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Empirical Mode Decomposition based Classification Method for Seizure/Non-Seizures Signals

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ABSTRACT

Disease identification could be a major task within the field of medical specialty. To perform it the analysis of Electroencephalogram signal is to be performed. The projected technique presents for feature extraction from EEG signals exploitation empirical mode decomposition (EMD). Its use is actuated by the very fact that the EMD provides an efficient time-frequency analysis of non-stationary signals. The intrinsic mode functions (IMF) obtained as a results of EMD offer the decomposition of a proof per its frequency elements. during this gift the analysis of up to third order temporal moments, and spectral options together with spectral center of mass, constant of variation and therefore the spectral skew of the IMFs for feature extraction from Electro-encephalogram signals. Options are physiologically relevant to traditional EEG signals. Traditional EEG signals have completely different temporal and spectral centroids, dispersions and symmetries. The performance of the projected technique is studied on an in public obtainable dataset that is meant to handle numerous classification issues together with the identification of brain disease patients additionally detection of seizures and non-seizures. The calculated options are fed into the quality support vector machine (SVM) for classification functions. The Experimental results show that sensible classification results are obtained exploitation the projected methodology for the classification of EEG signals.

KEY WORDS: Empirical mode decomposition, intrinsic mode function, feature extraction, classification.

1. INTRODUCTION

Electroencephalogram (EEG) could be a set of electrical potential variations that contain the data concerning the human brain activity. It exhibits the information relating to the quantity currents that unfold from a neural tissue throughout the semiconducting media of the brain. These measurements are often obtained mistreatment sensors placed on the scalp or mistreatment the intracranial electrodes. The graphical record signals are often effectively used for numerous applications like feeling recognition, brain–computer interfaces (BCIs), and etc. one among the foremost necessary applications of the analysis of graphical record signals is its use in neurobiology to diagnose diseases and brain disorders. Convulsion is one among the foremost common medical specialty disorders worldwide. Its detection is often done by the physicians employing a visual scanning of the graphical record signals that could be a time overwhelming method and will be inaccurate. These inaccuracies are significantly vital for durable length graphical record signals.

More recently, new techniques for analysis of non-linear and non-stationary graphical record signal are planned, that are supported the Empirical Mode Decomposition developed particularly for non-linear and non-stationary signal analysis. The mean frequency (MF) live of intrinsic mode functions has been used as a feature so as to spot the distinction between non-seizure and seizure graphical record signals. In this work fast frequency has been used as a feature of IMFs for the classification between healthy and convulsion graphical record signals.

The parameters extracted from the graphical record signals are terribly helpful for nosology numerous. The spectral parameters supported the Fourier remodel are helpful for analyzing the graphical record signals and have shown sensible results on their classification. Like many ways mentioned as use of short time Fourier remodel (STFT) and riffle remodel within the literature. Though sensible results are obtained mistreatment these ways, the STFT doesn't yield a multi-resolution analysis of the signals. This is often owing to the actual fact that the STFT uses the filters of identical information measure for signal decomposition in the slightest degree frequencies. This limitation is often resolved mistreatment the riffle analysis within which a multi-resolution time-frequency analysis is expedited by forming band pass filters with varied bandwidths. Researchers have found the riffle analysis to be a really useful gizmo for numerous signal process applications and it's performed in frequency domain.

In this paper, we have a tendency to propose a completely unique feature extraction methodology for the classification of graphical record signals involve it 3 stages. The primary stage of the formula involves the calculation of EMD of the graphical record signal, thereby giving a collection of IMFs. The primary 3 IMFs are elect for more process. The second stage involves feature extraction that is finished by conniving the temporal and spectral characteristics of the IMFs, that is that the main contribution of this paper. For the calculation of spectral options, we've got used power spectral density (PSD). The temporal and spectral options are obtained from the Hilbert remodeled IMFs. Thus, mistreatment this transformation will take away the DC offset from the spectral content of the signals that is one among the sources of non-stationary within the signals. The third stage involves the employment of support vector machine (SVM) for the classification of graphical record signals.

