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Feature Extraction ElectroEncephaloGram (EEG) using wavelet transform for cursor movement

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Feature Extraction ElectroEncephaloGram (EEG) using wavelet transform for cursor movement

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Abstract. This study aims to extract features related to human brain signals associated with ElectroEncephaloGraph (EEG) signal measurements and EEG signal classification extracted to relevant brain regions. EEG brain signals from 6 electrodes / channels placed on human scalp are recorded non-invasively using an EEG recorder with a 256 Hz sampling rate. The EEG data of the human brain function associated with the motor image task generated consists of two distinct activity classes, namely the Subject is asked to move the cursor up and down on the computer screen. The data used comes from the data set 1a BCI 2003 competition, consisting of two classes of class 0 as much as 135 experiments, 1st class of 133 experiments and trial data of 293 experiments. From the EEG signal data is processed using wavelet transform as feature extraction. Extract value of the characteristic value of the average, maximum, minimum and standard deviation. As for the classification using artificial neural network backpropagation. As a result, identification accuracy level using discrete Wavelet Transformation is 75%.

1. Introduction

ElectroEncephaloGram (EEG) is the impact of rapid technological advances and generates data acquisition analysis techniques of brain signals, thus having a major impact on research on brain waves. To control the movement of unhealthy / defective body parts made possible by technological advances, such as Brain-Computer Interface (BCI) gives humans to control effectively against devices such as computers, aids, or neurophysiological disorders [1]. Although in its infancy, BCI has begun to make a difference in helping one to gain self-confidence, so as to cultivate a quality of human life. In 1929, a German psychiatrist named Hans Berger, announced it was possible to record the weak electrical current generated in the brain, without opening the skull, and to write it onto a paper. Berger named this new recording format as EEG. So, to connect between the brain and the object that will be controlled by the thought tool called BCI, so that the object to be controlled can be controlled through the brain in this signal. BCI can also communicate with the mind without having to use human muscle [2]. BCI systems can also send commands from subjects to control electronic equipment using EEG signal activity [3]. The BCI system can also use subjects to play simple mobile games [4]. The wave of EEG signal activity can be grouped by frequency band, such as delta waves, theta waves, alpha waves and beta waves [5]. Frequency wave delta is at a frequency of 0 - 3 Hz. This delta frequency wave has the lowest frequency. Theta waves correspond to "slow activity", at a frequency of 3.5 - 7.5

Hz. this Theta waves are normal of children in a state of sleep. Alpha waves in the range 7.5 - 13 Hz. Beta waves according to fast activity have frequency 14 Hz - 30 Hz. High-frequency activity is classified on gamma waves in the range of 30 - 80 Hz.

Applications involving EEG Signals are widely used including neurological disorders, Brain Computer Interface and others. Research using EEG data related to BCI [6]. Many research papers have been researched and published, which relate to the awake and falling asleep of human of the EEG signal [7]. Research in the field looks for features of the EEG signal, a method that has been studied using wavelet decomposition package [8]. The characteristics associated with left and right-hand movements are extracted from EEG signal data using wavelet transforms [9] and features associated with cursor movement using Fast Fourier Transform [10]. The motor cortex section, or M1, is the back of the frontal lobe of the brain area, this section shown in Figure 1, has responsibility for all human body movements.

Figure 1. Cortical mapping to different parts of the body [11].

In this study, a new approach based on Artificial Neural Networks is presented to classify cursor movements. However, the main contribution of our paper to bioelectromagnetism and knowledge of digital signal processing is the use of the wavelet method for the extraction of the EEG signal feature to move the cursor up or down on the computer screen when its SCP is recorded. BackPropagatioan is used to classify cursor movements whose input comes from a set of statistical features retrieved from the Wavelet subband.

2. Materials and methods

2.1. Materials
The EEG signal dataset taken from the BCI 2003 competition data comes from Dr. Birbaumer and his team at the University of Tuebingen, Germany [12]. Six EEG channels were recorded from a healthy subject and the sampling rate of 256 Hz and a 3.5 second recording time [12]. Subjects were asked to imagine moving the cursor up or down on the computer screen when the SCP was recorded. Subjects receive visual feedback from SCPs (feedback phases). The dataset is divided into training (268 experiments) and trials (293 experiments), The dataset is divided into training (268 experiments) and trials (293 experiments) [12].

