Research Journal of Applied Sciences, Engineering and Technology 4(21): 4245-4251, 2012
ISSN: 2040-7467

Submitted: December 20, 2011 Accepted: April 23, 2012 Published: November 01, 2012

A Novel Spectrum Detection Scheme Based on Dynamic Threshold in Cognitive Radio Systems

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Abstract: In cognitive radio networks, nodes should have the capability to decide whether a signal from a primary transmitter is locally present or not in a certain spectrum in short detection period. This study presents a new spectrum detection algorithm based on dynamic threshold. Spectrum detection schemes based on fixed threshold are sensitive to noise uncertainty, the proposed scheme can improve the antagonism of noise uncertainty, get a good performance of detection while without increasing the computer complexity. However, for schemes which are not sensitive to noise uncertainty, the proposed scheme, in essence, did not improve the detection performance. Computer simulation results show that the proposed algorithm enhances the robust of anti-noise uncertainty and improves detection performance for schemes are sensitive to noise uncertainty in lower signal-to-noise-ratio and large noise uncertainty environments, but not help to schemes which are not sensitive to noise uncertainty.

Keywords: Cognitive radio, dynamic threshold, energy detection, matched filter detection, noise uncertainty

INTRODUCTION

Nowadays wireless systems are based on fixed spectrum allocations, allocated fixed spectral bandwidth to licensed user at any time. This leads to a wasteful use of scarce and expensive spectral resources and result in un-efficiency utilizing spectral resource. Dynamic spectrum access techniques promise greater spectral-usage efficiency and enhanced access to frequency spectrum based on cognitive radio systems. Cognitive radio is a resource sharing strategy which allows the licensed owner to share part of his licensed spectrum with a Rental System (RS) (Weiss and Jondral, 2004), cognitive radio users quit until licensed users need it themselves. The goal of the cognitive radio is to improve spectral efficiency by overlaying new wireless radio systems on a licensed one (the Licensed System, LS) without interfering to the LS and without changing its operations. In order to keep co-existing and no harmful interference with LS, cognitive radios nodes must have the capability to detect unused spectrum, which is a very important process in cognitive radio systems.

Spectrum detection is based on the detection of weak signals from primary users through the local observations of CR users. Three schemes are generally used, such as: Matched filter detection (Akyildiz *et al.*, 2006; Akyildiz *et al*., 2008; Cabric *et al.*, 2004; Cabric *et al.*, 2006; Ghasemi and Sousa, 2005), Energy detection (Akyildiz *et al*., 2006; Akyildiz *et al.*, 2008; Cabric *et al*., 2004; Cabric *et al*., 2006; Ghasemi and Sousa, 2005; Mishra *et al*., 2006), Feature detection (Akyildiz *et al.*, 2006; Akyildiz *et al*., 2008; Cabric *et al*., 2004; Cabric *et al*., 2006; Ghasemi and Sousa, 2005; Mishra *et al*., 2006; Tang, 2005; Gardner and Spooner, 1992). This study mainly investigated matched filter detection and energy detection.

METHODOLOGY

Matched filter detection: When the information of the primary user signal is known to the CR user, the optimal detector in white Gaussian noise is the matched filter, it maximizes received signal-to-noise ratio. However, the matched filter requires a priori characteristics knowledge of the primary user signal, e.g., modulation type and order, pulse shaping, packet format.

Energy detection: If the receiver cannot gather sufficient information about the primary user signal, the optimal detector is an energy detector. However, the performance of the energy detector is susceptible to the uncertainty of noise power. Also, energy detector often generates false alarms triggered by unintended signals because they cannot differentiate signal, noise and interference. The critical technique is how decide the threshold. Energy detector does not work for spread spectrum and hop-frequency signals (Hillenbrand *et al*., 2005).

A high spectrum detection probability must be achieved as the amount of interference that the LS encounter from the RS is directly linked to the detection probability. The detection process has to be repeated periodically at time intervals that are short enough to guarantee a more upper bound interference duration at the

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beginning of an LU's access. At the same time, the detection duration and the false alarm probability should remain as low as possible for the sake of the RS's efficiency (Hillenbrand *et al*., 2005).

