Analysis Of Alpha And Beta EEG Signal Pattern In Trypophobia Condition With Wavelet Method

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Abstract. A phobia is a human fear of things that are sometimes very simple for some people. One of them is Trypophobia which is a fear of visualizing small holes. The effect of the trypophobia effect can be analyzed by his brain waves using an Electroencephalograph. In this study, a system was developed to classify a person’s condition without Trypophobia (normal) and the condition of a person with Trypophobia based on analysis of alpha and beta EEG signals. In this study, the Artificial Neural Network (ANN) is used for classifying conditions. Discrete Wavelet Transform (DWT) is used to reduce the raw dimensions of EEG signals and retrieve signal features. The test results show that the best performance obtained in beta signals which have the highest diagnostic parameter accuracy, namely Maximum, Standard Deviation and Variance with 100% accuracy, with computation time 0.027 and 0.037 seconds. While for alpha signals obtained with Variance and Interquartile Range parameters of 96.42% with a time of 0.03 and 0.032 seconds.

1. Introduction
Phobias are defined as strong fears and continuously with the presence of certain objects or situations. Exposure to a feared object or situation constantly causes anxiety, disgust, and rapid heartbeat. Individual behavior, when given, feared stimuli in the form of panic, run away from these stimuli, and even faint. This makes phobias such as personal trauma to certain people [1]. While the trauma from the medical understanding is an injury both psychologically and physically [2, 3], trauma can occur in all parts of the human body, including the most commonly found is part of the human brain [4].

Electroencephalogram (EEG) is one of the tools that can be used to read and monitor brain wave conditions directly. EEG can be used to monitor patients with traumatic brain injury. The results of the study show that as many as 26% of patients who experience trauma-induced seizures indicated by intracerebral contractions [5]. In a study of EEG-based severity index in cases of traumatic brain injury showed that EEG signals could be used to distinguish between mild and severe types of traumatic brain injury in the post-acute period. EEG analysis, which is used for detection of Drug Effects, proves that there are differences in brain electrical activity in addicted people reported in the study [6]. Differences in EEG wave characteristics on psychological emotions can also be applied to human BCI as reported in research [7]. EEG signal analysis is related to wave characteristics when a person is relaxed and listening to music reported in research [8].

Other research by Jalilifard et al [9] has been carried out research to find out human emotions by classifying them into two classes namely fear and relaxation. The process of recording brain signals using a one-channel EEG, where the method used in the study is SWT (Stationary Wavelet Transform) with the classification of SVM and K-NN. From the research, it was found that the gamma signal spectrum tended to have a higher accuracy when classifying relaxation and fear data. The literature study provides the knowledge that EEG waves have distinctive characteristics in accordance with one’s psychological condition. So that the EEG signal analysis becomes an interesting research to find out the psychological condition of a person.
In this study, we observed the condition of brain signals in participants who experienced psychological trauma. The stimulation is given to objects in the form of digital images and videos by the traumatic conditions experienced by participants. The type of trauma that the data are taken is trauma to the hole or pattern of holes in an area (trypophobia), trauma to height and trauma to unfortunate events that occurred in the past.

Brain signals are taken by using the Muse Sensing headband EEG device through electrodes placed on the frontal scalp. A total of 4 channels of EEG signals were obtained from four different electrode points, Muse EEG channels are divided into AF7, AF8, TP9, TP10 [10]. Then the recording process is carried out for approximately two and a half minutes, as long as the subject is given a stimulus in the form of an image that is indicated to be able to trigger a person against the fear of Trypophobia. When the recording process is complete, save the results in the form of .csv and become the raw data. The raw data is then taken as part of the desired channel’s raw data. The raw data taken is then cut into five seconds so that it matches the time the subject is given per stimulus. The data acquisition phase has been completed and then makes a system to detect trypophobia with initial processing using Normalization and Fill missing value, analyzed using. The Discrete Wavelet Transform method for feature extraction and the results of feature extraction will be classified using the Artificial Neural Network method. The results of this study are expected to be used as an initial detection of traumatic symptoms which then becomes a reference to determine the right healing therapy.

