Adaptive MAC-layer Sensing of Spectrum Availability in Cognitive Radio Networks

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Abstract

In the recently-suggested dynamic spectrum allocation policy of cognitive radio networks [1]–[3], sensing/monitoring of spectrum availability is identified as a key requirement. To meet this requirement we address an important MAC-layer sensing issue: which of proactive and reactive sensing is more energy-efficient? An algorithm is proposed to dynamically determine which sensing mode to use. For proactive sensing, sensing-period adaptation to maximize discovery of opportunities and optimal-ordering of channels to minimize the delay in finding an available channel are proposed. Channel-usage patterns are also estimated. Our simulation results demonstrate the efficacy of the proposed sensing scheme, as well as its performance improvements over the previously-proposed schemes. The sensing-period adaptation discovers up to 98% of the analytical maximum of spectral opportunities, regardless of choice of the initial sensing period. For the testing scenario and simulation parameters we used, the proposed scheme is shown to discover up to 20% more opportunities than the previous sensing schemes without sensing-period adaptation. This improvement may become greater as the initial sensing period grows. The delay in finding an idle channel with the proposed channel-ordering is around 0.02 second, which is a half of the delay without channel-ordering, and the proposed scheme yields steady performance over a wide range of the number of channels.

Index Terms

Cognitive radios, spectral agility, MAC-layer sensing, proactive and reactive sensing, channel-usage patterns.

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I. INTRODUCTION

There have been numerous protocol standards on wireless spectrum that rely on a *static* spectrum allocation policy, under which each licensed spectrum band is statically assigned to the specific licensed service and its users. Once a spectrum band is assigned to a certain service, its allocation is not allowed to be changed dynamically. However, a new concept of *dynamic* spectrum allocation has become necessary to overcome critical limitations of the traditional static-allocation scheme. Recent studies have shown that use of static spectrum allocation has degraded spectral efficiency significantly [4]. Moreover, current standards cannot guarantee prevention of unexpected interruptions by wireless network users [5].

To alleviate these problems, FCC has recently suggested a new concept of cognitive radio networks that includes dynamic spectrum allocation. This requires the enhancement of current PHY and MAC protocols to adopt spectral-agile features. The basic idea of spectral agility is to allow *secondary* (unlicensed) users to access licensed spectrum bands provided it only incurs minimal tolerable interference to *primary* (licensed) users. To achieve this goal, secondary users should monitor each channel's usage pattern by its primary users to identify *spectrum holes* or *opportunities* [6] to utilize. Whenever secondary users/nodes find a channel that can be utilized without interfering with its primary users, it is assigned to a specific wireless data link. Secondary users are responsible for monitoring the return of any primary user on that channel so that they can stop their transmission and vacate the channel upon the primary user's return.

This new concept of protocol has been given different names, such as *Dynamic Spectrum Access* (DSA) protocol [7] or *neXt Generation* (XG) protocol [1], [2]. However, *sensing* the status of each channel/spectrum is commonly recognized as the most fundamental element due to its crucial role of discovering spectral opportunities. The PHY-layer sensing adapts modulation schemes and parameters to measure and detect the primary users' signals on different channels. Several PHY-layer detection methods, such as *energy detection*, *matched filter* and *feature detection* [8]–[10], have been proposed. Among them, *feature detection* is considered as a good candidate for detecting the primary user's presence on a channel since it differentiates the unique characteristics of modulation by using *cyclostationary* features [8]. The detection result on a channel would be one of the following three possibilities: (i) the channel is idle, (ii) the channel is occupied by its primary users, but secondary users are allowed to transmit their packets with some power constraints, or (iii) the channel is not available to secondary users at all. On the other hand, the MAC-layer sensing determines when a secondary user/node has to sense which channels. This type of sensing, despite its importance, has received far less attention than other related topics.

In this paper, we focus on important issues of the MAC-layer sensing. Recently, many MAC-layer researchers have considered fair channel allocation and secondary user coordination under the assumption of the availability of sensing results. However, they have not considered how the MAC-layer sensing works and which mode of sensing should be used to efficiently discover spectrum opportunities. To address these important issues, we first introduce two modes of MAC-layer sensing, *reactive* and *proactive*, and then propose an *energy-efficient*[1] mechanism to determine the type of sensing to use. For the proactive sensing, we also derive (i) the optimal sensing period that maximizes the discovery of

[1]A (proactive or reactive) sensing scheme A is said to be more *energy-efficient* than another scheme B if A consumes less energy while achieving the same performance as B. A more formal (mathematical) definition of energy-efficiency will be given in Section III.

opportunities, and (ii) the order of sensing channels that minimizes the delay in finding an idle channel.

There have been a limited number of publications on the MAC-layer sensing. Chou [11] proposed a non-adaptive proactive sensing algorithm that uses pre-determined sensing periods. This approach did not consider how to maximize the chance of discovering opportunities since the assigned sensing periods are not optimal (in the sense of minimizing the delay in locating an idle channel). Zhao *et al.* [12] proposed a Decentralized Cognitive MAC (DC-MAC) with reactive sensing. Their approach focused on slotted-time CSMA-based channel access with synchronized slot information. Sankaranarayanan *et al.* [13] proposed an Ad-hoc Secondary system MAC (AS-MAC) which is intended solely for TDMA/FDMA-based GSM cellular networks. AS-MAC is a proactive scheme with slotted-time-based channel access. The authors of [12] and [13] did not consider the essential tradeoff between reactive and proactive sensing, and they only targeted a specific type of primary user networks.

The contributions of this paper are threefold. First, our approach provides a general framework for the MAC-layer sensing which is not confined to any specific primary user networks. Second, we highlight a fundamental tradeoff between reactive and proactive sensing, and propose an energy-efficient sensing mode selection algorithm. Finally, we propose an optimal proactive sensing architecture with sensing-period adaptation and channel-ordering techniques.

The rest of the paper is organized as follows. Section II presents a system overview and a channel-usage model. Section III introduces reactive and proactive sensing modes, followed by development of a sensing mode selection algorithm. Section IV presents sensing-period adaptation and channel-usage pattern estimation for proactive sensing. Section V describes how to determine the order of sensing channels so as to minimize the delay in locating an idle channel. The MATLAB-based simulation results are presented and analyzed in Section VI. Finally, we conclude the paper and suggest future directions in Section VII.

II. System Overview

Before delving into the proposed techniques, we give an overview of the system under consideration, state the assumptions and present the channel-usage model to be used throughout this paper.

A. Network Topology

A wireless multi-hop ad-hoc network is considered as the network of secondary users. A group of secondary users/nodes share N licensed channels with their primary users. The network topologies or protocols of primary users could be different from those of secondary nodes. Although a multi-hop network is considered, packet transmission on the secondary network is performed in a hop-by-hop fashion. This is because sensing and allocation of channels should be done hop-by-hop due to the fact that primary users' channel-usage patterns may be observed differently depending on their locations.

In Figure 1, we therefore consider a secondary node N_0 which has M neighbors $(N_1, \ldots, N_M)$ where N licensed channels can be used by N_0 when they are left unused by their primaries. A data link L_j ($j = 1, \ldots, M$) is pre-assigned for communication between N_0 and N_j. We assume that each secondary node is equipped with one widely-tunable antenna that covers N licensed channels. This is to reduce hardware cost and RF-end complexity. Under this assumption, both sensing and data transmission cannot be done at the same time [10]. Moreover, a secondary node can sense only one channel at a time.

Each secondary node is responsible for sensing N licensed channels, and the availability of a channel is determined based on the PHY-layer sensing result. The timing of sensing and the channel to be sensed are controlled by the MAC-layer sensing. In case N_0 wants to communicate with node N_j, the two nodes have to exchange their sensing results via a dedicated control channel and negotiate the channel assignment to link L_j. The channel-allocation problem gets far more complicated when there exist fading channels or if there is any conflict/interference in assigning channels to nearby data links. There have been many proposed approaches to resolving these difficulties, often treating them as a secondary users coordination problem [14]. Note, however, that the channel-allocation issue is *not* within the scope of this paper.

