Distributed Sea Clutter Denoising Algorithm Based on Variational Mode Decomposition

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Abstract: In order to improve the detection accuracy of chaotic small signal prediction models under the background of sea clutter, a distributed sea clutter denoising algorithm is proposed, on the basis of variational modal decomposition (VMD). The sea clutter signal is decomposed into variational modal functions (VMF) with different center bandwidths by means of VMD. By analyzing the autocorrelation characteristics of the decomposed signal, we perform instantaneous half-period (IHP) and wavelet threshold denoising processing on the high-frequency and low-frequency components respectively, and regain the sea clutter signals. Based on LSSVM sea clutter prediction model, this research compares and analyzes the denoising effects of VMD. Experiment results show that, the RMSE after denoising is reduced by two orders of magnitude, approximating 0.00034, with an apparently better denoising effect, compared with the root mean square error (RMSE) of the prediction before denoising.

Key words: Sea Clutter, Variational Modal Decomposition, Autocorrelation Properties, Instantaneous Half-Period

1 Introduction

Sea clutter signal[1] has always played a vital role in the field of weak signal detection. Sea clutter characteristics study and analysis is to improve the reliability and accuracy of radar detection. There emerge higher and higher requirements for the reliability of radar detection technology, but all kinds of radars are susceptible to internal and external noise interferences. Therefore, denoising becomes an inevitable step[2]. In actual work, sea radars are interfered by its own measurement noise and external noise (such as sea clutter). Due to the significant non-linear, non-Gaussian, and non-stationary characteristics of sea clutter, the impact on radar target detection is particularly prominent. Therefore, the study of sea clutter denoising has naturally become the primary task in sea radar target detection[3].

Denoising is to assign high weight to signal and low weight to noise to achieve the effect of highlighting the signal itself. Traditional denoising methods, such as low-pass filtering and Wiener filtering, use statistical theory to design weights. These methods require certain prior knowledge and have no significant effects[4]. In 1965, Fast Fourier Transform (FFT) was proposed by J.W.Tuky[5] ,which is widely used in signal processing. Unfortunately, the denoising effect of non-stationary signals is not as expected. Until 1997, Huang et al.[6] proposed the Hilbert-Huang transform (HHT) from the signal itself, which can adaptively decompose, analyze and process nonlinear and non-stationary signals. Meanwhile,the method can obtain the instantaneous frequency. In 1999, Huang[7] discovered when studying nonlinear water waves that the empirical mode decomposition (EMD) theory in HHT is prone to modal aliasing, which leads to errors in the intrinsic mode function (IMF) and loss of specific physical significance[8]. After that, J. Tang and others[9] discussed the empirical mode decomposition and instantaneous frequency solution theory of HHT, studied the denoising effect of decomposing the ECG signal using EMD, and verified the feasibility of HHT to remove ECG noise. In order to improve the EMD adaptive decomposition ability, Wu[10] changed the extreme point distribution by adding white noise to eliminate the modal aliasing effect, and obtained the upper and lower envelopes in line with the signal characteristics. In 2007, EMMD algorithm was introduced when X.Sun and others[11] studying the signal detection of weak harmonics embedded in chaotic noise. It is suitable for the background of chaotic signals and strong Gaussian white noise[12]. In addition, on the basis of noise-assisted data analysis, Ye et al.[13] proposed the CEEMD method. By adding N pairs of noises with opposite signs to the signal to change the distribution of extreme points to suppress modal decomposition and save calculation time. In 2014, a new adaptive decomposition theory: VMD was proposed by K. Dragomiretskiy[14], which can compensate for the defects of modal aliasing, false components and end effects in EMD, and has a solid theoretical foundation and better noise robustness[15].

