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Licensed user activity estimation and track in mobile cognitive radio ad hoc networks ☆

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ABSTRACT

In cognitive radio (CR) networks, a static activity model fails to capture the dynamic and time-varying behavior of the licensed or primary users (PUs). In this paper, a distributed scheme is proposed that allows mobile CR users to learn about the activity of the PUs, and disseminate this information to the neighboring nodes that also function as information repositories. In order to guarantee sensing precision and transmission efficiency, the proposed method switches between time-intensive "fine sensing" and quick "normal sensing". Our approach uses the maximum likelihood estimator to learn average busy and idle periods in the fine sensing stage. These identified activity patterns are then used during normal sensing, where the mean square error (MSE) value of PU on–off times is continuously monitored to ensure that the estimation is sufficiently accurate. When PU activity changes significantly, the MSE is considered as the indicator to re-start the fine sensing. Simulation results reveal that our proposed method can efficiently track the dynamics of the PU activity.

1. Introduction

Cognitive radio (CR) is envisaged to support the increasing demand of spectrum for wireless communications, by allowing CR users (i.e., secondary users, SUs) to operate on the vacant parts of the spectrum allocated to licensed users (i.e., primary users, PUs) [1,2]. Here, SUs require frequent sensing to determine the state of the radio environment, and adaptively choose transmission parameters for avoiding interfering with PUs [3,4].

Many sensing schemes require a priori knowledge of the statistical behavior of PUs. The exponential distribution model is a common example for PU activity [5,6]. In [5], the authors model the channel usage through the semi-Markov process, but do not point out how to leverage the detection history to improve the estimation of PU activity. In [7], a theoretical framework was developed to jointly optimize the sensing and transmission periods with the aim of maximizing the spectrum efficiency subject to interference avoidance constraints. However, the PU activity parameters, such as the statistical average idle and busy periods, were assumed to be fixed and known a priori to SUs. Furthermore, there is a considerable body of work relying on a constant PU activity statistical model to optimize the sensing in CR networks [8–12], without actually obtaining or inferring them. In most of these papers, the fixed and known average idle and busy periods are vital in the calculation of the detection probability and false alarm probability. Hence, it is advantageous to obtain the PU activity statistics during the operation of the network, by collecting periodic measurements from the environment. Such a primary activity prediction

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approach can be found in [13], where the authors use frame structure and time slots, and activity prediction was limited to estimating the remaining time of the idle period, but not the average busy and idle periods that together influence the choice of the spectrum. Therefore, in our paper, PU activity parameters are assumed to be unknown to the SUs in advance, and our objective is to estimate the average idle and busy periods and to track PU activity change.

The approach in [14] is most relevant to our scheme. Here, the authors not only utilize the ON/OFF spectrum usage model, but also present an estimation technique to process the detection history and learn the traffic pattern of PUs. Nevertheless, they assume that the SUs already have a set of PU usage pattern samples without detailing (i) how to collect these samples, and (ii) how many samples should be enough to guarantee the sensing precision. In summary, in order to ensure that the spectrum sensing schemes work accurately, deriving an accurate PU activity model is a key concern, which needs further attention for the research community. Additionally, this model must be able to adapt to the changes of PU activity over time.

We would also like to point out the relevance of our approach in light of recent rulings by the FCC on spectrum sensing in the TV whitespace [15]. The FCC ruling in 2011 states that local sensing (without geo-location and spectrum database access) is only permitted for certified devices. This requirement necessitates revisiting the sensing models and new approaches that are able to function without pre-conditions and location-specific assumptions. It is likely that CR devices using models that do not capture the exact spectrum usage activity at the testing site will be unable to get the necessary permits for future operation.

Recent results in [16] introduced a scheme to model the primary user activity. However, the authors focus on the bursty and spiky traffic during short-term activity fluctuations. Each SU is required to monitor the spectrum band and send the observed samples to the base station. A first-difference clustering and correlation scheme is used to capture the short fluctuation transmission opportunities during the PU's ON period, which can maximize the CR network performance. However, the idle fluctuation time during ON period is very short and runs a greater risk of interfering with PU transmissions. Therefore, the short-term fluctuation is not considered in this paper. In addition, we assume a CR mobile ad hoc network, in which there is no base station.

CR ad hoc networks constitute additional challenges in estimating PU activity and modeling on account of node mobility [2], not seen in static environments, such as [17]. In addition, many estimation schemes require considerable memory (in case a history of measurements needs to be stored), which is difficult given the local hardware capability of a single node [18].

Most aforementioned previous works assume a priori knowledge of activity distributions, and for such cases, the practical channel usage statistics are very different when regions of overlap exist for the PUs. The final decisions based on such static models in the overlapping regions are likely to be wrong. Different from this, in our proposed approach, we do not care about a single PU's distribution. Rather, we base estimate of the channel availability using current, real time measurements. If more than one PU is present in the region, the distribution that we "learn" will be the combination of the two random variables that determine their individual on (or off) times. Without loss of generality and for the simplicity, we consider SUs cooperatively detect one PU in the CR network [19].

In this paper, we make three important contributions for estimating the PU activity and tracking the PU activity change.

- We optimize the number of measurements needed to accurately estimate the PU activity, which will be used later to tweak the performance of spectrum sensing algorithms. For this, we define two activity detection durations. The fine sensing phase occurs in the early stages when the current estimates are totally absent or very coarse. The normal sensing phase is during the continuous operation of the network, and serves to detect any changes in the existing levels of PU activity. Based on mean square error (MSE), we devise *stopping* and *restarting* rules for the fine sensing, which allow the SUs to switch between these two phases.
- We develop a cooperative weighted activity estimation scheme where SUs share their own locally obtained estimates of the PU activity with neighboring SUs around the PU activity region. Thus, these prior measurements serve as a starting point for the new SUs, which further contribute towards refining the estimate. Our scheme takes into account not only the previous activity estimates derived by the predecessors, but also the number of samples and channel conditions that may have contributed to errors in calculation of these earlier estimates.
- Finally, we also propose a distributed storage mechanism where the sensing data is saved in the local region of the PU, thereby reducing memory requirements of each SU.

The rest of this paper is organized as follows: In Section 2, the CR system model is presented. Our proposed mobile sensing model is described in Section 3. Section 4 presents the numerical and simulation results. Finally, Section 5 concludes the paper.

