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Classification of Epileptic EEG Signals using Wavelet-EMD-Domain Features and Improved Multi-class SVM

[1]Mohammad J. Arif, [2]Ramakrishnan S, [3]Ibrahiem M. M. El Emary, [4]Hassan A. Alsuraihi, [5]Muthanantha Murugavel A. S.

[1,3,4]Information Science Dept, Faculty of Arts and Humanities, King Abdulaziz University, Jeddah, Saudi Arabia
[2,5]Department of Information Technology,
Dr. Mahalingam College of Engineering and Technology, Pollachi, Tamilnadu, India

Abstract. Epilepsy is a chronic neurological disease caused by a disturbance in the electrical activity of the brain. In this paper, a novel approach based on multi-domain features, a selection of significantly important features from three domains namely time, wavelet and wavelet-EMD and combining them to classify EEG signals for epileptic seizure detection is proposed. The statistical time-domain features such as minimum, maximum, mean, standard deviation from time-domain, non-linear features namely largest Lyapunov exponent (LLE), approximate entropy (AE), and correlation dimension (CD) from the wavelet-EMD domain are extracted and used for the classification process. For feature selection, inter-class and intra-class based entropy is applied. Appropriate class-specific features that characterize the sub-band are selected to improve classification accuracy and to reduce computation time. An improved multi-class support vector machine is employed for the classification of epileptic EEG signals. The performances of the proposed methods are evaluated using two different benchmark EEG datasets such as Freiburg and Bonn. The performance measures namely classification accuracy, sensitivity, specificity, execution time and receiver-operating characteristics (ROC) are used to evaluate and analyze the performances of the proposed classifier. It is learned from the experiments conducted that the proposed method provides better performance in terms of improved classification accuracy with reduced execution time compared to that of the existing methods.

Keywords. Electroencephalogram signal classification, Epileptic seizure detection, Multi-domain feature extraction, Empirical mode decomposition, Wavelet Transformation, Support vector machine

1. Introduction

Approximately 1% of world's population suffers from the brain disorder called epileptic seizure [1]. The brain being command centre of the human body exercises control over the functioning of various organs in the body. The detection of epileptic seizures is possible by analyzing Electroencephalogram (EEG) signals. Diagnosis of an epileptic seizure is carried out by visual inspection of EEG records of long duration and is a very tedious and error-prone task.

Hence several researchers are working on developing efficient computerized seizure detection systems [2]. Recently many research works are carried out on feature extraction [3-4], feature selection [5-6] and classification methods [7-8] for epileptic seizure detection. Normally features are extracted in time, frequency and wavelet domains. Using all the features extracted from EEG may not be relevant or important for classification, and also take more computation time especially in epileptic seizure detection.

The existing classifiers provide reasonable classification accuracy but take more time for classification. Thus developing a new approach for extracting features and selecting significant features from the extracted features and classifying EEG signals is much essential. The detection of epileptic seizures is possible by analyzing Electroencephalogram (EEG) signals. EEG is a potential bio-signal which contains details of the electrical activity of the brain produced by the neurons. EEG is captured using surface and scalp electrodes with 18 or 24 channel systems [9]. Since EEG signals are a function of time, directly estimating features from time-domain are used to measure the EEG rhythmicity [10]. The classifiers such as Linear Discriminant Analysis (LDA), Multi-Layer Perceptron Neural Network (MLPNN), Probabilistic Neural Network (PNN), Elman Neural Network (ENN), Radial Basis Function Neural Network (RBFNN), Naive Bayes, Mahalanobis Distance, K-NN (K-Nearest Neighbor), Decision Trees, Logistic Regression, Bayes Quadratic, Hidden Markov Model (HMM), Support Vector Machine (SVM) are prominently used in EEG classification techniques for epileptic seizure detection [11].

In this paper, extraction of multi-domain features with entropy-based feature selection method is proposed for epileptic seizure detection. An improved multi-class SVM is used for the classification of EEG signals for seizure detection. The paper is organized as follows: in section 2, some of the important related works are described while section 3 describes benchmark EEG dataset used in this work. Section 4 explains in detail the various proposed methodologies such as multi-domain feature extraction, entropy-based feature selection and multi-class SVM classifier. Section 5 provides a description of various experiments carried out with results and discussion. Finally, Section 6 presents conclusion and possible future work.

2. Existing Seizure Detection Methods

Recent years number of research works have been conducted in the field of seizure detection. Alotaiby et al presented an overview of existing seizure detection and prediction algorithms with comparisons [12]. Figure 1 illustrates categories of various feature extraction, feature selection and classification methods applied in seizure detection. For epileptic seizure detection, time domain features such as amplitude difference and time separation between peak values as well as minima were used with SVM as classifier [13]. Yoo et al. used an 8 channel scalable EEG acquisition system-on-chip (SoC) with patient-specific seizure classification and recording processor for detecting epileptic seizures [14]. An efficient resource with three interdependent components such as PhysioBank, PhysioToolkit, and PhysioNet has been developed in the field of biosignal processing [15]. The classifier is well suited for the hardware implementation. The SoC was tested on CHB-MIT scalp EEG database. A remote monitoring system for monitoring and detecting epileptic-seizures based on accelerometer kinematic sensors

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was developed [16]. The data were gathered from subjects undergoing medication titration at the Beth Israel Deaconess Medical Center. Siuly et al proposed a framework based on samplings and machine learning techniques for the detection of multi-category EEG signals where random sampling and optimal allocation sampling were explored [16]. In this, three well-known classifiers such as a k-nearest neighbour, multinomial logistic regression with a ridge estimator, and support vector machine (SVM) [17-18] were employed to evaluate the performance of the dataset.

