VOL. 10, NO. 19, OCTOBER 2015 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

www.arpnjournals.com

WAVELET ENERGY DISTRIBUTIONS OF P300 EVENT-RELATED POTENTIALS FOR WORKING MEMORY PERFORMANCE IN CHILDREN

Siti Zubaidah Mohd Tumari and Rubita Sudirman
Department of Electronic and Computer Engineering, Faculty of Electrical Engineering, Universiti Teknologi Malaysia, Johor, Malaysia
E-Mail: rubita@fke.utm.my

ABSTRACT

The purpose of this study is to investigate the P300 event-related potentials (ERP) from background Electroencephalograph (EEG) of working memory performance by visual stimuli task. The proposed analysis for each channel at the prefrontal cortex is to compare the energy distribution via wavelet scalogram with the change of time and frequency of ERP signals. Wavelet energy distribution gives a lot of information for decomposing the frequency bands with necessary wavelet coefficient. This method was applied to data of normal children's with age groups (7, 8 and 9 years old) in a visual stimulation. Results showed that an alpha band was chosen for ERPs analysis according to the high energy level in the scalogram graph. This consequence of the alpha band was supported by the theory of chose the suitable frequency for working memory task. From the P300 signals in alpha band, the young children (7 years old) have a significant increase of amplitude variability rather than others. During the working memory task, the alpha band was increased when age increase: 7yo (4.88 Hz), 8yo (6.84 Hz) and 9yo (7.81 Hz). In conclusion, it is verified that the alpha band varies as a function of working memory performance.

Keywords: working memory, EEG, P300 ERP, wavelet transform, energy distribution.

INTRODUCTION

Nowadays, children have difficulty to remember the things in a short of time. One of the crucial issues in memory is to classify the relevant frequency bands, at which frequency bands the memory performance give more information. The working memory ability might be different according to the specific factors such as age, arousal and the type of cognitive demands during stimuli performances. Working memory performance states have been studied for almost 12 years, but the result focus on the abnormal children such as (ADHD, Autism, Obesity and Dementia) rather than normal children development (Liu *et al.* 2014). In order to acquire sustained attention, sensory modulations of visual stimuli assessments were given toward normal children to explore their working memory performance. The purpose of this stimulus is to investigate the responses of the abnormal levels of brain activity while remembering the sequence of the pictures. Based on this stimulus response, Electroencephalograph (EEG) signal was recorded and captured at the prefrontal cortex. This was done by investigating the early stages of working memory problem in children.

The electroencephalograph (EEG) is used to measure the electrical activity in the brain. The EEG frequency rhythm contains some characteristic waveforms which are typically categorized in specific bands such as delta (< 4 Hz), theta (4 to 8 Hz), alpha (8 to 13Hz), beta (13 to 30 Hz) and gamma (> 30 Hz) which decomposed using mathematical approaches (Sanei and Chambers, 2007). Delta wave lies below than 4 Hz with an amplitude < 100 μV that normally detected during the deep sleep, serious brain disorder and in the waking state. During the cognitive developments, the delta waves have relatively small amplitudes. Theta wave lies between 4 and 8 Hz with an amplitude > 20 μV. Theta observed from emotional stress, frustration and in condition of quiet focus, such as meditation. They are also apparent during short term memory tasks and memory retrieval for analyzing in learning procedures (Stella and Treves, 2011). Alpha lies between 8 to 13 Hz, with 30 to 50 μV amplitude. That appears in the posterior regions of the head (occipital lobe) when the subject in a relaxation state with eyes closed. It was proved that the activity on alpha waves reproduces the vision function of an individual. Beta wave lies between 13 to 30 Hz and has low amplitude that detecting on both sides of the brain varying symmetrical on the frontal area. The activity on beta wave usually with active attentions, concentrating out of box, solving problems and busy. Meanwhile, gamma wave lies more than 30 Hz that have very low amplitudes of less than 2 μV. The signal active exchanged information between cortical and subcortical areas during the conscious or anesthesia. Alpha, beta and gamma have been possible on increases of high power in frontal and parietal regions in attention and executive aspects of working memory (Palva *et al.* 2011). Some researchers have suggested that the EEG frequency within the alpha band should be related to memory performance were induces the neural activity in the cortex (Stam, Anne-Marie, and Micheloyannis, 2002). Thus, in order to utilize alpha band that is really suitable for cognitive processing, the wavelet energy distribution was used. This wavelet energy distribution will indicate which frequency band has the higher energy level at the positive peak of the P300 component after the stimuli. This analysis will be supported by the theory of choosing the suitable frequency for working memory task.

