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SPECIAL ISSUE

Adaptive wideband sensing scheme based on Bayesian experimental design

Keyu Wu[1] · Xingchen Hu[1] · Hang Du[1] · Kuihua Huang[1]

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Abstract
In this paper, we investigate the problem of wideband sensing for cognitive radio. Due to resource constraint, a cognitive node targets at finding a given number of spectrum holes, which is studied under a novel wideband sensing architecture. Specifically, the cognitive node can dynamically focus its sensing measurements on different portions of contiguous channels. An adaptive wideband sensing scheme is proposed under the standard Bayesian experimental design framework via three steps: (1) define a Bayesian cost that incorporates the numbers of desired spectrum holes, (2) design hypothesis testing rule to detect access opportunities, and (3) identify a scheme to adapt the measurements during the sensing process. In order to facilitate implementation, we further propose an approximated Bayesian experiment design scheme to reduce the computational complexity. The performance gain of our wideband sensing scheme is demonstrated via numerical simulation.

Keywords Wideband Sensing · Cognitive Radio · Bayesian Experimental Design

1 Introduction

Cognitive radio (CR) technique can opportunistically utilize channels that are not temporally unoccupied by primary users (PUs), and it provides an attractive solution to tackle the spectrum scarcity [1–3]. Compared with single-band CR, wideband CR can explore and exploit spectrum holes over a broad range of spectrum, which promises better utilization of access opportunities and higher achievable throughput [4]. Spectrum sensing identifies available spectrum holes, and therefore, is pivotal for the design of wideband CR [5].

With the concept of “divide and conquer”, the wideband sensing task can be accomplished via sampling and detecting the channels separately with single band sensing techniques. However, when channels are sensed one-by-one, the sensing time required for sweeping the whole spectrum band can be very high. In the contrast, simultaneously sensing all channels requires a bank of filters to cover the whole spectrum band [6], which can cause great hardware expenses.

Another approach is to sample the wideband signal directly, e.g., [7], and as long as the sample rate is at least twice of the signal bandwidth (known as the Nyquist rate), the information of each individual band can be recovered. However, because the bandwidth of the wideband signal is usually high, this approach often results in an unaffordable sampling rate.

Recently, compressive sensing (CS) technique has received considerable attention with the application for wideband spectrum sensing [8]. Given the wideband signal is sparse at the frequency domain, i.e., there are small amount of channels are occupied, the wideband spectrum signal or its spectrum power can be recovered from samples obtained at a rate smaller than the Nyquist rate. After information at each channel recovered, the spectrum occupancy detection is made accordingly. However, the sparsity level, which is defined as the number of occupied channel, is crucial for CS recovery algorithm and is typically time varying for wideband signal. Therefore, it is non-trivial to accomplish CS when the sparsity level information is unknown [9].

It can be seen that, all above schemes are targeting at detecting the spectrum occupancy of each individual channel. However, in many cases, the CR is only able to utilize up to certain number of channels. Therefore, it is possible

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Keyu Wu
keyuwu@nudt.edu.cn

[1] National University of Defense Technology, Changsha, Hunan 410073, China

to ease the complexity burden of WSS, since only the correct detection of a portion of channels is of interest. With this motivation, we investigate the WSS problem under an architecture that was first studied in [10], and we name it as the “sweep-zoom” architecture. The key components are an adjustable local oscillator (LO) and an adjustable bandpass filter (BF), and it is able to sweep to different location of the spectrum according to the frequency the LO and to measure different number of channels according to the bandwidth of the BF. This architecture is of interest, due to its low implementation complexity of offering the flexibility of adapting measurements.

We study the WSS problem with the framework of Bayesian experimental design [11], which consists of two dimensions: one is how to make detection decision given the initial belief about channel’s occupancy and a sequence of observations taken over different portions of channels; the other is how to adaptively take measurements based on current belief about channel’s occupancy. These two processes boost each other with the total goal to detect the given number of access opportunities.

The most related work in literature is [12], and its difference with our work is two-fold. First, in [12], the CR only interests in finding a given number spectrum holes as a whole. In the contrast, we also value partial discovery, since a cognitive node may be able to adapt its transmission rate according to the number of available channels via, for example, orthogonal frequency division multiplexing techniques. Second, work [12] focused on spectrum detection problem under a fixed measure process, while this paper further improves spectrum sensing performance via adapting sensing measurements based on real-time sensing observations.

