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ARTIFACT REMOVAL AND BRAIN RHYTHM DECOMPOSITION FOR EEG SIGNAL USING WAVELET APPROACH

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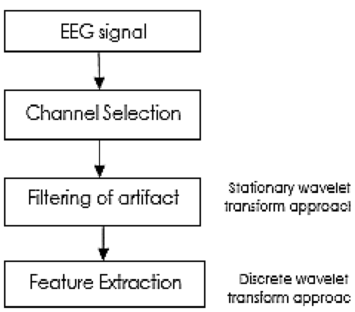
Graphical abstract



Abstract

This recent study introduces and discusses briefly the use of wavelet approach in removing the artifacts and extraction of features for electroencephalography (EEG) signal. Many of new approaches have been discovered by the researcher for processing the EEG signal. Generally, the EEG signal processing can be divided into pre-processing and post-processing. The aim of processing is to remove the unwanted signal and to extract important features from the signal. However, the selections of non-suitable approach affect the actual result and wasting the time and energy. Wavelet is among the effective approach that can be used for processing the biomedical signal. The wavelet approach can be performed in MATLAB toolbox or by coding, that require a simple and basic command. In this paper, the application of wavelet approach for EEG signal processing is introduced. Moreover, this paper also discusses the effect of using db3 mother wavelet with 5th decomposition level of stationary wavelet transform and db4 mother wavelet with 7th decomposition level of discrete wavelet transform in removing the noise and decomposing of the brain rhythm. Besides, the simulation result are also provided for better configuration.

Keywords: Artifact, brain signal, electroencephalography, feature extraction, filtering, wavelet approach

Abstrak

Kajian terbaru ini memperkenalkan dan membincangkan secara ringkas tentang kegunaan kaedah ubahan untuk menapis artifak dan menguraikan ciri-ciri isyarat elektroensifalograpi (EEG). Pelbagai kaedah telah ditemui oleh penyelidik untuk memproses isyarat EEG ini. Secara umumnya, pemprosesan isyarat EEG boleh dibahagikan kepada pra-pemprosesan dan pemprosesan selepas. Tujuan utama pemprosesan adalah untuk membuang isyarat yang tidak dikehendaki dan mengurai ciri-ciri penting yang terdapat dalam isyarat. Walau bagaimanapun, pemilihan kaedah yang tidak sesuai memberi kesan terhadap keputusan sebenar dan hanya membuang masa dan tenaga. Kaedah ubahan adalah antara kaedah yang berkesan digunakan untuk memproses isyarat biomedikal. Kaedah ubahan ini boleh dilakukan dalam MATLAB atau secara pengekodan yang hanya menggunakan arahan yang mudah dan asas. Dalam kajian ini, kaedah ubahan untuk memproses isyarat EEG diperkenalkan. Selain itu, kertas kerja ini juga membincangkan kesan penggunaan ibu ubahan db3 dengan tahap penguraian ke-5 dan ibu ubahan db4 dengan tahap penguraian ke-7 dalam membuang artifak dan penguraian irama otak. Selain itu, hasil simulasi juga disediakan untuk memberi konfigurasi yang lebih baik.

Kata kunci: Artifak, isyarat otak, elektroensifalographi, penguraian ciri, penapisan, kaedah ubahan

1.0 INTRODUCTION

The advancement of brain imaging technique attracts researcher to involve in the signal processing field. There are various non-invasive methods for acquisition of human brain signals such as magnetoencephalography (MEG), near infra-red spectroscopy (NIRS), electroencephalography (EEG) and functional magnetic resonance imaging (fMRI) [1]. However, among the techniques electroencephalography with 10-20 placement electrodes is popular for recording the brain signal. Generally, there are two types of EEG which are scalp or intracranial and electrocorticogram (ECoG).

In this article, the focus is on scalp or intracranial EEG which is widely used for experimental purpose. EEG is the combination of three words that are electro (refer to the recording of brain signal), encephalon (refer to the emission of the signal from the head) and graphic/gram (refer to drawing or writing) [2]. Advantages of using this technique are it able to record the signal in short time, non-invasive, high temporal resolution, less spatial resolution, and low cost [3]. Hans Berger was the first person who recorded the human brain signal using EEG in 1929 [4].

EEG obtains the brain signal by measuring the voltage fluctuations resulting from the flows of ionic current within neurons of the brain [5]. Thus, EEG technique is the most sensitive indicators reflecting thousands of brain respond towards certain stimulus and discover the brain functions [6-7]. During the EEG experiment, by using 10-20 placement electrodes there are about 19 active and 2 references channel of small discs known as electrodes are placed at different locations on the scalp surface [8].

