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Adaptive Spectrum Sensing for Very Low SNR in Cognitive Radio Networks

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Abstract: Cognitive Radio (CR) is a self-adaptive wireless technology that can detect available channels automatically in a wireless spectrum and configured dynamically. Spectrum sensing in CR is the fundamental activity to detect unused spectrum holes in an opportunistic manner. In Spectrum sensing, various methods have been proposed and studied exhaustively by the CR researchers. Blind spectrum sensing methods such as an Eigenvalue based Detection (EVD) and Energy Detection (ED) does not require any information of the transmitted signal characteristics, the channel or the noise-power, which are unknown at the receiver. The main aim of this work is to sense the spectrum at very low Signal to Noise Ratio (SNR) under frequently changing wireless environment. A combined blind spectrum sensing is proposed based on an adaptive SNR threshold calculation which achieves better sensing accuracy than the two individual detectors. In this paper spectrum sensing is done for DVB-T signals in the VHF band which has been declared as an operating band for Cognitive users.

Keywords: Cognitive Radio, Eigenvalue based detection, Energy detector, low SNR, Spectrum sensing.

I. INTRODUCTION

Wireless services have been experiencing a huge expansion and evolution in recent years. Besides, there has been a continuously increasing demand of higher bandwidths to serve the needs of higher data rates, which creates a phenomenon known as spectrum scarcity. Wireless networks are regulated by a fixed spectrum assignment policy and is assigned to license holders or services on a long-term basis for large geographical regions [1]. In addition, the assigned spectrum is used at irregular intervals of time. A slice of spectrum is more concentrated like 900 MHz, while a significant amount of spectrum remains unutilized. This paradox has led to the introduction of a dynamic spectrum access (DSA). In DSA, there are two types of users: primary user (PU) and secondary user (SU). The PU is the licensed owner of the spectrum. The SU is the unlicensed user, but can access the radio spectrum opportunistically when it is not being used by its PU.

A primary challenge that DSA faces is how to find the unused portion called spectrum hole. Spectrum holes can be found using spectrum sensing which is basically measuring a signal inside a specific frequency band and accordingly declaring whether a signal is present or not [2]. Spectrum sensing techniques can be grouped into two categories: non-blind and blind. In non-blind spectrum sensing, the SU or the CR device has to know some of the PU signal characteristics [3] [4]. Additionally, most of the non-blind spectrum sensing techniques require accurate synchronization, which is difficult to maintain especially in the low SNR values [5].

Blind sensing techniques like Energy Detection (ED) [6] and Eigenvalue-based Detection (EVD) [7] algorithms are developed, basically tests the extent of the received signal Gaussianity. Of these methods ED is semi-blind detection, which is optimal for detecting independent and identically distributed (iid) signal. The major drawback of ED is that it requires knowledge of the noise power causes SNR wall problem [8] and it is not optimal for highly correlated signals. To address the drawbacks, in [7], Zeng et al. presented EVD which showed immunity to noise-power uncertainty for maximum-minimum eigenvalue (MME) ratio detection based on random matrix theory (RMT). Moreover, these eigenvalue schemes do not require accurate synchronization. In this paper, a combination of ED, MME, and MX-GM is introduced based on adaptive SNR threshold λ which switches between the different spectrum sensing schemes in a frequently varying wireless environment. Simulations based on randomly generated signals and digital television (DTV) signals are considered to verify the efficiency of the adaptive method.

The rest of this paper is structured as follows: Section II presents the system model with the existing hypothesis used, in Section III, we discuss the adaptive spectrum sensing technique using ED and EVD. Section IV shows the simulation results of real life signals. Finally, Section V concludes the paper.

II. SYSTEM MODEL

This section of the paper presents the system model and some of the theoretical aspects used through the paper.

A. *Signal Model*

Consider a received signal, $x(k)$, which can be either: (a) only noise components, $\eta(k)$; or (b) a PU signal $s(k)$

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with channel response *h(k),* bearing noise *η(k).* Both (a) and (b) can be put in a binary hypothesis framework as

$$x(k) = \begin{cases} \eta(k), & H_0 \\ h(k)s(k) + \eta(k), & H_1 \end{cases} \quad (1)$$

with H_0 representing the spectrum hole denoting the existence of only noise and H_1 denoting the existence of a PU signal bearing noise.

