Wideband Spectrum Sensing in Cognitive Radio Networks

Zhi Quan[†], Shuguang Cui[‡], Ali H. Sayed[†], and H. Vincent Poor[§]

[†] Department of Electrical Engineering, University of California, Los Angeles, CA 90095
[‡]Department of Electrical and Computer Engineering, Texas A&M University, College Station, TX 77843
[§]Department of Electrical Engineering, Princeton University, Princeton, NJ 08544
Email: {quan, sayed}@ee.ucla.edu; cui@ece.tamu.edu; poor@princeton.edu

Abstract— Spectrum sensing is an essential enabling functionality for cognitive radio networks to detect spectrum holes and opportunistically use the under-utilized frequency bands without causing harmful interference to legacy networks. This paper introduces a novel wideband spectrum sensing technique, called *multiband joint detection*, which jointly detects the signal energy levels over multiple frequency bands rather than consider one band at a time. The proposed strategy is efficient in improving the dynamic spectrum utilization and reducing interference to the primary users. The spectrum sensing problem is formulated as a class of optimization problems in interference limited cognitive radio networks. By exploiting the hidden convexity in the seemingly non-convex problem formulations, optimal solutions for multiband joint detection are obtained under practical conditions. Simulation results show that the proposed spectrum sensing schemes can considerably improve the system performance. This paper establishes important principles for the design of wideband spectrum sensing algorithms in cognitive radio networks.

I. INTRODUCTION

Spectrum sensing is an essential functionality of cognitive radios since the devices need to reliably detect weak primary signals of possibly-unknown types [1]. In general, spectrum sensing techniques can be classified into three categories: energy detection [2], matched filter coherent detection [3], and cyclostationary feature detection [4]. Since non-coherent energy detection is simple and is able to locate spectrum-occupancy information quickly, we will adopt it as a building block for constructing the proposed wideband spectrum sensing scheme.

There are previous studies on spectrum sensing in cognitive radio networks with focus on cooperation among multiple cognitive radios [1] [5] [6] via distributed detection approaches [7] [8]. However, they are limited to the detection of signals on a single frequency band. In [9], two decision-combining approaches were studied: hard decision with the AND logic operation and soft decision using the likelihood ratio test [7]. It was shown that the soft decision combination of spectrum sensing results yields gains over hard decision combining. In [10], the authors exploited the fact that summing signals from two secondary users can increase the signal-to-noise ratio (SNR) and detection reliability if the signals are correlated. In [11], a generalized likelihood ratio test for detecting the presence of cyclostationarity over multiple cyclic frequencies was proposed and evaluated through Monte Carlo simulations.

Along with these works, we have developed a linear cooperation strategy [12] [13] based on the optimal combination of the local statistics from spatially distributed cognitive radios. Generally speaking, the quality of the detector depends on the level of cooperation and the bandwidth of the control channel.

The literature of wideband spectrum sensing for cognitive radio networks is very limited. An early approach is to use a tunable narrowband bandpss filter at the RF front-end to sense one narrow frequency band at a time [14], over which the existing narrowband spectrum sensing techniques can be applied. In order to operate over multiple frequency bands at a time, the RF front-end requires a wideband architecture and the spectrum sensing usually involves the estimation of the power spectral density (PSD) of the wideband signal. In [15] and [16], the wavelet transform was used to estimate the PSD over a wide frequency range given its multi-resolution features. However, none of the previous works considers making joint decisions over multiple frequency bands, which is essential for implementing efficient cognitive radios networks.

In this paper, we introduce the multiband joint detection framework for wideband spectrum sensing in individual cognitive radios. Within this framework, we jointly optimize a bank of multiple narrowband detectors in order to improve the opportunistic throughput capacity of cognitive radios and reduce their interference to the primary communication systems. In particular, we formulate wideband spectrum sensing into a class of optimization problems. The objective is to maximize the opportunistic throughput in an interference limited cognitive radio network. By exploiting the hidden convexity of the seemingly non-convex problems, we show that the optimization problems can be reformulated into convex programs under practical conditions. The multiband joint detection strategy allows cognitive radios to efficiently take advantage of the unused frequency bands and limit the resulting interference.