Dataset: During this study, we've used associate EEG dataset that's in public on the market online (Sample EEG signals area unit shown in Fig.1). The dataset consists of 5 subsets fig.1 (denoted as sets A-E) every containing one

hundred single channel EEG signals, every one having a length of twenty three.6 s. These signals are hand-picked from continuous multichannel EEG recording once visual review of artifacts. The Sets A and B carries with it surface EEG segments collected from 5 healthy volunteers in awaken and relaxed state with their eyes opened and closed severally. Segments in Sets C, D, associated E area unit obtained from an archive of EEG signals of pre-surgical identification. 5 patient's area unit hand-picked WHO have achieved complete management of seizure once surgical procedure of 1 of the hippocampal formations. The subsequent fig. one shows sample of EEG signals with 5 totally different sets A, B, C, D and E severally. Sample EEG signals from 5 totally different sets from rows one to five (A, B, C, D, and E, respectively) were recorded throughout seizure free intervals (i.e., interictal) severally. Set E contains signals similar to seizure attacks (i.e., ictal EEG), recorded exploitation all the electrodes. The signals area unit recorded in a very digital format at a rate of 173.61 Hz. Thus, the sample length of every phase is 173.6 × 23.6 ≈ 4097.

2. METHODOLOGY

Empirical Mode Decomposition: The EMD could be an information dependent methodology of mouldering a sign into variety of periodical elements, referred to as intrinsic mode functions (IMFs). EMD doesn't create any assumptions concerning the stationary or dimensionality of the info the aim of EMD is to decompose signals into variety of IMFs, all of them satisfying the 2 basic conditions: The range of extrema or zero crossings should be constant or disagree by at the most one; At any purpose, the common price of the envelope outlined by native maxima and also the envelope outlined by the native minima is zero.

Only if we've a sign, the calculation of its IMFs involves the subsequent steps: Identify all extrema (maxima and minima) in x(t); Interpolate between minima and maxima, generating \the envelopes $E_l(t)$ and $E_m(t)$; Determine the local mean as a (t) =Em(t) +El(t)/2; Extract the detail h1(t) =x(t)-a(t) i.e.; Decide whether h1(t) is an IMF or not based on two basic conditions for IMFs mentioned above; Repeat step 1 to 4 until an IMF is obtained.

