SVM based Automated EEG Seizure Detection using 'Coiflets' Wavelet Packets

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***Abstract*—Manual classification of ictal and non-ictal activities continues to be very perplexing even for any experienced neurophysiologist. Mostly due of the presence of considerable heterogeneity in the seizure patterns. Extensive research efforts have gone in solving this issue. But, the shortcomings and complexity of the deployed methods till date have been noteworthy to realize their practical applications. Present study showcased an expert system design for automated classification of ictal activities in electroencephalogram signals. The development used 'coiflets' wavelet packets for decomposition of signals to extract energy, standard deviation and Shannon entropy as features. Followed by support vector machine classifier with feds of various feature sets combinations. In the presented scheme, standard deviation feature set proved to be the best input features. It showed mean classification accuracy = 99.46 %, sensitivity = 99.40 % and specificity = 99.48 % with computation time = 5.60e-04 s. These outcomes demonstrated an improvement over the existing expert systems and also shed light on using different features. Proposed scheme hold promises for deployment in clinics and also for improvement in existing expert system designs.**

Keywords*—*Electroencephalogram (EEG), seizures, support vector machines (SVM), coiflets, wavelet packet transform (WPT).

I. Introduction

Epilepsy is a common neurological disorder characterized by persistent sensory disturbances, loss of awareness, or seizures. The irregular ephemeral electrical activities in the brain are called seizures. This briefly disturbs the rhythmicity of the brain. Since, more than fifty million people are affected by epilepsy (as per survey by World Health Organization [28, 14]), it is one of the most common neurological disorders. The diagnostic procedures for epilepsy can be classified into four major types. They are: a) History taking from patient and observers; b) Physical and neuropsychological tests; c) Clinical lab tests like blood test, liver and kidney function test, etc.; and d) Neuroimaging tests like electroencephalography, magnetic resonance imaging, computed tomography, etc. Out of all these methods available, electroencephalogram (EEG) forms to be the most important and commonly used method. However, due to high non-stationarity of EEG signals added with mixed nature of seizure patterns makes its visual inspection extremely difficult. The analysis issue worsens in underdeveloped and developing countries like India with high population of patients. Due to inadequate resources and shortage of experienced neurophysiologists, quite often the diagnosis could be improper. Thus, there is a dire need to automatize the EEG seizure detection process.

In the past, rigorous research efforts have gone in addressing this issue. Seminal works of Gotman [8, 9] utilized descriptive attributes of time-delays between spikes, slopes and sharpness measures of seizure patterns, etc. to categorize ictal and non-ictal events. The application of artificial neural networks (ANNs) was much realized in 2004 from the research work of Nigam and Graupe [25]. In 2005, Kannathal and his group [13] used entropy measures for classification of epileptic waveforms. The application of discrete wavelet transform (DWT) for extraction of time-frequency features [1] was an important landmark for seizure detection. This was further supported by the works of Tzallas and his group [2, 3]. Later in 2010, Guo's team [11] also suggested application of DWT-ANN based classification. Realization of decision tree and hybrid model designs [10] for seizure detection was also an important contribution in this domain. Since 2011, noteworthy results from the work of Orhan et al. [24], made k-mean clustering with ANN model as a popular approach for seizure detection. Application of support vector machine (SVM) for seizure detection was a notable contribution by Nandan's team [12], first performed on animal model. SVM's similar utilization was further supported by works on human EEG signals [15, 17, 29]. During the same period Wang, Miao and Xie [5] first demonstrated the benefits of using discrete wavelet packet transform (WPT) over the conventional DWT. They too used entropies as feature sets. Our previous work [15, 17, 20-22] successfully supported their proposals. Additionally, we also demonstrated the use of parallel network architectures like Probabilistic Neural Network (PNN) [20-22] and selection of proper mother wavelet for feature extraction [20]. Later in 2013, Xie and Krishnan [19] showed sparse function model for automated analysis which was also based on wavelets. In 2014, pioneering work by Chen [6] showcased the applicability of phase information in seizure patterns. Despite several efforts and noteworthy contributions, few discrepancies continues to be associated with seizure detection research. First, the amount of training involved to come up with proposed classification accuracy (CA) remains to be unclarified. Second, many findings compromise between the statistical measures i.e., true positives and true negatives. Third, unexpected high or non-elucidated computation time makes the implementation doubtful in practical scenario. This paper, presented improved expert system design with high classification accuracy (CA), sensitivity (SN) and specificity (SP) rates in negligible time lag.

In this study, EEG signals were segmented and their time-frequency domain coefficients till sixth level of wavelet packet decomposition tree were extracted. Further, based upon the literature survey, most reliable parameters viz. energy, standard deviation and Shannon entropy were calculated. These feature sets were grouped in seven different combinations and were fed into the SVM classifier. Based upon the cross-validated results (with 10-folds) [7], it was confirmed that the proposed model improved upon the existing expert systems.

