EEG Signal Classification Using Ensemble Empirical Mode Decomposition

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Abstract: A method for feature extraction from electroencephalogram (EEG) signals using ensemble empirical mode decomposition (EEMD) is developed. Its use is motivated by the fact that the EEMD gives an effective time-frequency analysis of non-stationary signals. The existing work makes use of EMD which involves in taking third order IMFs and also mode mixing is the one of the major problem in EMD. The proposed method overcomes the problem of mode mixing by applying a white noise to the signal on decomposition. Five different datasets are collected and used for analysis. The result of EEMD is the intrinsic mode functions which give the decomposition of a signal according to its frequency components. Temporal moments, and spectral features including spectral centroid, coefficient of variation and the spectral skew of the IMF is used for feature extraction from EEG signals. The calculated features are fed into the standard support vector machine (SVM) for classification purposes.

Keywords: EEMD, EMD, Support vector machine, Temporal and Spectral features.

I. INTRODUCTION

The epilepsies are chronic neurological disorders in which clusters of nerve cells, or neurons, in the brain sometimes signal abnormally and cause seizures. Neurons normally generate electrical and chemical signals that act on other neurons, glands and muscles to produce human thoughts, feelings and actions. During seizure, many as 500 time a second, much faster than normal. This surge of excessive electrical activity happening at the same time causes involuntary movements, sensations, emotions and behaviors and the temporary disturbance of normal neuronal activity may cause a loss of awareness. In general, a person is not considered to have epilepsy until he or she has had two or more unprovoked seizures separated by at least 24 hours. A number of tests are used to determine whether a person has a form of epilepsy, and if so, what kind of seizure the person has. Electroencephalogram (EEG) is one of the main diagnostic tests for epilepsy. EEG is a non-invasive technique used to measure and record the electrical activity in various region of the brain. An EEG can assess whether there are any detectable abnormalities in the person's brain waves and may help to determine if anti-seizure drugs would be of benefit.

II. METHOD

A number of tests are used to determine whether a person has a form of epilepsy and if so, what kind of seizures the person has. So, methods may be based on:

1. Blood test
2. Medical history
3. Imaging and Monitoring

Blood Test: There are a number of blood tests that may be recommended as part of epilepsy diagnosis and treatment. Blood test such as a CBC and chemistry panel helps doctors to assess overall health and identify conditions that may be triggering the seizures.

Medical History: A neurologist uses all responses of asked questions and details surrounding each episode of the seizure to determine the most probable cause of seizure or point to epilepsy.

Imaging and Monitoring: An Electroencephalogram, or EEG, can assess whether there are any detectable abnormalities in the person's brain waves and many help to determine if antiseizure drugs would be of benefit.

III. RELATED WORK

M. Niknazar et al., presented a method of applying recurrence quantification analysis (RQA) on EEG recordings and their subbands: delta,theta, alpha, beta, and gamma for epileptic seizure detection. RQA was adopted since it does not require assumptions about stationarity, length of signal, and noise. The decomposition of the original EEG into its five constituent subbands helps better identification of the dynamical system of EEG signal. This leads to better classification of the database into three groups: Healthy subjects, epileptic subjects during seizure-free interval (Interictal) and epileptic subjects during a seizure course (Ictal). The proposed algorithm is applied to an epileptic EEG dataset. Combination of RQA-based measures of the original signal and its subbands results in an overall accuracy of 98.67% that indicates high accuracy of the proposed method.

Neethu Robinson et al., proposed that a brain–computer interface (BCI) acquires brain signals, extracts informative features, and translates these features to commands to control an external device. The paper investigates the application of a non invasive electroencephalography (EEG) - based BCI to identify brain signal features in regard to actual hand movement speed. This provides a more refined control for a BCI system in terms of movement parameters. An experiment was performed to collect EEG data from subjects while they performed

right-hand movement at two different speeds, namely fast and slow, in four different directions. The informative features from the data were obtained using the Wavelet-Common Spatial Pattern (W-CSP) algorithm that provided high-temporal-spatial spectral resolution. The applicability of these features to classify the two speeds and to reconstruct the speed profile was studied. The results for classifying speed across seven subjects yielded a mean accuracy of 83.71% using a Fisher Linear Discriminant (FLD) classifier. The results achieved promises to provide a more refined control in BCI by including control of movement speed.

