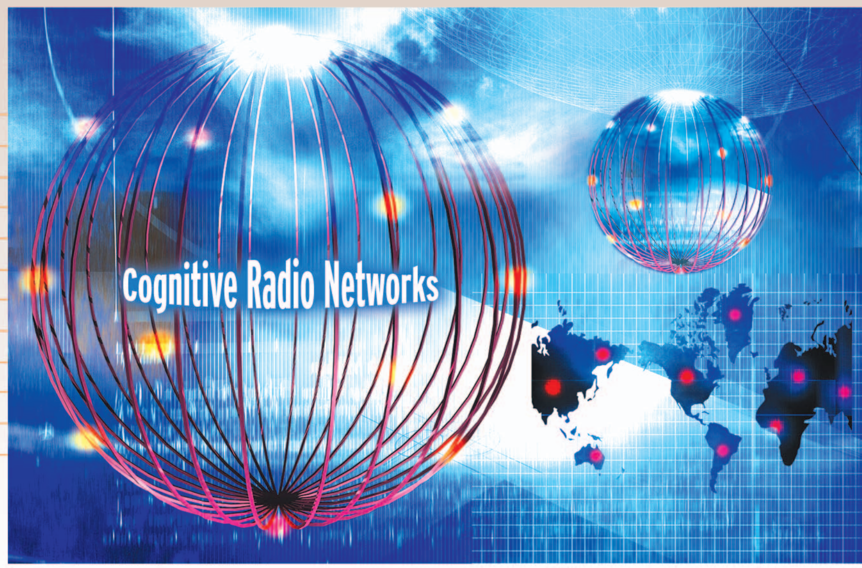
Zhi Quan, Shuguang Cui, H. Vincent Poor, and Ali H. Sayed

Collaborative Wideband Sensing for Cognitive Radios



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An overview of challenges and solutions

Cognitive radio (CR) has recently emerged as a promising technology to revolutionize spectrum utilization in wireless communications. In a CR network, secondary users continuously sense the spectral environment and adapt transmission parameters to opportunistically use the available spectrum. A fundamental problem for CRs is spectrum sensing; secondary users need to reliably detect weak primary signals of possibly different types over a targeted wide frequency band in order to identify spectral holes for opportunistic communications. Conceptually and practically, there is growing awareness that collaboration among several CRs can achieve considerable performance gains. This article provides an overview of the challenges and possible solutions for the design of collaborative wideband sensing in CR networks. It is argued that collaborative spectrum sensing can make use of signal processing gains at the physical layer to mitigate strict requirements on the radio frequency front-end and to exploit spatial diversity through network cooperation to significantly improve sensing reliability.

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COGNITIVE RADIOS

Traditional spectrum allocation policies are facing scarce radio frequency (RF) resources due to the proliferation of wireless services. Recently, the Federal Communications Commission (FCC) is developing policies for unlicensed wireless devices to opportunistically use vacant frequency bands (see Figure 1),

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especially vacant TV broadcast bands [1]. In this context, the emerging CR technology is considered to be a promising technique to improve spectrum utilization by seeking and opportunistically utilizing resources in time, frequency, and space domains without causing harmful interference to legacy systems [2]. In the literature, CR networks are also referred to as next generation (XG) or dynamic spectrum access (DSA) networks [3]. This technology is promising for the friendly coexistence of heterogeneous wireless networks such as cellular networks, wireless personal area networks (PANs), wireless local area networks (LANs), and wireless metropolitan area networks (MANs).

CR technology has already been adopted as a core platform in emerging wireless access standards such as the IEEE 802.22-Wireless Regional Area Networks (WRANs) [4]. The most important application of IEEE 802.22 WRANs is wireless broadband access in rural and remote areas, delivering performance comparable to that of existing broadband access technologies, e.g., digital subscriber line (DSL) and cable modems, serving urban and suburban areas [5], [6]. IEEE 802.22 networks are expected to exploit the unused ultra-high frequency (UHF) TV bands to provide wireless services such as data, voice, audio, and video traffic with appropriate quality of service (QoS) support [7].

CR implementations face many technical challenges, including spectrum sensing, dynamic frequency selection, adaptive modulation, and wideband frequency-agile RF front-end circuitry [8]. These challenges are compounded by the inherent transmission impairments of wireless links, user mobility, nonuniform legacy radio resource allocation policies, and user-dependent economic considerations. We focus on spectrum sensing issues and describe possible solutions for some of the design challenges.

SIGNAL DETECTION FOR SPECTRUM SENSING

Obviously, spectrum sensing is a critical functionality of CR networks; it allows secondary users to detect spectral holes and to opportunistically use under-utilized frequency bands without causing harmful interference to legacy systems. The spectrum sensing problem can be formulated as follows.

To detect a weak primary signal confined inside some a priori known bandwidth B, one could pose a binary hypothesis testing problem as follows:

$$\begin{aligned} \mathcal{H}_0 &: x(n) = v(n) \\ \mathcal{H}_1 &: x(n) = s(n) + v(n), \quad n = 1, 2, \ldots, N, \end{aligned} \tag{1}$$

where $\mathcal{H}_0$ represents the absence of the primary signal, i.e., the received baseband complex signal $x(n)$ contains only additive white Gaussian noise (AWGN), $v(n) \sim \mathcal{CN}(0, \sigma_v^2)$, and $\mathcal{H}_1$ represents the presence of the primary signal, i.e., $x(n)$ consists of a primary signal $s(n)$ corrupted by $v(n)$. Moreover, N corresponds to the number of available measurements. We initially review and comment on three signal detection techniques for spectrum sensing before moving on to motivate collaborative sensing.

ENERGY DETECTION

The noncoherent energy detector (or radiometer) [9] is one of the simplest approaches for deciding between $\mathcal{H}_0$ and $\mathcal{H}_1$. Let $\mathbf{x} = [x(1), x(2), \ldots, x(N)]^T$ and $\mathbf{s} = [s(1), s(2), \ldots, s(N)]^T$. The decision rule in this case is given by

$$T(\mathbf{x}) \triangleq \sum_{n=1}^{N} |x(n)|^2 \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \gamma, \tag{2}$$

where $T(\mathbf{x})$ is the test statistic and γ is the corresponding test threshold. Although $T(\mathbf{x})$ has a chi-square distribution [10], according to the central limit theorem $T(\mathbf{x})$ is asymptotically normally distributed if N is large enough ($N \geq 20$ is often sufficient in practice). Specifically, for large N, we can model the statistics of $T(\mathbf{x})$ as follows:

$$T(\mathbf{x}) \sim \begin{cases} \mathcal{N}\left(N\sigma_v^2,\ 2N\sigma_v^4\right) & \text{under } \mathcal{H}_0 \\ \mathcal{N}\left(N\sigma_v^2 + Np_s,\ 2N\sigma_v^4 + 4N\sigma_v^2 p_s\right) & \text{under } \mathcal{H}_1 \end{cases} \tag{3}$$

where $p_s = \|\mathbf{s}\|^2/N$ represents the average primary signal power. In this way, for large N, the probability of false alarm, P_f,and the probability of detection, P_d, can be approximated as

$$P_f = P(\mathcal{H}_1|\mathcal{H}_0) = Q\left(\frac{\gamma - N\sigma_v^2}{\sigma_v^2\sqrt{2N}}\right) \tag{4}$$

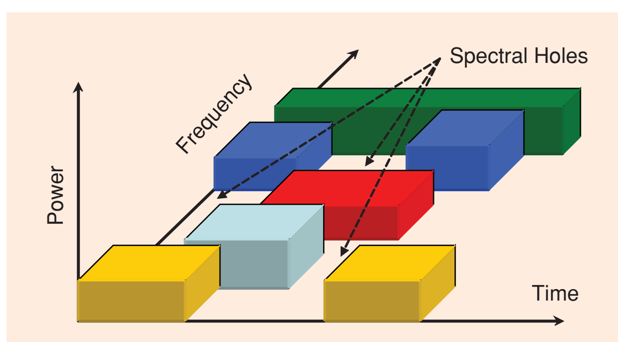
and

$$P_d = P(\mathcal{H}_1|\mathcal{H}_1) = Q\left(\frac{\gamma - N\sigma_v^2 - Np_s}{\sigma_v\sqrt{2N\sigma_v^2 + 4Np_s}}\right), \tag{5}$$

respectively, where

$$Q(x) = \frac{1}{\sqrt{2\pi}} \int_x^{+\infty} e^{-\tau^2/2} d\tau$$

is the tail probability of a zero-mean unit-variance Gaussian random variable.



[FIG1] A conceptual illustration of spectrum utilization over time and frequency. Within a certain geographical region and at a certain time, some frequency bands are not used by legacy systems.

Let

$$\text{SNR} \triangleq \frac{p_s}{\sigma_v^2} = \frac{\|\mathbf{s}\|^2}{N\sigma_v^2}$$

denote the signal-to-noise ratio (SNR). Using relations (4) and (5), it is easy to see that in order to ensure certain values for P_f and P_d, the required number of samples, N, is given by

$$N = 2\left[Q^{-1}(P_f) - Q^{-1}(P_d)\sqrt{1+2\text{SNR}}\right]^2 \text{SNR}^{-2}. \qquad (6)$$

In the large SNR regime (i.e., when SNR $\gg 1$) we conclude that $O(1/\text{SNR})$ samples are needed to meet the desired (P_f, P_d) performance level. (The notation $y = O(g(n))$ signifies that there exits a constant κ such that $\lim_{n\to\infty}(y/g(n)) \le \kappa$.) On the other hand, we see that $O(1/\text{SNR}^2)$ samples are needed in the low SNR regime (i.e., when SNR $\ll 1$). In other words, the energy detector needs a detection time on the order of $O(1/\text{SNR}^2)$ to achieve a desired operating point (P_f, P_d) at low SNR. It is worth noting that when the only known a priori information is the noise power, the energy detector is optimal in terms of the Neyman-Pearson criterion [10].

