Feature Selection and Interpretation of GSR and ECG Sensor Data in Biofeedback Stress Monitoring

Tamás D. Gedeon
Research School of Computer Science
Australian National University
Canberra Australia
tom@cs.anu.edu.au

Xuanying Zhu, Leana Copeland, Nandita Sharma
Research School of Computer Science
Australian National University
Canberra Australia

***Abstract*—We have used sensor data previously to detect the stress status of observers of stressful environments. In this work we describe the process of conversion from a passive and post-facto detection of this stress status to a dynamic and real-time or close to real-time process for control of stress using biofeedback. We describe the changes required to feature selection and interpretation of galvanic skin response (GSR) and electrocardiograph (ECG) sensor data for the new setting, using training on data from the post-facto dataset filtered to match, and as far as possible simulate a real-time dataset. We then compare 3 alternatives including a control component.**

Keywords- observer stress; physiological signals; biofeedback; human centred computing.

I. INTRODUCTION

Our previous work demonstrated that we could construct reliable computational models for observer stress extracted from a range of physiological signals. In that work, we used physiological recordings of the entire experiment to detect the observer's stress level, the experiment consisting of showing a number of short video clips of known stressfulness, as validated by user surveys. This data forms the ANU Stress DB.

We have extended our previous work, and sampled the ANU Stress DB to mimic real-time or close to real-time data collection, to form training data for a biofeedback model. For usefulness in biofeedback the model needs to display results no slower than 1 Hz, based on some preliminary experiments with subjects. Using only the last 2 seconds of data produces a model in 80% in accord with our previous full model using the entire experiment recording.

We then tested this new model in a new experiment, to compare our model with the use of EEG as the biofeedback target, as well as a control curve which displays the stress curve of a randomly chosen prior subject. That is, the stress curve is synchronized with the experiment and is a valid stress curve, but is not the curve of the current subject and so does not reflect any changes made by the current subject.

II. STRESS AND REDUCTION OF STRESS

The term *stress* was coined by Hans Selye in 1936, and defined as "the non-specific response of the body to any demand for change" [1]. There is evidence that too much stress has significant health effects, e.g. [2].

We concentrate on objective measures of stress [3].

A. Observer Stress

We concentrate on a viewer of events, hence the stress encountered is observer stress. In this century, more and more our interactions with the world are virtual or mediated via screens, or for other reasons we have no ability to change what we see. Hence this is a valuable area for stress research. We have done previous work on computational models for stress in a range of environments: abstract (reading) [4], virtual (screens - including video / cctv) [5], and real environments [6].

B. Stress reduction - biofeedback

There are a number of stress management techniques, from meditation [7] to biofeedback. Biofeedback is the process of making unconscious body functions perceptible for individuals so that they can learn and manipulate these physiological activities for the purpose of improving health [8]. Neuro-feedback, which uses EEG data, has been shown to be one of the most effective stress management methods [9].

C. Measures and Sensors

1) Galvanic Skin Response (GSR)

Skin conductance, also known as electro-dermal response or psycho-galvanic reflex, measures the electrical conductance of an individual's skin, which varies due to the amount of sweat on the skin. When the individual is under stress, skin conductance will increase; oppositely, the skin conductance will reduce when the individual encounters less stress [10]. We used the Neulog GSR Logger Sensor [11].

2) Heart Rate Variability

Heart rate variability (HRV) is the variation in the interval between heartbeats. HRV has been shown to be one of the most reliable indicators of stress in nearly a

 ISBN: 978-1-61208-425-1

quarter-century of clinical research [12]. Methods to measure HRV include Electrocardiogram (ECG) and Blood Pressure, but ECG is considered superior as it excludes unnecessary heartbeats and displays a clear waveform. We used the Neulog ECG Logger Sensor [13].

3) Brain Signals

The brain is the key organ of responding to stress, as it perceives what is threatening and thus potentially stressful [14]. Electroencephalography (EEG) is one of the primary methods for brain activity analysis. It re-cords the electrical voltage fluctuations resulting from ionic current flows within the neurons of the brain via multiple electrodes placed on the scalp [15]. EEG equipment usually produces a high degree of intrusion since participants need to wear a head cap attached to specific positions of the scalp with electrically conductive gel. The Emotiv EPOC headset [16] is a less intrusive device with a lighter headset, which is placed on rather than attached to the head. It is still noticeably more intrusive than the GSR and ECG sensors.