2. System model

In our approach, the PU transmitter is operating on a licensed spectrum band modeled as an ON–OFF source, alternating between ON (busy) and OFF (idle) periods. Assume ON and OFF periods follow exponential distribution, with the respective averages of α and β [5]. Moreover, as the activity of the PU transmitter can change over time [20], α and β may also exhibit long-term variations.

Further, we define the PU's transmission region, called A_p, approximated as a circle around the PU transmitter (the circular white disc around the PU transmitter in Fig. 1), where the SUs must carefully choose transmission opportunities. The PU activity estimation becomes important in this region A_p. The ON and OFF sample period measurements are gathered by the SU as it moves through the activity region (see paths of SU2 and SU3), and on reaching the circular boundary, it disseminates its own estimates to the surrounding nodes via broadcast messages. We assume that there is a common control channel (CCC) for the information exchange between SUs [21]. Consider the shaded ring around the PU activity region, denoted by A_s, which represents the area in which all SUs save and propagate the broadcast message of the last known activity estimates. Thus, a new SU, entering the shaded ring A_s from outside at any point, can obtain the last few estimates of the PU activity that were broadcast by its predecessors. In turn, this new SU will update the estimates and spread this knowledge when it exits the region A_p at the other end of its path.

In the mobile CR network, only mobile SUs who enter the PU's transmission region A_p can sense the licensed spectrum band and broadcast the latest detected average $\bar{\alpha}$ and $\bar{\beta}$. The extent of the broadcast is limited to the other SUs within the ring A_s. The SUs undertake two types of sample collections, which are *fine sensing* and *normal sensing*. If there is no information about PU transmitter at all, or the MSE of detected average $\bar{\alpha}$ and $\bar{\beta}$ is greater than a threshold, the sensing cycle must be short and repeated often. This type of detection is called as *fine sensing*. If SU has considerably accurate mean busy period and mean idle period, *normal sensing* will be used. In either case, the final estimates will be broadcasted at the boundary of the regions A_s and A_p. Consider that η SUs have disseminated their detection packets including their detected mean estimates in the region A_s, which are represented by $\bar{\alpha}_i, \bar{\beta}_i, i = 1, \ldots, \eta$, and also including the number of ON samples N_i and the number of OFF samples M_i that were used for this estimation. Assume that the network has a "memory" of η_s, i.e., a new SU entering the region A_s can receive at most η_s sets of the tuple $\{\bar{\alpha}_i, \bar{\beta}_i, N_i, M_i\}$.

The broadcast packet that disseminates the PU activity estimate contains the following fields: packet time-stamp, a sensing status bit (0 or 1), final average ON period $\bar{\alpha}$, final average OFF period $\bar{\beta}$, η (number of earlier SUs who have broadcasted the average detection results and $\eta \leqslant \eta_s$), η sets of $\{\bar{\alpha}_i, \bar{\beta}_i, N_i, M_i\}$, the maximum number of ON period samples (out of total possible η), the actual number of combined ON period samples, all ON sample durations, the maximum number of OFF period samples, the actual number of combined OFF period samples, and all OFF sample durations. Here, packet time-stamp will be used to avoid broadcast loop, $\bar{\alpha}$ and $\bar{\beta}$ are computed by the η sets of $\{\bar{\alpha}_i, \bar{\beta}_i, N_i, M_i\}$. If the sensing status bit is set to 1, SUs can perform normal sensing. Otherwise, fine sensing needs to be undertaken as the estimate is not accurate. If a SU obtains very few samples, these samples will be inserted into the packet. Once the combined samples become large, they will be used to compute the average periods, and then, they will be deleted from the packet.

Generally, false alarm and miss detection probabilities are used to analyse average interference time and lost spectrum opportunity in the spectrum sensing [7]. In this paper, instead, we focus on the estimation of the ON/OFF average periods and tracking the PU activity change, which precedes the normal operation of the network.

3. Proposed mobile sensing model

In this section, we focus on how to choose the durations of the fine and normal sensing, how to process and combine samples collected by SUs, how to stop and restart fine sensing, and the sharing of information among the SUs.

3.1. Sensing cycles and types

The probability of the period used by primary users is give as [4],

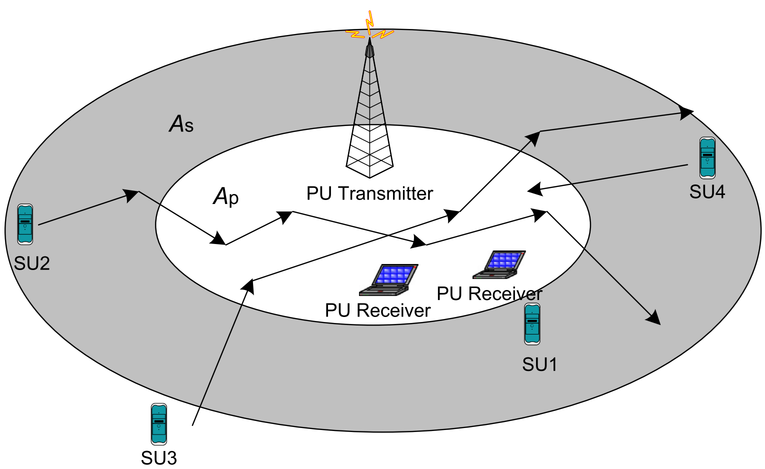

Fig. 1. Mobile CR ad hoc network.

$$P_{on} = \frac{\alpha}{\alpha + \beta} \tag{1}$$

And the probability of the idle period is

$$P_{off} = \frac{\beta}{\alpha + \beta} \tag{2}$$

In addition, the *lost spectrum opportunity ratio* T_L is defined to indicate the expected minimum fraction of the OFF state undetected by SUs, the *maximum outage ratio* T_P is the maximum fraction of interference that primary networks can tolerate.

