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Sleep Disorder Detection and Identification

Dennis E.B. Tan, Ren Sin Tung, Wai Yie Leong, Joel Chia Ming Than

University Tunku Abdul Rahman (UTAR),
Jalan Genting Kelang, 53300 Setapak, Kuala Lumpur, Malaysia

Abstract

Electroencephalogram (EEG) has been widely used for capturing the electrical human's brain activities for diagnosis and treatment purposes. One of the applications of EEG is to detect the sleep disorders include insomnia and stress-related-disorder depend on the severity of the disorders. In this study, Ensemble Empirical Mode Decomposition (EEMD) method which is modified original Empirical Mode Decomposition (EMD) algorithm will be employed for recognition and identification of the EEG patterns and features. Besides that, ICA was applied to assist the process of isolating noise components and to explain the functions of different brain parts through the topographical scalp map. The application of ICA has shown to be an efficient tool for artifact extraction from EEG. Finally, with the combination of EEMD and ICA methods, the music stimulation has been proved that it can enhance the sleep quality of human compare to non-music stimulation.

Keywords: Electroencephalogram (EEG); Empirical Mode Decomposition (EMD); Ensemble Empirical Mode Decomposition (EEMD); Independent Component Analysis (ICA); music stimulation.

1. Introduction

Empirical Mode Decomposition (EMD) is an adaptive time-frequency data analysis method for analyzing non-linear and non-stationary signals. Basically, EMD will decompose the EEG data into a set of Intrinsic Mode Decomposition (IMF) components as the basis representing data. Due to the major drawback of original EMD algorithm, so called mode mixing effect, the improved Ensemble Empirical Mode Decomposition (EEMD) which is employ noise-assisted data analysis (NADA) method in this study to ameliorate the efficiency of the EMD and alleviate the effect of mode mixing [1]. Independent Component Analysis (ICA) is a popular technique that used widely for separating the noise or artifacts from the EEG signals. ICA technique not only able to separate the brain activities from non-brain activities, it is also used to study the brain activities by an EEG analyst in order to determine the brain disorders. By using ICA as a tool to blindly separate overlapping EEG signals and artifacts into independent sources, one's is able to perform elimination on the unwanted signal such as noise or artifacts and reconstruct the noiseless EEG recording which is then used for diagnosing the brain disorder [2].

2. Methodology

2.1 Experiment Setup

In this experiment, the music will be applied onto the test subject to observe and analyze the sleep pattern. The main objective of this study is to recognize the sleep patterns and analyze the effect of music to human sleep quality by EEMD method and ICA which is provide the time-frequency domain. Test subjects who are participated in the experiment should

* Corresponding author. Tel.: +603-41079802; fax: +603-41079803.
E-mail address: milktea1226@hotmail.com，hotohori_sin@hotmail.com, waiyie@ieee.org, joeltc1@mail2.utar.edu.my

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at least remain 12 hours of incessant wakefulness and after a day of normal activity. The EEG gold plate electrodes will place according to the 10-20 EEG electrode placements to capture the brain signals. There are five channels of the scalp which are C3, C4, O1, O2 and A1 (mastoid area) had been chosen for the collection of EEG signal. C3 and C4 are the locations which related to the electrical activity in somato-sensoric brain areas [3]. O1 and O2 are related to electrical activity in the primary and secondary visual areas [3]. A1 is serving as reference electrodes. CamNtech Actiwave EEG System is used to perform the data collection. The Actiwave Recorder is used to collect and record the EEG signal and the CamNtech Interface Dock acts as a reader to show the EEG data collection from the recorder. Before the experiment is carried out, the test subjects need to follow the construction as show in Fig 1. The scenario under condition of sleep with aid of music is shows in Fig 2.

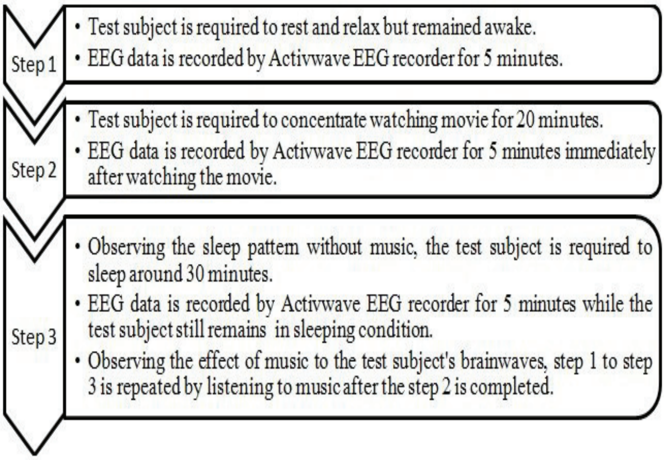


Fig 1: Procedures of the experiment.

