Control of a Virtual Reality Environment for Upper Limb Movement using a Motor Imagery-based Brain Computer Interface

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Abstract

This work presents the design, implementation and evaluation of a virtual reality (VR) environment controlled using a Motor Imagery (MI) based Brain Computer Interface (BCI). BCIs enhance the effective communication and interaction between humans and computers. Such systems are increasingly prevalent in diverse applications, including education, entertainment, and health. The aim of this system is to create a rehabilitation environment for upper limb motor recovery, in the form of a VR game. In the system, the user performs left and right arm MI, detected using machine learning algorithms to perform an ability within the virtual environment. The system was evaluated with five healthy participants in one experimental session each. Each experimental session consisted of a training and an evaluation routine, in which the participants were asked to imagine each MI task randomly to gather training data and then, with the trained classification algorithm, the users were evaluated by playing the game, needing to perform the correct ability to attack each enemy. The 3-class classification algorithms showed a ranged accuracy of 39.6% to 68.6%, with an average of 54.3%; the evaluation accuracy ranged from 46.2% to 76.9%, with an average of 59.2%.

1. Introduction

Neurodegenerative diseases, stroke, and spinal cord injury are the major causes of motor paralysis in adults and the elderly. Patients with these afflictions have severely impaired mobility and require assistance with daily activities such as eating, dressing, grabbing objects, and communicating. Due to the challenges these people face, there is a growing interest in developing novel technology-driven solutions to restore and recover mobility, as well as a need for innovative rehabilitation programs. Brain-Computer Interface (BCI) and virtual reality (VR) technologies are a new and compelling approach for neurorehabilitation on patients with motor loss.

A BCI is a system that allows communication between the brain and a computer or other external device [8]. Using BCIs is especially helpful for identifying motor commands via Electroencephalography (EEG). Some neurodegenerative affections, such as ALS, affect mainly superior and inferior motor neurons [15], meaning that the patient is unable to execute a movement but the brain keeps generating motor signals. This allows to identify movement commands using EEG, regardless of the ability of the patient to execute the motion. BCIs have long been used for neurorehabilitation, not only to aid movement but also to improve communication and for neuro-modulation [17].

In recent years the understanding and applications of BCIs have broadened, allowing users to control spellers, robots, drones, or wheelchairs [3]. EEG-based BCIs are mostly developed using visually evoked potentials, slow cortical potentials, event-related potentials, and sensorimotor rhythms. The last provides high degrees of freedom, potentially offering physical interaction for patients with motor loss, being an alternative to bodily motor pathways [7]. Sensorimotor rhythms are also easily detected in both healthy and disabled users. There are different methods used to analyze and process EEG data for BCI applications, two of the most common are P300 [4] and MI. In the MI paradigm, the user generates induced activity from the motor cortex while imagining they are performing a movement without doing it [19].

VR has been shown to have beneficial neurobiological effects. Georgiev et al. [6] demonstrated promising results in the use of VR for neurorehabilitation, describing increased cortical gray matter volumes in patients, a higher concentration of beta-waves in EEG readings, and enhanced cognitive performance. VR is regarded as a safe and controlled environment for rehabilitation activities [1], while also motivating patients complete rehabilitation in an enjoyable environment.

Both of these technologies have been extensively explored in recent years, and recently there has been an interest in combining BCIs with VR. Using BCIs can improve communication channels between the user and the virtual world, enhancing immersion and interaction [13]. Different clinical trials have been conducted for the use of BCI-VR technologies, showing promising results for rehabilitating patients with motor loss [8]. Integrating VR and BCIs involves the design of a system with immersive 3D graphics and feedback as well as a classification algorithm that is quick and accurate, allowing real-time interaction using the BCI, and being more intuitive than traditional VR controls [10].In a prior study involving VR and MI, users navigated a maze by imagining left or right movement [14]. Ten of the eleven participants achieved online performance superior to chance, and the majority of test subjects completed more than 70% of the tasks. Ferrero et al. [5] investigated the impact of using VR for MI improvement, analysing whether MI gait can be improved when subjects receive VR feedback rather than feedback from a screen. Visual feedback from VR was related to higher performances in the majority of cases.

