Wavelet Approach on Frequency Energy Distribution of Electrooculograph Potential towards Direction

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Abstract— **Biomedical signals recognition activity has been studied by many researchers. In this study, we describe the identification of Electro-oculography (EOG) signals of eye movement potentials by using wavelet transform which gives a lot of information than FFT. The capability of wavelet transform is to distribute the signal energy with the change of time in different frequency bands. This will show the characteristic of the signals since energy is an important physical variable in signal analysis. The EOG signals are captured using electrodes placed on the forehead around the eyes to record the eye movements. The wavelet features are used to determine the characteristic of eye movement waveform. This technique is adopted because it is non-invasive, inexpensive and accurate. New technology enhancement has allowed the EOG signals to be captured using the Neurofax EEG-9200. The recorded data is composed of an eye movement towards four directions, i.e. upward, downward, left and right. The proposed analysis for each eyes signal is analyzed by using Wavelet Transform (WT) by comparing the energy distribution with the change of time and frequency of each signal. A wavelet scalogram is plotted to display the different percentages of energy for each wavelet coefficient towards different movement. From the result, it is shown that the different EOG signals exhibit differences in signals energy with their corresponding scale such as left with scale 6 (8-16Hz), right with scale 8 (2-4Hz), downward with scale 9 (1-2Hz) and upward with scale 7 (4-8Hz).**

***Index Terms*—-** Electro-oculogram, Eye Movement, Signal Potentials, Scalogram, Wavelet Transform.

I. Introduction

The human eye is a spherical structure with a radius of 12mm. The signals that can be sensed from the movement of the human eyes can be known as *Electro-oculography* (EOG). The EOG is derived from the Cornea Retinal Potential (CRP) that is generated within the eyeball by the metabolically active retinal epithelium. The production of CRP comes from the hyper-polarization and de-polarizations of the nervous cells in the retina. EOG is the electrical recording corresponding to the eye movement. The eye has a resting electrical potential, with the front of the globe positive and the back with globe negative. This phenomenon was first observed by Emil du Bois-Reymond in 1848 and has been the foundation of electrooculography [1].

EOG are taken using bipolar electrodes on the outside of the eye. Exact electrode placements vary, but the electrodes are generally placed on the temples or on the distal ends of the forehead. When the eyes move, a differential potential result will occur. The magnitudes of the right and left eye movement can be seen between -75µV to 150µV respectively. The polarity of movement potentials is dependent on the electrode setup since the signal is positive when the eyes are moving toward positive electrode [1]. At present, EOG is used for the evaluation of occulomotor abnormalities such as nystagmus, strabismus, and supranuclear occulomotor dysfunction is briefly explained by [2].

EOG is a technique for measuring the resting potential of the retina. The resulting signal is called the electro-oculogram. The main applications are in ophthalmological diagnosis and in recording eye movements [3]. The EOG is a potential produced by movement of the eye or eye lid. The generation of the EOG signal can be understood by envisaging dipoles located in the eyes with the cornea having relatively positive potential with respect to the retina [4].

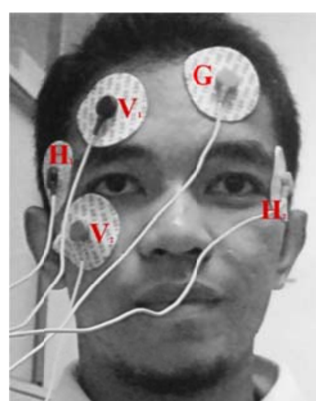


Fig. 1. Position of electrodes

This EOG signal is picked up by a bi-channel signal acquisition system consisting of the Horizontal (H) and Vertical (V) channels. The placement of the electrodes are shown in Figure 1. The EOG signals are obtained by placing two electrodes to the right and left of the outer canthi (H_1, H_2) to detect horizontal movement and another pair above and below the eye (V_1, V_2) to detect vertical movement. A reference electrode is placed on the forehead (G). The overall connection is illustrated in Figure 2.

