Secured Optimal Multiband Joint Detection Framework for Cognitive Radio Networks

Suwas Karki[1], I Santhi Prabha[2]
[1](M.Tech-C&C), Department of ECE, [2]Professor, Department of ECE,
University College of Engineering, JNTUK, Kakinada, India
[1]karkisuwas@gmail.com, [2]santiprabha@yahoo.com

***Abstract* – Spectrum sensing is an essential functionality that enables radios to detect spectral holes and to opportunistically use the under-utilized frequency bands without causing harmful interference to legacy (primary) networks. In this paper, the novel optimal multiband spectrum sensing framework referred as *multiband sensing time adaptive joint detection* is introduced which improves the overall secondary user performance while protecting the primary network, keeping the harmful interference below a desired low level and protecting the spectrum from the malicious attackers. Simulation results show that the proposed multiband spectrum sensing schemes can considerably improve system performance. An efficient iterative algorithm which solves the optimization problem with much lower complexity compared to other numerical methods is presented. The algorithm is evaluated via simulation and is shown to obtain the optimal solution in less number of iteration.**

***Keywords* - Cognitive radio, cooperative sensing, hypothesis testing, multiband sensing-time-adaptive joint detection, optimization, periodic sensing, spectrum sensing, throughput maximization, multiband sensing.**

I. INTRODUCTION

TRADITIONAL wireless networks are regulated by fixed (static) spectrum allocation policies to operate in certain time frames, over certain frequency bands, and within certain geographical regions. This regulation results in situations in which some radio bands are overcrowded while other bands remain moderately or rarely occupied. Over time, due to the ever-growing need for wireless communications and lack of unlicensed frequency resources, this fixed spectrum assignment policy has led to the spectrum scarcity problem. In order to realize efficient spectrum utilization, the static spectrum access must be replaced by dynamic spectrum access (DSA) [1]. The key technology behind the dynamic spectrum access is cognitive radio (CR), which has recently been proposed to revolutionize the wireless communication systems [2]. Since a cognitive radio network is designed to be aware of its surroundings, monitoring the primary user activities and sensing the spectrum is a critical task which must be accomplished. Also because of the dynamic nature of CR, the network is more vulnerable to be compromised. One serious threat is the primary user emulation attack (PUEA), in which the attacker sends out signal similar to that of primary users during the spectrum sensing period such that the secondary users will not use the spectrum even if there is no primary user. In order to utilize the available spectrum efficiently such type of issues must be avoided.

Effective spectrum sensing needs to identify suitable transmission opportunities without compromising the integrity of the primary network [3]. Generally, spectrum sensing techniques can be classified into three broad categories: energy detection [4], matched filtering (coherent) detection [5], and cyclostationary feature detection [6]. Energy detection has been shown to be optimal if the cognitive devices have no a priori information about the features of the primary signals except local noise statistics [7]. Since energy detection is simple and able to determine spectrum-occupancy information quickly, it is adopted as the building block for constructing the proposed wideband spectrum sensing framework.

A. Related Work

All of the above mentioned spectrum sensing strategies has been previously restricted to sensing narrowband channels. So there are limited prior works, when it comes to wide-band spectrum sensing. An early approach was to have a tunable narrowband band pass filter to sense a number of channels, one at a time [9]. In [10], [11], the authors have suggested using a wavelet transformation for sensing different frequency bands simultaneously. However, none of the aforementioned strategies have considered sensing multiple narrowband channels jointly, which is essential for implementing a most effective secondary network. Consequently, through a different approach, a novel “multiband joint detection” (MJD) framework for wideband sensing was proposed in [12] where the decisions are jointly made over multiple frequency bands.

More specifically, in the MJD framework [12], a bank of multiple narrowband detectors are optimized to improve the aggregate opportunistic throughput of a cognitive radio system while limiting the interference to the primary communication system. It is important to sense the channel periodically in order to vacate spectrum when a primary user reappears [13] - [17], however this feature is missing in the MJD framework. In addition, due to the wireless channel fluctuations and fading effects, it is essential to dynamically balance the quality and speed of sensing through an adaptive selection of the sensing time, which is assumed to be fixed in MJD.

