Physiological Signals Based Human Emotion Recognition: A Review

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***Abstract*— Recent research in the field of Human Computer Interaction aims at recognizing the user's emotional state in order to provide a smooth interface between humans and computers. This would make life easier and can be used in vast applications involving areas such as education, medicine etc. Human emotions can be recognized by several approaches such as gesture, facial images, physiological signals and neuro imaging methods. Most of the researchers have developed user dependent emotion recognition system and achieved maximum classification rate. Very few researchers have tried to develop a user independent system and obtained lower classification rate. Efficient emotion stimulus method, larger data samples and intelligent signal processing techniques are essential for improving the classification rate of the user independent system. In this paper, we present a review on emotion recognition using physiological signals. The various theories on emotion, emotion recognition methodology and the current advancements in emotion research are discussed in subsequent topics. This would provide an insight on the current state of research and its challenges on emotion recognition using physiological signals, so that research can be advanced to obtain better recognition.**

***Keywords*— Emotion, Inducement Stimuli, Physiological signals, Signal Processing Techniques.**

I. INTRODUCTION

The ability of computers to understand, discern human emotions, and perform the appropriate actions is one of the key focus areas of research in Human Computer Interaction (HCI). Picard states that "Emotions play an essential role in rational decision-making, perception, learning, and a variety of functions" [1]. Hence, empowering computers and robots to understand human emotions would make human computer interaction more meaningful and easier. For e.g. during online learning, the receptiveness of the student will be greatly increased if the computer knows the students emotional state and provides the appropriate learning. A psychologist can diagnose the disease easily with the knowledge of the patient's emotional state. Applications can be extended to missions involving very aged people, new born, patients with Autism etc., who will not be able to express their emotions explicitly [2, 3].

Several researches have been done to recognize emotions using various modalities like facial images, gestures, speech, physiological signals etc [4, 5]. These conventional emotion recognition methods using facial images or strength, tempo and tone of human speech lacks recognition accuracy, is not universal and depends on culture, gender and age [6, 7]. However, they have been reported widely because of its feature extraction methods which are easier compared to other modalities. Lighting conditions, accessories like glasses, auditory noise, etc makes these conventional classification methods challenging to be implemented in real time [8]. These modalities are also subject to social masking which would result in wrong recognition of emotional state [9].

Recently over the last decade, emotion recognition using physiological signals has gained its momentum. The subjective and complex nature of physiological signals, the sensitivity to movement artefacts and the inability to visually perceive emotions from the data makes it difficult to annotate and obtain the ground truth from the raw physiological data [9]. However, as they originate from the activity of the Autonomous Nervous System (ANS), they cannot be triggered by any conscious or intentional control. Therefore suppressing the emotions or social masking through physiological signals is impossible [9, 10]. In addition, it provides an avenue to recognize affect changes that takes place and are less obvious to perceive visually [7].

In this paper, we present a review of the recent advancements in emotion research using physiological signals; in specific to the emotion elicitation stimuli, feature extraction and classification methodologies. The goal of this review is to access and improve the efficiency of real time emotion detection system with the knowledge of the current advancement in this technology. The remaining part of this paper is organized as follows: Section II describes the theories of emotion and psycho physiological measures of human emotion recognition. Section III describes about the implementation of psycho physiological measures to evaluate the emotions. Section IV presents the overview of previous research works on physiological signals based emotion recognition. Section V concludes with the findings of this review on emotion recognition.

II. THEORY AND MEASURES OF EMOTION

A. *Theories of Emotion*

Emotions are present in our daily life and it affects our human consciousness dramatically [11]. In general, emotion is a mental state or feeling that occurs spontaneously rather than a conscious effort and it is reflected by physiological changes in our human body [12].

Psychologists and Neuroscientists have explained various theories of emotion [13]. However the two most applied models are the discrete emotional model proposed by Ekman [14] and the two dimensional valance arousal model proposed by Lang [15].

