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Working Memory Impairments Imitate Age-Related Behaviors in Children using Visual Stimulation Based on Event-Related Potentials

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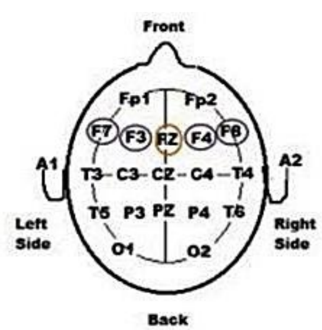
Graphical abstract



Abstract

The aim of this study is to examine the working memory impairments imitate age-related between 7 to 12 years old using Event-Related Potentials (ERP) signal. 97 normal children were selected to a visual stimuli assessment (Phase 1 and Phase 2) while their working memory response was recorded using Electroencephalograph (EEG) machine. Raw EEG signal were segmented and averaged into the ERP signal according to the event stimulus occur. Discrete Wavelet Transform technique is preferred to decompose the ERP signal into different frequency band. ERP signal at alpha frequency is used because of alpha is the most prominent component of brain waves activity. The necessary features were extracted as an input for the Logistic Regression (LR) and Support Vector Machine (SVM) classifier. Consequence indicated that the accuracy and mean performance results were significant in predicting either a child had working memory impairment or not. 7 years old have lower accuracy compared to other groups with 60% for LR and 86% for SVM. In conclusion, the study proposed that age-related changes and increasing level of visual stimuli affect working memory impaired. Thus, this study has provided empirical evidence in support for the assumption that younger children have working memory impaired through visual stimuli assessment.

Keywords: Working memory; ERP; EEG; visual stimuli; LR; SVM

Abstrak

Kajian ini bertujuan untuk mengkaji kemerosotan daya ingatan berdasarkan umur di antara 7 hingga 12 tahun dengan menggunakan isyarat *Event-Related Potentials (ERP)*. Seramai 97 kanak-kanak normal dipilih untuk penilaian visual stimuli (Fasa 1 dan Fasa 2) sementara kebolehan daya ingatan mereka direkodkan menggunakan mesin *Electroencephalograph (EEG)*. Isyarat EEG mentah telah dibahagikan dan dipuratakan ke dalam isyarat ERP berdasarkan rangsangan peristiwa yang berlaku. Teknik *Discrete Wavelet Transform* dipilih untuk menghuraikan isyarat ERP kepada beberapa frekuensi. Isyarat ERP pada frekuensi alpha digunakan kerana alpha merupakan komponen paling menonjol di dalam aktiviti gelombang otak. Beberapa pengelas diekstrak sebagai masukan bagi regresi logistik dan Mesin Vektor Sokongan. Keputusan menunjukkan ketepatan dan purata prestasi pencapaian adalah penting untuk meramalkan sama ada kanak-kanak itu mempunyai kemerosotan daya ingatan atau pun tidak. Kanak-kanak 7 tahun mempunyai ketepatan yang lebih rendah berbanding dengan kumpulan lain dengan 60% LR dan 86% bagi SVM. Kesimpulannya, kajian ini mencadangkan bahawa umur berkait berubah dan peningkatan tahap visual stimuli menjejaskan kemerosotan daya ingatan. Oleh itu, kajian ini telah menyediakan bukti-bukti empirikal dalam sokongan bahawa kanak-kanak di usia muda mempunyai kemerosotan daya ingatan melalui penilaian visual stimuli.

Kata kunci: Daya ingatan; ERP; EEG; visual stimuli; LR; SVM

1.0 INTRODUCTION

Nowadays, there are an increasing number of children facing short term memory impairments. This is a kind of mental disorder that refers to the condition where the working brain can only retain information consciously for a short period of time (in a few seconds) [1]. Working memory impairments among normal children can be evaluated through physician observation and based on their performance in the classroom. However, this assessment sometime can lead to human error which the teacher cannot identify accurately because of child's society and activation. Thus, the difficulties of normal children who impair with working memory development may happen faulty. The children's responsiveness to visual stimuli concerns their ability to interpret the surrounding environment after processing the information that is reflected in visible light. By using visual stimuli, the behavioural and neuronal consequences or reflexive orienting were investigated [2].

Working memory is the central processing unit of the nervous system, a temporary memory storage which depends on individual capacity. The term of working memory is defined as a structure of human brain which is able to store information temporarily and can manipulate some specific information [3]. As a multi-component system, it is also the central lobe that plays an important role in complex cognitive activities such as learning, comprehending and reasoning. Moreover, there are two important areas about the nature of working memory where the major area acts as a storage system while the other as the important information which is used in intellectual tasks. Recent researches include differentiating between what the brains develop and perceive as simple or complex spans. Tasks recognized as complex span are things that are remembered using numerous frameworks of disturbing task, for example, answering mathematics question and interpreting sentences. On the other hand, simple span tasks are about unloading primary and secondary memory such as words and letters [4]. In this study, more attention is given to complex span events in children.

Human are able to store about 1 to 10 items for a short period of time in the active state for about 0 to 60 seconds, depending on the individual cognitive memory capacity [5]. In addition, working memory capacities can increase with age. For example, younger children (4 to 7 years old) have smaller working memory capacity than children age 8 to 12 years old [6]. Some children have difficulties in memorizing and manipulating a given problem for a short time period.

