Manas K. Mandal · Avinash Awasthi
Editors

Understanding Facial Expressions in Communication

Cross-cultural and Multidisciplinary Perspectives

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Foreword

Faces are special. As seen in ancient coins and television's talking heads, we implicitly take the face to be what we need to see. Your face tells me who you are. Identifying someone from their face is an essential skill developed very early in life. The face also tells me where you are looking, whether you are speaking or listening or eating or sniffing, whether you are attending to me or ignoring me or failed to notice me. To know what you are doing—your thoughts, perceptions, emotions, plans, and actions—your face is where I look first.

The scientific study of what the face conveys was pioneered by Charles Darwin. Ancient and medieval writers simply stated what must have seemed obvious to them about all that the face does. Some instructed actors and artists how to use the face to express what they wanted it to express. It might be Darwin's greatest contribution to the study of facial expression to challenge this approach. He aimed to overthrow certain traditional views of the face assumed by the anatomist Charles Bell. Self-evident commonsensical truths were questioned and replaced with scientific hypotheses. Darwin's original hypotheses may not have fared well, but making the face a topic for scientific research was a grand idea.

The evolutionary line of research that Darwin founded has advanced, as in work by Fridlund and Owren. The scientific study of the face has now been taken up not just by behavioral biologists, but by, among others, psychologists, anthropologists, neuroscientists, and computer scientists. New topics have emerged, such as asymmetry and microexpressions. Faces can conceal—or even deceive—as well as reveal. Questions once thought answered are being raised again. The traditional either-or thinking of nature-nurture is being replaced with interactionist accounts. Just in the last decade, much new and exciting work on the face has emerged.

This book edited by Avinash Awasthi and Manas K. Mandal brings together many of these recent and fascinating lines of inquiry, with state-of-the-art chapters by leading researchers. For established researchers and new students, in basic research and applied, these chapters challenge old assumptions and suggest new ideas. All of us have to read and study this book.

James A. Russell
Professor of Psychology
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Chapter 1
Facial Expressions of Emotions: *Research Perspectives*

Avinash Awasthi and Manas K. Mandal

Facial expressions of emotions have always drawn the attention of researchers, primarily because of its importance in understanding human behavior, in general, and emotions, in particular. Facial expressions are considered to be the most significant nonverbal language to communicate emotions since the beginning of human evolution. These expressions are not only relevant for communication of emotions among humans, but also to other species, as Darwin (1872/1998) explained that emotions have evolved from the animals.

The psychological theory of emotional expression perhaps began with Darwin's seminal work *The Expressions of Emotions in Man and Animals* (1872) based on his theory of evolution. Since then, facial expressions have been studied through multiple theoretical and empirical perspectives, from evolutionary theory to computational sciences. The present chapter aims to examine the existing theoretical and empirical approaches being utilized in the researches on facial expressions of emotions.

Two theoretical approaches have dominated the researches in this area: *evolutionary-biological approach* and *sociocultural approach.* While researchers have presented evidence in favor of each of these theoretical approaches, they have generally argued upon which single theoretical perspective is capable of conclusively explaining the multitude of findings in the research on facial expressions of emotion. Theoretical approaches have been developed based upon the observers' responses (as an outcome measure) to different facial expressions of emotions. The evolutionary-biological approach believes that emotions are biologically triggered, as proposed by Darwin. This approach was further supported by the numerous biological and neuroscientific findings. On the other hand, the sociocultural approach defines social construction as

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the basis of development of facial expressions of emotions. In this chapter, we will revisit some of the evidence that forms the basis of the evolutionary-biological perspective of emotion expression, which has led to the development of universality thesis. We will then revisit the studies that oppose the universality thesis and, instead, advocate for the culture-specific influences on expression and recognition of emotions. The chapter will also discuss the attempts made by interactionist perspective in order to resolve the theoretical debates while emphasizing the in-group advantage of facial expressions of emotions.

Applications of the theory are based upon resolving the theoretical underpinning in order to establish the concept into measurable constructs. Contradictory theoretical findings and unresolved debates about the facial expressions of emotions have been widely attempted to resolve the controversies related to its origin and measurement by transforming theoretical underpinning into measurement-based approaches. Yet it has led to more contradictions than solutions. Major measurement approaches may include *anatomical* and *computational* perspectives. The present chapter will highlight these perspectives where facial expressions have been treated as predictor measures. Anatomical perspective emphasizes that the anatomy of facial muscles is responsible for production of facial expressions of emotions. This further provides the basis for developing the computational modeling of face from automated recognition to make expressions of emotions possible among virtual characters, for example, animated characters and virtual *avatars* with facial expressions of emotion.

The sociocultural perspective of facial expressions of emotions considers the recognition tendency above chance-level accuracy in order to formulate the universality of facial expressions of emotions. Similarities of the facial expressions have been attributed to the innateness of the biological basis, whereas the differences have been considered to be a result of differences in the sociocultural factors. It is believed that since similar biological structures are shared by the individuals across cultures, localization of the specific behavior in the brain may also be universally similar. Facial expressions of emotions and experience of emotions have been undertaken as an automatically associated process except the lying and deceptive behaviors. Brain, behavior, and computational sciences may not be capable enough of understanding behavior, in general, and facial expressions, in particular, from a unidirectional perspective. Rather, these perspectives are complementary to each other; for example, observable changes in the facial expressions are the result of the activation in the neural architecture. Further, these muscular changes are being automatized through an anatomical measure (FACS; Ekman and Friesen 1978). So, in order to understand the incongruence between the observable behaviors and neural stimulations, a comprehensive and interdisciplinary approach would be more suitable. In the end, the present chapter proposes an integrative perspective of cultural–computational neuroscience to understand facial expressions of emotions.

Most of the researches on facial expressions have followed a unidimensional perspective. However, in the recent past, some attempts have been made to understand facial expressions through interdisciplinary perspectives. The ultimate aim of each perspective is to generate generalizability and objectivity of facial expressions of emotions, while acknowledging the differences. This chapter aims to present the major perspectives utilized to understand the basic issues of facial expressions of emotions.

1.1 Theoretical Approaches

1.1.1 Evolutionary-Biological Perspective: Universality of Facial Expressions of Emotions

The evolutionary-biological perspective of emotions has started from Darwin's (1872) evolutionary theory of emotions. It suggests that expressions of emotions help in regulating the social interaction and increase the likelihood of survival (see Westen 1996). Knapp (1963) later on noted that "emotional phenomena were among the evolving attributes of man which had developed like man himself from antecedents in his animal forebears" (p. 5). Since then, the unique patterns of neural and physiological activity that accompany different emotions have been a central subject of research in the study of human emotion. The evolutionary-biological perspective was further supported by Izard (1971, 1994) and Ekman (1984) who found that individuals across cultures display the same facial expressions when experiencing the same emotion, till the culture-specific display rules do not interfere. Ekman (1972) suggested that emotions are expressed in universally equal manner. He suggested that emotions are expressed through different combinations of facial muscles, which are governed by a subset of neural network. Ekman followed the universality thesis of Darwin and explained emotions as the result of facial affect program that may be modulated by cultural display rules. To study the nature–nurture debate of emotions, researches have been conducted on facial expressions of congenitally blind and people with eyesight. Dumas (1932) found that congenitally blind people express spontaneous expressions adequately, similar to people with a normal eyesight, but they are not able to express posed expressions adequately. Matsumoto and Willingham (2009) have compared the expressions of congenitally and non-congenitally blind athletes of Paralympic Games 2004 with normal athletes of 2004 Olympic Games and found no significant differences in the level of facial emotion configurations.

Empirical evidences for the universality thesis come mostly from a series of cross-cultural judgement studies conducted mostly by Ekman and others. Universality refers to accurate recognition of facial expressions across cultures at better-than-chance levels (Ekman et al. 1987). Ekman conducted a series of experimental studies and concluded that emotions are recognized cross-culturally in Western–Oriental populations (Ekman 1972; Ekman et al. 1969, 1987; Izard 1971), and literate and preliterate populations (Boucher and Carlson 1980; Ekman et al. 1969; Ekman and Friesen 1971). To eliminate the exposure and familiarity factor, Ekman et al. (1987) studied the isolated and preliterate South Fore and Dani people of New Guinea. The participants were given different situations (e.g., "pretend your son has died") and were asked to express themselves. Photographs of these expressions were then shown to the Western literate populations. High recognition accuracy was found across ten different cultures (Estonia, Germany, Greece, Hong Kong, Italy, Japan, Scotland, Sumatra, Turkey, and United States) for all emotions except sadness. In another study, literate participants from Hungary, Japan, Poland, Sumatra, United States, and Vietnam were shown photographs of facial expressions of emotions. A high degree of agreement was recorded in the recognition of facial expressions among the cultural groups (Biehl et al. 1997). Izard (1971) conducted a multination study among American, European, African, Indian, and Japanese observers for judgement of facial expressions of emotions, and over 78 % cross-cultural agreement was observed in terms of accuracy of recognition (for details of universality thesis, see chapter by Hwang and Matsumoto).

However, this universality theory has been criticized by the cross-cultural studies on facial expressions of emotions, which suggest that facial expressions are not universal, but differ across cultures (Russell 1994). Indeed, universality theorists (Ekman 1972; Izard 1971) emphasized the similarities of facial expressions and recognition across cultures, but ignored addressing the differences across cultures (Matsumoto and Assar 1992). The universality thesis has faced several criticisms, yet in its support, Shariff and Tracy (2011, p. 407) have suggested universality as "easily recognizable signals" of facial expressions of emotions even in "geographically and culturally isolated populations." Ekman (1982) further proposed a *neurocultural theory*, in order to address the universal cultural differences, which suggests that the expression of emotion via face is the outcome of an elicitor that generates the innate facial affect program. It is proposed by the universality theorists that elicitors may change from one culture to another (as a function of the social situation and prevalent norms), but the facial behavior in response to that situation conveys the same meaning in all cultures. Ekman, therefore, proposed a set of primary/basic expressions of emotions—happiness, sadness, fear, anger, surprise, and disgust—and the recognition of which he believed to be universal.

1.1.2 Sociocultural Perspective: Culture Specificity of Facial Expressions of Emotions

Although the relationship between emotion and neurobiological processes has been established beyond doubt, the social significance and origins of emotions cannot be overlooked. The claim of the universalists that facial expressions of emotions are expressed or understood pan-culturally has been challenged by the cultural psychologists or social constructivists. It is commonly believed that an individual's emotional response is often guided by the evaluation of their social situation. Oatley et al. (2006) posit that all emotions are social in nature because their evolution is a result of the need of individuals to deal with the complexities of human social life.

The basic assumption of the sociocultural approach is that emotions are the result of socialization process and are constructed primarily by the process of culture with aspects ranging from how emotions are elicited, shaped, and valued by cultural beliefs and practices. Individuals learn to express subjective feelings through the process of socialization, in the process individuals learn about self and others through different social and emotional communications (Markus and Kitayama 1991; Mesquita and Albert 2007). Evolutionary-biological perspective believes that emotions are innate in nature and are universal, whereas sociocultural approach explains that some elements of emotions may be universal. Findings in support of both approaches also reveal the existence of remarkable cultural differences in emotions, which are learned according to the culture-specific meanings of identity, morality, and social structure (Averill 1985; Mesquita 2003; Sweder and Haidt 2000). The sociocultural environment influences one's expressions of emotion in a systematic manner right from birth. Socialization differs from one culture to another since cultures differ in their characteristics and nature, and these differences further influence individual's expressions of emotion. Researchers believe that emotions are not the result of innate programs solely, but are the result of different types of cultural variations across its components (e.g., Frijda 1986; Mesquita and Frijda 1992; Scherer 1984). Kitayama and Markus (1994) suggested that emotions depend upon the cultural situations and cannot be separated from cultural influences. The individualistic and collectivistic characteristics of culture have also been studied as variables influencing facial expressions and recognition of emotion.

Mead (1975) described the importance of culture in emotions and explained that nature is not the only factor responsible for emotions. The cultural school of thought grew as a challenge to the "universal" (i.e., emotion is the basic function of human beings that is relatively invariant across cultures) or "differential" (i.e., emotions are differentiated on the basis of accompanying physiological response patterning) theories in the experience of emotion (Scherer and Wallbott 1994). Russell (1994) posited in favor of culture specificity in the recognition of facial emotion. His arguments were based on the facts that (a) recognition accuracy for facial emotions in all cultures is not equal and (b) there are cultural variations in semantic attribution to facial expressions of emotion. In a meta-analysis of emotion studies, Russell (1994) concluded that facial emotion recognition accuracy differs from one culture to another. Certain emotions, such as happiness and sadness, are recognized equally accurately across cultures. Emotions such as fear and anger are not recognized equally accurately across different cultures (Mandal et al. 1986; Russell 1994). Evidences from studies (see Biehl et al. 1997; Elfenbein and Ambady 2002; Mandal et al. 1996; Russell 1994; van Hemert et al. 2007) reveal that there is cross-cultural difference in facial expression recognition. Universal affect program of the facial expressions may be characterized by the differences across cultures, and as the contact between cultures increases, familiarity becomes high (Elfenbein and Ambady 2003b). Individuals are able to recognize familiar faces easily across large variations in image quality, though our ability to match unfamiliar faces is strikingly poor (Burton et al. 2005). Kitayama and Markus (1994) illustrated that emotions depend upon the dominant culture frame.

1.1.3 Interactionist Perspective: In-Group Advantage

This perspective suggests that facial expressions of emotions are the result of the interaction between biological and social/cultural factors. There are certain innate programs which are molded by social/cultural determinants. It seems clear that there are strong innate components for facial expressions as well as cultural rules which exert strong influence on facial expressions and recognitions. Young-Browne et al. (1977) experimented on 3-month-old infants on their ability to discriminate facial expressions and found significant differences between control and experimental groups. Infants were able to discriminate surprise expressions with happiness and sometimes with fear also. Fear and surprise expressions have been found to create more confusion in discrimination tasks. Developmental studies suggest that infants are able to express emotions in extreme ways and, as being developed in a social environment, they learn to modulate, minimize, and exaggerate expressions according to social demands. Infants follow the expressions of their caregiver and innate program of facial expressions, later modulated by cultural display rules.

Though many studies have been conducted to resolve the controversy of universality and culture specificity, yet little progress has been made toward arriving at a consensus. One of the major reasons behind this state of controversy is probably the reliance on a single set of photographs depicting facial expressions of different emotions. Such a set of photographs is usually shown to observers of different cultures, and the responses are examined to conclude in terms of culture specificity or universality. Relatively fewer studies have been conducted with sets of photographs displaying facial emotions within different cultures with the purpose of examining the universality hypothesis in a given culture. This perspective is important because the recognition accuracy for "in-group" (same ethnic group) and "out-group" (different ethnic groups) may be compared to isolate the elements of universality and culture specificity. It is, therefore, believed that facial emotions "are a combination of biologically innate, universal expressions and culturally learned rules for expression management" (Matsumoto et al. 1998; p. 148). Dailey et al. (2010) explored the in-group advantage reproduced by using computational model for Japanese and American cultural context.

Elfenbein and Ambady (2002) reported that emotions are universally recognized at better-than-chance accuracy; however, within cultures, there is an "in-group advantage," that is, accuracy of recognition becomes higher when the perceiver and expresser have the same cultural background. Individuals recognize facial expressions displayed by members of their own culture (in-group) more accurately than those displayed by members of other cultures (out-group) (Beaupre and Hess 2006; Elfenbein and Ambady 2002; Thibault et al. 2006). Individuals recognize more accurately and take less response time while judging emotional expressions of in-group members (Elfenbein and Ambady 2003b). The greater accuracy of facial emotion recognition for one's own culture is referred to as in-group advantage. In the meta-analysis, Elfenbein and Ambady (2002) revealed that in-group advantage exists in the recognition of facial expressions of emotions. (for details of in-group advantage, see the chapter by Elfenbein in this volume).

Elfenbein and Ambady (2003a) proposed a dialect theory in support of in-group advantage. According to the dialect theory, there is a universal pattern of emotion recognition better-than-chance level, but because of the cultural differences, the recognition of facial expressions varies across cultures. Similar to the variation in language accents across different cultures, facial expressions too are unique to a specific culture and result in slightly different signals of facial expressions. These dialects are the result of learning and are developed in the context of the attunement of expression between individuals within the culture (Leach 1972 in Niedenthal et al. 2006). According to this account, in-group advantage occurs because members of a given culture are used to perceiving a particular expression (dialect) of universal expressions of emotion and are therefore more accurate in recognition of in-group facial expressions.

"The individual who moves from one class to another or from one society to another is faced with the challenge of learning new 'dialects' of facial language to supplement his knowledge of the more universal grammar of emotions" (Tomkins and McCarter 1964, p. 127). Individuals recognize more accurately and take less response time while judging emotional expressions of in-group members (Elfenbein and Ambady 2003a). Children correctly recognize fear and happiness at lower intensity, but they recognize fear, anger, and disgust less accurately in familiar faces (Herba et al. 2008). Herba et al. (2008) found less accuracy in children of 4–15 years in recognizing familiar faces. Familiarity with the other culture facilitates the recognition of other-culture facial emotions (Beaupre and Hess 2006; Elfenbein and Ambady 2003b). Familiarity, as a construct, further needs to be studied in order to minimize the miscommunication of facial expressions of emotions. Ekman et al. (1969) studied the preliterate and isolated tribe from New Guinea to ascertain the minimum effect of cross-cultural exposure on facial emotion recognition. They observed significant differences between the isolated and Western population, yet happiness, anger, and sadness achieved 50 % of recognition accuracy, but the remaining 50 % for these emotions and other emotions may be attributed to the lack of exposure to the other-race facial emotions. Achieving recognition accuracy above chance level has always been considered as a parameter to determine universality, whereas recognition differences have been ignored in order to attain cross-cultural agreement.

Matsumoto (2005) opined that the use of different muscle contractions leads to the differences in facial expressions across cultures. He further stated that any face expressing the emotion in a way specific to a culture is more accurately recognized by the members of that culture. The use of "any" face might be important because "culture" has often been confounded with the race. Since members from different races have slightly different facial morphology, morphological differences in facial expressions have also been confounded with culture. Cultural norms and patterns create the difference in the level of recognition across cultures. An individual learns recognition through the culture.

1.1.4 Theoretical Approaches: Comments

Either the evolutionary-biological perspective or the sociocultural perspective cannot be the sole contributor in the development of facial expressions of emotions. Facial expressions evolve through the process of evolution (Darwin 1872), so they may be considered universal. According to social construction, social environment determines an individual's behavior. Since social norms are different across cultures, facial expressions of emotions also vary across cultures. The central theme of the universality thesis of Darwin was that certain physical movements in the face and body are evolved for adaptations that are biologically basic in their form and function. Facial expressions of emotions might be learned like other socially learned symbolic communication. So, social evolution and its influence on the recognizability of facial expressions of emotions may not be negated in order to establish the universality. "It is more likely that evolution produced a generative, multipurpose set of mechanisms that work together in each instance to produce a variety of emotional responses that are exquisitely tailored to each situation" (Barrett 2011, p. 403).

Although many issues pertaining to the facial channel of emotion communication are discussed (such as universality, dimensionality, context specificity, and individual difference), some areas of research remained little explored. One such area is "eliciting condition" for facial expression. Most researchers deal with simulated expressions for the convenience of and suitability to experimental purpose and utilized posed facial expressions of emotions. Spontaneous expressions, on the other hand, are difficult to achieve in experimental conditions. Because spontaneous expressions are not quite free from cultural display rules, experiments with these stimuli do not permit generalization. Some theorists even believe that "pure" uninhibited facial emotions are rarely expressed, and therefore, we seldom perceive these expressions (Russell 1994). On the other hand, simulated facial expressions lack the "felt" component of emotion to a great extent. Ekman (1992), however, noted that subjective feelings may be evoked by instructing the encoder to move facial musculature in a definite way.

1.2 Measurement-Based Approach

Face has always been considered as the key to understand emotions, so attempts have been made to measure facial expressions and to classify expressions into emotions. Measurement of facial expressions in order to minimize the variability of facial emotions through different expressions has been always a challenge among the researchers. Facial expressions are easy to observe and understand, but it is difficult to develop a measurement system for facial expressions of emotions, since facial expressions vary in terms of frequency, intensity, and durations of certain types of changes in facial expressions. Researches to understand emotions through facial expressions have primarily been based on the individual's ability to recognize static and dynamic stimuli of facial expressions, for example, pictures of facial expressions and videos of facial expressions. Measurement of expressions is primarily based upon the anatomical changes in facial muscles during different affective states. Anatomy-based facial expressions have further provided the basis to the computational sciences in order to develop the automated system for the recognition of facial expressions.

Considering facial expressions as a dependent measure, quantification and measurement of facial expressions of emotions have been a challenge for the empirical researches conducted on this subject. Research has been conducted to identify facial expressions of emotions through behavioral measures in order to develop constancy and model facial expressions of a particular emotion, for example, self-report, rating systems, judgmental, and video analysis, or by electrophysiological approaches, for example, electromyography (EMG), electroencephalogram (EEG), and galvanic skin response (SCR), or by anatomically based coding systems, for example, Facial Action Coding System (FACS; Ekman and Friesen 1978) and MAX (Izard 1979), and mathematical and computational coding of facial expressions. In the judgemental method, observer's judgement is considered as an independent and his facial behavior as a dependent measure. Based on the observers' judgement, facial behaviors are calibrated and inferences are drawn (Ekman 1982). In electrophysiological method, the movements of muscles during the actions in face are measured either by EMG recordings (Brown and Schwartz 1980; Philipp et al. 2012) or by EEG.

1.2.1 Anatomical Perspective

The perspective has been evolved in order to develop a model set of expressions of various emotions. Anatomical perspective believes that different combinations of facial muscles communicate specific category of emotions. Human facial musculature structure has been known to the researchers for a long time (Duchenne 1859/1990). Initial attempts were made by Sir Bell (Bell 1824; in Loudon 1982) in the field of medicine through "*Essays on the Anatomy of the Expression in Painting.*" The anatomical basis of facial expressions has been developed in order to develop objectivity in understanding the facial expressions of emotions. Anatomically based coding system outlines the specific production of expressions based on the differential combination of activation of facial muscles. Carl-Herman Hjortsjo (1969) proposed first measurement system based on the facial muscles associated with different expressions (in Niedenthal et al. 2006). Further, Ekman et al. (1971) developed an objective coding system Facial Affect Scoring Technique (FAST) to measure emotion categories (happiness, anger, etc.) than emotion dimensions (pleasantness, unpleasantness, etc.). FAST provides 77 descriptors in three parts of face, i.e., forehead, eyes, and lower face to observe six basic emotions. Observers compare facial expressions with the FAST atlas and attribute corresponding scores, which further indicates the emotions mostly expressed. Izard (1979) developed Maximally Descriptive Facial Movement Coding System (MAX) on the similar pattern based on the 27 descriptors and used it with infants. These systems categorize facial expressions into different emotions such as happiness and surprise, but these systems did not code the intensity and dynamicity of the expressions.

Ekman and Friesen (1978) further developed a purely anatomically based FACS that relies on minimal facial muscle actions. FACS not only provides the coding, but also focuses on the intensity and temporality of muscular activity. FACS coding is based upon the 44 facial action units that singularly and in combination contribute to different facial muscle movements. FACS is not restricted to the emotion-specific measurements, but it also measures all facial movements (Rosenberg 1997). This system outlines specific actions produced by particular facial muscles. The quality of these actions, however, likely varies with differences in the facial muscles. Different facial muscles produce different types of movements, and they are most likely heterogeneous in their structure and innervation.

1.2.2 Electrophysiological Support

Physiological measures such as EEG and EMG have been initially applied to explore the brain architecture responsible for understanding emotion. During the past few decades, the emergence of brain-imaging technologies has redefined the biological and neural basis of emotional behavior. Facial EMG involves measuring electrical potentials from facial muscles in order to infer muscular contraction. Most studies were conducted with facial electromyographic technique. These data indicated that different emotional reactions induce facial electromyographic activities of different sorts. For instance, electromyographic activity of the brow region increased with unpleasant thoughts. The emotional valence-specific facial muscle activity is documented by many (Cacioppo et al. 1986; Hu and Wan 2003; Jancke and Jancke 1990). The finding was replicated in a recent study with an additional observation that the cheek muscles of the lateral halves (right or left) covary during pleasant expressions (Jancke 1994). The study designed to examine "how rapidly emotion-specific facial muscle reactions are released" revealed that the electromyographic activity of zygomatic major muscle (muscle used for smiling) sets in within 500 ms of the exposure of the pleasant stimuli. Activity of the corrugator supercilii (muscles used for frowning) sets in within 500 ms of the exposure of the unpleasant stimuli. Reviewing a large body of research in this domain, Dimberg 1997 commented that "humans have a pre-programmed capacity to react to facial expressions and that facial reactions are automatically evoked and controlled by fast operating facial affect programs" (p. 59). Facial EMG has extensively been utilized in the recent researches (Philipp et al. 2012; Tan et al. 2012) because it is noninvasive yet sensitive enough to record subtle changes in facial muscles during facial expressions (Neta et al. 2009; Tassinary et al. 2007).

Further there are great individual differences in the physical characteristics, resulting in variation in electrophysiological activation. Methodologically, it is difficult to establish baseline data for every subject being tested. The reliability of measurement is also affected by the quality of emotion being experienced. Categories of emotion are differentially related to electrophysiological measures. Emotion categories reduced to dimensions (e.g., positive–negative) revealed a variable picture. For example, happiness (positive) and sadness (negative), despite having opposite emotion qualities, derive similar kinds of cardiovascular activities as measured by heart rate and blood pressure (Rusalova et al. 1975; Ekman et al. 1983). To avoid such difficulties, it is important to develop a profile of electrophysiological record for each primary emotion. For instance, fear-provoking stimulus is accompanied by accelerated heart rate (Fredrikson 1981), increased electrodermal reactivity (Ohman and Soares 1994), vasoconstriction in the upper face (Hare 1973), and characteristics of facial reactions (Dimberg 1990; cited in Dimberg et al. 1998). Observable behavioral characteristics during emotional states are even more variable than reliable. Nonverbal expressions, especially facial behaviors, are modulated to a great deal by culture-specific display norms. Other forms of expressive behaviors also depend considerably on an individual's strategy to respond to a social situation.

1.3 Computational Perspective

Advances have recently been made in mathematical and computational coding of facial behavior. The computational modeling and automatic facial expression recognition have been the interest of the researchers since last two decades. There have been several advances in terms of face and facial feature detection mechanism, but developing the perfect system still has been the challenge among the computational researchers. The automatic facial expression recognition system requires robust face detection and facial feature tracking systems. In an earlier attempt, Thornton and Pilowsky (1982) tried to quantify facial expression mathematically. In this method, 60 key points on the face that may produce visible emotion behavior were identified with the help of a computer graphic procedure. These key points were joined with smooth curves to obtain a graphic model of facial expression. Pilowsky and Katsikitis (1994) attempted to calibrate facial behavior with numerical taxonomy program. Artificial neural network rules [such as, adaptive resonance theory 2 (ART-2); learning vector quantization (LVQ)] were also applied to reliably discriminate facial emotions (Driscoll et al. 1995). Some investigators used cascade correlation neural network and achieved 87.5 % success rate in the discrimination of six facial emotions: happiness, sadness, fear, anger, surprise, and disgust (Zhao et al. 1995).

The problem of Automatic Facial Expression Analysis is broadly divided into three stages, though some other steps may need to be performed in between these three stages depending upon the approach taken (Gunn and Nixon 1994). The three stages are as follows:

1. Face acquisition
2. Feature extraction
3. Classification

In the first stage, a face is detected in the given image. Once the face has been detected, features, which contain the information required for facial expression analysis, are extracted from the facial image in a feature vector, and, finally, the extracted feature vector is passed through classifier for classification/recognition. The classifier might be a two-class or a multiclass classifier.

An important functionality of these interfaces will be the capacity to perceive and understand the user's cognitive appraisals, action tendencies, and social intentions that are usually associated with emotional experience. Because facial behavior is believed to be an important source of such emotional and interpersonal information, automatic analysis of facial expressions is crucial to human–computer interaction. Face can depict numerous expressions at a given time, but each expression may not be an indicator of the emotional state of the individual. Separating emotions from other facial expressions is a challenge while developing an automated facial expression recognition system.

Facial expressions are the results of different combinations of facial musculature and depend upon the craniofacial characteristics of the individual. There are some permanent dispositions reflected on an individual's face—isolating the permanent characteristics of the individual face with the model face and increasing accuracy regardless of individual differences is another challenge. Culture-specific display and decoding rules play a major role in facial expressions and recognition of facial emotions. Embedding display and decoding rules in the automated system is another challenge in order to develop a universal automated facial expression of emotion recognition system. Recently, Dailey and colleagues (2010) have made an effort to develop a neurocomputational model trained in specific cultural context, i.e., Japanese and American in order to study in-group advantage. They attempted to model culture-specific display rules, the effect of encoder–decoder distance, and the effect of culture-specific decoding rules. They concluded that the encoder–decoder distance, culture-specific display, and decoding rules and other factors contribute in an integrated manner to create the differences in facial expressions across cultures.

To develop an interface between anatomical and mathematical models of facial measurement, more researches are necessary with experimental and clinical data for generalization and psycho-diagnosis in terms of emotional behavior. The major challenge for the computational sciences is to develop the system for spontaneous expressions. Developing the authentic database for spontaneous expressions is another challenge as the laboratory setting itself made the subjects pose their expressions. Emotions are not a sudden emerging state, but expressions emerge suddenly on the face, so capturing the real expressions associated with the subject's internal state is another challenge. Minimizing the individual and cultural differences in developing the model emotion expressions may further be a challenge among the researchers.

1.4 Conclusion

"Face" is a multidisciplinary subject matter, and it demands understanding from various perspectives both at macro- (such as social and cultural) and at micro (such as neuroscientific and computational)-levels, and understanding the facial expressions of emotions is one of the greatest challenges facing the twenty-first-century psychological, behavioral, and computational sciences. If we can rise to the challenge, we can gain fundamental insights into what it means to understand human behavior, in general, and emotions, in particular. In order to understand the complete gamut of facial expressions of emotions, an integrative and interdisciplinary approach is needed, which includes the three basic approaches based on social, biological, and computational sciences. Most of the researches in this area have been conducted independently with a unidimensional perspective, whereas researches need to be conducted with a complimentary approach. These approaches do not need to be considered in isolation, but should be treated complimentary to each other. The understanding will help researchers uncover the role of facial emotions in day-to-day interactions.

Emotions are a gradual stimulation process in human beings, and it becomes a challenge to decipher them among the localization, regionalization, and lateralization processes of facial expression processing. The neural circuit helps us understand the development of emotional processes among human beings and other species. Accurate assessment of facial expressions of emotions will further help develop new diagnostic tools, such as an automated behavioral assessment system based on the facial expressions of emotions. The major obstacle that hinders our understanding of the brain architecture behind facial expressions of emotion is the fragmentation of brain research and the enormous data it produces. Modern neuroscience has been enormously productive but unsystematic. It further needs revalidation through sociocultural and behavioral approaches. A recent field of cultural neuroscience (Chiao and Ambady 2007) studies the bidirectional relationship between cultural influences on neural architecture of brain and vice versa. Cultural neuroscience tries to bridge the gap between theory and the methods of psychology and genetics. Cross-cultural differences in neural architecture will further enable computational sciences to develop neural network for machines based on the foundations provided by the cultural neuroscientific findings.

Attempts have been made to automate facial expressions of emotions in order to utilize the systemic interface between technology and society. FACS has been used primarily by the researchers in the area of computational sciences to develop such systems, though developing a zero-error system is still a challenge. Based on the studies, six basic emotions, which are universal in nature, have already been tested in automation of facial expressions of emotions. Other existing concepts, such as in-group advantage, self-conscious emotions, and culture-specific emotions, need to be taken care of while transforming behavioral cues within the technological advancement. Transforming cultural differences into computational models has been an emerging issue among computational researches. Computational models may help researchers in validation of sociocultural and neurological models with state-of-the-art technologies.

Automated system for detecting deception and lying may be developed by involving the neural basis of deception with the help of computational sciences. Such system may further be utilized by an interviewer during an interview or interrogation. Studies of micro-momentary expressions have been of interest to the researchers in the recent past due to its relevance in deciphering deception and lying (for details, see chapter by Mark Frank and Elena Svetieva in this volume). Micro-expressions occur when an individual consciously tries to conceal the signs of true feelings (Ekman 2003; Freitas-Magalhães 2012). Recent research findings (Abe et al. 2007; Johnson et al. 2008; Yokota et al. 2013) have identified biological and neural structures involved in deception. Further attempts can be made to decipher deception through an integrative approach, by involving cultural, computational, and neuroscientific perspectives. Similar attempts can also be made to perform preliminary assessment of chronically ill psychotic patients in day-care center or at out-patient department of hospital through automated computational models (see chapter by Poria, Mondal and Mukhopadhyay in this volume).

All of the three approaches need to look into some basic issues for future research: For example, it would be interesting to find (a) the dominance of context, content of interaction, and intent of judges while perceiving facial expressions of emotions, (b) emotion-specific laterality and its effect on brain–behavior relationship (an integrative approach through behavioral and biological sciences may help us understand), (c) cultural differences in hemispheric dominance in triggering the expression of an emotion (biological and sociocultural sciences can help us understand), and (d) developing an automated behavioral diagnosis system (behavioral and computational sciences can help us understand). While micro-level perspectives, such as biological or computational, will help uncover the bases of facial emotions, macro-level perspective, such as sociocultural, will add meaning to it. Thus, an integrative perspective of cultural and computational neuroscience will help provide a comprehensive understanding of facial expressions of emotion.

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Chapter 2
Recognition of Facial Expressions: Past, Present, and Future Challenges

José-Miguel Fernández-Dols and Carlos Crivelli

This chapter focuses on the recognition of basic emotions through facial expression, challenging some of the commonsense assumptions related to this research paradigm. In the first section, we review the concepts that constitute this field: "emotion", "recognition", "facial expression", and "universality". In the second section, we discuss the data and methodological challenges from the most crucial test of the universal recognition of facial expressions: field experiments in remote cultures.

Our take-home message is clear: there are still a large number of conceptual and empirical issues that must be solved before arriving at any definitive conclusion on what "recognition of emotion" means. Each concept (i.e., "emotion", "recognition", "facial expression", and "universality") is plagued with unfounded assumptions and inconclusive evidence. Furthermore, the ultimate test for a more sophisticated version of "universal recognition" (studies in remote cultures) needs more careful attention and a prominent position in researchers' agendas.

2.1 What Do Psychologists Mean by "Recognition of Universal Facial Expressions of Emotion"?

2.1.1 Emotion

The concept of emotion is an elusive one. By using the term "emotion", we may be covering at least six different meanings (Fig. 2.1):

1. The subjective experience of emotion.
2. The observable emotional behavior (including facial behavior).

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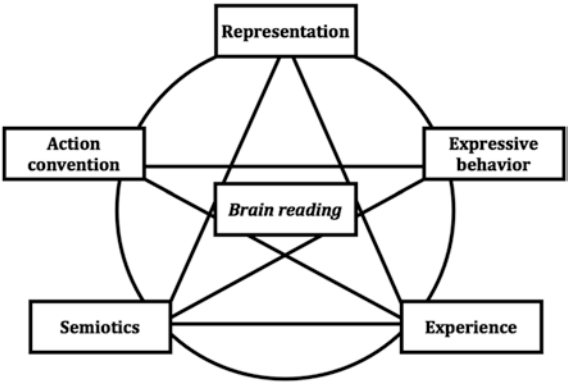

Fig. 2.1 Multiple referents of "emotion". Nodes and links are self-contained referents and constitute different, albeit related, research problems

3. The cognitive representation of emotional experience.
4. The semiotic resources of a particular culture when it deals with emotion.
5. The social rules that prescribe some conventional emotions.
6. The neural mechanisms and brain systems underlying these processes.

For example, for "happiness", we may refer to (a) a phenomenological identifiable inner experience, (b) to happy people's observed facial behavior, (c) to the constitutive features of the concept "happy" in English, (d) to the repertoire of signs (in Peirce's sense, icons, indexes and symbols[1]) that signify *happiness* in English—as compared to other languages, (e) to the conventional forms of "happiness" in social events (see Fernández-Dols et al. 2007), and finally, (f) to inferences about the related activity of some brain systems (i.e., the dopamine pathway to the *nucleus accumbens*).

All of these phenomena, as well as the logical and empirical relationships among them, are autonomous—although not independent—research goals. If something has to be learned from the study of emotions is that there is no simple, straightforward causal link between any of Fig. 2.1's nodes. For example, there is no automatic, two-way relationship between emotional experience and cognitive representation. Bilinguals tend to switch languages depending on the emotion they want to communicate (Fields 2012). Additionally, there is no simple relationship between cognitive representation and emotional experience, making bilinguals to experience higher levels of emotionality when talking their first language (Caldwell-Harris and Ayçiçegi-Dinn 2009).

In Fig. 2.1, each potential connection between two or more nodes is actually a complex and fascinating research goal and we are still far away from providing convincing responses to most of them. Indeed, the apparently obvious and simple link between "primitive" emotional experiences and their corresponding basic primitive brain systems is, most likely, mediated by other complex structures (Lindquist et al. 2012).

[1] We use "sign" following Peirce's typology of signs: icons, indices, and symbols. Icons share some quality with its object (e.g., physical resemblance of a picture of fire with its object, actual fire). Indices' relation to their objects is a factual correspondence (e.g., smoke as an index of fire). Finally, symbols keep an arbitrary correspondence with their objects (e.g., the words "fuego", "fire", "kova", etc.).

The emotion of disgust is illustrative of the complexities that researchers will face when studying the links of Fig. 2.1 nodes. Widen and Russell (2013) questioned the apparent monolithic, biological "basicness" of emotions, such as disgust. For example, disgust is absent in nonhuman primates, and it could be based on a functional response (i.e., distaste) that lacks emotional meaning (Rozin et al. 2000). Thus, if the emotion of disgust is a cultural evolution of a nonemotional behavior—the distaste response, it makes the disgust expression a cultural demonstration of a highly abstract and ideational emotion. Consequently, disgust would not be a constituent of a mere basic affect program (Ekman 2003), but the result of a complex process related to a Western cultural development that has adopted the expression of distaste (a nonemotional facial reaction like the startle reaction) as an expression of moral rejection. Therefore, there may be different kinds of disgust faces linked to nonemotional and emotional elicitors (Rozin et al. 1994).

The research on the development of emotion concepts and expression recognition supports Rozin et al.'s (1994) claims. For example, children up to 7 years tend to associate the prototypical "disgust face" (AU 9, and AU 10, see Ekman and Friesen 1978) with anger (Widen and Russell 2008, 2010). Additionally, the so-called sick face (AU 6, AU 7, AU 10, and AU 26, see Ekman and Friesen 1978) seems to be a better prototype for disgust than the "disgust face" (Widen et al. 2013).

In our view, recognition studies' primary location within Fig. 2.1 should be represented by the link connecting signs of emotion with the cognitive representation of emotions (i.e., participants' concepts of emotion). A basic, preliminary problem for interpreting recognition studies' findings is that researchers usually do not acknowledge this link. Recognition studies are typically characterized as testing the link between actual facial expression and the experience of emotion.

2.1.2 Recognition

The most influential sources of inspiration for contemporary studies on recognition (Basic Emotion Theory, BET, see Ekman 1982; Ekman and Oster 1979) assume that "recognition" means detecting a message with adaptive value for senders (and potentially for receivers). Thus, for BET, the sender's expression launches some sort of essential and immediate connection between the sender's and the receiver's emotional experience. Tomkins (1982), the main inspirer of this approach, considered emotion and expression as a unitary phenomenon. In the same vein, Ekman (1997, p. 334) pointed out that:

> The initial translation of an expression into some meaning (…) is likely to be so immediate that we are not aware of the process we go through (…) I think we use emotion words—anger, fear, disgust, sadness, etc.—as a shorthand, an abbreviated way to refer to the various events and processes which comprise the phenomenon of emotion.

Recognition studies are based on two incompatible hypotheses (see Fernández-Dols 2013). On the one hand, recognition studies are aimed at showing that some facial expressions are, for evolutionary reasons, universal adaptations shared with other primates since at least six million years ago. On the other hand, recognition studies assume that these primitive facial expressions have specific meanings (i.e., a precise correspondence with some concepts of emotion and the words that refer to these concepts).

By supporting the above-mentioned assumptions (i.e., recognition has preverbal and evolutionary roots allowing us to apply specific verbal referents to expressions) we would be falling into a theoretical hindsight bias. We would be assuming that, six million years ago, hominids with preverbal brains were already capable of segmenting their facial behavior into a precise set of fixed facial expressions, foretelling—several million years later—*Homo sapiens*' categories of emotion such as contempt (Ekman and Friesen 1988; Izard and Hayes 1988) or shame (Tracy and Matsumoto 2008).

We propose two ways for overcoming such hindsight bias and its corresponding illogical conclusions:

1. A first possibility would be to assume that facial expressions are remains of our primate ancestors' tools for animal communication. As a consequence, facial expressions, as any other kind of animal communication resources, are just instances of social influence with no precise, stable, and univocal meaning (Dawkins and Krebs 1978). Following a classic principle in animal ethology, the "recognition" of emotions (i.e., attribution of meaning to facial expressions) only makes sense when the signal is perceived within a specific context. Thus, this position may be summarized in Smith's equation for animal communication: message + context = meaning (Smith 1965, 1977).
2. A second possibility would be to assume that hominids' facial behavior underwent a process of coevolution with language, connecting the two phenomena—facial behavior and language. In such a case, facial expressions do not necessarily keep any homology with other primates' facial behavior. Accordingly, the recognition of facial expressions may be characterized by the cognitive processes involved in language and conceptualization (Lindquist and Gendron 2013; Lindquist et al. 2014).

Currently, most researchers have moved away from views of recognition as an automatic emotion detection process. Thus, "recognition" is regarded as a more complex inferential process with direct or indirect links to emotion (for contemporary accounts of the traditional view, see Matsumoto et al. 2013). BET advocates like Rosenberg and Ekman (1994) acknowledged "the problem of symbolic representation". Likewise, Haidt and Keltner (1999) found, in an intriguing study with American and Indian subjects, that recognition was affected by the experimental procedure (based on words or situations), the subjects' cultural or educational background, and some unknown features of expressions themselves. For these authors, expressions are best viewed as falling along a gradient of recognition, rather than as being members of a set with clear boundaries (Haidt and Keltner 1999, p. 263).

Additionally, researchers from other theoretical perspectives have provided a shift in the field when proposing new alternative accounts to the *readout view*. For example, Frijda and Tcherkassof (1997) have explored facial behaviors as expressions of action readiness indirectly linked to emotional states. Likewise, Russell

(1997, 2003) has approached facial expressions as manifestations of affect along two dimensions: pleasure and arousal.

Another group of researchers have discussed the effects of in-group advantages on emotion recognition, proposing a theory of "emotion dialects" (Elfenbein 2013; Elfenbein and Ambady 2002b; cf. Matsumoto 2002). In a meta-analysis of published and unpublished literature on emotion recognition, Elfenbein and Ambady (2002a) found that, beyond a certain consensus on the affective content of expressions of emotion, emotional meaning loses part of their connotations across cultures. These authors—relying on a robust phenomenon for those receivers who shared their cultural beliefs about emotion with the posers—suggest that research on emotional expression should take into account the "emotional dialects" in which each culture express some universal affective phenomena.

Researchers relying on mainstream recognition studies of facial expressions of *emotion* work neither with spontaneous and natural expressions nor with concepts of emotion taken from non-Western cultures. Actually, studies on the recognition of spontaneous expressions (Fernández-Dols and Ruiz-Belda 1997; Matsumoto 2006) are scarce and inconclusive—specifically if we do not consider the "spontaneous" facial expressions produced as experimental demands in laboratory settings. Likewise, recognition studies in remote cultures raise serious doubts on the apparently universal recognition of emotions through facial expression (Ekman 1972; Ekman et al. 1969; Nelson and Russell 2013; Sorenson 1975, 1976; cf. Ekman and Friesen 1971).

All in all, the conclusion that can be drawn is that recognition studies are not about actual expressions and emotional experience. Current research on the correspondence between the actual experience of emotion and the predicted standard facial expressions confirms that such correspondence is weak or nonexistent (Fernández-Dols and Crivelli 2013; Reisenzein et al. 2013).

In our view, recognition studies should consider three questions: (a) which facial behaviors should be considered as expressions, (b) how big is the magnitude of agreements, and (c) to what extent this consensus is universal. As the previous discussion suggests, researchers have not provided definitive answers to the first question, making the other two questions less decisive and important for understanding the relationship between facial behavior and emotion. Consequently, universal agreement on verbal categorization of a particular preselected face says little about its role in the experience of emotion. In this case, universal agreement means that people make similar attributions, but not that people are accurate intuitive scientists, capable of discerning which are the clearest manifestations of emotion. Psychological wisdom about people as intuitive scientists is rather pessimistic on their accuracy.

Additionally, the magnitude of this agreement and its universality has elicited a hot debate (Russell 1994, 1995; Ekman 1994, 1999; Izard 1994) and a series of methodologically oriented studies to support BET (Rosenberg and Ekman 1994; Haidt and Keltner 1999; Frank and Stennett 2001). Russell (1994) pointed out that there are no conclusive data of free-of-culture studies on verbal recognition of emotion. Verbal categorization is subject to potential methodological problems such as the use of within-subjects designs (Yik et al. 2013), the response formats (e.g., forced choice formats), or the lack of contextual information in most of the studies.

None of these problems could be decisive for questioning the internal validity of these studies, but, all together, they put their internal validity in jeopardy.

Beyond the methodological debate raised by Russell (1994, 1995; cf. Ekman 1994, 1999), empirical studies have provided new arguments for a serious reconsideration of the research on recognition of expressions. Nelson and Russell (2013) suggest that the recognition scores in standard experimental studies do not support the allegedly strength of BET claims. Agreement rates' percentages on the emotion displayed by an expression vary depending on the emotion displayed, the order of presentation, and participants' culture and language. In Nelson and Russell's review, percentages of recognition are far from consistent. Agreement rates range from 45 to 100 % for "happiness", from 43 to 94 % for "surprise", from 29 to 97 % for "sad", from 33 to 92 % for "anger", from 16 to 92 % for "fear", and from 20 to 94 % for "disgust". Figure 2.2 (adapted from Nelson and Russell 2013) represents the average recognition scores for six categories of emotion across Western literate, non-Western literate, as well as preliterate and remote cultures.

As a concluding remark, the results of a number of studies on the categorical perception of facial expressions have been used by BET advocates to claim the existence of discrete boundaries between facial expressions of *emotion* (Calder et al. 1996; Etcoff and Magee 1992). These studies included tasks in which emotion conceptualization was apparently unnecessary (for example, by asking participants to press a button if a trial face matched one of two faces; see Calder et al. 1996). Unfortunately, these studies basically dealt with the way in which our brains detect patterns on facial stimuli, but they did not test the emotional meaning of such stimuli. Currently, a growing amount of evidence suggests that these tasks require a significant amount of conceptual processing (Fugate 2013). This new evidence supports our previous remarks on how recognition is necessarily connected to language due to the coevolution of language and facial expression (Fernández-Dols 2013; Lindquist and Gendron 2013).

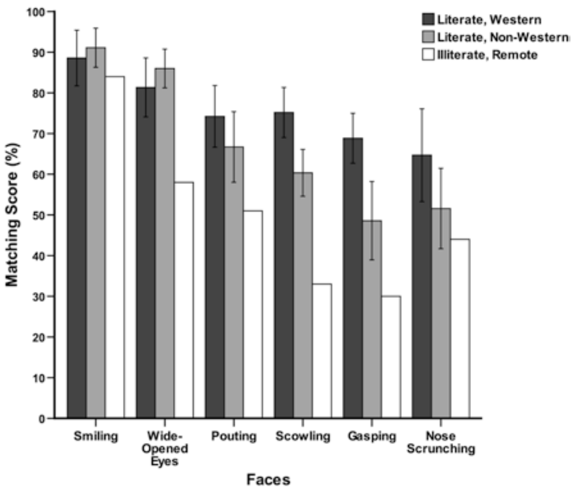

Fig. 2.2 Matching scores are the percentage of observers who selected the predicted label from studies published between 1992 and 2010 for six facial expressions. Error bars represent 95 % CIs. Data source: Nelson and Russell (2013)

2.1.3 Expression

The list of emotions that elicit spontaneous facial expressions is mostly linked to the historical trajectory of commonsensical and lay theories about emotion (Russell 2009). The most innovative contribution of Tomkins (1982) and his followers to contemporary psychology was not the prediction that some facial expressions were related to emotions—what was already a commonsensical assumption, but the creation of a contemporary repertoire of universal expressions of emotion (i.e., the assumption that human beings have a limited repertoire of basic and fundamental emotions that can be read out from faces). In the early 1970s, this restricted view of facial expressions as readouts of basic emotion was a powerful incentive for empirical research, making these studies less difficult to conduct (Davis 2001). The unquestioned existence of a closed list of universal emotions led psychologists to take for granted that the translations of emotion terms used as recognition criteria were always possible across cultures as far as they were restricted to those emotions within the "basic" set.

The mainstream approach to the verbal recognition of facial expressions has pivoted on a set of posed facial expressions selected accordingly to an a priori criterion (Ekman 1994, p. 276). Even though Ekman claims that this a priori criterion has been dictated by theoretical and methodological reasons, a careful reading of BET's first theoretical papers shows that the original references for this selection were Darwin's intuitions (1972/1965), and the later reinterpretations of Darwin made by Allport (1924) and Tomkins (1982). These authors based their intuitions on Western modern commonsense beliefs about facial expressions. Hence, the selection and refinement of the expressions of basic emotion was grounded on judgment studies in which facial expressions were filtered and shaped up to reach high agreement rates in the attribution of emotion. Accordingly, the expressions of basic emotion were stimuli designed a priori to elicit high levels of consensus in verbal attributions. They were not designed as precise descriptions of people's average facial behavior during intense emotional situations. Unfortunately, as the studies on spontaneous expressions have revealed, the role of the facial expressions of basic emotion as descriptors of such spontaneous behaviors is rather dubious (Fernández-Dols and Crivelli 2013).

The idea of a closed set of universal expressions of *emotions* is founded on a philosophical and esthetic tradition that can be traced back to the 17th century. A French painter—Charles Le Brun—proposed a set of rules (backed on drawings) for describing (and pictorially representing) the expression of passions through the face. Le Brun provided descriptions for wonder, esteem, veneration, rapture, scorn, horror, terror, love, desire, hope, fear, jealousy, hatred, sorrow, pain, joy, laughter, weeping, anger, despair, and rage. Le Brun's method did not consist of empirically observing facial behavior, but of deducting the expressions by reasoning from a few physiological principles mostly taken from Descartes' philosophical theories on passions (Montagu 1994). In the 19th century, Bell and Darwin's discussions on the number and appearance of facial expressions were still founded on philosophical and esthetic traditions such as Le Brun's. Bell and

Darwin's lists were strikingly heterogeneous, given the supposed basicness of such repertoires. They included expressions of hunger, determination, love, devotion (Darwin 1872/1965), remorse, revenge, and madness (Bell 1924). As an example of Darwin's *Zeitgeist*, physician and anthropologist Paolo Mantegazza (1883) was determined to find, among others, the facial expressions that were indexes of benevolence, religious feelings, or vanity.

Contemporary researchers providing sets of facial expressions of *emotion* also adopted such deductive and speculative approach, carrying out a disturbing and often unexplained variability in their suggested lists (see Ortony and Turner 1990). For example, Tomkins and McCarter's (1964) pioneering study on the recognition of emotion through facial expressions included eight primary affects (interest, enjoyment, surprise, distress, fear, shame, contempt, and anger) with two different levels of intensity. In Tomkins and McCarter's set, sadness was not even mentioned, and disgust was mentioned as intense contempt. The first validation of the Facial Affect Scoring Technique (FAST, Ekman et al. 1971), an observational method for describing facial behavior, included only six emotion categories (i.e., happiness, sadness, surprise, anger, disgust, and fear).

The continuity in the choice of a restricted set of exaggerated expressions, from Le Brun through Darwin to Tomkins, raises the question of whether this research tradition captures something other than emotional behavior—perhaps just human miming. For example, uniform verbal attributions of emotion to an expression might be part of an emotional program, a cultural script, or even a particularly fortunate way of providing human ideograms (in the same way that film editing has turned to be an artificial but easily understood way of representing action and movement in films).

In this line, Wierzbicka (2000) proposed that researchers should distinguish the "semantics of human faces" from the "psychology of human faces", developing research on the semantic properties of human faces as a natural language capable of providing primitive messages. These messages should be decoded in terms of a larger and more complex code, rather than be decoded in terms of basic emotions. The code may include a larger number of affective and non-affective messages modulated by the context of the utterance.

A decisive empirical test of these assumptions consists in testing the recognition of actual expressions of emotion without of all the requirements arbitrarily imposed by the a priori typologies of prototypical expressions. Aviezer et al. (2012) conducted an experiment with isolated real positive and negative intense expressions of emotion during sport events. They found that expressions, isolated from their respective contexts, were "non-diagnostic", only increasing their attributed meaning as a function of the context (see also Hassin et al. 2013).

2.1.4 Universality

The concept of a universal expression is generally used as a synonym of "true" signal of emotion, opposing it to "false" and learned displays that people produce for social convenience (e.g., following display rules). For decades, researchers have considered that social displays are voluntary, whereas "true" expressions are universal and involuntary readouts of innate basic emotion programs (Matsumoto et al. 2008).

The concept of true universal expression also implies a number of important methodological prescriptions. Buck's (1982, pp. 32–33) summary of such prescriptions includes three points: (a) "the subject must be made to experience a real emotion", (b) "[the subject] must be observed as unobtrusively as possible", and (c) "it is preferable that the subjects not to be in a social situation and that if they are in a social situation they should not be engaged in conversation". Since the late 1970s and early 1980s, the concept of "expression" has kept this prescriptive asocial feature, becoming increasingly more accentuated as time went by. True universal expressions have been characterized not just as private and involuntary, but as impossible to feign, visible only within a short temporal window (four seconds), and—through supposed microexpressions—impossible to conceal (Ekman 2001, 2003).

One of the obvious methodological consequences of these prevalent views was that laboratory studies were considered the only legitimate way for studying universal facial expressions of *emotion*. The more artificial the experimental setting, the truer the elicited expression. However, the search for true expressions following such premises has been inconclusive. Reviews on available experimental evidence (Fernández-Dols and Ruiz-Belda 1997; Reisenzein et al. 2013) conclude that there is no support for the popular assumption of a consistent causal link between the experience of a basic emotion and its predicted prototypical facial expression. According to Reisenzein et al. (2013), the only feeling that seems to elicit a consistent expressive pattern—a non-Duchenne smile—is amusement. However, amusement is not a clear example of a positive basic emotion and it cannot be equated with happiness or enjoyment.

This uncertain state of affairs probably cannot be solved if researchers insist on looking for universal expressions exclusively in the laboratory. Even if prototypical expressions existed, researchers would be looking for such expressions at the wrong place. Besides the sometimes insurmountable methodological problems posed by laboratory studies (e.g., the practical and ethical impossibility to elicit intense emotions), the concept of universal expression is basically flawed from a conceptual point of view.

The definition of universal expression as an asocial readout that can be elicited by extremely artificial stimuli is probably throwing the baby out with the bath water. Such approach ignores some basic warnings about universal psychological processes. In a thorough review on the concept of universality, Norenzayan and Heine (2005, p. 772) pointed out that psychologists "rarely encounter psychological processes at the more abstract, universal level directly". Indeed, as Norenzayan and Heine (2005, p. 771) suggested, "naturally selected psychological processes do not preclude the possibility that such adaptations are expressed in different forms", because they are contingent on ecological variations. This observation implies that "universal" is a nearly empty concept without a test of cross-situational functional and causal robustness.

If we extrapolate Norezayan and Heine's (2005) analyses on cognitive processes to the study of facial expressions of basic emotion, BET assumptions revealed theoretically ungrounded. The weakest version of universal expressions' claim—*existential universality*—states merely that all human beings can display some facial movements. A more demanding claim would characterize universal facial expressions as *functional universals* (does the same tool have the same use? Is a specific facial expression always aimed at transmitting sender's specific emotional state?), and a*ccessibility universals* (how big are the effect sizes of the relationships between prototypical expressions and basic emotions independently of content and context?).

The approach to expression as an asocial readout produced by a limited set of artificial stimuli excludes any feasible test of *functional* and *accessibility universals*. Even if studies on prototypical facial expressions would be able to find a consistent pattern of expression in laboratory settings—what clearly is not the case (Reisenzein et al. 2013)—such findings would just confirm the existence of such coherence for responses elicited in very artificial contexts. In other words, researchers conducting studies in laboratory settings could find occasions in which the emotion and its hypothesized facial expression co-occur, but such findings would not test whether emotion causes the facial expression or how often the two co-occur in nature. Such tests require very stringent checks of emotion-expression covariation across a wide range of natural situations.

Unfortunately, the concept of universal "true" expressions is misleadingly commonsensical. The distinction between true, genuine, involuntary universal expressions and false, voluntary, culturally variable displays has become a truism in the study of facial behavior (Ekman et al. 1980; Niedenthal et al. 2010). Nevertheless, its fatal flaws become evident when one tries to put current empirical findings on "true-involuntary" versus "false-voluntary" expressions into a coherent whole (Fernández-Dols and Carrera 2010).

We can exemplify the above-mentioned problem with two illustrations on the psychological relevance of "spontaneous false" facial expressions. Chong et al. (2003) found that Chinese-speaking and English-speaking mothers, when interacting with their 4- to 7-month-old babies, displayed three types of "spontaneous false" facial expressions (two displays were mocked facial expressions of basic emotion). The first display—which the authors called OOCHIEE—consisted of puckered lips and an open mouth (a *caricature* of a kiss that may mean love, concern, and emotional availability). The second display—called WOW—may be a mocked expression of surprise conveying pride and amazement. The third display, an *exaggerated* version of the prototypical expression of happiness—called JOY—may convey a message of playful love. These "spontaneous false" prototypical expressions are probably a key tool in the early emotional communication between infants and their caregivers, but cannot fit into the dichotomy between spontaneous versus posed expressions. The two mocked and exaggerated expressions of surprise and happiness are, paradoxically, the mothers' most intense "true" or "spontaneous" displays.

A second example of the apparently paradoxical combination of true but voluntary displays is Vazire et al. (2009) study. Men and women were simply asked to pose for a photograph. Vazire et al.'s (2009) goal was to capture "spontaneous posed" expressions due to its psychological relevance as spontaneous displays. Actually, the authors found a higher prevalence of "spontaneous posed" smiles in women (76 % female, 41 % male). Furthermore, "spontaneous posed" smiling was positively correlated with positive affect in women, but with negative affect in men. Again, these findings about an apparent oxymoron—"spontaneous posed" expressions—are extremely informative about the patterns of emotional expressivity and the evolution of emotional expression in men and women.

"False social displays versus true universal expressions" or "spontaneous universal expressions versus voluntary social displays" are not feasible scientific distinctions, and empirical tests of the covariance between facial expressions and the experience of basic emotions need a less simplistic conceptual framework. New approaches to recognition and universality should not take for granted the same assumptions that were usually accepted by most of psychology textbooks during the last twenty years (Matsumoto 2001; Matsumoto and Juang 2008; Myers 2011).

An important source of evidence for exploring the *functional*, and *accessibility universality* of facial expressions of basic emotion would consist in testing the robustness of the coherence between expression and emotion in remote and visually isolated cultures. Such studies would provide a new way of asking whether the hypothesized prototypical expressions of basic emotion are strongly related to the experience of the corresponding basic emotions beyond culture. The next section is aimed at showing how little we know about the right answer to this fundamental question.

2.2 Studies in Remote Cultures

The main idea that summarizes the previous section is that the "recognition of universal expressions" is not an innate and immediate way of connecting with others' emotions. Instead, it is a language-dependent categorization of some icons of emotion that have been successfully infectious across cultures—not innate adaptations.

Humans can develop universal non-innate solutions across cultures. One conspicuous example is counting. Although counting seems to be a universal solution, it is not an innate capacity. In fact, individuals who have not acquired a language for numbers (e.g., deaf individuals without a proper training in language of signs) cannot represent large exact numbers even if they are integrated in a numerate culture (Gordon 2004; Spaepen et al. 2011).

As the case for counting, the "recognition of facial expressions" is probably a cultural solution for segmenting the dynamic and unstable flow of facial movements into a few fixed and static icons. However, "recognition" can only be accomplished if individuals are socialized in an "expressional" culture (i.e., a society with a language for expressions).

Besides some experiments conducted in laboratory settings (Fernández-Dols et al. 2008; Gendron et al. 2012; Jack et al. 2012), the crucial test of these two antagonistic hypothesis—recognition of universal expressions versus language-dependent categorization of expressive icons—should be carried out in visually isolated and preliterate cultures. In this type of cultures, individuals are not socialized in an "expressional" culture.

On the one hand, if people from visually isolated and preliterate cultures (a) share our concept of "expression", and (b) categorize such expressions as members of less visually isolated cultures do, then there is some chance for inferring the existence of a truly innate way of emotion recognition. On the other hand, if individuals in visually isolated cultures fail to pass any of the two aforementioned tests, the hypothesis of recognition of emotions as a form of language-dependent categorization would be reinforced.

The aim of this section is to show how classic studies on recognition of emotion in visually isolated cultures were afflicted by a number of methodological problems that made the testing of these pre-conditions of universality inconclusive.

2.2.1 Closing the Door to Naturalistic Studies

At the end of 1960s, the research advances of anthropologists, psychologists, linguists, ethologists, and systems theory scientists were synthesized by some prominent scholars in *The Natural History of an Interview* (Bateson et al. 1971). *The Natural History* reflects some of the methods and the theoretical grounds of that time: the interest on microanalysis of behavior, the need to study contextual information, and the indivisible nature of social interaction when describing and explaining human communication (Bateson 1971).

Scholars like Birdwhistell, Mead, or Hinde addressed issues like the importance of naturalistic observation, the need to incorporate context in the *explanans*, the study of social interaction to explain behavior, or a direct criticism on the assumption that a set of facial expressions would be indexes of basic emotions (Birdwhistell 1970; Hinde 1982, 1985; Mead 1975). But these criticisms to a poorly grounded theory were misinterpreted. For example, Birdwhistell was depicted as an anti-Darwinian for rejecting Darwin's claims on universal facial expressions of *emotions* (Ekman 1973, 1980; Ekman et al. 1972). These assertions have led BET theorists to self-proclaim themselves as the only truly representatives of the evolutionary approach (Izard 1971; Tracy, in press; see rebuttal by Barrett, in press).

Not surprisingly, when prominent ethologist Robert Hinde (1982, p. 220) declared that "in so far as nonverbal communication is not merely a matter of the expression of the emotions, but of negotiation between individuals, the title of Darwin's (1872) book has biased research", psychologists did not pay attention to his remarks.

Since the late 1970s, behavioral ecology developed a theoretical ground for explaining animal communication as a tool for manipulating other's behaviors in social interactions (Dawkins and Krebs 1978; Seyfarth and Cheney 2003). Behavioral ecology was quickly accepted in disciplines like ethology, becoming one mainstream approach for explaining animal communication. Contrariwise, psychologists continued citing BET evolutionary explanations for the universality of facial expressions of *emotion* as the prescriptive approach, although ethological evidence supported behavioral ecology's claims instead of BET's reformulations of Darwin's original ideas (Fridlund 1994, 1997). This fact has influenced the low prevalence of naturalistic studies in emotion research programs and the editorial reluctance to publish this type of studies. Consequently, while ethology has developed a rich descriptive ground for further explanations on animal communication, psychologists have self-neglected this possibility.

2.2.2 Anthropologists: The Forgotten

It has been largely claimed—even for closing any debate on the universality of facial expressions of *emotion*—that the studies conducted among visually isolated and remote cultures were the definitive proof for rebutting criticisms on BET assumptions (Ekman 1999; Matsumoto et al. 2008). According to Matsumoto (2001, p. 173) "the universal basis for emotional expression is no longer debated in contemporary psychology and is considered a pancultural aspect of psychological functioning".

