Spectrum Sensing Based on Dynamic Primary User with Additive Laplacian Noise in Cognitive Radio

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Abstract. In this paper, spectrum sensing techniques with dynamic primary user (PU) are considered in the environment of Laplacian noise. It means the PU may not be present or absent during the whole sensing time. However, PU arrives or departs randomly in the sensing time interval. We consider three different detection schemes such as energy detection, absolute value cumulation detection (AVCD) and improved AVCD (i-AVCD). We present the performance in terms of receiver operating characteristic (ROC) and detection probability versus average signal-to-noise ratio (SNR) using simulations. We conclude that the detection performance in the dynamic scenario is better than the performance in the static scenario, when the arrival/departure parameter ($\theta_A T/\theta_D T$) is beyond one, where θ_A and θ_D are corresponding to arrival rate and departure rate of the PU respectively, and T is the sampling interval. Furthermore, the i-AVCD scheme outperforms AVCD and energy detection in the considered scenario.

Keywords: Spectrum sensing · Cognitive radio · Dynamic primary user · Detection probability · False alarm probability

1 Introduction

In the today's scenario of 5G communication, scarcity of microwave spectrum is the biggest bottleneck for introducing real time services. In this case, use of millimeter (mm) wave can provide enough spectrum but it demands for drastic change in the Radio Access Network (RAN), Air interface, physical layer and MAC Layer of cellular networks. On the other side, it has been observed that the microwave spectrum is not utilized effectively. Major part of this spectrum has been found vacant, we call it as spectrum holes. Thus, the spectrum holes indicate segments of the spectrum which are not utilized by the licensed users, also known as primary users (PU). In this case, the spectrum holes can be utilized by unlicensed users, also known as secondary users (SU) without introducing any interference to the PU [1]. This is popularly known as cognitive radio. The process of detecting spectrum holes is known as spectrum sensing in cognitive radio.

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In the literature, various detection schemes for spectrum sensing with their performance in terms of receiver operating characteristic (ROC) is well documented. Increase in the sensing period can improve the detection performance but reduce the throughput [2]. Hence, there always exists a trade-off between the detection performance and the throughput [3]. The conventional spectrum sensing methods assume the static behaviour of PU during sensing period. It means that PU remains active or inactive throughout the whole sensing period [4–6]. In this scenario, it is a simple binary hypothesis testing problem, in which the assumed static model of PU is valid for slowly varying PU traffic such as in television broadcast [7]. However, when PU traffic varies fastly or PU is dynamic as in cellular communication or Wireless LAN [8,9], the performance of these schemes degrade.

The case of one transition of PU signal during spectrum sensing interval is considered in [4–9], while multiple transitions of PU signal were considered in [10,11]. In [12], two transitions of PU signal were considered during sensing period and dynamic programming was introduced to reduce the computation time. In [13], random arrival or random departure of PU is considered over the sensing period and it is assumed that the arrival and departure of the PU follows Poisson process. The effect of deep sensing is proposed in [14]. Two-state Markov chain is used in [15], where Markov model is used for the on-off status of the PU. Partially observed Markov decision process is discussed in [16], where occupancies of the vacant licensed band follows Markovian evolution. Cooperative spectrum sensing in dynamic PU environment is discussed in [17] with the aim of throughput maximization. The effect of dynamicity of the PU under both sensing period and transmission period is discussed in [18].

Furthermore, most of the schemes assume additive noise as Gaussian [12–18], which usually models thermal noise of the receiver. However, in the multiuser environment, dominant source of noise is interference such as multiple access interference (MAI). The MAI can be modelled by Gaussian mixture model (GMM), Middleton Class A model (MCA) or Laplacian noise model. The Laplacian model is used in [19] to model the distribution of MAI in time-hopped ultra-wideband (TH-UWB) communication system.

In this paper, we consider dynamic primary user (PU) with additive Laplacian noise [19,20]. We have used conventional energy detection along with absolute value cumulation detection (AVCD) [21] and improved AVCD (i-AVCD) [22] detection schemes. In AVCD, sum of the absolute values of the received samples over the sensing period is considered, while in case of i-AVCD, the sum of absolute value of each sample raised to a positive exponent P, $0 \leq P < 2$ is used. Thus, AVCD is a special case of i-AVCD with $P = 1$. Further, we have modelled the random arrival or the random departure of the PU using Poisson distribution. The arrival time or departure time of the PU is assumed to follow exponential distribution.

