# Self Paced Brain Computer Interface On Sensorimotor Rhythms For Virtual Objects Controlling

***Abstract*—Non-invasive electroencephalogram (EEG) based Brain-Computer Interface (BCI) systems have been an interesting research area for many fields. However, most of the research done on this subject is synchronous, therefore the state of mind of the user is not similar to its natural behaviour. Considering to provide possible experience in practical applications, self-paced BCI systems started gaining popularity in recent years. However, there are certain challenges yet to be addressed when following this method. Out of the research done on self-paced BCI systems, most of them are focused on motor-imagery control whereas research on non-motor imagery mental tasks is limited. In this research, we analyse the possibility of using the techniques used in the motor-imagery method for non-motor imagery mental tasks to be fed into virtual object controlling applications. Research was done with 5 different classification models with the use of features from Fast Fourier Transform (FFT) and Wavelet Transform (WT). K-nearest neighbor model with features obtained with FFT sustained its performance continously with a 0.56 cross validation value.**

***Index Terms*—Brain Computer Interface, BCI, self-paced, EEG, sensorimotor rhythms, machine learning**

## I. Introduction

Brain computer interfaces (BCI) have been thrust into the limelight in recent years as a source of innovative applications for many fields like medicine and gaming industry. New directions are introduced to the BCI applications often and, using BCI to control virtual environments is one of them. Unlike the early days, hardware components had to be built to test and develop applications, with virtual environments researchers get a good testing ground to develop their applications. Identifying and classifying the thought commands of a person is a major task of a BCI system. The laboratory-based BCI systems often use a synchronous method where the subjects are guided towards certain intentions by visual or verbal cue. Not only this method is far from the natural behaviour of the mind but also can have certain limitations when it comes to practical applications. Alternatively, researchers have introduced self-paced systems where the subjects are free to decide when to have controlling commands. Here the BCI recognizes them based on the state of their thought commands which may belong to either intentional-control (IC) state or no-control (NC) state. However, self-paced BCI systems are more challenging than the former as there are major concerns with the false positive rate (FPR) that comes with signal classification.

The most common approach that has been used in research is non-invasive EEG based devices [1]. The key advantages of non-invasive techniques are the maturity of the technology, relative ease of use and low cost, as well as the robustness, portability and versatility of recent EEG devices [2]. Among the different EEG brain activity patterns used for BCI approaches, there are P300 [3], [4] steady state visual evoke potentials (SSVEP) [5] and event–related desynchronization/synchronization (ERD/ERS) [6], [7]. This research is based on ERD, where the ability to controlling virtual objects using mind intent is used, rather than mapping it to a external visual or verbal cue.

However, there are major concerns regarding receiving distorted signals as the devices are located far from the neurons. So far, the motor imagery and motor execution methods have been the most used asynchronous methods in BCI research. In the motor imagery (MI) method, the subjects imagine the movement of their arm or leg without moving them physically, whereas in the motor execution (ME) method they execute a movement of a limb. In 2007, Graz university of technology [8] conducted a ERD-based research where MI was used to operate a person in a virtual environment which resulted in 50% in TPR and average FPR to be less 10%. The classification method used here was LDA. In 2010 Graz university of technology was able to increase TPR to 79% and reduce the FPR down to 0.67% per minute [9] with the usage of SVMs. However, there are cases where some subjects like patients who have been paralyzed for long periods were not able to obtain the expected results. Researchers are interested in controlling virtual objects using thoughts of changing the spatial transformation of the object rather than motor imagery (MI) or motor execution (ME). For example, thoughts of moving an object into a predefined direction, rotating around an axis or scaling the object are considered as spatial transforms or non-motor imagery mental tasks in this research [10]. However, this area is still novel to the field of BCI research. In research by Faradji et al. [11], they explored the idea of rotation of a virtual object in 3D space using self-paced mind-intent. They used auto scalar auto-regressive methods for feature extraction and the classification was done with quadratic discriminant analysis. They obtained true positive rate (TPR) values within the range of 27.36% - 64.73% and 0.01% FPR. Although there are numerous researches on using motor imagery to control virtual objects that give us higher accuracy [10], research done by Faradji et al. [11] explores the possibility of controlling objects in a more natural way. Therefore, although the TPR is relatively

