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Research Article

A Method for Extracting Fingerprint Feature of Communication Satellite Signal

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Satellite communications have historically played a vital role in a variety of industries, including maritime communications. The marine communication environment is exceedingly complicated, and extracting the characteristics of communication equipment signals is difficult. This research proposes a method for extracting satellite signal fingerprint characteristics based on the maritime complex communication environment. To create the signal fingerprint feature vector, the marginal spectral entropy is determined using the HHT (Hilbert-Huang transform) time-frequency analysis approach. Furthermore, by merging the Mahalanobis distance approach with the EEMD (ensemble empirical mode decomposition) algorithm, this study enhances it. The improved EEMD algorithm decomposes the original signal using EEMD, calculates the Mahalanobis distance between each IMF (intrinsic mode function) component and the raw data, optimizes the adaptive threshold using MPA (marine predators algorithm), and then analyzes the IMF components and redundant IMF components. It was decided to eliminate superfluous IMF components. Finally, this article mimics the Iridium satellite signal. The results of the experiments suggest that using this strategy minimizes the computational cost of the next step in fingerprint feature extraction while ensuring the accuracy of signal fingerprint feature recognition.

1. Introduction

The development of signal processing theory and technology has brought great changes and far-reaching influence on people's daily life. Electronic systems in many fields (such as communication, medicine, and radar) have achieved rapid development, and satellite communication technology has also achieved rapid development. There are rapid breakthroughs in various scenarios transportation management business, positioning function, smart grids, telecommunication systems, fishing operations, oil exploration, and defense applications such as weapon precision strikes [1, 2]. Since 1960, many new signal processing methods have appeared, and as the complexity of the research object has increased, the study of the subtle characteristics of the signal has become more and more important. At the same time, the research in the field of machine learning has also made great breakthroughs, and the signal processing technology can combine many new clustering and classification methods [3]. Communication signals must contain both conscious modulation and unconscious modulation. The phase noise of unconscious modulation will change with different hardware. Therefore, unconscious modulation can be used to extract signal fingerprint features, and the source of different signals can be judged according to the fingerprint features. Due to the urgency and complexity of extracting signal fingerprint features, it is necessary for developing communication satellite signal fingerprint feature extraction method to realize effective ocean signal feature extraction technology and accurate satellite signal identification, which has always been a key subject in the field of signal processing. Therefore, it is very important to design a practical communication satellite signal feature extraction method in the marine environment.

More and more nonlinear analysis techniques can be applied to signal processing and recognition [4]. Examples are combining high-order spectrum [5], wavelet packet transform [6], Hilbert transforms [7], extracting eigenfrequencies from signals, empirical mode decomposition, and other advanced signal processing techniques. EMD has become a popular method due to its inherent properties and adaptability to nonstationary signals [8]. Aiming at the shortcomings of traditional EMD methods, improved methods such as weighting [9], wavelet threshold denoising [10], ensemble empirical mode decomposition [11], and partial ensemble empirical mode decomposition [12] have appeared. Later, with the development of artificial intelligence [13], pattern recognition is gradually combined with signal recognition technology. The most important thing in signal recognition technology is the selection of feature vectors, which determine the practicability and validity of signal recognition. These feature vectors can show the subtle features of signals. Later, some entropy-based methods were proposed, such as hierarchical entropy [14], fuzzy entropy [15], sample entropy [16], approximate entropy [17], hierarchical fuzzy entropy [18], and mixed entropy of different features [19], which can extract the dominant feature vector from the signal.

In this research, a method for extracting fingerprint features from maritime satellite signals them is proposed in the context of marine satellite communication. The EEMD (ensemble empirical mode decomposition) method is used to address the problems of modal aliasing and excessive redundant IMF (intrinsic mode function) components in the EMD (empirical mode decomposition) method in the traditional HHT (Hilbert-Huang Transform) decomposition method. MPA (marine predators algorithm) [20] was introduced for threshold optimization to remove redundant IMF components, which greatly reduces the computational complexity, to effectively solve the modal aliasing problem by calculating the Mahalanobis distance between each IMF component and the raw data. The signal will be evaluated using the modified EEMD approach in this study. The HHT time spectrum will be generated by HT (Hilbert transform) transformation of the nonredundant IMF components acquired by the analysis, the marginal spectrum will be obtained by calculation, and the marginal spectral entropy will be obtained as the signal fingerprint characteristic. Finally, simulation tests are used to verify the practicality of the fingerprint feature extraction approach for marine satellite signals.

2. Signal Fingerprint Feature Extraction Principle

2.1. The Principle of Ensemble Empirical Mode Decomposition Algorithm. HHT is mainly divided into two steps. First, EMD decomposes the raw data, the IMF component can be decomposed from the raw signal data, and then, Hilbert transform was performed on each of the obtained IMF components. This paper will improve the modal aliasing problem and the redundant component problem of EMD in HHT.

