Towards Emotion Aware Computing: a study of Arousal Modulation with Multichannel Event-Related Potentials, Delta Oscillatory Activity and Skin Conductivity Responses

Christos A. Frantzidis, Chrysa D. Lithari, Ana B. Vivas, Christos L. Papadelis, Costas Pappas and Panagiotis D. Bamidis

Abstract—**Emotion identification has recently been considered as a key element in contemporary studies for advanced human-computer interaction. The achievement of this goal is usually attempted via methods incorporating facial expression and speech recognition, as well as, human motion analysis. In this paper it is attempted to fuse multi-modal physiological signals of the autonomic (skin conductance) and central nervous systems (EEG), through the use of appropriate feature extraction procedures discriminating emotional arousal modulations, to a neural network classifier. Thus, skin conductivity responses, evoked-related potential peaks, and delta frequency oscillatory patterns are analyzed for a comparatively large number of subjects exposed to different emotions, evoked by pictures selected from the International Affective Picture System. The achieved neural network classifications were encouraging. It was found that fear was successfully differentiated (100%), pleasant emotions differing in their arousal level were well distinguished (80%), but the discrimination of low arousing negative feelings such as melancholy was more difficult (70%). It is argued that physiological patterning of multimodal recordings may successfully contribute to the enhancement of human computer interaction and emotion aware computing.**

I. Introduction

THE improvement of the interaction between humans and computers is essential for the development of intelligent interfaces which may be useful in a wide range of applications such as e-health, education and learning, and elderly care [1]. For example, a virtual tutor can adjust the lesson according to the individual skills and abilities, as well as, the current state and circumstances of each student. Moreover, such interfaces can be extremely useful in web applications, where they can cope with emotions such as frustration or anger when facing difficulties to fill in an electronic form or to complete a task or even to navigate through a web interface. To achieve this goal, human computer interaction (HCI) should get closer to human-human interaction (HHI). Humans communicate each other mainly due to their skill of emotional understanding. According to [2] the successful interaction of computers with humans will adopt basic principles required for the communication among human beings. Therefore, a subset of human emotional skills should be embedded to machines in order to facilitate them with adequate intelligence for adapting their behavior more suitably to the interacting with them people.

However, the task of discriminating human emotions is not a simple one to achieve. This is due to many reasons. First, the inherent emotion related physiology has not been well researched yet. In addition, there are problems in human-human interactions: e.g. the inability to understand emotions and needs of family, friends and colleagues, is the most common cause of conflict in one's daily lives. Furthermore, in many cases some innermost emotions remain completely unrecognizable even by humans. Last but not least, the human body responds in almost a similar way to certain emotions which are very different, like erotic lust and fear.

In order to succeed in giving computers the ability to discriminate the human feelings, we should think about the ways that we use to understand the mood of the person with whom we want to interact. For example, a teacher can alter her tone of voice in order to encourage her students or to keep them silent. Furthermore, she could change her facial expression or her posture when she recognizes the boredom or the frustration of the students. Gestures or different postures may be used to emphasize an important fact. Consequently, it is desirable to envisage the interaction richness of computers to all the aforementioned ways used by people upon communicating with each other. Apart from the use of human natural senses, as mentioned in [3] emotions can efficiently be recognized by means of physiological recording heart rate, the electrodermal activity measured in palmar or plantar surfaces, the respiration rate, the electromyographic activity of certain muscles and the cerebral activity as recorded by the Electroencephalogram (EEG).

The study of electric potentials measured on the human scalp can lead to a unique richness of neurophysiological

Manuscript received July 5, 2008
Christos. A. Frantzidis is with the Lab of Medical Informatics, Medical School, Aristotle University of Thessaloniki, P.O. Box 323, 54124 phone: +30-2310-999-332; fax: +30-2310-999-263; e-mail: christos.frantzidis@gmail.com.