low compared to MI related research, this method is more preferable in real-time applications.
In this research, we explore the possibility of using motor imagery signal acquisition, feature extraction and classification techniques in signals related to non-motor imagery mental tasks to be fed into virtual object controlling applications through a self-paced BCI system. We tested different artifact removal methods such as Independent Component Analysis (ICA), filtration methods, and wavelet transformation with threshold. Feature extraction was done using signals representations such as fast Fourier transformation and wavelet transformation of EEG data. Their ability to perform in real-time manner and their information resolution were obtained using different methods. For classification we used Random Forest, Quadratic Discriminant Analysis (QDA), KNearest Neighbour Algorithm (KNN), Support Vector Machine (SVM) and Catboost. According to the results obtained in this research, we present a comparison between the results of different approaches that were tested out.

## II. Methodology and Experiments

In the methodology section first we discuss the experimental protocol that was followed. Afterwards, we take a look at different signal representations that were implemented for the feature extraction purposes. The artifact removal mechanisms of EEG data that were followed and classification methods that were implemented are also included in this section.

### A. Experimental setup

Our subject was a male volunteer, of age 24. First we trained the subject to train three mind intents which are left, right, and none with a virtual stationary object (sphere). This training was done in a limited time trial like 0-10 seconds, because the performance of the mental task degrades over time. We used an OpenBCI Cyton board which has 8 EEG channels to capture the subjects' brain waves. This setup is visualized in Figure 1. EEG signals were fed for processing and denoising. We used the OpenBCI GUI to send EEG time series signals into a Python application through Lab Streaming Layer (LSL), where we did the post processing and classification of data. Signal processing and classification are done in computer with Intel Core i5-6200U processor.

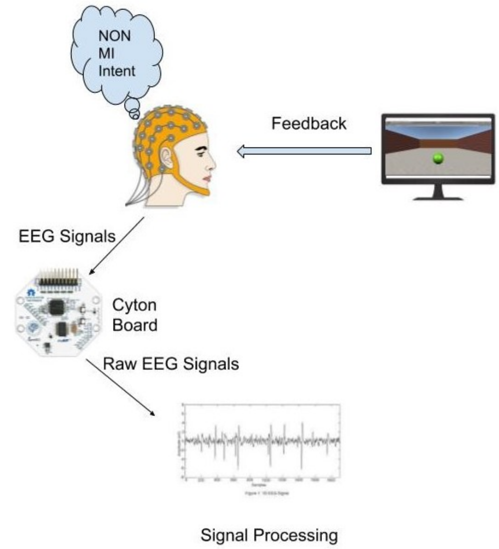


Fig. 1. Experimental setup to acquire EEG signals

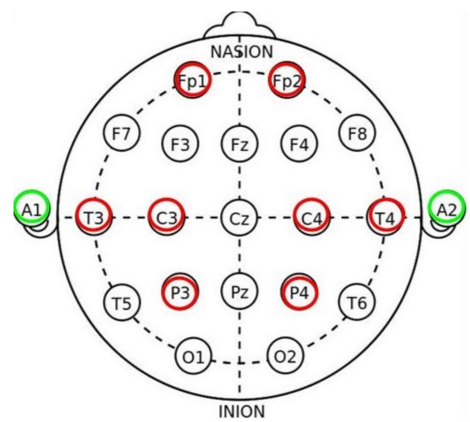


Fig. 2. 10-20 experimental electrode placement

### B. Electrodes and electrode placement

We used eight Golden cup electrodes to sample EEG data. We placed those on the subject according to the 10-20 method. The 10–20 system is an internationally recognized method to describe and apply the location of scalp electrodes in the context of an EEG exam. The brain waves related to controlling virtual objects are induced in the motor cortex, so electrode placement positions are chosen to extract the maximum amount of information. In our experiment, we placed electrodes on the positions indicated by the red circles in Figure 2.