Assume that observation time t_s in one sensing cycle is fixed. When PU transmitter is idle, transmission time in one sensing cycle is denoted by t_t, then the sensing cycle T_s^{off} in PU's idle state is expressed as

$$T_s^{off} = t_s + t_t \tag{3}$$

where the maximum transmission time t_t is bounded by [4]

$$t_t \leqslant -\mu \log\left(1 - \frac{T_P}{P_{off}}\right), \quad \mu = \min(\bar{\alpha}, \bar{\beta}) \tag{4}$$

In previous works such as [4,9], only one sensing cycle is used in PU's idle and busy states. However, when PU transmitter is busy, a different sensing cycle T_s^{on} is defined in this paper, composed of observation time t_s and quiet time t_q, as follows:

$$T_s^{on} = t_s + t_q \tag{5}$$

where the maximum quiet time t_q is bounded by

$$t_q \leqslant -\mu \log\left(1 - \frac{T_L}{P_{on}}\right), \ \mu = \min(\bar{\alpha}, \bar{\beta}) \tag{6}$$

If there are several licensed channels, the quiet time t_q in a sensing cycle can be scheduled to detect other licensed channels [7,14]. While our model can be easily extended in these scenarios, the multiple-channel estimation is out of scope of this paper.

When a SU enters the range A_p and receives no information about PU, the SU must perform fine sensing, in which the sensing cycles of T_s^{off} and T_s^{on} are same and fixed to a comparatively small value $T_s^{\min}$. This allows frequent sampling of the environment by the SU in its initial entry into the PU activity region. Later, when the fine sensing phase ends (i.e., the PU statistics are accurately known), T_s^{off} and T_s^{on} will be computed by Eqs. (3) and (5), respectively, which is defined as normal sensing. In dynamic environments, however, if the final averages $\bar{\alpha}$ and $\bar{\beta}$ deviate in accuracy from α and β beyond a certain threshold as indicated by the following MSE, the sensing cycles will be reduced to $T_s^{on} \times \gamma$ and $T_s^{off} \times \gamma$, where T_s^{on} and T_s^{off} are also computed by Eqs. (3) and (5), and $\gamma \in (0.5, 1)$. This forces the SU to re-start the fine sensing and quickly gather additional information about the environment.

3.2. Case I. Estimation for single user

When SU i first moves into the region A_p, it broadcasts a request message on the CCC to other neighboring SUs to inquire about the PU's operational characteristics, namely, the average ON period and OFF period. The neighboring SUs who have this information will send back this PU activity information, including the sensing status bit and the last η estimates, to the requesting SU. The SU will then select the latest information based on the packet time-stamp. According to the sensing status bit, the SU can determine to perform either fine sensing or normal sensing.

During ongoing activity estimation in the area A_p, SU i records each detected ON period sample and OFF period sample. Assume the number of ON period samples is N_i and the number of OFF period samples is M_i, which are the respective cardinality values of the sets of $\{t_{on}(1), t_{on}(2), \ldots, t_{on}(N_i)\}$ and $\{t_{off}(1), t_{off}(2), \ldots, t_{off}(M_i)\}$ (Fig. 2). Then, the maximum likelihood estimator (MLE) is used to calculate the average ON period $\bar{\alpha}_i$ and OFF period $\bar{\beta}_i$ [22,23].

The PU's busy time and idle time can be modeled by the exponential distribution. The probability density function (PDF) of ON state is

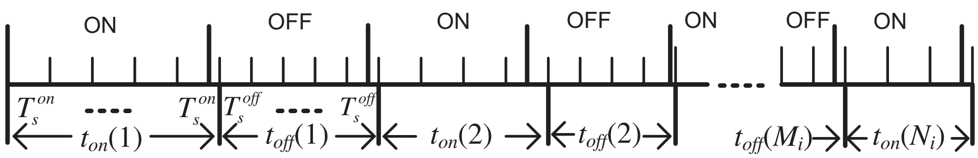

Fig. 2. SU i detects the PU's ON/OFF periods.

$$p(t_{on};\alpha) = \frac{1}{\alpha} e^{-\frac{t_{on}}{\alpha}} \tag{7}$$

Then, the likelihood function is

$$L(t_{on};\alpha) = \prod_{j=1}^{N_i} \frac{1}{\alpha} e^{-\frac{t_{on}(j)}{\alpha}} = \alpha^{-N_i} e^{-\frac{1}{\alpha}\sum_{j=1}^{N_i} t_{on}(j)} = \alpha^{-N_i} e^{-\frac{N_i \overline{T}_{on}}{\alpha}} \tag{8}$$

According to MLE algorithm,

$$\frac{d \ln L(T_{on};\alpha)}{d\alpha} = \frac{d\left\{-N_i \ln\alpha + \frac{-N_i \overline{T}_{on}}{\alpha}\right\}}{d\alpha} = -\frac{N_i}{\alpha} + \frac{N_i \overline{T}_{on}}{\alpha^2} = 0 \tag{9}$$

Then the optimal mean busy period $\bar{\alpha}_i$ of MLE can be calculated by,

$$\bar{\alpha}_i = \overline{T}_{on} = \frac{1}{N_i} \sum_{j=1}^{N_i} t_{on}(j) \tag{10}$$

Similarly, the optimal mean idle period $\bar{\beta}_i$ is,

$$\bar{\beta}_i = \overline{T}_{off} = \frac{1}{M_i} \sum_{j=1}^{M_i} t_{off}(j) \tag{11}$$

where $|N_i - M_i| = 0$ or 1.

Intuitively, the numbers of ON and OFF samples are related to the length of PU's true α and β, the SU's speed and the travel distance in the area A_p. If SU i obtains only a few samples, $\bar{\alpha}_i$ and $\bar{\beta}_i$ may suffer from considerable deviation from the true α and β. Therefore, if the set of samples is less than a *threshold number* N_t, SU can broadcast these samples instead of the average values alone, i.e., $\{\bar{\alpha}_i, \bar{\beta}_i, N_i, M_i\}$.

3.3. Case II. Estimation for multiple users

Assume that there are η mobile SUs broadcasting their individual estimations of PU activity. Generally, the arithmetic mean approach, called as *non-weighted average* in the paper, can be used to estimate the final $\bar{\alpha}$ and $\bar{\beta}$ with Eqs. (10) and (11) in this case. However, since the numbers of ON and OFF period samples of various SUs should be different, we introduce a *weighted average* approach to compute the final $\bar{\alpha}$ and $\bar{\beta}$ for multiple SUs, as follows:

$$\bar{\alpha} = \sum_{i=1}^{\eta} \bar{\alpha}_i \frac{N_i}{\sum_{j=1}^{\eta} N_j} \tag{12}$$

$$\bar{\beta} = \sum_{i=1}^{\eta} \bar{\beta}_i \frac{M_i}{\sum_{j=1}^{\eta} M_j} \tag{13}$$

We assign a weight to the final estimation made by a SU as proportional to the numbers of ON and OFF samples it uses for the calculation. Moreover, due to the dynamic nature of PU activity and the limited memory, the network only stores the latest η_s sets of $\{\bar{\alpha}_i, \bar{\beta}_i, N_i, M_i\}$.

