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Radar signal Analysis Using EMD and CEEMD

Engineering

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ABSTRACT

Data analysis is an vital part in pure research and practical applications.. Basically it's defined as a method of evaluating data using analytical and logical reasoning to examine every component of the information provided. It is accepted proven fact that linear and stationary processes are easy to analyze through (TF) representation methods of time domain signal like Fourier transform (FT), Short Time Fourier transform (STFT), wavelet transform etc., however the real world signals are mostly non-linear and non-stationary in nature. Analysis of such time varied signals isn't an easy method. Breaking out a complex method into separate components is named decomposition. Hilbert Huang Transform (HHT) is used for processing non-stationary and nonlinear signals. HHT is one among the time- a frequency analysis technique that consists of 2 parts: Empirical Mode Decomposition (EMD) and instantaneous frequency solution. However, EMD experiences some issues, like "mode mixing". To Solve these issues, a brand new technique was projected, the Ensemble Empirical Mode Decomposition (EEMD). EEMD relies on averaging the modes obtained by EMD applied to many realizations of Gaussian white noise superimposed to the original signal. The resulting decomposition solves the EMD mode mixing problem, but it introduces new ones. The EMD properties like completeness and fully data driven number of modes are lost by EEMD. To resolve this drawback, a brand new technique known as Complete Ensemble Empirical Mode Decomposition (CEEMD) technique is introduced. This technique depends on averaging the modes obtained by EMD applied to several realizations of Gaussian white noise superimposed to original signal. Its decomposition is complete with numerically negligible errors. It will solve mode mixing problems in EMD and improve resolution of EEMD when the signal has low signal to noise (SNR) ratio. It provides higher spectral separation of the modes and a lesser number of sifting iterations, reducing the computational price.

I. INTRODUCTION

Following the advent of traditional Fourier analysis, several new methods have been developed to accommodate for non-stationary signals. These vary from short-time Fourier transforms (STFT), which allow a signal to be non-stationary as long as it is piece-wise stationary or wavelet analysis which can sift out particular signatures from a signal on a variety of size scales.

Hilbert-Huang Transform (HHT) is an effective method to extract the properties of non- linear and non-stationary signals. When performing the HHT, first, empirical mode decomposition (EMD) is applied to analyze fault signal. That is, the signal is decomposed into a number of independent components called Intrinsic Mode Functions (IMF). Secondly, the instantaneous frequencies and amplitude of the signal can be derived by utilizing Hilbert Transform (HT) on the IMF. EMD experiences a drawback called "Mode Mixing".

To overcome this problem, a new method is proposed called Ensemble Empirical Mode Decomposition (EEMD). EEMD relies on averaging the modes obtained by EMD applied to several realizations of Gaussian white noise added to the original signal. The resulting decomposition solves the EMD mode mixing problem, however it introduces new ones. The EMD properties such as completeness and fully data driven number of modes are lost by EEMD. To solve this problem, a new technique called Complete Ensemble Empirical Mode Decomposition (CEEMD) method is introduced. This method relies on averaging the modes obtained by EMD applied to several realizations of Gaussian White Noise added to original signal. Its decomposition is complete with numerically negligible errors. It can solve mode mixing problems in EMD and improve resolution of EEMD. The numbers of iterations are greatly reduced in CEEMD compared to EEMD. Hence it is very fast.

II. EMPERICAL MODE DECOMPOSITION:

Empirical Mode Decomposition is an adaptive technique introduced to investigate non-linear and non-stationary signals. It consists in a local and fully data-driven separation of a signal in fast and slow oscillations. EMD is a method of breaking down an signal without neglecting the time domain. It has been compared with alternative analysis like Fourier Transforms and wavelet decomposition. This method is useful for analyzing natural signals, that are most often non- linear and non-stationary.[4]

EMD filters out functions that form an entire and nearly orthogonal basis for the original signal. Completeness depends on the methodology of the EMD. The methodology in which it's decomposition implies completeness. The functions, named as Intrinsic Mode Functions (IMFs), are therefore enough to describe the signal, although they're not essentially orthogonal. The actual facts that the functions into that a signal is decomposed are all in the time-domain and of the same length because the original signal permits variable frequency in time to be preserved. Getting IMFs from real world signals is very important because natural processes often have multiple cause, and every of those causes may happen at specific time intervals. This sort of data is obvious in an EMD analysis, however quite hidden in the Fourier domain or in wavelet coefficients