Although a detailed criticism and analysis of Ekman's results on recognition studies with visually isolated and remote cultures has been published by Russell (1994, 1995) and contested by Ekman (1994, 1999), we will review this controversy bridging the gap between psychology and anthropology.

BET foundational field studies (Ekman 1972; Ekman and Friesen 1971; Ekman et al. 1969) have constructed an idea of interdisciplinary and methodological novelty around their different expeditions. For example, Matsumoto (2004, p. 46) stated that "his [Paul Ekman's] studies in New Guinea bridged the gap between anthropological ethnography and psychological experimentation". But unfortunately, when taking a close look at the primary (Ekman 1972; Ekman and Friesen 1971; Ekman et al. 1969) as well as secondary sources (Ekman 1973, 1980, 1982, 1994, 1999, 2003; Ekman et al. 1972) on those three expeditions it is not possible to find nor anthropological ethnographies neither any fieldwork that would resemble anthropologists' standard procedures (for an introduction to ethnographic methods, see Agar 1996).

For example, Ekman's *The face of man* (1980) was meant to be the ethnography for his three remote culture's expeditions. After the primary sources were published (Ekman 1972; Ekman and Friesen 1971; Ekman et al. 1969), and several secondary sources were available for emotion researchers (Ekman 1973; Ekman et al. 1972), the publication of a book related to those expeditions with 69 pictures and its corresponding commentaries was highly anticipated. But apparently, what was meant to be the awaited "bridging of the gap between anthropology and psychology" was just another secondary source showing the typical prejudices on anthropology, as well as repeating the same introduction, methods, and results from previous sources (Ekman 1972, 1973; Ekman et al. 1972).

What makes *The face of man* (1980) strikingly appalling for anthropologists—specially for visual anthropologists—is the ethnocentric and *etic* approach taken by these studies. They dismissed ethnography , and *exported* experimental psychology to an alien territory where psychologists move in the dark (Leys 2010; Rosenwein 2010).

Psychologists' preference for approaching cross-cultural studies on remote cultures as mere descriptions of facial expressions clashes with the most basic principles of the ethnographic method (Malinowski 1922/1984, 1935/1965; for new developments in the field, see also Agar 1996, pp. 1–51). For example, ifwe inspect Malinowski's visual ethnographical collection, the absence of close-ups is noticeable. Instead, natives are always portrayed within a setting, a situation, or background. This fact allows other ethnographers to use those sources as secondary data—in a similar fashion as psychologists will use meta-analyses (Rosenthal 1991)—as well as to obtain an accurate description of the context in which the behavior was displayed. Anthropologists are able to reconstruct accurately these scenes when observing contextual information such as the type of decorations (e.g., providing information of chieftainship and rank). Likewise, the tools and elements of material culture surrounding the people can inform of their occupation, their belonging to one of the different clans and sub-clans, and these contextual elements can even provide information on the month of the year in which the picture was taken (Young 1998).

These methods contrast with the surmises made in *The face of man* (1980), where the psychologist makes (Western) commonsensical inferences on what emotions might feel the person portrayed by assessing the facial expression displayed. For example, in plate 33E, Ekman remarks on a woman displaying a Duchenne smile after Sorenson kneeled down to take her a picture are that "she probably does not understand the function of the camera but enjoys the situation". In the same sequence, we can observe a picture of the same woman (plate 33F) with tightened lips and her shoulder raised, being commented upon as showing clear signs of embarrassment. On logical grounds, if the woman previously did not know about the function of the camera, although enjoying the situation, it is not plausible that a moment after, nor changing the woman's understanding of the camera's function neither the gaze of the photographer, the woman's felt emotion would have switched from enjoyment to embarrassment. Ethnography of emotion concepts would have accounted for the embarrassment's antecedents, the usual reactions when feeling embarrassment, or even if the Western embarrassment concept itself is suitable for that culture.

2.2.3 Ethnography and Sorenson

Although there are no traces of any ethnography made in BET foundational field studies, we can indirectly assess the quality of their qualitative data when reviewing the stories devised for the recognition task of emotional antecedents (i.e., assigning stories, instead of words, to expressions; Ekman and Friesen 1971). The authors stated that previous pilot studies, conducted during their first expedition (Ekman et al. 1969), provided themes to create the stories, except for the surprise and fear stories. But such search of themes seem to be based in a ethnocentric and Westernized approach. For example, in the fear story, the Fore main character remains completely alone in the village, and tools for everyday labor (e.g., knives, axes) are absent. It is highly unlikely that a village will remain completely empty, but it is extremely unlikely the combination of the former statement with the sudden disappearance of knives and axes—considered by the authors as self-defense weapons, instead of tools for daily life activities. Likewise, the stories that were supposed to be provided by the Fore were circular while including a semantic context—an emotion term (e.g., for the story of anger, "he is angry"; for the story of happiness, "he is happy"), although Ekman's new method was designed to avoid translation problems (Ekman and Friesen 1971, p. 125).

Another issue worth discussing is the collaboration of the anthropologist Richard Sorenson in BET foundational field studies. Previous criticisms on the need to acknowledge anthropological wisdom, advices, and methods could be easily dismissed by BET advocates when stating that they had an anthropologist among the expedition members. That line of reasoning would eventually lead us to believe that Sorenson not only spoke the local language (Bahinemo and Fore), but he also conducted an ethnography of emotion concepts while helping the psychologists of the expedition to avoid frequent ethnocentric errors that could have been made in the field. Unfortunately, Sorenson was just the *man with the movie camera*. Ekman (1999, p. 310) refers to Sorenson as just a "cinematographer" and "not a trained social scientist".

But Sorenson (1975, 1976) reported that the moderate to high agreement rates for the recognition of basic emotions through facial expressions shown in the first and second BET foundational expeditions (Ekman and Friesen 1971; Ekman et al. 1969) were due to method artifacts. Sorenson argued that (a) the translators leaked the "correct" responses, (b) researchers thought that their participants were noble savages, ignoring the "eagerness with which the economically opportunistic Fore were ready to change their activities and beliefs according to the Western model" (Sorenson 1976, p. 140), (c) researchers followed an ethnocentric approach to data collection, and (d) researchers were the center of attention and the Fore "were quick to seize on the subtlest cues for an indication on how they should respond and react" (Sorenson 1976, p. 141).

2.2.4 From the Field: Lessons from the Trobriand Islands

Using our own experience in the fieldwork conducted in Papua New Guinea (2013 Trobriand Islands' expedition), we will provide an illustrative example to account for the importance of ethnographic data and anthropological methods to prepare a solid ground for conducting hypothesis-testing studies on facial expression.

When dealing with preliterate cultures anthropologists usually develop an informal grammar and vocabulary on which upcoming anthropologists will rely on. As a dynamic system, this linguistic corpus will be modified and validated with the passing of generations of researchers conducting fieldwork in the area (for the case of Kilivila language in the Trobriand Islands, see Fellows 1901; Malinowski 1935/1965; Senft 1986). This opened-source knowledge is probably built on a limited network of informants—normally high ranked chiefs and their relatives.

Due to the oral nature of the language, the well-educated and higher ranked Trobrianders of certain sub-clans (e.g., Tabalu, Mulabwema, Toliwaga) are the holders of the ancestral knowledge (i.e., the stories, the myths, the language) that is transmitted orally to certain sub-clans' members. By this custom, we may find that there is one Kilivila language for the elders, whereas the less *educated* commoners (*tokai*) use other variant of Kilivila language. This two-language system may entail some problems for the ethnographer, but namely it can invalidate a psychologist's research if he disregards ethnographic methods and relies solely on local translators for gathering data. The *educated* people will provide the emotion terms and the defining features of the emotion concepts in the elders' variant of Kilivila, whereas the commoners will rely on a different variant of Kilivila.

For example, in Kilivila language, the term *mwasila* works as the descriptor for shame (Senft 1986), whereas *badegila* is used for describing embarrassment. In a context in which the translators are the well-educated elders, the production of an ethnography of those concepts would not be probably validated by a sample of commoners. In fact, commoners tend to confuse the concept of shame and embarrassment, because the term *badegila* is unfamiliar to them (i.e., it is from the elder's Kilivila variant). Under the descriptor *mwasila* (shame), commoners will mix up stories and examples of women falling over in front of men with stories on moral transgressions. Thus, *mwasila* is used by commoners as a global category that will include the features of shame and embarrassment.

One of the main problems that a psychologist faces when conducting studies in remote cultures is that we behave differently than anthropologists, and locals are only *accustomed* to anthropologists' way of doing things. We are continuously being observed by the villagers. They gossip, hypothesize, and make predictions on every single detail of our behavior. We are a single case study for the whole population of our potential participants (DeVita 1990).

For example, the first thing Trobrianders acknowledge is that we do not sit down with the elders and chiefs to *talk* (*bigatona*). *Bigatona* is one way of building rapport with the informants and getting access to chunks of information while doing exchanges of betel nuts or tobacco. Unlike anthropologists, psychologists are a type of *Dim Dims* (a way Trobrianders have to refer to Caucasians and Europeans) mainly interested in studying the commoners (*tokai*). Thus, anthropologists aim at reaching the best group of sources reliable enough to gather the information they need for their ethnographic data, whereas psychologists urges to find a large representative sample from a population of commoners.

2.3 Conclusion

This chapter has described some definitional and methodological problems at the core of the concept of "recognition of universal facial expressions of emotion". A thorough analysis of each of the terms that constitute that concept raises important questions.

Current empirical evidence supports that *emotion* is a polysemous term that refers to a complex network of phenomena and their corresponding mutual links (Fig. 2.1). In this network, *recognition* is not a nonverbal instantaneous categorization of the sender's experience, but a semiotic task in which the receiver connects "emotions as signs" (artificial icons of emotions such as prototypical facial expressions) with emotions as "cognitive representations" (language-dependent concepts of emotion).

One of the reasons of this characterization is that prototypical *expressions* of basic emotion are not observed when people experience such emotions nor in natural (Fernández-Dols and Crivelli 2013) neither in laboratory settings (Reisenzein et al. 2013). This fact, strongly suggests that *expressions* are actually icons of emotional behavior. *Expressions* would work out like infectious signs adopted in many cultures, but not *universal* in a strict sense (i.e., they are not innate adaptations shared with other primates for millions of years).

The main conclusion of this analysis is that research on recognition has still to answer a basic preliminary question about universality. The mainstream approach is that recognition is an instantaneous and innate process of nonverbal categorization. We hypothesize that recognition of emotion is a successful cultural device for segmenting the flow of a complex behavior (facial muscles' movement) into a number of memorable, salient prototypes.

The appearance of universality in the recognition of expressions would be similar to the appearance of universality of counting systems based on precise numbers. While numbers are apparently universal today, researchers (Gordon 2004; Pica et al. 2004) have concluded that there is a probably innate representation of quantity (*one*, *two*, *many*), but numerating is dependent on cultural contexts that, through explicit socialization, combine the primitive representation of quantity with other cognitive competencies (see Norenzayan and Heine 2005).

In the same vein, recognition of emotion might be based on a basic, maybe innate, perception of core-affect (e.g., pleasure vs. displeasure). This fact, combined with other cognitive abilities through socialization, would eventually lead to the categorization of emotional events in terms of signs such as words and icons (prototypical expressions).

A crucial test of these two competing hypotheses would consist in carrying out tests of recognition in isolated, preliterate cultures in which this *infectious* cultural device ("recognition") should be absent. Unfortunately, such tests have rarely been performed in a proper way (for a recent promising development in field studies see Gendron et al., 2014). They require a truly interdisciplinary integration of ethnographic and experimental methods that was not accomplished in the few studies carried out with remote cultures during the 1960s and early 1970s. We believe it is time for carrying out these tests.

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Chapter 3
Evidence for the Universality of Facial Expressions of Emotion

Hyisung Hwang and David Matsumoto

Nonverbal communication is often considered merely body language, but researchers have defined nonverbal communication as almost all of human communication except the spoken or written word (Knapp 1972). We broadly define nonverbal communication as the transfer and exchange of messages in any and all modalities that do not involve words. One of the major ways by which nonverbal communication occurs is through nonverbal behaviors, the dynamic behaviors that occur during communication that include facial expressions, gestures, tone of voice, and body postures.

Of the various nonverbal behaviors, facial expressions are one of the most complex signal systems in the body. The face is a channel that can produce both voluntary movements and involuntary reactions. These two facets make research on the face complicated. Facial signals that are involuntarily produced are universal, whereas voluntary or learned facial expressions can vary across cultures. Voluntary and involuntary facial signals often confuse communicators, but they can be differentiated.

This chapter explores the scientific evidence for the universal expression and recognition of facial expressions of emotions. We first discuss the history of research on facial expressions of emotion, including early debates and positions, and review the ample scientific evidence for the universal expression and recognition of facial expressions of emotions. We then discuss how the universality of facial expressions of emotion informed our understanding of emotions, and in particular, a category of emotions known as basic emotions. We also discuss how facial signals of emotions interact with culture to demonstrate how

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biologically innate expressions can be modified by cultural learning. As a first step of understanding this area, we begin by describing the original debate about the universality of facial expressions of emotion.

3.1 Early Debates Concerning the Universality Versus Culture Specificity of Facial Expressions of Emotion

Modern day work in this area started with Darwin's (1872) seminal thesis about emotion and expression, who posited that all humans, regardless of race or culture, possessed the ability to express emotions on faces in similar ways because emotions and their expressions are evolutionarily adaptive and biologically innate. Darwin insisted that emotions exist panculturally and that all humans possess the ability to express emotions in the same ways through their faces and other nonverbal channels such as voice. He also claimed, in his principle of serviceable associated habits, that facial expressions are the residual actions of more complete behavioral responses. Relying on advances in photography and anatomy (de Boulogne 1862/1990), Darwin engaged in a detailed study of the muscle actions involved in emotion and concluded that the muscle actions are universal and their precursors can be seen in the expressive behaviors of nonhuman primates and other mammals.

Darwin's work drew heavy criticism, especially from anthropologists such as Birdwhistell (1970). They noted vast differences in expressive behavior across cultures and concluded that facial expressions could not be universal. Instead they argued that emotional expressions had to be learned differently in every culture, and just as different cultures have different spoken languages they must have different expressive languages of the face as well.

Between Darwin's original writing and the 1960s, only seven studies attempted to test the universality of facial expression. Unfortunately, these studies were inconclusive (Ekman et al. 1972). Thus, an influential review of the literature (Bruner and Tagiuri 1954) concluded that facial expressions were not universal but learned. It was not until almost a century after Darwin that the first systematic evidence for the universality of facial expressions of emotion appeared.

3.2 Evidence for the Universality of Facial Expressions of Emotions

In the mid-1960s, Sylvan Tomkins resurrected interest in the study of emotions and faces with the publication of his landmark volumes entitled *Affect, Imagery, and Consciousness* (Tomkins 1962, 1963). Tomkins conducted the first study demonstrating that facial expressions were reliably judged to be associated with certain emotional states (Tomkins and McCarter 1964) and later studies showed consistent findings (Ekman 1972; Ekman et al. 1969; Izard 1971). Those initial findings were criticized, however, because the evidence for universality (i.e., the high levels of cross-cultural agreements in judgments) might have occurred because of influences of social media (e.g., TV) and shared visual input (e.g., Hollywood movies, magazines, etc.). To address these potential limitations, Ekman and his colleagues conducted two studies with two visually isolated, preliterate tribes in the highlands of New Guinea (Ekman and Friesen 1971; Ekman et al. 1969). In the first study, the tribespeople could reliably recognize facial expressions of emotion (anger, disgust, fear, happiness, surprise, sadness) posed by westerners; in the second study, films of the tribespeople expressing emotions were shown to Americans who had never seen New Guineans before, and the Americans were able to recognize the expressions of the New Guineans. Thus, the ability to recognize facial expressions of emotion did not occur because of learning through mass media or other shared visual input as the New Guineans had had no exposure to the outside world.

One limitation of the above studies was that they all examined judgments of facial expressions of emotions and did not investigate their spontaneous production. Friesen's (1972) study, however, addressed this limitation. In that study, American and Japanese participants were presented with neutral and stressful films. During the experiment, the same expressions associated with the six emotions mentioned previously were identified via facial coding systems. The coded facial behaviors from the participants in the study corresponded to the facial expressions tested in the previous judgment studies supporting the universality of emotions. Members of both the American and Japanese cultures showed the same expressive patterns, providing the first evidence that facial expressions of emotion were universally produced.

Since the original evidence for the universality of facial expressions of emotions described above, numerous studies have replicated their findings (Ekman et al. 1987; Matsumoto 2001; Matsumoto et al. 2002, 2008). These studies have included both studies examining judgments of facial expressions of emotion (Elfenbein and Ambady 2002) as well as studies investigating the production of facial expressions of emotion (Matsumoto et al. 2008a, b). For example, one recent study examined the expressions of 84 judo athletes from 35 countries at the 2004 Athens Olympic Games (Matsumoto and Willingham 2006). The spontaneous facial expressions of winners and losers that were first observed at the completion of their final medal match were consistent with the universal expressions. In particular, winners displayed Duchenne smiles while losers displayed sadness, disgust, anger, and other negative emotions. Duchenne smiles are smiles that involve not only the smiling muscle (zygomatic major), which raises the lip corners, but also the muscles surrounding the eyes (orbicularlis oculi), which raise the cheeks, thin the eyes, and narrow the eye cover fold. That these spontaneous expressions were documented in a real-life, naturalistic setting and were produced by individuals from many different cultures of the world spoke to the universality of those facial expressions of emotion.

Fig. 3.1 Seven basic emotions and their universal expressions. Reprinted with permission © David Matsumoto 2008

In addition to the six universal emotions, contempt was identified as a universal expression in various studies (Ekman and Heider 1988; Matsumoto 1992, 2005). The evidence for the universality of the contempt expression was first documented in a study involving 10 cultures and later replicated in an additional seven cultures, including the Minangkabau in Sumatra, Indonesia (Ekman and Heider 1988; Matsumoto 1992). Thus, today there is strong evidence for the universal facial expression of seven emotions (see Fig. 3.1 for seven basic emotions and their universal expressions). In the next section, the source of the evidence of universal facial expressions of emotion will be introduced in detail.

3.3 The Source of Universal Facial Expressions of Emotions

Merely documenting the universality of emotional expression in many cultures around the world does not resolve questions concerning the source of the universality. Facial expressions of emotion may be universal because of at least two reasons. First, emotional expressions may be a biologically innate skill that all humans are born with. Or second, they may be a skill that is learned in the same way all around the world in different cultures through a mechanism known as culture constant learning. Demonstrating cross-cultural agreement in either the production or judgment of expressions does not address which of the two sources may produce the agreement; other methodologies are necessary to do so including studies of blind individuals, twins, infants, and animals. In this section, we briefly review some of the representative studies in these areas, all of which point to a biologically innate source of universality.

3.4 Studies with Blind Individuals

One of the critical challenges to the notion of the biological innateness of emotion is that humans can easily (or entirely) learn and imitate emotional expressions from others. Blind individuals who are limited in observing and imitating others' behaviors compared to sighted people are a suitable group to explore the pure effect of biologically wired systems on the universality of emotions. This is especially true for studies involving congenitally blind individuals because they are expected to be have limited social learning about how to produce sophisticated facial muscle movements of each emotion because they could not visually learn them from birth.

Many similarities between blind and sighted individuals in their spontaneous facial expressions of emotion have been reported in studies of congenitally blind individuals. For example, researchers have measured the spontaneous facial behaviors of blind individuals when emotions were aroused studying blind children (Cole et al. 1989) and adults of many different cultures (Galati et al. 2001; Galati et al. 2003) and have reported similarities in facial expressions between blind individuals and nonblind individuals. This evidence is compelling to show the existence of universal emotions because it is impossible for blind persons to simply imitate others and produce the complicated facial expressions involved in complex muscle combinations fired spontaneously in less than a second when they experience an emotion. They would not have these automatic reactions unless they were born with the capability of experiencing and expressing the emotions in a certain way.

More recent studies reported similar findings when comparing congenitally and noncongenitally blind judo athletes at the 2004 Athens Paralympic Games with the sighted athletes from the 2004 Olympic Games (Matsumoto and Willingham 2009). The blind athletes, who came from 23 cultures, produced the same facial configurations of emotion as sighted athletes in the same emotionally evocative situations. The study also found high concordance between the blind and sighted athletes in their expressions. Winners displayed all types of smiles, especially Duchenne smiles, more frequently than the defeated athletes, who displayed more disgust, sadness, and combined negative emotions. When receiving the medal, all athletes smiled, but winners of the last match (gold and bronze medalists) displayed Duchenne smiles more frequently than did the defeated (silver medalists), who displayed more non-Duchenne smiles. Because congenitally blind individuals could not have possibly learned to produce these expressions by imitation, we believe that these studies provided strong evidence for a biologically based emotion–expression linkage that is universal to all people of all cultures.

3.5 Evidence from Twin and Family Studies

Another source of evidence for the possible biological origins of emotion–expression linkages comes from studies of twins and family relatives. Facial behaviors of blind individuals are more concordant with their kin than with strangers (Peleg et al. 2006); in this study's facial movement analysis during an individual interview, the correlation between movements of 21 congenitally blind subjects with those of their 30 relatives especially in relation to such expressions as sadness or anger was significantly more similar to each other than with nonfamily members. The results provided evidence for a unique family facial expression signature, indicating a hereditary component for facial expressions. Moreover, some facial expressions in response to emotionally provocative stimuli are more concordant among monozygotic twin pairs than dizygotic twins (Kendler et al. 2008). These studies are strongly suggestive of a hereditable, genetic component to facial expressions of emotion.

3.6 Evidence from the Developmental Literature

More evidence for the biological base of facial expressions of emotion comes from the developmental literature. The same facial musculature that exists in adult humans exists in newborn infants and is fully functional at birth (Ekman and Oster 1979). Infants have a rich and varied repertoire of facial expressions including those that signal not only emotional states but also interest and attention (Oster 2005, 2010). There is widespread consensus that smiling; distaste, the infant precursor of adult disgust; and crying, the universal signal of sadness/distress, occur in neonates (Oster 2005).

There is some controversy as to when other differentiated and discrete negative emotions occur. Some authors suggest that discrete negative emotions exist from birth or shortly thereafter and emerge according to a maturational timetable (Izard 1991; Izard and Malatesta 1987; Tronick 1989). Others suggest that infants, at least within the first year of life, display relatively undifferentiated or modulated negative expressions, which ultimately transform into more differentiated, discrete expressions later (Camras et al. 2003; Oster 2005). Discrete expressions of anger and sadness have been reported in the early part of the second year of life (Hyson and Izard 1985; Shiller et al. 1986). Regardless, by the time of preschool, children display discrete expressions of the other emotions as well (Casey 1993). It is difficult to conceive of how this occurs if the children did not have the biological capability to do so in the first place, which again points to the innateness of facial expressions of emotion.

3.7 Evidence from Nonhuman Primates

The facial expressions considered to be universal among humans also have been observed in nonhuman primates (de Waal 2003). Chimpanzees have a fully functional facial musculature that, while not as differentiated as that of humans, include the same muscles that are used in human emotional expressions (Bard 2003; Burrows et al. 2006). Moreover, the chimpanzee facial musculature produces many of the same appearance changes as does the human musculature, according to a comparison of the human and chimpanzee versions of the Facial Action Coding System (Vick et al. 2007; Shepherd et al. 2012). Chimpanzees as well as Rhesus Macaques can categorize facial expressions of emotion much as humans do (Parr et al. 2008; Parr et al. 2010; Waller et al. 2012). Consistently, chimpanzees produce distinct laughs depending on contexts and interactants like human beings (Davila-Ross et al. 2011).

Following all the evidence stated above, we speculate that the emotions that are universally expressed and recognized are dominantly biologically wired. These findings have led to research that has suggested that the universally expressed and recognized emotions belong to a specific class of emotions that has certain specific and unique characteristics. This class of emotions is known as basic emotions. In the next section, we discuss how the universality of facial expressions of emotion has informed our understanding of emotions in general and of basic emotions in particular.

3.8 Emotions and Basic Emotions

The documentation of the evidence for the universality of some facial expressions of emotion led to the increased study of emotions in general, and especially to the study of universal emotions that have a biological basis, which are called basic emotions. The increased attention to emotion has led to the need for defining "emotion." However, it is difficult to define emotions in a simple word that can be equally understood by and for everybody even after so much research has been conducted in emotion and nonverbal behavior. For us, emotions are as *transient, bio-psycho-social reactions to events that have consequences for our welfare and potentially require immediate action* (Matsumoto and Hwang 2012).

Basic emotions include the emotions that have been shown to be universally expressed and recognized and are akin to biological systems and reactions. Basic emotions are discrete, unique, and rapid information processing systems that aid us to act with minimal conscious deliberation (Tooby and Cosmides 2008; Izard 2009). If humans did not have emotions, they could not make rapid decisions concerning whether to attack, defend, flee, care for others, reject food, or approach something useful. Emotion response is adaptive and aids in our ultimate survival and allows us to take action immediately without much thinking, and its expression promptly conveys this valuable information to others. This does not mean that emotions continue to occur all the time because humans consciously or unconsciously scan and evaluate our environments constantly but only selected stimuli evoke an emotional reaction (Ekman 2003; Ellsworth and Scherer 2003; Frijda et al. 1989; Roseman 1984; Roseman et al. 1995; Scherer et al. 2001). If selected events are expected to have any consequences, they trigger emotion in order to prime action and motivate behavior (Frijda et al. 1989; Tomkins 1962, 1963). Once emotions are triggered, they coordinate multiple bodily and psychological systems such as perception, attention, inference, learning, memory, goal choice, motivational priorities, physiological reactions, motor behaviors, and behavioral decision making (Cosmides and Tooby 2000).

The expressions of those biologically innate, basic emotions of course interact with culture, and there are many spaces for cultural variations in how to socially express facial reactions after these emotions have been triggered, based on social/cultural norms. And we also do not mean to imply that basic emotions are the only emotions that humans experience. There are many other emotional states that humans experience that are much more culturally grounded, both in terms of origin as well as moderation. For those emotions that can be culturally and socially cultivated, what triggers them in the first place, what happens when they are triggered, and their meanings afterward are influenced by culture (see Matsumoto and Hwang 2012, for a more detailed discussion). In the next section, we address cultural variations in the display of the universal facial expressions of emotion.

3.9 Cultural Differences in Expressing Facial Emotions

Despite the existence of universal facial expressions of emotion, people around the world use the universal expressions differently. The first evidence for cultural differences in expressions was in a second condition in Friesen's study (1972). In that study, Americans and Japanese viewed the stressful films alone, and then in the presence of an older, presumably higher-status male experimenter. In the latter condition, the Americans continued to express their negative emotions consistently regardless of the other's presence, whereas the Japanese were more likely to smile in the presence of others than when they were alone.

The concept of cultural display rules was used to explain these cultural differences in emotional expressions. Display rules are social norms learned early in childhood to help individuals manage and modify their emotional expressions depending on social circumstances. They provide a way of behaving that is consonant with the normative behaviors within a social role. They serve a vitally important function in culture by helping to regulate emotional expressions, which aids social coordination and group survival (Matsumoto and Juang 2013). When the participants in Friesen's (1972) experiment viewed the stressful films alone in the first condition, there was no reason for display rules to modify the expressions because there was no one else present; thus, the Americans and Japanese produced the same facial expressions (providing evidence for the universality of facial expressions of emotion, as discussed earlier). When viewing the films in the presence of a higher-status person, however, display rules were activated. Because the Japanese had a display rule not to express their negative feelings to a higher-status person, they masked their negative feelings by smiling. Because the Americans did not have such a display rule, they did not change their expressions much. Thus, cultural differences in the expressions were produced because of the different social contexts in which the expressions occurred.

After the original inception of the concept of display rules, cross-cultural research on them was dormant until Matsumoto's (1990) study examining display rules in Americans and Japanese, and a similar study documenting differences in display rules among four ethnic groups within the USA (Matsumoto 1993). Later Matsumoto and colleagues created the Display Rule Assessment Inventory (DRAI), where participants choose one of six behavioral responses (corresponding to the ways expressions are managed in real life, as described above) when they experience different emotions with family, friends, colleagues, and strangers (Matsumoto et al. 1998, 2005). They demonstrated cultural differences in display rules and provided evidence for its internal and temporal reliability and for its content, convergent, discriminant, external, and concurrent predictive validity with personality.

Matsumoto et al. (2008a, b) then administered a more comprehensive version of the DRAI in over 30 countries, examining universal and culture-specific aspects to display rules, and linking the cultural differences to culture-level individualism (vs. collectivism). Most countries' means on overall expression endorsement suggested a universal norm for expression management. Individuals of all cultures had a display rule norm for greater expressivity toward in-groups than toward out-groups, indicating another universal effect. Collectivistic cultures were associated with a display rule norm of less expressivity overall than individualistic cultures, suggesting that overall expression management for all emotions is central to the preservation of social order in these cultures (Fig. 3.2). This finding is commensurate with the behavioral findings from previous findings (Friesen 1972; Matsumoto and Kupperbusch 2001;

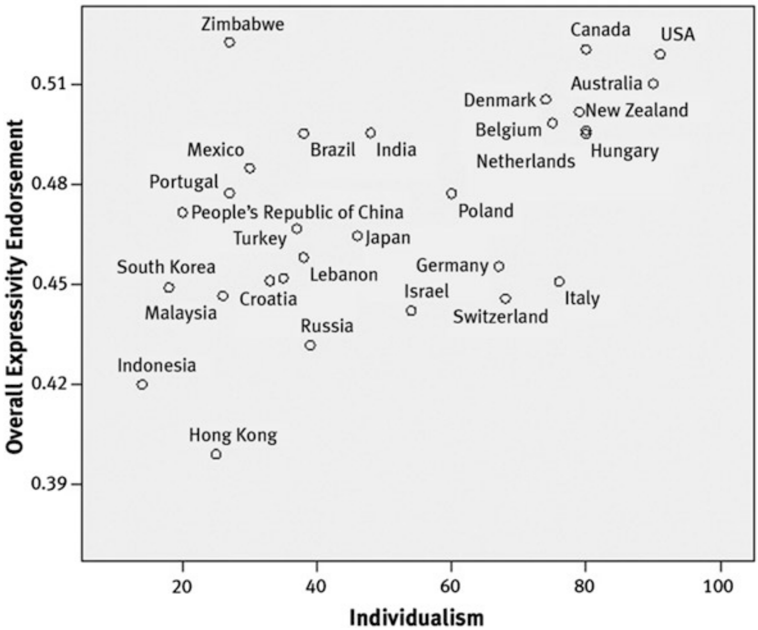

Fig. 3.2 Graphical representation of the relationship between individualism and overall expressivity endorsement in Matsumoto et al. (2008a, b)

Matsumoto et al. 2009). Individualism was also positively associated with higher expressivity norms in general and for positive emotions in particular. Individualism was positively associated with endorsement of expressions of all emotions toward ingroups, but negatively correlated with all negative emotions and positively correlated with happiness and surprise toward outgroups. Cumulatively, these findings suggest a fairly nuanced view of the relationship between culture and display rules that varies as a function of emotion, interactant, and overall expressivity endorsement levels.

As studies documenting cultural differences in expression peppered the literature (Argyle and Cook 1976; Edelmann et al. 1987; Gudykunst and Nishida 1984; Gudykunst and Ting-Toomey 1988; Matsumoto and Kupperbusch 2001; Noesjirwan 1978; Szarota 2010; Waxer 1985), a consensus emerged that when emotions are aroused, the displays are either universal or culture specific, depending on context. A recent study (Matsumoto et al. 2009), however, showed that emotional displays can be both for the same person in the same context, if displays are examined *in sequence across time.* In this study, changes in Olympic athletes' expressions after their initial reactions were classified into one of several regulation strategies, and the relationship between these expressive styles and cultural variables such Hofstede's (2001) cultural dimensions (i.e., country level scores on the dimensions Individualism, Power Distance, Uncertainty Avoidance, Masculinity, and Long Term Orientation) and country demographics such as population density and affluence were examined. Although the athletes' initial reactions were universal, their *subsequent* expressions were culturally regulated and associated with population density, affluence, and individualism. Athletes from urban, individualistic cultures expressed their emotions more; athletes from less urban, more collectivistic cultures masked their emotions more. The average length of time from an initial, universal emotional expression to a culturally moderated modification was less than 1 s.

In summary, culture plays an important role in how to manage emotions and their expressions when they occur. However, spontaneous and immediate reactions of universal emotions are often produced prior to the cultural reactions that modify the initial emotional expressions in socially desirable ways. The universal expressions of emotions are very rapid and often unconsciously produced, mostly occurring in less than a second. These two facets of universal emotions and their expressions highlight the critical part of research on the topic; ongoing arguments about whether biological emotions exist or not have occurred because the subsequent expressions of emotions are easily mistaken as evidence of cultural variations of emotional expressions (Matsumoto and Hwang 2012). How to disentangle these different expressions of emotions would be the key to understanding the universality of emotions in research.

3.10 Future Directions

In the future, researchers need to more clearly define emotions and the specific emotion domains in which they are interested in order to approach conducting research and understanding their findings with greater specificity and sophistication.

For example, research based on evolutionary theory, as stated above, may focus on spontaneous expressions on the face that immediately occur right after emotional events because facial expressions are part of the evolutionarily derived, biologically innate package of emotion components. Research based on self-reports of emotions that are based on memory or recall, however, represents a different domain of emotion, measuring emotions after immediate reactions. Thus, comparing findings from the two different approaches may not make sense. Researchers should fairly evaluate studies considering the domain of emotion being examined.

Second, evolutionary theory does not neglect the effects of context. In contrast, evolutionists believe that universal behavioral reactions and cultural-specific management of those reactions interact in specific contexts. Yet, very few studies have systematically attempted to directly examine these effects of context. To disentangle the unidentified and seemingly contradicted layers produced by different contexts, examining how culture specifically interacts with universal behavioral reactions across a wide variety of targeted contexts is an on-going task in future research on facial expressions of emotions.

Furthermore, the stimuli used in studies to test judgments of facial expressions of emotions should be carefully considered. This is a critical issue to resolve because many previous studies showing culture-specific findings in facial expressions of emotions used stimuli that may have been questionable in terms of their ecological validity to portray emotional expressions. Also, the expressive intensities of the stimuli are often not considered, thus rendering definitive conclusions about statistically significant differences in agreement rates among tested emotions is very difficult.

More studies concerning spontaneous facial expressions of emotion in real-life situations should be considered for future research. Although research in laboratory-based, experimental environments is understandable and has a scientifically unique meaning, conducting studies in real-life contexts provide solid and practical results that can enhance the applicability of research findings to the real life. This is especially true of the facial expressions of basic emotions, which are rooted in spontaneous behavioral reactions that usually occur in natural settings than in experimental ones. Therefore, scientists must continue to make efforts to conduct research in real-life contexts.

Finally, examining the training of facial expression recognition in practical applications will be beneficial in a practical research perspective (e.g., see Matsumoto and Hwang 2011, for a study on the benefits of facial expression training). It is a fact that basic emotions are universal and commonly recognizable across cultures. Thus, being skillful in understanding and catching other's emotions on the face in social interactions may be useful in many practical and applied contexts. As individual variations always exist, there must be some room for people to acquire and develop their ability of recognizing other's emotions on face. Acknowledging the possible consideration of facial expressions of emotion to real life will elucidate how to apply research findings appropriately in reality.

3.11 Conclusion

Darwin (1872) originally suggested that emotions and their expressions had evolved across species, were evolutionarily adaptive, biologically innate, and universal. Darwin's idea has been fully examined in numerous studies as discussed above. We started by reviewing the original and subsequent evidence for the universal expression and recognition of facial expressions of emotion. We then reviewed evidence concerning the source of the universality of facial expressions on emotions, examining research findings on blind individuals, twins, infants, and children as well as nonhuman primates. Those reports provided a solid and consistent conclusion that universal facial expressions of emotions are biologically innate. This characteristic of facial expressions of emotion has led to a greater understanding of the class of emotions known as basic emotions, which we then described. At the same time, we did not intend to undervalue the role of culture in moderating emotions and their expressions and discussed cultural display rules that indicated how cultures cause individuals to modify the initial universal facial expressions of emotions on social circumstances.

Not only are the seven basic universal facial expressions panculturally recognized, but cultures are similar in other aspects of emotion judgment as well. For example, there is cultural similarity in judgments of relative intensity among faces; that is, when comparing expressions, people of different countries agree on which is more strongly expressed (Ekman et al. 1987; Matsumoto and Ekman 1989). There is also cross-cultural agreement in the association between perceived expression intensity and inferences about subjective experiences, as well as in the secondary emotions portrayed in an expression (Biehl et al. 1997; Ekman et al. 1987; Matsumoto and Ekman 1989). This agreement may exist because of overlap in the semantics of the emotion categories, antecedents and elicitors of emotion, or in the facial configurations themselves.

There are cultural differences in emotion judgments as well, such as in the absolute levels of recognition across cultures; for example, Americans typically have higher agreement rates when judging emotions than other countries (Biehl et al. 1997; Elfenbein and Ambady 2002; Matsumoto 1992; Matsumoto et al. 2002). There are also cultural differences in ratings of the intensity of expressions; for example, Japanese tend to rate expressions lower in intensity than Americans (Biehl et al. 1997; Ekman et al. 1987; Matsumoto 1992; Matsumoto et al. 2002). Other cultural differences have led to interesting debates and controversies (see in particular Chap. 4 on the possible ingroup advantage of emotion recognition). However, it is extremely important to recognize that the cultural variations in how to display facial expressions is not interpreted as cultural control over immediate behavioral reactions on the face as these are likely very difficult to control. Instead, culture is an essential guideline for people to socially modify their more voluntarily based facial behaviors, which occur after the immediate behavioral reactions, in order to smooth their social interactions for well-being and social survival.

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Chapter 4
In-Group Advantage and Other-Group Bias in Facial Emotion Recognition

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Most introductory psychology textbooks tell the vivid story about how Ekman (1972) and Izard (1971) took a collection of black-and-white photographs of American facial expressions on round-the-world tours to see whether individuals across distant cultures could recognize the intended emotions. Their original goal was to demonstrate that emotions are universal. Notably, the participants chose among six multiple choices and achieved far better performance than the score of 1/6 (16.7 %) that would be expected by chance guessing alone. Ekman and Izard interpreted this finding in favor of the universality of emotions—which is a conclusion that was initially controversial, came to be accepted, and has become controversial again in recent years. Newer integrationist theoretical perspectives have attempted to reconcile cultural universals and cultural differences together in order to incorporate findings beyond this broad conclusion of universality that was inferred from the original round-the-world tour. Indeed, other observations relating to cultural differences could be made from the very same data that were collected to demonstrate cultural universals. The first of these is that some cultures did better than others on this task (Matsumoto 1989). The second of these is that the best performers in these studies were from the nation where the photographs originated, followed by the cultures that were the most culturally similar. This observation—namely, that there is an *in-group advantage* in recognizing others' emotions—has been at the center of integrationist theories of emotion recognition across cultures.

In-group advantage is a widely replicated empirical finding, and theories about cultural differences in emotion recognition need to be able to explain this finding.

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This chapter discusses the evidence in favor of two distinct explanations for in-group advantage and argues that both of these explanations can act singly or simultaneously. Both are supported by empirical data. The first explanation is the dialect theory of emotion, and the second is out-group bias. Both are discussed below.

4.1 Dialect Theory

In Tomkins and McCarter (1964), articulated the metaphor that cultural differences in emotional expression are like “dialects” of the “more universal grammar of emotion” (p. 127). Dialect theory starts with this linguistic metaphor for communicating emotion through verbal cues and attempts to apply this metaphor to nonverbal cues. Dialects of a verbal language can differ subtly in accent, grammar, and vocabulary—such as English from the USA versus Britain or French from Quebec versus Paris. When speaking a verbal language, it is more challenging to understand someone who uses a different dialect. It is crucial to the metaphor that the dialects of a language are still mutually intelligible. The majority of the message still gets through, but it is more challenging to understand people who speak a different dialect. There can be inadvertent misunderstandings and lost meanings.

There are two interconnected processes within dialect theory: First, members of different cultural groups have different styles of generating nonverbal cues, which are systematic even if subtle. This process is also called *encoding* or expression. Second, individuals tend to judge other people’s cues based on the knowledge of their own cultural style. This judgment process is also called *decoding* or recognition. According to the dialect theory, accuracy breaks down through mirror-image cultural differences on both sides of the encoding and decoding process. Ultimately, communication accuracy suffers to the extent that there is a mismatch between the style of display produced and the style expected by the perceiver.

It is important to note that, in dialect theory, not every difference in expression style is necessarily a dialect. Again, drawing from the linguistic metaphor, the theory makes a distinction between *nonverbal accents* and dialects. Nonverbal accents are any difference across cultures in the appearance of an emotional expression. Nonverbal dialects are a subset of these accents—namely, the accents that also impede accurate recognition. In the linguistic metaphor, typically, an accent is something that we notice but that we can still understand, whereas we typically do not use the term “dialect” until there is at least some difficulty in understanding another person’s speech. Note that this distinction cannot be made a priori from the properties of the facial expression itself—that is, it is a matter of how easily perceivers can overcome differences in the facial expressions produced across cultures. Notably, individuals who are familiar through cross-group contact can overcome even large differences in expression style, whereas some subtle differences can trip up perceivers who do not know how to interpret them.

4.2 Empirical Evidence in Favor of Dialect Theory

The dialect theory developed out of a need to explain empirical evidence for the in-group advantage. My colleague Nalini Ambady and I demonstrated this in a meta-analysis that included 182 independent samples of participants whose data appeared in 87 separate sources, including journal articles, unpublished dissertations, book chapters, and unpublished technical reports (Elfenbein and Ambady 2002b). The majority of the data included were based on studies examining facial expressions. It is noteworthy that the data set was so large in part because—ironically—researchers thought that the topic did not matter. First, many samples came from the very same classic papers that were intended to demonstrate universality. In these studies, the information necessary to make cross-cultural comparisons was not provided. In the famous round-the-world tours in which Ekman (1972) and Izard (1971) sampled multiple cultural groups judging American photographs, the data were analyzed for whether people could achieve accuracy that was greater than what would be expected by chance. However, these papers did not provide the statistical tests that could show, additionally, whether any cultural differences emerged in accuracy. Even simple descriptive statistics such as standard deviations to accompany the descriptive statistics would have been sufficient, but these were never provided. In fact, this information was deliberately hidden, because the researchers did not want to call attention to cultural differences when their agenda was to highlight universals (Matsumoto and Assar 1992). A second demonstration that researchers thought the topic did not matter is that many studies were not deliberately cross-cultural. In this work, researchers borrowed stimuli from colleagues abroad without apparently being concerned about potential cultural differences. Overall, we felt that it was an asset for our project that other researchers were not necessarily looking for in-group versus out-group differences in emotion recognition. After all, the likely extent of experimenter bias should be reduced when an experimenter is not trying to support your hypothesis. In examining the results across so many different studies done by so many different researchers using so many different methods, we found it reassuring that the study attributes did not appear to change the results in any systematic way. The in-group advantage did not differ across the particular research teams conducting the work, which is important because different teams have different theoretical perspectives and use different methodologies. In addition, we tested directly the influence of methodology, and none of the features tested had an influence on the size of the in-group advantage.

Indeed, the only significant moderator was the amount of cross-cultural exposure. In particular, there is lower in-group advantage when an individual perceives emotional expressions from a cultural group that is more familiar. This observation strongly fits the dialect theory, in that greater familiarity with a cultural group would imply greater familiarity with culture-specific elements of nonverbal style. Because there is no perfect measure of cross-cultural exposure—particularly when the analyses could only be conducted at the level of entire groups of participants—we attempted to triangulate around the concept of cultural exposure in two different ways. The first was in terms of the amount of communication between the two nations. We operationally defined this in terms of the volume of telephone traffic that flowed between the two nations. These telephone data are published by large-scale business clearinghouses that track the directional flow of calls due to the need for the telephone company that originates the call to reimburse funds to the telephone company that connects the call in the second country. On an interesting note, we attempted to do the same thing for postal mail, but learned that these data are kept secret by national postal departments in an attempt to prevent third parties from entering the market to send letters on the international routes with the highest volume. It is important to note that the research included in the meta-analysis largely pre-dated the Internet—today, there might be new tools to measure cross-cultural exposure, such as Facebook and Twitter, but cross-cultural exposure is also harder to identify in a world where communication flows outside of traditionally measurable boundaries. The second measure of cross-cultural exposure we used was the physical distance between nations. This measure was more of a proxy: We can assume that citizens have more contact with a physically nearby nation than a physically distant nation. This is, of course, an imperfect assumption. Another nation can be far away, but have excellent telecommunications and entertainment broadcasts that transmit far and wide—notably, the USA tends to have asymmetric cultural exposure because it exports television, movies, and music around the world. Other nations can be right next door, but have little cultural flow, notably when there are border wars or other diplomatic tension. It is reasonable to imagine that these two aspects of exposure are acting simultaneously: We have a smaller gap to overcome with our nearby neighbors, and when there is a gap, it is easier to overcome with greater exposure.

Another benefit of the large diversity of studies that were included in this meta-analysis is that it gave us the opportunity to begin to test some hypotheses about the origin and nature of these cultural differences. For example, we could examine how verbal language might influence the in-group advantage in nonverbal behavior. In doing so, we found that in-group advantage still existed across cultural groups that shared the same native language. This is important because perhaps otherwise the in-group advantage is merely an artifact of some kind. Further, we were able to look at the small number of studies that could start to disentangle the potential influence of actual culture versus visible ethnic group membership. Notably, there was in-group advantage in studies of facial expressions across members of Caucasian groups. This is crucial in beginning to distinguish the influence of in-group advantage and other-group bias, which is elaborated later in this chapter. If participants still show in-group advantage when there is no clear marker that the other person is foreign, then the cause must relate to their expression style rather than solely prejudice against out-group members. Even to the extent that individuals in these studies may have been able to detect that the facial expression was from an individual outside of their own cultural group (Marsh et al. 2003)—despite that person also being Caucasian—there was still a linear association in these studies between cultural exposure and decreased in-group advantage. We interpret this evidence to suggest that in-group advantage still exists when it cannot be explained away entirely in terms of other-group bias and return to this point in the discussion below.

In the decade since this meta-analysis, there has been mounting evidence for dialect theory, and this evidence has increasingly tested the specific theoretical mechanisms of dialect theory: namely, that there are culture-specific elements in expressive style and that familiarity with these culture-specific elements leads to greater accuracy. First, my colleagues and I used a novel methodology that linked the in-group advantage directly to differences in the appearance of expressions (Elfenbein et al. 2004). Collaborator Manas Mandal had created composite facial expressions based on the left and right hemispheres of a face—that is, he took one photograph and turned it into two pictures, one that showed the left side twice and one that showed the right side twice. This methodology provided a rare opportunity, in that it drew from research showing that the left hemisphere of the face tends to be more easily moved and intense in its display of emotional expressions, whereas the right hemisphere tends to be less easily moved. In a balanced 3x3 design testing photographs and judgments from Indian, Japanese, and American participants, we found greater in-group advantage when participants judged the left versus right hemisphere of the face. The only possible explanation for these findings was that in-group advantage was linked with emotional expression style. After all, this was a fully within-subjects design in which the left and right hemispheres were posed by the same people. This rules out many alternative explanations, such as posing ability, ethnic group differences in appearance, and possible ethnic bias in responding to the photographs. In another study, colleagues and I documented a link between expression style and in-group advantage with two samples of French-speaking participants, from the French province of Quebec, Canada, and the African nation of Gabon (Elfenbein et al. 2007). In this study, we documented accents by identifying the specific facial muscle movements that varied across the groups' posed expressions. Some emotions had essentially no difference in muscle movement style between the two groups, such as sadness, contempt, and serenity, whereas other emotions differed systematically, such as surprise, happiness, and anger. Crucially, when we took these same expressions and showed them to perceivers, there was greater in-group advantage for the emotions that had shown greater cultural differences in expression style. These two studies together provide support for the notion that in-group advantage results from cultural differences in emotional expression style.

Other researchers have also continued to study cultural differences in emotion recognition and have increased the body of evidence in favor of the dialect theory. These studies include balanced designs in which the same cultural groups serve as both expressers and perceives—in which in-group advantage was documented among Americans and Japanese viewing facial expressions (Dailey et al. 2010), Americans and Namibian villagers judging nonlinguistic vocalizations (Sauter et al. 2010), and European and Asian Americans viewing full-channel videos of spontaneous emotions (Kang and Lau 2013). Other studies showed in-group advantage for African students in the USA judging facial expressions and vocal tones (Wickline et al. 2009), English, German, Arabic, and Spanish speakers judging nonsense syllables from Spain (Pell et al. 2009), speakers of English, German, Chinese, Japanese, and Tagalog judging voices from the USA (Thompson and Balkwill 2006), and Japanese, Sri Lankans, and Americans judging Japanese postures (Kleinsmith et al. 2006).

In addition to increasing the evidence for in-group advantage itself, other recent studies have provided evidence for the key theoretical mechanisms behind the dialect theory. In support of the notion that subtle differences in expression style make out-group members less accurate, Kleinsmith et al. (2006) found that perceivers judging static postures in Japan, Sri Lanka, and the USA used different cues in making their judgments. Bringing a novel design into this area, Dailey et al. (2010) modeled the conditions that reproduce in-group advantage using a neural network that imitated the receptive fields in the visual cortex that "learn" how to represent objects visually. They were able to train the neural network with stimulus material from the USA or Japan. When they used training stimuli that were culturally normative for these two different cultures, the neural network developed slightly different visual representations.

In considering the potential value of this research stream outside of academia, there has also been applied use of the insights from dialect theory. Notably, Pinkham et al. (2008) studied emotional impairment in schizophrenics. In the past, studies found that there was greater emotional impairment for African American versus Caucasian schizophrenics, which was a concerning finding that researchers attempted to explain. When Pinkham and colleagues tested both ethnic groups with stimulus material that originated from both ethnic groups, they found that this observation no longer held. This means that the African American participants in past research had been seen as more impaired when no such difference in impairment necessarily existed. This is an important issue for monitoring patients, and to the extent that measured impairments may influence opportunities for independent living among clinical populations, this could be an important issue potentially for social justice.

The majority of the research cited above uses emotional expressions that were deliberately posed, which has led some critics to speculate that in-group advantage exists only for poses (Matsumoto et al. 2009). However, there are exceptions and some research has used spontaneous expressions—and in the cases, researchers still find evidence for in-group advantage. One of these studies showed in-group advantage for judging spontaneous full-channel videos (Kang and Lau 2013), and another showed spontaneous anxiety during interracial interactions (Gray et al. 2008). As mentioned earlier, Elfenbein et al. (2004) found greater dialects in the more spontaneous versus posed side of the face.

Taken together, the body of evidence in favor of the dialect theory has been increasing over time and it has been increasingly precise with respect to the basic foundation of the theory: Members of different cultural groups express their emotions using subtly different styles, and it is easier to recognize emotions that have been expressed in a familiar style.

4.3 Other-Group Bias

Dialect theory is a theory about accuracy: People are trying equally to recognize emotional expressions from individuals from every cultural group, and they simply have less information when people are from other groups. This is an *information-based* explanation, because it is a matter we are not trying to behave differently toward people from other cultural groups, but can simply understand some people better than others. However, dialect theory does not tell the full picture of what differs when we attempt to judge emotional expressions from our own cultural in-group versus cultural out-groups. In addition to the information-based failures of recognition that occur due to lower familiarity with culture-specific nonverbal cues, there are also *motivation-based* explanations that can be considered a kind of bias.

This chapter discusses two different motivation-based explanations for cross-cultural emotion recognition accuracy: first, the normative processes of display and decoding rules, and second, differences in the attention levels that we may pay to in-group versus out-group members.

4.3.1 Display and Decoding Rules

In attempting to explain away the in-group advantage, the most prominent alternative account for cultural differences in emotional expression and recognition focuses on perceiver bias. Klineberg (1938) first discussed the possibility that people expressing their emotions can use *display rules*, which are norms for people to regulate deliberately the appearance of their expressions. For example, the norm at a funeral is to appear sad and the norm at a celebration is to appear joyful. Ekman (1972) expanded this concept and defined display rules as conscious management techniques to deintensify, intensify, neutralize, and/or mask displays with qualitatively different displays. Ekman went so far as to argue that members of each culture would express their emotions in exactly the same way if some people were not constantly monitoring themselves and adjusting their displays to fit social norms. Taken to the extreme, using the dialect metaphor, this suggests that Americans would always sound British if they were not monitoring themselves at every moment with conscious techniques to hide their true style. Although the concept of display rules is universal, in that all cultural groups presumably have norms about which emotions should be displayed in which situations, Ekman (1972) emphasized that display rules are more pervasive and intense among individuals from interdependent cultures that emphasize social harmony.

Centuries of research from anthropologists supports the general concept that norms influence how we present ourselves in ongoing social interaction. Interestingly, the concept of emotion display rules has been discussed so pervasively and described across so many introductory psychology textbooks that it is not usually apparent how little empirical data support the appearance of display rules in laboratory settings outside of bona fide interpersonal interaction. This may seem like a merely technical point—that is, whether display rules can influence people in the laboratory versus real life—but the issue at stake is whether display rules are a potentially valid explanation for the in-group advantage that has been observed in the body of studies described earlier in this chapter. When one scratches the surface of the data, as Fridlund (1994) did in his landmark book, the results are surprising. Ekman (1972) grounded this discussion of display rules in a summary of Friesen's unpublished dissertation, in which Japanese participants purportedly masked their facial displays in the presence of an observer, while American participants did not. This has become a classic citation, although researchers cite Ekman's (1972) description of the work, rather than citing the work itself. Fridlund (1994) obtained a copy of the actual unpublished thesis and found that Ekman's summary was incomplete, notably in that there was an additional condition Ekman did not report.

From the description of display rules here, it should be clear that display rules and dialects can coexist alongside each other. Using a linguistic metaphor, there is no reason why we cannot both speak a different dialect and also take care to say the most socially appropriate words.

Decoding rules are the flip side of display rules—just as people might use conscious management techniques to display the most appropriate emotional expression, they might use conscious techniques to influence the way they perceive other people's expressions (Matsumoto, 1989). The idea of decoding rules is that we follow norms for what we should perceive—this can perhaps be described a "see-no-evil" approach to witnessing other people's emotional displays. Again, the distinction between decoding rules and dialect theory is that decoding rules are a matter of active deception. When using decoding rules, the perceiver actually does understand the expression as it was displayed, but the perceiver consciously puts aside this understanding and pretends that the expression was something else.

As with the description of display rules, it should be clear that decoding rules and dialects can coexist alongside each other. Using a linguistic metaphor, there is no reason why we cannot both speak a different dialect and also take care to ignore other people's words when that is the best strategy. According to dialect theory, cultural differences in recognition can still emerge when people are trying to be as perceptive as possible. People can be tripped up by differences in the styles of expressions from cultural out-groups without necessarily making a deliberate attempt to ignore someone else's emotions.

In this case, when they can coexist on theoretical terms, why have the two sets of phenomena been discussed in opposition? The reason is the inaccurate claim that display and decoding rules alone can explain away the body of findings on in-group advantage (Matsumoto 2002). In attempting to explain the cultural differences in Ekman's (1972) and Izard's (1971) studies, Matsumoto has argued that Americans are simply more effective at recognizing emotions, purportedly because Americans do not suppress their true understanding of emotional displays. One source of support he cites is his work with language (Matsumoto and Assar 1992), in which participants from India who were bilingual in English and Hindi performed better in a test of emotion recognition when they took the test in English. Their explanation was that the Hindi language is less suited to engage with these specific emotional categories and that being primed with an Indian cultural frame leads people to use decoding rules that reduce their ability to recognize emotional expressions. However, an alternative explanation that would be consistent with dialect theory is that being primed with an Indian cultural frame could make more accessible the nonverbal cues that are specific to the Indian nonverbal dialect.

Taken together, the theories of display rules and decoding rules are important sources of bias in the production and recognition of facial expressions. They form complementary perspectives to the dialect theory, rather than alternatives—even if they have sometimes been offered as alternatives erroneously in the literature.

4.3.2 Attention to Out-Group Members

A second motivation-based explanation for cross-cultural differences in emotion recognition is the likelihood that we pay greater attention to the emotions of our cultural in-group members. After all, communicating via emotion allows us to coordinate social activities for the sake of group living (for detailed discussions of the social functions of emotions, see, e.g., Frijda 1986; Van Kleef et al. 2010)—in which case, the emotions of our immediate social groups should be the most relevant to us. This is not to say that an opposing hypothesis is not plausible, particularly for those emotional states that might indicate challenges to group living such as navigating the fight-or-flight instincts via anger, fear, and pride, for which we may pay greater attention to members of our out-groups. Even so, in general, one might expect that in-group members would enjoy particular attention to their facial expressions and what meaning can be gleaned from them.

For this type of attentional bias to apply, it requires a mechanism: Do we even know always who is our in-group member? In daily life, this might seem like an odd question, but as discussed above, the bulk of the data comes from laboratory studies. In a typical study, the research participants serving as perceivers sit in front of a photograph on paper or a computer screen, view the facial expression, and respond with a multiple-choice judgment of what emotion was intended. No information is offered about the person they are judging—who they are, the situation at the time they are posing, whether they are posing deliberately, etc. Facial expressions do provide clues about a person's cultural group membership such as their ethnicity, but these are imperfect clues, particularly in light of centuries-old histories of cross-border immigration. My colleagues and I (Marsh et al. 2003) developed the concept of nonverbal accents, as described above, in order to articulate that perceivers can also use facial expressions to determine a person's cultural background, regardless of their apparent race. While preparing the 2002 meta-analysis described above, I noticed that the brochure for Matsumoto and Ekman's (1988) collection of Japanese and Caucasian facial expressions included a combination of Japanese and Japanese Americans. At first, this was a nuisance, in the sense that my goal was to code the data, which involved cataloging the cultural group of each expresser and each perceiver in a large pool of existing studies. Under the circumstances, having a set of studies in which two expresser cultural groups were mixed together was going to create extra work for this coding endeavor. One can imagine that a doctoral student would not be delighted by this.

David Matsumoto was kind enough to provide the list of which photographs came from which cultural origin, and this issue shifted from being a nuisance to an object of fascination: Collaborator Abby Marsh and I found that we could tell the Japanese apart from the Japanese Americans when we tested ourselves. We could not always "put our finger" on the reason why, but on an informal basis, we felt relatively confident that some photographs just did not seem "American" to us. These were ideal stimuli to test the notion that cultural group membership leaves a trace on our style of expressing emotion—that is, an accent. Because these stimuli were developed with the goal of having experimenter control on every dimension possible, many alternative explanations could be eliminated. These stimuli used the same lighting, the same clothing, similarly aged undergraduate student samples, etc. Indeed, the developers instructed participants exactly how to move their facial muscles, so that the emotional expressions themselves should be the same in every way other than the apparent cultural background of the poser. When we tested participants the way that we had tested ourselves—that is, to see whether they could identify the Japanese versus Japanese American ethnic origin of each photograph—participants could do this at accuracy levels better than chance guessing. Intriguingly, when we presented participants with the neutral photographs of the same targets, they were no longer accurate at detecting cultural group membership. Importantly, this observation eliminates alternative explanations such as dental health, hair style, skin care, or other possible influences on facial appearance. This suggests that it was the emotional expression itself that provided information about an individual's cultural group membership. We argue that our data provide strong evidence that there are detectable nonverbal accents: Even in a set of facial expressions for which researchers attempted to dampen every possible cultural difference in appearance, these cultural differences still leaked through.

Knowing that people can detect the cultural group membership of a person who is expressing their emotions, do we find that this always matters? Not necessarily. Returning to the large body of work reviewed in the 2002 meta-analysis described above, it is noteworthy that in-group advantage often disappeared when members of different cultural groups were somehow instructed to express their emotions using the same style. Such stimuli were developed in one of two ways. First, some researchers collected photographs by instructing members of different cultural groups to imitate the expressions in other photographs that the researchers provided. Second, some researchers—like Matsumoto—collected photographs by instructing members of different cultural groups to move their facial muscles in a particular pattern. We likened these types of designs as using a "cultural eraser" (Elfenbein and Ambady 2002a, p. 244). This is akin to asking British people to speak in exactly the same manner as Americans, and then finding out that Americans can understand both groups equally well. In these culturally erased studies, there was often little or no in-group advantage. The lack of in-group advantage in culturally erased studies has contributed to replicate over the years (Beaupre and Hess 2005, 2006; Kang and Lau 2013; Lee et al. 2005; Matsumoto et al. 2009; Tracy and Robins 2008)—consistent with the notion that forcing stimuli to have exactly the same appearance eliminates the cultural dialects that are at the heart of dialect theory. Indeed, in our study with Gabonese and Quebecois described above (Elfenbein et al. 2007), we had two different within-subjects conditions in the judgment study: a set of stimuli that contained dialects and a set of stimuli that had been culturally erased. The in-group advantage replicated with the dialect stimuli, but not with the culturally erased stimuli.

However, some researchers have found in-group advantage with culturally erased stimuli (e.g., van der Schalk et al. 2011). These findings have included specific and persuasive demonstrations of bias: Young and Hugenberg (2010) used minimal groups and Thibault et al. (2006) used false feedback about the group membership of the people in the stimulus materials. In these cases, it seems likely that participants paid greater attention to the emotions of individuals they believed to be members of their own cultural in-groups. Even so, attention itself has never been tested directly as the mechanism for such an effect—an important inconsistency between theorizing and the data that can support this theorizing. That is, we see there is lower accuracy in these cases but it is speculation that the lower accuracy results from lower attention. Decoding rules—the other motivation-based account—could equally explain these results. Perhaps people pay the same amount of attention, but differences in the stages of information processing or decisions about what judgment responses to record could contribute to lower accuracy. Future research could use eye-tracking or other methods to measure attention more directly than to infer differences in attention due to differences in accuracy.

4.4 When Should We Expect Information-Based Versus Motivation-Based Effects?

As the treatment above emphasizes, information-based influences such as dialect theory and motivation-based influences such as decoding rules and greater attention to in-group members can all exist alongside each other. These influences do not act in opposition to each other, but rather they act independently side by side. It may be possible in future research to develop an understanding for when to expect either or both types of influences. In doing so, it is worthwhile to continue reviving attention to Bühler's (1934/1990) Organon model (Scherer 1988) that outlines three distinct functions for emotional expressions. First, the "push" function in the Organon model is that expressions are symptoms of internal states. This is consistent with Ekman's (1972) neuro-cultural theory argument that individuals' faces read out their emotional experiences at all times except when they are consciously managing those facial expressions via display rules. The extreme version of notion has been considered problematic both for its lack of parsimony with respect to requiring the constant management of displays and for its lack of fit with data on actual expressiveness (Fridlund 1991; Parkinson 2005). However, the less extreme version of this statement is that sometimes our internal states push out into our expressive behavior—this is not a controversial statement when it is qualified as not occurring at every moment. Second, the "pull" function is that expressions are used as signals to produce a reaction in others (see also

Fridlund 1994; Owren and Rendall 2001). Third, the "symbolic" function is that expressions represent objects or events, similar to linguistic expressions. These different functions are not mutually exclusive. These functions can even reinforce each other over time—indeed, one would expect this, in that simple reflexes could produce reliable signals that later become used deliberately for communication (Russell et al. 2003). This model can assist in theorizing about cultural differences in emotion recognition.

To the question of when might we expect each type of influence to hold, one could speculate that information-based influences could be greatest for the second and third functions, which correspond more closely to the linguistic metaphor that is at the heart of dialect theory. In the case of emotional expressions produced as a part of "push" functions, these more biologically based expressions might be expected to show fewer elements of culturally specific emotion style. As a result, with a less culturally specific style, there should be less in-group advantage in recognizing that style. However, motivation-based influences might act similarly across the three distinct functions—to the extent that these motivation-based explanations rest on the perceiver herself, rather than resting on cultural differences in the stimuli. This relatively similar influence of motivation-based accounts across the three functions may not be the case, however, if the perceiver is able to identify which of the three functions is operating. In that case, people should be particularly motivated to recognize the pull functions, to the extent that these are appeals to someone more likely to be concerned with such appeals. All of these predictions are merely speculation and await further development and testing.

