Visual Motion Onset Augmented Reality Brain–computer Interface

Kensuke Shimizu, Takumi Kodama, Shoji Makino
Life Science Center of TARA
University of Tsukuba
Tsukuba, Japan

Tomasz M. Rutkowski[1 † ‡ ⋆]
†The University of Tokyo, Tokyo, Japan
‡Saitama Institute of Technology, Fukaya, Japan
⋆RIKEN Brain Science Institute, Wako-shi, Japan
tomek@bci-lab.info
http://bci-lab.info/

***Abstract*— The paper presents a pilot study of a visual motion onset and augmented reality (AR) brain–computer interface (vmarBCI) paradigm. We also evaluate a BCI classification accuracy using a step–wise linear discriminant analysis method using different event related potential (ERP) averaging scenarios. We discuss the novel visual motion in an AR set–up, which generates the vmarBCI stimuli. The AR set–up is created with a virtual reality cardboard with a regular smartphone as a display. Six visual motion patterns are presented to the user during the online vmarBCI experiments in an oddball style paradigm allowing for brainwave "aha–responses" elucidation, within ERPs carrying P300 modulations. A subsequent classification accuracy comparisons are also discussed in online and offline vmarBCI studies. A research hypothesis of the classification accuracy non–significant differences among various numbers of ERP response averaging scenarios is confirmed.**

***Keywords*— brain–computer interface (BCI); augmented reality (AR); motion onset brain response.**

I. INTRODUCTION

A brain–computer interface (BCI) is a modern neurotechnology employing the central nervous system (CNS) brain signals (brainwaves) of a user (paralyzed or able–bodied) to create a new communication channel with others or to control external devices without depending on any muscle activity [1]. The BCI technology has provided a support already to patients' life improvement who suffer from severe paralysis due to diseases like an amyotrophic lateral sclerosis (ALS) [1]. The contemporary BCI applications rely mostly on a static visual mode (no visual flow dynamics employed), which generates the most reliable event related potentials (ERP) so far [2]. Also many successful alternative options have been developed recently to utilize spatial auditory [2, 3], tactile (somatosensory) [4, 5] or mixed [6] modes. Meanwhile, the visual BCI still offers hard to beat communication options in comparison with the contemporary tactile and auditory modes in case of locked–in syndrome (LIS) patients [7, 8]. We present results of a new study employing an augmented reality (AR) environment realized with a headgear (a so–called "cardboard" set–up) as shown in Figure 1. We propose to utilize a visual motion onset BCI paradigm [9] realized in a low cost and simple cardboard AR environment with stereo vision display as shown in Figure 1c. The visual onset motion and augmented reality BCI (vmarBCI) head mounted display can generate various patterns to be applied in the AR environment (see Figure 1c), and therefore it could be adopted simply for those users with a good spatial vision. The presented approach allows for creation of visually rich and dynamic oddball paradigms [1, 9]. The goal of this pilot study, with five users so far, is to compare and test a performance (a BCI classification accuracy) of the novel vmarBCI paradigm in comparison to the state of the art spatial tactile and auditory modalities in function of various event–related potential (ERP) averaging scenarios. Namely we take the averaging scenarios into account of ten, five, three, two and single ERPs processed. The pilot study results obtained with five so far healthy users using a stepwise linear discriminant analysis (SWLDA) classifier [10] and five different averaging settings are analyzed and discussed in the paper.

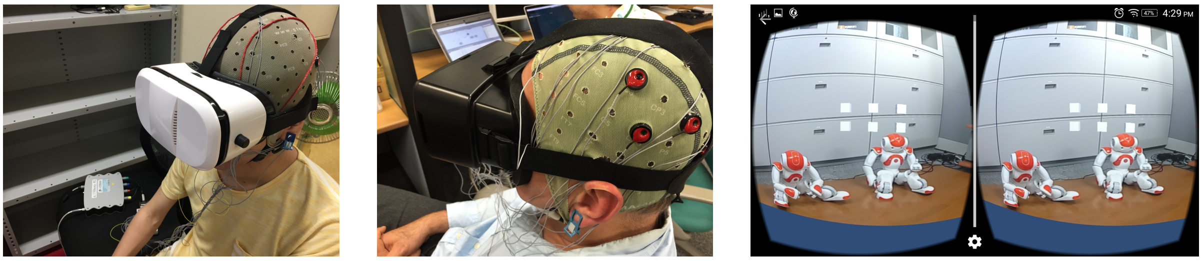
From now on the paper is organized as follows. In the next section we present methods developed in OpenVIBE [11] EEG experimental system together with Unity3D AR prototyping environment in order to capture, process and classify the brainwave responses in the online proposed vmarBCI application. Online and offline EEG analysis results together with conclusions summarize the paper.

