Emotion Recognition Through ANS Responses Evoked by Negative Emotions

Emotion Recognition based on Machine Learning Algorithms

Eun-Hye Jang, Byoung-Jun Park, Sang-Hyeob Kim, Chul Huh
BT Convergence Technology Research Department
Electronics and Telecommunications Research Institute
Daejeon, S. Korea
cleta4u@etri.re.kr; bj_park@etri.re.kr; shk1028@etri.re.kr; chuh@etri.re.kr

Yeongji Eum, Jin-Hun Sohn
Department of Psychology/Brain Research Institute
Chungnam National University
Daejeon, S. Korea
Yeongji_Eum@gmail.com; jhsohn@cnu.ac.kr

***Abstract*—Emotion recognition using physiological responses is one of the core processes to implement emotional intelligence in human-computer interaction (HCI) research. The purpose of this study was to investigate emotion-specific ANS responses and test recognition rate using classification algorithm when negative emotion such as fear, surprise, and stress was evoked. The results of one-way ANOVA toward each parameter, there were significant differences among three emotions in skin conductance response (SCR), number of SCR (NSCR), skin temperature (SKT), and high frequency of HRV (HF). Results of emotion recognition applied to statistical method, i.e. linear discriminant analysis (LDA) and 4 machine learning algorithm, i.e. classification and regression tree (CART), self organizing map (SOM), Naïve Bayes and support vector machine (SVM) for emotion recognition showed that an accuracy of emotion classification by SVM was the highest and by LDA was the lowest. This can be helpful to provide the basis for the emotion recognition technique in HCI as well as contribute to the standardization in emotion-specific ANS responses.**

Keywords-emotion recognition; machine learning algorithm; ANS responses

I. INTRODUCTION

Emotion plays an important role in contextual understanding of messages from others in speech or visual forms. In advanced human-machine interaction, for affective communication between user and computer, it has to consider how emotions can be recognized and expressed during human-computer interaction and emotion recognition is one of the key steps towards emotional intelligence. Emotion recognition is one of the core processes to implement emotional intelligence in human-computer interaction (HCI) research [1]. Particularly, in important HCI applications such as computer aided tutoring and learning, it is highly desirable (even mandatory) that the response of the computer takes into account the emotional or cognitive state of the human user [2]. Emotion recognition has been studied using facial expression, gesture, voice, and physiological signal [3-7]. Physiological signal may happen to artifact due to motion, and have difficulty mapping emotion-specific responses pattern, but this has some advantages which are less affected by environment than any other modalities as well as possible to observe user's state in real time. In addition, they also can be acquired spontaneous emotional responses and not caused by responses to social masking or factitious emotion expressions. Finally, measurement of emotional responses by multi-channel physiological signals offer more information for emotion recognition, because physiological responses are related to emotional state [8].

Many previous studies on emotion have reported that there is correlation between basic emotions such happiness, sadness, anger, etc. and physiological responses [9-15]. Also, experimental studies have been performed to distinguish specific emotions by autonomic nervous system (ANS) response and reported the emotion-specific ANS responses [10]. For example, in research reviewed 134 studies about ANS activity [11], ANS responses related to anger are a modal response pattern of reciprocal sympathetic activation and increased respiratory activity, particularly faster breathing. Studies on sadness report a heterogeneous pattern of sympathetic–parasympathetic coactivation and ANS responses of fear point to broad sympathetic activation, including cardiac acceleration, increased myocardial contractility, vasoconstriction, and increased electrodermal activity. Recently, emotion recognition using physiological signals has been performed by various machine learning algorithms, e.g., Fisher Projection (FP), k-Nearest Neighbor algorithm (kNN), Linear Discriminant Function (LDF), Sequential Floating Forward Search (SFFS), and Support Vector Machine (SVM). Previous works conducted a recognition accuracy of over 80% on the average seems to be acceptable for realistic applications [3-7]. Picard, Vyzas & Healey [3] classified 8 kinds of emotions (neutral, anger, grief, sadness, platonic love, romantic love, joy, & respect) by using kNN and it was verified 81.3% of accuracy. Haag, Goronzy, Schaich and Williams [4] applied MLP to categorize dimensions of arousal and valence in each emotion, and then it was reported as 80% of average accuracy. Also, Calvo, Brown and Scheding [14] reported 42% of accuracy by using SVM to differentiate 8 kinds of emotions (neutral, anger, grief, sadness, platonic love, romantic love, joy, & respect).