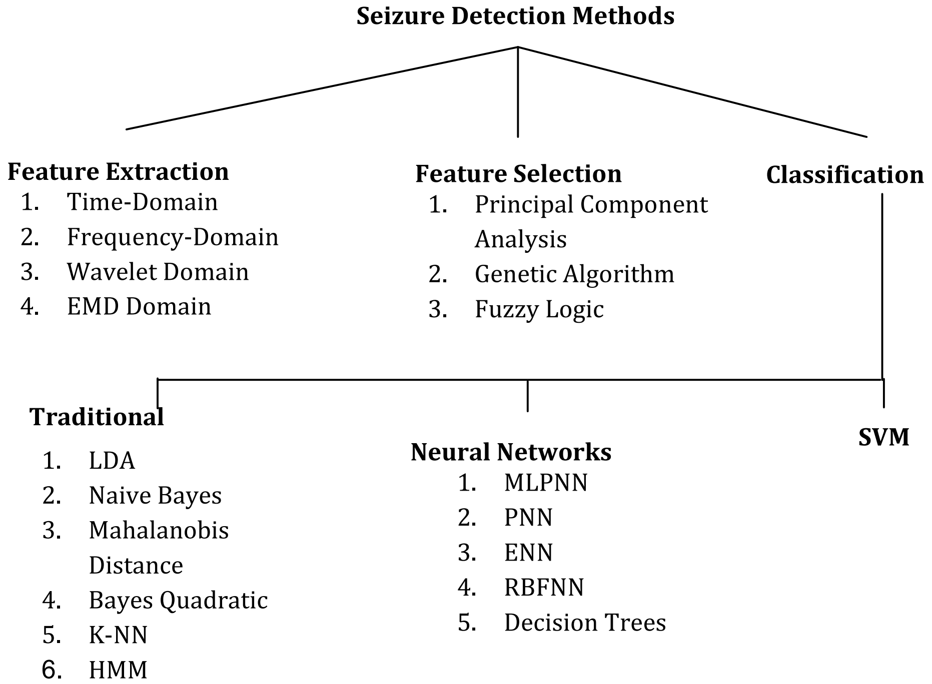

Figure 1 Categories of various feature extraction, feature selection and classification methods for seizure detection

3. Proposed Methods and Materials

The proposed approach consists of three stages namely feature extraction, feature selection and classification. The proposed methods are evaluated using two different benchmark EEG datasets such as Freiburg and Bonn.

3.1 Experimental Benchmark Dataset

3.1.1 Freiburg Dataset

The Freiburg database (http://epilepsy.uni-freiburg.de/database) is a collection of EEG recordings from 21 patients suffering from medically intractable focal epilepsy. The data have been taken from intracranial EEG recordings, conducted by the Epilepsy Centre of the University Hospital of Freiburg, Germany. The data have been captured at a rate of 256 Hz and quantized to 16 bits and has not undergone any sort of pre-processing. Each file in the records consists of a

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one-dimensional array of data representing data recorded in mV from one EEG channel. The recordings are split into 2 classes such as ictal (Set A) and inter-ictal (Set E). The Freiburg EEG Database have experimented in a number of research works [19 - 21].

3. 1.2 Bonn Dataset

The university of Bonn, Germany's EEG dataset is commonly used benchmark dataset for epileptic seizure detection and publically available [22]. It has five classes namely {A, B, C, D, E} and each class has 100 records. These 500 records are captured for the duration of 23.6 seconds each and digitized at 173.61 Hz sampling rate [27-28]. The description of the data set is summarized in Table 1.

Table 1 Summary of five-class EEG dataset (Bonn) with description

Subject	SET A	SET B	SET C	SET D	SET E
	Five healthy subject		Five epileptic patients		
Patient state	Awake and eyes open (normal)	Awake and eyes closed (normal)	Seizure free (inter-ictal)	Seizure free (inter-ictal)	Seizure Activity (ictal)
Electrode types	Surface	Surface	Intracranial	Intracranial	Intracranial
Electrode placement	International 10–20	International 10–20	Within epileptogenic zone	Opposite to epileptogenic zone	Within epileptogenic zone
No. of epochs	100	100	100	100	100
Epoch duration(s)	23.6	23.6	23.6	23.6	23.6

3.2 Wavelet-EMD-Domain Feature Extraction

Generally features are extracted in time, frequency and time-frequency domains. Time-domain features reveal exact location of the seizure but unable to disclose at which frequency it has that spike. Whereas the frequency domain features can reveal the identity of the frequency component but unable to detect the time of occurrence. In order to mitigate this problem, time-frequency domain features are extracted and successfully employed for detection of epileptic seizures. Even though time-domain, frequency-domain and wavelet-domain features have emerged as significant features, they have their own limitations when using them independently. This work proposes multi-domain features by combining all the three domains' significant features.

