Journal of Electronic Research and Application, 2024, Volume 8, Issue 1
http://ojs.bbwpublisher.com/index.php/JERA
ISSN Online: 2208-3510
ISSN Print: 2208-3502

Research on Modulation Signal Denoising Method Based on Improved Variational Mode Decomposition

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Abstract: In order to further analyze the micro-motion modulation signals generated by rotating components and extract micro-motion features, a modulation signal denoising algorithm based on improved variational mode decomposition (VMD) is proposed. To improve the time-frequency performance, this method decomposes the data into narrowband signals and analyzes the internal energy and frequency variations within the signal. Genetic algorithms are used to adaptively optimize the mode number and bandwidth control parameters in the process of VMD. This approach aims to obtain the optimal parameter combination and perform mode decomposition on the micro-motion modulation signal. The optimal mode number and quadratic penalty factor for VMD are determined. Based on the optimal values of the mode number and quadratic penalty factor, the original signal is decomposed using VMD, resulting in optimal mode number intrinsic mode function (IMF) components. The effective modes are then reconstructed with the denoised modes, achieving signal denoising. Through experimental data verification, the proposed algorithm demonstrates effective denoising of modulation signals. In simulation data validation, the algorithm achieves the highest signal-to-noise ratio (SNR) and exhibits the best performance.

Keywords: Micro-motion modulation signal; Variational mode decomposition; Genetic algorithm; Adaptive optimization

Online publication: January 18, 2024

1. Introduction

With the continuous development of detection technology, the collection environment with actual rotating component targets has become increasingly complex. Due to the presence of ground clutter and interfering noise, the collected modulated echo data is often mixed with various noise interferences, making the effective modulation information unclear and resulting in a low signal-to-noise ratio (SNR) [1-3]. In order to achieve the goal of high SNR for micro-motion modulated echoes, exploring and researching new denoising methods has become an inevitable trend. As a result, numerous domestic and foreign scholars have conducted research on methods to improve the SNR of radar echoes. Among them, the method based on signal decomposition and reconstruction has achieved good results in clutter suppression and denoising of Doppler signals collected from targets with rotating components [4-6].

Fourier transform denoising is a method of global transformation that lacks local descriptive ability. During denoising, it will lose a large amount of effective signal, resulting in poor processing results for non-stationary signals [7]. Wavelet threshold denoising transforms micro-motion modulated signals into the time-scale domain, but it requires the selection of appropriate wavelet functions and thresholds to achieve a better denoising effect [8]. However, these methods are all based on fixed transform basis functions and cannot adaptively process structurally complex modulated echo data. The Empirical Mode Decomposition (EMD) [9] method based on signal decomposition theory can adaptively decompose the signal itself, dividing it into a series of Intrinsic Mode Functions (IMFs) that represent local energy anomalies within different frequency bands. However, this method is prone to mode mixing, boundary effects, and other issues. The Ensemble EMD (EEMD) and Complete Ensemble EMD (CEEMD) methods are further improvements upon the EMD method. EMD, EEMD, and CEEMD are all recursive signal processing methods, but they have limitations when dealing with multi-component modulated signals [10]. The non-recursive signal decomposition method, Variational Mode Decomposition (VMD) eliminates the process of selecting components and transfers the acquisition process of signal intrinsic mode function (IMF) components to a variational framework [11]. This allows for adaptive and effective separation of the frequency domain portion of the signal and its components. Compared to methods like EMD, VMD has a solid theoretical foundation and effectively avoids mode mixing problems. It also exhibits better noise robustness. Although the VMD method effectively decomposes the signal into several sub-signals with different center frequencies, several parameter values must be set before the decomposition to achieve the best results. Typically, manually selecting parameters cannot produce optimal results. Sarangi and colleagues utilized a particle swarm optimization algorithm to simultaneously optimize the values of K and α for an optimal solution [12]. Naik and colleagues used the newly proposed orthogonal low sidelobe as an optimization objective and applied the firefly algorithm to search for optimal parameter combinations (K,α) [13].

Based on this, this paper combines the genetic algorithm with the VMD algorithm and applies it to denoise micro-motion modulated echoes. This method effectively extracts modulation information while adaptively selecting the determining parameters of VMD, minimizing signal loss as much as possible. Both theoretical models and practical verification results demonstrate that the application of the improved method proposed in this paper exhibits good performance in denoising, effectively improving the signal-to-noise ratio of micro-motion modulated signals. This lays a solid foundation for further analysis and processing of modulation components.