This study presents a new spectrum detection algorithm based on dynamic threshold. The proposed scheme can improve the antagonism of noise uncertainty and enhanced the robust of anti-noise uncertainty and un-increased computing complexity. The simulation results show that the proposed algorithm can have an accurate detection performance even if there is an evident noise uncertainty in the case of low signal-to-noise ratio and the algorithm enhanced the robustness of weak signal anti-noise uncertainty and improved the spectrum detection performance. Theoretical analysis and simulation results show that the dynamic threshold energy detection algorithm has a better robustness of anti-noise average power fluctuations.

Problem formulation: The problem of signal detection in additive noise can be formulated as a binary hypothesis testing problem with the following hypotheses:

$$\begin{aligned} &H_0: Y(n) = W(n) \qquad\qquad n = 1,\ 2, \cdots, N \\ &H_1: Y(n) = X(n) + W(n)\ n = 1,\ 2, \cdots, N \end{aligned} \tag{1}$$

where, Y(n), X(n) and W(n) are the received signals at CR nodes, transmitted signals at primary nodes and white noise samples, respectively. We assume that both signals and noise are independent each other. Noise samples W(n) are from a white Gaussian noise process with power spectral density σ_n^2, i.e., W(n) $\sim N(0,\ \sigma_n^2)$ and its statistics are completely know to the receiver.

Given a particular target probability of false alarm probability P_{FA}, probability of missed detection P_{MD} and probability of detection $P_D = 1 - P_{MD}$, our aim is to derive the sample complexities for various possible detectors, i.e., we are interested in calculating the number of samples required N, as a function of the signal-to-noise ratio (SNR).

Detection schemes:

Matched filter detector: We start with the most simplest version of the problem: when the signal X(n) is completely known to the receiver. In this case, the optimal detector is the matched filter detector or the correlation detector, initialized the decision model (Kay, 1998; Tandra and Sahai, 2008; Tandra, 2003):

$$D(Y) = \frac{1}{N}\sum_{n=0}^{N-1} Y(n)\,X(n) \underset{H_0}{\overset{H_1}{\gtrless}} \gamma \tag{2}$$

where, D(Y) is the decision variable and γ is the decision threshold, N is the number of samples.

If the noise variance is completely known, then we can get the following approximations according to the central limit theorem (Kay, 1998; Tandra and Sahai, 2008; Tandra, 2003):

$$\begin{aligned} &D\left(Y_{H_0}\right) \sim N\left(0, \left(P\sigma_n^2\right)/N\right) \\ &D\left(Y_{H_1}\right) \sim N\left(P, \left(P\sigma_n^2\right)/N\right) \end{aligned} \tag{3}$$

where, P is the average signal power and σ_n^2 is the noise variance. Using these approximations gives the following probability expressions (Tandra and Sahai, 2008; Tandra, 2003):

$$P_{FA} = \Pr\left(D\left(Y_{H_0}\right) > \gamma\right) = Q\left(\frac{\gamma}{\sqrt{\sigma_n^2 . P / N}}\right) \tag{4}$$

$$P_D = 1 - P_{MD} = Q\left(\frac{\gamma - P}{\sqrt{\sigma_n^2 . P / N}}\right) \tag{5}$$

Here $Q(\cdot)$ is the standard Gaussian complementary Cumulative Distribution Function (CDF) and $Q^{-1}(\cdot)$ is the inverse standard Gaussian complementary CDF. Eliminating threshold γ, then:

$$N = \left[Q^{-1}\left(P_{FA}\right) - Q^{-1}\left(1 - P_{MD}\right)\right]^2 (SNR)^{-1} \tag{6}$$

Energy detector: If we assume absolutely no deterministic knowledge about the signal X(n), i.e., we assume that we know only the average power in the signal. In this case the optimal detector is energy detector or radiometer:

$$D(Y) = \frac{1}{N}\sum_{n=0}^{N-1} Y^2(n) \underset{H_0}{\overset{H_1}{\gtrless}} \gamma \tag{7}$$

