Classification Improvement and Analysis of P300 Responses with Various Inter–stimulus Intervals in Application to Spatial Visual Brain–computer Interface

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***Abstract*—We report on a P300 based spatial visual brain–computer interface (BCI) application improvement based on an inter–stimulus–interval (ISI) optimization. The proposed system allows for nine commands' application using a non–invasive electroencephalography (EEG) brainwave monitoring. This paper presents the experiments results obtained by relying entirely on the visual oddball paradigm–based interaction. The visual stimuli are generated utilizing images on a computer screen arranged in a 3×3 matrix. The visual stimuli are used to elicit event related potentials (ERPs) with P300 components elicited to the intentional targets. The resulting ERPs are processed to extract the P300 responses in EEG features for a subsequent classification accuracy analysis. We propose to utilize a linear support vector machine (linSVM) classifier in offline EEG data post–processing analysis scenario. We discuss results of experiments conducted with five healthy users. We compare BCI accuracy results from two experimental setups with different ISI settings.**

I. Introduction

Brain–computer interface (BCI) is defined as a communication system in which messages or commands that an user sends to the external world do not pass through the brain's normal output pathways of peripheral nerves and muscles [1], [2]. There are already several BCI applications spanning from spellers [3] to online mental robot control implementations [4], [5].

Following the above ideas, we propose a spatial visual BCI for locked–in patients [6]. Figure 1 presents a diagram of the proposed BCI prototype that can perform the following functions: firstly, it creates a stimulus using the visual generation system that we developed; secondly, it captures and analyzes EEG event–related potential (ERP) responses to the attended and ignored spatial visual stimuli; finally, it classifies the brain responses to generate BCI commands for the user application. We also use an auditory feedback modality to keep the user visual sense dedicated to the visual stimuli.

From now on the paper is organized as follows: first section describes the general architecture of the proposed system and discusses the chosen methods, as well as conducted experiments; in the third section we compare results from two different experiments with varying ISI settings; finally we discuss results obtained from an offline analysis of EEG data recorded during online BCI sessions with five subjects; finally, conclusions and future research remarks summarize the paper.

II. Methods

In the proposed BCI paradigm in this paper, we employ a visual paradigm utilizing a fact that given a visual stimulus, the human brain generates the ERP pattern [1]. Additionally depending on user's intention the visual evoked potential (VEP), which is the modality specific ERP, is modulated creating the so–called P300 or "aha" response [8]. The P300 responses are usually evoked in an oddball paradigm, in which rare stimuli (targets) are presented together randomly with distractors (non–targets) [1].

When a machine learning algorithm accurately classifies the P300 brain response, it allows the user's intention to be translated, using the BCI application, to select a command mapped

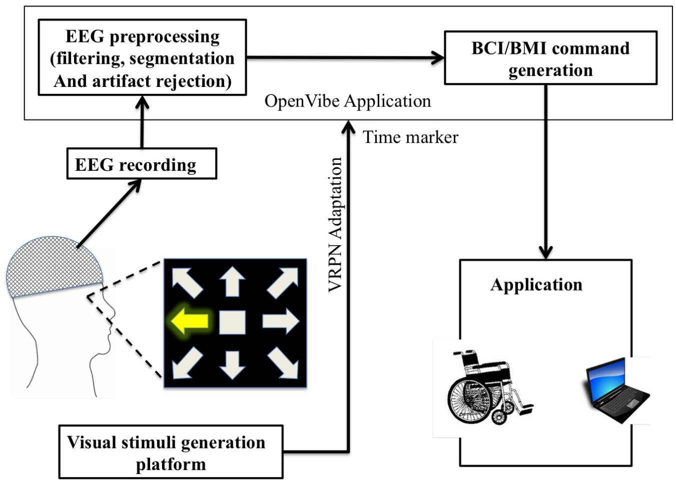

Fig. 1. Schematic diagram of the spatial visual BCI application. EEG signals are processed and classified by OpenVibe [7] software processing stages in synchrony with presented visual stimuli to generate interactive commands.

on an planned visual stimulus target. In this study, we focus on using a linear support vector machine (SVM) [9] as a classifier to improve our online system. State–of–the–arts BCI usually rely on a linear discriminant analysis (LDA) technique [7], [10]. We show classification accuracy improvement and an evaluation of our designed system in the next section. After that, we explain our proposed system architecture, experimental settings, and the chosen electroencephalography (EEG) data processing methods.

