Emotion Recognition using Autonomic Nervous System Responses

Emotion Recognition

Byoung-Jun Park, Eun-Hye Jang, Sang-Hyeob Kim, Chul Huh, Myoung-Ae Chung
IT Convergence Technology Research Laboratory
Electronics and Telecommunications Research Institute
Daejeon, Korea
{bj_park, cleta4u, shk1028, chuh, and machung}@etri.re.kr

Jin-Hun Sohn
Department of Psychology/Brain Research Institute
Chungnam National University
Daejeon, Korea
jhsohn@cnu.ac.kr

***Abstract*— Recently in HCI research, emotion recognition is one of the core processes to implement emotional intelligence. There are many studies using physiological signals in order to recognize human emotions. The purpose of this study is to recognize emotions using autonomic nervous system responses induced by three different emotions (boredom, pain and surprise). Three different emotional states are evoked by emotional stimuli, physiological signals (EDA, ECG, PPG and SKT) for the induced emotions are measured as the reactions of stimuli, and 27 features are extracted from their physiological signals for emotion recognition. The stimuli are used to provoke emotions and tested their appropriateness and effectiveness. Audio-visual film clips used as stimuli are captured originally from movies, documentary, and TV shows with the appropriateness of 86%, 97.3% and 94.1% for boredom, pain and surprise, respectively, and the effectiveness of 5.23 for happiness, 4.96 for pain and 6.12 for surprise (7 point Likert scale). Also, for the three emotion recognition, we propose a Fuzzy c-means clustering based neural networks using the physiological signals. The proposed model consists of three layers, namely, input, hidden and output layers. Here, fuzzy c-means clustering method, two types of polynomial and linear combination function are used as a kernel function in the input layer, the hidden layer and the output layer of neural networks, respectively. To evaluate the performance of emotion recognition of the proposed model, we use the 10-fold cross validation and a comparative analysis shows that the proposed model exhibit higher accuracy when compared with some other models that exist in the literature.**

Keywords-emotion; recognition; stimuli; physiological signal; autonomic nervous system responses; neural networks.

I. INTRODUCTION

Emotion recognition in human-computer interaction (HCI) studies is the one of topic that researcher are most interested in. To recognize human's emotions and feelings, various physiological signals have been widely used to classify emotion [1] because signal acquisition by non-invasive sensors is relatively simple and physiological responses induced by emotion are less sensitive in social and cultural difference [2]. 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, measurements of emotional responses by multi-channel physiological signals offer more information for emotion recognition, because physiological responses are related to emotional state [3]. 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 [4].

The objective of this study is to achieve emotion dataset including physiological signals for three emotions (boredom, pain and surprise) induced by emotional stimuli and to develop a recognizer based on neural networks, namely, fuzzy c-means clustering based neural networks.

To induce boredom, pain and surprise emotions, we use audio-visual film clip captured originally from movies, documentary, and TV shows. Electrodermal activity (EDA), skin temperature (SKT), electrocardiac activity (ECG) and photoplethysmography (PPG) are recorded from 200 undergraduate students; during they are exposed to visual-acoustic emotional stimuli. And participants classified their present emotion and assessed its intensity on the emotion assessment scale. As the results of emotional stimulus evaluation, emotional stimuli were shown to mean 92.5% of appropriateness and 5.43 of effectiveness; this means that each emotional stimulus caused its own emotion quite effectively. Also, 27 features are extracted from their physiological signals for emotion recognition.

In order to recognize three emotions, we propose a fuzzy c-means clustering based neural networks (FNN) with polynomial function as a new methodology of emotion recognizer. Neural networks (NNs) have been widely used to deal with pattern recognition problems. It has been shown that the NNs can be trained to approximate complex discriminant functions [5]. NN classifiers can deal with numerous multivariable nonlinear problems for which an

