Applied Data Science and Analysis
Vol.2024, **pp**. 69–81
DOI: https://doi.org/10.58496/ADSA/2024/007 ; ISSN: 3005-317X
https://mc04.manuscriptcentral.com/adsa

Research Article

Optimal Time Window Selection in the Wavelet Signal Domain for Brain–Computer Interfaces in Wheelchair Steering Control

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ARTICLEINFO

Article History

Received 25 Mar 2024
Revised 05 May 2024
Accepted 23 May 2024
Published 15 Jun 2024

Keywords

Brain–Computer Interface
Wheelchair
Pattern Recognition
Wavelet Domain
Motor Imagery

ABSTRACT

Background and objective: Principally, the procedure of pattern recognition in terms of segmentation plays a significant role in a BCI-based wheelchair control system for avoiding recognition errors, which can lead to the initiation of the wrong command that will put the user in unsafe situations. Arguably, each subject might have different motor-imagery signal powers at different times in the trial because he or she could start (or end) performing the motor-imagery task at slightly different time intervals due to differences in the complexities of their brains. Therefore, the primary goal of this research is to develop a generic pattern recognition model (GPRM)-based EEG-MI brain-computer interface for wheelchair steering control. Additionally, having a simplified and well generalized pattern recognition model is essential for EEG-MI based BCI applications. Methods: Initially, bandpass filtering and segmentation using multiple time windows were used for denoising the EEG-MI signal and finding the best duration that contains the MI feature components. Then, feature extraction was performed using five statistical features, namely the minimum, maximum, mean, median, and standard deviation, were used for extracting the MI feature components from the wavelet coefficient. Then, seven machine learning methods were adopted and evaluated to find the best classifiers. Results: The results of the study showed that, the best durations in the time-frequency domain were in the range of (4-7 s). Interestingly, the GPRM model based on the LR classifier was highly accurate and achieved an impressive classification accuracy of 85.7%.

1. INTRODUCTION

Recently, EEG-MI-based wheelchair control has attracted considerable attention because MI does not involve any physical body movement. Specifically, they depend on measuring brain patterns while the user performs a certain motor imagery movement [1, 2]. In an EEG-based motor imagery brain-computer interface (MI BCI), brain patterns are analyzed to forecast user intentions during tasks involving imagined movements [3, 4] or emotions [5-7]. Thus, MI is considered effective for paralyzed people because it does not require focus or gazing [8-10]. Fundamentally, a BCI-based MI pattern recognition system requires three essential processes, namely, preprocessing of the EEG signal, feature extraction, and classification [4, 8-10].
Segmentation is a vital preprocessing step for removing unwanted signals from EEG signals, and it has a large impact on the process of feature extraction and classification .However, in the segmentation process of the literature, different time courses have been investigated, and the best durations were four seconds [11], six seconds [12], and seven seconds [13]. No prior study has identified the optimal time window with the strongest MI signal features for hand movement using DWT and statistical feature extraction.

Essentially, another crucial process in the EEG-MI pattern recognition model is the process of feature extraction. In particular, the time-frequency information of EEG-MI signals is widely used as a feature for classification in brain-

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computer interface (BCI) applications, since it describes the density and intensity of the energy of signals at different times and frequencies by designing a joint function of time and frequency[14]. Principally, EEG signal analysis in the time-frequency-domain based on DWT has shown its ability and usefulness in handling brain signal characteristics compared to other methods, such as short-time Fourier transform (STFT), the autoregressive model (ARM), and the wavelet transform (WT)[15]. In addition, statistical features can be used to represent the characteristics of the original EEG-MI signal without redundancy and to minimize the feature vector [16, 17]. Therefore, this study utilized DWT and statistical methods for the feature extraction process in the GPRM.

