FEATURES OF SLEEP APNEA RECOGNITION AND ANALYSIS

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Abstract- Sleep apnea is a growing sleep disorder issue and estimate to affect 7% of the adult population in Malaysia. In this study, the electrical activity of the brain is studied using Electroencephalogram (EEG). The data obtained was then decomposed using three methods; Empirical Mode Decomposition (EMD), Bivariate EMD and finally Ensemble EMD. The Index of Orthogonatility (IO) was obtained which shows EMD performed the most poorly, EEMD the best and Bivariate in between. The performance of EMD greatly improves when the number of samples was greatly decreased and very high peaks and more complex parts of the signal were excluded in the analysis. Segmentation was also conducted and the segmentation error revealed when an Event Related Potential (ERP) has happened which is when apnea occurred.

Index terms*:* **Sleep apnea, Electroencephalogram (EEG), Empirical Mode Decomposition (EMD), Bivariate EMD, Ensemble EMD**

I. INTRODUCTION

Obstructive sleep apnea syndrome (OSAS) is a problem that involves two factors which are anatomical and neurological factors[1]. OSAS is characterised primarily by periodic collapses of the upper airway during sleep which contributes the main characteristic of the disease [2]. The airway calibre is smaller in the apneic compared to a normal subject. It is also noticeable that the soft palate and tongue area are larger in the apneic [2]. This problem leading to either complete or partial obstruction of the airway, will result in apneas, hypopneas, or both. This disorder causes daytime sleepiness, neurocognitive defects, and depression. It affects almost every system in the body, resulting in an increased incidence of hypertension, cardiovascular disease, stroke, pulmonary hypertension, cardiac arrhythmias, and altered immune function. It also increases the risk of having an accident, presumably as a result of associated somnolence [3].

It is estimated 7% of the adult population or 1.9 million people in Malaysia are affected by OSA [4]. The gold standard for the diagnosis of sleep apnea is an overnight polysomnogram. Split-night studies are becoming increasingly common and allow for quicker implementation of therapy at a reduced cost. Treatment options for sleep apnea include weight loss, positional therapy, oral devices, continuous positive airway pressure (CPAP), and upper airway surgery. One of the major components of PSG is the Electroencephalogram (EEG). EEG is able to pick up different electrical brain activities. The first recording of the electric field of the human brain was made by the German psychiatrist Hans Berger in 1924 in Jena. He gave this recording the name electroencephalogram (EEG). EEG measures namely three kinds of activity which are spontaneous activity, evoked potentials, and bioelectric events produced by single neurons [5].

In this study, 10-20 international electrode placement system is used. In this system, 21 electrodes are located on the surface of the scalp, as shown in Figure 1.1. The positions are determined from the reference points, which is the delve at the top of the nose, level with the eyes; and inion, which is the bony lump at the base of the skull on the midline at the back of the head. From these points, the skull perimeters are measured in the transverse and median planes. Electrode locations are determined by dividing these perimeters into 10% and 20% intervals. Three other electrodes are placed on each side equidistant from the neighbouring points, as shown in Figure 1.2 [5].

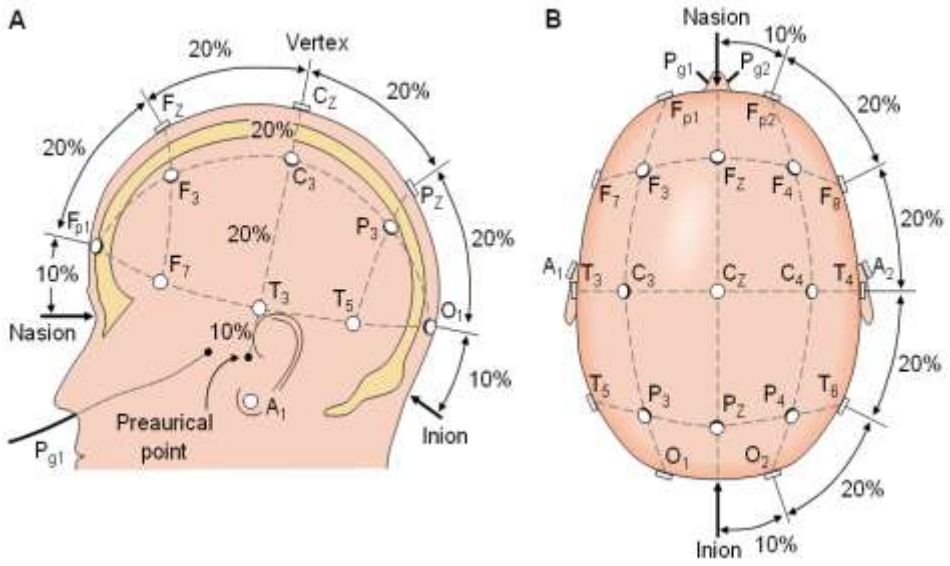


Figure 1.1: 10-20 Electrode Placement [5].