The rest of this paper is organized as follows. In Section II, we describe the system model for wideband spectrum sensing. In Section III, we develop the multiband joint detection algorithms, which seek to maximize the opportunistic throughput. The proposed spectrum sensing algorithms are examined by numerical examples in Section IV and conclusions are drawn in Section V.
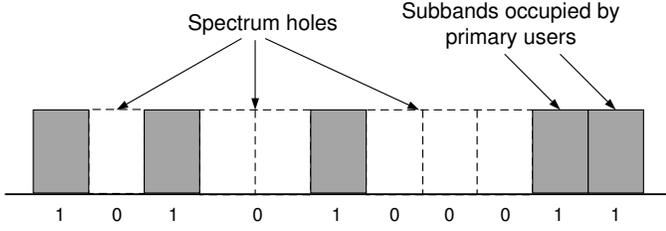
Fig. 1. A schematic illustration of a multiband channel.

II. SYSTEM MODELS

A. Wideband Spectrum Sensing

Consider a primary communication system (e.g., a multicarrier modulation based system) over a wideband channel that is divided into K non-overlapping narrowband subchannels. In a particular geographical region and time, some of the K subchannels might not be utilized by the primary users and are available for opportunistic spectrum access. Multiuser orthogonal frequency division multiplexing (OFDM) is an ideal candidate for such a scenario since it makes the subband manipulation easy and flexible.

We model the occupancy detection problem on subchannel k as one of choosing between $\mathcal{H}_{0,k}$ ("0"), which represents the absence of primary signals, and $\mathcal{H}_{1,k}$ ("1"), which represents the presence of primary signals. An illustrative example where only some of the K bands are occupied by primary users is depicted in Fig. 1. The underlying hypothesis vector is a binary representation of the subchannels that are allowed for or prohibited from opportunistic spectrum access.

The crucial task of spectrum sensing is to sense the K narrowband subchannels and identify spectral holes for opportunistic use. For simplicity, we assume that the high-layer protocols, e.g., the medium access control (MAC) layer, can guarantee that all cognitive radios keep quiet during the detection interval such that the only spectral power remaining in the air is emitted by the primary users in addition to background noises. In this paper, instead of considering a single subband at a time, we propose to use a multiband detection technique, which jointly takes into account the detection of primary users across multiple frequency bands. We next present the system model.

B. Received Signal

Consider a multi-path fading environment, where $h(l)$, $l = 0, 1, \ldots, L - 1$, denotes the discrete-time channel impulse response between the primary transmitter and cognitive radio receiver, with L as the number of resolvable paths. The received baseband signal at the CR front-end can be represented as

$$r(n) = \sum_{l=0}^{L-1} h(l) s(n-l) + v(n), \quad n = 0, 1, \ldots, N-1 \quad (1)$$

where $s(n)$ is the primary transmitted signal at time n (after the cyclic prefix has been removed) and $v(n)$ is additive complex white Gaussian noise with zero mean and variance σ_v^2, i.e., $v(n) \sim \mathcal{CN}\left(0, \sigma_v^2\right)$. In a multi-path fading environment, the wideband channel exhibits frequency-selective features [17] [18] [19] and its discrete frequency response is given by

$$H_k = \frac{1}{\sqrt{N}} \sum_{n=0}^{L-1} h(n) e^{-j2\pi nk/N}, \qquad k = 0, 1, \ldots, K-1 \quad (2)$$

where $L \leq N$. We assume that the channel is slowly varying such that the channel frequency responses $\{H_k\}_{k=0}^{K-1}$ remain constant during a detection interval. In the frequency domain, the received signal at each subchannel can be estimated by first computing its discrete Fourier transform (DFT):