Principally, machine learning and deep learning methods play a significant role in interpreting and analyzing brain signal patterns, which are naturally represented in a high-dimensional feature space [18-20]. The development of an efficient pattern recognition model with generalizability is one of the critical issues when attempting to develop an EEG-MI-based brain-computer interface (BCI) application [21-23]. Many machine learning algorithms, such as: linear discriminant analysis (LDA) [24-34], support vector machine (SVM) [12, 35-49], K-nearest neighbors (KNN) [50, 51], artificial neural networks (ANNs) [49-60], naive bases (NBs) [47, 50, 61, 62], decision trees (DTs) [63-66], and logistic regression (LR) [52, 53], have been proposed for BCW. Moreover, various studies have proposed hybrid learning models [67-70], novel machine learning methods [3, 71-76], and smart applications [7, 76-80]. However, none of the studies stated which one has a strong generalization capability to be deployed in a DWT-based GPRM for two-class EEG-MI signals. Therefore, this study aims to develop a GPRM for two-class EEG-MI signals of wheelchair steering control and considers the generalization capability of the three essential components of the MI pattern recognition system, namely, preprocessing, feature extraction, and classification. In the preprocessing stage, two steps were accomplished, namely, filtering, and segmentation. To filter the EEG-MI signal, a fourth-order Butterworth bandpass filter was used to extract signals with frequencies ranging from 8-30 Hz. Then, for the segmentation process, fifteen-time windows were studied to determine the optimal time segment, which is considered the main contribution of this study. Particularly, in the feature extraction stage, the statistical features that were used in [17] were used to extract feature components from the DWT coefficient that represent the original EEG-MI signal without redundancy. Principally, in the classification stage, seven classification algorithms, namely, LDA, SVM, LR, KNN, DT, MLP, and NB, were evaluated to find the best algorithms.

The remainder of this paper is organized as follows: Section 2 describes the methodological framework used to develop, evaluate, and validate the GPRM. Section 3 describes the results and discussion of the experiments on two different datasets, namely, the BCI Competition dataset IV/2b, and the Emotive EPOC dataset. Finally, Section 4 presents the conclusions of this study.

2. METHODOLOGY

The methodological framework of the GPRM for two-class EEG-MI-based wheelchair control is presented in Figure 1 below.

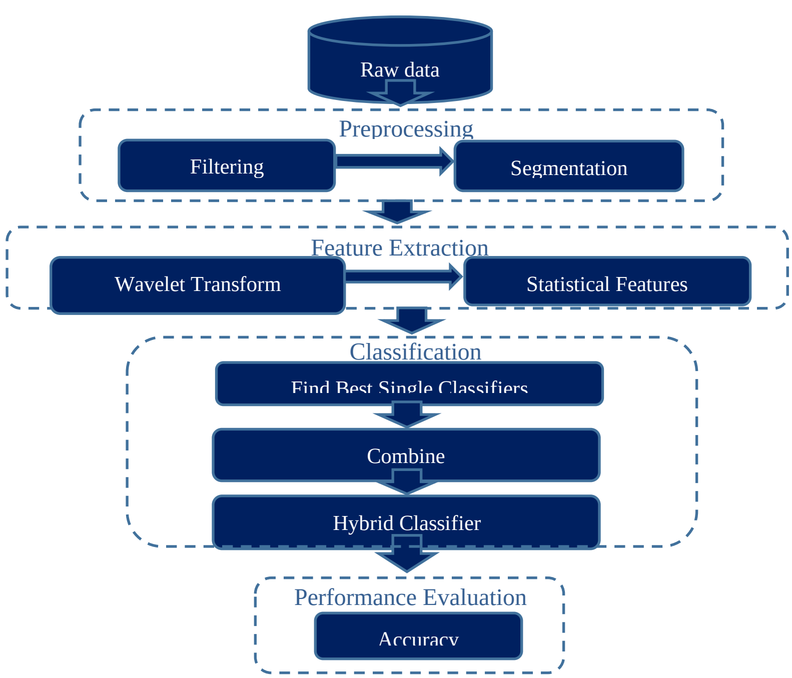

Fig. 1. Methodological Framework for GPRM Development

This framework describes the entire intelligent process of pattern recognition, starting from the preparation of the EEG-MI datasets and ending with the performance evaluation stage. The following subsections describe the methodology of this research in more detail.

2.1 Dataset-I

Two datasets were used in this study, the first dataset is a dataset that stands in the tradition of prior BCI competition datasets and belongs to Graz University. This dataset, which was collected using three channels, namely, C3, Cz, and C4 was used to acquire the EEG signals for two motor imagery hand movement right/left tasks collected from nine subjects at a 250 Hz sampling frequency. EEG data from 160 trials were collected from the nine subjects while they were watching a flat screen and sitting in an armchair.

