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Classification of motor imagery brain wave for bionic hand movement using multilayer perceptron

Sapto Budi Priyatno, Teguh Prakoso, Munawar Agus Riyadi*
Department of Electrical Engineering, Universitas Diponegoro, Indonesia

Abstract
Physical disability due to amputation can affect a person's quality of life due to limited movement in performing daily activities. Bionic hands are used to help someone with an amputation disability. This research developed a bionic hand control based on electroencephalography sensors capable of measuring the brain's bioelectric activity. The classified brain wave was then translated as activity pattern information. The alpha & beta waves were the focus of this work. This study demonstrated a method to extract and classify motor imagery of brainwave activity patterns. The Fast Fourier Transform (FFT) method extracts motor imagery characteristics. The extraction of features is then classified by the Multilayer Perceptron (MLP) method for five classes of bionic hand movement. Testing was conducted with two scenarios. The first test motor imagery without additional movement showed an accuracy of 77.20 %, while the second test motor imagery combined with head movement showed an accuracy of 84.40% for five classes. The system based on motor imagery has been implemented in a bionic hand that shows the applicability of the proposed method.

Keywords:
Bionic Hand;
Electroencephalograph;
Fast Fourier Transform;
Motor Imagery;
Multilayer Perceptron;

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Corresponding Author:
Munawar A Riyadi,
Department of Electrical Engineering, Universitas Diponegoro, Indonesia
Email:
munawar@elektro.undip.ac.id

INTRODUCTION

Restrictions on movement due to physical disabilities can affect a person's quality of life, which is caused by amputation [1]. Therefore, special attention is required to solve this problem. The rehabilitation of medical devices in hand prostheses [2] is one solution to this problem. The hand prosthesis resembles the original of a human hand but does not have a movement system. Then a bionic hand was developed with a mechatronic system [3] equipped with an electromyography sensor (EMG) [4]. However, the weakness of the EMG sensor is that the sensor cannot detect information signals for hand movements in amputees who have lost residual muscles under the elbow joint [3][4].

The solution overcomes these weaknesses by utilising a mechatronics system based on electroencephalography (EEG) sensors. The EEG-based system measures the bioelectrical activity of the brain and converts it into information about hand movements. The biological activity of the brain to command its limb to touch or move an object with its limb is called motor imagery [5]. EEG sensors offer a high temporal resolution, easy to transport [6], and available for monitoring the bioelectrical activity of the brain. It also can be measured and processed in real-time [7] and are not influenced by the use of residual amputation traces muscles under the elbow like EMG.

Researchers have developed several EEG-based classification and feature extraction methods. Hayashi et al. [8] applied Fast Fourier Transform (FFT) and the neural network classification method to recognize motor imagery patterns. The success rate reaches 80%, but the sensors require a cable to connect to a computing device [8] during the data extraction and processing process. This creates discomfort due to restricted mobility and lack of flexibility inactivity. Portable EEG was then used to overcome the problem. Riyadi et al. [9] conducted a study on five classes of movement pattern recognition with a portable EEG sensor using beta and gamma waves. The number of electrodes used is four channels using a support vector machine (SVM). In this study, five classes of motor movements could be identified. Subrata et al. [10] used a similar method to use the combined beta and gamma waves to move a class 5 bionic arm. Another study by Hamzah et al. [11] used 14-channel electrodes by combining the techniques of PSD feature extraction and Multilayer Perceptron (MLP) classification. A motor imagery accuracy of 86% could be achieved with alpha and beta waves to differentiate between the two classes. Shedeed et al. [12] also carried out a study with a portable EEG with 4-channel electrodes. Using the FFT feature extraction method and the MLP classification method, the motor imagery accuracy is 86.7% to distinguish between 3 classes. Chatterjee et al. [13] conducted a 2-channel hand-held EEG sensor study. Using the multilayer perceptron (MLP) method, the accuracy of the results was 85.71% for two classes of activity patterns [13].

