Blind Detection of Frequency Hopping Signal Using Time-Frequency Analysis

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Abstract—**The paper proposes a detection algorithm for the frequency hopping signals in intricate electromagnetic environment using time-frequency analysis. To overcome the difficulty brought by the unsteady distribution and energy fading, an adaptive time-frequency local threshold is applied to preprocess the spectrogram; And by the methods such as spectrogram modification and time-statistic, most of the interferences are successfully removed. And finally the detection of FH signals is realized.**

***Keywords-** intricate electromagnetic environment; time-frequency analysis; spectrogram; frequency-hopping signals; detection*

I. INTRODUCTION

Since the FH radios were widely equiped for military in many countries in 1980's, the scholars all over the world have successively started to do some deep researches on these hot questions. The detection methods, from the papers which are punished at present, can mainly be devided into two kinds: one is energy detection and the other is autocorrelation detection. The energy detection is the most common used FH signals detection method, and there are two main algorithms: one is based on multi-channel radiometry[1],[2],[3], the other based on multi-channel pulse-match[4],[5],[6]. The autocorrelation detection [7][,8],[9] includes single-hopping autocorrelation algorithms and multi-hopping autocorrelation algorithms. Compared with the energy detection algorithm, the latter has better detection performance, and reduces the operation complexity, but both the bandwidth and the least hopping period should be known in advance.

Though the detection methods above have got good performance, but they are mostly in the white noise condition, and need some prior knowledge of the signal to be detected. But in practical electromagnetic environment, for example the shortwave and ultra-shortwave environment, the circumstance is very complex: there are many interferential signals such as burst signals, which are mixed together with FH signals, and it is difficult to distinguish them; And there is serious energy fading, which causes the unsteadiness of the signals. Furthermore, as the incooperation side of the communication, there is no prior knowledge. Therefore, the methods above have some localization in the practice.

Because the signals of different kinds have different time-frequency characters in the spectrogram, according to these characters, signals of different kinds can be separated from the received mixture one by one[10],[11],[12].In this paper, we first analyze the signal components in the shortwave and ultra-shortwave environment and their different characters in the spectrogram, and then propose a new blind detection algorithm based on the spectrogram. It uses an adaptive time-frequency local threshold、power-detection、time-statistic and ect, to remove the influence caused by the interferences, and realize the blind detection of FH signals in the intricate electromagnetic environment.

II. PRINCIPLE OF THE ALGORITHM

For the surveillance of FH signals in the shortwave and ultra-shortwave environment, the signal denseness is very high, and the kinds are various. There are six main kinds: frequency-fixed signals, FH signals, burst signals, swept signals, radar signals and random noise. Figure 1 gives the spectrogram of the former five signals. Random noise is all kinds of channel noise and space interferences, in the spectrogram it behaves as random discrete points, which largely exist in Figure 1[13],[14].

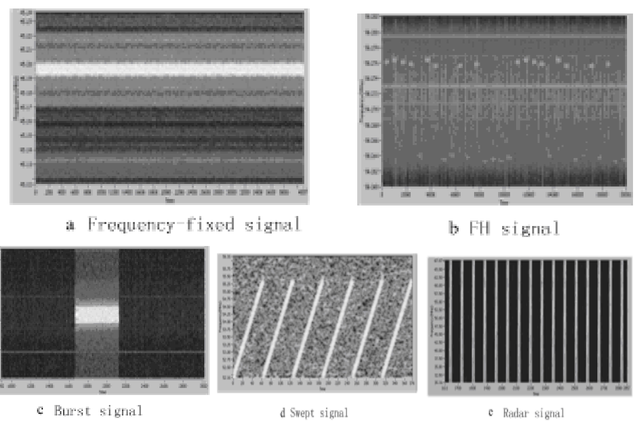

Figure 1 Spectrogram of common signals in shortwave and ultra-shortwave environment

From Figure 1, it is clear that the difference between the signals of different kinds is the way that signal instantaneous frequency changing with time: Frequency-fixed signals behave as one horizontal line with little wiggle; Burst signals behave as one short beeline or curve; Swept signals behave as several

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periodic diagonal lines in certain scope; Radar signals behave as a set of perpendicular lines of equi-distance; While the FH signals behave as a number of short line with the same length which could be linked-up along time domain on different frequencies.

Therefore, we can separate signals of different kinds according to different characters on the spectrogram, and finally realize the detection of FH signals. But due to the multi-path fading and the energy losing during the transmission, the energy of received signals is not steady. There are many broken points, and the amplitude changes with frequency and time greatly, and on some frequencies the FH signals is very weak. All the facts above make the detection very hard. So, before the separation of different signals, we need preprocess the spectrogram, to reduce the influence caused by the energy unsteadiness of the signal.