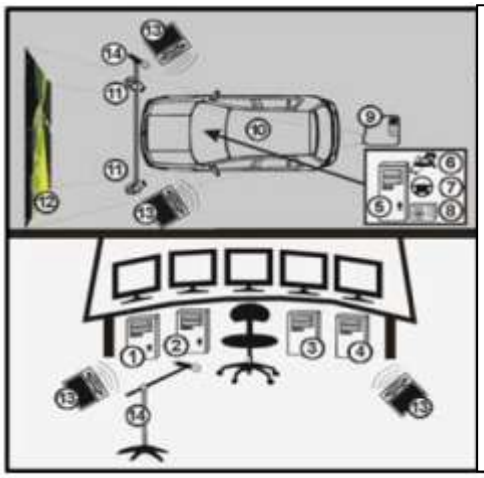
II. LITERATURE REVIEW

Micro sleep events can be defined as short periods of sleep during where a noticeable decrease in behavioural responsiveness is present [9]. EEG is widely used in the detection of micro sleep events. In a study by Peiris [10], EEG was used to detect several behavioural micro sleep events. Peiris [9] aim was to study the relationship between the Fractional Dimension (FD) EEG and micro sleep events.

The experimental data for the study by Peiris [9,10] were recorded from 15 normal healthy male volunteers aged 18–36 years with a mean of 26.5. None had a history of neurological or sleep disorders and all had visual acuities of (20/30) or better in each eye. EEG was recorded from electrodes at 16 scalp locations and digitized at 256 Hz with a 16 bit A-D converter. The following bipolar derivations were used in the analysis: Fp1–F7, F7–T3, T3–T5, T5-O1, Fp2–F8, F8–T4, T4–T6, T6–O2, Fp1–F3, F3–C3, C3–P3, P3–O1, Fp2–F4, F4–C4, C4–P4, P4–O2.

The subjects in the study by Peiris [10] were required to perform a tracking task which involves by the sensory-motor tests program SMTests which displayed a continuous target signal on a computer screen.. Volunteers controlled a steering wheel to move an arrow-shaped cursor, located at the bottom of the screen. The volunteer had to make sure was closest to the pseudo-random target. There was also video recording to record head and facial features of a subjects during the session. Tests were done twice on different days and each session lasted from 12.30 p.m. to 5.00 p.m.

EEG was also used in a system developed to detect micro sleep events. The study in a study by [11,14-21] developed a system integrating EEG features as well as other features causing a feature fusion to detect sleep events. The feature fusion includes brain electric activity, variation in the pupil size, and eye and eyelid movements.



1. Digital polygraphy PC
2. Eyetracing system PC
3. Experiment control PC
4. Video capture PC
5. Driving simulation PC & online questionnaires
6. Multi camera unit of the eye-tracing system
7. Recording of steering angle & lane deviation
8. Polygraphy head box
9. Video projector
10. Real car (GM Opel "Corsa")
11. Digital video camera

Figure Error! No text of specified style in document.1: Driving Simulation Setup[11].

The test subjects in [11] were 23 young adults started driving in s real car driving simulation lab (Fig. 2.1) at 1:00 A.M. after a day of normal activity and where there must be nonstop 16 hours of sleeplessness. The subjects had to accomplish seven driving sessions lasting 40 min, each followed by a 15 min long period of responding to sleepiness questionnaires and of vigilance tests and of a 5 min long break. The driving tasks were chosen intentionally monotonous to support drowsiness and occurrence of micro sleep events.

III. METHODOLOGY

Empirical Mode Decomposition (EMD) was introduced by Huang [6] for analysing nonlinear and non-stationary data. EMD processes complicated data set and decomposes into a finite number of `intrinsic mode functions' (IMF) that can further processed with Hilbert transforms. This method is adaptive and efficient where parameters can be changed according to the user. This method can process nonlinear and non-stationary processes. EEG data can be non-linear and non-stationary initially used for ocean wave signals it has found more and more interest in biomedical engineering [7].

