An improved method for blind detection of multi-node cooperative spectrum based on correlation coefficient

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Abstract. According to the problem that the detection performance of the whole cooperative spectrum detection system is reduced due to the low Signal to noise ratio(SNR) of some perceived nodes in complex electromagnetic environment, an improved method of multi-node cooperative spectrum blind detection based on correlation coefficient is proposed. This method uses the characteristics of the received signal correlation function, combines the square rate combination to construct a new test statistic and deduces the threshold formula. This method effectively improves the problem of degraded cooperative spectrum detection performance due to the different SNR of each sensor node, improves the spectrum detection probability, and the computer simulation results verify the effectiveness of the method.

1. Introduction
With the evolution of information-based warfare and the advancement of science and technology, combat platforms are gradually becoming more intelligent. The platform should have strong electromagnetic environment awareness, situational awareness, electronic warfare control, and multi-platform coordination[1-2]. Fast, correct and effective spectrum detection is the premise and foundation for the realization of the intelligence of electronic systems. The electromagnetic environment faced by modern electronic warfare is increasingly complex, making the requirements for electronic warfare technology increasingly high[3]. In a complex electromagnetic environment, due to the influence of uncontrollable factors such as wireless channel interference, fading, and shadow effects, it is difficult for a single sensing node to obtain reliable transient sensing information, and the data collection and processing capabilities are also limited, especially for high-speed transmission. With data, the processing speed drops quickly and cannot meet the real-time detection requirements. Compared with the detection results of a single sensing node, the cooperative spectrum sensing of multiple sensing nodes can effectively improve the detection reliability and overcome the physical limitations of single-node spectrum sensing. Therefore, the cooperative spectrum sensing technology is widely mentioned and attention[4-5].

The spectrum sensing technology based on the cooperation mode utilizes the perceptual information on each node and effectively improves the perceptual performance. How to efficiently to integrate the sensory information about each node is a key technology for cooperative spectrum sensing. According to the different fusion information, the fusion principle can be divided into decision fusion and data fusion. In the proposed phase of cooperative spectrum sensing, the decision fusion principle (hard decision) is adopted. In the decision fusion algorithm, each sensory node first detects the detected signal locally and makes a local decision, then sends the sensory result to the fusion center. Finally, the fusion center synthesizes the results of each node and completes the final decision according to the fusion rule. Commonly used fusion rules mainly include "OR", "AND"[6], "Majority"[7] and other criteria. Literature
[8] optimizes the voting threshold of the voting fusion principle. Based on the minimum principle of the global error probability value, the spectrum sensing performance is optimized. In the complex electromagnetic environment, the principle of decision fusion will have some uncertainty and cannot fully reflect the information obtained by the node, so the principle of data fusion (soft decisions) is proposed. In the data fusion algorithm, each sensor node does not directly judge the detected signal locally. Instead, it sends the preprocessed data onto the fusion center or other sensing nodes. Finally, the fusion center processes and analyzes all the data. Judgment. The most common fusion methods are Equal Gain Combining (EGC), Selective Combining (SC), and Maximal Ratio Combining (MRC). Their basic principles are all performed on the data of a single sensing node. Weighted processing, the difference lies in different weights [9].

A sensing algorithm based on the eigenvalue of the covariance matrix of the receiving signal [10-11] mainly has the ratio of the maximum minimum eigenvalue (MME) algorithm and the difference of the maximum minimum eigenvalue (DMM) algorithm. The problem of energy detection algorithm affected by noise uncertainty is overcome, but the feature value decomposition operation is needed, the complexity of the algorithm is higher, and it is difficult to obtain accurate distribution of the statistical data. Leads to inaccurate sentencing threshold. Literature [12] proposed based on multi-antenna cooperative blind detection algorithm correlation coefficient (SCC), characterized by using a sample of the correlation function, binding, etc. gain combining to construct a new test statistic, and deriving the formula for determining the threshold, clearly algorithm performance Better than MME, and the algorithm is less complex than MME. However, when the SNR of each sensory node is different, the addition of a sensor node with a low SNR will lead to a decrease in the performance of the entire spectrum sensing system.

This paper aims at the problem of the decrease of cooperative spectrum detection performance caused by different SNR of different sensing nodes in complex electromagnetic environment. Reference literature [12] proposes a multi-node cooperative spectrum sensing algorithm based on correlation coefficient, and uses the characteristics of the correlation function of the received signal. Combined with the square rate combination to construct a new test statistic, the method of determining the threshold was studied, and a computer simulation experiment was conducted.

