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Significant variables extraction of post-stroke EEG signal using wavelet and SOM kohonen

Esmeralda C. Djamal*[1], Deka P. Gustiawan[2], Daswara Djajasasmita[3]
[1,2]Department of Informatics-Universitas Jenderal Achmad Yani, Cimahi, Indonesia
[3]Faculty of Medicine-Universitas Jenderal Achmad Yani, Cimahi, Indonesia
*Coresponding author, e-mail: esmeralda.contessa@lecture.unjani.ac.id

Abstract

Stroke patients require a long recovery. One success of the treatment given is the evaluation and monitoring during recovery. One device for monitoring the development of post-stroke patients is Electroencephalogram (EEG). This research proposed a method for extracting variables of EEG signals for post-stroke patient analysis using Wavelet and Self-Organizing Map Kohonen clustering. EEG signal was extracted by Wavelet to obtain Alpha, beta, theta, gamma, and Mu waves. These waves, the amplitude and asymmetric of the symmetric channel pairs are features in Self Organizing Map Kohonen Clustering. Clustering results were compared with actual clusters of post-stroke and no-stroke subjects to extract significant variable. These results showed that the configuration of Alpha, Beta, and Mu waves, amplitude together with the difference between the variable of symmetric channel pairs are significant in the analysis of post-stroke patients. The results gave using symmetric channel pairs provided 54-74% accuracy.

Keywords: *EEG signal, post-stroke patient, significant variables, SOM clustering, wavelet*

1. Introduction

A stroke is a brain attack which can happen to anyone at any time. Stroke is the second leading cause of death worldwide and the leading causes of incidence, prevalence, mortality, and disability. Although almost 85% of patients survive the initial injury [1], approximately 65% of stroke survivors will experience residual disabilities that impair daily function and quality of life [2]. Amongst most physical defects, disorders for neuromuscular performance such as fine or coarse motor control, muscle strength, and strength are the features of stroke that have the most significant on functional ability [3].

The effort to improve the life quality of post-stroke patients is through rehabilitation such as physiotherapy, psychology, transcranial magnetic stimulation (TMS) and medicine to recover the physical ability [4]. So that required evaluation and monitoring. Electroencephalogram (EEG) can do it and contribute to a rapid evaluation of instantaneous brain function. The device is non-invasive functional neuroimaging which can be used to characterize the cortical activation difference between no-stroke subjects and post-stroke patients [4]. So EEG can be used as neurofeedback for monitoring and identification of electrical activity variables during rehabilitation which helps the neurologist analyzes. Besides, other research using fMRI neurofeedback to review stroke patients [5]. Although the accuracy was quite high, it is costly. The EEG signal usually is observed the rhythm of density, the magnitude, amplitude change and synchrony of the amplitude and rhythm of the symmetric channels pairs. However, its visual interpretation requires technical experience due to its low amplitude (1-100μV), complicated pattern, and non-stationary signal.

Analyzed ischemic stroke patients by involving alpha, beta, theta, and delta waves from an asymmetric channel pair [6], identifying the presence of the slow waves (theta-delta activity) as indication reduced cerebral blood flow of ischemic [7], and assessing traumatic brain injuries [8]. Some researches extracted the wave using Power Spectral Density [6, 8] and analyzed the variation of the pattern of every subband for each subject. Extracting frequencies of the EEG signal was used to analyze stroke patients. However, it was compared by finger movements recorded with EMG too [1, 9]. Other study using motor imagery variable of a brain-computer interface to provide neurophysiologic feedback and a robotic manipulation of the stroke-affected arm [3]. The extraction of 8-45 Hz frequency bands and inspection of a change in MI could identify post-stroke patients [10].

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In general, the EEG signal consists of wave components, differentiated by their frequency regions. They are alpha waves (8–13 Hz), beta wave (14–30 Hz), theta wave (4–7 Hz), delta wave (0.5–3 Hz), gamma wave (30-60 Hz). There Mu waves (8-13 Hz) associated with the presence of motor imagery, as the orders of the brain to move muscles. As a consequence, many kinds of research concerning EEG signal analysis represent the signal into frequency domain [8, 11]. Fourier transform is also less suitable for non-stationary signals such as EEG signals. It also becomes less feasible since the condition to be observed often occurs in a short period. In meanwhile, Wavelet transform can extract the needed signal components because it is scaling and shifting characteristic, so it is suitable for non-stationary signals [12].

