Research Article

Improved Energy Detector with Weights for Primary User Status Changes in Cognitive Radio Networks

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This paper presents an improved energy detector (ED) with weights to improve detection performance in this situation that the primary user’s status changes as arriving or leaving randomly in cognitive radio networks. The idea is derived from the concept of unequal scale sampling such that the instantaneous energy statistic of the sampling points in the sensing period is endowed with monotonic weights. The probabilities of false alarm and detection for our ED are deduced under the new detection model. Numerical simulation results show that the proposed ED offers better detection performances with a reduced probability of false alarm compared to conventional ED, and improved energy detector can improve the overall probabilities of detection, when spectrum sensing is performed for a network with high traffic.

1. Introduction

Cognitive radio (CR) [1] emerges as a way to improve the overall spectrum usage by exploiting spectrum opportunities in both licensed and unlicensed bands and its development has been widespread concerned by academia and industry. In cognitive radio networks (CRN), there are two types of users, (i) primary users (PU) who lease portions (channels or bands) of the spectrum directly from the regulator and have priority to use the spectrum and (ii) secondary users (SU) who lease channels from primaries and can use a channel when it is not in use by the primary or without interfering the PU [2]. Spectrum sensing is a critical functionality of CR. It enables SU to find the “spectrum holes.”

Energy Detection (ED) [3] (in this paper, we also call it the conventional ED) at the physical layer constitutes a preferred approach for spectrum sensing in CR owing to its simplicity and applicability as well as its low computational and implementation costs; it allows a quick sensing decision to be made within a short sensing period. Various kinds of improved ED versions [4–6] have been proposed to improve the performance of detection for CR system in recent years. In [4], an improved ED was proposed for random signals in Gaussian noise by replacing the squaring operation of the signal amplitude in the conventional ED with an arbitrary positive power operation. In [5], the authors proposed an improved version of ED algorithm and the proposed scheme outperformed the conventional scheme while preserving a similar level of algorithm complexity. In [6], an improved one was proposed in low SNR environment based on the trade-off between misdetection probability and false alarm probability under noise uncertainty [7].

However, all of these previous researches [3–7] assume that the PU is either absent or present during the whole sensing period [8]. However, in practice, the PU traffic could be high or the sensing period could be long such that the PU may arrive and depart during the sensing period. In this case, parts of the samples from the licensed channel contain noise only, while parts of the samples from the licensed channel contain PU signal plus noise, which is different from the conventional binary hypothesis testing problem for spectrum sensing. The effect of the PU traffic on the sensing performance is evaluated to show that the PU traffic causes significant performance degradation based on ED [9, 10].

A few of studies related to the above problem have been proposed recently [9–13]. Considering the effect of the PU traffic on the spectrum sensing performance, the conventional binary hypothesis testing problem for spectrum
sensing can be formulated into the quaternary hypothesis, and the probabilities of false alarm and detection are deduced under the new detection model [10]. Collaborative spectrum sensing is a promising method to alleviate the deleterious effects caused by PU traffic. Authors theoretically analyzed performances of four commonly used feature-based detectors for spectrum sensing as Maximum Eigenvalue (ME) detector, ratio of Maximum to Minimum Eigenvalue (MME) detector, ratio of average Energy to Minimum Eigenvalue (EME) detector, and COVariance (COV) detector that are compared by assuming that the PU may arrive or depart during the sensing period, a realistic case when the PU traffic is high or the sensing period is long. The effect of PU traffic on the performance of SU data transmission is investigated in [11]. The authors theoretically analyzed the achievable throughput for different sensing periods and proved that the degree of throughput degradation is related to the PU band which frequently changes between 1 (busy) and 0 (idle). The effect of multiple PUs on spectrum sensing performance has also been investigated [12]. They discussed multiple PU status changes during the SU sensing period. The spectrum sensing performance was significantly degraded by PU traffic and the degradation decreased when the number of PUs increased; also the extent of this degradation is related to how long the spectrum band was occupied by the PU and the SNR received at the SU. This other research [9–12] focuses on performance analysis; however, any new detection scheme has not been proposed to solve or resist this problem.

