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EEG based Stress Monitoring

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***Abstract*—Everyone experiences stress in life. Moderate stress can be beneficial to human; however, excessive stress is harmful to the health. To monitor stress, different methods can be used. In this work, an algorithm for stress level recognition from Electroencephalogram (EEG) is proposed. To validate the algorithm, an experiment is designed and carried out with 9 subjects. A Stroop colour-word test is used as a stressor to induce 4 levels of stress, and the EEG data are recorded during the experiment. Different feature combinations and classifiers are proposed and analyzed. By combining fractal dimension and statistical features and using Support Vector Machine (SVM) as the classifier, four levels of stress can be recognized with an average accuracy of 67.06%, three levels of stress can be recognized with an accuracy of 75.22%, and two levels of stress can be recognized with an accuracy of 85.71%. The algorithm is integrated into the system CogniMeter for stress state monitoring. Stress level of the user is visualized on the meter in real time. The system can be applied for stress monitoring of air-traffic controllers, operators, etc.**

Keywords-EEG; stress recognition; user interface; EEG, monitoring

I. INTRODUCTION

Most of the people experience stress from time to time in their daily life. Complex reasons can cause stress. It is a common physical response to the environment that makes people feel challenged or threatened. It can be observed while people are facing a challenging work, coping with a strained relationship or engaged in an intense competition [1]. Many health problems are also related to stress [2]. People under high pressure at work or in life may not only feel negative emotions, but also get depressed. On the other hand, moderate stress is beneficial to human because it helps to stay focused and alert. In this case, stress can be a way to improve performance during a presentation at work or during taking exams at school.

It is challenging to assess and monitor stress, because everyone experiences stress in different ways. Signs and symptoms of stress could be recognized using psychoanalysis, biosignals, and medical tests. Basic symptoms of high stress include headaches, tense muscles, insomnia, and rapid heartbeat [7]. There are many novel wearable devices such as Olive, Spire, BreathAcoustics, and Gizmodo integrated with various biosensors that help people monitor stress and organize accordingly their daily lives.

Electroencephalogram (EEG) signals are widely used in clinical diagnosis of mental diseases and in bioengineering research. EEG-based interfaces can be used in many applications including psychophysiology, psychology, serious games, etc. In this paper, we propose a novel algorithm to recognize different stress states from EEG signals. An experiment to induce different levels of stress using a Stroop colour-word test is designed and carried out. The EEG data recorded during the experiment are used to validate the proposed algorithm. Finally, a real-time stress-monitoring interface based on the proposed algorithm is implemented.

This paper is structured as follows: Section II introduces related works such as definition of stress, review on stress experiments, and existing EEG-based stress recognition algorithms. Section III introduces the experiment design, describes the proposed EEG-based stress recognition algorithm, and presents results of processing and analyses of EEG data collected from 9 subjects. Section IV introduces a real-time stress monitoring interface. Finally, conclusions are given in Section V.

II. RELATED WORK

A. *Stress Definition*

The definition of stress has been a subject of debate ever since it was proposed. There is no common accepted definition of stress. In previous researches, some definitions were proposed from different perspectives to give a general description of stress. According to Humphrey [3], stress is defined as a factor that makes people to feel difficult to adapt and maintain an equilibrium state both internally and with external environment. According to Koolhaas et al. [4], the term "stress" should be described from two dimensions: uncontrollability/unpredictability and life-threatening nature of the situation. Humans get stressed in particular environment when unpredictable and uncontrollable situations exceed the nature capacity of people. In this paper, we follow Lazarus and Folkman [5]'s definition of stress: psychological stress is defined as a particular relationship between people and environment that exceed their resources and endanger their well-being.

B. *Stress Experiments*

The stress response can be measured from perceptual and physical human responses [6]. There are various questionnaires for self-reviewing stress assessments that allow define the individual's level of stress. Some of the best known questionnaires include the perceived stress scale [7], the

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holmes rahe stress inventory [8], and the hamilton depression rating scale [9].

Apart from the perceptual responses, when the body is under the stress circumstances, it releases stress-related hormones to cause hormonal changes in the body. These hormonal changes can help the body to cope with the stress. Hence, the physical responses can be used as indicators to measure or diagnose the stress. It has been shown that stress can be assessed from physiological variables including EEG [10, 11], blood pressure [12], heart rate variability [6, 13], skin conductance level [14], and electromyography [15].

