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Improvement of Cooperative Spectrum Sensing in Rayleigh Fading and AWGN Environments for Cognitive Radio Networks

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Abstract: Cognitive Radios (CRs) improve spectrum efficiency by tracking users' movements using spectrum-aware devices. However, inadequate spectrum sensing can cause interference and incorrect detection. This paper explores cooperative spectrum sensing using OR-rule's detection performance in AWGN and Rayleigh fading channels, revealing that cooperative spectrum sensing only slightly improves detection in low signal-to-noise ratio situations. The authors propose an adaptive threshold method for CRN receivers, which outperforms fixed threshold approaches and reduces sensing errors in low SNR situations, highlighting the effectiveness of adaptive thresholds in improving CRN sensing performance to improve detection efficiency. The study uses MATLAB to analyse the relationship between signal to noise ratio (SNR), detection probability, and false alarm probability. Results show that adaptive detection thresholds improve detection efficiency, especially in low SNR cases, addressing the issue of interference and enhancing detection accuracy.

Keywords: Cognitive radio, cognitive cycle, signal-to-noise ratio, Receiver Operating Characteristic, probability of false alarm, software-defined radio.

تحسين الكشف التعاوني للطيف في بيئات تلاشي رايلي والضجيج الأبيض الإضافي لشبكات الراديو الإدراكي

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المستخلص: تعمل أجهزة الراديو الإدراكية (CRs) على تحسين كفاءة الطيف من خلال تتبع حركات المستخدمين باستخدام أجهزة تراعي الطيف. ومع ذلك، فإن الاستشعار غير الكافي للطيف يمكن أن يسبب تداخلاً واكتشافًا غير صحيح. تستكشف هذه الورقة الاستشعار التعاوني للطيف باستخدام أداء الكشف الخاص بقاعدة OR في قنوات الخبو AWGN وRayleigh، مما يكشف أن الاستشعار التعاوني للطيف لا يعمل إلا بشكل طفيف على تحسين الاكتشاف في حالات انخفاض نسبة الإشارة إلى الضوضاء. يقترح المؤلفون طريقة عتبة تكيفية لمستقبلات CRN، والتي تتفوق في الأداء على أساليب العتبة الثابتة وتقلل من أخطاء الاستشعار في حالات انخفاض نسبة الإشارة إلى الضوضاء (SNR)، مما يسلط الضوء على فعالية العتبات التكيفية في تحسين أداء استشعار CRN لتحسين كفاءة الكشف. تستخدم الدراسة MATLAB لتحليل العلاقة بين نسبة الإشارة إلى الضوضاء (SNR)، واحتمال الكشف، واحتمال الإنذار الكاذب. وتظهر النتائج أن عتبات الكشف التكيفية تعمل على تحسين كفاءة الكشف، خاصة في حالات انخفاض نسبة الإشارة إلى الضوضاء (SNR)، مما يعالج مشكلة التداخل ويعزز دقة الكشف.

الكلمات المفتاحية: الراديو المعرفي، الدورة المعرفية، نسبة الإشارة إلى الضوضاء، خاصية تشغيل المستقبل، احتمال الإنذار الكاذب، الراديو المحدد برمجياً.

1- Introduction:

The need for spectrum to provide more wireless services is rising in tandem with the rapid expansion of wireless communication technology. However, a major hurdle to meeting the growing demand for spectrum is the limited availability of radio resources. In order to assess the efficacy of spectrum usage, the FCC conducted a poll that accounted for differences in both time and geographical region [1]. The results of the study make it quite clear that the allowed spectrum is now underutilized. By re-purposing underutilized licensed frequency segments, cognitive radio (CR) shows promise as a solution to the growing demand for spectrum.

According to the FCC, a software-defined radio (SDR) is a type of radio that may change its maximum output power, frequency range, and modulation type through software changes, rather than modifying the hardware components that affect radio frequency emissions.

Users are able to alter their broadcasts in real-time, unrestricted by technological limitations; this is the main idea of SDR.

2- Literature Review:

he need for spectrum to provide more wireless services is rising in tandem with the rapid expansion of wireless communication technology. However, a major hurdle to meeting the growing demand for spectrum is the limited availability of radio resources. In order to assess the efficacy of spectrum usage, the FCC conducted a poll that accounted for differences in both time and geographical region[1,2,3].