The block diagram of the proposed multi-domain feature extraction approach is illustrated in Figure 2. The ability of classification approaches heavily depends on the type and nature of the features characterizing the signal under consideration. EEG signals are non-linear, non-stationary and highly complex bio-medical signals. Characterization of such a random signal requires features from various domains. In addition to the features from time and wavelet domain, this proposed work also consider the features from the wavelet-EMD domain.

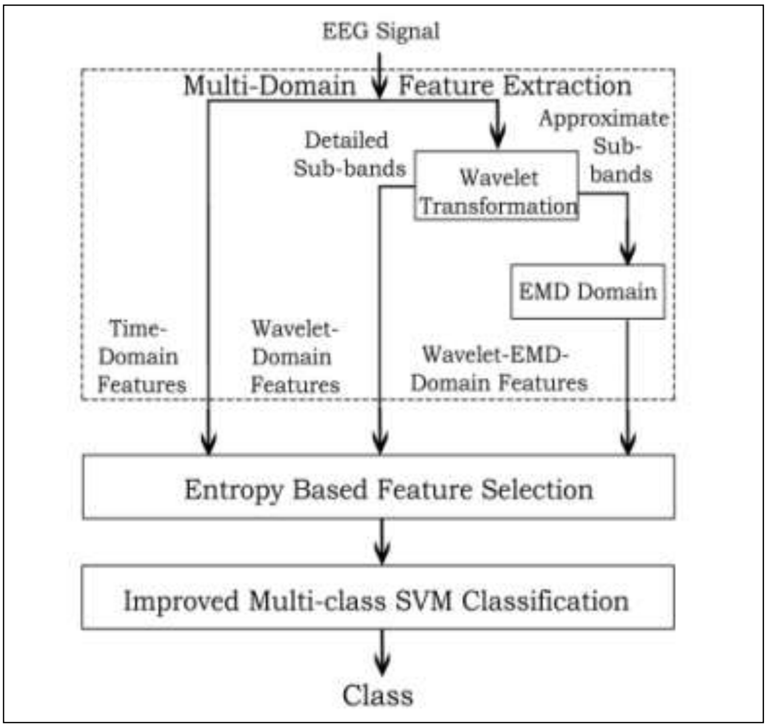

Figure 2 Block diagram of the proposed multi-domain feature extraction, selection and classification of EEG signals

3.2.1 Time-Domain Features

Characterizing signals in time-domain is computationally less expensive and not effective. However, the time-domain features when combined with other domains improve the classification rate. Proposed work extracts the following features from time-domain.

- Maximum Value
- Minimum Value
- Mean
- Standard Deviation

3.2.2 Wavelet-EMD Domain Features

Wavelet transformation (WT) is an efficient method to classify and analyze non-stationary signals [23]. Wavelet transform decomposes the signals into approximate and detailed sub-bands. The approximate sub-bands resemble the signals in the time domain and detailed sub-bands have

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high-frequency components. Both time and wavelet domain features are used by a number of researchers to characterize the EEG signals. The limitation of the wavelet domain in EEG signal characterization is a resemblance of the time domain signal in approximate sub-bands. Empirical mode decomposition (EMD) has the ability to model complex signals that are non-linear and non-stationary in nature [19]. EMD uses intrinsic mode functions to decompose signals. Intrinsic mode functions require computation of local maxima and local minima and connecting those points using suitable interpolation functions such as cubic spline [24]. Due to this EMD signals does not resemble time-domain signals, unlike wavelet-transformed signals.

In this work, the input EEG data is wavelet decomposed up to four levels using Daubechies 4 (DB4) wavelet basis function. The approximate sub-band of the wavelet decomposition is subjected to empirical mode decomposition to eliminate the resemblance of the time- domain signals. Following non-linear features are extracted from both wavelet and wavelet-EMD domain in addition to the linear time-domain features.

i. Approximate Entropy (AE)

The approximate entropy [22, 25] is a non-linear feature capable of predicting present amplitude values of EEG signal based on the previous amplitude values. The AE measures complexity or irregularity of the physiological system. The formula for computing approximate entropy is as follows.

$$AE = \frac{1}{N-p}\left[\sum_{i=1}^{N-p} \ln\left(\frac{C_i^p(r)}{C_i^{p+1}(r)}\right)\right] \quad (1)$$

where x are wavelet coefficients of each sub-band, N denotes the length of x, p represents the number of samples used for the prediction, and r represents the noise filter level. The parameter namely $C_i^p(r)$ is defined as follows.