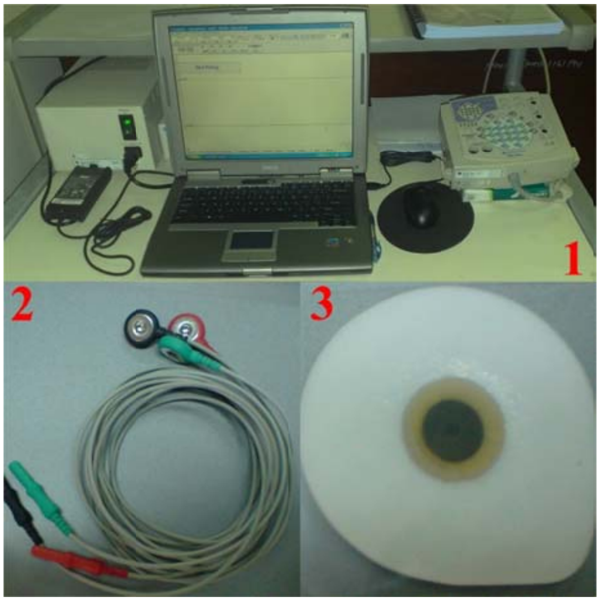


Fig. 2. (1) Data Acquisition system. (2) Electrode connector. (3) Disposable *Ag/AgCl* bioelectrode

Numerous other techniques from the theory of biomedical signal processing have been used to obtain representations and extract the features of interest for classification purposes. Dinesh [5] used the EOG signals for determining the angle of eye gaze for controlling a computer while Aysegul and Kara [6] used the EOG signals for the classification with Artificial Neural Network (ANN), and Sudirman [7] used the eye movement for the classification by using time frequency analysis. Study done by the Bhander [8] used the wavelet scalogram decomposition to determine the most energy in specific frequency bands of vertical eye movement. They found that 90% of the signal energy (90%) is concentrated in the lower or higher scales and signal denoising.

II. WAVELET TRANSFORM

Wavelet transform is a powerful tool in analyzing signals because of its ability to extract time and frequency domain information. The wavelet transform could be defined as an extension of the classic Fourier transform, except that, instead of working on a single scale (time or frequency), it works on a multi-scale basis [10]. Wavelet functions overcome the limitations of Fourier methods by employing an analyzing function that are localized in time and frequency. It has a finite energy function and can be represented on a transient signals.

In the previous studies as demonstrated by [11, 12, 13, 14, 15, 16, 17], wavelet analysis has developed excitement for the researchers in signal processing. It has been successfully implemented in various applications such as transient signal analysis, communication signals and other signal processing applications. Instead of Fourier analysis, wavelet analysis is set up within the expansion of functions in terms of a set of basic functions. Different from Fourier, it expands the function in terms of wavelets rather than the trigonometric polynomials in Fourier. It generates wavelets in the form of translation and dilation of a fixed function called the mother wavelet.

Wavelet functions overcome the limitations of Fourier methods by employing analyzing functions that are local in time and frequency. It is a finite energy function and can be represented on transient signals. In signal processing, wavelet analysis is used importantly in processing the non-stationary signals. The wavelet transform can be interpreted as a decomposition of the original signal into set of independent frequency channels. It is essentially the method of processing data from a continuous signal into series of signal decompositions represented at different frequency ranges. This is the use of the mother wavelet.

In signal processing, wavelet analysis is mostly used in processing non-stationary signals. The wavelet transform can be interpreted as a decomposition of the original signal into set of independent frequency compositions. The wavelet has a vanishing moment localized both in frequency and time. Assumption from the study done by Magosso [18] has brought us to this solution.

