FOURIER TRANSFORM FUR EEG SIGNAL

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Fourier Transform for Feature Extraction of ElectroEncephaloGraph (EEG) Signals

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Abstract

Electroensephalograph (EEG) is a device that can capture electrical activity in the brain and inform the mind's condition such as emotional, fatigue, alertness, health and concentration level. Modeling the EEG signal before classification needs to be done, several studies have been carried out using Wavelet, Power Spectral, or Autoregressive transformations as feature extraction. This study explains the application of K-Nearest Neighbor as a classification and Fourier transform by taking the value of Power Spectralfor feature extraction from the wave signal Electro Encephalo Graph (EEG). This study aims to identify EEG signals used for cursor movements. The data used are EEG data originating from the 2003 BCI competition (BCI 2003 Competition). The data contains data class 0 (for movement of the cursor up) and class 1 (for movement of the cursor down). Decision making is done in two stages. In the first stage, the Power Spectral value for each EEG signal is used to extract the feature. The feature is input to K-Nearest Neighbor. In the second stage of the identification process into two classes (class 0 and class 1) EEG signal data files, there are 250 EEG signal file training data and 25 from EEG signal file testing data, so that the total becomes 300 EEG signal data files. The results obtained for the classification of EEG signals are 84 % of the signal data tested.

Kata Kunci : EEG, BCI, Power Spectral, K-Nearest Neighbor

1. Introduction

Electroencephalography (EEG) is a method of electrophysiological monitoring to record electrical activity in the brain. Electrodes are placed along the scalp, although invasive electrodes are sometimes used as in electrocorticography. The EEG measures voltage fluctuations that result from ion currents in brain neurons. In the clinical context, EEG refers to the recording of spontaneous electrical activity of the brain over a period of time, as recorded from several electrodes placed on the scalp [1]. Diagnostic applications generally focus on the potential associated with EEG spectral content.

Placing electrodes on the scalp follows a predetermined system, namely the 10-20 system. Proper and good electrode placement is the main requirement to get good and reliable EEG recordings. Besides that the cleanliness of the scalp, the condition of the electrode, the EEG machine and the compliance of the subjects during recording are also very influential to get good results. Hans Berger stated that the human brain has continuous electrical activity that can be recorded. Brain activity can be possible to send commands to electronic equipment with the help of the Brain Computer Interface (BCI) [2]. Most BCI uses spontaneous mental activity (for example, imagining moving a finger, hand, or the entire arm, etc.) to produce a distinguishable electroencephalogram (EEG) signal [3]. EEG signals that can be distinguished are then converted into external actions. Over the past few years, various evidences have evaluated the possibility of recognizing some mental tasks of EEG signals [4]. However, how to improve the performance of EEG signal recognition in signal processing is still a major problem. The introduction procedure mainly includes feature extraction and classification, where feature extraction plays an important role for classification. This paper mainly focuses on feature extraction.

At present, the feature extraction method for EEG motorcycle images mainly includes several methods including using the fast Fourier transform (FFT) [5] [6] method, the Fourier spectral feature calculated by the Welch method using the windowed Fourier signal segment transformation. The main disadvantage of this method is that this method only uses frequency information and does not use time domain information. However, research shows that the combination of frequency information and time domain information can improve the performance of EEG signal classification [7]. Autoregressive (AR) is the motive of the AR spectrum, band power is calculated in several bands the frequency and amount of power is used as an independent variable [8]. In addition, the AR coefficient model or multivariate autoregressive (MVAR) model coefficient is used as a feature [9]. Time-frequency analysis by Wang et al. Used frequency-time analysis as a useful tool for oscillating EEG components during motor image [10]. As we all know, the oscillating EEG component produced during the image of the motor is the time and frequency associated, therefore, this method gets promising results. However, the oscillating EEG component can cause simultaneous shifts in slow cortical potential. Combination of two the associated signal might be used to increase the extracted information. The time-frequency method only considers oscillating EEG components. Utilizing the wavelet transformation coefficient, that is, extracting the wavelet transformation coefficient on a useful frequency band according to transcendent information [11]. However, the mechanism of EEG production is rather complicated, so it is difficult to get accurate and rather inflexible transcendent information.