2 System Model

In general, when PU is static, H_o denotes the null hypothesis when PU is absent and H_1 denotes the alternate hypothesis when PU is present. Here, we assume that PU randomly departs under hypothesis H_o and randomly arrives under hypothesis H_1 during the sensing time. Received signals at the cognitive terminal under the random arrival and the random departure of the PU can be expressed as [13]

$$\begin{aligned} H_0 : y_m &= \begin{cases} s_m + w_m & , m = 1, \ldots, \xi_o \\ w_m & , m = \xi_o + 1, \xi_o + 2, \xi_o + 3 \ldots, N \end{cases} \\ H_1 : y_m &= \begin{cases} w_m & , m = 1, \ldots, \xi_1 \\ s_m + w_m & , m = \xi_1 + 1, \xi_1 + 2, \xi_1 + 3 \ldots, N \end{cases} \end{aligned} \tag{1}$$

where $m = 1, 2, \ldots, N$, N indicates the total number of samples present during the sensing period. $N = BT$, where B is the bandwidth of the bandpass filter used to filter PU signal and T is the interval at which filtered PU signal is sampled. s_m is the unknown PU signal, w_m indicates Laplacian noise with mean 0 and variance $2b^2$ where b is the scale parameter of Laplacian noise. Average SNR is defined as $\gamma = (1/N) \sum_{m=1}^{N} (s_m^2)/(2b^2)$. ξ_o and ξ_1 indicate the first level alter points of the PU under hypotheses H_o and H_1 respectively. Transition of the PU occurs between the samples ξ_o and $\xi_o + 1$ under H_o (when PU randomly departs) and between the samples ξ_1 and $\xi_1 + 1$ under H_1 (when PU randomly arrives). The PDF of Laplacian noise is expressed as

$$f_{w_m}(x) = \frac{1}{2b} \exp\left(-\frac{|x|}{b}\right). \tag{2}$$

3 Dynamic PU Modeling

In this section, we present P_D and P_F for different detection schemes such as energy detection (ED) and i-AVCD detection.

3.1 Energy Detection

The ED is the classical and the simplest spectrum sensing method in cognitive radio. From (1), the likelihood function under the null-hypothesis H_o can be expressed as

$$f(\mathbf{y}|\mathbf{s}_{co}, H_o) = \frac{1}{(2b)^N} \exp\left\{ -\sum_{m=1}^{\xi_o} \frac{|y_m - s_m|^2}{b} - \sum_{m=\xi_o+1}^{N} \frac{|y_m|^2}{b} \right\}, \tag{3}$$

where $\mathbf{y} = [y_1, y_2, \ldots, y_N]$ and $\mathbf{s}_{co} = [s_1, s_2, \ldots, s_{\xi_o}]$. Similarly from (1), the likelihood function under the hypothesis H_1 can be expressed as

$$f(\mathbf{y}|\mathbf{s}_{c1}, H_1) = \frac{1}{(2b)^N} \exp\left\{ -\sum_{m=1}^{\xi_1} \frac{|y_m|^2}{b} - \sum_{m=\xi_1+1}^{N} \frac{|y_m - s_m|^2}{b} \right\}, \quad (4)$$

where $\mathbf{y} = [y_1, y_2, \ldots, y_N]$ and $\mathbf{s}_{c1} = [s_{\xi_1+1}, s_{\xi_1+2}, \ldots, s_N]$. As the parameter s_m is unknown, CR is not aware of any information about PU signal. Hence, it needs to be removed from the likelihood function. This belongs to the composite hypothesis testing problem where some of the parameters in the hypotheses are unknown and can be estimated using various estimation techniques. More specifically, Generalized likelihood ratio test (GLRT) is used for spectrum sensing and maximum likelihood (ML) estimation is used to find out the estimate of s_m. This gives

$$\frac{f(\mathbf{y}|\hat{\mathbf{s}}_{c1}, H_1)}{f(\mathbf{y}|\hat{\mathbf{s}}_{co}, H_o)} = \frac{\frac{1}{(2b)^N} \exp\left\{ -\sum_{m=1}^{\xi_1} \frac{|y_m|^2}{b} \right\}}{\frac{1}{(2b)^N} \exp\left\{ -\sum_{m=\xi_o+1}^{N} \frac{|y_m|^2}{b} \right\}} \underset{H_o}{\overset{H_1}{\gtrless}} \lambda, \quad (5)$$