As far as sea clutter denoising is concerned, Haykin[16] used the three-point moving average method to denoise in his study of the chaotic sea clutter characteristics. Since it would change the signal performances, it was questioned by some scholars. Flandrin[17] used EMD to decompose fractal Gaussian noise and found that EMD decomposition can be equivalent to a narrowband filter library to filter signals. In 2009, Kurian et al.[18] used reconstruction dynamic characteristics and chaotic synchronization methods to estimate and detect weak target signals. By selecting appropriate coupling coefficients, the mean square error of the detection results was significantly reduced. In 2018, when Y. Yan[19] studied the detection of low-altitude small targets under the background of sea clutter, she used the denoising method combined with CEEMD and wavelet transform to deal with target detection under different signal-to-noise ratios. The signal adaptive decomposition algorithm can only decompose the signal. And denoising makes use of noise signal distributions and useful signals for artificial screening. It is inevitable that some signal-containing components will be removed, which will affect the denoising effect.

Therefore, the frequency bands of component signals can be distinguished by analyzing autocorrelation characteristics of the decomposed signals. Denoising processing methods are adopted, according to the usefulness ratio of high- and low-frequency component signals. IHP denoising processing is used for high-frequency components with a high noise proportion. This method was proposed by Fang[20] in his study of pressure wave denoising methods, and it has a better effect on processing signals with high noise contents. For low-frequency components, wavelet threshold denoising is preferred on account of the reconstruction effects and method performance index selections.

This paper proposes a distributed sea clutter denoising algorithm based on VMD, which combines instantaneous half-period and wavelet transform to obtain pure sea clutter data. First, the low-dimensional sea clutter data is mapped to the high-dimensional phase space to facilitate the chaotic characteristics study of the sea clutter, through the chaotic phase space reconstruction. Then it checks the EMD adaptive decomposition ability to obtain the decomposition level K, and setting it as the VMD decomposition level. Then VMD is uses to decompose the sea clutter signal into VMFs with different center bandwidths. By analyzing the autocorrelation characteristics of the decomposed signal, this research performs IHP and wavelet threshold denoising for high-frequency and low-frequency components respectively. Finally, the sea clutter signals are regained. It uses the mature and stable LSSVM sea clutter prediction model to compare and analyzing the VMD denoising effect. The model uses the prediction error to detect chaotic small targets submerged in the sea clutter background. The effect of the proposed denoising algorithm is verified by comparing the RMSE before and after denoising.

2 Research Methodology

2.1 EMD Algorithm Preprocessing

As a time-frequency analysis method, EMD adaptively decomposes nonlinear and non-stationary signals [21]. This method adaptively decomposes the input signal into a finite number of linear and stable IMFs, in which each component contains the local characteristic signal of the original signal at different time scales. For a signal $x(n)$ to be decomposed after being processed by EMD, it can be expressed as the aftermath of the sum of the modal components [22]:

$$x(n)=\sum_{i=1}^{N}C_i(n)+R(n) \tag{1}$$

Where $C_i(n)$ is the i-th IMF component, N is the total number of IMFs, and $R(n)$ is the margin.

2.2 Variational Mode Decomposition

In order to solve the problems of modal aliasing, false components and end effects in EMD [23], it is assumed that each IMF has a limited bandwidth with different center frequencies. By converting to the construction and solution of the variational problem, the sum of the estimated bandwidth of each IMF is minimized.

Constructing the variational problems：After VMD performs modal separation on the input signal, it determines the frequency center and bandwidth of each VMF through continuous iteration to obtain a set of K VMFs: $\{u_k\}=\{u_1,u_2,...,u_k\}, k=1,2,...,K$. Perform the following three steps for each VMF:

Step1: Perform Hilbert-Huang transformation on each modal component to obtain the analytical signal of each modal component, the purpose is to obtain its unilateral frequency spectrum.

$$[\delta(t)+\frac{j}{\pi t}]*u_k(t) \tag{2}$$

Step2: Mix an estimated center frequency $e^{-jw_k t}$ with the analytical signal of each modal component, and convert the spectrum of the modal component to the corresponding base band.

$$[\delta(t)+\frac{j}{\pi t}]*u_k(t)e^{-jw_k t} \tag{3}$$

Step3: To estimate the bandwidth of each modal signal, the demodulated signal is processed by H1 Gaussian smoothing. The sum of the modal components is equal to the original input signal f as a constraint condition, so the following variational constraint model expression is obtained.