 ISBN: 978-1-61208-250-9

accurate analytical solution is difficult to derive or does not exist [6]. It is found however, that the quality and effectiveness of NN classifiers depend on several essential parameters whose values are crucial to the accurate predictions of the properties being sought. The appropriate NN architecture, the number of hidden layers and the number of neurons in each hidden layer are the important design issues that can immediately affect the accuracy of the prediction. Unfortunately, there is no direct method to identify these factors as they need to be determined on an experimental basis [6]. In addition, it is difficult to understand and interpret the resulting NNs. These difficulties increase once the number of variables and the size of the networks start to increase [7][8]. To alleviate the problems highlighted above, we propose to consider fuzzy c-means clustering based neural networks (FNN) with polynomial function exploiting a direct usage of Fuzzy C-Means clustering and involving polynomials in the description of relationships of the models. The proposed FNN model consists of three layers, namely, input, hidden and output layers. A neuron in input layer employs fuzzy c-means clustering method as a kernel function, namely, this layer relates to the partition function of input space using FCM clustering. Two types of polynomial and linear combination of input signals are used as a kernel function of a neuron in the hidden layer and the output layer of neural networks, respectively. Using two types of polynomial functions can help to improve the characteristic of basic neural networks recognizer and caries out the presentation of a partitioned local space. The proposed FNN recognizer generates a nonlinear discernment function in the output space and has the better performance of emotion recognition. The proposed recognizer is applied to the obtained emotional physiological signals with 27 features and its results are compared with performance of C4.5, SOM (Self-organizing map), Naïve Bayes and SVM (support vector machines) [9]-[13]. The study is organized as follows. In Section II, we discuss emotion stimuli and measurements of physiological signals obtained as autonomic nervous system responses by three emotions. A structure of the proposed FNN is presented with an overall description of a detailed design methodology in Section III. In Section IV, we report on results of emotion recognition for the proposed FNN and conventional models. Finally, concluding remarks are covered in Section V.

II. EMOTIONS AND AUTONOMIC NERVOUS SYSTEM RESPONSES

This section reports a presentation of emotional stimuli and the measurements of physiological signals of autonomic nervous system responses for boredom, pain and surprise emotions

A. *Subjects*

In this experiment, 200 college students (mean age: 21.7 ± 2.3 years) have participated. They have reported no history of medical illness due to heart disease, respiration, or central nervous system disorder or psychotropic medication. They were introduced to the experiment protocols and filled out a written consent before the beginning of experiment. Also, they were paid $30 USD per session to compensate for their participation.

Figure 1. Example of emotional stimuli

B. *Emotional Stimuli*

For the three emotions, emotional stimuli are selected the 2-4 min long audio-visual film clips, which are captured originally from movies and TV shows, and provoking pain. Figure 1 is the example of emotional stimuli using audio-visual film clips. The stimulus, which provokes pain, is that it's the more pressure an experimenter put on it after wearing a blood pressure cuff on subjects' arm during 1 minute. The boring stimulus is the combination a presentation of "+" symbol on screen and a repetitive sound of number from 1 to 10 during 3 minutes. The surprise provoking stimulus is the sudden presentation of above images and hog-caller, sound of breaking glass, and thunder during concentration on task during 1 minute. Audio-visual film clips have widely used because these have the desirable properties of being readily standardized, involving no deception, and being dynamic rather than static. They also have a relatively high degree of ecological validity, in so far as emotions are often evoked by dynamic visual and auditory stimuli that are external to the individual [14]-[17].

The audio-visual film clips have been used to provoke emotion and tested their appropriateness and effectiveness. The appropriateness of emotional stimuli means a consistency between the intended emotion by experimenter and the participants' experienced emotion. The effectiveness is an intensity of emotions that participants rated on a 1 to 7 point Likert-type scale, that is, 1 being "least boring" and 7 being "most boring". The appropriateness and effectiveness of these stimuli were as follows; appropriateness and effectiveness of boredom were 86.0% and 5.23±1.36, in pain 97.3% appropriateness and 4.96±1.34 effectiveness and 94.1% appropriateness and 6.12±1.14 effectiveness in surprise.

