Applied Data Science and Analysis
Vol.2024, **pp.** 82–100
DOI: https://doi.org/10.58496/ADSA/2024/008; ISSN: 3005-317X
https://mesopotamian.press/journals/index.php/ADSA

Research Article

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

Z.T.Al-Qaysi [1,2]*, M. S Suzani [2], Nazre bin Abdul Rashid [2], Reem D. Ismail [1], M.A.Ahmed [1,2], Wan Aliaa Wan Sulaiman [3], Rasha A.Aljanabi [1]

[1]Tikrit University, College of Computer Science and Mathematics, Computer Science Department, Iraq

[2]Data Intelligence and Knowledge Management Special Interest Group, University Pendidikan Sultan Idris, Tanjong Malim, Perak, Malaysia

[3]Department of Medicine, Faculty of Medicine and Health Sciences, University Putra Malaysia, Serdang, Malaysia

ARTICLEINFO

Article History
Received 27 Mar 2024
Accepted 29 May 2024
Published 20 Jun 2024

Keywords
Brain-Computer Interface
Wheelchair
Control
Transfer Learning
Pattern Recognition
Hybrid Model
Frequency-Domain

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.

**Corresponding author. Email: ziadoontareq@tu.edu.iq*

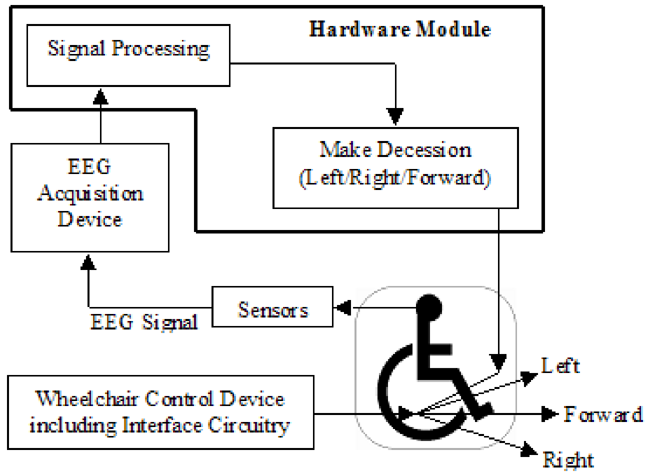

Fig.1. Architecture of BCI Controlled wheelchair system adapted from [14]

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 ß 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 smiley) 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.

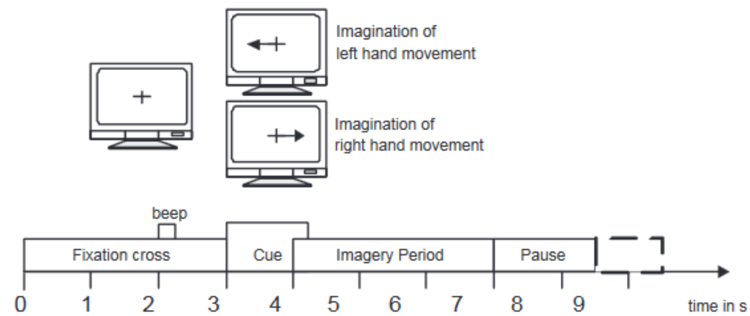

Fig.2. Timing scheme without feedback

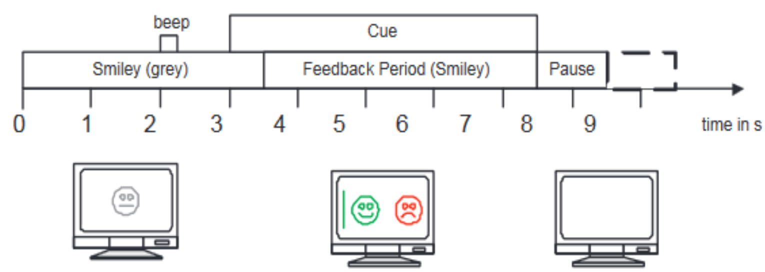

Fig.3. Timing scheme with Smiley Feedback

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.

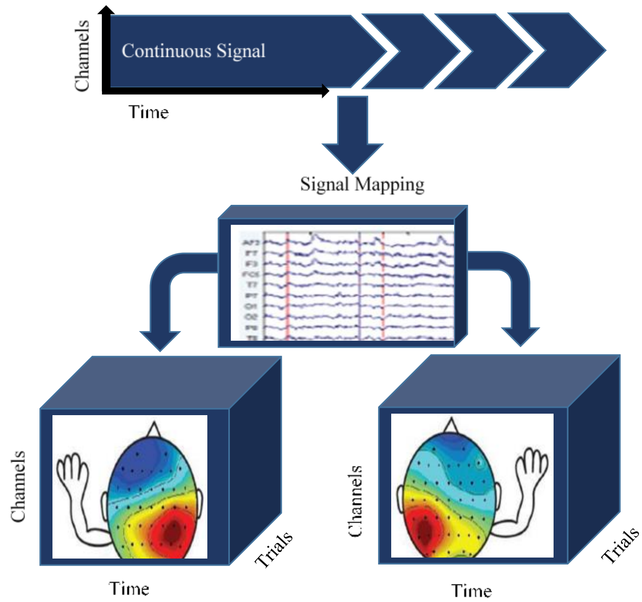

Fig.4. Generic Dataset Construction

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.

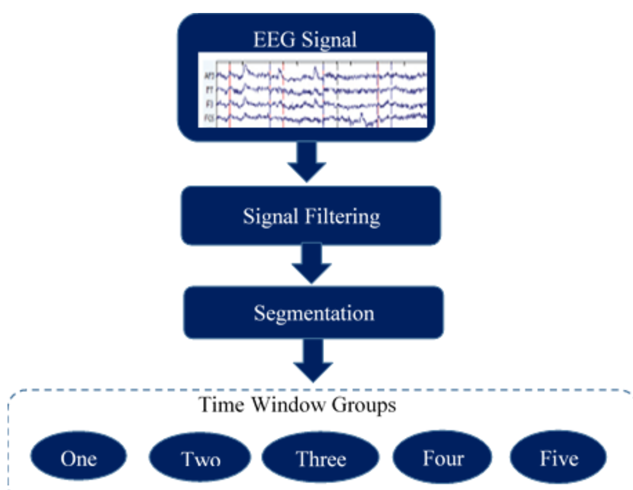

Fig.5. Preprocessing Steps

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---6s ,5---7s, and 6---8s). The last group is one second time window group which is divided further into five sub-groups (3--4s ,4--5s ,5--6s ,6--7s,7--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.

