Entropy-based Spectrum Sensing for Cognitive Radio Networks in the Presence of an Unauthorized Signal

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Received September 23, 2014; revised November 21, 2014; accepted December 13, 2014; published January 31, 2015

Abstract

Spectrum sensing is a key component of cognitive radio. The prediction of the primary user status in a low signal-to-noise ratio is an important factor in spectrum sensing. However, because of noise uncertainty, secondary users have difficulty distinguishing between the primary signal and an unauthorized signal when an unauthorized user exists in a cognitive radio network. To resolve the sensitivity to the noise uncertainty problem, we propose an entropy-based spectrum sensing scheme to detect the primary signal accurately in the presence of an unauthorized signal. The proposed spectrum sensing uses the conditional entropy between the primary signal and the unauthorized signal. The ability to detect the primary signal is thus robust against noise uncertainty, which leads to superior sensing performance in a low signal-to-noise ratio. Simulation results show that the proposed spectrum sensing scheme outperforms the conventional entropy-based spectrum sensing schemes in terms of the primary user detection probability.

Keywords: Cognitive radio, spectrum sensing, conditional entropy, unauthorized signal

This research was supported by the MSIP (Ministry of Science, ICT and Future Planning), Korea, under the C-ITRC (Convergence Information Technology Research Center) support program (NIPA-2014-H0401-14-1009) supervised by the NIPA (National IT Industry Promotion Agency). It was also supported by the Sogang University Research Grant of 2010 (No. 201010012).

http://dx.doi.org/10.3837/tiis.2015.01.002 **ISSN : 1976-7277**

1. Introduction

Cognitive Radio (CR) enables efficient use of a limited spectrum by allowing secondary users (SUs) to access licensed frequency bands of primary users (PUs) [1], [2]. Spectrum sensing is a key element to allow SUs to use a vacant frequency band in a CR network. Because of noise uncertainty, however, the performance of the traditional detectors is rapidly deteriorated at a low signal-to-noise ratio (SNR). The current prevailing spectrum sensing schemes are an energy detection-based scheme, a cyclostationary-based scheme, a matched filter-based scheme, and an entropy-based scheme [3], [4].

Many researchers have endeavored to increase the sensing performance of the detectors in CR networks. Some researchers have increased the spectrum sensing performance of the energy detector by adjusting parameters such as decision thresholds, sensing frequency, and the number of sensing operations [5]-[7]. Cooperative spectrum sensing can increase the PU detection performance by combining the sensing information from several SUs [2], [8]. The newly developed entropy-based spectrum sensing scheme generally outperforms the other spectrum sensing schemes [9]-[13]. In information theory, entropy is a measure of the uncertainty associated with a discrete random variable. The term usually refers to Shannon entropy [14]. The authors of [9] introduced an entropy-based approach for PU detection with uncertainty in noise and presented a likelihood ratio test for detecting a PU signal. To counteract the effect of noise uncertainty at a low SNR, the authors of [10]-[12] investigated an entropy-based spectrum sensing scheme in the frequency-domain. Estimating entropy in the time domain does not provide good performance under a low SNR, because the estimated entropy value is a constant regardless of the existence of PUs at a low SNR while the entropy can be estimated in the frequency-domain even at a low SNR. These studies identified the state of a PU solely from the current detected data set. The authors of [13] presented a new cross entropy-based spectrum sensing scheme that has two time-adjacent detected data sets of the PU. This scheme showed an enhanced discriminating ability due to the consideration of more information of the PU signal. The previous works approaches described in [9]-[13], on the other hand, showed the sensing performance in the CR network without the presence of an unauthorized user (UU), where the UU is known as a PU emulation attacker (PUEA). The PUEA emits a signal with a similar form to that of the PU so as to deter access to vacant channels by other SUs [15]. Several approaches have been studied to combat PUEAs. A location-based defence technique was employed in which a number of sensing nodes are deployed to pinpoint PUE attacks [16]. A cooperative spectrum sensing technique, where the existence of a PUEA in a CR network is considered, has been proposed wherein several SUs report the detected signal to the fusion center and the fusion center then calculates the decision statistic [17], [18]. However, the works of [15]-[18] fail to increase the detection performance of each SU because they employ the conventional energy detector.

