EEG SIGNAL CLASSIFICATION IN NON-LINEAR FRAMEWORK WITH FILTERED TRAINING DATA

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ABSTRACT

Electroencephalographic (EEG) signals are produced in brain due to firing of the neurons. Any anomaly found in the EEG indicates abnormality associated with brain functioning. The efficacy of automated analysis of EEG depends on features chosen to represent the time series, classifier used and quality of training data. In this work, we present automated analysis of EEG time series acquired from two different groups. Non-linear features have been used here to capture the characteristics of EEG in each case since it portrays the non-linear dependencies of different parameters associated with EEG. In the first case, we present the classification between alcoholics and controls. In the second case, we present classification between epileptic and controls. In the classification, we have addressed the issue of quality of training data. In the proposed scheme prior to classification, we filter the training data. This approach led to minimum 10% improvement in the classification accuracy.

***Index Terms*—** EEG, Non-Linear Analysis, k-Means Clustering, Support Vector Machine, Fuzzy k-NN

1. INTRODUCTION

Electroencephalography (EEG) signals are the electrical signals generated in the brain as a result of firing of neurons and hence provides a non-invasive measure of brain functioning. EEG is an important tool used in the diagnosis of various brain conditions including effect of alcoholism and epileptic seizure detection. Automatic diagnosis of various brain conditions depend on quality of the training set available, assumptions made about the data, features chosen to represent the time series and the classifier employed [1]. Alongside, several studies of the dis-orders also lend clues to be incorporated in the automation strategy.

In the problem of classification between alcoholics and non-alcoholic subjects, well-known facts that long term effects of alcohol abuse cause changes in brain like shrinkage, loss of neuronal connections resulting in abnormalities, have been utilized. EEGs show prominent differences between alcoholics and non-alcoholics in theta power [2] and beta power [3]. Sleep pattern also differs in alcoholics and non-alcoholics leading to differentiation between them using sleep EEG [4]. Multiple gamma bands of EEG can be used to distinguish alcoholics from non-alcoholics [5]. Slow alpha (7.5-10 Hz), fast alpha (10.25-12.75 Hz), slow beta (13-19.5 Hz) and fast beta (19.75-26 Hz) were utilized in a study [6].

Epilepsy is a well-studied brain disorder that manifests its signature in the EEG [7]. It is known that Epileptic seizures are abnormal,unprovoked firing of neurons. Different types of seizures have different characteristic patterns in the EEG. Spikes, polyspikes, spike-and-wave complex, sharp waves are the commonly seen rhythms in EEG pattern indicative of epileptic seizure [8]. Identification of the presence of these abnormalities from the given EEG data forms the base of any automated epileptic seizure detection system.

In the earlier works reported on EEG analysis, simple linear features [9] such as Entropy, Energy and statistical quantities such as median absolute deviation, inter-quartile range, standard deviation, kurtosis, skewness have also been employed. The authors have reported accuracies of 96 to 88 % on classification of epileptic seizure versus normal using classifiers such as Neural Networks (NN), Support Vector Machines (SVM). Several later works have been reported on analysis of epileptic EEGs that employ Time-frequency analysis [10] utilizing short-time Fourier transforms [11] and wavelet transforms [12]. On the other hand, several works have analyzed in the non-linear framework, calculating Lyapunov exponents, and have also combined wavelet analysis and Lyapunov exponents [13]. NNs [14] were also used in some approaches due to its learning ability but it suffered from large noise and sensitivity issues. Adaptive Neuro-Fuzzy Inference System (ANFIS) and SVM were also found effective in the classification of epileptic and normal EEG.

Chaos Theory finds the hidden interior regular rules and resolve the variable in the nonlinear systems. A small change at any one place of a chaotic system ends up being a drastic change in its later state. No two states of the system will be exactly same no matter how much time passes [15].

In this paper, we address the issue of the quality of training data in non-linear framework. Here, we present EEG time-series classification in two scenarios. In case (i), we look at classification between alcoholics and non-alcoholics, while in case (ii) we present classification between Epileptic and

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healthy controls. In both the cases, we use non-linear feature sets and also incorporate the step of filtering training data, prior to classification. A schematic illustrating the proposed method is shown in Fig. 1.