Chrysa. D. Lithari, Costas Pappas and Panagiotis D. Bamidis are with the Lab of Medical Informatics, Medical School, Aristotle University of Thessaloniki, P.O. Box 323, 54124

Ana B. Vivas is with the Psychology Department, City Liberal Studies(Affiliated Institution of the University of Sheffield), Greece

Christos L. Papadelis is with the Laboratory of Human Brain Dynamics, RIKEN, Japan

findings that will not only enhance the classification rates in emotion recognition tasks, but will also provide neuroscientists with useful information for the better understanding of various cognitive approaches during emotional processing. Event-related potentials and tomographic estimates of brain activity may map the temporal brain activity due to emotionally evocative stimuli, coupling the involved emotions to specific brain regions [4]. Time-frequency analysis of the cerebral oscillatory activity caused by an emotional stimulus may reflect the intrinsic membrane properties of single neurons as well as the organization and inter-connectivity of functioning networks, which result in coherent neuronal activity exercised by large neuronal pools in distributed or restricted brain regions [5].

The main theories about the processes that lead to emotional activation and modeling are the Darwinian, the cognitive and the Jamesian ones [6]. The Darwinian theory correlates the emotions with their contribution to survival. The cognitive approach attributes to the human brain a central role for emotional processing according to the situation judgment as either good or bad. The last theory regards emotions as the perception of body changes and favors the role of the physiological responses. Originating from cognitive theory, emotions are regarded as points in a 2D emotional space. The dimensions are valence, which divides emotions to pleasant and unpleasant, and arousal, which judges a specific emotion as either calm or excited.

To contribute to the research of finding ways to facilitate computers with the ability to recognize human emotions, we conducted an experiment that aimed to study the neurophysiological signatures of human emotions. The elicited motions differed in their arousal and valence dimensions as those were evoked by selected pictures from the International Affective Picture System (IAPS) [7]. The recordings of signals were obtained from both the autonomic and the central nervous systems. In this context, the present work aims at assessing the arousal dimension of human emotions by analyzing the multimodal recordings and classifying them by means of a neural network classifier.

So, in the remaining of this paper, necessary background knowledge is provided in section II, followed by a presentation of the experimental and preprocessing details. Theoretical and analytical steps of the feature extraction procedures are presented in section IV. The classification results achieved by the neural networks employed are subsequently provided and discussed in the last couple of sections.

II. PREVIOUS WORK

During the last few years there is growing evidence that fusing physiological recordings of the nervous system activities could lead to the formation of the scientifically sound signatures for a wide range of human emotions.

One decade ago, in the pioneering work of the MIT Media Lab [8] a single subject intentionally expressed eight affective states over a period of more than a month. During the experiment EMG activity on the masseter muscle, skin conductivity and respiration rate were recorded. From these signals a set of eleven features was extracted in order to discriminate between eight affective states by means of pattern recognition techniques such as the Fisher linear discriminant projection and the leave one out test method. Anger was fully discriminated from the peaceful emotions. Furthermore the eight emotions were separated into two classes according to their arousal dimension, but the study failed to distinguish between pleasant and unpleasant emotions. A later work of the same team [9], improved the results achieving 81% recognition accuracy by seeding a Fisher Projection with the results of Sequential Floating Forward Search. The latter was the first ever work to report similarities among physiological features for different emotions on the same day, which partially explains the difficulties on user-independent emotion recognition.

The aforementioned studies inspired the recent work conducted in [10]. More specifically, physiological data from the autonomic nervous system were gathered from a single subject on different days and different times of the day. Additionally to the previously used sensors, a Blood Volume Pressure (BVP) was used. A great number of data segments (1000) was extracted and used for training a neural network classifier. The duration of each segment was set at two seconds. Due to the large number of feature vectors (700 for training, 150 for testing and 150 for validation) it was feasible to robustly detect both arousal (96.58%) and valence (89.93%) dimensions of the emotions elicited by a single subject, when exposed to photos from the IAPS set.

Another study [11] used a long (45 min) show of slides and movie clips to elicit emotions in a fixed order. The emotion recognition task used non-invasive wearable sensors to gather data such as heart rate, skin temperature and phasic increases of the subject’s electrodermal activity. Unlike to previous studies, the sample included 29 participants. Twelve features were extracted and three supervised algorithms were implemented. The results were promising. Recognition rates greater than 85% were achieved for all the emotions except surprise and frustration.