However, Wagner, Kim and Andre [1] mentioned that it can be clearly observed that the accuracy strongly depends on the data sets which were obtained in laboratory conditions. That is, the results were achieved for specific users in specific contexts and it is very difficult to label emotion classes in physiological signals (waveforms) without uncertainty. Therefore, it is needed to recognize emotion

 ISBN: 978-1-61208-177-9

using manifold data sets obtained from different contexts and select the most optimal algorithm for emotion recognition. And in order to apply more elaborate feedback in HCI, it is necessary to discriminate the similar and vague emotions which are hard to be sorted. However, past studies is not a lot about discrimination of similar emotions under positive emotion or negative emotion likewise.

In this paper, to improve the limitation that it is result in specific context, we used 10 different emotional stimuli to induce one emotion under the same context conditions. And we verified the specific ANS responses of each emotion when negative emotions such as fear, surprise, and stress were evoked. The reason for selection of negative emotion was that in theory of evolution, it plays an important role in adaptation of living and surviving the evolution of human [16]. In particular, fear is associated with defensive aggression and is a kind of attempt to escape and people in fear emotion would attack only if escape is impossible [17-19]. Main function of surprise is to interrupt ongoing action and orient people to a possibly significant event. It has one core appraisal—appraising something as novel and unexpected—although other appraisals can shift the subjective feeling of surprise or shift the emotion from surprise to another emotion [20]. Stress are "constraining force or influence," "a physical, chemical, or emotional factor that causes bodily or mental tension and may be a factor in disease causation," and "a state resulting from stress-especially one of bodily or mental tension resulting from factors that tend to alter existent equilibrium [21]." Finally, we identified the optimal algorithm being able to classify three negative emotions. For this, we used a statistical method, linear discriminant analysis (LDA) which is one of the linear models, and 4 different machine learning algorithms, i.e., classification and regression tree (CART) of decision tree model, self organizing map (SOM) of Neural Network, Naïve Bayes of probability model, and SVM of non-linear model, which are used the well-known emotion algorithms.

II. METHODS

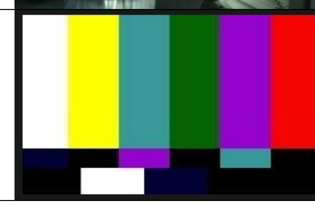
A. Participants

A total of 12 college students (6 males 20.8 years $\pm$1.26 and 6 females 21.2 years $\pm$2.70) participated in this study. They reported that they hadn't had any history of medical illness or psychotropic medication and any kind of medication due to heart disease, respiration disorder, or central nervous system disorder. A written consent was obtained before the beginning of the study from the participants and they were also paid $20 USD per session to compensate for their participation.

B. Emotional stimuli

Thirty emotional stimuli (3emotions x 10sets) which are the 2-4 min long audio-visual film clips captured originally from movies, documentary, and TV shows were used to successfully induce emotions (fear, surprise, and stress) in this study (TABLE 1). Fear-inducing films were the scene which had tense and dreary atmosphere. Surprise clips were a section in which startling accident occurred and stress clip was TV adjustment scene that was mixture of black and white with white noise sound; you may easily see that when after all daily programs ended.

TABLE I. THE EXAMPLES OF EMOTIONAL STIMULI

Emotion	***Contents***	***Examples***
Fear	ghost, haunted house, scare, etc.	
Surprise	sudden or unexpected scream etc.	
Stress	audio/visual noise on screen, etc.	

The used audio-visual film clips were examined their suitability and effectiveness by preliminary study which 22 college students rated the category and intensity of their experienced emotion on emotional assessment scale after they were presented each film clip. The suitability of emotional stimuli means the consistency between the experimentor's intended emotion and the participanats' experienced emotion (e.g., scared, surprise, and annoying). The effectiveness was determined by the intensity of emotions reported and rated by the participants on a 1 to 11 point Likert-type scale (e.g., 1 being "least surprising or least surprising or not surprising" and 11 being "most surprising").