Poor working memory in children, in general, can further agitates behavioral problems when it is at elevated level with its mean value more than 60 [7]. Higher mean value means that the child has more serious cognitive problem or inattentive symptoms that can cause him or her to have a shorter attention span than other children. Poor working memory is obvious when such child is given tasks in areas of reading, mathematics and sciences [8]. Children having poor working memory will face learning difficulties in distinct forms. Poor working memory can lead to discrimination by normal children. The learning performance of children depends on the individual's memory storage capacity. The ability of children to enhance their memory skills affects their academic performance. Therefore, this study intended to focus more on the complex span activities in children by interleaving to-be-remembered items with some forms of distracting task such as visual stimuli. Furthermore, sensory responsiveness of visual is used to investigate the working memory performance in neural computation of the various functional areas. However, this does not mean that they are abnormal since the comprised development of their working memory could have been caused by their environment, culture, or traumatic events that have distracted their attention during classroom learning [9]. Some studies have stated that visual pictures can represent a powerful modulator of cognitive performance for training the children to remember in a short period of time. The ordinary children chosen for this visual stimuli assessment are hypothesized to have certain degree of working memory impairment.

After that, the prefrontal cortex is responsible for organizing thoughts and information as compared to the inferior temporal cortex, which reacts more to stimuli. It is at the anterior part of the brain as shown in Figure 1 and focuses on problem solving, emotion and complex thought. It is common that children have difficulty in memorizing a solved task for a long period, and such incapability in coined as working memory impairment. This impairment is scientifically measurable through the brain signals, which permits the formulation of effective methods that can indicate the severity of working memory impairment in children.

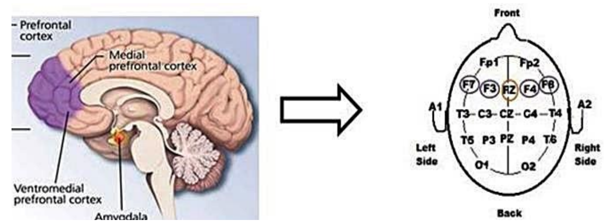


Figure 1 Medial view of prefrontal cortex at the channels: F7 and F3 (left midline), Fz (center midline)and right midline (F4 and F8) [10]

In order to investigate the working memory impairments in normal children, this study used Electroencephalograph machine to identify and classify who having and not having working memory impairment. Electroencephalography (EEG) is a medical imaging technique that reads scalp electrical activity generated by brain structure after being picked up by metal electrodes and conductive media. Due to capability to reflect both the normal and abnormal electrical activity of the brain, EEG has been found to be a very powerful tool in the field of neurology and clinical neurophysiology. As the EEG procedure is non-invasive and painless, it is being widely used to study the brain organization of cognitive processes such as perception, attention, language, memory and emotion in normal adults and children. The 10-20 electrode placement system is applied for electrode positioning to achieve standard reproduction of results. The EEG spectrum generated were within five frequency bands, i.e., delta (< 4 Hz), theta (4 to 8 Hz), alpha (8 to 13 Hz), beta (13 to 30 Hz), and gamma (> 30 Hz) [11]. Visual stimuli were given to the children through Phase 1: Study phase consisting of four pictures, and Phase 2; Working memory phase consisting of seven pictures.

Raw EEG signal was segmented according to the event responses and then average into Event-Related Potential (ERPs) signal so that a more conclusive diagnosis on the working memory performance of a particular respondent could be made. As such, ERP signal is used to identify the pattern of the children's while being engaged in two classes of respondents, i.e., pictures, to remember within a few seconds. Event-related potential (ERPs) is initiated by an external or internal stimulus and suitable for studying the aspects of cognitive processes of both normal and abnormal nature such as psychiatric disorders and neurological [12]. Such ERPs have their changes time-locked to a defined event, which could be detected before or immediately after stimuli. Analyzing the ERPs includes pre-processing; averaging the data time-locked to the stimulus or response; and averaging over the subjects for substantial properties. This kind of ERP technique can take in raw EEG segmented data to investigate cognitive processing. Generally, the ERPs can be either discrete or continuous. Discrete ERPs are analyzed in a short epoch (a few seconds) time-locked into the event (< 100 ms), while continuous ERPs are analyzed in a longer time segment (window) that is more than 100 ms. This also indicates that ERPs are the portion of the EEG that is both time and phase-locked to event onsets across a set of equivalent experimental events. Their high temporal resolution depicts the non-invasive signal of brain activity that is related to the processing of the stimuli (events). The peaks or components, on the other hand, are the experimental protocol that focuses on a part of the waveform containing significant local of maxima and minima. The ERP component in this study is P300 component which were mostly used in neuropsychiatric research to study cognitive processes [13].

This study used alpha band with frequencies between 8 Hz to 14 Hz for extracting useful parameters (mean, standard deviation, wavelet energy and wavelet entropy) to analyze normal children working memory performance. Thus, wavelet transform was proposed to perform the time-scale analysis of ERP signal. The suitable wavelet family selected for this study was Daubechies order of 4 to match the ERP properties which were orthogonal, symmetry, compact support, and non-stationary signals [14]. Numbers of level decomposition strictly depend on the sample rate of original signal. Since this study used frequency sampling of 1000 Hz, the ERP signal will decompose until 7th level decomposition (stop at alpha band). Discrete Wavelet Transform (DWT) will be computed into ERP signal for decomposing the signal into 5 different frequency bands (gamma, beta, alpha, theta and delta). The ERP signals will be decomposed into approximate coefficients (low-pass filter) and detailed coefficients (high-pass filter). ERP signal decomposition will be down sampling until the original ERP signals find all the frequency ranges (D5; gamma, D6; beta, D7; alpha, A7; theta).

