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by Hindarto Hindarto

Energy Subband Wavelet for Feature Extraction of ElectroEncephaloGraph (EEG) Signals

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Abstract

This research describes the application of Backpropagation Neural Network as a classification and Discrete Wavelet Transformation for feature extraction by taking energy values on each sub-band of the Electro Encephalo Graph (EEG) signal wave. The purpose of this study was to identify the EEG signal used in the cursor movement. The data used are EEG data derived from BCI competition 2003 (BCI Competition 2003). This data contains class 0 data (for upward cursor movement) and class 1 (for downward cursor movement). Decision-making is done in two stages. In the first stage, the energy values in each discrete wavelet subband are used to extract features of the EEG signal data. This feature as input on Backpropagation Neural Network. In the second stages of the identification process into two classes (class 0 and class 1) EEG signal data files, there are 260 training data files of EEG signals and 293 of the EEG signal data file testing, so the whole becomes 553 data files of EEG signals. The result obtained for the classification of EEG signals is 73.5% of the tested signal data.

Keyword: *EEG, BCI, Discrete wavelet, BackPropagation*

1. Introduction

To move a cursor on the computer screen, someone usually needs a keyboard or mouse to run it. This is not possible with someone who does not have a hand or someone who can move his hand. Initially, it may be just wishful thinking, but the creative and revolutionary ideas of researchers both from home and abroad to be able to move the cursor without using the hands.

Hans Berger was a German psychologist, in 1929 he claimed the existence of a weak electrical currents generated by the recording of the brain without opening the brain. The results of brain recording can be painted on a paper. He named the brain recording with the name Electroencephalography (EEG). So as to connect between the brain and the object to be controlled by the thought of using a tool called Brain Computer Interface (BCI). BCI is a system that can analyze and acquire neural signals to create a communication channel between the computer and the brain. BCI can be shaped into systems provided by human muscles [1]. With BCI one can make a command to an electronic device using the brain [2]. To play a simple game can also be done with BCI a by system [3].

Some research by taking data sample data set from BCI Competition 2003-Data Set Ia (EEG signal data to move the cursor up and down that is controlled by the human mind). Among them were Mensh, BD, Werfel, J, Seung, HS, in 2004. Their data consisted of four channels, four features (two of the average of the SPC and two of the gamma band power). The results of the classification process were 88,7% [4]. Subsequent research was Baojun Wang, Liu Jun, Jing Bai, Le Peng, Yan Li and Guang Li in 2005. Researchers used two channels, four features by combining slow cortical potentials (SCPs) and wavelet packet transforms. The results of the classification process 91.47% [5]. Other researchers were Wu Ting, Yan Guo-Zheng, Yang Bang-Hua and Sun Hong in 2007. The research they conducted using six channels and took 17 (seventeen) features with neural network as a classification process, The result of the classification process of 90.80% [6]. In 2005, Shiliang Sun and Changshui Zhang used the 2003 competition research data using six features and used seven features RMS, spectral centroid, bandwidth, zero crossing rate, spectral roll-off frequency, band energy ratio and delta spectrum magnitude with Bayesian as a classification process. The result of the classification process is 90.44% [7]. In 2010 Temel Kayikcioglu and Onder Aydemir also used BCI 2003 competition data using one channel (channel 1) as experimental data and took 2 features using polynomial

fitting method by taking feature of h value and b coefficient. KNN as the classification process. The result of the classification process is 92.15% [8].
So also with the EEG signal feature extraction using the wavelet method, many researchers use the wavelet method for EEG signal feature extraction, such as s Ale Proch azka and Jarom ır Kukal presents segmentation for EEG signal and analyzed using harmonic wavelet transform, so there is a feature for a scale of 1, 2 and 3 each includes three frequency bands with different time scales of resolution [9]. Analyzing EEG signal recording against epileptic patients using wavelet transform [10]. Take the value of the minimum, maximum, average and median of wavelet transforms for feature extraction of EEG signals against the disease epilepsy [11].
In this study, a new approach based on Artificial Neural Networks is presented to classify cursor movements. The signal processing method using the Wavelet feature features Transform EEG signals to move the cursor up or down on the computer screen when the SCP is recorded. Artificial Neural Networks are used to detect cursor movements when an energy as features retrieved from a subband Wavelet Transform is used as input.