A recent study used fusion of EEG and peripheral data for the arousal evaluation using emotionally evocative pictures selected from IAPS [12]. Peripheral signals included blood pressure, skin conductivity, heart rate, respiration and temperature. The data from the central nervous system included power values representing frequency bands from theta, beta, gamma, alpha and beta oscillations. The number of participants was very limited and the best performance achieved was 55%. Despite the fact of the poor arousal discrimination, this study shows that more research efforts should be done towards the integration of EEG (and perhaps MEG) data with the well studied signals derived from the autonomic nervous system.

III. MATERIALS & METHODS

A. The AFFECTION project context

This work is part of the AFFECTION collaborative project, between the Medical Informatics at the Medical School of the Aristotle University of Thessaloniki, Greece, and the Brain Science Institute of RIKEN in Japan. It aims at the robust identification of discrete human emotions elicited from selected IAPS pictures.

Healthy adults (13 men and 13 women) are being exposed to emotionally evocative-stimuli. The experiment consists of pictures, selected from IAPS, presented on a PC monitor in random order. Each picture has a specific (L for Low, H for High) Valence-Arousal dimension (HVHA, LVLA, LVHA, HVLA). There are 40 trials from each one of the four affective space conditions. Consequently, the participant passively views 160 pictures. Each photograph is presented during 1 second. Between two successive visual stimuli, a central fixation cross appears for 1500ms. During the experiment we recorded EEG (10/20 system) and Skin Conductance Responses (SCRs).

B. Recording & Pre-processing

EEG was recorded with Ag/AgCl electrodes from nineteen sites according to the international 10-20 system, with reference electrodes placed on the left and right ear lobe. The sampling frequency was set at 500Hz. All impedances were maintained at less than 20 KΩ. Vertical and horizontal eye movements were tracked with the same recording parameters as for EEG via four electrodes placed one above and one below the left eye and two at the outer canthus of both eyes. The signals were filtered of-line with a high-pass filter with cut-off frequency at 0.5 Hz, followed by a notch filter of 50Hz. Finally, a low-pass filter was applied with cut-off frequency at 40Hz. Then, the Infomax Independent Component Analysis (ICA) technique was applied to remove artifacts caused by eye blinks and eye or muscle movements. The pre-processing of EEG data was performed by means of the EEGLAB software coded in MATLAB

Skin conductance was recorded via a pair of silver-silver chloride electrodes. Gel was placed on the medial phalanges of digits II and III of the non dominant hand. Baseline removal took place as a first step in order to remove linear trends. Then the signal was digitally filtered by means of a low-pass short IIR with cut-off frequency at 2.5 Hz. The skin conductance data were synchronized with EEG data in order to form epochs according to stimulus onset. Then, the average signal was computed for each stage.

IV. FEATURE EXTRACTION

A. Theoretical Foundation

EEG analysis aimed at studying the brain mechanisms underlying human emotional processing by measuring event-related potentials (ERPs) and oscillatory activity. ERP analysis is focused on the detection of time-locked changes in the activity of large pools of neurons. The theoretical foundation of this type of analysis lies with the fact that cerebral activity induced by visual-stimuli, has an "almost" fixed, time-delay to the stimulus onset, while the rest of EEG activity can be regarded as "additive noise". For the reliable detection of the ERPs components an averaging process takes place in order to enhance the signal-to-noise ratio. Then, a single peak detection algorithm applied in a restricted time series region in order to encounter short declines among subjects can identify the local maxima and minima of interest.

