2017 24th national and 2nd International Iranian Conference on Biomedical Engineering (ICBME), Amirkabir University of Technology, Tehran, Iran, 30 November - 1 December 2017

Detection of Human Attention Using EEG Signals

Mitra Alirezaei
Dept. of Electrical Engineering
Sharif University of Technology
Tehran, Iran
mitralirezayii@gmail.com

Sepideh Hajipour Sardouie
Dept. of Electrical Engineering
Sharif University of Technology
Tehran, Iran
hajipour@sharif.edu

***Abstract*— Attention as a cognitive aspect of brain activity is one of the most popular areas of brain studies. It has significant impact on the quality of other activities such as learning process and critical activities (e.g. driving vehicles). Because of its crucial influence on the learning process, it is one of the main aspects of research in education. In this study, we propose a brand new protocol of brain signal recording in order to classify human attention in educational environments. Unlike other protocols used to record EEG signals, our protocol does not require strong memory and strong language knowledge to carry out. To this end, we have recorded EEG signals of 12 subjects using the proposed protocol in order to achieve a valid data set for classifying human attention in two classes: attention and non-attention states. The signals have been recorded using 8 forehead channels and different features were extracted from different frequency bands. The results show that the effective features were related to the beta band and the energy of the signals. The signals were classified using KNN (K=9), c-SVM, LDA, and Bayesian classifiers and the results were compared for each of the subjects individually. On average, c-SVM and LDA classifiers were more accurate than the other methods, with 92.8% and 92.4% accuracy, respectively.**

Keywords-component; Attention; Classification; Electroencephalography; Feature extraction

I. INTRODUCTION

Attention as a cognitive aspect of brain activity is one of the most usable areas of brain studies. In many branches of science, a great number of researches have been performed in order to determine how it operates and how it comes to existence. It has a significant impact on the quality of other activities such as learning process and critical activities (e.g. driving vehicles). Because of its crucial influence on the learning process, it is one of the main aspects of research in education. Due to its wide application, the quantification of human attention into different levels is inevitable. There are several ways to survey and recognize attention state, but utilizing surface brain signals, i.e. Electroencephalogram (EEG), has the most usage as it is cost effective, noninvasive, easy to recording, and it allows subjects to have much more freedom and mobility. In recent years, a great number of researches by using brain signals are done in this field such as:

1) Detecting and improving attention disorders such as Attention Deficit Hyperactivity Disorders (ADHD) [1,2,3]. In [1], the authors have proposed an alternative treatment for ADHD using BCI technology by EEG and Hemoencephalography (HEG) signals. In [2], a treatment using Virtual Reality (VR) technology and EEG biofeedback has been developed.

2) Designing a monitoring and alarming system based on level of attention in critical activities such as driving [4,5]. These studies proposed EEG-based monitoring systems used during driving.

3) Determining students' attention during class and facilitating distance learning [6,7]. In the study presented in [6], researchers classified EEG signals into two attention and non-attention classes with 76.82% accuracy. The protocol of signal recording was based on listening to English phrases and answering to related questions. In another study [7], a Self-Assessment Manikin (SAM) model has been used in order to classify and analyze learners' EEG signals during attention state.

In our study, we propose a brand new protocol of EEG signal recording in order to achieve a valid data set for classifying human attention in two classes: attention and non-attention states, in educational environments. The designed protocol is based on mathematical operations, which needs attention in order to carry out. Besides, unlike the other protocols used to record EEG signals, the designed protocol does not require strong memory, indeed subjects only should memorize mathematical outcomes in each step that a new number is shown. As a result, by utilizing this protocol we can record EEG signals related to different attention states of students.

This paper is organized as follows: first, a brand new protocol for recording EEG signals using an EMOTIV device [8] is proposed and a brief description of the data is provided. Our methodology, including feature extraction and classification methods, is presented in the second section. To evaluate the efficiency of our experiments, the obtained results are shown in the fourth section. This section is followed by the conclusion.