A. Proposed Visual BCI Architecture

We implement an experimental environment composed of two modules. The first module handles the visual stimulus generation and interaction with the user. The second module carries out EEG signals' acquisition and processing; P300 response feature classification; and the final generation of BCI commands. The second module is implemented in a new BCI open source development environment OpenVibe [7]. OpenVibe is very flexible visual programming environment that offers a possibility to expand and customize experimental blocks using Python, Java, Matlab or Lua scripting languages.

The two experimental modules interact together using virtual–reality peripheral network (VRPN) protocol. A developed visual stimuli platform (VSP) sends time triggers to the OpenVibe application when a new visual stimulus is presented to the user. Based on this trigger, the second experimental module analyzes the corresponding VEP signals to extract and classify the user intentional P300 responses.

B. EEG Experimental Settings

During the online BCI experiments, the EEG signals were captured with an EEG amplifier system g.USBamp by g.tec medical instruments GmbH, Austria. Eight active g.LADYbird electrodes (by the same manufacturer) were used. The electrodes were attached to the following head locations $Cz, CPz, POz, Pz, C3, C4, P3$, and $P4$ as in the $10/10$ extended international system [11] as shown in Figure 2. Ground and reference electrodes were attached at FCz position and a left earlobe, respectively. A sampling frequency was set to 512 Hz.

Each user accomplished eight sessions with two experimental settings as summarized in Table I. Each protocol consisted of four experiments. We extended the first experiment to 15 trials per target to gather more data to train a classifier (15 trials averaging procedure). After the training of a linear discriminative analysis (LDA) classifier [10], [12], the online test experiments were performed with shorted to five ERP averaging procedure. There were a total of nine up, up–right, right, down–right, down, down–left, left, up–left, and center target focus sessions. During the experiments, the users were instructed to focus and count the particular target stimulus appearances on the computer display. An auditory feedback with P300 classification results was provided to the users in order to avoid any visual distractions during the experiments.

The main difference between the protocols one and two was an inter–stimulus–interval (ISI) length, which is the major

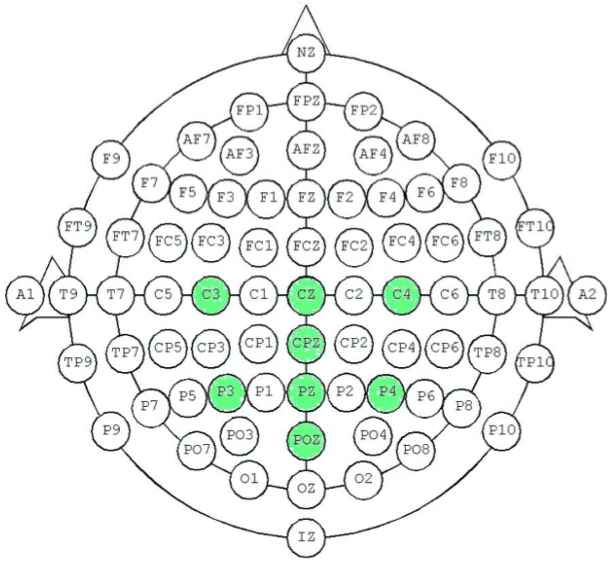

Fig. 2. EEG electrode positions in our experiments marked in green and localized within the the $10/10$ international system [11] layout.

research question tested in this paper. In the experiments reported in this paper, five volunteer BCI users took part (mean age of 27.6 years old with a standard deviation of 10.31). We conducted all the experiments in the BCI–lab [13] at Life Science Center of TARA, University of Tsukuba, Tsukuba, Japan. The online EEG BCI experiments were conducted in agreement with the *WMA Declaration of Helsinki - Ethical Principles for Medical Research Involving Human Subjects*. The psychophysical and EEG experiments were conducted in agreement with the ethical committee guidelines of the Faculty of Engineering, Information and Systems at University of Tsukuba, Tsukuba, Japan.

