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Comparison between a Passive and Active response task and their effect on the Amplitude and Latency of the P300 component for Visual Stimuli while using Low Fidelity Equipment

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Abstract— **In this paper, we investigate the effect, in terms of amplitude and latency, of the P300 component in a separate active and passive task response condition. This work is based on the P300 speller BCI (oddball) paradigm and the xDAWN algorithm, with five healthy subjects; while using a non-invasive Brain-Computer Interface (BCI) based on low fidelity electroencephalographic (EEG) equipment. Our results suggest that an active task yielded a larger P300 peak amplitude while there was no discriminable difference in the peak latency. The signal was also morphological consistent in both scenarios, even though they did not yield identical P300 components. This groundwork yields imperative data for future work where we plan to introduce several distractions, including communication with the user while performing the P300 speller paradigm.**

I. Introduction

In this paper we compare between a passive and an active task and the effect that these have on the amplitude and latency of the P300 component for visual stimuli while utilizing low fidelity equipment. Our research makes use of non-invasive Brain Computer Interface (BCI) on the basis of Electroencephalography (EEG). The work presented here is part of a larger EEG based project and in continuation of our previous papers [1, 2, 3].

Event-related potentials (ERPs) are slow voltage fluctuations or electrical potential shifts recorded from the nervous system. These are time-locked to perceptual events following a presentation of a stimulus being either cognitive, sensor or motor stimuli. The simplest paradigm for eliciting an ERP is by focusing attention on the target stimuli (occurs infrequently) embedded randomly in an array of non-targets (occurs frequently). The methodology used derives from the oddball paradigm; first used in ERPs by Squires N, Squires K and Hillyard [4], where the subject is asked to distinguish between a common stimulus (non-target) and a rare stimulus (target). The target stimuli elicit one of the most renowned ERP components known as P300, which is an exogenous and spontaneous component and was first described by Sutton [5]. The name is derived from the fact that it is a positive wave that appears approximately 300ms after the target stimulus. Unless otherwise noted in this paper, the term P300 (P3) will always refer to the P300b (P3b) which is elicited by task relevant stimuli in the centro-parietal.

In the scientific community, it is established that to heighten i.e. to increase the amplitude of the P300 component, the following can be performed: (1) decreasing the frequency of the target stimulus and (2) performing an 'active' task response i.e. a cognitive involvement of the subjects, for instance, the most commonly utilized are to either (2a) mentally count and/or (2b) button press; on the occurrence of a target stimuli. Conversely the term 'passive' implies that no action is taken by the subject i.e. merely focusing on the target stimuli.

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The need for this study originated as a precursor to our future work, where we plan to introduce a number of distractions, for instance, communicating and asking questions to the subject while performing a P300 visual experiment. This will of course limit the subject's ability to properly perform an 'active' task response such as counting the target stimuli. Due to the lack of a detailed study on the comparative effect, in terms of amplitude and latency on these two paradigms (active and passive) on a P300 speller while using low fidelity equipment, an evident necessity for this study was present. Our hypothesis based on preceding tantamount medical grade research is that the peak P300 amplitude should be higher in an active task when compared to a passive task while the latency should be somewhat analogous but not consistent. Because the major interest of the present study is the P300 component, only data related from the target stimuli will be considered.

In this work we report a study where five healthy subjects used Farwell and Donchin P300 speller paradigm; where we based the methodology on the xDAWN algorithm [6] while utilizing low fidelity equipment. The subject was asked to communicate five alphanumeric characters, referred as symbols, in each of the two separate scenarios i.e. in an active and passive task. Our aim is to assess the effect that counting (active) vis-à-vis focusing (passive) have on the amplitude and latency of the P300 component while using the aforementioned methodologies and equipment.

The experimental procedures involving human subjects described in this paper were approved by the Institutional Review Board.

II. METHODS

A. Research Background

The following study will assess the effect that active and passive tasks have on the amplitude and latency of the P300 component. As such it is important to understand these terms in the context of a P300 component. P300 **latency** is considered a measure of cognitive processing time, generally between 300-800ms [7] 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. The latency can increase, for instance, when you increase the difficulty of target detection. P300 **amplitude** is related to the distribution

of the subject's processing resources assigned to the task. P300 amplitude increases as the probability of the target stimulus decreases. Our study focuses on the effect that mental counting (active) vis-à-vis a just focusing (passive) has on these two terms.

