Computer-Aided Detection of Non-Focal and Focal EEG Signals using Flexible Analytic Wavelet Transform

A PROJECT REPORT

Submitted in partial fulfillment of the requirements for the award of the degrees

of

BACHELOR OF TECHNOLOGY

in

ELECTRICAL ENGINEERING

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December, 2016

CANDIDATE'S DECLARATION

We hereby declare that the project entitled **"Computer Aided Detection of Non-focal and Focal EEG Signals using Flexible Analytic Wavelet Transform"** submitted in partial fulfillment for the award of the degree of Bachelor of Technology in 'Electrical Engineering' completed under the supervision of **Dr. Ram Bilas Pachori, Associate professor, Electrical Engineering,** IIT Indore is an authentic work.

Further, we declare that we have not submitted this work for the award of any other degree elsewhere.

Signature and name of the student(s) with date

CERTIFICATE by BTP Guide

It is certified that the above statement made by the students is correct to the best of my knowledge.

Signature of BTP Guide(s) with dates and their designation

Preface

This report on **"Computer-Aided Detection of Non-focal and Focal EEG Signals using Flexible Analytic Wavelet Transform"** is prepared under the guidance of **Dr. Ram Bilas Pachori**, **Associate Professor, Electrical Engineering, IIT Indore.**

Through this report, we have tried to present a comprehensive analysis of focal and non-focal electroencephalogram (EEG) signals in the flexible analytic wavelet decomposition domain. We have calculated a number of entropy-based features such as sure entropy, log-energy entropy and correntropy on the basis of their efficacy in discriminating the focal and non-focal EEG signals. The main motivation behind this is to classify the focal and non-focal EEG signals which can be used to detect focal EEG signals automatically. The proposed automatic classification system in this work can be useful for a clinician in assisting them while performing the diagnosis of focal epilepsy. This method presented by us is a novel method for the computer aided detection of focal and non-focal EEG signals with improved accuracy, sensitivity and specificity against the existing techniques, and therefore has a potential of a big contribution to the world of Biomedical Signal Processing.

We have tried our best to explain the proposed concepts, techniques, results and conclusion in detail along with the comparison of our method with the already existing models.

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Acknowledgements

The long journey of this project that we undertook would have been impossible to complete without the kind support and help of many individuals and organizations. We would like to extend our sincere thanks to all of them.

We are highly indebted to Dr. Ram Bilas Pachori, Associate Professor, Electrical Engineering, Indian Institute of Technology Indore who let us work at our own pace, guiding us with his instructions whenever required and without whose support the report would not have been possible.

We would also like to thank Vipin Gupta, Research Associate at Indian Institute of Technology Indore, and Mohit Kumar, Research Scholar from Indian Institute of Technology Indore for their kind guidance and valuable supervision as well as for providing necessary information regarding the project and also for their support in completing the project.

We would like to express our gratitude towards our parents and friends for their kind co-operation and encouragement which helped us in completion of this project.

Our thanks and appreciations also go to our colleagues in developing the project and people who have willingly helped us out with their abilities.

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Abstract

A class of neurological disorder characterized by unpredictable seizures, epilepsy starts in the human brain and may lead to other health problems and may occur because of sickness, cerebrum damage, or unusual advancement of brain. According to world health organization (WHO), nearly 50 million people suffer with epilepsy worldwide. Approximately, more than 30% patients have generalized epilepsy which affects the entire brain, whereas, more than 48% patients have simple focal or dyscognitive partial epilepsy, which starts in a limited part of the affected area. This motivates for a research in this field to help recognize and locate the surgically removable epileptic zones in the brain. Study has shown that epilepsy is a neurological disease which is strenuous to medication. An automatic detection of focal epilepsy will help many doctors and patients to combat this disorder in a much efficient manner. Thus, development of an automatic detection system for non-focal and focal electroencephalograph (EEG) signals is very useful for epileptic diagnosis. In this work, we propound a 15 level flexible analytic wavelet transform (FAWT) method for detecting focal and non-focal EEG signals, wherein we use the 16 sub-bands produced and the original signal, which provides a total of 17 sub-signals corresponding to each signal. The EEG signals are collected from a publicly available database (Bern- Barcelona EEG database) that contains 3750 signal pairs recorded over approximately 80 hours with five focal epilepsy patients. This methodology employs time differencing of non-focal and focal EEG signals before decomposing them into sub-bands by employing FAWT. For feature extraction, we omit the less significant 13th sub-band signal based on Kruskal-Wallis statistical test and then a number of entropy measures such as correntropy, sure entropy and log energy entropy are extracted from the reconstructed sub-band signals. Eventually, all the three entropies are evaluated on the 16 sub signals which give a total of 48 features. The Wilcoxon ranking method was found the most effective in ranking the features in the proposed methods as compared to other ranking methods like entropy, t-test, receiver operating characteristic (ROC), and Bhattacharya space algorithm. Statistically significant features with ranking are given as input to two different classifiers, K-nearest neighbor (KNN) with different distances namely Euclidean, cityblock, cosine and correlation, and least squares-support vector machine (LS-SVM) with different kernels namely radial basis function (RBF) and polynomial, along with ten-fold cross validation method, wherein LS-SVM with RBF as kernel function provided best classification accuracy. In this proposed methodology, we have achieved classification accuracy of 94.41%, in the automated classification of focal and non-focal EEG signals.

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Chapter 1:
Introduction

1.1 General background

The EEG signal is utilized to examine the electrical activity of the brain and different frequency components are present in those signals that makes it complex in nature. These signals represent how human brain works and contain information related to the neurological disorder. A class of neurological disorder characterized by unpredictable seizures, epilepsy may occur because of sickness, cerebrum damage, or unusual advancement of brain, and can lead to other health problems. According to WHO, nearly 50 million people suffer with epilepsy worldwide [24]. Approximately, more than 20% patients have generalized epilepsy which affects the entire brain, whereas, more than 60% patients have simple focal or partial epilepsy, which starts in a limited part of the affected area [15]. When seizures cannot be managed with medications, it becomes important to localize that focal epileptic zone. However, scalp EEG may decline to gather ictal EEG changes in focal seizures which comes up from a small or deeply allocated focus [15]. This motivates for a research in this field to develop signal processing based methods in order to recognize and locate the surgically removable focal epileptic zones in the brain [17].

1.2 Literature survey

In [1], the outcomes imply that EEG signals from an epileptogenic brain are barely random, stationary and more nonlinear-dependent when contrasted with signals noted from non-epileptogenic brain areas. In this work, to examine the attributes of focal epilepsy, various non-linear arguments, such as linear correlation, phase synchronization and mutual information with surrogate inspection are used [14].

Several nonlinear chaotic measures, such as Renyi, Shannon, Tsallis, fuzzy, sample, log energy, phase, permutation entropy and central tendency measures have been presented to gather the dynamics of focal epileptic zones from EEG signals [20, 6, 4]. In [21], the features employed are average sample entropies and average variance of the intrinsic mode functions (IMFs) obtained by empirical mode decomposition (EMD) of EEG signals. These features are fed into least square support vector machine (LS-SVM) with radial basis function (RBF) as a kernel for classification of non-focal and focal EEG signals. This technique has been tested on 50 set of non-focal and 50 set of focal EEG signals from the entire database which was able to achieve an accuracy of 85%.

In [20], application of entropy measures on IMFs from the EMD of EEG signals are used as features, that is, Renyi wavelet, average Shannon wavelet, average Tsallis wavelet, average fuzzy, average phase and average permutation entropy based features are fed to the LS-SVM classifier to differentiate non-focal and focal classes. This method achieved 87% accuracy with 50 set of non-focal and 50 set of focal EEG signals. In [19], the detection of non-focal and focal EEG signals occupied on an integrated index is formulated employing discrete wavelet transform (DWT) and entropy based features. The entropy features are phase, fuzzy, average wavelet and permutation entropies provided to various classifiers, specifically fuzzy, K-nearest neighbor (KNN), probabilistic neural network (PNN) and LS-SVM, to distinguish between non-focal and focal classes. In [4], the area parameters based on central tendency measures (CTM) for various reconstructed phase space (RPS) plots are estimated to distinguish between 50 focal and 50 non-focal EEG signals, which lead to a classification accuracy of 90% and when same approach is used for 750 pairs of EEG signals then it was given an accuracy of 82.53%.