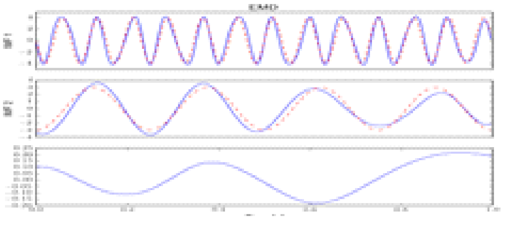


Fig (1) Representation of IMF's

EMD then means the following steps :

Step 1: Initialize: n = 1; r0(t) = x(t)

Step 2: Extract the nth IMF as follows:

a) Set h0(t) := rn 1(t) and k := 1

b) Identify all local maxima and minima of hk 1(t)

c) Construct, by cubic splines interpolation, for h k 1(t) the envelope Uk 1(t) defined by the maxima and the envelope Lk 1(t) defined by the minima

d) Determine the mean mk 1(t) =0.5 (Uk 1(t) Lk 1(t)) of both envelopes of hk 1(t). This running mean is called the low frequency local trend. The corresponding high frequency local detail is determined via a process called sifting.

e) Form the k th component hk(t) = hk 1(t) - mk1(t)

f) if hk(t) is not in accord with all IMF criteria, increase k to k + 1 and repeat the Sifting process starting at step[b]

g) if hk(t) satisfies the IMF criteria then set xn(t) = hk(t) and rn(t) = rn 1(t) -xn(t)

If rn(t) represents a residue, stop the sifting process; if not, increase n to n + 1 and start at step 1again.

DENOISING USING EMD:

The denoised signal is formed after noise removal and the harmful noise like process, which is the sum of IMFs whose energies are less than the threshold chosen earlier, is simultaneously defined.

DRAWBACKS IN EMD:

EMD is an adaptive signal process technique, that provides a powerful tool to extract intrinsic mode function from wideband signals. however as an empirical technique, EMD not only lacks the mathematical theoretical foundation, but also suffers end effect, overshoots or undershoots, IMF criteria problems during the sifting process. Especially due to the special sift technique, EMD always decomposes wideband signal from high frequency to low frequency, however not from high energy to low energy. These characteristics cause the incapability of separating components that include closely spaced frequencies or weak high frequencies .A large number of applications are conferred within the last decade, and plenty of publications have attempted to improve or at least to change the original methods. The most recent ensemble empirical mode decomposition (EEMD) technique largely overcomes the mode mixing drawback of the original EMD .Advanced approaches like complete ensemble empirical mode decomposition (CEEMD) reduce the degree of mode mixing.

III. ENSEMBLE EMPIRICAL MODE DECOMPOSITION:

(i).The Empirical Mode Decomposition (EMD) has been proposed recently as an adaptive time- frequency data analysis method. It has been proved quite versatile in a broad range of applications for extracting signals from data generated in noisy non-linear and non-stationary processes. As useful as EMD proved to be, it still leaves some annoying difficulties unresolved. One of the major drawbacks of EMD is occurence of mode mixing, which is defined as a single Intrinsic Mode Function (IMF) either consisting of signals of widely disparate scales, or a signal of a similar scale residing in different IMF components.

(ii). A collection of white noise cancels each other out in a time space ensemble mean, therefore only the signal can survive and persist in the final noise-added signal ensemble mean.

(iii). Finite, not infinitesimal, amplitude white noise is necessary to force the ensemble to exhaust all possible solutions; the finite magnitude noise makes the different scale signals reside in the corresponding IMF, dictated by the dynamic filter banks, and render the resulting ensemble mean more meaningful.

(iv). The true and physically meaningful answer of the EMD is not the one without noise; it is designated to be the ensemble mean of a large number of trials consisting of the noise-added signal.