$$R_k = \frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} r(n) e^{-j2\pi nk/N}$$
$$= H_k S_k + V_k, \qquad k = 0, 1, \ldots, K-1 \quad (3)$$

where S_k is the primary transmitted signal at subchannel k and

$$V_k = \frac{1}{\sqrt{N}} \sum_{n=0}^{L-1} v(n) e^{-j2\pi nk/N}, \qquad k = 0, 1, \ldots, K-1 \quad (4)$$

is the received noise in frequency domain. The random variable V_k is independently and normally distributed with zero mean and variance σ_v^2, i.e., $V_k \sim \mathcal{CN}\left(0, \sigma_v^2\right)$, since $v(n) \sim \mathcal{CN}\left(0, \sigma_v^2\right)$ and the DFT is a linear operation. Without loss of generality, we assume that the transmitted signal S_k, the channel gain H_k, and the additive noise V_k are independent of each other.

C. Signal Detection in Individual Bands

Here, we consider signal detection in a single narrowband subchannel, which will constitute a building block for multiband joint detection. To decide whether the k-th subchannel is occupied or not, we test the following binary hypotheses

$$\begin{aligned} \mathcal{H}_{0,k} &: R_k = V_k \\ \mathcal{H}_{1,k} &: R_k = H_k S_k + V_k, \qquad k = 0, 1, \ldots, K-1 \quad (5) \end{aligned}$$

where $\mathcal{H}_{0,k}$ and $\mathcal{H}_{1,k}$ indicate, respectively, the absence and presence of the primary signal in the k-th subchannel. For each subchannel k, we compute the summary statistic as the sum of received signal energy over an interval of M samples, i.e.,

$$Y_k = \sum_{m=0}^{M-1} |R_k(m)|^2, \qquad k = 0, 1, \ldots, K-1 \quad (6)$$

and the decision rule is given by

$$Y_k \underset{\mathcal{H}_{0,k}}{\overset{\mathcal{H}_{1,k}}{\gtrless}} \gamma_k, \qquad k = 0, 1, \ldots, K-1 \quad (7)$$

where γ_k is the corresponding decision threshold.

For simplicity, we assume that the transmitted signal at each subchannel has unit power, i.e., $\mathbb{E}\left(|S_k|^2\right) = 1$. This assumption holds when primary radios deploy uniform power transmission strategies given no channel knowledge at the transmitter side. According to the central limit theorem [20], Y_k is asymptotically in M normally distributed with mean

$$\mathbb{E}\left(Y_k\right) = \begin{cases} M\sigma_v^2 & \mathcal{H}_{0,k} \\ M\left(\sigma_v^2 + |H_k|^2\right) & \mathcal{H}_{1,k} \end{cases} \quad (8)$$

and variance

$$\text{Var}\left(Y_k\right) = \begin{cases} 2M\sigma_v^4 & \mathcal{H}_{0,k} \\ 2M\left(\sigma_v^2 + 2|H_k|^2\right)\sigma_v^2 & \mathcal{H}_{1,k} \end{cases} \quad (9)$$

for $k = 0, 1, \ldots, K - 1$. Thus, we write these statistics compactly as $Y_k \sim \mathcal{N}\left(\mathbb{E}\left(Y_k\right), \text{Var}\left(Y_k\right)\right), k = 0, 1, \ldots, K-1$.

Using the decision rule in (7), the probabilities of false alarm and detection at subchannel k can be respectively calculated as

$$P_f^{(k)}(\gamma_k) = \Pr\left(Y_k > \gamma_k | \mathcal{H}_{0,k}\right) = Q\left(\frac{\gamma_k - M\sigma_v^2}{\sigma_v^2\sqrt{2M}}\right) \quad (10)$$

and

$$P_d^{(k)}(\gamma_k) = \Pr\left(Y_k > \gamma_k | \mathcal{H}_{1,k}\right) = Q\left(\frac{\gamma_k - M\left(\sigma_v^2 + |H_k|^2\right)}{\sigma_v\sqrt{2M\left(\sigma_v^2 + 2|H_k|^2\right)}}\right) \quad (11)$$

where $Q(\cdot)$ denotes the complementary distribution function of the standard normal distribution.

