Extended Knowledge-Based Reasoning Approach to Spectrum Sensing for Cognitive Radio

Xiao Yu Wang, Alexander Wong, and Pin-Han Ho

Abstract—In this paper, a novel scheme for Cognitive Radio (CR) spectrum sensing in Medium Access Control (MAC) layer, called as Extended Knowledge-Based Reasoning (EKBR), is proposed. The target of EKBR is to improve the fine sensing efficiency by jointly considering a number of network states and environmental statistics, including fast sensing results, short-term statistical information, channel quality, data transmission rate, and channel contention characteristics. This is for a better estimation on the optimal range of spectrum for fine sensing so as to adaptively reduce the overall channel sensing time. Performance analysis is conducted on the proposed EKBR scheme using a multidimensional absorbing Markov chain to evaluate various performance metrics of interest, such as average sensing delay (or referred to as sensing overhead in the study), average data transmission rate, and percentage of missed spectrum opportunities. Numerical results show that the proposed EKBR scheme achieves better performance than that by the state-or-the-art techniques while yielding less computation complexity and sensing overhead.

Index Terms—Cognitive radio, dynamic spectrum access, spectrum sensing.

1 Introduction

The surging popularity of ubiquitous wireless devices in recent years has led to a significant strain on certain portions of the radio spectrum, particularly for the radio spectrum bands standardized for legacy voice and data transmission. This results in the situation where voice and data transmissions fail due to unavailability of spectrum resources for the devices to operate, despite the availability of strong wireless signals. In stark contrast, there is a large portion of licensed radio spectrum that is significantly underutilized, leading to used spectrum holes. For example, according to the statistics provided by Federal Communication Commission (FCC), up to 15 percent of the licensed spectrum is underutilized in highly populated regions and up to 85 percent is unused in thinly populated regions. To improve spectrum utilization, FCC has decided to deregulate these licensed spectrums for unlicensed use by ubiquitous wireless devices. This has brought up a significant interest in devising solutions to utilizing temporarily available portions of the licensed spectrum in an opportunistic fashion.

Cognitive Radio (CR) [1] is one of the most promising technologies that has been investigated for an efficient spectrum utilization. CR is an intelligent radio system that is capable of dynamically accessing various radio spectrum resources based on the knowledge of surrounding environment to allow user-centric communications [2]. For example, communication devices with CR capabilities are able to access spectrum bands licensed for other wireless services (e.g., television bands within 30 MHz-3 GHz) in an opportunistic fashion to meet the service requirement of the user. As such, such devices can be viewed as the "secondary" users to the "primary" licensed users of the licensed spectrum bands. Given its ability to greatly improve spectrum utilization, the CR technology has garnered a lot of interest as the solution to spectrum shortage problems experienced by users in highly utilized spectrum bands.

There are many challenges associated to the design of CR due to the wide range of available licensed spectrum. Many previous studies [3], [4], [5] assumed the existence of an ideal physical layer (PHY), which is capable of perfect detection and utilization of free spectrum. However, such an assumption is seldom true due to physical constraints. For example, a CR system should be equipped with radio frequency (RF) components capable of utilizing any portion of the multigigahertz wide radio spectrum. This requires the CR device to be equipped with extremely high-speed analog-to-digital converters (ADCs), which may not be feasible in many situations [6]. Furthermore, it is necessary that a CR is capable of detecting the presence of licensed primary users. This is very challenging particularly in a fading environment, where differentiating between a free channel and a deep fading channel is difficult. Commonly used energy detection methods are often insufficient for identifying the presence of primary users. More advanced feature detection methods provide improved primary user detection through better distinction between noise energy and modulated signal energy. However, this is at the expense of significantly increased computational complexity and longer spectrum sensing periods [7].

By observing the unsolved challenges associated with PHY design for CR in terms of primary user detection and spectrum sensing, we are motivated to investigate this topic

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and develop efficient and reliable spectrum sensing algorithms on the Medium Access Control (MAC) layer that can provide better control over the detection process based on the possible PHY constraints. Important design issues associated with spectrum sensing on the MAC layer are listed as follows:

1. **Efficiency**: It is necessary for a spectrum sensing algorithm to be able to sense an appropriate number of channels such that high sensing efficiency can be achieved. Since spectrum opportunities may occur across the entire spectrum, the CR is more likely to obtain the desired spectrum access by sensing more channels. However, provided with a time constraint for each data transmission, a lengthy sensing process results in reduced transmission time, and thus, increases the energy consumption and the chances of data transmission failure.
2. **Timing**: To allow reliable and efficient spectrum sensing, it is necessary for a spectrum sensing algorithm to elaborate the timing of spectrum sensing. *On-demand sensing* is efficient since CR only senses the spectrum upon arrival of a data transmission request. However, on-demand sensing introduces sensing latency to the end-to-end transmission delay because the data transmission cannot occur until the necessary available channels are found. *Proactive sensing* yields reduced sensing latency by providing spectrum availability information prior to transmission request. However, this comes at a cost of increased overall overhead [8].
3. **Reliability**: To enable unlicensed utilization of licensed spectrum resources, it is necessary that CR is capable of minimizing the possible interferences on any primary user. Therefore, a spectrum sensing algorithm should provide reliable channel availability information, given that reliable spectrum detection remains an issue in the PHY design.
4. **Computational complexity**: To achieve efficient spectrum access, a spectrum sensing algorithm should be as little computational complexity as possible. A complex algorithm leading to high energy consumption and computation latency is not desired.

Based on the aforementioned observations and design premises, we introduce a novel MAC layer spectrum sensing scheme, called Extended Knowledge-Based Reasoning (EKBR), in the application scenario of information exchange among distributed CR nodes across fully utilized licensed spectrum bands standardized for data and voice transmissions. In this scenario, the CR nodes are allowed to opportunistically access any available licensed band for peer-to-peer communications. It is assumed that there is no central controller, and thus, the CR nodes simply form an ad hoc network. The underlying goal of the proposed EKBR scheme is to perform stand-alone CR spectrum sensing at each CR node that intends to initiate a peer-to-peer communication session with another in a dynamic manner. The proposed EKBR algorithm is characterized by the ability of adapting to the ever-changing channel conditions and access opportunities in the radio spectrum, by assuming imperfect PHY that is capable of detecting the presence of free spectrum only within a certain probability. As a solid extension of the Knowledge-Based Reasoning (KBR) scheme in our previous work [9], the EKBR scheme takes advantage of both intrinsic and extrinsic knowledge about network states and environments to both prioritize channels and estimate the optimal range of radio spectrum to finely sense as well as dynamically refine the amount of fine sensing to achieve the desired performance requirements of the users while minimizing service processing time.

The new features of the proposed EKBR scheme are summarized as follows: First, the EKBR scheme jointly considers short-term statistical information, data transmission rate information, and contention characteristics as priors to facilitate the estimation of optimal range of channels for fine sensing. Second, the EKBR scheme takes advantages of a knowledge-based channel prioritization strategy based on short-term statistical information and fast sensing results to further enhance spectrum sensing efficiency. Simulation results show that the proposed EKBR scheme is capable of improved efficiency and performance over existing methods. The proposed EKBR scheme is designed to perform noncooperative, stand-alone MAC spectrum sensing for many application scenarios where the heterogeneous underlying technologies make it difficult for CRs to cooperate with each other.

The rest of this paper is organized as follows: The related work is presented in Section 2. The system model is described in Section 3. The proposed spectrum sensing scheme, EKBR, is introduced in Section 4. Performance analysis based on the developed multidimensional absorbing Markov chain model is presented in Section 5. Numerical results are provided in Section 6. Finally, conclusions are drawn in Section 7.

2 Related Work

Though the research initiatives on noncooperative MAC-layer spectrum sensing for CR just emerged in the past two years, a number of algorithms have been reported. Kim and Shin [8] proposed the use of two modes of MAC-layer spectrum sensing, reactive and proactive, as well as the associated trade-off between the two modes. They also introduced an energy-efficient approach for determining the appropriate mode of sensing, as well as a sensing-period adaptation technique for finding the optimal sensing period. More recently, Kim and Shin [12] proposed a spectrum sensing algorithm that attempts to determine a sensing sequence that minimizes the average delay of discovering idle channels based on channel capacity and probability of channel availability. Datla et al. [13] took a more heuristic approach to the problem of spectrum sensing, where a linear backoff scheme is employed to reduce the preference of sensing a channel whenever the channel is identified as being occupied. Jia et al. [14] introduced a spectrum sensing algorithm that takes some constraints on sensing and transmission into account. By considering the limitations associated with bandwidth and fragmentation (transmission constraints) and the limitations with sensing capacity (sensing constraints), Jia et al. formulate the trade-off between spectrum opportunities and sensing overhead as a stopping problem to determine whether the sensing process should proceed. More recently, Huang et al. [15] formulated the spectrum sensing and transmission problems together as an optimal stopping algorithm that aims to maximize the average reward per unit time, where an award is received