Original raw data can be expressed as an equation following [6]:

$$x(t) = s(t) + n(t) \tag{3.1}$$

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

When a signal $x(t)$ is given, the effective algorithm of EMD does the steps involved can be shown below [6]

a. Identify all extrema of $x(t)$;

b. Interpolate between minima (resp. maxima), ending up with some envelope $e_{min}(t)$ (resp. $e_{max}(t)$)

c. Compute the mean $m(t) = (e_{min}(t)+e_{max}(t))/2$

d. Extract the detail $d(t) = x(t) - m(t)$

e. Iterate on the residual $m(t)$

The main principle of EMD is to locally identify the most rapid oscillations in the signal, defined as a waveform interpolating interwoven local maxima and minima. The local maxima points and, respectively, the local minima points are interpolated with a cubic spline, to determine the upper (and, respectively, the lower) envelope. The mean envelope is then subtracted from the initial signal, and the same interpolation scheme is reiterated on the remainder. The sifting process stops when the mean envelope is reasonably zero everywhere, and the resultant signal is designated as the first IMF.

The higher order IMFs are iteratively extracted, applying the same procedure for the initial signal, after removing the previous IMFs[6]. For a set of data, for first iteration, the mean is set to be m_1, and the difference between the data and mean will give us the first component, h_1 . The formula to show this is as below:

$$x(t) - m_1 = h_1 \tag{3.2}$$

For the sifting process to continue h_1 is treated as data and iteration continues as shown in the equation below. The sifting process serves to remove riding waves; and to make the wave-profiles more symmetric. The sifting process has to be reiterated more times to achieve this. Below is the 2nd sifting process

$$h_1 - m_{11} = h_{11} \tag{3.3}$$

The sitting procedures can be for k times, until h1k is an IMF, that as shown in the equation below

$$h_{1(k-1)} - m_{1k} = h_{1k} \tag{3.4}$$

To ensure that the IMF components retain enough physical information of both amplitude and frequency modulations, there must be a stopping criterion for the sifting process to stop. This can be done by limiting the size of the standard deviation, SD, computed from the two consecutive sifting results as below:

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

The *SD* is usually set to be between 0.2 and 0.3. This is a very rigorous limitation for the difference between siftings. Huang [6] did a comparison and found that Fourier spectra, computed by shifting of only five out of 1024 points from the same data, can have an equivalent *SD* of 0.2-0.3 calculated point-by-point.

With any stoppage criterion, the c1 should contain the finest scale or the shortest period component of the signal. This is to allow the c_1 to be removed from the rest of the data by [6].

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

This gives the residue r_1 which contains all longer period variations in the data, it will become as new data and it is sifted, giving r_2 as shown below.

$$r_1 - c_1 = r_2 \tag{3.7}$$

The repeated processes will continue and expressed as below [6]

$$r_{(n-1)} - c_n = r_n \tag{3.8}$$

By summing up, the equation below is obtained (Huang, 1998a);

$$x(t) = \sum_{j=1}^{n} c_j + r_n \tag{3.9}$$

IV. EXPERIMENTAL SETUP

Figure 4.1 shows various stages involved in the entire experiment. The first stage of Data Acquisition involves the usage of EEG and test subjects to obtain the right data. It involves the preparation of the subject and placing of electrodes. The venue should be in a comfortable area to allow the subject to sleep and not be anxious. The second stage involves processing the data using different methods, EMD [6], EEMD [12] and Bivariate EMD [13]. Further processing can be done to see the effectiveness of the methods. Finally the third stage is the analysis of the processed data to identify characteristics of sleep apnea. This is where the features of sleep and sleep apnea are identified. The differences between each method are also determined.

