SLEEP DISORDER RECOGNITION SYSTEM

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A project report submitted in partial fulfilment of the requirements for the award of the degree of Bachelor (Hons.) of Mechanical Engineering

Faculty of Engineering and Science
Universiti Tunku Abdul Rahman

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DECLARATION

I hereby declare that this project report is based on my original work except for citations and quotations which have been duly acknowledged. I also declare that it has not been previously and concurrently submitted for any other degree or award at UTAR or other institutions.

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APPROVAL FOR SUBMISSION

I certify that this project report entitled **"SLEEP DISORDER RECOGNITION SYSTEM"** was prepared by **DENNIS TAN ENG BENG** has met the required standard for submission in partial fulfilment of the requirements for the award of Bachelor of Engineering (Hons.) Biomedical Engineering at Universiti Tunku Abdul Rahman.

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ACHIEVEMENT

Through this study, I have learned and able to analyze the results after applying signal processing techniques. Patterns recognition on EEG signals and the relationship between the effects of music to human sleep quality have been approached through several reliable and efficient results.

In addition, I was able to publish first journal, namely “Sleep Disorder Detection and Identification” in *Journal of Biomedical Science and Engineering (JBiSE)* which was accepted in February 2012. Another journal which the title is “Investigating the Effect of Music to Sleep Quality Performance” in *IEEE Transactions on Biomedical Engineering* is still under review (Both of the journals are put after last page of Appendix B). I also participated in the competition of Innovate Malaysia where the Agilent platform has been selected. Besides that, I have take part in the PRIDE competition where is held in Kuching Sarawak in July 2012 later.

SLEEP DISORDER RECOGNITION SYSTEM

ABSTRACT

Electroencephalogram (EEG) has been widely used nowadays as medical device in capturing the electrical activities of human brain for diagnosis and treatment purposes on stress related disorder especially sleep disorder. Since the severity of sleep disorder can be varies, there are different level and types of related disorder that allow us to carry out the research. In this study, the EEG was applied to mimic a scenario of a person who has light insomnia was take part in the experiment related to listen music during sleep condition through the observation of EEG signal channels. There are not only the EEG signals under condition of sleeping is investigation but also the conditions under relax and wakefulness, and after watching movie. The main purpose to conduct this experiment is to investigate and compare the effect of music to the human sleep quality and without aid of music during sleep condition. The wavelet method analysis was employed as fundamental before apply our signal processing techniques. Since the wavelet analysis is also carried out the decomposition process which is similar to our methods, the results shown by wavelet method have provided us a basis idea in processing the EEG signal. Empirical Mode Decomposition (EMD) and improved EMD so called Ensemble Empirical Mode Decomposition (EEMD) were employed to process the EEG signals from test subject. Comparison between performances in several aspects such as decomposed signals, Index of orthogonality (IO), Hilbert spectrum and so on was carried out by both of the signal processing techniques to determine the accuracy and reliability of the results. Since the EEMD method can lessen the effect of mode mixing, the results generated through EEMD are better compared to EMD method for analysis purposes. The decomposed signals which are Intrinsic Mode Functions (IMFs) whereby it is derived from both the methods were mainly used for recognition and identification of EEG patterns and features. Marginal Hilbert Spectrum which is in the form of amplitude-frequency distribution is able to provide us the results that related to the sleep stages of human in that particular time. With the capable of EEG patterns recognition and determination of sleep stages level, the determination of individual sleep quality can be analyzed and interpreted. Through this study, the demonstration of music stimulation during sleep indeed induces sleep condition to individual and the sleep quality was greatly improved compare to those without music stimulation.

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CHAPTER 1

INTRODUCTION

1.1 Background

With the advancement of the technology and competition of human being, the paces of human's life have been changed gradually. As consequences, the sleep disorder has been a major medical and psychiatric disorder among the people nowadays. According to the National Sleep Foundation (NSF), at least 40 million Americans are suffering from the sleep disorder. From these amounts, 60 percent of the adults are having sleep problems at night [1]. Another 40 percent experience daytime sleepiness which it can affect their performance in their daily activity [1]. The International Classification disorder, categories the sleep disorder into 4 major parts which are 1) dyssomnias include insomnias and excessive sleep, 2) parasomnias, 3) sleep disorders associated with medical or psychiatric disorders and 4) proposed sleep disorder [2].

In normal sleep of human, the hypothalamus is the main part to organize the sleep which involves regulation of intrinsic time clock and sleep-wake cycle (relying on cues from light) so called the circadian rhythm. Circadian rhythm is determined by an internal pacemaker which is located in suprachiasmatic nucleus (SCN) of hypothalamus. Thalamus also takes part in control of the sleep-wake cycle. Both of the hypothalamus and thalamus are primary site of origin for Rapid Eye Movement (REM) sleep which is regulated by acetylcholine from cholinergic neurons in brainstem. There are some stimulants such as amphetamines will reduce the total sleep and REM sleep time.

There are several stages for normal sleep as shows in **Table 1.1** [3]. These stages can be identified by using the Electroencephalogram (EEG), Electrooculogram (EOG) and Electromyogram (EMG). Besides that, each type of the brainwave represents different frequency ranges respectively which are shows in **Table 1.2**. In this project, the EEG is the main analysis equipment that used to capture the brain signals for verification of sleep disorder. EEG signal is the records of electrical signal that generated by the cortex and the deeper brain structure so called thalamus. Dream recall in REM frequently compare to the non-REM (NREM). Autonomic changes such as elevated blood pressure, irregular heart beat and respiration usually occur during REM. Therefore, some of the illness such as myocardial infarction and stroke usually happen during REM due to these changes. **Figure 1.1** shows that at least 10-20 electrodes are place for EEG measurement [4]. The **Figure 1.2** shows the signals that capture during each of the sleep stages by using EEG [4]. Each of the stages has their characteristic as shown in **Table 1.3** [5].

Sleep Stage	EEG Rhythms Contained
Awake	Beta, Alpha
Stage I: Drowsiness	Alpha, Theta
Stage II: Predominant sleep	Alpha, Theta, K complex, Sleep Spindles
Stage III & IV: Slow wave sleep	Delta, K complex, Sleep Spindle
REM sleep	Theta, Alpha

Table 1.1: Relationship among sleep stages and EEG rhythms.

Types of wave	Frequency (Hz)
Beta	≥ 14
Alpha	8~<14
Theta	4~<8
Delta	0.5~<4

Table 1.2: Ranges of frequency within each of the brainwave's types.

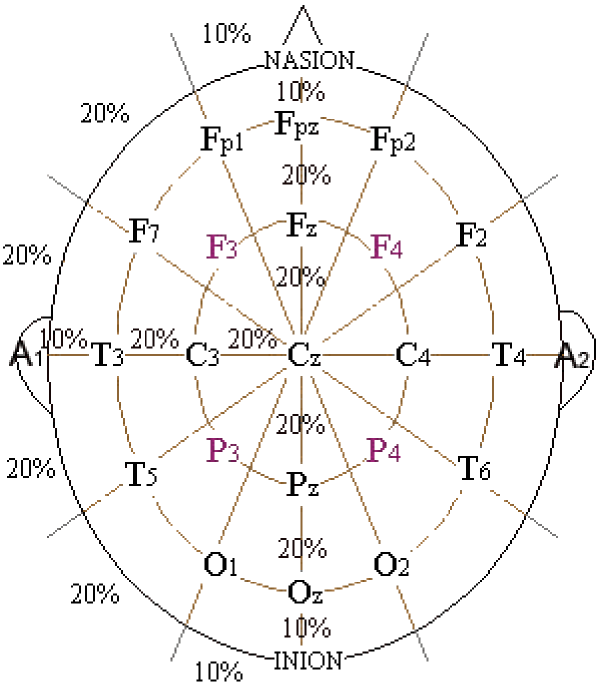

Figure 1.1: 10-20 electrodes placement system for EEG measurement.

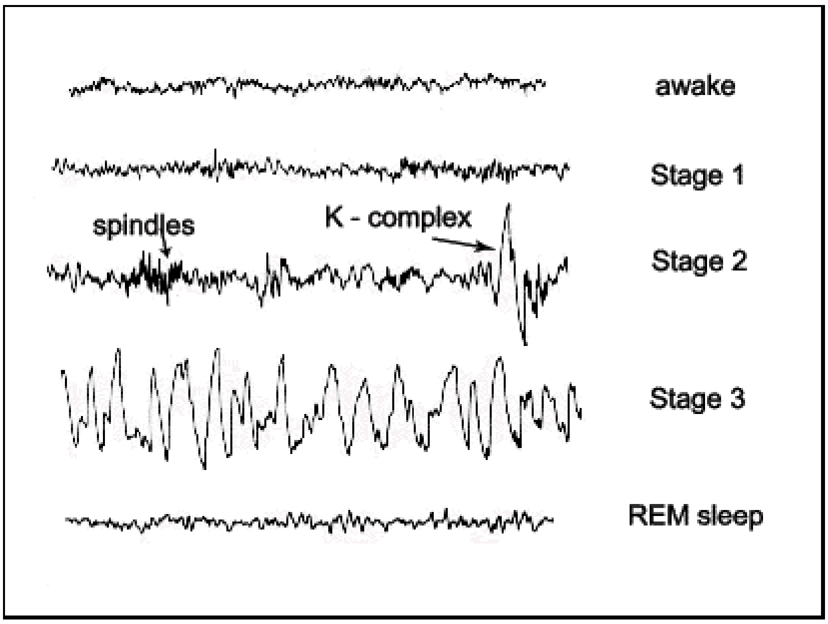

Figure 1.2: Wave pattern of different sleep stages.

Sleep stage	Characteristic each of stages
Stage I- NREM sleep	• Breathing become slowly and even. • Heartbeat becomes regular. • Blood pressure falls. • Brain temperature decreases. • Blood flow to the brain is reduced. • Little or no body movement. • Slow background activity compare to wakefulness.
Stage II- NREM sleep	• Bursts of EEG activity. • Large brain wave. • Easily be awakened by sound.
Stage III&IV- NREM sleep	• Deep sleep. • High amplitude, slow wave sleep. • Virtual oblivion. • Sleepwalker or bed wetter might begin.
REM sleep	• Brain wave small and irregular. • Dream might occur. • Cardiac problem in greater risks of heart attack. • Pulse rates increase irregular. • Blood pressure may increase drastically. • Breathing becomes irregular. • Oxygen consumption increase. • Large muscles are literally paralyzed.

Table 1.3: Characteristic of each the sleep stages.

According to the [6], sleep disorder are a group of syndromes characterized by disturbance in the patient's amount of sleep, quality or timing of sleep, or in behavior or physiological conditions associated with sleep. **Table 1.4** shows some of the main example of sleep disorder, description of each the example and factors that cause the sleep disorder [2].

Example of sleep disorder	Description	Factors and symptoms
Insomia	• Inability to initiate or maintain continuous sleep.	• Psychophysiologic factor. • Psychiatric disorder. • Anxiety (stress). • Travel across time zones or shift work.
Excessive daytime somnolence	• Excessive sleepiness.	• Sleep apnea. • Narcolepsy. • Neurologic illness. (eg. Head injury, Parkinson's disease, Alzheimer's disease and etc.)
Narcolepsy	• Chronic disorder of unknown etiology.	• Excessive sleepiness. • Sleep paralysis. • Hypnagogic hallucinations. • Cataplexy.
Circadian sleep-wake rhythm disorder	• Can be divided to delayed sleep phase syndrome, advanced sleep phase syndrome and irregular sleep-wake pattern.	• Sleep and awake lately. • Early evening sleep and early morning awakening. • Complete loss of circadian rhythm.

Parasomnias	• Undesirable motor or autonomic activity during sleep or upon arousal.	• Sleep paralysis • REM sleep behavior disorder. • Sleepwalking, night terrors and nightmares.

Table 1.4: Example of sleep disorder, description, factors and symptoms of each of disorder.

Music therapy is the clinical use of music interventional to accomplish individualized goals that address physical, emotional, cognitive and social needs. One of the designs of music therapy interventions is treatment on sleep disorder. In the recent years, a lot of researches have show that music has physiological effect to the human sleeping pattern. The researchers make use of EEG to verify the influence of music on human brain activity. Sound stimulation is one of variables which influence electrical wave occurrence in brain. Therefore, sound stimulation is applied in emotional and mental therapy to achieve the increment of certain type of wave in brain. As mention before in Table 1.4, there are a lot of factors can lead to have the sleep disorder. The severity of sleep disorder can be varying. According to the report published in the Journal of Advanced Nursing in 2009, the music-assisted relaxation is able to improve the sleep quality. Since the sleep disorder had been widely spread among public, the sleep scientists had recommend testing non-pharmacological methods that promote interaction between the mind and body to support sleep [7]. To promote sleeping condition, listening soothing music so called the music therapy had been proposed by [8] as a most frequent used strategy. The vibration created by music can have effect not only on eardrum but also other parts of bodies. It can change the way of our heart beats and the way of the blood flows around body. When listening to slow and softly strained relaxation music, mind and body is eased or lulled into a relaxed state, emptying out worrying thoughts and stressing concerns. Having the mind and body in a relaxed stage makes falling asleep easy and staying asleep a certainly. Besides that, according to the [9-11], music therapies not only induce the sleep among the human but also effectively intervention for managing stress in patient, improving subjective sleep in older adults and university students too. Music therapy offers a unique treatment approach, as music is a normal part of many facets of life. Music therapy provokes unique responses and positive outcomes due to the sense of familiarity, predictability, and feelings of security associated with music. Research indicates that music therapy is a viable treatment mode even for those who have no musical background or for those who have been resistive to other treatment approaches.

In this project, the signals that captured from brain were analyzed and processed. There are several methods to carry out the analysis. These methods can use to extract the characteristics and features of each segment of the signals. For example, Blind Source Extraction (BSE) which is a technique to extract the source signals sequentially from their mixture. Support Vector Machine (SVM) models are closely related to neural network which also performs the classification that separates the data into two categories by constructing an N-dimensional hyperplane. Learning Vector Quantization (LVQ) is a robust, very adaptive and rapidly converging classification method based on adaption of prototype vectors [12]. Besides that, wavelets transform are also one of the methods that use the mathematical functions to cut up data into different frequency components and then study each component with a resolution matched to its scale [13]. EEG data feature classification also can apply with modified fuzzy nearest neighbour. This is apply Polygon Feature Selection method which is based on the structural changes that give the unique signature of the data source to allow the discrimination of two or more sources if adequate features are extracted to represent them [14].

Since there are plenty of methods to classify the EEG signals, the Empirical Mode Decomposition (EMD) had been choose to identify the characteristic of the signals. Hilbert-Huang Transform (HHT) can be divided into EMD and Hilbert Spectral Analysis (HSA). Due to the signals that we capture from EEG which are contain a lot of noise, so HHT is applied to eliminate the noise and also identification of characteristic of signals. HHT is specifically for analyzing data from nonlinear and non-stationary processes [15]. To apply HHT, the EMD is needed to carry out the sifting process to decompose the signals to Intrinsic Mode Function (IMF) and make the wave profiles more symmetric. For HSA, it is used to obtain the instantaneous frequency of IMF and through the Hilbert Transform to present an energy-frequency-time distribution. HHT will further explain later in next sections.

1.2 Aims and Objectives

For this project, the main objective and aim is recognition of sleep disorder through collection of brain signals or data by EEG. The signals that capture from the sleep disorder patient can provide the essential information to healthcare provider for diagnosis and treatment purpose. With aid of the signal processing, the abnormal signal can be detect and determination on the patient whether he/she has specific sleep disorder. These results can be comparing with the signal which is capture from normal sleep for verification and classification of the disorder. Besides that, by carry out the analysis on the EEG signal, this project also offers the opportunities to find out some methods such as music therapy which will discuss later for improvement of human sleep quality.

CHAPTER 2

LITERATURE REVIEW

2.1 Experiment Study on Microsleep Event (MSE) to Detect the Sleep Disorder

2.1.1 Feature Fusion for the Detection of Microsleep Event (MSE)

According to the [12], the detection of sleep disorder is carried out by a scenario where is occur on a real-world problem. The methodology which applied on this experiment is to detect the sudden and non-anticipated lapses of attention in car drivers due to drowsiness so called the microsleep event (MSE). The signals are collect from several sources where is brain which observes the electric activity, pupil size variable and eye and eyelid movement. When the scientists are conduct this experiment, there are twenty-three young adults are started driving in real car driving stimulation lab as shows in **Figure 2.1** at 1.00am after a day of normal activity and of at least 16 hours of incessant wakefulness. They had to complete seven driving lessons lasting 40 minutes, each follow by a 15 minutes long period of responding to sleepiness questionnaires and of vigilance tests of a 5 minutes long break [12]. There are three video camera is used to observe these test subjects which are observe the subjects' left eye region, his/her head and upper part of body, and driving scene. There are several signs of MSE might occur such as prolonged eyelid closures, nodding off, driving accidents and drift-out-of-lane accidents.

Seven signals of EEG (C3, Cz, C4, O1, O2, A1, A2, common average reference) and two EOG channels (vertical, horizontal) were recorded by an electrophysiological polygraphy system at a sampling rate of 128 Hz. C3, Cz and C4 location of electrode is used to detect the electrical activity in somatic-sensory and motoric brain areas. O1 and O2 location are detected the electrical activity in the primary and secondary visual areas. A1 and A2 locations are served for electrode as reference electrode. Besides that, there are six signals were recorded by an eye tracking system. This device samples at a rate of 250Hz and is not restrict synchronized to the polygraphy system which is not problematic for later fusion on the feature level [12]. There are three signals are recorded for each of the eye, pupil size and two coordinates of eye gaze on the plane of projection.

In the feature extraction, the linear feature is obtained by the modified periodogram which used in quantitative biosignal analysis, whereas the nonlinear features are based on delay vector variance (DVV). To obtained suitable discrimination function, there are two classification methods are applied in this experiment which are LVQ and SVM. LVQ is a useful method for relatively quick optimization of free parameters in the preprocessing and feature extraction stages. SVM has good theoretical foundation and their coverage of complexity as demonstrated in different benchmark studies of several pattern recognition problems.

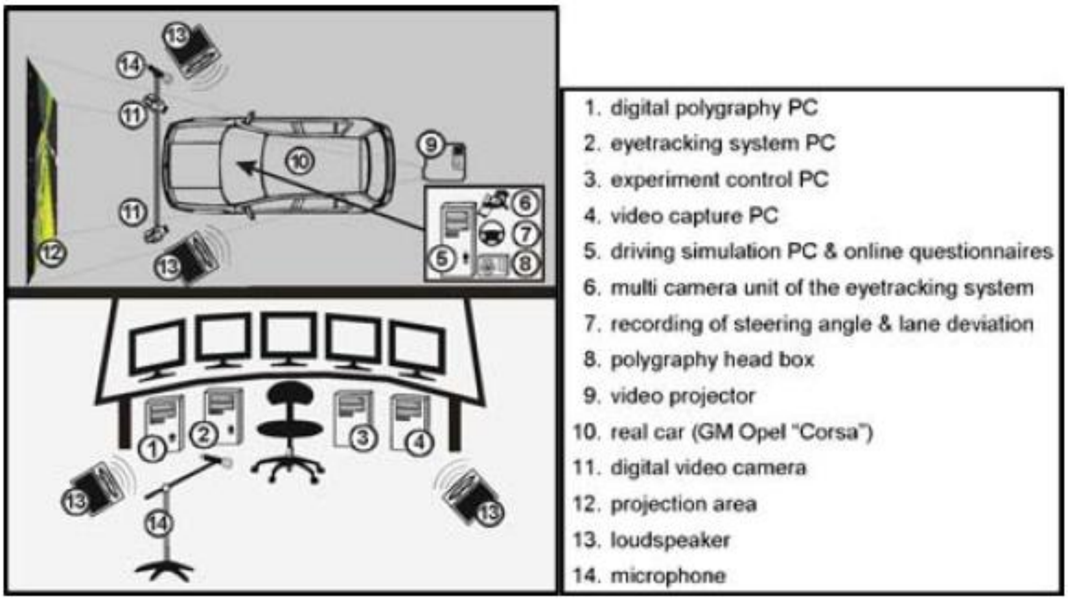

Figure 2.1: Real car driving stimulation lab.

2.1.2 Blind Source Extraction of Microsleep Event

According to the [16], a biosignal analysis method had been proposed for detection and extraction of the microsleep event. Through employing the method so called Blind Source Extraction (BSE) method based on cascaded nonlinear estimator, it is able to extract the relevant microsleep event. The experiment setup is involve twelve healthy volunteer (3 female, 9 male, between 21.4 ± 2.1 years) participated in an overnight study from 1 am to 8 am at the University of Applied Science Schmalkalden, Germany [16]. Wakefulness after normal daytime and evening activities was continued of at least 16 hours prior to first driving simulation, which was verified by wrist actometry. Karolinka Sleepiness Scale (KSS) was applied to perceive sleepiness of test subject after 40 minutes of them carried out experiment in real car interactive driving simulator for every 2 minutes. The EEG was recorded from occipital, central and frontopolar locations (O1, O2, O3, O4, Cs, Fp1, Fp2).

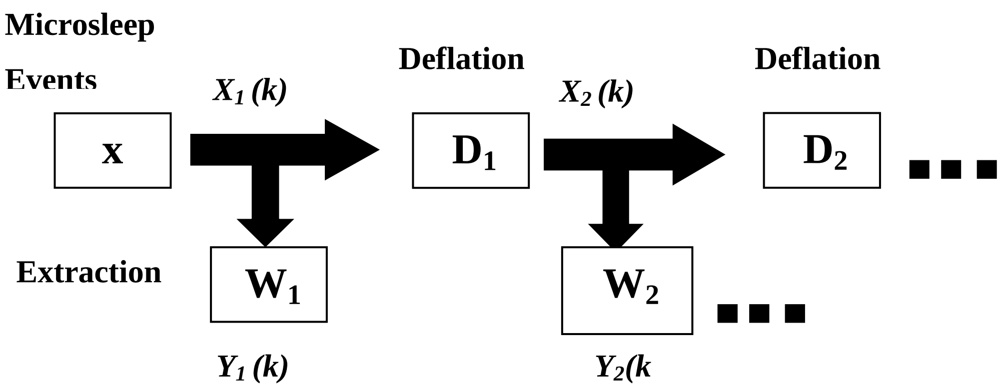

Figure 2.2: General structure of the BSE.

Figure 2.2 is shows a general structure of the BSE process which extracts one single source at a time, where there are two principle stages in this process which are extraction and deflation [16]. Basically, BSE is to extract only one or few microsleep event from the mixtures. It is nothing else but a variant of sequential estimation and extraction, whereby the sequential nature of the problem is represented by the so called "deflation" and it is achieved within the framework of the second order statistics [16]. For the BSE procedures, the mixtures will go through the extraction to have one source recovered. After the deflation, the contribution of the extracted source is removed from the mixtures. Then, these new “deflated” mixtures contain linear combination of the remaining sources and the next extraction process will recover the second source. This process will repeated until the last source of interest is recovered. Since the BSE will accumulate the error during the deflation process, so it has poorer performance compare to the Blind Source Separation (BSS). To solve this problem, the cascaded nonlinear estimator had been adopted in this procedure. With this approaches, the cascaded nonlinear estimator had successfully remove the artifacts, nonlinearities and noise. Besides that, the stimulation results also show the validity and performance of the algorithm.

2.2 Experimental Study on Depression Prevention by Employing Music Therapy

Since appearance of depression on human can be one of the factors to affect the quality of sleep, the investigations on integration of depression and related issues into a pervasive depression prevention system incorporating user-central design is necessary [17]. According to the [17], the author had proposed a treatment program where it is based on the EEG with music therapy system. The experiment involved 22 subjects and 4 subjects respectively in user identification and depression detection which shows in **Figure 2.3** to evaluate the EEG approach. At the initial phase, the user will be identified then follow by the depression prevention interface to allow the personalized feedback to the user for enabling depression relief.

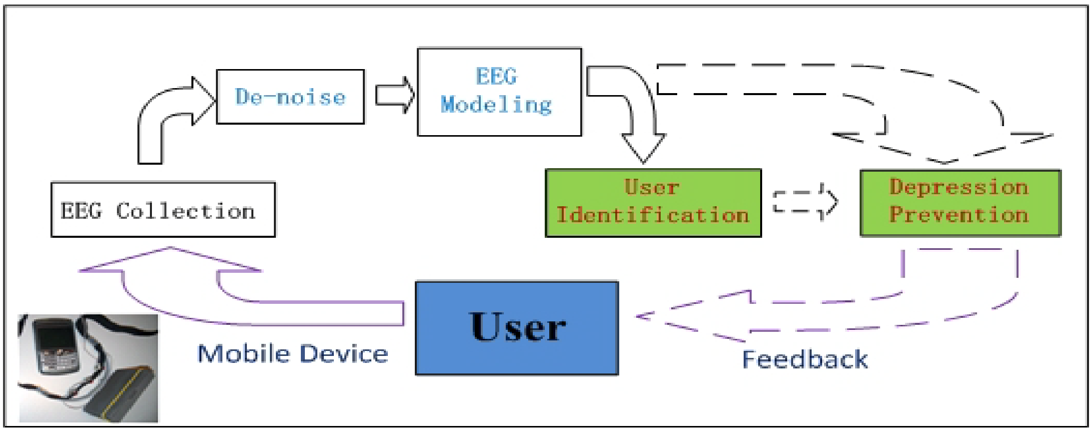

Figure 2.3: Methodology of EEG approach for depression prevention.

For user identification, channel Cz with M1 which is reference were used. Addition channel F3 and F4 were used to measure the depression level. The EEG signal that collected from test subjects had been pre-processing by discrete wavelet transform to detect the ocular artifacts with aid of high-order Haar wavelets. Stationary Wavelet Transform (SWT) was applied as basis function in ocular artifacts zone. Threshold for each level of decomposition had been selected to obtain de-noised EEG signals by Inverse Stationary Wavelet Transform (ISWT). For the evaluation based on user identification, k Nearest-Neighbour classifier (kNN) had been selected to apply in this system. For the evaluation based on depression prevention, this interface had been divided into two steps which are depression detection and depression treatment. In the depression detection process, the signals collected from Cz are used to inspect the brain activity activation while the signals recorded from F4 are used to measure the valence of emotion [17]. Besides that, the emotional response in subjects also been evoked to validate the feasibility of the system and effectiveness of algorithm. The results reported are provides an effective approach to user-centered depression prevention and also this music therapy system offers beneficial effects for the treatment of depression. There are still some improvements needed to meet the needs of user-centered and pervasive application. The main challenge is the system should be user-friendly and simple operation. Another one is the system should aliasing with multiple modal data fusion such as EMG, ECG and EOG due to the, especially ECG, had been proved that it has some interrelationship with the human’s mental states. This system also needs to consider the condition of the user such as in moving state or in excited state when the test was carried out.

2.3 Decomposition and Classification Methods

2.3.1 Fundamental of Wavelets Transform

In our project, we are mainly use EMD to decompose our EEG signal. However, there is another method which proposes in [18] which is discrete wavelet transform. To extract the individual EEG subbands, the wavelet filter is applied. According to the Nyquist sampling theorem, the maximum useful frequency is half of the sample frequency. The primary EEG signal contains sub bands such as delta, theta, alpha beta and gamma. They are using Haar wavelet transform to carry out the 6 level decomposition of the EEG segment.

Besides decompose the signals by using EMD method, we can also use wavelet method to obtain the desire result that we interest on. The wavelet decomposition of a data set takes as input of data values and outpus another set of transformed data values that has the same size as the input. For each of the new data, the value carried out some information on the original data set at some position and some scale. Instead of breaking the signal into its harmonics, which are global functions continuing forever, the signal is represented by breaking it into a series of local basic functions called wavelets [19]. These basic functions are derived from a mother wavelet which is single prototype wavelet by applying the dilation and translation (so called scaling and shifting). Therefore in wavelet transform, the notion of scale is introduced as an alternative to frequency, leading to a so called time-scale (time-frequency) representation. The **Figure 2.4** shows, for the left part, a 1D uniformly gridded domain, with one data value attached to each vertex, For the left part, shows the same data set “scanned” at half the original resolution [20]. The transition at the domain location indicated by a triangle is smooth at finest scale, and is sharp at the lower resolution. Since the lower resolution data set greatly differs from original data set that location, a wavelet transform would store a high value at that location and at the coarser scale [20].