The main steps of the EMD method can be expressed as follows:

(1) Find all extreme values of the original signal data $x(t)$, obtain the upper envelope $b_{\max}(t)$ and lower envelope $b_{\min}(t)$ of $x(t)$, and calculate the mean value of the two envelopes:

$$a_1 = \frac{b_{\max}(t) + b_{\min}(t)}{2} \tag{1}$$

(2) If the raw data $x(t)$ minus $a_1(t)$ meets the standard conditions of the IMF, it can be expressed as

$$p_1(t) = p_1(t) - a_1(t) \tag{2}$$

(3) If $p_1(t)$ does not meet the conditions in (2), take it as the new raw signal data, repeat (1) and (2), then obtain the mean value $a_{11}(t)$ of the upper and lower envelope, and then subtract the mean value from the new original data $p_1(t)$:

$$p_{11}(t) = p_1(t) - a_{11}(t) \tag{3}$$

(4) If $p_{11}(t)$ still does not meet the conditions in (2), repeat the operation in (3) until the IMF screening conditions are met, and then separate the first IMF component from the raw signal data $x(t)$:

$$d_1(t) = x(t) - \mathrm{imf}_1(t) \tag{4}$$

(5) Take $d_1(t)$ as the new raw data, and cycle the above steps to separate all qualified IMF components. The signal raw data $x(t)$ is finally decomposed into n IMF components and a residual component $d_n(t)$, which be as follows:

$$x(t) = \sum_{i=1}^{n} \mathrm{imf}_i(t) + d_n(t) \tag{5}$$

To reduce the phenomenon of modal aliasing, the EEMD method is used in this paper. EEMD adds randomly and uniformly distributed Gaussian white noise signal to the original signal, decomposes each IMF component by the EMD method, and finally generates a series of stable IMF components with different characteristic components and a residual component $d_n(t)$, which can be expressed as

$$x(t) = \sum_{i=1}^{n} \mathrm{imf}_i(t) + d_n(t). \tag{6}$$

2.2. The Principle of the Mahalanobis Distance Algorithm. Since the white noise signal used in the EEMD method has the characteristics of zero mean, the interference noise of the EMD can be effectively reduced, and the modal aliasing phenomenon in the EMD method is improved. However, both the original termination conditions in the EMD and EEMD methods are difficult to satisfy. Too many iterations will lead to overdecomposition of the original signal, resulting in a feature related to the original signal. For redundant IMF components with a very low degree, these components have very little reflection on the signal characteristics, have little effect on the subsequent signal identification, and increase the computational complexity of the Hilbert transform [21]. In response to this problem, this research proposes to use the Mahalanobis distance as an index to evaluate the effect of signal decomposition, reduce the computational complexity, calculate the optimal threshold of the IMF component through the ocean predator algorithm, and better deal with the noisy IMF component. Under the condition of ensuring the main features of the signal, a reasonable strategy is designed to remove redundant components and speed up the extraction of fingerprint features.

Mahalanobis distance is an effective method to calculate the similarity between two unknown sample sets, which has a certain degree of application in the field of navigation satellite systems [22–24]. Mahalanobis distance can judge the similarity between two one-dimensional signal probability density functions. Let M_1 and M_2 be two samples from population G, and the sample covariance matrix is Σ. Then, the Mahalanobis distance between M_1 and M_2 can be defined as

$$D_M(M_1, M_2) = (M_1 - M_2)^T \Sigma^{-1} (M_1 - M_2). \tag{7}$$

2.3. The Principle of Marine Predators Algorithm. MPA (marine predators algorithm) is a new metaheuristic optimization algorithm proposed in 2020. The algorithm simulates the movement of marine predators and prey. The optimal foraging strategy was chosen between the Levi walk or Brown walk. Prey also acts as a predator in the process of being preyed on, which makes MPA more dynamic and has a unique marine memory storage stage and ocean eddy influence stage, which can improve the updated population quality [25]. The optimization steps can be expressed as follows:

(1) Initial populations were randomly generated within the search space:

$$X_0 = X_{\min} + \text{rand}\,(X_{\max} - X_{\min}), \tag{8}$$

where $X_{\min}$ and $X_{\max}$ are the range of search space; rand () is a random number within $[0, 1]$

(2) If the predator is faster than the prey at the beginning of the iteration, the MPA optimization process is based on the exploration strategy:

$$\left.\begin{cases} \text{stepsice}_i = R_B \otimes (\text{Elite}_i - R_B \text{Prey}_i) \\ \text{Prey}_i = \text{Prey}_i + P \bullet R \otimes \text{stepsice}_i \end{cases}\right\}, i = 1, 2, 3, \cdots, n,$$
$$I < \frac{1}{3}\text{Max\_}I, \tag{9}$$

where stepsice is the moving step, R_B is a Brownian walk random vector with normal distribution, Elite_i is an elite matrix composed of top predators, Prey_i is the prey matrix, which has the same dimension as the elite matrix, $\otimes$ is a term-by-term multiplication operator, P equals 0.5, R is a uniform random vector within $[0, 1]$, n represents population size, I is the current number of iterations, and Max_I is the maximum number of iterations.

