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Research Article

Generalized Time Domain Prediction Model for Motor Imagery-based Wheelchair Movement Control

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ABSTRACT

Brain-computer interface (BCI-MI)-based wheelchair control is, in principle, an appropriate method for completely paralyzed people with a healthy brain. In a BCI-based wheelchair control system, pattern recognition in terms of preprocessing, feature extraction, and classification plays a significant role in avoiding recognition errors, which can lead to the initiation of the wrong command that will put the user in unsafe condition. Therefore, this research's goal is to create a time-domain generic pattern recognition model (GPRM) of two-class EEG-MI signals for use in a wheelchair control system. This GPRM has the advantage of having a model that is applicable to unknown subjects, not just one. This GPRM has been developed, evaluated, and validated by utilizing two datasets, namely, the BCI Competition IV and the Emotive EPOC datasets. Initially, fifteen-time windows were investigated with seven machine learning methods to determine the optimal time window as well as the best classification method with strong generalizability. Evidently, the experimental results of this study revealed that the duration of the EEG-MI signal in the range of 4–6 seconds (4–6 s) has a high impact on the classification accuracy while extracting the signal features using five statistical methods. Additionally, the results demonstrate a one-second latency after each command cue when using the eight-second EEG-MI signal that the Graz protocol used in this study. This one-second latency is inevitable because it is practically impossible for the subjects to imagine their MI hand movement instantly. Therefore, at least one second is required for subjects to prepare to initiate their motor imagery hand movement. Practically, the five statistical methods are efficient and viable for decoding the EEG-MI signal in the time domain. Evidently, the GPRM model based on the LR classifier showed its ability to achieve an impressive classification accuracy of 90%, which was validated on the Emotive EPOC dataset. The GPRM developed in this study is highly adaptable and recommended for deployment in real-time EEG-MI-based wheelchair control systems.

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1 INTRODUCTION

The use of a brain-controlled wheelchair (BCW) for paralyzed patients has attracted widespread attention due to its flexibility BCWs are suitable, relatively inexpensive, highly mobile, and easy to set up[1]. The BCW has been designed using different types of EEG signals, such as motor imagery (MI), P300 -evoked potentials, steady-state visual evoked potentials (SSVEPs), and some hybrid signals[2-4]. However, the efficiency of using EEG-based SSEPs and P300 has several limitations for patients with severe motor disabilities [5-10]. Additionally, people with disabilities easily become fatigued [8, 11-13]. Therefore, such a type of EEG signal is inappropriate for wheelchair control. MI is considered effective for paralyzed people because it does not require any voluntary muscle movement [14-16]. In wheelchair navigation with low-level control commands (e.g., forward, backward, or stop and turn left and right), EEG-based MI will be of particular interest [9, 17]. EEG-based MI BCI identifies brain patterns to forecast the user's intention during a specific movement imagination task [18, 19] or emotion [20, 21].

Principally, MI pattern recognition schemes include raw MI EEG signal preprocessing feature extraction [22], and classification [23, 24]. The MI pattern recognition model correlates the effectiveness of intelligent processes such as feature extraction and classification with the effectiveness of the preprocessing (segmentation) of the EEG signal[25, 26]. Feature extraction is another critical step in MI pattern recognition. It represents a distinguishing property, an identifiable measurement, and a functional component obtained from a section of a pattern [27-29]. Common EEG features include those in the time domain, frequency domain, time-frequency domain, and spatial domain [23]. In addition, statistical features can be used to represent the characteristics of the original EEG-MI signal without redundancy to reduce the dimensionality of the feature vectors [30, 31]. The classification process is very useful for analyzing brain pattern characteristics and interpreting EEG signal features represented in a high-dimensional feature space[32]. Numerous machine learning algorithms the BCW literature, including support vector machines (SVMs)[2, 14, 33-46], linear discriminant analysis (LDA) [47-57], decision trees (DTs) [5, 6, 58, 59], K-nearest neighbors (KNNs) [60, 61], naive bases (NBs)[43, 60, 62, 63], logistic regression (LR) [1, 64], and artificial neural networks (ANNs) [1, 45, 60, 61, 64-71]. Moreover, various studies have proposed hybrid learning models [72, 73], novel machine learning methods [74-78], and smart applications[79, 80].