Each of the electrodes is connected to the amplifier in order to amplify the signal to the readable data and to the EEG acquisition machine. Lastly, the signal was recorded and displayed on the graphic recorder. The arrangement of electrode is based on the lobes of cerebral regions of the brain; temporal, parietal, frontal and occipital. Figure 1 shows the arrangement of 10-20 placement of electrode. The biggest influence to EEG comes from electrical activity in cerebral cortex due to its surface position [9].

Brain rhythm or frequency band is an oscillation of the brain waves at specific frequencies. Brain rhythm is one of the most important elements for determining the abnormalities in people and discovering functional behaviour in cognitive research [10]. It can be divided into 5 types that are delta, theta, alpha, beta and gamma. Table 1 briefly discusses the frequency range and roles of the brain rhythm. The amplitude of EEG signal is about 1 to 100 µV in normal adult [10]. Since, the characteristics of EEG signal that have non-stationary and small amplitude it is easy to be corrupted by high and low artifact such as electromyography (EMG) signal (muscle movement), power line interference and electrooculography (EOG) signal (eye movement and blinking). Artifacts can be defined as the unwanted signals that presence in the acquisition process [2]. The presence of artifact could change the characteristics of the EEG signal and may lead to wrong interpretation of the data, thus affect the actual result [2].

Table 1 Descriptions of the human brain rhythm [2]

Brain Rhythm	Founder	Range (Hz)	Roles
Delta	Walter (1936)	0.5-4	Deep sleep or waking state
Theta	Wolter and Dovey (1944)	4-8	Access to unconscious material, creative inspiration and deep meditation
Alpha	Berger (1929)	8-13	Relaxed awareness without attention and concentration
Beta	Berger (1929)	13-30	Active thinking, active attention /concentration, focus on the outside world, or solving concrete problems
Gamma	Jasper and Andrew (1936)	Above 30	Related to the movement, sensory processing and solving high cognitive task

The subjects might blink during the experiment time, which cause the EOG artifact to appear in the EEG signal. Meanwhile, when the subject moves the EMG artifact will be generated. Due to these reasons, the raw EEG signal needs to be processed before further analyzing process. Objectives of EEG signal processing are to enhance and examine some interesting characteristics of the EEG signal that correlate with the brain functions. The basic flow involves in EEG signal processing are data acquisition, data processing (pre-processing and post-processing) and data analysis. There are three steps involved in data processing that are a digitization of raw data, filtering of artifacts and feature extraction.

1.1 Digitization of Raw Data

The brain signal was displayed and saved in analog data in the EEG signal. Analog signals are continuous in time domain. The analog data present at every point of the time. Meanwhile, the digital signals represent the signal in discrete point with time. Before further processing, the analog signals need to be converted to a digital signal. In EEG acquisition machine, the multichannel analog-to-digital converters (ADCs) will convert the analog signal to digital function by saving the data in ASCII format.

The aim of conversion is to make it to be readable by the signal processing software such as MATLAB and LABVIEW [11].

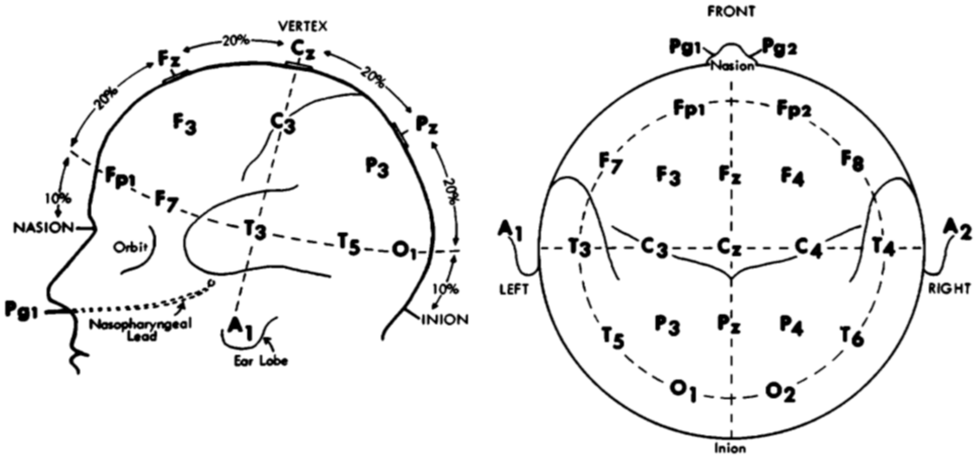


Figure 1 10-20 placement electrode system of Electroencephalography [2]