II. METHODS

The visual motion AR stimuli are delivered through a cardboard mobile phone set–up as shown in Figures 1a and 1b. Each visual motion stimulus pattern is generated in an oddball paradigm [1] style by OpenVIBE [11] scenario as shown in Figure 2. There are six oscillatory visual movement pattens delivered in random order in order to elicit P300 brainwave responses in an oddball style paradigm [1]. The visual motion events are of 100 ms long with inter–stimulus intervals (ISI) of 300 ms as summarized in Table 1 with experimental condition details. During the online BCI EEG experiments, the user wears the AR headgear attached with six moving patterns displayed randomly in the augmented vision environment programmed by our team in Unity3D as shown for a single box in Figure 1c. A smartphone camera is used to display a real room with augmented graphical stimuli. The vmarBCI users respond mentally by confirming/counting only to the instructed and spatially distributed visual motion patterns (see Figure 1c) while ignoring the others. The users are requested to spell sequences of six locations (six virtual digits represented by the boxes in the AR).

The EEG vmarBCI experiments were conducted with ethical permission of Ethical Committee of RIKEN Brain Sci-

[1]The corresponding author.



(a) The AR cardboard set–up #1 during the online BCI experiment with a first user.

(b) The AR cardboard set–up #2 during the online BCI experiment with a second user.

(c) The AR scene presented to the user within the cardboard with a room environment captured by a facing forward smartphone camera.

Figure 1: Users wearing the tested two different AR cardboard set–ups shown in panels (a) and (b) together with EEG caps during the online vmarBCI experiments.

ence Institute and in accordance with *The World Medical Association Declaration of Helsinki - Ethical Principles for Medical Research Involving Human Subjects*. In the online vmarBCI experiments the EEG signals are captured with an EEG amplifier g.USBamp by g.tec Medical Instruments, Austria. Eight EEG electrodes are attached to the head locations *O1, O2, Cz, CPz, CP5, CP6, P3*, and *P4* as in 10/10 intentional system. A reference electrode is attached to a left earlobe and a ground electrode on the forehead at *FPz* position respectively. The experimental details are summarized in Table 1.

The EEG signals are recorded and preprocessed online by an in–house extended OpenVIBE application [11] with Python programmed network communication and classification units (see Figure 2). The EEG signals are segmented ("epoched") as features drawn from ERP intervals of $0 \sim 800$ ms (see Figure 3 with averaged results). The sampling rate is set to 256 Hz, the high pass filter at 0.1 Hz, and the low pass filter at 40 Hz, respectively. Each user performs four sessions of selecting the six patterns (a spelling of a sequence of six digits associated with each visual motion pattern). In online vmarBCI experiments each target is presented ten times in a random series with remaining non–targets. We perform also an offline analysis of the collected online EEG datasets in order to test a possible influence of various ERP averaging scenarios by taking $10, 5, 3, 2$ or single responses. The stepwise linear discriminant analysis (SWLDA) [10] classifier is applied next in Python, with features drawn from the $0 \sim 800$ ms ERP intervals. A removal is performed of the least significant input features, having $p > 0.15$, and with the final discriminant function restricted to contain a maximum of 60 features.

III. RESULTS

The results of the SWLDA in different averaging scenarios have been summarized in Table 2. The accuracy results were dropping with lower ERP averaging settings, yet no statistically significant differences were observed among the results as evaluated with pairwise Wilcoxon rank sum tests. The grand mean averaged ERP responses for rare targets (red) and non–targets (blue) are depicted in Figure 3. The results allowed to draw a conclusion, based on the offline EEG analysis of five users, that less averaging steps could be used in order to boost the BCI interaction speed as suggested in Table 2.

