

## 2D VIRTUAL CURSOR CONTROL USING EEG BASED BRAIN COMPUTER INTERFACE

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### Abstract

This paper focuses on a Brain Computer Interface (BCI) system that allows for cursor control on a two-dimensional plane through Electroencephalography (EEG) indicators. Mu/Beta rhythms are associated with horizontal movement and P300 potentials are associated with the vertical movement. Existing classification techniques on EEG datasets are employed and K-means clustering is used for classification and big data integration tools are used to integrate the results into a Python-based graphical user interface (GUI). Even if there is signal noise as a limitation, the proposed method shows applicability for assistive technologies for motor disabled people. For future work, the recommendations are to fine tune the approach and consider real-world applications.



### INTRODUCTION

A Brain Computer Interface or BCI is a technology that uses signals from the brain to operate external devices with great advantage to individuals with motor disability. Among all types of BCIs, the EEG-based BCIs are valuable because they are invasive-free and can record brain signals related to mental activities. This research focuses on a Brain Computer Interface (BCI) system for controlling a 2-dimensional (2D) cursor using two distinct Electroencephalography (EEG) signal modalities: Mu/Beta rhythms for horizontal movement and P300 potential for vertical movement. The integration also helps to advance cursor control precision and speed while providing potential uses in assistive technology.

### Motivation:

Individuals with severe motor impairments face significant barriers in using conventional technology. Existing cursor control solutions often rely on single modalities, which limit precision and usability. This study bridges this gap by integrating motor imagery and P300 signals, enabling a more reliable and versatile cursor control system. Additionally, the proposed approach contributes to advancing hybrid BCI models, addressing a critical need in assistive technologies.

### Objectives:

Analyze Mu/Beta rhythms for horizontal movement and P300 potentials for vertical movement.  
Extract and classify Electroencephalography (EEG) features using machine learning techniques.

Enable two-directional cursor control.  
Evaluate the system's offline performance.

## Research Questions:

The key research questions addressed in this study are:

How can integrating Mu/Beta rhythms and P300 potentials improve the precision of 2D cursor control?

What are the practical challenges in implementing a hybrid BCI system using unsupervised learning methods?

How does the system performance compare with existing techniques, and what improvements can be made for real-time applications?

## Related Work

Brain Computer Interface (BCI) systems leveraging EEG signals for cursor control have been extensively studied. Research highlights the effectiveness of Mu/Beta rhythms in motor imagery tasks and P300 potentials for decision-making. For instance, studies by Li et al. [2] and McFarland et al. [11] demonstrated successful cursor control using these modalities. However, challenges such as signal interference and variability remain. This work builds upon prior research by employing unsupervised K-means clustering to integrate these modalities, offering a novel approach to hybrid BCI systems.

## Methodology

The present method depicts the sequential procedure that was utilized for designing and testing a 2D cursor control system in the context of EEG-based Brain-Computer Interface (BCI). The steps used in this process include, data input, data preprocessing, data feature extraction, modelling and classification, and incorporating it in a graphical user interface for visualization.

## Data Collection

Two distinct datasets were utilized to facilitate bidirectional cursor control:

### 1. Motor Imagery Dataset

The motor imagery dataset used in this paper was obtained from BCI Competition III Dataset 2b and contains EEG data collected from subjects while they performed motor imagery tasks which involve

imagining movements of the left or right hand. These tasks engage the sensorimotor cortex, with data captured from three key channels: These are C3, Cz, and C4 that are important in describing brain activity associated with these movements [3].

### 2. P300 Dataset

The data used here are from a P300 speller BCI Competition IV Dataset II where EEG signals are recorded in a P300 speller task. In this task, participants paid attention on target stimuli contained in a series of non-target stimuli, which produced different P300 waves. Such responses are recorded through basic electrode locations to make accurate measures of the P300 components that are essential in deciphering the attention-related decision-making mainly from the prefrontal region [4].

## Data Processing

For this purpose, there was a great emphasis on quality and reliability of the EEG signals obtained; therefore, there was an extensive preprocessing of the raw data before feature extraction and classification. The first intervention was bandpass filtering in the range of 1-50 Hz to filter out low frequency drifts and high frequency noise which was achieved while keeping the fundamental frequency bands of motor imagery (Mu/Beta rhythms) and the P300 components. Following this, the data was segmented into manageable epochs: for motor imagery, the segmentation was based on 1 second windows corresponding to task events, whereas for P300 signals, the segmentation was in epochs related to stimulus and response. Thereafter, Independent Component Analysis (ICA) was used to reject contaminating sources that include eye blinks and movements, muscle activity, and electrical interference that could otherwise distort the EEG data. Lastly, the StandardScaler tool in scikit-learn was used to normalize the features so that the scales for each of them in different datasets are the same. This remarkable transformation of the input instances during the preprocessing pipeline greatly improved data quality for higher feature accuracy and better classifying performance.

### Feature Extraction

Feature selection was done in the preprocessing step as it aids in selection of noticeable important features of the EEG signals which represent the real brain activity. For motor imagery the features were extracted using the Mu (8–12 Hz) and Beta (13–30 Hz) bands because they are seen in motor cortex when a person imagines to moving. Following the data acquisition process band power calculations using the PSD map were used to estimate the energy content of the data with respect to left and right-hand motor imagery. For P300 signals, measures of special characteristics were specified and computed to capture temporal and amplitude indexes. Besides the amplitude, the absolute value of which characterizes the height of signal, the P300 wave latency was also estimated, defines the time which occurs between the presentation of the stimulus and the appearance of the P300 wave. In addition, analyses of the AUC, a measure of overall P300 waveform attributing to amplitude and temporal sources, have also been performed for the primary analysis. These extracted features were vital to determine movement intentions for core formation during classifying Brain Computer Interface (BCI).