In [6], a new method namely log energy entropy (LgEn) supported feature was acquired after employing the EMD and the DWT on the EEG signals. KNN classifier was used to classify the two classes (focal and non-focal). This method accounted for 89.4% accuracy on 3750 set of non-focal and 3750 set of focal EEG signals.

In these works, focal epileptic EEG signals are found to be more nonlinear-dependent compared to non-focal records. Therefore, entropy based features are considered because of their successful importance in detecting focal epilepsy [21, 20, 19, 6]. The log energy, correntropy and sure entropy measures together have not been explored for the detection of focal and non-focal EEG signals. The log energy entropy is also considered in [6] to differentiate focal and non-focal EEG signals. The motivation behind correntropy nonlinear measures comes from its previous success in non-Gaussian signal processing [11]. The motivation for studying behind sure entropy has come from the wavelet packet entropy used in [5].

In the present work, the main focus is to propose a new methodology for computer aided detection of the non-focal and focal EEG signals employing studied features. These features are tested employing K-NN and LS-SVM with different distance methods and kernel functions respectively. On the basis of analysis of these features with two different classifiers, the LS-SVM with RBF kernel function is well suited for characterize the focal and non-focal EEG signals.

The rest of the organization of this report is as follow the Chapter 2 provide brief description about data collection, explanation about the designed methodology for classification of focal and non-focal EEG signals. It also provides description about the Flexible Analytic Wavelet Transform (FAWT), entropy based features, studied classifiers. In the Chapter 3 results and discussion have been provided. In the last, Chapter 4 concludes the work done and it also provides scope for future work.

Chapter 2:

Methodology

2.1. Data collection

EEG signals are acquired from Bern Barcelona database [13]. In [1], focal epilepsy is monitored among 5 patients and all the patients went through long-range intracranial EEG recordings at the Neurology Department of the Bern University. There are 3750 focal and 3750 non-focal EEG signals, which were sampled at a sampling rate of 512 Hz for 20 seconds, corresponding to 10240 samples. The main reason we use this data set is that we need relevant data that can easily be shared with other researches, allowing all kinds of techniques to be easily compared in the same database. The data set comprised bivariate EEG signals and are depicted as "X" and "Y". The plot of "X" time series of a focal and non-focal EEG signal are shown in Fig. 2.1 and Fig. 2.2 respectively.

2.2. Differencing of EEG signals

We have applied differentiation operation to the recorded EEG signals before transforming these signals by FAWT method.

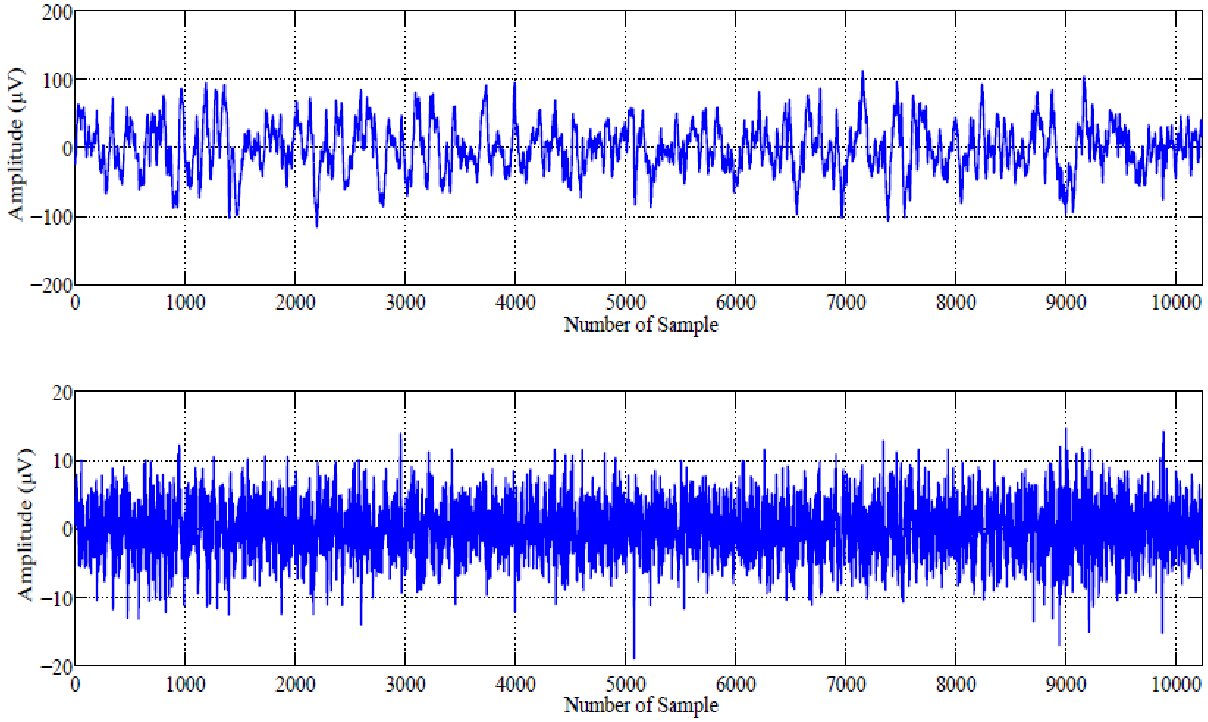

Figure 2.1: Plot of focal and differenced focal EEG signal for “X” time series

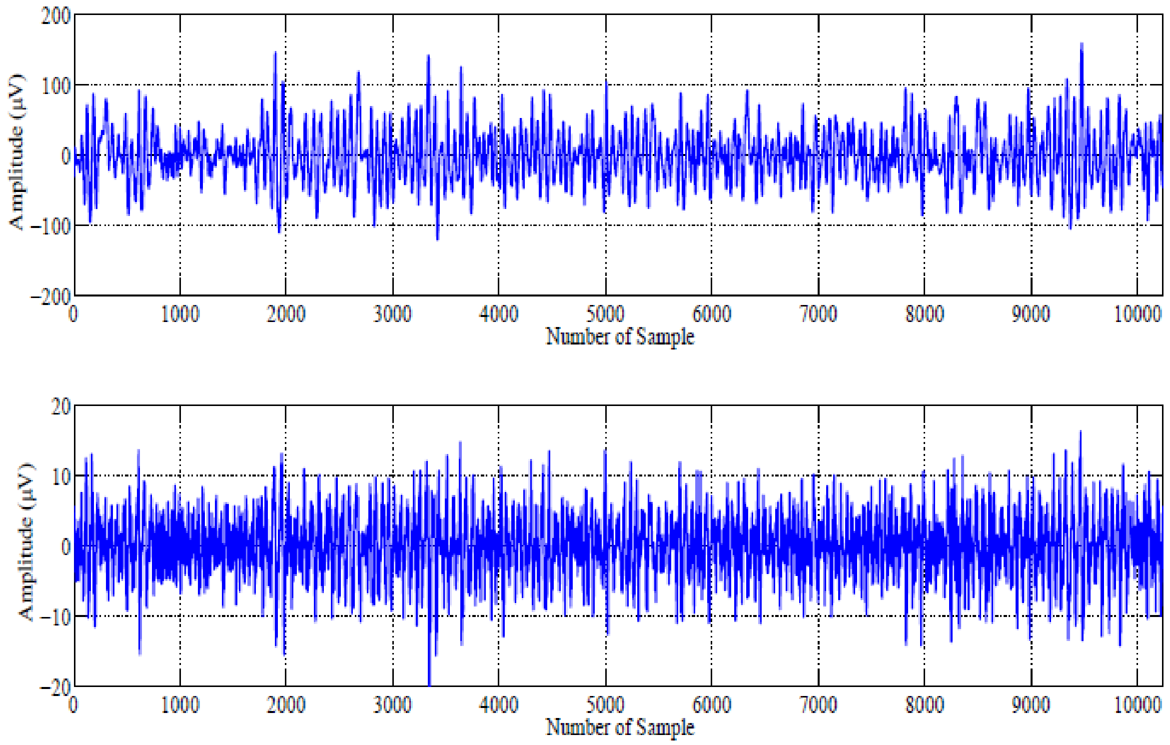

Figure 2.2: Plot of non-focal and differenced non-focal EEG signal for “X” time series

The differencing of EEG data is more suitable for further processing of focal and non-focal EEG signals, and also that the stationarity of the EEG signal is increased to a certain extent [3]. Fig. 2.1 and Fig. 2.2 depicts the differencing of “X” time series for focal and non-focal EEG signals respectively. Differencing of a signal is given as,

$$X_{diff}(i) = x(i) - x(i-1) \text{ for } i \in 1\ldots\ldots\text{N-1} \quad (1)$$

Where, X_{diff} is differencing signal, x is EEG signal and *N* is total number of EEG signal samples.