The choice of the threshold γ_k leads to a tradeoff between the probability of false alarm and the probability of miss[1], $P_m = 1 - P_d$. Specifically, a higher threshold will result in a smaller probability of false alarm and a larger probability of miss, and vice versa.

The probabilities of false alarm and miss have unique implications for cognitive radio networks. Low probabilities of false alarm are necessary in order to maintain possible high throughput in cognitive radio systems, since a false alarm would prevent the unused spectral segments from being accessed by cognitive radios. On the other hand, the probability of miss measures the interference from cognitive radios to the primary users, which should be limited in opportunistic spectrum access. These implications are based on a typical assumption that if primary signals are detected, the secondary users should not use the corresponding channel and that if no primary signals are detected, then the corresponding frequency band will be occupied by secondary users.

III. MULTIBAND JOINT DETECTION

In this section, we present the multiband joint detection framework for wideband spectrum sensing, as illustrated in Fig. 2. The design objective is to find the optimal threshold vector $\boldsymbol{\gamma} = [\gamma_0, \gamma_1, \ldots, \gamma_{K-1}]^T$ so that the cognitive radio system can make efficient use of the unoccupied spectral segments without causing harmful interference to the primary
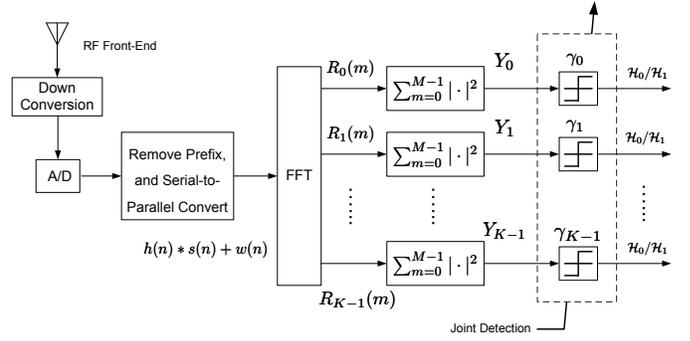
Fig. 2. A schematic representation of multiband joint detection for wideband spectrum sensing in cognitive radio networks.

users. For a given threshold vector $\boldsymbol{\gamma}$, the probabilities of false alarm and detection can be compactly represented as

$$\boldsymbol{P}_f(\boldsymbol{\gamma}) = \left[P_f^{(0)}(\gamma_0), P_f^{(1)}(\gamma_1), \ldots, P_f^{(K-1)}(\gamma_{K-1})\right]^T \quad (12)$$

and

$$\boldsymbol{P}_d(\boldsymbol{\gamma}) = \left[P_d^{(0)}(\gamma_0), P_d^{(1)}(\gamma_1), \ldots, P_d^{(K-1)}(\gamma_{K-1})\right]^T \quad (13)$$

respectively. Similarly, the probabilities of miss can be written in a vector as

$$\boldsymbol{P}_m(\boldsymbol{\gamma}) = \left[P_m^{(0)}(\gamma_0), P_m^{(1)}(\gamma_1), \ldots, P_m^{(K-1)}(\gamma_{K-1})\right]^T \quad (14)$$

where $P_m^{(k)}(\gamma_k) = 1 - P_d^{(k)}(\gamma_k)$, $k = 0, 1, \ldots, K - 1$, compactly written as $\boldsymbol{P}_m(\boldsymbol{\gamma}) = \boldsymbol{1} - \boldsymbol{P}_d(\boldsymbol{\gamma})$, with $\boldsymbol{1}$ the all-one vector.

