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CHARACTERIZATION OF YOUNG CHILDREN WITH PREFERRED AND NON-PREFERRED GRAPHIC RULE DURING DRAWING

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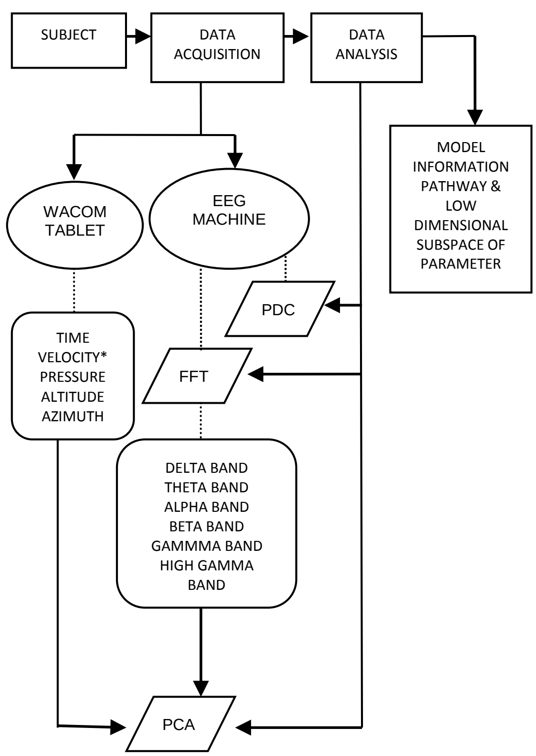
Graphical abstract



*The velocity of handwriting signals is calculated from extracted pen position data (position of x- and y- axes).

Abstract

This paper aims to investigate the functional connectivity in brain among young children during employment of preferred and non-preferred rule when drawing basic drawing task using Partial Directed Coherence (PDC) and to determine the most significant parameter in differentiating the two groups using handwriting dynamic features and brain activity based on statistical analysis and principle component analysis (PCA). Twelve subjects between 5 and 6 years old were selected randomly. All subjects were asked to gaze and trace four different unlined shapes. The brain signals were recorded using an electroencephalogram (EEG) machine during drawing tasks. Result showed that subjects who employed preferred graphic rule (Control) when performing gazing and tracing tasks were better at visual processing when compared to those that used graphic rule in haphazard fashion. Besides, significant difference was found in frequency domain when subjects used graphic rule in rule governed fashion when compared to relaxing activity. The contrast was found when subject used graphic rule in haphazard fashion. Results from PCA showed most significant parameter (gamma/high gamma) in differentiating between the two groups (employed graphic rule vs. non-graphic) was found in tracing task.

Keywords: Handwriting, electroencephalogram, partial directed coherence, fast fourier transform, principal component analysis

Abstrak

Tujuan kertaskerja ini adalah untuk menyiasat sambungan fungsi di dalam otak dalam kalangan kanak-kanak muda di antara peraturan pilihan dan bukan pilihan semasa tugas asas lukisan dengan menggunakan kaedah *Partial Directed Coherence* (PDC) dan bagi menentukan parameter yang paling penting dalam membezakan peraturan pilihan dan peraturan bukan pilihan dalam tulisan tangan dari ciri dinamik tulisan tangan dan aktiviti otak dengan menggunakan analisis statistik dan *Principal Component Analysis* (PCA). Dua belas kanak-kanak perlu merenung dan mengesan empat bentuk yang berbeza dan tidak bergaris dan pada masa yang sama isyarat otak direkodkan. Keputusan menunjukkan gelombang gamma dan gamma tinggi boleh membezakan kanak-kanak yang melakar mengikut aturan atau tidak. Perbezaan dalam merangka tugas ini boleh didapati ketika kanak-kanak sedang membuat kerja meniru asas lukisan.

Kata kunci: Tulisan tangan, elektroensefalogram, koheren separa terarah, jelmaan fourier pantas, analisa komponen prinsipal

1.0 INTRODUCTION

1.1 Graphic Rules

Handwriting is a complex human ability that requires integration of various skills. People start writing in the early stage of their life and children start developing their writing skills as early as the age of three [1]. As handwriting competency is important for academic success and self-esteem [2], children with handwriting difficulty may not excel in academic and less productive in daily life as compared to normal children [3, 4].