2.3 Proposed methodology

The proposed methodology shown in Fig. 2.3 has 8 subsections. The first subsection has been explained in 2.2, which is about differencing of EEG signals. The second section explains about the FAWT method to decompose the differenced EEG signals into 15th level decomposition. The third section is comprised of the reconstructed signals from the sub-bands. The fourth section includes the features extraction in which correntropy, log energy entropy and sure entropy are evaluated. The fifth section is about the statistical test i.e. Kruskal-Wallis test which evaluates the p values of these extracted features. In the sixth section, we selected the significant features which had p values less than 0.05. In the seventh section we ranked the features according to different ranking methods namely, Wilcoxon, ROC, Bhattacharyya, t-test and entropy. In the eight section we discuss about the automated classification system which included two different classifiers which are LS-SVM and KNN with different kernel functions and distances respectively. Finally, we are left with two different focal and non-focal classes.

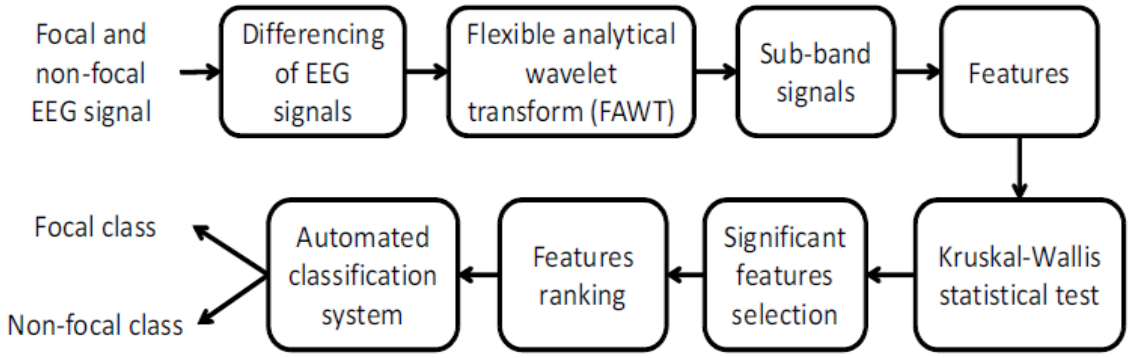

Figure 2.3: Block diagram of the designed methodology for classification of focal and non-focal EEG signals.

2.4 Signal decomposition using FAWT

FAWT is an effective method for analyzing the biomedical signals [9, 10]. The Hilbert transform pairs of atoms hosts by this transform and permits command over arguments like the redundancy, Q-factor and the dilation factor. FAWT delivers ability to test the signal with easily changeable arguments *a*, *b*, *c*, *d* and *β*, where, *a* and *b* are the up and down sampling arguments for low pass channel respectively and, *c* and *d* are the up and down sampling arguments for high pass channel respectively. *β* is a positive constant that evaluates the quality factor (QF) which is denoted as [2],

$$\mathrm{QF} = \frac{2-\beta}{\beta} \tag{2}$$

These arguments can regulate the dilation factor, quality factor and redundancy of FAWT [2]. *Jth* level of FAWT can be achieved employing iterative filter bank. Every level of achievement comprises two high pass channels and one low pass channel. One high pass channel deals with the positive frequencies and the other high pass channel deals with the negative frequencies.

Low pass filter frequency response is given as [2]:

$$\mathrm{H(w)} = \begin{cases} 3(ab)^{1/2} & |w| < w_p \\ (ab)^{\frac{1}{2}}\theta\left(\frac{w-w_p}{w_s-w_p}\right) & w_p \le w \le w_s \\ (ab)^{\frac{1}{2}}\theta\left(\frac{\pi-(w-w_p)}{w_s-w_p}\right) & -w_p \le w \le -w_s \\ 0 & |w| \ge w_s \end{cases} \tag{3}$$

High pass filter frequency response is given as [2]:

$$G(w) = \begin{cases} 4(2cd)^{\frac{1}{2}}\theta\left(\frac{\pi-(w-w_0)}{w_1-w_0}\right) & w_0 \le w \le w_1 \\ (2cd)^{\frac{1}{2}} & w_1 \le w \le w_2 \\ (2cd)^{\frac{1}{2}}\theta\left(\frac{\pi-(w-w_2)}{w_3-w_2}\right) & w_2 \le w \le w_3 \\ 0 & w \in [0, w_0)U(w_3, 2\pi) \end{cases} \tag{4}$$

where, $w_p = \left(\frac{(1-\beta)\pi}{a}\right) + \left(\frac{\varepsilon}{a}\right)$, $w_s = \frac{\pi}{b}$, $w_0 = \frac{(1-\beta)\pi+\varepsilon}{c}$, $w_1 = \frac{a\pi}{bc}$ and $w_2 = \frac{\pi-\varepsilon}{c}$, $w_3 = \frac{\pi+\varepsilon}{c}$, $\varepsilon \le \frac{a-b+\beta b}{a+b}\pi$. Then θ(w) can be given as [2]:

$$\theta(w) = \frac{[1+\cos(w)][2-\cos(w)]^{1/2}}{2} \text{ for } w \in [0,\pi] \tag{5}$$

To accomplish excellent reconstruction filter bank, subsequent prerequisites must be met [2]:

$$|\theta(\pi - w)|^2 + |\theta(w)|^2 = 1(1 - \frac{a}{b}) \le \beta \le \frac{c}{d} \tag{6}$$

On the basis of these conditions, we deduce the parameters for FAWT as, J=15, a=3, b=4, c=1, d=2, and based on these parameters the value for β is 0.4.

FAWT is employed to detect the weak fault signature from the rotating machinery [26] and for the detection of coronary artery disease (CAD) [9] [10]. MATLAB toolbox of FAWT is available at [7].

2.5. Entropy based features extraction from FAWT

2.5.1. Log energy entropy

The log energy entropy, which is presented in [6], is performed to evaluate the degree of EEG signals complexity. Log energy entropy of signal x is given by,

$$H_{LgEn(x)} = \sum_{i=0}^{N-1} (\log_2(p_i(x))^2 \tag{7}$$

2.5.2. Correntropy

Correntropy is determined as a generalization of correlation of arbitrary processes. The correntropy comprises second order as well as higher order moment knowledge of the arbitrary variables [18, 11]. A novel parametric correntropy is explained as the correntropy between a shifted and a scaled arbitrary variable. It provide a new measure of independence and is also capable to quantify the dependence measures among arbitrary variables [16, 32, 33].

Correntropy is a recent nonlinear and local similarity extent between two arbitrary variables X and Y, explained by [25]

$$V(X, Y) = E[<\emptyset(X), \emptyset(Y)>] = E[k(X-Y)] \tag{8}$$

Where $X=X_{t1}$ and $Y=X_{t2}$ $\{X_t, t \in T\}$ are stochastic processes with T being an index set. $\emptyset$ is a kernel mapping function and $k(X-Y)$ is a shift-invariant Mercer kernel. In this methodology, the kernel function in correntropy is selected as the following Gaussian kernel [25]:

$$k(X-Y) = exp(\frac{-\|X-Y\|^2}{2\sigma_1^2}) \tag{9}$$

Where, $\|.\|$ denotes the Euclidean norm and $\sigma_1 = 0.5$ is placed for the kernel size of the correntopy.

