Quickest Spectrum Sensing in Cognitive Radio

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***Abstract*— Quickest detection is applied to frequency spectrum sensing in cognitive radio systems. Distribution change in frequency domain is detected for vacating secondary radio networks from licensed frequency band. A successive refinement based quickest detection is proposed to tackle the problem of unknown parameters of primary radio signal. Cooperative quickest detection is used to enhance the performance of quickest spectrum sensing in secondary radio systems without data fusion centers. Performance is evaluated using theoretical analysis and numerical simulations.**

I. Introduction

In recent years, cognitive radio [9] [15] [22] has attracted intensive research because of pressing demand of efficient frequency spectrum usage. In a cognitive radio system, secondary radio users try to find 'blank spaces', in which the licensed frequency band is not being used by primary radio users, for communications. A key problem in cognitive radio is that the secondary users need to quit the frequency band as quickly as possible if the corresponding primary radio emerges. There have been plenty of research on frequency spectrum sensing. In [20], compressed sensing is used to sample the frequency spectrum efficiently. In [5], cycle frequency domain profile is used to detect the primary radio signal. The fundamental limits of spectrum sensing are discussed in [15] while wide band spectrum sensing is investigated in [8].

Essentially, the spectrum sensing is to detect the change of spectrum activity (emergence of primary radio). Therefore, we can apply the theory of quickest detection [2] [14], which performs a statistical test to detect the change of distribution in observations as quickly as possible, in order to attain an agile and robust spectrum sensing. However, it is insufficient to apply the well-known cumulative sum (CUSUM) test [13] directly. There exist unknown parameters after the primary radio emerges, e.g. the amplitude of received primary radio signal. Existing algorithms combatting the unknown parameters include generalized likelihood ratio (GLR) test [7], windowed GLR test [18] and parallel CUSUM test [11]. In this paper, we will combine both GLR and parallel CUSUM tests to propose a novel algorithm called successive refinement.

The remainder of this paper is organized as follows. The system model is explained in Section II. Then existing algorithms of quickest detection are briefly introduced in Section III. In Section IV, a novel quickest detection algorithm is proposed to tackle the problem of unknown parameters. Algorithms and performance analysis are investigated for the quickest spectrum sensing in secondary networks in Sections V. Numerical results and conclusions are provided in Sections VI and VII, respectively.

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II. System Model

Consider a time slotted secondary radio communication network containing K nodes, which are randomly deployed and have no base station. Suppose that the primary system is silent and the secondary network is using the frequency band licensed to the primary system. The secondary nodes need to monitor the activity in the 'borrowed' frequency band. In order to distinguish the signal from the primary and the secondary systems, the secondary network sets a guarding subband, within which the secondary network does not transmit signal, in the current frequency band. Once the primary system emerges and the secondary network detects sufficient activity in this subband, all secondary nodes that cause non-negligible impact on the primary radio need to be evacuated from the current frequency band. We assume that the primary radio signal in the guarding subband is a sinusoid, which is a reasonable assumption. Actually, in the standard of digital TV (DTV) system, made by advanced television standard committee (ATSC), there are multiple sinusoid pilots located at different frequency points. For simplicity, we consider monitoring only one sinusoid pilot. The algorithm and performance analysis can be easily extended to multiple pilots if we assume that each node can monitor all pilots simultaneously.

A. Signal Hypotheses

In a secondary network, we assume that each node senses the primary radio basing on only its own observations[1]. We can formulate the frequency spectrum sensing into a quickest detection problem, in which the two hypotheses for received signal $s(m)$ at time slot m and at a fixed node are given by

$$\left\{ \begin{array}{ll} H_0: & s(m) = n(m) \\ H_1: & s(m) = A\sin(m\omega t_s + \theta) + n(m) \end{array} \right. , \quad (1)$$

where A is the amplitude of the primary radio signal, which is confined within an interval $[A_{\min}, A_{\max}]$ (when $A < A_{\min}$, the impact of the secondary radio signal on the primary radio is negligible), ω is primary radio pilot frequency, t_s is sampling period, θ is the phase of the pilot signal and $n(m)$ is additive white Gaussian noise (AWGN) having power σ_n^2.