III. BINARY PREPROCESSING BASED ON THE ADAPTIVE TIME-FREQUENCY LOCAL THRESHOLD

In order to distinguish signals and noise in the spectrogram, we should make the binary preprocessing to normalize the points on the spectrogram to 0 or 1 according to a threshold.

$$Y(j,k)=\begin{cases}0 & ,X(j,k)\leq m\\ 1 & ,X(j,k)>m\end{cases} \tag{1}$$

In formula(1), $X(j,k)$ is the gray value of the jth time point and the kth frequency point (coordinate (j,k)) on the spectrogram, $Y(j,k)$ is the normalized value, and m is the threshold. After this processing, the value of every point on the spectrogram can mainly present the existence or not of the signals.

Due to the intricate electromagnetic environment of the shortwave and ultra-shortwave band, neither the energy of signal nor of the noise is stable. If we use a global threshold to normalize the spectrogram, wrong decisions may be made: when the energy of noise is strong, it may be considered as signal and be normalized to 1; When the energy of signal is weak, it may be considered as noise and be normalized to 0. Therefore, an adaptive time-frequency local threshold is adopted here, which can change according to the intricate electromagnetic environment.

First, a classical local binary algorithm, which is called Bernsen algorithm[15], is introduced. Consider one $(2d+1)\times(2d+1)$ area centered at the coordinate (j,k), the threshold is calculated as following:

$$m(j,k)=\frac{1}{2}\left(\max_{\substack{-d<n<d\\ -d<l<d}}\{X(j+n,k+l)\}+\min_{\substack{-d<n<d\\ -d<l<d}}\{X(j+n,k+l)\}\right) \tag{2}$$

Considering that the changing amplitudes of the signal gray values are bigger, while the noise gray values are much more flatter in practise, we improve the Bernsen algorithm as follows:

Calculate the mean minimum value of the local time-frequency area on the spectrogram, and add an appropriate value to it, then the sum is the threshold we need, its calculation expression is

$$m(j,k)=\frac{1}{\lambda(2d+1)^2}\sum_{i=1}^{\lambda(2d+1)^2} Z_i+\alpha \tag{3}$$

In this formula, Z_i is the value of the ith gray value of all the $(2d+1)\times(2d+1)$ points which are in ascending sort, $i=1,2,....,(2d+1)^2$, α is certain proper added value, which can preferably remove noise to some extent.

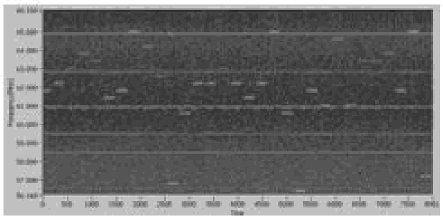

Figure 2 Original spectrogram of a practical signal

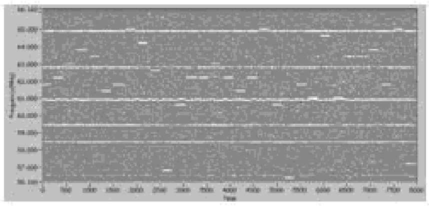

Figure 3 Spectrogram after binarization

Figure 2 and Figure 3 present the comparison of the spectrograms before and after the binarization. Figure 2 is the original spectrogram of a practical signal, from it, we can see the fading of even one FH signal is of great difference in different time and frequency band, the fading of signal between 63MHz and 64MHz is much greater than the signals in other bands. Figure 3 is the spectrogram after binarization. It is shown that using an adaptive time-frequency local threshold we can well distinguish signal and noise, and the signal distribution on the spectrogram is much clearly.

IV. SCANNING AND MODIFYING METHOD OF THE SPECTROGRAM

From Figure 3, we can see after binarization most of the signal and noise points are well distinguished, but not all the noise points are removed, there are still many random noise points. These points scatteredly distribute on the whole time-frequency platform, and have the character of isolation; While, due to the energy fading, the weak points in the signal may be considered as noise and binarized to 0, which will cause broken points in signals on the spectrogram.

To solve these two questions above, we adopt a parameter μ called scan-depth to modify the spectrogram in two facts:

1. To get rid of the noise points further

Choose certain proper scan-depth μ , and scan the spectrogram (after binarization) along every frequency row. When the length of 1 between two near 0 is less than μ , then replace these 1 with 0 of the same length; Otherwise, hold the original values on.

2. To remove the broken points in signals on the spectrogram

Choose a proper scan-depth μ , and scan the spectrogram along every time row. If the length of 0 between two near 1 is less than μ , replace these 0 with 1 of the same length; Otherwise, hold the original values on.

Figure 4 gives the processing of scanning and modifying sequence A with the scan-depth $\mu = 2$, and sequence B is the result.