$$\begin{cases}\min\limits_{\{u_k\},\{w_k\}}=\{\sum\limits_K\left\|\partial_t[(\delta(t)+\frac{j}{\pi t})u_k(t)]e^{-jw_k t}\right\|_2^2\} \\ s.t\sum\limits_K u_k=f\end{cases} \tag{4}$$

Where $\{w_k\}=\{w_1,w_2,...,w_k\}$ is the center frequency of each modal component u_k .

Variational problem solutions: In order to obtain the optimal solution of the above-mentioned variational constraint model, a secondary penalty factor and a Lagrange multiplication operator with strong constraint ability are introduced. The variational constraint problem is transformed into a variational unconstrained problem, and the following expression is obtained:

$$\begin{aligned}L(\{u_k\},\{w_k\},\lambda)&=\alpha\sum_K\left\|\partial_t[(\delta(t)+\frac{j}{\pi t})u_k(t)]e^{-jw_k t}\right\|_2^2 \\ &+\left\|f(t)-\sum_K u_k(t)\right\|_2^2+\left\langle\lambda(t),f(t)-\sum_K u_k(t)\right\rangle\end{aligned} \tag{5}$$

Where $\delta(t)$ is the Dirac distribution, and $f(t)$ represents the original input signal.

VMD uses the Alternating Direction Method of Multiplication Operator (ADMM)[24] to solve the variational problem, alternately thinking about u_k, w_k, λ_k, and seeking the result of modal decomposition that meets the constraints. The update formula of

u_k, w_k, λ_k as follows:

$$\hat{u}_k^{n+1}(w) = \frac{\hat{f}(w) - \sum_{i \neq k} \hat{u}_i(w) + \frac{\hat{\lambda}(w)}{2}}{1 + 2\alpha(w - w_k)^2} \tag{6}$$

$$w_k^{n+1} = \frac{\int_0^\infty w |\hat{u}_k(w)|^2 dw}{\int_0^\infty |\hat{u}_k(w)|^2 dw} \tag{7}$$

$$\lambda^{n+1}(w) \leftarrow \lambda^n(w) + \tau[f(w) - \sum_k u_k^{n+1}(w)] \tag{8}$$

3 Distributed Denoising Algorithm

In order to fit the decomposition signal ability of VMD and effectively retain useful signals, it is necessary to deal with all decomposition components in a targeted manner. The autocorrelation function [25] is used to reveal the correlation degree of the signal itself at different time points, and use the autocorrelation characteristics to filter high and low frequency components. For high-frequency components， noise is relatively high, and IHP is used for denoising. Considering the reconstruction effect and the choice of method performance indicators, the wavelet threshold method is preferred to process low frequency components.

3.1 Instantaneous Half-Period

In most general cases, the signal structure corresponds to the slow time-varying data and the useful signal frequency is often lower than that of the noise [26]. Thus, it can be assumed that the signal dominates the oscillation IHP longer than the noise does. According to this concept, a threshold is set to preserve the most important signal structure retrieved from noise. That is, the waveform between two adjacent zero-crossing points that is considered to be signal-dominated oscillation will be retained. And the waveform between two adjacent zero-crossing points that is considered to be noise-dominated oscillation will be replaced by zeros. The mathematical expression of this process is:

$$\hat{C}_i(n) = \begin{cases} C_i(n), T_i^j \geq thr \\ 0, others \end{cases}, ZP_i^j < n \leq ZP_i^{j+1} \tag{9}$$

Where $C_i(n)$ represents the i-th VMF, T_i^j is the middle j-th IHP in $C_i(n)$, and ZP_i^j represents the middle j-th zero-crossing point in $C_i(n)$.

The threshold choice in this method is matter great importance to the denoising effect. A large value thr will result in over-smooth denoising, so that the low-frequency oscillation containing the target signal will be eliminated. On the contrary, a too small thr will affect the quality of the denoising signal, that is, the noise is not completely removed.