Here D(Y), γ, N represent similar meanings as matched filter detection. If the noise variance is completely known and no noise uncertainty, the central limit theorem gives the following approximations (Tandra and Sahai, 2008; Tandra, 2003):

$$\begin{aligned} &D\left(Y_{H_0}\right) \sim N\left(\sigma^2,\ 2\sigma^4 / N\right) \\ &D\left(Y_{H_1}\right) \sim N\left(P + \sigma^2,\ \left(P + \sigma^2\right)^2 / N\right) \end{aligned} \tag{8}$$

where, the average signal power is P and σ_n^2 is the noise variance, therefore (Tandra and Sahai, 2008; Tandra, 2003):

$$P_{FA} = \Pr\left(D\left(Y_{H_0}\right) > \gamma\right) = Q\left(\frac{\gamma - \sigma^2}{\sqrt{2 / N\sigma^2}}\right) \tag{9}$$

$$P_D = Q\left(\frac{\gamma - \left(P + \sigma^2\right)}{\sqrt{2/N}\left(P + \sigma^2\right)}\right) \quad (10)$$

Here Q(×) is the standard Gaussian complementary cumulative distribution function (CDF) and Q^{-1}(×) is the inverse standard Gaussian complementary CDF. Eliminating threshold g, thus:

$$N = 2\left[Q^{-1}\left(P_{FA}\right) - Q^{-1}\left(P_D\right)\left(1 + SNR\right)\right]^2 SNR^{-2} \quad (11)$$

Matched filter detection based on dynamic threshold:
Noise uncertainty: We have discussed and analyzed the case of no noise uncertainty. Now, consider the case with uncertainty in the noise model. The distributional uncertainty of noise can be summarized in a single interval $\sigma^2 \in \left[\sigma_n^2/\rho, \rho\sigma_n^2\right]$, ρ is the noise uncertainty coefficient and ρ>1. It is required to achieve targets P_{FA}, P_D or P_{MD} robustly, (4) and (5) are modified to get:

$$P_{FA} = \max_{\sigma^2 \in \left[\sigma_n^2/\rho, \rho\sigma_n^2\right]} Q\left(\frac{\gamma}{\sqrt{\sigma^2 . P/N}}\right) = Q\left(\frac{\gamma}{\sqrt{\rho\sigma_n^2 . P/N}}\right) \quad (12)$$

$$P_D = \min_{\sigma^2 \in \left[\sigma_n^2/\rho, \rho\sigma_n^2\right]} Q\left(\frac{\gamma - P}{\sqrt{\sigma^2 . P/N}}\right) = Q\left(\frac{\gamma - P}{\sigma_n^2 . P/\left(\rho N\right)}\right) \quad (13)$$

Eliminating threshold g gives:

$$N = r\left[Q^{-1}\left(P_{FA}\right) - Q^{-1}\left(1 - P_{MD}\right)\right]^2 \left(SNR\right)^{-1} \quad (14)$$

Comparison (6) and (14), (14) augments a multiply factor of ρ, drawn the following conclusions: To get the same detection performance, relatively speaking, the detection duration in the noise uncertainty environment is a rather long than the case of no noise uncertainty.

Dynamic threshold: This section, we will introduce dynamic threshold on the detection performance. Supposing the dynamic threshold factor ρ′ and ρ′>1, the distributional of dynamic threshold can be summarized in a single interval $\gamma' \in \left[\gamma/\rho', \rho'\gamma\right]$, so (4) and (5) can be modified that:

$$P_{FA} = \max_{\gamma' \in \left[\gamma/\rho', \rho'\gamma\right]} Q\left(\frac{\gamma'}{\sqrt{\sigma^2 . P/N}}\right) = Q\left(\frac{\rho'\gamma}{\sqrt{\sigma_n^2 . P/N}}\right) \quad (15)$$

$$P_D = \min_{\gamma' \in \left[\gamma/\rho', \rho'\gamma\right]} Q\left[\frac{\gamma' - P}{\sqrt{\rho^2 . P/N}}\right] = Q\left[\frac{\rho'\gamma - P}{\sqrt{\sigma_n^2 . P/N}}\right] \quad (16)$$