TABLE II. THE SUITABILITY AND EFFECTIVENESS OF EMOTIONAL STIMULI

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**M**
Fear	75 (10)	100 (9.9)	83 (9.8)	92 (9.6)	92 (9.7)	92 (9.7)	83 (9.6)	100 (9.3)	100 (9.3)	75 (8.7)	89 (9.6)
Surprise	75 (9.3)	92 (9.7)	100 (9.7)	100 (9.9)	83 (9.6)	83 (9.6)	100 (9.5)	83 (9.4)	83 (8.6)	75 (10.3)	89 (9.5)
Stress	92 (9.3)	100 (9.1)	100 (8.8)	100 (8.9)	100 (9.3)	100 (8.8)	92 (9.3)	100 (9.3)	100 (9.1)	100 (9.3)	98 (9.1)

above: suitability (%), below ( ): effectiveness (point)

The result showed that emotional stimuli had the suitability of 89% and the effectiveness of 9.1 point on average. The suitability of each stimulus was ranged from 75 to 100% and from 8.6 to 10.3 point in the effectiveness (TABLE 2).

C. Procedure

Prior to the experiment, participants were introduced to detail experiment procedure and had an adaptation time to feel comfortable in the laboratory's environment. Then an experimentor attached electrodes on the participants' wrist, finger, and ankle for measurement of physiological signals. Physiological signals were measured for 60 sec prior to the presentation of emotional stimulus (baseline) and for 2 to 4 min during the presentation of the stimulus (emotional state), then for 60 sec after presentation of the stimulus as recovery term. Participants rated the emotion that they experienced during presentation of the film clip on the emotion assessment scale (Figure 1). This procedure was repeated 3 times for elicitation of 3 differential emotions. Presentation of each film clip was count-balanced across each emotional stimulus. This experiment was progressed by the same procedures over 10 times.

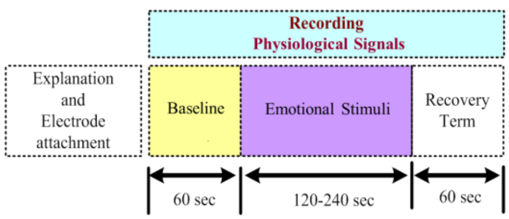


Figure 1. Experiment procedures

D. Experimental Settings

The laboratory was a sound-proof (lower than 35dB) room of 5m x 2.5m size where any outside noise or artifact was completely blocked. A comfortable chair was placed in the middle of the laboratory and 38 inch TV monitor for presentation of emotional stimuli was placed in front of the chair. An intercommunication device was located to the right side of chair for participant to communicate with an experimenter. A CCTV was installed on the top of the monitor set to observe participant's behaviours and their behaviours were storage through the monitor and a video cassette recorder outside the laboratory.

E. Physiological measures and data analysis

The physiological signals were acquired by the MP100 system (Biopac System Inc., USA). The sampling rate of signals was fixed at 256 samples for all the channels. EDA was measured from two Ag/AgCl electrodes attached to the index and middle fingers of the non-dominant hand. ECG was measured from both wrists and one left ankle (reference) with the two-electrode method based on lead I. PPG and SKT were measured from the little finger and the ring finger of the non-dominant hand, respectively. Appropriate amplification and band-pass filtering were performed.

The signals were acquired for 1minute long baseline state prior to presentation of emotional stimuli and 2-4 minutes long emotional states during presentation of the stimuli. The obtained signals were analyzed for 30 seconds from the baseline and the emotional state by AcqKnowledge (Ver. 3.8.1) software (USA) (Figure 2). The emotional states were determined by the result of participant's self-report (scene that emotion is most strongly induced during presentation of each stimulus).

Features extracted from the physiological signals and were used to analysis are as follows: meanGSR, meanSCR, NSCR, meanSKT, maxSKT, meanPPG, Mean RR(s), STD(s), Mean HR(1/min), RMSSD(ms), NN50(count), pNN50(%), SD1(ms), SD2(ms), CSI, CVI, RR tri index, TINN(ms), FFTap_LF, FFTap_HF, ARap_LF, ARap_HF, FFTnLF, FFTnHF, FFTL/Hratio, ARnLF, ARnHF, and ARL/Hratio.

