An Adaptive Window Time-Frequency Analysis Method Based on Short-Time Fourier Transform

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Abstract. Frequency hopping signal has the advantages of strong anti-jamming ability and low probability of interception. It can effectively improve communication quality and security. Therefore, frequency hopping technology is widely used in the field of information countermeasures, and has become one of the main anti-jamming technologies adopted by various countries. As a non-partner, how to quickly obtain the main parameters of frequency hopping signal in order to implement effective and timely interference is particularly important. In this paper, a blind estimation algorithm based on short-time Fourier transform (STFT) is proposed. STFT is a time-frequency analysis method with low complexity. The performance of this method depends largely on the length of the Fourier transform window. The algorithm in this paper roughly estimates the period of frequency hopping signal according to the Frequency domain characteristics of input signal, and uses this information to determine the length of local window. The obtained time-frequency distribution is purified by setting a reasonable threshold, and the purified time-frequency distribution is used to extract information and estimate the main parameters of frequency hopping signal. The results show that this method can roughly estimate the length of Fourier transform window in very low SNR environment, and fine estimation method has higher accuracy in estimating the Frequency hopping period of frequency hopping signal.

Keywords: Frequency hopping communication · Time-frequency analysis · Parameter estimation

1 Introduction

Frequency hopping communication systems are widely used in military communications and civil mobile communications due to their low interception rate, anti-fading and strong networking capabilities. In the field of communication countermeasures and radio monitoring, the analysis of frequency hopping signals is extremely significant in the study of parametric detection techniques. The analysis of FHSS signals required a method suitable for representing time-varying signals. Time–frequency (TF) analysis is suitable since it produces a representation for time varying signals jointly in both time and frequency.

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In paper [1], compressed sensing technology is applied to time-frequency analysis of frequency hopping signals. According to the model of frequency hopping signal, the sparse characteristics of frequency hopping signal are analyzed and a sparse dictionary is constructed. Then, a time-frequency analysis algorithm of frequency hopping signal is proposed by using partial reconstruction algorithm. For the spectrum estimation problem of multi-hop frequency hopping signals existing in random frequency hopping observation, paper [2] uses the signal structure inherent in the frequency hopping signal to design the corresponding time-frequency core, and represents the nucleation result in the instantaneous autocorrelation function domain, using redesign. The structure-aware Bayesian compressed sensing algorithm processes signals. Based on the basic approximation theory of scaling function, a new method for constructing the basis pairs of Hilbert transform (HT) wavelets is proposed in [3]. A kind of Bayesian algorithm based on sparse Bayesian reconstruction for approximate blind estimation is proposed to estimate multi-hopping signal parameters in [4]. For the non-stationary characteristics of frequency hopping signals, paper [5] proposes a blind detection and parameter estimation algorithm for single-hop signals in complex electromagnetic environment based on STFT. The frequency hopping signal can be identified by the same duration of the signal components on different frequencies, and the interference signal and noise can be effectively removed to achieve the purpose of blind detection. The fast Fourier transform can then be used to estimate the frequency hopping and frequency hopping periods. A kind of frequency hopping duration estimation algorithm for frequency hopping signals based on multi-window partially overlapping reallocation smoothing Pseudo-WVD and adaptive threshold detection technology is proposed in [6]. It divides the signal into several segments according to an analysis window, analyses each segment with connects the maximum values of all segments of each sampling time with multi-window partial overlap method, and estimates the hopping time of frequency hopping signal with adaptive threshold detection. A kind of resolution metrics for objective evaluation of secondary time-frequency distribution performance are given in [7]. This criterion considers key attributes of time-frequency distribution, such as main and side lobes and cross terms. And apply the defined criteria to analyze the advantages and disadvantages of different time-frequency distributions. An advanced time-frequency distribution of the extended modified-B distributions (EMBD) is given in [8]. The time-frequency distribution is designed with a variable Time-Frequency core, and an independent tightly supported hyperbolic cosine function is used as a kernel function to filter the fuzzy function to obtain a time-frequency diagram. Based on the traditional STFT, a new algorithm for extracting the frequency characteristics of frequency diversity signals is proposed. The algorithm combines STFT with false positives and detection probabilities to make full use of frequency domain information in [9]. The paper [10] proposes a globally adaptive optimal kernel smooth-windowed Wigner-Ville distribution. The autocorrelation function envelope of the signal and the localized weighted regression (LOWESS) is used to obtain the frequency hopping signal period. The power spectrum is obtained from the autocorrelation function. The information sets the length of the window function added to the Wigner transform. Based on the time-frequency diagrams of EMBD [8] and SWWVD [10], the paper [11] proposes a quadratic-based accurate FHSS signal parameter estimation method: TF moments method (TF moments method) and instantaneous frequency method

(IF method). Linear TFD like short time Fourier transform suffers from time–frequency resolution trade off. On the other hand, QTFDs like Wigner–Ville distribution provides a good time–frequency resolution at the drawback of cross terms [12]. Thus, a variety of TFDs which is much application dependent have been introduced. However, if the kernel function is chosen properly, the QTFD can provide an accurate representation.