B. Proposed Work

The major contribution of this work is three folds. First, for wideband spectrum sensing, an optimal framework is presented, known as multiband sensing-time-adaptive joint detection (MSJD). By adding periodic sensing to the system used in [12] and considering the aforementioned design concerns, the opportunistic throughput of secondary user can be maximized while keeping the interference to primary user to a reasonably low level.

Second, an efficient algorithm which computes the optimal sensing parameters quickly within the MSJD framework is proposed. Generally speaking, this paper demonstrates a practical and useful platform for designing a wideband spectrum sensing framework, as well as an efficient algorithm for the framework whose implementation is remarkably time and cost-effective.

Third, authorization of access is considered in the system for the security purpose. Each node has to supply access code before accessing the spectrum which is only known to the authentic nodes and the system. Only nodes with the valid access code are allowed to use the available spectrum

The remainder of the paper is organized as follows. In section II, the basic system models are presented. In section III, the wideband spectrum sensing framework is introduced. The theoretical results are given in section IV leading to the presentation of the proposed algorithm for solving the given framework in section V. In Section VI, authentication system is presented. Numerically evaluation of the framework and the algorithm are presented in section VII and finally conclusions are drawn in Section VIII.

II. CHANNEL SENSING

In this section, the general model for channel sensing and the periodic sensing model are presented.

A. *System Model*

Consider a primary communication system (e.g., multicarrier modulation based) operating over a wideband channel that is divided into N non overlapping narrowband sub bands and assume that J no. of primary user share this spectrum [12].

The detection problem on sub band N is modeled using binary hypothesis testing in which selection between a hypothesis $H_{0,k}$ ("0"), which represents the absence of primary signals, and an alternative hypothesis $H_{1,k}$ ("1"), which represents the presence of primary signals is done.

B. Periodic Sensing

Once a secondary user detects an opportunity for transmission it may tune its transmission parameters to access the channel. Yet, it should continue sensing the spectrum every τ seconds in order to vacate the channel if the primary user reappears. This is due to the fact that sensing a channel and transmitting in the same channel cannot be done simultaneously. The sensing period τ determines the maximum time that the secondary user disregards the primary user activity and may impose harmful interference on the legacy network. Therefore, the choice of τ forces a delay on the primary transmission and hence a degradation of the quality of service (QoS). On the other hand, a larger value of τ increases the secondary system's opportunity to access the underutilized spectrum. The selection of τ should depend on the type of the primary service and should be set by the regulator.

Fig. 1 represents the frame structure considered for the periodic spectrum sensing. Each frame consists of one sensing slot τ and one data transmission slot $T - \tau$. For a given sensing time τ, the number of samples used for sensing of one sub channel is $M = \tau f_s$ where f_s is the sensing sampling frequency in all sub channels.

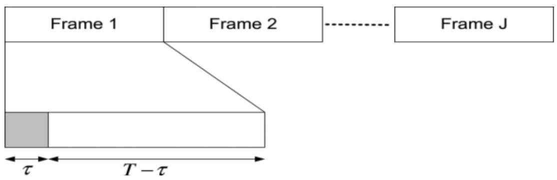


Fig. 1. Periodic spectrum sensing.

III. MULTIBAND JOINT DETECTION

In this section, the multiband sensing-time-adaptive joint detection framework is proposed, within which the detection thresholds $\{\epsilon_k\}_{k=1}^{N}$ and the sensing time τ will be found.

A. Problem Formulation

For the single primary user case, J=1. The objective of the proposed joint spectrum sensing framework is to jointly optimize the threshold vector ε and the sensing time τ so as to maximize the available throughput of the secondary user while keeping the weighted interference with primary users below a desired level. Mathematically, the optimization problem can be stated as

$$\max_{\varepsilon,\tau} \; R(\varepsilon,\tau) \tag{P1}$$

$$\text{s.t.} \quad I_j(\varepsilon,\tau) \le \xi_j, \quad j=1\ldots\ldots\ldots N \tag{1}$$

$$P_m(\varepsilon,\tau) \le \alpha_k, \quad k=1\ldots\ldots N \tag{2}$$

$$P_f(\varepsilon,\tau) \le \beta_k, \quad k=1\ldots\ldots N \tag{3}$$

where R is available throughput[18], α_k and β_k are the minimum requirements of each sub channel and ξ is maximum tolerable aggregate interference on primary network.