B. *Performance Metrics*

To evaluate an adaptive spectrum sensing technique, the sensing accuracy and the complexity of the technique are considered as performance metrics. The sensing accuracy is judged using two statistical measures, namely, the probability of false alarm and the probability of detection. The probability of false alarm is the probability of wrongfully detecting the existence of a signal when only noise is present [9]. In the binary hypothesis framework, the probability of false alarm p_{fa}, is formulated as

$$p_{fa} = P(H_1|H_0) \quad (2)$$

The probability of detection is defined as the probability of truly detecting an existing PU signal. Hence, the probability of detection p_d, is obtained statistically as

$$p_d = P(H_1|H_1) \quad (3)$$

III. ADAPTIVE SPECTRUM SENSING TECHNIQUE

The adaptive spectrum sensing scheme is proposed to adapt the sensing method according to the frequently changing wireless environment and the available information. The flow graph for the adaptive spectrum sensing technique is given below

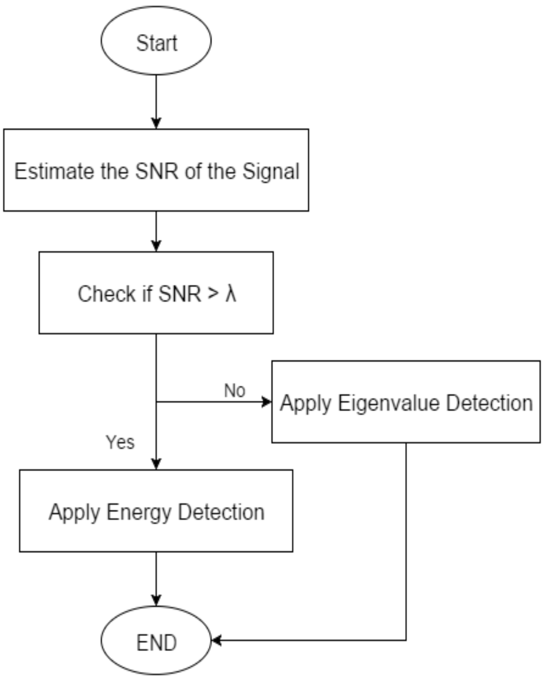

Fig. 1. Flow Diagram of Adaptive Spectrum Sensing

When prior knowledge about the PU signal is not available, then the adaptive spectrum sensing technique adapts to either ED or EVD depending on the SNR of the received signal.

The received signal *x(k)* is first pre-filtered by an ideal bandpass filter with transfer function to limit the average noise power and normalize the noise variance.

$$H(f) = \begin{cases} \frac{2}{\sqrt{N_0}}, & |f - f_c| \le B \\ 0, & |f - f_c| > B \end{cases} \quad (4)$$

The SNR of the filtered output is determined using a period gram uses a Kaiser window with $\beta = 38$. The computation of noise energy excludes the power of the first six harmonics, including the fundamental.

A. *Energy Detector*

The output of the filter is squared and integrated over a time interval *T* to produce a measure of the energy of the received signal. The output of the Integrator denoted by *E* will act as the test statistic to test the two hypotheses H_0 and H_1. Consequently, the decision is taken as

$$E \rightarrow \begin{cases} \left(\sum_{n=1}^{N} |x(n)|^2\right) < \rho, & H_0 \\ otherwise, & H_1 \end{cases} \quad (5)$$

where ρ is the threshold for detection. The output of the ED is Chi-square distributed which can be approximated as a Gaussian distribution under the assumption that $N \rightarrow \infty$ [9]. Based on this approximation, ρ is found as

$$\rho = 2\sqrt{2N}\sigma_z^2 Q^{-1}(p_{fa}) + N\sigma_z^2, \quad (6)$$

where $Q^{-1}(.)$ is the inverse *Q* function, σ_z^2 is the noise variance, p_{fa} is the probability of false alarm for the ED and *N* is the quantity of samples collected.

