Neurophysiological assessment of affective experience

Christian Mühl
Human Media Interaction,
University of Twente,
PO Box 217, 7500AE Enschede,
The Netherlands.
muehlc@cs.utwente.nl

Abstract

In the field of Affective Computing the affective experience (AX) of the user during the interaction with computers is of great interest. The automatic recognition of the affective state, or emotion, of the user is one of the big challenges. In this proposal I focus on the affect recognition via physiological and neurophysiological signals. Long-standing evidence from psychophysiological research and more recently from research in affective neuroscience suggests that both, body and brain physiology, are able to indicate the current affective state of a subject. However, regarding the classification of AX several questions are still unanswered. The principal possibility of AX classification was repeatedly shown, but its generalisation over different task contexts, elicitating stimuli modalities, subjects or time is seldom addressed. In this proposal I will discuss a possible agenda for the further exploration of physiological and neurophysiological correlates of AX over different elicitation modalities and task contexts.

Keywords: Emotions, Brain-Computer Interfaces, Affective Computing, Affective Signal Processing

1. INTRODUCTION

In this proposal I will outline the objective and structure of my PhD research project “Neurophysiological assessment of affective experience”. In the project I will explore how different affective states are reflected by physiological and neurophysiological indicators. Furthermore, I will study possible methods to automatically determine these states from the measured sensor modalities. Finally, the use of automatic affect classification will be explored in various gaming scenarios. I will focus on electroencephalography to assess neurophysiological activity, and on cardiovascular indicators, galvanic skin response, facial muscle activity and respiration to assess the state of the autonomous nervous system.

To clarify my motivation I will start the proposal by a very short introduction to emotion research, traditional approaches of affect assessment and a discussion of alternatives to the use of (neuro-) physiological sensors, pointing out the problems with this undertaking and the results obtained so far. In the second part I will then proceed with a concise review of physiological and neurophysiological measurements associated with certain affective states and of studies exploring the use of those features for the classification of emotions. Thereby I will detail a number of unexplored questions, such as the generalisation of classifiers over context, time and subjects. The third part will then outline the methods that I propose to approach these issues. Finally, first results and observed problems from a preliminary analysis of a first experiment will be presented to provide a starting point for the discussion of the research project proposed.

1.1 DEFINITION OF THE SUBJECT AND MOTIVATION

There are several reasons for the study of emotional processes and their physiological and neural correlates. One of the most important is certainly the purely scientific interest that already motivated studies in psychophysiology and more recently in affective neuroscience. This fundamental curiosity is spurred by questions about the nature of emotions. As example it should suffice to mention the old debate about the structure of emotions. Here the debate between proponents of a small number of discrete emotions and those that propose a continuous affective space, spanned by two or more affective dimensions, such as arousal, valence, dominance, stretches already over decades.

With the development of the relatively new domain of Affective Computing [26] another source of interest to the study of emotion has been established apart from the purely theoretic interest, adding a perspective on possible applications regarding our knowledge about affective experience. Here one of the main interests lies in the prediction of subjective experience and the development of an objective measure of experience. The aim of this domain is to enrich the interaction with applications by the automatic recognition of the affective user state. Further areas of application are the evaluation of experience in application or product design [23].

Before reviewing some studies of (neuro-) physiological correlates of affective states and their automatic recognition we will briefly discuss traditional approaches to emotion assessment and motivate the use of physiological and neurophysiological signals for this purpose.

