# Emotional stress recognition system using EEG and psychophysiological signals:

## Using new labelling process of EEG signals in emotional stress state

Seyyed Abed Hosseini
M.Sc. in Biomedical Engineering,
Islamic Azad University Mashhad Branch
Young Researchers Club,
Islamic Azad University Mashhad Branch
Mashhad, Iran
hosseyni_abed@mshdiau.ac.ir

Mohammad Ali Khalilzadeh
Assistant Professor, Biomedical Engineering dept.,
Islamic Azad University Mashhad Branch
Mashhad, Iran
makhalilzadeh@mshdiau.ac.ir

*Abstract*— **this paper proposes a new emotional stress recognition system using multi-modal bio-signals. Since electroencephalogram (EEG) is the reflection of brain activity and is widely used in clinical diagnosis and biomedical research, it is used as the main signal. In order to choose the proper EEG channels we used the cognitive model of the brain under emotional stress. We designed an efficient acquisition protocol to acquire the EEG and psychophysiological signals under pictures induction environment (calm-neutral and negative-excited) for participants. Qualitative and quantitative evaluation of psychophysiological signals have been tried to select suitable segments of EEG signal for improving efficiency and performance of emotional stress recognition system. After pre-processing the signals, both Linear and nonlinear features were employed to extract the EEG parameters. Wavelet coefficients and chaotic invariants like fractal dimension by Higuchi's algorithm and correlation dimension were used to extract the characteristics of the EEG signal which showed that the classification accuracy in two emotional states was 82.7% using the Elman classifier. This is a great improvement in results compared with other similar published work.**

***Keywords-EEG signals; psychophysiological signals; emotional stress; wavelet coefficients; nonlinear features; genetic algorithm; classification.***

### I. INTRODUCTION

A lot of research has been undertaken in assessment of stress over the last years. The main reason of which is the fact that feelings are present in many situations where humans are involved. Stress is often defined as the body's reaction to a perceived mental, emotional or physical distress. This definition may appear to be circular, but there are significant concepts contained in it [1]. A major problem in understanding emotion is the assessment of the definition of emotions. In fact, even psychologists have problem agreeing on what is considered an emotion and also how many types of emotions exist. The most well known theory represents emotions in 2 or 3 dimensional spaces, originating from cognitive theories, where valence-arousal space in emotions is expressed as a combination of two continuous variables: valence ranging from negative to positive (or unpleasant to pleasant) and arousal extending from calm to excited [2]. Psychologists agree that human emotions can be categorized into a small number of cases. For example, Ekman and et al. [3] found that six different facial expressions (fearful, angry, sad, disgusted, happy and surprised) were categorically recognized by humans from distinct cultures using a standardized stimulus set. In recognition of emotions brain activity plays a central role. Emotion plays a major role in motivation, perception, cognition, creativity, attention, learning and decision making [3, 4]. However, few works have used it to assess the emotional states. Recent researches on the human electroencephalogram (EEG), revealed the chaotic nature of this signal. To identify new features, we use the fact that the EEG signal reflects the interaction of millions of neurons and that the brain follows a chaotic behavior. Thus it is logical not to use conventional methods that assume emotion can be analyzed by linear models [5].

Previous studies have investigated the use of psychophysiological and brain signals separately [3, 6, 7] but little attention has been paid so far to the links between brain and psychophysiological signals. Analyzing the results of previous works is a difficult task, because to compare the results of the works which attempt to introduce emotion recognition systems as a classification problem, it is important to consider the way that emotions are elicited and the number of participants, the latter is important especially to introduce a user independent system.

In one study Chanel [6] asked the participants to remember past emotional events, and obtained the best result of 79% using EEG and 53% using peripheral signal for 3 categories,

978-1-4244-5316-0/10/$26.00 ©2010 IEEE

76% using EEG and 73% using peripheral signals for 2 categories. In another study, Hosseini [7] used EEG and psychophysiologcal signals to stimulate participants with two different emotions, resulting in 70% of correctly identified patterns. Kim [8] used the combination of music and story as stimuli and there were 50 participants, to introduce a user independent system, the results were 78.4%, 61% for 3 and 4 categories respectively. Takahashi [9] also used film clips to stimulate participants with five different emotions, resulting in 42% of correctly identified patterns.

