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Prioritized Spectrum Sensing in Cognitive Radio Based on Spatiotemporal Statistical Fusion

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***Abstract*—In this paper, a novel statistics-driven spectrum sensing algorithm is developed for improving spectrum sensing efficiency in the media access control (MAC) layer of cognitive radio (CR) systems. The proposed algorithm aims to achieve higher spectrum sensing efficiency and spectrum access opportunity by prioritizing channels for fine sensing based on the statistical likelihood of channel availability. The sensing priority is obtained by jointly exploiting the long-term spatiotemporal statistics recorded from the historical result of fine sensing, the short-term statistical information of channel condition obtained from a small-scale observation window, and the instantaneous statistical information obtained from fast sensing. Simulation results show that the proposed prioritization algorithm can achieve improved data transmission rates and reduced missed spectrum access opportunities when compared to the conventional non-prioritization spectrum sensing approach for situations where cooperative spectrum sensing is not suitable.**

I. Introduction

Cognitive radio (CR) [1], [2] has been a promising approach for solving the bandwidth insufficiency inherent in the legacy spectrum regulation by taking advantage of spectrum opportunities of licensed ("primary") user spectrum usage. The task of cognitive radios is to correctly and quickly identify the spectrum opportunities being held by licensed users and utilized the temporarily released spectrum in an efficient and opportunistic manner. One of the most challenging issues in CR MAC design is the development of efficient spectrum sensing, which is essential in the determination of spectral channels upon which communication can take place without interfering the primary users. Since it is very energy consuming and computationally intensive to perform fine sensing for all possible channels across the entire spectrum, the state-of-the-art CR spectrum sensing techniques rely on a "fast sensing" process to identify a range of spectrum for further fine sensing in order to reduce the scan space. The fast sensing process can help to give a better picture on the range of spectrum for the CR system to secure sufficient bandwidth for a transmission.

Although performing fast sensing can effectively improve the spectrum sensing efficiency without loss of much transmission quality, it is subject to a number of problems. Firstly, since fast sensing is a relatively inaccurate process, it often results in a poorly selected scan space for fine sensing, which could result in missed spectrum access opportunities. Secondly, the previously reported fast sensing techniques do not quantitatively measure/estimate how likely a channel in the scan space will be available and how good it will be. Thus, the CR system has no way to determine the sequence of the channels to be finely sensed in order to avoid the waste of time and energy during the fine sensing process. These problems make it insufficient to purely rely on fast sensing to determine the scan space for further fine sensing.

To compensate for the deficiencies of the fast sensing process, much of recent effort has been focused on developing cooperative approaches to spectrum sensing [3], [4], [5], [6], [7], [8], [9], where different CR peers cooperatively explore channel availability. These approaches exchange either informative sensing results [3], [4], [5] or local decisions [6], [7], [8], [9] to a decision node, or sharing local statistics in an ad-hoc manner [10] to make the overall decision on the presence of primary users. While research on cooperative sensing approaches show promising results, such algorithms are not well-suited in a number of situations. First, cooperative spectrum sensing might not be possible in situations where the CRs within an environment do not conform to the same communication protocols on a dedicated common control channel, making it difficult for them to exchange sensing results, local decisions, or local statistics to one another. Second, most cooperative spectrum sensing methods are not well-suited for situations where the density of CRs is low within the environment. This is because most cooperative sensing methods rely heavily on the density of CRs within an environment to improve sensing efficiency and accuracy. These two scenarios often occur in the real world environments, where a number of different primary and secondary users with different communication protocols co-exist within the same environment. Therefore, it is necessary to develop stand-alone spectrum sensing algorithms complementary to cooperative sensing methods that a CR can utilize in such situations. However, little attention has been paid to the development of efficient and accurate stand-alone spectrum sensing algorithms that rely on local observations and statistics to handle such situations. The goal of the proposed work is to achieve efficient and accurate stand-alone spectrum sensing for use as a complementary algorithm to existing cooperative spectrum sensing techniques in situations where cooperative spectrum sensing is not well-suited.