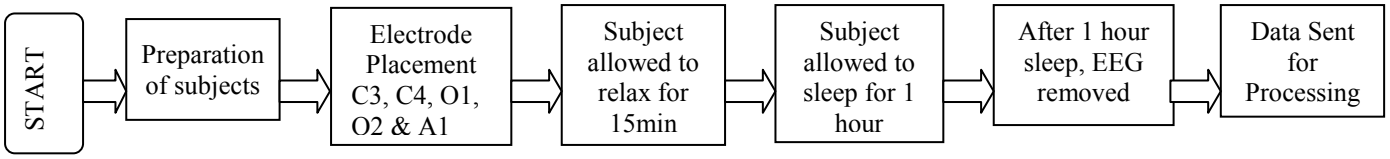


Figure 4.1 Data Acquisition using Actiwave EEG

The Actiwave EEG is a miniature biomedical waveform recorders are designed to capture EMG, EEG and ECG signals in daily living. Using miniatures recorders, EMG, EEG and ECG waveforms can be recorded discreetly without the need for a large belt mounted recorder or lengthy wires. Each recorder can be taped or glued to the skin near to the position of the electrodes. The very small size and weight of these units makes them ideal for paediatric and veterinary use. In this experiment it was chosen because of its mobility allowing the test subject to be practically anywhere to obtained the data and would not be restricted to the laboratory. It is quite versatile because of its maximum 13 hours of recording. It fully recharges in 4 hours and has non-volatile memory.

Firstly, the specific areas for electrode placed was marked by skin marker and cleaned by abrasive skin preparation gel called test subject preparation. Then, the adhesive and conductive paste was used to attach the electrode onto scalp. The electrode was secured also by adhesive tape. The test subject was advised not to consume any stimulants or depressants, such as alcohol, caffeine, and nicotine, during the 4 hours prior to the session. Also test subjects were asked to relax themselves as usual when they attempted to sleep as done in studies before.

Electrodes which detect the signal should place it according to the 10-20 electrode international placement system as shows in Figure 1.2. Electrodes were place in position C3, C4, O1, O2 and A1 were recorded by the CamNtech Actiwave EEG. The CamNtech Actiwave 4-channel Recorder (Figure 4.2) was used to collect and record the EEG signal. CamNtech Actiwave Interface Dock is used as the interface for the EEG recorder and the computer. Embedded system in the EEG device has a feature 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 locations were chosen because these regions are where electrical activity in somato-sensoric and motoric brain areas can be picked up. O1 and O2 are related to the primary and secondary visual areas to detect Rapid Eye Movement. A1 is serves as the reference electrode so that all the other electrodes can be referenced with. The EEG was sampled at 260 Hz.

The devices consist of as below:
(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 4.2: Devices and materials that used during experiment.

Data acquired from Actiwave EEG alone will limit the research capabilities and the outcome of this research. This is because Actiwave EEG only records just the EEG. A complete polysomnogram includes blood oxygen measurement, sound measurement as well as Electrocardiogram. With the limited materials this study was held to get a more extensive data. Therefore Actiwave EEG was used to measure EEG only if a person is normal.

Since a sleep study lasts for a few hours, the steps involved; processing the whole data of sleep followed selecting the data would be too time consuming. So this study looked for areas where there was a drop in oxygen level. A drop in oxygen level would indicate that an apnea might have happened. The second indicator would be to see if there are rises in sound level. Rises in sound level would indicate snoring or difficulty in bringing also another characteristic of apnea. After this two indicators are matched then the EEG timing is noted and the portion of EEG is then extracted for analysis.

V. RESULTS AND DISCUSSIONS

5.1 Comparison of Index of Orthogonatility

The data which is 1500 time samples from C3 channel sampled at 256 Hz was ran on all 3 algorithms EMD, EEMD, and Bivariate giving the values of Index of Orthogatility as below:

Table 5.1: Index of Orthogonatility for different decompositions

Decomposition Method	Index of Orthogonatility
EMD	0.2579
EEMD	0.1989
Bivariate EMD	0.2026

The 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 analysed result. In this report, the performance of IMF components that generated by EMD and EEMD methods respectively were compared to determine the reliability of the result. From the IO values, it can be seen that EMD performed the most poorly with a value of 0.2579. This shows there was most leakage of data in EMD when the EEG data was decomposed. Bivariate performance was in the middle between EMD and EEMD.

