A hybrid method based on time–frequency images for classification of alcohol and control EEG signals

A Hybrid Method based on Time-Frequency Images for Classification of Alcohol and Control EEG Signals

Varun BAJAJ[1], Yanhui GUO[2], Abdulkadir SENGUR[3], Siuly SIULY[4], and Omer F. ALCIN[5]

[1]Discipline of Electronics and Communication Engineering, PDPM Indian Institute of Information Technology, Design and Manufacturing, Jabalpur, India

[2]Department of Computer Science, University of Illinois at Springfield, Springfield, Illinois, USA.

[3]FiratUniversity, Technology Faculty, Electrical and Electronics Engineering Dept., Elazig, TURKEY.

[4]Centre for Applied Informatics, College of Engineering and Science, Victoria University, Melbourne, Australia

[5]Department of Electrical and Electronics Engineering, Faculty of Engineering and Architecture, Bingöl University, 12000, Bingöl, TURKEY

Email: bajajvarun056@yahoo.co.in, guoyanhui@gmail.com, ksengur@gmail.com, siuly.siuly@vu.edu.au, ofalcin@gmail.com

Abstract: Classification of alcoholic electroencephalogram (EEG) signals is a challenging job in biomedical research for diagnosis and treatment of brain diseases of alcoholic people. The aim of this study is to introduce a robust method that can automatically identify alcoholic EEG signals based on time-frequency image information as they convey key characteristics of EEG signals. In this paper, we propose a new hybrid method to classify automatically the alcoholic and control EEG signals. The proposed scheme is based on Time-Frequency (T-F) images, texture image feature extraction and non-negative least squares classifier (NNLS). In T-F analysis, the spectrogram of the Short Time Fourier Transform (STFT) is considered. The obtained T-F images are then converted into 8-bits gray-scale images. Co-occurrence of the Histograms of Oriented Gradients (CoHOG) and Eig(Hess)-CoHOG features are extracted from T-F images. Finally obtained features are fed into Non-negative least squares (NNLS) classifier as input for classify alcoholic and control EEG signals. To verify the effectiveness of the proposed approach, we replace the NNLS classifier by Artificial Neural Networks (ANN), k-nearest neighbor (KNN), Linear Discriminant Analysis (LDA) and Support Vector Machine (SVM) classifier separately, with the same features. Experimental outcomes along with comparative evaluations with the state-of-the-art algorithms manifest that the proposed method outperforms competing algorithms. The experimental outcomes are promising and it can be anticipated that upon its implementation in clinical practice, the proposed scheme will alleviate the onus of the physicians and expedite neurological diseases diagnosis and research.

Key-words: Electroencephalogram, Time-Frequency images; Texture image; Feature extraction; Classification; Alcoholism; Non-negative least squares classifier.

1. Introduction

Psychiatric phenotypes, brain disorders and metal tasks such as alcoholism can be detected by analysis and classification EEG signals. Alcoholism causes neurological deficiencies like impairment of decision making, learning and memory deficits, and suffering behavioral changes [1, 2] and also cause of some serious accidents during driving or operating machines where alertness and proper judgments are required. Brain weight reduces due to excessive alcohol consumption [1, 3, 4]. Permanent alcohol abuse produces hidden damages in the brain such as memory weakness and decision making impairments [5]. It has been also reported that after quitting alcohol consumption the disorders and weaknesses also remain same [6]. The EEG is the most frequently-used technique for studying the functional states of the brain. The EEG produces aperiodic and non-stationary time series data, which refers to the recording of the brain's spontaneous electrical activity. Vast amounts of multi-channel EEG signals are visually analyzed by experts to identify and understand abnormalities within the brain and how they propagate. However, the visual inspection of EEG signals is not a satisfactory procedure because there are no standard criteria for the assessment and it is time-consuming, error-prone, and subject to fatigue [7-8]. Therefore, need to develop automatic classification methods which can used to identify alcoholic people and it can help the psychiatrists to under brain activity.

