

Learning Style Classification via EEG Sub-band Spectral Centroid Frequency Features

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ABSTRACT

Kolb's Experiential Learning Theory postulates that in learning, knowledge is created by the learners' ability to absorb and transform experience. Many studies have previously suggested that at rest, the brain emits signatures that can be associated with cognitive and behavioural patterns. Hence, the study attempts to characterise and classify learning styles from EEG using the spectral centroid frequency features. Initially, learning style of 68 university students has been assessed using Kolb's Learning Style Inventory. Resting EEG is then recorded from the prefrontal cortex. Next, the EEG is pre-processed and filtered into alpha and theta sub-bands in which the spectral centroid frequencies are computed from the corresponding power spectral densities. The dataset is further enhanced to 160 samples via synthetic EEG. The obtained features are then used as input to the *k*-nearest neighbour classifier that is incorporated with *k*-fold cross-validation. Feature classification via *k*-nearest neighbour has attained five-fold mean training and testing accuracies of 100% and 97.5%, respectively. Hence, results show that the alpha and theta spectral centroid frequencies represent distinct and stable EEG signature to distinguish learning styles from the resting brain.

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1. INTRODUCTION

Learning styles and experiential learning have both been paramount to the constructivism theory in education, which proposes knowledge as being created through a process of interaction between experience and ideas. Although receiving criticism, the concept has been accepted due to its success in fostering effective teaching, which aims to provide optimal experience to learners with varying style preferences. Several learning style models have been established which include Curry's Onion Model, Riding and Cheema's Fundamental Dimensions, Dunn and Dunn's Learning Style Model, and Kolb's Experiential Learning Theory (ELT) [1]. Comparatively, Kolb's ELT has been widely adopted in the field of education and also implemented in management learning [2].

Kolb's ELT has defined that knowledge is created through the creative ability of individuals in grasping and transforming experience. The grasping dimension is represented by a pair of dialectically-related learning modes comprising of Concrete Experience and Abstract Conceptualisation. Meanwhile, the transformation dimension is described by another pair of dialectically-related learning modes which consists of Reflective Observation and Active Experimentation. In experiential learning, knowledge is being created through a process that implicates a creative tension between the learning dimensions which is responsive to the contextual demands. The model portrayed the learning process as a recursive cycle where individuals will experience, reflect, think and act [3].

Variations in individual learning style arise from unique preferences to resolve the conflict of being concrete or abstract, and active or reflective [3]. Such characteristics are attributed to individual specialisations in education, past experiences, context and gender [4]. Hence over a long period of time, the construct represents a stable trait of personality [5]. Individual learning style is assessable via Kolb's Learning Style Inventory (LSI), in which the dominant modes from the grasping and transformation dimensions are identified and mapped to either the Diverging, Assimilating, Converging or Accommodating styles [3].

Studies have shown that gender poses a significant impact on the grasping dimension, but is not significant in the transformation dimension [4]. Such characteristics are influenced by the differences in topological organisation of the brain's functional network which affects individuals in terms of behaviour and cognition [6]. Findings have also indicated that reliable patterns of brain deactivation are often complemented by increase in cognitive demands. Low level baseline conditions were active states and that pattern of activation and deactivation of the brain indicate shift in balance from a focus on the internal state of the subject and its ruminations, to the external environment. Hence, it is possible to characterise network dynamics without an explicit stimulus to drive brain activity [7]. It was also discovered that the anatomical structure and functional connectivity of the brain matures during adolescence. Although no significant differences have been observed between the adolescents and adults, subtle spectral electroencephalogram (EEG) differences exist between the two groups [8].

EEG is the bioelectrical recording of collective neuronal activity in the brain. The brain signal has been actively studied to enhance understanding on the underlying neurophysiological processes in the brain. These include characterisation of brain signatures during sleep [9], and psychological conditions such as schizophrenia, bipolar disorders [10] and autism [11]. Researchers have also attempted to unravel new theories in intelligence by studying various aspects of human cognition. It has been well-established that the frontal cortex is much related with cognitive functioning of the brain [12]. Hemispheric specialisation of the prefrontal cortex has been observed with the left hemisphere being involved with logical and sequential processes, while the right hemisphere is more immersed in emotional and social interaction capabilities [13].

