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A Proposed Scheme for Dynamic Threshold Versus Noise Uncertainty in Cognitive Radio Networks (DTNU)

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Abstract Cognitive radio essentially depends on optimum spectrum sensing for primary user detection. Noise uncertainty in spectrum sensing makes the detection process with fixed threshold unreliable due to thermal noise and interference from other remote communication systems, which in turn results in variation in the signal to noise ratio (SNR). In this paper, a dynamic detection threshold under noise uncertainty scheme is proposed for spectrum sensing to improve the detection performance in an environment characterized with noise uncertainty and low SNR. Hence, the detection threshold at each secondary user is dynamically changing according to the predefined detection and false alarm probabilities together with the received SNR at each node. Furthermore, our proposed integrated algorithm aims at finding the targeted number of samples, sensing time and user's throughput, while maintaining the detection performance metrics within the desired thresholds. A derived mathematical model and computer simulations are provided to show the influence of the dynamic threshold on system performance, and proof the robustness of our proposed scheme under noise uncertainty environment. Our results show a considerable reduction in number of sensed samples (up to 27%) compared to the approach in literature under low SNR.

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Keywords Cognitive radio · Dynamic threshold · Energy detection · Noise uncertainty · False alarm probability · Detection probability

1 Introduction

Cognitive Radio is used to improve the efficiency of radio spectrum utilization in wireless communications. The primary signal is monitored through spectrum sensing by the SUs to avoid harmful interference with PUs during the spectrum reuse [1]. This spectrum is reused by SUs once it is sensed idle. Therefore, spectrum sensing is the first step towards cognitive radio implementation [2].

In general, using a specific type of spectrum sensing is related to the environment surrounding SUs, and the amount of available information at the SU about the primary signal. In most applications, SU cannot reliably detect primary receivers; thus the focus is usually on transmitter detection. Energy Detection (ED) is widely adopted for spectrum sensing due to its simplicity and low cost implementation [3]. An ED measures the energy received on a primary band during sensing time duration (T_s) and decides the presence of a hole if the measured energy is less than the pre-defined threshold. According to this approach; it is assumed that no information exchange between the cognitive Fusion Center (FC) and the PUs exists, i.e. SUs do not have any prior information about the primary signal. Conventional studies such as [4] and [5] assume that all SUs receive the primary signal with the same SNR. In practice, communication environment is characterized with noise uncertainty due to many factors; such as thermal noise and interference from other remote communication systems, which has to be taken into consideration [1]. Hence, employing a fixed detection threshold (λ_{conv}) is not feasible in such environment. Furthermore, setting the threshold too high based on the wrong noise variance, would never allow the signal to be detected [6]. Accordingly, to make the utilization of CR more efficient; the spectrum sensing process should be optimized which critically depends on deciding the threshold. Given that the primary signal is received by different SUs with noise uncertainty, then the efficiency of CR system depends on determining the dynamic detection threshold and number of samples used to handle this signal.

Several authors have investigated the dynamic threshold in an environment characterized with noise uncertainty in CR networks. In [1], the authors propose two-threshold detector with confused region for local detection using only the false alarm probability as a performance metric. Two fixed detection thresholds are defined without mathematical model proof is proposed in [2]. The authors in [3], propose a heavily computational overhead sensing process, which involves several sensing stages and each stage employs two thresholds that are adjusted according to the number of samples. While in [7], two thresholds are arbitrarily built for each SU to increase detection performance metrics to a pre-defined noise uncertainty.

This paper presents the DTNU scheme, in which the dynamic threshold ($\lambda_{D,i}$) has been investigated and proved mathematically to improve the efficiency of spectrum sensing under noise uncertainty for each CR user, i. The required number of samples ($N_{D,i}$) that fits sensing process is defined as a function of $\lambda_{D,i}$ and SNR (γ_i) at each node. At the end of this work, the system throughput is examined and compared with the conventional and literature schemes. Finally; the main purpose of this paper is to handle spectrum sensing process in the critical situation, in which the received power (or noise) at each node is closed to the detection threshold. This can be considered as the contributions of the paper.

