Development of Proposed Algorithm for Neurometric Index (NI) Based on EEG Signals

A.Saidatul[1], Vikneswaran Vijean[1], M.Hariharan[2]
[1]*Biomedical Electronics Engineering, School of Mechatronics, Universiti Malaysia Perlis.*
[2]*Department of Biomedical Engineering, SRM University, Kattankulathur Campus, Tamil Nadu, India*
saidatul@unimap.edu.my

***Abstract*—Nowadays, stress is one of the major issues where too much stress may lead to depression, fatigue and insomnia. Stress can be divided into two types called Eustress and Distress. Eustress or positive stress refers to the positive stress which helps to improve the performance of an individual. In contrast, Distress or negative stress can devastate a person by creating depression and damage the quality of life. It is essential to comprehend and to figure out the state of current stress in the numerical index. This study aims to find a new algorithm which can represent the mental stress condition in the numerical index. A new algorithm has been proposed based on the more established index, Alpha Asymmetry Score (AAS), as a reference. Modifications have been made in term of the frequency band as a variable in the stress index calculation. The classification accuracy of the proposed Stress Asymmetry Score (SAS) is approximately 96% which is 10% higher than AAS. SAS offers larger marginal relative difference at fast beta and slow alpha wave between the right and the left hemisphere, thus, it becomes the best discriminator for mental stress features in EEG classification. The development of the stress index promises a new era of stress brain-related research for future people's benefit.**

***Index Terms*—Alpha Asymmetry Score (AAS); Electroencephalography (EEG); Mental Stress Index, Stress Asymmetry Score (SAS)**

I. Introduction

In modern society, it is impossible to live without stress. Stress is the emotional and physical strain caused by human body response to pressure from the outside world. Stress is the response to a stressor. Every people experienced different stressor daily in their life. A stressor can be physiologic (surgery, injection, disease, exercise, and trauma); environmental (prolonged heat, cold, chemical, radiation and noise); or psychological (threat, intense competition, prolonged conflicts, fear and unpredictability) [1][2]**.** For example, in working environment, stress may be triggered when people need to meet the deadlines to complete the task and overloading of the task given by the employer. Moreover, in personal view, the issues which are related to family relationship, financing problem, the death of family members and bad health status tend to excite the stress. If chronic, stress can have serious consequences and is a leading risk factor for heart diseases, diabetes, asthma and depression.

The human body is designed to cope with stress and react to it. Stress can become a positive and negative side to human health. Stress can be positive by keeping us alert and ready to avoid danger whereas stress becomes negative when a person faces continuous challenges without relief or relaxation between challenges. As a result, the person becomes overworked, and stress-related tension builds.

In recent years, there has been an increasing interest in studying the correlation between EEG signals to mental stress. To date, there are few agreements on assessing the severity of mental stress [3]–[5]. There are neither robust systems nor standard parameter to produce precise diagnosis on the mental stress status. This study presents a new proposed algorithm in developing neurometric index for assessing acute stress during Mental Arithmetic Task (MAT). Neurometric refers to the science of measuring the underlying organisation of the brain's electrical activity. This paper discussed some motivational issues, the comparison between the existing algorithm and proposed algorithm and problem intrinsic to the developed neurometric index.

II. Related Works

A considerable amount of literature has been published on stress and brain-related. The approach of these studies is varies depending on their discipline. For example, psychology field tends to investigate the severity of mental stress through questionnaire while medical field diagnoses the mental stress via laboratory specimens such as hormone in blood [3], saliva concentration [6] and blood pressure [7].

To derive an index, several attempts have been made to investigate the brain activity between two hemispheres during stress. EEG Alpha Brain Asymmetry is the most commonly used to study the effect of brain activity to stress [3], [8]. Theoretically, the alpha power in the right anterior hemisphere is greater compared to the left anterior hemisphere during low stress. However, the alpha power activity will be declined during the high stress [8]–[11].

Even though a lot of research had been done to identify stress level using physiological signals, researchers have yet to come out with a reliable index for stress level indicator using EEG signals from a healthy person. Obviously, stress index can be used to indicate the severity of stress so that the appropriate action can be taken at an early stage. Handri *et al.* (2008) demonstrated the classification of stress features into two classes which are low and high stress with the combination of three physiological signals namely EEG, ECG and skin temperature [12]. On the other hand, Sinha *et al.* (2007) employed EEG power spectra to classify the stress into three groups namely; acute, chronic and normal stress [13].

