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IMPROVEMENT IN COOPERATIVE SPECTRUM SENSING ON COGNITIVE RADIO NETWORKS IN AWGN AND RAYLEIGH FADING ENVIRONMENTS

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ABSTRACT

Cognitive radios (CRs) have lately emerged as promising possibilities for improving spectral efficiency by utilizing spectrum-aware systems that accurately monitor licensed users' activity. Spectrum sensing is used by CR users to detect potential white spaces in such activities. Local sensing, on the other hand, could be a useful tool. In fading situations, this is a difficult task. If spectrum sensing is ineffective, licensees may experience interference. They are detected incorrectly by CR users. Thus, cooperative spectrum sensing is proposed as a means to combat fading and enhance the accuracy of detection However, when such cooperation is used, the detection performance does not improve. A low-SNR environment is taken into account. Cooperative spectrum sensing with PSO-based threshold adaptation is discussed in this study is given as a solution to the aforementioned issue. Simulation results suggest that using a PSO-based adaptive detection threshold improves detection performance, especially in low-SNR environments.

KEYWORDS: cognitive radio, threshold, adaptation, OR rule, cooperative spectrum sensing.

INTRODUCTION

As wireless communication technology grows rapidly, the demand for spectrum is increasing consequently in order to support more wireless services. However, limited radio resources pose a significant challenge in meeting the growing demand for spectrum. The Federal Communication Commission (FCC) conducted a survey to assess spectrum usage efficiency in a temporal and geographical area variation.[1] According to the results of this survey, licensed spectrum is currently underutilized. As a result, cognitive radio (CR) has been offered as one of the most viable solutions for meeting the growing demand for spectrum by utilizing underutilized licensed spectrum segments.

According to the FCC, an SDR (software-defined radio) is a radio in which the operating parameters of frequency range, modulation type and maximum output power can be changed by making a mutation in software without making any changes to hardware components that affect the radio frequency emissions.

SDR's main premise is that users can change their broadcasts on the go, rather than being constrained by hardware limitations.

CR is characterized as a radio that can adapt and learn from its surrounding radio environment and alter network parameters to enhance spectrum consumption while enabling wireless access flexibility.[1] In other words, CR is a technology capable of detecting and identifying threats. gaining efficient access to under-utilized spectrums .For CR systems to have this capability, four key functions are proposed: spectrum sensing, spectrum decision, spectrum sharing, and spectrum mobility.[2] Spectrum sensing will be conducted first during CR operation to detect all available under-utilized spectrums, commonly known as spectrum gaps or white spaces.[3]

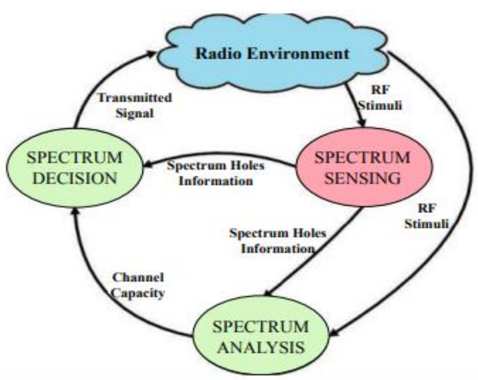

Figure 1: Cognitive Cycle.

Following the detection of all white spaces, the spectrum decision-making algorithm will be used to select the optimal white space for instantaneous transmission. In CR, the spectrum sharing function coordinates or schedules spectrum band sharing with other secondary users (SUs) and/or CR users. Finally, once recognized, the spectrum mobility function allows SU to smoothly release the spectrum band to its owner, also known as the primary user (PU), and migrate to another accessible white space.

In actuality, PU signals may be shaded and dimmed, resulting in fast signal fluctuation.

Many studies[2][4][5] [Due to probable fading and shadowing effects, local spectrum sensing by a single SU may not be able to reliably establish the presence of PU signal. Cooperative spectrum sensing[2][4] has been presented as a solution to this problem. The detection performance of cooperative spectrum sensing approaches appears to be improving.[6][7]

However, as shown in.[7], cooperative sensing does not significantly increase detection performance in low-SNR environments.