In order to make the analysis easier, the problem is reformulate as

$$\min_{\varepsilon,\tau}.\ R_{miss}(\varepsilon,\tau) \quad (P2)$$

where,

$$R_{miss}(\varepsilon,\tau) = r[P_f(\varepsilon,\tau)(1- \tau/T)+\tau/T] \quad (4)$$

is the opportunistic data rate loss due to inherent sensing impairment.

B. Convex Optimization

In general, it is difficult to find the global solution for problem (P2) since both objective and constraint functions are non convex, so a suboptimal solution is indicated for many cases. However, it is observed that this problem can be considered in the convex optimization category under some practical conditions [18]. Consequently, following results can be presented to take advantage of the convexity of (P2). From [18] and [19], the constraints of problem (P2) are convex given as

$$0 \le \alpha_k \le Q\ (1/\sqrt{3}) \quad (5a)$$
$$0 \le \beta_k \le Q\ (1/\sqrt{3}) \quad (5b)$$

for k=1,2…..N. Although the constraints are shown to be convex, the objective function is still non convex. To prove the convexity of the objective function, we use the following result [18]

$$\tau/T \le 0.5 \quad (6)$$

Under the conditions in (5) and (6), both the objective and constraint functions are convex, which implies that finding the global maximum is possible. Hence, some efficient numerical algorithms such as the interior-point methods [19] can be used to find the optimal solution.

IV. THEORETICAL ANALYSIS

In this section, some analytical results for solving the original problem (P1) are presented. The results are further exploited for presentation of the low-complexity algorithm.

A. Constant τ

Here, the case where τ is a predetermined value and unrelated to the optimization process is considered. Thus, the original problem (P1) can be simplified as

$$min.\, R_{miss}(\varepsilon) = \sum_{k=1}^{N} r_k\, p_f^{(k)}(\varepsilon_k) \quad (P3)$$

$$\text{s.t}\quad I_j(\varepsilon) \le \xi_j,\qquad j = 1,\ldots\ldots J \quad (7)$$

$$\varepsilon_{k,min} \le \varepsilon_k \le \varepsilon_{k,max},\ k = 1,2\ldots.N \quad (8)$$

where,

$$\varepsilon_{k,max} = \sigma_w^2\left[\frac{\sqrt{2\gamma_k+1}}{\sqrt{\tau f_s}}Q^{-1}(1-\alpha_k)+\gamma_k+1\right] \quad (9)$$

is the max detection threshold and

$$\varepsilon_{k,min} = \sigma_w^2\left[\frac{Q^{-1}(\beta_k)}{\sqrt{\tau f_s}}+1\right] \quad (10)$$

is the minimum tolerable threshold value. Note that the main difference between (P2) and (P3) is that the nonlinear constraints (2) and (3) are transformed to the linear constraint (8). In [12], it has been shown that the problem (P3) is a convex optimization problem. Therefore, it is possible to find the global optimal solution using numerical methods such as the interior-point methods. However, an iterative algorithm is proposed which computes the optimal threshold vector in less number of iterations.

