Original Article

An Efficient Method for Classification of Alcoholic and Normal Electroencephalogram Signals Based on Selection of an Appropriate Feature

Maryam Dorvashi[1,2], Neda Behzadfar[1,2], Ghazanfar Shahgholian[1,2]

[1]Department of Electrical Engineering, Najafabad Branch, Islamic Azad University, Najafabad, Iran, [2]Digital Processing and Machine Vision Research Center, Najafabad Branch, Islamic Azad University, Najafabad, Iran

Abstract

Background: Alcohol addiction contributes to disorders in brain`s normal patterns. Analysis of electroencephalogram (EEG) signal helps to diagnose and classify alcoholic and normal EEG signal. **Methods:** One-second EEG signal was applied to classify alcoholic and normal EEG signal. To determine discriminative feature and EEG channel between the alcoholic and normal EEG signal, different frequency and non-frequency features of EEG signal, including power of EEG signal, permutation entropy (PE), approximate entropy (ApEn), katz fractal dimension (katz FD) and Petrosion fractal dimension (Petrosion FD) were extracted from alcoholic and normal EEG signal. Statistical analysis and Davis-Bouldin criterion (DB) were utilized to specify and select most discriminative feature and EEG channel between the alcoholic and normal EEG signal. **Results:** Results of statistical analysis and DB criterion showed that the Katz FD in FP2 channel showed the best discrimination between the alcoholic and normal EEG signal. The Katz FD in FP2 channel showed the accuracies of 98.77% and 98.5% by two classifiers with 10-fold cross validation. **Conclusion:** This method helps to diagnose alcoholic and normal EEG signal with the minimum number of feature and channel, which provides low computational complexity. This is helpful to faster and more accurate classification of normal and alcoholic subjects.

Keywords: *Alcoholism, Davies–Bouldin criterion, electroencephalogram signal, K-nearest neighbor classifier, time–frequency features*

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Introduction

Consumption of alcohol has various effects on the central and peripheral nervous system, which depends on the usage pattern. This contributes to the lack of coordination between body and mind.[1] Memory and concentration weakness, lack of right decision, aggression, and loss of coordination are other detrimental effects of alcohol consumption in the brain even after quitting consumption of alcoholic drinks.[2] Decreased motor coordination and brain function impairment are short-term and long-term effects of alcohol consumption, respectively.[3]

Electroencephalogram (EEG) signal which is a noninvasive method for measuring and recording voltage fluctuations within brain neurons characterizes different brain states and actions. EEG signal is analyzed in various activities such as sleep, anesthesia, epilepsy, computational activities, and so on.[4]

In terms of diagnosis of alcohol and normal EEG signal, the power and coherence of EEG signal bands are important factors. While alcoholic subjects' theta band activity subjects increased, alpha band activity decreased in alcoholic subjects.[5,6] Increase in consumption of alcohol results in decrease of power and amplitude of the EEG signal in the frontal lobe, while the power of EEG signal increased in the central and occipital lobes.[7] Consumption of alcohol during cognitive tasks reduced brain coordination between different lobes significantly. Therefore, brain coordination during tasks can be considered as a distinguishable biomarker for the alcoholic and normal individuals.[8]

Bavkar *et al*. combined linear, nonlinear, and statistical features of EEG signal to differentiate alcoholic and normal EEG signal.[9] This combination of EEG signal's

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Address for correspondence:
Dr. Neda Behzadfar, Digital Processing and Machine Vision Research Center, Najafabad Branch, Islamic Azad University, Najafabad, Iran. E-mail: behzadfar_neda@yahoo.com

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data and extracted features from wavelet transformation including energy and entropy proposed a promising approach to classify alcoholic and normal EEG signals.[1] Various wavelet transformations including narrow band pass Butterworth filters,[12] orthogonal wavelet filter bank,[10] and the empirical wavelet transform (EWT)[4] have been applied in recent researches. Anuragi and Sisodia utilized EWT to classify EEG signal based on machine learning methods. Different statistical features such as mean, standard deviation, and variance were extracted using EWT. These features were classified by Least Square-Support Vector Machine (LS-SVM) classifier. An average accuracy of 98.75% was achieved by Least Square-Support Vector Machine (LS-SVM) classifier.[11] In previous studies, machine learning,[12] time-frequency images,[13] hybrid features,[9,14] and computer-aided diagnostic techniques[15] were applied to classify alcoholic and normal EEG signals. However, these studies did not provide information about the sensitive channels to alcohol. EEG channels showing the greatest discrimination between alcoholic and normal EEG signals are considered as the sensitive channels. Selection of discriminative channel for the determination of the alcoholic EEG signal is of prime importance. Appropriate selection of EEG signal channel can significantly reduce the computational complexity and computation time.[16,17]

Shooshtari and Setarehdan suggested selecting an optimal subset of EEG signal channels based on combination of model-based spectral analysis and correlation matrices which is a set of correlation coefficients between channels. Results showed that the F8 channel in international 10–20 system can be considered as an optimal channel for classification of alcoholic and normal individuals and the accuracy of 82.98% was achieved by SVM classifier.[18] According to Ahmadi *et al*. research, EEG signal was divided into five sub-bands by the wavelet decomposition to determine most discriminative features at different frequency bands for detection of alcoholic and normal EEG signals. The number of significant EEG channels got reduced through the principle component analysis method. Different features including mean synchronization, fractal dimension (FD), energy, and entropy were extracted to determine best discriminative feature. Results indicated that FD, entropy, and the energy of C1 channel in alpha sub-band were the most significant features for classification of alcoholic and normal individuals.[19] Combination of genetic algorithm and fuzzy art map were utilized for selection of the optimal EEG channel for classification of alcoholics and normal subjects.[20]