The goal of our research is to produce a multi-modal link between EEG and psychophysiological signals for emotion detection. The system was intended to recognize emotion from offline EEG signals. We investigated the recognition of two emotional states (calm and negatively excited) using Elman and we will discuss how multi-modal bio-signals are effective for emotion recognition. The design of emotional stress recognition system is shown in section 2-4 and the results of our emotional stress recognition experiments are presented in section 5.

## II. ACQUISITION PROTOCOL

### A. Stimuli

Several methods exist for subject stimulation. For example, participants could be looking at pictures, looking at movies, listening to sounds, stroop test or playing games. However, most experiments (e.g. [2, 3, 10-13]). That measure emotion from EEG signals use pictures from the subset of the International Affective Picture System (IAPS). The IAPS contains 956 emotionally evocative images evaluated by several American participants on two dimensions of nine points each (1-9) [11, 14]. In our study the stimuli to elicit the target emotions (calm and negatively excited) were some of the pictures in IAPS databases [14]. The use of IAPS allows better control of emotional stimuli and simplifies the experimental design. The images in these classes were picked according to the rules in (1) [3], where the arousal and valence scales were from 1 to 9. Particular images (for example erotic images) were removed from the selection.

$$\begin{aligned} &Calm : arousal < 4 \\ &\quad 4 < valence < 6 \\ &Negativeexiting : arousal > 5 \\ &\quad valence < 3 \end{aligned} \tag{1}$$

The participant sits in front of a computer displaying the images to inform him about the specific emotional event he has to think of. Each experiment consists of 8 trials. Each stimulus consists of a block of 4 pictures, which ensures stability of the emotion over time. And each picture is displayed for 3 seconds leading to a total 12 seconds per block. Prior to displaying images, a dark screen with an asterisk in the middle is shown for 10 seconds to separate each trial and to attract the participant's attention. The detail of each trial is shown in Fig. 1.

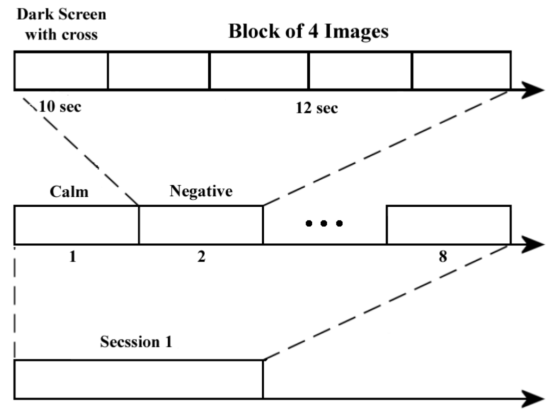

Figure 1. The protocol of data acquisition

### B. Subjects

Fifteen healthy volunteered subjects were right-handed males between the age of 20 and 24 years. Most subjects were students from biomedical engineering department of Islamic Azad University in Mashhad Branch. Each participant was examined by a dichotic listening test to identify the dominant hemisphere. All subjects had normal or corrected vision; none of them had neurological disorders. These were done to eliminate any differences in subjects. Then each participant was given a particulars questionnaire. All participants gave written informed consent. During the pre-test, several questionnaires have been evaluated in order to check the best psychological input to start the protocol phase; this test is State-Trait Anxiety Inventory (STAI, [15]). At the end of the experiment, each participant was asked to fill in a questionnaire about the experiment and give their opinions.

### C. Procedure

We used a Flexcom Infiniti biofeedback device for data acquisition. Data such as skin conductance (SC), photoplethysmograph (PPG), respiratory rate (RR) and EEG signals were continuously recorded through bio-sensors placed on the participant. In this study, we recorded SC by positioning two dedicated electrodes on the top of left index and middle fingers. RR was recorded by a respiration belt, counting the chest cavity expansions over time. Finally, a photoplethysmograph was placed on the thumb of the participant to record his blood volume pressure. The sample rate of the psychophysiological acquisition was 2048Hz. EEG was recorded using electrodes placed at 5 positions. In order to choose the proper EEG channels we used the cognitive model of the brain under emotional stress [16]. The scalp EEG was obtained at location FP1, FP2, T3, T4, Pz, as defined by the international 10-20 system. The sample rate of the EEG acquisition was 256Hz.