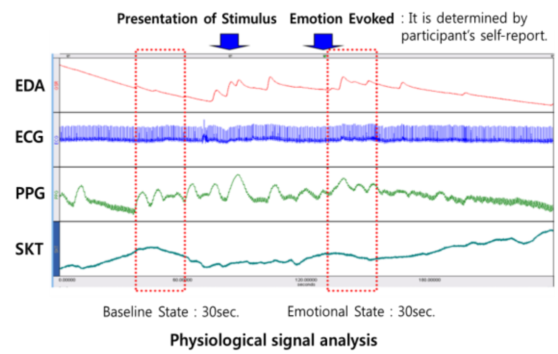


Figure 2. Analysis of physiological signals

270 physiological signal data (3 emotions x 10 stimuli x 9 cases) except for severe artifact effect by movements, noises, etc. were used for analysis. And differences of physiological signals among 3 emotions (alpha level at .05) were analyzed by one-way ANOVA (SPSS ver. 15.0). Also, to identify the emotion recognition algorithm being able to best recognize 3 different emotions by physiological signals, statistic method, LDA and 4 machine learning algorithms, i.e., CART which is a robust classification and regression tree, unsupervised SOM, Naïve Bayes classifier based on density, and SVM with the Gaussian radial basis function kernel were selected.

LDA, which is a statistical method to classify data signals by using linear discriminant functions, provides extremely fast evaluations of unknown inputs performed by distance calculations between a new sample and mean of training data samples in each class weighed by their covariance matrices [22]. CART is one of decision tree and nonparametric technique that can select from among a large number of variables those and their interactions that are most important in determining the outcome variable to be explained [23]. CART integrates the various information sources together for final decision. SOM, called Kohonen map, is a type of artificial neural networks in the unsupervised learning category and generally present a simplified, relational view of a highly complex data set [24]. The Naive Bayes algorithm is a classification algorithm based on Bayes rule and particularly suited when the dimensionality of the inputs is high [25]. SVM finds a hyperplane based on support vector to analyse data and recognize patterns. The complexity of the resulting classifier is characterized by the number of support vectors rather than the dimensionality of the transformed space [26]. Features' differences between emotional states and baseline extracted from physiological signals were used to apply these algorithms.

III. Results

A. Verification of the differences in ANS responses among emotions by one-way ANOVA

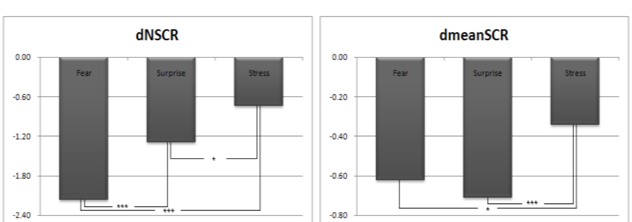
The results of one-way ANOVA using difference value of signals subtracting emotional states from baseline, there were statistically significant differences among three emotions in NSCR, mean SCR, mean SKT, max SKT and FFT ap_HF (which is value to integrate an absolute value power of HF extracted from FFT) (TABLE III).

TABLE III. The result on one-way ANOVA toward each parameters

ANOVA	*SS*	*df*	*MS*	*F*
dNSCR	100.398	2	50.199	20.886***
dmeanSCR	7.363	2	3.681	6.242**
dmeanSKT	94.884	2	47.442	5.827**
dmaxSKT	91.563	2	45.781	5.744***
FFTap_HF	2,322.00	2	1,161.00	3.833*

* $p < .05$, ** $p < .01$, *** $p < .001$

To verify the difference among three emotions in detail, data were analyzed by LSD post hoc test. Figure 3 shows the result. There were significant differences of NSCR among all emotions and mean SCR between fear and stress, and between surprise and stress. SCR and NSCR, which are extracted from EDA decreased while all emotions were evoked, compared to baseline. Also, mean and max SKT distinguished between fear and surprise and between fear and stress. SKT decreased during fear induction and increased during surprise and stress from baseline. Finally, significant difference between fear and surprise was in FFT ap_HF. There were an increase of FFT ap_HF in fear and decreases of FFT ap_HF in surprise and stress.



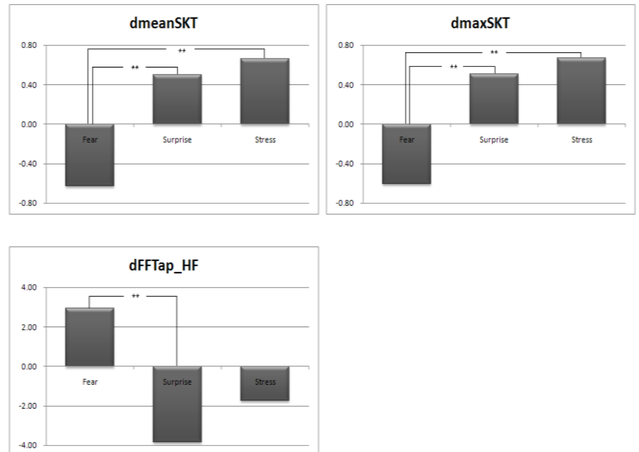


Figure 3. The results of LSD post-hoc test (*p<.05, **p<.01, **p<.001)