A person's daily activities require a lot of exercises, so many activity patterns are required in this case. Based on previous research, the FFT feature extraction method and the MLP classification method can well identify brain activity patterns. However, the previous studies were limited to two or three classes, insufficient to control bionic hands. Therefore, this study implemented the FFT feature and MLP for a larger class to classify five different hand moves and used four electrodes.

METHOD

Subject

The data was collected by recording brain waves with a Muse headband sensor. The recording is done on subjects that have been trained in using sensors and in recessed conditions. Five subjects were taken EEG signal data for the training and testing process. Data recording was carried out for a total time of 125 seconds for five classes.

The EEG sensor has four electrodes: TP9, TP10, AF7, AF8, and one reference, namely Fpz. The sensor electrode placement system complies with the international 10-20 system [14]. The sampling rate sent to each electrode is 256 Hz/10 bits. Figure 1 shows the location of the electrodes. The AF7 electrode is on the left front forehead, the AF8 electrode is on the right front forehead, the TP9 electrode is behind the left ear, the TP10 electrode is behind the right ear, and the Fpz electrode is called the reference of the use.

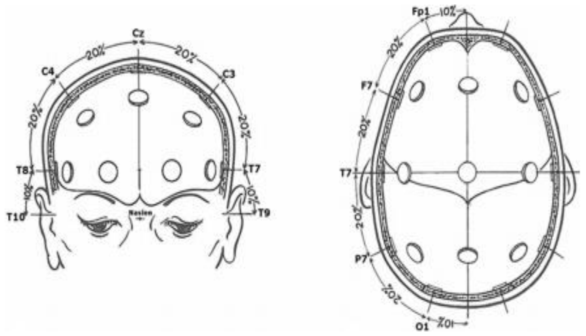


Figure 1. Position of the EEG electrodes according to international 10-20 system [15]

Electrodes AF8 and AF7 are located at the signal measuring point in the frontal lobe, which functions for movement planning [16]. The electrodes TP10 and TP9 are located in the frontal lobe, performing functions, perception, and detection [16]. This EEG sensor is equipped with Bluetooth, is easy to use and does not interfere with movement.

EEG Signal Acquisition

Based on the large frequency classification, the brain has five types of frequency waves, namely gamma (30-44 Hz), beta (13-30 Hz), alpha (8-13 Hz), theta (4-8 Hz), and Delta frequency waves (1-4 Hz) [14][17]. However, since each wave occurs under different brain activities, not all signals are used. Therefore, only alpha (8-13 Hz) and beta (13-30 Hz) signals are used in this study, as also suggested in [10].

A case study from [18] shows that alpha and beta signals experience desynchronisation when executing real and motor imagery movements. For example, alpha and beta generate signals when moving left and right hands show an accuracy of 97.77%. Similarly, alpha and beta signals were used in [13] to move left and right, which showed an accuracy rate of 85.71%. Therefore, this study focuses on alpha and beta signals. The stages of the whole system are described in the block diagram in Figure 2.

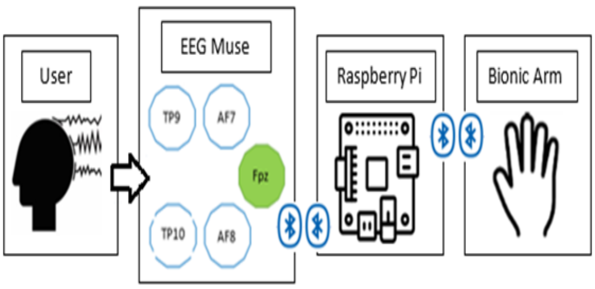


Figure 2. Block diagram of the system

Brain waves from the subject recorded by an EEG sensor are sent to the Raspberry pi via Bluetooth. The raspberry pi is a mini-computer that can perform arithmetic and data acquisition processes well and is portable. First, the raw alpha and beta signal data are calculated to obtain the characteristics and performance of the bandwidth.