Main study and innovation

There are still arguments over optimal selection of the suitable feature and EEG signal channel to classify alcoholic and normal EEG signal. It is essential to investigate the effect of diverse optimal algorithms on selection of the optimal EEG channel. This paper reports a novel method to select the most discriminative feature and channel between alcoholic and normal subjects. This paper utilizes two analysis methods including statistical analysis and DB criterion to determine the most discriminative feature and channel between alcoholic and normal subjects.

The main structure of the article

The general structure of this paper is as follows: section 2 explains materials and methods. In the section 3, the results of data analysis are investigated and section 4 provides the conclusion.

Materials and Methods

Participants

The dataset applied in this paper has been obtained from the experiments conducted at Center of Machine Learning and Intelligent Systems (UCI) at Neuro-dynamics laboratory at the State University of New York Health Center at Brooklyn. These datasets assessed EEG correlates of genetic predisposition to alcoholism. It includes 20 participants containing 10 alcoholic and 10 normal individuals. The EEG signals were recorded during 30 experiments by 64 electrodes with a sampling frequency of 256 Hz (3.9-msec epoch) for 1 s.[21] In these datasets, 1-s EEG signal was recorded while participants were exposed to either a single stimulus (S1) or to two stimuli (S2) which were pictures of objects selected from the 1980 Snodgrass and Vanderwart picture set.[22] S2 was presented in either a matched condition or in a nonmatched condition. While two stimuli were identical in matched condition, two stimuli were different in a nonmatched condition. Whereas participants only were exposed to S1 in the first 10 experiments, S2 contained 10 matched S2 and 10 nonmatched S2 were shown to participants in other 20 experiments. In this paper, EEG signals recorded during display of S1 and S2 were separately assessed.

Data processing

A flowchart of the proposed method has been shown in Figure 1. EEG signal was digitally filtered between 0.4 Hz and 45 Hz with a 6th order Butterworth band-pass filter to remove artifacts. The power of the frequency sub-bands, nonfrequency features, including approximate entropy (ApEn), permutation entropy (PE), FD based on Katz and Petrosion were extracted from EEG signal recorded during display of S1, S2, and both S1 and S2.[23] Statistical analysis was utilized to determine the significant differences between the extracted features from alcoholic and normal individuals. Moreover, DB criterion was applied to specify the most discriminating feature and channel between alcoholic and normal EEG signal. Finally, most discriminating feature was classified by SVM and KNN classifier. Matlab software was applied to analyze the data. Each section will be briefly explained.

Feature extraction

Power of electroencephalogram sub-bands

The power of EEG signal indicates the capacity of information processed in brain cortex.[24] Power of EEG

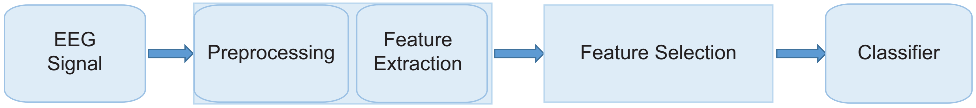

Figure 1: Block diagram of the proposed method

signal was calculated by Fast Fourier Transform. The EEG signal is composed of different kinds of bands with different frequencies including delta (0.1–4 HZ), theta (4–7 Hz), lower1 alpha (7–9 Hz), lower2 alpha (9–11 Hz), upper alpha (11–13 Hz), and beta (13–30 Hz).

Approximate entropy

ApEn quantifies the signal's complexity and irregularity. Low values of entropy show high regularity and predictability of a time series data. Conversely, high values of entropy indicate irregularity in a time series. With the signal embedded in an m-dimensional space, ApEn is calculated based on the correlation integral $C_i^m(r)$. Following that, the Ln function of all $C_i^m(r)$ (i) is calculated and averaged.[25]

$$\Phi^m(r) = [N-(m-1)]^{-1} \sum_{i=1}^{N-(m-1)} \ln(C_i^m(r)) \quad (1)$$

Then, the ApEn is calculated by adding a unit to m as follows: [25]

$$\text{APEn}(m, r) = \Phi^m(r) - \Phi^{(m+1)}(r) \quad (2)$$

In this study, m and r are set to 1 and 0.25% of the standard deviation of each time series, respectively. These values are selected based on the results of previous researches reported acceptable statistical validity for ApEn.[26]

Permutation entropy

PE index tracks the dynamics of brain activity. Nonstationary EEG series are transformed to an almost stationary ordinal series by PE**.** The time series $X_N = [X_1, X_2, ..., X_N]$ with N point is converted into the following vectors as follows with the embedding dimension, m, and the time lag s.[27]

$$Xi = [x_i, x_{i+\tau}, ..., x_{i+m\tau}] \quad 1 \le i \le N-(m-1)\tau \quad (3)$$