Some researches have used Wavelet transforms to the extraction of Alfa, Beta, Teta, Gama and Mu waves to classify of emotion in stroke patients [13] and in healthy individuals [14] which are obtained very effectively and obtain good accuracy values. In meanwhile, Kohonen's Self-Organizing Map (SOM) has been used to analyze EEG data equations [15]. Preliminary studies have used wavelets for the extraction of specific frequencies from EEG signals for the classification of three emotional states [16], recognizing the effect of sound stimulation [12], alertness classification [17], and identification of attention [18].

Based on the literature review, it is summarized that the variables for the analysis of stroke patients are rhythms, magnitude, and synchrony of the symmetric channel. This research analyzed EEG signal post-stroke patient using all these features. Rhythms are related to alpha, beta, theta, and gamma waves which extracted using Wavelet transformation. Besides motor imagery factor which relates to the Mu wave. Synchrony analysis included rhythms magnitude of all waves. All variables are features of Self-Organizing Map Kohonen clustering. Then compared to clinical of imaging of post-stroke patients and no-stroke subjects. This way proposed for extraction of the variables configuration until optimized accuracy.

2. Proposed Method

This research using Wavelet transformation to the extraction of EEG signal and SOM Kohonen to clustering.

2.1. Wavelet Transformation

The wavelet transform is an approach to extract signal into frequency bands that are alpha, beta, theta, gamma, and Mu. The method is appropriate to non-stationary signals such as EEG [12, 19]. Basis function Φ(n) called the mother Wavelet as (1).

$$\Phi_{j,k}(n) = 2^{j/2}\Phi(2^j n - k) \quad (1)$$

where j and k are an integer that indicates the scaling and dilate of the basis function. It depends on the shape or position of the signal. Φ(n) is wavelet family. The determinant of the mother Wavelet is a critical aspect depend on the characteristics of EEG signals to be decomposed. Previous studies generally used the Daubechies db4 mother Wavelets for seizure detection [19] and ischemic stroke [20]. The wavelet coefficient approximation, a(j,k) and detail d(j,k) and, are got from convolution signal x(n) with basis function as (2) and scaling function as (3).

$$a(j,k) = 2^{-j/2}\sum_{n} x(n) * \Psi\left(2^{-j} n - k\right) \quad (2)$$

$$d(j,k) = 2^{-j/2}\sum_{n} x(n) * \Phi\left(2^{-j} n - k\right) \quad (3)$$

where $\Psi_{j,k}(n)$ and $\Phi_{j,k}(n)$ are scaling function for low frequency and wavelet functions for high-frequency component respectively. Wavelet synthesis can be written as follows (4) [19].

$$x(n) = \sum_{j,k} 2^{-j/2} a_{j,k}\Psi\left(2^{-j} n - k\right) + \sum_{j,k} 2^{-j/2} d_{j,k}\Phi\left(2^{-j} n - k\right) \quad (4)$$

Using (4) signal can be decomposed into *j* scale level with narrower frequency interval, either for high frequency or low-frequency groups. The research has examined an experiment data with 128 Hz sampling frequency, with results as shown in Figure 1 that contains alpha, beta, and theta frequency for up to sixth levels [16].