The rest of paper is organized as follows. Section 2 discusses related work. Section 3 presents the PUs’ signal model, and the CR’s sensing architecture and sensing protocol. An adaptive WSS scheme is proposed in Sect. 4, and it is modified in Sect. 5 with in order to reduce complexity. Section 6 demonstrates the performance of proposed AWSS scheme. Section 7 concludes the paper.

2 Related work

2.1 Spectrum sensing and access

Reliable spectrum sensing is critical for cognitive radio, since it enables secondary nodes to correctly identify spectrum holes while minimizing interference to primary users. Various spectrum sensing schemes have been considered [13] for handling the reliability and agility tradeoff. For example, when primary activities have temporal correlation [14, 15], sensing observations can be used for predicting spectrum statuses. Spectrum sensing decision may need to balance between the two goals: identifying idle channel for immediate use and tracking primary activities to guide future decisions.

Given sensing results, cognitive radio network can improve spectrum utilization by intelligently exploiting identified spectrum holes. For example, work [16] proposed cooperative transmission scheme, which exploits intermediate nodes to relay message and enable data exchanging whenever there exists a multi-hop-multi-channel path between two communicating nodes. The cooperative transmission scheme reduces the likelihood of experiencing communication breakdown due to “spectrum outage”. Furthermore, work [17] considered dynamic spectrum management scheme for 5G Non Orthogonal Multiple Access (NOMA) wireless networks. The cognitive node attempts to optimize the power allocation between the licensed and unlicensed band in order to maximize throughput. The optimization problem was modeled as a Common Pool Resource game and a distributed algorithm was proposed to solve a Pure Nash Equilibrium solution.

2.2 Sequential wideband sensing

In general, for wideband cognitive radio, not all bands are equally important. For example, an SU may prefer to first sense channels with high idle possibility or good channel quality. Thus, by intelligently deciding the sensing order or sensing stopping rule, the throughput of SU system can be maximized [18, 19]. Furthermore, when there exists correlation among different channels, historical sensing results can be exploited to improve sequential sensing actions and detection reliability [20, 21].

In works [18–21], the sensing decision of each channel is made based on a fixed length of data samples. However, it is shown [22] that the sensing duration of each channel can be considerably reduced with Sequential Probability Ratio Testing (SPRT). Therefore, by combining the concept of SPRT [22] and the concept of sequential search over channels, works [23, 24] studied a sequential sensing scheme in frequency-temporal domain. Specifically, SU intelligently decides which channels to sample, and how many samples to collect at each channel, so as to minimize sensing cost (e.g., sensing time) under the premise of ensuring reliable detection.

In works [18–20, 23, 24], a cognitive node can only allocate sensing resource to one channel a time, which may limit the sensing performance. In this work, we will further study the wideband sensing scheme where a cognitive radio is capable of adapting its sensing resource over multiple channels.

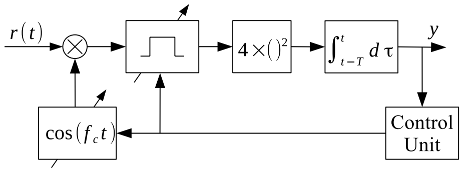

Fig. 1 Sweep-zoom sensing architecture

3 System model

3.1 Primary users' signal model

We assume the system consists of L channels, and each band has bandwidth W. The PUs operates in a slotted manner, and during each time slot, the wideband signal, denoted as $r_l(t)$, can be written as

$$r(t) = \sum_{l=1}^{L} \left[\lambda_l \cdot s_{I,l}(t) + n_{I,l}(t)\right] \cos(f_l t) + \left[\lambda_l \cdot s_{Q,l}(t) + n_{Q,l}(t)\right] \sin(f_l t), \tag{1}$$

where f_l is the angular frequency at the center of the l-th channel; λ_l is the indicator variable for the status of the l-th channel at current time slot, where $\lambda_l = 1$ if the l-th channel is occupied, and $\lambda_l = 0$, otherwise; and $s_{I,l}(t)$ and $s_{Q,l}(t)$ are the in-phase and quadrature components for the PU's signal at l-th channel, respectively; and $n_{I,l}(t)$ and $n_{Q,l}(t)$ are the in-phase and quadrature components of the noise at l-th channel, respectively. At each time slot, the occupancy of each channel is modeled as a Bernoulli random variable (r.v.) with $\mathrm{P}(\lambda_l = 0) = \bar{\omega}_0(l)$, and λ_l is independent with λ_n, $\forall n \neq l$. We assume $\bar{\omega}_0$ is known to the CR. The PU's signal $s_{I,l}(t)$ and $s_{Q,l}(t)$ are modeled as two independent Gaussian r.v.s with are with zeros mean and variances equal to $\sigma_l^2/2$. The noise $n_{I,l}(t)$ and $n_{Q,l}(t)$ are also modeled as two independent zero mean Gaussian r.v.s with variance $\sigma_0^2/2$, which implies the noise variance is the same for all channels[1]. We assume $\sigma_l^2/2$ and $\sigma_0^2/2$ are also known to the CR.