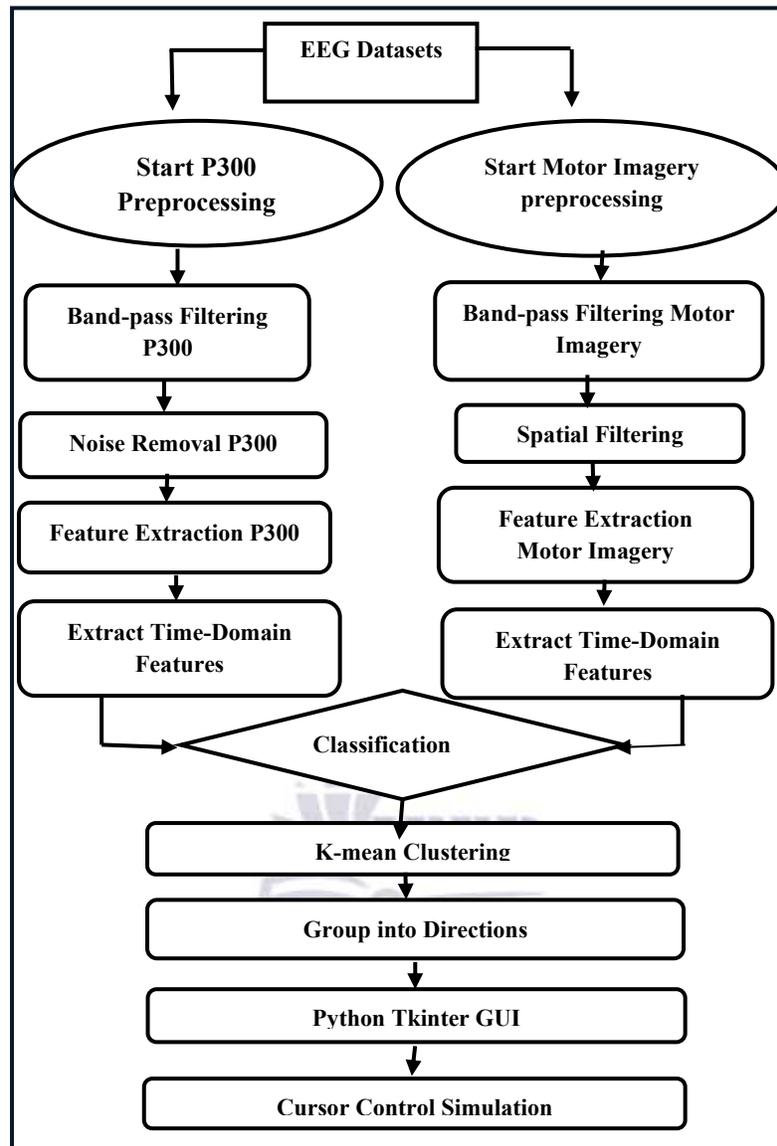
### 4.4. Classification

To categorize the calculated features, an unsupervised learning method was used, and the intention was to categorize the features according to the movement directions of the 2D cursor. Specifically, to split the extracted features, K-Means Clustering, where data points are summarized into four groups associated with cursors movements up, down, left and right were employed. K-Means clustering is carried out by linking the given data points with respect to the nearest centroid and then by finding averages of those centroids according to the points that belong to the centroid under consideration. It goes on until the algorithm ceases

to gain or decrease the variance within each of the clusters. These four clusters were useful in specification of the various directional movements which were needed in cursor control in 2D. Afterwards, the obtained cluster labels were converted to movement directions including up as Cluster 1, down as Cluster 2, left as Cluster 3 and right as Cluster 4. With this mapping it was possible to at feed the classified EEG data in the cursor control system and predict the direction of the cursor based on the classified features. The function of applying unsupervised learning with 'K-Means' was that: other than the restriction of labelled database; the best of EEG signals could be clustered quickly and easily which laid down the substitute of the effective cursor control system.

### 4.5. Cursor Control Integration and Implementation

From the motor imagery signals and P300 signals the 2D cursor was manipulated and navigated in both x and y axis. Motor imagery used for the horizontal movement was Mu/Beta rhythms which enabled the cursor to move either to the left or right side depending on hand movement imagery of the participant. By analysing the features of the P300 signal, vertical movement was predicted and the cursor followed up and down movements as subjects stared at target stimuli. For illustrating and enacting the cursor control, Python Graphical User Interface (GUI) based on the Tkinter toolkit was used. The processed EEG data and the classification results were integrated into the GUI, where cursor movements were the simulated using a 2D interface. This setup shown the real time response of the system to the classified Electroencephalography (EEG) signals which gave a clear representation of cursor movement in relation to the brain activity of the user.



The employment of the system was effective for the subjects to produce naturalistic communication with the interface to prove the feasibility of the EEG-BCI for cursor control in the context of assistive technologies.