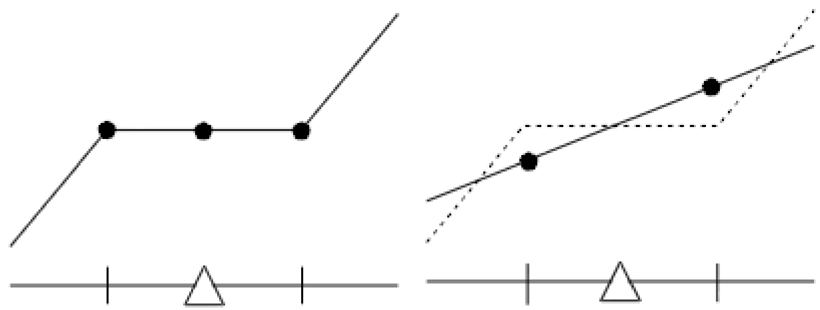

Figure 2.4: Wavelets encode informations at various scales; here a smooth transition at the triangle location and finest scale, and a sharp transition at the same

location and at the coarsest scale imply a high wavelet value at that location and at coarsest scale.

2.3.2 Fundamental of Support Vector Machine (SVM)

For signal processing such as analyzing the EEG data, there are several methods to classify the test data. One of the famous methods used to carry out the analysis is Support Vector Machine (SVM). According to [18], SVM is a type of an algorithm which supervised learning method for producing of input-output functions from a set of labeled training data. It is used to maximize the geometric margin between data classes and separate hyperplane [21]. SVM modeling is to find the optimal hyperplane to separate the test data by non-linear and linear boundaries. With the aid of kernel function, the SVM is able to define the boundaries by hyperplane and also classifying the overlapping and non-separable data. There are two parallel hyperplanes will be constructed on each side of the hyperplanes to maximize the distance between them for the purpose of obtaining better generalization error of the classifier. The **Figure 2.5** shows the simple example of SVM [18].

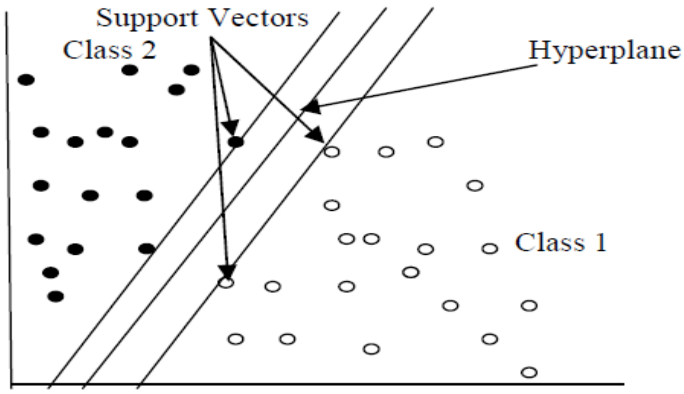

Figure 2.5: Simple kind of Linear SVM.

2.3.3 Fundamental of Empirical Mode Decomposition (EMD)

EEG signals that we capture from electrodes always contain the undesirable noise so called the artifact will affect the actual signals that we interested on. The artifacts can be occurred due to the movement of the testing subjects, environment conditions or part of the system and recording sensor. The data that obtained can be expressed as following [22]:

$$x(t) = s(t) + n(t), \tag{2.1}$$

where
$x(t)$ = data obtained
$s(t)$ = actual signal
$n(t)$ = noise

In signal processing of EEG data, the Fourier transform can use also to separate the noise from the actual signal. But, the premise is the process should be linear and noises have distinct time or frequency scales different from the actual signal [22]. In the case that processes are nonlinear, nonstationary and stochastic data, HHT can be applied to compensate the shortage of Fourier transform.

Like mention previously, the HHT consists of EMD methods and HSA. To begin analyse the signals that contain noises, EMD is used to decompose any data obtained into a set of IMF component as our represent data. From [22], the author state that although EMD is suitable for nonlinear and non-stationary data to analyze, this method still face difficulty and complicated to separate the actual signal with the noises. Therefore, the very first step that needs to understand is the characteristic of the noise before attach any specific sign to the actual signal in order to extract out undesirable noises. The EMD method is apply sifting process which is repeated until an IMF is obtained. IMF represents the oscillatory modes which having the same number of zero-crossing and extrema. Furthermore, the oscillation will also be symmetric with respect to the “local mean” which defined by local maxima and local minima [15]. For each the iteration, the envelope mean is subtracted from the data signal. The expression is shows as following:

$$h_1 = x(t) - m_1, \tag{2.2}$$

where

m_1 = mean of that sifting process

h_1 = first component that state the difference between the data and m_1

Basically, the concept is identifying all of the local extrema. All of the local maxima will be connect together to obtain the upper envelope while the local minima will also link by each other to produce the lower envelope as shows in **Figure 2.6** [15]. The **Figure 2.7** shows the repeated iterative (sifting) step is continue which show that the amplitude of signal is decreasing [15].

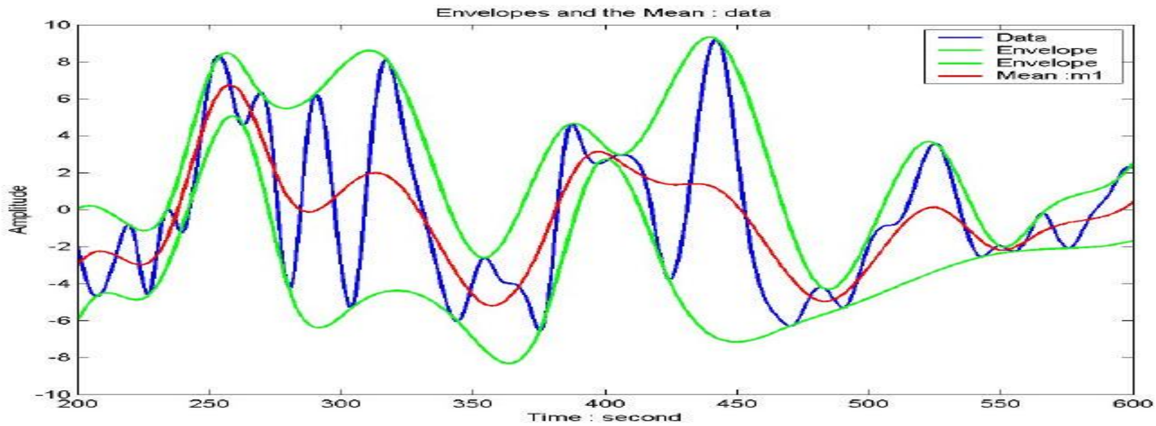

Figure 2.6: The data obtained (blue) is analysed by produce the upper envelope and lower envelope (green) which is defined by the local maxima and minima respectively. The mean value of both the envelope is indicated in figure also.

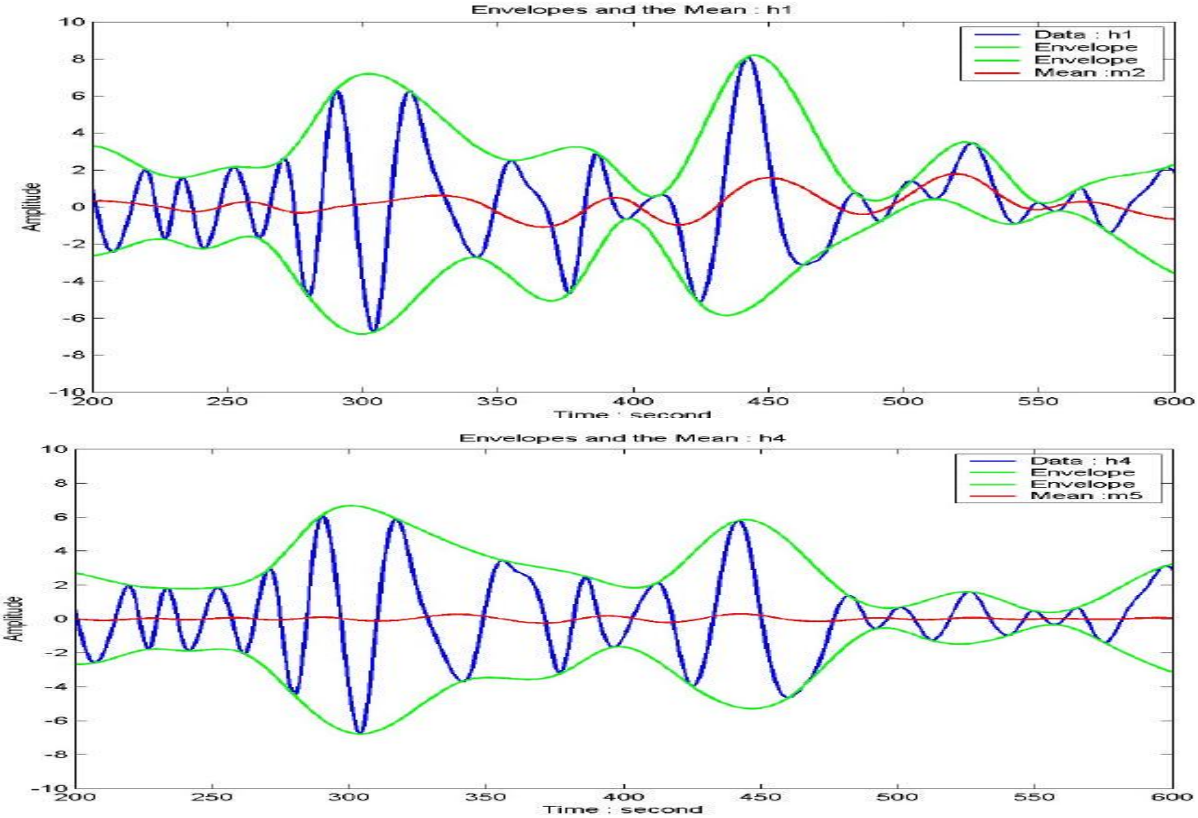

Figure 2.7: Repeated shifting steps with h_1 and m_2 (top) and h_2 and m_3 (bottom).

After the first round of sifting, a local hump near an inflection point will become local maxima and local minima when the coordinate system is changed to the curvilinear one with m_1 as the zero reference. Hence, h_1 only can be designated as proto-mode function (PMF) [23]. PMF have to process further to obtain the true IMF. After the sifting process had been done more than five times, the IMF would not change significant. h_1 expressed as the data as shows as following:

$$h_{11} = h_1 - m_{11}, \tag{2.3}$$

Since this form is repeated which shown in Figure 2.7 (bottom), up to k times, then the h_{1k} express as IMF,

$$h_{1k} = h_{1(k-1)} - m_{1k}\ , \tag{2.4}$$

where

$c_1 = h_{1k}$, which is the first IMF component from the data.

With limiting the size of standard deviation, SD as shows as following, the criterion for the sifting process to stop can be determined. This is ensure the IMF components can be guarantee that the physical sense of both amplitude and frequency modulations were retain efficient when gone through the sifting process.

$$SD = \sum_{t=0}^{T} \left[\frac{|(h_{1(k-1)}(t) - h_{1k}(t))|^2}{h_{1(k-1)}^2(t)} \right] \tag{2.5}$$

Typically, the value of SD is always set between 0.2 and 0.3 [24].

With any stoppage criterion, the c_1 should contain the finest scale or the shortest period component of the signal. Then, the c_1 can be removed from the rest of the data by [25].

$$x(t) - c_1 = r_1, \tag{2.6}$$

Since the residue r_1, contains all longer period variations in the data, it will become as new data and applied into the same sifting process as mention previously. We repeated the procedure to all the subsequent r_j's as

$$r_1 - c_1 = r_2, \tag{2.7}$$

and the process will continue and expressed as

$$r_{n-1} - c_n = r_n, \tag{2.8}$$

By summing up, we can obtain

$$x(t) = \sum_{j=1}^{n} c_j + r_n \tag{2.9}$$

After each of the IMF has been obtained, the examination of distribution of the energy will carried out with respect to the period in the form of HSA. Through the HHT, the signal can be analyzed and decomposed into as shows as **Figure 2.8** [15].

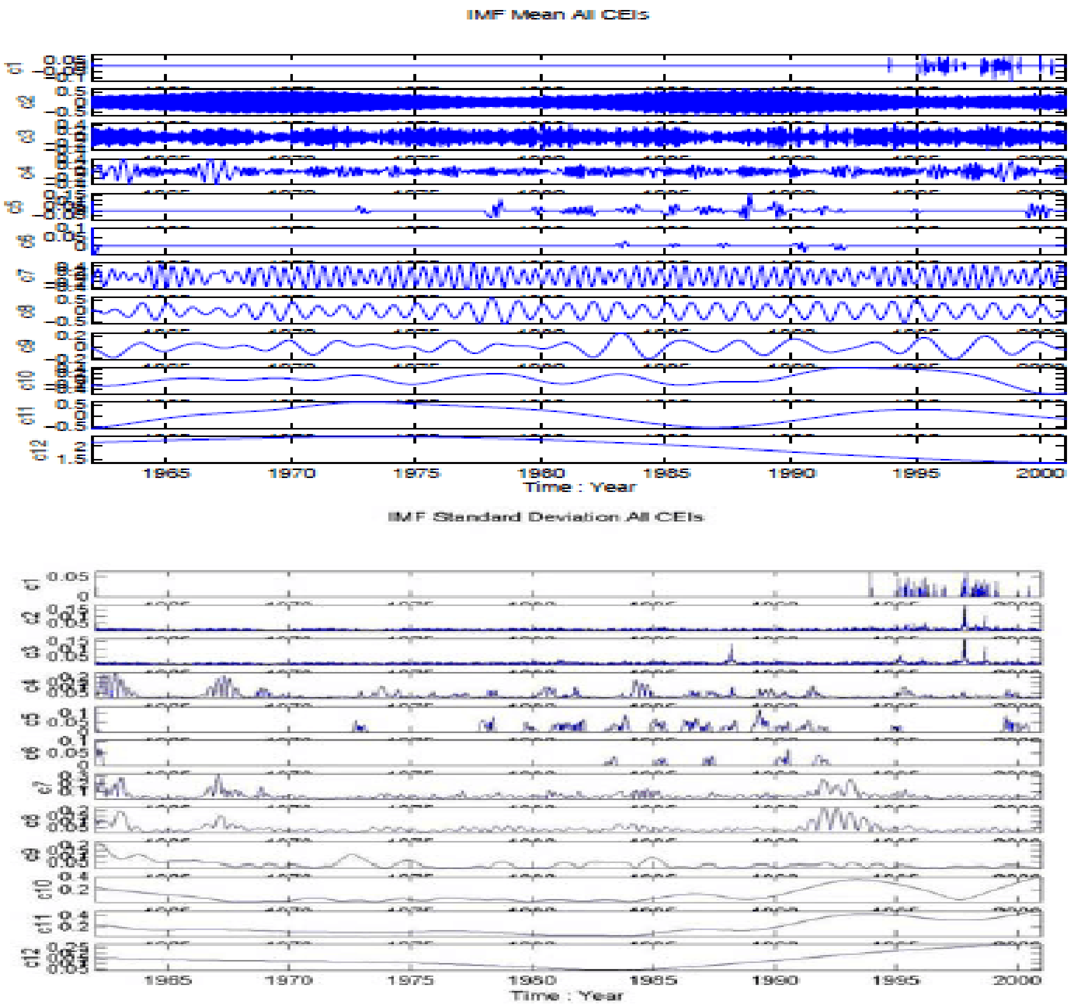

Figure 2.8: (Top) The mean IMF for nine different sifting. (Bottom) The standard deviation of the IMF for nine sifting.

2.4 Comparison between Fourier Transform (FT), Wavelets Transform (WT) and Hilbert-Huang Transform (HHT)

Once the IMF components are derive through the EMD method, the Hilbert spectra analysis can be applied to each of the IMF component. From **Table 2.1**, we can know that the HHT is the most powerful method compare to the fourier transform and wavelet transform.

	Fourier	Wavelet	HHT
Basis	A priori	A priori	Adaptive
Frequency	Convolution: global, uncertainly	Convolution: global, uncertainly	Differentiation: local, certainly
Presentation	Energy-frequency	Energy-frequency	Energy-time-frequency
Nonlinear	No	No	Yes
Non-stationary	No	No	Yes
Feature extraction	No	Discrete: no Continuous: yes	Yes
Theoretical base	Complete	Complete	Empirical

Table 2.1: Comparison between FT, WT and HHT.

2.5 Ensemble Empirical Mode Decomposition (EEMD)

Due to the drawback of EMD, Wu and Huang had proposed Ensemble EMD (EEMD) [26], a noise-assisted data analysis (NADA). In spite of a broad range of EMD application, the frequent appearance of mode mixing which is defined as a single IMF either consisting of signals of widely disparate scales, or a signal of a similar scale residing in different IMF component. EEMD is applied to define the true IMF components as the mean of an ensemble trial, each consisting of the signal plus a white noise of finite amplitude. Based on the [26], the proposed EEMD is developed as follows:

i. Add a white noise series to the targeted data.
ii. Decompose the data with added white noise into IMFs.
iii. Repeat step I and step ii again and again with different white noise series each time.
iv. Obtain the means of corresponding IMFs of the decompositions as the final result.

According to the [27], the authors have proposed EEMD-based SVMs enable learning approach as shows in **Figure 2.9**. After applied the EEMD method, the SVM is used to forecast each IMF component and the residual component. SVM also combine the prediction result of each IMF and residual component and generate an aggregated result as final prediction of the original time series.

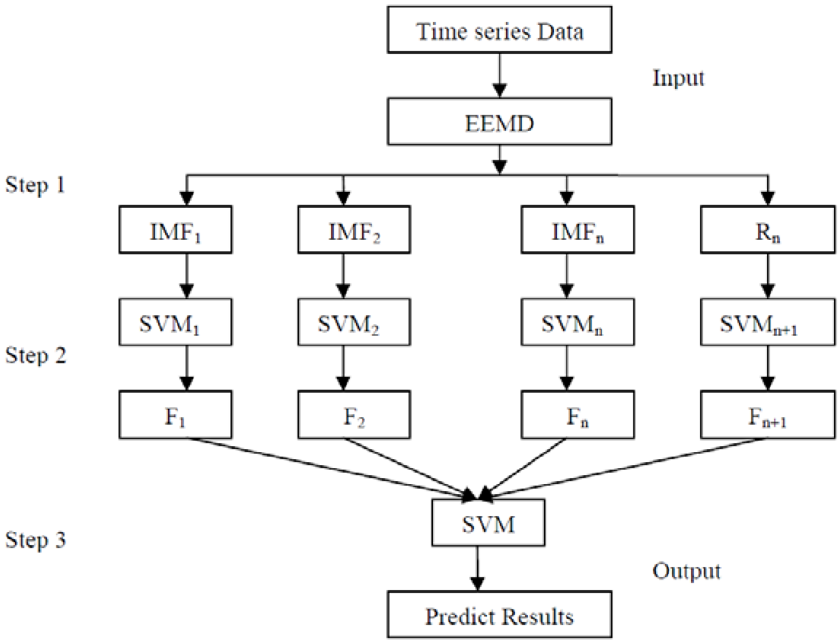

Figure 2.9: The framework of proposed EEMD – based SVMs learning approach.

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CHAPTER 3

METHODOLOGY

3.1 Experimental Study on Sleep Disorder Detection

Nowadays, more than millions of people are affected by the sleep disorder such as insomnia. Most of the people will intake the sleeping pill to help out with this condition. Although it might be a solution to treat the condition, it still will induce quite severe negative side effect on healthy. Sleeping pills usually are addictive and cause problem when interact with other medications and alcohol. People who take the pill have the high risk to cause high blood pressure, dizziness, nausea, confusion and so on. Recently, a lot of research had been done to verify that the music therapy can used as sleep disorder treatment. Music therapy uses binaural beats to stimulate the brain to high level of relaxation which can aid in falling sleep and stay asleep. Binaural beats is the music are set to certain frequencies to alter the brain frequency for induction of sleep condition.

Since the severity of insomnia has different levels, our intention is apply the music onto test subjects who are not so severe in insomnia. One of the factors of appearance of insomnia is the human's brainwaves are over excited which is the frequency is too high until that individual cannot fallen into sleep. Therefore, the experiment setup is modelling a scenario that could able to increase the excitation of the human's brainwave. The main purpose of the experiment is observing the effect of music that applied onto human when sleeping compare to the people who are sleeping without the music after having these types of excitation such as watching movie. The observation will focus on the recognition and determination of sleeping patterns and frequencies through EEG waveform, and compare and analyze the performance of stimulation result between EMD and EEMD methods. In this experiment, the music of sleep therapy will apply onto the test subjects to observe the brain signal that been produced. Test subject who is takes the experiment; he/she should at least 12 hours of incessant wakefulness and after a day of normal activity.

Figure 3.1 is shows the devices and materials that used during experiment. Before the electrodes are place onto the scalp, some cleaning processes need to be done. The interest areas on scalp was marked by skin marker and cleaned by abrasive skin prepping gel. Then, the adhesive and conductive paste was used to attach the electrode onto scalp. Earphone was needed to reduce any other sounds or noises from environment which will affect the auditory of test subject. He/She should relax themselves as usual when they attempt to sleep. Electrodes which detect the signal should place it according to the 10-20 electrode placement system as shows in Figure 1.1.There are five signals of EEG which are C3, C4, O1, O2 and A1 were recorded by the CamNtech Actiwave EEG System which been used to perform the task of data collection. The CamNtech Actiwave 4-channel Recorder was used to collect and record the EEG signal and the function CamNtech Actiwave Interface Dock is act as a reader to show the EEG data collection from the recorder. Embeded system in the EEG device was aided to filter undesirable noise and interference from the environment to provide more accurate and precise results for clinicians and researchers to carry out the analysis. The C3 and C4 are the locations which related to the electrical activity in somato-sensoric and motoric brain areas. O1 and O2 are related to the primary and secondary visual areas. A1 is serves as reference electrodes. A1 is the locations place at the mastoid areas.

Before applying music onto test subject, he/she need to follow several steps as well which shows in **Figure 3.2**. From Figure 3.2, the procedures of experiment can be divided into three steps. The purpose of step 1 is to show the different of the brainwave patterns and frequencies with the step 2 since the brainwave usually will be increased and stronger after watching a movie especially an exciting and emotional movie. Then, the step 3 and step 4 which are brainwave under sleeping condition provides us better analysis to distinguish with different scenario and condition. It is also performs the comparison of the effect of music during sleep condition to those without music. **Figure 3.3** shows the scenario of the procedure of experiment and the schematic of step 4 is shows as well in **Figure 3.4**. After signals have been recorded, we can use EMD method and EEMD method to decompose the signal for sleep pattern recognition and Hilbert Transform to determine the frequencies during sleep for determination of sleep stages.

Figure 3.1: Devices and materials that used during experiment. (1) Adhesive and conductive paste. (2) Abrasive skin prepping gel. (3) Medical Tape. (4) CamNtech Actiwave Interface Dock. (5) Gold plate electrodes. (6) CamNtech Actiwave 4-channel recorder.

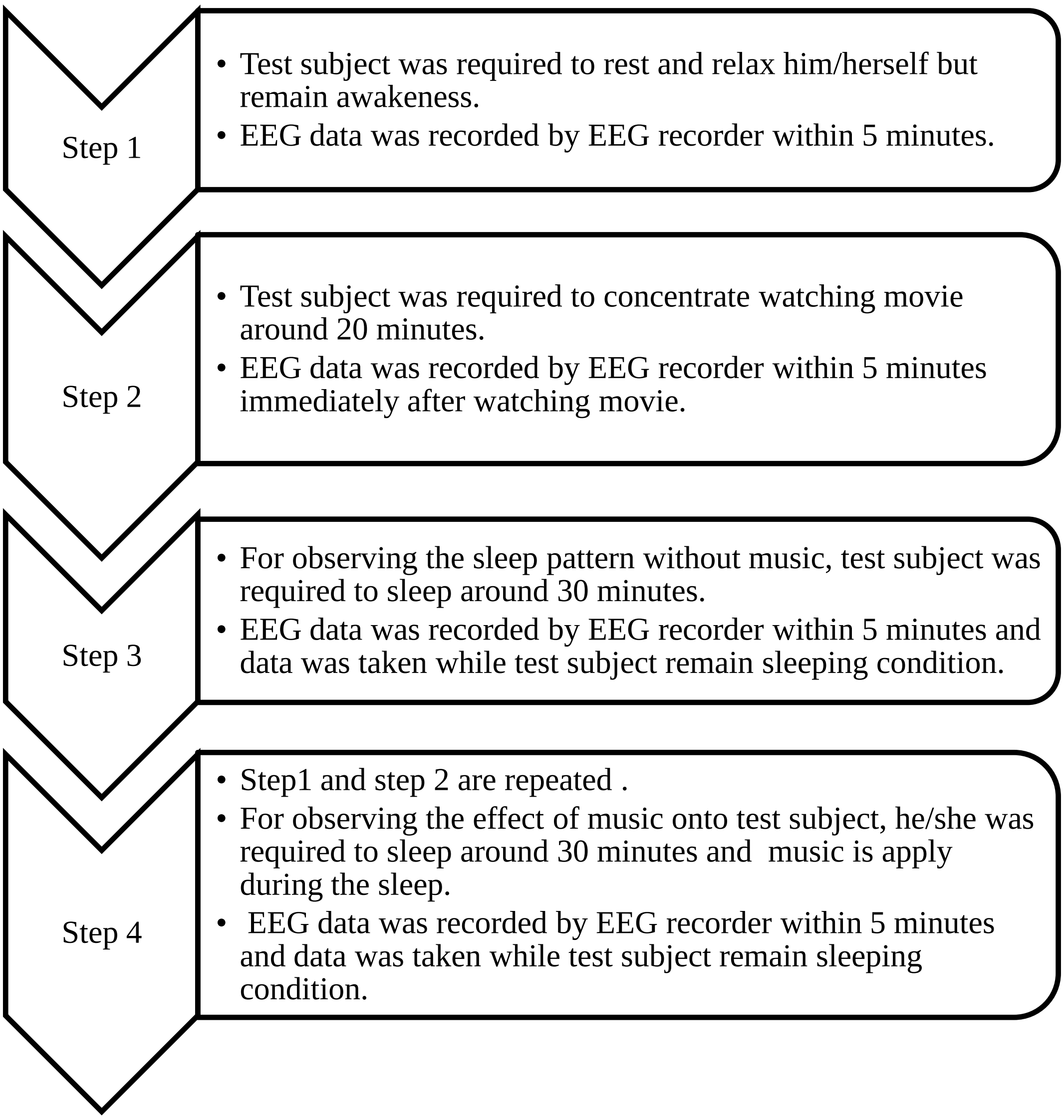


Figure 3.2: Procedures of the experiment.

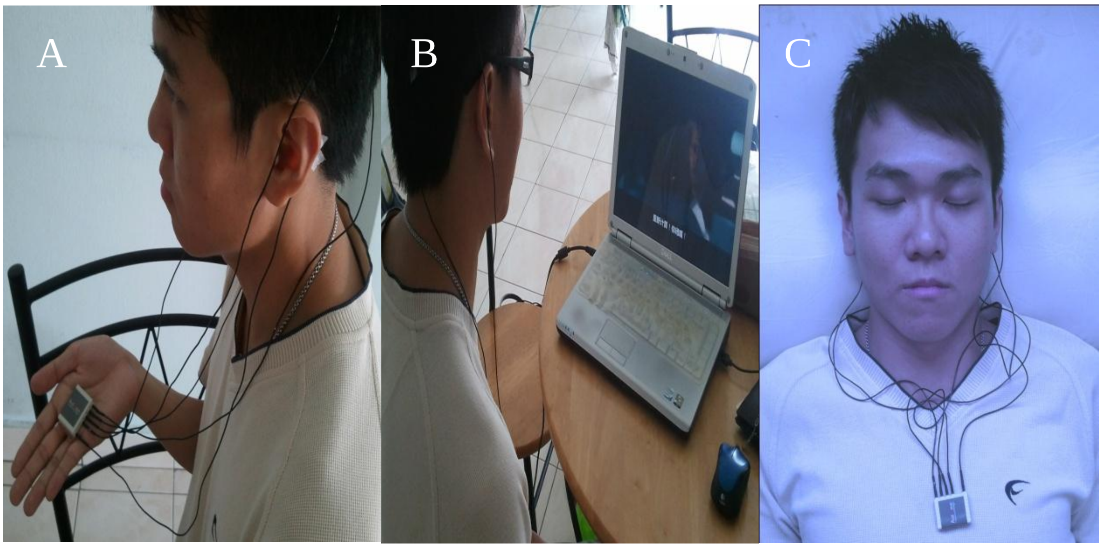


Figure 3.3: Scenario of the procedures of experiment. (A) Under condition of relax and wakefulness. (B) Under condition after watching movie. (C) Under condition of sleeping without music. For sleep with music, extra earphone with MP3 will added in figure C.