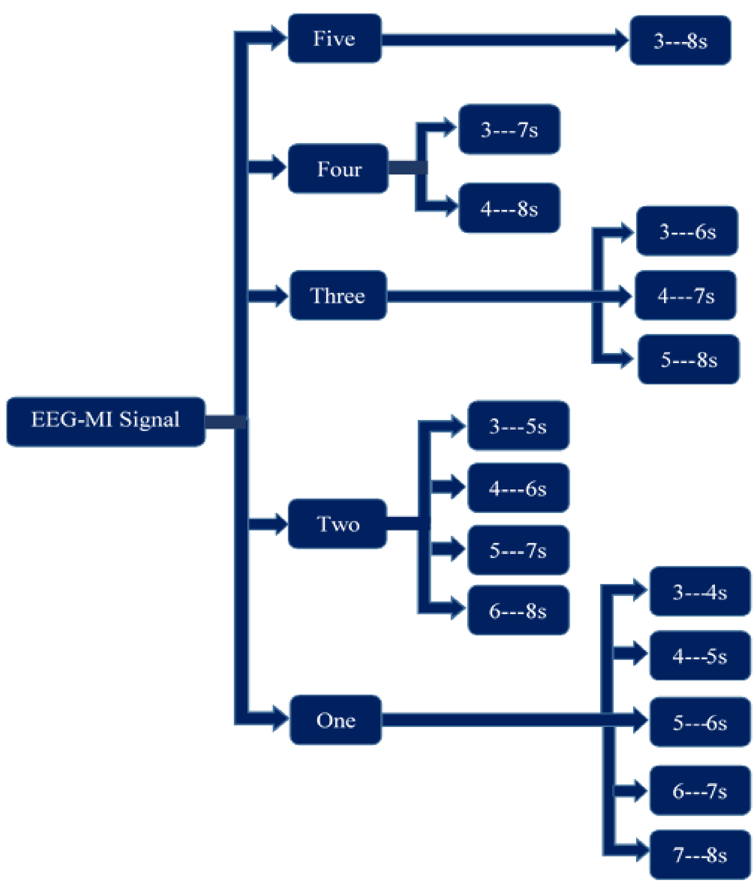

Fig.6. EEG-MI Segmentation

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 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 $2\,N\,log_2\,N$ [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 numberS $x_0, x_1, \ldots, x_{N-1}$ (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]:

$$x_k = \sum_{0}^{N-1} x_n e^{-j2\pi kN}/_N \qquad 1$$

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.**

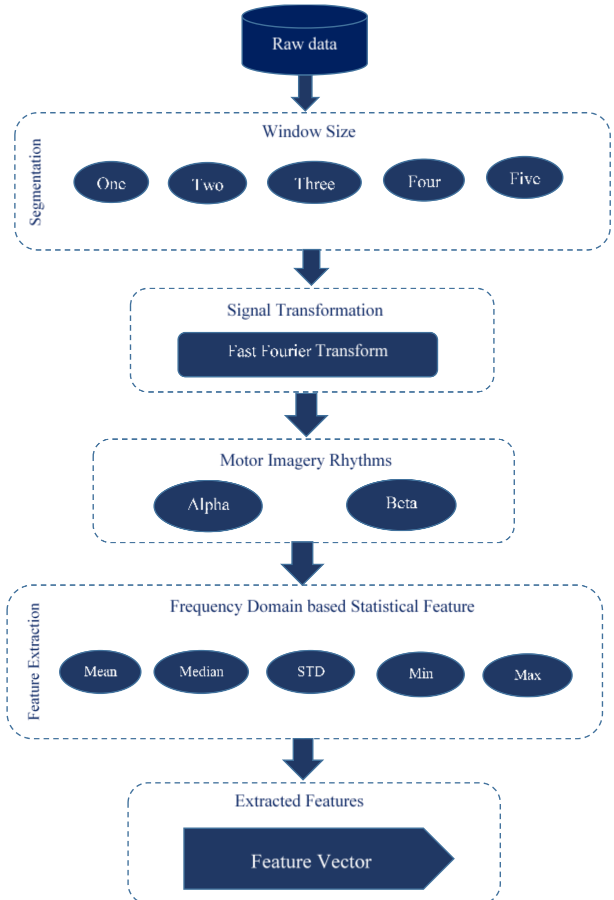

Fig.7. Feature Extraction Process

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.

1- $$\mu = \frac{1}{N} \Sigma_{i=1}^{N} A_i \qquad 1$$

The mean indicated by μ . 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
e
v
e
n

2- $$\overline{X} = \frac{\sum_{i=1}^{n} X_i}{n} \qquad 3$$

$\overline{X}$ 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.

n
u
m
b
e
r

o
f

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.

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2} \qquad 4$$

X is signal with mean μ, N is the number of sample and σ 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.

$$X_{Max} = \mathrm{Max}\,[Xn] \qquad 5$$

Where X_{Max} is the maximum value, and Xn 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.

$$X\ Min = \mathrm{Min}\,[Xn] \qquad 6$$

Where X_{Min} is the minimum value, and Xn 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 I. NUMEROUS FEATURE CLASSIFICATION METHODS IN THE ACADEMIC LITERATURE OF EEG-BASED WHEELCHAIR CONTROL

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

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.