C. *Measurements of Physisological Signals and Feature extraction*

To collect physiological signals for three emotions, the laboratory is a room with 5m x 2.5m size having a sound-proof (lower than 35dB) of the noise level where any outside noise or artifact are completely blocked. A comfortable chair is placed in the middle of the laboratory and 38 inch TV

 ISBN: 978-1-61208-250-9

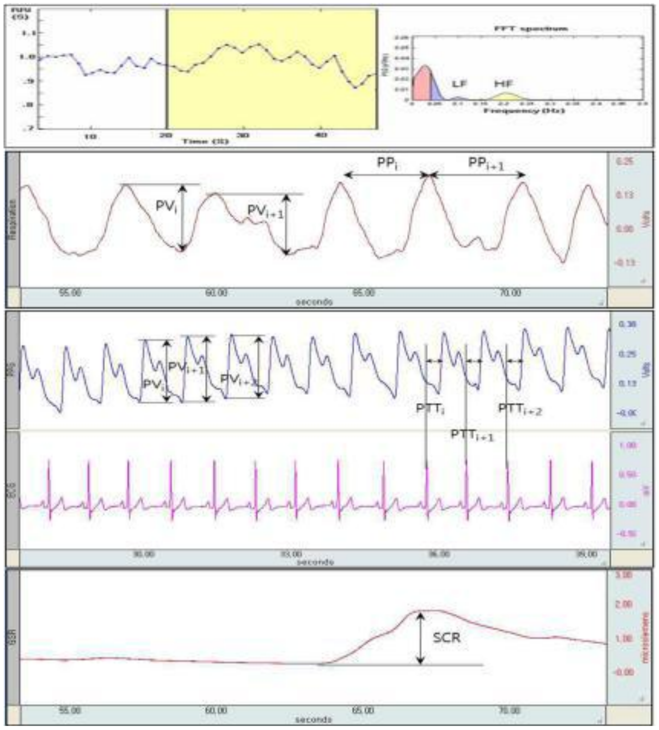

Figure 2. Physiological signals and feature extraction

monitor set for presentation of film clips is placed in front of the chair. An intercommunication device is placed to the right side of chair for subjects to communicate with an experimenter. A CCTV is installed on the top of the monitor set to observe participant's behaviors and their behaviors are storage through the monitor and a video cassette recorder outside the laboratory.

Prior to the experiment, subjects are introduced to detail experiment procedures and have an adaptation time to feel comfortable in the laboratory setting. Then they are attached electrodes on their wrist, finger, and ankle for measurement of physiological signals. Physiological signals are measured for 60 sec prior to the film clip presentation (baseline) and for 2 to 4 min during the presentation of the film clips (emotional state), then for 60 sec after presentation of the film clips as recovery term. Subjects rate the emotion that they experienced during presentation of the film clip on the emotion assessment scale.

The dataset of physiological signals such as skin temperature (SKT), electrodermal activity (EDA), photoplethysmography (PPG), and electrocardiogram (ECG) are collected by MP150 Biopac system Inc. (USA). SKT electrodes are attached on the first joint of non-dominant ring finger and on the first joint of the non-dominant thumb for PPG. EDA is measured with the use of 8 mm AgCl electrodes placed on the volar surface of the distal phalanges of the index and middle fingers of the non-dominant hand. Electrodes are filled with a 0.05 molar isotonic NaCl paste to provide a continuous connection between the electrodes and the skin. ECG electrodes are placed on both wrists and one left ankle with two kinds of electrodes, sputtered and AgCl ones. The left-ankle electrode is used as a reference.

The signals are acquired for 1 minute long baseline state prior to presentation of emotional stimuli and 1-2 minutes long emotional states during presentation of the stimuli as emotional state. To extract features, the obtained signals are analyzed for 30 seconds from the baseline and the emotional state by AcqKnowledge (Ver. 3.8.1) software (USA) as shown in Fig. 2. 27 features, namely, bSCL, bSCR, eSCL, eSCR, dSCL, and dSCR features from EDA signal, BmeanSKT, EmeanSKT and DmeanSKT from SKT, bHR, bLF, bHF, bHRV, eHR, eLF, eHF, eHRV, dHR, dLF, dHF and dHRV from ECG, and bBVP, bPPT, eBVP, ePPT, dBVP and dPPT from PPG are extracted from the obtained emotional physiological signals. These are the features that are commonly used in physiological signal analysis.