With xi being arranged in an increasing order, J = m! Would be the number of possible order patterns called permutations. The vectors xi can be represented by a symbol sequence, whose each permutation is considered as a symbol. In the time series X_N, the probabilities of different symbols are represented by P1., Pj. The PE is calculated with the following equation:[27]

$$H(d,\tau) = -\sum_{j=1}^{d!} p(j)\log p(j) \quad (4)$$

Fractal dimension

FD provides information about the complexity and irregularity of a signal. While higher FD value indicates more complexity in signal, lower FD value shows the more regular signal. FD can be calculated in several ways. In this study, two methods of Katz and Petrosian were employed. The Katz FD is calculated using the sum of the distances between the consecutive points (n) and the estimated diameter (d). This diameter is the distance between the first point of the sequence and the point providing the farthest distance. The equation of the Katz FD is represented below:[28]

$$D_{Katz} = \frac{\log_{10}(n)}{\log_{10}\left(d/L\right) + \log_{10}(n)} \quad (5)$$

Where L represents the length of signal.

The Petrosian FD is calculated using the length of signal (n) and the number of sign changes in the signal (N_D) as follows[29]:

$$D_{Petrosion} = \frac{\log_{10}(n)}{\log_{10}(n) + \log_{10}\left(\frac{n}{n+0.4N_D}\right)} \quad (6)$$

Feature selection

Statistical analysis

A Kolmogorov–Smirnov test was utilized to compare the extracted features with a standard normal distribution. Since none of the extracted features had normal distribution, a Mann–Whitney *U*-test was applied to specify the significant differences between the features in different conditions.

Davies-Bouldin as a discriminative criterion

DB was employed as an evaluation criterion to assess feature extraction space. This criterion was defined based on scattering matrix of clusters showing their separability level. The distance between each cluster is measured to choose the worst separability status. Then, the average of the worst separability status in all clusters would be the DB criteria. The DB criteria are calculated with the following equation, where C and R_{ij} show the number of clusters and the similarity of one cluster to other clusters, respectively:[30]

$$DB = \frac{1}{C}\sum_{i=1}^{C} \max(R_{ij}), \ i \ne j \quad (7)$$

Classification

Support vectors machine

SVM is an efficient supervised learning model showing consistently high performance in statistical pattern recognition and classification.[31] It maps feature vectors into high dimensional space and creates hyper plane to separate classes with linear approximation.[32] This method applies the structural risk minimization rule providing a trade-off between training error and modeling complication.[33,34] In this research, a binary classification technique based on SVM with radial basis function applied. Ten-fold cross-validation technique was utilized to divide feature vectors into training and testing sets.

K-Nearest Neighbor

KNN classifier is a nonparametric competitive classifier showing consistently high performance in supervised statistical pattern recognition.[35] In KNN classification, the input consists of the k closest training examples in the feature space and the output is a class membership. An object is classified by a plurality vote of its neighbors, with the object being assigned to the class most common among its KNN (k is a positive integer, typically small). If k = 1, the object is simply assigned to the class of that single nearest neighbor. After the determination of K, the distance of test data from all training data (X) is calculated and the first nearest distance from k is selected. Then, X is assigned to the class receiving the majority votes among the nearest K neighbors.[36]

Results

The results of statistical analysis of EEG signals recorded during display of S1 represented that power of Beta2, Upper_alpha, Lower2_alpha, Lower1_alpha, and Delta bands declined in alcoholic group compared to the normal group shown in Figure 2. Furthermore, PE, Katz FD, and Petrosion FD decreased in the alcoholic group compared to the normal group shown in Figure 3. The Power of Beta2, Lower2_alpha, PE, Katz FD, and Petrosion FD showed significant differences in all 64 channels whereas ApEn showed significant differences in 8 channels shown in Table 1. Moreover, the results of the DB criterion for frequency and nonfrequency features indicating significant differences in all 64 channels represented that the power of Lower2_alpha in TP8 channel and Katz FD in FP2 channel showed the best discrimination among all frequency and nonfrequency features, respectively. The results of the DB criterion for all frequency and nonfrequency features extracted from EEG signals recorded during display of S1 have been shown in Table 2.

Furthermore, the results of statistical analysis in EEG signals recorded during display of S2 showed that power of Beta2, Upper alpha, Lower2_alpha, Lower1_alpha, Delta, and Theta bands decreased in alcoholic group compared to the normal group shown in Figure 4. Moreover, PE, Katz FD, and Petrosion FD decreased in the alcoholic group compared to the normal group, while ApEn increased in the alcoholic group compared to the normal group shown in Figure 5. The Power of beta2, upper alpha, Lower2_alpha, Delta, PE, Katz FD, and Petrosion FD indicated significant differences in all 64 channels, whereas ApEn showed significant differences in 16 channels shown in Table 1. The results of the DB criterion for frequency and nonfrequency features showed that the power of Beta2 in FP1 channel and Katz FD in FP2 channel represented the best discrimination among frequency and nonfrequency features, respectively.