In general, the EEG can be segregated into four major frequency bands consisting of delta (0.5 Hz – 4 Hz), theta (4 Hz – 8 Hz), alpha (8 Hz – 13 Hz) and beta (13 Hz – 30 Hz) waves [14]. Each of the frequency sub-bands holds unique information pertaining different neurophysiological processes. The delta waves are essentially dominant in deep sleep and are often a precursor for comatose condition [15]. Meanwhile, the theta waves are generally associated with light sleep and are linked to creativity and emotion [16]. The brain in its resting state is marked by increase in alpha activity. Under intense mental activity however, the alpha wave is replaced with the faster beta rhythm [15]. In relation with the cognitive processes, it has been revealed that the theta sub-band contributes to working memory demands [17]. In addition, the theta and lower alpha sub-bands are also linked to attentional requirements that dominate during encoding of new information. Meanwhile, the upper alpha sub-band is predominant in semantic information processing [18].

In order to quantify the spectral information in each band, implementation of advanced signal processing approach would be required. As such, evaluation of spectral feature can be performed using the parametric and non-parametric methods. The parametric technique is dependent on model-based power spectrum estimation which includes auto-regressive, moving average or auto-regressive moving average methods. Meanwhile, the non-parametric approach utilises techniques such as the Welch's method to approximate the power spectrum of a time sequence. Albeit having its drawbacks, the power spectrum has been successfully implemented in a variety of EEG researches [19]. Such information is usually computed into quantifiable descriptors such as band power [18].

Spectral centroid frequency (*SCF*) is an established frequency-dependent feature that is an approximation of the spectrum's centre of gravity within each sub-band. Its advantages are attributed to its robustness against white Gaussian noise and reduced computational requirements. The feature has been successfully implemented for speech recognition [20], stress characterisation [21] and intelligence assessment [22]. Hence, being relatively new, implementation of spectral centroid features can be further extended to characterise brain signatures in relation with learning styles.

The EEG sub-band features are often used for classification purposes using techniques such as *k*-nearest neighbour (*k*-NN) classifier [23]. In *k*-NN, features are classified based on voting criteria. Through such method, the nearest neighbour features from the training set are considered, and the new features are being assigned to the class of the majority [24]. Various distance metrics can be used, with the Euclidean distance being among the most common. The classification technique has been implemented for various biomedical applications such as rehabilitation [25] and disease detections [23].

Current learning style assessment involves the use of established questionnaires. Such technique however is exposed to inconsistency issues when language proficiency becomes an obstacle. Hence in order to eliminate such limitation, EEG is proposed as a viable solution to assess learning styles from the resting

brain state. Following such proposition, the study attempts to characterise Kolb's learning styles using the robust spectral centroid frequency features. The investigation focuses only on the alpha and theta sub-bands as the inherent characteristics pertaining to differences in attentional demands and organisation of working memory exists at these frequency ranges. The features are then classified via k -NN to ascertain its validity as a stable EEG signature.

2. RESEARCH METHOD

This section elaborates extensively on the methods being implemented in this study. It comprises of EEG acquisition and implementation of Kolb's LSI for data clustering, signal pre-processing, extraction of alpha and theta sub-band SCF , removal of extreme outliers and pattern observation, generation of synthetic EEG, and classification of features via k -NN with k -fold cross-validation.

2.1. EEG Acquisition and Kolb's LSI

68 healthy university undergraduate and postgraduate students (male, right-handed, mean age / standard deviation = 23.9 / 3.1, range = 18 – 37 years) from various disciplines have volunteered in the EEG recording. Approval on the experimental protocol was obtained from the university's research ethics committee (600-RMI (5/1/6)). Prior to the recording session, subjects were initially briefed on the overall procedure. All the subjects have given written consent.

Subjects were required to seat in relaxed position with eyes closed. Next, EEG were recorded from the prefrontal cortex (scalp locations AF3 and AF4) using the Emotivneuroheadset with sampling rate of 128 Hz. A feedback loop was formed via the P3 and P4 scalp locations. The electrode placements conform to the 10-20 Electrode Placement System of the International Federation. Each session was recorded for duration of three minutes.

The subjects were also required to complete the online Kolb's LSI. The scores obtained were then used to cluster the subjects into Diverger, Assimilator, Converger and Accommodator [3].