The rest of the paper is organized as follows; spectrum sensing in CR network characterized with noise uncertainty is described in Sect. 2. Section 3 analyzes the impact of noise uncertainty on sensing process by performing fixed detection threshold, and then the dynamic detection threshold is presented as a function of SNR and noise together with pre-defined false alarm and detection probabilities. Then the number of samples, sensing time and normalized throughput that meet noise uncertainty are evaluated. Results and simulations are discussed in Sect. 4. Finally, Sect. 5 concludes the paper.

2 Spectrum Sensing in CR Network Characterized with Noise Uncertainty

Assume a centralized cognitive radio, which consists of a central fusion center and M mobile terminals (unlicensed users or SUs) included in the coverage area of this fusion center as shown in Fig. 1. The fusion center collects the local decisions from the SUs and updates the channel occupation information in real time and makes decisions on the spectrum use. Opportunistic spectrum sensing is performed by SUs to detect a transmission from PUs in order to find free bands (holes).

In the centralized network, SUs can only communicate and exchange their local decisions with the fusion center; those users are considered close to each other with respect to the primary node. The communication environment is characterized with noise uncertainty due to thermal noise, interference from other remote communications and other factors; thus, it is assumed that the primary signal is received by each SU with different SNR. The final decision on whether to access the spectrum or not is built at the fusion center and is broadcasted to all SUs. To make local decisions about the presence or absence of the primary user, each cognitive radio solves a binary hypothesis testing problem, by choosing H_1 in case the primary user is present and H_o when the primary user is absent [8]. The sensing problem for each detector is formulated as [1]:

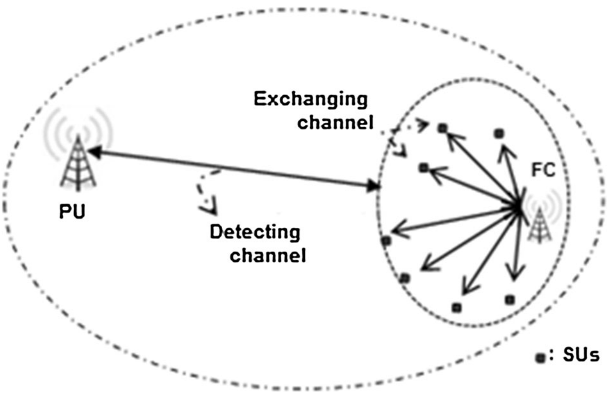


Fig. 1 System model of centralized cognitive radio network

$$\begin{Bmatrix} H_0 : X_i[n] = W_i[n], & i \in [1..M], n \in [1..N] \\ H_1 : X_i[n] = W_i[n] + S[n], & i \in [1..M], n \in [1..N] \end{Bmatrix} \tag{1}$$

where $X_i[n]$ denote the nth received sample by the ith SU, $W_i[n]$ is the noise received by the ith SU and $S[n]$ is the primary user signal. The noise and the primary signal are assumed to be i.i.d Gaussian-distributed random with zero mean and variance $\sigma^2_{w,i}$ and σ^2_s, respectively, and $\sigma^2_{m,i} = \sigma^2_{w,i} + \sigma^2_s$, where $\sigma^2_{m,i}$ represents the received power at the ith SU, and the primary signal received with SNR by each sensor (i) is denoted by $\gamma_i = \frac{\sigma^2_s}{\sigma^2_{w,i}}$, while $N = T_s f_s$ which equals the number of samples (or time-bandwidth product) [9].

Since SUs perform the sensing process individually; every SU should adopt a sensitive detection threshold in order to be robust against extremely rare events. Consider the sensed signals are sampled at sampling frequency f_s during sensing time frame, T_s, then the decision statistic at the ith ED is given by [10]:

$$Y_i = \frac{1}{N}\sum_{n=1}^{N} |X_i(n)|^2 \tag{2}$$

Therefore, the local decision strategy for the channel state can be formulated also as [10]:

$$D_i = \begin{cases} 1, & if\ Y_i \geq \lambda \\ 0, & if\ Y_i < \lambda \end{cases} \tag{3}$$

where D_i denotes the decision result about the channel state at the ith detector, λ is detection threshold.

