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Atmospheric Signal Processing using Wavelets and HHT

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Abstract

The HHT (Hilbert-Huang transform) and wavelet transform are both signal processing methods. This paper is based on comparing HHT and Wavelet transform applied to Radar signals. HHT can be used for processing non-stationary and nonlinear signals. It is one of the time-frequency analysis techniques which consists of Empirical Mode Decomposition (EMD) and instantaneous frequency solution. EMD is a numerical sifting process to decompose a signal into its fundamental intrinsic oscillatory modes, namely intrinsic mode functions (IMFs). In this paper wavelets and EMD has been applied to the time series data obtained from the mesosphere-stratosphere-troposphere (MST) region near Gadanki, Tirupati. The Algorithm is developed and tested using Matlab. Analysis has brought out improvement in some of the characteristic features like SNR, Doppler width of the atmospheric signals. SNR using wavelets and EMD has been compared and plotted for validation.

Keywords: Radar Signals, Wavelets, Hilbert Huang Transform, Empirical Mode Decompostion, Intrinsic Mode Functions.

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1 Introduction

Atmospheric Radar Signal Processing is one field of Signal Processing where there is a lot of scope for development of new and efficient tools for spectrum cleaning, detection and estimation of desired parameters. The echoes received from MST region represents atmospheric background information and are very weak and buried in noise, hence signal processing methods used for de-noising is necessary. Most of the approaches aim to enhance Signal to Noise Ratio (SNR) for improving the detection ability. The most common approach is the FFT, which is simplest and straightforward among all the methods. However, Fourier Transforms are unsuitable for applications that use nonlinear and non stationary signals. In addition, other technologies such as wavelet transforms, cannot resolve intra-wave frequency modulation, which occurs in signal systems composed of multiple varying signals. A new data analysis method based on the empirical mode decomposition (EMD) method, which will generate a collection of IMFs is applied to the radar echoes. EMD is a key part of Hilbert-Huang transform (HHT) proposed Norden E. Huang in 1996. HHT can be used for processing non-stationary and nonlinear signals. EMD has found a wide range of applications in signal processing and related fields. In this paper wavelet de-noising and EMD has been applied to the radar data and compared in terms SNR.

2 Literature Review

2.1 HHT

Hilbert-Huang Transform **(**HHT) can be used for processing non stationary and nonlinear signals. HHT is one of the time-frequency analysis techniques, which consists of two parts: the EMD, extracting IMFs from the data, and the associated HS (Hilbert Spectrum), providing information about amplitude, instantaneous phase and frequency. As the key part of HHT, EMD is a numerical sifting process to decompose a signal into its fundamental intrinsic oscillatory modes, namely, IMFs allowing IF to be defined. An IMF is defined as a function that must satisfy the following conditions:

(a) In the whole data series, the number of local extrema and the number of zero crossings must either be equal or differ at most by one;

(b) At any time, the mean value of the envelope of local maxima and the envelope of local minima must be zero.

These conditions guarantee the well-behaved HS. Thus, we can localize any event on the time as well as the frequency axis.

2.2 Wavelet de-noising

Wavelet analysis is one of the most important methods for removing noise and extracting signal from any data. The de-noising application of the wavelets has been used in spectrum cleaning of the atmospheric signals. There are many types of wavelets available. The wavelet families like symlets, coiflets, daubechies, haar etc., have their own specifications like filter coefficients, reconstruction filter coefficients. In the proposed work, Db9, Symlet7, boir3.5 wavelets have been used to eliminate noise embedded in the radar signal. The aim of this study is to investigate the wavelet function that is optimum to identify and de-noise the radar signal. Since Db9 wavelet has found to be optimum in the present case study, it was compared with EMD de-noising. The optimal wavelets are evaluated in term of SNR. In the recent wavelet literature one often encounters the term ‘de-noising’, describing in an informal way various schemes which attempt to reject noise by damping or thresholding in the wavelet domain. Wavelets are used as it provides a whole lot of advantages over FFT. Fourier analysis has a serious drawback. In transforming to the frequency domain, time information is lost. When looking at a Fourier transform of a signal, it is impossible to tell when a particular event took place. Wavelet analysis can often compress or de-noise a signal without appreciable degradation.