C. EEG Processing and Classification

An in–house expanded OpenVibe module was developed in order to record and process EEG signals. The goal of the software extension was to properly segment and classify P300 responses in the multi–module experimental environ-

TABLE I
BCI EXPERIMENTAL SETTINGS OF THE TWO TESTED PROTOCOLS

Experimental parameter	Protocol one setting	Protocol two setting
Stimulus length	0.05 s	0.05 s
ISI	200 ms	100 ms
Training trials	15	15
Testing trials	5	5
All training stimuli	1080 non–targets 135 targets	1080 non–targets 135 targets
All test stimuli	360 non–targets 45 targets	360 non–targets 45 targets
Experiment length	119.25 s	78.75 s
Classification speed	4.53 selections/minute	6.86 selections/minute

TABLE II
ONLINE BCI EXPERIMENT ACCURACY RATES (CHANCE LEVEL OF 11.11%) USING LDA CLASSIFIER FOR THE PROTOCOLS ONE AND TWO

Protocol one with $ISI = 200$ ms				
User	Online BCI accuracies			
	Test #1	Test #2	Test #3	Average
#1	44.44%	66.66%	77.77%	62.96%
#2	0.00%	11.11%	0.00%	3.70%
#3	11.11%	44.44%	33.33%	29.63%
#4	33.33%	11.11%	22.22%	22.22%
#5	22.22%	11.11%	11.11%	14.81%
			Grand average	26.66%
Protocol two with $ISI = 100$ ms				
User	Online BCI accuracies			
	Test #1	Test #2	Test #3	Average
#1	33.33%	33.33%	33.33%	33.33%
#2	0.00%	11.11%	11.11%	7.41%
#3	0.00%	22.22%	0.00%	7.41%
#4	11.11%	11.11%	11.11%	11.11%
#5	33.33%	33.33%	55.55%	40.74%
			Grand average	20.00%

TABLE III
OFFLINE BCI EXPERIMENT ACCURACY RATES (CHANCE LEVEL OF 11.11%) USING LINSVM CLASSIFIER FOR THE PROTOCOLS ONE AND TWO

Protocol one with $ISI = 200$ ms				
User	Offline BCI accuracies			
	Test #1	Test #2	Test #3	Average
#1	55.55%	33.33%	55.55%	48.14%
#2	55.55%	55.55%	88.88%	66.66%
#3	88.88%	77.77%	66.66%	77.77%
#4	66.66%	77.77%	77.77%	74.07%
#5	55.55%	55.55%	44.44%	51.85%
			Grand average	63.70%
Protocol two with $ISI = 100$ ms				
User	Offline BCI accuracies			
	Test #1	Test #2	Test #3	Average
#1	55.55%	66.66%	55.55%	59.25%
#2	66.66%	44.44%	66.66%	59.25%
#3	88.88%	77.77%	77.77%	81.47%
#4	88.88%	100.00%	100.00%	96.29%
#5	55.55%	88.88%	66.66%	70.36%
			Grand average	73.33%

ment developed by our team. As pre–processing and artifacts rejection steps we applied a band–pass filter in a range of $0.01 \sim 30.00$ Hz to separate the amplifier drift and the electromyographic (EMG) interferences from the EEG signals carrying the ERP responses. Additionally notch filter was used to filter the power line interference together with possible subharmonics in a rejection band of $48 \sim 52$ Hz. In order to further suppress eye–blink related muscular interferences an EEG amplitude–based thresholding identification and rejection technique was applied with an absolute value set to 80 μV.

Taking advantage of the time triggers marking VEP onsets we segmented the EEG signals to 600 ms long "epochs." Next the EEG signals were down–sampled to a sampling frequency equivalent to 32 Hz in order to reduce dimensionality of brainwave features subsequently used for classification. ERPs were next averaged in a final noise removal step. The so pre–processed brainwaves where next classified with the LDA classifier [7], [10]. The following section describes the results obtained from BCI online and offline post–processing experiments with five healthy users.

III. RESULTS

Figures 3 and 4 present the grand mean averaged ERP responses obtained from the two experimental protocols discussed in this paper. In the above figures positive deflections (the so–called P300 or "aha-responses") within latencies of $200 \sim 600$ ms could be observed.

Table II shows the results from the online BCI experiments (instant feedback given to the users) using the LDA for classification in two protocols using ISI of 200 ms and 100 ms. Overall observed accuracy was better in the first protocol using ISI of 200 ms. A chance level in all experiments was of 11.11 %.

We opted for the offline analysis of the EEG signals from the above analyzed online experiments (recorded data post–classification without a feedback given to the users) using a linear SVM (linSVM) [9], [14] classifier to improve the overall performance of the proposed BCI system.