A1 and A2 act as the reference voltage (ground) which will be references for all of the EEG electrodes placed on the head. Those were placed on earlobe as it is considered as a neutral electrical reference compared to other parts of the body. Nasion and inion were used as landmarks for the positioning of EEG electrodes.

### C. Virtual Environment

Virtual objects that were meant for controlling are created with Unity game engine. The subject is trained on a virtual environment where the display is a 15.6 inch monitor with a resolution of 1920 x 1080 p and refresh rate of 60Hz. Data of mind intent will be recorded where the subject will focus on moving the objects along horizontal axes. Figure 3 shows the virtual environment we created for the experiment.

### D. Signal Acquisition and Preprocessing

Initially, EEG time series signal is notched on 50Hz from the OpenBCI GUI and transferred to Python application. This

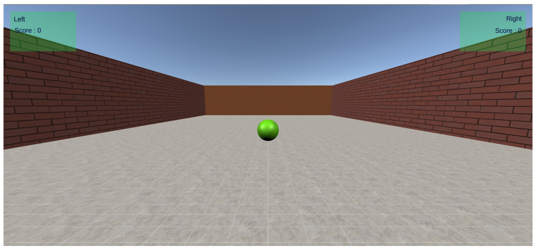


Fig. 3. Virtual environment

data was saved in .csv format. Data manipulation was done according to the different artifact removal methods that were followed. Unfiltered time series data was used for Independent Component Analysis (ICA) and post artifact removal signal representations. This range is chosen because the beta (13-30Hz) and gamma (30Hz and above) signal ranges are the interesting signal ranges in non motor imagery EEG signals [12]. The signals above 60 Hz are contaminated with other artifacts and do not contain interesting data, so information that can be extracted from them is low and noisy.

### E. Signal representations

We used two main signal representation methods in this research. They are Fast Fourier Transform (FFT) and Wavelet Transform (WT). Different researches in the BCI domain have used different representations of data for feature extraction [13]. Some of them are FFT, WT, time series data, statistical data and Surface Laplacian. Out of them we chose FFT and WT, since our focus is on exploring the behavior of EEG signals in frequency domain and how they behave when combined with time domain.

*1) **Fast Fourier Transform**:* FFT is a signal representation which contains a frequency spectral details of a time series signal. It contains the magnitudes related to each frequency component of the signal.

Given that the FFT function returns a symmetric spectrum for real signals, we extracted features from the positive frequencies. Since 15 - 60 Hz is the frequency band we focus on in this research, FFT for this bandwidth was extracted as shown in Figure 4.

*2) **Wavelet**:* Daubechies 4 (db4) wavelet is used as the mother wavelet in this research since it is most suitable to process biomedical signals [14]. The input signal has a frequency band of 0-250 Hz. In this research, our interest area is 15- 60Hz for EEG signals. Since the relevant frequency band lies in the Gamma and Beta (16-63Hz), the filtered signal will be decomposed only up to 5 levels to obtain the detailed coefficients related to beta and gamma bands. CD4 and CD3 are the detailed coefficients that represent Gamma and beta bandwidth that are relevant to the non motor imagery. Extracted features CD4 and CD3 are visualized in Figure 5. These coefficients can be used as features for the subsequent classification method. This method also can be

