

Hand and Foot Movement of Motor Imagery Classification Using Wavelet Packet Decomposition and Multilayer Perceptron Backpropagation

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ABSTRACT

The development of bionic aids for paralyzed patients leads to the Brain-Computer Interface (BCI) implementation with various obstacles, especially in interpreting brain signals as triggers for the bionic organ. The reading of electrical signal activity in the brain in the BCI system uses electroencephalography (EEG) signal, which comes from many electrodes in the head area and is non-stationary. The measured EEG signal contains much information, including information for the hands and feet motor imagery, so a classification system is needed to separate the information to be processed, such as hand and foot movements. This research aims to develop an imagery motor classification system for the hands and feet so that signals can be classified correctly. The system design is made through several stages of the signal processing process consisting of the pre-processing stage using centering, the feature extraction stage with wavelet packet decomposition (WPD), and multilayer perceptron back-propagation (MLP-BP) as the classifier. Based on the result, this study got the highest accuracy value, about 26.8% at level three, and gain above 0.02. This small accuracy is due to the large error due to under fitting.

Keywords: EEG, Motor Imagery, Wavelet Packet Decomposition, MLP-BP.

1. INTRODUCTION

The brain controlling all parts of the human body, including the hands and feet, has several nerve cells with various waves to control all the parts with different functions [1]. If one of the organs in humans, such as hands and feet, cannot be used, it is necessary to have a tool to replace these organs. Instead of unusable hands and feet, humans make bionic hands and feet that require communication with the brain through brain signal readers. Brain-Computer Interface (BCI) is a bridge to communicate between the brain and the external devices. BCI can translate language and convey user-desired controls into computer commands by classifying the brain activity associated with the task, usually measured by an Electroencephalograph (EEG) [2,3]. EEG signals are brain signals obtained by non-invasive methods. The EEG signal can function to measure bioelectric signals in brain tissue [4]. The brain waves are Alpha, Beta, Gamma, Theta, and Delta. Based on these five waves, the researcher used all available wave types [5]. The problems faced in signal processing are low frequency,

easily covered by noise when retrieving data, and have intricate patterns. It takes several appropriate stages to process a person's brain waves, starting from the extraction stage to the classification stage [6].

Akbar [7] showed that the discrete-time domain could analyze the human brain activities and frequency domain. Ersti [8] implement the discrete wavelet transform and deep neural network to classify EEG signals. Ersti showed the DWT based system not suitable to use in EEG classification. Wijayanto [9] implemented wavelet packet decomposition (WPD) and a support vector machine to analyze epilepsy. Our work implemented the WPD because of the Wijayanto work. Kevric [10] compared several classification methods for EEG signals. Kevric showed the WPD with the Sym4 mother wavelet gave the highest accuracy. Saddam [11] also showed high accuracy when the system implemented the WPD. Abdulrahman [12] showed the multilayer perceptron (MLP) gave higher accuracy than KNN and RNBF Network. We implemented the WPD for feature extraction and MLP for classification.

2. METHOD

This study aims to classify the hand and leg movements' motor imagery based on the EEG signal. The dataset used is data that contains a recording of the EEG motor imagery signal of the hand and foot movement, with a sampling frequency of 200 Hz. The number of datasets used is ten datasets, and the number of electrodes in the dataset is 22. The researchers used only 19 electrodes because, in the dataset, three of them were EOG channels while the rest were EEG channels. There are several classes in the dataset, but what researchers take is only four imagery motor classes. The four imagery motor classes are right hand, left hand, right foot, and left foot.

The classification system has several stages. The initial stage of a system is to provide an input signal in the form of an imagery motor EEG signal that will be processed and classified. After getting the input signal from each class, the signal pre-process in the form of centering. The centering signal will be processed to the decomposition stage with the WPD. The results from the decomposition stage will be taken based on the type of feature extraction used. The features obtained from feature extraction will be selected with information gain, leaving several features to be classified. The next process is the normalization of the values that are in the selected features. The last is the classification process using MLP-BP. The results of the classification will get an overall accuracy value.

The hand and foot movement EEG signal dataset will be decomposed using WPD. This study will use WPD with sym4 mother wavelet based on the journal [10]. The selection of the mother wavelet type from the symlet family also helps to maintain the decomposed EEG signal to obtain the optimal reconstruction signal [13]. The feature extraction stage generates the average (mean), min, max, and standard deviation of the two coefficients. Fig.1 shows an overview of the feature extracted decomposition signal process. The feature selection implemented information gain method to reduce the feature that will be used in classification stage. The value of the feature selection results can improve the level of accuracy during classification. The amplitude normalization process is obtained by dividing all digital sample values by the signal sample's maximum absolute value [14]. In this research scheme, the normalization process is carried out after the decomposition process.