There are many techniques that can be used to induce levels of stress in lab settings. A detailed review of the experiments to elicit stress is published in [16]. The most commonly used techniques to induce stress are the Stroop colour-word test [17], the Trier Social Stress Test (TSST) [18], the cold pressor test [19], as well as the mental arithmetic task [20].

Stroop colour-word test is often used as a psychological stressor [21], in which subjects are presented with lists of color words in matching and non-matching colors. It is proved to be one of the most effective methods for research in human psychophysiological reactivity under stress environment. In work [17], the research is aimed at inspecting whether the Stroop colour-word test is able to meet the basic four criteria to be conferred that the test can induce stress. The four criteria characterizing the adequate and successful stressors are physiological changes that reflect increased distress, sympathy-adrenal activation, human fight-or-flight mechanism, and neuronal changes. The analysis of all physiological indicators results confirmed that the Stroop colour-word test is reliable as stress stimulus since it meets all four requirements. In work [21], the research is aimed at validating Stroop colour-word test as an accurate experimental stressor by monitoring heart rate variability. Waldstein et al. [22] used the Stroop test to study the process of active coping and cardiovascular reactivity during the stressful situation.

TSST requires participants to deliver a free speech in front of a group of important audience for 10 minutes. It has been proved that it can induce stress responses with considerable changes in heart rate, cortisol, growth hormone and adrenocorticotropic hormone [18]. In [23], TSST is used to induce stress environment to explore the causes of false recognition.

Cold pressor test is an interesting test to induce stress where subjects are required to place their hands in ice cold water [19]. This test however is not desirable as it induces less hypothalamic-pituitary-adrenal axis activation and can be painful for the participants.

Mental arithmetic tasks, puzzles and IQ questions can also be used to induce different levels of stress. For example, the IQ questions are used to induce different stress states in the experiment [10]. In [24], a puzzle is used to induce mild uncontrollable stress situations.

As the Stroop colour-word test is one of the most effective methods to study human psychophysiological reactivity under stress environment, we propose to use it in our experiment to induce different levels of stress in participants.

C. *EEG-based Stress Recognition Algorithms*

EEG signal can be used to recognize human emotions [32, 37], mental workload, vigilance, etc. It can be used to identify human stress level as well since it is already proved that there is significant correlation between levels of psychological stress and EEG power. For example, in [6], the experiment shows that the stress is positively correlated with beta EEG power at anterior temporal lobe. Power spectrum features are often used in EEG-based stress recognition [11, 25]. In [11], higher order spectra is used, and genetic algorithm is applied to do feature selection. Support Vector Machine (SVM) with radial basis function kernel is chosen as a classifier, and the accuracy calculated with 5-fold cross validation for recognition of two stress states is 79.2%. [25] uses the features such as Gaussian mixtures of EEG spectrogram, fractal dimension and magnitude square coherence estimation in stress recognition. The classification of two levels of mental stress is done by k-NN and SVM classifiers and the best accuracy is 90% for two stress states. However, neither [11] nor [25] use standard stressor to induce stress in the experiments. Pictures are used in [11] to evoke different stress states. In [25], EEG data recorded before and after examination period are used in the data analysis.

In [26], a Stroop colour-word test is used to induce stress. The discrete cosine transform is applied to reduce the data size and extract features from frequency domain. Classification is done using artificial neural network, linear discriminant analysis and k-Nearest Neighbor (k-NN). The highest classification result for two stress states is 72% with k-NN. Calibo et al. [27] also explore human response to stress induced by the Stroop colour-word test. The theta band power, alpha band power, and beta band power are used as features for logistic regression and are fed into the k-NN classifier. The results show a median accuracy of 73.96% for recognition of the relaxed and stressed states.

III. STRESS RECOGNITION FROM EEG

A. *Experiment*

In our experiment, EEG data are collected from 9 subjects between the age 21 and 28 years from Nanyang Technical University. All subjects have no history of mental diseases and head injuries. A wireless EEG device Emotiv EPOC [28] is used to record EEG signals from 14 channels (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4), placed on the scalp following the international 10-20 system [29], sampled at 128 Hz with bandwidth from 0.16 Hz to 43 Hz.

