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Research Article

Effects of Learning Task Difficulties on the Prefrontal Brain Area

Amin Zammouri and Abdelaziz Ait Moussa
Department of Computer Sciences, Faculty of Sciences, Mohammed First University, Bd Med VI, B.P. 717, 60000 Oujda, Morocco

Abstract: This study addresses the issue of estimating mental efforts during a learning task based on brain signal measurements. The aim of this study is to describe how a Brain-Computer Interface (BCI) can be used as a direct communication tool between the human brain and a machine in the context of learning. Such devices are based on analyzing the electrical brain activity measurements using different brain exploration technics. In this study we describe an offline method to highlight effects of changing difficulty levels of a learning task on the prefrontal brain area status. Based on a single ElectroEncephaloGraphic (EEG) channel and using the Fisher-Snedecor test our proposed algorithm describes changes of Delta (0.5-3Hz), Theta (4-7Hz) and Alpha (8-11Hz) band powers. By using the Kappa coefficients, to assess the agreement rate between the algorithm decisions and those made by an expert, experimental results show a rate of 62% of agreement. This reflects the efficiency of the proposed method in distinguishing effects of difficulty levels of a learning task on the prefrontal brain area.

Keywords: Brain waves, cognitive task, mental effort, mental status

INTRODUCTION

Electroencephalography is an emergent technique allowing detection of the electrical brain activity resulting from the neurons functioning. The signal is recorded by placing electrodes on the scalp. Signals resulting from the brain activity are called Electroencephalograph. These signals are periodic and vary according to the brain activity. The electroencephalography discovery has given rise to new research areas such as Brain-Computer Interfaces, which are considered as new systems of direct communication between the brain and external devices such as computers or any electronic device (Wolpaw *et al*., 2002; Bell *et al*., 2008; Yasui, 2009). These systems can be designed to assist, improve, or repair functions of human cognition. Furthermore, BCI systems can be infinitely useful for people suffering from heavy motor disabilities (Farwell and Donchin, 1988). The application of this research field ranges from assistance for disabled people to the use in the video games field (Pires *et al*., 2012; Leeb *et al*., 2013). These communication and control systems do not depend on the standard brain neuromuscular outputs. The intention of the user is mediated by the brain signals instead of nerves and muscles. Currently, BCI systems are in the majority of cases unidirectional. Indeed, the brain signals are recorded and processed, but no feedback is directly transmitted to the brain. However, it does not mean that the user has no feedback at all. To be considered as a BCI, the system must provide a feedback to the user. This feedback reflects the result of the operation and may affect the next user's intention. There are many recording techniques to measure the brain activity and to convert it into signals which can be used by BCI. Some of these methods, called invasive, are mainly used in animals and require a neurosurgery implantation in the cortex. This type of recording methods allows a better signal quality. But over time, cysts could be formed and reduce the signal quality. The second technique, known as non-invasive, is described as “lightweight” since its implementation is simple, fast and without risks in the physical integrity. This makes it the most commonly used method for the development of a BCI.

In recent years, several researches have been conducted to study the brain behavior and the attention process during a cognitive task. In the Keller's ARCS model (Keller, 1987a, 1987b) attention is considered fundamental to achieve the motivation in the classroom. In this model, the components: Attention, Relevance, Confidence and Satisfaction should be achieved if the learner is going to be motivated. In order to recognize the students' attention in the computer mediated learning, several researches have been conducted. These studies were based on the Artificial Intelligence

Corresponding Author: Amin Zammouri, Department of Computer Sciences, Faculty of Sciences, Mohammed First University, Bd Med VI, B.P. 717, 60000 Oujda, Morocco

in EDucation (AIED). This field has dealt with two main problems (1) attention and motivation recognition (Başar *et al*., 2001; Conati and Merten, 2007), (2) Students' reactions. For attention and motivation recognition, researches were based on two main methodologies. The first aims at modeling using physiological markers and the second by using user-generated data. Results give an indication of physical interactions which are associated to the attention or motivation state during learner and educational system interactions.