In the proposed work, we illustrate the effectiveness in

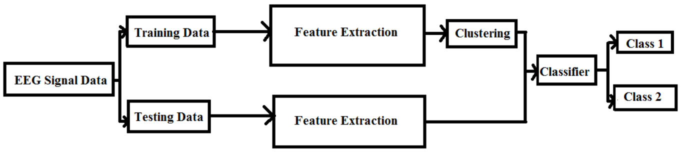

Fig. 1. Schematic Diagram

classification, after the refinement of training data, that ensures the removal of outliers. Here, we utilize the domain knowledge that the available samples can only come from the known set of classes.

The paper is divided into various sections. Section II details the methods employed and describes the data utilized. Section III discusses the results obtained. Section IV concludes this paper.

2. MATERIALS & METHODS

The block diagram depicting the proposed methodology is shown in the Fig. 2. In our experiments, the multichannel EEG data, undergo dimensionality reduction to extract the important channels containing information. From the reduced-channel data, we compute non-linear features, which are Hurst exponent, Approximate Entropy and Correlation Dimension. These features have been reported to perform well in EEG classification of different mental states [16].

In order to compute the non-linear features,the minimum

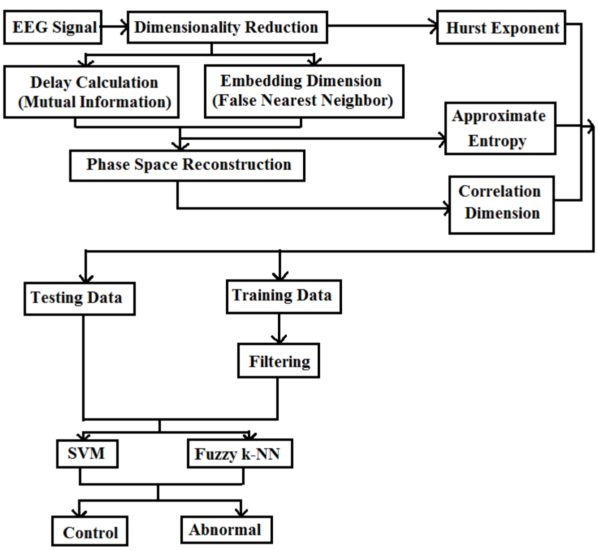

Fig. 2. Block Diagram

embedding dimension and optimal embedding delay are to be calculated and the phase space reconstruction is to be carried out.

1. *Embedding Dimension* : The optimum embedding dimension [17] is the minimum dimension at which the characteristics of the system completely unfolds. The idea is to identify the false nearest neighbours that appear to be nearest neighbours to a point due to the embedding dimension being too small. At the optimal embedding dimension, the *false* nearest neighbour drops to zero and the system characteristics have been completely unfolded.

2. *Embedding Delay* : Minimum embedding dimension and optimal embedding delay are required for phase space reconstruction. The optimum embedding delay is calculated using Mutual information (MI) criteria [18].
   The MI between $\mathbf{X}_T$ and $\mathbf{X}_{T+m}$ (m is the embedding delay)quantifies the information about $\mathbf{X}_{T+m}$ presuming the state $\mathbf{X}_T$ is known. Using Fraser and Swinney algorithm, initially, the minimum and the maximum of the input time series are found and the absolute value of their difference is partitioned into $\mathbf{N}_S$ equally sized bins (probability states). The MI coefficient ($\mathbf{I}_m$) is computed as as

$$I_m = \sum_{i=i}^{N_S} \sum_{i=j}^{N_S} P[\mathbf{X}_T(i), \mathbf{X}_{T+m}(j)]. \log_2 \frac{P[\mathbf{X}_T(i), \mathbf{X}_{T+m}(j)]}{P[\mathbf{X}_T(i)] P[\mathbf{X}_{T+m}(j)]} \tag{1}$$