3.2 Sweep-zoom sensing architecture

We augment the classical sweep architecture an adjustable BF (Fig. 1), which operates at medium frequency and can be adjusted to cover a bandwidth from W up to $B_{\max}W$. By setting the bandwidth of the filter as BW, and setting the operating angular frequency of the LO f_c as $f_l + \frac{B-1}{2}W$, the signal and noise at $\mathcal{L}(f_c, B) \triangleq \{l, l+1, ..., l+B-1\}$ channels can pass the filter. After squaring and integrating with duration T, which is set to $\frac{1}{W}$, the output after integration can be approximated via as [25]

$$y = \frac{1}{2} \sum_{l \in \mathcal{L}(f_c,B)} \lambda_l \cdot \left(s_{I,l}^2(t) + s_{Q,l}^2(t)\right) + n_{I,l}^2(t) + n_{Q,l}^2(t). \tag{2}$$

3.3 Adaptive wideband sensing

We assume among L channels, the CR can use up to d channels, and when the number of detected spectrum holes is less than d, the CR is still able to utilize these access opportunities for transmission, although with reduced throughput. At each time slot, the CR can use a fixed length sensing budget with time duration KT, i.e., it can get totally K measurements. Combining the initial belief $\bar{\omega}_0$ with all the K measurements, the CR makes decision about the channels' occupancy. If the number reported spectrum holes is more than d, the CR randomly picks d of them for transmission.

4 Adaptive wideband sensing via standard Bayesian experimental design

Bayesian experimental design (BED) addresses the problem of how to collect data in order to achieve (near) optimal result for certain Bayesian inference task. Here we formulate the adaptive wideband sensing as an BED with Bayesian hypothesis testing task.

A joint channel status is defined as the combination of all channel status, and a hypothesis is corresponding to a guess of a joint channel status. Therefore, there are $M = 2^L$ different hypotheses, and the set of the M hypotheses is defined as $\mathcal{M}$.

Before any measurement is conducted, the initial prior probability distribution over $\mathcal{M}$ can be calculated easily from $\bar{\omega}_0$. After observing K measurements, the CR can update its belief over the hypothesis space, and a proper decision should be made, such that it balances between the goal of finding d spectrum holes and protecting the PUs. We address this balancing problem via defining a proper Bayesian cost in Sect. 4.1. And with Bayes' theorem, the formula for CR iteratively update its belief after each observation is given in Sect. 4.2. After these preparation, the way for adaptively collecting the K measurements and the decision rule after the sensing budget is addressed in Sect. 4.3.

4.1 Bayesian cost design for wideband spectrum hole detection

When the status of each channel is decided separately, the cost of deciding hypothesis H_i while hypothesis H_j is true, denoted as $c_S(H_i, H_j)$, can be reasonably defined as

[1] This homogenous assumption is only for brevity, and the methods developed later holds for general noise models.

$$c_S(H_i, H_j) \triangleq \sum_{l=1}^{L} \mathbb{1}(H_i(l) \neq H_j(l)), \tag{3}$$

where $H_i(l)$ denotes the status of the l-th channel under hypothesis H_i.

However, we argue that, when the goal is to detect d spectrum hole out of L channels, it is more suitable to define the cost jointly as follows,

$$\begin{aligned} c_J(H_i, H_j) \triangleq & \Phi_{ij}(0,1) + \min\{\Phi_{ij}(1,0), \\ & \max\{d - \Phi_{ij}(0,0), 0\}\}, \end{aligned} \tag{4}$$

where $\Phi_{ij}(s,t)$ is defined as

$$\Phi_{ij}(s,t) \triangleq \sum_{l=1}^{L} \mathbb{1}(H_i(l) = s, H_j(l) = t). \tag{5}$$

In the design of $c_J(H_i, H_j)$, mistakenly deciding 0 as 1 will not be penalized, as long as enough spectrum holes has been discovered. However, deciding 1 as 0 will always be penalized, the CR is still obligated to protect the PUs.