GIVEN A SINGLE FREQUENCY BAND, THE FIRST CHALLENGE FOR CRs IS TO RELIABLY DETECT THE EXISTENCE OF PRIMARY USERS IN ORDER TO MINIMIZE THE INTERFERENCE TO LICENSED COMMUNICATIONS.

MATCHED FILTER

The coherent detector, also referred to as a matched filter, can improve detection performance if the primary transmitted signal, $\mathbf{s}$, is deterministic and known a priori [10]. The matched filter correlates the known signal $s(n)$ with the unknown received signal $x(n)$, and the decision is made through

$$T(\mathbf{x}) \triangleq \sum_{n=1}^{N} x(n)s^*(n) \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \gamma. \qquad (7)$$

The test statistic $T(\mathbf{x})$ is normally distributed under both hypotheses, i.e.,

$$T(\mathbf{x}) \sim \begin{cases} \mathcal{N}\left(0, Np_s\sigma_v^2\right) & \text{under } \mathcal{H}_0 \\ \mathcal{N}\left(Np_s, Np_s\sigma_v^2\right) & \text{under } \mathcal{H}_1 \end{cases} \qquad (8)$$

and the probabilities of false alarm and detection are now given by

$$P_f = Q\left(\frac{\gamma}{\sigma_v\sqrt{Np_s}}\right) \qquad (9)$$

and

$$P_d = Q\left(\frac{\gamma - Np_s}{\sigma_v\sqrt{Np_s}}\right), \qquad (10)$$

respectively. As before, the required number of samples, N, to achieve an operating point (P_f, P_d) can be found to be

$$N = \left[Q^{-1}(P_f) - Q^{-1}(P_d)\right]^2 \text{SNR}^{-1} = O(1/\text{SNR}). \qquad (11)$$

It is well known that the matched filter structure is the optimal detector that maximizes the SNR in the presence of additive noise if the transmitted signal, $\mathbf{s}$, is known a priori. However, the matched filter is not suitable for spectrum sensing in very low SNR regions since synchronization is difficult to achieve.

FEATURE DETECTION

Feature detection exploits the unique pattern of a specific signal to detect its presence. Most primary signals are modulated sinusoidal carriers, have certain symbol periods, or have cyclic prefixes, which result in built-in periodicity. Hence, cyclostationary feature detection can use the inherent periodicity of primary signals for more accurate detection [11]. The modulated signal, $s(n)$, can be characterized as a wide-sense second-order cyclostationary process since both its mean and autocorrelation exhibit periodicity. Specifically, let

$$\mu_s = E[s(n)]$$

and

$$R_s(n_1, n_2) = E[s(n_1)s^*(n_2)].$$

Then, for all n, n_1, and n_2, it holds that

$$\mu_s(n) = \mu_s(n + T_0)$$

and

$$R_s(n_1, n_2) = R_s(n_1 + T_0, n_2 + T_0),$$

where $T_0 > 0$ is a fundamental period. The cyclic autocorrelation function of a wide-sense second-order cyclostationary process with cyclic frequency $\alpha \neq 0$ is defined as

$$R_s^\alpha(m) \triangleq E[s(n)s^*(n+m)e^{-2\pi\alpha n}], \qquad (12)$$

which has the following property [12]:

$$R_s^\alpha(m) = \begin{cases} \text{finite} & \text{if } \alpha = i/T_0, \\ 0 & \text{otherwise} \end{cases} \qquad (13)$$

for any nonzero integer i. Thus, for a cyclostationary process $\{s(n)\}$, there exists an $\alpha \neq 0$ such that $R_s^\alpha(m) \neq 0$ for some value of m. The corresponding representation of $R_s^\alpha(m)$ in the frequency domain, referred to as the spectral correlation function, can be obtained through the discrete time Fourier transformation (DTFT)

COGNITIVE RADIO HAS RECENTLY EMERGED AS A PROMISING TECHNOLOGY TO REVOLUTIONIZE SPECTRUM UTILIZATION IN WIRELESS COMMUNICATIONS.

$$S_s^\alpha(e^{j\omega}) = \sum_{m=-\infty}^{+\infty} R_s^\alpha(m) e^{-j\omega m}, \quad (14)$$

where $\omega \in [-\pi, \pi]$ is the digital frequency corresponding to the sampling rate F_s.

The binary hypothesis test (1) can then be replaced by

$$\begin{aligned} \mathcal{H}_0 &: S_x^\alpha(e^{j\omega}) = S_v^\alpha(e^{j\omega}) \\ \mathcal{H}_1 &: S_x^\alpha(e^{j\omega}) = S_s^\alpha(e^{j\omega}) + S_v^\alpha(e^{j\omega}). \end{aligned} \quad (15)$$

Since the noise $v(n)$ is in general not periodic, we have $S_v^\alpha(e^{j\omega}) = 0$ for $\alpha \neq 0$.For a finite observation time N, an estimate for the spectral correlation function at $\omega = 2\pi k/L$ can be obtained as

$$\hat{S}_x^\alpha(k) = \frac{1}{N} \sum_{n=1}^{N} X_L\left(n, k + \frac{k_\alpha}{2}\right) X_L^*\left(n, k - \frac{k_\alpha}{2}\right), \quad (16)$$

where

$$X_L(n,k) = \frac{1}{\sqrt{L}} \sum_{l=n-L/2}^{n+L/2-1} x(l) e^{-j2\pi kl/L} \quad (17)$$

is the L-point discrete Fourier transform (DFT) around the nth sample of the received signal, and $k_\alpha = \alpha L/F_s$ is the index of the frequency bin corresponding to the cyclic frequency α. Suppose that the ideal spectral correlation function, $S_s^\alpha(k)$, is known a priori. The test statistic is then given by a single-cycle detector [13]

$$T_{sc}(\mathbf{x}) = \sum_{k=0}^{L-1} \hat{S}_x^\alpha(k) \left[S_s^\alpha(k)\right]^* \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \gamma, \quad (18)$$

or a multicycle detector

$$T_{mc}(\mathbf{x}) = \sum_\alpha \sum_{k=0}^{L-1} \hat{S}_x^\alpha(k) \left[S_s^\alpha(k)\right]^* \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \gamma, \quad (19)$$

where the sum is taken over all α's for which $S_s^\alpha(k)$ is not identically zero.

The performance of the cyclostationary feature detector in terms of P_f and P_d is generally mathematically intractable. One has to turn to Monte Carlo simulations to evaluate the performance and identify the optimal threshold [13]. The cyclostationary feature detector is noncoherent due to its quadratic transform, but its coherent detection of features results in a processing gain with respect to the energy detector if the noise power is known.

Since CRs usually have limited knowledge about the primary signals, energy detection becomes a most important technique for spectrum sensing. The more sophisticated techniques (coherent detection and feature detection) can be used for sensing refinement or signal classification if more a priori knowledge about the primary signal is available [14], [15]. In the rest of this article, we will focus primarily on energy detection and show how collaborative sensing strategies can be useful in improving the performance.

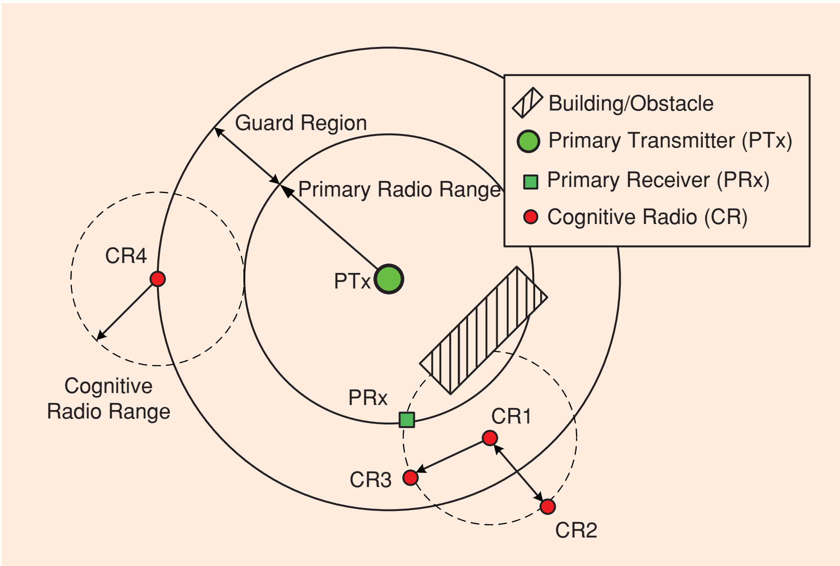
DESIGN CHALLENGES FOR SPECTRUM SENSING

We will consider two main challenges faced by spectrum sensing: reliable sensing and wideband sensing.

RELIABLE SPECTRUM SENSING

Given a single frequency band, the first challenge for CRs is to reliably detect the existence of primary users to minimize the interference to existing communications. Since the signals are usually undermined by channel shadowing or multipath fading between the target-under-detection and the CRs, it is generally difficult to distinguish between a white spectrum and a weak signal attenuated by a bad channel. Fading or shadowing may result in the hidden terminal problem, as illustrated in Figure 2, where one CR node (CR1) inside the protection region of a primary transmitter (PTx) cannot detect the primary signal due to shadowing; in this case, CR1 may assume that it is outside the protection region of PTx and may cause harmful interference by transmitting in the primary frequency band.