2.2. Signalpre-Processing and Feature Extraction

The recorded EEG signal were pre-processed offline using MATLAB R2012a. Baseline correction was accomplished using a 0.5 Hz highpass filter. Any amplitudes exceeding $\pm 100 \mu\text{V}$ is assumed as EOG artefact and hence rejected [26]. So as to standardise the signal duration for further analysis, only 2.5 seconds segment was considered [8]. Next, the pre-processed EEG were filtered into alpha and theta waves using equiripple bandpass filters [27]. In order to observe the hemispheric correlation, the study also considers both the left and right side of the prefrontal cortex.

Prior to SCF computation, power spectral density (PSD) for the respective sub-bands was first obtained via Welch technique using Hamming window with 50% overlapping epochs. As shown in (1), the sub-band SCF is then computed as the average of amplitude weighted frequencies, divided by the total amplitude, where N is the number of frequency bins, i is the EEG sub-band, and $S[f]w_i[f]$ is the power of the spectral distribution corresponding to frequency, f at bin i [20].

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

The SCF features were then clustered into Diverger, Assimilator, Converger and Accommodator groups, where significant pattern is observed via SPSS 19.

2.3. Synthetic EEG

It has been noted that performance of k -NN classifier deteriorates with small class separation and uneven sample distribution among the control groups [28]. Hence, in order to minimise such effect, generation of synthetic EEG has been recommended. It is important to note that EEG is stochastic in nature. Hence, its synthetic version can be generated by implementing white Gaussian noise with sufficiently conditioned signal-to-noise, SNR ratio to maintain similar characteristics. Alteration of EEG characteristics is imminent with very low SNR and thus, may lead to misclassification of samples. For these reasons, an SNR of 30 dB is implemented.

Noise array, V_{noise} , is obtained by multiplying the noise voltage, V_{attm} , and white Gaussian noise, W_{noise} , where V_{attm} , is the attenuated voltage derived from the SNR_{dB} relationship. With the 30 dB $_{SNR}$, the noise power, P_{noise} was computed via (2) where P_{signal} is the averaged power for the original EEG, V_{EEG} .

$$V_{attn} = \sqrt{\frac{P_{signal}}{SNR}} \quad (2)$$

The synthetic EEG, V_{synt} , was then computed by adding the generated noise, V_{noise} , to the original EEG, V_{EEG} . Such procedure can be expressed by (3) and (4).

$$V_{noise} = W_{noise} \times V_{attn} \quad (3)$$

$$V_{synt} = V_{EEG} + V_{noise} \quad (4)$$

The more detailed elaboration on the synthetic EEG has been previously reported [29]. In order to achieve statistically significant number of samples, synthetic EEG were generated, amounting to 40 samples per group and hence, totalling to 160 samples prior to k -NN classification [30].

2.4. k -nearest Neighbour and k -fold Cross-Validation

k -NN is a supervised learning algorithm, where new features are classified based on elective criteria. Initially, the algorithm stores the SCF features from the training dataset with its associated learning style labels. During testing, the unlabelled features will be classified by assigning the most frequent learning style label among those of k training samples nearest to it. In this study, Euclidean distance is utilised and the largest k value is set at 5. 80% of the data are used for training, while the remaining 20% was used for testing [31].

For both the training and testing phases, accuracy, positive predictivity and sensitivity were selected as performance indicators. Such method is common in gauging the performance of classifier for a selected set of features. Accuracy, Acc , positive predictivity, Pp , and sensitivity, Se , can each be expressed by (5), (6) and (7), where TP is the true positives, TN the true negatives, FP the false positives and FN is the false negative classifications.

$$Acc = \left(\frac{TP + TN}{TP + TN + FP + FN} \right) \times 100\% \quad (5)$$

$$Pp = \left(\frac{TP}{TP + FP} \right) \times 100\% \quad (6)$$

$$Se = \left(\frac{TP}{TP + FN} \right) \times 100\% \quad (7)$$

In order to determine the true performance of the classifier, k -fold cross-validation was incorporated with the k -NN. The accuracy estimates are made by constructing disjoint training and test sets using random sampling method. The cross-validation estimate of accuracy is the overall number of correct classifications, divided by the number of instances in the dataset. Hence, a feature is assumed stable for a given dataset and a set of perturbations, if it induces the classifier to make the same predictions when it is given the perturbed datasets [32].

For the purpose of the study, the fold value, k was set at 5. Hence at each instance, the data will be randomly divided into five segments, where four segments are used for training, while the remaining segment is used for testing. Through such implementation, the classifier will be trained and tested for five instances with randomly selected training and testing datasets.