4.2 Inference posterior probability distribution

Suppose the filter's bandwidth is BW and the central angular frequency of the LO is f_c. When the filtered out signal covers integer number of channels, we define the joint setting of the filter and LO as a valid measure action, denoted as a, i.e., $a \triangleq (f_c, B)$, and denote $\mathcal{L}(a)$ as the set of indices of covered channels. Refer to Sect. 3.2 for the relationship between $\mathcal{L}(a)$ and (f_c, B).

For any action a and hypothesis H_j, it is easy to show that the measurement y is the summation of positive weighted squared standard norm distribution, which has no closed form formula for the probability density function (PDF). But fortunately, via moment matching, Gamma distribution can be parametrized as an useful approximation as follows [26].

Define $k_{a,j} \triangleq |\mathcal{L}(a)| + \sum_{l\in\mathcal{L}(a)} H_j(l)$ and $\theta_{a,j} \triangleq \frac{1}{k_{a,j}}\left(|\mathcal{L}(a)|\sigma_0^2 + \sum_{l\in\mathcal{L}(a)} H_j(l)\sigma_l^2\right)$, the conditional PDF of y can be approximated as

$$\mathrm{f}(y|H_j, a) = \frac{1}{\Gamma(k_{a,j})\theta_{a,j}^{k_{a,j}}} y^{k_{a,j}-1} e^{-y/\theta_{a,j}}, \tag{6}$$

which is the Gamma distribution with shape parameter $k_{a,j}$ and scale parameter $\theta_{a,j}$.

With $\mathrm{f}(y|H_j, a)$, the posterior probability $\mathrm{P}(H_j|y, a)$ after y and prior probability $\pi(H_j)$ can be calculated as

$$\mathrm{P}(H_j|y, a) = \frac{\mathrm{f}(y|H_j, a)\pi(H_j)}{\mathrm{f}(y)}. \tag{7}$$

4.3 Hypothesis testing and sequential measurement adaptation

Here, we limit the scope to greedy measurement adaptation via ignoring the information of K, which gives non-trivial solution, and is the standard methodology in the field of BED [11]. That is, before a measure action needs to be chosen, it treats this measurement as the final measurement, and the action is chosen in a way such that the expected Bayesian cost is minimized under optimal decision rule given the action, which is formalized as follows.

Given action a and measurement y, define a decision rule $\delta(\cdot|a) : \mathbb{R}^+ \to \mathcal{M}$, i.e., $\delta(y|a)$ maps the measurement y to a joint channel status. Therefore, for any a and $\delta(\cdot|a)$, the expected Bayesian cost is

$$R_J(\delta|a) = \int \sum_{j=1}^{M} c_J(\delta(y|a), H_j)\, \mathrm{P}(H_j|y, a)\, \mathrm{f}(y) dy. \tag{8}$$

Define $\mathcal{L}_J(\delta(y|a))$ as

$$\mathcal{L}_J(\delta(y|a)) \triangleq \sum_{j=1}^{M} c_J(\delta(y|a), H_j)\, \mathrm{P}(H_j|y, a), \tag{9}$$

which is the expected Bayesian risk of decision $\delta(y|a)$ given measurement y under action a. Given function $\mathcal{L}_J(\delta(y|a))$, the best decision to take given y under a is simply to find the decision with smallest function value, i.e.,

$$\delta_J^*(y|a) = \arg\min_{x\in\mathcal{H}}\{\mathcal{L}_J(x)\}. \tag{10}$$

For fixed a, the optimal decision rule $\delta_J^*(y|a)$ divides the measurement space into different regions, and for measurement inside a region the same decision is made. Define $\mathcal{Y}_i(a)$ as the region where decision H_i is made, and we have

$$\begin{aligned} \mathcal{Y}_i(a) &\triangleq \{y \mid \delta_J^*(y|a) = H_i\} \\ &= \{y \mid \mathcal{L}_J(H_i) \leq \mathcal{L}_J(H_n), \forall n \neq i\}. \end{aligned} \tag{11}$$

Given $\mathcal{Y}_i(a)$, the expected risk of taking each action a, denoted as $R(a)$, can be formulated as

$$\begin{aligned} R(a) &\triangleq \inf_{\delta}\{R_J(\delta|a)\} \\ &= \sum_{i=1}^{M}\sum_{j=1}^{M} c_J(H_i, H_j) \int_{\mathcal{Y}_i(a)} \mathrm{f}(y|H_j, a) dy\, \pi(H_j), \end{aligned} \tag{12}$$

where the last equality comes via dividing the integration region of (8) into M regions according to $\mathcal{Y}_i(a)$.