II. MATERIALS AND METHODS

A. Data acquisition

First step toward automatic detection of attention is designing a new protocol for recording EEG signals in both attention and non-attention conditions. A total of 12 adults (5 men and 7 women aged 20-23) were examined in this study. According to the designed protocol, the subjects were seated in

978-1-5386-3609-1/17/$31.00 ©2017 IEEE

2017 24th national and 2nd International Iranian Conference on Biomedical Engineering (ICBME), Amirkabir University of Technology, Tehran, Iran, 30 November - 1 December 2017

front of a monitor at an appropriate distance (Fig.1) while a stream of images (presentation rate is almost 1Hz) is presented for them. In this experiment, using BCI2000 software [9], some numbers in different colors and brands (in both English and Persian forms) were shown in a random sequence (Fig. 2) while the subjects were asked to carry out simple mental mathematical tasks, e.g. summing up red odd numbers, multiplying even numbers written in circles, etc. The time interval between two consecutive images was not constant and the total time of each trial is about 180 seconds. During the experiment, EEG signals were recorded by an EMOTIV device, using 8 channels: AF3, F3, FC5, FC6, F4, AF4, F7 and F8. In this study, the forehead channels were used as this area of brain is shown to be one of the most active areas during attention state [10].

Since the aim of this study was automatic classification of human attention in two levels, all trials were done in two conditions, namely silent and non-silent conditions. In the non-silent case, some high-volume verbal and nonverbal sounds were played using an earphone to make distraction. The noises were not invariant and were changing intermittently.

At the end of each trial, the subjects were asked to express the result of the accomplished mathematical task and their mental state during the experiment: attention or non-attention. The final label of each trial (i.e. attention or non-attention) was determined based on the correctness of the mathematical task, the self-expression and the silent or nonsilent condition.

Figure 1. A subject conducting the experiment

Figure 2. A bunch of numbers displayed

B. Pre-processing

In this step, unwanted noises, which were produced by the movements of subjects or the neuroheadset during the experiment, were manually excluded. Then, a 0.5-49 Hz band-pass filter was used for noise reduction. To insure that subjects entered into attention or non-attention state, first 10 seconds of the recorded data in each trial were eliminated. Then, the obtained signals were divided into 10-second sections. Table 1 shows the total number of sections for each subject.

C. Feature extraction

After pre-processing, the next step is to extract features from the recorded signals. Typically, brain waves are classified into four basic groups: δ (0.5-3 Hz), θ (4-7 Hz), α (8-13 Hz) and β (14-20 Hz), which are active during human mental states [11]. According to the previous researches [10], alpha activity is intensified when we are in relaxation mode and our eyes are closed. The beta activity is related to the activation level of mental state. This feature is related to human attentive level [6]. Thus, in this paper we extracted features in the above-mentioned frequency bands. To this end, we filtered each channel of data, $x(t)$, in each of four frequency bands and called them $x_\delta(t)$, $x_\theta(t)$, $x_\alpha(t)$ and $x_\beta(t)$. Then, we computed features from these filtered signals in 6 different categories using the following feature expressions. To simplify our notations, in the following expressions, we show signals of different frequency bands with $x_{fb}(t)$ where fb can be δ, θ, α or β.

a) Entropy-based feature: We computed Shannon entropy for each channel of signal of each frequency band [12]. To this end, we considered each filtered signal, $x_{fb}(t)$, as samples of a random process and computed the probability distribution function related to it, namely $P(x_{fb})$. Then we computed Shannon entropy as follows:

$$H(x_{fb}) = -\sum_{x_{fb}} P(x_{fb}) log_2 (P(x_{fb})) \quad (1)$$

b) Maximum power of each frequency band: First we computed the Fourier transform of each frequency band as $X_{fb}(f)$ and then obtained maximum power of the corresponding band as follows:

$$P_{fb} = \max_f \frac{X_{fb}(f) X^*_{fb}(f)}{N} \quad (2)$$

where N is the number of points of Fast Fourier transform [6].

c) Energy of each frequency band: For each frequency band, energy is computed as follows [6]:

$$E_{fb} = \int_{fb} X_{fb}(f) X^*_{fb}(f) df \quad (3)$$

d) Peak-to-peak value of frequency bands: For each frequency band, we computed the maximum and minimum values of signal in time domain and then computed peak-to-peak value of the corresponding frequency band.

e) Mean value of frequency bands in time domain: For each frequency band, we computed the average of the signal in the time domain.