Moreover, the results of statistical analysis of all EEG signals recorded during display of both S1 and S2 (30 trials) showed that

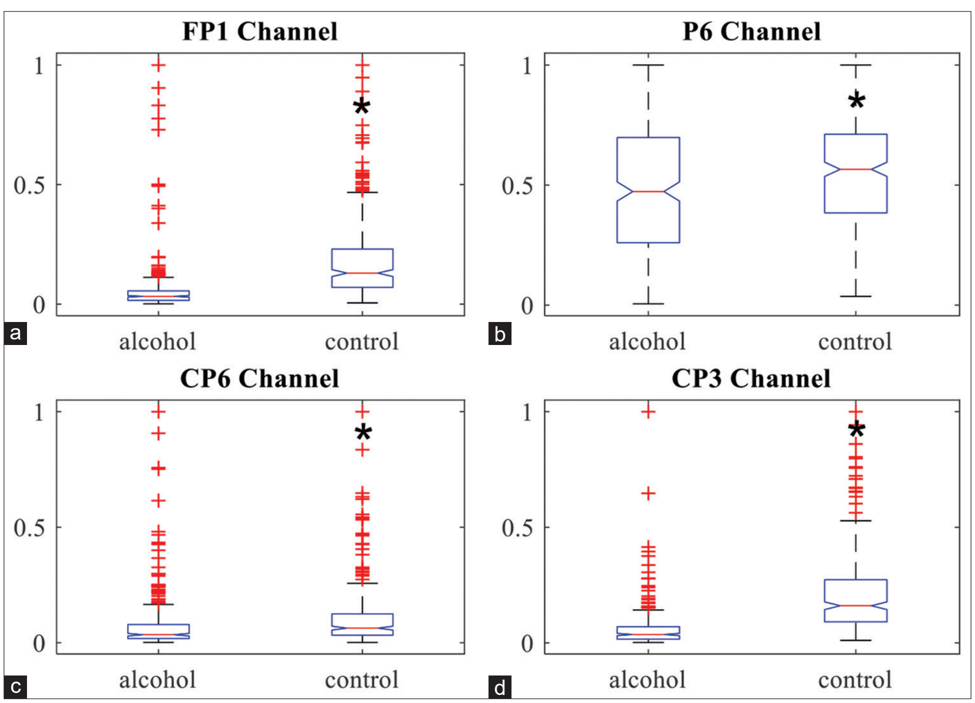

Figure 2: The results of paired t-test in the power of Beta2, Delta, Upper_alpha, and Lower2_alpha bands extracted from electroencephalogram signals recorded during display of both S1 and S2 (30 trials) in the channel indicating the most discrimination among all 64 channels have been shown in (a-d), respectively. Asterisks indicate significant differences between the two different conditions ****P* **< 0.05

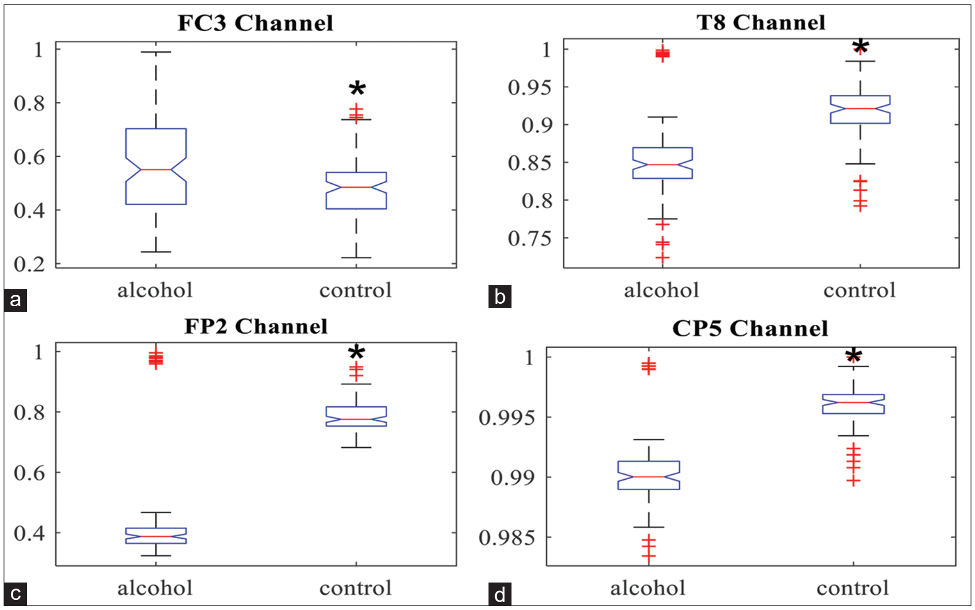

Figure 3: The results of statistical analysis of the approximate entropy, permutation entropy, Katz fractal dimension, and petrosion fractal dimension extracted from electroencephalogram signals recorded during display of S1 in the channel indicating the most discrimination among all 64 channels have been shown in (a-d), respectively

Table 1: Statistical analysis of all frequency and nonfrequency features in electroencephalogram signals recorded during display of S1, two stimulus and both single stimulus and two stimulus data (30 trials)

Feature	S1 data (P<0.05)	S2 data (P<0.05)	S1 and S2 data (P<0.05)
Delta	+	+	+
Theta	–	–	–
Upper_alpha	+	+	+
Lower 2_alpha	+	+	+
Lower 1_alpha	+	+	+
Beta2	+	+	+
ApEn	+	+	+
PE	+	+	+
Katz FD	+	+	+
Petrosion FD	+	+	+

S1 – Single stimulus; S2 – Two stimulus; FD – Fractal dimension; Katz FD – Katz FD; PE – Permutation entropy; ApEn – Approximate entropy

the power of upper alpha, Lower2_alpha, Beta2, and Delta bands declined in the alcoholic group compared to the normal group which have been shown in Figure 6. In addition, the results of statistical analysis showed that PE, Katz FD, and Petrosion FD decreased in the alcoholic group compared to the normal group, while ApEn increased in the alcoholic group compared to the normal group which have been shown in Figure 7. The PE, Katz FD, and Petrosion FD indicated significant differences in all 64 channels whereas ApEn represented significant differences in 10 channels shown in Table 1.