However, the above simple theoretical model even though widely used, is just a rough approximation of the reality. The basic model assumption that an event-related potential representation can be made by a signal added to uncorrelated noise, does not hold in cases where the amplitude of the ongoing EEG activity is reduced due to the visual stimulus. The above changes are not phase-locked to the picture onset and may be better detected by frequency analysis of the ERP components. This motivated us to study the oscillatory activity of the averaged ERPs on the delta frequency band. The motivation for the analysis of the specific frequency band was the fact that previous studies reported increase of delta oscillatory activity during sexual arousal induced by erotic films [13]. These waves centered around 4 Hz were mainly located on the right parietal lobe. Furthermore, delta waves are associated with the P300, which is an ERP component observed as a response to either unexpected or motivationally relevant tasks. Previous studies demonstrated that P300 amplitude is increased during the view of arousing visual stimuli [14]. Due to this fact, delta oscillations were chosen as indicators of arousing states.

Skin conductivity reflects the activity of sweat glands which are innervated by the sympathetic branch of the autonomic nervous system. They are located mainly on palmar and plantar surfaces of the human body. The electro-dermal activity measured on these surfaces is modulated by emotional stimuli and can be divided into the skin conductance level (SCL), which is a tonic level of autonomic arousal and the skin conductance response (SCR), which is a phasic arousal indicator as a response to an unexpected stimulus [15].

B. Features based on ERPs

The data from frontal (Fz), central (Cz) and parietal sites (Pz) distributed along the anterior-posterior midline of the brain, were analyzed and their main ERP components were extracted. As shown in Figure 1 a window from 100 to 200 ms can capture the local minimum which corresponds to the N100 component. This component is more pronounced for the negative stimuli as well as for pleasant pictures that cause excitation to the subjects. Subsequently, a prominent positive peak can be detected by means of a time window centered at 200 ms after stimulus onset. Then, N200 is observable between 200 and 300 ms. As for the late P300 event-related potential can be detected using a time window between 300 and 400 msec.

The described peak latencies are consistent to all three electrode sites that were analyzed. All the peaks were analyzed using the maximum and minimum values between the described time windows. Statistical analysis was applied to the obtained values in order to estimate the discrimination capacity with regards to the ERP components. Statistical analysis revealed several ERP components modulated by the arousal dimension of the human emotion model. The electrode sites found to mainly contribute to the discrimination task were the Pz and Cz. From the plethora of useful findings revealed by the analysis of variance (ANOVA), a selection was made according to their arousal discrimination. The five features selected were P300 and P100 recorded at the Pz electrode and P100, N100 and P300 recorded at the Cz electrode. The p-values for the selected features range from 0.00457 to 0.000002, which is an indication of their robustness.

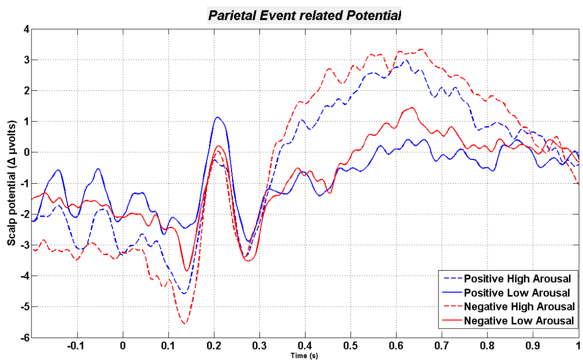

Fig.1. Stimulus synchronized grand average ERP waveform for Pz electrode during viewing of emotionally evocative pictures selected from International Affective Picture System (IAPS), separately for each

C. *Features Based on Delta Oscillatory Activity*

The average signals from all the electrode sites were digitally filtered by means of a second order band-pass Butterworth filter on the delta frequency band (0.5-4 Hz). As shown in Figure 2, the delta pattern is mainly modulated by the arousal dimension and could be used for discrimination purposes.