III. STRUCTURE AND DEVELOPMENT OF FUZZY C-MEANS CLUSTERING BASED NEURAL NETWORKS

Neural Network (NN) is a computational intelligence model inspired by the structure and functional aspects of biological neurons [11]. NN has been widely used to deal with pattern recognition problems. The generic topology of NN consists of three layers as shown in Fig. 1. A neuron in the input layer is connected to a layer of hidden neuron, which is connected to output neuron. The activity of the input neurons represents the raw information that is fed into the network, the activity of each hidden neuron is determined by the activities of the input neuron and the weights on the connections between the input and the hidden, and the behavior of the output depends on the activity of the hidden neurons and connection weights between the hidden and the output layer.

The proposed Fuzzy c-means clustering based neural networks (FNN) exhibit a similar topology as the one encountered in simple neural network. However the functionality and the associated design process exhibit some evident differences. In particular, the kernel fields of neurons do not assume any explicit functional form (say, Gaussian, ellipsoidal, etc.), but are directly reflective of the nature of the data and come as the results of fuzzy clustering in input layer, polynomials in hidden layer and linear combination of

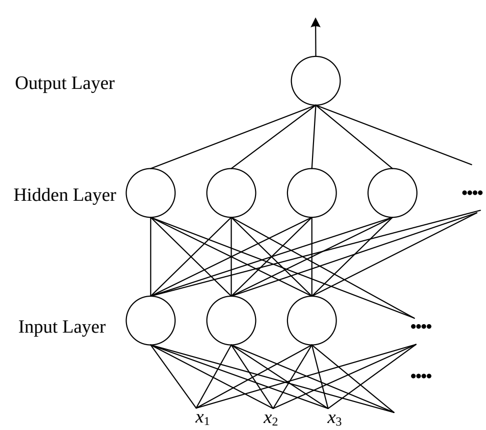

Figure 3. General structure of neural networks

activation signals in output layer. These networks results as a synergy between two other general constructs such as fuzzy c-means clustering [18][19] and neural networks [11].

In input layer, considering the prototypes v_1, v_2, …, v_c formed by the fuzzy c-means (FCM) clustering method, the kernel of a neuron is expressed in the following way

$$IK_i(\mathbf{x}) = 1 / \sum_{j=1}^{c} \left(\frac{\|\mathbf{x}-\mathbf{v}_i\|^2}{\|\mathbf{x}-\mathbf{v}_j\|^2} \right) \tag{1}$$

The FCM clustering method comes as a standard mechanism aimed at the formation of ‘c’ fuzzy sets. The objective function Q guiding this clustering is expressed as a sum of the distances of individual data from the prototypes v_1, v_2, …, and v_c,

$$Q = \sum_{i=1}^{c}\sum_{k=1}^{N} u_{ik}^{m} \|\mathbf{x}_k - \mathbf{v}_i\|^2 \tag{2}$$

Here, $\| \ \|$ denotes a certain distance function; ‘m’ stands for a fuzzification factor (coefficient), m=2.0. N is the number of patterns. The resulting partition matrix is denoted by $\mathbf{U}=[u_{ik}]$, i=1, 2,…,c; k=1, 2, …, N. While there is a substantial diversity as far as distance functions are concerned, here we adhere to a weighted Euclidean distance taking on the following form

$$\|\mathbf{x}_k - \mathbf{v}_i\|^2 = \sum_{j=1}^{n} \frac{(x_{kj}-v_{ij})^2}{\sigma_j^2} \tag{3}$$

with σ_j being a standard deviation of the j-th variable. While not being computationally demanding, this type of distance is still quite flexible and because of that commonly used.

The minimization of Q is realized in successive iterations by adjusting both the prototypes and entries of the partition matrix, that is min $Q(U, v_1, v_2, \ldots, v_c)$. The resulting partition matrix becomes output signals of kernel function in input layer, namely, U=IK.