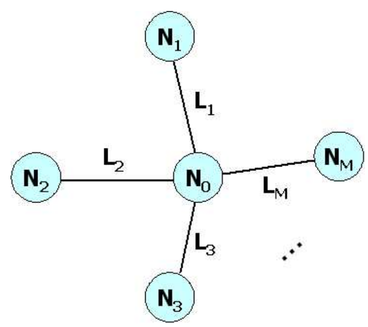

Fig. 1. The network topology used in sensing mode selection

B. Channel-Usage Model

"Sensing" mainly aims to check a channel's availability. Hence each channel is modeled as an ON-OFF source alternating between ON(busy) and OFF(idle) periods. An ON/OFF period models a time period in which the primary user signals can/cannot be detected on a channel.[2] Secondary users can utilize any portion of OFF periods for their own transmission. For a channel i, $i = 1, 2, \ldots, N$,[3] the length of an ON (or OFF) period is described by a random variable Y^i (or X^i) which is governed by its random distribution function $f_{Y^i}(y),\ y > 0$ (or $f_{X^i}(x),\ x > 0$). ON/OFF periods are assumed to be independent and identically distributed (i.i.d.), and ON and OFF periods are independent of each other. This random process forms a continuous-time semi-Markov chain and can be analyzed with the renewal theory [15]. A sample from an ON/OFF period corresponds to the value 1/0. Then, sensing produces a binary random sequence for each channel. The channel utilization, or load of channel i, u^i, is given as $u^i = E[Y^i]/(E[Y^i] + E[X^i])$. The channel-usage model is illustrated in Figure 2.

III. Sensing Mode Selection

The status of a spectrum/channel can be sensed *reactively* or *proactively*, depending on when the channel is sensed. In what follows, we will discuss the pros and cons of these

[2]Equivalently, an ON (or OFF) period can be considered as a time period in which the secondary users are prohibited from accessing (or allowed to access) the channel.

[3]We will use i as the channel index throughout the paper.

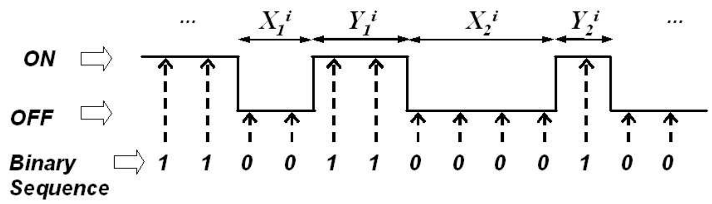

Fig. 2. The ON-OFF channel model

two sensing modes and then propose an algorithm for determining which sensing mode to use for energy-efficiency.

A. Reactive vs. Proactive Sensing

1) Reactive Sensing: This is on-demand sensing; whenever a secondary user/node has a packet to transmit/receive to/from its neighbor, it sequentially senses/monitors all licensed channels until it finds an idle channel. The thus-discovered idle channel is assigned to the wireless data link between itself and the neighbor. Although channel assignment must be negotiated between the two nodes, its detailed treatment is beyond the scope of this paper. Since packets arrive/depart randomly in time, it is difficult to process thus-collected sensing results to predict a channel's behavior. Without knowledge of channels' behaviors, one cannot determine their optimal order of sensing that minimizes the time required to locate an idle channel. Thus, a secondary user has to sense channels in random order. This scheme does not induce unnecessary sensing overheads, but incurs a greater channel-search delay than the optimally-ordered sensing based on the estimation of channels' behaviors.

2) Proactive Sensing: In the *proactive* sensing mode secondary users/nodes periodically monitor channels with their own sensing periods in addition to their on-demand sensing of likely-to-be-available channels.[4] The periodically-collected information is used to estimate channel-usage patterns so that a secondary node can determine the most desirable sensing order of channels whenever it needs to locate an idle channel (i.e., on-demand sensing). The periodic part of sensing operation can be considered as a common sampling procedure. Channel i is being sensed with its own *sensing period* (${T_P}^i$) and *listening interval* (${T_I}^i$) which resemble sampling period and sampling interval, respectively. These parameters have to be determined/adapted channel-by-channel since each channel may have its own unique usage pattern. An example in which a secondary user periodically senses two channels is illustrated in Figure 3.

The proactive sensing incurs a high sensing overhead since it periodically senses multiple channels even when no data transmission is necessary. However, it can reduce the time to search for an idle channel so that an end-to-end packet delay can be minimized.

B. Sensing Mode Selection

We now consider which of proactive and reactive sensing to choose to achieve high energy-efficiency. To define energy-efficiency formally, we (i) assume the amount of consumed energy to be proportional to the total sensing time; and (ii) consider the average

[4]Note that the on-demand sensing required in case of proactive sensing is the same as that of reactive sensing. In addition, a discovered available channel during the process of periodic (not on-demand) sensing is not necessarily assigned to a data link if there is no packet to transmit.

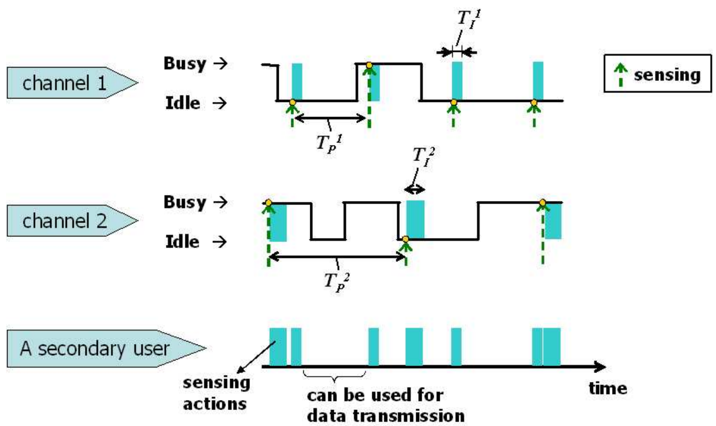

Fig. 3. Periodic sensing of two channels by a secondary user

time taken in locating an idle channel as a performance metric. Let E be the average time consumed for sensing per unit time, and let T_{idle} denote the average time taken to locate an idle channel per packet departure or arrival. Then, *energy-efficiency* is defined as $\frac{-E}{1/T_{idle}}$ since the performance is proportional to $1/T_{idle}$. A sensing mode that achieves a larger $\frac{-E}{1/T_{idle}}$ is considered to be more energy-efficient.

Intuitively, the proactive sensing consumes considerably more time than the reactive counterpart, but it can help find an idle channel faster (hence smaller end-to-end packet latency) by estimating and utilizing channel-usage patterns from the periodically-sensed information. On the other hand, the reactive sensing requires more time to search for an idle channel since no prior channel-usage information is available, and hence, it must rely on a random sequential search of channels. There is, therefore, a tradeoff between the periodic sensing overhead and the on-demand search overhead. This tradeoff must be optimized to determine which of the two sensing modes to be used.

As introduced in Section II, a wireless multi-hop ad-hoc network is considered for this optimization. It is assumed that the average packet inter-arrival time (A_j) and the average packet inter-departure time (D_j) on a data link L_j are known. It is not difficult to estimate A_j and D_j by recording and using packets' timestamps. It is also assumed that the utilization, or load of channel i, u^i, can be estimated, so we let $\hat{u}^i$ be the estimated utilization of channel i.

Let $E^p(E^r)$ be the average time consumed for sensing per unit time in proactive(reactive) sensing. In proactive sensing, on average a total of $\sum_{i=1}^{N} \frac{T_I^i}{T_P^i}$ per unit time is used for periodic sensing. In addition, T_{idle}^p must be spent every A_j or D_j units of time where T_{idle}^p denotes the average idle channel search time per packet departure/arrival in proactive sensing. Hence, E^p is given as

$$E^p = \sum_{i=1}^{N} \frac{T_I^i}{T_P^i} + \sum_{j=1}^{M} \left(\frac{T_{idle}^p}{D_j} + \frac{T_{idle}^p}{A_j} \right)$$