In both forms of wavelet analysis (continuous and discrete), the signal is decomposed into scaled and translated versions $\psi_{ab}(t)$ of a single function $\psi(t)$ called the mother wavelet:

$$\psi_{ab}(t) \triangleq \frac{1}{\sqrt{a}}\Psi\left(\frac{t-b}{a}\right) \qquad (1)$$

where a and b are the scale and translation parameters respectively, with a, b $\in \Re$ and a $\neq$ 0. The continuous wavelet transform (CWT) of a signal s(t) $\in L^2(\Re)$ (the space of the square integrable functions) is defined as:

$$\begin{aligned} C_{ab}(t) &= \int_{-\infty}^{\infty} s(t)\frac{1}{\sqrt{a}}\Psi^*\left(\frac{t-b}{a}\right)dt \\ &= \left\langle s(t), \psi_{a,b}(t)\right\rangle, \end{aligned} \qquad (2)$$

where the symbol * mean complex conjugation and < > the inner product. The discrete wavelet transform (DWT) is obtained by discretizing the parameters *a* and *b*. In its most common form, the DWT employs a dyadic sampling with parameters *a* and *b* based on powers of two: $a = 2^j$; $b = k2^j$, with j,k $\in$ Z. By substituting in Eq. (1), we obtain the dyadic wavelets:

$$\psi_{j,k}(t) = 2^{-j/2}\psi(2^{-j}t - k). \tag{3}$$

The DWT can be written as

$$d_{j,k} = \int_{-\infty}^{\infty} s(t)2^{-j/2}\Psi^*(2^{-j}t - k)dt = \left\langle s(t), \psi_{j,k}(t) \right\rangle, \tag{4}$$

By appropriately selecting the mother wavelet $\psi(t)$ the collection of functions { ψ j,k(t) j,k 2 Z} forms an orthonormal basis for $L^2(\Re)$. The correlated DWT allows the original signal to be reconstructed accurately and efficiently without any redundancy.

A. Wavelet Energy Distribution

The orthonormality of the set {$\psi_{j,k}$(t)j,k$\in$ Z} allows the concept of energy within the framework of the discrete wavelet decomposition to be linked with the usual notions derived from the Fourier theory. The energy series associated with coefficient series d $_{j,k}$ is given by

$$E_{j,k} = \left|d_{j,k}\right|^2 \tag{5}$$

and the overall energy at resolution j is

$$E_{j,k} = \sum_{k=0}^{2^{M-j}-1}\left|d_{j,k}\right|^2 \tag{6}$$

Hence, the total energy associated with the entire signal can be obtained as

$$E_{tot} = \sum_{j=1}^{M}\sum_{k=0}^{2^{M-j}-1}\left|d_{j,k}\right|^2. \tag{7}$$

Energy coefficients as computed by Eq. (7) have different localization and density over different frequency band depending on the scale. Therefore, in order to study and compare the different movement of energy at different scales, it is necessary to compensate for the halved time resolution at each scale due to the down sampling operation. These methods have been applied to the analysis of the EOG signals.

B. Wavelet Scalogram

Wavelet scalograms (refer to Figure 6 and Figure 7) represent the time frequency localization property of the discrete wavelet transform. In this plot each detail coefficient is plotted as a filled rectangle whose color corresponds to the magnitude of the coefficient. The location and size of the rectangle are related to the time interval and the frequency range for this coefficient. Coefficients at low levels are plotted as wide and short rectangles to indicate that they localize a wide time interval but a narrow range of frequencies in the data.

In contrast, rectangles for coefficients at high levels are plotted thin and tall to indicate that they localize small time ranges but large frequency ranges in the data. The heights of the rectangles grow as a power of 2 as the level increases. The bar shown on the scalogram plot indicates the range of energy for each scale. This energy is defined as the sum of the squares of the detail coefficient for each scale. The scalograms reveal that most of the energy of the signals in the data is captured in the details coefficient.

III. PROPOSED WORK AND METHODOLOGY

The system setting includes the EEG data acquisition system; Neurofax EEG-9100 software [19] with EOG electrodes set and the sampling interval is 1ms. The EEG data acquisition system is used to record EOG signals from the subjects. Independent measurements can be obtained from both eyes, but as both eyes move in the vertical direction, it is sufficient to measure the vertical motion of only one eye together with the horizontal motion of both eyes. *Ag/AgCl electrodes* are chosen as their half cell potential is closer to zero compared to other types such as silicon rubber electrodes. Figure 3 below shows the overall workings for the proposed study. This process was done in a quiet room to minimize the noise and hence get better recorded signals as shown in Figure 4.