The main contribution of the proposed work is a novel channel prioritization algorithm based on statistical information correlation to improving spectrum sensing efficiency and accuracy. The proposed algorithm takes advantage of long-term and short-term user behaviour within an environment by utilizing the long-term spatiotemporal statistics obtained from historical result of fine sensing, the short-term statistics obtained from an observation window (in a time scale of 100 milliseconds), as well as the instantaneous statistics obtained from the current fast sensing process. The use of statistical information of user behaviour is motivated by previous research analysis showing that channel occupancy exhibits behavioural patterns can be modelled statistically [11], [12]. The above three types of information are fused to prioritize channels based on the likelihood of channel availability for fine sensing in order to achieve better CR spectrum sensing efficiency and increase the opportunities of spectrum access. The proposed method is designed as a complimentary technique to the stochastic cooperative spectrum sensing algorithm proposed by Wang et al. [10], where the CR switches from the cooperative spectrum sensing algorithm to the proposed stand-alone spectrum sensing method for situations where there are no neighboring CRs in the network that supports the cooperative spectrum sensing technology. To the best of the authors' knowledge, there are no existing stand-alone spectrum sensing algorithms that utilize the concept of channel prioritization to improve spectrum sensing efficiency and accuracy. We will show that the proposed stand-alone spectrum sensing algorithm can achieve noticeably improved performance when compared with the conventional non-prioritized stand-alone approach in terms of transmission rate and missed spectrum opportunities in situations where cooperative spectrum sensing is not suitable.

The rest of this paper is organized as follows. The system model is presented in II. The proposed prioritized spectrum sensing algorithm is described in Section III. Numerical results are discussed in Section IV. Finally, conclusions are drawn in Section V.

II. System Model

In this study, we assume that there are M number of orthogonal and independent licensed channels $\{\mathbf{CH}|CH_i, i = 1, 2, ..., M\}$ shared by N_p number of primary users and N_s number of secondary users. The secondary users form an ad hoc network with low mobility. A licensed CH_i can be used by secondary users when the channel is not occupied by any of the N_p primary users.

We assume that the radio propagation of primary users is subject to small scale Rayleigh fading, which is commonly used to describe the rapid fluctuations of radio signal over a short period of time or transmission distance especially when multipath interference becomes the dominant influence in the radio propagation channel [17]. Mathematically, given a transmitter-receiver pair and the radio transmitting power P_t, the received signal-to-noise ratio X follows a chi-square distribution with two degrees of freedom:

$$p(X) = \frac{1}{\Gamma} \exp(-\frac{X}{\Gamma}) \quad (1)$$

with the mean value $\Gamma = \frac{P_t G}{d^\xi}$, where G is antenna gain, d is the distance between the transmitter and the receiver, and ξ is the path loss component.

The primary network formed by the primary users is independent of the secondary network. We assume that each channel alternates independently between busy and idle status due to the usage of primary users. Hence, the channel usage model of primary users can be represented as an ON/OFF traffic source model, where ON indicates channel occupancy by a primary user, and OFF indicates the absence of any primary user on the channel. In this study, the period that each channel stays in an ON or OFF state is assumed to be a random variable following an exponential distribution. Any portion of the OFF periods of a channel can be used by secondary users for their transmission. A dedicated common control channel CH_0 is allocated for secondary users to initiate channel negotiation and exchange control messages.

The secondary users perform fast sensing over the M channels according to an on-demand mode. Note that fast sensing is simply energy detection on the channel availability which may return very erroneous results. After the fast sensing is performed, fine sensing is then initiated based on the proposed prioritized spectrum sensing algorithm. Upon the identification of any one or more available channels, the available channels are accessed by the secondary users immediately. In this way, the effects of channel fluctuation, which can result in missed spectrum opportunities within the time in which the decisions of primary user absence and channel access are made, can be alleviated.

III. Prioritized Spectrum Sensing Algorithm

In the paper, an efficient and intelligent spectrum sensing algorithm for CR MAC that considers the sensing priorities is investigated. The proposed algorithm is a stand-alone spectrum sensing algorithm where the CR system learns from the channel historical behavior and fuses the obtained statistics instead of making decision of spectrum access based only on instantaneous channel information. The concept behind this approach is motivated by research analysis showing that channel occupancy exhibits behavioural patterns can be modelled statistically [11], [12].