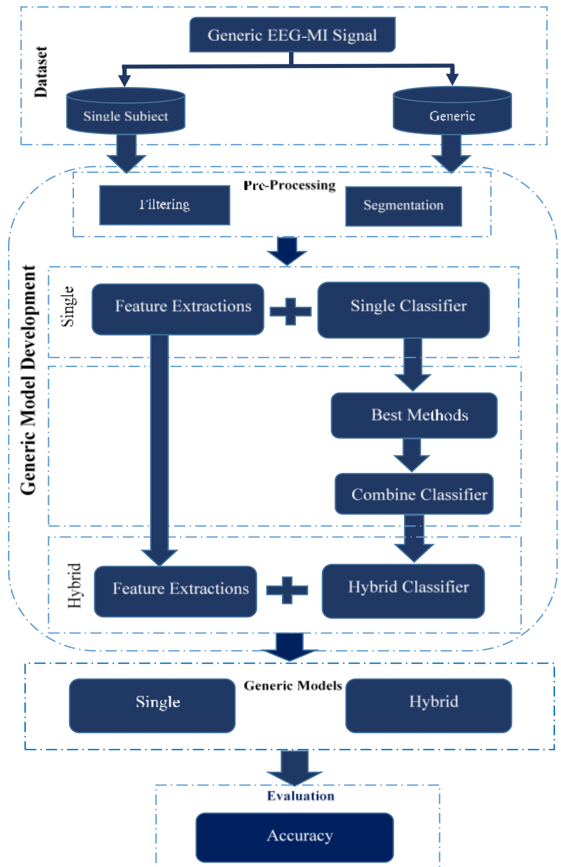

Fig.8. Generic Model Development Process

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 towards 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.

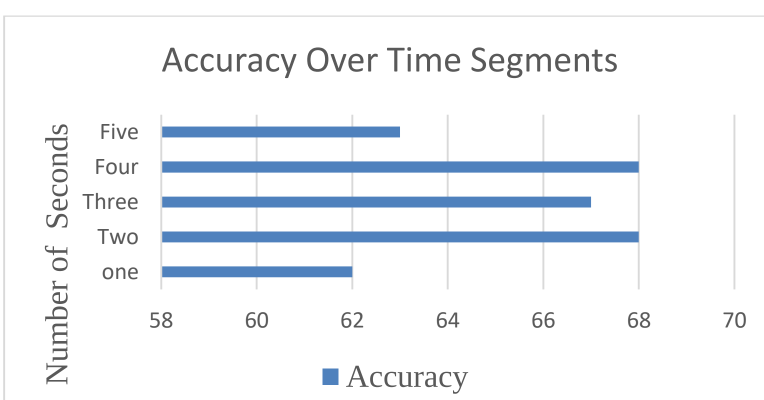

Fig.9. Accuracy Over Time Window

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 II. ACCURACY (%) OVER SUBJECTS DATASET IN FREQUENCY-DOMAIN MODEL

Time-Segment in Seconds (s)	***Accuracy of Machine Learning Algorithms (%)***						
One	***LR***	***NB***	***LDA***	***SVM***	***DT***	***MLP***	***KNN***
3-------4s	58	51	57	53	53	58	55
4-------5s	62	59	59	57	54	62	58
5-------6s	60	55	59	55	53	59	55
6-------7s	58	56	57	53	50	58	55
7-------8s	53	50	52	49	51	54	52
Two							
3-------5s	66	63	64	64	58	65	60
4-------6s	68	62	67	68	58	68	64
5-------7s	64	60	64	64	55	64	59
6-------8s	62	57	59	61	54	62	56
Three							
3-------6s	66	61	66	66	60	66	61
4-------7s	66	61	67	65	60	67	63
5-------8s	63	59	62	62	55	63	57
Four							
3-------7s	66	61	65	65	58	65	59
4-------8s	68	61	67	65	59	68	60
Five							
3-------8s	61	56	61	60	56	63	58

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 III. THE RESULT OF THE INDEPENDENTLY EXAMINATION EXPERIENCE BY THREE CLASSIFIERS: LR, MLP, AND LR-MLP

Dataset-I	***Development Accuracy (%)***					
	Using 4----6s Segmentation			***Using 4----8s Segmentation***		
Subjects	***LR***	***MLP***	***MLP-LR***	***LR***	***MLP***	***MLP-LR***
S1	70	69	73	70	70	71
S2	55	51	58	56	53	54
S3	36	48	42	60	51	61
S4	90	92	91	82	82	82
S5	72	74	70	67	72	68
S6	59	51	57	56	54	52
S7	76	77	75	68	67	65
S8	85	85	85	78	78	78
S9	76	76	75	74	76	65
Mean	68	69	69	67	67	66
Variance	273	251	227	86	135	99
P		0.99			0.94	

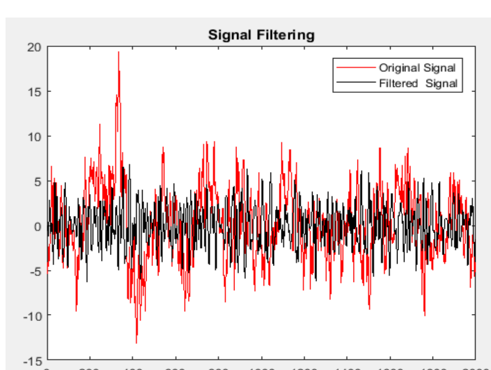

Fig.10. Signal Filtering

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

Dataset-I	*Classifiers Accuracy (%)*					
	Using 4----6s Segmentation			*Using 4----8s Segmentation*		
Subjects	*LR*	*MLP*	*MLP-LR*	*LR*	*MLP*	*MLP-LR*
S1	59	60	62	62	60	60
S2	54	51	56	45	51	45
S3	50	48	52	45	51	51
S4	81	86	83	83	84	85
S5	68	69	71	52	53	52
S6	64	63	63	56	58	52
S7	70	70	70	65	63	66
S8	94	93	94	87	87	89
S9	69	72	72	74	73	73
Mean	67	68	69	63	64	63
Variance	183	218	172	239	190	248
P		0.96			0.98	

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 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.

Funding

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

Acknowledgment

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

References

[1] O. S. Albahri, A. A. Zaidan, A. S. Albahri, B. B. Zaidan, K. H. Abdulkareem, Z. T. Al-qaysi, *et al.*, "Systematic review of artificial intelligence techniques in the detection and classification of COVID-19 medical images in terms of evaluation and benchmarking: Taxonomy analysis, challenges, future solutions and methodological aspects," *Journal of Infection and Public Health*, vol. 13, pp. 1381-1396, 2020/10/01/ 2020.