1.2 AUTOMATIC CLASSIFICATION VS TRADITIONAL METHODS TO MEASURE AX

The reliable measurement of affective states has been a known problem in the domains of psychology and psychophysiology for a long time. To assess emotional states and their interaction with other observations, researchers have developed several methods. One of the most widely used is the self-report, including techniques such as the Mood Adjective Checklist, the Profile Mood States, the Expanded Form of the Positive and Negative Affect Schedule, and the Differential Emotions Scale. A comprehensive overview can be found in [15]. Those self-reports are asking the subject (1) to observe and quantify their emotional experience, and (2) to honestly and accurately report it. These requirements are susceptible to several error sources. Firstly, retrospective reports can be distorted by effects of recency and duration neglect. Secondly, the subject's answers might be influenced by social desirability. Affect can also be measured by think aloud techniques and behavioural observations [23]. Think aloud techniques have the advantage to avoid the problems related to retrospective self-reports. However, they are unnatural and carry a high potential for distraction of the subject. Observations, e.g. by video recordings to code gestures, body language and verbalisations, are a rich data source, but the analysis is a time-consuming process not free of biases.

The advantages of an objective measure of the affective state via physiological signals are therefore obvious. It would be a continuous measure of the affective state of a subject, avoiding disturbances, and the risk of distortions known for retrospective reports. Furthermore, the ability to report emotions varies between subjects [30]. Objective measurement might allow one to assess emotions independent from the subject's ability to describe them. This would be interesting for basic and applied sciences. However, it is important to recognise that subjective reports remain in most cases the basis for the calibration of potential affect recognition systems as they provide the labels for the construction of physiological evaluation methods and the training of classifiers. Therefore, to gain from the advantages of physiological measures of affect, the problems innate to subjective reports have to be taken into account. Having motivated the search for an objective measurement of affective state we will now explore the advantages and disadvantages of the chosen sensors.

1.3 WHY TO USE PHYSIOLOGICAL AND NEUROPHYSIOLOGICAL SENSORS

I am focusing in this proposal on (neuro-) physiological attempts to classify affective experiences. While there is a multitude of physiological signals that might give valuable information about this experience, I explore mainly indicators of peripheral (e.g. muscle tension, galvanic skin response, and cardiovascular signals) and central nervous system functioning (i.e. electroencephalogram). Other physiological indicators of affective experience, e.g. visual and auditory analysis of subject behaviour, have also yielded promising results [10]. However, the use of (neuro-) physiological sensors has some advantages over those other, less intrusive sensors, as cameras or microphones. Firstly, one may observe state changes that are too subtle to find utterance in behavioural indicators. And, secondly, they appear to be less susceptible to voluntary deceiving. Thus, they are more robust indexes of affective state, as the behaviour can be easily manipulated, but the body state is harder to control [27].

The disadvantages, on the other hand, include the intrusiveness just mentioned, as it is yet not possible to measure (neuro-) physiological signals without the application of sensors to the body. Furthermore, there are variations of recording conditions, resulting from differences in hand washing, gel application, and sensor positions, which might lead to variations in the recordings themselves.

Another methodological problem arising in the study of (neuro-) physiological correlates of affective states is associated with the acquisition of the ground truth. While those studies that are centred on auditory and visual behaviour accompanying emotions can employ observer ratings to obtain the ground truth of a given sample, this is not possible when behaviour cannot be observed [27].

Despite the problems I believe that only the thorough understanding of emotional responses in body and brain can lead to robust classification of affective states. While there might be less intrusive alternatives for the observations of affective behaviour, the sensor technology in the focus of this proposal delivers important insights in otherwise non-observable facets of emotional states. Thereby valuable potential for the disambiguation of affective states might be gained. The next section will give an overview over physiological measurements and correlates of affective processes and first approaches of their classification. It will also reveal some hitherto unexplored issues that are in the focus of the proposed research.

2. RELATED WORK

In this section I will first show that the measured sensor modalities, physiological and neurophysiological, have been associated with emotional processes by several studies. Then I will discuss studies exploring their value for the training of automatic classifiers.

2.1 PHYSIOLOGICAL CORRELATES OF AFFECTIVE PROCESSES

The current project focuses on a limited range of physiological measurements to assess the state of the peripheral nervous system. Electromyography (EMG) assesses the somatic nervous system by the measurement of muscle activity. While the relation between muscle tension and emotional arousal seems straightforward, Cacioppo et al. [5] showed that facial EMG can differentiate valence *and* arousal. Magnée et al. [22] showed that the facial muscle activity reflects emotional processes, and is not just the result of facial mimicry.