The proposed Technique EEMD has considered all the vital statistical characteristics of noise. EEMD utilizes the scale separation principle of the EMD, and allows the EMD methodology to be a truly dynamic filter bank for any data. By adding finite noise, the EEMD eliminates mode mixing in all cases automatically. Therefore, the EEMD represents a significant improvement of the EMD methodology

The principle of the EEMD is simple: the additional white noise would populate the complete time-frequency space uniformly with the constituting components of different scales and are separated by the filter bank. when signal is additional to this uniformly distributed white noise background, the bits of signal of various scales are automatically projected onto proper scales of reference established by the white noise within the background. Of course, every individual trial might produce very noisy results, for each of the noise-added decompositions consists of the signal and also the added noise. Since the noise in each trial is totally different in separate trials, it is canceled out in the ensemble mean of enough trails. The ensemble mean is treated as the true answer, for, in the end, the only persistent part is the signal as more and more trials are added in the ensemble.

Steps for Ensemble Empirical Mode Decomposition [3]

The proposed Ensemble Empirical Mode Decomposition is developed as follows:

(I). Add a white noise series to the targeted data;
(ii). Decompose the data with added white noise into IMFs;
(iii). Repeat step 1 and step 2 again and again, but with different white noise series each time; and
(iv). Obtain the ensemble means of corresponding IMFs of all decompositions as the final result. The effects of the decomposition using the EEMD, the added white noise series cancel each other, and the mean IMFs stay back within the natural dyadic filter windows, significantly reducing the chance of mode mixing and preserving the dyadic property.

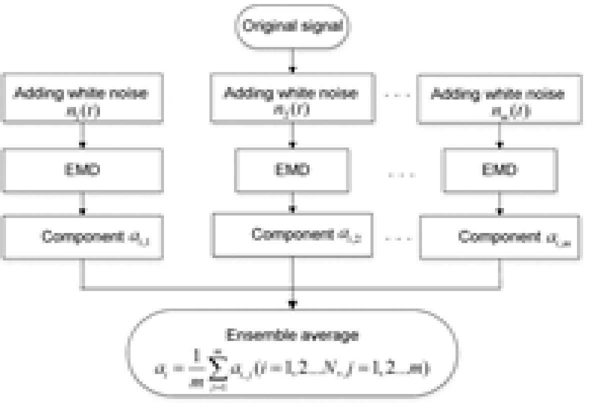


Fig.2. Flow chart representation of EMD

Drawbacks of EEMD

Although EEMD had greatly reduced the mode mixing problem significantly, it has not totally resolved the quandary. Unfortunately, exhausted search had failed to discover a solution. Several of the optimization schemes of the stoppage criterion test as a function of iteration number, n, end up in compact convex sets with the solution at the unacceptable n =∞.

IV COMPLETE ENSEMBLE EMPIRICAL MODE DECOMPOSITION

Empirical Mode Decomposition (EMD) is an adaptive methodology introduced to analyze non-linear and non-stationary signals. It EXISTS in a local and totally data-driven separation of a signal in fast and slow oscillations. [4]However, EMD experiences some issues, like the presence of oscillations of terribly disparate amplitude in a mode, or the presence of terribly similar oscillations in several modes, named as mode mixing. to overcome these issues, a brand new methodology was proposed. The Ensemble Empirical Mode Decomposition (EEMD). It performs the EMD over an ensemble of the signal plus white Gaussian noise. The addition of white Gaussian noise solves the mode mixing problem by populating the entire time-frequency space to take advantage of the dyadic filter bank behavior of the EMD. But it creates some new modes. Indeed, the reconstructed signal includes residual noise and different realizations of signal plus noise may produce different number of modes. so as to overcome these things, better solution was proposed, that could be a variation of the EEMD algorithm that provides an exact reconstruction of the original signal and a better spectral separation of the modes, with a lower computational cost.

[2]In EEMD, each $x^i[n]$ is decomposed independently from the other realizations and so for each one a residue $r_k^i[n]= r_{k-1}^i[n]-IMF_k^i[n]$ is obtained

In this method the decomposition modes will be noted as IMF and we propose to calculate a unique first residue as

$$r_1[n]=x[n]- IMF_1[n]$$

Where $IMF_1[n]$ is obtained in the same way as in EEMD

Then, compute the first EMD mode over an ensemble of $r_1[n]$ plus different realizations of a given noise obtaining IMF_2 by averaging. The next residue is defined as

$$r_2[n]=r_1[n]- IMF_2[n]$$

This procedure continues with rest of the modes until the stopping criteria is reached.