Eliminating threshold g and uncertainty coefficient ρ′:

$$N = \left[Q^{-1}\left(P_{FA}\right) - Q^{-1}\left(1 - P_{MD}\right)\right]^2 \left(SNR\right)^{-1} \quad (17)$$

Noise uncertainty and dynamic threshold: In front of two parts, we have discussed noise uncertainty and dynamic threshold with the relationship of detection performance respectively. This section will give detection performance expressions when consider noise uncertainty and dynamic threshold jointly. Set the parameters of variables: Noise uncertainty factor ρ and dynamic threshold factor ρ′. Therefore, the noise variance valued in set $\sigma^2 \in \left[\sigma_n^2/\rho, \rho\sigma_n^2\right]$ and threshold valued in $\gamma' \in \left[\gamma/\rho', \rho'\gamma\right]$. (4) and (5) can be revised:

$$P_{FA} = \max_{\gamma' \in \left[\gamma/\rho', \rho'\gamma\right]} \max_{\sigma^2 \in \left[\sigma_n^2/\rho, \rho\sigma_n^2\right]} Q\left(\frac{\gamma'}{\sqrt{\sigma^2 . P/N}}\right) = Q\left(\frac{\rho'\gamma}{\sqrt{\rho\sigma_n^2 . P/N}}\right) \quad (18)$$

$$P_D = \min_{\gamma' \in \left[\gamma/\rho', \rho'\gamma\right]} \min_{\sigma^2 \in \left[\sigma_n^2/\rho, \rho\sigma_n^2\right]} Q\left(\frac{\gamma' - P}{\sqrt{\sigma^2 . P/N}}\right) = Q\left(\frac{\rho'\gamma - P}{\sqrt{\sigma_n^2 . P/\left(\rho N\right)}}\right) \quad (19)$$

Removing parameters g, ρ and q ρ′, respectively:

$$N = r\left[Q^{-1}\left(P_{FA}\right) - Q^{-1}\left(1 - P_{MD}\right)\right]^2 \left(SNR\right)^{-1} \quad (20)$$

Comparison (6), (14), (17) and (20), it is clear that (17) and (6), (20) and (14) with the same expression, (14) and (20) than (6) by a multi-factor ρ. This shows that the noise uncertainty will lead to a slight decline in detection performance; however, no any help to detection performance with dynamic threshold in this case.

Energy detection based on dynamic threshold:
Noise uncertainty: Analyzing as the matched filter detection, supposing noise uncertainty factor ρ and r>1, noise variance valued range is $\sigma^2 \in \left[\sigma_n^2/\rho, \rho\sigma_n^2\right]$, we can find the expressions of false alarm probability, detection probability and missed detection probability:

$$P_{FA} = \max_{\sigma^2 \in \left[\sigma_n^2/\rho\sigma_n^2\right]} Q\left(\frac{\gamma - \sigma^2}{\sqrt{2/N\sigma^2}}\right) = Q\left(\frac{\gamma - \rho\sigma_n^2}{\sqrt{2/N}\rho\sigma_n^2}\right) \quad (21)$$

$$P_D = \min_{\sigma^2 \in \left[\sigma_n^2/\rho, \rho\sigma_n^2\right]} Q\left(\frac{\gamma - \left(P + \sigma^2\right)}{\sqrt{2/N}\left(P + \sigma^2\right)}\right) = Q\left(\frac{\gamma - \left(P + \sigma_n^2/\rho\right)}{\sqrt{2/N}\left(P + \sigma_n^2/\rho\right)}\right) \quad (22)$$

Ignored the manuscript processes and gets:

$$N = 2\left[\rho Q^{-1}\left(P_{FA}\right) - \left(1/\rho + SNR\right)Q^{-1}\left(1 - P_{MD}\right)\right]^2 \left(SNR - \left(\rho - 1/\rho\right)\right)^{-2} \quad (23)$$

Dynamic threshold: In the process of energy detection, it is very important that choose a suitable threshold.