[2] S. Garfan, A. H. Alamoodi, B. B. Zaidan, M. Al-Zobbi, R. A. Hamid, J. K. Alwan, *et al.*, "Telehealth utilization during the Covid-19 pandemic: A systematic review," *Computers in Biology and Medicine*, vol. 138, p. 104878, 2021/11/01/ 2021.

[3] W. Caesarendra, M. Ariyanto, S. U. Lexon, E. D. Pasmanasari, C. R. Chang, and J. D. Setiawan, "EEG based pattern recognition method for classification of different mental tasking: Preliminary study for stroke survivors in Indonesia," in *Automation, Cognitive Science, Optics, Micro Electro-Mechanical System, and Information Technology (ICACOMIT), 2015 International Conference on*, 2015, pp. 138-144.

[4] J. Li, J. Liang, Q. Zhao, J. Li, K. Hong, and L. Zhang, "Design of assistive wheelchair system directly steered by human thoughts," *International journal of neural systems*, vol. 23, p. 1350013, 2013.

[5] Z. Al-Qaysi, B. Zaidan, A. Zaidan, and M. Suzani, "A review of disability EEG based wheelchair control system: Coherent taxonomy, open challenges and recommendations," *Computer methods and programs in biomedicine*, vol. 164, pp. 221-237, 2018.

[6] Y. Xie and X. Li, "A brain controlled wheelchair based on common spatial pattern," in *Bioelectronics and Bioinformatics (ISBB), 2015 International Symposium on*, 2015, pp. 19-22.

[7] W. Budiharto, A. A. S. Gunawan, I. H. Parmonangan, and J. Santoso, "Fast Brain Control Systems for Electric Wheelchair using Support Vector Machine."

[8] Z. Al-Qaysi, M. Ahmed, N. M. Hammash, A. F. Hussein, A. Albahri, M. Suzani, *et al.*, "Systematic review of training environments with motor imagery brain–computer interface: coherent taxonomy, open issues and recommendation pathway solution," *Health and Technology*, vol. 11, pp. 783-801, 2021.

[9] C. Mandel, T. Lüth, T. Laue, T. Röfer, A. Gräser, and B. Krieg-Brückner, "Navigating a smart wheelchair with a brain-computer interface interpreting steady-state visual evoked potentials," in *Intelligent Robots and Systems, 2009. IROS 2009. IEEE/RSJ International Conference on*, 2009, pp. 1118-1125.

[10] A. Turnip, M. A. Suhendra, and M. S. WS, "Brain-controlled wheelchair based EEG-SSVEP signals classified by nonlinear adaptive filter," in *Rehabilitation Robotics (ICORR), 2015 IEEE International Conference on*, 2015, pp. 905-908.

[11] S. M. T. Müller, T. F. Bastos-Filho, and M. Sarcinelli-Filho, "Using a SSVEP-BCI to command a robotic wheelchair," in *Industrial Electronics (ISIE), 2011 IEEE International Symposium on*, 2011, pp. 957-962.

[12] R. H. Abiyev, N. Akkaya, E. Aytac, I. Günsel, and A. Çağman, "Brain-Computer Interface for Control of Wheelchair Using Fuzzy Neural Networks," *BioMed research international*, vol. 2016, 2016.

[13] M. A. Ahmed, B. B. Zaidan, A. A. Zaidan, M. M. Salih, Z. T. Al-qaysi, and A. H. Alamoodi, "Based on wearable sensory device in 3D-printed humanoid: A new real-time sign language recognition system," *Measurement*, vol. 168, p. 108431, 2021/01/15/ 2021.

[14] B. M. Faria, L. P. Reis, and N. Lau, "Cerebral palsy eeg signals classification: Facial expressions and thoughts for driving an intelligent wheelchair," in *Data Mining Workshops (ICDMW), 2012 IEEE 12th International Conference on*, 2012, pp. 33-40.

[15] T. Carlson, R. Leeb, R. Chavarriaga, and J. d. R. Millán, "The birth of the brain-controlled wheelchair," in *Intelligent Robots and Systems (IROS), 2012 IEEE/RSJ International Conference on*, 2012, pp. 5444-5445.

[16] T. Kaufmann, A. Herweg, and A. Kübler, "Toward brain-computer interface based wheelchair control utilizing tactually-evoked event-related potentials," *Journal of neuroengineering and rehabilitation*, vol. 11, p. 7, 2014.

[17] R. A. Hamid, A. S. Albahri, J. K. Alwan, Z. T. Al-qaysi, O. S. Albahri, A. A. Zaidan, *et al.*, "How smart is e-tourism? A systematic review of smart tourism recommendation system applying data management," *Computer Science Review*, vol. 39, p. 100337, 2021/02/01/ 2021.

[18] A. Widyotriatmo and S. Andronicus, "A collaborative control of brain computer interface and robotic wheelchair," in *Control Conference (ASCC), 2015 10th Asian*, 2015, pp. 1-6.

[19] N. Shinde and K. George, "Brain-controlled driving aid for electric wheelchairs," in *Wearable and Implantable Body Sensor Networks (BSN), 2016 IEEE 13th International Conference on*, 2016, pp. 115-118.

[20] M. Carra and A. Balbinot, "Evaluation of sensorimotor rhythms to control a wheelchair," in *Biosignals and Biorobotics Conference (BRC), 2013 ISSNIP*, 2013, pp. 1-4.

[21] M. Hadid, Q. M. Hussein, Z. Al-Qaysi, M. Ahmed, and M. M. Salih, "An Overview of Content-Based Image Retrieval Methods And Techniques," *Iraqi Journal For Computer Science and Mathematics,* vol. 4, pp. 66-78, 2023.

[22] A. S. Albahri, Z. T. Al-qaysi, L. Alzubaidi, A. Alnoor, O. S. Albahri, A. H. Alamoodi*, et al.*, "A Systematic Review of Using Deep Learning Technology in the Steady-State Visually Evoked Potential-Based Brain-Computer Interface Applications: Current Trends and Future Trust Methodology," *International Journal of Telemedicine and Applications,* vol. 2023, p. 7741735, 2023/04/30 2023.