With function $R(a)$, the optimal action to choose is the one minimizing $R(a)$, i.e.,

$$a^* = \arg\min_{a}\{R(a)\}. \tag{13}$$

4.4 Complexity analysis

The BED adapts sensing measurements by selecting the action with the smallest $R(a)$, which requires the information of $\mathcal{Y}_i(a)$ defined in (11) for all $i \in \mathcal{H}$ in order to compute the integral. However, solving $\mathcal{Y}_i(a)$ requires to solve following equation, for all $j, n \in \mathcal{H}$ and $n < j$,

$$\mathrm{EQ}_{jn} : \sum_{j=1}^{M} \xi_{jn} \frac{1}{\Gamma(k_{a,j})\theta_{a,j}^{k_{a,j}}} y^{k_{a,j}-1} e^{-y/\theta_{a,j}} = 0,$$

where $\xi_{jn} = \pi(H_j)\big(c_J(\delta(y|a), H_j) - c_J(\delta(y|a), H_n)\big)$. It can be seen that it requires to find all zeros for $4^L/2$ different transcendental equations, which is computationally unaffordable when L is large.

5 Approximated Bayesian experimental design

In order to reduce the complexity of the standard BED, we introduce two approximations. One is to allow the Bayesian cost adaptively changing after each measurement. The other is to allow the greedy action selection to be conducted approximately.

5.1 Adaptive Bayesian cost based on posterior distribution

Denote $\bar{\omega}_k$ as the marginalized posterior probability after the k-th measurement, such that $\bar{\omega}_k(l)$ denotes the probability that the l-th channel is idle. We drop the subscript k, whenever there is no ambiguity. Define $\phi_{ij}^l(s,t) \triangleq \mathbb{1}(H_i(l) = s, H_j(l) = t)$, and the adaptive Bayesian cost, denoted as $c_A(H_i, H_j)$, is constructed as

$$\begin{aligned} c_A(H_i, H_j) &= \sum_{l=1}^{L} \phi_{ij}^l(0,1) + \phi_{ij}^l(1,0) \cdot d_l \\ &\triangleq \sum_{l=1}^{L} \kappa(H_i(l), H_j(l)) \end{aligned} \tag{14}$$

where $0 \le d_l \le 1$, $\sum_{l=1}^{L} d_l = d$ and $d_l \ge d_n$ if $\bar{\omega}(l) \ge \bar{\omega}(n)$. And d_l represents how much it should be penalized when the l-th channel is mistakenly decided as 1 when it is actually 0, and it will be penalized more if it is more likely to be idle. Note that, although $c_A(H_i, H_j)$ separates the cost into each channel's decision, the penalty vector $\bar{d} \triangleq [d_1, \cdots, d_L]$ couples all channels together. One way to construct $\bar{d}$ is to set $d_l = 1$, if $l \in \mathrm{g}(\bar{\omega})$, and $d_l = 0$, otherwise, where $\mathrm{g}(\bar{\omega})$ returns the set of indices of the first d largest element of $\bar{\omega}$. And denote the $\bar{d}$ that constructed this way as $\bar{d}^{\max}(\bar{\omega})$ for the convenience of reference in Sect. 6.

5.2 Hypothesis testing with adaptive Bayesian cost

Following similar development as (8), we have

$$\begin{aligned} R_A(\delta|a) &= \int \sum_{j=1}^{M} c_A(\delta(y|a), H_j)\, \mathrm{P}(H_j|y,a)\, \mathrm{f}(y) dy \\ &\triangleq \int \mathcal{L}_A(\delta(y|a))\, \mathrm{f}(y) dy, \end{aligned} \tag{15}$$

Exploiting the structure of $c_A(H_i, H_j)$, $\mathcal{L}_A(\delta(y|a))$ can be further simplified as