When PU activity or SU mobility speed is high, then the number of collected samples for the estimation are few. In such a case, multiple sets of samples from different SUs who are passing through the activity region in near-overlapping times can be combined to compose a single set. Thus, if the ith SU gets a few samples, then these ON and OFF samples will be added into the broadcast packet instead of the statistical values $\{\bar{\alpha}_i, \bar{\beta}_i, N_i, M_i\}$. After the next SU, i.e., the $i + 1$th SU, finishes its sensing, its own samples are cumulatively considered for the analysis, along with the samples carried in the previous broadcast packet of the ith SU. If the total number of samples now is larger than the threshold number N_t, then the $i + 1$th SU calculates the average ON and OFF periods to generate the average set of $\{\bar{\alpha}_i, \bar{\beta}_i, N_i, M_i\}$. Henceforth, only these averages are included in the broadcast packet, in place of the actual sample values. Conversely, if the total number of samples is less than the threshold number N_t, then the new samples of $i + 1$th SU are also added into the broadcast packet.

3.4. Choosing start and stop conditions for fine sensing

In this section, we separately derive the start and stop conditions that allow the SU to switch between fine sensing and normal sensing.

3.4.1. Stop condition for fine sensing

The fine sensing can be stopped after the estimated mean of the PU activity converges to the true mean ON/OFF time. This implies that with progressive rounds of broadcast of the estimated values and continued refinement undertaken by subsequent SUs, the MSE of the samples will decrease. We need to choose a MSE threshold E_m for stopping the fine sensing process (which is time consuming) and consequently, increase the transmission efficiency.

Assume there are $\eta(\leqslant\eta_s)$ sets of $\{\bar{\alpha}_i, \bar{\beta}_i, N_i, M_i\}$, the MSE σ_{on} of the mean ON period can be computed by

$$\sigma_{on} = \sqrt{\frac{1}{\eta}\sum\nolimits_{i=1}^{\eta}[\bar{\alpha}_i - E(\bar{\alpha}_i)]^2} \tag{14}$$

where $E(\bar{\alpha}_i)$ is the latest average busy period computed by Eq. (12). Similarly, we can derive the MSE σ_{off} of the OFF period, which is given by

$$\sigma_{off} = \sqrt{\frac{1}{\eta}\sum\nolimits_{i=1}^{\eta}[\bar{\beta}_i - E(\bar{\beta}_i)]^2} \tag{15}$$

Only when both σ_{on} and σ_{off} are less than E_m, the fine sensing terminates and the *sensing status bit* will be set to 1 signaling the end of the fine sensing process.

3.4.2. Start condition for fine sensing

PU activity is dynamic and varies over time, possibly even with the time of the day. This requires periodically revising the activity estimations. As α and β vary over time, our approach is able to detect the change and restart the fine sensing.

A trivial option here is to use the MSE for detecting the change in PU activity, i.e., MSE will increase if there is a change in PU's activity. However, this technique does not work efficiently in slow-varying environments [24]. Thus, in order to capture the changes of PU spectrum usage efficiently and quickly, we introduce a new variable s_σ that exploits the variation of MSE. Here, the current $\sigma_{on}(t)$ and $\sigma_{off}(t)$ will be compared with the previous MSE values of $\sigma_{on}(t-1)$ and $\sigma_{off}(t-1)$. We define $s_{\sigma_{on}}(t)$ as:

$$s_{\sigma_{on}}(t) = \frac{|\sigma_{on}(t) - \sigma_{on}(t-1)|}{\sigma_{on}(t-1)} \tag{16}$$

Similarly, $s_{\sigma_{off}}(t)$ can be derived as:

$$s_{\sigma_{off}}(t) = \frac{|\sigma_{off}(t) - \sigma_{off}(t-1)|}{\sigma_{off}(t-1)} \tag{17}$$

If $s_{\sigma_{on}}(t)$ or $s_{\sigma_{off}}(t)$ is larger than the threshold S_{TH}, the fine sensing will be restarted.

Once the fine sensing stops, the estimated $\bar{\alpha}$ and $\bar{\beta}$ will not be changed until the next round of the fine sensing phase is triggered. When a SU enters the PU's transmission range A_p, it performs normal sensing because the *sensing status bit* is set to 1. Note that $\sigma_{on}(t-1)$ and $\sigma_{off}(t-1)$ can be calculated through the η sets of $\{\bar{\alpha}_i, \bar{\beta}_i, N_i, M_i\}$. After moving out from the range A_p, the oldest set of $\{\bar{\alpha}_1, \bar{\beta}_1, N_1, M_1\}$ will be discarded if $\eta = \eta_s$ (i.e., the limit on the sample history is reached), and the SU's own estimated values will be stored as the latest set. Thus, the current $\sigma_{on}(t)$ and $\sigma_{off}(t)$ can be calculated followed by $s_{\sigma_{on}}(t)$ and $s_{\sigma_{off}}(t)$ from Eqs. (16) and (17). If $s_{\sigma_{on}}(t)$ or $s_{\sigma_{off}}(t)$ is higher than the threshold S_{TH}, the *sensing status bit* will be set to 0. In addition, only the current sensing results will be broadcasted by the SU. Other SUs who receive this broadcast packet will be aware of the variation of PU's activity, thereby individually re-starting their own fine sensing.

Finally, in case that SU cannot obtain any information from neighboring SUs, it then performs fine sensing with sensing cycle $T_s^{\min}$. Otherwise, it uses $\bar{\alpha}$ and $\bar{\beta}$ to calculate the sensing cycles T_s^{on} and T_s^{off} by Eqs. (3) and (5), respectively. The consequent sensing procedures can be described as follows:

(1) If *sensing status bit* is 0, the SU will perform fine sensing with $T_s^{on} \times \gamma$ and $T_s^{off} \times \gamma$. Once it moves out of A_p, the new σ_{on} and σ_{off} will be computed. If σ_{on} and σ_{off} are less than E_m, then *sensing status bit* will be set to 1.
(2) On the contrary, if *sensing status bit* is 1, the SU will perform normal sensing. After it exits the range A_p, $s_{\sigma_{on}}$ and $s_{\sigma_{off}}$ will be calculated and compared with threshold S_{TH}. If $s_{\sigma_{on}}$ or $s_{\sigma_{off}}$ is larger than the threshold S_{TH}, the fine sensing will be restarted.