In our experiment, a Stroop colour-word test implemented using psychology experiment building language [30] is applied as the stressor to induce different levels of stress. According to [31], the Stroop colour-word test reliably induces stress in laboratory condition to the subjects. Different targeted stress levels are induced individually to each subject. The complete Stroop colour-word test based experiment consists of the following sections:

- **Introductory Section (IS)**: This section is to allow the subjects get familiar with the experiment environment. The experiment procedure is explained and instructions for administration of the Stroop colour-word test are given.

- **Resting Section (RS)**: This section is to let the subjects relax for a certain time. In this section, subjects are told to relax and remain still with eyes open for 3 minutes. The subjects are supposed to have the most relaxed state.
- **Congruent Section (CS)**: This section is to induce a low stress state with a simple task. In this section, the words' font color matches with the words' meaning. Subjects are asked to identify the words font color.
- **Incongruent Section 1 (ICS-1)**: This section is to induce a mild stress state. The words' font color and the words' meaning are different. The subjects are required to response to the words' font color. The subjects are supposed to be more stressed than in CS.
- **Incongruent Section 2 (ICS-2)**: This section is to induce a higher stress state. The basic test is the same with ICS-1, but the subjects are required to make the response to the words' font color within the limited time (1.5 seconds). This is the section where the highest stress is elicited in the subjects.

The protocol of our stress induction experiment is adapted from [6, 31]. As shown in Fig. 1 the experiment is designed to induce four different stress levels in sections RS, CS, ICS-1, and ICS-2. Each section is lasted for 3 minutes and the EEG signals are recorded during the whole experiment. At the end of each section, subjects are tasked to rate the level of stress they felt using a self-assessment questionnaire. In the questionnaire, stress is defined as a feeling of strain and pressure, and the subjects need to choose 1 rate from scale 1-9 where 1 represents the most relaxed state and 9 represents the most stressed state. For each subject, number of stress levels is decided based on the evaluations.

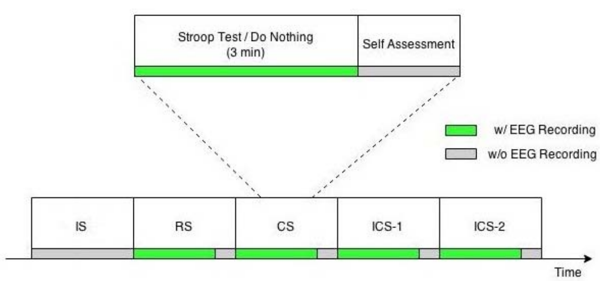

Figure 1. Protocol for collecting EEG data during our experiment.

B. Feature Extraction

According to [11, 25, 26], the EEG power spectrum features are correlated with stress levels. In addition, there are many similarities between the stressed state and negative emotion state [6]. Thus, we propose to apply in stress recognition Fractal Dimension (FD) and statistical features which were successfully used in emotion recognition algorithms [32, 37]. These features are extracted from EEG signals using 4 seconds sliding window with 3 seconds overlapping.

1) Power Feature

Power spectrum features are the most commonly used in EEG-based stress recognition algorithms. The power spectrum over a time interval is obtained by the Fast Fourier Transform (FFT). The EEG power spectrum is subdivided into bandwidths known as delta (0.5-4 Hz), theta (4-8 Hz), alpha (8-12 Hz), beta (12-30 Hz), and gamma (above 30 Hz). In our study, the power of theta band, alpha band and beta band are used as power features.

2) FD Feature

Fractal dimension is a measure of complexity and irregularity of time series [33]. FD can be used to analyze the nonlinear property of the EEG signal. Lower fractal dimension value corresponds to more regular signal; conversely, higher fractal dimension value corresponds to more irregular one. Wang et al. [34] proposed to use Higuchi fractal dimension to recognize arithmetic mental task from EEG. It was also used in application of EEG-based serious games [35] and emotion recognition [36]. In our work, the Higuchi algorithm [33] is used to calculate FD feature from the recorded EEG data.

3) Statistical Feature

Statistical features are simple yet widely used in classification of EEG signals. Statistical features were used in EEG-based emotion recognition [37, 38]. Six statistical features including mean, standard deviation, mean of absolute values of the first differences, mean of absolute values of the first differences of normalized signals, mean of absolute values of the second differences, and mean of the second differences of the normalized signal are extracted from the recorded EEG.

C. Data Processing and Analysis

In our experiment, the number of stress levels is defined according to the ratings in the self-assessment questionnaire. Subjects 1-7 have 4 levels of stress induced during the experiment. Subject 8 has 3 levels of stress induced. Subject 9 has only 2 levels of stress induced.

