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An Improved Cognitive Radio Spectrum Sensing Algorithm

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Abstract

To improve the cognitive radio user's detection performance and reduce the complexity, this paper composites the Fractal box dimension algorithm and the 3th-order cyclic-cumulate (TCC) algorithm and improves the TCC algorithm, so a novel detection algorithm is proposed that the Fractal box dimension is used when the signal to noise (SNR) is high, while the improved TCC algorithm is used when the SNR is low. This new algorithm not only avoids using TCC algorithm with high complexity when the channel environment is good, but also reduces the decision complexity of TCC algorithm. Simulation result shows that this algorithm obtains good detection performance with lower complexity than the traditional TCC algorithm.

Keywords: Cognitive radio, Spectrum sensing, Fractal box dimension, 3th-order cyclic-cumulate (TCC).

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1. Introduction

With the rapid development of communication technology, cognitive radio technology (CR) can fundamentally relieve the tension of the spectrum resources. Spectrum sensing is the key technology of CR. Classic spectrum detection technology includes: the matched filter detection, energy detection and cyclostationary feature detection [1-2]. The Matched filter detection requires a priori information of the signal. Energy detection can be largely restricted without the noise power and the presence of noise variance uncertainty is also a kind of defect. Cyclostationary feature detection can effectively distinguish between signal and noise, but its complexity is high $(O(N^2))$ [4]. Giannakis points that 3th-order cumulate assay can distinguish between signal and noise, but it builts on a stable signal, and there are more non-stationary signals or time-varying signal in the communication system [5]. Gardner proposes a higher order Cyclostationary theory, but its complexity is high [5-6]. According that the fractal box dimension can describe signal characteristics at high SNR with low complexity, this paper presents a new detection scheme that using Fractal box dimension algorithm in high SNR, and using TCC in low SNR detection [7]. This paper also improved the TCC to reduce its complexity. It can achieve to detect without noise information and with low complexity.

2. Spectrum Detection Algorithm Analysis

Considering the classical spectrum detection algorithms' defect, some new detection algorithms are continuous exploring. Fractal box dimension and high-order cyclic-cumulate, as classical algorithms of mathematical field, are also used in signal detection. This paper integrated the advantages of the two detection methods to detect signal.

2.1. Fractal Box Dimension

Fractal theory originated from research on system geometric structure which is complicated and irregular, thinks any internal relatively independent part can represent the global, Set up the part to analyze the overall thinking methods.

The fractal dimension can measure the irregularity of the signal, and box dimension is often used to describe the fractal signal's geometric scale in the practical [7].

(F, d) is a metric space, and R is the non-empty compact set family of F, ε is a nonnegative real number, B(f, ε) is a closed ball whose center is at the f and radius is ε , A is a nonempty set of F, then for every positive ε , the minimal closed ball number, which can cover A, is:

$$N(A,\varepsilon) = \{M: A \subset \bigcup_{i=1}^{M} B(f_i,\varepsilon)\}$$
(1)

 $f_{1}f_{2}...f_{M}$ are different points of F.

N/2

Definition 1: f is the continuous function of closed set T in R, F is the set of R^2 .

$$F = \{(x,y): x \subset T \subset R, y = f(x) \subset R\} \subset R^2$$
(2)

 $D_{B}(f) = \lim_{\epsilon \to 0} \{ \sup \frac{\lg N(F, \tilde{\epsilon})}{-\lg \tilde{\epsilon}} : \tilde{\epsilon} \in (0, \epsilon) \}$ If exists, then we named $D_{B}(f)$ is the box dimension of

function f.

We can simplify the calculation of the fractal box dimension for the digital point set of discrete signals in space. We assume the sampling sequence of the signal: $f(t_1)$, $f(t_2)$, $f(t_N)$, $f(t_{N+1})$, and N is even.

$$d(\Box) = \sum_{i=1}^{N} |f(t_i) - f(t_{i+1})|$$
(3)

$$d(2\Box) = \sum_{i=1}^{\infty} (\max\{f(t_{2i-1}), f(t_{2i}), f(t_{2i+1})\} - \min\{f(t_{2i-1}), f(t_{2i}), f(t_{2i+1})\}$$
(4)

Then the box dimension can be defined as:

$$D_{B}(f) = 1 + \log_{2} \frac{d(\Box)}{d(2\Box)}$$
(5)

The judgment rule as follows (H_0 represents the primer user signal is absence, while H_1 represents the primer user signal exists) :

$$D_{_{B}}(f) \begin{cases} >\lambda_{_{1}} & H_{_{0}} \\ \leq \lambda_{_{1}} & H_{_{1}} \end{cases}$$

 λ_1 is given according to the specific signal characteristics and specific false alarm probability.