where $\hat{\mathbf{s}}_{co} = [\hat{s}_1, \hat{s}_2, \ldots, \hat{s_{\xi_o}}]$ and $\hat{\mathbf{s}}_{c1} = [\hat{s}_{\xi_1+1}, \hat{s}_{\xi_1+2}, \ldots, \hat{s}_N]$. Maximum likelihood (ML) estimate of s_m is $\hat{s}_m$ which is calculated and found to be y_m, i.e., $\hat{s}_m = y_m$. The values of ξ_o and ξ_1 are also random and unknown at this point. Hence, they should be averaged out over the likelihood ratio obtained in (5). Taking logarithm from both the sides in (5), the expression becomes

$$Z = \sum_{m=\xi_o+1}^{N} |y_m|^2 - \sum_{m=1}^{\xi_1} |y_m|^2 \underset{H_o}{\overset{H_1}{\gtrless}} \lambda', \quad (6)$$

where λ' is the detection threshold of decision statistic Z, that needs to be determined using Neyman-Pearson (NP) test. Detection Probability P_D and false alarm probability P_F can be expressed as

$$P_D = Pr\left\{ Z > \lambda' | H_1 \right\},$$
$$P_F = Pr\left\{ Z > \lambda' | H_o \right\}. \quad (7)$$

In this paper, the arrival rate and the departure rate of the PU is assumed to follow Poisson process. The arrival rate and departure rate of the PU is denoted as θ_A and θ_D, respectively. The probability of the PU for not arriving or departing during the sample interval T is given by $e^{-\theta_A T}$ and $e^{-\theta_D T}$, respectively. Hence, the probability of arrival or departure of the PU is given by by $1 - e^{-\theta_A T}$

and $1 - e^{-\theta_D T}$ [13], respectively. Thus, the probability of the random arrival or the random departure in the ξ_o^{th} or ξ_1^{th} sample is given by [13]

$$Pr\{\xi_o\} = \Big\{1 - \exp\{\theta_D T\}\Big\}.\Big\{\exp\{-\theta_D T\}\Big\}^{\xi_o},$$
$$Pr\{\xi_1\} = \Big\{1 - \exp\{\theta_A T\}\Big\}.\Big\{\exp\{-\theta_A T\}\Big\}^{\xi_1}, \qquad (8)$$

where $Pr\{\xi_o\}$ and $Pr\{\xi_1\}$ denote the respective probability of random departure and random arrival, $\theta_A T$ and $\theta_D T$ denote the number of PU arrivals and departures, respectively. We consider three different decision statistics - ED, AVCD and i-AVCD. A case of static PU and two cases (arrival and departure) of dynamic PU are discussed in the following section using each of the three test statistics.

1) Static/Fixed PU: When PU is static or fixed at one place ED can be termed as conventional or classical ED. This denotes a case when $\xi_o = 0$ and $\xi_1 = 0$. When $\xi_o = 0$, PU is absent during the whole sensing period and when $\xi_1 = 0$, PU is present during the whole sensing period. This case complies with the case of low traffic scenario. Decision statistics under ED can be expressed as

$$C = \sum_{m=1}^{N} |y_m|^2 \underset{H_o}{\overset{H_1}{\gtrless}} \psi_c, \qquad (9)$$

where ψ_c is the detection threshold of ED based decision statistic C obtained using NP test. For large values of N, central limit theorem (CLT) can be applied to approximate the probability density function (PDF) of C as Gaussian with mean m_o and variance σ_o^2, i.e.,

$$C \sim N(m_o, \sigma_o^2), \qquad (10)$$

where $m_o = 2Nb^2$ and $\sigma_o = 2\sqrt{5N}b^2$ [22]. Using (10), ψ_c can be expressed as

$$\psi_c = Q^{-1}\big(P_F\big)\sigma_o + m_o, \qquad (11)$$

where $Q(.)$ is the Q-function given by $Q(v) = \frac{1}{\sqrt{2\pi}} \int_v^{+\infty} \exp\left(-\frac{t^2}{2}\right) dt$.