### Mathematical Modelling

K-Means is a clustering algorithm in which the datasets is divided into  $k$  clusters based on the given heuristic function trying to minimize within cluster variance. For the P300 dataset, the number of clusters,  $k = 2$  is adopted since the aim is to classify between the presence of the P300 signal, which relates to vertical movement and its absence. For the Motor Imagery dataset,  $k=4$  clusters represent the four movement directions: forward and backward

together with the conventional movements of up and down or sideways.

The aim of K-means is therefore to reduce the within-cluster variability, and this is approximated by sum of squares of the distance between any data point and its assigned cluster center. The total variance is given by:

$$J = \sum_{i=1}^k \sum_{x \in C_i} \|x - \mu_i\|^2 \tag{4.1}$$

Where  $C_i$  is the points belong to the cluster  $i$  and  $\mu_i$  is the center of the cluster  $i$ . The squared Euclidean

distance between a data point  $x$  and its centroid is  $\mu_i$  :

$$\|x - \mu_i\|^2 = \sum_{j=1}^n (x_j - \mu_{ij})^2 \quad (4.2)$$

Where  $x_j$  is the  $j^{\text{th}}$  feature of data point  $x$ , and  $\mu_{ij}$  is the  $j^{\text{th}}$  feature of centroid  $\mu_{ij}$ .

From the proposed algorithm the following algorithms are explained:

**Initialization:** Select  $k$  points randomly these are going to be initial centroids.

**Cluster Assignment:** The cluster each data point is going to be is the group that has the closest mean or centroid as defined by the Euclidean rule:

$$\text{Cluster}(x) = \arg \min_i \|x - \mu_i\|^2 \quad (4.3)$$

**Centroid Update:** The update of centroids means that one is required to compute the mean of those points that specific to a given cluster.

$$\mu_i = \frac{1}{|C_i|} \sum_{x \in C_i} x \quad (4.4)$$

**Iterative and convergence:** Repeat the second and third steps over the number of iterations until centroids are fixed or the maximum limit is completed.

For the P300 dataset, the number of clusters is  $k=2$  to classify the data in C1 intervening with presence of P300 signal and C2 intervening with its absence. The output is a binary label: Specifically, 1 was assigned to P300 indicators' presence and 0 - to its absence.

For the Motor Imagery dataset,  $k=4$  clusters correspond to the four movement directions: left, right, up, and down. The output for each point is a label where 0 represent left, 1 represent right 2 represent up and 3 represent down [6][7][8][9].