Proactive sensing can minimize T_{idle}^p by optimally-ordering channels to search. This optimization will be discussed in Section V. For now, we will assume that proactive sensing sorts channels in ascending order of channel utilizations. Without loss of generality, we can assume that $(1-\hat{u}^1) \geq (1-\hat{u}^2) \geq \cdots \geq (1-\hat{u}^N)$. In such a case, channel 1 is sensed first for T_I^1 units of time. If it appears to be idle, with probability $(1-\hat{u}^1)$, it is assigned to the data link. If not, channel 2 is sensed next for T_I^2 units of time and is assigned to the data link with probability $\hat{u}^1(1-\hat{u}^2)$ (i.e., probability that channel 1 is busy and channel 2 is idle). This process will continue for the rest of channels. If all channels turn out to be busy, with probability $\hat{u}^1\hat{u}^2\cdots\hat{u}^N$, the packet is buffered and will be transmitted later. Note that D_j and A_j should reflect the effect of packet buffering. Then, T_{idle}^p is given as

$$\begin{aligned}
T_{idle}^p &= T_I^1 \cdot \left(1-\hat{u}^1\cdots\hat{u}^N\right) + T_I^2 \cdot \hat{u}^1\left(1-\hat{u}^2\cdots\hat{u}^N\right) + \cdots \\
&\quad + T_I^N \cdot \hat{u}^1\cdots\hat{u}^{N-1}\left(1-\hat{u}^N\right) + \sum_{i=1}^{N} T_I^i \cdot \hat{u}^1\cdots\hat{u}^{N-1} \\
&= T_I^1 + \hat{u}^1 \cdot T_I^2 + \hat{u}^1\hat{u}^2 \cdot T_I^3 + \cdots + \hat{u}^1\cdots\hat{u}^{N-1} \cdot T_I^N \\
&= T_I^1 + \sum_{k=2}^{N}\left\{\left(\prod_{m=1}^{k-1}\hat{u}^m\right)T_I^k\right\}
\end{aligned}$$

In case of reactive sensing, T_{idle}^r is spent every A_j or D_j units of time in which T_{idle}^r denotes the average idle channel search time per packet departure/arrival in reactive sensing. Hence, E^r is given as

$$E^r = \sum_{j=1}^{M}\left(\frac{T_{idle}^r}{D_j} + \frac{T_{idle}^r}{A_j}\right)$$

The derivation of T_{idle}^r is similar to that of T_{idle}^p. The only difference is that sensing is performed in random order. Hence, $N!$ cases of all possible channel orders must be considered. Let S_k be the k-th set of ordered channels, among $N!$ possible sets. For example, $S_1 = \{(1-\hat{u}^1) \geq (1-\hat{u}^2) \geq \cdots \geq (1-\hat{u}^N)\}$. Let $S_k(m)$ be the channel index of an m-th element in S_k. Since S_k can be chosen equally-likely with probability $\frac{1}{N!}$, T_{idle}^r is given as

$$\begin{aligned}
T_{idle}^r &= \sum_{k=1}^{N!}\frac{T_{idle}^{S_k}}{N!} \\
\text{where}\quad T_{idle}^{S_k} &= T_I^{S_k(1)} + \sum_{n=2}^{N}\left\{\left(\prod_{m=1}^{n-1}\hat{u}^{S_k(m)}\right)T_I^{S_k(n)}\right\}
\end{aligned}$$

Now, the sensing mode can be dynamically determined by comparing the energy-efficiency of two schemes such that

$$\frac{-E^r}{1/T_{idle}^r} \underset{proactive}{\overset{reactive}{\gtrless}} \frac{-E^p}{1/T_{idle}^p}.$$

Or equivalently,

$$E^r \cdot T_{idle}^r \underset{reactive}{\overset{proactive}{\gtrless}} E^p \cdot T_{idle}^p.$$

IV. Sensing-Period Adaptation

In proactive sensing, two sensing parameters (T_P^i and T_I^i) must be determined. T_I^i is determined by the PHY-layer sensing since it depends on the modulation scheme used to detect primary users. Hence here we consider only T_P^i and propose a sensing-period adaptation technique to find the optimal sensing period of a channel to maximize the discovery of its existing opportunities. The optimal sensing period is uniquely determined for each channel according to its unique characteristics. For this optimization, channel-usage patterns must be estimated first using the prior sensing results. Based on this estimation, optimal sensing periods are determined and adapted repeatedly. The procedure is overviewed in Figure 4.

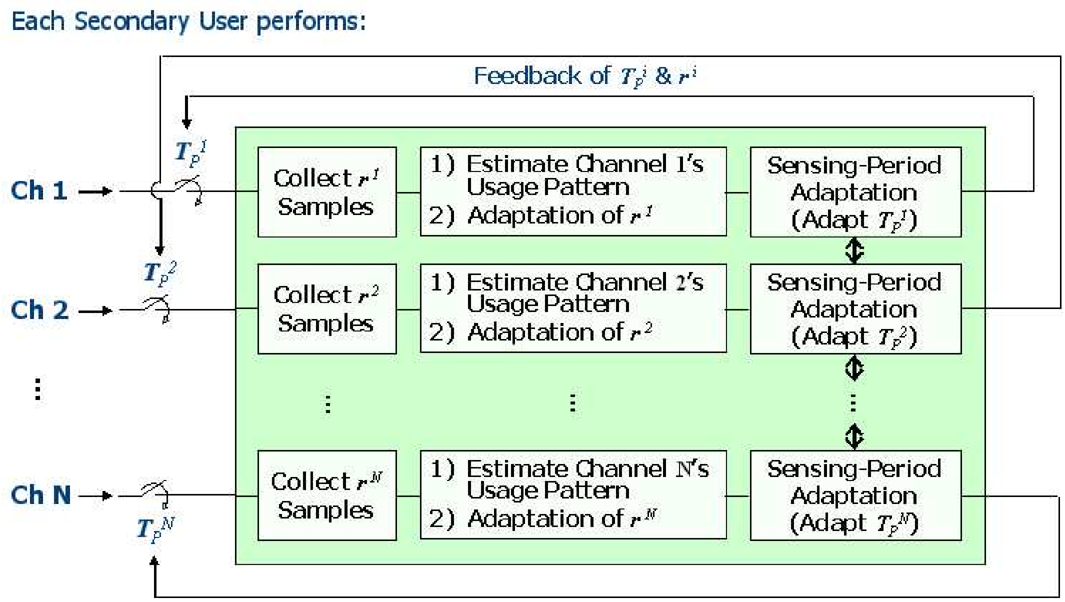

Fig. 4. System diagram of sensing-period adaptation

Since proactive sensing samples a channel's state (busy or idle) at discrete time points, it is not always possible to identify when an opportunity begins and ends. In fact, an opportunity is discovered when an idle sample is collected from the channel. Therefore, some opportunities may go undiscovered in case the sensing period is relatively large. However, blindly reducing the sensing period is not desirable either, as it will increase the sensing overhead, which is proportional to T_I^i/T_P^i. This tradeoff must be captured in building an equation to find an optimal period. So, we introduce two terms, *Unexplored Opportunity* ($UOPP^i$) and *Sensing Overhead* ($SSOH^i$). $UOPP^i$ is defined as the average fraction of time during which channel i's opportunities are not discovered. On the other hand, $SSOH^i$ is defined as the average fraction of time during which channel i's discovered opportunities cannot be utilized due to the sensing of other channels. We assumed that a secondary user/device is equipped with one widely-tunable antenna. Under this assumption, the secondary user must stop utilizing a discovered channel while it is sensing one of the other channels. In addition, a utilization factor u^i is defined as the average fraction of time during which channel i is busy. So, the average total sum of opportunities per unit time is $(1 - u^i)$. Our objective function is then defined as

$$\underline{T_P} := ({T_P}^1, ..., {T_P}^N),$$

$$
\begin{aligned}
\text{Find } \underline{T_P}^* &= \arg\max_{\underline{T_P}} \left\{ \sum_{i=1}^{N} \left\{ (1-u^i) - SSOH^i - UOPP^i \right\} \right\} \\
&= \arg\min_{\underline{T_P}} \left\{ \sum_{i=1}^{N} \left(SSOH^i + UOPP^i \right) \right\} \qquad (1)
\end{aligned}
$$

where $\underline{T_P}^*$ is a vector of optimal sensing periods.

To simplify our discussion, a few assumptions are made which render mathematical tractability while addressing the heart of the problem. First, in case there exist simultaneous opportunities on multiple but possibly non-adjacent channels, secondary users can assign them selectively and simultaneously to one or more data links by using the OFDM technique [11]. Second, we assume that every secondary user performs consistent transmission. That is, there always exists an incoming/outgoing packet from/to a secondary node. In this case, every discovered idle channel is assigned to one of the data links and is utilized until its current idle period ends. The end of an idle period is detectable by the *LISTEN-before-TALK* policy. That is, a secondary user is responsible for checking any primary user's reappearance on the channel before transmitting the next packet.

Note that throughout the analyses in Sections IV and V, the channel-usage model introduced in Section II will be used.