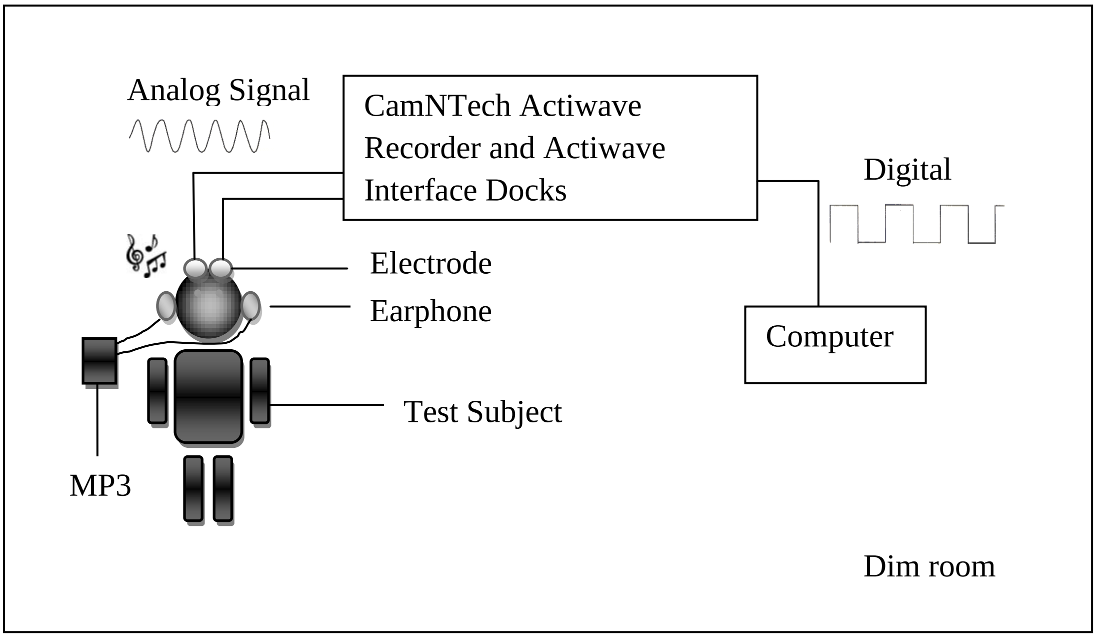


Figure 3.4: Schematic of the experiment for step 4.

3.2 Overall Process of the Experiment

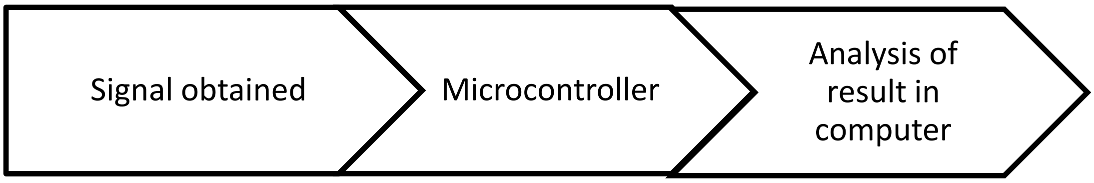


Figure 3.5: Flowchart of overall process.

From **Figure 3.5**, it shows the flowchart of the process to perform the recognition of sleep disorder. The signals are obtain from the brain wave through the electrode that attach onto the scalp of test subject. The electrodes we use can be either silver chloride or aurum (Au) electrodes. The electrodes are position onto scalp based on the 10/20 System of electrode placement. Besides following the positioning system, the reference electrodes are also need to place at the mastoid region. During place the electrodes onto the proper position, we should aware that the impedance of electrodes have to as low as possible to ensure high connectivity between electrodes and the scalp. The microcontroller is used to establish the communication between the electrodes with computer. The main role of our CamNtech EEG Devices is to convert signals that derive from brain wave to the signals which can be interpret and analyze in the computer.

In process the signal in computer, we are mainly focus on the EMD and EEMD methods. EMD is used to decompose the signal by a process so called the sifting process into a finite set of oscillatory components which called IMF, represent the oscillation modes embedded in the data. EEMD is the modification of EMD method due to the drawback of EMD which is mode mixing. EEMD can ameliorate the effect of mode mixing which may lead to misinterpretation the analyzed data by research or physician. EMD and EEMD method will explain later in the next part. From [28], there are several stages which are shows in **Figure 3.6** can be achieved based on EMD either by inspection or by post-processing in the form of some machine learning algorithm. With aid of the flowchart which shows in **Figure 3.7**, the signals obtained from electrode can be decompose into the data we interested on. After that, the result obtained from the processing of EMD method will be compare with those by EEMD method to show the differences and each of performance respectively.

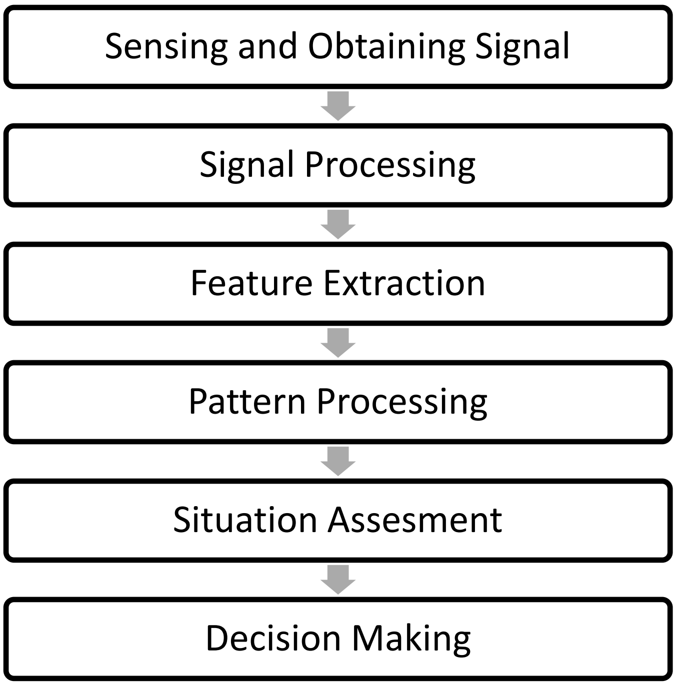


Figure 3.6: The “waterfall model” of information fusion.

3.3 Fundamental of Signal Processing

Before apply the EMD method into our signal processing, there are some EEG signal analysis had been done by using wavelet transform. We are process the signal by using wavelet method as our fundamental signal processing before carried out the EMD methods. The decomposition pattern of EMD method is quite similar with the wavelet. EMD have no basic functions and is dependent on the signal itself, while the wavelet transform scales frequency content is always fixed and depends on sampling frequency content and decomposition level. The most common utilization of wavelets is related to data denoising, data modelling, data compression and shape or contour recognition.

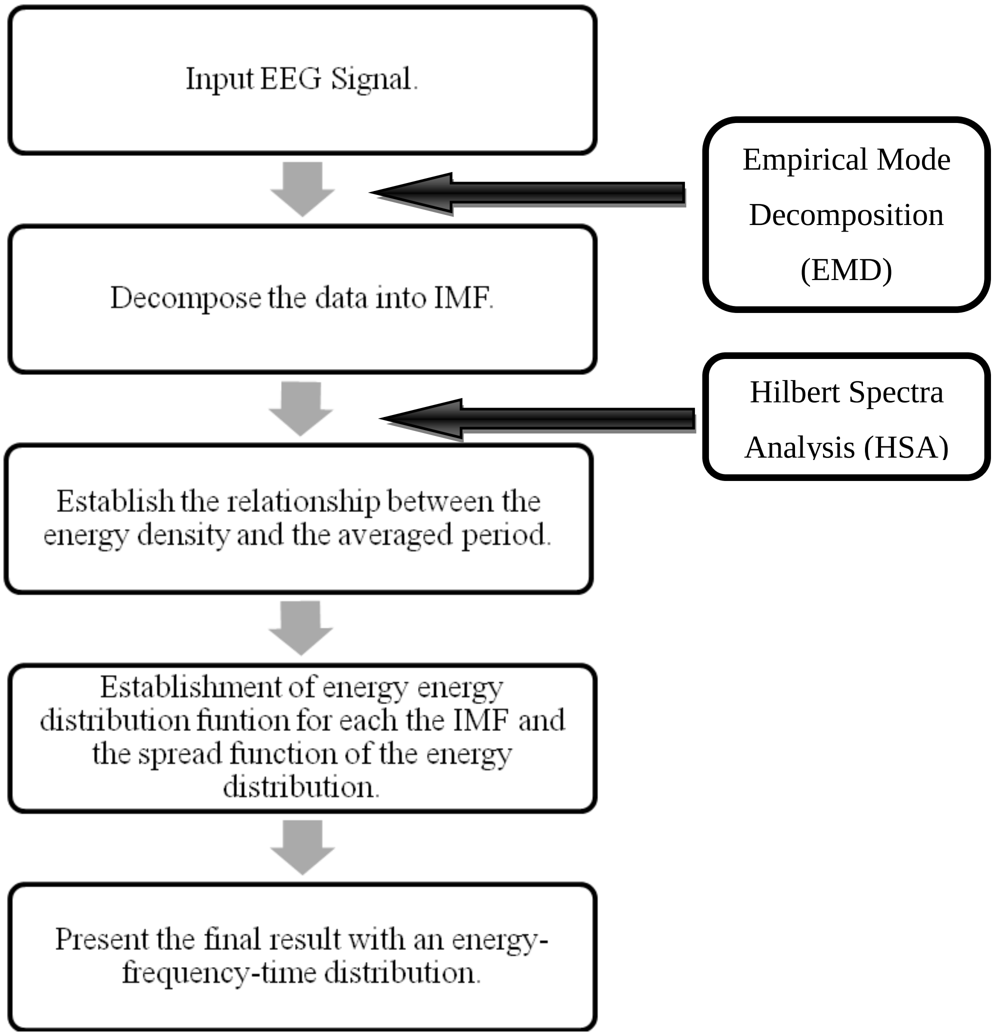


Figure 3.7: Flowchart of signal processing by applied EMD.

3.3.1 Denoising Signal

The basic principle underlying the denoising signal by using wavelets is the thresholding. The main task is used to decompose the wavelet components which exceed some predetermined thresholds threshold T_i for each scale S_i. Reconstruction is performed these wavelet components yielding a denoised version of the original signal without unacceptable distortion provided that the thresholds have been adequate selected [29]. There are two basic methods which are hard and soft thresholding. For the hard thresholding, any value of signal S_i decomposition level which exceeds T_i will be eliminated. While the soft thresholding, also trace for the signal S_i decomposition level which excess T_i, but is reduced by T_i instead of eliminating. After that, the signal will reconstructed from the threshold component.

Figure 3.8 shows the wavelet decomposition of the noisy signal while **Figure 3.9** shows wavelet tree of discrete wavelet transform.. In figure 3.8, the decomposition of the noisy signal is in an approximately a_5 and these signal is decompose at level 5 of Daubechies (dB) wavelet transform by using 5 dB. Besides that, there are five details level d_1, d_2, d_3, d_4 and d_5. S is the original noisy signal which is combination of a_5 and these five details.

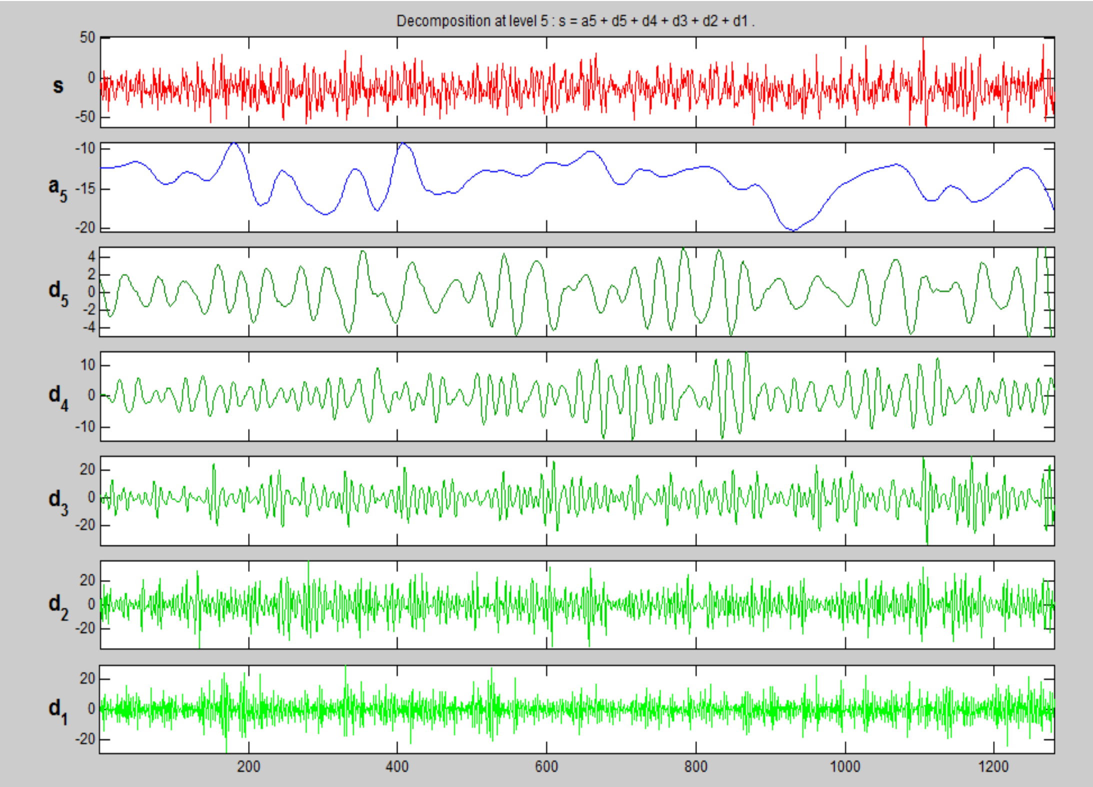


Figure 3.8: Decomposition of EEG signal by using dB wavelet transform.

Among the Haar wavelet transform and Daubechies (dB) wavelet transform, the dB wavelet has been chosen to analyze the EEG signal. This is due to the limitation of the Haar wavelet transform. However, Haar Wavelet transform also has several advantages [30] such as simple concept, faster, memory efficient since it can be calculated in place without a temporary array and exactly reversible without the edge effects that are a problem with other wavelet transform.

Haar transform can cause problem to some application [30]. In generating each of averages for the next level and each set of coefficient, the Haar transform performs an average and difference on a pair of values. The algorithm will shift over by two values and calculate another average and difference on the next pair. The high frequency coefficient spectrum should reflect all high frequency changes. Since Haar window is only two elements wide, if there is big changes take place from an even value to an odd value, the changes will not be reflected in the high frequency coefficient. Therefore, Haar wavelet transform is not so suitable in denoise and compression of signal.

This limitation can be solved by using the Daubechies wavelet transform. This wavelet type applied overlapping windows, so the high frequency coefficient spectrum reflects all high frequency changes. It has balanced frequency responses but non-linear phase response. Therefore, dB wavelets are useful in compression and denoise of signal processing [30].

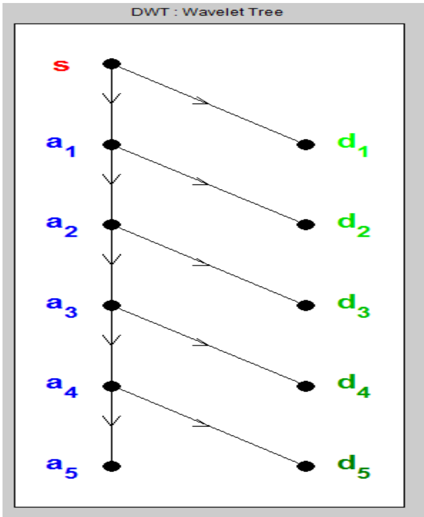


Figure 3.9: Wavelet tree of discrete wavelet transform.

From figure 3.9, *s* represents the original signals, *a* is take a low pass version of curve for scaling function and *d* is take a high pass version of curve for wavelet function. Both of them are mainly used to separate the high pass and low pass information. The iteration of the signal will be direct to downward along the low pass subband. Then, the next low pass data will continue subdivide itself into another low pass and high pass subbands. The iteration will be stop at a_5 since that level 5 has been set in decomposition of data.

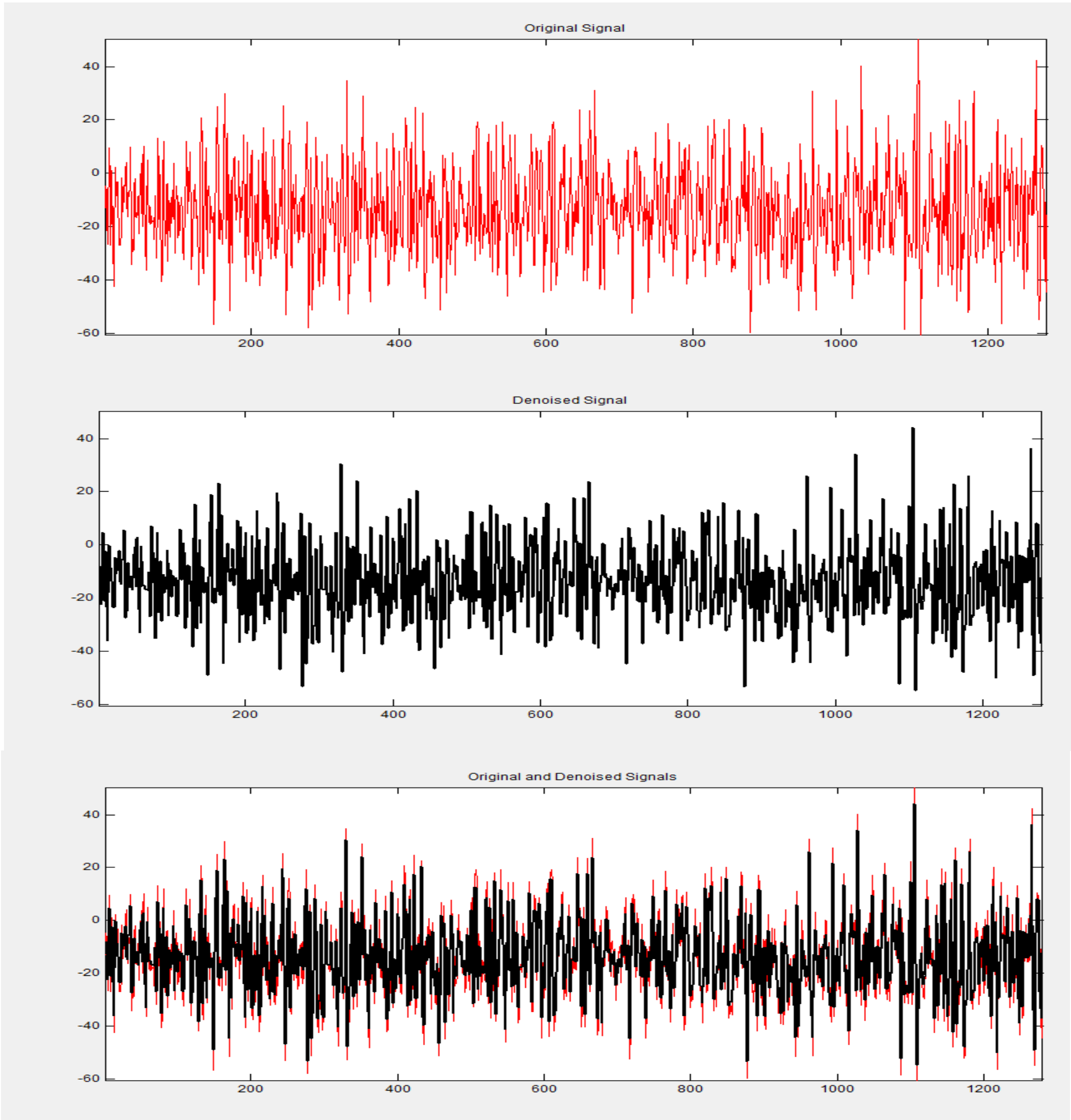


Figure 3.10: Top: Original signal before denoise. Middle: Original signal after denoise. Bottom: Comparison the signal before and after denoise. Red colour represent original signal while black colour represent denoise signal.

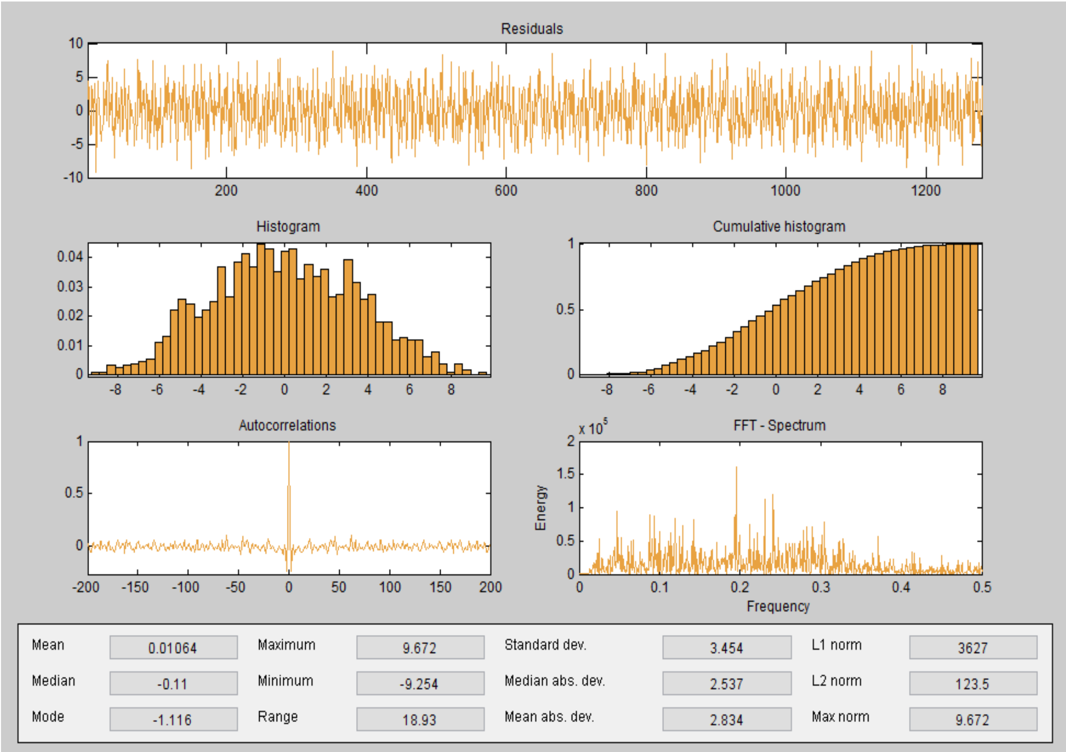


Figure 3.11: Residual, histogram and cumulative of denoising signal. Autocorrelations and FFT transform has been applied also onto the signal.

The general wavelet procedure which carried as shows in **Figure 3.10** is decompose the noisy signal by wavelet transform, remove the noise by selection of the appropriate threshold limit and inverse wavelet transform of the threshold wavelet coefficient to obtain a denoise signal. These techniques are significant step forward in handling noisy data because the denoising is carried out without smoothing out the sharp structures. During process the signal, we also can present the result in different aspect as shows in **Figure 3.11**. The residual of the signal is shows the error of the information which had been detected and mix with the exact signal that we interest on. Autocorrelation is the correlation of a signal with itself. Correlation function shows how similar two signals are and for how long they remain similar when one is shifted with respect to each other. In general, the real and imaginary parts of one-pulse spectrum display no specific pattern and their shape depends on the pulse position. From Figure 3.11, since the signal has high randomness, it has only one autocorrelation peak when the shift equals to the signal length. Fast Fourier transform is also applied onto the result to obtain the signal.

3.3.2 Compress Signal

Wavelets are widely used in compression. This is due to the wavelets have very good approximation properties for presenting classes of signals like piecewise smooth signals. The data can be compressed since the signal is separated which provide easier pathway to threshold and remove information. From **Figure 3.12**, the graph of retain energy versus number of zeros had been plot where the range between them is 82.03% to 81.98%. Retain Energy (RE) and Number of Zero (NZ) are determined for noiseless and noisy signal for compression. One can decide the threshold level to have complete control over de-noising the signal by choosing different threshold for different level [31]. From **Figure 3.13**, we can found that it is difficult to determine the absolute great threshold value. This is because small threshold which is equal to 10 will yields a result close to the input, but this result might be noisy [32]. While choosing the large threshold which is equal to 70, it will produce large number of zeros of wavelet coefficient. But, the disadvantage is some signal will be affected which might cause blurs and artifacts [32]. The RE and NZ are determined for different threshold values. In dB transform, the RE will decrease when we increase the threshold value. At the same time, the NZ will increase also. It represents that once the threshold value is increase, the compression ratio will be higher for both noisy and noiseless signal.

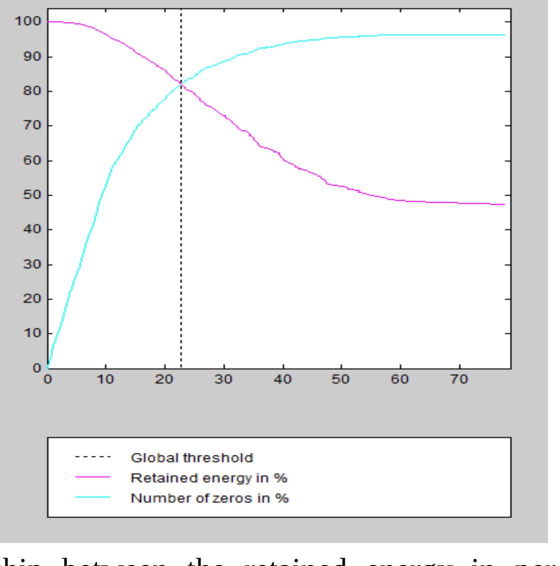


Figure 3.12: Relationship between the retained energy in percentage (%) and number of zeros in percentage (%) in order to obtain the compression ratio

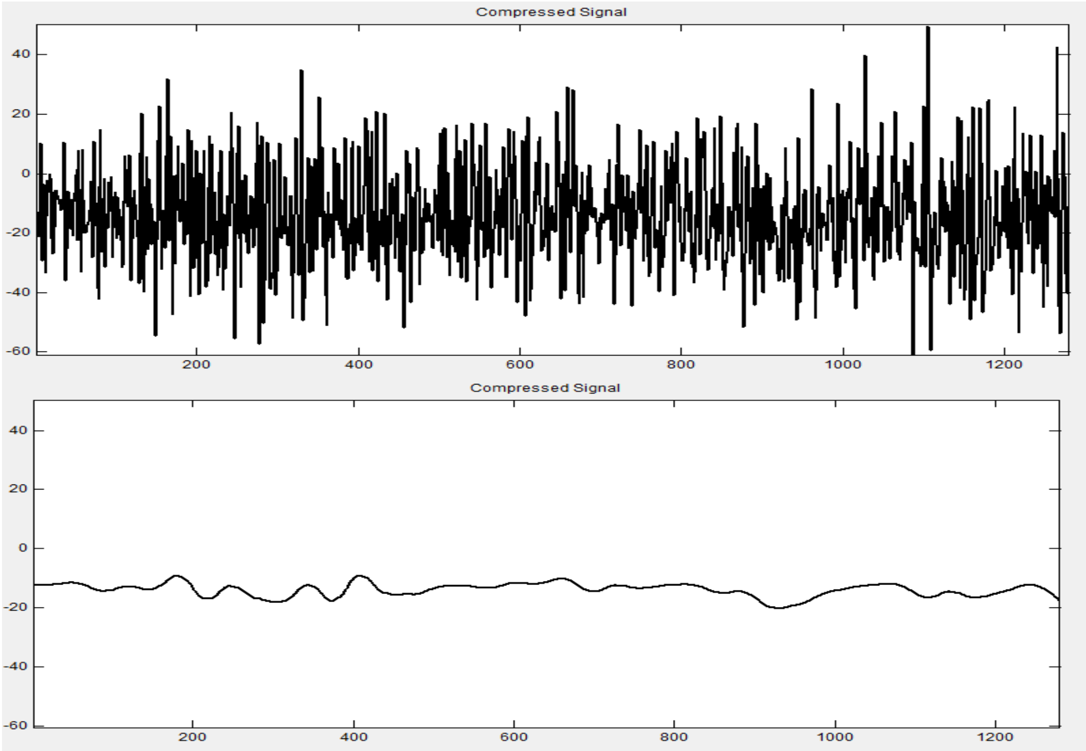


Figure 3.13: Global threshold of compress signal at 10 (top) and 70 (bottom).