Table III shows the classification accuracy of each test experiment using the two protocols with two ISIs of 200 ms and 100 ms. An open source toolbox *libSVM* [9] was used in Matlab to implement the libSVM classification algorithm. For the both experimental protocols the proposed linSVM method scored higher than the original used LDA method (compare Tables II and III). In this case again the overall observed BCI accuracy was better in the second protocol.

We also computed the information transfer rates (ITRs) [15] in bits per minute (bit/min) to evaluate the two protocols and the evaluated two classification techniques. The ITR scores have been summarized in Tables IV and V.

TABLE IV
ITR RESULTS OF THE PARTICIPATING USERS FOR THE BOTH PROTOCOLS USING LDA CLASSIFIER (MAXIMUM ITRS WERE OF 16.91 BIT/MIN AND 28.18 BIT/MIN FOR ISIS OF 200 MS AND 100 MS, RESPECTIVELY)

User number	ITR in protocol one [bit/min]	ITR in protocol two [bit/min]
#1	5.90	2.24
#2	0.28	0.00
#3	0.97	0.00
#4	0.39	0.00
#5	0.05	3.71
Average	1.52	1.19

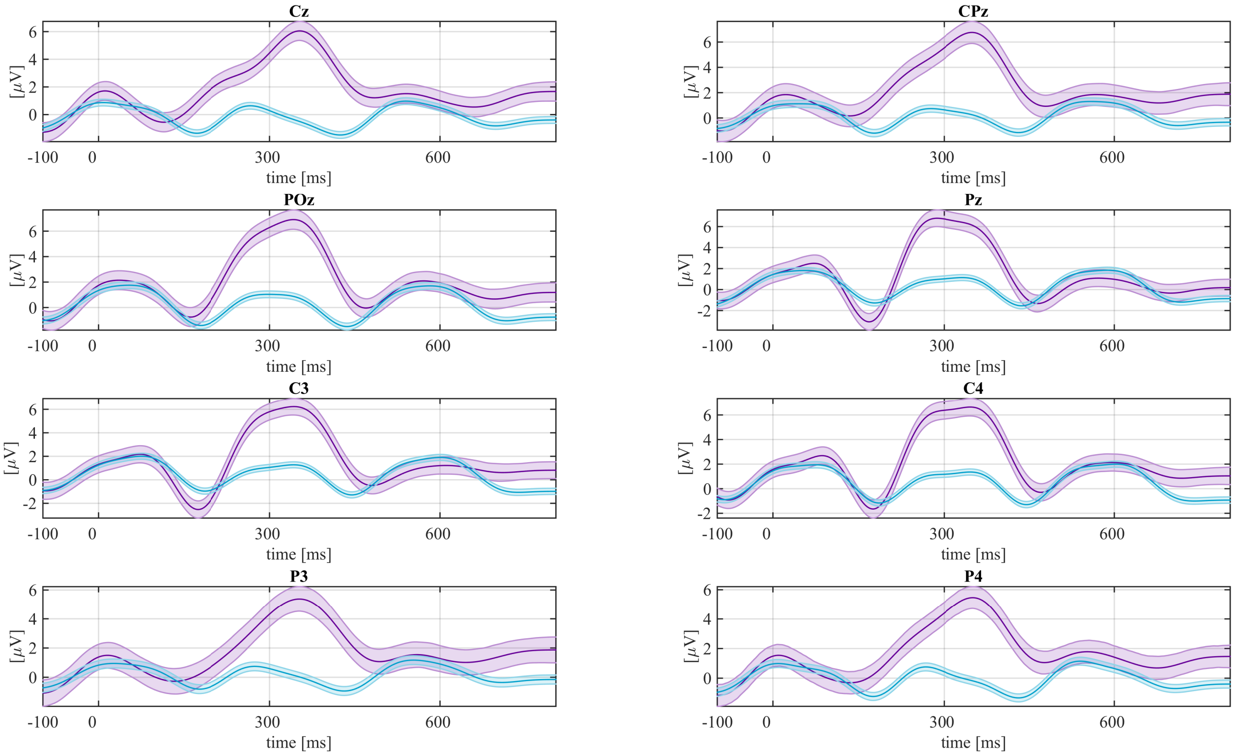

Fig. 3. The grand mean average ERP brain responses of the protocol one ($ISI = 200$ ms) with purple and blue middle lines depicting targets and non–targets, respectively. Standard error intervals are visualized also around the mean traces.