A. Sensing-Period Adaptation

1) Analysis of $UOPP^i$: We define $T_d^i(t)$ $(d = 0, 1)$ as the average opportunities on channel i during (t_s, $t_s + t$) provided a sample d is collected at time t_s. If t_s is the end/start time of an idle period, we use $\tilde{T}_d^i(t)$ instead of $T_d^i(t)$. Four possible cases are illustrated in Figure 5. Note that $T_d^i({T_P}^i)$ implies the average amount of channel availability between two consecutive samples in case the first sample is d.

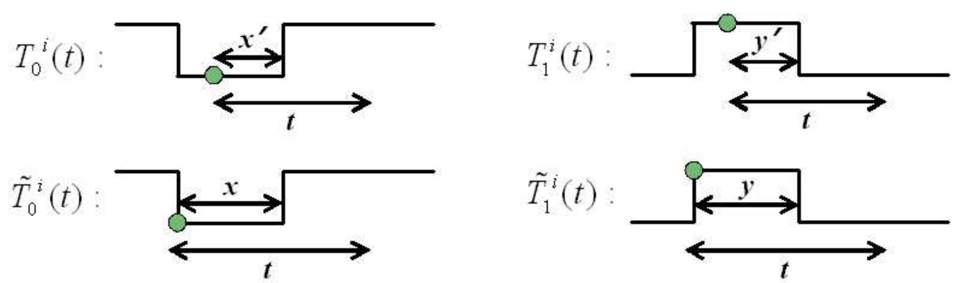

Fig. 5. Illustration of $T_d^i(t)$ and $\tilde{T}_d^i(t)$

In Figure 6, the distribution of $\tilde{X}^i$, which is the remaining time of an OFF period at the sampling time t_s, is given as $\mathbb{F}_{X^i}(\tilde{x})/E(X^i)$ [15]. Here $\mathbb{F}_{X^i}(\tilde{x}) = 1 - F_{X^i}(\tilde{x})$. Similarly, that of an ON period is given as $\mathbb{F}_{Y^i}(\tilde{y})/E(Y^i)$. Using these facts, the following equations are derived.

$$
\begin{aligned}
T_0^i(t) &= t \int_t^{\infty} \frac{\mathbb{F}_{X^i}(x)}{E(X^i)} dx + \int_0^t \frac{\mathbb{F}_{X^i}(x)}{E(X^i)} \left(x + \tilde{T}_1^i(t-x) \right) dx \\
T_1^i(t) &= \int_0^t \frac{\mathbb{F}_{Y^i}(y)}{E(Y^i)} \tilde{T}_0^i(t-y) dy
\end{aligned}
$$

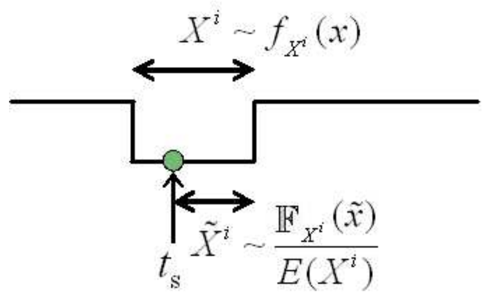

Fig. 6. The distribution of remaining time of an OFF period

$$\tilde{T}_0^i(t) = t\int_t^\infty f_{X^i}(x)dx + \int_0^t f_{X^i}(x)\left(x + \tilde{T}_1^i(t-x)\right)dx$$
$$\tilde{T}_1^i(t) = \int_0^t f_{Y^i}(y)\tilde{T}_0^i(t-y)dy$$

By performing Laplace transforms, we get

$$E(X^i)\cdot T_0^{i*}(s) = \frac{\mathbb{F}_{X^i}{}^*(0) - \mathbb{F}_{X^i}{}^*(s)}{s^2} + \mathbb{F}_{X^i}{}^*(s)\tilde{T}_1^{i*}(s)$$
$$E(Y^i)\cdot T_1^{i*}(s) = \mathbb{F}_{Y^i}{}^*(s)\tilde{T}_0^{i*}(s)$$
$$\tilde{T}_1^{i*}(s) = f_{Y^i}{}^*(s)\tilde{T}_0^{i*}(s)$$
$$\tilde{T}_0^{i*}(s) = \frac{f_{X^i}{}^*(0) - f_{X^i}{}^*(s)}{s^2} + f_{X^i}{}^*(s)\tilde{T}_1^{i*}(s)$$

Hence it follows that

$$T_0^{i*}(s) = \frac{1}{E(X^i)\cdot s^2}\cdot\left[\mathbb{F}^*_{X^i}(0) - \mathbb{F}^*_{X^i}(s)\cdot\frac{1 - f^*_{X^i}(0)f^*_{Y^i}(s)}{1 - f^*_{X^i}(s)f^*_{Y^i}(s)}\right]$$
$$T_1^{i*}(s) = \frac{\mathbb{F}^*_{Y^i}(s)}{E(Y^i)\cdot s^2}\cdot\frac{f^*_{X^i}(0) - f^*_{X^i}(s)}{1 - f^*_{X^i}(s)f^*_{Y^i}(s)}$$

Now, we develop an expression of $UOPP^i$ in terms of $T_0^i(t)$ and $T_1^i(t)$.[5] $UOPP^i_{(d)}$ is defined as the average fraction of time during which usable opportunities are not discovered between any sample d and its next sample. Then, $UOPP^i = UOPP^i_{(0)} + UOPP^i_{(1)}$. In case $d = 1$ is collected at time t_s, the total opportunity of $T_1^i(T_P{}^i)$ units of time is not discovered in $(t_s, t_s + T_P^i)$ since there is no additional sensing during that period. Hence,

$$UOPP^i_{(1)} = u^i\cdot\left[\frac{T_1(T_P^i)}{T_P^i}\right]$$

where u^i is the probability that a sample 1 is collected from channel i [15].[6] In case $d = 0$, the opportunity is discovered at time t_s and it starts to be utilized until any primary user

[5]Note that $\tilde{T}_d^i(t)$ can be derived from $T_d^i(t)$.
[6]A channel is assumed to be in its equilibrium state.

reappears on the channel. If the opportunity lasts until $t_s+T_P^i$, the total opportunity of T_P^i is discovered and utilized. However, if a primary user emerges at t_e, where $t_s < t_e < t_s+T_P^i$, any opportunities in $(t_e, t_s+T_P^i)$ could not be explored. Hence,

$$UOPP_{(0)}^i = \left(1-u^i\right) \cdot \left[\frac{1}{T_P^i}\int_0^{T_P^i} \frac{\mathbb{F}_{X^i}(x)}{E(X^i)} \tilde{T}_1^i(T_P^i - x)dx\right]$$

which completes the derivation of $UOPP^i$.

Two examples of $UOPP^i$ are introduced here. For a channel with Erlang-distributed ON/OFF periods such as $f_{X^i}(x) = xe^{-x}\ (x>0)$ and $f_{Y^i}(y) = ye^{-y}\ (y>0)$, $UOPP^i$ is given as

$$UOPP^i = \frac{1}{2} - \frac{3}{4T_P^i} + \frac{e^{-T_P^i}}{4}\left(\frac{3}{T_P^i}+1\right).$$

For a channel with exponentially-distributed ON/OFF periods such as $f_{X^i}(x) = \lambda_{X^i} e^{-\lambda_{X^i} x}\ (x > 0)$ and $f_{Y^i}(y) = \lambda_{Y^i} e^{-\lambda_{Y^i} y}\ (y>0)$, $UOPP^i$ is found to be

$$UOPP^i = (1-u^i)\left\{1 + \frac{1}{\lambda_{X^i} {T_P}^i}\left(e^{-\lambda_{X^i} {T_P}^i} - 1\right)\right\}.$$

Note that these results are reasonable in the sense that $\lim_{{T_P}^i \to \infty} UOPP^i = 1 - u^i$. As ${T_P}^i \to \infty$, no opportunity is discovered since no sensing is performed. Therefore, $UOPP^i$ becomes $(1-u^i)$.

2) Analysis of $SSOH^i$: As defined earlier, $SSOH^i$ is the average fraction of time during which channel i's discovered opportunities cannot be utilized due to sensing on other channels. Since it is assumed that a secondary user is equipped with one widely-tunable antenna, the secondary user must stop utilizing a discovered channel to sense another channel. This situation is depicted in Figure 7.