Combined with the Nyquist sampling theorem, a method for selecting the best threshold is proposed. According to the sampling theorem, the signal is sampled at a sampling rate f_s that is not less than twice the highest frequency f_m of the signal[27], and the discrete sampling value obtained can accurately determine the original signal. The optimal threshold selection expression is:

$$thr = \frac{1}{2 f_m} \tag{10}$$

Considering that the frequency range of the target signal is 0~5kHz, the optimal threshold is set to 0.1ms.

3.2 Distributed Denoising Algorithm for Sea Clutter Based on VMD

Using chaotic phase space reconstruction to preprocess the sea clutter signal, and then obtain VMFs through VMD processing. According to the autocorrelation characteristics of the signal components, we perform IHP and wavelet threshold denoising processing on the high-frequency and low-frequency components respectively. Finally, the denoising signal is reconstructed. The steps are as follows:

Step1: Use the classic C-C method to reconstruct the phase space, and use the processed chaotic time series as the denoising signal;

Step2: Initialize $\{u_k^0\}、\{w_k^0\}、\{\lambda^0\}$ and n;

Step3: Iteratively update in the frequency domain according to formula (6) and (7), and iteratively update y according to formula (8);

Step4: Determine whether the decomposed variable meets the given precision ε, if $\sum_{K}\left\|\hat{u}_k^{n+1}-\hat{u}_k^{n}\right\|_2^2 / \left\|u_k^{n}\right\|_2^2 < \varepsilon$, the iteration stops; otherwise, return to step (3);

Step5: At the end of the iteration, the VMFs after VMD decomposition are obtained;

Step6: Analyze the autocorrelation characteristics of VMFs to filter out high-frequency noise components and low-frequency signal components;

Step7: Perform IHP processing on high frequency noise components, and perform wavelet threshold denoising on low frequency signal components;

Step8: Reconstruct the processed high-frequency and low-frequency components, and output denoising sea clutter. Use LSSVM to establish a time series forecast model, and compare and analyze the forecast effect before and after denoising.

4 Experiments and Analyses

In order to verify the distributed sea clutter denoising algorithm based on VMD, the chaotic phase space reconstruction and the single-step prediction based on the LSSVM sea clutter prediction model are used to evaluate the denoising effect by comparing the RMSE of the prediction before and after denoising.

The sea clutter data comes from the IPIX measured radar [28], the transmitting frequency is 9.39GHz, the antenna height is 30m, the pulse repetition frequency is 1kHz, and the VV polarization method is adopted. Each group of data contains 131072 sampling points, the antenna gain is 45.7db, and the signal-to-noise ratio of the selected data is in the range of 0-16db.