Based on the background above, this study was designed as follows, section 2 describes the materials and methods used in searching for EEG signals and classification of EEG signals, section 3 explains the results of feature extraction and the EEG signal classification process, and section 4 describes the conclusions of this study .

2. MATERIALS AND METHODS

2.1. Materials

The dataset is taken from healthy subjects. Subjects are asked to move the cursor up and down on the computer screen, while the physical potential is taken. During the recording, subjects receive visual feedback from their slow cortical potential (Cz-Mastoids). Cortical positivity leads to movement the cursor down on the screen. Negative cortical causes the movement of the cursor up. Each experiment takes place 6s. During each experiment, only a 3.5-second interval for each trial is provided for training and testing. The sampling rate of 256 Hz and the recording length of 3.5 produced 896 points of data [20].

2.2. Fast Fourier transform

Fast Fourier transformation is a mathematical technique that functions to transform signals in the time domain into signals with a frequency domain. The fourier equation is as follows :

$$X(f) = \int_{-\sim}^{\sim} x(t).\, e^{-2\pi f t}\, dt \qquad (1)$$

In this equation there is time, f is the frequency and x represents the signal to be transformed. x is a signal in the time domain and X is a signal in the frequency domain [12]. Fourier transform is used to find the frequency spectrum from EEG signal data that is related to motor movement and imagination to move the cursor up and move the cursor down.

2.3 Power Spectral Dencity

EEG signals are recorded in the form of signals in the time domain, while to get alpha waves, beta and teta need to know the frequency of the signal. To change the time domain into a frequency domain, signal processing is needed to transform the signal. The method that can be used to get frequencies based on spectrum estimation calculations using the Welch method. Previous research used to identify the effect of 20 different sound stimuli after the signal was extracted with Wavelet. The results of these studies can identify relaxed conditions [13]. While other studies are analysis of mind conditions using power spectral [14]. Power Spectral is used to analyze EEG wave increases, namely the appearance of 75% alpha waves, while theta and beta waves decrease around 48% and 56% [15].

2.4 K-Nearest Neighbor Classification Method

K-NN is a simple machine learning algorithm. This is only based on the idea that an object that is 'close' to each other will also have similar characteristics. This means that if we know the characteristics of one object, we can also predict other objects based on their closest neighbors. K-NN is an advanced improvisation of the Nearest Neighbor classification technique. This is based on the idea that each new instance can be classified by the majority vote of neighbor k, where k is a positive integer, and usually with a small number [16]. The K-NN classification algorithm predicts sample test categories according to the training sample k is the closest neighbor to the test sample, and includes it in the category that has the largest probability category [17].

In pattern recognition, the KNN algorithm is a method used to classify objects based on the closest training example in the feature space. KNN is a type of institutional-based learning, or lazy learning where this function is only approached locally and all calculations are deferred to classification [18]. The K-NN classification method has several stages, the first being the k value which is the number of closest neighbors that will determine which new query goes to which class is determined. The second stage, k the nearest neighbor is searched by calculating the distance of the query point with the training point. The third stage, after knowing the distance of each training point with the query point, then see the smallest value. The fourth stage takes the smallest k value, then see the class. The class that is the most is the class of the new query. The distance or distance of a point with its neighbors can be calculated using the Euclidean distance. The euclidean distance is represented as follows [19]:

$$j(a,b) = \sqrt{\sum_{k=1}^{k_n}(a_k - b_k)^2} \qquad (2)$$

J (a, b) is the distance between point a which is the point known to its class and b is a new point. The distance between the new point and the training points is calculated and taken by the nearest point. The new point is predicted to enter the class with the highest classification of these points.

