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An Implicit Brain Computer Interface Supported by Gaze Monitoring for Virtual Therapy

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***Abstract*— Advanced Brain-Computer Interface (BCI) paradigms aim to solve some problems as BCI illiteracy and unfamiliarity of the subjects to be able to control their elicited motor imagery (MI) successfully, hence improving training time and performance of BCI systems. This work evaluates the effect and performance of an Implicit BCI supported by the Gaze Monitoring (IBCI-GM) paradigm for virtual rehabilitation therapy of patients suffering from partial or total paralysis of their upper limbs; this paradigm also was compared with alternative forms of advanced BCI methods such as Virtual Reality-based BCI (VR-BCI) with a head-mounted display (HMD) and a computer screen (CS). Eight subjects participated in the experiments; four subjects tested the VR-BCI with a CS, and the rest of them tested both BCI advanced methods (IBCI-GM and VR-BCI with an HMD). The subjects were asked to control a virtual arm through MI of flexion and extension movements. The VR-BCI HMD was the approached best method; however, IBCI-GM had significant results and was more practical for users, but it depends on the ability to perform eye movements to be applied by patients. Therefore, these methods should be tested with more subjects to have definitive results.**

I. INTRODUCTION

Virtual rehabilitation is an effective procedure for patients with chronic or severe patterns due to a disease, such as post-stroke paralysis, musculoskeletal disorders, and cognitive impairment. It presents some advantages concerning user motivation and in improving concentration in the brain-computer interface (BCI). However, as a result of the advanced computer skills required on the part of the therapists and some patient safety concerns, the adoption of these systems may be compromised [1].

The most used paradigm in rehabilitation BCI systems is motor imagery (MI), it consists of brain wave pattern recognition of the movement imagination without generating real movement, activating premotor and association brain areas; and inducing activities related to brain plasticity with a potential impact in motor restoration. The visual feedback is typical in MI BCI tasks; another possibility is to use an immersive environment using virtual reality (VR); VR keeps the patient more focused on MI tasks, and allows adding elements to facilitate it [2].

Eye-tracking has been suggested in several works as an alternative or comparative method to Electroencephalogram (EEG) powered BCI [3], [4]. Other works implement active BCI controlled by commands triggered by gaze movements, which are captured by an eye-tracking and EEG decoding [5]–[7]. Eye-tracking also has been proposed as an effective way of controlling devices to perform daily living activities [8]. For rehabilitation, the ability to elicit the correct brain responses and trigger the neuro-plasticity effect by lowering abnormal brain activity is even more important than the control itself [9]. An important factor to be considered in the development of a BCI application, it is to improve the attentional state and engagement of participants without being intrusive in their perception, it can be achieved by not generating external distracting events [10].

An implicit BCI is a paradigm that uses passive interactions or unconscious actions to support a main goal action command [11]. In our work, a BCI that uses gaze monitoring (IBCI-GM) by an eye-tracker is proposed to implicitly improve the performance of extension and flexion MI tasks of an arm. Instead of accounting for gaze as a mechanism of control, it is a metric of the subjects attentional focus. The IBCI-GM performance is compared with a virtual reality (VR) BCI using a head-mounted display (HMD) and a computer screen (CS). Therefore, it is possible to obtain a comparable performance with advanced methods of BCI based on VR exploiting implicit bio-signal cues obtained from eye-trackers.

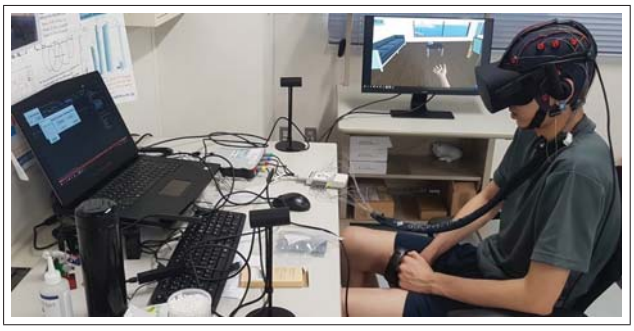

Fig. 1. Subject in test stage with the Oculus Rift.