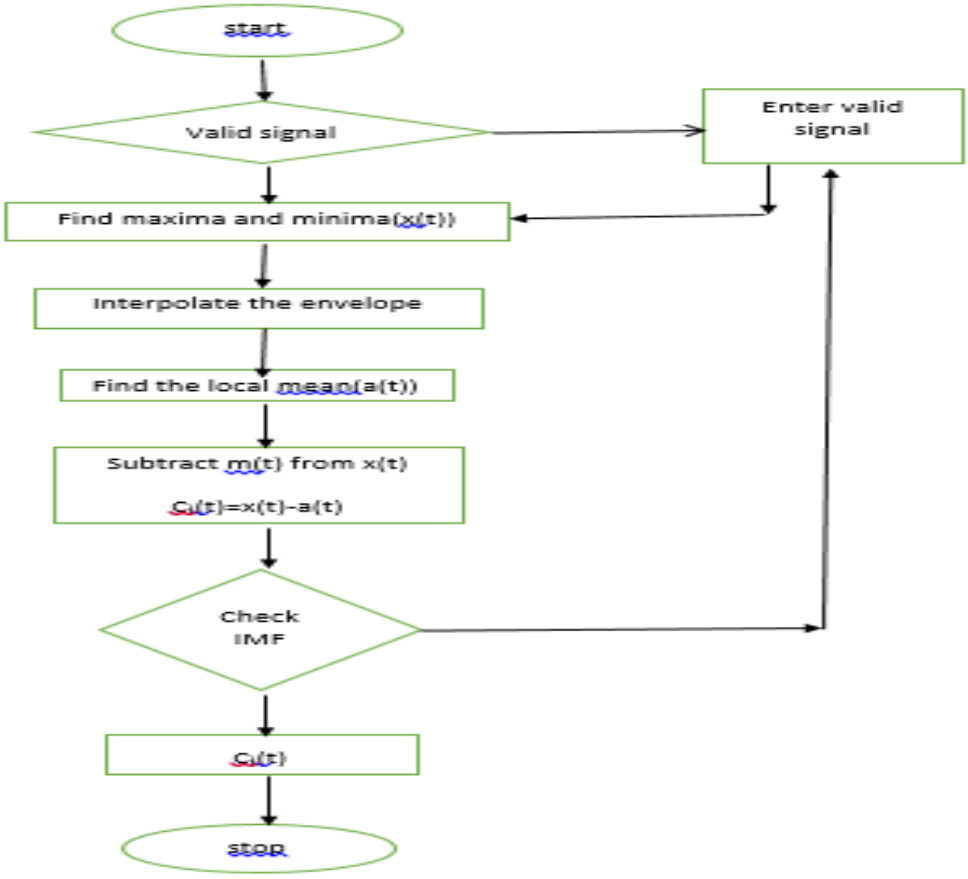


Fig.1. Flow chart of EMD algorithm

Once the primary IMF is obtained, outline c1(t)=h1(t), that is that the smallest temporal scale in x(t). A residual signal is obtained as r1(t)=x(t)-c1(t). The residue is treated because the next signal and therefore the higher than mentioned method is continual till the ultimate residue may be a constant (having no additional IMFs) three at the top of the decomposition.

Features: Thus the initial signal are often painted as follow:

$$X(t) = 1/N \sum\_(i-1)^N \text{▒} 〖Cm(t)+Rm(t)〗 .$$

Where m is that the variety of IMFs, Cm(t) is that the ordinal IMF and Rm(t) is that the final residue. So any signal are often enforced as total of IMFs and a residue.

Temporal Statistics of analytic IMFs: Statistical options of IMFs are helpful for discriminating between traditional and pathological EEG signals. A visible analysis of the IMFs obtained from healthy and encephalopathy patients throughout interictal and ictic periods once David Hilbert rework reveals that they're quite totally different from each other. Apparently, these variations are suitably captured mistreatment the statistics of the IMFs for AN IMF, these statistics are often obtained by the subsequent quantities:

Mean (μ(t)):= 1/*N*∑_(i=1)^N▒〖y(i)〗

Variance (σ(t)):= √(1/N) ∑_(i=1)^N▒(y(i)-μ(t))^2

Skewness(β(t)):-1/N ∑_(i=1)^N▒〖(〖(y(i)-μ(t))/(σ(t)))〗 ^3 〗

Where N is that the variety of samples within the IMF.

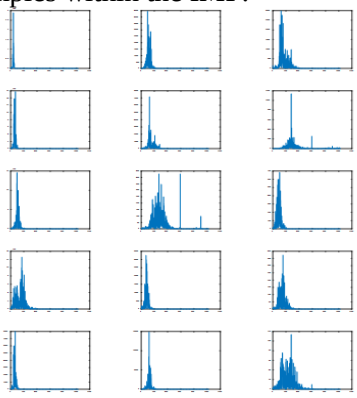


Fig.2.Plots of temporal signals obtained from the IMFs once EMD decomposition

Spectral statistics of Analytic IMFs: Strength of EMD is that it's the flexibility to perform a spectral analysis of the signals. A frequency based mostly analysis will so be helpful for feature extraction from EEG signals. The spectral options obtained from IMFs will so provide a made clue regarding the physiology of the EEG signals. Normally, using EMD, this spectral analysis is finished mistreatment the calculation of fast frequencies (IF). As an alternate, we've resorted to the calculation of PSD for feature extraction functions. The discrimination power of the PSD options are often visually analyzed by their various plots for 3 IMFs from the traditional and pathological EEG signals. The PSD are often calculated as follows:-

P(w) = ∑_(-∞)^∞▒〖Ry(n) e^(-jwn) 〗

Where Ry(n) represents the autocorrelation of y(n), outlined as Ry(n) = E(y(m)y*(m)).

Spectral Centroid: The center of mass frequencies of the IMFs extracted from EEG signals type distinct teams once supervised clump is applied on the EEG signals. The center of mass frequency is so a particular feature that may be used for the characterization of EEG signals. It's outlined as:-

Cs = (∑_w▒〖wP(w)〗)/(∑_w▒〖P(w)〗)

Where P(w) is that the amplitude of wth frequency.

Variation Coefficient: It provides info regarding spectral variation within the IMFs. It's totally different for traditional and pathological EEG signals. This variation are often calculated as follows:

σ2s= (∑_w▒〖(w-Cs)^2 P(w)〗)/(∑_w▒〖P(w)〗)

Spectral Skew: Skewness is that the third order moment and it measures the symmetry/asymmetry of a distribution. Visual scrutiny of the plot of PSD of IMFs shows that the asymmetry of the ability of IMFs for the traditional and pathological EEG signals differs so doubtless yielding a helpful feature for the classification of EEG signals. Asymmetry of the PSD are often calculated a:

Bs = (∑_w▒〖((w-Cs)/σs)^2 P(w)〗)/(∑_w▒〖P(w)〗)

Its feature vector are often obtained by their concatenation as follows:-

F = [μ(t) σ(t) β(t) Cs σ2s Bs].

