Advancing Real-time Brain Computer Interface with Electroencephalography

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Abstract and/or Background

The purpose of this research is to develop an asynchronous motor imagery brain-computer interface (BCI) using electroencephalography (EEG) data for real-time applications in robotics and virtual environments. There are many documented paradigms that can be detected in EEG data, but motor imagery is unique to EEG analysis in that it requires no bodily movements and cannot be detected by a camera or other means. The implications of motor imagery based BCI suggest that people who have limited or lost motor function would be able to gain control of a prosthetic limb or a virtual avatar, which may be able to benefit that person's quality of life or emotional state. The majority of recent studies focus on synchronous or cue-based motor imagery analysis, which has been shown to have a high rate of classification accuracy. A synchronous motor imagery classifier involves giving the participant some kind of prompt and then classifying the data that follows for a defined period. However, for a BCI to function in real time, it must be able to classify asynchronous, continuous EEG data so that the user can control the application at any desired time, rather than predefined windows. A reliable, asynchronous motor imagery BCI that can be easily adjusted for different users could greatly benefit people who have limited or lost motor function. Thus, this research focuses on the initial development of an asynchronous BCI with at least three different motor imagery paradigms. Future BCI research may also be applicable in virtual reality or mixed reality environments to benefit the emotional state or mood of persons with limited or lost motor function, or for rehabilitation purposes.

Introduction and/or Research Question

Electroencephalography (EEG) is the process of using electrodes placed on the scalp to record spontaneous electrical activity in the brain. EEG has been used to study many different phenomena, but an increasingly researched area of EEG is that of brain-computer interface (BCI). Typically, a BCI will involve applying a filter to the EEG data, focusing on a specific brainwave frequency relating to the activity that the user is performing, and then training a machine learning algorithm to classify the user's intended action. Motor imagery (MI) is the process of mentally executing the motor control of an appendage without any physical muscle movement (Abiri et. al., 2019). It involves imagining the sensation or feeling of a certain movement, rather than picturing what that movement looks like or physically moving a part of the body. MI is unique to EEG processing because it cannot be detected by any other means, e.g., a camera or eye tracker. Thus, it may be possible for persons with limited or lost motor function to be able to gain control over assistive devices using imagery (Ang et. al., 2015). MI-based BCI training involves providing instruction via visual cues to the user on what imagery task should be performed, with the user having been informed which cues represent each MI task. A machine learning classifier is then created and trained on the EEG data recorded from these cue-based, or synchronous, training sessions. Extensive training sessions may be necessary in order to train an accurate classifier, as EEG data can be inconsistent and difficult to process. When sufficient training data has been collected, the BCI can be tested in real time with live EEG data following a synchronous BCI system. Most current research involves synchronous MI-BCI systems, which cannot be practically applied to any form of control, as they require a cue for the classifier to correctly identify the data (Han et. al., 2020). There is significantly less research available on asynchronous BCI systems, as they are more complex and difficult to create. For a BCI to be fully asynchronous, it must classify the non-control state in addition to any motor imagery events. This initial research works toward advancing the field of asynchronous motor imagery BCI systems for use in applications such as assistive devices.

Methods

We begin by configuring the electrodes in locations on the scalp for an 8-channel electrode system, in accordance with the International 10-10 electrode system (Figure 1). A bias and reference electrode are also used, placed on the earlobe and forehead respectively. The electrodes are positioned around the motor cortex of the brain as well as the occipital lobe, with some positional limitations due to hardware. OpenViBE, which is an application created for designing real-time brain computer interfaces, is used to create the BCI. The training session begins with 20 seconds of inactivity to capture the user's baseline power. The trials begin by first displaying a fixation cross for 3 seconds, then displaying a left or right arrow for 1.25 seconds, instructing the user to start exercising motor imagery of the respective hand (Figure 2). The feedback duration lasts 3.75 seconds and the trial ends with a randomized resting duration from 2.5-4.5 seconds. There are 20 trials per class in a randomized order, for a total of 40 trials per training session. The data is bandpass filtered from 8-30hz to capture the mu and beta frequencies, and is used to train 3 separate Common Spatial Pattern (CSP) spatial filters: Left vs. Non-Control, Left vs. Right, and Right vs. Non-Control (Figure 3-A). The bandpass filter is applied to the data as well as the previously generated CSP spatial filters, and epochs are created using the cues from the training session with a five second duration and a one second offset to capture the time frame containing the data of interest. Time-based epochs are then created with intervals of 0.125 seconds and duration of 1.5 seconds, and the logarithmic band power is computed. The matrices can then be converted into feature vectors to train a Linear Discriminant Analysis (LDA) algorithm classifier (Figure 3-B). Finally, new EEG data can be classified asynchronously and in real time by using the previous filtration pipeline in addition to the trained LDA classifiers (Figure 3-C). Each classifier's confidence is displayed in a visualization window, with a taller bar indicating higher confidence (Figure 4). The overall accuracy can then be determined by taking the average of the two relevant classifiers' accuracies.

