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Electroencephalography-based brain-computer interface using neural networks

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ABSTRACT

This study aimed to develop a brain-computer interface that can control an electric wheelchair using electroencephalography (EEG) signals. First, we used the Mind Wave Mobile 2 device to capture raw EEG signals from the surface of the scalp. The signals were transformed into the frequency domain using fast Fourier transform (FFT) and filtered to monitor changes in attention and relaxation. Next, we performed time and frequency domain analyses to identify features for five eye gestures: opened, closed, blink per second, double blink, and lookup. The base state was the opened-eyes gesture, and we compared the features of the remaining four action gestures to the base state to identify potential gestures. We then built a multilayer neural network to classify these features into five signals that control the wheelchair's movement. Finally, we designed an experimental wheelchair system to test the effectiveness of the proposed approach. The results demonstrate that the EEG classification was highly accurate and computationally efficient. Moreover, the average performance of the brain-controlled wheelchair system was over 75% across different individuals, which suggests the feasibility of this approach.

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1. INTRODUCTION

Brain-computer interfaces (BCI) are devices that acquire and analyze brain activities, then convert them into output signals to control desired actions. BCI technology has found applications in several fields, including rehabilitation robotics [1], [2], driver fatigue monitoring [3], [4], gaming [5], and cognitive biometrics [6], [7]. Several techniques can be used to measure brain signals, such as electroencephalography (EEG) [8], magnetoencephalography (MEG) [9], and functional magnetic resonance imaging (FMRI) [10]. Among these methods, EEG is widely used in many applications because it is cost-effective, easy to use with minimal training, and can be used for mobile testing. EEG measures the electrical activity of the brain through electrodes placed on the scalp and is divided into six main frequency bands: delta (0.5−4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), gamma (30–50 Hz), and high gamma (80−150 Hz). Two key challenges in improving the performance of EEG classification are how to use spectral analysis techniques to extract useful features from EEG signals and how to design a robust classifier.

With spectral analysis of the EEG signals, there are various techniques used. For example, Adeli *et al.* [11] proposed the wavelet transform to analyze and characterize the EEG signal of the 3-Hz spike and slow-wave epileptic discharges. Li *et al.* [12] proposed a quantum wavelet packet transformation (QWPT) module to extract the wavelet packet energy entropy feature of the multi-channel and multi-sample EEG signal. Rahman *et al.* [13] introduced a hybrid principal component analysis (PCA) and t-statistical approach for feature extraction of emotion from multichannel EEG signals. Bajaj *et al.* [14] proposed a tunable Q-factor wavelet transform (TQWT) to extract the non-stationary characteristic of the EEG signal for identifying a neurological change in alertness and drowsiness states. A short-time Fourier transform (STFT) was used to analyze EEG signals to obtain time-frequency representations [15], [16]. Li and Chen [17] applied a fast Fourier transform (FFT) to generate the EEG matrix and PCA neural network to learn the hidden information from the frequency matrix of EEG signals. FFT was also used to extract features of stroke patients' EEG signals [18]. The choice of the appropriate spectral analysis technique depends on the complexity and characteristics of the EEG signals to be analyzed. FFT is a suitable method due to its time-shift invariance in both time and frequency domains and its computational efficiency.

To design a powerful classifier, machine learning (ML) techniques have been applied for EEG classification. For example, Sharma *et al*. [19] showed the performance of the multi-layered perceptron (MLP) model classified the EEG signals with 90% accuracy and half the classification time compared to traditional ML-based models (i.e., support vector machines, k-nearest neighbors, random forest, logistic regression, and Bayes). In [15], [20]–[23] introduced a convolutional neural network (CNN) for EEG classification. In addition, many other ML techniques were also used for classification such as extreme learning machine (ELM) [3], [24], ensemble support vector learning (ESVL) [25], quantum machine learning (QML) [12], long short-term memory (LSTM) and variants [26], [27], recurrent neural network (RNN) [28], you only look once (YOLO) algorithm [29]. These classifiers can be trained on either raw EEG signals or meaningful features extracted from pre-processed signals in the time and frequency domains. However, a dataset is a set of images or series, so the computational cost is quite large. By selecting appropriate features and classifiers, the classification performance of EEG signals can be greatly improved.