$$\begin{aligned} \mathcal{L}_A(\delta(y|a)) &= \sum_{j=1}^{M} \sum_{l=1}^{L} \kappa(\delta_l(y|a), H_j(l))\, \mathrm{P}(H_j|y,a) \\ &= \sum_{l=1}^{L} \left(\prod_{n=1}^{L} \sum_{\lambda_n=0}^{1} \right) \kappa(\delta_l(y|a), \lambda_l)\, \mathrm{P}(\lambda_1, ..., \lambda_L|y,a) \\ &= \sum_{l=1}^{L} \sum_{\lambda_l=0}^{1} \kappa(\delta_l(y|a), \lambda_l) \left(\prod_{n \ne l} \sum_{\lambda_n=0}^{1} \right) \mathrm{P}(\lambda_1, ..., \lambda_L|y,a) \\ &= \sum_{l=1}^{L} \sum_{\lambda_l=0}^{1} \kappa(\delta_l(y|a), \lambda_l)\, \mathrm{P}(\lambda_l|y,a) \\ &= \sum_{l=1}^{L} \mathbb{1}(\delta_l(y|a) = 0)(1 - \bar{\omega}(l)) + \mathbb{1}(\delta_l(y|a) = 1)\, d_l\, \bar{\omega}(l), \end{aligned} \tag{16}$$

where $\delta_l(y|a)$ denotes the decision of the l-th channel.

With the structure of $\mathcal{L}_A(\delta(y|a))$ in (16), it is easy to see that the decision of each channel is decoupled. And the optimal decision for the l-th channel is

$$\delta_l^*(y|a) = \begin{cases} 0, \text{ if } 1 - \bar{\omega}(l) \le d_l(\bar{\omega})\, \bar{\omega}(l) \\ 1, \text{ if } 1 - \bar{\omega}(l) > d_l(\bar{\omega})\, \bar{\omega}(l) \end{cases}, \tag{17}$$

where $d_l(\bar{\omega})$ is used to denote d_l for reminding that d_l is constructed via $\bar{\omega}$.

5.3 Approximated sequential measurement adaptation

Given the decision rule (17), the smallest risk of making decision given measurement y under action a is

$$\mathcal{L}_A^*(y|a) = \sum_{l=1}^{L} \min \left\{ 1 - \bar{\omega}(l), d_l\, \bar{\omega}(l) \right\}. \tag{18}$$

Therefore, the risk of taking action a is

$$R_A(a) = \int \mathcal{L}_A^*(y|a)\,\mathrm{f}(y)dy = \mathbb{E}[\mathcal{L}_A^*(Y|a)]. \tag{19}$$

Due to the complicated way of constructing $\bar{d}$, it is unlikely the evaluation of $R_A(a)$ can be done in closed form. However, for any given y, the evaluation of $\mathcal{L}_A^*(y|a)$ is easy. Therefore, for each action a, we choose to first sample y for Q times, and then evaluate $\mathcal{L}_A^*(y|a)$ with these samples, and finally use sample average to evaluate the risk of each given action. After this approximated evaluation is done, the action with smallest averaged risk is selected.

5.4 Complexity analysis

It can be seen that, for our proposed the approximated BED scheme, the measurement adaptation decision, as shown in (17), can be easily made by evaluating the value of $\bar{\omega}(l)$ at each channel l. Therefore, the remaining computation complexity is for computing the marginalized posterior probability $\bar{\omega}$ after each measurement, which can be implemented with belief propagation (a.k.a. sum-product message passing) algorithm [27]. It is known that, the computation complexity of applying belief propagation algorithm for a probability distribution with size S is of order $\mathcal{O}(2^S)$.

Hence, considering that the size of joint hypothesis distribution is with size $2^{B_{\max}}$, and the number of sequential time slot in K, the overall time complexity is of order $\mathcal{O}(K4^{B_{\max}})$. We argue that $B_{\max}$ should not be set too large: with the increase of the BF's bandwidth, the likelihood functions will becoming indistinguishable for different statuses of covered channels, and therefore, it may increase the number of required sensing measurements. Therefore, it can be seen that, the complexity of the proposed approximated BED scheme is significantly smaller than that of the conventional BED scheme.

6 Numerical experiment

This section investigates the performance of our proposed wideband sensing scheme by comparing to three alternatives. To be specific, four different wideband sensing schemes are investigated: (1) ABED, the proposed approximated BED with the Bayesian cost c_A constructed via $\bar{d} = \bar{d}^{\max}(\bar{\omega})$, and action evaluation is done with $Q = 10$ samples; (2) SBED, the standard BED using Bayesian cost c_S; (3) ASweep, an sensing scheme that measures the first K channels individually and sequentially, and makes hypothesis testing decision with the Bayesian cost c_A constructed via $d_l = \bar{d}^{\max}(\bar{\omega})$; (4) CS, an sensing scheme based on ideal CS signal recovery algorithms, where if the number of occupied channels is less than half of the number of measurements, the joint status for the whole channels can be perfectly recovered and also perfectly detected [28], and otherwise, signal recovery fails and all channels are reported as occupied. The simulation is concluded with $d = 6$, $B_{\max} = 5$, $\sigma_0^2 = 0.1$, $\forall l$, $\sigma_l^2 = 3.1$ $\bar{\omega}_0(l) = 0.7$, and the number of measurements K varying from 1 to 8.