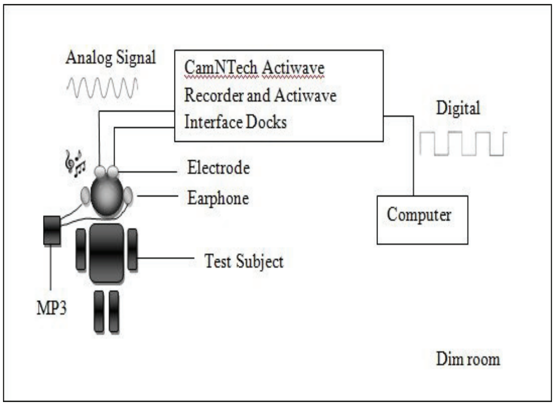


Fig 2: Schematic of the experiment in step 3.

2.2 Signal Processing Techniques

2.2.1 Empirical Mode Decomposition (EMD)

EMD is a method that can be adaptively decomposed any complicated data set into IMF component. IMFs are functions that need to satisfy two conditions [1]:

a) In the whole time series, the number of extrema and the number of zero crossings must be either equal or differ at most by one.
b) At any point in the time series, the mean value of the envelopes which is defined by local maxima (upper envelope) and local minima (lower envelope) is equal to zero.

For EMD method, the sifting process is repeated until an IMF is obtained. ‘Stopping criteria’ is the determination of number of sifting steps to produce IMF. Basically, the concept is to identify all of the local extrema which is defined by local maxima and local minima. All of the local maxima will be connected together to obtain the upper envelope while the local minima will also linked by each other to produce the lower envelope [4]. Their mean is designated as m_1 and the difference between original data, $x(t)$ and m_1 is the first component, h_1 as shows as following:

$$h_1 = x(t) - m_1 \quad (1)$$

Elimination of the riding wave and produce more symmetrical wave-profile is actually done by sifting process [5]. This is the reason of sifting process is required to repeat several times. For the second sifting process, h_1 is treated as the data:

$$h_{11} = h_1 - m_{11} \quad (2)$$

Sifting process will be continued up to k times when h_{1k} has fulfilled the two conditions of IMF to become first IMF component, c_1 :

$$h_{1k} = h_{1(k-1)} - m_{1k} \quad (3)$$

where $$c_1 = h_{1k} \quad (4)$$

Determination of criterion to stop the sifting process is important to ensure the IMF components contain enough physical sense of both amplitude and frequency modulations. Therefore, standard deviation, *SD*, criteria is applied by limiting its size:

$$SD = \sum_{t=0}^{T}\left[\frac{|(h_{1(k-1)}(t) - h_{1k}(t))|^2}{h_{1(k-1)}^2(t)}\right] \quad (5)$$

The typical value of *SD* can be set between 0.2 and 0.3. The original signal, $x(t)$ then is separated with the first IMF component, c_1 through

$$x(t) - c_1 = r_1 \tag{6}$$

Residue r_1 is taking as new data since still contains information of longer period components. The process will be repeated:

$$r_1 - c_1 = r_2$$
$$\ldots\ldots$$
$$r_{n-1} - c_n = r_n \tag{7}$$

Finally, the equation (6) and (7) are summing up and express as sun of all the IMF components and the residue signal:

$$X(t) = \sum_{i=1}^{n} c_i + r_n \tag{8}$$

2.2.2 Ensemble Empirical Mode Decomposition (EEMD)

EEMD is the improved EMD method to eliminate and reduce the effect of the mode mixing as mentioned before. When the signal is intermittent, means not continuous, will result as affecting the characteristic component of different time scales, an IMF component can crease their physical meaning of the original signal since the interruption of signal is occur to perturb the time-frequency distribution. EEMD is a method which applied the white noises in the original signal where the true IMFs components act as the mean of an ensemble of trials. The added white noise would populate the whole time-frequency space uniformly, facilitating a natural separation of the frequency scales that alleviate exist of mode mixing [6]. The collection of white noise will cancels each other out in a time space ensemble mean, so only the signal can survive in the final noise-added signal ensemble mean [7]. According to the [8], there are two situations will be shown as mode mixing exist, which are:

a) A Single IMF component of the signal contains a various component of scales;
b) Same components exist in different scales of IMF.