Power, statistical and FD features are first extracted from the EEG labeled with different stress levels (the labeling was done by the analysis of self-assessment questionnaire) and then, the features are fed to the classifier.

In our study, classifiers are implemented in Python based on Scikit-learn library [39] which includes a wide range of state-of-the-art machine learning algorithms. SVM and k-NN classifiers are used in the classification step. For SVM classifier, the polynomial kernel is chosen with penalty parameter $C=10$, degree $d=3$, gamma $g=1$, and coefficient $r=1$. For k-NN classifier, the number of neighbor k is set to 1. 5-fold cross validation is used to calculate the accuracy. First, the data are partitioned to 5 folds in which four folds are used as the training data and one fold is used as the testing data. Each fold of the data has a chance to be the testing data, the entire process runs for 5 times and an average accuracy is obtained.

The mean classification accuracy of SVM and k-NN classifiers using combination of FD and statistical features are shown in Table I and II. A comparison of average accuracy across all subjects is given in Figure 2. It can be seen that the classification accuracy declines when the number of levels of stress increases. The classification of two levels of stress has the highest accuracy for both SVM and k-NN, while the classification of four levels of stress has the lowest accuracy (Table I and II). The accuracy of stress recognition using SVM is higher than using k-NN for all subjects except for subject 5 (Table I and II). When we compare the mean accuracies obtained by different classifiers, SVM classification results are significantly higher than k-NN (Fig. 2): for two levels of stress recognition, SVM achieves an average accuracy of 85.17% and k-NN achieves an average accuracy of 76.72%; for three levels of stress recognition, SVM achieves an average accuracy of 75.22% and k-NN achieves an average accuracy of 63.24%; for four levels of stress recognition, SVM achieves an average accuracy of 67.06% and k-NN achieves average accuracy 54.31%.

TABLE I. SVM CLASSIFICATION RESULTS FOR 9 SUBJECTS (%).

	2 levels	3 levels	4 levels
Subject 1	74.44	63.27	56.30
Subject 2	83.70	75.37	69.07
Subject 3	92.22	85.99	81.30
Subject 4	92.72	87.90	83.89
Subject 5	85.12	76.36	70.74
Subject 6	76.91	66.67	60.74
Subject 7	70.93	55.86	47.41
Subject 8	93.46	90.37	—
Subject 9	97.04	—	—
Mean Accuracy (SD)[a]	85.17 (9.39)	75.22 (12.53)	67.06 (13.20)

a. SD: Standard Deviation

TABLE II. K-NN CLASSIFICATION RESULTS FOR 9 SUBJECTS (%).

	2 levels	3 levels	4 levels
Subject 1	66.67	50.43	40.00
Subject 2	72.47	60.86	53.89
Subject 3	84.51	75.00	68.15
Subject 4	82.41	72.65	65.56
Subject 5	86.60	79.01	73.52
Subject 6	62.96	50.43	43.89
Subject 7	62.47	44.94	35.19
Subject 8	82.35	72.59	—
Subject 9	90.00	—	—
Mean Accuracy (SD)[a]	76.72 (10.67)	63.24 (13.26)	54.31 (10.74)

a. SD: Standard Deviation

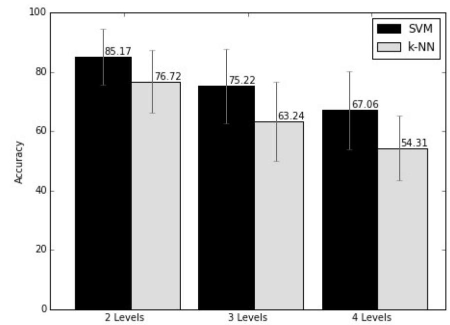

Figure 2. Average accuracies of stress recognition across all subjects using SVM and k-NN.

The traditional power features, combination of FD and statistical features, and the combination of power, fractal dimension and statistical features are evaluated and compared using SVM and k-NN classifiers for 2, 3, and 4 levels of stress recognition as shown in Table III. It can be seen that the combination of FD and statistical features gives the best accuracy in all cases. In Table I and II, it is shown that SVM outperforms k-NN in 8 of 9 subjects. In Table III, the recognition accuracy of SVM is also higher than k-NN in cases. Thus SVM is finally chosen as the classifier in the stress recognition algorithm.

TABLE III. FEATURE ANALYSIS (%).