The second dataset was collected using an Emotive EPOC EEG device to acquire the relevant data for the two classes of the EEG-MI signal, which were used for validating the applicability of the developed GPRM equipped with such a device. Given the nature of the data collection that could be deemed intrusive, the procedure for collecting the data in this study had to be approved by the ethical approval committee of University Pendidikan Sultan Idris. Specifically, the recording protocol of the two-class EEG-MI-based wheelchair control for the right and left commands was similar to the Graz protocol used in the BCI competition IV/dataset-2b. The dataset, consisting of EEG data, was obtained from four healthy male volunteers (subjects with normal vision). Additionally, each subject's task was recorded in four sessions, with each session consisting of two runs. Essentially, each run consisted of 20 trials, resulting in a total of 160 EEG-MI signals for each participant.

2.2 Preprocessing

Preprocessing of the raw EEG signal is one of the three vital processes that must be performed prior to developing an EEG-MI pattern recognition model for wheelchair steering control. Therefore, in this study, preprocessing was carried out via two main processes, namely, filtering and segmentation. The aim of the filtering process was to remove unwanted artifacts from the EEG-MI signal and to improve the signal-to-noise ratio. On the other hand, the segmentation process was carried out to remove the unwanted time window from the EEG-MI signal, excluding the feature components, to improve the classification accuracy. The fourth-order Butterworth filter was used in this study for the EEG-MI signal filtering process to remove the signal contaminated by various noise sources and to detect the rhythms within the range of 8 Hz to 30 Hz given that the EEG-MI method relies on the alpha rhythms (8-13 Hz) and beta rhythms (14-30 Hz) of the sensorimotor cortex. However, for segmentation, 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.

2.3 Time-Frequency Domain Feature Extraction

Essentially, the time-frequency domain is a hybrid type of brain signal representation. In principle, this type of domain considers neurophysiological EEG-MI signal properties in both the temporal and frequency domains. Fundamentally, the decomposition level and the choice of mother wavelet play a significant role when using the DWT method for analyzing brain signals [81]. Primarily, the frequency of interest determines the decomposition levels required to find spatial brain signal patterns. As such, in this study, the use of five decomposition levels in the wavelet transform helped extract the rhythms of the alpha and beta bands. Hence, the alpha and beta bands were located at levels five and four, respectively, and the power of these rhythms changed while the subjects simulated their hand movements. Practically, five statistical features used in [17] and mentioned in [16, 82], namely, the maximum, minimum, median, mean, and standard deviation, were utilized in this study, to minimize-the high dimensionality of the feature space extracted from the wavelet coefficients. Such statistical methods could represent the characteristics of the original EEG-MI signal-without redundancy [16]. Finally, the feature vector can be fed to the machine learning algorithm for training and testing.

2.4 Classification

Fundamentally, EEG signals require a high-dimensional feature to represent the characteristics of the brain signal. In addition, these features cannot be analyzed and interpreted without using machine learning methods[18]. The classification method plays a major role and has a direct impact on the discrimination between two EEG-MI mental commands. Therefore, by choosing the appropriate feature classifier, high rates of classification accuracy will be achieved. This research aimed to develop a GPRM for two-class EEG-MI signals using machine learning methods used in all the papers listed in literature.

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-frequency domain. Therefore, two classifiers, namely, single and hybrid classifiers, were developed, evaluated, and validated in this study. For the single classifier, seven machine learning methods that have been cited in the literature, namely, LDA, SVM, LR, KNN, DT, MLP, and NB, were evaluated to find the best algorithms using the developed generic dataset. Then, the best two single classifiers, which had been developed, were combined to produce the hybrid classifier using the voting technique. The single and hybrid classifiers were evaluated and validated using a single subject dataset individually acquired from BCI Competition IV/2b and Emotive EPOC datasets. As an evaluation method, a 10-fold cross-validation technique was used, and for this purpose, the dataset was partitioned into 10 equally sized mutually exclusive subsets (folds). The procedure was then repeated for 10 iterations to evaluate all the GPRMs based on single and hybrid classifiers over the generic and single subject datasets.

3. RESULTS AND DISCUSSION

Fundamentally, six experiments were conducted in this study to develop, evaluate, and validate a time-frequency domain-based GPRM for EEG-MI-based wheelchair steering control. Table 1 shows the classification accuracies of the time windows and the highest accuracy achieved by each time window.

