WIRELESS COMMUNICATIONS AND MOBILE COMPUTING
Wirel. Commun. Mob. Comput. 2016; **16**:1603–1611
Published online 16 September 2015 in Wiley Online Library (wileyonlinelibrary.com). DOI: 10.1002/wcm.2615

RESEARCH ARTICLE

A selective decision–fusion rule for cooperative spectrum sensing using energy detection

Ala Abu Alkheir[1]* and Mohamed Ibnkahla[2]

[1] School of Electrical Engineering and Computer Science, University of Ottawa, 800 King Edward Avenue, Ottawa, ON K1N 6N5, Canada

[2] Department of Electrical and Computer Engineering, Queen's University, 19 Union St., Kingston, ON K7L 3N6, Canada

ABSTRACT

Increasing the number of terminals in a cognitive radio network is known to improve the accuracy of cooperative spectrum sensing at the cost of reducing the useful communication time. This downside can be partially mitigated using decision-based fusion and/or sequential reporting. This paper proposes a novel selective decision-based cooperative spectrum sensing strategy that limits the reporting time to a single reporting slot with a possibility for retransmissions using automatic repeat request. The terminal with the highest energy estimate sends its local decision to the fusion center to make a final decision. Potential decoding errors are mitigated using threshold-based automatic repeat request. The performance of the proposed strategy is studied using rigorous mathematical analysis and intensive computer simulations. Results show observable performance enhancements compared with some benchmark strategies in terms of detection accuracy and agility. Copyright © 2015 John Wiley & Sons, Ltd.

KEYWORDS

cognitive radio networks; cooperative spectrum sensing; automatic repeat request; energy detection

***Correspondence**

Ala Abu Alkheir, School of Electrical Engineering and Computer Science, University of Ottawa, 800 King Edward Avenue, Ottawa, ON K1N 6N5, Canada.

E-mail: ala.abualkheir@uottawa.ca

1. INTRODUCTION

Cognitive radio networks (CRNs) rely on cooperative spectrum sensing (CSS) to locate unused spectrum bands through the collaboration of a number of dispersed sensing terminals. In this collaborative endeavor, every sensing terminal examines the status of a particular spectrum band using some sensing method, for example, energy detection, makes a local report (which can be a binary decision or raw data), and forwards it to a fusion center (FC), which can be an access point or a base station, to make and broadcast a final decision about the status of the examined spectrum band [1,2].

In time division multiple access CRNs, like IEEE 802.22 wireless regional area networks [3], a single channel is used for both control signaling and data transmission. Hence, the continued availability (i.e., idleness) of this channel is examined through periodic CSS. In particular, the FC launches a periodic listening time, known as a quiet period (QP), during which network terminals cease all communications and start the three-step CSS process shown in Figure 1. The duration of this process,† denoted by t_{CSS}, consists of t_s seconds for local spectrum sensing, Kt_r seconds for the K network terminals to send their reports to the FC, and t_d seconds for the FC to make and broadcast the final decision, hence, $t_{\text{CSS}} = t_s + Kt_r + t_d$.

Using this periodic CSS approach to monitor the status of the operating channel‡ causes a throughput loss because $\frac{t_{\text{CSS}}}{T}$ of the time is wasted for CSS, where T is the time between two consecutive QPs. This observation had encouraged a growing number of researchers to search for methods to reduce this throughput loss while not

†The IEEE 802.22 standard specifies two classes of QPs, intra-frame and inter-frame, corresponding to fast sensing and fine sensing, respectively. The local sensing duration of these two classes is set at a maximum of 1 ms for fast sensing and a minimum of 25 ms for fine sensing [3]. However, the reporting time is left unspecified as it depends on the number of network terminals, the spectrum access strategy (reservation based or contention based) in addition to the transmission data rate.

‡An operating channel is the channel used for communication by the CRN [4].

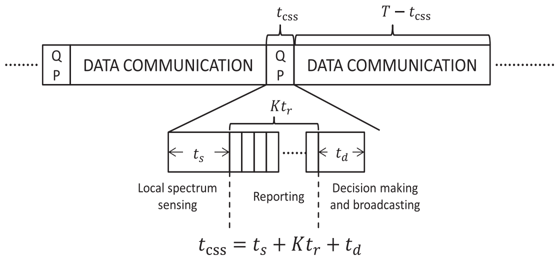


Figure 1. Periodic quiet period (QP) scheduled to perform cooperative spectrum sensing (CSS).

jeopardizing the accuracy of the sensing process. The first of these works was Kim and Shin [5], who proposed adapting the QP scheduling based on the predicted activity of the primary user (PU). As such, the ratio $\frac{t_{CSS}}{T}$ is reduced because the average value of T is increased. The authors, similar to [6], have also studied reducing the loss by finding the smallest t_s needed to maintain a prespecified detection performance. Hence, reducing the throughput loss by decreasing t_{CSS}. While this approach guarantees the minimum t_s, it comes at the cost of a computational complexity because an optimization problem has to be solved whenever the network characteristics change, for example, the average signal-to-noise ratio (SNR) of the PU. This cost can be avoided using sequential detection where the sensing process is terminated as soon as the network terminal receives enough evidence about the status of the examined spectrum band [7–10]. Unfortunately, minimizing t_s using either of these two approaches (the optimization approach and the sequential approach) cannot be translated into a reduction of t_{CSS} in the absence of a dedicated reporting channel. This is because reporting can only start after all K network terminals make final decisions. Accordingly, t_{CSS} depends on the maximum of the local sensing times, that is, $t_{CSS} = \max\{t_{s,1}, t_{s,2}, \ldots, t_{s,K}\} + Kt_r + t_d$, where $t_{s,k}$ is the sensing time of the k^{th} terminal.

Another group of researchers have focused on reducing t_{CSS} by decreasing the reporting time because this parameter scales with the network population. An intuitive way of achieving this is reducing t_r by limiting the content of reported data. In particular, if each terminal sends a single binary digit representing its local decision to the FC, then Kt_r will decrease [11,12]. This solution does not only come at the cost of a performance loss but also suffers from a scaling problem when K is large. This latter problem was tackled by Peh *et al.* [13] and Zhang *et al.* [14] who managed to find the minimum K needed to achieve a prespecified sensing accuracy. However, this comes at the cost of computational complexity and can only be applied when the network has abundance of sensing terminals. To avoid this complexity, sequential detection was extended to the FC side to give it the ability to early terminate the reporting process once it receives enough evidence about the status of the examined spectrum [15,16]. Reducing K using either approach increases the effect of reporting errors especially when the FC uses the OR rule [17]. This could be reduced using cooperative communications techniques, like relaying, clustering, space-time coding, and transmit diversity [17–19]. Nonetheless, because these techniques are based on half-duplex communication, the reporting time will be doubled. Alternatively, censoring techniques can be used to filter terminals based on the quality of their reporting channels. In this case, only terminals who have good reporting channels are allowed to send their reports to the FC [20,21]. However, because the identity and number of these terminals change based on the unpredictable fluctuations of the reporting channels, the reporting time cannot be smaller than Kt_r even if some reporting slots are not used.