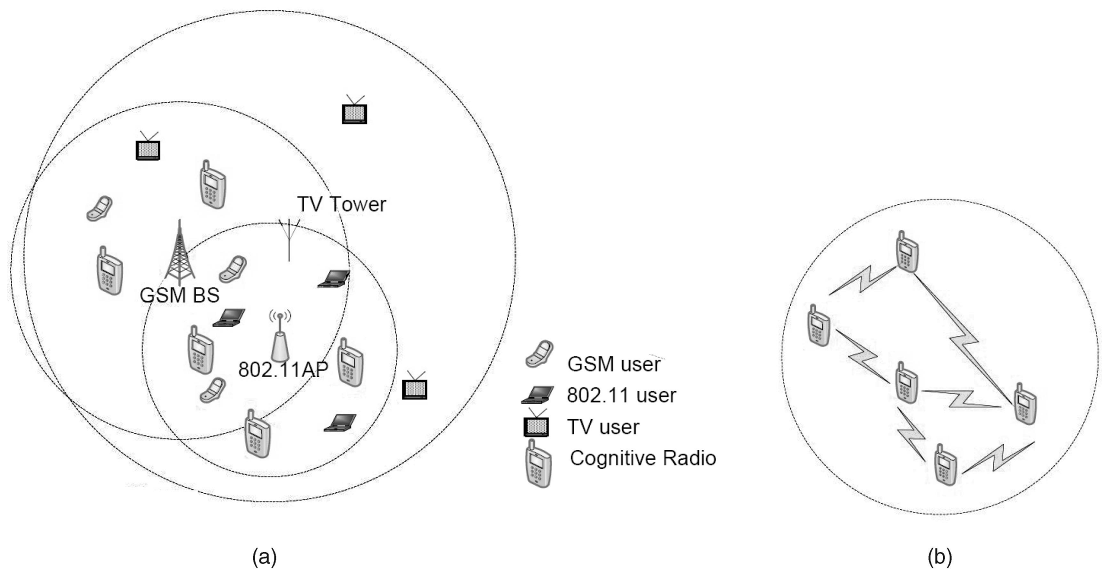


Fig. 1. Cognitive Radio network architecture. (a) A heterogeneous network. (b) A cognitive radio network.

by a secondary user for each successful transmission. Chang and Liu [16] also employed a joint channel sensing and transmission strategy that aims to maximize reward using a threshold-based structure.

This work differs from previous spectrum sensing approaches in that it takes advantage of both intrinsic and extrinsic knowledge about network states and environmental statistics, including fast sensing results, short-term statistical information, channel quality, data transmission rate, and channel contention characteristics in the channel prioritization, optimal channel range estimation, and fine sensing processes. Furthermore, the proposed EKBR system combines an optimal channel range estimation process with a channel prioritization strategy, which allows the system to provide an improved ordered list of channels for enhancing spectrum sensing efficiency. This integrated knowledge-based approach allows the system to achieve the desired performance requirements of the user in a dynamical manner while minimizing overall channel sensing time.

3 System Model

Before presenting the proposed EKBR scheme, it is important to provide an overview of the network architecture, the channel model, spectrum sensing model, access model, as well as assumptions made in the design of the proposed spectrum sensing scheme. The notation used in the remainder of this paper is listed in the Appendix.

3.1 Network Architecture

The architecture for a typical heterogeneous wireless network is illustrated in Fig. 1a. In such a heterogeneous network, many different devices operating under various wireless access technologies (e.g., IEEE 802.11, GSM, TV broadcast, etc.) may coexist within the same environment. These devices form a number of primary user networks, and the underlying infrastructure of each primary user network is not required to allow for spectrum sharing with other networks. However, a CR device may access network resources in other networks (as secondary users to the licensed users of the primary user networks) when unable to allocate resources within its own network to maintain services, hence forming a wireless ad hoc network.

Let us describe a practical scenario in which CR technology can be utilized to improve spectrum utilization in such a heterogeneous network. Due to the large number of devices utilizing IEEE 802.11 and GSM technology, the spectrum resources associated with these technologies can become saturated. This leaves such devices depraved of spectrum resources for transmission purposes. However, IEEE 802.11 and GSM devices with CR technology gain the capability of utilizing free spectrum on 400-800 MHz Ultra High-Frequency (UHF) TV bands, which will be available in the near future for use by CRs [6]. As such, the devices with CR technology act as the secondary users to the primary users on the TV band. This utilization of free spectrum resources on the TV bands has been demonstrated to be practically viable by many researchers [4], [6], [7], as well as promoted by the FCC and has led to the deregulation of spectrum resources on the TV bands.

In the CR network architecture upon which EKBR is built, the aforementioned wireless ad hoc network is denoted as the secondary user network, as shown in Fig. 1b.

3.2 Channel Model

In this study, we assume that there are M nonoverlapping channel $\{\mathrm{CH} \mid CH_i, i = 1, 2, \dots, M\}$ centered at $\{f_c^i\}_{i=1}^M$ over a license spectrum assigned to a primary user network. Users equipped with CR are considered as the secondary users to the primary networks, and form a network in an ad hoc manner. The secondary users with CR capability can opportunistically access channels that are not occupied by primary users. Without the loss of generality, it can be assumed that the channel usage model of the primary users follows an ON/OFF traffic model, where the secondary users are restricted to channel access only during OFF periods, while no primary users are using the channels.

3.3 Spectrum Sensing Model

In the spectrum sensing model used by the proposed EKBR scheme, it is assumed that the sensing process and the data

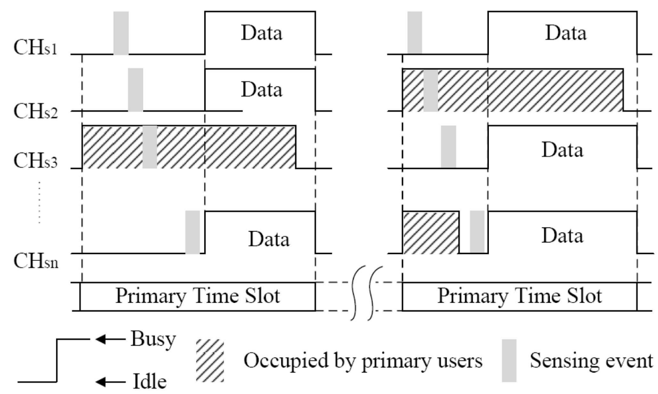


Fig. 2. Access model.

transmission process cannot be processed in a simultaneous manner. As such, each secondary user detects the presence of primary users independently of other secondary users through spectrum sensing. The first stage of spectrum sensing involves performing a fast but relatively inaccurate sensing process using energy detection over the entire radio spectrum. The instantaneous statistics is obtained based on a fast sensing process. In a Rayleigh fading channel model, at the time instance ζ, the detection probability, i.e., the aforementioned instantaneous statistics $P_{inst}(CH_i, \zeta)$ is given in [17] as

$$P_{inst}(CH_i, \zeta) = \frac{1}{\bar{\mu}} \int_0^{\infty} \int_{\epsilon}^{\infty} f(u_i) \exp\left(-\frac{\mu}{\bar{\mu}}\right) du_i d\mu, \quad (1)$$

where $\bar{\mu}$ is the average Signal to Interference plus Noise Ratio (SINR), μ is the instantaneous SINR, ϵ is the decision threshold, and $f(u_i)$ is the probability density function (PDF) of the test statistics u_i of observed signals.

The second stage of sensing, known as fine sensing, is performed using a feature detection process, which is more accurate but requires a longer observation time. In a typical system, the CR performs fine sensing on each channel within the range of channels determined based on the knowledge obtained during fast sensing to identify channel conditions and appropriate modulation schemes. As such, it is necessary to not only determine when to initiate and terminate the fine sensing process, but also determine how the data transmission rate is selected. All of these issues are addressed in the proposed EKBR scheme in Section 4.

3.4 Access Model

An Orthogonal Frequency Division Multiple Access (OFDMA) system is utilized as the underlying multiple access technique for data transmission across multiple free channels in the spectrum, as shown in Fig. 2. This access model is well suited for time-slotted primary user systems, such as IEEE 802.11, slotted GSM system, and digital TV system. Thus, channels that are successfully identified as available will be used by the secondary users in the remaining time of the primary time slot. Furthermore, the state of channel availability is assumed to be constant within each time slot. This assumption is practical since most digital systems such as GSM, IEEE 802.11, and digital TV system are time-slotted systems and are widely used in sensing-based MAC protocols such as those presented in [5], [14], [18]. Moreover, in the access model used by the EKBR scheme, a channel is a subcarrier in the OFDMA system and is categorized into γ different modulation schemes with corresponding data transmission rates based on the perceived SINR of the channel obtained through fine sensing process.

4 Proposed Spectrum Sensing Scheme

The proposed spectrum sensing scheme can be described as follows: When a secondary user $\aleph_\chi$ initially enters a primary user network, it possesses no statistical information about the primary user network upon which it can rely on for spectrum sensing. Therefore, it performs fine sensing in a proactive manner to determine an initial set of probabilities regarding channel availability $\hat{P}_s(CH_1), \hat{P}_s(CH_2), \ldots, \hat{P}_s(CH_M)$ in a short time scale τ prior to the current time. Upon the request of data transmission, $\aleph_\chi$ retrieves its short-term statistics, i.e., $\hat{P}_s(CH_1), \hat{P}_s(CH_2), \ldots, \hat{P}_s(CH_M)$, and initiates fast sensing immediately on entire channels $CH_1, CH_2, \ldots, CH_M$ to obtain the instantaneous statistical information $P_{inst}(CH_1)$, $P_{inst}(CH_2), \ldots, P_{inst}(CH_M)$, both of which can be used to obtain the sensing priority $\Theta = \{CH_{s_1}, CH_{s_2}, \ldots, CH_{s_M}\}$. The sensing prioritization process is performed for fine sensing based on the statistical likelihood of channel availability by jointly exploiting short-term statistics and instantaneous statistical information. The details of the sensing prioritization process can be found in [10], [11]. Based on results of the sensing prioritization process, $\aleph_\chi$ estimates the number of prioritized channels for fine sensing by comprehensively considering the short-term statistics, data transmission rate information, and contention characteristics, which is then used as the upper bound of the fine sensing process in order to secure at minimum the slowest required data transmission. Finally, fine sensing is performed according to the prioritized sensing results in a dynamic manner, where the fine sensing process is adaptively terminated based on additional prior knowledge, such as instantaneous channel quality information determined by actual fine sensing process, to satisfy the necessary performance requirements while minimizing sensing overhead. The short-term statistics used in the system, knowledge-based estimation process, as well as the reasoning approach of the proposed EKBR spectrum sensing scheme are further elaborated in the following sections.