2. GA-VMD denoising method

2.1. Variational mode decomposition

The goal of VMD is to decompose the original signal into intrinsic mode functions (IMFs) with fixed bandwidth and center frequencies. The decomposition process of the original signal is essentially a solving process of a variational problem.

The expression for the intrinsic mode functions is as follows:

$$u_k(t) = A_k(t)\cos\left(\Phi_k(t)\right) \qquad (1)$$

where $A_k(t)$ represents the instantaneous amplitude of $u_k(t)$. $\Phi_k(t)$ represents the phase, which is non-monotonically decreasing.

If the demodulation method is used to estimate the bandwidth of IMF, it will lead to a variational constrained problem. The expression for the variational constrained model is as follows:

$$\begin{gathered} min_{\{u_k\},\{w_k\}}\left\{\sum_k \left\|\partial_i\left[\left(\delta(t)+\frac{j}{\pi t}\right)*u_k(t)\right]e^{-jw_kt}\right\|_2^2\right\} \\ s.t.\sum_k u_k = f \end{gathered} \quad (2)$$

where $\{u_k\}=\{u_1,\ldots, u_k\}$ and $\{W_k\}=\{W_1,\ldots, W_k\}$ represent the IMFs and their corresponding center frequencies, respectively. K represents the number of decomposition layers.

To obtain the optimal solution of this variational constrained model, the algorithm introduces the Lagrange multiplier λ operator and quadratic penalty function term α. The expression of the augmented Lagrange function is as follows:

$$\begin{gathered} L(\{u_k\},\{w_k\},\lambda) = \\ \alpha\sum_k \left\|\partial_t\left[\left(\delta(t)+\frac{j}{\pi t}\right)*u_k(t)\right]e^{-jw_kt}\right\|_2^2 + \\ \left\|f(t)-\sum_k u_k(t)\right\|_2^2 + \left\langle\lambda(t), f(t)-\sum_k u_k(t)\right\rangle \end{gathered} \quad (3)$$

Finally, the variational constrained model is solved using the Alternating Direction Method of Multipliers (ADMM). The expressions for the updated formulas of $\{u_k\}$, $\{W_k\}$, and λ are as follows:

$$u_k^{n+1}(W) = \frac{f(W)-\sum_{i+k}\hat{u}_i(W)+\frac{\lambda^n(W)}{2}}{1+2\alpha(w-w_k)^2} \quad (4)$$

$$w_k^{n+1} = \frac{\int_0^\infty w|\hat{u}_k(W)|^2dw}{\int_0^n |\hat{u}_k(W)|^2dw} \quad (5)$$

$$\lambda^{n+1}(W) - \lambda^n(W) + \tau\left[f(W)-\sum_k u_k^{n+1}(W)\right] \quad (6)$$

The termination constraint condition is as follows:

$$\sum_k \|u_k^{n+1} - \frac{u_k^n\|_2^2}{\|u_k^n\|_2^2} < \varepsilon \quad (7)$$

where ε represents the convergence accuracy.

2.2. Genetic algorithm-based parameter optimization for VMD

In the VMD algorithm, the penalty parameter and the number of mode components K need to be preset based on prior experience. When the value of K is too large, it can lead to excessive decomposition of the signal. On the other hand, when K is too small, it becomes difficult to effectively separate the correct center frequencies of the modes, resulting in mode mixing phenomena. Therefore, selecting the appropriate parameter combination is crucial for denoising using VMD. Here, a genetic algorithm is employed to optimize the values of parameters K and α, ensuring that each detection of the micro-vibration modulation signal is optimal and effectively reducing the randomness in parameter selection.

The genetic algorithm is an adaptive optimization algorithm with excellent global probability search capability. The process of optimizing parameters mainly includes steps such as initial coding, generating initial population, setting fitness parameters, selection, crossover, and mutation.

(1) The punishment parameter α and the number of mode components K are encoded and initialized for chromosome initialization, generating an initial population that contains different combinations of (K,α) individuals.

(2) The signal is decomposed using different combinations within each individual, and the multiscale sample entropy of each decomposed mode function is calculated to determine the corresponding fitness. The local minimum is defined as the minimum value of the sample entropy.