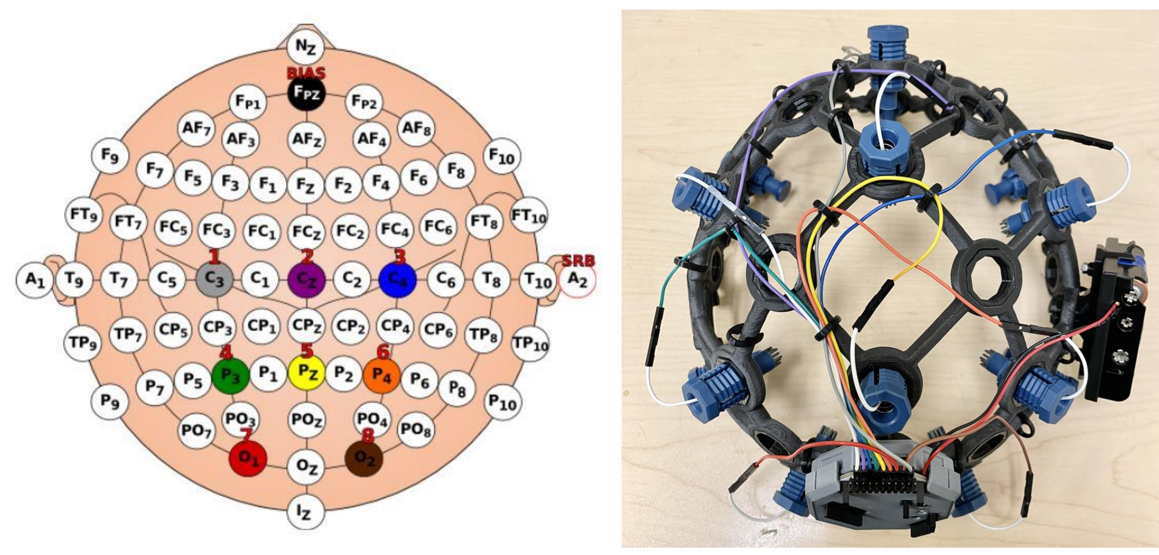

Figure 1. Electrodes configurated in locations C3;Cz;C4;P3;Pz;P4;O1;O2. A bias electrode is placed at FPz, and the SRB electrode is placed at A2.