The eccrine glands involved in the production of Galvanic skin response (GSR) are innervated by the sympathetic branch of the autonomous nervous system. GSR is therefore thought to be a trustworthy measure of sympathetic activation. Emotional arousal, for example, was shown to robustly express itself in the GSR response for affective pictures [21, 9] film clips [13], environmental sounds [4], and musical pieces [17]. However, it was found that emotional arousal in an erotic context is associated with a parasympathetic activation and thus not reflected by GSR.

Cardiovascular measures, like heart rate, blood pressure, blood volume and blood flow, assess the function of the heart and vasomotor activity. Lang et al. [21] measured electrocardiography (ECG) during the presentation of low and high arousal pictures. They found an increase of heart rate with emotional arousal. However, heart rate seems to be no robust measure, as exercise, stimulus, and design characteristics showed very influential on the heart rate. No heart rate increase was found for briefly presented arousing pictures or sounds [9]. And Aftanas and colleagues [1] measured even a decrease of heart rate for arousing pictures. Sammler et al. [29] observed a decrease for negatively valenced stimuli, but not for positive stimuli (distorted versus non-distorted music pieces). Heart rate variability (HRV), on the other hand, is supposed to be a more robust measure, at least in terms of exercise. From the three frequency ranges HRV can be divided into, the highest, respiratory sinus arrhythmia (RSA), which is associated with the effects of respiration on the heart rate, is supposed to be a good indication of parasympathetic activation. Interestingly, Frazier and colleagues [13] observed a decrease of RSA with increasing emotional arousal. Respiration has also been more directly associated with affective manipulations in different contexts [12, 14].

In general it might be said that it is difficult to make clear predictions of the response of a certain physiological measurement after affective stimulation. Autonomic response patterns can be highly subject- and context-specific. Nevertheless, some studies succeeded in identifying robust patterns for given experimental contexts. In the next section we will discuss neurophysiological responses associated with different affective states.

2.2 NEUROPHYSIOLOGICAL CORRELATES OF AFFECTIVE PROCESSES

In the last twenty years many studies explored the neurophysiology of emotions. The findings are manifold and complex. This might be due to differences in stimulus characteristics, experiment design, subject populations and finally the complexity of emotional responses in the brain. Most EEG studies on affect have focused on event-related responses to emotional stimuli. Those correlates are valuable for the spatial and temporal localisation of emotional processes, but only of limited value for the classification of affective states in a natural environment. Thus we will focus here on findings in the frequency domain, first those for valence and then for arousal.

According to the "hemispheric valence hypothesis" positive approach-related emotions are mainly processed in the left frontal cortex. Negative withdrawal-related emotions, on the other hand, are processed in the right frontal cortex. As activity in cortex is inverse to alpha activity, this translates to a decrease of alpha power in the right frontal cortex for positive emotions and in the left frontal cortex for negative [11]. However, Mueller and colleagues [25] did not find hemispheric interactions with valence for alpha or beta bands. Instead they found a left hemisphere

increase of gamma activity for negative valence and a right hemisphere increase of gamma activity for positive valence. A role for fronto-medial theta power in emotional processes was suggested by Sammler et al. [29]. They observed an increase of theta for positive valenced music pieces.
Arousal, on the other hand, is supposed to activate neural structures, and therefore to decrease the overall level of alpha power and increase power in beta and gamma bands. Choppin [8] found this general alpha power decrease and a parietal beta power increase for arousing picture stimuli. Marosi et al. [24] showed an overall decrease of low alpha power for emotional sentences. However, Aftanas et al. [1] found an increase in the occipital low alpha band synchronisation for arousing picture stimuli. Furthermore, Keil and colleagues [16] found enhanced gamma responses toward arousing pictures. A similar gamma increase was shown by Mueller et al. [25] for emotional compared to neutral stimuli.