$$C_i^p(r) = \frac{\sum_{j=1}^{N-p} k_j}{N-p} \quad (2)$$

where $k = \begin{cases} 1, & \text{if } |x(i) - x(j) \text{ for } 1 \le j \le N-p \\ 0, & \text{otherwise} \end{cases}$

ii. Largest Lyapunov Exponent (LLE)

The largest Lyapunov exponent [23] represents system chaoticity and quantifies the non-linear chaotic dynamics of the data. The formula of the largest Lyapunov exponent is given below.

$$LLE = \frac{1}{N\Delta t}\left[\sum_{i=1}^{N} \log_2 \frac{|\Delta x_{ij}(\Delta t)|}{|\Delta x_{ij}(0)|}\right] \quad (3)$$

Where x are wavelet coefficients of each sub-band, N denotes the length of x, $\Delta x_{ij}(0) = x(t_i)-x(t_j)$ is the displacement vector at the time point t_i.

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iii. Correlation Dimension (CD)

Correlation dimension is another important non-linear feature used to measure the dimensionality of the space occupied by a set of random points [23]. The correlation dimension has the advantages of fast computation time and less noisy. The formula for computing Correlation Dimension is given below.

$$CD = -\left[\frac{2}{N(N-1))}\sum_{i=1}^{N}\sum_{j=1}^{N}\log\left(\frac{x_i(d_M)-x_j(d_M)}{\varepsilon}\right)\right]^{-1} \quad (4)$$

where x are wavelet coefficients of each sub-band, N denotes the length of x, d_M denotes embedding dimension and ε is the radius of the measuring unit.

iv. Feature Vector

The multi-domain features extracted from all the three domains namely time, wavelet and wavelet-EMD are listed below.

- Time-domain: Minimum, Maximum, Mean, Standard deviation (4 features)
- Wavelet-domain: AE, LLE, CD (3 X 4 sub-bands = 12 features)
- Wavelet-EMD domain: AE, LLE, CD for the sub-band A4 (3 features)
- Total number of features: 19

3. 3 Entropy based Feature Selection

In pattern classification, feature selection is the important process as it is used for improving classification accuracy, reducing required storage and computational time. In this proposed work, selection of feature subset that is reduced in size and capable of discriminating samples that belong to different classes, are selected based on Entropy. Every sub-band has its own characteristics. If the appropriate features which characterize the specific sub-band are selected then the classification accuracy is improved and computational complexity is reduced. Hence, entropy based feature selection algorithm is used in this work.

The class similarity and dissimilarity can be analyzed using inter-class and intra-class entropy and are calculated using the following entropy formula.

$$\text{Entropy} = -\sum_{i=1}^{k} P(\text{value}_i).\log_2(P(\text{value}_i)) \quad (5)$$

where $P(\text{value}_i)$ is the probability of getting i_{th} value.

Inter-class and Intra-class entropy is computed for each extracted feature. Table 2 presents intra-class entropy and inter-class entropy for the multi-domain features. Class-wise similarity and dissimilarity are analyzed for selecting features. The logic to select features is that inter-class entropy should be maximum and intra-class entropy should be minimum.

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Table 2 Intra-Class Entropy and Inter-Class Entropy for the Different Multi-Domain features

Features	Domain	Intra-class Entropy					Inter-class Entropy
		Class A	Class B	Class C	Class D	Class E	
Minimum	Time	0.24	0.33	0.37	0.29	0.13	0.74
Maximum		0.37	0.21	0.23	0.32	0.12	0.87
Mean		0.24	0.34	0.38	0.22	0.29	0.84
Standard Deviation		0.15	0.27	0.13	0.22	0.19	0.73
D4_AE	Wavelet	0.28	0.30	0.37	0.43	0.13	0.48
D4_LLE		0.13	0.29	0.25	0.25	0.23	0.43
D4_CD		0.08	0.26	0.09	0.26	0.34	0.68
D3_LLE		0.38	0.25	0.14	0.34	0.21	0.88
D3_CD		0.15	0.35	0.17	0.28	0.17	0.55
D2_CD		0.47	0.18	0.28	0.34	0.21	0.77
D1_AE		0.24	0.27	0.35	0.16	0.26	0.54
D1_LLE		0.68	0.39	0.23	0.23	0.31	0.68
A4_AE	Wavelet-EMD	0.18	0.28	0.37	0.43	0.13	0.48
A4_LLE		0.12	0.29	0.23	0.24	0.23	0.42
A4_CD		0.09	0.28	0.08	0.26	0.33	0.66

Table 3 presents selected class-specific multi-domain features based on entropy. Class-wise similarity and dissimilarity are analyzed for selecting features. The logic to select features is that inter-class entropy should be maximum and intra-class entropy should be minimum. Finally using this feature selection method, 2 to 13 class specific multi-domain features have been selected as potential features.

