Impact of Mental Fatigue during Repetitive Exercises of a Visual P300 Speller

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Abstract: In this paper, we investigate the effect that mental fatigue during repetitive exercises of a visual P300 Speller has on the P300 component, in terms of accuracy, amplitude, latency, signal morphology, and overall signal quality. This work is part of a larger EEG based project and is based on the P300 speller BCI (oddball) paradigm and the xDAWN algorithm, with eight healthy subjects; while using a non-invasive Brain-Computer Interface (BCI) based on low fidelity electroencephalographic (EEG) equipment. Herein, eight channels through the initial task (6 minutes), additional tasks (50 minutes) and final task (6 minutes) states, recorded the subjects' signal. Our results show that the accuracy was best for the initial task (*IT*) at 100%, followed closely by the final task (*FT*) at 98%. In addition, our ANOVA analysis showed that the amplitude exhibited a statistical significance between *IT* and *FT*, while the latency did not indicate any statistical difference. This paper provides initial results into the practicability of the aforementioned P300 speller methodology and low-cost equipment to be used repetitively and continually and the effect thereof on accuracy and signal characteristics. Our aim is to assess the effect of prolonged usage and exposure to the aforementioned methodology and equipment, with the aim of broadening its use in a real-world context.

1 INTRODUCTION

In this paper, we analyse the possible impact of mental fatigue during repetitive exercises, explicitly on that of a visual P300 Speller, and the effect that this has on the accuracy, amplitude, latency, signal morphology, and overall signal quality of the P300 component. Our research makes use of non-invasive Brain-Computer Interface (BCI) based on Electroencephalography (EEG) while utilising low fidelity equipment. The work presented here is part of a larger EEG based project and in continuation of our latest papers (Schembri, et al., 2019) (Schembri, et al., 2019).

In the past decade, P300-based BCI research has been predominantly focused on the speed and accuracy of communication for both healthy subjects and especially to those individuals with severe neuromuscular disabilities such as amyotrophic lateral sclerosis patients (Londral, et al., 2015). However, the effect of mental fatigue with prolonged usage of BCI has been unheeded and neglected. Only a few research papers such as (Sargent, et al., 2018) and (Hammer, et al., 2018) focus on mental fatigue in conjunction with the P300 speller, however they were either utilizing expensive medical and/or research-grade equipment (Oken, et al., 2019) and/or focusing on a way to detect, evaluate and measure mental fatigue (Fujita, et al., 2018) (Sabeti, et al., 2018), rather than the effect that mental fatigue has on the accuracy and on the signal characteristics of the P300 component in a P300 Speller application.

The research aim of this paper is to analyze the effects that mental fatigue during repetitive exercises of a visual P300 Speller have on the P300 component, in terms of the aforementioned accuracy and signal characteristics. Due to the lack of a detailed study on this effect, an evident necessity for this study was present. Our null hypothesis (H_0) states that that the independent variables i.e. initial task (*IT)* and final task (*FT*) have no effect and/or no statistical impact on the dependent variables (accuracy, amplitude, and

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latency). Our alternate hypothesis (H_1) based on preceding related medical-grade research is that there should be a decrease in BCI performance over time which comprises a drop in accuracy and a reduction in amplitude, however, the latency should not show any statistically significant effect.

In this work, we report a study where eight healthy subjects communicated five alphanumeric characters, referred to as symbols, in the *IT* which lasted approximately six minutes, other additional tasks (*AT*) which lasted around fifty cumulative minutes which analysis is not included in this study, and the *FT* which lasted around six minutes, respectively. Our comparison was based on the *IT* and *FT* tasks i.e. on the first task when the subject was rested and alert when compared to the last task when the subject was tired and bored.

This paper is structured as follows: the research background, equipment, experimental procedures and participants are described in Section 2. The offline and online ERP results are presented in Section 3. Conclusions and future work are given in Section 4.

2 METHODOLOGY

The following segment/s of the methodology is the author's previous work and are adopted and outlined in the current paper for readers' convenience. A more thorough explanation can be found in our previous paper (Schembri, et al., 2018).

2.1 Research Background

Fatigue can be broadly divided into two categories i.e. physical and mental fatigue, depending on the task being performed. In previous studies such as (Marcora, et al., 2009), it was discovered that mental fatigue affects the physical performance of the subject, but contrariwise physical fatigue does not affect mental alertness. In simplest terms, mental fatigue refers to a psychobiological state caused by prolonged periods of demanding cognitive activity and characterized by subjective feelings of *tiredness* and *lack of energy* (Boksem & Tops, 2008), and, from boredom.