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II. Materials and Methods

A. Participants

Eight healthy subjects have participated in this study; they are between 21 and 26 years old. The experiments were conducted according to the guidelines of the Declaration of Helsinki. There are two groups of 4 subjects each one; the first group tested the VR-BCI with a CS. While the second one tested the VR-BCI with an HMD and the IBCI-GM systems, this last group has a subject with a mobility impairment, an amputated arm. All subjects signed informed consent before the beginning of this experiment and were BCI illiterates with no previous experience using a similar device.

B. Experimental Setup

The EEG data were recorded using a 16-channel g.USBamp (g.tec Medical Engineering GMBH) amplifier with active electrodes. The electrodes were distributed over the scalp according to the 10/10 international system, using electrode positions AF3, AF4, FC3, FCz, FC4, C3, Cz, C4, T7, T8, CP3, CPz, CP4, Pz, O1, O2; using Fz as the ground electrode and reference on the right ear lobe. The EEG amplifier was connected to a computer (OS: Windows 10, CPU: Intel Core i7-8750H at 4.1 GHz, RAM: 16 GB, Graphics: Nvidia GTX 1070) to record and process all the data in a C# application.

Furthermore, a 24" computer screen with an eye-tracker (ET) Tobii 4C (Tobii Gaming) with a frequency of 90 Hz; and an Oculus Rift HMD with a frequency of 90 Hz are used to test the system, see Fig. 1. The virtual arm and its animations were developed using MakeHuman and Blender respectively; they are integrated into the virtual environment using Unity 3D Engine (Unity Technologies). The virtual environment simulates a peaceful scenario, and it is composed of a living room with a beach view in the background.

C. Experimental Procedure

Equipment setup and calibration are carried out before to start the experiment, and they last 15 minutes. The experimental protocol consists of two sessions: training and test.

The training session is composed of 3 runs; each run lasts 1 minute and 30 seconds of BCI tasks and consists of 10 trials (5 trials/MI task), followed by 2 minutes of resting time. In this session, each participant was seated in front of a computer screen with arms resting on their legs. The protocol is the following, a black screen (BS) is displayed for the first 2 seconds; then a cross signal as a fixation stimulus (FS) alerts the subject that the MI task will start, it is shown for 1 second. Then, EEG data are recorded for 6 seconds, while an image of a virtual arm is presented (see Fig. 2.a); there are two possible images, an arm with an arrow pointing up or down, it suggests extension or flexion MI respectively. The IBCI-GM processing schema is displayed in the Fig. 3; the EEG and gaze data are processed in parallel, for MI decoding and to determine the level of focus on the target independently.

The test session is performed after the training session with a break of 5 minutes between them. The test session consists of runs of MI tasks with a break time of 2 minutes between them, each run lasts 2 minutes and 30 seconds and consists of 10 trials (5 trials/MI task). The first group carried out a run of the VR-BCI with a CS; and the second group carried out 2 runs, a run of the VR-BCI with an HMD and a run of the IBCI-GM. Calibration lasts 3 minutes for the HMD Oculus Rift and 2 minutes for the ET Tobii 4C. The protocol is the following; during the first 5 seconds, a word was displayed in front of the subject, being either flexion or extension. Then, the subject has 10 seconds to imagine it; then, the virtual arm performs the desired movement for 5 seconds, see Fig. 2.b. But the virtual arm movement angle is determined by the Support Vector Machine (SVM) classifier accuracy of MI data; then, the virtual arm completes its movement.

D. Signal Processing

EEG data were sampled at 512 Hz and filtered by an eight order Butterworth bandpass filter with cutoff frequencies 0.5 and 30 Hz, and a 50 Hz notch filter. Then, 3 pair spatial filter from common spatial patterns (CSP) transformation matrix of dimension 16x16 [12], [13] was calculated to reduce dimensionality. Then, the logarithm of the variance is computed to get 6 features by trial [2]; MI task features are grouped for the first class and relax state features for the second class from the training session, both feature groups were used to train a SVM classifier.

The SVM was configured with a radial basis function (RBF) kernel using the library LibSVM [14] in C#. SVM classifier has demonstrated to be efficient to discriminate between two motor-imagery classes, and due to its fast and computationally efficient training capabilities, it is the standard classification method used for binary-class MI BCIs [2].