Recently, numerous methods have been proposed for determination of alcoholic EEG signals. The variance and event-related potential of EEG signals increases with increases the level [9-10]. The second order autoregressive model [11] and Wavelet Transform (WT) [12] based features used for classification of normal and alcoholic EEG signals. Principal Component Analysis (PCA) based pre-processing and WT based features used for analysis of alcoholic and controls EEG signals [13]. Quantitative such as frequency analysis, absolute and relative powers of the four classical bands used for determine alternation in alcoholic patients [14]. Correlation dimension used as measures to discrimination of alcohol and normal EEG signals [15]. Chaotic measures are used as features to alcoholic from normal EEG signals [16]. The fast Fourier transform (FFT) and auto regressive (AR) method based power density used as features for classification of alcohol and control EEG signals [17]. The nonlinear features used as input to support vector machine (SVM) classifier for classification of alcohol and normal EEG signals [18]. Energy measures has been extracted from wavelet packet decomposition with various classifier for computer based identification of alcohol EEG signals [19].

2. Proposed Method

In this work, a new hybrid method is presented for EEG signal classification which combines T-F representation, co-occurrence of the Histograms of Oriented Gradients (CoHOG), and Sparse Representation based classifier (SRC). T-F image based features give more inside information of EEG signals. An illustration is given in Fig. 1. The EEG signals are firstly transformed into T-F domain by using the spectrogram of Short Time Fourier Transform (STFT). Obtained T-F images are then converted into 8-bits gray-scale images. Two different gradient based algorithms are employed to characterize the texture information of the T-F images. These methods are CoHOG and Eig(Hess)-CoHOG, respectively. The CoHOG combines the gradient orientations with different offsets to describe the shapes and provides features about objects. On the other hand, the Eig(Hess)-CoHOG algorithm employs the Hessian matrix and eigenvalues to extract local texture features. The feature vector for each T-F image is obtained by concatenation of CoHOG and Eig(Hess)-CoHOG features. When the feature vector for each T-F images is examined, a sparse structure can be seen. Thus, a sparse representation based classifier is considered in the classification phase of the proposed method. The NNLS method is used in sparse classifier.