(Lee, et al., 2018) reports that after prolonged use of visual attention-based BCI, most participants report the uncomfortable symptoms of physiological fatigue, which include tiredness, drowsiness, and a loss of attention which degraded the signal quality and performance of the BCI system. Similarly, (Oken, et al., 2019) reports that there was a decrease in BCI performance over time that related to increases in sleepiness and boredom. This worsened performance was only partly explained by decreases in P300 amplitude. Thus, drowsiness and boredom have a negative impact on BCI performance.

(Chen, et al., 2017) reports that the P300-Speller was shown to be significantly impaired once applied in practical situations due to effects of mental workload, where his aim was to provide a new method of building training models to enhance the performance of P300-Speller under mental workload. On the other hand, (Yu, et al., 2017) merged a motor imagery (MI)-based brain switch into a P300-based BCI speller which allowed the subjects to voluntarily turn on/off the P300 system when the mental workload was high. This was especially aimed for subjects with severe neuromuscular disabilities.

2.2 Hardware

The work reported herein is based on an OpenBCI 32-bit board (called Cyton) connected with an Electro-Cap using the international 10/20 system for scalp electrode placement in the context of EEG experiments. The Cyton board's microcontroller is the PIC32MX250F128B with a 32-bit processor and a maximum speed of 50MHz; storage of 32KB of memory and is Arduino compatible. The board uses the ADS1299 IC developed by Texas Instruments, which is an 8-Channel, 24-Bit, simultaneous sampling delta-sigma, Analogue-to-Digital Converter used for biopotential measurements. The system comes with a pre-programmed USB dongle for wireless communication, which communicates with the low-cost RFDuino RFD22301 microcontroller built on the Cyton board. A more thorough explanation of the hardware components of the Cyton board can be found in our previous paper (Schembri, et al., 2017). The Electro-Cap being used in our experiments has the fabric, which is made from elastic spandex and has recessed pure tin wet electrodes directly attached to the fabric. The term wet electrodes type implies that the use of an electrolyte gel is required to make effective contact with the scalp otherwise, it may result in impedance instability.

2.3 Participants

We enlisted a total of N = 10 healthy subjects, six males and four females, aged 29-38 which voluntarily participated in this study. The mean age (SD) was 33.75 years (3.65) and the total averaged reported sleep the night before the experiment was 442.5 minutes (31.05). Nine out of the ten subjects' native language was Maltese and the tenth subject's native language was English. All subjects were fluent in the English language and were familiar with the alphanumeric symbols presented on the P300 Speller. Moreover, nine out of ten subjects had previous experience performing P300-BCI experiments. The subjects were given written instructions describing all procedures related to the study but were not aware of the aims and hypothesis.

Data from eight subjects were analyzed. Two subject's (S2 and S7) were excluded from the study since (a) he/she was unable to complete the experiments due to the discomfort with the electrode cap after approximately 30 minutes, and (b) he/she was very anxious and panicked several times during the experiments. It was later known that he/she was claustrophobic and was uncomfortable in a closed environment of a lab setting. Additionally, this was the only subject that had never performed a P300-BCI experiment. An additional two subjects assisted in the preliminary testing and configuration of the equipment and methodology; however, they were not part of the official experiments and hence their data is not included in the results.

2.4 Data Acquisition

The EEG signals were sampled at 250Hz, while the sampling precision was 24-bit. The recordings were stored anonymously as raw data in OpenVIBE (Renard, et al., 2010) .ov format. These were later converted to a comma-separated value (CSV) files for offline analysis. Eight EEG electrodes were used in different regions of the scalp according to the International 10-20 System. The electrode positions C3, Cz, C4, P3, Pz, P4, O1 and O2 were selected. This is because the spatial amplitude dispersal of the P300 component is symmetric around Cz and its electrical potential is maximal in the midline region (Cz, Pz) (Ogura, et al., 1995). A referential montage was selected with the reference electrode being placed on the left earlobe A1 given that, in general, a mastoid or earlobe reference will produce a robust P300 response. The right ear lobe A2 was used as ground. The electrodes are referenced to electrode A1 as follows: Ch1: C3; Ch2: Cz; Ch3: C4; Ch4: P3; Ch5: Pz; Ch6: P4; Ch7: O1; Ch8: O2.