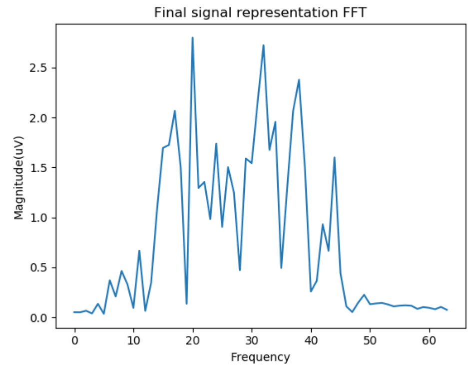


Fig. 4. Extracted FFT representation 15-60Hz

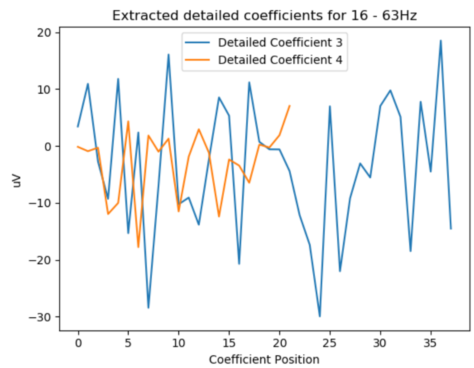


Fig. 5. Extracted Features CD4 and CD3

used for extracting required frequency bands by reconstructing the signals after removing unwanted detailed coefficients and artifact ranges.

### F. Artifact removal

Ocular artifact is one of the main artifacts that we were focused on in this research. For removing those artifacts ICA and Wavelet Transform Threshold Method were used. We tested out the ICA algorithm to remove EOG artifact. We applied the ICA algorithm to time series signal after arranging into 2D array (channel count x time series signal length) and resulted in separate independent components that were plotted as shown in Figure 6.

In Figure 6, the signal intensity of the independent component is high in the red area and low in the blue area. Each brain area shown in this figure represents a separate independent component. We identified ICA001 to be the independent component that contaminates the EOG artifact. We used ICA algorithm to remove EOG artifact as shown in Figure 7. to acquire the real signal representation.

We used the Wavelet Transform Threshold Method for removing high frequency noises. However artifacts of EEG signals cannot be removed using the universal threshold method directly. FFT and Wavelet transform also can be used

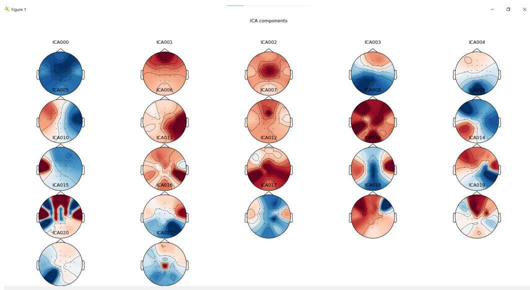

Fig. 6. Independent components Mapped to brain area

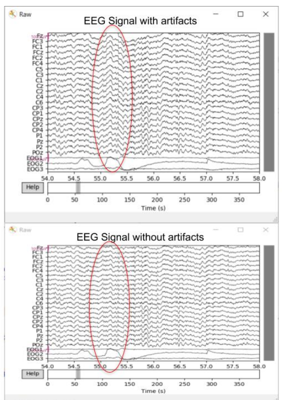


Fig. 7. EEG signals after removing EOG artifact

as artifact removal methods (after post signal representation). FFT can be used to reconstruct the signal after removing unwanted frequency coefficients that are related to artifacts. WT can be used to reconstruct the signal after removing unwanted detailed coefficients that are related to artifacts.

### G. *Feature extraction*

Frequency bins from 15Hz to 60Hz (i.e., 15Hz, 16Hz, 17Hz, ...) is used as features extracted from FFT for training classification models. Detailed coefficients on 4th and 3rd levels are used as features extracted from the wavelet transform method.

### H. *Classification*

The extracted features were applied to the models after performing model based feature selection methods. We used Random Forest classifier, QDA, KNN, SVM and Catboost models for classification. The classification is based on three classes Left, Right and None. The evaluation of classification models is done by cross validation. For training the model we used 4800 data points and for the test set we used 480 data points. To select the test set we used randomly picked data points from 5 days selecting 96 data points from each day.
Following were used as evaluation metrics.

$$\text{Accuracy} = \text{Number of correct predictions} \; / \; \text{Total number of predictions} \quad (1)$$

$$\text{True Positive Rate (TPR)} = \text{True Positives} \; / \; (\text{True Positives} + \text{False Negatives}) \quad (2)$$

## III. Results

### A. *Real-time requirement results*

In Table I, we have compared the different artifact removal and feature extraction methods on computational cost and time taken to calculate 25 instances of 8-channel EEG data. From the results it is observed that FFT frequency coefficient removal method has the lowest computational time so it is more preferable for real-time usage.