To prevent the hidden terminal problem, the CR network could fuse the sensing results of multiple CRs and exploit spatial diversity among distributed CRs to enhance the sensing reliability [8], [16]. In this way, a network of spatially distributed CRs, which experience different channel conditions from the target, would have a better chance of detecting the primary radio by exchanging sensing information. Therefore, collaborative spectrum sensing can alleviate the problem of corrupted detection by exploiting the built-in spatial diversity to reduce the probability of interfering with primary users. Since collaborative sensing is generally coordinated over a control channel, efficient cooperation schemes should be investigated to reduce bandwidth and power requirements while optimizing the sensing reliability. Important design



[FIG2] The hidden terminal problem in CR networks, in which the guard region and the area covered by the primary radio range together form the protection region of the primary transmitter.

considerations include the overhead reduction associated with sensing information exchange and the feasibility issue of control channels. In general, operating characteristics (such as false alarm versus missed detection probabilities) of the detector should be selected by considering the achievable opportunistic throughput of secondary users and the probability of colliding with primary users.

HIGH-RESOLUTION WIDEBAND SENSING

Another critical challenge for CR systems is to monitor and process ultra-wide frequency bands (up to several gighertz) in order to reliably find spectral holes for opportunistic spectrum access. Such a requirement presents unique challenges to both hardware design at the RF front-end and the development of reliable signal processing algorithms. First, spectrum sensing requires a wideband RF front-end with a high-resolution high-speed analog-to-digital (A/D) converter, which is expensive to implement [17]. In addition, spectrum sensing should accurately identify both occupied and unoccupied frequency segments in real time to improve spectrum utilization and avoid introducing harmful interference to the primary radios. These observations motivate the need for efficient wideband spectrum sensing algorithms that can mitigate the severe requirements on the RF front-end circuitry and enable CRs to maximize the opportunistic throughput in an interference-limited secondary network.

The existing literature on wideband spectrum sensing for CR networks is limited. One known approach is to use a tunable narrowband bandpass filter (BPF) at the RF front-end to sense one band at a time [18], over which 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 spectrum sensing usually involves the estimation of the power spectral density (PSD) of the wideband signal. In [19] and [20], a wavelet transform was used to estimate the PSD over a wide frequency range given its multiresolution features. However, these previous works do not consider joint decisions over multiple frequency bands, which is essential for implementing efficient wideband CR systems.

This article will discuss practical solutions for wideband spectrum sensing in CR systems. In particular, we introduce a wideband sensing technique, termed multiband joint detection (MJD) [21]. This technique, instead of considering one frequency band at a time, takes into account the detections of primary signals across multiple frequency bands and enables secondary users to make better overall decisions to optimize the CR system performance such as the aggregate opportunistic throughput. Moreover, collaboration among multiple spatially distributed CRs can relax the sensitivity constraint on the RF front-end by enhancing the detection signal energy at the fusion center and may even broaden the frequency range of spectrum sensing.

NARROWBAND COLLABORATIVE SENSING FRAMEWORKS

We start with the collaborative spectrum sensing problem over a single narrow band. Consider a CR network with M secondary users. User i $(i = 1, 2, \ldots, M)$ collects N measurements and formulates the binary hypothesis test problem:

$$\begin{aligned} \mathcal{H}_0 &: x_i(n) = v_i(n) \\ \mathcal{H}_1 &: x_i(n) = h_i s(n) + v_i(n), \end{aligned} \quad (20)$$

where h_i is the channel gain between the PTx and the ith secondary user, and $v_i(n) \sim \mathcal{CN}(0, \sigma_i^2)$ is the noise at the ith CR receiver. Without loss of generality, it is assumed that h_i is constant during the detection interval (N samples) and the value of N should be much less than the coherence time of the channel between the primary transmitter and the secondary receivers. With energy detection, secondary user i $(i = 1, 2, \ldots, M)$ uses the following decision rule:

$$T_i(\mathbf{x}_i) \triangleq \sum_{n=1}^{N} |x_i(n)|^2 \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \gamma_i, \quad (21)$$

where $\mathbf{x}_i = [x_i(1), x_i(2), \ldots, x_i(N)]^T$, $T_i(\mathbf{x}_i)$ measures the total energy, and γ_i is the local threshold at the ith secondary user.

To evaluate the sensing performance, we define the probability of detecting the spectral hole as

$$P(\mathcal{H}_0 \mid \mathcal{H}_0) = 1 - P_f$$

and the probability of interference as

$$P(\mathcal{H}_0 \mid \mathcal{H}_1) = 1 - P_d,$$

where P_f and P_d denote the probabilities of false alarm and detection, respectively. Specifically, $P(\mathcal{H}_0|\mathcal{H}_0)$ is the probability that the secondary users successfully identify the unoccupied spectral segment and is an important measure of opportunistic spectrum utilization. Likewise, assuming that the CRs always transmit in spectral segments on which they do not detect primary signals, the quantity $P(\mathcal{H}_0|\mathcal{H}_1)$ measures the probability that the secondary users cause harmful interference to the primary users. Of course, $P(\mathcal{H}_0|\mathcal{H}_1)$ is simply the probability of a missed detection.

TRADITIONAL SPECTRUM ALLOCATION POLICIES FACE SCARCE RADIO FREQUENCY RESOURCES DUE TO THE PROLIFERATION OF WIRELESS SERVICES.

Our objective is to design efficient cooperation schemes for the M spatially distributed nodes to improve the sensing reliability, i.e., to maximize $P(\mathcal{H}_0|\mathcal{H}_0)$ while maintaining $P(\mathcal{H}_0|\mathcal{H}_1)$ as small as possible. In practice, collaborative spectrum sensing can be implemented in either a centralized or distributed manner, as shown in Figure 3. The centralized implementation uses a fusion center to fuse the sensing results from multiple CRs and arrive at the final decision. In the distributed case, each CR collects the sensing results from its neighbors and performs its own local decision fusion. Collaborative spectrum sensing can achieve different levels of performance by exchanging different amounts of data: hard decisions and summary statistics (soft decisions).

HARD DECISION FUSION

With hard decision fusion, each CR makes a local decision about the presence of primary users and then sends the binary decision (i.e., a single bit) to the fusion center for decision fusion. The voting rule [22] is one of the simplest suboptimal fusion rules that can be used; it counts the number of nodes that vote for the presence of the signal and compares the vote to a given threshold. Alternatively, the OR logic operation can be used to combine decisions from several secondary users [23], where the fusion center decides $\mathcal{H}_1$ if any one of the users claims that $\mathcal{H}_1$ is true. Likewise, an AND logic operation can be used [24], which decides $\mathcal{H}_1$ if, and only if, all the nodes claim that $\mathcal{H}_1$ is true. Considering the case of correlated noises, these three decision fusion schemes were numerically evaluated with the assumption of identical thresholds at individual nodes in [25].

It is known that approaches based on the likelihood-ratio test (LRT) provide the optimal performance according to the Neyman-Pearson criterion [9], [10]. Denote the decisions from the individual nodes by a binary vector $\mathbf{u} = [u_1, u_2, \ldots, u_M]^T$, where

$$u_i = \begin{cases} 0 & \text{if the } i\text{th node decides } \mathcal{H}_0 \\ 1 & \text{if the } i\text{th node decides } \mathcal{H}_1. \end{cases} \tag{22}$$

Let $P(\mathbf{u}|\mathcal{H}_0)$ and $P(\mathbf{u}|\mathcal{H}_1)$, respectively, represent the probability distribution functions of $\mathbf{u}$ under hypotheses $\mathcal{H}_0$ and $\mathcal{H}_1$. Then the LRT detector is given by

$$L(\mathbf{u}) = \frac{P(\mathbf{u}|\mathcal{H}_1)}{P(\mathbf{u}|\mathcal{H}_0)} \mathop{\gtrless}_{\mathcal{H}_0}^{\mathcal{H}_1} \gamma^* \tag{23}$$

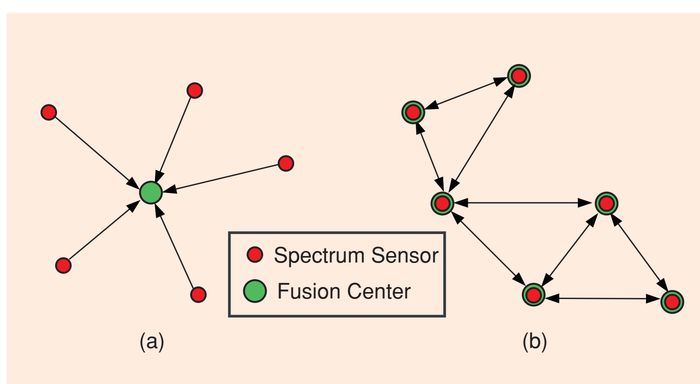
where γ^* is the optimal threshold determined by the targeted probability of detecting the spectral hole. Computing the optimal local decision thresholds $\{\gamma_i\}$ under the Neyman-Pearson criterion is mathematically untractable, and the problem becomes NP-complete if the measurements at the individual nodes are correlated [26], [27]. Hence, one must turn to suboptimal solutions [28]. Note that the hard decision fusion schemes require minimum bandwidth for the control channel but need a local detector at each CR.

