Efficient method for classification of alcoholic and normal EEG signals using EMD

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Abstract: The electroencephalogram (EEG) signal is an electrical representation of brain's working that reflects various physiological and pathological activities such as alcoholism. Alcohol can affect whole parts of the body but, it particularly affects the brain, heart, liver, and the immune system; its effects on the brain are called brain disorders. Nowadays, automatic identification of alcoholic subjects based on EEG signals has become one of the challenging problems in biomedical research. In this study, an automatic classification method for classifying alcoholic and normal EEG signals, based on empirical mode decomposition (EMD), is proposed. The uniqueness of EMD method is to decompose non-stationary and non-linear signals into a set of stationary intrinsic mode functions (IMFs) that are band limited signals. These IMFs are transformed into analytic representations by applying the Hilbert transform. From these analytic IMFs, various features namely mean, kurtosis, skewness, entropy, and negentropy are extracted; these features are used as input to least squares support vector machines (LS-SVMs) classifier with radial basis function (RBF) kernel and polynomial kernel. The accuracy results achieved for LS-SVM classifier with polynomial and RBF kernels are found to be 96.67 and 97.92%, respectively, which are found to be better as compared with other state-of-the-art methods.

1 Introduction

Alcoholism and alcohol abuse can affect all aspects of a person's life. It also brings him a lot of difficulties and discomfort in his social life [1], and particularly on his physical health, it brings forth a lot of harmful effects that include, to name a few, lack of co-ordination between body and mind, loss of vision, imbalance in walking, incoherent speech, memory slips, and depression and so on. Due to alcoholism, ∼2.5 million people die every year; it is the third highest risk factor for causing diseases as reported by the World Health Organization (WHO) [2]. Long-term consumption of alcohol impairs the development of human brain [3], whereas short-term consumption causes effects of memory impairment, black out, recklessness, impaired decision making and so on. According to the national institute on alcohol abuse and alcoholism, chronic consumption of alcoholism causes diminished ability to think, loss of visuospatial abilities, Wernicke–Korsakoff syndrome, memory loss, and loss of attention span [4].

The identification of alcohol in subjects is a challenging task because the standard devices are based on the smell of drink, which can be easily influenced. Recently, it has been observed that the consumption of alcohol changes the brain activities of a person from the normal condition and these changes are synchronised with excitation and inhibition situation of the alcoholic brain [5]. Various methods have been proposed for the classification of alcoholic and normal electroencephalogram (EEG) signals. The methods include, but not limited to, the support vector machines (SVMs) and neural network (NN) classifiers based method for classification of EEG signals using power spectrum of Haar-mother wavelet for features' extraction [6], computer-based identification method using features extracted from the wavelet packet decomposition (WPD) and energy measures for classification of normal and alcoholic subject's EEG signals [7, 8], and wavelet transform-based method from which five different frequency bands (alpha, beta, theta, gamma, and delta) are recognised with their power spectrum; the method observes that the value of power for theta and delta rhythms increases in alcoholic subject's EEG signal, whereas alpha rhythm's power decreases in normal EEG signal [9].

The optimal selection of features is carried out based on separability and correlation analysis for classification of alcohol and normal EEG signals [10]. In [11], computer aided diagnosis system with features based on energy and power of EEG signal has been used for the diagnosis of alcoholic and normal signals. The second-order autoregressive (AR) method has been proposed in [12] to discriminate alcoholics using Visual Evoked Potential (VEP) signals and single trial gamma band. An automatic machine learning method involving quantitative electroencephalography (QEEG) features has been proposed in [13] for automatic classification of alcoholic disorders. In [14], the reflection coefficients, which are extracted by using autocorrelation values, have been used as features to discriminate characteristic of alcoholic and normal EEG signal. Another method to classify alcoholic and normal EEG signals, on the basis of features extracted from VEP NN, has been proposed in [15], whereas Palaniappan [16] proposes a method that uses multiple gamma bands of EEG signal to discriminate chronic alcoholic EEG signals from non-chronic alcoholic signals. The latest research trend is in the exploration of features based on signal entropies [17], relative energy [18], and time–frequency images [19, 20].