In this paper, we revisit the problem of reducing the reporting time for decision-based CSS using the OR rule. Unlike all previous works, we choose the terminal with the highest energy estimate to send a report to the FC who employs a threshold-based automatic repeat request (ARQ) to mitigate decoding errors. The FC makes a final decision by combining the decision of the chosen terminal with its own decision. The performance of the proposed strategy is analyzed in terms of the detection and false alarm probabilities. We also study the average number of retransmissions needed to obtain a reliable replica of the chosen decision and use that to calculate the average reporting time. In doing so, we also include the additional waiting time needed to implement terminal selection in a distributed manner. The performance of the proposed strategy is compared with the performance of the conventional strategy [14], the sequential reporting strategy [16], and the selective strategy [22], all based on the OR rule. It is shown that the proposed strategy outperforms the other strategies in terms of detection performance as well as the average reporting time.

The remainder of this paper is organized as follows. Section 2 describes the system model. The proposed strategy is presented in Section 3, and its performance is analyzed in Section 4. Results and discussions are reported in Section 5, while conclusions are drawn in Section 6.

2. SYSTEM MODEL

2.1. Energy detection

Consider a CRN consisting of K terminals, $\mathrm{R}_1, \mathrm{R}_2, \ldots, \mathrm{R}_K$, and an FC, R_0, as shown in Figure 2. These terminals use energy detection to obtain local energy estimates, $\{\phi_k\}_{k=0}^{K}$, and make local decisions, $\{d_k\}_{k=0}^{K} \in \{0, 1\}$, about the status of the operating channel.

The cumulative distribution functions (CDFs) of $\{\phi_k\}_{k=0}^{K}$ when the PU is inactive, denoted by $\mathcal{H}_0$, and active, denoted by $\mathcal{H}_1$, over Rayleigh fading are given by Umar *et al.* [23]

$$F_{\phi_k|\mathcal{H}_0}(\phi) = 1 - \frac{\Gamma\left(u, \frac{\phi}{2}\right)}{\Gamma(u)} \tag{1a}$$

$$F_{\phi_k|\mathcal{H}_1}(\phi) = 1 - e^{-\frac{\phi}{2}} \sum_{i=0}^{u-2} \frac{\phi^i}{2^i i!} - \left[\frac{1 + \rho_p \Omega_{p,k}}{\rho_p \Omega_{p,k}}\right]^{u-1} \times$$

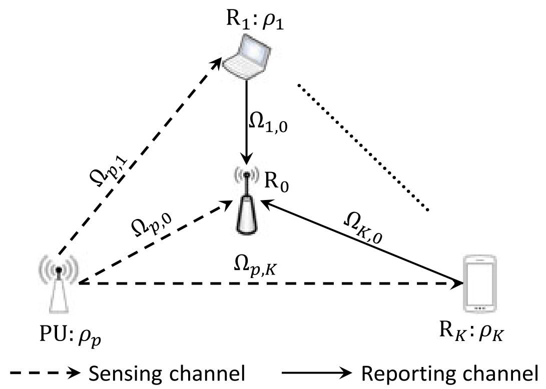


Figure 2. System model. PU, primary user.

$$\left\{ e^{-\frac{\phi}{2(1+\rho_p\Omega_{p,k})}} - e^{-\frac{\phi}{2}} \sum_{i=0}^{u-2} \frac{1}{i!} \left[\frac{\phi\rho_p\Omega_{p,k}}{2(1+\rho_p\Omega_{p,k})} \right]^i \right\} \quad \text{(1b)}$$

respectively, where $\Gamma(\alpha)$ and $\Gamma(\alpha, x)$ are the Gamma and the lower incomplete Gamma functions [24], respectively, u is the number of samples used to calculate $\{\phi_k\}_{k=0}^K$, $\rho_p = \frac{E_p}{\sigma^2}$ is the transmission SNR of the PU, E_p is the PU's transmission energy, σ^2 is the variance of the additive white Gaussian noise at $\{R_k\}_{k=0}^K$, and $\{\Omega_{p,k}\}_{k=0}^K$ is the average of the exponentially distributed PU $-$ $\{R_k\}_{k=0}^K$ channel gain, denoted by $\{g_{p,k}\}_{k=0}^K$, that is, $g_{p,k} \sim \mathcal{E}(\Omega_{p,k})$.

Using a decision threshold λ, every terminal calculates its local decision $\{d_k\}_{k=0}^K$ as follows. If $\phi_k \geq \lambda$, then $d_k = 1$, otherwise, $d_k = 0$. Choosing the same λ and u for all terminals makes $F_{\phi_0|\mathcal{H}_0}(\phi) = F_{\phi_1|\mathcal{H}_0}(\phi) = \cdots = F_{\phi_K|\mathcal{H}_0}(\phi)$ and $P_{\mathrm{fa},0} = P_{\mathrm{fa},1} = \cdots = P_{\mathrm{fa},K} = P_{\mathrm{fa}}$, where $\{P_{\mathrm{fa},k}\}_{k=0}^K$ is the probability of false alarm of R_k, defined as $P_{\mathrm{fa},k} \triangleq \Pr[\phi_k \geq \lambda|\mathcal{H}_0] = 1 - F_{\phi_k|\mathcal{H}_0}(\lambda)$, and $\Pr[\cdot]$ is the probability operator. This decision threshold, λ, is chosen such that all terminals operate at a preset probability of false alarm, P_{fa}, [23]. On the other hand, assuming that the sensing channels[§] are different, that is, $\Omega_{p,0} \neq \Omega_{p,1} \neq \cdots \neq \Omega_{p,K}$, then $F_{\phi_0|\mathcal{H}_1}(\phi) \neq F_{\phi_1|\mathcal{H}_1}(\phi) \neq \ldots \neq F_{\phi_K|\mathcal{H}_1}(\phi)$, and hence, $P_{\mathrm{d},0} \neq P_{\mathrm{d},1} \neq \cdots \neq P_{\mathrm{d},K}$, where $\{P_{\mathrm{d},k}\}_{k=0}^K$ is the detection probability of $\{R_k\}_{k=0}^K$ defined as $P_{\mathrm{d},k} \triangleq \Pr[\phi_k \geq \lambda|\mathcal{H}_1] = 1 - F_{\phi_k|\mathcal{H}_1}(\lambda)$.