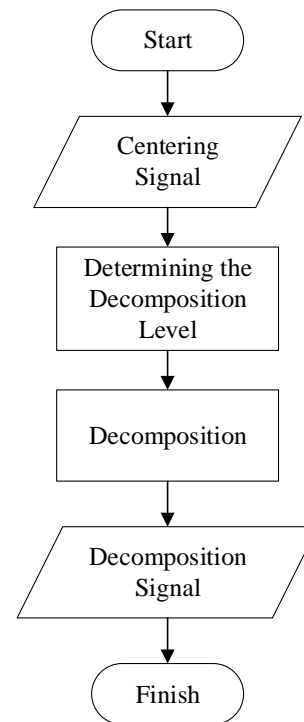


Figure 1 Signal Decomposition Process

The approximation coefficient results and the detail coefficient that have gone through the normalization process will be the input value in the Multilayer perceptron classification with the back-propagation algorithm. This classification's input value is a combination of the four classes whose feature extraction has been taken and has gone through the normalization process. Fig. 2 shows the flow of the training and testing process when performing classification. The use of K-Fold Cross Validation can minimize random samples in comparing accuracy. In k-fold cross-validation, data is separated into two subsets: training data and data validation (testing). There are three rules for the number of K, namely Representative, $K = 10$, and $K = n$ [15].

The result data from the K-Fold Cross Validation process will be processed using the Confusion Matrix. A confusion matrix compares the predicted value with the actual value and creates a measure of misclassification. The lower the number of classification errors in the Confusion matrix, the better the performance [16]. The error value can be displayed and the level of accuracy of each class, so that it can be added and produces an overall level of accuracy. The higher the accuracy obtained in each class, the higher the overall accuracy, and it can be interpreted that the better the classification system

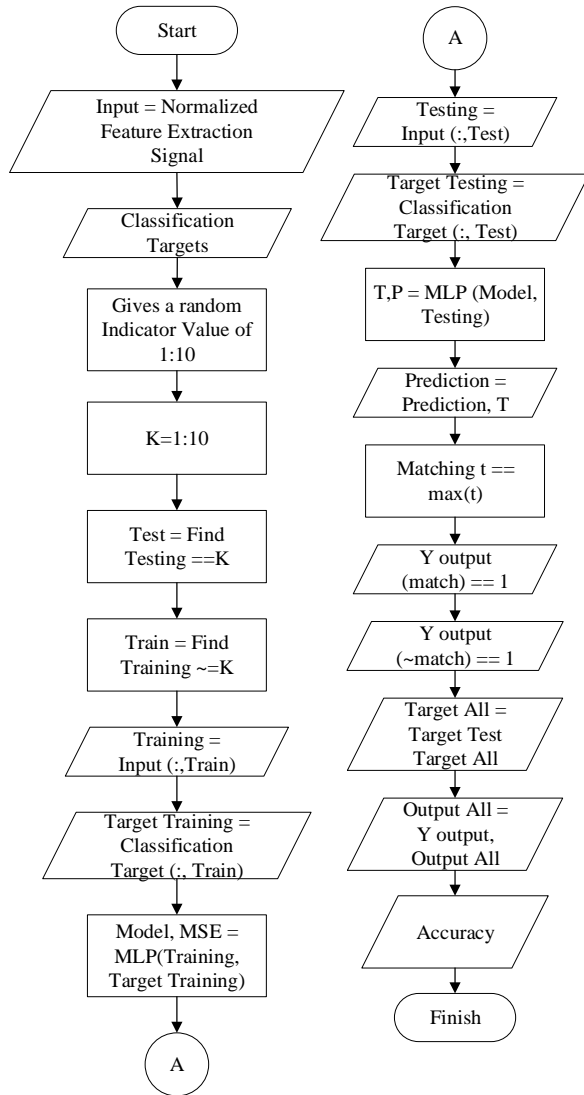


Figure 2 Classification Process

3. RESULT AND DISCUSSION

The table 1 shows the classification result of several types of features used in WPD with the decomposition level at level four without using feature selection. The average value feature is better than other features. The accuracy value obtained is the result of the entire class. The number of features used when classification is all features at level four, namely 304 features. This amount is obtained from the number of each electrode at each coefficient in the level four decomposition. The feature selection was not used because each feature can produce different gain values, so it would be fair if the number of features were not selected and equalized.

Table 1. Level of Accuracy in Each Feature

Features	Accuracy
Mean	25.6%
Standard Deviation	25.2%
Minimum	24.9%
Maximum	24.3%

The components to be compared are the accuracy of each type of feature. It can be seen that the type of feature, on average, produces the highest accuracy value of 25.6%. This accuracy level is a representation of the accuracy of the types of features used in the classification. Although this accuracy is still relatively low, the value is still higher than other types of features. Our works used the average feature by varying the level of decomposition and feature selection to determine which level was suitable for classification and the impact of feature selection.