2.3 Classification of (neuro-)physiological correlates of affective processes

In the last sections plenty of evidence for the existence of (neuro-) physiological correlates of emotional processes was presented. This section will discuss studies that explore the automatic classification of affective states via these correlates. Physiological signals were classified with very high accuracy rates. Benovoy et al. [3] showed that four different emotions, elicited by method acting and visualisations, could be separated by their physiological characteristics with an accuracy of 90%. Kim et al. [18] even achieved for four musically induced affective states an average classification ratio of 95%. Neurophysiological signals, on the other hand, only reached relatively low classification accuracies. The differentiation between three emotional states (calm neutral, excited positive, excited negative) via neurophysiological signals was with an accuracy of 67% possible, for two classes with 76 - 79% accuracy [6]. Comparable rates were achieved for arousal classification in single subjects using affective pictures to induce emotions [7]. The direct comparison of physiological and neurophysiological studies is rather difficult as they apply different methods for the affect elicitation and different signal intervals (minutes vs. seconds).
Once the subject-specific distinguishability of different emotional states is shown the question arises, whether a classifier can be generalised to function for different subjects. In the above-mentioned study of Kim et al. [18] the authors also trained a subject-independent classifier that differentiated emotional states by physiological signals with an accuracy of 70%. Kim and colleagues [19] trained a classifier on the physiological signals of 50 children aged between seven and eight years. They achieved correct classification ratios of 61% and 78 % for four (sadness, anger, stress, and surprise) and three (all but surprise) classes, respectively. To date no study compared subject-specific and general classifiers build from neurophysiological features. However, Choppin [8] found a great variation between subjects' EEG responses co-occurring with affective states, suggesting a strong subject-specificity of neurophysiological emotional responses.
Another aspect of classifier generalisation to consider is whether the patterns of affective states that are collected over time can be used to obtain a stable classifier. In other words, are the potential day-to-day variations in our physiological responses accompanying affective states hindering the training of reliable classifiers? This question was addressed indirectly by two studies. Picard and colleagues [27] collected the physiological data over several weeks from the same subject. A classifier that was trained on the data discriminated among eight classes of emotion with an accuracy of 81%. Interestingly, this high accuracy was achieved despite a great variation between the daily measurements, probably originating from differences in sensor-placement and daily background mood.
Also Kim et al. [18] collected their physiological data over a period of several weeks. As already reported they recognised four affective states with 95% and 70% accuracy with a subject-dependent and -independent classifier, respectively. The high classification ratios show that autonomic nervous system patterns that co-occur with affective states are stable enough to train time-independent classifiers on them. Again no EEG study invested the generalization of a classifier over several days or weeks.
Summarising, it might be said that there is strong evidence for robust (neuro-) physiological features associated with affective processes. Classification studies employing physiological measurements achieved high rates and showed that physiological patterns of affective states generalise over subjects and time. While classification of affective states was shown for neurophysiological measurements, no study to date explored its generalisation over subjects and time. Furthermore, most studies were conducted in a limited and controlled experimental context. This is especially true for the few EEG studies and leaves several fundamental questions about the viability of (neuro-) physiological affect classification open: (1) generalisation over different stimulus modalities and (2) over different contexts. The next part will introduce the current state of the discussed research project and the broad agenda, which is intended to deal with at least some of the mentioned issues.

3. Current and planned research

In the last section several unanswered questions regarding the generalisation of affect classification were presented. Here I will outline approaches that are suited to answer some of the questions to a certain degree. The first experiment is already conducted and the data currently analysed. It will also be in the focus of the discussion section. Therefore the first experiment will be described in more detail, while the other ideas will only be sketched.