### Results

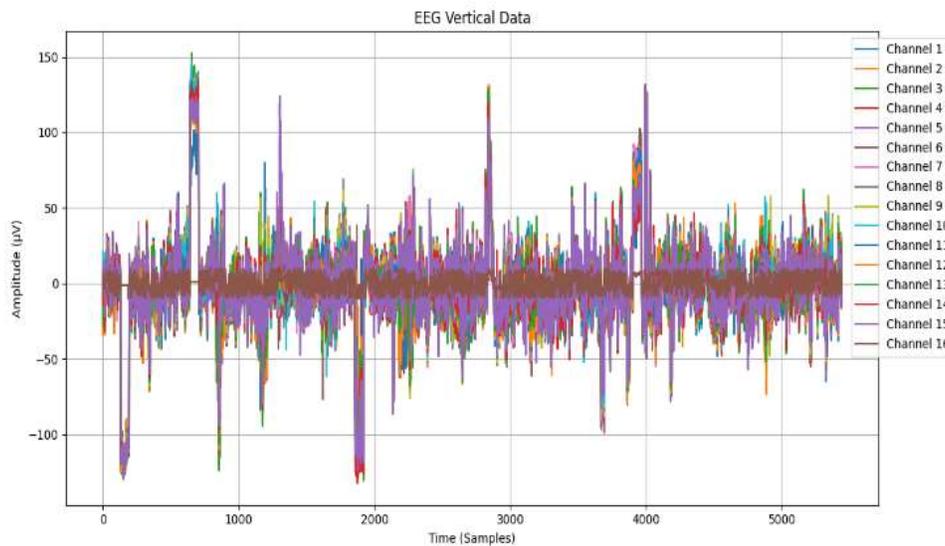


Figure 1 Methodology Flowchart Preprocessing

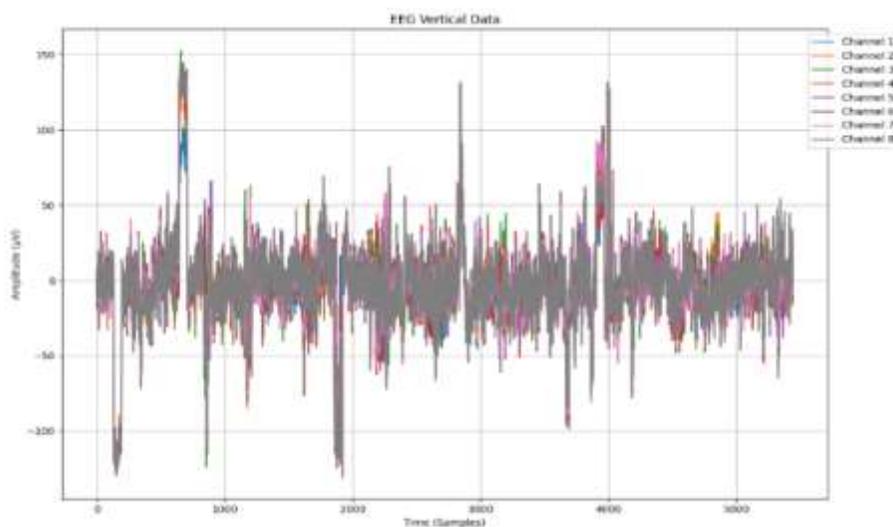


Figure 2 Processing and Cleaning of P300 data

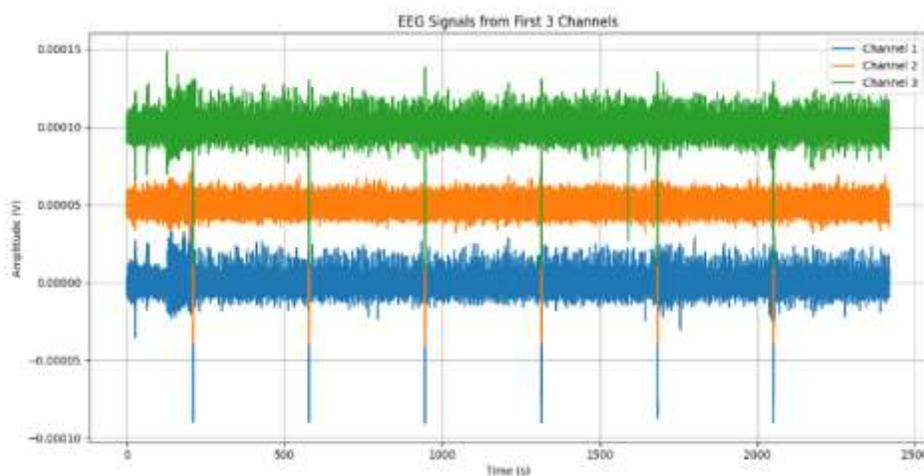


Figure 3 Selected channels of P300 data

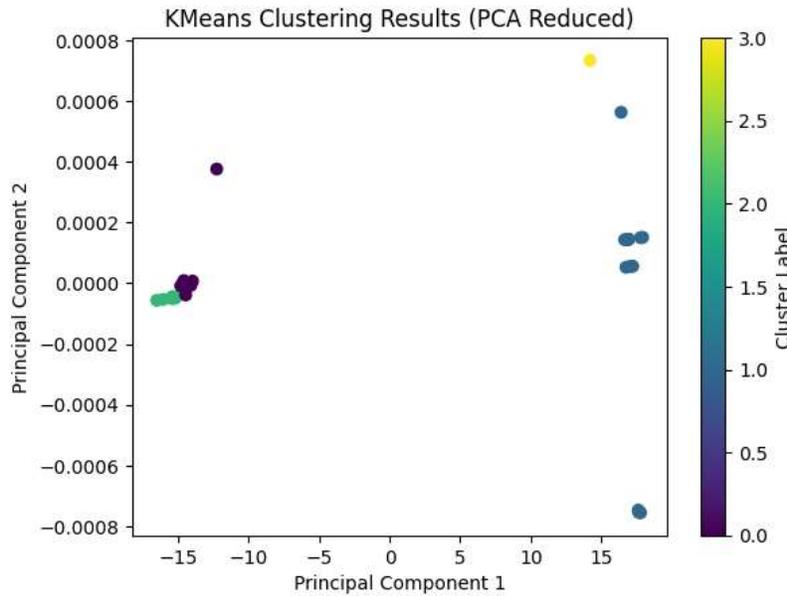


Figure 4 Preprocessing and cleaning of Motor Imagery data

Figure 2,3 and 4 shows Filtered and normalized signals demonstrated improved feature quality. Key channels for motor imagery and P300 signals were effectively isolated.

**Extracted Features**

Vertical features shape: (80,)

Horizontal features shape: (30,)

Feature extraction completed successfully

Shape of combined features: (2, 30)

Distinct patterns in Mu/Beta rhythms and P300 responses were identified, supporting reliable classification.

**Classification using K-mean Clustering**

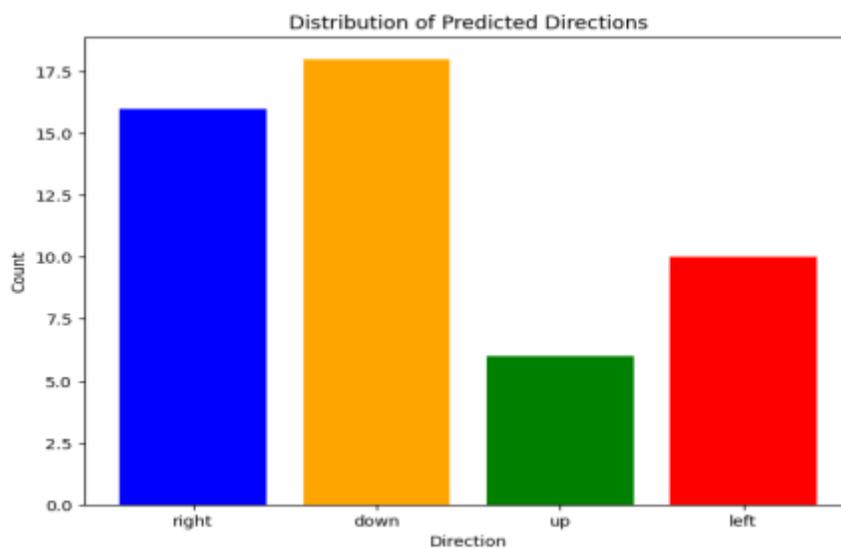


Figure 5 PCA Visualization of Clusters from K-mean Clustering

K-Means Performance: Clusters were visualized using PCA, showing clear separations between movement directions and P300 presence/absence.