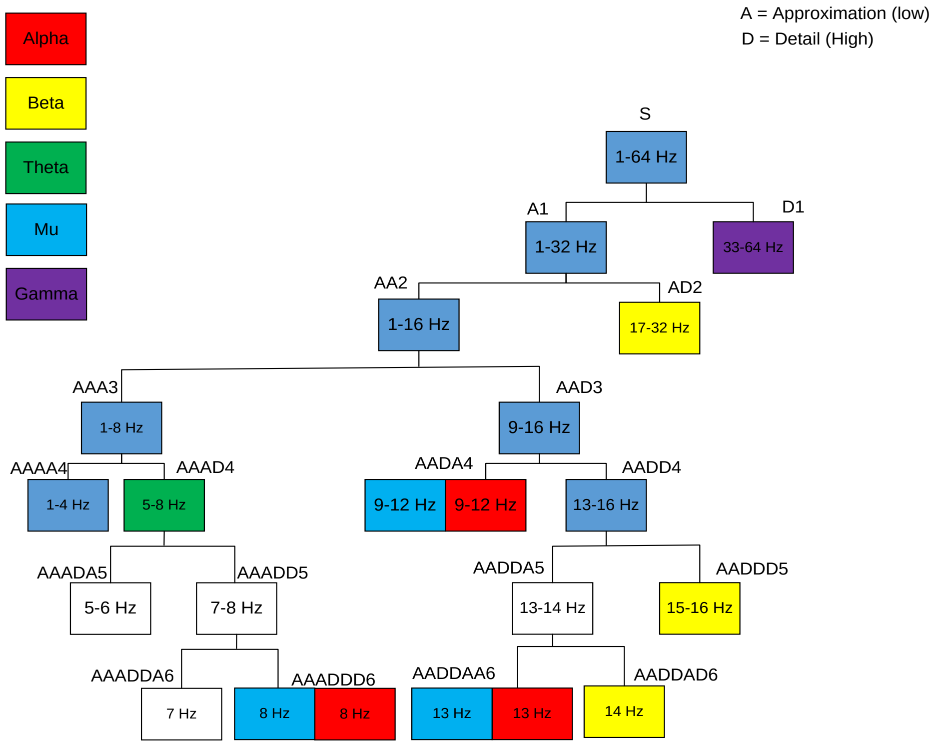

Figure 1. The sixth level of wavelet extraction

2.2. Self Organizing Map Kohonen

Clustering models the EEG signal which is the development of the cross correlation based simillariy that using the centroid. Previous research using multi-trial EEG clustering to partition similar EEG trials into the same cluster and distinguish clusters as far as possible [21]. One technique of unsupervised learning as clustering is the Self-Organizing Map (SOM). In previous studies compared supervised learning and unsupervised learning [15, 22] with each unit of four and ten clusters. Others, identification, and labeling have also been performed on the signal EEG epilepsy patients [23, 24]. SOM architecture is a network consisting of two layers (layer), namely the input layer and the output layer. Each neuron in the input layer is connected to each neuron in the output layer. Each neuron in the output layer represents the cluster of given inputs, as shown in Figure 2.

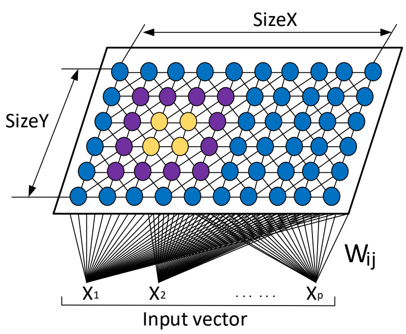

Figure 2. SOM Architecture

SOM has a structure there are the dataset, size, and topology as input many p and output a number n cluster. SOM perform unsupervised learning to classify data based only distinguishing features pattern. SOM cluster results should be compared to actual clusters if there are available. It is used to to to evaluate features that can be a good pattern differentiator.

3. Research Method

This study extracted the variables of the EEG signal from the post-stroke patient using the Wavelet transform and the Kohonen SOM clustering, as in Figure 3. Extraction model started with the data acquisition which then by designing the system extraction of variables of the EEG signal of post-stroke patients. Wavelet works for the extraction of Alfa, Beta, Teta, and Mu waves as part of the feature. In meanwhile, the SOM role for evaluation of features as a differentiator of EEG signals from patients post-stroke compares no-stroke people.