So, novel improved ED structure was proposed in [13]. In [13], the authors assumed that the arrival or departure of the PU followed a Poisson process and the detection performances under both statuses were discussed by using the generalized likelihood ratio test to improve the conventional ED. However, under the model proved by the authors, the probability of a PU’s status change was low for the later time slots without considering the equal probability of PU arrival and departure within each time slot. Additionally, the performance did not satisfy the CRN’s needs in a low SNR environment.

To solve the aforementioned problems, the authors here present a new improved ED with weights to improve the performance of detection for PU status changes. Firstly, we theoretically analyze the limitations of conventional ED and introduce the concept of unequal scale sampling, and then our proposed ED is obtained. Secondly, the probabilities of false alarm and detection for our ED are deduced under the proposed ED is obtained. Secondly, the probabilities of false alarm and detection for our ED are deduced. The corresponding simulation results and our analyses are showed in Section 5. Finally, we conclude the paper in Section 6.

2. System Model for Primary User Status Changes

In the conventional model [3], the PU is assumed to be either present or absent during the entire sensing frame duration. In practice, a PU may arrive or leave during the sensing period, especially when a long sensing period is used to achieve good sensing performance or when spectrum sensing is performed for a network with high traffic. Therefore, to accurately and effectively detect whether or not the PU band is free, the PU’s status changes during the SU sensing period should be considered.

When spectrum sensing is carried out using ED during the sensing period, where the received signal from the licensed channel is prefiltered by a band-pass filter, and is squared and integrated over the sensing period $T_{sens}$, the total number of samples collected from the channel during $T_{sens}$ is $I = f_s T_{sens}$, where $f_s$ is the sample frequency for ED. The conventional ED test is $Y = \sum_{i=1}^{I} y_i^2$, where $y_i^2$ is instantaneous energy statistic of the discrete received signal at the SU.

Considering the effect of PU traffic on the spectrum sensing performance, the conventional binary hypothesis testing problem for spectrum sensing can be formulated into the quaternary hypothesis [10] shown in Figure 1.

In Figure 1, $H_{0,1}$ and $H_{1,1}$ are the conventional binary hypotheses obviously that a PU is either absent or present during the whole sensing period. $H_{0,2}$ is the hypothesis that the PU is present for $d$ samples and then departs from the licensed channel during the sensing period. $H_{1,2}$ is the hypothesis that the PU is initially absent for $I - a$ samples and then arrives at the licensed channel during the sensing period. The hypothesis testing problem of conventional ED on additive white Gaussian noise (AWGN) channel can be given by

$$Y = \begin{cases} \sum_{i=1}^{d} n_i^2 & H_{0,1} \\ \sum_{i=1}^{d} (s_i + n_i)^2 + \sum_{i=d+1}^{I} n_i^2 & H_{0,2} \\ \sum_{i=1}^{d} (s_i + n_i)^2 & H_{1,1} \\ \sum_{i=1}^{I-a} n_i^2 + \sum_{i=d+1}^{I} (s_i + n_i)^2 & H_{1,2} \end{cases}$$

where $s_i, i \in [1, 2, \ldots, I]$ are the samples of the PU signal, $n_i, i \in [1, 2, \ldots, I]$ are the samples of the AWGN. As $d$ represents the number of signal samples in which the licensed channel...
is busy before it becomes vacant in $H_{0,2}$, $a$ represents the number of signal samples in which the licensed channel is occupied by the PU after it becomes busy in $H_{1,2}$.