Table 3 Selected Class-specific Multi-Domain Features based on Entropy

Class Name	Selected Features	No. of Features
A	Mean, Standard Deviation, LLE_D1	3
B	Mean, Standard Deviation, LLE_D1	3
C	Minimum, Maximum, LLE_A4, CD_A4, AE_D4, LLE_D3, CD_D3, CD_D2, AE_D1, LLE_D1	10
D	Class D: Standard Deviation, LLE_A4, CD_A4, AE_D4, LLE_D3, CD_D3, CD_D2, AE_D1, LLE_D1	9
E	Class E: Minimum, Maximum	2

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3.4 Improved Multi-class SVM Classifier

In the proposed work, the improved multi-class SVM is modelled by combining several binary SVMs. There are major existing multi-class implementations such as One Vs Rest and One Vs One. The One Vs Rest method and One Vs One use n(n-1) SVMs where n is the number of classes, whereas the proposed multi-class SVM uses only n(n-1)/2 SVMs for the multi-classification problems. During the training phase, the number of the training samples are decreased in the proposed classifier, when comparing with One Vs One and One Vs Rest multi-class support vector machines which use all the training data. A problem with both One Vs Rest and pairwise support vector machines is unclassifiable regions. The proposed multi-class SVM is much faster than conventional pairwise SVMs. The structure for the proposed five-class SVM is shown in Figure 3.

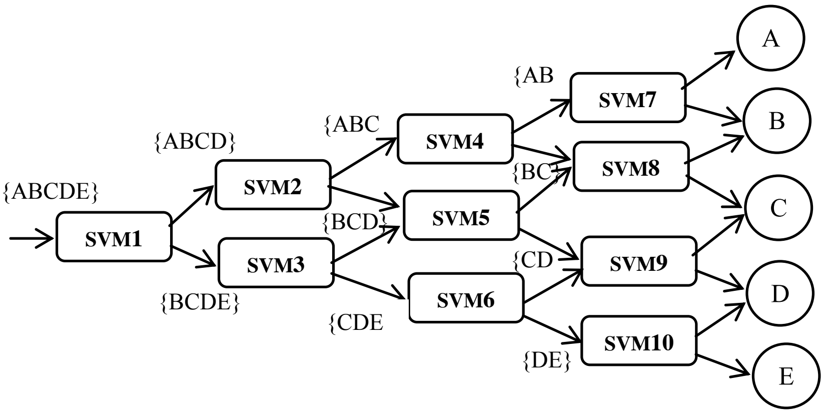

Figure 3 Structure of proposed multi-class SVM

4. Results and Discussion

In this work, benchmark datasets namely Freiburg and Bonn datasets have been used for the classification of EEG signals. The proposed methods have been implemented by using the MATLAB software package (Version R2013b). For classification of EEG signals, 50% of the non-overlapped data have been used for training and remaining 50% of the non-overlapped data have been used for testing.

4.1 Performance Analysis based on Feature Extraction

To evaluate the performance of multi-domain features, two different benchmark EEG dataset have been used. Figure 4(a), (b) and Figure 5(a), (b), illustrate scatter plot diagrams for time-domain and multi-domain features for the datasets Freiburg and Bonn respectively. For plotting to scatter plot, all the features are normalized between 0 and 1. Features are randomly selected and plotted for comparing various domains with different features. In using multi-domain features, the features of the classes are clustered separately, but not that much clustered in using time domain. Thus the extracted multi-domain features are much useful in discriminating the different types of EEG data.

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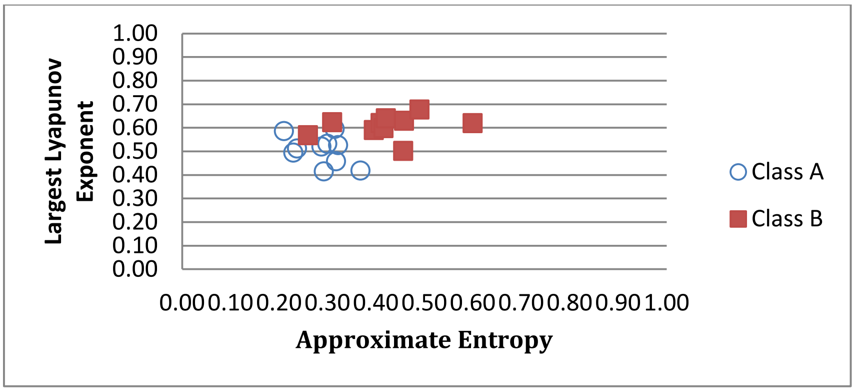

Figure 4(a) Scatter plot using time-domain features such as Maximum and Minimum (Freiburg)

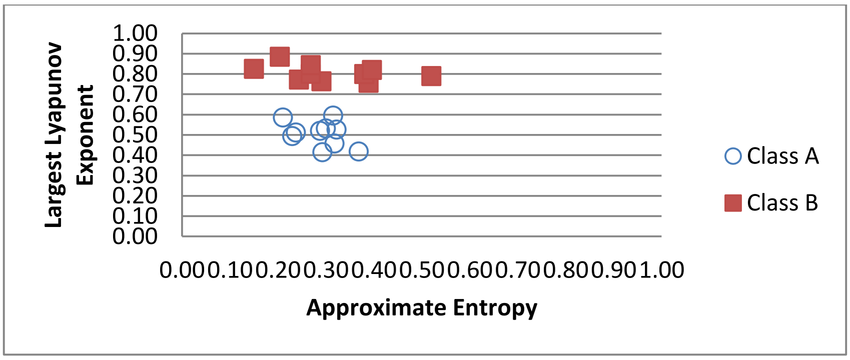

Figure 4(b) Scatter Plot using multi-domain features such as Approximate Entropy and Largest Lyapunov Exponent (Freiburg)