There have been many research papers stating that the action of counting (active) heightens the ERP component such as [8] and similarly by [9] and [10], apart from others. However there are no detailed qualitative analysis, especially in the context of mental counting (active) vis-a-vis just focusing (passive) for a visual P300 utilizing low fidelity equipment. Other research papers, such as [11] focused on comparing active and passive tasks; however it was aimed at auditory-event-related potentials and compared between two passive tasks i.e. button pressing and mental counting, where it was determined that endogenous potentials such as N200 and P300 can be elicited by mental counting. Several studies such as [12, 13] reports that the P300 potential can be obtained with auditory 'passive' oddball paradigms where an intentional discrimination was not required i.e. aimed at non-compliant subjects such as children or demented patients. However no study was done on visual P300.

Comparably Bennington & Polich [14] focused on comparing 'passive' versus 'active' oddball paradigms for auditory and visual stimuli. Their visual paradigm presented black and white stripped (non-target) and checked (target) patterns while it was unclear which EEG amplifier was used for the study. The study reports that P300 amplitude was smaller in the passive compared to active task conditions, however was larger for the auditory compared to visual stimulus conditions. It also reports that the latency was somewhat but not constantly shorter for passive tasks. This implies that when passive and active tasks are compared, they do not yield identical P300 components.

B. 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 bio potential measurements. The system comes with a pre-programmed USB dongle for wireless communication which connects with the low cost RFDuino RFD22301 microcontroller built on the *Cyton* board. An additional feature which is included in the board is a 3-axis accelerometer from ST with model LIS3DH. This can prove to be quite useful; such as, for sensing change in orientation of the head or sensing rough motion. A more thorough explanation of the hardware components of the *Cyton* board can be found in our previous paper [1]. 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.

C. Participants

We enlisted a total of $N = 5$ healthy subjects, three males and two females, aged 29-38 ($M = 33.8$) which voluntarily participated in this study. Four of the five subjects' native language was Maltese and the fifth subject's native language was English. All subjects spoke fluent English and were familiar with the symbols displayed on the P300 speller. All subjects had previous experience using BCI and formerly performed P300 speller experiments.

One subject assisted in the initial configuration and testing of the equipment; however he/she did not take part in the official experiment and hence isn't included in the results.

D. Procedure and Stimuli

The work presented in this paper will make use of Farwell & Donchin P300 speller based on the xDAWN algorithm, where thirty-six alphanumeric characters are presented in a six by six grid as depicted in Fig. 1. This methodology uses visual stimuli, where each row and column of the spelling grid is augmented in a 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 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 does not generate a P300 component and *target* i.e. row/column stimuli that generate a P300 component.

In any recorded EEG signal, the P300 component which has a typical peak potential between 5-10µV, is embedded and masked by other brain activities (typical EEG signal +-100µV) such as muscular and/or ocular artefacts [1] leading to a very low Signal-to-Noise Ratio (SNR) of the P300 component. This indicates that it would be very difficult to detect the target stimuli from a single trial, which is denoted by a series of augmentation, in random order, of each of the six rows and six columns in our matrix (i.e. twelve augmentations per trial). 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 be averaged over a number of trials, thus cancelling components unrelated to stimulus onset.

The xDAWN process of spatial filtering is (1) a dimensionally 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 can be found in our previous paper [3] or [6].

Apart from using low fidelity equipment, the experiments were performed in lab conditions (no distractions) in two distinct paradigms. The first paradigm consisted of an 'active' task i.e. the subject was asked to focus and mentally count the number of times the row and column comprising the desired symbol (target) is augmented. The second paradigm consisted of a 'passive' task i.e. the subject was asked to focus on the target stimuli without taking any action.