The performance of local spectrum sensing and cooperative spectrum sensing under different radio environments, such as Additive White Gaussian Noise (AWGN) and Rayleigh fading channels, is investigated in this study. Because of its ease of implementation, energy detection-based spectrum sensing is used in this paper. In addition, in compared to soft fusion techniques, an OR-rule hard decision fusion scheme is used to realize cooperative sensing while preserving low communication overhead. Finally, to overcome the issue of inefficient performance of cooperative spectrum sensing in low-SNR scenarios, a cooperative spectrum sensing with particle swarm optimization PSO-based threshold adaptation is developed.[8]

- **Energy detector-based local spectrum sensing**

The primary user PU signal is initially received and sampled in energy detection. Two assumptions can be inferred from the sampled received signals using SU, as shown below.

H0: PU is idle.

H1: PU is active.

The received signal for the i-th SU can be represented as follows based on the two possibilities above.[8]

$$y1(t) = \begin{cases} hi(t), & H0 \\ hixi(t) + ni(t), & H1 \end{cases}$$

where yi (t) denotes the signal received by the i-th SU, x(t) is the PU signal, and ni(t) denotes the received AWGN noise by means of the i-th SU The channel gain is hi. To determine if H0 or H1 is correct, and the energy of The received signal, yi(t), is calculated from the received signal.[9]

licensed channel of interest within an observation It is possible to obtain a test/decision statistic.[8] states that Zi is a decision statistic derived from the energy data. The detector for the i-th SU is as follows.

$$Z_i = \frac{1}{2w} + \sum_{k=1}^{2TW} \left(\frac{{y^2}_i K}{N_o W} \quad \right) \qquad (2)$$

Where $y_{i,j}$ =y(k/2w) and N_o is the one-sided noise power spectral density. The decision statistic for the i-th SU, Z_i, obtained from the energy detection is found to have chi-square distribution[8] and can be characterized as.

$$Z_i \left\{ \begin{matrix} {X_2}^2 \\ {X_{2m}}^2(2\gamma_2) \end{matrix} \middle| \begin{matrix} H_o \\ H_1 \end{matrix} \right\} \qquad (3)$$

Where m=TW The energy detector's time-bandwidth product is this. For the sake of simplicity, m is assumed to be an integer. Equation 3 ${X_{2m}}^2$ denotes a central chi-square distribution with 2m degrees of freedom, whereas ${X_{2m}}^2(2\gamma_2)$ denotes a central chi-square distribution with 2m degrees of freedom depicts a 2m degree of freedom noncentral chi-square distribution with a non centrality $2\gamma_2$ for H1 where Ûi is the instantaneous SNR received at the i-th SU.[9]

In general, the probability of false alarm and probability of detection for the i-th SU are, respectively, given as.

$$P_{f,j} = P_r(Z_i > \lambda_i | H_o) \quad (4)$$

$$P_{d,j} = P_r(Z_i > \lambda_i | H_1) \quad (5)$$

Where λ_i is the detection threshold for the i-th SU. Hence, from Equations 3 and 4, the closed-form expression for probability of detection over AWGN channel can be obtained from[9] as.

$$P_{d,j} = Q_m \sqrt{2\gamma_2} , \sqrt{\lambda} \quad (6)$$

where Q_m(a,b) refers to the generalized Marcum Q-function defined:

$$Q_m(a,b) = \frac{1}{a^{m-1}} \int_b^{\infty} x^m \, e^{\frac{x^2+a^2}{2}} |_{m-1} \, (ax)dx \quad (7)$$

The probability of missed detection is simply defined as

$$P_{m,j} = 1 - P_{d,j} \quad (8)$$

Using Equations 3 and 5, the chance of a false alert over the AWGN channel is calculated as.[9]

$$P_{m,j} = \frac{\Gamma(m, \frac{\lambda_i}{2})}{\Gamma(m)} \quad (8)$$

Where Γ (.) and Γ (.,.) are the complete gamma function and the upper incomplete gamma function, respectively. It was noted that Equation 9 is independent of γ_i; the instantaneous channel SNR. For fading channels, the probability of detection, $P_{d,i}$, for the i-th SU over fading channels can be, respectively, given as.[6]

$$P_{d,j} = \int Q_m\left(\sqrt{2\gamma_i} , \sqrt{\lambda}\right) f_{\gamma_i}(x) \, dx \quad (9)$$

Where $f_{\gamma_i}(x)$ is the PDF for which changes depending on the fading model. The probability of false alert, on the other hand, will stay the same as in Equation 9 because it is unaffected by γ_i. The PU signal experiences multipath fading when it is subjected to scattering produced by the environment. Rayleigh distribution is used to explain the degraded PU signal as a result of this phenomena.[5]