3 Radar data specifications

The MST Radar is located at Gadanki, near Tirupati (13.47°N, 79.18°E). MST radar operates continuously for different type of experimental observations. Here the signal is used on the data recorded corresponds to experiments related to lower atmosphere; i.e. the region of 3.6 km to 20 km. Only sample data is used for analysis to demonstrate the technique. Radar records data for each range gate and the resolution of sample can vary depends on experimental specification. Here the sampling interval corresponds to 150m (1 micro sec.) in space is used and number of samples taken on each range gate is about 512 points. Radar echoes are recorded in 6 beam directions, viz. East, west, zenith x, zenith y, north and south directions. These data are complex in nature and hence the method adopted is complex signal analysis. Each channel (I and Q) is independently treated for all preliminary processes and combined in the final stage while computing Hilbert transforms and FFT. In this paper, EMD has been applied for the data derived from MST regions on two different days and for 6 beam directions. Data set1 is the time series data of good SNR which is recorded during clear weather conditions on 22nd July 2009 and data set II of low SNR is recorded during bad weather on 28th May 2009.

4 Methodology and Implementation

4.1 Empirical Mode Decomposition: The Sifting Process

EMD is a new signal processing method for analyzing the non-linear and non-stationary signals [2]. EMD is one of the time-frequency analysis techniques which is used for extracting IMFs from the data. EMD is a numerical sifting process to decompose a signal into its fundamental intrinsic oscillatory modes, namely, IMFs allowing IF (Instantaneous Frequency) to be defined. Being different from conventional methods, such as Fourier transform and wavelet transform, EMD has not specified ”bases” and its ”bases” are adaptively produced depending on signal itself. There has better joint time-frequency resolution than Wavelet analysis and the decomposition of signal based on EMD has physical significance, [4]. The EMD algorithm has been designed for the time-frequency analysis of real-world signals .Thus, we can localize any event on the time as well as the frequency axis. The decomposition can also be viewed as an expansion of the data in terms of the IMFs. Then, these IMFs, based on and derived from the data, can serve as the basis of that expansion which can be linear or nonlinear as dictated by the data, and it is complete and almost orthogonal. Most important of all, it is adaptive. We focus on using the EMD to radar echoes which can be decomposed into a limited number of intrinsic mode functions. Different thresholds are used to treat intrinsic mode function to achieve de-noising and then compared with the effect of wavelet transform de-noising. EMD is demonstrated to be effective in removing the noise.

4.2 EMD Algorithm

Given a non-stationary signal $x(t)$, the EMD algorithm can be summarized into following steps:

Step(1) Finding the local maxima and minima; then connecting all maxima and minima of signal $X(t)$ using smooth cubic splines to obtain the upper envelop $Xu(t)$ and the lower envelope $Xl(t)$, respectively.

Step(2) Computing local mean value $m_1(t) = \frac{1}{2}(Xu(t) + Xl(t))$ of data $X(t)$, subtracting the mean value from signal $X(t)$ to get the difference:

$$h_1(t) = X(t) - m_1(t).$$

Step(3) Regarding $h_1(t)$ as new data and repeating steps (1) and (2) for k times,

$$h_{1k}(t) = h_{1(k-1)}(t) - m_{1k}(t),$$

where $m_{1k}(t)$ is the local mean value of $h_{1(k-1)}(t)$ and $h_{1k}(t)$. It is terminated until the resulting data satisfies the two conditions of an IMF, defined as $c_1(t) = h_{1k}$.

The residual data $r_1(t)$ is given by $r_1(t) = X(t) - c_1(t)$.