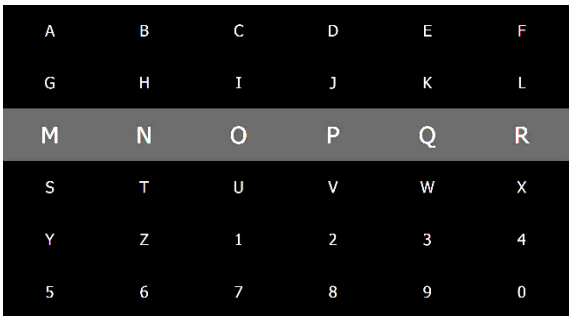

Figure 1. BCI "P300 Speller". The screen as shown to the subjects with the 3rd row highlighted.

In the induction session, each subject was re-educated on the P300 speller paradigm and the hardware utilized. Subsequently, the subjects' were informed on the following: (1) they would be performing the experiment three consecutive times; (a) in the training phase, (b) with an 'active' task and (c) with a 'passive' task as explained above; (2) the symbols to spell were "BRAIN" for (1b) and (1c) and fifteen random symbols for (1a). 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 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 electrodes impedance was confirmed to be less than 5KΩ.

The display presented to the subjects is shown in Fig. 1 were 36 symbols presented 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 no inter-repetition delay. However there was a 3s inter-trial period between the end of the trials of one symbol and the beginning of trials of the next symbol. This allowed the subject to focus the attention on the next symbol. At the end of each symbol run, the predicted symbol was presented with a green cue, which indicated whether the subject got the correct target symbol. The subjects were given a short break between experiments

The training phase 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 9 minutes. The 'active' and 'passive' task experiments consisted of one session each with the aforementioned conditions and configurations while spelling the symbols "BRAIN" consecutively. Similarly to the training phase, each symbol had fifteen trials each. The recording of each task lasted approximately 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 900 flashes in each task (900 * 2 tasks), amongst which 150 (150 * 2 tasks) were targets. These values are per subject. The data was stored anonymously by referring to the subjects as subject1-5 respectively.

The EEG signals where sampled at 250Hz, while the sampling precision was 24-bit. The recordings were stored anonymously as raw data in OpenVIBE .ov format. These were later converted to a comma separated value (csv) files for offline analysis. Eight EEG electrodes where 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) [15]. 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 as shown in Fig. 2.

E. 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 experiment paradigm was controlled by the OpenViBE *designer* where a number of scenarios in the "*P300: Basic P300 Speller demo with xDAWN Spatial Filter*" were executed in succession.

In the *offline analysis*, the captured raw data was converted from the proprietary OpenVIBE .ov extension to a more commonly used .csv format using a particular scenario aimed for this task. The outputs were two files in .csv format which contained the raw data and stimulations respectively. These files were later imported into MATLAB R2014a via the *readtable* command into MATLAB tables called *samples* and *stims* and were then converted to arrays via the table2array command. Subsequently any unnecessary rows

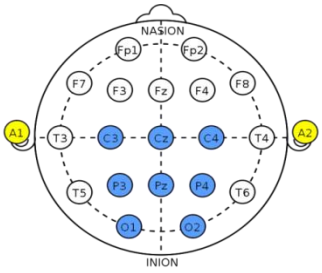

Figure 2. Electrode placement following the 10-20 system.

and columns in the samples array were removed. These consisted of the first rows which contained the time header, channel names and sampling rate; the first column which contained the time(s) and the last three columns which stored the auxiliary data of the accelerometer. Next, we filtered out the stims array 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. Additional data such as the *sampleTime*, *samplingFreq* and *channelNames* variables were extracted from the data and stored in the workspace. Next, we had to perform a signal inversion due to the hardware and driver implementation. The samples array was later imported into EEGLAB for processing and for offline qualitative and quantitative analysis. The first process was to apply a band pass filter of 1-20HZ to eliminate the environmental electrical interference (50Hz or 60Hz dependent on the country), to remove any signal harmonics and unnecessary frequencies which are not beneficial in our experiments and to remove the DC offset. Subsequently we import the event info (the stimulations – stim array) in EEGLAB with the format {latency, type, duration} in milliseconds. Next, the imported data was used in ERPLAB which is an add-on of EEGLAB, and is targeted for ERP analysis. Although the dataset in EEGLAB already contains information about all the individual events, we have created an eventlist structure in ERPLAB that consolidates this information and makes it easier to access and display; and also allows ERPLAB to add additional information which is not present in the original EEGLAB list of events. Subsequently we take every event we want to average together and assign that to a specific bin via the *binlister*. This must contain 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 criteria is met, it is place in the appropriate BIN; in our case BIN1 for target and BIN2 for non-target. Subsequently 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 artefact 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 artefacts. Lastly, we averaged our dataset ERPs to produce the required results. Fig. 3 is generated from ERPLAB by the *Plot ERP waveforms* while the values of Table II are generated by the *ERP measurement tool*. A more thorough explanation on segments of the signal processing can be found in our previous paper [3].