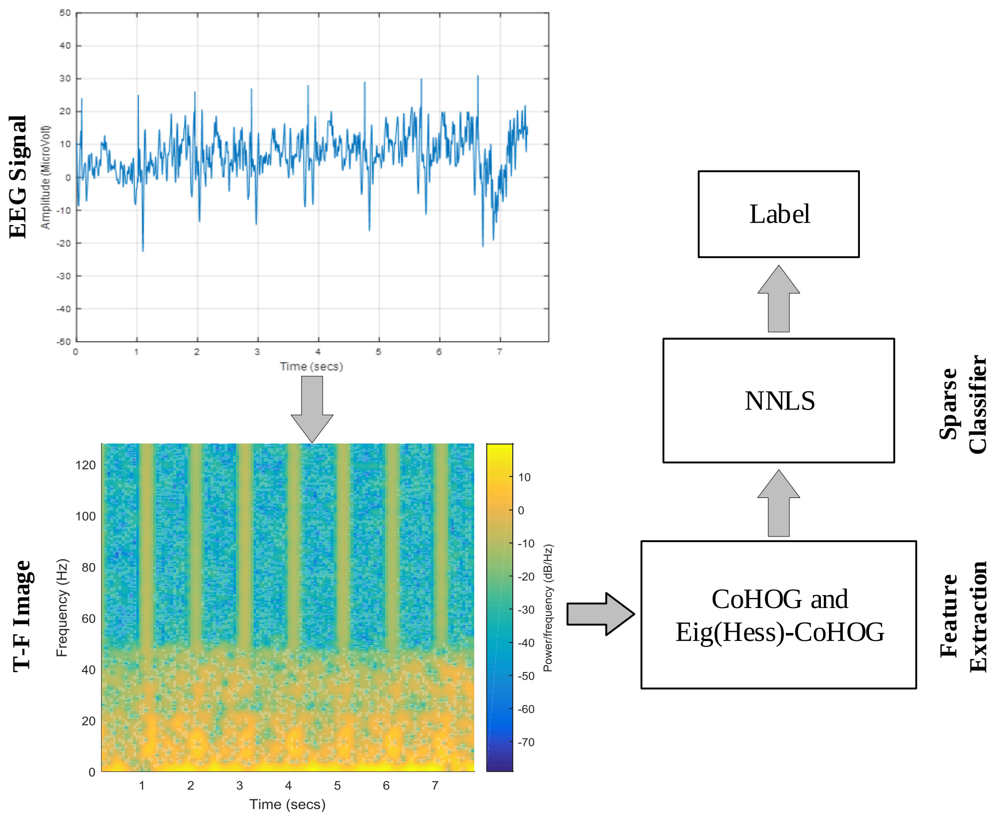


Fig. 1 Proposed Method

3. Background

3.1. Spectrogram

The discrete time STFT of $x[m]$ is defined as;

$$X(n,\omega) = \sum_{m=-\infty}^{m=\infty} x[m]w[n-m]e^{-j\omega n} \tag{1}$$

The discrete STFT is defined as [20];

$$X(n,k) = X(n,\omega)\Big|_{\omega=\frac{2\pi k}{N}} \tag{2}$$

where the window function $w[m]$ centered at time n is multiplied with the signal $x[m]$ before the Fourier transform. The window function is viewing the signal just close to the time n and the Fourier transform will be an estimate locally around n. The usual way of finding the STFT is to use a fixed positive even window, $w[m]$, of a certain shape, which is centered on zero and has unity power. Similar to the ordinary Fourier transform and spectrum we can formulate the spectrogram as;

$$S(n,k) = \left|X(n,\omega)\right|^2 \tag{3}$$

which is used very frequently for analyzing time-varying and non-stationary signals.

3.2 CoHOG and Eig(Hess)-CoHOG features

HOG is known as popular rotational invariant texture descriptors based on local gradients [21]. HOG outlines the distribution of gradient orientations in image and is particularly helpful in classification of textured objects having deformable shapes. A HOG feature is computed locally on each key point from a block. A key point is a center of the central cell of block. Neighbor region of each key point is divided into different cells. A histogram on gradient orientations is built over all the pixels of the cell. The histogram entries of all cells constitutes the feature on all key points [22]. Simple one-dimensional mask ($\left[-1;0;1\right]$) is used to compute gradient magnitude on gray scale image as:

$$f_x(x,y) = I(x+1,y) - I(x-1,y) \quad \forall x,y$$

$$f_y(x,y) = I(x,y+1) - I(x,y-1) \quad \forall x,y \tag{4}$$

where f_x and f_y denotes image gradient on x and y components. $I(x,y)$ is the pixel intensity at position (x,y). The magnitude and orientation are calculated as:

$$m(x,y) = \sqrt{f_x(x,y)^2 + f_y(x,y)^2} \tag{5}$$

$$\theta(x,y) = \tan^{-1}\left(\frac{f_y(x,y)}{f_x(x,y)}\right) \tag{6}$$

The orientation is assigned into eight bins. The corresponding orientation bins are built and orientation's magnitude $m(x,y)$ is voted on each bin. Orientation histogram of every cell and spatial blocks are normalized as:

$$h'_{(i,j)} = \frac{h'_{(i,j)}}{\sqrt{\left|v\right|^2 + \varepsilon}} \quad (\varepsilon = 1) \tag{7}$$

where v denotes feature vector and $h_{(i,j)}$ is un-normalized histogram of the cell at the position (i,j). The co-occurrence histogram of oriented gradient (CoHOG) feature is based on a co-occurrence matrix obtained from a 2D histogram of pairs of gradient orientations [23, 24]. The combinations of neighbor gradient orientations provide reliable features of objects in classification problems. The CoHOG is employed on grayscale image in the proposed method as:

$$C_{i,j} = \sum_{p=0}^{n-1}\sum_{q=0}^{m-1}\begin{cases} 1 & \text{if } I(p,q) = i \text{ and } I(p+x, q+y) = j \\ 0 & \text{otherwise} \end{cases} \tag{8}$$

where I is a gradient orientation image, i and j indicates gradient orientations, and x, y denotes the offsets on vertical and horizontal orientations. The orientations of gradient are computed as:

$$\theta = \arctan \frac{v}{h} \tag{9}$$

where v and h are the vertical and the horizontal components of gradient obtained using appropriate filters.