In the middle of the iteration, if the speed of the predator and the prey is the same, the prey is responsible for the development based on the Levy walk strategy; the predator is responsible for the exploration based on the Brown walk strategy and gradually changes from the exploration strategy to the development strategy:

$$\left.\begin{cases} \text{stepsice}_i = R_L \otimes (\text{Elite}_i - R_L \text{Prey}_i) \\ \text{Prey}_i = \text{Prey}_i + P \bullet R \otimes \text{stepsice}_i \end{cases}\right\}, i = 1, 2, 3, \cdots, \frac{n}{2},$$
$$\frac{1}{3}\text{Max\_}I < I < \frac{2}{3}\text{Max\_}I,$$
$$\left.\begin{cases} \text{stepsice}_i = R_B \otimes (R_B \otimes \text{Elite}_i - R_B \text{Prey}_i) \\ \text{Prey}_i = \text{Elite}_i + P \bullet \text{CF} \otimes \text{stepsice}_i \end{cases}\right\}, i = \frac{n}{2}, \cdots, n,$$
$$\frac{1}{3}\text{Max\_I} < \text{I} < \frac{2}{3}\text{Max\_I}, \tag{10}$$

where R_L is a random vector with a Levy distribution, CF is an adaptive parameter that controls the predator's moving step size, $\text{CF} = (1 - \text{Iter}/\text{Max\_iter})^{(2\bullet\text{Iter}/\text{Max\_Iter})}$.

At the end of the iteration, if the speed of the predator is slower than that of the prey, the predator adopts the development strategy based on the Levy walk:

$$\left.\begin{cases} \text{stepsice}_\text{i} = \text{R}_\text{L} \otimes (\text{R}_\text{L} \otimes \text{Elite}_\text{i} - \text{Prey}_\text{i}) \\ \text{Prey}_\text{i} = \text{Elite}_\text{i} + \text{P} \bullet \text{CF} \otimes \text{stepsice}_\text{i} \end{cases}\right\}, i = 1, 2, 3, \cdots, n,$$
$$I > \frac{2}{3}\text{Max\_}I \tag{11}$$

(3) The foraging behavior of marine predators will be affected by FADs (fish aggregation devices) or eddy

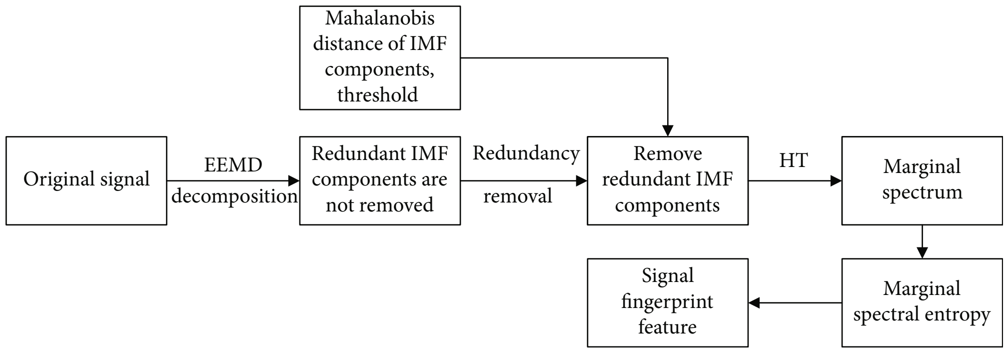

Figure 1: Signal processing based on improved EEMD algorithm.