## III. LABELLING PROCESS OF EEG SIGNALS

The process of labelling EEG signals consists of three stages: first self-assessment, second the qualitative analysis and third the quantitative analysis of psychophysiological signals. Fig. 2 shows the different stages of the process. After the experiment, there was also a self-assessment stage, which is a good way to have an idea about the emotional stimulation "level" of the subject because emotions are known to be very subjective and dependent on previous experience [3]. In this research, we will be able to get a general idea of the quality of the data, i.e. if the data are good or bad.

One kind of this data is respiration. Slow respiration, for example is linked to relaxation while irregular rhythm, quick variations, and cessation of respiration correspond to more aroused emotions like anger or fear [6]. Another one is skin conductance, which basically measures the conductivity of the skin. SC increases if the skin is sweaty, for example when one is experimenting emotions such as stress. Lang discovered that the mean value of the SC is related to the level of arousal [6, 17]. Moreover blood pressure and heart rate variability are variables that correlate with defensive reactions, pleasantness of a stimulus, and basic emotions [6]. We obtained HRV using PPG signal [18], because analysis of HRV provides an effective way to investigate the different activities of autonomic nervous system. In order to analyze the psychophysiological signals quantitatively, we need to pre-process them, to remove environmental noises by applying filters. We used a common set of feature values for the signals. The respiration features are from time and frequency domains, the skin conductance features and the photoplethysmograph features are from time domain, and the heart rate variability features are from time, frequency domains and fractal dimension (Table 1).

TABLE I. FEATURES EXTRACTED FROM PSYCHOPHYSIOLOGICAL SIGNALS

| Signal | Extracted features |
|---|---|
| Respiration | Mean, variance, Standard deviation, Kurtosis, Skewness, Maximum minus Minimum value, Mean of derivative and calculating the power 5 frequency band of 0.25 to 2.75Hz. |
| Skin Conductance | Mean, variance, Standard deviation, Kurtosis, Skewness, Maximum response, Mean of derivative, energy response and proportion of negative samples in the derivative vs. all samples. |
| Photo plethysmograph | Mean, variance, Standard deviation, Kurtosis, Skewness, Mean of trough variability, Variance of trough variability, Mean of peak variability, Variance of peak variability, Mean of amplitude variability, Variance of amplitude variability, Mean value variability, Variance of mean value variability, Mean of baseline variability, Variance of baseline variability |
| Heart Rate Variability | Mean, variance, Standard deviation, Maximum value, Minimum value, Low power frequency of 0.05-0.15Hz, Proportion low power frequency vs. all power frequency, fractal dimension by Higuchi's algorithm |

After extracting the features we need to classify them using a support vector machine (SVM) [19]. There are several approaches to apply the SVM for multiclass classification. In this study, the one-vs.-all method was implemented [20]. Two SVMs that correspond to each of the two emotions were used. The *i*th SVM was trained with all of the training data in the *i*th class with calm labels, and the other training data with negative labels.

