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A Novel Energy Detection Algorithm for Spectrum Sensing in Cognitive Radio

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Abstract: This study focuses on a novel energy detection algorithm for spectrum sensing in cognitive radio networks. How to set the decision threshold is the key part of the energy detection and our novel energy detection gives out a new method to set the threshold via the experiment results. In the conventional energy detection, the threshold is set by the energy that changes with the SNR, however, the ratio of the maximum energy to the mean energy of the received signal, which is dimensionless and nearly a constant, is used to set it in this study. At the same time, the fourth-order moments are used in the novel energy detection algorithm. The performance of this novel algorithm is investigated by Monte-Carlo simulation and compared with that of the conventional energy detection and enhanced energy detection algorithms. The simulation results show that the performance of the proposed algorithm is enhanced by at least 3 dB, when P_d is lager than 0.8, comparing with the enhanced energy detection in Hao's study.

Key words: Spectrum sensing, energy detection, threshold, fourth-order moments, Monte-Carlo simulation

INTRODUCTION

To solve the dilemma of spectrum scarcity and spectrum underutilization, Cognitive Radio (CR) firstly proposed by Mitola as an upgraded version of the normal Software Defined Radio (SDR) in 1999 (Mitola and Maguire, 1999), can opportunistically utilize the unoccupied spectrum without harmful interference to Primary User (PU). In Cognitive Radio Network (CRN), the challenges exist on many aspects such as spectrum sensing, spectrum accessing, spectrum sharing and resource allocation (Pei *et al*., 2010).

Spectrum sensing is therefore a fundamental requirement in CRN. Many signal detection techniques can be used in spectrum sensing in order to enhance the detection probability. Generally, spectrum sensing techniques can be classified into three broad categories (Cabric *et al*., 2004) energy detection, matched filter and cyclostationary feature detection (Enserink and Cochran, 1994; Turunen *et al*., 2009). When prior knowledge of the PU signal is not available, the energy detection method is optimal for detecting any zero-mean constellation signals. Matched filter has been shown to be optimal signal detection if a secondary user has a prior knowledge of the PU signal. If the modulation schemes of the primary signals are known, then the cyclostationary feature detector can differentiate primary signals from the local noise by exploiting certain periodicity exhibited by the mean and autocorrelation of the corresponding modulated signals (Quan *et al*., 2009).

Earlier studies on spectrum sensing of energy detection have focused primarily on single or cooperation detection, but are limited to the detection of signals in the time domain. A closed-form expression to the optimal threshold of local detection that can be adjusted to different applications as needed is shown (Xie *et al*., 2009). Digham *et al*. (2007) presented an analytical approach and obtain closed-form expressions for the probability of detection over Rayleigh and Nakagami fading channels. Hao and Zu (2009) proposed an enhanced energy detection algorithm. However, the authors just increase the parameter E_s/N_0, however, the algorithm of energy detection does not enhance. The double-threshold energy detection algorithm was derived and the detection performance was analyzed (Srivastava and Banerjee, 2009). However, the double-threshold energy detection algorithm is not always better than signal version. It can be shown that cooperative double-threshold energy detection algorithm is better than the single version; on the contrary, the performance of single-threshold detection is better than the double version when they detect independently (Wu *et al*., 2009).

A novel energy detection algorithm is proposed in this study in order to solve the problem essentially in Hao's study. The contribution of this study is twofold. First, the fourth-order moments framework for the energy detection was proposed. In addition, we derive a novel method to set the threshold used in the energy detection.

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CONVENTIONAL ENERGY DETECTION

In order to avoid being interfered with the primary users when the bands are already occupied, detection should be made before the cognitive radio to access the frequency bands. So the most critical point is the spectrum sensing which decides success or failure of the following steps. In the cognitive ratio scenario, the information of the PU signal is hardly available, so the use of the matched filter can be severely limited. At the same time, cyclostationary detection is more complex to implement than the energy detection and requires a prior knowledge of PU signal such as modulation types. However, energy detection is simple and able to determine spectrum-occupancy information quickly, so it is adopted as the building block for constructing the proposed wideband spectrum sensing techniques. The target of cognitive radio spectrum sensing is to determine if a licensed band is currently used by its primary user or not. This can be formulated into a binary hypotheses testing problem (Digham *et al*., 2007).

