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Recovery of low frequency Signals from noisy data using Ensembled Empirical Mode Detection.

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ABSTRACT: *Recovery of low frequency signal from observed noisy data is usually regarded as an important preprocessing and has been as area of research for a long time. The different methods used to resolve this problem of noise added to the original signal during transmission were traditional Linear Filters. Their effectiveness for removing the unwanted noise components have also been observed. Some of the examples that can be considered here are removal of Aliasing effect on the original step edge response curve, removal of impulses of short duration and filtering of the signal containing sharp edges. For the wavelet based de-noising techniques it is difficult to select the basis of wavelet, optimal threshold values scale threshold function and other parameters.*

Empirical Mode Decomposition technique[1] was designed by Wu and Huang in 1998 for decomposing the nonlinear and non stationary signals into a series of Intrinsic Mode Functions (IMF)[5]. The main advantage of EMD is that it depends entirely on the data itself. The observations of the result showed the target signal with full non stationary characteristics which proved the Empirical Mode Decomposition results at a greater approximation of original signal that was lacking in wavelet analysis. The property of EMD to behave as a filter bank has been useful in signal denoising. Apart from the advantages given by EMD method there is one drawback that is of mode mixing. The Ensemble Empirical mode detection has been proved to very useful for removing this problem. This method[2] adds some white noise of same standard deviation and limited amplitude to the researched signal sufficiently taking advantage of statistical Characteristic of white noise whose energy density is uniformly distributed throughout the frequency domain, then projects the signal components on to the proper frequency bands and finally added white noise can be counteracted by ensemble mean of enough corresponding components. Therefore EEMD method is significantly improved and efficient method for recovery of original signal from its envelop.

KEYWORDS: *Empirical Mode Detection, Ensemble empirical Mode Detection, Intrinsic Mode Function, Filter Bank, Sifting.*

I. I INTRODUCTION

Data recovery for analysis is necessary for scientists and engineers. The received signal is the only way we have with the real information. Therefore Data recovery and analysis is required for:

(I) For justification and validation of our research and theory.
(II) Guiding for discovery creation or improvements of theories and models.

In other simple words the aim of data recovery and analysis is to find correct information and make it available for the analysis of electrical signals in the time, frequency and modal domains.

Traditional data analysis methods are based on linear and stationary assumptions. And time frequency analysis methods follow the well established mathematical rules. The methods start with a definition of a basis and mixes the signal with the bases to get a new signal for viewing it in new form that is available for analysis in amplitude and frequency domain either for distribution or for filtering. Therefore restricts to linear and stationary assumptions.

As the data comes from all sources like complicated biological process or social economic phenomenon. The methods developed for nonstationary and non linear data are also introduced eg. Wavelet analysis, spectrogram for linear and Wagner vile distribution for non stationary . Various non-linear time series analysis methods were designed for nonlinear, and not found suitable for stationary and deterministic systems.

The available methods for nonstationary but linear data were based on apriori basis approach, where all the analysis is based on convolution of data with the established bases. The convolution process is entirely based on integration and limitations are imposed by the uncertainty principle, and prevents from examine the details of the data.

The signal analysis can be done using different adaptive methods but these methods are found suitable for only linear process.

The EMD method developed by Wu and Huang or Hilbert Huang Transform method is a solution for non-stationary and nonlinear Signals for analysis in Time and Frequency domain.

II. II THE EMPIRICAL MADE DECOMPOSITION

The Empirical Mode Decomposition is necessary to reduce any data from nonstationary and non linear processes into simple oscillatory function that will yield meaningful instantaneous Frequency through the Hilbert transform. EMD is empirical, intuitive, direct and adaptive with a posteriori defined bases derived from the data. The decomposition is based on the assumption that any data consists of different intrinsic mode functions. Any Intrinsic mode function is an oscillation linear or non linear that have the same number of extrema and zero crossing. The Intrinsic mode function is symmetric with respect to local mean of ensemble signal. Any Signal can have many different coexisting modes of oscillation at any given time. The collection or sequence of these oscillation is the final and complicated data and thes oscillatory modes are known as Intrinsic Mode Functions.

Intrinsic Mode Function

An IMF represents a simple oscillatory mode as a counterpart to the simple Harmonic function, Instead of constant amplitude the and frequency, as in a simple Harmonic component, IMF can have a variable amplitude and frequency as functions of time. The definition of IMF can be given as

(i) In the complete data set, the count of extrema and number of zero crossings must either be equal or differ at most by one.

(ii) The mean value of envelope calculated by the local maxima and the envelope calculated by local minima is zero at any point.

The total number of the IMF components is limited to ln2N where N is the total number of data points which satisfies all the necessities for a meaning for direct frequency, using Hilbert transform.