II. METHODOLOGY

A. *Signal acquisation*

For the present work, two EEG data sets were used. First set was taken from an open access database of University of Bonn, Germany [16]. The signals in these data sets were acquired with 173.61 Hz sampling rate. And it compromised of five subsets, namely: set A and set B acquired from five normal individuals; set C and set D acquired from five epilepsy patients during 'non-seizure' condition; and set E acquired from epilepsy patients during 'seizure' condition. Second set was collected from Neurology & Sleep Centre, India. The EEG signals in these data sets were acquired with 200 Hz sampling rate from four normal subjects with seizure-free activities and five epilepsy patients during ictal events. Both the databases used gold plated electrodes and surfaced recordings involved using 10-20 international electrode placement system [26].

B. *Feature extraction using 'coiflets' wavelet packets*

Here we used WPT for calculation of time-frequency domain coefficients. This technique offers processing of full bands of frequencies, hence produces precisely better results [5, 15, 22]. During the process, the input signals were simultaneously passed from low and high pass filters (as shown in Fig. 1). These filter series are called quadrature mirror filters (QMFs). At each recursive level, the signals were down-sampled into details and approximates. Assuming, the coefficients of wavelet packets be denoted by ${D_m}^n$ where, 'm' represented level and 'n' represented node. At the first decomposition level, the EEG signals with half of their sampling rates were sub-divided through high pass filter (denoted as HF) and low pass filter (denoted as LF) into band ranges of 0-43.40 Hz (i.e. ${D_1}^0$) and 43.40-86.80 Hz (i.e. ${D_1}^1$). This was followed by sub-divisions into 0-21.70 Hz (i.e. ${D_2}^0$), 21.70-43.40 Hz (i.e. ${D_2}^1$), 43.40-65.06 Hz (i.e. ${D_2}^2$) and 65.06-86.80 Hz (i.e. ${D_2}^3$). Fig. 1, illustrated wavelet packet decomposition till second level but, this process was repeated till sixth decomposition level during the study. At each m^{th} decomposition level, $2^(m-1)$ nodes

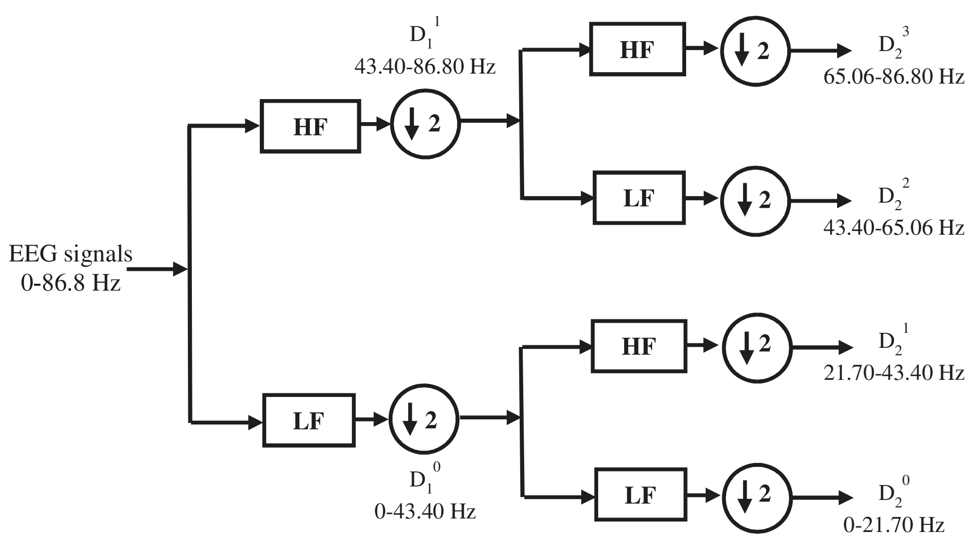

Fig. 1. Decomposition of EEG signals using discrete wavelet packet transform (WPT) after selecting 'coif1' as the mother wavelet.

(i.e. n) existed. The repetitions till sixth level yielded sixty-four nodal points. The extracted coefficients for the sixth level i.e. ${D_6}^n$ were processed to evaluate energy (ERD), standard deviation (SD) and entropies (ENT). Following equations were used for the calculations:

$$Energy\ (ERD) = \sum_{n=0}^{N} |{D_6}^n|^2 \qquad \ldots(1)$$

$$Shannon\ Entropy\ (ENT) = -\sum_{n=0}^{N} [{D_6}^n]^2 \log([{D_6}^n]^2) \qquad \ldots(2)$$

$$Standard\ Deviation\ (SD) = \sqrt{\frac{1}{N-1}\sum_{n=0}^{N}[{D_6}^n - (\frac{1}{N}\sum_{n=0}^{N} {D_6}^n)]^2} \qquad \ldots(3)$$

where, N represented coefficients at each m^{th}level and n is 0, 1, 3, …, 63 nodes. Fig. 2, represented the decision boundary for STD feature set at sixth decomposition level (D6) vs. fifth decomposition level (D5). It was observed that the ictal and non-ictal signal features had indecisive multidimensional boundaries which made it difficult to segregate them manually. Similar problem was also observant for other feature sets. In order to draw comparisons among feature sets evaluated, different combinations of features viz. ERD, ENT, SD, ERD-ENT, ENT-SD, ERD-SD and all feature sets combined (ERD-ENT-SD) were fed into the SVM classifier.