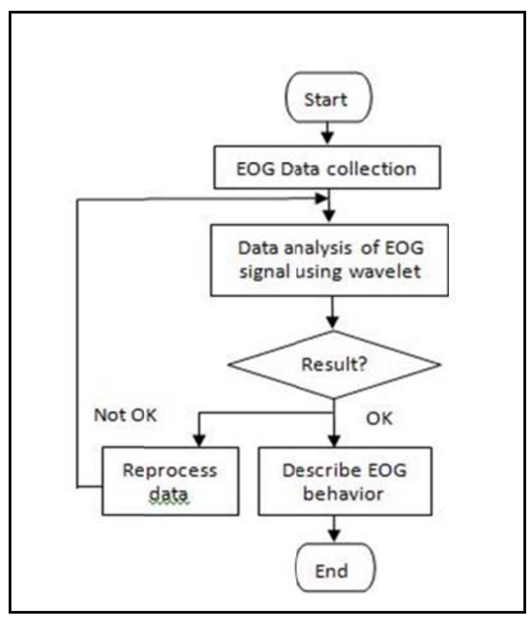


Fig. 3. Flow works of EOG signal processing

Subjects were seated on a chair and supervised by an instructor who gave instructions on how to move their eyes. The instruction composed of four movements that are upward, downward, left and right. The recording was done in four successive eye movements for 10 subjects and each subject repeated for three times. Initially, EOG was recorded for 20 to 30 seconds for each eyes movement. Unfortunately, since the subjects were showing signs of tiredness, the recording duration was reduced to 10 seconds which was free from artefacts observed in longer traces by visual inspection.

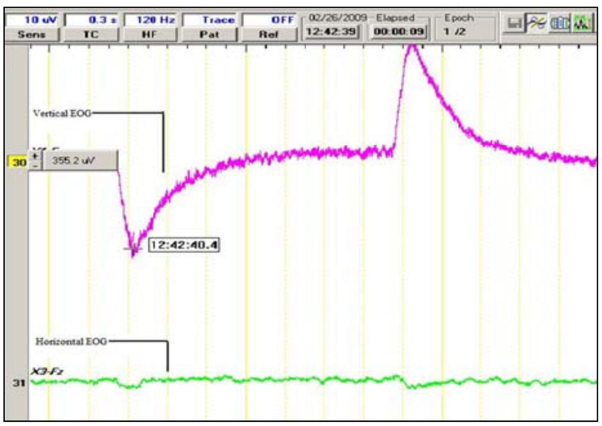


Figure 4: Vertical (pink) and Horizontal (green) EOG signal displayed from data acquisition system

The eyeball moved to the desired direction and the centre or static eye becomes the reference point. Furthermore, subjects were also asked to avoid blinking, body movements or any disturbances during the recording to minimize the unwanted artefacts. EOG signal captured was then analysed by using wavelet analysis from MATLAB software and toolbox application. Figure 5 is the real signal of the right movement of EOG signals by using MATLAB. It shows the basic characteristic of EOG potentials.