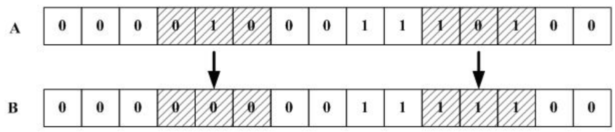

Figure 4 Principle of the scanning modification

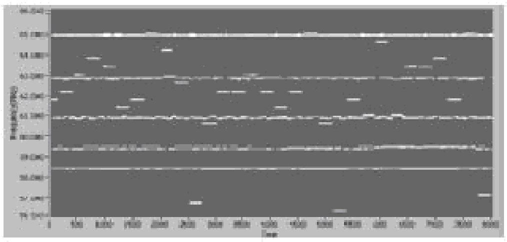

Figure 5 Spectrogram after modification

In the application, the scan-depth μ chosen to get rid of noise and broken points in signals is usually not the same. Therefore, we often scan and modify the spectrogram twice with different μ : First to remove noise points and later to remove the broken points in signals. Using this method, we modify the spectrogram after binarization (Figure 3), and get the new spectrogram as Figure 5. It can be seen that after the modification, the isolated noise points are mostly removed, and the broken points in signals almost disappeared.

V. ALGORITHMS OF REMOVING DIFFERENT INTERFERENCES

As aforementioned, different signals have different characters in the time-frequency domain, so we can adopted different methods for different interferences to remove them effectively. Combined with analysis of signal components in shortwave and ultra-shortwave band, this paper uses the spectrogram to get rid of the interferences from time domain、frequency domain and time-frequency domain, and finally realizes the auto blind detection of FH signal.

In time domain, compared with other signals, the time that FH signals stay on certain frequency is very short, but the time on different frequencies is of the same length, which is quite different from the frequency-fixed signals. Therefore, we can measure the signal energy in a longer time, with choosing an energy threshold, when the energy value is above the threshold, we consider it as frequency-fixed signal. The staying time of burst signals is also not long, but its staying time has no rules, which is different from FH signals, so we can make statistic of the staying time of the signals to distinguish FH signals and burst signals.

In frequency domain, although the band of FH signals is wide, but the bandwidth of single hop is narrow, which is different from radar signals and swept signals. Therefore, we can adopt a bandwidth threshold to distinguish FH signals from radar signals and swept signals.

In time-frequency domain, the near two hop can be linked up in time, and in spectrogram they behave as a group of short lines which can be connected to each other. Therefore, when the staying time of the burst signal happens to be the same with that of the FH signals, we can get rid of it in time-frequency domain.

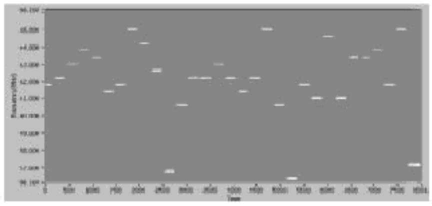

Figure 6 Spectrogram after removing the interferences

VI. THE FLOW OF THE DETECTION ALGORITHM

According to the methods above, we can get the flow of the detection algorithm of FH signals in the intricate electromagnetic environment:

Step1. Set the related parameters of short time frequency analysis, compute the spectrogram.

Step2. Binarize the spectrogram by the adaptive local time-frequency threshold to remove noise.

Step3. Scan and modify the spectrogram by the scan-depth to remove noise completely and to get rid of the broken points in signals.

Step4. Make statistic of the signal energy for a long time on every frequency to get rid of frequency-fixed signals by the energy threshold.

Step5. Set the bandwidth threshold to remove radar signals and swept signals.

Step6. Make statistic of the rule of signals' staying time and the link-up property on different frequency to delete burst signals, and finally realize the detection of FH signals.

VII. PERFORMANCE OF THE DETECTION ALGORITHM

Because the electromagnetic environment we analyzed is very intricate, it is hard to build a mathematic model for the signal detection to analyze the detection performance by quantitative analysis. Here, combined with the application of our system, we analyze it from the view of practice.

In this detection algorithm, many threshold parameters are referred, whether these parameters are chosen properly is the most important fact that impacts the detection performance. In our system, all these parameters are chosen by a large number of experiments by certain practical signals. The algorithm can correctly detect FH signals in shortwave and ultra-shortwave band with the hopping rate less than 10000 hop/s.

Furthermore, this algorithm making the final decision on whether FH signals exist mainly depends on the time statistic characters, so the number of hops in the surveillance band should be enough for the algorithm to find out the rule. If there are only a few hops in surveillance, it will be considered as burst signals, and a wrong decision will be made. In application, we find that the number of hops no less than five is enough to this algorithm.

VIII. CONCLUSION

The paper analyzes the signal components in the shortwave and ultra-shortwave environment and their different characters in the spectrogram, and proposes a blind detection algorithm based on the spectrogram. This algorithm can automatically detect FH signals without any prior knowledge. The operation complexity of the algorithm is low, it is easy to be realized in project, and has significant practical meaning.

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