D. Extraction of features

Some 59 representative features were derived by calculating the statistics and measures values of two-seconds data (as our preliminary experiments showed that 1 sec data was too little, but 5 secs was too long to still ‘feel’ like real-time). Such summary statistical values included the mean, standard derivation, kurtosis, skewness, interquartile range, minimum and maximum, where measures included the number of peaks for periodic signals.

III. HYBRID GENETIC ALGORITHM AND EXTREME LEARNING MACHINE MODEL

The 59 derived features are too many for good results on this data, hence we must engage in feature selection [17]. The issue is that there is a limited number of subjects for whom we have data, and with many features and a sizeable neural network, the number of free parameters well exceeds the number of data points available.

TABLE I. GA REPRESENTATION AND USE

	Vector of best representative features filtered by GA	0	0	**1**	0	**1**	…
×	Vector of derived representative features	.1	.2	**.3**	.4	**.5**	…
	Vector for best representative features in the current data segment	0	0	**.3**	0	**.5**	…

We used a genetic algorithm with feed-forward neural networks as individuals in the population to perform feature selection and training. A simple 59-bit string representation was used to determine whether a feature is used by a particular neural network. Figure 1 shows how the representation was used to construct the train and test sets for each neural network.

A standard 3 layer neural network with two layers of processing elements was used, as shown in Figure 1. There are up to 59 input neurons, some 20 (say) hidden neurons, and one output neuron indicating the degree of stress.

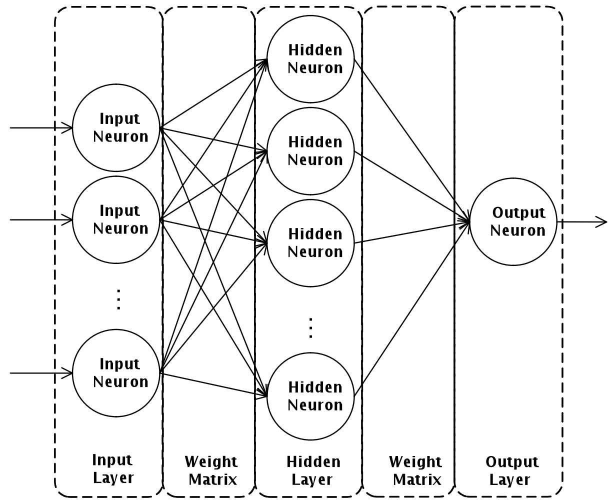

Figure 1. Neural network structure.

We validated our final networks against our previous work in virtual environments (stressful and calm video clips) [5], and using 10 fold cross validation we showed we can achieve 81% reliability.

This is less than our previous results which used the full sensor recording from a participant watching the entire clip, rather than just the preceding 2 seconds. This 81% reliability proved sufficient for our experiment (to be reported below) to be successful.

Our initial approach was to use back-propagation training for our neural network. We observed that it took one week to finish approximately 8% of the whole process, so the overall time for training this classifier was predicted to be more than three months. Instead, we trained our neural networks using the Extreme Learning Machine (ELM) method [18].

The ELM method in this case works as follows: the input weight matrix is assigned random values which are then frozen and not trained (the left ‘weight matrix’ shown in Fig. 1), and only the output weight matrix is trained.

This is possible to do via the delta rule normally used for output layers, but it is even faster to use the Moore-Penrose pseudo-inverse as the input matrix does not change, allowing a much higher efficiency in the process of estimating (training) output layer weights, by computing a 'best fit' (least squares) solution.

It is necessary to significantly increase the number of hidden neurons using the ELM approach. In this case, we

 ISBN: 978-1-61208-425-1

increased the number to 400. Then, we were able to complete the training in one week, faster by a multiple of about 15, notwithstanding the 20 fold increase in the number of hidden neurons.

How does it work? Essentially, the random weights provide some random functionality to each hidden neuron, and the training of the output layer selects from these the neurons with useful functionality and then their outputs are combined using the output weights to provide the optimized output value. This explains why we need so many hidden neurons, as we now just select from a menu rather than training individuals.