Comparison: K-means results were benchmarked against existing methods like SVM and ANN,

demonstrating comparable accuracy but with faster computational times.

### Cursor Control Simulation

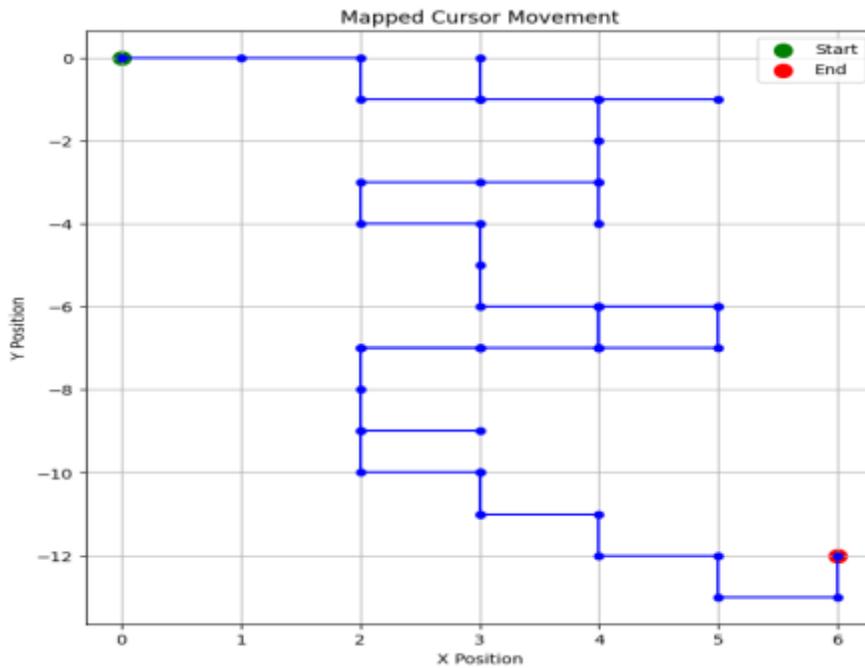


Figure 6 Distribution of Predicted Directions

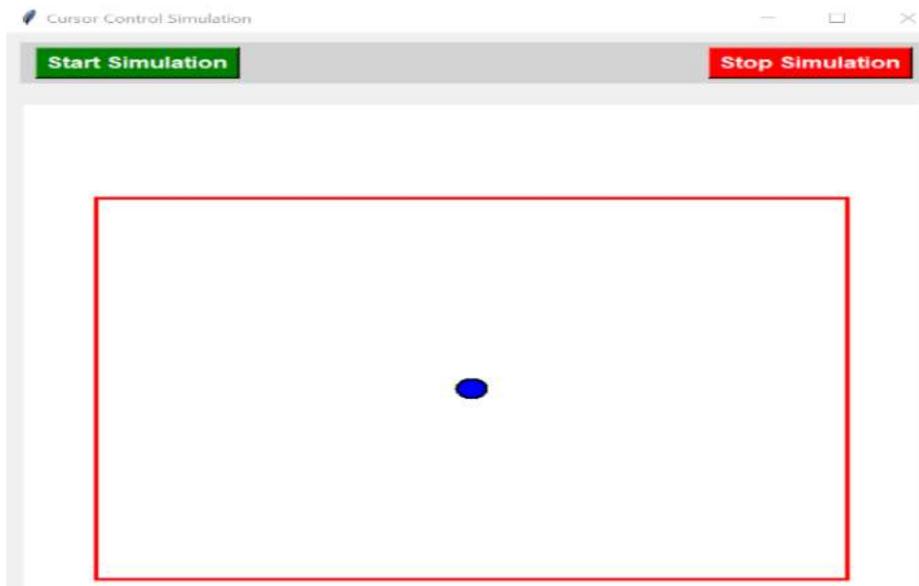


Figure 7 Mapped Cursor Movement

Simulated cursor movements accurately reflected classified directions, demonstrating the system's feasibility.

### Visualization of Cursor Movements along Different Directions

Each figure (from Figure 9 to Figure 14) contains nine subplots representing different iterations of the K-means

