Extraction of EEG signals using the discrete wavelet transforms

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Extraction of EEG signals using the discrete wavelet transforms

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Abstract. This study focuses on feature extraction for Electro Encephalo Graph (EEG) signals using the Discrete Wavelet Transform method. The EEG signal is used to move up the cursor and the down cursor. In each subband of the EEG signal wave the average value is taken to characterize the EEG signal. Backpropagation Neural Network is used as an EEG signal classification to determine whether the up cursor or the down cursor. The data used in this study are EEG data derived from BCI competition 2003 (BCI Competition 2003). Decision-making is done in two stages. In the first stage, the mean value of each wavelet subband is used as a feature extraction of the EEG signal data. This feature is an input to the Backpropagation Neural Network. In the second stage of the classification process into two classes of class 0 (for the up cursor) and class 1 (for the down cursor), there are 260 training data file of EEG and 293 signals from EEG signal data testing file, so the whole becomes 553 data file of EEG signals. The result obtained for EEG signal classification is 77.2% of the tested signal data.

Keywords: EEG, Mean, Discrete Wavelet Transform, BackPropagation

1. Introduction

Electroencephalography (EEG) is a method of monitoring of Electrophysiology to record electrical activity in the brain. The electrodes are placed along the scalp electrodes are invasive, although is sometimes used as in electrocorticography. EEG measures the voltage fluctuations resulting from the flow of ions in the neurons of the brain. In the context of clinical, EEG refers to the spontaneous electrical activity of brain recordings during the time period, as recorded from multiple electrodes placed on the scalp [1]. Diagnostic applications generally focus on the potential associated with EEG spectral content.

Placement of electrodes on the scalp following the system specified already 10-20 System. The proper electrode placement and good are the main requirements for obtaining EEG recording are good and trustworthy. In addition, the cleanliness of the scalp, the condition of the electrodes, and EEG machine compliance subjects while recording is also very influential to get good results. Hans Berger stated that human brains have electrical activity that is continuous and can be recorded. Brain activity may be possible to transmit the order to the electronic equipment with the help of Brain-Computer Interface (BCI) [2]. Most of BCI using spontaneous mental activity (for example, imagine moving the fingers, hands, or the entire arm, etc.) To generate an electroencephalogram (EEG) signals that can be distinguished [3]. EEG signals that can be distinguished from later converted into external actions. During the last few years, a variety of evidence has been evaluating the possibility to recognize some
mental task EEG signals from [4]. However, how to improve the performance of the EEG signal recognition in signal processing is still a major problem. The procedure of introduction mainly includes classification and feature extraction, where the extraction of features plays an important role in classification. This paper mainly focuses on the extraction of features.

Currently, the feature extraction method for image motor EEG mainly includes some methods include using the method of Fast Fourier transform (FFT) [5] [6], Fourier spectral features are calculated by the method of Fourier transformation using Welch windowed segment signal. The main disadvantage of this method is the method using only information and not to use the frequency domain information time. However, research shows that the combination of information frequency and time domain information can improve the performance of the classification of EEG signals [7]. Autoregressive (AR) is a method of the spectrum of AR, band power calculated in multiple frequency bands and the amount of power used as independent variables [8]. In addition, model multivariate autoregressive coefficient model used as a feature [9]. Time-frequency analysis by Wang et al, use of time-frequency analysis as a useful tool for the components of the EEG during motor imagery oscillating [10]. As we all know, the components of the EEG oscillating produced during motor imagery is a time and frequency related, therefore, this method of obtaining promising results. However, the components of the EEG oscillating simultaneously can cause a shift in the slow cortical potentials. A combination of two related signals may be used to enhance the information being extracted. Methods of time-frequency EEG components considering only oscillates. Utilizing wavelet transform coefficients, i.e., extracting coefficients of wavelet transform on the useful frequency bands according to the transcendent information [11]. However, the mechanism of production of EEG is rather complicated, so it is difficult to get accurate information on the transcendent and somewhat inflexible.

Based on the above research after the background was designed as follows, section 2 describes the materials and methods used in the search feature and classification of EEG signal, part 3 describes the result of the extraction feature process and the classification EEG signals, and section 4 describe the conclusions of this research.