The results of the DB criterion for frequency and nonfrequency features indicated that the power of Lower2_ alpha band in CP3 channel and Katz FD in FP2 channel showed the best discrimination among frequency and nonfrequency features, respectively. The results of the DB criterion for all frequency and nonfrequency features have been shown in Table 2. Table 2 indicates channels showing the best discrimination for every single feature among all 64 channels. Moreover, Table 3 provides the qualitative comparative analysis of the proposed method with existing methodologies.

According to Table, While power of Lower2_alpha indicated the best discrimination among frequency features during display of s1 and both S1 and S2 data, Katz FD in FP2 channel indicated the best discrimination among all frequency and non-frequency features between alcoholic and normal EEG signals recorded during display of S1, S2 and both S1 and S2 data.

To determine the best feature and channel discriminating among all the nonfrequency and frequency features, SVM and KNN classifiers were applied. 70% of data were assigned as the training data, 15% as validation data, and 15% as the test data. The results of SVM and KNN classifiers for these features have been illustrated in Tables 3 and 4, respectively. According to the results of the DB criterion and SVM and KNN classifier, Katz FD in FP2 channel indicated the best discrimination in the alcoholic and normal EEG signals. Table 5 provides comparative analysis of the proposed method and other studies.

Conclusion

Consumption of alcohol leads to excessive risk-taking, poor judgment, weakening frontal lobe function, and lack of development of the frontal lobes. Furthermore, fear

Table 2: Davies–Bouldin criterion for all frequency and nonfrequency features in electroencephalogram signals recorded during display of single stimulus, two stimulus, and both single stimulus and two stimulus data (30 trials). Asterisks indicate features showing the best discrimination among frequency and nonfrequency features in terms of Davies–Bouldin criterion

Feature	S1 data		S2 data		S1 and S2 data	
	Channel	DB criterion	Channel	DB criterion	Channel	DB criterion
Delta	P6	5.8762	P1	5.8722	P6	6.3162
Theta	P8	6.5703	P8	6.6667	P8	6.5667
Upper_alpha	CP1	16.2772	PO2	6.0939	CP6	7.9203
Lower 2_alpha	TP8	1.3418*	P6	1.9115	CP3	1.7638*
Lower 1_alpha	Y	6.0068	Y	9.6723	Y	9.6867
Beta2	OZ	3.0786	FP1	1.8042*	FP1	2.3095
ApEn	FC3	3.4686	C6	3.4777	FC3	3.5578
PE	T8	1.5310	CP5	1.7466	CP5	1.6797
Katz FD	FP2	0.6738*	FP2	0.8581*	FP2	0.8062*
Petrosion FD	CP5	0.9520	CP5	1.0302	CP5	1.0071

S1 – Single stimulus; S2 – Two stimulus; FD – Fractal dimension; Katz FD – Katz FD; DB – Davis-Bouldin criterion; PE – Permutation entropy; ApEn – Approximate entropy

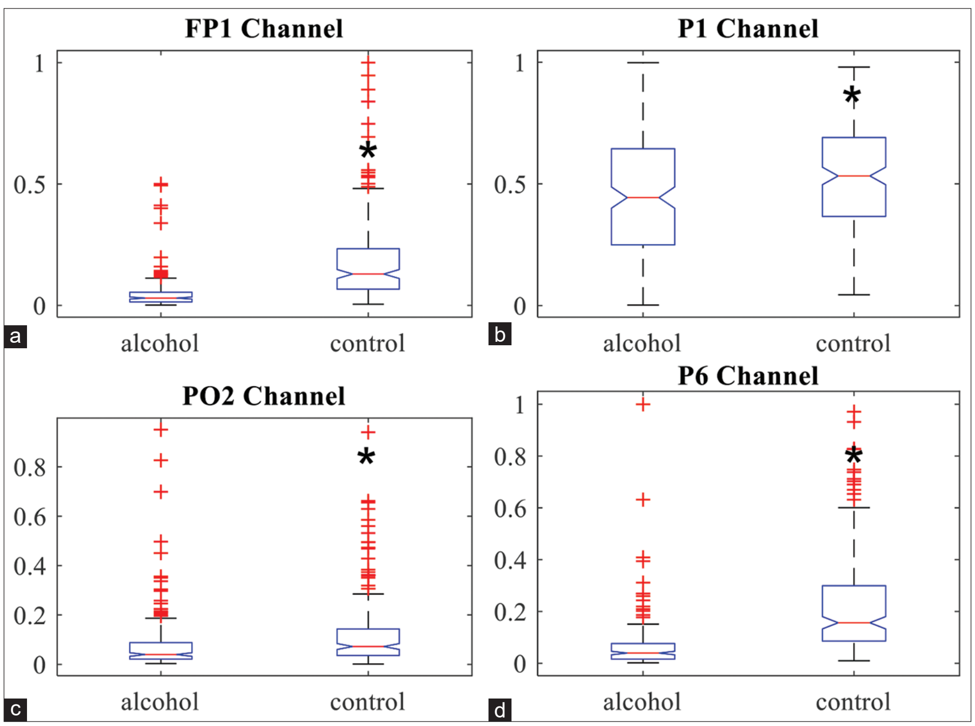

Figure 4: The results of statistical analysis of power of Beta2, Delta, Upper_alpha, Lower2_alpha bands extracted from electroencephalogram signals recorded during display of S2 in the channel indicating the most discrimination among all 64 channels have been shown in (a-d), respectively

response in temporal lobe is ignored, rejecting possible consequences of the actions. Alcoholism increases the risk of anxiety, mental disorders, and depression and reduces the safety of society[35] The effect of over-consumption of alcohol on the prefrontal cortex would be uncontrollable and improper behaviors and reduction in metabolism.[37]