The above literature mainly studies the performance of methods and often ignores the complexity of the algorithm. Although the quadratic time-frequency distribution solves the problem that the time-frequency resolution cannot be improved at the same time, it also brings the interference of the cross-term, and the complexity of the algorithm is also greatly improved. This method is no longer applicable in the case of rapid frequency hopping. When we are in a non-partner, there is no a priori information, and the performance of some methods is difficult to guarantee. In this paper, the complexity of the algorithm is considered, and a low-complexity hopping period blind estimation method based on STFT is proposed. The method utilizes the frequency domain characteristics of the received signal, first roughly estimates the frequency hopping period, and then appropriately sets the Fourier transform window length according to the obtained information. At the same time, this paper also makes full use of the obtained information to optimize the frequency hopping period estimation method and obtain better performance.

2 Problem Definition

Frequency hopping system only adds carrier frequency hopping ability in conventional communication system, which widens the whole working frequency band greatly, and improves the anti-interference and anti-fading ability of communication system. The anti-jamming ability of frequency hopping system is "evasive", which is different from DSSS system. DSSS system improves anti-jamming ability by spectrum expansion and de-spreading processing. Obviously, the frequency hopping signal is non-stationary, and the time-frequency analysis method is a powerful tool for frequency hopping analysis and estimating the parameters of frequency hopping signal.

2.1 Signal Mode

Frequency hopping communication is a kind of communication mode that periodically changes the carrier of transmitting signal under the control of frequency hopping sequence. Frequency hopping sequence is a pseudo-random sequence. The function of frequency hopping sequence is to control carrier frequency hopping, which is generally a multi-valued pseudo-random sequence. For this paper, prime frequency hopping sequence is used. Frequency hopping modulation is secondary modulation and primary modulation can be any common modulation mode, such as phase shift key (PSK), quadrature phase shift key (QPSK), frequency shift key (4FSK) and so on. This paper adopts 4FSK modulation mode. The expression of frequency hopping signal is as follows.

$$S_i(t) = S_d(t) \sum_{-\infty}^{\infty} 2P(t - nT_c)\cos(w_n t + \phi_n) \tag{1}$$

Where $S_d(t)$ is 4FSK signal, P is a rectangular pulse, T_c is the duration of each hop frequency, w_n is the hopping frequency within a kth hopping duration, ϕ_n is phase at the beginning of a kth hopping duration.

The signal parameters of the signals used in this paper are given as follows.

(1) 4FSK: $[f_1\ \ f_2\ \ f_3\ \ f_4] = [500\,\text{Hz}\ \ 1\,\text{kHz}\ \ 1.5\ \text{kHz}\ \ 2\ \text{kHz}]$
(2) Frequency hopping duration: 0.004 s
(3) Frequency hopping set: Taking 10 FH points at equal intervals from 3 kHz to 30 kHz

2.2 Analytical Form of Signal

In the signal spectrum analysis method, people often prefer to choose the analytical form of signal to eliminate the negative frequency effect of signal. Assuming that the signal $s(t)$ to be processed is a real signal, its corresponding spectrum is given as.

$$S(f) = \int_{-\infty}^{+\infty} s(t)e^{-j2\pi ft}dt \tag{2}$$

Signal spectrum is conjugate

$$S^*(f) = \int_{-\infty}^{+\infty} s(t)e^{j2\pi ft}dt = S(-f) \tag{3}$$

From the perspective of effective bandwidth utilization of information, the negative frequency spectrum of real signal is redundant, because the negative frequency component can be obtained from the positive frequency part of the spectrum. Therefore, the negative frequency spectrum of the real signal is removed and the positive frequency spectrum is retained, which can reduce the bandwidth of the signal and improve the bandwidth utilization. However, if only the positive frequency spectrum part of the signal is retained, the receiver spectrum will no longer have conjugate symmetry, and the corresponding time-domain signal is complex. If we want to remove the negative frequency component of the signal and keep the total energy of the signal unchanged, the spectrum of the analytic form $z(t)$ of the signal should be given as.