In this paper, an effective methodology for classification of alcoholic and normal EEG signal is proposed, where features are extracted from the EEG signal by applying empirical mode decomposition (EMD) over it that yields various intrinsic mode functions (IMFs). These IMFs are then transformed into analytic signals. From the analytic IMFs, five significant features namely entropy, negentropy, kurtosis, skewness, and mean of the IMFs are extracted, which are then fed as input to the least-squares SVMs (LS-SVMs) classifier that uses radial basis function kernel and polynomial kernel for the discrimination of alcoholic EEG signal with normal. Since, the performance of any classifier depends upon the selection of its features, which in the proposed method have been meticulously selected; as a result, they yield a classification accuracy of 97.92% for LS-SVM classifier with RBF kernel, which is found to be better than the other existing methods. The remaining of the paper is organised as follows. Section 2 gives details about the dataset of EEG signals, the EMD method, and the features description. Section 3 presents the proposed methodology. Results and discussion are given in Section 4. Finally, Section 5 concludes the paper.

2 Material and methods

2.1 Dataset

The EEG dataset used in this paper contains two classes of EEG signal data: alcoholic and normal as denoted by the symbols A and NA, respectively. The database is collected from 122 subjects taking 120 trials from each subject with different stimuli. The signals are measured by placing 64 electrodes on the subject's scalp. The database is sampled at the sampling frequency of 256 Hz. In this paper, a signal of length 2000 samples is considered for testing. The database is obtained from an online source reported in [21]. Fig. 1 depicts the example of an alcoholic and normal EEG signal, where Fig. 1*a* shows the plot of alcoholic EEG signal and Fig. 1*b* shows the plot of normal EEG signal.

2.2 Empirical mode decomposition

EMD is a data dependent and adaptive method that does not require any prior information about the linearity and stationarity of the signal. It is the most powerful and useful technique for decomposition of real-time signals into a small and finite set of amplitude and frequency modulated oscillating components, which are called as intrinsic mode functions (IMFs). These IMFs can be considered as a set of narrow-band symmetric waveforms. These IMFs have two basic characteristics, defined as [17]

(i) The difference between the count of zero crossings and the count of peaks (minima or maxima) is either zero or utmost differ by one.
(ii) At any instant of time, the mean of the envelopes defined by local maxima and local minima is zero.

A signal through EMD undergoes following steps [22, 23]:

- At first, maxima, and minima of the signal ($x(t)$) are identified.
- Then, envelops of local minima and maxima, denoted as $e_h(t)$ and $e_l(t)$, respectively, are obtained by using cubic spline interpolation. Then local mean is calculated as $h(t) = [e_l(t) + e_h(t)]/2$.
- Now, the detail is extracted from the basic signal as $I_1(t) = x(t) - h(t)$.
- Now, the $I_1(t)$ signal is checked for the aforementioned two basic conditions of IMFs.
- Steps 1–3 are repeated until an IMF is obtained.

Once the first IMF, which is defined as $m_1(t) = I_1(t)$ and which is the smallest temporal scaling of $x(t)$, is derived, a residue ($r_1(t) = x(t) - m_1(t)$) gets generated, which is then treated as a new signal for calculating remaining IMFs. The above process is repeated until either the final residue has a constant value or if no more IMFs can be extracted from the signal. EMD plots for alcoholic and normal EEG signals are depicted in Figs. 2 and 3, respectively.