Consider a cognitive radio sensing the K narrowband subchannels in order to opportunistically utilize the unused ones for transmission. Let r_k denote the throughput achievable over the k-th subchannel if used by cognitive radios, and $\boldsymbol{r} = [r_0, r_1, \ldots, r_{K-1}]^T$. Since $1 - P_f^{(k)}$ measures the opportunistic spectrum utilization of subchannel k, we define the aggregate opportunistic throughput capacity as

$$R(\boldsymbol{\gamma}) = \boldsymbol{r}^T\left[\boldsymbol{1} - \boldsymbol{P}_f(\boldsymbol{\gamma})\right] \quad (15)$$

which is a function of the threshold vector $\boldsymbol{\gamma}$. Due to the inherent trade-off between $P_f^{(k)}(\gamma_k)$ and $P_m^{(k)}(\gamma_k)$, maximizing the sum rate $R(\boldsymbol{\gamma})$ will result in large $\boldsymbol{P}_m(\boldsymbol{\gamma})$, hence causing harmful interference to primary users.

The interference to primary users should be limited in a cognitive radio network. For a widband primary communication system, the impact of interference induced by cognitive devices can be characterized by a relative priority vector over the K subchannels, i.e., $\boldsymbol{c} = [c_0, c_1, \ldots, c_{K-1}]^T$, where c_k indicates the cost incurred if the primary user at subchannel k is interfered with. Suppose that J primary users share a portion of the K subchannels and each primary user occupies a subset S_j. Consequently, we define the aggregate interference to primary user j as $\sum_{i \in S_j} c_i P_m^{(i)}(\gamma_i)$. In special cases where each primary user is equally important, we may have $\boldsymbol{c} = \boldsymbol{1}$.

To summarize, our objective is to find the optimal thresholds $\{\gamma_k\}_{k=0}^{K-1}$ of these K subchannels, collectively maximizing the aggregate opportunistic throughput subject to constraints on the aggregate interference for each primary user and individual constraints on the subbands. As such, the optimization problem for a multi-user primary system can be formulated as

$$\max \quad R(\boldsymbol{\gamma}) \tag{P1}$$
$$\text{s.t.} \quad \sum_{i \in S_j} c_i P_m^{(i)}(\gamma_i) \leq \varepsilon_j, \ j = 0, 1, \ldots, J-1$$
$$\boldsymbol{P}_m(\boldsymbol{\gamma}) \preceq \boldsymbol{\alpha} \tag{16}$$
$$\boldsymbol{P}_f(\boldsymbol{\gamma}) \preceq \boldsymbol{\beta} \tag{17}$$

with the optimization variables $\boldsymbol{\gamma} = [\gamma_0, \gamma_1, \ldots, \gamma_{K-1}]^T$. The constraint (16) limits the interference on each subchannel with $\boldsymbol{\alpha} = [\alpha_0, \alpha_1, \ldots, \alpha_{K-1}]^T$, and the last constraint in (17) dictates that each subchannel should achieve at least a minimum opportunistic spectrum utilization that is proportional to $1 - \beta_k$. For the single-user primary system where all the subchannels are used by one primary user, we have $J = 1$.

Intuitively, we could make some observations on the multiband joint detection. First, the subchannel with a higher opportunistic rate r_k should have a higher threshold γ_k (i.e., a smaller probability of false alarm) so that it can be highly used by cognitive radios. Second, the subchannel that carries a higher priority primary user should have a lower threshold γ_k (i.e., a smaller probability of miss) in order to prevent harmful interference by secondary users. Third, a little compromise on those subchannels carrying less important primary users might boost the aggregate rate considerably. Thus, in the determination of the optimal threshold vector, it is necessary to strike a balance among the channel condition, the opportunistic throughput, and the relative priority of each subchannel.

The objective and constraint functions in (P1) are generally nonconvex, making it difficult to efficiently solve for the global optimum. In most cases, suboptimal solutions or heuristics have to be used. However, we find that this seemingly nonconvex problem can be made convex by reformulating the problem and exploiting the hidden convexity.