2.2. EEG signal processing and feature extraction
Training for classification can be done well if the feature extraction scheme to select features or information is done well [13]. The selection of feature extraction is a requirement that feature extraction is important for the process of classifying EEG signals [14]. Principal Component Analysis (PCA), Independent Component Analysis (ICA), Autoregression (AR), Fast Fourier Transform (FFT), Wavelet Transform (WT), Tensor Decomposition (TR) techniques are examples for EEG signal

feature extraction. In this research, writer will extract feature of EEG signal using discrete wavelet transform method by taking energy value on each subband.

2.3. Wavelet Transform (WT)
WT is an important method of research in terms of recognition and diagnostics, WT can compress biomedical signals that vary over time, consisting of multiple data points, into several small parameters representing signals [14]. The EEG signal is a non-stationary signal [15], so in order to find the appropriate feature extraction usually using the method at the frequency domain and WT is the method included in this. WT has a frequency domain that is an infinite wavelet [16]. To get better low-frequency resolution, the old WT window is used; Instead of obtaining high frequency information, a short time window is used [17]. Using the WT method, the recorded EEG signal in the form of the original signal is represented by a simple building block known as the wavelet. The mother wavelet is a derivative function through translation and widening, i.e. shifting and stretching along the time axis [18].

2.4. Method of Discrete Wavelet Transformation (DWT)
DWT has been defined based on multiscale feature representation. Each scale of DWT is a unique representation of brain signals [19]. The decomposition of the DWT of the EEG signal $x(n)$ is shown in Figure 2. The convolution is a two-function multiplication process using the low-pass filter or high-pass filter coefficients which is then processed down sampling. Down sampling is the process of reducing the sample signal to half (reduction). Signals on the wavelets are divided into two types: approximation and detail. An approximation is a signal obtained from the convolution process of the original signal to the low-pass filter, whereas the detail is a signal obtained from the convolution process of the original signal to the high-pass filter. In Figure 2, each output generates the detail of the signal D and the approximate signal A, where the most recent one becomes the input for the next step. The number of levels decomposed by the wavelet is selected depending on the component of the EEG signal with the dominant frequency.
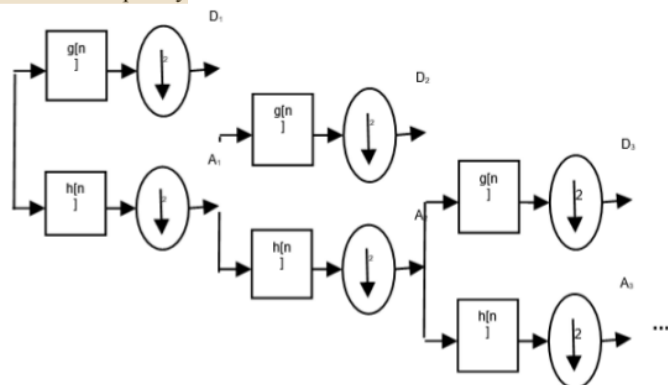
Figure 2. Implementation of decomposition of DWT.

Formula of WT and filter h, is a low pass, can be formulated in the formulation as follows:

$$H(z)\,H(z^{-1}) + H(-z)\,H(-z^{-1}) = 1 \qquad (1)$$

In the above formula, $H(z)$ is used to represent the hz-transform filter and the complement transformation of this high-pass filter is expressed as:

$$G(z) = zH(-z^{-1}). \qquad (2)$$

DWT is used to analyze spectral of EEG signals as described in Section above. Using of WT in the appropriate wavelet selection and number of decomposition levels are critical in EEG signal analysis.

The number of decomposition levels is selected based on the dominant frequency component of the EEG signal. Levels are chosen in such a way that the signal sections correlate well with the frequency required for signal classification are maintained in the wavelet coefficients. In this study, the number of decomposition levels is chosen to be 5. Thus, the EEG signal is decomposed into D1-D5 details and one final approach, A5. Typically, tests are performed with different types of wavelets and that provide maximum efficiency selected for a particular application. The Daubechies wavelet feature of the 2nd order (db2) smoothing makes it more suitable for detecting changes in the observed signal. Therefore, wavelet coefficients were calculated using db2 in this study. Band frequency corresponding different decomposition rates for Daubechies wavelet 2nd order (db2) with sampling frequency 256 Hz are: D1 (64 - 128 Hz); D2 (32 - 64 Hz); D3 (16 - 32 Hz); D4 (8 - 16 Hz); D5 (4 - 8 Hz); and A5 (0 - 4 Hz). Discrete wavelet coefficients are calculated using MATLAB software.

