EEG SUB-BAND SPECTRAL CENTROID FREQUENCY AND AMPLITUDE RATIO FEATURES: A COMPARATIVE STUDY IN LEARNING STYLE CLASSIFICATION

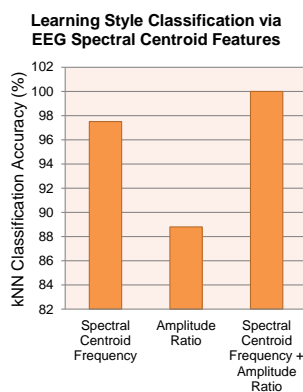Megat Syahirul Amin Megat Ali*, Aisyah Hartini Jahidin, Mohd Nasir Taib, Nooritawati Md Tahir

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Graphical abstract

Learning Style Classification via EEG Spectral Centroid Features

Abstract

Learning styles are critical element in constructivism that facilitates the process of knowledge creation. Conventional methods to evaluate the psychological trait however are exposed to reliability issues which stem from cultural and language barriers. Hence, a new assessment approach based on the resting EEG is proposed. The paper presents a comparative study between EEG spectral centroid frequency and ratio features in learning style classification. A total of 68 university students have participated in the study. Kolb's Learning Style Inventory has been implemented to establish the control groups. EEG is then recorded from the antero-frontal region and preprocessed for noise removal. Subsequently, the spectral centroid frequency and amplitude features are extracted. The amplitude component is further normalized via the ratio method. Synthetic EEG is implemented for dataset enhancement. In general, separate investigation via k-nearest neighbor classifier has shown that the spectral centroid frequency outperforms the amplitude ratio components. Alternatively, combination of both features concurrently can effectively improve the overall classification performance.

Keywords: EEG, learning style, spectral centroid frequency, amplitude ratio, k-nearest neighbor

Abstrak

Gaya pembelajaran merupakan elemen kritikal dalam konstruktivisma memudahcara proses penciptaan ilmu. Namun, kaedah-kaedah lazim bagi menilai ciri psikologi ini terdedah kepada isu-isu kebolehharapan yang berpunca daripada halangan kebudayaan dan bahasa. Justeru, suatu pendekatan baru berdasarkan EEG berehat dicadangkan. Kertas ini membentangkan kajian pembandingan antara ciri frekuensi sentroid spektrum dan nisbah sentroid spektrum. Sejumlah 68 peserta telah pengambil bahagian kajian ini. Inventori Gaya Pembelajaran Kolb telah pun dilaksanakan bagi menubuhkan kumpulan-kumpulan kawalan. EEG kemudiannya direkod daripada kawasan antero-frontal dan diproses untuk pembuangan hingar. Seterusnya, ciri frekuensi dan amplitud sentroid spektrum disari. Komponen amplitud selanjutnya dinormalkan melalui kaedah penisbahan. EEG sintesis dilaksanakan untuk penambahan set data. Secara umumnya, penyiasatan berasingan melalui pengelas jiran terdekat-k telah menunjukkan bahawa frekuensi sentroid spektrum mengatasi prestasi komponen nisbah amplitud. Selain itu, penggabungan kedua-dua ciri serentak dapat meningkatkan keseluruhan prestasi pengkelasan secara berkesan.

Kata kunci: EEG, gaya pembelajaran, frekuensi sentroid spektrum, nisbah amplitude, jiran terdekat-k

1.0 INTRODUCTION

Constructivism has long established itself as among the most prominent philosophies in education. Its principles, which is grounded in experiential learning and learning styles proposes that knowledge is created through a collaborative interaction between idea and experience. Albeit receiving criticism, the concept has been widely acknowledged due to its success in promoting effective teaching. Through such approach, instructors are able to provide optimal experience by actively matching suitable teaching methods with students' preferred learning styles. For the past 60 years after its initial conception, numerous experiential learning models have been established. These include Curry's Onion Model, Riding and Cheema's Fundamental Dimensions, Dunn and Dunn's Learning Style Model, as well as Kolb's Experiential Learning Theory (ELT) [1]. Comparatively, the later has widely established itself in educational research and management learning [2].