When $I$ is relatively large, according to the central limit theorem, the probability of false alarm and the probability of detection can be calculated as follows [10]. In $H_{0,1}$ and $H_{0,2}$, the probability of false alarm is

$$P_{fH_{0,1}} = P_r \{ Y > \eta \mid H_{0,1} \} = Q\left( \frac{\eta - I}{\sqrt{2I}} \right),$$

(2)

$$P_{fH_{0,2}} = P_r \{ Y > \eta \mid H_{0,2} \} = Q\left( \frac{\eta - I - dy}{\sqrt{2I + 4dy}} \right).$$

(3)

In $H_{1,1}$ and $H_{1,2}$, the probability of detection is

$$P_{dH_{1,1}} = P_r \{ Y > \eta \mid H_{1,1} \} = Q\left( \frac{\eta - I - Iy}{\sqrt{2I + 4Iy}} \right),$$

(4)

$$P_{dH_{1,2}} = P_r \{ Y > \eta \mid H_{1,2} \} = Q\left( \frac{\eta - I - ay}{\sqrt{2I + 4ay}} \right),$$

(5)

where $\eta$ is the decision threshold, $\gamma$ denoted the received signal-to-noise ratio (SNR) of the PU measured at the secondary receiver of interest, when PU is active. $Q(\cdot)$ denotes the standard gauss complementary cumulative distribution function defined as $Q(x) = (1/\sqrt{2\pi}) \int_x^{\infty} e^{-t^2/2} dt$.

Here, we undertake to analyze the PU traffic on the performance of SU’s spectrum detecting. Obviously, $H_{1,2}$ poses a major threat to the PU’s data transmission. In (5), if $a$ is small, the PU’s spectrum band is idle as judged by the SU. As a result, the probability of misdetection, which equals $1 - P_{dH_{1,2}}$, in the CRN will be higher and the PU’s priority cannot be protected reliably. In a similar way, $H_{0,2}$ will lead to a systemic spectrum efficiency decline. In (3), if $d$ is large, the probability of false alarm will be higher.

3. Sampling Points and Weights

The squaring and integrating process of sampling points using conventional ED over the sensing period is considered as a constant amplitude operation, in which all samples have the same coefficient, which is $1$. For example, $Y = 1 \times y_1^2 + 1 \times y_2^2 + \cdots + 1 \times y_I^2 = \sum_{i=1}^{I} y_i^2$. From Figure 1, we can see that, to avoid interfering with a PU link, samples of the PU signal in the latter part of the sensing period play an important role in the probability of detection. It means that, in (5), $P_{dH_{1,2}}$ is affected by $a$. If $a$ is small, the probability of misdetection will be higher in the CRN. Similarly, the samples of the PU signal in first half part of sensing period are important to the probability of false alarm. In (3), if $d$ is large, the probability of false alarm will be higher.

From this analysis, considering the effect of PU traffic on the spectrum sensing performance, conventional ED has its limitations. It does not recognize that the sampling points in different positions affect the detection performance. As a matter of fact, the proportion of energy statistics in the former part of $Y$ is the smaller, the better; on the contrary, the one in the later part is the bigger, the better. Figure 2 shows the importance of sampling points in $Y$ in the sensing period.

Based on the above analyses, we introduce the idea of unequal scale sampling, which is the instantaneous energy statistic of sampling point endowed with weights $\omega_i$ ($0 < \omega_i \leq 1$, $i \in [1, 2, \ldots, I]$). We choose the function elementary power of $p$, which is the monotonically increasing function with $i$

$$\omega_i = f(i, p) = \left( \frac{i}{I} \right)^p, \quad p > 0.$$
The problem of the optimal weights is finding the best power \( p \). In theory, searching the optimal power can be modeled as an optimization problem:

\[
\begin{align*}
\mathcal{P}_\text{best} &= \arg \left\{ \min_p \left\{ p \left| \mathcal{P}_{d,\text{new}} \geq p_{\text{DES}} \right\} \right\} \\
\text{s.t.} \quad & \mathcal{P}_{f,\text{new}} \leq \mathcal{P}_{f,\text{conv}}
\end{align*}
\]

where \( p_{\text{DES}} \) is the target probability of detection of CRN. \( p_{d,\text{new}} \) and \( p_{f,\text{new}} \) are the probabilities of detection and false alarm for ED with weights \( \omega_i \) under \( H_{1,2} \) and \( H_{0,2} \), respectively.