Step(4) Regarding $r_1(t)$ as new data and repeating steps (1),(2) and (3) until finding all the IMFs. The sifting procedure is terminated until the n-th residue $r_n(t)$ becomes less than a predetermined small number or the residue becomes monotonic.

Step(5) Repeat steps 1 through 4until the residual no longer contains any useful frequency information. The original signal is, of course, equal to the sum of its parts. If we have 'n' IMFs and a final residual $r_n(t)$. Finally the original signal $X(t)$ can be expressed as follows:

$$X(t) = \sum_{i=1}^{n} c_i + r_n.$$

4.3 Intrinsic mode functions

An intrinsic mode function (IMF) is a function that satisfies two conditions:

(1) In the whole data set, the number of extrema and the number of zero crossings must either be equal or differ at most by one; and

(2) at any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero

We can repeat this sifting procedure k times, until h_{1k} is an IMF.

$$h_{1(k-1)} - m_{1k} = h_{1k}.$$

Then, it is designated as

$c_1 = h_{1k}$; the first IMF component from the data.

As described above, the process is indeed like sifting: to separate the finest local mode from the data first based only on the characteristic time scale. We can separate c_1 from the rest of the data by

$$X(t) - c_1 = r_1 .$$

Since the residue, r_1, still contains information of longer period components, it is treated as the new data and subjected to the same sifting process as described above.

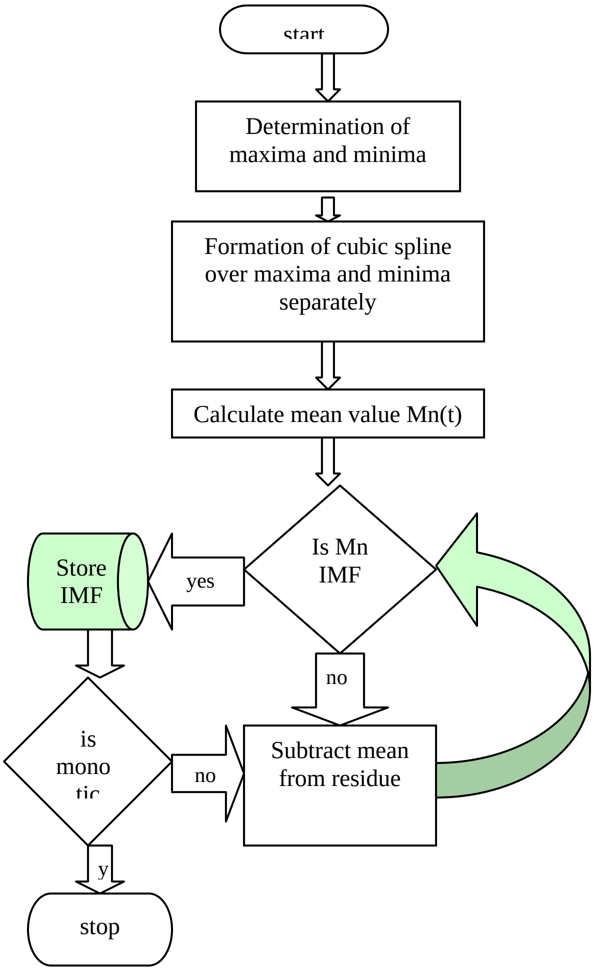

Figure 1: Flow Chart of Empirical Mode Decomposition

The sifting process is illustrated in Figure 2. The sifting process can be stopped by any of the following predetermined criteria: either when the component, c_n , or the residue, r_n , becomes so small that it is less than the predetermined value of substantial consequence, or when the residue, r_n becomes a monotonic function from which no more IMF can be extracted. To guarantee that the IMF components retain enough physical sense of both amplitude and frequency modulations, we have to determine a criterion for the sifting process to stop. This can be accomplished by limiting the size of the standard deviation, SD, computed from the two consecutive sifting results.