4.5 Turning Cross-Cultural Misunderstanding into Cross-Cultural Understanding

It is easy to become pessimistic about research findings that show cultural differences. We live in an increasingly multicultural world, and it is impossible to live a full and complete life without interacting on a daily basis with individuals from all kinds of backgrounds. It is important to be able to recognize other people's emotional expressions (Elfenbein et al. 2002) for the sake of healthy and productive interaction. Given that people tend to be less accurate at recognizing emotional expressions from members of foreign cultural groups, what can we do?

In the case of motivation-based accounts, it is challenging to find a simple way to intervene. Our norms about how to manage our emotions are so ingrained and over-learned that there is no clear quick fix. Developing positive attitudes toward members of other groups can help, and one recalls Allport's (1954) classic *contact hypothesis*, which enumerates conditions that can contribute toward improvement in inter-group relations.

In the case of information-based accounts, the situation is more reassuring. Given that the cross-cultural challenge is a simple lack of information, it can be overcome by providing that information. This is as simple as increasing cross-cultural exposure. Recall that the in-group advantage was lower in samples that were more physically nearby or that had greater cross-cultural communication (Elfenbein and Ambady 2002b). Other research has shown that individuals who move to a host culture quickly learn to recognize the emotions from that host culture as well as they understand the emotional expressions of their own cultural group (Elfenbein and Ambady 2003). In a training program that tested people of Chinese and European backgrounds with stimuli from China and the USA, after providing feedback about correct answers, participants in the post-training condition showed no apparent in-group advantage (Elfenbein 2006). As such, in-group advantage that results from a knowledge-based mechanism is easier to correct. These findings suggest that greater cross-cultural exposure can help to pave the way for healthy relationships in our increasingly global and multicultural societies that depend on these relationships to thrive.

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Chapter 5
Asymmetry of Facial Expressions of Emotion

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5.1 Introduction

The human face has traditionally been the primary way humans communicate emotion and inner feelings. Facial expressions of emotion are universal among human populations (Ekman 1999) and have provided a critical method of nonverbal communication that has served as an evolutionary adaptive behavior (Waller et al. 2008). These behaviors include the facilitation of social interaction, group bonding, and appropriate responses to others, such as mates, predators, and caregivers (e.g., Plutchik 2000; Waller et al. 2008). The human face is rich in communicative potential. Among the mammals, humans have the most extensively developed facial musculature (e.g., Roberts 1966). As such, in many cases, facial expressions of emotion are relatively easy to comprehend. It has been well documented that the basic facial emotions of sadness, happiness, surprise, anger, disgust, and fear are universally understood and expressed by all humankind.

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This evidence comes from cross-cultural examinations (e.g., Ekman 1999; Ekman et al.1969; Izard 1977), infant displays of facial expressions of emotion (e.g., Hauser 1996; Plutchik 2000), and facial expressions displayed by congenitally blind individuals (Cole et al. 1989). The term *emotion* has been described as a reaction to appropriately evocative stimuli that encompass cognitive appraisal, subjective experience, expressive behavior, physiological arousal, and goal-directed behavior (Borod 1993b; Borod et al. 2000, 2001; Plutchik 1984).

Asymmetry in facial emotional expression has been documented for over a century and has been interpreted as evidence of brain laterality since the late 1970s (e.g., Borod and Caron 1979). Facial asymmetry is defined as greater expression intensity or muscular involvement on one side of the face (i.e., "hemiface") as compared to the other side (e.g., Borod et al. 1997). As described in Borod and Koff (1984) and in Borod et al. (1997), the first mention of facial asymmetry during emotional expression appears to date back to Darwin (1890) who, in his 1872 discussion "Sneering and Defiance," noted that snarls (i.e., baring one's teeth or the canine tooth) and sneers (i.e., insincere [half] smiles indicative of defiance) seemed only to occur on one side of the face. In an attempt to understand this asymmetry in expression, Darwin asked four Australian natives to produce a sneer, in the absence of any eliciting stimuli. Two individuals could only sneer on the left side, and one individual could only sneer on the right side, while the fourth individual could not voluntarily produce a sneer.

Over 65 years later, researchers performed the first detailed study of facial asymmetry during emotional expression tasks (Lynn and Lynn 1938). In this seminal study, Lynn and Lynn (1938) introduced the term "facedness" to indicate which side of the face is dominant during facial expressions of emotion. For example, a person with left facedness is a person whose left hemiface is more expressive and intense during emotional expression. Interestingly, Lynn and Lynn (1938) coined the term "facedness" to correspond to the term for dominant hand use, "handedness." This corresponded well with their aim to examine facedness/handedness concordance or divergence and how it related to personality traits. Although research focusing on the relationship between facedness and personality traits has not been continued over the years, this body of work paved the way for future research on facial emotional asymmetry and brain laterality. Facial asymmetry was less researched during the 1950s and 1960s, but regained newfound interest and attention by researchers in the 1970s due to advances in technology and medicine

The modern era of systematic examination of facial expression in patients with lateralized brain damage (Buck and Duffy 1980; Ross and Mesulam 1979; see, also, Gainotti 1972; for a review of the early brain lesion literature, see Borod and Koff 1989) and healthy individuals began in the mid-to-late 1970s and very early 1980s (Borod and Caron 1979, 1980; Campbell 1978; Chaurasia and Goswami 1975; Ekman et al. 1981; Heller and Levy 1981; Sackeim and Gur 1978; Strauss and Kaplan 1980). The seemingly qualitative behavior of facial emotion is being studied in the laboratory using quantitative measures, such as the Facial Action Coding System (FACS) developed by Ekman and Friesen (1978). However, the study of lateralization of emotional facial expression has been dominated by three approaches: observation of patients with lateralized brain damage, assessment of asymmetry in whole faces of normal adults either by direct observation or through video recordings, and evaluation of unaltered photographed, composite, or chimeric faces.

The following chapter covers much of the current research to date on facial emotional asymmetry in terms of the prevailing theories (e.g., the right hemisphere hypothesis and the valence hypothesis). Special attention is paid to addressing consensus or discrepancies in the literature with regard to elicitation condition (i.e., posed vs. spontaneous), emotional valence (e.g., positive vs. negative), clinical populations (e.g., split-brain patients and stroke patients), age, gender, and methodological considerations. This chapter will conclude with suggestions for future research.

This chapter is based on and includes information about facial asymmetry studies from literature reviews and about neuropsychological approaches to theories of emotional processing from papers written over the past 35 years by Dr. Joan Borod and her colleagues.

5.2 How are Emotional Facial Expressions Captured and Studied?

There are a few ways to produce expressions of facial emotion stimuli that can be quantified by researchers or naïve raters. Studies of induced facial expression in normal adults have generally fallen into two categories: spontaneous expression and posed expression. Eliciting a posed emotional expression that is valid and reliable without running the risk of capturing an expression that does not actually portray the emotion of interest is a concern when utilizing this type of stimulus. Therefore, many researchers rely on validated sets of posed facial emotions that have been created using a standardized system. The most common and frequently used set of posed facial emotions is Ekman's *Pictures of Facial Affect* (Ekman and Friesen 1976). Alternatively, researchers can give oral commands indicating a specific emotion to be displayed. While this method risks ecological validity, there are notable exceptions discussed in the review of the literature below. See Borod and Koff (1990) for a detailed description of elicitation procedures for producing facial emotional expressions. For a methodological perspective on how to study facial emotional expression in terms of procedures with humans and brain laterality, see Borod and Koff (1990).

Spontaneous emotions have a bit more ecological validity as they occur naturally and are brought about via an eliciting stimulus (i.e., an emotional film, emotionally provocative slides, a comic strip, etc.) or can be elicited by recalling previously experienced emotional events (i.e., "Tell me about the saddest day of your life."). For procedures designed to elicit spontaneous facial emotional expression, see Borod et al. (1992), Malatesta and Izard (1984), and Montreys and Borod (1998). Studies investigating emotional facial expressions rely on posed and spontaneous expressions and, in some cases, can result in different experimental findings. Viewing a posed picture of a sad face can be very different from viewing a spontaneous emotional face in motion, either in person or via a video recording. Studies utilizing spontaneous facial emotions, as described above, need multiple, extensively trained raters to make facial ratings or comparisons and require high interrater agreement (Borod and Caron 1980; Borod et al. 1983).

Facial composite photographs may, in some ways, be viewed as a successor to the posed expression approach. The origins of this approach were with chimeric photographs that were presented to split-brain (i.e., commissurotomy) patients (Levy et al. 1972); also, see work by Heller and Levy (1981). For some studies of expressions of facial emotions, chimeric faces are created using photographs of posers demonstrating specific facial emotions; these photographs are divided vertically down the middle of the face. Each hemiface is then reproduced as a mirror image and combined with the original hemiface to form a full and perfectly symmetrical face. Variations on this include reversing the hemiface (i.e., creating a mirror image of the original photograph). Greater lateralized expressiveness may then be judged by having raters evaluate overall expressiveness for each doubled hemiface (e.g., original face vs. left–left face vs. right–right face). In numerous studies, left–left facial composites have been found to be more emotionally expressive for both positive and negative emotions as judged by naïve raters.

A major advantage of this technique is that it helps eliminate perceiver bias generated by the right hemisphere's well-established involvement in the perception of emotion (for a review of lateralization for emotion perception in healthy adults, see Borod et al. 2001). Specifically, the right hemisphere's preferential processing of facial emotion means that an observer would be more sensitive to emotional expression in their left hemispace (Borod et al. 1990; Levy et al. 1983; Moreno et al. 1990), which would be occupied by the subject's right hemiface, leading to greater sensitivity for expressions generated by the left hemisphere of the subject being observed. It also obviates any need for extensive training of naïve raters, generally used in these studies.

5.3 The Right Hemisphere Hypothesis of Facial Emotional Expression

The past four decades have since given rise to multiple theories of facial emotional expression. Two of the major hypotheses concerning the lateralization of emotion are the right hemisphere hypothesis and the valence hypothesis. The right hemisphere hypothesis proposes that the right hemisphere (RH) is specialized for the production and perception of emotion, regardless of valence (for reviews, see Borod 1992, 1996; Borod et al. 1998). Much of the current research supports the right hemisphere hypothesis, finding the left side of the face to be more emotionally expressive than the right side (e.g., Borod et al. 1988, 1997; Campbell 1978; Sackeim and Gur 1978; Sackeim et al. 1978).

In some of the earlier research utilizing tachistoscopic methodology with healthy individuals, several studies demonstrated left visual-field (right hemisphere) superiority for discriminating emotional faces among individuals without brain damage (Landis et al. 1979; Ley and Bryden 1979; McKeever and Dixon 1981). Yet, studies using posed faces have yielded conflicting results. While judging the lower face in posed facial emotional expressions, several studies found that the lower left hemiface was perceived as more expressive for negative emotions as compared to the lower right hemiface (Borod and Caron 1980; Koff et al. 1983; Moreno et al. 1990). While these results do support the RH hypothesis, the evidence is mixed. For example, using both posed and spontaneous expressions, Wylie and Goodale (1988) found that the left side of the mouth moved more during spontaneous compared to posed expression. This finding may suggest that spontaneous emotions are more realistic/genuine, therefore, demonstrating an RH bias as compared to what occurs for posed emotions.

However, more recently, some interesting techniques have been used to capture and analyze the posed face. In a study by Nicholls et al. (2004), researchers were able to capture "posers" (i.e., the facial expression producer) digitally while they posed intense facial expressions of happiness and sadness and also produced a neutral expression. No eliciting stimulus was given to drive the emotion the posers were asked to express; they were just told to produce the most intense expressions they could. The researchers found that both the sad and happy expressions had greater movement in the left hemiface. These judgments were not made by raters but by specialized computer software that captured and digitized the face and head in 3 dimensions (3-D). This program could then digitally detect which hemiface displayed greater movement.

5.4 The Right Hemisphere Hypothesis: Studying Spontaneous Facial Expressions of Emotion in Healthy Adults

For spontaneous facial expressions of emotion in the lower face, Brockmeier and Ulrich (1993) and Borod et al. (1983) found that the lower left hemiface, compared to the lower right hemiface, exhibited greater expressiveness for negative emotions. In addition, positive facial emotions were found to be consistently more expressive on the left side of the lower face in four different studies (Borod et al. 1983 [for male subjects]; Chaurasia and Goswami 1975; Wyler et al. 1987; Wylie and Goodale 1988). In contrast, Brockmeier and Ulrich (1993) found the lower right hemiface to be more expressive than the lower left hemiface. However, no differences in lower face expressivity were observed in two of the studies reviewed (Ekman et al. 1981; Remillard et al. 1977).

Whole face examinations of spontaneous emotional expressions provide the most mixed results. In a literature review by Borod et al. (1997), whereas negative emotions were found to be lateralized to the left hemiface in four studies

(Dopson 1984; Moscovitch and Olds 1982; Schiff and MacDonald 1990; Wemple et al. 1986), no lateralized difference was found in three other studies reviewed (Cacioppo and Petty 1981; Ekman et al. 1981; Monserrat 1985). Positive emotions were lateralized to the left hemiface in three studies (Dopson 1984; Monserrat 1985; Moscovitch and Olds 1982), whereas no differences in facial expressivity for positive emotions were found by Hager and Ekman (1985), Lynn and Lynn (1938), and Sackeim and Gur (1978). Also, using spontaneous emotional expressions, Schiff and MacDonald (1990) found that the right hemiface was significantly more expressive than the left hemiface.

5.5 The Right Hemisphere Hypothesis: Evidence from Composite Faces in Healthy Adults

Results from composite face studies more consistently support the RH hypothesis than the valence hypothesis. In a review by Borod et al. (2001), six of seven studies that examined both positive and negative emotions reported greater emotional expressivity for facial composites of left–left than right–right hemifaces (Asthana and Mandal 1997, 1998; Braun et al. 1987; Mandal et al. 1993, 1995; Moreno et al. 1990). Heller and Levy (1981) reported a similar finding but only examined one positive emotion. By contrast, one study found greater expressivity for positive emotions in the right–right composite faces (Brockmeier and Ulrich 1993). Of note, this study used only a single rater, whereas the other studies utilized multiple raters. Also, Brockmeier and Ulrich (1993) used “mouth deviation” as their outcome measure of facial asymmetry.

Interesting results have been found when three-dimensional faces are viewed. Indersmitten and Gur (2003) found that 3-D chimeric left–left faces were viewed as more emotionally intense as compared to 3-D right–right chimeric faces. Another study (Bourne 2011) investigated the effect of hemispheric lateralization for inverted chimeric faces. It is commonly accepted that the right hemisphere is specialized for gestalt processing or recognizing an image as a whole, whereas the left hemisphere processes information in more of a componential manner. In the study by Bourne (2011), chimeric faces expressing anger, disgust, fear, happiness, sadness, or surprise were presented in either an upright or an inverted orientation. When presented upright, a significant RH bias was found for all six emotions. However, when inverted, a significant left hemisphere bias was found for the processing of happiness and surprise, but not for the processing of negative emotions. These findings support the right hemisphere hypothesis and further elucidate that each hemisphere processes emotional faces differentially.

For comprehensive reviews of facial asymmetry literature in healthy adults, see Borod and Koff (1984, 1989), Borod (1993a), Borod et al. (1997, 1998, 2001), and Assuras et al. (2005).

5.6 The Right Hemisphere Hypothesis: Evidence from Brain-Damaged Individuals

Some of the most compelling support for the RH hypothesis, in terms of facial emotional expression, has come from studies using unilateral brain-damaged populations. Among three studies using right brain-damaged (RBD), left brain-damaged (LBD), and healthy control participants, researchers found greater expressiveness for both positive and negative emotions in the LBD participants (Borod et al. 1988; Buck and Duffy 1980). This demonstrates that facial emotions, regardless of valence, were more expressive when the RH was spared. Two studies examining the role of positive emotions on facial expression and lateral dominance (Blonder et al. 1993, 2005) found greater expressiveness among individuals with left hemisphere (LH) brain damage. It is important to note that the studies mentioned above requested posers to recount previously experienced emotional events or emotional monologues. Trained raters, naïve to the study conditions, then rated the video segments for emotional expressivity in the face. For a detailed description of elicitation and rating procedures for emotional, as well as nonemotional, monologues, see the New York Emotion Battery (Borod et al. 1992).

However, not all studies support a right-hemisphere advantage for facial emotional expression. For example, in a study by Mammucari et al. (1988), researchers did not find differences between RBD and LBD groups in facial expressiveness; however, they found both lesion groups to be less expressive than normal controls for negative emotions only, when facial expressions were evaluated using FACS (Facial Action Coding System; Ekman and Friesen 1978). It should be noted that in this study, posers expressed emotions alone in a room while being video-recorded. However, in the studies mentioned in the previous paragraph, posers were in a room with another individual and a camera during emotion recollection. The discrepant findings between these two sets of studies could be due to the fact that the posers were alone in the second set. This is not as externally valid if one is interested in the social display of emotions as recounting an emotional event to another individual, but could elicit private emotion more effectively, which is considered to be closer to genuine emotion.

Earlier studies have also been able to show that asymmetries are more likely to occur in the presence of an observer or when the subject knows that he or she is being watched (e.g., Buck 1984; Hager and Ekman 1985). Of the above-mentioned studies, nearly all used right-handed individuals, but this may not be true for the Mammucari et al. (1988) study where handedness information is not provided. In another study using FACS (Ekman and Friesen 1978) to quantify the muscle movements of the face, Weddell et al. (1988) found that both RBD and LBD patients were less facially expressive while performing a neuropsychological card sorting task as compared to healthy controls.

In a similar vein, studies that have examined the accuracy of identifying facial emotions (e.g., Borod et al. 1986; Mandal et al. 1999; for a review, see Borod et al. 2002) found patients with RBD to be less accurate in identifying facial emotional expressions as compared to the LBD patients or healthy controls. This supports the idea that facial emotions (i.e., both expressive and receptive) are lateralized to the RH.

In epileptic populations, the Wada test (intracarotid sodium amobarbital procedure) has been able to provide researchers a unique window into elucidating the lateralization of emotion and mood. By individually inactivating each hemisphere of the brain, researchers can observe each participant's emotional state or expression while selectively "knocking out" the function of the left or right hemisphere during a variety of experimental tasks. Kolb and Milner (1981) took advantage of this phenomenon and compared facial expressions resulting from RH versus LH injections. Using the FACS method of measurement (Ekman and Friesen 1978), Kolb and Milner (1981) did not find a difference in the degree of facial expressivity between RH and LH inactivations. More recently, in a review of the literature on the Wada test and emotion laterality (Trimble 2010), a majority of the studies indicated that inactivating the RH frequently leads to a feeling of euphoria (among other behaviors); however, there is no clear pattern of emotion experienced with LH inactivation. Whereas some studies mentioned in that review found that LH inactivation led to feelings of depression and despair, this phenomenon was not seen in the majority of studies. This area of research is relatively rare, in part, because the Wada test is typically performed on presurgical epilepsy patients. As such, generalizations to the general population are difficult, due to disease state (i.e., epilepsy) and the inherent mood-altering nature of sodium amobarbital.

Experimental outcomes and anecdotal observations from Wada testing are seemingly inconsistent with other lesion research, as the euphoria often seen with right hemisphere inactivation is in contrast to the relative lack of positive emotional expression seen in patients with RH lesions. One possible explanation for this would be that it is a result of disorientation, considering the patient is receiving a powerful dose of an intoxicating and anesthetic drug. Further, when the right hemisphere is injected, certain perceptual distortions are likely to occur, such as unilateral visual neglect (Ahern et al. 1998).

5.7 The Valence Hypothesis of Facial Expression of Emotion

The valence hypothesis pertaining to emotional expression has undergone minor conceptual changes over the years as new research has emerged. Early clinical observations of brain-damaged patients (Jackson 1880; Mills 1912) noted differences in emotional dysfunction dependent on the side of the lesion. Later case studies (Goldstein 1952; Hecaen 1962) reinforced the idea that emotional function was related to the right cerebral hemisphere. Gainotti (1972), however, noted that patients with RH damage could often be indifferent, euphoric, or anosognosic, whereas those with LH damage might catastrophize or be depressed.

One of the earliest descriptions of the valence hypothesis (Silberman and Weingartner 1986) considered the LH to be specialized for the perception and expression of positive emotions and the RH for negative emotions. A variation of that hypothesis, according to Borod (1992, 1996), posited that the RH is specialized for the perception of emotions of both valences, whereas both hemispheres are responsible for experiencing and expressing emotion as a function of valence (Bryden 1982; Davidson 1984; Ehrlichman 1987; Hirschman and Safer 1982; Sackeim et al. 1982). Another conceptualization is that both hemispheres process emotion but that each hemisphere is specialized for particular types of emotion, particularly in the anterior cerebral cortex (Davidson et al. 1990). A majority of the literature on the valence hypothesis suggests that the LH is dominant for positive emotions and that the RH is dominant for negative emotions (Davidson 1992; Gur et al. 1994; Starkstein and Robinson 1988; Sackeim et al. 1978). For a discussion of potential mechanisms, both psychological and neuroanatomical, underlying the valence and right hemisphere hypotheses, see Borod (1992, 1996, 2000) and Borod et al. (1998).

Using EEG, Davidson and colleagues (1990) found that the traditional dichotomy of the valence hypothesis (e.g., the LH is dominant for positive emotions and the RH is dominant for negative emotions) did not hold true when analyzing neural activations during the experience of various emotions. Based on these data, Davidson et al. (1990) conceptualized the LH as involved in approach emotions (e.g., happiness) and the RH in withdrawal emotions (e.g., disgust). Although this conceptualization overlaps substantially with the idea that positive emotions are processed in the LH and negative emotions in the RH, Davidson's theory (1990, 1992) considers the emotion of "anger" (i.e., a negative emotion) to be LH dominant. Other EEG experiments have provided additional support that positive and negative emotions are differentially lateralized, especially in the frontal cortex (e.g., Davidson and Fox 1982; Tucker et al. 1981). Somewhat later, Davidson et al. (Davidson 1993, 1998; Davidson and Sutton 1995) proposed that lateralization, particularly in the anterior frontal cortex, may depend on either personality traits or transient mood (e.g., Tomarken et al. 1992). As stated, both valence and approach/withdrawal dimensions have been used to conceptualize the valence hypothesis. The aforementioned studies tend to support the approach/withdrawal conceptualization of valence-dependent laterality, although the evidence supporting the valence lateralization hypothesis is still debated. For example, in another set of EEG studies, several groups of investigators failed to demonstrate valence-dependent lateralization (e.g., Collet and Duclaux 1987; Gotlib et al. 1998; Hagemann et al. 1998; Reid et al. 1998). Additionally, lesion data have not always supported the hypothesis (for a review, see Borod et al. 2002).

In a review of the literature by Borod et al. (1997), only two studies were found that used EMG recordings in place of visual observations for measuring facial activity (Schwartz et al. 1979; Sirota and Schwartz 1982). Both studies recorded activity in the zygomatic muscle on each hemiface. Both found no lateral differences for either positive or negative emotions in posed expression. Both found greater right hemiface activity for spontaneous positive emotions, and one (Schwartz et al. 1979) found greater left than right hemiface activity for spontaneous negative emotions. A more recent study (Zhou and Hu 2004) found higher activation in the left than right facial musculature during negative emotions and greater activity in the corrugator than zygomatic muscle. In a follow-up study that examined positive emotion produced by posing happiness, the mean value of EMG activity in the left zygomatic muscle region was the highest, followed by the right zygomatic, left corrugator, and right corrugator muscle regions (Zhou and Hu 2006).

One study by Smith et al. (2006) used the approach of applying intracranial stimulation to specific cerebral locations. Presurgical epilepsy patients were stimulated with subdural electrodes across the cortex. Along with changes in facial expression, motor responses and patient reports of subjective feelings were recorded. Although the investigators did not report facial expressivity findings separately from dysphoria or motor responses, they found negative emotional responses of some type when stimulation was applied to the right mesial frontal, insular, and orbitofrontal areas. Positive emotional responses to stimulation at any site were extremely infrequent, as were responses of any type to left hemisphere stimulation.

Using the region of interest (ROI) method with fMRI, Beraha et al. (2012) compared left and right hemispheric functioning in terms of emotional face processing. They found LH, but not RH, region-specific lateralization during passive viewing of stimuli from the *International Affective Picture System (IAPS;* Lang et al. 1997). Specifically, their data showed that asymmetry was left-lateralized for negative stimulus processing in subcortical brain areas, in particular, the amygdala and uncus; however, activation to positive stimuli was bilateral in differing brain regions.

Further, Schiff and Lamon (1989) had subjects perform muscle contractions on each side of the mouth that replicated positive and negative emotions (e.g., smiling and frowning); subjects then reported what emotions they felt. In two of three conditions, they found that contractions on the right side of the face, reflecting predominantly left hemisphere innervation, led to reports of positive emotion. This finding, however, was not supported in two later studies by other investigators (Fogel and Harris 2001; Kop et al. 1991). In an interesting study by Nicholls and colleagues (2004), researchers found that when posed expressions were rotated by 35° so that the left hemiface was featured more than the right hemiface, the rotated left hemifaces were evaluated by human raters as more expressive of negative emotion (i.e., sadness), whereas the rotated right hemifaces were seen as more expressive of positive emotion (i.e., happiness), supporting the valence hypothesis. Of note, when the same hemifaces were analyzed for movement using computerized measurement, the left hemiface had significantly greater movement than the right hemiface, which actually provides support for the RH hypothesis. On the other hand, although the face side by emotion-type interaction was not significant ($p = 0.11$), post hoc analyses (on a theoretical basis) showed that the left hemiface moved significantly more than the right hemiface for the sadness emotion, whereas there were no differences between the left and right face sides for the happiness emotion—findings providing partial support for the valence hypothesis.

5.8 The Upper–Lower Facial Axis Theory of Emotional Expression

The left versus right hemiface distinction is not the only facial delineation noted in the literature. In the 1940s, research into the nature of facial emotion production was studied by comparing the upper versus the lower hemiface (e.g., Coleman 1949; Hanawalt 1944). More recently, Ross et al. (2007) have argued that emotional displays in the upper hemiface are preferentially processed by the right hemisphere, whereas the lower hemiface displays are processed by the left. See, also, Ross et al. (2013). This argument is related to the theory that the left hemisphere preferentially processes voluntary, social emotional displays, which are enacted by the lower hemiface (see Ross et al. 1994, 2007). Studies in which observations were restricted to the lower face were primarily intended to test the right hemisphere hypothesis, as the efferent nerves to the lower face are predominantly contralateral, whereas the muscles for the upper face are bilaterally innervated (for reviews, see Borod and Koff 1984; Morecraft et al. 2004).

One part of the argument is that social displays of emotion are mediated by the left hemisphere. The idea that facial expressions may be mixed or in conflict goes back to Darwin. Research has supported the existence of a social (also called "voluntary," "false," or "non-Duchenne") smile simultaneously with an unemotional upper face (e.g., Ekman 2003). Early lesion research (Buck and Duffy 1980) found that social display rules are impaired by LH lesions but not by RH lesions.

Research on split-brain patients by Gazzaniga and Smylie (1990) found that when patients were commanded to smile, the left side of the face lagged the right by 90–180 ms, implying that smile simultaneity (i.e., the lack of a lag time between hemifaces) in healthy individuals would be mediated by subsequent right-to-left transmission across the corpus callosum.

Asthana and Mandal (1997) asked healthy subjects to observe blended composites of upper and lower faces (i.e., each composite had two left lower faces and two right upper faces and the reverse) to compare to unchanged, reversed, and symmetrical faces. Using the emotions happiness and sadness, they found that symmetrical left lower faces provided the most expressiveness, supporting the RH hypothesis.

The amount of literature relevant to this hypothesis is somewhat limited. The theory that the LH may be involved in social displays seems uncontroversial but may reflect the navigation of social situations more than the expression of true emotion. Studies using clinical neurological populations have addressed left hemiface and right hemiface lateralization (e.g., Borod and Koff 1991), but, to our knowledge, have yet to address the upper face versus lower face distinctions in terms of brain lateralization.

5.9 Description of Table

The following Table 5.1 highlights much of the research mentioned in this chapter as a way to summarize a number of studies that have been carried out to date on facial asymmetry and/or hemispheric laterality during the expression of facial

Table 5.1 Summary of facial emotional expression studies

Study	Participants (posers)			Methods			Hemisphere advantage	
	Gender	Health status		Emotional valence	Expression elicitation	Stimulus evaluation	Pleasant emotions	Unpleasant emotions
		NH	UBD					
Asthana and Mandal (1996)	5 Male 5 Female	✓		P, U	Posed	Rated intensity	RH	RH
Asthana and Mandal (1997)	10 Male 8 Female	✓		P, U	Posed	Rated intensity	RH	RH
Asthana and Mandal (1998)	5 Male 5 Female	✓		P, U	Posed	Rated intensity	RH	RH
Blonder et al. (1993)	22 Male	✓	✓	P, U	Interview (natural conversation)	Rated expressiveness	RH	–
Blonder et al. (2005)	16 Male 7 Female		✓	P, U	Interview (conversational discourse)	Rated expressiveness	RH	–
Borod, Kent, Koff, Martin, and Alpert (1988)	16 Male	✓		P, U, N	Verbal command and visual imitation	Rated intensity	RH	RH
Borod et al. (1988)	43 Male	✓	✓	P, U	Spontaneous (slide presentation) and Posed (verbal command and visual imitation)	Rated responsivity Rated appropriateness Rated intensity	RH RH =	RH = =
Borod et al. (1990)	16 Male	✓		P, U	Verbal command	Rated intensity	RH	RH
Braun et al. (1987)	14 Male* 14 Female*	✓		P, U, N	Verbal command	Rated expressiveness	RH (multivariate analysis) = (binomial analysis)	RH =
Brockmeier and Ulrich (1993)	24 Male	✓		P, U	Mood induction, recollection, and imagination	Mouth deviation	LH	RH

(continued)

Table 5.1 (continued)

Study	Participants (posers)			Methods			Hemisphere advantage	
	Gender	Health status		Emotional valence	Expression elicitation	Stimulus evaluation	Pleasant emotions	Unpleasant emotions
		NH	UBD					
Davidson et al. (1990)	11 Female	✓		P, U, N	Short film clips	EEG	LH	RH
Ekman et al. (1981)	?? Male [a, HU] ?? Female [b, HU] 71 (total)	✓		P	Visual imitation and examiner provocation	FACS	RH (visual imitation) = (examiner provocation)	– –
Kowner (1995)	22 (total) [GU]	✓		P	Posed	Rated intensity	RH	–
Mammucari et al. (1988)	?? Male [HU] ?? Female [HU] 90 (total)	✓	✓	P, U, N	Spontaneous (short movie viewing)	FACS, Rated involvement, Rated intensity	=	=
Mandal and Singh (1990)	?? Male [HU]	✓		U	Posed	Rated accuracy	–	RH
Mandal et al. (1992)	5 Male 7 Female	✓		N	Neutral pose	Rated pleasantness	RH	–
Mandal et al. (1995)	?? Male [AU, HU] ?? Female [AU, HU]	✓		P, U	Posed	Rated expressiveness	LH (high intensity) RH (medium intensity) RH (low intensity)	LH = RH
Mandal et al. (1993)	?? [GU, HU]	✓		P, U	Posed	Rated intensity	RH	RH
Moreno et al. (1990)	90 Female	✓		P, U, N	Verbal command	Rated intensity	RH	RH
Sackeim and Grega (1987)	4 Male 4 Female	✓		P, U	Posed unilateral expression	Rated intensity	=	RH

(continued)

Table 5.1 (continued)

Study	Participants (posers)			Methods			Hemisphere advantage	
	Gender	Health status		Emotional valence	Expression elicitation	Stimulus evaluation	Pleasant emotions	Unpleasant emotions
		NH	UBD					
Schuetze and Reid (2005)	18 Male [c] 23 Female [c]	✓		P, U	Examiner provocation	Mouth asymmetry	=	RH (stronger RH bias at 24 months than 12 or 18 months)
Wyler et al. (1987)	23 Male 23 Female	✓		P	Cartoon viewing	Mouth asymmetry	RH	–
Wylie and Goodale (1988)	13 Male* 18 Female*	✓		P	Verbal command	Displacement of mouth corner	=	–
						Displacement of upper lip	LH (men) RH (women)	– –
	14 Male* 18 Female*	✓		P	Examiner provocation	Displacement of mouth corner and upper lip	RH	–

(continued)

Table 5.1 (continued)

Study	Participants (posers)			Methods			Hemisphere advantage	
	Gender	Health status		Emotional valence	Expression elicitation	Stimulus evaluation	Pleasant emotions	Unpleasant emotions
		NH	UBD					
Zhou and Hu (2004)	15 Male 25 Female	✓		P, U, N	Photograph viewing	EMG	RH	RH
Zhou and Hu (2006)	11 Male 26 Female	✓		P, U, N	Verbal command	EMG	RH	RH

Note All participants in each study were right-handed adults unless otherwise noted.
Note This table includes facial expression studies, some of which appear in Borod et al. (2001).
* Right handedness was not 100 %.
[a]All participants were children.
[b]Participants consisted of children and adults.
[c]Participants were either infants or toddlers, and 100 % of their parents were right-handed.
P Pleasant, *U* Unpleasant, *N* Neutral, *NH* Neurologically healthy, *UBD* Unilateral brain damage, *LH* Left hemisphere, *RH* Right hemisphere, = No significant hemisphere advantage. *??* Number of individuals not reported, *FACS* Facial Action Coding System (Ekman and Friesen 1978), *AU* Age information was unreported, *GU* Gender information was unreported, *HU* Handedness information was unreported.

emotion. In the table, for each study, one can see poser information, the valence expressed, elicitation and evaluation procedures, and hemispheric advantage.

5.10 Gender Differences in Facial Expressions of Emotion

There is little consensus in the literature regarding gender differences in facial asymmetry. Some studies have found no significant differences in facial asymmetry or brain lateralization between men and women, whereas others have reported significant gender differences with respect to emotional valence (Borod et al. 1986; Burton and Levy 1989; Bowers and LaBarba 1988; Crucian 1996; Hines et al. 1992; Russo 2000; Steele 1998; Witelson and Kigar 1988). Some studies have shown that female and male subjects process emotions differently. Women have been found to be more emotionally expressive than men (Grunwald et al. 1999; for a review, see Borod and Madigan 2000). Grossman and Wood (1993) note that this may be due to societal factors, whereas others support a more biological theory that women show stronger activations than men in limbic structures during tasks related to emotional expression (Wager et al. 2003). Levenson et al. (1991) studied emotional expression in old age and found no significant sex differences in facial expression, although elderly women reported more intense emotional experiences during this study than elderly men. Borod and Caron (1980) found that women were more lateralized for positive emotions and that men were more lateralized for negative emotions. By contrast, another study found that women showed increased facial asymmetry (i.e., greater lateralization) during sad expressions than did men (Asthana and Mandal 1998). However, many studies have reported that men show more lateralization of brain function than women (Bowers and LaBarba 1988; Crucian 1996; Hines et al. 1992; Russo et al. 2000; Steele 1998).

In an analysis of 33 studies comprehensively reviewed by Borod et al. (1998), they found no significant gender differences in 23 of the 33 (≈70 %) studies reviewed. Six studies showed that men were more left-faced (i.e., RH dominant) than women, and 4 studies showed that women displayed greater left-faced emotion as compared to men. The authors concluded that there were no significant gender differences with regard to facial emotion expression. In another review by Borod et al. (1997), 14 experiments did not display significant differences in facial asymmetry with regard to gender, and 7 experiments showed significant overall gender differences related to facial asymmetry; however, there were no systematic patterns. When gender and laterality have been assessed in infant populations, the same lack of a pattern has been found. Schuetze and Reid (2005) examined lateralization in 12-, 18-, and 24-month-old infants and did not find any gender differences in facial asymmetry for positive or negative emotional expressions.

In a study of 37 right-handed men and women (Borod et al. 1983), positive and negative emotions were elicited through two posed conditions (i.e., verbal and visual command) and one spontaneous condition (i.e., viewed emotionally provocative slides). The researchers found that the left hemiface moved significantly more than the right hemiface regardless of condition or gender.

In summary, the research on gender differences in facial asymmetry has not reached a solid consensus but seems to suggest no reliable sex differences.

5.11 Age and Facial Expressions of Emotion

At the present time, there is not much concurrence in the literature regarding aging and facial expression of emotion. Schuetze and Reid (2005) examined oral asymmetry in positive and negative facial expressions for 12-, 18- and 24-month-old full-term infants. Their results indicated that 24-month-old infants showed stronger left-faced oral (mouth movement) asymmetry during negative facial expressions than the 12- or 18-month-old infants. Although 12- and 18-month-old infants displayed distinct left-sided oral asymmetry for negative facial expressions, these asymmetries were significantly stronger by 24 months of age. No oral asymmetry patterns were detected for positive facial expressions for any of the infants. These results, although limited, provide some support for the right hemisphere hypothesis, indicating that these asymmetries may be present very early in life (Schuetze and Reid 2005). In order to interpret these results within the context of the valence hypothesis, which claims that the RH is associated with negative emotions and that the LH is dominant for positive emotions, one can speculate that lateralization of positive emotions, or left hemisphere emotional development, is delayed until after 2 years of age. The researchers noted that children begin developing complex negative emotions, such as shame and guilt, between 18 and 24 months of age, the same point where they found a significant increase in lateralization for negative expressions (Schuetze and Reid 2005).

In contrast, two studies have found greater LH (i.e., right hemiface) activation during emotional expression among infants within their first year of life (Best and Queen 1989; Rothbart et al. 1989). Moscovitch, Strauss, and Olds (1980) found an inconsistent right hemiface bias in 2–3-year-old children, and suggested that this age is likely a transitional period for facial emotional expression hemispheric specialization. This discrepancy suggests that emotional expression patterns and lateralization may change as the cortex matures.

Research shows that there is a decline in many RH-mediated functions as we age (Albert and Kaplan 1980; Borod and Goodglass 1980a; Borod et al. 2004; Brown and Jaffe 1975; Ellis et al. 1989; for a review, see Borod and Goodglass 1980b). According to the RH aging hypothesis, RH-related functions (e.g., facial asymmetry and expression) decline faster than activities mediated by the left hemisphere (Albert and Kaplan 1980). Moreno et al. (1990) tested the RH aging hypothesis by examining whether there were age-related changes in facial asymmetry in 30 young (21–39 years of age), 30 middle-aged (ages 40–59), and 30 elderly (ages 60–81) adult women. The researchers used trained raters to evaluate photographs of positive and negative posed facial expressions and found that all participants demonstrated left-sided facial asymmetry. Therefore, there were no significant lateralization differences as a function of age.

A more recent study by Magai et al. (2006) examined the intensity and duration of emotional expressions and found that young, middle-aged, and older adults did not differ in the intensity of spontaneous prompted facial expressions of surprise, joy, anger, sadness, contempt, disgust, fear, shame, or guilt. Older adults in this study reported that they experienced the emotion of interest with greater intensity than middle-aged and young adults. Facial expression duration differed between the age groups for shame, contempt, and joy, with younger adults expressing longer expressions of these emotions during their monologues.

The research in this area does not seem to reach a firm or consistent conclusion on how facial and emotional expression differ throughout the life span, with some studies reporting significant changes and others finding differences based on valence.

5.12 Nonhuman Primates

Primates have some of the most complex facial musculature of all the mammals and make the most intricate facial displays (Burrows 2008). A large body of research suggests that baboons, macaques, vervet monkeys, and chimpanzees routinely use facial expressions as a means of communication within their complex social environment, much like humans do. In fact, some facial features of nonhuman primates may be homologous to facial expressions in humans, such as laughing and smiling (Burrows 2008). As we have discussed in this chapter, human emotional displays of the face are, at least, in large part due to RH specialization. New research indicates that chimpanzees may also have an RH bias when it comes to facial displays of emotion. Through careful study, Fernández-Carriba et al. (2002) found that the facial expressions of play, silent bared-teeth, the scream face, and pant-hooting in chimpanzees all show greater mouth expressions on the left, as compared to the right, hemiface. These expressions are of both positive and negative valence and tend to accompany vocalizations, as well. It is clear that the right hemisphere plays a part in chimpanzee facial emotions or at a minimum, the lower half of the face. In a second study by the same researchers in the same year, they furthered their investigation by not only having naïve raters view chimeric chimpanzee faces (as was done in the study above) but by also measuring and quantifying the distance of expressions from midline of the face. These two variables could then be looked at separately or taken together. They found that humans judging the chimeric faces were just as good as the measurement techniques used when judging "play" and "silent bared-teeth." Again, the authors were able to demonstrate that silent bared-teeth and play were consistently asymmetrical toward the left on all measures of rater judgments and on all measurements taken. The lack of asymmetry for the other facial expressions was thought to be due to a small sample size.

Further, in a study investigating the vocal and expressive characteristics of the rhesus monkey, Hauser and Akre (2001) found that there is also a RH bias in facial expressions on the rhesus. In adults, the left side of the mouth and face is first to display a facial expression when adult rhesus monkeys are producing copulation grimaces, fear grimaces, lip smacks, and open-mouth threats. This study implicates the RH as possibly dominant for facial expression in the rhesus monkey, as well. The authors pointed out that this asymmetry was not valence-specific as both negative and positive expressions presented with left-sided activity before the right side of the face began to move. Of interest, this left side bias has also been reported for screeching in infant and adult baboons (Lindell 2013).

In sum, it appears that there is RH dominance in nonhuman primates; however, it remains to be seen, without further study and investigation, whether a valence-specific model can be applied. These findings suggest that the right hemisphere's specialization for the control of emotional expression must have emerged early in primate evolution. So far, the evidence is consistent with the human literature that suggests that functional lateralization of emotional facial displays may not be solely human but of the primate species.

5.13 Conclusions and Future Directions

Understanding the relationship between asymmetry of facial expressions and the lateralized brain is critical, because it can inform neuropsychological theory and answer discrepancies that remain in the emotion literature. There are some aspects we first must consider. Through what we have learned from studies with brain-damaged individuals and through clinical observations, the relationship between the expression of positive emotions and the right hemiface/left hemisphere has not been found as consistently as that between negative emotions and the left hemiface/right hemisphere. One problem may be that emotional expression in the face does not occur in isolation. More studies need to focus on facial emotion and body position (e.g., posture and gesture). An attempt should be made to maintain an atmosphere that mimics real-life social interactions in order to truly understand expressions of facial emotion. We live and interact in a three-dimensional social world, and more studies should focus on replicating a more natural environment for obtaining and recording the emotional expressions of both genders and all age groups. It may be possible that three-dimensional computerized facial imagery, such as that pioneered by Cohn and Kanade (e.g., Cohn et al. 1999), may be used to minimize human biases and error while capturing the face in motion. There is another factor to be considered in evaluating these studies. It has been pointed out (Etcoff 1986) that smiling is the easiest expression to consciously produce and is the most commonly invoked for social communication. This would suggest that the left hemisphere may have some involvement in intentional control of emotional expression, rather than positive emotions. This would be consonant with the high emotional reactivity seen in patients with Broca's aphasia (and left hemisphere damage in general; Gainotti 1972).

We are just beginning to understand the complexity of emotional functioning in the brain and how it relates to facial expressions of emotion. Despite there being an enormous number of imaging studies of lateralized brain activation in response to emotional stimuli, we are unaware of any such studies that measure activation as it relates to true (or genuine) facial emotional expression. More sophisticated imaging techniques and creative paradigms would help elucidate the underlying functional connectivity and neural network that mediate the expression of facial emotion.

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Chapter 6
Facial Expressions in Empathy Research

Christina Regenbogen and Ute Habel

6.1 Introduction

Every day, we experience a multitude of situations in which we infer more or less automatically, how people around us may be feeling. Some of them make it easy for us, verbally informing us by telling straight away whether they are in a good or bad spirit. With others, it is more subtle, they just 'look sad.' And even on the phone, a cheerful tone of voice may guide us to think that the person on the other end could be in a good mood. Yet, simply recognizing or 'knowing' about someone else's state of mind does not do it all. We have to experience to some extent the other person's feeling in order to be emotionally engaged ourselves, in order to feel some relevance to act upon. What happens when we do this? When we share the emotion of the other person and show a proactive and caring response to their happiness, sadness, anger, or surprise, this is called empathy. Empathy is a central construct in social cognition and is defined as the ability to recognize and adequately react emotionally to an affective message transferred by a human counterpart by sharing—to a certain degree—their emotion (de Vignemont and Singer 2006).

To study empathy and those subprocesses (e.g., emotion recognition) that eventually lead to a state of mutual understanding and social coherence, experiments can target those cues that transport emotions and that were mentioned above. The face is such an empathy cue and—being a central feature of a human being—facial

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expressions are relatively easy accessible to create experimental stimuli from. Whether in the shape of real-life photographs (Ekman and Friesen 1976), face symbols (Fox et al. 2000) or avatar creations (Moser et al. 2007), studies have used a multitude of facial aspects as stimulus material. The basic idea of these experiments is to study participants' responses to the exposure of such stimuli, e.g., as valence ratings, physiological responses, or brain activation and to characterize them as correlates of empathy. However, not all studies in which participants are exposed to facial stimuli targeted empathy explicitly, but focused more on *specific* aspects of it, such as emotion recognition. In order to keep the scope of this chapter on experiments that meet the definition of empathy, we will thus only briefly mention studies that target only aspects or components of the social construct.

We will first present different theoretical assumptions regarding empathy and then try to sketch out an overview consisting of experiments that explicitly included facial expressions as stimuli. We then introduce some of our own studies that targeted empathy with a more holistic approach, taking into account different components of empathy in a multileveled approach. We conclude by presenting work in which we created and applied ecologically valid naturalistic stimulus material of emotional and of neutral facial expressions and assessed empathy within a multimodal setup along with speech prosody and content.

6.2 Theoretical Considerations of Empathy

What is empathy in the first place and what role do facial expressions play more specifically?

Empathy, as a mental process, which is aimed at establishing social coherence, is heterogeneous (Batson 2009). As Batson states, at least eight different phenomena relate to a typical situation in which we may feel empathic, and therefore, all correspond to the various definitions of empathy. Without the claim for completeness, we will roughly cluster them into three groups: Definitions that lead to theories which (a) focus on emotional mirroring and shared representations and that include simulation aspects, that (b) highlight cognitive-oriented aspects based on perspective-taking as well as theory-theories of mind, either focusing on the imagination of being another person or imagining to be in the other person's situation, and lastly, theories that (c) focus on responses that are not necessarily isomorphic (such as pity in response to sadness rather than sadness itself), bordering on a conceptual overlap with sympathy.

Definitions within group (a), e.g., 'knowing another person's internal state' and 'posture or expression matching' are much influenced by research investigating the (human) mirror neuron system (hMNS). Its basic idea aims at tangling out the processes that become relevant when observing another person performing an action and it is based on revolutionary macaque monkey work by the Italian neuroscientists around di Pellegrino and colleagues (1992) and Rizzolatti and colleagues (1996) who found a premotor cortex neuron excitation to be shared by both, observing and executing actions. Developed further and in its current shape, the hMNS is proposed to underlie humans' ability to understand actions, but also beliefs and feelings by simulating aspects of the respective observed construct (for review please refer to Blakemore and Decety 2001; as well as Grezes and Decety 2001). This simulation aspect is also central in the multitude of 'perception-action models' of empathy that date back to the early works of Lipps (1903), who introduced empathy or 'Einfühlung' at the dawn of the twentieth century as a concept of intense feeling—not related to the self but another object.

An early theory within this framework that explicitly introduced to use facial expressions in the experimental setting to assess empathy was proposed by Meltzoff and colleagues by the Active Intermodal Mapping Hypothesis (AIM) (Meltzoff and Moore 1977) in which facial mapping was proposed to be based on intermodal mapping, i.e., matching-to-target behavior, originally carried out by infants interacting with their first bonding objects. This was already described by the social psychologist McDougall (1908). Preston and de Waal (2002) further developed the assumptions of the hMNS regarding empathy into a complex perception-action model. They proposed a shared neural network responsible for navigating in a physical environment that also helps us to navigate socially.

Group (b) composed of empathy definitions focusing on perspective-taking aspects which are needed to put onself into the shoes of the other person. They can be described as more general and cognitively driven in the concepts of mindreading, 'Theory-of-mind' (Frith and Frith 1999; Perner 1991) or mentalizing (Hooker et al. 2008) that cover cognitive aspects of perspective taking and processing of mental states. Hence, empathy was divided into a more emotional and a more cognitive part. Some authors even set 'Theory-of-mind' as equal to cognitive empathy. Others propose affective aspects of 'Theory-of-mind' to be *supportive of establishing* empathy (Hooker et al. 2008) such that people who use emotional information when inferring the mental states of others show higher empathy than those who do not use this information. A differentiation into more cognitive versus more emotional aspects of empathy can also be found on a neural level as recent neuroimaging studies (Fan et al. 2011) present activation networks, which are either consistently activated by affective-perceptive forms of empathy (e.g., right anterior insula, right dorsomedial thalamus, supplementary motor area, right anterior cingulate cortex, midbrain) or consistently activated by cognitive-evaluative forms of empathy (e.g., midcingulate cortex, orbitofrontal cortex, left dorsomedial thalamus) while the left anterior insula represents a shared neural region.

Lastly, group (c) definitions point to aspects of empathy that do not necessarily involve isomorphic feelings. This is sometimes translated with 'empathic concern' (Batson 1991) and is, regarding to some classifications (Preston et al. 2007), positioned toward a more basic response level of empathy, not involving matching of the emotional state. The latter group proposes this interesting classification system along the axes of 'self-other distinction,' 'state matching,' and 'helping' that enables yet another categorization in which the existing definitions and theories of empathy can be placed (Table 6.1).

Table 6.1 Overview on empathy terminology. Modified from Preston and de Waal (2002), with friendly permission from Cambridge University Press (license number 3243540864655)

Term	Definition	Self–other distinction?	State matching?	Helping?	Synonyms
Emotional contagion	Subject's state results from the perception of the object's state	No	Yes	None	Personal distress, vicarious emotion, emotional transfer
Sympathy	Subject feels 'sorry for' the object. Focused more on object's situation than physical state	Yes	No	Depends	
Empathy	Subject's state results from the attended perception of the object's state	Yes	At representation level, not necessarily visible	Increasing with famili-arity, similarity, and salience	
Cognitive empathy	Subject represents state of object through top–down processes	Yes	No	Depends	True empathy, perspective-taking
Prosocial behaviors	Actions taken to reduce the object's distress	Usually	Not necessarily	Yes	Helping, succorance

6.3 Neuroscientific Theories of Empathy

The rise of the neurosciences at the turn of the centuries has certainly influenced conceptual approaches to empathy. The 'social brain' (Adolphs 2009; Dunbar and Shultz 2007; Gobbini et al. 2007; Kennedy and Adolphs 2012) is a term both innovative and promising as well as vague and a target of criticism at the same time, e.g., regarding its anthropocentric constructions (Barrett et al. 2007). Against the framework of a newly and rapidly developing 'social neuroscience' branch, empathy theories that explain the social construct on a neural level have become popular and influential as already evident in the previous section's overview. Regarding simulation aspects, it is a common notion in the *neuroscience of empathy* to assume certain neural networks that are mutually corresponding to an emotional state originating in the self as well as an emotional state originating in observing or imitating another person. Perspective-taking aspects are included when proposing distinct neural networks that are serving self versus other processing explicitly (Ochsner et al. 2004). The list of studies that integrate brain imaging techniques into the experimental investigation of social constructs can be continued. Apart from testing the existing constructs and definitions, the social neurosciences have on the one hand provided physiological evidence of the phenomena that up to then remained a subject of verbal self-report or measurements in the periphery (e.g., galvanic skin response or heart beat). They have also extended our knowledge about mental processes while providing heuristic constructs that sketch out new frameworks in which empathy and related constructs can be placed. For example, in the 'social-emotional-processing-stream' by Ochsner (2008), the focus is on intertwining social and emotional phenomena through which social and emotional input is encoded, understood, and acted upon. Another prerequisite for the inclusion into the stream is that phenomena have a measurable and reliable neural correlate as well as a significant behavioral end. On a functional level, Ochsner differentiates into bottom–up and top–down processing within these areas and connects a neural network to these functional abilities. While structures such as the superior temporal sulcus integrate incoming information and evaluate it, other areas central in emotion processing such as the extended amygdala complex and the anterior insula are proposed to serve emotion recognition aspects as well as remapping by relaying interoceptive processing. The latter is proposed by Adolphs (2009) in his review on the 'social brain.' At this point, it may be appropriate to mention this almond-shaped group of nuclei with specific regards to facial expression. A long time ago, lesion studies have already shown that bilateral damage to the amygdalae can result in impairments to recognize emotional facial expressions (Adolphs and Tranel 2004) not last due to their strong anatomical connections to the visual system, as found in macaque monkeys (Freese and Amaral 2005; Stefanacci and Amaral 2002). This finding paved the way to the structures' evaluative function, specifically in mostly appetitive and aversive emotional processing (Aggleton 2000; Balleine and Killcross 2006; Paton et al. 2006), but see other studies (Moessnang et al. 2013) that show its role in aversive conditioning of other modalities (here: olfaction). Moreover, a more general role in basic arousal and vigilance functions (Whalen 1999) has been proposed, even on an unconscious level (Whalen et al. 1998). Work by Kennedy and Adolphs (2012) includes the amygdala's functions and relevance in an 'amygdala network' that coexists next to a 'mentalizing,' 'empathy,' as well as a 'mirror/simulation/action-perception' network. Each of these networks, including the amygdala's, consists of structures that have been recognized either because of their significance in lesion studies or repeated findings in functional imaging studies focusing on social cognition. Again, due to its connections to occipito-temporal cortices, an exposed role in visually focused emotional processing, especially regarding a broad role in salience detection and evaluation, is stated, while the authors stress the importance of the amygdala's role in networks that it subserves, rather than tagging it with a stand-alone functionality.

While neuroscientific models are impressive and can integrate a lot of psychobiological theories, the underlying method must not be over-estimated. It has to be kept in mind that structures do not exclusively correspond to a single function. Neural structures and networks that are activated when subjects experience a certain emotional state, respond to the expressed emotion of another person, or try to cognitively infer the mental state of someone else are convergent zones that cross a statistical threshold after averaging a number of trials and subjects to increase the signal-to-noise ratio. They cannot provide insight into individual phenomenological experiences, they do not necessarily correspond to behavior (Ochsner 2008), and they are not exclusive in their nature but take part in many other related and sometimes (against the current state of knowledge) unrelated concepts.

Concluding, twenty years into empathy research, the seemingly simple and straightforward definition by de Vignemont and Singer (2006) that we presented in the introduction is by far not the only one that exists nor does one unifying theory explain it all. However, as these authors state, their definition is one that narrows down empathy from a broader concept that includes all kinds of affective reactions to someone else's state of mind including cognitive perspective taking to one that explicitly requires an affective state that is isomorphic to another person's state and is causally related to the latter while being able to differentiate into self and other within this process. The definition is presented with a theory of early and late contextual appraisal occurring either simultaneously with the emotional cue presentation (early appraisal model), or later on, modulating an earlier automatically elicited response to the emotional cue (late appraisal model). Summarizing, emotional cues profit from a contextual embedding so they can be interpreted correctly and justify empathy by the receiver.

6.4 Studying Empathy: From Theory into Experiments

How can empathy be operationalized to be studied and what is the difference between the multitudes of study protocols against the specific background of eliciting empathy by showing facial expressions?

Experimental investigations in the field of social cognition become increasingly popular. A recent search via PUBMED on the number of articles stating 'emotional facial expressions empathy' yields almost 100 hits, and this number even increases by almost 50 % when leaving out the keyword 'emotional.' As this chapter can only introduce an overview on the different approaches to study empathy, we hereby try to group them into studies that investigate various empathic responses by presenting facial displays of emotions such as pain, disgust, or fear, and studies that research motor aspects of empathy. These studies explicitly include a definition of empathy that goes beyond the mere perception, recognition, or evaluation of a facial stimulus which all have a relevance to empathy without explicitly aiming to assess it. We will conclude by introducing recent meta-analyses that shed light on the neural correlates of (not only) facially transported empathy. We will present exemplary studies that are representative of their group.

A *direct* stimulation[1] approach assumes that emotional states can be transferred via the presentation of various channels such as prosody, body language, facial expressions, empathy-eliciting stories, or, with respect to pain empathy, by presenting harmed body parts. The underlying assumptions, especially in those studies targeting the neural correlates, were that feelings or emotions should be neurally represented by a network sensitive to the subjective feeling of someone else's emotion as well as to the compassionate feeling *for* them. Applied to pain this means, watching a person being hurt should trigger at least to some degree the other person's feeling. This is even suggested to take place on an automatic and unconscious level (Adolphs 2009). Although the majority of studies investigating the responses to pain used visual displays of body extremities (e.g., feet or hands) in painful positions or undergoing painful treatment (Decety et al. 2008; Lamm et al. 2011; Morrison et al. 2013; Singer et al. 2004), some studies provided facially expressed pain (Botvinick et al. 2005; Lamm et al. 2007) and some used both (e.g., Vachon-Presseau et al. 2012; Fig. 6.1).

Other emotions in direct stimulation approaches included disgust (Jabbi et al. 2007; Wicker et al. 2003), happiness (Hennenlotter et al. 2005; Jabbi et al. 2007), sadness (Harrison et al. 2006), or anger (de Greck et al. 2012), just to name a few. Apart from presenting these faces directly, gaze directionality (directed vs. averted) was also sometimes measured (Schulte-Rüther et al. 2007). Gaze did not yield activation differences on a neural level but showed effects on electrophysiological correlates of face perception as well as behavioral effects such as higher recognition accuracy (Soria Bauser et al. 2012) and higher emotion intensity ratings (Schulte-Rüther et al. 2007) for directed faces.

Besides the stimulus material, further methodological factors are relevant: What is the instruction for the participant, which responses are measured and recorded and what exactly defines a response as empathic?

[1] *Indirect* stimulation protocols in which facial expressions were used, are rare. Most studies in this category presented complete social vignettes (Chisholm and Strayer, 1995; Krach et al. 2011); here, we focused on emotional facial expressions.

Fig. 6.1 Modified from Vachon-Presseau et al. (2012), with friendly permission from Elsevier (license number 3243541056141)

Some studies merely instructed participants to passively view the presented emotions; for example, Wicker et al. (2003) presented subjects with visual displays of disgust and pleasantness as well as actual affective odors of disgusting or pleasant stimuli, to compare empathy to own emotional experiences. Although the task instruction was not to explicitly empathize, neural activation patterns suggested a shared network of own and vicarious affective experience when comparing observed with experienced disgust.

Others (Hennenlotter et al. 2005; Kircher et al. 2013) focused on executing and observing certain (emotional) facial expressions. Again, a common neural circuit of motor-, somatosensory, and limbic processing emerged, which is important for empathic understanding. In a recent study by Moore et al. (2012), it was shown that EEG mu component desynchronization took place toward happy and disgusted facial expressions, representing action simulation. This was irrespective of empathic task instruction (either try to experience emotions felt and expressed by the facial stimuli or to rate the faces' attractiveness). In a task that consisted of observing or imitating emotional facial expressions, superior temporal cortex, amygdala, and insula may reflect the process of relaying information from action representations into emotionally salient information and empathy (Carr et al. 2003). Using an imitation/execution task, Braadbaart et al. (2014) associated imitation accuracy with trait empathy and replicated central structures of the human mirror neuron system during imitation. In addition, they could associate external trait empathy with brain activation in somatosensory regions, intraparietal sulcus, and premotor cortex during imitation, while imitation accuracy values correlated with activation in insula and motor areas. Shared activity was found in premotor cortex. Again, these findings strengthen the role of simulation or 'action plans' for empathy via a joint engagement of premotor and somatosensory cortices as well as the insula, holding an important role in socially regulating facial expressions.

Apart from studies based on human mirror neuron system assumptions, in which participants' main task was motor-related by observing, imitating, or expressing certain emotional states, other studies required explicit ratings of the emotions presented. For example, Harrison et al. (2006) piloted their fMRI study by presenting emotional expressions in combination with different pupil sites and measuring behavioral responses regarding valence, intensity, attractiveness, but concentrated on age judgments during the functional measurement, combined with pupil diameter measurements. Pupil size influenced intensity ratings of sad emotional facial expressions and was mirrored by the participants, interpreted as a sign of emotional contagion. Another study (Hofelich and Preston 2012) challenged this view by stating that facial mimicry and conceptual encoding occurred automatically as a natural consequence of attended perception but should not be equated to trait empathy. Lamm et al. (2008) provided physiological and explicit rating data after focusing on electromyography to assess automatic facial mimicry in response to painful facial expressions in participants who were explicitly told to either imagine to be an observed person or to put him or herself into the situation of the observed person. They focused on the self-other differentiation within the empathy concept by manipulating the point of reference (see also Schulte-Rüther et al. 2008). Here, participants indicated the pain's intensity and (un)pleasantness, which were not associated with the respective point of reference, but showed sensitivity to whether the painful stimulation was associated with an effective treatment or not. Brain imaging results (Lamm et al. 2007) revealed parts of the so-called 'pain matrix' (Derbyshire 2000) in the insula, anterior cingulate cortex, and the secondary somatosensory cortex to be activated as a function of perspective taking (here: the contrast 'self' vs. 'other').

Other groups used an explicit empathic task instruction to feel with another person's facial expression and share their emotional state (de Greck et al. 2012). Participants then consciously rated how well they had managed to do so. The results showed the inferior frontal cortex as well as the middle temporal cortex to be involved in intentional empathy that complemented the literature regarding more controlled aspects of empathy.

Although task instructions in empathy studies varied to a great amount, a recent neuroimaging meta-analysis by Fan et al. (2011) explicitly required one of the following criteria to be considered in the study design: observing an emotional or sensory state of another person in a defined empathic context; sharing the emotional state of this other person or imagine the other's feeling and actively judge the latter two, respectively; or brain activation, which was associable with a dispositional measure of empathy (e.g., questionnaire). As already stated, they summarized 40 fMRI studies and presented several empathy networks, cognitively driven or affectively driven, respectively, with a neural overlap in the left anterior insula.

One essential problem was, however, still obvious in this meta-analysis, namely the definition and operationalization of empathy remained heterogeneous, and only a few studies included more than one or two aspects of the complex construct. However, this endangered empathy to be lost in experiments targeting only emotion recognition or mere emotion perception without controlling for the subjective experience of the participants. In several studies, we therefore targeted three components of empathy experimentally, namely emotion recognition, affective responses as well as emotional perspective taking. The major advantage of this novel task combination was the simultaneous assessment of the different empathy components within one experiment including control tasks. This was, last but not least, the basis for studying specific impairments in disorders associated with altered social cognitive functions such as paranoid schizophrenia (Derntl et al. 2009, 2012) and enables a more detailed characterization of empathy deficits in this disorder while controlling for the well-known emotion recognition deficits in patients. For the emotion recognition task, we presented 60 colored Caucasian facial expressions of five basic emotions (happiness, sadness, anger, fear, disgust) and neutral expressions (Gur et al. 2002). Half of the stimuli were used for emotion recognition, the other half for the age discrimination control task. Subjects evaluated the emotion by selecting from two emotion categories; the correct emotion depicted or had to judge, which of two age decades was closer to the poser's age, respectively. The affective responsiveness included 150 short written sentences describing real-life emotional situations, which are expected to induce basic emotions (the same emotions as described above), and situations that were emotionally neutral (25 stimuli per condition). Participants were asked to imagine how they would feel if they were in those situations. Again, to facilitate task comparisons, responses required subjects to choose the correct emotional facial expressions from two presented alternatives. For the emotional perspective taking task, participants viewed 60 items depicting scenes with two Caucasians involved in social interaction reflecting five basic emotions and neutral scenes (10 stimuli per condition). The face of one person was masked, and participants were asked to infer the respective emotion of the covered face. Responses were made similar by presenting two different emotional facial expressions or a neutral expression as alternative response categories.

The task revealed the differential underlying cerebral correlates of empathy components (Derntl et al. 2010), with the amygdala playing a major role. Generalizing over tasks and gender, activation in the inferior frontal and middle temporal gyri, the left superior frontal gyrus and the left posterior as well as middle cingulate gyrus, and the cerebellum characterized the common nodes of the empathy network.