2) Dynamic PU (Random Arrival): It is now known that when $\xi_o = 0$, PU is absent during the whole sensing period. However, it also signifies the initial phase of the potential transmission of the PU. Using (6) and (8), averaged likelihood ratio (ALR) can be obtained as [13]

$$A = \sum_{\xi_1=0}^{N-1} \{1 - \exp\{\theta_A T\}\}\{\exp\{-\theta_A T\}\}^{\xi_1} \left[\sum_{m=1}^{N} |y_m|^2 - \sum_{m=1}^{\xi_1} |y_m|^2\right] \underset{H_o}{\overset{H_1}{\gtrless}} \psi_a$$
$$= \sum_{m=1}^{N} \Big\{1 - \exp\{-\theta_A T m\}\Big\} |y_m|^2 \underset{H_o}{\overset{H_1}{\gtrless}} \psi_a, \qquad (12)$$

where ψ_a is the detection threshold of ED based decision statistic A when PU arrives in random fashion. Applying CLT, A tends to be Gaussian with mean μ_A and variance σ_A^2. Thus, ψ_A can be expressed as

$$\psi_a = Q^{-1}(P_F)\sigma_A + \mu_A, \tag{13}$$

where μ_A and σ_A^2 denote the mean and the variance, respectively of the decision statistic A obtained in (12) under hypothesis H_o. The expression of μ_A and σ_A^2 can be derived and expressed as

$$\begin{aligned}
\mu_A &= N\mu_o - \mu_o\left[\frac{\exp\left(-\theta_A T\right)\left\{1 - \exp\left(-\theta_A TN\right)\right\}}{1 - \exp\left(-\theta_A T\right)}\right], \\
\sigma_A^2 &= N\sigma_o^2 - \sigma_o^2\left[\frac{\exp\left(-2(\theta_A T + 1)\right)\left\{1 - \exp\left(-(N-1)\right)\right\}}{1 - \exp\left(-1\right)} + \exp\left(-2\theta_A T\right)\right],
\end{aligned} \tag{14}$$

where μ_o and σ_o^2 are the mean and variance of the decision statistic C based on conventional/classical ED in Laplacian noise. They can be obtained from (11) with $\mu_o = 2Nb^2$ and $\sigma_o^2 = 20Nb^4$.

3) Dynamic PU (Random Departure): When $\xi_1 = 0$, PU is present during the whole sensing period. However, it also signifies the final or last phase of the active transmission of the PU. Using (6) and (8), ALR can be obtained as [13]

$$\begin{aligned}
D &= \sum_{\xi_o=0}^{N-1}\left\{1 - \exp\{\theta_D T\}\right\}\left\{\exp\{-\theta_D T\}\right\}^{\xi_o}\sum_{m=\xi_o+1}^{N}|y_m|^2 \\
&= \sum_{m=1}^{N}\left\{1 - \exp\{-\theta_D Tm\}\right\}|y_m|^2 \underset{H_o}{\overset{H_1}{\gtrless}} \psi_d,
\end{aligned} \tag{15}$$

where ψ_d is the detection threshold of decision statistic D based on ED when PU departs in random fashion. Applying CLT, D tends to be Gaussian with mean μ_D and variance σ_D^2. Thus, ψ_D can be expressed as and it can be expressed as

$$\psi_d = Q^{-1}(P_F)\sigma_D + \mu_D, \tag{16}$$

where μ_D and σ_D^2 denote the mean and the variance, respectively, of the decision statistic D obtained in (15) under hypothesis H_o. Expression of μ_D and σ_D^2 is derived and expressed as

$$\begin{aligned}
\mu_D &= N\mu_o - \mu_o\left[\frac{\exp\left(-\theta_D T\right)\left\{1 - \exp\left(-\theta_D TN\right)\right\}}{1 - \exp\left(-\theta_D T\right)}\right], \\
\sigma_D^2 &= N\sigma_o^2 - \sigma_o^2\left[\frac{\exp\left(-2(\theta_D T + 1)\right)\left\{1 - \exp\left(-(N-1)\right)\right\}}{1 - \exp\left(-1\right)} + \exp\left(-2\theta_D T\right)\right].
\end{aligned} \tag{17}$$