With the \( p \) increasing, the rate of convergence of this optimization problem is becoming much slower. Because of simplicity and low implementation costs of ED, for analytical simplicity, this paper chooses the elementary function listed as follows:

\[
\omega_i = f(i) = \frac{i}{I}.
\]

### 4. Improved Energy Detector with Weights

#### 4.1. Improved Detection Model.

According to (1) and (8), the quaternary hypothesis testing problem of improved ED becomes

\[
Y = \begin{cases} 
\sum_{i=1}^{I} \left( \frac{i}{I} \right)^2 n_i^2 & H_{0,1} \\
\sum_{i=1}^{I} \left( \frac{i}{I} \right)^2 (s_i + n_i)^2 + \sum_{i=d}^{I} \left( \frac{i}{I} \right) n_i^2 & H_{0,2} \\
\sum_{i=1}^{I} \left( \frac{i}{I} \right)^2 (s_i + n_i)^2 + \sum_{i=I-a+1}^{I} \left( \frac{i}{I} \right) (s_i + n_i)^2 & H_{1,1} \\
\sum_{i=1}^{I} \left( \frac{i}{I} \right)^2 n_i^2 + \sum_{i=I-a+1}^{I} \left( \frac{i}{I} \right) (s_i + n_i)^2 & H_{1,2}
\end{cases}
\]

Now, we analyze its probabilities of detection and false alarm. According to (9), \( y_i = (i/I)n_i^2 \) is the sample of AWGN; without loss of generality, \( n_i \) follows a standard Gaussian distribution with zero mean and unit variance indicated by \( n_i \sim N(0, 1) \). So, \( n_i^2 \) follows a central chi-square distribution with one degree of freedom [14]. Therefore, the mean and variance of \( y_i \) are \( E(y_i) = (i/I) \) and \( D(y_i) = 2(i/I)^2 \), respectively. The same approach is applied when the signal \( s_i \) is present with the replacement of each of \( n_i \) by \( (s_i + n_i) \sim N(0, 1 + \gamma) \). So, \( (s_i + n_i)^2 \) follows a noncentral chi-squared distribution with one degree of freedom and a noncentrality parameter \( 2\gamma \). Therefore, \( E((i/I)(s_i + n_i)^2) = (i/I)(1 + \gamma) \) and \( D((i/I)(s_i + n_i)^2) = 2(i/I)^2(1 + 2\gamma) \).

In \( H_{0,1} \), according to the central limit theorem,

\[
Y \sim N \left( \frac{1}{I} \sum_{i=1}^{I} (i), \frac{2}{I^2} \sum_{i=1}^{I} (i)^2 \right).
\]

Therefore, the probability of false alarm is

\[
P_{f,\text{H}_{0,1}} = P(Y > \eta \mid H_{0,1}) = Q \left( \frac{\eta - (1/I) \sum_{i=1}^{I} (i)}{\sqrt{2/I^2} \sum_{i=1}^{I} (i)^2} \right).
\]

In \( H_{0,2} \),

\[
Y \sim N \left( \frac{1}{I} \left( \sum_{i=1}^{I} (i) + \gamma \sum_{i=d}^{I} (i) \right), \frac{2}{I^2} \left( \sum_{i=1}^{I} (i)^2 + 2\gamma \sum_{i=d}^{I} (i)^2 \right) \right).
\]

The probability of false alarm is

\[
P_{f,\text{H}_{0,2}} = P(Y > \eta \mid H_{0,2}) = Q \left( \frac{\eta - (1/I) \left( \sum_{i=1}^{I} (i) + \gamma \sum_{i=d}^{I} (i) \right)}{\sqrt{2/I^2} \sum_{i=1}^{I} (i)^2} \right).
\]

The probability of detection is

\[
P_{d,\text{H}_{1,1}} = P(Y > \eta \mid H_{1,1}) = Q \left( \frac{\eta - (1/I) \left( \sum_{i=d}^{I} (i) \right)}{\sqrt{2/I^2} \sum_{i=d}^{I} (i)^2} \right).
\]

In \( H_{1,2} \),

\[
Y \sim N \left( \frac{1}{I} \left( \sum_{i=1}^{I} (i) + \gamma \sum_{i=d+1}^{I} (i) \right), \frac{2}{I^2} \left( \sum_{i=1}^{I} (i)^2 + 2\gamma \sum_{i=d+1}^{I} (i)^2 \right) \right).
\]