$$Z(f) = \begin{cases} 2S(f), & f > 0 \\ S(f), & f = 0 \\ 0, & f < 0 \end{cases} \tag{4}$$

The complex analytic signal satisfying the above formula is composed of two signals, real part and imaginary part. The analytic signal $z(t)$ corresponding to real signal $s(t)$ can be defined as.

$$z(t) = s(t) + jHilbert[s(t)] \tag{5}$$

Compared with the narrowband stationary signal, the spectrum obtained by traditional Fourier transform can well describe its physical characteristics. However, for non-stationary signals, the frequency is time-varying. In this case, the concept of frequency and Fourier analysis method cannot achieve good analysis results, so the concept of instantaneous frequency is introduced. From the physical point of view, signals can be divided into single and multi-component signals. Multicomponent signal means that the signal has several different instantaneous frequencies at some time; single component signal has only one frequency at any time. Vile gives a generally accepted definition of instantaneous frequency:

For real signals.

$$s(t) = a(t)e^{j\theta(t)} \tag{6}$$

Where $\theta(t)$ is the instantaneous phase and $a(t)$ is the instantaneous amplitude, the analytic signal can be expressed.

$$z(t) = a(t)\cos[\theta(t)] \tag{7}$$

The derivative of the phase of the analytic signal is the instantaneous frequency.

$$f_i(t) = \frac{d[\arg z(t)]}{dt} \tag{8}$$

Vile also proposed that since the instantaneous frequency is time-varying, the corresponding instantaneous spectrum should also exist. The instantaneous frequency is the average frequency of the instantaneous spectrum.

$$Z(f) = \int_{-\infty}^{+\infty} z(t)e^{-j2\pi ft}dt = \int_{-\infty}^{+\infty} a(t)e^{j[\theta(t)-2\pi ft]} \tag{9}$$

The characteristic of signal energy concentration along instantaneous frequency plays an important role in signal reconstruction, identification, parameter estimation, target tracking and modeling.

3 Time–Frequency Analysis

Traditional Fourier transform is a commonly used spectrum analysis tool, which has great significance in the analysis and processing of stationary signals. But Fourier transform has one obvious disadvantage, that is, Fourier transform decomposes the whole signal into different frequency components. This is to observe the signal from a global perspective, lacking local information, and any part of the signal change or loss will have a huge impact on the entire spectrum. It can't tell us which time period the various frequency components occur, and we can't establish the time-frequency domain joint relationship. Therefore, the Fourier transform is only applicable to the stationary signal whose statistics do not change with time. However, in reality, signals are confidential, anti-interference, etc., and many of them are non-stationary signals, such as frequency hopping signals. For such signals, the traditional Fourier transform is no longer adapted, and its local performance requires a two-dimensional joint representation of the time domain and the frequency domain in order to obtain an accurate description. Therefore, non-stationary signals usually use a two-dimensional function with two-dimensional variables of time and frequency.

3.1 Short-Time Fourier

Based on the traditional Fourier transform, STFT is proposed based on the non-stationary signal characteristics [9]. Add different window functions to the signal, propose local information, and then perform Fourier transform. The STFT uses a linear transformation method of signals. When analyzing a signal containing multiple components, there is no interference of cross terms, and it also has a small amount of calculation.

For non-stationary signals, people usually pay more attention to the instantaneous frequency of signals. Thus, the concept of "local spectrum" is introduced. The signal is extracted with a very narrow window function, and the signal outside the window is suppressed. Then, the signal is Fourier transformed in the window. The basic idea is to divide the signal into many small intervals and then use the Fourier transform for each small interval. In order to study the local characteristics of the signal at time t, it is necessary to strengthen the signal at time t, compress or filter the others. This is equivalent to extracting the signal with a finite length window.

$$s_t(\tau) = s(\tau)h(\tau - t) \tag{10}$$

Moving the window function continuously, this processing is used for all moments, and the result is STFT, defined as.

$$STFT_s(t,f) = \int_{-\infty}^{+\infty} s(\tau)h(\tau - t)e^{-j2\pi f\tau}d\tau \tag{11}$$

Where $h(t)$ is Hamming window

The corresponding STFT inverse transform is.

$$s(t) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} STFT_s(u,f)h(u - t)e^{j2\pi ft}dudf \tag{12}$$

In the STFT process, the length of the window determines the time resolution and frequency resolution of the spectrogram. The longer the length of the window function, the higher the frequency resolution after Fourier transform and the worse the time resolution. Conversely, the shorter the intercepted signal, the worse the frequency resolution, and the better the corresponding time resolution. Therefore, we should consider the time resolution and frequency domain resolution together. For non-stationary signals, the width of the selected window is preferably close to the length of each hop of the frequency hopping signal, and is compatible with local stationarity.

