Spectrum Sensing on High Density Cognitive Radio Vehicular Ad Hoc Network

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Abstract —Intelligent Transport System (ITS) has emerged as the most probable technology for improved transport experience more so in environments with high vehicular density. Effective vehicular communication is however hindered by spectrum scarcity due to the already crowded licensed spectrum. This has led to the emergence of Cognitive Radio (CR) systems as a solution to the spectrum scarcity problem. A crucial component in CR is spectrum sensing. Various spectrum sensing techniques including Cyclostationary, Matched Filter, and Energy detection have been proposed and applied with varied outcomes. In this paper, the above mentioned detection techniques are discussed and an improved energy detection based cooperative spectrum sensing scheme is proposed for improved communication in vehicular ad hoc networks (VANET). The proposed scheme showed an improvement in the performance of a network which in turn could lead to more efficient utilization of spectrum.

Index Terms—Cognitive Radio, Spectrum Sensing, Vehicular ad hoc network

I. Introduction

Increase in vehicular communication applications and high data rate traffic flows in vehicular ad hoc networks (VANETs) leads to more and more information exchange facilitated by wireless communications. More and more vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) information exchange, shall be facilitated by wireless communications through the use of wireless access in vehicular environments (WAVE) [1], [2]. With these requirements for additional radio resources for use in VANETs, the already crowded communication spectrum is bound to be overstretched thus, necessitating additional radio resources for vehicular communication through other technologies like Cognitive Radio (CR).

Some of the licensed radio spectrum is underutilized, as recent experiments by the FCC shows that the spectrum utilization varies from 15%-85% with frequency, time and geographical location [3], [4]. CR technology is one solution for utilizing the underutilized spectrum opportunistically [4]. CRs can detect unused spectrum bands (spectrum holes), and can access these holes opportunistically. CR systems involve Primary Users (PU) and Secondary Users (SU) of the spectrum; PUs are license holders, while SUs seek to opportunistically use the spectrum through CR when the PUs are idle. This allows the unlicensed SUs to utilize the temporarily unused licensed spectrums without interfering with the licensed PUs [5]–[9].

The cognition cycle of CR consists of multiple phases: Observe, Analyze, Reason, and Act [6], [10]. The goal is to detect available spectrum, select the best spectrum, select the best operational parameters, coordinate the spectrum access with other users, reconfigure the operational parameters, and vacate the frequency when a PU appears. Therefore, there are four important functionalities in CR networks: spectrum sensing, spectrum management, spectrum sharing, and spectrum mobility or spectrum handoff. In this work, the process of spectrum sensing is investigated. Spectrum sensing is the process of detecting the PUs by sensing the radio frequency (RF) environment. The CR user should efficiently identify and exploit the spectrum holes for required throughput and quality-of service, while taking precaution to ensure that they do not cause harmful interference to PUs by either switching to another available band when a PU appears, or limiting its interference with the appearing PU to an acceptable level [5], [6], [11].

In CR, each SU must sense the surrounding spectral environment to learn about incumbents or interferers, from which it determines which frequency bands to use [5], [6]. SUs with limited sensing capabilities in CR ad hoc networks strive to discover and share available spectrum resources without impairing PU transmission. Sensing strategy design objectives include high CR network throughput, resolution of SU competition, distributed implementation, and reliable performance under node mobility. Achievement of these objectives is further complicated by the high mobility nature of nodes in VANETs [11], [12].

There are three fundamental requirements for spectrum sensing [5], [6], [11], [12].

a) Continuous spectrum sensing to monitor the absence or presence of the PUs.
b) Precautions to avoid interference to potential PUs.
c) Independent detection of the presence of PUs without their help.

Such spectrum sensing can therefore be conducted non-cooperatively (individually), in which each SU

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conducts radio detection and makes decisions by itself. However, the sensing performance for one cognitive user will be degraded when the sensing channel experiences fading and shadowing. It has been proposed in the recent past that collaboration among SUs can improve the spectrum sensing, and thus may significantly enhance secondary spectrum access [4], [11], [12].

In this paper, Cyclostationary, Matched Filter, and Energy based spectrum detection techniques are discussed, and an improved energy detection based cooperative spectrum sensing scheme is proposed for improved communication in VANETs. The novel contributions here include the development of a triple threshold energy detection technique for improve sensing efficiency.