Currently, designing powerful pattern recognition methods with strong generalizability is one of the vital issues in the field of BCI-based applications[81, 82]. The literature has established several different time courses as optimal, including two seconds in the frequency domain[46] and seven seconds in the time-frequency domain [83]. To carry out the segmentation processes in the BCI-based EEG-MI signal, however, none of the studies identified the time window with the most robust MI signal features for generalization in the time domain using five statistical methods. Furthermore, no studies in the literature have identified a classifier with strong generalization capabilities suitable for deployment in a pattern recognition model.

Therefore, this study aimed to develop a time-domain generic pattern recognition model (GPRM) for two-class EEG-MI signal-based wheelchair steering control. Three vital components of the generalization capability of such GPRMs have been considered, namely preprocessing, feature extraction, and classification. In the preprocessing of the EEG-MI signal, a fourth-order Butterworth bandpass filter was used to extract signals with frequencies ranging from 8 to 30 Hz. While excluding time windows, not including feature components, in the segmentation process, fifteen-time windows were studied to find the optimal time window. Particularly, feature extraction using statistical methods that were used in [31] was used in this study for the feature extraction process to extract feature components from the EEG-MI signal without redundancy. Primarily, for classifying the two-class EEG-MI signal as either left or right, seven classification algorithms, namely, LDA, SVM, LR, KNN, DT, MLP, and NB, which have been mostly reported in the literature, were adopted, evaluated, and validated to find the best algorithm with strong generalization power. The remainder of this paper is organized as follows: Section 2 describes the research methodology of this study. In Sections 3 and 4, the results and discussion of GPRM development, evaluation, and validation using two datasets are described. Finally, the conclusions of this study are described in Section 5.