The capacity to adapt and learn from one's radio environment is what defines a CR radio. In order to increase spectrum use and provide flexible wireless access, it may change network properties [1]. To put it plainly, CR is a tool that can spot dangers. Acquiring effective exploitation of under-utilized spectrum's .There are four basic actions that are thought to be required for cognitive radio systems to have this capacity [2]. These tasks include spectrum sensing, decision-making, spectrum sharing, and spectrum mobility. Cognitive radio (CR) systems do initial spectrum sensing to discover any underutilized frequency bands. These frequency regions are sometimes referred to as white spaces or gaps in the spectrum [3].

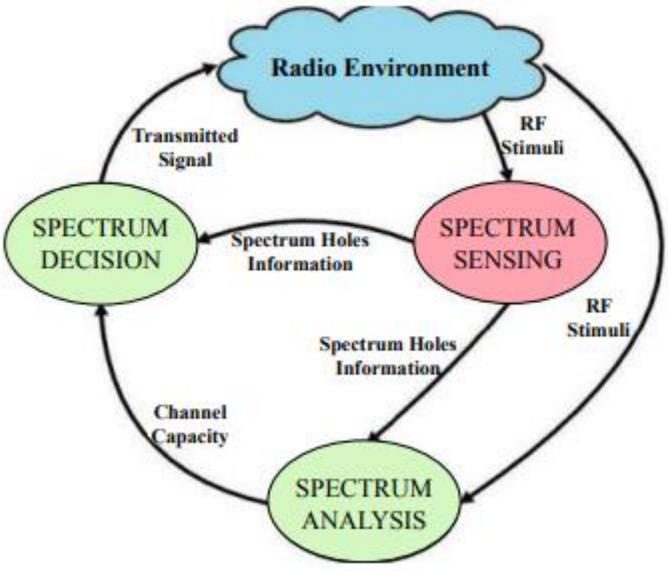

Figure 1 cognitive cycle

Upon identifying all feasible places, the spectrum decision-making approach will be employed to choose the white space most conducive to quick transmission. Spectrum sharing technology allocates and regulates frequency bands for many users, encompassing cognitive radio (CR) and secondary users (SUs). The spectrum relocation capabilities facilitate the transfer of a spectrum band from a secondary user (SU) to a primary user (PU) by transitioning to a more accessible white zone.

It is possible that the intensity of muted or entirely silenced PU signals will alter unexpectedly.

Related Works :

several investigations have been conducted on several occasions, using numerous methods. Tags are quite important for ensuring the security of the user's words.The user's material contains the following citations: [4], [5].The author clearly failed to complete their job because they neglected important details.When a secondary user relies on local spectrum sensing to identify a signal from a primary user, the secondary user may fail to detect the signal. The two most significant contributors to this issue are shadow and fading, which are inextricably linked. It is thought that using a combination of spectrum sensors might be one of the potential options. The employment of mixed band sensing technologies has resulted in considerable improvements in object localization [6, 7].

[7]shows that when the signal-to-noise ratio is low, simultaneous sensing does not significantly improve indication identification. This occurs when the ratio in question is low[8].

The key problems related to cooperative spectrum sensing (CSS) in Rayleigh fading and AWGN environments for cognitive radio networks:

1. Impact of Rayleigh Fading
   - Signal Attenuation: Rayleigh fading causes significant variations in signal strength, making accurate detection of primary users (PUs) challenging.
   - Hidden Node Problem: Fading can result in some secondary users (SUs) failing to detect the PU's presence, leading to missed detections.
   - Unreliable Sensing: Rapid changes in the fading environment can reduce the reliability of local spectrum sensing.
2. Low Signal-to-Noise Ratio (SNR)
   - Weak PU Signals: In low SNR conditions, primary signals are often buried under noise, making detection more difficult.
   - Increased False Alarms: Noise can be mistaken for PU signals, leading to unnecessary interruptions in secondary transmissions.
3. AWGN Impact

- Interference from Noise: Additive white Gaussian noise affects sensing accuracy, particularly in environments with low SNR.
- Threshold Selection: Determining the optimal detection threshold is challenging, as it must balance false alarms and missed detections under noisy conditions.