[1]We can investigate collaboration across different secondary nodes; however, in this paper, we consider only single-node detection.

We assume that the frequency ω is known to all secondary nodes since it is a configuration parameter of the primary radio system. In practical systems, A and θ are usually unknown since they are determined by many random factors such as distance, fading channel and initial phase of oscillator.

B. Performance Measure

We use two average run lengths (ARL), which have been used in many literatures [7] [2] [14], to measure the performance of the quickest detection. For a fixed node, the ARLs are defined as

$$\bar{T}_1 = \text{esssup}_{\mathcal{F}} \left(E_1 \left[T^* | \mathcal{F}_{-1} \right] \right), \quad (2)$$
$$\bar{T}_0 = E_0 \left[T^* \right], \quad (3)$$

where E_1 denotes the expectation under the assumption that the change happens at time slot 0 (without loss of generality, we assume that the detection also begins from time slot 0; the esssup guarantees that the performance is the same if we begin the detection earlier [10] [14].), $\mathcal{F}_{-1}$ is the filtration at time slot -1 and E_0 is the expectation under the assumption that the change never happens. Note that the esssup in $\bar{T}_1$ means the worst-case delay [10] [14]. T^* denotes the stopping time of detecting a distribution change at node n, measured in time slots. Obviously, we want to obtain a small $\bar{T}_1$ and a large $\bar{T}_0$.

III. Algorithms of Quickest Detection

In this section, we discuss several algorithms of quickest detection for general purposes. For simplicity, we assume a single-node system, in which the observation distributions of H_0 and H_1 are denoted by p_0 and p_1[2]. We denote the log likelihood ratio at time slot m by

$$l_m \triangleq \log \left(\frac{p_1(X_m)}{p_0(X_m)} \right),$$

where X_m is the observation at time slot m. For performance analysis, we define the following quantities: $I \triangleq E_1 \left[l_0 \right]$, $J \triangleq -E_0 \left[l_0 \right]$, $W \triangleq V_1 \left[l_0 \right]$, and $U \triangleq V_0 \left[l_0 \right]$. Note that the first two quantities are the Kullback-Leibler divergences under H_1 and H_0, respectively.

A. CUSUM Test and Page's Procedure

In CUSUM test [13], the stopping time for detecting the change is given by

$$T^* = \inf \left(m | s_m \geq \gamma \right), \quad (4)$$

where γ is a threshold and s_m is the metric at time slot m, which can be computed recursively:

$$s_m = \max \left(s_{m-1} + l_m, 0 \right). \quad (5)$$

It is easy to verify that the stopping time T^* is equal to the one determined by Page's procedure [13], in which the stopping time is determined by a family of random walks, namely

$$T^* = \inf \left(T_k, k = 0, 1, 2, ... \right), \quad (6)$$

where

$$T_k = \inf \left(m \Big| \sum_{r=k}^{m} l_r \geq \gamma \right). \quad (7)$$

For a sufficiently large threshold γ, the random walks can be approximated by Brownian motions and the performance analysis can be carried out by Brownian motion approximation [2] [14] [19]. The details can be found in the above literatures and references therein. When $\gamma \to \infty$, the ARL of detection delay can be approximated by [2] [14] [19]

$$\bar{T}_1 \approx \frac{\gamma}{I}. \quad (8)$$

And the ARL of false alarm is given by

$$\log \bar{T}_0 \approx \frac{J\gamma}{U}. \quad (9)$$

B. GLR Algorithm and Parallel CUSUM Algorithm

The CUSUM test is based on the perfect knowledge of the distributions. However, in many situations, the distribution parameters of H_1 are unknown (e.g. the amplitude and phase in the spectrum sensing of the primary radio signal). In such a scenario, we can apply the following two detection schemes. For simplicity, we assume that there is only one unknown parameter, denoted by ψ (the set of possible values of ψ is denoted by Ψ), and we use l_r^{ψ} to indicate the dependence of the log likelihood ratio on ψ.