2. Multi-node cooperative spectrum blind detection algorithm based on correlation coefficient

2.1. System Model

Some text In general, signal detection can be expressed as a binary hypothesis test problem [13], that is, there are two kinds of assumptions: \( H_0 \) indicates that the signal to be detected does not exist, and the frequency band is free; \( H_1 \) indicates that the signal to be detected exists, and the frequency band is occupied. Therefore, the mathematical model of cooperative spectrum sensing is given by

\[
s_i(n) = \begin{cases} \frac{w_i(n)}{h x(n)} + w_i(n), & H_1, n = 1, 2, \cdots, N \\
\end{cases}
\]

In the formula, \( s_i(n) \) is the signal that the first sensing node sampled at the first moment; \( N \) is the number of samples in the observation interval; \( w(n) \) is the independent identically distributed additive Gaussian white noise with mean zero and variance is \( \sigma^2 \); \( x(n) \) is Detection signal; \( h \) indicates the channel amplitude fading factor.

Ideally, when the signal to be detected exists, the result of the decision is hypothesis \( H_1 \), whereas the result of the decision is hypothetical \( H_0 \). However, in the actual spectrum sensing process, due to the existence of various interference factors, the judgment of the presence or absence of the signal may cause errors. This leads to missed or false alarms. When the signal to be detected exists, the spectrum sensing result is zero hypothesis \( H_0 \), which will lead to the occurrence of missed detection and cause
the mutual interference of signals in the channel; and when the sensed channel is idle, the spectrum sensing result is hypothesis $H_1$, which will lead to virtual the emergence of the police reduced the spectrum utilization. The performance of the spectrum sensing algorithm can be measured by the following two probabilities: detection probability $P_d = P(H_1 | H_1)$; false alarm probability $P_f = P(H_1 | H_0)$. There is a certain balance between $P_d$ and $P_f$. To improve one performance index means to decrease the other performance index. Therefore, the reception operating characteristic (ROC) curve reflecting the relationship between $P_d$ and $P_f$ can better measure the influence of the parameters in the spectrum sensing algorithm and other factors on the performance of the algorithm.

2.2. Determination of test statistics

The correlation coefficient defining the received signal of the first sensing node and the second sensing node is

$$
\rho_{i,j} = \frac{\sum_{n=1}^{N} x_i(n)x_j(n) - N\bar{x}_i\bar{x}_j}{\sqrt{\sum_{n=1}^{N} x^2_{i}(n) - N\bar{x}^2_{i}}} \cdot \sqrt{\sum_{n=1}^{N} x^2_{j}(n) - N\bar{x}^2_{j}}, i \neq j
$$

According to the formula (2), $\rho_{i,j} = \rho_{j,i}$ can be obtained. Therefore, the correlation coefficient of the signals received by the $i$ sensing node and the $j$ sensing node need only be calculated once. Assuming $i > j$, if there are $L$ sensing nodes under this premise, $M = L(L - 1) / 2$ different $\rho_{i,j}$ can be calculated.

When the signal to be detected does not exist, the signal received by any sensing node is Gaussian white noise with a mean value of 0 and a variance of $\sigma^2$. At this time, the received signals between the sensing nodes are statistically independent, and in the Gaussian distribution, independent and the irrelevance is equivalent, when the sampling point tends to infinity, $\rho_{i,j} = 0$ can be obtained; when the signal to be detected exists, there is a certain correlation between the received signals between the sensing nodes due to the presence of the signal to be detected, and in this case, with the signal As the noise ratio increases, the correlation coefficient also increases ($\rho_{i,j}$ is a positive correlation). Therefore, when the sampling point $N$ tends to infinity, $\rho_{i,j} > 0$ can be obtained

$$
\begin{align*}
\rho_{i,j} &= 0, H_0 \\
\rho_{i,j} &> 0, H_1
\end{align*}
$$

(3)