B. Dual Problem

In order to further explore the optimization problem (P3), the advantage of the Lagrangian duality properties are exploited, presented in [19]. The Lagrangian of the problem (P2) is defined as

$$L(\varepsilon,\lambda_1,\lambda_2,\lambda_3)=r^T P_f(\varepsilon)+ \lambda_1 (I(\varepsilon)-\xi)+ \lambda_2^T(\varepsilon - \varepsilon_{max})+\lambda_3^T (-\varepsilon + \varepsilon_{min}) \quad (11)$$

where $\lambda_1,\lambda_2 = [\lambda_2^{(1)},\ldots,\lambda_2^{(N)}]$ and $\lambda_3 = [\lambda_3^{(1)},\ldots,\lambda_3^{(N)}]$ are nonnegative Lagrangian dual variables associated with the constraint function. Accordingly, the Lagrangian dual function is defined as

$$g(\lambda_1,\lambda_2,\lambda_3) = \inf_{\varepsilon}.\ L(\varepsilon,\lambda_1,\lambda_2,\lambda_3) \quad (12)$$

Recall that the dual function is a lower bound on the optimal solution of (P3), p’, which is achieved by the primal optimal variable ε’. Consequently, the dual optimization problem is defined as

$$\max.\ g(\lambda_1,\lambda_2,\lambda_3)$$
$$\text{s.t. } \lambda_1 \ge 0,\ \lambda_2 \ge 0,\ \lambda_3 \ge 0 \quad (13)$$

which is formulated to reduce the gap between the optimal solution p’ and the Lagrangian function $g(\lambda_1,\lambda_2,\lambda_3)$. Denote the optimal solution of the dual problem (13) as d’ which is achievable by the optimal dual variables λ_1,λ_2 and λ_3 i.e. d’= $g(\lambda_1,\lambda_2,\lambda_3)$. Since the original problem (P3) is convex and Slater’s condition is satisfied, strong duality holds for this problem which means that the duality gap p’- d’ is zero [19] and consequently, any primal and dual optimal variables ε’, λ_1,λ_2 and λ_3 must satisfy the Karush- Kuhn- Tucker(KKT) conditions[18]. On the other hand, given the fact that the primal problem is convex, satisfying the KKT conditions is sufficient for finding the primal and dual optimal points. That is, any primal and dual variables ε', λ'_1,λ'_2 and λ'_3 set which satisfies the KKT conditions

$I(\varepsilon') \leq \xi$ (14a)

$\varepsilon_{k,min} \leq \varepsilon' \leq \varepsilon_{k,max}$, k = 1,2,…..,N (14b)

$\lambda_1' \geq 0, \lambda_2' \geq 0, \lambda_3' \geq 0$ (14c)

$\lambda_1' (I(\varepsilon') - \xi) = 0$ (14d)

$\lambda_2'^{(k)}(\varepsilon'_k - \varepsilon_{k,max}) = 0$, k = 1,2,…….,N (14e)

$\lambda_3'^{(k)}(-\varepsilon'_k + \varepsilon_{k,min}) = 0$, k = 1,2,…….,N (14f)

$\nabla L (\varepsilon', \lambda'_1, \lambda'_2, \lambda'_3) = 0$ (14g)

is the optimal solution and results in zero duality gap. Generally, there is no conventional method for solving KKT conditions and only a few special cases result in a closed-form solution. In our problem, since the KKT conditions (14a) and (14g) are nonlinear equations, finding a closed-form solution is extremely difficult and thus, a numerical algorithm is indicated.

V. LOW COMPLEXITY ALGORITHM

In this section, first, assuming that the sensing time τ is constant which restricts the multiband joint detection framework, we present an efficient algorithm for calculating the optimal threshold vector ε. Then, taking advantage of the algorithm, we propose another efficient algorithm for solving the original multiband sensing-time-adaptive joint detection framework in which ε and τ are both optimization variables.

A. Multiband Joint Detection

Here, the aim is to find the optimal primal and dual parameters ε', λ'_1, λ'_2 and λ'_3 by satisfying the KKT conditions given in (14). It is assumed that (14b) is valid even if the equality is removed. This assumption may not be generally valid and some of the thresholds must assume the boundary values in order to satisfy all the KKT conditions. However, for the interim, the results are presented based on the aforementioned assumption and the boundary thresholds are dealt in [18]. Based on above assumptions and after few substitutions and simplifications [18], the expression for detection threshold ε'_k can be written as