B. The results of emotion recognition by machine learning algorithm

28 features extracted from physiological signals were applied to 5 algorithms for emotion recognition of fear, surprise and stress. LDA, CART, SOM, Naïve Bayes and SVM were tested to confirm emotion recognition rate. The result of emotion recognition is like TABLE IV. 57.3% of originally grouped cases were correctly classified by LDA, 87.2% by CART, 59.5% by SOM, 80.9% by Naïve Bayes, and 100.0% by SVM. Three emotions, i.e., fear, surprise and stress were classified by SVM optimally.

TABLE IV. The result of emotion recognition by SVM

Algorithm	*Accuracy (%)*	*Features (N)*
LDA	57.3	28
CART	87.2	28
SOM	59.5	28
Naïve Bayes	80.9	28
SVM	100.0	28

The more detail results of emotion recognition accuracy by each algorithm are like from TABLE V to IX. In analysis of LDA, accuracy of each emotion had range of 49.5% to 62.0%. Fear was recognized by LDA with 60.6%, surprise 49.5%, and stress 62.0% (TABLE V).

TABLE V. The result of emotion recognition by LDA

	Fear	*Surprise*	*Stress*	*Total*
Fear	60.6	20.2	19.1	100.0
Surprise	22.2	49.5	28.3	100.0
Stress	16.0	22.0	62.0	100.0

CART provided accuracy of 87.2% when it classified all emotions and the recognition rate of each emotion was range of 84.0% to 92.2%. In fear, recognition rate of 92.2%

was achieved with CART, 85.4% in surprise, and 84.0% in stress (TABLE VI).

TABLE VI. THE RESULT OF EMOTION RECOGNITION BY CART

	Fear	***Surprise***	***Stress***	***Total***
Fear	92.2	5.0	3.0	100.0
Surprise	8.8	85.4	5.8	100.0
Stress	6.0	10.0	84.0	100.0

The result of emotion recognition using SOM showed that accuracy to recognize all emotions was 59.5%. According to orders of fear, surprise, and stress, recognition rates of 71.3%, 59.2%, and 48.0% were obtained by SOM (TABLE VII).

TABLE VII. THE RESULT OF EMOTION RECOGNITION BY SOM

	Fear	***Surprise***	***Stress***	***Total***
Fear	71.3	19.8	8.9	100.0
Surprise	26.2	59.2	14. 6	100.0
Stress	30.0	22.0	48.0	100.0

The accuracy of Naïve Bayes algorithm to classify all emotion was 80.9%. And each emotion was recognized by Naïve Bayes with 83.2% of fear, 67.0% of surprise, and 93.0% of stress (TABLE VIII).

TABLE VIII. THE RESULT OF EMOTION RECOGNITION BY NAÏVE BAYES

	Fear	***Surprise***	***Stress***	***Total***
Fear	83.2	4.9	11.9	100.0
Surprise	15.5	67.0	17.5	100.0
Stress	4.0	3.0	93.0	100.0

Finally, accuracy of SVM was 100.0% and classifications of each emotion were 100.0% in all emotions (TABLE IX).

TABLE IX. THE RESULT OF EMOTION RECOGNITION BY SVM

	Fear	***Surprise***	***Stress***	***Total***
Fear	100.0	0.0	0.0	100.0
Surprise	0.0	100.0	0.0	100.0
Stress	0.0	0.0	100.0	100.0

