Motor Imagery Approach for BCI Game Development

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***Abstract*—Brain-computer interface (BCI) is a rapidly growing field with various applications in many domains such as medical, gaming and lifestyle. This paper presents a 3D non-invasive BCI game. Muse 2 headband is used for acquiring electroencephalogram (EEG) data and OpenViBE platform for processing the raw signals and classification. The game is developed in Unity game Engine. Several subjects are included in the study and EEG signals are recorded for three different mental states i.e. left and right Motor Imagery and eye blink, before playing the game for ten times, aiming to collect coins. Average classification result is 94.86% and average coins collected from the users is 30.8 out of 50 coins. Furthermore, longer periods of playing the game leads to increased control over the game.**

Keywords*—Brain computer interface (BCI); Electroencephalography (EEG); 3D Game; Motor Imagery; Muse 2; OpenViBE; Unity

I. Introduction

Brain-computer interface (BCI) is a sub-class of human-computer interaction (HCI) that requires minimum amount of physical movement. This technology establishes a communication pathway between the brain and a computer device [1]. BCI research was mainly focused on paralyzed or disabled patients, but new developments like wireless commercial electroencephalogram (EEG) devices make BCI viable for everyone. The main advantage of BCI is the hands-free interaction to accurately control machines with the power of the brain.

BCIs can be divided into two categories, invasive and non-invasive. Invasive techniques require electrodes that have been surgically implanted on the human brain. It can produce better signal quality regarding the noise, amplitude and raw data. The main target of invasive BCI are paralyzed and blind patients, because neurosurgery is a dangerous process.

Non-invasive BCIs record information from electrodes placed on the scalp. No surgery is required to implant the sensors and this technique do not use any hazardous methods. The most common BCI recording mechanism is the EEG, which uses scalp positioned sensors that measure the brain electrical potentials with millisecond resolution. There are two types of EEG devices, clinical caps and commercial headbands. Clinical caps usually have 32 or 64 electrodes positioned over distinct brain regions and produce high quality EEG signals. However they are not portable and their applications are limited. On the other hand, electrodes on the commercial EEG devices range from 1 to 32 and they are used in applications where portability is required i.e. BCI controlled vehicles, gaming etc. Researchers are mainly focusing on the non-invasive category because it is a more secure technique. The drawback of this category is that the signals are distorted and contain artifacts.

BCI has seen progress in the medical field, for example for prosthesis control or as biofeedback therapy for the treatment of neurological disorders [2]. Because of this progress, researchers are trying to expand BCI beyond the medical field. In the last years several studies have been published that shifts BCI research towards gaming.

In this work, a 3D BCI controlled game is developed with three different Motor Imagery commands. Unity Engine is used to create the 3D game and OpenViBE platform is employed for the BCI development. Seven subjects participated in the experiment and Muse 2 headband is used for recording the raw EEG data. The goal of the game is to collect as many coins as possible using motor imagery for left and right movement.

II. Related Work

Gezgez and Kaçar [3] developed a 2D game with two levels that controls an avatar with BCI. For translating the brain signals and the facial expressions into avatar movement they used Emotive Epoc+. The BCI was trained with two commands, shoot and forward. The BCI was trained with brain commands ”Push” and ”Right”, matching shoot and forward for the avatar. The same process was applied for ”Clench” and ”Smile” corresponding to shooting and goind forward. The average time to finish level 1 and level 2 with brain commands is 41.9 and 56.5 seconds while for facial expressions is 39.4 and 41.4 respectively.

Pires *et al.* [4] developed a Tetris based game controlled by a non-invasise BCI. It has three unique levels, two of them are based on P300 and one that combines the P300 and sensorimotor rhythms. Two participants with no BCI experience performed the online sessions. Version 1 can be controlled effectively with a small amount of event repetitions. Version 2 has a higher target probability, therefore is harder t control. It was observed that the player mainly fails on selecting the position so the addition of MI to control the pieces in version 3 is a good option.

Bordoloi *et al.* [5] developed a motor imagery based BCI maze game. The game has four different MI mental commands, both hands up for moving forward , tighten both fists for moving backwards, right hand up for moving right and left hand up for moving left. The EEG data acquired with an EEG cap that has only two electrodes C3, C4 from thirteen subjects. RBF kernel Support Vector Machine was used to classify the processed EEG data and the classification accuracy is between 60% to 70%. As for the gameplay the user has to drive from his initial position (”Start”) to a target position (”Goal”). The results of this work indicates that subjects could achieve a significant level of mental control and they managed to drive around the maze.