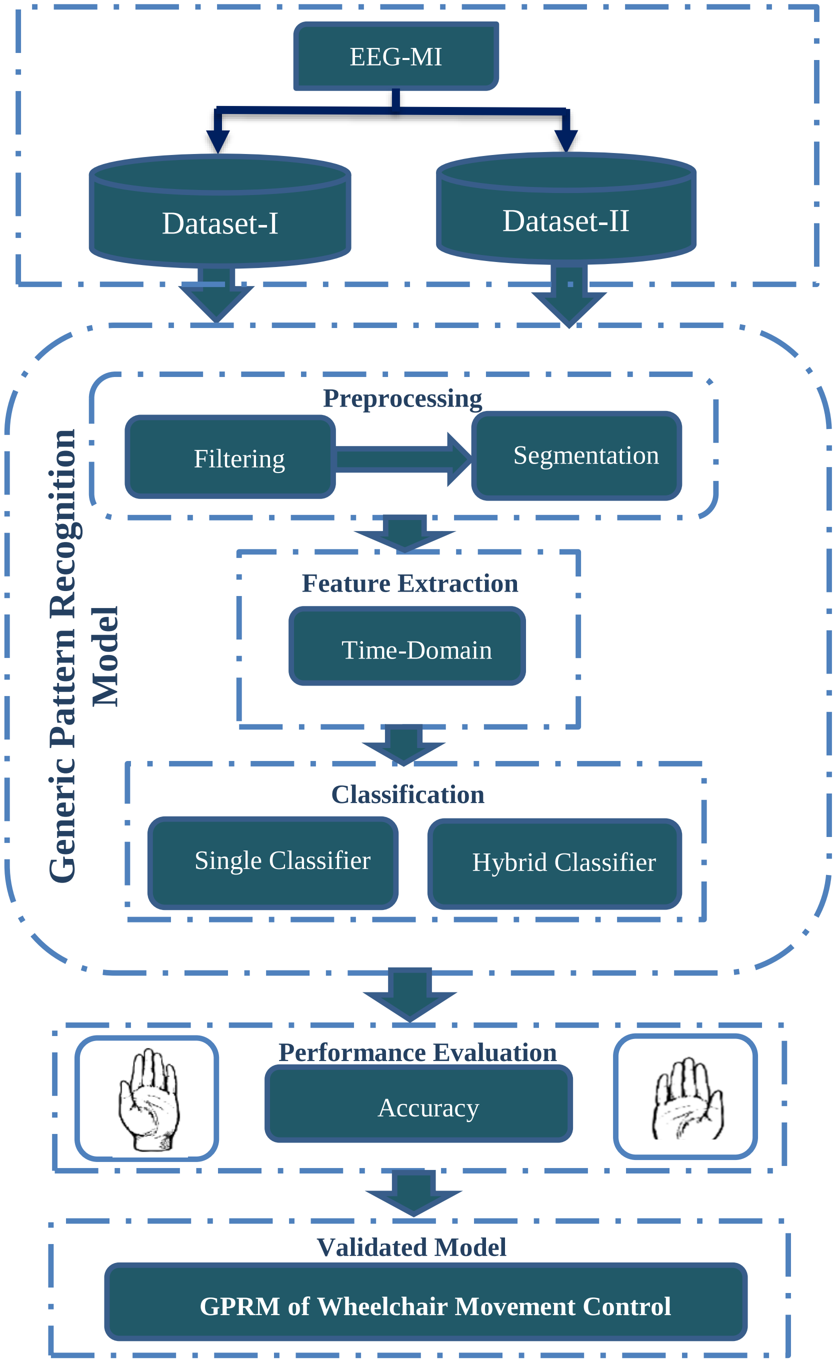

Fig. 1. Research Methodology of the Time Domain GPRM

2 METHODOLOGY

The following subsections describe the methodological framework of the GPRM for two classes of EEG-MI-based wheelchair controls developed, evaluated, and validated in this study. They provide more details about the methods and materials used, including the EEG-MI signal dataset, preprocessing, feature extraction, and classification. Figure 1 depicts the research methodology used for this research.

2.1 Dataset-I

Developers from the Graz University collected a dataset, known as dataset IIb, during the IV BCI competition. This dataset contains EEG signals acquired from three channels, namely, C3, Cz, and C4, from nine subjects performing two motor imagery hand movement tasks with their left and right hands. The dataset contains 160 trials for each participant. Clearly, the lack of a large dataset to develop, evaluate, and validate a GPRM to address the complexity of subjects' specific brain signals, such as inter- and intrasubject differences, was a significant obstacle. Therefore, these datasets of all nine subjects involving different brain complexities were combined (union) to form a large generic dataset. This dataset illustrates the timing scheme of the recording techniques used.

2.2 Dataset-II

The dataset-II had three channels of electroencephalogram (EEG) data (C3, Cz, and C4) that recorded signals for two different motor imagery tasks: movements performed with the left and right hands. They gathered the data from a group of nine different individuals at a sample frequency of 250 Hz. They obtained an electroencephalogram (EEG) from an individual who sat in an armchair and stared on a flat screen for 160 trials. There were two separate recording sessions: one for training with no feedback and the other for evaluation with positive feedback. During the first two sessions, the participants received a concise auditory signal in the form of a warning tone. The subjects conducted four seconds of motor-imaging exercises in response to this cue.

This task involved participating in a cognitive simulation of a specific movement guided by an auditory signal in the form of a pointing arrow displayed on a screen devoid of physical components. Over the course of the following three sessions, the participants received comprehensive guidance on modifying the gray smiley feedback located at the center of the monitor. After a brief auditory signal, the system instructed individuals to move the feedback left or right. Four seconds passed before the smiling emoticon transmitted the feedback. The smiling face turns green while it is heading in the right direction, but turns red when it is going the wrong way. As shown in Figure 2:

2.3 Preprocessing

One of the three essential processes for developing an EEG-MI pattern recognition model for wheelchair steering control is the preprocessing of the raw EEG signal. Therefore, this study carried out preprocessing with two main processes, namely, filtering and segmentation. The aim of the filtering process was to remove unwanted artifacts from the EEG-MI signal and improve the signal-to-noise ratio. Noise from various sources, including body movements, eye blinks, and facial muscle movements, along with artifacts from the surrounding environment, such as electromagnetic fields generated by electrical devices, inevitably contaminates the EEG-MI signal. Therefore, it was vital to filter the EEG-MI signal to remove such noise and artifacts. In this study, we specifically used the fourth-order Butterworth filter to filter the EEG-MI signal, removing contaminated signals from various noise sources and detecting rhythms within the 8 Hz and 30 Hz range, as the EEG-MI method depends on the alpha rhythms (8–13 Hz) and beta rhythms (14–30 Hz) of the sensorimotor cortex. On the other hand, they carried out a segmentation process to eliminate unwanted time windows from the EEG-MI signal while excluding the feature components, thereby enhancing the classification accuracy. Therefore, we employed the segmentation process to enhance the classification accuracy by eliminating periods and feature components from the EEG-MI signal. Figure 2 presents the preprocessing procedure for this research.

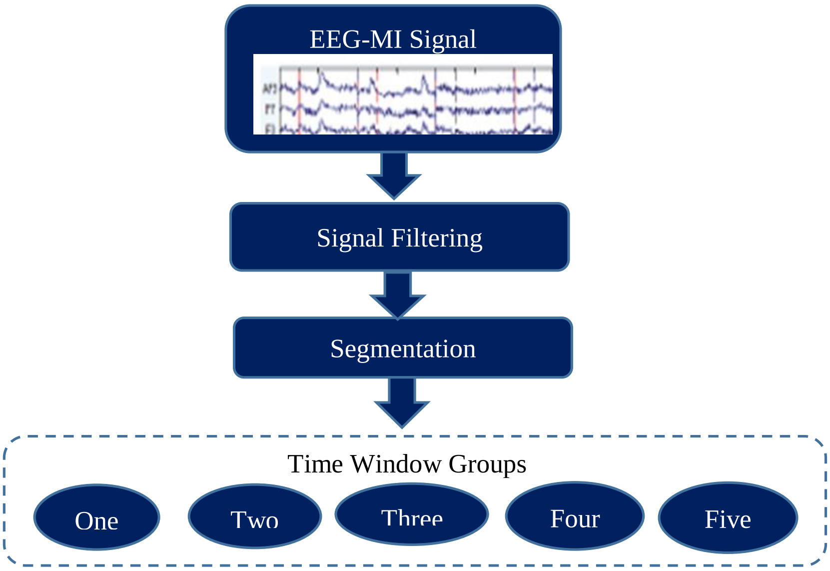

Fig. 2. Preprocessing Steps of the EEG-MI Signals

Each subject may exhibit varying motor-imagery signal power at different times during the trial, as their brain complexities may cause them to start or end the motor-imagery task at slightly different time intervals. Therefore, it is essential to perform feature extraction and classification for brain waves by segmenting motor-imagery signals into different time frames or windows. In this study, five different time-segment groups were used to study the different time windows or time frames based on one, two, three, four, and five seconds of the EEG-MI signal, as shown in Figure 3. The reason for these divisions was to make it possible to examine the different durations of the EEG-MI signal, which could help provide greater insight into the importance of motor-imagery feature components. In addition, the optimal time window of EEG- Mis containing the maximum number of feature components would help develop real-time hardware for applications based on the embedded system, which could be generalized to any two classes of the EEG-MI system using the eight-second Graz recording protocol.