IV. CONCLUSION

This study was to identify the difference among fear, surprise and stress emotions using physiological responses induced by these emotional stimuli and to find the optimal emotion recognition algorithm for classifying these three emotions. In our results, there were the differences of NSCR, mean SCR, mean SKT, max SKT, and FFT ap_HF among emotions by one-way ANOVA. EDA index, i.e., NSCR and mean SCR, is signal that represents the activity of the autonomic nervous system (activity of sweat glands) [27]. SKT variation reflects ANS activity and is effective indicator of emotional status. Variations in SKT mainly come from localized changes in blood flow, which is caused by vascular resistance or arterial blood pressure. The mechanism of arterial blood pressure variation can be described by a complicated model of cardiovascular regulation by the autonomic nervous system. Features of FFT ap_HF extracted from ECG reflect the activity of cardiac activity. The sino-atrial (SA) node, which acts as pacemaker of cardiovascular activity, receives inputs from both branches (sympathetic and parasympathetic) of the autonomic nervous system. The activity level of the sympathetic nervous system is presented to the SA node by a postganglionic fibre, and that of the parasympathetic nervous system is given by a vagal nerve. The SA node can be thought of as a spike train generator whose inter-spike interval is modulated by the integration of the activity levels of the sympathetic and parasympathetic nervous system [12].

Our result showed that SVM is the best algorithm being able to classify fear, surprise and stress emotions. SVM is designed for two class classification by finding the optimal hyperplane where the expected classification error of test samples is minimized [28]. The SVM shows a recognition ratio much higher chance probability, i.e. 100.0% for three emotion categories, when applied to physiological signal databases. This was utilized as a pattern classifier to overcome the difficulty in pattern classification due to the large amount of within-class variation of features and the overlap between classes, although the features were carefully extracted [12]. However, LDA and SOM had the lowest accuracy in emotion recognition. We think that this result in variability of physiological signals. The basic assumption that different emotions have a more or less unique and person-independent physiological response remains questionable. This could be reflected in the fact that the recognition rate falls off with the number of emotion categories [12]. These uncertainties could be an important cause that deteriorated the recognition ratio and troubled the model selection of the LDA or SOM.

Although some algorithm showed lower accuracy of emotion recognition, our results led to better chance to recognize human emotions and to identify the optimal emotion recognition algorithm by using physiological signals. In particular, SVM algorithm for classification of emotions can be helpful to provide the basis for the emotion recognition technique such as realization of elaborate and emotional man-machine interaction and will be applied to play an important role in several applications e.g., the human-friendly personal robot or other devices needed for various emotions recognition including how to develop effective robot control or adaptation behavior pattern using recognized emotion and product natural avatar's emotional behavior for interaction.

However, for more accurate and realistic applications, a novel method to identify not only basic emotions but also more various emotions such as boredom, frustration, and

 ISBN: 978-1-61208-177-9

love, etc. must be devised before it is mentioned that emotion recognition based on physiological signals is a practicable and reliable way of enabling HCI with emotion-understanding capability. Although, various physiological signals offer a great potential for the recognition of emotions in computer systems, in order to fully exploit the advantages of physiological measures, standardizations of experimental methods have to be established on the emotional model, stimulus used for the identification of physiological patterns, physiological measures, parameters for analysis, and model for pattern recognition and classification [29]. Finally, more research is needed to obtain stability and reliability of this result compare with accuracy of emotion classification using other algorithms.

ACKNOWLEDGMENT

This research was supported by the Converging Research Center Program funded by the Ministry of Education, Science and Technology (No. 2011K000655 and 2011K000658).

REFERENCES

[1] J. Wagner, J. Kim, and E. Andre, “From physiological signals to emotions: Implementing and comparing selected methods for feature extraction and classification,” 2005 IEEE International Conference on Multimedia and Expo, Amsterdam, pp. 940-943, July 2005.

[2] N. Sebe, I. Cohen, and T.S. Huang, “Multimodal emotion recognition,” in Handbook of Pattern Recognition and Computer Vision, Amsterdam: Publications of the Universiteit van Amsterdam, 2005, pp. 1-23.

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

[4] R. Cowie, E. Douglas-Cowie, N. Tsapatsoulis, G. Votsis, S. Kollias, W. Fellenz and J. G. Taylor, “Emotion recognition in human computer interaction,” IEEE Signal Process. Mag., vol. 18, pp. 32-80, January 2001.

[5] A. Haag, S. Goronzy, P. Schaich, and J. Williams, "Emotion recognition using bio-sensors: First steps towards an automatic system," Affective Dialogue Systems, vol. 3068, pp. 36-48, 2004.

[6] J. A. Healey, "Wearable and automotive systems for affect recognition from physiology," Doctor of Philosophy, Massachusetts Institute of Technology, Cambridge, MA, 2000.

[7] F. Nasoz, K. Alvarez, C. L. Lisetti, and N. Finkelstein, "Emotion recognition from physiological signals for user modeling of affect," International Journal od Cognition, Technology and Work-Special Issue on Presence, vol. 6, pp. 1-8, 2003.