1) GLR Algorithm: As proposed by Lorden [7], we can apply GLR algorithm to approximate the likelihood ratio in the Page's procedure, in which the unknown parameter ψ is replaced with a maximum likelihood ratio estimate. Then, Eq. (7) can be rewritten as

$$T_k = \inf \left(m \Big| \max_{\hat{\psi} \in \Psi} \left(\sum_{r=k}^{m} l_r^{\hat{\psi}} \right) \geq \gamma \right). \quad (10)$$

However, there is no recursive expression like (5) for the GLR computation. Therefore, all observations need to be stored and the metrics need to be recomputed in all time slots. This makes the GLR algorithm infeasible for practical system implementation.

2) Parallel CUSUM Algorithm: As proposed by Nikiforov in [11], we can also apply the principle of the Page's procedure, in which the family of random walks is indexed by time slots, to the set of unknown parameters, namely choosing a set of typical values of ψ, denoted by $\psi_1, ..., \psi_n$, and setting a family of random walks on this set. The metric for each random walk can be recursively computed similarly to (5) in the CUSUM test. Then, the stopping time T^* is given by

$$T^* = \inf \left(T_k, k = 1, ..., n \right), \quad (11)$$

[2]In this section, we suppose that p_0 and p_1 do not change in all time slots. Note that in our spectrum sensing problem, p_1 changes for different time slots since $\sin(m\omega t_s + \theta)$ is not a constant for different m's.

where $T_k = \inf \left(m \middle| s_{\psi_k}(m) \geq \gamma \right)$ and the metric is computed recursively, which is given by

$$s_{\psi_k}(m) = \max\left(s_{\psi_k}(m-1) + l_m^{\psi_k}, 0\right).$$

However, the parallel CUSUM algorithm does not achieve the optimal performance while the GLR algorithm is asymptotically optimal, as shown in [7].

IV. Successive Refinement Test with Unknown Parameter

In this section, we propose a novel algorithm for quickest detection with unknown parameters and analyze the corresponding performance. For simplicity, we assume that there is only one unknown parameter ψ. It is straightforward to extend the algorithm and performance analysis to the general case of multiple unknown parameters.

A. Algorithm

We list the features of GLR and parallel CUSUM algorithms as follows:

- GLR algorithm carries out joint parameter estimation (implicit) and change detection. When there are sufficiently large numbers of samples, a sufficiently good parameter estimation can be obtained such that the change detection is asymptotically optimal. The problem is how to determine the set of samples for estimating the parameter ψ since the change point is unknown. This is implicitly done by taking infimum in (10) in the GLR algorithm.
- The reason why parallel CUSUM algorithm is suboptimal is that the possible candidates of the unknown parameter are not changed. The impact of imperfect ψ remains throughout the detection procedure.

Based on the above analysis, we can borrow the principle of 'estimating while detecting' from the GLR algorithm. When the unknown parameter can be estimated incrementally, namely a statistic (not necessarily sufficient) can be accumulated for estimation, we can carry out an explicit estimation of the parameter. This incremental estimation can remove the requirement of storing all samples in the GLR algorithm. Such an incremental estimation can be embedded in the parallel CUSUM test to narrow down the range of unknown parameters in multiple stages. In the j-th stage ($j > 1$), the candidate set of the unknown parameter is obtained from the incremental estimation in the $j-1$-th stage. Note that the first stage is the same as the parallel CUSUM test.

Then, we propose the following algorithm called *successive refinement algorithm*, which is carried out in p stages (suppose that the tolerable ARL of detection delay is sufficiently large).

- Step 1: Set p thresholds $\gamma_1 < \gamma_2 < ... < \gamma_p = \gamma$, where all thresholds are sufficiently large and $\gamma_i = o(\gamma_{i+1})$.
- Step 2: Set n possible values of ψ and do the first parallel CUSUM test using threshold γ_1.
- Step 3: When the first parallel CUSUM test stops, begin to accumulate the statistic for estimating ψ and carry out the second parallel CUSUM test using threshold γ_2. Note that, Ψ, the candidate set of ψ, is still the same as that in the first stage.
- Step 4: When the second parallel CUSUM test stops, select an interval around the estimate of ψ, e.g. a confidence interval with a fixed confidence level. Choose n candidates for ψ within this interval and do the third parallel CUSUM test.
- Repeat the above steps until the p-th parallel CUSUM test is stopped.