[23] R. Chai, S. H. Ling, G. P. Hunter, and H. T. Nguyen, "Toward fewer EEG channels and better feature extractor of non-motor imagery mental tasks classification for a wheelchair thought controller," in *Engineering in Medicine and Biology Society (EMBC), 2012 Annual International Conference of the IEEE*, 2012, pp. 5266-5269.

[24] M. M. Salih, Z. T. Al-Qaysi, M. L. Shuwandy, M. A. Ahmed, K. F. Hasan, and Y. R. Muhsen, "A new extension of fuzzy decision by opinion score method based on Fermatean fuzzy: A benchmarking COVID-19 machine learning methods," *Journal of Intelligent & Fuzzy Systems,* vol. 43, pp. 3549-3559, 2022.

[25] M. A. Ahmed, Z. T. Al-qaysi, M. L. Shuwandy, M. M. Salih, and M. H. Ali, "Automatic COVID-19 pneumonia diagnosis from x-ray lung image: A Deep Feature and Machine Learning Solution," *Journal of Physics: Conference Series,* vol. 1963, p. 012099, 2021/07/01 2021.

[26] K. Amarasinghe, D. Wijayasekara, and M. Manic, "EEG based brain activity monitoring using Artificial Neural Networks," in *2014 7th International Conference on Human System Interactions (HSI)*, 2014, pp. 61-66.

[27] A. S. Albahri, R. A. Hamid, J. k. Alwan, Z. T. Al-qays, A. A. Zaidan, B. B. Zaidan*, et al.*, "Role of biological Data Mining and Machine Learning Techniques in Detecting and Diagnosing the Novel Coronavirus (COVID-19): A Systematic Review," *Journal of Medical Systems,* vol. 44, p. 122, 2020/05/25 2020.

[28] M. M. Salih, M. Ahmed, B. Al-Bander, K. F. Hasan, M. L. Shuwandy, and Z. Al-Qaysi, "Benchmarking framework for COVID-19 classification machine learning method based on fuzzy decision by opinion score method," *Iraqi Journal of Science,* pp. 922-943, 2023.

[29] A. Albahri, M. M. Jassim, L. Alzubaidi, R. A. Hamid, M. Ahmed, Z. Al-Qaysi*, et al.*, "A Trustworthy and Explainable Framework for Benchmarking Hybrid Deep Learning Models Based on Chest X-Ray Analysis in CAD Systems," *International Journal of Information Technology and Decision Making,* 2024.

[30] J. d. R. Millán, F. Galán, D. Vanhooydonck, E. Lew, J. Philips, and M. Nuttin, "Asynchronous non-invasive brain-actuated control of an intelligent wheelchair," in *Engineering in Medicine and Biology Society, 2009. EMBC 2009. Annual International Conference of the IEEE*, 2009, pp. 3361-3364.

[31] Z. T. Al-Qaysi, M. A. Ahmed, N. M. Hammash, A. F. Hussein, A. S. Albahri, M. S. Suzani*, et al.*, "A systematic rank of smart training environment applications with motor imagery brain-computer interface," *Multimedia Tools and Applications,* vol. 82, pp. 17905-17927, 2023/05/01 2023.

[32] A. Al-Saegh and A. F. Hussein, "Wavelet-based Hybrid learning framework for motor imagery classification," 2022.

[33] I. H. Parmonangan, J. Santoso, W. Budiharto, and A. A. S. Gunawan, "Fast brain control systems for electric wheelchair using support vector machine," in *First International Workshop on Pattern Recognition*, 2016, p. 100111N.

[34] S. Mohamad Samuri, T. V. Nova, B. Rahmatullah, S. L. Wang, and Z. T. Al-Qaysi, "CLASSIFICATION MODEL FOR BREAST CANCER MAMMOGRAMS," *IIUM Engineering Journal,* vol. 23, pp. 187 - 199, 01/04 2022.

[35] M. A. Ahmed, Z. T. Al-Qaysi, A. S. Albahri, M. E. Alqaysi, G. Kou, O. S. Albahri*, et al.*, "Intelligent Decision-Making Framework for Evaluating and Benchmarking Hybridized Multi-Deep Transfer Learning Models: Managing COVID-19 and Beyond," *International Journal of Information Technology & Decision Making,* p. 2350046, 2023.

[36] M. Li, Y. Zhang, H. Zhang, and H. S. Hu, "An EEG based control system for intelligent wheelchair," in *Applied Mechanics and Materials*, 2013, pp. 1540-1545.

[37] A. A. Rasha, Z. T. Al-Qaysi, M.A.Ahmed, and M. S. Mahmood, "Hybrid Model for Motor Imagery Biometric Identification," *Iraqi Journal For Computer Science and Mathematics,* vol. 5, pp. 1-12, 12/27 2023.

[38] R. Chai, S. H. Ling, G. P. Hunter, and H. T. Nguyen, "Mental non-motor imagery tasks classifications of brain computer interface for wheelchair commands using genetic algorithm-based neural network," in *Proceedings of the International Joint Conference on Neural Networks,(IJCNN), Brisbane, Queensland, Australia, 10-15 June 2012*, 2012.