Kolb's ELT outlines that knowledge is created via ability of individuals to absorb and comprehend experience. The absorption dimension is formed by dialectically-related modes of Concrete Experience and Abstract Conceptualization. Meanwhile, the comprehension dimension is formed by dialectically-related modes of Reflective Observation and Active Experimentation. The theory also highlights that knowledge is formed through a process involving creative interaction between the learning dimensions that are responsive to contextual demands. As shown in Figure 1, the learning process is portrayed as a recursive cycle in which individuals will experience, reflect, reason and act [3].
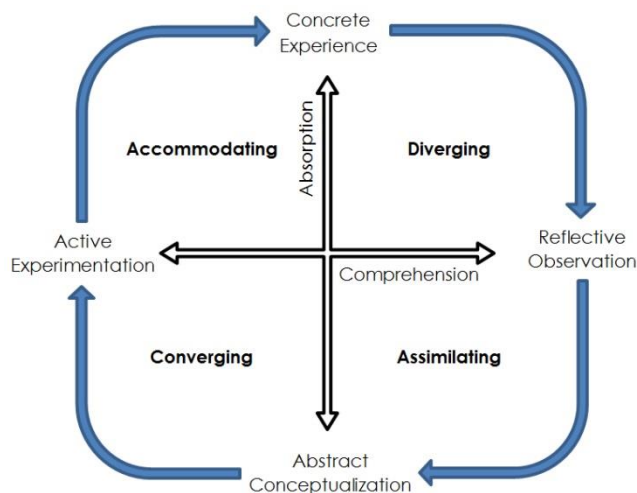

Figure 1 The experiential learning cycle [2]

Unique individual preferences to resolve the conflicting learning modes result in varying learning style inclinations [3]. These are mainly attributed to past experiences, educational specializations, context and gender [4]. Thus, as individuals mature, the construct becomes a stable trait of personality [5]. Learning styles are assessable conventionally via Kolb's Learning Style Inventory (LSI). Essentially, the technique ascertains the prevalent modes from the absorption and comprehension dimension and classifies the individuals into Diverging, Assimilating, Converging and Accommodating styles [3].

Studies have revealed that gender presents a substantial influence on the absorption dimension, but is not significant in the comprehension dimension [4]. These are attributed to the topological differences in brain's functional network; which are evident in the asymmetry of white matter connectivity [6]. Such finding relates well to the variations in local and long range coding of information, as well as in the excitability dynamics of the cortical arrangements. Hence, these affect individuals in terms of cognition and behavior [7]. Findings have also shown that baseline conditions are active states, while pattern of brain activation and deactivation results as a shift of balance from focus of the internal state to the external environment. Thus, even without an explicit stimulus to drive the brain, characterization of network dynamics is still feasible [8]. Other studies have revealed that structural configuration and functional connectivity of the brain fully develops during adolescences. Albeit no substantial differences in the electroencephalogram (EEG) of adolescence and adults, subtle spectral variations have been observed [9].

EEG is a non-invasive electrical recording of cerebral activity. The physiological signal has been extensively studied to unravel the underlying processes in the brain [10]. These include characterization of pathological conditions such autism [11], bipolar disorders, schizophrenia [12], and epilepsies [13]. The technique is also widely implemented in biobehavioral studies; encompassing intelligence, cognition and development, as well as emotional function and dysfunction [14]. Findings have established the frontal region as being involved with cognitive processes [15]. Studies have also revealed that the left hemisphere specializes in logical and sequential processes, while the right side is associated with social interaction capabilities and emotion [16].