Classification: Feature extraction is followed by the classification of EEG signals mistreatment support vector machines (SVM). The SVM, chiefly consists of constructing Associate in nursing optimum hyper-plane that maximizes the margin of separation margin between 2 completely different categories. It uses a kernel to remodel the input file to a better dimensional area followed by Associate in nursing improvement step for the development of Associate in nursing optimum hyper-plane. This approach builds the classification models having wonderful generalization capability and so is employed during a} very wide selection of pattern recognition applications. The choice operate of SVM is as follows:

D(x) = ∑_i▒αi K(Xi,F)+b

Where K(.) is that the kernel operate and F is that the input vector. For implementation, liner kernel for SVM classification has been used.

3. RESULTS AND DISCUSSION

The performance of the projected methodology for feature extraction from EEG signals is studied mistreatment commonplace measures like overall accuracy and space underneath receiver operative characteristics (ROC) curve. Additionally to the analysis of results created by the methodology projected during this paper, we've enforced many different descriptors of EEG signals. These ways embrace temporal statistics of IMFs from EMD, instant frequency (IF) options, the modulation (FM) and AM (AM) information measure options and wavelets. This choice has been done supported a high degree of accuracy achieved by these ways within the classification of EEG signals. The options obtained mistreatment all the descriptors are classified mistreatment four completely different classifiers i.e., 1-nearest neighbor (1NN), call trees, artificial neural networks (ANN), and support vector machine (SVM) based mostly classifiers for an expensive analysis. The take a look at bench is unbroken consistent for of these ways to make sure a good comparison of their performance. For the 5 sets of EEG recordings delineated in Section II, we've thought-about 5 completely different cases of classification issues during this Paper shown in fig.3. These cases are developed supported their clinical relevancy yet as their wide usage by numerous researchers for EEG signal classification. Consistent with experimental results we have a tendency to calculate the applied mathematics parameter of seizure and non-seizure. That's shown in table one and table a pair of.