This paper proposes a conditional entropy-based spectrum sensing scheme to detect the PU in a CR network with an UU. The proposed spectrum sensing scheme uses the mutual information between the expected primary signal and the unauthorized signal; it thereupon enhances the sensing performance by reducing the noise uncertainty. In particular, the proposed spectrum sensing scheme substantially increases the sensing performance at a low SNR in comparison with the previous entropy-based spectrum sensing schemes. This paper is organized as follows. In Section 2, the system model is introduced. In Section 3, a conditional entropy-based spectrum sensing scheme is proposed and analyzed. Simulation results are presented in Section 4, and conclusions are drawn in Section 5.

2. System Model

We consider a CR network with PUs and SUs along with an UU that influences the CR network, as shown in **Fig. 1**. The UU is assumed to be an attacker who is malicious and does not belong to the CR network. In the spectrum sensing period of each time slot, the UU may generate a PU emulation signal in order to deceive SUs. An UU has ability to mimic the behavior of the PU and therefore the unauthorized signal shows similar properties to a primary signal.

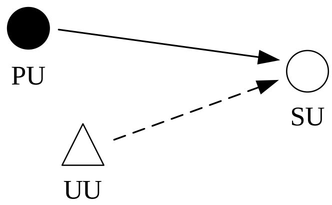

Fig. 1. A CR network with an UU

We consider a frequency bandwidth B_W, with central frequency f_c and sampling frequency f_s. Each SU senses the signal during N samples. The signal received by SUs at the nth sample is

$$y(n) = \alpha s(n) + \beta z(n) + w(n), \qquad n = 1, 2, \cdots, N \tag{1}$$

where $s(n)$ is the primary signal, $z(n)$ is the unauthorized signal, and $w(n)$ represents background noise, which follows a Gaussian distribution $\mathcal{N}(0, \sigma_0^2)$, and N is the sample size. α and β are binary indicators, where $\alpha = 1$ or $\beta = 1$ indicates the presence of the PU or UU and $\alpha = 0$ or $\beta = 0$ implies their absence.

The spectrum sensing problem can be formulated as the following hypotheses: H_0 denotes the absence of a primary and unauthorized signal; H_1 denotes the presence of a primary signal when there is no UU; and H_2 denotes the presence of an unauthorized signal when there is no PU, i.e., the detected signal was transmitted by UUs. The observed signal of a SU can then be expressed as

$$y(n) = \begin{cases} w(n), & H_0 \\ s(n) + w(n), & H_1 \\ z(n) + w(n), & H_2. \end{cases} \tag{2}$$

When we consider two hypotheses, H_1 that a PU transmits a signal and H_2 that an UU transmits a signal, two kinds of risks are incurred in the hypothesis test:

- False alarm: Although the actual transmission is made by the UU, the SU decides that the transmission is due to the PU. In other words, a PUEA occurs.

- Miss detection: Although the actual transmission is made by the PU, the SU decides that the transmission is due to the UU. In other words, the SU unintentionally violates the spectrum sensing rule.

From the Wald's sequential probability ratio test (SPRT), we can specify the desired thresholds λ_1 and λ_2 for the false alarm and miss detection probabilities, respectively. The space of all observations is the sample space of the received power measured at the SU. Let the sequence of the measured power at the SU for N samples be denoted by $\{x_1, x_2, \cdots, x_N\}$, where x_n is the measured power at the nth sample. According to the Wald's SPRT, we can decide which hypothesis is correct [19]. The SPRT is based on considering the likelihood ratio as a function of the number of observations. After N samples, the likelihood ratio (LR) is given by [20]

$$\Lambda_N = \sum_{n=1}^{N} \frac{f^{(UU)}(x_n)}{f^{(PU)}(x_n)}, \tag{3}$$

where $f^{(PU)}(\cdot)$ is the probability density function (pdf) of the received power at a SU from the PU and $f^{(UU)}(\cdot)$ is the pdf of the received power at a SU from the UU. As shown in **Fig. 2**, if $\Lambda_N \le T_1$, we decide H_1, if $\Lambda_N \ge T_2$, we then decide H_2, otherwise, we decide H_0. The decision criteria can then be expressed as follows [19], [20]:

$$\begin{cases} \Lambda_N \le T_1 = \dfrac{\lambda_1}{1-\lambda_2} & , H_1 \\ \Lambda_N \ge T_2 = \dfrac{1-\lambda_1}{\lambda_2} & , H_2 \\ \text{otherwise} & , H_0. \end{cases} \tag{4}$$

In (4), as two thresholds, λ_1 and λ_2, decrease, the threshold T_1 decreases and the threshold T_2 increases. Hence, as shown in **Fig. 2**, it is more likely that a SU makes another decision H_0 that there is no signal although there is a PU or UU. To correctly detect the presence of the PU, when H_1 is true, the LR of (3) should be small enough that it is less than or equal to T_1. Similarly, when H_2 is true, the LR of (3) should be large enough that it is greater than or equal to T_2. However, in the SPRT, there is a tradeoff between a reliable decision and the time to detect.

