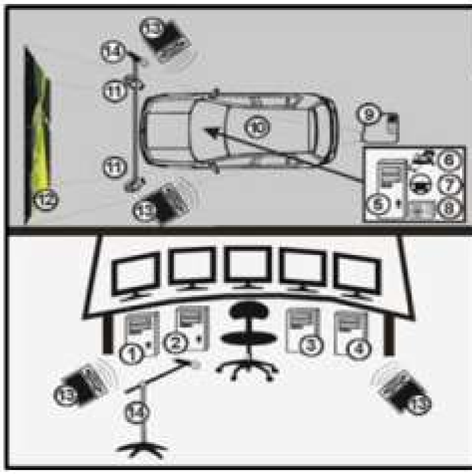
I. INTRODUCTION

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].

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]:

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

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

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.

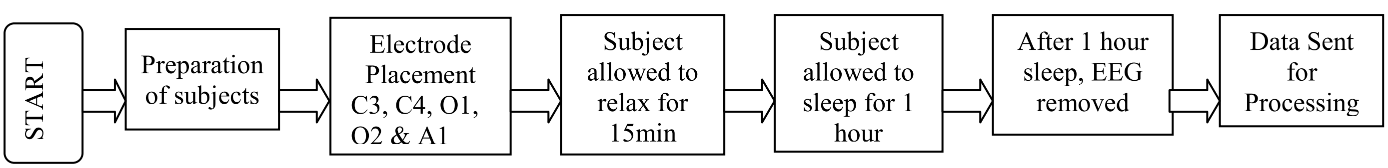


Figure 4.1 Data Acquisition using Actiwave EEG

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.

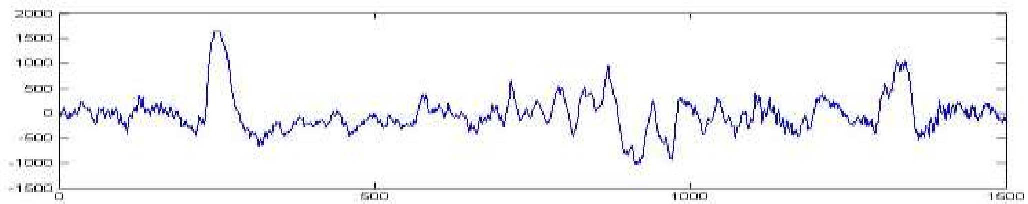


Figure 5.2: Original EEG data

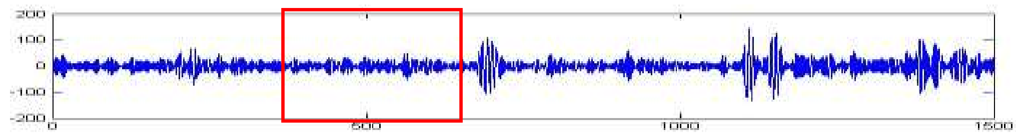


Figure 5.3: First IMF of EMD method

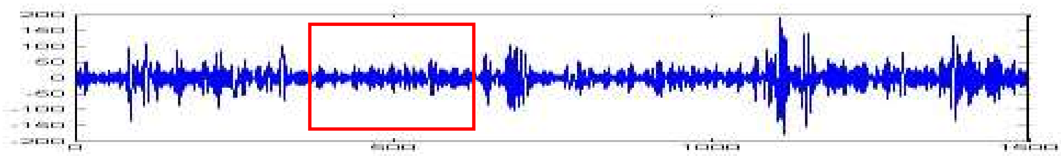


Figure 5.4: First IMF of Bivariate EMD method

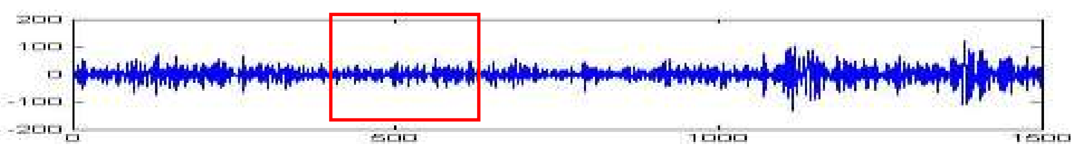


Figure 5.5: First IMF of EEMD method

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.

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

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.