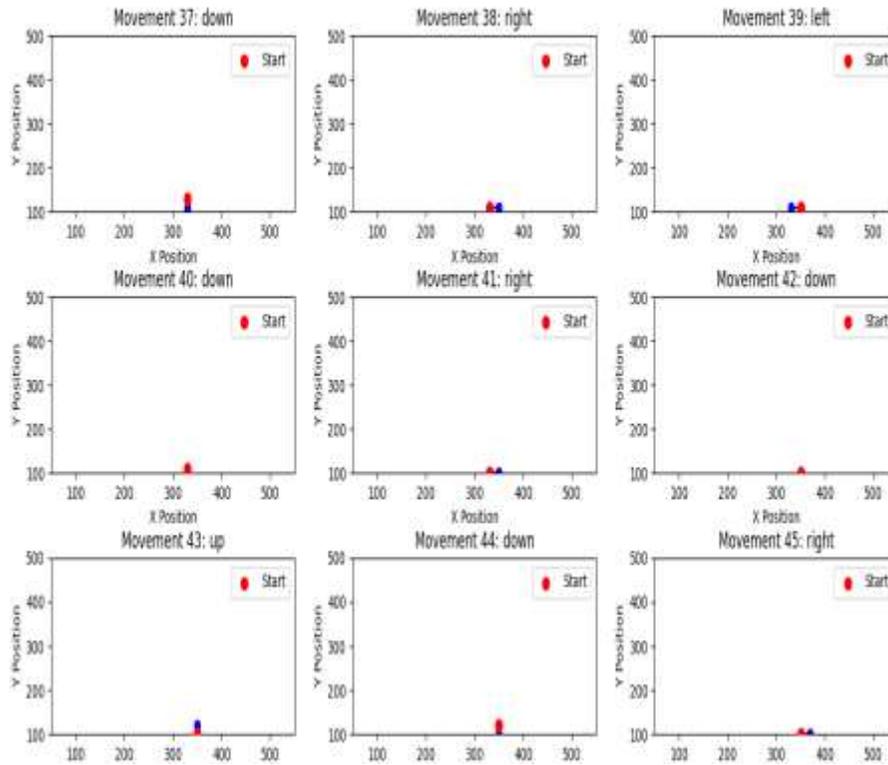


Figure 8 GUI for Simulation of Cursor Movement using Predicted Directions

clustering and cursor movement classification. These subplots visualize the cursor trajectories for all four directions (left, right, up, and down) in each

iteration. The figures demonstrate the system's progressive improvement in clustering accuracy and cursor control across iterations.

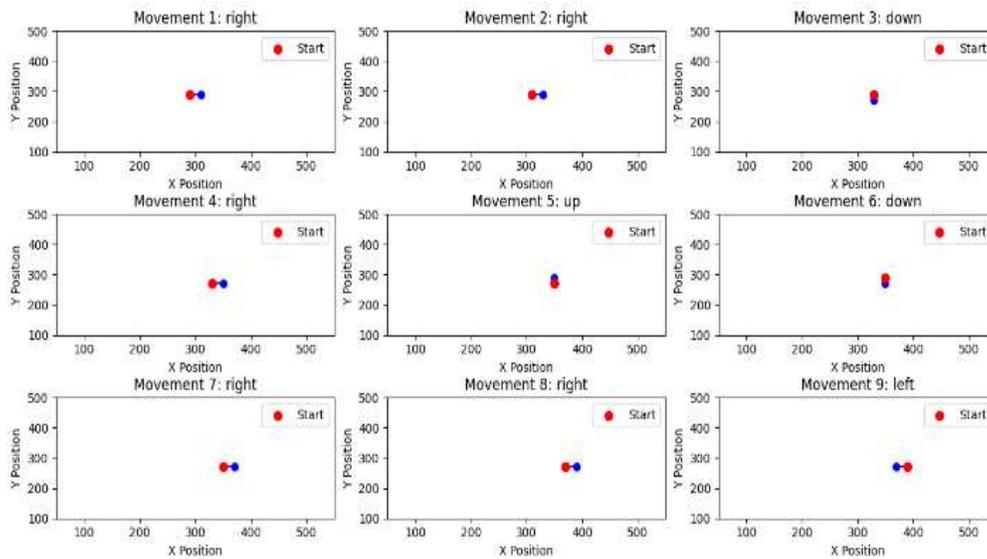


Figure 9 Visualization of Cursor Movements along Different Directions

In figure 9, the subplots illustrate the first iteration of K-means clustering. Clustering errors and

overlapping trajectories may be evident due to initial centroid placement and signal noise.

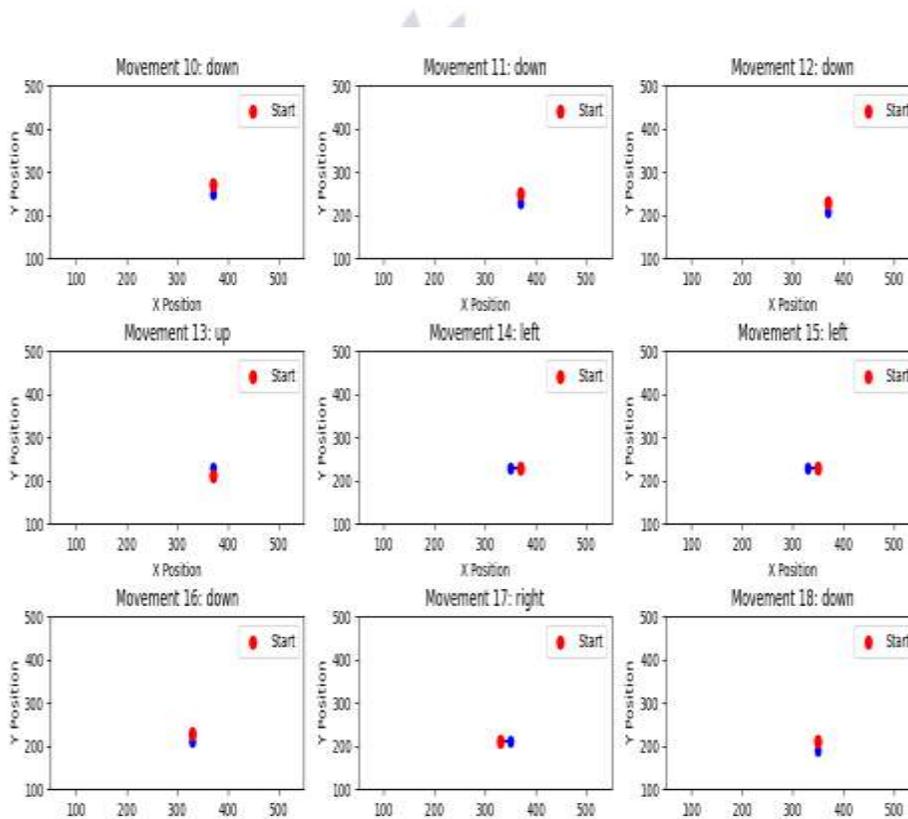


Figure 10 Visualization of Cursor Movements along Different Directions

In figure 10, the subplots show improved separation of movements as centroids adjust and clustering refines the predictions. Cursor trajectories begin to align more accurately with the intended directions.