Assuming ρ′ is the noise uncertainty coefficient and ρ′ >1, the distributional of dynamic threshold can be summarized in a single interval $\gamma' \in [\gamma/\rho', \rho'\gamma]$, this sub-section considered dynamic threshold only, (9) and (10) are modified to get:

$$P_{FA} = \max_{\gamma' \in [\gamma/\rho', \rho'\gamma]} Q\left[\frac{\gamma' - \sigma^2}{\sqrt{2/N}\,\sigma^2}\right] = Q\left(\frac{\rho'\gamma - \sigma_n^2}{\sqrt{2/N}\,\sigma_n^2}\right) \quad (24)$$

$$P_D = \min_{\gamma' \in [\gamma/\rho', \rho'\gamma]} Q\left(\frac{\gamma' - (P+\sigma^2)}{\sqrt{2/N}\,(P+\sigma^2)}\right) = Q\left(\frac{\gamma/N\rho' - (P+\sigma_n^2)}{\sqrt{2/N}\,(P+\sigma_n^2)}\right) \quad (25)$$

We can get the relationship of P_D, P_{FA}, N ρ′ and SNR:

$$N = 2\left[Q^{-1}(P_{FA}) - \rho'^2(1+SNR)Q^{-1}(1-P_{MD})\right]^2\left(\rho'^2 SNR + (\rho'^2-1)\right)^{-2} \quad (26)$$

Noise uncertainty and dynamic threshold: We have discussed two cases that existing noise uncertainty and dynamic threshold respectively, this sub-section will give the expressions that considering noise uncertainty and dynamic threshold together, revised (9) and (10), we got expressions of false alarm probability and detection probability:

$$P_{FA} = \max_{\gamma' \in [\gamma/\rho', \rho'\gamma]} \max_{\sigma^2 \in [\sigma_n^2/\rho, \rho\sigma_n^2]} Q\left(\frac{\gamma' - \sigma^2}{\sqrt{2/N}\,\sigma^2}\right) = Q\left(\frac{\rho'\gamma - \rho\sigma_n^2}{\sqrt{2/N}\,\rho\sigma_n^2}\right) \quad (27)$$

$$P_D = \min_{\gamma' \in [\gamma/\rho', \rho'\gamma]} \min_{\sigma^2 \in [\sigma_n^2/\rho, \rho\sigma_n^2]} Q\left(\frac{\gamma' - (P+\sigma^2)}{\sqrt{2/N}\,(P+\sigma^2)}\right) = Q\left(\frac{\gamma/\rho' - (P+\sigma_n^2/\rho)}{\sqrt{2/N}\,(P+\sigma_n^2/\rho)}\right) \quad (28)$$

Eliminating threshold g and gets inter-relationship of P_D, P_{FA}, N, ρ′, r and SNR:

$$N = 2\left[(\rho/\rho')Q^{-1}(P_{FA}) - \rho'(1/\rho + SNR)Q^{-1}(1-P_{MD})\right]^2\left(\rho' SNR + \rho'/\rho - \rho/\rho'\right)^{-2} \quad (29)$$

Comparing (23) and (11), by the property of $Q^{-1}(.)$, a small change to the front part of the expression almost no effect on the whole results, the second half SNR^{-2} and $(SNR-(\rho-1/\rho))^{-2}$should be considered mainly. When ρ≈1, then $SNR^{-2} \approx (SNR-(\rho-1/\rho))^{-2}$, (23) and (11) almost the same; When ρ value larger and suppose ρ = 1.05, thus (ρ −1/ρ) = 0.0976≈0.1, in the case of low signal-to-noise ratio, that is, SNR = 0.1, so $(SNR-(\rho-1/\rho))^{-2} \approx 0$, substitution (23) to be N→∞. In other words, only and only if an infinite detection duration can complete detection, which is inconsistent with the actual situation, the noise uncertainty affect detection performance greatly. A similar analysis, comparison (26) and (11) equivalent compared with the latter parts of SNR^{-2} and $\left(\rho'^2 SNR + (\rho'^2-1)\right)^{-2}$ mainly. When ρ′≈1 and $\rho'^2 \approx 1$, therefore $SNR^{-2} \approx (\rho'^2 SNR + (\rho'^2-1))^{-2}$, (26) and (11) almost the same; When ρ′ = 1.01, if SNR = 0.1, at this time we can get $\rho'^2 SNR + (\rho'^2-1)$ = 0.102+ 0.0201 ≈ 0.122 >SNR, substitution (26) and compared to (11), if variables P_D and P_{FA} unchanged, the value of N has been reduced, in other words, detection duration have been shorten and didn't loss of detection performance. It is in line with the actual situation, the dynamic threshold can improve the detection performance. In (29), when ρ′ ≈ρ and ρ′/ρ≈ρ/ρ′ ≅1, then $(\rho' SNR + \rho'/\rho - \rho/\rho')^{-2}$ and ρ′(1/ρ+SNR)≅(1+SNR), substitution (29) with the above approximate expressions, (29) almost the same with (11); Comparing (29) and (23), it is clear that $(\rho' SNR + \rho'/\rho - \rho/\rho')^{-2} \gg (SNR-(\rho-1/\rho))^{-2}$, detection duration has been shorten largely. By analyzing and we can draw a conclusion: Even if there is noise uncertainty, as long as set dynamic threshold factor suitably, we can get a better spectrum detection performance.