This NADA method, so called EEMD is developed as following [7,8]:

a) A white noise series is added into the signal,

$$X_i(t) = x(t) + w_i(t) \tag{9}$$

where $w_i(t)$ is i^{th} copies of white noise.

b) The added white noise's signal is process to decompose into IMF components.
c) Step 1 and step 2 are repeated with different white noise series each time.
d) Obtain the (ensemble) means of corresponding IMFs of the decomposition as final result.

$$c_j(t) = \lim_{N\to\infty} \frac{1}{N} \sum_{k=1}^{N} C_{jk}(t) \tag{10}$$

2.2.3Fast Independent Component Analysis (ICA) Algorithm

The basic idea is to first whiten the data using PCA and then, based on the whitened data matrix **X**, search for a solution in the form of $\mathbf{s} = \mathbf{w}^T\mathbf{x}$, where **s** and **x** are columns of the source matrix and whitened data matrix, respectively. Or equivalent in matrix from:

$$S = WX \tag{11}$$

where $\mathbf{W} = \mathbf{A}^T$ is the demixing matrix. The algorithm optimizes the objective function, which estimates the sources **S** by approximating statistical independence. The algorithm starts from an initial condition, e.g. random demixing weights **w**. Then, on each iteration step, the weights **w** are first updated, so that the corresponding sources become more independent and then normalized, so that **W** stat orthonormal. The iteration is continued until the weights converge. For example, when using *cubic* nonlinearity, which corresponds to estimating kurtosis, the fixed-point update rule becomes:

$$\mathbf{w}^+ = E\,\{\mathbf{x}(\mathbf{w}^T\mathbf{x})^3\} - 3\,\|\mathbf{w}\|^2\mathbf{w} \tag{12}$$

To begin with derivation of the algorithm, we shall show the one-unit version of FastICA whereby the one-unit refer to a computational unit, eventually an artificial neuron, having a weight vector **w** that the neuron is able to update by learning rule. The FastICA learning rule will find a direction, ie. a unit vector **w** such that the projection $\mathbf{w}^T\mathbf{x}$ maximizes nongaussianity. The variance of $\mathbf{w}^T\mathbf{x}$ must be constrained to unity; for whitened data this is equivalent to constraining the norm of **w** to be unity.

The FastICA is based on fixed-point iteration scheme for finding a maximum of the nongaussianity of $\mathbf{w}^T\mathbf{x}$**.** The derivation of FastICA is as follows. First note that the maxima of the approximation of the negentropy of $\mathbf{w}^T\mathbf{x}$ are obtained at certain optima of E $\{G(\mathbf{w}^T\mathbf{x})\}$. According to the Kuhn-Tucker conditions (Luenberger, 1969), the optima of $E\{G(\mathbf{w}^T\mathbf{x})\}$

under the constraint E $\{(\mathbf{w}^T\mathbf{x})^2\} = \|\mathbf{w}\|^2 = 1$ are obtained at points where

$$\mathrm{E}\ \{\mathbf{x}g(\mathbf{w}^T\mathbf{x})\} - \beta\mathbf{w} = 0 \tag{13}$$

In order to solve the equation, the method that we apply here is called Newton's method. The function on the left side of equation (13) is denoted as F, we obtain its Jacobian matrix JF ($\mathbf{w}$) as

$$JF\ (\mathrm{w}) = \mathrm{E}\ \{\mathbf{x}\mathbf{x}^T g(\mathbf{w}^T\mathbf{x})\} - \beta\mathbf{I} \tag{14}$$

To simplify the inversion of this matrix, we decide to approximate the first term in equation (14). Since the data is sphere, a reasonable approximation seems to be E $\{\mathbf{x}\mathbf{x}^T g(\mathbf{w}^T\mathbf{x})\} \approx$ E $\{\mathbf{x}\mathbf{x}^T\}$ E$\{g(\mathbf{w}^T\mathbf{x})\}$ = E$\{g(\mathbf{w}^T\mathbf{x})\}\mathbf{I}$. Thus the Jacobian matrix become diagonal and can be easily inverted. Thus, we obtain the following approximate Newton iteration: [9]

$$\mathbf{w}^+ = \mathbf{w} - [\mathrm{E}\{\mathbf{x}g(\mathbf{w}^T\mathbf{x})\} - \beta\mathbf{w}] \,/\, [\mathrm{E}\{\ g(\mathbf{w}^T\mathbf{x})\} - \beta\ ] \tag{15}$$