The development of neuroimaging techniques has certainly enabled to map and localize the structures and network underlying empathy on a neural level (see as a recent meta-analysis by Moya-Albiol et al. 2010). Still, an obvious lack of homogeneous operationalizations across studies and (conscious) accessibility in an experimental setting pose difficulties on the neuroscientific approaches to empathy. Also, the existing subconceptualizations within the field of social cognition and specifically empathy suggest still new categorization options of the processes leading to empathy. Hypotheses-free approaches for data analysis could be one option to further advance the field and might present one solution for this dilemma. One example for this is the work by Nomi et al. (2008), who analyzed their fMRI data in a facial expression viewing paradigm with principal component analysis and presented principal components explaining distinct neural networks comprising of 'mediating facial expressions,' 'identification of expressed emotions,' 'attention to these expressed emotions,' and 'sense of an emotional state.'

6.5 Facial Expressions in Social Communication: Multimodal Empathy

As stated before, empathy, more specifically, the contents leading to empathic responses are transmitted via different communication channels. As described in the previous paragraph, numerous studies used static facial displays to study empathy and its subcomponents (such as emotion recognition Adolphs 2002). In the last decade, the increasing requests for ecological validity together with the advancements in methods available for testing and recording human physiological responses demanded dynamic displays of emotion rather than static ones. Thecall came especially from those research groups, which initiated to study static and dynamic modalities within one experiment and encouraged to study 'emotions in motion' (Trautmann et al. 2009). This was motivated by the interest in dynamics of sensory processing and biological motion, but also implies a high relevance for empathy. The specific tasks ranged from investigating passive viewing (Sato et al. 2004), emotion recognition abilities (Trautmann et al. 2009; Weyers et al. 2006), emotion intensity ratings (Kilts et al. 2003), or affective responsiveness (Simons et al. 1999), respectively. Other studies restricted themselves to the use of dynamic displays only, such as Leslie et al. (2004), who used short video clips of emotional facial expressions in order to find a mirroring system for emotive actions.

These approaches paid tribute to the dynamic nature of facial expressions. Along with an increase in ecological validity, these studies also showed beneficial effects of dynamic stimulion behavioral responses (Ambadar et al. 2005) as well as autonomous parameters (Weyers et al. 2006).

This expands the field of empathy research to multimodal integration of different sources of sensory information. Multiple senses interact when we make sense of the (social) world. In order to include other communication channels than visually presented faces, our group has developed an approach to study multimodal contributions to empathy stemming from different emotion cues, facial expressions, prosody, and speech content (Regenbogen et al. 2012a, b). We developed and evaluated naturalistic stimulus material (video clips of 11-s duration), which consisted of different social communication situations of sad, happy, disgusted, or fearful content. The combinations of emotionality in facial expressions, prosody, and speech content differed between several experimental conditions. Emotionality was presented via three channels or via two channels with the third held neutral or unintelligible. This enabled to study the joint presence of two emotional channels with and the effect of keeping one channel neutral, respectively. As previous results showed that the given attitude toward the stimulus material can significantly modulate the results (Kim et al. 2009) and also that presenting complete strangers can be aversive and lead to the opposite effect (Fischer et al. 2012), we instructed participants to simply regard the presented actor as a familiar communication partner and to rate their own and the other's emotional state after the video. Empathy was operationalized by the congruence of participants' ratings on the other's and their own emotional experience (Fig. 6.2).

Behaviorally, facial expressions were central for recognizing the other person's emotion. Once facial expressions were experimentally held neutral, the recognition rates of 38 healthy participants decreased to approximately 70 % (compared

Condition	Prosody	Facial expression	Speech content
All emotional	1)E	E	E
All neutral	N	N	N
Neutral prosody	N	E	E
Neutral facial expression	E	N	E
Neutral speech content	E	E	N
Foreign language	E	E	E

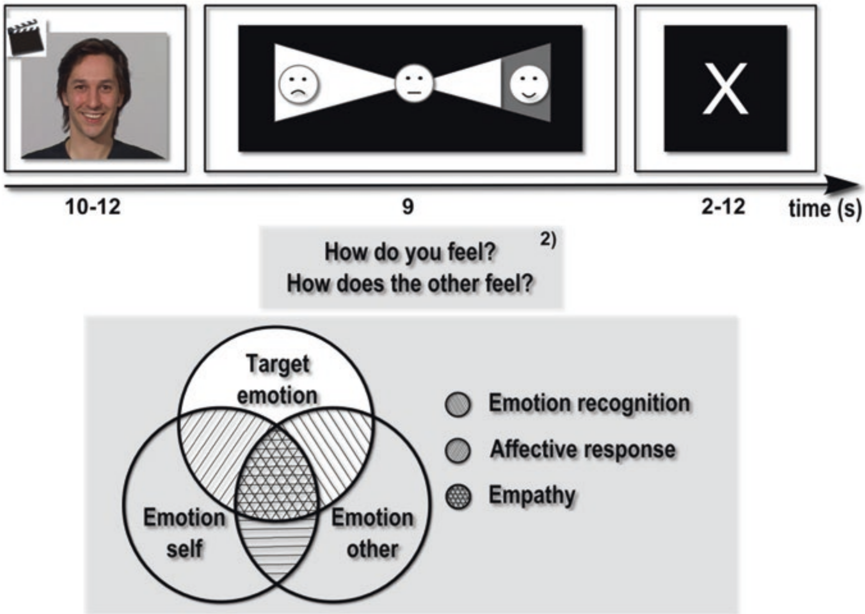

Fig. 6.2 Modified from Regenbogen et al. (2012a, b), with friendly permission from Elsevier (license number 3243690538277) and Taylor & Francis (license number 3243691330032). *1*. Abbreviations: *E* emotional, *N* neutral. *2* In the behavioral study, this was an explicit emotion and emotion intensity rating, in the fMRI study, this was shortened to a valence and intensity rating of self and other

to >95 % emotion accuracy when facial expressions were emotional). This was paralleled by participants' autonomous arousal to video clips as measured by galvanic skin responses on the left-hand palm. The number of electrodermal responses significantly decreased once facial expressions did not transport emotionality anymore. From these results, we concluded a central role of emotional facial expression when establishing an empathic response in a social communication situation, first by positively influencing the ability to correctly recognize another person's affective state, and second, by a beneficial role for multimodal integration of signals coming from other modalities (here, speech content and prosody).

In a subsequent study, using the same stimuli, we targeted the effects of emotional facial expressions and other cues on a neural level. In an fMRI design, we presented the same clips to participants while again refraining from an explicit empathy instruction. Explicit self and other valence and intensity ratings were acquired while whole-brain activation was measured in a design with events ranging between 9 and 11 s. Focusing on only face-related results, we could show that emotionality in the face specifically resulted in widespread activation of temporo-occipital areas, medial prefrontal cortex, as well as subcortical activation in basal ganglia, hippocampus, and superior colliculi. This was in line with the literature on dynamic face processing (Sato et al. 2004; Trautmann et al. 2009; Weyers et al. 2006) and confirmed that emotion in the human face enhanced arousal and salience. At the same time, experimental empathy and its components toward stimuli with a neutral facial expression were significantly lower compared to fully emotional stimuli. Facial expressions thus seem to be a major source of information for inferring the emotional state of a counterpart, especially when verbal information is neutral or incomprehensible as the latter conditions yielded the strongest activation in the fusiform gyri (Regenbogen et al. 2012b).

6.6 Outlook

The human face enables us to project inner subjective states to the outside world. Via fast detection mechanisms, our counterparts are able to perceive and recognize an emotional expression, its intensity, and react upon it. Via shared network representations, emotional states are to some degree mirrored by the other person, which, along with perspective-taking mechanisms and evaluation procedures, helps to create empathy. However, faces do not exist in empty space. Studies on multimodality or multisensory processing demonstrate this convincingly while at the same time pointing to the high relevance of a facial expression also in enhancing sensory acquisition of other cues (e.g., olfactory ones Susskind et al. 2008). Along with a challenge of the visual dominance effect (Collignon et al. 2008), it becomes clear that other emotional cues such as prosody and speech content are equally, if not significantly more related to the subjective affective experience within empathy (Regenbogen et al. 2012a).

Considering several components of empathy certainly helps to target the construct in a more holistic way. Further, external validation measures such as trait empathy questionnaires (e.g., Williams et al. 2013) help to characterize the concept in more detail and further support the experimental results. The biological bases can be analyzed with the variety of brain imaging methods available.

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Chapter 7
The Role of Social Context for the Interpretation of Emotional Facial Expressions

Ursula Hess and Shlomo Hareli

7.1 The Role of Social Context for the Interpretation of Emotional Facial Expressions

The scientific study of emotion expressions is usually traced to Darwin's seminal work "On the expressions of the emotions in man and animal" (1872/1965). Darwin understood emotion expressions as the visible part of an underlying emotional state, which are evolved and (at least at some point in the past) adaptive. Yet, Darwin's view has been disputed and rejected by those who considered facial expressions as exclusively or predominantly social or cultural signals. Also, a number of studies in the early years of the twentieth century came to the conclusion that emotions can only be recognized at chance levels, whereas other studies found good recognition rates. This disparity in findings led Bruner and Tagiuri in their 1954 *Handbook of Social Psychology* article to state that "… the evidence for the recognizability of emotional expressions is unclear" (p. 634). They concluded that, if anything, emotional facial expressions are culturally learned. This view remained basically unchanged until the early 1970s when research by Ekman and colleagues (Ekman 1973; Ekman et al.1969, 1972; Ekman and Friesen 1971) as well as Izard (Izard 1971a, b) vindicated Darwin's idea that at least some basic emotional expressions are universal and directly associated with an underlying

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emotional state. A number of discussions in leading journals took issue with the methodology employed in the studies that found support for universality (e.g., Ekman 1994; Izard 1997; Russell 1991, 1994, 1995) and social constructivist approaches to emotion emphasized differences in emotion vocabularies and disputed universality on these grounds.

Fridlund's Behavioral Ecology Theory (Fridlund 1994) contradicted Darwin's assumption of the usefulness of the honest communication of emotional states. He claimed that for emotion expressions to be truly useful as a communicative signal, they should be linked to the organism's social motives rather than to quasi-reflexive emotions. Hence, emotion expressions should be considered as expressions of social motives and not of emotions. In turn, Parkinson (2005) questioned the notion that communicating motives should be more adaptive than communicating emotions since when such motives are feigned they can also be used to cheat. His extensive review concludes that facial expressions may well serve as both symptoms of an underlying state and communicative signals. This notion was first empirically tested by Hess et al. (1995) who showed in a partial replication of Fridlund (1991) that smiles vary both as a function of social context (and thus social motives) and of the emotional content of the stimulus. These findings were extended by Jakobs and colleagues to different contexts and emotions (Jakobs et al. 1999a, b, 2001). In sum, the question of whether and to what degree emotion expressions express emotions or motives and intentions may in fact be a spurious one as the two options are not mutually exclusive and there are good reasons to believe both to be the case.

However, in some ways, the question of what emotions actually express is less important when considering how they are interpreted. Specifically, as is amply demonstrated by the use of facial expressions in the arts, films, and literature people understand emotional facial expressions to express emotions and they react in function of this understanding (Niedenthal and Brauer 2012). This is also relevant to the conclusions they draw from facial expressions, that is, the inferences about a person's character, their goals, and intentions, which can be drawn from observing or learning about an individual's emotional reaction to an event. That is, people treat emotion expressions as if they express emotions and act in accordance.

Yet, an expression does not occur in a vacuum. It occurs in a social context and even when emotions are felt when a person is alone, the source of the emotion may well be another real or imagined person. Nonetheless, much of the research on the recognition of emotional facial expressions has been conducted in ways that minimize context information. Typically, participants see faces or sometimes only ovals of faces (which also exclude hairstyle and with it considerable gender information) with the task to label the emotion shown in the face. However, a completely context-free presentation of facial expressions is in fact impossible, as the face on which facial expressions are shown does itself provide context. Faces signal the social group membership of the person, including not only such obvious aspects as gender, age, and ethnicity, but also social dominance (Mueller and Mazur 1997) and even sexual orientation (Rule et al. 2009). Much of this information can also be gleaned from the voice or from body postures. And all of these factors impact on our understanding of the emotion and its larger meaning.

In what follows, we will first discuss the process of understanding facial expressions and drawing inferences based on these expressions. We will then discuss the elements of context, which in our conceptualization extends over current discussions of context in terms of information about the emotion-eliciting situation or concurrent emotion information provided by other channels (Barrett et al. 2011; Hassin et al. 2013) to include the tacit information that the perceiver has about relevant social rules and norms as well as the perceiver's own goals, motives, and emotions.

7.2 Why Context Is Needed for the Decoding of Facial Expressions

The present chapter focuses on facial expressions. However, much of what we discuss can be applied to emotion decoding processes in general, both those based on nonverbal cues such as postures, tone of voice, and gestures and those based on secondhand information such as verbal descriptions of the expresser's behavior. In the early years of emotion research, the role of context was essentially constrained to the *expression* of emotions, which was thought to be influenced by culture-specific socially learned display rules (Ekman 1972) and even though Buck (1984) early on concluded that the existence of culturally shared display rules implies the possibility of their use as decoding rules, this observation generated little research. Yet, context is an integral part of the emotion decoding process as we outline below.

7.2.1 Two Ways to Decode Emotion Expressions

There are two ways to identify emotions from nonverbal cues. Most research on emotion recognition implicitly assumes a pattern-matching process, where specific features of the expression are associated with specific emotions (Buck 1984). For example, upturned corners of the mouth or lowered brows are recognized as smiles or frowns, respectively, and a perceiver can thus conclude that the individual is happy or angry. In this process, the perceiver is a passive decoder, who could and in fact can (e.g., Dailey et al. 2002) be replaced by an automated system and context information does play no role or only a minimal one.

However, when the perceiver knows the expresser, he/she can adopt an active role in the emotion identification process. Knowing the goals and values of others allows the perceiver to take their perspective and to infer their likely emotional state. Knowing about the temperament and emotional dispositions of the expresser further allows to refine predictions. For example, learning that someone's car was vandalized typically leads to the expectation that the person is angry. However, we may expect more intense anger from a choleric person than from an easygoing one and more anger if the car was cherished than if it was not.

Whereas a pattern-matching approach to decoding emotion expressions works well for the intense and unambiguous expressions that are typically depicted in standardized sets of emotion expressions such as the Pictures of Facial Affect (Ekman and Friesen 1976), it breaks down in many everyday situations where the nonverbal signal is often weak and ambiguous (Motley and Camden 1988). In this case, perspective taking can allow an observer to deduce the likely emotional reaction based on both the ambiguous expression and the context information.

But what happens if the expresser does not know the other person well or at all? In this case, any social category that the perceiver is aware of and for which expectations regarding emotional reactions exist can affect emotion identification (Kirouac and Hess 1999) in that the perceiver is more likely to attribute the more expected emotion evidenced in the ambiguous expression. For example, knowing that a (male) expresser is black or of high status leads observers to more readily label their expression as angry (Hugenberg and Bodenhausen 2003; Ratcliff et al. 2012).

So far, our discussion implicitly assumed "pure" emotion expressions, that is, expressions that can accurately be described by a single emotion label. Yet, such "pure" expressions are rare. In fact, most emotional situations elicit more than one emotion, with some being more prominent than others (Izard 1971a; Plutchik 1980). More importantly, observers tend to see multiple emotions even when judging emotional expressions considered to be "pure" (Russell and Fehr 1987; Russell et al. 1993; Yrizarry et al. 1998). This is especially the case in naturally occurring social interactions where people are likely to exhibit subtle expressions that are open to different interpretations (Ekman 2003; Motley and Camden 1988).

Thus, the identification of emotions also involves the identification of secondary emotions and these can be influenced by stereotype expectations as well. In this vein, Algoe et al. (2000) have shown that observers perceived fear expressions as reflecting more intense anger and contempt when targets were described as the boss (i.e., high status) rather than as employees (i.e., low status). In a social interaction, it can be expected to make a difference whether a person is seen as only fearful or as both fearful and angry. Thus, the identification—or misidentification—of secondary emotions can be expected to have implications for everyday interactions. This was demonstrated recently by Hess et al. (2014) who found that a tendency to (mis)attribute more secondary emotions to "pure" expressions was associated with diary reports of less positive social interactions.

Conversely, stereotype expectations based on social group membership not only bias the perception of emotions such that some emotions are preferentially associated with some groups but can also influence the intensity of the perceived emotions. For example, Hareli et al. (2013) found that the very same emotion expression was rated as expressing less intense emotions when purportedly shown by women wearing a surgeon's mask then when shown by women wearing a niqab, demonstrating the effect of the occupational stereotype of doctors as unemotional.

In sum, the identification of emotions can be accomplished via either a passive pattern-matching process or a process where the perceiver actively generates a label for the likely emotional state of the expresser based on both the expression and their knowledge of the context, either in the form of individualized knowledge about the expresser or based on the expresser's social group. The social group information can be used by observers to generate information about the likely emotions of members of this group and this information can then be applied to the emotion identification process.

7.2.2 Some Complexities in Decoding Facial Expressions

The above discussion made another implicit assumption, namely that observers in everyday life will in fact decode emotional facial expressions in the form that is assumed by decoding research—that is, they will apply an emotion label to the expression. However, as Frijda (1953) already notes, perceivers often identify emotional expressions in terms of components of the expression or of outcomes associated with such states. For example, the perceiver may identify the emotion conveyed by an anger expression by referring to its action tendency ("looking as if she wants to hit someone") or their own reaction ("he makes me feel scared"). Further, in addition to recognizing and labeling an emotional behavior, observers may often also identify its object, intensity and/or cause. Thus, for example, perceivers may conclude from a frown and clenched teeth not only that the expresser is angry but also that the anger is quite intense and when combined with a direct stare that the object of that anger is the perceiver (Adams et al. 2003; Hess et al. 2007).

7.2.2.1 The Authenticity of Emotion Expressions

This also raises the issue of the perceived authenticity of the expression. In fact, standard sets of emotion expressions that are used to assess decoding ability generally use posed facial expressions and obviously the expressers are readily labeled by participants as "feeling" the emotion expressed. Even studies that assess the difference in perception between authentic and inauthentic expressions (typically smiles) often use posed expressions (Thibault et al. 2012) or even artificial computer-generated faces (Maringer et al. 2011) and find that participants react differently to these expressions. Most research on expression authenticity has been conducted on smiles and it should not surprise anyone that smiles can be readily produced by most that include "markers" of authenticity (Krumhuber and Manstead 2009) and that people spontaneously use such smiles even in situation where genuine positive affect can be excluded (Hess and Bourgeois 2010).

However, research showing that participants do not show mimicry (the spontaneous imitation of the facial expressions of others, which fosters affiliation) to facial expressions when they suspect that these may be fake (Hess et al.1998; Stel and Vonk 2009) suggests that perceived inauthenticity and, in fact, even suspected inauthenticity have an impact on social communication. The limited research on the inferences drawn from inauthentic expressions suggests that the perception of inauthenticity also has an impact there. For example, Krumhuber et al. (2007) found that smiles that were created with the dynamic parameters of a fake smile were perceived as less trustworthy and led to less cooperation.

In this context, both stereotype expectations and context are relevant. Thus, when a child witness's crying in a court room is perceived as too much her credibility suffers (Golding et al. 2003) and generally any mismatch between an expression and the context in which it was perceived may be taken as a sign of its inauthenticity (Grandey et al. 2005). Thus, even though sometimes expression authenticity can be detected from markers such as the Duchenne smile (the wrinkles around the eyes that have been proposed as markers of smile authenticity, Ekman et al. 1988) in many situations, these markers may not be reliable and context may provide useful hints to authenticity.

7.3 Drawing Inferences from Emotions: A Model of the Reverse Engineering of Appraisals

As already hinted at above, people do not stop once they have labeled an emotion. Rather, knowing that another person feels a certain way is information that is used in social communication to further guide the interaction as emotional facial expressions provide information about the behavioral intentions of others in terms of threat or affiliation, the type of information that Frijda (1986) more generally refers to as action tendencies. But people do also very readily infer stable characteristics from facial expressions. Our reverse engineering model (see Fig. 7.1) (Hareli and Hess 2010) uses appraisal theory (Frijda 1986; Scherer 1987) to explain this process.

Appraisal theories of emotion posit that emotions are elicited by the spontaneous and intuitive appraisal of (internal or external) relevant stimulus events according to the perceived nature of the event (Arnold 1960; Scherer 1987). Importantly, appraisals relate to the subjective perception of the stimulus and not its objective characteristics.

Thus, the mere fact that someone reacts with an emotion to an event, signals that the event is relevant to that specific person, which in turn provides information about the person's goals and values. For example, the fact that a person reacts with anger to a perceived injustice signals that the person cares about this fact. When a relevant change in the environment is detected by an organism, it is evaluated according to whether it is pleasant or unpleasant and to what degree it is in line with the motivational state of the individual or obstructs the individual's goals. Thus, the second information that is encoded in the resulting emotion is information about preferences (the pleasant/unpleasant evaluation) and motivational goals. The appraisal of coping potential provides information about a person's resources and the evaluations regarding the correspondence of the event with the relevant social and personal norms provide information about a person's values. All of this

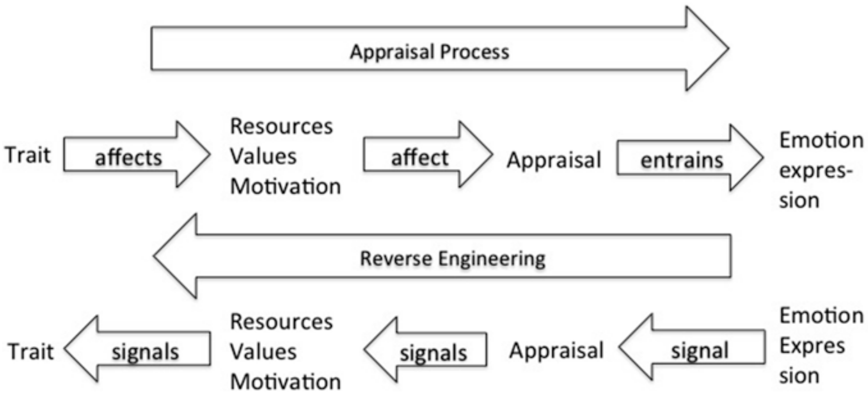

Fig. 7.1 Reverse engineering of appraisals

information is therefore encoded in the emotional expressions that are generated in this process. In fact, it has been proposed that facial expressions of emotions are a direct readout of appraisals (Scherer 1992; Smith and Scott 1997).

Importantly, even though appraisals are typically not the product of reasoning processes, people can and do reconstruct appraisal patterns consciously after the fact (Robinson and Clore 2002) and they can do so for other people's emotions as well (e.g., Roseman 1991; Scherer and Grandjean 2008). As such, emotions can be seen as encapsulated or compacted signals that tell a rather complex story about the emoter.

Thus, an angry person experiences a motivation incongruent (low goal conduciveness), unpleasant state, but considers the situation to be potentially under their control (high coping potential). In turn, an observer, who sees a person react with anger to an injustice can conclude that the person has values according to which the event in question appears unjust, perceives this injustice as incongruent with their own motivational state (which would be to see justice done) and also feels endowed with enough resources to act accordingly. Thus, in a very real sense, emotion expression can also provide information about the situational context and not only vice versa.

Importantly, however, as mentioned above, the information provided by emotional reactions refers not only to the situation at hand, but also to relatively stable characteristics of the person. Specifically, stable traits such as dominance, affiliation, and competence impact the motivational goals, preferences, and resources of a person. Thus, a person who is competent may be expected to have more resources to deal with potential problems than a person who is not. Likewise an affiliative person can be expected to have affiliative goals. Conversely, seeing a person react with anger in a difficult situation suggests that this person is high in resources in this situation and likely in other situations as well. Thus, emotion expressions provide information that can be used—and is used—to derive stable characteristics of a person (Hareli and Hess 2010).

This attribution also depends on context factors. For example, the attribution of dominance and affiliation depends not only on the emotion shown but also on such factors as gender and ethnicity as well as the social norm expectations associated with these factors (Hess et al. 2000). In what follows, we will further explain what we mean by context.

7.4 Some Elements of Context

As discussed above, the process of perspective taking necessarily implies the use of context information (Kirouac and Hess 1999). A first step consists in delineating what is meant by context or rather to define the different elements of context. The first element is what most often is meant by context in common parlance, that is, information about the situation in which an emotion was elicited (cf. Barrett et al. 2011). As is obvious from our preceding discussions, this is, however, not the only type of context information. A second aspect of context regards who the person who expresses the emotion is. As mentioned above, this can be either a specific individual known to the perceiver or a member of a specific social group that is known to the perceiver. Finally, an often overlooked aspect of context regards the social rules and norms that guide the expression of emotions. We propose that the information contained in the expression and the information provided by the context elements that are present in a specific situation is processed by a dynamic system involving continuous interaction between context information and the low-level processing of cues provided by the stimulus. Such a system permits lower-level sensory perception and higher-order social cognition to dynamically coordinate across multiple interactive levels of processing to give rise to stable identification of a cue (see Freeman and Ambady 2011).

However, in our view, this conceptualization of context is still incomplete; a more comprehensive view of context based on a conceptualization of the perceiver as an active "constructor" of the emotion label should include the perceiver as well. Specifically, we propose to consider the perceiver's goals and motivations in the situation as part of the context. In what follows, we will discuss each of the elements of context in more detail.

7.4.1 Situational Context

After some early research pointing to the importance of context information for the perception of emotions (Wallbott 1988), research in this domain was dormant until quite recently. From the above two paths to emotion recognition model, we would expect that any information on the cause of an emotion would be helpful in identifying an emotion expression. Thus, individuals who see both the situation which elicited the emotion and the emotion expression can use both sources of information to derive an emotion judgment and rely more on the situation when the expressive information provided is ambiguous (Wallbott 1988). Not only the emotion-eliciting situation, but also other communication channels can serve as context for facial emotion expressions. Whereas early research on cross-modal ambiguity found that observers preferentially used facial information for their judgments (Hess et al. 1988; Noller 1985), recent studies found a strong effect of body posture on emotion identification (Aviezer et al. 2008; Kret and de Gelder 2013).

The use of context information is also dependent on culture. Thus, Masuda et al. (2008) found that Japanese but not Western participants' judgment of a central character's emotional state was affected by the emotions expressed by a surrounding group. Using a similar paradigm, Hess et al. (2014) found that both primed and chronic self-construal affected the influence of the surrounding group on the decoding of the emotions of the central character. These and other findings (e.g., Barrett et al. 2011) have led to recent calls for research in emotion perception to include context (Hassin et al. 2013). We agree, but feel that this research should not stop at only considering situational context.

7.4.2 Social Group Membership

In fact, we already mentioned indications of the importance of social group membership for emotion perception. Thus, knowing that a person is a man or a women or a member of a specific ethnic group or has high versus low status all impacts on emotion perception (Hess et al. 1997; Hugenberg and Bodenhausen 2003; Ratcliff et al. 2012). From our perspective, these findings are special cases of the larger influence of social rules and norms.

7.4.3 Social Rules and Norms

The social and cultural rules which guide the appropriate expression of emotions in a specific social context are usually referred to as display (Ekman 1972) or feeling rules (Hochschild 1979). Display rules vary both with the type of emotion and the context. For example, anger expression is more acceptable for office staff than for service agents (Diefendorff and Greguras 2009; Mann 2007). Also, rules to suppress negative affect are more strongly normative for women than for men, whereas rules to suppress positive emotions are more commonly applied to men (Simpson and Stroh 2004). These rules have a strong impact on the expresser's emotional behavior. In fact, interpersonal situations in general are highly rule-governed (Gallois 1994) and these rules are not only perceived as normative for the interactions but also even as correct in a moral sense (Hall 1959). Consequently, people expect costs and rewards as a function of adhering to display rules (Davis et al.1992; Stoppard and Gruchy 1993) as even minor violations of rules guiding emotional behavior can create substantial problems for the interaction process.

Yet, research on display rules considers the observer mostly as a normative force, that is, the perceiver is a source of enforcement of these rules. In fact, social norm violations activate in perceivers not only brain systems associated with the representation of the mental state of others, but also brain regions that respond to aversive emotions (especially anger) in others (Berthoz et al. 2002).

However, what is largely missing is the study of the influence of the social norm knowledge on the *perception* of emotions, what Buck (1984) calls the application of decoding rules (exceptions are Matsumoto and Ekman 1989; McAndrew 1986). However, as the research on the influence of the social group membership of the expresser discussed above, already hints at—the expectations that we have regarding the "proper" behavior of another person should impact on how we interpret emotional signals, especially when these signals are ambiguous. In the same vein, knowledge of emotional rules and norms should impact on inferences drawn about people who violate such norms (Szczurek et al. 2012).

That these social norm expectations are already socialized very early in childhood is demonstrated by the observation that not only adults but also even children as young as 5 years, tend to consider a crying baby as "mad" when the baby is purported to be a boy but not when the same baby is purported to be a girl (Condry and Condry 1976; Haugh et al. 1980), for whom the behavior was attributed to fear. As the face of the expresser already provides information about the social group membership of the expresser, and different social groups are subject to differing social rules and hence differing expectations regarding their "proper" behavior, emotion identification should be guided by social norms and rules even when little or no situational context information is provided.

7.4.4 The Perceiver's Goals and Motives

The perceivers' goals, needs, expertise and even their own emotional state (Showers and Cantor 1985), also affect emotion identification. A first source of influence is provided by the degree of effort that the perceiver invests in attending to the available cues. A highly motivated perceiver tends to pay more attention to the cues emitted by the target, whereas if motivation is low, less attention may be paid. In this vein, Thibault et al. (2006) found that perceivers who strongly identified with members of a group were better at labeling emotion expressions from members of that group. In a related finding, drawings of emotional faces purportedly done by children were rated more accurately than when the same drawings were purportedly the product of a computer program (Dietrich et al. 2013). This finding fits well the more general idea that people often invest relatively less effort in learning about the characteristics of out-group others (Park and Rothbart 1982). In a similar vein, research on gender differences in emotion recognition shows that motivational factors may have a substantial impact on recognition accuracy (Ickes and Simpson 2004).

Yet, the perceiver's goals and motives as well as emotional state scan affect the identification of the emotion also indirectly by determining the extent to which the perceiver recruits available context information in order to make a judgment. Thus, the emotional state of the perceiver influences how social information is processed (e.g., Bower and Forgas 2000, 2001). Specifically, according to Forgas' "affect infusion model" (1995), perceivers' information processing strategies differ with regard to the extent to which a full search of information occurs and how open or closed this search is, that is, in the extend that perceivers use their knowledge. At one extreme of this process, the perceiver may directly and automatically retrieve a preexisting identification label when encountering a stimulus. This should in fact be the case when a highly stereotypical expression—for example, an intense smile—is encountered. At the other extreme, the perceiver may engage in substantive processing using preexisting knowledge in a relatively unbiased manner (Bower and Forgas 2000). And it is precisely the needs, goals, emotions, and the experience of the perceiver that has been shown to determine the strategy employed. For example, the smile of another person is usually perceived positively as happiness. But when perceivers know the other person to be in competition with them, and hence the expresser's goal is to achieve success at the expense of the perceiver, the perceiver might search for sinister motives on the part of the expresser, and the same smile may become a smirk and the happiness becomes glee in their mind.

Next to the varying goals and motives of perceivers, there is also individual variation in the extent to which observers are good at "correctly reading" others' emotions (e.g., DePaulo and Rosenthal 1978, 1979; Matsumoto et al. 2000) and the degree to which they are observant of situational cues. Such differences in emotional competence or "expertise"—often referred to as emotional intelligence (Salovey and Mayer 1990)—are also expected to influence the outcomes of emotion identification.

Individual differences in personality also can affect identification. Thus, traits such as hostility and aggression can bias emotion perception (Hall 2006; Larkin et al. 2002). Individual epistemic style may also determine the extent to which an individual is attentive to others' emotions. In a related vain, van Kleef et al. (2004) have shown that individuals who were low on need for closure were affected more by the emotions expressed by an opponent in a negotiation than were individuals high on need for closure. This can be explained by the tendency of people high on need for closure to ignore information, which may in part also make them less attentive to the emotions of the other.

To summarize, characteristics of the perceiver such as more fleeting goals, motives, and emotions but also more stable characteristics such as ability and cognitive style impact the identification stage in two principal ways. First, by making certain types of cues more accessible (Higgins and King 1981), and second by leading perceivers to engage in a more purposeful strategy and to actively choose the information on which they base their judgments (Showers and Cantor 1985). More generally, this notion implies that perceivers will play an active role, privileging, usually unconsciously, some interpretations over others, by choosing the "right" background information.

7.4.5 The Role of the Face

So far we have discussed a number of elements of context for emotion perception, which are more or less closely associated with the facial emotion expression itself. These range from truly external aspects such as the situation in which the emotion was elicited to such aspects as other expressive channels, which are indeed part of the overall expression. However, all of these aspects can in fact be transmitted not only via our bodily senses but also through words. Thus, the author of a novel can describe the expression on the face and provide information about the situation and who the people involved are and the reader would likely draw the same conclusions as if the scene had been witnessed first-hand. The last element of context that we would like to discuss, however, is different in that it is inexorably confounded with facial expressions of emotions and its influence is not readily described in words: the morphology of the face. This term refers to both the bone structure of the face as well as to other stable facial features such as eye brow and lip shape (which arguably are somewhat less stable for women than for men) and the wrinkles and folds of the face as we age.

In recent years, research has accrued showing that these stable features interact with facial expressions both in regard to the identification of emotions and when it comes to drawing inferences from facial expressions (Hess et al. 2009). Thus, fear is better recognized in immature than in mature faces, whereas anger is better recognized in mature and male faces (Becker et al. 2007; Sacco and Hugenberg 2009). Also smiles shown by women are perceived as more appetitive than smiles shown by men, whereas angry frowns shown by men are perceived as more threatening than angry frowns shown by women (Hess et al. 2007). In fact, it can be shown that anger, dominance, and male sex markers on the one hand and happiness, affiliation, and female sex markers on the other overlap perceptually in face space and are functionally equivalent. That is, anger, dominance and male sex all look sufficiently similar that they can and do convey the same meaning with the converse for happiness, affiliation, and female sex markers (Becker et al. 2007; Hess et al. 2009). In what follows, we will detail these notions.

7.4.6 Facial Dominance and Affiliation

People rapidly and spontaneously make judgments about the personality of others (see e.g., Kenny 2004; Todorov and Uleman 2002, 2003) and these judgments are often made on the basis of very little information (Ambady et al.1995; Ambady and Rosenthal 1992), including fleeting glimpses of the face (Rule et al.2009). As mentioned above, these also include the behavioral tendencies of dominance and affiliation (Zebrowitz 1997). At the same time, facial emotion expressions also signal dominance and affiliation, such that anger and disgust are perceived as signals of dominance and low affiliation, happiness signals high affiliation and high dominance, and sadness and fear signal submission and somewhat higher affiliation (Hess et al.2000; Knutson 1996). Thus, facial morphology and facial expression can signal the same behavioral intentions. This leads to the hypothesis that these signals may interact.

7.4.7 Functional Equivalence Hypothesis

Darwin (1872/1965) first noted the equivalence between certain emotional behaviors in animals and more enduring morphological appearance characteristics. Thus, he proposed that piloerection and the utterance of harsh sounds by "angry" animals are "voluntarily" enacted to make the animal appear larger and hence a more threatening adversary (see for example, pp. 95, 104).

Taking up this notion, Hess et al.(2007) proposed that some aspects of facial expressive behavior and morphological cues to dominance and affiliation are equivalent in both their appearance and their effects on emotional attributions. Such a functional equivalence between morphology and expression also implies that there are important interactions between facial expressions and facial morphology in the decoding of expressions of emotion. Hess and colleagues initially tested the functional equivalence hypothesis by examining differences in the attribution of emotions to men and women (Hess et al.2004, 2005). This, because men's and women's facial morphology differs in ways that make men appear more dominant and women appear more affiliative. Facial expressions can also make faces appear more dominant and affiliative and thereby more or less male or female. This, because smiling enhances the appearance of the roundness of the face, a female sex marker and a marker of baby-facedness, which signals warmth and affiliative intent. Conversely, those aspects of the face that make a face appear both dominant and masculine are made more salient by anger expressions. Specifically, the tightening of the lips in anger makes the mouth region appear more square and the drawing together of the eyebrows enhances the apparent thickness of the eyebrows. Thus, these expressions resemble both the morphological markers for the perceived behavioral intentions of dominance and affiliation. In addition, they are among the markers for sex. Thus, persons with dominant appearing faces may not only be perceived as particularly capable of anger (Tiedens 2001) and when anger is expressed on such a face it should be seen as quite intense, but the face should also appear as more likely to be male. Likewise, a more affiliative appearing face displaying happiness should be seen as more positive than would a less affiliative face displaying the identical facial movement (Hess et al.2007), as well as more likely to be female.

In fact, this relation between emotion expression, dominance and affiliation, and gender is so strong that it can produce the reverse bias, that is, the facial expression shown on an androgynous face can bias the assignation of gender to this face. Thus, an avatar who shows a happy or fearful expression is perceived as more likely to represent a woman and an avatar who looks angry is considered to be less likely to represent a woman and in a sex detection task participants are slower to decide that a women is indeed a women when she shows anger (Hess et al.2009).

Interestingly, these morphology-based associations are also in-line with stereotype beliefs about men and women which attribute higher levels of emotional expressivity to women than to men with the exception of anger, which is seen as more frequent in men (Fischer 1993). This pattern is also found when participants are presented with vignettes describing a specific emotion-eliciting event (Hess et al. 2000). These stereotypical expectations regarding men and women's emotionality seem to be strongly normative (Hess et al. 2005). This raises the question of how information based on facial morphology and information based on social rules interact.

This was the goal of a study by Hess et al. (2010). As it is impossible in our society to fully untangle the influence of these factors since they are highly confounded, we created an alien society where these factors could be unconfounded. In this alien world, Deluvia, child rearing is exclusively assumed by a third gender, the caregiver, whereas men and women share the same social roles. The facial appearance of the Deluvians was varied along the dominance continuum. The results showed that facially dominant Deluvians, regardless of gender, were expected to show more anger, disgust, and contempt and less happiness, fear, sadness, and surprise. Also, the nurturing caregivers were expected to show less anger, contempt, and disgust as well as more fear, sadness, and surprise, regardless of facial appearance. No effect of gender per se on perceived emotionality was found. That is, both facial morphology and beliefs drove the inferences drawn from the faces. Thus, the face is not an empty canvas on which emotions appear and disappear but rather provides its own context to the expression.

7.5 The Two Paths Model of Emotion Recognition

Figure 7.2 summarizes the two paths model of emotion recognition. The basic message is that emotion expressions can sometimes be quite directly identified through pattern matching. However, in general, facial expressions are only part of the relevant information, the other part is provided by the context, which consists of situational information, and information on the social group membership of the expression, the relevant social rules, and norm as well as the goal, motives, emotions, and ability of the decoder. These elements will provide on one hand the necessary information for the decoder to deduce the emotion of the expresser, by either applying the logic of likelihood based on stereotype knowledge or by taking the perspective of the expresser. On the other hand, these elements also impact on the decoder's motivation to actually engage in that process and on the biases the decoder may introduce as a function of their own congruent or divergent goals. Finally, in the case of facial expressions (but likely also for other, as yet unstudied channels), the medium of the expression itself influences both the perceptional basis of pattern matching (as for example, anger is easier detected in male and happiness in female faces, due to the perceptual overlap between expression and gender marker) and the choice of context information. As such, no expression is ever decoded without context.

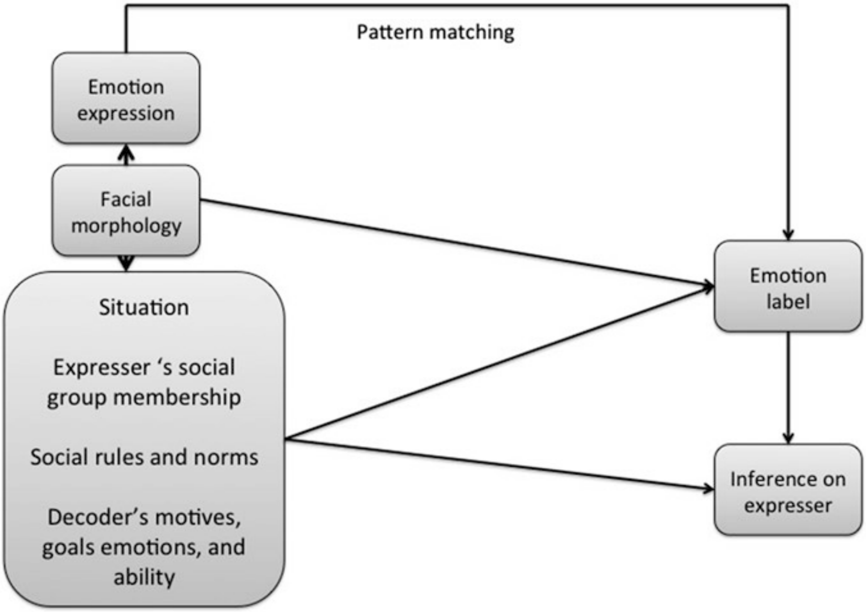

Fig. 7.2 The two paths model of emotion perception

7.6 Conclusions and Future Research

The present chapter has the goal to outline the importance of context in emotion communication. The definition of context, in our view should be expanded to not only include the scenes in which the expressions occur and the people who may witness the emotion expression, but should acknowledge the active role of the perceiver in constructing their understanding of the emotional signal by taking recourse to their tacit knowledge about social norms and rules and the likely emotionality of members of different social groups. In a wider sense the perceivers own goals, motives and states also provide a context to emotion perception. We finally point out, that the notion that facial expressions in particular could be studied without context, as was recently expressed in calls for more context in emotion research (Barrett and Kensinger 2010) is not realistic as facial expressions carry their own context with them—the face.

The research on the role of context information for emotion perception is in its infancy. In what follows we will discuss a few directions and questions that in our view merit further research as well as mention some methodological issues that need attention.

The identification of emotions is multifaceted. Most of the research on the identification of emotions focuses on the nonverbal manifestations that are associated with specific emotions and how accurate perceivers are in identifying emotions from such manifestations (Ekman et al.1969, 1972, 1987; Ekman and Friesen 1971; Izard 1971b). Yet, the correct "emotion label" is not the only aspect of the reaction that needs to be identified by the observer. Thus, the intensity of an emotional expression, its cause, and object are usually identified together with the expression. Importantly, "pure" emotion expressions are rare and hence secondary emotions are often also identified from a given expression (Algoe et al.2000). Little is known about how secondary emotions, emotion intensity, cause, and object are influenced by context and how in turn they contribute to the perception of the emotion.

We suggest that the a-priory knowledge that the perceiver has about the situation and the emoter influences the identification of the emotions by a perceiver. However, at the same time, the emotional facial expressions of others are usually understood to be authentic expressions of their feelings. What happens when the two sources of information conflict? In extreme cases, where the emotion and the purported elicitor are highly incompatible (e.g., a happy smile when seeing a mutilation), this results in a negative attitude toward the expresser (Szczurek et al.2012). However, more research is needed to understand how the expression conveyed by the expresser interacts with observer's expectations regarding the "proper" emotion to be shown in the given situation.

Related to the above is the question of cultural decoding rules. Whereas considerable research has addressed the impact of cultural display rules on emotion production, there is considerably less research on the reverse impact of decoding rules. The role that knowledge about those rules plays in the identification stage, however, this is of increasing relevance in our increasingly multicultural world. Specifically, emotional display rules are both culture specific (Boucher 1974; Matsumoto 1990) and, like most rules, not explicitly taught but implicitly acquired during socialization (Malatesta and Haviland 1982). Our model predicts that differences in display rule knowledge should lead to cultural misunderstandings when these rules are applied to the identification of emotions.

7.6.1 Methodological Concerns

Research on emotion perception in context also needs to consider a few methodological issues. First, one important aspect that needs to be considered in this context is the normativeness of the expressions examined. In many cases, researchers manipulate an emotional expression of a target embedded in a certain context (e.g., Szczurek et al.2012; Van den Stock et al.2013). Yet, these expressions are not always equally normative for the context examined. For example, it may seem more normative for a high status person to express anger rather than sadness at a failure (Tiedens 2001). Differences between these expressions in terms of their effect on perceivers may be, thus, not only a function of the signal value of the emotion as such but also its normativeness. Yet, because the participants respond to the stimuli by using their naïve knowledge and experience, it is also possible that they simply have less knowledge about non-normative behaviors. In such a case, they may respond to the different emotions by using different knowledge structures. This implies that research on emotion perception in context needs to carefully consider which emotions are to be contrasted and to what degree a given emotional reaction can be considered normative for the given situational context.

Finally, given that not all aspects of the context can be controlled, it is important to employ multiple stimuli in each condition so that any idiosyncratic aspect of the expresser that cannot be controlled will vary sufficiently so that the chances that it will be a confound will be reduced. Although this claim may appear quite trivial, in many studies exploring the perception of emotions these precautions are not employed and for example only one expresser is used or only expressers of one sex.

7.7 Conclusion

We offered a discussion of the kind of context factors that potentially intervene in the perception of emotions and some of the conditions under which these context factors are more likely to affect this process. Yet, our analysis is not the only one to discuss the perception of emotions. Other models such as the EASI by van Kleef (2009) also aim to describe this process. Yet, this model is less of a competing model than a complimentary one as it mainly focuses on the types of outcomes of this process. Among other things, it shows that expressions of emotions can affect observers' own emotions as well as inferences about the expresser. It also describes some individual differences characterizing observers that affect this process. Our model completes this picture by stressing the effect of context on this process and by offering a mechanism by which inferences are drawn.

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Chapter 8
Automatic Facial Expression Analysis

Michel Valstar

Automatic Facial Expression Analysis has come a long way since the earliest approaches in the early 1970s. We are now at a point where we see the first approaches that are commercially applied, most notably in the shape of smile detectors included in digital cameras and as marketing research tools such as those developed by companies including CrowdEmotion, RealEyes and Affectiva. But although facial expression recognition is maturing as a research field, research and development in this area is far from finished as there remain both a number of obstacles to overcome as well as a large number of exciting opportunities to explore.

To overcome the remaining obstacles to wide-spread adoption of automatic facial expression analysis, new techniques continue to be developed on all aspects of the processing pipeline: from face detection, via feature extraction all the way through to machine learning and evaluation. Nor is the field blind to the progress made in the social sciences with respect to emotion theory. No longer do people attempt to detect six discrete expressions only, which are turned-on and of like the switching of lights. Far from being switch-like binary detectors, modern analysis approaches dissect expressions into their temporal phases (Jiang et al. 2013; Valstar and Pantic 2012), analyse intensity, symmetry and micro-expressions, and detect dynamic differences between morphologically similar expressions (Valstar et al. 2006, 2007). The theory of Social Signal Processing (Vinciarelli et al. 2012) is a recent addition that is used in conjunction with the classical six-basic emotions theory, and the recognition of mixed discrete emotions and dimensional affect (Gunes et al. 2011) are now active sub-fields.

The shores of brave new worlds are within reach—Automatic Facial Expression Analysis is poised to revolutionise medicine with the advent of behaviomedics, an

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area that I define as the diagnosis, monitoring and treatment of medical conditions that either alter human behavior or can be treated more efficiently with technology that senses or synthesises human behavior. Other exciting new application areas are gaming with enriched player–non-player interactions, teleconference meetings with automatic trust and engagement analysis and human–robot interaction with robots displaying actual empathy.

In this chapter, I will give a step by step overview of all the aspects involved in creating successful automatic facial expression analysis systems. I will discuss the various approaches that are currently considered to be state-of-the-art, and provide a number of applications. Finally, I will discuss what lies ahead: challenges to be faced and advances in science waiting to be made possible.

8.1 State-of-the-Art

It is always hard to give an overview of what is currently the state-of-the-art in a highly active field such as Automatic Facial Expression Analysis, as it is bound to change before long. There may also be advances that are purely theoretical or merely incremental, and many works have not or cannot be proven to work in real time on realistic data sets. While these works may turn out to be highly valuable in the longer term, it is the works that work now in the wild that are about to revolutionise our world. The overview below will, therefore, focus on works that have proven to work in (near) real-time and/or in realistic, so-called in the wild scenarios (Crabtree et al. 2013; Rogers 2011), as it is these that are most likely to be adopted into commercial systems and publicly available services before long.

8.2 The Processing Pipeline

Facial expression recognition systems generally follow the processing pipeline displayed in Fig. 8.1, although variations on this theme exist. It starts with illumination normalisation, followed by face detection, face registration, feature extraction and finally classification or regression [formally speaking hypothesis testing (Mitchell 1997)]. We will discuss the state-of-the-art in each of these steps in some detail below, as they all play a crucial role in automatic facial expression analysis.

8.2.1 Face Detection

The first step in any facial expression analysis system will be face detection, as we need to be able to constrain the feature extraction to the area of the image that contains the face, rather than the background or any other part of the body. There has

Fig. 8.1 Typical processing pipeline for facial expression analysis

been a long history of research in this area, which is essentially an object detection problem in computer vision. Many systems nowadays use the Viola and Jones cascade detector (Viola and Jones 2002), at first because of its speed and reliability at the time, and currently because it has been widely implemented in products such as Matlab and OpenCV. But although that detector is relatively fast and robust, it is not perfect and there have been a number of recent advances in the area of face detection that address its shortcomings. In particular, the Viola and Jones detector cannot deal well with non-frontal faces, and it has a rather high false positive rate, i.e. non-face objects or elements of the background that are classified as being a face.

There have been a number of recent successful approaches to deal with non-frontal, or multi-view face detection. Typically this is achieved by using a combination of multiple view-specific detectors. Recently, Zhu and Ramanan (2012) proposed an algorithm capable of performing reliable multi-view face detection. While the work primarily targets facial point detection, their work is interestingly not that accurate in terms of facial point detection (Jaiswal et al. 2013), but the face detection and a rough head pose estimation which come as a by-product of their algorithm are extremely robust and accurate. Given a high enough image resolution, the Zhu and Ramanan method offers superior performance to the Viola and Jones algorithm and is capable of dealing with head poses with a range of [90, −90] yaw rotation.

A similar model was proposed for the specific task of face detection by Orozco et al. (2013). This results in better performance and faster execution at the expense of the facial point detection. A further speed-up is attained without significant performance loss by adopting a cascaded detection strategy. Both works are publicly available from the respective author's website. For an extensive overview of recent advances in face detection, please see the survey by Zhang and Zhang (2010).

8.2.2 Face Registration

Finding the location of the face in an image is not sufficient to produce accurate expression analysis. Looking ahead to the feature extraction and machine learning steps, it is crucial that our descriptors describe the variation of face shape and appearance that are caused by facial expression, not by dynamic changes in e.g. the head pose or static differences between groups defined by traits such as gender, age or ethnicity. In the face registration step, the face is transformed to remove such geometric differences. In other words, the face is rotated so that it is upright and frontal facing, and scaled so that shape differences between individuals are minimised. The process can be decomposed into two independent steps—intra-subject registration and inter-subject registration, where intra-subject registration eliminates the shape variation within one subject, that is, the variation caused by head pose. Inter-subject registration aims to remove the differences in shape between subjects. This is usually done by mapping a subject's face to that of a reference face.

The simplest yet most commonly adopted way to normalise faces is to apply a Procrustes transformation to register each face to a common pre-defined reference coordinate system based on a set of facial landmarks (e.g. Jiang et al. 2011; Zhu et al. 2011), or some inner facial components such as the eyes (e.g. Bartlett et al. 2006; Gehrig and Ekenel 2011; Tong et al. 2010). This process eliminates rigid motions such as translation, isotropic scaling and in-plane head rotations. An anisotropic scaling can be used instead, which can reduce the effect of identity variations and small out-of-plane rotations.

However, in real-world scenarios, the observed subjects cannot be assumed to remain static and removing variations due to head pose variability is a beneficial step. Normalising for the head pose means warping the face shape and texture to, ideally, its equivalent in the frontal view. To this end, the facial points are localised in every frame of the sequence, a mapping between each non-frontal shape and a frontal shape equivalent is defined. This defines a piecewise affine transformation on the face texture through the use of a mesh defined by the points. That is to say, an affine transformation is applied to the image texture within each of the mesh triangles. The accuracy of this transformation relies on the accuracy of the face tracker, and a large number of facial points (e.g. 60 or more) are required. Alternatively, the detected head pose could be used to learn a mode-specific model for each pose. However, while this avoids complicated 3D registration of the face, it does require training data of expressions from every possible head pose.

Different shape transformations can be obtained, and might or might not depend on the shape model used. If a 3D shape model is used, eliminating head pose can be achieved by applying a rigid rotation. However, the 3D coordinates of the shape might not be fitted accurately to the physical 3D of the face, so it is, therefore, not clear how accurate this warping would be. Of course, the advent of new consumer-grade RGB-D sensors such as the Microsoft Kinect might make the entire 3D shape modelling much simpler.

When using a 2D statistical shape model, its PCA basis vectors encode information of 3 modes of variation; non-frontal head pose variations, identity and facial expressions. Therefore, eliminating head pose from the shape means also eliminating facial expressions from it. However, applying this same transformation to the face texture does not eliminate all the expression of information, as everything contained within a triangle of the mesh undergoes only an affine transformation. For example, Lucey et al. (2011) use an AAM tracker and morph the face texture at every frame to that of a neutral frontal face template. Although some information might be lost in the process, the texture information is highly registered. It has been shown that, when used in combination with geometric features based on the untransformed face shape, it yields superior performance compared to the use of non-frontal textures (Kaltwang et al. 2012; Lucey et al. 2011).

8.2.3 Feature Extraction

It is theoretically possible to go directly from image grey scale intensities to a machine learning solution of facial expression analysis, in which abstract concepts such as edges, motion or eye-lid opening are learned implicitly. But in practice higher accuracy can be obtained by employing pre-defined features. The goal of using features is to reduce the dimensionality of the problem (i.e. the total possible variations of a face descriptor), and to encode aspects of the face that are known to be important for facial expression analysis while ignoring aspects that are irrelevant. Another reason for using features is that they may provide some form of robustness against failings of the earlier steps in the pipeline, such as misaligned faces or imperfect illumination normalisation.

Over the years, researchers have been swaying back and forth between so-called geometric- and appearance-based descriptors. Geometric (or shape)-based features describe a facial expression based on a set of fiducial facial landmarks [often 20 (Valstar and Pantic 2012) or 64 (Lucey et al. 2011)]. They are defined in terms of distances between facial points, motion of facial points, angles between pairs of points, etc. The main benefit of geometric features is that they are intuitive, there is a direct relation between the features and expression intensity and temporal dynamics (as argued by Valstar and Pantic 2012), and they allow for easier registration in case of non-frontal head pose. The main criticism is that they depend on accurate facial point localisation, which has for a long time been a serious problem. However, recent advances in facial point detection allow robust and accurate detection even in realistic scenarios (Jaiswal et al. 2013; Martinez et al. 2013; Saragih et al. 2011), and therefore the only remaining obstacle for the serious adoption of these features is reducing the still significant computational resources required by these approaches.

Filter banks: Gabor wavelets are most commonly used for automatic expression analysis, as they can be sensitive to finer wave-like image structures as those corresponding to wrinkles and bulges, provided that the frequency of the filters used match the size of the image structures. If this is not the case (typically because the face image is too small), Gabor filters will respond to coarser texture properties and miss valuable information. For automatic expression analysis, only Gabor magnitudes are used, as they are robust to misalignment (e.g. Bartlett et al. 2006; Mahoor et al. 2011; Savran et al. 2012b, c). Both holistic and local approaches use similar Gabor parametrisations, as the ideal parameters relate to the size of the facial structures. Typical parametrisations in the literature use 8 orientations, and a number of frequencies ranging from 5 to 9. Gabor filters have been applied both in a holistic manner in (Littlewort et al. 2009; Tong et al. 2007; Wu et al. 2011, 2012; Zhang et al. 2008) and in a local manner in (Baltrusaitis et al. 2011; Cohn et al. 2004; Hamm et al. 2011; Tian et al. 2002; Zhu et al. 2011). However, they require a significant optimisation effort, as their dimensionality is very large, especially for holistic approaches. Furthermore, their high computational cost is a burden for real-time applications. It has been recently shown, however, how to significantly speed-up their computation when only inner products of Gabor responses are needed (Ashraf et al. 2010).

Haar-like filters (Papageorgiou et al. 1998; Whitehill and Omlin 2006), that respond to coarser image features, are robust to shift, scale and rotation variations, and are computationally very efficient. Haar filters are not responsive to the finer texture details, so their use should be limited to detecting expressions related to the more obvious facial muscle actions, usually expressed in terms of the Facial Action Coding System's Action Units (AUs, Ekman et al. 2002).

The discrete cosine transform (DCT) features (Ahmed et al. 1974) encode texture frequency using pre-defined filters that depend on the patch size. DCTs are not sensitive to alignment errors, and their dimensionality is the same as the original image. However, higher frequency coefficients are usually ignored, therefore potentially loosing sensitivity to finer image structures as wrinkles and bulges. DCTs have been used for automatic AU analysis by Gehrig and Ekenel (2011) and Kaltwang et al. (2012), being computed in a block-based holistic manner by Gehrig and Ekenel (2011) and holistically but without being block-based by Kaltwang et al. (2012).

Binarised local texture: Local binary pattern (LBP) (Ojala et al. 1996) and local phase quantisation (LPQ) (Ojansivu and Heikkila 2008) belong to this group. Their main characteristics are (1) real-valued measurements extracted from the image intensities are quantised to increase robustness (especially against illumination conditions) and reduced intra-class variability (2) histograms are used to eliminate the spatial information of the distribution of patterns, increasing the robustness to shifts.

The local binary pattern of a pixel is defined as an 8-dimensional binary vector that results from comparing its intensity against the intensity of each of the neighbouring pixels. The LBP descriptor is a histogram where each bin corresponds to one of the different possible binary patterns, resulting in a 256-dimensional descriptor. However, the so-called uniform pattern LBP is normally used. It results from eliminating some pre-defined bins from the LBP histogram that are more likely to code spurious structures, also reducing the feature dimensionality (Ojala et al. 2002). Many works successfully use LBP features for automatic facial expression analysis. They are typically used in a block-based holistic manner (Chew et al. 2011; Jiang et al. 2011; Smith and Windeatt 2011; Wu et al. 2012), and Jiang et al. (2013) found 10×10 blocks to be optimal for uniform LBPs. The main advantages of LBP features are their tolerance to illumination changes, their computational simplicity and their sensitivity to local structures while remaining robust to shifts (Shan et al. 2008). They are, however, not robust to rotations, and a correct normalisation of the face to an upright position is necessary. A review of LBP-based descriptors can be found in Huang et al. (2011).

The LPQ descriptor (Ojansivu and Heikkila 2008) uses local phase information extracted using the 2D short-term fourier transform (STFT) computed over a rectangular M-by-M neighbourhood at each pixel position. It is robust to image blurring produced by a point spread function. The phase information in the Fourier coefficients is quantised by keeping the signs of the real and imaginary parts of each component. LPQs were used for automatic facial expression analysis by Jiang et al. (2011), Jiang et al. (2013), and the latter found that when applied in a holistic manner, 4×4 blocks perform best.

There is a glaring shortcoming associated with the static appearance descriptors outlined above. Essentially, facial expression recognition is concerned with facial action detection. It is a dynamic event that needs to be detected. As such, static appearance descriptors are not the ideal descriptors for this task. Consider someone with a particular physiognomy that makes it look like she is smiling when in fact her muscles are not activated, or an older man who has permanent wrinkles between or above the eyebrows. A static appearance descriptor may mistake this for an activation of the zygomaticus major (i.e. a smile) for the smiley lady, or the corrugator supercilii (i.e. brow lowerer) for the older man, when in fact there was no facial action at all. There is a direct dual in geometric features, where it is usually required to look at the displacement of facial points over time or with respect to a neutral face.

To detect facial actions, and thus expressions, it would make much more sense to look at appearance *changes* over time. This is exactly what dynamic appearance descriptors do. They consider small cubic space-time video volumes, and calculate a feature that describes the changes of appearance over time, often together with static appearance for each of the frames in the video volume.

Zhao and Pietikainen (2007) proposed a dynamic extension of LBPs that did exactly this. To make the approach computationally simple, LBP features are computed only on Three Orthogonal Planes (TOP): XY, XT, and YT, resulting in the LBP-TOP descriptor. The same extension was proposed for LPQ features (Jiang et al. 2011), and later with the highly successful LGBP features (Almaev and Valstar 2013) (see Fig. 8.2). Yang et al. (2009) proposed dynamic features based on Haar-like features. During a training phase, the distribution of values of each Haar-like feature is modelled using a Normal distribution. The dynamic descriptor is built by thresholding the values of each Haar-like feature within a temporal window using the Mahalanobis distance, resulting in a binary pattern. This has been extended by Yang et al. (2011).

Many dynamic features can be defined to be a generalisation of their static counterparts, resulting in more powerful representations, and they can distinguish actions characterized by their temporal evolution (e.g. onset vs. offset). This has been shown in (Almaev and Valstar 2013; Jiang et al. 2013), where the performance of the LBP, LPQ, LGBP features, and their TOP variants were evaluated for automatic AU detection. It showed a significant and consistent performance improvement when using spatio-temporal features for each of several databases

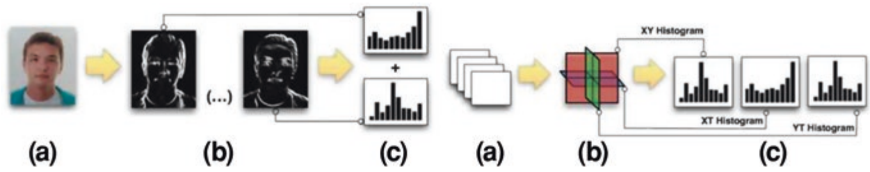

Fig. 8.2 Extraction of local gabor binary patterns from three orthogonal planes (Almaev and Valstar 2013). *Left* the original image is convolved by a bank of Gabor filters, resulting in an equal number of Gabor Pictures. *Right* Local binary patterns are extracted from three orthogonal planes of a small number of subsequent Gabor Picture frames

tested. However, important challenges still exist in relation with the design of spatio-temporal features.

First of all, the dimensionality of the feature vector can be large, which has a negative impact on generalisation ability and thus accuracy of the facial expression recognition system. Secondly, spatio-temporal features are computed over fixed-length temporal windows, so that the possible speeds of an action produce different patterns and increase the intra-class variability.

Interestingly, it appears that TOP features are not as sensitive to misalignment of faces in the registration phase as one would expect. While the contiguity of pixels in the spatial plane is given by the image structure, temporal contiguity depends on the face registration. Therefore, TOP features should theoretically be sensitive to registration errors, as activations in the temporal planes may now be caused by spurious face rotations caused by alignment errors rather than by the motion of facial features caused by facial expression. Interestingly, this does not appear to be the case. While investigating the sensitivity of LGBP-TOP to facial misalignments, it was found that TOP features are actually more robust to rotational misalignments than their static counterparts. To assess the sensitivity to misalignments, we performed an experiment in which images in a spatio-temporal video volume were artificially rotated by a degree a that was sampled from a Gaussian distribution with mean 0 and standard deviation σ. Results, reproduced here in Fig. 8.3, showed that the TOP feature performance degraded much less than the static appearance descriptors (Almaev and Valstar 2013).

8.2.4 Machine Analysis of Facial Expressions

Once an appropriate feature representation of a facial expression has been obtained, it is the task of the machine learning component to learn the relation between the feature representation and the target facial expressions. Facial expressions can be described in terms of discrete expressions of emotions, FACS AUs, or dimensional affect. Below we will limit the discussion to discrete machine learning approaches, and will not go into the details of regression-based dimensional affect recognition.