In figure 11, further refinement is visible in the subplots. The system demonstrates better discrimination between left, right, up, and down movements, reducing overlaps and misclassifications.

Figure 11 Visualization of Cursor Movements along Different Directions

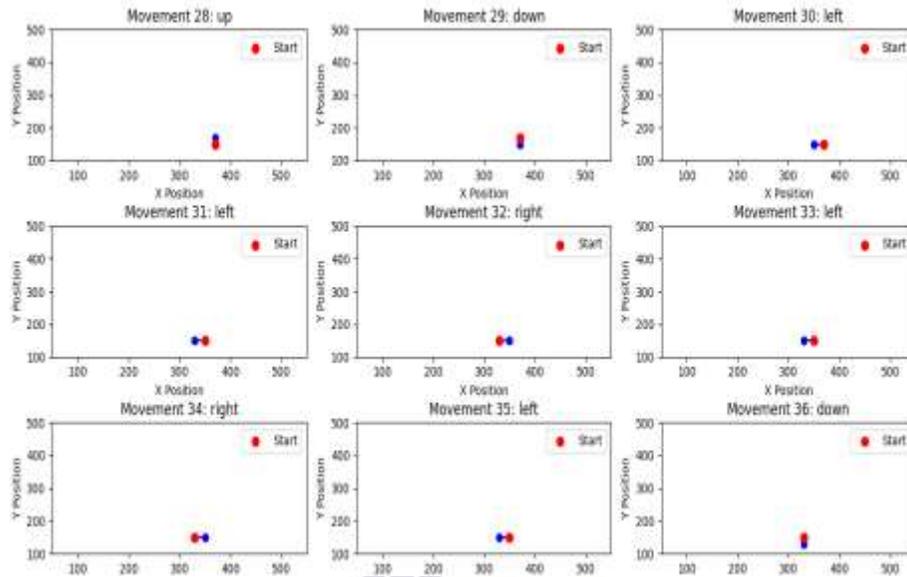


Figure 12 Visualization of Cursor Movements along Different Directions

In figure 12, subplots show near-optimal clustering results, with cursor trajectories aligning closely with

the expected movement directions. Errors are minimal, and movements appear smoother.

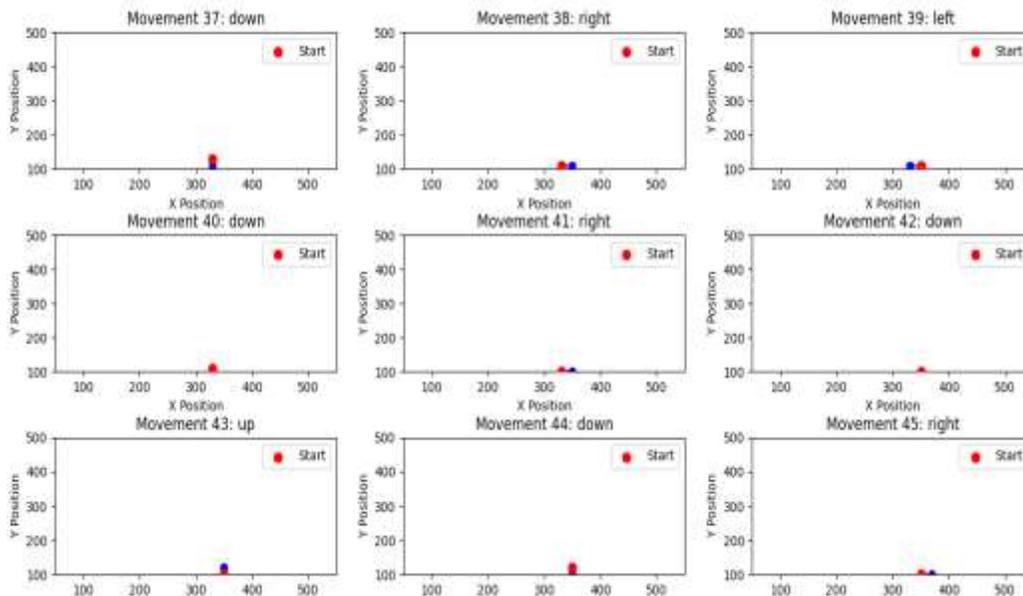


Figure 13 Visualization of Cursor Movements along Different Directions

In figure 13, subplots illustrate a highly refined state, with clear separation of movements. This iteration

confirms the system’s capability to classify EEG features accurately.