5.2 Comparison of IMFs

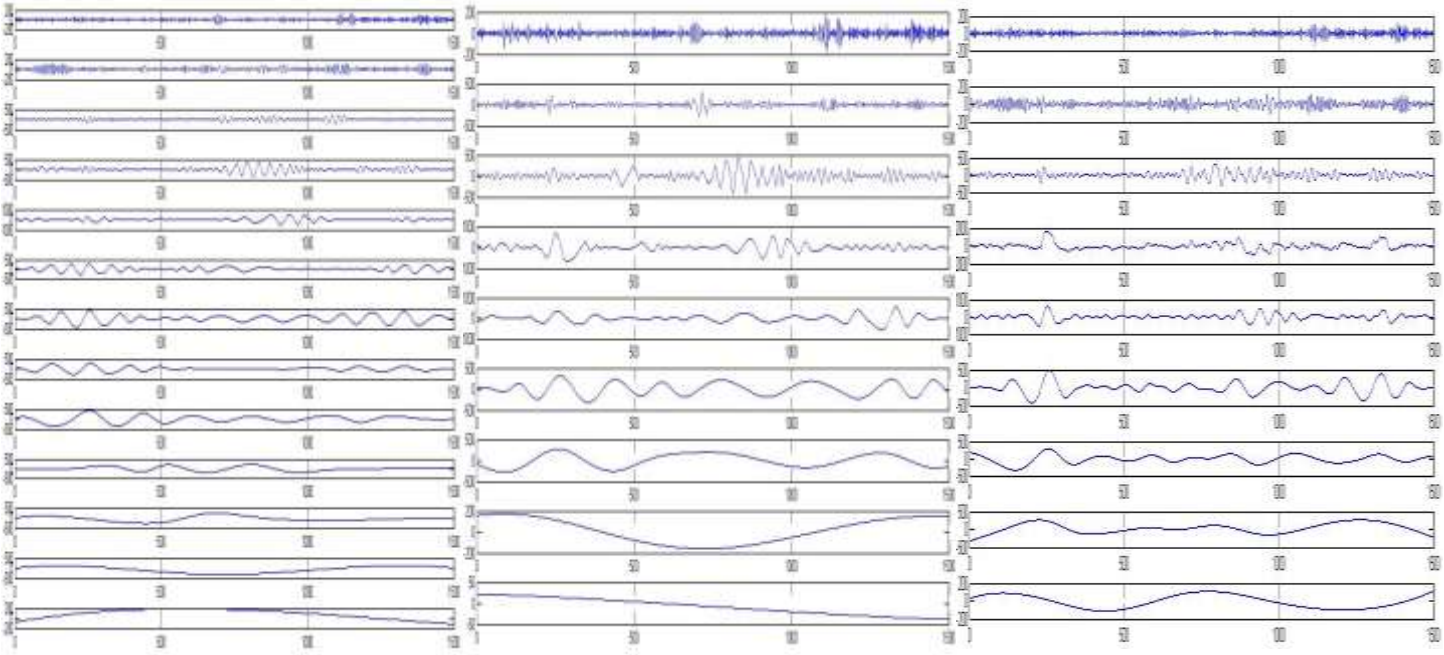


Figure 5.1: IMFs of decomposed EEG data using EMD (Left) , EEMD (Middle) and Bivariate (Right)

The Figures 5.1 shows the decomposed IMFs of the original EEG signal. It is noticeable that the signal is slowly reduced to a trend line. Below shows the original data EEG that was sampled at 256 Hz from the C3 electrode.

From Figure 5.2, it can be seen that the original data that there are very high peaks as well as low peaks. This raw data presents a problem for analysis because there is no mean zero for reference. The local minima can be above zero and local maxima can be below zero. One thing can be said of this character is that the waveform is not uniformed. After applying the decomposition methods it can be seen that the waveform became more uniform primarily. Thus, it is now an IMF. Looking into the first iteration or first IMFs in Figures 5.3, 5.4 and 5.5 the difference even after the first decomposition is quite considerable compared to the original in 5.2. It can be seen that all local maximas and minimas are above zero and below zero respectively. Now the waveforms are more uniformed and analysis can be done.

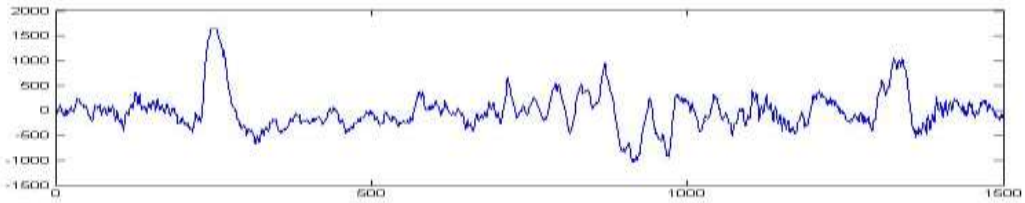


Figure 5.2: Original EEG data

Figure 5.3: First IMF of EMD method

Figure 5.4: First IMF of Bivariate EMD method

Figure 5.5: First IMF of EEMD method

There are noticeable differences in the first iteration when comparing all three methods. When comparing first IMF of EMD and Bivariate, notice the red box labelled, there are actually two regions of peaks in the Bivariate compared to only one in the EMD, this shows that more information was retained in the Bivariate. Another thing noticeable when comparing these two methods is that the peaks are higher in the Bivariate method. When comparing the EEMD with the rest it is noticeable that the peaks are not as high as the others. However there are more regions of peaks compared to the other methods. The first iteration alone is not enough to see the difference in the three methods. In the third example, the difference is clearer and supports the initial results of Index of Orthogonatility.