2. Materials And Methods

The EEG signal dataset taken from the BCI 2003 competition data comes from Dr. Birbaumer and his team at the University of Tuebingen, Germany (Blankertz 2004). Six EEG channels were recorded from a healthy subject and the sampling rate of 256 Hz and a 3.5 second recording time. The result of each experiment of each channel is 896 samples. 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), according to the BCI 2003 Ia description [18].

Wavelet Transform

The Wavelet theory provides an integrated framework for a number of techniques developed for various signal processing applications. In particular, it is of interest for non-stationary signal analysis, such as EEG, as it provides an alternative to the classic short time Fourier Transform (STFT) or Gabor transformation. The fundamental difference is that, unlike STFT, which uses a single analysis window, Wavelet Transform (WT) uses short windows at high frequencies and long windows at lower frequencies. This is similar to "Constant Q" or the relative bandwidth of the Conventional bandwidth [12][13].

Discrete Wavelet Transform

Stationary signals are signals that do not change much over time. In signal processing, all stationary can use Fourier Transform method. But for EEG signals are a signal that has many signals. EEG signals are can contain non-stationary signals. Therefore the fourier transform is not ideal to apply to EEG signal. To overcome this, the wavelet method can be used. In wavelet analysis, relating to different probing functions can be used. This analysis leads to a decisive equation for continuous wavelet transform (CWT):

$$W(a,b) = \int_{-\infty}^{\infty} x(t) \frac{1}{\sqrt{a}} \psi\left(\frac{t-b}{a}\right) dt \quad \ldots\ldots \quad (1)$$

Where b is used in x (t), and the action variable to vary the time scale of the probing function, ψ. If larger than one, the wavelet function, ψ, is withdrawn at all times, and if not smaller than one (but still positive) contact function. While the probing function can be one of several different functions, and the oscillatory form is always taken, with the term "wavelet". Complex conjugation operation, and normalization factor 1 / √ | a | ensuring the same energy for all values a. In applications requiring bilateral transformations, more so that the transformation produces the minimum number of required coefficients accurately. Discrete wavelet transforms (DWT) achieve this by parsimony by limiting variations in scale and translation, usually to power 2. Mostly for signal processing and image applications, DWT-based analysis is best described in the form of a filter bank. The use of a group of filters to divide the signal into various spectral components is called sub-band coding. This procedure is known as the multi-resolution decomposition of the signal x [n]. Each of the first filters, h [.] Is the discrete, high-pass in nature, and the second, g [.] Is a reflective, low-in-nature version. The bottom output of the sample from the first high-pass and low-pass filters provides detail, approximation A1 and respectively D1 [14][10].

By using DWT, the proper wavelet selection and number of decomposition levels are very important in signal analysis. The dominant frequency component of the signal is used to select the number of decomposition levels. The decomposition rate is chosen so that portions of the signal are correlated well with the frequency required for signal classification to be maintained in the wavelet coefficients. The number of levels is chosen to be 5 because the EEG signal has no useful frequency components above 30 Hz. Thus the signal is decomposed into details D1-D5 and one last approach, A5. These detailed estimates and records are reconstructed from the Daubechies 4 (DB4) wavelet filter [15][16]. The extracted wavelet coefficient provides a concise representation showing the distribution of EEG signal energy in time and frequency. To further reduce the dimensions of the extracted feature vector, the EEG signal characteristic extraction is obtained by decomposing the signal up to 5 levels using discrete wavelet transforms. The wavelet function used is db4. Illustration of decomposition of a 5-degree EEG signal with a 256 Hz snap frequency as shown in Figure 2. Each EEG signal is decomposed up to 5 levels to obtain a detailed signals D1, D2, D3, D4, and D5 and approximation signals A5. The average decomposition energy of the detailed signal per sub-band is calculated by the equation:

$$E_{Di} = \sum \frac{Di(k)^2}{Lenght\ Di} \tag{2}$$

Where :
k = 1, 2, ... Lenght D_i.
i= 1, 2,...N=5

The average decomposition energy of the approximation signal A5 is calculated by the equation :

$$E_{A5} = \sum \frac{A_5(k)^2}{Lenght\ A_5} \tag{3}$$

Where :
k = 1, 2, .. . lenght A_5

Since it will be the neural network input, the average energy of each decomposition signal is normalized by dividing by the largest average energy between the decomposition average energy in each signal :

$$E_{nj} = \frac{E_i}{Maks\ (E_{Di}, E_{A5})} \tag{4}$$

Where :
j= 1, 2, 3, …..n=4

As a result of normalization, the value of extraction of Enj properties is between 0 and 1.