For Eig(Hess)-CoHOG features, the Hessian matrix H is computed as a second-order partial derivative matrix of grey scale image I for a scale σ.

$$H_{\sigma}(x,y) = \begin{bmatrix} D_{xx} & D_{xy} \\ D_{yx} & D_{yy} \end{bmatrix} = \begin{bmatrix} I * G_{xx} & I * G_{xy} \\ I * G_{xy} & I * G_{yy} \end{bmatrix} \tag{10}$$

where $*$ operator shows the convolution operation, D_{xx} , D_{yy} and D_{xy} are the second-order derivative of the image along x , y and xy directions, respectively. G_{xx} , G_{yy} and G_{xy} are the second-order derivative filter of the image along x , y and xy directions, respectively. Eigenvalues and eigenvectors of the Hessian matrix are used to obtain the principal directions and principal curvatures on surface of image.

$$\lambda = \pm \sqrt{\frac{\left(I * G_{xx} - I * G_{yy}\right)^2}{4} + \left(I * G_{xy}\right)^2} + \frac{I * G_{xx} - I * G_{yy}}{2} \tag{11}$$

where λ are the Eigenvalues of the Hessian matrix. The Eigen analysis of the Hessian matrix is important for texture analysis. In [24], gradient magnitude and orientations were calculated using the Eigenvalues λ_1 and λ_2 .

Thus, the Eig-HOG feature, the gradient magnitude and orientation can be calculated as:

$$I_{\theta gradient} = \sqrt{(\lambda_1)^2 + (\lambda_2)^2} \tag{12}$$

$$\theta = \arctan\left(\frac{\lambda_2}{\lambda_1}\right) \tag{13}$$

3.3 Non-negative least squares (NNLS) classifier

Let's suppose a set of training data $X \in R^{m\times n}$ and a set of test data $S \in R^{m\times p}$ are given, where the columns of the data sets show the sample and each row shows a feature.The corresponding class labels for these n training data samples are $\{0,1,\dots,C-1\}$respectively, where C denotes number of classes. The non-negative matrix factorization (NMF) can be formulated as;

$$\min_{A,Y} \frac{1}{2} ||X - AY||_F^2 ,\ \text{s.t. } A,Y \geq 0 \tag{14}$$

where X must be non-negative and $||.||_{\mathrm{F}}^2$ is the *Frobenius* norm. Similarly, semi-NMF can be defined as;

$$\min_{A,Y} \frac{1}{2} ||X - AY||_F^2 ,\ \text{s.t. } Y \geq 0 \tag{15}$$

In the above equations negative values are allowed in X and A. In NMF each sample is approximated by the non-negative superposition of the basis vectors [25]. In NNLS, the training dataset is firstly replaced with the basis vectors, thus Eq. (15) can be redefined as;