In essence, the EEG comprises of delta (0.5 Hz – 4 Hz), theta (4 Hz – 8 Hz), alpha (8 Hz – 13 Hz) and beta (13 Hz – 30 Hz) waves [11]. Each of these frequency bands hold exclusive information that can be related to different neurophysiological processes [10]. Delta and theta waves are each associated with deep and light sleep [17]. Meanwhile, alpha rhythms are apparent when the brain is in resting but conscious state. As the brain engages in intense mental activity, the alpha waves are replaced by the faster beta rhythms [10]. Studies focusing on cognitive processes have revealed that theta band contributes to working memory demands [18]. Moreover, it was also discovered that theta and lower alpha band is associated with attentional requirements that prevail during encoding of new information. Meanwhile, the upper alpha band is inherently dominant in semantic information processing [19].

By implementing innovative signal processing techniques, the spectral information for each of the frequency bands can then be quantified. The spectral features can be evaluated via parametric or non-parametric methods. Essentially, the parametric technique relies on estimation of model-based power spectrum via auto-regressive, moving average or auto-regressive moving average approaches. Meanwhile, non-parametric method includes Welch's technique for estimating power spectrum from time series. Even with its inherent limitations, the non-parametric approach has been widely implemented in numerous EEG studies [20]. For analysis purposes, the spectral information is usually computed into quantifiable features such as band power [19].

Spectral centroid is defined as the center of gravity for the spectrum of each frequency bands. The feature is practical due to its reduced computational requirement and robustness against white Gaussian noise [21]. In addition, the feature which can be segregated into its frequency and amplitude components provide an accurate description regarding the spectral behavior [22]. Its successful implementation ranges from intelligence assessment [23], speech recognition [21], and stress characterization [24]. Thus, being comparatively new, the spectral centroid features can also be used to characterize learning styles from the resting EEG [25].

Machine learning algorithms such as k-nearest neighbor (kNN) have been increasingly utilized to classify brain signatures. In kNN, the features are classified based on polling measures. During training, the closest neighboring features are considered. The testing phase then, assigns the set of features according to class of majority. Several distance metrics have been established, with the Euclidean being among the commonly implemented. To date, kNN has been widely applied in various biomedical studies such as disease detections [26] and rehabilitation [27].

Currently, conventional technique for assessment of learning style involves the use of questionnaires. The approach however, is subject to inconsistency issues that are attributed to cultural and language barriers [4]. To eliminate such limitations, a new method for assessing learning styles has previously been proposed via the EEG spectral centroid frequency (SCF) features. Albeit yielding excellent performance [25], the impact of spectral centroid amplitude (SCA) as the second derivative component has yet to be observed.

Hence, this paper proposes a comparative study on the implementation of EEG spectral centroid frequency and amplitude features in learning style classification. The study focuses on a group of healthy young adults. Such age range has been included as a control criterion to ensure that the brain structure of subjects under study is sufficiently matured and not in ageing state. In adolescents, the brain still experiences neuronal maturation via synaptic pruning and myelination [28]. Such phenomenon may indirectly affect EEG readings and influence the findings of the study [9]. Similarly, old aged group is not included to minimize impact of cognitive decline which affects attention, memory and executive functioning [29].

Past studies have shown that handedness can be correlated with white matter anisotropy of the frontal region [6]. Hence, to control the brain structure variation, only right-handed subjects have been considered. The approach has been a standard practice; particular in psychological researches that specializes into cognition and intelligence [30-32]. The study is also restricted to the alpha and theta bands as the intrinsic characteristics relating to variations in attentional requirements and working memory organizations exists at these frequency ranges. kNN with k-fold cross-validation is implemented to assess the reliability of spectral centroids as stable EEG signatures.

2.0 METHODS

This section describes on the methods employed throughout the entire study. It encompasses EEG acquisition and data clustering technique, signal pre-processing and extraction of spectral centroid features, removal of outliers and pattern observation, implementation of synthetic EEG, classification via kNN, as well as performance comparison between the SCF and SCA features. An extended investigation is also provided using a combination of both feature components for classification. It is important to note however, that the methods used for analysis of alpha and theta SCF features have been replicated from previous publication [25].