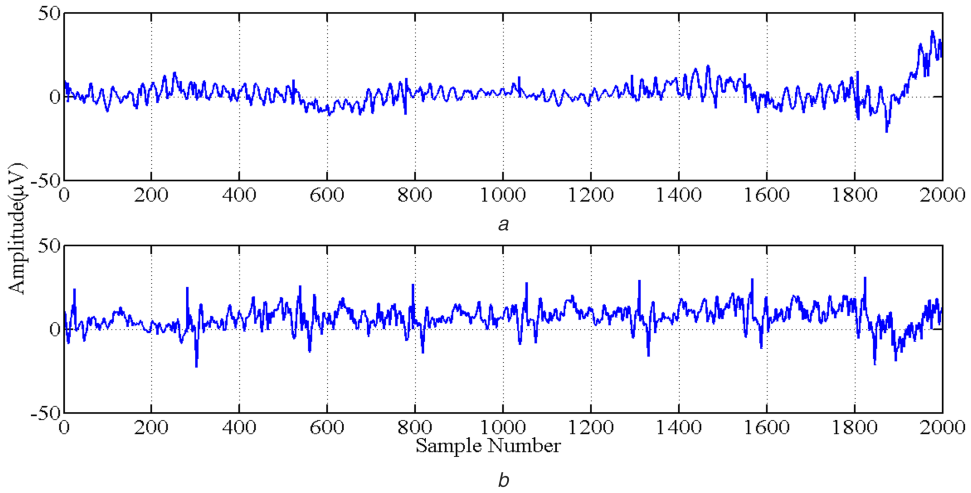

Fig. 1 *EEG signals*
a Alcoholic
b Normal

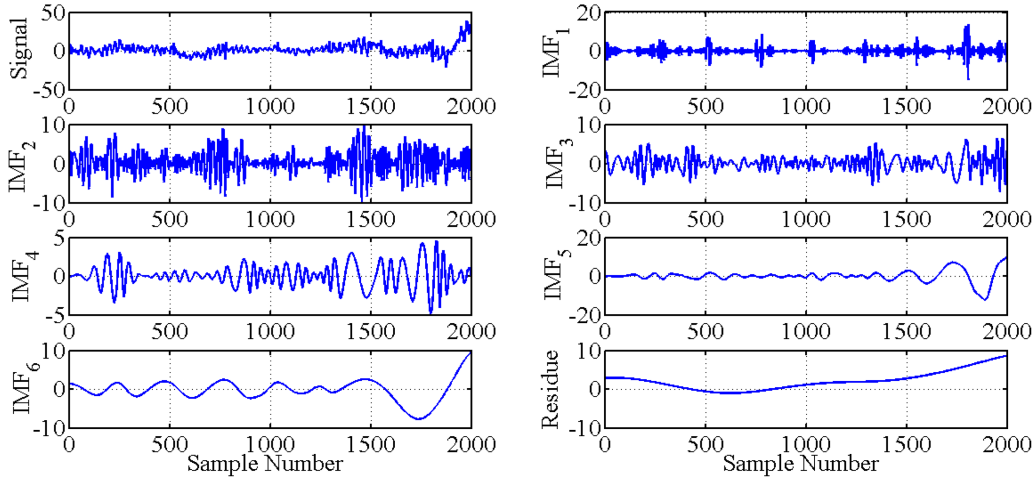

Fig. 2 *EMD of alcoholic EEG signal*

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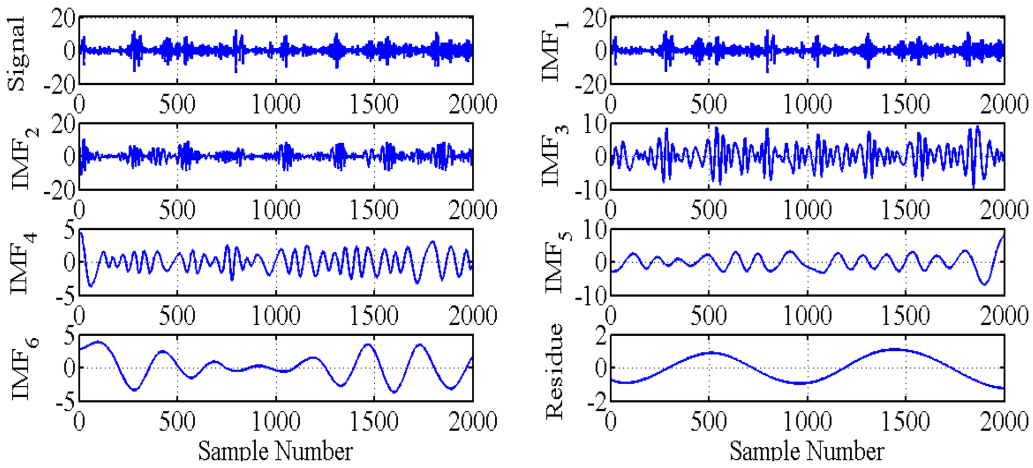