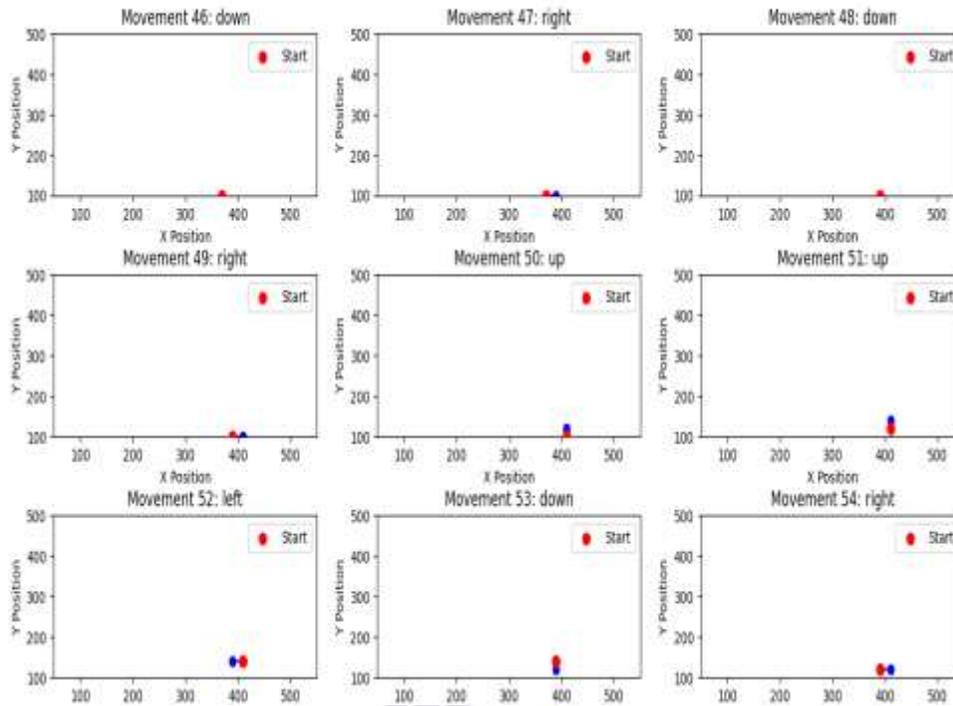


Figure 14 Visualization of Cursor Movements along Different Directions

This figure 14, represents the final iteration, consolidating all adjustments from previous iterations. The subplots exhibit well-defined

trajectories for all directions, showcasing the system's optimal performance. Minor variations may still exist but are within acceptable limits.

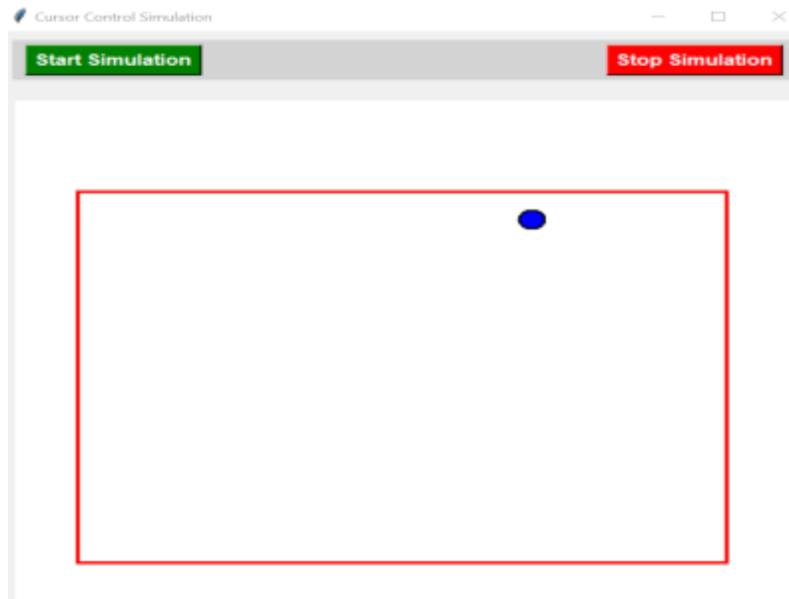


Figure 15 End Position of Cursor

**Discussion**

The proposed system effectively integrates Mu/Beta rhythms and P300 potentials for 2D cursor control. While K-means clustering provided efficient classification, its reliance on unlabelled data limited accuracy compared to supervised methods.

Additionally, noise and feature overlaps impacted performance. Future work should explore real-time systems, advanced feature extraction techniques like wavelet transforms, and supervised algorithms to improve accuracy and applicability.

**K-mean Clustering Comparison with other Algorithms**

Algorithm	Accuracy	Type	Strengths	Weaknesses
K-means Clustering	N/A (Unsupervised)	Unsupervised	Simple, fast, good for identifying patterns	Sensitive to initial centroids, requires predefined clusters
Support Vector Machine	85-90%	Supervised	Effective with high-dimensional data, good for small datasets	Computationally expensive, sensitive to hyperparameters
Random Forest	80-90%	Supervised	Robust, less prone to overfitting, handles large datasets	Slow in real-time, less interpretable
Convolutional Neural Networks (CNNs)	90%+	Supervised	Learns complex patterns, no need for feature engineering	Needs large dataset and powerful hardware

**Conclusion**

This study shows that EEG signals can indeed be used for 2D cursor control is possible. Overall combining Motor Imagery (MI) and P300 potentials the current system provides a very stable base for the development of assistive technologies. This research is inherently offline based, yet it offers a reference point for building real-time BCI systems.

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