Analysis of EEG using Ensemble Empirical Mode Decomposition

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Abstract— This work provides the back ground for analysis of non-linear and non-stationary brain signals by using Ensemble Empirical Mode Decomposition. The electroencephalogram (EEG) is a representative signal which contains information about the condition of the human brain. The disorder in brain is characterized by recurrent electrical discharge of the cerebral cortex. Detection of such disorders by visual scanning of EEG signal is a time consuming task andit may be inaccurate, particularly for long recording data set. In this paper an algorithm is presented which is based on the concept of Ensemble Empirical Mode Decomposition (EEMD). The main idea is White Gaussian Noise is added to the original signal and then EMD is performed. This realization is done several times and by averaging the modes we obtain the true values of modes. Empirical Mode Decomposition is being done over an ensemble of the Gaussian white noise plus signal. Hence Mode mixing problem is being resolved by populating the time frequency space plane.

Key words: EEG, EEMD, Ensemble Empirical Mode Decomposition

I. INTRODUCTION

The electroencephalogram (EEG) is a representative signal which contains information about the conditions of the human brain. EEG is non-linear and non-stationary signal. Most of the methods developed in the literature for EEG signal analysis and classification are based on time domain, frequency domain, and time-frequency domain.Several individual processing techniques and also combinations of those were employed and refined for analysis, quantification and recognition. Neural Networks (NN) have been used to detect abnormal patterns in the EEG [2]. Wavelet Transform is also widely used for disorder detection [4].Others concepts combine Approximate Entropy and Lempel-Ziv Complexity [5], and Time Frequency Distributions. Recently a new technique for analysis of nonlinear and non-stationary EEG has been introduced which is based on the Ensemble Empirical Mode Decomposition (EEMD) of EEG.

Ensemble Empirical Mode Decomposition (EEMD) [6] is adata adaptive method which is used for the analysis of non-stationary and non-linear signals. It comprises of a local and completely data-driven separation of a signal into slow and fast oscillations. It performs the EMD over an ensemble of the signal plus Gaussian white noise. This methodology resolves the problem of mode mixing by populating the whole time-frequency space.The main focus of this approach is sifting an ensemble of white noise and added signal, hence mean value obtained is treated as final result. Mode mixing is defined as a single Intrinsic Mode Functions (IMFs) [4] consisting of signals of widely disparate scale or a signal of un-comparablescale residing in different IMFs. Mode mixing [6] is a consequence of intermittency. Intermittency means signal is stopped or cease for some time. Intermittency can cause aliasing problems and also responsible for losing the meaning of IMFs. As we go from lower order IMFs to higher order IMFs, the scaling increases. This means scaling factor increases hence the signal decomposes. With this ensemble mean concept, we can separate scaleswithout any a priori subjective criterion selection. This new approach utilizes the advantage of the statistical characteristics of white noise which slightly modifies the signal in its true solution neighborhood, and to cancel itself out after serving its purpose.

II. DATASET

An EEG dataset, which is available online in [3] and which includes recordings for both epileptic and healthy subjects, is used. The dataset includes five subsets (denoted as O, Z, N, S, and F). Each of them comprises of 100 single-channel EEG signals, having 23.6 second duration. The subsets F, N and S have been recorded intracranially, whereas sets Z and O have been recorded extracranially.

Number of Epileptic Subjects	SF Class (N,F)	S Class (S)
Electrode Type	Intracranial	Intracranial
Electrode placement	Epileptogenic zone	Epileptogenic zone
Subject’s State	Seizure Free(Inter Ictal)	Seizure(Ictal)
Number of EEG signals	200	100
Signal Duration	23.6 sec	23.6 sec
Sampling Frequency	173.61 Hz	173.61Hz

Table 1: Summary of EEG Data Set

These subsets are linked with the conditions, recording regions, and activities of the brain as: subset Z (healthy eyes open), subset O (healthy eyes closed), subset F (epileptogenic zone), N (hippocampal formation of opposite hemisphere), and subset S (epileptic seizure). The EEG signals of subsets F and N were taken from all contacts of the depth electrode.

The sampling frequency of the data is 173.61 Hz. There are 4097 data points in each data set.In this project, the subset Sforms seizure (S) class and subsets N and F are combined to form the seizure (S) class.Typical EEG signals (one from each subset) are shown in Figure 1.