2.5 P300 Speller and xDAWN

In this paper, we make use of Farwell & Donchin P300 speller (Farwell & Donchin, 1988), which is based on visual stimuli, in conjunction with the xDAWN algorithm. The subject was presented with a six by six grid, made up of thirty-six alphanumeric characters referred to as symbols. In this methodology, each row and column of the spelling grid is augmented in random order and the subject is asked to distinguish between a common stimulus (nontarget) and a rare stimulus (target). As a result of the (target) stimuli, an exogenous and spontaneous ERP potential known as P300; which is a positive deviation around 300ms after the stimuli; is evoked in the brain. The desired symbol is determined and predicted by the intersection of the (target) row and column. This prediction entails distinguishing between non-target i.e. rows/columns stimuli that do not generate a P300 component and target i.e. row/column stimuli that generate a P300 component. Since the peak potential of a P300 component is between 5-10µV, this is embedded and masked by other brain activities (typical EEG signal +-100µV) leading to a very low Signal-to-Noise Ratio (SNR). A popular way to address the limited SNR of EEG is for each symbol to be spelled numerous consecutive times and the respective column/row epochs are averaged over a number of trials, thus canceling components unrelated to stimulus onset.

The xDAWN process of spatial filtering is (1) a dimensional reduction method that creates a subset of pseudo-channels (referred to as output channels) by a linear combination of the original channels and (2) it promotes the appealing part of the signal, such as ERPs, with respect to the noise. This is applied to the data before performing any classification such as LDA (Linear Discriminant Analysis) which was used in this paper. A more thorough explanation of the xDAWN algorithm can be found in our paper (Schembri, et al., 2017) or (Rivet, et al., 2009).

2.6 Experimental Design

In this study, there were two independent variables manipulated: (a) initial task (*IT*) and (b) final task (*FT*), within-subjects variables. In addition, there were several dependent measures used which can be categorized into two types of dependent variables: online performance (accuracy), offline performance (amplitude and latency).

2.6.1 Independent Variables

In this study, there were two manipulated (independent) within-subjects variables: (a) Initial Task abbreviated as *IT*, which was based on the first task i.e. immediately after the training phase, and when the subject was rested and alert. (b) Final Task abbreviated as *FT*, which was based on the last task i.e. after approximately 60 minutes of cumulative P300 spelling tasks (including resting time between experiments which amounted to approximately 6 minutes), and when the subject was tired and/or bored. The *IT* and *FT* tasks were performed in a sound-attenuated room with no distractions i.e. lab conditions.

2.6.2 Dependent Variables

Online Performance (Accuracy): is the number of correctly spelled symbols over the number of planned target symbols to be spelled; in our case five symbols, which make up the word BRAIN.

Offline Statistics (Amplitude and Latency): *P300 amplitude (µV)* is related to the distribution of the subject's processing resources assigned to the task. It is defined as the voltage difference between the largest positive peak from the baseline within the P300 latency interval. *P300 latency* is considered a measure of cognitive processing time, generally between 300-800ms poststimulus i.e. after target stimulus. In simplest terms, it is the time interval between the onset of the target stimulus and the peak of the wave.

2.7 Experimental Procedure

Prior to the study, all participants consented and a written informed consent was obtained. Subsequently, each subject was invited and attended an induction session that was aimed to re-educate all subjects on the P300 speller paradigm and the hardware utilized. The subjects' were informed on the following: (1) they would be performing the experiment a number of consecutive times, which amount to approximately sixty to seventy minutes in total, and that these will be performed entirely in a sound-attenuated room i.e. lab conditions. (a) in the training phase, (b) *IT*, (c) additional tasks *AT* (which are not part of this study), and (d) *FT*; as explained in the independent variable section; (2) the symbols to be spelled were "BRAIN" for (1b) to (1d) and fifteen random symbols for (1a). The experiment (1a) was always done first since it was the training and required for the other experiments, while (1b) to (1d) were done in sequential order. Any subjects' query was answered at this stage. Before the start of the experiments, each subject was asked to relax for a few minutes in a seated position. The subject was seated approximately one meter away from the display. The researcher and his equipment were situated on the left side of the subject. The speakers were situated one meter away and facing the subject at a 15-degree angle. The experiment was started when the subject was able to properly perform the task at hand and had no additional questions. Prior to the start of every experiment, the impedance of the electrodes was confirmed to be less than 5KΩ.