Feature selection is an important component in designing artificial neural networks based on pattern classification because even the best classifier will perform poorly if the feature used as input is not well chosen. The calculated wavelet discrete coefficient gives a representation showing the distribution of signal energy in time and frequency. Therefore, the discrete wavelet coefficient calculated from the EEG signal of each record is used as the feature vector representing the signal. To reduce the extracted feature vector dimension, the statistics above the set of wavelet coefficients are used. The following statistics feature is used to represent the time frequency distribution of the signals studied:

- Mean of the wavelet coefficients in each subband.
- Maximum of the wavelet coefficients in each subband.
- Minimum of the wavelet coefficients in each subband.
- Standard deviation of the wavelet coefficients in each subband.

There are 268 data training and 293 total data testing records performed for EEG. For EEG recordings, there are 6 recorded channels (EEG). Due to the large number of factors that need to be processed and analyzed, such as the wavelet coefficient of 5 subband, 6 channels, it is necessary to use a data reduction. Basic statistics features, such as maximum deviation, mean, minimum and standard are calculated for the above factors.

2.5. Artificial Neural Network (ANN)
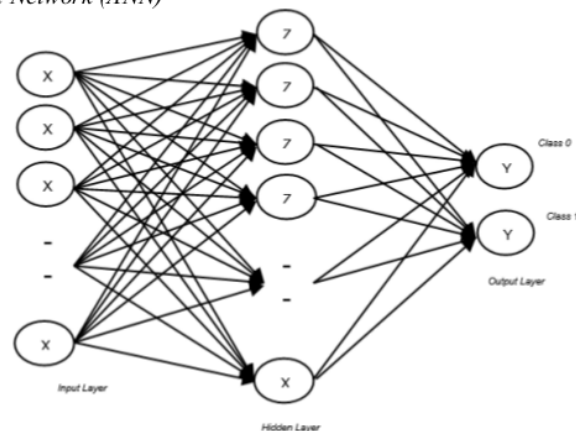
Figure 3. Backpropagation neural network architecture.

Artificial Neural Network (ANN) is a computational architecture and operation based on the knowledge of biological neurons in the brain. One of the ANN architecture is BackPropagation which can be seen in Figure 3. In this study the input count is 16 neurons, with one hidden layer, and two classes as output.

In ANN specified behaviors such as weights, inputs, outputs, and activation functions. There are several activation functions that can be used such as Binary activation function, Bipolar, Linear, Sigmoid Binary and Sigmoid Bipolar. The activation function is used to ensure the output of a neuron is within a certain range according to the activation function used. As a classifier used Artificial Neural Network method with Backpropagation learning. Data classification is done by separating EEG signals into two parts, i.e. data for training and data for testing. 268 data vectors DWT EEG signals into training data and 293 data into test data. This network has input 16 (x_1, x2, ..., x16) derived from DWT feature, 32 hidden nodes (z1, z2, ... z32), and Binary type output for identification condition (y1, y2). Network architecture can be seen in Figure 3. Output pattern is 2 target outputs in binary form to be trained so that the network can recognize this pattern. 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

In this study, Backpropagation neural networks for the detection of cursor movements up and down were investigated. Data to evaluate the cursor motion classification model was obtained by analyzing EEG recordings. This study explains the cursor movement detection of EEG signals using statistical features taken from the frequency of the DWT sub-band. Preprocessing via DWT, training using artificial neural network.
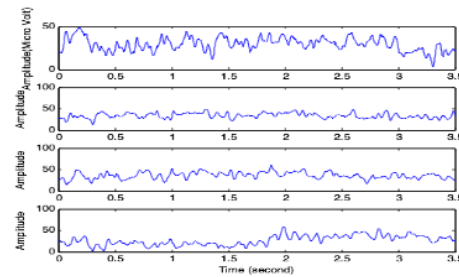

Figure 4. EEG signal for class 0 (up cursor) taken from healthy subject.
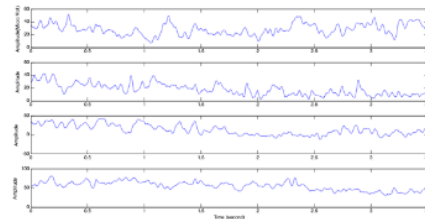
**Figure 5.** EEG signal for class 1 (down cursor) taken from healthy subject.

Therefore, EEG signal detection boils down to the problem of recognizing EEG waves and classifying them as cursor movements up or down. Well-distributed, adequate, and accurate distributed input data is a basic requirement for finding accurate models. Input Option Artificial Neural Network

Backpropagation is a key component in designing classification based on pattern classification because even the best classifier will appear inadequate if the input is not properly selected. The input selection has two meanings: (1) the pattern component, or (2) which input circuit best represents the given pattern.
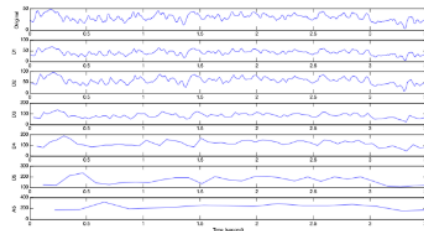
Figure 6. Approximate and detailed coefficients of EEG signal taken from a healthy subject.