The organization of the rest of the paper is as follows. Section II discusses various spectrum detection techniques that are used in VANETs environments. Sections III proposed an improved detection technique based on energy detection method while section IV and V discusses the simulation results and concludes the work respectively.

II. Spectrum Detection Techniques

The essence of CR systems is to provide a licensed channel that belongs to the PU for use by SU when the channel is idle. This means that the SUs must have the capability to perform spectrum sensing. Spectrum sensing is a process of obtaining awareness about the spectrum usage and existence of PUs in a certain geographical area [13]–[15]. An effective spectrum sensing scheme is desirable for detection of the presence of spectrum holes and, most importantly, for detection of the presence of PUs. Real-time decisions about which bands to sense, when, and for how long is a requirement for any CR system. Also, the sensed spectrum information must be sufficient for the cognitive radio to reach accurate conclusions regarding the radio environment. With constant changes in the environment, the spectrum sensing must be fast in order to be useful. Energy Detection, Cyclostationary, and Matched Filter detection are the most common PU signal detection methods [16].

The probability of detection (P_d), probability of false alarm (P_{fa}), and probability of missed detection (P_m) are the most commonly used performance metrics when analyzing the performance of spectrum detection techniques. P_d is probability of a vacant frequency channel being declared vacant leading to utilization of the spectrum band. P_{fa} is the probability that a vacant frequency channel is declared occupied, and consequently the free band is not utilized by the CR. The P_m on the other hand is the probability that an occupied channel is declared vacant, causing interference to the PU, if the CR then utilizes the occupied channel. Challenges like hidden PU problem, fading, multipath, and shadowing, may lead to PU interference by SU. Cooperative spectrum sensing by exploiting multiple CR users to improve the sensing network performance has emerged as a possible solution to these challenges [17].

The spectrum sensing of primary signal can be expressed mathematically as [18]–[21];

$$y(n) = \begin{cases} w(n) & , H_0 \\ s(n) + w(n), & H_1 \end{cases} \tag{1}$$

where, $y(n)$ is the signal received at the cognitive radio terminal, $w(n)$ is the additive white Gaussian noise (AWGN) with zero mean and variance δ_w^2 , $s(n)$ represents the primary user signal, H_o represents absence of licensed PU, and H_1 represents the presence of a licensed PU.

The Signal-to-Noise Ratio (SNR), γ can be given as [18] [21];

$$\gamma = \frac{\sigma_s^2}{\sigma_w^2} \tag{2}$$

where σ_s^2 is the variance of the signal and σ_w^2 is the variance of the noise.

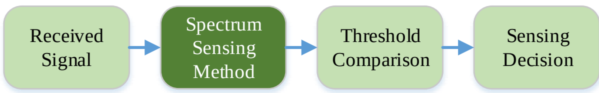

Fig. 1. Spectrum sensing model

Fig. 1 [21] illustrates the spectrum detection general model where the block representing spectrum sensing method is varied depending on the detection technique employed.

A. *Matched Filter Detection Technique*

Matched filter detection requires accurate synchronization and *a priori* knowledge of the PU's features used to demodulate the received signal, such as bandwidth, modulation type and order, operating frequency, and pulse shaping. This information can be obtained from the PU if it intends on leveraging cooperation. With proper synchronization, this method can achieve a shorter sensing time for a given probability of false alarm or probability of detection [21].

The test statistic $\phi(y)$ is given as;

$$\phi(y) = \sum_{n=0}^{N-1} y(n)x^*(n) \tag{3}$$

where $y(n)$ is the received signal and $x^*(n)$ represent the correlation coefficient which is a copy of known signal $x(n)$.

Based on Neyman-Pearson hypothesis, the P_d and P_{fa} can be are expressed as [21];

$$P_d = Q\left(\frac{\lambda_m - E}{\sqrt{E\sigma_w^2}}\right) \tag{4}$$

$$P_{fa} = Q\left(\frac{\lambda_m}{\sqrt{E\sigma_w^2}}\right) \tag{5}$$

where E is the PU signal energy and Q is the Marcum Q-function. Sensing threshold λ_m is giving as a function of PU signal energy and noise variance expressed as [21];

$$\lambda_m = Q^{-1}(P_{fa})\sqrt{(E\sigma_w^2)} \quad (6)$$

Cumbersome and large algorithms are used in this method leading to difficulties in implementation and high computation power requirements. These are its major drawbacks coupled by the fact that knowledge of PU features is necessary.