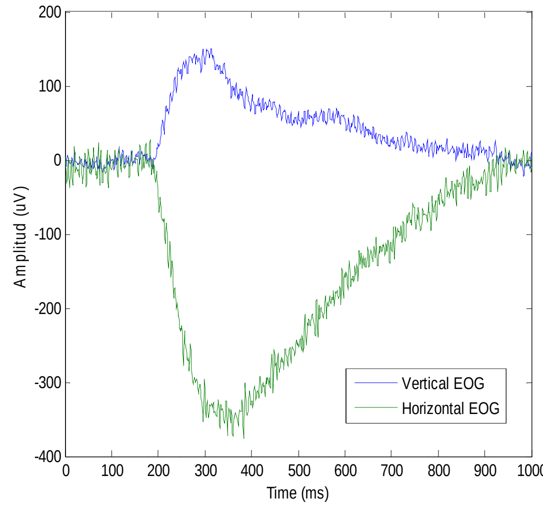
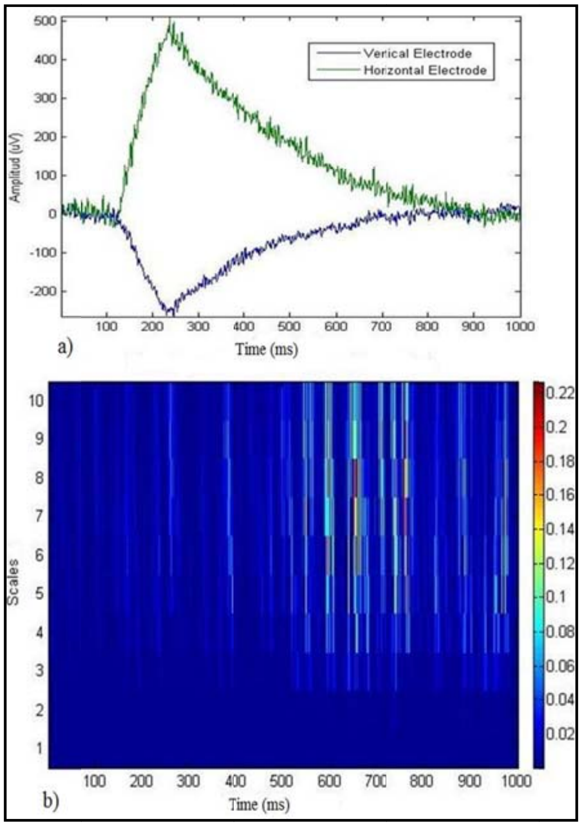


Figure 5: Right EOG signal plotted using MATLAB

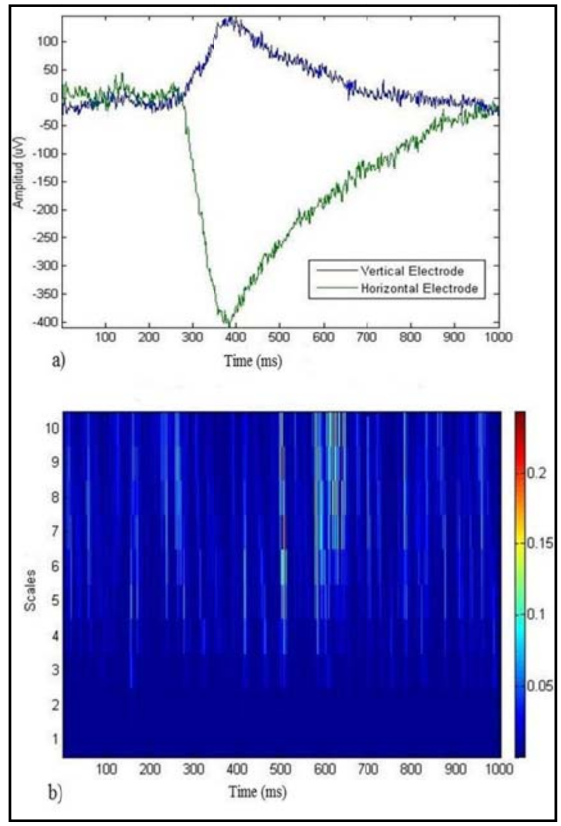
It was then uploaded into a program that runs a wavelet scalogram in order to present the signal in the wavelet coefficient energy in scale and space or time. The signals is decomposed down to 10 level of details using Daubechies order 4 (db4) as a mother wavelet. The db4 has been chosen because it has two vanishing moment, i.e. constant and linear component. The numbers of level decomposition strictly depend on the sample rate of original signal recorded.

IV. RESULTS AND DISCUSSION

When it comes to the time frequency analysis in wavelet transform, we are interested in knowing the distribution of signal energy of wavelet details coefficient with the change of time. Hence, we plotted a scalogram for each movement in order to identify the dominant scales over the maximum wavelet energy coefficient for the signal. The scalogram is used because it represents the time frequency localization property of wavelet transform. In this plot, each details coefficient is plotted as a filled rectangle whose colors correspond to the magnitude of the coefficient. The bar on the scalogram plot indicates the range of energy for each level. This energy is defined as the sum of the squares of the details coefficient for each scale. Figure 6 and Figure 7 show the scalogram of signals of four different movements from a subject; left, right, downward and upward.