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

Time-Segment (s)	*Classification accuracy of GPRM (with Single Classifier) (%)*						
Number of Seconds	***LR***	***NB***	***LDA***	***SVM***	***DT***	***MLP***	***KNN***
3-------4	59	57	60	54	53	58	52
4-------5	70	64	69	70	65	68	67
5-------6	67	59	66	60	58	67	62
6-------7	62	55	62	57	55	62	55
7-------8	58	58	58	56	54	56	56
3-------5	67	62	67	61	60	64	62
4-------6	71	62	71	68	66	69	67
5-------7	68	59	68	62	61	65	61
6-------8	62	58	62	60	56	61	58
3-------6	68	67	67	66	62	66	63
4-------7	71	70	70	67	62	67	64
5-------8	66	65	65	62	58	64	59
3-------7	70	59	68	62	61	64	62
4-------8	69	61	68	64	63	65	62
3-------8	69	60	67	62	63	64	61

This section discusses the six experiments that have been conducted to develop, evaluate, and validate the time-frequency domain-based GPRM for EEG-MI-based wheelchair steering control. Evidently, in Experiment 1 in the time-frequency domain involving a large dataset, LDA and LR had the best generalization capability compared to the other classifiers for classifying two mental tasks (the right and left tasks). These experiments also revealed differences in the motor-imagery feature components of the subjects based on their EEG-MI signals. Overall, the research findings suggest that the two most critical time windows or time intervals for the classification of tasks are the two second (4–6 s) time window and three-second (4–7 s) time window, as presented in Table 2, Table 3, and Table 4, which present the results of the evaluation, the validation with the BCI Competition dataset, and the validation with the Emotive dataset, respectively.

In addition, the experimental findings of the time-frequency domain GPRM revealed that the delay after each command cue while utilizing the eight-second EEG-MI signal recorded by the Graz protocol was approximately one second. This delay was inevitable because it was practically impossible for the subjects to imagine their MI movement instantly. As such, they needed at least one second to start initiating the EEG-MI mental movements. In addition, the proposed GPRM achieved better classification accuracy in three second time windows (3–7 s) than in the literature, as shown in Table 5 and Table 6, indicating that better accuracy can be achieved with four-, six-, and seven-second time windows. Additionally, comparing the findings of Experiment-2 with those of Experiment-1 revealed that the highest accuracies achieved with the use of single and hybrid classifiers were 71% using a time window of 4–7 s. Therefore, it can be deduced that in the time-

frequency domain, the EEG-MI GPRMs based on single and hybrid classifiers have the same strong generalization capability when applied to large datasets. Therefore, both classifiers (single and hybrid) can be deployed in GPRM for wheelchair steering control based on the EEG-MI signal. In particular, compared with the results of Experiment-1, the classification accuracy of LR decreased by 1% and 2% based on the time windows of 4–6 s and 4–7 s, respectively.
A similar trend of percentage decrease was also observed for LDA, with percentages of classification accuracy decreasing by 2% and 3%, respectively. In contrast, the percentage of classification accuracy of LR-LDA was consistent throughout the experiments (there was no decrease in the percentage of classification accuracy) in the time window of 4–6 s. However, the same was not replicated in the time window of 4–7 s, in which the percentage of classification accuracy of such a hybrid classifier decreased by 4%. Similarly, compared with models based on other classifiers, the LR-based GPRM achieved the highest accuracy in classification tasks involving two different generic datasets of the same subjects. Taken together, all the above findings suggest that the LR-based GPRM model is more efficient and consistent than models based on LDA and LR-LDA and has better generalizability in handling the complexity of subjects' brain signals using a number of different generic datasets.

Table II. CLASSIFICATION METRICS USING SINGLE AND HYBRID CLASSIFIERS FOR A SINGLE-SUBJECT TRAINING DATASET

Classifier	***Subjects***	***Time Window***							
		4-6 s				***4-7 s***			
		Precision	***Sensitivity***	***Specificity***	***Accuracy***	***Precision***	***Sensitivity***	***Specificity***	***Accuracy***
LR	S1	59	74	52	62	68	74	68	70
	S2	56	56	52	54	68	68	65	66
	S3	33	30	44	37	54	61	52	56
	S4	100	100	100	100	100	97	100	97
	S5	79	76	78	77	79	92	74	83
	S6	36	47	55	52	50	53	71	64
	S7	88	84	87	85	78	72	78	75
	S8	95	91	96	93	95	91	96	93
	S9	83	80	83	81	74	82	67	75
	Mean	69.8	70.8	71.8	71.2	74	76.6	74.5	75.4
LDA	S1	67	78	64	70	75	78	76	77
	S2	67	78	64	70	64	64	61	62
	S3	40	35	52	43	52	61	48	54
	S4	100	100	100	100	97	94	94	93
	S5	77	80	74	77	75	84	70	77
	S6	35	53	45	47	53	59	71	66
	S7	81	88	78	83	73	76	70	72
	S8	91	91	92	91	91	87	92	89
	S9	74	68	74	70	72	72	70	70
	Mean	70.2	74.5	71.4	72.3	72.4	75	72.4	73.3
LR-LDA	S1	62	87	52	68	67	78	64	70
	S2	60	72	48	60	62	72	52	62
	S3	36	35	44	39	52	65	44	54
	S4	100	100	100	100	97	97	94	95
	S5	77	80	74	77	73	96	61	79
	S6	33	53	42	45	53	59	71	66
	S7	79	88	74	81	74	80	70	75
	S8	92	96	92	93	92	96	92	93
	S9	74	80	70	75	72	84	65	75
	Mean	68.1	76.7	66.2	70.8	71.3	80.7	68.1	74.3