$$\varepsilon_k' = \sigma_w^2\left[\frac{1}{2}+\sqrt{\left[\frac{2\gamma_k+1}{\gamma_k}\left[\frac{-1}{\tau f_s}log\left(\frac{\lambda_1' c_k}{r_k\sqrt{2\gamma_k+1}}\right)+\frac{\gamma_k}{4}\right]\right]}\right] \tag{15}$$

which is a closed-form function of λ_1'. Having such a function enables us to substitute (15) into the KKT condition (14a) and obtain the optimal λ_1'. Note that (14a) is an equality condition and can easily be solved using various fast and efficient numerical root-finding methods such as the Newton-Raphson method, fixed point iteration method, etc. Once λ_1' is obtained, the detection thresholds $\{\epsilon_k'\}_{k=1}^{N}$ are accordingly obtained.

B. Multiband Sensing-Timing-Adaptive Joint Detection

In this section, an algorithm which computes the optimal detection threshold vector ε and sensing time τ as given in (P2) is presented. The basic idea is that, instead of jointly optimizing the optimization variables, they are optimized in a disjoint two-stage algorithm. In the first stage of the algorithm, the sensing time τ is assumed as a constant value. Therefore, the original problem is reformulated as the one stated in (P3). In the second stage, the sensing time τ based on the information obtained from the previous stage is updated. Iteration is used in the algorithm in order to refine the information used in each stage.

Some information from the previous stage is needed to implement stage 2. For this purpose specifically probabilities of missed detection is exploited. There are four main parameters which are effective in determining probabilities of missed detection $P_m(\varepsilon,\tau)$. These parameters are the achievable throughput r_k, the interference cost c_k, the channel SNR γ_k and the sensing time τ. This is an intuitive result which can be easily extracted from the objective and constraint functions in the problem (P1).

It is observed that the parameters are channel dependent value and can vary in each sub channel but the sensing time τ is a global value and is the same in each sub channel. Therefore, it can intuitively conclude that the channel depended parameters are more effective in determining sensing time τ. On the other hand, it is seen that these so called channel-dependent parameters are fixed values and depend only on the system model. Thus, the computed missed detection probabilities in the first stage will remain almost unchanged even if the sensing time τ changes in the next iteration. This information is used to implement the second stage of the algorithm. Accordingly, in the second stage, the probabilities of missed detection are assumed to be fixed at the values $P'^{(k)}_m$ obtained from the first stage. Thus, the probability of false alarm can be written as

$$P_f^{(k)}(\tau) = Q\left(\sqrt{(2\gamma_k+1)}Q^{-1}\left(1-P_m'^{(k)}\right)+\sqrt{\tau f_s}\gamma_k\right) \tag{16}$$

Accordingly, the optimization problem is converted to

$$min.\, R_{miss}(\tau) = \sum_{k=1}^{N} r_k\left(\left(1-\frac{\tau}{T}\right)P_f^{(k)}(\tau)+\frac{\tau}{T}\right) \tag{P4}$$

s.t $P_f(\tau) \leq \beta$ (17)

which has been proved to be convex if $0 \leq \beta_k \leq 0.5$. Since the only optimization variable is τ, the problem can be rewritten as

$$\min_{\tau}.\ R_{miss}(\tau) \tag{P5}$$

$$\text{s.t. } \tau \geq \text{argmax}\{ \tau^{(1)}_{min}, \tau^{(2)}_{min},\ldots, \tau^{(N)}_{min}\} \tag{18}$$

in which,

$$\tau_{min}^{(k)} = \frac{1}{\gamma_k^2 f_s}\left[Q^{-1}(\beta_k)-\sqrt{2\gamma_k+1}\,Q^{-1}\left(1-P_m'^{(k)}\right)\right]^2 \tag{19}$$

is the minimum required sensing time at sub channel obtained from (16). The optimization problem (P5) can easily be solved by taking the derivative of the objective function and setting it to zero in order to obtain the optimal value of τ. The calculated value of τ is the optimal solution if it satisfies constraint (18), otherwise the boundary value given in (18) is chosen. After solving the problem (P5), the first stage is repeated based on the updated value of τ until the solution is accurate enough. However, required numbers of iterations are very small.