3.2 AVCD and i-AVCD

AVCD and i-AVCD are the two important test-statistics used actively in Laplacian noise. As discussed before, AVCD is a special case of i-AVCD with exponent $P = 1$. Hence, in this section we particularly describe i-AVCD. Corresponding parameters of AVCD can be obtained by putting the value of $P = 1$ in the expressions obtained for i-AVCD. Removing the squaring operation and substituting it with P in (3)–(5), decision statistics can be expressed as

$$Z = \sum_{m=\xi_o+1}^{N} |y_m|^P - \sum_{m=1}^{\xi_1} |y_m|^P \underset{H_o}{\overset{H_1}{\gtrless}} \lambda^{'}, \tag{18}$$

where λ' is the detection threshold of the test-statistic Z obtained in (18). Three different cases under dynamic modeling of i-AVCD based spectrum sensing are discussed in the following section.

1) Static PU: When PU is static, i-AVCD can be termed as conventional or classical i-AVCD. This denotes the case when $\xi_o = 0$, $\xi_1 = 0$. The decision statistic under this case can be expressed as

$$C = \sum_{m=1}^{N} |y_m|^P \underset{H_o}{\overset{H_1}{\gtrless}} \psi_c, \tag{19}$$

where ψ_c is the detection threshold of i-AVCD based decision statistic C obtained in (19) using NP test and it can be expressed as

$$\psi_c = Q^{-1}\big(P_F\big)\sigma_o + \mu_o, \tag{20}$$

where μ_o and σ_o^2 denote the mean and the variance, respectively of the decision statistic C obtained in (19) expressed as [22]

$$\begin{aligned} \mu_o &= b^P \Gamma(P+1), \\ \sigma_o^2 &= b^{2P} \Gamma(2P+1) - \mu_o^2, \end{aligned} \tag{21}$$

where $\Gamma(v) = \int_0^{+\infty} e^{-t} t^{v-1} dt$.

2) Dynamic PU (Random Arrival): Similar to the ED, in this case, the ALR can be obtained as

$$\begin{aligned} A &= \sum_{\xi_1=0}^{N-1} \{1 - \exp\{\theta_A T\}\}\{\exp\{-\theta_A T\}\}^{\xi_1} \left[\sum_{m=1}^{N} |y_m|^P - \sum_{m=1}^{\xi_1} |y_m|^P\right] \underset{H_o}{\overset{H_1}{\gtrless}} \psi_a, \\ &= \sum_{m=1}^{N} \Big\{1 - \exp\{-\theta_A T m\}\Big\} |y_m|^P \underset{H_o}{\overset{H_1}{\gtrless}} \psi_a, \end{aligned} \tag{22}$$

where ψ_a is the detection threshold of i-AVCD based decision statistic A, when PU arrives randomly which can be expressed as

$$\psi_a = Q^{-1}(P_F)\sigma_A + \mu_A, \tag{23}$$

where μ_A and σ_A^2 denote the mean and the variance respectively, of the decision statistic obtained in (22) under hypothesis H_o. The expression of μ_A and σ_A^2 can be derived and expressed as

$$\begin{aligned} \mu_A &= N\mu_o - \mu_o\left[\frac{\exp\left(-\theta_A T\right)\left\{1 - \exp\left(-\theta_A TN\right)\right\}}{1 - \exp\left(-\theta_A T\right)}\right], \\ \sigma_A^2 &= N\sigma_o^2 - \sigma_o^2\left[\frac{\exp\left(-2(\theta_A T + 1)\right)\left\{1 - \exp\left(-(N-1)\right)\right\}}{1 - \exp\left(-1\right)} + \exp\left(-2\theta_A T\right)\right], \end{aligned} \tag{24}$$