Handwriting process includes the mechanical and visual perceptual processes of graphics. A developmental sequence of graphomotor skills is normally seen as children evolve their scribbling and picture drawing into handwriting [5]. The outcome measures of drawing performance have been used to create a profile of behavioral traits in children who are at risk of handwriting difficulty [1]. In addition, kinematic analysis of drawing has also been shown could quantitatively highlight the characterization of handwriting movement that disrupt normal handwriting process [2]. All these diagnostic information from drawing activities can be used in the assessment of handwriting proficiency [6].

The most consistent and significant findings in empirical studies of handwriting performances is the influence of Visual Motor Integration (VMI) skills [7]. VMI has been operationally defined as the ability to allow eyes and hands to work together in a smooth, organized and efficient way when copying geometric shapes. One of the tests often used for development assessment of children's VMI skills is the Beery Development Test of Visual Motor Integration. The test requires children to copy an ordered sequence of geometric shapes. It is claimed that VMI is a significant predictor of handwriting performance in a group of first graders [7, 8].

Drawing a pattern appears simple but the sequence of movement to produce the pattern varies [9]. To copy geometric pattern consisting of several segments, one can usually select many possible combination of start position, stroke directions and stroke orders [10]. In most cases, when children were asked to copy geometrical pattern, they will organize their movement sequences such that they could employ the strokes that demand the fewest total movement. Apparently their aim is to minimize the complexity of the copying task which may correspond to their joint-coordination demand [11]. Starting at the bottom and moving upwards or at the right and moving leftward is known as non-preferred sequencing strategy associated with high-joint control demand [12]. On the other hand, starting from the top and moving downward with low joint-coordination demand is known as preferred rule [12]. Children preferred strategies are start either at the top or left and progress downward or rightward [13].

Copying a figure or shape does not require memorization but it always requires translation process. Children with handwriting difficulties were found not to be able to translate the visual information into motor actions [14, 15]. As children seem to follow a set of rule when copying geometric figures [12, 16] and their chosen sequences of movement are normally based on their motor capabilities, difficulties with handwriting may relate to strategy implementation and may have been influenced by the use of graphic rules (stroke sequences and directions) in a haphazard fashion rather than rule-governed fashion [2, 9].

In order to understand the complex functional organization of the motor system, it is essential to know the anatomical and functional connectivity among cortical motor areas of an individual [17]. Nowadays, there has been an explosive growth of interest on investigating handwriting difficulties based on human brain activity [18]. However, the difference in brain activity in relation to the use of graphic rules has not yet been explored. Therefore, this paper focuses on determining parameters that can characterize young children who perform drawing using preferred graphic rule from those who do not based on not only dynamic features of drawing process but also brain activity during such task. Methods involved in this research include partial directed coherence (PDC), frequency analysis and principle component analysis (PCA).

1.2 Partial Directed Coherence (PDC)

PDC is the latest concept in neural structure determination [19]. PDC is the combination of Granger causality and coherence to process numerous time series for determination of the functional connectivity in brain [18]. The Granger causality can be illustrated in term of multivariate Vector Autoregressive process (VAR). Vector autoregressive model of order *p*, VAR [*p*] is generalized given by x ,

$$x(t) = \sum_{n=1}^{p} a_n x(t-n) + \xi(t) \qquad (1)$$

with *p* coefficient matrices a_n,n = 1,2, …, p, each of dimension M X M . The term ξ Gaussian white noise process with covariance matrices (t) represents an M-dimensional Σ, i.e ξ (t) ~ N (0,Σ).