(3) Using the fitness values obtained in step (2), selection is performed on the superior individuals in the initial population, followed by crossover and mutation to form a new generation population. This process is iterated continuously, comparing the local fitness values to find the global minimum.

(4) Stop the iteration and determine the optimal solution for the parameter combination (K,α) .

2.3. Combining genetic algorithm with VMD for denoising

Given the nonlinear and non-stationary characteristics of micro-vibration modulation signals, as well as the suboptimal performance of a single VMD denoising method, this paper proposes a VMD decomposition approach for denoising modulated noisy signals. By optimizing the decomposition parameters using the GA algorithm, the reconstructed modulated signal is obtained. The following is the specific implementation process of the proposed method in this paper.

(1) Using genetic algorithm to optimize VMD parameters, enabling accurate decomposition of the original signal.

(2) Using the VMD method to decompose the acquired modulated signal.

(3) Reconstructing the original signal to obtain the denoised result.

To verify the effectiveness of the proposed algorithm, two objective performance indicators, SNR and root mean square error (RMSE), are used to evaluate the denoising performance of various methods. The SNR parameter reflects the denoising ability of the method, with a larger SNR indicating better denoising performance. The RMSE reflects the difference in the signal amplitude before and after denoising, with a smaller RMSE indicating better denoising performance.

$$SNR = 10lg\frac{\sum_{i=1}^{n} f(t_i)^2}{\sum_{i=1}^{n}\left[\hat{f}(t_i) - f(t_i)\right]^2} \tag{8}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left[\hat{f}(t_i) - f(t_i)\right]^2}{n}} \tag{9}$$

3. Experimental data verification

The performance of the denoising method is evaluated using two objective parameters, SNR and RMSE. Gaussian white noise with variances ranging from 0.01 to 0.09 is added to the simulated helicopter echo data with a diameter of 5.029 m and a rotational speed of 6.8 r/s.

Table 1. Comparison of SNR values

Noise variance	VMD	GA-VMD
0.01	15.127	15.489
0.02	14.527	15.153
0.03	14.425	14.857
0.04	14.127	14.852
0.05	13.256	13.527
0.06	12.775	13.578
0.07	12.084	12.578
0.08	10.852	11.575
0.09	10.052	11.425

Table 1 lists the comparison of values between the traditional VMD denoising method and the proposed method in this paper for noise variances ranging from 0.01 to 0.09. From the table, it can be observed that the GA-VMD method proposed in this paper has the lowest SNR value. Moreover, because VMD itself is a powerful tool for analyzing non-stationary and nonlinear signals, it has a solid mathematical theoretical foundation. As long as the parameters are properly selected, the issue of mode mixing can be avoided. Therefore, in this paper, a genetic algorithm is used to optimize the two parameters that affect the decomposition performance, achieving accurate signal decomposition. The VMD method operates in the frequency domain, which also results in relatively high computational efficiency. The decomposed components can be considered as stable signals. By reconstructing the original signal, the denoising effect is achieved. When the noise variance ranges from 0.01 to 0.09, the proposed method achieves a maximum SNR value. Compared to the traditional VMD denoising method, it is higher by 0.271 to 0.803. As the noise intensity increases, this difference also increases.

Table 2. Comparison of RMSE values

Noise variance	VMD	GA-VMD
0.01	0.0387	0.0325
0.02	0.0395	0.0311
0.03	0.0414	0.0411
0.04	0.0426	0.0419
0.05	0.0448	0.0438
0.06	0.0458	0.0442
0.07	0.0462	0.0458
0.08	0.0483	0.0467
0.09	0.0502	0.0481

Table 2 presents the RMSE values of the two methods when the noise variance ranges from 0.01 to 0.09. From the table, it can be observed that at the same noise variance, the proposed method achieves the lowest

RMSE value. Compared to the traditional VMD denoising method, the RMSE value of the proposed method is reduced by 0.004 to 0.0021. As the noise intensity increases, this difference also increases.

To validate the effectiveness of the proposed algorithm for denoising real measurement data, the Robinson R44 helicopter is taken as an example. The target is hovering under the far-field conditions of an S-band radar. At this time, the azimuth angle α=149° and the elevation angle β=9.15°. The specific radar parameters are shown in **Table 3**.