The data collected by the subjects was carried out for 15 seconds to imagine the motion for each class and 10 seconds of rest breaks. Each recording session was carried out with a duration of 135 seconds. The data obtained are saved in CSV (*.csv) format. The movement pattern is determined to be considered a reference dataset for a particular feature. The movements chosen in this study are the first class of the "release" movement, the second class of the "key grip" movement, the third class of the "finger point" movement, the fourth class of the "precision open" movement., the fifth class of the "spoon hold" movement.

The bandwidth calculation is then sent to the classification system as a control command. After going through the classification process, the final results were used to distinguish five classes of bionic movements.

The bionic hand system uses the microcontroller as a control centre. The bionic hand is manufactured using a 3D printing technique with a drive as the main motor and an energy source in a battery. The communication system between the bionic hand and the raspberry pi uses Bluetooth. The Raspberry Pi acts as a master controller for processing and classifying brain wave signals.

Fast Fourier Transform

The system's success is inextricably linked to the feature recognition pattern, so feature extraction is required. Feature extraction is an important step in the BCI system to remove irrelevant signals from artefacts or noise that affect clustering results [19][20]. The EEG signal recorded by the EEG sensor contains information about time since patterns of brain activity are assigned to the time range. Since the recorded EEG signal is time-dependent, it must be converted to the frequency domain before it is extracted. The feature extraction process uses the FFT method, which has computational speed in changing the signal [21]. The result of feature extraction is used to characterise the different patterns of the signal [16].

The feature extraction process is carried out to obtain absolute mean power as input to the classification process. Absolute mean power is the average value of the results of the FFT process in each segment. There are several steps to get absolute mean power: frame blocking, windowing, FFT, and the final result is absolute mean power.

The frame blocking process using (1) and (2).

$$N = sampling \text{ x } fs \qquad (1)$$

$$M = N \text{ x } overlap \qquad (2)$$

where N is the amount of data per frame, fs is the sampling frequency, and M is the overlap in the signal. The next stage is the windowing process with the hamming type. Hamming windowing process using (3) and (4) [9].

$$w\,(n) = 0.54 - 0.46\cos\left(\frac{2\pi n}{N-1}\right), \quad 0 \le n \le N-1 \qquad (3)$$

$$w\,(n) = y * w\,(n) \qquad (4)$$

The next stage is FFT. At this stage, the sample frames N = 15.360 point in the time domain converted into the frequency domain with (5). After doing the computation with FFT, it got k = 9.600 feature points.

$$X(k) = \sum_{n=0}^{N-1} x(n).e^{-j2\pi k\frac{n}{N}} \qquad (5)$$

The last stage is calculating the absolute mean power process using (6).

$$Sk = \frac{1}{x}\sum_{n=1}^{x} y(k) \qquad (6)$$

where k is the FFT index, x is the number of frames used in each segment, and $y(k)$ is the resulting FFT-k to data at the time of frame -x. Then calculate the standard deviation to determine whether the sample data represents the total amount of data and calculate the standard deviation process using (7).

$$\delta x = \frac{1}{N-1}\sum_{n=1}^{N-1} |X(\text{n}+1) - X(n)| \qquad (7)$$

Figure 3 illustrates the raw signal at four electrodes to be processed using FFT. Figure 4 illustrates the result of FFT signal for the beta wave in each electrode.

