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TIME AND FREQUENCY DOMAIN DECOMSPOTION MODELS FOR IMPROVED EEG EPILEPTIC SEIZURE DETECTION AND CLASSIFICATION

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Abstract

In Epileptic seizure detection, classification of EEG signals are essential measures and allows detecting various causes and symptoms from appropriate EEG signal measures. In this paper, we introduce the design of appropriate Ensemble Empirical Mode Decomposition model with most appropriate parametric measures to accomplish Epileptic event detection in EEG signal with minimized the false rate caused by signal interferences. In addition to this DWT based EEG signal decomposition is also introduced which can categorize the input EEG signal into five different types in accordance with frequency ranges. The proposed model integrates SVM machine learning model for fully automated CAD system with improved classification rate. EEG signal detection and analyzes, on the other hand, uses signal decomposition models for accurate signal detection by smartly rejecting false alarms arise. This system comprised of EMD based IMF band decomposition which requires no human intervention to detect epileptic measures. It allows for prompt accessibility, efficient usage of EEG signal characteristics and provides user convenience. The performance metrics in terms of final classification accuracy and detection rate are experimented with real time data sets extracted from most realistic EEG benchmark epilepsy datasets which considers signal measures from different environmental conditions.

INDEX TERMS EEG, Empirical mode decomposition (EMD), DWT, Epilepsy detection, CAD, Classification accuracy etc..

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I INTRODUCTION

In recent years the demands for most appropriate diagnostic measurement system for EEG signal classification measures is emerging steadily and introduced several optimal methodologies to analyzes the brain signals [1-2]. As compared to other signal and biomedical image modalities the applications of EEG signal measurements ranging from brain computer interface to next generation AI system developments [3] which require most advanced signal processing methodologies and most appropriate feature attribute models. In general EEG signal analyzes is carried out using multi modal sensor nodes for reliable brain activity measures [4]. Thus, EEG signal classification is one of the prominent things needs to be introduced and also difficult task to achieve with traditional signal processing algorithms for following reasons: i) Typical electrode set up used for signal measurement comprise of several sensor computing device that collect information which may causes severe interference. ii) Memory and lack of discrimination among input classes. iii) Demands high classification accuracy. Conventional EEG signal classifications are not optimal for detecting epilepsy due to its computation inefficiency.

In many existing works several DWT models are investigated [5-6] to explore the unique characteristics of EEG features attributes. Moreover, the electrodes are placed all over open heads, adding further noise interferences to CAD system. To ensure the EEG epilepsy detection system as economically viable, the entire CAD system should be comprised with minimal hardware components and computation capabilities which use traditional classification methodologies not suitable one for EEG signal analyzes. The inherent EEG signal aggregation and data collection properties of classification networks render all FIR filter and other transformation-based EEG measurements models are impractical.