Besides that, Hinrikus *et al.* (2009) produced an index for depression which is based on EEG spectral asymmetry index [14]. Depression index has been derived by computing relative difference in EEG power spectrum at two frequency bands. Teplan (2006) proposed a model to estimate human stress level. He used the dynamic Bayesian network to develop stress level estimator [15]. Holm *et al.* (2009) reported the development of stress type based on theta and alpha ratio. This study has produced an index to classify the EEG signal into three types namely; cognitive workload, mental fatigue and stress [16]. Tran *et al.* (2007) produced an indicator for fatigue and stress based on the change of spectral analysis and sample entropy for sub frequency bands [17].

Based on the previous literature, it can be seen that researchers have applied different approaches to develop stress indicator. However, there are some shortcomings have been found in their studies where only alpha waves have been considered in the algorithm. Other components of frequency band waves such as fast alpha, slow alpha, fast beta and slow beta must be considered since mental stress may are reflected not only from alpha waves. Therefore, it would have been desirable to develop an index for measuring mental stress states by considering other bands such as beta, theta and delta waves instead of focusing alpha waves only.

III. METHODOLOGY

A. Dataset

There were 30 healthy subjects (15 males and 15 females) aged between 21 and 23 years old with the mean age of 22.4 years participated in this experiment. All the subjects were university students without any previous history of medical, neurological and psychiatric illness. All the selected subjects are right handed. This is because there are different mechanisms of understanding between right and left-handed subjects [18]. Thus, this study focused on the right-handed subject to avoid any biased during data analysis.

To develop the neurometric for acute stress, the dataset from non-stress subjects was considered. Depression Anxiety Stress Score (DASS) was used to classify the stress and non-stress subject [19]. This is to standardise the response of stress towards stimuli. People with a degree of stress are predicted to react with different stress-response compared to the subjects who are under no stress condition. From 30 subjects, 26 subjects (11 males and 15 females) and four subjects (1 male and three females) were classified under non-stress and stress group. EEG signals were collected from 26 non-stress subjects while performing Mental Arithmetic Task (MAT) for 5 minutes. EEG signal processing was applied to extract EEG signals into different frequency bands such as fast alpha, fast beta, slow alpha and slow beta.

B. Development of New Algorithm of Neurometric Index

A new algorithm of the Stress Asymmetry Score (SAS) was proposed for classifying EEG signals. The diagram of the proposed methodology for SAS development is shown in Figure 1. The stages are discussed as follows:

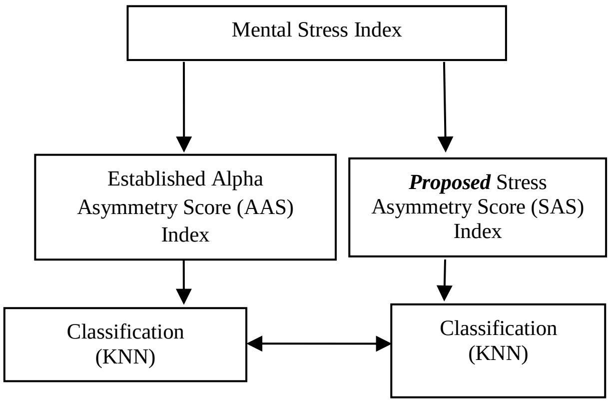


Figure1: Diagram in developing mental stress index

Step 1:

Firstly, the brain Alpha Asymmetry Score (AAS) is calculated as Equation (1). The concept of the AAS, $\xi(P_\alpha)$ is measuring the difference between log alpha density in the right hemisphere and log alpha density in the left hemisphere [8], [14], [20].

$$\zeta(P_\alpha) = \log(P_\alpha)_R - \log(P_\alpha)_L \qquad (1)$$

where P_α is power of alpha waves which is represented by $\frac{1}{N}\sum_{n=k}^{k+N-1}|x[n]|^2$, N is number of data, $x[n]$ is the discrete EEG data signal, n is the i^{th} signal (i= integer numbers), k = 1,2,3……..,k (integer numbers), α refers to band power for alpha wave (8-13 Hz), R refers to channel F4 and L refers to channel F3.