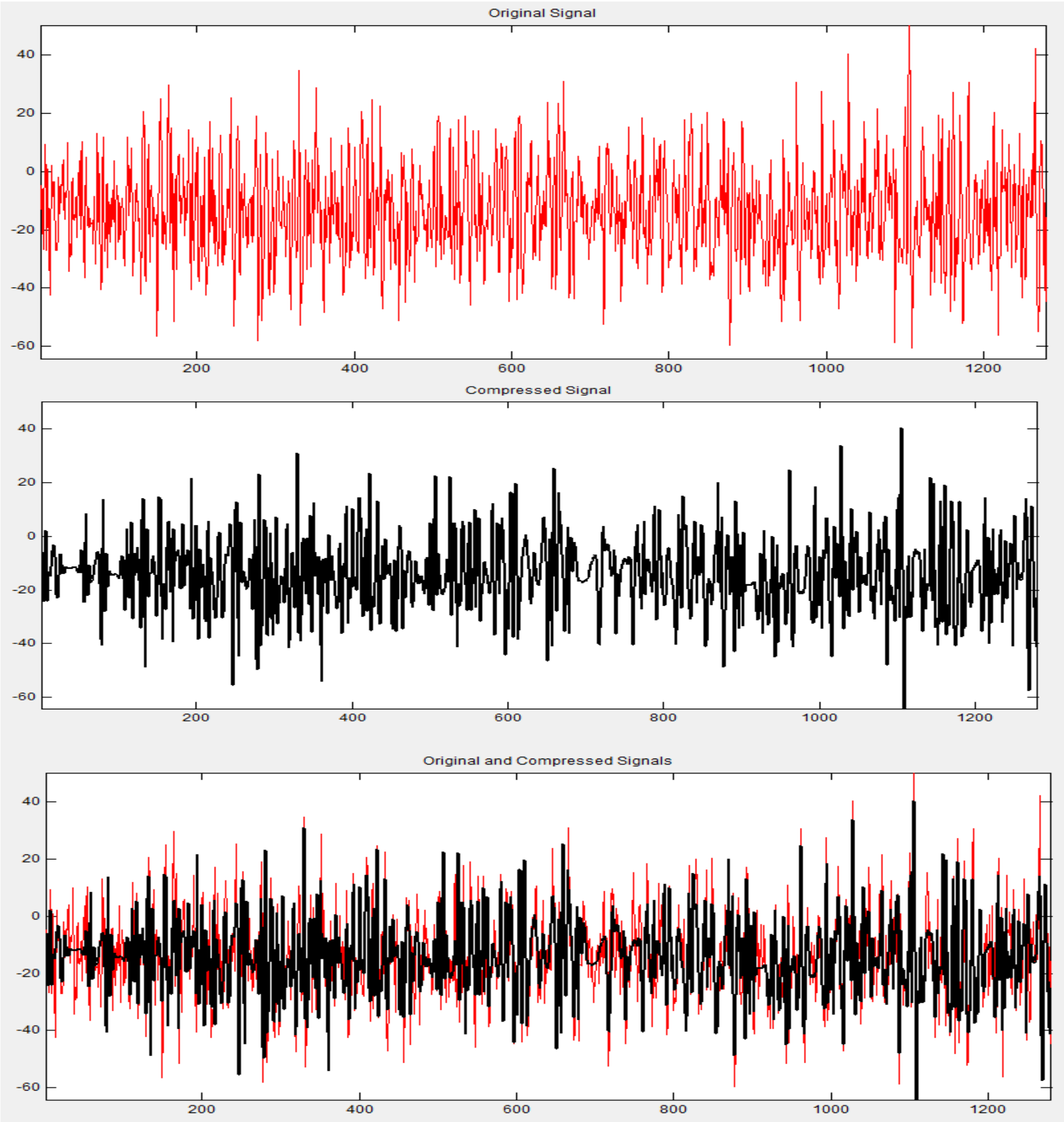


Figure 3.14: Top: Original signal before compress. Middle: Original signal after compress. Bottom: Comparison the signal before and after compress. Red colour represent original signal while black color represent compress signal.

For **Figure 3.14**, the signal shows it had been compress and compare with the original signal. The main three steps of compression procedure are decomposition of signal, selection of threshold for each level and hard thresholding is applied to detail coefficient, and reconstruction the data. For **Figure 3.15**, the results have been display in different aspects and the interpretation of autocorrelation and FFT is quite similar with that of the denoising signal.

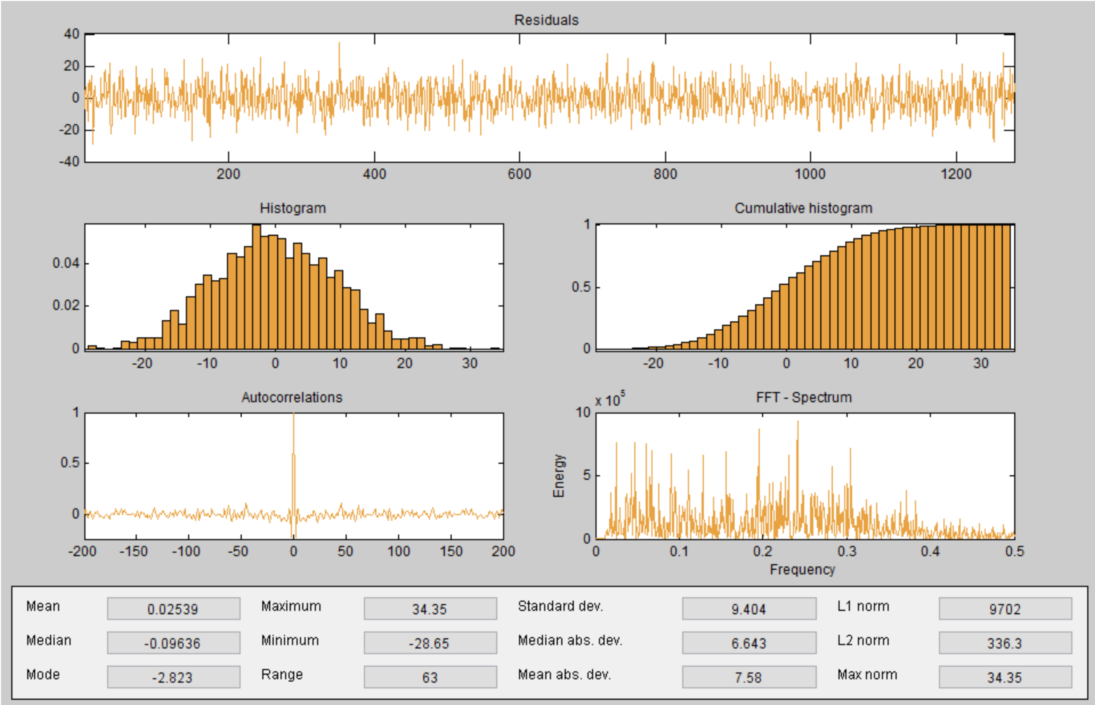


Figure 3.15: Residual, histogram and cumulative of compressed signal. Autocorrelations and FFT transform has been applied also onto the signal.

3.4 Signal Processing Technique

After applying wavelet method as our fundamental knowledge toward the signal processing as discussed before, we can actually applied the signal processing technique that we want which are the EMD and EEMD methods to analyzed the EEG data that obtained from our test subject.

3.4.1 Empirical Mode Decomposition (EMD) Method

In the literature review, we know that signal processing can be done by various techniques and methods. One of the method that mention before is EMD method which is a method that can be adaptively decomposed any complicated data set into IMF component. IMFs are functions that need to satisfy two conditions [24]:

1. 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.
2. At any point in the time series, the mean value of the envelopes which define by local maxima (upper envelope) and local minima (lower envelope) is equal to zero.

EMD method is applying sifting process which is repeated until an IMF is obtained. The 'stopping criterion' is act as the determination of the number of sifting steps to produce IMF [23]. The envelopes are defined by local maxima and local minima. When these extrema are identified, all the local maxima and local minima will be connected by spline line as upper envelope and lower envelope which should cover all the data between them respectively. 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:

$$h_1 = x(t) - m_1 \tag{3.1}$$

Sifting process is necessary because it can eliminate the riding wave and produce more symmetrical wave-profile [e]. Therefore, the sifting process is required to repeat several times. For the second sifting process, h_1 is treated as the data:

$$h_{11} = h_1 - m_{11} \tag{3.2}$$

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

$$h_{1k} = h_{1(k-1)} - m_{1k} \tag{3.3}$$

where $$c_1 = h_{1k} \tag{3.4}$$

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

$$SD = \sum_{t=0}^{T} \left[\frac{|(h_{1(k-1)}(t) - h_{1k}(t))|^2}{h_{1(k-1)}^2(t)} \right] \tag{3.5}$$

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

$$x(t) - c_1 = r_1 \tag{3.6}$$

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

$$\begin{aligned} r_1 - c_1 &= r_2 \\ &\cdots\cdots \\ r_{n-1} - c_n &= r_n \end{aligned} \tag{3.7}$$

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

$$X(t) = \sum_{i=1}^{n} c_i + r_n \tag{3.8}$$

3.4.2 Ensemble Empirical Mode Decomposition (EEMD)

EEMD is the modified EMD method to eliminate the effect of 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 defines the true IMF components as the mean of an ensemble of trials, each consisting of the signal plus a white noise of finite amplitude. The added white noise would populate the whole time-frequency space uniformly, facilitating a natural separation of the frequency scales that reduced exist of mode mixing [27]. 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 [26]. According to the [26], there are two situations will be shown as mode mixing exist, which are:

1. A Single IMF component of the signal contains a various component of scales;

2. Same components exist in different scales of IMF.

This NADA method, so called EEMD is developed as following [26, 33]:

1. A white noise series is added into the signal,

$$X_i(t) = x(t) + w_i(t) \tag{3.9}$$

   where $w_i(t)$ is i^{th} copies of white noise.
2. The added white noise's signal is process to decompose into IMF components.
3. Step 1 and step 2 are repeated with different white noise series each time.
4. Obtain the (ensemble) means of corresponding IMFs of the decomposition as final result.

$$c_j(t) = \lim_{N\to\infty} \frac{1}{N} \sum_{k=1}^{N} C_{jk}(t) \tag{3.10}$$

3.4.3 Index of Orthogonality

By theoretically, all of the decomposed IMF components should be able to reconstruct into the original data set to indicate that they are orthogonal to each other [23] to ensure the completeness and orthogonality of the decomposition by both of the EMD and EEMD methods. According to the [6], define an index based on the most intuitive way to check the orthogonality of the IMFs from EMD and EEMD as following:

1. Rewrite equation (3.8) as

$$X(t) = \sum_{j=1}^{n+1} c_j(t) \tag{3.11}$$

   In which the r_n is included as an additional element.

2. Form the square of the signal

$$\mathrm{X}^2(t) = \sum_{j=1}^{n+1} c_j^2\,(t) + 2\sum_{j=1}^{n+1}\sum_{k=1}^{n+1} c_j\,(t) c_k(t) \tag{3.12}$$

3. With this expression, overall index of orthogonality, IO, is defined as

$$\mathrm{IO} = \sum_{t=0}^{T}\left(\sum_{j=1}^{n+1}\sum_{k=1}^{n+1} c_j\,(t) c_k(t)/\mathrm{X}^2(t)\right) \tag{3.13}$$

Although the index of orthogonality act as the guarantee to evaluate the completeness of the data set, it still might appear some leakages of the data when it tend to reconstruct back to the original signal in real life. Hence, the performance of index of orthogonality is strongly depending on the leakage of the decomposed signal during the reconstruction of original data. These leakages which will bring the drawback to the performance of decomposition's methods should be ameliorated as much as possible. Higher the value of index of orthogonality means that the severity of leakage also higher. The value of index of orthogonality should as low as possible (nearly to zero) to ensure the accuracy and efficiency of the analyzed result. In this report, the performance of IMF components that generated by EMD and EEMD methods respectively will be compare later to determine the reliability of the result.

3.4.4 Hilbert Spectral Analysis

After obtained the IMF components from decomposition of EMD and EEMD methods respectively, Hilbert Transform can be applied to each component to obtain the instantaneous frequency. The instantaneous frequency of original signal is defined as [34]

$$w_j(t) = \frac{d\theta_j(t)}{dt} \tag{3.14}$$

Where $\Theta_j(t)$ is instantaneous phase.

After performing the Hilbert-Huang transform (HHT), we can express the data in the following form [34]:

$$X(t) = R_e \sum_{i=1}^{n} a_j (t) exp\left(i \int w_j (t) dt\right) \tag{3.15}$$

Where $a_j(t)$ is the instantaneous amplitude.

Since the Hilbert spectrum had been defined, it is able for us to define the Hilbert marginal spectrum which shows as following:

$$h(w) = \int_0^T H(w,t) dt \tag{16}$$

where T is the total data length. Hilbert marginal spectrum offers a measure of total amplitude or energy contribution from each frequency value. It represents the cumulated amplitude over the entire data span in a probabilistic sense. It is also the time integration of Hilbert spectrum, $H(w,t)$which is a reduced frequency-energy representation [23].

CHAPTER 4

RESULTS AND DISCUSSIONS

4.1 Comparison between Performance of EMD Method and EEMD and EEMD Method

As mention previously, EEMD method is the modified EMD method to ameliorate the drawback of the original EMD algorithm which is the mode mixing effect. This effect will greatly affect and reduce the accuracy and efficiency of the analyzed data which may bring the consequences of misinterpretation on these results by physicians and researchers. Therefore, EEMD method is able to produce more reliable and precise information from a large sum of EEG raw data compare to the performance of the EMD method. Next, the performance of both the methods will be compared to determine the accuracy and efficiency after the EEG raw data had been processed. The EEG data set used was created and contributed by the developers of the BCI2000 instrument system and downloaded from the PhysioNet [35]. This data set whose sampling rate is 100Hz had been collected by EEG device from an obstructive sleep apnea syndrome (OSAS) patient. From the original raw EEG OSAS patient's data, only 1500 time samples of the data which is show in **Figure 4.1** will be extracted to do the comparison due to the large amount of EEG data in channel C3. To compare the performance of both the methods, not only the IMF will be emphasize but also, these IMF components were applied into Hilbert transform to present the result in Hilbert Spectrum and Marginal Hilbert Spectrum. Although one of the method that act as performance indicator which is Index of Orthogonality (IO) is the simplest way and short of novelty, it still can be employed to ensure the completeness and orthogonality of the decomposition after the EEG data had been processed by EMD and EEMD methods [36]. There are several aspects that mention before will be applied to determine the performance of EMD and EEMD methods in the next few sections.

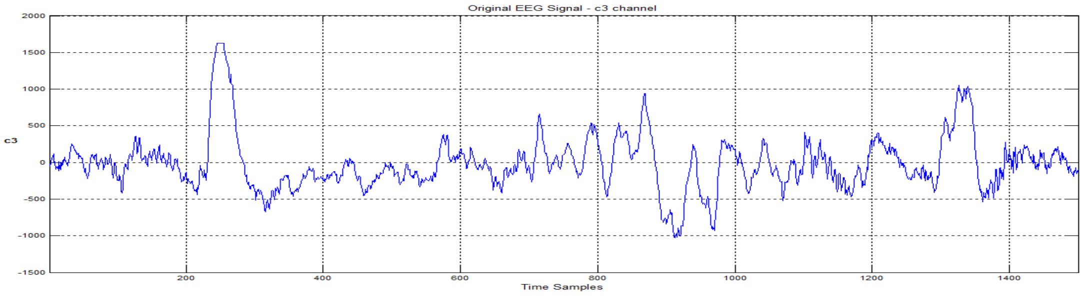


Figure 4.1: Original 1500 samples EEG Data from C3 channel of severe OSAS patient.

4.1.1 Details in the IMF Components

The original C3 channel EEG data which is shows in Figure 4.1 had been decomposed by EMD method and EEMD methods respectively. These IMF components based on EMD method where shows in **Figure 4.2** and EEMD method in **Figure 4.3** were arranged from low to high order. The EEMD method was implemented with the added noise which is having amplitude of 0.1 standard deviation of C3 channel EEG data. Through the observation onto these IMFs, these frequencies of each individual IMF are decreases as the order of IMF increases. The IMF components based on EEMD method also retain more physical meaning of the signal compare to those based on EMD method. This is happen significantly by comparing third IMF of EMD and EEMD methods which are show in Figure 4.2 and Figure 4.3. From the time samples 600th to 1000th, the third IMF based EMD method is contain less useful information compare to those based EEMD method.

Now, we are look more into details of the IMF components based on EMD and EEMD methods. **Figure 4.4** and **Figure 4.5** are show the fifth IMF component based on EMD and EEMD methods while **Figure 4.6** and **Figure 4.7** are show the sixth IMF component of both the method respectively. The red frames of the figure are used to carry out the comparison between the EMD and EEMD methods. Significantly, the fifth and sixth IMF component based on EEMD method is containing more physical meaning compare to those based on EMD method. During the decomposition process along to the highest order, the IMF components based on EMD method is unable to avoid the mode mixing problem since the dyadic property is comprised which means that it had loss the physical meaning of the data. Conversely, the EEMD had proved that it can present well the inherent physical properties of the original EEG signal with the aid of added white noise. Therefore, the EEMD is enabling EMD to reform the compromised dyadic property for the effectiveness on regulation of mode mixing effect.

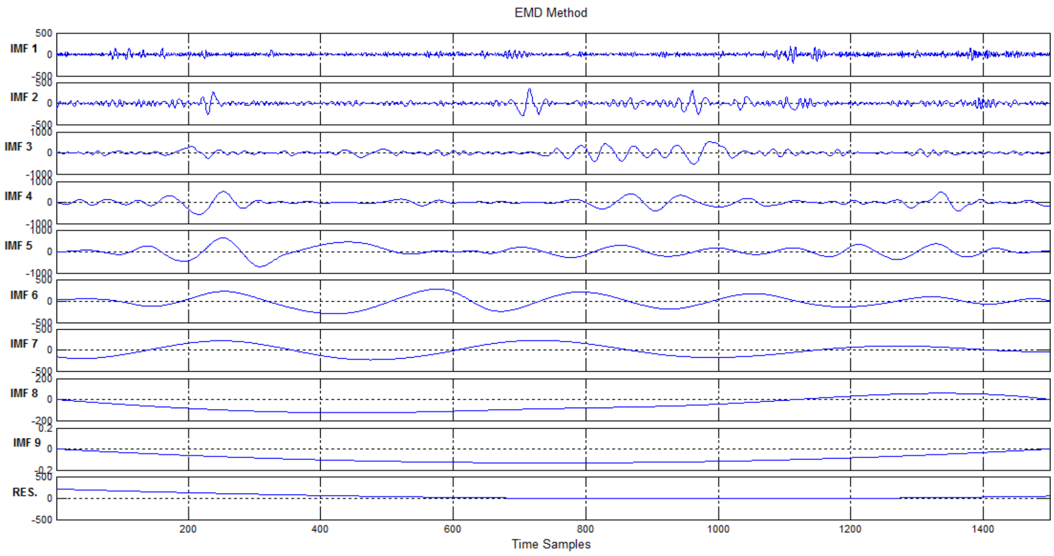


Figure 4.2: IMF components of EMD method.

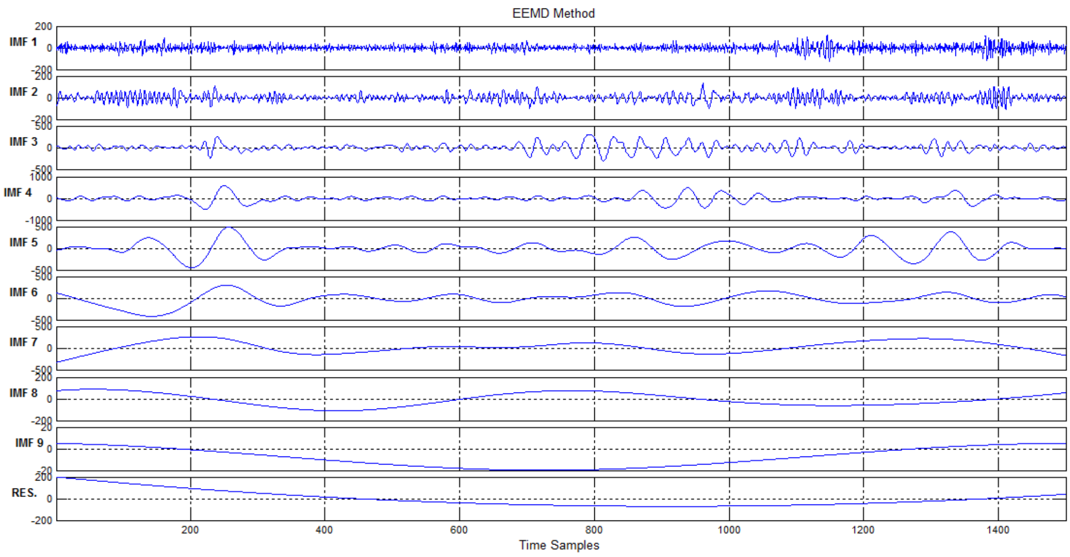


Figure 4.3: IMF components of EEMD method.

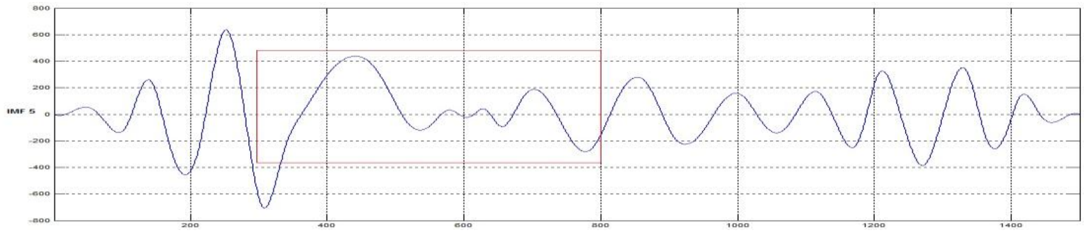


Figure 4.4: IMF5 of EMD.

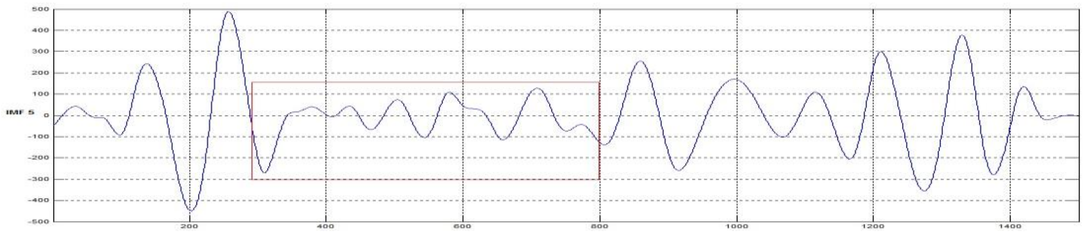


Figure 4.5: IMF5 of EEMD.

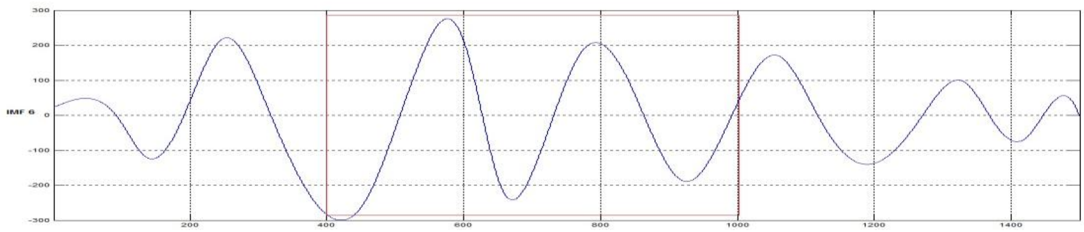


Figure 4.6: IMF6 of EMD.

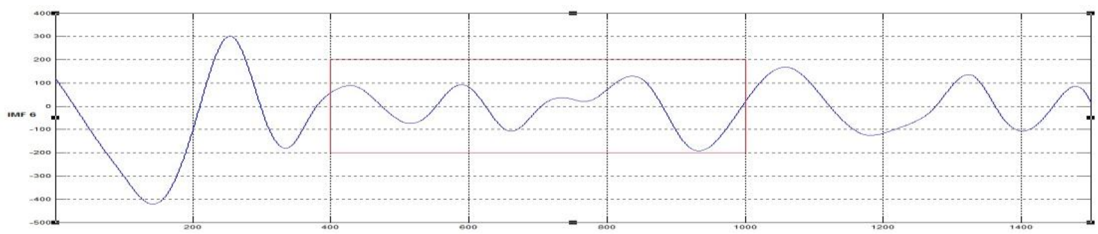


Figure 4.7: IMF6 of EEMD.

4.1.2 Index of Orthogonality (IO)

From the decomposed signals through the observation, how can we guarantee the validity and reliability of the EMD and EEMD algorithms? In other words, how can ensure the IMF components that generated by both the EMD and EEMD methods are fulfil the requirement of completeness and orthogonality or differences between the reconstructed data from sum of all IMFs and the original data? One of the simplest ways that mention previously is by calculated the value of Index of Orthogonality (IO) and evaluates the interpolation techniques from the component orthogonality point of view based on EEG data to ensure the completeness of the EEG data.. According to the [24], the orthogonality is requirement only for linear decomposition systems. It might not make physical sense for nonlinear decomposition as in EMD and EEMD. But, in most cases encountered, the leakage is still considered small. However, we still can compare the index of orthogonality (IO) in both methods since the data which been carried out the analysis is the same EEG signal from C3 channel.

Decomposition method	Index of orthogonality (IO)
EMD	0.2579
EEMD	0.1989

Table 4.1: Comparison of IO values between EMD and EEMD methods.

Table 4.1 shows the IO values of EMD and EEMD methods respectively. These IO values were used to indicate the level of leakage during the decomposition process appeared by both of the methods. Although the IO values that been provided are “less orthogonal”, the result shown still can be a part of reference values to determine which signal processing technique is the best method to apply in EEG data. From Table 4.1, the IO value based on EMD method is 0.2579 which is quite high compare to the EEMD method which the IO value is 0.1989. Theoretically, the IO value should be zero to prove the completeness of the data after decomposition had been employed. But in real life, it can be said is impossible due to the leakage will still appear no matter how perfect the algorithms are. Therefore, the obtained IO value should as low as possible to ensure the level of leakage is very low. Through the IO values of EMD and EEMD methods from the result, it can be concluded that the EEMD method can retain more physical meaning and less leakage information will be loss in the IMF components.