Fig. 3 *EMD of normal EEG signal*

Mathematically, the signal ($x(t)$) after EMD can be expressed as

$$x(t) = \sum_{p=1}^{Q} I_p(t) + r_Q(t) \tag{1}$$

where $I_p(t)$ is the pth IMF and $r_Q(t)$ is the final residue for total Q number of IMFs. The analytic representation ($z(t)$) of any IMF ($I(t)$) can be defined as

$$z(t) = I(t) + \mathrm{j}I_{\mathrm{H}}(t) = A(t)\,\mathrm{e}^{\mathrm{j}\varphi(t)} \tag{2}$$

where $I_{\mathrm{H}}(t)$ indicates the Hilbert transform of any IMF ($I(t)$). The amplitude of an analytical signal is calculated as

$$A(t) = \sqrt{I^2(t) + I_{\mathrm{H}}^2(t)} \tag{3}$$

The phase ($\varphi(t)$) and instantaneous frequency ($\omega(t)$) of the analytic signal ($z(t)$) are represented by the expressions, given as

$$\varphi(t) = \tan^{-1}\left[\frac{I_{\mathrm{H}}(t)}{I(t)}\right] \tag{4}$$

$$\omega(t) = \frac{\mathrm{d}\varphi(t)}{\mathrm{d}t} \tag{5}$$

2.3 Features extraction from IMFs

This section gives an explanation about the features that have been extracted from the analytic IMFs and are used with LS-SVM classifier as input; the description is as follows:

(i) *Mean:* It is the statistical mean of the analytic IMF ($z(t)$), which is defined as

$$\mu_i = \frac{1}{M}\sum_{t=1}^{M} z(t) \tag{6}$$

where μ_i is the mean of ith IMF and M is the total number of samples in the IMF. In this paper, higher-order statistical features like kurtosis and skewness are also used for the classification of EEG signal in EMD domain.

(ii) *Skewness:* It is a measure of the asymmetry of the probability distribution of a real-valued random variable about its mean. It can be positive or negative or even undefined. The skewness for a normal distribution is zero and any symmetric data should have skewness to be nearly zero. The negative value for the skewness indicates that the data are skewed left, whereas the positive value indicates that the data are skewed right. The mathematical expression for skewness (β_i) is given as

$$\sigma_i = \sqrt{\frac{1}{M}\sum_{t=1}^{M}\left(z_t - \mu_i\right)^2} \tag{7}$$

$$\beta_i = \frac{1}{M}\sum_{t=1}^{M}\left(\frac{z_t - \mu_i}{\sigma_i}\right)^3 \tag{8}$$

where σ_i is the standard deviation of analytic signal ($z(t)$).

(iii) *Kurtosis:* It is a measure of the 'tailedness' of the probability distribution of a real-valued random variable; it is denoted as $\boldsymbol{k}_i$. Its mathematical representation is given as [24]

$$\boldsymbol{k}_i = \frac{1}{M}\sum_{t=1}^{M}\left(\frac{z_t - \mu_i}{\sigma_i}\right)^4 \tag{9}$$

(iv) *Entropy:* It is a measure of randomness of a signal. Here, two random variables are used to extract the uncertainty. The large entropy of a random variable indicates its large uncertainty and vice versa. Mathematically, entropy is defined as

$$H(P) = -\sum_{i=1}^{N} P_i \log\left(P_i\right) \tag{10}$$

where $P_i = [P_1, P_2, \ldots, P_n]$ is probability distribution obtained for each IMF ($c_i(t)$).

(v) *Negentropy:* It is the difference between the differential entropy of Gaussian density ($H(\boldsymbol{P}_{\mathrm{G}})$), having same mean and variance as that of P, and the differential entropy of P ($H(P)$). It is defined as [25]

$$H(P_{\mathrm{G}}) = \frac{1}{2}\log\left((2\pi e)^n \sigma^2\right) \tag{11}$$

$$J(P) = H(\boldsymbol{P}_{\mathrm{G}}) - H(P) \tag{12}$$

where $\boldsymbol{P}_{\mathrm{G}}$ is the Gaussian random vector of the same mean and variance (σ^2) as that of P, and n is the dimension of P.

3 Methodology

In this paper, a two-class classification method for classifying normal and alcoholic EEG signals is proposed. The overall

methodology has been explained in the block diagram given in Fig. 4. According to it, firstly EEG signal is decomposed with EMD algorithm so as to obtain IMFs, then on IMFs Hilbert transform is applied to obtain their analytic representations. Then five features, given as skewness, kurtosis, entropy, negentropy, and mean of IMFs, are extracted from analytic IMFs. These features, then undergo Kruskal–Wallis (KW) statistical test for checking of their class discrimination abilities. After KW test, the features are fed as input to the LS-SVM classifier, which is used with RBF and polynomial kernel for classification of normal and alcoholic EEG signals. Detailed description of LS-SVM classifier and its kernel functions can be found in [26].