4.1 Short-Term Statistics

The short-term statistics are used to estimate the likelihood of channel availability at time instance ζ based on a short observation window of previous τ seconds. The use of short-term statistics of channel behavior is motivated by previous work demonstrating that channel availability demonstrates patterns can be modeled using a statistical approach [19], [20]. In the proposed EKBR scheme, each CR node maintains the observations for a channel CH_i $\Omega_i^\tau = \{\omega_i(\tau_1), \omega_i(\tau_2), \ldots, \omega_i(\tau_n)\}$, which represents the observations of primary user channel occupancy as successfully identified by the node. Based on Ω_i^τ, assuming that the observations are independent and identically distributed (i.i.d.) with a Poisson distribution during τ as not to lose generality, the arrival rate of primary users $\hat{\Lambda}_i$ on CH_i can be estimated as

$$\hat{\Lambda}_i = \sum_{t=\tau_1}^{\tau_n} \omega_i(t)/\tau. \tag{2}$$

Therefore, based on $\hat{\Lambda}_i$, the likelihood of channel availability $\hat{P}_s(CH_i)$ based on the observations over τ can be estimated as

$$\hat{P}_s(CH_i) = 1 - \int_0^{\tau} \hat{\Lambda}_i e^{-\hat{\Lambda}_i t} dt. \tag{3}$$

4.2 Knowledge-Based Estimation

During the fine sensing process, $\aleph_\chi$ senses a set of prioritized channels $\Theta = \{CH_{s_1}, CH_{s_2}, \dots, CH_{s_M}\}$ to identify the availability of a channel as well as the underlying channel conditions. $\aleph_\chi$ continues to perform the fine sensing process from one channel to another until sufficient channels for data transmission are found. It is observed that as the number of channels sensed is increased, the likelihood of obtaining channels with better quantity and quality is increased. This results in an improved data transmission rate, and thus, higher data throughput. Unfortunately, sensing too many channels during the fine sensing process results in significantly increased overall processing time T_Σ, and consequently, decreased throughput ρ, which is defined as $\rho = L/T_\Sigma$, where L is the length of the data packet (frame). Furthermore, a long fine sensing process increases the likelihood of unsuccessful transmissions within the primary time slot T and lost opportunities due to the time-sensitive nature of spectrum sensing. Hence, the optimal number of channels to be finely sensed should be determined in such a way that the total processing time T_Σ is minimized. Furthermore, by minimizing T_Σ, the throughput ρ is effectively maximized. The knowledge-based estimation on n for determining the number of channels to be finely sensed can be formulated as

$$n = \arg\min_n \left\{ T_\Sigma \mid T_\Sigma = nt_s + \frac{L}{\bar{R}} + \Delta t + T_b \right\}, \tag{4}$$

where t_s is the time consumed by each fine sensing iteration, Δt is the processing time of the proposed scheme and other time consumed by the system, T_b is the backoff time determined by backoff mechanism during channel access, and $\bar{R}$ is the expected basic data transmission rate obtained in n iterations fine sensing. The basic data transmission rate R_k can be determined based on the information rate of modulation symbols N_ξ, number of available channels k obtained by $\aleph_\chi$ after performing the fine sensing process for n iterations, and sample time ϱ. We note that N_ξ is dependent on the channel quality, i.e., a bigger SINR suggests a better quality channel so that a faster modulation scheme can be used. However, at this estimation stage, no fine sensing process is involved so that $\aleph_\chi$ is not able to determine the modulation schemes. If taking Binary Phase Shift Keying (BPSK) as the slowest modulation scheme at the estimation stage in the OFDMA system, it can be expressed as [21]

$$R_k = \frac{N_1 k}{\varrho}, \tag{5}$$

where N_1 is the information rate of BPSK. $\aleph_\chi$ will refine the decision on modulation schemes on the fly at the reasoning stage.

It can be observed that the number of identified available channels k is highly dependent on the channel availability and the estimated n iterations of fine sensing. The channel availability of a channel, which is prioritized as CH_{s_i}, at time instance ζ is estimated by using (3) during the short-term observation as $\hat{P}_s(CH_{s_i})$. By using this prior information, the probability representing the likelihood of CH_{s_i} being available with respect to the other channels at time instance ζ is normalized as

$$\bar{P}_s(CH_{s_i}) = \hat{P}_s(CH_{s_i})/n \tag{6}$$

and the aggregate probability that the channel $\{CH_{s_i}, \forall s_i\}$ is not available is normalized as

$$\bar{P}'_s = \frac{1}{n}\sum_{i=1}^{n} [1 - \hat{P}_s(CH_{s_i})]. \tag{7}$$

With probability $\bar{P}_s(CH_{s_1}), \bar{P}_s(CH_{s_2}), \dots, \bar{P}_s(CH_{s_n})$ and $\bar{P}'_s$ so that $\sum_{i=1}^{n} \bar{P}_s(CH_{s_i}) + \bar{P}'_s = 1$, the fine sensing of n channels (where each iteration of sensing involves the sensing of a single channel) resulting in k identified available channels follows a multinomial distribution. Since the number of times outcome $CH_{s_i}, i = 1, 2, \dots, n$ can be observed at most once over n fine sensing iterations, for the purpose of notation simplification, let the random variable x_i represent the ith identified available channel found over the n iterations based on the channel prioritization results. The probability mass function of $i = k$ with parameters n and $\bar{\mathbf{P}}$, where $\bar{\mathbf{P}} = (\bar{P}_s(CH_{s_1}), \dots, \bar{P}_s(CH_{s_n}), \bar{P}'_s)$, is, therefore, given by

$$\begin{aligned} &f(k; n, \bar{P}_s(CH_{s_1}), \dots, \bar{P}_s(CH_{s_i}), \bar{P}'_s) \\ &= \frac{n!}{(n-k)!} \prod_{i=1}^{n} \bar{P}_s(CH_{s_i})^{I(i)} \bar{P}'^{(n-k)}_s, \end{aligned} \tag{8}$$

where indication function is defined as

$$I(i) = \begin{cases} 1, & CH_{s_i} = x_i, \\ 0, & CH_{s_i} \neq x_i. \end{cases} \tag{9}$$

By averaging k, the expected basic data transmission rate is given by

$$\begin{aligned} \bar{R} &= \int_0^n f(k; n, \bar{P}_s(CH_{s_1}), \dots, \bar{P}_s(CH_{s_i}), \bar{P}'_s) R_k dk \\ &= \sum_{k=0}^{n} \left[\frac{N_1 k}{\varrho} \cdot \frac{n!}{(n-k)!} \prod_{i=1}^{n} \bar{P}_s(CH_{s_i})^{I(i)} \bar{P}'^{(n-k)}_s \right]. \end{aligned} \tag{10}$$

Substituting (10) into (4), $\aleph_\chi$ can then estimate the number of channels that should be finely sensed.

4.3 Fine Sensing under Reasoning

Although the estimated number of channels n to be finely sensed is estimated, simply performing fine sensing n iterations on the channels given by the channel prioritization process could still be an expensive process. Note that a lengthy sensing process could lead to unsuccessful channel access due to the dynamic nature of channel conditions. To improve sensing efficiency while maintaining the desired transmission rate, the EKBR scheme introduces an extended knowledge-based reasoning approach that takes advantage of additional prior knowledge such as instantaneous channel quality information to dynamically terminate the fine sensing process. With the proposed reasoning approach, the $\aleph_\chi$ has the intelligence and knowledge necessary to determine whether the fine sensing process should be terminated.

The proposed reasoning approach under EKBR can be explained using a "seashell collection" analogy described as follows: Suppose that a person walks along a beach, looking for seashells to collect. When the person comes upon a seashell, he or she can either collect the seashell or not. For any seashell that is not collected, it will never be considered again. Further, the person knows little about the type of seashell he or she will come upon next nor does he or she knows how far to walk to come upon the next seashell as the tide may either wash a seashell ashore or away at any time. Hence, the person needs to decide whether to pick up and collect an encountered seashell based on limited observations and knowledge after each step.

In the case of EKBR, the person is analogous to $\aleph_\chi$, the seashells are taken as spectrum resources, and the tide is analogous to the dynamic nature of channel availability. To decide whether the next channel is finely sensed, $\aleph_\chi$ evaluates the possible outcomes prior to the next fine sensing iteration. Each spectrum fine sensing iteration will either find an available channel or not. Either of the outcomes imposes a profound influence on the subsequent fine sensing iterations. If $\aleph_\chi$ decides to sense the next channel and find an available channel, the aggregate data transmission rate is increased based on (5), which may increase the success probability in data transmission within the remaining time in the primary time slot. However, if the CR decides to proceed the next iteration, and unfortunately, fails in finding any available channel, the time spent in the iteration is totally wasted, which decreases the success probability in data transmission within the remaining time. Therefore, the reasoning approach should be designed at each iteration of fine sensing based on whether or not $\aleph_\chi$ can gain better success probability of data transmission by continuing finely sensing the next channel. If there is no any marginal return by performing the next iteration of fine sensing, the fine sensing process should be terminated, and $\aleph_\chi$ should immediately start the channel access and subsequent data transmission by using the currently collected channels.