Table 3. Main parameters of the linear frequency modulation (LFM) pulse signal

Parameters	Values	Unit
Radio frequency	2.94912	GHz
Bandwidth	120	MHz
Pulse width	2.0835	**μs**
Pulse repetition frequency	3.7202	kHz
Number of range samples	8,192	piece
Slow time dimension	4,096	piece
Sampling frequency	491.52	MHz

The specific parameters of the rotating components of the Robinson R44 helicopter are shown in **Table 4**.

Table 4. Structural parameters of the R44 helicopter

Parameters	Values	Unit
Number of rotor blades	1	piece
Number of blades on a single rotor	2	piece
Blade length	5.029	m
Blade rotational speed	6.8	rad/s

Performing a short-time Fourier transform directly on the modulated component echoes yields their spectrogram, as shown in **Figure 1(a)**. From the figure, it can be seen that due to the presence of background noise and clutter interference, the signal-to-noise ratio of the modulated component's spectrogram is not high, and the noise interference is mixed in the echo signal. To eliminate these effects and better reflect the characteristics of the micro-motion modulated signal, traditional VMD and the method proposed in this paper are used for denoising and comparison. **Figures 1(b)** and **(c)** respectively show the modulated signals obtained after denoising using the traditional VMD method. The traditional VMD method, due to its lack of adaptability in the selection of , often resulting in either over-decomposition or under-decomposition of the signal, leading to less-than-ideal denoising results.

From **Figure 1**, it can be seen that the method proposed in this paper achieves more thorough noise removal. The processed in-phase axis is clearer, and some information that was masked by high-frequency noise is effectively recovered. The denoising effect is relatively ideal. To further demonstrate the superiority of the method proposed in this paper, 1,841 distance units on the flight route were selected for analysis. **Figure 2** shows the optimization curves of the Genetic Algorithm-VMD for each of these distance units.

From **Figure 2**, it can be observed that the fitness value of the data becomes stable when the genetic algorithm reaches generation 6, indicating the best decomposition effect. Moreover, compared to other methods,