2.1 EEG Acquisition and Data Clustering

A total of 68 undergraduate and postgraduate students (male, right-handed, mean age / standard deviation = 23.9 / 3.1 years, age range = 18 – 37 years) from various disciplines have participated in the study. Matters pertaining to experimental protocol and recording procedure have been approved by the university's research ethics committee (600-RMI (5/1/6)). Prior to EEG recording, subjects were initially briefed on the overall experimental procedure and have given written consent.

Subjects were required to relax in seated position with both eyes closed. EEG is then recorded from scalp locations AF3 and AF4 via the Emotiv neuroheadset. Sampling rate of the device is 128 Hz. A feedback loop was completed via scalp locations P3 and P4. The positions comply with the International 10-20 System for electrode placement. Resting EEG was recorded once from each subject for duration of three minutes. For data clustering purposes, subjects were needed to answer the Kolb's LSI online [3].

2.2 EEG Pre-processing and Feature Extraction

The acquired EEG was pre-processed offline using MATLAB 2012a. Rectification of baseline was performed via 0.5 Hz high-pass filter. Electrooculogram

(EOG) artifact is then performed via automatic rejection of amplitudes exceeding ±100 μV [33]. Normalization of signal duration was achieved by considering 2 minutes 30 seconds EEG segment prior to further analysis [9]. Next, the signals were filtered into alpha and theta waves via equiripple band-pass filter [34].

Power spectral density for alpha and theta bands were then estimated via Welch method using Hamming window with 50% overlapping epochs. As mathematically shown in (1), the SCF for each band is computed as the mean of amplitude weighted frequencies divided by the total amplitude. i represents the respective frequency band, N is the number of frequency bins and $S[f]w_i[f]$ is the power of the spectral distribution in relation to frequency, f at bin i [21].

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

Meanwhile, as expressed in (2), SCA is also obtained as the total of amplitude weighted frequencies, but is divided by the total frequency in the respective bands [22].

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

Normalization of SCA is performed using the ratio technique; in which the inter-relationship between alpha and theta amplitude components is being considered [35]. The alpha and theta amplitude ratio can each be computed via (3) and (4), where α and θ represents alpha and theta SCA, respectively.

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

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

Both the SCF and amplitude ratio features were then clustered into the Accommodator, Diverger, Assimilator and Converger groups. Patterns of the feature distribution were then observed via SPSS 19.

2.3 Generation of Synthetic EEG

Studies have shown that performance of kNN classifier declines with uneven sample size between the control group and small class separation [36]. To overcome such limitation, implementation of synthetic EEG is proposed. EEG is inherently stochastic. Thus, its synthetic form can be produced by adding white Gaussian noise with adequately controlled signal-to-noise ratio (SNR). Such requirement is essential to maintain similar signal characteristics. For the purpose

of this study, an SNR of 30 dB has been implemented [35].

Via such technique, the noise array, V_{noise}, is obtained as the product of white Gaussian noise, W_{noise}, and noise voltage, V_{attn}; in which V_{attn} represents the attenuated voltage resulting from the SNR relationship. Hence, as expressed in (5), V_{attn} is then derived as the square root of the noise power, where P_{signal} is the mean power of the original signal, V_{EEG}.

$$V_{attn} = \sqrt{\frac{P_{signal}}{SNR}} \tag{5}$$

Subsequently, the synthetic version of the signal, V_{synt}, was obtained by adding V_{noise} to V_{EEG}. The procedure can be mathematically expressed by (6) and (7).

$$V_{noise} = W_{noise} \times V_{attn} \tag{6}$$

$$V_{synt} = V_{EEG} + V_{noise} \tag{7}$$

A more comprehensive elaboration on generation of synthetic EEG has been previously reported elsewhere [35]. Prior to kNN classification, the synthetic EEG has been used to increase the number of samples to 40 per group and thus, totaling up to 160 samples [37].

2.4 k-Nearest Neighbor and k-Fold Cross-Validation

kNN is a supervised machine learning classifier. The technique adopts a statistical approach in which unlabelled features are identified based rule of majority. During training, the classifier stores the spectral centroid features with its corresponding learning style labels. Subsequently, the unlabelled features from the testing dataset will be classified by assigning the most frequent learning style label with k nearest training samples. In this study, the classification tasks were performed for k=1 to k=5 with Euclidean as the distance metric. The train-to-test split ratio for the dataset was set at 80:20 [38].