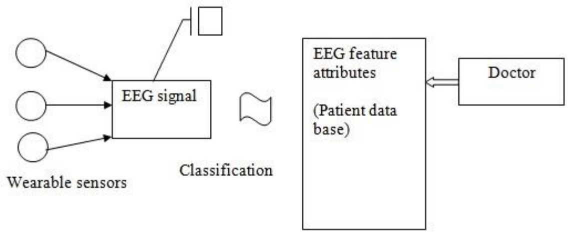

FIGURE 1 EEG processing architecture for health care system

The rapid rise of brain computer interfaces and brain signal analyzes requires multi channel EEG signal incorporation and classification measures as shown in Figure 1.1 for improved detection and signal classification measurements. This EEG epilepsy detection framework is organized as follows. Section 2 includes the detailed analyzes of FIR design models and DWT transformation model various signal decomposition models used in EEG epilepsy detection and its performance metrics analyzes. Section 3 discussed proposed time and frequency domain decomposition models and associated feature extraction techniques which includes optimal hybrid feature subset generation techniques Section 4 summarize the classification measure analyzes of proposed EEG epilepsy detection framework with SVM classifier model. Section 5 concludes the details. Researchers have been driven to create efficient automated seizure detection techniques since the visual examination of common neurological illnesses, such as epilepsy in electroencephalography (EEG), is an oversensitive procedure and prone to errors. This study suggests a reliable automatic seizure detection technique that can provide a conclusive diagnosis of these illnesses. The suggested procedure consists of these three steps: In order to overcome the non-linearity and non-stationarity of EEG signals, one must (i) remove artefact from EEG data using the filter and multi-scale principal component analysis (MSPCA); (ii) extract features from EEG signals using signal decomposition representations based on empirical mode decomposition (EMD), discrete wavelet transform (DWT), and dual-tree complex wavelet transform (DTCWT). On the other hand, a number of time-frequency (FT) analysis techniques have also been used to identify epileptic seizures. In the seizure classification experiments, the wavelet transform and its derivatives, discrete WT (DWT) and wavelet-packed decomposition (WPD), were successfully applied. Another TF analysis method, the smoothed pseudo-Wigner-Ville distribution (SPWVD), the Hilbert-Huang transform (HHT), the short-time Fourier transform (STFT), the analytic time-frequency flexible wavelet transform (ATFFWT), and the Wigner-Ville distribution (WVD), has been used frequently in seizure detection and prediction studies. The term "time domain" describes how a signal's value changes over time; in other words, the time parameter is the signal's independent variable. Time domain approaches typically analyse discrete time, analyse the supplied epochs, and are patient- or problem-specific (time window). As a result, the signal x being analysed here is value-time (t). Below is a summary of seven papers. Here, the major goal is to show how different approaches interact with one another and how diverse options exist in the temporal domain so that seizure detection technology can be further improved. In order to do this, we chose seven distinct papers with various concepts. The key factors affecting the detection rate of the methods listed below are the chosen classifiers, features, and basic concepts.

II RELATED WORKS

In many EEG signal classification systems includes different versions of DWT architecture is introduced to maximize the abnormality and optimize the final feature subsets which includes both time and frequency domain features. In most cases DWT architecture comprises of high and low frequency bands and associated multi level decomposition models [7]. In some works, to ensure the performance trade-off is optimal time domain decomposition models [8] are introduced to overcome the all-parametric constraints.

The epileptic seizures detection model proposed in [9] for EEG epileptic patients CAD system used discrete wavelet transform (DWT) based signal decomposition and high end fully approximated entropy measure-based feature extraction. Here overall EEG Seizure detection is achieved using hierarchical processing stages namely DWT signal decomposition stage which is determined approximation and detail coefficients and feature extraction stage where ApEn values of the DWT coefficients are formulated. Finite discrimination is achieved in determined ApEn values among epileptic and the normal EEG which produce 100 % classification accuracy in ANN ML based classification. The discrete wavelet transform (DWT) framework developed in [10] classify the EEG signals using both linear and nonlinear classifiers. The performance validation includes various combinations epilepsy/non epilepsy using naïve Bayes (NB) and k-nearest neighbor (k-NN) classifiers. For improved classification accuracy detailed statistical analyzes is carried out over extracted DWT band outputs. From the experimental results it is well proved that the NB classifiers shows classification rate up to 100% and outperform the KNN classifier model. The performance validation is carried out over epileptic EEG datasets extracted from the University of Bonn, Germany. The database compiled at the Boston Children's Hospital (CHB), which was utilized to validate the experimental findings, served as the basis for all experiments and simulations. This "CHB-MIT" database has 23 separate subsets that each contain pediatric patients' EEG information. There are 182 seizures in it. All signals were sampled with a resolution of 16 bits at 256 Hz per second. The majority of files have 23 EEG signals. These recordings were made using the worldwide 10-20 EEG electrodeposition and nomenclature standard. The electroencephalography (EEG) is used to examine neurological problems. One of the most common neurological conditions, epilepsy is characterized by recurrent seizures. In order to increase the precision of seizure identification, this research will decompose EEG signals using iterative filtering. Both the online CHB-MIT surface EEG database and the Patna EEG database from the All India Institute of Medical Science (AIIMS) are used to assess the suggested method. The iterative filtering decomposition method is used to separate the EEG signal's components. Dynamic mode decomposition power, variance, and Katz fractal dimension are among the time-domain variables and 2-D power spectral density that may be extracted from each segmented intrinsic mode function. The probabilistic model is based on the Hidden Markov Model (HMM).

For next generation brain computer interaction (BCI) in [11] extract features from EEG signal and classified using DWT transform. Here extraction of features directly from EEG motor activities affects the classification accuracy which is mitigated by discriminating the left- and right-hand imagery movement using Artificial Neural Network (ANN) ML model. Here only beta band from input EEG signal is considered as reference input the Feed-forward neural network training phase. Here the final feature subset includes attributes like mean, standard deviation and peak power showed classification accuracy of 80.71%.