We observe the fact that the Q-function is monotonically non-increasing allows us to transform the constraints in (16) and (17) into linear constraints. From (16), we have

$$1 - P_d^{(k)}(\gamma_k) \leq \alpha_k, \qquad k = 0, 1, \ldots, K-1. \tag{18}$$

Substituting (11) into (18) gives

$$\gamma_k \leq \gamma_{\max,k} \qquad k = 0, 1, \ldots, K-1 \tag{19}$$

where

$$\gamma_{\max,k} \triangleq M\left(\sigma_v^2 + |H_k|^2\right) +$$
$$\sigma_v \sqrt{2M\left(\sigma_v^2 + 2|H_k|^2\right)} Q^{-1}(1 - \alpha_k). \tag{20}$$

Similarly, the combination of (10) and (17) leads to

$$\gamma_k \geq \gamma_{\min,k} \qquad k = 0, 1, \ldots, K-1 \tag{21}$$

where

$$\gamma_{\min,k} = \sigma_v^2 \left[M + \sqrt{2M} Q^{-1}(\beta_k)\right]. \tag{22}$$

Consequently, the original problem (P1) has the following equivalent form

$$\min \quad \sum_{k=0}^{K-1} r_k P_f^{(k)}(\gamma_k) \tag{P2}$$
$$\text{s.t.} \quad \sum_{i \in S_j} c_i P_m^{(i)}(\gamma_i) \leq \varepsilon_j, \ j = 0, 1, \ldots, J-1 \tag{23}$$
$$\gamma_{\min,k} \leq \gamma_k \leq \gamma_{\max,k}, \ k = 0, 1, \ldots, K-1. \tag{24}$$

Although the constraint (24) is linear, the problem is still nonconvex. However, it can be furthermore transformed into a tractable convex optimization problem in the regime of low probabilities of false alarm and miss. To establish the transformation, we need the following results.

Lemma 1: The function $P_f^{(k)}(\gamma_k)$ is convex in γ_k if $P_f^{(k)}(\gamma_k) \leq \frac{1}{2}$.

Proof: Taking the second derivative of $P_f^{(k)}(\gamma_k)$ from (10) gives

$$\frac{d^2 P_f^{(k)}(\gamma_k)}{d\gamma_k^2} = \frac{-1}{\sqrt{2\pi}} \frac{d}{d\gamma_k} \exp\left[-\frac{\left(\gamma_k - M\sigma_v^2\right)^2}{4M\sigma_v^4}\right]$$
$$= \frac{\gamma_k - M\sigma_v^2}{2M\sigma_v^2\sqrt{2\pi}} \exp\left[-\frac{\left(\gamma_k - M\sigma_v^2\right)^2}{4M\sigma_v^4}\right]. \tag{25}$$

Since $P_f^{(k)}(\gamma_k) \leq \frac{1}{2}$, we have $\gamma_k \geq M\sigma_v^2$. Consequently, the second derivative of $P_f^{(k)}(\gamma_k)$ is greater than or equal to zero, which implies that $P_f^{(k)}(\gamma_k)$ is convex in γ_k. ∎

Lemma 2: The function $P_m^{(k)}(\gamma_k)$ is convex in γ_k if $P_m^{(k)}(\gamma_k) \leq \frac{1}{2}$.

Proof: This result can be proved using a similar technique to that used to prove Lemma 1. By taking the second derivative of (11), we can show that $P_d^{(k)}(\gamma_k)$ is concave, and hence $P_m^{(k)}(\gamma_k) = 1 - P_d^{(k)}(\gamma_k)$ is a convex function. ∎

Recall that the nonnegative weighted sum of a set of convex functions is also convex [21]. The problem (P1) becomes a convex program if we enforce the following conditions:

$$0 < \alpha_k \leq \frac{1}{2} \ \text{ and } \ 0 < \beta_k \leq \frac{1}{2}, \quad k = 0, 1, 2, \ldots, K-1. \tag{26}$$

This regime of probabilities of false alarm and miss is that of practical interest in cognitive radio networks.