The subjects were presented with 36 symbols in a 6x6 matrix. The target symbol was preceded by a cue i.e. one of the symbols was highlighted in blue at the beginning of the symbol run. Each row and column in the matrix was augmented randomly for 100ms and the delay between two successive augmentations was 80ms. This led to an interstimulus interval (ISI) of 180ms. For each symbol, six rows and six columns were augmented for fifteen repetitions and there was a 100ms inter-repetition delay and a 3000ms inter-trial period between the end of the trials of one symbol and the beginning of trials of the next symbol, which allowed the subject to focus on the next symbol. At the end of each symbol run, the predicted symbol was presented with a green cue, which indicated whether the system predicted the correct target symbol. The subjects were given a short break between experiments.

The training phase (1a) consisted of one session with 15 random symbols by 15 trials each (i.e. 12 flashes of columns & rows per trial*15 trials=180 flashes per symbol). The recording of the training phase took approximately 10 minutes. The *IT* and *FT* experiment consisted of one session each with the aforementioned conditions and configurations while spelling the symbols "BRAIN" consecutively. The *AT* experiments consisted of repetitive experiments in different settings, but with the same configuration as *IT* and *FT*; however, they are not part of this study. Similarly, to the training phase, each symbol had fifteen trials each. The recording of each task lasted around 6 minutes. In total, there were 15 symbols spelled in the training phase and 5 symbols spelled in each task, per subject. Hence due to the matrix disposition, there were in total 2700 flashes in the training phase, amongst which 450 were targets; and 1800 flashes in each task i.e. *IT* and *FT* (900 * 2 tasks), amongst which 300 (150 * 2 tasks) were targets; per subject. The data was stored anonymously by referring to subjects as subject1-10 respectively, with the exclusion of subjects 2 and 7.

2.8 Signal Processing

The online system was controlled by OpenViBE 2.0.0 which is a C++ based software platform designed for real-time processing of biosignal data. The acquisition server interfaces with the Cyton board and generates a standardized signal stream that is sent to the designer which in turn is used to construct and execute signal processing chains stored inside scenarios. The signal was obtained via the acquisition server which does not communicate directly with the Cyton board. Instead, it provides a specific and dedicated set of drivers that does this task. The signal was obtained at a sampling rate of 250Hz with 8 EEG channels and 3 accelerometer (auxiliary) channels. The experimental paradigm was controlled by the OpenViBE designer where a number of scenarios in the "P300 Speller xDAWN Spatial Filter" were executed in succession.

In the offline analysis, the following procedure was done for *IT* and *FT*. The captured raw data was converted from the proprietary OpenVIBE .ov extension to a more commonly used .csv format and was later imported into MATLAB R2014a. Then, any unnecessary rows and columns such as headers and auxiliary data were removed. Next, we filtered out the data to include the target stimulations with code 33285; non-target stimulations 33286; and visual stimulation stop 32780, which is the start of each flash of row or column. Subsequently, we had to perform a signal inversion due to the hardware and driver implementation. The data (samples and event info) were later imported into EEGLAB (Delorme & Makeig , 2004) for offline processing. The first process was to apply a bandpass filter of 1-20HZ to eliminate the environmental electrical interference, to remove any signal harmonics and unnecessary frequencies which are not beneficial in our experiments, and to remove the DC offset. Next, the imported data was used in ERPLAB (Lopez-Calderon & Luck, 2014) and we took every event we wanted to average together and assigned that to a specific bin via the binlister. This contained an abstract description of what kinds of event codes go into a particular bin. In our experiments we have used the following criteria: ".{33285}{t<50-150>32780}" for the target and ".{33286}{t<50-150>32780}" for the non-target. This implies that it is time-locked to the stimuli event 33285 (target) or 33286 (non-target) and must have the event 32780 that happens 50 to 150ms after the target/non-target event. If this criterion is met, it is placed in the appropriate BIN. Next, we extracted the bin-based epochs via ERPLAB (not the EEGLAB version) and set the time period from -0.2s before the stimulus until 0.8s after the stimulus. We have also used baseline correction (pre) since we wanted to subtract the average pre-stimulus voltage from each epoch of data. Next, we passed all channels epoch data through a moving window peak-to-peak threshold artifact detection with the voltage threshold set at 100µV, moving window width at 200ms and window step at 100ms to remove unwanted signals such as blinking and moving artifacts. Subsequently, we averaged our dataset ERPs and performed an average across ERPsets (Grand Average) to produce the results shown in Table 2, generated by the ERP measurement tool.