C. *Classification using support vector machine (SVM) design*

SVM is an established machine learning tool. It is based on Vapnik-Chervonenkis dimension theory [27]. In this technique, different classes of data are separated using a hyper-plane. This plane basically maximizes the margin [4, 12] which results in segregating the classes. Here, we employed it for automatically classifying the two classes i.e. ictal and non-ictal feature sets, represented by equation

$$\{x_j, y_j\}_{j=1}^{N}$$

The inputs to the SVM design with dimension d were seven different combinations of the extracted features sets $x_j \in R^d$ and targets $y_j \in \{0, 1\}$. The SVM classifier equation considered was:

$$y(x) = sign[w^T + b] \qquad \ldots(4)$$

where, $x_j \in R^d$, b is real.

The results were cross-validated using K folds [7] (with K as 10). During each run of fold, total seven training samples were used for training and rest for testing.

III. Results & Discussion

The parameters considered for evaluating the performance of the expert system designed were: classification accuracy (CA), sensitivity (SN), specificity (SP) in terms of percentage and computation time (CT) in terms of seconds (s) for each fold. Averaged values of these parameters evaluated after the 10-folds were highlighted the overall performance of the expert model. Analysis were performed on MATLABR2014a running on Corei7 processor with 8 GB RAM. Fig. 3, represented the error

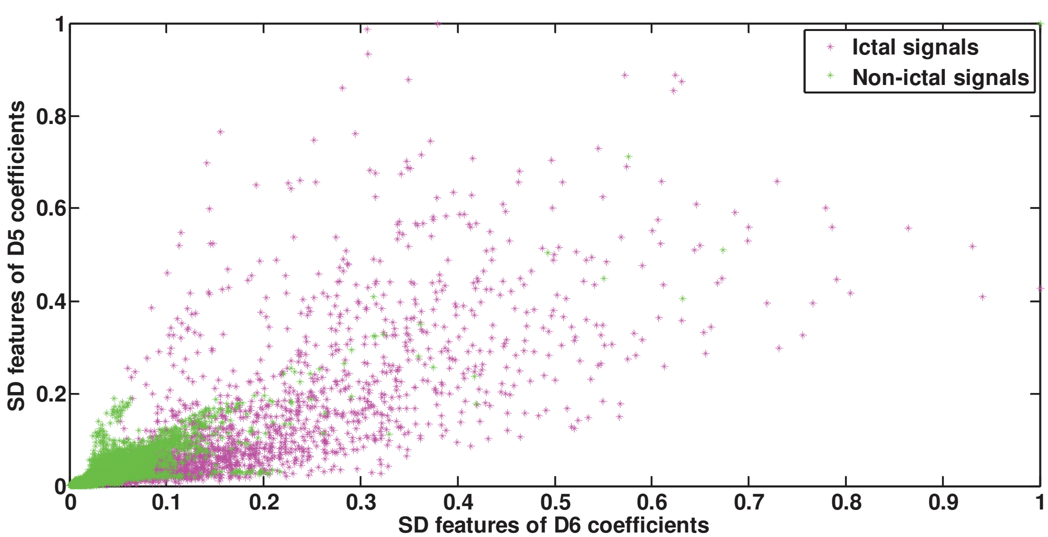

Fig. 2. Decision boundary for standard deviation (SD) feature set at sixth decomposition level (D6) vs. fifth decomposition level (D5) for ictal and non-ictal signal coefficients

bar plots of CA, SN, and SP rates after ten folds. Bar graphs in Fig. 4, represented the mean CT values.

It was observed from Fig. 3, that the CA and SP rates for every feature sets were greater than 99 %. SD and ERD-ENT feature sets showed SN higher than 99 %. Mean performance with the SD feature set were: CA = 99.46 %, SN = 99.40 %, and SP = 99.48 %. While mean performance with ERD-ENT combination feature set were: CA = 99.60 %, SN = 99.10 %, and SP = 99.70 %. The findings were supported with negligible standard error variations over each fold. These results were at par with CA = 99.53 %, SN = 99.21 % and SP = 99.34 % obtained from our last study reported [15]. From Fig. 4, the SD feature set inputs displayed CT = 5.60e-04 s while, ERD-ENT combination inputs displayed CT = 6.50e-04 s. The time elapses reported in this study were less than 6.59e-04 s, hence, outmatched out previous best testing CT = 0.02 s [19].