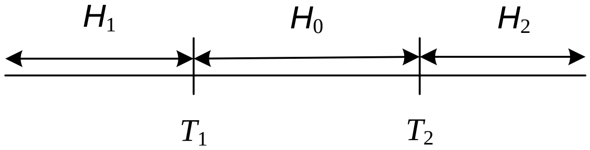

Fig. 2. Decision criteria in SPRT

3. Proposed Conditional Entropy-based Spectrum Sensing

3.1 Frequency-Domain Entropy

The structure of the proposed conditional entropy-based detector is shown in **Fig. 3**, where the detector consists of three blocks: a frequency-domain converter, a conditional entropy estimator, and a test statistic. The frequency-domain detector is generally superior to the time domain detector [10], [11]. Applying the discrete Fourier transform (DFT) to (1), we have

$$\vec{Y}(k) = \alpha\vec{S}(k) + \beta\vec{Z}(k) + \vec{W}(k), \qquad k = 1, 2, \cdots, K \tag{5}$$

where K, which is the DFT size, is equal to the sample size N; the parameters, $\vec{Y}(k)$, $\vec{S}(k)$, and $\vec{W}(k)$, represent the complex spectrum of the received signal, the primary signal, and the background noise, respectively. Hence, in the frequency-domain, we have the following hypotheses:

$$\vec{Y}(k) = \begin{cases} \vec{W}(k), & H_0 \\ \vec{S}(k) + \vec{W}(k), & H_1 \\ \vec{Z}(k) + \vec{W}(k), & H_2 \end{cases} \tag{6}$$

The complex spectrum of the received signal can be expressed as follows [11]:

$$\begin{aligned} \vec{Y}(k) &= Y_r(k) + jY_i(k) \\ &= \frac{1}{N}\sum_{n=0}^{N-1} y(n)\exp(-j\frac{2\pi}{N}kn), \end{aligned} \tag{7}$$

where $Y_r(k)$ and $Y_i(k)$ represent the real part and the imaginary part of $\vec{Y}(k)$, respectively. The spectrum magnitude can then be expressed as $Y(k) = \sqrt{Y_r^2(k) + Y_i^2(k)}$.

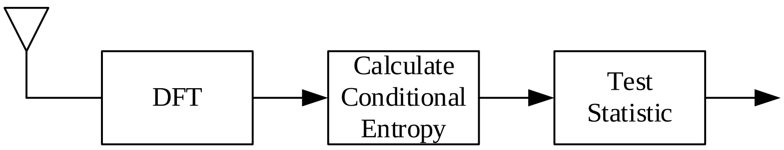

Fig. 3. A block diagram of the conditional entropy-based frequency-domain detector

In information theory, the conditional entropy quantifies the amount of information needed to describe the outcome of a random variable Y given that the value of another random variable Z is known. The distribution of Z is assumed to be estimated by observing UUs [17]. The conditional entropy is

$$H(Y \mid Z) = -\sum_{y \in Y, z \in Z} p(y,z)\log\frac{p(y,z)}{p(z)}, \tag{8}$$

where $H(Y \mid Z)$ is estimated from the probability mass function of Y and Z, and is compared with a threshold to decide the current knowledge of the PU. $p(y)$ and $p(z)$ denote the probability mass function of discrete random variables, Y and Z, respectively. $p(y, z)$ denotes the joint probability mass function of Y and Z.

