An Improved Denoising Method for Optical Fiber Signal

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Abstract. In the large-capacity FBG sensor network demodulation system, the process of collecting the light source is often accompanied by noise interference. Signal denoising is an important factor that affects the accurate demodulation of the FBG sensor system. Aiming at the problem of constant deviation of soft and hard threshold functions in denoising of traditional wavelet threshold algorithm and the shortcomings of modal aliasing easily in empirical mode decomposition, a modified semi-soft threshold-VMD denoising algorithm is proposed. The simulation results show that the function in this paper is better than the traditional threshold function in continuity and signal reduction degree, and has achieved good results.

1. Introduction
Fiber Bragg gratings are used as sensing elements to measure physical quantities such as temperature and strain. It is widely used in bridge, subway, tunnel monitoring, building health monitoring and other projects [1]–[4]. For a large-capacity FBG sensor network measurement system, the process of collecting fiber grating sensor signals is usually accompanied by noise interference. How to remove the noise to the maximum extent, improve the wavelength resolution, and maintain the accuracy and stability of the demodulated signal is crucial important.

Wavelet denoising has powerful time-frequency analysis capabilities and high-resolution characteristics, and has achieved good results in signal, image processing and other fields. Wavelet denoising algorithms mainly include spatial correlation denoising algorithm and wavelet threshold denoising algorithm. At present, the wavelet threshold denoising algorithm has been widely used because of its good effect. However, the effects of traditional wavelet soft threshold and hard threshold denoising algorithms can no longer be satisfied with today's practical engineering applications.

Variational mode decomposition was first proposed by Konstantin and Zosso in 2014 [5]. It overcomes the frequent occurrence of modal aliasing in empirical mode decomposition [6] and the shortcomings of lack of mathematical theory when extracting IMF (intrinsic mode functions). VMD has a good basic theory and is more robust to noise samples. It is widely used in fault diagnosis, signal noise reduction, voice signal processing and so on.
2. Adjustable semi-soft threshold denoising

Suppose the noisy signal of the grating demodulation system is expressed as:

\[ s(t) = f(t) + n(t) \]  \hspace{1cm} (1)

Among them, \( s(t) \) is the noisy signal, \( f(t) \) is the initial noise-free signal, \( n(t) \) is the noise signal, \( J \) is the maximum number of decomposition layers, and \( N \) is the signal length. Here we take \( n(t) \) as the Gaussian white noise with variance \( \sigma^2 \), which obeys the normal distribution \( N(0, \sigma^2) \). \( \omega_f(j,k) \) and \( \omega_n(j,k) \) are the wavelet coefficients of the original signal and noise in the \( j \)-th layer, respectively.

The hard threshold function and the soft threshold function were first proposed by Professor Donoho [4], which are respectively shown in formulas (2) and (3);

\[
\hat{\omega}^{\text{hard}}_{j,k} = \begin{cases} 
\omega_{j,k}, & |\omega_{j,k}| \geq \lambda \\
0, & |\omega_{j,k}| < \lambda 
\end{cases}
\]  \hspace{1cm} (2)

\[
\hat{\omega}^{\text{soft}}_{j,k} = \begin{cases} 
\text{sgn}(\omega_{j,k})(|\omega_{j,k}| - \lambda), & |\omega_{j,k}| \geq \lambda \\
0, & |\omega_{j,k}| < \lambda 
\end{cases}
\]  \hspace{1cm} (3)

\( \omega_{j,k} \) is the wavelet coefficient, and \( \lambda \) is the threshold value \( \sigma \sqrt{2 \ln N} \). Since the wavelet transform coefficient of noise will decrease as the scale increases, when denoising the signal, the selection of thresholds for different decomposition layers is different. The threshold selected in this paper is:

\[
\lambda_j = \frac{\sigma \sqrt{2 \log_2 N}}{\ln(j + 1)}
\]

\( j \) is the decomposition scale; \( N \) is the length of the wavelet transform coefficients of each layer; \( \sigma \) is the variance of the noise.

The traditional wavelet threshold has two shortcomings. One is that the threshold is discontinuous everywhere and is not high-order derivable, which results in the reconstructed signal is not smooth enough to produce oscillations. The second is that the adjustment factor is fixed, which will cause this function to process some other signals even inferior to the traditional soft and hard threshold function for denoising.

In response to the above problems, this paper proposes a new threshold function;

\[
\hat{w}^{\text{ad}}_{j,k} = \begin{cases} 
\beta \omega_{j,k} + \frac{2k}{2k + 1} (1 - u) \text{sgn}(\omega_{j,k}) \cdot (|\omega_{j,k}| - \beta \cdot \lambda), & |\omega_{j,k}| \geq \lambda \\
0, & |\omega_{j,k}| < \lambda 
\end{cases}
\]  \hspace{1cm} (4)

\[
u = 1 - e^{-|w_{j,k}|^2}, \beta = \tan\left(\frac{|w_{j,k}| - \lambda}{|w_{j,k}| - \lambda}^2\right)
\]

\( k, \alpha \) is the adjustment factor. \( k, \alpha \) is a positive number. The function is shown in Figure 1:
Fig. 1 Function diagram

The asymptotic line of the new threshold function is \( \omega_{j,k} = \omega_{j,k} \), which means that the larger the value of the new threshold function, the more it fits the hard threshold function, and the smaller the constant error. As the value of the threshold function increases, the function is getting closer and closer to the hard threshold function, which solves the problem of constant deviation between the threshold and the wavelet coefficient.

