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Noise reduction in Lidar signal using correlation-based EMD combined with soft thresholding and roughness penalty

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ABSTRACT

Empirical mode decomposition (EMD) is widely used to analyze the non-linear and non-stationary signals for noise reduction. In this study, a novel EMD-based denoising method, referred to as EMD with soft thresholding and roughness penalty (EMD-STRP), is proposed for the Lidar signal denoising. With the proposed method, the relevant and irrelevant intrinsic mode functions are first distinguished via a correlation coefficient. Then, the soft thresholding technique is applied to the irrelevant modes, and the roughness penalty technique is applied to the relevant modes to extract as much information as possible. The effectiveness of the proposed method was evaluated using three typical signals contaminated by white Gaussian noise. The denoising performance was then compared to the denoising capabilities of other techniques, such as correlation-based EMD partial reconstruction, correlation-based EMD hard thresholding, and wavelet transform. The use of EMD-STRP on the measured Lidar signal resulted in the noise being efficiently suppressed, with an improved signal to noise ratio of 22.25 dB and an extended detection range of 11 km.

1. Introduction

Lidar is a powerful remote sensing technology that has been extensively used in observations of the Earth's atmosphere, including atmospheric aerosols, clouds, water vapor and wind [1–4]. However, the intensity of the Lidar signal decays with the square of the distance; thus, the signal demonstrates both non-linear and non-stationary characteristics. When the detection range is large, the Lidar signal become extremely weak [5], and the signal is overwhelmed by background noise and the noise from the optical detection system [6]. Efficiently extracting the true signal from a signal with large amounts of noise is a challenge that remains to be solved.

In the past few decades, several denoising methods, such as moving average (MA), Fourier transform (FT), wavelet transform (WT), and empirical mode decomposition (EMD) have been extensively investigated for noise reduction of the Lidar signal. The MA technique is a low-pass filtering method that averages several points from the input signal to produce each point in the output signal. This method, however, cannot eliminate meaningless values (especially negative values) that result from noises produced by the detectors [7]. FT is a suitable denoising method for the linear and the stationary signals, but signal distortion can easily occur when denoising the non-linear and non-stationary signals owing to the lack of time–frequency localization. Although WT overcomes the limitations of FT to a certain extent [8], it is hampered by the required selection of a suitable basic wavelet function [9].

Recently, EMD, which was originally proposed by Huang et al. [10], has demonstrated outstanding performance when applied to the non-linear and non-stationary signals. The method can adaptively decompose a given signal into a finite sum of components, called intrinsic mode functions (IMFs) and a residual. The conventional EMD denoising method consists of partially reconstructing the signal from the IMFs that contain useful information and discarding those IMFs that primarily carry noise [11]. However, the signal reconstruction lacks explicit criteria for determining which modes are relevant. Moreover, the partially reconstruction usually misses some useful information that is present in the discarded modes. To improve the denoising abilities of EMD, a series of EMD-based denoising methods have been developed [9,12–16]. Tian et al. [9] proposed an automatic denoising method that treated the typical range and the low-frequency fraction as the reference principles for deciding which IMFs should be removed as noise. Unfortunately, calculation errors are introduced when the Lidar signal

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fluctuates greatly. In addition, wavelet thresholding and smoothing techniques [13–16] have also been proposed to handle the irrelevant modes, thereby maintaining the integrity of the useful information. Gong et al. [16] proved that EMD combined with a soft thresholding is effective in preserving the useful information related to sudden changes in the Lidar signal for the near-field and low-altitude with high signal to noise ratio (SNR) [17].

In this study, we propose a new method for denoising Lidar signals that combines the correlation coefficient, the soft thresholding and the roughness penalty. The proposed method is referred to as EMD-STRP owing to the inclusion of the soft thresholding and the roughness penalty. The correlation coefficient between the IMFs and the original signal is used to distinguish the relevance of each IMF. Further, the soft thresholding and the roughness penalty techniques are, respectively, applied to the irrelevant and relevant modes to effectively extract the useful information. To verify the feasibility of EMD-STRP, three typical signals contaminated by white Gaussian noise were treated with several different techniques, and their denoising effects were compared. Finally, signal denoising was performed on the real Lidar signal.

2. Basic theory of EMD

EMD is a time–frequency analysis method that is particularly suitable for analyzing the non-linear and non-stationary signals. The method can adaptively decompose any signal into a series of IMFs based on the local characteristic time scale of the signal itself. The IMFs are required to satisfy two conditions: (1) the number of extrema and the number of zero-crossings must either be equal or differ by one at most; (2) at any point, the mean value of the envelope defined by the local maxima and minima is zero. IMFs obtained via a sifting process are shown in Fig. 1. The original signal is then decomposed into a number of IMFs and a residual, as follows:

$$x(n) = \sum_{i=1}^{L} h^{(i)}(n) + res(n) \tag{1}$$

where $h^{(i)}(n)$ stands for the decomposed IMF, L is the number of extracted IMFs, and res (n) represents the final residual.