In an upper limb rehabilitation therapy; flexion and extension movements are performed at different times, and they are indicated by the therapist. In our work, these directions are replaced by a message in the test session, it is considered to choose a SVM classifier with two outputs instead of one SVM classifier with three outputs. The EEG data of 10 seconds is split into 1-second segments with an overlap of 90%; then, all segments are evaluated by the SVM classifier to determine its accuracy, it also could give a measurement of how focused the subject was during 10 seconds to perform MI tasks.

E. Eye Tracking

The eye-tracking is activated to interact with the participant while MI tasks are performed and brain activity is recorded, see Fig. 4; a neighborhood is defined around the target points, these points are set according to the virtual arm movement endpoint in each MI task, flexion and extension. All subjects were asked to observe these points to do a more intuitive interface, the distance between the target point and

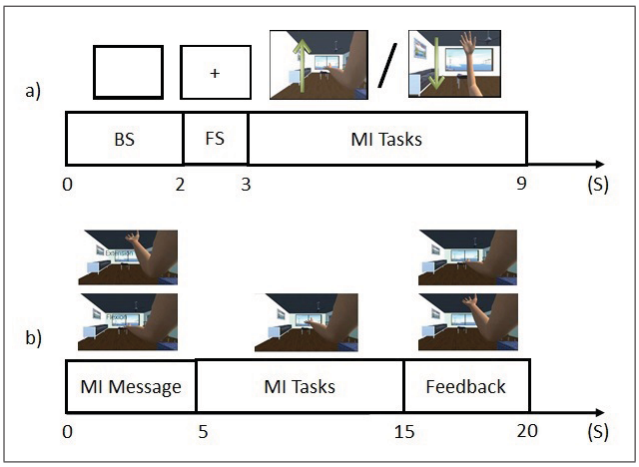

Fig. 2. Timelines. a) Training stage. b)Test stage.

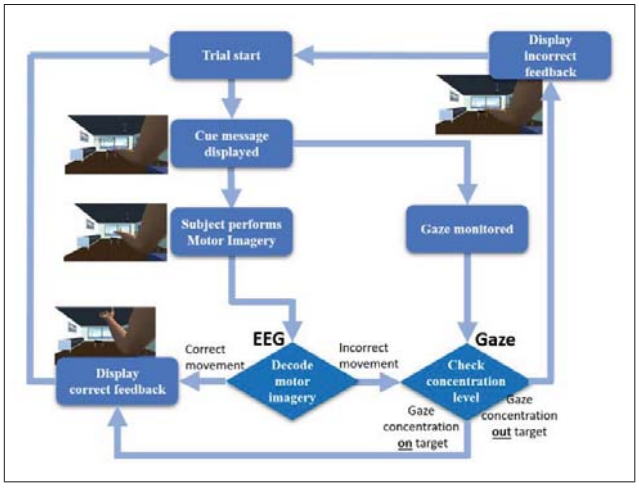

Fig. 3. Schema of processing steps of the IBCI-GM

the observed point was calculated with a frequency of 90 Hz and its average was scaled to add a compensation to the SVM classifier accuracy; the maximum compensation was 10%, it was chosen arbitrarily but this chosen will be approached in future works based on sensor fusion methods.

III. Results

An SVM classifier was trained using a 5-fold cross-validation for each subject, the Table I shows mean accuracies for each approached methods and the Fig. 5 shows mean accuracies by subject; the VR-BCI CS approach had the lower mean test accuracy than the IBCI-GM and the VR-BCI HMD approaches. The training stage is the same for all subjects, and the cross-validation and validation accuracies are close between the groups. Analysis of variance (ANOVA) between the groups accuracies found statistical differences ($p > 0.05$) between the VR-BCI CS and the IBCI-GM groups ($p = 0.0004$), and the VR-BCI HMD and the IBCI-GM groups ($p = 0.0183$).

The spectrogram was calculated to find some differences between the IBCI-GM and the VR-BCI HMD for all channels; then, ANOVA of EEG signal power is calculated to determine statistical differences between both groups. There is a significant difference in the mu band over motor cortex, specifically in the channels FCz, FC4, C3, Cz, C4, CP3, and CP4; but only for 2 of 4 subjects. It could be due to the level of immersion of Oculus Rift; the HMD produces a better ownership perception than an eye-tracker, a questionnaire was answered by all subjects, it is related to ownership sense and immersion level. The subjects mentioned that the use of HMD produces greater fatigue and the virtual environment causes more distraction than the case with eye-tracker. The subjects mentioned that the use of HMD produced fatigue; and in some cases, they lost concentration due to the virtual environment details.