With the conditions in (26), the feasible set of problem (P2) is convex. The optimization problem takes the form of minimizing a convex function subject to a convex constraint, and thus a local maximum is also the global maximum. Efficient numerical search algorithms such as the interior-point method can be used to solve for the optimal solutions [21].

Alternatively, we can formulate the multiband joint detection problem into another optimization problem that minimizes

the interference from cognitive radios to the primary communication system, subject to some constraints on the aggregate opportunistic throughput, i.e.,

$$\text{minimize} \quad \boldsymbol{c}^T \boldsymbol{P}_m(\boldsymbol{\gamma}) \qquad \text{(P3)}$$
$$\text{st.} \quad \boldsymbol{r}^T \left[\boldsymbol{1} - \boldsymbol{P}_f(\boldsymbol{\gamma})\right] \geq \delta$$
$$\boldsymbol{P}_m(\boldsymbol{\gamma}) \preceq \boldsymbol{\alpha}$$
$$\boldsymbol{P}_f(\boldsymbol{\gamma}) \preceq \boldsymbol{\beta}$$

with δ the required minimum aggregated rate and $\boldsymbol{\gamma}$ the optimization variables. Like problem (P1), this problem can be transformed into a convex optimization problem by enforcing the conditions in (26). The result will be illustrated numerically later in Section IV.

IV. Simulation Results

In this section, we numerically evaluate the proposed spectrum sensing schemes. Consider a multiband single-user OFDM system in which a wideband channel is equally divided into 8 subchannels. Each subchannel has a channel gain H_k between the primary user and the cognitive radio, a throughput rate r_k if used by cognitive radios, and a cost coefficient c_k indicating a penalty incurred when the primary signal is interfered with by the cognitive radio. For each subchannel k ($0 \leq k \leq 7$), it is expected that the opportunistic spectrum utilization is at least 50%, i.e., $\beta_k = 0.5$, and the probability that the primary user is interfered with is at most $\alpha_k = 0.1$. For simplicity, it is assumed that the noise power level is $\sigma_v^2 = 1$ and the length of each detection interval is $M = 100$. This example studies multiband joint detection in a single cognitive radio. The proposed spectrum sensing algorithms are examined by comparing with an approach that searches a uniform threshold to maximize the aggregate opportunistic throughput. We randomly generate the channel condition between the primary user and the cognitive radio, the opportunistic throughput over each subchannel, and the cost of interference of each subchannel. One realization example is given in Table I.

We maximize the aggregate opportunistic throughput over the 8 subchannels subject to some constraints on the interference to the primary users, as formulated in (P1). Fig. 3 plots the maximum aggregate opportunistic rates against the aggregate interference to the primary communication system. It can be seen that the multiband joint detection algorithm with optimized thresholds can achieve a much higher opportunistic rate than that achieved by the one with uniform threshold. Note that in the reference algorithm, the uniform threshold is searched to maximize the achievable rate for a fair comparison. That is, the proposed multiband joint detection algorithm makes better use of the wide spectrum by balancing the conflict between improving spectrum utilization and reducing the interference. In addition, it is observed that the aggregate opportunistic rate increases as we relax the constraint on the aggregate interference ε.

An alternative example is depicted in Fig. 4, showing the numerical results of minimizing the aggregate interference subject to the constraints on the opportunistic throughput as