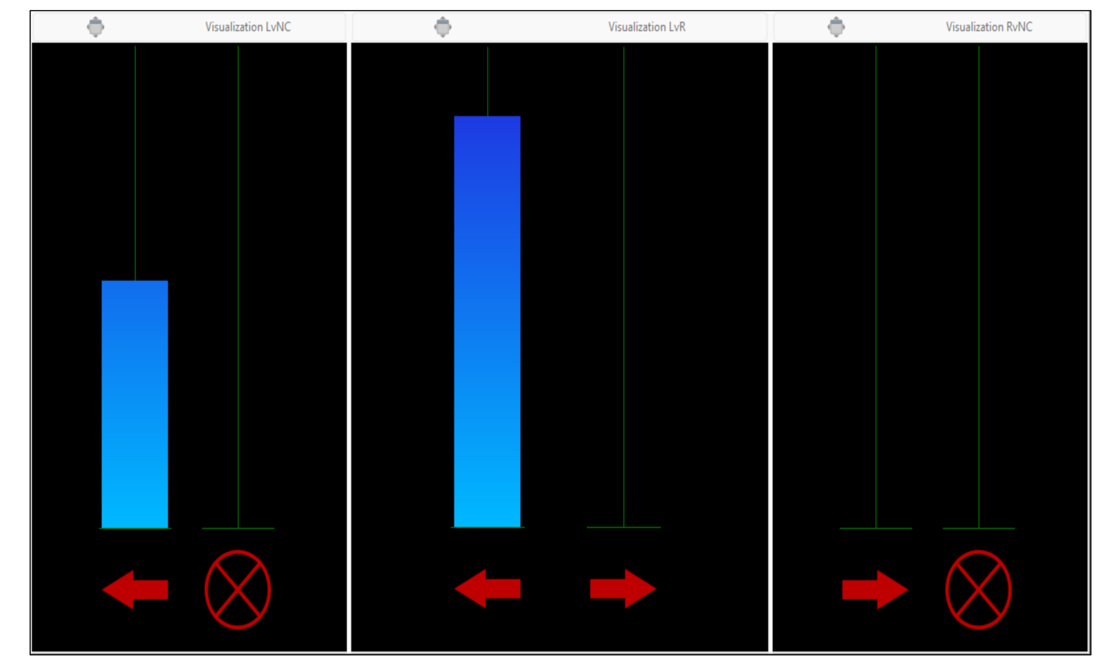

Figure 4. Graz Visualization classifier probability being output in real time. Left and right arrows represent left- and right-hand motor imagery respectively, and the ⊗ symbol represents the non-control state. The blue bars represent probability vs. the alternative class, from 0-100%.

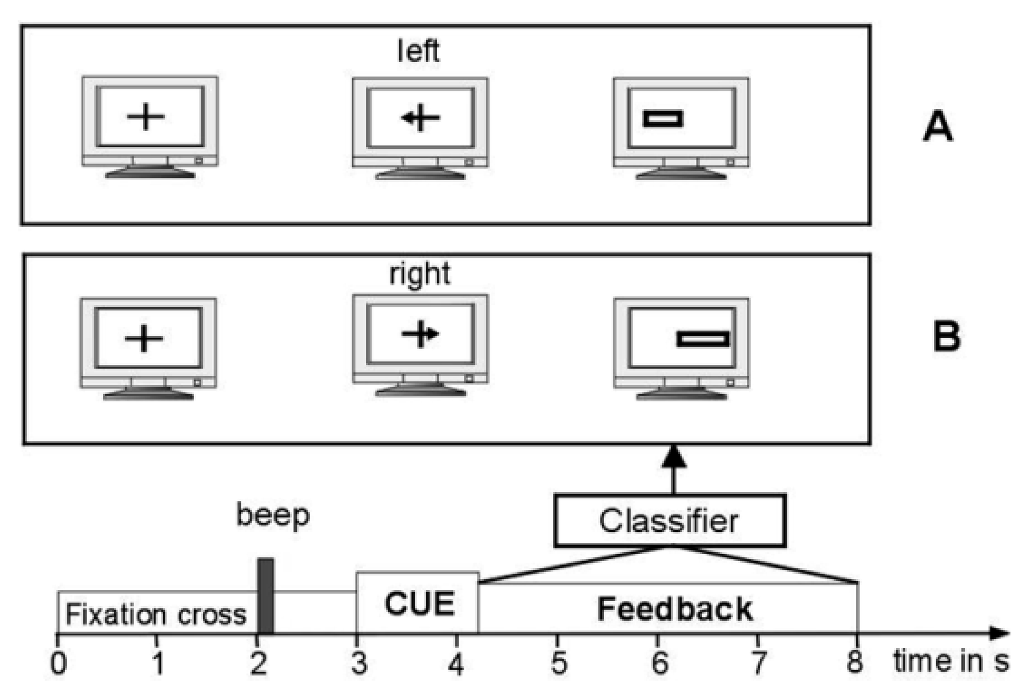

Figure 2. Example of a similar cue-based visualization used for training and feedback of the motor imagery classifier (Townsend et. al., 2004).

Confusion Matrix of Each Classifier

	Left vs Non-Control	
Target→ Result↓	Left	NC
Left	20	0
NC	0	0

	Left vs Right	
Target→ Result↓	Left	Right
Left	19	8
Right	1	12

	Right vs Non-Control	
Target→ Result↓	Right	NC
Right	16	0
NC	4	0

Figure 5. Confusion Matrix of each classifier at the end of 40 trials.

