NOISE REDUCTION IN LIDAR SIGNAL BY EMPIRICAL MODE DECOMPOSITION

Songhua Wu, Zhishen Liu, Bingyi Liu

Ocean Remote Sensing Laboratory of Ministry of Education of China,
Ocean Remote Sensing Institute (ORSI), Ocean University of Qingdao,
No. 5 Yushan Road, Qingdao, China, 266003. Email: wush@orsi.ouc.edu.cn

ABSTRACT

LIDAR is a remote sensing tool of great practical importance in environmental monitoring sciences. Signal processing for LIDAR applications involves highly nonlinear models and consequently nonlinear filtering. In this paper, we applied a new method, empirical mode decomposition to LIDAR signal pre-processing. Performance evaluation of the EMD denoising approach shows that it is very effective and superior to the traditional averaging method.

Keywords: lidar, empirical mode decomposition, denoise

1. Introduction

Lidar technology makes it possible to obtain profiles of meteorological parameters and atmospheric constituents. Lidar backscatters contain a variety of noise and interferences, such as thermal noise, background noise and atmospheric turbulence. Attenuating this kind of noise is essential for the precise measurement and for subsequent data analysis. Lidar researchers usually just adapt a multiple-pulse average or running-average approach to remove noise in lidar signal [1-3]. But in practice, such average approach is inefficient to handle the nonstationary noise especially in the far distance.

The conventional multiple-pulse average approach is a kind of low-pass filtering process based on least squares. System errors are assumed to have a Poisson distribution, and average over n pulses decrease the noise magnitude from 1 to $1/\sqrt{n}$, However, such a process has a large bandwidth and poor cut-off spectral property. It is also difficult to distinctly define the statistical properties of the signal because the statistical properties of lidar signal are unknown *a priori*.

The Fourier smoothing technique has also long been used to reduce noise. A common assumption of this process is that the information of a signal can be separated from the noise because the signal varies slowly in comparison with the noise. Since lidar signals represent spatially varying information, setting a particular cutoff frequency may result in signal distortion. Even wavelet analysis is essentially an adjustable window Fourier spectral analysis.[4] Because of the limited length of the basic wavelet function, it is difficult for wavelets to quantitatively define the energy-frequency-time distribution.

Recently, a new nonlinear technique, Empirical Mode Decomposition (EMD), has been developed by Huang et al. for adaptively representing nonstationary signals as sums of intrinsic mode functions (IMFs).[4, 5] They are derived directly from the data and are not restricted by linearity or a priori conceptions. The method allows the modes to be nonlinear while still requiring local orthogonality in a least squares sense. In this work, the lidar data obtained from our Doppler lidar are analyzed by EMD. We propose to use the power spectrum of the intrinsic mode functions to determine how to process the denoising. The results by removal of the high frequency IMF are evaluated by comparing the SNR and the power spectrum.

2. Lidar System

The Doppler lidar receiver in our MIDWiL system (Mie-Rayleigh Doppler wind lidar) is based on the iodine edge filter. The details of the lidar system design have been described elsewhere [6] and will be briefly summarized here. The laser is an injection seeded, lamp pumped, frequency doubled Nd:YAG laser which can be tuned and locked to the iodine absorption spectrum. The laser pulse energy is around 100 mJ at 10 Hz repetition rate. The wind speed is retrieved from the ratio of signals from frequency discrimination channel (iodine filter) and energy reference channel. The lidar returns can be processed under a varied mixture of the Rayleigh and Mie scattering. Because of this unique property, the lidar data cover the low altitude atmosphere that varies more rapidly and is more sensitive to the ground interference than the high altitude atmosphere. The lidar signal is a combination of non-stationary noise, such as instrumental DC offset, thermal noise, atmospheric background radiation and other stochastic turbulences, etc. Therefore, signal processing calls for rapid and efficient techniques.