2.2. Reporting channels

At the end of the local sensing process, $R_k, k = 1, 2, \ldots, K$, sends d_k to the FC. Upon receiving this transmission, R_0 uses coherent detection to obtain a decoded version of d_k, denoted by $\hat{d}_k$. In doing so, it perceives either an SNR (under $\mathcal{H}_0$) or a signal-to-interference-plus-noise ratio (SINR) (under $\mathcal{H}_1$). If we let ψ_k denote this SNR/SINR, then it can be shown that $\psi_k = \rho_k g_{k,0}$ under $\mathcal{H}_0$ and $\psi_k \triangleq \frac{\rho_k g_{k,0}}{\rho_p g_{p,0}+1}$ under $\mathcal{H}_1$, where ρ_k is the transmission SNR of R_k, while $g_{k,0}$ and $g_{p,0}$ are the gains of the $\{R_k\}_{k=1}^K - R_0$ and PU $- R_0$ channels, respectively. Assuming Rayleigh fading, $g_{k,0}$ becomes an exponential random variable with a mean value of $\Omega_{k,0}$, that is, $g_{k,0} \sim \mathcal{E}(\Omega_{k,0})$. Hence, under $\mathcal{H}_0$, $\psi_k \sim \mathcal{E}(\rho_k\Omega_{k,0})$, while under $\mathcal{H}_1$, ψ_k has the CDF [25]

$$F_{\psi_k|\mathcal{H}_1}(\psi) = 1 - \frac{\rho_k\Omega_{k,0}}{\rho_k\Omega_{k,0} + \psi\rho_p\Omega_{p,0}} \exp\left(\frac{-\psi}{\rho_k\Omega_{k,0}}\right) \quad (2)$$

3. THE PROPOSED STRATEGY

Instead of allowing all K terminals to send their reports to the FC, which results in a proportional throughput loss, we shall select a single terminal, denoted by R_*, to transmit its local decision to R_0. This decision, denoted by d_*, shall convey information about the remaining decisions. Such a selection can be made in a number of ways. For instance, selecting R_* based on the median energy estimate gives a good idea about the distribution of the energy estimates. However, identifying the terminal with the median value cannot be achieved without costly reporting overhead. Alternatively, R_* can be chosen based on the minimum energy estimate, but this will lead to excessive misdetection because it would resemble the AND voting rule [12]. After exploring a number of possibilities, we found that a suitable approach to make this selection is to choose R_* based on the maximum energy estimate. In doing so, we are selecting the most informing terminal to participate in the decision-making process at R_0 on behalf of the rest of the terminals. A reporting strategy that capitalized on this selection is described in Algorithm 1.

Algorithm 1 . The proposed strategy

for $k = 0, 1, \ldots, K$ **do**
  Calculate ϕ_k, d_k.
end for
Set $\phi_* = \max\{\phi_1, \phi_2, \ldots, \phi_K\}$,
Send d_* to R_0
Calculate ψ_*,
if $\psi_* \geq \tau$ **then**
  $\Theta = d_0 + \hat{d}_*$
else
  Retransmit d_*
end if
if $\Theta \geq 1$ **then**
  Choose $\mathcal{H}_1$
else
  Choose $\mathcal{H}_0$
end if

The proposed strategy works as follows. At the beginning of every sensing cycle, every terminal calculates an energy estimate, ϕ_k, and makes a corresponding decision, d_k. To identify the terminal with the highest energy estimate, every terminal sets a timer inversely proportional to

[§]A sensing channel is the channel between the PU and $\{R_k\}_{k=0}^K$.

its energy estimate such that the timer corresponding to the highest ϕ_k expires first. Once this happens, the corresponding terminal, which will be R_*, transmits d_* to R_0. When detecting this ongoing transmission, the remaining terminals cancel their transmissions and remain silent. To guarantee this, it is assumed that all terminals are within the transmission range of each other.

To reduce the impact of decoding errors when receiving d_*, R_0 employs a threshold-based ARQ protocol. In particular, the instantaneous SNR or SINR (depending on the status of the PU), denoted by ψ_*, is compared with a quality threshold τ. If $\psi_* \geq \tau$, R_0 sends an acknowledgment to R_* and uses the decoded version of d_*, denoted by $\hat{d}_*$, to calculate a decision metric Θ as $\Theta = d_0 + \hat{d}_*$. Otherwise, R_0 sends a negative acknowledgment to R_* asking for a retransmission. Once this retransmission is received, R_0 reexamines ψ_* and repeats the same procedure. This process continues until τ is exceeded. Finally, R_0 compares Θ to a decision threshold $\Theta_{\text{th}} = 1$. If $\Theta \geq \Theta_{\text{th}}$, R_0 deems the PU active, otherwise, it is deemed inactive.

The computational complexity of the proposed strategy is much smaller than that of the optimized techniques in [6,13,14] because it relies on distributed selection of a single terminal. However, because the proposed strategy uses the OR voting rule, it remains vulnerable to the misbehavior of the reporting terminal, R_*. This can be mitigated by coupling the received reports to the terminal's reputation, which is built over a period of time. This allows the network to exclude reports from known misbehaving terminals [26].

The notion of using backoff counters to select R_* resembles selecting random backoff timers in contention-based medium access networks, for example, IEEE 802.11, [27]. In these networks, random timers are chosen as integer multiples of the slot time, which results in a non-negligible probability of collision. To avoid this, we mandate that timers are chosen to have continuous values between 0 and ∞ (this will be discussed further in Section 4.2.1). Accordingly, because these timers are continuous random variables (because the corresponding energy estimates are continuous random variables), then the probability that two terminals have the same value is zero. Moreover, even when two energy estimates are very close to each other, the fact that R_* only sends a single bit, that is, d_*, makes the probability of a collision due to the hidden terminal problem virtually zero. For these two reasons, we shall assume that the proposed reporting strategy is collision-free.

4. PERFORMANCE ANALYSIS

The performance of the proposed strategy is measured using the probability of detection and the probability of false alarm at the FC side in addition to the average reporting time. These metrics are studied in the following subsections.

