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Multiplayer video game control via motor imagery BCI using consumer-grade EEG-headset

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Abstract — Motor imagery (MI) is a commonly used brain response for a variety of Brain-Computer Interface (BCI) applications, one of them being controlling video games. In this project, we investigated whether it is possible to allow a competitive multiplayer gaming experience using the non-invasive recording method of electroencephalogram (EEG). For this purpose, a Unicorn Hybrid Black EEG headset was used to gather and then label raw data from different subjects. After pre-processing the gathered data, random forest classifiers were trained for each subject. The trained model could thus make online predictions about the intended game controls and had a prediction accuracy better than random guessing (33%). The setup was finally used to allow two players to compete against each other in a simple video game we developed.

1 Introduction

A system that establishes a communication pathway between the brain and a specific device, by measuring central nervous system activity and enabling measured signals to control or enhance an external feature or activity is known as a Brain-Computer Interface (BCI). Primarily, BCIs are used for medical applications, such as neuronal rehabilitation and assistive devices for physically challenged or locked-in patients [1]. However, nowadays non-invasive EEG based BCIs are getting adopted in other fields as well, for example in the entertainment sector.

In the scope of this report, a use case for gaming purposes was investigated. This is of great interest, because BCIs are one of the most rising technologies in the video game industry. This shouldn't be surprising, since the promise of this emerging technology is to enable players to tap into games using only their brain signals, resulting in a brand-new gaming experience.

At this stage, the most feasible option to incorporate BCIs to gaming is by using non-invasive recording techniques, simply because these recording methods do not require the skin or the skull to be penetrated. In this project, being one of the most widely used and easily accessible non-invasive recording methods, the electroencephalogram (EEG) was used. We utilized the Unicorn Hybrid Black EEG headset, which is a consumer-grade 8 channel EEG system that is able to measure and output raw EEG data in real-time to a host personal computer (PC).

EEG-based BCIs come with many limitations. Most notably, the measured EEG signals are uniquely person-specific and relatively noisy. The used EEG system adds a number of challenges on top of these. Firstly, we had to use dry electrodes even though conductive gel can be applied to the electrodes to use them as wet electrodes. Not applying any conductive gel and thus using the electrodes as dry electrodes resulted in larger impedances. Secondly, the low number of electrodes and the big gaps between them (unlike research-grade systems) allow only relatively large-scale neural activity measurements, resulting in a more generalized gathered data.

To compensate the low signal quality and the scarcity of measurement zones in the used EEG system, the motor imagery (MI) BCI paradigm was relied upon. The captured EEG data was then pre-processed and used to train machine learning (ML) models. Finally, the probabilistic predictions of the ML models would serve as players' inputs for controlling the game.

2 Theory

2.1 EEG

As mentioned before, EEG is a popular non-invasive technique for recording signals from the brain by placing electrodes on the scalp with the help of a fabric cap. The signals reflect the summation of postsynaptic potentials from many thousands of neurons that are oriented radially to the scalp. EEG predominantly captures electrical activity in the cerebral cortex and typically has a good temporal resolution but a poor spatial resolution. Furthermore, the measured signals are in the range of a few tons of microvolts meaning that they can be easily corrupted by muscle activity and nearby electrical devices, for example the power lines. Due to this reason, the very high and very low noise are typically filtered out using a band-pass filter. [2]

2.2 Motor Imagery

Motor imagery can be defined as a dynamic state during which a subject mentally simulates a given action [3] and it is widely used as a BCI paradigm. It typically produces neural activity that is spatiotemporally similar to the activity generated during actual movement, but smaller in magnitude. [4]

It is shown that primary sensorimotor areas are activated by MI, accompanied by a desynchronization of the mu-rhythm (10–12 Hz) with a circumscribed "event-related desynchronization" (ERD) for the hemisphere contralateral to the used arm. [2] [5] Thus, the left and right hand imagery can be distinguished by placing electrodes on the sensorimotor cortex. This concept was already put into use for other gaming applications. [6]

3 Experimental Setup

3.1 Gathering the data

To be later used during the offline training, raw data had to be gathered from each subject. It is noteworthy to mention that before coming to this conclusion, we considered two other options. First was to use the data provided by the Berlin BCI group (data set 1d) for the fourth BCI Competition that is available at http://www.bbci.de/competition/iv/#download. Since the downsampled data had a sampling rate of 100 Hz, we considered either upsampling it to 250 Hz to match the sampling rate of our recordings or downsampling our data to 100 Hz. In the end, the problem was not with the sampling rate but rather due to the low accuracy of the predictions when the model was trained on this data set. The second consideration was to record extensive data from one subject and use this data to train one model to use for predicting each subject's intentions. This attempt also resulted in a low performance. Eventually, it was decided to record raw data from each subject and to build separate models for each of them, thus personalizing the gaming experience in the progress.