3. Empirical Mode Decomposition

EMD method decomposes the time series data into IMFs that have a zero local mean. The local mean is extracted by calculating the mean of the envelope of the data. This mean is iteratively subtracted from the current data until the residual has a local mean. This residual is then the first IMF that contains the highest frequencies of the time series. This process is so called ‘sifting’ process. The subsequent IMFs can be found by subtracting the first IMF from the original data and repeating the above ‘sifting’ process. In this way all the IMFs can be extracted and the last IMF usually is a monotonic trend. Due to the limit of space in this paper, the process of decomposition is not shown and can refer to reference 4.

The lidar data is a kind of typical non-stationary time series. In lidar inversion studies, the lidar signal is usually normalized to the transmitting range. The noise components are also amplified in this range calibration process so that the real signals at far distances may be submerged by the background noise. The necessary conditions needed to describe a nonlinear and non-stationary time series in terms of basis function are completeness, orthogonality, locality and adaptiveness. The empirical mode decomposition (EMD) method was developed to address these conditions and has since been found to be very useful.

4. Experiments and analysis

We herein use a wind profile to illustrate the EMD process. Fig. 1 shows the original wind profile.

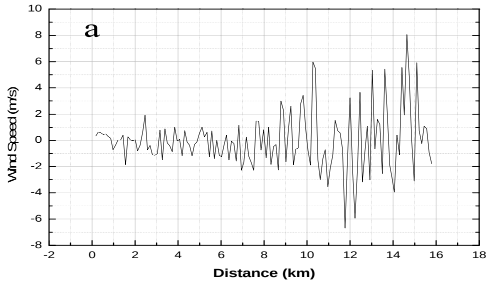

Fig. 1. The original wind profile.

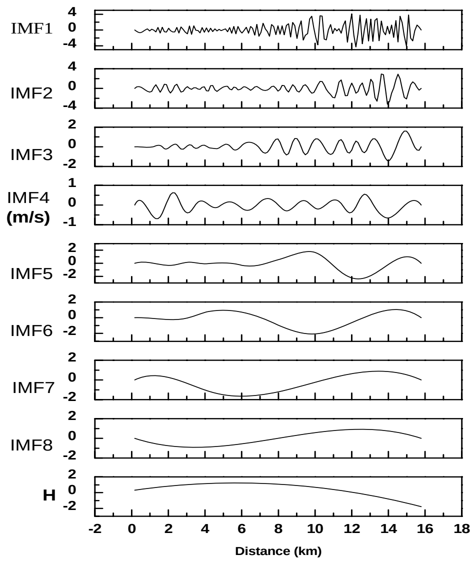

Fig. 2. The intrinsic mode functions of the data: IMF1~IMF8 are IMFs; H is the trend.

Fig. 2 summarizes all the IMFs obtained from EMD processes. In this way the IMFs will generally be ordered from high to low frequency although they will rarely have a constant frequency and the last IMF often contains a trend. Comparing this with the traditional Fourier expansion, one can immediately see the efficiency of the EMD: the expansion of a turbulence data set with only nine terms. From the result, one can see a general separation of the data into locally non-overlapping time scale components.

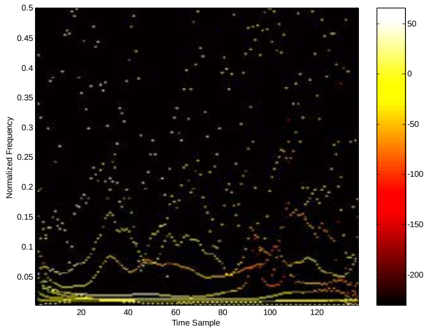

Fig. 3. Hilbert spectrum of the IMFs

Once the modes are defined, a Hilbert Transform can be used to calculate local frequencies. [4, 7] The Hilbert spectrum of the IMFs is an energy-frequency-time distribution. We assume the high frequency IMFs to contain only noise and turbulence. This is a conservative estimation because those IMFs may contain useful signal. Whereas the energy of the high frequency IMFs are of little weight in the Hilbert spectrum, especially the first IMF, it is still practicable to improve SNR by subtracting high frequency modes from the data. In addition, the high order IMFs often contain small spatial (or time) scale fluctuations much less than that of the wind speed we concerned. Therefore, the high frequency modes can also be removed to get proper signal resolution.