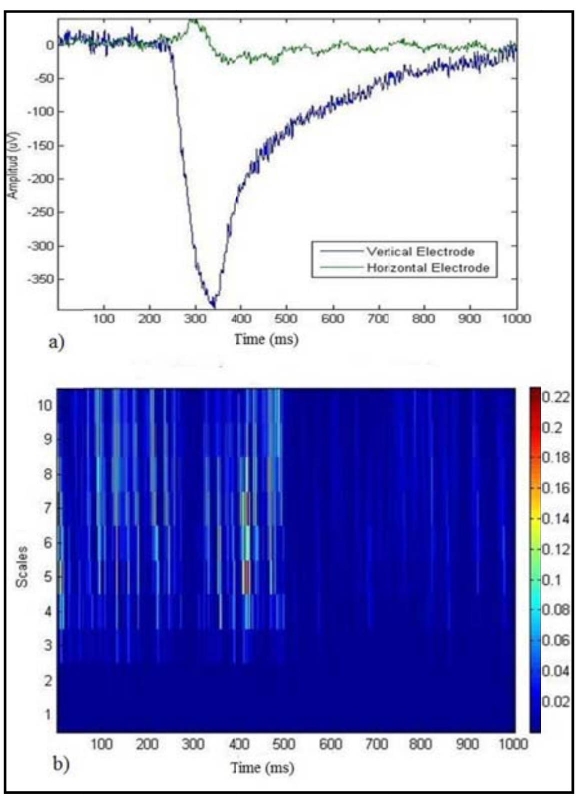


i) Left eye Movement

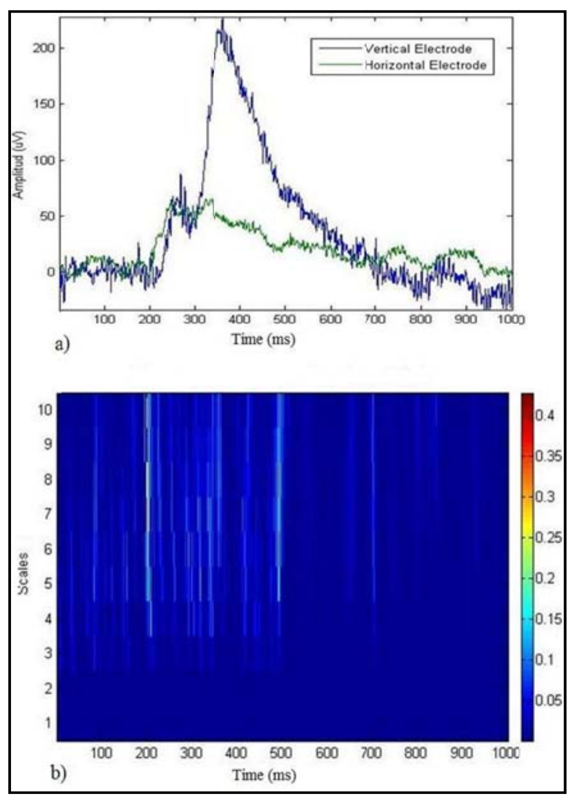


ii) Right eye Movement

Fig. 6. Scalogram of horizontal eye movements



i) Upward eye Movement



ii) Downward eye Movement

Fig. 7. Scalogram of vertical eye movements

The scalograms reveal that highest energy of the signals is captured in the different scale of details coefficient for different EOG signals. Frequency component extracted by details move from high frequencies to low frequencies as scale of wavelet coefficient increases from 1 to 10, with frequency content being halved at each increment in accordance to the sampling rate which is 1000 Hz (see Table I).

About 15 data for each eye movement have been analyzed by using wavelet scalogram in order to extract the most dominant energy details coefficient and it frequencies. The number of extracted detail coefficients from each level is calculated and plotted as shown in Figure 8. From Figure 8, it is noticed that the average percentage for each movement data is slightly different from their energy level. This means that different eye movements are associated with different frequency bands.