III. RESULTS

A. Online Analysis

Following the online experiments, the results achieved per subject are shown in Table I. The symbols to be spelled were BRAIN consecutively and all percentages are rounded to the nearest one. It must be noted that in the passive task, subject 3 had a success rate of 80% with the symbol *A* predicted as symbol *G* i.e. the column prediction was correct but not the row. Similarly, anew in the passive task, subject 4 had a success rate of 80% with the symbol *I* predicted as symbol *7* i.e. the column prediction was correct but not the row. All other subjects had a 100% success in both active and passive tasks. This imparts a strong indication that performing an active task yields better results with some subjects when compared to performing a passive task. However further in-depth analysis is provided in the following (offline) section of this paper.

B. Offline Analysis

In this section, we process and analyse the averaged epoch signal of five subjects in an active and passive task response. The processing to achieve these results is thoroughly explained in the section - *Signal Processing*. Fig. 3 represents the signals for Subject 1 which include all eight channels and an average channel (AVG). We have opted to show the signal of Subject 1 since it represented the best morphological quality for illustration. Fig. 3 shows four overlapping signals, (i) BIN1 - Target for active task shown in black (solid for grayscale), (ii) BIN2 - Non-Target for active task in red (dash-dot in grayscale) (iii) BIN3 - Target for passive task in blue (dotted in grayscale) and (iv) BIN4 - Non-Target for passive task in green (dashed in grayscale). BIN1 and BIN2 represent the active task experiment, while BIN3 and BIN4 represent the passive task experiment and are done in a separate experiment from BIN1 and BIN2. Our main concern is the comparison in terms of latency and amplitude for BIN1 and BIN3 i.e. the targets for active and passive task response. However for illustration purposes we have left BIN2 and BIN4 i.e. the non-targets. The data for Fig. 3 is comprised of averaged raw signals i.e. 5 symbols with 15 trials per symbol; with 12 flashes of columns/rows per trial i.e. 900 flashes amongst which 150 were targets.

The presented results are passed through a band pass filter (1-20Hz) since this is needed to reduce the noise and unwanted frequencies, but it does not change the P300 signal i.e. it is essentially a pre-processing / conditioning step, it doesn't contribute directly to the analysis of the P300. In addition, the signal is passed through an artefact detection of the epoched data via a moving window peak-to-peak threshold as explained previously, since this is needed to remove unwanted signals such as blinking that might alter the quality of our results.

TABLE I. ONLINE RESULTS

Subject	Active	Passive	Description
S1	5 / 5 predicted	5 / 5 predicted	
S2	5 / 5 predicted	5 / 5 predicted	
S3	5 / 5 predicted	4 / 5 predicted	BR*G*IN was predicted
S4	5 / 5 predicted	4 / 5 predicted	BRA*7*N was predicted
S5	5 / 5 predicted	5 / 5 predicted	
	100% predicted	92% predicted	

TABLE I shows the performance of our subjects in the online system.