$$x(k) = \begin{cases} n(k), & H_0(\text{absent}) \\ s(k)+n(k), & H_1(\text{present}) \end{cases} \quad (1)$$

where, n = 1 ,..., K; K is the number of samples. The primary user's signal, the noise and the received signal are denoted by s(k), n(k) and x(k), respectively. The noise is assumed to be Additive White Gaussian Noise (AWGN) with zero mean and variance of σ_n^2, whereas the signal is also assumed to be independent and identically distributed (IID) random process of zero mean and variance of σ_s^2. The signal to noise ratio is defined as the ratio of the signal variance to the noise variance:

$$\gamma = \sigma_s^2/\sigma_n^2 \quad (2)$$

The collected energy x is taken as a decision statistic which has the following distribution:

$$x = \begin{cases} \chi^2_{2\mu} & H_0(\text{absent}) \\ \chi^2_{2\mu}(2\gamma) & H_1(\text{present}) \end{cases} \quad (3)$$

where, μ is the degree of freedom which equals to the time-band product TW and $\chi^2_{2\mu}$ and $\chi^2_{2\mu}(2\gamma)$ represents central and non-central Chi-square distributions each with 2μ degree of freedom and a non-centrality parameter 2γ for the later one. T is the observation time interval and W is the bandwidth of the pre-filter. Figure 1 depicts the block-diagram of the typical energy detector.

From Fig. 1, we can see that, there are three or four parts in the traditional energy detector. In Fig. 1a, the traditional energy detector in time domain is

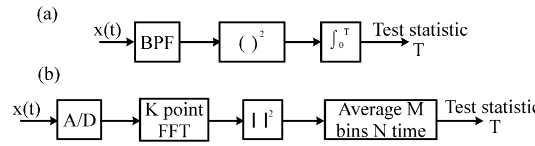

Fig. 1: The block of traditional energy detector. (a) The block of traditional energy detector in time domain and (b) the block of traditional energy detector in frequency domain

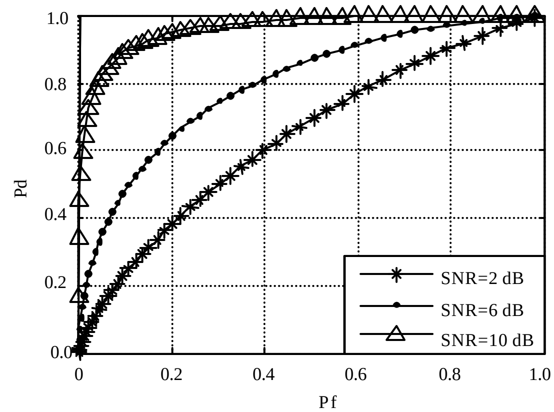

Fig. 2: ROC curves under different SNR

demonstrated. In it, the received signal is squared after the band-pass filter and then integrated in the integrator. In Fig. 1b, the band pass filter is replaced by the A/D converter and K points of FFT and the others remain the same. The final result is compared with the threshold and made the decision.

When the detecting channels are assumed to be the AWGN channels, probabilities of detection, miss-detection and false alarm of local spectrum sensing at a single SU can be expressed, respectively as:

$$P_d = Q_u(\sqrt{2\gamma}, \sqrt{\lambda}) \quad (4)$$

$$P_m = 1 - P_d \quad (5)$$

$$P_f = \frac{\Gamma(u, \lambda/2)}{\Gamma(\lambda)} \quad (6)$$

where, $Q_u(\,,\,)$ is generalized Marcum Q-function, $\Gamma(\,,\,)$ and $\Gamma(\,)$ are incomplete and complete gamma functions respectively and λ is the threshold of the energy detection. In Fig. 2, computer simulations were performed to the complementary Receiver Operating Characteristic (ROC) curves, which are given in Eq. 4 and 6.

From Fig. 2, we can get the relationship between the probabilities of false alarm and the probabilities of the detection under different SNR.

A NOVEL ENERGY DETECTION ALGORITHM

Although, the energy detection approach has some drawbacks, such as poor performance under low SNR conditions and the difficulty of setting the threshold used in energy selection that influenced by the noise power estimation errors, it still can be implemented without any prior knowledge of the PU signal and so it is widely used in practice, especially in cooperative spectrum sensing. In order to improve the detection performance, a lot of method had been given. The detection performance can be improved, when the parameter SNR is increased by restrain the noise power spectrum density (Hao and Zu, 2009). In this study, the authors get the idea from Fig. 2. They did not improve the algorithm of the energy detection and just improve the SNR by decreasing the noise width, so it is not the real way to improve the detection performance in virtually. Some others use different methods to set the threshold to improve the detection performance. Under the hypothesis of the dynamic range of the noise power is known, the authors analyze and simulate the impact of noise uncertainty on the performance of spectrum sensing (Tandra and Sahai, 2005). However, they did not show how to derive the dynamic range. An estimated noise variance is used to set the threshold in energy detection (Ye *et al*., 2008). But the noise variance is changing with the noise, so it is not easy to estimate the exact value. In this study, we use the experimental method to set the threshold, after taking a lot of measurements of the noise power.