The resulting of P300 ERP signal at alpha frequency will be extracted the useful feature as an input (independent variable) for Logistic Regression (LR) and Support Vector Machine (SVM) classifier to reveal the working memory impairment among different ages. Experimental results from the LR and SVM classifier were compared to the post-stimulus result from to-be-remembered questionnaire given. The consequence would further the knowledge of the neurophysiology of memory recognition.

1.1 Related Research

The present study is not really using children as a subject to investigate the working memory impairments towards visual stimuli using ERPs signal among children development. Although various researcher using children as the subject, but the finding area is more focus on the abnormal children such as (Autism, Hyperactive, Obesity and Dementia) rather than normal children development. Normal children are only used as a control group to compare with the abnormal children that who already diagnose. The working memory of normal and abnormal children is different which led to the existence of different ERP patterns. Furthermore, working memory and visual responsiveness are also different between normal and abnormal children that might affect the children's behavior. At the current level of research, the environmental factors do not affect the working memory performance but there is evidence that working memory is genetic [15].

Several researchers studied about the working memory performance using children towards visual stimuli task. However, there is a problem for the ineffectiveness to identify working memory performance related with visual stimuli of currently study implementation. Previous research is concerned with the development of cognitive functions with the standardized material of visual-naming with adults and children. Because of the researcher involve a large group of age (7 to 28 years old), they failed to interpret the age-related differences in cognitive functions which can be made only when age-appropriate pictorial stimuli is chosen [5].

In 2004, a researcher use ERPs signal to investigate the relation between different aged from 8 to 16 years old using the face recognition stimulation. However, the results indicated that there is no difference of cognitive impairment was found in different aged [16].

Another research used mathematical arithmetic to identify the contribution of working memory in children without recording the EEG signal. Therefore, the results only represent the pattern regression among the score of children without comparison with the EEG signal during the stimulation. Thus, the result failed to relate the contributions of working memory and mathematics [17].

The motivation for the present research was to obtain a normative database for pictorial material that will be helpful in future studies with normal children as a main subject. 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 ERPs brain activity among normal children while remembering the sequence of the pictures. Based on this stimulus response, Electroencephalograph (EEG) signal was recorded and captured from channel positions at F8, F7, F4, F3, and Fz. For children, working memory has its limits where the child will lose some information when there is too much information. If that is the case, then the child is known as having impairment in his or her working memory.

2.0 MATERIAL AND METHODS

2.1 Subjects

97 children aged 7 to 12 years old are designated in this study comprise of 57 boys and 40 girls. Concerning this determination, 60 subjects are those with good results, and 37 subjects have a moderate result in their academics record. They had no record of neurological problem and mental abnormalities. Interviews were held with the teachers to understand the ability and performance of children in the classroom.

2.2 Research Design and Procedure

Figure 2 shows the summary of the entire flow process implemented in this study. First, one child was selected and the examiner set 2 different assessments. Each assessment will record the EEG signal from the EEG data acquisition machine. The subject was given two phases of study to be focused that are Phase 1: The Study Phase and Phase 2: The Working Memory Test Phase. The recorded raw EEG data were saved in ASCII code, and converted into .Mat file format to analyze the signal using MATLAB coding. After that, the study proceeds to pre-processing to remove noise inside the acquired signal using ICA and wavelet filtering. Then, the EEG signal was segmented and averaged among the event stimuli to become ERP P300 component. This ERP signals are compared between different ages. ERP technique allows taking the raw EEG data, in order to investigate cognitive processing, where by the ERPs signal was generated as a response to specific stimuli and averaged over the number of samples. From the wavelet decomposition, at the level of D7, alpha rhythm value was determined by amplitude of 8 to 12 Hz. An explanatory analysis will carry on into feature extraction at P300 component as an independent variable. Meanwhile, a dynamic feature like mean, standard deviation, wavelet energy and wavelet entropy will be extracted from P300 component. Logistic regression and SVM will be invoked as a classifier to make a comparison between the proposed method and recent study is based on accuracy of percentage. Finally, the hypothesis can be predicted based on the dependent variable (1 and 0), either the normal children having working memory impairment or not.

For post-stimulus stage, the subject needs to recall the sequence of the pictures after the stimulus presented. The answer will be recorded with label (1: can answer correctly the sequence of picture; 2: cannot answer correctly the sequence of picture). Then the score of performance will be calculated using Microsoft Excel. The limitation of developmental trending is obtained between age and visual stimuli phases. The comparison between stimulus and post-stimulus results is discussed based on the age-related differentiate. The aim of this stage is to investigate if there are any significant difference or not between a group of age with visual stimuli phases (Phase 1 and Phase 2).