In this study, we use Mind Wave Mobile 2 to measure raw EEG signals from the surface of the scalp. The signals are then transformed into the frequency domain using FFT. To extract meaningful features for classification, we analyze the signals in both the time and frequency domains and obtain 9 features including amplitude, peak frequency, phase, period, and root mean square for 5 action gestures: opened-eyes, closed-eyes, blink per second, double blink, and lookup. Before analysis, noise in the appropriate frequency bands is removed through filtering. Subsequently, these features are fed into MLP neural networks for classification of 5 signals to control wheelchair movement: forward, backward, turn left, turn right, and stop. Finally, we test the experimental wheelchair system on 5 different individuals to evaluate the effectiveness of our proposed approach.

The rest of this paper is structured as: in section 2, we present our methodology for feature extraction and classification using neural networks. Section 3 provides an in-depth analysis of our EEG classification results, along with the brain-controlled wheelchair. Finally, in section 4, we draw our conclusions based on the findings of this study.

2. METHOD

2.1. EEG-based brain-controlled wheelchair approach

The diagram in Figure 1 illustrates the process of measuring, extracting, analyzing, and classifying EEG signals. It includes components such as data acquisition, feature extraction, classifier-based MLP neural networks, and a wheelchair system. In which, the MindWave Mobile 2 is used to measure EEG signals from the surface of the scalp, and to transmit power spectrum data to a computer via Bluetooth. The analysis is focused on 5 action gestures: opened-eyes, closed-eyes, blink per second, double-blink, and gaze direction (look-up). The features of the EEG signals are analyzed in both the time and frequency domains and are then used as inputs for the neural network classifier. The output of the classifier is sent as control signals through RF networks to operate a wheelchair.

2.2. EEG feature extraction

After collecting the EEG data, it was analyzed and filtered to monitor changes in attention and relaxation. The frequency domain was transformed using FFT, and a set of potential features was extracted, which included 4 time-domain and 5 frequency-domain features. The time-domain EEG feature extraction comprised the maximum, minimum, mean, and root mean square (RMS) of frequency components less than 30 Hz. In the frequency domain, the EEG feature extraction involved the mean and maximum of the alpha band within the range of 8–13 Hz, the mean and maximum frequencies of the delta and theta bands in the range of 1–7 Hz, and the peak frequency. These 9 features were then inputted into the MLP neural network, which classified them into 5 control signals for the wheelchair.

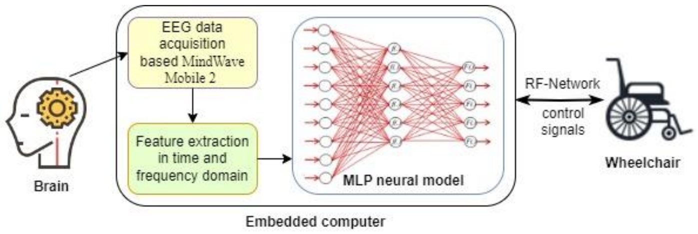


Figure 1. Block diagram of EEG-based brain-controlled wheelchair

2.3. EEG classification using MLP neural model

This section employs MLP neural networks for EEG classification. The architecture of the MLP neural classifier includes the input layer $x(k) = [x_1(k), x_2(k), \ldots, x_9(k)]$ represents the 9 features of the EEG signal. The output layer $y(k) = [y_1(k), y_2(k), \ldots, y_5(k)]$ consists of the 5 output signals of the classified neural network, namely opened-eyes, closed-eyes, blinks per second, double blink, and look-up, respectively. v_{jn} denotes the weighting value of the input layer, w_{mj} represents the weighting value of the hidden layer. $fj(.)$ denotes a sigmoid function at the hidden layer, $F(.)$ represents a linear activation function at the output layer, respectively. We determine the output neural model as:

$$y_i(v, w) = F_i\left(\sum_{j=1}^{q} w_{ij} f_j\left(\sum_{l=1}^{m} v_{jl} x_l\right)\right) \quad (1)$$

In the training process, both the input vector x and the output vector y_{ref} are known and the synaptic weights (v, w) are adapted to obtain appropriate functional mappings from the input x to the output y_{ref}. Generally, the adaptation process can be carried out by minimizing the network error function which is based on a measure of closeness in terms of a mean sum of square error (MSSE) criterion:

$$MSSE((v, w), Z^N) = \frac{1}{2N} \sum_{t=1}^{N} \left[y_{ref}(k) - y(k|(v, w))\right]^T \left[y_{ref}(k) - y(k|(v, w))\right] \quad (2)$$

Where, the training data Z^N is specified by $Z^N = \{[x(k), y_{ref}(k)] | k = 1, \ldots, N\}$.