IV. Biofeedback Experiment

Ethics approval to perform the experiment was received from the ANU Human Research Ethics Committee.

Eighteen undergraduate and masters students were recruited for the experiment. The participant cohort was made up of twelve males (57.1%) and nine females (42.9%) between the ages of 20 and 35 years. The average age was 25.1 years old with a standard deviation of 3.7.

A. Experiment aim

Our goal was to compare effects of our GA-ELM calculated stress curve, EEG curve, and a (plausible) random curve on stress reduction.

B. Experiment Data Collection

Figs 2. and 3. display the experiment setups required for the stress curve / random curve settings, and for the EEG setting, respectively.

Multiple computers were required, as the computational intensiveness of both our own real time stress curve and the Emotiv EEG stress curve were such that a separate data acquisition computer was required. For smooth display of the film clips, we needed yet another computer

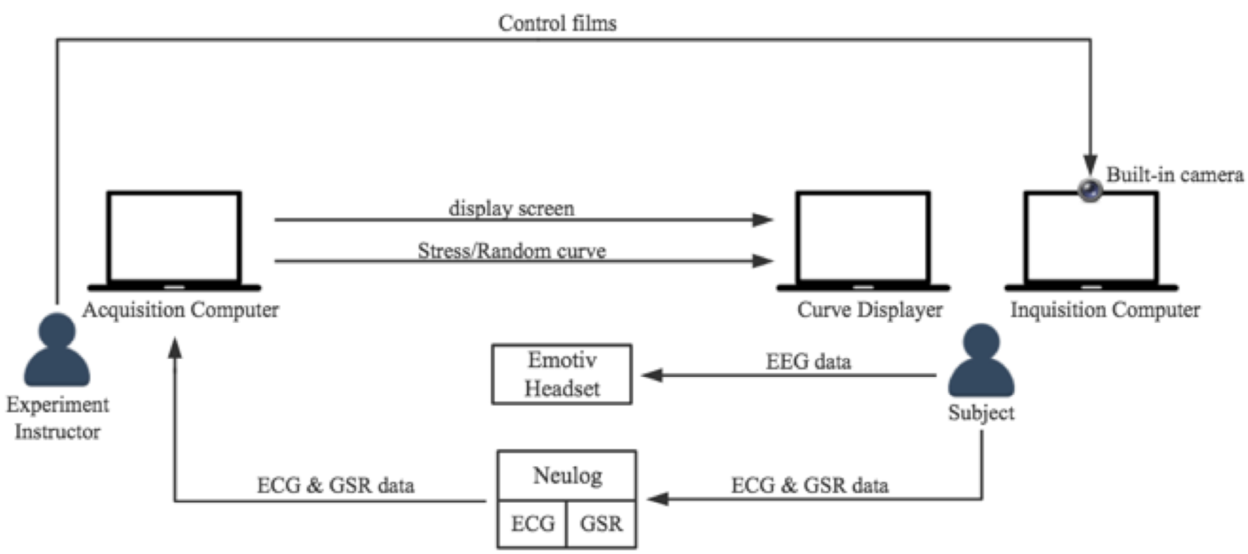

Figure 2. Schematic diagram of equipment setup for stress and random curve group.