1.2 Artifact Removing

The main objective of signal filtering is to remove or eliminate the unwanted signal from EEG. This step is essential before analyzing processes to avoid the misinterpretation of the result. There are several methods have been introduced and discussed in the literatures for signal filtering. The simple filter such as low-pass filter, high-pass filter, band-pass filter, adaptive filters and visual inspection has been introduced by the researchers [12, 13]. According to Palendeng, [14] the simple filtering technique cannot fully remove the noise in the EEG signals. Currently, the independent component analysis (ICA) method has been applied to EEG signal for removing the noise. ICA method proves that it is effective to be used for removing the muscle artifact that generated by the eye-movements. However, ICA method cannot be applied for certain cases and requires much time to process the signal [1].

1.3 Feature Extraction

The most important part to study the effect of stimulus on brain signal is by analyzing the features extracted from EEG signals. This process is usually done after the filtering process. The extraction can be done in time domain or frequency domain depends on the requirement of the study. The examples of time domain features are mean, standard deviation, range, mode and median. Meanwhile, the examples of frequency domain features are energy, power and entropy. The method such as fast fourier transform (FFT), adaptive auto regressive parameters (AAR), Genetic algorithms (GA), independent component analysis (ICA) and wavelet transformations (WT) are widely used for extracting the required features [1, 15].

The aim of this study was to introduce the application of the wavelet transform in filtering and feature extraction process. The wavelet approach was selected since it is suitable to be used for biomedical signal such as EEG signal for processing purposes. The raw signal obtained from the EEG acquisition machine is in time-domain which only provides the signal amplitude and time information [14]. Thus, the time domain signal should be transformed to frequency domain for getting more information about the signal characteristics. The wavelet transform is able to obtain the information in time or frequency domain. Thus, it provides the user to select which particular information they required. Besides, it is also effective in removing the EMG and EOG artefacts in the EEG signals. In this study, the steps flow involved in stationary wavelet transform and discrete wavelet transform for EEG signal processing are discussed. Some of the important commands used in MATLAB are also provided as a reference for the reader.

1.4 Wavelet

The wavelet transform is the best technique for signal filtering process. The method provides high quality and flexibility in removing the noise of images and signals [16]. Furthermore, it was the simplest method for extracting the brain rhythm at a specific frequency by decomposition process. The advantage of using wavelet approach is it capable to disclose important information in EEG signal [15]. The discontinuities, self-similarity, breakdown points and trends are among the disclose information of the signal [17].

1.4.1 Discrete Wavelet Transform (DWT)

The multiresolution analysis was used in discrete wavelet transform to present the information of the signal [14]. The signal in discrete wavelet transform is computed using high pass filter and low pass filter. Besides, from being used as a filter to remove the artefact, it also can decompose the EEG signal to the alpha, beta, theta, delta and gamma rhythm. According to Mallat [18], fastest algorithm of approximation and detail of discrete wavelet transform can be defined as:

$$A_k(n) = \sum_{i=-\infty}^{\infty} g(l-2n)A_{(k-1)}(l) \quad (1)$$

$$D_k(n) = \sum_{i=-\infty}^{\infty} h(l-2n)A_{(k-1)}(l) \quad (2)$$

where, *k* and *l* are the discrete points of the data, $A_k(n)$ represents the approximation at level *k*, $D_k(n)$ is the detail at level *k*, g is the low pass filter, *h* is the high pass filter and *n* is the number of sample [19].

The filtering process of discrete wavelet transform involve of down-sampling method. It decomposes the signal through a low pass filter and high pass filter to produce approximation and detail coefficient (see Figure 2). The approximation contains low frequency of signal, but the detail contains high frequency of signal. The decomposition process will decrease the frequency of coefficient into half. This process continues until the required frequency band is obtained for analysis purpose.

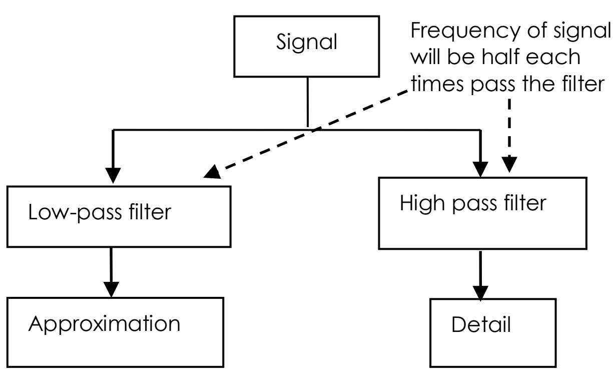


Figure 2 Approximation and detail derived by passing through low-pass and high pass filter [20]