In this paper, the most discriminative feature and channel between alcoholic and normal individuals were specified. The applied dataset was 1-s EEG signal recorded within display of a S1 or S2 from 20 participants, including 10 alcoholics and 10 normal individuals during 30 experiments.[24] EEG signals recorded within display of S1 and S2 were separately assessed. Frequency and nonfrequency features including power of EEG signal, ApEn, PE, FD based on Katz and Petrosion were extracted from EEG signals recorded during display of S1, S2, and both S1 and S2 data. In feature selection step, statistical analysis was applied to specify the notable differences between features extracted from alcoholic and normal individuals. The most discriminating feature and channel between alcoholic and normal individuals were specified by DB criterion.

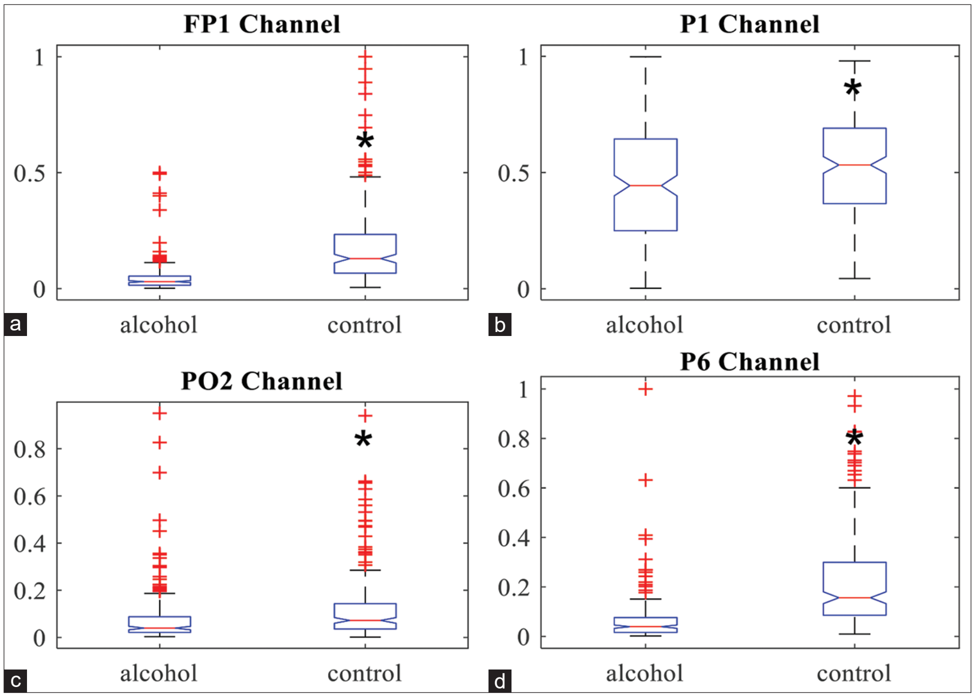

Figure 5: The results of statistical analysis of the approximate entropy, permutation entropy, Katz fractal dimension, and Petrosian fractal dimension extracted from electroencephalogram signals recorded during display of S2 in the channel indicating the most discrimination among all 64 channels data have been shown in (a-d), respectively

Table 3: Results of support vector machine classifier with 10-fold cross-validation for electroencephalogram signals recorded during display of single stimulus, two stimulus, and both single stimulus and two stimulus data (30 trials)

Feature - channel	S1 data			Feature	S2 data			Feature	S1 and S2 data		
	Accuracy (%)	Sensitive (%)	Specify (%)		Accuracy (%)	Sensitive (%)	Specify (%)		Accuracy (%)	Sensitive (%)	Specify (%)
Katz FD-FP2	98.33	100	96.7	Katz FD-FP2	95.83	100	92.3	Katz FD-FP2	98.77	100	87.37
Lower 2_ alpha-TP8	78.33	93.3	90.4	Beta2-FP1	75.83	67.81	92.30	Lower 2_ alpha-CP3	78.33	71.79	90.47
Combination of Katz FD and Lower 2_alpha	73.3	66.27	91.1	Combination of Katz FD and beta2	74.16	66.86	92.64	Combination of Katz FD and Lower 2_alpha	78.33	69.76	92.64

S1 – Single stimulus; S2 – Two stimulus; FD – Fractal dimension; Katz FD – Katz FD

Table 4: Results of K-nearest neighbor classifier with 10-fold cross-validation for electroencephalogram signals recorded during display of single stimulus, two stimulus and both single stimulus and two stimulus data (30 trials)