4.1. Probability of detection and probability of false alarm

The probabilities of detection and false alarm are defined as $Q_{\text{d,prop}} \triangleq \Pr[\Theta \geq \Theta_{\text{th}}|\mathcal{H}_1]$ and $Q_{\text{fa,prop}} \triangleq \Pr[\Theta \geq \Theta_{\text{th}}|\mathcal{H}_0]$, respectively. In other words, an event of detection (false alarm) occurs when at least one of d_0 and $\hat{d}_*$ has a value of one under $\mathcal{H}_1$ ($\mathcal{H}_0$). Consequently, $Q_{\text{d,prop}}$ and $Q_{\text{fa,prop}}$ can be expanded as

$$Q_{\text{d,prop}} = P_{\text{d},0}\left(1 - \Pr\left[\hat{d}_* = 1|\mathcal{H}_1\right]\right) + \left(1 - P_{\text{d},0}\right) \times \Pr\left[\hat{d}_* = 1|\mathcal{H}_1\right] + P_{\text{d},0}\Pr\left[\hat{d}_* = 1|\mathcal{H}_1\right] \tag{3a}$$

$$Q_{\text{fa,prop}} = P_{\text{fa}}\left(1 - \Pr\left[\hat{d}_* = 1|\mathcal{H}_0\right]\right) + (1 - P_{\text{fa}}) \times \Pr\left[\hat{d}_* = 1|\mathcal{H}_0\right] + P_{\text{fa}}\Pr\left[\hat{d}_* = 1|\mathcal{H}_0\right] \tag{3b}$$

where $P_{\text{d},0}$ and P_{fa} are the detection and false alarm probabilities of R_0, respectively. Using the total probability theorem, $\Pr[\hat{d}_* = 1|\mathcal{H}_j], j = 0, 1$, can be written as

$$\Pr\left[\hat{d}_* = 1|\mathcal{H}_j\right] = \sum_{k=1}^{K}\Pr\left[\hat{d}_* = 1, R_* = R_k|\mathcal{H}_j\right] \tag{4}$$

Because ϕ_k and ψ_k are mutually independent, (4) can be rewritten as

$$\begin{aligned}\Pr\left[\hat{d}_* = 1|\mathcal{H}_j\right] = &\sum_{k=1}^{K}\Pr\left[\phi_* \geq \lambda, R_* = R_k|\mathcal{H}_j\right] \\ &\times\left(1 - p_{e,k|\mathcal{H}_j}\right)\left[1 - F_{\psi_k|\mathcal{H}_j}(\tau)\right] \\ &+ \sum_{k=1}^{K}\Pr\left[\phi_* < \lambda, R_* = R_k|\mathcal{H}_j\right] \\ &\times p_{e,k|\mathcal{H}_j}\left[1 - F_{\psi_k|\mathcal{H}_j}(\tau)\right]\end{aligned} \tag{5}$$

where $p_{e,k|\mathcal{H}_j}$ is the decoding error probability of the $\{R_k - R_0\}_{k=1}^{K}$ channel under $\mathcal{H}_j$, $j = 0, 1$. To calculate (5), we need to calculate both $p_{e,k|\mathcal{H}_j}$ and $\Pr[\phi_* > \lambda, R_* = R_k|\mathcal{H}_j]$.

4.1.1. Calculating $p_{e,k|\mathcal{H}_j}$.

Because $d_* \in \{0, 1\}$, Binary Phase Shift Keying (BPSK) modulation is a reasonable choice to reduce decoding errors. In this case, $p_{e,k|\mathcal{H}_j}$, $j = 0, 1$, can be calculated by averaging the conditional error probability, given by $Q(\sqrt{2\psi_k})$, where $Q(x)$ is the Gaussian Q-function, over the conditional probability density function of ψ_k given that $\psi_k \geq \tau$ under $\mathcal{H}_j$. Alternatively, this can be written using the moment generating function (MGF) approach as [28]

$$p_{e,k|\mathcal{H}_j} = \frac{1}{\pi}\int_0^{\pi/2}\mathcal{M}_{\psi_k|\mathcal{H}_j,\psi_k\geq\tau}\left(\frac{-1}{\sin^2\theta}\right)d\theta \tag{6}$$

Wirel. Commun. Mob. Comput. 2016; 16:1603–1611 © 2015 John Wiley & Sons, Ltd.
DOI: 10.1002/wcm

where

$$\mathcal{M}_{\psi_k|\mathcal{H}_j,\psi_k\geq\tau}(-s) = s\int_\tau^\infty e^{-s\psi}F_{\psi_k|\mathcal{H}_j,\psi_k\geq\tau}(\psi)d\psi \quad (7)$$

is the conditional MGF, and $F_{\psi_k|\mathcal{H}_j,\psi_k\geq\tau}(\psi)$ is the conditional CDF written as

$$F_{\psi_k|\mathcal{H}_j,\psi_k\geq\tau}(\psi) = \begin{cases} 0, & \psi < \tau \\ \frac{F_{\psi_k|\mathcal{H}_j}(\psi)-F_{\psi_k|\mathcal{H}_j}(\tau)}{1-F_{\psi_k|\mathcal{H}_j}(\tau)}, & \psi \geq \tau \end{cases} \quad (8)$$

For the case of $j = 0$, this CDF can be easily calculated using $F_{\psi_k|\mathcal{H}_0}(\psi) = 1 - e^{-\psi/\rho_k\Omega_{k,0}}$. Hence, after some manipulations, a closed-form expression for $p_{e,k|\mathcal{H}_0}$ can be obtained as

$$\begin{aligned} p_{e,k|\mathcal{H}_0} = {} & Q\left(\sqrt{2\tau}\right) - e^{\frac{\tau}{\rho_k\Omega_{k,0}}}\sqrt{\frac{\rho_k\Omega_{k,0}}{\rho_k\Omega_{k,0}+1}} \\ & \times Q\left(\sqrt{2\tau\left(1+\frac{1}{\rho_k\Omega_{k,0}}\right)}\right) \end{aligned} \quad (9)$$

On the other hand, given $F_{\psi_k|\mathcal{H}_1}(\psi)$ in (2), a closed-form expression for $p_{e,k|\mathcal{H}_1}$ is hard to obtain, and hence, we resort to numerically integrating (6) using the conditional MGF

$$\begin{aligned} \mathcal{M}_{\psi_k|\mathcal{H}_1,\psi_k\geq\tau}(-s) = {} & e^{-s\tau} - s\frac{\rho_k\Omega_{k,0}}{\rho_p\Omega_{p,0}} \\ & \times \frac{1}{1-F_{\psi_k|\mathcal{H}_1}(\tau)}\exp\left(\frac{\rho_k\Omega_{k,0}s}{\rho_p\Omega_{p,0}} + \frac{1}{\rho_p\Omega_{p,0}}\right) \\ & \times \mathsf{E}_1\left[\left(s+\frac{1}{\rho_k\Omega_{k,0}}\right)\left(\frac{\rho_k\Omega_{k,0}}{\rho_p\Omega_{p,0}}+\tau\right)\right] \end{aligned} \quad (10)$$

where $\mathsf{E}_1[x]$ is the exponential integral function [24].