In practical processing, how many IMFs to be removed are determined by the noise level and range resolution of lidar signal. The Power Density Spectrum (PDS) herein is used to analyze the IMFs of lidar signal and denoised data. Fig. 4 shows the lidar signal with 100 shots averaged. The PDS of its first six IMFs are shown in Fig. 5.

In this work, the centre of 5th IMF's PDS locates at the 0.02 Hz corresponding to 50 m spatial resolution that satisfies the resolution requirement of line-of-sight velocity retrieval. In other words, regardless of noise distribution there are five high frequency IMFs at most that can be subtracted in order to obtain 50 m resolution.

Denoised signal here is achieved by subtracting the first 5 IMFs from the original signal (Fig. 6). The denoised signal is more smooth and less of fluctuations than the original signal (gray dash line). The fluctuations with large magnitude but small spatial-scale are sufficiently suppressed in far distance. At the same time, local structures of lidar return are preserved. For example, a strong backscattering at 8 km is not distorted after denoising. As mentioned in section 2, wind speed is calculated from the ratio of backscattered returns. EMD denoising can improve the retrieve accuracy especially in far distance.

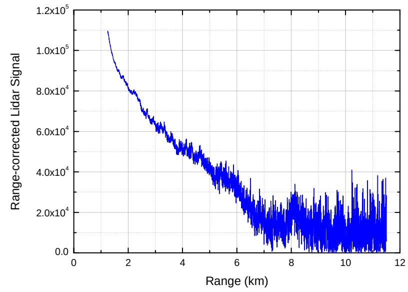

Fig. 4. The range corrected lidar return signal

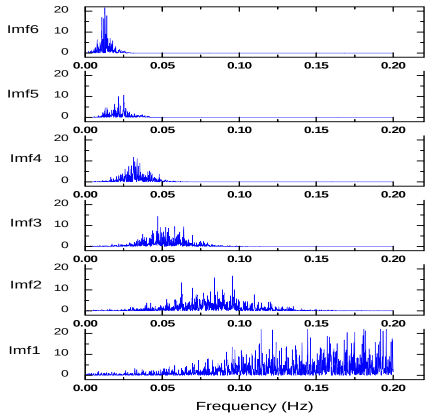

Fig. 5. The power density spectrum of the first six IMFs of the lidar signal.

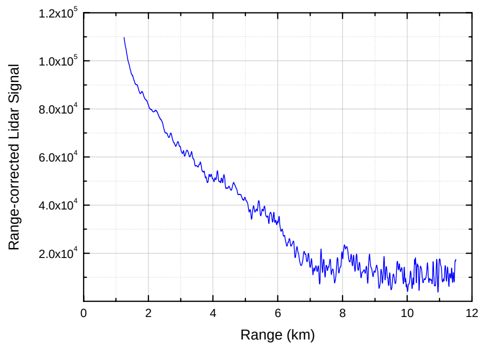

Fig. 6. 100 shots averaged data denoised by EMD.

We compared this method with the multi-pulse average. The 1000 shots averaged data successive to the 100 shots averaged lidar signal in Fig. 4 are compared.

The PDS of 100 shots averaged, 1000 shots averaged and denoised data are shown in Fig. 7. The most attractive specific is the EMD denoising approach only needs a small quantity of data for average when it achieves comparative results and obtains instantaneous atmospheric motion. With this method, lidar researchers may reduce the measurement time and the system can be less power consuming, which are important for the real-time monitoring and the low cost laser transmitter.