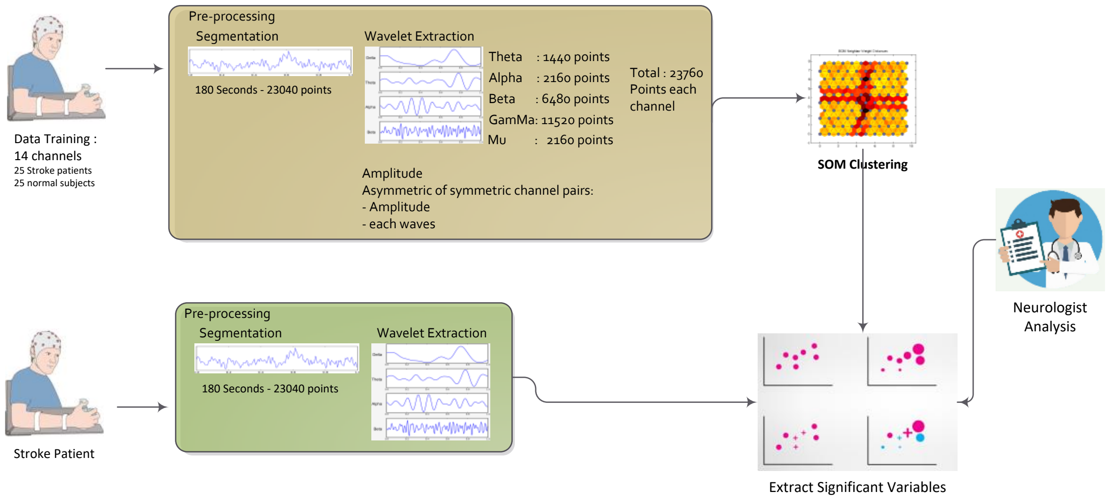

Figure 3. Extract significant variables of stroke patients using Wavelet and SOM Kohonen

3.1. Data Acquisition

Data were collected on 25 post-stroke patients while on therapy at the neurology clinic of Al Islam hospital in Bandung. As a comparison also recorded 25 people with healthy subjects as participants with 25-70 years old. For healthy subjects no previous history of stroke or called no-stroke subject. The Ethics Committee of Padjadjaran University has approved data collection of patients.

The signal was recorded using Emotiv EEG wireless by placing the electrode using a Modified Combinatorial Nomenclature (MCN) system which is a 10-20 system development. Selection of channels was also determined in the post-stroke patient analysis. Previous research analyzed from 12 channels to select the most optimal channel configuration [25]. This research used 14 channels (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4) and determined the channel configuration that provided the best clustering accuracy. The patient sat down and faced a prepared laptop video containing and execute the instructions as in Figure 4. First, a black layer for a minute is an instruction to open eyes. Then, the next minute was a command to imagine raising the hand and left hand. Moreover, the patient's last minute was instructed to close his eyes.

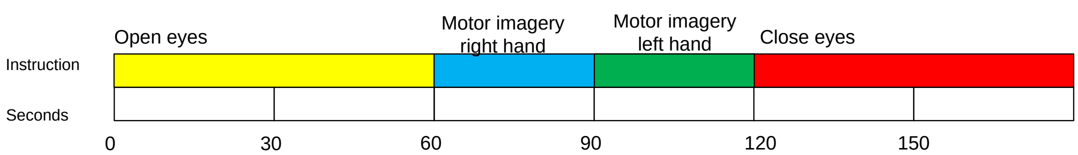

Figure 4. Instruction of patient while EEG recording

3.2. Extraction Wavelet

EEG signal in 180 seconds was extracted into Alpha, Beta, Theta, Gamma, and Mu waves using (4). Mu wave has a frequency similar to Alpha waves but is in the central area or FC5 and FC6 in Figure 3. The decomposition process like Figure 1 which can be seen as in Table 1.

3.3. SOM Kohonen

Besides the five waves, the features in the SOM clustering used magnitude feature. Amplitude observation was done by dividing into eight segments every second. So we got 1440 segments in 180 seconds. Each segment was calculated the maximum of amplitude magnitude, so that obtained 1440 data points of a channel and 20.160 points of 14 channels. Moreover, the system used asymmetrical of 7 pairs of symmetric channels of each wave and amplitude. So obtained as in Table 2. Feature Mu wave and Asymmetric of Mu wave only in FC5 and FC6 channels.