4.1.2. Calculating $\Pr[\phi_* \geq \lambda, \mathrm{R}_* = \mathrm{R}_k|\mathcal{H}_j]$.

Because the events $\mathrm{R}_* = \mathrm{R}_k$ and $\phi_* \geq \max_{i=1,\ldots,K;i\neq k}\{\phi_i\}$ are equivalent, then using a random variable Z_λ, defined as $Z_\lambda \triangleq \max_{i=1,\ldots,K;i\neq k}\{\phi_i,\lambda\}$, one can write $\Pr\left[\phi_* \geq \lambda, \mathrm{R}_* = \mathrm{R}_k|\mathcal{H}_j\right] = \Pr\left[\phi_i \geq Z_\lambda|\mathcal{H}_j\right]$. Hence, this probability can be calculated as

$$\Pr\left[\phi_k \geq Z_\lambda|\mathcal{H}_j\right] = \int_\lambda^\infty f_{\phi_k|\mathcal{H}_j}(z)F_{Z_\lambda|\mathcal{H}_j}(z)dz \quad (11)$$

where $f_{\phi_k|\mathcal{H}_j}(z)$ is obtained by differentiating $F_{\phi_k|\mathcal{H}_j}(z)$ in (1), while

$$F_{Z_\lambda|\mathcal{H}_j}(z) = \begin{cases} 0, & z < \lambda \\ \prod_{\substack{i=1\\ i\neq k}}^{K} F_{\phi_i|\mathcal{H}_j}(z), & z \geq \lambda \end{cases} \quad (12)$$

4.1.3. Calculating $\Pr[\phi_* < \lambda, \mathrm{R}_* = \mathrm{R}_k|\mathcal{H}_j]$.

Because $\Pr\left[\phi_* \geq \lambda|\mathcal{H}_j\right] + \Pr\left[\phi_* < \lambda|\mathcal{H}_j\right] = 1$, then we can calculate $\Pr\left[\phi_* < \lambda, \mathrm{R}_* = \mathrm{R}_k|\mathcal{H}_j\right]$ as

$$\begin{aligned} \Pr\left[\phi_* < \lambda, \mathrm{R}_* = \mathrm{R}_k|\mathcal{H}_j\right] = {} & \Pr\left[\mathrm{R}_* = \mathrm{R}_k|\mathcal{H}_j\right] \\ & - \Pr\left[\phi_i \geq Z_\lambda|\mathcal{H}_j\right] \end{aligned} \quad (13)$$

Now, by defining $Z_0 \triangleq \max_{i=1,\ldots,K;i\neq k}\{\phi_i\} \equiv Z_\lambda|_{\lambda=0}$, we can write $\Pr\left[\mathrm{R}_* = \mathrm{R}_k|\mathcal{H}_j\right] = \Pr\left[\phi_k \geq Z_0|\mathcal{H}_j\right]$, which can be calculated using (11) with $\lambda = 0$.

4.2. Average reporting time

A schematic diagram of the reporting process is shown in Figure 3. This figure illustrates the three components of the reporting process, which are the average initial waiting time prior to the first transmission, denoted by $\bar{t}_0$, the transmission duration of d_*, which is t_r, and the additional waiting time t_w. This latter is the time that R_* waits to obtain a response from R_0 about the quality of the received decision. The last two components, that is, t_r and t_w, are repeated an average of $\overline{M}_j$ times for R_0 to receive a reliably decoded version of d_*. Accordingly, the average reporting time of the proposed strategy under $\mathcal{H}_j$ can be written as

$$t_{\mathrm{rep}|\mathcal{H}_j} = \bar{t}_0 + (t_r + t_w)\left(1 + \overline{M}_j\right) \quad (14)$$

While t_r and t_w are design parameters that depend on the system parameters, $\bar{t}_0$ depends on the specific formula used to calculate the timers, while $\overline{M}_j$ depends on the statistical characteristics of the reporting channels. These two parameters are studied subsequently.

4.2.1. Calculating $\bar{t}_0$.

The value of t_0, the time waited before R_* starts its transmission, is inversely proportional to ϕ_*. However, because ϕ_* can take any arbitrary positive value, then using

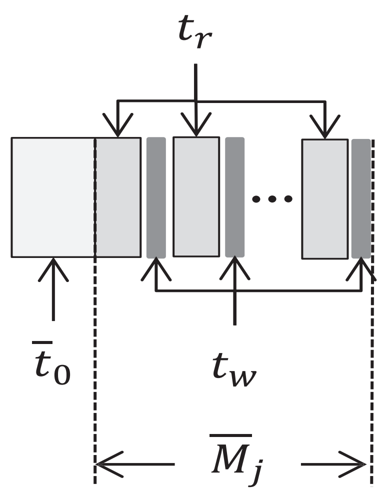


Figure 3. Reporting time of the proposed strategy.

something like $t_0 = \frac{1}{\phi_*}$ will result in very long waiting times, which is undesirable. This can be avoided by mapping ϕ_* into a monotonically increasing function like the logarithm function $\ln(\phi_*)$. Hence, by writing $t_0 = \frac{1\mu s}{\ln \phi_*}$, we can limit t_0 to a few microseconds while maintaining monotonicity [29]. Based on this selection, t_0 becomes a random variable whose mean value can be calculated by numerically evaluating the integral

$$\bar{t}_0 = \int_0^{\infty} \frac{1}{\ln \phi} f_{\phi_*|\mathcal{H}_j}(\phi) d\phi, \tag{15}$$

where $f_{\phi_*|\mathcal{H}_j}(\phi_*) = \frac{d}{d\phi} \prod_{k=1}^{K} F_{\phi_k|\mathcal{H}_j}(\phi)$.