The proposed approach is described as follows. When the CR system joins a primary network at the beginning, it has no temporal or spatial statistics about spectrum sensing upon which it can rely on. Therefore, it simply performs fine sensing in a proactive manner to determine an initial set of probabilities regarding channel availability that can be further used to obtain the sensing priority of each channel. Upon the request of data transmission, fine sensing is performed based on the sensing priority of each channel until the required number of available channels is obtained. The proposed method records the channel usage information of primary users in the database according to the result of each fine sensing process, by which the spatiotemporal probability distribution for channel usage can be created and updated. In the proposed CR spectrum sensing process, the channel availability and sensing priority decisions are made not only according to the long-term spatiotemporal probability distribution of primary users, but also by taking advantage of the short-term statistics obtained from an observation window. Along with the fast sensing result, the CR system can quantify the channel availability using the fused channel statistics and prioritize the channels accordingly in the subsequent fine sensing process.

After each fine sensing process, the result regarding channel usage of primary users at that instance is then used to update both long-term statistics and short-term statistics of channel access. Firstly, the long-term statistics for channel access is described by using a spatiotemporal probability distribution $\hat{f}_L(\mathbf{CH}, t)$, which keeps track of the channel occupancy by primary users within a significantly longer window of time T_{cycle} (e.g., 24 hours). The use of T_{cycle} for $\hat{f}_L(\mathbf{CH}, t)$ also enables the long-term observation of channel availability over a larger time window such as days or weeks. Secondly, $\hat{f}_s(\mathbf{CH}, t)$ abstracts the short-term statistics in a short time scale τ (e.g., 10ms) prior to the current time with respect to channel availability. Finally, $P_{inst}(CH_i, \zeta)$ represents the likelihood of channel CH_i being available at time instant ζ based on the on-demand fast sensing. The three types of channel statistics used in the proposed algorithm are further elaborated in the following paragraphs.

A. Long-term statistics

When the system is initialized at the beginning (i.e., $t = 0$), the system has no past experience about spectrum sensing upon which it can rely on. Therefore, the CR proactively and periodically performs fine sensing to obtain the initial channel usage statistics of the primary users over the spectrum in its sensing range during the initial learning period. After the initial spatiotemporal probability distribution is obtained, the CR performs sensing according to an on-demand mode and keeps updating the distribution according to the fine sensing results. We assume feature detection is used for fine sensing, based on which the decision of the presence of primary users is made. Fine sensing of a specific channel CH_i returns a set of sample patterns $\Omega_{CH_i} = \{x(t_1), x(t_2), ..., x(t_n)\}$, which is used to estimate the probability distribution, $\hat{f}_L(CH_i, t)$, of channel CH_i with regards to the absence of primary users across the time axis.

For a specific channel CH_i, the feature space is divided into k equal sized bins (i.e., sampling time slots), and v_i counts the number of decisions pertaining to the absence of primary users that fall into bin B_i. Therefore, the probability of v_i (of $V = \sum_{i=1}^{k} v_i$) learning samples falling into B_i is given by the binomial density [18]:

$$P_{B_i} = \begin{pmatrix} V \\ v_i \end{pmatrix} P^{v_i}(1-P)^{V-v_i} \quad (2)$$

The expected number of v_i is $E[v_i] = \sum_{i=0}^{k} v_i P_{B_i} = VP$. Therefore, the estimation of $E[v_i]$ by observed v_i leads to estimated $\hat{P}_L(CH_i, t) = v_i/V$. A set of probabilities of channel availability across the time axis can be obtained as follows:

$$\hat{P}_L(\mathbf{CH}, t) = \vec{v}_i \cdot \vec{V}^{-1} \quad (3)$$

The estimated spatiotemporal probability distribution constructed using the Parzen window density estimator can be expressed as follows:

$$\hat{f}_L(\mathbf{CH}, t) = \frac{1}{nh} \sum_{i=1}^{n} K(\frac{x(t) - x(t_i)}{h}) \quad (4)$$

