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Research Paper

Coefficient of Subband Discrete Wavelet Transforms for Feature Extraction of Electro Encephalo Graph (EEG) Signals

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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 the cursor up and down the cursor. In each sub band of the Electro Encephalo Graph (EEG) signal waves the means and Maximum value are taken to characterize the EEG signals. Backpropagation Neural Network is used as an EEG signal classification to determine whether the cursor moves up or the cursor moves down. 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 and maximum values 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 cursor up) and class 1 (for the cursor down), there are 260 training data files of EEG and 293 signals from EEG signal data testing files, so the whole becomes 553 data files of EEG signals. The result obtained for EEG signal classification is 75.8% of the tested signal data

Keywords: *EEG, Mean, Maximum, Discrete Wavelet Transformation, BackPropagation*

1. Introduction

Placement of electrodes on the scalp following a predetermined system of 10-20 systems. Proper and good electrode placement is a key requirement for obtaining good and reliable EEG recordings. Besides the cleanliness of the scalp, electrode condition, EEG machine and subject compliance during recording is also very influential to get good results. Hans Berger states that the human brain has a continuous and recordable electrical activity. Brain activity can be possible to send commands to electronic equipment with the help of Brain Computer Interface (BCI)[1]. In addition to playing games on mobile devices can also use BCI System[2].

Several relevant studies have been identified using EEG signals from BCI. Application of Adaptive Neuro Fuzzy Inference System (ANFIS) model used for EEG signal classification. The application for decision making is done in two stages, the first step is Wavelet Transformation (WT) used for character search. The second stage is the ANFIS training process using Backpropagation Gradient Descent method in combination of Least Squares method. Decision making can doing not only by Wavelet Transformation and ANFIS but also we can using ARIMA, α-Sutte and other methods [3]–[9]. Data subject used In the application comes from set A, set B, set C, set D, and set E[10]. To predict the degree of drowsiness by using frequency δ, frequency θ, frequency α, and frequency β sub-frequency of EEG signals are taken using Wavelet Transform. The spectrum of wavelets in EEG signals is used as inputs for Artificial Neural Networks. Predictions that can be used to distinguish alert, drowsy and sleeping parts reach the Accuracy of Artificial Neural Networks are 96 ± 3% alert, 95 ± 4% drowsy and 94% ± 5% sleep.

The sampling technique (TS) is applied to detect features of EEG data. EEG signal characteristics can be taken using the sample size of the EEG signal. Many different sampling techniques in EEG signal research are used in statistical analysis[11]. Simple Random Sampling (SRS) is one of the sampling techniques used to extract the characteristics of EEG signals into two different classes in normal people and people with epilepsy. Classification using Least Square Support Vector Machines (LS-SVM) is designed to be implemented on the feature vector extraction obtained from the two classes. For training data The accuracy of LS-SVM classification reaches 80.31% accuracy and for test data achieves 80.05% accuracy[12]. Classification using artificial neural networks and EEG signal analysis methods using relative energy wavelets has also been studied. The accuracy of the classification obtained mentions for the proposed scheme to have potential in classifying the EEG signal[13]. Another study by taking data from the BCI Competition 2003, from six electrode channels embedded in the scalp, the study used only four channels (ch 1, ch 2, ch 4 and ch 6). Features used there are four features (two of the gamma band power and two of the means of the SPC). Results from the classification process were 88.7%[14].

In this study designed as follows, Section 2 describes the materials and methods used in the search for EEG feature extraction and EEG signal classification, Section 3 describes the results of feature extraction and EEG signal classification processes, and Section 4 illustrates the conclusions of this study.

2. Materials and Methods

A. Material

The dataset is taken from a healthy subject. Subjects are asked to move the cursor up and down on the computer screen, while the cortical potential is taken. During recording, subjects receive visu-

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al feedback from their slow cortical potential (Cz-Mastoids). Positive cortical leads to downward cursor movement on the screen. The cortical negative causes the cursor to move upwards. Each trail takes 6s. During each trial, only 3.5 second intervals per trial are provided for training and testing. The sampling rate of 256 Hz and the length of the 3.5 recording yielded 896 data points[15].

B. Discrete Wavelet Transform

The Compared with Continuous Wavelet Transform (CWT), discrete wavelet Transform (DWT) is considered relatively easy to implement. How to obtain the time and a scale representation of a signal using digital filtering techniques and sub-sampling operations is a basic principle of DWT. The high-pass and low-pass filter circuit is the first circuit used to pass the signal. The sub sampling operation is used to sample the output of the EEG signal taken half of each EEG signal output, the process being a one-level decomposition process. Outputs of low-pass and high-pass filters are used as input in the next level decomposition process. This process is repeated until the desired level of decomposition process. The output of a high-pass filter and a low-pass filter are combined into one, called the wavelet coefficient, which contains the compressed signal information[16].