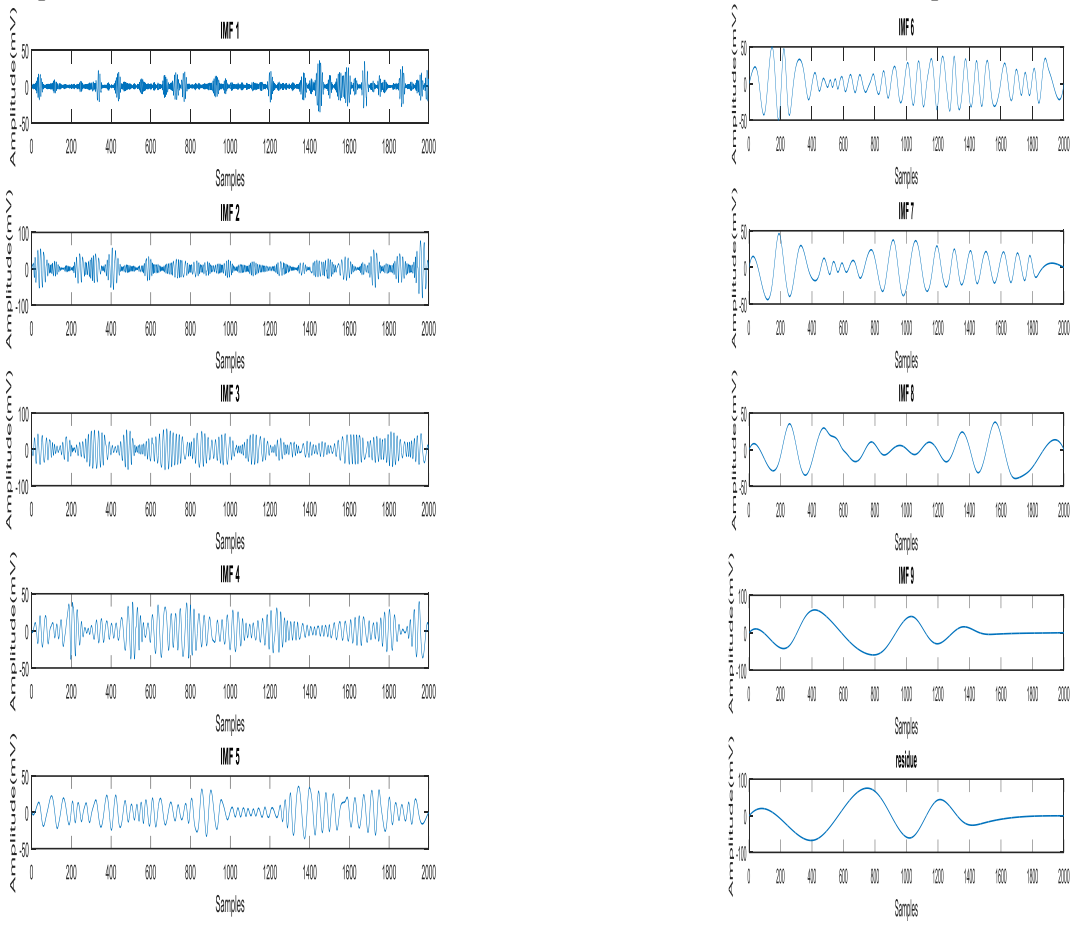


Fig.3. Decomposed Normal EEG signal using EMD

Table.1. Provides simulation results of statistical parameter for non-seizure signal

Parameter	Imf1	Imf2	Imf3	Imf4	Imf5
Mean	-0.03074	-0.04457	0.087518	-0.1015	0.025631
Variance	3.897988	16.53824	30.74322	57.30674	98.81519
Skewness	0.055057	-0.18944	-0.04159	-0.22685	0.185288
Autocorrelation	1	-0.17747	-0.02816	-0.25909	-0.10483
Power spectral density	0.300719	0.632448	2.438035	3.278997	0.209109
Standard deviation	1.974332	4.066724	5.544657	7.570121	9.940583
Instantaneous frequency	310.7551	215.5773	234.8645	224.8956	182.4685
Spectral centroid	10	10	10	10	10
Variation coefficient	6.72E-33	9.26E-33	7.68E-34	3.46E-31	8.20E-35

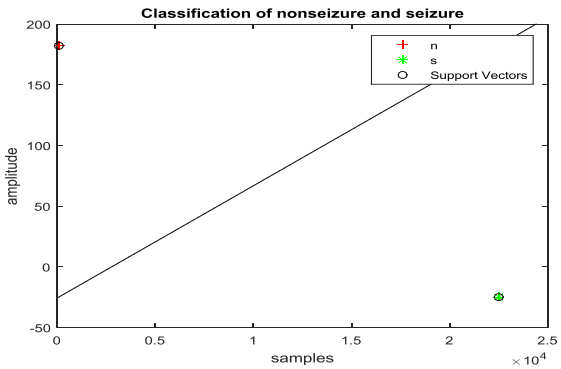
Parameter	Imf6	Imf7	Imf8	Imf9
Mean	0.220189	-0.25231	0.581286	2.084131
Variance	156.3765	148.7804	138.6543	301.1271
Skewness	0.122848	-0.02109	-0.35402	0.031714
Autocorrelation	0.067859	0.086789	0.101296	-0.05081
Power spectral density	15.4327	20.26397	107.555	1382.611
Standard deviation	12.50506	12.19756	11.77516	17.35301
Instantaneous frequency	223.997	301.3318	-456.834	353.3534
Spectral centroid	10	10	10	10
Variation coefficient	2.76E-31	1.32E-33	9.07E-31	7.01E-31

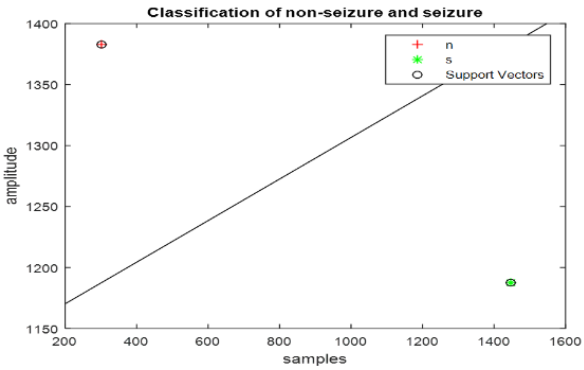
For classification of seizure and non-seizure EEG signals, it's been shown in fig. five that the strategy of Liang et al. provides higher classification accuracy eighty fifth to ninetieth than the opposite existing ways in. the strategy supported line length feature of the sub-band signals conferred in has provided nearly similar classification accuracy that's obtained with lower machine complexness. So as to assess the performance of the projected methodology for classification of seizure and non-seizure EEG signals, comparison with methodology of Liang et al. has been done.