[8] P. D. Drummond, and S. H. Quah, “The effect of expressing anger on cardiovascular reactivity and facial blood flow in Chinese and Caucasians,” Psychophysiology, vol. 38, pp. 190-196, 2001.

[9] G. Stemmler, "The autonomic differentiation of emotions revisited: convergent and discriminant validation," Psychophysiology, vol. 26, pp. 617-632, 1989.

[10] P. Ekman, R. W. Levenson, and W. V. Friesen, "Autonomic nervous system activity distinguishes among emotions," Science, vol. 221, p. 1208, 1983.

[11] S. D. Kreibig, "Autonomic nervous system activity in emotion: A review," Biological psychology, vol. 84, pp. 394-421, 2010.

[12] K. H. Kim, S. W. Bang, and S. R. Kim, “Emotion recognition system using short-term monitoring of physiological signals,” Medical & Biological Engineering & Computing, vol. 42, pp.419-427, 2004.

[13] J. N. Bailenson, E. D. Pontikakis, I.B. Mauss, J. Gross, M. E. Jabon, C. A. C. Hutcherson, C. Nass, and O. John, "Real-time classification of evoked emotions using facial feature tracking and physiological responses," International journal of human-computer studies, vol. 66, pp. 303-317, 2008.

[14] R. Calvo, I. Brown, and S. Scheding, "Effect of experimental factors on the recognition of affective mental states through physiological measures," AI 2009: Advances in Artificial Intelligence, vol. 5866, pp. 62-70, 2009.

[15] C. Liu, K. Conn, N. Sarkar, and W. Stone, "Physiology-based affect recognition for computer-assisted intervention of children with Autism Spectrum Disorder," International journal of human-computer studies, vol. 66, pp. 662-677, 2008.

[16] C. Darwin, The expression ofthe emotions in man and animals. London: John Murray, 1872.

[17] D. C. Blanchard, and S. N. Takahashi, "Affect and aggression: An animal model applied to human behavior," Advances in the Study of Aggression, vol. 1, pp. 1-62, 1988.

[18] K. M. J. Lagerspetz, "Aggression and aggressiveness in laboratory mice," in Aggressive behavior, S. Garattini and E. B. Sigg, Eds., ed New York: Wiley, 1969, pp. 77-85.

[19] K. E. Moyer, The Psychobiology of aggression. New York: Harper & Row, 1976.

[20] K. R. Scherer, "Appraisal considered as a process of multilevel sequential checking," in Appraisal processes in emotion: Theory, methods, research, K. R. Scherer, et al., Eds., ed New York: Oxford University Press, 2001, pp. 92-120.

[21] Merriam-Webster. (2001, Februry 22). *WWWebster Dictionary [Online]*. Available: http://www.m-w.com/dictionary.htm

[22] M. Murugappan, R. Nagarajan, and S. Yaacob, “Classification of human emotion from EEG using discrete wavelet transform,” Journal of Biomedical Science and Engineering, vol. 3, pp. 390-396, April 2010.

[23] J. R. Quinlan, C4.5 Programs for Machine Learning, San Mateo, CA: Morgan Kaufmann, 1992.

[24] F. Fdez-Riverola, E. L. Iglesias, F. Diaz, J. R. Mendez, and J. M. Corchado, “SpamHunting: an instance-based reasoning system for spam labeling and filtering,” Decision Support Systems, vol. 43, pp. 722-736, 2007.

[25] D. W. Aha, D. Kibler, and M. K. Albert, “Instance-based learning algorithms,” Machine Learning, vol. 6, pp. 37-66, 1991.

[26] P. D. Wasserman, Advanced Methods in Neural Computing, New York, Van Nostrand Reinhold, pp. 35–55, 1993.

[27] W. Boucsein, “Electrodermal activity,” Plenum Press, NewYork, 1992.

[28] K. Takahashi, “Remarks on emotion recognition from bio-potential signals,” 2nd International Conference on Autonomous Robots and Agents, Palmerston North, pp. 186-191, December, 2004.

[29] J. Arroyo-Palacios, and D. M. Romano, “Towards a standardization in the use of physiological signals for affective recognition systems,” Proceedings of Measuring Behavior 2008, 2008.

 ISBN: 978-1-61208-177-9