Classifier	Features	2 levels	3 levels	4 levels
SVM	Power (SD)[a]	73.18 (10.20)	58.39 (11.32)	49.66 (12.20)
	FD+Statistical (SD)[a]	85.71 (9.39)	75.22 (12.53)	67.06 (13.20)
	Power+FD+ Statistical (SD)[a]	80.96 (8.86)	69.82 (11.88)	60.71 (11.50)
k-NN	Power (SD)[a]	66.36 (8.96)	50.98 (10.99)	41.35 (9.64)
	FD+Statistical (SD)[a]	76.72 (10.67)	63.24 (13.26)	54.31 (10.74)
	Power+FD+ Statistical (SD)[a]	69.93 (9.44)	54.44 (10.63)	44.97 (11.42)

a. SD: Standard Deviation

IV. STRESS MONITORING

A. Implementations

A real-time stress recognition application is implemented with Visual Studio 2010 in C++. By using the Emotiv API [28], the application receives the EEG signals at 128 Hz. The FD and six statistical features are calculated using a 4 seconds sliding window with 3 seconds overlapping.

B. User Interface

This application is used to monitor the individual's real-time stress state. As the algorithm is subject-dependent, it includes a training/calibration module and a real-time stress recognition module. The screenshot of the interface of the training module is shown in Fig. 3. When "Start Training" button is clicked, the subject needs to complete a series of Stroop colour-word tests which can induce different levels of stress. At the same time, the EEG data are recoded. After each test, the subject needs to fill a prompted questionnaire to evaluate and describe his/her current state. After all recordings, the "Train SVM" button is clicked. By doing this, the SVM model is trained with the labeled recorded EEG data. This model is saved and can be loaded again for the future use. When "Start Recognition" button is clicked, the software starts real-time stress recognition. The real-time stress levels are recognized and visualized in CogniMeter, as shown in Fig. 4. The current level of stress is shown on the meter with a pointer changing its position, the color (green, yellow, red), and the corresponding word description is given at the bottom of the meter.

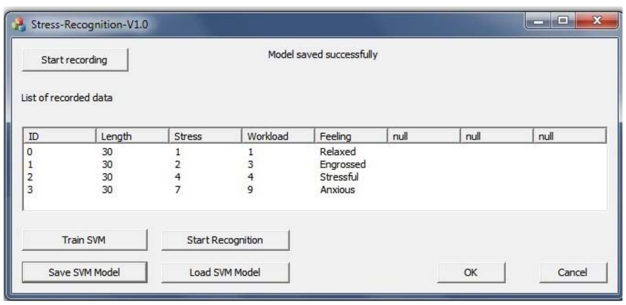

Figure 3. Screenshot of the training interface.

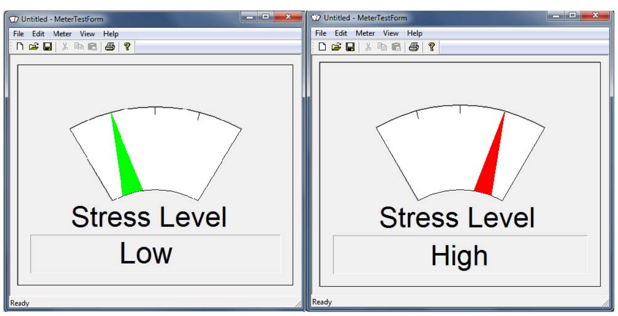

Figure 4. Screenshots of CogniMeter for real-time stress monitoring. Left meter shows the low stress level. Right meter shows the high stress level.

V. Conclusion

In this work, we proposed a real-time EEG-based stress recognition algorithm. To validate the proposed stress recognition algorithm, we designed an experiment to induce 4 levels of stress and recorded EEG data. We analysed different combinations of features (power, FD and statistical) using SVM and k-NN classifiers. By combining FD and statistical features and using the SVM classifier, four levels of stress can be recognized with the average accuracy of 67.07%, three levels of stress can be recognized with the accuracy of 75.22%, and two levels of stress can be recognized with the accuracy of 85.17%. In addition, the CogniMeter system to monitor stress in real time is implemented based on the proposed algorithm. In future, we plan to acquire EEG data from more subjects and set up a database for EEG-based stress recognition.

References

[1] D. S. Goldstein, K. Pacak, and I. J. Kopin, "Nonspecificity versus primitive specificity of stress responses." Stress: Harwood Academic Publishers,R McCarty, G Aguilera, E Sabban, R Kvetnansky (Eds.), Amsterdam, New York, USA: S.A., pp. 3-20, 1996.