[39] M. D. Salman and R. Adel, "An intelligent attendance system based on convolutional neural networks for real-time student face identifications," *Journal of Engineering Science and Technology,* vol. 17, pp. 3326-3341, 2022.
[40] Z. T. Al-Qaysi, A. S. Albahri, M. A. Ahmed, and S. M. Mohammed, "Development of hybrid feature learner model integrating FDOSM for golden subject identification in motor imagery," *Physical and Engineering Sciences in Medicine,* vol. 46, pp. 1519-1534, 2023/12/01 2023.
[41] J. Li, H. Ji, L. Cao, D. Zang, R. Gu, B. Xia*, et al.*, "Evaluation and application of a hybrid brain computer interface for real wheelchair parallel control with multi-degree of freedom," *International journal of neural systems,* vol. 24, p. 1450014, 2014.
[42] L. Jiang, E. Tham, M. Yeo, Z. Wang, and B. Jiang, "Motor imagery controlled wheelchair system," in *Industrial Electronics and Applications (ICIEA), 2014 IEEE 9th Conference on*, 2014, pp. 532-535.
[43] A. H. Alamoodi, B. B. Zaidan, A. A. Zaidan, O. S. Albahri, K. I. Mohammed, R. Q. Malik*, et al.*, "Sentiment analysis and its applications in fighting COVID-19 and infectious diseases: A systematic review," *Expert systems with applications,* vol. 167, p. 114155, 2021.
[44] "Multi-Tiered CNN Model for Motor Imagery Analysis: Enhancing UAV Control in Smart City Infrastructure for Industry 5.0," *Applied Data Science and Analysis,* pp. 88-101, 2023.
[45] Z. T. Al-qaysi, A. S. Albahri, M. A. Ahmed, and M. M. Salih, "Dynamic decision-making framework for benchmarking brain–computer interface applications: a fuzzy-weighted zero-inconsistency method for consistent weights and VIKOR for stable rank," *Neural Computing and Applications,* 2024/03/16 2024.
[46] Y. Li, J. Pan, F. Wang, and Z. Yu, "A hybrid BCI system combining P300 and SSVEP and its application to wheelchair control," *IEEE Transactions on Biomedical Engineering,* vol. 60, pp. 3156-3166, 2013.
[47] M. H. Jasim, M. M. Salih, Z. T. Abdulwahhab, M. L. Shouwandy, M. A. Ahmed, M. A. ALsalem*, et al.*, "Emotion detection among Muslims and non-Muslims while listening to Quran recitation using EEG," *Int J Acad Res Bus Soc Sci,* vol. 9, p. 14, 2019.
[48] M. A. Ahmed, B. B. Zaidan, A. A. Zaidan, A. H. Alamoodi, O. S. Albahri, Z. T. Al-Qaysi*, et al.*, "Real-time sign language framework based on wearable device: analysis of MSL, DataGlove, and gesture recognition," *Soft Computing,* vol. 25, pp. 11101-11122, 2021/08/01 2021.
[49] N. Saad Baqer, H. A. Mohammed, A. S. Albahri, A. A. Zaidan, Z. T. Al-qaysi, and O. S. Albahri, "Development of the Internet of Things sensory technology for ensuring proper indoor air quality in hospital facilities: Taxonomy analysis, challenges, motivations, open issues and recommended solution," *Measurement,* vol. 192, p. 110920, 2022/03/31/ 2022.
[50] J. Long, Y. Li, H. Wang, T. Yu, J. Pan, and F. Li, "A hybrid brain computer interface to control the direction and speed of a simulated or real wheelchair," *IEEE Transactions on Neural Systems and Rehabilitation Engineering,* vol. 20, pp. 720-729, 2012.
[51] Á. Fernández-Rodríguez, F. Velasco-Álvarez, and R. Ron-Angevin, "Review of real brain-controlled wheelchairs," *Journal of neural engineering,* vol. 13, p. 061001, 2016.
[52] M. L. Shuwandy, A. S. Jouda, M. A. Ahmed, M. M. Salih, Z. T. Al-qaysi, A. H. Alamoodi*, et al.*, "Sensor-based authentication in smartphone: A systematic review," *Journal of Engineering Research,* 2024/02/09/ 2024.
[53] C. R. Hema, M. Paulraj, S. Yaacob, A. Adom, and R. Nagarajan, "Single trial motor imagery classification for a four state brain machine interface," in *Signal Processing & Its Applications, 2009. CSPA 2009. 5th International Colloquium on*, 2009, pp. 39-41.
[54] K. Kaneswaran, K. Arshak, E. Burke, and J. Condron, "Towards a brain controlled assistive technology for powered mobility," in *Engineering in Medicine and Biology Society (EMBC), 2010 Annual International Conference of the IEEE*, 2010, pp. 4176-4180.
[55] M. E. Abdalsalam, M. Z. Yusoff, N. Kamel, A. Malik, and M. Meselhy, "Mental task motor imagery classifications for noninvasive brain computer interface," in *Intelligent and Advanced Systems (ICIAS), 2014 5th International Conference on*, 2014, pp. 1-5.
[56] K. Choi and A. Cichocki, "Control of a wheelchair by motor imagery in real time," in *International Conference on Intelligent Data Engineering and Automated Learning*, 2008, pp. 330-337.
[57] M. Tangermann, K.-R. Müller, A. Aertsen, N. Birbaumer, C. Braun, C. Brunner*, et al.*, "Review of the BCI competition IV," *Frontiers in neuroscience,* vol. 6, p. 55, 2012.
[58] K. Belwafi, R. Djemal, F. Ghaffari, and O. Romain, "An adaptive EEG filtering approach to maximize the classification accuracy in motor imagery," in *Computational Intelligence, Cognitive Algorithms, Mind, and Brain (CCMB), 2014 IEEE Symposium on*, 2014, pp. 121-126.

[59] H. Azami and J. Escudero, "Combination of signal segmentation approaches using fuzzy decision making," in *Engineering in Medicine and Biology Society (EMBC), 2015 37th Annual International Conference of the IEEE*, 2015, pp. 101-104.

[60] Z. Mu, D. Xiao, and J. Hu, "Classification of Motor Imagery EEG Signals Based on Time-Frequency Analysis," *JDCTA*, vol. 3, pp. 116-119, 2009.

[61] A. Ferreira, T. F. Bastos Filho, M. Sarcinelli Filho, J. L. M. Sanchez, J. C. G. García, and M. M. Quintas, "Evaluation of PSD Components and AAR Parameters as Input Features for a SVM Classifier Applied to a Robotic Wheelchair," in *BIODEVICES*, 2009, pp. 7-12.

[62] R. Chai, S. H. Ling, G. P. Hunter, Y. Tran, and H. T. Nguyen, "Brain–computer interface classifier for wheelchair commands using neural network with fuzzy particle swarm optimization," *IEEE journal of biomedical and health informatics,* vol. 18, pp. 1614-1624, 2014.