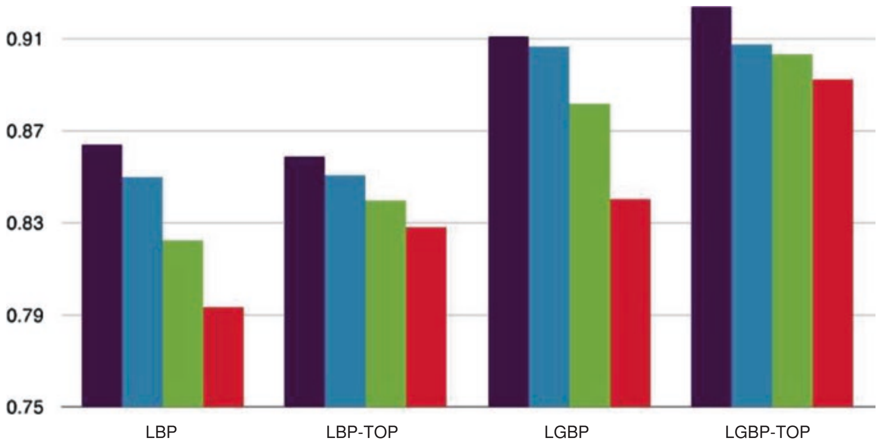

Fig. 8.3 Analysis of sensitivity to errors in alignment. Images are rotated randomly from a Normal distribution with std 0, 3, 7 and 11°. Accuracy measured in 2AFC

AU activation detection aims to assign, for each AU, a binary label to each frame of an unsegmented sequence indicating whether the AU is active or not. Therefore, *frame-based A U detection* is typically treated as a multiple binary classification problem, where a specific classifier is trained for each target AU. This reflects the fact that more than one AU can be active at the same time, so AU combinations can be detected by simply detecting the activation of each of the AUs involved. It is also important to take special care when dealing with non-additive AU combinations; such combinations need to be included in the training set for all of the AUs involved. An alternative is to treat non-additive combinations of AUs as independent classes (Tian et al. 2001). That makes the patterns associated with each class more homogeneous, boosting the classifier performance. However, more classifiers have to be trained/evaluated, especially because the number of non-additive AU combinations is large. Finally, the problem can be treated as multi-class classification, where a single multi-class classifier is used per AU. AU combinations (either additive or non-additive) are treated as separate classes, as only one class can be positive per frame, which makes this approach only practical when a small set of AUs is targeted (Smith and Windeatt 2011).

Discrete expressions of emotion detection on the other hand is a multi-class problem. It is possible to have a facial display that signals a mixture of emotions, making it desirable for the chosen machine learning methods to output a level of likelihood or intensity for each possible expression rather than a single emotion. In general, mixtures of emotions are not simply additive as is the case with AUs, making it important that sufficient training data of expressions of mixed emotions are available, something that is generally hard to obtain.

Common binary classifiers applied to the frame-based AU detection problem include artificial neural networks (ANN), Ensemble learning techniques and support vector machines (SVM). ANNs were the most popular method in earlier works (Bazzo and Lamar 2004; Donato et al. 1999; Fasel and Luettin 2000; Smith and Windeatt 2011; Tian et al. 2002). ANNs are hard to train as they typically involve many parameters, they are sensitive to initialisation, the parameter optimisation process can end up in local minima and they are more prone to suffer from the curse of dimensionality, which is particularly problematic as data for AU analysis is scarce. Some of the advantages of ANN, such as naturally handling multi-class problems or multidimensional outputs, are of less importance in case of frame-based AU detection, but can be very useful for detection of discrete expressions of emotion.

Ensemble learning algorithms, such as AdaBoost and GentleBoost, have been a common choice for AU activation detection (Hamm et al. 2011; Yang et al. 2009; Zhu et al. 2011). Boosting algorithms are simple and quick to train. They have fewer parameters than SVM or ANN, and are less prone to overfitting. Furthermore, they implicitly perform feature selection, which is desirable for handling high-dimensional data. However, they might not capture more complex non-linear patterns. SVMs are currently the most popular choice (e.g. Chew et al. 2012; Gonzalez et al. 2011; Jiang et al. 2011; Wu et al. 2012; Yang et al. 2011) as they often outperform other algorithms for the target problem (Bartlett et al. 2006; Savran et al. 2012b, c). SVMs are non-linear methods, parameter optimisation is relatively easy, efficient implementations are readily available (e.g. the libsvm library; Chang and Lin 2011), and the choice of various kernel functions provides flexibility of design.

Temporal consistency: facial expression detection is by nature a temporally structured problem as, for example, the label of the current frame is more likely to be active if the preceding frame is also labelled active. Considering the problem to be structured in the temporal domain is often referred to as enforcing temporal consistency. Graphical models are the most common approach to attain this. For example, Valstar et al. (2007) used a modification of the classical Hidden Markov Models. In particular, they substituted the generative model that relates a hidden variable and an observation with a discriminative classifier. In terms of graph topology, this consists of inverting the direction of the arrow relating the two nodes, and results in a model similar to a Maximum Entropy Markov Model (McCallum et al. 2000).

Van der Maaten and Hendriks (2012) applied a conditional random field (CRF), which represents the relations between variables as undirected edges, and the associated potentials are discriminatively trained. In the simplest CRF formulation, the label assigned to a given frame depends on contiguous labels, i.e. it is conditioned to the immediate future and past observations. Van der Maaten and Hendriks (2012) trained one CRF per AU, and each frame was associated to a node within the graph. The state of such nodes is a binary variable indicating AU activation. Chang et al. (2009) used a modified version of the hidden conditional random field (HCRF), where the sequence is assumed to start and end with known AU activation labels. The hidden variables represent the possible AU activations, while the labels to be inferred correspond to prototypical facial expressions. In other words, observations provide evidence regarding the activation of AUs (the hidden variables), while facial expressions are inferred from the binary information on AU activations. In this way, the detection of AUs and prototypical expressions is learnt jointly.

Dimensionality reduction: Due to the potentially high dimensionality of the input features, it is often recommended (but not necessary) to reduce the input dimensionality prior to the application of other learning techniques. This can be done through either feature selection or manifold learning. The former aims to find a subset of the original features that are representative enough. The latter consists of finding underlying lower-dimensional structures that preserve the relevant information from the original data (e.g. PCA). Therefore, manifold learning uses a (typically linear) combination of the original features instead of a subset of them. Dimensionality reduction can lower the computational cost for both training and testing and can even improve performance by avoiding the curse of the dimensionality. For example, Smith and Windeatt (2011) adopted the fast correlation-based filtering algorithm, which operates by repeatedly choosing the feature that maximises its correlation to the labels and minimises its correlation with previously selected features.

AdaBoost/GentleBoost has also been used as a feature selection technique (e.g. Bartlett et al. 2006; Littlewort et al. 2009; Jiang et al. 2011; Valstar et al. 2006, 2012). At each iteration of a Boosting algorithm, one feature is used to build a weak classifier. Then the examples are re-weighted to increase the importance of previously misclassified examples, so that the new weak classifier uses a feature which is complementary to the previously selected features. Such linear methods might not be optimal for feature selection when used in combination with a non-linear classifier such as SVM. However, such combinations have been experimentally shown to be effective (Jiang et al. 2011).

Common unsupervised manifold learning approaches such as PCA (Bazzo and Lamar 2004; Khademi et al. 2010; Valstar et al. 2011), ICA and LFA (Donato et al. 1999) have been applied to automatic AU analysis. Non-negative matrix factorisation was recently applied in Jeni et al. 2012. The authors argue that each dimension corresponds to a different part of the face. Manifold learning techniques such as PCA are common for face analysis, as it has been argued that the intensity values of face images lie on a linear manifold. However, more often than not the eigenvectors explaining most of the data covariance actually relate to other factors such as alignment errors or identity, while the most relevant eigenvectors for automatic AU analysis represent a much smaller part of the energy.

Alternatively, discriminant methods can be used, for example discriminant analysis (DA) (Donato et al. 1999). The aim was then not to keep as much energy from the original signals as possible, but to find a manifold (typically a linear subspace) over which to project the feature vectors so that the separability between classes is maximised. Other methods compute either non-linear or locally linear embeddings. For example, Rudovic et al. (2012) used a kernelised (non-linear) version of linear locality preserving projections to project data from a graph structure to a lower-dimensional manifold. Similarly, Mahoor et al. (2009) employed Laplacian Eigenmaps to obtain a non-linear embedding with locality preservation properties.

The most widely used manifold learning methods (e.g. PCA), and the currently explored feature selection techniques, are designed for linear cases. However, they have been shown to be effective even when combined with non-linear classification methods such as SVM (Bartlett et al. 2006; Valstar et al. 2011). Furthermore, manifold learning methods are most commonly unsupervised. This might result in the loss of AU-related information, as alignment errors or identity variations typically produce larger appearance variation than facial expressions. Therefore, expressive information might be encoded in the lower-energy dimensions, which are usually discarded. The practical advantage of using supervised manifold learning methodologies has not been systematically compared to the unsupervised setting, and the practical impact of these considerations is still unclear.

Unsupervised detection of facial events: In order to avoid the problem of lack of training data, which impedes development of robust and highly effective approaches to machine analysis of AUs, some recent efforts focus on unsupervised approaches to the target problem. The aim was to segment a previously unsegmented input sequence into relevant 'facial events', but without the use of labels during training (De la Torre et al. 2007; Zhou et al. 2010). The facial events might not be coincident with AUs, although some correlation with them is to be expected, as AUs are distinctive spatiotemporal events. A clustering algorithm is used in these works to group spatiotemporal events of similar characteristics. Furthermore, a dynamic time alignment kernel is used by Zhou et al. (2010) to normalise the facial events in terms of the speed of the facial action. Despite of its interesting theoretical aspects, unsupervised learning traditionally trails behind in performance to supervised learning, even when small training sets are available. A semi-supervised learning setting might offer much better performance, as it uses all the annotated data together with potentially useful unannotated data.

Transfer learning: Transfer learning methodologies are applied when there is a significant difference between the distribution of the learning data and the test data. In these situations, the decision boundaries learnt on the training data might be sub-optimal for the test data. Transfer learning encompasses a wide range of techniques designed to deal with these cases (Pan and Yang 2010). They have only very recently been applied to automatic AU analysis. For example, Chu et al. (2013) proposed a new transductive learning method, referred to selective transfer machine (STM). Because of its transductive nature, no labels are required for the test subject. At test time, a weight for each training example is computed as to maximise the match between the weighted distribution of training examples and the test distribution. Inference is then performed using the weighted distribution. The authors obtained better a remarkable performance increase, beating subject-specific models. This can be explained by the reduced availability of subject-specific training examples. However, Chen et al. (2013) evaluated standard methodologies for both inductive and transductive transfer learning for AU detection, finding that inductive learning improved the performance significantly while the transductive algorithm led to poor performance. It is important to note that, for the case of inductive learning, subject-specific labelled examples were available at training time.

Transfer learning is a promising approach when it comes to AU analysis. Appearance variations due to identity are often larger than expression-related variations. This is aggravated by the high cost of AU annotation and the low number of subjects present in the AU datasets. Therefore, techniques that can capture subject-specific knowledge and transfer it at test time to unseen subjects are very suited for AU analysis. Similarly, unsupervised learning can be used to capture appearance variations caused by facial expressions without the need for arduous manual labelling of AUs. Both transfer learning and supervised learning have, thus, a great potential to improve machine analysis of AUs with limited labelled data.

The dynamics of facial actions are crucial for distinguishing between various types of behavior (e.g. pain and mood). The aim of AU temporal segment detection is to assign a per-frame label belonging to one of four classes: neutral, onset, apex or offset. It constitutes an analysis of the internal dynamics of an AU episode. Temporal segments add important information for the detection of a full AU activation episode, as all labels should occur in a specific order. Furthermore, the AU temporal segments have been shown to carry important semantic information, useful for a later interpretation of the facial signals (Ambadar et al. 2005; Cohn and Schmidt 2004).

Temporal segment detection is a multiclass problem, and it is typically addressed by either using a multiclass classifier or by combining the output of several binary classifiers. Some early works used a set of heuristic rules per AU based on facial point locations (Pantic and Patras 2004, 2005, 2006), while further rules to improve the temporal consistency of the label assigned were defined by Pantic and Patras (2006). In Valstar and Pantic (2012), a set of one versus one binary SVMs (i.e. six classifiers) were trained, and a majority vote was used to decide on the label. Similarly, Koelstra et al. (2010) trained GentleBoost classifiers specialized for each AU and each temporal segment characterized by motion (i.e. onset and offset). These last two works use a score measure provided by the classifier to represent the confidence of the label assignments.

Probabilistic graphical models can be adapted to this problem to impose temporal label consistency by setting the number of states of the hidden variables to four. The practical difference respect to the AU activation problem is that the transitions are more informative, as for example an onset frame should be followed by an apex frame and cannot be followed by a neutral frame. Markov models were applied to this problem by Valstar and Pantic (2012) and Koelstra et al. (2010). An extension of CRF, and in particular a kernelised version of Conditional Ordinal Random Fields, was used instead by Rudovic et al. (2012). In comparison to standard CRF, this model imposes ordinal constraints on the assigned labels. It is important to note that distinguishing an apex frame from the end of an onset frame or beginning of an offset frame by its texture solely is impossible. Apex frames are not characterized by a specific facial appearance or configuration but rather for being the most intense activation within an episode, which is by nature an ordinal relation.

While traditional classification methodologies can be readily applied to this problem, they produce suboptimal performance, as it is often impossible to distinguish between the patterns associated to the different temporal segments at a frame level. Therefore, the use of temporal information, both at the feature level and through the use of graphical models, is the most adequate design. In particular, the use of graphical models has been shown to produce a large performance improvement, even when simpler methods like Markov Chains are applied (Koelstra et al. 2010; Jiang et al. 2013). The use of CRFs, however, allows to jointly optimise the per-frame classifier and the temporal consistency, while the use of ordinal relationships within the graphical model add information particularly suited to the analysis of the AU temporal segments.

When it comes to automatic analysis of temporal co-occurrences of AUs, the relations between AU episodes are studied, both in terms of co-occurrences and in terms of the temporal correlation between the episodes. To this end, Tong et al. (2007) modelled the relationships between different AUs at a given time frame by using a Static Bayesian Network. The temporal modelling (when an AU precedes another) is incorporated through the use of a dynamic bayesian network (DBN). They further introduced a unified probabilistic model for the interactions between AUs and other non-verbal cues such as head pose (Tong et al. 2010). The same group later argued that the use of prior knowledge instead of relations learnt from data helps to generalise to new datasets (Li et al. 2013). Although traditionally unexploited, this is a natural and useful source of information as it is well known that some AUs co-occur with more frequency due to latent variables such as for example prototypical facial expressions. In particular, graph-based methodologies can readily incorporate these relations. However, it is necessary to explore the generalisation power of these models, as they are likely to have a strong dependency on the dataset acquisition conditions.

Annotations of intensity are typically quantised into A, B, C, D and E levels as stipulated in the FACS manual. Some approaches use the confidence of the classification to estimate the AU intensity, under the rationale that the lower the intensity is, the harder the classification will be. For example, Bartlett et al. (2006) estimated the intensity of action units by using the distance of a test example to the SVM separating hyperplane, while Hamm et al. (2011) used the confidence of the decision obtained from AdaBoost.

Multi-class classifiers or regressors are more natural choices for this problem. It is important to note, however, that, for this problem, the class overlap is very large. Therefore, the direct application of a multi-class classifier is unlikely to perform well and comparably lower than when using a regressor. That is to say, for regression, predicting B instead of A yields a lower error than predicting D, while for a classifier this yields the same error. Mahoor et al. (2009) made an attempt of using a multi-class classifier for this task. The authors employed six one vs all binary SVM classifiers, corresponding to either no activation or one of the five intensity levels. The use of a regressor has been a more popular choice. For example, Jeni et al. (2012, 2013), and Savran et al. (2012b, c) applied support vector regression (SVR) for prediction, while Kaltwang et al. (2012) used relevance vector regression (RVR) instead. Both methods SVR and RVR are extensions to regression of SVM, although RVR yields a probabilistic output.

Expression intensity estimation is a relatively recent problem within the field, in particular for AUs. It is of particular interest due to the semantic richness of the predictions. However, it is not possible to objectively define rules for the annotation of AU intensities, and even experienced manual coders will have some level of disagreement. Therefore, the large amount of overlap between the classes should be taken into consideration. Regression methodologies are particularly suited, as they penalise a close (but different) prediction less than distant ones. Alternatively, ordinal relations can alleviate this problem by substituting the hard label assignment with softer ones (e.g. greater than). There is also a large degree of data imbalance, as high intensity AUs are much less common.

8.3 Performance and Challenges

Facial Expression Recognition, in particular FACS AU detection (Ekman et al. 2002) and classification of facial expression imagery in a number of discrete emotion categories, has been an active topic in computer science for some time now. And since the first workshop on automatic dimensional affect recognition held during FG 2011 (Gunes et al. 2011) there has been intense interest in that area as well. Yet although there have been a number of surveys on automatic facial expression recognition over the years (e.g. Fasel and Luettin 2003; Pantic and Rothkrantz 2000; Samal and Iyengar 1992; Zeng et al. 2009), the question remains as to whether the approaches proposed to date actually deliver what they promise. To help answer that question, a few years ago we felt it was time to take stock, in an objective manner, of how far the field has progressed.

Researchers often do report on the accuracy of the proposed approaches using a number of popular, publicly available facial expression databases (e.g. The Cohn-Kanade database; Kanade et al. 2000, the MMI-Facial Expression Database; Valstar and Pantic 2010, or the JAFFE database; Lyons et al. 1998). However, only too often publications fail to clarify exactly what parts of the databases were used, what the training and testing protocols were, and hardly any cross-database evaluations are reported. All these issues make it difficult to compare different systems to each other, which in turn hinder the progress of the field. A periodical challenge in Facial Expression Recognition would allow this comparison in a fair manner. It would clarify how far the field has come, and would allow us to identify new goals, challenges and targets.

It is in this spirit that we organised the first Facial Expression Recognition and Analysis challenge (FERA 2011; Valstar et al. 2011), followed by a series of Audio-Visual Emotion recognition challenges (AVEC 2011, 2012, 2013; Schuller et al. 2011, 2012; Valstar et al. 2013). FERA 2011 focused on the detection of AUs and displays of discrete emotions from video only. AVEC 2011 had as target audio-visual analysis of the affective states arousal, valence, power and expectancy in binary form (i.e. either high or low affect). AVEC 2012 extended this to fully continuous audio-visual affect recognition on the same dataset. Finally, AVEC

2013 had as task the recognition of both dimensional affect and a mental health condition, i.e. the severity of major depressive disorder. Below we will give an overview of the four challenges and their outcome.

8.3.1 Facial Expression Recognition and Analysis Challenge 2011

The Facial Expression Recognition and Analysis challenge 2011 was the first challenge in automatic recognition of facial expressions, held during the 9th IEEE conference on Face and Gesture Recognition 2011. This section provides details of the challenge data used, the evaluation protocol that participants had to follow, and the results attained in two sub-challenges: AU detection and classification of facial expression imagery in terms of a number of discrete emotion categories. A summary of the lessons learned and reflections on the future of the field of facial expression recognition in general and on possible future challenges in particular are given in the end.

A dataset needs to satisfy two criteria in order to be suitable as the basis of a challenge. Firstly, it must have the relevant labelling, which in the case of FERA 2011 means frame-by-frame AU labels and event-coding of discrete emotions. Secondly, the database cannot be publicly available while the challenge is being held. The GEMEP corpus (Banziger and Scherer 2010), which was used for FERA 2011, is one of the few databases that meet both conditions.

The GEMEP corpus consists of over 7,000 audiovisual emotion portrayals, representing 18 emotions portrayed by 10 actors who were trained by a professional director. The actors were instructed to utter 2 pseudo-linguistic phoneme sequences or a sustained vowel aaa.

Figure 8.4 shows an example of one of the male actors displaying an expression associated with the emotion anger. A study based on 1,260 portrayals showed that portrayed expressions of the GEMEP are recognised by lay judges with an accuracy level that, for all emotions, largely exceeds chance level, and that inter-rater reliability for category judgments and perceived believability and intensity of the portrayal is very satisfactory (Banziger and Scherer 2010). At the time of organising the challenge, the data had not been made publicly available yet, making it a suitable dataset to base a fair challenge on. A detailed description of the GEMEP corpus can be found in Banziger and Scherer (2010).

The GEMEP-FERA dataset was created for FERA 2011 and is a fraction of the GEMEP corpus that has been put together to meet the criteria for a challenge on facial action units and emotion recognition. By no means does the GEMEP-FERA dataset constitute the entire GEMEP corpus. In selecting videos from the GEMEP corpus to include in the GEMEP-FERA dataset, the main criterium was the availability of a sufficient number of examples per unit of detection for training and testing. It was important that the examples selected for the training set were different than the examples selected for the test set.

Fig. 8.4 An example of the GEMEP-FERA dataset: one of the actors displaying an expression associated with the emotion 'anger'

The twelve most commonly observed AUs in the GEMEP corpus were selected. To be able to objectively measure the performance of the competing facial expression recognition systems, the dataset was split into a training set and a test set. A total of 158 portrayals (87 for training and 71 for testing) were selected for the AU sub-challenge. All portrayals are recordings of actors speaking one of the 2 pseudo-linguistic phoneme sequences. Consequently, AU detection had to be performed during speech. The training set included 7 actors (3 men) and the test set included 6 actors (3 men), half of which were not present in the training set.

For the emotion sub-challenge, portrayals of five emotional states were retained: anger, fear, joy, sadness and relief. Four of these five categories are part of Ekman's basic emotions. The fifth emotion, relief, was added to provide a balance between positive and negative emotions but also to add an emotion that is not typically included in previous studies on automatic emotion recognition. Emotion recognition systems are usually modelled on the basic emotions, hence adding relief made the task more challenging.

A total of 289 portrayals were selected for the emotion sub-challenge (155 for training and 134 for testing). Approximately 17 % of these were recordings of actors uttering the sustained vowel aaa while the remaining portrayals were recordings of actors speaking one of the 2 pseudo-linguistic phoneme sequences. The training set included 7 actors (3 men) with 3 to 5 instances of each emotion per actor. The test set for the emotion sub-challenge included 6 actors (3 men), half of which were not present in the training set. Each actor contributed 3–10 instances per emotion in the test set.

The goal of the AU detection sub-challenge was to identify in every frame of a video whether an AU was present or not (i.e. it is a multiple-label binary classification problem at frame level). The goal of the emotion recognition sub-challenge was to recognise which emotion was depicted in that video, out of five possible choices (i.e. it is a single label multi-class problem at event level). The

Table 8.1 Average classification rates over all emotions for the Emotion recognition sub-challenge and average F1-measure over all AUs for the AU detection sub-challenge

Participant	Emotion detection		
	Person-independent	Person-specific	Overall
ANU	0.649	0.838	0.734
KIT	0.658	0.944	0.773
MIT-Cambridge	0.448	0.433	0.440
Montreal	0.579	0.870	0.700
NUS	0.636	0.730	0.672
Riverside	**0.752**	0.962	**0.838**
QUT	0.624	0.554	0.600
UCLIC	0.609	0.837	0.700
UCSD	0.714	0.837	0.761
UIUC-UMC	0.655	**1.00**	0.798
Baseline	0.440	0.730	0.560

High scores are printed in bold

challenge protocol was divided into four stages. First, interested parties registered for the challenge and signed the EULA to gain access to the training data. Then they trained their systems. In the third stage, the participants downloaded the test partition and generated the predictions for the sub-challenges they were interested in. They then sent their results to the FERA 2011 organisers who calculated and returned their scores.

The challenge data was downloaded by 20 teams, of which 15 participated in the challenge and submitted a paper to the FERA 2011 workshop. Of the 15 papers, 11 papers were accepted for publication, based on a double-blind peer review process. In total, 10 teams participated in the emotion recognition sub-challenge, and five teams took part in the AU detection sub-challenge (three teams participated in both sub-challenges). Demographic statistics of the participants were as follows: Teams were from many countries and often spanned multiple institutes. The participating institutes were dispersed over 9 countries (USA, Australia, Canada, Germany, Singapore, Sweden, UK, Belgium and France). In total, 53 researchers participated in the challenge, with a median of 6 researchers per paper. Five entries were multi-institute endeavours. This indicates that the research community is not entrenched in local enclaves, instead there appears to be a large amount of cooperation and communication between researchers of automatic facial behavior understanding. With four authors being psychologists, the challenge indicated a certain level of interdisciplinary collaboration as well.

Table 8.1 shows the scores attained in the emotion recognition sub-challenge. As can be seen, 9 out of 10 participating systems outperform the baseline approach on the full test set. The winning team, Yang and Bhanu of the University of California Riverside, attained an overall 83.8 % classification result (Yang et al. 2011).

Table 8.2 F1 measures per AU, for every participant in the AU detection sub-challenge

AU	ISIR	KIT	MIT-Camb.	QUT	UCSD	Avg
1	**0.809**	0.606	0.681	0.780	0.634	0.702
2	**0.731**	0.520	0.635	0.723	0.636	0.649
4	0.582	0.529	0.446	0.433	**0.602**	0.518
6	**0.833**	0.822	0.739	0.658	0.759	0.762
7	**0.702**	0.554	0.323	0.553	0.604	0.547
10	0.475	0.467	0.328	0.468	**0.565**	0.460
12	0.803	0.798	0.658	0.778	**0.832**	0.774
15	**0.245**	0.065	0.114	0.156	0.193	0.155
17	**0.557**	0.518	0.300	0.471	0.499	0.469
18	0.431	0.329	0.127	**0.448**	0.345	0.336
25	**0.850**	0.800	0.815	0.311	0.815	0.718
26	**0.576**	0.515	0.475	0.537	0.515	0.524

Last column shows average over all participants, and high scores are printed in bold

The results for the AU detection sub-challenge are shown per partition in Table 8.1, and overall results per AU for each team are shown in Table 8.2. The winner of the AU detection sub-challenge was the team of Senechal et al., from the Institut des Systemes Intelligents et de Robotique, Paris (Senechal et al. 2011). Their method attained an F1 measure of 63.3 %, averaged over all 12 AUs. This is well above the baseline's 45.3 %, but still very far off from a perfect AU recognition.

Looking at individual AUs, we can see that AU1, AU2, AU6 and AU12 are consistently detected well by all participants, while AU4, AU5, AU10, AU17, AU18 and AU26 were consistently detected with low accuracy. AU25, parting of the lips, is detected with high accuracy by all participants except QUT (Chew et al. 2011). Chew et al. (2011) noted that this may have been due to an inability to deal with speech effectively. AU7, narrowing of the eye aperture caused by contraction of the orbicularis occuli muscle (pars palpebralis), was only detected with high accuracy by Senechal et al. (2011). Valstar et al. (2012) did a full meta-analysis of this challenge, including per-AU results.

8.3.2 Audio/Visual Emotion Challenge 2011/2012

The Audio/Visual Emotion Challenge and Workshop (AVEC) series is aimed at the comparison of multimedia processing and machine learning methods for automatic audio, visual and audio-visual emotion analysis, with all participants competing under strictly the same conditions. The goal of the challenge series is to provide a common benchmark test set for individual multimodal information processing and to bring together the audio and video emotion recognition communities, to compare the relative merits of the two approaches to emotion recognition under well-defined and strictly comparable conditions and establish to what extent fusion of the approaches is possible and beneficial. A second motivation is the need to advance emotion recognition systems to be able to deal with naturalistic behavior in large volumes of unsegmented, non-prototypical and non-preselected data as this is exactly the type of data that both multimedia retrieval and human–machine/human–robot communication interfaces have to face in the real world.

The 2011 and 2012 challenges used the SEMAINE corpus (McKeown et al. 2012) as the source of data. This database was recorded to study natural social signals that occur in conversations between humans and artificially intelligent agents, and to collect data for the training of the next generation of such agents. It is freely available for scientific research purposes from http://semaine-db.eu. The scenario used in the recordings is called the sensitive artificial listener (SAL) technique (Douglas-Cowie et al. 2008). It involves a user interacting with emotionally stereotyped characters whose responses are stock phrases keyed to the users emotional state rather than the content of what (s)he says. For the recordings, the participants are asked to talk in turn to four emotionally stereotyped characters. These characters are Prudence, who is even-tempered and sensible; Poppy, who is happy and outgoing; Spike, who is angry and confrontational; and Obadiah, who is sad and depressive.

Different from FERA, the AVEC series uses affective dimensions rather than discrete emotion categories. In AVEC 2011 and 2012, the dimensions used are arousal, expectation, power and valence, which are all well established in the psychological literature. An influential recent study (Fontaine et al. 2007) argues that these four dimensions account for most of the distinctions between everyday emotions categories. Arousal is the individual's global feeling of dynamism or lethargy. It subsumes mental activity as well as physical preparedness to act as well as overt activity. Expectation (Anticipation) also subsumes various concepts that can be separated as expecting, anticipating, being taken unaware. Again, they point to a dimension that people find intuitively meaningful, related to control in the domain of information. The Power (Dominance) dimension subsumes two related concepts, power and control. However, people sense of their own power is the central issue that emotion is about, and that is relative to what they are facing. Valence is an individuals overall sense of weal or woe: Does it appear that, on balance, the person rated feels positive or negative about the things, people or situations at the focus of his/her emotional state? All interactions were annotated by 2–8 raters, with the majority annotated by 6 raters: 68.4 % of interactions were rated by 6 raters or more, and 82 % by 3 or more. The raters annotated the four dimensions in continuous time and continuous value using a tool called FeelTrace (Cowie et al. 2000), and the annotations are often called traces.

The dataset was split into three partitions, a training, development and test partition. Raw audio and video data, labels and baseline features were given for the training and development partitions, but for the test partition the labels were held back. Declaring a development partition allows participants to report on the

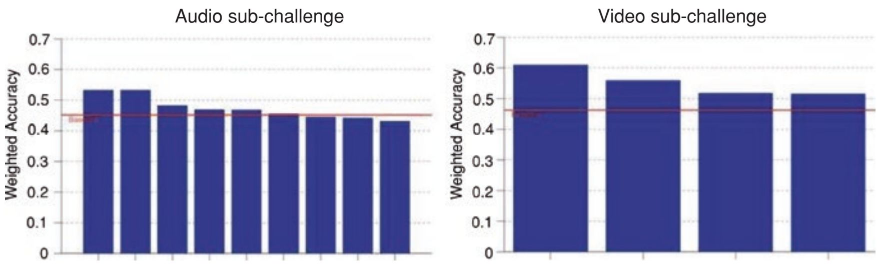

Fig. 8.5 Audio-based (*left*), and video-based (*right*) detection results of binarised affect on the SEMAINE database from participants of AVEC 2011

performance of various subsystems on a common subset of the given data. This would not be possible on the test data as the test labels are not provided and participants have a limited number of results submission opportunities. While both AVEC 2011 and 20112 were based on affective dimensions, the 2011 edition had a somewhat easier goal to determine only whether the affect was higher or lower than average at any given time, reducing it to a binary classification problem. The 2012 edition had as goal the prediction of the real values of affect, making it a regression problem, which is in general harder to solve. The results for AVEC 2011 are shown in Fig. 8.5, and for AVEC 2012 in Fig. 8.6.

You can find more details about each participants' entry in their own works. For AVEC 2011: UCL (Meng and Bianchi-Berthouze 2011), Uni-ULM (Glodek et al. 2011), GaTechKim (Kim et al. 2011), LSU (Calix et al. 2011), Waterloo (Sayedelahl et al. 2011), NLPR (Pan et al. 2011), USC (Ramirez et al. 2011), GaTechSun (Sun and Moore 2011), I2R-SCUT (Cen et al. 2011), UCR (Cruz et al. 2011) and UMontreal (Dahmane and Meunier 2011a, b). For AVEC 2012: UPMC-UAG (Nicolle et al. 2012), Supelec-Dynamixyz-MinesTelecom (Soladie et al. 2012), UPenn (Savran et al. 2012a), USC (Ozkan et al. 2012), Delft (van der Maaten 2012), Uni-ULM (Glodek et al. 2012), Waterloo2 (Fewzee and Karray 2012). The results obtained by I2R, Cubic-ASU, and the University of Aberystwyth did not result in a publication. Interestingly, the binary problem of AVEC 2011 should have been the easier problem, yet participants hardly improved over the baseline, barely over 52 % correct for the winners. On the other hand, for the continuous dimensional affect challenge, 7 out of 10 participants attained scores higher than the baseline, many of them significantly higher. The winners attained a score of 0.45 Pearson's correlation, which is about 4 times as high as the baseline. Correlation may be somewhat hard to interpret as a raw number. We therefore show the prediction and ground truth on some of the AVEC 2012 recordings of the winner's system in Fig. 8.6.

One of the aims of the challenges was to encourage audio-visual emotion recognition, and while only two out of nine participants combined audio and video information in the 2011 edition, in the 2012 edition six out of eight participants submitted fully audio-visual systems (Fig. 8.7).

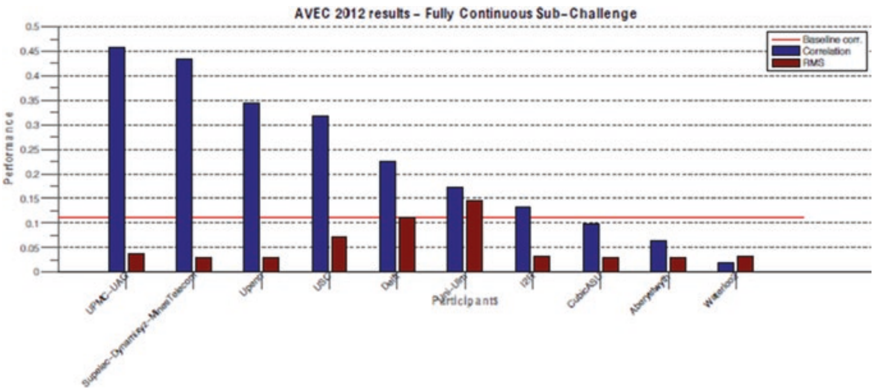

Fig. 8.6 Average Pearson's Correlation and root mean square error for recognition of four affective dimensions on the SEMAINE database for all participants of AVEC 2012

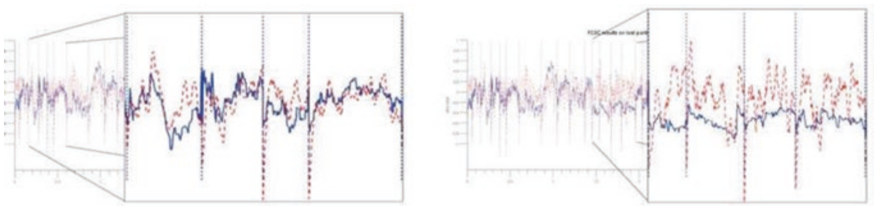

Fig. 8.7 Ground truth (*blue*) and prediction (*red*) of prediction of Arousal by the winners of the AVEC 2012 challenge. Vertical dotted lines delineate separate video recordings. *Figure left* shows 4 consecutive recordings that are predicted very well, while the *figure right* shows 4 recordings that are not predicted well at all

8.3.3 Challenge Conclusions

The FERA 2011 challenge made clear that recognition of the displays of prototypical, discrete emotions can be considered to be a solved case if the recording conditions are reasonably good and some data of the person to perform recognition on is available. Even for person-independent emotion recognition high recognition accuracy can be obtained and it is thus possible to start implementing emotion recognition in real consumer applications. For automatic FACS coding, the picture is less positive—it is clear from the literature and the results of FERA 2011 that we are still some way off from reliable AU detection in realistic conditions. A few of the more explicit AUs can be detected with reasonably high accuracy though, most notably AU1 and AU2 (inner and outer brow raisers), AU12 and AU6 (smile and the frequently co-occurring cheek raiser), and AU25 (lips parted). It is thus possible to start implementing some of these AUs in commercial applications.

Fig. 8.8 Facial expressions of two Blue Peter presenters analysed using head-mounted camera footage on the new Alton Towers ride 'The Smiler'

8.4 Wild Facial Expression Analysis

As the results from the FERA and AVEC challenges pointed out, some early applications of facial expression analysis are now ready to be deployed 'in the wild'. Resounding evidence of this is the smile-triggered photo capture that is integrated into many modern consumer cameras. Another example of this is a recent marketing stunt we performed for Alton Towers' new roller coaster ride 'The Smiler'. There we deployed our LGBP-TOP based emotion recognition system (Almaev and Valstar 2013) on footage captured by head-mounted cameras worn by journalists and presenters of the popular children's television programme 'Blue Peter'. The footage of their emotional expressions was captured while going through the 14 consecutive loops in the ride (see Fig. 8.8). This was used to describe how some people really enjoy a ride, thrill seekers who love nothing more than an exciting experience such as a roller coaster, while others experience mostly fear with moments of relief, and generally strong happiness as the ride ends.

With the maturing of automatic facial expression recognition, opportunities are becoming evident to researchers in other areas as well as industries in areas in marketing, healthcare and security. With the availability of both commercial and academic tools for face analysis having extensive knowledge of computer vision and machine learning is no longer an obstacle. Our Automatic Human Behavior Understanding team at the Mixed Reality Lab of the University of Nottingham has released their own API for face and facial expression analysis under an academic license, which includes the code used for the Alton Towers emotion recognition, but also AU detection (Almaev and Valstar 2013) facial point detection (Jaiswal et al. 2013), head pose detection and includes all the intermediate steps of the processing pipeline outlined in Sect. 8.2. The API is written in C++ and includes extensive documentation. For those who do not want to integrate an API into their own programs, we have made some of our research output available through a cloud-based web service called affective computing tools on the cloud (ACTC) (Almaev et al. 2013). Both the API and ACTC can be found online on http://actc.cs.nott.ac.uk.

Despite the positive tone of this chapter and the encouraging results presented here, it is becoming increasingly clear that current approaches to facial expression recognition, while capable of dealing robustly with a limited set of facial displays, cannot scale to cover all 7,000+ possible facial expressions, encountered under all possible environmental conditions, for all possible demographics. Even if data of all such expressions would be recorded (which in itself would be no mean feat), manual annotation of such an extensive dataset would be impossible given the high level of training that is required of manual FACS annotators. Therefore, it is essential that researchers in this field turn to approaches such as online, unsupervised, semi-supervised and transfer learning, which require at most a small part of the dataset to be labelled while still learning all possible facial appearances. Only then can we hope to truly apply facial expression analysis in the wild.

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Chapter 9
Facial Expressions to Emotions: A Study of Computational Paradigms for Facial Emotion Recognition

Dipti Deodhare

9.1 Introduction

The crown jewel of nonverbal communication is facial expression. Facial expressions are reflective of the emotional state of a person's mind and provide nonverbal cues for effective everyday communication. Apart from indicating affective state, they also lend insight into a person's personality and psychopathology. Facial expression cues usually complement speech, enabling a listener to better elicit the intended meaning of spoken words.

Facial emotion recognition is one of the final frontiers of the man–machine interface. Computational methods that enable this capability in machines are being actively researched and are gaining significant importance particularly when taken in context to the notion of *technological singularity.* Technological singularity or simply singularity is currently a much discussed and hotly debated topic by philosophers, computer scientists, physicists, etc. Simply speaking, technological singularity is a theoretical prediction that artificial intelligence (AI) would have progressed to a greater than human intelligence, and machines driven by AI would have radically changed human civilization and even biology and intelligence as the way we know it. Irrespective of whether one agrees with this view or not, a machine's ability to read and interpret human emotions using visual cues clearly creates an important new paradigm in computational advancement. Cognitive systems that respond to human behavior, and intelligent systems that attempt to interact with humans, need to incorporate the ability to read and interpret human facial expressions. Use of computational technologies for recognition and interpretation

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of facial emotions is a thriving area of research and has drawn substantial attention from researchers for over a decade now. Literature survey reveals a vast body of research in the field. Various methods and tests have been formulated by researchers over the last few years, and today, these methods demonstrate some ability to perform interpretations of human expressions and emotions. In what follows, we touch upon some of the landmark contributions in this rigorously researched field.

This chapter is organized as follows: In this, the Introduction Section, besides making some general contextual comments, we also introduce one of the most popular methods for detection of faces in an image. Needless to say, detection of faces in an image is the first important step towards detection of emotions from facial expressions in a computational process. In Sect. 9.2, we give a brief overview of the various approaches discussed in recent literature for automatic detection of emotions from facial expressions. Section 9.3 discusses mechanisms for recognizing emotions from faces, as proposed by psychological and neurological studies. Tools and constructs from computer science that maybe relevant in realizing these theories on a computer are briefly discussed. In Sect. 9.4, we delve into the algorithmic and mathematical details of how typical automatic algorithms are constructed to obtain emotions from images of faces. These technologies are heavily anchored in advanced AI techniques such as neural networks, machine learning, particle swarm optimization, genetic algorithms, and principal component analysis. For the sake of completeness, simple and intuitive descriptions of these techniques have been included where relevant. Section 9.5 presents a specific algorithm from the literature that describes a mechanism of identifying emotions from faces in videos. Finally, Sect. 9.6 offers some concluding comments.

Several technological approaches have been proposed for facial emotion recognition to classify human emotions successfully. Most of these approaches focus on *seven* basic emotions owing to their constancy across culture, age, and other identities. These emotions are as follows: joy, sadness, anger, surprise, disgust, fear, and neutrality. Facial hair, eye glasses, and headwear, etc, affect computational analysis. Further complexities emerge when the subject has a facial injury, or the face is unnaturally constricted due to tight turbans or scarves. Finally, the context of the emotion being expressed also becomes a critical aspect of computational classification. The computational classification may not show the actual emotions in case the subject becomes aware of scrutiny and surveillance and if the subject tries to hide or mask his or her emotions. It is, therefore, critical that such computational analysis techniques and algorithms be developed in close concert with experts in the field of psychology and psychiatrics to arrive at an accurate analysis.

Adolphs (2002) showed in his work that recognition requires some knowledge about the world; it thus requires memory of some sort. One of the simplest forms of recognition is recognition memory, which basically involves the ability to retain information about the perceptual properties of a visual image, to which another image can be compared. This form of recognition may be sufficient to discriminate between two faces that are presented at separate points in time. For an AI-based system to "recognize" emotions, it needs a large memory bank of correlational database. The efficiency with which visual cues are detected, compared,

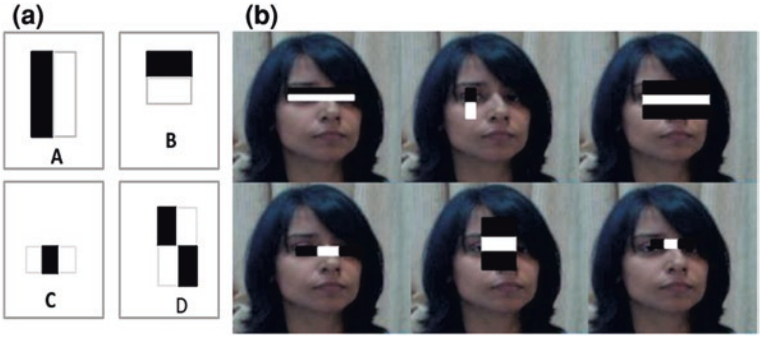


Fig. 9.1 **a** Four basic Haar-like feature extractors. **b** Feature extraction from an image

and lead to an inference is a direct function of the size of the database. Unless large volumes of data are made available to the algorithm for training and correlation, computational intelligence algorithms and reasoning methods cannot produce accurate results. Every instance of an analysis revealed as accurate can be added to the database and gradually help the system "learn." Emotion recognition involves three stages of computation.

Step 1: Face Detection—The Viola–Jones face detection algorithm is of importance and is discussed below.
Step 2: 3D modeling of the face—The active appearance method described by Cootes and Taylor is popular, though other methods are also described here.
Step 3: Computational intelligence-based analysis, using a large databank (at least 2,000 annotated images).

The Viola–Jones algorithm is a popular algorithm for face detection that can detect faces in an image in real time. Proposed by Viola and Jones (2001), the approach, in fact, describes a generic framework for object detection. However, it was first motivated by the problem of face detection in a digital image. The Viola–Jones algorithm works by looking for Haar-like features. All the features are rectangles. Four basic feature extractors are shown in Fig. 9.1a. These rectangular Haar features are positioned at various locations in a detection window. The sum of the pixel intensities in the region below the rectangles is computed. The difference between the sums of adjacent rectangles is then calculated to obtain the feature. The algorithm works on the premise that a human face has contrast patterns organized in a particular manner. For instance, the hairline is darker than the forehead; the eyes are darker than the cheeks, etc. Each of these rectangular patterns is compared with a portion of the image underneath (see Fig. 9.1b) to check how much that particular part of the image matches that pattern. This way the algorithm basically looks for a signature contrast pattern that might be one particular part of the face. To begin with, the tests are coarse so that parts of the image that have no contrast are eliminated very quickly. The feature detection mechanism iterates as a cascade so that more matching requirements are added in more specific spaces.

If a combination of matches passes a threshold comparison, that portion of the image is assumed to potentially contain a face. Each Haar-like feature gives a very weak cue to the potential existence of a face in the image. Therefore, a very large number of Haar features are organized into a classifier cascade to form a strong classifier. A special representation of the image sample, called the integral image, makes feature extraction faster. Typically, a basic classifier operates on 24 × 24 sub-windows. To detect faces at different scales, the detectors are scaled usually by factors of 1.25. Hence, features are easily evaluated at any scale. The detectors are moved around the image, by one pixel increments, for example. As a result, a real face may result in multiple nearby detections. To suppress these multiple detections into a single detection, the detected sub-windows are post-processed to combine overlapping detections.

A computational technique for facial emotion recognition, essentially, maps key points of the face and derives information from the geometry of these points. The features for emotion recognition can be static, dynamic, point-based (geometric), or region-based (appearance). Geometric features are extracted from the shape of important facial components, such as the mouth and eyes, using salient point locations. Facial states, such as the state of eyes, shape of key points of the mouth and eyebrows, and head orientation, are some of the aspects that are used for analysis. The computational approach needs large volumes of data, essentially graphic images with tags and metadata, which can then be used to correlate the expressional characteristics of the target subject. The expression identification is complicated by possibly small inter-subject variations. Various imaging parameters, such as aperture, exposure time, and lens aberrations, can compound the problem by increasing the intra-subject variability. All these factors are confounded in the image data so that variations between the images of same face are almost always larger than image variations due to the change in face identity. There are a number of face databases available which incorporate these variations in images, for example, Japanese Female Facial Expression (JAFFE) and Cohn—Kanade AU coded facial expression database. Care has to be taken to group data phylogenetically, based on gender, age, ethnicity, culture, geographical origin, literacy levels, and background of the subject, etc.

In the next section, we proceed to give an overview of various approaches that have been attempted to establish algorithms for recognition of emotions from faces in an image.

9.2 An Overview of Computational Algorithms for Emotion Recognition

There is a vast body of literature on the topic of face recognition and analysis. Zeng et al. (2009) classified facial features for the purpose of feature recognition under two broad categories: (i) geometric features and (ii) appearance-based features. Geometric features are extracted from the shape or salient point locations of some important facial components, such as mouth and eyes. Suwa et al. (1978) presented an early attempt to automatically analyze facial expressions by tracking the motion of twenty identified spots on an image sequence. In the work of Chang et al. (2006), 58 landmark points were used to construct an active shape model. These landmark points were then used to obtain valid facial emotions across faces.

Appearance-based features, such as *texture,* have been employed in the work of Lyon and Akamatsu (1998) using Gabor filters. In computer programming, a filter is a program or a section of code that is designed to examine each input for certain qualifying criteria and then process or forward it accordingly. Gabor filters are band-pass filters that allow signals between two specific frequencies to pass, but discriminate against signals at other frequencies. These filters are used in image processing for feature extraction, texture analysis, and stereo disparity estimation. A set of Gabor filters with different frequencies and orientations can be helpful for extracting useful features from an image. Gabor filters gained importance when it was discovered that simple cells in the visual cortex of mammalian brains can be modeled by Gabor functions (Daugman 1985). Thus, image analysis by the Gabor functions is similar to perception in the human visual system. The effort proposed a methodology for coding facial expressions with multi-orientation and multi-resolution set of Gabor filters that are ordered topographically and aligned approximately with the face. Similarity values and semantic ratings were calculated using the Gabor coding. The degree of correlation obtained was significantly high, without any parameter fitting. The work of Gu et al. (2012) is also motivated by some characteristics of the human visual cortex (HVC). The authors proposed a new scheme for facial expression recognition, which involved the statistical synthesis of hierarchical classifiers. The method subjects images to multi-scale, local Gabor filter operations. The resulting images are encoded using radial grids. This is similar to the mapping structure displayed in the HVC. The coded images are further processed by local classifiers to result in global features, which represent facial expressions. This hybrid approach that combines the HVC mapping structure with a hierarchy of classifiers has been experimentally demonstrated to improve accuracy on a large number of databases. Lyons et al. (1998) coded facial expression images using a multi-orientation, multi-resolution set of Gabor filters, which are aligned approximately with the face. They derived the similarity space from this representation and compared it with the similarity space derived from the semantic ratings of images by human observers. This representation using Gabor filters shows a noteworthy consistency with human psychology, which can prove very relevant for human–computer interface design.

Feature geometry is an explicit and precise function of facial deformation occurring due to expression, but it does not capture any textural changes. Although addition of grid points enhances the performance of a geometric measure, the overall computational complexity increases exponentially. Azcarate et al. (2005) devised an algorithm based on the piecewise Bezier volume deformation tracker along with a Haar face detector, which was used to initially locate the human face automatically. Experiments in this work were conducted with Naive Bayes and the Tree-Augmented-Naive Bayes (TAN) classifiers in person-dependent and person-independent tests on the Cohn—Kanade database. The results obtained through this approach were better for person-dependent experiments as compared to those for person-independent experiments.

Habibizad and Mirnia (2012) proposed an algorithm to classify emotions through eyes and lips using particle swarm optimization. Particle swarm optimization (PSO) is an artificial intelligence technique to find optimal solutions to really complex problems. In this approach, a population of candidate solutions is represented by a swarm of particles. These particles move around in the search space based on simple mathematical formulae. These formulae take into cognisance a particle's best-known position so far in the search space and guide the particle toward better-known positions in the search space as updated using results contributed by other particles in the swarm. Convergence capabilities of PSO algorithms are demonstrated through empirical results, since there is really no sound mathematical analysis of their convergence properties. PSO algorithms do not require the objective function of the optimization problem to be differentiable. They can search very large spaces and hence can be used in domains where the problems are noisy, change over time, etc. This approach was employed to optimize eyes and lips elliptical characteristics. The results obtained in this approach suggest a high success rate and a high processing speed. Ioannou et al. (2005) proposed an algorithm to recognize emotions using a neuro-fuzzy approach. This approach is robust to facial expression variations among different users. Mpiperis et al. (2008) present a novel approach for expression recognition, which was inspired by the advances in an ant colony and particle swarm optimization techniques. Anatomical correspondence between faces was established using a genetic 3D face model, which was deformed elastically to match the facial surfaces. They achieved a recognition rate of 92.3 % with the BU-3DFEDB database. Kaushik and Mohamed (2012) in their latest research proposed a new lip boundary localization scheme using game theory to elicit lip contour accurately from a facial image. They applied a feature subset selection scheme based on particle swarm optimization to select the optimal facial features. They could achieve recognition rates of 93 % on the JAFFE database. Ghandi et al. (2009) presented an approach which was based on tracking the movements of facial action units placed on the face of a subject. They defined some swarm particles, so that they have a component around the neighborhood of each action unit.

Huang et al. (2012) proposed an algorithm for emotion recognition by a novel triangular feature extraction method that uses statistical analysis and genetic algorithms to extract a set of optimal triangular facial features. In artificial intelligence, genetic algorithms are a type of evolutionary algorithms that help obtain solutions to complex optimization problems, through mechanisms inspired by nature's process of natural selection. The method starts off with generating a set of feasible solutions that acts as the initial population. The objective function of the optimization problem acts as what is described as the fitness function and helps assess if particular samples in this parent population are good. The best are selected to generate a new set of offspring by selecting two parents and taking part of the solution they represent and combining them to create a new possible solution. This mechanism is described as crossover or recombination. Sometimes, the elements in the offspring are slightly changed to represent the mechanism of mutation. Mutation is caused in nature by errors in copying genes from parents. If the new offspring are feasible solutions to the objective function, they are accepted. The process starts again with a suitably selected new population. The algorithm stops if the end criterion is met or a preset number of iterations are completed. The best fitting sample in the current population is returned as the solution. The emotion recognition algorithm proposed is claimed to be robust against noisy features and feature rotations. It also shows a significant dimension reduction in facial features.

Londhe and Pawar (2012) proposed a statistics-based approach combined with artificial neural network (ANN) techniques for analyzing facial expressions. An artificial neural network is a computing model that seeks to emulate the style of computing of the human brain. Its architecture comprises a massively parallel interconnection of simple units called "neurons." These interconnections are weighted, and the long-term knowledge of the network is encoded in the strengths of these connections. Depending on their architecture, neural networks can be classified into two basic types: (i) *feedforward* neural networks and (ii) *recursive* or *recurrent* neural networks. In feedforward networks, signals flow in only one direction, and hence, the network can be represented by an acyclic graph. On the other hand, in recursive networks, a unit may be influenced by its own output directly or indirectly through other units. The *multilayer perceptron* or the MLP is the most widely used feedforward network. It falls in the category of static networks, i.e., their output is a function only of the current input and not of past and future inputs or outputs. In the referred paper (Londhe and Pawar 2012), the authors have studied the changes in the curvatures on the face and the intensities of corresponding pixels of images. They have used statistical parameters to compute these changes, and the computed results were recorded as feature vectors. An ANN was used to classify these features into six universal emotions such as anger, disgust, fear, happiness, sadness, and surprise. A two-layered feedforward neural network was trained and tested using the scaled conjugate gradient back-propagation algorithm to obtain a 92.2 % recognition rate.

Saudagare and Chaudhari (2012) gave an overview of facial expression recognition techniques using neural networks. They used neural networks for face recognition, feature extraction, and categorization. Karthigayan et al. (2008) used the eye and lip regions for the study of emotions. They performed their study on a Southeast Asian face database. They applied genetic algorithms to get the optimized value of the minor axis of an irregular ellipse corresponding to the lips and the minor axis of a regular ellipse related to the eye. Their successful classification went to a maximum of 91.42 %. In order to classify six basic facial expressions of emotions, Dailey et al. (2002) proposed a simple yet plausible neural network model. Their model matched a variety of psychological data on categorization, similarity, reaction times, and recognition difficulty without any parameter tuning. Kobayashi and Hara (1992) investigated the methods of machine recognition of human expressions and their strength. They used back-propagation algorithm for neural network learning and obtained a correct recognition ratio of 90 %. Anam et al. (2009) proposed a face recognition system for personal identification and verification using genetic algorithm and back-propagation neural network. They applied some preprocessing on the input images followed by facial features extraction. These features were taken as the input to the neural network and genetic algorithm for classification. Agrawal et al. (2011) proposed a highly efficient facial expression recognition system using PCA, optimized by a genetic algorithm. They could achieve reduced computational time and comparable efficiency. Yen and Nithianandan (2002) proposed an automatic feature extraction method that was based on edge density distribution of the image. The face is approximated to an ellipse in the preprocessing stage. Consequent to this, a genetic algorithm is applied to search for the best ellipse region match.

Busso et al. (2008) describe visual-feedback-based emotion detection for natural man–machine interaction. Their paper introduces an emotion detection system realized with a combination of a Haar cascade classifier and a contrast filter to detect and localize facial features. The detected feature points are then used to estimate the emotional state using the action units. Based on the exact position of these features, a probability for each of the six basic emotions—fear, happiness, sadness, disgust, anger, and surprise—is assigned. The final test experiments with reference images show correct detection rates of about 60 % for the emotions happiness, sadness, and surprise.

This section has presented some of the more discussed methods in the literature for emotion recognition. The literature landscape is indicative of the state of the art. A large variety of mechanisms have been tried out, and there are several researchers across the globe working in this domain. However, computational paradigms still remain fragile and much more needs to be done to establish robust paradigms. It is not difficult to motivate the conjecture that mechanisms for emotion recognition will also have to include large knowledge bases and fast learning and reasoning mechanisms that operate on them in real time to provide the necessary background and contextual knowledge that would be important to arrive at the correct classification of the emotion through a computational paradigm. The next section discusses this aspect briefly.

9.3 Mechanisms for Recognizing Emotion from Faces

While in an attempt to engineer robust computational paradigms for detecting emotions from facial expressions, we are not necessarily committed to biological plausibility; literature from psychological and neurological studies can contribute effectively in the generation of algorithms. Mechanisms for recognizing facial emotions are tied to specific neural structures and their interconnections. A given brain structure typically participates in multiple strategies. Thus, a recognition task needs disparate strategies and, hence, disparate sets of neural structures. The strategies suggested by Adolphs (2002) are outlined below with brief companion comments on the relevant computational mechanisms that could be potentially used and even effectively combined to realize these mechanisms on the computer.

9.3.1 Recognition as a Part of Perception

The first strategy is to consider recognition as a part of perception. Recognition of basic topographies of a stimulus, and thus recognition that one stimulus differs from another, is fundamentally a matter of perception. To recognize an emotion, we need to be able to discriminate, categorize, and identify emotions on the basis of the geometric visual properties of a stimulus image.

Computer models of psychological studies are evidence that meaningful processing can be carried out from the information present in the geometric properties of a human stimulus. Mathematical analyses reveal that the structure present in images of facial expressions is sufficient in principle to generate some of the structure of the emotion categories that humans perceive (Calder et al. 2001). Network models can judge a sharp perceptual difference between different expressions, even when the expressions are structurally very similar, provided they straddle the boundary of an emotion category (analogous to the way in which we segment a rainbow into bands of color despite linear changes in wavelength). Categorization of morphed images generated from the expressions of two different emotions has been explored in normal subjects (Calder et al. 1996; de Gelder et al. 1997; Etcoff and Magee 1992) and has been investigated in a neural network model trained to classify faces (Cottrell et al. 2001; Padgett and Cottrell 1998).

9.3.2 Recognition Through Associated Knowledge

Recognition typically involves more than just perceptual information. It has associated information. When we see a facial expression, we associate it with a particular type of event or occurrence—past, present, or future (expected). This knowledge is not present in the topographical structure of the stimulus; it is retrieved from our past experience with the emotion (and to a limited extent, may even be present innately). To obtain comprehensive knowledge of the emotion being experienced, we need the means to train the network to store such associated knowledge either as metadata with the emotion data, or in any other form, and retrieve the same when the emotion is encountered. The means to reconstruct with accuracy the knowledge associated with an emotion is a complex aspect of AI-based systems and deals with representation of knowledge.

Knowledge representation and reasoning are important branches of symbolic artificial intelligence and aim to design intelligent computer systems that can reason on machine interpretable representations of knowledge and arrive at conclusions autonomously. Knowledge representation is a substitute representation of the real world that enables determining consequences by "thinking" rather than "acting", i e., by reasoning about the world rather than taking action in it. It is a set of ontological commitments that embody what is important and what can be ignored. Philosophically, ontologies are specifications of what exists or what can be said about the world. They are discussed in the context of the science of being. Modern AI and natural language processing mostly define ontologies to be hierarchical knowledge structures that represent relations between various entities and their combinations, parts/wholes, sets, and individuals. Going back to our discussion on recognition through associated knowledge, ontological representations are best suited for such a task. The advantage of an ontological representation is its ability to build associations across different categories of parameters, which may be geometric, lexical, or semantic, involving varying data structures. This provides a neural scheme for implementing the above representation mechanisms, which can bind information between separate neural representations, so that they can be processed as components of knowledge about the same concept. Extensive feedback connections as well as feedforward connections between different neural regions are needed for integrating the neural representations that are spatially separated in the brain. Another advantage is the ability to build on associated knowledge through "learning" and "training." The representation of the stimulus and its associated knowledge evolves abreast. One continuously modulates and is simultaneously influenced by the other, and perception and recognition become coupled parts of the same process.

9.3.3 Recognition Via Generation of a Simulation

The above two mechanisms are direct methods, which categorize and link together the various components of perceptual and conceptual knowledge about an emotion, signaled by a stimulus. This provides all the information, and all that is now required to complete the recognition task is to reconstruct the perceptual and conceptual knowledge and provide a categorized inference. But imagine a situation where the explicit knowledge obtained from an expressed emotion is itself insufficient to trigger recognition. This may be because the particular emotion has never been encountered before, or the associated knowledge available in the network is insufficient to reconstruct the emotion. An indirect method—*simulation*—is found to succeed in such instances.

Simulation uses the concept of inverse mapping to generate some conceptual knowledge and thereby trigger the states normally antecedent to producing a given facial expression. This is also the concept of *synthesis*, explained below. By simulating an emotional state (based on a partially informed presumption) and generating the motor representations associated with that emotion, this mechanism attempts to trigger conceptual knowledge within the network and complete the task of recognition. Simulation thus provides a mechanism to trigger conceptual knowledge, but the trigger is not the motor stimulus of an easily recognizable emotion, but a conceptual presumption (based on a superficial recognition) that may trigger a full-blown recognition.

This undoubtedly is a hugely complex and advanced recognition task, and it requires extensive inherent conceptual knowledge to be contained within the network. The simulation hypothesis is actually modeled on the biological model (as many computational models are), wherein a suggestion of an emotion triggers the emotion. In the experimental findings of Rizzolatti et al. (1996), they have shown that in the pre-motor cortex of monkeys, neurons not only respond when the monkey prepares to perform an action itself but also respond somatotopically, when the monkey observes the same visually presented action performed by someone else (Gallese et al. 1996; Rizzolatti et al. 1996).

The theory of confabulation, as described in an article at www.scholarpedia.org, offers a detailed comprehensive explanation of the mechanism of thought, e.g., vision, reasoning, language, cognition, planning, origin of thought process, and hearing in humans and other vertebrates and also potentially in some invertebrates, such as bees and octopi. This theory estimates that the gray matter of a human cerebral comprises roughly 4,000 largely mutually disjoint, localized modules. Each module has an area of roughly 45 mm^2. It is further conjectured that a process of genetic selection connects pairs of these modules through knowledge bases of which humans have roughly 40,000 in number. These are rough estimates and would of course vary from individual to individual. The individual module and knowledge base also include a uniquely dedicated, small zone of thalamus. These modules and knowledge bases constitute the thought hardware. The principle of computation is called confabulation and is designed to *maximize cogency*. Simply speaking, confabulation theory works by processing lots of information and then from this information finds out which symbols belong together. Those symbols that are often seen together constitute the information contained within the network. The proponent of this theory Hecht-Nielsen (2007a, b) describes this as the duck test—if a duck-sized creature quacks like a duck, walks like a duck, swims like a duck, and flies like a duck, then we accept it as a duck, because duck is the symbol that most strongly supports the probability of these assumed facts being true; there is no logical guarantee that this creature is a duck; but maximization of cogency makes the decision that it is and moves on. Confabulation can now produce new associations by continuously generating possible symbols based on the context that is seen prior to that. In effect, the confabulation theory uses an architecture that can produce entirely new associations, which are plausible in the context by maximizing cogency.

Computational approaches to interpret facial emotions are based on the mechanisms of *analysis* and *synthesis*. Broadly speaking, in analysis, given a facial expression, computational mechanisms identify what the underlying emotion is. This is a direct classification task based on available data sets. There is a need to examine each aspect of classification and organize data before computational techniques can be applied. In the synthesis approach, soft embodied agents are created, which generate the facial expression based on the emotions presented. The synthesis approach acquires importance when the explicit information from stimulus cannot be recognized by the network. There is, therefore, a need to build a trigger to enable further evaluation. An important aspect of the synthesis approach is to give weights to each of the multiple emotions the subject may be expressing, as humans rarely feel just one emotion at a given point in time. They might be blended based on the weights given to each of the basic emotions from a predefined set. In both approaches, when a face is presented, the system identifies its closeness to a cluster of expressions in a generated bank of the same to infer the blend of expression. Computational solutions that can accurately identify the emotion of the target subject may need a hybrid of the classification and synthesis approach. Some of the mechanisms are discussed in the following sections.

9.4 Basic Computational Processes

In this section, we plunge into the actual computational mechanisms that are the current state of the art for recognition of emotions from facial expressions. The basic computational process of recognizing emotions consists of two phases—**Training** the algorithm and **Classification** of data. Training consists of *labeling* and *modeling*, while Classification consists of *model-fitting* and *emotion classification*. In labeling, facial images of different emotions are collected from databases, and the landmark points of face are hand-labeled in a prescribed manner. These set of landmark points are then fed into the modeling stage where shape models for each class of emotions are constructed. The shape models of each class of emotions, its corresponding mean, and the eigenvectors are stored in files for further reference. The mean face and the eigenvectors for each class of emotions are then read by the model-fitting module, and a test image is fed into this module. Once an appropriate representation is obtained from the model-fitting stage, the final emotion classification stage is carried out.

Cootes (2000) devised the active shape model for modeling. The Cootes method for modeling used in conjunction with the Euclidean distance model for final emotion recognition is reproduced in Fig. 9.2.