Step 2:

Secondly, the SAS is calculated based on these three *proposed* Equations (2) to (4), $\zeta(P_{\alpha1,}P_{\beta2}), \zeta(P_{\beta1,}P_{\beta2})$and $\zeta(P_{\alpha1,}P_{\alpha2})$ are expressed as follows:

$$\zeta(P_{\alpha1}, P_{\beta2}) = \log(\tfrac{P_{\beta2}-P_{\alpha1}}{P_{\beta2}})_R - \log(\tfrac{P_{\alpha2}-P_{\alpha1}}{P_{\alpha2}})_L \qquad (2)$$

$$\zeta(P_{\beta1}, P_{\beta2}) = \log(\tfrac{P_{\beta2}-P_{\beta1}}{P_{\beta2}}) \qquad (3)$$

$$\zeta(P_{\alpha1}, P_{\alpha2}) = \log(\tfrac{P_{\alpha2}-P_{\alpha1}}{P_{\alpha2}})_R - \log(\tfrac{P_{\alpha2}-P_{\alpha1}}{P_{\alpha2}})_L \qquad (4)$$

where P is band power, which is represented by $\frac{1}{N}\sum_{n=k}^{k+N-1}|x[n]|^2$, N is the number of data, $x[n]$ is the discrete EEG data signal, n is the i^{th} signal (i=integer numbers), k = 1,2,3……..,k (integer numbers),$\alpha_1$is the slow alpha wave (8 < α_1 < 10 Hz), α_2 the is fast alpha wave (10 <α_2< 13) Hz), $\beta_1$is the slow beta wave (13 <β_1< 20 Hz), β_2 is the fast beta wave (20 <β_2< 30Hz), R refers channel F4 and L refers to channel F3.

The proposed Equation of (2) – (4) are based on the original idea of established Alpha Asymmetry Score in Equation (1). Equation (2) – (6) are derived from expanding the knowledge of the understanding of mental stress between two hemispheres. Thus, the proposed Equation is designed to study the activity of sub-frequency bands which may offer larger margin between two frequency bands for selected combination. In hindsight, larger marginal scores indicate better discriminator features between stress levels.

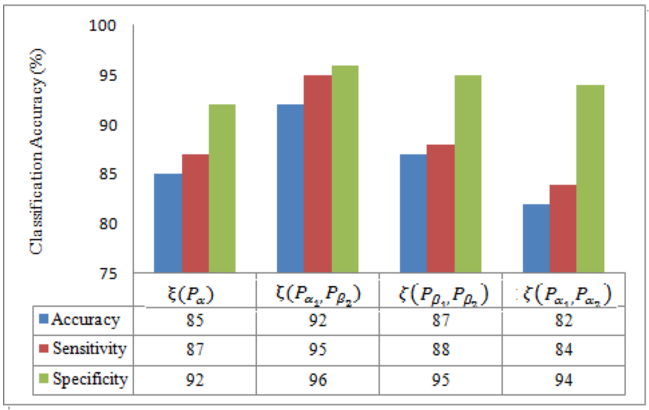
Step 3:

In this study, the master data set consists of 830 samples. KNN classifier is used to classify the features vector input from established Alpha Asymmetry Score (AAS) and *proposed* SAS. The classifier is validated using *k*-fold cross-validation with the *k*- value is 2, 4, 6, 8 and 10. The classification accuracies are compared between these equations.

IV. Result and Discussions

Figure 2 presents the classification performance for the established Alpha Asymmetry Score (AAS) and the proposed Stress Asymmetry Score (SAS). From Figure 2, it can be seen that the average classification accuracy is 85 % for Equation (1), 92 % for the Equation (2), 87% for the Equation (3) and 82% for the Equation (4) of the Proposed SAS. Among four SAS sets, Equation (2) gives the highest classification performance which is 92%. The relative difference between fast beta wave and slow alpha wave for right and left brain hemisphere shows the best combination of two frequency bands that can represent mental stress features.

An average value of sensitivity of 98% is obtained for Equation (1) while for Equation (2), Equation (3) and Equation (4) attained sensitivity of 95%, 88% and 84%, respectively. Equation (1) achieved a 92% average specificity while for the AAS Equation (2), Equation (3) and Equation (4) obtained specificity of 96%, 95% and 94%, respectively. It is noticeable that Equation (2) attained slightly higher classification accuracies (sensitivity, specificity, accuracy) compared to the other Asymmetry Score's.