After all these considerations, the EEG signals were recorded in 1 second chunks over 8 electrodes with a sampling rate of 250 Hz determined by the EEG system being used. Thus, each second of recorded data corresponded to a 250x8 matrix with the columns representing the different electrodes and the rows representing each measurement. For the sake of convenience, from now on such a matrix will be referred to as a "sample".

For recording purposes a custom Python script was written. When run, the script would start off with a 6 seconds resting state, in which the subject had to relax. The first few seconds of this initial trial would then be discarded, taking the adjusting period into consideration. After the initial resting state, either left or right hand imagery was picked randomly by the script and the result was displayed on the screen with the help of arrows showing in the picked direction. The subject had to focus on the corresponding MI for a duration of 4 seconds. After each trial there was another 4 seconds of resting state. The script would also automatically label the gathered data to one of the three labels: idle, left and right. This process was repeated until the predefined number of trials was reached.

3.2 Implementation of the game

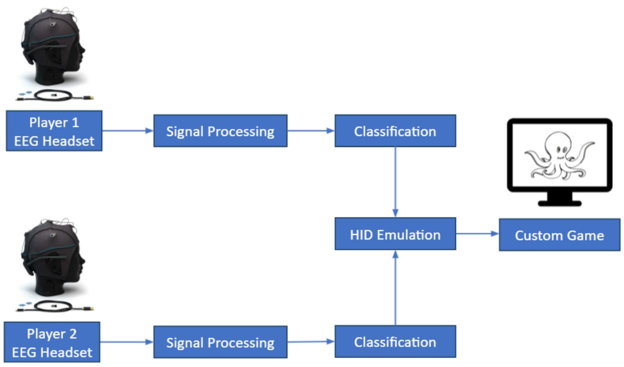

Figure 1 Overview of the implemented BCI system for the two player game control

Figure 1 provides a graphical overview of the implemented EEG-based BCI system. During gaming, both of the players were wearing Unicorn Hybrid Black headsets. Raw EEG data recorded from the headsets were sent over Bluetooth to a common host PC, which performed the necessary signal processing and subsequently online prediction based on the pre-trained classifiers. Lastly, as the players imagined moving their right or left hands depending on where they wanted to move the octopus avatar residing in the middle of the custom game designed using the Unity engine, the predicted outputs from both of the players were compared and the "stronger" signal was used to emulate the corresponding Human Interface Device (HID), for example the keyboard controls in this case.

4 Signal Processing

As mentioned before, the gathered data was very noisy. Moreover, different electrodes had different sensitivities and bias values. Due to these reasons, pre-processing of the acquired signals was necessary.

As discussed above, MI generates rather low frequency signals and to filter out the unwanted high frequency noise, a band-pass filter between 0.1 and 30 Hz was applied to the data. This automatically eliminated the 50 Hz noise from the electric grid.

Using a common heuristic [7], the logarithm of the variance of the band-pass filtered data was computed. This transformation will be denoted as "logvar", where i denotes the channel index:

$$x_{i,logvar} = log(var(x_i)) \tag{1}$$

This transformation allowed computing how strongly the signal varies at different channels during 1 second time intervals. The logarithm helped with bringing these computed variances within a confined range. This transformation also reduced the dimensionality in which each sample was reduced from a matrix to a vector. So each sample was now just a vector of length 8. In Figure 2, we depict the signals after the logvar transformation averaged over all signals of the same label, in this case for the subject 1. One can immediately detect two problems. First, different electrodes have different sensitivities and therefore different average variances overall. Second, it is very hard to differentiate between different types of MI. However, for example at the C4 electrode, one can already observe a stronger signal for the left hand imagery.