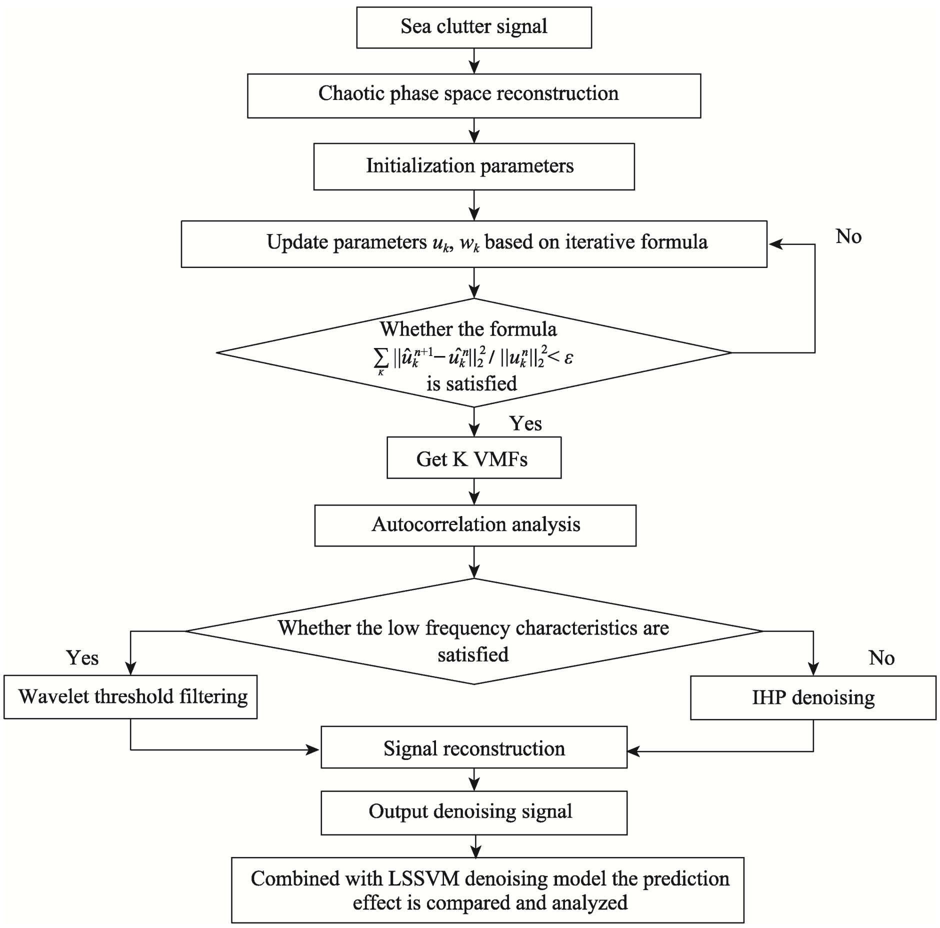

Fig.1 Flow Chart of Distributed Sea Clutter Denoising Based on VMD

4.1 Sea Clutter Prediction of LSSVM Model Before Denoising

In order to verify the effectiveness of the distributed sea clutter denoising algorithm based on VMD, it is in contrast with the predicted results after denoising, so the sea clutter prediction without denoising LSSVM model is carried out.

The experiment uses 54# sea clutter target distance unit with 2000 sample points, selects the first 1000 points as the training sample set, and the last 1000 points as the prediction verification set. And perform phase space reconstruction and LSSVM prediction. The experimental results are shown in Fig.2. The predicted signal and the verification signal are basically consistent. The prediction error at the 500th to 550th point is large, indicating that there is a small target. In Fig.3, it can be seen that there are obvious spikes in the prediction error, which shows that the LSSVM model can detect the weak signal submerged in the sea clutter background, and the RMSE of the prediction result is 0.0125.