B. Cyclostationary Detection Technique

In cyclostationary based detection technique, the algorithms are used to differentiate noise from primary users' signals since the noise is wide-sense stationary with no correlation while modulated signals are cyclostationary with spectral correlation due to the redundancy of signal periodicities. The cyclostationary feature detector does not require transmitter information at the CR, but it requires excessive signal processing capabilities and is computationally very complex to implement. It also introduces an element of time delay [22].

Cyclic Spectral Density (CSD), a cyclic correlation function, is used in this method instead of Power Spectral Density (PSD) for signal detection [18]. The autocorrelation function, $R_y(t,\tau)$, and mean, $E_y(t)$, are used to determine cyclostationary property of the received signal, $y(t)$ as;

$$E_y(t) = \mu(t + mT_0) \quad (7)$$

$$R_y(t,\tau) = R_y(t + mT_0, \tau + mT_0) \quad (8)$$

where T_0, t, τ, and m are the time period, time index, autocorrelation function lag, and integer, respectively. Considering the Fourier series, the CSD function is given by the expression;

$$s(f,\alpha) = \sum_{t=-\infty}^{\infty} R_y^{\alpha}(\tau)e^{-j2\pi ft} \quad (9)$$

$$R_y^{\alpha}(\tau) = E[y(n-\tau)y^*(n-\tau)e^{-j2\pi\alpha n}] \quad (10)$$

where $R_y^{\alpha}(\tau)$ is the cyclic autocorrelation function and α is the cyclic frequency.

C. Energy Detection Technique

In the energy detection technique, the signal is detected by comparing the output of the energy detector with a threshold which depends on the noise floor [16], [23], [24]. This is the most widely used spectrum sensing method since prior knowledge of the licensed user signal is not required and it performs well with unknown dispersive channels with less computational and implementation complexity. Fig. 2 shows a block diagram of the energy detection technique.

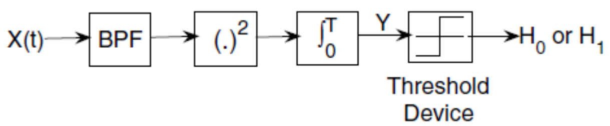

Fig. 2. Energy detection scheme

A band-pass filter in CR system is applied to the received signal for power measurement in a particular frequency region in the time domain. The power of received signal samples is then measured. The input band pass filter of the energy detector selects the center frequency, f_s and the bandwidth of interest, W. This filter is followed by a squaring device to measure the received energy and an integrator that determines the observation interval, T. Finally, the output of the integrator, Y is compared with a threshold, λ to decide whether the primary user signal is present or not. The energy of the received signal, E can be estimated as [9], [25], [26];

$$E = \sum_{i=1}^{N} |y_i|^2 \quad (11)$$

where y_i is the i^{th} sample of the received signal, and $N = 2TW$ is the time bandwidth product.

Some of the challenges with energy detector based sensing include, selection of the threshold for detecting PUs, and the challenge in differentiating from PUs and SUs already occupying the spectrum holes. Also, as this method relies on the knowledge of accurate noise power, it suffers from noise uncertainty.

III. Improved Energy Based Spectrum Detection Technique

A. Single Threshold Energy Detection

Single threshold energy detection technique is a conventionally method where the received signal energy, E_i, as measured over a specified observation time, is compared with a threshold λ, to determine the presence or absence of a PU [27], [28]. Under this method, the only two possible results are absence or presence of PU denoted by H_0 and H_1, respectively, in Fig. 3. Decision H_0 will be made when E_i is less than the threshold value λ, and H_1 will be made when E_i is greater than the threshold value λ, as seen in Eq. (1).