where h is the smoothing parameter, $K(\cdot)$ is a standard Gaussian function with mean of zero and variance of 1: $K(y) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}y^2}$. The Parzen window density estimator is used to obtain probability estimations at a set of specific time instants rather than at specific time intervals. Taking a cross section of the above spatiotemporal probability distribution at time T, the probability representing the likelihood of a specific channel CH_i being available compared with the other channels at the specific time T is given by

$$P_L(CH_i)_T = \frac{f(CH_i, T)}{\sum_{j=1}^{M} f(CH_j, T)} \quad (5)$$

B. Short-term statistics

The short-term channel usage statistics is used to estimate how likely a channel is available at time t based on the observation of previous τ seconds. The short-term statistics presents a microscopic view of channel usage of primary users, aiming to compensate for inaccuracies made in the long-term, macroscopic view of the channel usage statistics. The short-term statistics can also be useful when there are insufficient samples collected to form well-learned long-term statistics.

The CR system maintains the channel usage statistics of primary users for a time window of τ up to the current time instant. For channel CH_i, assume that all samples $\Omega_\tau = \{y_1, y_2, ..., y_{N_{CH_i}}\}$ representing events of channel occupancy of primary users follow a Poisson distribution during τ. The mean $\hat{\lambda}_{CH_i}$ during τ can be evaluated by

$$\hat{\lambda}_{CH_i} = N_{CH_i}/\tau \quad (6)$$

Therefore, based on $\hat{\lambda}$, the CR can further predict how likely each channel is available for a secondary user in a short period of time τ as follows:

$$\hat{P}_s(\mathbf{CH}) = 1 - \int_0^\tau \hat{\lambda} e^{-\hat{\lambda} t} dt \quad (7)$$

It can be seen that the reliability of the estimation is dependent on the frequency of fine sensing. Secondary users with a high volume of traffic demands have more channel usage information with regards to the primary users since fine sensing is performed in a higher frequency. Therefore, in this case, the estimation by Eq. (7) can more practically model the real-world situation. This issue will be addressed in Section III-D.

C. Instantaneous statistics

Upon a data transmission request (at time $t = \zeta$), the CR will first perform fast sensing over the spectrum. According to the perceived signal-to-noise ratios (SNR) in the fast sensing process (i.e. energy detection), each of the M channels is categorized either into one of four classes corresponding to a specific modulation scheme and transmission rate or as not available. Therefore, the probability that a specific channel CH_i falls in any one of the four classes, denoted as $\chi_j, j = 1, 2, 3, 4$, can be determined based on Eq. (1) as follows:

$$\gamma(CH_i) = \int_{\chi_j} p(X)dX \tag{8}$$

Thus, the probability that a specific channel CH_i is available at time $t = \zeta$ for secondary users can be determined as follows:

$$P_{inst}(CH_i, \zeta) = \sum_{j=1}^{4} \int_{\chi_j} p(X)dX \tag{9}$$

D. Fusion function

Based on the instantaneous statistics,$P_{inst}(\mathbf{CH}, \zeta)$, the short-term channel usage statistics, $\hat{P}_s(\mathbf{CH})$, and long-term statistics $\hat{P}_L(\mathbf{CH})_\zeta$, the CR MAC comprehensively prioritizes the channels to be finely sensing using the following statistical fusion formulation:

$$\begin{aligned} F(CH, \zeta) = \; & (1 - \alpha - \beta)\hat{P}_L(\mathbf{CH})_\zeta + \\ & \beta\hat{P}_s(\mathbf{CH}) + \alpha\gamma(\mathbf{CH})P_{inst}(\mathbf{CH}, \zeta) \end{aligned} \tag{10}$$

where α is a weighting factor that balances the impact of long-term/short-term statistics and the instantaneous statistics, and β is a dynamic weighting factor that balances the impact of short-term statistics based on the quantity of samples learned during τ.

$$\beta = \frac{\breve{\beta} n_{\text{samples}}}{n_{\max}} \tag{11}$$

where $\breve{\beta}$ is the base factor, n_{samples} is the number of samples acquired, and $n_{\max}$ is the maximum number of samples that can be stored within the short window of time. If the quantity of samples is not sufficient to estimate the channel available, the weighing of the short-term estimation has little impact on the prioritization of channels for fine sensing. What this fusion function does is aggregate the long-term, short-term, and instantaneous statistics adaptively based on their importance to the prediction of channel availability. One of the main advantages to the use of a weighted sum is that it has low computational complexity and can be performed in an efficient manner. The determination of weighting factors are further investigated in the numerical experiments.