So as to gauge the classification performance during training and testing, indices such as accuracy (Acc), positive predictivity (Pp) and sensitivity (Se) have been utilized. The performance indicators can each be expressed by (8), (9) and (10), where TP, TN, FP and FN represent the true positives, true negatives, false positives and false negatives in classification.

$$Acc = \left(\frac{TP + TN}{TP + TN + FP + FN} \right) \times 100\% \tag{8}$$

$$Pp = \left(\frac{TP}{TP + FP} \right) \times 100\% \tag{9}$$

$$Se = \left(\frac{TP}{TP + FN} \right) \times 100\% \tag{10}$$

k-fold cross-validation is incorporated with the kNN to assess its true performance. Prior to feature classification, the method forms a disjointed training and testing datasets via random sampling technique. The cross-validation estimate of accuracy is the total amount of correct classification, divided by the number of folds in the dataset. Thus, a feature is deemed reliable stable for a particular dataset and a set of perturbations, if similar prediction is being induced with different perturbed datasets [39].

In this study, the fold value, k has been set to 5. The data is randomly divided into five segments, in which four segments are allocated for training, while the remaining segment is used for testing. Hence, these matches the train-to-test split ratio that is implemented in the kNN. With varying k, different combination of segments will form the training and testing datasets. Hence, the classifier will be trained and tested for five instances and averaged to obtain its true performance.

In an attempt to compare the effectiveness of spectral centroid features in classifying learning styles, the kNN classifier will be trained and tested separately using SCF and amplitude ratio components. Additionally, an extended investigation is also conducted using combination of both the feature components.

3.0 RESULTS AND DISCUSSION

Initially, the patterns of SCF and amplitude ratio features with synthetic EEG are elaborated. This is followed by classification of SCF, followed separately by the ratio features via kNN. An extended investigation on combination of both features for classification is also discussed.

3.1 EEG Acquisition and Data Clustering

Subjects were clustered into the respective learning style groups based on the results from Kolb's LSI. 14 subjects have been identified as Accommodators, 20 subjects as Divergers, 20 subjects as Assimilators, and the remaining 14 subjects as Convergers. Two extreme outliers, each from Accommodator and Assimilator group has been identified and removed. Table 1 summarizes the distribution of subjects in Accommodating, Diverging, Assimilating and Converging learning style groups prior to pattern observation.

Initial observation on the implementation of synthetic EEG revealed that the pattern of SCF and amplitude ratio features are similar between the original (N=66) and enhanced (N=160) datasets. Thenceforth, the ensuing discussion will focus on dataset with the synthetic EEG. Figure 2 shows the

previously published results on pattern distribution of alpha and theta SCF.

Table 1 Subject distribution in the original dataset (N=66) [25]

Learning style group	Number of subjects
Accommodator	13
Diverger	20
Assimilator	19
Converger	14