PDC is estimated with the condition in equation (2) according to equation (3) while the coefficient matrices a_{ij} are evaluated by fitting a VAR model of order *p* as shown in equation (1).

$$\overline{A}_{ij} = \begin{cases} 1 - \sum_{n=1}^{p} a_{ij}(r) e^{-i2\pi fr}, i = j \\ -\sum_{r=1}^{p} a_{ij}(r) e^{-i2\pi fr}, otherwise \end{cases} \qquad (2)$$

$$\pi_{ij}(f) = \frac{|\bar{A}_{ij}(f)|}{\sqrt{|\bar{A}_{1j}(f)|^2 + |\bar{A}_{2j}(f)|^2}} \qquad (3)$$

M of the linear VAR model contain the information about Granger–causal interactions between the components of multivariate process.

1.3 Fast Fourier Transform (FFT)

FFT is mathematical procedures which are thought of transforming a function from time domain to frequency domain. It is a faster version of the Discrete Fourier Transform (DFT) that can be applied when the number of samples in the signal is power of two [9]. The N point DFT can be computed using (4)

$$x_n = \frac{1}{N}\sum_{k=0}^{N-1} X_k \cdot e^{i2\pi kn/N}, \; n \in Z \tag{4}$$

where x_n is discrete–time signal with a period of N. The Fourier transform operates in continuous function. In EEG application, FFT is extremely important in extracting useful information from EEG signal based on the type of brain waves generated. FFT normally gives the result in the form of power distribution of six frequency band. Each frequency band has different mental condition. The types of brain waves generated that are related to the mental condition of a subject are shown in Table 1.

Table 1 EEG Frequency band and associated condition

EEG Frequency Bands	Frequency Ranges (Hz)	Mental Condition
Delta	0-4	Deep sleep
Theta	4-8	Intuitive, creative
Alpha	8-13	Relax
Beta	13-31	Active thinking
Gamma	31-51	Motor function (fine motor control)
High Gamma	51-120	

1.4 Principle Component Analysis (PCA)

Principal Component Analysis involves mathematical procedure that transforms number of possibly correlated variable into smaller number uncorrelated variables. Quantitative analysis using the dataset can be obtained by using multivariate analysis to identify the most effective parameter [20]. PCA can be calculated using the formula below:

$$\mathrm{PC}_1 = \sum_{i=1}^{p} a_{ij} X_j \tag{5}$$

Where PC_1 refer to principal component, and a_{ij} is the factor loading. The greater the factor loading the greater the degree of indicator variables associated with the main component. X_j is the indicator variable. The most important objective of PCA is to represent multivariate data as low dimensional data. By projecting all observation onto this low-dimensional subspace and plotting the result, it is possible to visualize the structure of dataset. To avoid redundancy and identify the features that are most sensitive to locomotors performances, a dimensionality reduction is performed through this analysis. From the new low-dimensional constructed principal component, the variable that contributes most to the pattern among the observation could be determined [20]. The variable that influence most among variable are important. Some of the low-performances variables might therefore be removed from consideration to simplify the overall analysis. The operation of PCA can be used in open source R software.

2.0 EXPERIMENTAL

2.1 Participants

A total of four (4) experiments were conducted with a total of 12 young participants, aged 5 and 6 years old. The number of participants who performed the drawing with a non-preferred graphic rule were 3 in task 1 and task 4, and 4 in task 2 and task 3. These subjects were grouped into test group and those who performed the drawing task in accordance to graphic rules were grouped into control group as shown in Table 2. All subjects were selected randomly.

Table 2 Number of participants according to group

Task	1	2	3	4
Preferred (Control group)	9	8	8	9
Non-Preferred (Test group)	3	4	4	3
Total subjects	12	12	12	12

2.2 Data Acquisition and Analysis

Portable digitizing tablet (WACOM) with a wireless electronic inking pen connected to a computer via a USB port, detect and record the subjects' drawing process. The time and position of the pen tip were recorded while the subject performing the task.

At the same time, electrode cap (Electro-Cap International, Inc, Eaton, OH) with 19 channels was applied to the subject's scalp with the reference connected to the subject's ear lobe. The cap was then connected to an EEG machine (Neurofax μ EEG-9100J/K Nihon Kohden) for data acquisition. The acquired EEG waveform reflected the cortical activity in the brain. Linux Fedora 20 was used to compile and analyze the EEG data based on Partial Directed Coherence Method (PDC) and Fast Fourier Transform (FFT) using C language.