Table 1. Wavelet Extraction

No	Wave (Freq, Hz)	Length of 180 seconds (a channel)	Length of 180 seconds (14 channels)
1.	Delta (1-4)	1,440	20,160
2.	Theta (5-7)	1,080	15,120
3.	Alpha (8-14)	2,520	35,280
4.	Beta (15-32)	6,480	90,720
5.	Gamma (33-64)	11,520	161,280
6.	Mu (8-14)	2,520	5,040

Table 2. SOM Features

No	Feature	Length of 180 seconds
1.	Delta (1-4)	20,160
2.	Theta (5-7)	15,120
3.	Alpha (8-14)	35,280
4.	Beta (15-32)	90,720
5.	Gamma (33-64)	161,280
6.	Mu (8-14)	5,040
7.	Amplitude	20,160
8.	Asymmetric of Delta wave	10,080
9.	Asymmetric of Theta wave	7,560
10	Asymmetric of Alpha wave	17,640
11.	Asymmetric of Beta wave	45,360
12.	Asymmetric of Gamma wave	80,640
13.	Asymmetric of Mu wave	2,520
14.	Asymmetric of Amplitude	10,080
	Total	521,640

SOM clustering used Figure 2 with X_1 ... X_{521640} as input and two clusters, i.e., post stroke and no-stroke person. The parameters for the SOM clustering were learning rate (α) of 0.05 and subtraction every 0.1 times multiplied by the learning rate of every epoch. Meanwhile, minimum learning rate (Eps) was 0.0001 and maximum 1000 epochs. Clustering was done with Kohonen SOM compared with actual clusters. The feature as Table 2 is a full combination. The analysis of significant variables based on concerning the highest accuracy of the combination of features used in Table 2 by reducing some features.

4. Results and Analysis

EEG signals post-stroke patients and no-stroke people generally differ concerning amplitude and rhythmic as in Figure 5. There are two colour, red of post-stroke patients and blue of no-stroke people. Observations are limited to amplitude although not easy to observe the pattern. Therefore, processing begins with wave extraction based on the frequency range to obtain rhythm or speed.

4.1. Wavelet Extraction

Wavelet extraction used Symmlet 2 by Wavelet filtering of 5-64 Hz as illustrated by Figure 6. Using wavelet filter reconstructed the signal in the frequency range. The red line for the original EEG signal is compared to the blue line for Wavelet extraction signals. It can be seen that the extraction signal reduces the high frequency of the sampling results.

4.2. Parameter Optimized

Clustering parameter test was conducted to determine the effect of learning rate on learning the quality of training data using 1000 epoch, learning rate 0.05 and reduced constants of Learning rate of 0.1 as shown in Table 3. Based on Table 3, it can be seen the comparison of learning rate and learning rate reduction constant based on clustering accuracy. From the result of comparison of learning rate value got to result in 74% accuracy data according to the cluster using a learning rate of 0.05.