5.3 Extracting Sleep Bands using Wavelet

Next the common features of sleep study that are able to be extracted are the bands of sleep from the processed signals. Wavelet is the most readily used method to extract the frequency bands of sleep and therefore is used as the reference method to compare the extracted bands of suitable frequency. Sleep bands are a common feature of sleep to see the brain activeness in different stages.

Figure 5.6 shows all the five bands that could be extracted from the same original EEG data using Wavelet transformation.

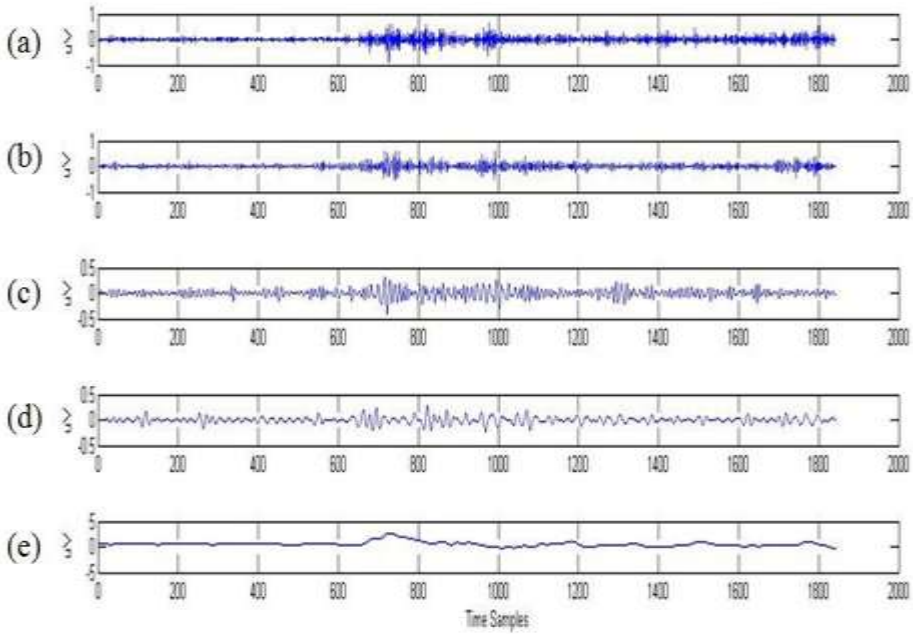


Figure 5.6**: Frequency bands of Sleep using Wavelet Method:**
(a) Gamma (b) Beta (c) Alpha (d) Theta (e) Delta

Frequency (Hz)		
IMF	**EMD**	**Band**
1st	42.66666667	Gamma
2nd	23.48751357	Beta
3rd	13.34201954	Alpha
4th	7.852334419	Theta
5th	4.447339848	Delta
6th	2.640608035	Delta
7th	1.667752443	Delta
8th	0.833876221	Delta
9th	0.555917481	Delta
10th	0.347448426	Delta
11th	0.208469055	Delta
12th	0.13897937	Delta
13th	0.13897937	Delta
14th	0.069489685	Delta

Table 5.2: Decrease of Frequency using EMD

The wavelet transforms the frequency of the original signal into half and each transform further transform into another half. Therefore since the frequency is 128 Hz using wavelet, the frequency is transformed from 128Hz to 64Hz for Gamma band, 64 to 32Hz Beta band, 32Hz to 16Hz for Alpha band and 16Hz to 8Hz for Theta band. The delta band is obtained reconstructing from the coefficients of the theta band which is the fourth level of decomposition. Therefore four levels of decomposition is only needed to obtain the five bands Figure 5.6.