2. Method

2.1. Data Acquisition

EEG signal retrieval is done on subjects who have trypophobia and without trypophobia as a normal subject. For comparison, we also made a condition where each subject was also given a stimulus in the form of images related to trypophobia and took other conditions in the form when the subject was relaxed and when stressed. Relax is a condition of the subject when not thinking about anything and not given any stimulus so that the brain condition is stable for approximately 2.5 minutes. Then for stress conditions, the subject is given a stimulus in the form of questions with complex levels and given time to do it in a short time, so the brain is forced to work hard, this aims to make stress data as comparative data with trauma data. For recording, use the Muse Sensing Headband to track changes in brain signals that occur during experiments. The sampling frequency used is 256 Hz.

2.2. Signal Processing

The experiment was carried out using the Muse Sensing Headband device. Muse Sensing Headband records EEG signals with four channels from 10 respondents. Data acquisition was obtained by each respondent seeing videos showing traumatic conditions as well as from each respondent’s acknowledgment. Raw data is separated based on the level of subject mapping into three classes. Each class represents a relaxed, traumatic, and stressful condition. There are two conditions for the algorithm that are used as processing training data and test data. Each processing of training data and test data is shown in Figure 1.

![Figure 1 System Design](image)
There are several artifacts and noise attached to the EEG signal. Some conditions experienced include incomplete data. This condition occurs in the inappropriate Muse Sensing Headband placement or excessive movement noise. Figure 2 is an example of the EEG raw data signal. Fill Missing Value is done by filling in an empty value or NaN in the data set with the closest value. Then the signal needs to go through the signal normalization stage. Normalization aims to change the range of signal amplitude to 0 and 1 without changing the signal pattern itself. This is because the back propagation algorithm is usually the activation function used is the sigmoid function. This function will bring input values with a range that is not limited to limited output values, namely 0 and 1. The examples of signals after preprocessing shown in Figures 3.

\[ x_{\text{norm}} = \frac{X}{\max X} \]  

2.3. Signal Processing
Discrete Wavelet Transform (DWT) is a linear transformation that operates vector data that has a length of 2^n, then converts it into several different vectors with the same length. DWT is a method for separating data based on frequency and then analyzing each part with a resolution that matches the scale. DWT is calculated by a filter cascade and is followed by 2 subsampling. There are several wavelet bases namely Haar, Coiflet, Daubechies, and Morlet [11]. In the case of this study, we chose to use the Daubechies 8 (Db8) wavelet base. Wavelet is a basis derived from a scaling function, where the scaling is generated from the decomposition and reconstruction process. In general, decomposition is an extraction process at a certain frequency, while reconstruction returns the signal to its original condition. DWT is a suitable method for separating data based on its frequency and then analyzing each part with characteristics each signal produces variations that vary from the emotional condition of the respondent. EEG signals are in the frequency band (0-4) Hz Delta, (4-8) Hz Theta, (8-12) Hz Alpha, (12-30) Hz Beta, (30-50) Hz Gamma. The variation of frequency bands is used in the separation of raw data produced by Muse Sensing Headband. This study focuses on the analysis of Alpha and Beta waves because these signals are closest to when the brain transitions from passive to active mode. The wavelet function \( \psi_{a,b}(t) \) can be represented as follows:

\[ \psi_{a,b} = \frac{1}{\sqrt{a}} \psi \left( \frac{t-a}{b} \right) \]  

where \( a, b \in R, a > 0 \) and \( R \) is wavelet space. Element a and b are scale and shift factors. The wavelet decomposition process can be simply illustrated in Figure 4.
The Discrete wavelet transformation will describe the signal into two components, Approximation Coefficients (AC) and Detailed Coefficients (DC). This process will be carried out repeatedly and produces Approximation Coefficients and Detailed Coefficients to different decomposition levels. That way, we can obtain the value of the frequency band power feature of the signal. The decomposition process in this research is shown in Figure 5.