3.1 Eliciting affect via multimodal stimuli

In a first experiment the influence of different affect eliciting modalities was studied. On the one hand the question is how well the classification of affect generalises over different elicitation contexts, in this case auditory or visual. On the other hand I am interested in the classification of the affect eliciting modality itself. To study the effects that the different modalities have on neurophysiological affective responses, 180 multimodal stimuli were combined from the auditory and visual affective stimuli sets IADS and IAPS. The stimuli were combined in a way that allowed a grouping into auditory negative and positive, visual negative and positive, and multimodal neutral. The auditory negative consisted of a negative auditory stimulus and a neutral visual stimulus. The auditory positive group contained positive auditory and neutral visual stimuli. This way the affect elicitation was supposed to result from the auditory stimulus. Correspondingly, the visual negative and positive stimuli were created from a neutral auditory and a valence-holding visual stimulus. The multimodal neutral stimuli consisted of a neutral auditory and a neutral visual stimulus. This group was important as a control group, which enables the analysis of the specific effects of positive and negative stimulation, respectively. While the grouping is based on the distribution of the stimuli on the valence axis, the group differences on the arousal axis are kept comparable to avoid confounding effects. To assess the effect of the stimuli on the participant's affective state, a self-assessment manikin (9 point Likert scale) for the dimensions of valence (SAMv) and arousal (SAMa) is used. Each trial had therefore the following sequence of presentations: (1) a pre-stimulus period of 2 seconds only showing the fixation cross, (2) 6 seconds in which the multimodal stimulus is presented, (3) 2 seconds in which only the fixation cross is presented, (4) SAMv, (5) SAMa, and (6) 5 seconds of black screen. Thus a trial took about 20 seconds.

In case clear features and good classification results are yielded, the experiment could be extended by a temporal dimension. The repeated recording of participants over a longer period can inform about the generalization of (neuro-) physiological pattern over time, i.e. how robust a classifier would work after some time is passed.

3.2 Eliciting affective states via computer games - Pacman

For the elicitation of emotions in a more natural (task) context a modified version of the game Pacman was used [28]. The experiment described in that paper induced frustration by manipulation of the game flow and control responsiveness. Other manipulations of game speed or opponent intelligence might induce states of boredom, flow, and stress, to assess (neuro-) physiological differences between them and explore methods for their classification.

3.3 Assessing affective state via probe stimuli – testing a N400 approach

Another approach to emotion recognition could be based on the response of the central nervous system to certain probe stimuli. For example Allison and Polich [2] use probe stimuli to assess work load in video games via P300 ERP analysis. This probing is made possible by a negative relationship between attention response (indicated by P300 amplitude) and work load. For the analysis of emotional responses I plan to explore the N400 ERP. This potential is associated with semantic processing and appears when a (probe) stimulus semantically mismatches a preceding stimulus. Koelsch et al. [20] have shown that the effect of the N400 occurs in very broad contexts, for example when words expressing moods are succeeding excerpts of classic music. This might qualify the N400 response for the assessment of affective experience in movies or games by the exclusion of non-matching states.

3.4 Applying affect classification and neurofeedback approaches in games

To study the dynamics of conscious and unconscious affective feedback and its effect on the user experience in a computer game I will use the Pacman game just mentioned, which will be controlled in a traditional manner and by affective neurofeedback. The affective state of the user thereby integrated by a game logic to manipulate one or more parameters of the game. As a simple feature representing affective state one can use alpha activity over central or frontal electrodes. However, the described research on (neuro-) physiological correlates of affect is supposed to reveal further potential methods and features to determine the affective state of the user. These will provide more precise and robust means of affect classification.

4. DISCUSSING RELEVANT METHODOLOGICAL ISSUES

I would like to use the discussion to bring some specific issues related to my first experiment to the attention of the committee. First I will lay out problems related to the grouping of the trials using the self-assessment method. Then I will address the conflicts for experiment design introduced by the use of physiological *and* neural measurements. Finally, the issue of temporal precision in the analysis of neurophysiological features will be discussed.

