Chapter 13
Study of Facial Micro-expressions in Psychology

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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

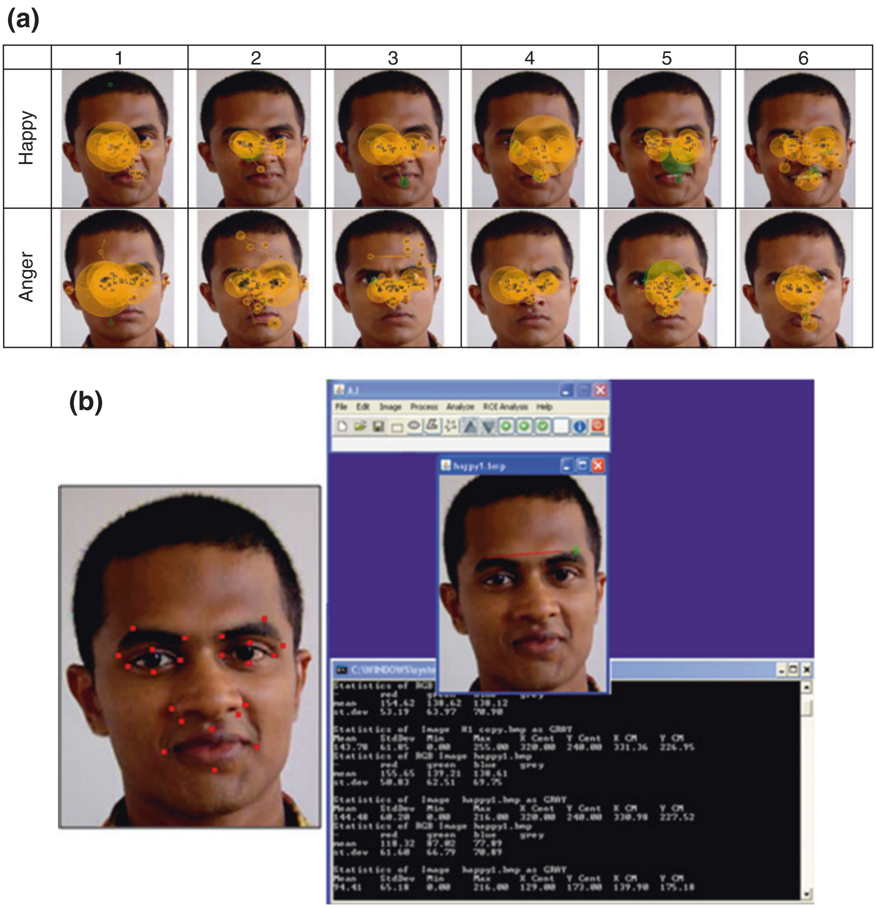

Fig. 13.3 **a** Eye-tracking outcome for facial expressions. **b** Points of interest on the face. Points on the face and the distance/angle calculation between any two points (© Braj Bhushan)

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.

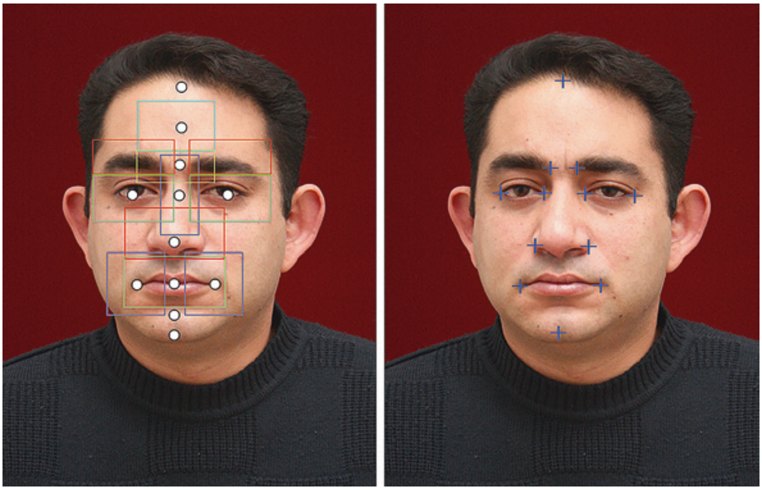

Fig. 13.4 Points on face and derivation of facial regions (adapted from Pfister et al. 2011)

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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