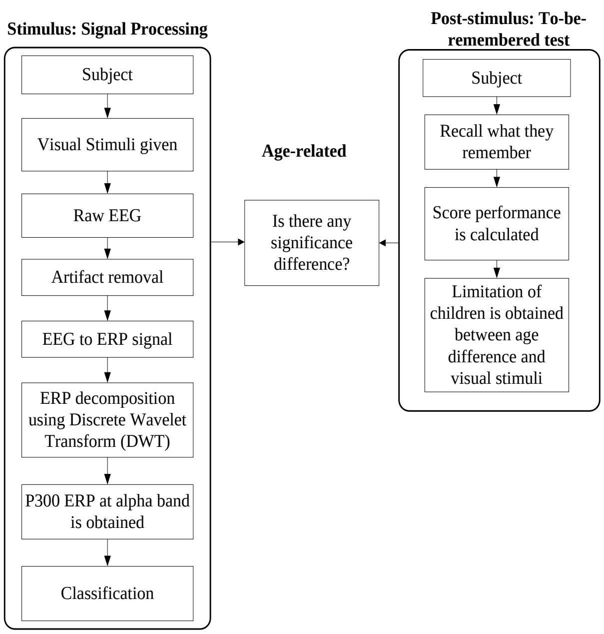


Figure 2 Work flow of the study

2.3 Behavioral Assessment: Visual Stimuli

The behavioral task that was given to the subject are using visual stimuli assessment. The assessments were divided into two-phases which are Phase 1: The Study Phase and Phase 2: The Working Memory Test Phase.

Phase 1 is originated with four black and white pictures. This assessment started with the sequential presentation of four different pictures about 5 second per picture and repeated two-times. The screen will be automatically backed into the fixation block (white color background) after all pictures obtainable.

While, Phase 2 contain of seven pictures with old (from Phase 1) and new pictures (as inter-stimulus pictures). The new picture (inter-stimulus) will be presented for a minimum of 1 second between any two old pictures. The purpose of inter-stimulus picture is to interrupt the subject to-remember the sequence of pictures.

2.4 Electroencephalography (EEG) Recording

EEG data were recorded using Neurofax-EEG 9200 when the subject doing their assessment. EEG recording can be attained by placing electrodes on the scalp which attached to the skin of head using wires. Scalp electrodes are placed according to the standard 10-20 Electrode Placement at channels of F3, F4, Fz, F7 and F8 for working memory development. The sampling frequency is set to 1000 Hz. Each subject was adjusted to 25 cm from the screen which displays the visual stimulus. Then, the electrode board adapter was plug in to DAQ EEG machine according to the standard color coded (see Figure 3). Before recording session, subject was asked to avoid any movements such as blinking eyes and tongue movement in order to reduce the biological artifacts.

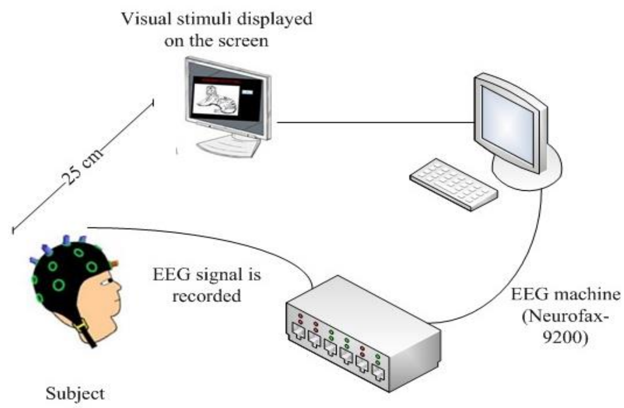


Figure 3 Experimental setup

2.5 Data Analysis

2.5.1 Electroencephalography (EEG) Signal Analysis

EEG signal recorded were analyzed using MATLAB software. First, raw EEG signal that are contaminated with a lot of artifact such as biological artifact (eye movement, muscle movement and blinking) and external artifact (line noise and power noise) were filtered using Independent Component Analysis (ICA) technique. The purpose of ICA is to filter the unnecessary signal activity that is not related to the visual stimuli response, since EEG data are recorded continuously.

Next stage, the brain signals were segmented correspond to each stimulus according to the event responses (Phase 1: 5s, 10s, 15s, and 20s; Phase 2: 5s, 6s, 11s, 12s, 17s, 18s and 23s). Then, the event responses were averaged to produce the Event-related Potentials (ERP) signal for diagnosis on working memory impairment of a particular respondent. By doing this averaging at each time point according to the stimulus, the P300 component of ERP could be made.

2.5.2 P300 Event-related Potentials (ERPs) Signal Analysis

The P300 might occur due to allocation of attention resources to stimulus attended by memory updating. P300 manifests itself as a positive voltage approximately 300 ms after the stimulus. In cognition terms, P300 is deemed to represent stimulus evaluation time (latency) and attention engagement (amplitude). For stimulus complexity, P300 component has a more expressive behavior for complex span while doing visual stimuli. P300 intended as the most positive peak in the time window between 200 ms to 500 ms after the stimulus onset, which is maximal over the frontal lobe.

2.5.3 Discrete Wavelet Transform (DWT) Analysis

This study used alpha rhythm because it is the most prominent component of brain waves. The frequency and amplitude are known to be affected by external stimuli such as memory tasks and mental arithmetic. On the other hand, positive change in P300 ERP in alpha increases the speed of processing information and enhances cognitive performance.

In sustained of this attention, DWT is used to decompose the P300 ERP signal into several level of decomposition with the sampling frequency of 1000 Hz. DWT is more suitable in area of biomedical applications. DWT decomposed the signal at different frequency bands with different resolutions by decomposing the original signal into Approximation coefficients (cA) and Detailed coefficients (cD). Consequently, this algorithm gives precise analysis of frequency domain at low frequency and time domain at high frequency [18].

