Research Article

A Frequency-Domain Pattern Recognition Model for Motor Imagery-Based Brain-Computer Interface

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ARTICLEINFO

ABSTRACT

Brain-computer interface (BCI) is an appropriate technique for totally paralyzed people with a healthy brain. BCI based motor imagery (MI) is a common approach and widely used in neuroscience, rehabilitation engineering, as well as wheelchair control. In a BCI based wheelchair control system the procedure of pattern recognition in term of preprocessing, feature extraction, and classification plays a significant role in system performance. Otherwise, the recognition errors can lead to the wrong command that will put the user in unsafe conditions. The main objectives of this study are to develop a generic pattern recognition model-based EEG –MI Brain-computer interfaces for wheelchair steering control. In term of preprocessing, signal filtering, and segmentation, multiple time window was used for de-noising and finding the MI feedback. In term of feature extraction, five statistical features namely (mean, median, min, max, and standard deviation) were used for extracting signal features in the frequency domain. In term of feature classification, seven machine learning were used towards finding the single and hybrid classifier for the generic model. For validation, EEG data from BCI Competition dataset (Graz University) were used to validate the developed generic pattern recognition model. The obtained result of this study as the following: (1) from the preprocessing perspective it was seen that the two-second time window is optimal for extracting MI signal feedback. (2) statistical features are seen have a good efficiency for extracting EEG-MI features in the frequency domain. (3) Classification using (MLP-LR) is perfect in a frequency domain based generic pattern recognition model. Finally, it can be concluded that the generic pattern recognition model-based hybrid classifier is efficient and can be deployed in a real-time EEG-MI based wheelchair control system.

1 INTRODUCTION

Mobility is one of the challenges faced by stroke survivors[1, 2]. A wheelchair can assist these patients to become partially independent in performing certain daily activities [3-5]. However, People with disability and the elderly will find steering and driving a wheelchair with electrical and mechanical schemes challenging [6]. Brain-controlled wheelchair (BCW) is the appropriate device for completely Paralyzed patients with a healthy brain to navigate their environment [7, 8]. Techniques based on brain-computer interface (BCI) are currently used to develop electric wheelchairs [9-11]. Using human brain control in wheelchairs for people with disability has elicited widespread attention due to its flexibility [6], convenience, relatively low cost, high mobility and easy setup [12, 13]. One can see in Figure 1 the architecture of an intelligent wheelchair system.

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Moreover, in complex and real environments, driving a wheelchair safely is essential and recommended for people with disability due to the requirement of sending commands on time [15]. Therefore, dependable navigation control systems are required for the wheelchair user to comfortably and freely navigate around and ensure his/her safety [16, 17]. For example, placing the user in an unsafe condition, the wheelchair control system must be sensitive to checking if the extracted commands from the BCI system is accurate and will place the user in a safe zone [18]. A BCI system can pose a threat to the user or nearby people due to unwanted navigation controls of the wheelchair resulting from using the wrong commands or being unfamiliar with the machine interface or if the machine misunderstands the gesture of the user [19]. Therefore, the processes of pattern recognition in term of feature extraction and classification are vital in BCI design, and they have a significant effect on the performance of the BCI system. Otherwise, the presence of errors can cause the initiation of a wrong command that can lead to dangerous situations [12]. In general, any BCI system requires an efficient signal processing which mainly are three necessary steps, namely preprocessing, features extraction, and classification [20, 21]. However, efficient signal processing and machine learning techniques in feature extraction and classification can also improve the accuracy of extracting high-dimensional EEG features [22-25]. Also, mapping the brain signal once measured into a feature vector containing useful information is a very challenging task [26, 27]. Therefore, rapidly and efficiently extracting features from various signals are necessary to realize BCI systems [6].

Also, while designing a wheelchair for stroke survivors, the most important thing that has to be considered is how accurate the classification is to distinguish a couple of mental tasks such as thinking forward, backward, right, and left [26]. Furthermore, the BCI depends on its classification algorithm to decode the extracted signal features for interpreting the user’s intent into device commands to control the wheelchair. Therefore, the better the classification is, the better the application of any BCI system will be [6, 28, 29]. Consequently, fast decision-making is required in a wheelchair control system-based BCI signal because of the amplified communication in the BCI channel [30-32]. However, achieving high classification accuracy is challenging in a BCI-based system due to the complexity of the brain signal [33-35].