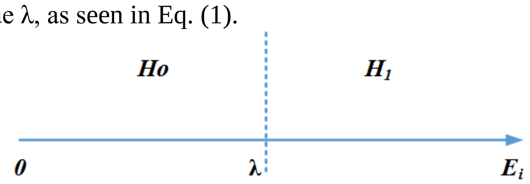

Fig. 3. Single threshold energy detection

For hypothesis H_0, PU is absent and only noise is detected. Here, the test statistic γ is the sum of the squares of $2u$ Gaussian variables with zero mean and σ_n^2 variance. In this case, statistic E follows a central chi-square (χ^2) distribution with $2u$ degrees of freedom. For hypothesis H_1, the received signal comprises of PU signal and noise. Here, the decision statistic E_i will follow a non-central (χ^2) distribution with $2u$ degrees of freedom and a non-centrality parameter 2γ as shown in Eq.(12) [12], [28].

$$E_i \approx \begin{cases} \chi_{2u}^2 & , H_0 \\ \chi_{2u,2\gamma_i}^2 & , H_1 \end{cases} \quad (12)$$

Probabilities of Detection, Missing , and False Alarm can be given as [29]–[31];

$$P_d = P\{E > \lambda | H_1\} = Q\left(\sqrt{2\gamma}, \sqrt{\lambda}\right) \quad (13)$$

$$P_m = P\{E \le \lambda | H_1\} = 1 - P_d \quad (14)$$

$$P_{fa} = P\{E > \lambda | H_0\} = \frac{\Gamma\left(n, \lambda/2\right)}{\Gamma(n)} \quad (15)$$

where, λ is the threshold value, γ is the SNR, $Q(a,b)$ is the generalized Marcum function Γ(a) is the complete gamma function, and Γ(a,b) is the incomplete gamma function.

For a given P_{fa}, the threshold λ can be computed as;

$$\lambda = 2\sigma_n^2 \Gamma^{-1}\left(u, P_{fa}\,\Gamma(u)\right) \quad (16)$$

Single threshold detection greatly suffers from high interference problems.

B. Double Threshold Energy Detection

The double threshold method has been proposed [23], [27], [28], [32], [33] to avoid the unwanted interference by introducing a fuzzy region (uncertainty region) as seen in Fig. 4.

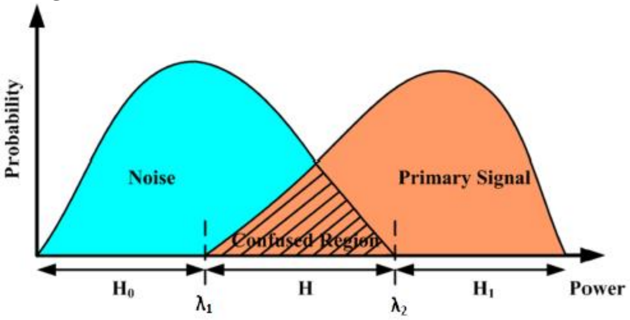

Fig. 4. Illustration of double threshold energy detection regions

The place on uncertainty where the noise and PU signals overlaps illustrates the uncertainty region where the SU scanning the spectrum is not 100% sure of the presence or absence of PU. This region is called region of uncertainty, confused region, or fuzzy region as shown in Fig. 5.

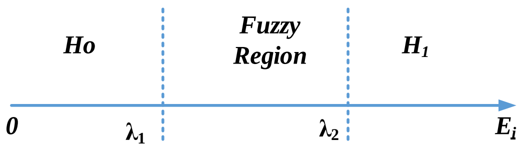

Fig. 5. Double threshold energy detection

Under the double threshold energy detection method, the user reports H_1 if the energy value, E_i exceeds λ_2. If E_i is less than λ_1, the decision H_0 will be made. Otherwise, if E_i is between λ_1 and λ_2, then the SU reports its observational energy value E_i for further decision making at the fusion center.

$$x(n) = \begin{cases} H_0, & E_i > \lambda_1 \\ No\ Decision, & \lambda_1 \le E_i \le \lambda_2 \\ H_1, & E_i > \lambda_2 \end{cases} \quad (17)$$

By using the lower and upper limit of noise variance, the lower threshold λ_1 and the upper threshold λ_2 respectively are chosen as;

$$\lambda_1 = 2(1-\rho)\sigma_n^2 \Gamma^{-1}\left(u, P_{fa}\,\Gamma(u)\right) \quad (18)$$

$$\lambda_2 = 2(1+\rho)\sigma_n^2 \Gamma^{-1}\left(u, P_{fa}\,\Gamma(u)\right) \quad (19)$$

where, the estimated noise variance is assumed on the interval $[(1-\rho)\sigma_n^2,\ (1+\rho)\sigma_n^2,]$ where $0<\rho<1$ is a parameter that quantifies the noise power uncertainty [19].