4.2.2. Calculating $\overline{M}_j$.

The average number of retransmissions needed for R_* to deliver a signal with $\psi_k \geq \tau$ depends on the identity of R_*. This implies that $\overline{M}_j$ has to be written as a function of the average number of retransmissions assuming that $R_* = R_k$, $k = 1, 2, \ldots, K$, using the total probability theorem, that is,

$$\overline{M}_j = \sum_{k=1}^{K} \overline{m}_{j,k} \Pr[R_* = R_k|\mathcal{H}_j] \tag{16}$$

where $\overline{m}_{j,k}$ is the average number of retransmissions when $R_* = R_k$. The number of retransmissions that R_k makes to achieve $\psi_k \geq \tau$ follows a geometric distribution with a success probability of $p_{j,k} \triangleq \Pr[\psi_k \geq \tau|\mathcal{H}_j] = 1 - F_{\psi_k|\mathcal{H}_j}(\tau)$. As a result, the average number of retransmissions, that is, $\overline{m}_{j,k}$, can be written as

$$\overline{m}_{j,k} = \frac{1}{p_{j,k}} - 1 = \frac{F_{\psi_k|\mathcal{H}_j}(\tau)}{1 - F_{\psi_k|\mathcal{H}_j}(\tau)} \tag{17}$$

More specifically, using $F_{\psi_k|\mathcal{H}_0}(\tau) = 1 - e^{-\tau/\rho_k \Omega_{k,0}}$ and $F_{\psi_k|\mathcal{H}_1}(\tau)$ in (2), $\overline{m}_{0,k}$ and $\overline{m}_{1,k}$ can be written as

$$\overline{m}_{0,k} = \exp\left(\frac{\tau}{\rho_k \Omega_{k,0}}\right) - 1 \tag{18a}$$

$$\overline{m}_{1,k} = \left(1 + \frac{\psi \rho_p \Omega_{p,0}}{\rho_k \Omega_{k,0}}\right) \exp\left(\frac{\tau}{\rho_k \Omega_{k,0}}\right) - 1 \tag{18b}$$

5. NUMERICAL AND SIMULATIONS RESULTS

Consider a two-dimensional network where the distances between the PU and R_0, denoted $d_{p,0}$, and between R_k, $k = 1, \ldots, K$, and R_0 are chosen from a uniform distribution on the range (0, 1), hence, $d_{p,0}, d_{k,0} \leq 1$; see Figure 4. Using these distances, we can write $\left\{\Omega_{p,k} = d_{p,k}^{-n}\right\}_{k=0}^{K}$ and $\left\{\Omega_{k,0} = d_{k,0}^{-n}\right\}_{k=1}^{K}$, where $n = 4$ is the path loss exponent.

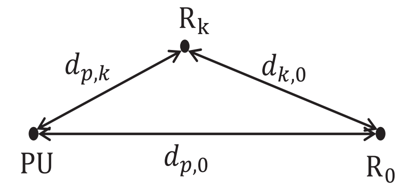


Figure 4. Two-dimensional network model.

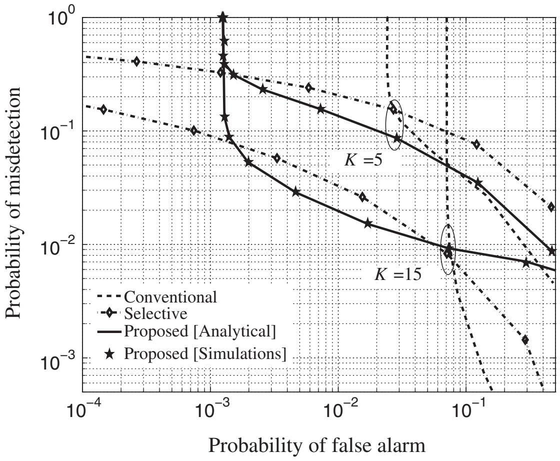


Figure 5. Complementary receiver operating characteristics for the proposed, conventional, and selective strategies for $K = 5$ and 15, $u = 40$, $\tau = 0$ dB, $\rho_p = 0$ dB, $\{\rho_k\}_{k=1}^{K} = 5$ dB, and $\{d_{p,k}\}_{k=0}^{K} = \{d_{1,k}\}_{k=1}^{K} = 0.5$.

Let us first compare the complementary receiver operating characteristics of the proposed strategy with that of the conventional strategy as described in [14] and the selective strategy proposed in [22] for different values of K as shown in Figure 5. This figure shows that the proposed strategy outperforms the other strategies when the probability of false alarm is between 10^{-1} and 10^{-3}, which is a practical range for most standards, for example, IEEE 802.22 [3]. Another interesting observation is that ARQ significantly reduces the error floor of the proposed strategy compared with the conventional strategy.

The effect of increasing K on the probabilities of detection and false alarm is shown in Figures 6 and 7, respectively. In Figure 6, the proposed strategy is shown to have a probability of detection between the selective and conventional strategies, while in Figure 7, the probability of false alarm of the proposed and selective strategies is shown to be very close and significantly outperforms the conventional strategy. This last observation is very important because throughput mainly depends on the probability of false alarm. Hence, the proposed and selective strategies promise more accurate detection of spectrum opportunities compared with the conventional strategy.

Next, let us look at the corresponding average reporting times of the proposed strategy under $\mathcal{H}_0$ and $\mathcal{H}_1$ and

Wirel. Commun. Mob. Comput. 2016; 16:1603–1611 © 2015 John Wiley & Sons, Ltd.
DOI: 10.1002/wcm

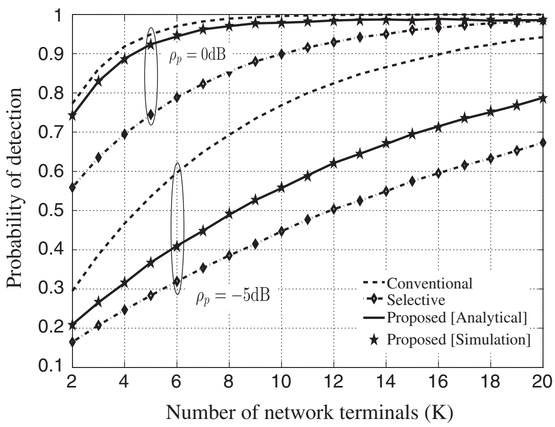


Figure 6. Probability of detection as a function of K for $\rho_p = -5$ and 0 dB, $u = 20$, $\tau = 0$ dB, $\{\rho_k\}_{k=1}^{K} = 0$ dB, $\{d_{p,k}\}_{k=0}^{K} = \{d_{k,0}\}_{k=1}^{K} = 0.5$, and $P_{fa} = 10^{-3}$.