B. *Eigenvalue Detection*

To reduce complexity of EVD method, the signal model of received signal considered as

$$\hat{x} = \begin{bmatrix} x_1(1) & x_2(1) & \cdots & x_L(1) \\ x_1(2) & x_2(2) & \cdots & x_L(2) \\ \vdots & \vdots & \vdots & \vdots \\ x_1(n) & x_2(n) & \cdots & x_L(n) \end{bmatrix} \quad (7)$$

where $\hat{x} = s + \eta$, be $N \times L$ received PU signal, where *N* is no of samples collected and *L* is the consecutive samples or multiple receiver model. Here noise η assumed to be a stationary process satisfying with zero mean and variance $\sigma_\eta^{\,2}$.

The statistical covariance matrix of the received signal defined as:

$$R_{xx} = E\left((\hat{x} - \bar{\hat{x}})^T(\hat{x} - \bar{\hat{x}})\right) \quad (8)$$

where *T* denotes transpose. The sample covariance matrix R_{xx} is of order $L \times L$ which requires less computational complexity compared to Zeng. [7] which yields *L* eigenvalues. Based on the calculated *L* eigenvalues, we propose two detection methods as follows:

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1. Maximum Minimum Eigenvalue (MME) Detection:

Obtain the maximum and minimum eigenvalues of the matrix R_{xx}, that is, λ_{max} and λ_{min}.

Decision threshold of MME can be given as: if $\lambda_{max}/(\lambda_{max}+\lambda_{min}) > \gamma_1$, then signal exists ($H_1$); otherwise, signal does not exist (H_0), where $\gamma_1 > 0.5$ is a threshold, and will be given in the next section.

Detection Threshold: To find the threshold for this statistical test, it is important to study the statistical distribution of the covariance matrix when there is no PU signal. The sample covariance matrix of the noise $R_\eta(N)$ is nearly a Wishart random matrix.

Using the theory [7], we can analyse the threshold for MME as per eq. (9)

$$\gamma_1 = \frac{(\sqrt{N}+\sqrt{L})}{2(N+L)}\left(1+\frac{(\sqrt{N}+\sqrt{L})^{-2/3}}{(NL)^{1/6}}\ F_1^{-1}(1-P_{fa})\right) \tag{9}$$

where γ_1 is the threshold for detection, F_1^{-1} is Tracy Widom distribution [10].

2. Maximum Geometric Mean (MX-GM) Detection:

Similarly, λ_{max} and λ_{GM} are calculated based on sample covariance matrix R_{xx}.

Decision threshold can be given as: if $(\lambda_{max}/\lambda_{GM}) > \gamma_2$, then signal exists ($H_1$); otherwise, signal does not exist (H_0), where $\gamma_2 > 1$ is a threshold, and will be given as eq. (10)

$$\gamma_2 = \frac{(\sqrt{N}+\sqrt{L})}{N}\left(1+\frac{(\sqrt{N}+\sqrt{L})^{-2/3}}{(NL)^{1/6}}\ F_1^{-1}(1-P_{fa})\right) \tag{10}$$

The above equations for threshold shows threshold is not dependent on noise power or noise level and can be evaluated from a number of samples N, L and false alarm probability p_{fa} whatever be the noise, interference and signal characteristics. The threshold is independent of noise power is the basic advantage due to which eigenvalue detection is the most reliable method.

IV. SIMULATION RESULTS AND DISCUSSION

Most of the spectrum in the range 700 MHz and 2.6 GHz have already been allocated for use. From [11], Television band (TV 2-6) is utilized less than 15% of the users which leads to underutilization of the electromagnetic spectrum. Here we present the simulation results and evaluate the performance of the blind spectrum sensing algorithms considering the parameters such as probability of detection, probability of false alarm and SNR for DVB-T signal which uses 64 QAM OFDM at VHF band. In addition to the presence of AWGN, multipath fading like Rayleigh fading and time dispersion are applied to PU to generate real-time environment. Then we have shown the adaptive spectrum sensing scheme to adapt the method according to the frequently changing wireless environment and the available information. All the results are averaged over 1000 Monte Carlo realizations (for each realization, random channel, and random noise).