[63] D. A. Craig and H. Nguyen, "Adaptive EEG thought pattern classifier for advanced wheelchair control," in *Engineering in Medicine and Biology Society, 2007. EMBS 2007. 29th Annual International Conference of the IEEE*, 2007, pp. 2544-2547.

[64] A. S. Al-Fahoum and A. A. Al-Fraihat, "Methods of EEG signal features extraction using linear analysis in frequency and time-frequency domains," *ISRN neuroscience*, vol. 2014, 2014.

[65] M. K. Odziej, A. Majkowski, and R. J. Rak, "A new method of feature extraction from EEG signal for brain computer interface design," *Przegl D Elektrotechniczny,* 2010.

[66] D. A. Rojas, L. A. Góngora, and O. L. Ramos, "EEG signal analysis related to speech process through BCI device EMOTIV, FFT and statistical methods," *ARPN Journal of Engineering and Applied Sciences,* pp. 3074-3080, 2016.

[67] M. M. Shaker, "EEG waves classifier using wavelet transform and Fourier transform," *brain,* vol. 2, p. 3, 2006.

[68] J.-S. Lin and W.-C. Yang, "Wireless brain-computer interface for electric wheelchairs with EEG and eye-blinking signals," *Int. J. Innov. Comput. Inf. Control,* vol. 8, pp. 6011-6024, 2012.

[69] T. Instruments, "“FFT Implementation on the TMS320VC5505, TMS320C5505, and TMS320C5515 DSPs," *Tech. Rep,* 2013.

[70] W. Sałabun, "Processing and spectral analysis of the raw EEG signal from the MindWave," *Przeglad Elektrotechniczny,* vol. 90, pp. 169-174, 2014.

[71] L. Wang, W. Xue, Y. Li, M. Luo, J. Huang, W. Cui, *et al.*, "Automatic epileptic seizure detection in EEG signals using multi-domain feature extraction and nonlinear analysis," *Entropy,* vol. 19, p. 222, 2017.

[72] T. N. Thieu and H.-J. Yang, "Diagnosis of Epilepsy in Patients Based on the Classification of EEG Signals Using Fast Fourier Transform," in *International Conference on Industrial, Engineering and Other Applications of Applied Intelligent Systems*, 2015, pp. 493-500.

[73] S. Siuly and Y. Li, "Improving the separability of motor imagery EEG signals using a cross correlation-based least square support vector machine for brain–computer interface," *IEEE Transactions on Neural Systems and Rehabilitation Engineering,* vol. 20, pp. 526-538, 2012.

[74] A. F. Hussein, N. Arunkumar, C. Gomes, A. K. Alzubaidi, Q. A. Habash, L. Santamaria-Granados, *et al.*, "Focal and non-focal epilepsy localization: A review," *IEEE Access*, vol. 6, pp. 49306-49324, 2018.

[75] A. Hamad, E. H. Houssein, A. E. Hassanien, and A. A. Fahmy, "Feature extraction of epilepsy EEG using discrete wavelet transform," in *2016 12th international computer engineering conference (ICENCO)*, 2016, pp. 190-195.

[76] M. Chandani and A. Kumar, "Classification of EEG Physiological Signal for the Detection of Epileptic Seizure by Using DWT Feature Extraction and Neural Network," *International Journal of Neurologic Physsical Therapy,* vol. 3, pp. 38-43, 2017.

[77] P. Bhuvaneswari and J. S. Kumar, "Support vector machine technique for EEG signals," *International Journal of Computer Applications,* vol. 63, 2013.

[78] A. N. Belkacem, H. Hirose, N. Yoshimura, D. Shin, and Y. Koike, "Classification of four eye directions from EEG signals for eye-movement-based communication systems," *life,* vol. 1, p. 3, 2014.

[79] Z. Tareq, B. Zaidan, A. Zaidan, and M. Suzani, "A review of disability EEG based wheelchair control system: Coherent taxonomy, open challenges and recommendations," *Computer methods and programs in biomedicine,* 2018.

[80] T. L. Fan, C. Ng, J. Ng, and S. Goh, "A brain-computer interface with intelligent distributed controller for wheelchair," in *4th Kuala Lumpur International Conference on Biomedical Engineering 2008,* 2008, pp. 641-644.

[81] A. B. Benevides, T. F. Bastos, and M. Sarcinelli Filho, "Proposal of Brain-Computer Interface architecture to command a robotic wheelchair," in *Industrial Electronics (ISIE), 2011 IEEE International Symposium on*, 2011, pp. 2249-2254.

[82] K.-T. Kim, T. Carlson, and S.-W. Lee, "Design of a robotic wheelchair with a motor imagery based brain-computer interface," in *Brain-Computer Interface (BCI), 2013 International Winter Workshop on*, 2013, pp. 46-48.

[83] F. Galán, M. Nuttin, E. Lew, P. W. Ferrez, G. Vanacker, J. Philips, *et al.*, "A brain-actuated wheelchair: asynchronous and non-invasive brain–computer interfaces for continuous control of robots," *Clinical neurophysiology,* vol. 119, pp. 2159-2169, 2008.

[84] G. Gentiletti, J. Gebhart, R. Acevedo, O. Yáñez-Suárez, and V. Medina-Bañuelos, "Command of a simulated wheelchair on a virtual environment using a brain-computer interface," *Irbm,* vol. 30, pp. 218-225, 2009.

[85] I. Iturrate, J. M. Antelis, A. Kubler, and J. Minguez, "A noninvasive brain-actuated wheelchair based on a P300 neurophysiological protocol and automated navigation," *IEEE transactions on robotics,* vol. 25, pp. 614-627, 2009.

[86] K.-T. Kim and S.-W. Lee, "Towards an EEG-based intelligent wheelchair driving system with vibro-tactile stimuli," in *Systems, Man, and Cybernetics (SMC), 2016 IEEE International Conference on*, 2016, pp. 002382-002385.