Wavelet transformation has become one of the most reliable data compression methods. The high-pass and low-pass filter pair used should be a Quadrature Mirror Filter (QMF), a filter pair that satisfies the following equation:

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

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

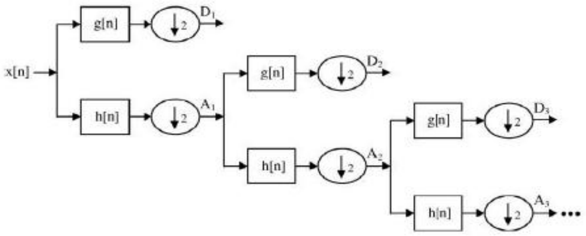

Fig.1: Sub-decomposition of Discrete Wavelet Transforms

The wavelet coefficient is calculated using daubechies 2 wavelet because its smoothing feature is more suitable for detecting changes in EEG signals. In this study, the EEG signal was decomposed into D2 details. To reduce the dimension of the feature vector, statistics on the set of wavelet coefficients are used. The following statistics feature is used to represent the time - frequency distribution of EEG signals:

a. Mean of wavelet coefficients on each sub band.
b. Maximum of wavelet coefficients on each sub band

C. Back propagation Neural Network

Artificial neural network (ANN) is an information processing system that has characteristics similar to biological neural networks [17][18]. This means that ANN is one information processing system designed by mimicking the workings of the human brain in solving a problem by making the learning process through the synapse of weight changes. The ANN is a method that can find non-linear relationships between loads and varied economic factors and other factors that can make adjustments to changes that occur. The ANN can be applied well is forecasting field[19]. To predict what will happen, we need forecasting techniques to determine the planning and decision-making process. Backpropagation Neural Network is a technique that can be used for forecasting. The back propagation is mostly used on multiple layer networks or it can be called multi-layer in hopes of minimizing errors in the results of calculation techniques performed by the network. There are three main steps: entering data into the input network, performing Backpropagation calculations and propagation and updating the weights and the bias (adjustment). After finding the network pattern that is weight and bias values, the network can be used to determine the output of any input (testing).

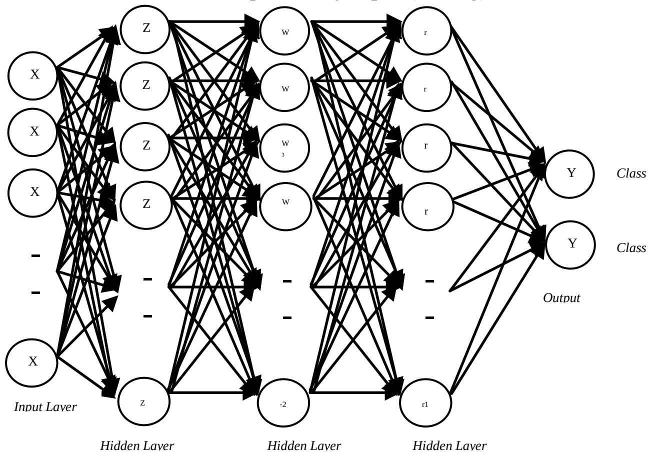

Fig.2: Backpropagation Neural Network Architecture with 3 hidden layers

In this study, the data classification process is done by separating the EEG signals into two parts, ie data for the training process as much as 268 vector data and data for the data testing process used as many as 293 data. This network has an input of 8 nodes (x 1, x2, ..., x8) derived from DWT feature, 10 nodes for hidden layers 1 (z1, z2, ... z10), 20 nodes for hidden layers 2 (w1, w2, ... w20), 10 nodes for hidden layers 3 (r1, r2, ... r10), and Binary type output for identification of conditions (y1, y2). Network architecture in research can be seen in Figure 2. Output pattern with 2 target output in binary form. These types of patterns can be seen in Table 1.

Table.1: Output Vector Patterns

No	Data Classification	Output Patterns
1.	Up Cursor Movement	0
2.	Down Cursor Movement	1

3. Results and Discussion

The data used is using data from BCI competition 2003 Data set Ia. This data set consists of 6 channels (electrode mounted on the scalp of 6 pieces of electrode sensor, resulting in 6 pieces of signal channel EEG). Data set It consists of Training data and Testing data.

A large amount of data, will cause the old computing process caused by a lot of data is processed, so that the presence of features that result in a little quick computing process. In this study, EEG signal takes only the average and maximum values of each sub band of the DWT process to be a feature extraction for the identification process.

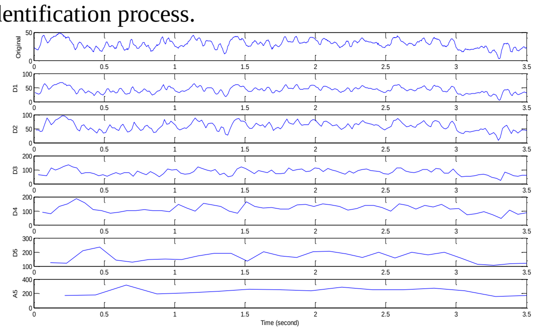

Fig.3: Approximate and detailed coefficients of EEG signal taken from a healthy subject

Figure 3 is an EEG recording divided according to sub-band frequency, resulting in wavelet coefficients A5, D5, D4, and D3 of the DWT process. The frequency of wavelet sub-bands (0-4 Hz), (4-8 Hz), (8-16 Hz) and (16-32 Hz) are used as a feature extraction sets taken from each sub band of EEG signals.