2.4. Feature Extraction
The feature extraction used in this research is based on statistic features. They are maximum value, minimum value, mean, standard deviation, variance, interquartile range, skewness, and kurtosis
2.4.1. Maximum Value
Maximum value is the highest value in an array of data.

\[ M = \max(n) \]  

(3)

where \( n \) is an input in the form of an array of data so that the highest value can be determined in the data array.

2.4.2. (b) Minimum Value
Minimum value is the lowest value in an array of data

\[ m = \min(n) \]

(4)

where \( n \) is an input in the form of an array of data so that the lowest value can be determined in the data array.

2.4.3. Mean
Mean is the average input value from the data array.

\[ \mu = \frac{1}{N} \sum_{i=1}^{N} n \]

(5)

\( N \) shows many samples from input data \( n \) starting from array 1 to \( N \).

2.4.4. Standard Deviation
Standard deviation is a statistical value parameter used to determine how the data is distributed in the sample, and how close the individual data points are to the average sample value.

\[ \sigma = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N} (n - \mu)^2} \]

(6)

\( n \) which is input, while \( N \) is the number of samples of data \( n \) which starts from 1 and \( \mu \) is the mean of \( n \).

2.4.5. Variance
Variance is another way to measure how the data is spread in a data set. Variance is almost the same as the standard deviation, but variance is the square of the standard deviation. Following is the formula of variance.

\[ \sigma^2 = \frac{1}{N-1} \sum_{i=1}^{N} (n - \mu)^2 \]

(7)

2.4.6. Interquartile Range
Interquartile Range (IQR) is a statistical parameter that divides a collection of data into quartiles. The quartile divides the data collection ranked into four equal parts. The values that separate parts are called the first, second, and third quartiles; and they are denoted by Q1, Q2, and Q3, respectively.

\[ Q3 - Q1 = IQR \]

\[ Q1 = (\sigma z1 + \mu) \]

\[ Q3 = (\sigma z3 + \mu) \]

(8)

Q1 is the upper quartile of the array and Q3 is the bottom quartile of the array while \( z1 \) is the standard value of quartile one (-0.67) and \( z3 \) is the standard value of the third quartile (+0.67) and \( \mu \) as the mean while \( \sigma \) is the standard deviation.
2.4.7. Skewness
Skewness is a form of measurement that shows the slope level of a curve which if the curve deviates to the right (seen from the mean) then it is said to be positive if the opposite is called negative skew.

\[ \beta_2 = \frac{N}{(N-1)(N-2)} \sum_{i=1}^{n} \left( \frac{n - \mu}{\sigma} \right)^3 \]  

(9)

2.4.8. Kurtosis
Kurtosis is a form of measurement that shows the level of shedding from relative curves.

\[ \beta_4 = \sum_{i=1}^{n} \left( \frac{n - \mu}{n \sigma} \right)^4 \]  

(10)

2.5. Backpropagation Neural Network
Artificial neural networks (ANN) are models inspired by the workings of the human brain. The modelling process can provide stimulation, process, and provide output [12]. Backpropagation is one type of ANN that is widely applied to classify or predict output based on input features [13]. When the network provides input, then the forward value will also be activated which comes from the input layer in the units that are processed. Then each internal layer is given to the output layer that is processed by the output units. The units of the output will respond to the network. If the network has corrections to the parameters inside, the repair mechanism will start from the output unit, and the Back Error Propagation will then return to each internal unit to be used in the input layer.