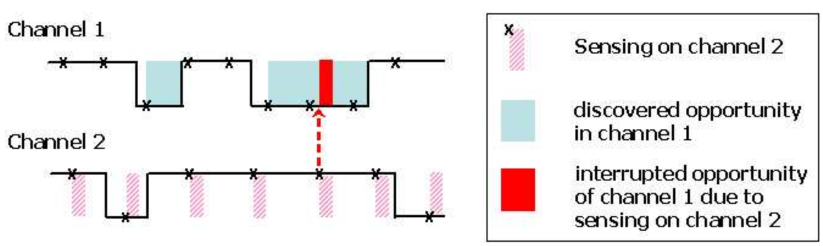

Fig. 7. Interruption of channel 1's discovered opportunity due to sensing on channel 2

To express $SSOH^i$ mathematically, we introduce the *observed* channel model. Since we do not know if a channel is idle or not until sample 0 is collected, the observed channel usage pattern is different from the real one. Hence, we consider a new channel-usage model based on what we observe from samples. Figure 8 illustrates the concept of the observed channel. This channel model has the modified channel utilization $\tilde{u}^i$ which is given as $\tilde{u}^i = u^i + UOPP^i$. Using the new model, $SSOH^i$ can be derived as

$$SSOH^i = (1-\tilde{u}^i)\sum_{\substack{j=1\\ j\neq i}}^{N}\left(\tilde{u}^j \cdot \frac{T_I^j}{T_P^j}\right).$$

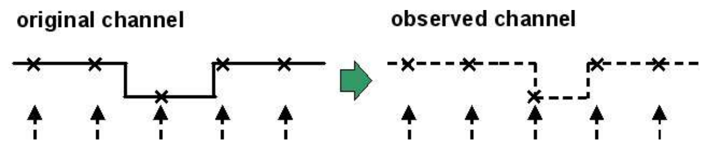

Fig. 8. The observed channel model

3) Sensing-Period Adaptation Algorithm: Based on the derived expressions of $UOPP^i$ and $SSOH^i$, optimal sensing periods can be determined. As shown in Figure 4, our proposed algorithm adapts sensing periods asynchronously. That is, when one of N sensing periods is to be updated, we use most-recently determined sensing periods of other $(N-1)$ channels so that Eq. (1) becomes an equation with only one variable. Note that u^i and other channel parameters in Eq. (1) should be replaced with their estimates.

B. Channel-Parameter Estimation

The forms of $UOPP^i$ and $SSOH^i$ are expressed with distribution functions of ON and OFF periods which must be estimated beforehand. Here we introduce an estimation technique for exponentially-distributed ON/OFF periods. Although our objective is to estimate λ_{X^i} and λ_{Y^i} of each channel, λ_{X^i} and u^i will be estimated instead for simplicity. ML estimation is used to achieve the goal since it is consistent and asymptotically unbiased. Two estimators and the corresponding confidence intervals will be derived. The overall estimation procedure works as follows. First, a likelihood function is built with most recent r^i samples that were collected with a fixed sensing period T_P^i. From the likelihood function, λ_{X^i} and u^i are estimated. These estimates are used to adapt and produce a new sensing period. r^i is also adapted to maintain the designed level of confidence. Finally, using the new r^i and T_P^i, the next stage of sample-collection/estimation/adaptation is started. This process repeats itself forever.

Suppose we have r^i samples, $\underline{Z} = (Z_1, Z_2, \ldots, Z_{r^i})$, collected with the sensing-period of ${T_P}^i$. The joint probability mass function is expressed with four types of transition probabilities:

$$\begin{aligned}
\underline{\theta} &= (u^i, \lambda_{X^i}) \\
L(\underline{\theta}) &= P(\underline{Z}; \underline{\theta}) \\
&= \Pr(Z_1 = z_1; \underline{\theta}) \prod_{k=2}^{r^i} \Pr(Z_k = z_k | Z_{k-1} = z_{k-1}; \underline{\theta}) \\
&= \Pr(Z_1 = z_1; \underline{\theta}) \cdot \\
&\quad \left[P_{00}^i(T_P^i)\right]^{n_0} \left[P_{01}^i(T_P^i)\right]^{n_1} \left[P_{10}^i(T_P^i)\right]^{n_2} \left[P_{11}^i(T_P^i)\right]^{n_3}
\end{aligned}$$

where the Markovian property is applied. $P_{d_1 d_2}^i(t)$ denotes the probability that a sample d_1 is followed by a sample d_2. The total occurrence of 4 different transition types such as $(d_1, d_2) = (0,0), (0,1), (1,0), (1,1)$, is counted and denoted by n_0, n_1, n_2 and n_3. The renewal theory [15] says that for a renewal process alternating between state I (OFF) and II (ON), the probability $P_{00}^i(t)$ that state I is in use at time t provided the process starts from state I is given as

$$P_{00}^i(t) = \frac{\lambda_{Y^i}}{\lambda_{X^i} + \lambda_{Y^i}} + \frac{\lambda_{X^i}}{\lambda_{X^i} + \lambda_{Y^i}} e^{-(\lambda_{X^i} + \lambda_{Y^i})t}.$$

If we switch the role of two states, $P_{11}^i(t)$ is easily derived as

$$P_{11}^i(t) = \frac{\lambda_{X^i}}{\lambda_{Y^i} + \lambda_{X^i}} + \frac{\lambda_{Y^i}}{\lambda_{Y^i} + \lambda_{X^i}} e^{-(\lambda_{Y^i}+\lambda_{X^i})t}.$$

Now, the derivation of four transition probabilities is trivial since $P_{01}^i(t) = 1 - P_{00}^i(t)$ and $P_{10}^i(t) = 1 - P_{11}^i(t)$. They are given as

$$\begin{aligned}
P_{00}^i(t) &= (1 - u^i) + u^i \cdot e^{-(\lambda_{X^i}+\lambda_{Y^i})t} \\
P_{01}^i(t) &= u^i - u^i \cdot e^{-(\lambda_{X^i}+\lambda_{Y^i})t} \\
P_{11}^i(t) &= u^i + (1 - u^i) \cdot e^{-(\lambda_{X^i}+\lambda_{Y^i})t} \\
P_{10}^i(t) &= (1 - u^i) - (1 - u^i) \cdot e^{-(\lambda_{X^i}+\lambda_{Y^i})t}.
\end{aligned}$$

1) u^i Estimator: The ML estimator $\hat{u}^i$ can be derived by solving the equation $\partial \log L(\underline{\theta})/\partial u^i = 0$ which does not yield any closed-form solution. Although a numerical analysis could be used, it is not conducive to provide a confidence interval. Instead, a sample mean estimator is proposed as an alternative estimator:

$$\hat{u}^i = \frac{1}{r^i} \sum_{k=1}^{r^i} Z_k.$$

Although this is not optimal, it is unbiased and tractable to derive a confidence interval. The unbiasedness can be shown as

$$E[\hat{u}^i] = \frac{1}{r^i} \sum_{k=1}^{r^i} E[Z_k] = u^i.$$

We now derive the confidence interval. The correlation coefficient for any two samples Z_{k_1} and Z_{k_2} $(k_1 \neq k_2)$ is found to be

$$\begin{aligned}
E[Z_{k_1} Z_{k_2}] &= \begin{cases} \Pr(Z_{k_1} = 1 | Z_{k_2} = 1) \Pr(Z_{k_2} = 1) \ , \ k_1 > k_2 \\ \Pr(Z_{k_2} = 1 | Z_{k_1} = 1) \Pr(Z_{k_1} = 1) \ , \ k_1 < k_2 \end{cases} \\
&= P_{11}^i(|k_1 - k_2| \cdot T_P^i) \cdot u^i \\
\Rightarrow \rho_{k_1 k_2} &= \frac{E[Z_{k_1} Z_{k_2}] - (u^i)^2}{u^i - (u^i)^2} = e^{-(\lambda_{X^i}/u^i) \cdot |k_1 - k_2| T_P^i}.
\end{aligned}$$

This shows that the correlation is decaying exponentially fast as the separation of two samples becomes large. Since the rate of decrease is proportional to $(\lambda_{X^i}/u^i)T_P^i$, r^i samples can be assumed to be weakly-correlated as long as $(\lambda_{X^i}/u^i)T_P^i$ and r^i are large. Using this fact, we can derive the confidence interval. When $(\lambda_{X^i}/u^i)T_P^i$ is large, $\frac{\overline{\mathrm{Z}} - E[\overline{\mathrm{Z}}]}{\sqrt{\mathrm{var}[\overline{\mathrm{Z}}]}} \to \mathrm{N}(0, 1)$ as $r^i \to \infty$ by the Central Limit Theorem. Hence, $100(1 - \alpha)$ $(\%)$ confidence interval is given as

$$\left[\overline{\mathrm{Z}} - \sqrt{\mathrm{var}[\overline{\mathrm{Z}}]} \cdot \mathrm{N}^{-1}(1 - \alpha/2), \overline{\mathrm{Z}} + \sqrt{\mathrm{var}[\overline{\mathrm{Z}}]} \cdot \mathrm{N}^{-1}(1 - \alpha/2) \right]$$

where α is a design parameter and $\mathrm{var}[\overline{\mathrm{Z}}]$ is a function of r^i. To relate r^i with the confidence interval, we introduce another design parameter β such that $\beta = \sqrt{\mathrm{var}[\overline{\mathrm{Z}}]} \cdot \mathrm{N}^{-1}(1 - \alpha/2)$. Then, an appropriate r^i can be found to guarantee the level α of confidence with the interval length of 2β. In general, we need more samples (i.e., bigger r^i) to achieve a higher level of confidence (i.e., smaller α or β).