The entire mobile cooperative sensing procedure is illustrated in the flowchart in Fig. 3.

4. Numerical and simulation results

In this section, we conduct simulation studies to evaluate the performance of our proposed PU activity estimation algorithm. In the mobile CR network, there is only one PU operating on a licensed spectrum band. The location of the PU transmitter is at the center coordinates of (2000 m, 2000 m). The transmission radius of PU transmitter is 800 m, which covers the region A_p while the broadcasting area of SUs is within the ring A_s, which spans 1200 m further from A_p boundary. The speed

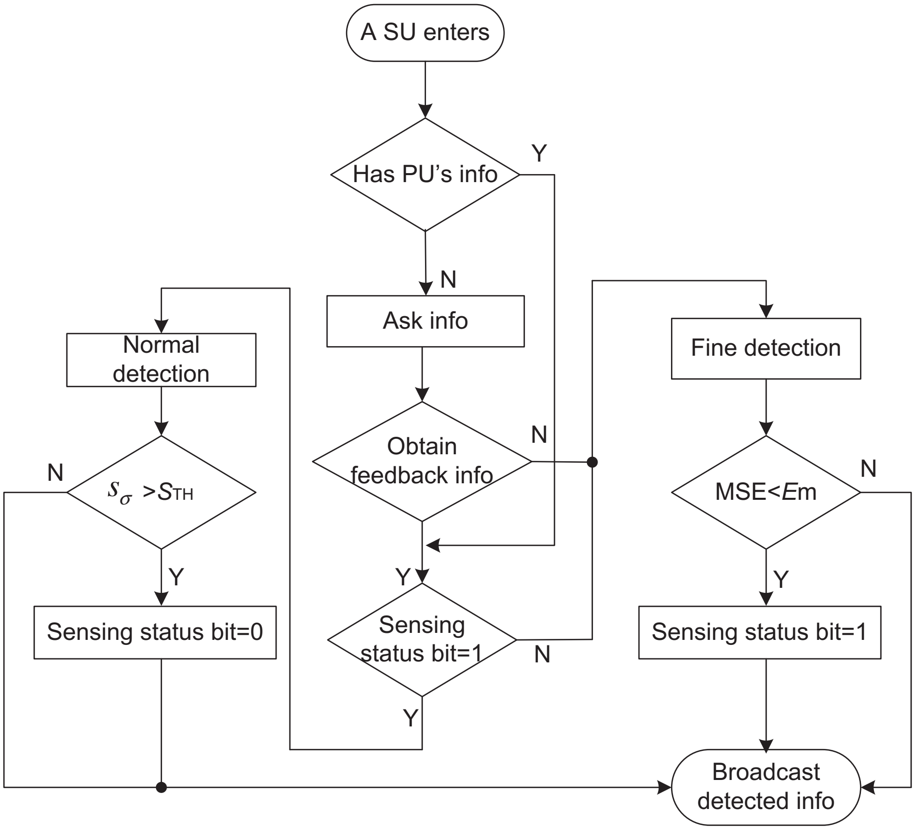

Fig. 3. Sensing flowchart for one single SU.

of mobile SU is uniformly distributed from 3 m/s to 20 m/s, and the moving direction is also uniformly distributed in $[0, 2\pi)$. The random walk model was adopted to model the movement of SUs. As per the IEEE 802.22 standard [25], the observation time t_s for one time sensing is less than 2 ms when using energy sensing method. Consequently, t_s is set to 2 ms, and the minimum fine sensing cycle $T_s^{\min}$ is set to 8 ms.

In order to examine the protocol convergence with regard to the number of samples obtained by individual SU detection, we gradually injected 20 SUs into region A_p successively to detect the PU transmitter with $\alpha = 1$ s, $\beta = 0.5$ s. As a result, there were 5 SUs that obtained more than 100 samples. From Fig. 4, we observe that when the number of ON period samples is more than 30, the mean ON periods of all the 5 SUs fluctuate around the true mean ON period by 15%. However, when the number of samples is less than 30, the average ON period $\bar{\alpha}_i$ has a large deviation from the true α. Therefore, in a practical application, when a SU obtains few samples, these samples can be broadcast allowing us to set the sample threshold number N_t as 30. Moreover, when a SU has no information about the PU, it can utilize the shortest sensing cycle $T_s^{\min}$ for detection. After it obtains more than a certain number of samples, the sensing cycles can be increased to enhance the sensing efficiency.

The cooperative sensing efficiency of multiple SUs can be demonstrated by letting 50 SUs move into the PU's transmission range A_p successively. This implies that the number of samples collected by individual SU may differ as well. Two previously mentioned average approaches, *non-weighted average* and *weighted average*, were employed to evaluate the performance. In the beginning of this simulation, the first SU uses fine sensing with minimum sensing cycle $T_s^{\min}$. Once the number of samples reaches 30, the sensing cycles will be set to $T_s^{on} \times \gamma$ and $T_s^{off} \times \gamma$, where $\gamma = 0.8$. It is clear from Fig. 5 that when more than 10 SUs use fine sensing to sense the licensed band, the average ON period $\bar{\alpha}$ is very close to the accurate average ON period, which is $\alpha = 0.4$ s. Additionally, the weighted average approach obviously outperforms the non-weighted average approach throughout the range.

It is also crucial to evaluate the performance of MSE and the relative error in our approach. We define relative error as $|\bar{\alpha} - \alpha|/\alpha$. As shown in Fig. 6, MSE σ_{on} decreases as more SUs sense the PU transmitter and it asymptotically converges to the true mean. Additionally, the relative error also exhibits the similar behavior. However, the fluctuation of relative error is much larger than that of MSE, and SUs cannot determine the true α when using relative error. The σ_{on} is almost equal to 4% when there are more than 25 SUs, which indicates that not all the SUs' detected information $\{\bar{\alpha}_i, \bar{\beta}_i, N_i, M_i\}$ are required to be stored and broadcasted. This is another reason why we introduce η_s which is the maximum number of $\{\bar{\alpha}_i, \bar{\beta}_i, N_i, M_i\}$ stored.