VI. AUTHENTICATION SYSTEM

The dynamical spectrum access mechanism, particularly the spectrum sensing mechanism, in CR also incurs vulnerabilities for the communication system. One serious threat is the primary user emulation attack (PUEA), in which the attacker sends out signal similar to that of primary users during the spectrum sensing period such that the secondary users will not use the spectrum even if there is no primary user, since it is difficult to distinguish the signals from primary users and the attacker.

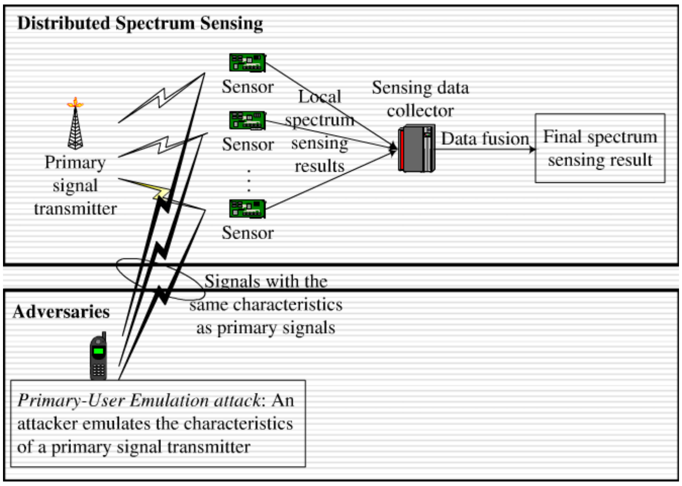


Fig. 2. Primary Emulation Attack (PUEA) [21]

To prevent such issues, secret access codes are being shared between authentic nodes and the system via secured channel using any existing cryptography techniques. Only nodes with valid access code are allowed to use the spectrum whereas others are rejected.

VII. SIMULATION RESULTS

In this section, computer simulation results are presented to verify the effectiveness of our proposed work. Consider a single primary user communication (i.e., J = 1) over a wide band spectrum where the wideband channel is equally divided into six sub bands. For each sub band k, we assume an achievable throughput rate r_k if used by CRs and a cost coefficient c_k indicating the penalty if the primary signal is interfered with by secondary users, also γ_k, denote the received SNR. Furthermore, in each sub channel k, we assume a minimum primary user protection level of 90%, i.e., α_k = 0.1and an opportunity detection margin of β_k = 0.2. For simplicity it is assumed that the noise power level is $\sigma^2_v = 1$ and the maximum time for which the secondary network is unaware of the primary activity (i.e.T) is chosen such that f_sT = 3000.

k	1	2	3	4	5	6
γ_k,	0.21	1.30	2.52	3.24	4.35	5.271
r_k(kbps)	207	306	485	600	711	808
c_k	3.94	5.68	6.81	7.91	9.01	10.07

Table 1: Parameter set used for simulation

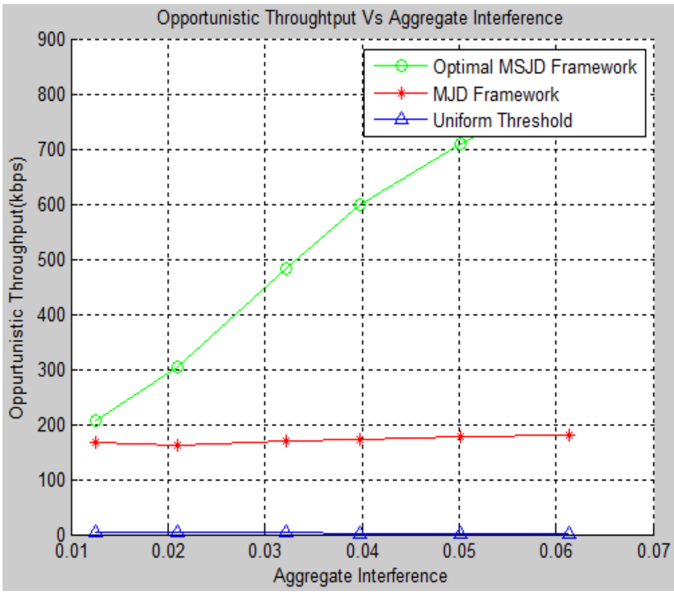


Fig. 3. The available opportunistic throughput for cognitive radio transmission versus the aggregate interference to the primary network