In Figure 4, Daubechies of 4 (*db4*) is used as a mother wavelet with the 7th level of wavelet decomposition. The mother wavelet is chosen according to the criteria of EEG signal that can be categorized into orthogonal, symmetry, compact support, and non-stationary signals. The chosen of mother wavelet have been discussed on the previous study [14].

From the original signal of P300, the signal will be down sampling by 2 through a low pass filter (Approximation coefficient: cA) and a high pass filter (Detailed coefficient: cD). Down sampling occurs when the original signal, *x(n),* passes through a half band high-pass filter, *g(n),* and then a low pass filter, *h(n)*. A one level of decomposition can be mathematically expressed in Equation (1), (2) and (3) [19].

$$y(n) = x(n) \times h(n) \quad (1)$$

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

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

where *x(n)* is the original signal, *h(n)* is low pass filter, *g(n)* is high pass filter, $y_{high}(k)$ is the outputs of the high pass filter and $yl_{ow}(k)$ is the output of the low pass filter. Equation (2) represent the detailed coefficient defined by the scalar product raw signal, *x(n)* with the scaling function, *g(2k-n)*. While, Equation (3) is the approximation coefficient for down-sampling by scalar product between raw signal *x(n)* and down-sampling *h(2k-n)*.

For the first down sampling, a low pass filter contents a length from 0 to 500, name as A1, and a high pass filter (500 to 1000) as D1. Then, A1 will continue be down sampled by 2 which produce A2 (0 to 250) and D2 (250 to 500). The down sampling process will resolve interchange until the original signals find the necessary frequency ranges (D5: gamma; D6: beta; D7: alpha). For representation, D1, D2, D3, and D4 are named as noise signal.

In this case, the alpha rhythm is chosen, thus the decomposition analysis will stop at the level of 7 (D7: 8 to 16 Hz). For each subject, the alpha coefficients were averaged to obtain a grand average of P300 ERP by a group of age, see Figure 4 and Table 1.

2.6 Feature Extraction and Selection

Feature extraction is the key for classification method which is to reduce the pattern vector such as an original waveform into a lower dimension, that contains most of the useful information from the original vector [20].

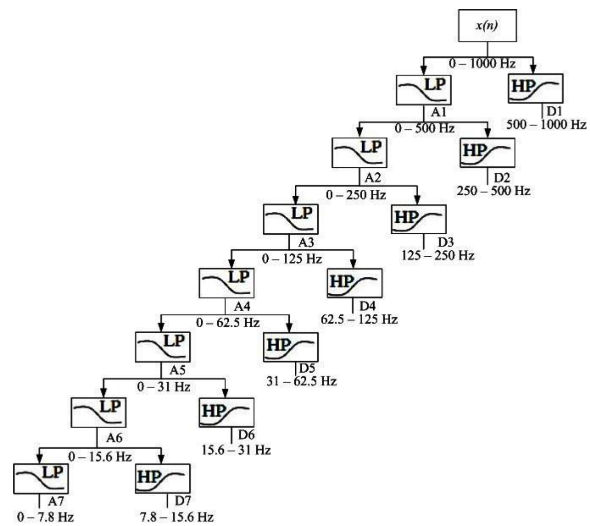


Figure 4 Original signal is decomposed into 7th of level decomposition with detail and approximation coefficient of signal. The original signal *x(n)* is down-sampling by 2 through a low-pass filter (LP) and high pass filter (HP) and produces output of cA and cD.

Table 1 Decomposition of ERP signal into different frequency bands (Fs = 1000 Hz)

Frequency Range (Hz)	Decomposition Level	Frequency Band
1000 - 500	D1	Noise
250 – 500	D2	Noise
125 – 250	D3	Noise
63 – 125	D4	Noise
31 – 63	D5	Gamma
16 – 31	D6	Beta
8 – 16	D7	Alpha

Based on the ERP signal, useful parameters such as mean, standard deviation, wavelet energy, and wavelet entropy were extracted at the time window of 250 ms until 350 ms (see Figure 5). Since, the responses to target stimuli were considered correct if the responses at the positive peak of P300.

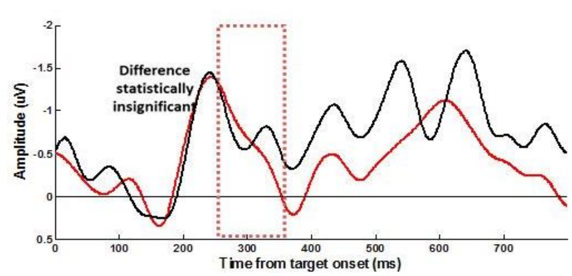


Figure 5 P300 component of ERP signal at the time window of 0 ms to 800 ms.

2.6.1 Mean

The mean is the average of the summation of observed values that is divided by the total number of observations. Equation (4) indicates the mathematical formula for finding the mean value.

$$\overline{\mathrm{X}} = (\textstyle\sum_i X_i) \div N \tag{4}$$

where $\bar{X}$ is the mean value, X_i is the observed values and N is the total number of observations.