Two metrics are used to estimate the performance of spectrum sensing process for each SU; those metrics are: *false alarm* ($P_{f,i}$) and *detection* ($P_{d,i}$) probabilities. $P_{f,i}$ is the probability such that the local decision is busy while the channel is actually free, while $P_{d,i}$ refers to the probability of considering the channel is busy when it is actually busy. Hence, the performance of ED for each secondary user can be estimated by using these probabilities under the two hypotheses H_0 and H_1, respectively, as [11]:

$$\begin{Bmatrix} P_{f,i} = \Pr\{Y_i > \lambda | H_0\} \\ P_{d,i} = \Pr\{Y_i > \lambda | H_1\} \end{Bmatrix} \tag{4}$$

$P_{f,i}$ and $P_{d,i}$ are the integrations of Probability Density Function (PDF) of the Chi square distributions with N degrees of freedom for the signal and noise under H_0 and H_1, respectively. Since the proposed communication environment is characterized with low SNR of the primary user; large number of samples N should be used. Thus, the statistic Chi square distribution can be approximated as a Gaussian distribution based on the Central Limit Theorem (CLT) [9]. In other words, the PDF of Y_i under H_0 and H_1 can be approximated by a Gaussian distribution as [12]:

$$\begin{Bmatrix} H_0 : Y_i \sim Normal\left(\sigma^2_{w,i}, \dfrac{2}{N}\sigma^4_{w,i}\right) \\ H_1 : Y_i \sim Normal\left(\sigma^2_{m,i}, \dfrac{2}{N}\sigma^4_{m,i}\right) \end{Bmatrix} \tag{5}$$

then, $P_{f,i}$ and $P_{d,i}$ are given by [11]:

$$P_{f,i} = Q\left(\frac{\lambda - \sigma_{w,i}^2}{\sqrt{2/N}\sigma_{w,i}^2}\right) \tag{6}$$

$$P_{d,i} = Q\left(\frac{\lambda - \sigma_{m,i}^2}{\sqrt{2/N}\sigma_{m,i}^2}\right) = Q\left(\frac{\lambda - \sigma_{w,i}^2(1+\gamma_i)}{\sqrt{2/N}\sigma_{w,i}^2(1+\gamma_i)}\right) \tag{7}$$

where $Q(.)$ is the complementary distribution function of the Gaussian distribution, and has the following form:

$$Q(x) = \frac{1}{\sqrt{2\pi}}\int_x^\infty exp\left(\frac{-t^2}{2}\right).dt \tag{8}$$

3 Analysis and Problem Formulation

Since a performance in noise uncertainty environments decline sharply, cognitive nodes that access temporarily will have a serious interference to licensed users, which is absolutely not allowed in dynamic spectrum access technology [13]. Under noise uncertainty, using fixed number of samples and fixed detection threshold to all SUs leads to unreliable sensing process. Furthermore, utilizing high number of samples leads to higher network energy consumption, longer sensing time and lower achievable throughput. Therefore, it is a persistent need to apply a dynamic detection threshold and number of samples that satisfy a certain detection performance constrained by pre-defined acceptable detection and false alarm probabilities. We will start by analyzing the performance of sensing process in CR network under noise uncertainty using fixed detection threshold (λ_{conv}) and fixed number of samples (N). Then, we will present the proposed scheme by considering the dynamic detection threshold in order to meet the trade-offs between CR network parameters. Finally; it is worth to mention that the adopted values of detection threshold and noise power are chosen to fit the actual noise uncertainty environment as in [14] and [15]. For instance, In [14], the authors adopted a detection threshold to be between −120 and −90 dBm with noise uncertainty ranging from 0.5 to 2 dB, and between −112.9 and −110.5 dBm with DTV signal of −116 dBm. While in [15], the detection threshold in spectrum sensing for wireless microphone signals is −114 dBm, averaged over a 200 kHz bandwidth.