978-1-5386-3609-1/17/$31.00 ©2017 IEEE

TABLE1. TOTAL ATTENTION AND NONATTENTION 10 SECONDS SECTIONS OF EACH SUBJECT

Subject	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12
Attention	70	43	53	56	40	55	132	76	73	58	95	80
Non-attention	81	33	58	63	56	60	122	64	63	65	73	68

f) The ratio of alpha-band energy to beta-band energy: By computing the energy of signal in alpha and beta bands using (3), we computed the ratio of alpha-band energy to beta-band energy as:

$$R = \frac{E_\alpha}{E_\beta} \tag{4}$$

By computing the above-mentioned features for each channel, 21 features were extracted and totally, 168 features were extracted for each subject. After that, all of the features were normalized by computing the signed distance between the raw feature and the population mean in units of the standard deviation.

D. Feature Selection

Feature selection is used to reduce the number of extracted features to the effective ones, in order to increase the accuracy of classification. In this paper, the Forward Feature Selection (FFS) method with Fisher criterion has been utilized.

a) Forward Feature Selection

In this method, the criterion is computed for each of the features. Then, the feature with the best value is selected. In the next step, all possible two-dimensional vectors that contain the winner from the previous step are formed, and the criterion for each of them is computed and the best one is selected. This procedure continues until the desired feature vectors are obtained [13].

b) Fisher Criterion

To define an appropriate criterion for the FFS method, we used the Fisher criterion. To this end, we defined within-class and between-class scatter matrices as follows:

Within-class scatter matrix is defined as:

$$S_w = \sum_{i=1}^{M} p_i \Sigma_i \tag{5}$$

where $\sum_i$ is the covariance matrix for class ω_i and defined as follows:

$$\Sigma_i = E[(x-\mu_i)(x-\mu_i)^T] \tag{6}$$

and μ_i and p_i denote the sample mean and the a priori probability of class ωi, respectively. Between-class scatter matrix is defined as:

$$S_b = \sum_{i=1}^{M} p_i(\mu_i-\mu_0)(\mu_i-\mu_0)^T \tag{7}$$

where μ_0 is the global mean vector and defined as follows:

$$\mu_0 = \sum_{i=1}^{M} p_i \mu_i \tag{8}$$

Trace of within-class scatter matrix, $tr\{S_w\}$, is a measure of the average variance of the features over all classes. On the other hand, trace of between-class scatter matrix, $tr\{S_b\}$, is a measure of the average (over all classes) distance of the mean of each individual class from the respective global value. Therefore, smaller values of $tr\{S_w\}$ represent that the corresponding features produce denser classes and larger values of $tr\{S_b\}$ show the ability of them to scatter different classes.

In this stage, we used the ratio $tr\{S_b\}/tr\{S_w\}$ as an appropriate criterion for feature selection. The greater ratio represents better discrimination ability of the corresponding group of features.

By applying this criterion in the FFS method, the most effective groups of 3, 4, … and 10 features were selected for each subject from all 168 features. We refer to them as effective feature groups in the following sections [13].

III. CLASSIFICATION

The next step after feature extraction and selection is data classification. In this paper, four classification methods were applied, namely KNN (K Nearest Neighbors) [13], Bayesian [13], Support Vector Machine (c-SVM) [13], and Linear Discriminant Analysis (LDA) [13]. For each person, individually, the classification procedure has been done on each of the effective feature groups. The k-fold cross validation (k=5) used to validate the accuracy of classifiers [13]. In this method, the data is divided into k subsets. One of the k subsets is used as the test data and the other k-1 subsets are used as the training data, and this method is repeated k times. Then the average error across all k trials is computed.

IV. RESULTS

In this part, the results of the applied processing methods are presented. Due to innate differences between the signals of subjects, all the processing methods have been done for each subject individually (subject-dependent).