IV. CONCLUSIONS AND FUTURE SCOPE

For the present study, maximum CA was elicited using ERD-ENT feature sets combination with mean value equal to 99.60 %. However, considering the overall better synchronization of performance parameters, SD features resulted in best classification rates. This was further supported by proved measures of extremely less computation timings. Thus, making its application highly reliable for practical settings. Overall, this research work successfully demonstrated an improvement over existing designs [15, 17, 20-23]. Further assisting in eradication of impediments faced during time-consuming manual inspection of seizure events. Its deployment will be of at-most help in underdeveloped and developing countries. Furthermore, the proposed methodology will also help to improve other expert system designs used in clinical diagnosis.

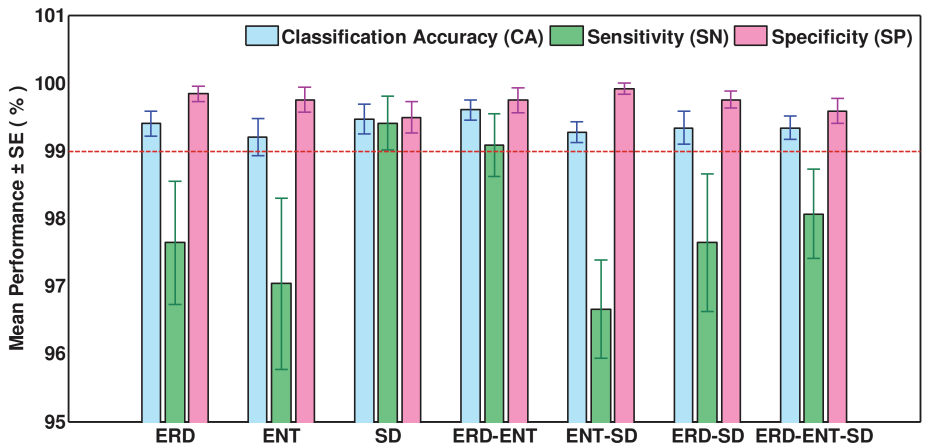

Fig. 3. Mean performances (in %) elicited from different combinations of feds viz. energy (ERD); entropy (ENT); standard deviation (SD); energy and entropy (ERD-ENT); entropy and standard deviation (ENT-SD); energy and standard deviation (ERD-SD); and energy, entropy and standard deviation concatenated together (ERD-ENT-SD) into the support vector (SVM) classifier. The acronyms CA, SN, SP and SE referred to classification accuracy, sensitivity, specificity and standard error, respectively.

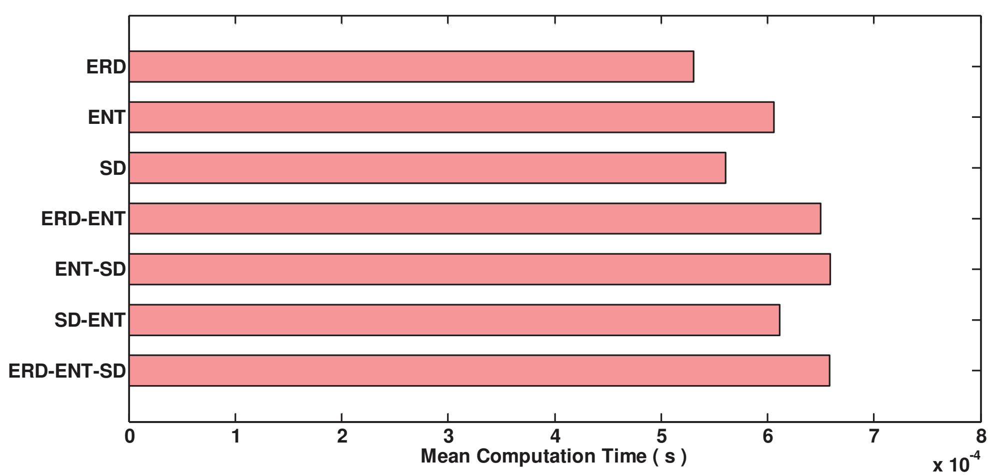

Fig. 4. Mean computation time (in s) elicited from different combinations of feds viz. energy (ERD); entropy (ENT); standard deviation (SD); energy and entropy (ERD-ENT); entropy and standard deviation (ENT-SD); energy and standard deviation (ERD-SD); and energy, entropy and standard deviation concatenated together (ERD-ENT-SD) into the support vector (SVM) classifier.

Present work needs further validation with more out-of-sample data sets. This proposal can be further backed by nature-inspired optimization. The future work involves application of this model for seizure prediction to generate warning messages.

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