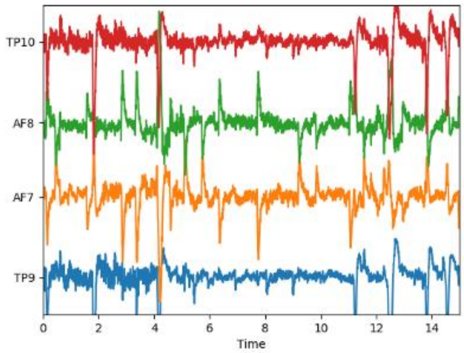
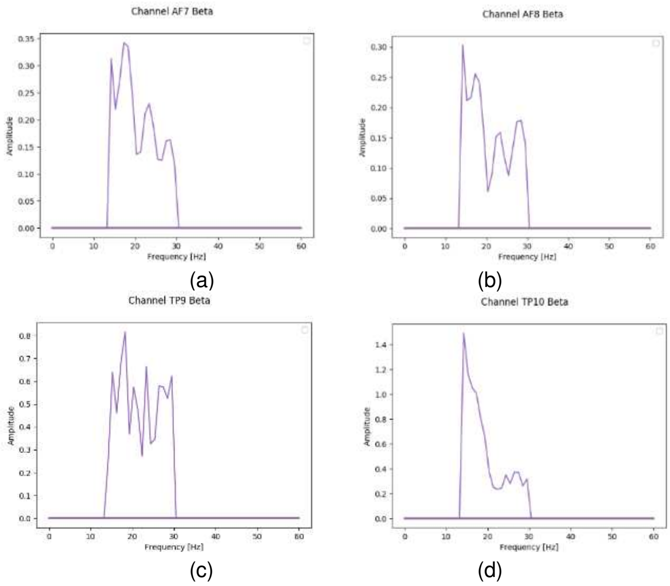


Figure 3. The raw signal generated by the beta frequency at four electrodes (time domain)



(a) (b) (c) (d)

Figure 4. The process of calculating the signal with FFT on each channel : (a), AF7 channel, (b) AF8 channel, (c) TP9 channel, and (d) TP10 channel

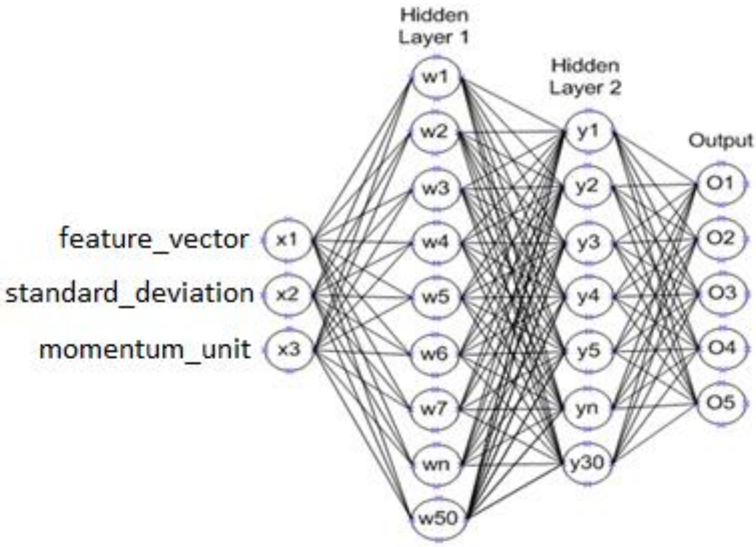


Figure 5. Multilayer Perceptron with two hidden layers

Multilayer Perceptron

The multilayer perceptron algorithm (MLP) is an algorithm that adopts the workings of an artificial neural network in the human brain. This algorithm is reliable because of its directed learning process [11][13]. The training algorithm used is feed-forward. MLP uses an activation function, where the weighted sum of the input and bias is entered into the activation level via the transfer function to produce the output, and the units are arranged in the feed-forward layer.

MLP is generally composed of input, hidden, and output layers. Input neurons can consist of one neuron to several neurons depending on each case [12]. The input level receives information in the form of the value of a variable that affects the learning outcome. Hidden layers serve to connect the input layer and the output layer. The number of shifts in an MLP can be different in each case. This influences the probability of success.