The percentage of each detail coefficient of four eye movements is illustrated in Figure 8. Statistically, the dominant energy is: scale 6 for left eye movement; scale 7 for upward; scale 8 for right and scale 9 for downward. They are summarized in Table II.

Dominant energy level means the maximum details coefficient energy that can be derived by scalogram for each signal. We use this parameter as the benchmark to classify the different movement of EOG signals.

SCALE	FREQUENCY RANGE (Hz)
1	250-500
2	125-250
3	62.5-125
4	31.25-62.5
5	15.6-31.3
6	7.8-15.6
7	3.9-7.8
8	1.9-3.9
9	0.9-1.9
10	0.5-1.0

Table 1: Frequency Content 10 Level Decomposition

EOG Signals	**Dominant Energy Scale**	**Average Percentage (%)**	**Estimated Frequency**
Left	Scale 6	80.0	8-16 Hz
Right	Scale 8	98.2	2-4 Hz
Up	Scale 7	99.2	4-8 Hz
Down	Scale 9	95.4	1-2 Hz

Table 2: Dominant energy level for 15 EOG Data

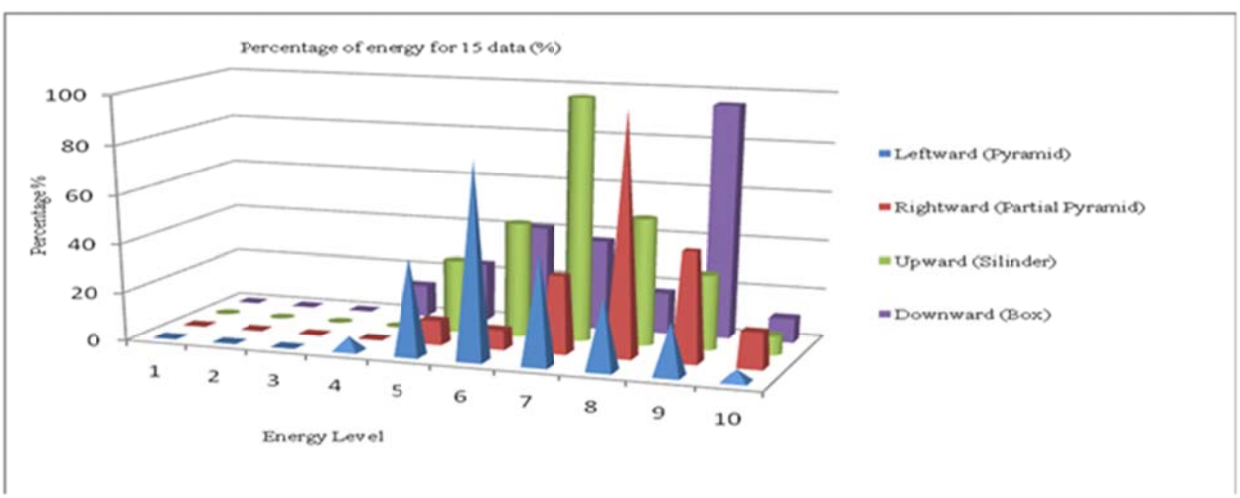


Fig. 8: Average percentages of energy level for 15 data of vertical and horizontal eye movements

V. Conclusion and Future Recommendations

This study has classified each EOG signals movement based on its estimated frequency using wavelet scalogram decomposition. This is different to previous studies in which they only focused on the overall wavelet decomposition and not specifically into the details of each EOG signals of each frequency bands. Hence, this paper proposes and targets the researcher to look into details of the energy and frequency bands distribution within four eye movement signals for better interpretation of EOG signals analysis by using wavelet scalogram. Result obtained indicates that each eye movement has different frequency bands and could be integrated to design a support machine for paralyzed people to move their wheelchair by using eye movements.

Acknowledgment

The authors are so indebted and would like to express our thankfulness to the Biomedical Instrumentation and Electronics Research Group (BMIE) at the Universiti Teknologi Malaysia for their ideas and comments to improve this paper.

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