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Slow and Fast Eeg Waves Analysis for Kolb's Learning Style Classification

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Abstract: This research is meant to classify learners based on the combination of Kolb's learning style information and Electroencephalogram (EEG) dataset. Slow waves and fast waves EEG of a learners (N = 131) were captured using the waverider pro hardware and processed using the accompanied software called waveware to generate the summative EEG as a final dataset. Next, the learners LS were determined using Kolb's Learning Style Inventory (KLSI) which clustered them into the LS of diverger assimilator, converger and Accommodator respectively. The SPSS 16 Modules of 2-steps cluster analysis is used to analyze the summative EEG dataset of beta and alpha (fast waves); theta and delta (slow waves). As to establish the LS classification on both waves condition. In term of single EEG band, all LS are correctly clustered (100%) in a homogenous group notwithstanding fast wave or slow wave EEG. On the other hand, in combined EEG bands, both waves group had demonstrated a best classification (100%) for LS diverger. Concurrently, best classification (100%) also obtained for LS accommodator but only in EEG Fast wave condition. Based on the overall findings, the fast wave EEG is found to be a better classifier for Kolb's LS compared to the slow wave EEG. The research findings could be utilized to impart further attention and focus on Beta and Alpha EEG waves in order to infer the learner's learning preference based on KLSI.

Key words: EEG, learning style, classification, summative, demonstrated

INTRODUCTION

Electroencephalography (EEG) is the recording of electrical activity along the scalp produced by the firing of neurons within the brain's cortex (Teplan, 2002). EEG activity is quite small, measured in microvolt (μV) with the main frequencies of interest up to approximately 70 Hz which are alpha activity (8-13 Hz), delta (1-4 Hz), theta (4-under 8 Hz), beta (14-30 Hz) and Gamma (30-70 Hz) (Sanei and Chambers 2007). Recent advancements in EEG technology have empowered researchers all around the world to limitlessly look into the current information about the human's brain cerebrum and obtained more profound bits of knowledge into brain procedures and structures which translated in to various research applications (Rossini *et al*., 2015; Butler *et al*., 2015). One of the common applications that EEG is being employed is in Psychology and Neuroscience research which included the study on attention, memory, learning and Learning Style (LS) (Mazher *et al*., 2015; Rashid *et al*., 2011a, b).

The LS hypothesis is grounded in research studies of Piaget, Allport, Gullford and Thurson. These scholars were concerned principally with the formative parts of individual differences and learning builds of intelligence (Keefe, 1987). In educational psychology domain, LS generally refers to consistent individual differences in the way individuals set about learning something (Schmeck, 2013). One of the LS theorist, Davis A. Kolb defined LS as typical individual differences in the learning process that originate from consistent blueprint of transaction between the individual and their surroundings (Kolb and David, 1981). Kolb's theory is that, through their yesteryear and current experiences, learners prepare themselves to grasp reality through a particular learning pattern (Kolb and David, 1981). Under

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Kolb, The Learning Style Inventory (KLSI) was created to appraise these preferences towards learning.

Purpose of the study: This research is meant to classify learners based on the combination of LS and slow and fast waves EEG dataset. First, the learners LS would be determined and classified using KLSI. Then, their EEG would be probed and segregated into beta, alpha, theta and delta bands. Beta and alpha EEG bands are considered as a fast waves while theta and delta are the slow waves. These characteristics are adopted based on the wave's frequency rate. Finally, the best classification of LS would be analysed and compared between the slow and fast waves.

MATERIALS AND METHODS

Sampling and participants: The convenience sampling technique had been adopted in the research (Robinson, 2014). This imparted to the involvement of mini. 30 participants per LS to allow for a substantial data analysis (VanVorhis *et al*., 2007). The participants were healthy 131, 1st year undergraduates from Sultan Idris Education University, Malaysia. A pre-experiment instruction had been conducted to convey the research's scope and activities to all the participants concerned.

Kolb's Learning Style Inventory (KLSI): The KLSI version 3.1 was applied in the research to determine the participant's LS (Kolb and Kolb, 2005). This KLSI had been tested by 6977 LSI users which comprised of on-line users and university researchers. Hence, the KLSI reliability and validity had been proven to be at the best standard. The KLSI had a format of brief questionnaire of 12 items that asks participants to rank four sentence with 4 (most suited), 3, 2 and 1 (least suited) endings that correspond to the four learning style of Diverger assimilator, converger and accommodator (Kolb, 1984).