   where the variables N_S,$P[\mathbf{X}_T(i)]$, $P[\mathbf{X}_{T+m}(j)]$ and $P[\mathbf{X}_T(i), \mathbf{X}_{T+m}(j)]$ represents respectively the number of probability states, the probability of $\mathbf{X}_T$ belonging to the i^{th} probability state, the probability of $\mathbf{X}_{T+m}$ belonging to the j^{th} probability state and the joint probability of $\mathbf{X}_T$ belonging to the i^{th} probability state and $\mathbf{X}_{T+m}$ belonging to the j^{th} probability state simultaneously.
   The probability $P[\mathbf{X}_T(i)]$ is computed as the ratio of total number of data points of $\mathbf{X}_T$ belonging to probability state *i* to the total number of data points in $\mathbf{X}_T$. The other probabilities are computed in a similar manner. Different values of MI coefficients are obtained by varying the embedding delay*m*. The optimum embedding delay is the first minimum of MI coefficients ($\mathbf{I}_m$) Im since $\mathbf{X}_{T+m}$ adds the largest amount of information to the information already known due to knowledge about $\mathbf{X}_T$ at the first minimum of MI coefficients $\mathbf{I}_m$ without completely losing the correlation between them.

3. *Phase space reconstruction* : EEG signal being non-linear tends to gravitate towards specific regions in phase space [19]. Chaoticity and complexity form the two main aspects of phase space. The method of delays is used for phase space reconstruction when equations of system are unknown. According to this method, a vector is formed in an embedding space from time delayed values of the

scalar inputs.

$$\mathbf{X}_T = \{x_{T-(d_0-1)m_0}, x_{T-(d_0-2)m_0}, ..., x_T\} \tag{2}$$

where d_0 and m_0 are the optimum embedding dimension and optimum embedding delay respectively. Takens embedding [20] theorem states that if the sequence $\mathbf{X}_T$ consists of scalar observations of the state of a dynamical system, the time delay embedding provides a one-to-one image of the original observations, provided embedding dimension is large enough.

The features set, comprising of Hurst exponent (H), Approximate entropy (ApEn) and Correlation dimension (υ) are computed as below :

1. *Hurst Exponent (H)* : Hurst exponent evaluates the self similarity of a time series [21]. In EEG, Hurst exponent is used to characterize the non-stationary behaviour. Initially the EEG data is divided into : two segments of half the length of the original EEG data, four segments of 1/4th length of the original EEG data and so on but minimum length chosen for segment must be atleast 8 data points. For each segment, mean is calculated and the segment is centred. Cumulative deviation is calculated and the difference between maximum and minimum value of the cumulative deviation is taken as the range(R). The rescaled range is calculated as the ratio of the range and standard deviation (S) of the centred segment.

$$H = \frac{log(R/S)}{log(n)} \tag{3}$$

R/S = rescaled range and n = length of the segment

2. *Approximate Entropy (ApEn)* : The approximate entropy reflects the intra-cortical information flow in the brain according to [22] and is a measure of complexity which enables the quantification of the unpredictability of fluctuations in EEG. Three important parameters are required for the calculation of the approximate entropy, namely, embedding dimension (d_0), embedding time delay (m_0) and tolerance (r). Tolerance is taken default as 0.2*standard deviation of the data and is the distance within which neighbouring trajectories must lie. Embedding dimension is calculated using false nearest neighbour method and embedding time delay is calculated using mutual information method.

The correlation integral can be calculated as [23]:

$$C_i^{m_0}(r) = \sum_{j=1}^{N-m_0-1} \frac{\Theta(r- \parallel y_[i] - y_j \parallel)}{N-(m_0-1)} \tag{4}$$

where, $i = 1, 2, ..., N-(m_0-1)d_0$, N is the length of EEG, y_i, y_j are the vectors in phase space and $\Theta(.)$ is a heaviside function.