2.6.2 Standard Deviation

A standard deviation is the distance between one point to the mean value and a measure of dispersion. A standard deviation with a smallest value is considered better because of the estimation will be consistent. Equation (5) indicates the mathematical formula to determine the value of standard deviation.

$$\sigma = (\,\Sigma(\mathrm{X_i} - \overline{\mathrm{X}})^2) \div \mathrm{N} \tag{5}$$

2.6.3 Wavelet Energy

Wavelet energy is defined as the sum of the squared values of all ERP samples in an epoch (one continuous time series, usually in a few seconds). The coefficients from each resolution level of j correspond to different frequency bands. The energy of E_j for each frequency range in each time window of 1000 ms can be computed as the corresponding squared coefficients. Then, the energy at each resolution level j = -1, -2, …, -N, will be the energy of the detailed signal that follow in Equation (6) [21].

$$E_j = \textstyle\sum_k \left|C_j(k)\right|^2 \tag{6}$$

where C_j is the coefficient series in each level of j. This time window being the minimum one including at least one coefficient in each level denoted with the index of k. Then, the total energy, E_{tot} can be measured by using Equation (7):

$$E_{tot} = \textstyle\sum_{j<0} E_j \tag{7}$$

2.6.4 Wavelet Entropy

Wavelet entropy is considered to be the measurement of deviation from the mean entropy of the background of ERPs signal. Wavelet entropy is measured for analyzing and comparing the probability distribution that provides information of any distribution that underlying the signal. The total wavelet entropy is defined as in Equation (8) [22]:

$$WE = -\textstyle\sum_j p_j . \ln p_j \tag{8}$$

where p_j is the relative energy as in Equation (9) which is computed as the ratio between the energy of each level, E_j and the total energy of the signal, E_{tot} in the respective time window.

$$p_j = \frac{E_j}{E_{tot}} \tag{9}$$

2.7 Classification

Classification can be appealed as diagnosis and outcome predictions for the problem specified [23]. There are two main types of classification which are supervised classification and unsupervised classification. Supervised classification is used to observe a set of data that associated with class labels. In other hands, supervised procedure assumes that a set of training data has been provided and the ERP dataset were divided into training and testing set. The training set is used to train the classifier, while testing is used to evaluate the performance of the classifier.

Unsupervised classification involves grouping data into classes based on some measure of inherent ability. This procedure predicts training data has not been hand-labeled, and any information about the class labels of the measurements is not available for a small dataset [24].

Thus, in the area of biomedical research, supervised classification is more preferred as the classification type. This study used Logistic Regression (LR) and Support Vector Machine (SVM) as a classifier to predict the ability of working memory. The main issues using LR and SVM are to compare their accuracy. Accuracy is the reliability of the rule, usually represented by the proportion of correct classification to control the error rate.

2.7.1 Logistic Regression (LR)

Logistic regression (LR) as a multilayer perceptron neural network based classifiers were developed and associated in relation to their accuracy in classification of ERP signals [25]. The major advantage of the LR is it can create a simple probabilistic principle of classification. The logistic function, defined as the logit, is shown in Equation (10):

$$g(x) = \beta_0 + \beta_1 x \tag{10}$$

where $g(x)$ refers to the logit function of some given predictor of X, β_0 is the intercept from the linear regression equation (the value of the standard when predictor is equal to zero), $\beta_1 x$ is the regression coefficient multiplied by some value of the predictor.

The LR predicts the variants that have a probability value between 1 and 0. If the subject had the probability of 0.5 and above, it was taken that the probability was having working memory impairment and vice versa.

2.7.2 Support Vector Machine (SVM)

SVM is a large margin binary classifier. The classes (input data) are described by a vector of features, which is a description of parameter characteristics [23].The training set is used to train the classifier, while the testing set is used to evaluate the performance of the classifier.

■3.0 RESULTS AND DISCUSSION

3.1 Behavioral Task Performance

The hypothesis is to determine which group among a group of age 7 to 12 years old has more impaired in working memory. The prediction was made to determine whether the null hypothesis had been accepted or rejected with reference to the inputs of the independent variables (mean, standard deviation, wavelet energy and wavelet entropy). Dependent variable (1 = having working memory impairment; 0 = do not having working memory impairment).

In this case study, two hypotheses have been made:

H0: There is no supported relationship between ages and working memory performance.

H1: There is supported relationship between ages and working memory performance.

The mean performance was analyzed supported on the total score for each two-phase. The scoring is divided into two variables (1: if the subject can answer correctly the name of pictures in array; 2: if the subject cannot answer correctly). Analysis of scoring is using Microsoft Excel by mathematical formula to compute the percentage of each picture in an array. The mathematical formula ((Total number of correct picture ÷ Total number of subject for a group of age)) × 100). An example, for 7 years old children, only one subject out of 15 cannot answer correctly the first picture in Phase 2; the score performance is (14 ÷ 15) × 100 = 93.3%.

For the first phases, there is no significant difference for the first three pictures, all subject in each group can remember precisely, but for the fourth array picture, the mean performances were diverged significantly for the 7 years old. But for children of 12 years old, their working memory performance maintains until the end of the session. Within age groups, the performance of 12 years old shows significantly different with the Phase 2. It can be seen that the mean performance on the task improved with age and for all age groups, mean performance decreased as task difficulty increased. This decrease was most marked in the youngest children and the least for the oldest children. By comparing the result between Phase 1 and Phase 2 stimuli, 7 years old children indicated working memory impaired when the number of stimuli increased. While 12 years old children performed well even-though the occurrence of visual stimuli in assessment increasing (see Figure 6).