1.4.2 Stationary Wavelet Transform (SWT)

According to Palendeng, [14], the stationary wavelet transform is the best wavelet transform approach for filtering the time domain signal since it is able to improve the power of the filtering signal. It uses the sample method at each level of decomposition for the signal [20]. The stationary wavelet transform produces the approximation and details coefficient at the same length as the original signal during decomposition process [14] (see Figure 3). The approximation is produced when original signal convolves with the low pass filter, whereas detail level is produced when original signal convolves with the high pass filter [14]. According to [21], the coefficient of stationary wavelet transform can be defined as:

$$cA_{j,k}^{SWT} = \sum_n cA_{j-1,k+2^j(n)}^{SWT} g(n) \quad (3)$$

$$cD_{j,k}^{SWT} = \sum_n cD_{j-1,k+2^j(n)}^{SWT} h(n) \quad (4)$$

where, $cA_{j,k}^{SWT}$ represents the approximation coefficient, $cD_{j,k}^{SWT}$ is the detail coefficient, *g(n)* is the low pass filter, *h(n)* is the high pass filter, and *j*, *k* is the number of level decomposition level.

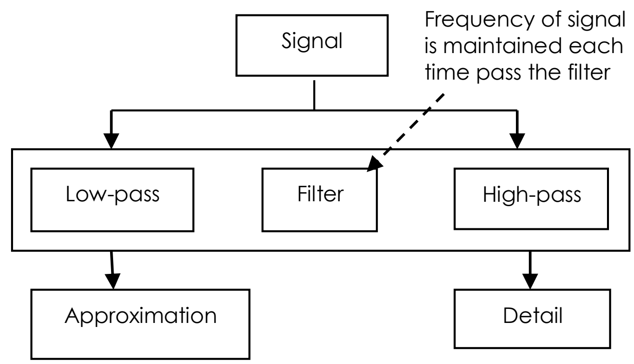


Figure 3 Decomposition of stationary wavelet transform

2.0 PROPOSED METHODOLOGY

The datasets used in this study are taken from an experiment conducted at the laboratory using EEG acquisition machine with 10-20 placement electrode system. The volunteer subject needs to memorize the visual working memory task in 2 minutes at silence condition. The EEG signal was recorded during the memorizing process. Each set contains 19 channels of EEG segments of 2 minutes duration. The signal was sampled at 500 Hz. The dataset was saved in ASCII format for easily to be processed in the MATLAB software. Figure 4 shows the block diagram of the EEG processing for this study. There are 4 steps involved that are acquisition of the EEG signal, channel selection, filtering noise and feature extraction.

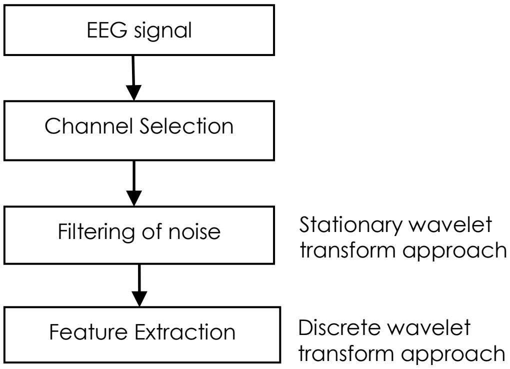


Figure 4 Block diagram of proposed methodology

2.1 Channel Selection

Among the nineteen channels only 10 (Fp1, Fz, F8, T3, T4, T5, Pz, T6, O1 and O2) of them were selected for processing stage. These channels are selected since they are related with the human memory, attention level and cognitive processing. Each of the channels represents different roles in the brain that are:

a) Fp1: Attention
b) Fz: Working memory
c) F8: Emotional expression (joy, happy, happiness)
d) T3: Verbal memory
e) T4: Emotional memory
f) T5: Verbal understanding
g) Pz: Cognitive processing
h) T6: Emotional understanding and motivation
i) O1: visual processing
j) O2: visual processing

2.2 Filtering of Artifact

In this study, the SWT is proposed to remove the EOG and EMG using Daubechies 3 (db3) of mother wavelet [19]. The original signal is decomposed to five levels. The following are commands used to call the wavelet function [19].

```
% Decomposed using swt
[swa,swd]=swt(s,5,'db3');

% Denoise the signal using thresholding method
[thr,sorh]=ddencmp('den','wv',s);
dswd=wthresh(swd,sorh,thr);

% Reconstruct the denoised signal
signal=iswt(swa,dswd,'db3');
```

There are four steps involved in removing the artifact as shown in Figure 5. At first, the signal was decomposed to five levels and will be split into two parts using low pass and high pass filter. The approximation and details were produced at different frequency resolution component as in Figure 6 [14]. Then, the EMG is removed from details signal.