3.2 Adaptive Window

By analyzing the spectrum characteristics of frequency hopping signals, this paper proposes a kind of method for estimating window length in frequency domain. This method can still work in low SNR environment.

In frequency hopping communication, no matter which pseudo-random sequence is adopted, the carrier frequency will not be repeated in a short time. In this way, the frequency hopping period can be roughly estimated according to the spectrum characteristics of some intercepted signals, and the window length can be designed according to this information (Fig. 1).

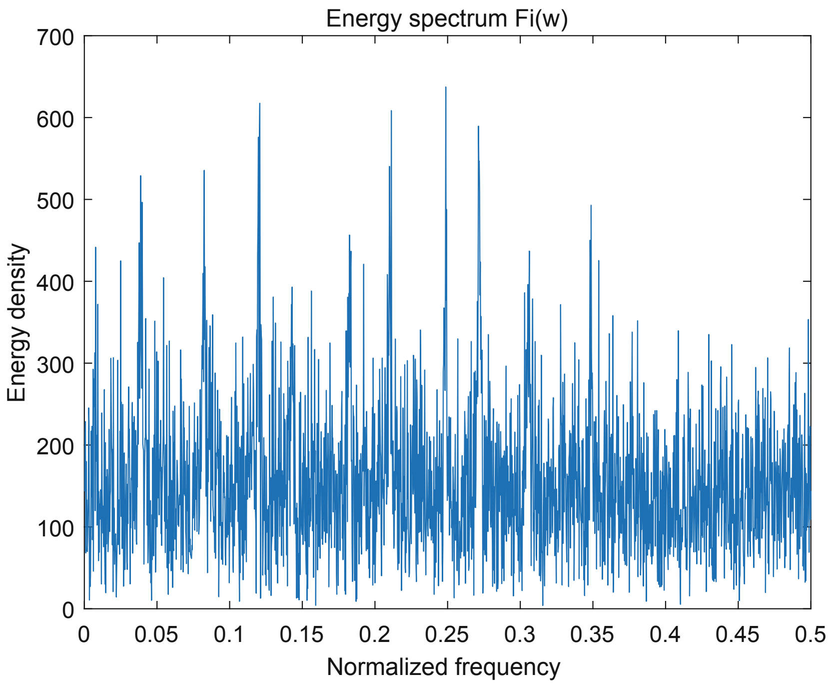

Fig. 1. Frequency domain characteristics of signals.

The specific steps are as follows.

Assuming that the received radio signal has completed the down conversion operation, and is an intermediate frequency signal. Divide the signal into N segments.

Select a fragment of data $x_i(n)$ and find the analytical form $z_i(n)$ of this data fragment, then DFT transform for segment of data and Get frequency domain Information of Signal $F_i(w)$.

$$z_i(n) = x_i(n) + jHilbert[x_i(n)] \tag{13}$$

$$F_i(w) = DFT[z_i(n)] = \sum_{n=0}^{N-1} z_i(n) W_N^{kn} \tag{14}$$

Choose half of the maximum value of $F_i(w)$ as the threshold λ to filter the noise. The value greater than λ in $F_i(w)$ is retained and the value less than λ is set to zero, and then get $G_i(w)$.

$$G_i(w) = \begin{cases} 0, & F_i(w) < \lambda \\ F_i(w), & F_i(w) > \lambda \end{cases} \tag{14}$$

Smooth $G_i(w)$ with Locally Weighted Regression, which is discussed in detail in [10]. According to the instantaneous frequency theory, the signal energy is concentrated along the instantaneous frequency in the frequency domain, while the noise is relatively dispersed. Sum $G_i(w)$ every few data points on frequency domain direction.

$$S_i(w_1) = \sum_{j=1}^{a-1} G_i(aw + j) \tag{15}$$

Among them, the length of $G_i(w)$ data is an integer multiple of a.