The probability of detection is

\[
P_{d,\text{H}_{1,2}} = P(Y > \eta \mid H_{1,2}) = Q \left( \frac{\eta - (1/I) \left( \sum_{i=d+1}^{I} (i) \right)}{\sqrt{2/I^2} \sum_{i=d+1}^{I} (i)^2} \right).
\]

In the Neyman-Pearson criterion, when the constant false alarm rate (CFAR) strategy is adopted [15], the threshold \( \eta \) is calculated by assigning a predetermined probability of false alarm. So, according to (11), \( \eta \) for improved ED is

\[
\eta = Q^{-1} \left( P_{f,\text{DES}} \right) \sqrt{\frac{2}{I^2} \sum_{i=1}^{I} (i)^2} + \frac{1}{I} \sum_{i=1}^{I} (i).
\]
4.2. The Average Probability Affected by PU’s Traffic. Assuming that the PU traffic is modeled as a 1-0 random process [16], where “1” and “0” states represent the busy and idle channel, respectively. The holding time of each status obeys the Exponential Distribution, with mean parameter $\lambda_b$ for “1” and mean parameter $\lambda_i$ for “0”, respectively.

Therefore, we can obtain that at any time instant, the channel is busy with probability $p_b = \lambda_b/(\lambda_b + \lambda_i)$; in a similar way, the probability of idle status is $p_i = 1 - p_b$. Given the $T_s$ seconds ago, the transition probability of channel from state “$\phi \in \{0,1\}$” to “$\theta \in \{0,1\}$” is given by

$$P_{\phi \theta}(T_s) = \begin{pmatrix} p_{00}(T_s) & p_{01}(T_s) \\ p_{10}(T_s) & p_{11}(T_s) \end{pmatrix} = \frac{1}{\lambda_b + \lambda_i} \begin{pmatrix} \lambda_b + \lambda_i e^{-(\lambda_b + \lambda_i)T_s} & \lambda_i - \lambda_i e^{-(\lambda_b + \lambda_i)T_s} \\ \lambda_b - \lambda_b e^{-(\lambda_b + \lambda_i)T_s} & \lambda_i + \lambda_b e^{-(\lambda_b + \lambda_i)T_s} \end{pmatrix}, \tag{19}$$

where $T_s$ is the sampling interval of ED. Therefore, by using the transition probabilities, the probabilities of each hypothesis happening in the new detection model can be calculated as

$$P(H_{0,1}, T_s) = p_b p_{00}^l(T_s),$$

$$P(H_{0,2}, T_s) = \sum_{d=1}^l \left[ p_b p_{11}^d(T_s) p_{01}(T_s) p_{00}^{l-d}(T_s) \right],$$

$$P(H_{1,1}, T_s) = p_b p_{11}^l(T_s),$$

$$P(H_{1,2}, T_s) = \sum_{d=1}^l \left[ p_b p_{00}^{l-a}(T_s) p_{01}^a(T_s) p_{11}^{a-1}(T_s) \right]. \tag{20}$$

So, by combining the conditional probabilities of detection, false alarm, and the transition probabilities of the licensed channel state, the overall probabilities of detection for the new sensing model by using our improved ED can be given by

$$P_{d\text{Avg}} = \frac{P(H_{0,1}, T_s) P_{H_{0,1}}}{P(H_{1,1}, T_s) + P(H_{1,2}, T_s)} + \frac{\sum_{a=1}^l \left[ p_b p_{00}^{l-a}(T_s) p_{01}^a(T_s) p_{11}^{a-1}(T_s) P_{dH_{12}} \right]}{P(H_{1,1}, T_s) + P(H_{1,2}, T_s)}. \tag{21}$$

In a similar way, the overall probabilities of false alarm can be derived as

$$P_{f\text{Avg}} = \frac{P(H_{0,1}, T_s) P_{fH_{0,1}}}{P(H_{0,1}, T_s) + P(H_{0,2}, T_s)} + \frac{\sum_{d=1}^l \left[ p_b p_{11}^d(T_s) p_{00}(T_s) p_{00}^{l-d-1}(T_s) P_{fH_{12}} \right]}{P(H_{0,1}, T_s) + P(H_{0,2}, T_s)}. \tag{22}$$

5. Simulations and Analyses

In Section 4, we have derived the probabilities of detection and false alarm for our improved ED. In this section, the MATLAB simulation results will be investigated.