As an ARCS model-based study, (Rebolledo-Mendez *et al*., 2009) conducted a study to test the usability of NeuroSky EEG headset to detect the attention level in an assessment exercise in Second Life. The approach used in this study fuses EEG recordings with the user-generated data. The adopted model combines attention readings with other information such as the number of correct answers or the taken time to answer each question. The aim of this combination is modeling attention during an assessment exercise.

On another hand, estimating the attention level and the cognitive load from the EEG requires objective methods to determine the cognitive overload of the brain mental fatigue during the work performance. In Holm *et al*. (2009), authors have determined an index ρ, based on the prefrontal theta (4-7 Hz) oscillation (electrode Fz) and the parietal alpha (8-11 Hz) oscillation (electrode Pz):

$$\rho = \frac{Theta\ (F_Z)}{Alpha\ (P_Z)} \tag{1}$$

The ρ index increases with the increasing number of tasks to perform and the time awake. Determining the workload status increasing would provide the opportunity to either prevent or help subjects with automated systems. The main results are focused on the information from the EEG spectrum and particularly on the theta oscillation increasing in the prefrontal area and the alpha oscillation decreasing in the parietal area.

In this study we propose an offline method to illustrate effects of the learning task difficulty on the prefrontal brain area using only a single EEG electrode and based on the Fisher-Snedecor test. The experimentations are based on solving a matrix problem. Furthermore, we highlight the brain oscillations which enter into interaction to describe the increase or decrease in vigilance and mental efforts during a learning task.

MATERIALS AND METHODS

In our application, we are interested at discovering a side of the human brain behavior when performing a cognitive task based only on a single EEG electrode placed in the brain prefrontal area.

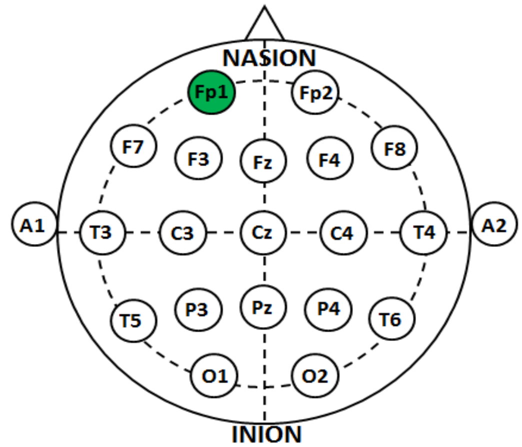

Fig. 1: Fp1 electrode placement in the 10-20 international system

Protocol and experimentations: EEG data used in this study were recorded on 11 subjects from the Departments of Mathematics, Computer Science and Biology at the Mohamed First University, Morocco. The population consisted of 3 females and 8 males aged between 20 and 32 years old. In the general case of a BCI-based experiment the number of subjects does not exceed 5 in average. The experimentations conducted in this study consist of two tests in which the user must solve a set of matrix products with different difficulties. EEG data were recorded using the OpenViBE (Renard *et al*., 2010) acquisition server with a sampling frequncy of 512Hz and applying the filter band-pass 0.5-30 Hz.

EEG data filtering: The brain signals acquisition was performed using the NeuroSky headset with a single $Ag/AgCl$ electrode placed at the prefrontal brain area as it is depicted in Fig. 1. We decided to work on the Fp1 electrode for various reasons. From a practical point of view, it allows to set the electrode on the facial skin, which enables a better signal quality. On another hand, the prefrontal brain area is the more supposed to contain the working memory which allows performing cognitive processes. This memory is deeply involved in the reasoning-based processes such as reading, writing and calculates. In contrast, given its position, the Fp1 electrode is influenced by certain noises, especially ocular artifacts. An effective way to deal with these disturbances is by asking subjects to restrict their eye movements fixating on a stable point (Klados *et al*., 2011). However, this fixation may affect the neuroscience interpretation of the results. To overcome this problem, we use an eye blinks rejection method that we have developed in a previous work (Zammouri *et al*., 2015). For the sake of completeness, we briefly explain this method.

