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COMPUTING EMOTION AWARENESS THROUGH GALVANIC SKIN RESPONSE AND FACIAL ELECTROMYOGRAPHY*

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Abstract To improve human-computer interaction (HCI), computers need to recognize and respond properly to their user's emotional state. This is a fundamental application of affective computing, which relates to, arises from, or deliberately influences emotion. As a first step to a system that recognizes emotions of individual users, this research focuses on how emotional experiences are expressed in six parameters (i.e., mean, absolute deviation, standard deviation, variance, skewness, and kurtosis) of not baseline-corrected physiological measurements of the galvanic skin response (GSR) and of three electromyography signals: frontalis (EMG1), corrugator supercilii (EMG2), and zygomaticus major (EMG3). The 24 participants were asked to watch film scenes of 120 seconds, which they rated afterward. These ratings enabled us to distinguish four categories of emotions: negative, positive, mixed, and neutral. The skewness and kurtosis of the GSR, the skewness of the EMG2, and four parameters of EMG3, discriminate between the four emotion categories. This, despite the coarse time windows that were used. Moreover, rapid processing of the signals proved to be possible. This enables tailored HCI facilitated by an emotional awareness of systems.

1 Introduction

Computers are experienced by their users as coldhearted; i.e., 'marked by lack of sympathy, interest, or sensitivity' (Merriam-Webster, 2007). However, 'during the past decade rapid advances in spoken language technology, natural language processing, dialog modeling, multi-modal interfaces, animated character design, and mobile applications all have stimulated interest in a new class of conversational interfaces' (Oviatt et al., 2004). The progress made in this broad

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range of research and technology enables the rapid computation and modeling of empathy for human-computer interaction (HCI) purposes. The latter is of importance since conversation is, apart from being an information exchange, a social activity, which is inherently enforcing (Oviatt et al., 2004). Futurists envision embodied, social artificial systems that interact in a natural manner with us. Such systems need to sense its user's emotional state.

Empathic artificial systems can, for example, prevent user frustration in HCI. Users feel frequently frustrated by various causes; e.g., error messages, timed out/dropped/refused connections, freezes, long download time, and missing/hard-to-find features (Ceaparu et al., 2004). Picard (1999) posed the prevention of user frustration as one of the main goals in HCI. When prevention is not sufficient, online detection and reduction of frustration is needed. Psychophysiological signals are expected to be useful in the detection of frustration (Picard, 1997). According to Hone, Akhtar, and Saffu (2003), an (embodied) affective agent, using techniques of active listening and empathy, could reduce user frustration.

The current paper discusses the emotions people can experience and their expression in and detection through psychophysiological measures, in Section 2 and Section 3. Next, in Section 4, affective wearables are introduced in which the proposed apparatus for the measurement of the psychophysiological signals can be embedded. In Section 5, we present an experiment into the appropriateness of various statistical measures derived from psychophysiological signals, followed by a reduction of the data in Section 6. The experimental results are described in Section 7. The paper ends with Section 8 in which the results are discussed, limitations are denoted, and future research is described.

2 Emotion

Despite the complexity of the concept of emotion, most researchers agree that emotions are acute affective states that exist in a relatively short period of time and are related to a particular event, object, or action (Ortony et al., 1988; Picard, 1997). In relation with physiology, emotions are predominantly described as points in a two-dimensional space of affective valence and arousal, in which valence represents overall pleasantness of emotional experiences ranging from negative to positive, while arousal represents the intensity level of emotion, ranging from calm to excited (Ball and Breese, 1999; Lang 1995). This allows us to tell the difference between four rough categories of emotions, when differentiated between both high and low valence and high and low arousal. Some researchers even differentiate between nine categories by including a neutral section on both the valence and arousal axis. However, an, in principle, infinite amount of other arbitrary number of categories can be defined, where the valence and arousal axes are not necessarily are divided with the same precision (Bosma and Andre, 2004).

The valence-arousal model, however, does not account for mixed emotions: positive and negative at the same moment. In order to be able to cope with mixed emotions, Larsen et al. (2003) and Konijn and Hoorn (2005) suggest that valence should be unipolar instead of bipolar. When valence is rated on two scales, one for the intensity of positive affect and one for the intensity of negative affect, mixed emotions, in the sense of both positive and negative emotions, will show. As an extension to the valence-arousal model, a unipolar valence axis, with separated positive and negative axes, might allow for a better discrimination between different emotions.