By adding two parameters $\Delta_{0,i}$ and $\Delta_{1,i}$ to represent the probability of $\lambda_1 \le E_i \le \lambda_2$ for the i^{th} secondary user under hypothesis H_0 and H_1 respectively, we have;

$$\Delta_{1,i} = P\{\lambda_1 \le E_i \le \lambda_2 | H_1\} \quad (20)$$

$$\Delta_{0,i} = P\{\lambda_1 \le E_i \le \lambda_2 | H_0\} \quad (21)$$

So it can be derived that:

$$P_d = P\{E > \lambda_2 | H_1\} = Q\left(\sqrt{2\gamma}, \sqrt{\lambda_2}\right) \quad (22)$$

$$P_m = P\{E \le \lambda_1 | H_1\} = 1 - \Delta_{1,i} - P_{d1} \quad (23)$$

$$P_{fa} = P\{E > \lambda_2 | H_0\} = \frac{\Gamma\left(n, \lambda_2/2\right)}{\Gamma(n)} \quad (24)$$

Each SU performs spectrum sensing individually and make a decision depending on the fusion rule adopted. For cooperation of the nodes, the spectrum sensing results E_i from SU is sent to the fusion center with the results designated as R_i and D_i. The result R_i is where E_i satisfies $\lambda_1 < E_i < \lambda_2$ otherwise D_i, where $E_i < \lambda_1$ and $E_i > \lambda_2$ represents H_0 and H_1 respectively.

$$R_i = \begin{cases} E_i, & \lambda_1 \le E_i \le \lambda_2 \\ D_i, & Otherwise \end{cases} \quad (25)$$

$$D_i = \begin{cases} 0, & E_i < \lambda_1 \\ 1, & E_i > \lambda_2 \end{cases} \quad (26)$$

C. Improved Triple Threshold Energy Detection

For improved spectrum performance and utilization, it would be crucial to have proper classification of the region of uncertainty in spectrum sensing results, as well as avoiding the use of small scale PUs, like WIFI, which are unreliable as they span over a short distance, leading to constant reallocation of spectrum space to SU if used for VANETs. Thus, the region of uncertainty can be expanded to include all uncertain spectrum sensed results with different thresholds. Fig. 6 and 7 illustrates the proposed improved triple energy detection method with the three threshold levels indicated.

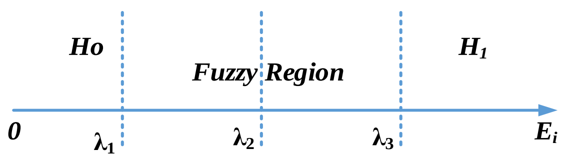

Fig. 6. Triple energy detection threshold levels

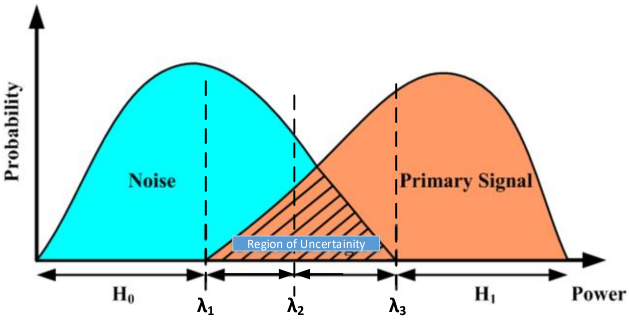

Fig. 7. Illustration of triple energy detection regions

The region of uncertainty is from the first threshold λ_1 to the third λ_3. The uncertainty region can be analyzed further to determine whether there is presence or absence of small scale PU, presence or absence of PU, or absence of both. All the nodes will relay all the spectrum scanned information to the Fusion Center (FC).