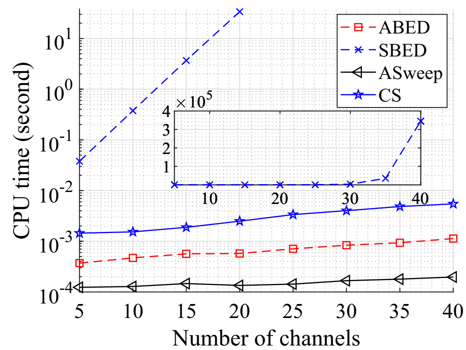

Fig. 2 The CPU time of algorithms

6.1 Computation and energy cost evaluation

Here, we investigate algorithms' performance in terms of computation and energy consideration. Specifically, algorithms' computation burden is measured via considering the CPU running time with L varying from 5 to 40. In addition, as sensing measurement is the main source of energy consumption in cognitive radio nodes' spectrum sensing, the number of sensing measurements is further considered for evaluating algorithms' energy cost.

Figure 2 shows the CPU running time required for one measurement adaptation as L taking values from 5 to 40. Algorithms are implemented via Matlab R2017a on a computer with Intel i7-3770 cores and 16GB RAM. It can be seen that SBED consumes the most of computation, since SBED requires to compute the Bayesian decision region for all hypothesis, which increases exponentially as the number of channels L increases. In contrast, thanks to cost construction and approximated measurement adaptation, the ABED shows considerably computational improvement compared to SBED. The CS algorithm accomplishes wideband sensing via solving sparse signal recovery problem via, for example, minimizing the L1-norm, whose computation burden appears to be larger than that of ABED. Lastly, it can be seen that ASweep requires the least amount of computation, since ASweep limits its measurement adaptation to choosing one of the L channels, which can be efficiently achieved by posterior belief updating.

Figure 3 shows algorithms' sensing measurements, which is the main source of cognitive radio's energy consumption in spectrum sensing. It can be seen that ASweep enjoys the lowest energy consumption, as the ASweep algorithm always chooses to measure one channel at each sensing