4 Results and discussion

EMD is a suitable technique used for the decomposition of nonlinear and non-stationary signals like EEG signal into a set of narrow band frequency IMFs. These narrow band IMFs ease the computation of instantaneous frequencies that are helpful for further analysis. Five features, namely, kurtosis, skewness, entropy, negentropy, and mean of IMFs are used in this paper for the discrimination of alcoholic and normal EEG signals. KW statistical test is performed on the aforementioned features of first six IMFs for discriminating the two classes. KW plots of their *p*-values, which act as a measure of their discrimination performances, are shown in Figs. 5–9 for the features given as entropy, negentropy, kurtosis, skewness, and mean, respectively. From the KW plots of all features, it is noticed that the entropy and negentropy features have the best discrimination capability for classifying the two classes of alcoholic and normal EEG signals. The *p*-values of these features entropy, negentropy, kurtosis, skewness, and mean of the IMFs for the first six IMFs are presented in Table 1. It is also validated from the table that the features, entropy, and negentropy, show the best discrimination capability for discriminating the two classes of EEG signals. The *p*-values for these two features for all six IMFs prove to be statistically significant, as they are nearly equal to zero. The rests of the features also exhibit very low *p*-values, so they also give good performance in discriminating the two classes of EEG signals.

These five features of six IMFs of EEG signal are used as input in LS-SVM classifier with polynomial kernel and RBF kernel functions for classification of the normal and alcoholic EEG signals. For testing the performance of the proposed method, the fidelity parameters given as, sensitivity (SEN), specificity (SPE), accuracy