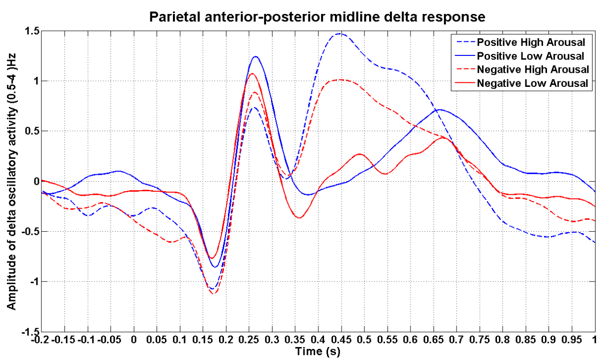

Fig.2. Stimulus synchronized grand average delta oscillatory response for Pz electrode during viewing of emotionally evocative pictures

The feature evaluation process indicates that there are more features that can discriminate arousal among pleasant pictures than among negative pictures. So, three features were selected for the arousal discrimination of unpleasant photographs, whereas one more was selected for the pleasant ones. However, for both categories the vast majority of features associated with the delta oscillations are found in parietal locations.

D. *Skin Conductance Features*

The averaged filtered signal representing the electro-dermal activity during the experiment which was obtained by the pre-processing step was served as an input to a peak-detection algorithm. This algorithm, based on derivative changes, was used for the computation of the skin conductance characteristics that may serve as features for the discrimination of the autonomic arousal. The computed features were the latency, rise time, amplitude and SCR duration. Latency was defined as the temporal interval between stimulus onset and SCR peak. As SCR amplitude was regarded the phasic increase in conductance from SCR initiation till the time of the peak response. The SCR rise time was set as the temporal interval between stimulus onset and SCR initiation. As shown in Figure 3, there are noticeable differences between the signals obtained from each one of the four different emotional categories. The most prominent increase in the electro-dermal activity was observed during the viewing of positive and excited pictures, which mainly are erotic photographs. Negative stimuli elicit great increases, irrespectively of their arousal dimension. On the other hand, pleasant and calm photographs elicit delayed responses that present significantly smaller amplitudes in comparison to the other categories of visual stimuli. Consequently, the skin conductance amplitude served as feature only for the arousal discrimination between pleasant pictures.

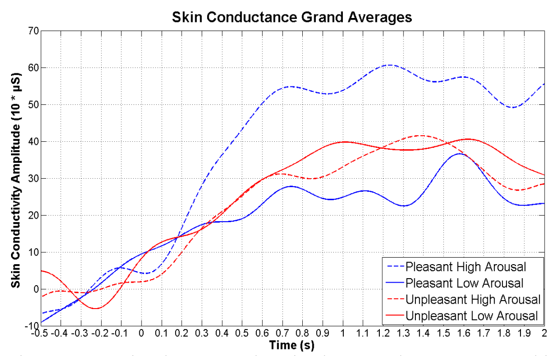

Fig.3. Stimulus synchronized grand average skin conductivityresponse during viewing of emotionally evocative pictures selected from IAPS, separately for each one emotional category

E. *Features Fusion*

The statistical analysis of variance (ANOVA) revealed statistically significant or marginally significant gender by arousal interaction for almost all the features used for the discrimination task. Consequently, a new feature describing the subject's gender was introduced.

Summarizing, there were seven features used for the arousal identification among the unpleasant pictures and nine features for discriminating arousal among the pleasant ones.

V. CLASSIFICATION & RESULTS

After the extraction of the features, a neural network classifier was used for the arousal discriminating task. Two different networks were used according to the valence dimension of the visual stimulus. Avoiding, the use of the same features or the same network for both positive and negative pictures was the appropriate choice to account for the role of the valence effects expressed by the different cerebral networks used by the human brain upon processing fearful or pleasant stimuli.

The two distinct networks were both multiple-layer consisting of an input vector, one hidden layer and a single output layer. The feed-forward architecture was selected. The type of the learning rule they both used was the back propagation. The target vector was 0 for low arousal stimuli and 1 for high arousal. Similarly, the gender feature was consisted of ones for female subjects and zeros for males. All the other features consisted of their values as obtained by the analysis, since no normalization process took place. Due to the binary output, the log-sigmoid transfer function, which generates outputs ranging from zero to one, was used. For each network there are 26 feature vectors available. Each vector corresponds to a single subject. Sixteen vectors were used for training and the remaining ten for the network evaluation procedure. Equal number of male and female subjects was used both for training and testing. The traditional back-propagation training algorithms were not preferred due to their extremely slow convergence. Moreover, their performance was limited at almost 70% of correct arousal discrimination. Consequently, the appropriate choice was to use faster and more robust algorithms for training the networks.