Meanwhile, Figure 3 shows the pattern of mean alpha and theta ratio with 95% confidence interval for the respective learning style groups. As examined from Figure 3(a), the Assimilators attained the highest alpha ratio and hence, indicating that its brain state is the most relaxed compared to the other groups. This is followed by the Convergers and then, the Diverger group. The Accommodators attained the lowest alpha ratio. Figure 3(b) shows an inversed theta relationship to that of the alpha ratio. These complement the findings on theta SCF; in which the variations in normalized theta content are credited to the different strategies in maintenance of working memory.
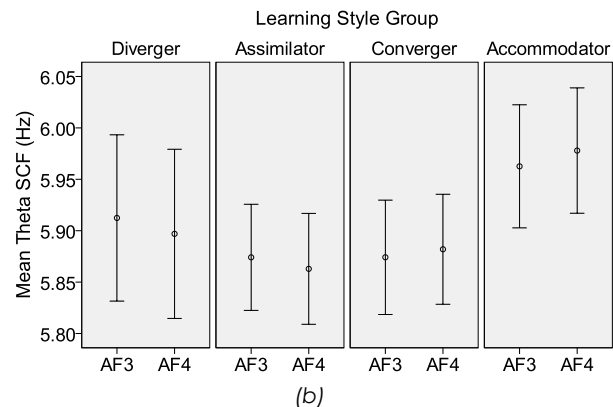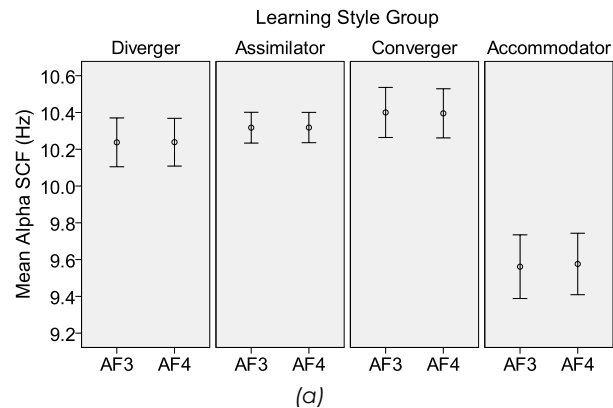

(a)

(b)

Figure 2 Mean (a) alpha and (b) theta SCF with 95% confidence interval (N=160) [25]
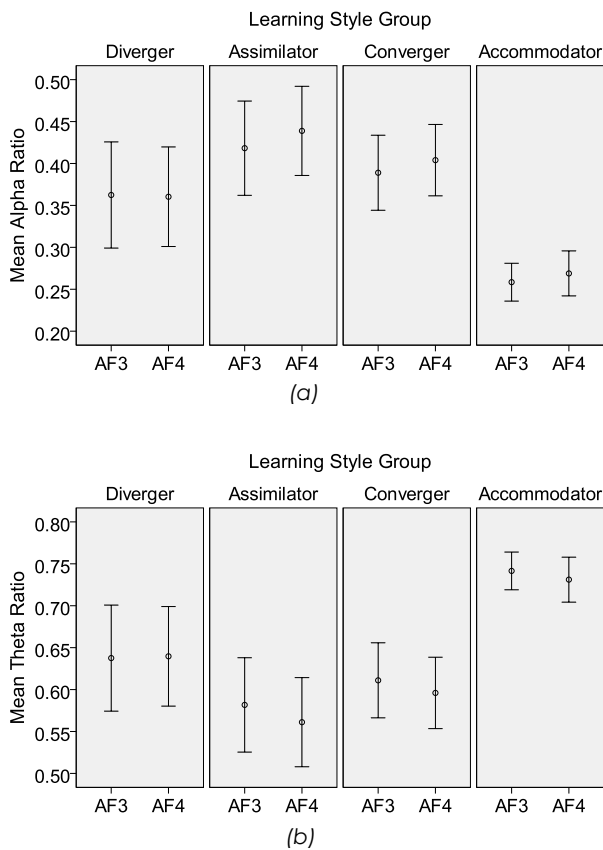
(a)

(b)

Figure 3 Mean (a) alpha and (b) theta ratio with 95% confidence interval (N=160)

Visually, a high degree overlapping between the learning style groups has been observed for SCF and amplitude ratio features. However, a remarkably good separation with the least of distribution overlap has been observed for alpha SCF and ratio features, particularly for the Accommodator group.

3.2 Classification – Alpha and Theta SCF

kNN classification were initially performed separately for SCF and amplitude ratio features. Figure 4 shows the replicated five-fold average training and testing accuracies for alpha and theta SCF. In theory, k=1 represents classification of similarly labelled features for the nearest neighboring distance. Hence, this would produce optimal results with minimal disturbance from other differently labelled features. As the distance increases, probability of disturbance will also increase. This will be reflected in reduced classification performance. However, should similar performance be recorded with the increasing distance, this would indicate that the feature has a high degree of separation between the control groups. Hence, in this study, the optimal performance is selected based on the highest accuracy at the largest value of k.