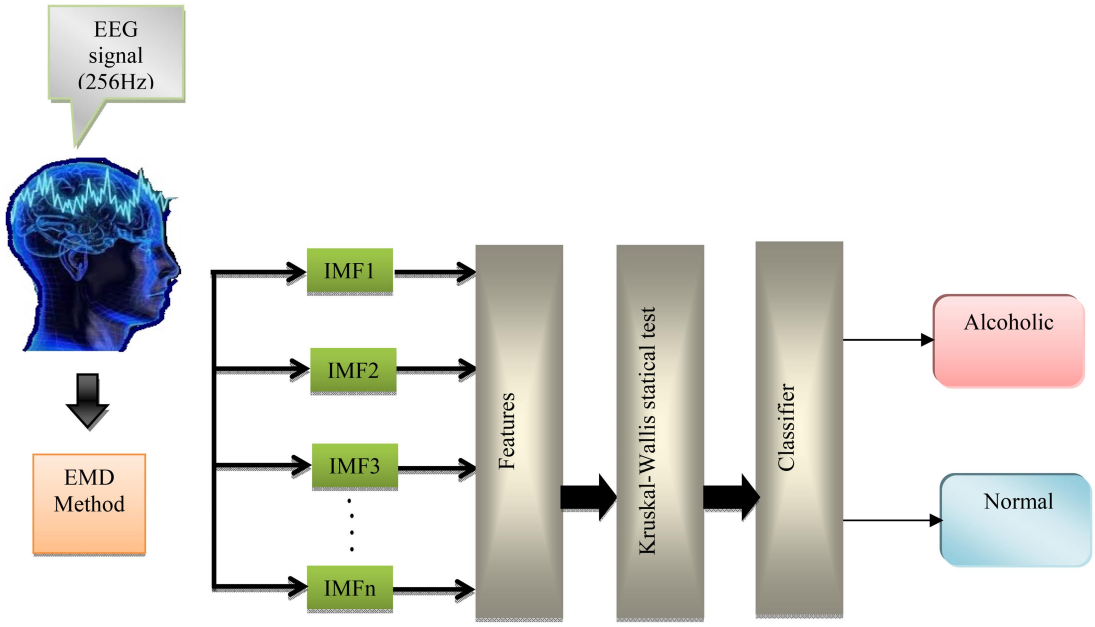

Fig. 4 *Block diagram of proposed methodology*

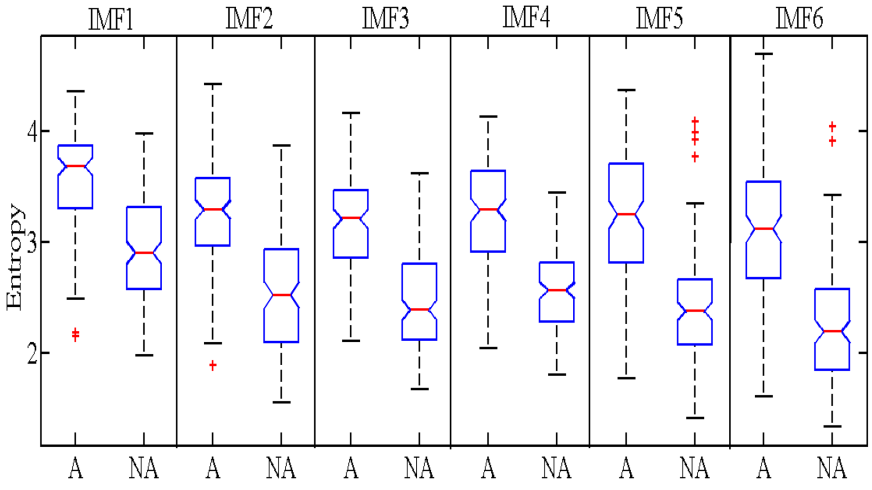

Fig. 5 *KW test performance of entropy feature for classifying alcoholic (A) and normal (NA) EEG signals*

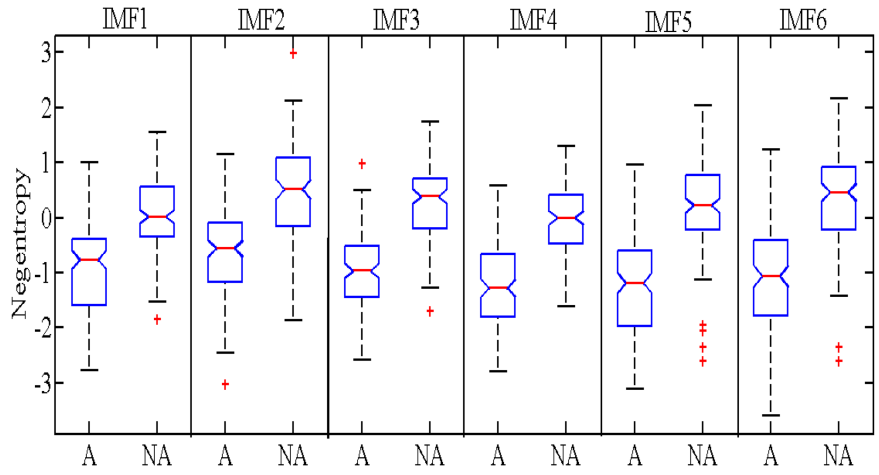

Fig. 6 *KW test performance of negentropy feature for classifying alcoholic (A) and normal (NA) EEG signals*

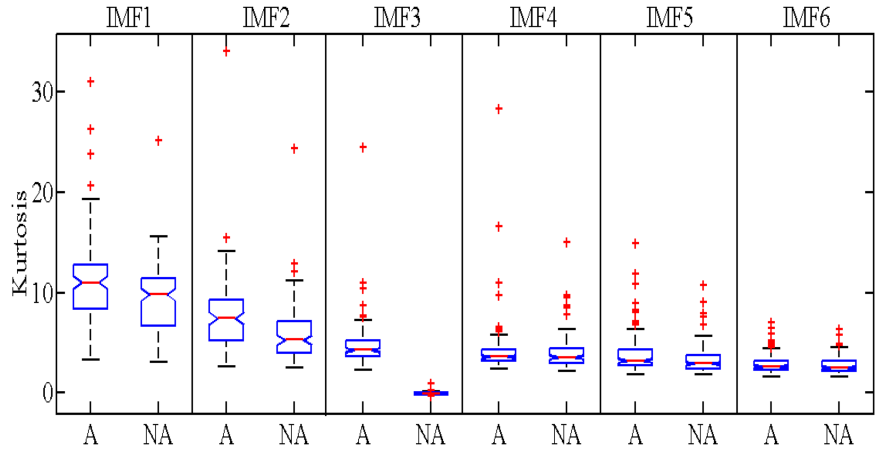

Fig. 7 *KW test performance of kurtosis feature for classifying alcoholic (A) and normal (NA) EEG signals*

