Intra-User Analysis Based on Brain-Computer Interface Controlled Game

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***Abstract*—Brain computer interface (BCI) technology represents a growing field of research with extensive applications. This paper focuses on the use of brain signals as a direct communication pathway to an external device. Our goal was to implement a 2D game and control it using a commercially available electroencephalography (EEG) device, by developing an appropriate BCI. The proposed method consists of recording and processing EEG data using the Muse 2 headband, in order to control a 2D game built on Unity game engine. Five subjects were included in the study and each of them played the game when it was trained using EEG data from all other participants (including themselves). Results indicate that participants tend to achieve better scores when the BCI has been trained with their own EEG data, however this is not applicable for all subjects. Furthermore, longer periods of playing the game led to increased control.**

***Keywords*—Brain computer interface (BCI); Electroencephalography (EEG); Game; Muse; 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 a computing device and the brain's electrical activity [1]. Research on BCIs began in the 1970s and was mainly directed towards medical applications. Nowadays BCI research is very wide including various non-medical applications, such as gaming. Through all these years of research, now it is possible to accurately control machines with the power of the brain.

In general, BCIs can be divided into two categories, invasive and non-invasive. Invasive techniques require an electrode array positioned directly in contact with the human brain. This category produces a high quality signal in terms of noise, amplitude and raw data. However, it is mainly used in severely disabled patients because of the dangers that involves.

On the other hand, the non-invasive techniques are based on electrodes positioned on the scalp in order to measure the brain's electrical potentials (EEG) or the magnetic field (MEG). It is a safer, cheaper and faster technique and most of research is focusing on this method. These devices have been successful in giving a patient the ability to move muscle implants and restore partial movement [2]. Techniques' main drawback is, is that the signals are distorted and contain several artifacts. The most common non-invasive device is known as an electroencephalograph (EEG). The electrodes can read brain signals. Regardless of the number or location of the electrodes, the fundamental BCI mechanism is the same, i.e. it processes the EEG signal to identify specific patterns.

In this paper a method to build a BCI controlled game is presented. Interaxon's Muse 2 headband is used to collect EEG signals from several users. OpenViBE software is used for recording the EEG data of the players, the offline signal processing and classification and for the real-time acquisition and online EEG analysis and classification. Unity software was used to develop the 2D game in which the player has to overcome certain obstacles using the Muse 2 headband and the BCI software.

II. Related Work

Several studies, aiming to connect BCI's with gaming, have been published. Their main goal was, to build a game controlled by the brain from start to finish, improving the overall experience of the user.

Malete *et al.* [3] discusses the use of brain signals as a primary communication pathway to external hardware. They designed a game in Unity 3D where the character walks inside a maze and collects coins to earn points while trying to solve the maze and discover hidden treasures to score points. The proposed method consists of recording and processing the EEG data using the Emotiv Epoc+ headset. Support vector machine (SVM), linear neural network (NN) and decision trees (DT) were used for EEG features classification. The overall system performance was promising.

This work has been co-financed by the European Union and Greek national funds through the Operational Program Competitiveness, Entrepreneurship and Innovation, under the call RESEARCH – CREATE – INNOVATE: "Intelli– WheelChair" (Project Code: T 2EK-02438). Also, this work is partially supported from project "AGROTOUR - New Technologies and Innovative Approaches to Agri-Food and Tourism to Boost Regional Excellence in Western Macedonia" (MIS 5047196) which is implemented under the Action "Reinforcement of the Research and Innovation Infrastructure", funded by the Operational Programme "Competitiveness, Entrepreneurship and Innovation" (NSRF 2014-2020) and co-financed by Greece and the European Union (European Regional Development Fund).

Cao and Yun [4] developed an online human-agent interaction system using a BCI to control an avatar in Unity platform. Also, the system provides the capacity to visualize the EEG signals including the pre-processed temporal data and the power spectrum in three frequency bands. The designed scenario in Unity is a kart game, where the avatar requires to complete three checkpoints within sixty seconds to finish the game. In the testing phase, the agent used the processed signals and managed to win the game.

Gezgez and Kaçar [5] designed a two level 2D game that provides virtual character control with both BCI and HCI. Emotiv Epoc + was used to translate mental commands and facial expressions into in-game character movement. The system was trained to be able to execute two commands, ”forward” and ”shoot”, which were assigned to the buttons M and F respectively. Initially, the system was trained with the mental commands ”Right” and ”Push”, corresponding to forward and shoot for the character and then with the facial expressions ”Smile” and ”Clench”, again matching the forward and shoot commands. The results showed that BCI is temporally delayed compared to HCI. The average completion time for level 1 and level 2 is 8.4 and 10.6 seconds using the HCI. When using the BCI with mental commands the completion time increased to 41.9 and 56.5 seconds for levels 1 and 2. Likewise, facial expressions completion time was 39.4 and 41.4 seconds for the two levels.