As discussed before the details consist of high frequency component, whereas approximation has a low frequency signal. The third step is the reconstruction of signals. Lastly, the threshold method was applied to remove the EOG signal. The EEG signal was considered clean after going through the steps.

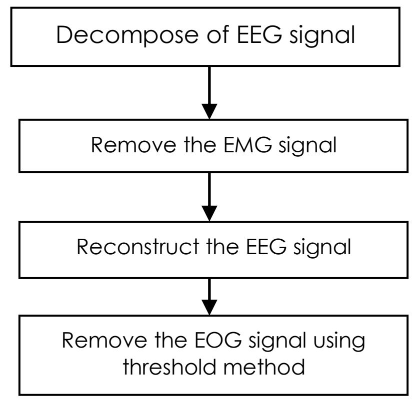


Figure 5 Filtering steps of stationary wavelet transform

2.3 Feature Extraction

After filtering process, the signal was passed to discrete wavelet approach. Since, the EEG data has 500 Hz of frequency, thus 7 levels of decomposition were chosen for gamma (D4), beta (D5), alpha (D6), theta (D7) and delta (A7). The EEG signal is decomposed to approximation and details after passing through low pass filter and high pass filter. The frequency will be reduced to half every time the signal pass through the filter as illustrated in Figure 7. The MATLAB commands for the DWT approach are:

```
% To perform 7 level decomposition of a signal
[C,L]=wavedec(signal,7,'db4');
[cD1,cD2,cD3,cD4,cD5,cD6,cD7]=detcoef(C,L,[1,2,3
,4,5,6,7]);

% Reconstruct the level 7 approximation from c
A1=wrcoef('a',C,L,'db4',1);
A2=wrcoef('a',C,L,'db4',2);
A3=wrcoef('a',C,L,'db4',3);
A4=wrcoef('a',C,L,'db4',4);
A5=wrcoef('a',C,L,'db4',5);
A6=wrcoef('a',C,L,'db4',6);
A7=wrcoef('a',C,L,'db4',7);

% Reconstruct the level 7 details from c
```

```
D1=wrcoef('d',C,L,'db4',1);
D2=wrcoef('d',C,L,'db4',2);
D3=wrcoef('d',C,L,'db4',3);
D4=wrcoef('d',C,L,'db4',4);
D5=wrcoef('d',C,L,'db4',5);
D6=wrcoef('d',C,L,'db4',6);
D7=wrcoef('d',C,L,'db4',7);
```

The last step is feature extraction from the brain rhythm. The mean and standard deviation are extracted for time domain as shown in equation (5) and (6) and energy and power are extracted for

$$Mean: xi' = \frac{\sum_{j=1}^{n} x_{ij}}{n} \tag{5}$$

$$Standard\ deviation: \sigma_i = \left(\frac{1}{n-1}\sum_{i=1}^{n}(x_{ij} - x_i')^2\right)^{\frac{1}{2}} \tag{6}$$

$$Energy: E = \sum_{j=1}^{n} |x_{ij}|^2 \tag{7}$$

$$Power: P = \left(\frac{\sum_{i=1}^{n} x_{i2}}{n}\right)^{\frac{1}{2}} \tag{8}$$

where, x_{ij} represents the elements of the transform and n represents the length of the wavelet transform.