In this work, the joint probability density function (PDF) is unknown and due to the availability of finite number of data samples $\{(x_i, y_i), i= 1,2,\ldots\ldots,N\}$, it leads to sample estimator of correntropy, which is as follows [28]:

$$V(X,Y) = \frac{1}{N}\sum_{i=1}^{N} k(x_i - y_i) \tag{10}$$

2.5.3. Sure entropy

Sure entropy is a common measuring tool for quantifying information related properties for an accurate representation of a given signal. Sure entropy of a signal is defined as [29],

$$|x_i| \leq \varepsilon \rightarrow E(x) = \sum_i min(x_i^2, \varepsilon^2) \tag{11}$$

Where, the sure entropy E is a real number, x is the EEG signal and (x_i) i^{th} sample of EEG signal. In sure entropy, ε is a positive threshold value and must be greater than or equal to 0. Here, we choose ε = 0.2.

2.6. Classifiers

2.6.1. Least-squares support vector machine

The support vector machine (SVM) is formulated by applying statistical learning theory [23]. It is a machine learning approach, and is efficiently utilized to identify the patterns [22]. In this approach, first the data is mapped into a higher dimensional input space and a hyperplane is constructed into higher dimensional space to discriminate the dissimilar set of patterns [22]. The LS-SVM is the least square formulation of the SVM. For two class classification problem in SVM, the discrimination function can be written as [22]:

$$v(x) = sign[w^T u(x) + b] \tag{12}$$

Where *w*, *b* and *u(x)* represent the *d*-dimensional weight vector, bias and mapping function, respectively. To optimize the hyperplane in SVM algorithm, the distance from any one of the classes to the hyperplane is maximized. This is an optimization issue and can be fabricated as the quadratic programming problem subject to inequality constraints [22]. In the present methodology, LS-SVM along with two different kernel function, namely polynomial and RBF are used.

2.6.2. K-nearest neighbors

The K-nearest neighbors (K-NN) classifier is based on the assumption that the classification of an instance is most similar to the classification of other instances that are nearby in the vector space [19]. K-NN does not rely on prior probabilities, and it is computationally efficient. The main computation is the sorting of training data in order to find the K-nearest neighbors for the testing data. More importantly, in a dynamic environment that requires frequent additions to the training data collection, incorporating new training data is easy for the K-NN classifier. K-NN classifier, classifies the testing data by measuring the distance from the near one training data. There are mainly two parameters to optimize the classification performance; first one is K which decides how many neighbors influence the classification. Its default value is 1 but we varies it from K = 1 to 5. The second parameter is distance, here, we used Euclidean, cosine, correlation and city-block distances to gather the optimized performance of the classifier [6].

In the present method, to estimate the efficacy of the classifiers, six distinct arguments are involved, which are accuracy (ACC), sensitivity (SEN), specificity (SPF), positive predictive rate (PPR), negative predictive rate (NPR), Matthew's correlation coefficient (MCC) [30].

Chapter 3:
Results and discussion

In this study, we have performed differencing operation to EEG signals in order to make them suitable for further processing. Furthermore, to increase the discrimination between these differenced EEG signals, a FAWT is employed to decompose these signals into fifteen sub-bands and one approximation band (15 level decomposition). The reconstruction of these sub-bands along with signal reconstructed with all bands are used to evaluate nonlinear features namely log energy entropy, correntropy, and sure entropy. To improve the realization, statistically significant features with $p < 0.05$ are decided using the Kruskal-Wallis statistical test [12], which motivated us to omit the 13th sub-band. The p values are shown in Table 3.1 for 3750 pairs of EEG signals and the box plot corresponding to these significant features are shown in Figs. 3.1-3.6. Now the significant features extracted, which were summed up to 48 are tested with various ranking methods namely t-test, entropy, Bhattacharyya space algorithm, receiver operating characteristic (ROC) and Wilcoxon [19]. After ranking with these methods, two well-known classifiers are used to perform classification i.e. LS-SVM with different kernels and K-NN with different distances. The classification performance of two different classifiers with all three entropy together and individually are shown in the Tables 3.2-3.9. The presented methodology was simulated using MATLAB.

Finally, when these extracted essential features were applied to the LS-SVM classifier, it provided good classification. To assure the reliability of classification, ten-fold cross validation technique is used [8]. For performance estimation of LS-SVM classifier, six distinct type of arguments namely, ACC, SEN, SPE, ACC, PPV, NPV and MCC are used. The result corresponding to the maximum accuracy i.e., the method used by us is displayed in the Table 3.2. The maximum value of accuracy, sensitivity, specificity, PPR, NPR and MCC using our method are 94.41%, 93.25%, 95.57%, 95.47%, 93.41% and 0.89, respectively.

In [27] classifiers are used to classify the focal and non-focal EEG signals of patients, which achieved a maximum accuracy of 84% using SVM classifier with RBF kernel function. In [19], entropy features are extracted and fed into LS-SVM classifier which reported a classification accuracy of 84%.

In [21], authors used nonlinear features, entropy and variance of instantaneous frequencies as an input to the LS-SVM classifier. They obtained a maximum accuracy of 85% using RBF as kernel function. Maximum classification accuracy of 87% is achieved in [20] where, for the classification of focal and non-focal EEG signals, entropy features were used. In [6], log-energy entropy is extracted using EMD-DWT and are fed to various classifiers. They achieved maximum accuracy of 89.4% using k-nearest neighbor (KNN) classifier. In the present work, features are extracted from reconstructed signals, and then fed to the

classifier. The maximum classification accuracy of 94.41% is achieved using LS-SVM classifier with RBF kernel. Therefore, the proposed methodology is more accurate as compared to the earlier works.
The main advantage of our method is that, we have obtained a maximum classification accuracy of 94.41% on 3750 focal and 3750 non-focal EEG signals using forty eight features. The limitation of this work is that, we have used reconstructed signals with 14 sub-bands, one approximation sub-band and all sub bands, which increased the size of the feature matrix (7500x16). This technique can be utilized for other types of epilepsy as well as early stages of epilepsy can also be diagnosed.

Furthermore, the performance of this work can be enhanced using different features, kernel functions and classifiers.

Table 3.1: p value for 3750 focal and non-focal EEG signals by Kruskal-Wallis statistical test

Reconstructed signal	Correntropy	Log energy	Sure entropy
All-bands	2.45E-72	1.54E-54	1.65E-73
Sub-band(1)	1.22E-03	4.89E-05	0.00026364
Sub-band(2)	1.48E-55	5.89E-58	2.37E-64
Sub-band(3)	7.68E-64	1.76E-60	1.17E-66
Sub-band(4)	4.16E-61	8.32E-52	1.28E-63
Sub-band(5)	4.04E-43	1.57E-32	4.37E-47
Sub-band(6)	4.80E-54	3.45E-44	3.45E-61
Sub-band(7)	2.22E-28	5.32E-21	5.41E-32
Sub-band(8)	4.22E-43	4.35E-35	3.36E-47
Sub-band(9)	8.97E-55	3.48E-46	1.55E-58
Sub-band(10)	1.31E-64	1.30E-56	2.66E-69
Sub-band(11)	1.34E-38	1.50E-34	8.62E-43
Sub-band(12)	2.81E-15	9.33E-14	2.00E-17
Sub-band(13)	7.04E-01	0.5922634	0.71735811
Sub-band(14)	1.35E-37	3.90E-37	8.12E-37
Sub-band(15)	1.80E-65	1.47E-64	1.14E-64
Approximation-band	1.70E-78	3.83E-79	4.23E-83

Table 3.2: LS-SVM classifier performance with correntropy, Log energy entropy and sure entropy involving 48 statistically significant features.