3.1 Impact of Noise Uncertainty on $P_{f,i}$ and $P_{d,i}$ Using Fixed Threshold (λ_{conv}) and Different N

Equation (6) is depicted as shown in Fig. 2 using 20 SUs with different values of noise ($\sigma_{w,i}^2$) for each and ranges from less than, equal to and larger than λ_{conv}, and for two different numbers of samples, N, which denoted by N_l and N_h. It can be deduced that for all values of $\sigma_{w,i}^2 < \lambda_{conv}$, then $P_{f,i}(N_l) > P_{f,i}(N_h)$ and $P_{f,i} < 0.5$. While for $\sigma_{w,i}^2 > \lambda_{conv}$; then $P_{f,i}(N_l) < P_{f,i}(N_h)$ and $P_{f,i} > 0.5$. In an environment characterized with noise uncertainty, and in terms of $P_{f,i}$; adopting a fixed detection threshold leads to unreliable spectrum sensing process for all values of $\sigma_{w,i}^2 > \lambda_{conv}$ regardless of N. On the other hand; when $\sigma_{w,i}^2 < \lambda_{conv}$ and N is high (N_h); more spectrum utilization and throughput can be achieved.

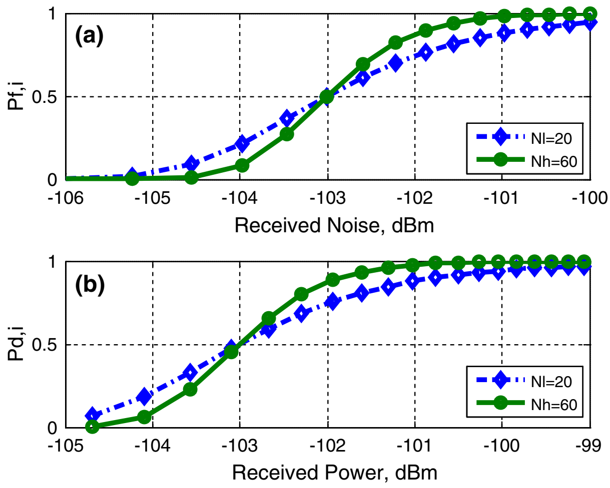


Fig. 2 **a** $P_{f,i}$ versus different values of noise,$\sigma_{w,i}^2$; $\sigma_{w,i}^2 < \lambda_{conv}$, $\sigma_{w,i}^2 = \lambda_{conv}$ and $\sigma_{w,i}^2 > \lambda_{conv}$. **b** $P_{d,i}$ versus different values of received power, $\sigma_{m,i}^2$; $\sigma_{m,i}^2 < \lambda_{conv}$, $\sigma_{m,i}^2 = \lambda_{conv}$ and $\sigma_{m,i}^2 > \lambda_{conv}$. ($\lambda_{conv} = -103$ dBm)

In terms of numerical analysis and referring to Fig. 2a, where $\lambda_{conv} = -103$ dBm, $N_l = 20$ sample and $N_h = 60$ sample; the impact of N vanishes in three regions; for $\sigma_{w,i}^2 < < \lambda_{conv}$ (<-106 dBm), at $\sigma_{w,i}^2 = \lambda_{conv}$ and for $\sigma_{w,i}^2 > > \lambda_{conv}$ (>-99 dBm).

Each SU receives the same primary signal but with different noise power. Since the proposed CR network characterized with low SNR; the adopted detection threshold should be very sensitive to this environment. If the primary signal is present; it will be received by each node with noise uncertainty ($\sigma_{m,i}^2 = \sigma_{w,i}^2 + \sigma_s^2$). On the contrary of $P_{f,i}$; $P_{d,i}$ should be as large as possible to achieve more accurate detection process and to avoid interference to primary user. Equation (7) is depicted in Fig. 2b. For $\sigma_{m,i}^2 < \lambda_{conv}$ $P_{d,i}(N_l) > P_{d,i}(N_h)$ and $P_{d,i} < 0.5$, While for $\sigma_{m,i}^2 > \lambda_{conv}$; then $P_{d,i}(N_l) < P_{d,i}(N_h)$ and $P_{d,i} > 0.5$. It is clear that the targeted high $P_{d,i}$ can be achieved by increasing N and keep $\lambda_{conv} < \sigma_{m,i}^2$. As a result, the analysis show that the system performance in terms of $\mathrm{P_{f,i}}$ and $\mathrm{P_{d,i}}$ can be improved by increasing N and let the threshold to be dynamically changing according to received power.