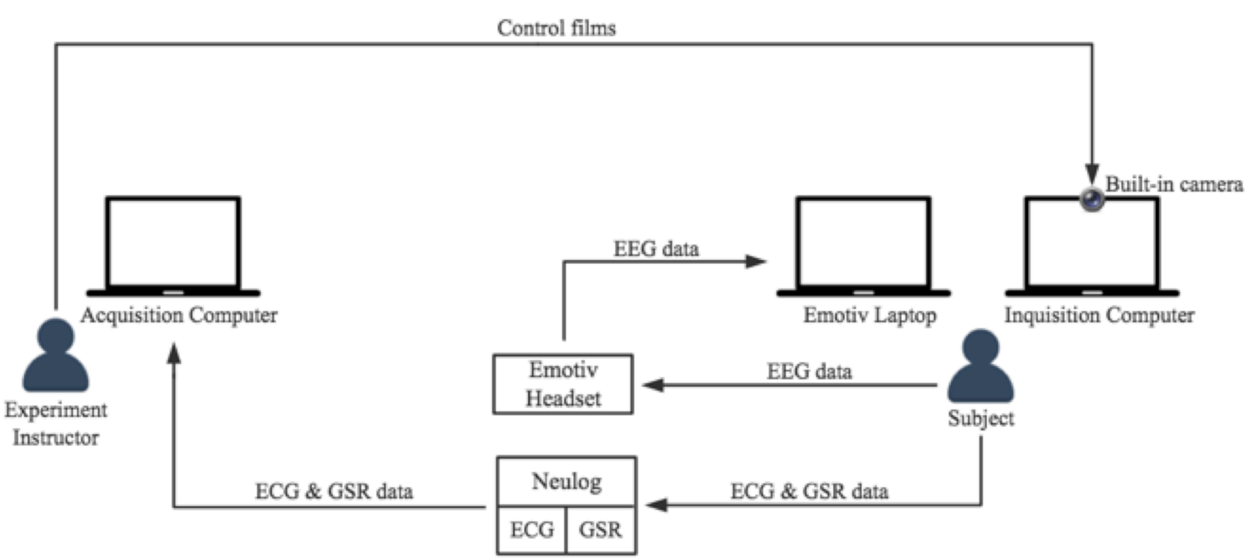

Figure 3. Schematic diagram of equipment setup for EEG curve group.

C. *Experiment process*

After a countdown display, a blank screen was shown for 15 seconds, which was followed by a sequence of film clips with five-second blank screens in between.

The film clips consisted of stressful and non-stressful film clips and each was approximately one minute in length. These film clips were categorized by the type of environment they create. Some had stressful content in the direction towards distress, fear and tension, see Fig. 4 for a sample screenshot from one of the stressful film clips.

Figure 4. Stressful film clip: Dark Knight.

The non-stressful clips had content that created an illusion of meditation or comfortable environments, see Fig. 5 for a sample screenshot from one of the non-stressful film clips. In total there were three stressful films and three non-stressful film for each experiment session, presented in an order balanced fashion.

Figure 5. Non-stressful film clip: Ducks on the lake.

One third of the participants were shown their own real-time stress curve as calculated from the their preceding 2 secs of data as described in §1.4, while watching the sequence of film clips.

Another third were shown their EEG stress curve as calculated by the Emotiv Affectiv Suite [19] (see Fig. 4), again while watching the film clips. Since the clips were order balanced, the participants watched them in different orders, to reduce or eliminate any effects from the sequence of presentation of the film clips.

The final third were shown a 'random' curve. This curve was based on the ECG and GSR of two subjects from our previous work [5], using the same film clips. Thus, the curves were completely valid stress curves and were in good synchrony with the experiment, they were just not from the participant viewing them.