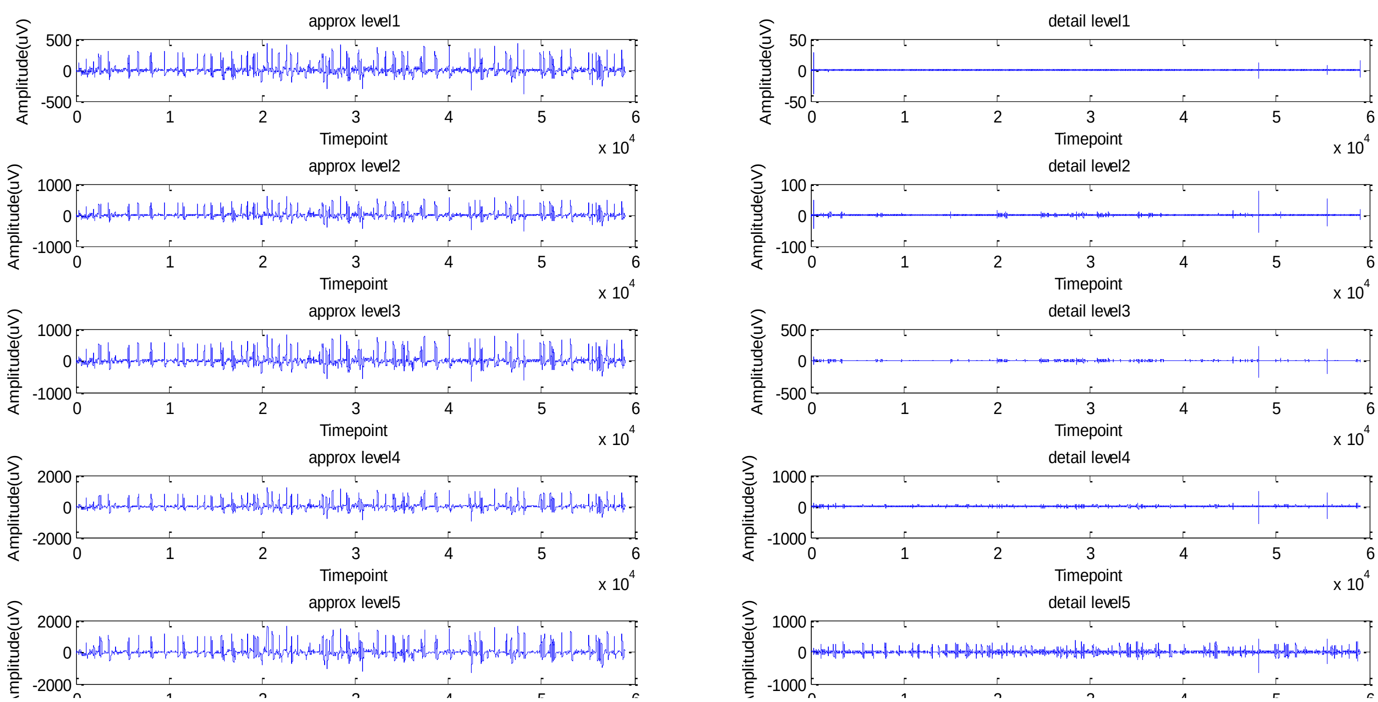


Figure 6 Approximation and detail signal after decomposition process of SWT approach

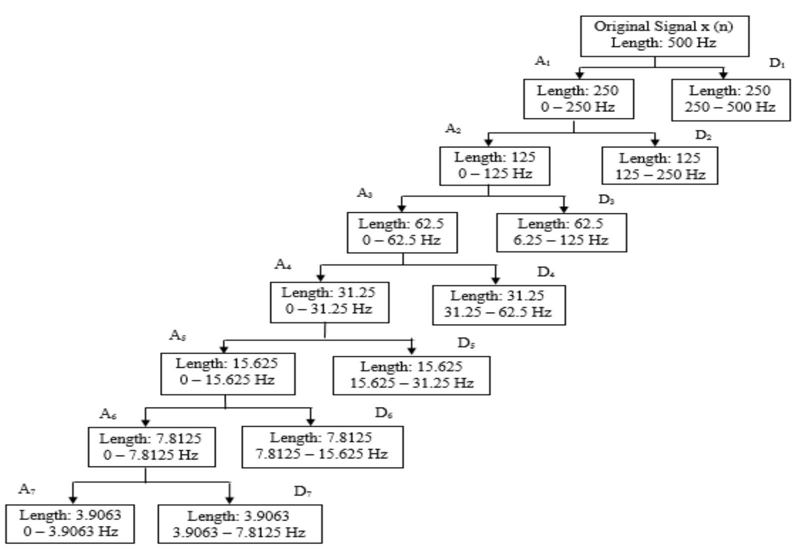


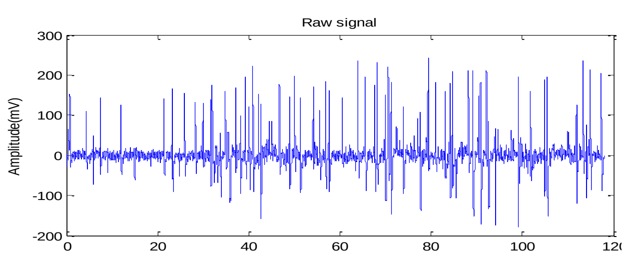
Figure 7 Decomposition level of DWT approach for 500 HZ frequency sampling of EEG signal