3 RESULTS

3.1 Online Analysis

Following the online experiments, the results achieved per subject are shown in Table 1 which depicts the correct symbols predicted out of five (i.e. symbols BRAIN) and the percentage in parentheses, rounded to the nearest one, for the accuracy dependent variable. It must be noted that in an incorrect symbol prediction, it might be the case that the column was predicted correctly, whilst the row was predicted incorrectly or vice versa. For instance, subject10 had a success rate of 80% in the *FT* scenario; with the symbol, A predicted as symbol G i.e. the column prediction was correct but not the row. However to avoid ambiguity we have decided to assume that both row and column prediction were incorrect when the symbol is predicted incorrectly.

Table 1: Symbols spelled (out of 5) and percentage (in parentheses) for the accuracy dependent variable.

Subject	IT	FT
S1	5 (100%)	5 (100%)
S3	5 (100%)	5 (100%)
S4	5 (100%)	5 (100%)
S5	5 (100%)	5 (100%)
S6	5 (100%)	5 (100%)
S8	5 (100%)	5 (100%)
S9	5 (100%)	5 (100%)
S10	5 (100%)	4 (80%)
Grand Avg	100%	98%

3.2 Offline Analysis

In this section, we process and analyse the averaged epoch signal of eight subjects in relation to the independent variables (*IT* and *FT*). Table 2 shows the means and standard deviations in parentheses, for the dependent variables (amplitude and latency) according to levels of the independent variable rounded to the nearest hundredth. This data includes

Table 2: Means and Standard Deviations (in Parentheses) for Two Dependent Measures (Amplitude and Latency).

Subject	**IT**		**FT**	
	Amplitude (μV)	*Latency (ms)*	*Amplitude (μV)*	*Latency (ms)*
S1	4.90 (0.54)	466.5 (2.98)	3.58 (0.53)	342.5 (21.37)
S3	3.39 (1.53)	391.0 (87.29)	3.68 (0.74)	441.5 (93.39)
S4	3.74 (0.92)	445.5 (110.44)	3.81 (0.96)	437.0 (83.38)
S5	3.95 (0.77)	444.5 (90.57)	4.30 (0.80)	457.0 (99.34)
S6	5.39 (1.64)	483.0 (1.85)	2.87 (0.93)	477.0 (44.12)
S8	3.00 (1.25)	387.0 (79.07)	3.02 (0.75)	420.0 (86.35)
S9	4.80 (1.92)	380.5 (89.91)	2.96 (1.90)	356.0 (76.26)
S10	2.72 (0.49)	446.0 (45.31)	3.08 (0.43)	405 (68.11)
Grand Avg	3.99 (1.48)	430.5 (79.31)	3.41 (1.04)	417.0 (84.14)

Table 3: ANOVA test on Amplitude and Latency.

	Source of Variation	**SS**	**df**	**MS**	**F**	**P-value**	**F crit**
Amplitude	*Between Groups*	10.502	1	10.502	6.442	0.012	3.916
	Within Groups	205.395	126	1.630			
	Total	215.897	127				
Latency	*Between Groups*	5832.0	1	5832.0	0.872	0.352	3.916
	Within Groups	842256.0	126	6684.571			
	Total	848088.0	127				

the average of all eight recorded electrodes throughout the five symbols and is shown per subject.