Also, individual differences in EEG signals can also affect the stability of a control system, given that the signals are not ideal [36]. Furthermore, the EEG based system has the disadvantage of a higher sensitivity to noise including ocular, muscular and electromagnetic noises [37]. The noise problem can be reduced, and the classification accuracy can be improved by using better computational intelligent methods in both features extraction and classification algorithms to extract high dimensional EEG feature [38-40].

Recently, EEG-based MI signals have been used in various types of applications, such as sports, psychology, neuroscience and rehabilitation technology, as well as wheelchair control [41-45]. MI-based BCI signals provide a rapid response [46, 47]. Therefore, these signals support the dynamic movements of an electrical wheelchair by turning over and crossing a path during navigation. MI does not require any voluntary muscle movement[48]. Thus, MI is considered effective for people with severe disability [4, 49]. Recently, EEG-based MI signals have been used in various types of applications, such as sports, psychology, neuroscience and rehabilitation technology, as well as wheelchair control [41, 42]. This approach does not require gazing or focus. Also, MI-based BCI signals provide a rapid response [46]. Therefore, these signals support the dynamic movements of an electrical wheelchair by turning over and crossing a path during navigation [30, 50]. MI-based BCI signals will be of particular interest in shared and low navigation because they
can offer continuous control of BCW with few low-level commands (e.g., forward, backward or stop and turn left and right) [51, 52]. Although many studies in the literature using different techniques and methods of preprocessing, feature extraction, and classification for recognizing EEG patterns of EEG-MI based wheelchair control commands, however, up to what extent, none of those above studies stated or recommended the best method and technique for distinguishing a couple of EEG-MI commands to be deployed in a wheelchair control system.

Therefore, this study aims to develop a generic pattern recognition model of two class EEG-MI signals in frequency domain based on fast Fourier transform, statistical feature methods as a feature extraction methods, as well as select the best machine learning technique for the classification of EEG-MI wheelchair control commands.

### 1.1. EEG Motor Imagery

Motor imagery (MI), is one of the most common methods used in BCI-based EEG control systems [53, 54]. MI also is known as movement imagery is a mental process through which a person imagines a physical action, such as jump, moving hands, etc. MI is used as a BCI strategy. In particular, event-related desynchronization (ERD) and synchronization (ERS) structures caused by MI are analyzed [42]. Many factors suggest that μ and β rhythms can be good signs to be used in BCI systems. They are associated with cortical areas more directly linked to brain motor activity. Furthermore, it was verified that the SMR occur both at the imagination movement realization as in its and may help people with severe disabilities to perform tasks only with the movements’ imagination[20]. The primary sensory and motor cortices create sensorimotor rhythms (SMR). SMR based BCI’s divided into two: event-related synchronization (ERS) and event-related desynchronization (ERD), which detected as mu rhythm and beta [55]. One of the most processing paradigms in BMI is motor imagery paradigm in which the mu (8-13 Hz) and beta rhythm (14-30Hz) of the sensorimotor cortex are used. The oscillations of the mu and beta rhythm of the sensorimotor cortex decrease when a movement is being prepared or during movement-this is called event-related desynchronization (ERD). After a movement occurs, the oscillations increase-this is called event-related synchronization (ERS). If a person imagines that she/he is moving the left hand, a strong ERD occurs at the right side of the sensorimotor cortex.

On the other hand, if a person imagines that s/he is moving the right hand, ERD occurs on the left side [56]. Event-related Synchronization and Desynchronization (ERS and ERD, respectively) are the EEG patterns characterized by meaningful changes in the signal energy in specific frequency bands. An energy increase is associated with an ERS, while an energy decrease is associated with an ERD.