3. Experimental Results

3.1. Pattern Recognition of EEG Signal by Applying EEMD

From the path flow of experiment which is shows in Figure 1, the test subject had been carried out the experiment under three different conditions. In this paper, we were only discussed and emphasized the pattern recognition based on EEMD methods under conditions of sleep with aid of music and without the music. IMFs which generated by both of the methods are provide us a set of data that easier for us to carry out the analysis onto original signals itself. Since the EEG pattern of channel C3 and O1 are similar to the C4 and O2, so only channel C3 and O1 will be analyzed and interpreted for pattern recognition.

Through EEMD method, the sleep patterns of test subjects without the aid of music can be detected as show in Fig 3 and Fig 4. For channel C3, the slow waves around 2-7 Hz were showed in the red frames of Fig 3A. Basically, the slow waves will occur in light sleep stage. A slow wave is less persistent, more asynchronous, lower amplitude and faster frequency compared to deep sleep [10]. For Fig 3B, it shows the occurrence of sleep spindle in the green frame of the figure. Sleep spindles normally have frequency range around 11-14Hz and widely distributed in the EEG signals. They are always appearing simultaneously over both hemispheres and approximately symmetric [10]. For channel O1, the red frames of Fig 4 also shows the appearance of slow waves around 2-7Hz. Apperance of slow waves in channel C3 and O1 always indicate the symptoms of drowsiness has been detected. From the features and characteristics of sleep patterns without music that we determined, it can be said that the test subject is in the sleep stage I after 30 minutes sleep condition since the symptoms of the drowsiness has been detected. Besides, the test subject was more likely enter to sleep stage II where the alpha rhythms do not exist and the sleep spindles are appeared. Up to sleep stage II, the sleep pattern can be consists of various mixture of rhythms such as delta, theta and alpha wave. At the initial part of this stage I, the amplitude is shown with mixed frequencies. During deeper part of stage I, the slow waves are shown in medium amplitude and may form irregularly spaced bursts. At the end of the stage I, Positive Occipital Sharp Transients (POSTs) will occur which will be emphasized later in sleep pattern with music.

A B

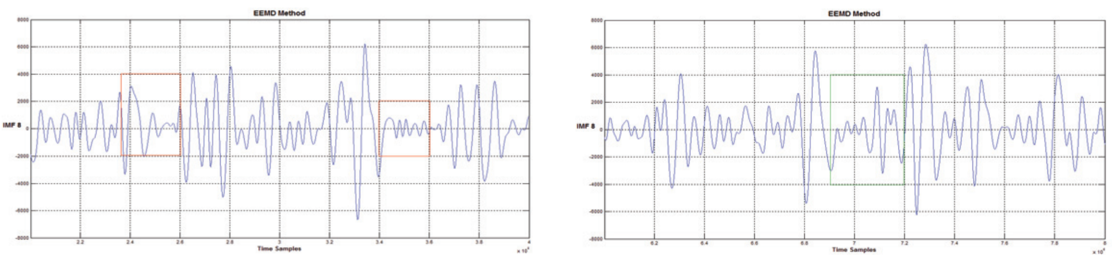


Fig 3: EEG patterns of sleeping without music in channel C3 of test subject. (A) Red frame represent slow wave occur between 2-7Hz. (B) Green frame represent sleep spindle occur.

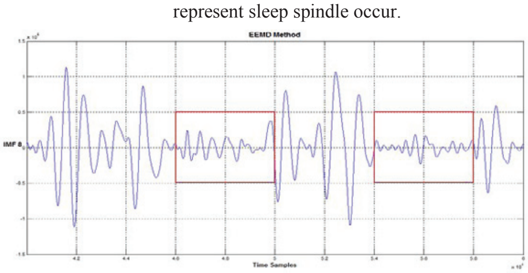


Fig 4: EEG patterns of sleeping without music in channel O1 of test subject. Red frame represent slow wave occur between 2-7Hz.