5.4 Extracting Sleep Bands using EMD

Unlike wavelet, EMD, Bivariate and EEMD approach to finding the sleep bands are not as straightforward as the wavelet. This is because the underlying principle of decomposition of these three methods is different than wavelet. The frequency after each level of decomposition changes not in a fixed rate of halves as the Wavelet method. The frequency definitely decreases after decomposition. However the decrease is usually less than half the frequency therefore it cannot straightaway be utilised for all levels of decomposition for the energy bands as in wavelet method. The first method is to determine the frequency of all IMFs of each method. Another constraint is that since there is no fixed numbers of IMFs per method therefore the parameters of frequency have to be changed when changing data. Therefore the frequency of each IMF must be evaluated to see how they can be represented into energy bands.

	Frequency (Hz)	
IMF	**EEMD**	**Band**
1st	43.36156352	Gamma
2nd	21.26384365	Beta / Beta + Alpha
3rd	10.56243214	Alpha + Theta
4th	4.864277959	Theta
5th	2.293159609	Delta
6th	0.903365907	Delta
7th	0.416938111	Delta
8th	0.208469055	Delta
9th	0.069489685	Delta
10th	0.069489685	Delta

Table 5.3: Decrease of Frequency

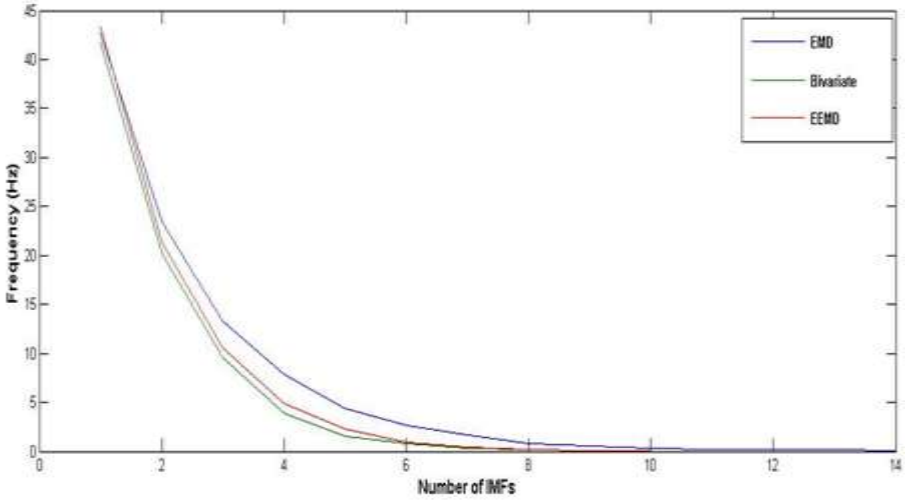


Figure 5.7**: Decreasing Trend of Frequency**

Table 5.2 shows the frequency for all IMFs using three methods and Figure 5.7 shows the decreasing trend of frequency of IMFs. The trend shows that it is nonlinear and the degree of decrease is different for each method IMFs. The trend shows that it is non linear and the degree of decrease is different for each method. Beginning with EMD method, the frequencies were analysed to see which can be readily used to represent frequency bands of sleep.

The 1st IMF has a frequency of 42.66666667 Hz and is the only IMF in the region of Gamma band therefore it can be used to show Gamma band. Next the 2nd IMF has a frequency 23.48751357 Hz and is in the region of Beta band and can be used to represent the Beta band. The 3rd IMF has a frequency 13.34201954 Hz which fits into the Alpha Band. The 4^{th} IMF has a frequency of 7.852334419 Hz which also fits into the Theta Band. Coincidentally all four of the first IMFs can correspond with the frequency band but this is only a coincidence and should not be seen as a trend. The fifth band which is the delta band should not be retrieved straight away but be reconstructed just as the wavelet method this is because there is no one singular IMF to show the delta wave. The delta wave utilises all the IMFs that are less than 4Hz. Since the 6^{th} until the 14^{th} IMF has frequency has a frequency less than 4Hz it is suitable to be reconstructed together to obtain the delta wave.

5.5 Extracting Sleep Bands using EEMD

The approach for the EEMD method for obtaining all the sleep bands also includes finding the frequencies of each IMF as shown in Table 5.3.

For the EEMD method, 5th to the 10th IMFs were chosen for Delta wave reconstruction because they have frequencies that fit into the Delta frequency band which is 4 – 0 Hz. A clear distinction here from the EMD, is that EEMD decomposes lower frequencies more vigorously and therefore there will be less IMFs in this range of 4 - 0 Hz.