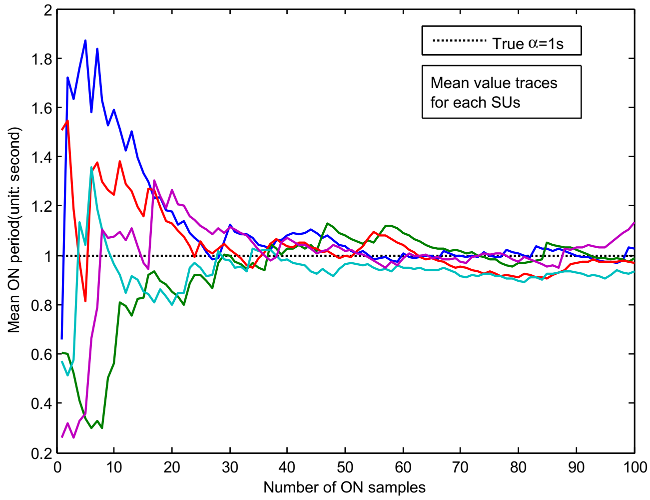

Fig. 4. Convergence of the estimated mean ON period of five individual SU (α = 1 s, β = 0.5 s).

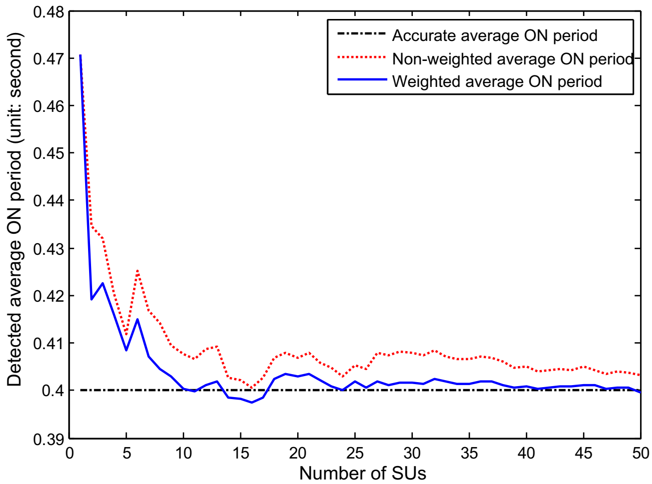

Fig. 5. Multiple SUs detect PU (α = 0.4 s, β = 0.5 s).

After the fine sensing is completed by 20 SUs, the final mean ON period and mean OFF period are used to calculate the sensing cycles for the subsequent normal sensing. As shown in Fig. 7, it is obvious that based on the $\bar{\alpha}$ and $\bar{\beta}$ estimated by our proposed sensing model, both the *maximum outage ratio* T_P and *lost spectrum opportunity ratio* T_L are below the predefined threshold 0.04 after a short period of operation.

We next evaluate the detection sensitivity. Here η_s is set to 20. We let 100 SUs successively detect the PU's activity. After the 50th SU finishes its detection, α varies from 0.4 s to 0.5 s and 0.6 s. On the contrary, β is constant at 0.5 s. As depicted in Fig. 8, MSE of σ_{on} is almost constant when the number of SUs increases from 20 SUs to 50 SUs. However, σ_{on} starts increasing slowly from the 51th SU because of the change of PU activity. This is because when the 51th SU finishes its detection, the estimated average ON period of this SU is close to the current real average ON time ~0.5 or 0.6, while other estimated ON periods used converge to 0.4. Hence, the impact of this specific SU on the estimate $\bar{\alpha}$ is slight, and the final estimated ON period $\bar{\alpha}$ is still dominated by the previous SUs, before the 51th SU. Consequently, if MSE is used to restart a new fine sensing procedure, it will have a considerable delay and cause interference with PU. It should be pointed out that the values of $\sigma_{on}(50)$ and $\sigma_{on}(51)$ are very small, but the increment of $\sigma_{on}(51) - \sigma_{on}(50)$ is in the same order of magnitude and is less than $\sigma_{on}(50)$ and $\sigma_{on}(51)$. On the contrary, the ratio of $(\sigma_{on}(51) - \sigma_{on}(50))/\sigma_{on}(50)$ is large. From Fig. 8, we observe that the value of $S_{\sigma_{on}}(51)$ is more than 35%. As a result, the variation of PU's activity can be quickly detected by the 51th SU, which can be used to restart fine sensing within a very short time. In addition, we can find that when the activity of PU does not change, $s_\sigma(t)$ fluctuates within acceptable bounds, which is a direct result of combining multiple samples and reducing the sudden impact of an outlier measurement. Finally, from the 52th SU, fine sensing is restarted. Therefore, alternatively we use $s_\sigma(t)$ to monitor the PU activity since it is more sensitive to the changes in PU activity pattern.

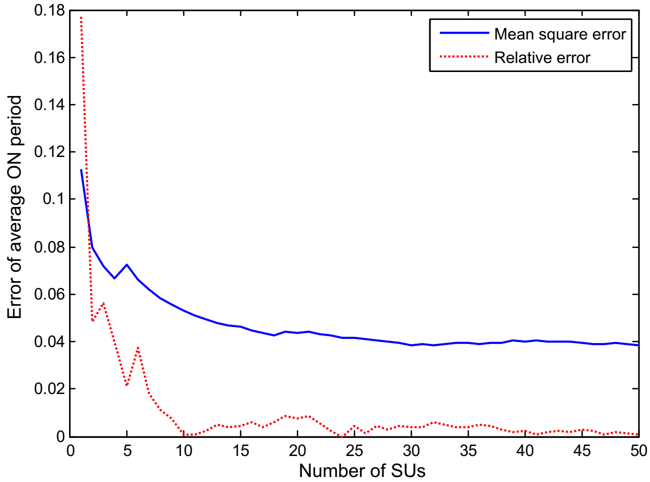

Fig. 6. Multiple SUs detect PU (α = 0.4 s, β = 0.5 s).