The discrete emotional model claims the presence of some basic emotions universally among all cultures. Several psychologists have suggested different categories of emotions. But there has been a considerable agreement in the following six emotions – happiness, sadness, surprise, anger, disgust, and fear [16]. The Dimensional model categorizes emotions based on the scales and can be characterized by their valance and arousal. Valance represents the pleasantness and ranges from negative to positive. Arousal indicates the activation level and ranges from low to high [10]. Figure 1 shows the six basic emotions plotted on valance-arousal place. For example, sadness has negative valance and low arousal.

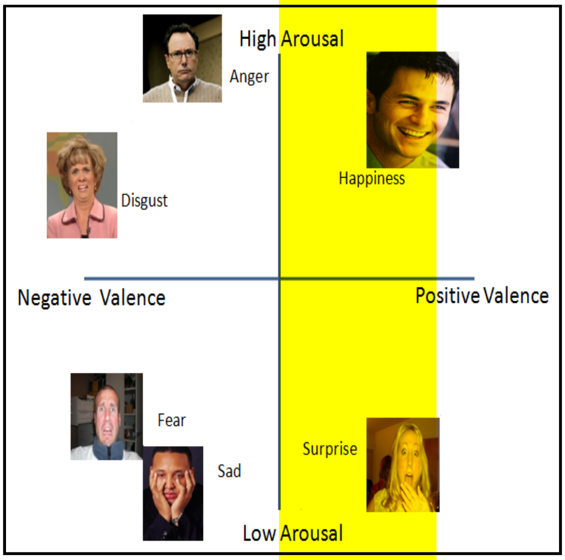

Fig.1 Basic Emotions on the Valance Arousal Dimensional Model [10]

B. Physco physiological measures of Emotion Evaluation

Psychophysiology is the branch of psychology that is concerned with the physiological bases of psychological process. Even if a person does not overtly express his/her emotion though speech, gestures or facial expression, a change in physiological pattern is inevitable and detectable [17] because the sympathetic nerves of the ANS get activated when a person is positively or negatively excited. This sympathetic activation raises heart rate, increases respiration rate, raises blood pressure and decreases heart rate variability [18]. The most common measures of psychophysiology used in human robot interaction studies include: 1. Cardiovascular system – Heart Rate Variability (HRV), Respiratory Sinus Arrhythmia (RSA), Cardiac Output, Inter Beat Interval (IBI), Blood Pressure(BP); 2. Electrodermal Activity – Skin Conductance (SC), Galvanic Skin Response (GSR); 3. Respiratory System – Breaths per minute, Respiration Volume; 4. Muscular System – Electromyography (EMG); 5. Brain Activity – Electroencephalography (EEG) and Brain imaging methods such as positron emission tomography [19, 20].

The Cardiovascular system measures the contractile activity of the heart and differentiates between positive and negative emotions. HRV, which is the oscillation interval between two consecutive heart beats, is a useful measure in indicating the stress and mental effort in adults [10]. Electrodermal activity describes the changes in skins ability to conduct electricity as it is interpreted to measure the overall arousal of the sympathetic nervous system [21]. Respiratory System depicts how deep and fast a person is breathing and indicates negative valance and arousal. However, it is not suited for online applications due to the slow physiological response of the signal [22]. EEG signals refer to the activity of the Central Nervous System(CNS) [11]. However, they are not suited for practical implementations because of high sensitivity to physiological artefacts such as eye blinks and electrostatic artefacts due to the usage of large number of electrodes [23].

III. Implementation Of Psycho Physiological Measures Of Emotion Evaluation

A. Emotion Elicitation Stimuli

Gathering a high quality database of physiological signals is vital for the development of emotion recognition system[9]. It is easy to gather meaningful data in case of image and audio recognition as the integrity of the data can be seen or heard by non-specialists. However, a good physiological data cannot be determined by non-specialists[24]. The physiological signals being the activity of ANS, the emotions must be naturally elicited on the subjects in order to obtain good data. Various emotion elicitation methods such as visual using pictures – [International Affective Picture System (IAPS)][25, 26], Audiovisual using movie/film clips [27, 28], Audio using music/sound clips[10], Personalized Imagery [24], Recall Paradigm [29] and Multimodal approach[9] are used by researchers to elicit the target emotions. The aim of the emotion elicitation method if to induce the target emotion in the subject by eliminating the chances of inducing multiple emotions. The studies done by Gross and Levenson indicate that emotionally categorized films achieve better results due to its dynamic profile [30].