Mathematically, X_i is denoted as a spectrum offer at the ith fine sensing, which is a set of identical and independent random variables with a cumulative distribution function F, which is known as the *profile function* of the spectrum. The net spectrum offer return $Y_{(i)}$ at the ith fine sensing step is given by

$$Y_{(i)} = \sum_{i=1}^{i} X_i - iC \quad 0 < i < n, \tag{11}$$

where C is the cost associated with each fine sensing. Therefore, the expected return of the next move $Y_{(i+1)}$ is given by

$$\begin{aligned} E[Y_{(i+1)}] = \hat{P}_s(CH_{s_i}) \left[\sum_{i=1}^{i+1} X_i - (i+1)C \right] \\ + (1 - \hat{P}_s(CH_{s_i})) \left[\sum_{i=1}^{i} X_i - (i+1)C \right] \quad 0 < i < n. \end{aligned} \tag{12}$$

$\aleph_\chi$ continues finely sensing the next channel as long as the following condition is satisfied:

$$E[Y_{(i+1)}] > Y_{(i)} \quad 0 < i < n. \tag{13}$$

Equation (13) is equivalent to

$$\hat{P}_s(CH_{s_i}) X_{i+1} - C > 0 \quad 0 < i < n. \tag{14}$$

What (14) means is that any additional fine sensing should provide a certain desired marginal return. If the required return cannot be obtained, the reasoning process of EKBR terminates the fine sensing process. One possible definition of the cost is the time consumed on each fine sensing iteration, i.e., t_s, and the spectrum offer X_i is the saved time through increased data transmission rate, i.e., $(L/R_{(i)} - t_s)N_1/\varrho/R_{(i)}$. Therefore, (14) can be rewritten with respect to time as

$$\frac{L}{R_{(i)}} > \frac{L}{R_{(i)} + \frac{N_1}{\varrho} \hat{P}_s(CH_{s_i})} + t_s \quad 0 < i < n, \tag{15}$$

where $R_{(i)}$ is the aggregate data transmission rate after ith fine sensing, and it is determined adaptively on channel quality by $\aleph_\chi$ based on SINR level through fine sensing. This channel quality information is taken into account by classifying the individual channels into γ classes with corresponding spectrum sensing thresholds to further aid in the decision-making process. This prior knowledge of network states can further aid $\aleph_\chi$ determine whether to continue fine sensing on the next channel by comparing the expected throughput gained in the next move with present throughput; therefore, $R_{(i)}$ can be rewritten as $R_{(i)} = \sum_i N_\xi^{(i)}/\varrho$, where $N_\xi^{(i)}$ is the ith N_ξ. Equation (15) can be interpreted as that any additional fine sensing should only be performed if it can compensate for the additional fine sensing time cost t_s through increased data transmission rates by taking the slowest modulation. Equation (15) serves as the "reasoning" process, by which $\aleph_\chi$ determines whether to proceed with additional fine sensing efforts in an attempt to achieve the desired throughput.

5 Performance Analysis

For the purpose of performance analysis, the proposed EKBR scheme is modeled as a multidimensional absorbing finite Markov chain [22] process, where the average transmission delay and resultant average data transmission rate are evaluated by solving the formulated Markov chain. Because each fine sensing iteration only scans one channel, there is at most one channel that could possibly be identified as available and labeled with a certain class ξ among γ classes according to SINR level when $\aleph_\chi$ decides to proceed to the next fine sensing iteration. Once a channel is labeled, the channel state will not be changed during the remaining time in the primary user time slot. This assumption is practical since most digital systems such as GSM, IEEE 802.11, and digital TV system are time-slotted systems. In such primary systems, the secondary users can either detect, and then, use the time slots that are not assigned to the primary users or use up the remaining time in the time slot that have already been assigned to the primary users but is not being used up by the primary users. We denote $\eta_\xi, (s = 1, 2, \ldots, \gamma)$ as the number of

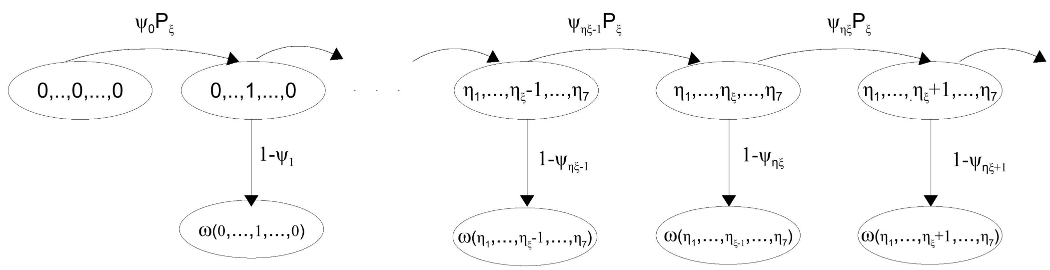


Fig. 3. A cross section of multidimensional absorbing Markov chain.

available channels of class ξ collected at the $i\mathrm{th}$ fine sensing. Hence, the transition state space S consists of a set of integers $\eta_1, \eta_2, \ldots, \eta_\gamma : \sum_{\xi=1}^{\gamma} \eta_\xi = k$, and the number of mutually exclusive states is denoted as

$$\Phi = \sum_{k=0}^{k} \binom{k+\gamma-1}{k}.$$

Furthermore, there are Φ absorbing states $\Re$ associated with all the transition states. This is due to the fact that the fine sensing process could terminate at any state, and then, enter the corresponding absorbing state if $\aleph_\chi$ decides not to proceed. Hence, both transition state space S and absorbing state space $\Re$ form a γ-dimensional absorbing Markov chain with a finite set of 2Φ mutually exclusive states. The probability that a process moves from state S_i to S_j is only determined by state S_i.

Based on the above descriptions, the objectives of the performance analysis are formulated as follows:

1. To evaluate the conditional probability that the fine sensing process enters state S_j, given that it is leaving state S_i.
2. To evaluate the average number of transitions that remain in a particular active state before absorption. Using this information, the average number of reasoning iterations required by the fine sensing process before terminated as well as the average overall delay due to the fine sensing process and data transmission can be evaluated, respectively.
3. To estimate the probability that the process is stopped at an absorbing state, which can facilitate the evaluation of average data transmission rate.

A cross section of the γ-dimensional Markov chain is shown in Fig. 3. For ease of presentation, we will first describe a one-dimensional Markov chain case. Each reasoning iteration of fine sensing will result in either: 1) an increment on η_ξ or 2) no available channel. We have the transition probabilities $P_{(\eta_1,\eta_2,\ldots,\eta_\xi,\ldots,\eta_\gamma)(\eta_1,\eta_2,\ldots,\eta_\xi+1,\ldots,\eta_\gamma)}$ that represent the cases of gaining channel $P_{(\eta_1,\eta_2,\ldots,\eta_\xi,\ldots,\eta_\gamma)(\eta_1,\eta_2,\ldots,\eta_\xi,\ldots,\eta_\gamma)}$ that represent the cases of getting no channel, and $P_{(\eta_1,\eta_2,\ldots,\eta_\xi,\ldots,\eta_\gamma)(\varpi(\bullet))}$ that represent the cases of stopping fine sensing to enter the corresponding absorbing state $\varpi(\bullet) = \varpi(\eta_1, \eta_2, \ldots, \eta_\xi, \ldots, \eta_\gamma)$. Upon each reasoning iteration, the CR decides whether or not to continue the fine sensing toward the next iteration. If it decides to continue, there is a probability that an available channel of certain quality is obtained. Therefore, the transition probability $P_{(\eta_1,\eta_2,\ldots,\eta_\xi,\ldots,\eta_\gamma)(\eta_1,\eta_2,\ldots,\eta_\xi+1,\ldots,\eta_\gamma)}$ and $P_{(\eta_1,\eta_2,\ldots,\eta_\xi,\ldots,\eta_\gamma)(\eta_1,\eta_2,\ldots,\eta_\xi,\ldots,\eta_\gamma)}$ are determined by two factors: 1) the probability ψ_{η_ξ} that the CR decides to continue the fine sensing process based on the proposed reasoning approach and 2) the probability P_ξ of getting channels of class ξ. Therefore, we have the following expression:

$$P_{(\eta_1,\ldots,\eta_\xi,\ldots,\eta_\gamma)(\eta_1,\ldots,\eta_\xi+1,\ldots,\eta_\gamma)} = \psi_{\eta_\xi} P_\xi, \tag{16}$$

where ψ_{η_ξ} is determined by how likely the inequality (15) holds, which can be expressed as

$$\begin{aligned}\psi_{\eta_\xi} &= P\left(\frac{L}{R_{(i)}} > \frac{L}{R_{(i)} + \frac{N_1}{\varrho}\hat{P}_s(CH_{s_i})} + t_s\right)\\ &= P\left(R_{(i)} < \sqrt{\frac{N_1 L}{\varrho t_s}\hat{P}_s(CH_{s_i}) - \left[\frac{N_1}{2\varrho}\hat{P}_s(CH_{s_i})\right]^2}\right.\\ &\qquad \left. - \frac{N_1}{\varrho}\hat{P}_s(CH_{s_i})\right).\end{aligned} \tag{17}$$

Then, the probability of entering the absorbing state is

$$P_{(\eta_1,\ldots,\eta_\xi,\ldots,\eta_\gamma)(\varpi(\bullet))} = 1 - \psi_{\eta_\xi}. \tag{18}$$

The probability P_ξ of getting channels of class ξ is determined by SINR level. The probability that the CR decides to continue for the next reasoning iteration but eventually gets no available channel is formulated as

$$P_{(\eta_1,\ldots,\eta_\xi,\ldots,\eta_\gamma)(\eta_1,\ldots,\eta_\xi,\ldots,\eta_\gamma)} = \psi_{\eta_\xi} P_{-\xi}, \tag{19}$$

where $P_{-\xi}$ is the probability of the noise that is not in any range of class ξ, which means that the channel is not available.