SUMMARY STATISTICS COMBINATION

To avoid optimizing the local thresholds $\{\gamma_i\}$ for binary decision fusion, the nodes can instead send the summary statistics $\mathbf{y} \triangleq [T_1(\mathbf{x}_1), T_2(\mathbf{x}_2), \ldots, T_M(\mathbf{x}_M)]^T$ to the fusion center in which an optimal test can be performed as

$$L(\mathbf{y}) = \frac{P(\mathbf{y}|\mathcal{H}_1)}{P(\mathbf{y}|\mathcal{H}_0)} \mathop{\gtrless}_{\mathcal{H}_0}^{\mathcal{H}_1} \gamma^*, \tag{24}$$

where γ^* again denotes the optimal threshold selection as determined by the desired probability of detecting spectral holes.



[FIG3] Data fusion for cooperative sensing. (a) In centralized implementation, the sensing results of individual CRs are sent to a fusion center in which a global decision is made. (b) In distributed implementation, each CR acts as a fusion center, collecting the sensing measurements from its neighboring nodes and making its decision independently.

From the central limit theorem, it can be argued that $\mathbf{y}$ is asymptotically normally distributed for large N [10], say $\mathbf{y} \sim \mathcal{N}(\boldsymbol{\mu}_0, \boldsymbol{\Sigma}_0)$ under $\mathcal{H}_0$ and $\mathbf{y} \sim \mathcal{N}(\boldsymbol{\mu}_1, \boldsymbol{\Sigma}_1)$ under $\mathcal{H}_1$. With energy detection, we have from (3) that

$$\boldsymbol{\mu}_0 = N\left[\sigma_{v_1}^2 \ \sigma_{v_2}^2 \ \cdots \ \sigma_{v_M}^2\right]^T$$

and

$$\boldsymbol{\Sigma}_0 = 2N \begin{bmatrix} \sigma_{v_1}^4 & & \\ & \ddots & \\ & & \sigma_{v_M}^4 \end{bmatrix}$$

for hypothesis $\mathcal{H}_0$, and that

$$\boldsymbol{\mu}_1 = N\left[\sigma_{v_1}^2 + p_{s_1} \ \sigma_{v_2}^2 + p_{s_2} \cdots \sigma_{v_M}^2 + p_{s_M}\right]^T$$

and

$$\boldsymbol{\Sigma}_1 = 2N \begin{bmatrix} \sigma_{v_1}^2 \ (\sigma_{v_1}^2 + 2p_{s_1}) & & \\ & \ddots & \\ & & \sigma_{v_M}^2 \ (\sigma_{v_M}^2 + 2p_{s_M}) \end{bmatrix}$$

for hypothesis $\mathcal{H}_1$. Please note that $\boldsymbol{\Sigma}_0$ and $\boldsymbol{\Sigma}_1$ are positive semi-definite matrices, denoted by $\boldsymbol{\Sigma}_0 \succeq 0$ and $\boldsymbol{\Sigma}_1 \succeq 0$.

The statistics of $\mathbf{y}$ under both hypotheses $\mathcal{H}_0$ and $\mathcal{H}_1$ can be estimated in practice. For $\mathcal{H}_0$, the noise power $\{\sigma_{v_i}^2\}_{i=1}^M$ can be calibrated in a given band when it is known for sure that it is not being used. The information about the deterministic quiet periods is usually available in TV bands (e.g., TV channel 37 is currently always empty) [27]. For $\mathcal{H}_1$, the statistics can be learned a priori during the period when the primary transmitter was known for sure to be working. Again, obtaining such a priori information about the primary signal is possible since most current TV stations transmit pilot signals periodically at a fixed power level. This method is also applicable to the downlinks of certain cellular networks, where base stations periodically transmit pilot signals at known power levels. The received primary signal power p_{s_i} can be estimated by subtracting the noise power $\sigma_{v_i}^2$ from the total received power at the ith node during the period when we know for certain that the primary user is transmitting since the primary signal is generally independent of the noise.

The diagonal covariance matrices $\boldsymbol{\Sigma}_0$ and $\boldsymbol{\Sigma}_1$ imply that the statistics received at the fusion center are independent of each other. This assumption is reasonable for IEEE 802.22 networks, whose service coverage has a radius of 33–100 km and in which consumer premise equipments (CPEs) are usually separated far away. One would like to further model the correlation between these statistics provided that sufficient channel information is available.

Given the distributions of $\mathbf{y}$ (24) becomes

$$\frac{P(\mathbf{y}|\mathcal{H}_1)}{P(\mathbf{y}|\mathcal{H}_0)} = \frac{\det^{-\frac{1}{2}}(\boldsymbol{\Sigma}_1)\exp\left[-\frac{1}{2}(\mathbf{y}-\boldsymbol{\mu}_1)^T\boldsymbol{\Sigma}_1^{-1}(\mathbf{y}-\boldsymbol{\mu}_1)\right]}{\det^{-\frac{1}{2}}(\boldsymbol{\Sigma}_0)\exp\left[-\frac{1}{2}(\mathbf{y}-\boldsymbol{\mu}_0)^T\boldsymbol{\Sigma}_0^{-1}(\mathbf{y}-\boldsymbol{\mu}_0)\right]} \quad (25)$$

A FUNDAMENTAL PROBLEM FOR COGNITIVE RADIO IS SPECTRUM SENSING.

where $\det(\mathbf{A})$ denotes the determinant of the matrix $\mathbf{A}$. By taking the natural logarithm, the LRT detector $L(\mathbf{y})$ can be simplified into a quadratic form:

$$L_q(\mathbf{y}) = \mathbf{y}^T\left(\boldsymbol{\Sigma}_0^{-1} - \boldsymbol{\Sigma}_1^{-1}\right)\mathbf{y} + 2\left(\boldsymbol{\mu}_1^T\boldsymbol{\Sigma}_1^{-1} - \boldsymbol{\mu}_0^T\boldsymbol{\Sigma}_0^{-1}\right)\mathbf{y}. \quad (26)$$

Since this LRT-based fusion usually involves nonlinear (quadratic) operations, performance analysis and threshold optimization continue to be a complex task.

Alternatively, a simpler detector structure can be used by linearly combining the local energy levels from the individual CRs for global decision making [30]. Specifically, the test statistic can be chosen to be of the form

$$L_l(\mathbf{y}) = \mathbf{w}^T\mathbf{y} \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \gamma, \quad (27)$$

where $\mathbf{w}$ is a weight vector (to be chosen) representing the contribution of the individual nodes to the global decision. For example, if a node generates a high SNR observation that is more likely to result in a correct decision, then it should be assigned a larger weighting coefficient. Since the linear combination of several Gaussian random variables is still Gaussian, the performance of the linear detector (27) can be evaluated as

$$P(\mathcal{H}_0|\mathcal{H}_0) = 1 - Q\left(\frac{\gamma - \boldsymbol{\mu}_0^T\mathbf{w}}{\sqrt{\mathbf{w}^T\boldsymbol{\Sigma}_0\mathbf{w}}}\right) \quad (28)$$

and

$$P(\mathcal{H}_0|\mathcal{H}_1) = 1 - Q\left(\frac{\gamma - \boldsymbol{\mu}_1^T\mathbf{w}}{\sqrt{\mathbf{w}^T\boldsymbol{\Sigma}_1\mathbf{w}}}\right). \quad (29)$$

We can then pose the problem of maximizing the probability of detecting the spectral hole (i.e., the opportunistic spectrum utilization of the targeted frequency band) subject to a constraint on the interference probability. (Depending on the specific application, one may formulate an alternative optimization problem that minimizes $P(\mathcal{H}_0|\mathcal{H}_1)$ subject to a constraint on $P(\mathcal{H}_0|\mathcal{H}_0)$. Mathematically, this alternative problem belongs to the same category as (30) and can be solved using the algorithms developed in this article with trivial modifications.) The problem can be formulated as

$$\begin{aligned} \max_{\gamma, \mathbf{w}} \quad & P(\mathcal{H}_0|\mathcal{H}_0) \\ \text{s.t.} \quad & P(\mathcal{H}_0|\mathcal{H}_1) \leq \varepsilon. \end{aligned} \tag{30}$$

Since the Q-function (6) is monotonically decreasing (see Figure 4), it can be shown that the weight vector w and the threshold γ can be jointly optimized by solving an unconstrained optimization problem of the form [30]:

$$\max_{\mathbf{w}} \quad f(\mathbf{w}) = \frac{Q^{-1}(1-\varepsilon)\sqrt{\mathbf{w}^T \boldsymbol{\Sigma}_1 \mathbf{w}} + (\boldsymbol{\mu}_1 - \boldsymbol{\mu}_0)^T \mathbf{w}}{\sqrt{\mathbf{w}^T \boldsymbol{\Sigma}_0 \mathbf{w}}} \tag{31}$$

with

$$\gamma = Q^{-1}(1-\varepsilon)\sqrt{\mathbf{w}^T \boldsymbol{\Sigma}_1 \mathbf{w}} + \boldsymbol{\mu}_1^T \mathbf{w}. \tag{32}$$

Directly solving problem (31) is difficult. Nevertheless, we can apply a divide-and-conquer strategy to divide the problem into several subproblems and then consolidate their solutions [30]. First, we consider the case where $f(\mathbf{w}) \geq 0$, i.e., $P(\mathcal{H}_0|\mathcal{H}_0) \geq 1/2$, and the CR system is *aggressive* in seeking spectral holes for opportunistic transmission. The unconstrained problem (31) is actually equivalent to the following constrained optimization problem:

$$\begin{aligned} \max_{\mathbf{z}} \quad & Q^{-1}(1-\varepsilon)\sqrt{\mathbf{z}^T \boldsymbol{\Sigma}_1 \mathbf{z}} + (\boldsymbol{\mu}_1 - \boldsymbol{\mu}_0)^T \mathbf{z} \\ \text{s.t.} \quad & \mathbf{z}^T \boldsymbol{\Sigma}_0 \mathbf{z} \leq 1 \end{aligned} \tag{33}$$

where

$$\mathbf{z} = \frac{\mathbf{w}}{\sqrt{\mathbf{w}\boldsymbol{\Sigma}_0 \mathbf{w}}}. \tag{34}$$

For $Q^{-1}(1-\varepsilon) \leq 0$ (i.e., $\varepsilon \leq 1/2$), the above problem is a convex optimization problem that can be easily solved [31]. For $\varepsilon > 1/2$ and $Q^{-1}(1-\varepsilon) > 0$, problem (33) becomes one of maximizing a convex function (or minimizing a concave function) over an ellipsoid, which can be efficiently solved through an iterative algorithm using quadratic-constraint quadratic-programming (QCQP) reformulations [30].