Therefore, γ_i would have an exponential distribution and thus the probability of detection over Rayleigh fading channel can be found as.[9]

$$P_{d,j} = e^{\frac{\lambda_i}{2}} \sum_{K=0}^{m-2} (\frac{\lambda_i}{2})^k + (\frac{1+\gamma_i^-}{\gamma_i^-})^{m-1} * (e^{\frac{\lambda_i}{2(1+\gamma_i^-)}}) - e^{\frac{\lambda_i}{2}} \sum_{K=0}^{m-2} (\frac{\lambda_i \gamma_i^-}{2(1+\gamma_i^-)})^k \quad (11)$$

- **Cooperative spectrum sensing**

To detect the presence of a PU signal, each SU uses spectrum sensing. The signal strength fluctuates at different times and locations when the PU signal experiences deep fading and shadowing, based on the channel circumstances indicated by the appropriate noises and gains imposed.[5]

In the literature, many different decision fusion strategies have been presented. The so-called one-out-of-N rule, or ORrule, is a well-known decision fusion strategy, where N is the total number of cooperating SU.[5]

All collaborating SUs communicate their local sensing decisions to a shared fusion center for final decision fusion in this hard decision fusion method. If all N participating SUs indicate that the PU is absent, a final decision corresponds to H0[9], however if at least one out of N SUs indicates that the PU is present, a final decision corresponds to H1.[11] The probability of detection, the probability of missed detection, and the probability of false alarm of cooperative spectrum sensing, indicated by Qd, Qm, and Qf, respectively, can be described as[7], assuming that all judgments are independent.[6]

$$Q_d = 1 - \prod_{i=1}^{N} (1 - P_{d,j}) \quad (12)$$

$$Q_m = 1 - \prod_{i=1}^{N} (1 - P_{d,j}) \quad (13)$$

$$Q_f = 1 - \prod_{i=1}^{N} (1 - P_{f,j}) \quad (14)$$

- **Dynamic threshold adaptation with cooperative spectrum sensing**

the cooperative is a group of people who work together to achieve a common .the use of spectrum sensing did not yield any noteworthy results. In a low-SNR setting, the detection performance has improved. This is being done in order to address the problem[7]. A cooperative spectrum sensing system is presented in this study for finding the best detection a detection threshold at which there is a high possibility of detection and a low probability of false alert is achieved by working together.[15] The Each SU's computed decision statistic will then be when compared to the optimal threshold and all SUs' corresponding decisions will be sent.to an OR-rule common fusion center for developing a final global decision on PU availability.[6]

- **Threshold adaptation**

Low chance of missed detection and low probability of false alarm must always bemaintained in an SNR varying environment to maximize detection performance.[9] This is because minimizing the probability of missed detection protects the PU from prospective SU transmissions, whilst minimizing the probability of false alarm helps SUs to make efficient use of the unused spectrum bands. As a result, the decision threshold must be adaptively modified to meet the two competing needs outlined above for diverse channel conditions.[6] The complete CRN performance goal can be reduced to a single optimization problem of minimizing the total sensing error as defined by.[11]

$$\varepsilon = (1 - \delta)P_m + \delta P_f \quad (15)$$

Where δ is a weighting constant that ranges from 0 to 1 for the probability of missed detection vs false alert. Because a low chance of a false alert and a high chance of detection are desired.[12] The threshold must be constrained in some way. The probability of a false alert is confined in this research to the range [0.001, 0.1]. It is fair to set a maximum limit on the chance of false alarm in order to maintain a low probability of false alarm.[13] A minimum limit is also imposed since a very low probability of false alarm implies a very low possibility of detection, therefore establishing a minimum limit on the probability of false alarm could maintain a respectable probability of detection. As a result, the optimization problem takes on a new dimension.[14]

$$\lambda = argmin\varepsilon(\lambda)$$

so 0.001<=pf<=0.1 (16).

- **Simulation environment:** Simulation environment is set as follows.

Table 1: Simulation environment.

Parameters	Values
Time bandwidth factor	1000
threshold	-
Number of samples	2000
Number of cognitive radio uses	10
Probability of false alarm	Changed -From 0.01 to 1 (increament by 0.01)

The simulation code had implemented Using MATLAB to find the relationship between probability of missed detection pmd & Probability of False Alarm PFA for cooperative spectrum sensing algorithm. also the relationship among probability of detection and signal to noise ratio in dB had implemented.