III. Methods

The proposed method was developed using the OpenViBE BCI software [6], which is a free and open-source platform for designing, testing and using Brain-Computer Interfaces. OpenViBE provides both an Acquisition Server and a Scenario Designer. The Acquisition Server provides drivers for communication between software and some BCI devices. The users can develop their data flows in a tree view environment with Scenario Designer . The platform consists of software modules, “Box algorithms”, which can be integrated to create BCI for both real and VR applications. These Boxes implement existing algorithms, which the developer can use to start an OpenVibe scenario.

A. *Offline Processing and Classification*

1) Acquiring EEG Data: In this paper, the Muse 2 headband, which is an accessible EEG device, was used for data acquisition. It is a commercial EEG headband that connects to a computer via (Bluetooth). It is lightweight, flexible and easily worn. Muse 2 uses four EEG electrodes, two on the left, two on the right and a ground electrode as it is shown in fig. 1. OpenViBE acquisition server is used for acquiring the EEG data. The Muse 2 is not in the list of the default headsets that OpenViBE can connect to so a lab streaming layer [7] (lsl) stream was created through BlueMuse [8]. Then the ”Acquisition client” box is used and the raw data are being saved in CSV files.

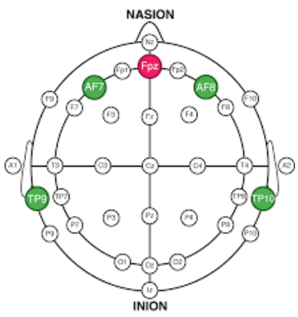

Fig. 1. Muse 2 electrodes on 10-20 electrode positioning system.

2) Input Signal: To import the training signals the “CSV file reader” box is used. Features extracted from the pre-recorded EEG signals were used as a training dataset. In the current scenario two different EEG signals should be imported (one for each class). The time of the off-line phase is equal to the duration of the entire EEG input signal plus the execution time of the classification algorithm.

3) Time Epoching: Time epoching is a frequently used method in EEG analysis. Epoching is a procedure in which specific time-windows are extracted from the continuous EEG signal. The proposed approach employs a “Time Based Epoching” box, where each epoch last for 2 seconds, while the epoch interval offset is 1 second.

4) Signal Processing and Feature Extraction: After importing the raw data from the EEG recordings a temporal filter is applied to reduce the artifacts. The ”Temporal filter” box applies a Band Pass filter between 8-40 Hz. Then spectral features are extracted. In this scenario ”Spectral Analysis” box is used which is the Fast Fourier Transform. Then the ”Frequency Band Selector” is used which splits the EEG spectrum into three bands: 1) Alpha waves 8-13 Hz 2) Beta waves 13-30 Hz and 3) Gamma waves 30-40 Hz. Finally, the average spectral amplitude per band is calculated and then used as input to “Feature Aggregator” Box.

5) Classification: For the classification, the linear discriminant analysis (LDA) algorithm is used [9]. The results of the trained classifier are stored in an XML file to be used in the real time training. Training Scenario is presented in detail in Fig.2.

B. *Real Time Classification*

After the off-line processing and classification have been completed, the real-time testing can start via the Acquisition Server. All the boxes except, the ”Time based epoching” box, that have been used in the training scenario are used again but in this case only one time is enough. Fig. 3 illustrates the Testing Scenario, where the results of the classifier are exported through the ”LSL Export” box as a Markers stream.

IV. Game design

In order to build the game used in this study, Unity game engine was employed. Unity is a popular cross-platform game-