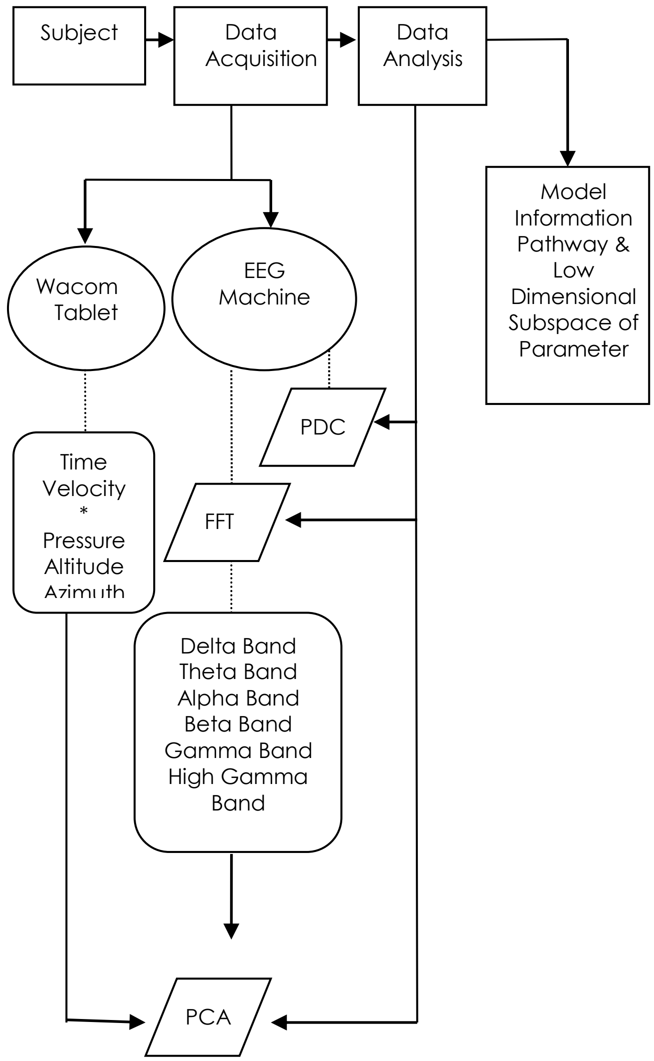
2.3 Experimental Procedure

The experiment was done in a small room with a quiet environment to avoid people's interferences as it can affect the acquired EEG signal and the subject may lose focus. The subject wore an EEG cap with electrodes attached to the scalp while performing simple drawing task on the digitizing tablet. Each participant was given a brief explanation of the experimental procedure. The experiment consisted of two tasks, i.e. Control Task and Drawing Task. For Control Task, subjects were required to be at rest and relax mind while their brain activity was recorded for 10 seconds. After that, the experiment continued with the drawing task. In the drawing task, participants need to perform two sub tasks: gaze task and trace task. In gaze task, subjects were asked to gaze eleven different unlined shapes which included the first nine form of VMI while their brain activity was recorded within 10 seconds. In trace task, subjects need to trace the shape directly on top of printed image on digitizing tablet while their brain activity was recorded. There is no specific end time for trace task. The subjects could freely choose their own preferred sequences and direction when tracing the shapes. Their sequences and direction for each task was noted. Each shape was printed on separated A4 paper and the paper was overlaid on the digitizing tablet for the subjects to perform the tracing activity. However, this paper presented four different unlined shapes only that include vertical line, horizontal line, right oblique line and a triangular shape for Task 1, Task 2, Task 3 and Task 4 respectively as shown in Table 3. Other shapes will be reported elsewhere.