As already mentioned, the self-assessment is the basis of the classifier training, as it determines the ground truth for the training samples. Analysis of the mean stimulus valences suggested that the emotion induction did work (Table 1 left). The mean values behaved according to the group membership (N+: positive, Nn: neutral, N-: negative). However, for many stimuli the induced emotions differed from the emotions the stimuli were supposed to induce. This was also reflected by participants' reports after the experiments. For example, a starving African child on a blue blanket was perceived as cared for and elicited a calm and rather positive response, while it was intended to elicit a negative reaction. These deviations from the original grouping of the stimuli are natural taking the individual differences between participants into account. Those differences are already reflected in the standard deviations that characterise the (norm) ratings of the individual stimulus sets, IAPS and IADS. Therefore, the overall grouping of trials into the three emotion classes, independent from the elicitating modality, is not straightforward. Grouping the trials according to the ratings, we observe a trend towards the middle, thus toward the neutral class (S1n), while the positive (S1+) and negative (S1-) classes are underrepresented in the data (Table 1 upper right). However, by assuming each rating that deviates from the middle of the Likert scale by one scale unit towards one end of the scale to result from a negative or positive affective response, the S2 grouping is obtained (Table 1 lower right). Here the responses are equally distributed over all 3 classes (S2+, S2-, and S2n), as the neutral class is narrowed down to 1 Likert point. Of course, this results in smaller differences of the mean valences between the emotion conditions.

Group	Valence mean (std)	Arousal mean (std)
N+	5.29 (1.58)	4.01 (1.84)
Nn	4.49 (1.35)	3.75 (1.86)
N-	3.04 (1.70)	5.02 (2.03)
S1+	6.79 (0.64)	3.71 (1.94)
S1n	4.4 (0.74)	3.76 (1.78)
S1-	1.79 (0.75)	5.88 (1.59)
S2+	6.22 (0.81)	3.79 (1.89)
S2n	4.47 (0.13)	3.41 (1.70)
S2-	2.37 (0.98)	5.34 (1.79)

	N+	Nn	N-	sum
S1+	270	104	38	412
S1n	386	519	313	1218
S1-	60	97	369	526
sum	716	720	720	2156
S2+	426	216	92	734
S2n	162	308	140	610
S2-	128	196	488	812
sum	716	720	720	2156

Figure 1. The left table shows the mean and standard deviations of the self-assessments for the emotion conditions according to the different grouping methods (N, S1, S2). The right table shows the relations between the intended grouping of trials and the grouping according to the 3-point sized neutral class (upper right) and the 1-point sized neutral class (lower right).

The combination of auditory and visual stimuli complicates the matter further. In the experiment I constructed the emotional stimuli from one emotion inducing part and one neutral part. A preliminary analysis suggests that the planned fragmentation of the trials into groups of 30 stimuli for each emotion-modality pair does not coincide with the self-assessments. Therefore the direct comparison of the effect of an eliciting modality for a certain emotional reaction, positive or negative, is not viable if the self-assessment data is used as ground truth. However, the comparison of the effect of the eliciting modality of emotional reactions in general might still deliver valuable information. Eventually, a classification of an emotional reaction might not only be helped by a better understanding of modality specific parts, but might guide the determination of potential emotion eliciting events.

A more general problem of all approaches to correlate neurophysiological and physiological measurements to affective processes are the different requirements of the recording methods. The low signal-to-noise ratio of EEG signals requires many trials of affective responses. As neurophysiological processes are fast paced and relatively short this high number of trials can be gained by a fast-paced presentation of affective stimuli. However, the response of physiological sensors, as ECG or GSR, is rather sluggish and needs several seconds to start and several more to reach its peak. Thus, both sensor groups have conflicting requirements. A fast-paced presentation of many affective stimuli is also contraindicated by a potential habituation of the participants to the emotional content of the stimuli. A longer and more intense induction of affective states might be a viable EEG paradigm if the lengthy trials could be split in subtrials, resulting in a higher number of features per condition. However, the features extracted in this fashion could be highly dependent or, on the other hand coincide with different consecutive cognitive processes. Furthermore, the analysis of neurophysiological responses toward affective stimuli is often focused on the few 100 milliseconds after stimulus presentation. This makes sense in the context of the analysis of fast affective processes that follow stimulus presentation. The component process theory [30], for example, assumes that affective responses are a chain of evaluation processes conducted partially automatically within very short intervals. Each of these processes is supposed to have its own neural signature. Therefore, an evaluation of neural responses that takes several seconds into account sees only a rough summation of different response correlates, instead of the individual affective responses. However, without the use of probe stimuli as is the case in natural gaming scenarios, no information about onset of the affective process is available and thus an analysis with temporal precision impossible.