Ranking method	Kernel function	ACC	SEN	SPF	PPR	NPR	MCC	Parameter for kernel
T-test	RBF	94.36	93.31	95.41	95.31	93.45	0.89	1.40
Entropy	RBF	94.35	93.25	95.44	95.34	93.42	0.89	1.40
Bhattacharya	RBF	94.40	93.31	95.49	95.40	93.47	0.89	1.20
ROC	RBF	94.39	93.25	95.52	95.42	93.42	0.89	1.30
Wilcoxon	RBF	94.41	93.25	95.57	95.47	93.41	0.89	1.40
T-test	Polynomial	93.27	91.71	94.83	94.66	91.97	0.87	3.00
Entropy	Polynomial	93.45	91.73	95.17	95.00	92.02	0.87	3.00
Bhattacharya	Polynomial	93.21	91.47	94.96	94.80	91.77	0.86	3.00
ROC	Polynomial	93.60	91.87	95.33	95.18	92.14	0.87	3.00
Wilcoxon	Polynomial	93.37	91.60	95.15	94.99	91.91	0.87	3.00

Table 3.3: K-NN classifier performance with correntropy, log energy entropy and sure entropy involving 48 statistically significant features.

Ranking method	Distance	ACC	SEN	SPF	PPR	NPR	MCC	Number of nearest neighbors
T-test	Euclidean	93.09	91.12	95.07	94.87	91.48	0.86	4.00
T-test	Cityblock	93.35	91.25	95.44	95.25	91.62	0.87	3.00
T-test	Cosine	93.20	91.20	95.20	95.00	91.55	0.86	4.00
T-test	Correlation	93.13	91.36	94.91	94.73	91.68	0.86	4.00
Entropy	Euclidean	93.12	91.09	95.15	94.95	91.45	0.86	4.00
Entropy	Cityblock	93.57	91.92	95.23	95.08	92.19	0.87	4.00
Entropy	Cosine	93.15	91.20	95.09	94.91	91.54	0.86	4.00
Entropy	Correlation	93.09	91.15	95.04	94.85	91.49	0.86	4.00
Bhattacharyya	Euclidean	93.05	91.01	95.09	94.89	91.37	0.86	4.00
Bhattacharyya	Cityblock	93.33	91.28	95.39	95.20	91.64	0.87	4.00
Bhattacharyya	Cosine	93.20	91.12	95.28	95.09	91.48	0.86	4.00
Bhattacharyya	Correlation	93.01	91.15	94.88	94.70	91.48	0.86	4.00
ROC	Euclidean	93.12	90.91	95.33	95.13	91.31	0.86	4.00
ROC	Cityblock	93.25	91.44	95.07	94.90	91.75	0.87	4.00
ROC	Cosine	93.23	91.36	95.09	94.90	91.69	0.87	4.00
ROC	Correlation	93.05	91.17	94.93	94.73	91.51	0.86	4.00
Wilcoxon	Euclidean	93.12	90.85	95.39	95.18	91.26	0.86	4.00
Wilcoxon	Cityblock	93.44	91.41	95.47	95.29	91.76	0.87	4.00
Wilcoxon	Cosine	93.24	91.09	95.39	95.18	91.47	0.87	4.00
Wilcoxon	Correlation	93.36	91.60	95.12	94.98	91.91	0.87	4.00

Table 3.4: LS-SVM classifier performance with log energy entropy involving 16 statistically significant features

Ranking method	Kernel function	ACC	SEN	SPF	PPR	NPR	MCC	Parameter for kernel
T-test	RBF	94.19	92.96	95.41	95.30	93.14	0.88	1.00
Entropy	RBF	94.31	92.91	95.71	95.59	93.12	0.89	1.00
Bhattacharya	RBF	94.25	92.80	95.71	95.58	93.01	0.89	1.00
ROC	RBF	94.23	92.83	95.63	95.52	93.03	0.89	1.00
Wilcoxon	RBF	94.21	92.85	95.57	95.45	93.05	0.88	1.00
T-test	Polynomial	92.71	90.99	94.43	94.24	91.29	0.85	4.00
Entropy	Polynomial	92.56	90.53	94.59	94.37	90.92	0.85	4.00
Bhattacharya	Polynomial	92.48	90.43	94.53	94.31	90.82	0.85	4.00
ROC	Polynomial	92.76	90.91	94.61	94.41	91.25	0.86	4.00
Wilcoxon	Polynomial	92.49	90.56	94.43	94.21	90.92	0.85	4.00

Table 3.5: K-NN classifier performance with log energy entropy involving 16 statistically significant features

Ranking method	Distance	ACC	SEN	SPF	PPR	NPR	MCC	Number of nearest neighbors
T-test	Euclidean	93.16	90.96	95.36	95.16	91.35	0.86	4.00
T-test	Cityblock	93.52	91.84	95.20	95.06	92.12	0.87	4.00
T-test	Cosine	92.63	90.72	94.53	94.34	91.09	0.85	4.00
T-test	Correlation	89.11	87.33	90.88	90.55	87.79	0.78	5.00
Entropy	Euclidean	93.03	90.88	95.17	94.97	91.27	0.86	4.00
Entropy	Cityblock	93.44	91.57	95.31	95.13	91.88	0.87	3.00
Entropy	Cosine	92.63	90.80	94.45	94.25	91.17	0.85	4.00
Entropy	Correlation	89.00	87.41	90.59	90.29	87.81	0.78	4.00
Bhattacharyya	Euclidean	93.05	90.88	95.23	95.02	91.28	0.86	4.00
Bhattacharyya	Cityblock	93.57	91.71	95.44	95.27	92.03	0.87	4.00
Bhattacharyya	Cosine	92.61	90.75	94.48	94.29	91.08	0.85	4.00
Bhattacharyya	Correlation	88.99	87.44	90.53	90.27	87.83	0.78	4.00
ROC	Euclidean	93.15	90.99	95.31	95.10	91.38	0.86	4.00
ROC	Cityblock	93.61	91.84	95.39	95.23	92.14	0.87	4.00
ROC	Cosine	92.63	90.64	94.61	94.40	91.00	0.85	4.00
ROC	Correlation	89.03	86.96	91.09	90.73	87.50	0.78	5.00
Wilcoxon	Euclidean	93.01	90.80	95.23	95.03	91.22	0.86	4.00
Wilcoxon	Cityblock	93.64	91.79	95.49	95.33	92.09	0.87	4.00
Wilcoxon	Cosine	92.64	90.80	94.48	94.28	91.14	0.85	4.00
Wilcoxon	Correlation	89.00	87.63	90.37	90.13	87.98	0.78	3.00

Table 3.6: LS-SVM classifier performance with correntropy involving 16 statistically significant features

Ranking method	Kernel function	ACC	SEN	SPF	PPR	NPR	MCC	Parameter for kernel
T-test	RBF	92.95	91.52	94.37	94.23	91.77	0.86	1.00
Entropy	RBF	92.99	91.57	94.40	94.26	91.82	0.86	1.00
Bhattacharya	RBF	93.12	91.57	94.67	94.51	91.84	0.86	1.00
ROC	RBF	92.83	91.55	94.11	93.96	91.78	0.86	1.00
Wilcoxon	RBF	92.95	91.57	94.32	94.18	91.80	0.86	1.00
T-test	Polynomial	92.47	90.83	94.11	93.93	91.13	0.85	4.00
Entropy	Polynomial	92.69	91.07	94.32	94.14	91.37	0.85	4.00
Bhattacharya	Polynomial	92.73	91.25	94.21	94.06	91.52	0.86	4.00
ROC	Polynomial	92.55	90.96	94.13	93.95	91.26	0.85	4.00
Wilcoxon	Polynomial	92.59	91.33	93.84	93.70	91.56	0.85	4.00

Table 3.7: K-NN classifier performance with correntropy involving 16 statistically significant features