9.4.1 Training

Training consists of labeling, shape modeling, alignment of shapes, and model extraction using principal component analysis. Each of these steps is discussed in some detail below.

Labeling—Labeling is a stage in which each landmark point of a face is annotated manually (A landmark is a point of correspondence on each object that matches between and within populations). Figure 9.3 is an example of a hand-labeled facial image. A face is represented as a set of n landmark points defined in (usually) two or three dimensions. It is any shape that is defined as the quality of the configuration of points and is invariant over the Euclidean similarity transformation.

Shape is all the geometrical information that remains when location, scale, and rotational effects are filtered out from an object. Mathematically, a shape is defined by n landmark points in k-dimensional space and is represented by a nk

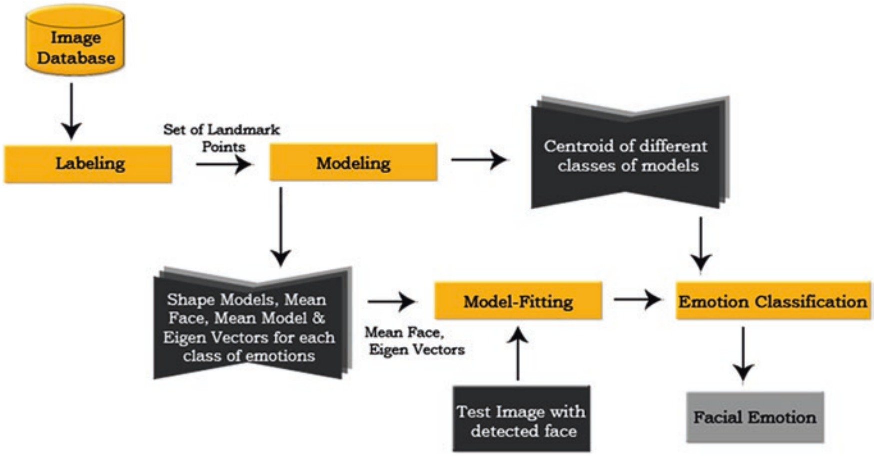
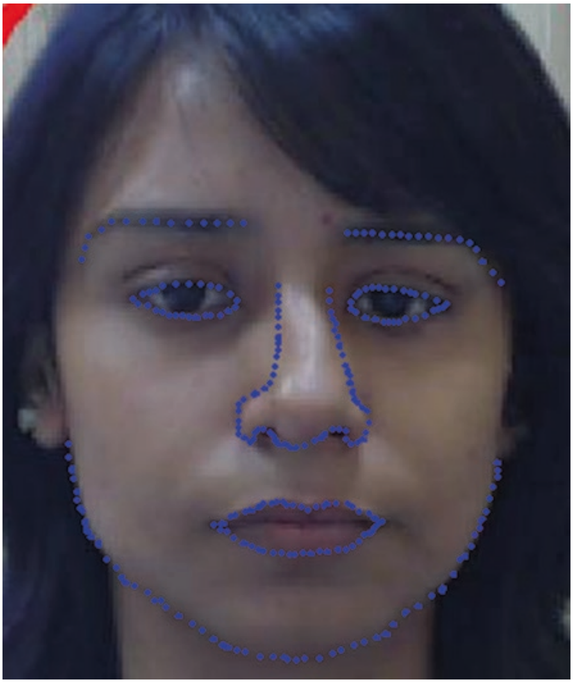


Fig. 9.2 Cootes methodology for emotion recognition

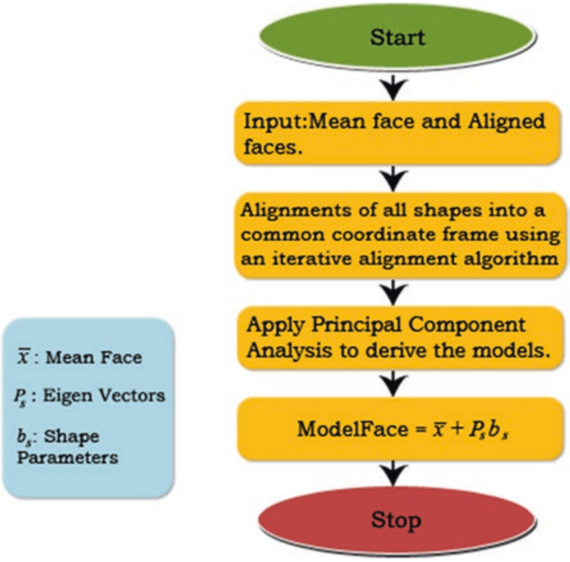
Fig. 9.3 Example of a hand-labeled image



vector. In two-dimensional images ($k = 2$), n landmarks, $\{(x_i, y_i)$: $i = 1,\ldots, n\}$, define the 2 n vector $\boldsymbol{x}$ as follows:

$$\boldsymbol{x} = (x_1, y_1, x_2, y_2, \ldots, x_n, y_n)'$$

Fig. 9.4 Flowchart of shape modeling



Shape Modeling—In shape modeling, face models for different emotions are constructed. Models for each emotion are varied in terms of shape parameters. Different landmark points are selected for different emotions and are varied between specific ranges to derive models for each emotion. The algorithm for shape modeling is as follows (Fig. 9.4):

Alignment of Shapes—The alignment of two shapes comprises of finding the similarity parameters (scale, rotation, and translation) that best maps one shape to another by minimizing a given metric. A classical solution to align two shapes is the **procrustes analysis** method. Procrustes analysis is the most popular approach to aligning shapes in a common reference frame. This aligns each shape such that the sum of the distances of each shape to the mean ($D = \sum |\boldsymbol{x}_\mathrm{i} - \bar{\boldsymbol{x}}|^2$) is minimum. An iterative approach for aligning shapes into a common coordinate frame is depicted in the flowchart below (Fig. 9.5):

Convergence is declared if the estimate of the mean does not change significantly after a single iteration. On convergence, all the examples are aligned in a common coordinate frame and can be analyzed for shape change. After the alignment of faces, principal component analysis is performed on the aligned faces.

Model Extraction Using Principal Components Analysis (PCA)—Principal component analysis (PCA) is a statistical technique for data dimensionality reduction. In this method, the directions in the data that have the largest variance are searched for. The data are projected along directions of large variance resulting in a linear transformation of data into a new coordinate system that orients the axes based on the spread of the data in the high dimensional space. Coordinates along the axes with high variance are taken and the remaining are ignored. This results in dimensionality reduction.

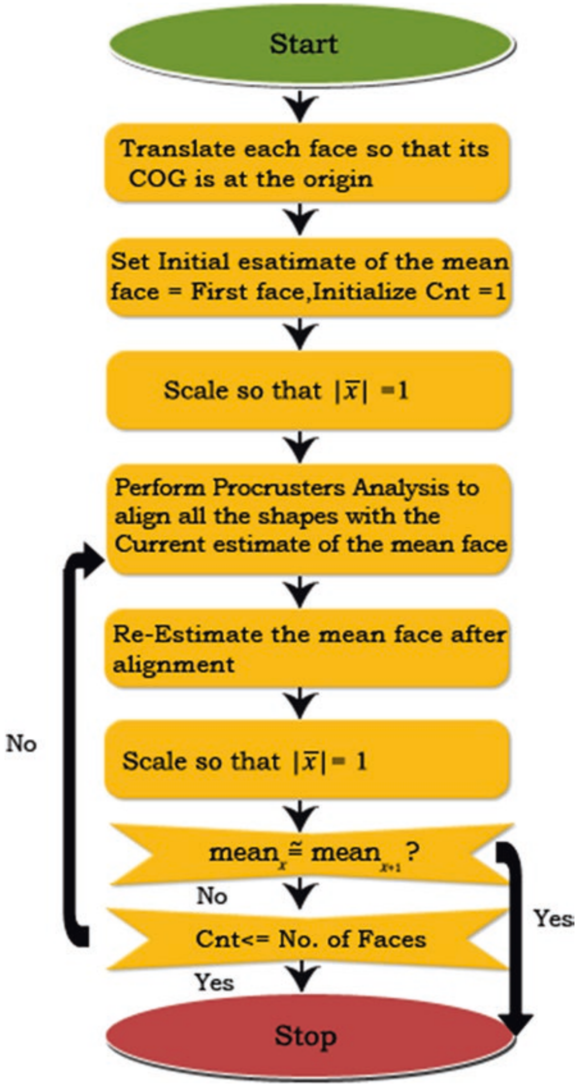


Fig. 9.5 Flowchart for alignment of shapes

Consider a data set with N vectors $\boldsymbol{x}_i$: $i = 1,\ldots, N$, where each $\boldsymbol{x}_i$ is an n-dimensional vector. PCA is performed in the following manner:

(i) Compute the N vectors average,

$$\bar{\boldsymbol{x}} = \frac{1}{N}\sum_{i=1}^{N}\boldsymbol{x}_i$$

(ii) Subtract the mean from each data vector to form the matrix $\mathbf{D}$ as follows:

$$\mathbf{D} = ([\boldsymbol{x}_1 - \bar{\boldsymbol{x}}]|\ldots|\ldots|[\boldsymbol{x}_N - \bar{\boldsymbol{x}}])$$

(iii) Calculate the covariance

$$\boldsymbol{S} = \frac{1}{N}\mathbf{D}'\mathbf{D}$$

$\boldsymbol{S}$ is an $N \times N$ matrix. Calculate the eigenvectors $\boldsymbol{P_s}$ of $\boldsymbol{S}$. $\boldsymbol{P_s}$ should be orthonormal.

(iv) Calculate the shape parameters using the following equation

(v) Model face can be calculated using the following equation

$$\boldsymbol{b_s} = \boldsymbol{P_s}(\boldsymbol{x} - \bar{\boldsymbol{x}})$$

$$\boldsymbol{x}_{\text{model}} = \bar{\boldsymbol{x}} + \boldsymbol{P_s} * \boldsymbol{b_s}$$

Variations in shapes are usually incorporated by varying each element of $\boldsymbol{b_s}$ between $[\pm 3]$ (Fig. 9.6).

9.4.2 Classification

The Classification process includes model-fitting and emotion classification.

Model-Fitting—Model-fitting is performed to obtain a suitable representation of a new image for further classification. In this stage, every test image fed into the module is hand-labeled to obtain the geometrical features or the landmark points of the face. The labeling of landmark points is performed in an orderly fashion and in a consistent manner. These landmark points are then aligned with the mean face using procrustes analysis. Using this mean face, eigenvectors of the models, and the landmark points obtained after alignment of the shapes, the shape parameters are obtained. Then, using an iterative approach, a model is created using the equation described in step (v) in the previous section. The process of model-fitting is depicted in the Fig. 9.7:

Emotion Classification—This is the final stage, in which the model representation obtained from the model-fitting stage is used for further classification under one of the 5 classes of universal emotions, namely *neutral, joy, sadness, surprise,* and *anger*. Emotion classification is carried out by calculating the Euclidean distance between the centroid of each group and the model obtained from the model-fitting stage. The image is placed under the class of emotion where the Euclidean distance between the representation of the test image and the mean model of that class is a minimum. In cartesian coordinates, if $\boldsymbol{p} = (p_1, p_2, \ldots, p_n)$ and $\boldsymbol{q} = (q_1, q_2, \ldots, q_n)$ are two points in Euclidean n-space, then the distance from $\boldsymbol{p}$ to $\boldsymbol{q}$ or from $\boldsymbol{q}$ to $\boldsymbol{p}$ is given by:

$$d(\boldsymbol{p},\boldsymbol{q}) = d(\boldsymbol{q},\boldsymbol{p}) = \sqrt{(\boldsymbol{q}_1 - \boldsymbol{p}_1)^2 + (\boldsymbol{q}_2 - \boldsymbol{p}_2)^2 + \cdots + (\boldsymbol{q}_n - \boldsymbol{p}_n)^2}$$

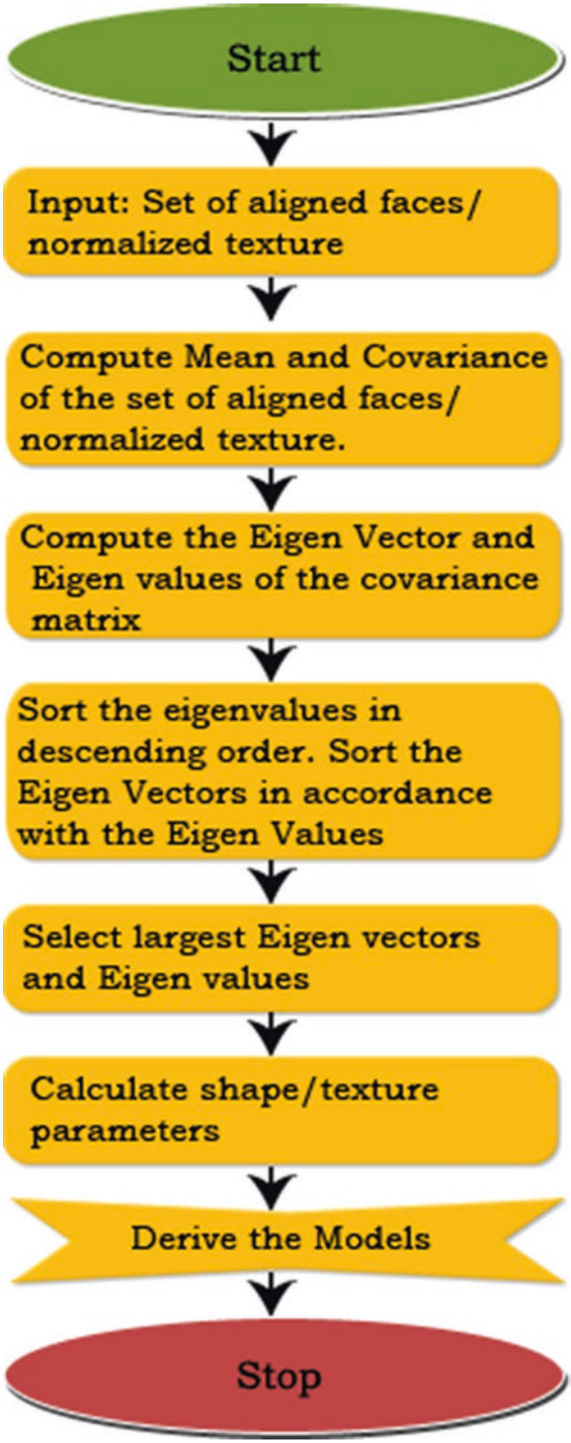


Fig. 9.6 Flowchart depicting the process of PCA

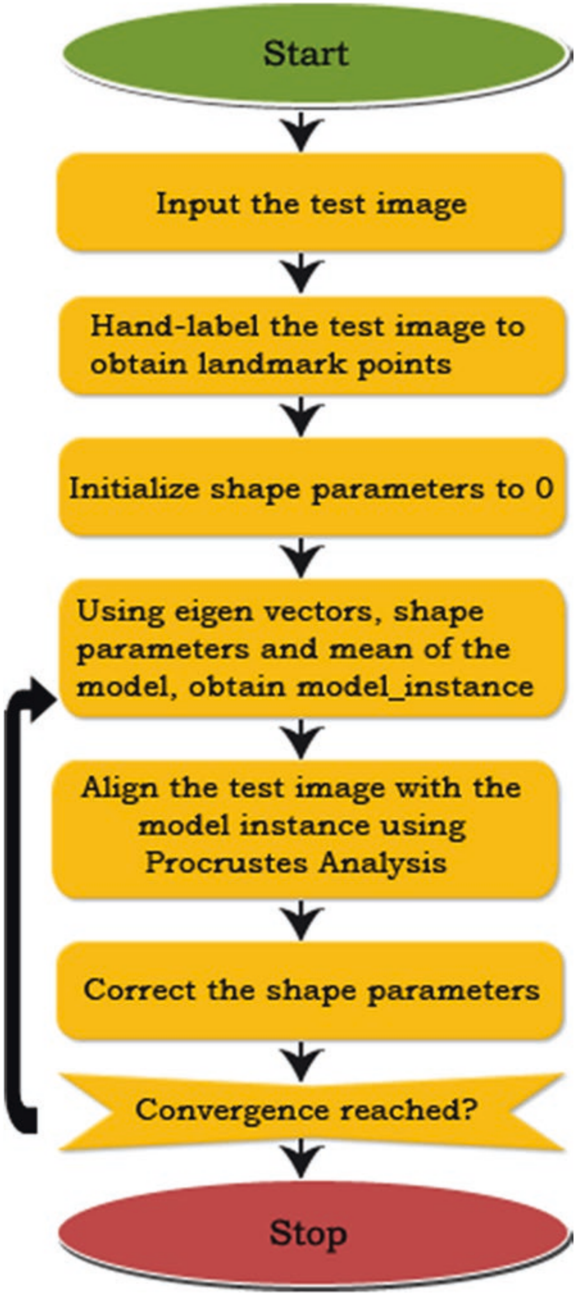


Fig. 9.7 Flowchart depicting the procedure of model-fitting

The new image is classified under that class in which the distance is the minimum. The process of emotion classification is further elucidated in the algorithm below:

(i) Input the model representation obtained from model-fitting stage.
(ii) Read the mean models, i.e., centroids of a set of models for each class of emotions.
(iii) Determine the Euclidean distance between each of the 5 centroids and the model representation.
(iv) Classify the test image under that class in which the Euclidean distance is the minimum.

The approach discussed in this section deals with methods for handling static data repositories. The classifiers are trained a priori on labeled data and used later for classifying new data. The next section discusses a recent algorithm that demonstrates an online processing in the context of videos.

9.5 A Computational Technique Using Static and Dynamic Information

This section discusses a recent mechanism for detecting emotions from facial expressions in videos.

9.5.1 The Approach

Metallinou et al. (2010) investigate the role of static and dynamic information conveyed by the face during speech for emotion recognition. Their focus is twofold: first, to compute compact facial representations by capturing usable information from the facial shape and facial movements and second, to model and recognize emotions by conditioning on knowledge of speech-related lip movements (*visemes*), which occur in parallel.

Their use of direct facial marker data enables the overcoming of some of the present challenges in feature processing from video data and focuses on establishing feasibility bounds for emotion classification using visual features. They rightly premise that facial information obtained from multiple markers across the face is redundant; neighboring markers tend to be highly correlated because they are controlled by the same underlying muscle movements. As the human face has a specific configuration, the possible range of physical movement of each facial marker is also limited.

They apply principal component analysis (PCA) for dimensionality reduction. In an alternative method, they select face markers using either Principal Feature Selection (PFA), a recently proposed technique motivated by PCA, or apply Fisher criterion in order to select features that better discriminate between different emotional classes. In order to constrain the speech-related variability of facial movement, they use the concept of *viseme*, which represents the lip shape during the articulation of a phoneme. Visemes are widely used for speech analysis and audio–visual recognition of speech, especially under noisy conditions and animation. While averaging can be used to smooth the speech-related face movements, in contrast, they incorporate these movements in their analysis by modeling the evolution of emotional visemes. Dynamic modeling of information streams using HMMs has been shown to be a powerful method for audio–visual recognition.

In their work, they use a multi-speaker database and perform speaker-independent cross-validations. Facial features resulting from averaged, de-correlated, and normalized marker information (PFA features) achieve good performance. Happiness is the most recognized emotion using facial cues, with a recognition performance of the order of 75 %, in leave-one-speaker-out cross-validation experiments. Anger and happiness have performance of the order of 50–60 %, while neutrality has performance of the order of 35 %.

The Interactive Emotional Dyadic Motion Capture (IEMOCAP) database has been used in these experiments (Busso et al. 2008). This database contained approximately 12 h of audio–visual data from five mixed gender pairs of actors—male and female. IEMOCAP contained detailed facial information is obtained from motion capture as well as video, audio, and transcripts of each session. In comparison to other acted emotion databases where actors are asked to read out sentences displaying a specific emotion, in IEMOCAP, two techniques of actor training are used in order to elicit emotional displays—scripts and improvisation of hypothetical scenarios. The sessions are approximately 5 min in length. During these sessions, actors displayed various emotions according to the content of the session and the course of the interaction. The sessions were later manually segmented into utterances and annotated into categorical (anger, happiness, neutrality, etc.) and dimensional tags (valence, activation, and dominance). This study uses facial motion capture data, as well as the transcripts from all 10 speakers used in the corpus. Classes of anger, happiness, excitation, neutrality, and sadness were examined.

The IEMOCAP data contain detailed facial marker coordinates from the actors during their emotional interaction. For details on the layout of the face markers and the actual setup used for creating the corpus refer to (Busso et al. 2008). A total of 53 markers were attached to the faces of the subjects during the recordings. The markers were normalized for head rotation and translation. The nose marker is defined as the local coordinate center of each frame. There were five nose markers, and these were excluded from the computation because of their limited movement. In total, information in the form of (x, y, z) coordinates from 46 facial markers was used. This resulted in a 138-dimensional facial representation, which tends to be redundant because it does not exploit the correlations of neighboring marker movements and the structure of the human face.

9.5.2 Feature Extraction

Four feature extraction approaches were examined in order to find compact facial representations well suited for emotion recognition applications in terms of recognition accuracy.

Speaker Face Normalization—While examining various speakers, individual speaker face characteristics that were not related to emotion were smoothed out. The speaker normalization approach consists of finding a mapping from the individual average face to the general average face. The mean value of each marker coordinate of each speaker is shifted to the mean value of that marker coordinate across all speakers to achieve the normalization. The mean of each face feature (marker coordinate) is computed across all emotions m_{ij} (where "i" is the speaker index and "j" is the feature index) for each speaker. The mean of each feature is also computed across all speakers and all emotions, M_j (where "j" is the marker coordinate index). To obtain the set of normalized features, each feature is further multiplied with the coefficient $c_{i,j} = M_j m_{ij}$.

Principal Component Analysis—As already discussed in Sect. 9.4 above, PCA is a widely used method for dimensionality reduction. This method finds the projection of data into a lower dimensional linear space in which the variance of the projected data is maximized. The application of PCA for facial emotion recognition is inspired by the technique of eigenfaces. In eigenfaces, a feature vector is constructed from pixel values of facial image. PCA finds the principal faces, which can be linearly combined to reconstruct any face. Similarly, in this approach, the feature vector consists of the facial marker coordinates, and the principal projections can be interpreted as the directions of facial movement along which the variance is the maximum.

After performing the PCA, the face is reconstructed from the first 30 principal components, as they encode more than 95 % of the total variance. Some projections correspond to recognizable directions of facial movement, which affects either the lower or the upper facial parts or both. The PCA transformation matrix is computed, using data from all available speakers. Therefore, individual speaker characteristics are indirectly taken into account. Speaker normalization, either prior to or after the PCA transformation, does not improve recognition performance, and, therefore, it is not done. The window used for feature extraction is 25 ms with an overlap of about 16 ms. The choice of a short window enables further dynamic modeling of the visemes (as the average phoneme lasts about 100 ms).

Principal Feature Selection—The transformation space in PCA is a linear combination of the initial space of face marker coordinates. It has no inherent intuitive interpretation. The projections can be interpreted as directions of the specific face gestures and movements, but it is difficult to find meaning behind these projections. Principal feature analysis can be used to find more meaningful facial representations. In this method, the PCA transformation matrix is computed and used to cluster together highly correlated facial marker coordinates. After this, a representative feature is selected from each cluster, which performs feature selection while using similar criteria as PCA.

Normalization smoothes out the individual face characteristics that are unrelated to emotion and focus on emotional modulations. As in PCA, about 30 features are selected for this analysis. Principal feature analysis shows that the facial features are clustered together in a meaningful way. For example, same coordinates of neighboring or mirroring markers, as in left and right cheek, are clustered together. After 100 repetitions of PFA, it was found that, on an average, 28 % x coordinates, 39 % y coordinates, and 33 % z coordinates were selected. This is indicative of the fact that all the 3 coordinates demonstrate significant variability in the context of emotional speech.

The jaw movements are mainly in the vertical direction which explains the comparatively high percentage of selected y coordinates selected. On an average, 22 % of the selected y coordinates are from mouth markers, while only 14 % of the initial markers are placed around the mouth. The z coordinates come from lip protrusion during articulation. The distribution of initial markers across the face regions is (chin, mouth, cheeks, eyebrows, and forehead) = (11, 14, 28, 36, and 11 %), wherein the distribution of the selected markers is (13, 23, 25, 31, and 8 %). This clearly shows a bias toward selecting lower face marker coordinates (especially mouth). This is expected because the movement of the jaw conveys a great amount of variability. Since the mouth can be automatically tracked more reliably than other face regions, such as cheeks and forehead, this is a useful result.

Feature Selection Using Fisher Criterion—The features described before are selected so as to capture maximum variance in the data. Such a set of features do not necessarily separate the different emotion classes well. To overcome this, Fisher criterion is used to extract a set of features, which maximizes the between-class variability and minimizes the within-class variability. Ad hoc averaging of neighboring markers is performed on these features to reduce from 46 to 28. After this, speaker face normalization is performed. In the final stage, 30 best marker coordinates are selected according to this criterion. The Fisher criterion value of each feature is computed on the training set, where the emotion classes are known. The Fisher criterion values are slightly different in each fold, so the features selected in different folds may vary slightly. The 30 ad hoc features are chosen so that this feature set is comparable with the previous two sets. From the selected features, across the 10-fold, on an average, 29 % are x, 34 % are y, and 37 % are z coordinates. On an average, about 34 % of the markers come from upper face including eyebrows and forehead, and 66 % come from lower face. Similar tendencies with PFA concerning the feature selection are observed, in general.

9.5.3 Viseme Information

The lip shape during the articulation of a phoneme is called a viseme. The viseme is conditioned to constrain the variability related to speech, which recognizes the underlying emotion better. Visemes provide a reasonable time unit for HMM training, besides incorporating speech-related information and associated dynamical models of the facial movement. The phoneme-to-viseme mappings are many to one, and various such mappings exist in the literature depending on the desired detail. The authors here used 14 visemes. They have the word transcription for each utterance, and through forced alignment, they obtain the phoneme-level transcription. They use this transcription to group facial data corresponding to each viseme.

Through their experiment, Metallinou et al. (2010) find that emotion recognition accuracy is highly speaker dependent. Also, the lower face seems to convey more information as compared to the upper face. Explicitly modeling articulation movements improves recognition for anger, happiness, and neutrality, but decreases performance for sadness.

9.6 What the Future Holds

This research has utilization in the domains of human–computer interaction, medical applications, nonintrusive interrogation, etc. It can be used for building cognitive systems that read and respond to human behavior and actions (including intent), for military and security applications such as surveillance and analysis, intelligent robotic systems, and medical diagnosis. Health professionals can develop better rapport with patients and make the right diagnosis by obtaining more complete information.

Computational analysis based on video and image analysis is used in numerous real-world applications particularly those that are security-related. Findings can be based on either silent surveillance or analysis of video frames/images during a face-to-face interaction. Typical examples are cited below:

(a) Airport surveillance using surveillance cameras can help detect any suspicious behavior in a passenger prior to boarding the aircraft. The most relevant analysis will be when the subject is clearing a security check or the subject's baggage is being screened. Subjects communicating on phone or on the Internet will also reveal emotions in case some information of value is received that affects the subject either adversely or positively.

(b) During questioning or interrogation, a subject will experience numerous emotions that a video analysis can interpret. The polygraph lie-detector test which uses heart rate monitors for emotion interpretation is highly inaccurate and not admissible as evidence usually. However, video analysis-based advanced algorithms for emotion detection may eventually come to be admitted, if they can prove their accuracy.

There are many potential directions for future work. One immediate step is to include multiple modalities, such as speech and gestures, to improve emotion recognition performance. The dynamic statistical modeling of multiple modalities and their effective fusion is an interesting and challenging problem and needs more work. *Affective computing* is a modern evolving interdisciplinary domain that consolidates work in this area. Affective computing is about inducing empathy in a machine, so that it understands human emotions and adapts and responds to these perceived emotions in an empathetic manner. Although facial expressions of emotion are presently categorized into discrete categories, and although there is even evidence for categorical perception of such facial expressions, it is also clear that expressions are typically members of multiple emotion categories and that the boundaries between categories are fuzzy at the level of recognition (Russell and Bullock 1986). Further, it is evident that the categorization of an emotional facial expression depends to some extent on the contextual relation to other expressions with which it may be compared (Russell and Fehr 1994). Some mathematical models further argue that emotions shown in facial expressions could be thought of as exhibiting features both of discrete emotions and continuous dimensions (Calder et al. 2001).

As researchers across the world evolve techniques for recognizing emotions from facial expressions, one fact is abundantly clear. Any computational technique for recognising emotions will, to begin with, be limited by our own understanding of human emotions. Even though humans themselves have enormous exposure to the world and can therefore form concepts around explicit facial expressions, they still remain handicapped in their understanding of human emotions. But as computational systems evolve, they will slowly assist humans in their perception of emotions. And then a new, more complex frontier of machine-based human emotion recognition may be breached.

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Chapter 10
Evaluation of the Intricacies of Emotional Facial Expression of Psychiatric Patients Using Computational Models

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10.1 Introduction

Over the past two decades, understanding of spontaneous human behavior has attracted a great deal of interests among the scientists across different domains of science, such as clinical and social psychology, cognitive science, computational science, and medicine, because of its possible wide range applications in the spheres of mental health, defense, and security. Individuals' own spontaneous facial expressions and their appraisal of facial expressions of others with little or no effort in their daily encounters are adjudged to be one example of spontaneous human behavior. Facial expression being such a fine index of one's inner experience could be considered as a very important tool for understanding the varied underlying emotional states of human mind. Facial expression classification can be effectively used in understanding prevailing affect and mood states of the individual under any pathological condition or in a deviant state of mind, particularly in the diagnosis of psychiatric disorders or in identifying the underlying affect and motives of criminals, alcoholics, and even in individuals with psychiatric disorders. Human facial expression is a prominent means that communicates one's underlying affective state and intentions (Keltner and Ekman 2000) almost instantaneously. Two main streams in the current research on automatic analysis of facial expressions are facial emotion detection and feature-based expression classifier. Facial action coding system (FACS; Ekman and Friesen 1978) is an objective measure used to identify facial configurations before interpreting displayed affect. Although different approaches such as facial motion

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(Essa and Pentland 1997) and deformation extraction (Huang and Huang 1997) have been adopted, the existing facial expression analysis methods still require considerable modification to increase their accuracy, speed, and reliability in identifying emotional expression, considering both the unconstrained environmental conditions and intra- and inter-personal variability of facial expressions. Existing behavioral studies indicate that there is a significant relevance of emotional facial expressions (EFEs) in psychiatric diagnosis in two ways:

(i) The extent to which the patient is capable of expressing specific emotions and,
(ii) The extent to which they can accurately assess the facial emotional expression in others.

In spite of dramatic developments in the research on automatic facial expression with the advancement in techniques of image and video processing (Pantic and Bartlett 2007), application of computational model in psychiatric illness is a relatively new domain of research. Therefore, it is imperative to examine various aspects of EFE analysis from the perspective of psychiatric diagnosis through computational approach.

Computational techniques have proved to be powerful tools to complement the human evaluation of EFEs (Wehrle and Scherer 2001). In the early 60s, revolutionary work started with the Abelson's model of hot cognition (1963), Colby's model of neurotic defense (1963), Gullahorns' model of a homunculus (1963), and Toda's Fungus Eater (1962). However, these models were developed based on the appraisal theories of emotion (Wehrle and Scherer 2001). According to these authors, the limitation of neglecting the time dimension of models of appraisal theory could be overcome through the development of process theory, which considers multi-level processes than single-shot configurational predictions of labeled emotions. This process modeling is important as EFE constantly shows dynamic changes as the human brain in dynamic contexts receives continual input with an automatized demand on the changing of emotions.

In the backdrop of this increased understanding of the computational analysis of emotion, its application in the psychiatric diagnosis was considered to be important. Computer-based automatic facial action coding system (AFACS) enables researchers to process volumes of data in a short time in a more systematic manner with high accuracy, once the system secures the parameters for a model. Kanade (1973) was the first to implement computational modeling approach for automatic facial expression recognition.

The work presented here addresses how the database may be framed and what type of information could be stored in order to provide with concrete input for computational analysis. This could aid in development of computational model that infers diagnosis from facial expressions observed through real-time video to obtain accurate output through computational analysis.

The following will be the major objectives of this chapter:

- The importance of facial expression as a measure in psychiatric diagnosis.
- The effectiveness of computational models of automatic facial expression analysis (AFEA) to aid in diagnosis.
- Finally, the usefulness of computational approach in facial expression analysis as a measure of psychiatric diagnosis.

10.2 Importance of Facial Expression in Psychiatric Diagnosis

10.2.1 Emotional Facial Expressions

Emotional expression is a specific constellation of verbal and nonverbal behavior. Emotional messages mediated through nonverbal behaviors include facial expression, paralanguage, gesture, gaze, and posture. Face is thought to have primacy in signaling affective information since it portrays the significance of emotions to both basic survival and communication (Mandal and Ambady 2004). A schematic diagram of usefulness of facial expressions is shown in Fig. 10.1. Facial expressions owing to their deep phylogenetic origin are expected to have greater innate disposition to reflect true psychic reality through spontaneous and genuine emotional expressions, that is, EFE.

Darwin (1872) in "The Expression of the Emotions in Man and Animals" opined that human expressions of emotions have evolved from similar expressions in other animals, which are unlearned innate responses. He emphasized on genetically determined aspects of behavior to trace the animal origins of human characteristics, such as the contraction of the muscles around the eyes in anger or in putting efforts to memorize, or pursing of the lips when concentrating on any task. The study of Sackett (1966) on nonhuman primates also indicates that the evocation of emotional reactions to a threat display is controlled by "innate releasing mechanisms" that are indices of inborn emotions. Spontaneous facial muscle reactions that occur independent of conscious cognitive processes (Dimberg 1997; Ekman 1992a, b; Schneider and Shiffrin 1977; Zajonc 1980) are functions of biologically determined affect programs for facial expressions (Tomkins 1962). Wide range of cross-cultural research also confirmed the spontaneity (Dimberg 1982) and universality (Ekman and Friesen 1971; Ekman et al. 1969; Izard 1971) of facial expressions. More universality in EFE, owing to its phylogenetic underpinning, has possibility of being more accurately detected across the culture. But social display rules applied to basic emotions are culture bound. Ekman and Friesen (1975) proposed the existence of culture-specific display rules which govern the expressions of emotions. Consideration of the concept of these rules is relevant here to understand spontaneous facial expressions. Social display rules are informal norms of the social groups about expressing emotions.

Felt spontaneous emotion is also an expression of display rules when it is internalized and becomes apart of one's spontaneous emotional repertoire. In contrast to the felt emotion, when social display rules are not automatized, the nonfelt emotional expressions using these rules are posed emotions. In this context, it

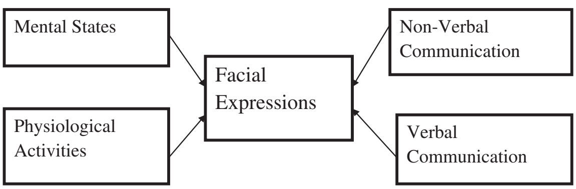

Fig. 10.1 Usefulness of facial expression

could be assumed that since patients with psychotic symptoms are not able to utilize environmental feedback immediately using the display rules, this in turn makes them unable to modify their spontaneous emotional expressions.

Automatized spontaneous emotion, which is involuntary in nature, may be mediated by subcortically initiated facial expression characterized by synchronized, smooth, symmetrical, consistent, and reflex-like facial muscle movements, in contrast to cortically initiated facial expressions those are subject to volitional real-time control, and tend to be less smooth, with more variable dynamics (Rinn 1984). This distinction between biologically disposed emotional expression and emotional expression that is modified in congruence with environmental feedback explains the possibility of spontaneous emotional expression in psychiatric patients who have poor reality-, self-, and source-monitoring capacity (Hermans et al. 2003; Radaelli et al. 2013). For example, in case of schizophrenia, one can structure diagnostic formulation by developing suitable computational model incorporating the database so far obtained from research outcome. It has been evident from neuropsychological studies that hemi-facial differences (Rinn 1984; Sackeim et al. 1978; Wolff 1943) give a direction of assessment of emotional expression in psychiatric population. Since, in psychiatric illness, spontaneous emotional expression is expected, it could be more rational to make computational program based on the information from the left (Wolff 1943) and lower regions of the face (Borod and Koff 1984), considering the degree of facial symmetry (Borod et al. 1997), which reflects the true inner emotional state of the patient that is beyond modification by social display rules. The more one is self-absorbed and less reality-oriented, the less will be the difference between the activation of the regions of the face responsible for involuntary expressions and voluntary modification of emotional expressions, in favor of involuntary expression. It makes the facial expression more symmetrical.

But the assessment of conscious control of emotional expression is also to be taken into account. It itself can be an index of one's ability to appraise social situations that directs one to modify the emotional facial expression, which, if detected through measures of facial affect in course of psychiatric treatment, could also be considered as a valid prognostic indicator of positive treatment outcome.

Since patients are reared up in a given culture and learn to express emotions following culture-specific display rules, so culture-specific facial expressions cannot be totally ignored in diagnostic assessment. At this juncture, it is important to consider whether the culturally learnt emotional expression is automatized in patients or has employed display rule to suppress genuine emotional response. Comprehensive database relating the emotional facial expressions with the hemifaces may help to solve this problem.

Spontaneous facial expression analysis as a diagnostic tool in psychiatric illness is important as it may be the true reflection of the patients' inner psychic reality. Since facial expressions help to better understand the present mental status of the patient, it could be an important marker for clinical diagnosis. In general, clinical diagnosis is being done by clinical observation of the patients using the observation method, using the case study method, and by using different psychometric tools. Assessment of facial expressions through computational models definitely would have a significant contribution in confirming the diagnosis. Different types of facial expression measurements include observer's judgment, electrophysiological recording, and componential coding schemes.

In case of observer's judgment, observers view behavior and make judgments on the extent to which they see emotions in the target face. However, even though this method seems to be easy to execute, it is not free from its limitations. There is the possibility of subjective bias in judgment, which makes them neglect certain subtle morphological characteristics of facial expressions. The inevitability of instantaneous classification of facial expressions for diagnosis of different disorders is another major disadvantage of human judgment concerning facial expression.

Emotional facial expressions can also be measured through facial electromyography (EMG), which measures electrical potential from facial muscles in order to infer muscular contraction via the placement of surface electrodes on the skin of the face. But it may increase one's self-conscious behavior and minimize genuine emotional expressions. Another problem in EMG signal measure is "cross talk," that is, surrounding muscular contraction (potentials) interferes with the signal of a given muscle group. For emotional expressions, such changes in muscular contraction of adjacent muscle groups may misrepresent the picture of facial muscle movements, which may delude emotional interpretations (Tassinary et al. 1989).

By contrast, in componential coding schemes, coders follow some prescribed rule to detect subtle facial actions. The two most popular systems are the FACS, developed by Ekman and Friesen (1978), and the maximally discriminative facial movement coding system (MAX), developed by Izard (1979). MAX is a theoretically driven system where only that facial configuration can be coded, which corresponds to universally recognized facial expressions of emotions, whereas FACS is a comprehensive measurement system, which measures all the observable movements in the face. This system is not limited to the behaviors that are theoretically related to emotions. It allows discovering new configurations of movements.

With the advancement of technologies, recently FACS has become a more objective automatic facial expression componential coding analysis. This is an interesting and challenging area of research. It has important application in many areas such as emotional and paralinguistic communication, pain assessment, lie detection, and multimodal human computer interface. AFACS, in addition to processing volumes of data in a short time in a more systematic manner, performs with a higher accuracy than human coders who have large margins of error and may overlook important information. Acquisition of the data of parameters for a model and prediction of behavior (vs. simple detection and classification) using only a small sample are other advantages of automated facial detection technology when coupled with computational models.

To differentiate clinical population from normal controls, computational models identify differential features or action units involved in the patient's facial expression. Patients with schizophrenia, for example, those with impairment in source monitoring (Arguedas et al. 2012) as well as reality monitoring (Radaelli et al. 2013), are not capable of appraising the situational demand to modify their felt emotional expressions, which are governed by the extrapyramidal tracts of subcortical origin (Van Gelder 1981, cited in Borod and Koff 1991). Thus, the identification of the more pronounced felt emotion in the hemi-face or symmetrical emotional expression between the two hemi-faces and information of the relative level of activation of the tracts of subcortical and cortical regions of the brain could be a strong database for computational analysis of facial expression in diagnosis of psychiatric illness.

Since accuracy of judgment of EFE increases with more pronounced emotion (in either directionless or more than usual expression), the efficiency of detection is presumed to be more in diagnosis of psychotic cases. In this context, Borod et al. (1997) suggested that asymmetry of facial action is not observed during spontaneous expression because subcortical structures innervate the face with bilateral fiber projections. This strong biological disposition suggests that facial symmetry for the felt emotion (governed by either automatized social display rules or innate disposition) is expected to characterize psychotic patients and may be considered as an important part of the database for computational analysis of EFE. In addition, patients with schizophrenia display more negative than positive emotions (Martin et al. 1990), exhibit expressions of contempt more frequently than other emotions (Steimer-Krause et al. 1990), and show a lower proportion of joyful expressions (Schneider et al. 1992; Walker et al. 1993) across the situations, which could be considered as idiosyncratic characteristics of schizophrenia and requires due attention for diagnosis during computational analysis. Gruber et al. (2008) in their research also suggested that participants at high risk of mania reported irritability and elevated positive emotion. Such information of disorder-specific emotional biasness can also be incorporated to distinguish different types of disorders.

Neuroanatomical research suggests relatively independent neuroanatomical pathways for posed or nonfelt and spontaneous emotional facial expression. These independent pathways produce facial asymmetry when one puts conscious effort in modifying felt emotion (Campbell 1978, 1979) in contrast to facial symmetry in case of spontaneous expression (Remillard et al. 1977). Posed emotional expressions are governed by the pyramidal tracts of the facial nerves that descend from the cortex (Van Gelder 1981, cited in Borod and Koff 1991), which suggests the voluntary cortical control over felt emotion. This information indicates the importance of considering the ratio of posed emotion in comparison with the felt affect in psychiatric cases to create the database. The greater the monitoring capacity, the less severe the disorder and the better the prognosis.

However, efficient monitoring capacity, in some psychiatric disorders characterized by manipulativeness, could be one of the diagnostic indicators of that disorder instead of being a positive quality of the individual. Consideration of this sort of overlapping of information in the database is also necessary for relevant differential diagnosis.

Even in anxiety disorders, in spite of putting effort to monitor emotional expressions according to the demand of reality and social display rules (Hermans et al. 2003), their intrinsic emotional force causes a veridical leakage in emotional expression failing to totally suppress the ingenuity of emotional expression. In an early observation, Dunchenne, a nineteenth-century neurologist, claimed that genuinely happy smiles as opposed to false smiles involve contraction of a muscle near the eyes, the lateral part of the *orbicularis oculi*. According to him, zygomatic major muscle obeys the volition and its volitional disposition is so strong that the lateral part of the *orbicularis oculi* cannot be evoked by deceitful laugh (Dunchenne 1862/1990). Ekman confirmed this early observation (Ekman 1992a, b). Neurobiological disposition of the upper face is less voluntarily controlled than that of the lower face because the upper face has neural link with the motoric speech center (Rinn 1984). Again, it has been reported in early literature that being monitored by the respective opposite hemisphere, the left side of the face is more under unconscious control, expressing hidden emotional content (Wolff 1943), and the right side of the face is more under conscious control revealing interpersonally meaningful expressions (Wolff 1943, cited in Sackeim et al. 1978).

Like patients with anxiety disorder, depressive patients also show intact reality monitoring (Benedetti et al. 2005) but selective source monitoring (Ladouceur et al. 2006). The most prominent finding in depression so far has been the attenuation of smiles produced by zygomatic major activity (Girard et al. 2013). This led many researchers to conclude that depression is marked by attenuation of expressed positive affect.

It follows from the above discussion that bio-behavioral understanding of identification of such robust indices, such as facial asymmetry and facial areas in emotional expression, if properly utilized, may enhance the efficiency of the computational diagnostic tool. Not only facial asymmetry in general but the database of onset, latency of expression, apex duration (how long it remains), time distance between hemi-facial expressions, primarily occurred hemi-facial expression, and intensity dominance of the hemi-face also could be of immense diagnostic importance.

Understanding of one's inner state through the analysis of emotional expressions can be strengthened by corroborating analysis of facial expression of patients with the database of their appraisal of others' emotions.

10.2.2 Appraisal of EFE

As it is understood, another source to obtain information regarding the patient's understanding of emotion is to study the accuracy of their appraisal of others' emotional expression. The spontaneous emotional reaction, which is controlled by biologically driven affect program, also suggests that this facial affect program aids in spontaneous recognition of emotion in others. The reports (Benson 1999; Girard et al. 2013) of deficits in portraying emotional expressions in different groups of psychiatric patients have implied that they could have some experiential problems that get reflected when different groups of psychiatric patients appraise others' emotions.

It has been evident that schizophrenic patients are significantly inferior to normal controls in the ability to decode universally recognized facial expressions of emotions. The findings of impairment in schizophrenia, in their own emotional expressions and in recognition of emotions, imply that a person with impairment in one's own facial expressions finds it difficult to decode facial expressions of emotion in others. According to Hall et al. (2004), besides deficits in other aspects of face perception in schizophrenia, deficit in expression recognition performance is also an important index to be related to their social dysfunction (Hooker and Park 2002), thereby inducing research interest from the perspective of appraisal of emotional expression in others.

In a meta-analysis, Uljarevic and Hamilton (2013) also found that individuals with autism have trouble in classifying emotions. Disorder of social functioning in autism that is associated with impairment of automatic mimicry may be the reflection of impairment in the functioning of mirror cells in this disorder (McIntosh et al. 2006).

Skill deficits in the appraisal of facial expressions or in decoding EFE are also evident from the EFE recognition deficits in detoxified alcoholics but for different etiological factors. Deficit in detoxified alcoholics is correlated more with interpersonal problems compared to normal control (Kornreich et al. 2002). Thus, interpersonal difficulties could also serve as a mediator of EFE accuracy problems.

When such overlapping features are present in the appraisal of EFE by patients with different disorders, the profile of symptomatic and etiological features of the disorder and detailed clinical evaluation is to be incorporated for the accurate computational analysis for differential diagnosis in addition to database of EFE. This would give direction to diagnosis with inclusion of both the clinical and empirical approaches together to reach a final decision.

10.2.3 Differential Diagnosis

When the areas of facial expressions overlap across the diagnosis, differential diagnosis is required. For example, in case of anxiety disorder and affective disorder, signal value of facial expression of patients can produce equivocal results. Since patients with these disorders have reality contact and can modify their felt expression in accordance with situational demand, the signal value becomes overshaded by the attempt by the patients to mask the spontaneous EFE. When particular facial markers cannot differentiate the disorders, differential diagnosis is suggested based on strong theoretical groundwork of these disorders. For example, in depression, the patients' facial expression can be explained by the social risk (SR) hypothesis, which states how depressed mood minimizes social communication to restrict any negative outcome variability, which is not within the depressed persons' acceptable zone. They tend to show reservation in help-seeking behavior in reciprocal interactions even with their relatives and close ones who are likely to provide the requested help. In competitive contexts, however, their interaction is dominated by submission and withdrawal (Girard et al. 2013), whereas for patients with anxiety disorder, researchers (Barlow et al. 1996; Mineka and Zinbarg 1996) hypothesize that the patients may perceive situations as unpredictable or uncontrollable. They always have a tendency to look for signs of threat; this hyper-vigilant activity can be reflected in their facial expressions. Thus, a detailed analysis of facial expression along with its assimilation with theoretical foundation and symptom manifestation can reduce the ambiguity of facial expression analysis among anxiety- and depression-related patients.

From the perspective of differential diagnosis, research studies claimed that acute schizophrenia showed greater emotion decoding impairment than the depressive and normal controls (Gessler et al. 1989). Paranoid schizophrenia subjects were more accurate than the nonparanoid subjects in judging facially displayed emotions (Kline et al. 1992; Lewis and Garver 1995). Anstadt and Krause (1989) used primary affects in portraits and concluded that schizophrenic patients were more impaired in terms of the quality and diversity of the action unit (AU) (the cluster of muscles in an area of the face during expression) drawn in facial expressions. Borod et al. (1993) suggested that these patients have difficulty specifically in comprehending facial emotional cues (facial expressions of emotions) but not in nonemotional facial cues. Domes et al. (2008) indicated that borderline individuals more or less accurately perceive others' emotions and show a tendency toward heightened sensitivity in recognizing specifically anger and fear in social context. Negative response bias in depressed patients may explain their tendency to attribute neutral faces as sad and happy faces as neutral (Stuhrmann et al. 2011). Their findings imply selective attentional bias in recognition of emotions among individuals with different disorders. Since decoding deficit of facial expression is evident across different diagnostic categories, computational analysis may help identify even subtle differential points necessary for accurate diagnosis and also for understanding diagnostic specificity, if any, in appraisal of emotions in others.

Thus, the specific ways in which an individual processes and attributes emotional information can be a strong determinant of psychiatric diagnosis, especially for affective and anxiety disorders. The accuracy with which a patient can assess the expression of emotion in others is another way to determine the severity of the psychiatric disorder, which can be utilized for framing the database for diagnostic computational modeling.

10.3 Computational Models for Automatic Facial Expression Analysis

Machine analysis of facial expressions attracted the interest of many researchers because of its importance in cognitive and medical sciences. Although humans detect and analyze faces and facial expressions with little effort, development of an automated system for this task is very difficult. Since 1970s, different approaches are proposed for facial expression analysis from either static facial

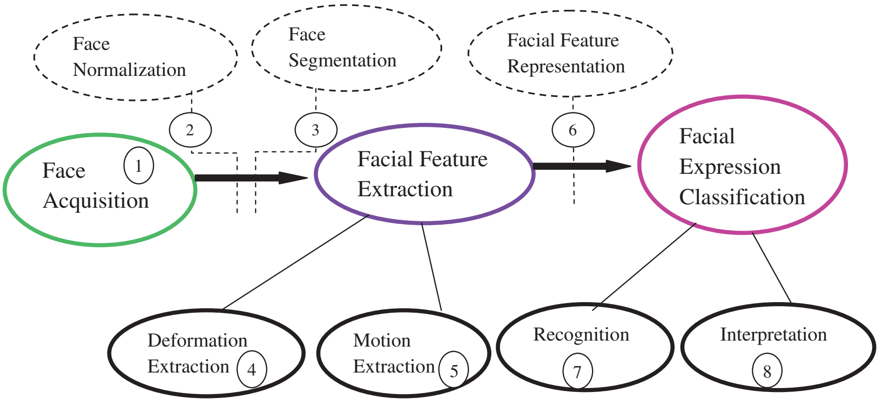

Fig. 10.2 A generic facial expression analysis framework

images or image sequences. AFEA is a complex task as physiognomies of faces vary from one individual to another considerably due to differences between age, ethnicity, gender, facial hair, cosmetic products, and occluding objects, such as glasses and hair.

According to Shenoy (2009), the first objective and scientific study of facial expression was done by Bell in (1844). Darwin (1872) argued that emotional expressions are universal and the same for all people based on his theory of evolution. Ekman has proposed the existence of six basic prototypical facial expressions (anger, disgust, happiness, sadness, surprise, and fear) that are universal. Though many facial expressions are universal in nature, but the way these are displayed depends upon culture and the upbringing. Kanade (1973) published the first work on automatic facial expression recognition. The first survey of the field was published by Samal and Iyengar in (1992) followed by others (Fasel and Luettin 2003; Pantic and Rothkrantz 2000a, b). An automatic face analysis (AFA) system was developed by Fasel to analyze facial expressions based on both permanent facial features (brows, eyes, and mouth) and transient facial features (deepening of facial furrows) in a nearly frontal-view face image sequence. He used Ekman and Friesen's FACS System to evaluate an expression. Many computational models have been developed for facial expression classification over the last few years. In general, any facial expression classification system would have the three basic units: face detection, feature extraction, and facial expression recognition. A generic facial expression analysis framework proposed by Fasel and Luettin (2003) is shown in Fig. 10.2.

Any computational model performs facial feature extraction and then uses dimensionality reduction techniques followed by a classification technique. A flowchart of computational models of facial expression analysis is shown in Fig. 10.3. Facial feature extraction consists of localizing the most characteristic face components such as eyes, nose, and mouth within images that depict human faces. This step is essential for the initialization of facial expression recognition or face recognition.

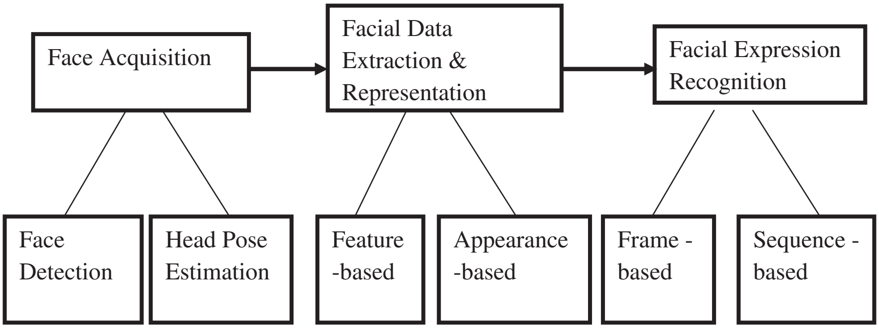

Fig. 10.3 Flowchart of computational models of facial expression analysis

There are many techniques for dimensionality reduction, such as principal component analysis (PCA) or singular value decomposition (SVD), independent component analysis, curvilinear component analysis (CCA), linear discriminant analysis (LDA), Fisher linear discriminant, multidimensional scaling, projection pursuit, discrete Fourier transform, discrete cosine transform, wavelets, partitioning in the time domain, random projections, multidimensional scaling, and fast map and its variants. PCA is widely being used for data analysis of varied areas, such as neuroscience, computational graphics, for extracting relevant information from confusing datasets because it is a simple, nonparametric method. PCA transforms higher-dimensional datasets into lower-dimensional uncorrelated outputs by capturing linear correlations among the data, and preserving input by output as much information as possible in the data. CCA is a nonlinear projection method that attempts to preserve distance relationships in both input and output spaces. CCA is a useful method for redundant and nonlinear data structure representation and can be used in dimensionality reduction. CCA is useful with highly nonlinear data, whereas PCA or any other linear methods fail to give suitable information. Fisher linear discriminant analysis (FLDA) has been successfully applied to face recognition, which is based on a linear projection from the image space to a low-dimensional space by maximizing the between-class scatter and minimizing the within-class scatter. It is most often used for classification. The main idea of the FLD is that it finds projection to a line so that samples from different classes are well separated. LDA is a special case of FLD in which both classes have the same variance. Belhuemer was the first to use the LDA on faces and used it for dimensionality reduction (Belhumeur et al. 1997). Different techniques have been proposed to classify facial expressions, such as neural network (NN), support vector machine (SVM), Bayesian network, and rule-based classifiers. SVMs introduced by Boser et al. in (1992) have become very popular for data classification. SVMs are most commonly applied to the problem of inductive inference, or making predictions based on previously seen examples. An SVM is a mathematical entity, an algorithm for maximizing a particular mathematical function with respect to a given collection of data. In the SVM classifier, there are a number of parameters that must be chosen by the user. It is necessary to make the right choices of these parameters in order to yield the best possible performance. The basic concept underlying the SVM is quite simple and intuitive and involves separating our two classes of data from one another using a linear function that is the maximum possible distance from the data.

To understand the essence of SVM classification, one needs only four basic concepts: (1) the separating hyper-plane, (2) the maximum-margin hyper-plane, (3) the soft margin, and (4) the kernel function. But there exist free and easy-to-use software packages which allow one to obtain good results with a minimum of effort. Viola and Jones (2001) devised Haar Classifiers algorithm using AdaBoost classifier cascades that are based on Haar-like features and not pixels for rapid detection of objects including faces. Wavelet transform could extract both the time (spatial) and frequency information from a given signal, and the tunable kernel size allows it to perform multi-resolution analysis. Among different wavelet transforms, the Gabor wavelet transform has some impressive mathematical and biological properties and has been used frequently on researches of image processing. The Gabor wavelet is a linear filter where impulse response is defined by a harmonic function multiplied by a Gaussian function. This filter can be used to detect line endings and edge borders over multiple scales and with different orientations. Gabor wavelet is used for facial feature extraction in computational models of facial expression analysis.

Recently, Shan et al. (2009) studied facial representation based on local binary pattern (LBP) features for person-independent facial expression recognition. Recently LBP features have been introduced to represent faces in facial images analysis. The most important properties of LBP features are their tolerance against illumination changes and their computational simplicity.

Automatic pain recognition has received attention in the recent past because of its relevance in health care, ranging from monitoring patients to assessment of chronic lower back pain (Prkachin et al. 2002). Lucey et al. (2011, 2012) address AU and pain detection based on SVMs. Details of computational methods for AFEA are reported by Pantic and Rothkrantz (2000a, b). We discuss briefly the fundamentals of AFEA.

10.3.1 Face Detection

The first step in facial information processing is face detection. Determining the exact location of a face within a large background is a very difficult job for a computational system. An ideal face detection system should be capable of detecting faces within a noisy background and in complex scenes. Facial components, such as eyes, nose, eyebrows, are the prominent features of the face. In holistic face representation, face is represented as a whole, while on the other hand, in analytic face representation, face is represented as a set of facial features. Face can also be represented as a combination of these, and such a representation is called hybrid representation. Many face detection methods have been developed to detect faces in an arbitrary scene (Li and Gu 2001; Pentland et al. 1994; Rowley et al. 1998; Schneiderman and Kanade 2000; Viola and Jones 2001). Most of them can detect only frontal and near-frontal views of faces. A neural-network-based system to detect frontal-view face has been developed by Rowley et al. (1998). Viola and Jones (2001) developed a robust real-time face detector based on a set of rectangle features. Modular eigenspace method for face detection was developed by Pentland et al. (1994). Schneiderman and Kanade (2000) developed a statistical method for 3D object detection that can reliably detect human faces. Li and Gu (2001) proposed an AdaBoost-like approach to detect faces with multiple views.

Huang and Huang (1997) apply a point distribution model (PDM) to represent the face. Huang and Huang utilize a Canny edge detector to obtain a rough estimate of the face location in the image. Pantic and Rothkrantz (2000b) detect the face as a whole unit—they use dual-view facial images. Kobayashi and Hara (1997) use a CCD camera in monochrome mode to obtain brightness distribution data of the human face. Yoneyama et al. (1997) use an analytic approach for face detection in which the outer corners of the eyes, the height of the eyes, and the height of the mouth are extracted automatically. Liu (2003) presents a Bayesian discriminating features (BDF) method. Kimura and Yachida (1997) use potential net for face representation.

In order to perform a real-time tracking of the head, Hong et al. (1998) utilized the person spotter system proposed by Steffens et al. (1998). Steffens et al. (1998) system performs well in the presence of background motion, but fails in the case of covered or too much rotated faces. To locate faces in an arbitrary scene, Essa and Pentland (1997) use the eigenspace method of Pentland et al. (1994). The method employs eigenfaces approximated using PCA on a sample of facial images.

10.3.2 Facial Expression Data Extraction

After face detection, the next step is to extract the features that may be relevant for facial expression analysis. In general, three types of face representation are used in facial expression analysis: holistic (Kato et al. 1992), analytic (Yuille et al. 1989), and hybrid (Lam and Yan 1998). For facial expression data extraction, a template-based or a feature-based method is applied. Template-based methods fit a holistic face model, and feature-based methods localize the features of an analytic face model in the input image or track them in the input sequence.

10.3.2.1 Static Images

Edwards et al. (1998) utilized a holistic face representation method. They used facial images coded with 122 points around facial features to develop a model known as active appearance model (AAM). Edwards et al. (1998) aligned training images into a common coordinate frame and applied PCA to get a mean shape for generating statistical model of shape variation. The AAM search algorithm failed to converge to a satisfactory result (Cootes et al. 1998) in 19.2 % of the cases. The method works with images of faces without facial hair and glasses, which are hand-labeled with the landmark points beforehand approximated with the proposed AAM (Pantic and Rothkrantz 2000b). To represent the face, Hong et al. (1998) utilize a labeled graph. They defined two different labeled graphs known as big general face knowledge (GFK) and small GFK. A big GFK is a labeled graph with 50 nodes, and a small GFK is a labeled graph with 16 nodes. The small GFK is used to find the exact face location in an input facial image. On the other hand, the big GFK is used to localize the facial features. Hong et al. (1998) utilized the person spotter system, and the method of elastic graph matching proposed by Wiskott (1995) to fit the model graph to a surface image. Hong et al. (1998) utilize the person spotter system (Steffens et al. 1998) for facial expression analysis from static images.

Huang and Huang (1997) utilize a PDM developed by Cootes et al. (1998) to represent the face. The PDM is a model for representing the mean geometry of a shape and some statistical modes of geometric variation inferred from a training set of shapes. The mouth is included in the model by approximating the contour of the mouth with three parabolic curves. Success of the method is strongly constrained.

Padgett and Cottrell (1996) used a holistic face representation, but did not deal with information extraction through faces in an automatic way. They used the facial emotion database assembled by Ekman and Friesen. Yoneyama et al. (1997) used a hybrid approach for face representation. Their method will fail to recognize any facial appearance change that involves a horizontal movement of the facial features. For correct facial expression analysis using this method, the face should be without facial hair and glasses and no rigid head motion is allowed. Zhang et al. (1998) use a hybrid approach to face representation, but do not deal with facial expression information extraction in an automatic way. A similar face representation was recently used by Lyons et al. (1999) for expression classification into the six basic plus neutral emotions.

Kobayashi and Hara (1997) proposed a geometric face model of 30 facial characteristic points (FCPs). Later, they utilized a CCD camera in monochrome mode to obtain a set of brightness distributions of 13 vertical lines crossing the FCPs. A major drawback of the method is that the facial appearance changes encountered in a horizontal direction cannot be modeled. A real-time facial expression analysis system, developed by Kobayashi et al. (1995), works with online taken images of subjects with no facial hair or glasses facing the camera while sitting at approximately 1-m distance from it (Pantic and Rothkrantz 2000b). Pantic and Rothkrantz (2000b) use a point-based model composed of two 2D facial views for the frontal and the side view. They apply multiple feature detectors for each prominent facial feature (eyebrows, eyes, nose, mouth, and profile) to localize the contours of the prominent facial features and then extract the model features in an input dual view. The system cannot deal with minor inaccuracies of the extracted facial data, and it deals merely with images of faces without facial hair or glasses.

10.3.2.2 Image Sequences

Black and Yacoob (1995, 1997) used local parameterized models of image motion for facial expression analysis by using an affine, a planar, and an affine-plus-curvature flow model (Pantic and Rothkrantz 2000b). Otsuka and Ohya (1996) estimate the motion in the local facial areas of the right eye and the mouth by applying an adapted gradient-based optical flow algorithm (Black and Yacoob 1995). After the optical flow algorithm, a 2D Fourier transform is utilized to the horizontal and the vertical velocity field, and the lower-frequency coefficients are extracted as a 15D feature vector, which is used further for EFE classification (Pantic and Rothkrantz 2000b). This method is not sensitive to unilateral appearance changes of the left eye. Essa and Pentland (1997) used a hybrid approach to face representation. They applied the eigenspace method (Essa and Pentland 1997) to automatically track the face in the scene and extract the positions of the eyes, nose, and mouth. The method for extracting the prominent facial features employs eigenfeatures approximated using PCA. Essa and Pentland (1997) use the optical flow computation method proposed by Simoncelli (1993). This approach uses a multi-scale coarse-to-fine Kalman filter to obtain motion estimates and error-covariance information. The method used for frontal-view facial image sequences. Kimura and Yachida (1997) utilize a hybrid approach to face representation. The method seems suitable for facial action encoding. Wang et al. (1998) also use a hybrid approach to face representation. The face model used by Wang et al. (1998) represents a way of improving the labeled-graph-based models (e.g., Hong et al. 1998) to include intensity measurement of the encountered facial expressions based on the information stored in the links between the nodes.