5. Conclusion

In this proposal I motivated and outlined a project for the study of (neuro-) physiological correlates of affective experience and their classification. It was shown that physiological and neurophysiological measurements can inform about affective states and are suited for automatic classification approaches. However, several open questions regarding the (task) context-, (elicitation) modality-, subject-, and time-independent classification of affective experience were detailed. I proposed three approaches to investigate the (neuro-) physiological correlates over different elicitation-modalities and task context.

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References

[1] Aftanas, L. I., Reva, N. V., Varlamov, A. A., Pavlov, S. V., and Makhnev, V. P. (2004). Analysis of evoked EEG synchronization and desynchronization in conditions of emotional activation in humans: temporal and topographic characteristics. *Neuroscience and behavioral physiology*, 34(8), pages 859-867.

[2] Allison, B. Z. and Polich, J. (2008). Workload assessment of computer gaming using a single-stimulus event-related potential paradigm. *Biological psychology*, 77(3), pages 277-283.

[3] Benovoy, M., Cooperstock, J. R., and Deitcher, J. (2008). Biosignals analysis and its application in a performance setting - towards the development of an emotional-imaging generator. *IEEE International Conference on Bio-Inspired Systems and Signal Processing*, pages 253-258, Funchal, Portugal.

[4] Bradley, M. M. and Lang, P. J. (2000). Affective reactions to acoustic stimuli. *Psychophysiology*, 37(2), pages 204-215.

[5] Cacioppo, J. T., Petty, R. E., Losch, M. E., and Kim, H. S. (1986). Electromyographic activity over facial muscle regions can differentiate the valence and intensity of affective reactions. *Journal of personality and social psychology*, 50(2), pages 260-268.

[6] Chanel, G., Asl, K. A., and Pun, T. (2007). Valence-arousal evaluation using physiological signals in an emotion recall paradigm. *In Proceedings of the IEEE SMC and International Conference on Systems, Man and Cybernetics, Smart cooperative systems and cybernetics: advancing knowledge and security for humanity*, pages 2662-2667, Montreal, Canada.

[7] Chanel, G., Kronegg, J., Grandjean, D., and Pun, T. (2005). Emotion assessment: Arousal evaluation using eeg's and peripheral physiological signals. *Technical report*, Computer Vision and Multimedia Laboratory, Computing Centre, University of Geneva, Switzerland.

[8] Choppin, A. (2000). EEG-based human interface for disabled individuals: Emotion expression with neural networks. *Unpublished master's thesis*. Information processing, Tokyo institute of technology, Yokohama, Japan.

[9] Codispoti, M., Bradley, M. M., and Lang, P. J. (2001). Affective reactions to briefly presented pictures. *Psychophysiology*, 38(3), pages 474-478.

[10] Cowie, R., Douglas-Cowie, E., Tsapatsoulis, N., Votsis, G., Kollias, S., Fellenz, W., and Taylor, J. G. (2001). Emotion recognition in human-computer interaction. *IEEE Signal Processing Magazine*, 18(1), pages 32-80.

[11] Davidson, R. J. (1992). Anterior cerebral asymmetry and the nature of emotion. *Brain and Cognition*, 20(1), pages 125-151.

[12] Etzel, J., Johnsen, E., Dickerson, J., Tranel, D., and Adolphs, R. (2006). Cardiovascular and respiratory responses during musical mood induction. *International Journal of Psychophysiology*, 61(1), pages 57-69.