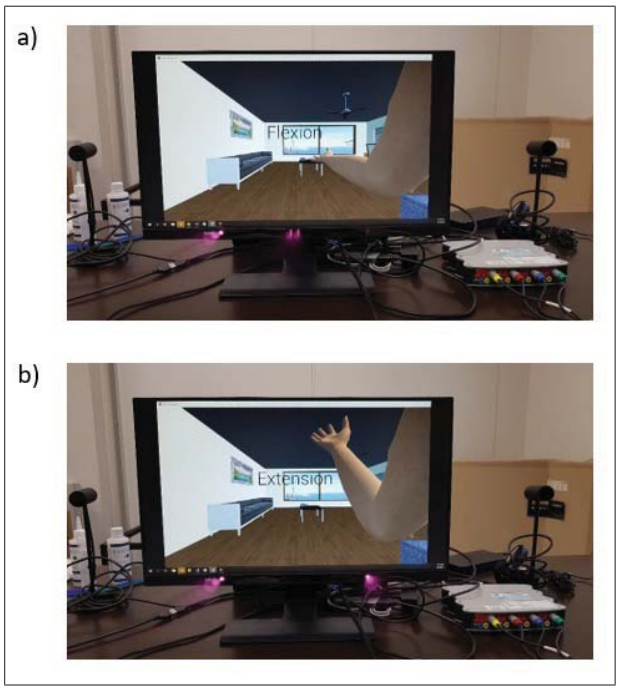

Fig. 4. Eye tracking interaction. a) Flexion stimuli. b) Extension stimuli.

IV. Discussion

The eye-tracking compensation has a maximum of 10%; it was chosen arbitrarily based on the average accuracy of the VR-BCI CS approach, it could be adaptive based on the subject BCI performance or a complex method of sensor fusion could be applied, gaze map or pupil dilation could be useful to achieve it. The positions to be followed by the eye-tracker on the IBCI-GM approach are pointed out before to start the experiment but the subjects could learn them when the protocol started in an intuitive way.

Another aspect is that the VR-BCI CS method test was carried out in a different country (Peru) than the other methods approached (Japan), it could influence the results due to electrical noise in spite of the same protocol was followed; an analysis of signal-noise ratio (SNR) would be suitable to evaluate this effect. Furthermore, cultural factors could affect the experiment development; although

all subjects accomplished with the exclusion criterion, which is healthy persons without mental disease antecedents, there are distinct personality patterns according to nationality.

TABLE I

MEAN ACCURACIES FOR APPROACHED METHODS

Methods	VR-BCI CS	IBCI-GM	VR-BCI HMD
Cross-val. Acc. (%)	99.71	97.46	
Validation Acc. (%)	100.00	99.31	
Test Acc. (%)	84.64	92.30	97.85

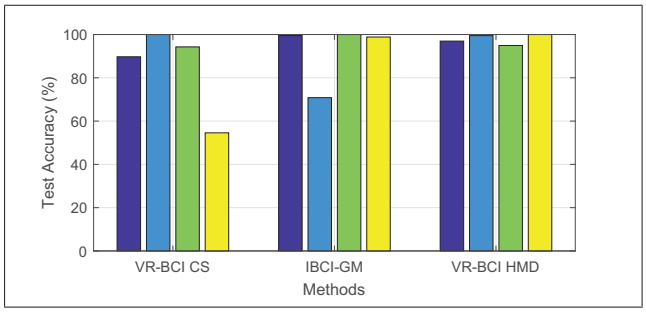

Fig. 5. Comparison of methods.

V. CONCLUSIONS

An IBCI-GM system is proposed and was compared with VR-BCI using a CS and an HMD; it had closer results to the VR-BCI HMD, being this last one the best method approached. However, the IBCI-GM is done using an eye-tracker, it is more practical than an HMD according to the subjects perception; it only requires to put an EEG for brain data recording over the subject scalp.

The IBCI-GM approach could be useful and intuitive to disable post-stroke patients; the gaze monitoring could compensate for some BCI problems due to the severity of the patient paralysis, although they should be able to perform eye movements.

This work presents preliminary results that should be extended with more subjects to have definitive results.

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