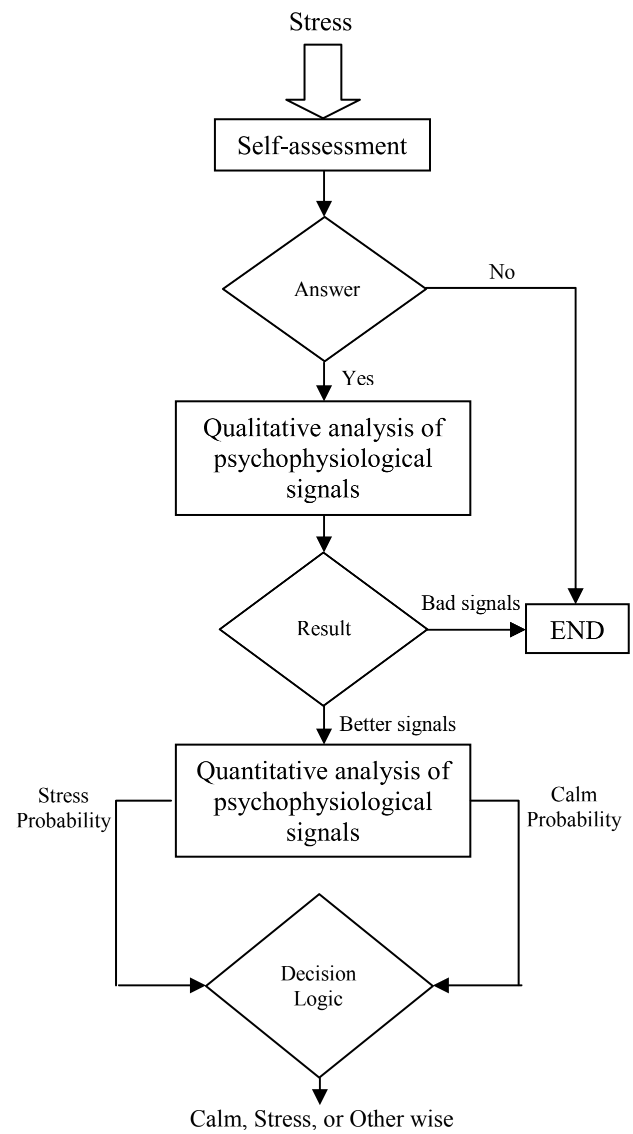


Figure 2. Labelling process of EEG signals

In the emotion recognition process, the feature vector was simultaneously fed into all SVMs and the output from each SVM was investigated in the decision logic algorithm to select the best emotion (Fig. 3). In the SVM classifier, was used a Gaussian Radial Basis function (RBF) as a kernel function. RBF projects the data to a higher dimension [19].

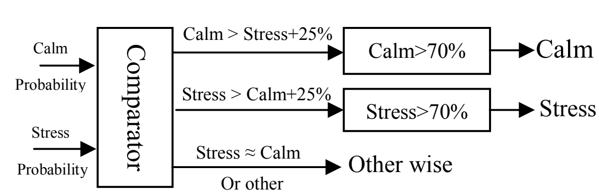


Figure 3. decision logic algorithm

The best results are the accuracy of 84.1% for two categories, using the psychophysiological signals. Method at this stage it has been tried to select suitable segments of EEG signal for improving efficiency and performance of the classifier.

## IV. Analysis of EEG signals

### A. Pre-processing

The brain produces electrical activity in the order of microvolt. Because these signals are very weak, it usually contains a lot of noise. We need to pre-process EEG signals, remove environment noises and drifts by applying a 0.5-35Hz band pass filter. This band is selected because the frequency intervals of interest in EEG are the $\delta$ (1-4Hz), $\theta$ (4-8Hz), $\alpha$ (8-13Hz) and $\beta$ (13-30Hz) bands. This filter will remove all high frequency noise, and also removes most of the artifacts. Before analysis, we first remove the data segment which contains obvious eye blinking through electrooculogram (EOG).

### B. Normalization

In order to normalize the features in the limits of [0, 1], we used (2).

$$Y_{norm} = \frac{-2Y_s^{'} + Y_{s\max}^{'} + Y_{s\min}^{'}}{Y_{s\min}^{'} - Y_{s\max}^{'}} \qquad (2)$$

In this equation $Y_{norm}$ is the relative amplitude.

### C. Feature extraction

Feature extraction is the process of extracting useful information from the signal. Features are characteristics of a signal that are able to distinguish between different emotions. We use a common set of feature values for brain signals. Nonlinear measures have received the most attention in comparison with the measures mentioned before, for example time domain, frequency domain and other linear features. The nonlinear set of features used include fractal dimension and correlation dimension signals. Features are extracted for each electrode of EEG signals

*1) Fractal dimension:* The term "fractal dimension (FD)" refers to a noninteger or fractional dimension of a geometric object. Fractal dimension analysis is frequently used in biomedical signal processing, including EEG analysis [5]. Higuchi's algorithm unlike many other methods requires only short time intervals to calculate fractal dimension. This is very advantageous because EEG signal remains stationary during short intervals and because in EEG analysis it is often necessary to consider short, transient events (for a review in equation, see [5]).

*2) Correlation dimension:* Correlation dimension ($D_2$) is one of the most widely used measures of a chaotic process. We used the Grassberger and Procaccia algorithm (GPA) [21] for estimating $D_2$ in our work (for a review in equation, see [21]). The choice of an appropriate time delay r and embedding dimension d is important for the success of reconstructing the attractor with finite data. We calculated $D_2$ with $d_E$ values varying from 2 to 10 for all the subjects. It can be seen that $D_2$ saturates after the embedding dimension of 7. Therefore we have chosen $d_E$=8 for constructing the embedding space and estimation of the invariants. The determination is based on calculating the relative number of pairs of points in the phase-space set that is separated by a distance less than r. For a self-similar attractor, the local scaling exponent is constant, and this region is called a scaling region. This scaling exponent can be used as an estimate of the correlation dimension. If the $d_E$=8 plots C(N, r) vs. r on a log-log scale, the correlation dimension is given by the slope of the log C(r) vs. log r curve over a selected range of r, and the slope of this curve in the scaling region is estimated by the least slope fitting.

