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Characterization of Resting Brainwave at Different Developmental Stages of Human Learning

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ABSTRACT

An investigation has been made to characterize resting brainwave at different developmental stages of human learning. A total of 68 university students have participated in the study. Initially, resting EEG is recorded from the antero-frontal region of the brain. The signal is then pre-processed for noise removal. Subsequently, spectral centroid features are extracted from the alpha and theta band. Control groups are established via Kolb's Learning Style Inventory. Pattern observation has revealed distinct characteristics in Acquisition, Specialization and Integration stages. It is also revealed that subjects in the Integration stage are in more relaxed state compared to the other groups. Classification of developmental stages via spectral centroid features and k-nearest neighbor has yielded satisfactory results for training and testing, each with 100% and 91.7% accuracies, respectively. Reliability of the findings is ascertained via k-fold cross-validation.

Keywords: EEG, learning, spectral centroid, kNN.

1. INTRODUCTION

Kolb's Experiential Learning Model theorizes that knowledge is being created through unique ability of individuals to absorb and comprehend experience. Ideally, an individual will go through four learning modes comprising of Concrete Experience, Reflective Observation, Abstract Conceptualization and Active Experimentation. A two-dimensional dialectical tension between the learning modes has been proposed to resolve the conflicting modes of adaptation to the real world. The learning cycle is modelled in a recursive manner; in which individuals will experience, reflect, reason and act. Knowledge formation, thus, requires unique interaction between the learning dimensions which are responsive to contextual demands [1]. Essentially, learning styles can be gauged via Kolb's Learning Style Inventory (LSI). The technique determines the dominant modes from absorption and comprehension dimensions and categorizes individuals into Converging, Assimilating, Diverging and Accommodating styles [2].

Apart from providing framework for conceptualizing individual differences in learning styles and social adaptation, Kolb's Experiential Learning Model has also suggested normative directions for human growth and development. The human growth can be divided into three broad developmental stages. The first is Acquisition phase, which extends from birth to adolescence. This stage marks the attainment of elementary learning abilities and cognitive structures. The second stage, Specialization, develops via formal education and early experiences of adulthood. The environment in which individuals live then forces increased competence in a specialized mode of adaptation.

The chronology of transition into the third stage however, varies between individuals. In the third stage, Integration, the non-dominant learning styles are re-asserted and expressed in the form of new career interests,

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changes in lifestyles or creativity in selected career. The progression of the three stages is marked by increasing complexity and relativism in dealing with experience [3].

In the past, learning styles have successfully been correlated with brain activity. These were made possible via the use of electroencephalogram (EEG) [4]. Generally, EEG is a non-invasive recording of electrical activity from the brain [5]. It is relatively superior to other brain imaging modalities due to its practicality and very high temporal resolution [6]. Combined with innovative signal processing and feature extraction algorithms, the EEG has been widely applied to characterize sleep patterns [5] and study psychological conditions such as schizophrenia and bipolar disorders [7]. As yet, no study has been conducted to characterize brain behavior for different developmental stages of human learning. Hence, this paper proposes to investigate brainwave features at Acquisition, Specialization and Integration stages. Since the study only focuses on the resting brain, the scope will be limited to the alpha and theta bands. This is because at these frequency ranges, the inherent attributes related to organization of working memory and attentional demands can be found [8]. It is important to note that alpha and theta bands have also been used to characterize mental stress [9].

2. METHODS

The study comprises of EEG recording and segregation of control groups, signal pre-processing and extraction of spectral centroid features, pattern observation, dataset enhancement, and classification of the developmental stages via k-nearest neighbor (kNN) technique.

2.1. EEG Recording and Segregation of Control Groups

The protocols adopted in this study have been approved by the university's research ethics committee (Ref. No.: 600-RMI (5/1/6)). A total of 68 university students (male, right-handed, age range = 18 – 37 years, mean age / standard deviation = 23.9 / 3.1 years) from different fields have volunteered for the EEG recording. Subjects were briefed regarding the experimental procedure and have given prior written consent. They were then required to seat in relaxed position with both eyes closed and the Emotiv neuroheadset fixed to the scalp. Next, resting EEG was recorded from locations AF3 and AF4 for duration of three minutes.