B. Pre-processing

The raw physiological signals are always contaminated with noises and other external interferences. In addition to the noises, artefacts due to electrostatic devices and muscular movements affect the raw signals [9]. This noise and artefacts are removed from the raw physiological signal before processing. In general different types of Low-pass filters such as Adaptive filters, Elliptic filters, Butterworth filters etc., are used to pre-process the raw ECG and Facial EMG signals. Smoothing filters are used to pre-process the raw GSR signals [25, 31, 32]. Kim et al., segmented the physiological signals (ECG, EMG, GSR and Respiration Rate) into samples of 160 s each and considered the middle part of the signal by ignoring the beginning and the end of each recording which are highly prone to movement artefacts [9]. Cong Zong et al., re-sampled the signal at 4 Hz, subtracted the baseline and considered only the relative amplitudes for GSR [33]. Mandryk et al., normalized each physiological signal(ECG, EMG and GSR) to a percentile between 0 and 100 and continued further processing [34].

C. Feature Extraction

Once the signals are pre-processed, it is necessary to extract statistical information or features from the signal which can be used to detect the emotional content of the signal. A large number of statistical, time domain, frequency domain and time-frequency domain features can be extracted from the various physiological signals. A maximum of 110 features were extracted by J. Kim et al., [10] using four physiological signals (ECG, EMG, Skin Conductance and Respiratory signal). These features included conventional statistics in time series, frequency domain, geometric analysis, power, multiscale sample entropy, sub-band spectra etc. A number of feature extraction methods such as Fourier transform [17], Wavelet Transform (Mexico wavelet, Morlet Wavelet[35] and Daubechies Wavelet [36, 37]), Empirical Mode Decomposition (EMD) and Hilbert Huang Transform (HHT)[33], Robust Singular Spectrum Transform (RSST) [38] etc., were used by various researchers to extract the features for emotion classification. Andreas Haag et al., computed the running mean and running standard deviation using a rectangular window, the size of which depends on the type of physiological signal (ECG, BVP, EMG, SC or Respiration). This would distinguish between the tonic and phasic components of the analysed signal[26, 37] . Honig et al., used moving and sliding features such as moving mean, sliding mean, moving median, sliding median etc., Moving features are recursively computed over the analysis window and depends on the previous value of the feature. Sliding features are approximations of the moving features and does not depend on the sample history. These sliding features require less memory and are suitable for emotion classification system applications that has constraints in terms of memory [39].

D. Feature Reduction

The features that are extracted from the various bio-signals may or may not be correlated with the emotion. Hence, it is important to remove the features that might not have any correlation between the different emotional states. Such uncorrelated features reduce the performance of the classifiers [10]. In order to select the relevant features for efficient emotion classification, various feature reduction algorithms such as Sequential Forward Selection (SFS) [1], Sequential Backward Selection (SBS), Sequential Forward Selection Search (SFFS) [1] and Fischer Projection [1, 9, 27] etc., has been used by various researchers. E. Leon et al. insists on detecting the signal attributes or features that contribute to optimal separation of emotional states based on Davies-Bouldin Index(DBI) [40].

E. Classification

After selecting the features that are relevant to the emotional states, they must be used to train a classifier so that it can classify the various emotional states using the features presented [41]. Various classifiers such as K-Nearest Neighbour (KNN)[17, 25], Regression Tree, Bayesian Networks, Support Vector Machines(SVM)[17, 33], Canonical Correlation Analysis (CCA) [27], Artificial Neural Network (ANN) [26], Linear Discriminant Analysis (LDA) [10] and Marquardt Back Propagation(MBP) [28] etc., are used by various researchers for classifying emotions. The comparison of the different classification algorithms is difficult as the systems use different training/testing data sets, which differ in the way the emotions are elicited. For the same data base, classification accuracy is higher when the features from all the physiological signals are used to classify the various emotions[42]. When only one physiological signal (EMG) is used the classification accuracy is low [10, 36].