The implementation of KLSI is administered using Google Form system. The form's URL was exclusively shared among the participants and they were required to complete the on-line questionnaire in the lab with the guidance of the officially appointed facilitators. Nevertheless, the participants who had an invalid response would be contacted and asked to attend and complete the questionnaire at their own convenient.

Participant's responses were stored in google drive server and downloaded as spreadsheet. The bi-polar value calculation of the KLSI was done off-line. Ultimately, the participants LS were determined by mapping the calculated value to the learning style type Grid found in Kolb's LSI 3.1 workbook (Kolb, 2007).

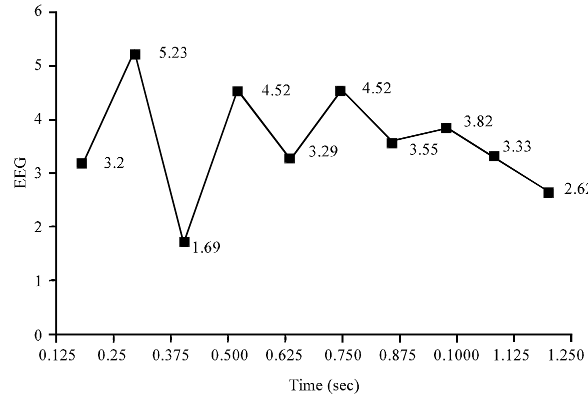

Fig. 1: Excerpt of alpha band EEG occurrences (Rashid *et al*., 2010, 2014)

Brain EEG acquisition: The WaveRider Pro of Mindpeak (www.mindpeak.com) is used to acquire the participants EEG signals. The EEG signal probed is at the frontal locations (Fp1 and Fp2) area of the participant's scalp. The EEG were recorded to the processing hardware (Computer Notebook) using a USB port input and processed by the WaveRider corresponding software "WaveWare" Version 2.5 .

The WaveWare interface configuration, General Graph (GG) window is used for the EEG acquisition and recording process. The GG window allows segregated EEG recording of the participant's left and right sides scalp. Every window is configured by Waverider's Digital filter module according to the pre-set beta, alpha, theta and delta frequency value.

Each participant undergone a base-line open eyes EEG recording experiment for 5 min (300 sec). The EEG value was recorded in the occurring time of 0.125 sec. Only 290 sec data were processed as the 1st and last 5 sec were excluded in order to conserve the constancy of the data. As a result, 2320 EEG occurrences were recorded for each band at left and right side. The excerpt of the recorded alpha band EEG could be seen as in Fig. 1.

Based on Fig. 1, the EEG occurrence in full recorded 290 sec would be summed up to gain the final Summative EEG. The calculation led to 1048 Summative EEG values articulated from Participants 131×Band 4×Condition 1× Scalp Location 2 (Table 1 and 2).

Statistical analysis: The two-step cluster analysis module of SPSS 16 is used to group the observations (LS) into clusters such that each cluster is as homogenous as possible with respect to the clustering variables (slow and

Table 1: EEG Dataset information

EEG band 4	Condition 1	Scalp locations 2	Each participant	Overall participant
Beta	Open eyes	Left	1×4×1×2 = 8	8×131 = 1,048
Alpha		Right		
Theta				
Delta				

Table 2: Participants LS classification

Learning style	Count	Percentage
Diverger	33	25.2
Assimilator	36	27.5
Converger	32	24.4
Accommodator	30	22.9
Total	131	100

Table 3: LS clustering by EEG (single wave)

Cluster/EEG band	1	2	3	4
Beta	Diverger	Accommodator	Assimilator	Converger
Left	(33 = 100%)	(30 = 100%)	(36 = 100%)	(32 = 100%)
Beta	Diverger	(Accommodator	Converger	Assimilator
Right	(33 = 100%)	(30 = 100%)	(32 = 100%)	(36 = 100%)
Alpha	Assimilator	Diverger	Accommodator	Converger
Left	(36 = 100%)	(33 = 100%)	(30 = 100%)	(32 = 100%)
Alpha	Diverger	Accommodator	Converger	Assimilator
Right	(33 = 100%)	(30 = 100%)	(32 = 100%)	(36 = 100%)r
Theta	Converger	Assimilator	Diverger	Accommodator
Left	(32 = 100%)	(36 = 100%)	(33 = 100%)	(30 = 100%)
Theta	Assimilator	Diverger	Accommodator	Converger
Right	(36 = 100%)	(33 = 100%)	(30 = 100%)	(32 = 100%)
Delta	Diverger	Accommodator	Converger	Assimilator
Left	(33 = 100%)	(30 = 100%)	(32 = 100%)	(36 = 100%)
Delta	Assimilator	Diverger	Accommodator	Converger
Right	(36 = 100%)	(33 = 100%)	(30 = 100%)	(32 = 100%)