4.1.3 Hilbert Spectrum

After obtaining the IMF components of EMD and EEMD, the Hilbert Spectrum can be derived by employing Hilbert transform to construct the time-frequency-energy distribution [37]. Hilbert spectra analysis can be used in exploring the full physical meanings of complicated data such as EEG data we analyzed here. Hilbert spectrum can perform the high time-frequency resolution; the signal can characterize the local features of the signal effectively by combining the instantaneous spectrum of each IMF component [33]. According to the [26], Hilbert spectra can be used to identify the basis frequency and ranges of variation but not in quantitative measurement.

The Hilbert spectrum based on EMD method and EEMD method are show in **Figure 4.8** and **Figure 4.9** respectively. For the EEMD method, we can observe that the comprehensible and unmistakable were appeared on the characteristics of Hilbert spectrum compare to those with EMD method. As we can see in Figure 4.8, the Hilbert spectrum based on EMD method had been affected and the trace was separated from one scale to another in certain distance due to the mode mixing effect in EMD method. Conversely, the Hilbert spectrum based EEMD method in Figure 4.9 are less or almost no transitional gap occur. The basis frequency traces are continuously to indicate that the inherent physical information can be retained and capable to reduce the effect of mode mixing.

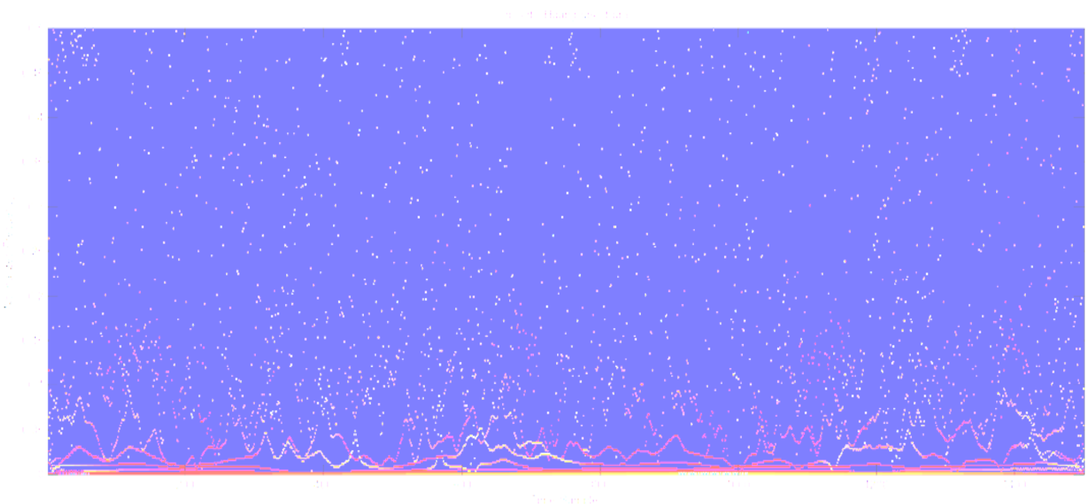


Figure 4.8: Hilbert spectrum of EMD method.

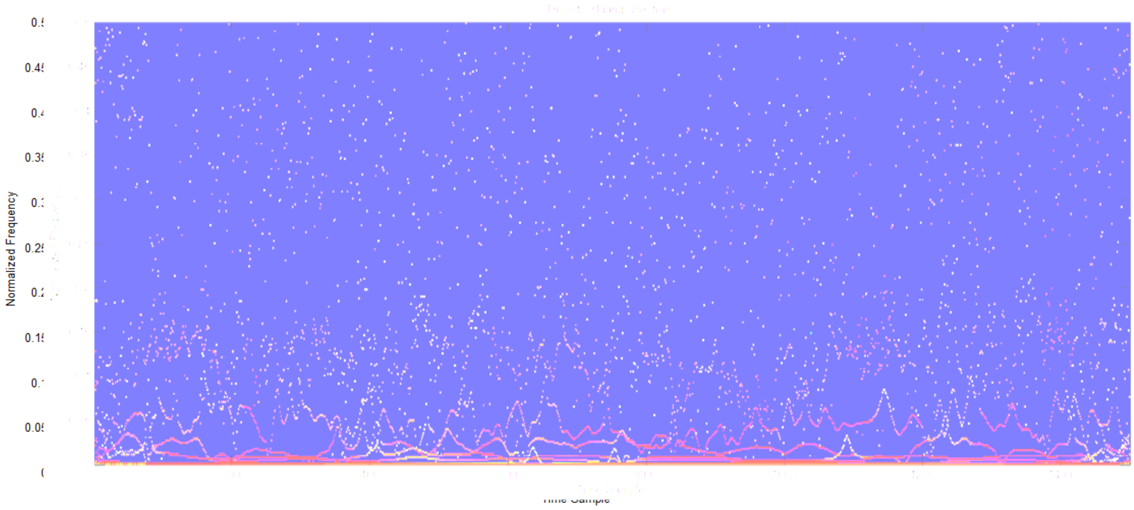


Figure 4.9: Hilbert spectrum of EEMD method.

According to the [38], the instantaneous frequency is employed to understand the details mechanisms of nonlinear and non-stationary signal. Through the Hilbert transform, the instantaneous frequency also can derive to compare the accuracy of the result based on these two methods. The instantaneous frequency of EEG signals based on EMD and EEMD methods has been showed in **Figure 4.10** and **Figure 4.11** respectively. Observe that red colour line which is IMF 3, the mode mixing was appeared obviously from the time samples 500th to 1000th based on EMD compare to the EEMD. For instantaneous frequency based EEMD, at the same ranges of time samples, it provide more information to analyze the EEG signal. Finally, the last method to compare the performance of these two methods is marginal Hilbert Spectrum. Marginal Hilbert spectrum will be presented to describe the total amplitude (or energy) contribution of EEG signal from each frequency value. **Figure 4.11** and **Figure 4.12** are show the marginal Hilbert spectrum based on EMD and EEMD methods respectively. The characteristics of the EEG signal are more significant in EEMD method compare to the EMD method. Recognition of characteristics of EEG signal is essential for medication prescription, diagnosis and treatment purposes by healthcare provider especially physician.

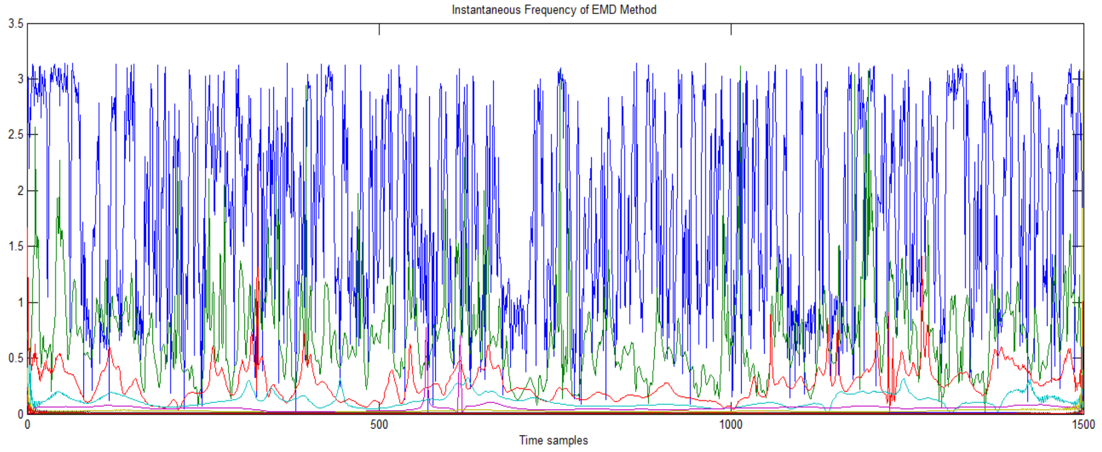


Figure 4.10: Instantaneous frequency of EMD method.

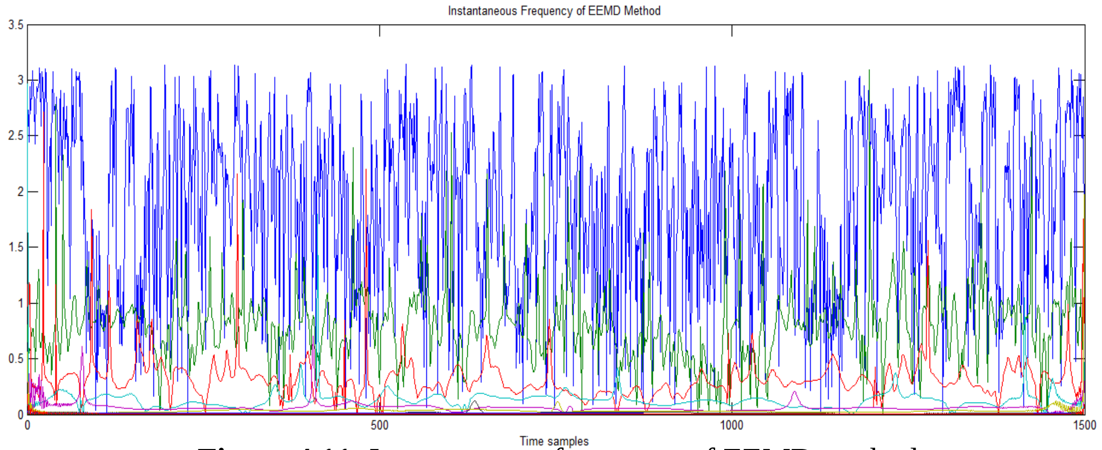


Figure 4.11: Instantaneous frequency of EEMD method.

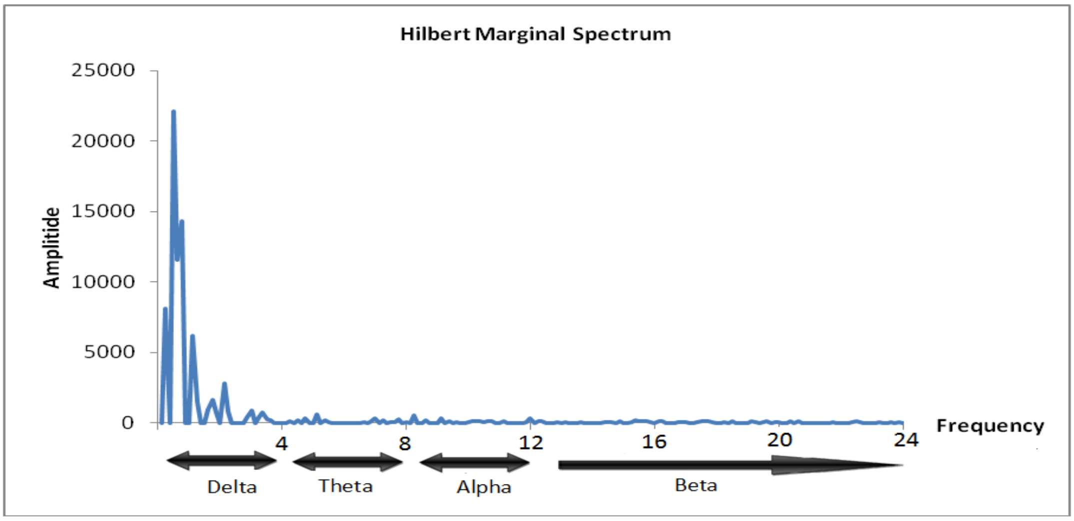


Figure 4.12: Marginal Hilbert spectrum by EMD method.

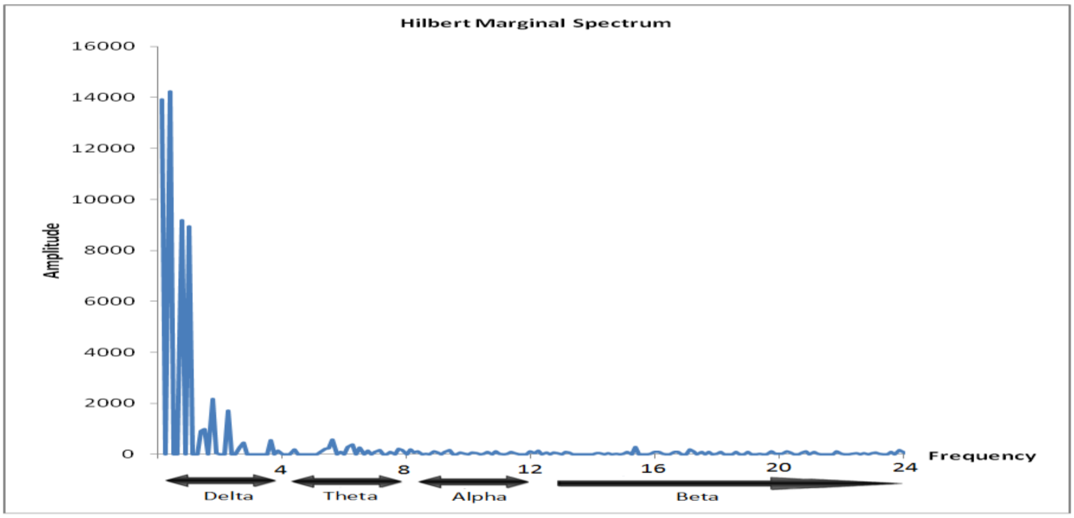


Figure 4.13: Marginal Hilbert spectrum by EEMD method.

4.2 Experimental Study on the Relationship between Effect of Music Therapy and Human Sleep Quality

The experiment related to the music therapy and the human sleep quality had been successfully conducted under three different conditions as follow the procedures that show in Figure 3.1 and 3.2. With aid of the CamNtech Actiwave EEG System, the EEG data are able to be collected and captured from the test subject. In this experiment, we are mainly focus in the recognition and identification of the EEG patterns, and the determination of quality of sleep through marginal Hilbert Spectrum which is amplitude-frequency distribution. 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 emphasized for EEG pattern's recognition. The original raw EEG data that collected under different conditions from test subject will be presented in Appendix A (I)-A (IV). Due to the IMF components that generated by EMD and EEMD methods have a lot of decomposed results, these IMFs will be put in the Appendix B (I)-B (VIII). At the last section, the performance between the EMD and EEMD method had been compared by using the EEG data that downloaded from PhysioNet. For the comparison by using the EEG data from our test subject, there are several aspect had been done to determine the performance. Of course, the result shown was the EEMD method has better performance compare to the EMD method. The IMF components obtained can provide the better analysis and understanding onto the EEG signal itself. At the same time, the comparison between EMD and EEMD in detecting the features and characteristics of IMFs will emphasize also to show the accuracy and efficiency of these methods.

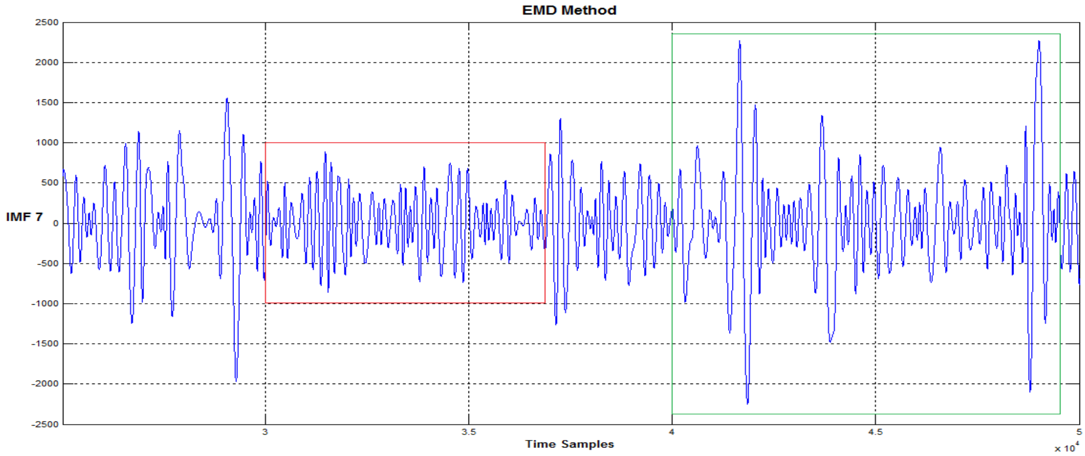
4.2.1 Recognition and Identification of EEG Patterns

4.2.1.1 Under Conditions of Relax and Wakefulness

By following the sequences of the experiment's procedure, first step is the test subject should relax him/herself but remain wakefulness. The EEG data that collected in this stage is to identify the EEG pattern under wakefulness condition. The features and characteristics of decomposed signal by EMD and EEMD methods are show in **Figure 4.14** for channel C3 and **Figure 4.15** for channel O1 based on 10-20 EEG placement of electrode respectively.

For channel C3, the beta rhythms where the ranges are more than 13Hz have usually quite low amplitude depend on the value of frequency. Higher the frequency will lead to lower the amplitude. From the Figure 4.14A and 4.14C, the red frames in the figures indicate that it is the beta rhythms which have quite low amplitudes compare to the green frames in the Figure 4.14A and 4.14B which are alpha rhythms that have higher amplitudes. The alpha rhythm always consists of regular waveforms that have sharp points at the top or bottom or sinusoidal [39]. The alpha rhythm is usually repetitive in the same recording with high amplitudes where are often waxes and wanes and middle-high frequency which are between 8Hz to 13Hz. At this stage, the EMD method still could recognize the alpha and beta rhythm as EEMD shown. For the channel O1, the decomposed signal had detected the symptoms of short while of light drowsiness with some irregular waveforms which shows in green frames of Figure 4.15A and 4.15B. Basically, these irregular waveforms are around 5-7Hz during relaxation. Compare between the Figure 4.15A and 4.15B, the decomposed signal of EEMD method had showed the irregular waveform and slow wave compare to the EMD method.

A



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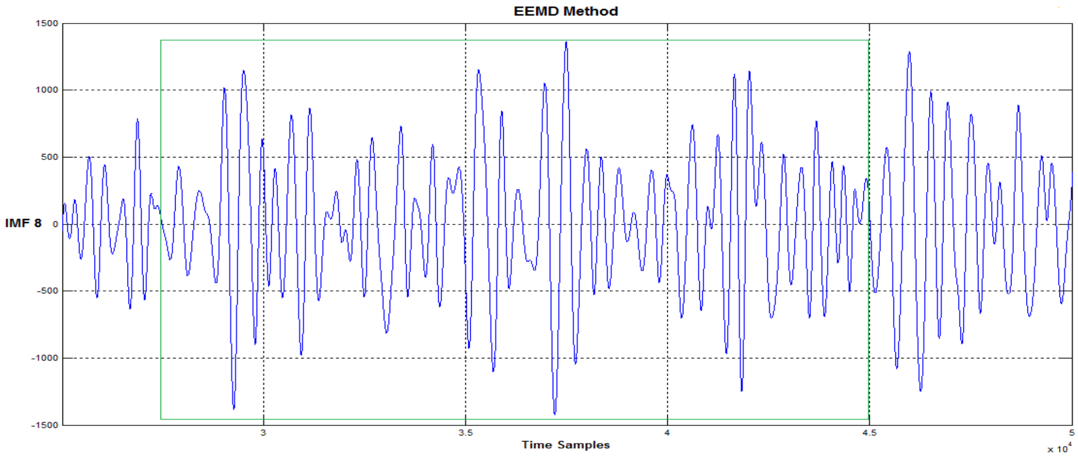

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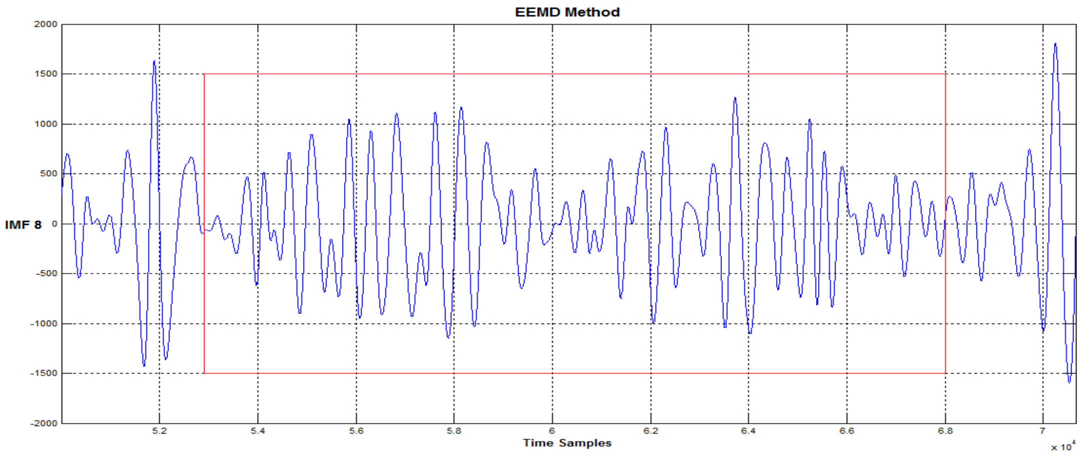
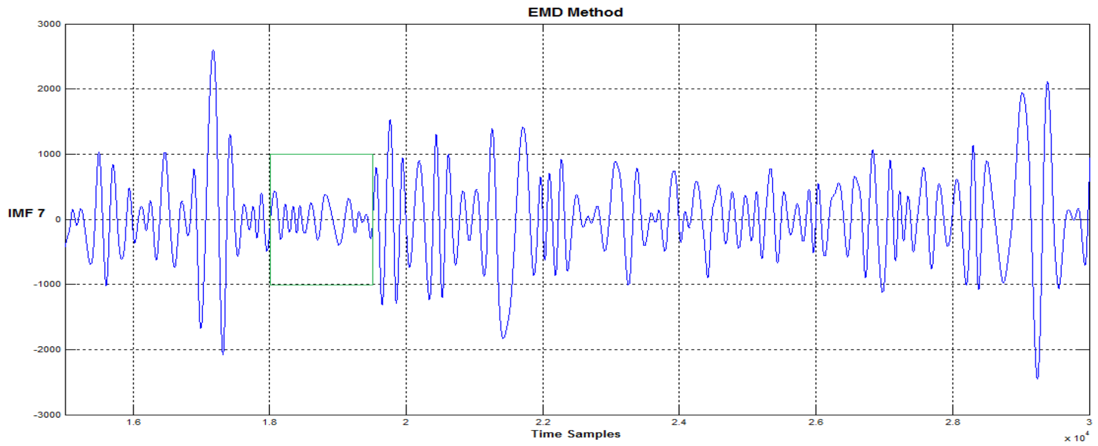


Figure 4.14: Normal patterns of wakefulness and relax in channel C3 of test subject. (A) IMF 7 of EMD method. (B&C) IMF 8 of EEMD method. Red frames represent beta rhythm while Green frames represent alpha rhythm.

A



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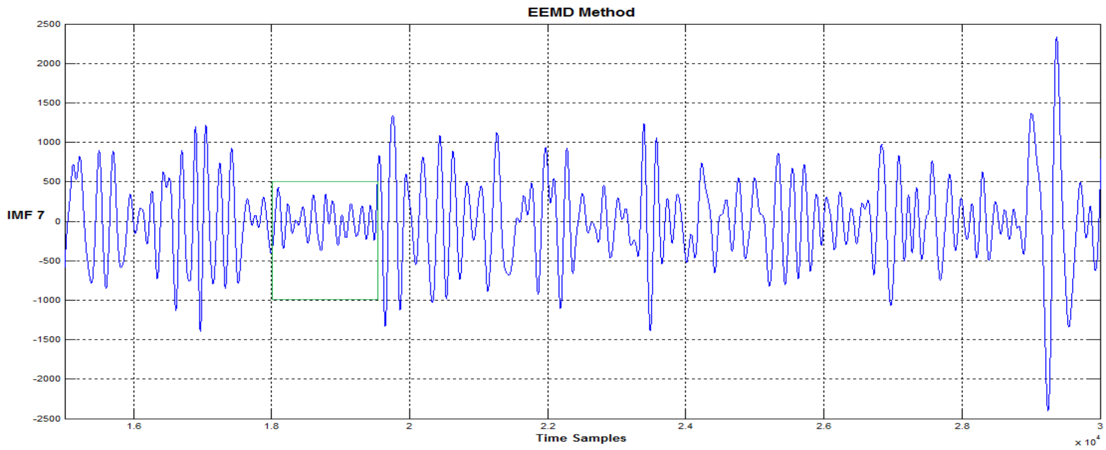


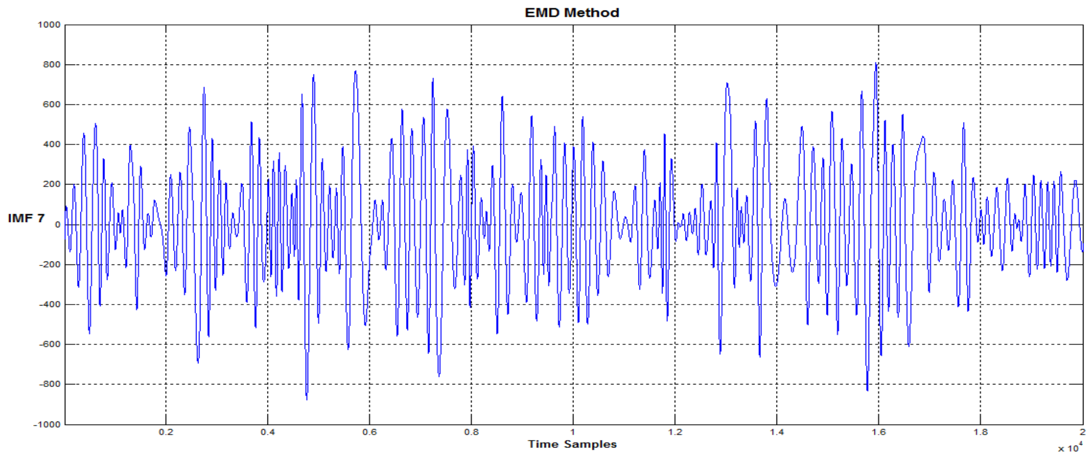
Figure 4.15: Normal patterns of wakefulness and relax in channel O1 of test subject. (A) IMF 7 of EMD method. (B) IMF 7 of EEMD method. Green frames represent light drowsiness occurs during relaxes.

4.2.1.2 Under Conditions after Watching Movie

After complete the analysis of EEG signals under conditions of wakefulness and relax, it is the turn to identify the features and characteristics of decomposed EEG signal under condition after watching movie. By theoretically, the frequencies of human's brainwave will be gradually increases after have some activities that can trigger the neuron in the brain cell. Therefore, to prove this statement is undeniable, an exciting and emotional movie will be test onto our subject. **Figure 4.16** and **Figure 4.17** are shows the IMF components by applying EMD and EEMD method respectively after movie's condition.

For channel C3, the decomposed EEG signals were mainly found that the test subject was in the beta rhythms. As Figure 4.16A and 4.16B shown, the beta rhythms had occupied a lot in the signals. The beta rhythm shows in both the figures are very high in frequencies and low in amplitudes which are less than 800. These beta rhythms that found from the test subject indeed proved that the after watching movie's condition, the human's brainwave can be activated and gradually increased. For channel O1, the red frames of Figure 4.17 and 4.18 had showed the fast alpha variant of around 15Hz in the posterior head regions and fast beta rhythm elsewhere occurs. Posterior beta rhythm or fast alpha variant has a frequency about twice that of the alpha rhythm and either intermixes or alternates with the alpha rhythm or replace it [39]. This beta rhythm is blocked by the same maneuvres that block the alpha rhythm [39].