IV. Previous Works

Over the last decade, several research works have been done on emotion recognition using physiological signals. Table 1 below shows the details of the work that has been done so far in classifying the various emotions using physiological signals. As like many other bio signal processing research, emotion recognition also started with user dependent approach which highly depends on the subject. Focus is now shifted towards user independent emotion recognition where unknown physiological data was used for testing. In case of user dependent system, a maximum of 95 % accuracy has been obtained for recognizing four emotions (Joy, Anger, Sad, Pleasure) and 92% accuracy for recognizing six emotions (Amusement, Contentment, Disgust, Fear, Sad, Neutral) has been obtained[10, 41]. The user independent approach has a obtained accuracy of 86% for classifying two emotions(Joy, Sadness), 70% for classifying four emotions (Joy, Anger, Sad, Pleasure) and 50% for classifying nine(Anger, Interest, Contempt, Disgust, Distress, Fear, Joy, Shame , Surprise) emotions [9, 10, 41, 43].

We can also observe that the emotion elicitation stimuli play an important role in emotion classification. In subjective emotion recognition 92% classification accuracy has been obtained for visual emotion elicitation [34]. Audio mode of emotion elicitation has obtained 95% classification accuracy when the features from four physiological signals (ECG,EMG,SC and Resp) are used for classification [10]. However when only one physiological signal (EMG) is considered the classification accuracy is 83% [36]. Though studies by Gross and Levenson indicate that audio visual stimuli using film clips elicits the target emotion better, the classification accuracy is only 86% which is considerably less compared to other modes of emotion elicitation [10, 30, 31, 41]. It should also be noted that the feature extraction methods used by the researchers in emotion elicitation using audio visual modes are relatively simple [27, 44]. This indicates that simple algorithms also give considerable classification accuracy in audio visual emotion elicitation. Hence, applying better feature extraction and classification algorithms may provide better results. Some of the researches have used the data base of MIT Media Lab in which the emotions are elicited using audio mode (Music) and a maximum of 95% classification accuracy has been obtained [10].