Table 1: Conditions and details of the vmarBCI EEG experiment

Condition	**Detail**
Number of users	5
Visual motion stimulus length	100 ms
Inter-stimulus-interval (ISI)	300 ms
EEG recording system	g.USBamp active wet electrodes
Number of the EEG channels	8
EEG electrode positions	O1, O2, Cz, CPz, CP5, CP6, P3, and P4
Reference electrode	Behind the user's left earlobe
Ground electrode	On the forehead (FPz)
Sampling frequency	256 Hz
Classification method	Stepwise LDA (decimation filter by a factor 10)
Number of trials	10
Number of sessions	5 (first session used for training)

IV. CONCLUSIONS

The aim of this study was to test the ERP responses variability impact on the vmarBCI classification accuracy results. The offline results obtained with the SWLDA classifier did not resulted with significant differences although lower averaging settings caused accuracy drops as summarized in Table 2. One of the users could score the perfect accuracies with 10 trials averaging. All the obtained BCI accuracy results, with the limited number of users so far (we continue hiring subjects), were above a theoretical chance level of 16.67%.

The preliminary results from the reported pilot study have been very promising for future online applications with users suffering from neurodegenerative diseases as well as for healthy people allowing for enriching the visual BCI stimuli presentation by introducing the spatial dynamic features in the AR set–up, as well as without significant classification drops in relation to ERP averaging scenarios.

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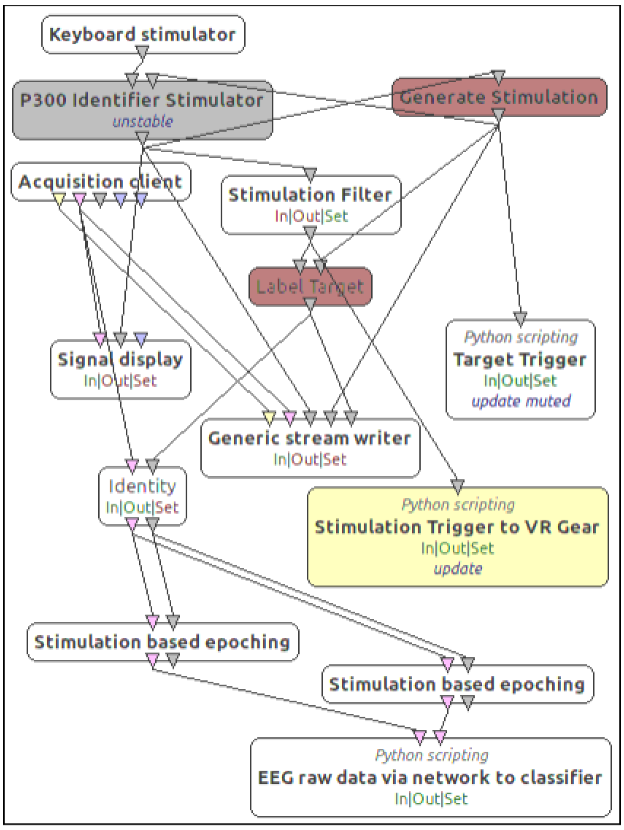

Figure 2: The vmarBCI paradigm EEG acquisition and processing steps in OpenVIBE [11] environment. The yellow "Python processing" box was responsible to sending visual motion onset trigger to the AR cardboard headgear shown in Figure 1.

Table 2: The vmarBCI accuracy results using ten, five, three, two and single ERP averaging scenarios

Number of averaged ERPs = 10				
User number	Session			
	#1	#2	#3	#4
1	100.00%	100.00%	100.00%	66.67%
2	100.00%	83.33%	66.67%	83.33%
3	66.67%	83.33%	50.00%	100.00%
4	66.67%	50.00%	100.00%	50.00%
5	83.33%	66.67%	100.00%	83.33%
Average	**80.00%**			

Number of averaged ERPs = 5				
User number	Session			
	#1	#2	#3	#4
1	83.33%	83.33%	66.67%	66.67%
2	66.67%	83.33%	75.00%	66.67%
3	66.67%	33.33%	58.33%	75.00%
4	66.67%	50.00%	91.67%	25.00%
5	66.67%	66.67%	75.00%	66.67%
Average	**66.67%**			

Number of averaged ERPs = 3				
User number	Session			
	#1	#2	#3	#4
1	72.22%	66.67%	61.11%	44.44%
2	55.56%	77.78%	55.56%	50.00%
3	50.00%	44.44%	50.00%	50.00%
4	44.44%	33.33%	72.22%	38.89%
5	38.89%	50.00%	55.56%	72.22%
Average	**54.17%**			