A number of schemes have been proposed by earlier researchers for estimating the entropy of a continuous random variable based on a finite number of observations [10], [11], [14]. To reduce the computational complexity, we use the simplest approach, histogram-based estimation of the density function. The histogram-based method estimates the probability of each state. Let Y and Z represent the distribution of the spectrum magnitude of the measured signal in the presence of a primary signal and in the presence of an unauthorized signal, respectively. We divide the range of Y and Z into L_y bins and L_z bins, respectively. Hence, the bin widths are $\Delta_y = Y_{\max} / L_y$ and $\Delta_z = Z_{\max} / L_z$, where $Y_{\max}$ and $Z_{\max}$ denote the maximum value of the random variables, Y and Z, respectively. The probability mass function can then be approximated as the frequency of occurrences in each bin width. Hence, we have $p(y) \approx k_y / N$ and $p(z) \approx k_z / N$, where k_y and k_z are respectively the total number of occurrences in the yth bin of Y and in the zth bin of Z; N is the number of observations. As described above, a SU can estimate the distribution of Y based on the observations of the received signals. However, in practice, it is difficult to estimate the distribution of Z without the help of the primary system or without the location information of UUs. Some works analytically derived a distribution of unauthorized signals when UUs are uniformly located in a cell [20], while other works assumed that the channel information, both for the PU and for the UU, can be obtained [17]. In this paper, we assume that a primary system has a periodic duration for the pilot transmission or the silence. A SU can then receive unauthorized signals for every the periodic duration and it may estimate the distribution of Z based on the cumulative observations of the unauthorized signals.

3.2 Spectrum Statistics of the Received Signal

In hypothesis H_0, the received signal, $y(n) = w(n)$, consists of noise. Both the real part W_r and the imaginary part W_i of the spectrum follow a Gaussian distribution. Hence, $Y(k) = \sqrt{W_r^2(k) + W_i^2(k)}$ follows a Rayleigh distribution with the parameter σ_y, and the differential entropy of Y can be expressed as [10], [14]

$$h(Y) = 1 + \ln\frac{\sigma_y}{\sqrt{2}} + \frac{\gamma}{2}, \tag{9}$$

where γ is the Euler-Mascheroni constant.

In hypothesis H_1, the received signal, $y(n) = s(n) + w(n)$, consists of both the primary signal and the noise. The entropy of the spectrum amplitude in the presence of the primary signal is much smaller than in the absence of the primary signal. Let D be the distance of the estimated entropies between hypothesis H_0 and hypothesis H_1. If $D \geq \delta$, we decide H_1 and otherwise, we decide H_0, where δ is the threshold determined by false alarm and miss detection probabilities [11]. Because the entropy of the noise signal has almost a constant value, we can do the test statistic with the estimated entropy of the received signal in hypothesis H_1; i.e., if $H(Y \mid Z) \leq \delta'$, we decide H_1 and otherwise, we decide H_0, where δ' is the difference between the entropy of the noise signal and the value of δ.

3.3 Reduction of Noise Uncertainty

The proposed spectrum sensing uses the conditional entropy with mutual information between the primary signal and the unauthorized signal. On the basis of the mutual information, the conditional entropy, $H(Y \mid Z)$, is obtained as [14]

$$H(Y \mid Z) = H(Y) - I(Y;Z), \tag{10}$$

where $H(Y)$ is the entropy of Y, and $I(Y;Z)$ is the mutual information between Y and Z. The mutual information is equal to the relative entropy which measures the distance between probability distributions of Y and Z. The mutual information can be expressed as

$$\begin{aligned} I(Y;Z) &= D(p(y,z) \,\|\, p(y)p(z)) \\ &= \sum_{y \in Y, z \in Z} p(y,z) \log\left(\frac{p(y,z)}{p(y)p(z)}\right), \end{aligned} \tag{11}$$

where $D(p(y,z) \,\|\, p(y)p(z))$ is the Kullback-Leiber divergence of the product, $p(y)p(z)$, of the two marginal probability distributions from the joint probability distribution of Y and Z, i.e., the expected number of extra bits that must be transmitted to identify Y and Z if they are coded using only their marginal distributions instead of the joint distribution. In the following, we derive how to reduce the noise uncertainty with the conditional entropy between the primary and unauthorized signals.