TABLE I
REVIEW OF PREVIOUS WORKS ON EMOTION RECOGNITION USING PHYSIOLOGICAL SIGNALS

Ref No	Biosignals Used	No of Subjects	Emotions	Stimuli Used	Feature Extraction	Classification	% accuracy
[9]	Electrocardiogram Skin Temperature Electrodermal Activity	125	Sad Anger Stress Surprise	Multimodal	Mean, Standard deviation of raw signals and their first derivative, High Frequency and Low frequency powers	Support Vector Machine	78.4(User Independent,3 emotions)
							61.8(User Independent,4 emotions)
[10]	Electromyogram Electrocardiogram Skin Conductance Respiration	3 (22 trials) MIT database	Joy Anger Sad Pleasure	Music	Statistical and Energy based features- Sub band Spectrum, Entropy	Linear Discriminant Analysis	95(User Dependent) 70(User Independent)
[17]	Electrocardiogram Electromyogram		Anxiety Boredom, Engagement Frustration Anger	Anagrams, Pong task	Fourier Transform, Wavelet Transform, Thresholding, Peak detection	K Nearest Neighbor	75.6 (User Dependent)
						Regression Tree	83.5 (User Dependent)
						Bayesian Networks	74.03 (User Dependent)
[22]	Skin Conductance Heart Rate Electromyogram	36	Valance Arousal	Robot Actions		Hidden Markov Model	83 Arousal ,80 Valance (User Dependent)
							66 Arousal , 66 Valance (User Independent)
[24]	Electromyogram Blood Volume Pulse Skin Conductance Respiration	1	Neutral Anger Hate Grief Platonic love Romantic love Joy Reverence	Personalized Imagery	Statistical Features(mean, Standard deviation of raw signals, absolute values of first and second differences of raw signals), Sequential Forward Selection Search, Fischer Projection	Hybrid Linear Discriminant Analysis	81(User Dependent)
[25]	Electromyogram Electrocardiogram Electrodermal Activity Respiration	9	Happiness Disgust Fear	Visual (International Affective Picture System)	Mean, Standard deviation, Difference Simba Algorithm, Principal Component Analysis	K Nearest Neighbor	62.70 (User Independent)
						Random Forest	62.41(User Independent)
[26]	Electromyogram Electrocardiogram Electrodermal Activity Skin Temperature Blood Volume Pulse, Respiration	Not specified	Valance Arousal	Visual (International Affective Picture System)	Running mean, Running standard deviation, Slope	Neural Network Classifier	Valance 89.7 (User Dependent) Arousal 63.76(User Dependent)
[27]	Electrocardiogram Skin Temperature Skin Conductance Respiration	60	Fear Joy Neutral	Movies	Mean, Difference, Low frequency power, High frequency power, ratio of powers	Canonical Correlation Analysis	85.3 (User Dependent)
[28]	Galvanic Skin Response Heart Rate	14	Sad Anger Surprise Fear Frustration Amusement	Movies	No specific features stated	K Nearest Neighbor	71(User Dependent)
						Discriminant Function Analysis	74(User Dependent)
						Marquardt Back Propagation	83(User Dependent)
[33]	Electrocardiogram Electromyogram Skin Conductance Respiration	MIT database	Joy Anger Sad Pleasure	Music	Hilbert Huang Transform (Fission and Fusion)	Support Vector Machine	76 (Fission , User Dependent) and 62 (Fusion, User Dependent)
[35]	Electromyogram	MIT database	Joy Anger Sad Pleasure	Music	Daubechies5 Wavelet transform	Neural Network	82.29 (User Dependent)

[36]	Electromyogram	MIT database	Joy Anger Sad Pleasure	Music	Six scale Daubechies Wavelet Transform	Support Vector Machines	83.30 (User Dependent)
[39]	Electrocardiogram Electromyogram Skin Conductance Respiration	MIT database	Joy Anger Sad Pleasure	Music	Moving features and sliding features (Recursive)	Linear Discriminant Analysis	83.4 (User Dependent)
[41]	Blood Volume Pulse Electromyogram Skin Temperature Skin Conductance Respiration rate	10	Amusement Contentment Disgust Fear Sad Neutral	Visual (International Affective Picture System)	Time domain statistical features (mean, Standard deviation of raw signals, absolute values of first and second differences of raw signals)	Support Vector Machine, Fisher Linear Discriminant Analysis	90(User Dependent) and 92(User Dependent)
[43]	Electrocardiogram Blood Volume Pulse, Skin Conductance Electromyogram Respiration rate	28	Anger Interest Contempt Disgust Distress Fear Joy Shame Surprise	Visual (International Affective Picture System)	One subject model using Maximum a Posteriori (MAP) rule, Sequential Floating Forward Search, Fischer Projection	K Nearest Neighbour ,	50(User Independent) 90.7(User Dependent)
[44]	Electrocardiogram	154	Joy Sadness	Movies	Fast Fourier Transform	Tabu search	86(User Independent)

V. Conclusion

In this paper, we have reviewed and presented the different stages of human emotion recognition using physiological signals. It can be very well noted that the real-time emotion recognition using physiological signals is still in its early stages of growth. As emotions are highly subjective, a generalized system for classifying all the basic emotions remains a challenge. Most of the systems developed till date is user dependent and the user independent systems lack accuracy. Hence, in order to obtain a user independent, robust and reliable emotion recognition system, more amounts of physiological signal data is required. However, the emotional changes in the physiological signals can be observed for a very small time ranging between 3 -15 seconds [45, 46]. Hence extracting the data at the instant of emotion elicitation inside the subject would provide better results. This would require a window based approach during the processing of the various physiological signals. In addition, employing a robust and novel feature extraction, feature selection and classification techniques would help in developing a user independent emotion recognition system with higher classification accuracy.