The network used for the arousal detection among positive pictures consists of an input layer with six neurons and three hidden neurons. The output layer as mentioned above consists of a single neuron. The conjugate gradient algorithms search along conjugate directions and converge faster. However, they require a line search at each iteration, which is computationally expensive. The scaled conjugate gradient algorithm was selected for trainining this network because it avoids this type of search by combining the model-trust region approach with the conjugate gradient approach. The learning rate was set at 0.01 and the network's goal was to achieve mean square error smaller than 0.00001.

The network used to discriminate the arousal dimension among unpleasant photographs consisted of an input vector with seven neurons and a hidden layer of four neurons. The gradient descent with momentum was selected as the training algorithm for this network, because it responds not only to the local gradient, but also to recent trends in the error surface. This feature allows the network to circumvent shallow local minima. The learning rate in this case was set at 0.03.

The network's performance depends partially to the initial values assigned to the neurons' weights. For improving the network's performance an initial training took place and the network was evaluated using the ten vectors that were not used for training. In case of recognition rates greater than 70%, the network's weights were saved and served as an input to a new training.

The classification results, which are shown in Table I, indicate that unpleasant and highly arousal photographs, related to anger, fear and threat-related stimuli produce a distinct neurophysiological signature. So, the discrimination process of these stimuli was achieved with 100% success, whereas the recognition of emotions such as melancholy was more difficult. On the other hand, pleasant pictures were distinguishable in a sufficient way according to their arousal dimension..

TABLE I
CLASSIFICATION RESULTS

Emotion	Size	Classification Rate
Joy	10	80%
Fear	10	100%
Happiness	10	80%
Melancholy	10	70%

Classification results for pleasant and unpleasant emotionally evocative stimuli selected from International Affective Picture System (IAPS) indicates that multimodal recordings from peripheral and EEG data can lead to successful emotion recognition according to the arousal dimension

VI. DISCUSSION & FUTURE WORK

This paper has suggested that physiological patterning of multimodal recordings can contribute to the enhancement of human computer interaction providing the computers with the ability to recognize the user's emotional state and adapt their behavior in order to interact more sufficiently and successfully with people. The novelty of our contribution is the development of a user-independent classifier instead of gathering physiological data from one subject over many weeks. Most of the previous attempts of emotion recognition with the use of physiological signals have mainly focused on collecting data from the autonomic nervous system. They used features obtained by first order statistics like mean values, standard deviation and first derivatives. These characteristics are mainly quantitative, whereas the features used in our study are mostly quantitative (e.g. skin conductance amplitude). In general, the use of features from the central nervous system has been very limited in past literature, thereby limiting access to the understanding of emotion elicitation due to fear, anger, joy or sexual lust. In one study [12], researchers used the fusion of EEG and peripheral data, acquired from only four participants. Three of them were males. The EEG analysis focused only on obtaining the power values of the various frequency bands and no ERP analysis took place. The best performance achieved by this approach was only 72% arousal discrimination. Consequently, to the best of our knowledge no other method previously proposed the emotion recognition based on peripheral (Skin Conductivity) and central nervous system (EEG, event-related potentials and event-related oscillations) data collected from many subjects by means of emotionally evocative pictures selected from the IAPS and differing both in their arousal and valence dimension. The fusion of features which was obtained by three different aspects of the nervous system enhanced the robustness of the proposed classifier which is suitable to efficiently detect the subject's level of arousal regardless of his/her personality.

Our results imply successful arousal discrimination and are promising in terms of creating affective applications with adapting learning abilities. However, much further work needs to be done. Even if the task of adequately discriminating arousal is achieved, serious efforts should be done to distinguish between pleasant and unpleasant pictures. The combination of both dimensions will provide a physiological signature for a range of discrete human emotions. We expect that including recordings from other signals such as ECG or EMG and further analysis of the existing signals will lead to significant improvements in the machine recognition of user emotion. More sophisticated classification techniques based on unsupervised learning as well as with the use of fuzzy architectures will be adopted in order to enhance the method's robustness.