TABLE III. CLASSIFICATION METRICS OF GPRM USING SINGLE AND HYBRID CLASSIFIERS FOR A SINGLE-SUBJECTS VALIDATION DATASET

	Subjects	Time Window 4-6 s Precision	4-6 s Sensitivity	4-6 s Specificity	4-6 s Accuracy	4-7 s Precision	4-7 s Sensitivity	4-7 s Specificity	4-7 s Accuracy
LR	S1	60	58	55	56	64	62	59	60
	S2	63	65	55	60	60	58	55	56
	S3	52	42	55	47	60	58	55	56
	S4	92	96	92	93	92	96	92	93
	S5	79	85	71	79	79	70	76	72
	S6	45	36	52	43	79	44	87	64
	S7	60	41	77	60	58	50	69	60
	S8	88	95	88	91	83	86	85	85
	S9	63	89	66	75	64	84	69	75
	Mean	66.8	67.4	67.8	67.1	71	67.5	71.8	69
LDA	S1	64	62	59	60	58	54	55	54
	S2	56	58	45	52	67	62	64	62
	S3	61	42	68	54	67	62	64	62
	S4	100	88	100	93	92	92	92	91
	S5	81	81	76	79	73	70	67	68
	S6	45	36	52	43	55	44	61	52
	S7	50	45	62	54	59	59	65	62
	S8	81	95	81	87	81	100	81	89
	S9	71	89	76	81	62	79	69	72
	Mean	67.6	66.2	68.7	67	68.2	69.1	68.6	68
LR-LDA	S1	73	55	67	59	63	65	55	60
	S2	57	71	40	56	62	62	55	58
	S3	46	35	53	43	62	62	55	58
	S4	88	94	88	90	92	96	92	93
	S5	77	94	64	81	75	78	67	72
	S6	69	53	73	62	57	52	57	54
	S7	56	60	59	59	58	64	62	62
	S8	77	91	86	87	81	100	81	89
	S9	60	92	58	71	57	84	59	68
	Mean	67	71.6	65.3	67.5	67.4	73.6	64.7	68.2

Contrasting the findings of Experiment-6 with previous findings showed that the highest classification accuracies achieved by such models were in the time window of 4–7 s. Collectively, the findings of the conducted experiments provide enough evidence to argue that operating with different datasets of identical subjects in the time window of 4–7 s will help the GPRM to consistently achieve high classification accuracy compared to that of the same models operating in the time window of 4–6 s. As demonstrated, the development and validation of the GPRM in the time-frequency domain using five different datasets yielded promising results in terms of preprocessing, feature extraction, and classification. Particularly, the classification accuracy of the LR-based GPRM model far surpassed those of the same models based on other classifiers in the time-frequency domain.

TABLE IV. CLASSIFICATION METRICS OF GPRM USING SINGLE AND HYBRID CLASSIFIERS BASED ON AN EMOTIVE EPOC SINGLE-SUBJECT DATASET

	Procedure	***Dataset***		***No. of Samples***	***Segmentation***	***Classifier***	***Accuracy***
[12]	Development	BCI Competition II	Single	1	6 s	SVM	91.4%
	Validation	Proprietary	Single	4	6 s	SVM	71%
[24]	Development	BCI Competition III	Single	3	4 s	ANN	76%
[26]	Development	Proprietary	Single	10	7 s	ANN	73.5%