4. Inefficient Fusion of Data
   - Diverse Channel Conditions: Cooperative sensing relies on combining data from multiple SUs, but channel conditions vary among users, complicating data fusion.
   - Communication Overhead: Sharing sensing data among SUs increases bandwidth usage and energy consumption, especially in noisy environments.
5. Delay in Decision-Making
   - Slower Response Time: Cooperative sensing introduces latency as data from multiple users must be collected, transmitted, and processed.
6. Trade-Off Between Detection and False Alarm Rates
   - Competing Objectives: Improving detection rates often increases false alarms, while reducing false alarms may compromise detection accuracy.
7. Resource Constraints
   - Power Consumption: Cooperative sensing requires significant energy, which can be a problem for battery-powered devices.
   - Hardware Limitations: Devices may lack the processing power to handle advanced sensing algorithms in real-time.

The goal is to enhance sensing performance by reducing error rates and increasing detection reliability, even in challenging conditions like random fading or high noise levels. This can be achieved through various approaches:

1. Enhanced Fusion Techniques:
   - Traditional Fusion Rules: Use conventional methods like OR Rule, AND Rule, or Majority Voting to process data from multiple sensors.
   - Improved Fusion Algorithms: Apply optimal algorithms such as Weighted Cooperative Sensing, which assigns weights to sensors based on signal quality.

2. Modeling and Adapting to Rayleigh Fading:
   - Employ precise mathematical models to represent the multipath Rayleigh fading environment accurately.
   - Use signal processing techniques like Diversity Reception or Equalization to mitigate the effects of fading.
3. Minimizing Noise Impact (AWGN):
   - Implement algorithms to improve the signal-to-noise ratio (SNR), such as Noise Filtering techniques.
   - Develop algorithms that analyze the variance between signal and noise for better detection accuracy.
4. Machine Learning and AI-Based Approaches:
   - Deep Learning Models: Use neural networks to identify patterns in noisy environments and enhance detection performance.
   - Reinforcement Learning: Optimize sensing strategies dynamically based on environmental feedback.
5. Energy-Efficient Cooperative Sensing:
   - Design protocols to minimize energy consumption in cooperative sensing while maintaining high accuracy.
   - Optimize the number of cooperative sensors to balance resource usage and detection reliability.
6. Hybrid Sensing Techniques:
   - Combine cooperative sensing with non-cooperative methods for improved performance in dynamic environments.
   - Integrate spectrum prediction models to anticipate spectrum availability and reduce sensing overhead.

3- Methodology :

1- The goals and assumptions of this paper :

The goals of this study is to look at the effectiveness of local and joint spectrum sensing in a range of radio scenarios, including those with AWGN and Rayleigh fading channels. Spectrum sensing, or more specifically energy detection, is used in this study due of its ease of implementation. Furthermore, in contrast to the usage of soft fusion solutions, the installation of a hard decision fusion approach that employs the OR-rule promotes cooperative sensing with minimal additional interaction. Particle swarm optimization was developed to improve the efficiency of combined spectrum sensing in conditions with a low signal-to-noise ratio (SNR). a threshold that may be changed was necessary.

Energy sensors keep track of the frequency ranges prevalent in the nearby region.

2- **The Importance of this paper** :Cognitive Radio Networks (CRNs) are designed to enhance spectrum utilization by allowing secondary users (SUs) to opportunistically access underutilized spectrum bands without interfering with primary users (PUs). Spectrum sensing is a critical functionality in CRNs to detect the presence of PUs. Improving cooperative spectrum sensing (CSS) in challenging environments like Rayleigh fading and AWGN (Additive White Gaussian Noise) is essential for several reasons:

1. Mitigating Fading Effects
   - Rayleigh fading models the random variations in signal strength caused by multipath propagation in wireless environments. This can result in deep signal fades, making it difficult for individual nodes to reliably detect the PU's signal.
   - Cooperative spectrum sensing helps mitigate these effects by aggregating observations from multiple SUs. Improving CSS ensures better handling of fading, reducing the likelihood of false alarms or missed detections.
2. Enhancing Detection Accuracy
   - AWGN environments introduce noise that can degrade the performance of individual sensing nodes. CSS combines observations from multiple SUs, averaging out noise and improving the overall detection probability.
   - Optimized CSS algorithms (e.g., weighted fusion or machine-learning-based methods) further enhance accuracy by accounting for varying channel conditions and SU reliability.
3. Maximizing Spectrum Utilization
   - Improved CSS ensures that spectrum opportunities are detected accurately and quickly, maximizing the spectrum's availability for SUs.
   - This reduces the underutilization of the spectrum while avoiding interference with PUs, leading to more efficient spectrum usage.
4. Reducing Energy Consumption

- Advanced CSS techniques minimize redundant sensing by optimizing the selection of cooperating nodes, leading to energy-efficient operation in battery-constrained CRNs.
- In fading and noisy environments, improving CSS can reduce unnecessary sensing cycles triggered by unreliable single-node detections. And Improving Network Reliability and QoS

Analytical and Statistical tools :

- Energy detector-based local spectrum sensing

The main user (PU) provides the initial data sample that is used in the process of constructing power consumption monitors. With the aid of Spectrum Utilization (SU), two inferences can be drawn from the dataset provided in the example.

The initial assumption is that the central processing unit enters sleep mode. The processing equipment is now operating at peak efficiency.

We previously explored both strategies for conveying the signal received by the i-th secondary user (SU). a number that is eight.

The primary user receives the signal x(t), whereas the i-th secondary user receives the signal yi(t) as well as additive white Gaussian noise. The service's revenue has significantly increased.

The energy of the received signal, represented by yi(t), may be used to determine which of the two hypotheses,

H0: PU is idle.
H1: PU is active.

H0 or H1, is accurate. I really apologize, but the actual count is nine.

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

An effective method for maintaining attention while doing an analysis The number of tests or selections is not difficult to calculate. According to reference [8], energy data was used to calculate Zi, which is a decision-making statistic. The following may be regarded a justification for the discovery of the i-th secondary user

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

Where (SU).$y_{i,j}$ =y(k/2w) and N_o represents the power spectral density of noise that occurs only in one direction. Equation (3) shows the chi-square distribution for the i-th secondary user's choice statistic in order to calculate the quantity of energy.

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

The number TW represents the letter M, m=TW . Within the boundaries of this debate, the energy analyzer's time-bandwidth product is quite important. Consider the possibility that m is a real number to make the argument more obvious and correct. Equation 3 presents $X_{2m}{}^2$ its an alternate central chi-square distribution with 2m degrees of freedom, as stated before. Equation 4 represents a mathematical expression

$X_{2m}{}^2(2\gamma_2)$ for a non-centered chi-square distribution with 2m degrees of freedom. According to the alternative hypothesis H1, the noncentrality constant is responsible for the distribution's alteration. The noncentrality measure (i) may be used to calculate the signal-to-noise ratio at the i-th secondary user (SU).A precise count of nine.

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

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

Let's go further into the problem of false alarms and the possibility of being detected λ_i by the i-th secondary user (SU). Equations (4) and (5) allow us to calculate the detection level of the i-th specified unit (SU). As a result, using Equations 3 and 4 from Reference [9] yields the precise mathematical equation defining the likelihood of detecting a signal over the Additive White Gaussian Noise (AWGN) channel. This equation can be interpreted as a mathematical expression

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

One definition of the Marcum Q-function Q_m(a,b) is that the sum of A and B is equal to 7.

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

This definition is global.

The mathematical formula (8) can be used to show the probability of missing a discovery.

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

The information presented in [9] can be used to estimate the probability of a false alarm occurring in an AWGN channel using Equations 3 and 5.

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

The number "(8)" is represented in text on the current page. For example, the sign Γ (.) and Γ (.,.) represents the gamma function, but the symbols (.,.) show the higher incomplete gamma function. Equation 9 remains same at all times, γ_i irrespective of the channel's signal-to-noise ratio (SNR). Calculating the probability density function (PDF) , $P_{d,i}$ by summing the values represented by dx is a method for determining the i-th secondary user in fading channels.

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

The PDF value $f_{\gamma_i}(x)$ is determined using the fading model. However, Equation 9 states that any other element has the same likelihood of causing a false alert. This is the general consensus among specialists. There is a link between the transmission of a principal user (PU) signal via its surroundings and the development of multipath fading. The Rayleigh distribution [5] explains this trend, which is characterized by a decrease in the intensity of the main user signal.