3. RESULTS AND ANALYSIS

3.1. Characterisation of Alpha and Theta SCF

Samples have been clustered into four learning style groups in accordance with the assessment via Kolb's LSI. The Accommodator and Converger groups each consists of 14 samples. Meanwhile, the Diverger and Assimilator groups comprises of 20 samples each. One extreme outlier each from the

Assimilator and Accommodator group was identified and removed. Figure 1(a) and Figure 1(b) shows the mean alpha and theta *SCF* (with 95% confidence interval) for each learning style group.

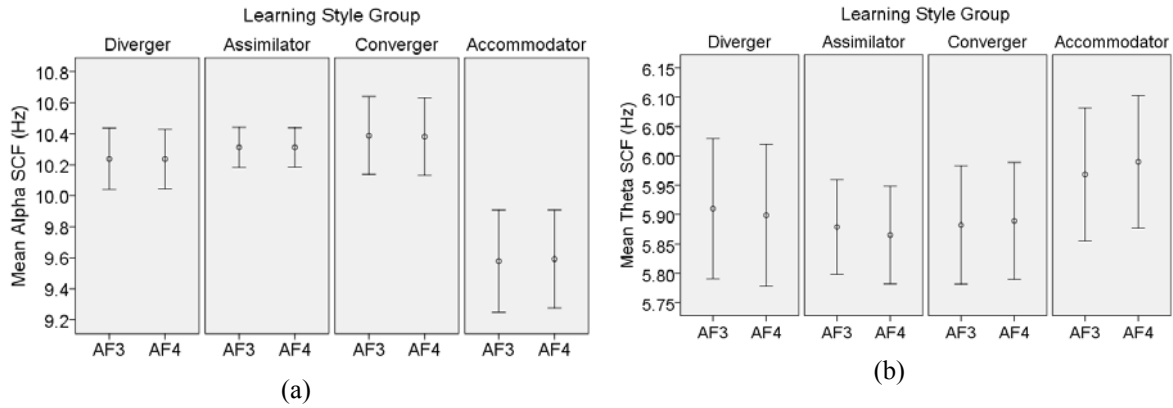


Figure 1. Mean (a) alpha and (b) theta *SCF* in Kolb’s learning style group, N = 66 samples (original dataset)

As observed from Figure 1(a), the Convergers yield the highest mean alpha *SCF*, followed by the Assimilators and then, the Divergers. The Accommodators on the other hand, attained the lowest mean for the alpha *SCF*. Variations in the alpha *SCF* is attributed to the different approaches being adopted in information processing, where a high alpha *SCF* would indicate state of semantic information while a low alpha *SCF* signifies a state encoding of new information. Balanced mean alpha *SCF* between the left and right hemisphere has been observed for all learning style groups.

Meanwhile, Figure 1(b) revealed that Accommodators attained the highest mean theta *SCF*, followed by the Divergers and Convergers. Meanwhile, the Assimilators yielded the lowest theta *SCF*. Variations of *SCF* between the left and right hemisphere was notable for the theta band. Comparatively, the Accommodators and Convergers displayed higher *SCF* for the right hemisphere, while both Divergers and Assimilators attained higher *SCF* for the left side of the prefrontal cortex. Such findings can be related to the different attentional requirements and strategies in working memory organisation between the left and right hemisphere.

3.2. Synthetic EEG

Each of the learning style groups were enhanced with synthetic EEG, amounting to 40 samples per group. The synthetic EEG underwent similar signal preprocessing and feature extraction method as the original dataset. As shown in Figure 2(a) and Figure 2(b), similar pattern of mean alpha and theta *SCF* (with 95% confidence interval) has been observed with the enhanced dataset.