SIMULATION RESULTS

Setting variables used in simulations: Signal-to-noise ratio SNR; Detection probability P_D; Probability of false alarm P_{FA}; Number of samples N; Noise uncertainty factor ρ; Dynamic threshold factor ρ′.

Figure 1 and 2 are the numerical simulations of (6) and (11), respectively, compared with (6) and (11), by the

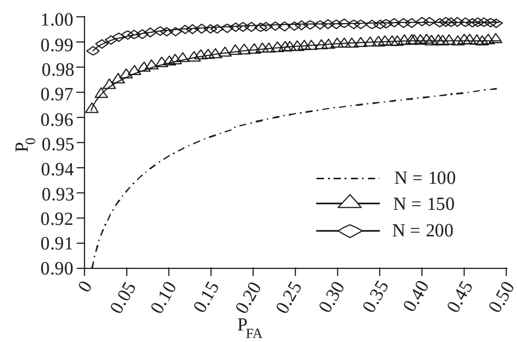

Fig. 1: Matched filter detection

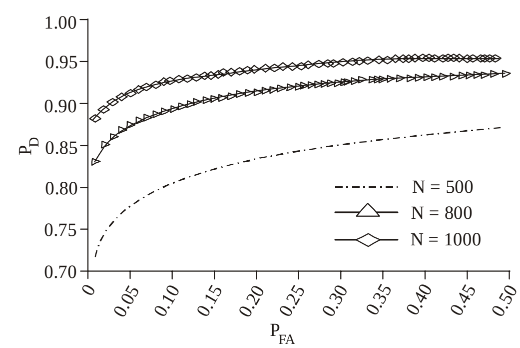

Fig. 2: Energy detection

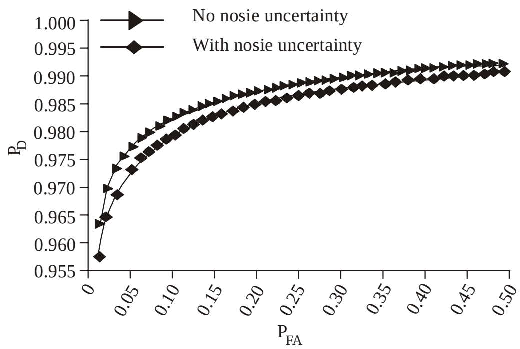

Fig. 3: Matched filter detection: N = 150, r = 1.05

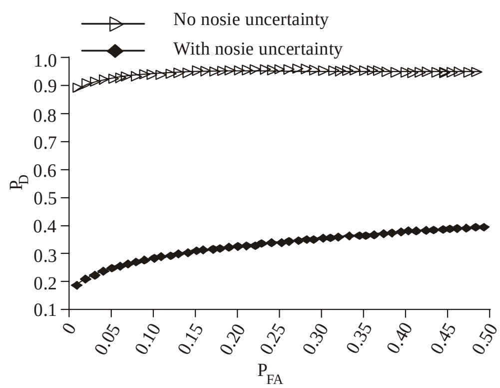

Fig. 4: Energy detection: N = 1000, r = 1.05

nature of Q^{-1}(.), the front part almost no change of the whole expression results, however, depending on the latter part of SNR^{-1} and SNR^{-2}.