Table 3 Drawing task with preferred and non-preferred graphic rule

Task	Shape	Preferred rule	Non-preferred rule
1			
2			
3			
4			

In total, there were 119 parameters were extracted ((19 EEG channels x 6 frequency bands) + 5 tracing dynamic features (tracing time, pen position (velocity), pen pressure, as well as altitude and azimuth from portable WACOM digitizing tablet)). All of these parameters were analyzed based on PCA. The significant difference between preferred and non-preferred graphic rules was based on these 119 parameters. Figure 1 shows the block diagram for the whole process.



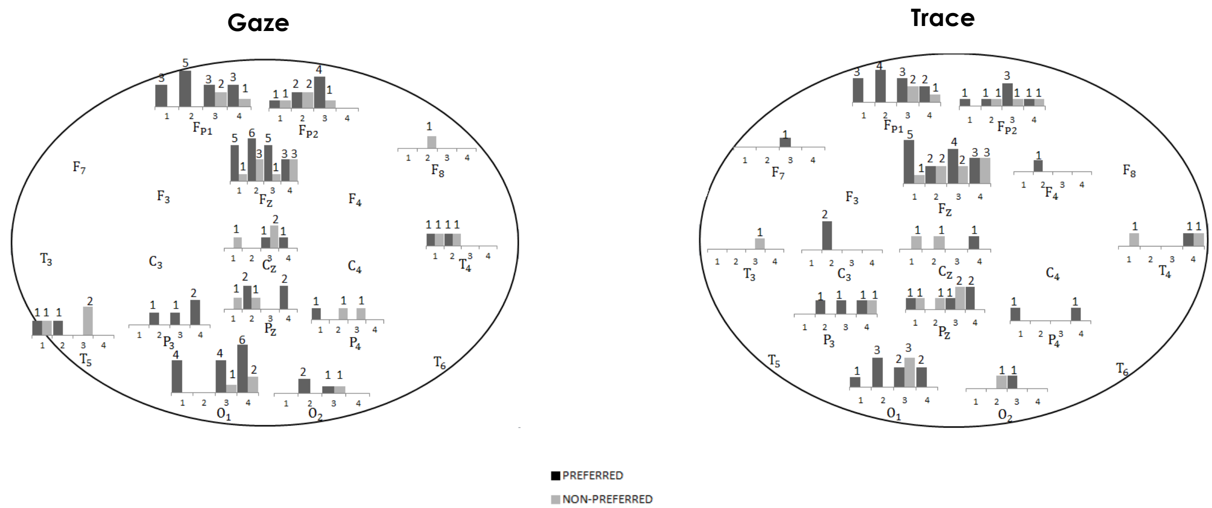
* The velocity of handwriting signals is calculated from the Extraction of pen position data (x and y positions).