Figure 5 shows the MLP architecture used. The MLP architecture consists of 3 input layers, two hidden layers, and five output layers. The data entered consists of the result of the feature extraction process, namely *Feature Vector*, *Standard Deviation,* and *Momentum Unit*. Hidden layer one totals 50 nodes, hidden layer two totaling 30 nodes, and output layer totals five neuron classifications. Later, each class will be presented in a bionic hand movement. Table 1 summaries the architecture.

The training process aims to find the best weight with the smallest error value obtained from the desired output target. The 'relu' activation function activates the neurons to get the error value. The learning rate uses a 'constant' and a maximum iteration of 200. The optimisation function 'adam' is used in this network to update the weights.

Table 1. Multilayer perceptron network architecture

Characteristics	Specification
Number of input layer	3
Number of hidden layer 1	50
Number of hidden layer 2	30
Number of output layer	5
Activation function	*Relu*
optimization function	*Adam*
Max Epoch	200
Learning Rate	0,2

RESULTS AND DISCUSSION

This study uses a brainwave classification to control a bionic hand with five-class motor imagery. A previous study [10] indicates that additional movement increases the accuracy of the brainwave classification. Therefore, this study was conducted with two testing sessions by motor imagery without movement and motor imagery with additional head movement.

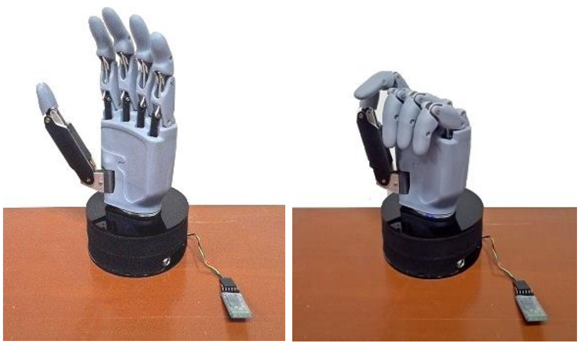
Each session in this research was conducted into two stages, namely the training and testing process. The first session of the training process was conducted by recording brain waves from motor imagery activities. Subjects were initially given 10 seconds to prepare, followed by 1-second pause, 15 seconds to record the pattern, and 10 seconds to rest on each pattern recording. The training data was obtained from a streaming muse headband EEG sensor sent to Raspberry pi via Bluetooth.

EEG signal extraction feature data from the FFT process: Feature Vector, Standard Deviation, and Momentum Unit. EEG signal data that has been processed using FFT consists of alpha and beta signal features. First, the dataset goes through the FFT process and has been reviewed in other forms. Then the classification process is carried out using the MLP method by assuming that each variable's attribute is independent. Finally, a classification model is created to trigger bionic hand control.

The device is supplied with a tone that signals preparation, recording, rest, and end during the recording process. The subject is in a relaxed sitting position facing a screen during each training and test. An icon is displayed on the monitor screen that supports the subject during training to concentrate better. After completing the training process, the monitor shows the percentage of successful training units.

The testing process re-recorded data from subject streams using the same headband sensor with the same flow of training process. The subject must move the bionic hand according to the motor imagery pattern during the initial training session. This process also applies to the second session, which differs only in the addition of head movement.

The activity patterns that have been trained at the beginning represent five classes of bionic hand movements, namely: class 1 "release," class 2 "key grip," class 3 "finger point," class 4 "open precision," class 5 "spoon hold". Several samples of hand movement are shown in Figure 6. The initial movement is the "release" before moving to the next one in the testing process. This aims to determine whether the bionic hand can execute commands and avoid collisions between bionic fingers. The release movement also makes it easier to position the bionic hand with the object to be grabbed.



(a) (b)

Figure 6. (a) The position of the bionic hand for "release" movement. (b) The position of the bionic hand for the "hold the spoon" movement

Brain activity patterns were predicted and divided into five classes using a raspberry pi device. After the training session is completed, the processing results are shown on the monitor board. The tests were carried out by subjects in 10 tests in each class. The final result of this test is determined ten times in each class by the command to move the bionic hand.