Find the number of peaks for $S_i(w)$, If the two peaks are close together, treat them as one. According to the number of frequencies and the length of the data, each frequency duration can be derived. You can set the window length N based on this information.

$$num_i = \text{findpeaks}(S_i(w)) \tag{16}$$

Perform 2–7 operations on all data segments and find the average of N_{aver} (Fig. 2).

$$N_{aver} = \frac{1}{N} \sum_{i}^{N} num_i \tag{17}$$

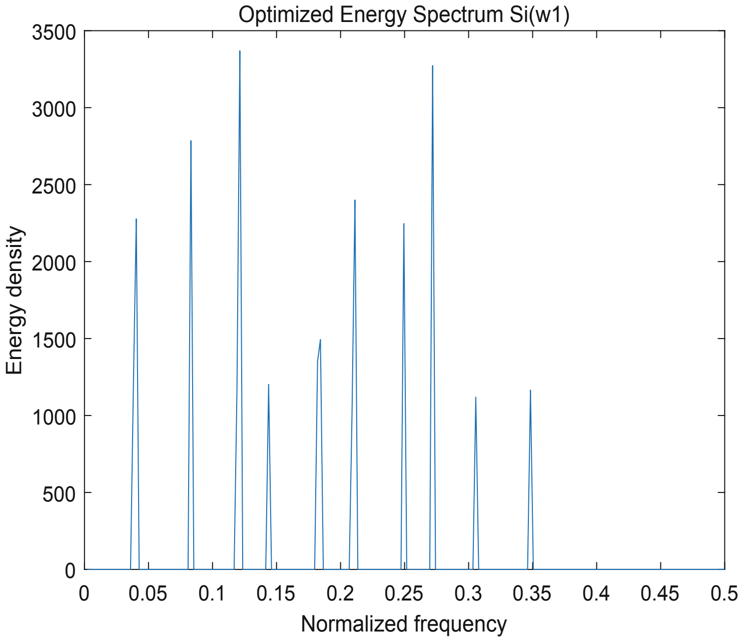

Fig. 2. Rough estimation of frequency number based on frequency domain characteristics

4 Hopping Parameters Estimation

Once the Time-frequency distribution of the signal is obtained, the next step is to estimate the FHSS signal parameters: hopping frequencies, hopping duration and hopping sequence.

Two methods for estimating parameters of frequency hopping signals have been proposed which are instantaneous frequency method [23] and maximum curve method [21]. Furthermore, according to the rough estimation information of frequency hopping period and the maximum curve method, the frequency hopping period estimation method is optimized (Fig. 3).

4.1 Instantaneous Frequency Method

The use of IF estimation is to characterize time-varying signals and estimate the signal parameters [11]. Extending its use for FHSS signals, the IF estimation from the peaks of the TFD

$$f_i(t) = \arg\{\max_f[\rho_z(t,f)]\} \quad 0 \leq t \leq T \tag{18}$$

Find the histogram of the instantaneous frequency and estimate the frequency hopping frequency set from the histogram.

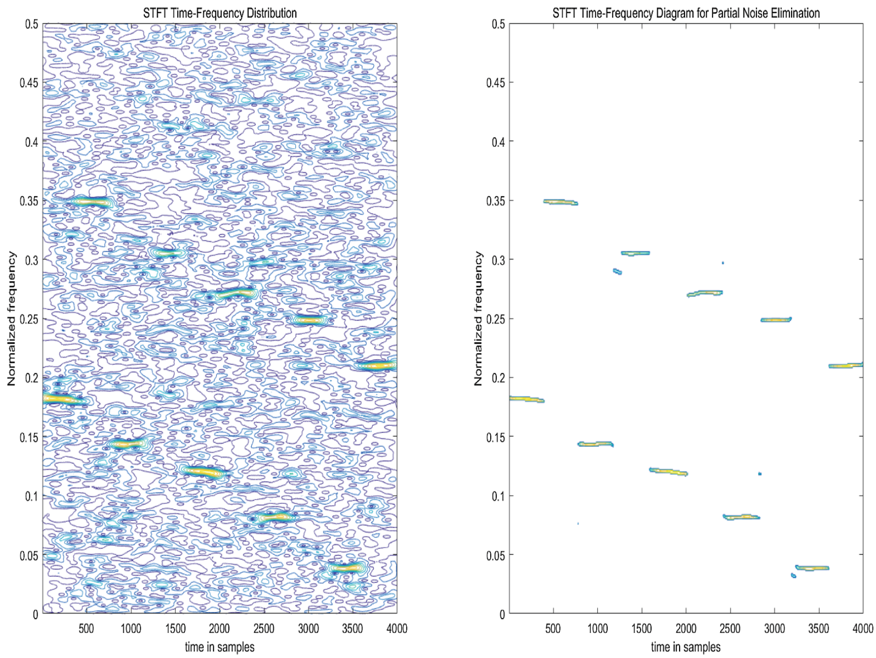

Fig. 3. Time-frequency distribution before and after noise removal

$$\hat{f}_h = \arg\{\max_f [hist(\hat{f}_i)]\} \quad 1 \le h \le M_h \tag{19}$$

Estimate the transition time by finding the reciprocal of $f_i(t)$.