While the description of the one-dimensional Markov chain case is useful for illustrative purposes, it is insufficient for modeling the proposed scheme because there are γ possible classes for channel quality. Therefore, to consider all the γ classes of channel qualities in the performance analysis, a γ-dimensional Markov chain is developed as follows: The transition probabilities as listed in objective (1) are as follows:

$$\begin{aligned}&P_{(\eta_1,\eta_2,\ldots,\eta_\xi,\ldots,\eta_\gamma)(\eta_1+1,\eta_2,\ldots,\eta_\xi,\ldots,\eta_\gamma)} = \psi_{\eta_1,\eta_2,\ldots,\eta_\xi,\ldots,\eta_\gamma} P_1,\\ &P_{(\eta_1,\eta_2,\ldots,\eta_\xi,\ldots,\eta_\gamma)(\eta_1,\eta_2+1,\ldots,\eta_\xi,\ldots,\eta_\gamma)} = \psi_{\eta_1,\eta_2,\ldots,\eta_\xi,\ldots,\eta_\gamma} P_2,\\ &\ldots\\ &P_{(\eta_1,\eta_2,\ldots,\eta_\xi,\ldots,\eta_\gamma)(\eta_1,\eta_2,\ldots,\eta_\xi+1,\ldots,\eta_\gamma)} = \psi_{\eta_1,\eta_2,\ldots,\eta_\xi,\ldots,\eta_\gamma} P_\xi,\\ &\ldots\\ &P_{(\eta_1,\eta_2,\ldots,\eta_\xi,\ldots,\eta_\gamma)(\eta_1,\eta_2,\ldots,\eta_\xi,\ldots,\eta_\gamma+1)} = \psi_{\eta_1,\eta_2,\ldots,\eta_\xi,\ldots,\eta_\gamma} P_\gamma,\\ &P_{(\eta_1,\eta_2,\ldots,\eta_\xi,\ldots,\eta_\gamma)(\eta_1,\eta_2,\ldots,\eta_\xi,\ldots,\eta_\gamma)} = \psi_{\eta_1,\eta_2,\ldots,\eta_\xi,\ldots,\eta_\gamma} P_{-\xi},\\ &P_{(\eta_1,\eta_2,\ldots,\eta_\xi,\ldots,\eta_\gamma)(\varpi(\bullet))} = 1 - \psi_{\eta_1,\eta_2,\ldots,\eta_\xi,\ldots,\eta_\gamma},\end{aligned}$$

where

$$\psi_{\eta_1,\eta_2,\ldots,\eta_\xi,\ldots,\eta_\gamma} = P\left(R_{(i)} < \sqrt{\frac{N_1 L}{\varrho t_s}\hat{P}_s(CH_{s_i}) - \left[\frac{N_1}{2\varrho}\hat{P}_s(CH_{s_i})\right]^2} - \frac{N_1}{\varrho}\hat{P}_s(CH_{s_i})\right). \tag{20}$$

One possible approach in solving the γ-dimensional Markov chain is to project it into two-dimensional space so as to allow the problem to be solved using a wider range of approaches. In this study, we put all possible γ-dimensional states into a canonical form, and the resultant transition probability $\mathbf{P}$ can be arranged as follows:

$$\mathbf{P} = \begin{array}{c c} & \begin{array}{cc} TR. & ABS. \end{array} \\ \begin{array}{c} TR. \\ ABS. \end{array} & \begin{pmatrix} \mathbf{Q} & \mathbf{R} \\ \mathbf{0} & \mathbf{I} \end{pmatrix} \end{array}, \tag{21}$$

where

1. $\mathbf{Q}$ is a $\Phi \times \Phi$ matrix, whose elements are the transitional probabilities between nonabsorbing states,
2. $\mathbf{R}$ is a $\Phi \times \Phi$ matrix, whose elements are the probabilities from transient state S_i to the absorbing states,
3. $\mathbf{0}$ is a $\Phi \times \Phi$ zero matrix, and
4. $\mathbf{I}$ is a $\Phi \times \Phi$ identity matrix.

The fundamental matrix $\mathbf{N}$ for $\mathbf{P}$ can be defined as follows:

$$\mathbf{N} = (\mathbf{I} - \mathbf{Q})^{-1}. \tag{22}$$

The entry n_{ij} of $\mathbf{N}$ gives the expected number of times that the process enters the transient state S_j if it starts in the transient state S_i. The fundamental matrix $\mathbf{N}$ possesses many interesting properties, with which we can obtain the results listed in the objectives. The following theoretical results are thus obtained to fulfill the objectives of the performance analysis:

1. The conditional probabilities of objective (1) are given by (20).
2. The average number of iterations that the sensing process is in state S_j given that it starts in state S_i is given by the elements of the fundamental matrix $\mathbf{N}$. The expected step to absorption given that the chain starts in state S_i is given by

$$\vec{\Delta} = \mathbf{N}\,\vec{c}, \tag{23}$$

where $\vec{c}$ is an all "1" column vector. Here, the first element Δ_0 is of particular interest since it represents the average number of steps taken before the fine sensing being terminated. Using this information, we can estimate the average sensing delay as

$$\bar{T}_s = t\Delta_0. \tag{24}$$

3. Let $\mathbf{B}$ be the absorption probabilities with entries b_{ij}, which states that an absorbing chain will be absorbed if it starts in the transient state S_i. Then, the $\Phi \times \Phi$ matrix can be defined as

$$\mathbf{B} = \mathbf{NR}. \tag{25}$$

TABLE 1
Relationship between SINR and Information Rate of Different Modulation Schemes

SINR (dB)	Information rate of different modulation Scheme, N_s , (bits/channel)
<0	0[1]
0-5	0.5
5-8	1
8-12	1.5
12-15	2
15-18	3
18-23	4
>23	4.5

[1] This channel cannot be used to carry data signals.

The probabilities b_{0j} of absorption in state S_j, starting from the initial state, can be obtained from the first row of matrix $\mathbf{B}$. The average data transmission rate is then determined as

$$\Gamma = \sum_{(\eta_1,\eta_2,\ldots,\eta_\gamma)\in S}\left[b_{(0)(\eta_1,\eta_2,\ldots,\eta_\gamma)}\sum_{\xi=\gamma}^{\gamma}\frac{\eta_\xi N_\xi}{\varrho}\right]. \tag{26}$$

6 Numerical Results

A series of simulations were conducted to evaluate the efficiency of the proposed EKBR scheme, where the performance of the proposed scheme was compared with a number of previously reported schemes, such as the spectrum sensing approach without the use of reasoning, as well as the state-of-the-art stopping algorithm proposed in [14].

The simulations of the proposed EKBR scheme, along with the other sensing schemes under consideration, were evaluated via an event-driven simulation program written in C++. The Distributed Coordination Function (DCF) was used as the underlying MAC protocol in a multichannel environment to achieve channel access. The channel usage of primary users follows the channel model we discussed in Section 3.2. Each spectrum sensing event is triggered by the arrival of a secondary user data transmission request. Observations are made at randomly selected secondary users placed over the network. The analytical results were calculated using MATLAB. The parameters adopted in the simulation are summarized as follows: The symbol size ϱ of the OFDMA system is set as 0.31 ms [18], and the fine sensing time for each channel is set as 92.5 ms [23]. The time window for obtaining the short-term statistics was set to $\tau = 1{,}000$ ms. The data length is assumed to be uniformly distributed from 0 to 2,048 bytes based on IEEE 802.16-2001 and IEEE 802.11 specifications. The individual channels are classified into γ channel quality classes along with the corresponding spectrum sensing thresholds. Each of the γ SINR levels is obtained by assuming the maximum transmitting power for each transmission, where a CR node can select an appropriate modulation scheme corresponding to the SINR level. The transmission rates in terms of bits per symbols and the corresponding SINR taken in the numerical analysis are summarized in Table 1 [21], [24]. The relationship may vary according to the underlying specification or modulation technology.

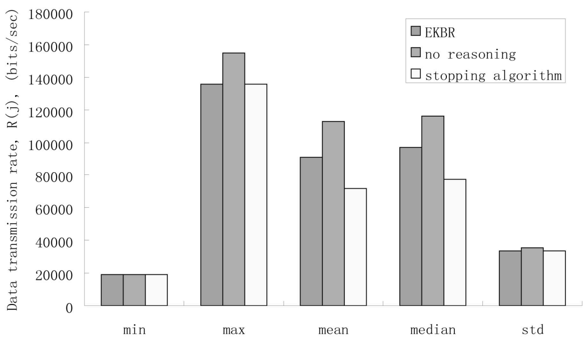


Fig. 4. Statistics pertaining to data transmission rate comparison between EKBR, nonreasoning approach, and the stopping algorithm.

The performance measurements are defined as follows:

- Data transmission rate $R_{(j)}$: the aggregate data transmission rate when fine sensing process terminated at $j\mathrm{th}$ iteration.
- Percentage of missed spectrum opportunities θ_m: the ratio between the number of missed available channels and the number of actual available channels to be finely sense.
- Sensing overhead o: the ratio of total time consumed on spectrum sensing to the data transmission time.
- Throughput ρ: the ratio of data packet (frame) length to the overall process time, i.e., the amount of data bits transmitted every second.