To mitigate all these issues, the mean of the idle state was subtracted from all the signals. The resulting averaged signals for three subjects are shown in Figure 3.

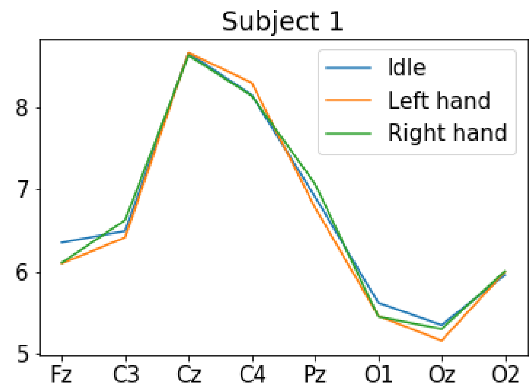

Figure 2 In this graph the signals after the logvar transformation are shown. They are averaged over all samples with the same label. As one can see, it is hard to differentiate between different types of signals due to the different sensitivities and biases of different electrodes.

After all these transformations one can immediately observe a stronger signal at the C4 electrode for left hand imagery and at the C3 electrode for right hand imagery. To summarize, the pipeline for the pre-processing can be seen in Figure 4.

5 Machine Learning

5.1 Offline Learning

As one can see in Figure 3 signals for different subjects drastically differ, even though exactly the same transformations were applied to each subject's data. So, to use these features in the game we decided to train a separate classifier for each subject. This step allowed the personalization of the gaming experience for each player. In the following, the processing done on the data from Subject 1 is demonstrated, but the exact same processing is done for the rest of the subjects as well.

As the first step, the data was scaled using a standard scaler and then divided into representative training and test sets. There was nearly 2-3 times more data for the idle state than for both of the MI tasks combined. This resulted in an unbalanced data set. To tackle this issue, data for the idle state was randomly eliminated until there were nearly equal data points for each class. A corresponding representation of the split after balancing out the data set can be seen in Figure 5.

To determine the best model for this particular application, the accuracies of different classifiers provided in the scikit-learn package were compared

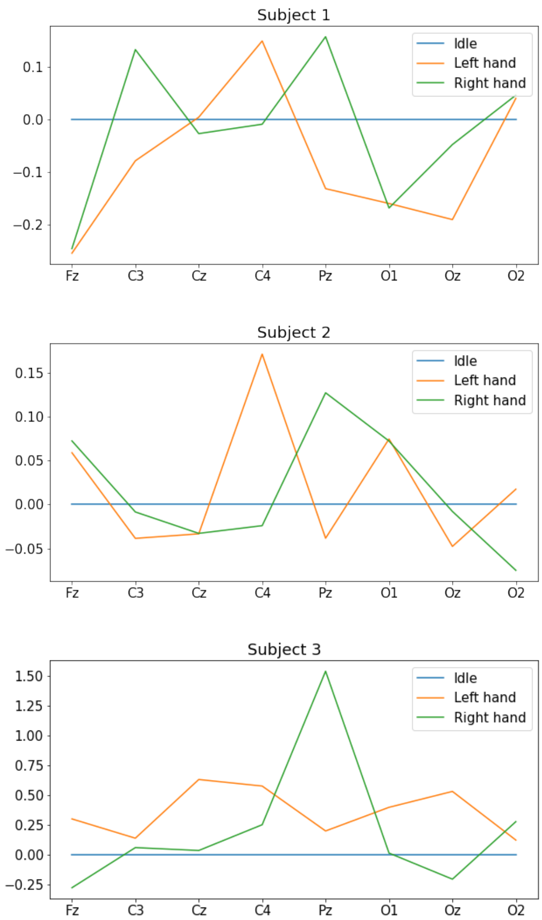

Figure 3 The resulting signals for each subject after the mean of the idle state is subtracted from the average over all the logvar transformed samples with the same label.

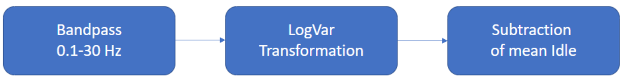

Figure 4 Schematic visualization of the signal processing pipeline

without any hyperparameter tuning. This comparison of "out-of-the-box" models, that can be seen in Figure 6, gave an overview of the best possible models to consider. Based on this comparison we decided to proceed with the random forest classifier.