The schematic diagram of the novel energy detector is shown in Fig. 3.

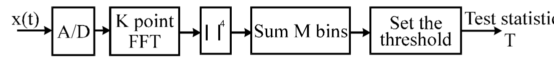

Fig. 3: The block of the novel energy detector

From Fig. 3, we can see that there are five parts in the whole novel energy detector and the K points FFT are used. The main reason is that the FFT is easy to implement and can improve the estimate of the signal energy by increasing the number of points K, which is equivalent to changing the analog pre-filter, or increasing the number of averages M. On the other hand, a band-pass filter, which is matched to the bandwidth of the signal, is needed for a given signal bandwidth. In the case of narrowband signals, however, it is quite inflexible to implement.

The implementation procedure of our novel scheme according to Fig. 3 is shown in Fig. 4.

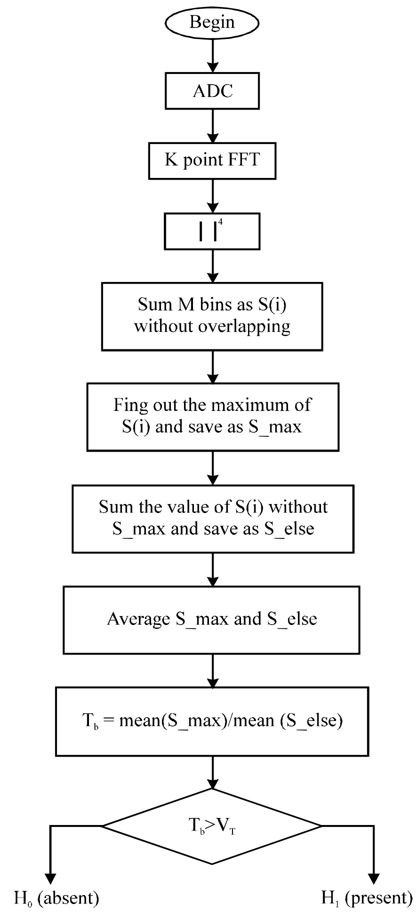

Fig. 4: The implementation procedure of the novel scheme

In the traditional energy detector, we use the square to finish the energy detection, whereas we use the fourth-order moments in this study. The square describes the degree of dispersion around the mean, however, the fourth-order moments, which is also called coefficient of kurtosis, depicts the degree of centralization and decentralization, which is our purpose to find the maximum in the observed spectrum. In order to illustrate the fourth-order moments is better than the square method in searching the maximum value in the whole spectrum. The result of the ideal signal and the receive signal is given in Fig. 5 a-c.

In Fig. 5 a, the signal is the ideal signal which is send out from the signal source, while the others are the receive signal, which are show in Fig. 5 b and c. The purpose is to search the maximum in the observed spectrum, which means that we should find out the maximum of the parameter T_b which is shown in Fig. 4. Comparing these three figures, we can get the conclusion that parameter

T_b with the fourth-order moments is lager than the one with the square. As a result, the fourth-order moments are the algorithm that will be used in the novel energy detection.

The decision statistic for Fig. 1b and 3, respectively, is:

$$T_a = \sum_{N} (X[n])^2 \tag{7}$$

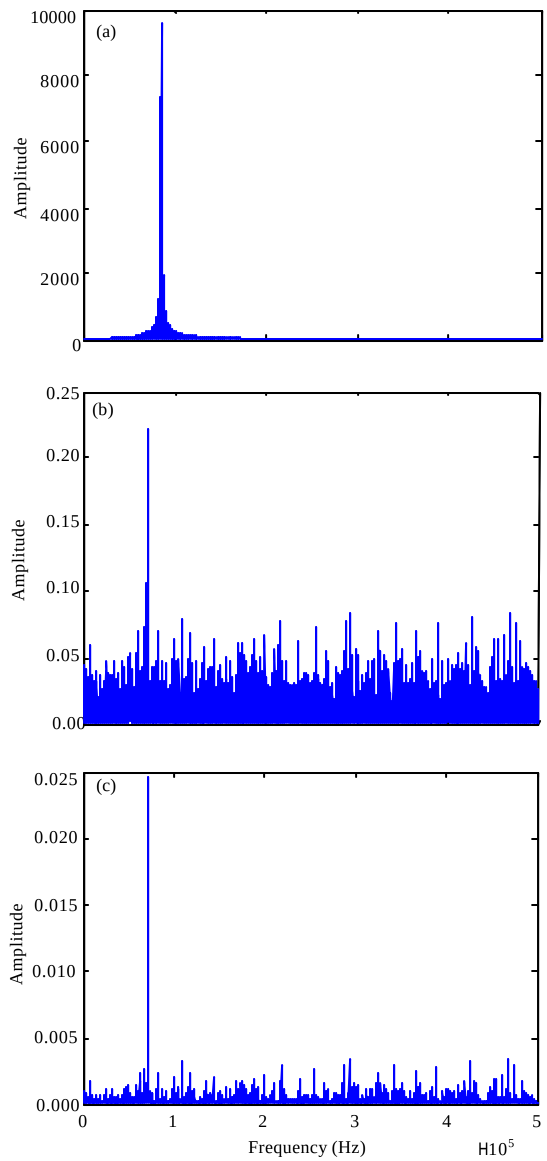

Fig. 5: The receive signal of different moments. (a) The ideal signal without noise, (b) the receive signal of square and (c) the receive signal of fourth-order moments

$$T_b = \text{mean}(S\_max) / \text{mean}(S\_else) \tag{8}$$

where, S_max is the maximum of S(i), S_else is the value that subtract S_max from the sum of S(i) and $S(i) = \Sigma (X[n])^4$.

In the traditional energy detector, we have to calculate the value of T_a and then we compare it with the threshold that we set before, which is hard to set because of the noise uncertainty and some other reasons. After comparing the values that we measured with the threshold, we could get the conclusion whether there is a primary user or not. In order to solve the problem that is difficult to set the value of the threshold, we introduce the novel algorithm. At the beginning, we have to do plenty of measurements in order to set the threshold which is the radio not the value of the noise power that in the traditional energy detector. The result will be given in the next part. And then, we could compare the value of T_b with the threshold that we set according to many measurements and make the final decision.

SIMULATION RESULTS

Here, the simulation results will be provided to demonstrate the improvement of the novel algorithm. The signal of interest is a 1 MHz QPSK signal upconverted to 70 MHz.

In Fig. 6, we illustrate the noise of AWGN channel obtained via Monte-Carlo simulation. When the SNR is from -28 to 30 dB, the ratio of the novel algorithm is plotted in Fig. 6 for N = 1000 (the simulation times) times. If we set the threshold T_b as 10, there are 34 times that larger than the threshold T_b and so the probability of false alarm (P_f) is 0.034.