Let $x(t)$ be the EEG signal vector. We draw the graphical representation of the distribution of the vector x as a histogram. In all cases, the histogram was a

Gaussian cloche. This information allows assuming that the EEG signal is a Normal Gaussian distribution:

$$x(t) \sim \mathcal{N}(\mu_x, \sigma_x^2) \tag{2}$$

The Eq. (2) defines the range of the EEG recordings that are not contaminated by eye movements. Besides this range we find the large amplitudes which represent eye movements. In below, we give the pseudo algorithm of this filtering method:

Algorithm *Eye blinks rejection*

Require: $x \in \mathbb{R}^N$ (EEG data vector)

1: $H \leftarrow \text{Histogram}()$

2: $\mu_x \leftarrow \text{mean}(x)$, $\sigma_x \leftarrow \text{standard} - \text{deviation}\ (x)$

3: Choose k (to determine $\mu_x - k * \sigma_x$ and $\mu_x + k * \sigma_x$)

4: For $i = 0$ to N

6: Detect P points: $P < (\mu_x - k * \sigma_x)$ or$P > (\mu_x + k * \sigma_x)$

7: End for

8: Reject all the detected eye blinks

End

The comparison of the eye blinks detection algorithm using the ROC curves method revealed that the algorithm performs well in the detection of eye blinks. The performance characteristics parameters calculated on all subjects are presented in Table 1.

The True Positive Rate (TPR) or detection rate is the ratio between the number of annotations of true eye blinks made by the algorithm and the number of true annotations of true eye blinks made by the expert. The false positive rate (FPR = 1-SPC) represents the ratio between the number of false decisions made by the algorithm and the number of the expert's annotations concerning non-eye blinks. These rates are calculated as presented in the two Eq. (3) and (4):

$$TPR = \frac{TP}{TP+FN} \tag{3}$$

$$TPR = \frac{FP}{FP+TN} \tag{4}$$

Changes detection algorithm: The principle of our method to illustrate the effects of a learning task difficulty on the prefrontal brain area is shown in Fig. 2. The subject performs the two tests of two different levels of difficulty. The recorded EEG data during the two tests are then filtered using the eye blinks rejection method described above. Based on a Short Time Fourier Transform (STFT), the EEG power spectrum is computed in order to distinguish the different EEG oscillations. The Fisher-Snedecor test is then applied in order to compare brain oscillations in the two tests.

The STFT is used to calculate the EEG power spectrum and extract the different brain oscillations. The power spectrum is calculated every second using an averaged periodogram with a Hanning window. Applying an eye blinks rejection method at the beginning of our approach is justified by the reduction of the effects of these disturbances on the brain oscillations. Then, the power of each band is computed every second. For sake of completeness we describe the use of this comparison test in our approach.

Let x and y be two independent and normal samples with lengths n_x and n_y respectively and let s_x^2 and s_y^2 be their experimental variances respectively.

Table 1: ROC parameters for the filtering algorithm

	ROC Parameters		
Subjects	TPR (%)	SPC (%)	PPV (%)
Subject 1	90.00	99.30	98.30
Subject 2	97.80	99.30	95.74
Subject 3	91.41	99.20	100.0
Subject 4	100.0	99.10	90.00
Subject 5	100.0	97.80	78.04
Subject 6	92.50	97.60	88.10
Subject 7	94.11	97.50	84.00
Subject 8	96.00	96.80	84.84
Subject 9	85.13	93.90	87.27
Subject 10	90.00	90.90	71.42
Subject 11	92.40	96.30	87.02
Average	93.57	97.06	87.70

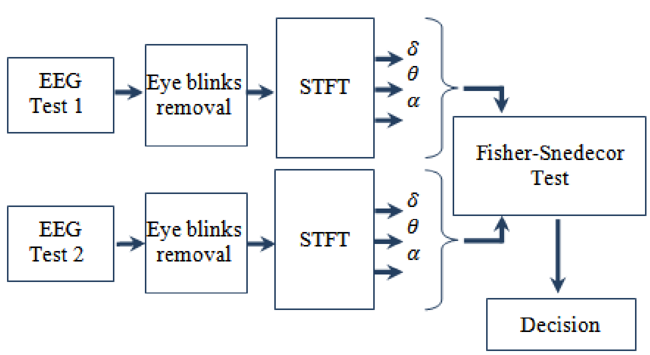

Fig. 2: Flowchart of our methodology to illustrate effects of changing difficulty levels on the prefrontal brain area during a learning task