Figure 1 Block diagram for data acquisition and analysis

3.0 RESULTS AND DISCUSSION

3.1 Partial Directed Method

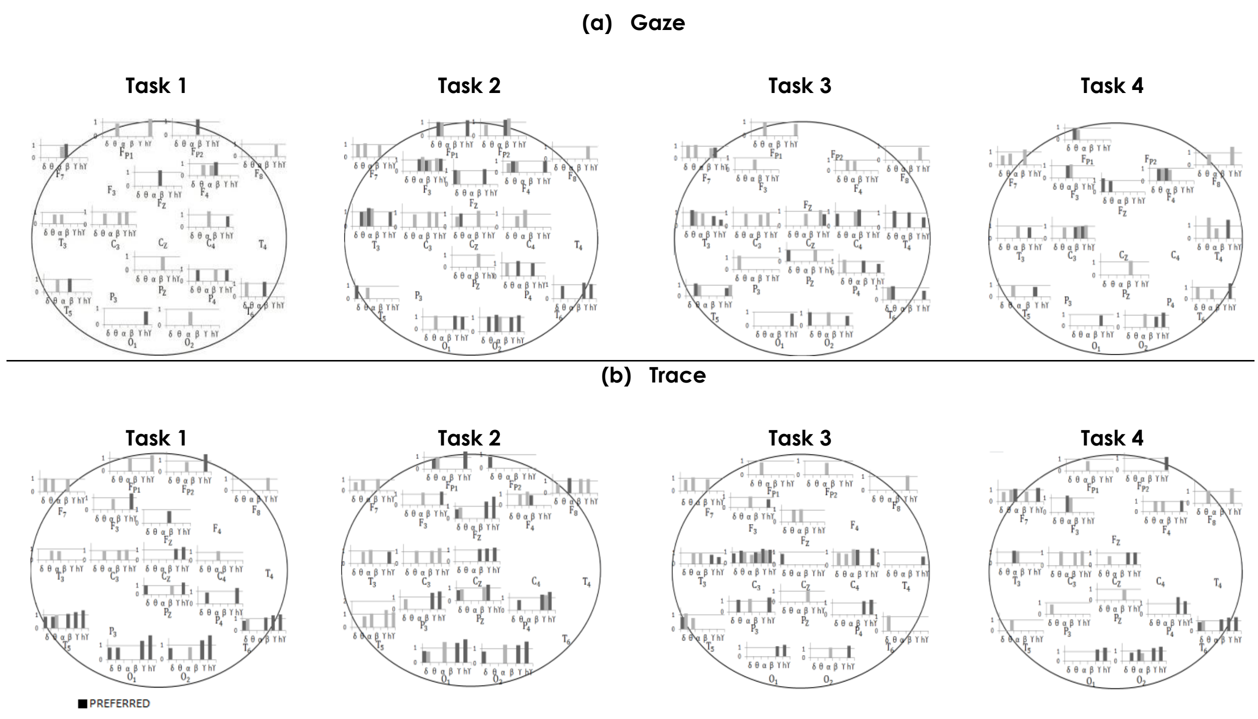
Figure 2 shows the total number of PDC sources of cortical information pathway during gazing and tracing activities for all tasks and for all scalp locations. In general, the control group, i.e. subjects who traced based on preferred graphic rule, showed higher numbers than the test group (subject who traced using non-preferred graphic rule) for generating information sources during both gazing and tracing. It can be seen that the control group used more occipital area, mainly in O_1 region to complete the gazing and tracing activities. It can be said that the occipital region as the source of EEG information flow during gazing and tracing activities is proportional to the subject cognitive performances, i.e. develop skills to follow certain rule and occipital region is where primary visual processing take place. It is concluded that the control group performed better in visual information processing than the test group.



Note: X-Axis = Task1, Task2, Task3, Task4

Y-Axis = Total number of subjects

Figure 2 PDC sources of information pathway for all tasks

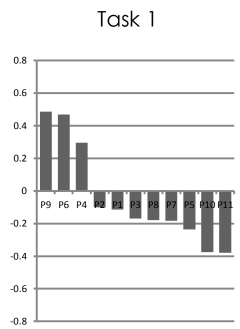


Note:

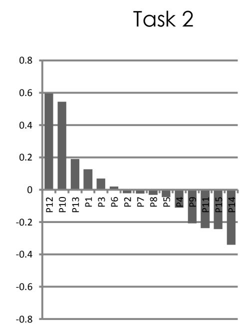
x-axis = delta band (δ), theta band (θ), alpha band (α), beta band (β), gamma band (γ), high gamma band (hγ)

y-axis = normalized peak ratio

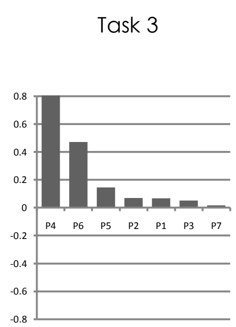
Figure 3 Control task (brain in relax condition) to drawing task (with significant difference) ratio of EEG frequency band during (a) gaze and (b) trace conditions



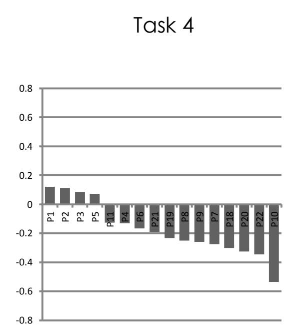
	Parameter
P1	Delta band C_3 gaze
P2	High Gamma band C_3 gaze
P3	Gamma band P_3 gaze
P4	Theta band T_3 gaze
P5	High Gamma band T_3 gaze
P6	Delta band C_z gaze
P7	Gamma band C_z gaze
P8	High Gamma band C_z gaze
P9	**High Gamma band F_3 trace**
P10	Beta band C_3 trace
P11	Beta band C_z trace