3. RESULTS AND DISCUSSION

3.1. Extracted features dataset

The data was collected by measuring each person's actions for 30 minutes, corresponding to five different gestures: opening their eyes, closing their eyes, blinking per second, double blinking, and looking up. EEG raw data was collected and pre-processed to remove electrical signal noise at 30 Hz. The detailed analysis of one participant's features is as: the base state is the opened-eyes gesture, and the features of the remaining four action gestures were compared to the base state to identify potential gestures. Figure 2 displays both the EEG raw signal in the time domain and the EEG signal in the frequency domain after FFT.

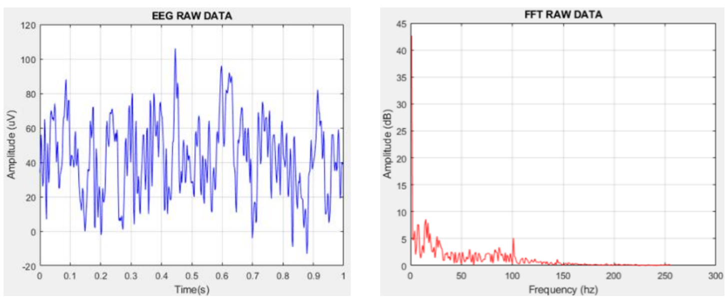


Figure 2. EEG signal pattern when opened-eyes

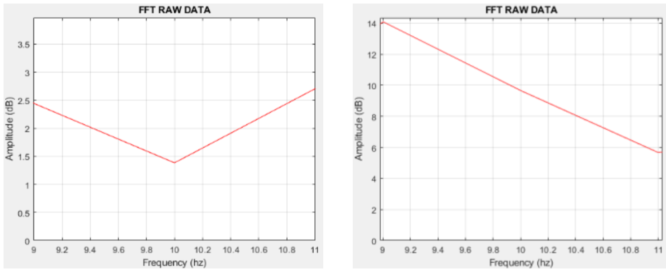
After analyzing numerous signal samples, it was found that the "eyes-closed" features differ from the eyes-opened features in the alpha frequency range (8‒13 Hz), particularly in the frequency range of 9‒11 Hz, as depicted in Figure 3(a) and Figure 3(b). Table 1 shows the extracted features, including the maximum and mean amplitude of the alpha frequency range (9‒11 Hz). We see that mean amplitude of eyes-closed signal is 4.5 times larger than eyes-opened signal.

When analysing the blink action gesture, it becomes evident that the blink per second and double blink features differ from the opened-eyes features in the time domain and in the frequency range of 1−7 Hz, as shown in Figure 4(a), Figure 4(b), Figure 4(c), Figure 5(a), Figure 5(b) and Figure 5(c). Table 2 provides the feature extraction details for the opened-eyes, blink, and double blink gestures, including the maximum and mean amplitude, peak frequency (fmax) in the 1−7 Hz range, and maximum, minimum, and mean amplitude in the time domain. The results show that the features are sufficiently different to distinguish between the blink per second and double blink features.

Only one gaze direction gesture called the look-up, which involves moving the gaze from the center to the top. The EEG signal analysis in the frequency domain does not differ from the base state of opened-eyes, except in the time domain, as shown in Figure 6(a) and Figure 6(b). To extract features in this case, a low-pass filter was utilized to eliminate the component signal with a frequency greater than 30 Hz. After completing the filtering process, the root mean square (RMS) amplitude in the time domain was 141.96 and 1817.51 for opened-eyes and look-up, respectively.