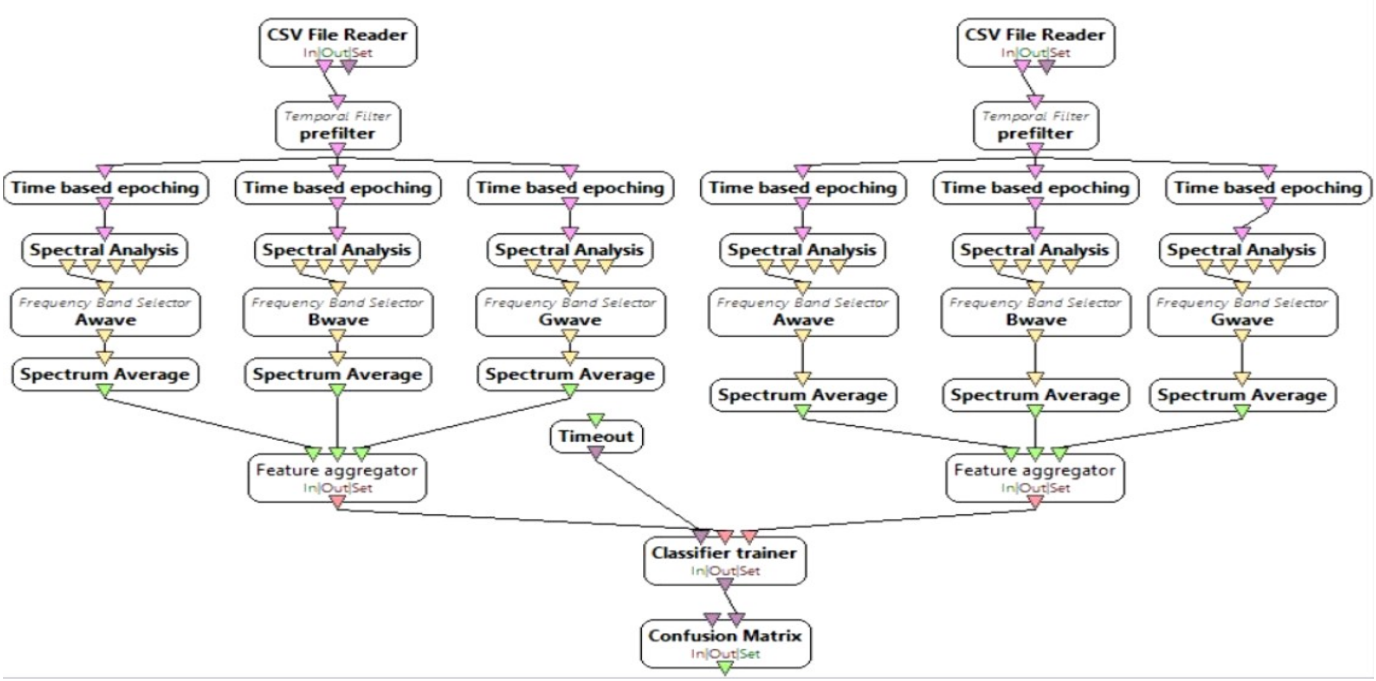

Fig. 2. OpenViBE training scenario for the EEG processing and classification (offline).

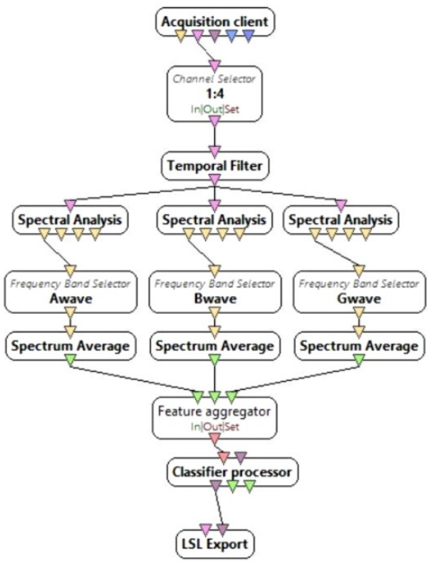

Fig. 3. OpenViBE real time EEG processing and classification scenario.

developing engine, developed by Unity Technologies Company, and is widely used in 2D and 3D game developing[10]. The engine can be combined with the BCI software in order to produce BCI controlled games that replace standard control options with EEG signals.

The developed game is a 2D game (a snapshot is presented in Fig. 4). The game consists of a platform on which there is a character that the player must move. The objective of the game is to reach the end of the path by bypassing the obstacles. Obstacles are ”ghost” and ”monster” characters. At the top right of the screen is the score, which increases as the player progresses.

A. Game scenario

For this paper, the ordinary movement commands usually given via the keyboard are replaced with brain commands. The installation of the lab streaming layer library (LSL) allows the application to obtain data from a live stream (Muse 2 Headband in our study). More specifically, the stream outlet component from the LSL library is used, which enables data streams of time series on the lab network. The data is pushed sample-by-sample into the outlet (our game). The samples received from the stream are divided into two categories depending on the command given by the user.

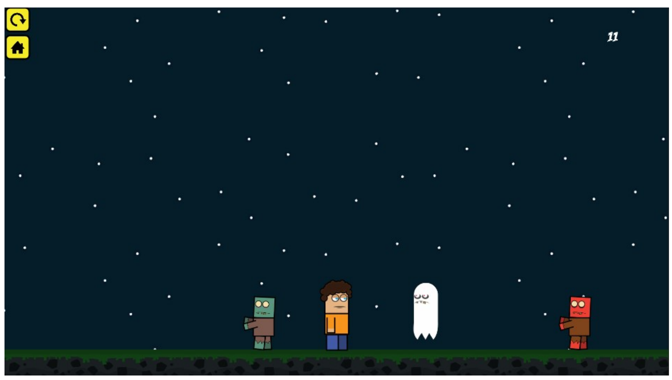

Fig. 4. A snap of the 2D game.