A typical value for SD can be set between 0.2 and 0.3. The process will repeat till the function become monotonic. This can be accomplished by limiting the size of the standard deviation, SD, computed from the two consecutive sifting results as

$$\mathrm{SD} = \sum_{t=0}^{T} \left[\frac{\left| h_{1(k-1)}(t) - h_{1k}(t) \right|^2}{h_{1(k-1)}^2(t)} \right]$$

A typical value for SD can be set between 0:2 and 0:3. A SD value of 0:2 for the sifting procedure is a very rigorous limitation for the difference between siftings. The IMF components obtained are designated as c_1, the first IMF component from the data, c_2, the second IMF component and so on. The nth IMF component is designates as c_n . We finally obtain

$$X(t) = \sum_{i=1}^{n} c_i + r_n \, .$$

Thus, we achieved a decomposition of the data into n-empirical modes, and a residue, r_n, which can be either the mean trend or a constant.

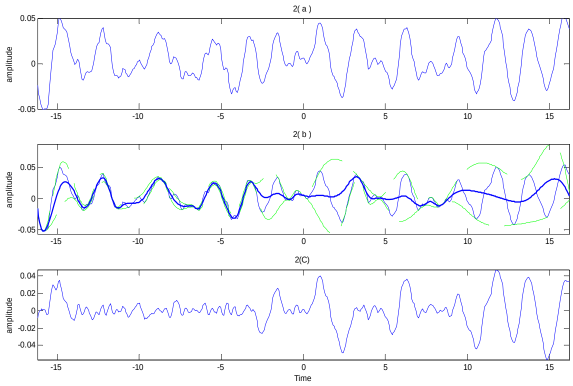

Figure 2: Illustration of the sifting process
(a) The original data (b) the data in thin blue line with the upper and lower envelopes in dot-dashed green and the mean in thick solid line;
(c) the difference between the data & mean m1.

5 Results and discussion

EMD algorithm has been applied to all the 6 beams viz. east, west, zenith x, zenith y, north and south beams. Sifting process has been illustrated in figure 2 for the 1st bin of the data of 22 July 2009. The shifting process is illustrated for 1st IMF only. The Intrinsic mode functions obtained by applying EMD on two sets of the atmospheric data for beam 3 are illustrated by the Figure 4(a) & 4(b). Similar results have been obtained for all the 6 beams. Figure 4(a) shows the IMFs extracted from radar data with better SNR during clear weather conditions (22 July 2009) and Figure 4(b) shows the IMFs extracted after applying the EMD algorithm to the radar data of low SNR during cloudy and noisy weather (28 May 2009). 'C1' is the first IMF component from the data. 'C2' is the second IMF component and so on. The Doppler profile of the data has been plotted in Figure 3(a) and 3(b). For validation of results, SNR has been plotted for the two data sets using Db9 wavelet and then compared with EMD. The results are plotted in Figure 7(a) and 7(b). The results showed an improvement of SNR when EMD is used compared to wavelet de-noising using Db9.

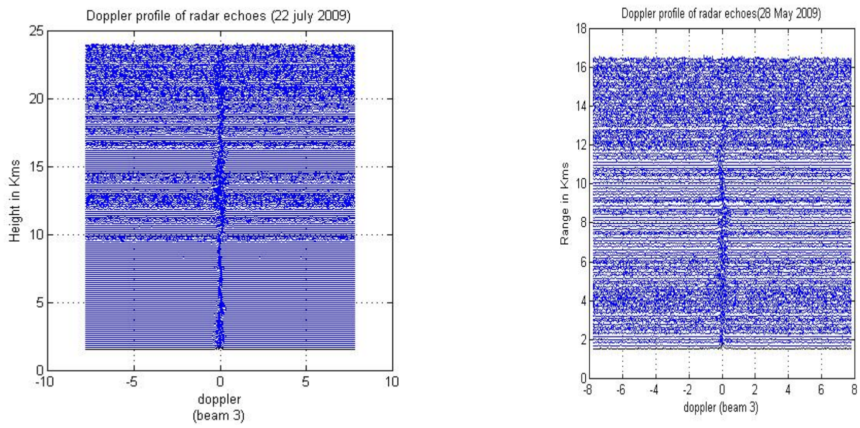

Figure 3: (a) Doppler profile radar data of good SNR (22 July 2009-zenith x).
(b) Doppler profile radar data of low SNR (28 May 2009-zenith x).