Proposition 1. *The mutual information of entropy reduces the uncertainty of the primary signal due to the knowledge of the unauthorized signal. With a fixed bin number, L_z, the entropy of the spectrum of WGN can be approximated by a constant; the proposed spectrum sensing technique on the basis of the mutual information is hence intrinsically robust to noise uncertainty.*

Proof. The maximum values of Y and Z, $Y_{\max}$ and $Z_{\max}$, can be expressed as $Y_{\max} = C_y\sigma_y$ and $Z_{\max} = C_z\sigma_z$, respectively, where C_y and C_z are constant values [10]. The bin width can then be expressed as $\Delta_y = Y_{\max} / L_y = C_y\sigma_y / L_y$ and $\Delta_z = Z_{\max} / L_z = C_z\sigma_z / L_z$, respectively. If the density $f(y)$ of the random variable Y is Riemann integrable, then the entropy of the quantized version $H(Y^{\Delta})$ is [14]

$$H(Y^{\Delta}) \approx h(Y) - \log \Delta_y. \tag{12}$$

Hence, from (9), (10), and (12), with the natural logarithm, the conditional entropy $H(Y \mid Z)$ can be expressed as

$$
\begin{aligned}
H(Y\,|\,Z) &= H(Y) - I(Y;Z) \\
&\approx \{h(Y) - \log(\Delta_y)\} - \{i(Y;Z) - \log(\Delta_y \Delta_z)\} \\
&= \left\{1 + \ln\frac{\sigma_y}{\sqrt{2}} + \frac{\gamma}{2} - \ln\left(\frac{C_y \sigma_y}{L_y}\right)\right\} - \left\{1 + \ln\frac{\sigma_y \sigma_z}{\sqrt{2}} + \frac{\gamma}{2} - \ln\left(\frac{C_y C_z \sigma_y \sigma_z}{L_y L_z}\right)\right\} \\
&= \ln\left(\frac{C_z}{L_z}\right).
\end{aligned}
\tag{13}
$$

where $i(Y;Z)$ represents the differential entropy of the mutual entropy $I(Y;Z)$. From (13), it is seen that the conditional entropy is approximated by a constant for a given bin number L_z, which implies that the proposed conditional entropy-based detection is robust against noise uncertainty.

4. Simulation Results

We evaluate the performance of the spectrum sensing schemes in a cognitive radio network with the existence of UUs. The performance of the proposed spectrum sensing has been compared with that of [11] and [13] in the frequency-domain. MATLAB is used as a tool for evaluating the performance of the proposed spectrum sensing scheme though extensive simulations in Gaussian and Rayleigh fading channel environments. The simulation parameters are identical to those in the work of [11]. A single sideband signal is selected as a candidate PU signal. The UU is assumed to mimic the PU signal with a half power of the PU signal. The nominal noise power is -90 dBm with ± 5 dB fluctuation. In the simulation, all channel information is assumed to be known to the SUs [17]. To estimate the probability mass functions, the probability space is partitioned into equal bin numbers, L_y = 15 and L_z = 10. The probabilities for hypotheses in SPRT are assumed to be λ_1 = 0.1 and λ_2 = 0.2. Moreover, the threshold for the test statistic is assumed to be δ = 0.3. The false alarm probability is no more than 0.1. The other simulation parameters used in this paper are summarized in **Table 1**. The terms "E-based scheme" and "CE-based scheme" in the figures denote the entropy-based and cross entropy-based spectrum sensing scheme, respectively. In the conventional E-based scheme, SUs decide the presence of a primary signal based on the estimated entropy $H(Y)$ and in the previous CE-based scheme, SUs decide the presence of a primary signal based on the estimated cross entropy $H(Y_i, Y_{i\text{-}1})$ between the current detected data set Y_i and the previous detected data set $Y_{i\text{-}1}$ [11], [13]. In the proposed spectrum sensing scheme, SUs decide the presence of a primary signal based on the estimated conditional entropy $H(Y\,|\,Z)$.

Table 1. Simulation parameters

Items	Values
Bandwidth, B_W	12 KHz
Carrier frequency, f_c	40 KHz
Sample frequency, f_s	100 KHz
DFT size, K	128
Sample size, N	5000
Average noise power	-90 dBm

4.1 Gaussian Channel

Fig. 4, 5, and **6** shows the performance of the spectrum sensing schemes under Gaussian channel environments. As shown in **Fig. 4**, the distances between the estimated entropies of the noise and signal in [11] and [13] are smaller than that of the proposed spectrum sensing scheme. A higher gap between the noise and the signal ensures better performance in distinguishing the signal from the noise regardless of the absolute value of the estimated entropy. For example, the distance between the noise and the signal of the estimated entropy in the proposed spectrum sensing is about ten times greater than that of [11] and twice that of [13] at a SNR of -10 dB. The entropy detector is based on the characteristic that the entropy of a stochastic signal is maximized if the signal is Gaussian. If the received signal contains the PU signal, the entropy is reduced. Hence, the signal in the estimated entropy degrades smoothly as the value of the SNR increases. From **Fig. 4** it can be concluded that the proposed detector can better distinguish the signal from the noise even at a low SNR as compared with the conventional entropy detectors.