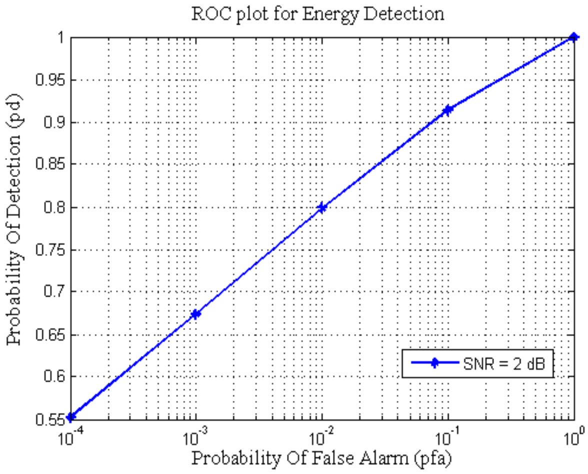

Fig. 2. Plot of p_d vs p_{fa} for Energy detection

Figure 2 shows a plot of p_d vs p_{fa} for SNR = 2 dB for energy detection. It is observed that there is a trade-off between p_d and p_{fa} values. For p_{fa} values from 0.07 to 0.8 the detection probability is optimum. After that the detection probability approaches 1.

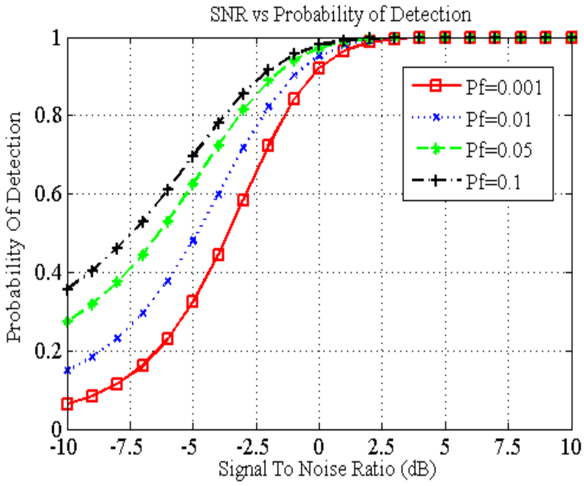

Fig. 3. Plot of p_d vs SNR for Energy detection

Figure 3 shows the plot of p_d vs SNR for various p_{fa} for $N = 1000$. As p_{fa} increases, the detection probability also increases.

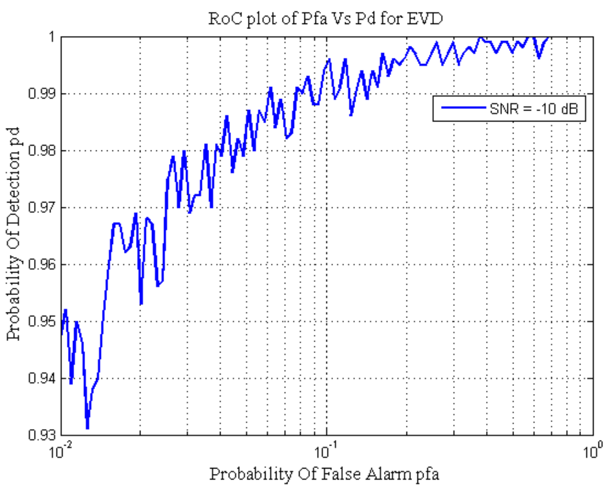

Fig. 4. Plot of p_d vs p_{fa} for Eigenvalue detection

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But, in a general wireless environment, maximum allowable p_{fa} is 0.1. ED with noise uncertainty almost does not change with an increase in the number of samples *N*. From the graph it is observed that in increasing SNR values there is a linear increase in the probability of detection. For low values of SNR, the detection probability is almost 0. Above 2 dB the detection probability approaches 1.

Figure 4 shows a plot of p_d vs p_{fa} for SNR = -10 dB for EVD for sample size *N = 5000*. It is observed that the detection probability is optimum for EVD which almost approaches to 1 for p_{fa} values greater than 0.01 which states that it doesn't affect with noise uncertainty.