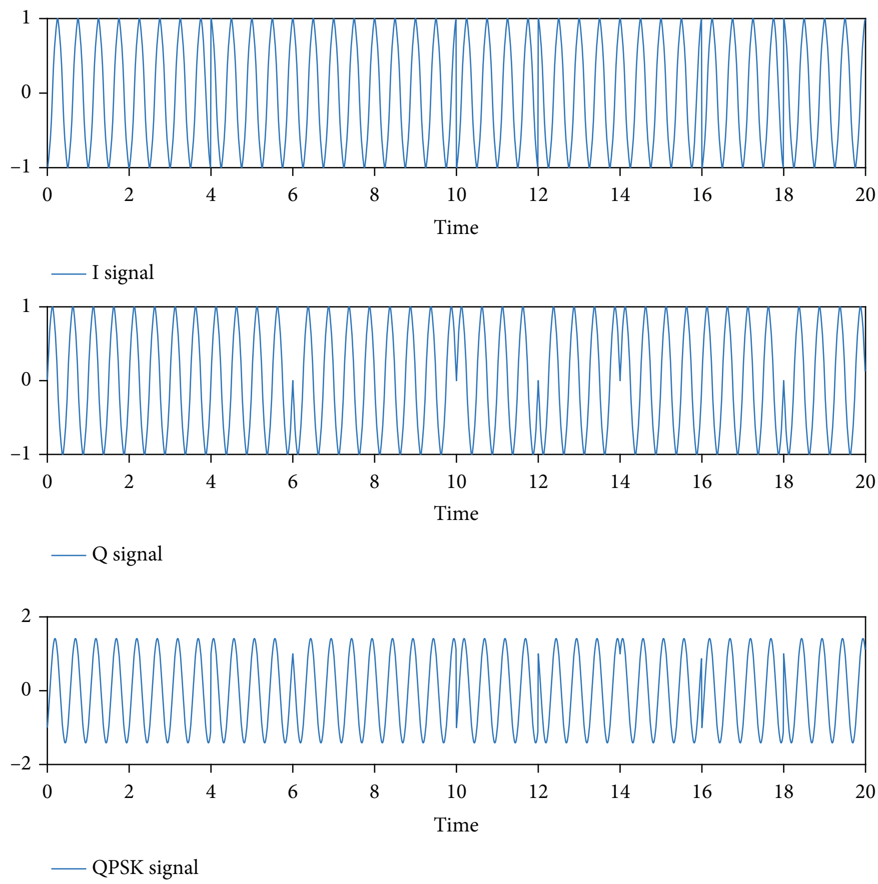

Figure 2: QPSK modulation waveform diagram.

effects. Based on this strategy, MPA can overcome the problem of premature convergence and escape from local extremes in the optimization process:

$$\text{Prey}_i = \begin{cases} \text{Prey}_i + \text{CF}[X_{\min} + R_L \otimes (X_{\max} - X_{\min})] \otimes U, & a \leq \text{FADs}, \\ \text{Prey}_i + [\text{FADs}(1-a) + a](\text{Prey}_{a1} - \text{Prey}_{a2}), & a > \text{FADs}, \end{cases} \quad (12)$$

where H is a binary vector; FADs represent the impact probability, taken as 0.2; a is a random number within $[0, 1]$; and $a1$ and $a2$ are the random indexes of the prey matrix, respectively.

3. Signal Fingerprint Feature Extraction Method

In this section, the signal fingerprint feature design is based on the HHT time spectrum. After the EEMD algorithm decomposes the signal, according to the principle of the improved EEMD algorithm, the obtained IMF components are redundantly removed, and the Hilbert transform is performed on the redundant IMF components. The time