Prefrontal cortex area was selected to measure the brain activity while doing the stimulus activity. The functions of the prefrontal cortex are for problem solving, emotion, and complex thought. The continuous activity through the event activity was proven that the prefrontal

cortex can present the signal activity (Freedman *et al.* 2001) (Ramnani and Owen, 2004). Each channel has their own functions, so in the prefrontal cortex were preferred to record the performance of working memory in visual stimuli representations.

The generation of the EEG signal can be understood by changing the dipoles location at the right point for working memory ability. According to the 10-20 Electrode Placement, F7 and F3: lateral frontal (left midline) and F4 and F8: medial frontal (right midline) were attached as a motor planning. In the meantime, at the center point of Fz was attached to the working memory and absent mindless as showed in Figure-1. According to this midline, 5 channel locations were used to analyze the activation of energy based on the different frequency bands via visual stimuli.

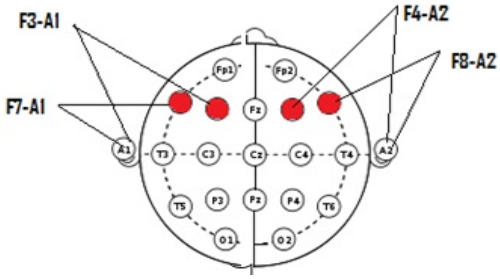

Figure-1. 10-20 electrode standard placement of frontal montage (Mohd Tumari, Sudirman, and Ahmad, 2012a).

If the EEG activity is recorded to the certain event or stimulus, Event Related Potential (ERP) is used to determine the electrical brain activity to internal and external stimuli response (Markazi *et al.* 2006). ERPs are the portion of the EEG both time and phase-locked to event onsets across a set of equivalent experimental events. Their high temporal resolution provides for non-invasive signal of brain activity that related to instruments, which processing the stimuli (events) (Ventouras *et al.* 2004). ERP also allow to perceive a series of cognitive operations before the delivery of sensory information sending to the peripheral nervous system until the behavioral response is made (Woodman, 2010). Peaks or component is defined as an experimental protocol that focused on the part of the waveform containing significant local of maxima and minima. Since ERPs are non-stationary signals, wavelet transforms more suitable techniques filtering because of its ability to adjust to signal components, as speed as their computation (Markazi *et al.* 2007).

MATERIALS AND METHODS

Data collection and experimental setup

Respondents of 41 children's within 7 to 9 years old were selected for these experiments. Respondents were selected into 14 children aged 7 years old, 14 children aged 8 years old and 13 children aged 9 years old respectively. The respondents have not been recorded on brain injury history and healthy.

EEG data were recorded on 10-20 Electrode Placement systems but 5 channels at the prefrontal cortex were considered to be the analysis with the frequency sampling of 1000 Hz. The electrode scalp was attached on the respondent's forehead with impedance less than 10 kΩ and respectively tightens with the body harness. This experiment was done in the close room to minimize the environment noise and hence to get the improved signals. The experiment was started after all the EEG procedure was done, and the respondents need to sit comfortably in front of the screen monitor with the distance between 25 cm for all subjects (see Figure-2).

The visual task which is Phase 1 (The study phase) was presented on the monitor using MATLAB: Graphic User Interface (GUI). Phase 1 consists of 4 individual animal pictures in the black and white color. The presentation of pictures will start with the white block as the fixation screen. Then the pictures will display one by one accordingly 5 second per pictures. At the same time, the EEG signal was recorded while the children remembering the sequence of the pictures. The recorded of EEG signal done when the fixation block appears on the screen.

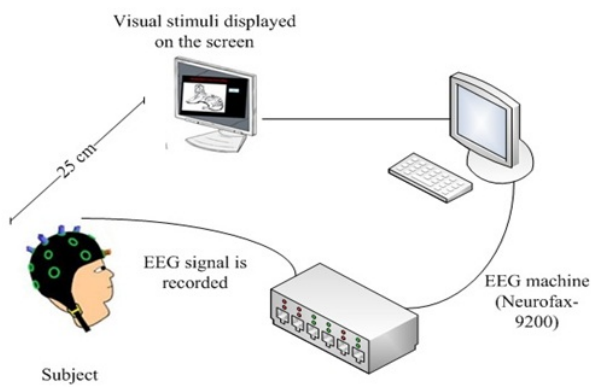

Figure-2. Experimental setup.