Subjects were then required to answer Kolb's LSI online under guided supervision. Instead of assigning subjects into their respective learning style, the questionnaire was used to segregate them into the Acquisition,

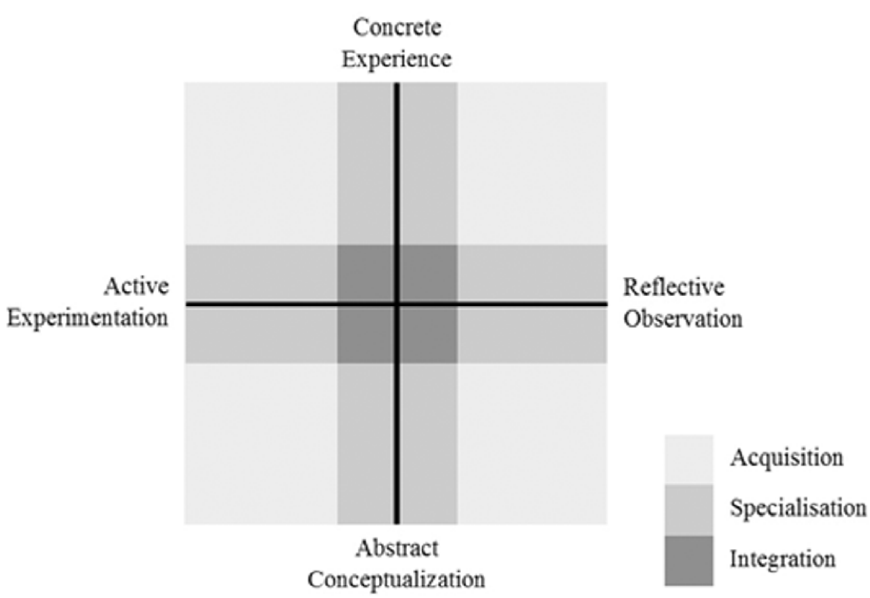


Figure 1: Developmental Stages and Its Designated Regions on Kolbs' LSI

Specialization and Integration stages. Figure 1 shows the different developmental stages and its designated regions on Kolb's LSI.

2.2. Signal Pre-processing and Extraction of Spectral Centroid Features

All processing, analysis and classification tasks were performed in MATLAB. Initially, baseline rectification is performed via 0.5 Hz high-pass filter. Elimination of electrooculogram (EOG) artefact is then conducted via automatic rejection method. Signal amplitudes exceeding ± 100 μV are considered as EOG and thus, removed from the EEG. Next, only 2 minutes 30 seconds segment is retained for further processing. The pre-processed signal is then filtered into theta (4 Hz – 8 Hz) and alpha (8 Hz – 13 Hz) bands using equiripple band-pass filters [10]. Power spectral density for each frequency component was further estimated via Welch method using Hamming window with 50% overlapping epoch.

Spectral centroid is defined as the center of gravity of the power spectral density in each frequency band. The feature which can be resolved into frequency and amplitude components is selected due to its robustness against random white Gaussian noise. Spectral centroid frequency (SCF) and amplitude (SCA) is each represented by (1) and (2), where i is the respective EEG band, N represents the number of frequency bins and $S[f]w_i[f]$ is the power of the spectral distribution at frequency, f and bin, i [11].

$$SCF_i = \frac{\sum_{i=1}^{N} f \times S[f]w_i[f]}{S[f]w_i[f]} \tag{1}$$

$$SCA_i = \frac{\sum_{i=1}^{N} f \times S[f]w_i[f]}{f} \tag{2}$$

Subsequently, the amplitude component is normalised into spectral centroid ratio via (3) and (4). α each θ each represents the alpha and theta SCA, respectively. The obtained features were then segregated into the respective developmental stages and observed for distinct pattern.

$$\text{Alpha Ratio} = \frac{\alpha}{\alpha + \theta} \tag{3}$$

$$\text{Theta Ratio} = \frac{\theta}{\alpha + \theta} \tag{4}$$

2.3. Dataset Enhancement

Studies have shown that uneven sample distribution among the control groups and small class separation negatively affects classifier performance. To overcome such limitation, the use of synthetic EEG is proposed. The synthetic version is generated by adding white Gaussian noise with sufficiently conditioned signal-to-noise ratio (SNR). This is to ensure that similar signal characteristics are maintained for each predefined group. In this study, an SNR of 30 dB has been selected. A more detailed elaboration on synthetic EEG has been reported elsewhere [12]. The total number of samples prior to classification was enhanced to 40 per group (N = 120).