2) λ_{X^i} Estimator: The ML estimator $\hat{\lambda}_{X^i}$ can be derived by solving the equation $\partial \log L(\underline{\theta})/\partial \lambda_{X^i} = 0$ which gives

$$\hat{\lambda}_{X^i} = -\frac{u^i}{T_P^i} \log \left[\frac{-B + \sqrt{B^2 - 4AC}}{2A} \right]$$

$$\text{where} \begin{cases} A = (u^i - (u^i)^2)(r^i - 1) \\ B = -2A + (r^i - 1) - (1 - u^i)n_0 - u^i \cdot n_3 \,. \\ C = A - u^i \cdot n_0 - (1 - u^i)n_3 \end{cases}$$

The remaining task is to find a confidence interval of $\hat{\lambda}_{X^i}$. Unfortunately, the high nonlinearity of $\hat{\lambda}_{X^i}$ makes it difficult to find a confidence interval. Instead, an upper bound of T_P^i will be provided to ensure a reasonable level of confidence. Note that each of four transition probabilities tends to converge to a constant, u^i or $1 - u^i$, as T_P^i goes to infinity. Since $\log L(\underline{\theta})$ is expressed with transition probabilities, an ML estimator cannot guarantee accurate estimation with a large T_P^i. Hence we will bound the value of $P_{01}^i(T_P^i)$ below a certain threshold $(1 - \gamma)u^i$ to ensure the probability would not be too close to its limit. This concept is shown clearly in Figure 9. Then, an upper bound of T_P^i is determined as

$$|u^i - P_{01}^i(T_P^i)| \geq \gamma \times u^i \quad \Rightarrow \quad T_P^i \leq -\frac{u^i}{\lambda_{X^i}} \log \gamma.$$

In case a new sensing period to be adapted is larger than this bound, T_P^i must be set to $-\frac{u^i}{\lambda_{X^i}} \log \gamma$.

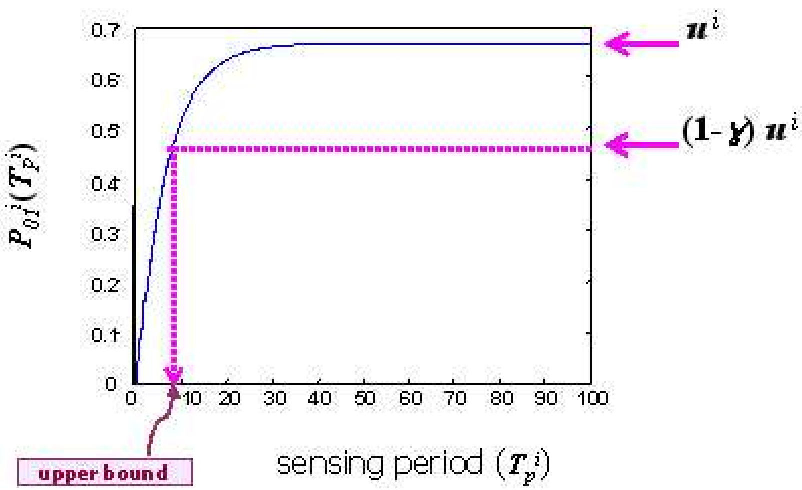

Fig. 9. The graph of $P_{01}^i(T_P^i)$ and upper bound of T_P^i

V. Ordering Channels

As discussed in Section III, a secondary user has to sense N licensed channels to find an idle channel and assign it to one of data links to transmit/receive a packet to/from its neighbor. Here, our main objective is to minimize the idle channel search time so as to reduce the end-to-end packet delay. As a simple solution, channels may be arranged in ascending order of channel utilizations. However, this is not an optimal solution. Instead, we must consider $P^i_{idle}(t)$, the probability that channel i would be idle at time t based on the previous sample history. By setting t to be the time when an idle channel needs to be found, we can build an optimal sensing order as described below.

$$\begin{cases} \text{Find } P^i_{idle}(t) = \Pr(Z^i_t = 0 | Z^i_s, s < t), \text{ for all } i = 1, \dots, N \\ \text{Sense N channels in descending order of } P^i_{idle}(t) \end{cases}$$
$$\text{where } \begin{cases} Z^i_t\text{: channel } i\text{'s sensing result at time } t \\ t\text{: the time when an idle channel search is required} \end{cases}$$

Again we consider ON-OFF alternating channels. According to the renewal theory, we only need the most recent sample to derive $P^i_{idle}(t)$. Hence, $P^i_{idle}(t)$ becomes the transition probability between the most recent sample and its following sample which will be collected by the idle channel search: $P^i_{idle}(t) = \Pr(Z^i_t = 0 | Z^i_s = d)$, where Z^i_s is the most recent sample of channel i. Since $d = 0$ or 1, P^i_{00} and P^i_{10} are considered. In this section, the general form of transition probabilities, not only for the exponential case, will be derived. The theory suggests that $P^i_{11}(\Delta_i)$, where Δ_i implies the time difference between the most recent sample's collection time and the time when an idle channel search is required, is expressed as

$$P^i_{11}(\Delta_i) = \int_{\Delta_i}^{\infty} \frac{\mathbb{F}_{Y^i}(u)}{E[Y^i]} du + \int_0^{\Delta_i} h^i_{10}(u) \mathbb{F}_{Y^i}(\Delta_i - u) du$$

where $h^i_{10}(u)$ is the renewal density of state I (OFF) given that the renewal process started from state II (ON) [15]. It is proven that $h^{i*}_{10}(s)$ is expressed as

$$h^{i*}_{10}(s) = \frac{f^*_{X^i}(s)\left\{1 - f^*_{Y^i}(s)\right\}}{E[Y^i] \cdot s \left\{1 - f^*_{Y^i}(s) f^*_{X^i}(s)\right\}}.$$

By using the above form and the Laplace transform, we get

$$P^{i*}_{11}(s) = \frac{1}{s} - \frac{\left\{1 - f^*_{Y^i}(s)\right\}\left\{1 - f^*_{X^i}(s)\right\}}{E[Y^i] \cdot s^2 \left\{1 - f^*_{Y^i}(s) f^*_{X^i}(s)\right\}}.$$

$P^i_{10}(\Delta_i)$ can be derived by the inverse Laplace transform and the following relationship: $P^{i*}_{10}(s) = 1 - P^{i*}_{11}(s)$. By switching the role of state I and II, $P^i_{00}(\Delta_i)$ can be easily derived by the inverse Laplace transform of the following term:

$$P^{i*}_{00}(s) = \frac{1}{s} - \frac{\left\{1 - f^*_{X^i}(s)\right\}\left\{1 - f^*_{Y^i}(s)\right\}}{E[X^i] \cdot s^2 \left\{1 - f^*_{X^i}(s) f^*_{Y^i}(s)\right\}}$$

For example, for a channel with Erlang-distributed ON/OFF periods such as $f_{X^i}(x) = xe^{-x}\ \ (x > 0)$ and $f_{Y^i}(y) = ye^{-y}\ \ (y > 0)$,

$$\begin{aligned} P^i_{00}(\Delta_i) &= \frac{1}{2} + \frac{1}{2} e^{-\Delta_i} \cos(\Delta_i) \\ P^i_{10}(\Delta_i) &= \frac{1}{2} - \frac{1}{2} e^{-\Delta_i} \cos(\Delta_i). \end{aligned}$$

On the other hand, for a channel with exponentially-distributed ON/OFF periods such as $f_{X^i}(x) = \lambda_{X^i} e^{-\lambda_{X^i} x}\ \ (x > 0)$ and $f_{Y^i}(y) = \lambda_{Y^i} e^{-\lambda_{Y^i} y}\ \ (y > 0)$,

$$\begin{aligned} P^i_{00}(\Delta_i) &= (1 - u^i) + u^i \cdot e^{-(\lambda_{X^i} + \lambda_{Y^i})\Delta_i} \\ P^i_{10}(\Delta_i) &= (1 - u^i) - (1 - u^i) \cdot e^{-(\lambda_{X^i} + \lambda_{Y^i})\Delta_i}. \end{aligned}$$

The complete channel-ordering algorithm is given below.