Parameters: Signal to noise ratio SNR = 0.1, that is, snr = 10lg(SNR) = −10DB, the range of false alarm probability meet $P_{FA} \in (0, 0.5)$. From Fig. 1 and 2, in the same false alarm probability P_{FA} and detection probability P_D, the detection duration of energy detection is almost 10 times of matched filter detection, so the matched filter detection is superior to the energy detection in the same detection performance.

Figure 3 and 4 are the numerical simulation results of (14) and (23) and corresponding to the matched filter detection and energy detection, respectively.

Parameters: Signal to noise ratio SNR = 0.1, that is, snr = 10lg(SNR) = −dB, let false alarm probability $P_{FA} \in (0, 0.5)$ and valued in it, noise uncertainty factor $\rho = 1.05$. In the case of existing the same noise uncertainty, matched filter detection scheme by the noise uncertainty was not obvious, almost no effect; while the energy detection scheme is sensitive to the noise uncertainty. Figure 4 shows that it can not complete the detection, that is to say, the noise tiny fluctuations will lead to the detection performance of energy detection scheme falling sharply.

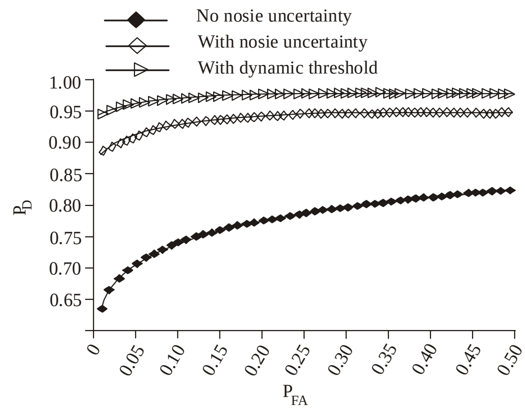

Fig. 5: Energy detection: N = 1000, r = 1.02, r¢ = 1.001

In the fourth part, we have discussed the noise uncertainty and the dynamic threshold on the effect of matched filter detection performance, respectively. Compared with (6), (14), (17) and (20), we can know that the threshold of uncertainty is no help to matched filter detection performance, however, the existence of noise uncertainty will lead to a small decline in detection performance, in other words, matched filter detection scheme is not sensitive to noise uncertainty. When considered dynamic threshold alone, the detection performance is the same as not consider the uncertainty; When considered the noise uncertainty only, the detection performance drop a little compare with no uncertainty case; While taking into account noise uncertainty and dynamic threshold together, get the same results as considering noise uncertainty alone. Therefore the introduction of dynamic threshold does not help on the detection performance of matched filter detection, that is to say, dynamic threshold did not give any help to noise un-sensitive detection programs.

In the fifth section, the noise uncertainty and dynamic threshold on the impact of energy detection performance discussed separately. Compared with (11), (23), (26) and (29), the results shown that the energy detector are very sensitive to the noise uncertainty, a small fluctuation of noise uncertainty factor will cause a sharp decline in detection performance. Figure 4 is the performance curves in the condition that noise uncertainty factor valued ρ = 1.05 and the number of signal samples are N = 1000. When $P_{FA} = 0.1$, the detection probability is $P_D < 30\%$, even if the probability of false alarm gets to an intolerable value, that is, $P_{FA} = 0.5$, the probability of detection is still very low, it is show that $P_D \approx 40\%$. Signals can not be detected. This shows that the energy detection scheme is very sensitive to noise uncertainty.