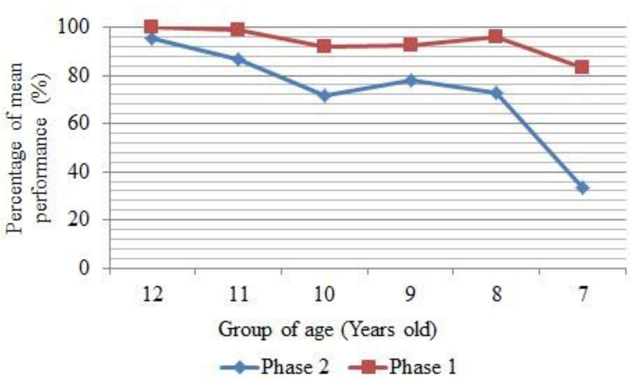


Figure 6 Percentage of mean performance changes is detected by a group of age between Phase 1 and Phase 2

3.2 ERP Results

ERP signal was carried out to identify the pattern of children stimuli events according to two different phases. Focus of ERP pattern is more on to investigate the children's responsiveness to visual stimuli. It concerns their ability to interpret the surrounding environment after processing the information. The performance on cognitive tasks showed working memory impaired when the task increasing. This also showed that the P300 component had increased with amplitude variability in the visual stimuli responsiveness. Even though, for 7 and 10 years old that indicated higher amplitude Phase 2, but their significantly different only away from zero values. Different subjects give different results, but the grand means for ERPs at P300 are rather close to each other. Phase 2 had slight delay on latency and had lower amplitude rather than Phase 1 when the children were exposed to new pictures.

P300 components signal in alpha band was selected to identify which group has the higher amplitude and latency. Figure 7 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 (10 years old) exhibited higher positive P300 peak amplitude than other groups. There was also significant difference between six groups within the range of the time window of 250 ms to 350 ms. Age differences were observed that for 7 years old has amplitude at 0.0037 µV. Meanwhile, the older children (12 years old) indicated the amplitude at the 0.004 µV. At the same time, group of 8 years old slightly has similarity when drop in peak amplitude (0.045 µV) to the latency of 333 ms (see Figure 7).

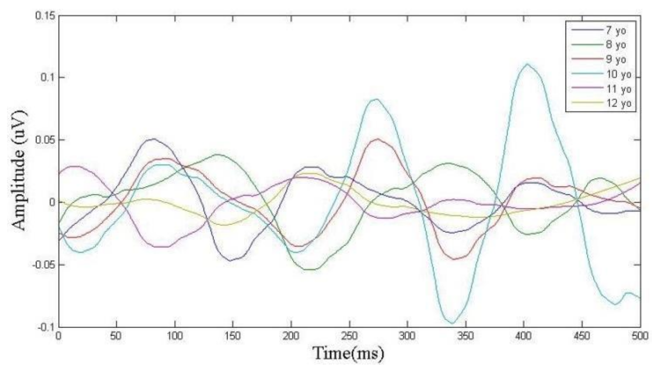


Figure 7 Grand averaged ERP at alpha band for a group of age in a time window from 0 to 500 ms. The significant difference of the amplitude within the range of the time window of 250 ms to 350 ms

3.3 Classification

Classification was performed by means of LR and SVM. This supervised learning algorithm can seek to provide the best possible separation of predefined groups on the basis of a number of training samples.

All the experiments in this section were done over parameter of P300 component of 97 samples data for each subject with 4 different features (mean, standard deviation, wavelet energy and wavelet entropy). There were two diagnosis classes: Having working memory (Label: Yes or 1) and does not have working memory impairments (Label: No or 0).

Classification results of this model were analyzed by using cross-validation technique. 97 data sets were randomly partitioned into subset; one of the subset was used as the test set and the other subset were put together as the training sets. Then, in order to reduce their variability, the average classification results were computed.

Logistic regression classifier was used for validation of the model with the independent variable of feature parameters (mean, standard deviation, energy and entropy). By using the same input of features, SVM is used to classify the output data. In these combinations of feature, we train and test with various features likes mean, standard deviation, energy and entropy. According to this procedure, the SVM classifier was trained using feature vectors from dataset (97 sample data per features; 388 sample data for combined features), except from one dataset (does not matter whether it corresponds to a 1 or 0 classes), that was used for testing. The generalization ability of the SVM was then tested using the feature vector in a singled out. The training-testing procedure was repeated until each one of the feature vector has a chance to be the testing data. The classification accuracy was computed by the sums of correctly classified or misclassified pattern of 1 and 0 classes.

The correct classification of the results would be comparable between a group of age using LR and SVM. Table 2 and Figure 8 show the comparative of percentage of accuracy for a group of age with combined feature for two-phases. In Phase 1, children aged 7 years old have a lower accuracy compared to other groups with 60 % of accuracy for LR and 86 % for SVM. While, children aged 10 years old raised about 99 % of accuracy for LR and 100 % for SVM. The results show that, there is not one of the data for aged 10 years goes to misclassified observations. In Phase 1, SVM-based classifier shows higher than using LR-based classifier, so possibility of misclassified observations was less. Hence, the majority of subjects had no problem memorizing the sequence because Phase 1 consists of 4 pictures only. However, Phase 2 shows that there is small difference between LR and SVM. Additions of pictures affected the working memory performance in children.