In addition, the kernel functions of hidden layer come in the product of polynomials of inputs and activation signals which are output signals of input layer.

$$HK_i = f_i(\mathbf{x}) \cdot IK_i(\mathbf{x}) \tag{4}$$

Here, $f_i(\mathbf{x})$ is a certain polynomial coming from the following family of relationships

$$\begin{aligned} &\text{Constant}: \ f_i(\mathbf{x}) = a_{i0} \\ &\text{Linear}: \ f_i(\mathbf{x}) = a_{i0} + \sum_{j=1}^{n} a_{ij} x_j \end{aligned} \tag{5}$$

These functions are activated by partition matrix and lead to local regression models. The proposed FNNs governed by (5) are furnished with a great deal of degrees of freedom which may result with improved their emotion recognition rates when contrasted with conventional models.

The neuron located at the output layer completes a linear combination of the activation levels of the hidden layer.

$$\begin{aligned} y &= \sum_{i=1}^{c} HK_i = \sum_{i=1}^{c} f_i(\mathbf{x}) \cdot IK_i(\mathbf{x}) \\ &= \sum_{i=1}^{c} f_i(\mathbf{x}) \cdot \left(1 / \sum_{j=1}^{c} \left(\frac{\|\mathbf{x}-\mathbf{v}_i\|^2}{\|\mathbf{x}-\mathbf{v}_j\|^2} \right) \right) \end{aligned} \tag{6}$$

y is a representation of FNNs as a discriminant function.

IV. RESULTS OF EMOTION RECOGNITION

Our objective is to quantify the performance of the proposed FNNs recognizer and to compare it with the performance of some other recognizer reported in the literature. In the assessment of the performance of the recognizer, we use the recognition accuracy for three emotions. The experiments completed in this study are reported for the 10 fold cross-validation for assessing how the results of a statistical analysis will generalize to an independent dataset.

For the recognition of boredom, pain and surprise emotions, Table I contrasts the recognition accuracy (%) of the proposed FNNs with other well-known methods (C4.5, SOM, Naïve Bayes and SVM) studied in the literatures [9]-[14]. The experimental results reveal that the proposed approach and the resulting model outperform the existing methods in terms of better prediction capabilities on feature space.

C4.5 developed by R. Quinlan is one of statistical classifier algorithms and builds decision trees from a set of training data. C4.5 starts with large sets of cases belonging to known classes. The cases, described by any mixture of nominal and numeric properties, are scrutinized for patterns that allow the classes to be reliably discriminated. These patterns are then expressed as models, in the form of decision trees or sets of if-then rules, which can be used to classify new cases, with emphasis on making the models understandable as well as accurate.

SOM (self-organizing map), 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. This is called a topology-preserving map because there is a topological structure imposed on the nodes in the network. A topological map is simply a mapping that preserves neighbourhood relations. The goal of training is that the “winning” unit in the target space is adjusted so that it is more like the particular pattern. Others in the neighbourhood of output are also adjusted so that their weights more nearly match that of the input pattern.

The Naïve Bayes algorithm is a classification algorithm based on Bayes rule and particularly suited when the dimensionality of the inputs is high. When the dependency relationships among the features used by a classifier are unknown, we generally proceed by taking the simplest assumption, namely, that the feature are conditionally independent given the category, that is,

$$p(\omega_k \mid \mathbf{x}) \propto \prod_{i=1}^{d} p(x_i \mid \omega_k) \tag{7}$$

This so-called naïve Bayes rule often works quite well in practice, and it can be expressed by a very simple belief net.

SVM (support vector machine) finds a hyperplane based on support vector to analyze data and recognize patterns. The complexity of the resulting recognizer is characterized by the number of support vectors rather than the dimensionality of the transformed space. The goal in training SVM is to find the separating hyperplane with the largest margin. We expect that the larger the margin, the better generalization of the recognizer.