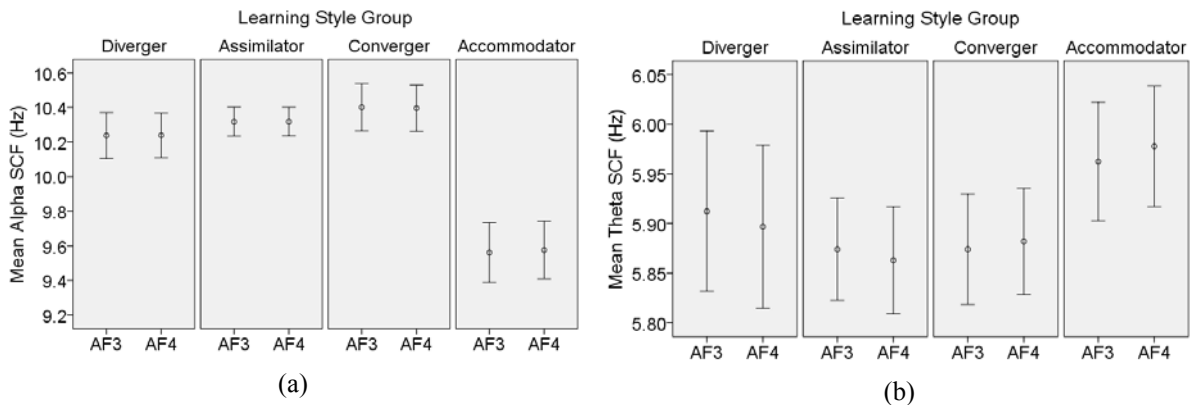


Figure 2. Mean (a) alpha and (b) theta *SCF* in Kolb’s learning style group, N = 160 samples (original dataset)

3.3. k -nearest Neighbour and k -fold Cross-Validation

The five-fold mean training and testing accuracies for $k = 1$ to $k = 5$ is shown in Figure 3. The best accuracies were obtained at $k = 2$, with the training and testing yielding 100% and 97.5% accuracies, respectively. As k increases, both the training and testing accuracy decreases. This is mainly contributed by the fact that the classification technique works based on voting criteria. With increasing k , interference from other neighbouring but differently labelled features would be introduced and hence, affecting the classification accuracies.

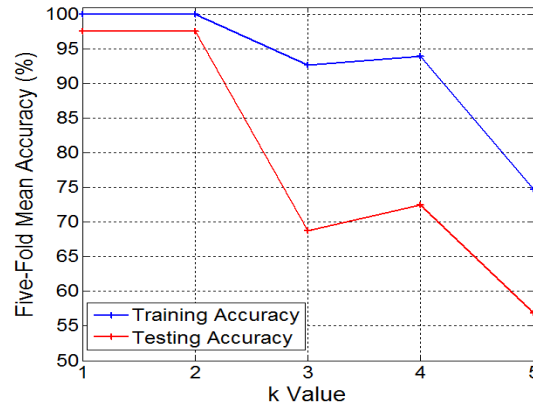


Figure 3. Five-fold mean training and testing classification accuracies for alpha and theta *SCF* features

Positive predictivity and sensitivity for each learning style group for $k = 2$ are as shown in Table 1. Overall, findings indicate that the five-fold mean indices yielded reliable results. During training, all learning style groups attained perfect positive predictivity and sensitivity. In the testing stage however, acceptable performance have been observed. The Accommodators yielded 100% positive predictivity and sensitivity. Meanwhile, the Diverger group attained the lowest positive predictivity and sensitivity at 95.6% and 95.0%, respectively.

Table 1. Five-Fold Mean Positive Predictivity and Sensitivity Measures for Classification at $k = 2$

Learning Styles	Training		Testing	
	Pp (%)	Se (%)	Pp (%)	Se (%)
Diverger	100	100	95.6	95.0
Assimilator	100	100	97.1	95.0
Converger	100	100	97.8	100
Accommodator	100	100	100	100

The results are deemed reliable since the k -NN classifier has been incorporated with k -fold cross-validation. The consistency of the features in classifying the learning styles were tested with five randomly assigned training and testing datasets that on average resulted in excellent performance in terms of accuracy, positive predictivity and sensitivity.

4. CONCLUSION

Findings have proven that resting EEG from the prefrontal cortex contains brain signatures that can be related with learning styles. The study has provided a first-hand insight into the characterisation of alpha and theta sub-band *SCF*, where distinct differences can be observed between the learning style groups. Such findings are attributed to the variations in attentional requirements, information processing strategies and organisation of working memory during the resting state.

Classification of the alpha and theta sub-band *SCF* via k -NN technique has attained excellent accuracy, positive predictivity and sensitivity for all learning style groups. Hence, the results support the initial observations which indicate alpha and theta sub-band *SCF* as distinctive and stable EEG signatures for

identifying individual learning styles. Reliability of the features was also confirmed via the k -fold cross-validation.

Future work will focus on modelling of the resting EEG in relation with Kolb's learning styles. Comparative study between different modelling techniques will also be performed so as to provide the most feasible solution for a real-time EEG-based learning style assessment system.

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