[2] U. Lundberg, "Stress and public health," in Mental and Neurological Public Health: A Global Perspective, A. W. Vikram Patel, Valery L. Feigin, H.K. Heggenhougen, and Stella Quah, Ed., ed, 2010, pp. 496-504.

[3] J. H. Humphrey, "Teenagers Will be Teenagers: Teenagers Under Stress." New York: Nova Science Publishers, pp. 111, 2002.

[4] J. M. Koolhaas, A. Bartolomucci, B. Buwalda, S. F. de Boer, G. Flügge, S. M. Korte, et al., "Stress revisited: A critical evaluation of the stress concept," Neuroscience & Biobehavioral Reviews, vol. 35, pp. 1291-1301, 2011.

[5] R. S. Lazarus and S. Folkman, "Stress, appraisal, and coping". New York: Springer Pub. Co, pp. 19, 1984.

[6] S.-H. Seo and J.-T. Lee, "Stress and EEG," . Convergence and Hybrid Information Technologies, Marius Crisan (Ed.): InTech, pp. 413-426, 2010.

[7] C. Sheldon, T. Kamarck, and R. Mermelstein, "A Global Measure of Perceived Stress," Journal of Health and Social Behavior, vol. 24, pp. 385-396, 1983.

[8] T. H. Holmes and R. H. Rahe, "The social readjustment rating scale,"Journal of Psychosomatic Research, vol. 11, pp. 213-218, 1967.

[9] J. W. Williams, "A structured interview guide for the hamilton depression rating scale," Archives of General Psychiatry, vol. 45, pp. 742-747, 1988.

[10] N. Sulaiman, M. N. Taib, S. Lias, Z. H. Murat, S. A. M. Aris, M. Mustafa, et al., "Development of EEG-based stress index," in 2012 International Conference on Biomedical Engineering (ICoBE), 2012, pp. 461-466.

[11] S. A. Hosseini, M. A. Khalilzadeh, M. B. Naghibi-Sistani, and V. Niazmand, "Higher Order Spectra Analysis of EEG Signals in Emotional Stress States," in 2010 Second International Conference on Information Technology and Computer Science (ITCS), 2010, pp. 60-63.

[12] S. S. Hassellund, A. Flaa, L. Sandvik, S. E. Kjeldsen, and M. Rostrup, "Long-term stability of cardiovascular and catecholamine responses to stress tests: An 18-year follow-up study," Hypertension, vol. 55, pp. 131-136, 2010.

[13] S. Ssanghee, G. Yeongjun, and L. Jungtae, "The Relation between Affective Style of Stressor on EEG Asymmetry and Stress Scale during Multimodal Task," in Third International Conference on Convergence and Hybrid Information Technology, ICCIT '08, pp. 461-466, 2008.

[14] S. C. Jacobs, R. Friedman, J. D. Parker, G. H. Tofler, A. H. Jimenez, J. E. Muller, et al., "Use of skin conductance changes during mental stress testing as an index of autonomic arousal in cardiovascular research," American Heart Journal, vol. 128, pp. 1170-1177, 1994.

[15] R. Luijcks, H. J. Hermens, L. Bodar, C. J. Vossen, J. v. Os, and R. Lousberg, "Experimentally Induced Stress Validated by EMG Activity," PLoS ONE, vol. 9, p. e95215, 2014.

[16] N. Skoluda, J. Strahler, W. Schlotz, L. Niederberger, S. Marques, S. Fischer, et al., "Intra-individual psychological and physiological responses to acute laboratory stressors of different intensity," Psychoneuroendocrinology, vol. 51, pp. 227-236, 2015.

[17] J. H. M. Tulen, P. Moleman, H. G. van Steenis, and F. Boomsma, "Characterization of stress reactions to the Stroop Color Word Test," Pharmacology Biochemistry and Behavior, vol. 32, pp. 9-15, 1989.

[18] C. Kirschbaum, K. M. Pirke, and D. H. Hellhammer, "The 'Trier Social Stress Test' - A Tool for Investigating Psychobiological Stress Responses in a Laboratory Setting," Neuropsychobiology, vol. 28, pp. 76-81, 1993.