Backpropagation Neural Network

Artificial neural networks (ANN) have certain performance characteristics such as biologists neural network, so it can be used as an information processing system. ANN has been developed as a generalization of the mathematical model of human cognition or biological nerves. The neural network is characterized by an interconnect pattern between neurons (architecture), the method of weighting the connection (learning or algorithm), and its activation function. The learning about counterfeit neural networks includes three stages: forward propagation, backward propagation and weight changes [17]. There are two main learning parameters in the reversal of learning rate α and momentum μ. The rate of learning is used to regulate the rapidity of learning. Momentum is used to avoid significant changes in weight due to different data from others.

The classification process consists of two stages, first the learning process or training. Both testing / testing processes. The training process is to find the best weight value by obtaining the smallest error value from the desired output target. In backpropagation algorithm to change the weight value using an output error with backward direction. Previously you have to do the forward propagation stage (forward) to get an error value.

Neuron- neurons will be activated using the sigmoid activation function. If the backward output in the hidden layer is not the same as the desired output, it will be forwarded to the input layer. In the backpropagation algorithm the error value can be minimized by using the following equation:

$$MSE = \frac{1}{2}\sum_{i=1}^{n}(d_{lk} - O_{lk})^2 \tag{5}$$

Information:
n = total data.
d_{lk} = target input value.
O_{lk} = Output actual.

1. Backpropagation Error

To correct the weight between layers and minimize error values in the backpropagation algorithm can be explained as follows:
Each output unit (Y_k, k = 1, 2, 3..., m) will receive the same target pattern as the pattern entered in the training process and the error value is calculated by the equation:

$$\delta_k = (t_k - y_k)f^{i}(y_{-ink}) \tag{6}$$

Look for correction values on the weight first (then to correct the w_{jk}).

$$\nabla w_{jk} = \alpha \partial_k Z_j \tag{7}$$

Look for equations in the correction of correction values :

$$\nabla W_{ok} = \alpha \partial_k \tag{8}$$

Each unit in the hidden layer (Zj, j = 1,2,3... , p) will be added to delta input from the layer above it.

$$\partial\_in_j = \sum_{k=1}^{m} \partial_k \, w_{jk} \tag{9}$$

And then, each unit hidden layer (Zj, j = 1, 2, 3..., p) the bias and value values will be updated (j=0,1,2...,p).

$$\delta_j = \delta_{in_j} f^1(y\_in_j) \tag{10}$$

Then do the calculation to fix the weight value (used to update V_{ij}).

$$\nabla v_{ij} = \alpha \delta_j X_i \tag{11}$$

That look for the refinement bias value (used to update V_{oj})

$$\nabla v_{oj} = \alpha \delta_j \tag{12}$$

2. Update weight dan bias

Improve weight and bias values in each output unit (Yk, k = 1, 2, ..., m) bias values and weight values will be corrected (j=0,1,...,p).

$$\nabla w_{jk}(baru) = w_{jk}(lama) + \nabla w_{jk}$$

Each unit in the hidden layer (Zj, j= 1,2,...,p)) the bias and value values will be updated (j=0,1,...,p).

$$v_{jk}(baru) = v_{jk}(lama) + \nabla_{jk}$$

Test repair conditions (final iteration) With a list of notations :
X_p= input pattern in p-learning, p = 1, 2, ..., p-1
X_p=(X_1,X_2,...,Xn)

tp= output patterns targeted at learning, tp = t1, t2, ..., tn
xi= unit i for the input layer.
X_i= activation value in the unit Z_j
Z_j= unit j in the hidden layer
Z_in_k= output for the unit Z_j
Y_k= the k unit in the output layer
Y_in_k= input for the unit Y_k
y_k= activation value of the unit Y_k
Wk_o= the connection weight value to the bias for the unit Y_k
W_{kj}= connection weight value of the units Z_{ij} to units Y_k
ΔW_{jk}= the difference between $V_{ij}(t)$ with $W_{kj}(t+1)$
V_{jo}= the connection weight value to the bias for the units Z_j
V_{ij}= connection weight value of the units X_i to units Z_j
ΔV_{ij}= difference between $V_{ij}(t)$ with $V_{ij}(t+1)$