The steps of the backpropagation algorithm are as follows [14]:

1. Problem definition, for example input matrix (P) output matrix (T)
2. Initiation, determine the network shape and specify the synaptic values of W1 and W2 and learning rate (lr).
3. Network training:
   a. Forward Computation
      Output for hidden layer:
      \[ A_i = \frac{1}{1 + e^{-\sum_j w_{ij} A_j}} \]  
      (11)
      The output of the hidden layer is used to get the result of the output layer:
      \[ A_i = \frac{1}{1 + e^{-\sum_j w_{ij} A_j}} \]  
      (12)
      Gate (E) is the difference between the desired output value (T) and the actual output (A2), as follows: \( E = T - A_i \) Sum Square Error (SSE) stated by the following equation:
      \[ SSE = \sum E^2 \]  
      (13)
   b. Back Computation
      \[ D2 = A_i \ast (1 - A_i) \ast E \]
      \[ dW2 = dW2 + (lr \ast D2 \ast A_i) \]
      \[ D1 = A_i \ast (1 - A_i) \ast (W2 \ast D2) \]
      \[ dW1 = dW1 + (lr \ast D1 \ast P) \]  
      (14)
c. Weight correction

\[
TW^2 = W^2 + dW^2 \\
TW^1 = W^1 + dW^1 \\
W^2 = TW^2 \\
W^1 = TW^1
\]  

(15)

4. The steps above are for one training cycle (one epoch), so it must be repeated until the number of epochs that have been determined or has reached the desired SSE (Sum Square Error).

5. The end result of network training is getting W1 and W2 weights which are then stored for network testing.

3. Result and Discussion

In this research, there are two classes which are separated. Experiments were carried out with varying neuron parameters, namely 20, 40, 60, 80 and 100 so that the best accuracy can be known between the use of these neurons. We use 2 hidden layers for each variation of neurons. The results of this test can be seen in Table 1 to 5.

The trial with 20 neurons obtained the best accuracy 96.42% and 100% for alpha and beta signal respectively by using standard deviation as the feature. The standard deviation feature also had a good result in trial with 40 and 80 neurons. In trial with 40 neurons, we acquired 89.28% and 100% of accuracy for alpha and beta signal respectively. While in trial with 80 neurons we obtained 82.14% for alpha signal and 96.42% for beta signal.

### Table 1 Accuracy with 20 neurons

| Feature    | Alpha Signal Accuracy (%) | Computation Time (s) | Beta Signal Accuracy (%) | Computation Time (s) |
|------------|---------------------------|----------------------|--------------------------|----------------------|
| Max        | 50                        | 0.22                 | 96.42                    | 0.023                |
| Min        | 85.71                     | 0.196                | 96.42                    | 0.029                |
| Mean       | 64.28                     | 0.075                | 64.28                    | 0.023                |
| StDv       | 96.42                     | 0.094                | 100                      | 0.233                |
| Variance   | 96.42                     | 0.026                | 96.42                    | 0.029                |
| IQR        | 85.71                     | 0.029                | 50                       | 0.043                |
| Kurtosis   | 39.28                     | 0.278                | 50                       | 0.026                |
| Skewness   | 57.14                     | 0.026                | 39.28                    | 0.028                |

### Table 2 Accuracy with 20 neurons

| Feature    | Alpha Signal Accuracy (%) | Computation Time (s) | Beta Signal Accuracy (%) | Computation Time (s) |
|------------|---------------------------|----------------------|--------------------------|----------------------|
| Max        | 75                        | 0.108                | 100                      | 0.028                |
| Min        | 82.14                     | 0.037                | 92.85                    | 0.035                |
| Mean       | 75                        | 0.032                | 75                       | 0.03                 |
| StDv       | 89.28                     | 0.036                | 100                      | 0.027                |
| Variance   | 96.42                     | 0.03                 | 100                      | 0.037                |
| IQR        | 96.42                     | 0.032                | 50                       | 0.029                |
| Kurtosis   | 46.42                     | 0.05                 | 71.42                    | 0.029                |
| Skewness   | 53.57                     | 0.027                | 42.85                    | 0.084                |
Table 3 Accuracy with 60 neurons