In the current research, solely the valence axis was explored. The reason is that the simplest differentiation of emotions is a differentiation between positive and negative emotions. In most cases of HCI, this is sufficient to improve the dialog between user and computer; e.g., when a user has a negative emotion, the computer can adapt its dialog to that, depending on the context.

3 Psychophysiological measures

The roots of psychophysiological aspects of emotions lay in Darwin's book 'The expression of emotions in man and animals', which he wrote in 1872. The overall assumption is that emotion arouses the autonomic nervous system (ANS), which alters the physiological state. This is expressed in various physiological measures, often stimulated through the ANS; e.g., heart rate, blood pressure, respiration rate, galvanic skin response, and muscle activity (Scerbo et al., 2001). The main advantage of using autonomic physiological measures is that autonomic variables are regulated by the ANS, which controls functions outside individual's conscious control (Scerbo et al., 2001).

In this research, we focused on how emotional experiences, rated to their positive and negative affect, are expressed in four physiological signals:

- Galvanic Skin Response (GSR), also often termed electrodermal activity (EDA; Boucsein, 1992), which is a measure of the conductivity of the skin: arousal of the ANS influences sweat glands to produce more sweat; consequently, skin conductivity increases. GSR was chosen because it is an autonomic variable; hence, it can not be controlled by the user.

- Three electromyography (EMG) signals: frontalis, corrugator supercilii, and zygomaticus major. EMG measures muscle activity of a certain muscle. Facial EMG is related to affective valence; however, the type of relation depends strongly on the muscle that is measured. The corrugator supercilii, which causes a frown when activated, increases linearly with a decrease in valence, while the zygomaticus major, which is responsible for smiling when activated, increases with an increase in valence (Lang et al., 1998). These measures were chosen because a great deal of emotional expression is located in the face (Larsen et al., 2003), as can be measured using facial EMG.

These measures have extensively proven their use to detect emotional experiences in laboratory settings, mostly in group-averaged, baseline-corrected paradigms. In order to make them useful for emotion-aware systems, three aspects will have to change:

- The measurements will have to be done in a less obtrusive manner,
- the interpretation of the signals will have to be meaningful on an individual (not a group-averaged) level,
- and robust signal interpretation algorithms will have to be developed that are baseline-free or incorporate automatic (non-manual) baseline correction.

The first issue is dealt with in the next paragraph, where we discuss the advent of unobtrusive affective wearables. Our focus for the remainder of the paper is on the search for robust signal interpretation algorithms that do not need a manual baseline correction.

4 Affective wearables

Using the GSR and EMG signals, a system will be able to determine the emotional state of its user, certainly if that system also possesses a user-profile. Affective wearables will facilitate such a system in monitoring the user in an unobtrusive manner. Direct physiological measures are often considered to be obtrusive to the user, but this is not necessarily true. In the field of affective computing, some efforts have been made to design unobtrusive measurement technology: affective wearables. Picard (1997) defines an affective wearable as “a wearable system equipped with sensors and tools which enables recognition of its wearer’s affective patterns”. Affective wearables become smaller in time, due to improved design and smaller technology components. Especially when hidden in daily used tools and objects, affective wearables could make a huge difference in user acceptance of direct physiological measures.

The acceptance of direct physiological measurements is of great importance since indirect physiological measurements are much more subject to noise. Indirect physiological measurements (e.g., through voice analysis; Van den Broek, 2004) have been applied in controlled settings such as telepsychiatry (Hilty et al., 2004) and evaluation of therapy effectiveness (Van den Broek, 2004).

However, outside such controlled conditions these measures have not proved to be reliable.

Measurement of physiological signals have already been embedded into wearable tools; e.g., Picard and Scheirer (2001) designed the 'Galvactivator', a glove that detects the skin conductivity and maps its values into a led display. In an overview of previous work of the Affective Computing Research Group at MIT, Picard (2000) describes several affective wearables. One affective wearable that is of interest in this research is the expression glasses. The expression glasses sense facial movements, which are recognized as affective patterns.