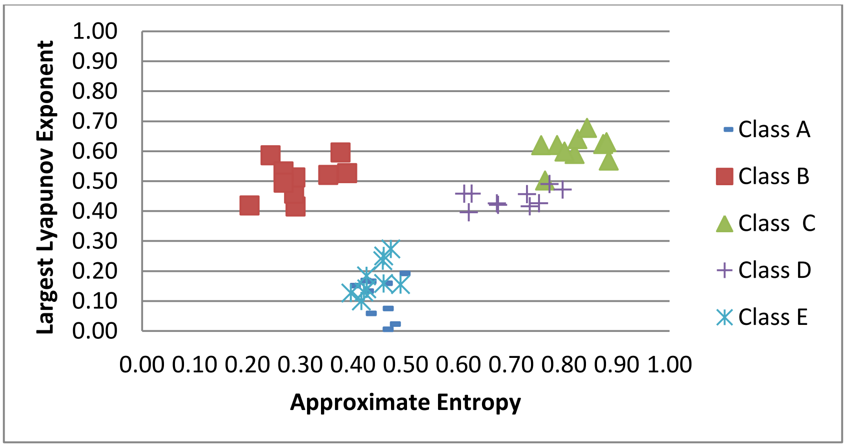

Figure 5(a) Scatter plot using time-domain features such as Standard Deviation and Mean (Bonn)

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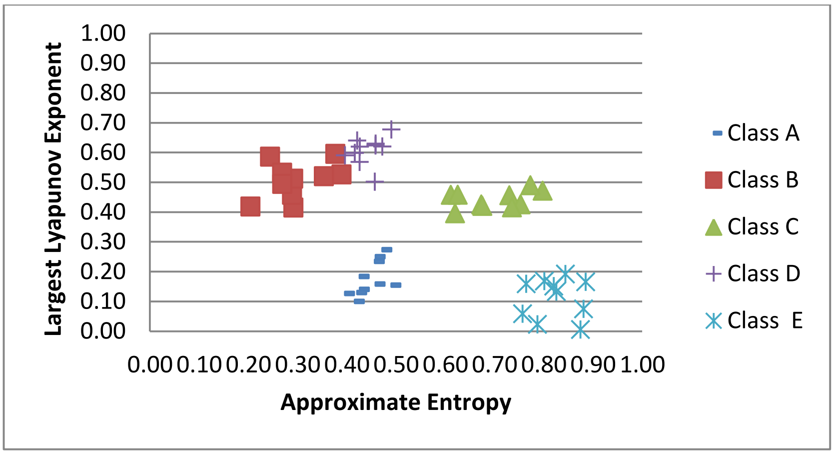

Figure 5(b) Scatter Plot using multi-domain features such as Approximate Entropy and Mean (Bonn)

4.2 Performance Analysis based on Feature Selection

Figures 6(a) and 6(b) illustrate box plots that are measure to analyze the performances of the multi-domain features based on with and without feature selection. The experiments have been conducted using five-class Bonn and two-class Freiburg datasets respectively. From the figures, it can be observed that the median value is higher for before feature selection than for the after feature selection. From this variation, it is observed that the selected multi-domain features are useful in improving the classification performance.