After tuning the hyperparameters of the random forest classifier we arrived at an accuracy of 51.1% for Subject 1 with the following hyperparameters: ['bootstrap': True, 'min_samples_leaf': 1, 'min_samples_split': 2, 'n_estimators': 100]

In Table 1 you can see the results for all three of the subjects.

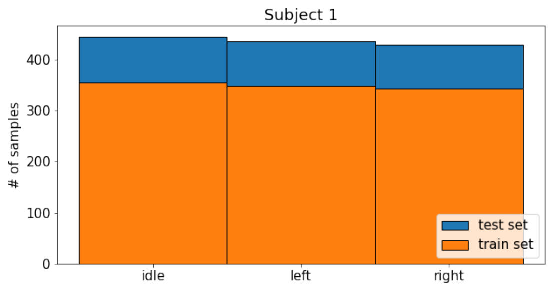

Figure 5 Exemplary training and test set split for the Subject 1

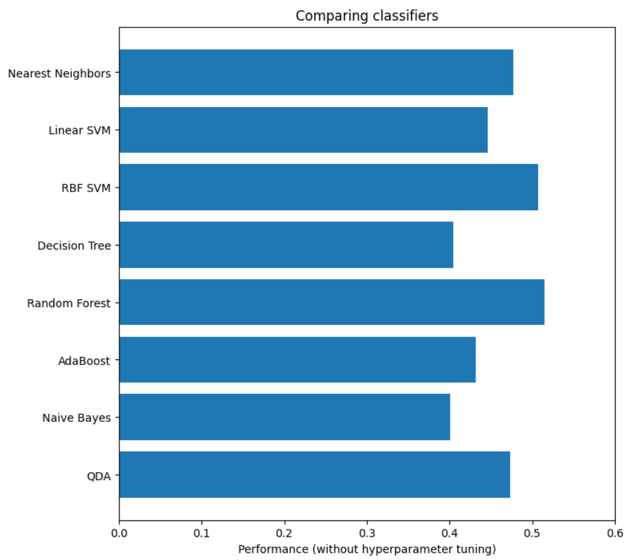

Figure 6 Comparing classifiers for three different classes (idle, left, right). Random Forest classifier performed best with the accuracy of around 50%.

5.2 Online Prediction

Once again for the online prediction, the pre-trained classifiers of each subject were used. Before the game started, the subjects were asked to sit still for a few minutes to gather "idle" data. This data was averaged and then subtracted from each signal sample to reproduce the form of the data used for offline training.

6 Results

This project aimed to allow a competitive multiplayer gaming experience using EEG-based BCI by utilizing MI paradigms to control the video game. Towards this aim, the gathered data from each subject was pre-processed and trained using random forest classifiers. After this offline learning, the trained models were put into use for online predic-

Sbj.	# samples	Best	Confusion matrix
1	1877	51.1%	$\begin{pmatrix} 0.56 & 0.24 & 0.2 \\ 0.32 & 0.46 & 0.22 \\ 0.27 & 0.23 & 0.5 \end{pmatrix}$
2	753	48.9%	$\begin{pmatrix} 0.53 & 0.26 & 0.21 \\ 0.32 & 0.58 & 0.1 \\ 0.41 & 0.26 & 0.33 \end{pmatrix}$
3	1004	63.4%	$\begin{pmatrix} 0.49 & 0.12 & 0.39 \\ 0.14 & 0.76 & 0.1 \\ 0.23 & 0.05 & 0.73 \end{pmatrix}$

Table 1 In this table we summarise results of classifier training for all 3 subjects (Sbj.). "# of samples" is the total number of samples used for training and tasting classifiers. "Best" is the best accuracy achieved after hyperparameter tuning with a corresponding confusion matrix.

tion. Hence, the two players could play against each other by imagining the hand movement to direct the octopus avatar in the desired direction. Whoever had a "clearer" signal that could be easily and correctly classified with the trained model would win in the end.

Our findings show that, even with simple models accuracy rates over random guessing can be achieved. The possible explanation to the rather low performance of the designed BCI system could be that the captured signal quality was not good enough to be used as features. This shows the importance of developing systematic methods to analyze the signal quality of the captured EEG data.