The test of Fisher-Snedecor aims to determine whether the two samples belong to the same population. Hence, we have two hypotheses. The Null Hypothesis (H_0) corresponds to $s_x^2 = s_y^2$. Alternative Hypothesis H_A corresponds to $s_x^2 \neq s_y^2$. From this, a statistic F is calculated:

$$F = \frac{s_x^2}{s_y^2} \tag{5}$$

The statistic F follows a Fisher law with $n_x - 1$ and $n_y - 1$ degrees of freedom. Therefore the equality of variances can be tested using a bilateral test with a specific confidence threshold λ. If $F > \lambda$ we can reject H_0 with a ρ risk of having reject it. If $F < \lambda$ we accept H_0. For a given ρ and degrees of freedom, we seek the theoretical value in the Fisher's table. In our approach, the Fisher-Snedecor's test is applied to each brain oscillation to make a comparison between the two tests.

RESULTS AND DISCUSSION

The automatic system proposed in this study provides a classification of two different levels of mental efforts while it is possible that the EEG data set contains other subclasses in each of the two distinguished main classes. This assumption is justified by the fact that our algorithm compare variances of the wholly tow tests. Results of the Fisher-Snedecor test, presented in Table 2 and Fig. 3, demonstrate that our method performs well in distinguishing the two main classes of mental efforts induced by the two experimental tests. On another hand and in order to highlight effects of changes in difficulty levels of the learning task, in each of the two experimental tests the mean of each band power is computed. The aim is to find a correlation with decisions made by the Fisher-Snedecor test. Results presented in Fig. 3 show and illustrate the decisions made by the Fisher-Snedecor test. Indeed, when the statistic F moves away from the threshold $\lambda$the difference of averaged powers of each band increases.