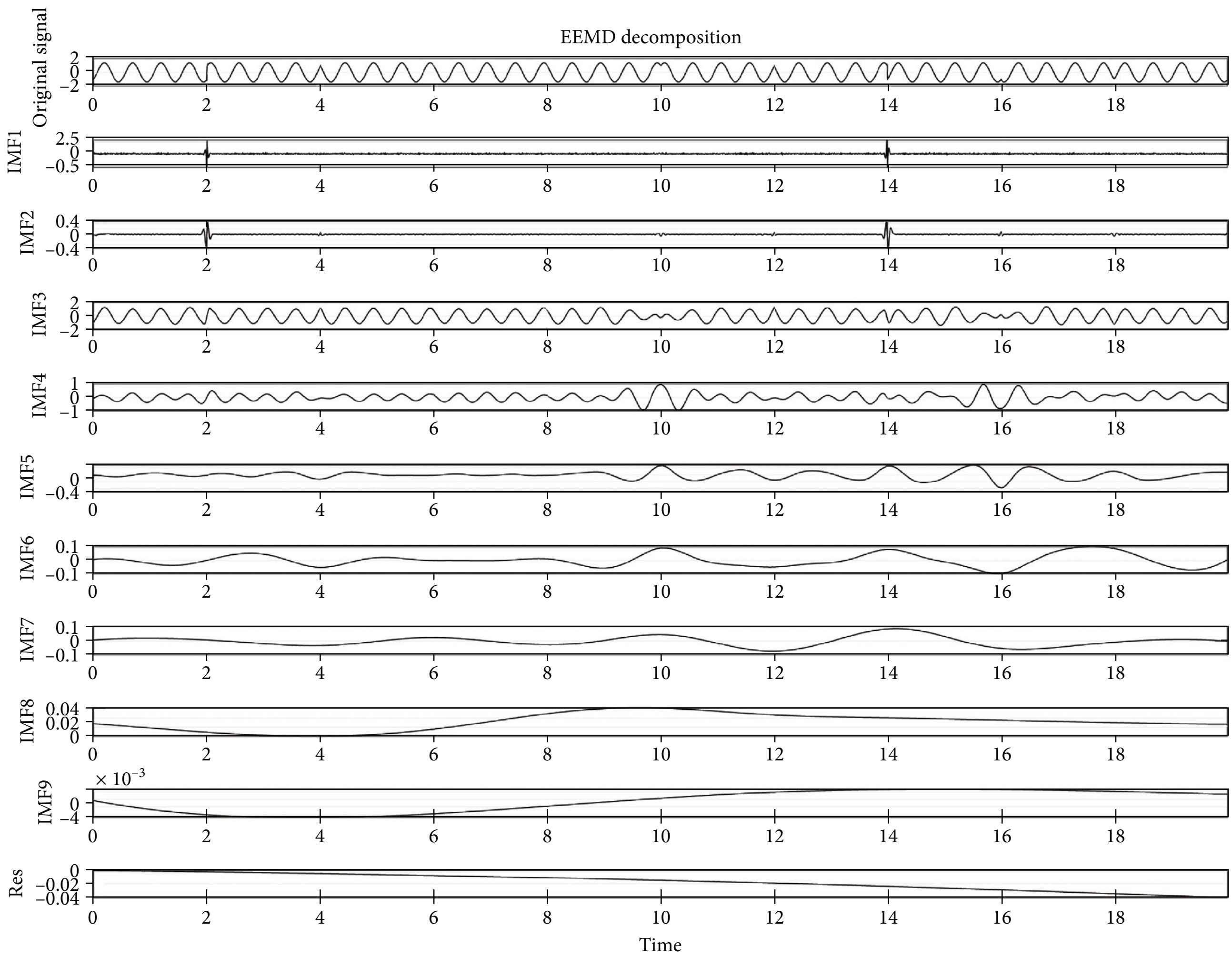

Figure 3: IMF component.

spectrum difference is analyzed, and the edge spectrum entropy is extracted as the signal fingerprint feature. Constructing the eigenvectors of edge spectral entropy can be used for signal identification. Figure 1 shows the specific steps.

3.1. Signal Processing Based on Improved EEMD Algorithm. The EEMD algorithm decomposes to obtain multiple IMF components, including components reflecting modulation information and redundant components, sets thresholds in all IMF components for screening, and removes redundant components whose Mahalanobis distance is less than the threshold. The specific steps of the removal method can be expressed as follows:

(1) Preprocess the original signal to obtain the original signal data $x(t)$

(2) $x(t)$ is decomposed by EEMD to obtain $\mathrm{imf}_1(t) \sim \mathrm{imf}_n(t)$ components

(3) The method based on PDF (probability density function) and MD (Mahalanobis distance) is used to judge the components and redundant components reflecting modulation information and calculate the Mahalanobis distance between each component $\mathrm{imf}_i(t), i = 1, 2, \cdots, n$ and the original signal:

$$d(i) = \mathrm{MD}(\mathrm{PDF}(x(t)), \mathrm{PDF}(\mathrm{imf}_i(t))) \tag{13}$$

(4) Determine the threshold between the component reflecting the modulation information and the redundant component $\gamma = (\mathrm{argmax}/1 \le i \le N)\{d(i)\}$, MPA is used to optimize the threshold globally. Remove the components whose Mahalanobis distance is greater than the threshold in $\mathrm{imf}_1(t) \sim \mathrm{imf}_n(t)$ components and retain the remaining components

The above method can effectively retain the main modulation information of the signal and reasonably remove redundant components that do not affect subsequent identification.

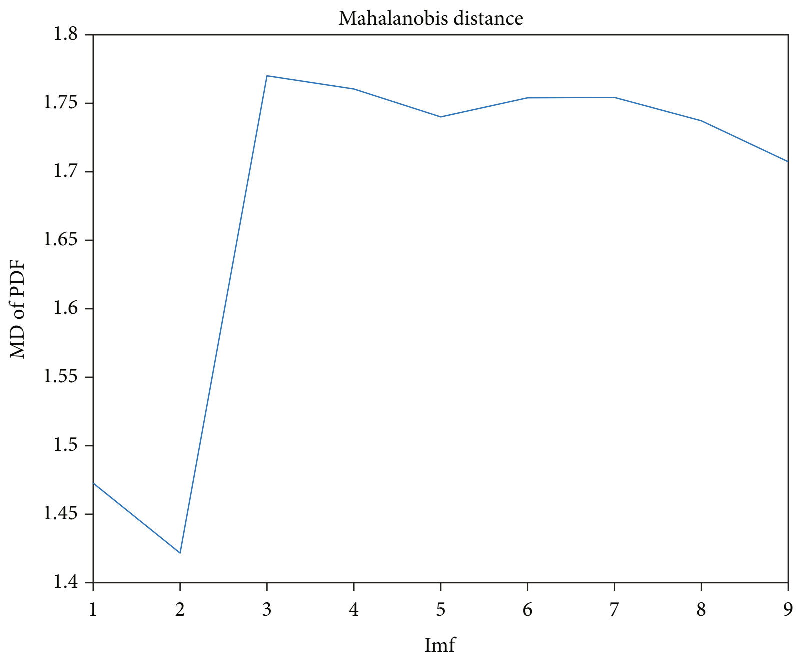

Figure 4: IMF component Mahalanobis distance.

3.2. Signal Fingerprint Feature Extraction Based on Marginal Spectral Entropy. There are subtle differences in the marginal spectrum between different signals. These differences are the signal fingerprint features carried by the signal. The signal fingerprint features can be extracted based on the marginal spectrum of the signal. The specific process can be expressed as follows:

(1) Use the improved EEMD decomposition algorithm to decompose the original signal, obtain the HHT time spectrum according to the HHT correlation theory, and normalize the HHT time spectrum:

$$\mathrm{TF}_n(t, f) = \frac{\mathrm{TF}(t, f)}{E} \tag{14}$$

(2) Obtain the marginal spectrum according to the normalized HHT time spectrum:

$$J_n(f) = \sum_t \mathrm{TF}_n(t, f) \tag{15}$$

(3) Calculate the marginal spectral entropy to represent the uniformity of the marginal spectral energy distribution:

$$\mathrm{Hse} = -\sum_f J_n(f) \ln J_n(f) \tag{16}$$

Table 1: Signal HT time comparison.