Another explanation could be that, not enough data was gathered to make meaningful predictions. Even if this is the case, one has to bear in mind that there is not always a direct correlation between the amount of gathered data and the performance of the model. This can most easily be seen in the Table 1. Even though the Subject 1 has the highest number of collected samples, his model's accuracy is lower than the model of Subject 3.

Also worth mentioning is that, an estimated 15-30% if the BCI users are "BCI illiterate", meaning that BCI control does not work well with these users. But fortunately this can be increased over time with the help of more focusing from the BCI user and also by "coadaptive calibration" done during ML. [8] It is not out of question that the subject were not very BCI literate.

One last thing to note is that, at this stage gathering the data takes a long time. Each subject had to do MI tasks for ca. an hour to gather the data we used for the project. Since it is a necessary step for individual model training, that cannot be skipped so easily, developing new methods to decrease training time will be of crucial value in future applications.

7 Conclusions

In this project we have shown a feasible way of using non-invasive BCI to allow a multiplayer gaming experience. Even though the accuracy was not high enough to use this system as a main gaming platform yet, the results are promising. We are comfortable that with slight tweaks, this system could develop into a technology that would allow an even more enjoyable gaming experience.

8 The Future of Brain-Computer/Machine Interfaces

While most certainly BCIs will be used more frequently in the future, the video game industry is a particularly thrilling and promising sector. Valve Corporation, which is nowadays among the leading video game companies in innovation, is researching and developing real-time adaptive gameplay features powered by BCIs [9]. Engagement in a video game creates a strong emotional response, which can then be theoretically measured by recording methods, such as EEG, and precisely represented on an arousal-valence emotion plane. Based on this knowledge, a lot of aspects can be incorporated into video games. Some examples that can be adjusted depending on the player's current state could be the difficulty level, the environment or the general appearance of the game. Endless possibilities of alterations to the game could make them more personalized and thus ensure a more enjoyable gaming experience. The emotional recognition could also play a huge role in neuromarketing, such as sellers basing their recommendations for entertainment products according to the short- and long-term emotional data gathered about consumers.

The results of the project have verified, that even relatively low-cost EEG hardware can be viable replacements for traditional video game controllers. It might take many years, perhaps decades, until BCI based game controllers can compete on a consumer market however, this could most certainly become out new reality. For instance, Microsoft actively conducts research on mainstream BCIs for healthy users, utilizing comfortable and affordable BCI systems. Mainstream adoption would create higher competition, which in turn would bring BCI system costs down. The main challenge that remains is to create user-friendly and seamless devices and develop better classification methods with mass data sets.

Another important aspect to mention is that, with each new study, the BCI applications are becoming more feasible to use. For example, in a recently published paper a high-performance handwriting BCI is introduced which can achieve up to 90 characters per minute with a raw accuracy of 94.1%. [10] Although it is still not on par with the current typing speeds of average smartphone users (with ca. 180 characters per minute [11]), with big companies like Facebook jumping into the BCI game we can most probably see dramatic increases to the innovation rate of these technologies. This highlights the fact that the future of BCI applications is bright.

9 Human-Centered Engineering

As mentioned, emotion recognition can be a notable research topic in the BCI field along with BCIs being used as game controllers, like explored in this project. While the player controls the game via some sort of BCI, emotional data can be collected and it could provide an insight on the user's internal mental state. There are a lot of techniques for emotional recognition based on facial expressions, verbal speech, or body language. But none of them could be as effective as directly tapping into somebody's internal state. This could open the doors to a novel game testing and quality assurance methods as well as a lot of marketing ideas, as previously discussed, but also to an era of empathy. If emotions end up to be transferable information, in the future people may not need to bother with explaining themselves to others and might just occasionally allow others to connect directly to their internal state to show how they feel. Feeling first-hand what another person feels will hopefully make people realize what other people are going through. Although, this technology could of course be used in malignant ways, it is up to our society to show how new technologies are going to be adapted.

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Appendix

The documented source code for the implemented BCI system setup is available under following link: https://gitlab.lrz.de/ge57yog/hackathon-bci-multiplay

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