2.4. K-nearest Neighbor Classifier

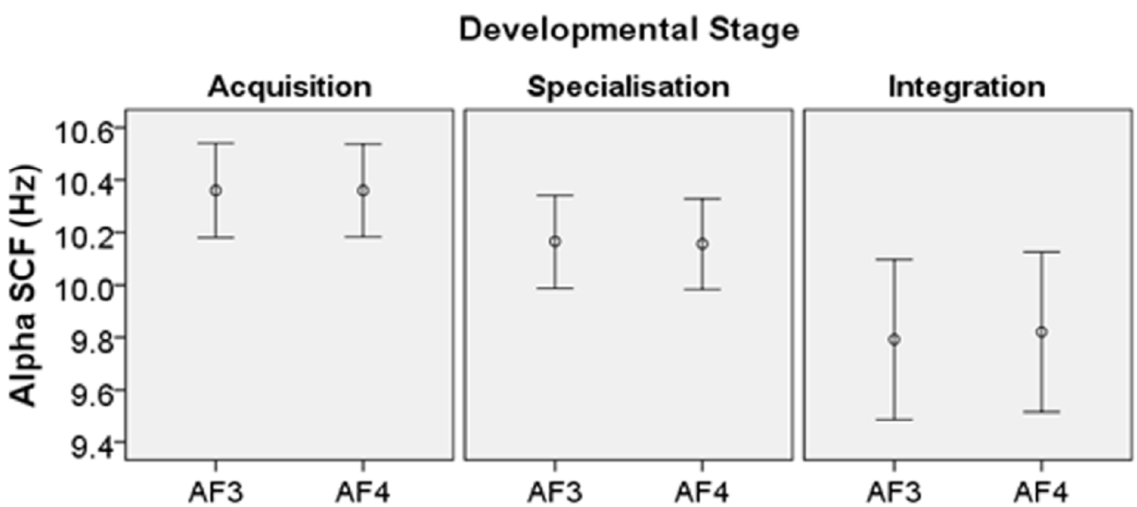
kNN is a simple and supervised machine learning classifier. It adopts a statistical approach, whereby the unlabeled features are assigned based on rule of majority [13]. In the training phase, the classifier identifies and assigns the spectral centroid features to its designated developmental stages. Consequently, during testing, the remaining unlabeled features are classified based on the most frequent developmental stage label with k nearest training samples. Euclidean distance has been selected as the distance metric. Classification was performed for k = 1 to k = 5. Meanwhile, the features have been randomly assigned to the respective training and testing dataset with 80:20 ratio. Accuracy (*Acc*), positive predictivity (*Pp*) and sensitivity (*Se*) have been utilized to gauge classifier performance.

Reliability of the results is ascertained by incorporating the classifier with k-fold cross-validation technique. Through random sampling, the method forms a disconnected training and testing datasets. The cross-validation estimate of true performance is therefore, defined as the average accuracy over the number of folds in the dataset. Thus, the result is assumed reliable, if similar prediction is induced with different test data [14]. The fold value has been set to five to match the ratio of training to testing dataset.

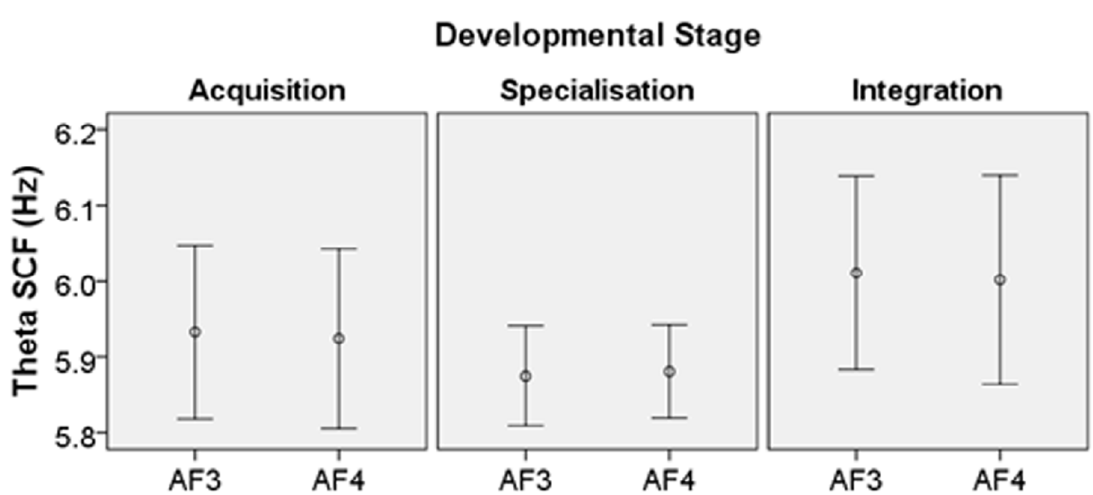
3. RESULTS AND DISCUSSION

3.1. Pattern Observation

Kolb's LSI have identified 22 samples in the Acquisition, 31 samples in the Specialization and the remaining 15 samples in the Integration stage. Mean pattern for alpha and theta SCF in different developmental stages are as shown in Figure 2.