These results indicate that multimodal recordings from both the autonomic and the nervous system can be combined and discriminate subsets of discrete human emotions, which differ according to their arousal dimension.

ACKNOWLEDGMENT

This work has been benefited by a grant from the Greek GENERAL SECRETARIAT FOR RESEARCH & TECHNOLOGY, and the MSc in Medical Informatics Programme, at the Aristotle University of Thessaloniki, Greece.

REFERENCES

[1] A. Luneski, P. Bamidis, M. Hitoglou-Antoniadou, "Affective Computing and Medical Informatics: State Of The Art in Emotion-Aware Medical Applications", in Stud Health Technol Inform. 2008;136:517-22

[2] B. Reeves and C. Nass, "The Media Equation" ,Cambridge University Press; Center for the Study of Language and Information, 1996.

[3] P. D. Bamidis et. al., "Multi-channel physiological sensing of human emotion: insights into Emotion-Aware Computing using Affective Protocols, Avatars and Emotion" in *Proc. of Medinfo 2007.Brisbane*, Australia, 2007, pp.106 8–1072.

[4] P. D. Bamidis et. al., "Affective computing in the era of contemporary neurophysiology and health informatics", *Interacting with Computers*, vol.16, pp. 715–721, 2004.

[5] C. Neuper and G. Pfurtscheller, "Event-related dynamics of cortical rhythms: frequency-specific features and functional correlates", Internatiional Journal of Psychophysiology, vol. 43, 2001, pp. 41-58

[6] R.R. Cornelius, "Theoretical approaches to emotion", ISCA Workshop on Speech and Emotion, Belfast 2000

[7] P.J. Lang, M.M. Bradley and B.N Cuthbert "International Affective Picture System (IAPS): Technical Manual and Affective Ratings" , NIMH Center for the Study of Emotion and Attention, 1997

[8] J. Healey and R. W., "Digital Processing of Affective Signals", in *Proc. of ICASSP, Seattle, 1998, pp.3749-3752*

[9] R.W. Picard, E. Vyzas and J. Healey, "Toward Machine Emotional Intelligence: Analysis of Affective Physiological State" *IEEE Trans. Pattern Analysis and Machine Intelligence* , vol.23, no. 10, pp. 1175–1191, Oct. 2001.

[10] A. Haag, S. Goronzy, P. Schaich and J. Williams "Emotion recognition Using Bio-Sensors: First Steps Towards an Automatic System" in Lecture Notes in Computer Science,Affective Dialogue Systems, vol 3068/2004, Springer Berlin/Heidelberg, pp. 36-48

[11] C. L. Lisetti and F. Nasoz, "Using Noninvasive Wearable Computers to Recognize Human Emotions from Physiological Signals" , EURASIP Journal on Applied Signal Processing, vol. 2004 (11), 2004, pp. 1672–1687.

[12] G.Chanel, J. Kronegg, P. Schaich and J. Williams "Emotion recognition Using Bio-Sensors: First Steps Towards an Automatic System" in Lecture Notes in Computer Science,Multimedia Content Representation, Classification and Security, vol 4105/2006, Springer Berlin/Heidelberg, pp. 530-537

[13] H. D. Cohen, R. C. Rosen, L. Goldsten, "EEG hemispheric asymmetry during sexual arousal: psychophysiological patterns in responsive, unresponsive and dysfunctional men", Journal of Abnormal Psychology, vol. 94, 1985, pp. 580-590.

[14] G. G. Knyazev, "Motivation, emotion, and their inhibitory control mirrored in brain oscillations", Neuroscience and Biobehavioral Reviews,vol. 31, 2007, pp.377-395

[15] D. M. Alexander et. al., "Separating individual skin conductance responses in a short interstimulus-interval paradigm", Journal of Neuroscience Methods, vol. 146, pp. 116-123