The exponential distribution(γ_i) may be used to calculate the probability of signal detection in a Rayleigh fading channel [9].

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

Collaborative spectrum sensing

Spectrum sensing is implemented by each SU to identify the presence of a PU signal. Based on the channel circumstances indicated by the appropriate noises and gains imposed, the signal intensity fluctuates at various times and locations when the PU signal experiences profound fading and shadowing.Five.

Numerous decision fusion strategies have been proposed in the literature. ORrule, or the "one-out-of-N rule," is a widely recognized decision fusion strategy, where N represents the total number of cooperating SU[5].

In the hard decision fusion method, all collaborating SUs communicate their local sensory decisions to a shared fusion center for final decision fusion. If the PU is absent from all N participating SUs, a final decision corresponds to H0[9]. Conversely, if at least one out of N SUs indicates that the PU is present, a final decision corresponds to H1, the eleventh Using Qd, Qm, and Qf, respectively, one may quantify the detection, missed detection, and false alarm probabilities in cooperative spectrum sensing. The assumption that all decisions are autonomous underpins this .[6]:

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

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

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

The combination of spectrum detection and adaptive thresholding results in Collaboration is the defining trait of a cooperative, which is why it is so important.Through the use of spectral sensing, no significant findings were seen. In an environment with a low signal-to-noise ratio, we have improved the performance of the detecting system. This is being carried out in order to put an end to the problem [7]. Through the utilization of a cooperative spectrum sensing technique, this work works to determine the optimal detection threshold. It is possible for us to improve the likelihood of correct detections and decrease the risk of false alarms if we work together [15]. OR guidelines are used by a widespread fusion center in order to determine a definitive worldwide assessment of the availability of PUs. This is accomplished by comparing the approximated decision statistic of each SU to the optimum threshold [6].

Keeping the rates of false alarms and missed detections as low as possible is absolutely necessary in order to improve detection performance in an environment with a changeable signal-to-noise ratio [9]. The reason for this is that secondary users (SUs) can exploit the underutilized spectrum bands more efficiently when the likelihood of false alarms falls, while primary users (PUs) are safeguarded from excessive SU transmissions when the risk of missed detections diminishes. As a result, the decision threshold needs to be continuously adjusted in order to accommodate the two competing requirements that were indicated before for various channel circumstances. By reducing the total sensing error to its minimum, the entire Cognitive Radio Network performance target may be condensed into a single optimization issue, as described in [11].

For the purpose of computing the chance of missed detection in the context of false alarms, how may a weighting constant that ranges from 0 to 1 be utilized? Given that the likelihood of a false warning is minimal and the likelihood of detection is high[12].The barrier must be restricted in some way. The limited possibility of a false alarm is defined by the range [0.001, 0.1] in this study. In order to mitigate the risk of false alarms[13], it is advisable to establish a maximal threshold for the likelihood of a false alarm. Moreover, a minimal restriction is enforced, as a very low probability of false alert indicates a very low potential for detection. Consequently, establishing a minimum probability of false alarm may assist in maintaining a reasonable likelihood of detection. The optimization issue is subsequently confronted with a new perspective.Fourteen

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

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

The Simulation Environment

The simulation environment is configured 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 MATLAB simulation code was utilized to determine the correlation between the probability of missed detection (PMD) and the probability of false alarm (PFA) for the cooperative spectrum sensing technique. The link between the chance of detection and the signal-to-noise ratio in decibels has been incorporated.