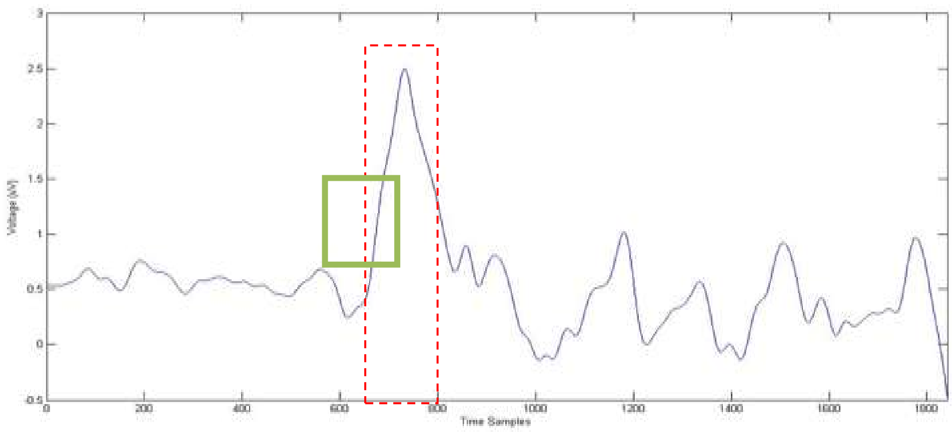


Figure 5.8: Delta Wave using EEMD method

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

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

REFERENCES

[1]Pack, A. I., *2002. Sleep Apnea: Pathogenesis, Diagnosis and Treatment. 1st ed. s.l.:CRC Press.*

[2] Tung, R. and Leong, W.Y, 2013, *Processing obstructive sleep apnea syndrome (OSAS) data*. Journal of Biomedical Science and Engineering, 6, 152-164. doi: 10.4236/jbise.2013.62019.

[3] Caples, S. M., Gami, A. S., & Somers, V. K., 2005. Obstructive sleep apnea. *Annals of internal medicine,* 142(3), pp. 187-197.

[4] TheStar Publications, 2011. *Sleep Well.*

[5] Harrison, Y., & Horne, J. A., 1996. Occurrence of 'microsleeps' during daytime sleep onset in normal subjects. *Electroencephalogr. Clin. Neurophysiol.,* Volume 98, pp. 411-416.

[6] Huang, N. E. et al., 1998a. The empirical mode decomposition and the Hilbert spectrum for nonlinear and nonstationary time series analysis. *Proceedings of the Royal Society of London. Series A: Mathematical, Physical and Engineering Sciences,* 454(1971), pp. 903–995.

[7] Huang, W. et al., 1998b. Engineering analysis of biological variables: an example of blood pressure over 1 day. *Proceedings of the National Academy of Sciences,,* 95(9), pp. 4816-4821.

[8] Golz, M. et al., 2007. Feature Fusion for the Detection of Microsleep Events. *Journal of VLSI Signal Processing,* Vol.49, pp.329-342.

[9] Peiris, M. T. R. et al., 2006a. Detecting behavioral microsleeps from EEG power spectra. *Engineering in Medicine and Biology Society, 2006. EMBS'06. 28th Annual International Conference of the IEEE,* p. 5723.

[10] Peiris, M.T.R. et al., 2006b. *Fractal dimension of the EEG for detection of behavioural microsleeps.* Shanghai, IEEE, pp.5742-5745.

[11] Poudel, Govinda R., et al., 2010. *The Relationship Between Behavioural Microsleeps, Visuomotor Performance and EEG Theta.* Bueno Aires, IEEE, pp. 4452-4455.

[12] Rilling, G. et al., 2007. Bivariate empirical mode decomposition. *Signal Processing Letters IEEE,* 14(12), p. 9360939.

[13] Wu, Z., & Huang, N. E., 2009. Ensemble empirical mode decomposition: A noise-assisted data analysis method. *Advances in Adaptive Data Analysis,* 1(1), pp. 1-41.

[14] Leong W.Y,, Mandic D.P., Liu W., 2007, *Blind Extraction of Noisy Events Using Nonlinear Predictor*, ICASSP 2007, IEEE, Pages:657-670, 1520-6149.

[15] Leong W.Y., Homer J., 2004, *Implementing ICA in blind multiuser detection*, IEEE International Symposium on Communications and Information Technology (ISCIT) 2004., Vol.2, pp.947-952.

[16] Leong WY, Mandic DP, M Golz, D Sommer, 2007, *Blind extraction of microsleep events*, 15th International Conference on Digital Signal Processing, pp.207-210.

[17] Leong WY, 2006, *Implementing Blind Source Separation in Signal Processing and Telecommunications,* PhD Thesis, The University of Queensland.

[18] Leong WY, Mandic DP 2007, *Noisy component extraction (noice)*, IEEE International Symposium on Circuits and Systems, IEEE, Pages:3243-3246.

[19] E. B. Tan, D. and Leong, W. (2012) Sleep disorder detection and identification. *Journal of Biomedical Science and Engineering*, 5, 330-340. doi: 10.4236/jbise.2012.56043.

[20] B. Ginzburg, L. Frumkis, B.Z. Kaplan, A. Sheinker, and N. Salomonski, 2008, Investigation Of Advanced Data Processing Technique In Magnetic Anomaly Detection Systems*, International Journal On Smart Sensing and Intelligent Systems*, Inaugural Issue VOL. 1, NO. 1, MARCH 2008, Pages: 110-122.

[21] Xu Xiaobin, Zhou Zhe, Wen Chenglin, Data Fusion Algorithm of Fault Diagnosis Considering Sensor Measurement Uncertainty, *International Journal On Smart Sensing and Intelligent Systems*, VOL. 6, NO. 1, FEB 2013, Pages: 171 – 190.