### 2 METHODOLOGY

#### 2.1 Dataset

The BCI competition IV stands in the tradition of prior BCI competitions that aim to provide high-quality neuroscientific data for open access to the scientific community. As experienced already in previous competitions not only scientists from the narrow field of BCI compete, but scholars with a broad variety of backgrounds and nationalities. They include high specialists as well as students. The goals of all BCI competitions have always been to challenge concerning novel paradigms and complex data[57]. This dataset belongs to Graz university and contains EEG signals on channel C3, Cz, and C4 from nine subjects performing two different imagery tasks of Left/Right hands. The datasets include 160 trials for each subject. The signals were sampled at 250 Hz and applied the band-pass filter between 0.5-100 Hz. A 50 Hz notch filter was also applied to suppress the power line noise. All volunteers were sitting in an armchair, watching a monitor. At the beginning of each session, a cross was shown on the black screen, and a short warning tone was given. Then, an arrow pointing to either the left or right side was presented. Finally, the subjects were prompted to perform the corresponding motor imagery task throughout four seconds. For the evaluation session, the feedback (a gray smiling) was centered on the screen, and a short warning beep was given at the beginning of each trial. Then, the cue was presented in four seconds. Finally, the subjects were required to move the smiley towards the left or right side by imagining left or right-hand movements respectively.

During the feedback period, the smiley changed to green when moved in the correct direction. Otherwise, it became red.

One can see in Figure 2 and Figure 3 the timing scheme of the recording technique without and with smiley feedback respectively.
2.2 Identifying and Constructing Generic Dataset

The aim of this step is to do a feasibility study about the available BCI competition datasets for their applicability to be used in the development and validation of the generic pattern recognition model. Therefore, it has been studied from their number of participant’s, number of classes, number of channels, and dataset format. The number of participant’s is very important in developing the generic model to handle the subject specific brain signal complexity and intra-subject differences. Therefore, it is vital to find the dataset with the largest number of participants. On the other hand, regarding to the number of classes, hence the scope of this study is to discriminate between two class EEG-MI signal to be deployed in a wheelchair steering control system. Therefore, two class EEG-MI signal is our target in this feasibility study. In addition, regarding to the number of channels, minimum number of channels is the third important factor in the designing of the BCI based system. Hence, BCI system with a minimum number of channels is preferred to be deployed in a real life with a least cost and easy to setup on the participant’s head. Another important factor is the format of the datasets. Hence dataset formats that is supported by signal processing and machine learning tools such as MATLAB software is preferred.

On the other hand, the EEG-MI signal was stored in the dataset in the continuous from. Besides the continuous signal itself, there are also some labels and markers in the dataset. These markers show the starting of each trial. The labels indicate which kind of motor imagery movement the trial is about. However, in order to feed the EEG signal to the machine learning algorithm, the continuous EEG signal needed to be separated into trials. shows graphically how the continuous EEG signal mapped into trials to build a generic dataset for two class motor imagery EEG signal. Moreover, in order to test a generic pattern recognition model for their efficiency to overcome subjects’ differences brain complexity, therefore, a subject independent dataset should be used. consequently, for this purpose the dataset of all subjects will be combined (Stacked) to build a large dataset from all trials as a generic dataset for different brain complexities as shown in Figure 4. To the best of our knowledge, none of the studies in the academic literature of EEG signal-based wheelchair control used the stacking techniques to build a generic dataset for developing and validating a generic pattern recognition model of two class EEG-MI wheelchair control commands.
2.3 Preprocessing

In the preprocessing stage as shown in Figure 5, three significant processes were implemented. The first process was filtering the two-class EEG-MI signal to remove unwanted artifacts from the signal and for improving the signal to noise ratio. The second process was to remove unwanted time window to extract the maximum power of motor imagery feedback in an EEG signal using multi-segments techniques.

2.3.1. EEG Signal Filtering

The purpose of EEG signal filtering is to increase the signal-to-noise ratio of the raw brainwaves and enhance the relevant information in the motor imagery EEG signal to be used in wheelchair control. The EEG signal contaminated by noise from various sources such as body movements, eye blink, facial muscle movement and artifacts from the surrounding environment such as electromagnetic fields generated by electrical devices. Therefore, it is essential to filter the EEG signal to remove noise and artifacts. Consequently, filters such as band-pass filters are widely used to restrict the analysis to frequency bands in which we know that the neurophysiological signals for motor imagery are within the alpha and beta band. Therefore, this study uses the Butterworth band-pass filter with fourth order as suggested by [58] to filter the EEG signal from the unwanted frequencies located outside the band of interest.
2.3.2. Segmentation