The simplest method for changing weights is the gradient descent method. Bias and weights can be changed in the direction in which the function of the function decreases the fastest, IE the gradient in the negative direction, with the equation:

$$W_{k+1} = W_k - \alpha_k g_k$$

W_k = weight vector in the k iteration.
g_k = gradient.
α_k = learning rate

Generally in the training process, the results of bacpropagation training will not produce MSE = 0 (with a lot of training data), but most people are quite satisfied with the results of MSE = 0.1. If the MSE value is increased from 1 to 0.000000001 it will increase the rate of understanding, and backpropagation training will be faster, but if the understanding rate is too large it will have an impact on unstable algorithms (MSE does not decrease or even rises) which means this network does not recognize patterns and researchers will look for the best MSE values.
Part of the Artificial Neural Network is BackPropagation, where the architecture can be seen in Figure 1. To research the input count of 4 neurons, with Three hidden layers, and two classes as output.

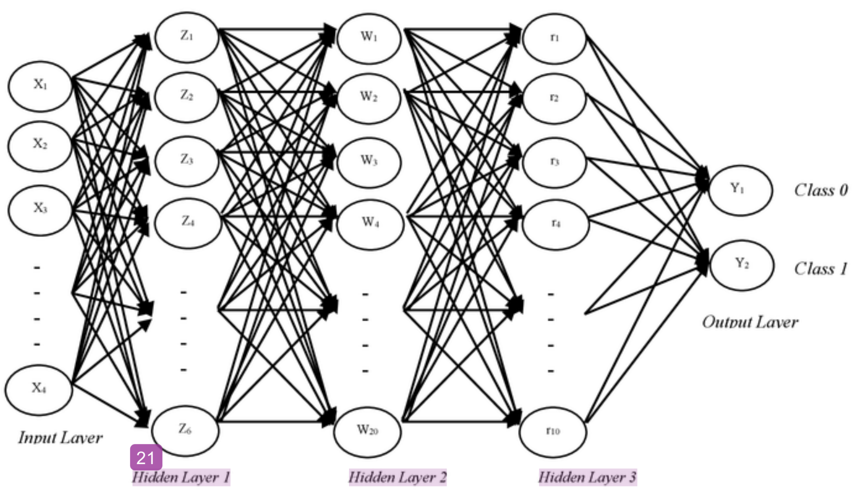

Figure 1. Backpropagation Neural Network Architecture with 3 hidden layers

In this study, the data classification process is done by separating the EEG signals into two parts, the 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 the input 4 (x1, x2, x3, x4) derived from the DWT feature, hidden layer 1 has 10 nodes (z1, z2, ... z10), hidden layer 2 has 20 nodes (w1, w2, ... w20), hidden layer 3 has 10 nodes (r1, r2, ... r10) and Binary type outputs for condition identification (y1, y2). Network architecture in research can be seen in Figure 1. 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 Analysis

This study explains the detection of cursor movement of EEG signals obtained from BCI dataset Competition 2003. The EEG data is processed using DWT as a feature extraction of EEG signals. In the DWT Process, the value of the EEG feature is derived from energy at the frequency of the DWT sub-band.

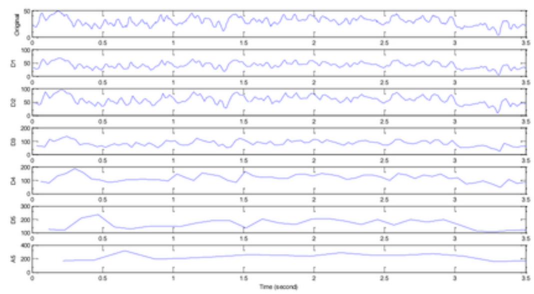

Figure 2. Approximate and detailed coefficients of EEG signal taken from a healthy subject

In Figure 2 EEG recording is shown divided into sub-band frequencies such as wavelet coefficients A5, D5, D4, and D3 uses DWT. Frequency sub-band wavelets (0-4 Hz), (4-8 Hz), (8-16 Hz) and (16-32 Hz) are extracted to become EEG signal feature sets. The following features are used to represent the time, frequency distribution of the observed signal is the energy of the wavelet coefficients in each subband.