*3) Wavelet coefficients:* Discrete wavelet transform (DWT) based feature extraction has been successfully applied with promising results in physiological pattern recognition applications [22]. Choice of suitable wavelet and the number of levels of decomposition is very important in analysis of signals using DWT. In this study, we used Daubechies wavelet function with order db4 for extracting the statistical feature from the EEG signal [22]. The number of levels of decomposition is chosen based on the dominant frequency components of the signal. The levels are chosen such that those parts of the signal that correlate well with the frequencies required for classification of the signal are retained in the wavelet coefficients. Since the EEG signals do not have any useful frequency components above 32Hz, the number of levels was chosen to be 5. Thus the signal is decomposed into the details D1-D5 and one final approximation, A5. The range of various frequency bands are shown in table 2.

TABLE II. Frequencies corresponding to different levels of decomposition for "db4" wavelet with a sampling frequency of 256 Hz

| Decomposition levels | Frequency Bandwidth (Hz) | Frequency bands |
|---|---|---|
| D1 | 64-128 | Noises |
| D2 | 32-64 | Noises (Gama) |
| D3 | 16-32 | Beta |
| D4 | 8-16 | Alpha |
| D5 | 4-8 | Theta |
| A5 | 0-4 | Delta |

The extracted wavelet coefficients provide a compact representation that shows the energy distribution of the EEG signal in time and frequency. Table 2 presents frequencies corresponding to different levels of decomposition for db4 wavelets with a sampling frequency of 256Hz. It can be seen from table 2 that the components A5 are within the delta (0-4Hz), D5 are within the Theta (4-8Hz), D4 are within the alpha (8-13Hz) and D3 are within the beta (13-30Hz). Lower level decompositions related to higher frequencies have negligible magnitudes in a normal EEG. In order to further diminish the dimensionality of the extracted feature vectors, statistics over the set of the wavelet coefficients was used.

- Mean of the absolute values of the wavelet coefficients in each sub-band
- Average power of the wavelet coefficients in each sub-band
- Standard deviation of the wavelet coefficients in each sub-band

### D. Feature selection

The problem of the vast number of features is solved by using Genetic Algorithm (GA) as a feature selection method [23]. The emphasis on using the genetic algorithm for feature selection is to reduce the computational load on the training system while still allowing near optimal results to be found relatively quickly. The GA uses populations of 100 sizes, starting with randomly generated genomes. The probability of mutation was set to 0.01 and the probability of crossover was set to 0.4. The classification performance of the trained network using the whole dataset was returned to the GA as the value of the fitness function. We attempted to detect the feature sets related to negative/calm emotion response from EEG signals.

### E. Classification

After extracting the desired features, we still have to find the emotion. This process will be done by a classifier. A classifier is a system that divides some data into different classes, and is able to learn the relationship between the features and the emotional state. One very useful classifier is an Elman network [24, 25] which is a two-layer back-propagation neural network, with the addition of a feedback connection from the output of the hidden layer to its input. This feedback path allows Elman network to learn to recognize and generate temporal patterns, as well as spatial patterns. The Elman network has tansig neurons in its hidden (recurrent) layer, and purelin neurons in its output layer. This combination is special in that the two-layer networks with these transfer functions can approximate any function (with a finite number of discontinuities) with arbitrary accuracy. The Levenberg-Marquardt back-propagation algorithm is used for training. The Levenberg-Marquardt algorithm will have the fastest convergence compared with other training functions [25]. The error ratio for stop training was considered 0.001.

## V. Results

The simulations were implemented in MATLAB software. We used a 2-second rectangular window without overlap for data segmentation. The gathered data was be used to teach our system the details about recognizing emotion from the EEG and psychophysiological signals. We used around 65% of the data for the training, and 25% of the data for testing whether the learned relationship between the EEG signals and emotion is correct and the last 10% was used for validating the data. Our best results were the accuracy of 82.7% for the two categories (calm vs. negative exited), using the EEG signals. The system was tested using the 5-fold cross-validation method. This method divides the training data into five parts. One of the parts is used for testing the classifier, and the four others are used for training. The process was repeated five times, every time with another part of the data. This method reduces the possibility of deviations in the results due to some special distribution of training and test data, and ensures that the system is tested with different samples from those it has seen for training. Using a 5-fold cross validation method for training and testing, we reached an accuracy of 79.2% for the two categories of emotional stress using the EEG signals.