5 Experiment

5.1 Aim

The goal of the present experiment was to enable a search for robust (e.g. baseline-free) algorithms for use in future emotional awareness systems, which interpret positive or negative emotions from psychophysiological signals.

5.2 Subjects

24 Subjects (20 female) were invited from a volunteers database. They signed an informed consent form, and were awarded with a small incentive for their participation. They were aged between 27 and 59 years (average 43 years).

5.3 Materials

Sixteen film sequences were selected for their emotional content. Several of these sequences were described by Gross and Levenson (1995) for their capability of eliciting one unique emotion among various viewers. They were edited with Dutch subtitles, as is normal on Dutch TV and in Dutch cinemas. Since not enough material of Gross and Levenson (1995) was available with Dutch subtitles in acceptable quality, the set was completed with a number of similar sequences. The resulting video fragments each lasted between 9 seconds and 4 minutes[1]. If the fragment lasted less than 120 sec, a plain blue screen was added to make a total of 120 sec.

The video fragments were presented on a large 42″ 16:9 flat panel screen mounted on the wall of the room. Print-outs for significant scenes of each of the film fragments were used to jog the subjects memory of each film fragment after the viewing session.

[1] From Gross and Levenson (1995): Silence of the lambs (198 sec), When Harry met Sally (149 sec), The champ (153 sec), Sea of love (9 sec), Cry freedom (142 sec), The shining (80 sec), Pink Flamingoes (30 sec). Additional: Jackass the movie - paper-cut scene (51 sec), Static TV color bars (120 sec), The bear - intro (120 sec), Sweet home Alabama – wedding scene (121 sec), Tarzan - orchestra scene (133 sec), Abstract shapes – screen saver (120 sec), Lion King – dad's dead (117 sec); Nature documentary (120 sec), Final destination – side-walk café scene (52 sec).

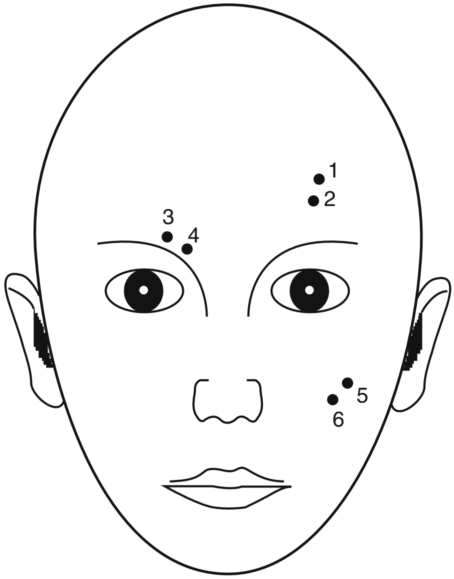

Figure 1. The points indicate the electrodes that were placed on the face of the participants to determine the EMG signals. The EMG signals of the frontalis, corrugator supercilii, and zygomaticus major were respectively measured through electrodes 1–2, 3–4, and 5–6.

The psychophysiological measurements were performed with a TMS International Porti5–16/ASD measurement system connected to a computer, in combination with TMS Portilab software. A ground electrode was attached to the right-hand lower chest area. Three EMG measurements were done: at the right-hand corrugator supercilii muscle, the left-hand zygomaticus major muscle, and the frontalis muscle above the left eye. At each site 2 electrodes were placed in the direction of the muscle (see Figure 1). These signals were first high pass filtered at 20 Hz and then the absolute difference of the two electrodes was average filtered with a time constant of 0.2 sec.

For the skin conductivity (GSR) measurements, two active electrodes were positioned on the distal phalanges of the index and ring finger of the right hand (see Figure 2). Skin conductivity was calculated from the measured signal with a time constant of about 2 sec, thus capturing GSR signal variations reliably in first order.