In [12] developed optimal DWT settings for EEG classification framework which can automatically determine the discriminate feature sets. Here final subset dimensions are greatly reduced for improved classification with least memory space and computational cost overhead. Here input EEG signal is decomposed into EEG sub bands using 7 level DWT decomposition using different wavelet families, which are derived from the core mother wavelet. To attain highest possible classification accuracy exhaustive selection of frequency bands are carried out iteratively and finally determined optimal set for peak accuracy and reduces the computational cost by suppressing the 40% of redundant blocks and associated DWT feature values [13].

In [14] proposed a novel wavelet-based envelope analysis (EA) for multi class EEG classification which includes classes namely normal, interictal and epileptic EEG and used neural network ensemble (NNE) classified to overcome the limitation of ANN. Here DWT output results are processed using EA to formulate potentially significant features from the input EEG signals. Finally for epilepsy detection NNE classifier is introduced which showed improved classification rate which reduced intra class variation and inter class similarity measures.

In [15] focal and non-focal EEG signals are classified using variation mode EEG signal decomposition and discrete wavelet transform (DWT) multi-level frequency domain decomposition. For improved classification extracted features are refined using composite multi scale fuzzy entropy, multi scale dispersion entropy and accurate autoregressive model (AR) models. Here detailed parametric analysis is formulated to validate the improved discrimination levels and associated in variance measures of proposed hybrid feature subset.

In [16] carried out fully automatic identification of epileptic seizures using combined improved intrinsic time-scale decomposition (ITD), multi level DWT decomposition, phase space reconstruction (PSR) and finally used ANN classifier for classifying the input EEG signals. The computer aided diagnostic (CAD) system proposed in [17] combined discrete wavelet transform (DWT) and arithmetic coding to maximize the epileptic seizure detection accuracy. Here input EEG signal is decomposed EEG into approximations and detail coefficients and used optimal threshold values to retain most discriminate feature subsets. In [18-19] emotion states of different individuals are classified and recognized using state spiking neural networks (SNNs) and DWT decomposition model. Here DWT transform is combined with fast Fourier transform (FFT) to extract unique EEG feature sets. Finally, to validate the performance metrics the final subsets datasets include arousal, valence and dominance measures.

III RECONFIGURABLE NOC ARCHIETECTURE

The proposed epileptic seizures detection model shown in Figure 2 allows to detection EEG epileptic event from EEG signal monitored form patients. The proposed system includes optimal discrete wavelet transform (DWT) based signal decomposition and high end fully automated EMD IMF measure-based feature extraction. Here overall EEG Seizure detection is achieved using hierarchical processing stages namely DWT signal decomposition stage which is determined approximation and detail coefficients and time domain signal decomposition stage where LMF band values are generated from all generated time scales. Finite discrimination is achieved between normal and abnormal classes by combining both time-frequency domain extracted feature attribute values from both epileptic and the normal EEG and carried out final classification using SVM based ML classification. The discrete wavelet transform (DWT) framework developed to decompose the EEG signals into alpha, beta, gamma, delta and theta signals using multiple levels of DWT decompositions. The paramedic validation of time domain decomposition includes various IMF band generation using EMD model. For improved classification accuracy detailed statistical analyzes is carried out over extracted DWT and EMD outputs. Here for detailed performance metric is carried out over epileptic EEG datasets obtained from the University of Bonn, Germany. The topology is the first important component of the NoC architecture, and it has a significant impact on both the cost and performance of the entire network. The physical arrangement and connections between nodes and channels are determined by the topology. Moreover, the topology affects the number of message traversal hops and the number of channels per hop. Hence, the topology has a big impact on latency and power usage. The topology also impacts the distribution of network traffic, which in turn affects the network's bandwidth and performance. This is because the number of alternate paths between nodes is determined by the topology.