3) Dynamic PU (Random Departure): In this case, the ALR can be obtained as [13]

$$\begin{aligned} D &= \sum_{\xi_o=0}^{N-1}\{1 - \exp\{\theta_D T\}\}\{\exp\{-\theta_D T\}\}^{\xi_o}\sum_{m=\xi_o+1}^{N}|y_m|^P \underset{H_o}{\overset{H_1}{\gtrless}} \psi_d \\ &= \sum_{m=1}^{N}\Big\{1 - \exp\{-\theta_D Tm\}\Big\}|y_m|^P \underset{H_o}{\overset{H_1}{\gtrless}} \psi_d, \end{aligned} \tag{25}$$

where ϕ_d is the detection threshold of i-AVCD based decision statistic D, obtained in (25), when PU departs randomly. It can be expressed as

$$\psi_d = Q^{-1}(P_F)\sigma_D + \mu_D, \tag{26}$$

where μ_D and σ_D^2 denote the mean and the variance respectively of the decision statistic, obtained in (25) under hypothesis H_o. The expressions of μ_D and σ_D^2 can be derived and expressed as

$$\begin{aligned} \mu_D &= N\mu_o - \mu_o\left[\frac{\exp\left(-\theta_D T\right)\left\{1 - \exp\left(-\theta_D TN\right)\right\}}{1 - \exp\left(-\theta_D T\right)}\right], \\ \sigma_D^2 &= N\sigma_o^2 - \sigma_o^2\left[\frac{\exp\left(-2(\theta_D T + 1)\right)\left\{1 - \exp\left(-(N-1)\right)\right\}}{1 - \exp\left(-1\right)} + \exp\left(-2\theta_D T\right)\right]. \end{aligned} \tag{27}$$

The mean and variance, obtained under dynamic scenario, are dependent on the parameters T and N. The random arrival and random departure are dependent on the respective arrival rate θ_A and departure rate θ_D, total number of sensing samples N and sample interval T.

4 Results

In this section, performance of the proposed spectrum sensing in dynamic PU environment with additive Laplacian noise is presented in terms of receiver operating characteristic (ROC) and detection probability versus average signal-to-noise ratio (SNR) γ using Monte Carlo simulations. The values of ξ_o and ξ_1 are taken to be 10 and 15 respectively. For static PU environment, $\xi_o = 0$ and $\xi_1 = 0$, whereas for dynamic PU environment both are less than N.

Figure 1 shows the ROC for ED, AVCD and i-AVCD (for $P = 0.8$) under both static and dynamic scenarios of the PU at $\gamma = -5$ dB, $\theta_A T = 1$, $\theta_D T = 1$ and $N = 50$. It can be seen that the performance in the dynamic scenario is better than the performance in the static scenario in all the three schemes. We have further observed that the performance with i-AVCD improves, when P reduces in the range $0 \leq P < 2$.

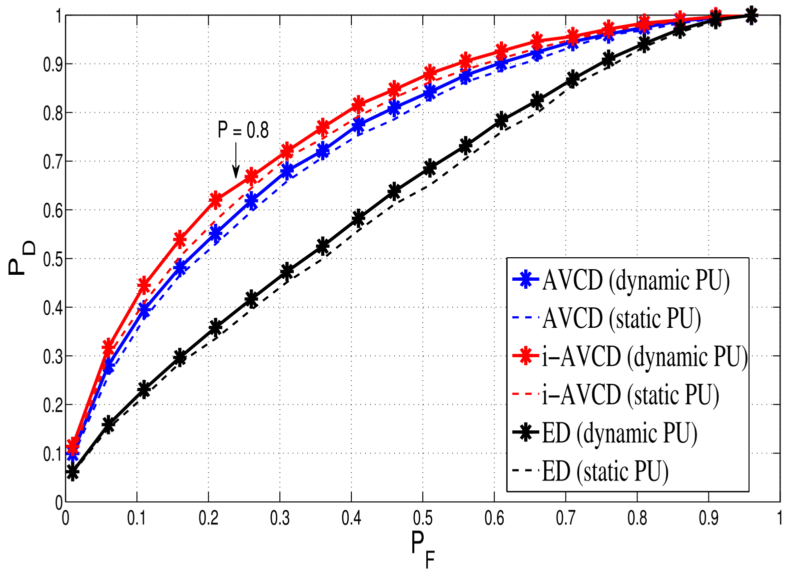

Fig. 1. Comparison of ROC plot for different test statistics with $N = 50$, $\gamma = -5$ dB, $\theta_A T = 1$ and $\theta_D T = 1$.

Figure 2 presents the detection probability (P_D) versus average SNR γ for all the three schemes: ED, AVCD and i-AVCD for $P_F = 0.1$, $\theta_A T = 1$, $\theta_D T = 1$ and $N = 50$. Here, also i-AVCD outperforms other two schemes.