A



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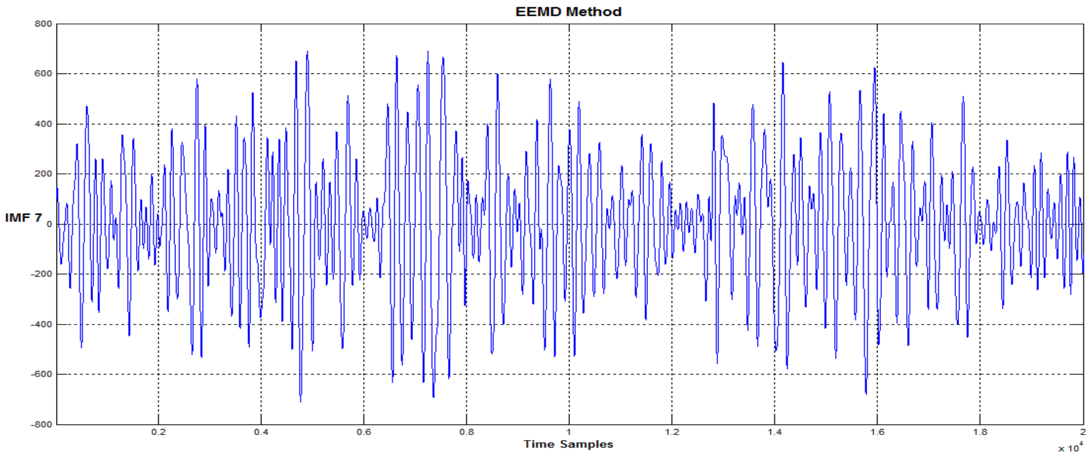
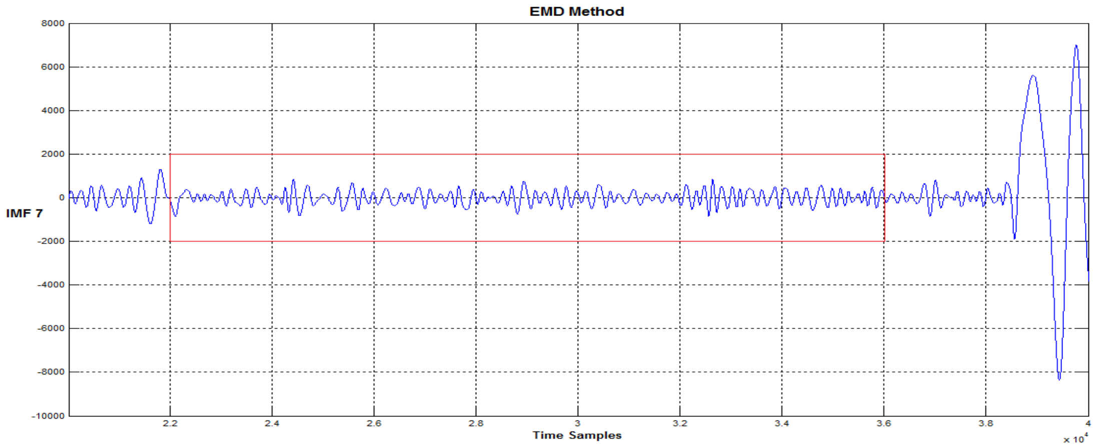


Figure 4.16: EEG patterns after watching movie in channel C3 of test subject. (A) IMF 7 of EMD method. (B) IMF 7 of EEMD method. The overwhelming majority of beta rhythm had been found.

A



B

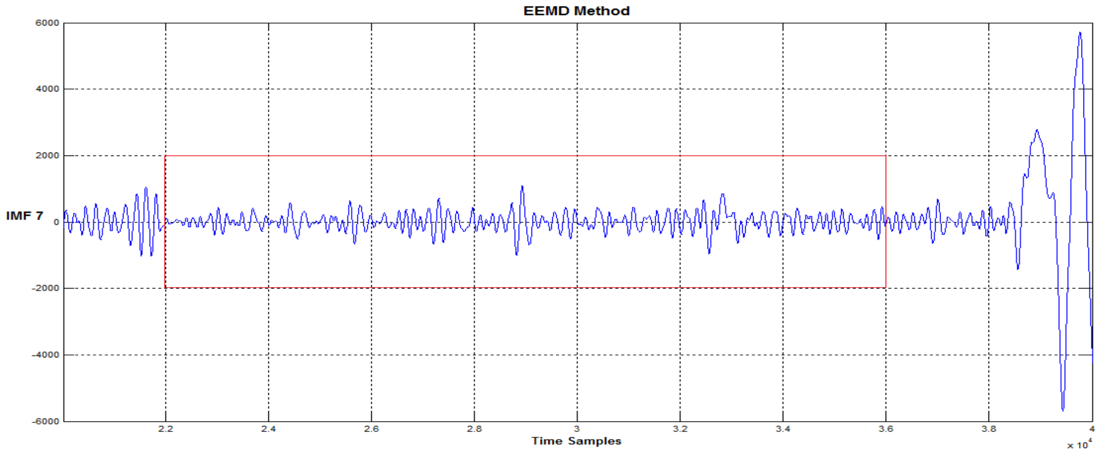


Figure 4.17: EEG patterns after watching movie in channel O1 of test subject. (A) IMF 7 of EMD method. (B) IMF 7 of EEMD method. Red frames represent fast alpha variant of around 15Hz in the posterior head regions and fast beta rhythm elsewhere.

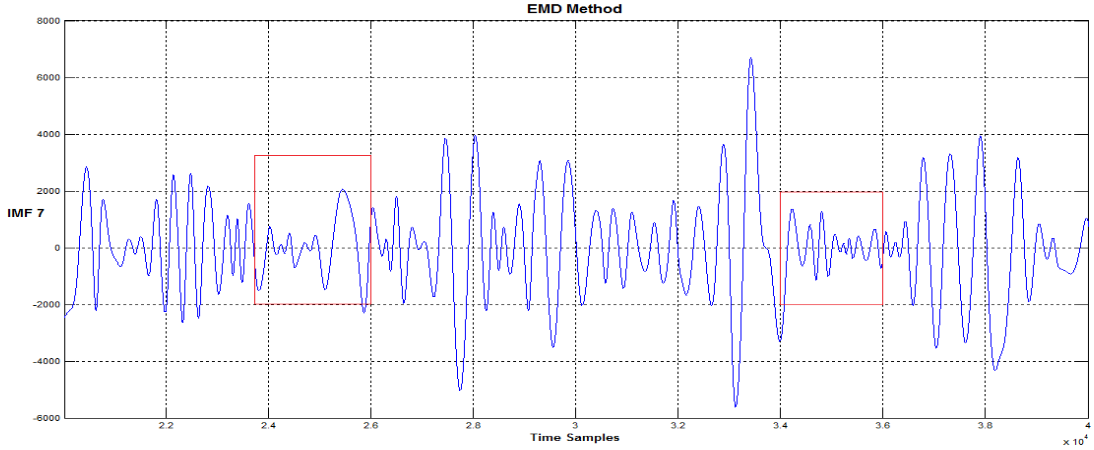
4.2.1.3 Conditions of Sleep without Music and within Music

For the final stage of the experiment which is also the main purpose of this report, the analysis was done on the effect of music toward human sleep quality compare to those without music. Through the result that we obtained by EMD and EEMD method, the pattern recognition will focus on the features of sleep pattern in different sleep stages to determine how deep the test subject is sleep with aid of music and without music.

For the channel C3, **Figure 4.18** and **Figure 4.19** are shown the sleep patterns of test subject without aid of music. There are several features and characteristics of sleep pattern had been detected through EMD and EEMD methods. In the red frames of Figure 4.18A and 4.18B, the slow wave around 3-7Hz has been detected. The slow waves usually are widely distribution in the EEG signals. The slow waves that occur here can be defined as light sleep or sleep stage I. The slow wave generally less persistent, more asynchronous, lower amplitude and faster frequency compare to the deep sleep [40]. However, for the red frames in Figure 4.18A, it is difficult to recognize the EEG signals is under condition of slow wave because the frequencies show is more likely higher compare to the slow wave's frequencies. Since the EMD method is not likely to present the slow waves symptoms, we can do some investigations onto the EEMD method at the same time samples. Indeed, the EEMD method is able to show the slow wave in the red frames of 4.18B significantly. Both of the EMD and EEMD methods are able to show the appearance of light sleep and sleep spindle in the Figure 4.18C and 4.18D respectively. The green frames of both the figures represent the sleep spindle occur. Sleep spindles have quite high frequency range around 11-14Hz. They are widely distributed and always appear simultaneously over both hemispheres and approximately symmetric [40].For channel O1, the appearance of slow wave around 3-7Hz also been detected which shows in red frame of Figure 4.19A and 4.19B. by comparing both of the figures, the EMD method is lead to confuse and mistake for determination of slow wave's features due to the contained signals have some high frequency signal appear in the red frame of figure. Conversely, the EEMD method had showed the features of slow wave significantly. These slow waves which appear in channel C3 and O1 are the symptoms of drowsiness occur.

From the features and characteristics of sleep patterns without music that had been recognized and identified, these can be concluded that after 30 minutes remain sleeping condition, the test subject is sleep under condition of stage I since the slow wave between 2-7Hz (drowsiness) occur and disappearance of alpha rhythms, and began to enter stage II where the sleep spindle is appear just before the end of EEG data recorder. Sometimes, there are quite numbers of sleep pattern consists various mixture of rhythms such as delta, theta and alpha wave up to stage II. The awareness of misinterpretation and repeating carried out the analysis need to be done to obtain the accurate and precise conclusion. At the initial part of this stage I, the amplitude is show with mixed frequencies. When reach to the deeper part of stage I, the slow waves are show 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



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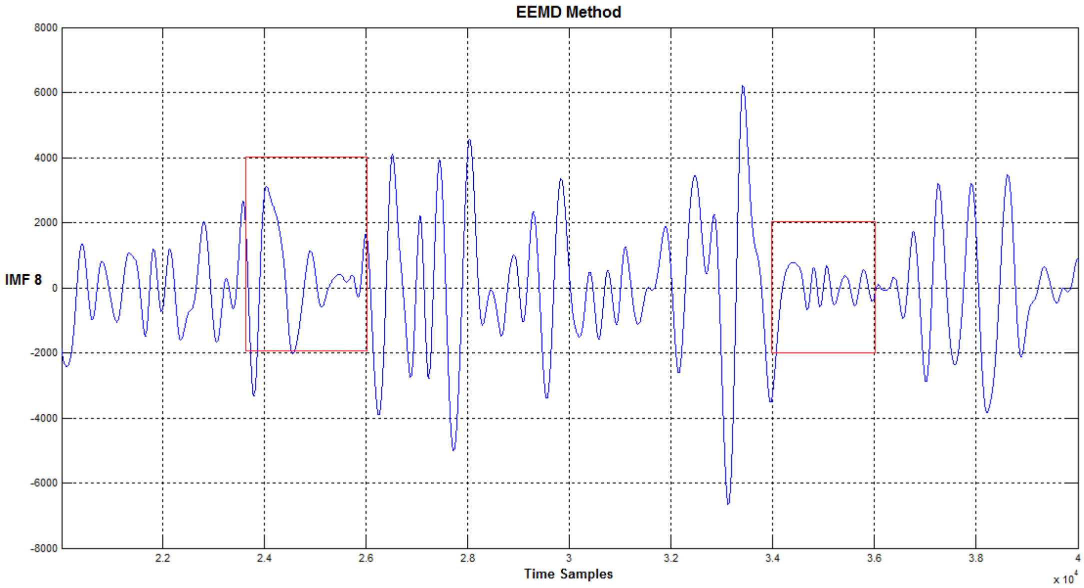

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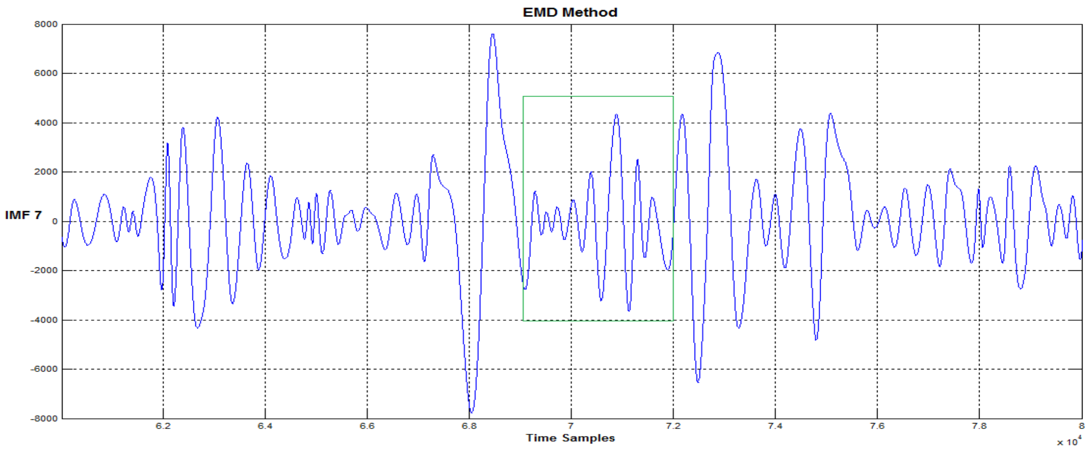

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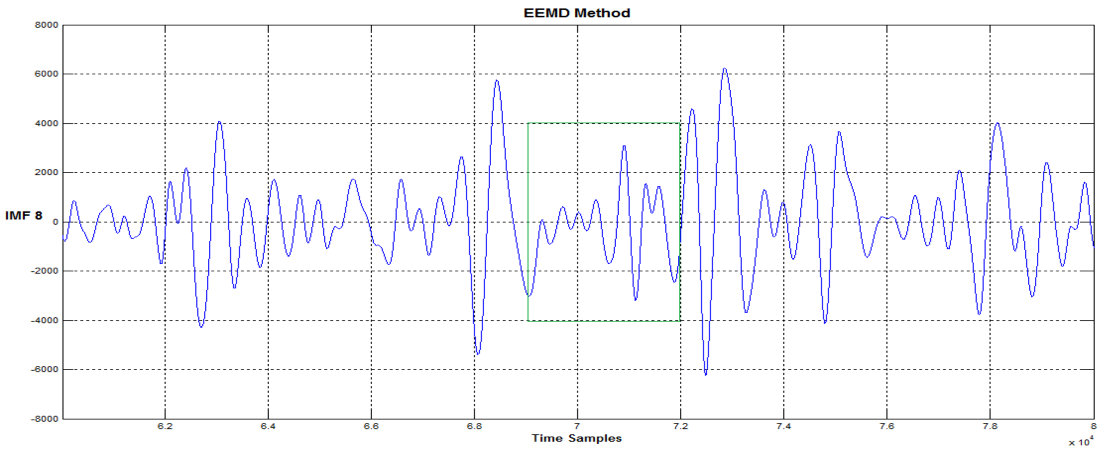
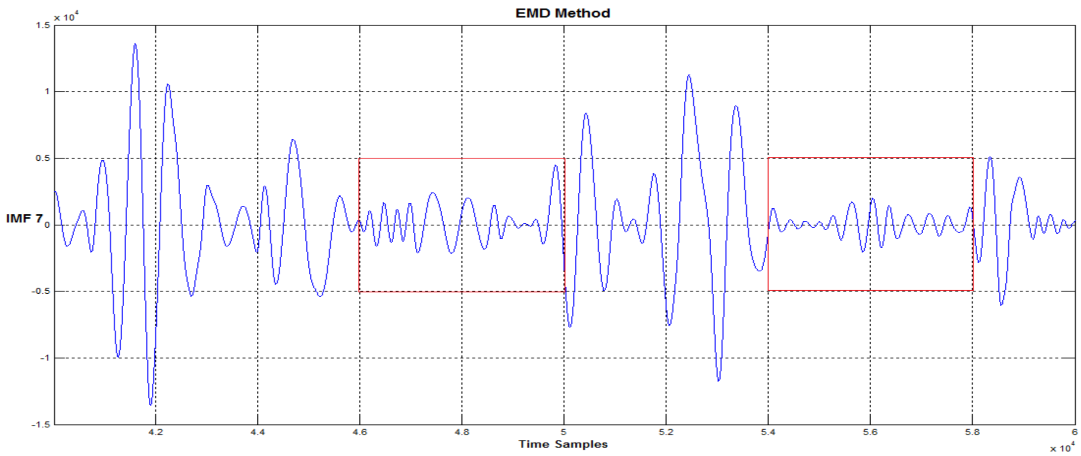


Figure 4.18: EEG patterns of sleeping without music in channel C3 of test subject. (A&C) IMF 7 of EMD method. (B&D) IMF 8 of EEMD method. Red frames represent slow wave occur between 2-7Hz. Green frames represent sleep spindle occur.

A



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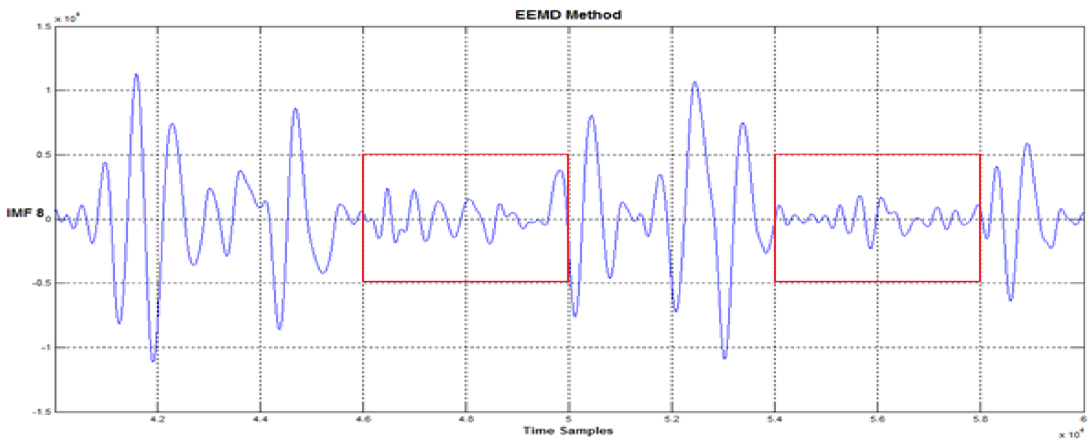


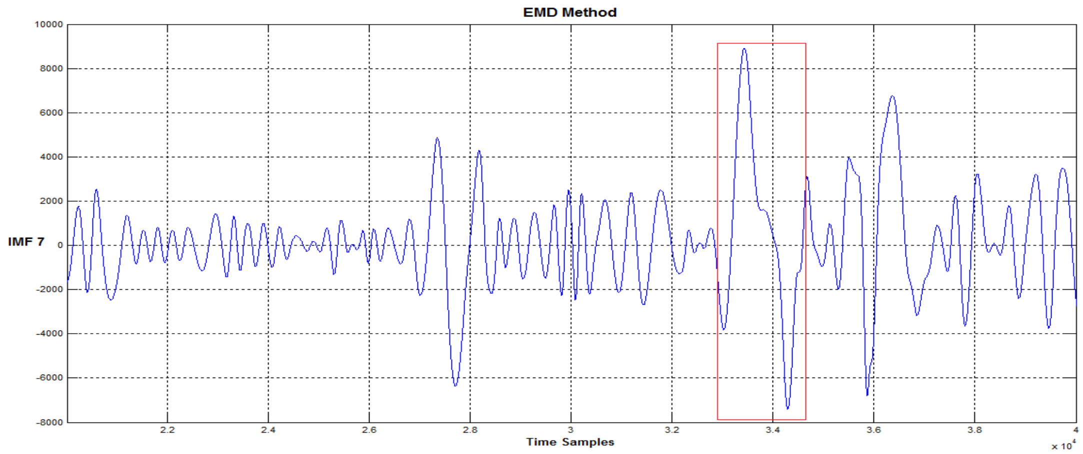
Figure 4.19: EEG patterns of sleeping without music in channel O1 of test subject. (A) IMF 7 of EMD method. (B) IMF 8 of EEMD method. Red frames represent slow wave occur between 2-7Hz.

Lastly, the analysis on sleep patterns with aid of music which are show in **Figure 4.20** and **Figure 4.21** was carries out by EMD and EEMD method respectively to compare the effectiveness of music therapy with the sleep pattern without music that we emphasized previously. For channel C3, both of the EMD and EEMD are able to detect the features of K-complex which are show in red frames of Figure 4.20A and 4.20B while the features of sleep spindle in green frames of 4.20C and 4.20D. 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 [40]. The details on features and characteristics of the sleep spindle had been emphasized previously. For channel O1, the red frame of

Figure 4.21B which is based on EEMD method was showed more obviously the very slow wave EEG signals where can be less than 2Hz had been captured compare to the EMD method which is shows in red frame of Figure 4.21A. The K-complexes are also been presented in the green frames of both the figures. But, the EMD method (Figure 4.21A) is containing lack of the features of K-complex compare to the EEMD method (Figure 4.21B). Besides these features that detected from the EEG signal, there is still has another sleep pattern so called the positive occipital sharp transient (POSTs) which is shows by the black arrows in the Figure 4.21C based EMD method and 4.21D based EEMD method respectively. POSTs are monophasic or biphasic, triangle wave in occipital regions. POSTs resemble the lambda waves in shape and distribution and sometime it name as 'lambdoid waves' [40]. 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 [40].

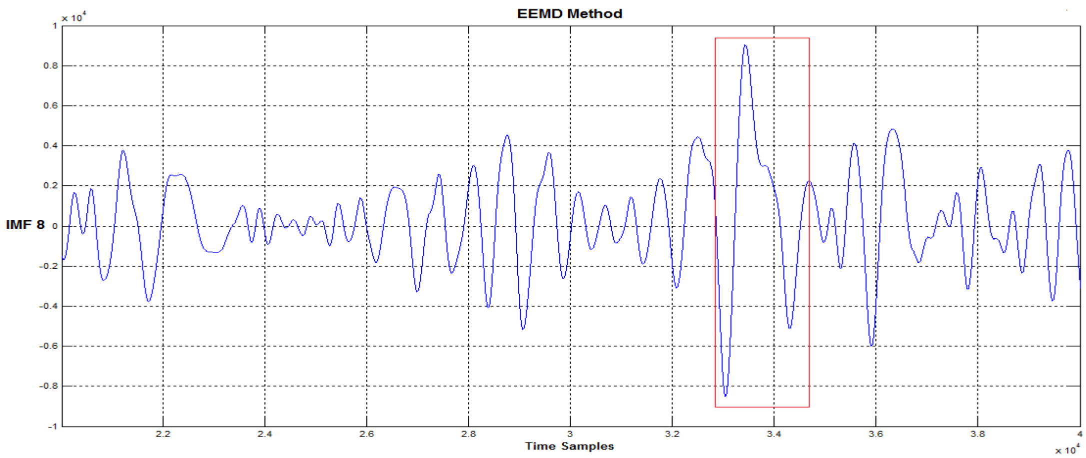
Through the observation of sleep pattern with aid of music, we can conclude that the test subject is sleep under condition of stage II and stage III after 30 minutes remain sleep condition. The stage II is characterized by the presence of K-complexes and sleep spindles. Slow wave between 2-7Hz is able to be seen and often bilaterally synchronous. POSTs could be appeared in both stage II and stage III. Stage III will presence of very slow waves of high amplitude occur. In this experiment, K-complex and sleep spindle were occurred in this stage also. The disappearance of drowsiness and existence of slow wave less than 2 Hz had ensured the test subject had entered the deep sleep (Stage III). Therefore, by comparing the conclusion of the results which are sleep with music and without music, the music therapy indeed can improve the sleeping quality of human through observation on the individual sleep patterns recognition and identification.

A



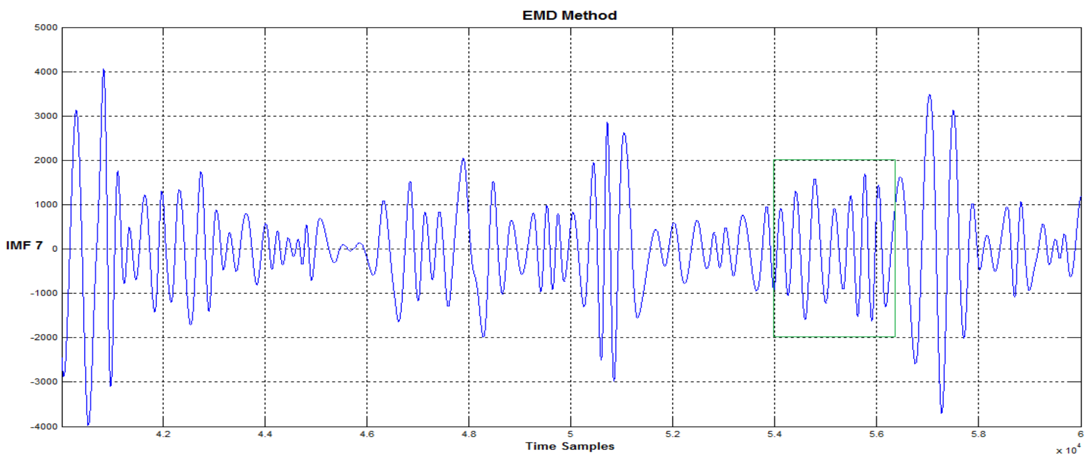
EMD Method
IMF 7
Time Samples
x 10^4
10000
8000
6000
4000
2000
0
-2000
-4000
-6000
-8000
2.2
2.4
2.6
2.8
3
3.2
3.4
3.6
3.8
4

B



EEMD Method
IMF 8
Time Samples
x 10^4
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-1
2.2
2.4
2.6
2.8
3
3.2
3.4
3.6
3.8
4

C



EMD Method
IMF 7
Time Samples
x 10^4
5000
4000
3000
2000
1000
0
-1000
-2000
-3000
-4000
4.2
4.4
4.6
4.8
5
5.2
5.4
5.6
5.8
6

D

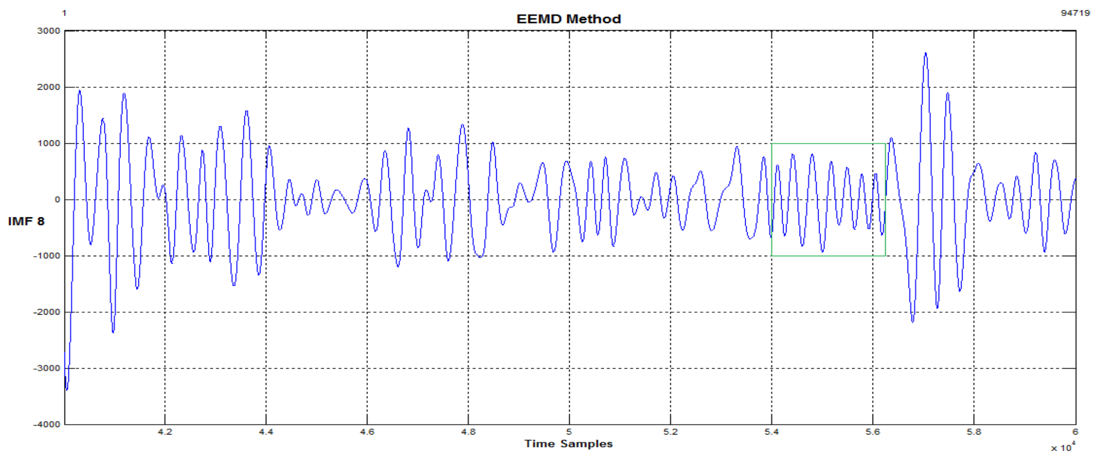
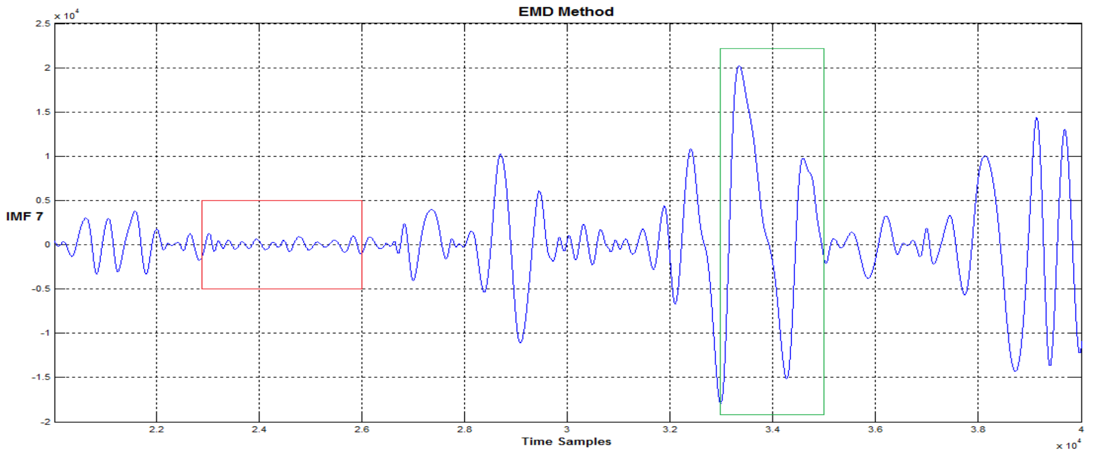
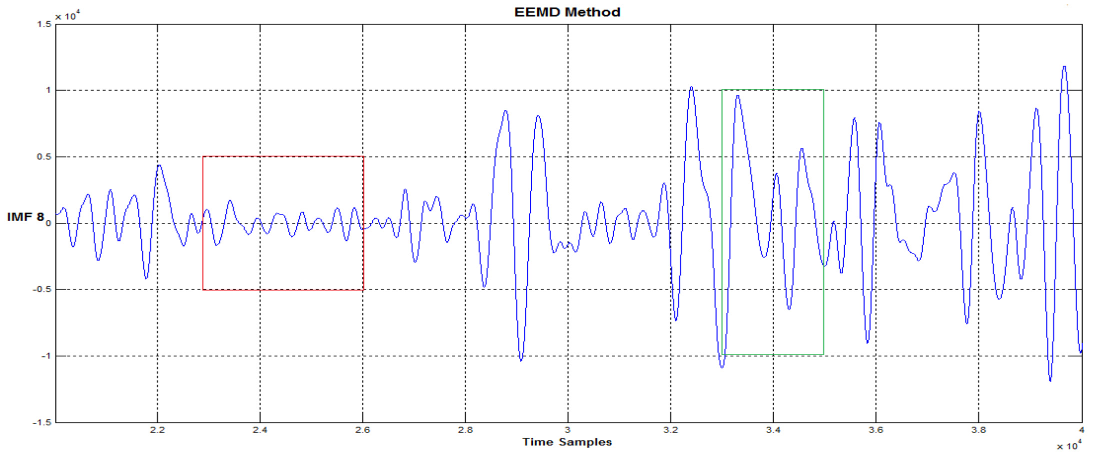


Figure 4.20: EEG patterns of sleeping with music in channel C3 of test subject. (A&C) IMF 7 of EMD method. (B&D) IMF 8 of EEMD method. Red frames represent K-complex occurs. Green frames represent sleep spindle occur.