3. RESULTS AND DISCUSSION

The data used is using data from BCI comptetion 2003 Data set Ia. The Ia data set consists of 6 channels (electrodes affixed to the scalp totaling 6 electrode sensors, resulting in 6 EEG signal channels). The data set consists of Trainning data and Testing data.

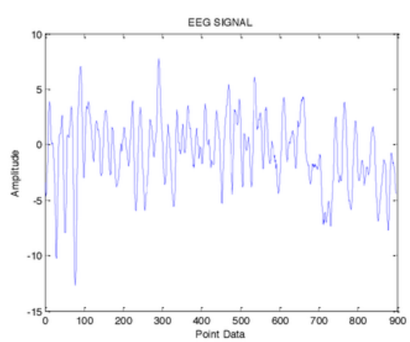

Figure 1. EEG signals from healthy subjects

The large amount of data will cause the old computing process to be caused by a lot of data being processed, so that with few features it results in a fast computing process. In this study, an EEG signal is taken from the average energy value of each Fourier process to be used as a feature extraction for the identification process.

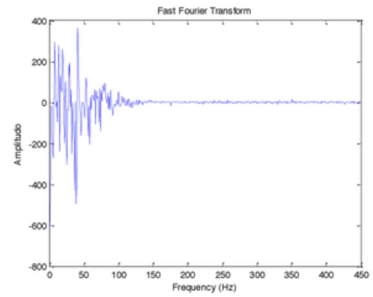

Figure 2. Fourier transform process of EEG signals in healthy subjects

Figure 2 is an EEG signal after the Fourier Transform process to convert EEG signals from time domain signals to frequency domain signals.

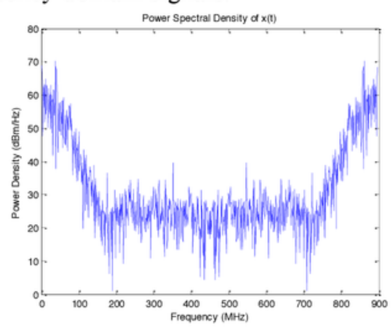

Figure 3. Power Spectral Density of EEG signals

By transforming the signal into the frequency domain, using fft and logarithmic processes we will get the power spectral density (PSD) value shown in Figure 3. The EEG signal that has been done by the process to get the PSD value, the average value will be searched. energy for each EEG signal. The average value of this energy will be used as an extract of the characteristics of the EEG signal.

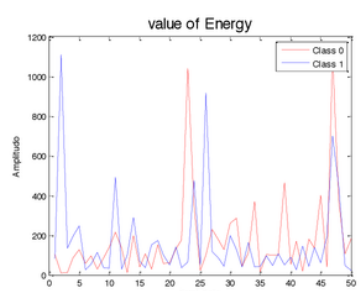

Figure 4. Comparison of the average value of energy from class 0 and class 1

In Figure 4 shows the average value of EEG signal energy, each EEG signal for the cursor movement up and the cursor movement down has a difference value. With differences in values that are not the same, it shows that the level of classification by taking the average

value of energy is quite good. Classification using K-NN is implemented by using the average energy value feature of the FFT process as input. In this study, the training set amounted to 250 EEG signal data and trial data of 50 EEG signal data. In table 2 is the distribution of sample classes in the training and trial data collection. Data obtained from different subjects in the training process is a way to improve the ability of K-NN. To train K-NN, use training data sets, while to verify the accuracy and effectiveness of K-NN test data to detect cursor movements up and down.
The test will be carried out with a variation of the K value in the KNN system and variations in training data and test data used. The accuracy in question is the accuracy of the classification results carried out by the program with the results of manual classification. The level of accuracy can be formulated with equation 3.

$$Level\ of\ accuracy = \frac{The\ number\ of\ EEG\ signals\ is\ correctly\ classified}{Total\ amount\ of\ test\ data}\ x\ 100\% \quad (3)$$

In this test variations in the number of k are performed on the KNN function. k is the number of closest neighbors. The k values tested are one, three, five, seven, and nine. Odd values are chosen to avoid similarities in proximity to two different points of class. Because KNN will classify based on the most class voting. From this test the average accuracy value for each k value is determined.