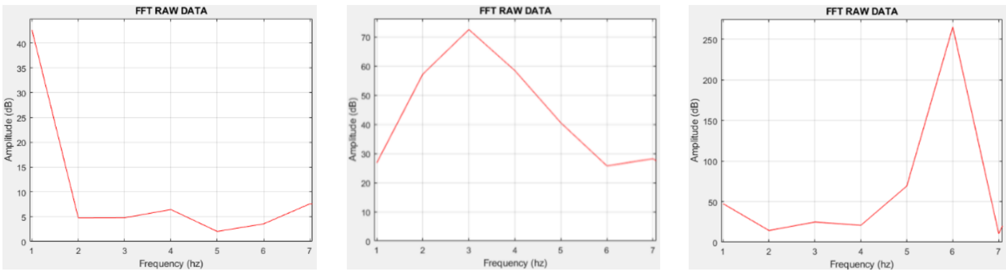
Table 1. Opened-eyes and closed-eyes feature extraction

Gesture	Alpha signal in (9-11Hz) range	
	Max (dB)	Mean (dB)
Opened-eyes	2.70	2.17
Closed-eyes	14.09	9.80



(a) (b)

Figure 3. EEG alpha signal pattern in (9−11 Hz) domain: (a) opened-eyes and (b) closed-eyes



(a) (b) (c)

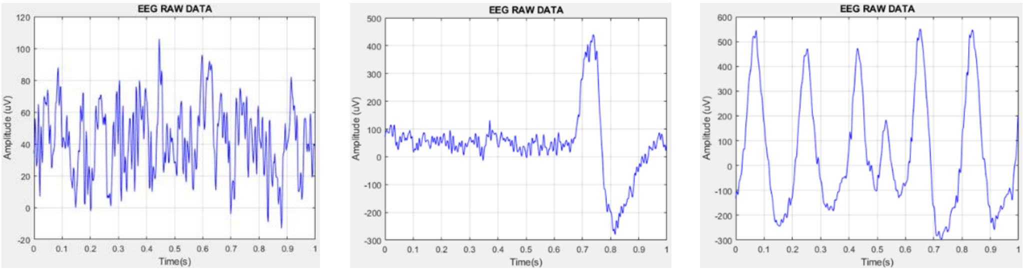
Figure 4. EEG pattern of opened-eyes, blink, double blink in (1-7 Hz) domain: (a) opened-eyes, (b) blink per second, and (c) double blink

Table 2. Opened-eyes, blink, and double-blink feature extraction

Gesture	1−7 Hz frequency domain (dB)			Time-domain (uV)		
	Max	Mean	fmax	Max	Min	Mean
Opened-eyes	42.65	10.27	1 Hz	106.00	-13.00	42.65
Blink	72.54	44.23	3 Hz	440.00	-280.00	44.39
Double blink	264.98	64.62	6 Hz	551.00	-297.00	47.51

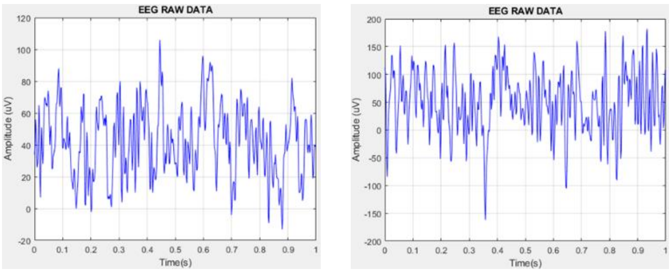
In summary, a total of 300 samples were collected from 1 participant shows as Table 3. The dataset was split into two categories: 210 samples for training data and 90 samples for validating and testing data. The table includes $x1$ and $x2$, which represent the maximum and mean amplitude in the 9–11 Hz range, respectively.

$x3$, $x4$, and $x5$ indicate the maximum, mean, and peak frequency in the 1–7 Hz range, respectively. $x6$, $x7$, $x8$, and $x9$ denote the maximum, minimum, mean, and RMS in the time domain, respectively. Finally, $y1$ to $y5$ are the five gestures considered in this study, namely opened-eyes, closed-eyes, blink per second, double-blink, and look-up.