Table.2. Provides simulation results of statistical parameter for seizure signal

Parameter	Imf1	Imf2	Imf3	Imf4	Imf5
Mean	9.434779	7.716412	5.491209	2.38973	-0.07229
Variance	124897.3	62937.98	47526.46	43768.23	22504.55
Skewness	-0.05152	-0.0688	-0.02749	0.085695	0.012142
Autocorrelation	1	0.881769	0.579875	0.203951	-0.12786
Power spectral density	28334.37	18953.13	9598.119	1817.807	1.663226
Standard deviation	353.4081	250.8744	218.0056	209.2086	150.0152
Instantaneous frequency	0.027936	1.669903	4.525657	-1.64388	-24.7024
Spectral centroid	10	10	10	10	10
Variation coefficient	7.90E-32	1.97E-30	7.04E-32	1.01E-32	4.84E-34

Parameter	Imf6	Imf7	Imf8	Imf9
Mean	6.177517	-1.15301	-3.63838	-1.93148
Variance	7631.689	2572.267	4319.178	1445.276
Skewness	0.092552	0.067623	0.114994	0.174252
Autocorrelation	-0.33954	-0.40794	-0.35112	-0.21435
Power spectral density	12147.25	423.1722	4213.72	1187.495
Standard deviation	87.35954	50.71752	65.72046	38.01679
Instantaneous frequency	-39.808	14.22582	31.72948	42.37548
Spectral centroid	10	10	10	10
Variation coefficient	3.01E-30	1.59E-33	3.77E-32	0





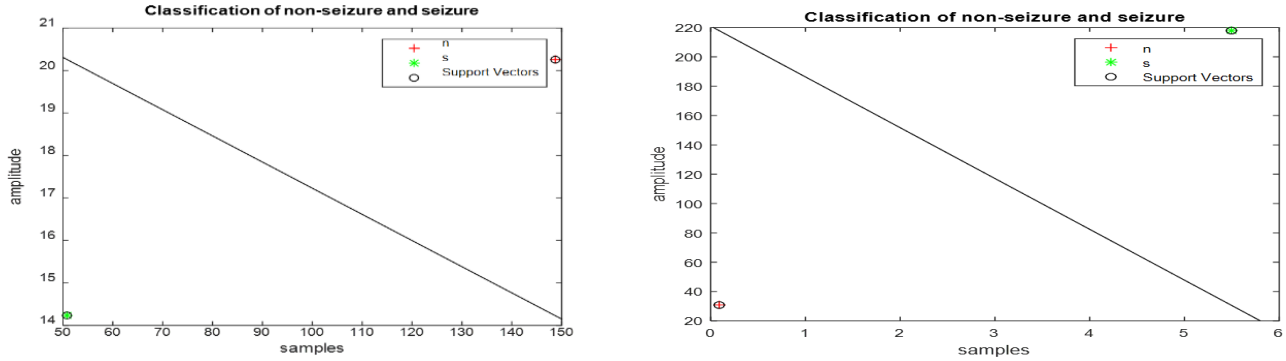


Fig.4. Experimental results of classification

4. CONCLUSION

The EMD method could be a helpful and powerful methodology to decompose EEG signal into a group of IMFs. These IMFs may be diagrammatical by the amplitude and frequency modulated (AM–FM) signal model, that makes it potential to cipher AM and FM bandwidths of the IMFs. These information measure parameters of the IMFs of EEG signals are used as a feature so as to classify seizure and non-seizure EEG signals. The classification accuracies and mythical monster curves of the classifier were used for evaluating the classification performance of the LS-SVM classifier. The classification results and values of applied mathematics parameters indicated that the Morlet moving ridge kernel operate of LS-SVM classifier had provided higher classification accuracy in classification of seizure and non-seizure EEG signals. The projected methodology could also be applied for analysis and classification of different non-stationary signals. Future directions of this analysis embrace the impact of oftenness of EEG signals on the classification accuracy, and verify mechanically parameters of the kernel functions for good classification of seizure and non-seizure EEG signals.

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