	Original EEMD algorithm	Improved EEMD algorithm
HT time	0.091 s	0.066 s

The marginal spectral entropy of different satellite signals is different. The marginal spectral entropy of different satellite signals varies in a small range and is relatively stable. Therefore, the marginal spectral entropy of the signal can be used as a signal fingerprint feature.

4. Simulation Experiments and Analysis

To verify the satellite signal fingerprint extraction method proposed in this paper, this paper will use the simulation experiment mode to verify the improved EEMD method. The experimental platform used is MATLAB built on Windows 10. To simulate the satellite communication in the real ocean environment, we will simulate the Iridium satellite signal as the original signal of the experiment. The iridium communication system is a global mobile personal communication satellite system based on low-orbit satellites. The iridium mobile phone establishes a communication link with the space satellite of the iridium communication system, which can be transmitted through the forwarding of the satellite constellation. The iridium communication system supports global wireless digital communication. The iridium communication system uses QPSK (quadrature phase-shift keying) for debugging at gateway stations and user terminals, so the original simulated signal in this experiment is based on QPSK modulation. Figure 2 shows the waveforms of the I channel, Q channel, and original signal

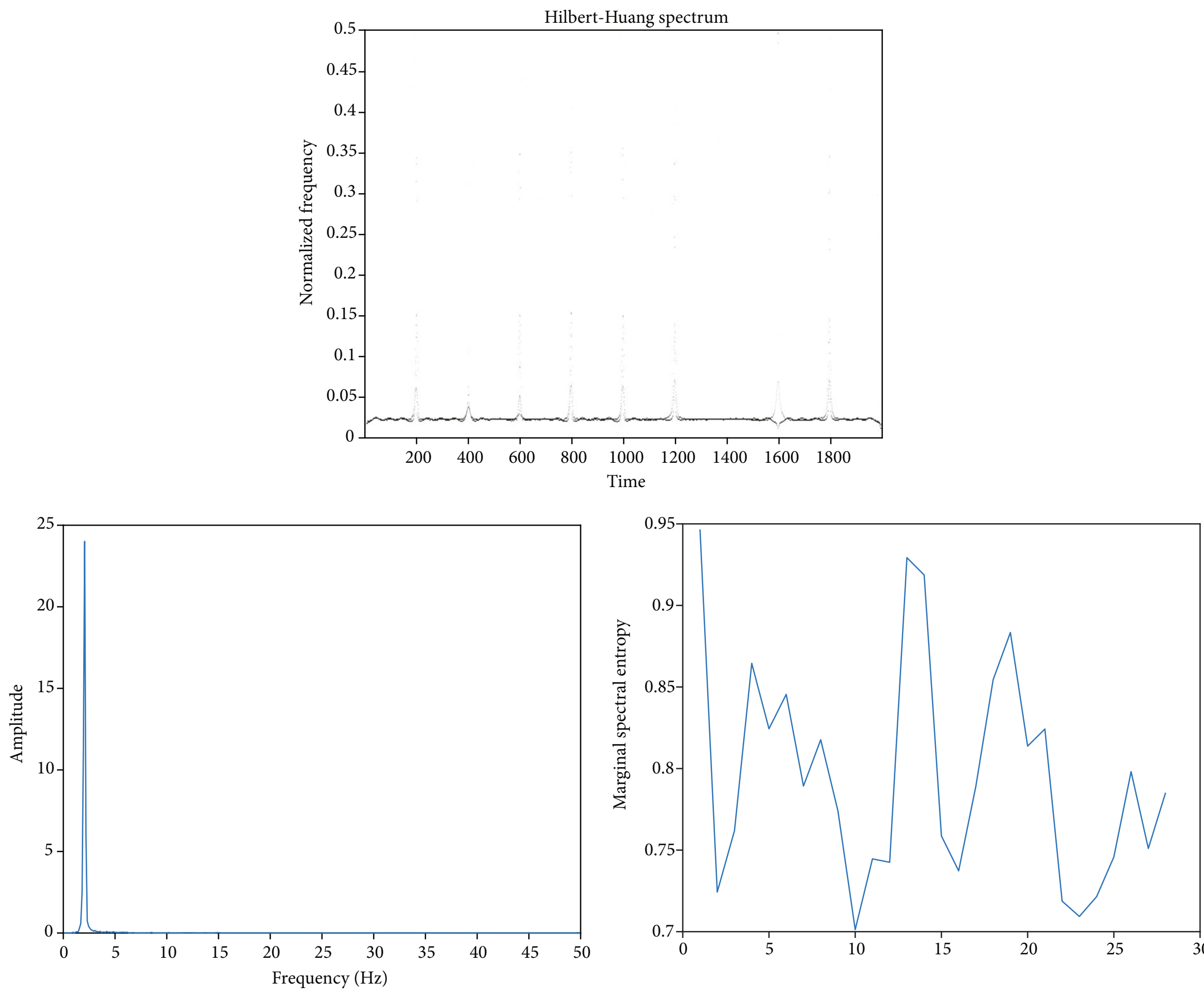

Figure 5: Hilbert spectrum, marginal spectrum, and marginal spectral entropy with redundant components removed.