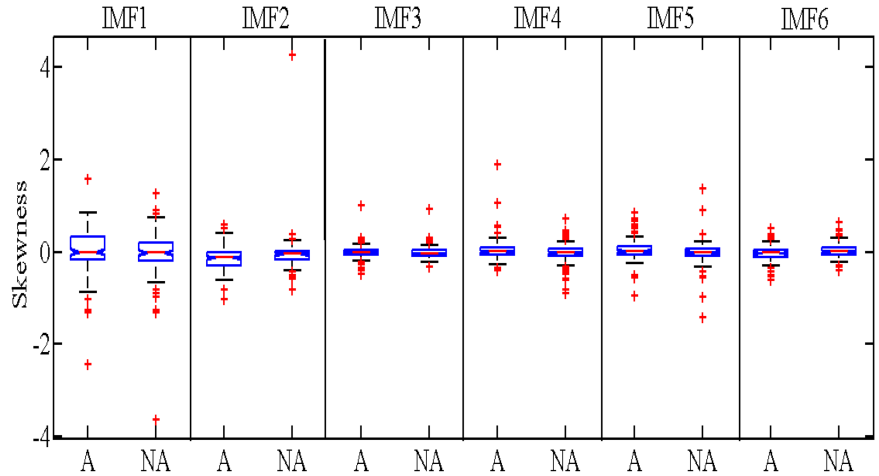

Fig. 8 *KW test performance of skewness feature for classifying alcoholic (A) and normal (NA) EEG signals*

(Acc), positive predictive value (PPV), negative predictive value (NPV), and error rate detection (ERD), are evaluated. These fidelity parameters (in percentage (%)) are defined as

$$\mathrm{SEN}(\%) = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \times 100 \tag{13}$$

$$\mathrm{SPE}(\%) = \frac{\mathrm{TN}}{\mathrm{TN} + \mathrm{FP}} \times 100 \tag{14}$$

$$\mathrm{Acc}(\%) = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}} \times 100 \tag{15}$$

$$\mathrm{VPP}(\%) = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}} \times 100 \tag{16}$$

$$\mathrm{NPV}(\%) = \frac{\mathrm{TN}}{\mathrm{TN} + \mathrm{FN}} \times 100 \tag{17}$$

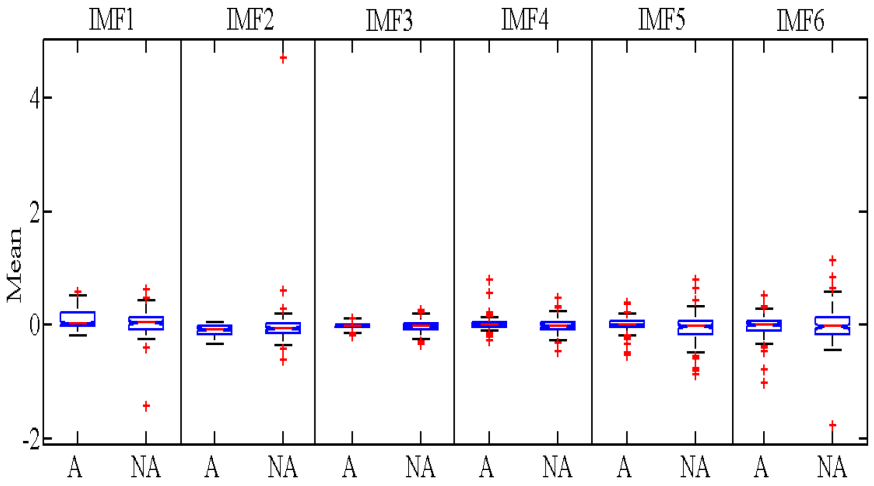

Fig. 9 *KW test performance of mean feature for classifying alcoholic (A) and normal (NA) EEG signals*

Table 1 Probability values (p-values) of features of the first six IMFs

Features	IMF1	IMF2	IMF3	IMF4	IMF5	IMF6
entropy	1.806×10^{-17}	7.825×10^{-19}	7.125×10^{-22}	5.197×10^{-23}	1.21×10^{-23}	8.792×10^{-22}
negentropy	5.473×10^{-18}	5.128×10^{-18}	2.919×10^{-23}	2.413×10^{-24}	1.976×10^{-26}	2.467×10^{-23}
kurtosis	0.0023	3.279×10^{-6}	0.0036	0.4581	0.005	0.1776
skewness	0.4525	0.0164	0.2694	0.0828	0.0736	0.0043
mean	0.063	0.2239	0.3652	0.0586	0.0224	0.6621