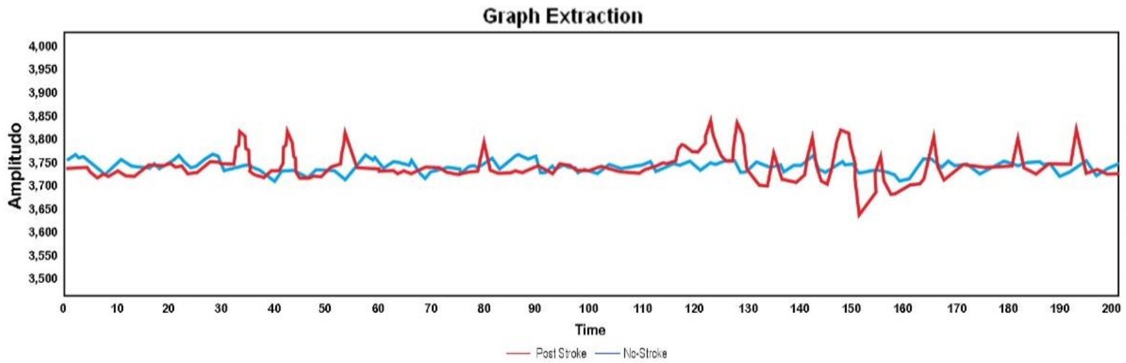

Figure 5. EEG signal of post-stroke patient and no stroke subject

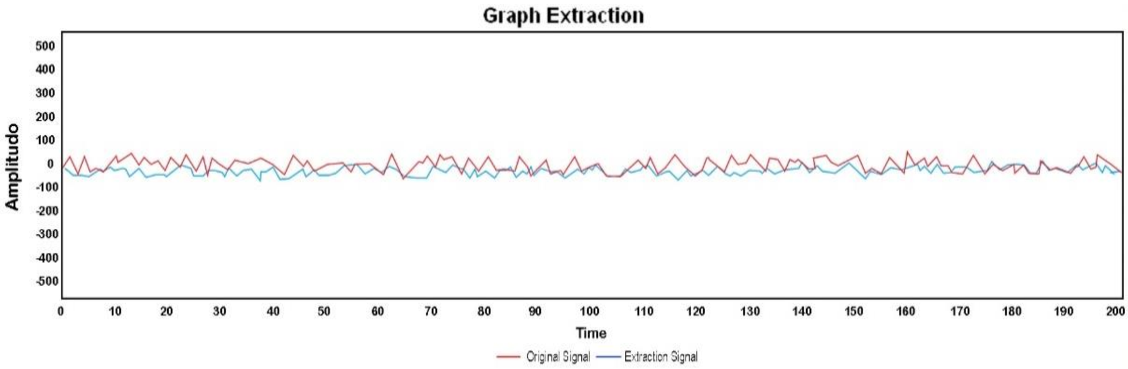

Figure 6. EEG signal compared Wavelet extraction

Table 3. Optimization of SOM Parameters

Learning rate	Reduced constants of Learning rate	Epoch	Time of Clustering (seconds)	Accuracy (%)
0.10	0.1	1000	40	58
0.05	0.1	1000	40	74
0.02	0.1	1000	76	60
0.01	0.1	1000	78	56

4.3. Testing of a single feature

This study used training data from 25 post-stroke patients and 25 no-stroke respondents. Clustering using SOM Kohonen was performed by grouping variables based on similarities which rule of SOM for post-stroke patients and no-stroke subjects. This term used a single feature of 14 groups of features in Table 4 which has different accuracy. Based on the clustering results, the amplitude variables have the highest real cluster of 68% of single features.

Table 4. The Accuracy of Single Features

No	Feature	Accuracy (%)
1.	Delta wave	60
2.	Theta wave	52
3.	Alpha wave	58
4.	Beta wave	54
5.	Gamma wave	56
6.	Mu wave	52
7.	Amplitude	68
8.	Asymmetric of Delta wave	50
9.	Asymmetric of Theta wave	55
10	Asymmetric of Alpha wave	54
11.	Asymmetric of Beta wave	53
12.	Asymmetric of Gamma wave	55
13.	Asymmetric of Mu wave	60
14.	Asymmetric of Amplitude	67

4.4. Testing of Feature Configurations

Furthermore, this study also needs to test the configuration of the features used. This sub-section is a development test of sub-section 4.3 that was only single feature testing. If there is, there will be 2^n combinations. By eliminating the single feature as much as n, and the configuration of without features, then there are 2^{14}-14-1=16,369 combinations that are tested for their accuracy as shown in Table 5.

Of the 16,369 combinations of non-single features as in Table 5 showed that the accuracy of clustering increased. The highest accuracy was obtained with a configuration that features Alpha-Beta-Mu-Amplitude-Asymmetric of Alpha-Asymmetric of Beta-Asymmetric of Amplitude that is 74%. In meanwhile, using all features obtained an accuracy of 70%. These results showed that need further feature configuration development more than a single feature configuration. These configurations are significant variables of EEG signals of post-stroke patients. Morover, the combinations as Table 5 was better compare single feature of Table 4.

Table 5. The Accuracy of Features Configuration

No	Feature	Accuracy (%)
1.	Alpha – Beta	61
2.	Alpha – Theta	59
…	….	
66.	Asymmetric of Mu- Asymmetric of Amplitude	56
67.	Alpha-Beta-Theta	54
68.	Alpha-Beta-Gamma	68
…	…	…
75	Alpha-Gamma-Amplitude	72
76	Alpha-Mu-Amplitude	72
…	…	…
4083	Alpha – Beta – Mu - Amplitude Asymmetric of Alpha - Asymmetric of Beta - Asymmetric of Amplitude	74
…..	….	…
16,369	All features	70

This increase of Tables 5 occurs according to the hypothesis that alpha waves appear when relaxed which distinguishes post-stroke patients. While the thinking ability is reflected with Beta waves, and imagining movements marked by Mu waves are also a characteristic of post-stroke patients. Besides, the amplitude variables and balance of the two waves and the amplitude are those characteristics. This result is relevant compared the analysis of Neurologists in the form of standard tests and previous research.