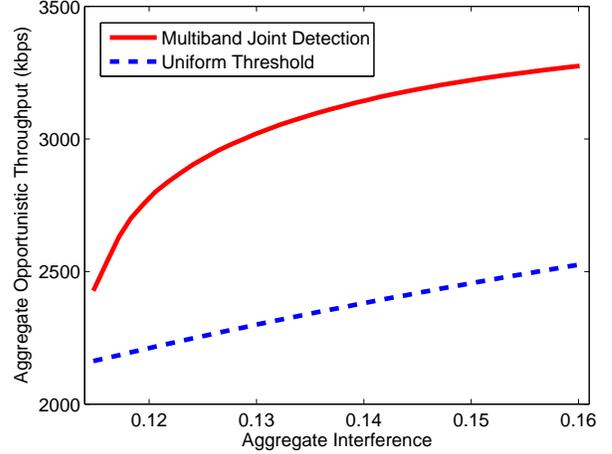| $|H_k|^2$	.50	.30	.45	.65	.25	.60	.40	.70
r (kbps)	612	524	623	139	451	409	909	401
c	1.91	8.17	4.23	3.86	7.16	6.05	0.82	1.30

Fig. 3.   The aggregate opportunistic throughput capacity vs. the constraint on the aggregate interference to the primary communication system.

formulated in (P3). It can be observed that the multiband joint detection strategy outperforms the one using uniform thresholds in terms of the induced interference to the primary users for any given opportunistic throughput. For illustration purposes, the optimized thresholds and the associated probabilities of miss and false alarm are given in Fig. 5 for (P1) and (P3). To summarize, these numerical results show that multiband joint detection can considerably improve the spectrum efficiency by making more efficient use of the spectral diversity.
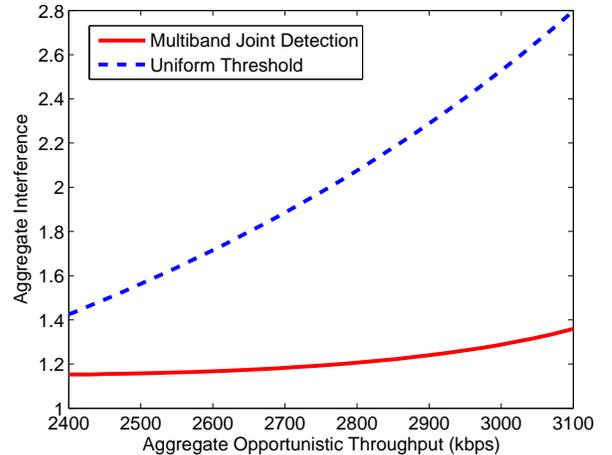

Fig. 4.   The aggregate interference to the primary communication system vs. the constraint on the aggregate opportunistic throughput.
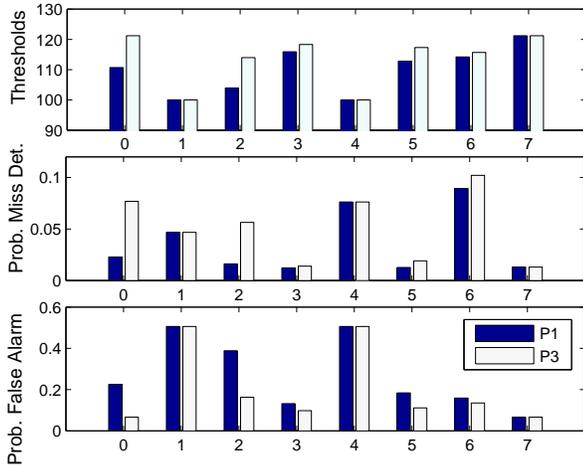
Fig. 5. The optimized thresholds and the associated probabilities of miss and false alarm: (P1) $\varepsilon = 1.25$ and (P3) $\delta = 3224$ kbps.

V. CONCLUSION

In this paper, we have proposed a multiband joint detection approach for wideband spectrum sensing in cognitive radio networks. The basic strategy is to take into account the detection of primary users across a bank of narrowband subchannels jointly rather than to consider only one single band at a time. We have formulated the joint detection problem into a class of optimization problems to improve the spectral efficiency and reduce the interference. By exploiting the hidden convexity in the seemingly nonconvex problems, we have obtained the optimal solution under practical conditions. The proposed spectrum sensing algorithms have been examined numerically and shown to be able to perform well.

ACKNOWLEDGMENT

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