$$\min_Y \frac{1}{2}||S - XY||_F^2, \text{ s.t. } Y \geq 0 \tag{16}$$

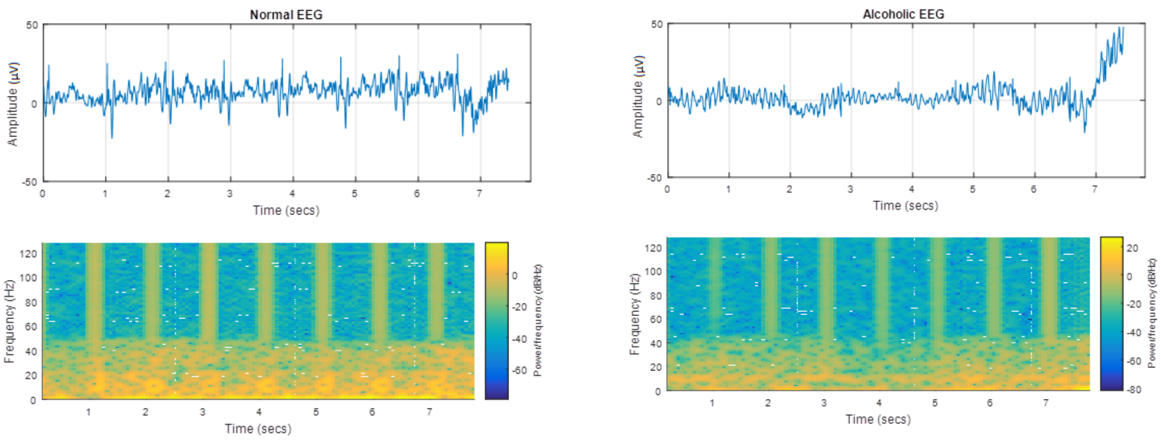
The approximation is handled by a non-negative and sparse superposition of the training samples. The class labels are then predicted by a sparsity interpretation as given;

$$p_i \leftarrow \text{MAX}(y_i) \tag{17}$$

where p_i shows the *ith* test data.

4. Results and Discussions

To show the efficiency of our proposal, the experiments were conducted on the EEG dataset which contains both alcoholic and control persons' EEG signals. The EEG dataset which is available online in [26] is used. In this section, a short description is given and please refer to [27] for further detail. 64 electrodes are used to acquire EEG signals, sampling frequency is 256 Hz. The dataset used in proposed method contains 120 files with the length 2048 samples from each alcoholic and control EEG signals.



(a) (b)

Fig. 2 T-F representation of EEG signals. (a) Control EEG signal, (b) Alcoholic EEG signal

The EEG signals were firstly converted to T-F domain by using the spectrogram method. T-F domain provides more inside information of EEG signals. The T-F representation of control and alcoholic EEG signals is given in Fig 2 (a) and (b), respectively. In spectrogram presentation, Hamming window was considered. T-F domain representations were then converted to gray scale images. The T-F representation of the alcoholic and control EEG signals have texture. These texture nature can be used to differentiate control and alcoholic EEG signals. Nowadays, HOG is known as a robust texture descriptor and consequently, CoHOG characterises the occurence of HOG in a given texture. in addition recently proposed Eig(Hess)-CoHOG is another powerfull texture descriptor. Thus, we considered these features for classifiying the control and alcoholic EEG signals that is represented by T-F images. For computing CoHOG and Eig(Hess)-CoHOG features, the number of orientation bins was selected as 8 and 4x4 squared grid was chosen for each key point. Thus a 128 element HOG feature vector was obtained. The orientations in the range $(0, 2\pi)$ are quantized into eight labels thus the co-occurrence matrix size became 8x8. Six offsets were considered in experimental works. Thus, the dimensionality of the CoHOG descriptor became 1536 [28]. On the other hand, for calculating the Eig(Hess)-CoHOG features, the orientations labels in the range $(0,2\pi)$are quantized into seven labels. These caused a reduction in the dimensionality of the obtained feature vector. The total dimensionality of the Eig(Hess)-CoHOG became 1176. Finally, CoHOG and Eig(Hess)-CoHOG features was concatenated. The final dimensionality of each feature vector was 2712 and each feature vector was normalized according to the zero mean and unit variance criteria.