The results of the feature selection step show that the effective features for each subject are different with each other. To investigate the results of this step, these results are summarized in figures 3 to 7. In Fig. 3, the percent of utilization of different feature categories is shown. As shown in this diagram, the features related to three categories, namely

978-1-5386-3609-1/17/$31.00 ©2017 IEEE

energy, entropy and peak-to-peak features, are the most usable ones. But we should note that the total number of features in the sixth category (the ratio of alpha-band energy to beta-band energy, called R) is one-quarter of the number of features in the other categories. Therefore, from another point of view, we can conclude that the most effective feature is R. Fig. 4 shows the percent of utilization of features related to different frequency bands. Similar to previous studies, features of the beta band are the most effective ones.

Fig. 5 shows the percent of utilization of features extracted from different channels. Nearly, all the recording channels have involved in the selection of effective features.

To investigate the differences between EEG signals of men and women in the proposed protocol, we calculate the percent of utilization of different feature categories for the male and female subjects as shown in Fig. 6 and Fig. 7. According to these diagrams, there is no significant difference between these two groups. By recording signals from much more subjects, we may find meaningful differences in EEG signals of male and female subjects in attention and non-attention states.

Table 2 shows the best classification accuracy obtained by using the four classifiers for each subject.

The highest accuracy was achieved for subject 6 which is almost 100% using all four classifiers. A probable reason for this is that the subject has been completely indifferent to carry-out desired tasks in the non-attention condition. The lowest accuracy was achieved on the data of subject 10. This may result from the fact that the subject has been hardly distracted in the non-attention condition. According to Table 2, on average, c-SVM and LDA classifiers with 92.8 and 92.4 percent accuracy have the best performances.

Fig. 8 shows the classification results for subject 9 (as an example) in terms of the number of effective features. According to this figure, the best result is obtained by LDA classifier with 8 effective features. In addition, Fig. 8 shows that by increasing the number of the features, the performance of classifiers will not increase as well.

V. DISCUSSION AND COLCLUSION

In this study, the EEG signals of 12 subjects were recorded in two attention and non-attention conditions using a new protocol that was based on mathematical operations. The protocol does not require strong memory and strong language knowledge to carry out. The signals were recorded using 8 forehead channels which all of them had impact on the feature selection part. After signal recording and pre-processing, the effective features of each subject were extracted. The best features were related to the beta band and the energy of the signals.

Four different classifiers, namely KNN (K=9), c-SVM, LDA, and Bayesian classifiers were applied on the selected effective features and their results were compared for each of the subjects individually. On average, c-SVM and LDA classifiers were more accurate, with 92.8% and 92.4% accuracy of 5-fold cross validation, respectively.