Let us define the operator Ej(.) which, given a signal, produces the j^{th} mode obtained by EMD. [5]

Let w^i be white noise with N(0,1). If x[n] is the targeted data then the CEEMD algorithm is as follows:[1]

1. Decompose by EMD I realizations $x[n]+\varepsilon 0w^i[n]$ to obtain their first modes

$$\overline{IMF_1}(n) = \frac{1}{I}\sum_{i=1}^{I} \overline{IMF_k^i}(n)$$

- Calculate first residue as $r_1(n) = x(n) - \overline{IMF_1(n)}$

3. Decompose $r_1(n) + \varepsilon_1 E_1\left(w^i(n)\right)$ where i=1, 2,--I realizations, until their first EMD mode define as second mode.

$$\overline{IMF_2}(n) = \frac{1}{I}\sum_{i=1}^{I} E_1\left(r_1(n) + \varepsilon_1 E_1\left(w^i(n)\right)\right)$$

Similarly

$$\overline{IMF_{K+1}}(n) = \frac{1}{I}\sum_{i=1}^{I} E_1\left(r_K(n) + \varepsilon_K E_K\left(w^i(n)\right)\right)$$

4. Continue this process until residue no longer feasible. Final residue

So the given signal can be expressed as

$$R(n) + \sum_{k=1}^{K} \overline{IMF_k}.$$

Above equation makes the proposed decomposition complete and provides an exact reconstruction of the original data. Observe that the Ɛi coefficients allow to select the SNR at each stage. Concerning the amplitude of the added noise, Wu and Huang suggested to use small amplitude values for data dominated by high frequency signals, and vice versa

V RESULTS:

The figure shows the radar signal obtained in EAST direction

fig 3. Radar original signal

Ensemble empirical mode decomposition algorithm is applied on radar signal. The signal is decomposed into 8 IMFs as shown in figure

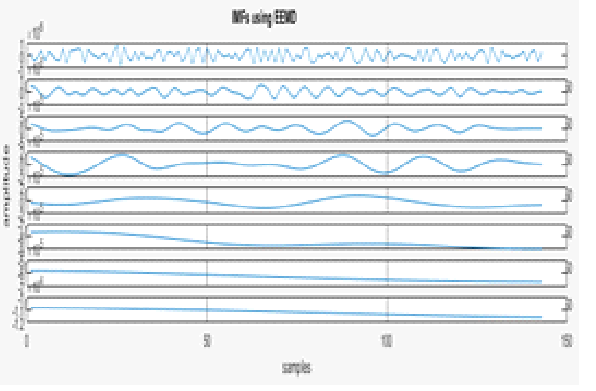


Fig 4. Decomposition of East beam using EEMD (10 July 2008)

CEEMD Decomposition :

CEEMD algorithm is applied on radar signal, it gets decomposed into 5 IMFs as shown in figure

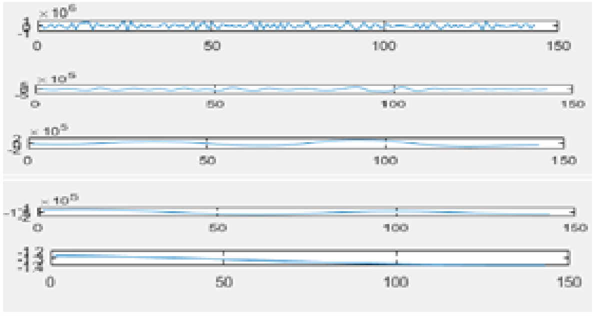


Fig 5. Decomposition of East beam using CEEMD (10 July 2008)