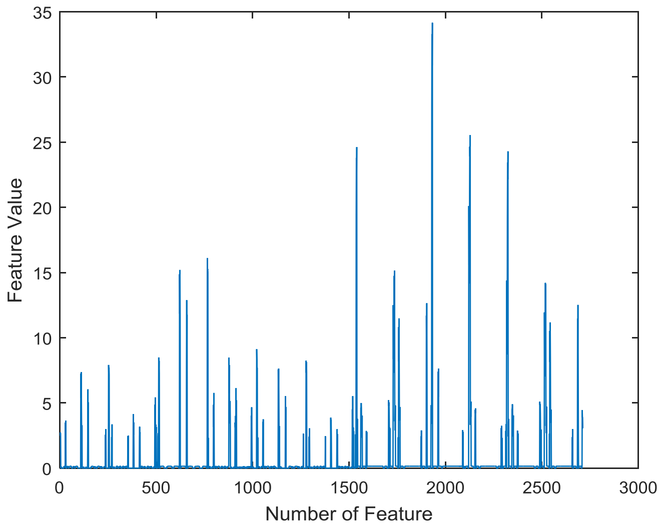


Fig. 3 A feature vector for control EEG signal

As it was mentioned earlier, NNLS classifier was used due to the sparse nature of the feature matrix. A feature vector for control EEG signal is represented in Fig. 3. As can be seen in Fig 3, most of the feature values are zero. In other words, 63.86% of the feature vector is 0. In the experiments, the following parameters were used; the kernel function was chosen as linear, the prediction rule was chosen as nearest neighbor and sparsity threshold was chosen as 0.0001. We also experimented with other parameters, but we did not get any performance improvement. The performance of the proposed algorithm was computed by classification accuracy, sensitivity and specificity. It is worth to mentioning that the experimental results were recorded using 10-fold cross validation. The experimental results were tabulated in Table 1.

Table 1 Performance evaluation results with different feature set

Features set	**Classifier**	**Sensitivity (%)**	**Specificity (%)**	**Accuracy (%)**
CoHOG		91.67	91.67	91.67
Eig(Hess)-CoHOG	**NNLS**	100	83.33	91.67
CoHOG &CoHOG Eig(Hess)		100	91.67	95.83

As can be seen in Table 1, concatenation of the CoHOG and Eig (Hess)-CoHOG features yielded the highest accuracy and sensitivity values (95.83 % and 100%) while individually CoHOG and Eig (Hess)-CoHOG features yielded same accuracy and sensitivity value (91.67%).

In order to asses the effectivess of the proposed NNLS classifier, we performed more experiments for comparing the performances of some well-known classifiers such as, Artificial Neural Networks (ANN), k-nearest neighbor (KNN), Linear Discriminant Analysis (LDA) and Support Vector Machine (SVM). We achieved highest performance for the proposed NNLS classifier with the CoHOG & CoHOG Eig(Hess) features. All classifier's parameters were tuned accordingly. The ANN had a single hidden layer and it trained with Levenberg-Marquardt learning rule. The activation function in the hidden layer was chosen as sigmoid. In KNN classifier, we performed several experiments with various K values. The best performance was obtained with K=5. The Euclidean distance was used for similarity measure. On the other hand, for LDA, we used the Fisher method for minimizing the errors in the least square sense. Finally, for SVM, Radial Basis Function was used as kernel. The parameters of the RBF were set based on the experiments. The optimum sigma=0.01 and C=100 values were assigned.

Table 2 A Comparison report for various classifiers

	Classifiers				
	ANN	KNN	LDA	SVM	**NNLS**
F-measure	0.8750	0.8333	0.7730	0.9285	**0.9538**
Kappa	0.7500	0.6667	0.5417	0.8333	**0.9167**
Specificity	0.8750	0.8750	0.8333	**0.9583**	0.9167
Sensitivity	0.9583	0.7500	0.7500	0.9167	**100**
Accuracy	91.67%	81.25%	79.17%	93.75%	**95.83%**

We compared the classifiers based on Receiver operating characteristics (ROC) curve, F-measure and Kappa values. Higher F-measure and Kappa values show the efficiency of the classifier. According to the Table 2, the proposed method yielded the best results. 0.9538 F-measure value and 0.9167 Kappa value was tabulated in Table 2 for NNLS classifier. The second best results were obtained with SVM. ANN and KNN obtained the third and fourth best results respectively. The worst result was yielded with LDA classifier. These evaluation results were supported by the ROC curves that were illustrated in Fig. 4. When we consider the area under the ROC curve by visually, the biggest area under the ROC curve was constructed by NNLS which showed the efficiency of our proposed method.