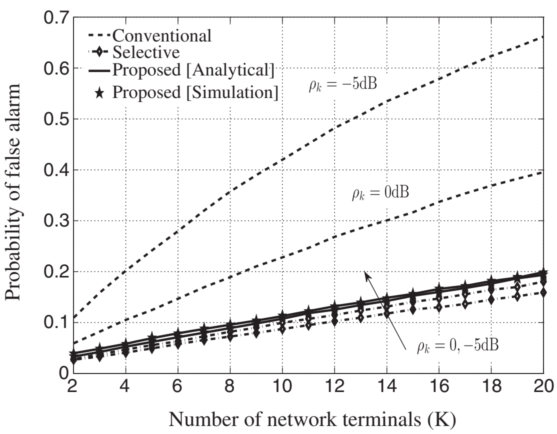


Figure 7. Probability of false alarm as a function of K for $\rho_k = -5$ and 0 dB, $u = 20$, $\tau = 0$ dB, $\rho_p = 0$ dB, $\{d_{p,0}\}_{k=0}^{K} = \{d_{k,0}\}_{k=1}^{K} = 0.5$, and $P_{fa} = 10^{-2}$.

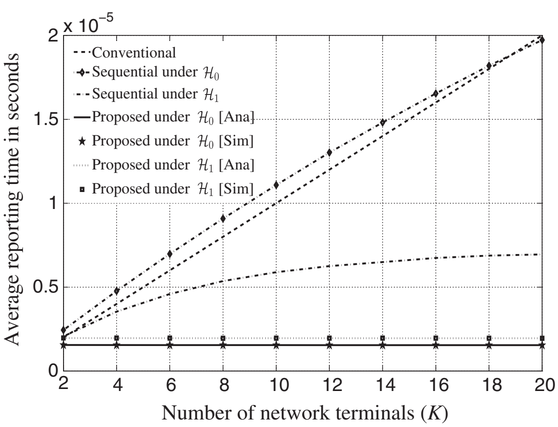


Figure 8. Average reporting time under $\mathcal{H}_0$ and $\mathcal{H}_1$ as a function of K for $t_r = 1$ µs, $t_w = \frac{1}{4}t_r$, $\rho_p = -5$ dB, $u = 40$, $\tau = 0$ dB, $\{\rho_k\}_{k=1}^{K} = 0$ dB, $\{d_{p,k}\}_{k=0}^{K} = \{d_{k,0}\}_{k=1}^{K} = 0.5$, and $P_{fa} = 10^{-2}$.

compare it with that of the conventional strategy and the sequential reporting strategy proposed in [16]. As Figure 8 shows, the proposed strategy outperforms both strategies regardless of the status of the PU. Moreover, the figure shows that unlike other strategies, the proposed strategy maintains a low reporting time that is independent of K. Hence, this strategy brings considerable throughput gain to well-populated networks.

6. CONCLUSION

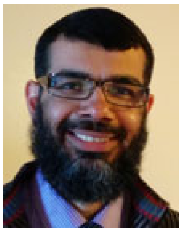
This paper studied the problem of reducing the reporting time of decision-based CSS while achieving reliable sensing. In particular, we have proposed a novel selective reporting strategy for CSS using energy detection. The proposed strategy allows the terminal with the highest energy estimate to send a binary decision to the FC, which uses threshold-based ARQ to mitigate decoding errors. The proposed strategy is shown to offer observable enhancements to the sensing accuracy and to significantly outperform other strategies in terms of sensing agility.

REFERENCES

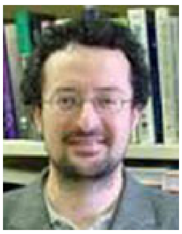
1. Akyildiz IF, Lo BF, Balakrishnan R. Cooperative spectrum sensing in cognitive radio networks: a survey. *Physical Communications* 2011; **4**(1): 40–62.
2. Chen X, Chen HH, Meng W. Cooperative communications for cognitive radio networks: from theory to applications. *IEEE Communications Surveys Tutorials* Third Quarter 2014; **16**(3): 1180–1192.
3. IEEE draft standard for information technology—telecommunications and information exchange between systems—local and metropolitan area networks—specific requirements—part 22.1: standard to enhance harmful interference protection for low power licensed devices operating in the tv broadcast bands. *IEEE Unapproved Draft Std P802.22.1/D6*, 2009.
4. Ko G, Franklin A, You SJ, Pak JS, Song MS, Kim CJ. Channel management in IEEE 802.22 WRAN systems. *IEEE Communications Magazine* 2010; **48**(9): 88–94.
5. Kim H, Shin K. Efficient discovery of spectrum opportunities with MAC-layer sensing in cognitive radio networks. *IEEE Transactions on Mobile Computing* 2008; **7**(5): 533–545.
6. Liang YC, Zeng Y, Peh E, Hoang AT. Sensing-throughput tradeoff for cognitive radio networks. *IEEE Transactions on Wireless Communications* 2008; **7**(4): 1326–1337.