Now consider the case in which $f(\mathbf{w}) < 0$, i.e., $P(\mathcal{H}_0|\mathcal{H}_0) < 1/2$, where the CR system is *conservative* in sharing the spectrum with primary users. Problem (31) becomes equivalent to

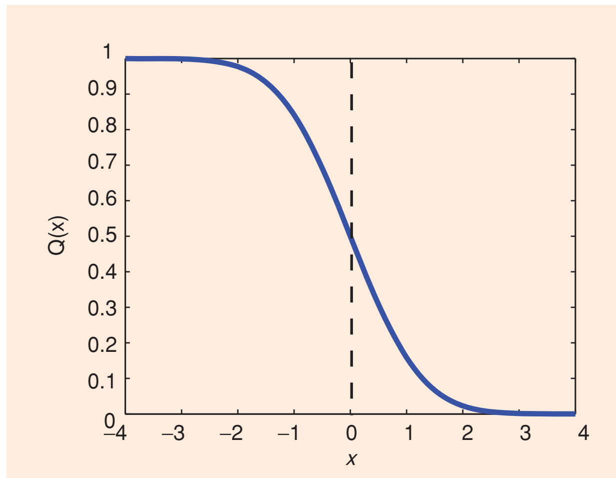
$$\begin{aligned} \max_{\mathbf{z}} \quad & Q^{-1}(1-\varepsilon)\sqrt{\mathbf{z}^T \boldsymbol{\Sigma}_1 \mathbf{z}} + (\boldsymbol{\mu}_1 - \boldsymbol{\mu}_0)^T \mathbf{z} \\ \text{s.t.} \quad & \mathbf{z}^T \boldsymbol{\Sigma}_0 \mathbf{z} \geq 1 \end{aligned} \tag{35}$$

which can also be solved using the iterative alogrithm developed in [30]. Thereafter, a faster algorithm exploiting semidefinite programming (SDP) to solve such nonconvex optimization problems has been developed in [32].

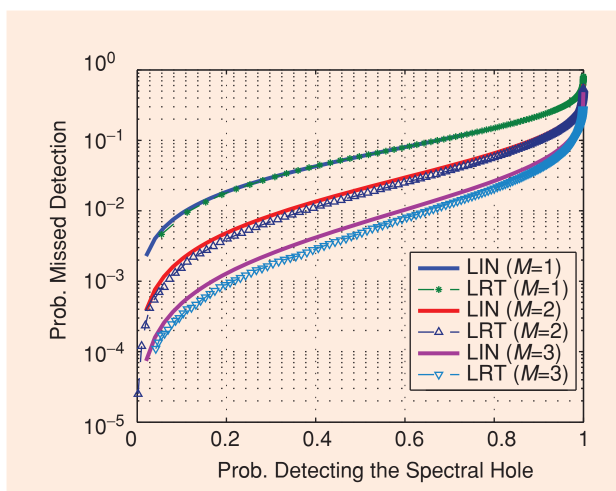
Compared with the optimal LRT detector (26), the linear structure (27) is simple and efficient. As shown in Figure 5, the optimal linear detector (27) can provide performance comparable to the optimal LRT-based scheme (26). In general, the combination of summary statistics from the spatially distributed nodes yields gains over hard-decision fusion but requires a relatively higher bandwidth for the control channel. Other suboptimal linear fusion rules such as maximum deflection combining and maximum ratio combining for collaborative sensing can be found in [30], [33] and [34].

COLLABORATIVE WIDEBAND SENSING

In a particular geographical region and at a particular time, some licensed frequency bands might not be used by the primary users and are available for opportunistic spectrum access. For example, the ultra high frequency (UHF) bands



[FIG4] The Q-function is monotonically decreasing; it is concave if $x \leq 0$ and convex if $x > 0$.



[FIG5] The probability of interference versus the probability of detecting spectral holes for $M = 1$, 2, and 3. The primary signal is a BPSK signal with $N = 20$. The SNR levels are respectively (-1), $(-1, -2)$, and $(-1, -1, -3)$ in decibels.

from 470 to 890 MHz are reserved for TV broadcasting channels, each with a bandwidth of 6 MHz, but some of them are empty at a particular time and location. Wideband spectrum sensing is thus critical since the CRs need to detect spectral holes from such an ultra-wide frequency band for opportunistic communications.

The sensing techniques discussed so far are applicable to a single frequency band, for which a BPF is needed to extract the target signal. Deploying the narrowband detector for wideband spectrum sensing requires a tunable BPF at the RF front end to scan one band at a time. This mechanism is slow and inflexible. To improve the sensing agility (e.g., processing multiple bands in parallel), efficient wideband sensing algorithms become a necessity in the design of wideband CR systems.

[THIS ARTICLE HAS SURVEYED THE EXISTING COLLABORATIVE SPECTRUM SENSING TECHNIQUES.]

We will describe a cross-layer design principle for collaborative wideband sensing, in which spectrum sensing at the physical (PHY) layer, and the maximization of opportunistic throughput at higher layers, are integrated into a unified framework based on the multiband joint detection (MJD) scheme introduced in [21] and [35]. Unlike the traditional spectrum sensing techniques that scan one band at a time, multiband joint detection jointly processes multiple narrow frequency bands from a network of spatially distributed CRs. Within the collaborative wideband sensing framework, the multiband joint detection is formulated into a class of optimization problems, which maximize the aggregate opportunistic throughput of the CR system subject to certain constraints on the spectrum utilization of individual bands and interference to the primary users [35]. The wideband sensing strategy enables secondary users to efficiently take advantage of the unused frequency bands in an interference-limited CR network.

MULTIBAND JOINT DETECTION

Consider a primary communication system operating over a wideband channel that is divided into K nonoverlapping narrow subbands. At a particular time and in a geographical location, some of the K subchannels might not be used by the primary users and are available for opportunistic communication by secondary users. To monitor the activities of the K subbands, the wideband signal is transformed into the frequency domain (say, via an FFT) and the signal energy at each subband is then measured.

The wideband spectrum sensing technique will jointly optimize a bank of narrowband detectors instead of processing only one narrow band at a time [35]. The objective is to maximize the aggregate opportunistic throughput of a CR network subject to some interference constraints. We model the detection problem on subband k as one of choosing between $\mathcal{H}_{0,k}$ ("0"), which represents the absence of the primary signal in subband k, and $\mathcal{H}_{1,k}$ ("1"), which represents the presence of the primary signal in subband k. To decide whether the kth subband is occupied or not, we again test the following two hypotheses:

$$\begin{aligned}&\mathcal{H}_{0,k} : X_k(n) = V_k(n)\\ &\mathcal{H}_{1,k} : X_k(n) = H_k S_k(n) + V_k(n), \quad k = 1, 2, \ldots, K, \end{aligned} \tag{36}$$

where $X_k(n)$ is the received signal, $V_k(n)$ represents the additive channel noise, H_k signifies the channel gain, and $S_k(n)$ stands for the primary transmitted signal (the capital letters refers to frequency domain signals). Let $\mathrm{X}_k = [X_k(1), X_k(2), \ldots, X_k(N)]$. Using energy detection, the decision rule is given by

$$T_k(\mathrm{X}_k) \triangleq \sum_{n=1}^{N} |X_k(n)|^2 \underset{\mathcal{H}_{0,k}}{\overset{\mathcal{H}_{1,k}}{\gtrless}} \gamma_k, \quad k = 1, 2, \ldots, K, \tag{37}$$

where γ_k is the decision threshold of subband k. As before, the sensing performance of (37) at subband k can be measured in terms of the probability of detecting the spectral hole, $P(\mathcal{H}_{0,k}|\mathcal{H}_{0,k}, \gamma_k)$, and the probability of interference, $P(\mathcal{H}_{0,k}|\mathcal{H}_{1,k}, \gamma_k)$, which are both functions of the threshold γ_k. For both hypotheses, $T_k(\mathrm{X}_k)$ has a chi-square distribution with N degrees of freedom. To simplify the analysis, we again apply the central limit theorem to approximate $T_k(\mathrm{X}_k)$ with a Gaussian random variable when N is large as before, i.e., $T_k(\mathrm{X}_k) \sim \mathcal{N}(\mu_{0,k}, \sigma_{0,k}^2)$ under $\mathcal{H}_{0,k}$ and $T_k(\mathrm{X}_k) \sim \mathcal{N}(\mu_{1,k}, \sigma_{1,k}^2)$ under $\mathcal{H}_{1,k}$. Under the decision rule (37), the sensing performance of subband k can be evaluated by

$$P(\mathcal{H}_{0,k}|\mathcal{H}_{0,k}, \gamma_k) = 1 - Q\left(\frac{\gamma_k - \mu_{0,k}}{\sigma_{0,k}}\right) \tag{38}$$

and

$$P(\mathcal{H}_{0,k}|\mathcal{H}_{1,k}, \gamma_k) = 1 - Q\left(\frac{\gamma_k - \mu_{1,k}}{\sigma_{1,k}}\right). \tag{39}$$