4.5. Testing of Feature Configurations

Results in sub-section 4.4 were tested against seven symmetric channel pairs. In this case, the features used, are configurations that have the highest accuracy, i.e., Alpha-Beta-Mu-

Amplitude-Asymmetric of Alpha-Asymmetric of Beta-Asymmetric of Amplitude. The channel configuration is 2^7-1 or 127 combinations. The results can be seen in Table 6. In Table 6 each symmetrical channel pair shows the highest percentage is 74%, i.e., AF3-AF4, F7-F8, FC5-FC6, T7-T8, and P7-P8. When all channels were used together, it produced the best clustering percentage of 72%. It appears that the channel configuration AF3-AF4, F7-F8, FC5-FC6, T7-T8, and P7-P8 were nearly accurate compared using all channels.

4.6. Testing Patient Condition

The result gave the configuration of the best features and best channels. It is also necessary to test the accuracy of the patient's condition. The results are shown in Table 7. There were 25 post-stroke patients. The conformity between models built with the actual class of 25 post-stroke patients, there were only 12 patients appropriate classified. In meanwhile the no-stroke subjects were 100% recognized. These results indicated the possibility of such patients already showing recovery become minor stroke or approaching no-stroke people based on the EEG signal. A neurologist has also justified these results and concerned about the patient's medical records. Computing time must be review. The results showed that the computational time required for new patient EEG data was 277.5 seconds or 4.62 minutes. This time is reasonable if using to a neurologist.

Table 6. Accuracy of Channel Configuration

No	Channel	Accuracy (%)
1.	AF3-AF4	58
2.	F7-F8	61
…	..	..
7.	O1-O2	60
8.	AF3-AF4; F7-F8	57
9.	FC5-FC6; F7-F8	70
..		
111	AF3-AF4, F7-F8, FC5-FC6-T7-T8, and P7-P8	74
..	..	..
127	All Channel	72

Table 7. Accuracy of Patient's Condition

Condition	Subject	Amount of Appropriate Class	Amount of Appropriate Class
	P1		1
	P2		
	P3		
	P4		
	P5		1
	P6		
	P7		1
	P8		1
	P9		
	P10		1
	P11		1
	P12		
Post-stroke Patient	P13		1
	P14		
	P15		1
	P16		
	P17		
	P18		1
	P19		
	P20		
	P21		1
	P22		
	P23		
	P24		1
	P25		1
Normal Subject	All		25
Total	All		37

5. Conclusion

The proposed method of Wavelet transformation and Self Organizing Clustering Kohonen can be used for the extraction of significant variables in the analysis of post-stroke patients. These features have been tested and validated one by one using SOM to find out how the effect on the supposed supervised data. The research gave an accuracy of 74%. Configuring the best SOM training parameters needs to be done to get the best accuracy. The parameter is the learning rate of 0.05 and reduced constants of learning rate of 0.1.

The results of the analysis showed that only 52% of EEG post-stroke patient data recognized in the original cluster and 48% recognized as a wrong cluster or no-stroke subject. In meanwhile, 100% of the no-stroke subject was correct. The weakness of the built system only divides the cluster into two, namely post-stroke patients and no-stroke subjects, without considering approaching patients cured or minor stroke. The outcome of the system has also been compared with the validation of a neurologist. The difference between post-stroke patients and no-stroke subjects can be seen in the slowdown in each wave.

The results showed that the use of configuration over single features could increase accuracy from 68% to 74%. The best accuracy is obtained with the feature configuration was Alpha-Beta-Mu-Amplitude-Asymmetric of Alpha-Asymmetric of Beta-Asymmetric of Amplitude of the channel AF3-AF4, F7-F8, FC5-FC6, T7-T8, and P7-P8. However, the configuration of the channels gave almost the same accuracy if all channels are used.

Signal analysis of all the variables for the medical team can be viewed directly using the chart provided on the menu extraction and identification of post-stroke patients EEG variables. The time needed to process new data extraction stroke patients is 4-5 minutes. It is reasonable to support the neurologist in post-stroke analyzing. Moreover, the model used, which is implemented in the system or software can be tested for EEG signal measurement data in other post-stroke patients. This system is done for further system testing by a Neurologist.

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