TABLE II. OFFLINE RESULTS

		Subject 1		Subject 2		Subject 3		Subject 4		Subject 5	
		Active	***Passive***	***Active***	***Passive***	***Active***	***Passive***	***Active***	***Passive***	***Active***	***Passive***
AVG	***Amplitude (μV)***	3.324	2.421	2.730	1.882	2.424	1.780	1.900	1.683	3.358	1.542
	Latency (ms)	452	444	456	456	460	472	452	492	456	444
C3	***Amplitude (μV)***	3.758	2.613	3.175	2.043	2.764	1.517	2.152	2.706	3.982	2.437
	Latency (ms)	448	444	456	444	476	468	452	500	452	440
Cz	***Amplitude (μV)***	3.780	2.506	3.158	2.890	2.903	1.819	2.837	2.669	4.851	2.636
	Latency (ms)	444	444	452	440	460	416	436	500	452	436
C4	***Amplitude (μV)***	3.648	2.439	3.063	1.964	3.430	1.524	2.123	2.439	3.495	1.848
	Latency (ms)	448	440	452	444	452	464	436	500	460	440
P3	***Amplitude (μV)***	3.230	2.651	2.748	1.377	2.403	2.071	1.831	1.832	3.205	1.512
	Latency (ms)	460	448	456	460	472	476	460	496	456	444
Pz	***Amplitude (μV)***	3.404	2.807	2.836	2.048	2.236	1.926	2.501	1.151	3.654	1.368
	Latency (ms)	456	448	460	464	464	476	456	492	460	448
P4	***Amplitude (μV)***	3.158	2.289	2.434	1.935	2.578	2.018	1.866	1.760	3.539	1.874
	Latency (ms)	456	444	452	468	452	476	452	488	460	464
O1	***Amplitude (μV)***	3.087	2.603	2.438	1.719	1.985	1.788	1.382	1.074	2.095	0.626
	Latency (ms)	460	448	456	464	464	472	460	480	460	464
O2	***Amplitude (μV)***	2.937	2.346	2.197	1.955	2.120	2.294	1.543	1.109	2.524	1.221
	Latency (ms)	456	448	452	456	456	468	460	480	460	464

TABLE II show the amplitude (μV), rounded to three decimal points, and latency (ms) of all subjects in all eight electrodes/channels and the averaged channel (AVG) of all eight electrodes.