Considering that all simulations are conducted using a BPSK modulation on the AWGN channel, the carrier frequency is 500 MHz, sample frequency is 6 MHz, the smallest possible probability of false alarm $P_d^{\text{DES}}$ is 0.1, and the target probability of detection $P_d^{\text{DES}}$ is 0.9. The contrasting simulation experiments are performed among conventional ED, our proposed ED, the improved ED in [4], and the ED proposed in [13]. To conventional ED, the statistical energy test is $Y = \sum_{i=1}^f y_i^p$, and the probabilities of detection and false alarm under simulation circumstance that PU randomly arriving or departing are presented in Section 2 from (2) to (5). To Chen’s novel ED, its principle is replacing the squaring operation with an arbitrary positive power operation; that is, $Y = \sum_{i=1}^f y_i^p$, and we choose that the power operation $p$ is 3 based on Chen’s analysis in [4]. According to [13], the theoretical probabilities of detection and false alarm were not deduced, so we only test its simulation results. When the Beaulieu’s ED test of [13] is $Y = \sum_{i=1}^f (1 - e^{-\lambda T_{\text{sens}}}) y_i^2$, it denotes the PU arrival and $\lambda_b = 1/(a \cdot T_{\text{sens}})$ indicates the arrival rate. In a similar way, when the PU departs, the ED test is $Y = \sum_{i=1}^f (1 - e^{-\lambda T_{\text{sens}}}) y_i^2$ and $\lambda_i = 1/(b \cdot T_{\text{sens}})$ denotes the departure rate. The arrival or departure of the PU followed a Poisson process. The curves labeled as “sim” and “analy” represent simulation results and theoretical analysis results, respectively.

Choosing the SNR of −5 dB, −10 dB, and −12 dB, the sampling time is 1 ms, so the total number of samples $I$ is 6000. In $H_{1,2}$, the number of PU signal samples $a$ in the sensing period lies between 0 and $I$. Figure 3 shows the probability of detection versus $a$ compared among the four kinds of EDs under $H_{1,2}$ and the theoretical results are based on (5) and (17) for conventional ED and our ED, respectively.

From Figure 3, we can infer a match between the simulation and numerical results which indicates that the theoretical analyses of proposed ED are correct. The probability of detection increases as the PU signal samples increases. Thus, one can achieve a larger probability of detection for larger values of $a$ and one can achieve a high probability of misdetection for smaller $a$, as expected.

Figures 4 and 5 show the probability of detection among four kinds of EDs in high SNR and low SNR environment, respectively. We can achieve that Beaulieu’s scheme in [13] has limitation and it only can improve the performance in high SNR environment such as SNR = −5 dB depicted in Figure 4. However, when in the low SNR environment such as SNR = −10 dB showed in Figure 5, the performance of [13] is similar to the conventional one. The performance of Chen’s ED proposed in [4] is less than other ones on matter what the SNR is. However, our ED significantly outperforms its counterparts in all kinds of cases considered. That is to say, our ED needs less number of PU signal samples to fulfill the target probability of detection $P_d \geq P_d^{\text{DES}}$ under the situation of PU status changes.
The probability of detection
Conventional sim
Conventional analy
Our improved sim
Our improved analy
Ref [4] sim
Ref [13] sim

Figure 3: The probability of detection comparison versus $a$ among four kinds of ED in different SNR environments for $T_{\text{sens}} = 1$ ms under $H_{1,2}$.