3.0 RESULT AND DISCUSSION

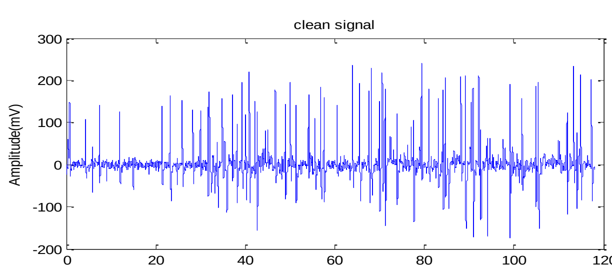
This section shows the simulation result of EEG signal after filtering and decomposing using stationary wavelet transform and discrete wavelet transform. Besides, the time domain and frequency domain features also are extracted from the EEG signal

3.1 Artifact Removing

Figure 8 shows the simulation result for EEG signal before and after filtering process using stationary wavelet transform approach. The db3 mother wavelet was chosen because it has spiky characteristic. It is suitable to be applied to EEG signal because the EMG and EOG artefact have spiky characteristic, thus this mother wavelet can remove the noise effectively compare to others. The other wavelets that might suitable for filtering process are symlets and coiflets [23]. Besides, the stationary wavelet transform is in time invariant and has a better sampling rate in the low frequency band. The advantage of using stationary wavelet transform in filtering process is the time invariant property does not lose [14]. It is because this approach does use down-sampling on its decomposition compare to other approaches such as independent component analysis and fourier transform. Preserving the time invariant property of the signal is important because it determines the characteristics of the signal. According to study in [22], the decomposition at level 5 is better since it has lower mean square error value and high peak-to-signal noise ratio compare to other decomposition level. It indicates that more noise are removed from the signal [22].



(a)



(b)

Figure 8 Electroencephalography signal at channel Fp1 (a)Before filtration (b) After filtration

3.2 Decomposition of Brain Rhythm

Figure 9 shows the simulation result of alpha, beta, theta, delta and gamma rhythm after decomposition process for 120 seconds duration. This rhythm shows the activity of the brain during the subject memorize the task. Brain rhythm represents the oscillation of neuron in the brain. Thus, to determine its activity, the brain rhythm signal should be simulated first before feature extraction. Discrete wavelet transform is among the approach that able to decompose the brain rhythm. The db4 mother wavelet was chosen because it is more appropriate to detect the changes of EEG signals and give better accuracy [24].

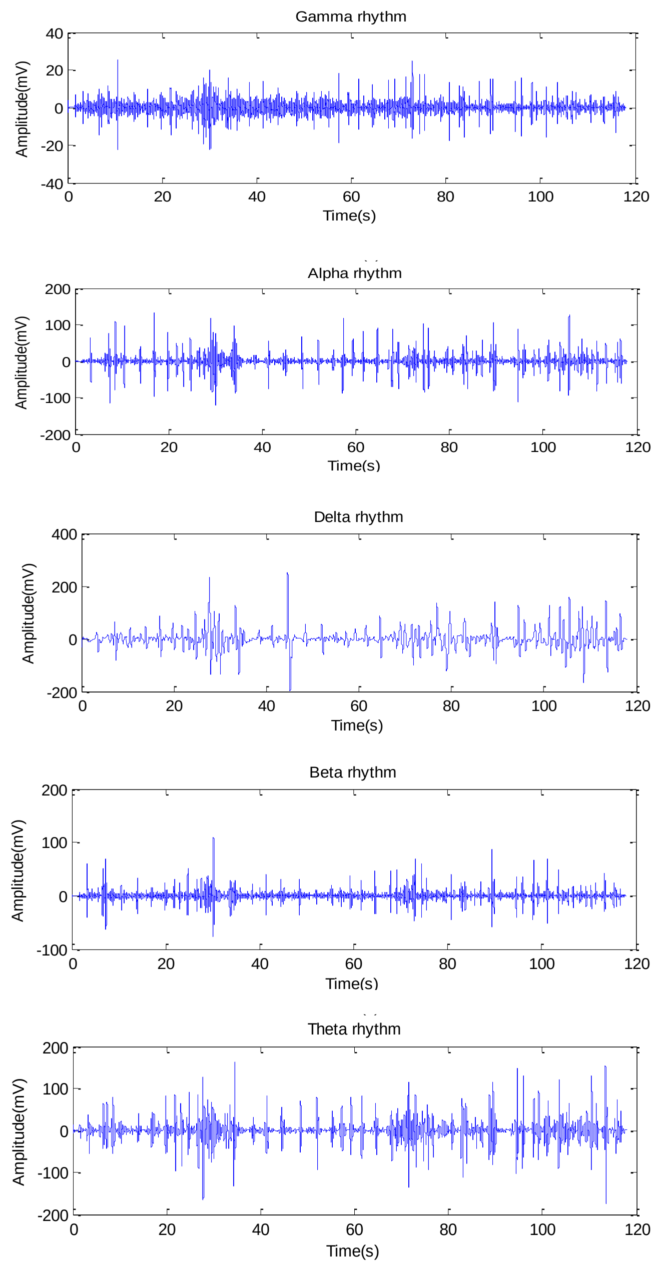


Figure 9 Brain Rhythm signal after decomposition using discrete wavelet transform