Note that this successive refinement algorithm is suitable for only parameters that can be estimated incrementally. Otherwise, we have to store all samples; thus having no advantages over the GLR algorithm.

B. Asymptotic Performance Analysis

We will analyze the asymptotic performance of $\bar{T}_1$ and $\bar{T}_0$, separately. For simplicity, we assume $p = 3$, namely, the detection procedure contains three stages: initial detection, parameter refinement and final detection. It is easy to extend the results to cases in which $p > 3$. We denote the estimate of parameter ψ by $\hat{\psi}$. We also assume that an incremental maximum likelihood (ML) estimation for ψ is used. Then, the estimation converges to the true value in the large sample limit since ML estimation is consistent. Other consistent estimation approaches follow the same argument.

1) $\bar{T}_1$: First, we need to study the impact of the mismatched parameter $\hat{\psi}$ on the CUSUM test. Suppose that an imperfect $\hat{\psi}$ is used as the true value in the CUSUM test. It is easy to verify that, by applying the Brownian motion approximation, $\bar{T}_1$ is approximated by

$$\bar{T}_1 \approx \frac{\gamma}{E_1\left[l_m^{\hat{\psi}}\right]}, \tag{12}$$

where

$$l_m^{\hat{\psi}} = \log\left(\frac{p_1^{\hat{\psi}}(X_m)}{p_0(X_m)}\right). \tag{13}$$

Then, we have (note that here E_1 is the expectation with respect to p_1^{ψ})

$$\begin{aligned} & E_1\left[l_m^{\hat{\psi}}\right] \\ = \; & E_1\left[\log\left(\frac{p_1^{\hat{\psi}}(X_m)}{p_0(X_m)}\right)\right] \\ = \; & E_1\left[\log\left(\frac{p_1^{\psi}(X_m)}{p_0(X_m)}\right)\right] - E_1\left[\log\left(\frac{p_1^{\psi}(X_m)}{p_1^{\hat{\psi}}(X_m)}\right)\right] \\ = \; & D\left(p_1^{\psi}||p_0\right) - D\left(p_1^{\psi}||p_1^{\hat{\psi}}\right), \end{aligned} \tag{14}$$

where $D(\cdot||\cdot)$ denotes Kullback-Leibler divergence. By applying the Information Inequality (Theorem 2.6.3 in [4]), which states

$$D\left(p_1^{\psi}||p_1^{\hat{\psi}}\right) \geq 0, \tag{15}$$

we have

$$E_1\left[l_m^{\hat{\psi}}\right] \leq E_1\left[l_m^{\psi}\right]. \quad (16)$$

Therefore, we can draw the following two conclusions when γ is sufficiently large:

- An imperfect $\hat{\psi}$ always increases $\bar{T}_1$;
- In the parallel CUSUM algorithm, the procedure using parameter ψ_i, given by

$$i = \arg\min_j\left(D\left(p_1^{\psi}||p_1^{\psi_j}\right)\right), \quad (17)$$

  stops first.

Now we return to the three stage algorithm. Similar to (17), we define

$$\psi_i^* \triangleq \arg\min_{\hat{\psi}\in\Psi_i}\left(D\left(p_1^{\psi}||p_1^{\hat{\psi}}\right)\right), \quad (18)$$

where Ψ_i denotes the set of parameters used for the i-th parallel CUSUM test. Then, $\bar{T}_1$ is given by (recall that $I = D\left(p_1^{\psi}||p_0\right)$ and the same candidates are used in stages 1 and 2)

$$\begin{aligned}\bar{T}_1 \approx & \quad \frac{\gamma_1}{I + D\left(p_1^{\psi}||p_1^{\psi_1^*}\right)} \\ & + \frac{\gamma_2}{I + D\left(p_1^{\psi}||p_1^{\psi_1^*}\right)} \\ & + \frac{\gamma}{I + D\left(p_1^{\psi}||p_1^{\psi_2^*}\right)}. \end{aligned} \quad (19)$$

Due to our assumption of ML estimation, $D\left(p_1^{\psi}||p_1^{\psi_2^*}\right)$ converges to 0 as γ_1 and γ_2 tend to infinity. Moreover, since γ is of higher order than γ_1 and γ_2, we obtain the same approximation of $\bar{T}_1$ as in (8), which means that we can achieve approximately the same ARL of detection delay as in the case of known parameter.