10.3.3 Facial Expression Classification

The last step of facial expression analysis is to classify the facial features conveyed by the face. Many classifiers have been applied to expression recognition such as NN, SVMs, LDA, *K*-nearest neighbor, multi-nomial logistic ridge regression (MLR), hidden Markov models (HMM), tree augmented naive Bayes, and others. The surveyed facial expression analyzers classify the encountered expression as either a particular facial action or a particular basic emotion. Independent of the used classification categories, the mechanism of classification applied by a particular surveyed expression analyzer is either a template-based or a neural-network-based or a rule-based classification method.

10.3.3.1 Classification of Static Images

At first, automatic expression analysis from static images applies a template-based method for expression classification. The methods in this category perform expression classification into a single basic emotion category. Edwards et al. (1998)

introduce a template-based method for facial expression classification. The main aim of Edwards et al. (1998) is to identify the observed individual in a way which is invariant to confounding factors such as pose and facial expression. The achieved recognition rate for the six basic and neutral emotion categories was 74 %. Edwards et al. (1998) explain the low recognition rate by the limitations and unsuitability of the utilized linear classifier (Edwards et al. 1998). Success of the method for identifying expressions of an unknown subject is not known.

To achieve expression classification into one of the six basic plus neutral emotion categories, Hong et al. (1998) proposed another method. The achieved recognition rate was 89 % in the case of the familiar subjects and 73 % in the case of unknown persons. As indicated by Hong et al. (1998), the availability of the personalized galleries of more individuals would probably increase the system's performance. In order to perform emotional classification of the observed facial expression, Huang and Huang (1997) perform an intermediate step by calculating 10 action parameters. The achieved correct recognition ratio was 84.5 %. It is not known how the method will behave in the case of unknown subjects. Also, the descriptions of the emotional expressions, given in terms of facial actions, are incomplete. For example, an expression with lowered mouth corners and raised eyebrows will be classified as sadness. Lyons et al. (1999) report facial expression classification technique based on complex-valued Gabor transform. In general, the generalization rate is 92 %, whereas the generalization rate is 75 % for a novel subject. Yoneyama et al. (1997) extract 80 facial movement parameters, which describe the change between an expressionless face and the currently examined facial expression of the same subject. To recognize four types of expressions (sadness, surprise, anger, and happiness), they use 2 bits to represent the values of 80 parameters and two identical discrete Hopfield networks. The average recognition rate of the method is 92 %.

Now, we review methods for AFEA from static images applying a NN for facial expression classification. Except the method proposed by Zhang et al. (1998), the methods belonging to this category perform facial expression classification into a single basic emotion category. For classification of expression into one of the six basic emotion categories, Kobayashi and Hara (1992) used neural-network-based method. The average recognition rate was 85 %. For emotional classification of an input facial image into one of 6 basic plus neutral emotion categories, Padgett and Cottrell (1996) utilize a back-propagation NN. The average correct recognition rate achieved was 86 %. Zhang et al. (1998) employ a NN that consists of the geometric position of the 34 facial points and 18 Gabor wavelet coefficients sampled at each point. The achieved recognition rate was 90.1 %. The performance of the network is not tested for recognition of expression of a novel subject. Zhao and Kearney (1996) utilize a back-propagation NN for facial expression classification into one of the six basic emotion categories. The achieved recognition rate was 90.1 %. The performance of the network is not tested for recognition of the expression of a novel subject.

Just one of the surveyed methods for AFEA from static images applies a rule-based approach to expression classification. The method proposed by Pantic and

Rothkrantz (2000b) achieves automatic facial action coding from an input facial dual view in few steps. First, a multi-detector processing of the system performs automatic detection of the facial features in the examined facial image. From the localized contours of the facial features, the model features are extracted. Then, the difference is calculated between the currently detected model features and the same features detected in an expressionless face of the same person. Based on the knowledge acquired from FACS (Ekman and Friesen 1978), the production rules classify the calculated model deformation into the appropriate AUs-classes. The average recognition rate was 92 % for the upper face AUs and 86 % for the lower face AUs. Classification of an input facial dual view into multiple emotion categories is performed by comparing the AU-coded description of the shown facial expression to AU-coded descriptions of six basic emotional expressions, which have been acquired from the linguistic descriptions given by Ekman (1982). The classification into and, then, quantification of the resulting emotion labels are based on the assumption that each subexpression of a basic emotional expression has the same influence on scoring that emotion category. A correct recognition ratio of 91 % has been reported.

10.3.3.2 Classification from Image Sequences

The first category of the surveyed methods for AFEA from facial image sequences applies a template-based method for expression classification. The facial action recognition method proposed by Cohn et al. (1998) applies separate discriminant function analyses within facial regions of the eyebrows, eyes, and mouth. Predictors were facial point displacements between the initial and peak frames in an input image sequence. Separate group variance–covariance matrices were used for classification. The images have been recorded under constant illumination, using fixed light sources and none of the subjects wear glasses (Lien et al. 1998). Data were randomly divided into training and test sets of image sequences. They used two discriminant functions for three facial actions of the eyebrow region, two discriminant functions for three facial actions of the eye region, and five discriminant functions for nine facial actions of the nose and mouth region. The accuracy of the classification was 92 % for the eyebrow region, 88 % for the eye region, and 83 % for the nose/mouth region. The method proposed by Cohn et al. (1998) deals neither with image sequences containing several facial actions in a row, nor with inaccurate facial data, nor with facial action intensity (yet the concepts of the method makes it possible).

Essa and Pentland (1997) use a control-theoretical method to extract the spatio-temporal motion-energy representation of facial motion for an observed expression. By learning ideal 2D motion views for each expression category, they generated the spatio-temporal templates for six different expressions two facial actions (smile and raised eyebrows) and four emotional expressions (surprise, sadness, anger, and disgust). Each template has been delimited by averaging the patterns of motion generated by two subjects showing a certain expression. Correct frontal-view image sequences recognition rate of the method is 98 %. Kimura and Yachida (1997) fit a potential net to each frame of the examined facial image sequence. The proposed method is unsuccessful for classification of image sequences of unknown subjects. Otsuka and Ohya (1996) match the temporal sequence of the 15D feature vector to the models of the six basic facial expressions by using a left-to-right hidden Markov model. The method was tested on image sequences shown by the same subjects. Therefore, it is not known how the method will behave in the case of an unknown expresser. Wang et al. utilize a 19-points labeled graph with weighted links to represent the face. The average recognition rate was 95 %.

Just one of the surveyed methods for AFEA from image sequences applies a rule-based approach to expression classification. Black and Yacoob (1995, 1997) utilized local parameterized models of image motion to represent rigid head motions and nonrigid facial motions within the local facial areas. The achieved recognition rate was 88 %. Lip biting is sometimes mistakenly identified as a smile (Black and Yacoob 1997).

10.4 Computational Method for Psychiatric Diagnosis

EFE is not restricted only to gross changes of facial expressions, but involves continual subtle changes in activation of facial muscles resulting in continuous modification in emotional expressions, in response to dynamic changes in the internal and external context of the individual. Thereby, the tool for understanding the psychiatric diagnosis from the EFE should have to be very sophisticated and sensitive to detect multi-level changes in emotion. Computational models for automatic face recognition could provide such improved methodology.

Computational method for understanding EFE is the development of the formulas or algorithms that are used to calculate the output on the basis of concrete input, given a concrete set of parameters (Wehrle and Scherer 2001). Any computational model, like those developed based on appraisal theory (Wehrle and Scherer 2001), requires determination of parameters to obtain input from all the relevant variables necessary for identification and digitization of location, intensity, and symmetry of hemi-faces in a diagnostic category to understand concrete affective response from EFE. Substantial database will finally help to formulate the digital version of the EFE and can predict the profile of affective response in a given psychiatric illness.

Though psychiatrists usually follow definite diagnostic procedure to diagnose psychiatric disorders by the method of interview, it could be one of the reasons for differences in opinion among them regarding diagnosis. By using facial images of a subject which dynamically changes over time during interview, we can acquire rich supplementary information from the changes in facial expressions that may immensely enhance the accuracy of the diagnosis. Kobayashi et al. (2000) also opined that conversation, behavior, and facial expressions are important in psychiatric diagnosis. They emphasized on the designing of automatic interview system in order to unify the contents and interpretations of psychiatric diagnosis. But as automatic interview system may cause an artificial ambience, recording of video-based automated facial expression in natural ambience, subsequently translating it into digital version, appears to be the more justified approach for input of genuine data of EFE of the psychiatric patients for more accurate diagnosis. Wang et al. (2008) were the first to apply video-based automated facial expression analysis in neuropsychiatric research. They presented a computational framework that creates probabilistic expression profiles for video data and can potentially help to automatically quantify emotional expression differences between patients with neuropsychiatric disorders and healthy controls. Their results open the way for a video-based method for quantitative analysis of facial expressions in clinical research of disorders that cause affective deficits. The automated AU recognition system was also applied to spontaneous facial expressions of pain by Bartlett et al. (2006) where they used automated AU detector within AFACS to differentiate faked from real pain.

For automatic psychiatric diagnosis, video analysis of the EFE, as it happens during the period of interview, also could be incorporated to acquire the information of the change in facial expressions by using dynamically changing facial images of a subject. There are many methods for automatic extraction from different regions of face, such as eyes, eyebrows, and mouth. Frame-by-frame AU intensity analysis could make investigation of facial expression dynamics possible, following the design adopted in pain management program (Bartlett et al. 2006). In their study, coding of each frame with respect to 20 action units automatic detection of faces in the video stream was done by applying SVMs and AdaBoost, to texture-based image representations, where the output margin for the learned classifiers predicted AU intensity.

Next step in automatic psychiatric diagnosis is calculation of the correlations among different parts of facial muscles movements based on the information with respect to the changes in facial expressions. Then, we have to compare these correlations with the corresponding correlations observed in normal healthy subjects (Kobayashi et al. 2000). If significant deviation is observed between two groups with respect to these correlations, the difference may be considered as an index of expression of psychopathology.

Figure 10.4 may help design computation models for automatic identification of psychiatric disorder.

Objective coding of emotional expression in diagnosis of psychiatric population through computational modeling also may incorporate:

1. The database to understand emotional expression bias of each diagnostic category, for example, indifference or flat affect in schizophrenia, negative emotion bias (sadness) in depression, or positive emotion bias in manic patients.
2. From the view point of decoding emotion, impairment of decoding emotional expression in autism (McIntosh et al. 2006) or differential perceptual bias for negative emotions in borderline personality disorder (Domes et al. 2008) or in patients with anxiety disorder (Barlow et al. 1996); (Mineka and Zinberg 1996), or in schizophrenia (Borod et al. 1993) suggest not only emotional expression of the patients but decoding of emotional faces of others by patients can also provide an important basis of computational diagnosis.

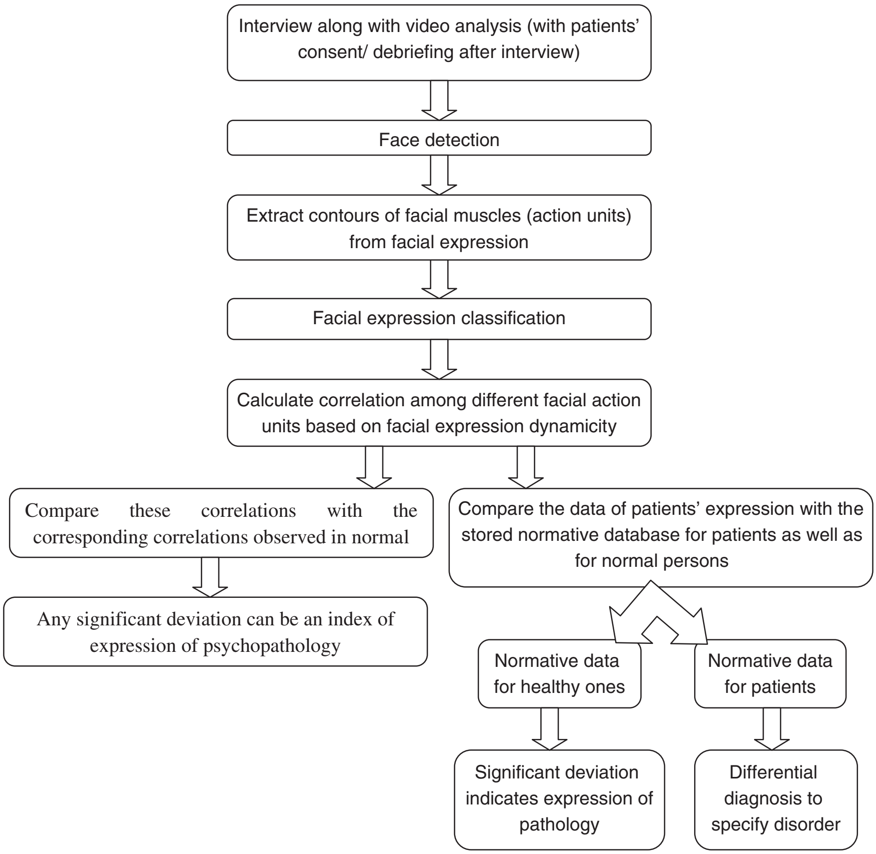

Fig. 10.4 Flowchart based on summarizing computational analytic procedures for psychiatric diagnosis

Following the above perspective, the data base can store three types of information regarding the appraisal of EFE of others by clinical population.

(i) Nature of appraisal of facial expressions of the psychiatric patients of different psychiatric diagnostic categories under investigation is necessary to understand their emotional valance. These appraisals by the patients could be used as the diagnostic index for them.
(ii) Nature of appraisal of facial expressions of at least six basic emotions of normal population by the psychiatric patients could serve as a reference point, to help us in analyzing patients' vulnerability in appraising basic normative emotional facial expression.
(iii) Nature of appraisal of facial expression, blended with display rules of normal population by the psychiatric patients, helps us in detecting whether patients are able to decode display rules or not.

The development of these normative sets of data for the patients of different diagnostic categories is necessary to understand the unique constellation of characteristics of EFE of each diagnostic category and the differential point of diagnosis of a given psychiatric illness from the other. Consideration of efficiency for monitoring emotional expressions in congruence with the situational demand in the model could be used as an index of better prognosis. Another important issue to be considered is reliability of computational models. In case of computational analysis, the signal value for correct diagnosis is pronounced enough for patients with psychotic symptoms, those who widely deviate from normal pattern of EFE. However, distinguishing the patients with intact reality contact from normal could enhance the probability of error in computational diagnosis. In such cases, reliability analysis is imperative in order to reduce diagnostic errors. This methodological crisis could be overcome by checking the reliability of computational models through signal detection paradigm.

In the context of diagnosis of psychiatric disorders, real-time dynamic facial expression analysis techniques seem to be very helpful. Subtle differentiation is not possible without the assistance of sophisticated computer analysis and mathematical explanation. It is expected in near future that facial expression recognition will become very useful for early diagnosis of mental illness. LBP-based facial image analysis has been one of the most popular methods in recent years. Happy et al. (2012) propose a facial expression classification algorithm that uses Haar classifier for face detection purpose. LBP histogram of different block sizes of a face image as feature vectors classify various facial expressions using PCA. The algorithm is implemented in real time for expression classification since the computational complexity of the algorithm is small. Happy et al. (2012) noted the following algorithm for real-time facial expression analysis.

Training Algorithm (Proposed by Happy et al. 2012) (Fig. 10.5):

(i) Detect face from the training image using Haar classifier and resize detected face image to N × M resolution.
(ii) Preprocess the face image to remove noise.
(iii) For each class (expression), obtain the feature vectors $\Gamma_{j,1}$, $\Gamma_{j,2}$, …, $\Gamma_{j,p}$ (jth class) of dimension $\left(\frac{M}{n} * \frac{M}{m} * b, 1\right)$ each.
   (a) Divide the face image to subimages of resolution n × m, find the LBP values, and calculate b—bin histogram for each block.
   (b) Concatenate the histograms of each block to get the feature vector ($\Gamma_{j,i}$) of size $\left(\frac{M}{n} * \frac{M}{m} * b, 1\right)$.
(iv) Compute the mean feature vector of individual class $\Psi_j = \frac{1}{P}\sum_{i=1}^{P}\Gamma_{j,1}$, $(j = 1{,}2,\ldots{,}6)$.
(v) Subtract mean feature vector from each feature vector $\Gamma_{j,i}$.

$$\varphi_{j,i} = \Gamma_{j,i} - \Psi_j, \quad (j = 1, 2, \ldots, 6).$$

(vi) Estimate the covariance matrix C for each class, given by

$$C_j = \frac{1}{P}\sum_{i=1}^{P}\phi_{j,1}\phi_{j,i}^{T} = A_jA_j^{T} \quad (j = 1, 2, \ldots, 6)$$

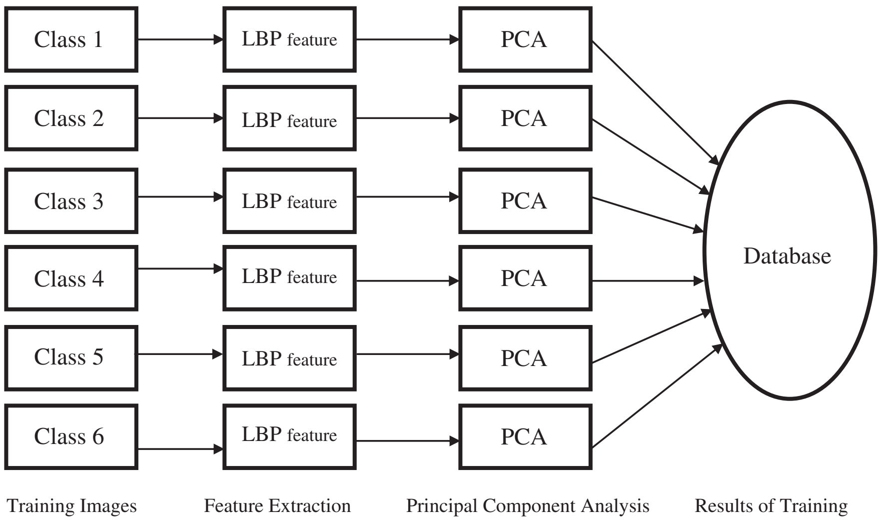

Fig. 10.5 Flowchart for training phase proposed by Happy et al. (2012)

where $A_j = [\phi_{j,1}\phi_{j,2}, \ldots, \phi_{j,P}]$ of dimension $\left(\frac{M}{n} * \frac{M}{m} * b \times P\right)$ which is very large. Compute $A_j^T A_j(P \times P)$ instead as $P \ll \frac{M}{n} * \frac{M}{m} * b$.

(vii) Compute the eigenvectors $v_{j,i}$ of $A_j^T A_j$ using the equation

$$\sigma_{j,i} u_{j,i} = A_j v_{j,i} \quad (j = 1, 2, \ldots, 6).$$

(viii) Keep only K eigenvectors corresponding to the K-largest eigenvalues form each class (suppose, $U_j = [u_{j,1}, u_{j,2}, \ldots, u_{j,k}]$).

(ix) Normalize the K eigenvectors of each class.

Algorithm for facial expression detection (proposed by Happy et al. 2012) (Fig. 10.6):

(i) Detect face with Haar classifier algorithm and resize face image to $N \times M$ resolution.

(ii) Preprocess the face image to remove noise.

(iii) Find feature vector (Γ) for the resized face using similar methods as used in training phase (Step 3).

(iv) Subtract the mean feature vector of each class form (Γ)

$$\phi_j = \Gamma - \Psi_j \quad (j = 1, 2, \ldots, 6)$$

(v) Project the normalized test image onto the eigen directions of each class and obtain weight vector

$$W = [w_{j,1}, w_{j,2}, \ldots, w_{j,k}] = U_j^T \phi_j \quad (j = 1, 2, \ldots, 6)$$

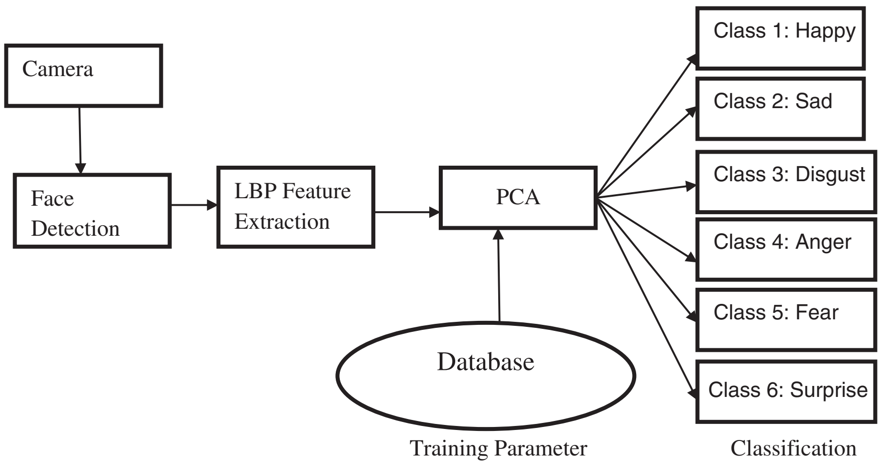

Fig. 10.6 Flowchart for testing phase proposed by Happy et al. (2012)

(vi) Compute $\cap\phi_j = \sum_1^k w_{j,i}u_{j,i}$ $(j = 1, 2, \ldots, 6)$
(vii) Compute error $e_j = \left\|\phi - \cap\phi_j\right\| j = 1, 2, \ldots, 6.$

The image is classified to the training set, to which it is closest (when the reconstruction error (e_j) is minimum).

It is envisioned that this algorithm will be very useful for diagnosis of psychiatric disorders.

10.5 Conclusion and Future Direction

Present review is an attempt to explore the possible methodologies of computational modeling of emotional facial expressions that may be finally developed into an objective psychiatric diagnostic tool in terms of fully automated facial action detection system of spontaneous facial expressions. The accuracy of automated facial expression measurement in spontaneous behavior may also be considerably improved by 3D alignment of faces. Bartlett et al. (2006) in his work with feature selection by AdaBoost though significantly enhanced both speed and accuracy of SVMs, but its application is still restricted to the field of recognition of basic emotions only. Expansion of its applicability in the task of AU detection in spontaneous expressions could be an important task in future. The computational analysis is capable of bringing about paradigmatic shifts in the field of psychiatric diagnosis by making facial expression more accessible as a behavioral measure and also may enrich the understanding of emotion, mood regulation, and social communication in the field of advanced cognitive neuroscience. We believe that a focused, interdisciplinary program directed toward computer understanding of human behavioral patterns (as shown by means of facial expressions and other modes of social interaction) should be established in order to achieve a major breakthrough.

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Chapter 11
Microexpressions and Deception

Mark G. Frank and Elena Svetieva

11.1 Microexpressions and Deception

The success of television programs like *Lie to Me* in the USA and elsewhere in the world has pushed the term *microexpression* into the common parlance. Microexpressions are often portrayed as strong indicators of deception and often spoken with a hushed reverence, as if some magical process. Some scientists have even referred to them as 'mysterious' (Zuckerman et al. 1981, p. 15). But what is a microexpression, exactly? And, how might it relate to deception? This chapter will describe why microexpressions occur, the history of the microexpression, their role in deception, and their role in detecting deception.

11.2 What Is a Microexpression?

We define a microexpression as a facial expression of emotion, full or fragmentary, that is expressed for 0.5 s or less. Thus, a microexpression is just a special case of a facial expression of emotion. Research has shown again and again that there are approximately six to nine basic human emotions, each with its own accompanying facial expression (Ekman 2003; Izard 1994). These emotions include anger, contempt, disgust, fear, enjoyment, sadness (or distress), and surprise; some

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also include interest (Izard 1977), or embarrassment (Keltner 1995). These facial displays of emotion seem biologically wired, produced involuntarily, and have similar meanings across all cultures (e.g., Ekman 2003, for a review). The reason for this universality, originally proposed by Darwin (1872/1998), and later elaborated by others, (e.g., Ekman 1994; Izard 1994; Plutchik 1994), is that social animals, such as humans, must communicate their emotions to others in their group because emotions express imminent behavior, such as striking out in anger, fleeing in fear, and other action tendencies (e.g., Frijda 1986). These signals allow other members to predict and thus react more appropriately to others in the group, and this can smooth social interaction. It can also spread signals that alert others to imminent danger, that others in the group need attention, that there is food that is acceptable or unacceptable to eat, to let others know when they have transgressed the social hierarchy, and so forth.

There is compelling evidence that these emotions are expressed and interpreted the same across all cultures (Ekman et al. 1987; Ekman 1994; Izard 1994). This 'universal' production and perception across cultures suggests that those emotions, and their specific facial expressions, are genetically determined rather than socially learned. They are unbidden, with a particular pattern of morphology and dynamic actions (Ekman and Friesen 1982; Frank and Ekman 1993). Moreover, a number of studies have since documented the relationship between these facial expressions of emotion and the physiology of the emotional response (Ekman et al. 1980, 1983; Levenson et al. 1990, 1992). Indeed, between 1972 and 2007, there were 74 published research studies showing the link between these specific facial expressions and internal physiological states associated with emotion (reviewed by Matsumoto et al. 2008).

Several additional lines of evidence suggest that the source of these expressions is biologically based. These include studies of congenitally blind individuals (Galati et al. 2001, 2003; Matsumoto and Willingham 2009); studies of the concordance in spontaneous expressions between kin versus non-kin (Peleg et al. 2006) and monozygotic versus dizygotic twins (Kendler et al. 2007); and studies of analogous and homologous expressions in non-human primates (de Waal 2003; Parr et al. 2005). Moreover, a growing body of research also shows that specific regions of the brain will activate in response to showing still photographs of specific facial expressions of emotion (e.g., Blair 2003). To date, researchers have discovered specific brain areas that respond to anger, disgust, fear, and happiness (reviewed by Matsumoto et al. 2008). This strongly suggests that these facial expressions of emotion are hardwired for production and perception. There are certainly debates concerning the source (Barrett 2006) and meaning (Fridlund 1994) of universal expressions, but little doubt remains about their existence or importance (Ekman 1999).

These universal facial expressions are part of a coherent emotional reaction that involves an individual's appraisals of events, physiological response, cognitions, and subjective experience. These components work together in an organized fashion to enable the individual, with little conscious thought, to address the threat or other stimulus that is provoking the emotion; these coherent responses have been demonstrated within many different cultures, but also in cross-cultural studies (e.g., 27 different countries; see review by Matsumoto et al. 2007).

The presence of these universal facial expressions predicts a large number of social phenomena (see Ekman and Rosenberg 2005, for a review of 28 different studies of spontaneous facial expressions of emotion). For example, the presence of enjoyment smiles, but not other smiles, on the part of a person who has survived the death of their romantic partner predicts successful coping with that traumatic loss (Bonanno and Keltner 1997). Clinically depressed patients show fewer facial expressions in general, and enjoyment smiles in particular (e.g., Berenbaum and Oltmanns 1992; Katsikitis and Pilowsky 1991). In fact, evidence shows that the increased proportion of enjoyment smiles compared to non-enjoyment smiles can foretell clinically depressed patients' successful response to therapy (Ekman et al. 1997). Moreover, patients with schizophrenia tend to show different, and sometimes, fewer or more disorganized facial expressions than normal patients (Krause et al. 1989) when experiencing an emotion. These patients seem to feel emotion, as measured by galvanic skin conductance measures, but they do not express these emotions (Kring and Neale 1996). At-risk aggressive adolescents respond with more facial expressions of anger, and less facial expressions of embarrassment, to the same stimuli than less aggressive adolescents (Keltner et al. 1995). Patients with myocardial ischemia, with Type A personalities, tend to show more elements of an anger face than others (Rosenberg et al. 1998). Mothers show different sorts of smiles to their difficult compared to their non-difficult children (Bugental 1986). People who score high in psychopathology show physiological responses to facial expressions of anger, but not sadness, suggesting they do not feel sympathy (Patrick 1994). Moreover, facial expressions of emotion are useful indicators of relationship status. The expression of disgust or contempt, but not anger, predicts marital divorce (Gottman 1994). Taken together, this research demonstrates that facial expressions of emotion are part of the emotional reaction and thus indicative of internal emotional states (Ekman 2003).

Although the microexpression is a special case of the more typical facial expression of emotion, we chose to use this term to define any expression of emotion that is shown at 0.5 s or less. The reason we selected that particular duration is that previous work had shown that spontaneous expressions of emotion tend to last between 1/2 and 4 (or 5) seconds—regardless of whether the duration was measured by human coders using videotape, or electromyographic (EMG) tracings of specific muscle movements (Ekman and Friesen 1982; Frank et al. 1993; Hess and Kleck 1990). Thus, it seemed defensible to label anything at or less than 0.5 s to be a microexpression, particularly in light of other work to be described later in this chapter. This particular duration cutoff is a new definition, and the history of work on this issue shows this definition has not always been the case.

11.3 The History of the Microexpression

These very brief expressions were first noted in a clinical context, where they were called *micromomentary expressions* (Haggard and Isaacs 1966). Specifically, they reported:

> The present report is concerned with one class of behaviors and processes which cannot be observed-namely facial expressions which are so short-lived that they seem to be quicker than the eye. These rapid expressions can be seen when motion picture films are run at about one-sixth of their normal speed. The film and projector thus become a sort of temporal microscope, in that they expand time sufficiently to enable the investigator to observe events not otherwise apparent to him.
>
> We first noticed the existence of micromomentary expressions (MMEs) while scanning motion picture films of psychotherapy hours, searching for indications of nonverbal communication between the therapist and patient (Haggard and Isaacs 1966, p. 154).

These researchers attempted to develop coding schemes for what they called micromomentary expressions—met by only partial success—and conducted some observational studies that suggested these micromomentary expressions were more likely to occur either during discussions of affective states or topics, or when their clinical subjects felt some conflict between the topic under discussion and the subjects' feelings. They concluded that these micromomentary expressions were due to unconscious repression on the part of the individual, and as can be seen in the quote above, they believed these expressions were not detectable in real time.

Three years later, researchers articulated more clearly the intrapersonal and emotionally conflicted nature of what they now called *microexpressions* (which they also called *microdisplays* within this same paper) through their analysis of filmed interviews of depressed inpatients (Ekman and Friesen 1969a). These researchers studied emotions not from a psychodynamic perspective—which suggested unconscious repression (cf. Haggard and Isaacs 1966)—but from an evolutionary perspective, first put forth by Darwin (1872/1998). Like Darwin, they had suggested that emotions were biologically hardwired, designed to reorganize the body's physiological priorities to address recurrent life events that had significance for the organism, such as fleeing danger and attacking obstacles. Moreover, these emotions also featured facial signals of such emotional states that were meaningful to conspecifics (Ekman 1972). Consistent with that notion, they had confirmed Darwin's methodologically shaky finding (i.e., sending photographs of posed expressions across the British empire and asking if informants had seen those expressions in the local residents) that some facial expressions of emotion are recognized across all cultures (known as *universality*; e.g., Ekman et al. 1969). Finally, in examining the films of psychiatric patient interviews, they took Darwin's idea that one could suppress these spontaneous facial expressions through the will (often called Darwin's *inhibition hypothesis*), but that those facial actions hardest to move deliberately would be also be those that are the hardest to control deliberately when spontaneously activated. Darwin wrote:

> Some actions ordinarily associated through habit with certain states of mind may be partially repressed through the will, and in such cases the muscles which are least under the separate

> control of the will are the most liable still to act, causing movements which we recognize as expressive. In certain other cases the checking of one habitual movement requires other slight movements; and these are likewise expressive (Darwin 1872/1998, pp. 34).

In one of the case studies, the researchers described a situation where a patient who was hospitalized for depression asked for a weekend pass when she claimed to have felt better. She had appeared to have improved but, nonetheless, later admitted both to wanting to take her life and lying about feeling better during the interview (Ekman and Friesen 1969a). In their real-time examination of the filmed interview, the research team did not see any behavioral clues to this patient's deception (i.e., actually feeling sad but feigning happiness), but upon review of the film in painstaking frame-by-frame detail, they saw a brief but intense expression of sadness that lasted only two frames (1/12th of a second), followed by a smile. This knowledge enabled them to find other examples of these extremely fast expressions in the same film. From these observations, they described what they alternately called *microexpressions* (p. 93) or *microdisplays* (p. 97) as:

> Micro displays may be fragments of a squelched, neutralized, or masked display. Micro displays may also show the full muscular movements associated with a macro affect display, but may be greatly reduced in time. We have found that such micro displays when shown in slow motion do convey emotional information to observers, and that expert clinical observers can see micro displays and read the emotional information without the benefit of slow motion projection.
>
> If the micro display results from squelching and that squelching is fast enough, the affect may be completely obscured, and the display may provide deception clues rather than leakage. If there is a brief but relatively complete display of affect, then the micro display may provide leakage. Such micro displays are often followed by or covered by simulated, antithetical, macro affect displays, and the untrained observer will usually miss or minimize micro displays (Ekman and Friesen 1969a, p. 97).

Thus, they concluded that these microexpressions convey emotional information and are due to the *conscious* suppression of the expression and not just *unconscious* repression, thus making microexpressions amenable to study as individuals would have some awareness of the process. They also found that microexpressions could be detected in real time, without slowing the image down to 1/6th its normal speed (as suggested by Haggard and Isaacs 1966). Finally, if expert clinical observers could detect microexpressions in real time, then they reasoned that non-experts could be trained to detect them as well (Ekman and Friesen 1969a). Finally, it was thus Ekman and Friesen's (1969a) exposition of the microexpression phenomenon that has driven the ensuing research.

We offer one more note on terminology. Although Ekman and Friesen (1969a) did acknowledge that microexpressions can be fragmentary, more recently scientists have distinguished a microexpression from a *subtle* expression—a subtle expression being the term used to describe the fragmentary microexpressions (e.g., Ekman 2003). This was driven by the development of training tools to facilitate facial expression recognition accuracy; thus, researchers had defined a *microexpression* as a full facial expression (that is, the complete set of the movement features) shown for a very brief duration (typically 1/15th to 1/25th of a second), whereas they defined a *subtle expression* as a partial facial expression, featuring fragments of the facial expression, such as just the movement features from the lower face, or just the movement features of the upper face (e.g., Ekman 2003; Matsumoto and Hwang 2011). However, we will refer to all expressions—partial or full—that are 0.5 s or less as microexpressions. We believe microexpressions can be as subtle to the eye as these *subtle* expressions, and those observations of rapid facial expressions in a number of social situations—particularly involving deception—show them more often to be partial rather than full (e.g., Frank and Ekman 2004; Frank et al. 2014a; Porter and ten Brinke 2008).

11.4 Why Do Microexpressions Occur?

Microexpressions are possible because the human face is a dual system. Neuroanatomical research confirms that facial expressions can be biologically driven, involuntary, and harder to control (as in the case of the basic emotions), and socially learned (as in the case of mimicked or posed facial expressions). There are two distinct neural pathways that mediate facial expressions, each one originating in a different area of the brain. The pyramidal motor system drives the voluntary facial actions and originates in the cortical motor strip, whereas the extrapyramidal motor system drives the more involuntary, emotional facial actions and originates in the subcortical areas of the brain (Meihlke 1973; Myers 1976; Tschiassny 1953). The research documenting these differences is so reliable (e.g., Brodal 1981; Karnosh 1945) that prior to modern methods that see through tissue, they served as the primary diagnostic criteria for certain brain lesions (DeMyer 1980). Not only do voluntary and involuntary facial actions differ by neural pathway, but the actions mediated by these pathways manifest themselves differently. In a normal person, voluntary pyramidal motor system-based movements are limited solely by individual effort. However, extrapyramidal motor system-based facial actions are characterized by synchronized, smooth, symmetrical, consistent, and reflex-like or ballistic-like actions on the part of the component facial muscles (Ekman and Friesen 1982; see review by Rinn 1984). Relatively speaking, these actions appear to be less under the deliberate control of people. Thus, these spontaneously expressed emotional expressions tend to have dynamic qualities different from non-emotional expressions, such as having smoother onsets, more symmetry, and a circumscribed duration lasting between 1/2 and 5 s in length (Ekman and Friesen 1982; Frank et al. 1993).

Although Darwin (1872/1998) proposed that facial expressions are part of an involuntary emotional impulse, they are not solely the product of involuntary emotional impulses. People can deliberately fabricate the appearance of an involuntary facial expression of emotion without experiencing the emotion. This means that people can pose facial expressions that resemble anger, contempt, disgust, fear, happy, sadness, and surprise when they have not actually experienced those emotions. Moreover, people can also use their face to display symbolic gestures (Ekman and Friesen 1969b), such as raising one eyebrow to indicate skepticism, or winking to indicate 'I'm kidding.' These facial expressions are culturally specific, learned like language (Ekman 1977), and tend to be more variable in their duration on the face than emotional expressions (Frank et al. 1993). What this all means is that people have the neuroanatomical infrastructure to suppress the emotional expression in the manner first proposed by Darwin (1872/1998) and later elaborated by Ekman and Friesen (1969a).

In social situations where people attempt to squelch, conceal, or mask their emotional expression, both the pyramidal and extrapyramidal motor systems can be activated simultaneously. When an emotion is triggered, the subcortical area of the brain sends an involuntary ballistic-like signal to the facial nerve. To conceal this response, the individual recruits his or her voluntary cortical motor strip area of the brain, which sends a signal to suppress, amplify, or disguise his or her expression in a socially and culturally acceptable way. This creates a 'tug of war' over control of the face, and when the subcortical impulse is strong enough, the expression will leak onto the face for a very brief time before the voluntary motor systems regains control of the expression. This competitive confluence of signals produces an emotional facial expression that is shorter in duration than the duration of 1/2 to 4 s originally identified (Ekman and Friesen 1982).

11.5 What Is the Role of Microexpressions in Lying?

A lie is a deliberate attempt to mislead, without prior notification of the target (Ekman 1985/2001). Virtually, all models of how lies are betrayed by behavior recognize that clues to deceit are caused by not only cognitive factors, such as mental effort, but also emotional factors, such as signs of fear, guilt/distress, or even enjoyment (Zuckerman et al. 1981). These emotional signals are proposed to occur when the liar feels fear of getting caught in their lie, or distress or guilt at telling the lie, or contempt or disgust toward the target of the lie (Frank and Svetieva 2013). To the extent that the lie situation generates emotions—typically through the stakes such as strong rewards for successful lying, and strong punishments for unsuccessful lying—one would predict that signs of the aforementioned emotions could betray a lie (Frank and Ekman 1997). However, most studies of behavioral clues to lying have not featured high-stakes lies. It is not surprising therefore that the most comprehensive meta-analysis of behavioral clues to lying has shown inconsistently significant effect sizes for some facial expression type clues. For example, liars have shown significantly less facial pleasantness, more chin raises, more lip pressing, and in general appeared more nervous; yet other facial clues such as brow lowering, brow raising, smiling, lip stretching, and general facial expressiveness have not shown consistently significant effect sizes (DePaulo et al. 2003). When this same meta-analysis separated the high-motivation (a stand-in for stakes) studies from the others, they did report stronger effects for emotion-based clues such as nervousness and higher voice pitch (Frank and Svetieva 2012).

Outside of the original work on concealing emotions, which showed differences in feigned happiness and subtle signs of distress (Ekman et al. 1988, 1991), it has only been recently that specific emotional expressions have been measured when individuals have been lying. This is likely due to the logistic benefits of cheap and durable videotape, along with cheap and durable VCR systems that enabled frame-by-frame coding of facial movement using the Facial Action Coding System (FACS, Ekman and Friesen 1978), a comprehensive system for measuring all visible facial muscle movement. FACS also enables one to measure those movements presumed to be associated with emotion, thus enabling one to predict the presence of an emotion within an individual (see Ekman 2003, for a description of movement features).

Studies using FACS (or a pseudo technique inspired by FACS; e.g., Porter and ten Brinke 2008) have shown that facial expressions of emotion can betray deception and that a significant portion of those expressions could be classified as microexpressions. Microexpressions have been reported in a number of studies featuring deception—in particular studies featuring individuals lying about their feelings, such as whether they were viewing pleasant ocean waves, or photographs designed to induce specific emotions, or individuals feigning sadness as the loss of a relative whom they killed (e.g., Ekman and Friesen 1969b; Ekman et al. 1991; Porter and ten Brinke 2008, 2010). They have also been identified in studies featuring individuals lying or telling the truth about their opinions, or a theft, under high-stakes conditions—that is, strong punishments for being judged a liar and strong rewards for successful lying (e.g., Frank and Ekman 1997, 2004; Frank et al. 2014a). Most of these studies employing frame-by-frame coding simply mentioned that many of the expressions were of very brief duration (e.g., Frank and Ekman 2004). However, two studies—Porter and ten Brinke (2008) and Frank et al. (2014a)—actually broke out the microexpressions by count and duration.

Porter and ten Brinke (2008) used a paradigm whereby participants had to facially respond to affective imagery produced by the International Affect Picture System (Lang et al. 2008). They found that more than 1/5th of their sample exhibited microexpressions, particularly in situations where individuals had to mask or conceal their emotional expression to the stimuli. In contrast to durations of microexpressions described by earlier accounts (1/25th of a second, 1/30th of a second; Ekman 1985/2001, 2003; Ekman and Friesen 1969a; Haggard and Isaacs 1966), they reported no expressions of such speed. They also reported that they found no full face examples of such expressions, only upper face or lower face components. However, this study simply asked people to feign emotional expressions or stifle them and did not burden them with creating and speaking falsified accounts as what would be found in other types of lies.

Frank et al. (2014a) instead asked participants who were members of politically active groups to choose whether to take a $100 check made out to their arch rival group. Participants were told that they were going to be interviewed by retired law enforcement officers, and if they took the check and lied to the officer successfully, they could tear up the $100 check, gain a $100 check made out to their group, as well as $75 for themselves personally. If they were judged as lying, they were told that the $100 would go to the arch rival group, they would receive nothing and instead face detention for 30 min while being exposed to 110-db blasts of white noise delivered by headphones. The results showed that 72 % of the 132 participants could be successfully classified as truthful and lying by the presence or absence of the emotions of fear, distress, contempt, and disgust (approximately the same rate of classification accuracy for truth tellers as liars). Moreover, of those emotions that betrayed deception in the liars, 51 % of them were 0.5 s or less in duration, and 30 % of them were less than 0.25 s in duration. Interestingly, the same rate of microexpressions occurred in those truth tellers who showed these emotions (and thus were classified as false-positives).

The involuntary nature of these expressions is demonstrated further by the fact that after the last questionnaire, the participants were asked what strategies they used to fool the interviewer. Those liars who stated that they used a 'poker face' or similar strategy of managing their facial expressions showed exactly the same rate of these negative emotions as those who did not indicate that they tried to deliberately manage their expressions. In contrast, those truth tellers who stated they used a 'poker face' strategy showed significantly less of these emotional expressions (18 %) than those who did not report such a strategy (35 %).

This suggests that liars would have a hard time concealing such microexpressions. This was tested when lying participants were specifically instructed to conceal their expressions of fear or happiness when being interrogated; the results showed that although participants were able to successfully decrease the intensity and the duration of their facial expressions, almost all of them nonetheless still showed signs of these emotions (Hurley and Frank 2011).

Taken together, this work shows that internal emotional states can betray deception when they contradict the verbal line—for example, signs of distress when describing pleasant ocean waves (Ekman 1985/2001), or signs of fear when saying one would never steal a check (Frank et al. 2014a), or signs of disgust when saying how smoking should not be banned (Frank and Ekman 1997). Given that individuals are motivated to conceal their emotions when they deceive (Frank et al. 2014a), these emotional expressions will often appear as a microexpression. Thus, an individual who can detect microexpressions would seem to be at an advantage when it comes to detecting lies.

11.6 Can Individuals Detect Microexpressions?

A US Department of Defense review of research on detecting deception from demeanor concluded that microexpressions may be a useful clue for detecting deception by intelligence officers, but stated that they could not be seen without specialized equipment:

> …Some of the more reliable clues to deception …included… some elements of a system developed by Ekman and associates for evaluating subtle, small, and short-lived shifts in facial expression. However, analysis of microfacial expressions … generally requires the use of recording equipment and represents methods that may not be practicable for field operatives (Hazlett 2006, p. 48).

The two studies that did delineate the specific microexpressions found evidence consistent with this speculation. Both asked lie catchers to judge truth and lie, and both found that lie catchers did not detect lies and truths at rates greater than chance (Frank et al. 2014a; Porter and ten Brinke 2008).

Other studies that contained microexpressions, but did not count them, also found that they are rarely detected. For example, nursing students were interviewed as they viewed 2 films—one featuring ocean waves, and a second showing a gruesome leg amputation—and tried to convince the interviewer that both films made them feel calm, pleasant, and relaxed. When these videos were subjected to frame-by-frame analysis of the facial and body behavior, many subtle and micro-momentary signs of concealed emotion were shown when the nurses viewed the amputation video (Ekman and Friesen 1974). However, untrained observers could not distinguish at rates greater than chance which video the nurse was watching. Interestingly, groups who were especially attuned to the nonverbal and emotional aspects of communication, such as physically abused children raised in institutions (Bugental et al. 2001), patients with left hemisphere brain damage such that they could not process speech (Etcoff et al. 2000), and the US Secret Service (Ekman and O'Sullivan 1991) were able to make this distinction at rates greater than chance.

Videos of truths and lies that featured microexpressions shown by individuals lying about their opinions or involvement in a mock theft showed that some groups of law enforcement could detect these lies at rates greater than chance (e.g., Ekman et al. 1999). In fact, a meta-analysis of lie studies that featured high stakes for the liars and truth tellers has shown that law enforcement officers exhibit much higher lie detection accuracy (67 %) than studies that present law enforcement officers with low-stakes lies (54 %; O'Sullivan et al. 2009). Other expert groups—such as the 'wizards'—show consistently high accuracy judging deception across a number of lie detection tests (O'Sullivan and Ekman 2004) including high-stakes materials. This is in contrast to studies that examined the ability of average people to detect lies from truths, which consistently show accuracy at approximately 54 % (reviewed by Bond and DePaulo 2006).

The ability to detect these microexpressions seems to be one component associated with the higher accuracy at judging lies and truths in these high-stakes lie situations. Researchers have created a number of tests that assess one's ability to detect microexpressions (e.g., Matsumoto and Hwang 2011; Matsumoto et al. 2000). These tests tend to feature still photographs of individuals showing no expression for one to three seconds and then flash an image of that same person showing a posed expression of anger, contempt, disgust, fear, happy, sadness/distress, or surprise for 1/15th of a second, followed by a backward mask of the same individual with a neutral facial expression. These 'flash' programs have been used in a number of studies and have consistently shown significant correlations such that individuals who are good at recognizing the 1/15th of a second flash of emotion are also better at detecting deception. For example, Ekman and O'Sullivan (1991) reported a correlation of $r = 0.27$ between accuracy at judging microexpressions and accuracy at judging emotional concealment lies. Frank and Ekman (1997) reported a correlation of $r = 0.34$ between microexpression accuracy and a high-stakes mock crime scenario, and $r = 0.30$ for a high-stakes false-opinion scenario for university students. Frank and Hurley (2014) reported a correlation of $r = 0.35$ for police officers and a mock crime scenario. Finally, Warren et al. (2009) showed microexpression tests (full-fledged facial expressions of emotion, or partial facial expressions) and reported a significant correlation of $r = 0.46$ for partial facial expressions and deception accuracy judging lies featuring emotional concealment.

It is possible to train people to detect microexpressions, and that training will persist over time (Hurley 2012). This training produces greater than chance-level improvements in one's ability regardless, whether it is self-instructional or instructor-led, although it tends to improve significantly better when it is instructor-led. University students, as well as Coast Guard officers, Australian Police and Customs, and Hong Kong Police and Customs, have also shown significant improvements in their abilities to detect microexpressions with as little as 30 min of training (Frank et al. 2014b, c). For the Coast Guard officers and university students, the training in microexpressions translates into significant improvements in their abilities to detect concealed emotions in real-time microexpressions shown by individuals in deception situations (Frank et al. 2014b). Finally, attendees at the FBI's National Academy, when trained to detect microexpressions as anomalous behavior, also showed an increase in their ability to detect deception (Matsumoto et al. 2012).

11.7 What Can We Conclude?

The evidence shows quite clearly that microexpressions do exist, but they are typically more fragmentary—that is, appearing on the top or bottom half of the face—and they are usually not as fast as the 1/30th of a second as original articulated (Ekman and Friesen 1969a; Haggard and Isaacs 1966). Of the 87 negative emotions shown by 71 liars in a recent study, only 1 was found to be 1/30th of a second in duration (although 30 % were less than 0.25 s; Frank et al. 2014a). They are so quick because of the tension between the pyramidal motor system, which controls deliberate movement, and the extrapyramidal motor system, that controls involuntary movements like those caused by emotion (see review by Rinn 1984). Microexpressions seem to be prevalent in situations in which facial expressions of emotions are elicited through deliberate emotion induction tasks (films of leg amputations, IAPS photos; e.g., Ekman et al. 1991; Porter and ten Brinke 2008) or through high-stakes lies (e.g., Frank and Ekman 2004). Those who are better at spotting microexpressions—through natural abilities (e.g., wizards; O'Sullivan and Ekman 2004), life experiences (e.g., Etcoff et al. 2000), or professional experiences such as law enforcement (e.g., O'Sullivan et al. 2009)—are better at spotting microexpressions. In addition, those who are specifically trained to detect microexpressions also show improvement in their abilities to detect lies (Frank et al. 2014b). Thus, in contrast to the supposition of the US government review, microexpressions can be detected in real time and can be detected without specialized equipment (c.f. Hazlett 2006).

Detecting microexpressions would be important in any domain in which individual may be motivated to conceal their true feelings, such as in physical and mental health, judicial and law enforcement, intelligence and counter terrorism, and the corporate world (Matsumoto et al. 2013). One must keep in mind though that at its core, a microexpression is a rapid signal that the individual is feeling an emotion, and they are trying to manage that emotion. There are many reasons why individuals may manage their emotions for reasons beneficial to others, such as when trying to be polite or respectful. However, there are other situations in which it is not the case and the emotion management is conducted to further some nefarious purpose and harm others, such as when concealing terrorist activity or involvement in some other crime. It is those situations in which they are particularly important to detect. But this detection is just one part of the process—one must not only detect the microexpression, but also interpret it properly (O'Sullivan et al. 2009). A person's microexpression of fear may be caused by his or her fear of being disbelieved when one is telling the truth (Ekman 1985/2001); or it may be caused by his or her fear of being caught in the lie. Thus, the only way to be certain is to ask further questions, ascertain the true reason behind the emotion (Frank et al. 2006), and use that to obtain enough unimpeachable corroborating evidence as to whether this person is lying or telling the truth.

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Chapter 12
The Detection of Deception in Cross-Cultural Contexts

Paola A. Castillo

12.1 The Detection of Deception in Cross-Cultural Contexts

Judgments about credibility and deception often have significant implications. In forensic contexts, the evaluation of a person's veracity could affect the decision-making of investigators, prosecutors, and jurors. In everyday situations, credibility judgments may have personal repercussions—for instance, being able to assess the honesty of a salesperson might have important economic consequences for the customer. Across a range of social, legal, and professional settings, people are likely to make judgments about whether someone is telling them the truth or not. However, factors such as the creation of new technologies, globalization of economies, and changes in immigration patterns (Samovar et al. 2005) make it more likely for these judgments to occur in cross-cultural contexts. Thus, being able to accurately detect truths and lies in cross-cultural environments is likely to be particularly important for immigration, customs, and national security.

Despite the commonplace occurrence of cross-cultural interactions, deception research conducted to date has occurred almost entirely in mono-cultural contexts, where individuals are asked to judge the veracity of messages from people with whom they share the same cultural background. As suggested by Kim et al. (2008), "deception appears to be regarded as a phenomenon that occurs in a *cultural vacuum*" (p. 24). However, this assumption seems questionable on at least two grounds. First, cultural norms, display rules, and beliefs about deception might influence the cognitive and affective processes of deceivers, the behaviors

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that accompany deceptive messages (i.e., behavioral correlates of deception), and the cues that observers use when making judgments of credibility. Second, in a cross-cultural interaction, factors that affect intergroup perceptions, such as stereotypes and prejudice, may influence one person's judgments about the other. Without a clear appreciation of the impact these cultural factors might have on the process and outcomes of credibility judgments, there is a considerable gap in our knowledge about deception assessments in cross-cultural contexts.

Given that the limited interest culture has received in the deception literature, this chapter consists of two parts. The first section will review a number of cultural factors that can influence cross-cultural judgments of credibility. It will be argued that there are several cultural factors which can hinder cross-cultural lie detection. This section will also review current studies that demonstrate that differences in cultural norms and display rules (including facial expression of emotion) hamper the lie detection process by increasing the potential for errors and biases with significant consequences. The second section will then explore a number of intergroup factors that can, theoretically, influence the way people make cross-cultural judgments of credibility. It will be argued that from a theoretical standpoint stereotypes, ethnocentric beliefs and out-group biases can also hamper the lie detection process in cross-cultural environments. Future research directions will be outlined in the conclusion.

12.2 Defining Deception

Vrij (2008) defines deception as a "successful or unsuccessful deliberate attempt, without forewarning, to create in another a belief which the communicator considers to be untrue" (p. 15). This definition suggests that "intention to mislead" and "consciousness of the act" are the key elements for deception to occur. Accordingly, someone who truly believes the information they are giving is true is not considered to be deceiving because there was no intention or conscious attempt to deceive the other. Bok (1999) further argued that deception can be conveyed through "any form of communication, such as gesture, disguise, action or inaction, exaggeration, or silence" (p. 13). Thus, deception is a complex and subtle form of behavior that does not simply equate to saying something that it is not objectively true.

While deception has been defined as an intentional deceptive message which is conveyed through any form of communication, lying has been defined as an intentional deceptive message which is stated and conveyed verbally, in writing, or through any form of language such as sign language (e.g., Barnes 1994; Bok 1999; Vrij 2008). In this sense, a person may not be considered to be lying if he or she hides or omits information even though it would be considered deception. Although scholars have pointed out the distinctions between these concepts, lying is often considered part of the larger category of deception (e.g., Barnes 1994; Bok 1999). In this chapter, lying and deception will be used interchangeably, because regardless of the type of communication used (i.e., whether language or any other form of communication), both terms imply the intention to convey a message that is not objectively true.

12.3 Theoretical Approaches to Behavioral Correlates of Deception

In addition to examining the nature and frequency of lying (e.g., DePaulo and Bell 1996; DePaulo and Kashy 1998; DePaulo et al. 1996), researchers have proposed a number of theoretical approaches that predict verbal and nonverbal behavioral differences between liars and truth-tellers, for instance, the multifactor model (Zuckerman et al. 1981), emotional and leakage cue approach (Ekman and Friesen 1969), and the interpersonal deception theory (Buller and Burgoon 1996). Overall, these approaches have suggested that although lying is not a distinct psychological process corresponding to a specific set of behavioral patterns (e.g., DePaulo et al. 2003; Vrij 2008), there are several psychological processes that are more likely to occur when lying than when telling the truth and that are likely to produce a number of behavioral responses in the body and face.

Firstly, liars are likely to experience emotions such as fear, anxiety, and guilt. These emotions can manifest behaviorally in the body as signs of arousal such as higher pitched voice, fidgeting, increased speech errors and hesitations, gaze aversion, and increased body movements (Ekman 2001; Ekman and Friesen 1969; Sporer and Schwandt 2007; Vrij et al. 2000; Zuckerman et al. 1981) and in the face as "microexpressions"—which are defined as "time-reduced remnants of interrupted or inhibited facial muscular movements" (Ekman and Friesen 1974, p. 289). Facial expressions are suggested to be far more difficult to control than the body or voice due to the involuntary nature of emotion expression (e.g., Ekman 2001; Hurley and Frank 2011). Therefore, attempts to conceal these emotions are more likely to "leak" in the face than the body. Ekman (2001) further argued that the presence of these behavioral responses is more evident if the liar is experiencing these emotions significantly, or the consequences of getting caught are serious enough. In other words, the guiltier the liar is feeling about their lie, the more he/she would display leakage signs of arousal and/or guilt (e.g., gaze aversion).

Secondly, lying is also a cognitively demanding task that requires greater cognitive effort than telling the truth (Buller and Burgoon 1996; Sporer and Schwandt 2006, 2007; Zuckerman et al. 1981). It is a cognitively demanding task because liars have to provide plausible answers, remember what was said, be consistent with what the observer knows or might find out (Vrij 2008), carefully monitor reactions and behaviors of the person being deceived, and suppress the truth (Spence et al. 2001; Vrij et al. 2008). Therefore, the more complex the lie is to fabricate, the more cognitive the resources are needed, thus decreasing the availability of resources for other communication processes such as the control of body or facial movements (Ekman and Friesen 1974). This notion has been supported by extensive empirical evidence which has demonstrated that engaging in a cognitively demanding task often leads to fewer illustrators and body movements, more speech errors and hesitations, more frequent and longer pauses when speaking, longer response latencies, greater pupil dilatation, and more gaze aversion (Buller and Burgoon 1996; DePaulo et al. 2003; Ekman 1997, 2001; Ekman and Friesen 1969, 1974; Goldman-Eisler 1968; Sporer and Schwandt 2007; Vrij et al. 2000; Zuckerman et al. 1981).

Thirdly, liars may also attempt to control their behavior (Vrij 2008; Zuckerman et al. 1981) as they might worry that some behaviors will give away their lies. Therefore, liars will try to control such cues and might engage in "impression management" in order to avoid getting caught (Memon et al. 2003, p. 13). However, this impression management is a complex and difficult task because there are numerous variables that a liar would have to take into account. For instance, the liar may need to suppress his or her nerves, mask evidence of cognitive load, and have knowledge about how an "honest" person behaves and the appropriate skills to effectively display such behavior (Memon et al. 2003). This suppression and control of behaviors will often result in behavior that looks planned, rehearsed, rigid, or too smooth (Vrij 2008). For example, if the liar believes that movement will give away the lie, he/she may try to make deliberate movements and avoid those which are not essential, resulting in behaviors that look unusual and rehearsed. Accordingly, liars would be more likely to display an overall decrease in body movements (e.g., hand and arm, leg and foot movements), less gaze aversion, fewer speech errors and hesitations, shorter response latency, and fewer pauses (Sporer and Schwandt 2006, 2007; Vrij 2008).

One important limitation of the predictions made by these theoretical approaches is that behavioral changes in the body and face that result from emotional and attempted control processes may not be exclusive to liars. It is possible that some truth-tellers experience the same emotions as liars—a phenomenon known as the *Othello error* (DePaulo et al. 2003; Memon et al. 2003; Vrij et al. 2010). For instance, consider the case of an innocent person in a police interrogation who feels nervous and afraid of not being believed by the police. Furthermore, truth-tellers may also attempt to control their behavior in the same way as liars because of their fear of making a dishonest impression (Fiedler and Walka 1993). Also, it may be plausible that not all liars experience negative emotions such as a liar feeling excitement for fooling someone (referred to as *duping delight* Ekman and Friesen 1969) or feeling guilt and anxiety for their deceptiveness. A person who does not experience these negative emotions may be less likely to leak cues in the body or face as there is no emotion that needs to be concealed or suppressed. Thus, it could be argued that while the occurrence of the behaviors predicted by these processes may indicate lying, their presence does not automatically suggest that the person is, in fact, being deceptive. Consequently, more recent research has focused in the cognitive load approach as a more fruitful avenue for finding reliable behavioral indicators of deception (Vrij et al. 2010).

Another limitation to this area of research that warrants further discussion, and which is the aim of this chapter, is the lack of cross-cultural focus. Current deception research has been limited in answering questions regarding the universality of behavioral correlates of deception and the way these cues are used to make judgments of credibility in cross-cultural contexts. It has been well documented that culture not only influences the display verbal and nonverbal communication but also the way it is interpreted (Matsumoto 2006; Matsumoto and Hwang 2013; Watson 1970). Therefore, it is plausible that deceptive behavior is no exception, and thus, cultural norms and practices could also potentially mediate the display and interpretation of such communication. It is possible that the way deception is expressed, the cues that liars display, and the cues that observers use, evaluate, and interpret when making judgments of credibility are culture-specific. For instance, a lie that is perceived as unacceptable in one culture may induce higher degrees of emotion or guilt in the deceiver and may result in a specific pattern of behaviors, whereas the same type of lie may not be perceived in the same way by another culture and hence may result in different types of emotional experiences and accompanying behavioral signs.

Cultural factors such as differences in normative behaviors and display rules, beliefs toward deception, and stereotypes toward other groups may potentially affect deception and lie detection in cross-cultural contexts. Specifically, cultural factors may influence the way deception is perceived and regarded and thus shape the behavioral cues that accompany these messages. These factors could then hinder or facilitate the observer's ability to accurately detect whether a person from a foreign culture is lying to them or not. The following section will discuss how culture could influence deception and lie detection in cross-cultural environments.

12.4 Culture and Correlates of Deception

In a cross-cultural context, the behavioral predictions made by the different theoretical approaches described above can be examined from two different perspectives: the "universal cue perspective" and the "specific discrimination perspective." The "*universal cue perspective*" (Bond et al. 1990) assumes that liars across the world experience the same psychological processes of guilt, fear, cognitive load, and attempted control while lying and thus display similar behavioral cues of deception. That is, all liars across the world will display a number of verbal and behavioral cues in the body and face. On the other hand, the "*specific discrimination perspective*" (Bond et al. 1990) suggests that communication and behavioral patterns differ across cultures, and thus, behavioral correlates of deception are also culture-specific. That is, the behaviors associated with lying and truth-telling will vary according to the cultural origin of the deceiver.

To date, the deception literature has assumed the "*universal cue perspective*" (Bond et al. 1990)—which suggests that there is no theoretical reason to believe that a liar's behavior is different across cultures (Vrij 2008). However, the assumption that the experience of these cognitive and emotional processes is universally shared (e.g., Sabourin 2007; Vrij 2008) ignores the differences in the way deception is perceived and regarded across cultures. According to Kim et al. (2008), the premise that liars experience emotions such as fear and guilt is only true if deception is believed to be an immoral act. Thus, if a culture's norms and practices consider lying acceptable under specific circumstances (e.g., when it is necessary to maintain relationships, to avoid conflict, or to show modesty), then there would be no reason for the liar to experience high levels of guilt or fear when communicating deceptively during such situations. Accordingly, if one does not experience high levels of guilt in response to communicating deceptively, one is not likely to exhibit behavioral cues of arousal or emotion as suggested by this approach.

Differences in the moral significance of deception and truth-telling have been found in many cultures (e.g., Lee et al. 1997; Yeung et al. 1999). For instance, Lee et al. (1997) studied Canadian and Chinese children's moral evaluations of lying and truth-telling in pro-social and anti-social situations. Children aged 7, 9, and 11 from Canada and mainland China were asked to read a series of vignettes that described a child that intentionally carried out a good and a bad deed. The vignettes also described when the child was questioned by a teacher about the deed and whether the child lied or told the truth. Overall, they found that Chinese children rated truth-telling less positively and lie-telling more positively in pro-social settings compared to their Canadian counterparts. Lee et al. (1997) concluded that the collectivistic nature of the Chinese culture promotes personal sacrifice for the social good and thus condones lying when it is use in conjunction with a good deed.

Similarly, Kim et al. (2008) found that in collectivistic cultures, the altering or rejection of truthful information is not typically considered deception but, instead, is seen as necessary in order to maintain harmonious relationships. Thus, when a person from a collectivistic culture alters the truth, he/she may not experience guilt or fear of lying because it is acceptable to do so according to cultural norms and practices. Likewise, if the communicator does not regard deception as an immoral practice that is to be avoided, it is less likely that he/she would try to engage in impression management techniques or attempted control processes (Memon et al. 2003).

If there are cultural differences in the way deception is regarded across cultures, it is also questionable to assume that there are no culture-specific cues to deception. To date, only few studies have been conducted in this area (e.g., Bond et al. 1990; Castillo and Mallard 2012; Vrij and Winkel 1991). One such study was conducted by Bond et al. (1990) who asked American and Jordanian students to either lie or tell the truth about a person they liked and a person they disliked. They then recorded the frequencies of eight verbal and nonverbal behaviors such as gaze aversion, self-manipulations, and movements. Bond et al. (1990) found that, regardless of veracity, American and Jordanian students differed in their behavior. Specifically, Jordanians displayed more eye contact, more movements, and more filled pauses per minute compared to Americans, regardless of whether they were lying or not. Interestingly, they also found that behaviors associated with deception were different across cultures. Jordanians were more likely to display filled pauses while lying than telling the truth, but Americans did not show this pattern. The results of this study not only support the idea that behavior is influenced by cultural norms and practices, but it also suggests that there may also be culture-specific indicators of deception.