	$\xi(P_\alpha)$	$\xi(P_{\alpha_2}, P_{\beta_2})$	$\xi(P_{\beta_1}, P_{\beta_2})$	$\xi(P_{\alpha_1}, P_{\alpha_2})$
Accuracy	85	92	87	82
Sensitivity	87	95	88	84
Specificity	92	96	95	94

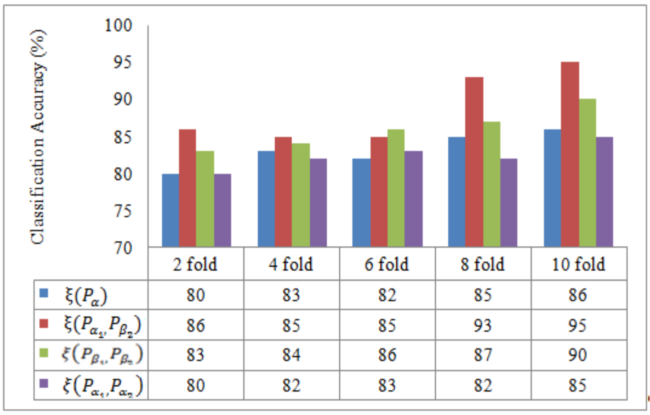
Figure 2: Classification Performance of Established (AAS) and Proposed Stress Asymmetry Score (SAS)

To make the classifier more robust and precise, the classifier was validated using k-fold cross-validation. Detailed information about the classification performance for each of the four sets of SAS, this study demonstrated the classification performance for each of the five different *k*-folds (*k* = 2,4,6,8 and 10) for all level of stress (low, moderate and high).

Figure 3 to Figure 5 present the overall classification accuracy of different *k*-fold values (*k* = 2, 4, 6, 8, 10) for the low, moderate and high level. From Figure 3 - 5, it is seen that the 10-folds via Equation (2), produces highest classification accuracy for all mental stress levels namely low, moderate and high.

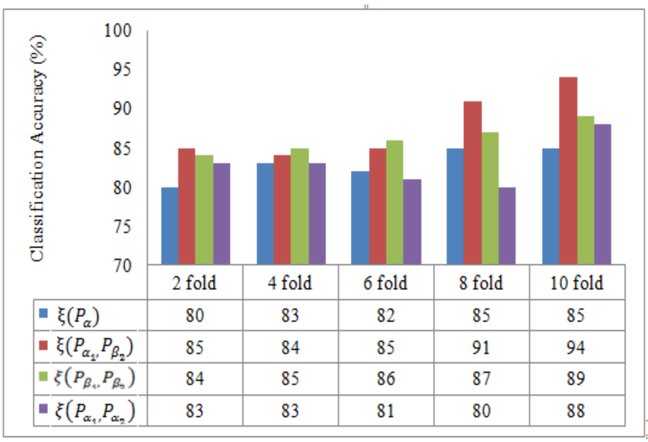
Figure 4 shows the percentage accuracy obtained from four sets of Stress Asymmetry Score for low level concerning the different k-folds value. It can be seen that Equation (2) with ten folds produces the highest classification accuracy rate which is 95% compared to others.

Figure 5 compares the percentage accuracies obtained from the moderate stress of mental states. The results show that the highest percentage accuracy is 94% for Equation (2) with 10-fold cross-validation. Besides that, Figure 5 compares the percentage accuracies obtained for high-stress level and it was found that Equation (2) achieves highest percentage accuracy which is 96%. In Figure 3 - 5, there is a clear trend that Equation (2) achieves average highest classification accuracies which are 95% for all level of stresses (low, moderate and high) with 10-folds cross-validation.



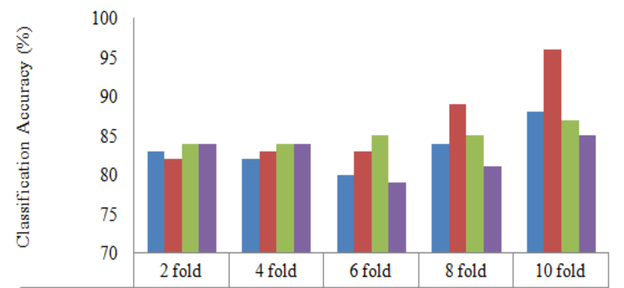
	2 fold	4 fold	6 fold	8 fold	10 fold
$\xi(P_\alpha)$	80	83	82	85	86
$\xi(P_{\alpha_2}, P_{\beta_2})$	86	85	85	93	95
$\xi(P_{\beta_1}, P_{\beta_2})$	83	84	86	87	90
$\xi(P_{\alpha_1}, P_{\alpha_2})$	80	82	83	82	85

Figure 3: Classification accuracy of different *k*-fold (*k*=2, 4, 6, 8, 10) for low-level stress.