Segmentation is a significant phase in signal analysis, and its performance plays a vital role in the efficiency of the subsequent steps, such as feature extraction and classification [59]. However, some of the studies in the field of BCI based EEG-MI signal used signal segmentation to increase system performance such as [60-63]. Though, each of the studies above used different time courses. Also, the purpose of segmentation is to improve the classification accuracy by removing periods, not including feature components and reduces the processing time of the classification algorithm. Therefore, to perform feature extraction and classification for brainwaves, it is essential to pre-process the raw brain waves by making segmentation process to study different time courses for the motor imagery signal. However, results from the fact, that each subject has his strongest motor imagery signal power at a different moment of time in the trial because each subject could start (or end) performing the motor imagery task at a slightly different time interval due to the difference in subjects’ brain complexities. Up to our knowledge, none of the studies in the academic literature of wheelchair control-based EEG-MI mentioned the best time window that includes the motor imagery feedback to be extracted with statistical features in the Frequency domain. Therefore, five different time segment groups have been used in this study as shown in Figure 6.

to check their influence on the classification accuracy and nominating the best time window that gives the highest accuracy in each signal domain. The proposed time windows are as follows: Five second time window group which is only (3---8s) that represent the entire signal from the start of the motor imagery cue until the end of the signal epoch. The next group is four second time window which is divided further into two sub-groups (3---7s, and 4---8s). The next group is three second time window which is divided further into three sub-groups (3---6s, 4---7s, and 5---8s). The next group is two second time window which is divided further into four sub-groups (3---4s, 4---5s, 5---6s, and 6---8s). The last group is one second time window group which is divided further into five sub-groups (3---5s, 4---6s, 5---7s, 6---8s). The reason behind this division is to study the existence of motor imagery feedback in the period of one, two, three, four, and five seconds respectively.

Fig.6. EEG-MI Segmentation
2.4 Feature Extraction

Technically, a feature represents a distinguishing property, a recognizable measurement, and a functional component obtained from a section of a pattern. Extracted features are meant to minimize the loss of relevant information embedded in the signal. This is necessary to reduce the complexity of implementation, to reduce the cost of information processing, and to cancel the potential need to compress the information. More recently, a variety of methods have been widely used to extract the features from EEG signals, among these methods, are time-frequency distributions (TFD), fast Fourier transform (FFT), eigenvector methods (EM), wavelet transform (WT), and autoregressive method (ARM), and so on[64]. To enable brain-computer interface construction an efficient way of feature extraction from EEG signal is needed [65].

FFT method is one of the most important and useful tools in fields like engineering, science, and mathematics because it is a domain transformation that allows temporal processing signals in the frequency domain, which implies some advantages like dimension reduction, feature extraction and normalized data lengths[66]. Brain signals are composed by a set of specific oscillations known as rhythms. However, performing a given mental task (such as motor imagery or another cognitive task) makes a variance in the amplitude of these different rhythms. These rhythms, which are mainly located in the alpha (8-13 Hz) and beta (14-30 Hz) frequency bands, therefore it appears as natural or even essential to exploit the frequency components embedded in the EEG MI signals. Therefore, this study uses FFT to transform the time domain signal into the frequency domain to extract the power spectrum of the alpha and beta band. Fourier analysis is extremely useful for data analysis, as it breaks down a signal into constituent sinusoids of different frequencies. However, For sampled vector data, Fourier analysis is performed using the discrete Fourier transform(DFT)[67]. Though, Fast Fourier Transform (FFT) is an efficient signal processing algorithm for computing the discrete Fourier transform of a digital signal because it minimizes the required time for computing the N points from $2N^2$ to $2N \log_2 N$ [68]. Since FFT can be implemented by a digital signal processor that include FFT hardware accelerator (HWAFFT) that is tightly coupled with The CPU, allowing high FFT processing Performance at very low power [69]. Therefore, it can be easily deployed for an EEG Based BCI embedded control system. DFT transforms the sequence of N complex number’s $x_0, x_1, \ldots, x_{N-1}$ (the time domain) into an N-periodic sequence $X_0, X_1, X_2, \ldots, X_{N-1}$ (the list of coefficients of a finite combination of complex sinusoids, ordered by their frequencies). It is according to the DFT formula [70]:

$$x_k = \sum_{n=0}^{N-1} x_n e^{-j2\pi kn/N}$$

Each $X_k$ element encodes amplitude and phase of a sinusoidal component of the function $x_n$. As for the frequency domain, the fast Fourier transform (FFT) is an effective common practice for signal analysis with different frequencies, which cannot be identified in the time domain [71]. Finally, by using Fast Fourier transform is possible to convert the EEGs signals into the simpler form, remove some noises and get better features [72].