3.2 DTNU Scheme

In order to obtain high detection accuracy in an environment characterized with noise uncertainty; two conditions should be satisfied: the first condition, false alarm probability should be kept as small as possible to obtain efficient spectrum sensing and utilization from SU's point of view. The second one, detection probability should be kept as large as possible to avoid interference to primary signal and obtain more efficient spectrum sensing from PU's point of view. Hence, from the results in Sect. 3.1, large number of samples to be detected, together with dynamic detection threshold are targeted to satisfy the two aforementioned conditions. In DTNU scheme we assume that the targeted number of collected samples and the dynamic detection threshold at the ith node are $N_{D,i}$ and $\lambda_{D,i}$, respectively. Each sensor constrained by the pre-defined probabilities; $\overline{P}_{f,i}$ and $\overline{P}_{d,i}$, such that $\overline{P}_{f,i} < \max\left(P_{f,i}\right)$ and $\overline{P}_{d,i} > \min\left(P_{d,i}\right)$. Starting from (6) and solve for $\sqrt{2/N}$:

$$\sqrt{2/N} = \frac{\lambda - \sigma_{w,i}^2}{\sigma_{w,i}^2 Q^{-1}(P_{f,i})} \tag{9}$$

From Eq. (9), if detection threshold equals noise, then infinite number of samples is needed to detect the signal. Substitute (9) in (7):

$$P_{d,i} = Q\left[\frac{\frac{\lambda}{1+\gamma_i} - \sigma_{w,i}^2}{\left(\frac{\lambda-\sigma_{w,i}^2}{Q^{-1}(P_{f,i})}\right)}\right] \tag{10}$$

Then, (10) can be solved to determine the dynamic detection threshold ($\lambda_{D,i}$) for each SU, which is constrained by $\overline{P}_{f,i}$ and $\overline{P}_{d,i}$ as follows:

$$\lambda_{D,i} = \frac{\sigma_{w,i}^2(1+\gamma_i)\left[Q^{-1}(\overline{P}_{f,i}) - Q^{-1}(\overline{P}_{d,i})\right]}{\left[Q^{-1}(\overline{P}_{f,i}) - (1+\gamma_i)Q^{-1}(\overline{P}_{d,i})\right]} = \frac{\sigma_{w,i}^2\left[Q^{-1}(\overline{P}_{f,i}) - Q^{-1}(\overline{P}_{d,i})\right]}{\left[\frac{Q^{-1}(\overline{P}_{f,i})}{(1+\gamma_i)} - Q^{-1}(\overline{P}_{d,i})\right]} \tag{11}$$

where $\lambda_{i,D}$ *satisfies the condition:* $\sigma_{w,i}^2 < \lambda_{D,i} < \sigma_{m,i}^2$. From (11) we can conclude that $\lambda_{D,i}$ directly proportional with $\sigma_{w,i}^2$, while it is inversely proportional with γ_i.

The targeted number of samples can be determined using $\lambda_{i,D}$ from (11) as follows:

$$N_{D,i} = 2\left[\frac{Q^{-1}(\overline{P}_{f,i})}{\frac{\lambda_{D,i}}{\sigma_{w,i}^2} - 1}\right]^2 = 2\left[\frac{Q^{-1}(\overline{P}_{d,i})}{\frac{\lambda_{D,i}}{\sigma_{m,i}^2} - 1}\right]^2 \tag{12}$$

Equation (12) assures that; either in presence or absence of primary signal, the number of samples to be sensed by each SU can be determined based on $\lambda_{D,i}$ and the pre-defined $\overline{P}_{f,i}$ or $\overline{P}_{d,i}$ together with $\sigma_{w,i}^2$ or γ_i, respectively. Hence, adopting $\lambda_{i,D}$ results in saving both time and power needed in spectrum sensing process.