(a) (b) (c)

Figure 5. EEG pattern of opened-eyes, blink, double blink in the time domain: (a) opened-eyes, (b) blink per second, and (c) double blink



(a) (b)

Figure 6. EEG pattern of opened eyes and look-up in the time domain: (a) opened-eyes and (b) look-up

Table 3. The data set extracted features for classification

No	x-input									y-output				
	$x1$	$x2$	$x3$	$x4$	$x5$	$x6$	$x7$	$x8$	$x9$	1	2	3	4	5
1	6	3	44	12	1	120	-40	44	216	1	0	0	0	0
…	…	…	…	…	…	…	…	…	…	-	-	-	-	-
60	10	8	40	13	1	106	-65	40	194	1	0	0	0	0
61	7	5	40	10	1	115	-40	40	455	0	1	0	0	0
…	…	…	…	…	…	…	…	…	…	-	-	-	-	-
120	8	7	54	12	1	167	-28	54	454	0	1	0	0	0
121	46	34	98	71	4	664	-350	44	293	0	0	1	0	0
…	…	…	…	…	…	…	…	…	…	-	-	-	-	-
180	87	75	93	52	3	691	-291	49	268	0	0	1	0	0
181	94	75	187	103	6	614	-305	55	358	0	0	0	1	0
…	…	…	…	…	…	…	…	…	…	-	-	-	-	-
240	91	63	248	90	5	677	-289	56	323	0	0	0	1	0
241	11	6	35	15	1	182	-110	35	1563	0	0	0	0	1
…	…	…	…	…	…	…	…	…	…	-	-	-	-	-
300	11	8	53	12	1	214	-156	53	1944	0	0	0	0	1

3.2. EEG classification results

In this section, the neural network toolbox of MATLAB is utilized to perform EEG classification using the data set described in Table 3. After a trial and error run, the number of suitably hidden layer neurons is determined to be 9. The MLP neural model is trained using 20 epochs, with mean squared error (MSE) value of 6.10–9 obtained for the training data and 1.10–8 for the testing data. The MSE value for EEG classification is 0.0065597. Figure 7 depicts the MSE achieved during the training of the MLP model. Following successful training, the MLP neural model is employed for EEG classification to control the electrical wheelchair.

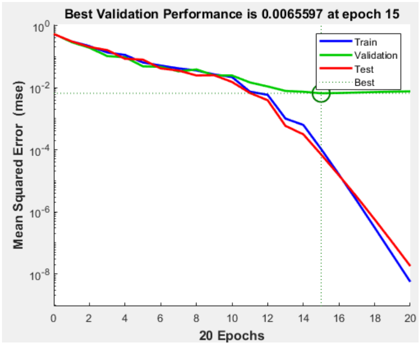


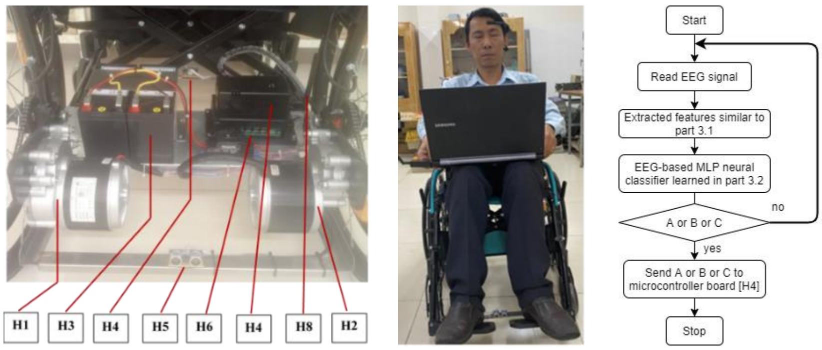
Figure 7. MSE in training MLP neural model for EEG classification

3.3. Controlling wheelchair

3.3.1. Experimental wheelchair configurations

In Figure 1, a flowchart of EEG data acquisition based on MindWave Mobile 2 to control a wheelchair is shown. The wheelchair is capable of moving in five different directions, namely forward, backward, left turn, right turn, and stopping. The experimental wheelchair's architecture is presented in Figure 8(a) and a flowchart of EEG classification is shown in Figure 8(b).