TABLE I
Feature extraction and artifact removal methods comparison

| Method | Computational Cost<br>K-number of sources<br>N-number of samples | Computational Time |
|---|---|---|
| ICA | $\mathcal{O}(kn\log n)$ | 86 ms |
| FFT frequency coefficient removal method | $\mathcal{O}(n^2)$ | 23 ms |
| WT Threshold Method (Universal/ Bayesian threshold) | $\mathcal{O}(n^2 \log_2 n)$ | 53 ms |
| WT Detail Coefficient Removal Method | $\mathcal{O}(n^2 \log_2 n)$ | 42 ms |

### B. *Classification results*

Frequency bin components extracted by FFT and detailed coefficients extracted by WT were used as features for the classification purpose. All the classifications have the ability to perform in real time. In Table II we have compared the accuracies between different classification models. Best hyper parameters combination for each model is determined by a grid search using 10 fold cross validation as evaluation method. KNN model with features obtained with FFT showed the highest accuracy. As shown in Table II the overall accuracies obtained when using FFT is higher than when using WT. We then obtained the accuracy with respect to each mind intent obtained with FFT. Table III gives the TPR of each class obtained with FFT with respect to each model. The confusion matrix of the KNN model is shown in Figure 8.
Since we have data collected over 5 days we used a 5-fold cross validation to get an estimation of the consistency of accuracies. This is shown in Table IV and Table V.

TABLE II
Accuracy comparison of each classification model

| **Random Forest** | | **Catboost** | | **QDA** | | **KNN** | | **SVM** | |
|---|---|---|---|---|---|---|---|---|---|
| FFT | WT | FFT | WT | FFT | WT | FFT | WT | FFT | WT |
| 0.473958 | 0.385417 | 0.5 | 0.380208 | 0.46875 | 0.40625 | 0.552083 | 0.40625 | 0.451875 | 0.432292 |

## IV. Discussion

### A. *Real-time requirements analysis*

Since EEG signals are in the micro voltage range, it is more vulnerable towards artifacts. As this is a real-time application,

TABLE III
TRUE POSITIVE RATES OF EACH CLASS WITH RESPECT TO MODEL

| Class | Random forest-FFT | Catboost-FFT | KNN-FFT | SVM-FFT | QDA-FFT |
|---|---|---|---|---|---|
| LEFT | 0.79 | 0.57 | 0.67 | 0.68 | 0.79 |
| RIGHT | 0.36 | 0.47 | 0.51 | 0.44 | 0.49 |
| NONE | 0.062 | 0.44 | 0.44 | 0.00 | 0.06 |

TABLE IV
FIVE-FOLD CROSS VALIDATION WITH FAST FOURIER TRANSFORM

| | KNN-FFT | CatBoost-FFT | Random Forest-FFT | SVM-FFT | QDA-FFT |
|---|---|---|---|---|---|
| CV_score | 0.56 | 0.54 | 0.55 | 0.54 | 0.55 |
| std_dev(+/-) | 0.02 | 0.01 | 0.07 | 0.07 | 0.09 |