E. Summary

A flowchart summarizing the prioritization process is shown in Fig. 1. When a secondary node enters into a primary network, it attempts to identify its closest neighboring nodes that share the cooperative spectrum sensing technology proposed in [10]. If no other secondary user is around, the cooperative spectrum sensing algorithm cannot be used and so it enters into its learning stage to build an initial spatiotemporal probability distribution. At time ζ when the secondary user has data to transmit and requires K number of channels, it performs a set of fast sensing to get the instantaneous channel statistics $P_{inst}(\mathbf{CH}, \zeta)$. The long-term statistics $\hat{P}_L(\mathbf{CH})_\zeta$ and the short-term statistics $P_s(\mathbf{CH})$ are retrieved from memory at the same time. By applying the statistical fusion described in Eq. (10), the CR MAC prioritizes the channels and performs a set of fine sensing according to the order. The data transmission is launched immediately on the channel that is identified as an available channel. This approach is computationally efficient and does not introduce noticeable additional delays. The results of the set of fine sensing are used to update both the long-term statistics and short-term statistics. In this way, the secondary user keeps updating the channel statistics until it leaves the network.

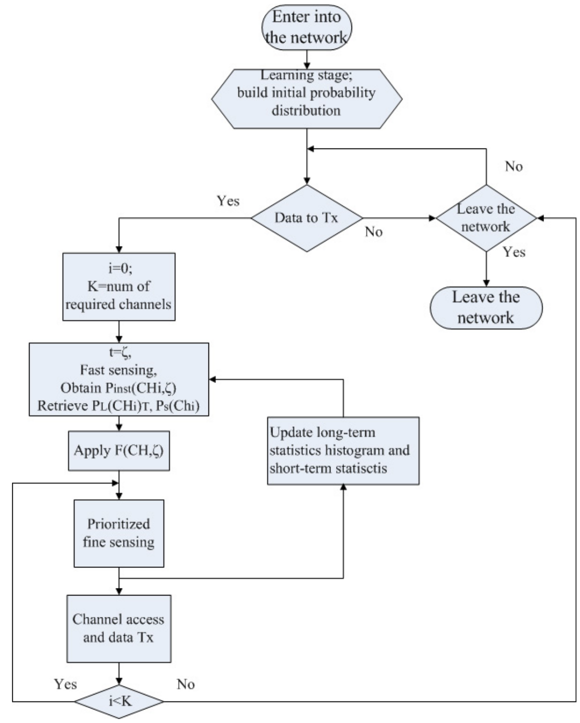

Fig. 1. Flowchart of the stand-alone prioritized spectrum sensing scheme

IV. Numerical Results

In the numerical experiments, we implement the prioritization of channels for fine sensing. The experimental parameters used in the simulation can be summarized as follows. Let the number of licensed channel be 40 ($M = 40$). Traffic is classified into four QoS classes with a corresponding spectrum sensing threshold. By assuming that any transmission will be at the maximum possible power, the four SNR levels can be defined solely based on the channel condition sensed, which further determines the transmission rate. Let the information bits N_s be denoted as $1, 2, 3, 4$ bits/(symbol$*$subcarrier) associated with different modulation carried by a single subcarrier