## VI. Discussion and Conclusion

Classically, the electroencephalogram has been the most utilized signal to assess brain function owing to its excellent time resolution. In this paper we propose an approach to classify emotion in the two main areas of the valance-arousal space by using physiological signals. During the last decade a variety of these analysis techniques have repeatedly been applied to EEG recordings during physiological and pathological conditions and were shown to offer new information about complex brain dynamics [21, 26, 27]. The nonlinear measures include: fractal dimension and correlation dimension. For most measures a dimension should be defined to visualize the attractor in phase space, but the problem associated with all of them is that defined dimension for the phase space is not constant for all channels of recorded EEG signals or for different subjects, and depending on the conditions, the chosen dimension can be different.

The results of our study show that the $D_2$ of negative emotional activity is less as compared to that of calm activity. It can also be observed that Higuchi's algorithm indicates similar trend of reduction in FD value for negative emotional EEG compared to calm EEG. The reduction in FD values and $D_2$ characterizes the reduction in brain system complexity [21] for participants with negative emotional state. Hence the application of nonlinear time series analysis to EEG signals offers insight into the dynamical nature and variability of the brain signals. The chaotic measures distinctly characterize the normal and negative emotional EEG signals. The results show that new fusion between EEG and psychophysiological signals are more robust in comparison to the signals separately [3, 6, 7]. Our results show the importance of EEG signals for emotion assessment by classification as they have better time response than psychophysiological signals. We used 2 second time intervals to analyze the brain signals which resulted in a time resolution of 2 seconds in emotional stress recognition. If we had used shorter time intervals with overlap, we could have achieved a greater but virtual time resolution, which, for example, can be useful in biofeedback applications. The classification accuracy in two emotional states was 82.7% using EEG signals. Due to the differences in the conditions of the experiment, we cannot compare our results with the results of the works which have attempted to introduce emotion recognition systems as a classification problem. But in comparison to similar works, we achieved an improvement of about 11% in our results [6, 7].

Future work to acquire data from more participants is underway to validate the current results. We are pursuing this track as it should lead to a better identification of emotions.

## REFERENCES


[1] S. Reisman, "Measurement of Physiological Stress", Proceedings of the IEEE, 23rd Northeast Bioengineering Conference, pp. 21-23, May 1997.

[2] R.R. Cornelius, "Theoretical approaches to emotion", Proc. Int. Speech Communication Association (ISCA) Workshop on Speech and Emotion, Belfast, Ireland, 2000.

[3] A. Savran, K. Ciftci, G. Chanel, J.C. Mota, L.H. Viet, B. Sankur, L. Akarun, A. Caplier, and M. Rombaut, "Emotion Detection in the Loop from Brain Signals and Facial Images", Final Project Report, eNTERFACE'06, Dubrovnik, Croatia, 2006.

[4] S.A. Hosseini, and M.A. Khalilzadeh, "Qualitative and Quantitative Evaluation of EEG signals in Emotional state with through higher order spectra", 3rd Iranian Congress on Fuzzy and Intelligent Systems, July 2009. (Article in Persian).

[5] A. Bashashati, R.K. Ward, G.E. Birch, M.R. Hashemi, and MA. Khalilzadeh, "Fractal Dimension-Based EEG Biofeedback Slystem", Proceedings of the 25th Annual Intemational Conference of the IEEE EMBS Cancun, Mexico, September 2003.

[6] G. Chanel, K. Ansari-Asl, and T. Pun, "Valence-arousal evaluation using physiological signals in an emotion recall paradigm", IEEE International Conference on Systems, Man and Cybernetics ISIC, pp. 2662-2667, October 2007.

[7] S.A. Hosseini, M.B. Naghibi-Sistani, and S. Rahati-quchani, "dissection and analysis of psychophysiological and EEG signals for emotional stress evaluation", 12th Iranian Students Conference on Electrical Engineering, August 2009. (Article in Persian).