5.4 Procedure

At the beginning of the session, the subject was invited to take place in a comfortable chair and the electrodes were positioned: first at the fingers, then at the face. Then, the recording equipment was checked and aligned

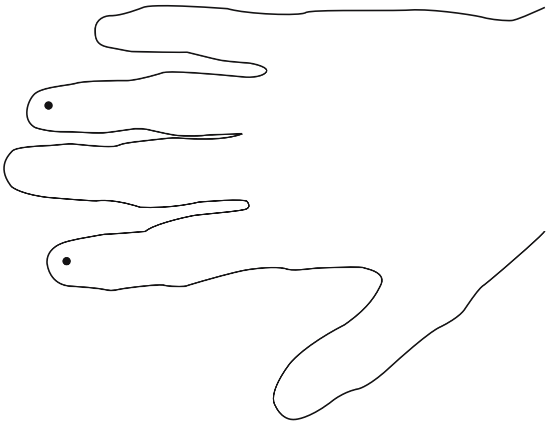

Figure 2. The points indicate the electrodes that were placed on the hands of the participants to determine the GSR signal.

when needed. A rest period of 5 minutes was taken into account. The subjects were presented with the 16 video fragments, each segment was presented only once.

A pseudo-random order of presentation was generated for the 16 video presentations. This order was designed to spread positive and negative scenes evenly over the session. It was presented to 12 subjects, each starting with a different scene in the list, but maintaining the same order. The reverse order was presented to the other 12 subjects, again each starting with a different scene while maintaining the same presentation order. In between two fragments, a plain blue screen was presented for 120 seconds.

After the measuring session, the electrodes were detached and the subject was requested to fill out a short questionnaire. In this questionnaire, representative pictures of the 16 video fragments were represented sequentially and the subject was requested to rate them according to two emotion-related axes: intensity of positive feelings and intensity of negative feelings, both on a 7-point Likert scale.

6 Data reduction

Average intensities for both positive and negative ratings were calculated for each of the film fragments, allowing for a classification of the fragments in 4 emotion categories: neutral, mixed, positive, negative. In each emotion category, the two fragments with a duration closest to 120 seconds were selected for further analysis (see Table 1).

The EMG data of 2 subjects appeared to be corrupt; therefore, these datasets were not analyzed. For the other subjects, the GSR signal and three EMG signals (of the frontalis, corrugator supercilii, and zygomaticus major) were

Table 1. The sixteen film scenes with the average ratings with the accompanying standard deviations (between brackets) given by the subjects (n=24) on both experienced negative and positive feelings. Based on the latter two dimensions, four emotion categories are founded: neutral, mixed, positive, and negative. The top eight film scenes were selected for further analysis.

Film scene	*Positive*	*Negative*	*Emotion category*
Color bars	1.60 (1.43)	2.20 (2.04)	neutral
Abstract figures	1.20 (0.70)	2.10 (1.94)	neutral
The bear	5.15 (1.50)	1.65 (0.88)	positive
Tarzan	5.10 (1.17)	1.50 (0.95)	positive
Final destination	3.11 (1.70)	4.32 (1.63)	mixed
Lion King	3.85 (2.21)	3.65 (1.93)	mixed
Cry freedom	1.95 (1.54)	6.25 (1.07)	negative
Pink flamingos	1.75 (1.20)	5.60 (1.54)	negative
Silence of the lambs	2.30 (1.38)	3.85 (1.73)	neutral
When Harry met Sally	4.60 (1.47)	1.80 (1.15)	positive
The champ	2.65 (1.46)	4.35 (1.05)	mixed
Jackass the movie	1.85 (1.57)	5.95 (1.47)	negative
Sea of love	2.15 (1.31)	3.90 (1.74)	neutral
Sweet home Alabama	4.35 (1.66)	1.70 (1.26)	positive
The shining	2.65 (1.39)	3.55 (1.47)	neutral
Nature documentary	4.50 (2.04)	1.45 (1.28)	positive

processed in order to determine their discriminating ability on the four emotion categories induced by the eight films. To determine the latter, six parameters (mean, absolute deviation, standard deviation, variance, skewness, and kurtosis) were derived from the four signals. Where the mean, standard deviation, and average deviation are well-known dimensional quantities (i.e., have the same units as the measured quantities x_j), the skewness and kurtosis are conventionally defined as non-dimensional quantities. Both skewness and kurtosis are less well known statistical measures and both are defined in several ways (Press et al., 1992; Weisstein, 2002). Therefore, we provide the definitions as adopted in the current research.