3. Principle of the EMD-STRP

3.1. Criterion of discriminating the IMF correlations

Consider a noiseless signal $y(n)$ contaminated by an additive noise $e(n)$:

$$x(n) = y(n) + e(n). \tag{2}$$

The objective is to solve the denoising problem by removing the noise and to determine an estimate $x^*(n)$ of the observed signal $x(n)$. For EMD-based denoising method, the main task is to select the relevant modes for partial reconstruction, called EMD-PR, which is given by

$$x^*(n) = \sum_{i=k_{th}}^{L} h^{(i)}(n) + res(n) \tag{3}$$

in which k_{th} is the first selected index for partial reconstruction, which can be determined by estimating the correlation coefficient between the original signal and decomposition modes. The estimated $x^*(n)$ can also be rewritten as

$$x_m^*(n) = x(n) - \sum_{i=1}^{m} h^{(i)}(n) \tag{4}$$

where $m = k_{th} - 1$. The correlation coefficient between $x(n)$ and $x_m^*(n)$ is calculated as follows:

$$\rho(m) = \sum_{n=1}^{N} x(n)\, x_m^*(n) \Big/ \sqrt{\sum_{n=1}^{N} x^2(n) \sum_{n=1}^{N} \left(x_m^*\right)^2(n)} \tag{5}$$

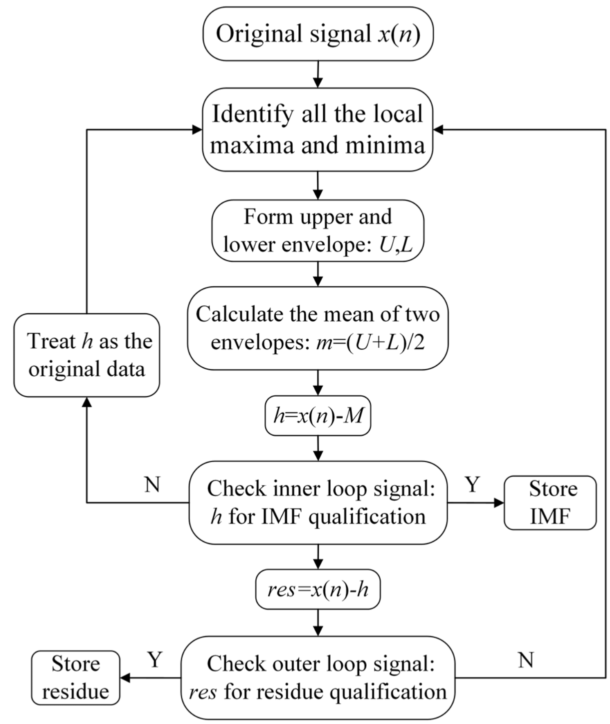

Fig. 1. Pictorial representation of EMD.

in which N denotes the length of the signal. The value of $\rho(m)$ is always decreasing until it reaches a minimum. The value for k_{th} is given by

$$k_{th} = \arg \underset{1\le m\le L}{last} \{\rho(m) \ge C\} + 1 \tag{6}$$

where "last" denotes the last value in $\rho(m)$ bigger than C. In general, C belongs to [0.75, 0.85] [18]. Based on EMD-PR, the denoising effects corresponding to different values of C within this range are compared and C is finally set to 0.85 in this study. From the above analysis, we can determine the value for k_{th}. Thus, the first $k_{th} - 1$ modes are irrelevant, and the rest are relevant. The two types of modes are then processed separately. Finally, the denoised signal can be realized by reconstructing the denoised modes and the residual.

3.2. Soft thresholding denoising

EMD-based denoising methods can be classified into two main categories: partial reconstruction and whole reconstruction with filtered modes. The conventional EMD-PR technique is not always effective when analyzing Lidar signals because the backscattering signal and the noise may be extracted into the same IMF. Thus, the removal of the irrelevant modes would lead to some useful information missing. Existing research results show that the combination of EMD and the thresholding techniques can significantly improve the denoising effect of the irrelevant modes [15,18]. Compared with the hard thresholding, the denoised signal processed by the soft thresholding has better smoothness. Thus, we use the soft thresholding technique to acquire the buried useful information in this paper [16]:

$$c_i(n) = \begin{cases} sgn\left(h^{(i)}(n)\right)\left(\left|h^{(i)}(n)\right| - T_i\right) & \left|h^{(i)}(n)\right| > T_i \\ 0 & \left|h^{(i)}(n)\right| \le T_i \end{cases} \tag{7}$$

$$\sigma = median\left(\left|h^{(i)}(n) - median\left(h^{(i)}(n)\right)\right|\right)/0.6745 \tag{8}$$

in which $c_i(n)$ denotes the buried useful information that is extracted from the irrelevant IMF, $T_i = \sigma\sqrt{2\ln(N)}$ is the universal threshold, σ