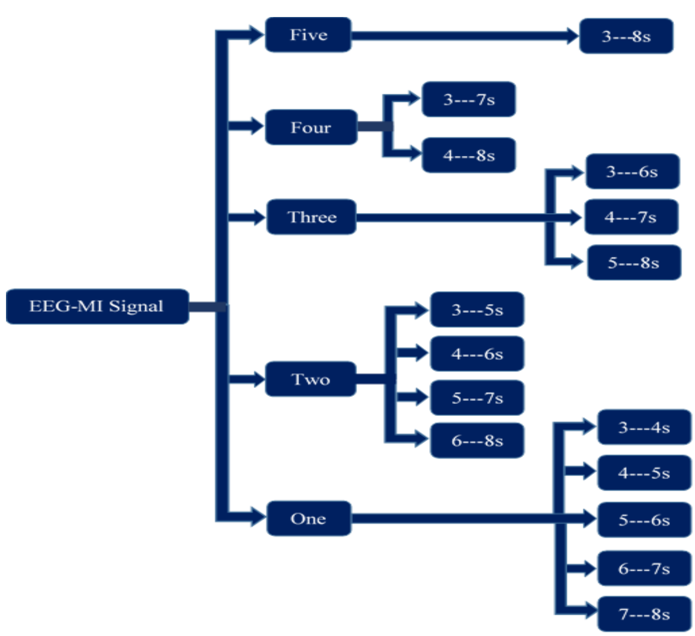

Fig. 3. EEG Signal Segmentation Groups

2.4 Time domain Feature Extraction

In general, biomedical engineering research uses features in the time domain extensively. The widespread use of time-domain features in signal classification is due to their simplicity in computation and rapid implementation in real-world applications. Additionally, they do not need any transformation because such features can be calculated based on the raw EEG signal. Nonetheless, the nonstationary property of the EEG signal, which changes in statistical properties over time, poses a major problem in the extraction of features in the time domain, given that time-domain features assume data to be a stationary signal. Compared with frequency-domain and time-frequency domain features, time-domain features have gained widespread use due to their superior signal classification performance in low-noise environments and their lower computational complexity. As a result, this study used the five statistical features in the extraction of temporal information directly from the EEG signal, as well as to build and reduce the dimensionality of the feature vectors[31], namely, the maximum, minimum, median, mean, and standard deviation. These features represent the characteristics of the original EEG-MI signal without redundancy. Such a feature vector was used to handle the extracted time-domain EEG-MI signal features, which were then fed into the next stage of the classification process.

Classification

In particular, classification methods play a significant role in understanding and distinguishing brain signal features represented in a high-dimensional feature space. In addition, choosing the appropriate classification method would increase the classification accuracy of the BCI-based wheelchair control system. Specifically, this study aimed to develop a GPRM for two-class EEG-MI-based wheelchair steering control. Such a GPRM offers the advantage of having a model that is applicable to unknown subjects. However, if a subject-specific model is developed, it will only fit one subject. Practically, all the papers listed employ seven machine learning methods for developing the GPRM. Various strategies have been implemented to identify the most effective single classifiers and hybrid classifiers. The literature on EEG-based wheelchair control has reported classification methods such as LDA, SVM, LR, KNN, DT, MLP, and NB.

To date, however, none of these studies have focused on the best classification method for EEG-MI signals consisting of two classes using statistical feature extraction in the time domain. The GPRM was assessed in three stages, namely, development, evaluation, and validation. Specifically, the best two single classifiers from the seven classification methods that had been developed were combined to produce the hybrid classifier using the voting technique. The GPRM-based single and hybrid classifiers were evaluated and validated using a single subject dataset individually acquired from the BCI Competition IV/2b and Emotive EPOC datasets. To evaluate the performance of the entire input dataset, it was portioned into subsets using k-fold cross-validation. In this technique, the sample data are divided into k subsets, and out of k subsets, k-1 subsets are used for training the GPRM, while the remaining subset is used for testing the accuracy. This study uses 10-fold cross-validation for evaluating all the PRMs based on single and hybrid classifiers over generic and single-subject datasets.

3 RESULTS

In this study, we conducted six experiments primarily to develop, evaluate, and validate a time domain-based GPRM for EEG-MI-based wheelchair steering control. Initially, we implemented the first three experiments for both development and evaluation purposes. We conducted the last three experiments solely for the validation process. Experiments 1 and 2 were conducted on the developed generic dataset to evaluate the recognition power of each model while being applied to a large dataset with different brain signal complexities. The purpose of the former experiment was to examine five groups of time windows and test them with seven machines to find the optimal time window as well as the best classifier. The results of Experiment-1 showed that the two-second time window achieved the highest classification accuracy compared to the other time windows (namely, one-, three-, four-, and five-second time windows), as shown in Figure 4. Table 1 shows the classification accuracies of the time windows and the highest accuracy achieved by each time window. The results indicate that a two-second (4–6) window achieved the highest classification accuracy. Examining such accuracy based on the different classifiers revealed that LR and LDA were the classifiers that achieved the highest classification accuracy of 62% at the time interval of 4-6 s, which was the highest percentage compared to those of the other classifiers.