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References

[1] W. R. Picard, "Affective computing: challenges," International Journal of Human-Computer Studies - Application of affective computing in human—Computer interaction, vol. 59, pp. 55-64, 2003.

[2] E. Bal, E. Harden, D. Lamb, A. Van Hecke, J. Denver, and S. Porges, "Emotion Recognition in Children with Autism Spectrum Disorders: Relations to Eye Gaze and Autonomic State," *Journal of Autism and Developmental Disorders,* vol. 40, pp. 358-370,2009.

[3] Y. Demazeau, F. Dignum, J. Corchado, J. Bajo, R. Corchuelo, E. Corchado, F. Fernández-Riverola, V. Julián, P. Pawlewski, A. Campbell, R. Martínez, K. de Ipiña, E. Irigoyen, N. Asla, N. Garay, A. Ezeiza, and I. Fajardo, "Emotion Elicitation Oriented to the Development of a Human Emotion Management System for People with Intellectual Disabilities," in *Trends in Practical Applications of Agents and Multiagent Systems*. vol. 71: Springer Berlin / Heidelberg, pp. 689-696,2010.

[4] L. Kessous, G. Castellano, and G. Caridakis, "Multimodal emotion recognition in speech-based interaction using facial expression, body gesture and acoustic analysis," *Journal on Multimodal User Interfaces,* vol. 3, pp. 33-48,2009.

[5] O. Kaynak, E. Alpaydin, E. Oja, L. Xu, A. Raouzaiou, S. Ioannou, K. Karpouzis, N. Tsapatsoulis, S. Kollias, and R. Cowie, "An Intelligent Scheme for Facial Expression Recognition," in *Artificial Neural Networks and Neural Information Processing — ICANN/ICONIP 2003*. vol. 2714: Springer Berlin / Heidelberg, pp. 182-182,2003.

[6] P. Cheonshu, R. Jungwoo, S. Joochan, and C. Hyunkyu, "An Emotion Expression System for the Emotional Robot," in *IEEE International Symposium on Consumer Electronics, 2007. ISCE 2007.*, pp. 1-6,2007.

[7] P. Rani and N. Sarkar, " A New Approach to Implicit Human-Robot Interaction Using Affective Cues, ," *Mobile Robots: towards New Applications, Aleksandar Lazinica (Ed.),I-Tech Education and Publishing,*2006.

[8] B. Apolloni, R. Howlett, L. Jain, K.-B. Sim, I.-H. Jang, and C.-H. Park, "The Development of Interactive Feature Selection and GA Feature Selection Method for Emotion Recognition," in *Knowledge-Based Intelligent Information and Engineering Systems*. vol. 4694: Springer Berlin / Heidelberg, pp. 73-81,2007.

[9] K. Kim, S. Bang, and S. Kim, "Emotion recognition system using short-term monitoring of physiological signals," *Medical and Biological Engineering and Computing,* vol. 42, pp. 419-427, 2004.

[10] K. Jonghwa and E. Ande, "Emotion Recognition Based on Physiological Changes in Music Listening,", *IEEE Transactions on Pattern Analysis and Machine Intelligence,* vol. 30, pp. 2067-2083, 2008.

[11] P. C. Petrantonakis and L. J. Hadjileontiadis, "Emotion Recognition from Brain Signals Using Hybrid Adaptive Filtering and Higher Order Crossings Analysis," *IEEE Transactions on affective computing,* vol. 1, pp. 81-97, 2009.

[12] "www.thefreedictionary.com/emotion," in *The free dictionary*.

[13] "http://en.wikipedia.org/wiki/Emotion," in *Wiki*.

[14] P. Ekman and W. V. Friesen, "Universals and Cultural Differences in the Judgments of Facial Expressions of Emotion," *Journal of Personality and Social Psychology,* vol. 53, pp. 712-714, 1987.

[15] P. J. Lang, "The Emotion Probe: Studies of Motivation and Attention," *American Psychologist,* vol. 50, pp. 372-385, 1995.