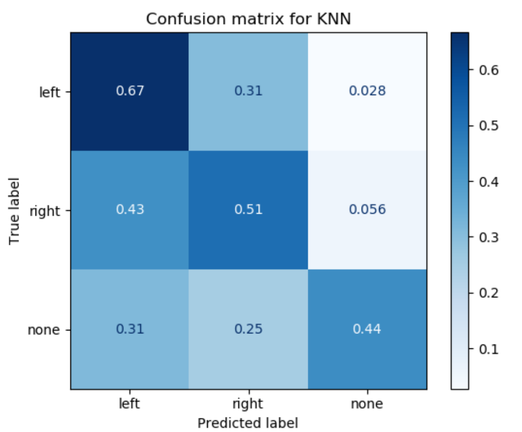


Fig. 8. Confusion matrix of KNN model

in this research we were more concerned about the time complexities and processing costs of each signal analysis and processing method concerned. ICA can be considered one of the best methods for offline applications since it is more sensitive to discovering artifacts and has the capability to preserve more information while removing them. But the ICA method had a higher computational time compared to other methods. Plus, in order to identify the signals that are related to the artifacts, it is a must that training data is contaminated with those artifacts. WT threshold method has a lower artifact removal ability compared to other methods that were implemented. In our research, we tested out the universal threshold method. Since the universal threshold is sensitive for higher frequencies, it is not applicable for eliminating lower frequency components. Due to the limitations of these two methods we have chosen WT detailed coefficient removal method and FFT frequency component removal method as our artifact removal methods.

### B. Feature extraction and classification analysis

Overall, FFT frequency components as features gave more accuracy than WT detailed coefficients as features when it comes to signal classification. The reason behind that is non-motor imagery signals are induced brain signals which are also known as time phase unlocked signals [9]. Therefore signal characteristics in the time domain variate. Due to this, features extracted from WT can misguide the classification trends. Another reason is that different filtrations that were done on EEG time series data would cause a phase shift which results in a change in the signal characteristics in the time domain. Hence classification becomes even less accurate when using wavelet features. Although both Catboost and KNN with FFT shows a significant accuracy compared to other models, all 5 classification models show high TPR on identifying categorical values left and right. But TPR of non-class (non-intended state) identification is low on QDA, SVM, and Random Forest algorithms. KNN and Catboost models show a significant TPR on identifying non-intended states. When comparing both KNN and Catboost models, KNN has overall high accuracy and TPR than other models. Another keen observation we had is that the Random Forest algorithm requires more memory; it also requires considerable time to predict instances. For one instance it approximately gets 110ms time. So it is not a very good approach for real-time classification. According to the results obtained by 5 fold cross-validation, Catboost algorithm and KNN sustain their performance continuously than other models.

TABLE V
FIVE-FOLD CROSS VALIDATION WITH WAVELET TRANSFORM

| | KNN-WT | CatBoost-WT | Random Forest-WT | SVM-WT | QDA-WT |
|---|---|---|---|---|---|
| CV_score | 0.47 | 0.50 | 0.47 | 0.49 | 0.47 |
| std_dev(+/-) | 0.03 | 0.05 | 0.09 | 0.09 | 0.06 |

In [11] Faradji et al. were able to obtain a 54.6% accuracy using auto scalar auto-regressive methods for feature extraction and quadratic discriminant analysis as the classification method with 29 EEG channels. However with the KNN algorithm with FFT feature extraction method, we were able to obtain 55% accuracy with 8 EEG channels.

## V. CONCLUSION

In our research, our main goal was to collect advancements done within MI-based research and see how much is applicable when it comes to self-paced non-MI-based applications. It is evident that there are novel signal analysis techniques that show an improved ability to identify and classify the thought commands of the subject but some of these methods are not applicable for a real-time self-paced BCI application. Compared to FFT features, WT features have far less reliability in non-motor imagery signals. The phase unlocked nature of non-motor imagery signals causes the signals within the same class to be distinguished from each other. Filtration techniques that were implemented in the hardware itself cause phase changes for signals which reduces the reliability of WT features. This proved that WT signals do not provide the best features when it comes to identifying thought commands in self-paced BCI. The subject needs to be properly trained prior to using the application. The subject should be able to properly concentrate on the thought commands related to controlling the virtual object. Change of thought patterns and lack of concentration will decrease the accuracy of the application immensely. Changes in the virtual environment also can cause reliability issues in virtual object controlling. Uncertainties of weights for inducing signal patterns for thoughts, from each cerebral area are hard to identify. Changes in the placement of electrodes can cause changes in signals related to thought commands in respective channels. Even the slightest change can cause a considerable impact. This is known as the error of uncertainties in the anatomical localization of electrodes [15]. In a self-paced BCI application, it is important to have more channels or have a proper headset for electrode placement. When the electrode density (number of electrodes) increases we can rectify the anatomical localization errors considerably using statistical methods.