Sifting Algorithm

Pursuant to the above description for IMF, the decomposition of any function known as sifting can be done as follow-

(I) Take the test data set x(t).
(II) Find the locations of all the extreme of the variable x(t).
(II) Interpolate between all the minima to obtain the lower envelope connecting the minima emin(t). Similarly obtain emax(t).
(IV) Compute the local mean m(t) = { emin(t)+ emax(t)}/2.
(V) Subtract the local mean from the loop variable x(t) to obtain the modulated oscillation d(t) = x(t) – m(t).
(VI) If d(t) satisfies the stopping criterion set IMFm = d(t) else set x(t) = d(t) and go to step 1.
(VII) Subtract the so derived IMF from the variable x(t) so that x (t) = x(t)-IMFm and go to step1.
(VIII) Stop the sifting process when the residual from step 6 becomes a monotonic function.

The sifting process

The Sifting algorithm known as sifting process serves two following purposes:

- to eliminate riding waves and
- to make the wave profiles more symmetric.

while the first condition is absolute necessary for Hilbert transform to give a meaningful instantaneous frequency, the second purpose shows its significance in case the neighboring wave amplitudes having too large a discrepancy. Therefore the sifting process needs to be continual many times to reduce the extracted signal an IMF.

III. ENSEMBLE EMD

The principle of EEMD is as follows**:** The added white noise constitutes components of different scales that uniformly inhabit the entire frequency space on the uniformly distributed white noise background. These different scale component of the signal are automatically projected onto proper scales of reference established by the white noise component. Because each of the component containing signal and white noise, each individual trial generates very noisy results. The noise level in each trial is kept different, that can be almost removed by calculating the ensemble mean of all trials. The ensemble mean is treated as true answer because only the signal is preserved as the number of trials added to the ensemble increases.

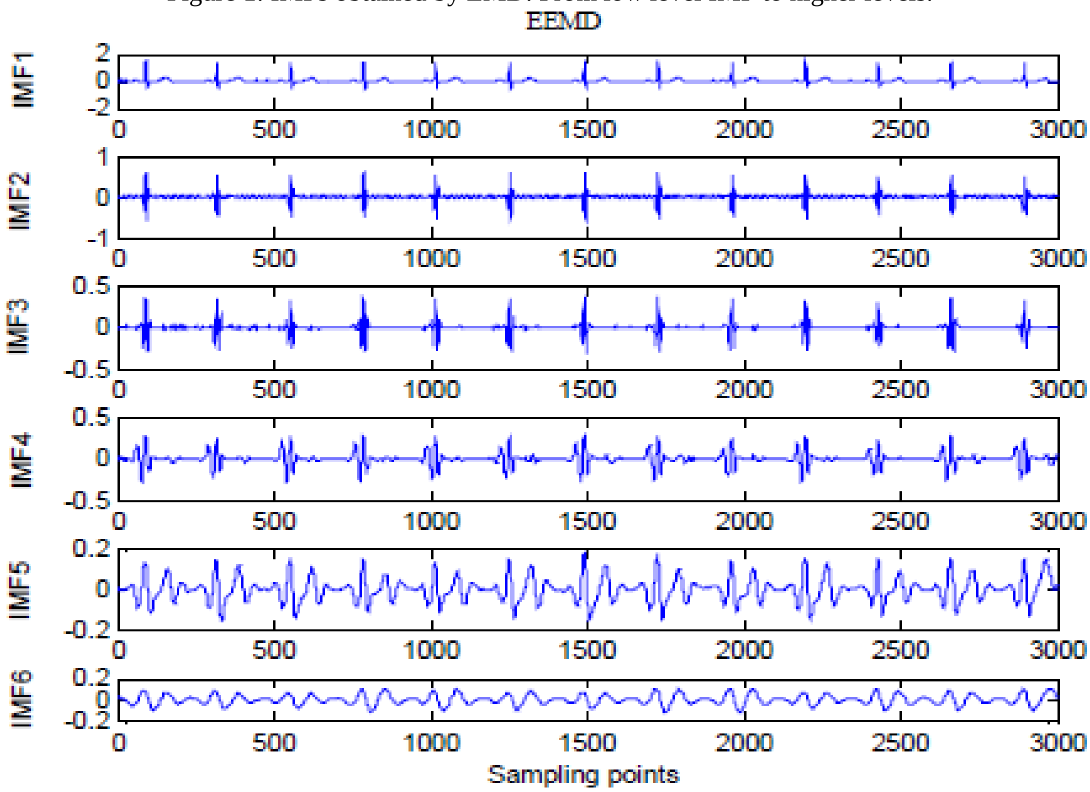
IV. Methodology

The essential principal of the proposed method is based on the following observation.