The best result for classification of alpha and theta SCF features was attained at k=2, with 100% accuracy for training and 97.5% for testing. The accuracies

however, decrease with increasing k. As k increases, disturbance from other neighboring but differently labeled features would be introduced and thus, influencing the performance. It was also observed that at each k, classification during testing yielded lower accuracy than with the training dataset. This is influenced by the smaller sample size being used for testing.
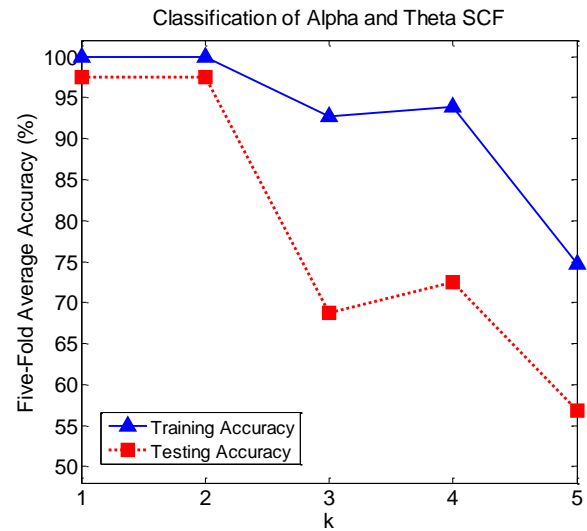

Figure 4 Average accuracies for alpha and theta SCF features [25]

Subsequently, Table 2 shows the replicated results for positive predictivity and sensitivity for each learning style group at k=2. The classifier yielded perfect results for all learning styles during training. During testing however, only the Accommodators attained perfect positive predictivity and sensitivity. This is due to excellent class separation via alpha SCF feature. Meanwhile, the Diverger, Assimilator and Converger groups attained relatively lower results due to the higher overlapping of features for both alpha and theta SCF.

Table 2 Five-fold average positive predictivity and sensitivity for classification of alpha and theta SCF features at k=2 [25]

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

3.3 Classification – Alpha and Theta Ratio

Separately, the performance of alpha and theta amplitude ratio features is initially assessed via the five-fold average accuracy. As shown in Figure 5, the best result was obtained at k=2, with training and testing each yielding 100% and 88.8% accuracy.
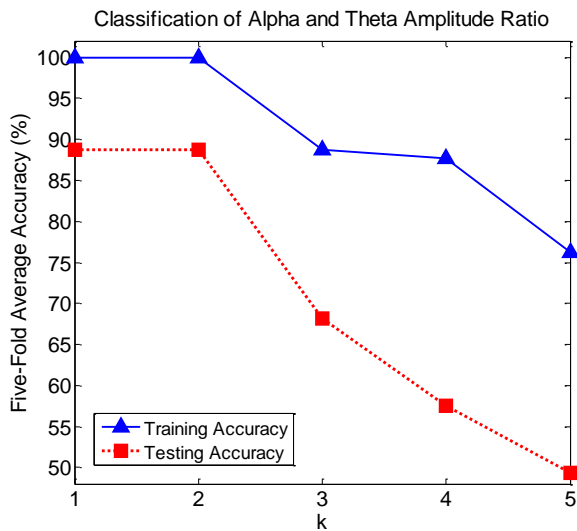
Figure 5 Average accuracies for alpha and theta ratio features

Similar pattern in classification performance has been observed as those of the SCF features; whereby the accuracy deteriorates with increasing k. It was also observed that for each k, the testing phase yielded inferior results compared with classification during training.

Meanwhile, Table 3 summarizes the positive predictivity and sensitivity for each learning style group at k=2. Overall, the five-fold average indices in training have attained perfect results. During testing however, Divergers, Assimilators and Convergers have yielded inferior results for positive predictivity and sensitivity. Despite the poor performance, the Accommodator group was able to retain 100% result for both indices. It has been noted that the proposed amplitude ratio features also suffers from poor class separation and high degree of overlapping features. Such observation is particularly true for the Diverger, Assimilator and Converger groups.