Amar R. Marathe developed a patterns of neural data obtained from electroencephalography (EEG) can be classified by machine learning techniques to increase human-system performance. In controlled laboratory settings this classification approach works well; however, transitioning these approaches into more dynamic, unconstrained environments will present several significant challenges. One such challenge was an increase in temporal variability in measured behavioural and neural responses, which often results in suboptimal classification performance. Previously, we reported a novel classification method designed to account for temporal variability in the neural response in order to improve classification performance by using sliding windows in hierarchical discriminant component analysis (HDCA), and demonstrated a decrease in classification error by over 50% when compared to the standard HDCA method. Here, we expand upon this approach and show that embedded within this new method is a novel signal transformation that, when applied to EEG signals, significantly improves the signal-to-noise ratio and thereby enables more accurate single-trial analysis. The results presented here have significant implications for both brain–computer interaction technologies and basic science research into neural processes**.**

IV. PROPOSED METHOD

A new Ensemble Empirical Mode Decomposition (EEMD) is presented for the classification of EEG signals. This new approach consists of sifting an ensemble of white noise-added signal (data) and treats the mean as the final true result. Finite, not infinitesimal, amplitude white noise is necessary to force the ensemble to exhaust all possible solutions in the sifting process, thus making the different scale signals to collate in the proper intrinsic mode functions (IMF) dictated by the dyadic filter banks. As EEMD is a time–space analysis method, the added white noise is averaged out with sufficient number of trials; the only persistent part that survives the averaging process is the component of the signal (original data), which is then treated as the true and more physical meaningful answer. The effect of the added white noise is to provide a uniform reference frame in the time–frequency space; therefore, the added noise collates the portion of the signal of comparable scale in one IMF. With this ensemble mean, one can separate scales naturally without any a priori subjective criterion selection as in the intermittence over the original EMD and is a truly noise-assisted data analysis (NADA) method. Test for the

original EMD algorithm. This new approach utilizes the full advantage of the statistical characteristics of white noise to perturb the signal in its true solution neighbourhood, and to cancel itself out after serving its purpose; therefore, it represents a substantial improvement.

V. METHODOLOGY

Initially the EEG datasets are collected. The dataset consists of five subsets (denoted as sets A-E) each containing 100 single channel EEG signals, each one having duration of 23.6 seconds. These signals have been selected from continuous multichannel EEG recording after visual inspection of artifacts. The Sets A and B consist of surface EEG segments collected from five healthy volunteers in awaken and relaxed state with their eyes opened and closed respectively. Segments in Sets C, D and E are obtained from an archive of EEG signals of presurgical diagnosis. Five patients are selected who have achieved complete control of seizure after resection of one of the hippocampal formations. These resection sites are thus diagnosed as epileptogenic zone. Sets C and D consist of EEG epochs recorded during seizure free intervals (i.e., interictal) from epileptogenic zone and hippocampal formation of the opposite hemisphere, respectively. Set E contains signals corresponding to seizure attacks (i.e., ictal EEG), recorded using all the electrodes. The signals are recorded in a digital format at a sampling rate of 173.61 Hz [8]. Thus, the sample length of each segment is 173.61*23.6=4097.
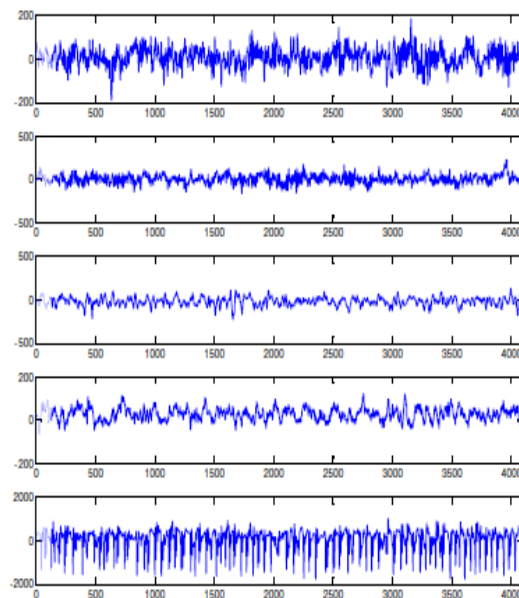

Fig 1.1 Sample EEG signals from five different sets from rows 1 to 5 (A, B, C, D and E respectively).