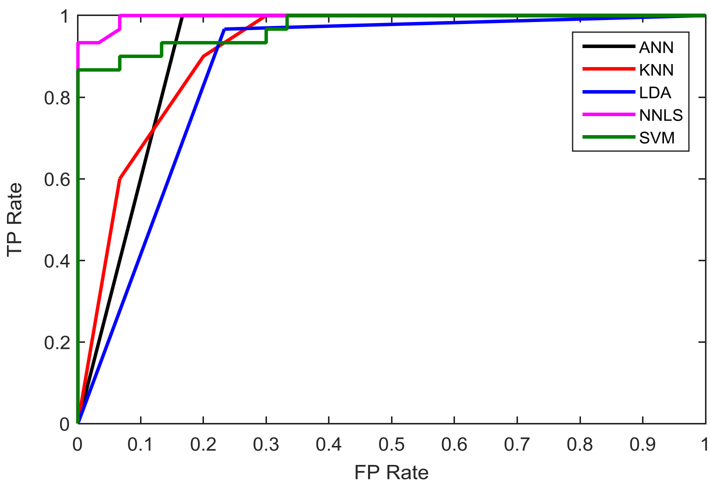


Fig. 4 Performance of the ROC curves for the reported classification methods

The performance results of proposed method are compared with other published methods handling the classification problem in the same datasets. It can be notice from Table 3, that our proposal yielded a better accuracy than the existing methods.

Table 3 A Comparison report for the proposed method with the existing methods

Authors	Features	Classifiers	Performance (Accuracy)
Ehlers et al. [15]	Correlation dimension	Discriminant analysis	88%
Kannathal et al. [16]	CD, LLE, entropy, H	Unique ranges	90%
Acharya et al. [18]	ApEn, SampEn, LLE, HOS	SVM with poly kernel	91.3%
Faust et al. [19]	WPD — Relative energy	kNN	95.8%
Proposed Method	**CoHOG and Eig(Hess)-CoHOG**	**NNLS**	**95.83%**

ApEn=Approximate entropy; SampEn=Sample entropy; LLE=Lyapunov exponent; HOS=Higher order spectra WPD=wavelet packet decomposition; CD=correlation dimension; H=Hurst's exponent;

5. Conclusions

In this paper, a hybrid method is proposed for classification of alcoholic and control persons along with their EEG signals. The proposed hybrid method is based on T-F images, texture image feature extraction and NNLS classifier. In T-F analysis the spectrogram of the STFT is considered. CoHOG and Eig(Hess)-CoHOG features are extracted from T-F images. The experimental results show the efficiency of our proposed method. One important observation from the results is that concatenated feature vector yields the best accuracy. It is also worth to mentioning that accuracy is the highest one between the reported results. In future, this proposed method can help psychologist to identify physiological states of the brain for better treatment. The method has used high dimensional features vector in future some features reduction technique can be analyzed.

Disclosure of potential conflicts of interest: No conflicts of interest
Research involving human participants and/or animals: The dataset of EEG signals used is online available.
Informed Consent: Yes

References

1. Harper C (2007) The neurotoxicity of alcohol. Hum Exp Toxicol 26: 251–257.
2. Brust JC (2010) Ethanol and cognition: indirect effects, neurotoxicity and neuroprotection: a review. Int J Environ Res Public Health 7: 1540–1557.
3. Harper C (2009) The neuropathology of alcohol-related brain damage. Alcohol 44: 136–140.
4. Zahr NM, Kaufman KL, Harper CG (2011) Clinical and pathological features of alcohol-related brain damage. Nat Rev Neurol 7: 284–294.
5. Misulis KE, Spehlmann's Evoked Potential Primer, Visual, Auditory and Somato sensory Evoked Potentials in Clinical Diagnosis, Butterworth-Heinemann, 1994.
6. Zhang XL, Begleiter H, Porjesz B, Litke A (1997) Electrophysiological evidence of memory impairment in alcoholic patients. Biological Psychiatry, 42: 1157-1171.