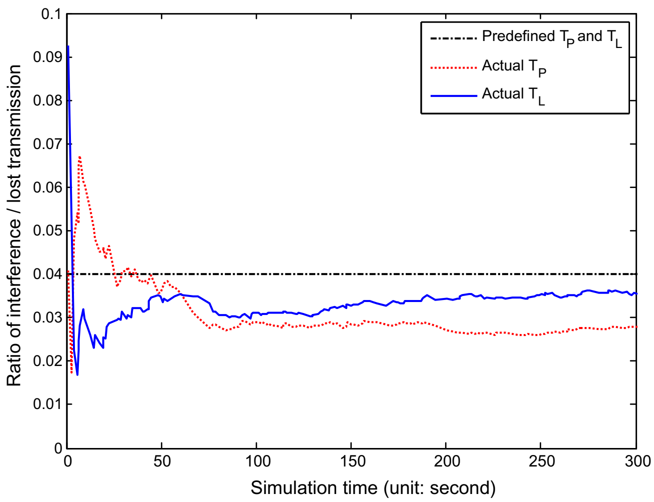

Fig. 7. Interference ratio and lost communication ratio with $T_P = T_L = 0.04$.

In [14], the authors utilized moving time window to track the variations of PU activity. The latest ON and OFF periods samples will be collected within a time window and the estimation procedure will be executed once every a period of time. In order to further demonstrate that our proposed scheme can quickly track the changes of PU activity, we compare it with the scheme in [14]. Our proposed scheme is called *Scheme* 1, the track method in [14] is called *Scheme* 2. In our proposed scheme, the maximum number of SUs that pass through the PU activity region and cooperate to estimate the final $\bar{\alpha}$ and $\bar{\beta}$ is η_s. Hence, we set the size of the moving window here is not the individual samples, but the number of collaborating SUs at a given time, i.e., $\eta_s = 20$. However, the total number of SUs that pass through the PU activity region from the start to the end of the simulation is 100. Further, we explore the response time of the system when α varies from 0.4 s to 0.5 s halfway through the simulation (i.e., when the 50th SU finishes its detection). From Fig. 9, we can find that our proposed *Scheme* 1 can quickly track the change of PU activity. This is because $s_\sigma(t)$ is used to restart the fine sensing, and the earlier η_s estimations are discarded. However, the tracking speed of *Scheme* 2 is much slower, as the outdated estimations from the 32th to 50th SUs are still used to compute the final average $\bar{\alpha}$ when the 51th SU finishes its own sensing. In addition, from the 70th SU, 20 ON estimations of *Scheme* 2 converge to 0.5 same as those of *Scheme* 1, so final average $\bar{\alpha}$ of two schemes converge to 0.5. When PU activity does not change, i.e., α = 0.4 s, same method is used to calculate $\bar{\alpha}$ in *Scheme* 1 and *Scheme* 2, and therefore the curves are overlapping. Hence, we conclude that our method provides enhanced responsiveness of the system when PU activity is subject to change.

The broadcast overhead is a concern in collaborative CR sensing. If all the raw sensing data, i.e., ON/OFF period samples, are broadcast between the SUs, then the broadcast overhead will be large. Therefore, the packet structure in Section 2 is used, which relies only on sending the average values. By using the statistical information in place of the actual raw samples, the

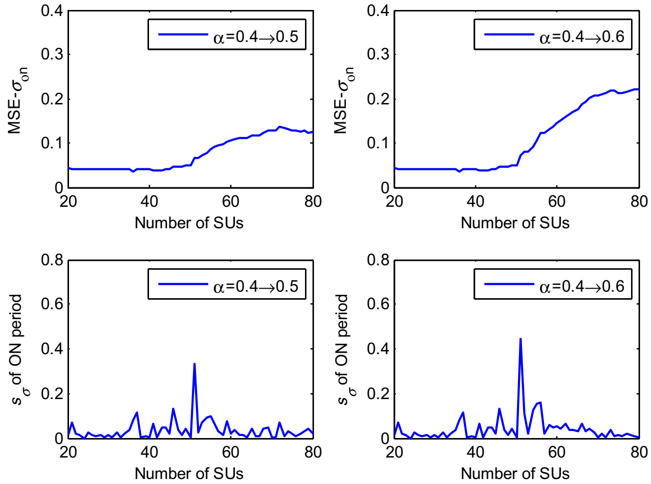

Fig. 8. MSE and its variation when α changes (β = 0.5 s).

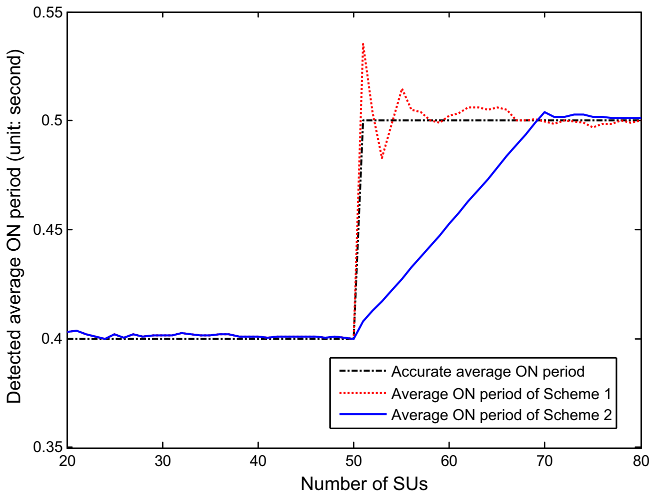

Fig. 9. Track speed comparison of PU activity (α = 0.4s → 0.5 s, β = 0.5 s).