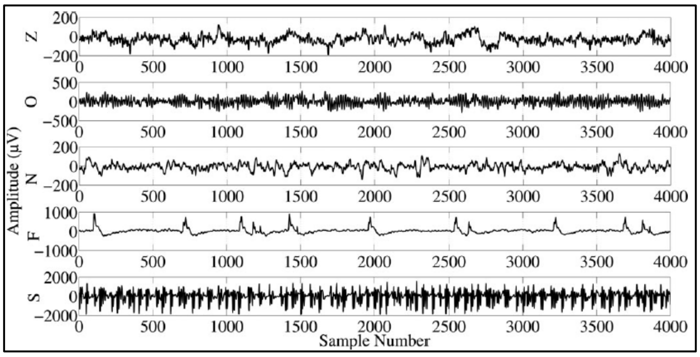

Fig. 1: An example of EEG signals from each of the five subsets

III. Problem and Method

Mode mixing is defined as a single IMFs consisting of signals of widely disparate scale or disorder in the scaling of IMFs. Mode mixing is a consequence of intermittency. Intermittency means signal is stopped or cease for some time. Intermittency can cause aliasing problems and also responsible for losing the meaning of IMFs. As we go from lower order IMFs to higher order IMFs the scaling increases. This means scaling factor increases hence the signal decomposes.To eliminate this Huang et al proposed the intermittence test but it is based on the concept of subjective selected scaling which violates the adaptive nature of EMD.To overcome the problem of mode mixing without introducing the concept of subjective selected scaling a Noise Assisted Data Analysis (NADA) [6] method was proposed known as Ensemble Empirical Mode Decomposition (EEMD).EMD [1] decomposes a signal $x(t)$ into a small number of Intrinsic Mode Functions (IMFs). A signal which is an IMF should satisfy two conditions given below [4]:

- The number of the zero crossing and the number of maxima should be equal or differ at most by one.
- The mean value of the lower and upper envelope is zero everywhere.

EEMD defines the “true” IMF components (here notated as IMF) as the mean of the corresponding IMFs obtained by performing EMD over an ensemble of trials which are generated by adding different realizations of white Gaussian noise of finite variance to the original signal $x[n]$. In this method Additive White Gaussian Noise is added to original signal in order to alleviate the disparate scale mixing problem and then EMD is performed to get the IMFs. EEMD defines the “true” IMF components (here notated as IMF) as the mean of the corresponding IMFs obtained via EMD over an ensemble of trials, generated by adding different realizations of white noise of finite variance to the original signal $x[n]$. EEMD algorithm [6] can be described as:

1) Generate$\mathrm{x^i[n] = x[n] + w^i[n]}$where $\mathrm{w^i[n]}$ $(\mathrm{i} = 1,2,3,4 \dots\dots \mathrm{I})$ are different realizations of white Gaussian noise.
2) Each $\mathrm{x^i[n]}(\mathrm{i} = 1,2,3,4 \dots\dots \mathrm{I})$ is completely decomposed by performing EMD getting their modes $\mathrm{IMF_k^i[n]}$ where $\mathrm{k} = 1,\dots,\mathrm{K}$indicates the modes.
3) Assign $\overline{\mathrm{IMF}}_\mathrm{k}$ as the k-th mode of$\mathrm{x^i[n]}$, obtained as the average of corresponding $\mathrm{IMF_k^i[n]}$: $\overline{\mathrm{IMF}}_\mathrm{k}[\mathrm{n}] = \frac{1}{\mathrm{T}}\sum_{\mathrm{i=1}}^{\mathrm{I}} \mathrm{IMF_k^i[n]}$.

To illustrate the procedure, the data in Figure 2 is used as an example. On the available dataset EEMDis implemented with the added noise having an amplitude of 0.1 standard deviation of the original data for just one trial, the result is given in Figure 3. Here the low frequency component is already extracted almost perfectly. The high frequency components, however, are buried in noise.

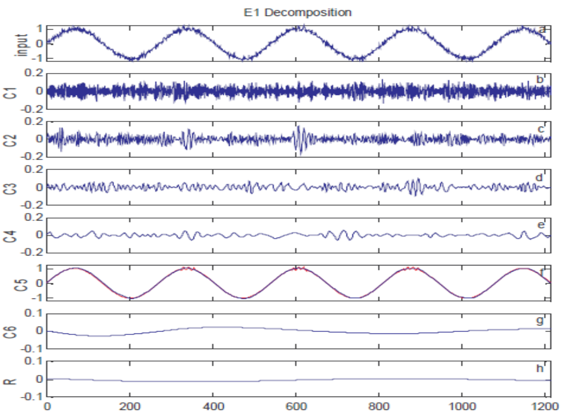

Fig. 3: Random White Gaussian Noise is added to input signal and EEMD is performed

IV. CONCLUSION

The use of EEMD to decompose signals into IMFs is a substantial method. It also alleviates the problem of mixing of disparate scales at different levels i.e. Mode Mixing by populating the time frequency plane with the white Gaussian noise. With this ensemble mean concept, we can separate IMFs at disparate scale without having any priori information. Hence this method is completely data driven. Therefore, it represents improvement over the other methods and it is a Noise Assisted Data Analysis (NADA) [6].

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