[16] C. Peter and A. Herbon, "Emotion representation and physiology assignments in digital systems," *Interacting with Computers,* vol. 18, pp. 139-170, 2006.

[17] P. Rani, C. Liu, N. Sarkar, and E. Vanman, "An empirical study of machine learning techniques for affect recognition in human–robot interaction," *Pattern Analysis & Applications,* vol. 9, pp. 58-69, 2006.

[18] T. Gross, J. Gulliksen, P. Kotzé, L. Oestreicher, P. Palanque, R. Prates, M. Winckler, G. van der Vloed, and J. Berentsen, "Measuring Emotional Wellbeing with a Non-intrusive Bed Sensor," in *Human-Computer Interaction – INTERACT 2009*. vol. 5727: Springer Berlin / Heidelberg, pp. 908-911,2009.

[19] C. L. Bethel, K. Salomon, R. R. Murphy, and J. L. Burke, "Survey of Psychophysiology Measurements Applied to Human-Robot Interaction," in *Robot and Human interactive Communication, 2007. RO-MAN 2007. The 16th IEEE International Symposium on 26-29 Aug. 2007,* pp. 732 - 737,2007.

[20] E. Fernandez-Egea, E. Parellada, F. Lomeña, C. Falcon, J. Pavia, A. Mane, G. Horga, and M. Bernardo, "FDG PET study of amygdalar activity during facial emotion recognition in schizophrenia," *European Archives of Psychiatry and Clinical Neuroscience,* vol. 260, pp. 69-76,2010.

[21] S. Blain, A. Mihailidis, and T. Chau, "Assessing the potential of electrodermal activity as an alternative access pathway," *Medical Engineering and Physics,* vol. 30, pp. 498 - 505, 2008.

[22] D. Kulic and E. A. Croft, "Affective State Estimation for Human–Robot Interaction," *IEEE Transactions on Robotics,* vol. 23, pp. 991-1000, 2007.

[23] M. Smith, G. Salvendy, and S.-H. Jeong, "Suggestion of Methods for Understanding User's Emotional Changes While Using a Product," in *Human Interface and the Management of Information. Methods, Techniques and Tools in Information Design*. vol. 4557: Springer Berlin / Heidelberg, pp. 59-67,2007.

[24] R. W. Picard, E. Vyzas, and J. Healey, "Toward machine emotional intelligence: analysis of affective physiological state," *IEEE Transactions on Pattern Analysis and Machine Intelligence,* vol. 23, pp. 1175 - 1191, 2001.

[25] G. Rigas, C. D. Katsis, G. Ganiatsas, and D. I. Fotiadis, "A User Independent, Biosignal Based, Emotion Recognition Method," in *Proceedings of the 11th international conference on User Modeling* Corfu, Greece: Springer-Verlag, 2007.

[26] E. André, L. Dybkjae r, W. Minker, P. Heisterkamp, A. Haag, S. Goronzy, P. Schaich, and J. Williams, "Emotion Recognition Using Bio-sensors: First Steps towards an Automatic System," in *Affective Dialogue Systems*. vol. 3068: Springer Berlin / Heidelberg, pp. 36-48, 2004.

[27] L. Lan and C. Ji-hua, "Emotion Recognition Using Physiological Signals from Multiple Subjects," in *International Conference on Intelligent Information Hiding and Multimedia Signal Processing, 2006. IIH-MSP '06.*, pp. 355-358, 2006.

[28] F. Nasoz, K. Alvarez, C. Lisetti, and N. Finkelstein, "Emotion recognition from physiological signals using wireless sensors for presence technologies," *Cognition, Technology & Work,* vol. 6, pp. 4-14, 2004.

[29] G. Chanel, J. J. M. Kierkels, M. Soleymani, and T. Pun, "Short-term emotion assessment in a recall paradigm," *International Journal of Human-Computer Studies,* vol. 67, pp. 607-627, 2009.

[30] J. J. Gross and R. W.Levenson, "Emotion Elicitation using Films," *Cognition and Emotion,* vol. 9, pp. 87-108, 1995.