First process involved in the proposed method is collecting the datasets which is already described above. Next the signal is decomposed using ensemble empirical mode decomposition. The result of empirical mode decomposition is the IMF, which is the time-frequency analysis of the non-stationary signals. As the proposed work involves in using EEMD the last IMF is considered

instead of taking third order IMF's as in the case of EMD. After that a Hilbert transform is applied to the signal for feature extraction. The temporal feature and spectral features like mean, variance, Skewness and spectral centroid, variance coefficient and spectral skew is calculated correspondingly. The calculated features are fed into SVM classifier. Finally, the output is displayed as Healthy, Pre-Seizure or Seizure accordingly.
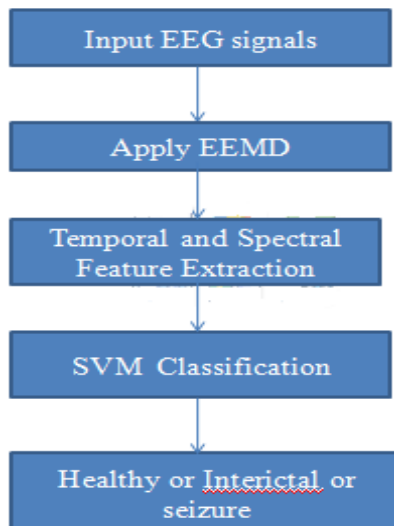

Fig 1.2 Flow Diagram of Proposed Work

VI. CONCLUSION

A method for the detection of seizures and epilepsy in the EEG signals was proposed. The foundation of this method lies on the extraction of temporal and spectral features from Ensemble Empirical Mode Decomposition (EEMD) of the EEG signals. The usage of EEMD was motivated by the fact that EEG signals are non-stationary and EEMD is a data dependent method exhibiting a better adaptability towards non-stationarity in the EEG signals. The work was extended in the spectral domain where the power spectrum density (PSD) has been observed to exhibit good discrimination power for the classification of EEG signals .Since the temporal and spectral characteristics of the signals represent complementary information, so concatenation of these features was proposed in order to extract the salient characteristics of EEG signals. The proposed feature set is embedded in a pattern recognition framework where Multilevel SVM is used for classification purposes. Thus with the proposed method better accuracy can be achieved than the existing methods.

REFERENCES

1. Mingsheng Liu, Wenzhe Liao and Shujing Sun, "Research on Applying the Theory of Wavelet Neural Network and Entropy-Grey Association to the Security Risk Assessment for E-Government Information System" , Journal of Computer, Vol. 6, pp. 1699-1706, 2011.
2. Anil Chacko and Samit Ari, "Denoising of ECG Signals Using Empirical Mode Decomposition Based Technique", Advances in Engineering, Science and Management (ICAESM), pp. 6-9, 2011.
3. Young-Bok Joo, Gyu-Bong Lee, Kil-Houm Park, " 2-D ECG Compression Using Optimal Sorting and Mean Normalization", 2009 International Conference on Machine Learning and Computing IPCSIT, Vol. 3, 2011
4. Pranob K. Charles, Rajendra Prasad K., " A Contemporary Approach for ECG Signal Compression Using Wavelet Transforms", Signal and Image Process: An International Journal (SIPIJ) Vol. 2, No. 1, March 2011
5. Anubhuti Khara, Manish Saxena, Vijay B. Nerkar, "ECG Data Compression Using DWT", International Journal of Engineering and Advanced Technology (IJEAT), Vol.1, Issue 1, Oct 2011
6. Geeta Kaushik and Dr. H.P.Sinha, "Biomedical Signal Analysis through Wavelets: A Review", International Journal of Advanced Research in Computer Science and Software Engineering, Vol. 2, pp. 422-428, 2012
7. Janett Walters-Williams and Yan Li, "Independent Component Analysis Based on B-Spline Mutual Information Estimation for EEG Signals", Canadian Journal on Biomedical Engineering & Technology, Vol. 3, No. 4, May 2012.
8. Babatunde S. Emmanuel, "Discrete Wavelet Mathematical Transformation Method for Non-Stationary Heart Sounds Signal Analysis", ARPN Journal of Engineering and Applied Sciences, Vol. 7, pp. 1021-1028, 2012
9. Doha Safieddine, Amar Kachenoura, Laurent Albera, Gwenael Birot, Ahmad Karfoul, Anca Pasnicu, Arnaud Biraben, Fabrice Wendling, Lotfi Senhadji and Isabelle Merlet, "Removal of Muscle Artifact from EEG Data: Comparison Between Stochastic (ICA and CCA) and Deterministic (EMD and wavelet-based) Approaches", Journal on Advances in Signal Processing, Vol. 127, pp. 1-15, 2012.