(QPSK) transmitted after QPSK modulation is multiplied by the carrier signal.

The original signal is decomposed according to the EEMD decomposition method, and 9 IMF components, and one residual component are obtained, as shown in Figure 3.

Due to the inherent decomposition error of the EEMD decomposition algorithm, the number of iterations is large. Overdecomposition of the signal occurs, resulting in redundant IMF components that are less correlated with the original signal. These redundant components have very little reflection on the signal characteristics and have very little effect on signal identification, which will also increase the subsequent computational complexity. Therefore, to reduce the computational complexity and speed up the extraction of subsequent signal fingerprint features, this paper proposes to use Mahalanobis distance to remove redundant components. To better calculate the Mahalanobis distance between each IMF component and the raw data, first calculate the one-dimensional signal probability density function PDF of the original signal and each IMF component, and then calculate the Mahalanobis distance between each IMF component and the original signal data PDF, the results are shown in Figure 4.

The curve increases sharply at the third IMF, indicating that the similarity becomes smaller. To more reasonably select the threshold for removing redundant IMF components, the marine predators algorithm intelligent optimization algorithm will be used to find the optimal threshold. The final optimal threshold is about 1.533. It can also be determined that the similarity of the IMF components after IMF3 is small and can be removed as redundant components.

Using the improved EEMD decomposition method to decompose the same original signal, the generated IMF components are reduced from 9 to 3, which can greatly reduce the amount of calculation. It can be seen from the previous analysis that the three IMF components have high similarity and can retain the original most of useful information of the signal. The EEMD algorithm before and after the improvement is used to perform HT transformation. The operating platforms are Windows 10 operating system, Intel Core i7-11800H CPU, and MATLAB R2018a. The test results are shown in Table 1. The improved EEMD algorithm reduces the computational complexity of the subsequent Hilbert transform and improves the efficiency of signal processing.

From the results of the above experiments, it can be concluded that using the improved EEMD method to remove