Noise or modulated signal has its inherent geometry, so its box dimension has fixed value. Classification feature can have a clear boundary in the decision space, and Fractal algorithm is not sensitive to fractal noise and Gaussian noise. In addition, the Fractal dimension algorithm doesn't need a priori knowledge of signal and noise.

2.2. 3th-Order Cyclic-Cumulate (TCC)

Definition 2: For a Cyclostationary signal s(t), the 3th-order cumulate is:

$$C_{3s}(t;\tau_1,\tau_2) = E\{s(t)s(t+\tau_1)s(t+\tau_2)\}$$
(6)

We assume the fixed time-delay τ_1 , τ_2 , if the 3th-order cumulate of s(t) exists its Fourier series expansion relative to t, then

$$C_{3s}(t;\tau_{1},\tau_{2}) = \sum_{\alpha \in \Omega_{s}} C_{3S}^{(\alpha)}(\tau_{1},\tau_{2}) e^{j\alpha t}$$

$$C_{3S}^{\alpha}(\tau_{1},\tau_{2}) = \lim_{T \to \infty} \frac{1}{T} \sum_{t=0}^{T-1} C_{3S}(t;\tau_{1},\tau_{2}) e^{-j\alpha t}$$
(8)

The $\Omega_3^{i} = \{ \alpha: C_{3s}^{\alpha} \neq 0, 0 \le \alpha \le 2\pi \}$, and α is the cyclic-frequency of signal's 3th-order cumulate. Fourier factor C_{3s}^{α} is 3th-order cyclic cumulant about α .

Due to the actual existence deviation of 3th-order cumulate. In practical application, we can only analysis and hand finite signal, then we can asymptotically consistent estimate with the following formula [6]:

$$C_{3y}^{\alpha}(\tau_{1},\tau_{2}) = \frac{1}{N} \sum_{t=0}^{N-1} y(t) y(t+\tau_{1})(t+\tau_{2})$$
(9)

The classic 3th-order cumulate algorithm is as Figure 1.



Figure 1. TCC Algorithm

We can get the judgment rule.We assume $\bar{\tau} = (\tau_1, \tau_2)$, and $f(t; \bar{\tau}) = y(t)y(t+\tau_1)y(t+\tau_2)$, then the cyclic-spectrum of $f(t; \bar{\tau})$ is:

$$\mathbf{S}_{3f_{\tau\bar{\tau}}}(\alpha,\omega) = \lim_{T \to \infty} \frac{1}{T} \sum_{t=0}^{T-1} \sum_{\varepsilon \to \infty}^{\infty} \operatorname{cum}\{f(t;\bar{\tau}), f(t+\varepsilon;\bar{\tau})\} e^{-j\omega\varepsilon} e^{-j\alpha t}$$
(10)

$$\mathbf{S}_{3f_{\tau\bar{\tau}}}^{*}(\alpha,\omega) = \lim_{T \to \infty} \frac{1}{T} \sum_{t=0}^{T-1} \sum_{\epsilon \to \infty}^{\infty} \operatorname{cum}\{f(t;\bar{\tau}), f^{*}(t+\epsilon;\bar{\tau})\} e^{-j\omega\epsilon} e^{-j\alpha t}$$
(11)

The prerequisite for judging is that we got $\frac{S_{3f}}{\tau\tau}^{(2\alpha,\alpha)}$, and $\frac{\sum \alpha}{3c}$ with the assumed α .

$$\sum_{3c} \alpha = \begin{pmatrix} R_{e} \{ \frac{S + S^{*}}{2} \} & I_{m} \{ \frac{S - S^{*}}{2} \} \\ I_{m} \{ \frac{S + S^{*}}{2} \} & R_{e} \{ \frac{S - S^{*}}{2} \} \end{pmatrix}$$
(12)

We use $T_{3c}^{\alpha} = TC_{3y}^{\alpha} \sum_{3c}^{-1} C_{3y}^{\alpha}$, get the detection probability $P_{D} = P\{T_{3c}^{\alpha} > \gamma; H_{1}\} = Q(\frac{\gamma \cdot NT}{2\sqrt{NT}})$, and get $P_{F} = P\{T_{3c}^{\alpha} > \gamma; H_{0}\} = Q_{x^{2}}(\gamma)$, $Q_{x^{2}}(\gamma)$ is the complementary cumulative distribution function, P_{F} is the false alarm probability.