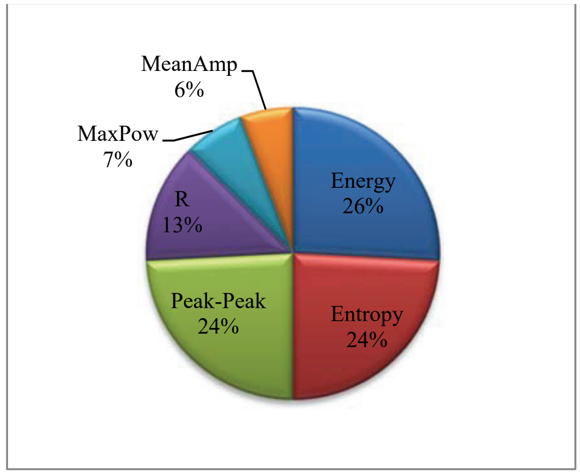

Figure 3. The percent of utilization of different feature categories

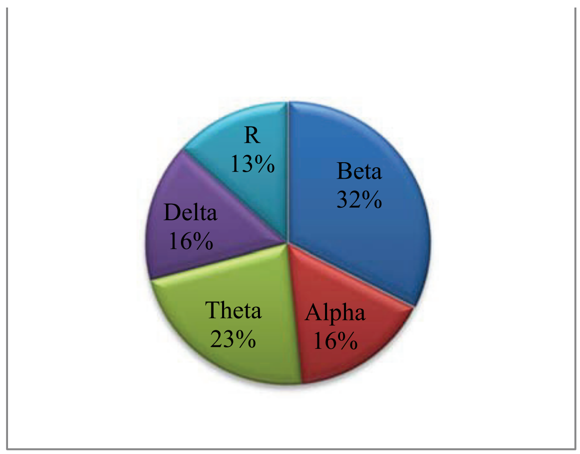

Figure 4. The impact of different frequency bands

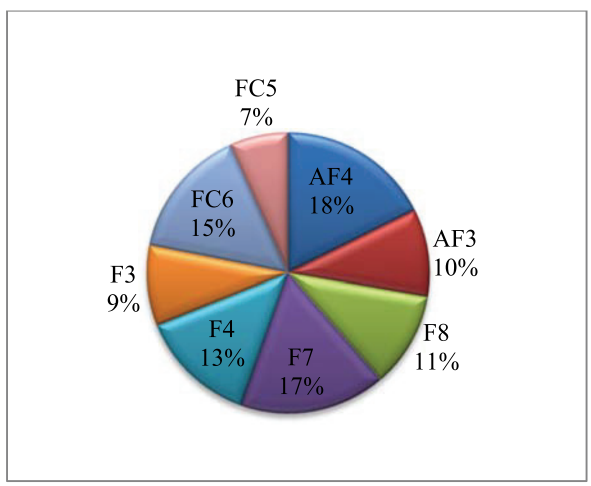

Figure 5. The impact of different channels

978-1-5386-3609-1/17/$31.00 ©2017 IEEE

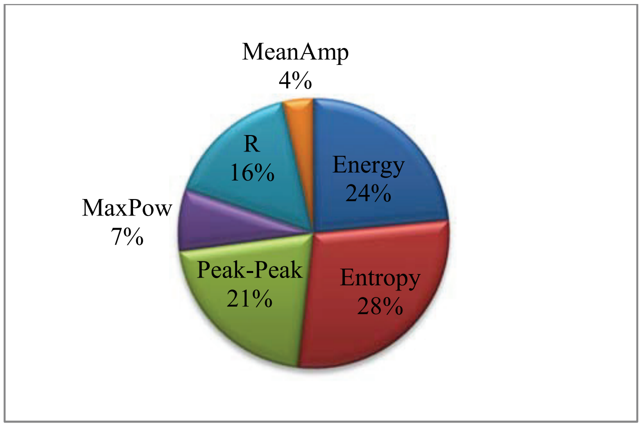

Figure 6. The impact of different categories features for women

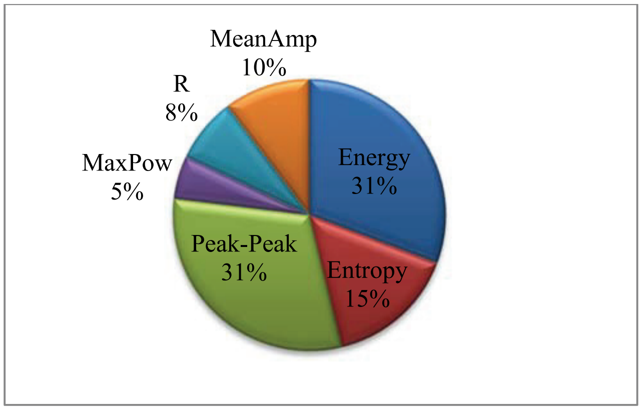

Figure 7. The impact of different categories features for men

TABLE 2. CLASSIFICATION RESULTS (5-FOLD CROSS VALIDATION) FOR EACH OF THE SUBJECTS

Subjects	C-SVM (%)	Bayes (%)	KNN (%)	LDA (%)
S1	80	68	76.8	80.1
S2	98.9	99	98.9	99
S3	96.4	90	94.6	97.3
S4	95.8	79	83.9	86.5
S5	91.6	78.1	88.5	90.6
S6	100	99.1	100	100
S7	92.8	87.5	90.1	92.8
S8	97.8	92.8	96.4	97.1
S9	96.3	92.75	94.1	97.7
S10	76	70	76.4	76.4
S11	94	80.1	93.3	95.3
S12	93.9	94	88.5	95.9
Mean	92.8	85.9	90.1	92.4