Given that all SUs use the same sampling frequency, f_s, this means that during the sensing time frame, the SU with high SNR can perform faster spectrum sensing process than that with low γ_i, in this situation reporting the local decision by each SU at the fusion center can be accomplished by using random access TDMA. Accordingly, the fusion center can build the final decision on whether to occupy or not the primary channel based on the *best* (faster) received local decisions. Assuming that the total time frame (T_T) is divided into two main sub-frames; sensing time (T_s) and transmission time (T_f), then less sensing time means more effective sensing process and more achievable throughput. For each user with its own γ_i, the targeted sensing time ($T_{sD,i}$) can be obtained from (12) as follows:

$$T_{sD,i} = \frac{N_{D,i}}{f_s} = \frac{2}{f_s}\left[\frac{Q^{-1}(\overline{P}_{f,i})}{\frac{\lambda_{D,i}}{\sigma_{w,i}^2} - 1}\right]^2 = \frac{2}{f_s}\left[\frac{Q^{-1}(\overline{P}_{d,i})}{\frac{\lambda_{D,i}}{\sigma_{m,i}^2} - 1}\right]^2 \tag{13}$$

while the targeted normalized throughput for each user ($C_{oD,i}$) can be calculated as follows:

$$C_{oD,i} = \left(1 - \frac{T_{sD,i}}{T_f}\right)(1 - \overline{P}_{f,i})P(H_0) \tag{14}$$

where $P(H_0)$ is the probability of the primary user being absent (inactive) in the channel [16, 17].

4 Simulations and Results

In order to make spectrum sensing more efficient and to accommodate the proposed communication environment; each sensor will update the dynamic threshold ($\lambda_{D,i}$) and the number of samples ($N_{D,i}$) according to the received power in the previous time frame (T_T). In this section, we present the simulation results of the proposed DTNU scheme compared with the conventional and Chabbra et al. schemes, using two scenarios; high and low detection accuracy. From the stated equations and the simulation results, we found that the DTNU scheme outperform the other schemes in terms of number of samples, detection accuracy and normalized throughput. The simulation parameters are shown in Table 1.

Figure 3a shows that $\lambda_{D,i}$ (in dBm) is directly proportional with $\sigma^2_{w,i}$. For instance, at low noise (i.e. -106 dBm), $\lambda_{D,i}$ is greater than $\sigma^2_{w,i}$ by 0.7 dBm at high detection accuracy and 0.3 dBm when low detection accuracy is adopted. On the other hand, at a certain value of noise, *less* detection accuracy in terms of $\overline{P}_{f,i}$ and $\overline{P}_{d,i}$ makes the detection threshold closer to noise, which ensures that the sensing process is neither unreliable nor robust. On the contrary of the impact of noise on detection threshold; Fig. 3b shows that $\lambda_{D,i}$ is inversely proportional with γ_i under noise uncertainty. For instance, at low γ_i (-22 dB), $\lambda_{D,i}$ is about -99 dBm, while its -105 dBm at $\gamma_i = -8.9$ dB. In both scenarios (low and high detection accuracy), the impact of detection accuracy vanishes as the received power increase, and $\lambda_{D,i}$ becomes closer to this power.

Figure 4 shows a comparison between DTNU scheme and the conventional schemes in terms of detection thresholds under the two scenarios together with the received power and noise versus the first 10 SUs. It is verify that for all values of received noise and power, the targeted condition $\sigma^2_{w,i} < \lambda_{D,i} < \sigma^2_{m,i}$ is satisfied in the DTNU scheme. Furthermore, $\lambda_{D,i}$ is more sensitive for small values of noise than the large ones. Whereas in conventional scheme, all received powers less than fixed threshold (λ_{conv}) are considered as a noise. In this case, detection probability become very small and the SU cannot recognize the presence of primary signal, which in turn leads to interfere with the primary signal and obtain inefficient spectrum sensing from PU's point of view.