III. Methods

The proposed method is developed using the OpenViBE BCI software [6], which is a free and open-source platform for designing, testing and using BCIs. OpenViBE provides a Scenario Designer where the users can process their data with ”Box algorithms” in a tree view environment and develop BCIs for real or virtual applications and an Acquisition Server which provides drivers for connecting BCI devices with the OpenViBE software.

A. Offline Processing and Classification

*1) **Acquiring EEG Data**:* Muse 2 headband is used for recording EEG data. This headband is a commercial EEG device that connects to a computer via Bluetooth. It was chosen due to it’s low price, it’s flexibility and it’s size. Muse 2 has four EEG electrodes, two on the left (TP9, AF7), two on the right (AF8, TP10) and a ground electrode as it is shown in fig. 1. For acquiring the EEG data OpenViBE’s acquisition server is used. This headband is not listed as a device that OpenViBE can connect to so lab streaming layer (lsl) [7] is being used to connect the whole system. Through BlueMuse [8] one lsl stream is created and connects with OpenViBE’s acquisition server.

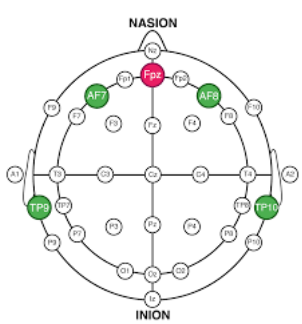

Fig. 1. Muse 2 headband electrodes.

*2) **Input Signal**:* One OpenViBE scenario in the Scenario Designer is created to import, process and classify the raw data. Features extracted from the imported signals are being used as training dataset. In this work three different EEG signals (left, right, blink) should be imported.

*3) **Time Epoching**:* Time epoching is a widely used method in EEG analysis. Specific time-windows are extracted from the continuous EEG signal and this creates more data samples for processing. The proposed approach employs windows that last three seconds without any overlap. This practically means that the classifier is giving a decision every three seconds. This time window was chosen after trial-and-error process.

*4) **Signal Processing and Feature Extraction**:* After importing the raw data from the EEG recordings, a Butterworth bandbass filter at 8-40 Hz is applied for each EEG channel to reduce the noise and the artifacts. Then the signal is epoched and splited into 5 frequency bands:

- Alpha waves 8-13 Hz
- Beta 1 waves 13-20 Hz
- Beta 2 waves 20-30 Hz
- Gamma 1 waves 30-35 Hz
- Gamma 2 waves 35-40 Hz

The energy of each band is calculated and the obtained features are used as an input to the classifier.

*5) **Classification**:* Linear discriminant analysis (LDA) algorithm is used to classify the EEG data [9]. The strategy that was used in this mutli-class BCI is ”One vs One” and the pairwise decision strategy is ”Voting”. When the classifier is trained the results are stored in an XML file to be used in the real time classification. Training Scenario is detailed presented in Fig. 2.

B. Real Time Classification

Acquisition Server is used for real-time testing after the off-line processing and classification. The same ”boxes” that have been used in the off-line process are used again and the classifier results are exported through the ”LSL Export” box as an OpenViBE-Markers stream and fed into Unity.

IV. Game Design

In order to develop the 3D game used in this paper, Unity game engine was employed. Unity can be connected with BCI technology and create games controlled by brain commands.

In this study a 3D game has been developed Fig. 4 that consists of a platform on which there is an avatar constantly moving forward. The objective of the game is to collect coins, located in several positions in the platform by moving left, right and jumping. The platform has 3 lanes where the coins can be, either on the ground or in the air. The number of total coins is 50 and they are divided into 17 clusters (16 clusters of 3 coins and 1 cluster of 2 coins).

A. Game scenario

For this work, the standard keyboard input is replaced by mental commands. The utilization of the LSL allows the game to receive chunks data from a Markers stream. The data is pushed sample-by-sample into the game and they are divided into three categories based on the user mental command.