4- Results:

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

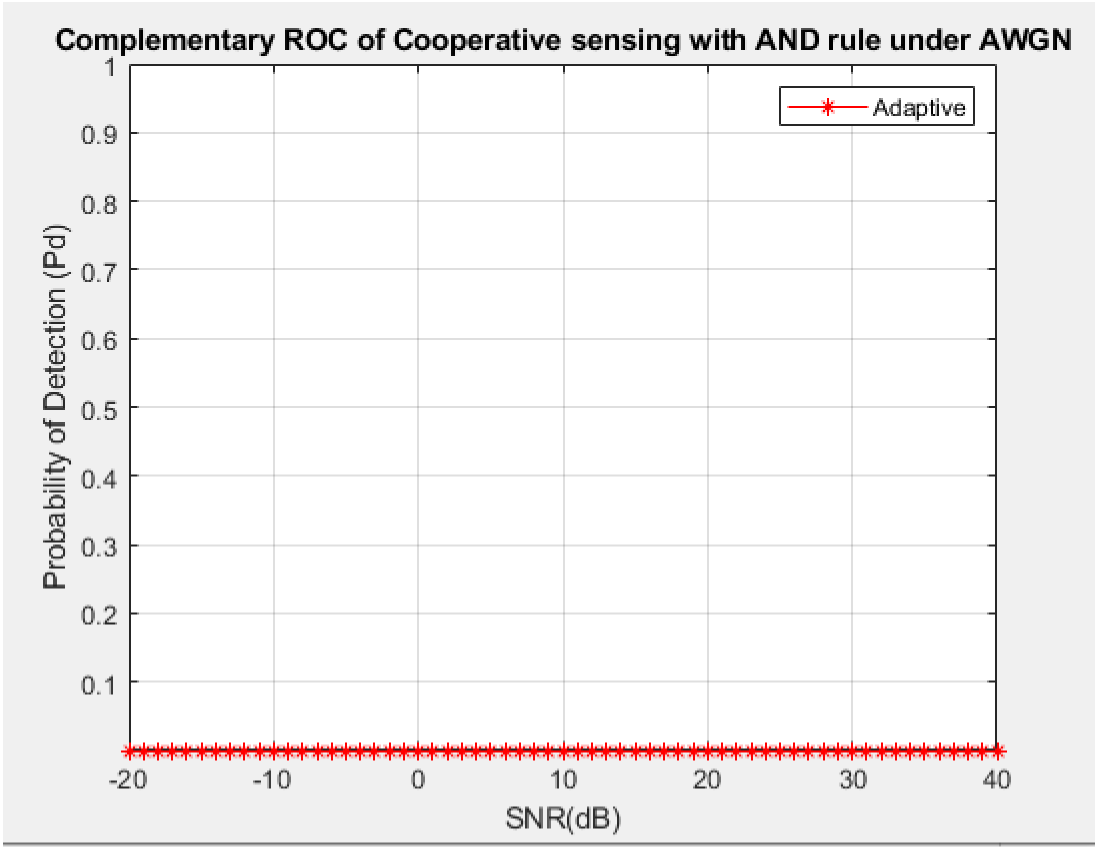

Figure 2 :Exploring signal-to-noise ratio and detection probability: Additive White Gaussian Noise (AWGN) with complementary features and AND rule receiver operating characteristic (ROC) study of cooperative sensing.