In $H_{0,2}$, the number of PU signal samples $b$ in sensing period is from 0 to $I$. Figure 6 shows the probability of false alarm versus $b$ compared among four kinds of EDs in different SNR environments under $H_{0,2}$. The theoretical probabilities of false alarm are based on (3) and (13) for conventional ED and our ED, respectively. Our improved ED can reduce the probability of false alarm no matter what the SNR is. The reason for this becomes clear when relative weights are considered.

In conclusion, considering the new detection model, the proposed ED is superior to the compared schemes. In other words, considering the effect of PU traffic on the spectrum sensing performance, our EDs not only can improve the probability of detection as shown in Figure 3, but also reduce the probability of false alarm as seen in Figure 6. Now, we compare the sensing performance in $H_{1,1}$.

Figure 7 shows the probability of detection versus SNR under $H_{1,1}$ and $T_{\text{sens}} = 1/3$ ms. Obviously, the simulation and numerical results match very well, which indicates that the theoretical analyses of proposed ED are correct. The probability of detection increases as the SNR increases. The detection performance of conventional and [13] method is close to each other. And the performance of our proposed ED lay close to them. We can be informed that our ED can achieve a good detection performance compared to the conventional one under $H_{1,1}$.

Figure 8 shows the receiver operating characteristic (ROC) curves of spectrum sensing performance among four types of EDs for different SNR received at SU in local spectrum sensing under $H_{1,1}$. The probability of detection increases as the probability of false alarm increases. The detection performances of four detectors are affected by SNR received at SU. Our proposed method can achieve a good detection performance as the conventional one under $H_{1,1}$.

Now, the performance of spectrum sensing based on the PU traffic is investigated. The average probability of detection is compared between conventional ED and improved ED with weights. The Neyman-Pearson rule is used to determine the detection threshold by maximizing the average probability of false alarm.

We choose simulation parameters $T_s = 0.5$ seconds, $\lambda_b = \lambda_i = 15$, $I = 100$, $y = 1$ dB, $-5$ dB, $-10$ dB, respectively, according to [10]. Figure 9 shows ROC curves of spectrum sensing performance for different SNRs received at SU in local spectrum sensing. In computing, the decision threshold
The probability of false alarm comparison versus $d$ among four kinds of ED in different SNR environments for $T_{\text{sens}} = 1$ ms under $H_{0,2}$.

Figure 6: The probability of false alarm comparison versus $d$ among four kinds of ED in different SNR environments for $T_{\text{sens}} = 1$ ms under $H_{0,2}$.

The probability of detection under $H_{1,1}$.

Figure 7: The probability of detection comparison versus SNR among four types of ED under $H_{1,1}$.

The average probability of detection increases as the average probability of false alarm increases, as we expect. Obviously, the detection performance of both detectors is affected by SNR $\gamma$ received at SU. However, our proposed improved ED with weights outperforms traditional one in different SNR environments.

The SNR is set to $-10$ dB. Larger values of $\lambda_b$ and $\lambda_i$ result in more frequent state transition in PU channel. Firstly, we can see that the frequent state transition in PU traffic degrades the sensing performance significantly. For example, when the desired average probability of false alarm is $P_{f,Avg} = 0.1$ in CRN, the conventional ED has an average probability of detection that is 0.45 when $\lambda_b = \lambda_i = 15$, while when $\lambda_b = \lambda_i = 25$, the average probability of detection is 0.31. However, our proposed improved ED with weights outperforms the traditional one in different PU traffic intensity environments.

In conclusion, from Figures 9 and 10, we can obtain that our ED can improve the overall probabilities of detection.
compared to conventional energy detector, when spectrum sensing is performed for a network with high traffic.

6. Conclusion

We propose an improved ED with weights to improve detection performance in the face of PU’s status changes when arriving or leaving randomly in cognitive radio networks. The idea is derived from the concept of unequal scale sampling such that the sampling points in the sensing period are endowed with monotonic weights. The probabilities of false alarm and detection for our ED are deduced under the new detection model. The simulation results show that our ED not only offers better detection performance but also reduces the probability of false alarm and can improve the overall probabilities of detection compared to conventional energy detector, when spectrum sensing is performed for a network with high traffic.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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