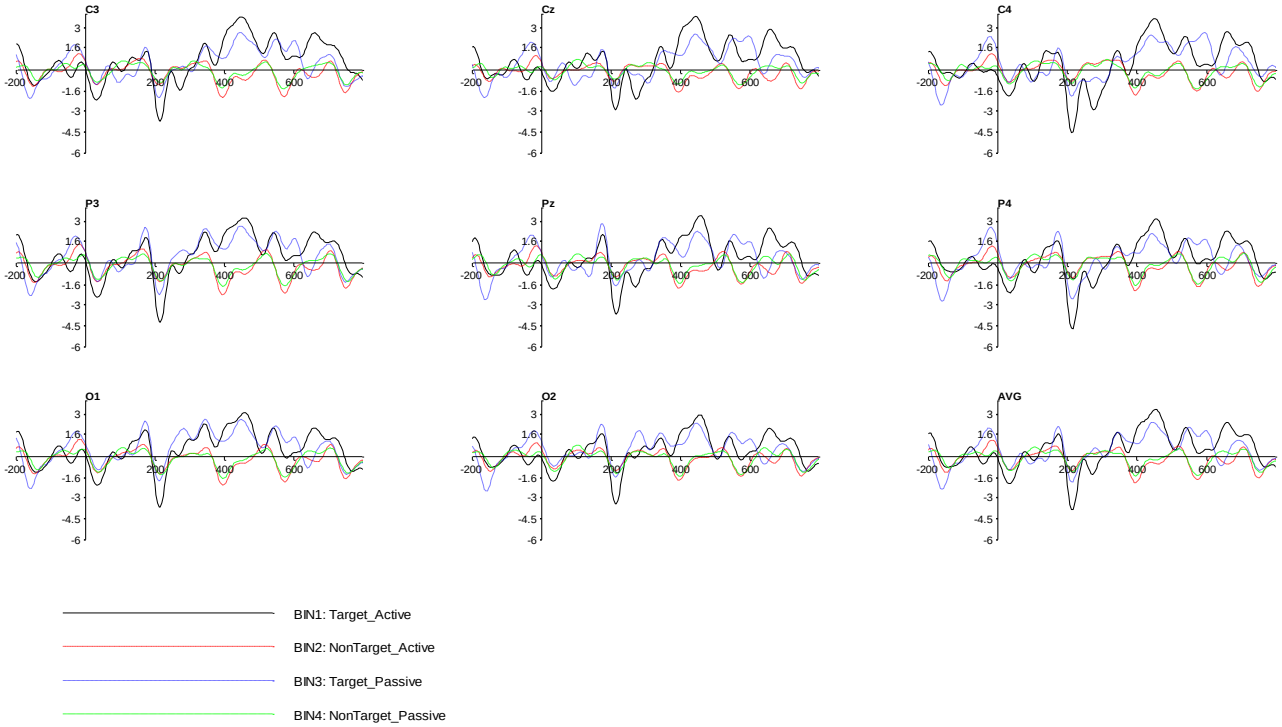

Figure 3. represents the signals for Subject 1 which include all eight channels and an average channel (AVG).

In Table II we show the amplitude (μV), rounded to three decimal points, and latency (ms) of all subjects in all eight electrodes/channels apart from the averaged channel (AVG) of all eight electrodes. Each electrode value is made up from the aforementioned 150 target flashes for each BIN1 (Target Active tasks) and BIN3 (Target Passive tasks). BIN2 and BIN4 are not represented in this table. When analysing the data in Table II, we have noted that this was in line with related medical grade research, other comparable research and to our original hypothesis that the peak P300 amplitude is higher in an active task when compared to a passive task. Even though, we were expecting the difference to be slightly higher. In regards to the latency we did not note any significant differences between the two tasks, whereas there was no discriminable outcome on either a passive or active task i.e. some subjects had earlier latency in the passive when compared to active, while other subjects had the opposite.

Summarizing our data, the peak P300 absolute differences between the passive and active task on the average channel for all subjects are (a) amplitude (μV) = $| 0.217 \leq y \leq 1.816 |$ and (b) latency (ms) = $| -40 \leq t \leq 12 |$. A grand average of all subjects in the average channel were (a) amplitude difference of 2.424μV for the active and 1.78μV for the passive, while (b) latency of 460ms for the active and 472ms for the passive.

IV. CONCLUSION

In this work, we compare the effect in terms of amplitude and latency of the P300 component for visual stimuli in an active and passive task response condition while utilizing low fidelity equipment. Our work is based on the P300 speller BCI (oddball) paradigm and the xDAWN algorithm, were a total of $N = 5$ healthy subjects where enlisted.

Even though in the scientific community, it is established that to heighten i.e. to increase the amplitude of the P300 component, the subject can perform an 'active' task such as counting, the research was always based on medical grade equipment. Moreover comparable research was frequently performed on auditory ERPs and only a handful of research papers focused on visual ERPs. Still, these were not aimed specifically for the effect that active and passive tasks have on the P300 component in a P300 speller paradigm. As a result, and due to the lack of a specific study on the comparative effect, in terms of amplitude and latency on these two response tasks (active and passive) on a P300 speller paradigm, while using low fidelity equipment, an evident necessity for this study was present.

Our hypothesis was that the effect should be similar to previous relatable research papers i.e. the amplitude should be higher in an active task, while the latency would not be consistent. Our main contribution is the comparative assessment in terms of amplitude and latency between an active response task, specifically counting, vis-à-vis a passive response task while utilizing the aforementioned equipment. Our results suggest that an active task yielded a larger P300 peak amplitude while the difference in peak latency was not statistically significant. The signal was also morphological consistent in both scenarios, even though they did not yield identical P300 components. The present results are tantamount to previous findings, such as [11] who however, focused on auditory-event-related potentials, specifically button pressing vis-à-vis mental counting and [14] who reports that the P300 amplitude was smaller in the passive compared to active task conditions in visual stimulus.

This work forms part of a wider project and in continuation of our previous papers [1, 2, 3] where we validated our equipment's suitability and performance, in the execution of the P300 speller domain. The need for this study arose in view of our future studies were we plan to perform qualitative and quantitative analysis on the effect that distractions (such as conversing with the subject, which would not allow him to perform an active task), have on the signal quality and online performance of the system using our aforementioned equipment, in the aims of contributing knowledge that would eventually lead to a broader utilization of this technology. Even though this work is qualitative in nature, we plan to perform a quantitative study in future work to validate our results. Nevertheless, these results will yield imperative data for future work.

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