EMD denoising is also an option for lidar working on the fast scanning mode such as the Doppler lidar on PPI (Planar Position Indicator) mode and the volume imaging lidar.

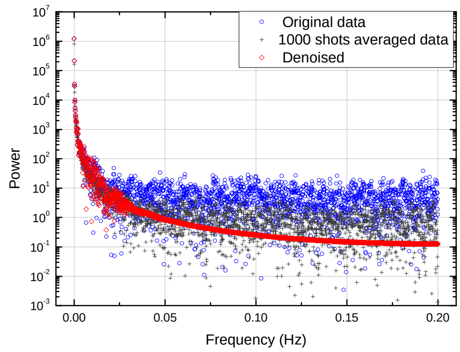

Fig. 7. The PSD of 100 shots averaged data, denoised data and 1000 shots averaged data.

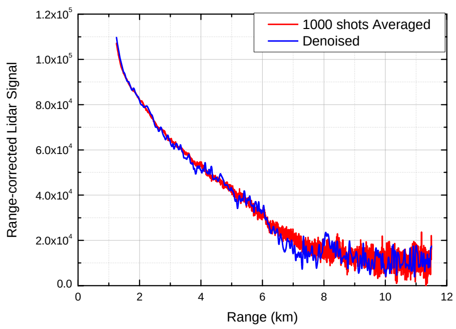

Fig. 8. 1000 shots averaged lidar return signal and 100 shots averaged data denoised by EMD.

5. Result and discussion

In conclusion, it is the first application of the Empirical Mode decomposition to the analysis of lidar data. EMD analysis is implemented to reduce the noise and keeps the significance of the signal, which is possibly the only computational method of real time lidar signal processing. Thus, EMD denoising is attractive in the case of scanning lidars demanding fast measurement. Of course, this analysis underestimates the signal to noise ratio because there often is some signal in the first mode. However, it can work as conservative estimate.

Acknowledgement

This work is supported by the Natural and Science Foundation of China No. 40505003 and No. 40427001 under grant and the research fundation of Information Science and Engineering Department, OUC.

Reference

1. Milton, M. J. T., and E T. Woods, "Pulse Averaging Methods for a Laser Remote Monitoring System Using Atmospheric Backscatter," Appl. Opt., 26, 2598, 1987.
2. Menyuk, N., D. K. Killinger, and C. R. Menyuk, "Limitations of Signal Averaging due to Temporal Correlation in Laser remote Sensing Measurements," Appl. Opt., 21, 3377, 1982.
3. J. M. Dias, E. S. Fonseca, D. P. Resendes, Time and Range Averaging of Lidar Echoes Using APD Based Receivers, SPIE: Application of Lidar to Current Atmospheric 3757, 158-166.
4. N.E. Huang, Z. Shen, S.R. Long, M.L. Wu, H.H. Shih, Q. Zheng, N.C. Yen, C.C. Tung and H.H. Liu, “The empirical mode decomposition and Hilbert spectrum for nonlinear and non-stationary time series analysis,” Proc. Roy. Soc. London A, Vol. 454, pp. 903–995, 1998.
5. Norden E. Huang, Man-Li C. Wu, Steven R. Long, Samuel S. P. Shen, Wendong Qu, Per Gloersen and Kuang L. Fan, A confidence limit for the empirical mode decomposition and Hilbert spectral analysis, Proc. Roy. Soc. London A, Vol. **459**, 2317－2345, 2003.
6. Zhi-Shen Liu, Dong Wu, Jin-Tao Liu, Kai-Lin Zhang, Wei-Biao Chen, Xiao-Quan Song, Johnathan W. Hair, Chiao-Yao She, “Low-Altitude atmospheric wind measurement from the combined Mie and Rayleigh backscattering by Doppler lidar with an iodine filter”, APPLIED OPTICS, Vol. 41, No. 33, 7079-7086, 2002.