In this system, [H1] and [H2] are permanent magnet motors that operate on 24 volts, with a power rating of 250 watts, and are equipped with a 75 RPM reduction gearbox. [H3] comprises a pair of power supplies that provide power to the wheelchair system. [H4] is a microcontroller board that transmits and receives EEG data from the computer via the ZigBee RF transceiver module [H8]. It also controls the speed of the two motors for movement and measures signals from the ultrasonic sensor [H5] located at the front and back of the wheelchair to avoid obstacles. [H6] is an integrated circuit consisting of two H-bridges that utilize Mosfet IRF3205 to drive two motors with a maximum current of 10 A for each motor (maximum current of up to 30 A).



(a) (b)

Figure 8. Wheelchair systems and flowchart of EEG classification: (a) photo of wheelchair and (b) flowchart

3.3.2. Flowchart to control a wheelchair

In sub-section 3.2, we extracted 9 features and utilized the MLP neural model to classify them into 5 gestures, namely opened-eyes, closed eyes, blink per second, double-blink, and look-up. However, in reality, only 3 gestures, namely closed eyes, look-up, and double-blink, are suitable for controlling a wheelchair. Two gestures consisting of opened eyes and a blink per second are not feasible, since these gestures are infrequent human occurrences. In light of this, the authors propose a method of controlling the wheelchair based on the 3 above gesture signals, as demonstrated in Table 4. In which, 3 gestures including closed-eyes, look-up, and double-blink are denoted as A, B, and C, respectively. Figure 8(b) shows a flowchart to read EEG signals via MindWave Mobile 2 and classification based on MLP neural model on the embedded computer to send signals to control the wheelchair.

Table 4. EEG signal frame to control a wheelchair

No	Control signal		Wheelchair
	Frame 1	Frame 2	
1	B	B	Move forward
2	B	C	Turn left
3	C	B	Turn right
4	C	C	Move backward
5	A		Stop

3.3.3. Wheelchair performance results

The wheelchair is operated by 5 participants, in which 1 person is got data set for training and validating MLP neural model in part 3.2, 1 disabled person, and 3 normal people. Each person controls the wheelchair 20 times. Table 5 shows the wheelchair performance results of 5 participants.

Based on the above results, an accuracy of 78% was attained for forward and backward movement, with 72% for turning right, 68% for turning left, and 70% for stopping. The highest accuracy of 92% was recorded for the 5th individual whose sample data was used for training and validating the MLP neural classifier. Conversely, the lowest accuracy of 50% was achieved by the 1st individual due to the limitations of using brain waves to control eye movements. The 2nd to 4th participants were not familiar with using brain waves to control eye gestures and had yet to undergo MLP neural network training, resulting in accuracies ranging from 68% to 80%. Although the wheelchair performed well overall, all participants should be trained before using it to increase accuracy.

Table 5. The wheelchair performance results

Operation	Disabled person	Normal people not yet training			Trained	Avarage
	1	2	3	4	5	
Move forward	6/10	7/10	8/10	8/10	10/10	78%
Move backward	5/10	7/10	9/10	8/10	10/10	78%
Turn left	4/10	6/10	8/10	7/10	9/10	68%
Turn right	4/10	7/10	8/10	8/10	9/10	72%
Stop	6/10	7/10	7/10	7/10	8/10	70%
Avarage	50%	68%	80%	76%	92%	73.2%

4. CONCLUSION

The study successfully extracted 9 features from 5 distinct action gestures, namely opened-eyes, closed-eyes, blink per second, double blink, and lookup, both in the time and frequency domains. These features were then processed and classified using MLP neural networks to effectively control the movement of a wheelchair, including forward, backward, left, right, and stopping. The experiment aimed to evaluate the effectiveness of this approach, which resulted in a remarkable 99% accuracy in EEG classification performance. Moreover, the average performance of the brain-controlled wheelchair achieved by 5 individuals was over 75%, indicating the system's robustness and practicality. However, due to the EEG device's fixed position with only one pair of sensors, it could only receive brain waves related to concentration and meditation, limiting its ability to receive signals from other brain regions. Additionally, collecting EEG data from stimuli that cause eye fatigue is not ideal. To address these limitations, future work will use EEG sensors that measure multiple points, specifically in the posterior brain regions, to directly collect Mu waves related to EEG motor imagery signals to better classification of motor intentions and enhanced control of the wheelchair.

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