In this work, we present the implementation and validation of a VR environment controlled by a BCI using the Motor Imagery paradigm. The BCI controls a character's movement within the VR environment, focusing on two movements: right-arm and left-arm movement. These movements prompt an animation and a special ability within the environment to attack a random enemy. The virtual environment was created in Unreal Engine and implemented on a Meta Quest 2 headset.

2. System Description

The developed system consists of a VR environment, a BCI based on Motor Imagery, and an EEG biosignal amplifier. Figure 1 depicts the system, including the setup diagram and communication lines between each component. The objective is to use the MI BCI to create a rehabilitation environment for upper-limb movement. The BCI and the VR environment communicate with json formatted messages sent via the User Datagram Protocol (UDP) communication protocol. The user manipulates a set of virtual arms inside the VR environment using this communication, allowing for immersive control during the game. The game is divided into two levels: training and evaluation, which are described in the following sections.

2.1. MI-based BCI

The BCI receives EEG signals directly from the amplifier. The EEG recording system (g.LADYbird active wet electrode arrangement and a g.USBamp amplier from g.tec medical engineering GmbH, Austria) consists of eight monopolar electrodes placed following the 10-20 system at positions FC3, FCz, FC4, C3, Cz, C4, CP3, CPz, CP4, P3, Pz, and P4. These electrodes were chosen because they are located over the left and right motor cortex. The ground electrode was located at AFz, and the reference electrode on the left earlobe. The sampling rate was 256 Hz.

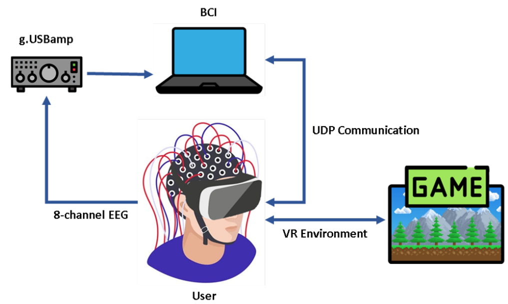

Figure 1. Set up diagram of the proposed VR-BCI system.

The BCI first needs to be calibrated to recognize between left, right and rest using a machine learning model. The model consists of a filter bank common spacial patter (FBCSP) feature extraction algorithm and a regularized linear discriminant analyzer (RLDA) classifier. After the calibration, the system can be used in a real-time experimental evaluation. These two steps are done during the training and evaluation levels respectively.

The EEG data goes through a processing sequence to differentiate between the MI tasks. The data is divided into 1.5-second EEG epochs. The pre-processing and feature extraction stages are applied on this epoch. The classification model then evaluates the features and labels the epoch class. There are three classes: left arm, right arm, and rest. An additional artifact class allows the system to identify a noisy EEG epoch. If a class is determined, the BCI sends a message with the corresponding movement to the virtual environment. The processing sequence was based on the classification approach presented in [11].

To distinguish between the three classes, the feature extraction stage employs the FBCSP algorithm. This algorithm to computes the best spatial filters for extracting useful features from EEG signals. This method is widely used to decode diverse motor-related tasks from EEG data [16, 21]. The feature extraction process consists of three sequential steps: *a*) selecting a filter bank for multiple frequency bands, *b*) using CSP to perform spatial filtering in each frequency band, and *c*) feature selection. This feature extraction procedure was applied independently to the binary conditions rest vs left, rest vs right, and left vs right.

The classification model was applied to the EEG epochs that passed an artifact rejection stage. The model is based on RLDA [2, 9], a popular algorithm for MI-based BCI applications [12, 18]. The RLDA algorithm was implemented as a multiclass model with a one versus one voting scheme. The model is used with automatically regularized covariance, so hyper-parameter tuning is unnecessary. To solve the multiclass problem, the model was trained with a $K(K-1)/2$ binary classifier.