Ranking method	Distance	ACC	SEN	SPF	PPR	NPR	MCC	Number of nearest neighbors
T-test	Euclidean	90.13	88.59	91.68	91.42	88.95	0.80	3.00
T-test	Cityblock	91.15	89.52	92.77	92.57	89.88	0.82	4.00
T-test	Cosine	90.49	89.41	91.57	91.40	89.68	0.81	4.00
T-test	Correlation	90.52	89.60	91.44	91.29	89.80	0.81	4.00
Entropy	Euclidean	89.96	88.45	91.47	91.21	88.82	0.80	3.00
Entropy	Cityblock	90.96	89.12	92.80	92.55	89.53	0.82	4.00
Entropy	Cosine	90.59	89.47	91.71	91.52	89.73	0.81	4.00
Entropy	Correlation	90.31	89.60	91.01	90.91	89.77	0.81	4.00
Bhattacharyya	Euclidean	90.01	88.93	91.09	90.91	89.18	0.80	4.00
Bhattacharyya	Cityblock	90.89	89.01	92.77	92.51	89.43	0.82	4.00
Bhattacharyya	Cosine	90.52	89.49	91.55	91.39	89.73	0.81	4.00
Bhattacharyya	Correlation	90.36	89.52	91.20	91.06	89.73	0.81	4.00
ROC	Euclidean	90.16	88.80	91.52	91.30	89.11	0.80	4.00
ROC	Cityblock	91.21	89.44	92.99	92.74	89.81	0.82	4.00
ROC	Cosine	90.51	89.49	91.52	91.37	89.71	0.81	4.00
ROC	Correlation	90.33	89.71	90.96	90.88	89.85	0.81	4.00
Wilcoxon	Euclidean	90.12	88.80	91.44	91.21	89.11	0.80	4.00
Wilcoxon	Cityblock	91.01	89.01	93.01	92.74	89.48	0.82	4.00
Wilcoxon	Cosine	90.67	89.55	91.79	91.61	89.80	0.81	4.00
Wilcoxon	Correlation	90.36	89.57	91.15	91.02	89.75	0.81	4.00

Table 3.8: LS-SVM classifier performance with sure entropy involving 16 statistically significant features

Ranking method	Kernel function	ACC	SEN	SPF	PPR	NPR	MCC	Parameter for kernel
T-test	RBF	91.45	89.55	93.36	93.11	89.96	0.83	1.00
Entropy	RBF	91.56	89.76	93.36	93.14	90.14	0.83	1.00
Bhattacharya	RBF	91.55	89.65	93.44	93.22	90.06	0.83	1.00
ROC	RBF	91.40	89.49	93.31	93.05	89.89	0.83	1.00
Wilcoxon	RBF	91.52	89.76	93.28	93.06	90.11	0.83	1.00
T-test	Polynomial	89.63	87.68	91.57	91.26	88.17	0.79	3.00
Entropy	Polynomial	89.57	87.55	91.60	91.28	88.07	0.79	3.00
Bhattacharya	Polynomial	89.79	87.95	91.63	91.32	88.41	0.80	3.00
ROC	Polynomial	89.56	87.76	91.36	91.06	88.21	0.79	3.00
Wilcoxon	Polynomial	89.51	87.71	91.31	91.00	88.14	0.79	3.00

Table 3.9: K-NN classifier performance with sure entropy involving 16 statistically significant features

Ranking Method	Distance	ACC	SEN	SPF	PPR	NPR	MCC	Number of nearest neighbors
T-test	Euclidean	89.57	86.77	92.37	91.95	87.50	0.79	5.00
T-test	Cityblock	90.65	88.67	92.64	92.36	89.11	0.81	4.00
T-test	Cosine	88.60	86.85	90.35	89.99	87.33	0.77	4.00
T-test	Correlation	86.52	86.61	86.43	86.48	86.60	0.73	4.00
Entropy	Euclidean	89.77	87.01	92.53	92.10	87.73	0.80	5.00
Entropy	Cityblock	90.60	88.45	92.75	92.43	88.95	0.81	4.00
Entropy	Cosine	88.81	87.04	90.59	90.27	87.52	0.78	4.00
Entropy	Correlation	86.17	86.11	86.24	86.26	86.15	0.72	3.00
Bhattacharyya	Euclidean	89.71	87.17	92.24	91.84	87.82	0.80	5.00
Bhattacharyya	Cityblock	90.71	87.71	93.71	93.30	88.42	0.82	5.00
Bhattacharyya	Cosine	88.79	87.12	90.45	90.16	87.56	0.78	4.00
Bhattacharyya	Correlation	86.19	86.11	86.27	86.26	86.14	0.72	4.00
ROC	Euclidean	89.81	87.20	92.43	92.02	87.86	0.80	5.00
ROC	Cityblock	90.69	88.69	92.69	92.40	89.13	0.81	4.00
ROC	Cosine	88.68	87.09	90.27	89.97	87.50	0.77	4.00
ROC	Correlation	86.51	86.59	86.43	86.47	86.60	0.73	4.00
Wilcoxon	Euclidean	89.73	87.63	91.84	91.49	88.14	0.80	4.00
Wilcoxon	Cityblock	90.45	88.08	92.83	92.47	88.63	0.81	4.00
Wilcoxon	Cosine	88.68	87.12	90.24	89.94	87.55	0.77	4.00
Wilcoxon	Correlation	86.28	86.21	86.35	86.35	86.28	0.73	4.00

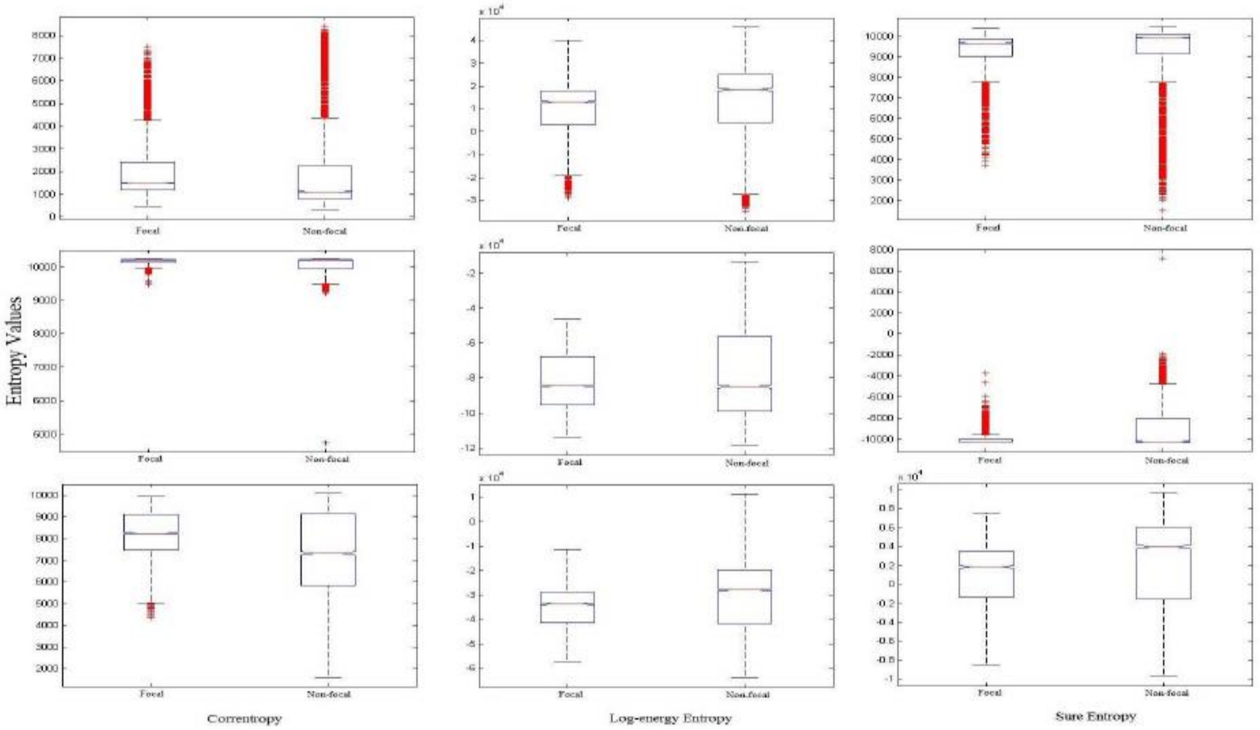

Figure 3.1: Box plots of reconstructed signals from all bands and 1st - 2nd detailed sub-bands in first, second and third row respectively for correntropy, log-energy entropy and sure entropy in first-third column respectively.