[13] Frazier, T. W., Strauss, M. E., and Steinhauer, S. R. (2004). Respiratory sinus arrhythmia as an index of emotional response in young adults. *Psychophysiology*, 41(1), pages 75-83.

[14] Gomez, P., Shafy, S., and Danuser, B. (2008). Respiration, metabolic balance, and attention in affective picture processing. *Biological Psychology*, 78(2): pages 138-149.

[15] Gray, E. and Watson, D. (2007). Assessing positive and negative affect via self-report. In J. A. Coan, and J. J. B. Allen (Eds.), *Handbook of Emotion Elicitation and Assessment*. New York: Oxford University Press, USA.

[16] Keil, A., Müller, M. M., Gruber, T., Wienbruch, C., Stolarova, M., and Elbert, T. (2001). Effects of emotional arousal in the cerebral hemispheres: a study of oscillatory brain activity and event-related potentials. *Clinical Neurophysiology*, 112(11), pages 2057-2068.

[17] Khalfa, S., Isabelle, P., Jean-Pierre, B., and Manon, R. (2002). Event-related skin conductance responses to musical emotions in humans. *Neuroscience letters*, 328(2), pages 145-149.

[18] Kim, J. and André, E. (2008). Emotion recognition based on physiological changes in music listening. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 30(12), pages 2067-2083.

[19] Kim, K., Bang, S., and Kim, S. (2004). Emotion recognition system using short-term monitoring of physiological signals. *Medical and Biological Engineering and Computing*, 42(3), pages 419-427.

[20] Koelsch, S., Kasper, E., Sammler, D., Schulze, K., Gunter, T., and Friederici, A. D. (2004). Music, language and meaning: brain signatures of semantic processing. *Nature Neuroscience*, 7(3), pages 302-307.

[21] Lang, P. J., Greenwald, M. K., Bradley, M. M., and Hamm, A. O. (1993). Looking at pictures: Affective, facial, visceral, and behavioral reactions. *Psychophysiology*, 30(3), pages 261-273, 1993.

[22] Magnée, M. J., Stekelenburg, J. J., Kemner, C., and de Gelder, B. (2007). Similar facial electromyographic responses to faces, voices, and body expressions. *Neuroreport*, 18(4), pages 369-372.

[23] Mandryk, R. L., Inkpen, K. M., and Calvert, T. W. (2006). Using psychophysiological techniques to measure user experience with entertainment technologies. *Behaviour & IT*, 25(2), pages 141-158.

[24] Marosi, E., Bazán, O., Yañez, G., Bernal, J., Fernández, T., Rodríguez, M., Silva, J., and Reyes, A. (2002). Narrow-band spectral measurements of EEG during emotional tasks. *The International Journal of Neuroscience*, 112(7), pages 871-891.

[25] Mueller, M. M., Keil, A., Gruber, T., and Elbert, T. (1999). Processing of affective pictures modulates right-hemispheric gamma band EEG activity. *Clinical Neurophysiology*, 110(11), pages 1913-1920.

[26] Picard, R. W. (1997). *Affective Computing*. Cambridge: MIT Press, USA, 1997.

[27] Picard, R. W., Vyzas, E., and Healey, J. (2001). Toward machine emotional intelligence: Analysis of affective physiological state. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 23(10), pages 1175-1191.

[28] Reuderink, B., Nijholt, A., and Poel, M. (2009). Affective pacman: A frustrating game for brain-computer interface experiments. *In Intelligent Technologies for Interactive Entertainment*, volume 9, pages 221-227.

[29] Sammler, D., Grigutsch, M., Fritz, T., and Koelsch, S. (2007). Music and emotion: Electrophysiological correlates of the processing of pleasant and unpleasant music. *Psychophysiology*, 44(2), pages 293-304.

[30] Sander, D., Grandjean, D., and Scherer, K. R. (2005). A systems approach to appraisal mechanisms in emotion. *Neural Networks*, 18(4), pages 317-352.