However, when $H_0$ is the case, $\rho_{i,j} = 0$ is the value obtained when the number of sampling points $N$ approaches infinity. In the actual spectrum sensing process, since the sensing time is limited, $\rho_{i,j}$ can only be calculated by a limited number of sample points, that is, in $H_0$. In this case, $\rho_{i,j}$ is only approximately equal to zero. Therefore, when $H_0$, the actual value and ideal value of $\rho_{i,j}$ will also have a certain deviation, that is, $\rho_{i,j}$ will not be equal to 0 in the actual situation but obey a certain probability density function. According to the literature [14], in the case of a limited number of sample points, $\rho_{i,j}$ is appropriately transformed and follows the distribution of students whose degree of freedom is $N - 2$, that is
\[
\frac{\sqrt{N-2}\rho_{i,j}}{\sqrt{1-\rho_{i,j}^2}} \sim t_{N-2} \tag{4}
\]

For the convenience of description, the definition is as follows
\[
\beta_{i,j} = \frac{\sqrt{N-2}\rho_{i,j}}{\sqrt{1-\rho_{i,j}^2}}, (j > i) \tag{5}
\]

Analysis by Section 2.1 shows that for \( L \) sensing nodes, \( M = L(L - 1)/2 \) different \( \rho_{i,j} \) can be obtained. Therefore, \( M \beta_{i,j} \) can also be obtained.

For the actual environment, the SNR of different sensing nodes are also different. The correlation coefficient between the sensing nodes with low SNR is small. This part of the sensing nodes cannot bring more useful information to the cooperative spectrum detection. Should allocate smaller weights; The correlation coefficient obtained between the sensing nodes with high SNR is relatively large. This part of the sensing node can bring more useful information to the cooperative spectrum detection, so it should be assigned a larger weight. Calculating the squares of \( \beta_{i,j} \) calculated by different nodes can make large \( \beta_{i,j} \) values be assigned larger weights, and smaller \( \beta_{i,j} \) values can be assigned smaller weights. In this way, you do not need any a priori information to get the weight value, but also reasonably assign weights. Therefore, this article decided to use square-rate mergers to form test statistics \( T \), that is
\[
T = \sum_{j>i, j=1}^{L} \beta_{i,j}^2 \tag{6}
\]

Therefore, the decision criterion of the algorithm can be described as
\[
\begin{align*}
H_0: & \quad T < \gamma \\
H_1: & \quad T \geq \gamma
\end{align*} \tag{7}
\]

\( \gamma \) in formula (7) is the detection threshold.

2.3. Determination of detection threshold

In the spectrum detection process, it is important to determine the detection threshold that can keep the system at a constant false alarm probability. In general, there are two ways to determine the decision threshold. One method is to use a computer numerical simulation method (such as MATLAB simulation, etc.), when the system parameters (such as sampling points, etc.) have changed, the need to re-computer numerical simulation to generate new decision threshold, so this method is not universal the second method is to obtain the theoretical expression of the constant false alarm threshold. This method is simple and relatively suitable for the actual spectrum detection system. Therefore, this section derives the formula for determining the threshold of the decision based on the previous section.

From Section 2.2, we can see that when the \( H_0 \) test statistic is the square sum of the \( M \) students who follow the degree of freedom of the \( N-2 \), the literature [13] shows that when the degree of freedom \( N-2 \) tends to be positive, the student The distribution is approximately equal to the standard normal distribution, so when the number of sampling points \( N \) is large enough, the test statistic is the sum of the squares of the \( M \) standard normal distributions, and the chi-square distribution with degrees of freedom is \( M \). So the probability density function of \( T \) at \( H_0 \) can be described as
\[
f_T(t) = \frac{1}{(M/2-1)!} \frac{1}{2^{M/2}} t^{(M/2-1)} e^{-t/2} \quad t > 0 \tag{8}
\]

The relationship between false alarm probability and detection threshold can be expressed as
\begin{equation}
P_T = \Pr \{ T > \gamma | H_0 \} = 1 - \Pr \{ T \leq \gamma | H_0 \} = 1 - F(\gamma)
\end{equation}

Among them, \( F(\gamma) \) can be expressed as
\begin{equation}
F(\gamma) = \int_{-\infty}^{\gamma} \frac{1}{(M/2-1)!} \frac{1}{2^{M/2}} t^{M/2-1} e^{-t^2/2} dt
\end{equation}

From the above analysis, the detection threshold \( \gamma \) can be expressed as
\begin{equation}
\gamma = F^{-1}(1 - P_T)
\end{equation}

From Equation (6) and Equation (11), it can be seen that the test statistic of the algorithm is only related to the received signal to be detected and has nothing to do with factors such as noise variance, so it does not need to know any prior information, so this algorithm is not subject to Impact of noise uncertainty.