3.3 Feature Extraction

Commonly, after obtaining the brain rhythm's signal, the features of the EEG signal were extracted. The reason is visualization on the signal only does not enough to interpret the information from the signal. Thus, the time domain or frequency domain is extracted from the signal for analysing stage. In this study, some of the features that can be extracted from the EEG signals are shown. Table 2 and 3 show the EEG features in time domain (mean and standard deviation). Meanwhile, Tables 4 and 5 show the frequency domain (energy and power).

Table 2 Mean (μV/Hz) of the brain rhythm

Channel	Gamma	Beta	Alpha	Theta	Delta
Fp1	0.0001	0.0000	0.0009	0.0016	0.1797
Fz	0.0000	0.0000	0.0003	0.0012	0.2107
F8	0.0001	0.0000	0.0009	0.0018	0.1707
T3	0.0000	0.0001	0.0026	0.0014	0.2018
T4	0.0000	0.0000	0.0003	0.0010	0.2037
T5	0.0000	0.0006	0.0027	0.0011	0.1548
Pz	0.0001	0.0001	0.0009	0.0012	0.2171
T6	0.0001	0.0003	0.0007	0.0011	0.2086
O1	0.0000	0.0007	0.0009	0.0015	0.2123
O2	0.0000	0.0004	0.0017	0.0012	0.2606

Table 3 Standard deviation ($\mu V/Hz^{1/2}$) of the brain rhythm

Channel	Gamma	Beta	Alpha	Theta	Delta
Fp1	2.37	7.73	16.94	24.68	36.35
Fz	1.39	4.54	8.66	10.04	16.12
F8	1.35	4.61	9.36	12.54	21.82
T3	1.41	4.05	7.52	7.85	13.67
T4	1.39	4.04	7.56	8.64	15.29
T5	1.77	4.61	7.67	7.69	13.62
Pz	1.52	4.46	7.89	8.40	14.09
T6	1.47	4.32	7.50	7.95	13.63
O1	1.89	5.04	8.03	8.16	13.77
O2	1.73	4.88	7.86	7.96	13.65

Table 4 Energy (μkV^2) of the brain rhythm

Channel	Gamma	Beta	Alpha	Theta	Delta
Fp1	331	3529	16929	35924	77962
Fz	115	1219	4424	5953	15330
F8	109	1256	5173	9285	28100
T3	117	968	3342	3638	11033
T4	114	965	3377	4404	13799
T5	185	1257	3470	3491	10952
Pz	136	1174	3674	4170	11713
T6	128	1104	3324	3730	10970
O1	212	1500	3805	3929	11196
O2	177	1405	3646	3736	11000

Table 5 Power ($\mu V/Hz^{1/2}$) of the brain rhythm

Channel	Gamma	Beta	Alpha	Theta	Delta
Fp1	5.63	59.84	287.05	609.13	1321.93
Fz	1.95	20.67	75.02	100.95	259.94
F8	1.85	21.30	87.72	157.44	476.47
T3	2.00	16.42	56.67	61.69	187.09
T4	1.94	16.38	57.27	74.69	233.98
T5	3.15	21.32	58.85	59.20	185.72
Pz	2.32	19.91	62.30	70.71	198.62
T6	2.18	18.73	56.37	63.26	186.02
O1	3.60	25.44	64.53	66.62	189.85
O2	3.02	23.84	61.83	63.36	186.52

4.0 CONCLUSION

In this paper, the application of wavelet approach on filtering the artifact and feature extraction for electroencephalography signal has been discussed. The stationary wavelet transform is applied in removing the muscle movement and eye blink/movement artifact. The result shows that the stationary wavelet transform able to remove this artifact after decomposition process. Meanwhile, the discrete wavelet transform is applied for decomposing the alpha, beta, delta, gamma and theta rhythm. After obtaining the brain rhythm the features likes mean, standard deviation, energy and power are extracted from the EEG signal. It shows that by applying wavelet approach on EEG signal the features can be extracted whether in time domain or frequency domain. The wavelet approach is suitable to be used for the beginner in processing the biomedical signal, since it does not need a deep knowledge to apply this approach.

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