The approximate entropy is calculated as:

$$ApEn = \Phi^{m_0}(r) - \Phi^{m_0+1}(r) \tag{5}$$

where,

$$\Phi^{m_0}(r) = \frac{1}{N-(m_0-1)} \sum_{i=1}^{N-(m_0-1)} ln[C_i^{m_0}(r)] \tag{6}$$

3. *Correlation Dimension(υ)* : The correlation dimension represents the complexity of the system [24]. Taken's estimator is used to find the correlation dimension. Accordingly, a total of $N_c(N_c-1)/2$ pairwise distances can be obtained given a signal consisting of $N_c = N - m_0 d_0$ points, where m_0 and d_0 are minimum embedding dimension and optimum time delay respectively. The Correlation Dimension is computed as $\upsilon = -Z^{-1}$, where

$$Z = \frac{2}{N_c(N_c-1)} \sum_{i=1}^{N_c}\sum_{j=1}^{N_c} \log\left(\frac{|\mathbf{Y}_i(d_0) - \mathbf{Y}_j(d_0)|}{\varepsilon}\right) \tag{7}$$

where $Y_i(d_0)$ and $Y_j(d_0)$ are the phase space locations of the i^{th} and j^{th} points respectively for the embedding dimension d_0, and ε is the radius of the measuring unit.

2.1. Quality of Training Data

Outliers present in the training set of any classification problem can cause misclassification since the classifiers learn features of the outliers. To achieve greater accuracy rate, it is necessary to remove outliers from the training set and enable proper learning for the classifiers. The method proposed here is outlier removal using k-means clustering.

Labelled training data are clustered using k-means clustering. The original label of the data and the label assigned to it after clustering are compared and those that do not match are identified as outliers and discarded. The remaining training samples are retained. To avoid loss of important information in the training set, the k-means clustering is carried out ten times independently. This ensures that the same samples are identified as outliers and discarded from the training set. Equal number of training samples from each class are retained to avoid any bias. The refined training data is used for classification. For classification, two commonly used classifiers are SVM and Fuzzy k-Nearest Neighbour.

2.2. Experimental Dataset

Alcoholic and control subject EEGs were obtained from UCI Machine Learning Repository [25]. The 64-electrode EEGs were sampled at 256 Hz. Total of 70 subject datasets containing 10 trials each were used for the experiment. 60 subjects(60*10=600 EEG time series) were used for training and remaining 10 subjects(10*10=100 EEG time series) for testing.

Epileptic Seizure and control EEG datasets were obtained from Bonn University [26]. 65 EEG time series of single channel control EEG and 65 data of single channel epileptic seizure EEG sampled at Hz were used. 70 EEG time series were used for training and remaining 60 time series for testing.

2.3. Dimensionality Reduction

The multichannel alcoholic EEG data requires dimensionality reduction to choose the most important channels for the classification problem. The method followed here is sparse principal component analysis [27]. Fig. 3 illustrates the sparse principal component analysis. The EEG channels are centred and normalized initially and covariance matrix is calculated. The normalized and centred input undergoes PCA to give eigen vectors corresponding to each principal eigen values. The eigen vectors undergo the following :

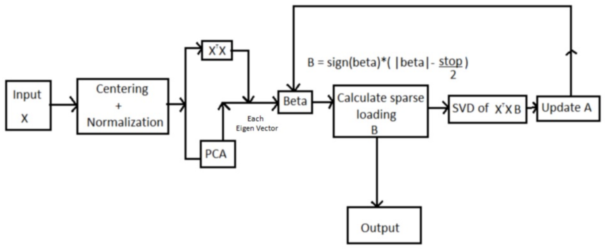

Fig. 3. Sparse Principal Component Analysis

1. Eigen vectors and covariance matrix are multiplied to give the resulting variable referred to as beta
2. Beta is then used to calculate the sparse loading B as

$$B = sign(beta) * (|beta| - \frac{stop}{2}) \tag{8}$$

   where $stop$ is the number of iteration and default is taken as 300.
3. The sparse loading is multiplied with covariance matrix and undergoes singular value decomposition to give the output as UDV^T
4. The original eigen vector is updated using the eigen vectors obtained from SVD as $A_{new} = UV^T$
5. Repeat steps 1-4 till the stop criteria is achieved (300 iterations).

This led to a significant reduction in the number of EEG channels.

3. RESULTS & DISCUSSION

The multichannel EEG signal initially underwent dimensionality reduction to obtain the important channels. The features extracted from the EEG were Hurst Exponent, Approximate Entropy and Correlation Dimension. Two experiments were carried out.