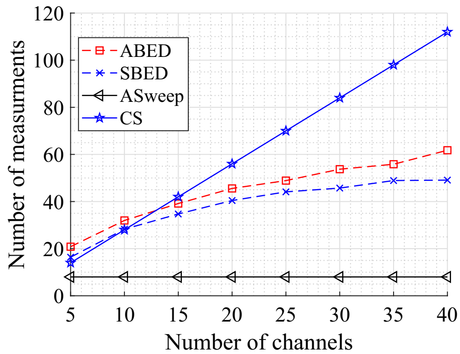

Fig. 3 The number of sensing measurements

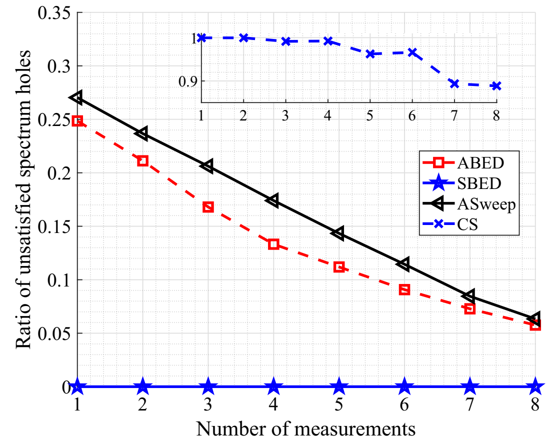

Fig. 4 The ratio of unsatisfied spectrum holes

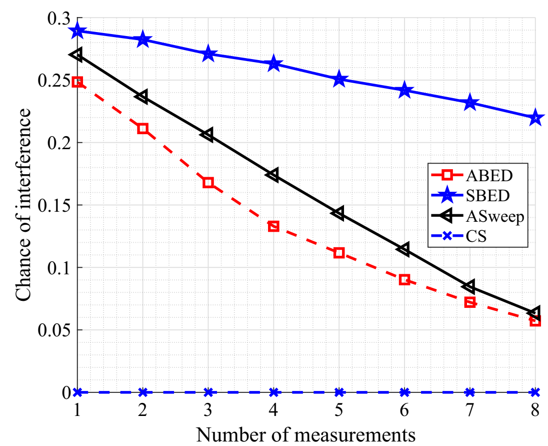

Fig. 5 The chance of interfering primary users

moment, regardless of the number of total channels in the system. In contrast, the CS algorithm's sensing measurement burden linearly increases as channels number increases, it is because that the number of measures required by the CS algorithm equals the sparse ratio times the number of total channels. SBED and ABED demonstrates similar sensing measurement cost, and shows sub-linear increase rate, which outperforms that of the CS algorithm as L increases. The reason is that SBED and ABED can exploit the Bayesian cost about spectrum hole requirement, and reduces sensing measurements whenever the requirement is satisfied during the sequential measurement adaptation process.

In summary, although ASweep appears to be the most attractive algorithm in terms of computation and energy cost, its sensing performance is inferior (as shown the next subsection) due to its inability of sensing adaptation. Thanks to Bayesian-based adaptation, SBED performs well in terms of sensing measurements, which, however, requires prohibitive computation. In contrast, CS and ABED algorithms show good balance between computation and energy cost. However, as shown in the next, the ABED algorithm outperforms the CS algorithm in terms of sensing performance.

6.2 Sensing performance evaluation

This part demonstrates algorithms' sensing performance with the number of channel L fixed to 20. For any sensing scheme, after K measurements collected, a detection decision is made, and define H_F as the number of mistakenly reported spectrum holes, and H_T as the number of correctly detected spectrum holes, and H_{TF} as the number of totally decided spectrum holes. With these definitions, two performance metrics are calculated: the ratio of unsatisfied spectrum holes, denoted as R_U, and the chance of interfering PUs, denoted as C_I, and they are defined as $R_U \triangleq \min\{1, H_T/d\}$, and $C_I \triangleq H_F/H_{TF}$.

Figures 4 and 5 show the results averaged over 5000 independent runs. It can be observed that, for ABED and ASweep, their individual metrics C_I and R_U are very close, and the reason is that in most of the time, they report exactly d spectrum holes, and therefore $C_I = R_U$. And with the increase of measurements, both ABED and ASweep can improve the detection result, and after 8 measurements, they demonstrates satisfactory performance for identifying spectrum holes and protecting PUs. ABED shows superior performance to ASweep, and it is because ABED can adapt its measurement during the sensing process and therefore provide richer information than the open-loop measurement allocation strategy of ASweep.

The benefit of the proposed cost c_A for detection can be observed via comparing ABED with SBED. Observing Fig. 4, it may be surprising that SBED is able to completely satisfy the spectrum holes requirement even with 1 measurement. The reason is that SBED reports all the channels that is not suspected as occupied as spectrum holes, and these reported spectrum holes include all unmeasured channels, since the belief for these unmeasured channels being idle is 0.7. This aggressive detection rule satisfies the spectrum holes requirement with high probability, but it also increases the risk of interfering the PUs, which can be observed from Fig. 5. Furthermore, since the detection rule of SBED treats the detection of occupancy and spectrum holes equally important, some measurements in its sensing budget will be used over the channels that have been measured and are shown to not likely be spectrum holes. Although to further confirm a channel is truly occupied make total sense when the goal is to detect the status of all channels, it is clearly unreasonable when the goal is to find a certain number of spectrum holes and there are some channels unmeasured and they are likely to be idle (with probability 0.7). And this is the reason why, when compared with ABED, SBED makes low progress with increase sensing budget.

Finally, although the design of CS ensure that there is not interference to PUs, its performance of discovering the given number of spectrum holes is poor. Although CS is able to recover and detect the status for all channels if the number of occupied channels is less than the half of the number of measurements, it receives no extra credit with the extra detected spectrum holes if the recovery succeeds, but it gets full penalty when the recovery fails. This confirms that, when the sensing goal is to discovery a portion of spectrum holes, sensing scheme aims at detecting the status for all channels can be completely unsatisfactory.

7 Conclusion

In this paper, we have proposed an adaptive wideband sensing scheme under the framework of standard BED, which considers the design of joint channel status detection rule, and measurement adaptation with the goal of detecting a given number of spectrum holes. In order to reduce the complexity of the standard BED, an approximated BED have been proposed via defining the cost adaptively based on posterior probability and allowing the measurement adaptation to be done approximately. Finally, the satisfactory performance of the proposed sensing scheme is demonstrated via simulation.

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