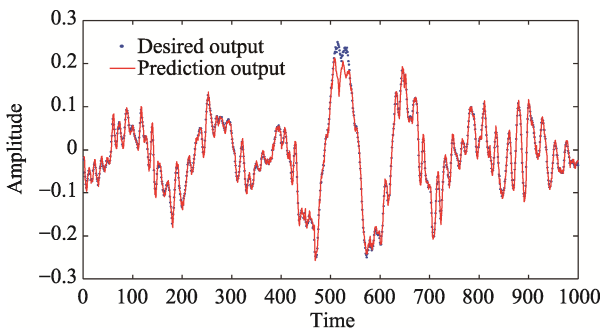

Fig.2 Real and Predicted Values of Unnoised Sea Clutter

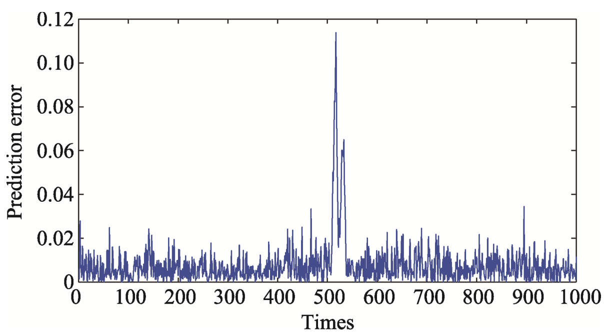

Fig.3 Prediction Error Spectrum before Denoising

4.2 LSSVM Model Prediction after VMD Denoising

In order to ensure the decomposition effect of VMD, first use EMD to adaptively decompose the 54# sea clutter to obtain the optimal decomposition level K, and use K as the number of decomposition levels for VMD, where K=9. Fig.4 is a decomposition diagram of the sea clutter signal based on the VMD algorithm. The figure indicates that the sea clutter is divided into 9 modal components m1-m9. In order to distinguish the high and low frequency bands of the decomposed components, the autocorrelation function of each component is calculated separately. In Fig.5, according to the characteristics of the autocorrelation function, the first four VMFs are divided into low-frequency components, and the last five VMFs are divided into high-frequency components.

According to the distinction between high and low frequencies, different denoising methods are selected for processing. For the four low-frequency components m1~m4, wavelet threshold denoising is