(a) Alpha SCF



(b) Theta SCF

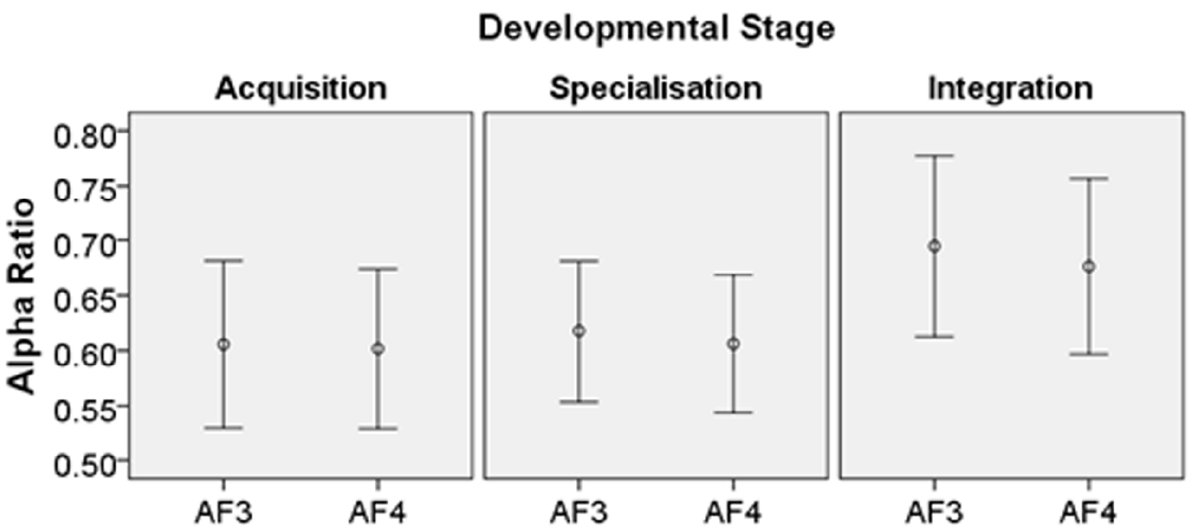
Figure 2: Mean Pattern with 95% Confidence Interval (N = 68)

Results indicate a decreasing alpha SCF from Acquisition to Integration stage. Meanwhile, the highest theta SCF is attained by the Integration stage, followed by Acquisition and then, the Specialisation group. The variations in SCF patterns are attributed to different strategies of information processing adopted at each developmental stage.

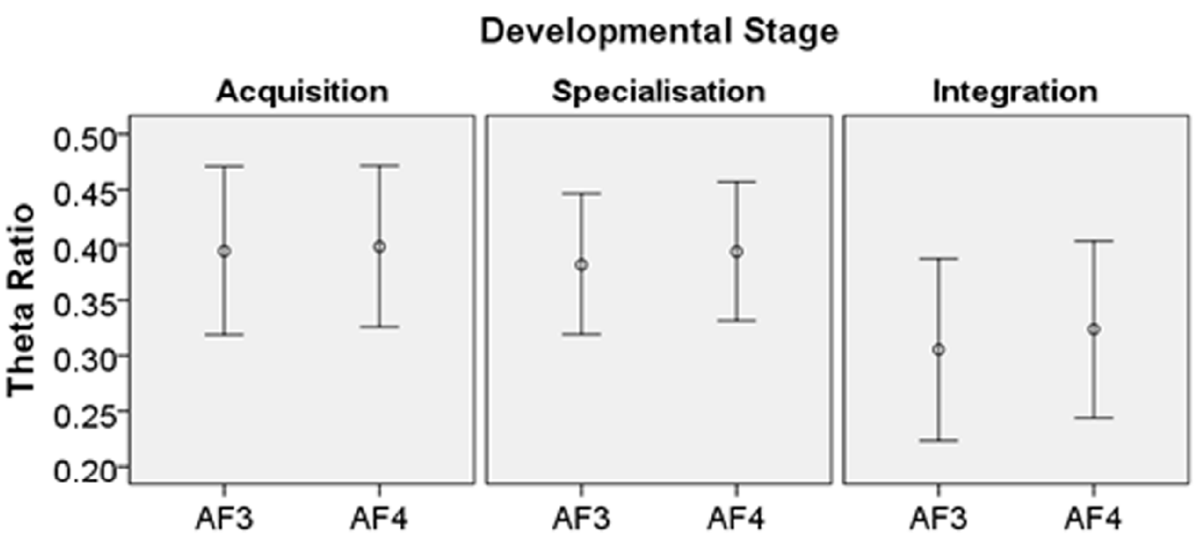
The pattern for alpha and theta ratio is shown in Figure 3. Results indicate increasing alpha ratio from Acquisition to Integration stage. Conversely, an inversed pattern has been obtained for theta ratio. Such discovery shows that subjects attaining the Integration stage of human learning have the most relaxed brain state. The observation is based on its comparatively higher alpha content. Additionally, the lower theta amplitude indicates that it is less prone to stress.