[8] 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.

[9] K. Takahashi, "Remarks on Emotion Recognition from Bio-Potential Signals", Proceedings of the 2nd International Conference on Autonomous Robots and Agents, Palmerson North (New Zealand), December 2004.

[10] J. Zhai, A.B. Barreto, C. Chin, and C. Li, "Realization of Stress Detection using Psychophysiological Signals for Improvement of Human-Computer Interactions", Proceedings of the IEEE Southeast Conference, pp. 415-420, Aprill 2005.

[11] R. Horlings, "Emotion recognition using brain activity", Delft University of Technology, Faculty of Electrical Engineering, Mathematics, and Computer Science, Man-Machine Interaction Group, March 2008.

[12] M. Soleymani, G. Chanel, J.J.M. Kierkels, and T. Pun, "Affective Characterization of Movie Scenes Based on Multimedia Content Analysis and User's Physiological Emotional Responses", Tenth IEEE International Symposium on Multimedia, 2008.

[13] Z. Dharmawan, "Analysis of Computer Games Player Stress Level Using EEG Data", Master of Science Thesis Report, Delft University of Technology, Netherlands, August 2007.

[14] http://www.unifesp.br/dpsicobio/adap/exemplos_fotos.htm

[15] S. Scotti, M. Mauri, S. Cerutti, L. Mainardi, and M. Villamira, "Quantitative evaluation of distant student psychophysical responses during the e-learning processes", Proceedings of the 27th Annual Conference of the IEEE Engineering in Medicine and Biology, Shanghai, China, pp. 1196-1199, September 2005.

[16] S.A. Hosseini, M.A. Khalilzadeh, S.M. Homam, and M. Azarnoosh, Presentation of description and computational model of brain behavior in emotional stress", 16th Iranian Conference on biomedical engineering, 2009. (Article in Persian).

[17] P.J. Lang, M.K. Greenwald, M.M. Bradley, and A.O. Hamm, "Looking at pictures: affective, facial, visceral, and behavioral reactions", Psychophysiology, vol. 30, pp. 261-273, 1993.

[18] R.D. Wan, and L.J. Woo, "Feature Extraction and Emotion Classification Using Bio-Signal", Transactions on Engineering, Computing and Technology V2 ISSN 1305-5313, pp. 317-320, December 2004.

[19] C.J.C. Burges, "A Tutorial on Support Vector Machines for Pattern Recognition", Data Mining and Knowledge Discovery 2, pp. 121-167, 1998.

[20] O. Chapello, P. Haffner, and V. Vapnik, "Support vector machine for histogram-based image classification", IEEE Transactions on Neural Networks, vol. 10, No. 5, pp. 1055-1064, 1999.

[21] N. Kannathal, K.S. Puthusserypady, and L.C. Min, "Complex Dynamics of Epileptic EEG", Proceedings of the 26th Annual International Conference of the IEEE EMBS San Francisco, CA, USA, pp. 604-607, September 2004.

[22] M. Murugappan, M. Rizon, R. Nagarajan, and S. Yaacob, "FCM clustering of Human Emotions using Wavelet based Features from EEG", International Journal of Biomedical Soft Computing and Human Sciences (IJBSCHS), vol. 14, No. 2, pp. 35-40, 2009.

[23] R.L. Haupt, and S.E. Haupt, "Practical Genetic Algorithms", Second Edition, John Wiley & Sons, Inc, pp. 189-190, 2004.

[24] J.L. Elman, "Finding Structure in Time", Cognitive Science 14, pp. 179-211, 1990.

[25] H. Demuth, M. Beale, and M. Hagan, "Neural Network Toolbox 5 User's Guide", by The MathWorks, 2007.

[26] Y. Wang, W. Wang, Y. Liu, D. Wang, B. Liu, Y. Shi, and P. Gao, "Feature Extracting of Weak Signal in Real-Time Sleeping EEG with Approximate Entropy and Bispectrum Analysis", 3rd International Conference on Bioinformatics and Biomedical Engineering (ICBBE), pp. 1-4, June 2009.

[27] S.C. Fang, H.L. Chan, and W.H. Chen "Approximate Entropy Analysis of Electroencephalogram in Vasovagal Syncope on Tilt Table Test", Proceedings of the 26th Annual International Conference of the IEEE EMBS San Francisco, CA, USA, pp. 590-592, September 2004.