The EEG record is divided into sub-band frequencies such as the wavelet coefficients A5, D5, D4, and D3 using DWT shown in Figure 6. Then a set of statistical features extracted from the wavelet sub-band frequency (0-4 Hz), (4-8 Hz), (8-16 Hz) and (16-32 Hz). After normalization, the EEG signal is decomposed using DWT and statistical features are extracted from the sub-band. The following statistical features are used to represent the time frequency distributions of the observed signals including Mean, Maximum, Minimum and Standard deviations of the wavelet coefficients in each subband.
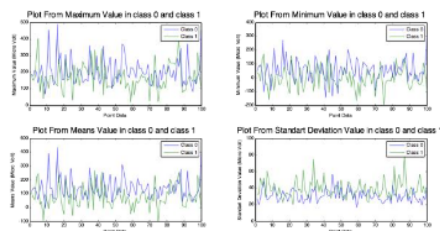
Figure 7. Mean, Maximum, Minimum dan Standard deviation of the wavelet coefficients in each subband.

Figure 7 shows that for the mean, maximum, minimum and standard deviation values for class 0 and class 1 still have almost the same grade-difference values. A similar value difference shows that the classification rate by taking the average, maximum, minimum and standard deviation values is still poor.

The Backpropagation based classification system is implemented using the statistical feature as input. The training set was formed by 260 sample data and trial of 293 sample data. 260 data samples (from normal subjects) for channel 1 were used for training and 293 samples of data (from normal subjects) for each channel were used for testing. The distribution of sample classes in the training and validation datasheets is summarized in Table 2. To improve the capability of backpropagation, the training and test series are shaped by data obtained from different subjects. The training data sets are used to train backpropagation, while the test data set is used to verify the accuracy and effectiveness of trained Backpropagation to detect the cursor movements up and down.

Tabel 2. Class distribution of the samples in the training and test data sets.

Class	Training sets	Test sets
Up Cursor (class 0)	130 x 6 Channel	293 x 6 Channel (mix)
Down Cursor (class 1)	130 x 6 Channel	
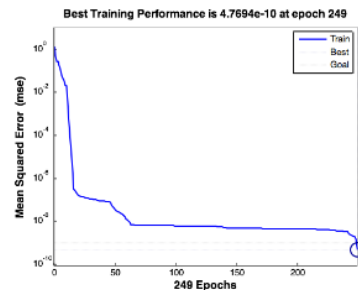
Figure 8. Performance Training of artificial neural networks using 1 hidden layer.

Backpropagation used 260 training data from channel 1 in 249 training periods and the step size for adaptation parameters had an initial value of $4,7694.10^{-10}$. In real-world domains, just as used in this study, all of the features used in case descriptions may have different relevance levels. After the training, 293 test data per channel and 260 training data were used to validate the accuracy of the Backpropagation network to detect cursor movements up and down. In the classification, the goal is to assign an input pattern to one of two classes, usually indicated by outputs that are restricted to be in the range of 0 and 1

Table 3. Backpropagation accuracy results with 1 hidden layer for all channels.

	Channel 1	Channel 2	Channel 3	Channel 4	Channel 5	Channel 6
Accuracy	75 %	72 %	73 %	73 %	74 %	73 %

From table 3 shows that channel 1 occupies a good degree of accuracy compared to other channels.

Table 4. Neural network performance against different hidden layer numbers.

	MSE (1 Hidden Layer)	MSE (2 Hidden Layer)	MSE (3 Hidden Layer)
Time	52 second	28 second	13 second
Iteration	249	132	21
MSE	$4,77.10^{-10}$	$9,98.10^{-10}$	$6,73.10^{-10}$
Accuracy	75 %	74 %	73 %

From table 4 it is seen that using only 1 hidden layer on backpropagation has been able to achieve the accuracy value of 75% of the testing process.

4. Conclusion

This study was used to extract and classify the resulting EEG signals in the main motor area of the cortex to imagine the cursor movements up and down. To identify the EEG Signals consisting of six electrodes / channels were analyzed using Wavelet and neural network methods. It can be concluded that the discrete Wavelet method gives a good enough result for feature extraction corresponding to

the signal generated. Testing with various hidden layers of backpropagation yields a 75% accuracy rate. For further research, researchers will look for better feature extraction methods.

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