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Adaptive Filtering Method Based on EMD

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Abstract. For non-linear and non-stationary signals, traditional signal processing methods cannot effectively capture their characteristics. For this purpose, time-frequency analysis algorithms are needed to analyze the frequency domain characteristics of the signal at different times. The traditional Empirical Mode Decomposition (EMD) algorithm is a non-linear non-stationary algorithm. Its time-frequency resolution adaptively changes with the signal, so it can have higher resolution in various situations, and medical denoising and other fields have been widely used. However, when the signal-to-noise ratio is low, the performance of the EMD method is degraded due to noise. In this paper, an adaptive filtering method is proposed. By estimating the noise power under different conditions, the denoising process is adaptively performed, and a better filtering effect is achieved compared to the conventional method.

Key words: EMD, Filtering, Adaptive denoising, IMF.

INTRODUCTION

The signal contains a variety of information, including useful information we need and unwanted interference information. In order to suppress unwanted signals such as noise, various algorithms have been proposed for signal filtering. For a long time, for a stable linear time-invariant signal, people use the Fourier transform to link the signal between the time domain and the frequency domain and filter the signal in the frequency domain to achieve signal denoising and filtering. However, for non-stationary nonlinear signals, the Fourier transform cannot be effectively applied. In order to solve this problem, people put forward various time-frequency analysis algorithms and jointly described the distribution relationship between signal time domain and frequency domain.

Various time-frequency analysis methods such as Gabor transform and wavelet transform have relatively fixed time-frequency resolution [1]. For complex and varied signals, these time-frequency algorithms often suffer from degraded performance, making it difficult to meet actual signal processing needs. To this end, Norden. E. Huang et al. proposed the EMD [2] algorithm (Empirical Mode Decomposition). The EMD algorithm does not require a reference signal but is based on the signal itself and has a high frequency domain resolution and adaptability [3][4]. However, when the signal-to-noise ratio is low, using the EMD algorithm to filter will cause some useful signals to be filtered out, and the denoising performance will be reduced [5].

PRINCIPLE AND METHOD

The EMD Principle Analysis

For the EMD decomposition algorithm, the idea is to decompose the signal into several high-order and low-order IMF (Intrinsic Mode Function) components according to the frequency. To meet the requirements of statistics and signal symmetry, this decomposition needs to satisfy the following two conditions: There is at most one difference between the local extreme points and the zero-crossing points, and the average value of the envelope formed by each extreme point is zero [6][7].

Specifically, the obtained signal $s(t)$ is subjected to EMD decomposition, and the following steps are performed:

(1) Find all the maxima and minima in the signal $s(t)$, Use cubic spline interpolation to obtain maximum envelope $e(t)_{\max}$ and minimum envelope $e(t)_{\min}$.

(2) Find the mean envelope $e(t)_{\text{mean}}$ from the maximum and minimum envelopes, and calculate the difference envelope $d_1(t)$

$$d_1(t) = s(t) - e(t)_{\text{mean}} \tag{1}$$

(3) Repeat the resulting $d_1(t)$ as $s(t)$ for (1)(2) steps, after m cycles,the difference envelope obtained for the m_{th} time is $d_{1m}(t)$,If they $d_{1m}(t)$ obtained at this time meets the requirements of the IMF component, $d_{1m}(t)$ is the first IMF component to be obtained as $I_1(t)$.

(4) Subtracting the $s(t)$ and IMF components and obtaining the residual signal component $R_1(t)$

$$R_1(t) = s(t) - I_1(t) \tag{2}$$

(5) $R_1(t)$ still contains useful information components and is still not used, then repeat N times for step of (1)~(4) ,until the standard deviation σ of the selected two adjacent components meets the Koch Convergence Criterion, $\sigma \subseteq [0.2, 0.3]$ [8][9],where the standard deviation is

$$\sigma = \sum_t \frac{\left| d_{1m}(t) - d_{1(m-1)}(t) \right|^2}{d^2_{1(m-1)}(t)} \tag{3}$$

Finally, N IMF components can be obtained. The N_{th} IMF component is $I_N(t)$.