Table 1. Characteristics of the two game levels of the virtual environment.

Game Levels	
Training Level	**Evaluation Level**
System trains classification algorithm	User performs online evaluation
User follows instructions	Users decides which movement to choose
Fixed duration	Fixed number of trials
No evaluation	User is evaluated right or wrong

2.2. Virtual Environment & Game Levels

The virtual environment and game levels were developed using Unreal Engine and the Meta Quest 2 headset. The game was divided into two levels, the Training Level and the Evaluation Level. In the first one, the user would calibrate the BCI for left, right or rest classification. In the second, the user would use the calibrated system to run an online evaluation and test their performance by imagining either right or left depending on what the virtual environment showed the user. The main differences of each level are shown in table 1. The game consists on attacking two different enemies, each is attacked with an ability assigned to the movement of the arms, the assigned abilities and enemy interactions are described on figure 2.

Figure 2. In-Game interactions between the user and the enemies. Left movement triggers a fire ability, right movement triggers an ice ability. The user attacks the enemies with these abilities; fire defeats the ice enemy and ice defeats the fire enemy.

The training level consists of a calibration routine in which the system randomly asks the user to imagine either left or right arm movement for 12 seconds in order to collect the training dataset. The routine lasts approximately 8 minutes and consists of 24 trials, 12 left and 12 right. The collected data is then sent into the processing pipeline. Finally, we obtain the accuracy score of each class by performing a five-fold cross validation. Based on these results, the calibration is used or discarded, depending on whether the classes are balanced and the accuracy is greater than random chance ($accuracy > 33\%$). During the training level, the user begins to associate the imagined movement, the assigned ability, and the corresponding enemy to attack with each ability.

In the evaluation level, the trained algorithm to classifies the EEG signals in real time. If the BCI detects a MI task in less than 12 seconds, it sends a message to the virtual environment to perform the corresponding ability. The evaluation routine has a maximum duration of 11 minutes and consists of 26 trials, 13 left and 13 right randomly selected. In game, enemies are spawned one by one in front of the user, and the user must decide which movement to imagine to correctly attack the enemy. During the evaluation, the user has three options: attack with fire (left class), attack ice (right class), or do not attack (rest class). The goal of the evaluation is to test both the user and the BCI classifier, so the system records correctly and incorrectly classified movements.

Figure 3. Experimental setup, user P3 during training level.

3. System Validation

3.1. Experiment Description

Experiments were conducted in a closed space with five healthy subjects to assess the performance and usability of the VR-BCI system. Participants sat in front of a desk, wearing the Meta Quest 2 headset and the EEG electrode cap, resting their arms on their legs. Initially, participants were given instructions on how to complete the MI tasks, and they were asked to avoid unnecessary movements while focusing on the interface. The EEG electrodes were connected to an amplifier, which in turn was connected to a laptop computer running the BCI.

The experimental task consisted of imagining raising either the right or left arm in response to visual and audio cues displayed in the virtual environment. An experimental session was divided into two stages: training level and evaluation level, completed one after the other. Figure 3 presents the experimental setup.

3.2. Participants

This study recruited the participation of five healthy individuals. The group consisted of three females and two males aged 20 to 24 (24, 24, 22, 22, 20 from P1 to P5). Four participants were right-handed, and one (P3) was left-handed, with normal or corrected vision and no prior experience with EEG recordings or BCI-related experiments.

All participants volunteered for the study and provided informed consent before the experimental session. This study followed the ethical principles of the World Medical Association (WMA) Declaration of Helsinki [20].

Table 2. Online evaluation performance of the five subjects and the overall average. For evaluation performance we reported the number of correctly classified trials (Succ. trials) and the rate (acc_{ev}) between the successful trials and the total trials conducted per session (26 trials, 13 left and 13 right).