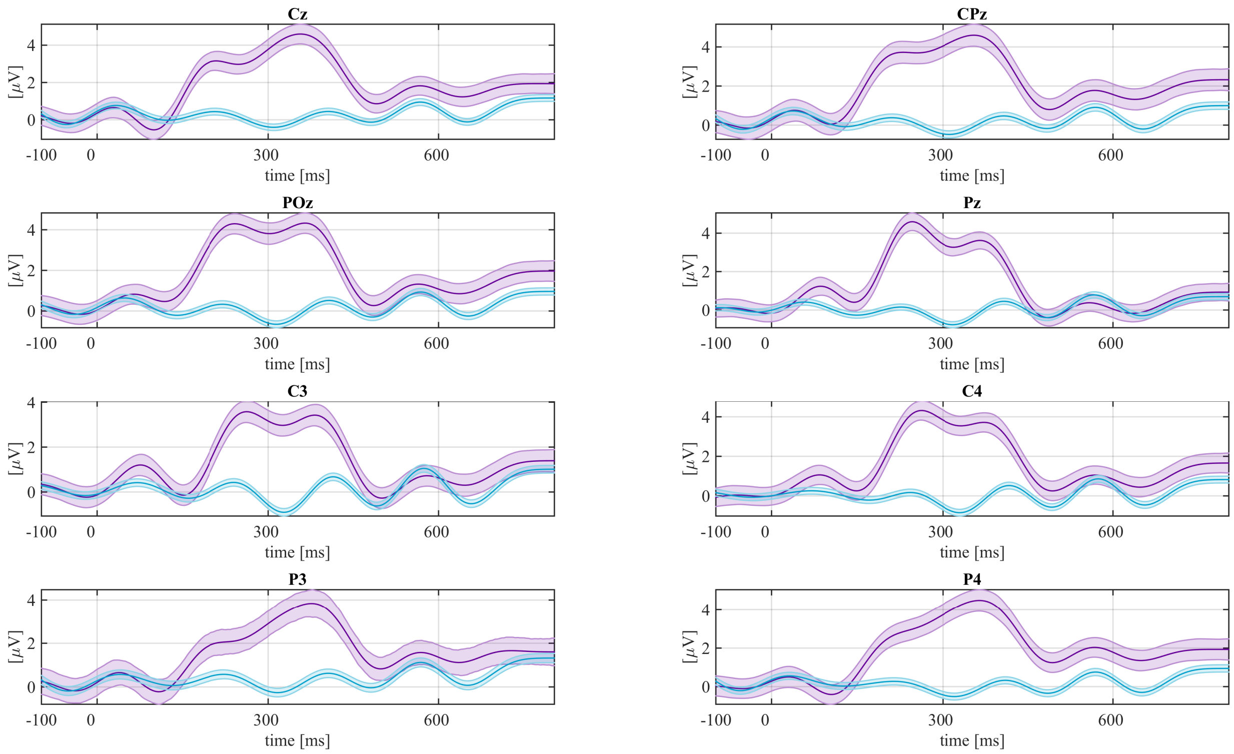

Fig. 4. The grand mean average ERP brain responses of the protocol one ($ISI = 100$ ms) with purple and blue middle lines depicting targets and non–targets, respectively. Standard error intervals are visualized also around the mean traces.

TABLE V
ITR RESULTS OF THE PARTICIPATING USERS FOR THE BOTH PROTOCOLS USING LINSVM CLASSIFIER (MAXIMUM ITRS WERE OF 16.91 BIT/MIN AND 28.18 BIT/MIN FOR ISIS OF 200 MS AND 100 MS, RESPECTIVELY)

User number	ITR in protocol one [bit/min]	ITR in protocol two [bit/min]
#1	3.28	8.64
#2	6.67	8.64
#3	9.27	17.09
#4	8.35	25.15
#5	2.73	12.48
Average	6.06	14.40

IV. Conclusions

We conducted a series of EEG experiments to evaluate our proposed spatial visual stimuli BCI system. Using the linSVM classification approach in offline analysis mode we managed to improve the BCI accuracy of the proposed system. The offline chosen method can be implemented next online, which is a target of our near future project. The results also have shown that the classification accuracies were better for the ISI of 200 ms.

We plan to continue this line of research or order to further improve and validate the proposed spatial visual BCI paradigm for locked–in patients in need.

Author Contributions

Performed the EEG experiments and analyzed the data: AB, TMR. Conceived the proposed system: AB, TMR. Designed the EEG experiments: AB, TMR. Supported the project: NB, wrote the paper: AB, TMR.

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