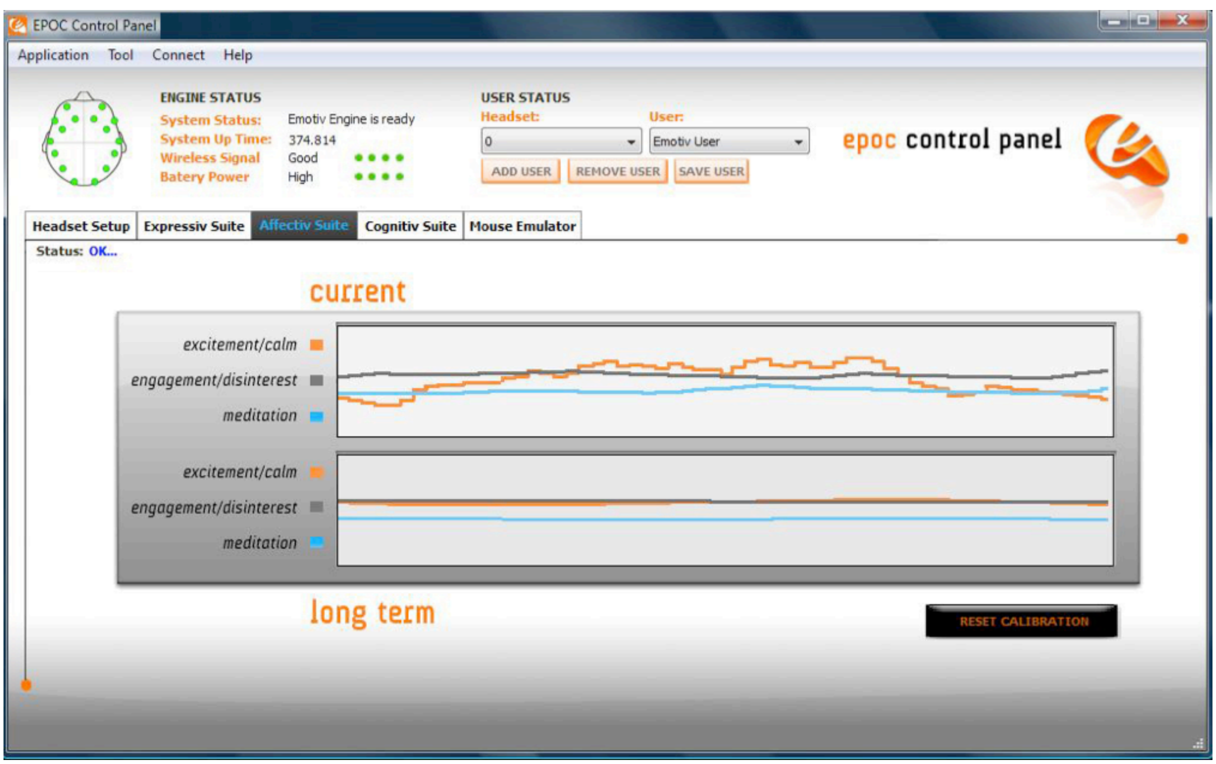

Figure 6. Emotiv Affectiv Suite: the top orange curve is the stress indicator for the EEG curve group.

 ISBN: 978-1-61208-425-1

The point of these 'random' curves is to provide a baseline – it is possible the mere intention to reduce stress will have an effect, so for our results to be meaningful we need to show a different (better) result than for this 'random' control curve.

V. Results and Discussion

The data was analysed by visual inspection and clustering analysis. Observation of the stress curve suggested that the stress curve does reflect individuals' stress in real time. It also revealed the correlation between the effectiveness of physiological biofeedback in stress control. This correlation was confirmed by the use of K-Means clustering. The clustering analysis was conducted on the 2 different stress data sets generated by watching stressful or non-stressful films. The result of clustering on stress data, which were produced when individuals were watching stressful films, showed that biofeedback with our physiological stress curve was effective and it was superior to neurofeedback.

We now provide the results of the clustering, in Table 2. The results are sorted by the curve provided to each participant. Clusters 2 and 3 have a purity of 83%, and correspond to our stress curve, and to the EEG curve, respectively. This is essentially the highest value we could have expected as our pre-experiment estimate for the correctness of our calculated stress curve.

These results show that both our stress curve and the EEG curve have good consistency in terms of their effects on the ability of participants to modify their stress. By observation, the direction of modification is as expected, to reduce their stress.

Cluster 1 has a purity of 50%, for the random curve. The *lack* of high purity in the case of the cluster which represents the random curve indicates that that curve is of some value in reducing the stress of participants, otherwise this cluster would have high purity due to its consistent uselessness in modifying stress levels.

TABLE II. CLUSTERING RESULTS ON STRESS DATA GENERATED BY WATCHING STRESSED FILMS.

Participant ID	Clustered label	Provided curve
p10	S3	Stress
p12	S2	Stress
p13	S2	Stress
p14	S2	Stress
p15	S2	Stress
p6	S2	Stress
p2	S3	Random
p7	S3	Random
p4	S2	Random
p1	S1	Random
p11	S1	Random
p5	S1	Random
p17	S3	EEG
p18	S3	EEG
p19	S3	EEG
p20	S3	EEG
p21	S3	EEG
p16	S2	EEG