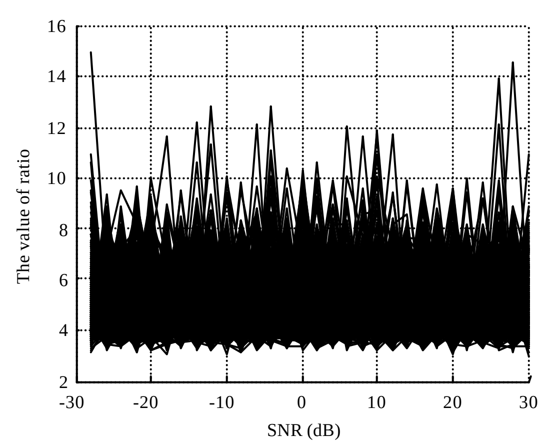

Fig. 6: The value of the ratio vs. SNR under AWGN

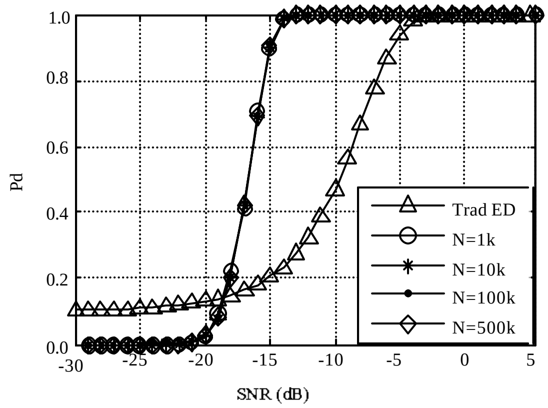

Fig. 7: The SNR vs. Pd of the NED under different times of simulation

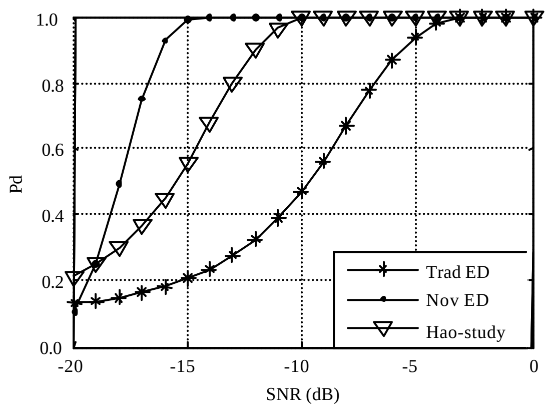

Fig. 8: The SNR vs. Pd under different algorithms

The most important conclusion, which we can get from the Fig. 6, is that the value of the ratio is almost a constant even though the SNR is changing from -28 to 30 dB, which is the reason that we adopt the experimental method to set the threshold.

In Fig. 7, the simulation result of the SNR versus P_d of the novel energy detection algorithm under different N is given, which is the result of P = 2048 (the point of FFT) and P_f = 0.034.

From Fig. 7, we can see that the curves are nearly the same, although the parameter N is respectively, N = 1000, N = 10000, N = 100000, N = 500000. At the same time, the difference of the novel energy detection and the traditional energy detection is given and illustrations of the detail will be given in Fig. 9 with the parameter N = 10000.

In Fig. 8, with the parameters of N = 10000, P = 1024 and P_f = 0.1, the curves are given, respectively as

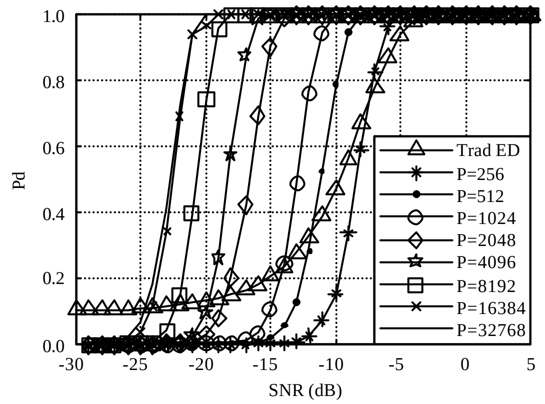

Fig. 9: The SNR vs. Pd of the NED under different point of FFT

traditional energy detection, novel energy detection and the enhanced energy detection which is given in Hao's study.

From Fig. 8, we can see that, the curve obtained by novel energy detection, when the SNR is lager than -19 dB, is better than the one obtained by the enhanced energy detection in Hao's study, while the curve obtained by the enhanced energy detection in all the scenarios is better than the one obtained by the traditional energy detection. The performance of the novel energy detection is enhanced at least 3 dB, when P_d is lager than 0.8, comparing with the enhanced energy detection.

In Fig. 9, with the parameters of N = 10000 and P_f = 0.034, the curves are given under the point of the FFT respectively, P = 256, P = 512, P = 1024, P = 2048, P = 4096, P = 8192 P = 16384, P = 32768. The curve is becoming better with the increasing of the point of the FFT.

From Fig. 9, we can see that the simulation result is worse than the traditional energy detection when the P = 256 and the SNR is lower than -9 dB, or P = 512 and the SNR is lower than -13 dB, or P = 1024 and the SNR is lower than -19 dB. However, the result is less important for us when P_d is less than 0.5, so the novel energy detection algorithm is better than the traditional one no matter what the value of P is (between 256 and 32768).

CONCLUSIONS

Under the constraint of the probability of miss detection, which is got from the simulation result, with the method of Monte-Carlo simulation, a novel energy detection algorithm is investigated in this study. The novel way of setting the threshold is the highlight of this study. The threshold is nearly a constant, which means that the value of the threshold is unchanged with the background noise and easy to set in practice. We have shown that the enhancement of the novel energy detection algorithm with different point of FFT, compared with the traditional energy detection algorithm and the enhanced energy detection algorithm which is given in Hao's study. We investigate the improved signal node novel energy detection algorithm in this study. And it will be our future work to develop the cooperative spectrum sensing with this novel energy detection algorithm.

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