2.3. The analysis of algorithm

2.3.1. The calculating complexity

This paper will measure the real addition number and the real multiplication number as the calculation complexity of algorithm. In Table 1, the B and B' respectively represent the multiplication number and the addition number of two-dimensional matrix inverse operation, as Table 1.

Table 1. Complexity Comparison			
Algorithm	Number of real	Number of real	
	multiplications	additions	
ED	4T	4T-1	
Box dimension	1	3T-2	
TCC	$24T+3L_{FFT}+B$	$21T+3L_{FFT}+B$	

 $L_{\rm FFT}$ and $L_{\rm FFT}$ respectively represents the multiplication number and addition number of FFT calculating [9], T is the total sampling points. Then the traditional TCC's calculating complexity is:

The real multiplication number is: ${}^{8T+L}_{\rm FFT} + 16T + 2L_{\rm FFT} + B = 24T + 3L_{\rm FFT} + B$

The real addition number is:

$$7T+L'_{FFT}+14T+2L'_{FFT}+B'=21T+3L'_{FFT}+B'$$
(13)

It is obviously that the complexity of box dimension is lower than ED detection algorithm, and TCC algorithm's complexity is the highest. Cognitive radio need fast effective detection to check whether the main user exists, so high demand for detective rate, and high complexity influence detective rate, obviously TCC is not suit for high speed detection.

2.3.2. The detection analysis

From Figure 2, the gauss noise's box dimension value is about 1.415. Along with the decreases of SNR, Signal is submerged in noise, its box dimension values is nearly same with the noise's box dimension values.



Figure 2. Different Signal's DB(f)

As the BPSK signal for example, we can distinguish the noise and signal when the SNR is greater than 5dB. We simulate the Fractal box dimension algorithm, ED algorithm and TCC algorithm under the same condition (BPSK modulation, sampling 4096 points, over sampling 4 points, 50MHz carrier, and gauss noise). The simulation result is showed as Figure 3.

From the above, the Fractal dimension's complexity is lower than ED, and its detection performance is good with high SNR (greater than 5dB); the TCC's complexity is the highest, but its performance is good when the SNR (lower than -10dB) is low.



Figure 3. Probability of Detection

3. The Improved Spectrum Detection Algorithm

Although Fractal dimension calculates easy, but poor performance in detection when SNR is low. TCC's good performance in detection, but complexity is high. This article proposed a new spectrum detection algorithm by integrating the advantages of box dimension and TCC. It means we use Fractal dimension when SNR is high, and when SNR is low we use TCC, we also improve the traditional TCC, decrease its complexity.

3.1. The improvement of TCC

In the formula (9), $\alpha \in \{\alpha_1, \alpha_3\}$ and $\{\alpha_1, \alpha_3\}$ is the possible cyclic-frequency by observing

the FFT of 3th-order cumulate, $\{\alpha_1, \alpha_3\}$ respectively represent the carrier's one-order cyclic-frequency and 3th-order cyclic-frequency. Then we get the 3th-order cyclic-cumulate value and statistics with α . Though this method can know the statistics' distribution, but the complexity is high. Since α can be measured by observing, we can simplify the following steps. It means that we do not need to return to find the corresponding 3th-order cyclic-cumulate and cyclic-spectrum for detecting. The improved TCC algorithm is showed in Figure 4.



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Figure 4. the improved TCC algorithm

The sampling dates are dividend to L parts (L_i represents the i-th part), in every part, we get FFT for P points, and divided by i+1, the result approximates the formula (13), ${}^{\omega_{max}}$ and ${}^{\omega_{max}}$ (${}^{\omega_{max}} \neq 0, \omega_{max} \neq 0$) are respectively corresponding to the highest amplitude in the frequency domain. If the primer user's signal exists and the signal's carrier frequency is ${}^{\omega_0}$, then the ${}^{\omega_{max}}$ will be constantly at the ${}^{\omega_0}$ or ${}^{3\omega_0}$ with the continuous superposition and the ${}^{\omega_{max}}$ will be constantly at the ${}^{\omega_0}$. If there is only the noise, the ${}^{\omega_{max}}$ and the ${}^{\omega_{max}}$ will be constantly at the 0. The ${}^{\omega_{max}}$ just plays a supporting role. If ${}^{\omega_{max}=\omega_{max}}$, then we can be more sure that the signal exists. The judgment rule is:

decision=
$$\begin{cases} H_0 \ (\alpha_m \text{change}) \text{and} (\alpha_m \neq \alpha_m) \\ H_1 \ (\alpha_m \text{unchange}) \text{or} (\alpha_m \equiv \alpha_m) \end{cases}$$
(14)