	2 fold	4 fold	6 fold	8 fold	10 fold
$\xi(P_\alpha)$	80	83	82	85	85
$\xi(P_{\alpha_2}, P_{\beta_2})$	85	84	85	91	94
$\xi(P_{\beta_1}, P_{\beta_2})$	84	85	86	87	89
$\xi(P_{\alpha_1}, P_{\alpha_2})$	83	83	81	80	88

Figure 4: Classification accuracy of different *k*-fold (*k*=2, 4, 6, 8, 10) for moderate level stress.



	2 fold	4 fold	6 fold	8 fold	10 fold
$\xi(P_{\alpha})$	83	82	80	84	88
$\xi(P_{\alpha_1}, P_{\beta_2})$	82	83	83	89	96
$\xi(P_{\beta_1}, P_{\beta_2})$	84	84	85	85	87
$\xi(P_{\alpha_1}, P_{\alpha_2})$	84	84	79	81	85

Figure 5: Classification accuracy of different *k*-fold (*k*=2, 4, 6, 8, 10) for high-level stress.

There are several possible explanations for this result. The derivation of Equation (1) – Equation (6) is quite revealing in several ways. Firstly, Equation (1) describes the measurement of the alpha asymmetry score which is based on the relative alpha power between right and left hemisphere. In neurophysiology, the most cited indicator of relaxation is the rise in alpha wave frequencies will be predominant [21]. Thus, this equation works by evaluating the gradual decline in alpha waves during stress between two hemispheres.

Secondly, Equation (2) presents the relative power difference ratio between the fast beta and the slow alpha waves for the right and the left hemispheres. Beta waves (13-30 Hz) represent the cerebral activities under tension, critical thinking, excitement, etc. while alpha wave represents the relaxation state of cerebral activities. Hence, the response of the beta waves to the stress is likely proportional to the tension and inversely proportional to alpha waves. Alpha waves become dominant waves during relaxation. However, alpha waves diminish while stress grows.

Thirdly, Equation (3) computes the relative power difference ratio between the fast beta wave and the slow beta wave. This Equation has considered the response of the brain to the mental stress based on the beta waves only. Finally, Equation (4) reflects the measurement of the relative power difference ratio between the fast alpha wave and the slow alpha wave.

Based on the result, Equation (2) shows the most potential equation compared to other equations which can be applied in developing neurometric for acute stress based MAT. A possible explanation for this might be that Equation (2) offers larger marginal relative difference at fast beta and slow alpha wave between the right and the left hemisphere, thus, it becomes the best discriminator for mental stress features in EEG classification.

V. Conclusions

A modified version of established Brain Alpha Asymmetry [8] where proposed SAS involving the combination of two frequency band be employed. This study investigates the best suitable SAS Equation for representing the distribution of EEG signals according to the severity of stress. The three sets of proposed SAS and an established Brain Asymmetry Score are tested as the input individually to the classifier. The results of this study indicate that new proposed SAS by using Equation (2) is increased by 10% compared to the established Alpha Asymmetry Score (AAS).

References

[1] N. T. Sawyer and A. Escayg, “Stress and epilepsy: multiple models, multiple outcomes.,” *J. Clin. Neurophysiol.*, vol. 27, no. 6, pp. 445–52, Dec. 2010.

[2] R. P. Van de Kar LD, Richardson-Morton KD, “Stress:Neuroendocrine and pharmacological mechanism,” *Methods Achieve Exp Pathol*, vol. 14, pp. 133–173, 1991.

[3] N. Weekes, R. Lewis, F. Patel, J. Garrison-Jakel, D. E. Berger, and S. J. Lupien, “Examination stress as an ecological inducer of cortisol and psychological responses to stress in undergraduate students.,” *Stress*, vol. 9, no. 4, pp. 199–206, Dec. 2006.