Implications

The first few IMFs, in Figure 4 correspond to the high-frequency noise embedded in the data. It is illustrated from Figure 4 that the EMD resulted in 8 imf components (C1–C8) corresponding to data collected for low SNR data during noisy weather. Where as for clear weather data, the application of the EMD algorithm resulted in 6 imf components (C1-C6) due to better SNR.

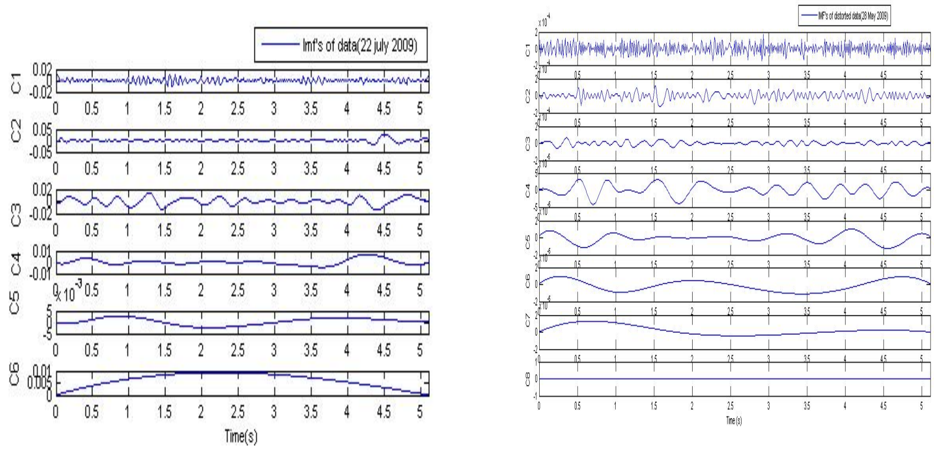

Figure 4: (a) IMFs of radar data with better SNR (22 July 2009).
(b) IMFs of radar data with low SNR (28 May 2009).

For verification and comparison, FFT has also been applied on the same data and the Doppler profile has been plotted. It is evident from the Doppler profile that the data on 28 May is contaminated with noise and the data on 22 July is better. The Doppler profile is very clearly visible up to 10Kms for data set I and not so clear above 10 Kms. This is due the low SNR of the echo signals at greater heights. The doppler profile for data set II is not so clear even below 10 Kms. This is due the low SNR of the echo signals due to bad weather conditions and clutter.