Electroencephalograph (EEG) signal processing

The raw EEG signal of working memory performance was filtering the contaminated artifact on the signals. Since EEG data are recording continuously, if the activity generated in response to visual stimuli, the EEG signal activity that is not related to the visual stimuli can be categorized as an artifact. The external artifact (power line) has to be removed by wavelet de-noising with the mother wavelet of Daubechies of 4. Then, for the internal artifacts which occur by eye movement; muscle movement and environment, Independent Component Analysis (ICA) is used to get the clean EEG signal (Xiong *et al.* 2014). In order to study the behaviour of ERP, the Discrete Wavelet Transform (DWT) were chosen to decompose the signal through the means of low-pass filter (Approximation coefficient: cAs) and high pass filter (Details coefficients: cDs) (Mohd Tumari, Sudirman, and Ahmad, 2012b) (Mohd Tumari, Sudirman, and Ahmad, 2013).

In order to perform the required decomposition, the output signals having half the frequency's bandwidth from the original ERPs signal that follows the Nyquist rule. Without losing any information, the down-sampling of a time domain signals can be divided into two: low and high frequency. Down-sampling occurs when the original signal, x(n), passed through a half band high-pass filter, g(n), (detailed coefficient) and a low-pass filter, h(n), (approximation coefficient). A one level of decomposition can be mathematically expressed as in equation (1), (2), (3) (Polikar, 1999):

$$y(n) = x(n) \times h(n) \tag{1}$$

$$y_{high}(k) = \sum x(n) \times g(2k-n) \tag{2}$$

$$y_{low}(k) = \sum_{n} x(n) \times h(2k-n) \tag{3}$$

x (n) = Original signal,
h (n) = Low-pass filter,
g (n) = High-pass filter,
yhigh (k) = Outputs of the high-pass filter,
ylow (k) = Outputs of the low-pass filter

Equation (2) shows the detailed coefficient defined by the scalar product of raw signal, x(n) with the scaling function, g(2k-n). However, equation (3) is the approximation coefficient for down-sampling by scalar product between raw signal x(n) and down-sampling h(2k-n).

The decomposition of level has been discussed on the previous study which is using db4 with level of decomposition of 8, since the length of the frequency is 1000 Hz (Mohd Tumari, Sudirman, and Ahmad, 2014). The Daubechies of 4 was chosen for this study because this wavelet has a shape similar to the average of P300 neuron action potentials and considerable degree of smoothness (Al-Nashash, Paul, and Thakor, 2003). Decomposition of ERP signal was decomposed into necessary frequency bands and scale of a, that being used on the energy distribution analysis.

The signal was decomposed by 2 until level decomposition of 8; mean that from the length of 1000, it will decompose by 2 which go to the high frequency of 1000 to 500 as detailed coefficient and low frequency as approximation coefficient (0 to 500). Then, the signal will decompose from the high frequency level (D1) to make another level of decomposition (D2). The process of decomposition will end until found all the frequency bands. At the higher frequency, the necessary frequency bands were indicated starting from the D5 (gamma rhythm), D6 (beta), D7 (alpha), and D8 (theta). For the last frequency bands which contain of delta rhythm (< 4Hz), the ERP signal that was to be taken by the approximation coefficient (cA8) which is at the low frequency. In this study, the coefficients of the scale level corresponding to the 5 frequency bands was submitted to find which frequency have the higher energy among 7, 9 and 10 years old children's.

Wavelet scalogram was representing the time frequency localization property of the discrete wavelet transforms (Daud and Sudirman, 2011). Scalogram is the square magnitude of wavelet transform that provides the energy distribution of the signal in the time-scale plane. Depending on this theory, the detail coefficients is plotted correspond to the frequency bands and the magnitude of the coefficient. The bar shown on scalogram was indicating the percentage of energy for each wavelet coefficient and plotted in the different color which is red for the high energy, lower energy (yellow) and little energy (blue) (Markazi *et al.* 2007). By using scalogram, it will interpret that the majority of the energy of the signals in the data are captured in the details coefficients.