[31] C. D. Katsis, N. Katertsidis, G. Ganiatsas, and D. I. Fotiadis, "Toward Emotion Recognition in Car-Racing Drivers: A Biosignal Processing Approach," *IEEE Transactions on Systems, Man and Cybernetics, Part A: Systems and Humans* vol. 38, pp. 502-512, 2008.

[32] C. Chuan-Yu, Z. Jun-Ying, and W. Chi-Jane, "Based on Support Vector Regression for emotion recognition using physiological signals,"*International Joint Conference on* in *Neural Networks (IJCNN)*, pp. 1-7,2010.

[33] Z. Cong and M. Chetouani, "Hilbert-Huang transform based physiological signals analysis for emotion recognition," *International Symposium on* in *Signal Processing and Information Technology (ISSPIT)*, pp. 334-339,2009.

[34] L. M. Regan and M. S. Atkins, "A fuzzy physiological approach for continuously modeling emotion during interaction with play technologies," *Int. J. Hum.-Comput. Stud.*, vol. 65, pp. 329-347, 2007.

[35] Cheng, B. Liu, and Guangyuan, "Emotion Recognition from Surface EMG Signal Using Wavelet Transform and Neural Network," in *The 2nd International Conference on Bioinformatics and Biomedical Engineering, 2008. ICBBE 2008.* Shanghai, China, pp. 1363-1366, 2008.

[36] X. Zhu, "Emotion Recognition of EMG Based on BP Neural Network," in *Proceedings of the Second International Symposium on Networking and Network Security (ISNNS '10)* Jinggangshan, P. R. China, pp. 227-229, 2010.

[37] Z. Long, G. Liu, and X. Dai, "Extracting Emotional Features from ECG by Using Wavelet Transform," in *International Conference on Biomedical Engineering and Computer Science (ICBECS), 2010* Wuhan, pp. 1-4, 2010.

[38] B.-C. Chien, T.-P. Hong, S.-M. Chen, M. Ali, Y. Mohammad, and T. Nishida, "Measuring Naturalness during Close Encounters Using Physiological Signal Processing," in *Next-Generation Applied Intelligence*. vol. 5579: Springer Berlin / Heidelberg, pp. 281-290,2009.

[39] F. Honig, J.Wagner, A. Batliner, and E.Noth, "Classification of user states with physiological signals: On-line Generic features vs. Specialized feature sets," in *17th European Signal Processing Conference 2009* Glasgow, Scotland, pp. 2357-2361, 2009.

[40] E. Leon, G. Clarke, F. Sepulveda, and V. Callaghan, "Optimised attribute selection for emotion classification using physiological signals," *26th Annual International Conference of the IEEE* in *Engineering in Medicine and Biology Society, IEMBS '04*, pp. 184-187,2004.

[41] C. Maaoui and A. Pruski, "Emotion Recognition through Physiological Signals for Human-Machine Communication," in *Cutting Edge Robotics 2010, Vedran Kordic (Ed.)*, 2010.

[42] MIT AUBT Database, "http://affect.media.mit.edu/share-data.php."

[43] Y. Gu, S.-L. Tan, K.-J. Wong, M.-H. R. Ho, and L. Qu, "A biometric signature based system for improved emotion recognition using physiological responses from multiple subjects,"in *8th IEEE International Conference on Industrial Informatics (INDIN), 2010* Osaka, 2010.

[44] W. Wan-Hui, Q. Yu-Hui, and L. Guang-Yuan, "Electrocardiography Recording, Feature Extraction and Classification for Emotion Recognition," in *WRI World Congress on Computer Science and Information Engineering* Los Angeles, CA, 2009.

[45] J. Kim, "Bimodal Emotion Recognition using Speech and Physiological Changes," *Robust Speech Recognition and Understanding,* pp. 265-280, 2007.

[46] H. Gunes, "Automatic Dimensional and Continuous Emotion Recognition " *International Journal of Synthetic Emotions,* vol. 1, pp. 68-99, 2010.