A. Example 1: Multiband Sensing-Time-Adaptive Joint Detection Framework

In this example, multiband sensing-time adaptive joint detection (MSJD) framework is evaluated. To make a fair comparison, two schemes are considered here. First, a multiband joint detection (MJD) framework [12] with the same constraints and the number of samples M = τf_s =150 is examined. Recall that the MJD framework maximizes the available secondary throughput by a joint optimization of the detection thresholds. Second, an algorithm which searches uniform thresholds to maximize the available throughput within the same framework is studied. In order to evaluate the performance, the simulation parameters are randomly generated like in [18] such as the channel condition, opportunistic throughput, and interference cost. One typical parameter set used for simulation is given in Table 1.

Fig. 3 plots the maximum available throughput for cognitive radio transmission versus the aggregate interference in the primary network. It is evident in the figure that our proposed framework achieves a performance superior to the other approaches. Two main observations are notable here. First, other than the detection thresholds, the sensing time is a critical parameter which should be dynamically assigned due to the channel fluctuations and fading effects. Second, in order to adjust a intelligent tradeoff between the available throughput and interference to the primary user, we need a unified approach which optimizes all of these parameters. These considerations are well adopted in the framework.

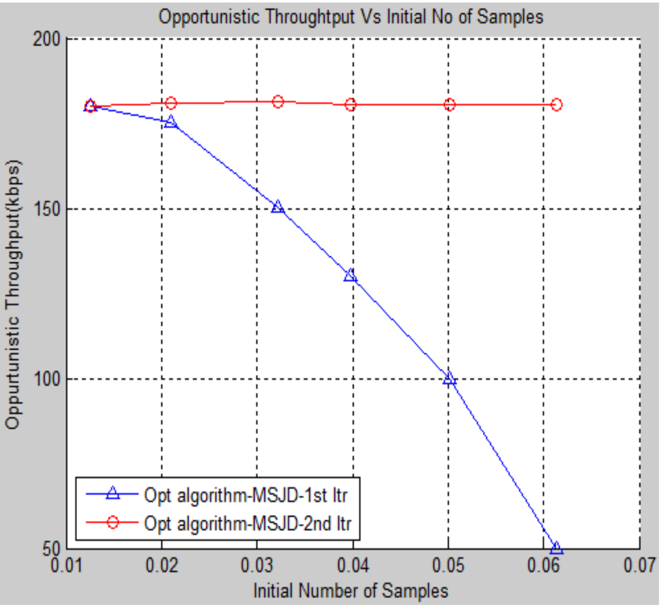


Fig. 4. The available opportunistic throughput for cognitive radio transmission versus the initial number of samples defined in Algorithm.

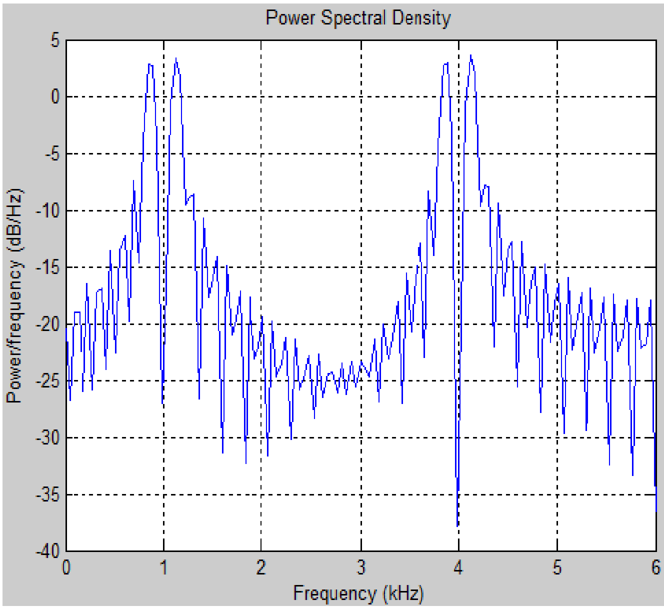
B. *Example 2: Low Complexity Wideband Sensing Algorithm*