- **RESULTS**

After execution of simulation code the results explained in form of graphs as follows.

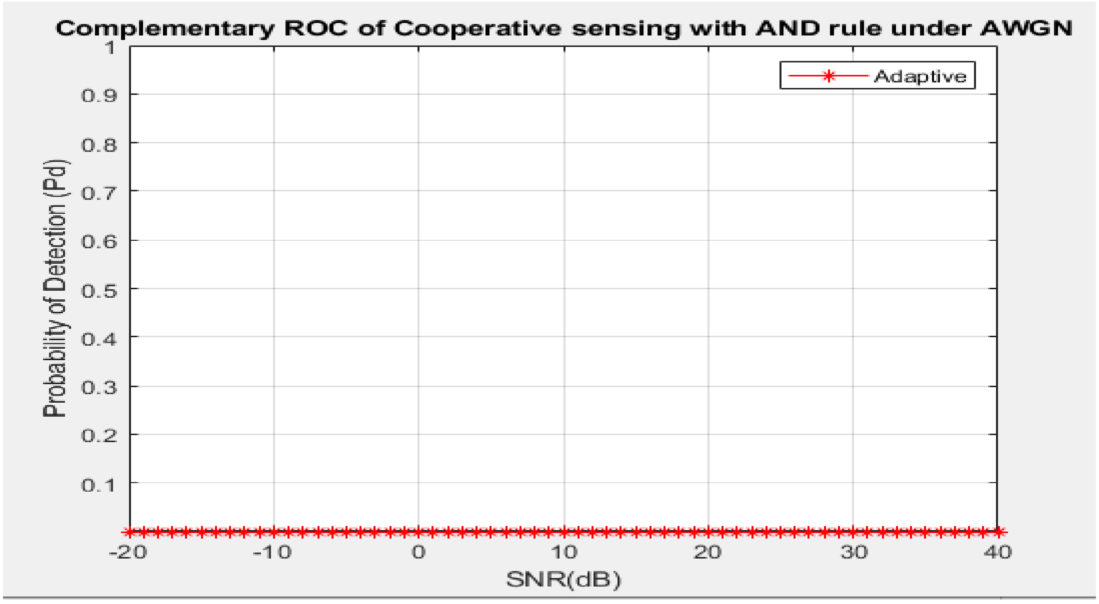

Figure 2: complementary ROC of cooperative sensing with AND rule under AWGN, relationship between probability of detection and signal to noise ratio.

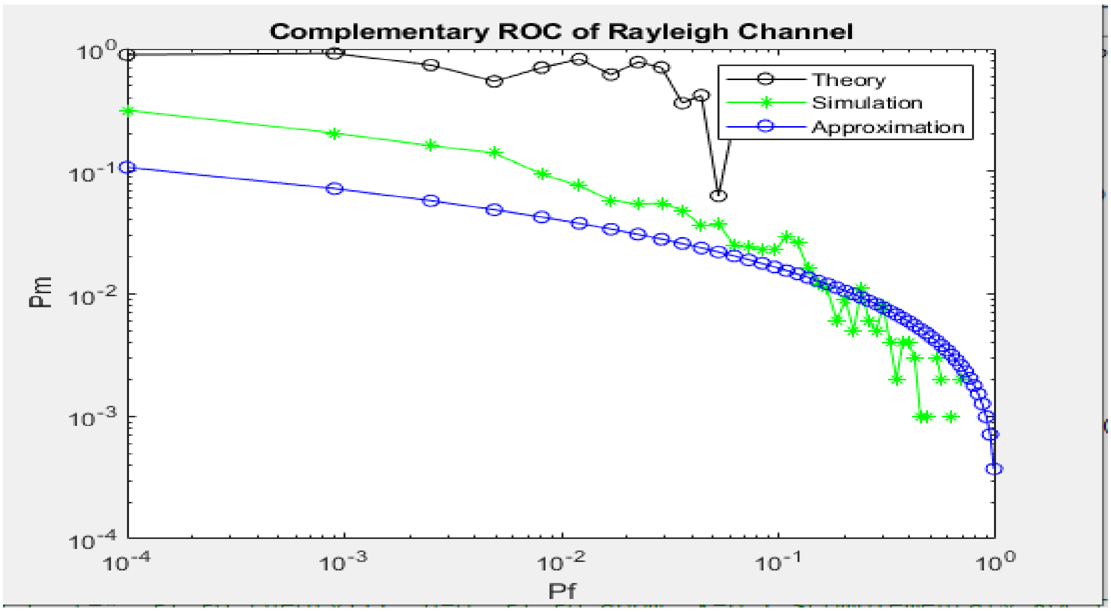

Figure 3: complementary ROC of Rayleigh channel, relationship between probability of detection and probability of false alarm.