6.1 Data Transmission Rate

In this set of simulations, we compare the performance of the proposed EKBR scheme with the other schemes under consideration in the study using the data transmission rate $R_{(j)}$. The statistical results pertaining to the simulated data transmission rate with the proposed EKBR scheme, where (15) is used, and the nonreasoning approach, where the fine sensing process is statically performed for all n channels, as well as the stopping algorithm are shown in Fig. 4. The statistical results consist of the minimum (min), mean, median, maximum (max), and standard deviation (std) of the data transmission rate. It can be observed that the nonreasoning approach is able to achieve higher overall data transmission rates than that achieved by both the EKBR scheme and the stopping algorithm. This is due to the fact that the CR performs lengthy sensing so that it has higher probability of getting more available channels. It can also be observed that the overall data transmission rate $R_{(j)}$ achieved using EKBR is comparable to that obtained by using the stopping algorithm. The data transmission rate is an important measurement for evaluating the performance of EKBR; however, it is important not to jump to a conclusion based on a single measurement of the performance.

6.2 Percentage of Missed Spectrum Opportunities

To provide a good indication of spectrum sensing efficiency, we evaluate the percentage of missed spectrum opportunities θ_m associated with the proposed EKBR scheme in this set of simulations. Comparison is made with the nonreasoning approach and the stopping algorithm in Fig. 5. It can be observed that the EKBR scheme is, in general, subject to the lowest missed spectrum opportunities when compared to the other tested spectrum sensing schemes. In Fig. 6, the statistics pertaining to the percentage of missed spectrum opportunities show that the proposed EKBR scheme showed improvements of 42 and 34 percent in terms of the missed spectrum opportunity reduction when compared to the nonreasoning approach and the stopping algorithm, respectively. This reduction in the missed spectrum opportunities can be contributed to the fact that the EKBR scheme jointly considers fast sensing results and short-term statistical information to further enhance the selection of optimal range of channels for fine sensing. These experimental results demonstrate the effectiveness of the proposed EKBR scheme in providing improved spectrum sensing accuracy and efficiency.

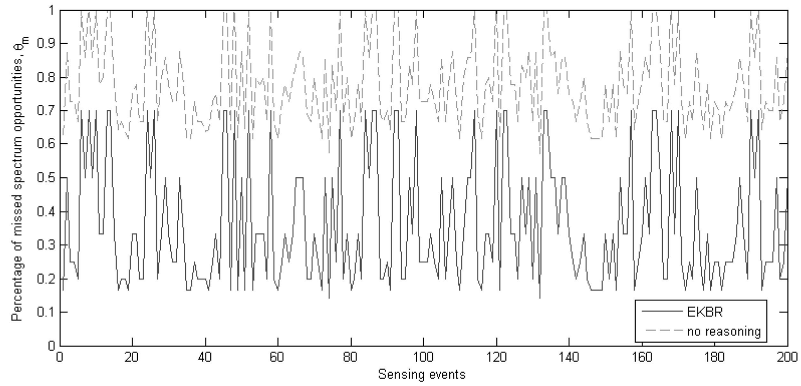
6.3 Sensing Overhead

To investigate the trade-off between the projected data transmission rate and sensing time, we compare the sensing overhead of the proposed EKBR scheme with the sensing overhead of the nonreasoning approach. The reason for not comparing the stopping algorithm is that EKBR has a fundamental difference with the stopping algorithm, where fine sensing process is artificially and statically truncating to K stages. Therefore, it is difficult to compare the sensing overhead between these schemes in this set of simulations.

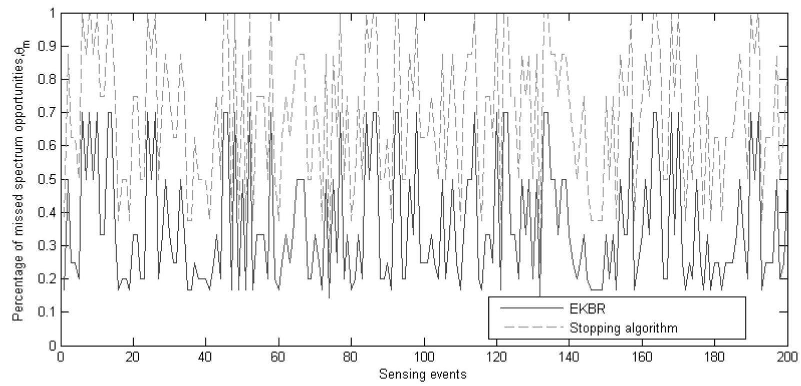
In Fig. 7, the statistics pertaining to the sensing overhead o for both the EKBR scheme and the nonreasoning approach are plotted. It can be observed that EKBR has significantly reduced overall sensing overhead when compared with the nonreasoning approach. Furthermore, Fig. 8 shows the simulation results on the estimated iterations of fine sensing under different channel conditions as determined by short-term statistics in (3). It can be observed that the estimated iterations of fine sensing are significantly reduced as the channel condition improves. This is because the CR only needs to finely sense a small number of channels until the transmission requirement is satisfied. Therefore, by intelligently reducing the number of channels for being finely sensed, the proposed EKBR scheme can achieve lower overhead by better saving sensing time and consumed energy. In addition, as the data length for transmission is increased, the CR has to finely sense more channels so as to improve the likelihood of getting better channels in terms of quantity and quality, and, in turn, to ensure successful data transmission.

6.4 Throughput

In this set of simulations, we further compare the performance of the proposed scheme with other sensing approaches under consideration in the study using throughput ρ, as shown in Fig. 9. It can be observed that while the data transmission rate $R(j)$ of the nonreasoning approach is higher than EKBR, the overall throughput is significantly higher for EKBR than the nonreasoning approach, as demonstrated in Fig. 9a. This is because finely sensing all the n channels take more than twice as much time in fine sensing as that by EKBR. The much longer fine sensing time for each data transmission dramatically



(a)



(b)

Fig. 5. Simulation results of percentage of missed spectrum opportunities in comparison. (a) EKBR versus no reasoning. (b) EKBR versus stopping algorithm.

impairs the throughput although the data transmission rate of identified channels could be higher. In Fig. 9b, it can be observed that the data transmission rate of EKBR is also noticeably improved when compared to that obtained by using the stopping algorithm, while performing fine sensing on much fewer channels. This is because EKBR takes advantage of prior knowledge of network states to intelligently prioritize channels and locate a spectrum range for fine sensing that can help the CR capture the pattern of channel variation. Therefore, in spite of comparable data transmission rates, the proposed EKBR scheme has achieved better throughput than the stopping algorithm, as shown in Fig. 9. Without using any prior knowledge of channel states, on the other hand, the stopping algorithm can less likely ensure that the qualities of channels identified in the fine sensing process will stay static and realizable in the subsequent data transmission stage.

To further compare EKBR with the other sensing approach, Fig. 10 shows the simulation results on the average throughput of these schemes with respect to the increasing traffic volume Λ in the whole network (measured in packet arrival rate). First of all, we found that the sensing

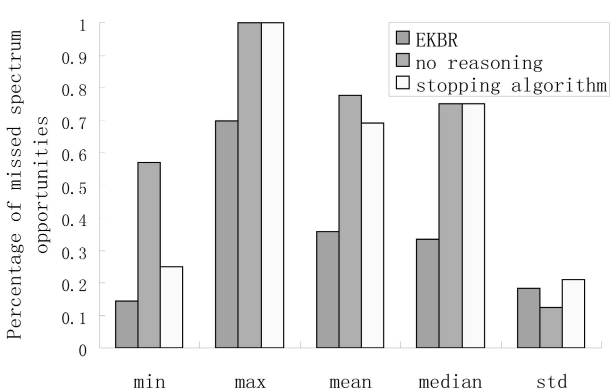


Fig. 6. Statistics pertaining to percentage of missed spectrum opportunities between EKBR, nonreasoning approach, and the stopping algorithm.