RESULTS AND DISCUSSION

Based on the wavelet scalogram, for the average mean of 7 years old children, it can be indicated that the alpha band has a lower energy level (yellow). Meanwhile, delta, theta, and beta show little energy (blue color) at P300 component. However, for 8 years old scalogram, the energy in the alpha band shows high energy (red) that spreads out between 300 ms and 400 ms. On the other frequency bands, the scalogram indicates the energy as little energy (blue). Furthermore, for 9 years old children, P300 component in the delta, theta, and beta band give high energy and spread out the energy in the time window between 200 ms and 400 ms. Meanwhile, lower energy level in the alpha band is detected on the P300 component. In summary, the most noteworthy of P300 component activity occurs in the alpha band activity. This is because, when taking the average of all 3 age groups, the alpha band was indicated to be spread at the higher energy level (red color) in the time window between 250 ms and 350 ms (see Figure-3). This energy level at the alpha band is consistent with the previous study. Meaning that, alpha band gives higher energy while doing the visual stimuli for the working memory performance.

Regarding this result, P300 component signal in alpha band was selected to identify which group has higher amplitude and latency. Figure-4 shows the grand average ERPs at alpha band for a group of age in a time window from 0 to 500 ms. The younger children (7 years old) exhibited higher positive P300 peak amplitude than other groups. There was also significant difference between three groups within the range of the time window of 320 ms to 380 ms that illustrated in Figure-4. Age differences were observed, as the 7 years old had an amplitude at 0.055 µV with latency at 364 ms. Meanwhile, the older children (9 years old) had an amplitude at 0.0354 µV with latency at 332 ms. At the same time, the 8 years old group had slightly similarity when drop in peak amplitude (0.045 µV) to the latency of 333 ms.

In order to see the performance on working memory processes, energy distribution analysis among the age groups are compared. Besides that, this analysis was done to acknowledge which frequency has the higher

VOL. 10, NO. 19, OCTOBER 2015 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

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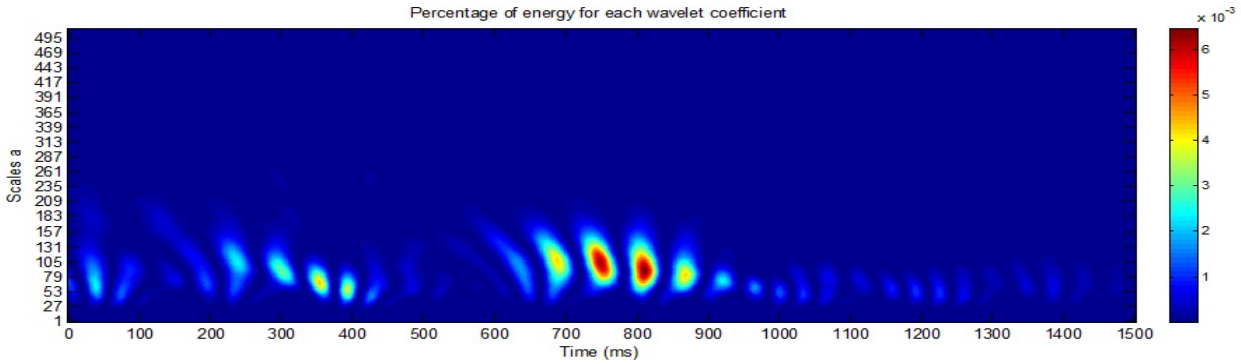
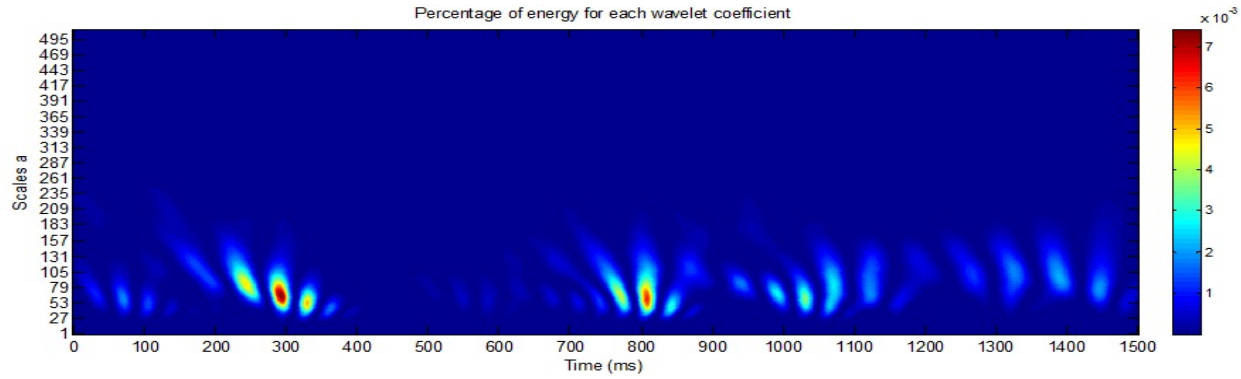
energy while doing the visual stimuli. Thus, ideas regarding wavelet energy distribution analysis have been developed to know the distribution of the ERP signal energy with the change of time in the wavelet scalogram illustrations.