3. Variational Mode Decomposition Algorithm
VMD is an adaptive and completely non-recursive method of modal variation and signal processing. The most critical problem of VMD is to constrain the eigenmode function components obtained by decomposition.

The bandwidth of the overall modal component is:

\[
\sum_{k=1}^{K} \left( \sum_{j=1}^{K} \omega_{k,j} \right) \left( \sum_{j=1}^{K} \omega_{k,j} \right) = \sum_{j=1}^{K} \omega_{j,k} \]

\[u_k\] is the real mode function, \( \{u_k\} \) is the K IMF components obtained by decomposition, \( \{\omega_k\} \) is the center frequency of each eigenmode function component obtained, and \( f(t) \) is the original signal. Introduce Lagrangian multiplier \( \lambda(t) \) and secondary penalty factor \( \alpha \) to solve the reconstruction constraint problem:

\[
L = \alpha \sum_{k=1}^{K} \left\| \frac{j}{m} u_k(t) e^{-j\omega_k t} \right\|^2 + \left\| f(t) - \sum_{k=1}^{K} u_k(t) \right\|^2 + \left\langle \lambda(t), f(t) - \sum_{k=1}^{K} u_k(t) \right\rangle
\]

\( \alpha \) represents the balance parameter in the data fidelity constraint, and corresponds to the bandwidth of the mode.

4. Adjustable semi-soft threshold-VMD algorithm
In order to improve the denoising effect, combining the advantages of VMD decomposition and wavelet threshold denoising, the two methods are combined, and the steps are as follows:

Stepl: performs VMD decomposition on the original signal to be processed to obtain the BLIMF component and margin;
Step2: Calculate the BLIMF components of each layer and normalize them.

Step3: select the appropriate wavelet base and decomposition level, respectively perform wavelet decomposition on BLIMF and obtain wavelet coefficients;

Step4: Calculate the thresholds of each layer, and perform threshold processing on the wavelet coefficients of each layer to obtain the decomposition coefficients;

Step5: performs inverse wavelet transform and reconstructs the signal.

According to previous research, sym5 is selected as the wavelet base, and the number of decomposition levels K is 6. VMD parameters are selected as follows: balance the tolerance of the parameter convergence criterion [7][8].

5. Experiment and analysis

In order to test the effect, we conducted a simulation test in MATLAB software. Introduce a section of optical signal, and perform denoising processing by the method proposed in this article. We use the signal-to-noise ratio and the root mean square error to identify the denoising effect. The formulas of SNR and RMSE are (7), (8);

\[
SNR = 10 \log \left( \frac{\sum f^2(t)}{\sum (f(t) - \hat{s}(t))^2} \right)
\]

\[
RMSE = \sqrt{\frac{1}{n} \sum (f(t) - \hat{s}(t))^2}
\]

\( f(t) \) shows the original signal, \( \hat{s}(t) \) represents the de-dyeing signal, and \( n \) is the sampling length.

Figure 2 shows the waveform and spectrogram before and after denoising using the method in this paper. From the figure, it can be seen more intuitively that good results have been achieved after variational modal decomposition and improved threshold denoising, and more signal characteristics are retained. Provide a more accurate original spectrum signal for the next large-capacity FBG sensor network demodulation.

Table 1 and Table 2 list the SNR and RMSE experimental data of the four methods in 5db to 25db noisy environment.
Tab.1 SNR of FBG sensor signal de-noised with different methods

| Noise   | SNR/db | SNR/db | SNR/db | SNR/db | SNR/db |
|---------|--------|--------|--------|--------|--------|
| Ivmd-Dwt| 22.4821| 26.1564| 31.5212| 35.8845| 37.3124|

Tab.2 RMSE of FBG sensor signal de-noised with different methods

| Noise   | SNR/db | SNR/db | SNR/db | SNR/db | SNR/db |
|---------|--------|--------|--------|--------|--------|
| Ivmd-Dwt| 0.0499 | 0.0385 | 0.0244 | 0.0169 | 0.0113 |

6. Temperature test experiment

In the experiment, the FBG sensor was placed in a constant temperature bath isolated from the outside world to adjust the temperature from 5 ℃ to 60 ℃ every 5 ℃, and the center wavelength was measured. Each temperature point was measured 5 times, and the average value was taken. The measurement result is shown in Figure 3.

![Fig.3 wavelength-temperature curve](image)

Fitting the experimental data to get the relationship between temperature and wavelength is shown in Figure 6. Temperature and wavelength have a good linear relationship, which can meet actual engineering needs.

7. Conclusion

This paper constructs a new threshold function based on soft and hard threshold functions and current denoising functions and combines with variational modal decomposition to improve the denoising effect. The new threshold function guarantees high-order divergence while achieving continuity, which overcomes the shortcomings of poor continuity and inherent deviation of soft and hard thresholds. In the MATLAB simulation experiment, the signal-to-noise ratio and the root mean square error are introduced for comparative experiments, which have achieved good results and have certain application value.

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