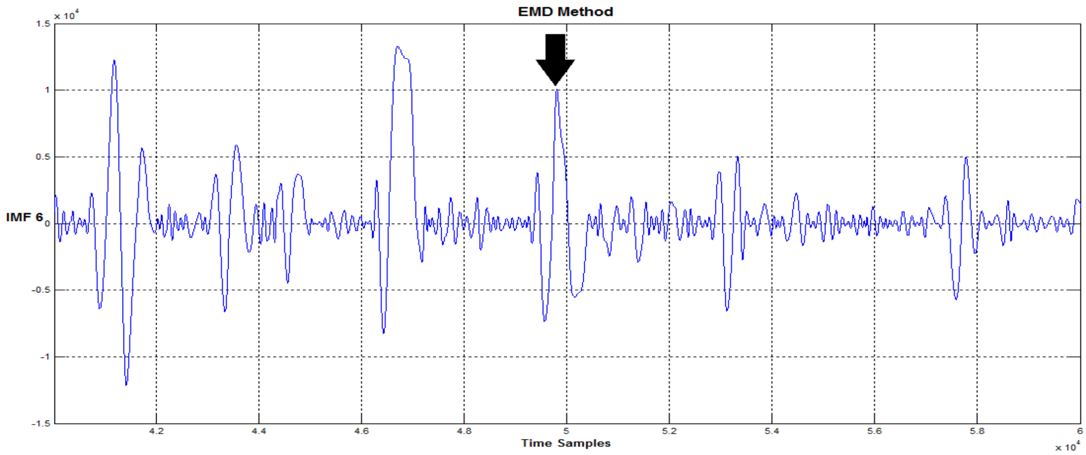
A



B



C



D

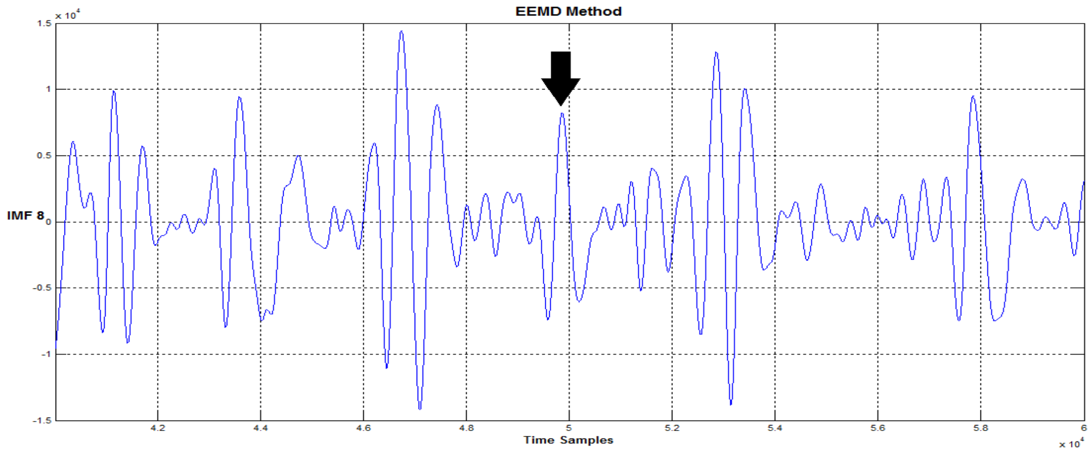


Figure 4.21: EEG patterns of sleeping with music in channel O1 of test subject. (A&C) IMF 7 of EMD method. (B&D) IMF 8 of EEMD method. Red frames represent slow wave less than 2Hz occur. Green frames represent K-complex occur. Black arrow represent POSTs occur.

4.3 Determination of Human Sleep Quality based on Amplitude-Frequency Distribution (Marginal Hilbert Spectrum)

Besides determine the sleep quality of human through observation by sleep pattern recognition and identification, the Marginal Hilbert Spectrum actually could provide us the results in amplitude-frequency distribution. Since the marginal Hilbert spectrum was employed to describe the total amplitude (or energy) contribution of EEG signal from each frequency value, it can told us most of amplitudes that contribute by EEG signals are actually within what ranges of frequencies to determine the sleep stages of test subject.

From the Section 4.2 where had carried out the comparison between performance of EMD and EEMD, we know that the EEMD method had better performance significantly in signal processing and analysis of EEG data. Therefore, in this section, the marginal Hilbert spectrum based on EEMD method which are showed in **Figure 4.22** and **Figure 4.23** will be carried out to compare the effect of music toward human sleep quality with those sleep quality without aid of music. Figure 4.22 was represented the marginal Hilbert spectrum under condition of sleep without music while Figure 4.23 was represented under condition of sleep with aid of music. From Figure 4.22, the main contribution of amplitudes in test subject's EEG signals were within the ranges of frequencies of approximately 7-12Hz. This means that, under condition of sleep without music, the alpha rhythms and theta rhythms were mostly detected in EEG signals. Alpha rhythms (8-12Hz) usually appeared in stage I which is drowsiness. For theta rhythms, it mainly shows in 7Hz which indicate that the test subject is slowly slept into stage II. For Figure 4.23, the contributions of amplitudes are mainly distributed within the ranges of frequencies approximately 3-10Hz. The rhythms that showed in graph within these ranges of frequencies are delta, theta and alpha rhythms. As mention before, alpha and theta rhythms always can be found in sleep stages I and II. Delta rhythm which in this case, is between 3-4Hz, this had indicate that the test subject had slept into deep sleep and can be defined as in the condition of sleep stage III.

Marginal Hilbert spectrum which presented results in the form of amplitude-frequency distribution had provide us better analysis to determine sleep stages of individually. The results had proved that the assist of music can actually improved the sleep quality of human. Sleep quality within music is much better compare to those sleep quality without music.

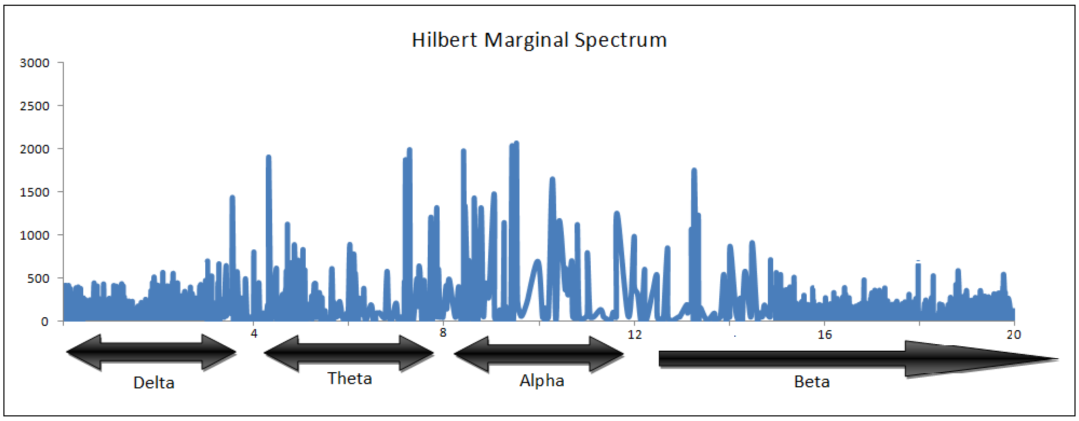


Figure 4.22: Marginal Hilbert Spectrum based EEMD method under condition of sleep without aid of music.

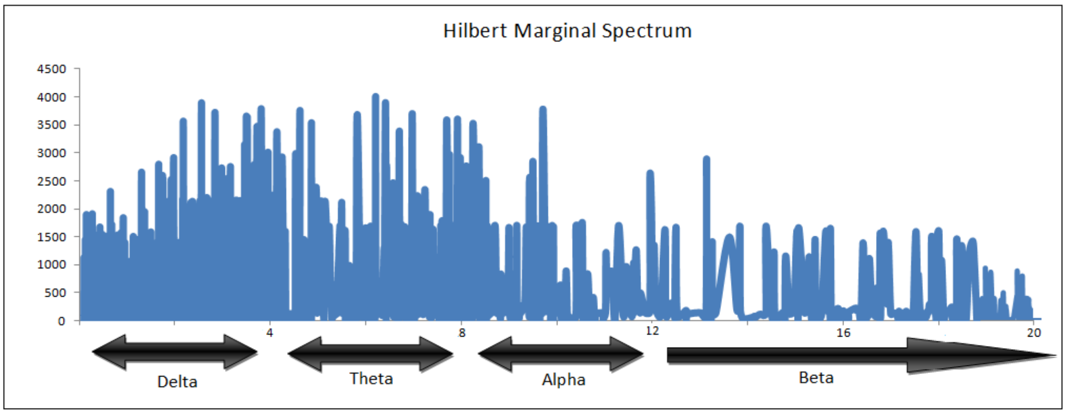


Figure 4.23: Marginal Hilbert Spectrum based EEMD method under condition of sleep with aid of music.

CHAPTER 5

CONCLUSION AND RECOMMENDATIONS

5.1 Challenges and Future Work

In this study, the main challenge of original EMD method is the effect of mode mixing. Mode mixing always creates the intermittency between one time scale to another and these discontinuous signals will affect the characteristic component of different time scales, an IMF component can reduce their inherent physical meaning of the original signal since the interruption of signal is occurred to perturb the time-frequency distribution. However, the effect of mode mixing was gradually eliminated by improved EEMD method. EEMD method has major improvement in retain the physical meaning of decomposed signals from original EEG signals. It has applied the NADA method which is adding the noise to populate the whole time-frequency space uniformly, facilitating a natural separation of the frequency scale. Since the added noise is zero mean, so the background of noise can be cancelled off each other without affect and destroy the physical features and characteristics in the original EEG signals.

Although the EEMD has been proven a good improvement of the EMD method, there are still remaining some drawbacks [26]. The multi-mode distributions of the IMF components remain as major challenge to the EEMD method. Referring to [26], the problem appeared due to the overlapping of scales in dyadic filter which is based on [22]. When the scale is located at the overlapping region, two different modes will occur. For the cases of bi-modal, there are two alternative ways to reduce the impact of this problem. The first one is number of sifting times must be low during the derivation of the IMF components in order to decrease the opportunity of increase and carry out some adjustment on the noise level to decrease the root-mean-square deviation. But, when both of the alternative ways were employed onto multi-mode distribution, the problem is still unable to eliminate which lead to decrease in accuracy of the analyzed results.

Since the EEMD method was not hundred percent guarantees the reliability of results after processing the signals, some improvement were needed to carry out. For analyzing the bivariant data, the rotation-invariant EMD (RIEMD) which proposed by [41] to obtain the local mean of bivariate signal by using component-wise spline interpolation and then averaging the local extrema. For the extension EMD for trivariate signal, the equi-longitudinal lines is used to produce a set of multiple direction vectors in 3D to project onto the trivariate signal for estimation of local mean and envelopes.

Recently, the multivariant EMD has been proposed by [42] is to alleviate the problem occur in original EMD algorithm which is computation of the local mean of the original signal. The standard EMD method in original EMD algorithm and EEMD algorithm may lacks of capability to process the complex signal especially by using the EMD algorithm. This multivariate EMD not only shows the great performance over than bivariate [28] but also for trivariant [43] processing. The multivariate EMD algorithm employed the concept of bivariate and trivariate as it taking signal projections along different directions in *n*-dimensional spaces to produce multiple *n*- dimensional envelopes and the further averaged them to derive the local mean. Further study will be carried out in this field to enhance the reliability and efficiency of standard EMD method for analysis the different kinds of complex signals purposes without misinterpret the results obtained.

5.2 Conclusion

In this study, we have applied two signal processing techniques to compare the performance of each other to determine the most adaptive and reliable method in processing the EEG data. The comparisons are actually done through observation and analysis of decomposed signal which is IMF components, index of orthogonality, Hilbert spectrum and marginal Hilbert spectrum. From the results shown, EEMD method has more superiority over the EMD method for the cases of reducing the effect of mode mixing. With aided of added noise with zero mean characteristics in EEMD algorithm, the background noises actually can be cancelled off each other to retain the inherent physical meaning of original EEG signals.

Besides that, both of the EMD and EEMD methods have been employed to derive the IMF components which contain the features and characteristics of EEG patterns in order to recognize and identify. Since the experiments are done under different conditions which conditions are under relax and wakefulness, after watching movie, and sleeping with and without music, the comparison of EEG patterns can be done by identify the features of EEG rhythms. During the process, we also found that the features and characteristics of the decomposed signals can be seen significantly through EEMD method rather than by applying EMD method.

To achieve the objective of this study, the effect of music toward sleep quality of human also been approached. Compare with the sleep quality without aid of music, the features that appear in decomposed signals are unable to indicate that individual was not enter the deep sleep stages. Conversely, the features of decomposed signals under condition of sleep with aid of music which is detected indicate that the sleep quality is quite good since the test subject was entered the deep sleep stages. Besides that, the marginal Hilbert spectrum which is presented the results in amplitude-frequency distribution by based on EEMD method also has proved the music actually can induce the sleep condition to human since the EEG frequencies during sleep were within the ranges of deep sleep.

As conclusions, EMD and EEMD methods are applicable signal processing techniques to detect and identify the features and characteristics of the EEG signals in EEG patterns recognition and also determination of sleep quality of human based on amplitude-frequency distribution. Through the application of both the methods, the results obtained have shown the music stimulation which is employed onto human is able to improve the sleep quality compare to those are not subjected to the music stimulation. Since the experiment is mainly design in mimic of scenario in the effect of music onto an insomnia person, it is also provide the sleep disorder related information as references for healthcare provider especially physician to reduce their burden in diagnosis and treatment purposes.

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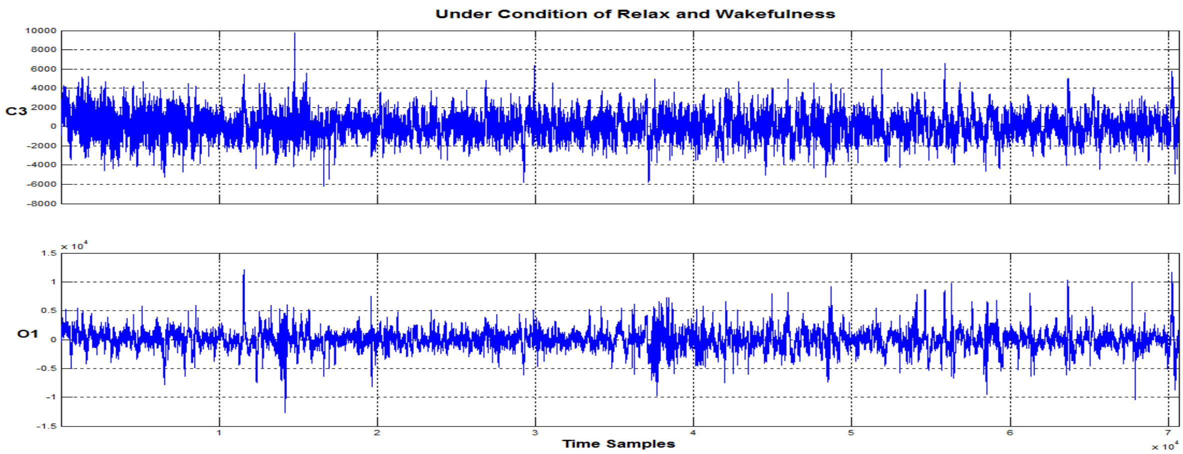
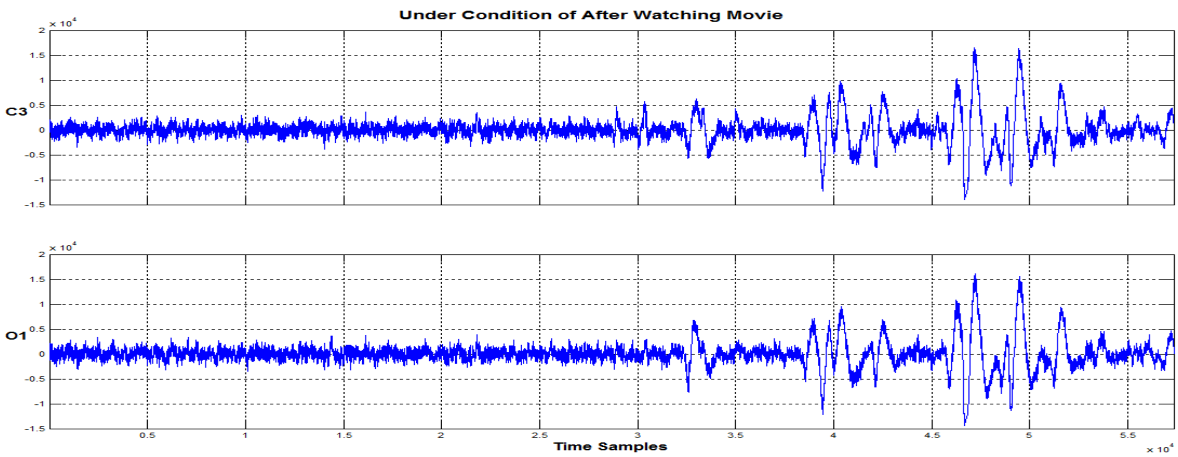
APPENDICES

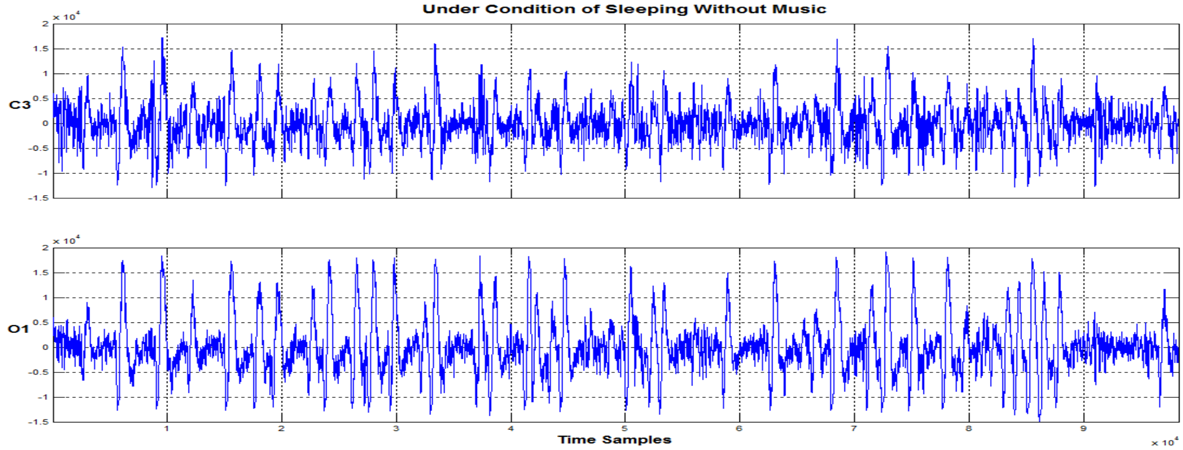
APPENDIX A: Original EEG Raw Data of Channel C3 and O1 under Different Conditions



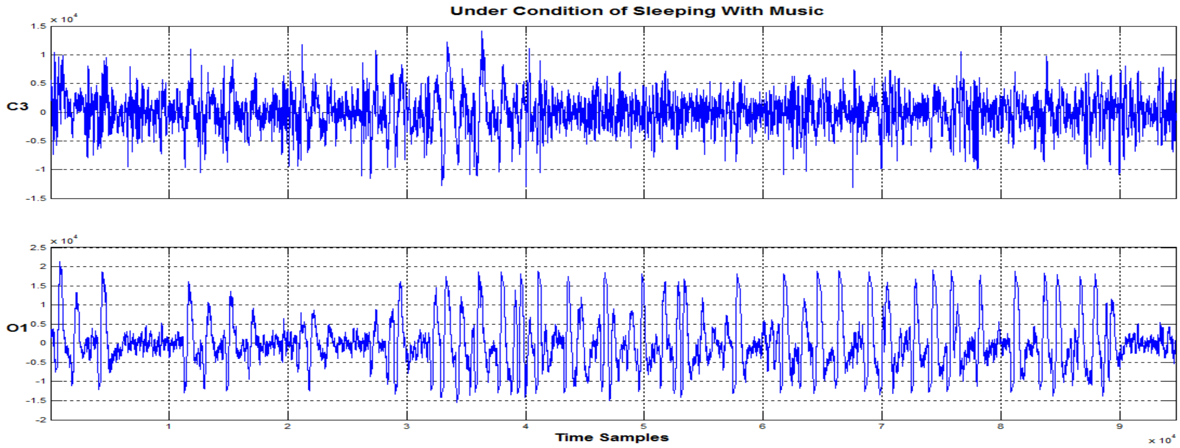
A (I): EEG data of channel C3 and O1 under condition of relax and wakefulness.



A (II): EEG data of channel C3 and O1 under condition after watching movie.

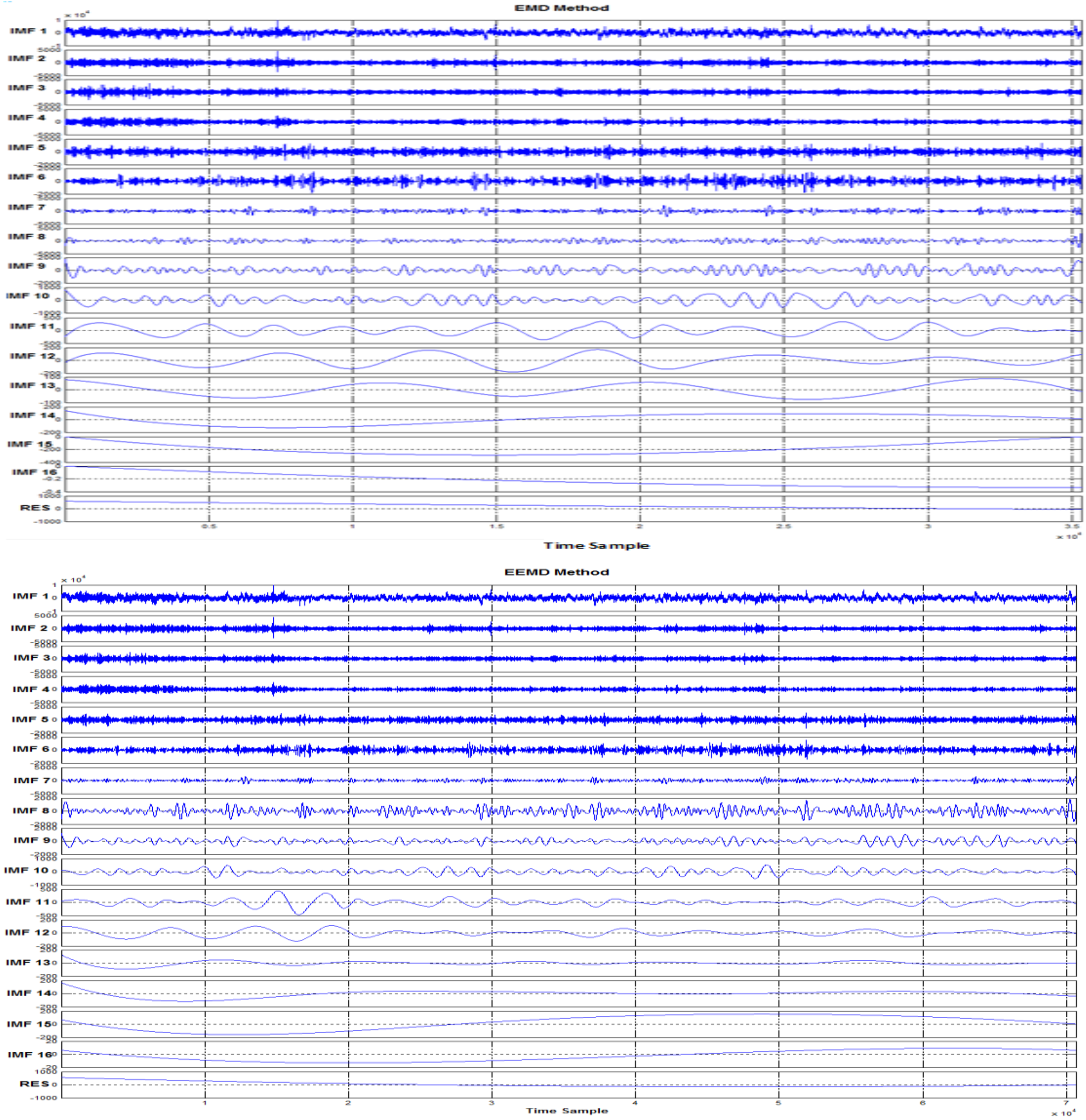


A (III): EEG data of channel C3 and O1 under condition of sleep without music.