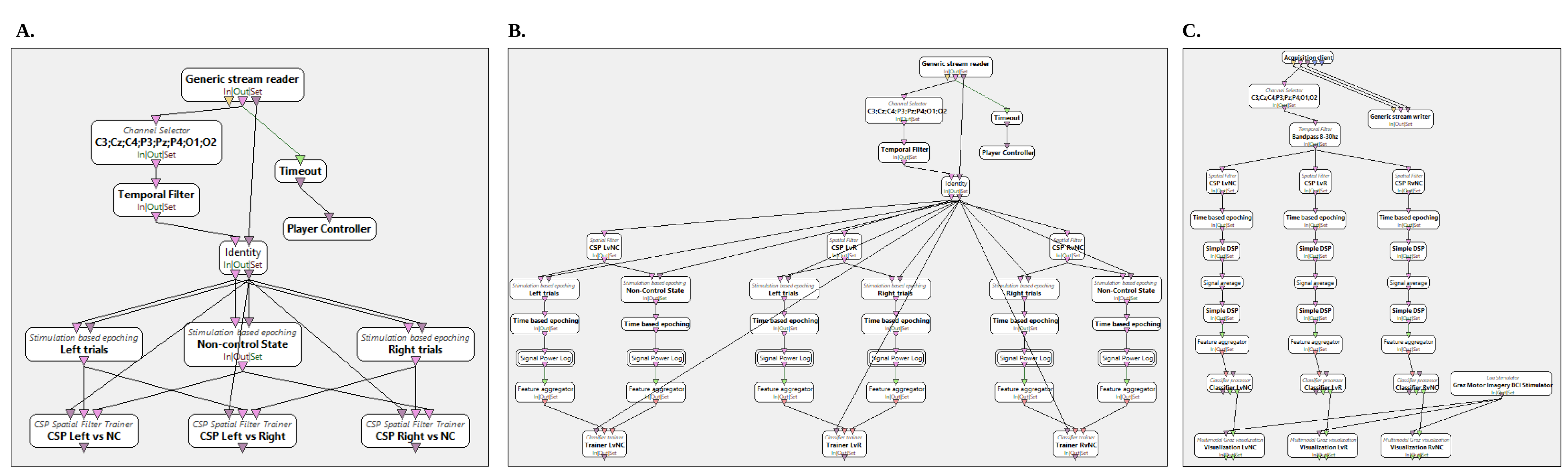

Figure 3. Scenarios created in the OpenViBE Designer, an application dedicated to the design, test, and usage of BCI in real time (Renard et. al., 2010). Scenario A creates a CSP spatial filter for each class comparison (Wang et. al., 2005). Scenario B trains the machine learning algorithms based on the epoched CSP data, using the LDA algorithm method. Scenario C then uses the trained LDA classifiers, along with the initial bandpass filter and CSP spatial filter, in order to classify continuous data in real time.

Results and/or Conclusion

Initial research shows that factoring in a non-control state allows a synchronous BCI to function asynchronously, though it introduces new challenges and can reduce the overall accuracy of the system if not processed correctly. After a session of 40 trials, each classifier resulted in a confusion matrix with accuracies greater than 75% (Figure 5). However, confusion matrices are not the best representation of an asynchronous BCI, since there are no real trials involved after the initial training sessions. The accuracy of an asynchronous BCI can be difficult to definitively measure for this reason and requires factors such as dwell periods and refractory periods to get a better result, which have not been utilized in this research at this point. However, what can be seen from the confusion matrices is that the BCI was able to distinguish left and right motor imagery with 77.5% accuracy. When this same pipeline is applied in a synchronous BCI design, it is able to achieve the same rate of accuracy. The BCI was also able to distinguish hand imagery intent versus the non-control state with accuracy of 80% or higher in both cases. The reason that the confusion matrices do not display trials for the non-control state is that the initial training session did not include set event markers for the non-control state. While those markers are not needed to create an asynchronous BCI, they are needed for a more accurate confusion matrix. During a real-time session using the asynchronous BCI system, it is much more apparent whether the classifiers are functioning with high accuracy or not. The process of motor imagery does bring its own challenges; imagery is not a skill that comes naturally to most people, so if an individual is not trained sufficiently then they will likely not have good results in the real-time BCI session. In contrast, training over time will generally result in improvement in an individual's imagery skill and the classifier accuracy as a result. If an individual is not skilled at imagery to begin with or is not performing the correct mental task during training, then the real-time classifier will not be able to accurately classify intended events. Future work should make corrections to the pipeline in order to implement stimulation markers for the non-control state so that the accuracy can be measured in a confusion matrix.

Conclusions

This research has shown that asynchronous BCI systems are possible to create and can classify events successfully with greater-than-chance accuracy. Future research should implement dwell periods and refractory periods in order to have a more accurate results from the system in a real control application. The data may also be improved by using a 16-channel EEG system rather than an 8-channel system, which would allow for more accurate placement of the electrodes and better spatial filters as a result. In future research, this method of asynchronous BCI may be capable of fully asynchronous control of an external application, such as a powered wheelchair or an avatar in a virtual environment.

Future Work

1. Implement a dwell period before confirming a motor imagery command in order to reduce false positives.
2. Create a more accurate method of measuring the accuracy of an asynchronous BCI involving dwell periods.
3. Apply the fully developed asynchronous BCI to an assistive technology, such as a powered wheelchair or a prosthetic.
4. Develop a virtual environment where the avatar can be controlled by a user solely through motor imagery.
5. Investigate how the usage of BCI affects emotional state or mood of persons with lost or limited motor function.

References and/or Acknowledgments

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