Table 2 Performance results of LS-SVM classifier with RBF kernel for classification of alcoholic and normal EEG signals in terms of fidelity parameters

IMFs	TN	TP	FN	FP	ACC, %	SEN, %	SPE, %	VPP, %	NPV, %	ERD, %
IMF1	108	110	12	10	90.83	90.83	90.83	90.83	90.83	90.833
IMF2	118	117	2	3	97.92	98.32	97.52	97.5	98.33	4.20
IMF3	118	115	2	5	97.08	98.29	95.93	95.83	98.33	5.98
IMF4	103	110	17	10	88.75	86.61	91.15	91.67	85.83	21.299
IMF5	112	111	8	9	92.92	93.28	92.56	92.5	93.33	14.29
IMF6	110	114	10	6	93.33	91.94	94.83	95	91.67	12.90

Table 3 Performance results of LS-SVM classifier with polynomial kernel for classification of alcoholic and normal EEG signals in terms of fidelity parameters

IMF	TN	TP	FN	FP	ACC, %	SEN, %	SPE, %	VPP, %	NPV, %	ERD, %
IMF1	95	114	25	6	87.08	82.01	94.06	95	79.17	22.30
IMF2	118	114	2	6	96.67	98.28	95.16	95	98.33	6.89
IMF3	112	119	8	1	96.25	93.70	99.12	99.17	93.33	7.09
IMF4	86	112	34	8	82.5	76.71	91.49	93.33	71.67	28.77
IMF5	112	119	8	1	96.25	93.70	99.12	99.17	93.33	7.09
IMF6	112	111	8	9	92.92	93.28	92.56	92.5	93.33	14.29

$$\mathrm{ERD}(\%) = \frac{\mathrm{FP} + \mathrm{FN}}{\mathrm{TP} + \mathrm{FN}} \times 100 \tag{18}$$

where TP stands for true positive and TN stands for true negative represent the total number of correctly detected alcoholic and normal EEG signals, respectively. The FP stands for false positive and FN stands for false negative represent a total number of incorrectly detected alcoholic and normal EEG signals, respectively. Tables 2 and 3 show the classification performance of LS-SVM classifier in terms of fidelity parameters for the two kernel functions, RBF, and polynomial, respectively, when used with LS-SVM classifier. Results from these tables indicate that the classification accuracy of LS-SVM classifier with kernels, RBF, and polynomial, for IMF2 is found to be the highest, which is valued at 97.92 and 96.67%, respectively. It is also proved that amongst both the kernels used with LS-SVM classifier for IMF2, the performance with RBF kernel is found to be the best for classifying alcoholic and normal EEG signals. Table 4 gives a performance comparison of this method with other state-of-the-art methods. To the best of our knowledge, the proposed method with an achieved classification accuracy of 97.92% gives better performance than other methods.

Table 4 Performance comparison of proposed method with state-of-the-art methods

Authors	Features	Classifiers	Accuracy, %
Ehlers *et al.* [5]	correlation discriminant	dimension analysis	88.00
Kannathal *et al.* [17]	CD, LLE, entropy, *H*	unique ranges	90.00
Faust *et al.* [18]	WPD – relative energy	k-nearest neighbour	95.80
Acharya *et al.* [19]	ApEn, SampEn, LLE,HOS	SVM with poly kernel	91.30
Bajaj *et al.* [20]	CoHOG and Eig(Hess)-CoHOG	NNLS	95.83
proposed method	entropy, skewness, negentropy, mean, kurtosis	LS-SVM with poly kernel	96.67
		LS-SVM with RBF kernel	97.92

5 Conclusion

EMD is a very useful technique for the decomposition of non-linear and non-stationary EEG signal into various stationary IMFs, from which various significant features can be extracted. In this paper, five features namely kurtosis, skewness, entropy, negentropy, and mean of IMFs are extracted from first six IMFs. With KW statistical test it has been found that these features are statistically significant for discrimination of alcoholic EEG signals from normal EEG signals. These features are fed as input to an LS-SVM classifier, which provides a classification accuracy of 96.67% with the poly kernel and 97.92% with RBF kernel when features of IMF2 are used. It is found that IMF2 provides better classification performance for classifying alcoholic and normal EEG signals. This method is proposed for the identification of alcoholic subjects by observation of their EEG signals, as EEG signals, unlike smell-tests, cannot be influenced by any external change. In future, this method can be extended for the study of other physiological and pathological stages of the human brain.

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