TABLE V. CLASSIFICATION ACCURACIES IN THE LITRATURE OF MI-BASED WHEELCHAIR CONTROL USING THE

Classifier	***Subjects***	***Time Window***							
		4-6s				***4-7s***			
		Pre cisi	***Sen sitiv***	***Spe cifi***	***Acc ura***	***Pre cisi***	***Sen sitiv***	***Spe cifi***	***Acc ura***
LR	S1	81	92	79	85	70	79	67	72
	S2	78	88	75	81	82	96	79	87
	S3	83	83	83	83	85	92	83	87
	S4	55	71	42	56	100	96	100	97
	Mean	74.2	83.5	69.7	76.2	84.2	90.7	82.2	85.7
LDA	S1	72	75	71	72	68	54	75	64
	S2	74	71	75	72	73	67	75	70
	S3	70	79	67	72	70	79	67	72
	S4	66	63	79	54	87	83	88	85
	Mean	70.5	72	73	67.5	74.5	70.7	76.2	72.7
LR-LDA	S1	67	83	58	70	67	83	58	70
	S2	73	100	62	81	73	100	62	81
	S3	67	100	50	75	67	100	50	75
	S4	89	100	80	93	89	100	88	93
	Mean	74	95.7	62.5	79.7	74	95.7	64.5	79.7

TABLE VI. CLASSIFICATION ACCURACIES USING THE PROPOSED GPRM

Study	*Procedure*	*Dataset*		*No. of Samples*	*Segmentation*	*Classifier*	*Accuracy*
Proposed GPRM	Development	BCI Competition IV Training Part	Generic	9	3 s	LR	71%
	Evaluation		Single	9	3 s	LR	73%
	Validation	BCI Competition IV Validation Part	Generic	9	3 s	LR	69%
			Single	9	3 s	LR	70.4%
		Emotive Dataset	Single	4	3 s	LR	85.7%

Clearly, with higher classification accuracy, the former model will be the best candidate for wheelchair steering control, the use of which is made more imperative by taking into account its generalization capability in dealing with different datasets of the same subjects, as well as the Emotive EPOC EEG-MI dataset. Overall, the findings of the six experiments involving the development, evaluation, and validation of the GPRM models indicate that the time window of 4-7 s is the best time window in the time-frequency domain. The preference for using a specific time window in a certain domain lies in the ability of the GPRM to include most of the feature components of the EEG-MI signal in each signal domain. For the classification of the two MI hand movements, LR is deemed the most appropriate classifier in the time-frequency domain, the choice of which is governed by the consistency of a particular classifier in achieving high classification accuracy with the use of different datasets.

4. CONCLUSION

This study proposed a new GPRM for two-class EEG-MI signals to be deployed in a wheelchair steering control system. Specifically, this model consists of a processing pipeline for EEG-MI signals, such as preprocessing, feature extraction, and classification. Clearly, the obtained results and findings in this study showed that, in the preprocessing stage, after filtering the EEG-MI signal and applying the segmentation process, the motor imagery feature component existed after one second from the cue and lasted for three seconds. This means that the delay after each command cue while utilizing the eight-second EEG-MI signal recorded by the Graz protocol was approximately one second. This delay was inevitable because it was practically impossible for the subjects to imagine their MI movement instantly. As such, they needed at least one second to start initiating the EEG-MI mental movements. In addition, it was deduced that the duration of the EEG-MI signal plays a substantial role in the classification accuracy, with the best durations in the time-frequency domain using DWT and five statistical features being in the range of 4 to 7 seconds (4-7 s). Specifically, this duration will minimize the computational complexity compared to using the whole signal, which may facilitate the hardware implementation of the intelligent control system-based EEG-MI scheme. Additionally, as a feature extraction step based on the statistical feature method and DWT, this technique is viable and effective in decoding the EEG-MI signal. Interestingly, the GPRM model based on the LR classifier was a powerful classifier with strong generalizability. In addition, the validation process of such a model with the use of the Emotive EPOC dataset showed that the LR-based GPRM attained an impressive percentage of classification accuracy of 85.7% and outperformed the model-based SVM in the literature by 14.7%. These findings confirm the adaptability of the developed GPRM for real-time EEG-MI-based wheelchair control. in real-time in EEG-MI-based wheelchair steering control systems as well as in other BCI-based disability applications.

Conflicts of interest

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

Funding

The author's paper does not provide any information on grants, sponsorships, or funding applications related to the research.

Acknowledgments

The author acknowledges the support and resources provided by the institution in facilitating the execution of this study.

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