Feature	S1 data			Feature	S2 data			Feature	S1 and S2 data		
	Accuracy (%)	Sensitive (%)	Specify (%)		Accuracy (%)	Sensitive (%)	Specify (%)		Accuracy (%)	Sensitive (%)	Specify (%)
Katz FD-FP2	98.97	100	97.30	Katz FD-FP2	98.3	100	96.6	Katz FD-FP2	98.5	100	83
Lower 2_ alpha-TP8	71.6	66.6	76.6	Beta2-FP1	75	75	75	Lower 2_ alpha-CP3	71	74	69
Combination of Katz FD and lower 2_alpha	83.3	83.3	83.3	Combination of Katz FD and beta2	78.3	78.3	78.3	Combination of Katz FD and lower 2_alpha	76.6	75.5	77.7

S1 – Single stimulus; S2 – Two stimulus; FD – Fractal dimension; Katz FD – Katz FD

The results of DB criterion demonstrated that the Katz FD in the FP2 channel showed the most discrimination between alcoholic and normal EEG signals recorded during display of S1, S2, and both S1 and S2 data. The accuracies of 98.33%, 95.83%, and 92.77% were achieved by SVM classifier with 10-fold cross validation in EEG signal recorded during display of S1, S2, and both S1 and S2, respectively. Furthermore, the Katz FD in FP2 channel indicated the accuracies of 98.97%, 98.3%, and 93% by KNN classifier with 10-fold

Table 5: Qualitative comparative analysis of the proposed method

Contribution	Dataset	Feature selection method	Number of features	Classifier	Accuracy (%)
Shri *et.al*.[35]	20 subjects (10 alcoholic and 10 control subjects)	Ranked ApEn	1	BPNN	90
				SVM	
Bavkar *et.al*.[16]	40 subjects (20 alcoholic and 20 control subjects)	Rhythm power, variance, skewness, kurtosis, SampEn, ApEn	7	Ensemble subspace KNN	95.1
Proposed method	20 subjects (10 alcoholic and 10 control subjects)	Rhythm power, ApEn, PE, katz FD Petrosion FD	5	KNN	98.33
				SVM	

ApEn – Approximate entropy; SampEn – Sample entropy; FD – Fractal dimension; Katz FD – Katz FD; BPNN – Backpropagation neural network; SVM – Support vector machine; KNN – K-nearest neighbor; PE – Permutation entropy

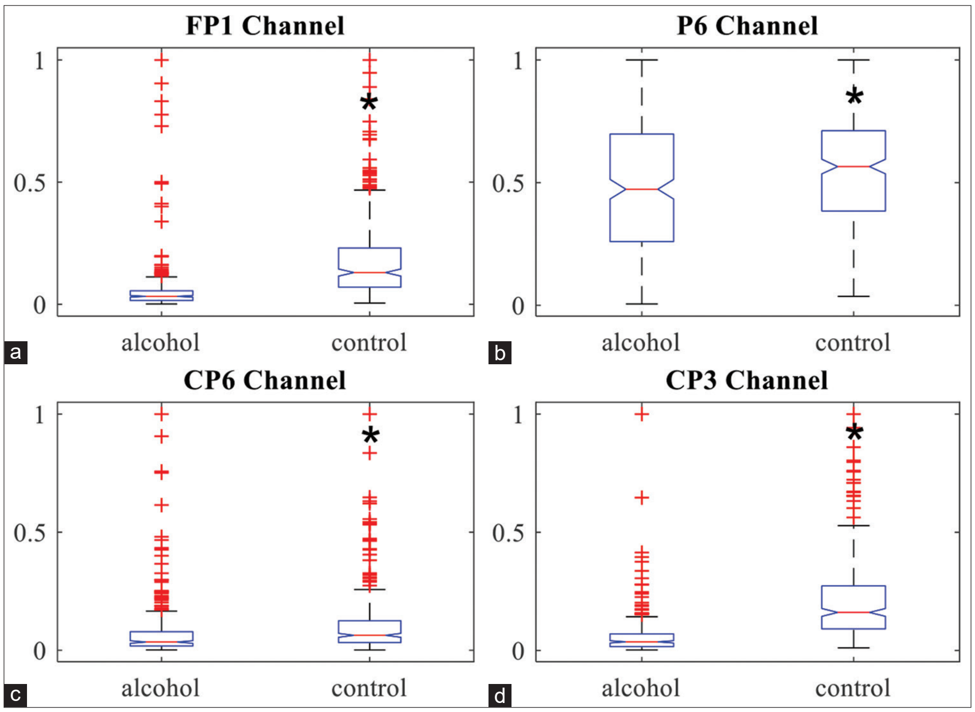

Figure 6: The results of statistical analysis of the power of Beta2, Delta, Upper_alpha, and Lower2_alpha bands extracted from electroencephalogram signals recorded during display of both S1 and S2 (30 trials) in the channel indicating the most discrimination among all 64 channels have been shown in (a-d), respectively

cross-validation in EEG signal recorded during display of S1, S2, and both S1 and S2, respectively.