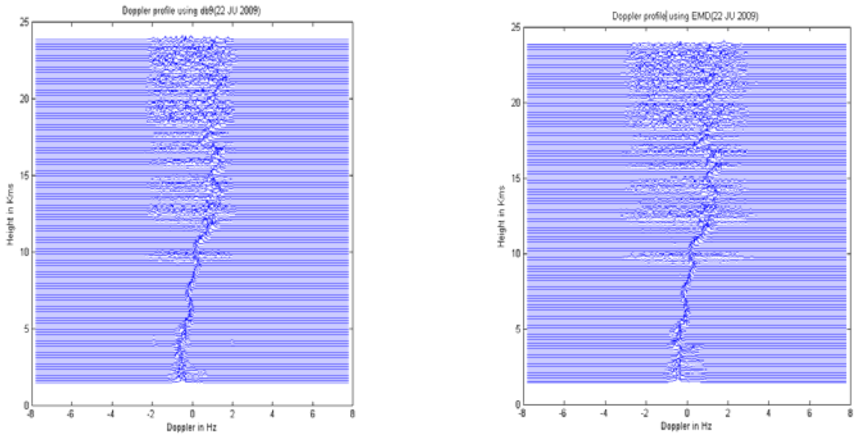

Figure 5: Doppler profile of zenith x beam using Db9 wavelet de-noising and EMD

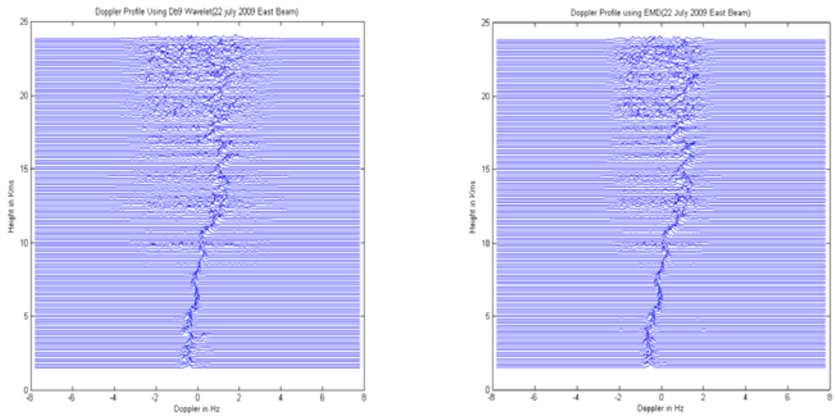

Figure 6: Doppler profile of east beam using Db9 wavelet de-noising and EMD.

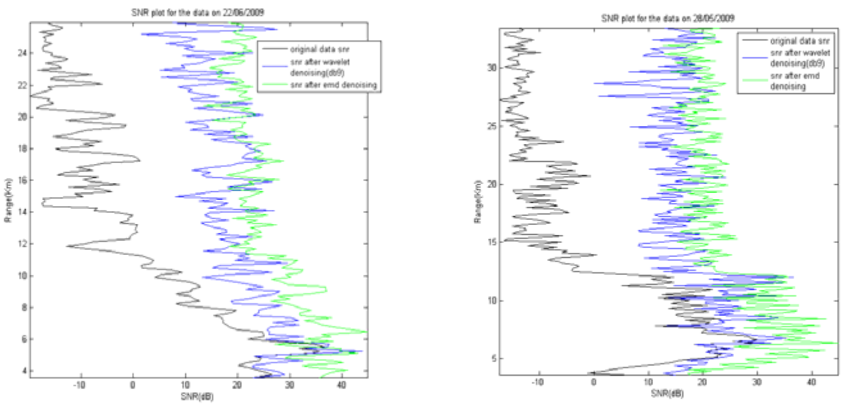

Figure 7: (a) SNR Plot of Radar Data (22 July 2009).
(b) SNR Plot of Radar Data (28 May 2009).

6 Comparison and Conclusions

In this paper, different thresholds are used to treat intrinsic mode function to achieve de-noising and then compared with the effect of wavelet transform de-noising. Hilbert-Huang Transform is demonstrated to be effective in removing the noise embedded in radar echoes. To compare results, wavelet transform and HHT methods are used to deal with the same data to show the effect of de-noising. We add up all the new IMFs which are treated with threshold, and reconstruction of radar signal is done.

We can get the following conclusions by comparison:

1) Both HHT and wavelet transform can be used to analyze non stationary signal and can achieve the desired effect of de-noising.

2) Because the basic functions which are extracted from original data and base on residue of the last filtering are alterable in HHT, the EMD is adaptive. But the basic function of wavelet transform is given, and the effect of de-noising is affected greatly by the choice of basic wavelet. It is demonstrated that HHT techniques are able to resolve frequency components with finer resolution. This is one of the important properties of this method and applied to non linear and non

stationary signals. Large set of data has been used for validating the performance of the algorithm. In all cases it is observed that HHT out performs the wavelets in extracting information. For all the beam directions, the results obtained were in correlation. This is a promising technique for enhancing the capability of detection of signals with finer details.

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