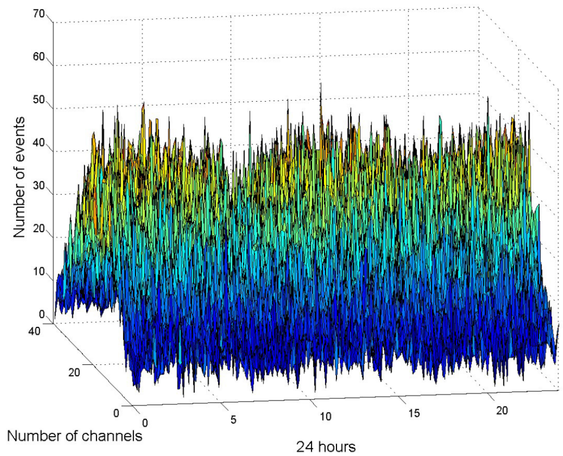

Fig. 2. Probability distribution built during both learning stage and update stage

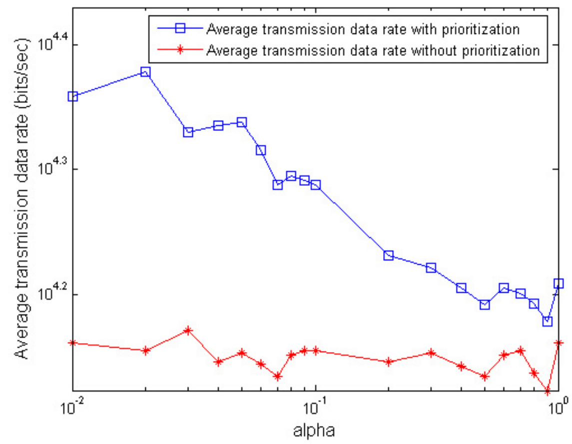

Fig. 5. Average transmission data rate with prioritized fine sensing vs. those without prioritized fine sensing with different α

in our quantitative analysis. We adopt 0.31ms/symbol [19] as the symbol size.

In our simulation, the spatiotemporal distribution of channel usage of primary users is built purely based on the samples without prior knowledge of the true distribution. Therefore, the spatiotemporal probability distribution shown in Fig. 2 depends on the number of samples obtained during both the learning stage and update stage.

The simulation results of data rate on the spectrum sensing with prioritization and without prioritization are shown in Fig. 3 with $\alpha = 0.1$ and number of channels to be sensed being $K = 5$. It can be observed that the data rate of the case with prioritization is almost twice as high as the case without prioritization. The corresponding percentage of missed spectrum opportunities with and without the proposed prioritized fine sensing are shown in Fig. 4. The percentage of missed spectrum opportunities reduces to 18% when compared with that obtained without prioritization. The improvements in data rate and reduction in missed spectrum opportunities can be largely contributed to the fact that the proposed prioritization technique gives channels with a higher likelihood of availability priority over other channels, thus improving the likelihood of channel acquisition. The results on data transmission rate with and without prioritized fine sensing associated with different α is further shown in Fig. 5. It is seen that the average data rate with prioritized fine sensing increases with the decrease of α, thereby indicating the importance of the proposed long-term and short-term statistics. When $\alpha = 1$, where the proposed algorithm depends solely on the instantaneous statistics, the results of average data rate with prioritized fine sensing remains higher than that without prioritized fine sensing, thereby indicating the importance of prioritization. When $\alpha \rightarrow 0$, where the proposed algorithm depend heavily on both the long-term and short-term statistics, the average transmission data rate is much higher than that without prioritization. With an error rate of fast sensing $q = 0.3$, the average percentage of missed opportunities associated with $K = 5$ required channels without prioritization

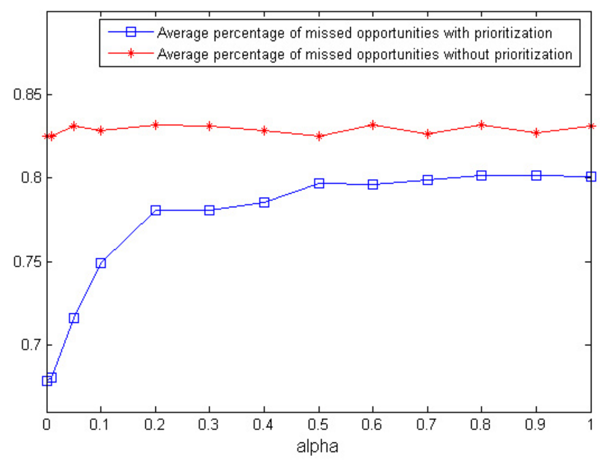

Fig. 6. Average percentage of missed opportunities with prioritized fine sensing vs. those without prioritized fine sensing with different α

is $p = 1-(1-q)^K = 0.83$. The average percentages of missed opportunities with different values of α are shown in Fig. 6. It is also seen that both the long-term/short-term statistics and prioritization increase the opportunities of spectrum.