After study on the analyzed decomposed signals of sleep patterns without aid of music, the sleep patterns with music by EEMD method are shown in Fig 5 and Fig 6**.** The red frame of Fig 5A shows that the features of K-complex were able to detect by EEMD method while the green frames of Fig 5B shows the features of sleep spindles. Basically, the K-complex resembles V waves in distribution, reaction to sensory stimuli and polarity of the major component, but they are significant longer in duration (≥0.5s) and less sharply contoured [10]. For the features of sleep spindles, we have discussed previously in the part of the sleep patterns without aid of music. For channel O1, EEMD algorithms is able to detect the very slow brainwave where less than 2Hz which shows in red frame and K-complex in green frame of Fig 6A respectively. In Fig 6B, the black arrow indicates that another sleep pattern so called Positive Occipital Sharp Transient (POSTs). POSTs are monophasic or biphasic, triangle wave in occipital regions. POSTs resemble the lambda waves in shape and distribution and sometime it is named as 'lambdoid waves' [10]. POSTs always occur intermittently and spontaneously, either simultaneously or independently. They can be recurring irregularly at intervals of over 1 second but may repeat up to 4-6 times per second [10]. Since the recognition of sleep patterns with aid of music has been done, the result shown can provide us the estimation and determination of the sleep quality of the test subjects. After 30 minutes sleep condition, the test subject is actually within the sleep stages II and III. Stage II is consists of K-complex and sleep spindle. The slow wave between 2-7Hz is able to be seen and often bilaterally synchronous. POSTs could be appeared in both stage II and stage III. Presences of very slow waves with high amplitude are the main symptoms of the test subject who is in the sleep stage III. Since the disappearance of drowsiness and existence of slow wave less than 2 Hz have been recognized, the test subject can be conclude that he had entered the deep sleep stages which is sleep stage III. Through the observation on these results shown by both of the conditions, music therapy actually can enhance the human's quality of sleeping.

A B

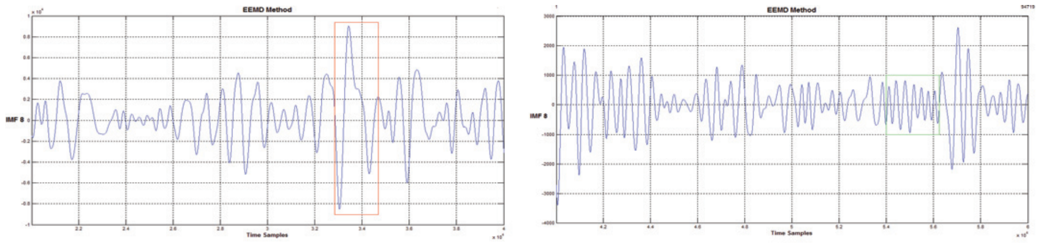


Fig 5: EEG patterns of sleeping with music in channel C3 of test subject. (A) Red frame represent K-complex occur. (B) Green represent sleep spindle occur.

A B

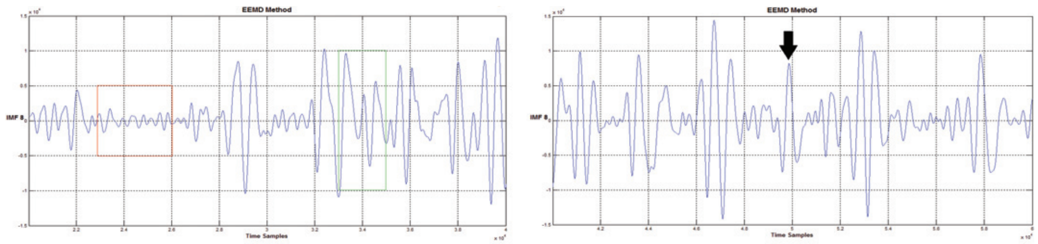
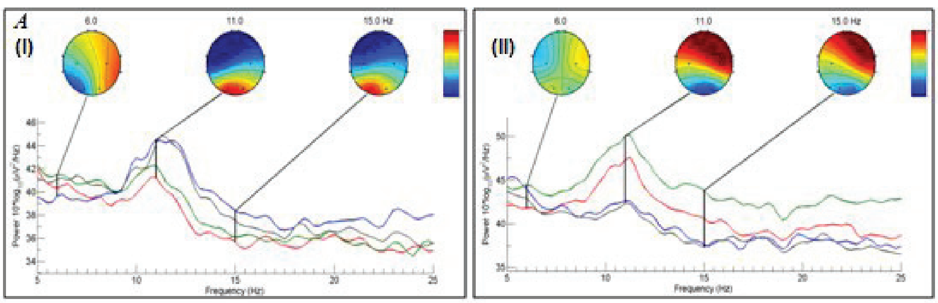