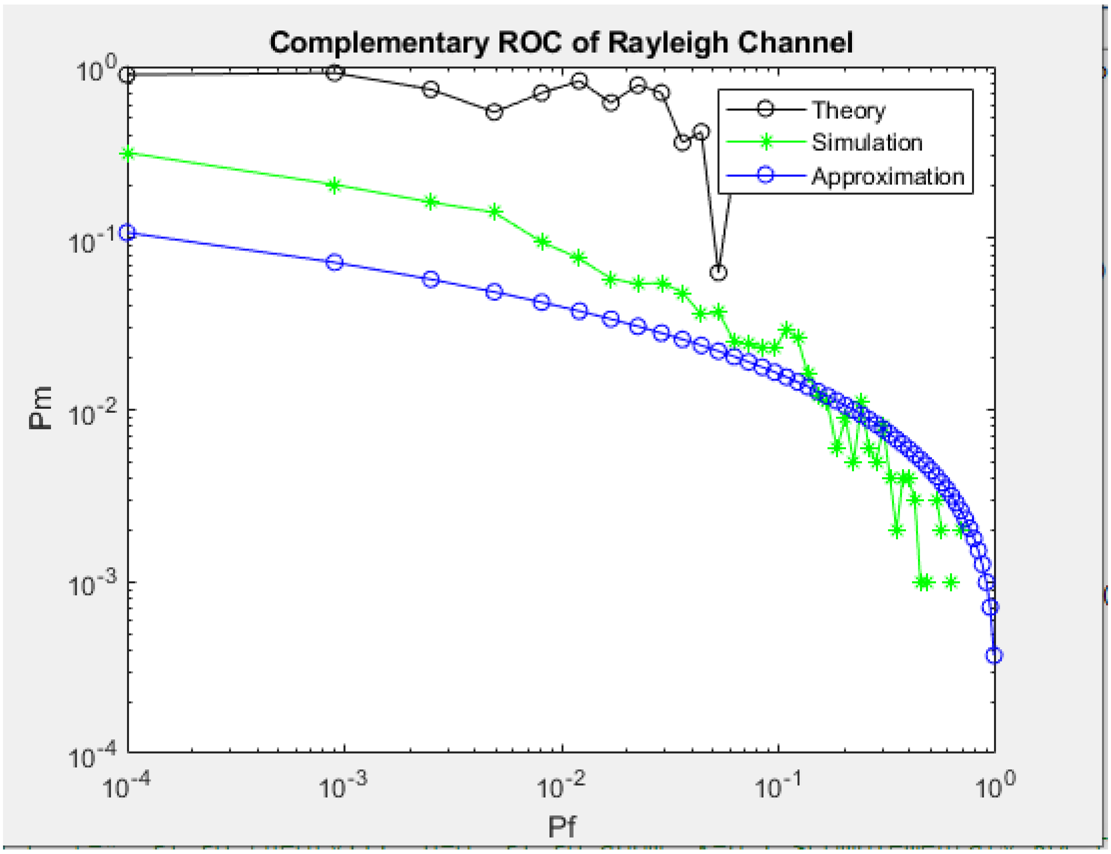

Figure 3 :The relationship between the probability of detection and the probability of false alarm in the complementary ROC of the Rayleigh channel.