The design objective is to find the optimal threshold vector $\boldsymbol{\gamma} = [\gamma_1, \gamma_2, \ldots, \gamma_K]^T$ such that the CR network can opportunistically use the unused spectral segments in an efficient way without causing harmful interference to primary users. Due to channel frequency diversity [36], a secondary user may experience different channel conditions (e.g., channel gain, interference, and noise) across the K subbands. For a CR exploiting the K narrowband subbands for opportunistic transmission, the supported throughput vector is denoted by $\boldsymbol{r} = [r_1, r_2, \ldots, r_K]^T$, which are the rates achievable when the bands are available to use. Therefore, as a spectrum efficiency measure, the aggregate opportunistic throughput of the CR system can be defined as

$$R(\boldsymbol{\gamma}) \triangleq \sum_{k=1}^{K} r_k P(\mathcal{H}_{0,k}|\mathcal{H}_{0,k}, \gamma_k). \qquad (40)$$

On the other hand, opportunistic sharing of the licensed spectrum should avoid harmful interference to the primary users. First of all, for a wideband channel consisting of multiple subbands, the probability of interference on each subband should be bounded by a tolerable level, say, $P(\mathcal{H}_{0,k}|\mathcal{H}_{1,k}) \leq \alpha_k$. Moreover, suppose that we represent the penalties of interference induced by secondary users across all the subbands by a predefined metric vector, i.e., $\boldsymbol{c} = [c_1, c_1, \ldots, c_K]^T$, where the metric c_k indicates the cost incurred if the primary user at the kth subband is interfered with by secondary users. For example, c_k can be defined as a function of the bandwidth of subband k since in some applications each subband does not have to occupy an equal amount of bandwidth. Consequently, an aggregate interference measure to the primary system is defined as

$$I(\boldsymbol{\gamma}) \triangleq \sum_{k=1}^{K} c_k P(\mathcal{H}_{0,k}|\mathcal{H}_{0,k}, \gamma_k). \qquad (41)$$

We would like to maximize the aggregate opportunistic throughput, $R(\boldsymbol{\gamma})$, subject to some constraints on the aggregate interference, and the individual interference and achievable spectrum efficiency at each subband

$$\begin{aligned} \max_{\boldsymbol{\gamma}} \quad & R(\boldsymbol{\gamma}) \\ \text{s.t.} \quad & I(\boldsymbol{\gamma}) \leq \varepsilon \\ & P(\mathcal{H}_{0,k}|\mathcal{H}_{1,k}, \gamma_k) \leq \alpha_k, \quad k = 1, 2, \ldots, K \\ & P(\mathcal{H}_{0,k}|\mathcal{H}_{0,k}, \gamma_k) \geq \beta_k, \quad k = 1, 2, \ldots, K, \end{aligned} \qquad (42)$$

where the last K constraints signify that the CR network would like to maintain a certain level of opportunistic spectrum utilization for each particular subband.

The optimization problem (42) is difficult to solve since both the objective function (40) and constraints are nonlinear and nonconvex functions in $\{\gamma_k\}$. Nevertheless, the problem can be reformulated into an equivalent form

$$\begin{aligned} \min_{\boldsymbol{\gamma}} \quad & \sum_{k=1}^{K} r_k Q\left(\frac{\gamma_k - \mu_{0,k}}{\sigma_{0,k}}\right) \\ \text{s.t.} \quad & \sum_{k=1}^{K} c_k Q\left(\frac{\gamma_k - \mu_{1,k}}{\sigma_{1,k}}\right) \geq \mathbf{c}^T \mathbf{1} - \varepsilon \\ & \gamma_{\min,k} \leq \gamma_k \leq \gamma_{\max,k}, \quad k = 1, 2, \ldots, K, \end{aligned} \qquad (43)$$

where

$$\gamma_{\min,k} = \mu_{0,k} + \sigma_{0,k} Q^{-1}(1 - \beta_k), \quad k = 1, 2, \ldots, K \qquad (44)$$

$$\gamma_{\max,k} = \mu_{1,k} + \sigma_{1,k} Q^{-1}(1 - \alpha_k), \quad k = 1, 2, \ldots, K \qquad (45)$$

and $\mathbf{1}$ is the all-one vector. Furthermore, we find that $Q(x)$ is convex if $x > 0$ and is concave if $x \leq 0$ [35] as illustrated in Figure 4. By exploiting this hidden convexity of the problem structure, the reformulated problem (43) becomes a convex optimization problem under the conditions

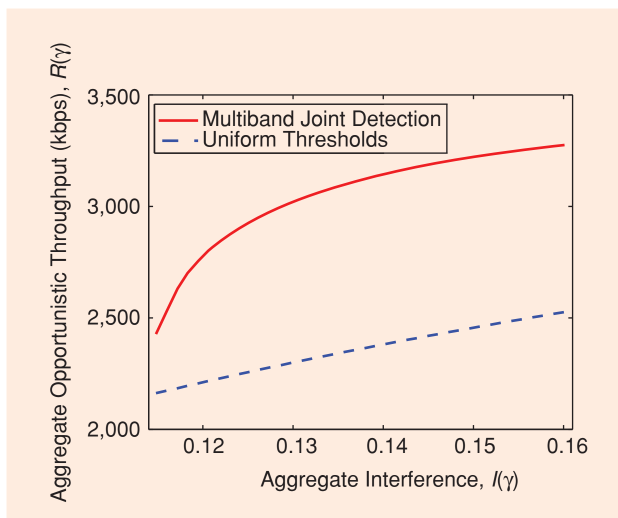
$$\alpha_k \leq 1/2 \text{ and } \beta_k \geq 1/2, \quad k = 1, 2, \ldots, K. \qquad (46)$$

This regime of $\{\alpha_k\}$ and $\{\beta_k\}$ is of practical interest since it requires that on each subband, the opportunistic spectrum utilization is greater than or equal to 50% and the probability of interference is less than 50%. The reformulated convex problem can then be solved using efficient numerical algorithms (i.e., the interior-point method) [31]. Consequently, the solutions provide the jointly optimal thresholds for these K narrowband detectors. Please note that the system parameters ε, $\{\alpha_k\}$, and $\{\beta_k\}$, should be properly chosen so that (43) is feasible.

The performance of the multiband joint detection algorithm is compared with that of a uniform-threshold ($\gamma_k = \gamma$ for all k) approach that maximizes the aggregate opportunistic throughput of the CR system subject to the same constraints on the interference. As illustrated in Figure 6, the optimal multiband joint detection with heterogeneous thresholds accommodating channel diversity for both primary and secondary users exhibits superior performance.

SPATIO-SPECTRAL JOINT DETECTION

As we did in the single band case, to exploit spatial diversity to prevent the hidden terminal problem, it is important to fuse



[FIG6] The throughput of a CR system versus the constraint on the interference cost ε. The wideband channel consists of eight subchannels, each with a unit primary signal power level and a unit noise power level. The squared channel gains between the primary and secondary users are (05, 0.3, 0.45, 0.65, 0.25, 0.6, 0.4, and 0.7), the opportunistic data rates of secondary users (612, 524, 623, 139, 451, 409, 909, and 401) in kB/s, and the costs of interference (1.91, 8.17, 4.23, 3.86, 7.16, 6.05, 0.82, and 1.30). For each subband k ($1 \leq k \leq 8$), 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 $N = 100$.

the sensing results from individual CRs to obtain a more accurate inference about the targeted wideband channel. Here, we describe a spatio-spectral joint detection (SSJD) strategy based on the linear combination of summary statistics from different CRs [37].

Consider again M spatially distributed CRs sensing a bank of K narrow subbands. Let $T_{k,i}$ represent the sensing result of the kth subband from the ith CR. Each CR sends its sensing results over multiple subbands to a fusion center where the final decision is made. For subband k, the sensing results from the M CRs can be represented in a vector $\mathbf{Y}_k = [T_{k,1}, T_{k,2}, \ldots, T_{k,M}]^T$. For energy detection, $\mathbf{Y}_k$ is normally distributed under both hypotheses according to the central limit theorem, i.e., $\mathbf{Y}_k \sim \mathcal{N}(\boldsymbol{\mu}_{0,k}, \boldsymbol{\Sigma}_{0,k})$ under $\mathcal{H}_{0,k}$ and $\mathbf{Y}_k \sim \mathcal{N}(\boldsymbol{\mu}_{1,k}, \boldsymbol{\Sigma}_{1,k})$ under $\mathcal{H}_{1,k}$. On each subband, these sensing results are linearly combined through a weight vector $\boldsymbol{w}_k = [w_{k,1}, w_{k,2}, \ldots, w_{k,M}]^T$ as

$$z_k = \boldsymbol{w}_k^T Y_k = \sum_{i=1}^{M} w_{k,i} Y_{k,i}, \tag{47}$$

which is also normally distributed under both hypotheses, i.e., $z_k \sim \mathcal{N}(\boldsymbol{w}_k^T \boldsymbol{\mu}_{0,k}, \boldsymbol{w}_k^T \boldsymbol{\Sigma}_{0,k} \boldsymbol{w}_k)$ under $\mathcal{H}_{0,k}$ and $z_k \sim \mathcal{N}(\boldsymbol{w}_k^T \boldsymbol{\mu}_{1,k}, \boldsymbol{w}_k^T \boldsymbol{\Sigma}_{1,k} \boldsymbol{w}_k)$ under $\mathcal{H}_{1,k}$. At the fusion center, the statistic z_k is compared with a test threshold to decide the presence or absence of a primary signal in subband k, i.e.,

$$z_k \underset{\mathcal{H}_{0,k}}{\overset{\mathcal{H}_{1,k}}{\gtrless}} \gamma^k \quad k = 1, 2, \ldots, K. \tag{48}$$