Fig 6: EEG patterns of sleeping with music in channel O1 of test subject. (A) Red frame represent slow wave less than 2Hz occur while green represent K-complex occur. (B) Black arrow represent POSTs occur.

3.2. Frequencies Determination of EEG Signals under Different Condition by Applying Fast ICA Algorithm

With the application of EEGLAB toolboxes, we have decided to choose the Spectra Analysis Method for identifying the types of brainwaves emitted by the test subject in the experiment. Spectral analysis is a mathematical approach to quantify the EEG signals and it does not provide a biophysical model of EEG generation. The purpose of using spectral analysis is the decomposition of EEG signals into constituting frequency components. Besides that, topographic EEG brain mapping is used to map the power changes across the brain regions.



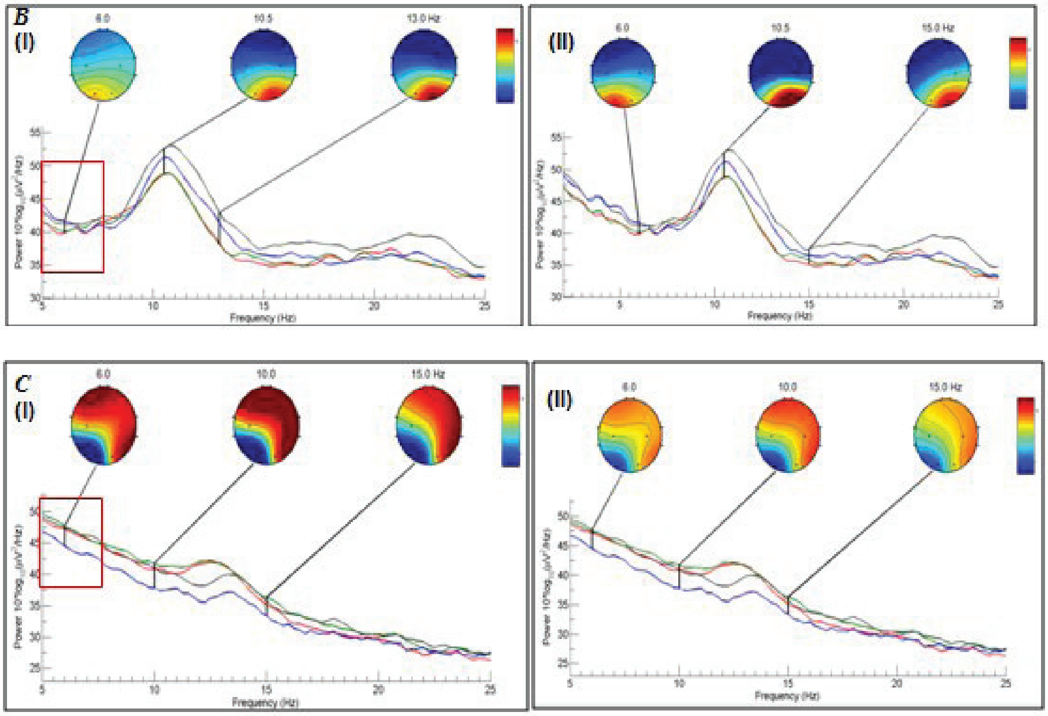


Fig 5: EEGLAB of Spectra power (μV^2/Hz) versus Frequency (Hz). 5*A* represent awakening state, 5*B* represent after 20 minutes of movie state and 5*C* represent sleeping state. Topographic brain maps of the normalized power without music stimulation and with music stimulation is shown in *C* (I) and *C* (II) respectively.

Each recorded EEG signals including awaked state, after 20 minutes of movie state and during sleeping state was processed with the FastICA algorithm. The spectra power (μV^2/Hz) versus frequency (Hz) is computed as shown in the Fig 5. As shown in the Fig 5A (I), the computed results show significant increased in amplitude approximately 45μV^2/Hz in the frequency range of 9Hz to 13Hz. As mentioned in the preceding section, higher amplitude recorded in frequency range of 8Hz to 12Hz showed that the person is in awaked state but with a relaxation mind. Hence, with the computed results support, the higher amplitude power spectra prove that the test subject was in awaked condition with a relaxing mind state.