A uniformly applied white noise background is cancelled out in a time frequency ensemble mean, hence the final signal remains in the final noise added ensemble mean. The added White noise of fixed amplitude automatically compels the ensemble to discover maximum solutions. The different scale signals due to added white noise reside in the corresponding IMFs controlled by the dyadic filter banks and renders the result of ensemble mean further meaningful. The EMD result with accurate physical meaning is not the one not including noise however it is the ensembles mean of many trials using noise added signals.
Based on the aforementioned interpretation, the EEMD algorithm can be stated as follows:

a. Execute the mth trial for the signal with added white noise.
b. Add the white noise series with the given amplitude to the investigated signal i.e. Ym(t) = y(t)+nm(t), where nm(t) represents the mth added white noise and ym(t) indicates the noise added signal of the mth trial.
c. Decompose the noise added signal ym(t) into IMFs Iim(i=1,2,3……..l, m= 1,2,3,……..M) using EMD method, where Iim indicates the ith IMF of the mth trial; l is he number of IMFs and M is the number of ensemble members.
d. If m<M, then let m=m+l and repeat the steps (a) and (b) until m= M using different white noise each time.
e. Compute the ensemble mean of the M trials for each IMF.
f. Report the mean of each trial of l IMFs as the final IMF.

Figure 1: IMFs obtained by EMD. From low level IMF to higher levels.



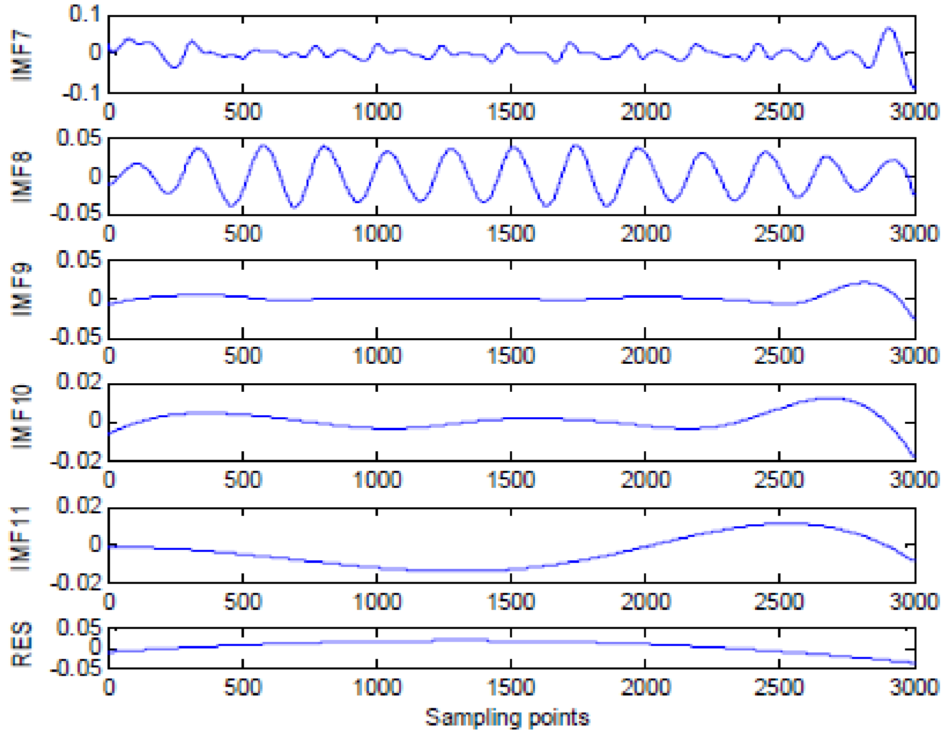


Figure 2: IMFs obtained by EEMD. From low level IMF to higher levels. Noise amplitude. To identify best many level of noise(randomly or systematically) required to be tried.

V. CONCLUSION

A weak signal taken for analysis and after the simulation of data using EMD and EEMD technique , it can be concluded: compared with other time-frequency analysis methods, the Ensembled Empirical mode detection method can be more comprehensive and accurate to analyze the nonlinear and non-stationary signals in the time frequency domain; and the Ensembled Empirical mode detection method with added white noise is found to be more effectively able to detect the weak signal component from the strong background of white noise, so this method is more significant in the detection of weak signals. The comparison of the Empirical mode decomposition and Ensembled empirical mode decomposition technique based on decomposition of signal without white noise and with added white noise respectively enhances the noisy weak signal more successfully in Ensembled Empirical Mode Detection Technique. .

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