2.4.1. Statistical Feature Extraction

This study examined five statistical feature extraction methods namely (Maximum, Minimum, Mean, Median, and Standard deviation (STD)) to extract signal features located in the alpha and beta band power of the EEG-MI signal. The reason behind choosing these five statistical features is to handle the signal features by studying five different statistical characteristics as the feature representatives ideally containing all important information of the original signal patterns. These characteristics are Maximum and minimum values are used to describe the range of observations in the distribution of the signal power. Mean corresponds to the center of a set of values while the median is the middle most observation. These two features give a fairly good idea about the nature of the data (shows the “middle value”), especially when combined with measurements on how the data is distributed. The Standard deviation describes how observations in a distribution are spread out around a typical value (mean). The standard deviation is the average distance between the actual data and the mean. The extracted statistical features values are considered as the most valuable parameters for representing the characteristics of the MI signals and representing the brain activities [73]. Finally, the feature vector can be fed to the machine learning algorithm for training and testing. One can see in Figure7 the process of frequency domain based statistical feature extraction.
Finally, many statistical methods have been seen in the academic literature [74-76] to extract the statistical features of the brain signals. However, statistical features that have been used in this study are explained briefly with their mathematical formula as:

1. **Mean**: Mean are fundamental statistical attributes of a signal. The arithmetic mean of a signal is the average expected value of that signal in time, frequency, or time-frequency. In some cases, the mean value of a signal can be the operating point or working point of a physical system that generates the time series. One can see in Equation 2, the arithmetic mean formula.

\[
\mu = \frac{1}{N} \sum_{i=1}^{N} A_i
\]

The mean indicated by \( \mu \). The value in the signal X, by letting the index, i, run from (0 to 1). Then finish the calculation by dividing the sum by N.

2. **Median**: The median is a simple measure of central tendency. To find the median, arrange the observations in order from smallest to largest value. If there are an odd number of observations, the median is the middle value. If there is an even

\[
X = \frac{\sum_{i=1}^{N} X_i}{n}
\]

\( X \) refers to the entire set of the numbers. Median are more robust than arithmetic mean and geometric mean if the raw data does not contain significant outliers.
3. **Standard Deviation:** The standard deviation is similar to the average deviation except the averaging is done with power instead of amplitude. This is achieved by squaring each of the deviation before taking the average. To finish the square root is taken to compensate for the initial squaring. One can see in Equation 3, the arithmetic standard deviation formula.

\[
\sigma = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (x_i - \mu)^2}
\]

X is signal with mean \( \mu \), N is the number of sample and \( \sigma \) is standard deviation.

4. **Maximum:** The maximum is a simple measure of the largest value of signal amplitude in time domain. However, in frequency and time-frequency domain it computes the maximum power spectrum of signal components. One can see in Equation 4, the arithmetic mean formula.

\[
X_{\text{Max}} = \text{Max} \{X_n\}
\]

Where \( X_{\text{Max}} \) is the maximum value, and \( X_n \) is the input signal.

5. **Minimum:** The maximum is a simple measure of the lowest value of signal amplitude in time domain. However, in frequency and time-frequency domain it computes the minimum power spectrum of signal components. One can see in Equation 5, the arithmetic mean formula.

\[
X_{\text{Min}} = \text{Min} \{X_n\}
\]

Where \( X_{\text{Min}} \) is the minimum value, and \( X_n \) is the input signal.

### 2.5 Classification

EEG signals will be generally represented in high dimensional features space, and it is very difficult to interpret. Machine learning methods are helpful for interpreting high dimensional feature sets and analyze the characteristics of brain patterns [77]. Many classification algorithms have been developed to distinguish brain activity states during different mental tasks [78]. Since 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 occupied. Numerous feature classification methods have been seen in the academic literature of EEG based wheelchair control that has been conducted by [79] and has been summarized in Table 1.