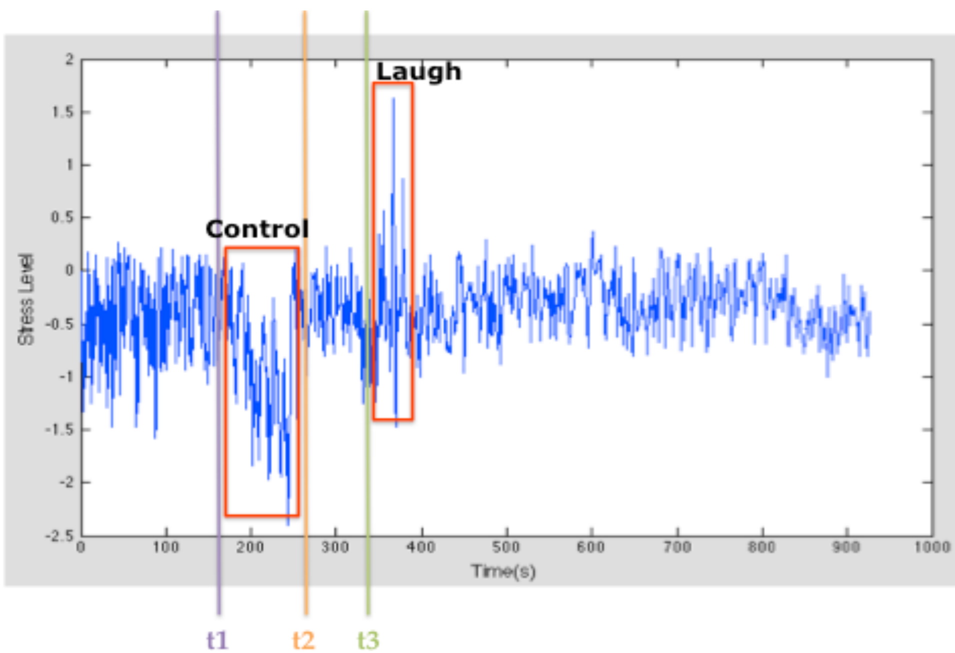

Figure 5. Participant 14: Using our stress curve. The stress axis has arbitrary units, the time axis is in seconds.

An example of the visual inspection analysis is shown in Fig. 5. In the period labeled from t1 to t2, the participant was actively trying to control his stress, as reported during the experiment. At time t2, a new clip started. Unfortunately, at time t3, he laughed and pounded on the table, partially dislodging the sensors.

We performed a statistical analysis of the clustering results to the categorisation of the stress levels of the fil clips. The calculation of the p-value derived from the Wilcoxon Statistical Test was: $p < 0.001$. Thus we can conclude that our results are highly statistically significant, as we accept $p < 0.05$ as statistically significant..

CONCLUSIONS, LIMITATIONS AND FUTURE WORK

We have shown via an experiment with 18 participants, and with high statistical significance, that participants could control or modify their stress well with an EEG curve (i.e., by neurofeedback, being an approach known to work well in the literature), which validates our approach.

More significantly, we have shown that with high statistical significance, that participants could control or modify their stress well with the use of our real time stress curve calculated only from the GSR and ECG. This is a novel contribution, as GSR and ECG is much less intrusive than EEG.

A limitation was that in our experiments, electrodes were attached to the hands of the participants, but in practice this may not be necessary. For example, the use of a GSR enabled mouse could be used (in more active settings than watching film clips). For ECG, a computer wrist rest could be wired to measure this. Alternatively, the wearable revolution in progress right now may soon provide wristwatches or other wrist or arm borne devices, which are both ubiquitous and effective in measuring ECG and GSR.

We modified our initial GA-NN approach for feature selection and training to use ELM training and achieved an approximately 15-fold increase in speed of training.

In future work we will consider the introduction of noise into the training regime [20], as well as the hierarchical structuring of the data [21], especially using fuzzy signatures [22-24].

REFERENCES

[1] H. Selye, A syndrome produced by diverse nocuous agents, *Nature*, 138:32, 1936.

[2] The-American-Institute-of-Stress, *Stress and Heart Disease*: www.stress.org/stress-and-heart-disease/, 2012.