	Left MI		Right MI		Evaluation
Participant	**Succ. Trials (#)**	**Accuracy (%)**	**Succ. Trials (#)**	**Accuracy (%)**	**Total Accuracy (%)**
P1	4	30.8%	10	76.9%	53.8%
P2	4	30.8%	12	92.3%	61.5%
P3	13	100.0%	7	53.8%	76.9%
P4	10	76.9%	5	38.5%	57.7%
P5	8	61.5%	4	30.8%	46.2%
Average	**7.8**	**60.0%**	**7.6**	**58.5%**	**59.2%**

3.3. Data Analysis

To assess the accuracy of the machine learning model trained by the BCI for each participant, we used five-fold cross-validation on the training data. In this study, the accuracy of each classifier trained in the one versus one strategy was reported, and the overall accuracy was calculated as the mean of the three class accuracies.

The performance of the online BCI system was measured with the evaluation level, in terms of percentage of successful detection of the requested MI task. The accuracy in the online evaluation (acc_{ev}) was computed as:

$$acc_{ev} = \frac{n_{sel}}{n_{att}} \times 100\% \qquad (1)$$

where n_{att} is the total MI tasks (13 left, 13 right and 26 overall) and n_{sel} is the number of successful detections. This was computed for both, left and right trials, and for the total trials.

4. Results and discussion

4.1. Classification Model Evaluation

Table 3 shows the training accuracies estimated with the five-fold cross-validation for each participant, along with the average results of the five participants. The mean accuracy for the left class was 58.5%, 58.2% for the right class, 46.1% for the rest class, and 54.3% overall. P3 had the highest classification accuracy, with 68.6%.

We observe that the left and right classes are balanced on average, and that the results obtained were sufficient to carry out the evaluation routine in all cases. The accuracy calculated was greater than chance for all subjects, in both overall accuracy and class accuracy results. Implying that the three-class classification paradigm used in training was able to differentiate between the MI tasks.

4.2. Online BCI Evaluation

Table 2 summarizes the evaluation level results. P3 and P4 obtained accuracies above 76% for the Left MI, which is more than 10 trials correctly classified. P1 and P2 had accuracies higher than 76% for the Right MI. The mean accuracy for Left MI was 60%, and 58.5% for Right MI was, equivalent to nearly 8 correct trials. P3 had the highest classification accuracy with 76.9% overall, with 20 out of 26 trials correctly classified and a 100% accuracy performance for Left MI. More than half of the evaluation trials are correctly classified according to the overall performance.

Table 3. Classification accuracies of the three tasks (Left, Right and Rest) and model accuracy (mean value).

Participant	Left Class (%)	Right Class (%)	Rest Class (%)	Mean (%)
P1	52.5%	53.3%	13.0%	39.6%
P2	64.1%	55.1%	50.0%	56.4%
P3	75.2%	68.6%	61.9%	68.6%
P4	56.7%	68.3%	70.8%	65.3%
P5	44.2%	45.8%	34.8%	41.6%
Average	**58.5%**	**58.2%**	**46.1%**	**54.3%**

Seemingly, users perform better with one movement than the other. P1 and P2 performed better on Right, with 76.9% and 92.3% accuracy, compared to 30.8% on Left. Both of these participants were right handed. P4 and P5, also right handed, achieved better results for Left, with 76.9% and 61.5% accuracy, compared to 38.5% and 30.8% for Right. There is no discernible correlation between the dominant hand and better performance on the MI task, more testing is required to reach accurate conclusions. Users were able to control both virtual movements and correctly attack the spawned enemies in at least half of the trials.

5. Conclusion

The system was proved able to perform the Motor Imagery task for people with no prior experience with BCIs or VR, properly classifying between left and right arm MI in more than half of the trials. More experimentation is required to achieve higher accuracy results so that the system can have a greater impact on upper limb rehabilitation. Future work will include testing the system with more participants and in multiple sessions to see if the user's performance can improve over time and determining whether a change in the processing pipeline is required to achieve better results.

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