2. Materials and Method

2.1. Materials

The DataSet is taken from a healthy subject. The subjects were asked to move the cursor up and down on the computer screen, while the potential of cortical taken. During recording, the subject receives visual feedback from the potential the slow cortical (Cz-Mastoids). Cortical leads to the positive movement of the cursor to the bottom of the screen. Cursor movement causes cortical negative up. Each experiment 6s. During each experiment, Only the interval of 3.5 minutes per experiment is provided for training and testing. 256 Hz sampling rate and record length of 3.5 produces 896 point data [15].

2.2. Discrete Wavelet Transform

Comparison Discrete Wavelet Transforms (DWT) with continued Wavelet transform (CWT), DWT is considered a relatively easier implementation. How to obtain a representation of the time and scale of a signal using digital filtering techniques and operations, sub-sampling is the basic principle of DWT. Series high-pass filter and low-pass is a series that is used first to missed signals. The operations, subsampling is used to sample the output signals from an EEG taken half of each output signals EEG, the process is the process of decomposition of one level (Figure 1). Filter the output low-pass and high-pass used as an insert in the decomposition process of the next level. This process is repeated until the desired level of the decomposition process. Output filter high-pass and low-pass filters are merged into one, referred to as the coefficients of wavelet signal information, containing the results of the transformation that has been compressed [12].
The operations, sub-sampling that eliminates redundant signal information, wavelet transform has become one of the most data compression methods that are reliable. High-pass filter pair off and low-pass that is used must be a Quadrature Mirror Filter (QMF), i.e. a pair of filters that meet the following equation:

\[ h[L - 1 - n] = (-1)^n \cdot g(n) \]  

(1)

Where \( h[n] \) is the filter high-pass, \( g[n] \) is the low-pass filter and \( L \) is the length of each filter.

Wavelet coefficients calculated using daubechies wavelet sequence 2 features more suitable for detecting changes in the EEG signals. In this study, the EEG signal is decomposed into the details of the D2.

To reduce the dimensions of the vector features, set up the statistical wavelet coefficient is used. The following statistics feature is used to represent the time, frequency distribution of EEG signals, i.e., the average value of the wavelet coefficients at each sub-band.

2.3. Backpropagation Neural Network

Neural network (ANN) is a system of information processing that has characteristics similar to a network of nerve Biology [13]. This means that the neural network is one of the information processing system designed by parroting the workings of the human brain in solving a problem by making the learning process through changes in the weighting of synopsis. JST is a method that can find a non-linear relationship between the load and the economic factors that vary as well as other factors that can make adjustments against the changes that occur. JST can be applied with good forecasting is the field [14]. To predict what will happen, we need a technique of divination to determine the process of planning and decision-making. JST backpropagation is a technique that can be used for forecasting. Mostly used in Backpropagation network many layers or can be called also multi-layer in hopes of minimizing the error on the result of the calculation technique conducted by the network. There are three main steps, i.e. enters data into the input network (feedforward), performs calculations and turning from error propagation (backpropagation) and performs renewal of weights and biases (adjustment). After discovering a pattern of network i.e. the values of the weights and biases, the network can be used to determine the output of any insert (testing).

In this study, the process of data classification is done by separating EEG signals into two parts, namely the data for the training process as many as 268 the data vector and the data for the test process data are used as much as 293 the data. This network has 4 input node \( (x_1, x_2, ..., x_4) \) comes from the feature DWT, 10 nodes in hidden layer 1 \( (z_1, z_2, ... the z_{10}) \), 15 nodes in hidden layer 2 \( (w_1, w_2, ... w_{15}) \), and outputs the binary type to identify conditions \( (y_1, y_2) \). Research on network architecture can be seen in Figure 2. The output pattern with 2 outputs in the form of binary target. The type of pattern can be seen in table 1.
Table 1. The Output Vector Patterns

| No | Classification Of Data | The Output Pattern |
|----|-------------------------|--------------------|
| 1. | Up Cursor               | 0                  |
| 2. | Down Cursor             | 1                  |

3. Results and Discussion

The data used for research that is using data from the BCI Data set He 2003 competition. Data set It is composed of 6 channels (the electrode taped in the scalp amounted to 6 electrode sensor, resulting in a 6 channel signal EEG). The data set is that it consists of the training and data Testing data.

The amount of data a lot, will cause long computation process is caused by lots of data that are processed, so with a little feature that results in a fast computing process. At the research, one signals EEG has only taken the average value and the maximum value of each subband extraction process of DWT untuk from the Foundation of the characteristics for the identification process.