We have performed a one-way ANOVA which is based on our independent variable with two levels/groups (*IT* and *FT*) as presented in Table 3, to determine if there is a significant difference between the two means of each group or if they are all the same. We have chosen to use a 5% significance level (0.05) denoted as α (alpha) and rounded all values to the nearest thousandth. Our ANOVA null hypothesis (H_0) states that the means are all equal i.e. the mean of *IT* and *FT* is the same. Our alternate hypothesis (H_1) states that at least two of these means are different. Even though we are comparing only two groups, we have opted to use one-way ANOVA rather than a T-test for comparison purposes to our previous results (Schembri, et al., 2019) and to avoid a statistical Type I error on multiple two-sample T-tests. Regardless, this should yield the same results. For instance, consider the results in Table 3 in the amplitude section. In the first column we have the source of variation, where ANOVA carries out an analysis between groups variation i.e. *IT* and *FT*, and also carries out an analysis of the within-groups variation i.e. the variation within each of our two groups. In the second column, we have the *sum of squares (SS)* of the variation, which is the spread between each individual value and the mean. The third column is the *degrees of freedom (df)* which is the (number of samples – 1). We have two samples of between groups which gives one and we have one-hundred and twenty-eight samples (eight channels * eight subjects * two groups) in total which give one-hundred and twenty-seven. That allows us to calculate the *within-group df* which is total less between groups i.e. a value of one-hundred and twenty-six. The fifth column we have the mean *Square Values (MS)* which is calculated by dividing *SS* by the corresponding *df*. The sixth column is the *F statistic* which is the key statistic where we divide the *MS between groups* by the *MS within group*. Since our *F statistic* got a result 6.442 which is larger than our *F-critical value* (8th column) i.e. 3.916, this implies that we reject the H_0 i.e. that all means are equal and accept H_1. Also, by analyzing that the *P-value* (7th column) which is 0.012 i.e. it is smaller than the alpha value of 0.05, so we can also accept H_1 and reject our null hypothesis H_0. The latency section results follow the same detailed description as above, which however accepts H_0 and rejects H_1.

4 CONCLUSION

In continuation of our previous papers (Schembri, et al., 2019), this work analyzed the effect that mental fatigue during repetitive exercises of a visual P300 Speller have on the P300 component, in terms of our dependent variables i.e. accuracy, amplitude and latency, and also on the signal morphology, and overall signal quality. N = 8 healthy subjects performed several experiments using Farwell & Donchin P300 speller in conjunction with the xDAWN algorithm, with a six by six matrix of alphanumeric characters, while utilising low fidelity equipment in concurrence with eight EEG channels. This paper is related to our current work where we have introduced (Schembri, et al., 2019) different categories of distractions alongside the continuous development (Schembri, et al., 2019) of taxonomy.

The experiments were explicitly done in three states i.e. the initial task (*IT*) which lasted 6 minutes, additional tasks (*AT*) which lasted around 50 cumulative minutes, in which data is not included in this study, and the final task (*FT*) which lasted 6 minutes, respectively. Our comparison was based on the independent variables, *IT* and *FT* tasks i.e. on the first task when the subject was rested and alert when compared to the last task when the subject was tired and bored.

The goal of our study is to develop and ensue on the development (Schembri, et al., 2019) (Schembri, et al., 2019) of a hierarchical taxonomy aimed at categorizing distractions in the P300b domain and the effect that these distractions have on the success rate, signal quality, reduction of amplitude, or any other change/distortion that occurs. This should give some insight into the practicability of real-world application of the current P300 speller with our aforementioned low-cost equipment. The aim of this paper was to assess the effect of prolonged usage and exposure to the aforementioned methodology and equipment, with the aim of broadening its use in a real-world context.

Our null hypothesis based (H_0) states that the independent variables have no effect and/or statistical significance on the dependent variables (accuracy, amplitude, and latency). Our alternate hypothesis (H_1) based on preceding related and tantamount medical-grade research state that there should be an effect on the *accuracy* and a statistical effect on the *amplitude*, while the *latency* should not have any statistically significant effect. The results show that the accuracy was slightly affected and that there was a statistically significant effect on the amplitude, but the latency was not statistically affected as shown in our ANOVA analysis in Table 3. In view of the results, we reject H_0 and accept H_1 for the accuracy and amplitude dependent variables, while we reject H_1 and accept H_0 for the latency dependent variable.

Non-statistical analysis shows that the dependent *accuracy* variable was highest in the *IT* (100%), followed closely by *FT* (98%) as shown in Table 1. The dependent variable amplitude was highest in the *IT* (M=3.99, SD=1.48), followed by *FT* (M=3.41, SD=1.04). Additionally, the dependent variable *latency* was shortest in the *FT* (M=417.0, SD=84.14), followed by *IT* (M=430.5, SD=79,31) as shown in Table 2. It seems that there is no correlation between amplitude and latency, while the signals were morphological consistent in both settings, even though they did not yield identical P300 components. Moreover, empirical results show a significant decrease in the activation of P300 sources in the *FT* mental fatigue level compared to the *IT*.

In this paper, we have analysed the P300 component of a visual P300 speller under the effect of mental fatigue during repetitive exercises. Explicitly, the effect that the aforementioned independent variables have on the dependent variables. In the future, we plan to expand on our study by performing extended and lengthier sessions, under the same conditions, and analyse the dependent variables of the experiments being performed on the hour every hour.

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