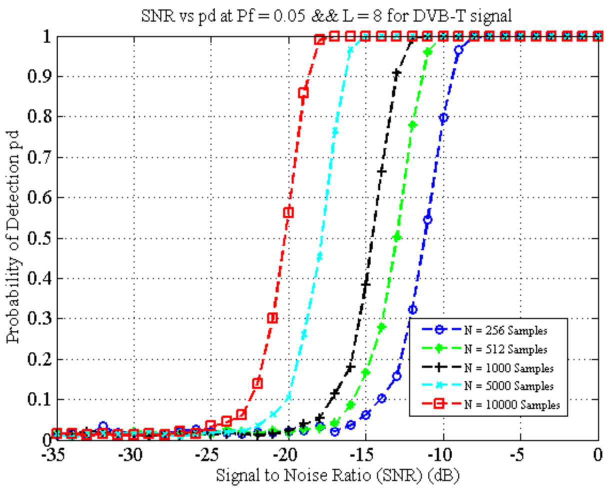

Fig. 5. Plot of p_d vs SNR for Eigenvalue detection

Figure 5 shows the plot of p_d vs SNR for p_{fa} = 0.05 and various no of samples for MME. It is observed that in increasing SNR values there is a linear increase in the probability of detection. The Probability of detection is high even for low values of SNR compared to ED. As the no of samples increases, the detection probability increases and computational complexity also increase. Above -17 dB the detection probability reaches 1 for *N = 10000* samples. The main drawback of EVD is the complexity compared to ED.

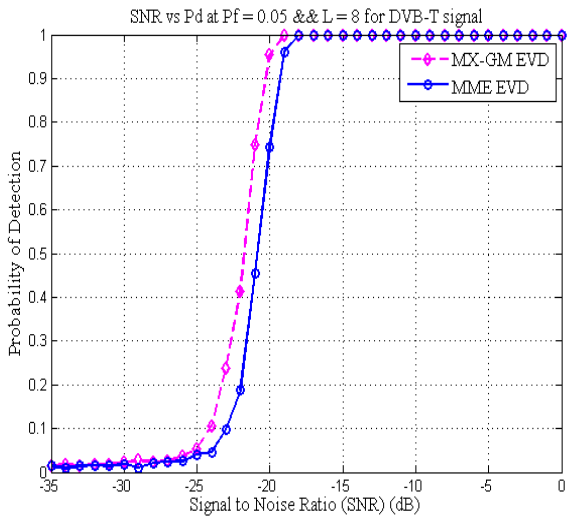

Fig. 6. Comparison of MME and MX-GM EVD method

Figure 6, compares the detection probabilities for *N = 20000* for EVD. Mx-GM is better compared to MME, but the additional complexity for calculation of the Geometric Mean of all Eigenvalues.

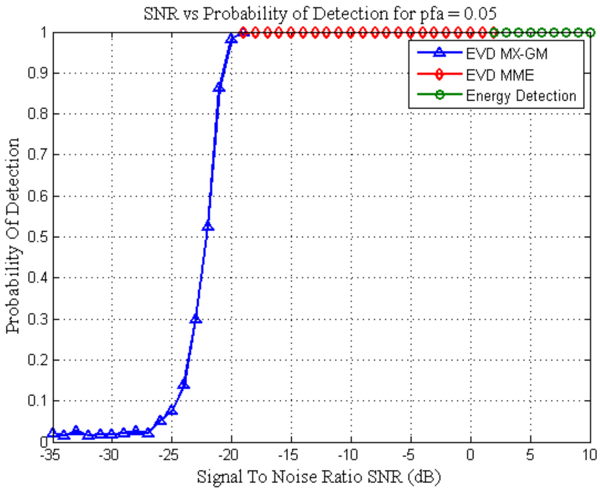

Fig. 7. Plot of Blind Adaptive Spectrum Sensing of primary user

Figure 7 shows a plot of blind adaptive spectrum sensing of the PU signal. When the prior knowledge about the primary user signal is not known, then the SNR of the signal is estimated. If the SNR value is less than the threshold λ = 2 dB, then Eigen value detection is applied. If the SNR value is less than the threshold λ, then EVD is applied. If the SNR value is greater than the threshold λ, then ED technique is applied.

Wireless networks, which are close to each other and transmitting on the same channel can cause some major drop outs and slow connections. In this scenario, the signal will on and off at the carrier frequency. To test in real time, Simulink based spectrum sensing in Cognitive Radio based on adaptive spectrum sensing is shown in Figure 8. The primary user of 100 MHz TV signal is passed through a channel with AWGN noise and then proposed scheme is applied for spectrum hole's detection.