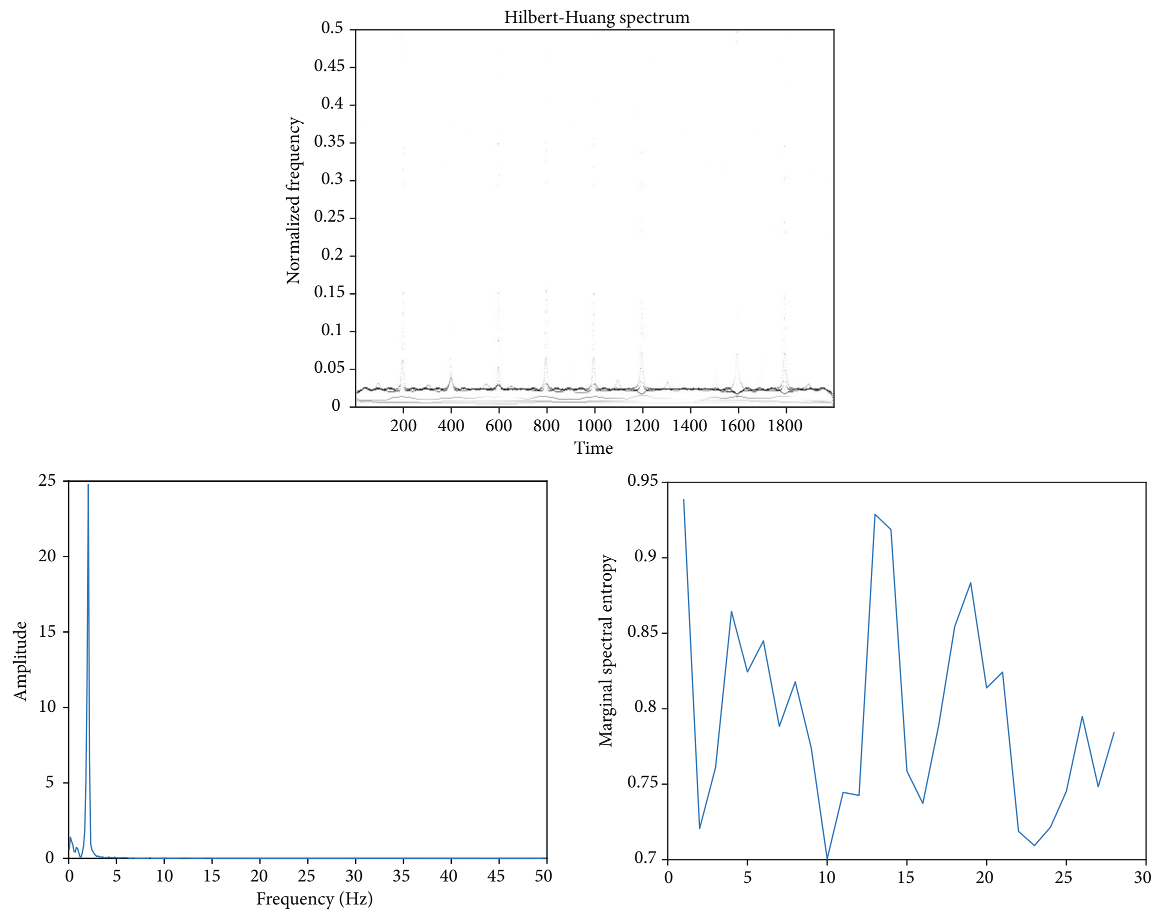

Figure 6: Hilbert spectrum, marginal spectrum, and marginal spectral entropy based on EEMD.

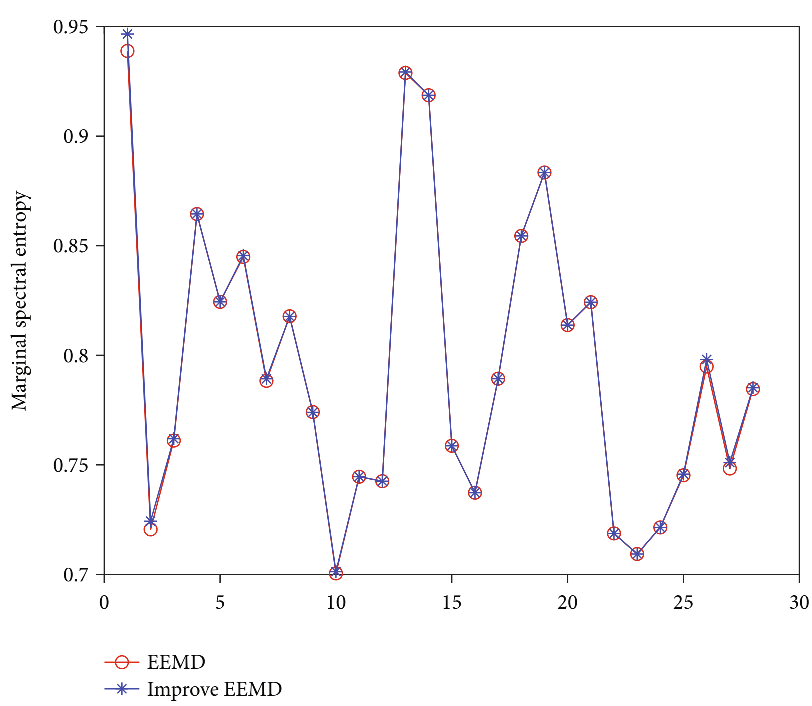

Figure 7: Comparison of the marginal spectral entropy.

redundant IMF components can reduce the computational complexity of subsequent feature extraction. Next, perform the Hilbert transform on the IMF components with redundant parts removed to obtain the Hilbert spectrum. Figure 5 shows the Hilbert spectrum with redundant components removed. Then, find and draw the marginal spectrum as shown in Figure 5. According to the marginal spectrum, the marginal spectral entropy is obtained as the signal fingerprint feature, and the marginal spectral entropy after removing redundant components is shown in Figure 5. To verify the accuracy of the improved EEMD method for removing redundant components based on Mahalanobis distance, the Hilbert spectrum, edge spectrum, and edge spectrum entropy based on the EEMD method were obtained, as shown in Figure 6. Figure 7 shows the comparison of the marginal spectral entropy based on the original EEMD method and the marginal spectral entropy based on the improved EEMD method. It can be seen that the two are similar, and the correlation coefficient between the two is 0.9996. Therefore, the signal fingerprint features extracted by the improved EEMD algorithm can ensure accuracy. To sum up, the improved EEMD method based on Mahalanobis distance for redundant IMF component removal can reduce the computational complexity of subsequent Hilbert transform and signal fingerprint feature extraction while ensuring the integrity of signal fingerprint features.

5. Conclusions

The above fingerprint extraction method can be applied to satellite communication scenarios in marine environment. The traditional Hilbert-Huang transform method is improved, the EEMD decomposition method is used to solve the modal aliasing problem, and the Mahalanobis distance method is used to distinguish redundant IMF components in the IMF components obtained by EEMD decomposition. The redundant IMF components are removed by the threshold optimized by the marine predators algorithm. The Hilbert-Huang transform time-frequency analysis method is used to extract the signal fingerprint features, and the marginal entropy is used to construct the signal fingerprint feature vector. The experimental results show that the improved EEMD algorithm reduces the computational complexity of subsequent Hilbert transform and signal fingerprint feature extraction while ensuring the accuracy of signal fingerprint feature recognition. However, improving the EEMD algorithm may have the problem of low recognition accuracy in some scenarios, and further improvement is needed, which is also the next research topic.

Data Availability

The data type used to support the findings of this study is included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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