Figure 5 is the detection performance curves comparison of three conditions that noise power knows completely, existing noise uncertainty and dynamic threshold, respectively. Noise uncertainty lost the energy

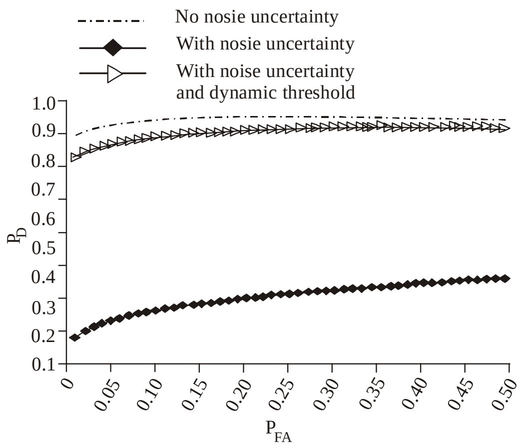

Fig. 6: Energy

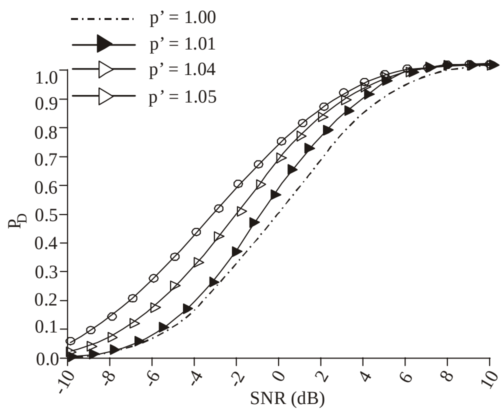

Fig. 7: Performance curves

detection performance and the using of dynamic threshold improved it.

When we were to consider the following three conditions: the case of no uncertainty, existence of noise uncertainty only and consider noise uncertainty and dynamic threshold jointly. From Fig. 6 can be shown that the used of dynamic threshold method have conquered the impact of noise uncertainty and improved the detection performance evidently:

Detection: $N = 1000$, $r = 1.05$, $\rho' = 1.03$

To further validate the above analysis, Fig. 7 is the computer Monte Carlo simulation result of energy detection. In the processing, 5×10^5 signals were used and the authorize users to use the probability of channel is 50%. Noise is AWGN. Simulation parameter settings: computer environment is $SNR\in(-10, 10)$(dB), false alarm probability is $P_{FA} = 0.01$, detection duration is $N = 500$, the average noise power fluctuation factor is $\rho = 1.02$.

In Fig. 7, curve labeled "Δ" is the fixed threshold detection algorithm, that is dynamic threshold factor is $\rho' = 1.00$; and "*" curve correspond to the dynamic threshold detection algorithm and the dynamic threshold factor is $\rho' = 1.01$; Marked "▹" is the curve correspond to the dynamic threshold factor is $\rho' = 1.04$; The last curve is $\rho' = 1.05$ and labeled with "O".

From the figure, when the noise is fluctuation, the dynamic threshold algorithm is superior to fixed threshold energy detection scheme. With the dynamic threshold factor value increases, detection performance improved significantly. The range of dynamic threshold factor increases is relatively small, while detection performance trends are obvious. When SNR close to 0(dB), the value of dynamic threshold detection probability is better than fixed threshold detection probability is [0.08 0.17 0.23]. It is very helpful to improve cognitive radio system detection performance, especially work in low SNR environment.

Theoretical analysis and simulation results show that the dynamic threshold energy detection algorithm has a better robustness of anti-noise average power fluctuations.

CONCLUSION

This study presents a new spectrum detection algorithm based on dynamic threshold. Spectrum detection schemes based on fixed threshold are sensitive to noise uncertainty; the proposed scheme can improve the antagonism of noise uncertainty. For spectrum detection schemes which are not sensitive to noise uncertainty, such as matched filter detection, the proposed spectrum detection scheme, in essence, did not improve the detection performance; however, for spectrum detection schemes which are sensitive to noise uncertainty, such as energy detection, the proposed scheme enhanced the robust of anti-noise uncertainty and un-increased computing complexity. The simulation results show that: The proposed algorithm can have an accurate detection performance even if there is an evident noise uncertainty in the case of low signal-to-noise ratio, the algorithm enhanced the robustness of weak signal anti-noise uncertainty and improved the spectrum detection performance. Theoretical analysis and simulation results show that the dynamic threshold energy detection algorithm has a better robustness of anti-noise average power fluctuations.

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