According to previous studies, alcohol affects the parietal and central lobes, which reduces the correlation between different lobes of the brain, stimulation of the cerebral cortex, and balance.[32] The most serious brain damages in alcoholics are associated with frontal lobe including neurological function disorder, reduction in bloodstream, and metabolism in the frontal lobe. These damages cause improper response to a special conditions and lack of emotion expression in the face, voice, and motivation in individuals. Furthermore, alcoholism has a detrimental effect on the cognitive performances, resulting in disorders in the frontal lobe.[33] The results of this paper demonstrated that Katz FD in the FP2 channel showed the highest discrimination between normal and alcoholic EEG signal indicating that alcoholics` frontal lobe has considerably changed compared to the normal group. The results of the present study are aligned with other quantitative studies into alcoholic and normal EEG signal.[33]

There is less power of alpha frequency band in alcoholic EEG signal than that of normal individuals.[5,6,34] Moreover, the values of nonlinear parameters including FD, entropy, were lower in alcoholic group compared to normal group.[15,19] This shows that the dynamic behavior is less random in the alcoholics, while normal EEG is more complex than alcoholic EEG signal. This shows reduction in active neural process in the brain due to alcohol consumption.[15]

According to the results of statistical analysis and DB criterion, the Katz FD in the FP2 channel showed the highest discrimination between normal and alcoholic EEG signal. It must be noted that SVM classifier yielded to the accuracy of 92.77% for Katz FD in the FP2 channel

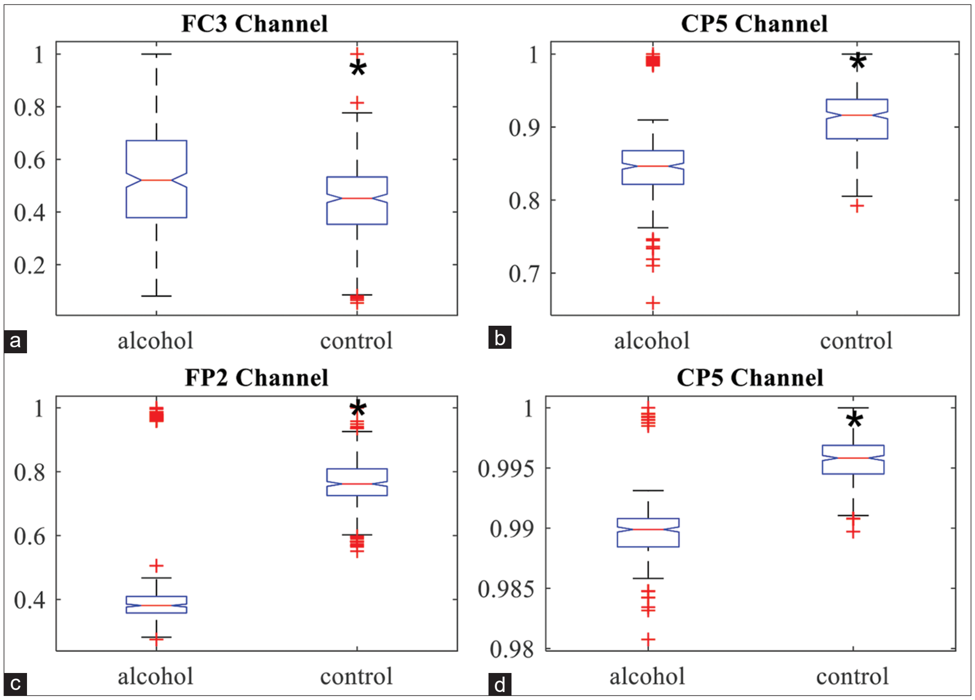

Figure 7: The results of statistical analysis of the approximate entropy, permutation entropy, Katz fractal dimension, and Petrosian fractal dimension extracted from electroencephalogram signals recorded during display of both S1 and S2 (30 trials) in the channel representing the most discrimination among all 64 channels have been shown in (a-d), respectively

for EEG signals recorded during display of both S1 and S2 data, while Shri *et al*. reached accuracy of 90% on the same dataset. In the paper of Shri *et al*., significant channel was selected by the ranked ApEn features based on the analysis of variance (ANOVA) test. The ApEn coefficients were ranked by ANOVA test to specify the discriminating channel between alcoholics and normal individuals. The ranked ApEn set was utilized to BPNN 40 hidden neurons and SVM classifiers with a polynomial kernel of order 3 performed with an accuracy of 90% with only 32 ranked ApEn coefficients.[35] Bavkar *et al*. extracted EEG hybrid features including linear, nonlinear, and statistical feature from the same dataset to measure the complexity and nonlinearity in EEG signal. Results showed that gamma and alpha rhythms are capable to differentiate alcoholic EEG signal from nonalcoholic EEG signal.[9] While Bavkar *et al*.[9] only utilized statistical analysis to discriminate the alcoholic and normal individuals, we applied both statistical analysis and DB criterion to determine discriminative feature and EEG channel between the alcoholic and normal EEG signal. In this study, both frequency and nonfrequency features were used to discriminate the alcoholic and normal individuals. Katz FD in the FP2 channel was determined as the best feature and EEG channel for the EEG signal classification. FD measure illustrates change in synchronization state under certain mental conditions related to the diversity of neural activities.[36] Determination of discriminative feature and EEG channel by statistical analysis and DB criterion provides low computational complexity, which can be applied in many applications, including accurate classification of normal and alcoholic subjects and neurofeedback training in the rehab program of alcoholic individuals to improve the cognitive abilities.[37] This proposed method helps to diagnose alcoholic and normal EEG signal with the minimum number of feature and channel, which is likely to be helpful to more investigation of the covert steps of brain signal processing.

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None.

Conflicts of interest

There are no conflicts of interest.

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