In the DTNU scheme, the number of samples ($N_{D,i}$) that need to be sensed depends on the strength of the received power together with $\lambda_{D,i}$ at each sensor. Hence, the proposed scheme demonstrates that a small number of samples are sufficient to sense a strong signal. Figure 5 compares between the DTNU, Chabbra et al., and the conventional schemes in terms of number of samples versus γ_i. The first former schemes show that the number of

Table 1 Simulation parameters

Parameter	Value
$\overline{P}_{f,i}, \overline{P}_{d,i}$	$0.02, 0.95$, *high detection accuracy*
$\overline{P}_{f,i}, \overline{P}_{d,i}$	$0.45, 0.65$, *low detection accuracy*
λ_{conv}	-103 dBm
$\sigma^2_{w,i}$	-106 to -99 dBm
σ^2_s	-110 dBm
f_s	100 kHz
$P(H_0)$	0.8
M	20
T_f	100 ms

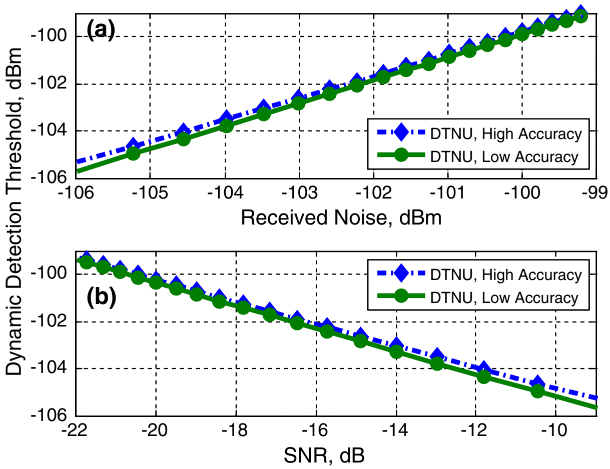


Fig. 3 **a** $\lambda_{D,i}$ versus received $\sigma_{w,i}^2$ in dBm. **b** $\lambda_{D,i}$ in dBm versus γ_i in dB ($\sigma_s^2 = -110$ dBm)

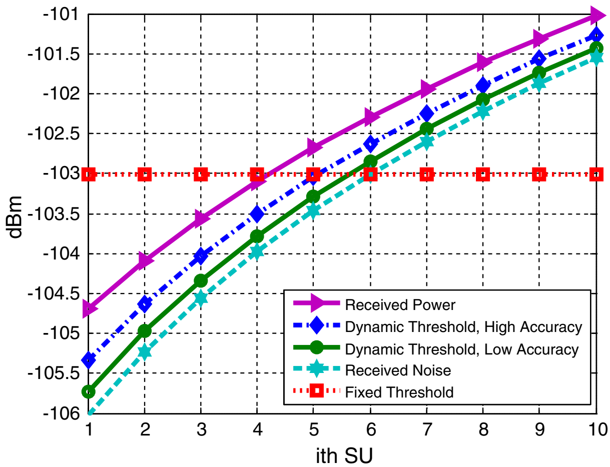


Fig. 4 $\sigma_{m,i}^2$, $\sigma_{w,i}^2$, $\lambda_{D,i}$ and λ_{conv} (in dBm) versus *i*th SU ($\sigma_s^2 = -110$ dBm)

samples is inversely proportional with γ_i. As a comparison between these two schemes; it is clear that the DTNU scheme outperform the other one and achieve reduction in number of samples by 27% at low SNR (-22 dB) and up to 44% as SNR increase to -10 dB. Since the conventional scheme adopts fixed detection threshold, the number of samples is sharply increases when the received power (or noise) is closed or equal to fixed threshold. However, less number of samples is needed in conventional scheme compared with high detection accuracy scenario in the DTNU scheme, but at expense of detection accuracy in terms of detection and false alarm probabilities.

Finally; Fig. 6 sum up the performance of the proposed DTNU scheme in terms of achievable normalized throughput by each SU ($C_{oD,i}$) and compared with two other schemes. Equation (14) implemented on the optimal formulas in [2] and on the conventional scheme using fixed threshold, then we compared the schemes with the proposed one. At low SNR (-22 dB), the DTNU scheme is extremely outperform the two schemes, which achieve up to 14% increment in throughput compared with the scheme in [2], and this gap decline as γ_i increase. Since the conventional scheme adopts fixed threshold, then