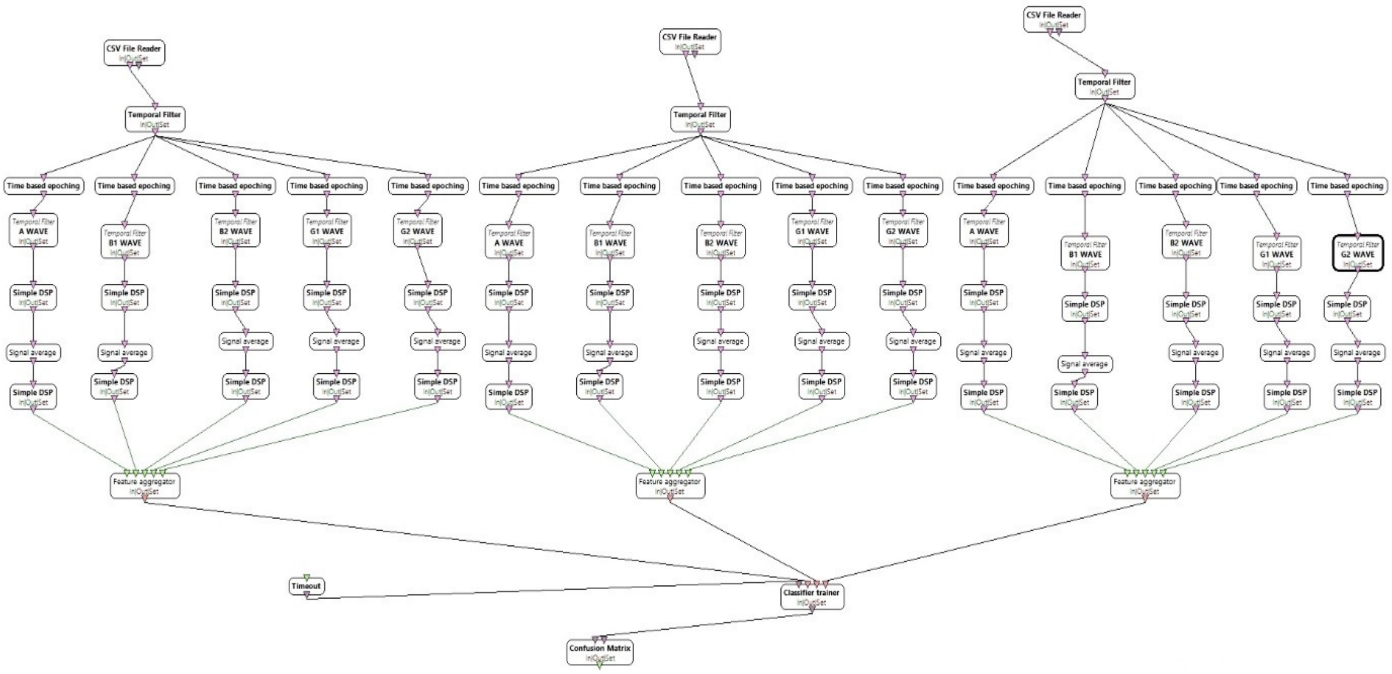

Fig. 2. OpenViBE offline scenario.

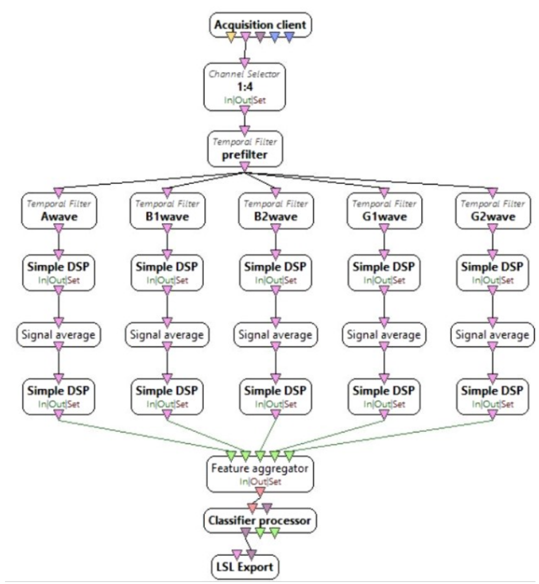

Fig. 3. Aqcuisition client and real time classification.

- If the user is looking right and thinking that he is moving his right hand then the in-game avatar slides right.
- If the user is looking left and thinking that he is moving his left hand then the in-game avatar slides left.
- If the user blinks, then the in-game avatar jumps.

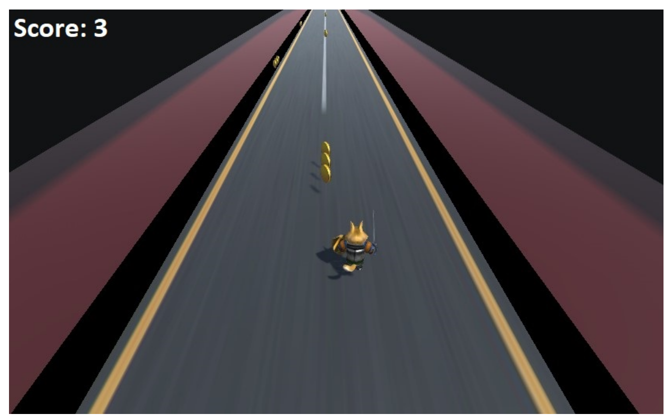

Fig. 4. Snapshot of the gameplay.