<table>
<thead>
<tr>
<th>References</th>
<th>Method</th>
</tr>
</thead>
<tbody>
<tr>
<td>[16, 20, 80-88]</td>
<td>LDA</td>
</tr>
<tr>
<td>[4, 33, 41, 46, 54, 56, 61, 89-97]</td>
<td>SVM</td>
</tr>
<tr>
<td>[3, 12, 14, 55, 97-104]</td>
<td>ANN</td>
</tr>
<tr>
<td>[14, 95, 105, 106]</td>
<td>Naive Base</td>
</tr>
<tr>
<td>[11, 107-109]</td>
<td>Decision Tree</td>
</tr>
<tr>
<td>[12, 55]</td>
<td>Logistic Regression</td>
</tr>
<tr>
<td>[14, 98]</td>
<td>KNN</td>
</tr>
</tbody>
</table>

Therefore, in this research, the aim is to develop a generic pattern recognition model two class EEG-MI signal based on single and hybrid classifier by using machine learning methods that are listed in Table 1. In addition, these classification methods have been tested towards nominating the best one that can work as a generic classifier. The generic classifier then will be deployed in a generic pattern recognition model-based EEG-MI of wheelchair steering control. The benefit of a generic classifier is to offer the opportunity to be also applied for unknown subjects. But, in the case of developing a subject-specific model that means it will fit only to one subject. The framework of the generic pattern recognition model of two class EEG-MI based wheelchair control is presented in Figure 8. This intelligent framework describes the whole of pattern recognition processes starting from the preprocessing and ending with the evaluation step.
3 RESULT

Six experiments have been conducted towards developing and validating the frequency domain based generic pattern recognition. Hence, the first three experiments have been conducted for the development purpose. However, the other three experiments are for the validation purpose. The purpose of experiment one is to examine the five groups of time window and test them with seven machine learning to find the optimal time window as well as the best classifier. Result of this experiment shows that, the highest accuracy was achieved with two and four second time window as shown in Figure 9. Hence, the accuracy is (68%) for (4—6s), and (4—8s) using (LR, and MLP) respectively.

![Fig.8. Generic Model Development Process](image)

![Fig.9. Accuracy Over Time Window](image)
Consequently, all the achieved accuracy of this experiment has been presented in Table 2. However, in experiment two, LR and MLP that were achieved the best result in experiment one was combined to develop a hybrid classifier (MLP+ LR). Result of this experiment shows that, the generic pattern recognition model based generic model-based hybrid classifier achieved (65%), and (68%) accuracy for two, and four seconds respectively.

<table>
<thead>
<tr>
<th>Time-Segment in Seconds (s)</th>
<th>Accuracy of Machine Learning Algorithms (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>One</td>
<td>LR</td>
</tr>
<tr>
<td>3-4s</td>
<td>58</td>
</tr>
<tr>
<td>4-5s</td>
<td>62</td>
</tr>
<tr>
<td>5-6s</td>
<td>60</td>
</tr>
<tr>
<td>6-7s</td>
<td>58</td>
</tr>
<tr>
<td>7-8s</td>
<td>53</td>
</tr>
<tr>
<td>Two</td>
<td></td>
</tr>
<tr>
<td>3-4s</td>
<td>66</td>
</tr>
<tr>
<td>4-5s</td>
<td>68</td>
</tr>
<tr>
<td>5-6s</td>
<td>64</td>
</tr>
<tr>
<td>6-7s</td>
<td>62</td>
</tr>
<tr>
<td>Three</td>
<td></td>
</tr>
<tr>
<td>3-4s</td>
<td>66</td>
</tr>
<tr>
<td>4-5s</td>
<td>66</td>
</tr>
<tr>
<td>5-6s</td>
<td>63</td>
</tr>
<tr>
<td>Four</td>
<td></td>
</tr>
<tr>
<td>3-4s</td>
<td>66</td>
</tr>
<tr>
<td>4-5s</td>
<td>68</td>
</tr>
<tr>
<td>Five</td>
<td></td>
</tr>
<tr>
<td>3-4s</td>
<td>61</td>
</tr>
</tbody>
</table>

Moreover, the aim of experiment three is to evaluate the performance of the generic pattern recognition model based single and hybrid classifier over single subjects’ dataset in this experiment. The results of this experiment are shown in Table 3. Independently, three classifiers namely, LR, MLP, and LR-MLP have been examined. The draw of Signal Filtering is shown in Figure 10.