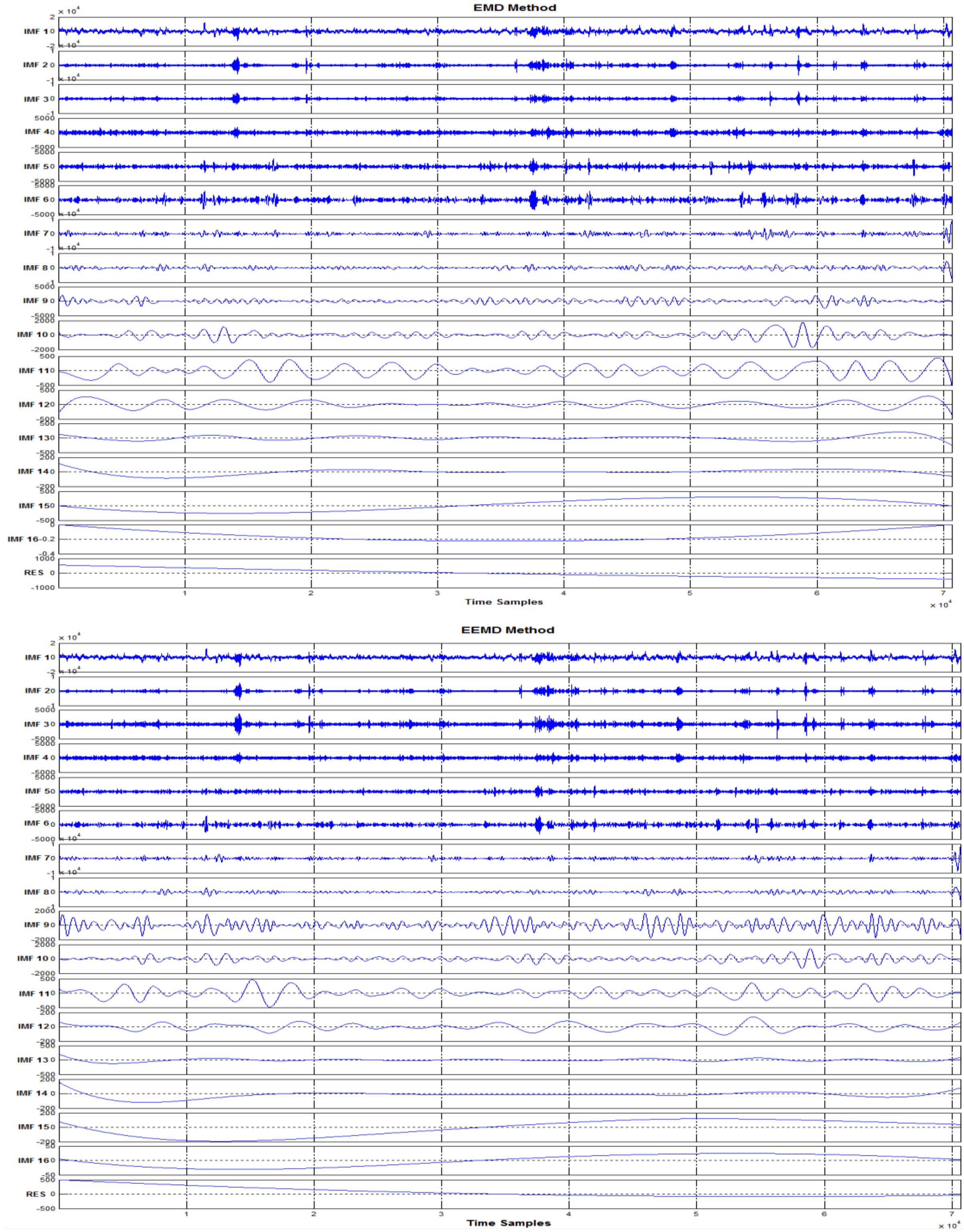


A (IV): EEG data of channel C3 and O1 under condition of sleep without music.

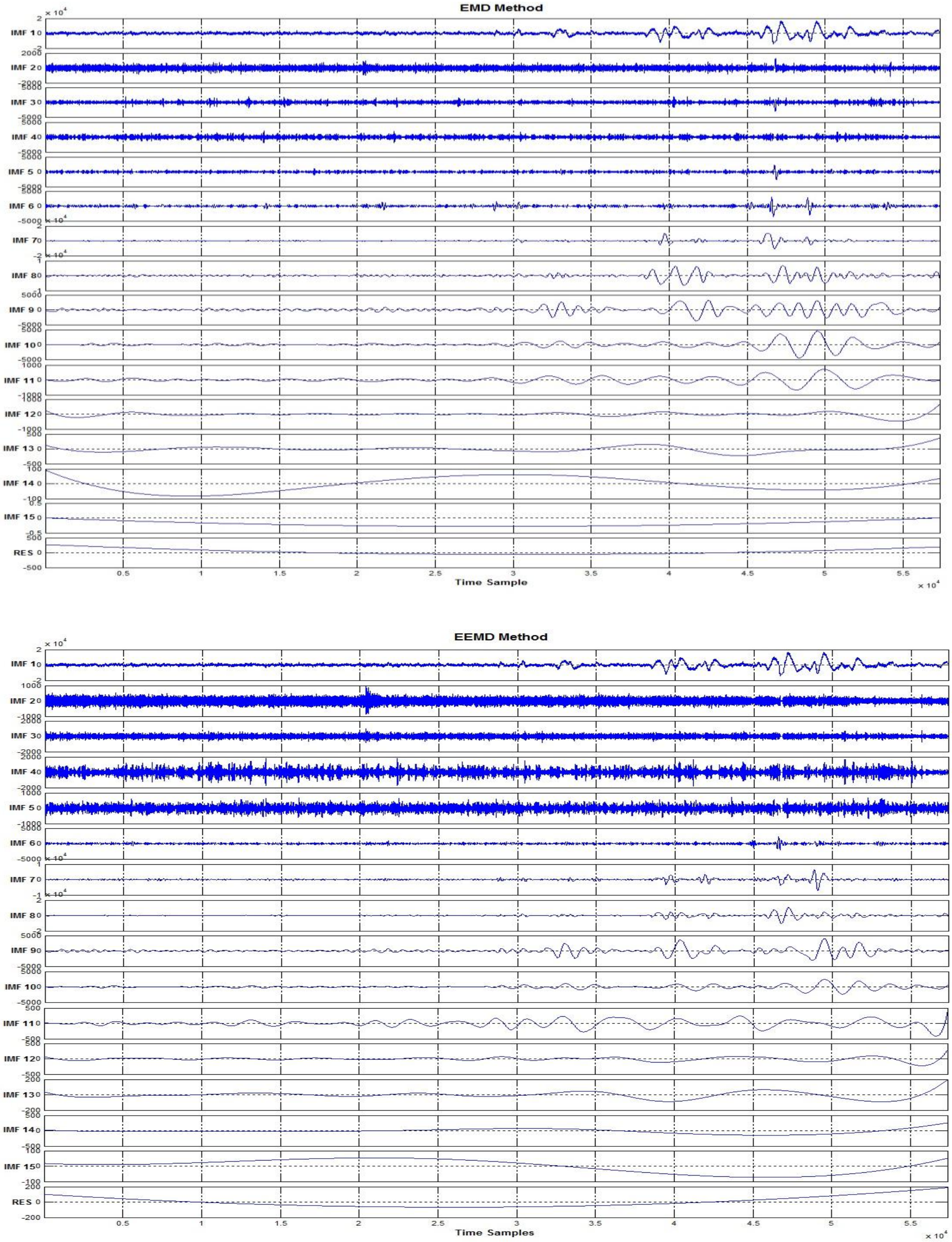
APPENDIX B: Intrinsic Mode Functions (IMFs) of EMD and EEMD Methods under Different Conditions



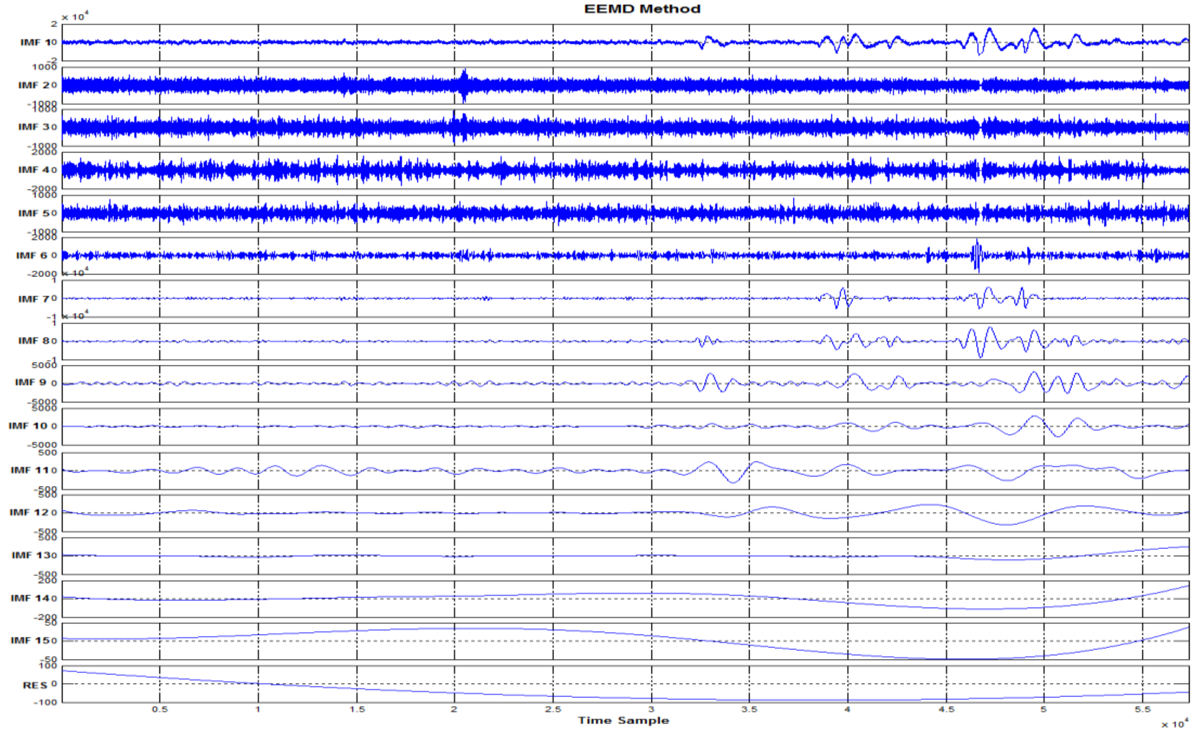
B (I): Channel C3 IMF components of (Top) EMD and (Bottom) EEMD methods under condition of relax and wakefulness.

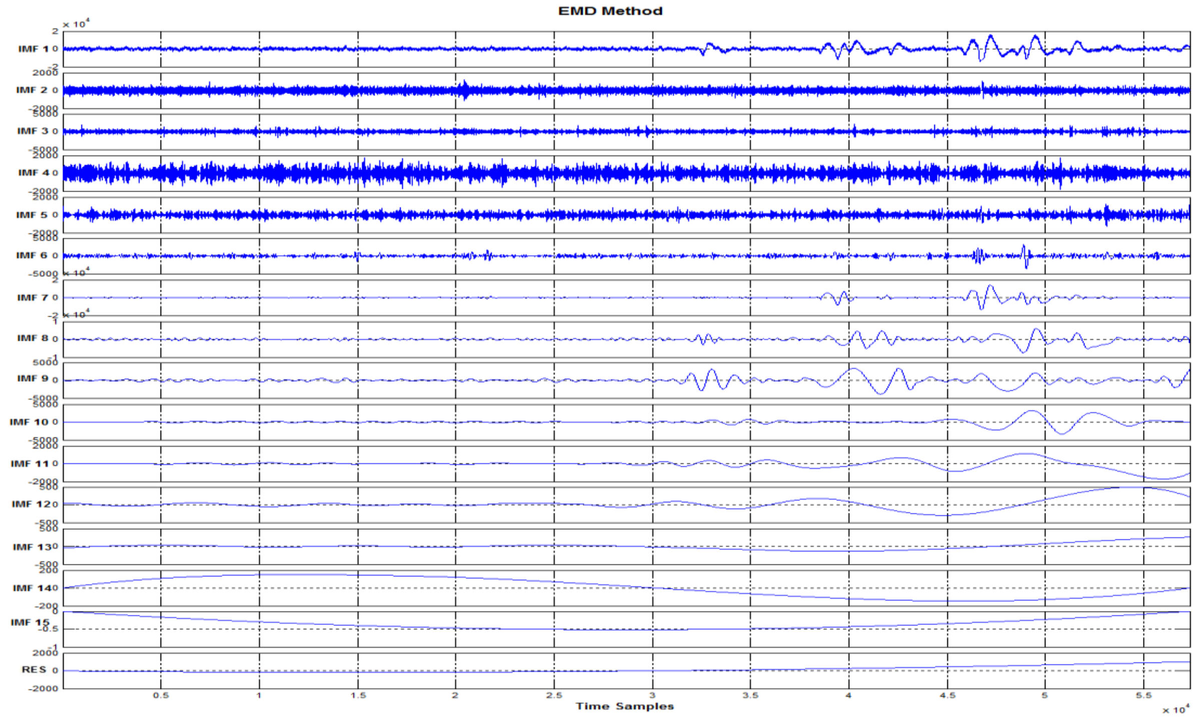


B (II): Channel O1 IMF components of (Top) EMD and (Bottom) EEMD methods under condition of relax and wakefulness.

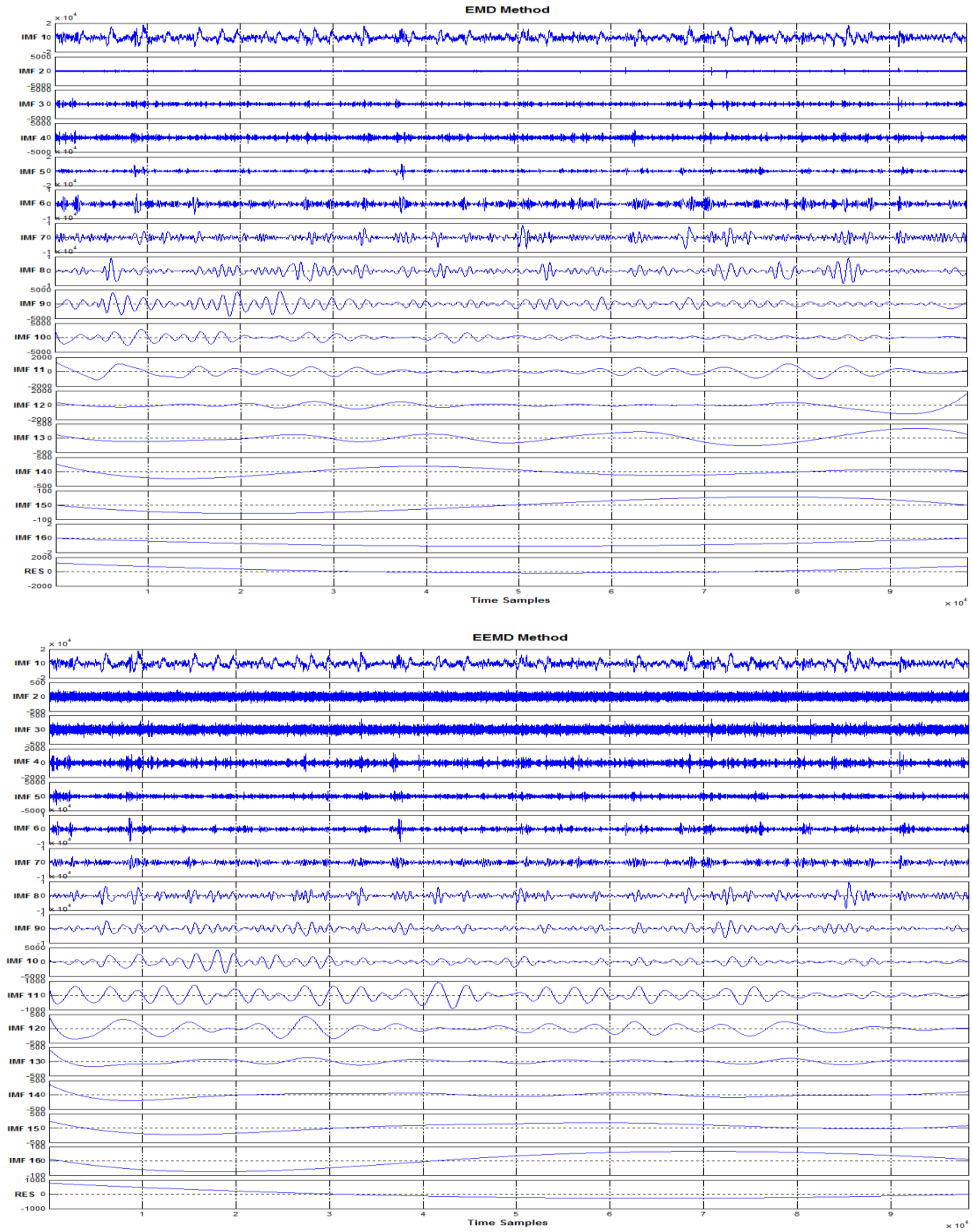


B (III): Channel C3 IMF components of (Top) EMD and (Bottom) EEMD methods under condition of after watching movie.

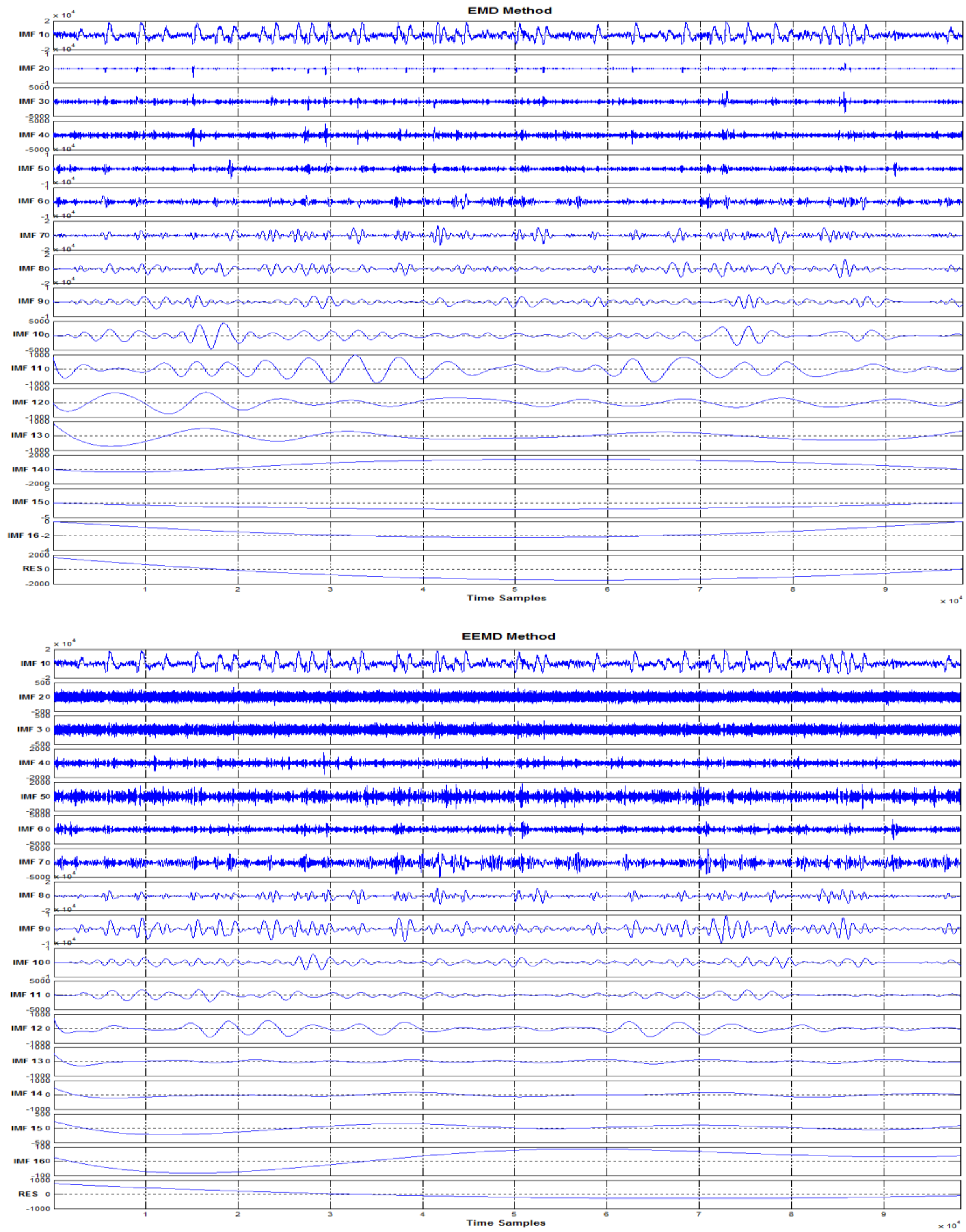




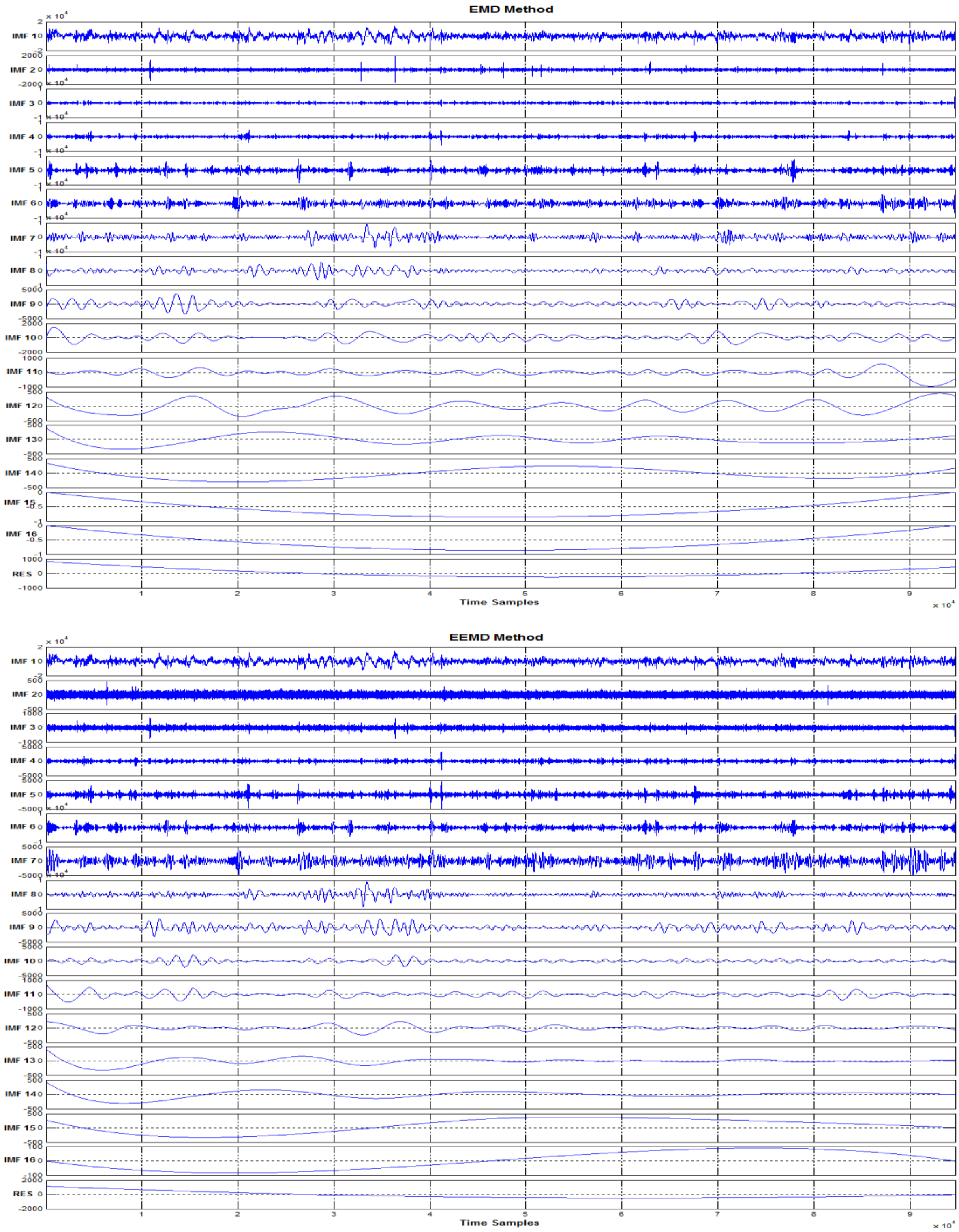
B (IV): Channel O1 IMF components of (Top) EMD and (Bottom) EEMD methods under condition of after watching movie.



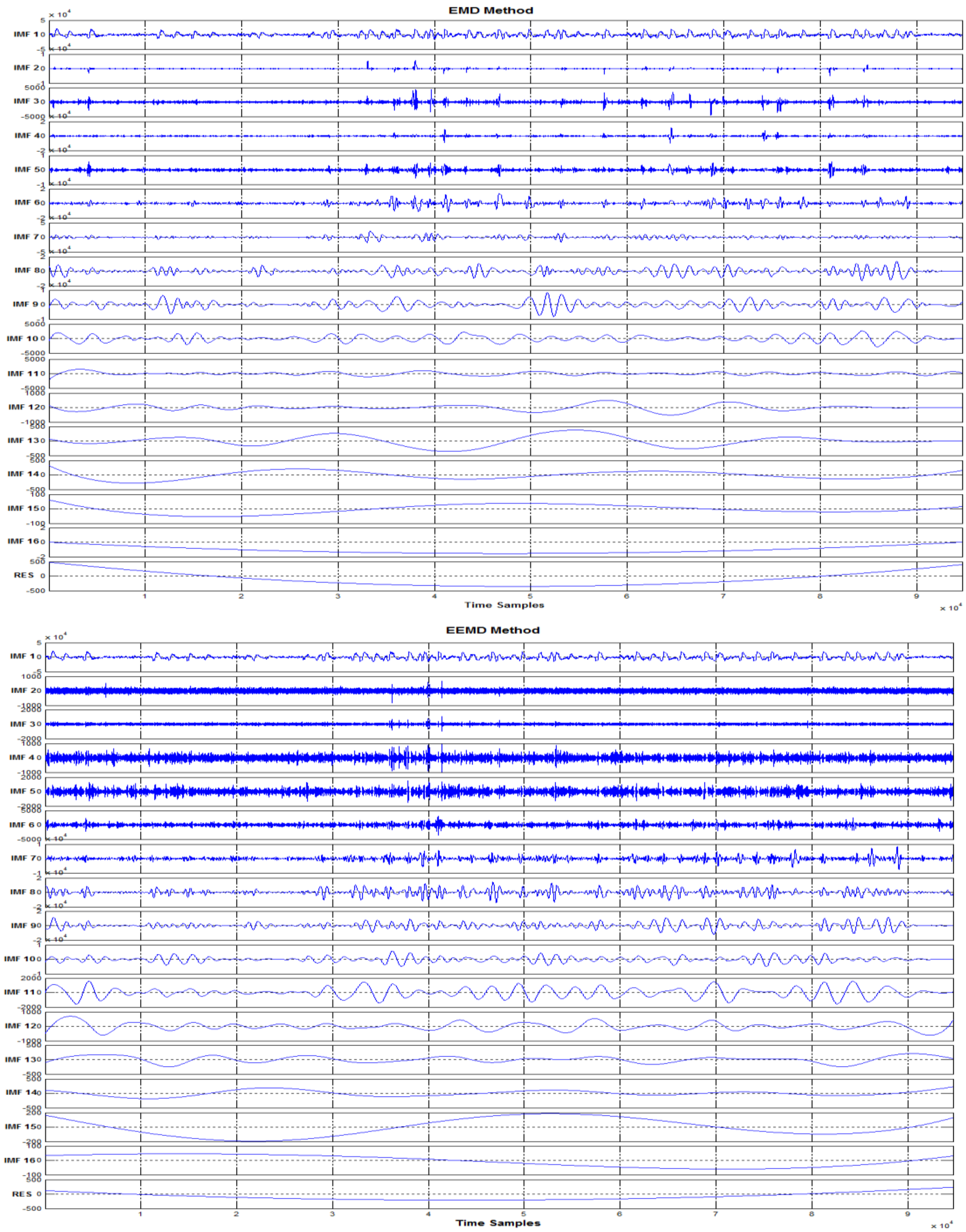
B (V): Channel C3 IMF components of (Top) EMD and (Bottom) EEMD methods under condition of sleeping without music.



B (VI): Channel O1 IMF components of (Top) EMD and (Bottom) EEMD methods under condition of sleeping without music.



B (VII): Channel C3 IMF components of (Top) EMD and (Bottom) EEMD methods under condition of sleeping with music.



B (VIII): Channel O1 IMF components of (Top) EMD and (Bottom) EEMD methods under condition of sleeping with music.