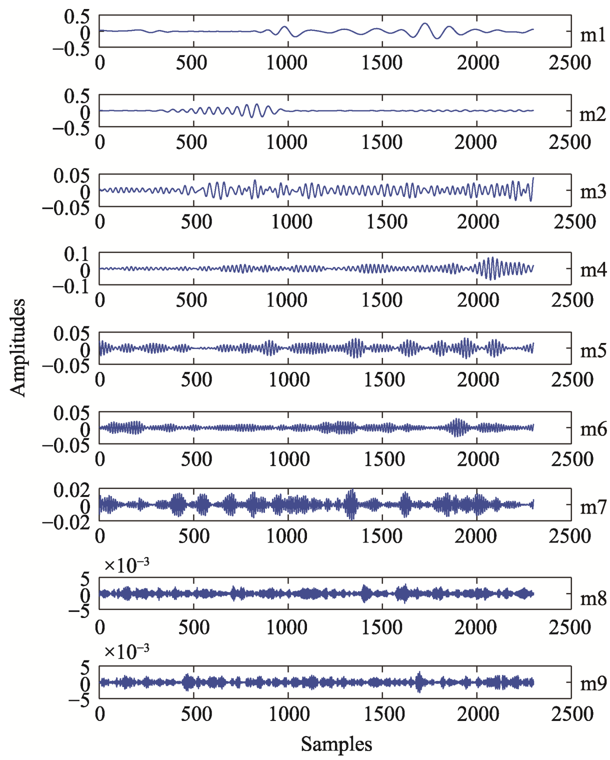

Fig.4 Sea Clutter Signal Decomposition Diagrams

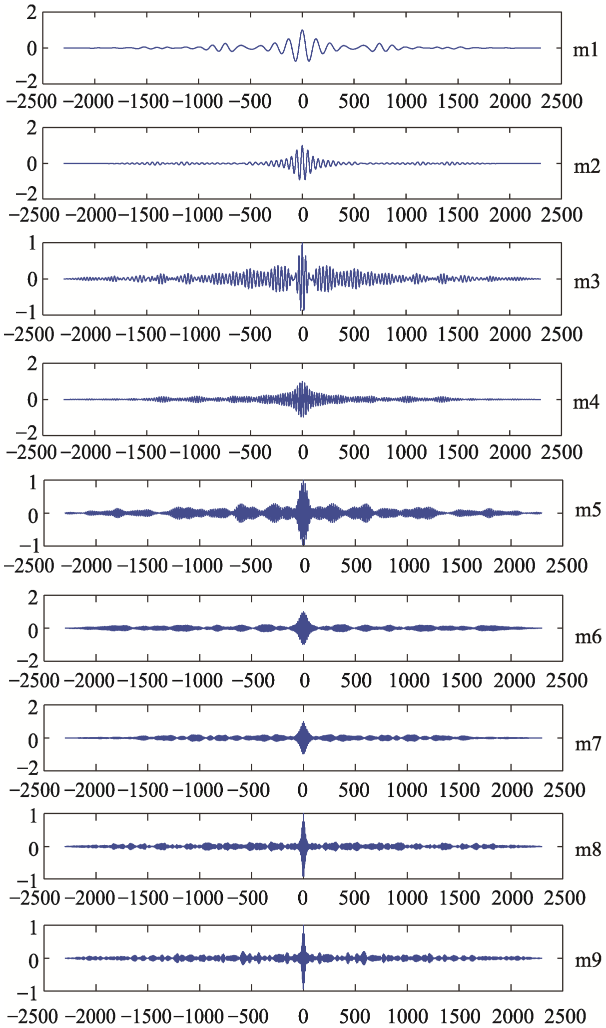

Fig.5 VMFs Autocorrelation Characteristic Diagrams

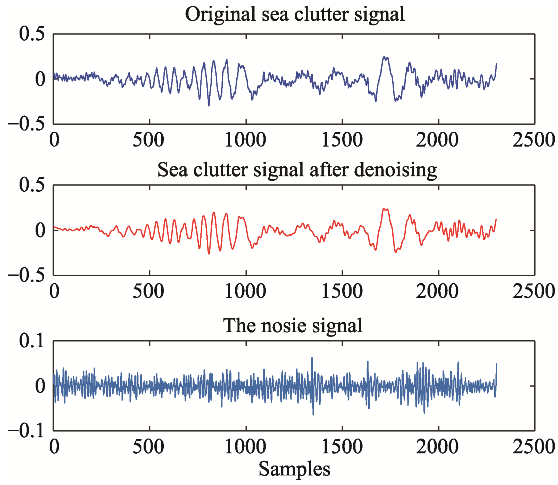

Fig.6 Original Sea Clutter Signal and Sea Clutter Signal after Denoising

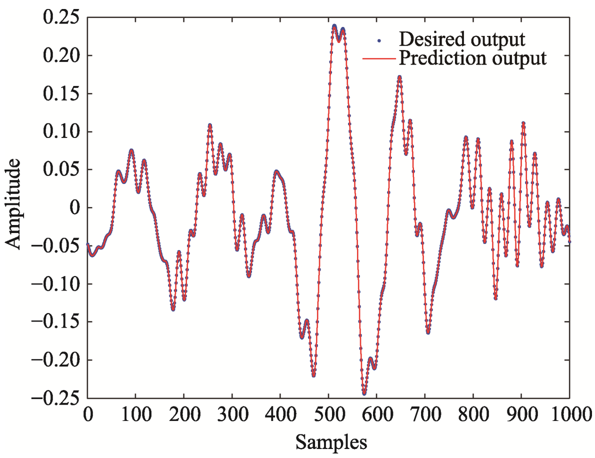

Fig.7 Real and Predicted Values after Denoising

selected, and the minimax threshold criterion suitable for most useful signals is adopted. For the five high-frequency components of m5~m9, the IHP method proposed in this paper is selected for processing. Reconstruct the processed components to get the denoising sea clutter signal. Draw the waveforms before and after the sea clutter denoising, and subtract the two signals to get the removed noise signal.

In Fig.6, some flaws in the sea clutter signal have been removed, and the overall signal has become much smoother than before, but the overall characteristics of the sea clutter without significant changes. In order to further verify the effectiveness of the distributed sea clutter denoising algorithm based on VMD, a sea clutter prediction model of LSSVM is established. After the chaotic phase space reconstruction of the denoised sea clutter signal, the prediction effect after denoising is analyzed.

According to the experimental steps of the control group, the denoised sea clutter data was normalized, phase space reconstructed, and single-step prediction based on the LSSVM model. It can be seen from Fig.7 that the LSSVM model can detect small target signals submerged in the background of sea clutter, and the signals of the prediction set and the test set are almost identical.

From the prediction error spectrum in Fig.8, it can be seen that the target signal position is between 500 and 550 sample points. At the same time, the spectral peak of this segment has fewer defects than before denoising, and the target signal position can be found more intuitively and accurately. The RMSE of the predicted result is 0.00034, which is lower than before denoising get RMSE0.0125 two orders of magnitude. It can prove the effectiveness of the distributed sea clutter denoising algorithm based on VMD.