Figure 3 shows ROC for AVCD scheme under different dynamic scenario with different values of $\theta_A T$ and $\theta_D T$ at SNR $\gamma = -2$ dB and $N = 50$. For $\theta_A T$ and $\theta_D T$ as 0.05, 0.1, 1, 10 and 20. We have also presented performance with static scenario also. It can be seen that the performance will improve as value of $\theta_A T$

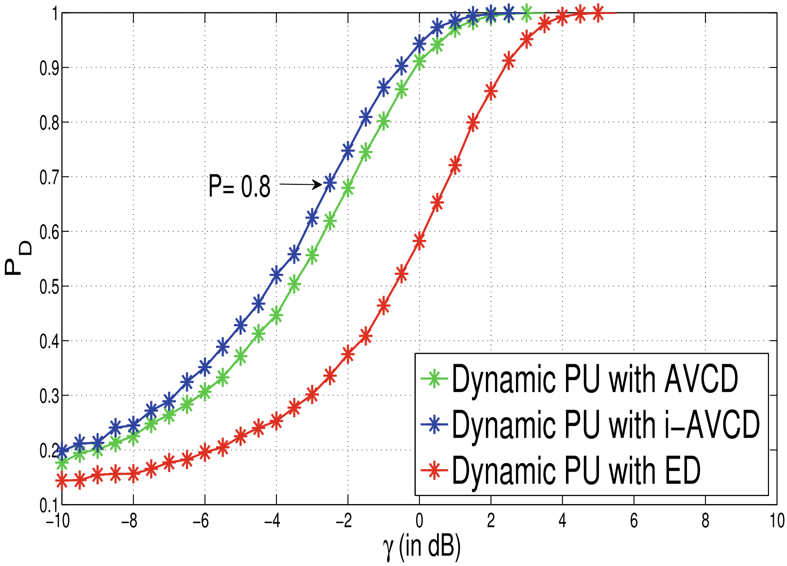

Fig. 2. P_D vs average SNR comparison with $N = 50$ and $P_F = 0.1$, $\theta_A T = 1$ and $\theta_D T = 1$ for randomly arriving or departing PU under different test statistic.

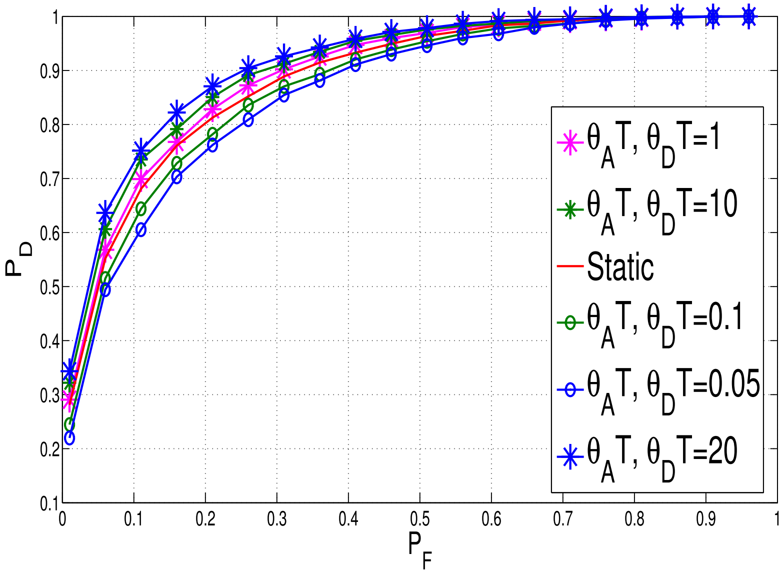

Fig. 3. P_D vs P_F plot at $N = 50$ and $\gamma = -2$ dB for randomly arriving or departing PU with AVCD based test statistic.