$$\frac{df_i(t)}{dt} \simeq |\mathrm{f}_i(t) - f_i(t + \Delta t)|, \quad 0 \le t \le T, \tag{20}$$

Where Δt is the adjacent instantaneous frequency difference. It changes immediately within each hop interval, so the reciprocal value of this instantaneous frequency will appear at the maximum value at the time of the transition.

$$\hat{t}_{h,k} = \arg\{\max_t [\frac{df_i(t)}{dt}]\}, \quad 0 \le k \le N_h - 1, \tag{21}$$

The hopping carrier duration of the Kth hop is obtained by finding the time difference between the signal hopping times.

$$\hat{T}_{h,k} = \hat{t}_{h,k} - \hat{t}_{h,k-1}, \quad 0 \le \mathrm{k} \le \mathrm{N}_h - 1, \tag{22}$$

The averaging of $\hat{T}_h$ for all hops Nh results in the estimate of the hopping duration.

$$\hat{T}_h = \frac{1}{Nh} \sum_{k=0}^{Nh-1} \hat{T}_{h,k} \tag{23}$$

Once this frequency hopping frequency set F and frequency hopping period t are estimated, the average power is first calculated in one hop period.

$$f_{IF,avg,k} = \frac{1}{\hat{T}_{h,k}} \int_{t=\hat{t}_{h,k-1}}^{\hat{t}_{h,k}} \hat{f_i(t)} dt \tag{24}$$

Find the absolute value of the difference between the average frequency and the sum of each hop period.

$$D_{h,k} = |f_{IF,avg,k} - \hat{f}_h| \tag{25}$$

The instantaneous frequency during each hop period is as follows (Fig. 4).

$$\hat{f}_{h,k} = \arg\min_k (D_{h,k}) \tag{26}$$

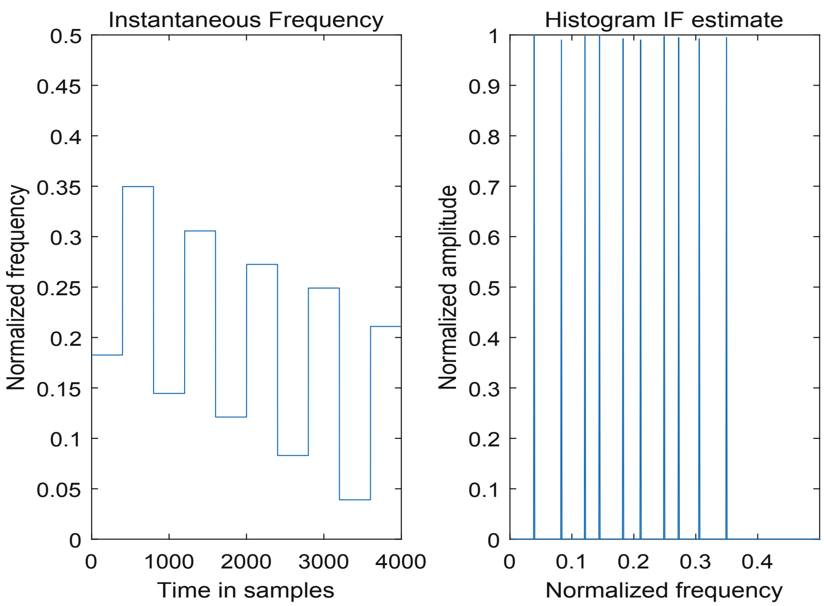

Fig. 4. IF estimation method: IF estimation from the peaks of TFD and Histogram of frequencies derived from the IF

4.2 Maximum Curve Method

The average power of additive Gauss noise may be much higher than that of signal. However, the noise is uniformly distributed on the time-frequency plane and the value of noise power distribution to every point on the time-frequency plane is very small. According to this characteristic, the maximum curve method is proposed [13].