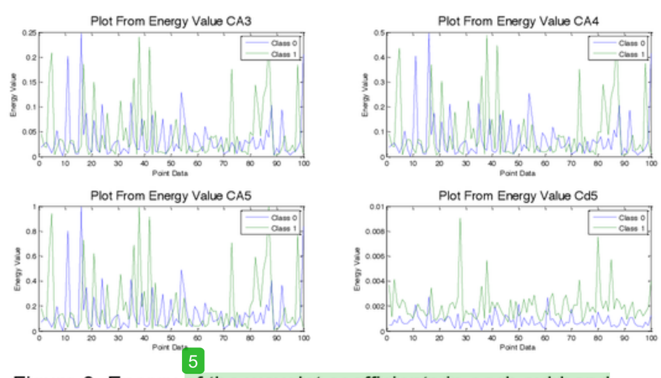

Figure 3. Energy of the wavelet coefficients in each subband

Figure 3 shows that for energy in each subband for class 0 and class 1 has a different value. Different scores of values indicate that the classification rate by taking the energy value is good enough. Classification using Artificial Neural Network Backpropagation is implemented using the energy value feature of the DWT process as input. In this study, the training set amounted to 260 sample data and trial data of 293 sample data. 260 data samples (from normal subjects) for channel 1 were used as training data and 293 sample data (from normal subjects) for each channel used for test data. The class distribution of sample data in training and testing is summarized in Table 2. To improve the capability of backpropagation, training and testing are shaped by data obtained from different subjects. The data set for the training process is used as training for backpropagatioan, while for the test data set is used as the accuracy and effectiveness of Backpropagation in detecting cursor movements up and down.

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

Class	Training set	Test set
Up Cursor (class 0)	130 x 6 Channel	293 x 6 channel (mix)
Down Cursor (class 1)	130 x 6 Channel	

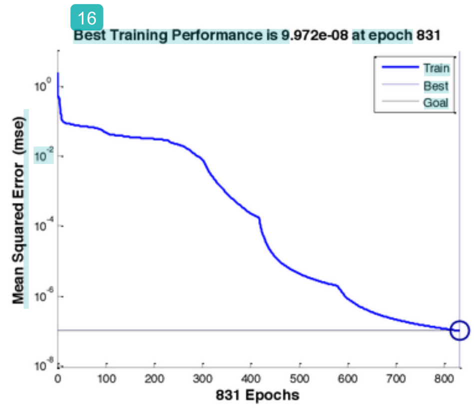

Figure 4. Performance training of artificial neural networks uses 3 hidden layers

In Figure 4 there are 260 training data from channel 1 in 831 training period and step size for adaptation parameter has initial value of $9{,}97.10^{-8}$. Performance Backpropagation using 3 hidden layers is able to perform the training process by passing the minimum error limit, so that 100% has the accuracy of the training process.

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

	Channel 1	Channel 2	Channel 3	Channel 4	Channel 5	Channel 6
Accuracy	70,0 %	72,7 %	72,3 %	73,5 %	72,2 %	71,0 %

The table 3 shows that channel 4 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	33 second	86 second	154 second
Iteration	1000	624	831
MSE	$1{,}70.10^{-2}$	$9{,}98.10^{-8}$	$9{,}97.10^{-8}$
accuracy	73,0 %	72,9 %	73,5 %

Table 4 shows the degree of accuracy of the various layers are hidden, the greatest degree of accuracy shown in backpropagation with either 3 hidden layer by reaching the level of accuracy of 73.5%.

The table 4 it can be seen that by using 3 hidden layers in backpropagation it can achieve 73.5% accuracy value from the testing process.

4. Conclusion

In this paper the researchers introduced the Discrete Wavelet to extract features by taking energy values on each subband. 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. The accuracy of Backpropagation classification reached 73.5% of test data. Future research work, will examine the search techniques suitable for feature extraction and EEG signal classification, so the accuracy level for the command move the cursor would be better. The results obtained will be compared with the methods already studied.

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