In the proposed model, the FC receives two kinds of information: local decisions and observational values of the SU, i.e. local energy values. The local sensing using energy detection for triple threshold method, $x(n)$ is determined as;

$$x(n) = \begin{cases} 0, & E_i \le \lambda_1 \\ 1, & E_i > \lambda_3 \\ k, & Otherwise \end{cases} \tag{27}$$

where k is the region of uncertainty given as;

$$k = \begin{cases} No\ Decision, & \lambda_1 < E_i < \lambda_2 \\ Unreliable, & \lambda_2 \le E_i \le \lambda_3 \end{cases} \tag{28}$$

Generally, Equation 27 and 28 can be written as;

$$x(n) = \begin{cases} 0, & E_i \le \lambda_1 \\ No\ Decision, & \lambda_1 < E_i < \lambda_2 \\ Unreliable, & \lambda_2 \le E_i \le \lambda_3 \\ 1, & E_i > \lambda_3 \end{cases} \tag{29}$$

For the i^{th} SU, the parameters $\Delta_{u0,i}$ and $\Delta_{u1,i}$ representing the probability of $\lambda_2 \le E_i \le \lambda_3$ under hypothesis H_0 and H_1 respectively, and $\Delta_{nd0,i}$ and $\Delta_{nd1,i}$ representing the probability of $\lambda_1 \le E_i \le \lambda_2$ under hypothesis H_0 and H_1 respectively, can be given as;

$$\Delta_{1,i} = P\{\lambda_2 \le E_i \le \lambda_3 | H_1\} = Q\left(\sqrt{2\gamma}, \sqrt{\lambda_2}\right) - Q\left(\sqrt{2\gamma}, \sqrt{\lambda_3}\right) \tag{30}$$

$$\Delta_{u0,i} = P_r\{\lambda_2 \le E_i \le \lambda_3 | H_0\} = \frac{\Gamma\left(n, \lambda_3/2\right)}{\Gamma(n)} - \frac{\Gamma\left(n, \lambda_2/2\right)}{\Gamma(n)} \tag{31}$$

$$\Delta_{nd1,i} = P_r\{\lambda_2 \le E_i \le \lambda_3 | H_1\} = Q\left(\sqrt{2\gamma}, \sqrt{\lambda_2}\right) - Q\left(\sqrt{2\gamma}, \sqrt{\lambda_1}\right) \tag{32}$$

$$\Delta_{nd0,i} = P_r\{\lambda_2 \le E_i \le \lambda_3 | H_0\} = \frac{\Gamma\left(n, \lambda_2/2\right)}{\Gamma(n)} - \frac{\Gamma\left(n, \lambda_1/2\right)}{\Gamma(n)} \tag{33}$$

The probabilities of detection, false alarm, and missing are given by the following equations;

$$P_d = P_r\{E > \lambda_3 | H_1\} = Q\left(\sqrt{2\gamma}, \sqrt{\lambda_3}\right) \tag{34}$$

$$P_m = P_r\{E < \lambda_1 | H_1\} = 1 - \Delta_{nd1,i} - P_{d1} \tag{35}$$

$$P_{fa} = P_r\{E > \lambda_3 | H_0\} = \frac{\Gamma\left(n, \lambda_3/2\right)}{\Gamma(n)} \tag{36}$$

Equations (25) and (26) can be modified to include the three thresholds where the result R_i is for E_i satisfying $\lambda_1 < E_i \le \lambda_3$, denoted as G_i, otherwise D_i. G_i can either be E_i or U_i representing no decision and unreliable region satisfying $\lambda_1 \le E_i < \lambda_2$ and $\lambda_2 \le E_i \le \lambda_3$ respectively.

$$R_i = \begin{cases} G_i, & \lambda_1 \le E_i \le \lambda_3 \\ D_i, & Otherwise \end{cases} \tag{37}$$

where,

$$G_i = \begin{cases} E_i, & \lambda_1 \le E_i \le \lambda_2 \\ U_i, & \lambda_2 \le E_i \le \lambda_3 \end{cases} \tag{38}$$

$$D_i = \begin{cases} 0, & E_i < \lambda_1 \\ 1, & E_i > \lambda_3 \end{cases} \tag{39}$$

IV. Simulation Results

To check the spectrum sensing performance of CR users, various performance metrics were simulated under different scenarios. Monte Carlo simulations under AWGN with mean 0 and noise variance 1 were simulated with the number of iterations set at 1000. A QPSK modulation technique with a modulation index of 4 was adopted in this simulation with the number of signal samples set at 1000. Probability of false alarm and signal-to-noise ratio are the common parameters that are used to estimate the probability of detection and the probability of missed detection in cognitive radio systems.