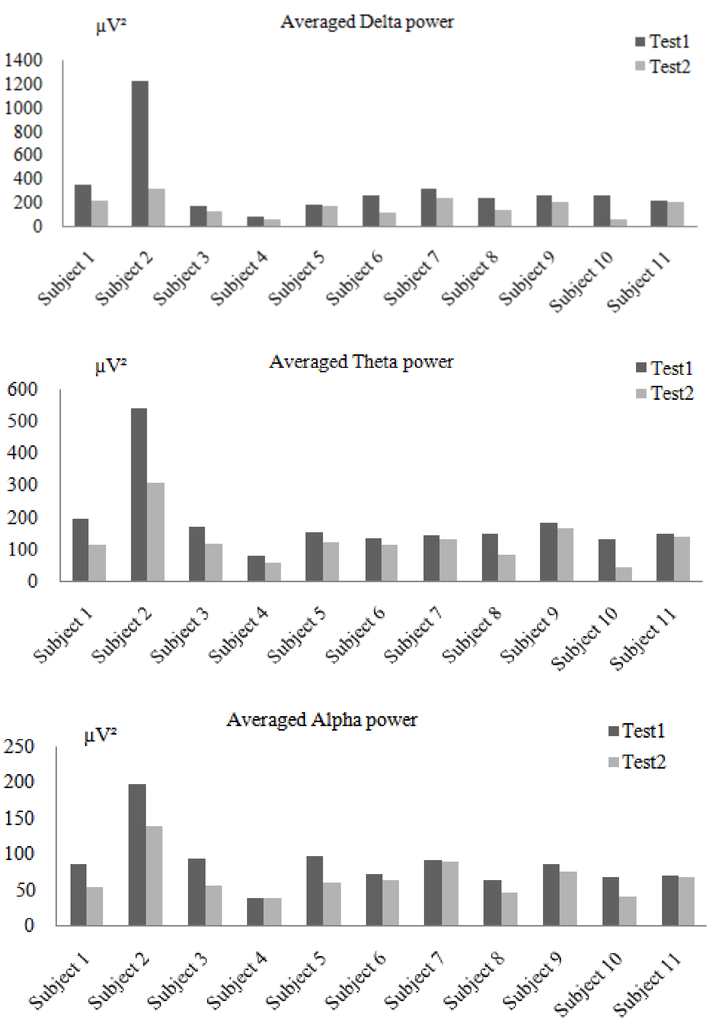

Fig. 3: Averaged band powers

Table 2: Statistic 'F' obtained for all subjects

	ROC Parameters			
Subjects	Delta (0.5-3 Hz)	Theta (4-7 Hz)	Alpha (8-11 Hz)	λ
Subject 1	3.9139	2.8327	2.386	1.44
Subject 2	24.1998	4.55150	3.3829	1.33
Subject 3	6.19990	2.76010	4.0466	1.52
Subject 4	1.11330	1.30360	1.1604	1.58
Subject 5	0.68800	3.04930	2.6374	1.66
Subject 6	11.6495	1.53170	1.5292	1.52
Subject 7	3.06320	1.09220	0.8722	1.48
Subject 8	7.63320	12.3728	4.4570	1.63
Subject 9	1.55030	1.19860	1.3397	1.19
Subject10	24.5368	15.4993	1.8420	1.63
Subject 11	0.93300	1.36200	0.7900	1.31

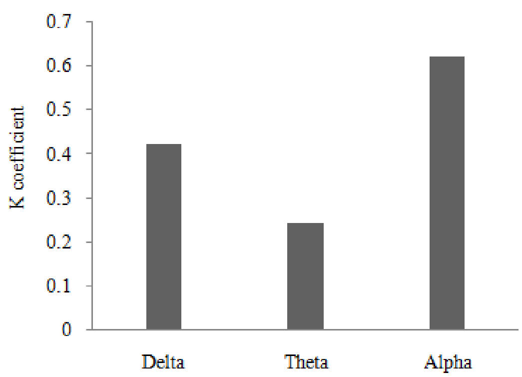

Fig. 4: Agreement coefficients between the expert and the proposed algorithm

On another hand, we find that increasing the level of difficulty in the learning task reduces the power of delta, theta and alpha bands in the prefrontal brain area. By comparing our results to those existing in the literature we find a strong correlation with findings of Otmani *et al*. (2005), Papadelis *et al*. (2006) and Kaida *et al*. (2007). From this comparison we deduce that the theta and alpha activities decrease, obtained from our experimental results when increasing the learning task difficulty, is an indicator of the subject's mental effort and vigilance increase. In order to evaluate the performance of the proposed method, an expert's annotations are used. For each band power, the expert identify whether the EEG data of the two tests correspond to two different classes or not. Therefore, the classification results of our method are compared to the expert's annotations. The agreement is assessed using the Cohen's Kappa test which represents a statistical metric of agreement:

$$k = \frac{P_r(a) - P_r(e)}{1 - P_r(e)} \tag{6}$$

where, $P_r(a)$ represents the agreement existing between the algorithm and the expert and $P_r(e)$ is the probability of a random agreement. The obtained results of the agreement assessment are reported in Fig. 4. These results show a strong agreement (k = 0.64) between the expert and the classifications of the algorithm regarding changes in the alpha band. For the delta band, the Kappa test give a value K = 0.42. This reflects a moderate agreement between the expert and the algorithm. Regarding the changes in the theta band., the agreement is weak and is justified by a coefficient k = 0.24.

Our results demonstrate that a single non-invasive EEG channel can be used to illustrate and highlight reactions of the prefrontal brain area to changes of difficulties levels in cognitive tasks. An automatic system such as the one described in our investigation could be used in different domains. For instance, in the medical field, it could represent for neurologist, a more subjective mean to assess improvements of a patient's status. In the learning area and the technologies associated with it, this classification system could be exploited in the development of new adaptive intelligent tutoring systems.

CONCLUSION

An algorithm for distinguishing two classes of mental efforts has been described in this study. Based on a Fisher-Snedecor test, this method highlights effects of learning task difficulties on delta, theta and alpha band powers in the prefrontal brain area. Using only one EEG channel, the Kappa coefficients, computed in order to assess the agreement rate between the algorithm decisions and those made by an expert reached 62% of agreement. As further works, we are considering to study the other different brain areas in order to highlight the effects of changing difficulty levels of a learning task on these brain areas. Moreover, we seek define new and optimal models which can describe the learning process and exploit only the brain information measured in a non-invasive way.

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