3.2. KNN Classification

Prior to kNN classification, sample enhancement to $N = 120$ has revealed similar feature distribution as to the original dataset. As shown in Figure 4, classification of developmental stages has revealed satisfactory results with 100% training and 91.7% testing accuracies at $k = 1$ and $k = 2$. Beyond $k = 2$, the classification accuracies deteriorate. With increase in the neighboring distance, interference from other



(a) Alpha Ratio



(b) Theta Ratio

Figure 3: Mean Pattern with 95% Confidence Interval (N=68)

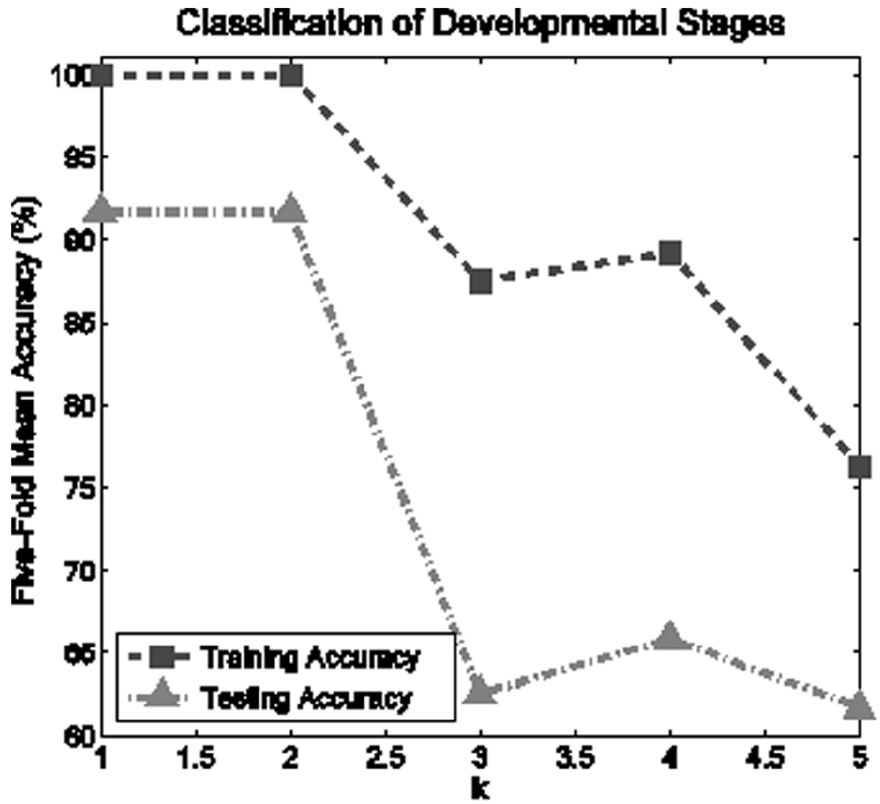


Figure 4: Five-Fold Mean Training and Testing Accuracies for $k = 1$ to $k = 5$ ($N = 120$)

Table 1
Positive predictivity and sensitivy measures at $k = 2$

Developmental Stage	*Training*		*Testing*	
	Pp (%)	*Se (%)*	*Pp (%)*	*Se (%)*
Integration	100	100	93.8	100
Specialization	100	100	96.7	80.0
Acquisition	100	100	86.8	95.0

differently labeled features also increases. This is expected since the feature distribution overlaps between the developmental stages. Findings are also supported by the positive predictivity and sensitivity measures shown in Table 1.

4. CONCLUSION

The study has successfully characterized resting brainwave at different development stages of human learning. Significant findings have revealed that there are distinct pattern of alpha and theta spectral centroids in Acquisition, Specialization and Integration stages. Subjects in Integration stage are in more relaxed state and less prone to mental stress. The proposed SCF and SCA features from resting EEG can also reliably classify developmental stages in human learning.

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