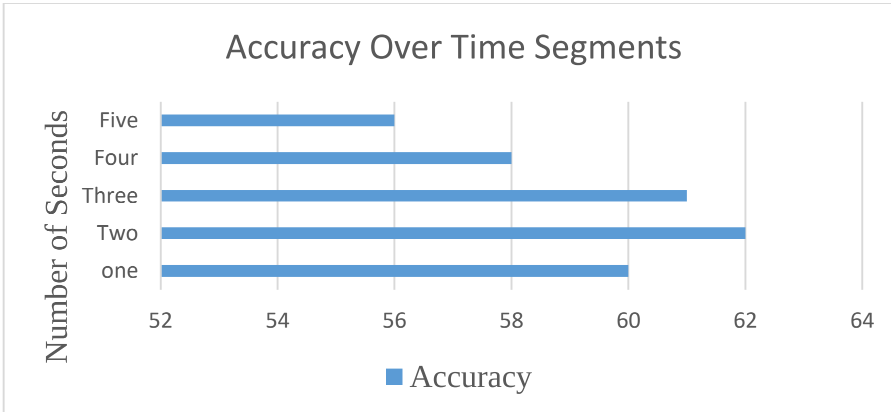

Fig. 4. Classification Accuracies Based on Time Segments

Table I. ACCURACIES OF GPRM USING SINGLE CLASSIFIERS WITH DIFFERENT TIME SEGMENTS

Time-Segment (s)	*Classification Accuracy of GPRM (with single classifier) (%)*						
One Seconds	***LR***	***NB***	***LDA***	***SVM***	***DT***	***MLP***	***KNN***
3-------4	59	51	59	53	54	56	54
4-------5	59	55	59	58	56	60	56
5-------6	59	55	59	58	56	58	56
6-------7	58	52	58	58	52	57	54
7-------8	54	51	55	53	52	53	50
Two Seconds							
3-------5	58	49	58	57	54	58	56
4-------6	62	57	62	60	56	60	56
5-------7	57	53	58	58	52	58	57
6-------8	54	52	54	55	51	56	56
Three Seconds							
3-------6	58	51	58	56	54	60	53
4-------7	61	55	60	59	57	61	59
5-------8	57	51	56	56	52	55	56
Four Seconds							
3-------7	58	55	58	58	54	58	55
4-------8	57	53	57	57	55	57	58
Five Seconds							
3-------8	55	51	55	54	53	56	56

TABLE II. CLASSIFICATION ACCURACIES USING SINGLE AND HYBRID CLASSIFIERS BASED ON A SINGLE-SUBJECT DATASET

Dataset-I	*Classification Accuracy of GPRM (with single and hybrid classifier) (%)*		
Subjects	***LR***	***LDA***	***LR-LDA***
S1	71	71	73
S2	68	69	69
S3	74	75	75
S4	88	88	87
S5	57	59	59
S6	56	51	52
S7	86	88	86
S8	84	83	83
S9	73	75	73
Mean	73	73.2	73
STD	11.6	12.5	11.8

In particular, the results of experiment- 2 using the hybrid classifier (LR-LDA) yielded a classification accuracy of 62%. Specifically, Experiment- 3 was conducted to evaluate the generalization capability of the time-domain EEG-MI GPRM developed in Experiment- 1 and Experiment- 2, which were based on single classifiers (LR and LDA) and hybrid classifiers (LR-LDA), respectively, in distinguishing two mental MI tasks (right and left tasks). In this experiment, the GPRM based on the above classifiers was evaluated on a single subject belonging to the BCI competition dataset (the training part) using a time window of 4–6 s, which had been shown to have the highest classification accuracy in Experiment 1. Moreover, this experiment employed the identical feature-extraction procedure from Experiment- 1 and Experiment- 2, feeding feature vectors to the single classifiers (LR and LDA) and the hybrid classifiers (LR-LDA), respectively.