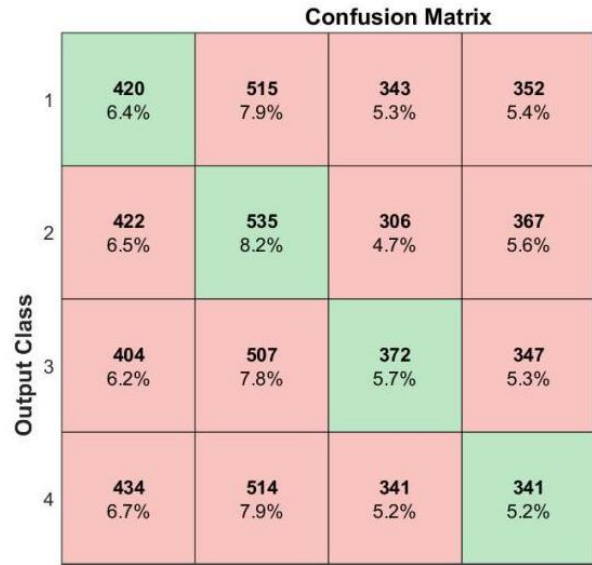


Figure 3 Confusion Matrix Average Data

Figure 3 show the result of this average with an accuracy value of 25.6%. This value is obtained from the sum of the actual positional values in each class. The highest accuracy value of the four classes is in the second class, namely the right hand, which reaches 8.2%.

Table 2 shows the accuracy resulted by various levels of decomposition stage and features selection stages. The accuracy obtained is a variation of the data with the gain obtained from the information gain. Gain is obtained from each feature available at each level. Based on several levels tested, it can be seen that the highest level of accuracy of all is at level three, with 26.8% when the gain used exceeds 0.02. Meanwhile, the lowest accuracy value is at level one, 25.5%, with no gain or more than 0. The result of a decomposition level that is higher than level three gets a smaller level of accuracy. At levels four and five, both produce an accuracy of 26.1% and 26.0% when the gain is more than 0.02. At a gain of more than 0.01, level 3 has the lowest accuracy value than the other four levels. So, the highest accuracy of all data is not necessarily the highest in every experiment. The accuracy of each level still looks very low if it is to be implemented in reality. The use of information gain as feature selection has no impact on increasing the classification's accuracy value. For example, in table 4.2

with an average feature level, four without using feature selection only gets an accuracy of 25.6%, while level four with a gain of more than 0.01 gets an accuracy of 26.4%. However, when the gain is more than 0.02, the accuracy value decreases to 26.1%. There is an increase in accuracy, although it is not too significant. Likewise, when the accuracy decreases, it does not decrease significantly.

Table 2. Level of Accuracy at Each Level

Level	Accuracy without feature selection	Accuracy with Gain > 0.01	Accuracy with Gain > 0.02
Level 1	25.5%	25.7%	26.3%
Level 2	25.9%	26.2%	26.4%
Level 3	26.1%	25.6%	26.8%
Level 4	25.6%	26.4%	26.1%
Level 5	25.8%	26.2%	26.0%

The results of several experiments that have been tested in this study have an insufficient level of accuracy. Researchers then find out that the error value obtained during classification is very high, as shown in Figure 4, where the highest error value is 8235.7 during the 3745 iterations. Not all of the error values are high, but there are some times where the error increases and suddenly decreases again. The smallest error value obtained is 110.2192 in the 17622nd iteration. Based on the error graph concept, it can be concluded that the classification system used by the researcher is underfitting. This can be caused by several things, including the pre-processing process that can change the value of the dataset and the extraction of features that have not yet obtained the characteristics of the dataset, so it is difficult to distinguish each class.

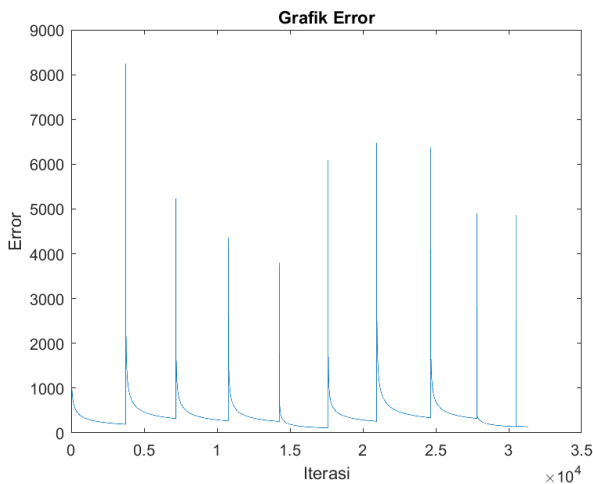


Figure 4 Error Graph

4. CONCLUSION

The hand and foot imagery motor classification system based on the EEG signal made includes several stages such as pre-processing, WPD as feature extraction by varying the level of decomposition, and information gain on feature selection, and MLP-BP as a classifier. Based on the test results, the accuracy level of the hand and foot imagery motor classification system using the WPD and MLP-BP method reaches 26.8% on average features and a gain limit of more than 0.02. The use of varying levels of decomposition and information gain does not affect the resulting accuracy because there is no significant increase in accuracy. The variation in the accuracy value seen is influenced by the initial weight when starting the classification.

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