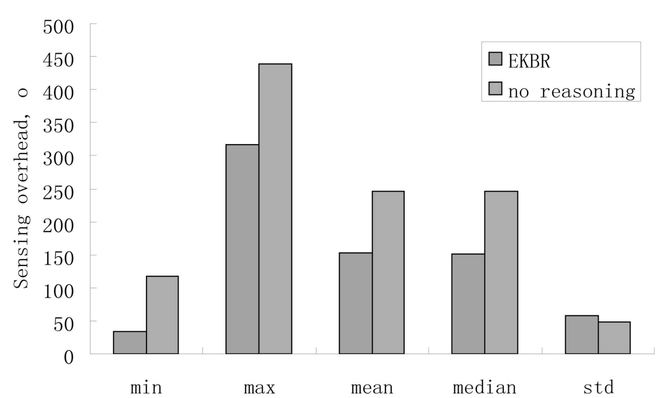
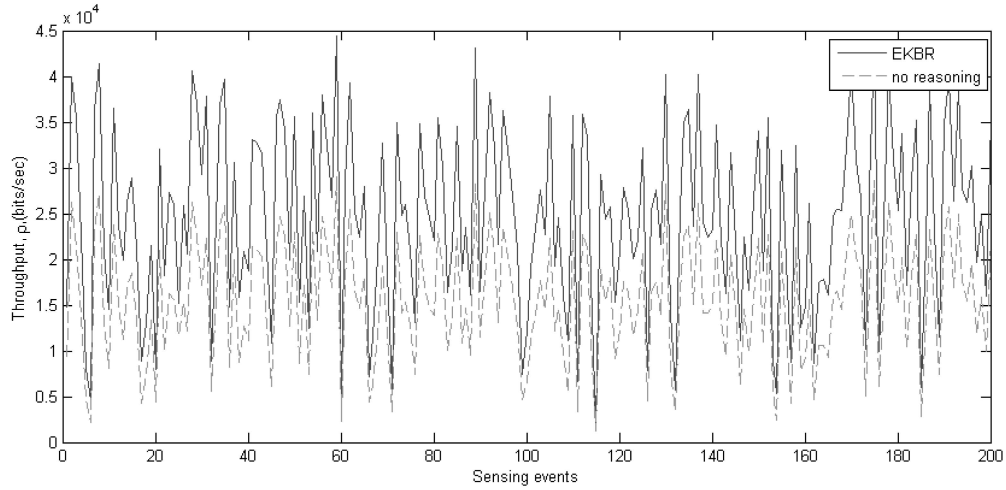
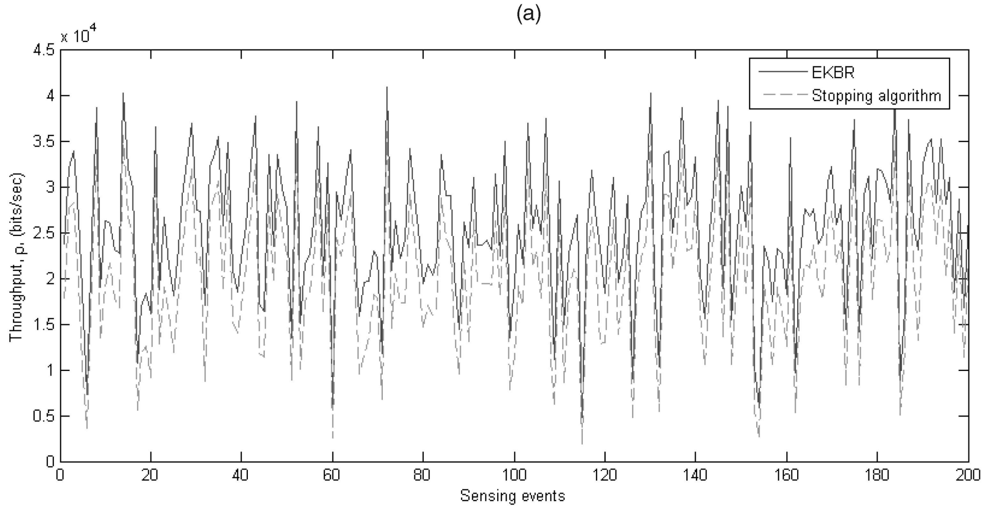


Fig. 7. Statistics pertaining to sensing overhead comparison between EKBR and the nonreasoning approach.



(a)



(b)

Fig. 9. Simulation results of throughput in comparison. (a) EKBR versus no reasoning. (b) EKBR versus stopping algorithm.

efficiency of each scheme in terms of average throughput is sensitive to the network load. It can be observed that the average throughput of EKBR decreases much slower than that by the stopping algorithm of $K = 5, 10$, and by the nonreasoning approach, when the traffic volume Λ of the network increases.

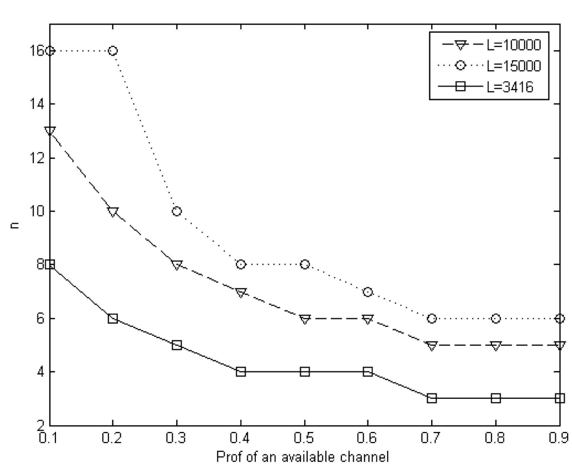


Fig. 8. Relationship between estimated fine sensing number and the channel condition.

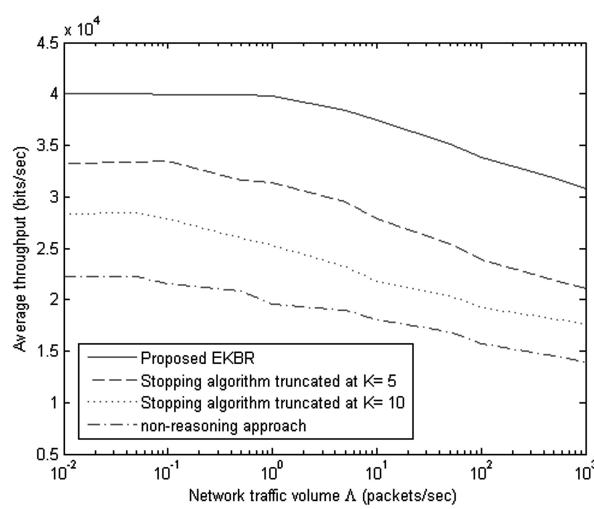


Fig. 10. Simulation results of average throughput in comparison.

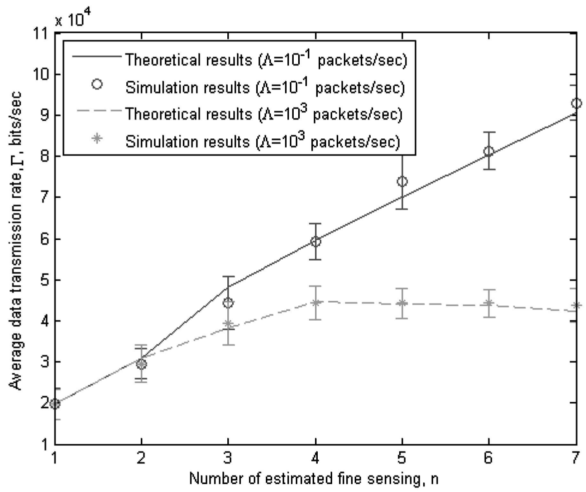


Fig. 11. Simulation and analytical results for average data transmission rate.

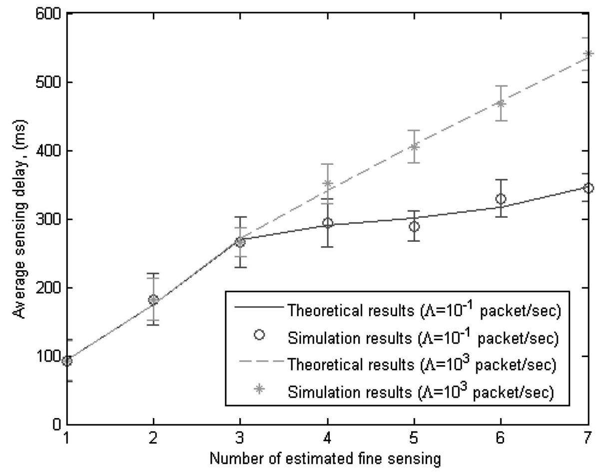


Fig. 12. Simulation and analytical results for spectrum sensing delay.

6.5 Average Data Transmission Rate and Average Sensing Delay

In this set of simulations, we validate the developed analytical model in Section 5 by making a comparison between the simulation and analytical results in terms of the average data transmission rate Γ and the average sensing delay $\bar{T}_s$. The analytical and simulation results on the average data transmission rate in the case where the EKBR operates in a low traffic volume scenario at $\Lambda = 10^{-1}$ packet/sec and high traffic volume scenario at $\Lambda = 10^3$ packet/sec are shown in Fig. 11 with the 93 percent confidence interval. A number of observations can be made as follows: First, the simulation and analytical results closely match with each other in both of the traffic volume scenarios, which validated the proposed analytical model. Second, in the scenario of a higher traffic volume scenario, the average data transmission rate increases until the estimated number of fine sensing (i.e., n) reaches a certain threshold (in this case, $n = 4$). The data transmission rate nonetheless stabilizes and decreases slightly as n continues to increase. The reason for this decrease is that the number of anticipated fine sensing is directly correlated with network traffic volume, which is, in turn, determined by the number of nodes in the network and their traffic loads. As such, the increase of n potentially increases the number of fine sensing iterations, and thus, damages the data transmission rate due to the interference of other nodes.

Fig. 12 shows the average sensing delay with different numbers of channels being finely sensed with the 93 percent confidence interval. We observed that in the case of a low traffic volume in the network, the average sensing delay increases very slowly when using EKBR. On the other hand, when a higher traffic volume in the network, the average sensing delay increases noticeably. This is due to the fact that as the number of anticipated fine sensing increases, the effect of interference increases, and as a result, the number of available channels decreases. Therefore, more fine sensing iterations are required by the CR under such a scenario in order to satisfy the data transmission quality requirements of the system.

7 Conclusions

In this paper, an EKBR scheme is introduced for efficient MAC layer spectrum sensing for CRs. By additionally employing prior knowledge of network sates such as fast sensing results, short-term statistics of channel availability/quality, and channel access, the proposed EKBR scheme can achieve efficient spectrum sensing by initiating a graceful trade-off between data transmission rate and sensing overhead. Our scheme is considered particularly effective when a rigid upper bound is imposed on the total processing time for each packet (frame). Performance analysis was conducted on EKBR by way of a multi-dimensional absorbing Markov chain. Simulations were conducted to validate the proposed analytical model and compare the proposed scheme with existing state-of-the-art spectrum sensing methods. The simulation results demonstrated that the proposed scheme noticeably outperforms the existing methods in terms of throughput due to the adoption of prior knowledge of network states. Abundant discussions were provided on the observations we made from the simulation results. Our future work will focus on the exploration of some other practical scenarios, such as when cooperative sensing is in place. We also plan to launch a CR testbed that can precisely and practically implement the proposed scheme.

Appendix

Table of Notation

See Tables 2 and 3.