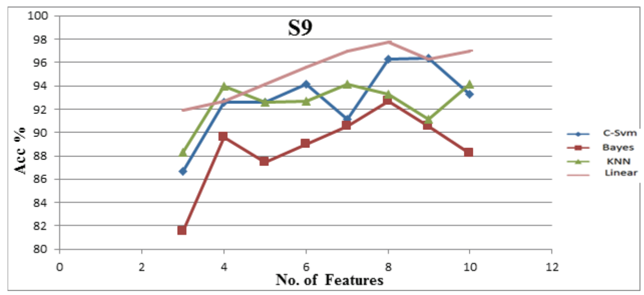

Figure 8. Classification results for subject 9

In this study, all applied methods and the obtained results were subject-dependent and were applied offline. It is suggested to compute a unit model for all the subjects in order to classify the signals, and also to adjust the project in order to be utilized for online detection of human attention. In addition, it is suggested to record data from more subjects and to find common features. In this case, one can more precisely draw a conclusion about the common characteristics of different subjects.

REFERENCES

[1] Rodrak, S., & Wongsawat, Y. (2012, December). On the classification of EEG/HEG-based attention levels via time-frequency selective multilayer perceptron for BCI-based neurofeedback system. In Signal & Information Processing Association Annual Summit and Conference (APSIPA ASC), 2012 Asia-Pacific (pp. 1-4). IEEE.

[2] Cho, B. H., Lee, J. M., Ku, J. H., Jang, D. P., Kim, J. S., Kim, I. Y., ... & Kim, S. I. (2002). Attention enhancement system using virtual reality and EEG biofeedback. In Virtual Reality, 2002. Proceedings. IEEE (pp. 156-163). IEEE.

[3] Miles, R. K., Smith, W. J., LaCourse, J. R., & Petrie, R. A. (1996, March). A system for the detection and non-pharmacological intervention in attention deficit/attention deficit hyperactivity disorder [EEG analysis]. In Bioengineering Conference, 1996., Proceedings of the 1996 IEEE Twenty-Second Annual Northeast (pp. 101-102). IEEE.

[4] Wan, Z., He, J., & Voisine, A. (2013, October). An attention level monitoring and alarming system for the driver fatigue in the pervasive environment. In International Conference on Brain and Health Informatics (pp. 287-296). Springer International Publishing.

[5] Sun, H., Bi, L., Chen, B., & Guo, Y. (2015). EEG-based Safety Driving Performance Estimation and Alertness Using Support Vector Machine. International Journal of Security and Its Applications, 9(6), 125-134.

[6] Liu, N. H., Chiang, C. Y., & Chu, H. C. (2013). Recognizing the degree of human attention using EEG signals from mobile sensors. Sensors, 13(8), 10273-10286.

[7] Li, X., Zhao, Q., Liu, L., Peng, H., Qi, Y., Mao, C., ... & Hu, B. (2012). Improve affective learning with EEG approach. Computing and Informatics, 29(4), 557-570.

[8] EMOTIV, last accessed January, 2017, Emotiv.com

[9] BCI2000, last accessed January, 2017, http://www.schalklab.org/research/bci2000

[10] Duann, J. R., Chen, P. C., Ko, L. W., Huang, R. S., Jung, T. P., & Lin, C. T. (2009, July). Detecting frontal EEG activities with forehead electrodes. In International Conference on Foundations of Augmented Cognition (pp. 373-379). Springer Berlin Heidelberg.

[11] Teplan, M. (2002). Fundamentals of EEG measurement. Measurement science review, 2(2), 1-11.

[12] Tong, S., Bezerianos, A., Malhotra, A., Zhu, Y., & Thakor, N. (2003). Parameterized entropy analysis of EEG following hypoxic–ischemic brain injury. Physics Letters A, 314(5), 354-361.

[13] Theodoridis, S., & Koutroumbas, K. (2001). Pattern recognition and neural networks. In Machine Learning and Its Applications (pp. 169-195). Springer Berlin Heidelberg.