The simulations were carried out in two phases. The first phase was to analyze the spectrum sensing performance under different values of P_{fa} and SNR using conventional single threshold method of checking for the presence or absence of PU. The same procedure was then repeated under double and triple thresholds and comparison drawn. The P_{fa} from 0.01 to 1 in steps of 0.01 was first used to check the P_d and the P_m. Also, the same procedure was repeated with the SNR set at -16 dB to 0 dB. The receiver operating characteristics (ROC) curves that depict the P_d and P_{fa} relationship at a specific SNR value and P_d and SNR relationship at a specific P_{fa} values are discussed below.

Fig. 8 shows the ROC of P_d vs P_{fa} at different SNR values, and based on conventional single threshold energy detection method. Liu, *et.al* [34] points out that the recommended P_{fa} of 0.1 indicates a confidence level is 95%, which corresponds to the IEEE 802.22 recommended and the acceptable values for P_{fa} and P_d as ≤ 0.1 and ≥ 0.9 respectively [35]–[37]. At the recommended P_{fa} level of 0.1, the highest SNR of 1dB has the highest P_d of approximately 0.988 as compared to *Pd* of 0.886, 0.39, and 0.169 at -5 dB, -10 dB, and -15 dB respectively.

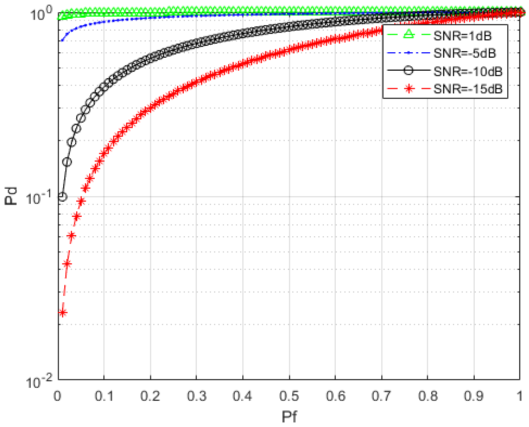

Fig. 8. P_d vs P_{fa} for different SNR

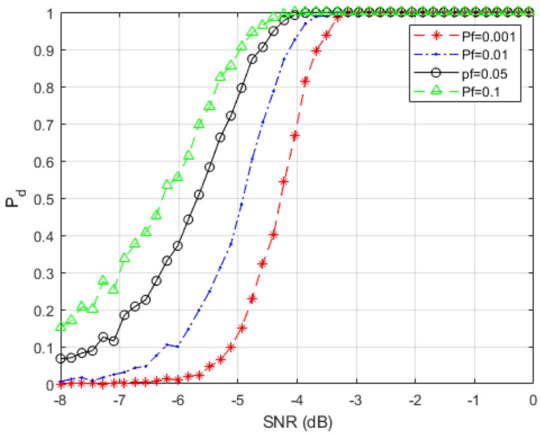

Fig. 9 P_d vs SNR for different P_{fa}

The results in Fig. 9 shows that the higher the SNR value, the higher the P_d . Also the lower the P_{fa}, the lower the P_d value for the same SNR. The detection performance for SNRs lower than -5 dB can be seen to degrade further. This degradation can be attributed to increase in noise levels received as well as the possibility of window shadowing. A P_{fa} of 0.1, 0.5, 0.01, and 0.001 at SNR of $-5\text{ dB}, -4.67\text{ dB}, -4.16\text{ dB}, \text{and} -3.46\text{ dB}$ respectively yields a recommended P_d of 0.9.

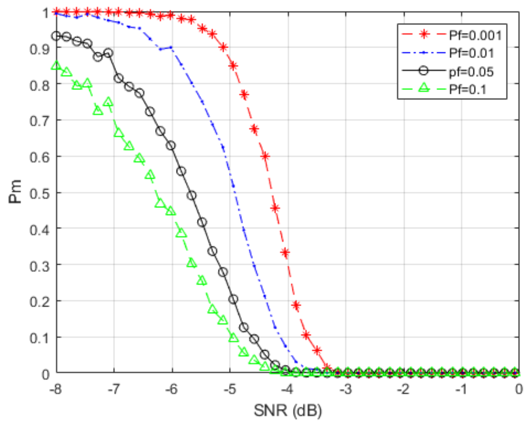

Fig. 10. P_m vs SNR for different P_{fa}

Similarly, in order to prevent underutilization of transmission opportunities, a lower P_{fa} with a lower P_m is recommended. A lower P_m with a higher SNR will provide better spectrum utilization. Fig. 10 shows a complementary ROC comparison of P_m with SNR under different values of P_f. It is observed that the higher the SNR, the lower P_m at different values of P_{fa}. This presents an ideal situation in which the CR user does not fail to note the presence of PU, and thus avoiding causing interference to licensed users.