fast EEG datasets) (Bacher *et al*., 2004). This statistical module usually employed using classification means and normally used to classify mixed attribute objects (Okazaki, 2006). In the analysis, the LS are set as the categorical variables while the EEG bands are set as continuous variable while the cluster indices would be automatically specified by the clustering tool using the Akaike's Information Criterion (AIC) (Koehler and Murphree, 1988) Table 3.

RESULTS AND DISCUSSION

Participants LS classification: As being mentioned in the earlier study, KLSI had been deployed on-line to the participants (N = 131). The number of participants was recorded at minimum number of 30 per group. LS Assimilator with 36 counts (27.5%) was the majority while the least number of participants went to LS Accommodators with 30 counts (22.9%). The diverger and converger were at 33 (25.2%) and 32 (24.4%), respectively. As such they were successfully grouped to their respective LS as depicted by following.

LS classification using EEG: The LS classification using EEG is made with the considerations below:

Table 4: LS Number of appearance in cluster (single wave)

Cluster LS	1	2	3	4
Diverger	4	3	1	0
Assimilator	3	1	1	3
Converger	1	0	3	4
Accommodator	0	4	3	1

- Beta and alpha are considered as fast waves while theta and delta as Slow waves
- Classification is used by single EEG waves and combination of all waves according to the fast and slow criteria

The LS classification using single EEG wave and the number of LS appear in a particular cluster are shown by the accompanying Table 4, respectively.

In Table 3, each LS had been correctly classified (100%) either in Cluster 1-4 but with different position and arrangement dependent to the EEG band. Hence, in general, both fast EEG waves and slow EEG waves are able to be a classifiers when used as single wave input. Meanwhile, the shaded rows showing Beta band (fast waves EEG) are consistent in classifying LS Diverger and Accommodator in Cluster 1 and 2, respectively for both scalp condition. This unique finding exhibit that Beta band is the best EEG to single out LS Diverger and Accommodator compared to the rest of the band.

Table 5: LS clustering by eeg (combined waves)

Cluster EEG band	1	2	3	4
(Fast waves) Beta left + Beta right + Alpha left + Alpha right	Assimilator (18 = 50%) Converger (12 = 37.5%)	Diverger (33 = 100%)	Accommodator (30 = 100%)	Assimilator (18 = 50%) Converger (20 = 62.5%)
(Slow waves) Theta left + Theta right + Delta left + Delta right	Diverger (33 = 100%)	Assimilator (24 = 64.77%) Converger (12 = 37.5%)	Converger (20 = 62.5%) Accommodator (15 = 50%)	Assimilator (12 = 33.3%) Accommodator (15 = 50%)

Meanwhile, the shaded cells in Table 4 expose diverger as a dominant LS in cluster 1 with 4 counts. The same premise happened to converger and accommodator in Cluster 4 and 2, respectively. In a contrary, no cluster is dominated by LS assimilator but still it had been classified as a second highest count for both Cluster 1 and 4.

Table 5 showing the LS classification result based on EEG Fast waves combined and EEG Slow waves combined. The shaded cells display a 100% classification obtained for LS Diverger and accommodator. Diverger is 100% classified in Cluster 2 based on EEG Fast waves and also in Cluster 1 but now based on EEG slow waves. At the same time, accommodator is 100% classified in Cluster 3 using the eeg fast waves. The other LS experienced a split classification between clusters. From the findings, EEG Fast waves successfully classified more LS compared to EEG slow waves and diverger is considered as the best LS as far as classification by both waves condition is concerned.

CONCLUSION

Throughout the research, the EEG Fast waves and Slow waves had been successful in classifying the participants LS especially when utilized as a single band input. Nonetheless, beta band which is the fastest EEG band (14-30Hz) is considered as the best single band classifier as it obtained a consistent and highest classification for most LS which is diverger and accommodator compared to the other bands. In term of combined band, fast waves incurred highest classification for two LS of Diverger and accommodator compared to only diverger for the slow waves. Therefore, EEG fast waves of beta and alpha bands are regarded as a better classifier of Kolb's LS compared to the Slow waves. Meanwhile, in term of LS, diverger is conceived as the best classified LS in both fast waves and slow waves condition.

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