The original signal can be reconstructed by using these IMF components [10] $s_E(t)$

$$s_E(t) = \sum_{i=1}^{N} I_i(t) + R_N(t) \tag{4}$$

EMD Adaptive Denoising

By filtering the signal $s(t)$ by the traditional EMD method, a series of IMF components can be obtained, and the noise components contained in these IMF components are different. The component with a large noise content will affect the reconstruction of the signal. Therefore, by analyzing the energy of each IMF component, it is necessary to select a component with strong noise and perform multiple filtering on it to obtain better results. To measure the noise component of each order IMF component, the IMF components of each order can be taken separately and sequenced to generate a new signal. The covariance matrix of the new signal is calculated to obtain the noise statistics of each component, that is, the noise energy distribution can be obtained [11] [12].

If each IMF component $I_N(t)$ has K snapshot data, the rearrangement of $I_N(t)$ is written as a $N \times K$ matrix $\mathbf{X}(\mathbf{t})$, and the covariance matrix calculated as $\mathbf{R} = E\left[\mathbf{X}(\mathbf{t})\mathbf{X}^H(\mathbf{t})\right]$, where the $[\bullet]^{\mathrm{H}}$ is a conjugated symbol, $E[\bullet]$ is the mean operator.

The covariance matrix $\mathbf{R}$ includes noise intensity information for each IMF component. Eigenvalue decomposition is performed on the $\mathbf{R}$ to obtain N eigenvalues and their corresponding eigenvectors. The i_{th}

eigenvalue is λ_i, and the value of the N eigenvalues represent the noise intensity of IMF components. Compare the size of each feature and take out the larger L IMF components for further filtering.

Because the signal and noise part of $s(t)$ are orthogonal to each other, the biorthogonal filter [13] [14] spline wavelet Biorthgonal 5.5 is used for adaptive filtering, and 6 layers are decomposed then i_{th} IMF components are expressed after filtering as $I'_N(t)$.

The IMF component of each order is superimposed as the last filtering result $s'_E(t)$, and the reconstructed signal is $s_E(t)$, which is better than the traditional EMD method.

$$s'_E(t) = \sum_{i=1}^{N} I'_i(t) + R_N(t) \tag{5}$$

DETERMINATION OF CRACK LENGTH

The appropriate signal is selected for experimental simulation, and the denoising performance of the traditional EMD algorithm and the improved adaptive EMD algorithm is compared. The square wave signal is selected as the original signal and the $s(t)$ is processed with noise.

In order to compare the performance of the two methods accurately, the N Monte Carlo simulation experiment is carried out in the case of different signal to noise ratio, and the root mean square error of the simulation results is RMSE. The smaller the RMSE value, the smaller the reconstruction error and the better the filtering effect.

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} \left[s_E(t) - s(t) \right]^2} \tag{6}$$

Set up 800 Monte Carlo simulations, and the RMSE curve contrast diagram shown in Figure 1, shows that the improved EMD algorithm has a smaller RMSE value and a more effective filtering effect.

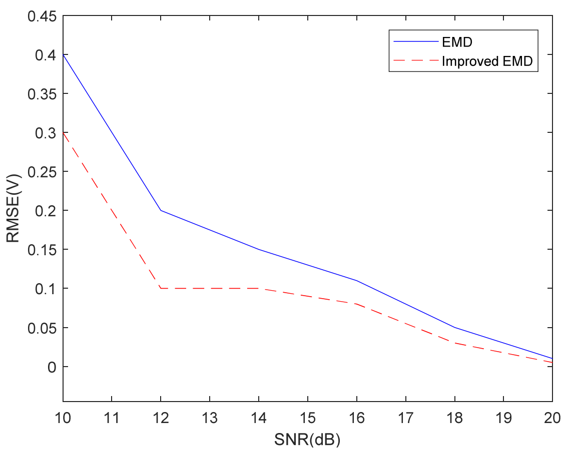

FIGURE 1. The contrast curve of RMSE

CONCLUSION

Aiming at non-stationary nonlinear signals, the EMD algorithm can achieve the denoising effect to a certain extent. Since the signal is nonstationary, the signal to noise ratio of different eigenmode components is different after superimposing noise. If the noise is too strong in an eigenmode component, the performance of the signal reconstruction will be worse. Therefore, by estimating the noise content in the different components, the multiple denoised components of the noise can be filtered and reconstructed, and the better performance of the signal reconstruction algorithm can be obtained compared with the EMD algorithm.

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