[87] K.-T. Kim, H.-I. Suk, and S.-W. Lee, "Commanding a brain-controlled wheelchair using steady-state somatosensory evoked potentials," *IEEE Transactions on Neural Systems and Rehabilitation Engineering,* vol. 26, pp. 654-665, 2018.

[88] I. Iturrate, J. Antelis, and J. Minguez, "Synchronous EEG brain-actuated wheelchair with automated navigation," in *Robotics and Automation, 2009. ICRA'09. IEEE International Conference on*, 2009, pp. 2318-2325.

[89] F. Aziz, H. Arof, N. Mokhtar, and M. Mubin, "HMM based automated wheelchair navigation using EOG traces in EEG," *Journal of neural engineering,* vol. 11, p. 056018, 2014.

[90] K. Choi, "Control of a vehicle with EEG signals in real-time and system evaluation," *European journal of applied physiology,* vol. 112, pp. 755-766, 2012.

[91] H. Wang, Y. Li, J. Long, T. Yu, and Z. Gu, "An asynchronous wheelchair control by hybrid EEG–EOG brain–computer interface," *Cognitive neurodynamics,* vol. 8, pp. 399-409, 2014.

[92] Z. Li, S. Lei, C.-Y. Su, and G. Li, "Hybrid brain/muscle-actuated control of an intelligent wheelchair," in *Robotics and Biomimetics (ROBIO), 2013 IEEE International Conference on*, 2013, pp. 19-25.

[93] B.-G. Shin, T. Kim, and S. Jo, "Non-invasive brain signal interface for a wheelchair navigation," in *Int. Conf. on Control Automation and Systems*, 2010.

[94] G. Reshmi and A. Amal, "Design of a BCI system for piloting a wheelchair using five class MI Based EEG," in *2013 Third International Conference on Advances in Computing and Communications (ICACC)*, 2013, pp. 25-28.

[95] S. He, R. Zhang, Q. Wang, Y. Chen, T. Yang, Z. Feng, *et al.*, "A p300-based threshold-free brain switch and its application in wheelchair control," *IEEE Transactions on Neural Systems and Rehabilitation Engineering,* vol. 25, pp. 715-725, 2017.

[96] L. Cao, J. Li, H. Ji, and C. Jiang, "A hybrid brain computer interface system based on the neurophysiological protocol and brain-actuated switch for wheelchair control," *Journal of neuroscience methods,* vol. 229, pp. 33-43, 2014.

[97] H. A. Lamti, P. Gorce, M. M. Ben Khelifa, and A. M. Alimi, "When mental fatigue maybe characterized by Event Related Potential (P300) during virtual wheelchair navigation," *Computer methods in biomechanics and biomedical engineering,* vol. 19, pp. 1749-1759, 2016.

[98] Z. Bahri, S. Abdulaal, and M. Buallay, "Sub-band-power-based efficient brain computer interface for wheelchair control," in *Computer Applications & Research (WSCAR), 2014 World Symposium on*, 2014, pp. 1-7.

[99] H. T. Nguyen, N. Trung, V. Toi, and V.-S. Tran, "An autoregressive neural network for recognition of eye commands in an EEG-controlled wheelchair," in *Advanced Technologies for Communications (ATC), 2013 International Conference on*, 2013, pp. 333-338.

[100] A. Ferreira, D. C. Cavalieri, R. L. Silva, T. F. Bastos Filho, and M. Sarcinelli Filho, "A Versatile Robotic Wheelchair Commanded by Brain Signals or Eye Blinks," in *BIODEVICES (2)*, 2008, pp. 62-67.

[101] T. A. Izzuddin, M. Ariffin, Z. H. Bohari, R. Ghazali, and M. H. Jali, "Movement intention detection using neural network for quadriplegic assistive machine," in *Control System, Computing and Engineering (ICCSCE), 2015 IEEE International Conference on*, 2015, pp. 275-280.

[102] C. Naijian, H. Xiangdong, W. Yantao, C. Xinglai, and C. Hui, "Coordination control strategy between human vision and wheelchair manipulator based on BCI," in *Industrial Electronics and Applications (ICIEA), 2016 IEEE 11th Conference on*, 2016, pp. 1872-1875.

[103] L. R. Borges, F. R. Martins, E. L. Naves, T. F. Bastos, and V. F. Lucena, "Multimodal system for training at distance in a virtual or augmented reality environment for users of electric-powered wheelchairs," *IFAC-PapersOnLine*, vol. 49, pp. 156-160, 2016.

[104] R.-M. Hjørungdal, F. Sanfilippo, O. Osen, A. Rutle, and R. T. Bye, "A game-based learning framework for controlling brain-actuated wheelchairs," in *30th European Conference on Modelling and Simulation, Regensburg Germany, May 31st–June 3rd, 2016*, 2016.

[105] G. Pires and U. Nunes, "A Brain Computer Interface methodology based on a visual P300 paradigm," in *Intelligent Robots and Systems, 2009. IROS 2009. IEEE/RSJ International Conference on*, 2009, pp. 4193-4198.

[106] A. C. Lopes, G. Pires, and U. Nunes, "Assisted navigation for a brain-actuated intelligent wheelchair," *Robotics and Autonomous Systems*, vol. 61, pp. 245-258, 2013.

[107] S. T. Müller, W. C. Celeste, T. F. Bastos-Filho, and M. Sarcinelli-Filho, "Brain-computer interface based on visual evoked potentials to command autonomous robotic wheelchair," *Journal of Medical and Biological Engineering*, vol. 30, pp. 407-415, 2010.

[108] T. Bastos-Filho, A. Ferreira, D. Cavalieri, R. Silva, S. Muller, and E. Pérez, "Multi-modal interface for communication operated by eye blinks, eye movements, head movements, blowing/sucking and brain waves," in *Biosignals and Biorobotics Conference (BRC), 2013 ISSNIP*, 2013, pp. 1-6.

[109] T. F. Bastos, S. M. Muller, A. B. Benevides, and M. Sarcinelli-Filho, "Robotic wheelchair commanded by SSVEP, motor imagery and word generation," in *Engineering in Medicine and Biology Society, EMBC, 2011 Annual International Conference of the IEEE*, 2011, pp. 4753-4756.