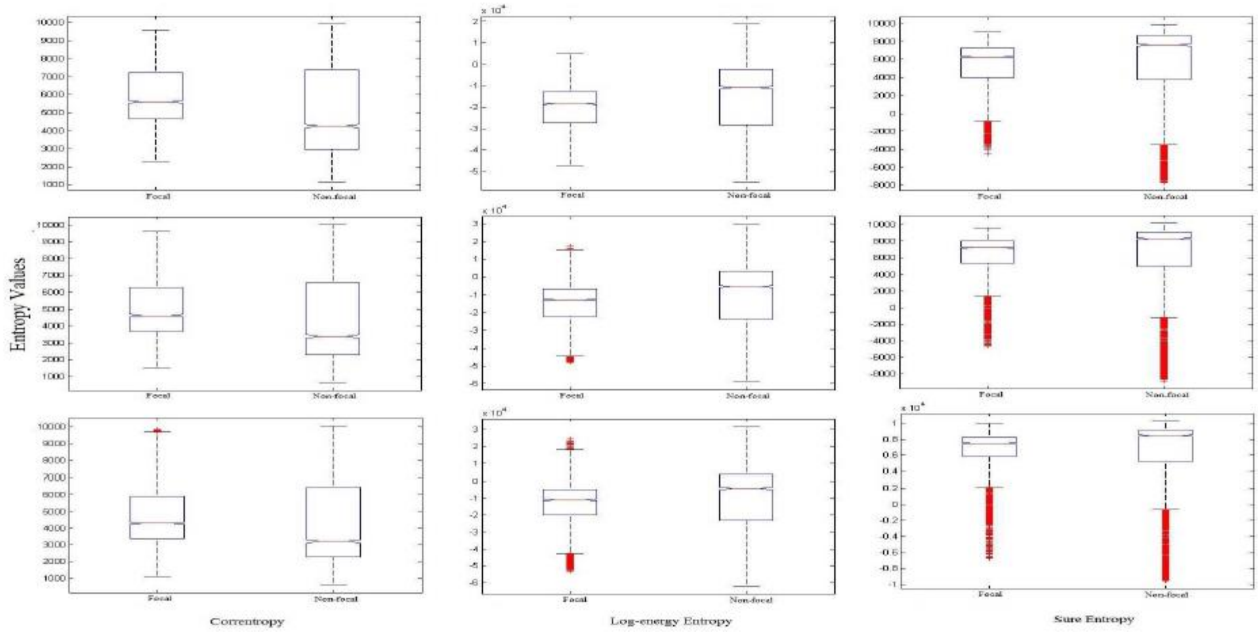

Figure 3.2: Box plots of reconstructed signals from 3rd to 5th detailed sub-bands in first, second and third row respectively for correntropy, log-energy entropy and sure entropy in first-third column respectively.

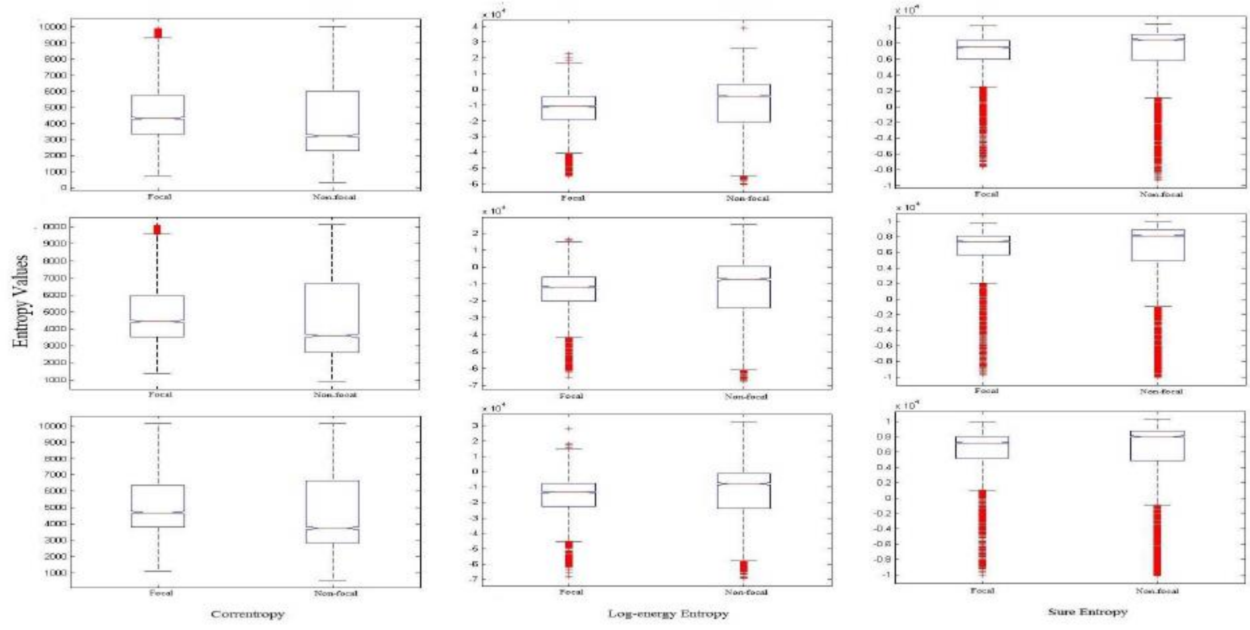

Figure 3.3: Box plots of reconstructed signals from 6th to 8th detailed sub-bands in first, second and third row respectively for correntropy, log-energy entropy and sure entropy in first-third column respectively.

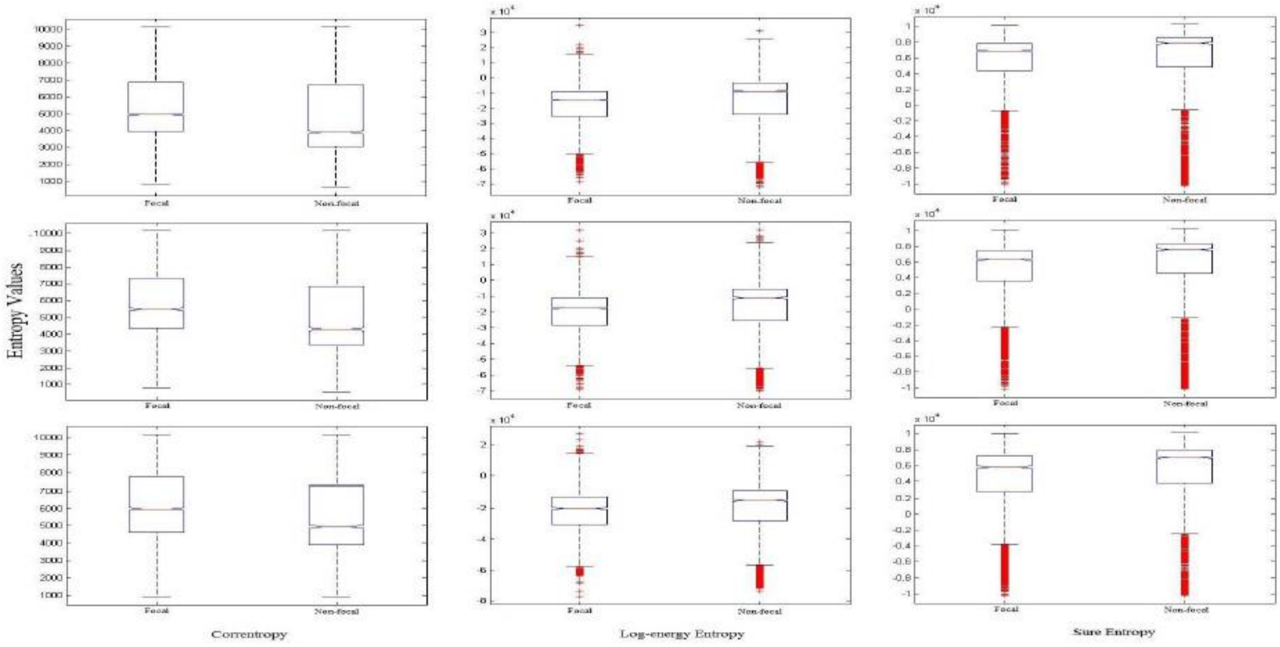

Figure 3.4: Box plots of reconstructed signals from 9th to 11th detailed sub-bands in first, second and third row respectively for correntropy, log-energy entropy and sure entropy in first-third column respectively.