Detailed steps are as follows:

Search for maximum amplitude at each time along the frequency axis and obtain the function between time and maximum amplitude as shown in Fig. 5.

$$y(n) = \max_k STFT(n,k) \tag{27}$$

Then the $y(n)$ is transformed by FFT to get $w(k)$. The abscissa k_f corresponding to the maximum value of $w(k)$ is the frequency hopping frequency, and its reciprocal is the frequency hopping period (Fig. 6)

$$w(k) = DFT[y(n)] = \sum_{n=0}^{N-1} y(n) W_N^{kn} \tag{28}$$

$$k_f = \arg\ \max w(k) \tag{29}$$

$$\hat{T} = 1/k_f \tag{30}$$

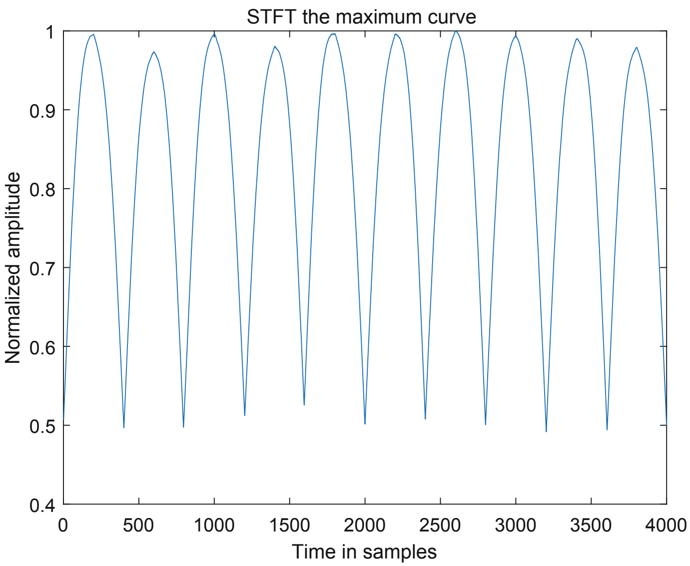

Fig. 5. Maximum curve method: the law of maximum signal amplitude conversion

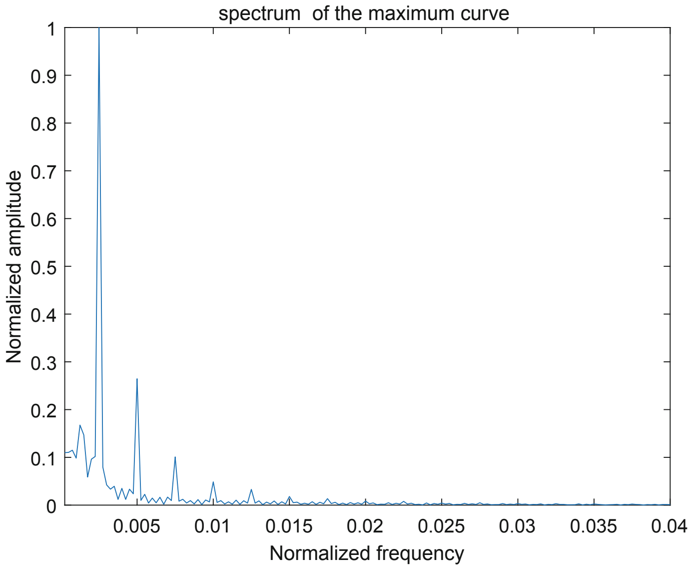

Fig. 6. Maximum curve method: frequency domain characteristics of maximum curve

Because the time-frequency diagram shows the local spectrum of the signal, the spectrum energy of the signal is larger than the noise energy near the instantaneous frequency of the signal at each moment. Therefore, the maximum curve $y(n)$ represents the law of the spectrum maximum changing with time, and equals to the component of the spectrum of the signal passing through the moving window. The period of the curve change is the frequency hopping period of the frequency hopping signal, and the corresponding time at the curve trough point is the time of carrier frequency hopping.

4.3 Optimizing Maximum Curve Method

According to the roughly estimated frequency hopping period, the method of estimating frequency hopping period by maximum curve can be optimized. After obtaining the maximum curve, Fourier transform is applied to the curve to obtain the frequency domain information. The frequency hopping period of the signal corresponds to the maximum amplitude in the frequency domain. Therefore, according to the number of roughly estimated frequencies, the searching range of maximum amplitude can be greatly reduced, and the accuracy of estimation can be improved.

5 Result

The performance of the method has been evaluated by simulation in the presence of additive white Gaussian noise.