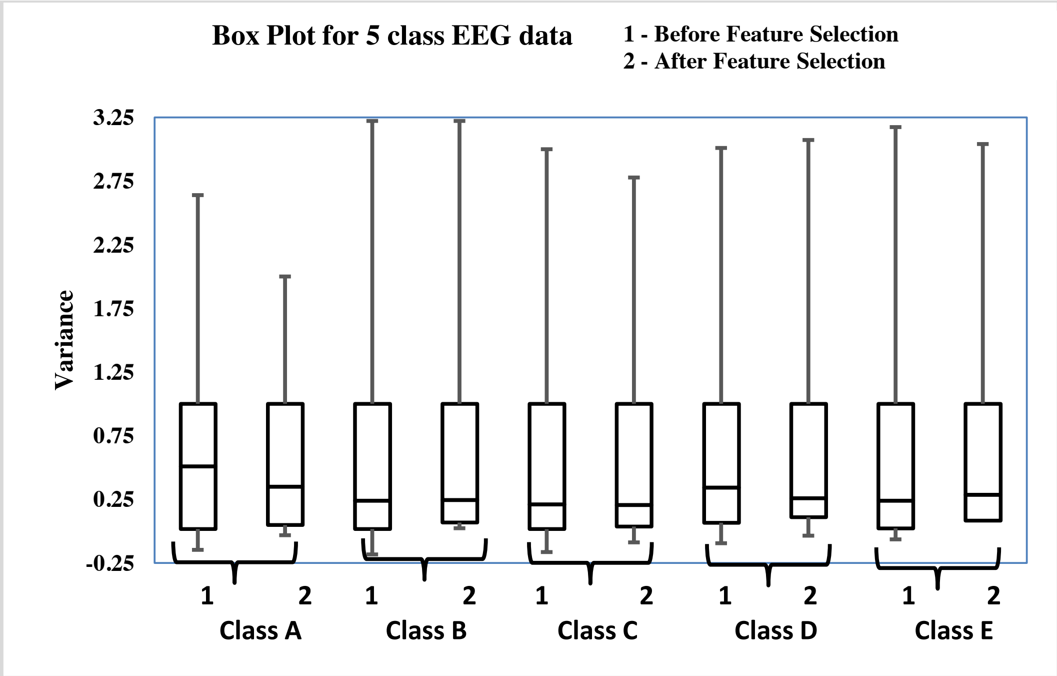

Figure 6(a) Box plots using multi-domain domain features before and after feature selection (Bonn)

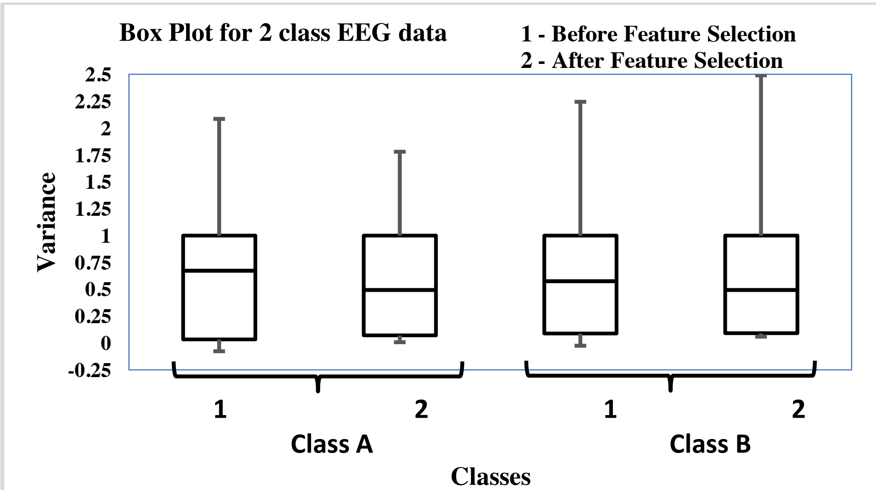

Figure 6(b) Box plots using multi-domain features before and after feature selection (Freiburg)

In class specific multi-domain features selection, hybrid features in time, wavelet and wavelet-EMD domains have been selected based on entropy. This method has the advantages of both class-wise variable length features as well as hybrid features. Features have been extracted from Freiburg and Bonn datasets and feature extraction time are calculated. Performances such as a number of features

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and computation time for extracting the features for various cases using the proposed feature selection methods is provided in Table 4. It is found from the table that the entropy-based multi-domain features selection takes lesser computation time and also provides better classification accuracy when compared with the other cases of features.

Table 4 Number of Features and Computation Time for Various Cases using the Proposed Multi-Domain Features Selection

Feature domain	Number of Features	Computation time for extracting the features (in mille seconds)	
		Freiburg	Bonn
Case 1 (Time-domain features)	4	36	133
Case 2 (Wavelet-domain features for all detailed sub-bands)	12	47	199
Case 3 (EMD-domain features for approximate sub-band)	3	126	431
Case 4 (Multi-domain features)	20	158	527
Case 5 (Selected multi-domain features based on Entropy)	Minimum 2 to Maximum 10	35 (maximum)	277 (maximum)

4.3 Performance Analysis based on Classifier

The performances analysis of entropy based selected multi-domain features with the proposed classifier is carried out with the two datasets. Figures 7(a) and 7(b) illustrate ROC curves based on 1-specificity Vs sensitivity for the ANN, SVM and proposed multi-class SVM using the selected multi-domain features, for the datasets Freiburg and Bonn respectively. Among the three classifiers, the proposed classifier with selected multi-domain features provides improved performances in terms of sensitivity and false alarms than the existing classifiers.

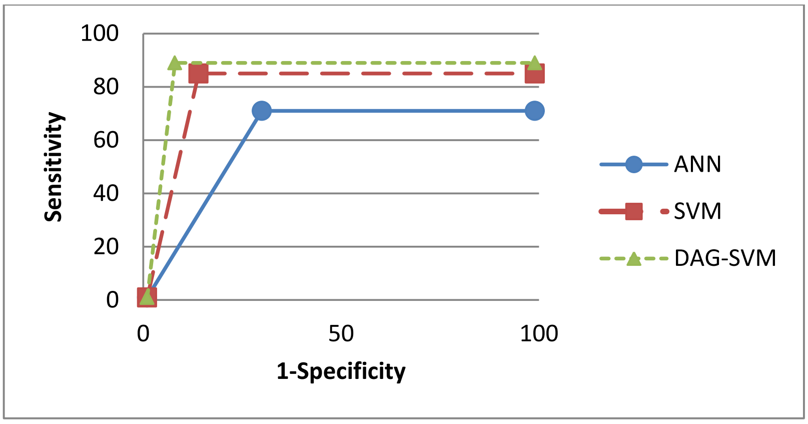

Figure 7(a) ROC for the Proposed multi-class SVM classifier Vs Various existing classifiers (Freiburg)