Classification Testing with Value k = 1
The classification results with a value of k = 1 are shown in Table 1. The results of testing with k = 1 obtained an average accuracy of KNN classification of 67%. With the lowest accuracy of 60% and the highest accuracy of 84%.

Tabel 1. Results of testing k = 1 classification

Test	Amount of training data	Amount of test data	Right	wrong	accuracy
1	50	50	21	4	84%
2	50	50	17	8	68%
3	50	50	16	9	64%
4	50	50	15	10	60%
5	50	50	15	10	60%
Average					67%

Classification Testing with Value k = 3
The classification results with values k = 3 are shown in Table 2. The test results with k = 3 obtained an average accuracy of 59%. The highest level of accuracy is found in the first test of 72%. The lowest level of accuracy is in the fifth test of 48%.

Table 2. Results of testing classification k = 3

Test	Amount of training data	Amount of test data	Right	wrong	accuracy
1	50	50	18	7	72%
2	50	50	15	10	60%
3	50	50	13	12	52%
4	50	50	15	10	60%
5	50	50	12	13	48%
Average					59%

Classification Test with Value k = 5

The classification results with a value of k = 5 are shown in Table 3. From the results of testing with k = 5, the average accuracy is 57%. The highest accuracy of 76% is in the first test. The lowest accuracy of 40% is found in the third test.

Table 3. Results of testing classification k=5

Test	Amount of training data	Amount of test data	Right	wrong	accuracy
1	50	50	19	6	76%
2	50	50	15	10	60%
3	50	50	10	15	40%
4	50	50	15	10	60%
5	50	50	12	13	48%
Average					57%

Classification Test with Value k = 7

The classification results with values k = 7 are shown in Table 4. Testing with k = 7 produces an average accuracy of 58%. The highest accuracy results are found in the first test with a value of 72% accuracy. The lowest accuracy of 52% is found in the third test.

Table 4. Results of testing classification k=7

Test	Amount of training data	Amount of test data	Right	wrong	accuracy
1	50	50	18	7	72%
2	50	50	15	10	60%
3	50	50	13	12	52%
4	50	50	15	10	60%
5	50	50	12	13	48%
Average					58%

Classification Test with Value k = 9

The results of classification testing with a value of k = 9 are shown in Table 5. The results of the classification test with a value of k = 9 show the average value of accuracy of five times the test of 59%. The lowest test value of 48% is found in the third test.

Table 5. Results of testing classification k =9

Test	Amount of training data	Amount of test data	Right	wrong	accuracy
1	50	50	19	6	76%
2	50	50	14	11	56%
3	50	50	12	13	48%
4	50	50	16	9	64%
5	50	50	13	12	52%
Average					59%

Comparison of the Average Value of Accuracy

From all tests with variations in the value of k obtained the highest accuracy value is found at the value of k = 1 with an average level of accuracy of 67%. The lowest accuracy value is found in testing with k = 5 with an average level of accuracy of 57%. Overall the value of accuracy has a value close to 60%. Classification of KNN with the description above, the value of k = 1 is the most optimal k value.

4. Conclusion

This study introduces Fast Fourier Transform to extract features by taking the average energy value of each EEG signal. The process of classifying EEG signals is divided into two classes namely class 0 and class 1. This study uses 300 EEG signal file data for training and testing. the accuracy of the K-NN classification reaches 84% for test data. To produce better results, the work of future researchers will examine suitable search techniques for feature extraction and classification of EEG signals for commands to move the cursor. The results of the research obtained will be compared with the methods studied.

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