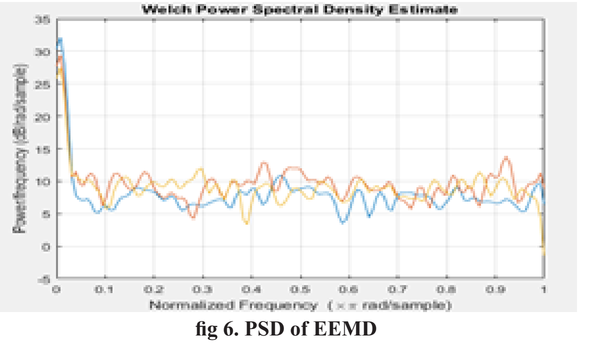
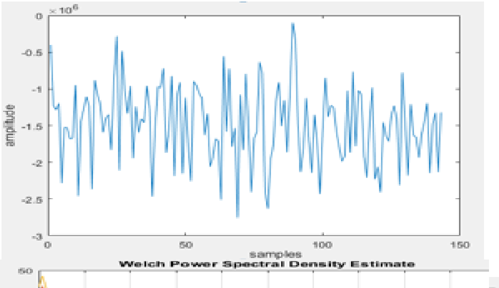


fig 6. PSD of EEMD



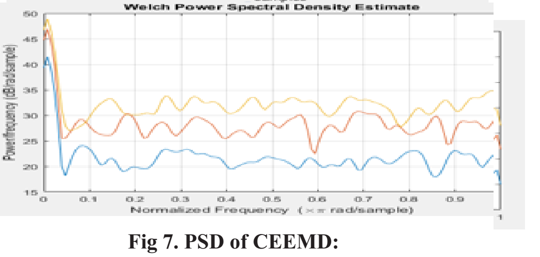


Fig 7. PSD of CEEMD:

VI CONCLUSION

In this work a new algorithm using Complete Ensemble Empirical Mode Decomposition is proposed for analyzing and processing non-linear and non-stationary signals. The method used here solves the mode mixing problem and has the advantages of requiring less number of sifting iterations than EEMD. The original signal can be exactly reconstructed by summing the modes. Hence a smaller ensemble size is needed, resulting in a significant computational cost saving. The new method indeed can separate signals of different scales without mode mixing. Also better spectral separation is obtained using this method. CEEMD utilizes all the statistical characteristics of the noise. As the number of sifting iterations has drastically reduced, it is very fast than EEMD. Therefore, CEEMD represents a major improvement of the EEMD method.

REFERNCES:

[1] Maria E. Torres, Marcelo A.Colominas, Gaston Schlotthauer, Patrick Flandrin, ―Complete Ensemble Empirircal Mode Deomposition with Adaptive Noise‖, Laboratoire de Physique (UMR CNRS 5672), EcoleNormaleSup`erieure de Lyon, France, 978-1-4577-0539- 7/11/$26.00 © 2011 IEEE.

[2] Norden E. Huang, Z. Shen, and S. R. Long, M.L.Wu, E. H. Shih, Q. Zheng, C. C. Tung, andH.H.Liu,―TheEmpiricalModeDecomposition and the Hilbert Spectrum for Nonlinear and Nonstationary Time Series Analysis,‖ Proceedings of the Royal Society of London A, (1998) vol. 454, pp903-995.

[3] N.E. Huang et al., ―The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis,‖ Proc. R. Soc. Lond. A, vol. 454, pp. 903–995, 1998.

[4] Z. Wu and N. E. Huang, ―Ensemble empirical mode decomposition: A noise-assisted data analysis method,‖ Advances in Adaptive Data Analysis, vol. 1, no. 1, pp. 1–41, 2009.

[5] Z. Wu and N. E. Huang, ―A study of the characteristics of white noise using the empirical Mode decomposition method‖. Proc. Roy. Soc London A, 2004, Vol. 460, pp. 1597-1611

[6] Kang-Ming Chang, "Ensemble empirical mode Decomposition for high frequency ECG noise reduction,"BiomedizinischeTechnik/Biomedical Engineering, vol.55, pp. 193–201, August 2010.

[7] Carle purdey, Harlod W. carter, Wen ben Jone Signal DenoisingUsing Wavelets‖ CINCINNATI 2003.

[8] P. Flandrin, P. Gonc¸alv`es, and G. Rilling, Hilbert-HuangTransform and Its Applications, chapter EMD Equivalent Filter Banks, from Interpretation to Applications, pp. 57–74, World Scientific, 2005.