[4] a. Kaklauskas *et al.*, “Recommended Biometric Stress Management System,” *Expert Syst. Appl.*, vol. 38, no. 11, pp. 14011–14025, May 2011.

[5] P. Karthikeyan, M. Murugappan, and S. Yaacob, “A review on stress inducement stimuli for assessing human stress using physiological signals,” *2011 IEEE 7th Int. Colloq. Signal Process. its Appl.*, pp. 420–425, Mar. 2011.

[6] G. Krantz, M. Forsman, and U. Lundberg, “Consistency in physiological stress responses and electromyographic activity during induced stress exposure in women and men.,” *Integr. Physiol. Behav. Sci.*, vol. 39, no. 2, pp. 105–18, 2004.

[7] T. Yamakoshi *et al.*, “A preliminary study on driver’s stress index using a new method based on differential skin temperature measurement.,” *Conf. Proc. IEEE Eng. Med. Biol. Soc.*, vol. 2007, pp. 722–5, Jan. 2007.

[8] T. H. Lewis, R. S., Weekes, N. Y., & Wang, “The Effect of Naturalistic Stressor on Frontal Asymmetry, Stress and Health,” *Biol. Psychol.*, vol. 75, pp. 239–247, 2007.

[9] N. Hayatee *et al.*, “Evaluation of Human Stress Using EEG Power Spectrum,” *Methods*, pp. 6–9, 2010.

[10] R. S. Lewis, N. Y. Weekes, and T. H. Wang, “The effect of a naturalistic stressor on frontal EEG asymmetry, stress, and health.,” *Biol. Psychol.*, vol. 75, no. 3, pp. 239–47, Jul. 2007.

[11] N. Sulaiman *et al.*, “Intelligent System for Assessing Human Stress Using EEG Signals and Psychoanalysis Tests,” *2011 Third Int. Conf. Comput. Intell. Commun. Syst. Networks*, pp. 363–367, Jul. 2011.

[12] K. N. S. Handri, S. Nomura, “Detecting stress based on the schedule of an intermittent mental workload using physiological sensor,” in *Proceedings of the 11th International Conference on Humans and Computers*, 2008, pp. 123–126.

[13] R. K. Sinha, “EEG power spectrum and neural network based sleep-hypnogram analysis for a model of heat stress,” *J. Clin. Monit. Comput.*, vol. 22, no. 4, pp. 261–268, 2008.

[14] H. Hinrikus *et al.*, “Electroencephalographic spectral asymmetry index for detection of depression.,” *Med. Biol. Eng. Comput.*, vol. 47, no. 12, pp. 1291–9, Dec. 2009.

[15] M. Teplan, “Fundamentals of EEG measurement,” *Meas. Sci. Rev.*, vol. 2, no. 2, pp. 1–11, 2002.

[16] A. Holm, K. Lukander, J. Korpela, M. Sallinen, and K. M. I. Müller, “Estimating Brain Load from the EEG,” *ScientificWorldJournal.*, vol. 9, pp. 639–651, 2009.

[17] Y. Tran, R. a. Thuraisingham, N. Wijesuriya, H. T. Nguyen, and a. Craig, “Detecting neural changes during stress and fatigue effectively: a comparison of spectral analysis and sample entropy,” *2007 3rd Int. IEEE/EMBS Conf. Neural Eng.*, pp. 350–353, May 2007.

[18] R. L. Kelly and L. A. Wheaton, “Differential mechanisms of action understanding in left and right-handed subjects: The role of perspective and handedness,” *Front. Psychol.*, vol. 4, no. DEC, 2013.

[19] P. F. Lovibond, S.H. & Lovibond, *Manual for the Depression Anxiety Stress Scales*, 2nd edition. Sydney: Psychology Foundation, 1995.

[20] J. L. Stewart, J. a Coan, D. N. Towers, and J. J. B. Allen, “Frontal EEG asymmetry during emotional challenge differentiates individuals with and without lifetime major depressive disorder.,” *J. Affect. Disord.*, Sep. 2010.

[21] K. Natarajan, R. A. U, F. Alias, T. Tiboleng, and S. K. Puthusserypady, “Nonlinear analysis of EEG signals at different mental states,” *Biomed. Eng. Online*, vol. 11, pp. 1–11, 2004.