After completing collection the EEG signals for the awaked state of the test subject, the test subject was then subjected to a 20 minutes of movie whereby he/she requires to pay full attention to the movie. After the 20 minutes of the movie, the EEG signals was then recorded for 5 minutes and the computed result showed in Fig 5B(I). After the movie stimulation to the brain area of the test subject, the result show significant amplitude changed in the frequency range of 9Hz to 13Hz. When the test subject was asked to relax at the stage 1st experiment, the computed power spectra amplitude is approximately 45μV^2/Hz. However, the power spectra amplitude is approximately 55μV^2/Hz after the test subject was exposed to a 20 minutes of movie. From the result that we obtained, we are able to prove that vision stimulation through computer screen is able to increase the brain activity of a person. Therefore, it is advisable to turn off or avoid the exposure of electronic gadgets such as iPad, iPhone or laptop whereby these devices emit radiation that would eventually lead to mild sleep disorder. [11]

For the result that shown in Fig 5C(I) whereby the test subject was in sleeping stage, the result shows that the test subject is in sleeping state as the brainwaves become slower in term of frequency and increase in amplitude during the transition from waking to sleeping. During sleeping stage, lower frequency (1Hz to 4Hz) recorded higher amplitude if compared to higher frequency (10Hz to 15Hz) which recorded lower amplitude. This shows that the test subject's brainwave become slower frequency at the sleeping stage. Furthermore, there is an increase of amplitude during the transition from waking to sleeping state. This can be shown in Fig 5B (I) (red square) and Fig 5C (I) (red square), respectively. During the sleeping state of the test subject, the spectra power amplitude is computed approximately 44μV^2/Hz in the frequency range of 1Hz to

4Hz. By comparing the result of Fig 5B (I) and Fig 5C (I), the result proves that human brainwaves become slower and increase in amplitude during the transition from waking to sleeping.

For a better insight of the EEG power changes across the brain region, a topographic EEG brain mapping is used to visualize which specific region of brain is affected during the experiment. As shown in the Fig 5A (I), the topographic mapping show a statistically mean power at the occipital region at the frequency of 10Hz to 15Hz. The increased mean power in the occipital region was due to the test subject was not closing his/her eyes during the recording EEG signals. However, the result was improved for the second repetition (with music stimulation), test subject's eyes was asked to closed and relax during the recording of the EEG signals. This improvement can be shown in Fig 5A (II) whereby the mean power of the brain mapping is distributed evenly at the frequency range of 10Hz to 15Hz.

After the 20 minutes of the movie, the topographic brain map was computed and it shows a significant power increase at the occipital region of the test subject's brain scalp. As mentioned in earlier section, occipital region of the human brain in responsible for the vision stimulation and it will become active if the vision is being stimulated.

On the other hands, Fig 5C (I) and Fig 5C (II) is showing the music effect inducing a better sleep quality to the test subject. Theoretically stated that the sleeping frequency is in between 0Hz to 4Hz, therefore, the brain mapping on the sleeping stage will be only concentrated in the frequency range of 0Hz to 4Hz. With the comparison of both figures, the brain mapping with music stimulation along the sleeping showed a significant decrease in mean power across the brain region. This result could simply imply that music is actually playing a calming role in reducing the brain activity so that one's can sleep better. [12]

4. Conclusions

To eliminate and reduce the mode mixing effect that created by original EMD algorithm, the EEMD method had been applied to increase the reliability and accuracy of the results. With the presence of NADA method, which is adding noise with zero mean in EEG data in order to protect the decomposed signals from altered or destroyed the inherent physical meaning of the original signals. By employ the EEMD method, the identification and recognition of features and characteristics under sleeping condition can be adopt well and provided useful analysis in effect of music towards the human sleep quality. The application of the ICA on the EEG data has been shown by emphasizing the power spectra analysis and human topographic maps. For the power spectra analysis, different types of brainwaves are able to identify through the computed amplitude at different stages of the experiment. In addition, the human topographic map has been plotted in order to show the specific region of the brain has been activated through a series of activity carried out by the test subject.

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