The more detail results of emotion recognition accuracy by each algorithm are like from Table II to VIII. In analysis of C4.5, accuracy of each emotion has range of 42% to 74%. Boredom is recognized by C4.5 with 73.9%, pain 42.0%, and surprise 58.9% as shown in Table II. In Table III and IV, the results of Naïve Bayes and SVM are shown for three emotions, respectively. Naïve Bayes provides accuracy of 71.88 % when it recognized all emotions. In boredom, accuracy of 73.9% is achieved, 71.6% in pain, 66.7% in surprise. The results of emotion recognition using SVM show recognition accuracy of 67%, 62.1%, and 57.3% according to orders of boredom, pain, and surprise. For the supervised and unsupervised SOM, 61.45% and 59.22% are obtained, respectively, as recognition accuracy for three emotions. For the each emotion, boredom, pain and surprise, 69.3%, 52.7% and 62% are obtained in supervised SOM and 68.2%, 56.8%, and 53.1% are resulted from unsupervised SOM. Finally, the recognition accuracy of the proposed FNN with constant and linear has 70.2% and 74.49%, respectively for three emotion recognition. In case of constant, each emotion is recognized by FNN with 79% of boredom, 61.5% of pain and 69.8% of surprise. 72.2%, 74.6% and 76.6% are shown as results of emotion recognition by FNN with linear for boredom, pain and surprise, respectively.

C4.5 and Naïve Bayes were coming from the Classification Toolbox of MATLAB. For SVM, we have used Duda's Toolbox (www.yom-tov.info/toolbox.html). SOM toolbox available in MATLAB has offered SOM algorithms, see www.cis.hut.fi/projects/somtoolbox/.

TABLE I. RESULT OF EMOTION RECOGNITION

Models		Accuracy (%)
C4.5		58.47
Naïve Bayes		71.88
SVM		62.01
SOM	Supervised	61.45
	Unsupervised	59.22
Proposed FNNs	Constant	70.2
	Linear	74.49

TABLE II. RESULT OF EMOTION RECOGNITION BY C4.5

	Boredom	Pain	Surprise
Boredom	73.9	2.3	23.9
Pain	22.5	42	35.5
Surprise	28.6	12.5	58.9

TABLE III. RESULT OF EMOTION RECOGNITION BY NAÏVE BAYES

	Boredom	Pain	Surprise
Boredom	77.8	2.3	19.3
Pain	8.3	71.6	19.5
Surprise	16.1	16.7	66.7

TABLE IV. RESULT OF EMOTION RECOGNITION BY SVM

	Boredom	Pain	Surprise
Boredom	67	8	25
Pain	5.9	62.1	32
Surprise	14.1	28.6	57.3

TABLE V. RESULT OF EMOTION RECOGNITION BY SUPERVISED SOM

	Boredom	Pain	Surprise
Boredom	69.3	10.2	20.5
Pain	3	52.7	44.4
Surprise	7.8	30.2	62

TABLE VI. RESULT OF EMOTION RECOGNITION BY UNSUPERVISED SOM

	Boredom	Pain	Surprise
Boredom	68.2	7.4	19.9
Pain	8.9	56.8	32.5
Surprise	14.1	30.7	53.1

TABLE VII. RESULT OF EMOTION RECOGNITION BY FNN WITH CONSTANT

	Boredom	Pain	Surprise
Boredom	79	4.5	16.5
Pain	4.1	61.5	34.3
Surprise	9.4	20.8	69.8

TABLE VIII. RESULT OF EMOTION RECOGNITION BY FNN WITH LINEAR

	Boredom	Pain	Surprise
Boredom	72.2	4	23.9
Pain	3	74.6	22.5
Surprise	4.2	19.3	76.6

V. CONCLUSION

In this study, we have discussed the acquisition of emotional physiology signals using emotion stimuli and the design of an emotion recognition methodology for boredom,