1) For $i = 1, \dots, N$,

calculate $P^i_{idle}(\Delta_i) = \begin{cases} P^i_{00}(\Delta_i) \text{ , if } d_i = 0 \\ P^i_{10}(\Delta_i) \text{ , if } d_i = 1 \end{cases}$

where $\begin{cases} d_i : \text{ most recent sample of channel } i \\ \Delta_i : \text{elapsed amount of time since} \\ \qquad \text{the most recent sensing} \end{cases}$

2) Optimal Sensing Order :

sense N channels in descending order of $P^i_{idle}(\Delta_i)$

VI. Evaluation

A. Simulation Setup

To measure the effectiveness of the proposed proactive sensing algorithm, especially for sensing-period adaptation and ordering of channels, we define three performance metrics: *estimation accuracy, achieved opportunity ratio,* and *channel-search delay*. The *estimation accuracy* represents how close the estimation results would be to the actual channel-parameters. The *achieved opportunity ratio* measures the ratio of the total amount of discovered spectrum availability (summed over all channels) to the total amount of existing availability (summed over all channels). The *channel-search delay* is defined as the average delay (in seconds) in finding an idle channel per packet transmission.

We considered the case where a secondary node N_0 tries to exchange packets with its neighbors. All channels are assumed to have exponentially-distributed ON/OFF periods. We conducted simulation using MATLAB, and all measurements are made by N_0.

To evaluate the algorithm's estimation accuracy, 5 heterogeneous channels are used. Since each channel has unique channel utilization and λ_{X^i}, it helps differentiate channel-usage estimation results.

To evaluate the achieved opportunity ratio, two scenarios are tested: 5 homogeneous channels and 5 heterogeneous channels. The results are compared to those of a non-adaptive proactive sensing scheme, such as those in [11], [13]. Both schemes start with a given initial sensing-period, ranging from 0.15 to 2 sec. Since the sensing period is not adapted in the non-adaptive case, the initially-determined T^i_P affects the overall system performance. By comparing the two schemes in this way, we can show the benefits of sensing-period adaptation in terms of the discovery of opportunities. As in Section IV, consistent packet transmission is assumed so that whatever idle channels discovered by N_0 via periodic sensing can be allocated to a data link and then utilized.

To measure the channel-search delay, our proactive-sensing scheme is compared to a proactive sensing without channel-ordering. The sensing-period adaptation is assumed to be used by both. Several environments with different numbers of channels, ranging from 3 to 15 heterogeneous channels, are studied. This test will show that the channel-ordering can reduce the delay in locating an idle channel and also improve the system scalability. Unlike in the achieved opportunity ratio, consistent packet transmission is not assumed; instead, the packet inter-arrival/departure time is assumed to be Poisson-distributed with mean 1 sec.

The following design and channel parameters are used for the simulation where EX^i and EY^i are measured in seconds.

α	β	γ	T_I^i
0.2	0.05	0.2	20(ms) (for all i)

TABLE I

THE VALUES OF DESIGN PARAMETERS IN THE SIMULATION

homogeneous: achieved opportunity ratio					
	Ch 1	Ch 2	Ch 3	Ch 4	Ch 5
EX^i	2.50	2.50	2.50	2.50	2.50
EY^i	0.50	0.50	0.50	0.50	0.50
heterogeneous: estimation accuracy and achieved opportunity ratio					
	Ch 1	Ch 2	Ch 3	Ch 4	Ch 5
EX^i	2.50	0.50	1.00	5.00	1.00
EY^i	0.50	2.50	1.00	2.50	2.00
heterogeneous: channel-search delay					
	Ch 1,6,11	Ch 2,7,12	Ch 3,8,13	Ch 4,9,14	Ch 5,10,15
EX^i	1.50	0.50	1.00	3.00	1.00
EY^i	0.80	2.50	1.00	2.50	2.00

TABLE II

THE VALUES OF CHANNEL PARAMETERS IN THE SIMULATION

B. The Simulation Results

1) Estimation Accuracy: Figures 10 and 11 show the accuracy of channel-usage estimation. Each point in the figures indicates an estimate produced in an estimation cycle. A dashed line implies the actual channel parameter. The estimator $\hat{u}^i$ is unbiased and its confidence interval was derived in an exact form in Section IV. As a result, the plot of $\hat{u}^i$ in Figure 10 follows the actual channel utilization very closely. On the other hand, we do not have the exact confidence interval of $\hat{\lambda}_{X^i}$ which is reflected in Figure 11 such that the variance of estimates varies with channel. However, the average behavior of the estimator shows that it follows the actual λ_{X^i} well.

Note that the estimation results do not converge in time since we don't accumulate samples to produce an estimate. That is, we discard previous samples when a new stage of sampling/estimation/sensing-period-adaptation begins and we use only r^i samples to estimate.

2) Achieved Opportunity Ratio: Figures 12 and 13 plot the achieved opportunity ratios of adaptive and non-adaptive schemes. The x-axis represents the initially-assigned sensing period, which is adapted in the former scheme. In the y-axis, 100 % is achieved only when all the existing opportunities in 5 channels, the sum of $(1-u^i)$, are discovered. However, it is unachievable in practice because each sensing operation requires a non-zero time, T_I^i, to listen to a channel and the discrete sensing may miss some opportunities. Hence, a dashed

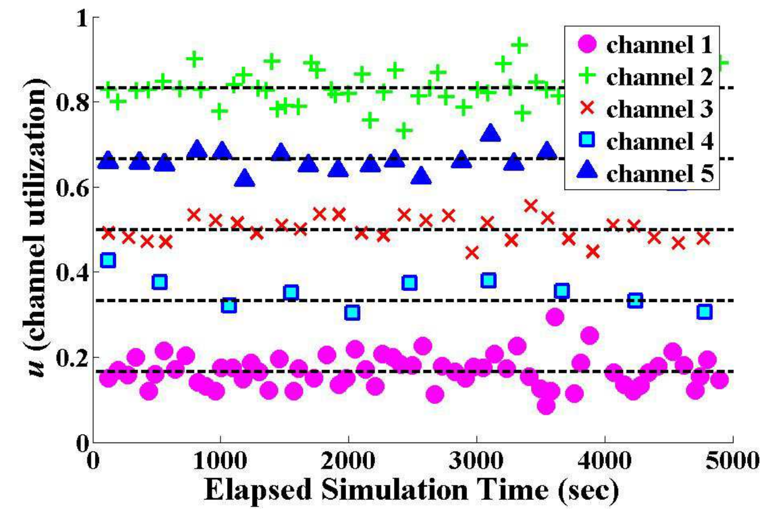

Fig. 10. Channel-utilization estimation

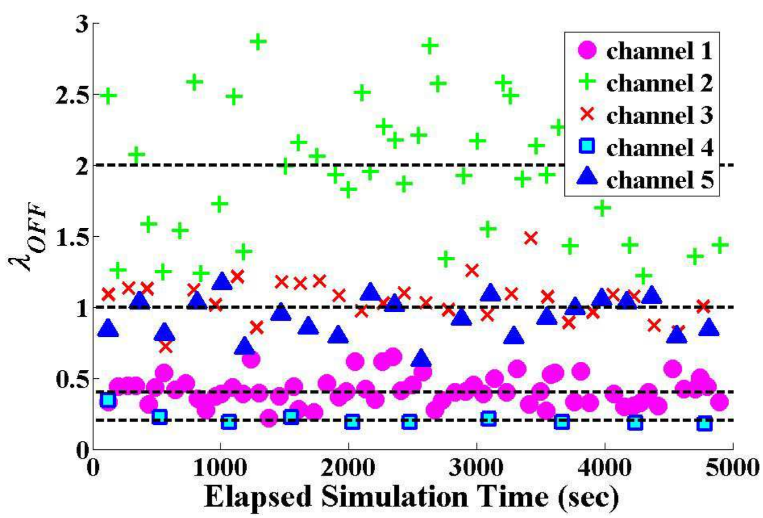

Fig. 11. λ_{OFF} estimation

line in each graph is used to indicate the analytical maximum of the ratio which can be derived from the Eq. (1).