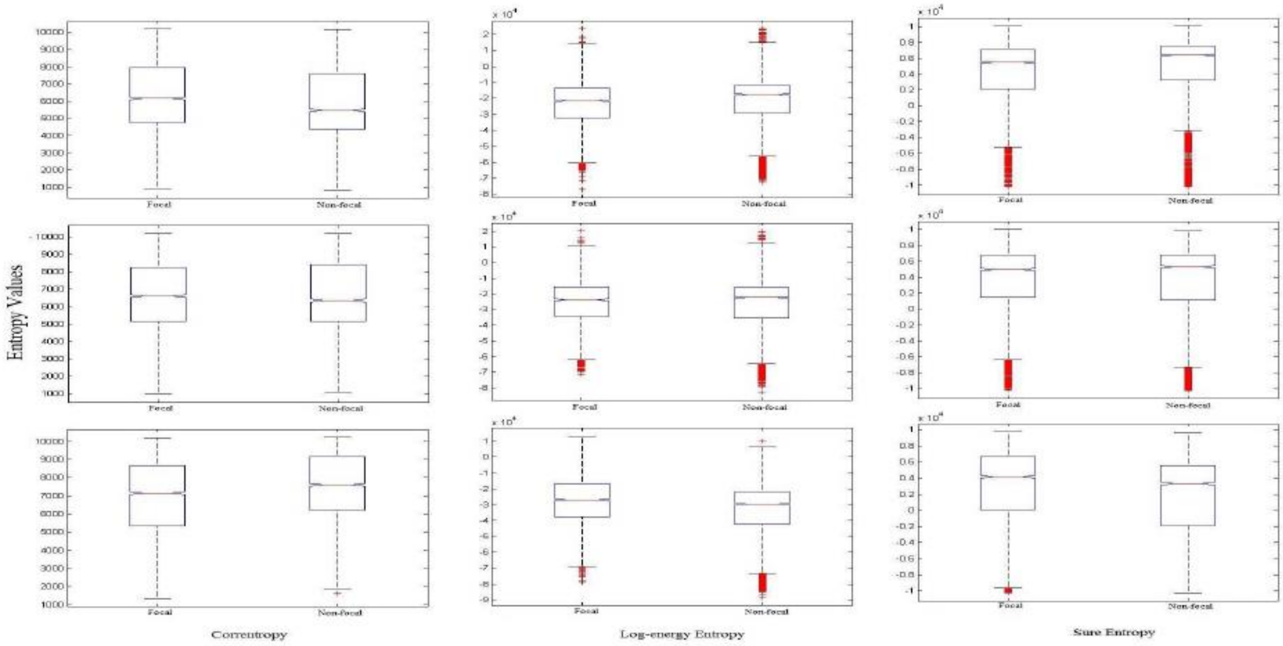

Figure 3.5: Box plots of reconstructed signals from 12th to 14th detailed sub-bands in first, second and third row respectively for correntropy, log-energy entropy and sure entropy in first-third column respectively.

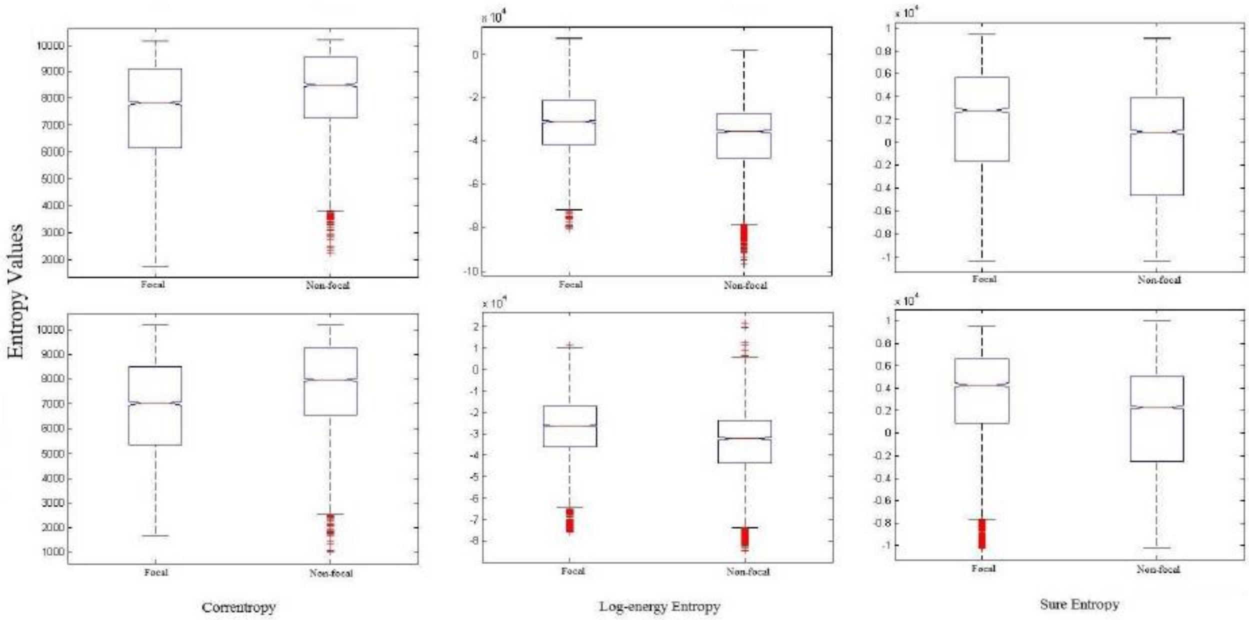

Figure 3.6: Box plots of reconstructed signals from 15th detailed sub-band and one approximate band in first and second row respectively for correntropy, log-energy entropy and sure entropy in first-third column respectively.

Table 3.10: Comparison of the classification performance of the proposed work with the existing work.

Authors, Year, Reference	Features	Classification method	Classification accuracy (%)
Zhu et al. (2013) [27]	Delay permutation entropy	SVM RBF Kernel	84%
Sharma et al. (2015) [19]	DWT, Entropy measures	SVM least square method	84%
Sharma et al. (2014) [21]	EMD, ASE, AVIF	SVM least square method	85%
Sharma et al. (2015) [20]	EMD, Entropy measures	SVM least square method	87%
Das et al. (2016) [6]	EMD-DWT, log-energy entropy	KNN city-block distance	89.4%
Bhattacharyya et al. (2016) [4]	RPS, CTM	LS-SVM method	90%
Sharma et al. (2016) [31]	Orthogonal wavelet filter banks, Entropy measures	LS-SVM method	94.25%
Present work	FAWT, correntropy, log-energy entropy and sure entropy	LS-SVM method with RBF kernel	94.41%

Chapter 4:

Conclusions and scope for future

A significant part of the population is affected by epilepsy which hinders their inclusion in the society. This provides a motivation for a research to come up with novel ideas for taking this challenge. The epilepsy is a serious brain related disease and the patients suffering from it are increasing day by day. Undetected epilepsy may lead to long term complications, causing severe disorder problems. Early detection of epilepsy may save the patients from these serious disorder issues. In the present work, only focal epilepsy is considered. FAWT method is used to decompose the differencing focal and non-focal EEG signals into sub-bands.

From these sub-bands, reconstructed signals are obtained which is used for feature extraction, namely correntropy, log energy entropy and sure entropy. Statistically significant features, decided using Kruskal-Wallis statistical test, are used as an input to the different classifiers for the discrimination of focal and non-focal EEG signals. Ten-fold cross validation algorithm is involved to confirm the reliability of the classifiers. The best classification accuracy of 94.41% is acquired using RBF kernel function with LS-SVM. The primary benefit of the proposed methodology is that it can help in automatically identifying the focal epileptic area of a patient with high accuracy and devoid of personal errors which in turn will reduce the work load of the clinicians.

In future work, several new features can be studied and may be utilized with the extracted features in the present work so that the classification accuracy may be further improved. Also, some new kernel functions may be defined and used with LS-SVM classifier. Artificial neural network (ANN) and other classification techniques may also be used with the proposed features.

The proposed methodology can also be applied for other physiological signals like phonocardiogram (PCG), electromyogram (EMG) and electrocardiogram (ECG) etc.

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