This example studies the low-complexity algorithms which are proposed for solving both the MSJD and MJD framework where the detection threshold vector ε is optimized when the sensing time τ is a predetermined value which better suits the MJD framework. Considering the design concerns presented in the MSJD framework, an efficient iterative algorithm is developed which computes the optimal values of both the detection threshold vector ε and sensing time τ.

Fig. 3 plots the maximum available throughput for cognitive radio transmission versus the aggregate interference in the primary network. As depicted in the figure, the optimal solutions can easily be achieved by the proposed algorithms. It should also be noted that only two iterations are used for implementing Algorithm which verifies that the required number of iterations is very small. In fig 4, the maximum available throughput for the cognitive transmission is plotted versus the initial number of samples (initial sensing time) given in Algorithm. It is evident in the figure that it is obtained the optimal solution by running at most two iterations. This is another validation of the small number of iterations required using Algorithm.

C. *Example 3: Authentication System*

This example studies the authentication system to prevent primary user emulation attack (PUEA) [20]. In order to utilize the spectrum as primary user, every node has to come up with correct access code. Those nodes that are able to provide correct codes are given chance to access the available spectrum. In fig. 5 only node at slot 1 and 3 are able to



provide correct access code and hence allowed to utilize the spectrum.

Fig.5. Power spectral density of spectrum with primary users

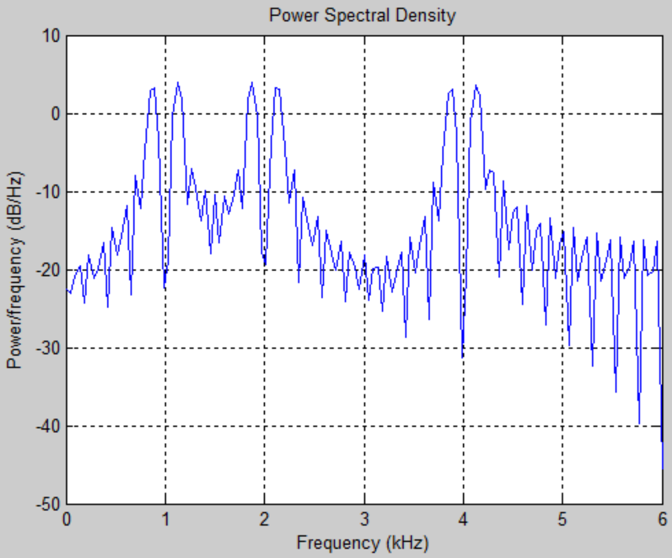


Fig.6. Power spectral density of spectrum after inserting secondary users

in respective slots. All other nodes at remaining slots are not able to provide correct access code and hence are rejected. So slot 2, 4 and 5 are empty slots and available for secondary user opportunistically transmission. Now when secondary users come to utilize available spectrum then it is allotted available empty slots in first come first serve basis. In fig. 7, slot 2 is assigned to newly arrive secondary user.

VIII. CONCLUSION

In this paper, optimal multiband sensing-time-adaptive joint detection (MSJD) framework was proposed for wideband spectrum sensing in CR networks. The basic strategy was to take into account the detection of primary users jointly across a bank of narrowband sub bands rather than considering only one single band at a time. The joint detection problem was formulated into a class of optimization problems to improve the spectral efficiency and reduce the interference. By exploiting the hidden convexity in the seemingly non convex problem formulations, the optimal solution was obtained under practical conditions. Moreover, an algorithm was proposed which solved the formulated optimization problem in less no of iteration. The proposed spectrum sensing algorithms have been examined numerically and have been shown to perform well. Also with the addition of the authorization of access in the system, the spectrum can be protected from the malicious intruders.

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