2) $\bar{T}_0$: Similar to the analysis of $\bar{T}_1$, $\bar{T}_0$ is dominated by the third stage. Consequently, the performance is determined by the parameter estimation in the second stage. Applying Sanov's theorem (Theorem 12.4.1 in [4]), the ML estimation of ψ in the second stage under H_0 is given by

$$\psi^* = \arg\min_{\hat{\psi}\in\Psi}\left(D\left(p_1^{\hat{\psi}}||p_0\right)\right). \quad (20)$$

Then, when $p_1^{\psi^*} \neq p_0$, the ARL of false alarm is given by

$$\log \bar{T}_0 \approx \frac{J^*\gamma}{U^*}, \quad (21)$$

where

$$J^* = E_0\left[\log\left(\frac{p_0(X_m)}{p_1^{\psi^*}(X_m)}\right)\right],$$

and

$$U^* = V_0\left[\log\left(\frac{p_0(X_m)}{p_1^{\psi^*}(X_m)}\right)\right].$$

V. Quickest Spectrum Sensing in Secondary Networks

In this section, we analyze the performance of quickest spectrum sensing in a secondary radio network. Since there is no collaboration, we can focus on only one node. Therefore, the analysis is the same as a single-node system and the quickest detection is a centralized one. We first analyze the performance of the CUSUM test in ideal case, namely the amplitude and phase of the primary radio signal are both known, and then apply the successive refinement algorithm to the more practical case with unknown amplitude and phase. Note that the performance analysis is based on Brownian motion approximation.

A. Known Amplitude and Phase

The algorithm and performance analysis are straightforward when the amplitude and phase are both perfectly known. Due to the normality of noise, the likelihood ratio at time slot m is given by

$$l_m = \frac{2X_m A\sin(m\omega t_s+\theta) - A^2\sin^2(m\omega t_s+\theta)}{2\sigma_n^2}. \quad (22)$$

Then, the stopping time can be computed using the CUSUM test in (4) and (5).

When $t_s \neq \frac{n\pi}{\omega}$ ($n \in \mathbb{N}$), $A\sin(m\omega t_s+\theta)$ has different values at different time slots. Then, the observations under H_1 are not identically distributed (but mutually independent). At time slot m, the divergence under H_1 is given by

$$I_m = \frac{A^2\sin^2(m\omega t_s+\theta)}{2\sigma_n^2}. \quad (23)$$

Then, we can use the time average of I_m to approximate I in (8). We have

$$\lim_{M\to\infty}\frac{1}{M}\sum_{m=1}^{M} I_m = \frac{A^2}{4\sigma_n^2}. \quad (24)$$

Therefore, the ARL of detection delay is approximated by

$$\bar{T}_1 \approx \frac{4\gamma\sigma_n^2}{A^2}. \quad (25)$$

When $t_s = \frac{n\pi}{\omega}$ ($n \in \mathcal{N}$, $\theta \neq n\pi$), it is easy to verify that

$$I = \frac{A^2\sin^2(\theta)}{2\sigma_n^2}, \quad (26)$$

which yields

$$\bar{T}_1 \approx \frac{2\gamma\sigma_n^2}{A^2\sin^2(\theta)}. \quad (27)$$

Similarly, for H_0 and $t_s \neq \frac{n\pi}{\omega}$ ($n \in \mathcal{N}$), we can obtain

$$J = \frac{A^2}{4\sigma_n^2}, \quad (28)$$

and

$$U = \frac{A^2}{2\sigma_n^2}. \quad (29)$$

Then, based on (9), the ARL of false alarm is given by

$$\log \bar{T}_0 \approx \frac{\gamma}{2}. \quad (30)$$

When $t_s = \frac{n\pi}{\omega}$ ($n \in \mathcal{N}$, $\theta \neq n\pi$), (30) still holds.