[3] N. Sharma and T.D. Gedeon, Objective measures, sensors and computational techniques for stress recognition and classification: A survey, *Computer methods and programs in biomedicine*, 108(3): 1287-1301, 2012. doi: 10.1016/j.cmpb.2012.07.003

[4] N. Sharma and T.D. Gedeon, Computational Models of Stress in Reading Using Physiological and Physical Sensor Data. In *Advances in Knowledge Discovery and Data Mining* (pp. 111-122). Springer Berlin Heidelberg, 2013.

[5] N. Sharma and T.D. Gedeon, Modeling stress recognition in typical virtual environments, *Pervasive Computing Technologies for Healthcare (PervasiveHealth), 7th International Conference*, pp. 17-24, IEEE, 2013.

[6] N. Sharma and T.D. Gedeon, Modeling Observer Stress for Typical Real Environments, *Expert Systems with Applications*, *41*(5):2231-2238, 2014.

[7] R.R. Michaels, M.J. Huber and D.S. McCann, Evaluation of transcendental meditation as a method of reducing stress, *Science*, 192:1242-1244, 1976.

[8] H.L. Epstein and E.B. Blanchard, Biofeedback, self-control, and self-management, *Biofeedback and Self*-regulation, 2(2):201-211, 1977.

[9] E. Hoffmann, Brain Training Against Stress, 2005.

[10] W. Liao, W. Zhang, Z. Zhu and Q. Ji, A real-time human stress monitoring system using dynamic bayesian network, *IEEE Computer Society Conference on Computer Vision and Pattern Recognition-Workshops*, 70, 2005.

[11] Neulog, *GSR logger sensor NUL-217*. At: neulog. com/gsr/, 2011.

[12] Z. Ori, G. Monir, J. Weiss, X. Sayhouni and D. H. Singer, Heart rate variability: Frequency domain analysis, *Cardiology clinics*, 10:499-537, 1992.

[13] Neulog, *Electrocardiogram logger sensor NUL-218*. At: neulog.com/electrocardiagram/, 2011.

[14] B. S. McEwen, Physiology and neurobiology of stress and adaptation: central role of the brain, *Physiological reviews*, 87:873-904, 2007.

[15] E. Niedermeyer, F. L. da Silva, Electroencephalography: basic principles, clinical applications, and related fields, Lippincott Williams & Wilkins, 2005.

[16] Emotiv, *Emotiv EPOC Headset.* At: emotiv.com/ epoc.php, 2011.

[17] T.D. Gedeon, Data mining of inputs: analysing magnitude and functional measures, *International Journal of Neural Systems*, 8(02):209-218, 1997.

[18] G.B. Huang, Q.Y. Zhu and C.K. Siew, Extreme learning machine: a new learning scheme of feedforward neural networks, *IEEE International Joint Conference on Neural Networks, 2004. Proceedings*, 2:985-990, 2004.

[19] S.F. Verkijikaand L. De Wet, Using a brain-computer interface (BCI) in reducing math anxiety: Evidence from South Africa. *Computers & Education,* 81:113-122, 2015.

[20] W.M. Brown, T.D. Gedeon and D.I. Groves, Use of noise to augment training data: a neural network method of mineral–potential mapping in regions of limited known deposit examples, *Natural Resources Research*, 12(2):141-152, 2003.

[21] Gedeon, T. D., and L. T. Koczy. "Hierarchical co-occurence relations." Systems, Man, and Cybernetics, 1998. 1998 IEEE International Conference on. Vol. 3. IEEE, 1998.

[22] K.W. Wong, T.D. Gedeon and L.T. Kóczy, Construction of fuzzy signature from data: an example of SARS pre-clinical diagnosis system, *Proceedings 2004 IEEE International Conference on Fuzzy Systems*, 2004.

[23] B.S.U. Mendis, T.D. Gedeon, J. Botzheim and L.T. Kóczy, Generalised weighted relevance aggregation operators for hierarchical fuzzy signatures, 2006.

[24] B.S.U. Mendis, T.D. Gedeon and L.T. Kóczy, Investigation of aggregation in fuzzy signatures, Proceedings International Conference on Computational Inteligence for Modelling Control and Automation and International Conference on Intelligent Agents Web Technologies and International Commerce (CIMCA'06). Sydney, 2006.

 ISBN: 978-1-61208-425-1