	Parameter
P1	Delta band F_7 gaze
P2	Gamma band F_7 gaze
P3	theta band T_4 gaze
P4	Gamma band T_4 gaze
P5	Gamma band T_5 gaze
P6	Theta band T_6 gaze
P7	Delta band T_4 trace
P8	Gamma band P_z gaze
P9	Beta band F_{p1} trace
P10	Delta band T_3 trace
P11	Beta band T_3 trace
P12	**Gamma band T_6 trace**
P13	Theta band T_4 trace
P14	Gamma band T_4 trace
P15	High Gamma band T_4 trace

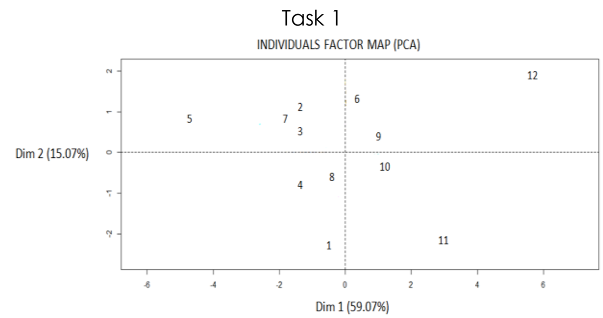


	Parameter
P1	Alpha band C_4 trace
P2	Gamma band P_3 gaze
P3	Gamma band P_z gaze
P4	**Gamma band F_4 gaze**
P5	Theta band P_4 trace
P6	Gamma band P_z trace
P7	Altitude

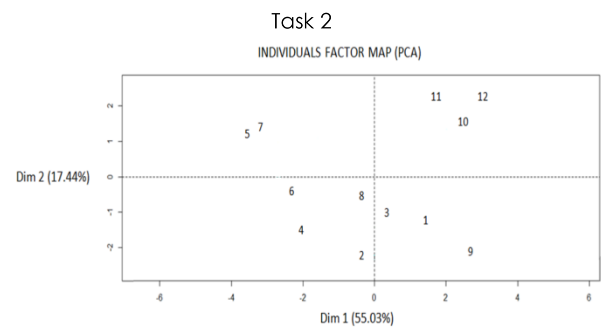


	Parameter
P1	**Gamma band F_3 gaze**
P2	High gamma band F_3 gaze
P3	Gamma band C_3 gaze
P4	Gamma band P_3 gaze
P5	High Gamma band P_3 gaze
P6	High Gamma band F_7 gaze
P7	Gamma band F_8 gaze
P8	High Gamma band F_8 gaze
P9	High Gamma band T_3 gaze
P10	Gamma band T_4 gaze
P11	High Gamma band F_z gaze
P12	High Gamma band T_3 trace
P13	High Gamma band T_6 trace
P14	High Gamma band C_z trace
P15	Gamma band P_z trace
P16	High Gamma band P_z trace

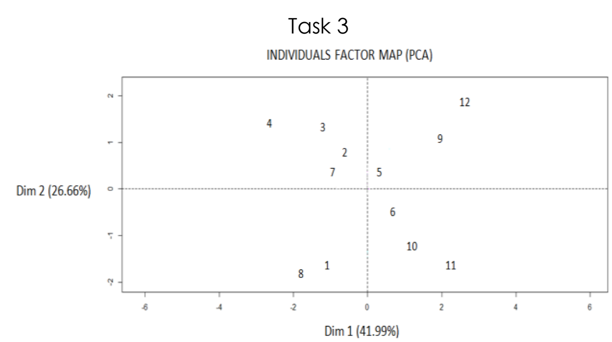
Figure 4 Ranking of important parameters in principal component using selected parameters that indicates statistically significance parameters (most positive value) between group that employed preferred and non-preferred graphic rule