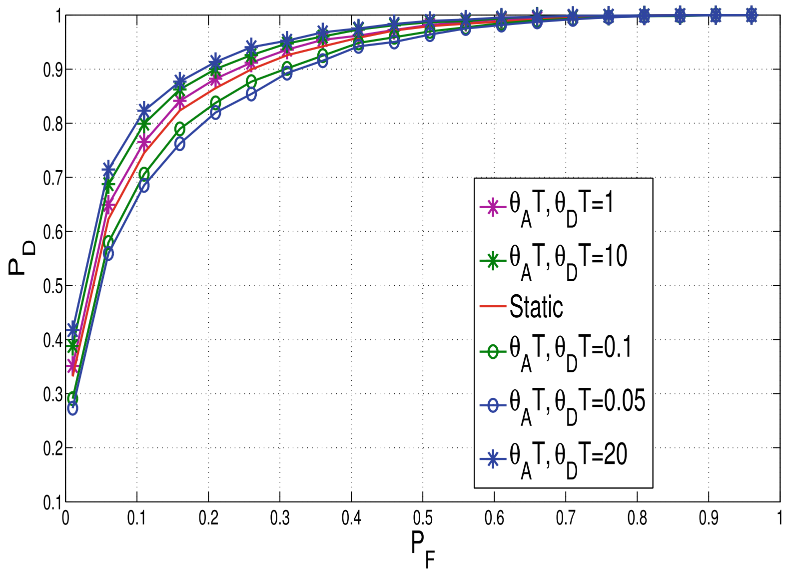

Fig. 4. P_D vs P_F plot at $N = 50$, $P = 0.8$ and $\gamma = -2$ dB for randomly arriving or departing PU with i-AVCD based test statistic.

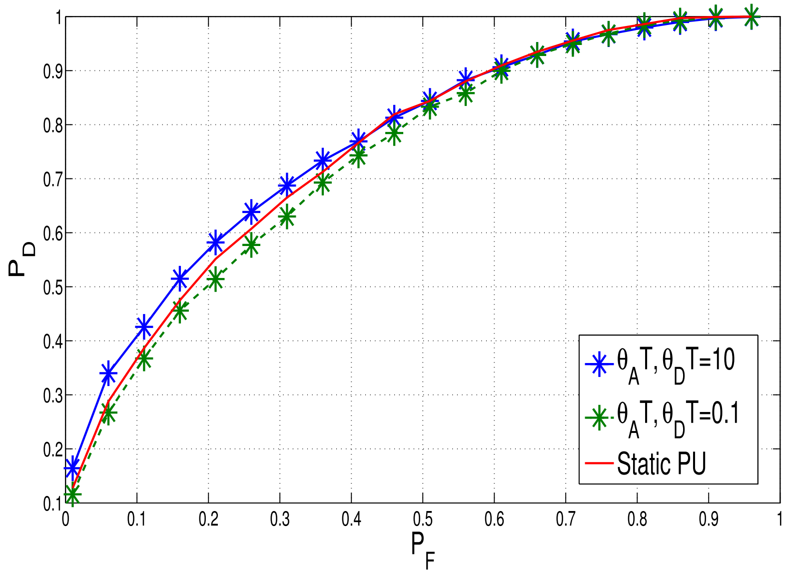

Fig. 5. P_D vs P_F plot at $N = 50$ and $\gamma = -2$ dB for randomly arriving or departing PU with ED based test statistic.

and $\theta_D T$ increases from 0.05 to 20. However, the performance for $\theta_A T$ and $\theta_D T$ of below 1 is worse than the performance with static scenario.

Similar to the above figure, in Fig. 4, we represent detection performance of i-AVCD based test-statistic for different values of $\theta_A T$ and $\theta_D T$ from 0.05 to 20 with $P = 0.8$, SNR $\gamma = -2$ dB and $N = 50$. We have observed the similar effect. Compared to the static case, the performance in dynamic case with $\theta_A T$ and $\theta_D T$ of 1, 10 and 20 is better. However, the performance with $\theta_A T$ and $\theta_D T$ of 0.05 and 0.1 is worse than the static case.

Similar the above-mentioned two figures, Fig. 5 shows the ROC performance with ED under both dynamic and static PU condition. We have again observed the similar trend.

5 Conclusion

In this paper, we considered spectrum sensing schemes such as energy detection, absolute value cumulation detection (AVCD) and improved AVCD (i-AVCD) in the additive Laplacian noise environment. Further, we considered the dynamic behaviour of primary user by assuming its random arrival and/or departure (in terms of $\theta_A T$ and/or $\theta_D T$) in the sensing interval. We present the performance using simulations in terms of receiver operating characteristics and detection probability versus average SNR. We conclude that the performance with dynamic scenario with $\theta_A T$ and/or $\theta_D T$ beyond 1 is better than the static scenario.

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