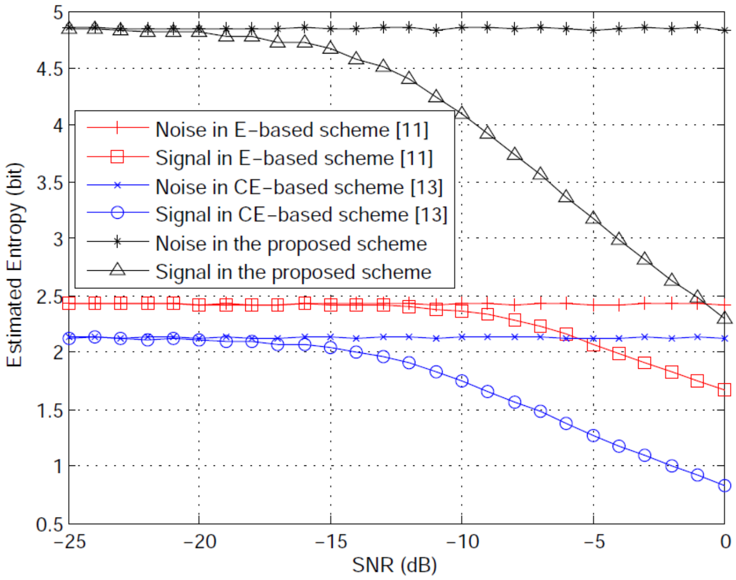

Fig. 4. Estimated entropy in the Gaussian channel

Fig. 5 shows the detection probabilities of the spectrum sensing schemes. The distance between the estimated entropies of the noise and signal in **Fig. 4** results in the difference of the detection performance seen in **Fig. 5**. For example, to satisfy the detection probability over 0.9, the detectors of the E-based scheme, CE-based scheme, and proposed scheme require a SNR of -0.9 dB, -4.1 dB, and -5.8 dB, respectively. When the SNR is -5 dB, the detection probability of the proposed spectrum sensing scheme is about 1304% greater than that of the E-based scheme of [11] and about 28% greater than that of the CE-based scheme of [13]. Consequently, the proposed spectrum sensing can detect the primary signal even at a low SNR.

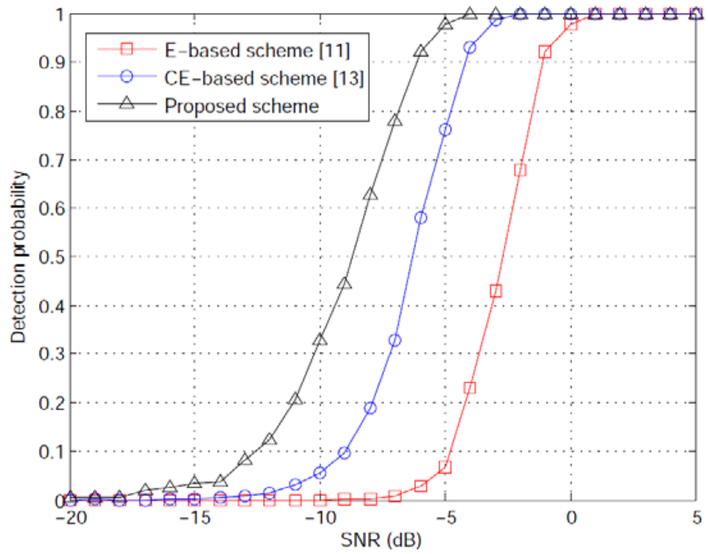

Fig. 5. Comparison of detection probability in the Gaussian channel

Fig. 6 shows the receiver operating characteristic (ROC) curves of each sensing scheme when SNR = -10 dB. When the false alarm probability $P_f = 0.2$, the detection probability of the proposed scheme outperforms the E-based scheme of [11] by about 150% and the CE-based scheme of [13] by about 10%.