Experiment 1 **Data type set**	**Accuracy(%)** **SVM**	**Accuracy(%)** **F k-NN**
Alcohol vs Control (Training = 600 time series, test = 100 time series)	90	80
Epileptic seizure vs control (Training = 70 time series, test = 60 time series)	78.33	76.6

Table 1. Classification accuracy without filtering training data

Experiment 2 **Data type set**	**Accuracy(%)** **SVM**	**Accuracy(%)** **F k-NN**
Alcohol vs Control (Training = 540 time series, test = 100 time series)	100	100
Epileptic seizure vs control (Training = 50 time series, test = 60 time series)	95	88.33

Table 2. Classification accuracy after filtering training data

1. *First experiment* : The training data were directly given to classifier for learning which then classified the test data into the classes associated with the classification problem. In the alcohol vs control case, 70 subjects with 10 trials each (total of 700 data) were used. The training constitute 60 subjects and test data constitute 10 subject. Accuracy of 90% and 80% were obtained with SVM and Fuzzy k-NN respectively. In epileptic seizure vs control, total of 130 time series were utilized. Among this, 70 were training data and remaining test data. SVM and Fuzzy k-NN gave an accuracy of 78.33% and 76.6% respectively.
2. *Second Experiment* : The training data were normalized and underwent filtering where those data which were filtered incorrectly are eliminated. This refined data were then used by the classifier for learning. In the alcohol vs control case, the training data constituting 600 time series were reduced to 540 time series after filtering. The testing data comprised of 100 time series as in experiment 1. SVM and Fuzzy k-NN gave an accuracy of 100% each. In epileptic seizure vs control, the training data reduced from 70 to 50 time series after filtering. The accuracy obtained using SVM and Fuzzy k-NN were 95% and 88.3% respectively.

The accuracy obtained in both experiments for two cases are shown in Table. 1 and 2. Filtering removed the outliers present in the training data which caused higher misclassification rate. An increase of about 10-20(%) was observed in the accuracy with the use of filtering.
The outliers in the training data can occur as illustrated in Fig.4. One variety of outliers denoted by '$' could occur close to data samples belonging to class 1 while a second variety of outliers denoted by '&' could occur close to data samples belonging to class 2. A third variety of outliers denoted by '+' could occur at the border close to both the classes, leading to confusion among testing data. Addressing the issue of these

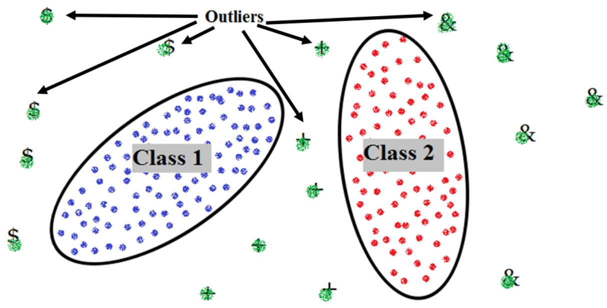

Fig. 4. Example scenario of possible types of outliers

outliers, and utilizing them rather than discarding could lead to better classification accuracy. This could be a possible extension of the proposed work. It is clear that merely increasing the number of clusters to tackle outliers, would not be an effective solution since it could alter the naturally-structured clusters.

4. CONCLUSION

In this work filtering of training data for effective classification of EEG time series is proposed. Clustering is utilized for outlier removal using prior knowledge of number of classes. The experiments carried out involve dimensionality reduction and non-linear feature extraction. In the first the experiment, the training data after feature extraction are used by classifier for learning while in the second experiment the training data undergo k-means clustering and the refined training data are utilized by the classifier. Two cases are considered: Alcoholic EEG vs Control and Epileptic Seizure EEG vs Control.
In both cases, it is observed that latter yielded higher accuracy than former. The outliers which cause increase in the misclassification rate are eliminated by k-means clustering. Accuracy have increased by about 10-20%. Clustering proves to be an effective way of refining the training data by eliminating the outlier and thus increasing the accuracy rate of the experiment.

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