Accordingly, the probability of detecting spectral holes, $P(\mathcal{H}_{0,k}|\mathcal{H}_{0,k}, \gamma_k, \boldsymbol{w}_k)$, and the probability of interference, $P(\mathcal{H}_{0,k}|\mathcal{H}_{1,k}, \gamma_k, \boldsymbol{w}_k)$, are respectively given by

$$P(\mathcal{H}_{0,k}|\mathcal{H}_{0,k}, \gamma_k, \boldsymbol{w}_k) = 1 - Q\left(\frac{\gamma_k - \boldsymbol{w}_k^T \boldsymbol{\mu}_{0,k}}{\sqrt{\boldsymbol{w}_k^T \boldsymbol{\Sigma}_{0,k} \boldsymbol{w}_k}}\right) \tag{49}$$

and

$$P(\mathcal{H}_{0,k}|\mathcal{H}_{1,k}, \gamma_k, \boldsymbol{w}_k) = 1 - Q\left(\frac{\gamma_k - \boldsymbol{w}_k^T \boldsymbol{\mu}_{1,k}}{\sqrt{\mathrm{w}_k^T \boldsymbol{\Sigma}_{1,k} \boldsymbol{w}_k}}\right), \tag{50}$$

which are both functions of the design parameters $(\gamma_k, \boldsymbol{w}_k)$. Consequently, the aggregate opportunistic throughput and the aggregate interference of the K subbands can be defined as

$$R(\boldsymbol{\gamma}, \boldsymbol{w}) \triangleq \sum_{k=1}^{K} r_k P(\mathcal{H}_{0,k}|\mathcal{H}_{0,k}, \gamma_k, \boldsymbol{w}_k) \tag{51}$$

and

$$I(\boldsymbol{\gamma}, \boldsymbol{w}) \triangleq \sum_{k=1}^{K} c_k P(\mathcal{H}_{0,k}|\mathcal{H}_{0,k}, \gamma_k, \boldsymbol{w}_k). \tag{52}$$

Thus, the optimal SSJD can be formulated into an optimization problem that maximizes the aggregate opportunistic throughput of the CR network subject to the same constraints as in the single-CR wideband sensing case, i.e.,

$$\begin{aligned} \max_{\boldsymbol{\gamma}, W} \quad & R(\boldsymbol{\gamma}, W) \\ \text{s.t.} \quad & I(\boldsymbol{\gamma}, W) \le \varepsilon \\ & P(\mathcal{H}_{0,k}|\mathcal{H}_{1,k}, \gamma_k, \boldsymbol{w}_k) \le \alpha_k, \quad k = 1, 2, \ldots, K \\ & P(\mathcal{H}_{0,k}|\mathcal{H}_{0,k}, \gamma_k, \boldsymbol{w}_k) \ge \beta_k, \quad k = 1, 2, \ldots, K, \end{aligned} \tag{53}$$

where $\boldsymbol{\gamma} = [\gamma_1, \gamma_2, \ldots, \gamma_K]^T$ and $W = [\boldsymbol{w}_1, \boldsymbol{w}_2, \ldots, \boldsymbol{w}_K]$ are the optimization variables.

Since the objective function and constraints are neither linear nor convex, it is difficult to solve (53). Through mathematical reformulation, the problem (53) can be transformed into the equivalent form [37]

$$\begin{aligned} \max_{\boldsymbol{\gamma}, W} \quad & \sum_{k=1}^{K} r_k Q\left[\left(\gamma_k - \boldsymbol{w}_k^T \boldsymbol{\mu}_{0,k}\right)\sqrt{\frac{\boldsymbol{w}_k^T \boldsymbol{\Sigma}_{1,k} \boldsymbol{w}_k}{\boldsymbol{w}_k^T \boldsymbol{\Sigma}_{0,k} \boldsymbol{w}_k}}\right] \\ \text{s.t.} \quad & \sum_{k=1}^{K} c_k Q\left(\gamma_k - \boldsymbol{w}_k^T \boldsymbol{\mu}_{1,k}\right) \le \boldsymbol{c}^T \mathbf{1} - \varepsilon \\ & \gamma_k - \boldsymbol{\mu}_{0,k}^T \boldsymbol{w}_k \le Q^{-1}(1 - \alpha_k)\sqrt{\boldsymbol{w}_k^T \boldsymbol{\Sigma}_{0,k} \boldsymbol{w}_k}, \\ & \gamma_k - \boldsymbol{\mu}_{1,k}^T \boldsymbol{w}_k \ge Q^{-1}(1 - \beta_k), \quad k = 1, 2, \ldots, K, \end{aligned} \tag{54}$$

which has a nonconvex objective function but a set of convex constraints under the conditions (46). Since $\boldsymbol{\Sigma}_{0,k} \succeq 0$, the Rayleigh Ritz inequality [38] gives

$$\frac{\boldsymbol{w}_k^T \boldsymbol{\Sigma}_{1,k} \boldsymbol{w}_k}{\boldsymbol{w}_k^T \boldsymbol{\Sigma}_{0,k} \boldsymbol{w}_k} \ge \lambda_{\min}\left(\boldsymbol{\Sigma}_{0,k}^{-T/2} \boldsymbol{\Sigma}_{1,k} \boldsymbol{\Sigma}_{0,k}^{-1/2}\right), \tag{55}$$

where $\boldsymbol{\Sigma}_{0,k}^{1/2}$ is chosen as the square root obtained from the Cholesky decomposition [38] and $\lambda_{\min}(\cdot)$ denotes the minimum eigenvalue. As a result, the objective function of (54) can be upper bounded by a convex function, i.e.,

$$\begin{aligned} & \sum_{k=1}^{K} r_k Q\left(\frac{\gamma_k - \boldsymbol{w}_k^T \boldsymbol{\mu}_{0,k}}{\sqrt{\boldsymbol{w}_k^T \boldsymbol{\Sigma}_{0,k} \boldsymbol{w}_k}}\right) \\ & \le \sum_{k=1}^{K} r_k Q\left[\left(\gamma_k - \boldsymbol{w}_k^T \boldsymbol{\mu}_{0,k}\right)\lambda_{\min}\left(\boldsymbol{\Sigma}_{0,k}^{-T/2} \boldsymbol{\Sigma}_{1,k} \boldsymbol{\Sigma}_{0,k}^{-1/2}\right)\right] \end{aligned} \tag{56}$$

since the Q-function is monotonically decreasing. By minimizing the upper bound of the objective function in problem (54), we can obtain a good approximation to the optimal solution of the original optimization problem. Figure 7 shows that the SSJD algorithm outperforms the MJD procedure without cooperation.

The formulations of MJD and SSJD exemplify a cross-layer optimization framework for CRs, which takes into account the channel conditions, interference, opportunistic throughput, and network cooperation.

DESIGN CONSIDERATIONS IN OPPORTUNISTIC SPECTRUM SHARING

Now we discuss some high-level design considerations in opportunistic spectrum sharing. There are two basic approaches for the secondary users to share the spectrum with the primary users. The first one is to deterministically use an underlay mechanism (e.g., a spread spectrum scheme), with which the CR devices use extremely low power to simultaneously share the spectrum with the primary users with zero probability of causing harmful interference. This mechanism needs to place severe restrictions on transmit power to limit interference. The other approach uses an overlay mechanism to opportunistically access the unused spectral segments identified via spectrum sensing, with finite probability of interfering with the primary users. As such, spectrum sensing is mostly used for overlay CR networks. With spectrum sensing, the secondary users opportunistically share the spectrum with the licensed primary users, and the unoccupied spectral segments are assigned to the secondary users according to their QoS requirements such as throughput, delay, and packet loss.

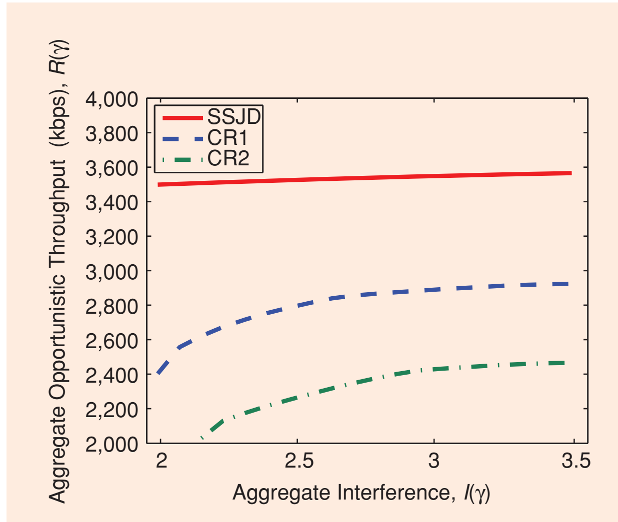
To implement the CR overlay system mentioned above, orthogonal frequency division multiplexing (OFDM) is an attractive candidate, since it can easily generate signals with arbitrary spectrum occupancy pattern [39], [17], [40]. With OFDM-based CRs, the interference to the primary users can be avoided by simply nullifying the subcarriers in the occupied spectral segments and modulating only the subcarriers in the spectral holes. With a sufficient number of subcarriers, an OFDM-based CR system can operate efficiently in any target licensed band regardless of its channelization scheme. Other advantages of an OFDM-based CR system include robustness against multipath delay spread (with the guard interval and cyclic prefix), insensitivity to sampling time drift (and thus no need for complex synchronization), and easy integration with multiantenna techniques [41].