| Feature | Alpha Signal Accuracy (%) | Computation Time (s) | Beta Signal Accuracy (%) | Computation Time (s) |
|---------|---------------------------|----------------------|--------------------------|----------------------|
| Max     | 64.28                     | 0.024                | 96.42                    | 0.024                |
| Min     | 71.42                     | 0.035                | 92.85                    | 0.038                |
| Mean    | 64.28                     | 0.038                | 75                       | 0.028                |
| StDv    | 89.28                     | 0.029                | 100                      | 0.028                |
| Variance| 75                        | 0.034                | 100                      | 0.027                |
| IQR     | 96.42                     | 0.029                | 50                       | 0.028                |
| Kurtosis| 50                        | 0.03                 | 75                       | 0.028                |
| Skewness| 50                        | 0.035                | 60.71                    | 0.023                |

Table 4 Accuracy with 80 neurons

| Feature | Alpha Signal Accuracy (%) | Computation Time (s) | Beta Signal Accuracy (%) | Computation Time (s) |
|---------|---------------------------|----------------------|--------------------------|----------------------|
| Max     | 78.57                     | 0.031                | 96.42                    | 0.03                 |
| Min     | 78.57                     | 0.024                | 82.14                    | 0.032                |
| Mean    | 60.71                     | 0.028                | 60.71                    | 0.03                 |
| StDv    | 82.14                     | 0.038                | 96.42                    | 0.027                |
| Variance| 67.85                     | 0.033                | 85.71                    | 0.032                |
| IQR     | 96.42                     | 0.317                | 50                       | 0.032                |
| Kurtosis| 53.57                     | 0.324                | 64.28                    | 0.028                |
| Skewness| 60.71                     | 0.029                | 53.57                    | 0.031                |

Table 5 Accuracy with 100 neurons

| Feature | Alpha Signal Accuracy (%) | Computation Time (s) | Beta Signal Accuracy (%) | Computation Time (s) |
|---------|---------------------------|----------------------|--------------------------|----------------------|
| Max     | 67.85                     | 0.029                | 89.28                    | 0.03                 |
| Min     | 78.57                     | 0.028                | 92.85                    | 0.031                |
| Mean    | 67.85                     | 0.031                | 85.71                    | 0.03                 |
| StDv    | 71.42                     | 0.029                | 96.42                    | 0.027                |
| Variance| 89.28                     | 0.026                | 82.14                    | 0.03                 |
| IQR     | 96.42                     | 0.031                | 50                       | 0.043                |
| Kurtosis| 46.42                     | 0.035                | 71.42                    | 0.03                 |
| Skewness| 67.85                     | 0.038                | 57.14                    | 0.029                |

4. Conclusion
This research has succeeded in simulating and analysing the conditions of Trypophobia based on EEG signals using the Discrete Wavelet Transform (DWT) method and Artificial Neural Networks (ANN). Some statistical parameters used in the test are maximum, minimum, mean, standard deviation, variance, interquartile range, kurtosis, and skewness. Based on the results of testing the feature parameters as a whole, the best condition of Trypophobia is in beta signals with 40 neurons. The maximum value, standard deviation, and variance parameters achieve 100% accuracy with epoch 500 and two hidden layers. The computing time of each feature is 0.027 and 0.037 seconds. Whereas for alpha signals with Variance parameters and Interquartile Range the accuracy is 96.42% with the computation time of 0.03 and 0.032 seconds. The number of neurons as a classification parameter affects the level of accuracy of a system, but the higher the number of neurons cannot determine whether a system is getting better, that is also because adding many neurons also affects the computing time on the system. Overall, the concentration detection system obtains optimal results in
the AF7 channel in Trypophobia conditions, where the brain signals that catch the most disorders and certain conditions are in the frontal brain area.

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