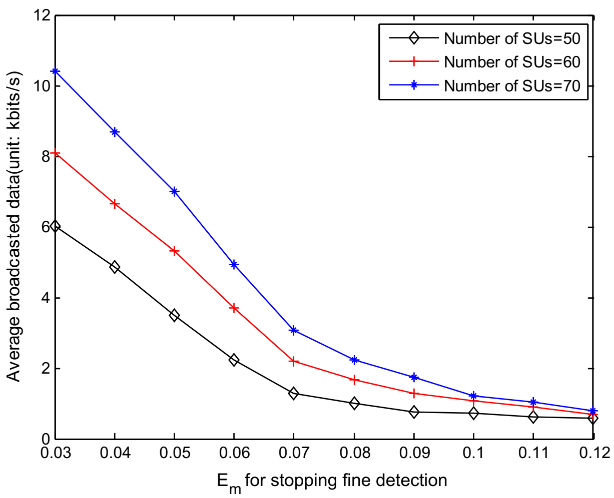

Fig. 10. Broadcasting overhead (α = 0.4 s, β = 0.5 s).

overhead is contained. In order to evaluate the overhead incurred by broadcast, we deployed varying number of SUs uniformly in the broadcasting region A_s at the beginning of simulation. In addition, we assume that each SU in A_s will broadcast the latest received detection results. Once σ_{on} and σ_{off} reach the threshold E_m, the overhead, defined as the total amount of broadcasted data divided by the corresponding required time, will be computed. As shown in Fig. 10, with the increase in detection precision, reduction in E_m from 0.12 to 0.03, the average broadcasted data per second increases. This is because more time and large number of SUs are required to yield the requested detection precision. Additionally, the broadcast overhead increases when the total number of SUs increases from 50 to 70. This implies that more SUs enter PU's transmission region A_p, as more detection information needs to be disseminated.

5. Conclusion

In this paper, we presented and evaluated a novel licensed user activity estimation algorithm to detect the average busy period and idle period of PUs in a mobile CR ad hoc network. The MLE and weighted average method were used to process the sensing results, and the MSE was used to decide stop and restart instants of fine sensing. Our approach demonstrated efficient tracking of the changes of PU's activity, resulting in convergence to the true activity with an acceptable overhead. The simulation results indicate that the proposed algorithm can accurately estimate the PU spectrum usage pattern by using the optimal number of measurements and through the cooperation of multiple SUs. Moreover, our proposed mobile cooperative sensing approach can be easily extended for static SUs and centralized CR networks.

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References

[1] Haykin S. Cognitive radio: brain-empowered wireless communications. IEEE J Select Areas Commun 2005;23(2):201–20.
[2] Akyildiz IF, Lee W, Chowdhury KR. CRAHNs: cognitive radio ad hoc networks. Ad Hoc Netw 2009;7:810–36.
[3] Cormio C, Chowdhury KR. A survey on MAC protocols for cognitive radio networks. Elsevier J Ad Hoc Netw 2009;7(7):1315–29.
[4] Song C, Zhang Q. Cooperative spectrum sensing with multi-channel coordination in cognitive radio networks. In: Proc. IEEE ICC; 2010. p. 1–5.
[5] Zhao Q, Tong L, Swami A, Chen Y. Decentralized cognitive MAC for opportunistic spectrum access in ad hoc networks: a POMDP framework. IEEE J Select Areas Commun 2007;5(3):589–600.
[6] Lee WY, Akyildiz IF. Joint spectrum and power allocation for inter-cell spectrum sharing in cognitive radio networks. In: Proc IEEE DySPAN; 2008. p. 1–12.
[7] Lee WY, Akyildiz IF. Optimal spectrum sensing framework for cognitive radio networks. IEEE Trans Wireless Commun 2008;7(10):3845–57.
[8] Chowdhury KR, Felice MD. Search: a routing protocol for mobile cognitive radio ad-hoc networks. Comput Commun 2009;32(18):1983–97.
[9] Huang S, Liu X, Ding Z. Opportunistic spectrum access in cognitive radio networks. In: Proc IEEE INFOCOM; April 2008. p. 1427–35.
[10] Felice MD, Chowdhury KR, Meleis W, Bononi L. To sense or to transmit: a learning-based spectrum management scheme for cognitive radio mesh networks. In: Proc IEEE WIMESH; 2010. p. 1–6.
[11] Yang L, Cao L, Zheng H. Proactive channel access in dynamic spectrum networks. In: Proc IEEE CrownCom, Orlando, FL, USA; August 2007. p. 487–91.
[12] Zarrin S, Lim TJ. Throughput-sensing tradeoff of cognitive radio networks based on quickest sensing. In: Proc IEEE ICC; 2011.
[13] Sung KW, Kim SL, Zander J. Temporal spectrum sharing based on primary user activity prediction. IEEE Trans Wireless Commun 2011;9(12):3848–55.
[14] Kim H, Shin KG. Efficient discovery of spectrum opportunities with MAC-layer sensing in cognitive radio networks. IEEE Trans Mobile Comput 2008;7(5):533–45.
[15] FCC Press release; 2011. <http://www.fcc.gov/Daily_Releases/Daily_Business/2011/db0126/DA-11-131A1.pdf>.
[16] Canberk B, Akyildiz IF, Oktug S. Primary user activity modeling using first-difference filter clustering and correlation in cognitive radio networks. IEEE/ACM Trans Netw 2011;19(1):170–83.
[17] Miao M, Tsang DHK. Impact of channel heterogeneity on spectrum sharing in cognitive radio networks. In: Proc IEEE ICC; 2008. p. 2377–82.
[18] Park J, Van Der Schaar M. Cognitive MAC protocols using memory for distributed spectrum sharing under limited spectrum sensing. IEEE Tans Commun 2011;59(9):2627–37.
[19] Peh ECY, Liang YC, Guan YL, Zeng YH. Cooperative spectrum sensing in cognitive radio networks with weighted decision fusion schemes. IEEE Trans Wireless Commun 2010;9(12):3838–47.
[20] Pursley MB, Royster TC. Low-complexity adaptive transmission for cognitive radios in dynamic spectrum access networks. IEEE J Select Areas Commun 2008;26(1):83–94.
[21] Chowdhury KR, Akyildiz IF. OFDM based common control channel design for cognitive radio ad hoc networks. IEEE Trans Mobile Comput 2011;10(2):228–38.
[22] Kay StevenM. Fundamentals of statistical signal processing: estimation theory. Prentice Hall; 1993. p. 157–214.
[23] Myung IJ. Tutorial on maximum likelihood estimation. J Math Psychol 2003;47:90–100.
[24] Sanna M, Murroni M. Nonconvex optimization of collaborative multiband spectrum sensing for cognitive radios with genetic algorithms. Intl. J Digital Multimedia Broadcast 2010:12.
[25] Cordeiro C, Challapali K, Birru D, Shankar S. IEEE 802.22: the first worldwide wireless standard based on cognitive radios. In: Proc IEEE DySPAN; 2005. p. 328–37.

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