A clear distinction between the presence and absence of PU may not be possible in some situations due to the impact of noise. To test the performance of the proposed triple threshold method for improved performance of VANET, the P_{fa} was set at 0.01 and SNR set at -15dB to 5dB at intervals of 0.5.

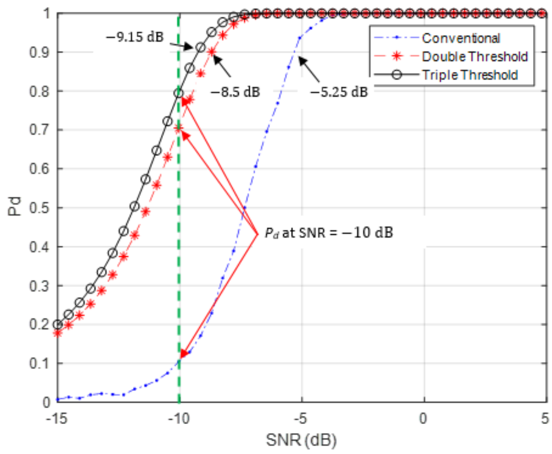

Fig. 11. P_d vs SNR with different thresholds

Fig. 11 compares the probabilities of detection versus SNR based on the three thresholds, conventional single threshold, double threshold, and triple threshold, techniques. Similar to Fig. 9, Fig. 11 shows that the P_d increases with the increase in the SNR value. Due to unclear fuzzy region, the P_d under single threshold was the lowest as compared with the double and triple thresholds. Double and triple threshold have comparable P_d with the triple threshold having a higher P_d. At -10 dB SNR, the P_d of 0.795, 0.705, and 0.104 for triple, double, and single thresholds, respectively, are obtained. This shows clearly that triple threshold method outperforms double threshold by P_d of approximately 0.09, an improvement of approximately 12.8%. The improvement over single threshold method is over 6 fold. This can be very significant given the high rate of operation of the users, and result in significant improvement in network data efficiency.

Fig. 12 compares the P_d versus the P_f. Based on the recommended P_{fa} of 0.1, the P_d of 0.95, 0.90, and 0.205 were noted for triple, double, and single threshold, respectively. These results shows that triple threshold method performed better that both the double and single threshold methods. The difference in P_d between triple and double threshold is 0.05 or 5.3%, and thus detections are likely to improve by this percentage.

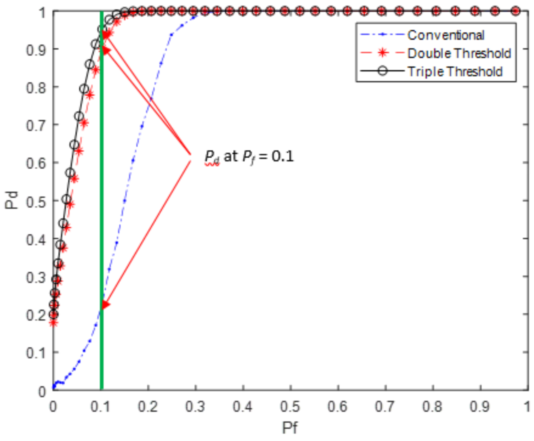

Fig. 12. P_d vs P_{fa} for varying threshold

V. Conclusion

Spectrum detection methods are discussed in this paper with emphasis on the proposed spectrum sensing method based on an energy detection method that improves the spectrum sensing performance for VANETs. Due to its advantages, energy detection method has been researched extensively and thus was analyzed further in this work. The use of triple threshold method in this work has be shown to significantly improve the performance of a network which in turn could lead to more efficient utilization of spectrum.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

All authors contributed to research and modelling the proposed spectrum sensing technique. K.V. Rop simulated the proposed technique under the guidance and advice of Dr. P.K. Langat and Prof. H.A. Ouma; All authors had approved the final version.

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