The complexities of algorithms are showed in Tab.2. From the table, the improved TCC algorithm's real addition number and the real multiplication number are all significantly reduced.

Table 2. Complexity Comparison		
Algorithm	Number of real	Number of real
	multiplications	additions
TCC	$24T{+}3L_{\rm FFT}{+}B$	$21T+3L_{FFT}+B$
Improving TCC	$8T+2L_{FFT}$	$7T+2L_{FFT}$

3.2. The improved detection algorithm

We assign λ_1 as the threshold, if $D_B(f) > \lambda_1$, it represents there is no signal, or the signal exists. The improved detection algorithm steps as follows:

Step1 assign λ_i , calculate the signal's $D_B(f)$, if $D_B(f) < \lambda_i$, then transmit 1bit result to fusion center, return to step6.

Step2 let the received signal y(n) to be zero mean, divide the sampling points to L parts,

and P points of every part. Calculate $s(n)=y(t)y(t+\tau_1+\tau_2)$. Then $Y(\omega)=\frac{1}{p}FFT(y(n))$ } and $Y'(\omega)=\frac{1}{p}FFT(y(n))$ }

for every part. α_m and α_m respectively represent the ω values which are corresponding to the highest amplitude of $|Y(\omega)|/i$ and $|Y'(\omega)|/i$.

Step3 Constantly overlay the $^{Y(\omega)}$ of every part, receive the $^{\alpha_m}$ and $^{\alpha_m}$ every part until the last part.

Step4 The judgment rule is:

 $\begin{array}{l} \text{decision} = \begin{cases} H_0 \; (\alpha_m \text{change}) \text{and} (\alpha_m \neq \alpha_m) \\ H_1 \; (\alpha_m \text{unchange}) \text{or} (\alpha_m \equiv \alpha_m) \end{cases}$

Step5 If the decision is H_0 , the CR user doesn't transmit any information to fusion center; if the decision is H_1 , the CR user transmits 1 bit information to the fusion center as there has primer user's signal.

Step6 The detection is over.

3.3. The analysis of the improved algorithm

We assume that the probability of high SNR of channel environment is Pa, and the probability of low SNR or just with noise of channel is 1-Pa, so the complexity of the improved algorithm is:

The real multiplication number: ${}^{L=1*P_a+(1-P_a)*(8T+2L_{\rm FFT})}$

The real addition number: $\dot{L} = (3T-2)*P_a + (1-P_a)*(7T+2L_{FFT})$

Because $^{0 \leq P_a \leq 1}$, then $^{1 \leq L \leq 8T+2L_{FFT}}$, $^{3T-2 \leq L \leq 7T+2L_{FFT}}$, it is obviously that its total minimum complexity can achieve the box dimension complexity. When the CR users are all in the good environment, the total complexity can be far less than the improved TCC algorithm's.

The simulation of the detection algorithm proposed in this paper is showed in Fig. 5. We divided the sampling points to 16 parts with 256 points every part, the primer user's signal is BPSK modulated signal, we also guarantee the probability of false alarm in box dimension algorithm is 0.1. The λ_1 is 1.41.



Figure 5. Probability of Detection

From the Fig.5, we can find that the improved algorithm reduces the calculating complexity, and at the same time guarantees the high detection probability at different SNR. It proves the effectiveness of the improved algorithm.

4. Conclusion

To guarantee the detection performance and reduce the calculating complexity, this paper had two aspects of the work, firstly it improved the TCC algorithm to reduce its complexity; secondly it proposed a new detection algorithm by integrating the advantages of box dimension algorithm and TCC algorithm, which adopted the Fractal box dimension algorithm when the SNR is high and adopted the improved TCC algorithm when SNR is low. The another character of the algorithm is that it is not sensitive to the gauss noise, and can still detect even the noise variance is unknown or the noise variance has the uncertainty.

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