B. Unknown Amplitude and Phase

We can apply the successive refinement algorithm to the product space of the unknown amplitude and phase. There has been plenty of research on estimating unknown amplitude and phase of sinusoid signals. One simple incremental approach is to convert the continuous signal $A\sin(wt+\theta)$ into complex discrete signal and set the sampling period $t_s = \frac{\pi}{\omega}$ (since ω is known), which is given by

$$X(m) = \int_0^{t_s} R(mt_s+t)\sin(wt)dt + j\int_0^{t_s} R(mt_s+t)\cos(wt)dt, \quad (31)$$

where $R(t)$ is the received continuous signal. It is easy to verify that

$$X(m) = Ae^{j\theta} + w(m), \quad (32)$$

where complex AWGN $w(m)$ has variance $2\sigma_n^2$. Then, the estimations of A and θ, denoted by $\hat{A}$ and $\hat{\theta}$, are given by

$$\hat{A}e^{j\hat{\theta}} = \frac{1}{M}\sum_{m=0}^{M-1} X(m), \quad (33)$$

in which we assume that $\{X(0),...,X(M-1)\}$ are used in the estimation.

Applying the argument in Subsection IV-B, we can obtain the ARL of detection delay is the same as (25). Under H_0, the estimation in (33) results in $\hat{A}=0$ as the number of samples tends to infinity, which implies $p_1^{\psi^*} = p_0$ and $l_m = 0$ when $A_{\min} = 0$. Therefore, we need to set $A_{\min} > 0$ and then $\bar{T}_0$ is exponential in γ.

VI. Numerical Results

A. Parameter Estimation

In this subsection, we show the performance of the parameter estimation in the quickest spectrum sensing. We adopt the successive refinement algorithm with three stages and consider three sets of threshold $\{\gamma_1,\gamma_2,\gamma_3\} = \{8,30,80\}$ (small threshold) or $\{50,100,200\}$ (moderate threshold) or $\{100,300,500\}$ (large threshold). We also tested three sets of signal-to-noise ratios (SNR), defined as $\frac{A^2}{2\sigma_n^2}$, namely 0dB, 5dB and 10dB. Fig. 1 shows the relative mean square error (MSE) of amplitude (normalized by the true value of amplitude) versus different threshold sets and SNRs. We observe that the amplitude is reduced by using large threshold since more samples are used for estimation. An interesting observation is that the estimation error is almost constant for different SNRs. The reason is that the stopping time can be reached faster with a higher SNR, which is equivalent to having less samples for estimation. Fig. 2 shows the relative MSE of phase with the same configuration as Fig. 1, from which we have the same observation.

Figure 3 shows the relative errors of amplitude and phase estimation versus different number of stages in the successive refinement. We use SNR=5dB and thresholds $\{10,80,500,1000,2000\}$ in the simulation. We observe that using more than three stages induces only marginal performance gain.

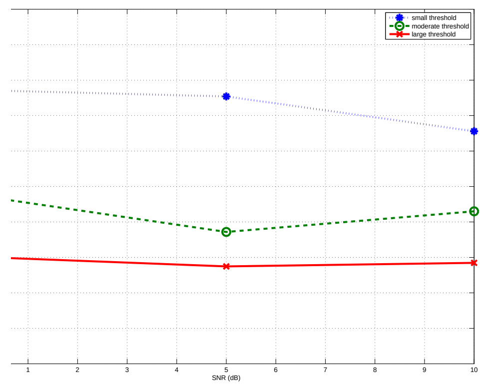

Fig. 1: Normalized MSE of amplitude with different SNRs and thresholds.

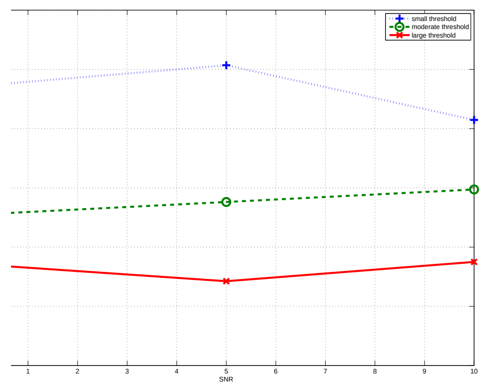

Fig. 2: Normalized MSE of phase with different SNRs and thresholds.