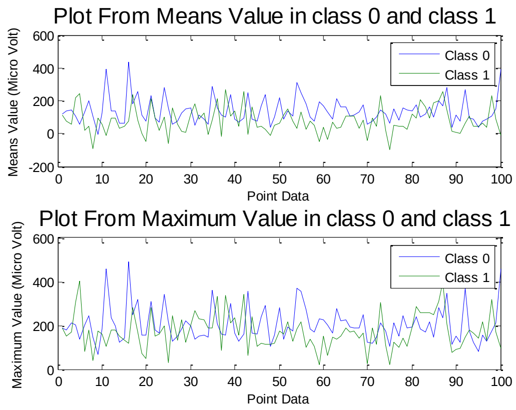

Fig.4: Mean and maximum of the wavelet coefficients

Figure 4 shows that for the mean and maximum values for each sub band for class 0 and class 1 has a difference in value. Different scores of values indicate that the level of classification by taking the average and maximum values is good enough.

Classification using Backpropagation Neural Networks is implemented using the mean and maximum value features of the DWT process as inputs. In this study, the training set amounted to 260 sample data and trial data of 293 sample data. In the training process used data as much as 260 samples of data (from normal subjects) for channel 1. For the test process used data of 293 samples of data (from normal subjects) for all channels. Table 2 is the distribution of the sample classes in the training and validation data set. Data obtained from different subjects in the training process is a way of improving Backpropagation skills. To train Backpropagation using Set training data, while To verify the accuracy and effectiveness of Backpropagation we use tested data trained to detect cursor movements up and down.

Table.2: The class distribution of the samples in the training and test data sets

Class	Training sets	Test sets
Up Cursor Movement (class 0)	130 x 6 Channel	293 x 6 Channel (mix)

The result of a characteristic extraction process with DWT used the input of neural network, this research uses Backpropagation method (8-10-20-10-2) which is 8 inputs that come from characteristic of EEG signal and 3 hidden layers. 3 hidden layers that are 10 nodes at 1 hidden layers, 20 nodes at 2 hidden layers, and 10 nodes at 3 hidden layers and 2 targets (up cursor movement for class 0 and down cursor for class 1). In addition to using the 8-10-20-10-2 network architecture, for pilot research it also uses addition and layer reduction.

The training process is the process of finding the best weight value by obtaining the smallest error value of the desired output target, this is the initial process done in the identification. The process of mapping is done after the training process is the identification of EEG signals from up movement of the cursor and down cursor movements based on the weight value already obtained in the training process.

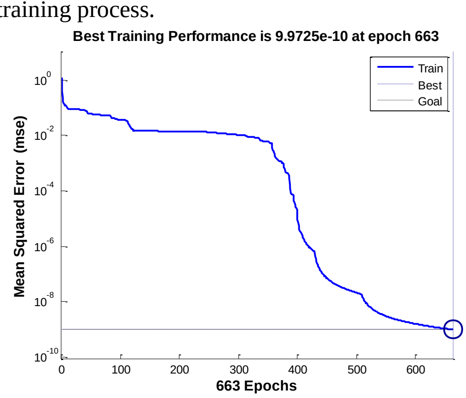

Fig.5: Training Performance of artificial neural networks using 3 hidden layers

260 training data from channel 1 in 663 training period and step size for adaptation parameter has initial value of $9.97.10^{-10}$. Performance Backpropagation using 3 hidden layers is capable of performing the training process by passing the minimum error limit, so that 100% has the accuracy of the training process.

Table.3: The Backpropagation accuracy results with 3 hidden layers for all channels

	Channel 1	Channel 2	Channel 3	Channel 4	Channel 5	Channel 6
Accuracy	58,0 %	58,2 %	68,4 %	75,8 %	72,2 %	71,6 %

Table 3 shows that channel 4 occupies a good level of accuracy compared to other channels with an accuracy of 75.8%.

Table.4: Effect of different Hidden Layer amounts on artificial neural networks

	MSE (1 Hidden Layer)	MSE (2 Hidden Layers)	MSE (3 Hidden Layers)
Time	44 second	30 second	61 second
Iteration	1000	733	663
MSE	$2,59.10^{-2}$	$9,99.10^{-10}$	$9,97.10^{-10}$
Accuracy	72,7 %	72,7 %	75,8 %

From table 4 it can be seen that by using 3 hidden layers in Backpropagation it can achieve the accuracy value of 75.8% of the testing process.

4. Conclusion

This study introduces Discrete Wavelet to extract features by taking the mean and maximum values on each sub band of an EEG signal. The process of classifying EEG signals is divided into two classes: class 0 and class 1. This study uses 553 EEG signal data files for training and testing. Classification accuracy reached 75.8% of test data using Backpropagation. To produce better results, the work of future researchers will examine the search techniques suitable for feature extraction and EEG signal classification for cursor movement commands. The results obtained will be compared with the methods already studied.

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