Acknowledgments

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TABLE 2
Table of Notation I

Notation	Definition
M	number of non-overlapping channels.
CH_i	channel i.
CH	vector of $CH_i, i = 1, 2, ..., M$.
γ	number of different modulation schemes.
$\aleph_\chi$	an example of secondary user node.
CH_{s_i}	the s_ith channel in sensing prioritization.
ζ	time instance.
τ	observation window.
$\omega_i(t)$	observation of primary user channel occupancy on CH_i.
$\bar{\mu}$	the average Signal to Interference plus Noise Ratio (SINR).
μ	the instantaneous SINR.
ϵ	decision threshold of power detection.
$P_{inst}(CH_i)$	instantaneous probability regarding CH_i availability.
$\hat{P}_s(CH_i)$	short-term probability regarding CH_i availability
T_Σ	overall processing time.
ρ	throughput.
L	length of data packet (frame).
n	estimated number of channels to be finely sensed.
k	identified k number of available channels.
t_s	time consumed by fine sensing on a single channel.
Δt	processing time of proposed scheme and other time consumed by the system.
T_b	back-off time determined by back-off mechanism during channel access.
R_k	basic data transmission rate on k number of available channels.
$\bar{R}$	expected basic data transmission at the estimation stage.
N_1	information rate of basic modulation scheme, Binary Phase Shift Keying.
$N_\xi^{(i)}$	i^{th} N_ξ.
ϱ	sample time.

TABLE 3
Table of Notation II

Notation	Definition
$\bar{P}_s(CH_{s_i})$	normalized $\hat{P}_s(CH_{s_i})$.
$\bar{P}'_s(CH_{s_i})$	normalized aggregate probability that $CH_{s_i}, \forall s_i$ is not available.
$I(i)$	indication function of CH_i availability.
x_i	random variables indicates the i^{th} identified available channel.
X_i	spectrum offer on i^{th} fine sensing.
$Y_{(i)}$	net spectrum offer return at the i^{th} fine sensing.
C	cost associate with each fine sensing.
$R_{(i)}$	aggregate data transmission rate after i^{th} fine sensing.
$R_{(j)}$	aggregate data transmission rate when fine sensing process terminated at jth iteration.
S	transition state space.
$\Re$	absorbing state space.
Φ	number of mutually exclusive states.
$P_{(\eta_1,\eta_2,...,\eta_\xi,...,\eta_\gamma)(\eta_1,\eta_2,...,\eta_\xi+1,...,\eta_\gamma)}$	transition probability from state $(\eta_1, \eta_2, ..., \eta_\xi, ..., \eta_\gamma)$ to $(\eta_1, \eta_2, ..., \eta_\xi + 1, ..., \eta_\gamma)$
$\varpi(\bullet) = \varpi(\eta_1, \eta_2, ..., \eta_\xi, ..., \eta_\gamma)$	absorbing state of state $(\eta_1, \eta_2, ..., \eta_\xi, ..., \eta_\gamma)$.
ψ	probability of continue fine sensing process based on the proposed reasoning approach.
P_ξ	probability of getting a channel of class ξ.
$P_{-\xi}$	probability of channel not available.
Γ	average data transmission rate.
$\bar{T}_s$	average sensing delay.
o	sensing overhead.

REFERENCES

[1] J. Miltola, "Cognitive Radio: Making Software Radios More Personal," *IEEE Personal Comm.*, vol. 6, no. 4, pp. 13-18, Aug. 1999.

[2] FCC, ET Docket No. 03-222, "A Cognitive Radio Is a Radio That Can Change Its Transmitter Parameters Based on Interaction with the Environment in Which It Operates," Dec. 2003.

[3] L. Ma, X. Han, and C. Shen, "Dynamic Open Spectrum Sharing MAC Protocol for Wireless Ad Hoc Networks," *Proc. IEEE Int'l Symp. Dynamic Spectrum Access Networks (DySPAN)*, Nov. 2005.

[4] P. Pawelczak, R.V. Prasad, L. Xia, and I.G.M.N. Niemegeers, "Cognitive Radio Emergency Networks—Requirements and Design," *Proc. IEEE Int'l Symp. Dynamic Spectrum Access Networks (DySPAN)*, Nov. 2005.

[5] L.-C. Wang, A. Chen, and D.S.L. Wei, "A Cognitive MAC Protocol for QoS Provisioning in Over Laying Ad Hoc Networks," *Proc. IEEE Consumer Comm. and Networking Conf. (CCNC)*, Jan. 2007.

[6] R.W. Brodersen, A. Wolisz, D. Cabric, S.M. Mishra, and D. Willkomm, "Corvus: A Cognitive Radio Approach for Usage of Virtual Unlicensed Spectrum," White paper, Berkeley Wireless Research Center, 2004.

[7] I.F. Akyildiz, W. Lee, M.C. Vuran, and S. Mohanty, "Next Generation/Dynamic Spectrum Access/Cognitive Radio Wireless Networks: A Survey," *Computer Networks J.*, vol. 50, pp. 2127-2159, Sept. 2006.

[8] H. Kim and K.G. Shin, "Adaptive MAC-Layer Sensing of Spectrum Availability in Cognitive Radio Networks," Technical Report CSE-TR-518-06, Univ. of Michigan, May 2006.

[9] X.Y. Wang, P. Ho, and A. Wong, "Towards Efficient Spectrum Sensing for Cognitive Radio through Knowledge-Based Reasoning," *Proc. IEEE Int'l Symp. Dynamic Spectrum Access Networks (DySPAN '08),* 2008.

[10] X.Y. Wang, A. Wong, and P. Ho, "Stochastic Channel Prioritization for Spectrum Sensing in Cooperative Cognitive Radio," *Proc. IEEE Consumer Comm. and Networking Conf. (CCNC '09),* 2009.

[11] X.Y. Wang, A. Wong, and P. Ho, "Prioritized Spectrum Sensing in Cognitive Radio Based on Spatiotemporal Statistical Fusion," *Proc. IEEE Wireless Comm. and Networking Conf. (WCNC '09),* 2009.

[12] H. Kim and K.G. Shin, "Fast Discovery of Spectrum Opportunities in Cognitive Radio Networks," *Proc. IEEE Int'l Symp. Dynamic Spectrum Access Networks (DySPAN '08),* 2008.

[13] D. Datla, R. Rajbanshi, A. Wyglinski, and G. Minden, "Parametric Adaptive Spectrum Sensing Framework for Dynamic Spectrum Access Networks," *Proc. IEEE Int'l Symp. Dynamic Spectrum Access Networks (DySPAN '07),* pp. 482-485, 2007.

[14] J. Jia, Q. Zhang, and X. Shen, "HC-MAC: A Hardware-Constrained Cognitive MAC for Efficient Spectrum Management," *IEEE J. Selected Areas in Comm.,* vol. 26, no. 1, pp. 106-117, Jan. 2008.

[15] S. Huang, X. Liu, and Z. Ding, "On Optimal Sensing and Transmission Strategies for Dynamic Spectrum Access," *Proc. IEEE Int'l Symp. Dynamic Spectrum Access Networks (DySPAN '08),* 2008.

[16] N.B. Chang and M. Liu, "Optimal Channel Probing and Transmission Scheduling for Opportunistic Spectrum Access," *Proc. 13th Ann. ACM Int'l Conf. Mobile Computing and Networking,* pp. 27-38, 2007.

[17] F.F. Digham, M.-S. Alouini, and M.K. Simon, "On the Energy Detection of Unknown Signals over Fading Channels," *IEEE Trans. Comm.,* vol. 55, no. 1, pp. 21-24, Jan. 2007.

[18] C. Cordeiro, M. Ghosh, D. Cavalcanti, and K. Challapali, "Spectrum Sensing for Dynamic Spectrum Access of TV Bands," *Proc. IEEE Int'l Conf. Cognitive Radio Oriented Wireless Networks and Comm. (CrownCom),* Aug. 2007.

[19] S. Geirhofer, L. Tong, and B. Sadler, "Cognitive Radios for Dynamic Spectrum Access—Dynamic Spectrum Access in the Time Domain: Modeling and Exploiting White Space," *IEEE Comm. Magazine,* vol. 45, no. 5, pp. 66-72, May 2007.

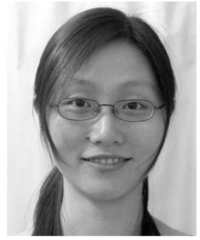
[20] S. Mangold, Z. Zhong, K. Challapali, and C. Chou, "Spectrum Agile Radio: Radio Resource Measurements for Opportunistic Spectrum Usage," *Proc. Global Telecomm. Conf. (GLOBECOM),* vol. 6, pp. 3467-3471, 2004.

[21] F. Hou, J. She, P.-H. Ho, and X. Shen, "A Cross-Layer Design Framework for Non-Real-Time Polling Service in IEEE 802.16 Networks," *ACM Wireless Networks,* June 2007.

[22] J.G. Kemeny and J.L. Snell, *Denumerable Markov Chains.* Springer-Verlag, 1976.

[23] H.-S. Chen, W. Gao, and D.G. Daut, "Signature Based Spectrum Sensing Algorithms for IEEE 802.22 WRAN," *Proc. IEEE Int'l Conf. Comm. (ICC),* June 2007.

[24] M. Shen, G. Li, and H. Liu, "Design Tradeoff in OFDMA Traffic Channels," *Proc. IEEE Int'l Conf. Acoustics, Speech, and Signal Processing (ICASSP),* vol. 4, pp. 757-760, May 2004.



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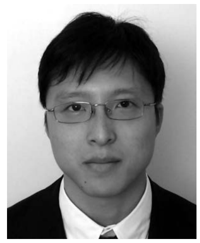

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