7. Kundargi N, Tewfik A. Hierarchical sequential detection in the context of dynamic spectrum access for cognitive radios. In *IEEE International Conference on Electronics, Circuits and Systems (ICECS)*, Marrakech, Morocco, 2007; 514–517.
8. Shei Y, Su YT. A sequential test based cooperative spectrum sensing scheme for cognitive radios. In *IEEE International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC)*, Cannes, France, 2008; 1–5.
9. Maleki S, Leus G. Censored truncated sequential spectrum sensing for cognitive radio networks. In *International Conference on Digital Signal Processing (DSP)*, Corfu, Greece, 2011; 1–8.
10. Nguyen-Thanh N, Koo I. Optimal truncated ordered sequential cooperative spectrum sensing in cognitive radio. *IEEE Sensors Journal* 2013; **13**(11): 4188–4195.
11. Mishra S, Sahai A, Brodersen R. Cooperative sensing among cognitive radios. In *IEEE International Conference on Communications (ICC)*, Istanbul, Turkey, 2006; 1658–1663.
12. Ben Letaief K, Zhang W. Cooperative communications for cognitive radio networks. *Proceedings of the IEEE* 2009; **97**(5): 878–893.
13. Peh E, Liang Y-C, Guan YL, Zeng Y. Optimization of cooperative sensing in cognitive radio networks: a sensing-throughput tradeoff view. *IEEE Transactions on Vehicular Technology* 2009; **58**(9): 5294–5299.
14. Zhang W, Mallik R, Letaief K. Optimization of cooperative spectrum sensing with energy detection in cognitive radio networks. *IEEE Transactions on Wireless Communications* 2009; **8**(12): 5761–5766.
15. Hesham L, Sultan A, Nafie M, Digham F. Distributed spectrum sensing with sequential ordered transmissions to a cognitive fusion center. *IEEE Transactions on Signal Processing* 2012; **60**(5): 2524–2538.
16. Luan H, Li O, Zhang X. Cooperative spectrum sensing with energy-efficient sequential decision fusion rule. In *Wireless and Optical Communication Conference (WOCC)*, New Jersey, U.S.A., 2014; 1–4.
17. Zhang W, Letaief K. Cooperative spectrum sensing with transmit and relay diversity in cognitive radio networks. *IEEE Transactions on Wireless Communications* 2008; **7**(12): 4761–4766.
18. Sun C, Zhang W, Letaief K. Cooperative spectrum sensing for cognitive radios under bandwidth constraints. In *IEEE Wireless Communications and Networking Conference (WCNC)*, Hong Kong, China, 2007; 1–5.
19. Sun C, Zhang W, Letaief K. Cluster-based cooperative spectrum sensing in cognitive radio systems. In *IEEE International Conference on Communications (ICC)*, Glasgow, Scotland, June 2007; 2511–2515.
20. Abu Alkheir A, Ibnkahla M. Selective cooperative spectrum sensing in cognitive radio networks. In *IEEE Global Conference on Telecommunications (GLOBECOM)*, Houston, U.S.A., 2011; 1–5.
21. Nallagonda S, Dhar Roy S, Kundu S, Ferrari G, Raheli R. Performance of MRC fusion-based cooperative spectrum sensing with censoring of cognitive radios in Rayleigh fading channels. In *International Wireless Communications and Mobile Computing Conference (IWCMC)*, Sardinia-italy, 2013; 30–35.
22. Zou Y, Yao YD, Zheng B. A selective-relay based cooperative spectrum sensing scheme without dedicated reporting channels in cognitive radio networks. *IEEE Transactions on Wireless Communications* 2011; **10**(4): 1188–1198.
23. Umar R, Sheikh A, Deriche M. Unveiling the hidden assumptions of energy detector based spectrum sensing for cognitive radios. *IEEE Communications Surveys Tutorials* Second Quarter 2014; **16**(2): 713–728.
24. Gradshteyn IS, Ryzhik IM. *Table of Integrals, Series, and Products* (7th edn). Academic Press: San Diego, CA, 2007.
25. Abu Alkheir A, Ibnkahla M. Performance analysis of decode and forward incremental relaying in the presence of multiple sources of interference. In *IEEE Vehicular Technology Conference (VTC Fall)*, Québec City, Canada, 2012; 1–5.
26. Ni X, Chen H, Xie L, Wang K. Reputation-based hierarchically cooperative spectrum sensing scheme in cognitive radio networks. In *IEEE/CIC International Conference on Communications in China (ICCC)*, Xi'an, China, 2013; 397–402.
27. Bianchi G. Performance analysis of the ieee 802.11 distributed coordination function. *IEEE Journal on Selected Areas in Communications* 2000; **18**(3): 535–547.
28. Simon MK, Alouini MS. *Digital Communication over Fading Channels* (2nd edn). John Wiley & Sons: New York, NY, 2005.
29. Blum R, Sadler B. Energy efficient signal detection in sensor networks using ordered transmissions. *IEEE Transactions on Signal Processing* 2008; **56**(7): 3229–3235.

AUTHORS' BIOGRAPHIES



Ala Abu Alkheir has earned his BSc and MSc in Electrical Engineering from the Jordan University of Science and Technology in 2004 and 2006, respectively. Between 2007 and 2008, he was with the Department of Electrical and Computer Engineering at Texas A&M University in Qatar as a research and teaching associate. In 2008, he joined the Department of Electrical and Computer Engineering at Queen's University as a PhD student working in the areas of wireless sensor network and cognitive radio networks. After finishing his PhD in 2013, Ala joined the School of Electrical Engineering and Computer Science at the University of Ottawa as a postdoctoral fellow. His research interests are in cognitive radio networks, wireless sensor networks, smart grids, vehicular networks, and the internet of things.



Mohamed Ibnkahla received his Engineering degree in Electronics and a Diplome d'Etudes Approfondies degree (equivalent to MSc) in signal and image processing, both in 1992, the PhD degree in 1996, and the Habilitation a Diriger des Recherches degree (HDR) in 1998, all from the National Polytechnic Institute of Toulouse (INP), Toulouse, France. He currently holds a full professor position at the Department of Electrical and Computer Engineering, Queen's University, Kingston, ON, Canada. He has been an assistant professor at INP (1996–1999) and Queen's University (2000–2004) and an associate professor at Queen's University (2004–2012). He is also the founding director of the Wireless Communications and Signal Processing Laboratory (WISIP) at Queen's University. He has published the following books: Signal Processing for Mobile Communications Handbook (Boca Raton, FL, USA: Taylor & Francis/CRC Press, 2004), Adaptive Signal Processing in Wireless Communications (Boca Raton, FL, USA: Taylor & Francis/CRC Press, 2008), Adaptive Networking and Crosslayer Design in Wireless Networks (Boca Raton, FL, USA: Taylor & Francis/CRC Press, 2008), Wireless Sensor Networks: A Cognitive Perspective (Boca Raton, FL, USA: Taylor & Francis/CRC Press, 2012), and Cooperative Cognitive Radio Networks: The Complete Spectrum Cycle (Boca Raton, FL, USA: Taylor & Francis/CRC Press, 2014). He has published more than 50 peer-reviewed journal papers and book chapters, 20 technical reports, 90 conference papers, and 4 invention disclosures. His research interests include cognitive radio, adaptive signal processing, cognitive networking, neural networks, and wireless sensor networks and their applications. Dr. Ibnkahla received the INP Leopold Escande Medal, France, in 1997, for his research contributions to signal processing and the prestigious Prime Minister's Research Excellence Award (PREA), Ontario, Canada, in 2001, for his contributions in wireless mobile communications. He is a registered professional engineer (PEng) of the Province of Ontario, Canada.