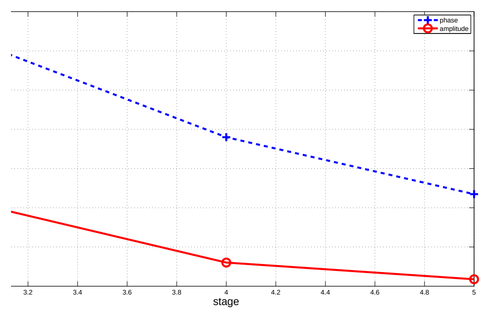

Fig. 3: Normalized MSE of phase with different numbers of stages.

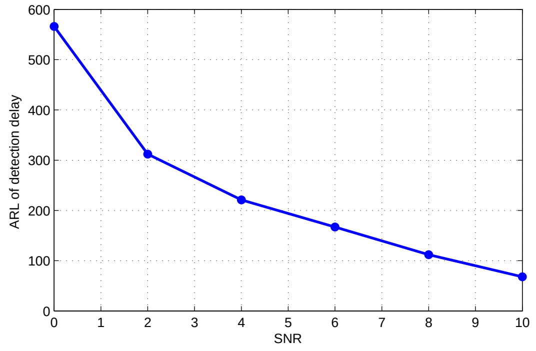

Fig. 4: ARL of detection delay versus different SNRs.

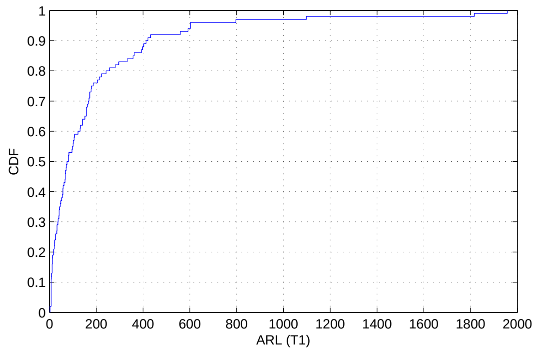

Fig. 5: CDF of ARL T_1 in a secondary network.

B. T_1: ARL of Detection Delay

Figure 4 shows the ARL of detection delay of a node using thresholds of 8,30, 80 in three-stage successive refinement, versus different SNRs. We observe that T_1 is substantially reduced when the SNR increases.

Figure 5 shows the cumulative distribution function within a secondary network. We assume that 100 secondary nodes are randomly distributed within a square while a primary radio base station (transmitting with power of 20W) is located at the center. To avoid too large or too small SNR, we assume that the distance between any secondary node and the primary base station is between 600m and 2600m. We also assume that the transmit power of primary radio is uniformly distributed in 5MHz bandwidth and the noise power spectral density is -174dBm/Hz. We use shadow fading with variance of 8.9dB and pathloss, which is given by $L = 28.6 + \log_{10}(d)$, where d is distance in meters, to compute the channel gain. In the simulation, the maximum and minimum SNRs are 24.8dB and -3.4dB, respectively. For simplicity, we ignore fast fading. From Fig. 5, we observe that most secondary nodes achieve good performance while a small portion of nodes perform much worst, due to bad SNR. This observation necessitates the study on collaboration across different secondary nodes.

VII. Conclusions

In this paper, we have studied the quickest spectrum sensing in secondary nodes of cognitive radio systems. The theory of quickest detection is applied to the spectrum sensing to achieve agile and robust performance. The problem of unknown parameters in primary radio signals is tackled by proposing the successive refinement test. The system performance has been analyzed by using Brownian motion approximation and has been evaluated by numerical simulations. Note that, in this paper, we do not consider collaboration across different secondary nodes, which can improve the robustness of the spectrum sensing. The algorithm and performance analysis of collaborative quickest spectrum sensing are still open problems and we are currently working on them.

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