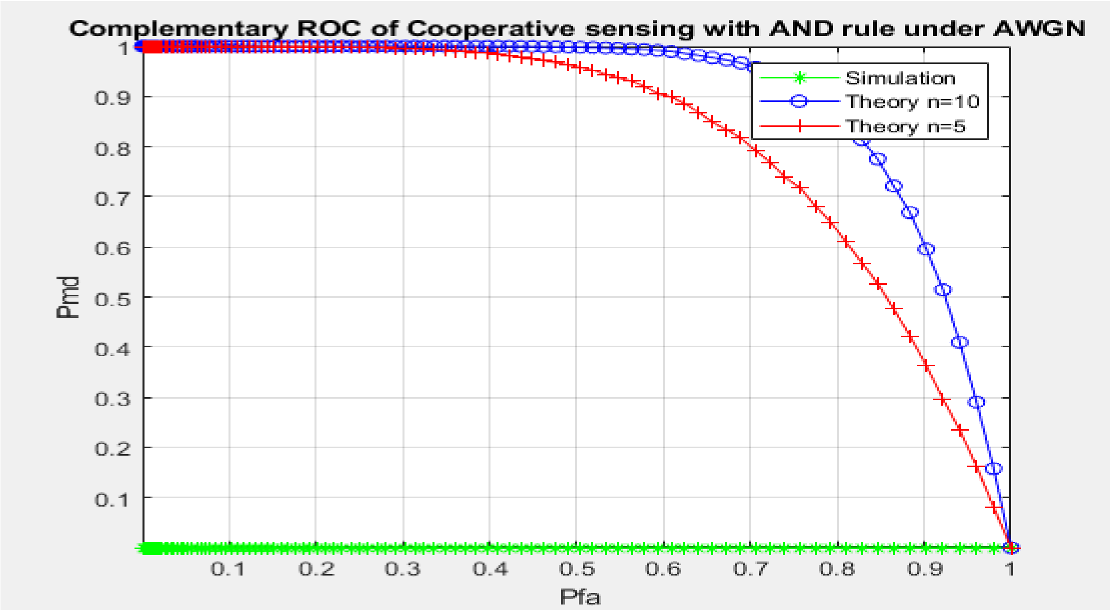

Figure 4: complementary ROC of cooperative sensing with AND rule under AWGN, relationship between probability of detection and signal to noise ratio with 10 cognitive users.

- **RESULTS AND DISCUSSION**

From equations.[6,7,8,9] the probabilities of detection are calculated .To found the relationship between its and signal to noise ratio. The probability of detection, the probability of missed detection, and the probability of false alarm of cooperative spectrum sensing, indicated by Qd, Qm, and Qf, respectively which were obtained from equations (12,13,14). From equation 15 the probability of missed detection vs false alert was found. So the relationship between them is inverse relationship, a low chance of a false alert and a high chance of detection are desired.

CONCLUSION

The detection performance of OR-rule for local spectrum sensing and cooperative spectrum sensing under AWGN and Rayleigh fading channels is examined in this work. It was shown that in a low-SNR setting, cooperative spectrum sensing can only marginally increase detection performance.

The CRN receivers are equipped with threshold adaptation algorithms. The goal of increasing CRN's detection performance in low-SNR environments was achieved by decreasing overall sensing error, which was achieved by minimizing both the chance of false alarm and the probability of missed detection at CRN's common fusion centre. Computer simulations revealed that the suggested technique outperforms fixed threshold schemes and provides lower sensing errors in low-SNR environments. It was also discovered that as the SNR decreases, the benefit of lowering the sensing error grows. As a result, these intriguing results showed the effectiveness of using adaptive thresholds to increase CRN sensing performance under worsened channel circumstances.

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