Previous study stated that early childhood has an increasing alpha band, and then starts to decline with age (Klimesch, 1999). For children, which aged 1, 3, 9 and 15 years old will increase the alpha band from 5.5 to 8, 9 and 10 Hz (Klimesch, 1999). According to this statement, this finding of this study approved that the children of 9 years old approximately at 7.8 Hz with peak amplitude of 0.0257 µV. Meanwhile for 7 years old, alpha band is 4.88 Hz with peak amplitude (0.0964 µV), for 8 years old, alpha band rises about 1.96 Hz and will be 6.84 Hz with peak amplitude is 0.0477 µV. As a consequence, alpha bands change when age increases.



(a)



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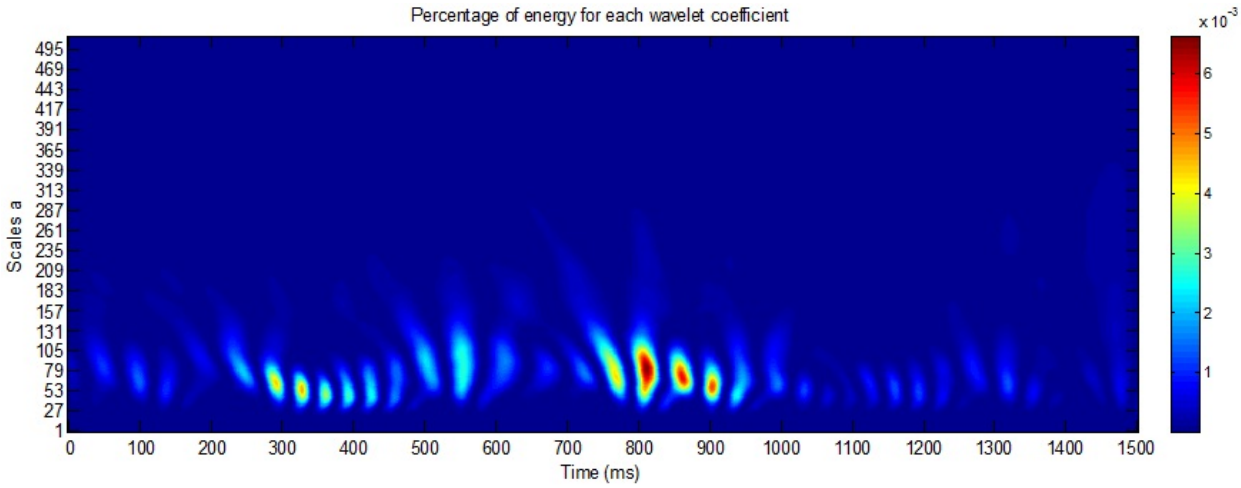