5.1 Rough Estimation Method

Figure 7 is a rough estimate of the frequency hopping period using the frequency domain characteristics of the received signal. From the error curve, it can be known that when the signal-to-noise ratio is −15 dB, the error is less than 15%. Since this estimate is to design the window length and optimize and correct the subsequent methods, there is a large allowable error range, and the 15% error ratio meets the required requirements. It can be concluded that the adaptive window design method can work in a very low signal to noise ratio environment.

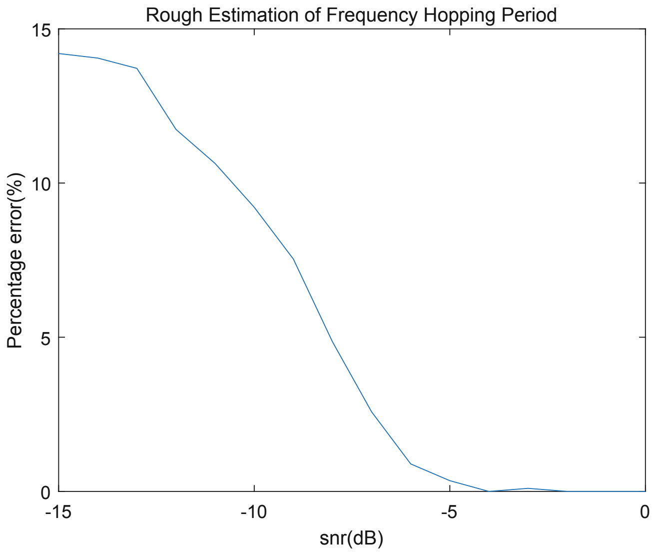

Fig. 7. Rough estimation error curve of frequency hopping signal period

5.2 Fine Estimation Method

After obtaining the STFT distribution, the maximum value curve method, the instantaneous frequency method and the improved maximum curve method are used to accurately estimate the frequency hopping period. As can be seen from Fig. 8, the improved method has a better performance improvement than the maximum curve method. Although the instantaneous frequency method performs better than the maximum curve method, the complexity is greater than it. The improved maximum curve method has the best performance and the complexity is lower than the instantaneous frequency method. As can be seen from Fig. 8, the improved method can achieve an error of zero at −8 dB.

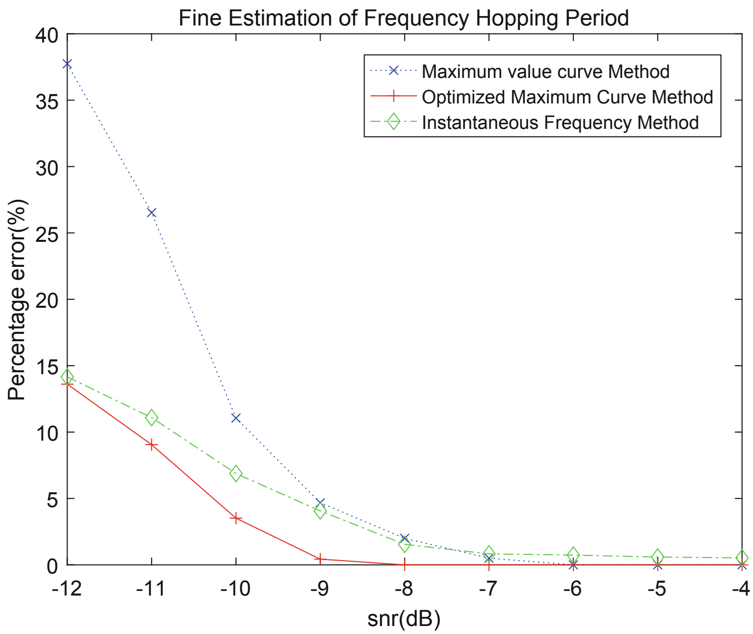

Fig. 8. Fine estimation error curve of frequency hopping signal period

6 Conclusion

In this article, we make full use of the frequency domain information of the received frequency hopping signal to design an adaptive window. At the same time, we use the rough estimation information to improve the frequency hopping period estimation method and obtain better estimation accuracy. Compared to other time-frequency analysis tools, such as the quadratic time-frequency distribution method, short-time Fourier changes have a very low complexity. And because the complexity of adaptive window design is also low, the overall complexity of the algorithm is low, and it has good performance. However, since the simulation environment is only an additive Gaussian channel, we also need to consider a more complex and realistic environment, such as Rayleigh channel, to fully estimate the feasibility of the method.

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