<table>
<thead>
<tr>
<th>Dataset-1</th>
<th>Development Accuracy (%)</th>
<th>Using 4-6s Segmentation</th>
<th>Using 4-8s Segmentation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Subjects</td>
<td>LR</td>
<td>MLP</td>
<td>MLP-LR</td>
</tr>
<tr>
<td>S1</td>
<td>70</td>
<td>69</td>
<td>73</td>
</tr>
<tr>
<td>S2</td>
<td>55</td>
<td>51</td>
<td>58</td>
</tr>
<tr>
<td>S3</td>
<td>36</td>
<td>48</td>
<td>42</td>
</tr>
<tr>
<td>S4</td>
<td>90</td>
<td>92</td>
<td>91</td>
</tr>
<tr>
<td>S5</td>
<td>72</td>
<td>74</td>
<td>70</td>
</tr>
<tr>
<td>S6</td>
<td>59</td>
<td>51</td>
<td>57</td>
</tr>
<tr>
<td>S7</td>
<td>76</td>
<td>77</td>
<td>75</td>
</tr>
<tr>
<td>S8</td>
<td>85</td>
<td>85</td>
<td>85</td>
</tr>
<tr>
<td>S9</td>
<td>76</td>
<td>76</td>
<td>75</td>
</tr>
<tr>
<td>Mean</td>
<td>68</td>
<td>69</td>
<td>69</td>
</tr>
<tr>
<td>Variance</td>
<td>273</td>
<td>251</td>
<td>227</td>
</tr>
<tr>
<td>P</td>
<td>0.99</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Fig. 10. Signal Filtering
Recently, frequency domain-based pattern recognition models have been engaged in a large number of biomedical engineering applications. Therefore, it is vital to validate a generic model to test their efficiency and applicability to be deployed in a real-time application. Consequently, two experiments have been conducted for the validation purpose. Moreover, the same procedure that have been used in the development process was repeated in the validation but with BCI competition IV-2B dataset evaluation version. In experiment one, the single and hybrid classifier have been validated over the generic dataset-2. Result of this experiment shows that, by using (4---6s) time window the achieved accuracy is (67.68%) by using single classifier (LR and MLP) respectively. However, by using hybrid classifier (MLP-LR) the archived accuracy is (67%). On the other hand, by using (4---8s) time window, the same accuracy has been archived by the single classifier (LR and MLP) as well as the hybrid classifier (MLP-LR) which is (63%). In experiment two, the aim is to find the generic pattern recognition model with the highest performance as well as better consistency among subjects. Therefore, the generic pattern model based single and hybrid classifier have been tested over single subject’s dataset. Result of this experiment is presented in Table 4.

### TABLE IV. THE RESULT OF THE GENERIC PATTERN MODEL-BASED SINGLE AND HYBRID CLASSIFIER EXPERIMENT OVER A SINGLE SUBJECT’S DATASET

<table>
<thead>
<tr>
<th>Dataset-I</th>
<th>Classifiers Accuracy (%)</th>
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<th>Using 4---6s Segmentation</th>
<th></th>
<th>Using 4---8s Segmentation</th>
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### 4 DISCUSSION AND STATISTICAL ANALYSIS OF THE DEVELOPMENT RESULT OVER SINGLE SUBJECTS DATASET

The achieved accuracy of the generic pattern recognition model based single and hybrid classifiers over single subject’s dataset has been analyzed statistically using ANOVA to test the classifiers variance over subjects as well as to check if there is any significant difference among the generic pattern recognition model based LR, MLP, and MLP-LR. The statistical result shows that by using (4---6s) time window, the P-value is (0.99). This indicates that there is no significant difference between the generic pattern recognition model based single classifiers (MLP, and LR) as well as a based hybrid classifier (MLP-LR). The highest average accuracy that was achieved is (69%) by the generic pattern recognition model is based on single classifier using MLP classifier as well as hybrid classifier using (MLP-LR). However, the lowest accuracy is based on LR classifier which is (68%). Also, the lower variance of the generic pattern recognition model-based hybrid classifier (MLP-LR) which is (227) compared with LR (273) and MLP (251). Even the same average accuracy achieved with generic pattern recognition model based on MLP and (MLP-LR) classifier but the generic pattern recognition model-based hybrid classifier model shows lower variance.