7. Siuly S, Li Y, (2015) Designing a robust feature extraction method based on optimum allocation and principal component analysis for epileptic EEG signal classification. Computer Methods and Programs in Biomedicine 119(1): 29–42.
8. Siuly S, Li Y. (2014) A novel statistical framework for multiclass EEG signal classification. Engineering Applications of Artificial Intelligence, vol. 34, pp. 154–167.
9. Ehlers CL, Havstad JW (1982) Characterization of drug effects on the EEG by power spectral band time series analysis. Psychopharmacol Bull 18: 43– 47.
10. Ehlers CL, Reed TK (1987) Ethanol effects on EEG spectra in monkeys: comparison to morphine and diazepam. Electroencephalogr Clin Neurophysiol 66: 317–321.
11. Yazdani A, Ataee P, Setarehdan SK, Araabi BN, Lucas C (2007) Neural, fuzzy and neurofuzzy approach to classification of control and alcoholic electroencephalograms, Proceedings of the 5th International Symposium on Image and Signal Processing and Analysis, 102 – 106, 2007.
12. Kousarrizi MRN, Ghanbari AA, Gharaviri A, Teshnehlab M, Aliyari M (2009) Classification of alcoholics and non-alcoholics via EEG using SVM and neural network, 3rd International Conference on Bioinformatics and Biomedical Engineering, Beijing, China, 1-4, June 2009.
13. Sun Y, Ye N, Xu X (2006) EEG analysis of alcoholics and controls based on feature extraction, 8th International Conference on Signal Processing, 2006.
14. Countin-Churchman P, Moreno R, Anez Y, Vergara F (2006), Clinical correlates of quantitative EEG alternations in alcoholic patients, Clinical Neurophysiology 117: 740-751.
15. Ehlers CL, Havstad J, Prichard D, Theiler J (1998) Low doses of ethanol reduce evidence for nonlinear structure in brain activity. J Neurosci 18(18):7474–86.
16. Kannathal N, Acharya UR, Lim CM, Sadasivan PK (2005) Characterization of EEG - a comparative study. Comput Methods Programs Biomed 80(1):17–23.
17. Faust O, Acharya UR, Alen A, Lim CM (2008) Analysis of EEG signals during epileptic and alcoholic states using AR modeling techniques. Innov Techn ol Biol Med (ITBM-RBM) 29(1):44–52.
18. Acharya UR, Sree SV, Chattopadhyay S, Suri JS (2012) Automated diagnosis of control and alcoholic EEG signals. Int J Neural Syst 22(3): 1250011 .
19. Faust O, Yu W, Kadri NA (2013) Computer-based identification of normal and alcoholic EEG signals using wavelet packets and energy measures. J Mech Med Biol 13(3):1350033 (17 pp).
20. Allen JB (1997) Short-term spectral analysis and synthesis and modification by discrete Fourier transform, IEEE Trans. Acoust., Speech, Signal Processing, 25(3): 235-238.
21. L. Liu, Fieguth P, Clausi D, Kuang G (2012) Sorted random projections for robust rotation-invariant texture classification, Pattern Recogn. 45: 2405–2418.
22. Chen PY, Huang CC, Lien CY, Tsai YH (2014) An efficient hardware implementation of HOG feature extraction for human detection, IEEE Trans. Intell. Transp. Syst. 15 (2): 656–662.
23. Watanabe T, Ito S, Yokoi K (2009) Co-occurrence histograms of oriented gradients for pedestrian detection. Lect. Notes Comput. Sci. 5414: 37–47.
24. Hanbay K, Alpaslan N, Talu MF, Hanbay D, Karci A, Kocamaz AF (2015) Continuous rotation invariant features for gradient-based texture classification. Computer Vision and Image Understanding, 132: 87-101.

25. Li Y, Ngom A (2013) Non-negative least squares for the classification of high dimensional biological data. IEEE/ACM Transactions on Computational Biology and Bioinformatics 10(2): 447-456.
26. American Electroencephalographic Association 1990. Standard electrode position nomenclature, <http://kdd.ics.uci.edu/databases/eeg/eeg.data.html/>; 2007.
27. Zhang XL, Begleiter H, Porjesz B,Wang W, Litke A (1995) Event related potentials during object recognition task. Brain Res Bull 38: 531–8.