Number of averaged ERPs = 2				
User number	Session			
	#1	#2	#3	#4
1	60.00%	66.67%	60.00%	43.33%
2	60.00%	60.00%	43.33%	43.33%
3	43.33%	43.33%	30.00%	53.33%
4	53.33%	33.33%	63.33%	40.00%
5	50.00%	46.67%	46.67%	56.67%
Average	**49.67%**			

Number of averaged ERPs = 1				
User number	Session			
	#1	#2	#3	#4
1	45.00%	46.67%	60.00%	43.33%
2	48.33%	53.33%	50.00%	35.00%
3	35.00%	31.67%	35.00%	45.00%
4	45.00%	33.33%	55.00%	33.33%
5	36.67%	35.00%	30.00%	51.67%
Average	**42.42%**			

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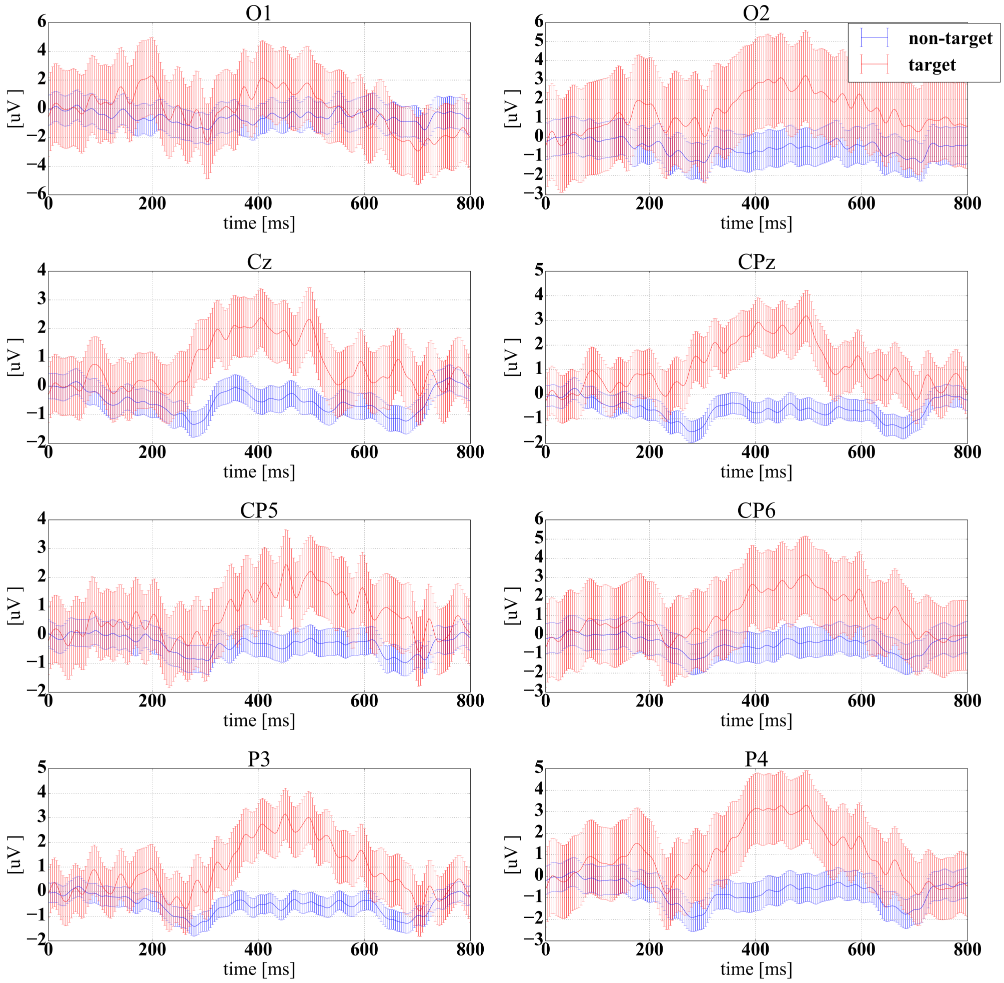

Figure 3: Grand mean averaged ERP responses for rare targets (red) and non–targets (blue). The clear P300 responses to the rare targets can be observed for EEG electrodes *Cz, CPz, CP5, CP6, P3*, and *P4*.

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