V. Conclusion

This paper introduced a novel spectrum sensing algorithm that exploits statistical channel prioritization in the fine sensing process. Through the fusion of long-term spatiotemporal statistics, short-term statistics, and instantaneous statistics through fast sensing, the proposed algorithm determines the order of each channel to be sensed such that the likelihood of channel access can be increased. Simulation results demonstrated that the proposed algorithm is capable of improving the CR spectrum sensing efficiency when compared to spectrum sensing approaches without prioritization in situations where cooperative spectrum sensing is not suitable. Our future research will focus on developing a more dynamic and intelligent approach for determining the base weighting factors.

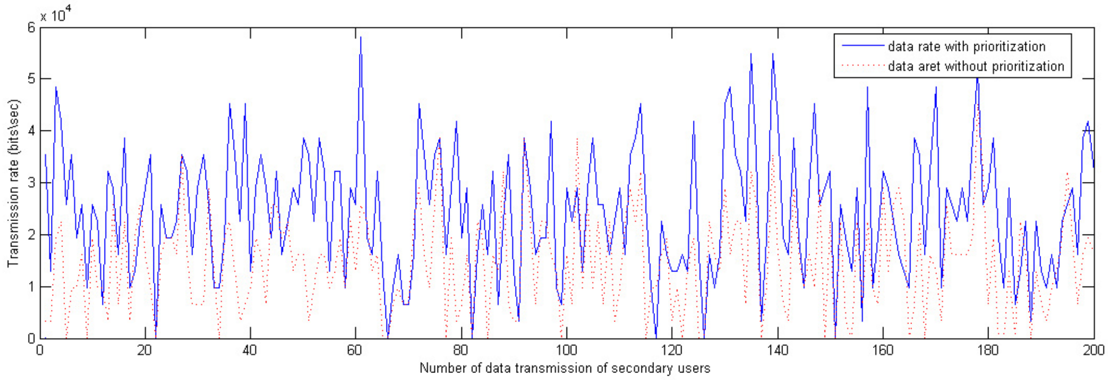

Fig. 3. Transmission data rate with prioritization and without prioritization

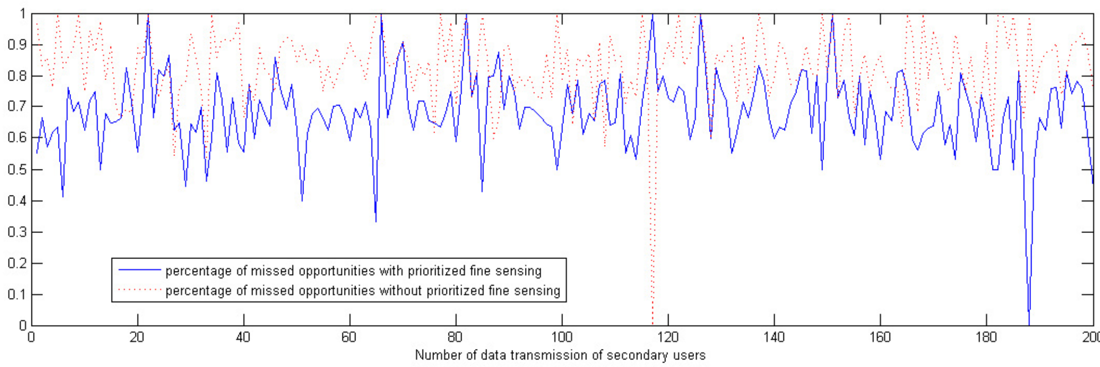

Fig. 4. Percentage of missed opportunities with and without prioritized fine sensing

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