The classification accuracies in Experiment- 3 were also examined, and it was found that the EEG-MI GPRM models using the single classifier LDA were 73.2% accurate. The single classifier LR and the hybrid classifiers (LR-LDA) were both 73% accurate. Two types of EEG-MI GPRM models—one with single classifiers and one with hybrid classifiers—achieve approximately the same average accuracy. However, the LR classifier had a lower standard deviation (11.6) than the 12.5 and 11.8 for the LDA and LR-LDA classifiers, respectively. Therefore, the time-domain EEG-MI GPRM model based on the single classifier (LR) was the most accurate model, with the highest classification accuracy, using a time window of 4–6 s. Table 2 summarizes the results of Experiment 3's statistical analysis.

TABLE III. CLASSIFICATION ACCURACIES FOR GPRM VALIDATION USING THE BCI COMPETITION SINGLE SUBJECT DATASET

Dataset-II	***Classification accuracy of GPRM (with single and hybrid classifier) (%)***		
Subjects	***LR***	***LDA***	***LR-LDA***
S1	61	65	62
S2	58	54	56
S3	53	52	53
S4	91	93	91
S5	65	60	65
S6	60	58	56
S7	71	71	69
S8	93	95	94
S9	77	78	78
Mean	69.8	69.5	69.3
STD	14.3	16	15.1

Essentially, experiment 4's main objective is to validate such GPRMs in terms of their ability to handle inter- and intrasubject differences in brain signals. They conducted this experiment on the second generic dataset, which we acquired from the validation part of the BCI Competition dataset IV/2b. The results of this experiment showed that the accuracy percentages of the GPRM based on LR and LDA were 69% and 66%, respectively. The accuracy percentage for the LR-LDA model was 67%. In experiment 5, they clearly validated such GPRM models using a single-subject dataset, specifically the BCI Competition IV dataset IIb (validation part). Table 3 displays the results of the GPRM validation involving the nine subjects. As shown, all the GPRMs based on the selected single and hybrid classifiers attained mean classification accuracies of 69.8%, 69.5%, and 69.3% for LR, LDA, and LR-LDA, respectively.

Furthermore, the standard deviation of the LR classifier was 14.3, which was smaller than those of the LDA and LR-LDA classifiers, which were 16 and 15.1, respectively. Finally, the goal of experiment 6 is to test these GPRMs to determine how well they can handle the EEG-MI dataset that the Emotion EPOC EEG device collected. Evidently, the results showed that the LR-based GPRM and LDA-based GPRM achieved the highest and lowest classification accuracies, with mean percentages of 90.2% and 77%, respectively. In contrast, the GPRM based on LR-LDA attained a mean percentage of classification accuracy of 84%, somewhat lying in the middle of the above mean percentages. Furthermore, the standard deviations of the LR- and LDA-based GPRMs (whose standard deviations were 9.2 and 9.1, respectively) were lower than those of the LR-LDA-based model (whose standard deviation was 10.3).

TABLE IV. CLASSIFICATION ACCURACIES OF GPRM VALIDATION USING THE EMOTIVE EPOC SINGLE-SUBJECT DATASET

Emotive	*Classification Accuracy (with single and hybrid classifiers) (%)*		
Subjects	***LR***	***LDA***	***LR-LDA***
S1	77	66	71
S2	95	75	89
S3	98	88	95
S4	91	79	81
Average	90.2	77	84
STD	9.2	9.1	10.3

4 DISCUSSION

This section primarily covers the six experiments conducted to develop, evaluate, and validate the time domain-based GPRM for EEG-MI-based wheelchair steering control. In experiment 1, the results revealed that there was a one-second latency after each command cue, and the maximum motor-imagery feature components emerged after one second of each cue, which lasted for two seconds. This delay was inevitable because it was practically impossible for the subjects to imagine their MI movement instantly. As a result, they needed at least one second to initiate the EEG-MI mental movements. This experiment also showed that the LDA and LR classifiers for the EEG-MI GPRM in the time domain are better at generalization than other classifiers in regard to working with a large dataset. Overall, the research findings suggest that the most critical time window or time interval for task classification is the two-second (4–6 s) time window. Particularly, the comparison of Experiment-1 and Experiment-2's findings in the time domain revealed that both the single classifier and the hybrid classifier achieved similar performance based on the two-second (4–6 s) time window. This finding suggests that both classifiers have the same classification capability for distinguishing the characteristics of the EEG-MI signal features. Therefore, it can be reasonably argued that both single and hybrid classifiers have the same ability to generalize large datasets, making them suitable for use in wheelchair steering control based on the EEG-MI GPRM.