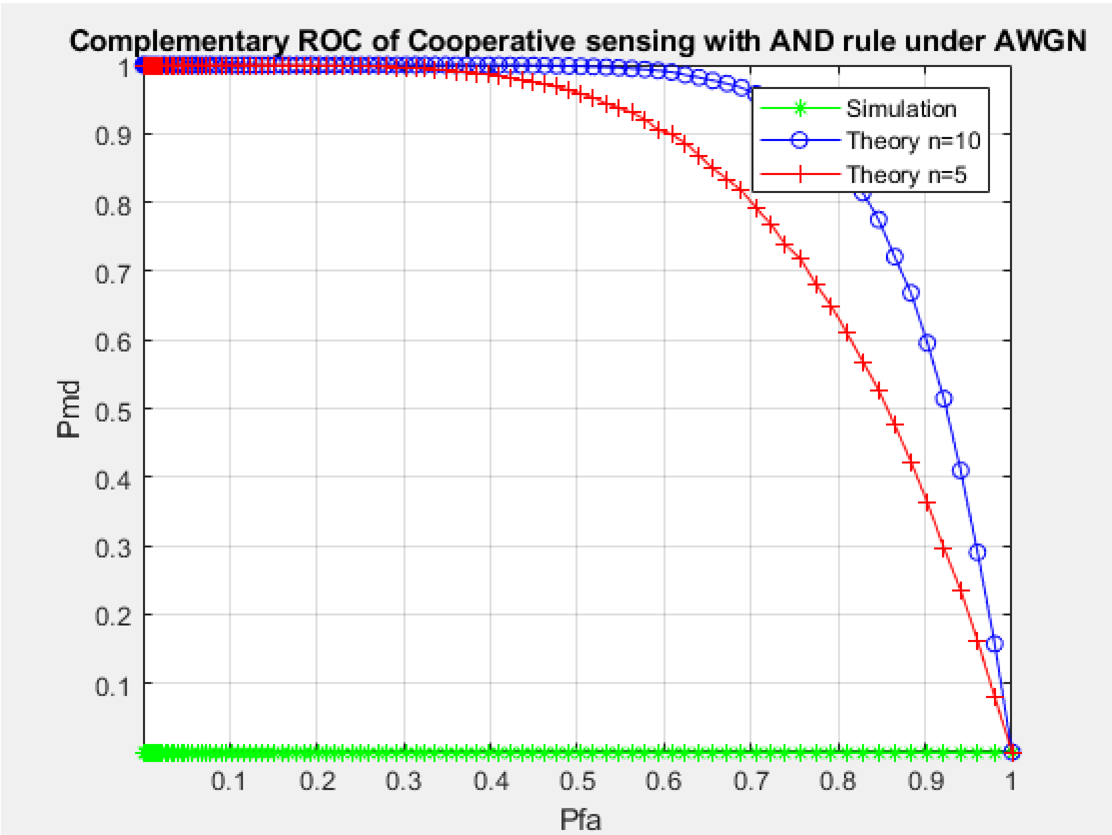

Figure 5: In cooperative sensing using the AND rule under AWGN, the complementary ROC of detection probability and signal-to-noise ratio with 10 cognitive users is analyzed.

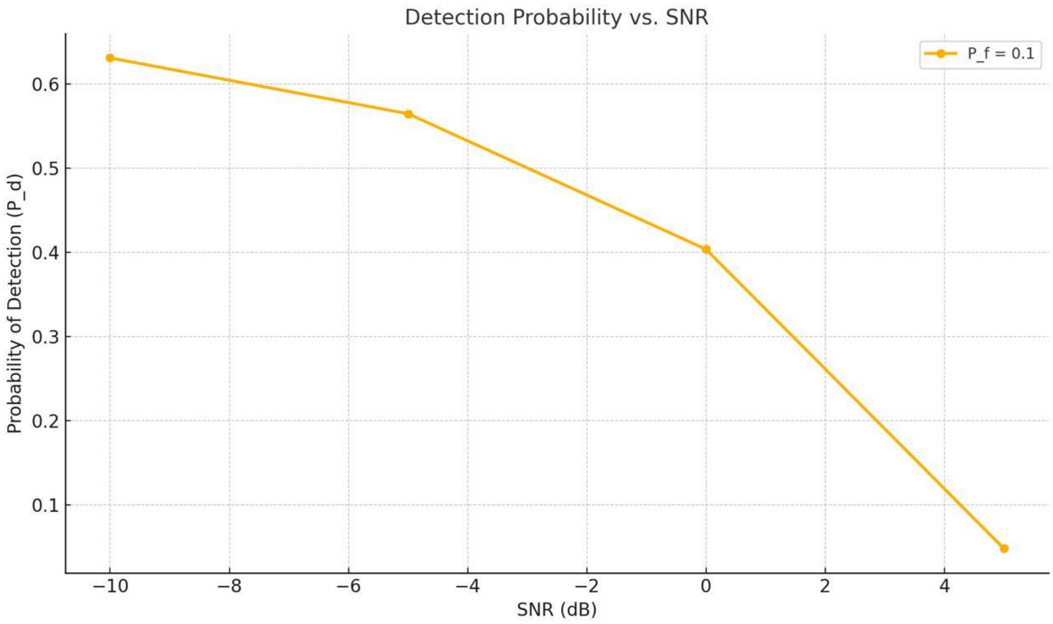

Figure 6: Detection Probability vs SNR at p_f =0.1

Results Discussion:

You can use equations 6, 7, 8, and 9 to figure out the chance of finding. to figure out how important it is in terms of signal-to-noise ratio. In joint spectrum sensing, equations 12, 13, and 14 figure out the chances of detection (Qd), missed detection (Qm), and false warning (Qf). Equation 15 showed the ratio of the chances of not finding anything to the chances of finding something wrongly. We should try to get a low rate of false alarms and a high rate of recognition because of this negative connection.

Higher SNR significantly improves detection probability.At very low SNR (e.g., -10 dB), the detection probability is poor, even with cooperative sensing

Conclusion:

This paper explores the OR-rule's detection performance in low signal-to-noise ratio (SNR) situations, focusing on cooperative and local spectrum sensing. It found that cooperative spectrum sensing only slightly improves detection performance in low SNR situations. The authors suggest that adaptive thresholds can improve CRN sensing performance under worse channel circumstances. Higher SNR improves detection performance but reduces noise and fading impact. Cooperative users significantly enhance spectrum sensing performance, while Rayleigh fading negatively impacts detection performance. The study suggests that optimizing system parameters to enhance SNR can significantly improve spectrum sensing.

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