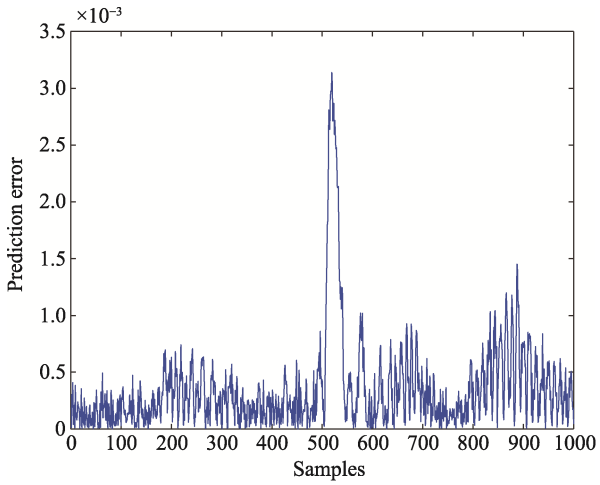

Fig.8 Prediction Error Spectrum after Denoising

4.3 Comparative Experiment

In order to further analyze the effectiveness of the distributed sea clutter denoising algorithm based on VMD, it is compared with Ref. [29],[30]. The results are shown in Table 1.

Table 1 Comparison of Sea Clutter Prediction Effects by Different Denoising Methods.

Contrast	EMD Hard Denoising [29]	EEMD+SG Filtering [30]	Proposed Algorithm
predict RMSE before Denoising	0.0124	0.0119	0.0125
predict RMSE after Denoising	0.0032	0.0028	0.00034

Although the algorithm proposed in the literature has improved the accuracy of the prediction before denoising, there is still a gap compared with the denoising algorithm proposed in this article. Ref. [29] uses EMD hard denoising, directly discarding the noise components that do not meet the signal characteristics, which is subjective and the denoising effect is unstable. Ref. [30] uses the EMMD algorithm combined with Savitzky-Golay (SG) to denoise, which only deals with the noise component and ignores the clutter in the signal component. It has a smaller improvement in denoising effect than the Ref. [29]. This paper uses the advantages of VMD to decompose the signal, and combines IHP and wavelet threshold to process all components. Compared with the previous two methods, the denoising effect is significantly improved. However, due to the preparation of pre-processing and the separate processing of components in different frequency bands, the complexity of the algorithm has also increased, and the denoising rate has been reduced. In the following research, we can consider optimizing the algorithm structure and writing an algorithm toolbox.

In summary, the distributed sea clutter denoising algorithm based on VMD has significantly improved denoising effect, and the algorithm complexity has also increased. Generally speaking, compared with the traditional decomposition and denoising algorithm, the denoising effect is outstanding, especially when dealing with chaotic small target signals under the background of sea clutter.

5 Conclusion

This paper proposes a distributed denoising algorithm based on VMD for sea clutter. By analyzing the autocorrelation characteristics of the decomposed components, combining IHP and wavelet threshold denoising to process high and low frequency component signals separately. Due to the non-recursive nature of the VMD algorithm, IHP and wavelet threshold denoising process the high and low frequency components simultaneously. Finally, the chaotic sea clutter sequence prediction model built by LSSVM verifies the effectiveness of the algorithm. The results confirm that small targets can be detected, and the predicted RMSE is 0.00055, which is two orders of magnitude lower than before denoising. Compared with the traditional decomposition denoising algorithm, the method proposed in this paper has better denoising effect and lower RMSE of the prediction result.

Although the VMD-based sea clutter distributed denoising algorithm has obvious denoising effects, the overall complexity of the algorithm has increased a lot due to the pre-processing preparation and the denoising of all components, resulting in a low signal processing rate. It is advised to consider optimizing the algorithm structure, improving the efficiency of algorithm processing, writing algorithm toolbox, and simplifying the difficulty of operation in future studies.

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