In Experiment- 3, the average accuracy of the EEG-MI GPRM obtained using single classifiers and hybrid classifiers was approximately the same. However, the LR classifier had a lower standard deviation than the LDA and LR-LDA classifiers. Therefore, the time-domain EEG-MI GPRM model based on the single classifier (LR) was the most accurate model, with the highest classification accuracy, using a time window of 4–6 s. It is possible that the LR classifier, which has a lower standard deviation, would be able to address the complex brain signals of the subjects more consistently and have a better ability to generalize than the LDA and LR-LDA classifiers. Basically, looking at the development results from Experiment-1 and Experiment-4 showed that both single and hybrid classifiers did about the same in the GPRM development over a two-second period of time (4–6 s). However, for the validation process, the single and hybrid classifiers achieved different performances. Specifically, the LR-based GPRM attained the highest classification accuracy compared to the models based on LDA and LR-LDA. In addition, the classification accuracy of the LR classifier was 7% higher than that of the classifier described in Experiment 1. This interesting finding, based on different generic datasets of the same subjects, suggested that LR can distinguish EEG-MI signal features in the time domain more accurately than can LDA and LR-LDA. Therefore, we deem the LR classifier to have better generalization capability when dealing with different datasets of the same subjects, making it the optimal classifier for EEG-MI GPRM-based wheelchair steering control. Additionally, comparing the results of Experiment-5 to the results of Experiment-3, the GPRM models based on LR, LDA, and LR-LDA lost as much as 4% of their ability to correctly classify things. Again, the LR standard deviation was relatively lower than that of LDA and LR-LDA. The results show that the LR-based EEG-MI GPRM is more consistent and accurate in the time domain than are the models based on the LDA and LR-LDA classifiers. It can also handle more complex brain signals from different subjects better. As shown in Table 4, the GPRM models that used the Emotion EPOC EEG-MI dataset in Experiment-6 were better at classifying people than the same models that used the BCI Competition dataset (see Experiments-3 and 5 for results). The collective findings strongly suggest that the primary components of the time-domain GPRM, particularly the LR-based GPRM (developed and validated using five different datasets), are best suited for real-time disability applications, such as the Emotive EPOC EEG device.

5. CONCLUSION

This research essentially aims to develop a time-domain GPRM of a two-class EEG-MI signal for use in a wheelchair control system. This GPRM consists of three crucial steps, namely, preprocessing, feature extraction, and classification. The experiments clearly showed that there was a one-second delay after each command cue when the eight-second EEG-MI signal of the Graz protocol was used. Additionally, the results show that the EEG-MI feature components last for two seconds after the one-second latency. This one-second latency makes it practically impossible for the subjects to imagine their MI hand movement immediately. Therefore, at least one second is required for subjects to prepare to initiate their motor imagery hand movement. In addition, the duration of the EEG-MI signal in the range of 4–6s (4–6 s) has strong impact on the classification accuracy when the signal features are extracted via five statistical methods. Interestingly, replacing the eight-second signal with a short signal lasting between 4 and 6s (4–6 s) will make computations easier than using the whole signal. This could make it easier to use the hardware in the EEG-MI-based wheelchair control system. The five statistical methods demonstrated practical efficiency and viability in decoding the EEG-MI signal within the time domain. Evidently, the GPRM model, based on the LR classifier, demonstrated its generalization capability by achieving impressive classification accuracy percentages of 90.2% during validation on the Emotive EPOC dataset. The findings of this study indicate that the developed GPRM is highly adaptable, and we recommend its deployment in real-time EEG-MI-based wheelchair control systems. Additionally, other BCI-based disability applications, such as prosthetic control, robotic arm control, and smart home appliance control, can utilize this GPRM.

Conflicts of interest

The author's disclosure statement confirms the absence of any conflicts of interest.

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