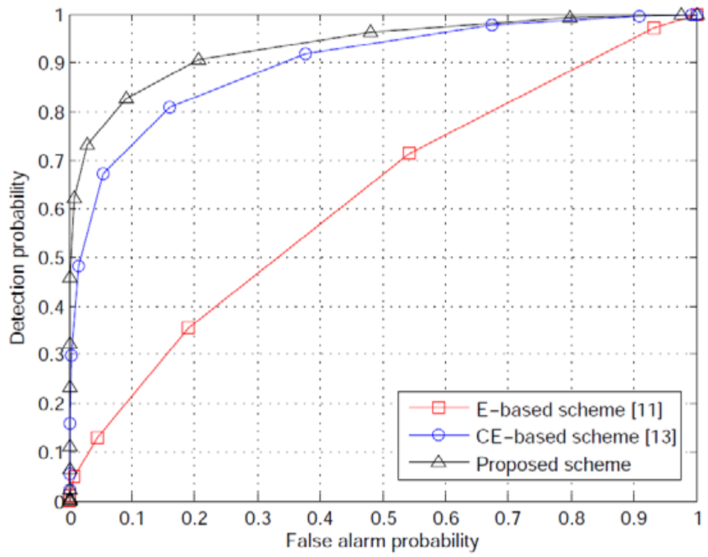

Fig. 6. Comparison of ROC curves in the Gaussian channel when SNR = -10 dB

4.2 Rayleigh Fading Channel

Fig. 7, 8, and **9** show the performance of the spectrum sensing schemes under the Rayleigh fading channel environments. The primary signal is a single sideband signal, which is assumed to experience deep fading such that the magnitude follows a Rayleigh distribution when the delay time of each path is 0.01 seconds and the number of the paths is 15.

As shown in **Fig. 7**, the proposed spectrum sensing scheme shows better performance than the previous spectrum sensing schemes of [11], [13] under a Rayleigh fading channel.

Superior performance in discerning signals from noise requires a greater gap between the noise and the signal regardless of the value of the estimated entropy. At any SNR value, the proposed scheme possesses higher gaps than others. For example, the distance between the noise and the signal of the estimated entropy is about three times greater than that of [11] and twice that of [13] at a SNR of -10 dB.

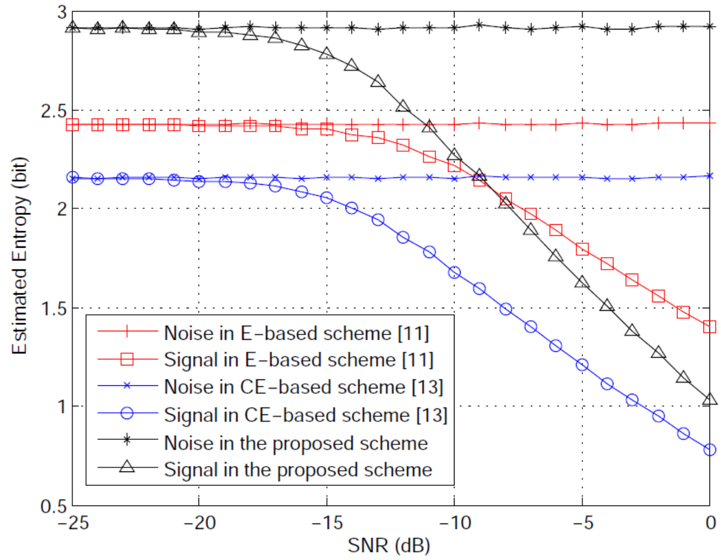

Fig. 7. Estimated entropy in the Rayleigh fading channel

Fig. 8 shows that the detection performance of the proposed scheme outperforms that of the conventional spectrum sensing schemes of [11] and [13]. For example, to satisfy detection probability over 0.9, the proposed spectrum sensing scheme has a SNR gain of about 7 dB and 1.4 dB in comparison with [11] and [13], respectively. Moreover, at a SNR of approximately -10 dB, the detector of [11] is unable to detect PU signals while the detector of [13] and that of the proposed spectrum sensing scheme show detection probability of 0.40 and 0.65, respectively.