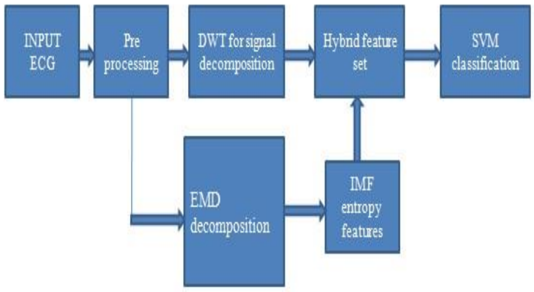

FIGURE 2 Proposed EEG epilepsy detection frameworks

SVM based EEG signal classification

Here final EEG signal classification used hyper lane SVM model which includes different versions of DWT and EMD output extracted feature values. And to maximize the correlation and discrimination level between normal – abnormal EEG signal measures, the extracted features are optimized to get final feature subsets which retained potentially useful feature values from both time and frequency domain features. Here finite classification performance is maximized with associated computational complexity trade-off with optimal time domain decomposition models. For the diagnosis of neurological illnesses like epilepsy and sleep disorders, support vector machine (SVM) has been frequently utilized to classify electroencephalogram (EEG) signals. The convex optimization challenge that SVM faces helps it perform well in terms of generalization for large dimensional data. A more optimal classifier is produced when prior knowledge about the data is incorporated. The distribution of EEG data is revealed by several EEG signal types. We present a novel machine learning strategy based on universal support vector machine (USVM) for classification in order to include past knowledge in the categorization of EEG data. In our method, the interracial EEG signals are chosen as universum from the EEG dataset itself to construct the universum data points. Support Vector Machine (SVM) classification is the second approach we can employ for training. The statistical learning theory is the source of the machine learning algorithm known as SVM. The capability of SVM classification to learn from a relatively small sample set is one of its characteristics.

According to their frequency range, the different types of EEG waves are classified as follows: delta: below 3.5 Hz (0.1-3.5 Hz), theta: 4-7.5 Hz, alpha: 8-13 Hz, beta: 14-40 Hz, and gamma: over 40 Hz. When a brain disorder arises, the EEG may display atypical electrical discharge.

IV EXPERIMENTAL RESULTS

In this section, the performance metrics of proposed EEG epilepsy detection framework is evaluated and validated the metrics both in terms detection rate and classification accuracy with associated parametric measures. As compared other single compound decomposition model-based EEG signal measure the proposed combined DWT - EMD based EEG signal measures form multiple channels showed significant improvement in discrimination level and detection rate with least possible hardware complexity overhead. The proposed system is modeled using SVM classifier and feature subset generation for performance analyzes. Here to suppress the influence of input signal interference in overall classification rate optimal FIR filter design is incorporated which can preprocess the input EEG signal and reduces the all kinds of signal interferences as shown in Figure 3.

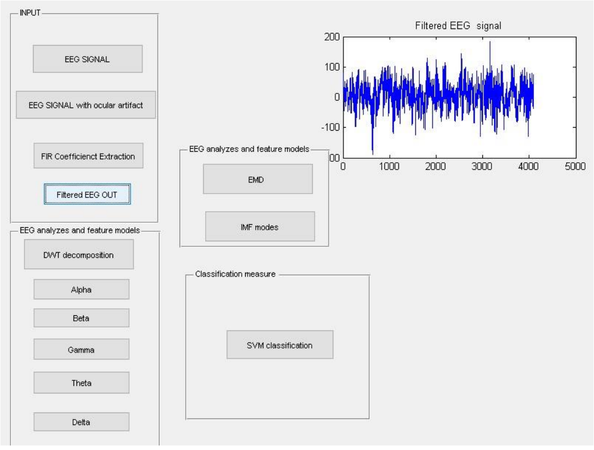

FIGURE 3 Filtered EEG signal output

Simulation results

In order to verify the functionality of the proposed DWT-EMD based EEG classification model input stimulus is generated using exhaustive test bench with Bonn dataset generation EEG signal input. Here CAM system is configured using dedicated DWT and EMD and associated feature extraction process. Based on high level signal decomposition the desired EEG signal type is optimally generated and separated using band selection. In DWT both high and low pass filter wavelet coefficients are determined and associated approximated and detailed coefficients are formulated as shown in Figure 4. In EMD IMF bands are generated using different time scale measures which packet comprise of time domain signal discrimination. During classification final feature subset evaluation is processed and final set is sent in accordance with class of object selected. Each decomposition mode is equipped with the parametric selection which can be dynamically altered and modified using input EEG signal characteristics. During performance validation optimal sets of parameters for each decomposition model is selected with other feature sets is. Here distance evaluation-based feature selection algorithm is used to allocate the priority to predominant features irrespective to the time and frequency domain. With the inclusion of hybrid feature sub set most approximated feature set is estimated and classification is performed accordingly.