Similarly, Vrij and Winkel (1991) investigated the behavioral patterns of white native Dutch and black Surinam citizens of the Netherlands during a simulated police interview. In the experiment, they approached Dutch and Surinam shoppers and asked them to participate in a study to determine how accurate police officers were at detecting deception in a short interrogation about the theft of a set of headphones. Half of the participants were given the headphones and were asked to hide them and convince the interrogating officer that they did not possess them. The other half of the participants were not given the headphones and were asked to tell the truth. The participants were then interviewed by a native Dutch police officer or Surinam police officer about the possession of the headphones. All interviews were videotaped, and participants' behaviors were scored. The results showed that regardless of whether they were lying or not, compared to native Dutch people, Surinamese people generally made more speech errors, spoke more slowly, spoke with higher pitched voice, smiled more, displayed more gaze aversion, and performed more self-manipulations, illustrators, and trunk movements.

A more recent study examined behavioral differences between Colombian and Australian liars and truth-tellers (Castillo 2011). In the study, participants were asked to either lie or tell the truth about a mock computer crime. Half of the participants were given details to break into a students' e-mail account and were asked to read a number of confidential e-mail messages. These participants were then asked to lie to the interviewer about what they did while they were using the computer. The other half of participants were not given the e-mail account details but were asked to search the Web for a few minutes. These participants were then asked to tell the truth to the interviewer about what happened while they used the computer. The interviews were videotaped, and the frequency of 14 verbal and nonverbal behaviors was recorded. It was found that there were significant behavioral differences between Australian and Colombian participants. Specifically, it was found that regardless of message veracity, Colombian participants smiled less and made fewer head nods and speech hesitations, and responses were generally shorter than their Australian counterparts. Moreover, Colombian participants were more likely to avert their gaze more, made more trunk movements and head shakes, and paused more frequently while speaking than Australians regardless of whether they were lying or telling the truth. The findings indicated that the cross-cultural differences in behavior were much greater than any differences associated with veracity.

The influence of culture can also be seen in the facial expressions of emotion. Recent research suggests that while there are basic commonalties in the way facial expressions of emotion are displayed and interpreted around the world, there are also important systematic differences across cultures (e.g., Elfenbein and Ambady 2002; Marsh et al. 2003; Matsumoto 1991). That is, there are specific, yet subtle, forms of facial expressions that may differ across cultures. These differences have been termed by Marsh et al. (2003) as "*nonverbal accents*." A recent study conducted by Jack et al. (2012) examined this issue and found that Chinese participants relied on eyes more to represent facial expressions compared to Western Caucasians. They argued that these cultural differences in the internal representations of emotions reflect cultural diversity in emotion signals. More importantly, they argued that these cultural distinctions could potentially lead to missed cues or misinterpreted signals about emotions during cross-cultural communications. This finding is important for deception and lie detection as it is theoretically plausible to assume that such cultural variations on the way emotions are expressed could be misinterpreted by observers as signs of deception. For example, Matsumoto and Kudoh (1993) conducted a study to compare American and Japanese people's attributions of personality based on smiles. In the study, American and Japanese participants were asked to judge smiling and neutral faces depicted by both Caucasians and Japanese male and females. It was found that Japanese people have a display rule to use smiles for social appropriateness more frequently than Americans do and relatively less frequently to display true feelings of pleasure and joy. Consistent with these display rules, they found that Americans were more likely than Japanese people to associate more positive traits (such as honesty, sociability, and sincerity) with smiling faces. Therefore, it appears that Japanese people believe, perhaps more than Americans, that smiles are not a manifestation of true emotions; rather, they believe that there exists an association between smiling faces and distrust and dishonesty (Matsumoto and Kudoh 1993).

More recently, Safdar et al. (2009) provided further evidence of cultural display rules of emotions. They found that Japanese display rules permitted the expression of powerful emotions such as anger, contempt, and disgust, significantly less than the North American and Canadian display rules. They also found that Japanese display rules for the expression of anger, contempt, and disgust differed between in-groups and out-groups. That is, the expression of such emotions was dependent on whether the interactant was a member of their in-group (e.g., family member) or out-group (e.g., stranger/interviewer). It was also found that Japanese people expressed positive emotions (e.g., happiness, surprise) significantly less than Canadians but not compared to North Americans. Overall, the literature on the universality of basic emotions and culture specificity of display rules demonstrates that the fundamental expression of emotions may be shared by people from different cultures, but the usage, meanings, and interpretations given to these emotions may not be as easily translated across languages and cultures. However, to date, research on facial cues to deception (or microexpressions) has not examined the impact these cultural differences may have on deception and lie detection accuracy in cross-cultural environments. To my knowledge, there are no studies that have examined this issue.

While the results of these studies do not provide sufficient evidence to indicate that there are culture-specific cues to deception, the findings are consistent with the premise that culture has a significant influence in the display of verbal and nonverbal behaviors and facial expression of emotion which can also impact deceptive communication (e.g., Matsumoto and Hwang 2013; Matsumoto and Kudoh 1993; Watson 1970). If there were culture-specific cues of deception, then current lie detection methods would need to be revisited in order to account for such cross-cultural variability of deceptive behavior. More importantly, the real question that these findings raise is whether cultural distinctions in behavior have an impact on cross-cultural lie detection accuracy. Is it possible to accurately detect lies and truths in cross-cultural contexts?

12.5 Lie Detection Accuracy in Cross-Cultural Environments

Bond and Rao (2004) proposed that cross-cultural differences in behavior may affect cross-cultural lie detection in two ways: (1) It may hamper the lie detection process by introducing biases and errors or (2) it may facilitate lie detection by providing observers more cues indicative of deception.

Bond et al. (1990) study described above also examined lie detection accuracy in cross-cultural contexts. In the study, they asked American and Jordanian students to judge the veracity of American and Jordanian's statements about a person they liked and a person they disliked. The results indicated that, within cultures, Americans achieved a lie/truth detection accuracy rate of approximately 58.5 % when lies were conveyed by American students. Similarly, Jordanians had a lie/truth detection accuracy rate of around 57.4 % when lies were told by Jordanian students. Interestingly, when lie detection was examined across cultures, it was found that American observers achieved a lie/truth detection accuracy rate of 50.89 % and Jordanian observers 49.3 %, both no different from chance. These results suggest that participants were particularly poor at making accurate lie/truth classifications in cross-cultural contexts and slightly better in within culture contexts.

However, Bond and Atoum (2000) pointed out that the no-audio presentation of videos in Bond et al. (1990) study may have undermined observers' attempts at cross-cultural lie detection. In order to address this limitation, Bond and Atoum (2000) conducted a series of studies. They videotaped American, Jordanian, and Indian students and community members either lying or telling the truth. The videotapes were then judged for deception by other American, Jordanian, and Indian students and community members. Contrary to Bond et al. (1990) findings, participants' detection accuracy rate across cultures was around 51.66 % and within cultures 54.27 %, both significantly higher than expected by chance alone (i.e., 50 %), although not impressive. They concluded that people can accurately detect lies of people with whom they do not share the same cultural background; however, judgments of credibility were still consistently higher within than across cultures.

The results of these studies suggest that lie detection across cultures may be possible, but cultural differences in behavior may complicate this process. In mono-cultural contexts, lie detection accuracy has been consistently found to be particularly poor (i.e., around 50–60 %) (for a review, see Bond and DePaulo 2006); in cross-cultural contexts, however, the picture is not any better because accuracy rates have been found to be similar or even worse, as demonstrated by Bond and Atoum's (2000) study.

Given the significant consequences of making accurate judgments of credibility in cross-cultural settings, it is important to investigate the problems that are likely to occur in such situations. It has been argued that these cultural differences may hamper cross-cultural lie detection by introducing a number of errors and biases (Bond and Rao 2004). When people from different cultures come into extensive contact, there is a potential for miscommunication and misunderstandings which lie in the nature of culture itself (Brislin 2001). For instance, what can be considered polite and effective in one culture may be considered rude and ineffective in another culture. Matsumoto et al. (2005) argued that cross-cultural communication is characterized by ambiguity and uncertainty because the ground rules by which the interaction occurs may not be similar between interactants. In other words, the meanings given to verbal and nonverbal codes are unknown and different for both the communicator and the receiver, which may produce opportunities for misunderstanding. Therefore, cultural differences in behavior may have the potential to introduce biases or errors when people are making attributions about a person's credibility from a foreign culture. Vrij et al. (2010) noted that these errors can easily occur because behaviors that are displayed by one culture may be interpreted as suspicious by the other culture.

12.6 Cultural Bias and Errors

Examining the potential for errors during cross-cultural judgments of credibility has received little attention. Vrij and Winkel (1992) conducted an experiment to examine whether differences in nonverbal behavioral patterns and skin color had an impact on perceptions of credibility. Data from their earlier study (Vrij and Winkel 1991) were used to establish behavioral norms for "white Dutch" and "black Surinamese" nonverbal behaviors. Surinamese and Dutch actors were then videotaped and were asked to display gestures and smiling behavior of typical white (Dutch) or typical black (Surinamese) while giving a statement. For example, the actors showed normative smiling behavior typical of black (Surinamese) people in one version and normative smiling behavior typical of white (Dutch) people in the other version. Dutch police officers were then shown these video clips and asked to indicate to what extent the people in the video made a suspicious impression, were nervous, and appeared unpleasant. It was found that skin color did not have a negative impact on impression formation but nonverbal behavioral differences did. Specifically, it was found that both Surinamese and Dutch actors were seen as more suspicious, nervous, and unpleasant when they showed nonverbal behavior that was consistent with Surinamese citizens than when they displayed normative Dutch nonverbal behavior.

Vrij and Winkel (1994) extended this line of research in a subsequent study in which they examined the influence of accent, skin color, speech style (i.e., direct or indirect), and spoken fluency on perceptions of credibility. They presented 175 Dutch police officers with a series of slides and an audiotape of a citizen being interrogated. They then asked the police officers to provide ratings of the perceived suspiciousness, nervousness, and unpleasantness of the citizen. Skin color and accent were manipulated by presenting slides depicting either a person of Dutch or Surinamese origin accompanied by audio recorded in a corresponding accent. The audiotapes were then manipulated to correspond to the typical speech style and spoken fluency of Dutch and Surinamese citizens, respectively.

They found that neither accent nor skin color produced an unfavorable assessment of the participants of Surinamese origin. However, consistent with their previous study (Vrij and Winkel 1992), it was found that when the communicators displayed the typical speech style and spoken fluency of Surinamese citizens, police officers were likely to rate them as more suspicious, nervous, and unpleasant than citizens displaying typical Dutch behavior. Thus, cultural differences in communication styles may have the potential to create biases when cross-cultural judgments of credibility are made.

There are two theories that can explain Vrij and Winkel's (1992, 1994) findings, the expectancy violation model (Bond et al. 1992), and the norm violation model (Levine et al. 2000). According to these models, violations of the observer's cultural norms and/or expectations would increase the likelihood that the observer will suspect the communicator of being dishonest if no other plausible explanation is available. Therefore, in a situation in which a communicator and an observer are from different cultures, the observer will apply social norms or beliefs concerning behavior that may differ from the communicator's own norms. This behavioral discrepancy may be interpreted as attempts to hide the truth by the communicator if the observer does not have an appropriate explanation for these behavioral differences. Thus, deception might be inferred from any behavior (or facial expression) that violates a social norm. For example, if the norm for a social interaction includes relatively high levels of eye contact, a person who avoids eye contact may be suspected of deception as a result of violating that norm. Considering Vrij and Winkel's (1992, 1994) findings, it is possible that because black Surinamese citizens have a distinct normative behavioral pattern compared to white Dutch citizens, the norm violations that occurred during these interactions may have aroused suspicion and thus resulted in more negative judgments compared to those communicators who did not violate these norms. However, it is difficult to determine whether these cultural differences did result in a heightened suspicion of the communicator as this was not investigated in their studies (Vrij and Winkel 1991, 1992, 1994).

More recently, Castillo, Tyson and Mallard (2014) conducted a study to investigate whether cultural differences in normative behavior would result in misinterpretations of a culture's baseline behavior and, consequently, in more dishonest judgments being made (i.e., deception bias). In order to do this, 71 Australian participants were asked to watch 24 video clips that depicted Australian and Colombian individuals either lying or telling the truth. Some of the Colombian video clips depicted individuals lying or telling the truth in their first language—Spanish—and some depicted Colombians lying or telling the truth in their second language—English. Participants were asked to watch the clips and then indicate whether they thought that the person in the clip was either lying or telling the truth (i.e., dichotomous answer). Interestingly, the results indicated that participants were likely to ascribe more truthful than deceptive judgments to the Australian clips than to the Colombian clips. Specifically, the average response bias for Australian clips indicated a *truth bias* (Mean $c = 0.32$), whereas the average response bias for Colombian clips (mean $c = 0.06$) indicated that participants took a neutral approach to judgment. The truth bias found for Australian clips is consistent with the literature on the detection of deception in mono-cultural contexts (e.g., Bond and Atoum 2000; Bond and DePaulo 2006; Bond and Rao 2004; Levine et al. 1999, 2006). However, while it was found that observers did not rate Colombian clips as significantly more suspicious than Australian clips, the absence of a truth bias for the Colombian clips suggested that, at the very least, participants' tendency to make more truth judgments was attenuated for clips that depicted someone from another culture.

Although these findings do not provide sufficient evidence of the presence of bias during cross-cultural judgments of credibility, they do indicate that observers need to be cautious and aware of culturally mediated behavioral differences in order to avoid the potential for errors and bias. Vrij et al. (2010) proposed that lie detectors should interpret the verbal and nonverbal behaviors displayed by communicators of a different ethnic origin in light of cultural differences. However, research (e.g., Castillo 2011) in this area has indicated that observers often have limited knowledge about the behavioral differences that exist between cultures, and thus, pointing out differences between cultures or informing lie detectors of such differences might be sufficient to reduce such errors.

Theoretically, based on the expectancy and norm violation models (Bond et al. 1992; Levine et al. 2000), it is possible that providing observers with an explanation for norm and expectancy violations could attenuate observers' tendency to judge any violations as attempts to hide the truth. Familiarization or sensitization to cross-cultural issues of individuals who are performing cross-cultural judgments of credibility may be the key to prevent or attenuate the presence of such biases. While the research in this area has been limited, a preliminary investigation (Castillo and Mallard 2012) has suggested that providing lie detectors with specific normative information about the communicators' behavior did not improve accuracy but did counteract/alleviate cultural bias. Future research in the prevention of such biases could therefore benefit from examining whether familiarity with a cultures' communicational style and normative behavioral patterns moderates the extent to which these biases operate (i.e., result in a greater or lesser degree of bias). For instance, future studies could examine cultures with closer geographical proximity (e.g., two European cultures) and familiarity.

12.7 Second Language Use and Bias

Another aspect that is particularly relevant during cross-cultural interactions is second language use. Often these interactions are characterized by at least one individual requiring to communicate in their second language (L2). Therefore, investigating whether behavioral differences between liars and truth-tellers are dependent on the language spoken (i.e., first or second language) is essential for our understanding of cross-cultural lie detection.

Numerous research studies on second language use have demonstrated that speaking in a non-native language is more cognitively taxing than speaking in a mother tongue (e.g., Fehringer and Fry 2007; Hongyan et al. 2010; Kroll and de Groot 2005). For instance, Fehringer and Fry (2007) provided evidence that second language use had a negative impact on speech production because of the cognitive demands it causes on working memory capacity. Therefore, speaking in a second language may result in a display of behaviors that suggest cognitive load and anxiety such as increase hesitations, repetitions, formulations, and filled pauses. Theoretically, it is plausible that despite the veracity of the message, communicating in a second language would result in differences in the baseline behavior of the second language speaker, and these differences would be in the direction that is indicative of increased cognitive capacity. Thus, a person who is communicating in a second language may display behaviors that are in accordance with deceptive cues but are the result of linguistic proficiency and not credibility.

This issue is particularly important for cross-cultural judgments of credibility. The literature has consistently demonstrated that lie detectors often associate lying with an increase of cognitive load and often look for cues that would indicate whether the person was thinking hard, feeling anxious, or nervous (e.g., Akehurst et al. 1996; Global Deception Research Team 2006; Granhag et al. 2004). Thus, if communicating in a second language is cognitively taxing and results in signs of cognitive load, a person communicating in their second language may be more likely to be judged as deceptive. In other words, the behavioral signs that arise from language demands may be interpreted by observers as attempts to hide the truth because these cues are stereotypically associated with deception. Therefore, if observers attribute deception based on the presence of behaviors that suggest cognitive load or arousal, then in a situation where the communicator is providing a message in their second language, the display of behavioral signs that are associated with language demands may be interpreted by observers as attempts to hide the truth. As a result, one would expect that behavioral differences that arise from second language use would increase the potential for errors in cross-cultural situations.

Only a few deception studies have examined this issue. One such study was conducted by Cheng and Broadhurst (2005). They asked 31 students from Hong Kong to either lie or tell the truth about their opinion of capital punishment. The students were interviewed in their mother tongue (i.e., Cantonese) or their second language (i.e., English), and the interviews were recorded. They then asked 27 students to watch the video clips and indicate whether the thought that the person was either lying or telling the truth. Consistent with the literature on second language use, they found that regardless of message veracity, speaking in a second language resulted in a different behavioral pattern compared to when speaking in a first language. Specifically, they found that participants speaking in their second language were more likely to display signs of nervousness and high cognitive demand (e.g., gaze aversion, increased body movements). More importantly, they found that observers were more successful in identifying liars speaking in their second language (English) than liars speaking in their native language (Cantonese). Interestingly, observers were more successful in identifying truth-tellers speaking in Cantonese than English, thus suggesting the presence of a language bias, such that people speaking in their first language were more likely to be judged as credible than people speaking in their second language, irrespective of veracity. However, the validity of Cheng and Broadhurst's (2005) behavioral analysis was questionable as they reported a description of these differences without appropriate inferential statistics.

Similarly, Castillo (2011) found that participants' baseline behavior differed markedly when communicating in their second language compared to when communicating in their first language, regardless of the veracity of the message. Specifically, it was found that Colombian participants made more functional hand and arm movements and their response latency was considerably shorter when speaking in their first language (Spanish) than their second language (English). These behaviors were also consistent with literature on second language use which suggests an increase of cognitive load (Fehringer and Fry 2007). Similar to Cheng and Broadhurst's (2005) study, Castillo, Tyson and Mallard (2014) found that observers were more suspicious of individuals speaking in their second language (i.e., Colombian English speaking clips).

More recently, Da Silva and Leach (2013) asked observers to make credibility assessments of individuals lying and telling the truth in their second language. Consistent with previous studies, they found that observers were more likely to judge speakers of a second language as less credible than native speakers. Interestingly, they also found that observers were better able to discriminate lies and truths from native language speakers than second language speakers.Thus, observers were not only more suspicious but also less accurate at detecting deceit from second language speakers.

The results of these studies provide preliminary evidence that behavioral distinctions that arise from second language use could potentially hinder the lie detection process by producing bias and errors in judgment. Liars are likely to display a number of behaviors as a result of experiencing cognitive and affective processes: emotion, cognitive load, and attempted control. However, as the studies described above suggest, these same processes and behaviors may also be experienced by someone speaking in their second language; in particular, the emotional and cognitive load processes may be associated with speaking in a language in which one does not have native fluency.

12.8 Cognitive and Affective Factors in Cross-Cultural Lie Detection

The previous section highlighted that cultural and language differences in behavior may result in errors or bias during cross-cultural environments. The focus on such cultural differences in behaviors and norms suggests that previous research has also consistently neglected the influence of other cognitive and affective factors on intergroup perceptions, such as stereotypes, ethnocentrism, and prejudice (Stephan and Stephan 2002; Wiseman et al. 1989). There is considerable evidence in the cross-cultural communication literature that suggests that many misunderstandings that arise during cross-cultural communications are rooted in the attitudes and beliefs people hold toward members of the out-group (Stening 1979). Wiseman et al. (1989) suggested that an individual's attitudes toward members of another culture not only influence how positive or negative their impressions of that culture are, but also determine the degree of mutual understanding that could be achieved during cross-cultural communication. However, the deception literature has largely disregarded the impact these factors may have during cross-cultural lie detection. Thus, it is argued that future research should explore the role of these issues in cross-cultural credibility judgments.

12.8.1 Stereotypes and Prejudice

Social psychologists have long been interested in stereotypes and prejudice because they are particularly important in understanding how people make sense of and react to each other (Stangor 2000). These two concepts have been widely viewed as interrelated (Devine 1989; Sherman et al. 2005). While stereotypes are commonly defined as the knowledge, beliefs, and expectations associated with social groups and their members, prejudice is defined as the positive or negative evaluations of social groups and their members (Sherman et al. 2005). Therefore, stereotypes are seen as the cognitive component and prejudice as the affective or evaluative component, of intergroup bias (Amodio and Devine 2006).

Stereotypes are particularly important in understanding intergroup relations because they help to create expectations of how a group and their members should behave and provide ways to explain and predict their behavior (Gudykunst 2004). Their influence can be pervasive, affecting the perceiver's attention to the information, their inferences, and interpretations of and judgments of behavior (Hamilton and Sherman 1996; Hamilton et al. 1990). Thus, stereotypes are particularly relevant during cross-cultural communication because they can affect the information that is noticed, remembered, stored, and recalled about individuals from a group (Stephan and Stephan 2002; Wiseman et al. 1989). However, it has been argued that stereotypes in and of themselves do not always lead to miscommunication or errors. According to Gudykunst (2004), inaccurate predictions of a person's behavior are particularly likely to occur when negative stereotypes of a group are rigidly held. For example, if a person has a strong belief that Americans are dishonest, seeing a man known to be American who takes a package from a car would likely lead that observer to assume that the American is stealing the package. Furthermore, people who hold rigid stereotypes of an out-group also tend to be negatively prejudiced toward that out-group. Consequently, rigidly held stereotypes and negative evaluations of an out-group are more likely to result in discriminatory behaviors (e.g., Hilton and von Hippel 1996; Jussim et al. 1987).

The role of stereotypes and prejudice would appear to be particularly important when cross-cultural judgments of credibility are made. It is plausible that holding negative stereotypes and prejudiced attitudes toward members of a cultural group may increase the likelihood of interpreting a behavior as indicative of deception. These cognitive and affective factors may increase the potential of a dispositional attribution being made. However, the impact of these factors on cross-cultural judgments of credibility has not been investigated yet in the deception literature.

12.8.2 Ethnocentrism

Another central concept in understanding group attitudes and intergroup relations is ethnocentrism. Ethnocentrism is commonly defined as "the view of things in which one's group is the center of everything, and all others are scaled with reference to it" (Sumner 1906 cited in Stephan and Stephan 2002, p. 130). Such views, according to Samovar et al. (2005), are the perceptual window in which cultures interpret and judge each other. Typically, ethnocentrism is exemplified by positive attitudes and behaviors toward the in-group and negative attitudes and behaviors toward out-groups (Hammond and Axelrod 2006; Neuliep and McCroskey 1997; Stephan and Stephan 2002; Wiseman et al. 1989). Ethnocentric groups see themselves and members of their in-groups as virtuous and superior and see their own standards of value as universal and true, whereas out-groups are seen as contemptible, immoral, inferior, suspicious, and weak (Neuliep and McCroskey 1997; Smith and Bond 1993).

Consistent with this, ethnocentrism has been commonly associated with negative stereotypes, negative affect, and prejudice toward the out-group (Dovidio et al. 2002; Perreault and Bourhis 1999). For instance, Gagnon and Bourhis (1996) found that individuals who identified strongly with their in-group were more likely to discriminate against an out-group than those who identified less strongly with their in-group. In cross-cultural interactions, ethnocentric views have also been thought to determine the extent to which a culture's behavior is judged and understood. Some researchers argue that interactants high in ethnocentrism may base their expectations on their own cultural social norms and rules, resulting in misunderstandings of the other interactant's intentions, values, and behavior (Lin and Rancer 2003; Neuliep and McCroskey 1997; Stephan and Stephan 2002). Similarly, Gudykunst (2004) noted that the more ethnocentric the people are, the more trouble they would have making accurate predictions of, and explanations for, a stranger's behavior.

Theoretically, it appears plausible that ethnocentric beliefs may also influence cross-cultural judgments of credibility. The degree of ethnocentrism a person holds may determine the way they interpret and judge the behavior of an individual from a different culture. For instance, people high in ethnocentrism may perceive foreigners as more deceptive than their compatriots.

In sum, it has been well documented that cognitive and affective factors such as stereotypes, prejudice, and ethnocentrism play an important role when people are trying to explain and predict a stranger's behavior and also have the potential to produce misunderstandings during cross-cultural interactions. Therefore, it is possible that these same factors play a part when people are trying to make judgments of credibility in cross-cultural contexts. However, research in this area is needed.

12.9 Conclusion

The literature reviewed above provides ample support for the idea that culture plays a role in the encoding and decoding of verbal and nonverbal behaviors including facial expressions of emotions, which are an important part of the communication process. However, it does not provide a clear explanation about the nature of such cultural influences in cross-cultural lie detection contexts. A number of studies have already provided an initial demonstration that such differences in display rules and normative behavior of behavior result in an increased suspicious of the speaker, yet it has not explained the extent of such influence or whether it can be prevented or not. Future research should examine the role of the cultural factors that were described in this chapter but more importantly on whether these biases and errors can be prevented or, at the very least, attenuated.

Existing literature has tended to regard deception as a "one-size-fits-all" phenomenon, where individuals from all over the world are thought to share a set of universally specific psychological processes that lead to similar behavioral cues to deception (e.g., Vrij 2008; Zuckerman et al. 1981). However, this chapter has challenged this view and argued that deception research needs to move away from this "*cultural vacuum*" perspective (Kim et al. 2008, p. 24) and start recognizing the cultural and cross-cultural factors that may impact deceptive communication and lie detection in cross-cultural contexts. It was argued that this view is problematic because it largely ignores the influence of culture in the communication process, particularly given that contemporary research has shown that culture has a significant impact on the way an individual communicates and that deceptive communication is not exempt from such influence (e.g., Gudykunst 2004; Sabourin 2007; Vrij and Winkel 1991, 1994).

The clear difficulties associated with accurately distinguishing truthful from deceptive messages in a cross-cultural context and the potential for biases that result from culturally and linguistically based behavioral differences have important implications for many social, legal, business, and national security settings. For instance, the tendency toward bias in cross-cultural judgments of deception could contribute to miscarriages of justice in which immigrants, asylum seekers, or foreign visitors are wrongly suspected of deception because their normative behavioral pattern may be misinterpreted as an attempt to hide the truth. Thus, the role of culture in deception and lie detection has been under-researched and are now long overdue.

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Chapter 13
Study of Facial Micro-expressions in Psychology

Braj Bhushan

Emotion has been studied in psychology as a multifaceted process involving physiological reactions, behavioral reactions, expressive reactions, and subjective experiences. Studies focusing on expressive reactions have extensively examined facial expressions of emotions with respect to the dimensional perspective. Valence, arousal, and motoric direction are the three dimensions examined by the researchers. Valence dimension categorizes emotions as those with positive valence (such as happiness) and those with negative valence (such as sadness). Some emotions involve greater level of arousal (such as happiness), whereas some others involve low arousal state (such as sadness). Motoric direction refers to approach or withdrawal behavior shown toward the stimulus.

There has been disagreement in terms of usage and relationship among the three dimensions. Some researchers do see conceptual intersection between valence and motoric direction (Gray 1994) because of the pleasure (happiness) component in approach emotions and unpleasantness in the withdrawal emotions (Bhushan 2006). Russell (1980) has advocated inverse relationship between positive and negative emotions, whereas Larsen et al. (2001) have argued that these two dimensions are independent of each other. This view has been supported by Tellegen et al. (1999) as well. Many researchers contest that approach and avoidance are by and large synonymous with positive and negative states of emotions.

The theories of emotions offering prediction for emotion-specific facial expressions can be divided into two groups—discrete theories of emotions (Ekman 1992a; Izard 1991) and appraisal theories of emotions (Kaiser and Wehrle 2001; Scherer 1984; Smith and Ellsworth 1985). Appraisal theories following componential approach (Scherer 1984; Smith and Ellsworth 1985) assume that we

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assess the situation by examining the precursor of any given event. This appraisal mechanism guides the physiological as well as expression outcomes. As proposed by Lazarus (1991), appraisal of an event for its personal significance is the precursor to emotional reaction. Referring to the theories of emotion, Lazarus (1991) has summarized five metatheoretical themes that these theories propound. Firstly, the emotion process has antecedent variable, mediating process, and a response. No single variable can explain the emotional outcome as they are interrelated. Secondly, emotions convey two mutually dependent principles—the process principle and the structure principle. The process principle refers to change, whereas the structure principle refers to the stable person–environment relationship which is seen in the form of repeated emotional pattern in an individual. Thirdly, the developmental principle refers to the biological and social variables influencing the emotions. Fourthly, the specificity principle endorses that the progression of emotion is unique for each emotion. Finally, the major premise of the theory is the relational meaning principle, i.e., each emotion is defined in terms of a distinctive and specific relational meaning. Lazarus has talked about how appraisal process is instrumental in deriving emotional meaning out of a person–environment relationship.

With this brief introduction to the metatheoretical themes embedded in the theories of emotions, this chapter will focus on the understanding of facial expressions with special reference to micro-expressions. Thereafter, it will focus on the methods used in behavioral studies and automatic analysis of micro-expressions, respectively. Finally, it would elucidate some of the neuropsychological evidences and the new technological advances that can further enrich this domain of knowledge.

13.1 Understanding Facial Expressions

In their attempt to understand the nuances of facial expressions, psychologists have taken various factors into account, such as culture, type of participants, types of expressions, nature of stimuli, and the response format. While looking at culture, one will find a good number of studies comparing the non-Western and Western cultures. Researchers have also compared the literate and the preliterate participants. In terms of nature of stimuli, researchers have compared posed versus spontaneous emotions. They have used either a static stimulus or a videotaped one. In terms of response format, studies have gone either for matching task where the task is to match the target expression with the available options or for labeling task where options are not provided, rather the respondent simply looks at the expression and assigns name to that very expression (label it).

Since Darwin (1872) offered the systematic findings about human facial expressions, several aspects of facial expressions have been scientifically examined by behavioral scientists. Historically, research on human facial expressions started in the seventeenth century and it attracted the attention of creative artists, physiognomists, and psychologists. Ekman (1973, 1992a) postulated that six basic emotions, namely happiness, sadness, anger, disgust, fear, and surprise, are universally recognizable. Since then, the cross-cultural study of facial expressions suggests that the recognition and production of these universal facial expressions are hardwired in the brain. Studies also endorse that the emotional state as well as social response of an individual is influenced by the intense expressions of others. Some researchers (Gusnard and Raichle 2001; Raichle and Gusnard 2005) argue in favor of a "default system" in human beings who constantly assess the environment for salient stimuli. Human expressions still engage physiognomists and psychologists, but now a new set of researchers have joined this group who intend to develop systems for automatic recognition of facial expressions. The automatic recognition of facial expressions began in 1978 by Suwa and his associates. Their system used a twenty-point tracking to analyze facial expressions from movie frames. 1990s saw a big change in two forms—human–computer interaction (HCI) and affective computing started becoming popular, and face-tracking algorithms came into being. A review of published literature does indicate that automatic recognition of facial expressions is considered extremely important by computer scientists (Fasel and Luttin 2003).

It is noteworthy that a host of information is communicated through nonverbal channels and face does work as an important source of information with its inherent properties such as the shape and size as well as the superfluous features such as wrinkles and sagging of the skin. Physiological processes such as change of blood flow, skin temperature, and muscle tonus further intensify the facial expression of the behavioral intent of the person. This will be discussed little later in the chapter. Face has permanent as well as transient features. For instance, eyes and lips are permanent features, whereas facial lines, wrinkles, and furrows are the transient features. Researchers adopting physiological measures for studying facial behavior have explained emotions in terms of two perspectives—dimensional and discrete perspectives. According to the discrete perspective (Ekman 1999; Panksepp 2007), each emotion corresponds to an exclusive profile of subjective experience, physiological state, and behavioral reaction. There have been attempts to resolve the distinction emerging from the two perspectives. As proposed by Haidt and Keltner (1999), each discrete emotion is an amalgamation of multiple dimensions. For instance, anger is a discrete emotion, but it can be characterized by negative valence, high arousal, and approach motive. On the other hand, fear as a discrete emotion can be characterized by valence, high arousal, and avoidance motive. Subjective experiences can be measured well by self-reports, whereas behavioral reactions can be assessed using vocal (such as amplitude and pitch) and facial behavior (rating scale or EMG). Both are sensitive to valence and arousal. Measures of the autonomic nervous system are also sensitive to valence and arousal. On the other hand, measures of the central nervous system (such as EEG) are sensitive to approach–avoidance dimension. There are studies looking at facial expressions in terms of hemispheric activity of the brain. Researchers have reported differential hemispheric involvement of facial emotion expression as a function of valence (Reuter-Lorenz and Davidson 1981). Studies show that positive emotions are processed by the left hemisphere, while the right hemisphere processes negative emotions (Silberman and Weingartner 1986). In terms of motoric direction, left hemisphere has been found to control approach emotions, while right hemisphere arbitrates withdrawal emotions (Kinsbourne and Bemporad 1984).

13.2 From Facial Expressions to Micro-expressions

Long after Darwin's (1872) proposition, Haggard and Isaacs (1966) studied micro-expressions by examining films of psychotherapy sessions. Later, Ekman and Friesen (1974) demonstrated the occurrence of micro-expressions in a frame-by-frame analysis of interviews with depressed inpatients. Micro-expressions are involuntary facial expressions that last between $^1/_5$ and $^1/_{25}$ of a second (Porter and Brinke 2008). According to Ekman and Friesen (2003), micro-expressions are "typically embedded in movement, often in facial movements that are part of talking. And they are typically followed immediately by a masking facial expression" (p. 151). As these expressions are apparent on one part of the face for a very short period of time, identification of such expressions is extremely difficult. Micro-expressions are classified into three categories—simulated expressions, masked expressions, and neutralized expressions (Ekman and Friesen 1975). If micro-expression is not followed by a true expression, it is referred to as simulated expression. Masked expression represents falsified expression replacing a genuine one, whereas neutralized expression is achieved after a genuine expression is suppressed to retain the face neutral.

Micro-expressions are brief involuntary expressions occurring in high-stake situations demanding concealing or repression of an emotion. On the other hand, macro-expressions are not concealed and typically exist between 0.5 and 4 s on the face. Unlike micro-expressions, it is expressed on the entire face (Ekman 2003). Macro-expressions typically last somewhere between ¾ of a second and 2 s in duration and are relatively easier for manual identification in videos (10–60 frames). Compared to these macro-expressions, micro-expressions hardly ever show motion except in the forehead and eye regions of the face.

Ekman (2001) has also talked about squelched expressions. These expressions are immediately curtailed by instantly changing one's expressions. It is important to note that micro-expressions are complete with respect to temporal parameters, but squelched expressions are not, although they last longer (Ekman 2001). This chapter will restrict itself only to the study of micro-expressions in psychology and how it has influenced development in the area of automatic processing systems for human expressions.

13.3 Methods for Studying Micro-expressions

Let us now look at the methods used in behavioral studies and thereafter the methods used for automatic analysis of micro-expressions. The intention is to show whether researchers in other domains working on micro-expressions were methodologically helped by the psychology community or not, and if yes, then to what extent.

Fig. 13.1 Anatomy of human facial muscles (© Braj Bhushan)

13.3.1 Behavioral Method

Paul Ekman first reported facial micro-expressions after examining a video of a patient who showed intense anguish and subsequent smile while attempting to conceal a suicide plan. Since then, several attempts have been made to evolve psychological as well as automated tools for the recognition of micro-expressions. Significant advance in this direction necessitated the development of a robust tool and that required derivation of the facial parameters. As is the case with most of the psychological measures, behavioral studies were largely dependent on the rating scales till the development of the facial action coding system (FACS). However, the development of FACS (Ekman and Friesen 1978) and the facial animation parameters (FAPs) (1998) played a crucial role in parameterization of human facial expressions. FACS is based on facial muscles (see Fig. 13.1) and their impact on changing the expressions on the face. The underlying muscle(s) and the apparent change on the face are called *action units* (AU).

The table given below shows some of the examples of facial expressions and the corresponding AUs.

As you can easily make out from Table 13.1, human facial expressions are the outcome of one or more additive or non-additive AUs. For instance, look at Fig. 13.2

Table 13.1 Illustration of FACS action units, corresponding muscles, and apparent changes on the face (© Braj Bhushan)

Action unit	Function	Muscles	Facial expressions
AU1	Raising the inner brow	Frontalis and pars medialis muscles	
AU2	Raising the outer brow	Frontalis and pars lateralis muscles	
AU26	Dropping the jaw	Masseter, temporal, and internal pterygoid muscles	

Fig. 13.2 Angry expression (© Braj Bhushan)

which illustrates an angry expression. Here, the actions suggesting fear expression include rising of the inner and outer eyebrows and dropping of the jaw. The muscles involved in rising of the eyebrows are *frontalis, pars medialis,* and *pars lateralis,* whereas *masseter*, *temporal* and *internal pterygoid* muscles underlie dropping the jaws. Hence, the three AUs involved are AU1, AU2, and AU26. These AUs are considered additive if the appearance of each of them is independent. If the appearance of one AU modifies the appearance of the other AU, then they are considered non-additive (Cohn et al. 2007).

The development of FACS can be considered one of the most significant steps toward understanding facial expressions, including micro-expressions. Few more coding systems were developed. Besides Infant/Baby FACS, the other observation-based coding schemes are as follows: facial action scoring technique (FAST), emotional facial action coding system (EMFACS), maximally discriminative facial movement coding system (MAX), facial electromyography (EMG), affect expressions by holistic judgment (AFFEX), FACS affect interpretation database (FACSAID), and Mondic Phases. References are needed to put up.

Behavioral scientists have also tried to develop tools for studying micro-expressions. For instance, Haggard and Isaacs (1966) developed a test of micro-expression detection ability. Little later, Ekman and Friesen developed the Brief Affect Recognition Test (BART; Ekman and Friesen 1974). BART required the participants to look at facial expressions using tachistoscope. However, this test had a problem. Although the images were tachistoscopically presented for short time duration, they remained on the retina for longer time than intended. Matsumoto et al. (2000) imbedded neutral expression of the same expressor within a 1-s presentation, thus solving this issue. This imbedding was useful as a forward–backward mask was created that abolished image aftereffect created in Ekman and Friesen's (1974) technique.

Micro-expression training tool (METT) was developed by Ekman using static facial micro-expressions. According to Ekman (1992b), micro-expressions occur in high-stake situation where one weighs loss and gain. Ekman (2009) has also referred to lie detection and micro-expressions. Behavioral studies have also empirically studied micro-expressions. Warren et al. (2009) have reported the significance of such expressions in detecting deception. They asked the participants to truthfully or deceptively describe an emotional (surgery) or non-emotional (sunny beach) video. Warren et al. (2009) found many micro-expressions during deception as well as truthful conditions.

The most significant attribute for behavioral scientists is the recognition accuracy of these micro-expressions. Using METT, Endres and Laidlaw (2009) compared two groups of medical students, good or poor communicators, for their ability to perceive micro-expressions. The participants were trained in the recognition of static facial micro-expressions using METT. The findings suggested that good communicators perceived facial micro-expressions more accurately as compared to the poor communicators. In their micro-expression recognition test with real-life videos, Frank et al. (2009) examined the recognition accuracy in undergraduate students and coast guards before and after training. The recognition accuracy was 32 % in the students which increased to 40 % after training. In the coast guards, it increased to 47 % from 25 % after training. Matsumoto and Hwang (2011) used micro-expression recognition training tool (MiX) to assess micro-expression recognition accuracy in participants of a training workshop, and the effect was positive, suggesting that recognition accuracy of micro-expressions can be improved by practice.

Behavioral studies have significantly contributed to the understanding and empirical examination of micro-expressions. The combination of computer vision research and psychology has made the area far more interesting. We shall now look at the development in the area of automatic analysis of the facial expressions in order to see the impact of behavioral tools and techniques on the automatic analysis.

13.3.2 Automatic Analysis

Automatic analysis of the facial expressions is comprised of three phases—acquisition of face, data extraction and representation, and expression recognition. Face acquisition is the stage of tracking and detection of expressions in the video. As far as data registration is concerned, two approaches are used for this purpose—geometric feature-based approach and appearance-based approach. In geometric feature-based approach, facial points such as corners of the lips, center of eyes, edges of the eyebrows, and tip of the nose are extracted using computer vision technique. The coordinates of these facial points create a feature vector, thus representing the facial geometry. Appearance-based methods analyze video frame by frame and use image filter to extract a feature vector. This can be applied to the full face or a specific region. For instance, the active appearance model (AAM) is based on manually tagged points on the face. The other approach uses direct tracking of twenty facial features such as eyes, nose, and mouth by particle filter. This has severe limitation for micro-expression recognition in terms of detecting subtle movement on the face as the points-tracking algorithm has limited accuracy.

Automatic recognition of the AUs has proven to be much more difficult. The automatic face analysis (AFA) system of Kanade et al. (2000) automatically recognizes six AUs from the upper face and ten AUs from the lower face from an image or a video. Recognition of AUs from profile view is a challenging task in real-time applications (Pantic and Patras 2004). Selection of parameters for recognizing facial movements and usage of computer-assisted systems was dominant model, followed even by the animation and graphics researchers (Pandzic and Forchheimer 2002). The facial animation (FA) specification in the MPEG-4 standard was an attempt by the moving picture experts group (MPEG) to have standardized facial control parameters. It became international standard in 1999. The FAPs are part of the MPEG-4 synthetic/natural hybrid coding (SNHC) standard. The FAPs were primarily designed for animating facial expressions. The recent attempts are directed toward recognition of expressions and emotions with the help of FAPs. The MPEG-4 takes neutral face as template with specific properties such as distance between the two eyes, iris diameter, and eyelids tangent to iris. Eighty-four key feature points (FPs) are defined on the neutral face, and movement of the FPs is recognized as expressions.

The real-life scenarios would include great degree of head movements, and thus, temporal segmentation of facial expressions becomes an intricate task in such scenarios. Large head movements leading to out-of-plane rotation and uneven lighting on the face are two major problems in segmentation. Researchers have used hand-segmented expression recognition adopting temporal as well as static approaches (De la Torre et al. 2000; Hu et al. 2004; Lee and Elgammal 2005). Very few studies have been conducted on temporal segmentation in face videos. Shreve et al. (2009) have proposed a method for temporal segmentation of facial expressions from videos. This is done on the basis of observed facial deformation by calculating facial strain maps and the magnitude of the strain. This takes care of the motion vectors arising out of in-plane head movements. Shreve et al. (2009) tested two datasets containing 100 expressions and found their algorithm robust enough for automatic spotting of micro-expressions even with moderate head movement. However, fast head and facial movements limit the outcome of their algorithm.

Polikovsky et al. (2009) used high-speed camera (200 fps camera) to capture facial motion. This was also based on the characteristics of the facial muscles. As human eyes have their own limitations, using a high-speed camera to take images and 3D-gradient descriptor to examine predefined regions of the face seems to be an alternative. They studied micro-expressions using 200 fps high-speed camera in order to get ten frames. This allowed capturing the faster facial movements. Thereafter, the motion in specific regions of the face was analyzed on the basis of 3D-gradient orientation histogram descriptor. It is important to note that Polikovsky et al. (2009) used FACS in order to see the 46 component movements in the facial expression and claim to have determined the most representative region of the face-depicting motion.

Optical flow method, a technique of motion estimation based on the brightness conservation principle, has been combined with FACS for calculating displacement induced due to various expressions on the face. Essa and Pentland (1995) have reported high classification accuracy for recognition of facial expressions in presegmented videos. They had used FACS and optical flow to represent muscle and motion which, in turn, represented facial motion.

However, the automatic analysis of the facial expressions has certain limitations. The first limitation, posed versus spontaneous expression of emotions, is also a topic of debate for psychologists. Behavioral scientists classify expressions into categories such as posed versus spontaneous expressions. Posed expressions are different from spontaneous expressions in terms of appearance and temporal characteristics. Its merits mention that researchers have largely focused on automatic facial expression recognition systems for posed expressions, whereas our day-to-day interactions have spontaneous facial expressions, and this is a major impediment in the recognition accuracy of such systems. Hence, there is a need for developing recognition system that can recognize spontaneous expressions. Secondly, a good database is needed for this purpose that takes care of factors such as race, sex, and ethnicity. This would immensely help the researchers develop robust systems with higher recognition accuracy across the globe. The existing ones, such as RU-FACS and Cohn and Kanade's DFAT-504 database, consist of one hundred participants each. The third dataset available is the Ekman and Hager dataset with 24 participants. Its merits mention that in Cohn and Kanade's DFAT-504 as well as Ekman and Hager dataset, the emphasis was on facial expressions and not the micro-expressions.

13.4 Micro-expressions and Neuropsychology

Neuropsychological studies suggest that the two sides of the human face are not equally pronounced during emotional expressions and emotions are more intense on the left side of the face. The study of facial asymmetry shows that socially appropriate cues are apparent on the right side of the face, while personalized feelings are visible on the left side of the face. We have already talked about posed and spontaneous expressions. The neuroanatomical basis of facial asymmetry also suggests difference between posed and spontaneous expressions. Researchers studying posed expression propose contralateral control of face by the neocortical structures. Movement of the upper facial muscles (forehead and upper eyelid) is controlled by precentral gyrus. This control is executed by the bilateral projections. On the other hand, the muscle movement of the lower face (lower eyelid, nose, cheeks, and lips) is controlled by contralateral projections. Clinical studies of unilateral lesions of the facial motor regions (Van Gelder and Van Gelder 1990) have not demonstrated weakening or paralysis of contralateral hemifacial region, indicating ipsilateral innervations controlling voluntary facial expression. In summary, for posed expressions, the upper face is bilaterally innervated and the lower face contralaterally innervated. On the other hand, spontaneous expressions are controlled by subcortical structures such as thalamus and globus pallidus. The muscle movement for such expressions is controlled by bilateral fibers.

The neural pathways controlling facial expressions help elucidate the inhibition hypothesis (Darwin 1872) explaining the existence of micro-expressions. Two distinct pathways—pyramidal tract and extrapyramidal tract—originate in different areas of the brain (Rinn 1984). The pyramidal tract originates in the cortical motor strip and has control over voluntary facial expressions. On the other hand, the extrapyramidal tract originates in the subcortical areas of the brain and controls the involuntary emotional expressions. Intense situations are likely to activate both the systems, leading to neural competition over the control of face. This neural competition explains leakage of micro-expressions on the face during intense emotional situations.

Neuropsychological studies also attempted investigation of static and dynamic processing of facial expressions. Using positron emission tomography (PET), Kilts et al. (2003) examined the neural correlates of facial expressions (happy and anger) presented as static or dynamic displays. They observed activation of motor, prefrontal, and parietal cortical areas for the perception of anger and happiness in static expressions. The dynamic expression of happiness showed activation of the cuneus, temporal cortex, and the middle, medial, and superior frontal cortexes. The dynamic expression of anger, on the other hand, showed increased right hemisphere activation in the medial, superior, middle, and inferior frontal cortexes and cerebellum. ERP studies suggest that threat is processes as early as 80 ms after the appearance of the stimulus (Keil et al. 2005; Pourtois et al. 2004; Williams et al. 2004). Threatening visual stimuli has been found to augment the occipital or occipitoparietal P1. Given the facts that neural competition leads to leakage of micro-expressions on the face and that the real-life situations would largely demand processing of dynamic displays, it might be interesting to find whether micro-expressions appear only on one half of the face, or the intensity is differentially distributed for various emotional states. Further, the issue of facial asymmetry needs to be examined with respect to motion, duration, and change. Thirdly, the role of facial muscles and the neural underpinning of voluntary and involuntary control over these muscles need to be examined in an integrated manner to decipher the nitty-gritty of micro-expressions.

13.5 Ahead of Methods and Approach

The available literature on psychology suggests universality of at least six basic emotions—happiness, sadness, fear, anger, surprise, and disgust. Irrespective of culture, these facial expressions are universally recognized (Ekman et al. 1987). The evidence for universality of emotions has come from cross-cultural studies on the recognition of emotions. It is important to note that expressions differ with respect to facial motion. Recognition of expression is relatively easier when one compares neutral state with any other emotional expressions. However, some emotions are more expressive than others. How does this affect micro-expressions? Further, behavioral as well as automatic recognition system studies suggest variation in the recognition threshold for different facial expressions of emotions.

As mentioned earlier, faces have permanent and transient features both. On the one hand, eyes and lips act as permanent features, whereas facial lines, wrinkles, and furrows act as transient features. Studies show that expressions of surprise, fear, disgust, and anger produce more facial motion. One of the questions to be examined is to whether higher facial movements are apparent in the permanent or the transient features. Research also suggests that the upper and lower halves of the face should be analyzed separately. Rothwell (2006) examined recognition of micro-expressions by segmenting the face into upper and lower halves. Earlier, Porter and Brinke (2008) had also validated the subsistence of micro-expressions by examining the upper and lower halves of the face separately.

Another important issue is the recognition threshold for identifying different emotional expressions. Esteves and Ohman (1993) found that 100–250 ms were required for confident recognition of facial expressions. They found that less time was needed for recognizing happiness as compared to angry expressions. Researchers have reported that anger, fear, and happiness can be detected at presentation time below 20 ms (Milders et al. 2008). Pardas and Bonafonte (2002) have reported high recognition rates for expressions of surprise (100 %), joy (93.4 %), and disgust (97.3 %). They argue that the eyebrows and mouth carry maximum information pertaining to an expression and these three emotions have clearer mouth and eyebrow motion. Bourel et al. (2001) found that sadness was largely recognized by looking at the mouth. Morris (1977) has categorically stated that our recognition response comprises a smile, eyebrow flash lasting 1/6th of a second, head tilt, call, wave, and intended hug. Mouth has been considered a significant indicator of affiliation.

Ekman and Friesen (1978) have also found confusion between anger and disgust and fear and surprise. Once again, there are common facial motions between these expressions, and the confusion can be attributed to this. Interestingly, outcome of the automatic facial expression recognition systems has also reported confusion between anger and disgust (Aleksic and Katsaggelos 2006; Kotsia and Pitas 2007; Sebe et al. 2007; Wang and Yin 2007). However, the confusion between fear and surprise has not been replicated. Studies have reported confusions in the automatic facial expression recognition systems' outcome between fear and happiness

(Aleksic and Katsaggelos 2006; Kotsia and Pitas 2007; Sebe et al. 2007; Wang and Yin 2007), fear and anger (Kotsia and Pitas 2007; Kotsia et al. 2008), and sadness and anger (Aleksic and Katsaggelos 2006; Sebe et al. 2007; Kotsia et al. 2008). The system-based outputs have shown ease of recognizing the expressions of happiness and surprise.

As micro-expressions are expressions that are inappropriate in their given context, it is equally interesting to see how such displays affect the viewers. There are interesting studies (Stewart et al. 2009) attempting to examine this phenomenon using the speeches of political leaders. It has been observed that if the expressions displayed violate the expectations of the viewer, then it affects their physiological, emotional, and evaluative response (Bucy 2000; Bucy and Bradley 2004).

Normally, certain emotions, such as surprise, fear, disgust, and anger, produce more facial motions compared to sadness and smile. We find multiple combinations of facial expressions in the real-life situation. They also vary with respect to intensity and duration. One has to factor in findings of the occlusion studies as these are very commonly observed in the real-life situation. Occlusion of the mouth has been found to reduce the recognition rate by 50 %. It is important to note that researchers in the field of automatic processing have argued that expressions are symmetrical along the vertical plane dividing the left and right halves of the face (Kotsia et al. 2008), while behavioral studies hold asymmetry on the two halves of the face. Similar to behavioral studies, studies based on automatic processing systems also hold two views. One view argues recognition by components (Biederman 1987), while the counter view advocates that recognition is a holistic process (Farah et al. 1998). Researchers have adopted both approaches. For instance, PCA is a holistic approach, while Gabor wavelet transform is a component-based approach.

13.6 Psychophysiology and Expressive Behavior

Several psychophysiological parameters have been used for the study of emotional states. All of them can prove vital for further exploring micro-expressions and correlating them with different psychophysiological states. One way of quantifying the facial expressions is the usage of electromyographies (EMG). EMG of corrugator supercilii and zygomatic muscles has proven to be another important index of expressive behavior. Corrugator supercilii is used to see furrowing of the eyebrows, whereas zygomatic muscle is used to see rising of the corners of the lips. Studies have measured electrical potential from the facial muscles. It is considered good for assessing the valence of an emotional state. The activity of corrugator muscle shows a linear decrease, while zygomatic muscle activities show a linear increase to the pleasantness of affective stimuli (Bradley and Lang 2000; Larsen et al. 2003). However, such measures have a limitation. EMG seems to be good only in studying discrete emotional reactions. The motor control system of the two muscles is also an indicator of the neural mechanism, and hence, EMG study of micro-expressions can be of great help. The relationship between the changes apparent on the forehead and eyes and other facial muscles can be benefited by the usage of EMG for all the three categories of expressions—simulated expressions, masked expressions, and neutralized expressions.

Studies reporting indices of autonomic nervous system functions concentrate on electrodermal or cardiovascular response. Electrodermal response is either galvanic skin response (GSR), also called skin conductance level (SCL), or short-duration skin conductance responses (SCRs). These responses are considered important because of its connection to the sympathetic nervous system. In a given emotional state, when the sympathetic nervous system is aroused, it leads to the release of sweat. This, in turn, increases skin conductance. Cardiovascular measures include heart rate (HR), blood pressure (BP), total peripheral resistance (TPR), cardiac output (CO), pre-ejection period (PEP), and heart rate variability (HRV). The blood flow from the heart is considered a good indicator of arousal. Of these many outcomes, one can choose any or many parameters based on their specific requirement. Cardiac output (CO) is the volume of blood pumped by the two ventricles in 1 min. Impedance cardiography is used to measure pre-ejection period (PEP). It tells the inotropic status of the heart. Medical research also uses total peripheral resistance (TPR) or pulmonary vascular resistance (PVR). TPR is the measure of resistance of the systemic circulation, whereas PVR is the measure of resistance of the pulmonary circulation. However, one does not find them being used in psychophysiological studies. Blood volume pulse (BVP) amplitude tells the magnitude of difference in blood flow in normal and emotional conditions. Respiration rate (RSP) is the measure of respiration with respect to time. RSP amplitude tells the magnitude of difference in respiration rate in normal and emotional conditions. HRV can be recorded by putting sensors on the chest or abdomen, and it estimates cardiac autonomic nerve activity. Typical HR for a relaxing person will have low values (60–70 bpm). This value changes under certain psychological state. The rhythms and patterns of HRV reflect emotional state of the individual.

The choice of electrodermal and cardiovascular measures described above depends on whether the researcher is interested in recording activities of the sympathetic or parasympathetic system. If one is predominantly interested in the sympathetic activities, then skin conductance level (SCL) and pre-ejection period (PEP) are suitable, but if one is interested in parasympathetic activity, then HRV is preferable. Heart rate (HR) and blood pressure (BP) reflect the combined activity of sympathetic and parasympathetic systems.

Magnitude of the startle response is also considered a measure of emotion. Sudden intense stimulus generates certain motor reflexes visible in the neck and back muscles and eye blinks. Amygdala is considered a key modulator of the startle response. It has been used to examine dimensional perspective. Mapping approach–avoidance onto positive–negatives dimensions, Lang (1995) has argued that the amplitude of startle response can be used as a measure of emotion. This is based on the assumption that negative emotions activate avoidance system. This should generate defensive reaction including startle reflex. It has been proven that the magnitude of startle response is sensitive to emotional valence for high-arousal stimuli only. Empirical findings suggest that startle response can be considered as a marker of the valence of emotional states.

These indicators of autonomic nervous system functions have been very well used in studies of emotion, but for some reasons, studies on micro-expressions have not done so. Micro-expressions and the autonomic responses both are involuntary in nature, and hence, the relationship between them deserves an in-depth investigation. Further, the appraisal mechanism is supposed to guide the physiological as well as expression outcomes. This would imply that these two functions should have a strong correlation. Even if these expressions are visible for a very small period of time on the face, it might be interesting to see whether their presence shows any change in the psychophysiological state as compared to the facial expression that follows/replaces it. It is well established that micro-expressions are the outcome of neural competition during intense emotional situations. Can this neural competition be mapped through the activities of the autonomous nervous system functions? It is also known that certain expressions such as surprise, fear, disgust, and anger produce more facial motion. What is the relationship between facial motion, neural competition, and the autonomous nervous system functions? Is this relationship same for all the facial expressions of all the emotions or it differs for simulated, masked, and neutralized expressions? Studies adopting the psychophysiological measures can open new roads to the scientific understanding of micro-expressions.

13.7 Some Applications

Besides proving its significance for researchers of behavioral sciences, understanding of facial expressions has consequence for animations, telecommunications, video games, safety tools, and so forth. Segmentation of human facial expression to extract micro- and macro-expressions has multiple applications. Such research is likely to be of immense help for security and surveillance. At the point in history of humankind when perceived threat of terrorist attacks is high throughout the world, the applied aspect of knowledge pertaining to micro-expressions can be used by law enforcement agencies in identifying possible suspects. Researchers argue that micro-expressions can also be helpful in revealing deception. Manohar et al. (2007, 2008) have proved that facial strain patterns can be used as supplementary biometric evidence, thus proving its forensic importance. Porter and Brinke (2008) have also demonstrated the existence of micro-expressions in deceitful conditions. Besides forensic applications, it also has relevance for various other settings. In the medical setup, it can assist caregivers detect real feeling of patients, thus improving care and compassion. It can be very helpful in counseling sessions as well. Micro-expressions can help understand the unease of the client with the situation, thus making the counselor to come forward with convincing explanations.

Analyzing facial expressions and voting decisions, Little et al. (2007) and Todorov et al. (2005) have concluded that facial characteristics exhibit personality traits. This can be further extended to personnel selection as a complimentary tool along with other psychological measures. On negotiation table, it can help understand the success of suggested alternatives. Another way of looking at these expressions could be to identify the mental state of an individual by seeing the expressions itself. Based on their study of British, Spanish, and Japanese participants, Baron-Cohen et al. (1996) have concluded that human adults can recognize a range of mental states through facial expression. These mental states include contempt, recognize, threaten, regret, astonished, worried, distrust, and revenge. The mental states that were not identified across culture were wary, guilt, and scheme.

There are newer technological developments, and one can contemplate that this knowledge could also be extended to the study of micro-expressions. The advances in robotics have gone to the extent of the development of humanoid robots. Similarly, the development of affect-sensitive HCI is a sought-after goal in affective computing. Both of them depend on the precise understanding of human facial expressions and replicating them in automatic recognition systems. Inputs from behavioral studies can be of use to this community. It is also important to note that we have come to the world of affect-sensitive jukeboxes. Bartlett et al. (2003) have developed real-time face detection and facial expression recognition system named *CU Animate* that mirrors the expressions of the user. Anderson and McOwen's (2006) *EmotiChat* is a chat application that automatically inserts emoticons during chatting. Here, the facial expression recognition system selects and inserts emoticons by identifying the facial expressions of the users. Interestingly, most of the educational software also makes use of it.

Advances in the area of speech recognition and the science of acoustics have made it possible to compare vocal characteristics and emotional state of the person. This can further be equated with facial expressions, including change in acoustic properties and micro-expressions. Besides amplitude and pitch of the voice, minute changes in vocal fold vibration have been analyzed by researchers. Studies have observed association between pitch and arousal inasmuch as higher arousal is correlated with higher pitch of voice (Bachorowski 1999).

One of the technologies giving new dimension to the understanding of many psychological phenomena is the eye-tracking technology. It is one of the fast growing technologies that are being used by many researchers. Bhushan's (2007) work on varying intensity of the facial expressions of six basic emotions had few interesting findings. Here, six still images were derived out of a video of a posed emotion. The first image showed the lowest intensity of that specific emotion, whereas the sixth image showed the highest intensity of that specific emotion. The remaining images represented intensity of a specific emotion in increasing order from 1 (minimum) to 6 (maximum). These expressions were shown to participants for labeling and rating, while the eye tracking was also performed. Further, the distance between two key points on the face was also calculated. Figure 13.3a illustrates the scan path for two of these emotions (happy and anger) for all six

Fig. 13.3 **a** Eye-tracking outcome for facial expressions. **b** Points of interest on the face. Points on the face and the distance/angle calculation between any two points (© Braj Bhushan)

images of variable intensity. Figure 13.3b illustrates the points on the face and the distance (horizontal, vertical, and diagonal) between any two given points.

The scan path analysis endorsed the way adult participants gaze a human expression in search of a possible emotional state. If you look at the work of Pfister et al. (2011) (Fig. 13.4), you can find the proximity between the behavioral approach and the automatic analysis approach.

Figure 13.4a illustrates the manually selected points on the first frame, and Fig. 13.4b shows the facial regions. The similarity in terms of selecting facial points has a scientific background, but face-scanning pattern validates the selection of facial regions for deciphering specific expression. This also indicates that the scientific understanding as well as development and refinement of micro-expression training tools can be benefited by using this technology.

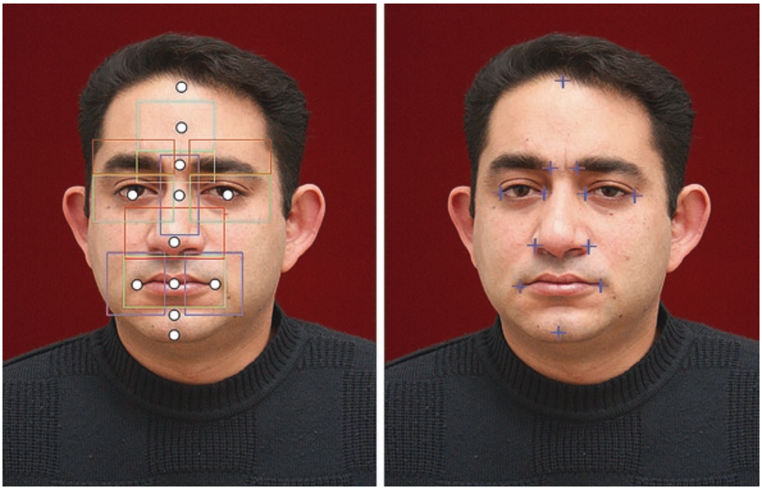

Fig. 13.4 Points on face and derivation of facial regions (adapted from Pfister et al. 2011)

However, there are many intricacies that need to be addressed. The technical problems in the study of micro-expressions are duration, intensity, and accuracy of judgment. As the micro-expressions are of low intensity and are visible for such brief period of time, recognizing them with accuracy is a major challenge. Another challenge is to go beyond the recognition of six basic emotions. Parrott (2000) has acknowledged 136 different emotional states and has divided them into classes and subclasses. AUs can play a significant role in identifying these finer changes in facial expressions. This will not only help the automatic processing systems but also be useful for psychologists in the area of training. Now, it seems that the AUs of FACS can be mapped to FAPs of MPEG-4 and expression analysis and expression synthesis might attract the researchers. Another challenge is to get spontaneous expressions under variable lighting and occlusion conditions. The third important concern is the recognition accuracy. The accuracy of recognizing these expressions is low, and even with training, the reported accuracy is only 47 % (Frank et al. 2009). Pfister et al. (2011) have used temporal interpolation along with multiple kernel learning (MKL) and random forest (RF) and reported high detection accuracy.

It might also be interesting to examine micro-expressions in the developmental perspective. Studies confirm that two-year-old babies can recognize facial expression of happiness and this expands to the recognition of sadness, anger, surprise, and fear by 3–4 years (Bullock and Russell 1984; Izard 1971; Michalson and Lewis 1985; Smiley and Huttenlocher 1989). By the fifth year, children can also discriminate expression of disgust (Bullock and Russell 1986; Michalson and Lewis 1985). Further, eye-tracking studies have reported difference in the eye movement pattern between children and adults. Besides enhancing our understanding of micro-expressions, such experimental findings might help the behavioral scientists as well as the experts in the technological domain to serve humanity in a better way.

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