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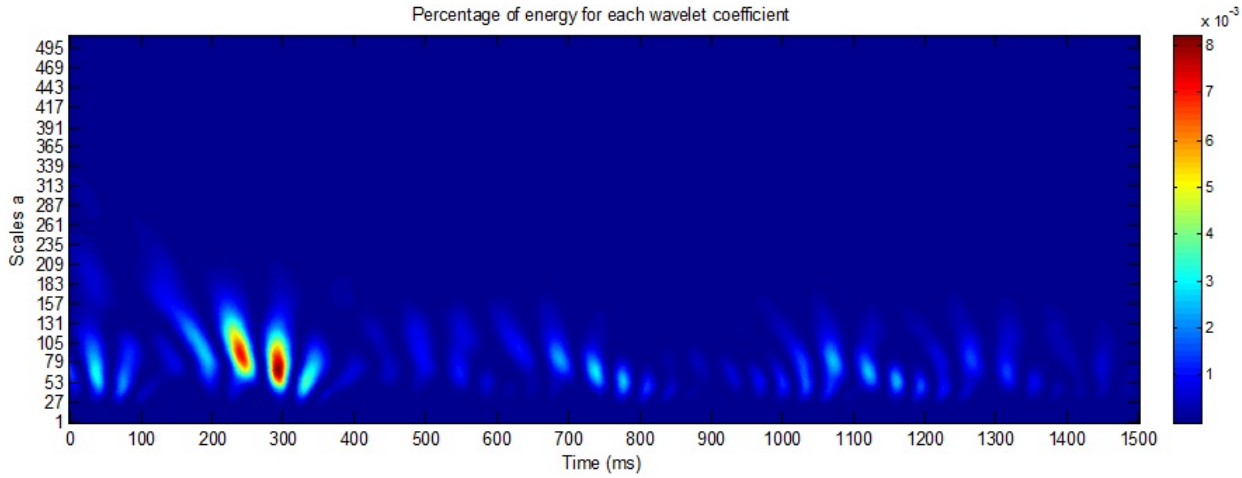

(d)

Figure-3. The wavelet scalogram graph of distribution of energy for each wavelet coefficient for a group of age. The wavelet scalogram graph for the mean group of age in a time window from 0 to 1500 ms. (a) 7 years old (b) 8 years old (c) 9 years old (d) Average all aged. Color scale of scalogram: red for the high energy, lower energy (yellow) and little energy (blue).

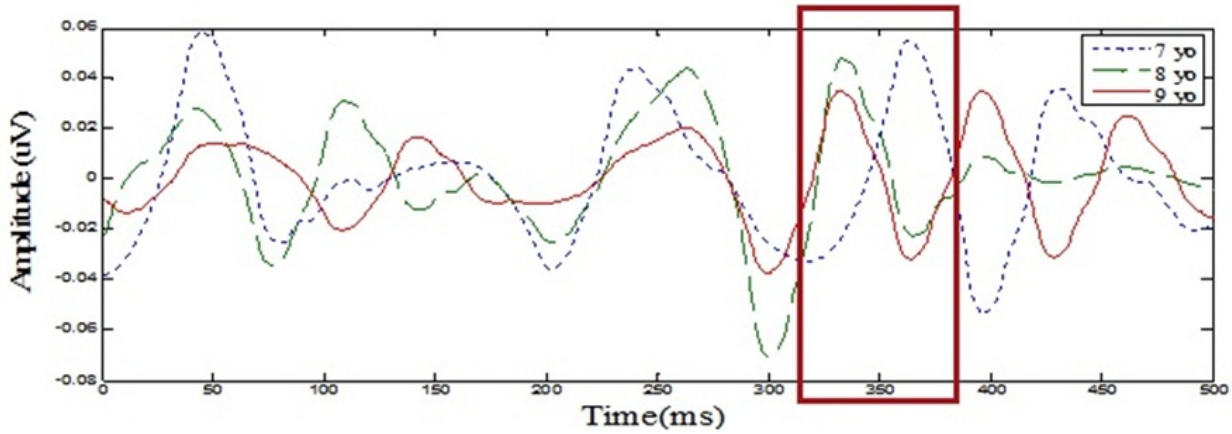

Figure-4. Grand averaged ERPs at alpha band for a group of age in a time window from 0 to 500 ms. The significant difference is within the range of the time window of 250 ms to 350 ms. Box marker shows the peak amplitude of working memory performance at the P300 component for each group of age in a time window from 320 ms to 380 ms.

CONCLUSIONS

This study has been classified each frequency band signals for working memory using visual stimuli based on the wavelet scalogram decomposition. The discrete wavelet transforms (DWT) were employed to decompose the signal in different frequency bands and with different temporal resolutions. Wavelet energy distribution is used to support that alpha band is suitable for the P300 ERP analysis. This alpha band was chosen as a reference for the analyzing method due to the credibility of working memory performance. This way will help to studies the P300 analysis more informative based on the EEG characteristics. In conclusion, the proposed study method could be used for ERP classification to find out the suitable frequency bands, to give an easier way for the further analysis.

ACKNOWLEDGEMENTS

The author would like to express thank all the teachers and students from primary school for collecting the EEG data. The second gratitude goes to the Ministry of Higher Education and Universiti Teknologi Malaysia for their funding this study under vote no. 4S094.

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