V. Results and Discussion

*1) **Dataset**:* Seven volunteers participated in the experiment. All participants were healthy with normal vision. They were instructed to sit comfortably in a chair, remain calm and minimize their movements to perform three separate recordings. In the first recording, the subjects were instructed to look left and think that they are moving their left hand. In the second recording they were looking right and thinking that they are moving their right hand. In the third recording they were instructed to blink every two seconds. All three recordings lasted for five minutes.

After processing the raw EEG data everyone has 97 feature vectors for each input of the classifier. The average classification accuracy is 94.86%, ranging from 88.73% to 100%.

*2) **Online Testing**:* All the participants had never been part of a BCI game experiment. An experienced researcher, familiar with the procedure, explained the protocol to the subjects before the beginning of the experimental process. After the recordings and the offline processing the subjects started to play the game. They had 10 game trials in order to get familiar with the game environment and the Unity engine. After the familiarization process, subjects played the game 10 times in order to evaluate the online procedure. Two evaluation metrics were used, being the total number of collected coins collected and the total number of coin clusters. A coin cluster is considered completed if at least one of its coins is collected from the player. Table I shows the results of the online testing (average number of coins and number of clusters for the trials for each subject).

TABLE I. MI BCI GAME

	Average #Coins	Average #Clusters	Classification Accuracy
Subject1	27.9 (55.8%)	10.2 (60%)	88.73%
Subject2	37.6 (75.2%)	13.5 (79.4%)	99.31%
Subject3	29.6 (59.2%)	10.7 (62.9%)	100%
Subject4	27.7 (55.4%)	10.2 (60%)	96.25%
Subject5	38.9 (77.8%)	13.5 (79.4%)	90.10%
Subject6	29.8 (59.6%)	11.2 (65.8%)	97.26%
Subject7	24.7 (49.4%)	9.1 (53.5%)	92.43%
Average	30.88 (61.77%)	11.2 (65.8%)	94.86%

It should be remarked that the subjects played the game 20 times, 10 for training and getting familiar with the environment and 10 for the testing phase. All 10 recordings from the testing phase were used in the analysis, unless there was an error with the equipment (EEG device moved or Bluetooth connectivity issues); in this case the recording was repeated. Although the participants played the game for testing strictly 10 times it was observed that they got better in every repetition. Subjects 2 and 5 had the best overall performance, with subject 2 achieving the highest score, collecting 47 coins in his final try. These two participants almost had perfect control of the in-game avatar and the only coins that they couldn't collect with ease was the coins in the air. Subjects 1, 2, 4 and 6 had quite good performance and they were able to collect at least 32 coins in their last tries . Subject 6 was able to collect 40 coins in his last round of playing. Subject 7 had the worst scores in the experiment because the classifier couldn't identify his left movement fast enough. The average coins collected from all participants is 30.88 (61.77%) and the average clusters is 11.2 (65.8%).

Table II presents a comparison between our paper and related work.

TABLE II. COMPARISON OF BCI CONTROLLED GAMES

Authors	Subj	Repetition per Subj	Results
Bordoloi *et al.* [5]	13	-	Classification results: 64%
Pires *et al.* [4]	2	-	Classification results: 70% - 75%
Gezgez & Kaçar [3]	1	8	Game score results: Game finished in 25 sec
Our Paper	7	10	Classification results: 88.73% - 100% Game score results: 30.88 (61.77%) coins 11.2 (65.8%) clusters of coins

Bordoloi *et al.* [5] developed a maze game to evaluate the BCI performance. Command accuracy was between 60% - 70%. Support vector machine (SVM) was used as the classifier. Pires *et al.* [4] designed a tetris game. They used Fisher linear discriminant (FLD) classifier that lead to 70% - 75% classification results. Both the participants managed to control the game with two motor imagery commands. Gezgez & Kaçar [3] used three classification algorithms, and for evaluating the game they created a time-based score which measures the time until a user completes the game.

VI. CONCLUSION

In this paper a BCI game with three different Motor Imagery commands is developed. Unity Engine was used to create the 3D game and OpenViBE platform was employed for the BCI development. For recording the raw EEG data, Muse 2 headband was used.

Seven subjects participated in the experiment and played the BCI game. The goal was to collect coins using mental commands. After getting familiar with the BCI environment, subjects were able to control the in-game avatar with high precision. It was observed that some subjects could fully control the avatar while the rest had difficulty using a certain mental command (left Motor Imagery). Nevertheless the results are very promising for future research on BCI game development.

In the future, the goal is to add one more mental command, Motor Imagery of moving both legs for going forward, so the movement of the in-game avatar would be entirely from mental commands. Lastly more subjects will participate in the experiment and different EEG devices will be used.

In this work the BCI application was based on a 3D MI game. In the future more BCI applications will be employed for commanding autonomous vehicle such as wheelchairs and for controlling augmented or virtual environments.

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