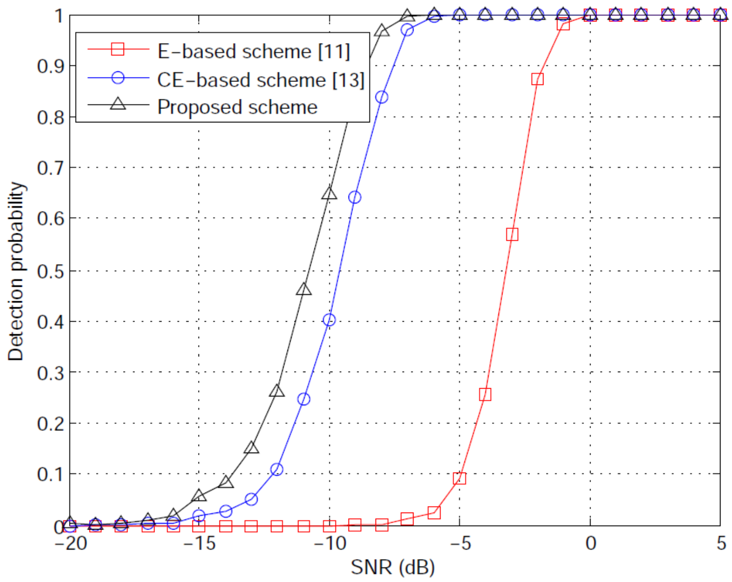

Fig. 8. Comparison of detection probability in the Rayleigh fading channel

Fig. 9 shows that the detection ability of the proposed scheme is more robust than that of the conventional entropy-based schemes. By selecting a SNR = -10 dB, we have simulated the ROC curves in a Rayleigh fading channel. This figure shows that the detection probability of the proposed spectrum sensing scheme is better than that of [11], [13] when the false alarm probability is identical.

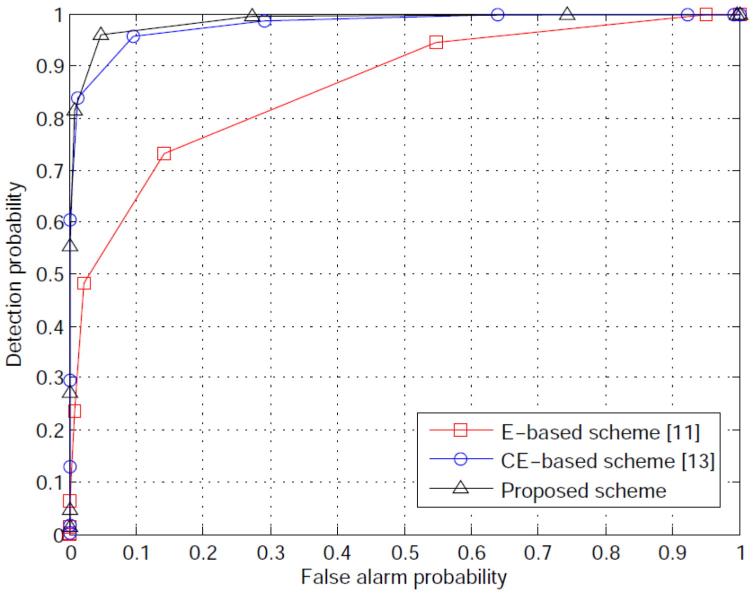

Fig. 9. Comparison of ROC curves in the Rayleigh fading channel when SNR = -10 dB

5. Conclusion

A conditional entropy-based spectrum sensing scheme has been proposed for a cognitive radio network with an unauthorized signal. The proposed spectrum sensing scheme uses the mutual information and exploits the difference between the primary signal and the unauthorized signal. The proposed spectrum sensing scheme in the frequency-domain is shown to be robust to noise uncertainty and presents good primary user detection performance at a low signal-to-noise ratio. Under the Gaussian channel, when the signal-to-noise ratio is -5 dB, the proposed spectrum sensing scheme increases the detection probability by more than 28% as compared with the conventional entropy-based sensing schemes. However, the proposed spectrum sensing has a limitation that the characteristic of the unauthorized signal can be estimated from the observations due to the help of the primary system. Our future work will study an entropy-based spectrum sensing scheme with the partial or blind information of the UU signal characteristic. Future work will also include comparisons with other detection schemes designed to combat PUEAs, where the proposed conditional entropy-based spectrum sensing will be extended into cognitive radio networks with cooperative spectrum sensing.

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