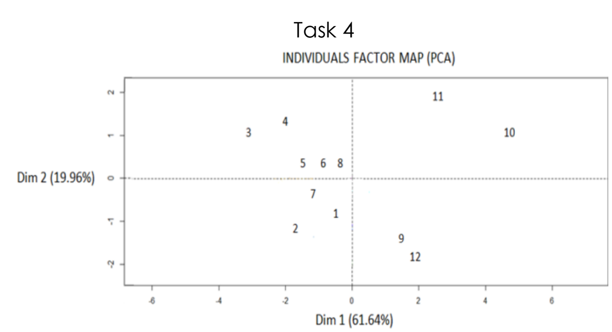
Note: n=12; 1- 9: preferred subjects; 10-12: non-preferred subjects



Note: n=12; 1-8: preferred subjects; 9-12: non-preferred subjects



Note: n=12; 1- 8: preferred subjects; 9-12: non-preferred subjects



Note: n=12: 1-9: preferred subjects; 10-12: non-preferred subjects

Figure 5 PCA individual factor map using significant parameters (most positive value) by task

3.2 Fast Fourier Transform

Figure 3 shows the differences in the change of power spectrum for all frequency bands involved during gazing and tracing activities that were directly related to the subject performances. Significant difference (P< 0.05) at frontal, parietal and occipital regions were observed between the control task and all tracing tasks, but the frequency bands in which the significant difference was found varied. The control group (preferred) showed better performance in tracing task compared to the test group (non-preferred) as the former exhibited higher gamma and high gamma power spectra that corresponded to higher motor function)

3.3 Principal Component Analysis

Based on PCA of the 119 parameters (tracing activity) and 114 parameters (gazing activity), the important parameters in differentiating preferred and non-preferred graphic rule can be described for both control and test groups. But, only the significant parameters were considered for further analysis. For task 1, the most important positive parameter was P9 which is the high gamma band at F_3 during tracing activity (Figure 4). The first and second component contributed 74.14% of the variance to the whole which sufficient to model the systemic variation of dataset that provides a meaningful visual representation of the subjects and parameters. It was assumed that the two components have a sufficient amount of the variance, allowing discovery of ~70% of the variance in the dataset. If Dim 1 (PC1) was insufficient to model the systematic variation of a dataset, the second component, Dim 2 (PC2) was considered as shown in all the tasks.

The most important parameter for task 2 was P12 which is gamma band at T_6, task 3 was P4 which is gamma band at F_4, while for task 4 was P1 which is gamma band at F_3. Note that all of the most positive parameter (gamma/high gamma) for all the tasks was found during tracing activity. Figure 4 used bar graphs to rank the important parameters of principal component. By projecting all observations onto lower dimensional subspace and plotting the result, it was possible to visualize the pattern of all subjects using parameters as illustrated in Figure 5. Using PCA, all subjects were distributed into two groups. The control group (preferred) for all task was plotted on the left side of the graph while the test group (non-preferred) was scattered on the right side of the graph, indicating a clear separation of the two groups.

4.0 CONCLUSION

The cortical information connectivity among young children in relation to the employed strategy (preferred versus non-preferred rule) while performing gazing and tracing basic shape activities was investigated and the findings may provide insight on how the brain functions among young children during the activities.

The pattern of information pathway in brain among the control subjects shows that the tracing activity is well planned as it involved occipital region. Members of the control group mostly used occipital area where visual processing and pattern recognition were executed during the gazing and tracing activities. This may indicates that the control group that employed preferred graphic rule showed better performance in both gazing and tracing tasks due to better execution of brain function. By projecting all of the observation (parameters) it was possible to visualize the structure of dataset by distributing the members of the control and test groups for predicting the most significant parameter in differentiating the control group that employed preferred graphic rule and group that employed otherwise in gazing and tracing basic geometry drawing. Our result showed that the most significant parameter in differentiating the subjects that used graphic rules in rule-governed fashion from those that used graphic rules in haphazard fashion were found during tracing activity and the parameters involved were gamma and high-gamma.

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