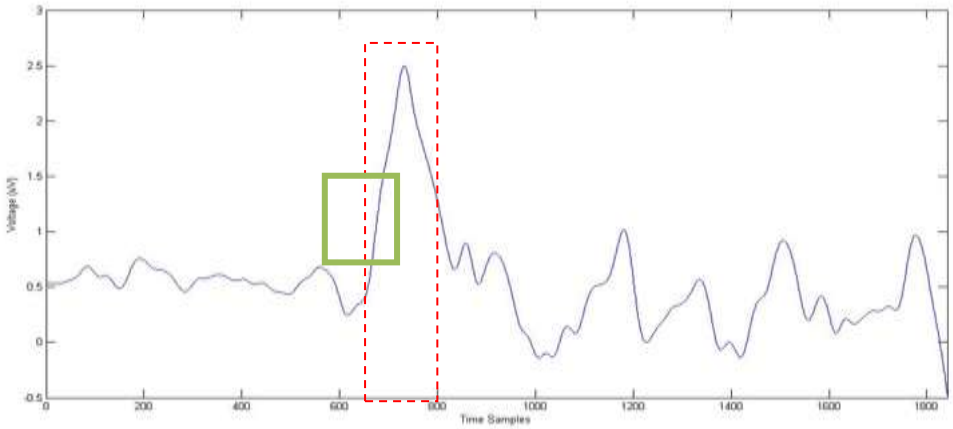


Figure 5.8: Delta Wave using EEMD method

Method	Delta Power
Wavelet	0.515884408
EEMD	0.505057628

Table 5.4: Comparison of Delta Power

In Figure 5.8 the Delta wave obtained using the EEMD method can be seen. The green box region on the graph shows where a missing peak is located, which is the Delta wave obtained using Wavelet. Thus it has sift out more information than the wavelet. Again the dotted (…) region of Figure 5.8 reveals the same occurrence of apnea that disrupts sleep using EEMD Method which is supported and shown repeatedly by results using Wavelet, EMD and Bivariate methods. Another similar observation is that there is a big rise of amplitude in the red region mirrored by all the differnet methods.

Again the wavelet proves to have a smoother signal. When comparing the Delta Power the Bivariate also underperforms to the EMD and wavelet. The difference when compared to the Delta Power of Wavelet is around 0.01 which is very simillar to the Delta power of the Bivariate. Again this difference is considered quite huge since EMD only differs from Wavelet by 0.001. Simillar with the explaination of Bivariate and EMD, the cause for the difference in Delta power is also due to the

limited number of IMFs used to reconstruct the Delta wave as seen in the Bivariate method. In the EMD method used 9 IMFs to reconstruct the Delta wave where as for the EEMD method, it used only 6 IMFs to reconstruct the delta wave. Since less IMFs are used, there are less sources to reconstruct. This results a loss in information for the Delta wave. Therefore this supports the notion that having more IMFs when used to reconstruct would produce more accurate reconstructions especially in the Delta wave and Delta power.

Thus it is important to have more IMFs to achieve the highest similarity of Delta wave if compared to the wavelet method. This can be a constraint especially when there are no more IMFs and the decomposition method decomposes vigorously IMFs of lower frequencies.

VI. CONCLUSIONS

In this study, signal processing using EMD, EEMD and bivariate EMD were analysed on EEG data from a sleep apnea patient. The milestone achieved is in comparing the index of Orthogonality, instantaneous frequency, amplitudes, energy and sleep bands of all 3 methods. This report shows the general view that Bivariate EMD is better than EMD however not as good as EEMD. All three methods manage to show certain features regarding the sleep data that were meaningful. All three methods manage to show the occurrence of apnea, sleep bands, correlation with sound waves as well as delta power. All three methods are effective in showing that apnea has happened. The Bivariate is more favourable is looking at the data as a whole, where as EEMD is more favourable if looking at specific IMFs and the EMD is more favourable especially at looking at Delta power only.

There are few major challenges faced for this project. The first is obtaining the data for all sleep apnea patients. This is quite a laborious task because effort and time needs to be taken to find these patients to obtain proper data. The conditions of obtaining the data must also be constant so that the results have the same constraints and may not be affected by changing environments. The second challenge would be in detecting the key features of the EEG data because EEG data are usually interpreted. Therefore, time and care needs to be taken to learn to interpret the EEG data.

To improve, firstly there must be a set up of a control experiment in order to compare results obtained. The control experiment must be independent of the variables that contribute to sleep apnea detection. For example, subjects who are female have less probability to have sleep apnea whereas

subjects with obesity have very high probability to have sleep apnea. Therefore the subjects chosen for the control experiment must be chosen carefully.

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