On the other hand, by using (4---8s) time window, the P-value is (0.94). This indicates that there is no significant difference between the generic pattern recognition model based single classifiers (MLP, and LR) as well as a based hybrid classifier (MLP-LR). The highest average accuracy that was achieved is (67%) by the generic pattern recognition model is based on single classifier using LR classifier as well as MLP. However, using hybrid classifier (MLP-LR) the average accuracy is lower which is (66%). Also, the lower variance of the generic pattern recognition model based LR classifier which is (86) compared with MLP (135) and MLP-LR (99). Even the same average accuracy achieved with generic pattern recognition model based on MLP and LR classifier but the generic pattern recognition model based LR classifier model shows a lower variance. One can conclude that the generic pattern recognition model-based hybrid classifier (MLP-LR) shows better accuracy with (4---6s) than using time (4---8s) time window. Consequently, the generic pattern recognition model-based hybrid classifier (MLP-LR) shows more consistency on inter-subject’s differences
compared with other classifiers. Therefore, the generic pattern recognition model-based hybrid classifier (MLP-LR) shows good and acceptable accuracy as well as more reliability than (MLP, and LR) classifier.

5 DISCUSSION AND STATISTICAL ANALYSIS OF THE VALIDATION RESULT OVER SINGLE SUBJECTS DATASET

The achieved accuracy results of the generic pattern recognition model based single and hybrid classifiers over an individual subject’s dataset has been analyzed statistically using ANOVA. This statistical analysis aims to test the classifiers variance over subjects as well as to check if there is any significant difference among the generic pattern recognition model based on LR, MLP, and MLP-LR classifier. The statistical result shows that using (4---6s) time window the P-value is (0.96). This indicates that there is no significant difference between the generic pattern recognition model based single classifiers (MLP, and LR) as well as a based hybrid classifier (MLP-LR). The highest average accuracy that was achieved is (69%) by the generic pattern recognition model is based on hybrid classifier using (MLP-LR). However, the average accuracy of the generic pattern recognition model based on MLP and LR is (68%) and (67%) respectively. Also, the lower variance of the generic pattern recognition model is based on hybrid classifier (MLP-LR) which is (172) compared with LR (183) and MLP (218).

On the other hand, using (4---8s) time window the P-value is (0.98). This indicates that there is no significant difference between the generic pattern recognition model based single classifiers (MLP, and LR) as well as a based hybrid classifier (MLP-LR). The highest average accuracy that was achieved is (64%) by the generic pattern recognition model is based on single classifier using (MLP). However, the average accuracy of the generic pattern recognition model based on MLP and MLP-LR is the same which is (63%). Also, the lower variance of the generic pattern recognition model is based on single classifier (MLP) which is (190) compared with LR (239) and MLP-LR (248).

One can conclude that the average accuracy of the generic pattern recognition model using (4---6s) shows better performance than (4---8s). However, in term of variability, the generic pattern recognition model using (4---6s) shows lower variability compared with (4---8s). Also, the generic pattern recognition model using hybrid classifier (MLP-LR) shows better accuracy using (4---6s) time window compared with other classifiers. Consequently, the generic pattern recognition model based (MLP-LR) classifier shows more consistency on inter-subject’s differences compared with other classifiers. Also, the generic pattern recognition model using (4---6s) time window based (MLP-LR) classifier shows good and acceptable accuracy. As well as the lower variance compared with other classifiers. Therefore, MLP-LR based generic pattern recognition model using (4---6s) time window suggested being deployed in a real-time standalone and IOT based BCI based systems.

6 CONCLUSION AND FUTURE WORKS

This study proposed a new generic pattern recognition model of two class EEG-MI signal to deployed in a wheelchair control system. As this generic pattern recognition model consist of processing pipeline for the EEG-MI signal. It was seen from the preprocessing stage that; the motor imagery feedback starting after one minute from the cue and lasting for two second. Therefore, it can be concluded by the achieved result with the founded optimal time window (4---6s) that; it would be possible to minimize the computation complexity and realize the hardware implementation of the intelligent control system-based EEG-MI scheme on an FPGA platform. However, as the feature extraction step is based on statistical feature method and Fast Fourier Transform, it was seen that; this technique is viable and effective in decoding the EEG-MI signal. Consequently, in the stage of feature classification, it was seen after testing seven machine learning algorithms, the hybrid model that is based on composite machine learning algorithm LR-MLP shows their ability in handling overlapped and crossed EEG signals by the achieved result. Finally, it can be concluded that, the proposed new generic pattern recognition model can provide a key solution to the problem of wheelchair steering control and can be deployed in standalone application as well as in an IOT based brain computer interface scheme.

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

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