The skewness characterizes the degree of asymmetry of a distribution around its mean. It characterizes only the shape of the distribution. The usual definition is (Press et al., 1992; Weisstein, 2002):

$$Skewness(x_1 \ldots x_N) = \frac{1}{N}\sum_{j=1}^{N}\left[\frac{x_j - \bar{x}}{\sigma}\right]^3,$$

where $\sigma = \sigma(x_1 \ldots x_N)$ is the distribution's standard deviation. A positive value of skewness signifies a distribution with an asymmetric tail extending out towards more positive x; a negative value signifies a distribution whose tail extends out towards more negative x.

Kurtosis measures the relative peakedness or flatness of a distribution relative to a normal distribution. We applied kurtosis as (Press et al., 1992; Weisstein, 2002):

$$Kurtosis(x_1 \ldots x_N) = \left\{ \frac{1}{N} \sum_{j=1}^{N} \left[\frac{x_j - \bar{x}}{\sigma} \right]^4 \right\} - 3,$$

where the −3 term makes the value zero for a normal distribution.

7 Results

For each of the six statistical parameters, for each film fragment, and for each subject, the complete GSR and EMG signals were processed over the last 120 seconds of the film fragment. The duration of 120 seconds was chosen because it was available for the majority of the scenes. Two film fragments were shorter than that, and for them we included measurements taken during the blue screen following it in order to add up to a section of 120 seconds as well (see also Section 5.3). Note that we deliberately did not correct these values for their baseline, because – however useful in academic research – the baseline-correction procedure is not easily applicable in future emotionally aware systems.

Due to corrupted recordings during a few films with two of the subjects, the measurements of these two subjects were not taken into account. Moreover, for the same reason, the recordings of one subject, during the film scene of the "Pink flamingos", were skipped. For each parameter of each physiological measure, a repeated measures ANOVA was conducted, with the four emotions, each measured with two film scenes, as within-subject factors. So, a total of 24 (4 * 6) repeated measures ANOVAs were conducted.

The EMG of the frontalis did not provide a significant discrimination between the four emotion categories on any of the statistical parameters. Of all physiological measures, the zygomaticus major signal is the most discriminative physiological signal (see Table 2). The mean, absolute deviation, standard deviation and variance calculated over the zygomaticus major EMG signal showed strong significant effects of emotions. Significant effects did also show in the skewness and kurtosis of the GSR signal and the skewness of the corrugator supercilii EMG signal (Table 2). For the skewness of the zygomaticus EMG signal a trend is present ($F(3,18) = 3.013$, $p = 0.057$) over the four emotions.

Table 2. The discriminating statistical parameters for the galvanic skin response (GSR), EMG corrugator supercilii, and EMG zygomaticus signals. For each parameter, the average value for all four emotion categories is provided as well as the strength and significance of its discriminating ability.

Physiological measure	*Statistic parameter*	*average value on*				*effect (F(3,18))*	
		neu-tral	*posi-tive*	*mixed*	*nega-tive*	*strength*	*signifi-cance*
GSR	skewness	0.46	0.01	–0.15	0.39	7.289	$p = 0.002$
	kurtosis	–0.66	–0.78	0.55	–0.19	3.812	$p = 0.028$
EMG corrugator supercilii	skewness	1.99	2.84	3.49	3.29	3.500	$p = 0.037$
EMG zygomaticus	mean	2.74	5.21	3.15	3.53	9.711	$p < 0.001$
	abs. dev.	1.64	3.77	2.10	2.42	8.369	$p < 0.001$
	SD	2.46	6.01	3.68	3.96	5.837	$p = 0.006$
	variance	7.23	63.82	18.69	23.21	4.064	$p = 0.023$

8 Discussion

8.1 Comparison with literature

Most 120 sec. averaged values of the physiological signals did not yield significant effects of emotion category, in contrast to what is generally reported in literature. One of the reasons might be that we chose not to correct our data for baseline values, as is common in psychophysiological literature. Another factor is that the present analysis was chosen to extend over a relatively long period of time including the beginning of the video fragment in which the targeted emotions were still in the process of getting elicited, which might have diminished the differences between categories of emotions.