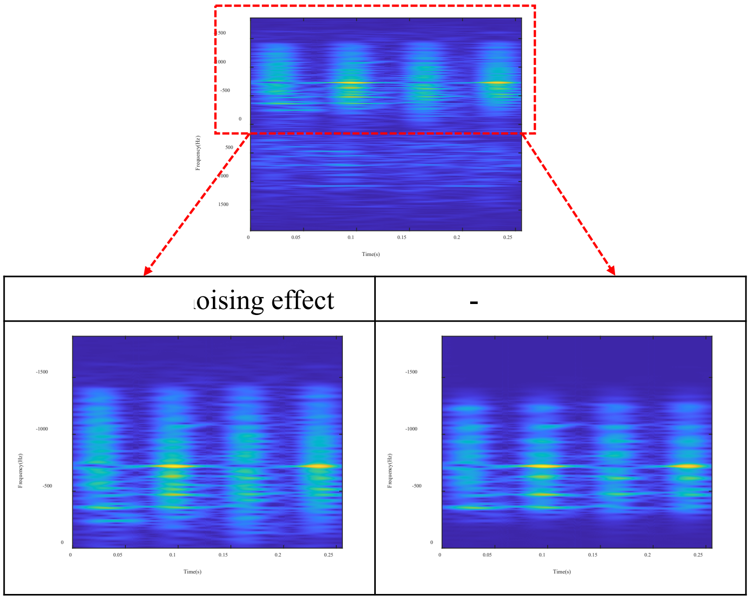

Figure 1. Comparison of measured denoising results

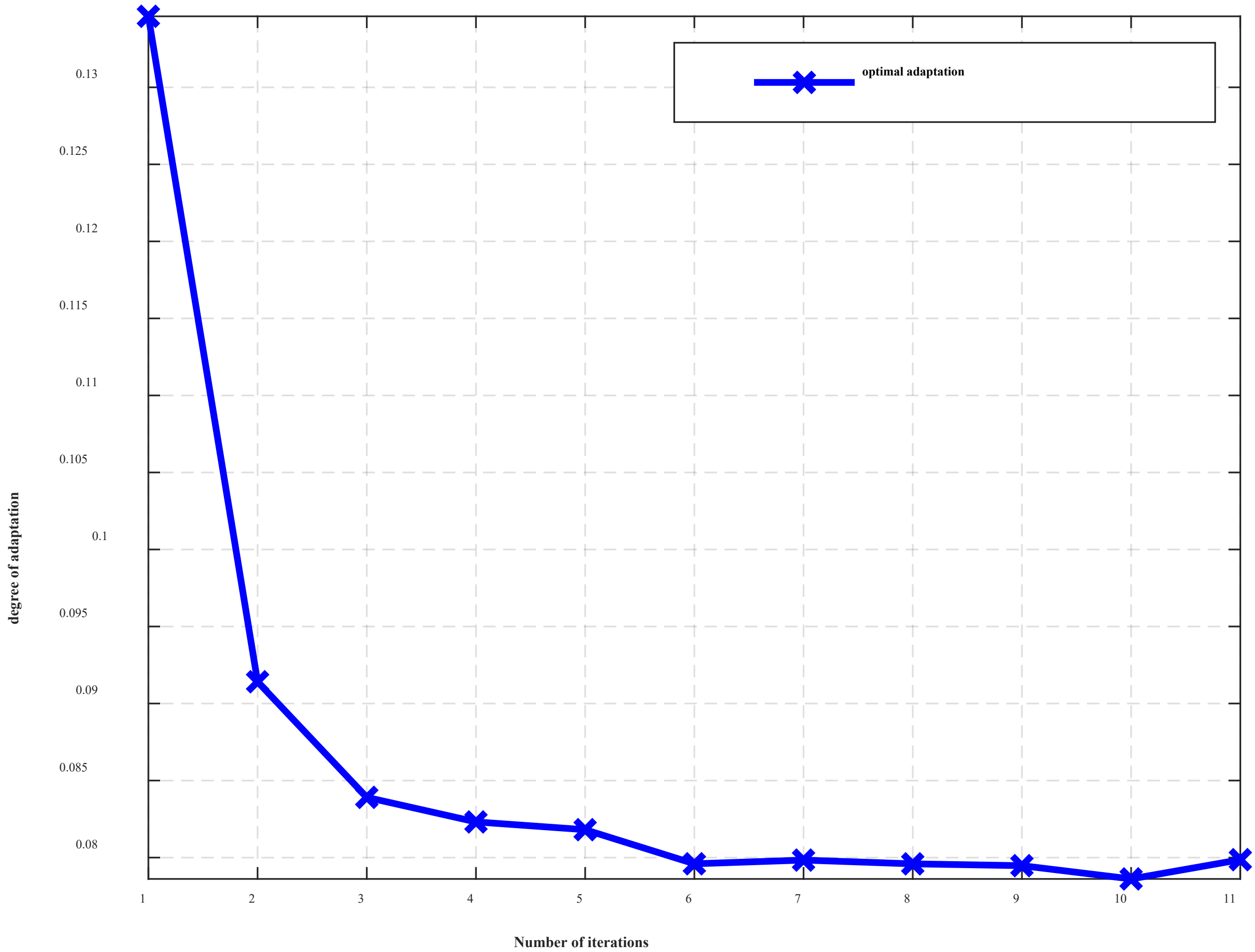

Figure 2. Optimization curves

the proposed method in this paper preserves a wider frequency band while effectively suppressing high-frequency noise, resulting in a relatively ideal denoising effect.

4. Conclusion

The proposed method in this paper adopts a combination of VMD and genetic algorithm to optimize the decomposition parameters. This approach leverages the adaptability of VMD decomposition, the strong mathematical theoretical foundation and the high-frequency noise suppression capability of the genetic algorithm itself. The effectiveness of the proposed method in practical application scenarios is validated through two objective parameters: SNR and root mean square error (RMSE). The experimental results indicate that the proposed method in this paper achieves a significant improvement in signal-to-noise ratio compared to other methods. Furthermore, as the noise intensity increases, the denoising effect becomes more pronounced.

The drawback of the proposed method in this paper is that the VMD method requires a lot of parameter settings, and it is necessary to select appropriate parameters for accurate signal decomposition, which, in turn, leads to better decomposition results. Although the genetic algorithm used in this paper is an intelligent optimization algorithm, it does have a significant computational complexity in terms of optimization.

Disclosure statement

The authors declare no conflict of interest.

Author contributions

Conceptualization: Canyu Mo
Formal analysis: Yuanduo Niu
Writing – original draft: Canyu Mo
Writing – review & editing: Qianqiang Lin, Haoran Du

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