Table 3 Five-fold average positive predictivity and sensitivity for classification of alpha and theta ratio features at k=2

Learning style group	Training		Testing	
	Pp (%)	*Se* (%)	*Pp* (%)	*Se* (%)
Accommodator	100	100	100	100
Diverger	100	100	88.0	82.5
Assimilator	100	100	88.3	82.5
Converger	100	100	85.7	85.1

Comparative study has revealed that the established SCF has significantly outperformed the proposed amplitude ratio features for classification of learning styles. The findings were not only based on the best classification accuracies obtained at k=2, but also considers at larger neighboring distances of k=3 to k=5. An evaluation via positive predictivity and sensitivity

measures has further shown that the class separation is much inferior for the amplitude ratio features.

3.4 Extended Investigation – SCF and Amplitude Ratio

The experiments conducted thus far, have provided valuable insights on the SCF and amplitude ratio features as reliable EEG signatures. By comparing the classifier performance at k=2, SCF has surpassed the amplitude ratio features, particularly in terms of classification accuracy, positive predictivity and sensitivity. In an effort to further increase the classification performance, a combination of both features is also investigated. Hence, by employing similar methodology, the resultant five-fold average accuracy during training and testing are as provided in Figure 6. The best classification performance has been obtained at k=2, with 100% accuracy for both training and testing. Further inspection into the larger neighboring distance of k=3 to k=5 has also revealed improvement over the preceding experiments.
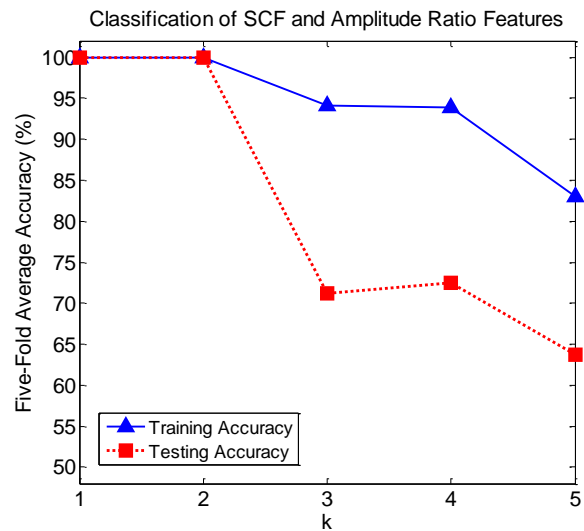

Figure 6 Average accuracies for combination of SCF with amplitude ratio features

Subsequently, the positive predictivity and sensitivity for each learning style group are also in agreement with the 100% classification accuracy during training and testing. All relevant information has been summarized in Table 4.

Table 4 Five-fold average positive predictivity and sensitivity for classification of alpha and theta SCF with amplitude ratio features at k=2

Learning style group	Training		Testing	
	Pp (%)	*Se* (%)	*Pp* (%)	*Se* (%)
Accommodator	100	100	100	100
Diverger	100	100	100	100
Assimilator	100	100	100	100
Converger	100	100	100	100

Increased dimensional space through the combination of SCF and amplitude ratio features has significantly improved the classification performance. Reliability of the results has also been ascertained via k-fold cross-validation algorithm. The method which is readily incorporated into the kNN classifier enables the assessment of true performance via the selected five-fold average indices. Hence, the obtained results are not merely obtained from single-trial experiment, but are averaged over five sequences of randomly assigned training and testing datasets.

4.0 CONCLUSION

In general, the study has analyzed the capabilities of SCF and amplitude ratio features to distinguish learning styles from the resting EEG. Comparatively, the alpha and theta SCF have proven to be more efficient in identifying learning styles as compared to the amplitude ratio components. However, further study has also shown that classification performance can be effectively enhanced through combination of both the SCF and amplitude ratio features.

Acknowledgement

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