For the zygomaticus major, we did find an effect for the average value, even when not corrected for baseline and averaged over 120 sec. This is in line with results of previous research of Larsen, Norris, and Cacioppo (2003), who concluded that valence influences both the corrugator supercilii and the zygomaticus major. They found that valence had a stronger effect on the corrugator supercilii than on the zygomaticus major in experiencing standardized affective pictures, sounds, and words, while our research shows a stronger effect of emotions on the mean zygomaticus major signal, than on the corrugator supercilii. In addition, the effect is present with four statistical parameters of the zygomaticus major, where it is only present in one statistical parameter (skewness) of the corrugator supercilii. The difference in strength of the effects found between the current research and that of Larsen, Norris, and Cacioppo (2003) can possibly be explained by the absence of a baseline correction in our procedure. Another difference between the two researches is the type of stimuli. Film scenes are dynamic and multi-modal, they induce emotions by both auditory and dynamic visual stimuli, as well as affective words, in some fragments. The dynamic and multi-modal characteristics of the film scenes also provide good means to build up emotions, or to create a shock effect. This is not possible with affective words, sounds or pictures of a static character. On the one hand, all these factors give film scenes a relatively high degree of ecological validity (Gross and Levenson, 1995). On the other hand, it can not be determined which modality influences the emotional state of the subjects to the highest extent.

For three of the four physiological signals the parameter skewness turned out to be important as a significant effect or as a trend. The skewness (and kurtosis) of EMG signals have been topic of previous research, although its use as discriminating descriptors is limited to only a few studies. In 1983, Cacioppo, Marshall-Goodell and Dorfman (1983) analyzed among a number of parameters, the skewness and kurtosis of skeletal muscle patterns, recorded through EMGs. Four years later, a paper of Cacioppo and Dorfman (1987) was published that discusses "waveform moment analysis in psychophysiological research" in general. In 1989, Hess et al. (1989) conducted research toward experiencing and showing happy feelings, also using video segments. Hess et al. (1989) recorded four facial EMG signals and extracted the mean, variance, skewness and kurtosis of these signals. The current research is distinct from that of Hess et al. (1989) since it distinguishes four emotion categories instead of the presence or absence of only one.

8.2 Use in products

Not all investigated parameters of all measures proved to be equally suited for sensing human's emotional state. This is no doubt due to the demanding analysis conditions we imposed: No baseline correction and averages over relatively long time intervals. Nevertheless, even under these demanding analysis conditions, still some of the measures succeed in distinguishing between the respective emotion categories.

For three of the four physiological signals used, the parameter skewness proved to be an interesting source of information. The skewness of the distributions of the data of two of the physiological signals differs significantly over the four emotions, where a trend is present for a third signal. The skewness characterizes the degree of asymmetry of a distribution around its mean. To inspect more distribution details of the signals, additional analyses could be conducted. Measures such as the slope of the signal and the peak density could be taken into account for further analysis.

In addition to adding more descriptors of the physiological signals, the time windows of measurement can be changed. In the current setup, the time window enclosed the complete length of the film scene. However, smaller time windows (e.g., 10 or 30 sec.) can be applied. Moreover, dynamic time windows can be applied that enclose the time directly after a critical event (if any) appeared in the film scene. The drawback of the latter approach is that it can not be applied in practice, while it can be expected to prove good results for data gathered through experimentation, as in the current research.

A more general notion that can have a significant impact on measurement of emotions is that the emotional state of people changes over time, due to various circumstances. Moreover, different persons have different emotional experiences during the same events, objects, or actions. The latter is determined by a person's personality. Personality traits correlate with affective states, especially with the personality traits extraversion and neuroticism, which have been linked both theoretically and empirically to the fundamental affective states of positive and negative affect, respectively (Matzler et al., 2005). Hence, to enable tailored communication strategies in HCI, not only the emotional state of a person should be determined but also his personality. When the system possesses a personality profile of its user, it will be able to react appropriately to its user's emotions by selecting a suitable communication strategy.

We conclude that the set of psychophysiological measures as introduced suits the vision of 'ambient emotion-aware intelligence', which is characterized as embedded, aware, natural, personalized, adaptive, and anticipatory. With the robust algorithms presented, the measurement of the psychophysiological signals can be embedded in wearables, can facilitate awareness for systems connected to it, can aim to mimic human empathy (i.e., is natural), can be connected to a user-profile, and can facilitate in utilizing knowledge to anticipate on people's mood and adapt its communication strategy.

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