MULTILAYER DESIGN ISSUES FOR COLLABORATIVE SENSING

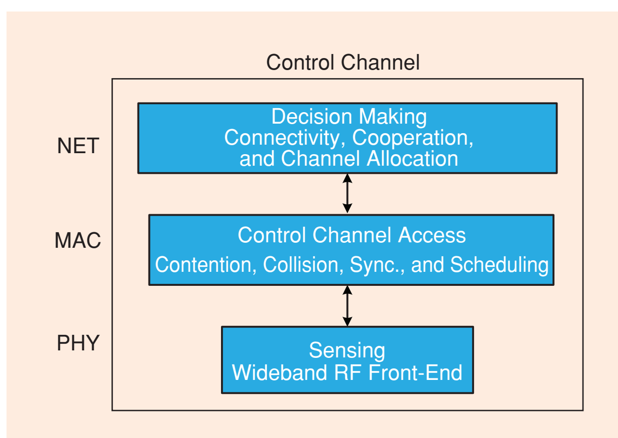
As we have demonstrated earlier, collaborative spectrum sensing is performed across multiple layers in the network, involving signal processing at the physical layer, channel sharing and opportunistic throughput maximization at the medium access control (MAC) layer, and node collaboration at the network (NET) layer. In Figure 8, we show a layered architecture of collaborative spectrum sensing in a CR network. We will discuss practical design issues across multiple layers in the remainder of the article.

HARDWARE CONSIDERATION AT THE PHYSICAL LAYER

Since a wideband CR system needs to scan a wide frequency range to reliably detect spectral holes, an individual CR device requires a high-resolution RF front-end with a high-speed A/D converter at a sampling rate up to several gigahertz, which is difficult to implement with current hardware technologies [17]. Collaborative sensing can alleviate the harsh requirements on the circuitry of the RF front-end in two ways. First, the collaboration among multiple CRs observing the same band can significantly increase the observation SNR at the fusion center and thus relax the sensitivity constraint on the CR receiver. Second, multiple CRs, each of which is responsible for sensing a portion of the target spectrum, can team up to perform spectrum sensing over an ultra-wide frequency band up to several gigahertz. Therefore, collaborative wideband sensing provides a practical solution to lessen the costly requirements on the RF front-end circuitry.



[FIG7] The throughput capacity of a CR system consisting of two secondary users versus the constraint on the interference cost ε. The wideband channel consists of eight subchannels, each with a unit primary signal power and a unit noise power. The squared channel gains between the primary and secondary users are (0.17, 0.21, 0.27, 0.14, 0.37, 0.38, 0.49, and 0.33) and (0.21, 0.17, 0.21, 0.21, 0.17, 0.43, 0.15, and 0.35). The opportunistic data rates of the secondary users are (356, 327, 972, 806, 755, 68, 720, and 15) in kB/s and the costs of interference (0.71, 5.95, 3.91, 4.21, 0.44, 2.03, 0.58, and 2.85). For each subband k ($1 \le k \le 8$), we set $\beta_k = 0.5$ and $\alpha_k = 0.1$. It is also assumed that the noise power level is $\sigma_v^2 = 1$ and the length of each detection interval is $N = 100$.



[FIG8] A layered structure for distributed wideband spectrum sensing in a cognitive radio network.

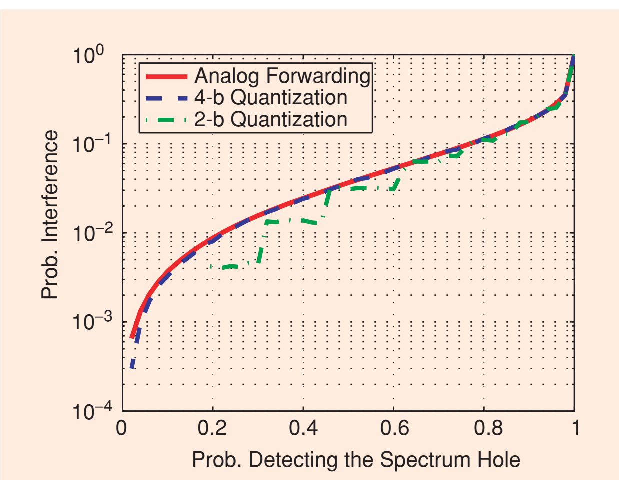
CONTROL CHANNEL BANDWIDTH VERSUS QUANTIZATION LEVEL

In practice, the summary statistics from individual CRs need to be quantized before being transmitted to the fusion center. The quantization level leads to a tradeoff between the sensing performance and the bandwidth requirement of the control channel. That is, a larger number of quantization bits will introduce less distortion into the transmitted summary statistics, while placing a heavier burden on the bandwidth of the control channel.

To illustrate the sensitivity of the proposed collaborative sensing to quantization levels, we quantize the summary statistics, i.e., the energy levels in (21), and then perform linear combination with three CRs according to (27) to form a global energy level. We consider implementing a Lloyd-Max quantizer for the measured energy level of each CR, where for a given number of quantization levels, the Lloyd-Max algorithm minimizes the mean square error (MSE) between the input and the output of the quantizer. From Figure 9, we find that a 4-b quantizer would provide sensing performance comparable to that of the ideal analog forwarding scheme. This observation is consistent with [30] in that the performance of collaborative sensing is insensitive to the error introduced by the control channel since quantization errors can be modeled as additive noise on the top of the channel noise. Therefore, collaboration among multiple CRs can improve the sensing reliability at the cost of only a small amount of bandwidth for the control channel.

MAC

Since there are multiple CRs sharing the control channel, the access to the control channel must be coordinated to prevent collision/interference and ensure reliable reception at the fusion center. Carrier sense multiple access (CSMA)-based protocols would provide simple solutions for sensing result exchange among CRs. The control channel can be implemented using either a dedicated channel or an underlay channel sharing the spectrum with the primary network. Spread spectrum is a good candidate technique for establishing the underlay channel for CRs but it needs to carefully control the transmit power or interference temperature to avoid creating harmful interference [8].



[FIG9] The effect of quantization level on the sensing performance in collaborative sensing with $M = 3$ cognitive radios. The SNR levels at individual cognitive radios are $(-1.8, -6.3, -3.8)$ in decibels with $N = 20$.

CONCLUSIONS

Motivated by the fact that collaborative wideband sensing techniques are an essential component of CR networks and are especially useful when individual CR devices cannot reliably detect weak primary signals, this article has surveyed the existing collaborative spectrum sensing techniques for CRs. We have introduced a linear fusion scheme for collaborative sensing and a multiband joint detection framework for wideband sensing. We have also presented efficient algorithms to optimize the sensing performance. Implementation issues of the proposed sensing algorithms in a wideband CR system have been discussed from a multilayer networking perspective.

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AUTHORS

Zhi Quan (quan@ee.ucla.edu) is working towards his Ph.D. in electrical engineering at UCLA. He received his B.E. degree in communication engineering from Beijing University of Posts and Telecommunications, China, and M.S. degree in electrical engineering from Oklahoma State University. He was a visiting researcher with Princeton University, New Jersey, in 2007 and an interim engineering intern with Qualcomm Incorporated in 2008. His current research interests include statistical signal processing, wireless communications, cognitive radios, and linear/nonlinear optimization.

Shuguang Cui (cui@tamu.edu) received the Ph.D. in electrical engineering from Stanford University in 2005, the M.Eng. in electrical engineering from McMaster University, Canada, in 2000, and the B.Eng. in radio engineering with the highest distinction from Beijing University of Posts and Telecommunications, China, in 1997. He is now an assistant professor in electrical and computer engineering at the Texas A&M University, College Station. His research interests include cross-layer optimization for resource-constrained networks and network information theory. He is an associate editor for *IEEE Communication Letters* and *IEEE Transactions on Vehicular Technology*.

H. Vincent Poor (poor@princeton.edu) is the dean of the School of Engineering and Applied Science at Princeton University, where he is also the Michael Henry Strater

University Professor of Electrical Engineering. His interests are in the area of statistical signal processing, with applications in wireless networks and related fields. Among his publications is the recent book, *MIMO Wireless Communications* (Cambridge, 2007). He is a Fellow of the IEEE and a member of the NAE. Recent recognition includes the 2007 Marconi Prize Paper Award, the 2007 IEEE Signal Processing Society Technical Achievement Award, and the 2008 IEEE Information Theory Society Wyner Award.

Ali H. Sayed (sayed@ee.ucla.edu) is professor and chair of the Electrical Engineering Department, UCLA, where he directs the adaptive systems laboratory. He served as editor-in-chief of *IEEE Transactions on Signal Processing*. He has authored or coauthored several books including *Adaptive Filters*, *Fundamentals of Adaptive Filtering*, and *Linear Estimation*. He has received several recognitions including the 1996 IEEE Donald G. Fink Award, 2003 Kuwait Prize, 2005 Terman Award, IEEE Signal Processing Society 2002 Best Paper Award and 2005 Young Author Best Paper Award. He served as a 2005 IEEE Signal Processing Society Distinguished Lecturer and as General Chair of ICASSP 2008. He is Fellow of the IEEE.

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