Conventionally, LR and SVM are used to find out the percentage of accuracy who having working memory impairments and to clarify which classifier has the better value of the percentage of accuracy. Regarding on the results or accuracy, SVM is more stable to classify the working memory impairment of normal children in a group of age according to the less of misclassified data.

Our hypothesis proved that ERPs features incremental between the age samples when the visual stimulus is at the highest levels. The combination of features gives the best features to find abnormalities of working memory development.

Table 2 Comparative of percentage of accuracy for a group of age with combined feature for Phase 1 and Phase 2 using LR and SVM

Age	Accuracy (%)			
	LR		SVM	
	Phase 1	Phase 2	Phase 1	Phase 2
7	60	60	86	71
8	69	69	83	100
9	92	85	100	83
10	99	67	100	100
11	75	79	89	89
12	71	59	75	69

4.0 CONCLUSION

The aim of this study is to discriminate of visual stimuli task effect on ERP signals. The alpha band was chosen as a reference for analyzing method due to the credibility of working memory performance. The necessary features can be used as an input for the logistic regression and SVM classifier. The useful parameter (mean, standard deviation, energy and entropy) and biological data were significant in predicting whether a child had working memory impairment or not. The mean performance indicated that there is significantly difference between the group of age and scoring of working memory performance.

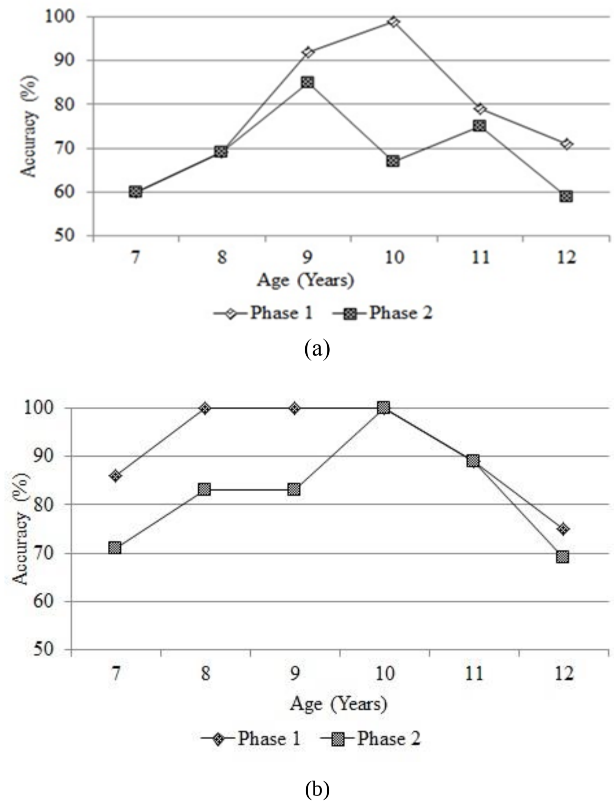


Figure 8 Comparative of percentage of accuracy for a group of age trending for Phase 1 and Phase 2 (a) LR-based classifier accuracy (b) SVM-based classifier accuracy

In conclusion, working memory is only a part of cognitive development but there is promising future approaches in this field. Brain activities were identified by using DWT and the quality of working memory performance was determined by the use of ERP patterns, scoring mean performance and classification analysis. ERP patterns for Phase 2 (including old and target pictures) that contains 7 pictures elicit greater positive amplitude at P300 component than Phase 1 (4 pictures). This observation proves to have an effectiveness of visual objects embedded in the working memory task based on the Event-Related Potentials (ERPs) signal response was determined.

This study also discussed the developmental trends for age-differentiate, whether normal children with no working memory difficulties have a working memory deficit. By using standardized proposed visual stimuli model for all group, their scoring of mean performance was recorded after the stimulus responses. 97 children were compared among a group of aged of children with 7 years old children performed worse on Phase 2 with scoring of 37%. More important, 7 years old children performed worse than the older children (12 years old: 95 %), whereas the all group performed worse score on the inter-stimulus task (representing for 1 second). Compared with the age-differentiate controls, both phases (Phase 1 and Phase 2) performed significantly worse on a second picture in array presented. These findings lend support for the assumption that younger children having working memory impairment. Thus, working memory performance and behavioural rating correlate significantly by aged for normal children deficit in visual stimuli assessment was discriminated.

The alpha rhythm pattern in normal children changes due to their ability to memorize picture sequences well. Alpha value for normal children that does not have working memory is greater than normal children who having working memory when both kinds of children were exposed to visual stimuli. Thus, EEG method can be used to record their brain signal in order to monitor their level of visual response through working memory performance. The younger children tend to working memory impaired rather than older children. Since, they are too young to learn how to remember things in a short of period time.

A classification of P300 ERP signal at alpha frequency had been discussed to obtain the necessary feature vector that can be used as independent variable (x) for the LR and SVM classifier. The useful parameter and biological data were significant in predicting whether a child had working memory impairment or not. Moreover, premised on a respondent's age, we can predict the increasing in working memory impairment. This also indicates that, even though a child may have performed well in lower grades, he or she may not be able to maintain the outstanding academic record if his or her reading and memorizing skills are not improved. Thus, the effectiveness between two-phases stimulus according to the percentage of accuracy had been classified.

Overall, this study has provided empirical evidence in support for the assumption that normal children have working memory impaired in young children through visual stimuli assessment.

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