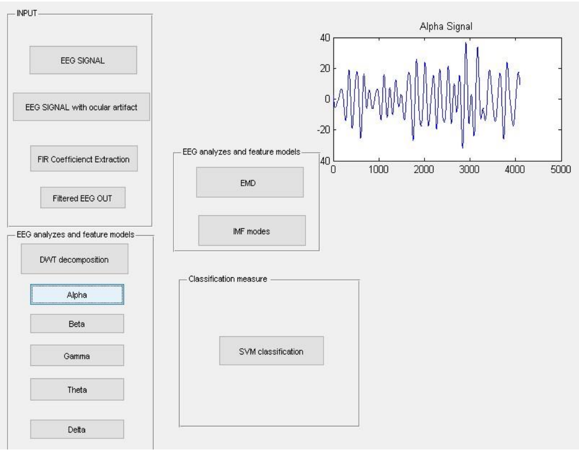

FIGURE 4 DWT decomposed- Alpha signal component

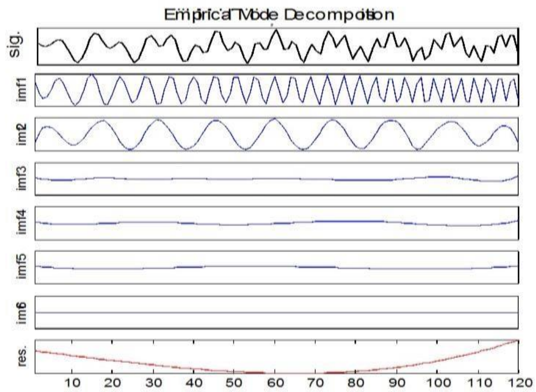

FIGURE 5 EMD decomposed IMF band signal

The efficiency of proposed EEG classification is maximized through time domain signal decomposition scheme using IMF band generation which shows improved discrimination in terms of time scale properties associated to the each EEG signal types as shown in Figure 5. To illustrate the performance efficiency of EMD during the evaluation of EEG classification experimentation has been carried out which will consider 100 data sampled form each class namely normal and epilepsy EEG signals. The dynamic variations are noted down during iterative computation and associated performance degradations are note down for classification measurements.

FIGURE 6 SVM CLASSIFICATION OUTPUT

As shown above the support vector machine is trained by passing necessary inputs, support vector machine is a machine learning algorithm , It will find the hyper plane according to the number of inputs features, hyper plane is a straight line if the input features are two, hyperplane becomes complex as the number of input features increases, after completion of the training phase, actual signal is passed to find out if any epileptic seizure contained in the signal, output is displayed as shown above , if the passed input signal contains seizure output will be displayed as epilepsy detected , otherwise it will show detection failed. A supervised machine learning approach called Support Vector Machine (SVM) is used for both classification and regression. Although we also refer to regression issues, categorization is the most appropriate term. Finding a hyperplane in an N-dimensional space that clearly classifies the data points is the goal of the SVM method. The number of features determines the hyperplane's size. The hyperplane is essentially a line if there are just two input features. The hyperplane turns into a 2-D plane if there are three input features. Imagining something with more than three features gets challenging. Finding a hyperplane that effectively divides data points from one class from those from another is the goal of the SVM algorithm. The hyperplane with the widest margin between the two classes is referred to as "best"; plus and minus are used to illustrate this. Margin is the maximum thickness of the slab that is perpendicular to the hyperplane but has no interior data points. The approach can only discover such a hyperplane for linearly separable problems; for the majority of real-world problems, it maximizes the soft margin, permitting a limited amount of misclassifications. SVM has a lower computational complexity than other conventional classification methods like k-nearest neighbor (KNN) and multi- layer perceptron (MLP). With the rise of parameter K, the computational complexity of KNN decreases, but so does the accuracy of its categorization. Deep learning has become a popular area of research in recent years with the emergence of the big data age. SVM, on the other hand, is still somewhat competitive in comparison. The fact that SVM is not a black box method and has a strong mathematical theoretical foundation is its most important quality. SVM is also simpler to modify and has fewer parameters than deep learning.

V CONCLUSION

Here in this paper combined time and frequency domain decomposition results are used to generate final subsets to formulate the EEG epilepsy detection. Here DWT transform is used to decompose the input EEG signal into 5 signal output and used EMP decomposition to decompose the input EEG signal into IMF bands. Here, in proposed EEG classification is completely automated using SVM based classification model and showed improved classification accuracy. By selecting prominent features and associated final subset evaluation finite discrimination level is achieved. From the simulation results it is well proved that the proposed EEG classification model offered improved performance efficiency as compared to convention EEG classification model. The findings of comparing the three EEG signal decomposition methods show that, when utilizing the two demonising methods, DTCWT performed better than DWT and significantly better than EMD when using S-Golay (DTCWT, 99%; DWT, 94%; and EMD, 91%). The approximate shift invariant characteristic, a key element in epileptic seizure detection, is responsible for the DTCWT's relatively high classification result with 100% accuracy classification rates. The experimental results demonstrate the superiority of the standard deviation and average power, which both provided a relatively high classification accuracy when compared to the mean of the sub-band features, in terms of the performance of feature extraction methods.

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