As shown in both figures, the plot of achieved opportunity ratio shows the superiority of the proposed algorithm. The sensing-period adaptation offers a maximal amount of discovered spectrum availability regardless of the initial sensing period. The adaptive sensing is found to achieve up to 98% (homogeneous) and 97% (heterogeneous) of the analytical maximum, and discover up to 20% more opportunities than the previous sensing schemes without sensing-period adaptation. This improvement may become greater as the initial sensing period grows. The reason for a slight performance degradation with large initial values in the adaptive case is that the initial sensing period is not adapted until the first estimation cycle ends, which took more than 50 seconds in our simulation. However, this tendency is negligible since the sensing period is quickly adapted to the optimal value in a few cycles as shown in Figure 14. In this figure, each plot represents a realization of sensing-period adaptation starting from a given initial period (7 variations: 0.15 to 2 seconds). It can be seen that every plot converges to the common adapted period which is very close to the optimal one (a dashed line).

On the other hand, choice of the initial sensing period is crucial for the performance of the non-adaptive sensing. In case the period is too small, the performance is degraded since the sensing overhead becomes significant. On the other hand, if the period is too large, most of the opportunities cannot be discovered, yielding a poor performance.

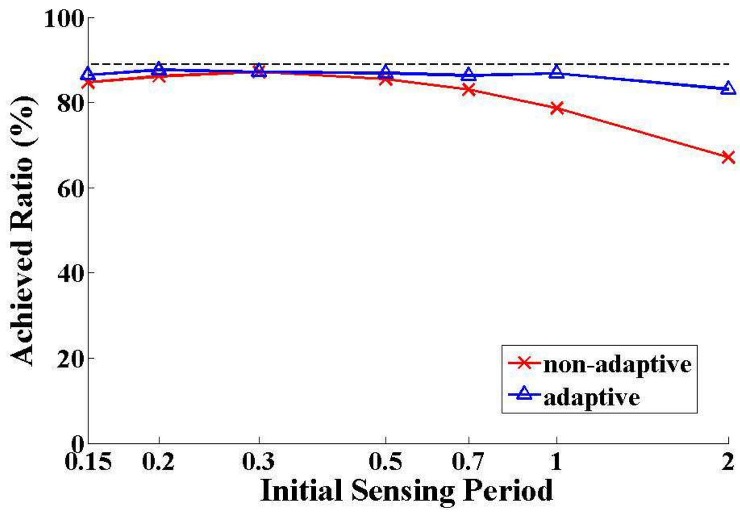

Fig. 12. Homogeneous case: achieved opportunity ratio

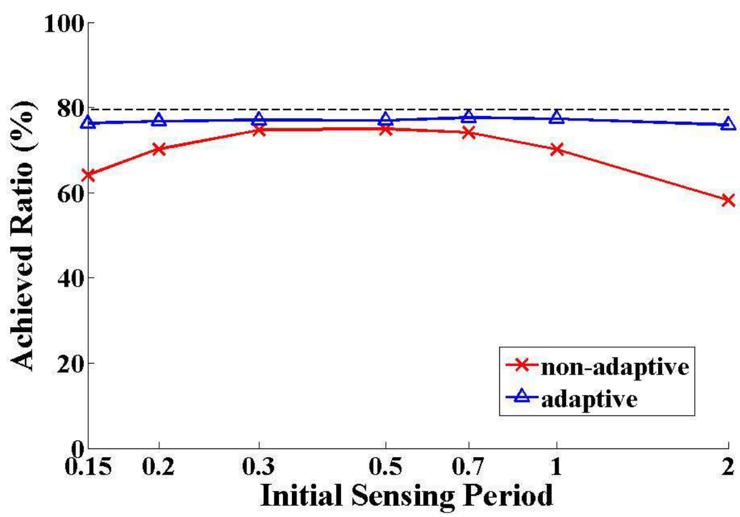

Fig. 13. Heterogeneous case: achieved opportunity ratio

3) Channel-Location Delay: In terms of the channel-search delay, our scheme also outperforms the sensing without channel-ordering as shown in Figure 15. In the case without channel ordering, the delay grows steadily as the number of channels to sense increases.

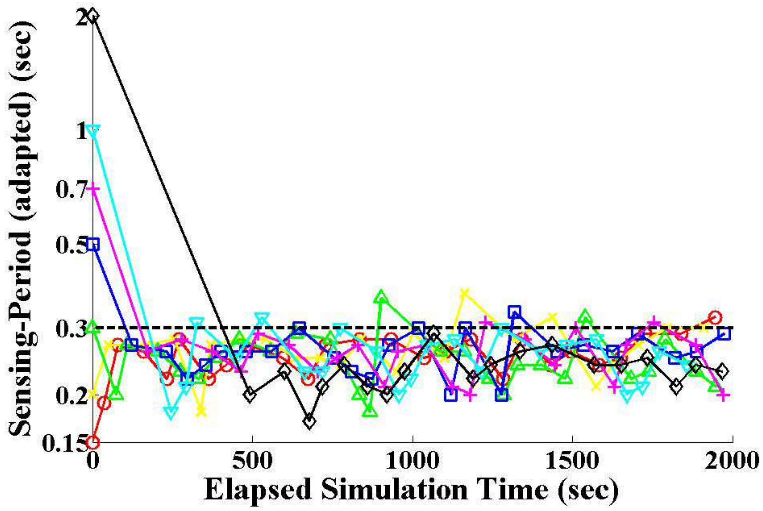

Fig. 14. Sensing-period adaptation (channel 3)

However, in case of ordering channels to sense, the delay in locating an idle channel is less sensitive to the number of channels, thanks to the optimal order of sensing channels. An idle channel can be located within 25 ms which corresponds to one or two times of sensing. Hence, the proposed channel-ordering enhances system scalability, enabling a secondary node to sense a large number of channels. Although the exact delay in locating an idle channel depends on the underlying channel parameters, the channel-ordering always reduces the location delay.

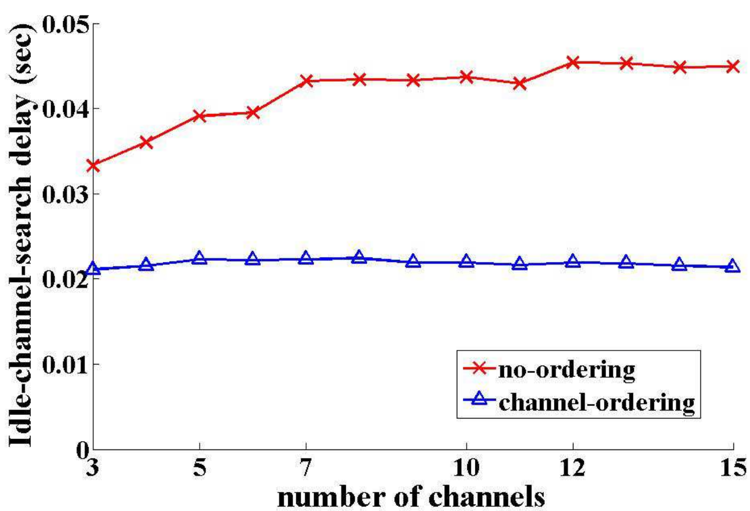

Fig. 15. Channel-search delay

VII. Conclusion

We investigated two typical modes of sensing, proactive and reactive, and developed a sensing mode selection algorithm to achieve better energy-efficiency. Proactive sensing was designed and analyzed in-depth, especially focusing on its optimal sensing adaptation. The proposed scheme strives to discover as much usable spectrum availability as possible. A channel-usage pattern estimation technique was also proposed by deriving ML estimators and their confidence intervals. Finally, the optimal order of sensing channels is constructed so as to minimize the delay in finding an idle channel. The simulation results demonstrated the advantages of the proposed algorithm, such as robustness of parameter estimation, a larger amount of discovered channel availability, and a smaller channel-searching delay.

In future, we would like to enhance reactive sensing by adding a channel estimation feature. Although it does not provide an organized way of sample collection, some channel information is collected during each idle channel search. We will focus on those samples to perform Bayesian estimation without any prior knowledge.

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