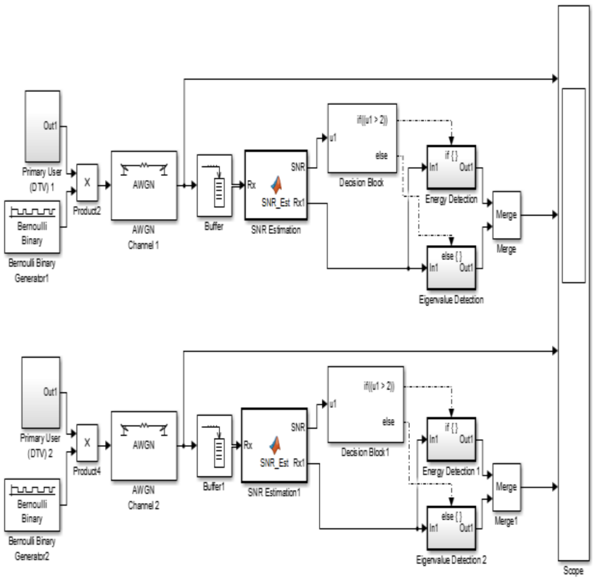

Fig. 8. Matlab Simulink schematic of adaptive spectrum sensing method

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The presence of primary user TV signal is decided using adaptive method.

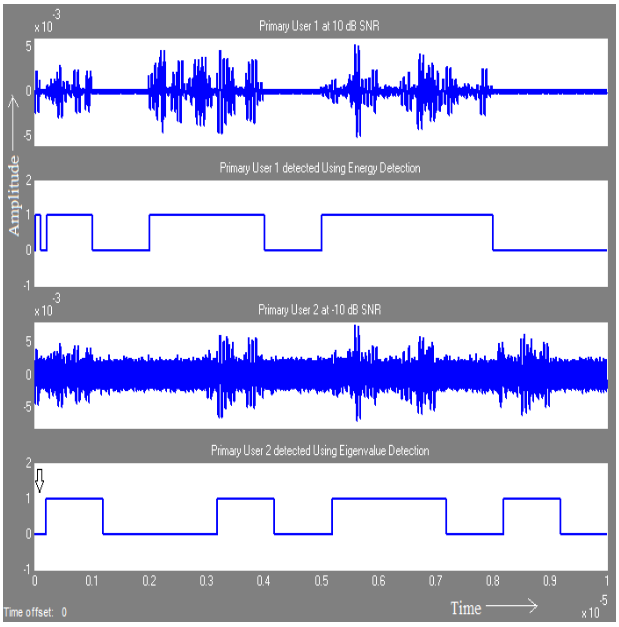

Fig. 9. Primary user activity detected with respect to time

Figure 9 describes the primary user activity in the channel 1 and channel 2 with respect to time, with white noise at 10 dB and -10 dB SNR. For channel 1, spectrum holes are detected using ED and channel 2 holes are detected by EVD. From figure 9, it can be observed the EVD method has more delay over ED for sensing because of complexity. The detected holes can be allocated to any secondary users by a frequency allocation process.

V. CONCLUSION

An adaptive spectrum sensing technique has been implemented in MATLAB. It is observed that Energy detection is the simplest technique, but it relies on the knowledge of accurate noise power, and inaccurate estimation of the noise power leads to SNR wall problem and high probability of false alarm i.e. the detection performance is high after a certain value of SNR (2 dB). Eigenvalue detection implementation is slightly complex compared to energy detection, but it shows good detection performance even under low SNR conditions where the energy detector doesn't work well. Therefore, energy detection is applied when the SNR value is greater than 2 dB and Eigenvalue detection is applied when the SNR is less than 2 dB. Time-based spectrum sensing has done using MATLAB Simulink. The primary user activity is observed and a decision is made, based on proposed adaptive spectrum sensing. This adaptive spectrum sensing technique reduces the overall complexity of the individual spectrum sensing process. It can be concluded that, Spectrum hole's map in a VHF broadcasting band can be built using the adaptive spectrum sensing. In future, a hardware implementation in FPGA of proposed adaptive spectrum sensing scheme can also be attempted.

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