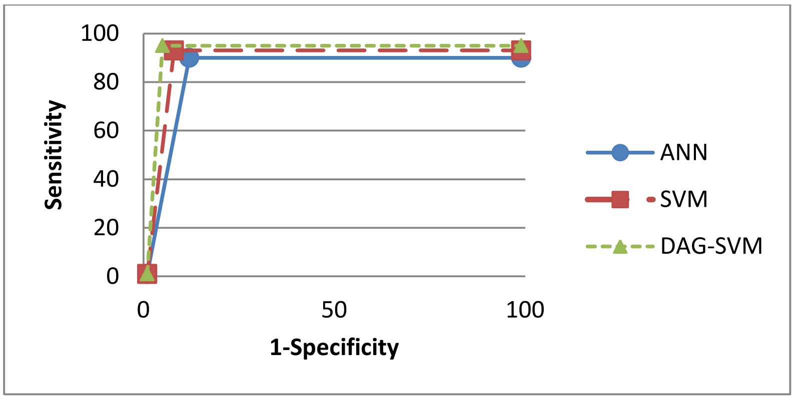

Figure 7(b) ROC for the Proposed multi-class SVM classifier Vs Various existing classifiers (Bonn)

The classification accuracy, number of SVMs required and execution time of the proposed multi-class SVM classifier is compared with other existing multi-class SVM classifier such as (One Vs One, One Vs Rest). The results are presented in Table 5. The proposed multi-class SVM achieves better classification accuracy with lesser number of SVMs required. Since it uses tree approach, the number of SVMs required is only 10 for the five class problem. For the other 2-class Freiburg dataset in proposed multi-class SVM classifier, the two classes are classified in the first level itself. Especially for the multi-class problem this approach is much suitable and provides better classification accuracy with lesser execution time.

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Table 5 Classification Accuracies, Number of SVMs and Execution Time Versus Various Classifiers (Bonn)

Classifiers	Classification Accuracy (%)	No. of SVMs required for N class problem	No. of SVMs required for the five-class EEG problem	Execution time (Seconds)
Multi-class SVM (proposed)	95	N(N-1)/2	10	53
Multi-class SVM (OneVsRest)	90	N(N-1)	20	78
Multi-class SVM (OneVsOne)	92			76

Table 6 compares classification accuracy and execution time of the proposed work with other existing research works which use Freiburg and Bonn EEG databases. In some cases, our proposed approach takes reasonable classification accuracy but takes lesser execution time. The proposed multi-class SVM with entropy based class specific selected multi-domain features in classifying the EEG signals provides better classification accuracy with lesser execution time when compared with existing research works.

Table 6 Comparison of Classification Accuracy of the Proposed Research Work and The Existing Research Works

Feature Extraction	Classification	Dataset	Classification Accuracy (%)
Freiburg			
Entropy based selected multi-domain features (This work)	An improved multi-class SVM	{A,E}	89
Wavelet Transform [26]	SVM	{A,E}	87
Bonn			
Entropy based selected multi-domain features (This work)	An improved multi-class SVM	{A},{E} {A,B,C,D},{E} {A},{D},{E} {A,B},{C,D},{E} {A}{B}{C}{D}{E }	100 98 97 97 95
Cross-correlation method [27]	Support Vector Machine	{A},{E}	99

Time frequency domain features [28]	Artificial Neural Network	{AB},{CD},{E} {ABCD}{E} {A}{C}{E} {A}{E}	98 98 99 100
Wavelet domain features with Independent Component Analysis [29]	Support Vector Machine	{A},{E}	99
Wavelet domain features with Recurrence Quantification Analysis [15]	Error-Correction Output Codes (ECOC)	{AB},{CD},E	99
Fuzzy Entropy [24]	SVM	{A},{D},{E}	98

5. Conclusion and Future Work

In this paper, extraction of multi-domain features with entropy based features selection method is proposed for epileptic seizure detection. For classification, an improved multi-class SVM is used for the classification of EEG signals for epileptic seizure detection. Two different benchmark EEG datasets namely Freiburg and Bonn have been experimented to compare and analyze the performances. The selected multi-domain features based on entropy is reduced in size when compared with the all extracted features. In this work, an improved multi-class SVM classifier has been proposed and experimented to analyze the performances using the measures such as classification accuracy, sensitivity, specificity, execution time and ROC. The proposed multi-class SVM with entropy based selected multi-domain-domain features provides better performance in terms of improved classification accuracy with reduced execution time when compared with the existing classifiers. Our future work will be an extension of this proposed work, to develop lightweight real-time epileptic seizure detection and monitoring system using wireless biosensors.

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