 ISBN: 978-1-61208-250-9

pain and surprise emotions. The emotion stimuli used to induce a participant's emotion were evaluated for their suitability and effectiveness. The result showed that emotional stimuli have the appropriateness of 92.5% and the effectiveness of 5.4 point (7 point Likert scale) on average. Twenty seven features have been extracted by means of the statistical and the geometric approaches in time and frequency domain from physiological signals such as EDA, SKT, PPG and ECG. These signals have been induced by emotional stimuli. In order to recognize the three emotions with physiological signals, we have proposed fuzzy c-means clustering based neural networks (FNNs) with three layers. Fuzzy c-means clustering method as a kernel function has used in a neuron in input layer. A kernel function of a neuron in the hidden layer used two types of polynomial functions and the linear combination of input signals were used in output layer of the proposed networks. Using two types of polynomial functions helped to improve the characteristic of a recognizer and carried out the presentation of a partitioned local space. The proposed FNN recognizer generates a nonlinear discernment function in the output space and has the better performance of emotion recognition. As shown in results, the proposed FNN with linear function has recognition accuracy 74.49% for the three emotions. The proposed recognizer will lead to better chance to recognize human emotions by using physiological signals in the emotional interaction between man and machine.

ACKNOWLEDGMENT

This research was supported by the Converging Research Center Program funded by the Ministry of Education, Science and Technology (No. 2012K001330 & 2012K001339).

REFERENCES

[1] J.Wagner, J. Kim, and E. Andre, "From physiological signals to emotions: Implementing and comparing selected methods for feature extraction and classification," IEEE International Conference on Multimedia and Expo, pp. 940-943, 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] P.D. Drummond, and S.-H. Quah, "The effect of expressing anger on cardiovascular reactivity and facial blood flow in Chinese and Caucasians," Psychophysiology, pp. 190-196, 2001.

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

[5] R. P. Lippman, "An introduction to computing with neural nets," IEEE ASSP Magazine, vol. 4, no. 2, pp. 4-22, 1981.

[6] Y. Al-Assaf, and H. El Kadi, "Fatigue life prediction of composite materials using polynomial classifiers and recurrent neural networks," Composite Structures, vol. 77, pp. 561-569, 2007.

[7] F. Ros, M. Pintore, and J.R. Chretien, "Automatic design of growing radial basis function neural networks based on neighborhood concepts," Chemometrics and Intelligent Laboratory Systems, vol. 87, pp. 231-240, 2007.

[8] C. Zhang, J. Jiang and M. Kamel, "Intrusion detection using hierarchical neural networks," Pattern Recognition Letters, vol. 26, pp. 779-791, 2005.

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

[10] C. Lim, and J.-H. Chang, "Adaptive Kernel Function of SVM for Improving Speech/Music Classification of 3GPP2 SMV", ETRI Journal, vol. 33, no. 6, pp.871-879, 2011.

[11] R.O. Duda, P.E. Hart, and D.G. Stork, Pattern classification, 2nd ed. Wiley-Interscience, New York, 2000.

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

[13] T. Kohonen, "Self-Organizing Maps," Proceedings of the IEEE, vol. 79, pp. 1464-1480, 1990.

[14] J.J. Gross, and R.W. Levenson, "Emotion elicitation using films," Cognition and Emotion, vol. 9, pp. 87-108, 1995.

[15] R.S. Lazarus, J.C. Speisman, A.M. Mordkoff, and L.A. Davidson, "A Laboratory study of psychological stress produced by an emotion picture film," Psychological Monographs, vol. 76, pp. 553, 1962.

[16] M.H. Davis, J.G. Hull, R.D. Young, and G.G. Warren, "Emotional reactions to dramatic film stimuli: the influence of cognitive and emotional empathy," Journal of personality and social psychology, vol. 52, pp. 126-133, 1987.

[17] D. Palomba, M. Sarlo, A. Angrilli, A. Mini, and L. Stegagno, "Cardiac responses associated with affective processing of unpleasant film stimuli," International Journal of Psychophysiology, vol. 36, pp. 45-57, 2000.

[18] A. Aiyer, K. Pyun, Y.Z. Huang, D.B. O'Brien and R.M. Gray, "Lloyd clustering of Gauss mixture models for image compression and classification," Signal Processing: Image Communication, vol. 20 pp. 459-485, 2005.

[19] J.C. Bezdek, Pattern Recognition with Fuzzy Objective Function Algorithms, Plenum Press, New York, 1981.

 ISBN: 978-1-61208-250-9