Table 2 shows the training and testing process for moving bionic hands from five classifications. The test accuracy obtained when motor imagery without movement is 77.2%, while motor imagery with movement is 84.4%. These test results are similar to the research conducted by [10], which experienced an accuracy improvement of up to 20% when the imagery motor was combined with movement. From this, it can be concluded that imagery alone is not enough to get maximum results. However, with the addition of movement, the results obtained increased, so the imagery motor combined with movement is very important and affects the success rate of accuracy.

Research to move the bionic hand of motor imagery, five classes, without movement and with movement in each class performed by the subject, is shown in Figure 7.

The highest classification test results for motor imagery without movement and with movement showed that class 1 was highest. In this study, grade 1 was implemented with a release movement. Because class 1 has a characteristic that is much different from other class imagery motors, the classification patterns can be recognised well. Characteristics of classes with similarities make the classification system detect many of the same. As class 5 has some similarities with class 2, the test results also show a similar lower level of accuracy. The feature's success influences testing accuracy in recognising patterns during the motor imagery training process.

Table 2. Comparison of accuracy with and without additional head movement

Subject			Accuracy without head movement		Accuracy with head movement	
No	Gender	Age	Training	Testing	Training	Testing
1	male	30	71%	76%	83%	86%
2	male	27	76%	78%	79%	84%
3	female	29	72%	76%	78%	80%
4	male	28	82%	80%	87%	86%
5	female	21	79%	76%	81%	86%
	average		76.0%	77.2%	81.6%	84.4%

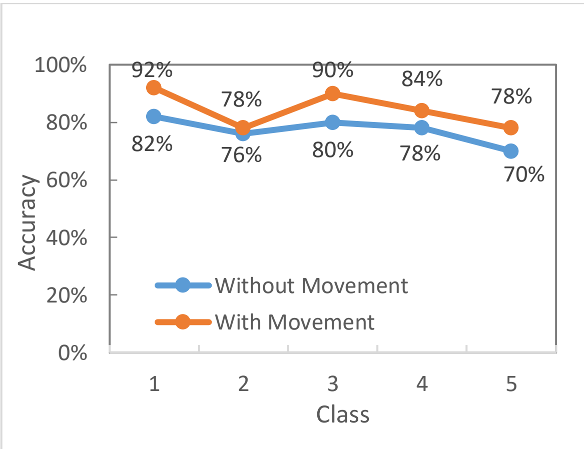


Figure 7. Test results of the average accuracy of without movement and with movement in each class

The overall system shows good results. A similar study using muse headband sensor with FFT feature extraction method proved good results for five classes [9]. Compared to the study [12], which used the same extraction and classification methods, they provided an accuracy success rate of 86.7% motor imagery of only three classes. At the same time, this study for five motor imagery classes gave a success rate of accuracy of 84.40%. Due to the higher complexity of more class classifications in our research, the results of the developed system are considered acceptable.

The results of this study suggest a higher presentation than one obtained by P. Yang et al. [22]. What distinguishes the two methods used is the choice of the activation function and the number of recognitions of classification patterns. The more pattern recognition is classified, the more difficult and complex it is for the system to classify them. The studies carried out in [22] in which the EEG signal was classified for four motor imagery patterns with the activation function' softmax' showed an accuracy of 76%. According to [23, 24, 25], a hidden layer consisting of 2 or more can improve the accuracy of the classification system but slow down the training system.

CONCLUSION

The experimental data shows that the brainwave classification system of 5-class motor imagery using FFT and MLP methods has run well compared to similar studies. The accuracy obtained in the testing stage achieved 77.20% without additional movement and 84.40% with head movement based on alpha and beta waves. In this study, it has been found that motor imagery with additional head movement as a support of the classification system can increase the yield by + 7%. Overall, the developed system has been successfully implemented in bionic hands, which is proof of the applicability of the proposed method.

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