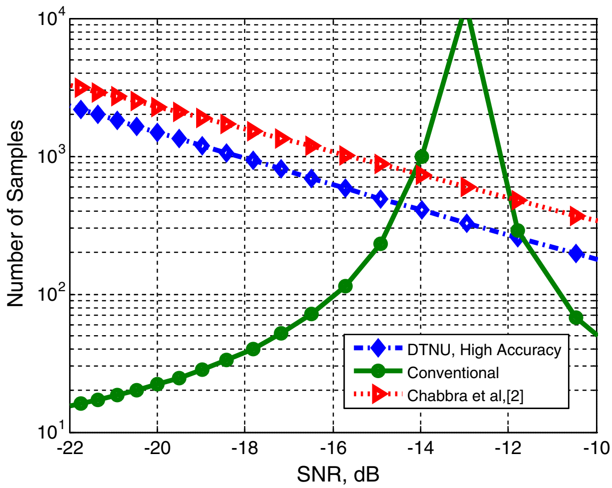
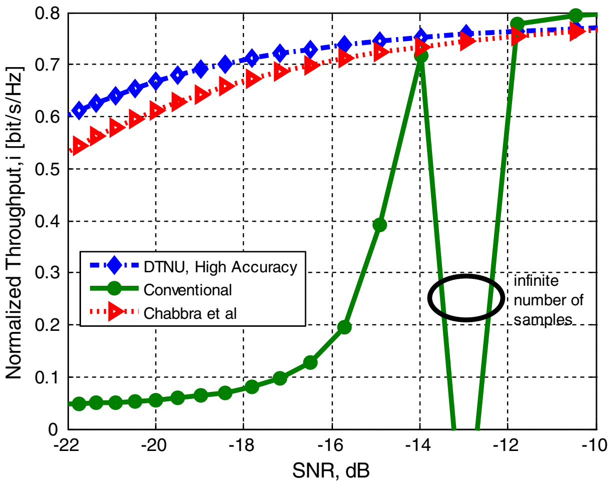


Fig. 5 A comparison between DTNU, Chabbra et al. and conventional schemes in terms of number of samples versus γ_i ($P_{d,i} = \overline{P}_{d,i} = 0.95, \lambda_{conv} = -103$ dBm, $f_s = 100$ kHz)

Fig. 6 A comparison between proposed, conventional and [2] schemes in terms of normalized throughput versus γ_i ($P_{d,i} = \overline{P}_{d,i} = 0.95, \lambda_{conv} = -103$ dBm, $f_s = 100$ kHz)



false alarm probability increase rapidly with noise, which decline the achievable throughput. This is because the throughput in conventional scheme is only constrained by detection probability $P_{d,i}$ whereas in the DTNU, $C_{oD,i}$ constrained by $\overline{P}_{d,i}$ and $\overline{P}_{f,i}$ while $N_{D,i}$ and $T_{sD,i}$ optimized based of these metrics. Even though the number of the samples in the conventional is less than the DTNU scheme for the majority of SUs, the false alarm probability in the conventional scheme is much larger than the DTNU scheme, which create a large gap between the DTNU and the conventional schemes in terms of throughput especially at low SNR and at $\lambda_{conv} = \sigma^2_{w,i} or \sigma^2_{m,i}$. In the last critical situation infinite number of samples is needed to sense the spectrum and throughput decline deeply.

5 Conclusion

The DTNU scheme with dynamic spectrum sensing scheme is presented in this paper. The proposed scheme based on building a dynamic detection threshold that attain acceptable pre-defined false alarm and detection probabilities and meet the uncertainty in received power by each sensor. Sensing time, number of samples and throughput are optimized accordingly. The conventional approach with fixed threshold is analyzed, then the proposed scheme is compared with the literature and conventional schemes and final results show that the proposed dynamic spectrum sensing (DTNU scheme) is more reliable and accurate in an environment characterized with noise uncertainty and low SNR.

Compliance with Ethical Standards

Conflict of Interest The authors declare that no conflict of interest exists in publishing this article.

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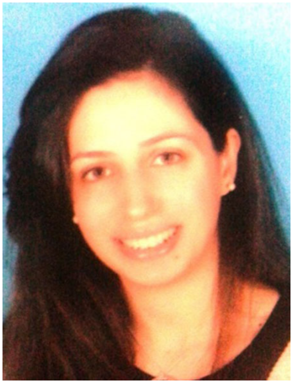

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