[19] L. Schwabe, L. Haddad, and H. Schachinger, "HPA axis activation by a socially evaluated cold-pressor test," Psychoneuroendocrinology, vol. 33, pp. 890-895, 2008.

[20] C. H. Poh, T. Hershcovici, A. Gasiorowska, T. Navarro-Rodriguez, M. R. Willis, J. Powers, et al., "The effect of antireflux treatment on patients with gastroesophageal reflux disease undergoing a mental arithmetic

stressor," Neurogastroenterology & Motility, vol. 23, pp. e489-e496, 2011.

[21] E. Siska, "The Stroop Colour-Word Test in Psychology and Biomedicine," Acta Univ. Palacki. Olomuc., Gymn., vol. 32, pp. 45-50, 2002.

[22] S. R. Waldstein, E. A. Bachen, and S. B. Manuck, "Active coping and cardiovascular reactivity: A multiplicity of influences," Psychosomatic Medicine, vol. 59, pp. 620-625, 1997.

[23] J. D. Payne, L. Nadel, J. J. B. Allen, K. G. F. Thomas, and W. J. Jacobs, "The effects of experimentally induced stress on false recognition," Memory, pp. 1-6, 2002.

[24] J. F. Brosschot, R. J. Benschop, G. L. Godaert, M. B. de Smet, M. Olff, C. J. Heijnen, et al., "Effects of experimental psychological stress on distribution and function of peripheral blood cells," Psychosomatic Medicine, vol. 54, pp. 394-406, 1992.

[25] R. Khosrowabadi, Q. Chai, A. Kai Keng, T. Sau Wai, and M. Heijnen, "A Brain-Computer Interface for classifying EEG correlates of chronic mental stress," in International Joint Conference on Neural Networks (IJCNN), pp. 757-762, 2011.

[26] C.-K. A. Lim and W. C. Chia, "Analysis of Single-Electrode EEG Rhythms Using MATLAB to Elicit Correlation with Cognitive Stress," International Journal of Computer Theory and Engineering, vol. 7, pp. 149-155, 2015.

[27] T. K. Calibo, J. A. Blanco, and S. L. Firebaugh, "Cognitive stress recognition," in IEEE International Instrumentation and Measurement Technology Conference (I2MTC), pp. 1471-1475, 2013.

[28] The Emotiv EEG device. Available: http://www.emotiv.com/eeg /features.php

[29] R. Oostenveld and P. Praamstra, "The five percent electrode system for high-resolution EEG and ERP measurements," Clinical Neurophysiology, vol. 112(4), pp. 713-719, 2001.

[30] S. T. Mueller and B. J. Piper, "The Psychology Experiment Building Language (PEBL) and PEBL Test Battery," Journal of Neuroscience Methods, vol. 222, pp. 250-259, 2014.

[31] A. Mehrabian, "Framework for a comprehensive description and measurement of emotional states," Genetic, Social, and General Psychology Monographs, vol. 121, pp. 339-361, 1995.

[32] Y. Liu and O. Sourina, "EEG-based subject-dependent emotion recognition algorithm using fractal dimension," in 2014 IEEE International Conference on Systems, Man and Cybernetics (SMC), , 2014, pp. 3166-3171.

[33] T. Higuchi, "Approach to an irregular time series on the basis of the fractal theory," Physica D: Nonlinear Phenomena, vol. 31, pp. 277-283, 1988.

[34] Q. Wang and O. Sourina, "Real-Time Mental Arithmetic Task Recognition From EEG Signals," IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 21, pp. 225-232, 2013.

[35] Q. Wang, O. Sourina, and M. Nguyen, "Fractal dimension based neurofeedback in serious games," The Visual Computer, vol. 27, pp. 299-309, 2011.

[36] Y. Liu, O. Sourina, and W. Chai, "EEG-Based Emotion Monitoring in Mental Task Performance," in The 15th International Conference on Biomedical Engineering. vol. 43, 2014, pp. 527-530.

[37] Y. Liu and O. Sourina, "EEG Databases for Emotion Recognition," in International Conference on Cyberworlds, 2013, pp. 302-309.

[38] Z. Lan, O. Sourina, L. Wang, and Y. Liu, "Stability of Features in Real-Time EEG-based Emotion Recognition Algorithm," in 2014 International Conference on Cyberworlds, 2014, pp. 137-144.

[39] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, et al., "Scikit-learn: Machine Learning in Python," Journal of Machine Learning Research, vol. 12, pp. 2825-2830, 2011.