2.4. Algorithm Steps

By calculating the correlation coefficient of the signals received by the different sensing nodes, and then deforming the correlation coefficient according to the demand, in view of the problem that different sensory noising ratio will lead to the reduction of spectrum detection performance, the fusion method of the square rate merger will be adopted to form the new survey statistics. The test statistic is greater than the detection threshold and the result of the determination is \( H_1 \), and when the detection threshold is less than the detection threshold, the result is \( H_0 \). The specific algorithm flow is as follows:

Step 1 According to formula (2), the correlation coefficient \( \rho_{i,j} \) between the detected signals received by different sensing nodes is calculated.

Step 2 According to equation (5), the obtained correlation coefficient is modified accordingly, and the test statistic is obtained according to formula (6).

Step 3 According to formula (11), the detection threshold is calculated.

Step 4 Judgment results are obtained based on the formula (7).

3. Simulation results and analysis

The simulation parameters and detection environment are set as follows: the signal to be detected is BPSK modulation, the symbol rate is \( R_s = 2 \text{Mbit/s} \), and the carrier center frequency after signal down conversion is \( f_c = 7\text{MHz} \). Under multipath fading conditions, the multipath fading channel obeys the Rice distribution, Rice factor \( K = 25 \), and each path delay differs by one sampling period in turn. The SNR of each channel is 0dB, and the number of multipaths is 3. On the receiving side, band-pass sampling processing is performed on the received signal, sampling frequency \( f_s = 20\text{MHz} \), Monte Carlo simulation times is 1000.
Figure 1. Two methods for detecting performance when the SNR is the same

Figure 1 shows the relationship between the detection performance and the signal to noise ratio in Gaussian channel environment in the case of that the number of sensing nodes is $L=10$, the number of sampling points is $N=1000$, and the false alarm probability is $P_f = 0.05$. As a result, the detection performance of both methods increases as the SNR increases. When the sensing nodes are in the same SNR environment, the detection performance of this method is better than that of [12], but the improvement of detection performance is not obvious.

Figure 2. ROC Curves of Two Methods with Different SNR

Figure 2 shows the ROC of the two methods when the sensing nodes are in different signal-to-noise environments under multipath fading environment conditions. The number of sampling points is $N=1000$; the number of sensing nodes is 10; the SNR of each sensing node is -20dB in sequence, -18dB, -16dB, -14dB, -12dB, -10dB, -8dB, -6dB, -2dB, -0dB. As can be seen from Figure 2, the ROC curve of the proposed method is above the ROC curve of the method [12], and when the false alarm probability is 0.05, the detection probabilities of the methods of this paper and the literature [12] are 0.921 and 0.482 respectively. Therefore, the detection performance of this method is better than that of the literature [12] method when the sensing nodes are in different SNR environments. The SNR for -10 dB to replace the perception of nodes SNR for -30 dB perception nodes, can be seen from the figure 2, due to low SNR perception nodes to join SCC perception performance degradation is serious, and the method detection performance decline is smaller. Therefore, the problem is that the detection performance of SCC method will be seriously reduced by the addition of perceived nodes in the environment of low SNR. The method in this paper can improve this problem.
Figure 3. The relationship between this method and $N, L$

Figure 3 shows the detection performance of the proposed method under different sensing nodes $L$ and different sampling points $N$ when the SNR is -10 dB and the false alarm probability $P_f = 0.05$ in Gaussian environment. As can be seen from Figure 3, when the number of sensing nodes is the same, the detection performance increases with the number of sampling points; when the number of sampling points is the same, the detection performance increases with the number of sensing nodes.

4. Summary

Aiming at the problem that the detection performance of the entire cooperative spectrum detection system is degraded due to the low SNR of some sensing nodes in complex electromagnetic environment, an improved multi-node cooperative spectrum blind detection method based on correlation coefficient is proposed. First, the correlation coefficients of the received signals between different sensing nodes are calculated. Secondly, the correlation coefficients are appropriately transformed to obey the student distribution. Finally, the squared rate of correlation coefficients after the transformation is combined as the test statistic, and its decision threshold is deduced. Simulations show that the proposed method has better detection performance under the condition that the SNR of sensing nodes are different.

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