With all the classification models that were trained, KNN algorithm with FFT feature extraction method would be the ideal choice for features and classification combination. We were able to obtain around 55% TPR value with this combination. In comparison to other approaches Catboost algorithm and KNN sustained their performance continuously. In comparison to the research that is done by Faradji et al. these models have been able to show consistence performance rates with much less standard deviation.

Deep learning methods are proved to have a lot of potential in MI-based research in recent history. The possibility of using deep learning approaches in non-motor imagery intent with self-paced brain-computer interfaces is something that can be explored as well. Performance of self-paced BCI with the combined features of WT and FFT is another approach that is yet to be explored.

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## References

[1] J. R. Wolpaw, N. Birbaumer, D. J. McFarland, G. Pfurtscheller, and T. M. Vaughan, "Brain–computer interfaces for communication and control," *Clinical neurophysiology*, vol. 113, no. 6, pp. 767–791, 2002.

[2] M. Kaya, M. K. Binli, E. Ozbay, H. Yanar, and Y. Mishchenko, "A large electroencephalographic motor imagery dataset for electroencephalographic brain computer interfaces," *Scientific data*, vol. 5, p. 180211, 2018.

[3] E. Sellers, Y. Arbel, E. Donchin, J. Wolpaw, and E. Wolpaw, "Bcis that uses 300event related potentials. brain-computer interfaces: Principles and practice," 2012.

[4] L. A. Farwell and E. Donchin, "Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials," *Electroencephalography and clinical Neurophysiology*, vol. 70, no. 6, pp. 510–523, 1988.

[5] C. S. Herrmann, "Human eeg responses to 1–100 hz flicker: resonance phenomena in visual cortex and their potential correlation to cognitive phenomena," *Experimental brain research*, vol. 137, no. 3, pp. 346–353, 2001.

[6] G. Pfurtscheller and F. L. Da Silva, "Event-related eeg/meg synchronization and desynchronization: basic principles," *Clinical neurophysiology*, vol. 110, no. 11, pp. 1842–1857, 1999.

[7] G. Pfurtscheller and C. Neuper, "Motor imagery and direct brain-computer communication," *Proceedings of the IEEE*, vol. 89, no. 7, pp. 1123–1134, 2001.

[8] R. Leeb, D. Friedman, G. R. Müller-Putz, R. Scherer, M. Slater, and G. Pfurtscheller, "Self-paced (asynchronous) bci control of a wheelchair in virtual environments: a case study with a tetraplegic," *Computational intelligence and neuroscience*, vol. 2007, 2007.

[9] G. Pfurtscheller, R. Leeb, J. Faller, and C. Neuper, "Braincomputer interface systems used for virtual reality control," *Virtual Reality*, vol. 1, pp. 3–20, 2011.

[10] C.-H. Han, K.-R. Müller, and H.-J. Hwang, "Brain-switches for asynchronous brain–computer interfaces: A systematic review," *Electronics*, vol. 9, no. 3, p. 422, 2020.

[11] F. Faradji, R. K. Ward, and G. E. Birch, "A self-paced two-state mental task-based brain-computer interface with few eeg channels," in *New Frontiers in Brain-Computer Interfaces*, IntechOpen, 2019.

[12] Y. Zhang and Q. Yang, "A survey on multi-task learning," *IEEE Transactions on Knowledge and Data Engineering*, 2021.

[13] J. F. Borisoff, S. G. Mason, and G. E. Birch, "Brain interface research for asynchronous control applications," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 14, no. 2, pp. 160–164, 2006.

[14] S. M. Tumari, R. Sudirman, A. Ahmad, *et al.*, "Selection of a suitable wavelet for cognitive memory using electroencephalograph signal," *Engineering*, vol. 5, no. 05, p. 15, 2013.

[15] D. J. Krusienski, M. Grosse-Wentrup, F. Galán, D. Coyle, K. J. Miller, E. Forney, and C. W. Anderson, "Critical issues in state-of-the-art brain–computer interface signal processing," *Journal of neural engineering*, vol. 8, no. 2, p. 025002, 2011.