Figure 3 is a recording of EEG is divided based on the frequency of the sub-band wavelet coefficient, resulting in A5, D5, D3, and D4 from the DWT. Frequency sub-band wavelet (0-4 Hz), (4-8 Hz), (8-16 Hz) and (16-32 Hz) was made into a set of feature extraction are taken from each sub-band EEG signals.

Figure 4 shows that for the average value in each subband for class 0 and class 1 has the value difference. The difference in value is not the same show that level of classification by taking the average value quite well. Classification using a Backpropagation Neural Network implemented using features of the average value of the DWT as input. In this study, a set of training amounted to 260 data samples and test data 293 sample data. On the training process used data as much as 260 sample data (from normal subjects) for channel 1. To test process data is used as many as 293 sample data (from normal subjects) for all channels. Table 2 is the distribution of the sample classes in the training data collection and validation. Data obtained from subjects in the training process is a way to improve the
ability of Backpropagation. To train a backpropagation using a training data set, whereas To verify the accuracy and effectiveness of Backpropagation was using a test data have been trained to detect the movement of the cursor moves up and down.

![Graph](image)

**Figure 3.** Approximate and detailed coefficients of EEG signal taken from a healthy subject

![Graph](image)

**Figure 4.** The mean value of the coefficient of the Sub Band Wavelet transforms

**Table 2.** The sampling distribution of the class at the training data and test data

| Class               | Training set | Test sets              |
|---------------------|--------------|------------------------|
| Up Cursor (class 0) | 130 x 6 Channel | 293 x 6 channels (mix) |
| Down Cursor (class 1)| 130 x 6 Channel | 293 x 6 channels (mix) |

The results of the extraction process characterized with DWT used a neural network, input for this study using the method of back Propagation (4-10-15-2) i.e. 4 input that comes from the
characteristics of EEG signal and 2 the hidden layer (Figure 5). Two hidden layers are 10 nodes in the hidden layer node on 15 dan hidden layer 2, and 2 targets (the movement of the cursor to the top of the class 0 and cursor movements down to grade 1). In addition to using the architecture network 4-10-15-2, to test the study also uses additional and subtraction hidden layers.

The process of training is the process of searching the best weight value with the smallest error value of the acquisition of the target output is desired, this is done in the initial process of identification. Process mapping is done after the process of training, namely the identification signals of the EEG up the cursor and down cursor movement based on the weights that already obtained in the process of training.

![Figure 5](image)

260 data training from channel 1 in 619 the training period and the size of the steps for adaptation parameter has a value of 9, initial 998.10-10. Performance Backpropagation using 2 hidden layers capable to perform the training process with minimal error limits, so 100% had the accuracy of the training process.

From table 3 to see that channel 6, which occupied a good degree of accuracy compared to the other channel with a value accuracy of 77.2%.

| Channel   | Accuracy |
|-----------|----------|
| Channel 1 | 60.0 %   |
| Channel 2 | 63.1 %   |
| Channel 3 | 67.1 %   |
| Channel 4 | 68.0 %   |
| Channel 5 | 73.4 %   |
| Channel 6 | 77.2 %   |

From table 4 visible that by using 2 hidden layers on backpropagation can already achieve the accuracy value of 77.2% of the testing process.

| Time (sec) | MSE (1 Hidden Layer) | MSE (2 Hidden Layer) | MSE (3 Hidden Layer) |
|-----------|----------------------|----------------------|----------------------|
| Channel 1 | 13 second            | 15 second            | 34 second            |
| Channel 2 | 1000                 | 619                  | 916                  |
| Channel 3 | 8.14.10-2            | 9.99.10-10           | 9.88.10-10           |
| Channel 4 | 67.7 %               | 77.2 %               | 74.1 %               |

![Figure 5](image)
4. Conclusion
The study introduced the Discrete Wavelet to extract features by taking the average value in each subband signals EEG. The process of classification of EEG signals is divided into two classes, namely class 0 and class 1. This research, using EEG signals 553 file data for training and testing. The accuracy of the classification of Backpropagation reaches 77.2% of test data. To generate better results, the work of researchers who will come will examine the appropriate search techniques for the extraction of features and classification of EEG signals to command moves the cursor. The research results obtained are compared with the methods already researched.

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