- If the user looks ahead then the sample goes to the first category and the in-game character moves forward.
- if the user blinks, the sample goes to the second category and the in-game character jumps.

V. Results and Discussion

1) Training Dataset: Five subjects, three males and two females, participated in the experiment. All subjects were healthy with normal or corrected to normal vision. They were instructed to sit comfortably in a chair, in an upright position, while trying to hold still as much as possible, and performed two separate recordings. During the first recording, the subjects were instructed to look at the center of the computer screen and think that they move forward and in the second they were instructed to blink every one second. Both of the recordings lasted for eight minutes.

All recorded data from every subject were included in the offline processing and the classifier input consist of 1350 feature vectors (450 for each class). The average classification accuracy is 96.8%, ranging from 89.8% to 99.8%.

2) Online Testing: All the subjects had zero experience in a brain computer interface and in the Unity engine environment. An experienced researcher informed the participants about the procedure and all the subjects got familiar with the device and the protocol before the beginning of the experimental process. After the offline training the subjects started to test the game. In the beginning they had five tries to play in order to get familiar with the unity and game environment. Then, every time they played a score was kept in order to rate the online procedure. The protocol of this online testing was that each subject should play twenty times with the classifier that was trained with their own data and with the classifiers that were trained with the other players data (twenty for each classifier and eighty in total). The average scores are shown in Table I (rows corresponding to the players and columns to the data).

TABLE I. Intra-user BCI-controlled game results

	Subject1	**Subject2**	**Subject3**	**Subject4**	**Subject5**
Subject1	28.30	21.40	16.65	22.30	29.70
Subject2	47	66.40	47.20	54.45	41.45
Subject3	37.60	23.05	44.80	19	25.95
Subject4	28.45	42.65	32.15	25.65	16.20
Subject5	46.25	29.20	52.10	55.70	34.70

TABLE II. Comparison of averaged scores

	Subjects Data	**All Others Data**	**All Subjects Data**
Subject1	28.30	22.51	23.67
Subject2	66.40	47.52	51.30
Subject3	44.80	26.40	30.08
Subject4	25.65	29.86	29.02
Subject5	34.70	45.81	43.59

Table II shows the average score of every subject with their own EEG data ("Subjects Data" column), with the EEG data of the other participants ("All Others Data" column) and with all the data that have been recorded for the experiment ("All Data" column).

After playing the game a few times, the participants gradually adapted and achieved better scores. It should be noted that the subjects had to play the game for 40 or more times until they managed to finish it successfully at least once. Subjects 1, 2 and 3 had overall better performance and finished the game with their own EEG data, while subjects 4 and 5 managed to score higher in a classifier that had been trained with someone else's data. The average game results for all subjects when playing the game trained with their own EEG data is 39.97, while respective results when playing the game trained with all other EEG data (except the current user) is 34.42.

Comparative study with other BCI controlled games presented in the literature is shown in Table III.

TABLE III. Comparison of BCI Controlled Games

Authors	**Subj**	**Repetition per Subj**	**Results**
Malete *et al.* [3]	11	-	Classification results: 49% - 56%
Cao & Yun [4]	1	-	-
Gezgez & Kaçar [5]	1	8	Game score results: Game finished in 25 sec
This work	5	100	Classification results: 89.8% - 99.8% Game score results: 39.97 with own EEG data 34.42 with other EEG data

The works from Malete *et al.* [3] and Cao & Yun [4] mainly focused on the EEG classification and did not present any results for the BCI controlled game. Cao & Yun [4] used a convolutional neural network (CNN) to build the classification model while Malete *et al.* [3] tested several classification algorithms. Gezgez & Kaçar [5] used three classification algorithms, and a time-based score was employed to evaluate the game, which measured the time until the player finished the game. In this work, both classification and game score results are measured and the intra-user correlation while playing the BCI controlled game is evaluated.

VI. Conclusion and future work

In this paper a BCI controlled game was developed and used to evaluate the intra-user variability in terms of game score. OpenViBE platform was used to develop the BCI while Unity game engine was employed for the creation of the game. The Muse 2 headband was used to record the raw EEG data and LSL was used to connect the data to the BCI.

Five subjects participated in the experiment, each one playing the game when it was trained with their own EEG data and with the EEG data from each other participant. The obtained results indicate that the results were significantly higher (on average) when playing the game trained with their own EEG data, however 2 participants achieved higher scores when playing the game trained with other user's EEG data.

In the future, more levels will be created with increased difficulty and more characters will be added for the players to choose. Additionally the goal is to increase the number of commands from two to four, so the character can move backwards and crouch. Another important addition will be the overall BCI game control, including all initial manual selections in order to enhance the BCI experience.

In this study the BCI application was based on a simple game. Further studies will include the application of BCI in different research areas such as interaction with various software applications, control of virtual or augmented environments and wheelchair or other autonomous vehicle navigation.

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