Stochastic Channel Prioritization for Spectrum Sensing in Cooperative Cognitive Radio

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***Abstract*—In this paper, a novel cooperative stochastic channel prioritization algorithm is presented for the purpose of improving spectrum sensing efficiency in cooperative cognitive radio systems. The proposed algorithm achieves the goal by prioritizing the channels for fine sensing based on both local statistics obtained by the cognitive radio as well as long-term spatiotemporal statistics obtained from other cognitive radios. Channel priority is determined in a stochastic manner by performing statistical fusion on the local statistics and statistics from neighboring cognitive radios to obtain a biasing density from which stochastic sampling can be used to identify the likelihood of channel availability. Therefore, the individual cognitive radios collaborate to improve the likelihood of each cognitive radio in obtaining available channels. Simulation results show that the proposed cooperative stochastic channel prioritization algorithm can be used to reduce both sensing overhead and percentage of missed opportunities when implemented in a complimentary manner with existing cooperative cognitive radio systems.**

I. Introduction

A major challenge faced in the design of cognitive radio (CR) systems is the problem of channel fading. Under channel fading, it is very difficult for cognitive radios to distinguish between a faded primary user signal and white noise [1]. This poor detection sensitivity to fading primary user signals can result in ill-informed secondary user with CR capability access of unavailable channels. Such scenarios are highly undesirable as it can lead to destructive interference of primary user transmission by secondary users. To tackle this important problem, much of recent research effort in cognitive radio systems have been focused on the design of cooperative spectrum sensing algorithms. The underlying goal of cooperative spectrum sensing algorithms [2] - [9] is to increase detection sensitivity and accuracy of fading primary user signals by collectively deciding on the presence of primary users.

The underlying assumption made by existing cooperative spectrum sensing algorithms is that the individual cognitive radio nodes within the secondary network sense for available channels at approximately the same time and exchange either local decisions [5], [6], [7], [8], [9] or sensing results [2], [3], [4] to collaboratively determine channel availability. What this assumption implies is that the level of sensing accuracy that can be achieved by the cooperative cognitive radio system is highly dependent on the density of secondary users. As such, cognitive radio nodes with few neighboring nodes may still suffer from poor detection sensitivity as a result of insufficient local measurements. The goal of the proposed cooperative channel prioritization algorithm, as a complementary technique to existing state-of-the-art cooperative spectrum sensing techniques, is to reduce the effect of the aforementioned limitation by utilizing long-term statistical information from neighboring secondary users to improve the accuracy of the spectrum sensing process. Furthermore, the exchange of long-term statistical information allows the knowledge gained by neighboring secondary users to be retained in the secondary user network even when neighboring secondary users leave the network.

To the best of the authors' knowledge, there are currently no techniques for cooperative prioritization of channels for spectrum sensing. Furthermore, this method is complementary to existing techniques and can yield improved performance when used in conjunction with existing cooperative sensing techniques.

The rest of this paper is organized as follows. Firstly, the system model is presented in II. The proposed cooperative channel prioritization algorithm is described in Section III. Numerical results are discussed in Section IV. Finally, conclusions are drawn in Section V.

II. System Model

The system model can be defined as follows. Assume that there are K non-overlapping channels $\{\mathbf{CH}|CH_i, i = 1, 2, ..., K\}$ centered at $\{f_c^i\}_{i=1}^K$ over a licensed spectrum assigned to a primary user network. Users equipped with cognitive radios are considered as the secondary users to the primary networks, and form a network in an ad-hoc manner. The secondary users with CR capability can opportunistically access channels that are not occupied by primary users. Without the loss of generality, it can be assumed that the channel usage model of the primary users follows an ON/OFF traffic model, where the secondary users are restricted to channel access only during OFF periods, where no primary users are using the channels. This traffic model is designed to minimize the likelihood of interference with the primary users on the primary user network. Given this traffic model, there exists two hypotheses H_1 and H_0, which indicate signal presence and signal absence for the primary networks respectively.

At each secondary user, spectrum sensing is performed over the K channels when there are data to transmit. Control information is exchanged on a dedicated control channel CH_0. The two stages of spectrum sensing as indicated in the latest draft of the IEEE 802.22 standard [10], i.e., a fast sensing stage and a fine sensing stage, are adopted. The fast sensing stage scans a wide range of spectrum in a fast but relatively inaccurate manner by measuring the energy received on the channels using an energy detector. Under the two aforementioned hypotheses, the received bandpass waveform on CH_i at the secondary user can be represented as [12],

$$x_i(t) = \begin{cases} Re\{[h_c S_{\mathrm{LP}}(t) + w_{\mathrm{LP}}(t)]e^{j2\pi f_c^i}\}, & H_1 \\ Re\{w_{\mathrm{LP}}(t)e^{j2\pi f_c^i}\}, & H_0 \end{cases}, i = 1, ..., K \tag{1}$$

where $Re\{\cdot\}$ indicates the real part of a complex value, h_c is the channel impulse response, f_c^i is the carrier frequency of CH_i, and $S_{LP}(t)$ and $w_{LP}(t)$ refer to an equivalent low-pass representation of the primary user's signal and additive white Gaussian noise (AWGN) with zero mean and a known power spectral density (PSD) respectively. Using a band-pass filter, given the observed signal $x_i(t)$ on CH_i, for $0 \leq t \leq T$, the test statistics can be expressed as

$$u_i \cong \frac{2}{N_0} \int_T x_i^2(t)dt, \tag{2}$$

which is a random variable with a chi-square (χ^2) distribution. Therefore, the probability density function (PDF) of u_i can be expressed as [12]

$$f(u_i) = \begin{cases} \frac{1}{2^{k/2}\Gamma(k/2)} u_i^{(k/2)-1} e^{-u_i/2}, & H_0 \\ \frac{1}{2} e^{-(u_i/2+\mu)} (\frac{u_i}{2\mu})^{k/4-0.5} I_{(k/2)-1}(\sqrt{2\mu u_i}), & H_1 \end{cases}, \tag{3}$$

where k is the degrees of freedom, μ is the instantaneous signal-to-noise ratio (SNR), Γ denotes the Gamma function, and I denotes a modified Bessel function.

After the fast sensing stage, a fine sensing stage is performed using a feature detection process, which is more accurate but requires a longer observation time. The fine sensing stage is performed to more accurately identify the presence of primary user signals to avoid interference by the secondary users. The technique of feature detection is beyond of the scope of this work, but an overview of feature detection can be found in [13]. The underlying goal of the proposed algorithm is to prioritize the channels to be finely sensed using both local statistics and statistics from neighboring secondary user to reduce the need to perform fine sensing on channels with lower likelihood of primary user absence. The fine sensing results regarding channel availability are recorded by each individual secondary user to form and revise spatiotemporal probability distributions of channel usage.

III. Proposed Algorithm

The proposed channel prioritization algorithm is designed to complement existing cooperative cognitive radio networks, particularly in situations characterized by insufficient neighboring secondary users to make accurate decisions based on instantaneous information from each secondary user. The proposed algorithm does not require each neighboring secondary user to perform collaborative sensing at the same instance in time to obtain local information from each other. Instead, an intended secondary transmitter consults with neighboring secondary users' long-term statistics of channel usage information to determine channel prioritization in a cooperative manner. Furthermore, each secondary user learns the channel long-term statistics results from other secondary users and built its own spatiotemporal probability distributions based on local sensing results as well as the long-term statistics of neighboring secondary users.

The proposed approach can be described as follows. When a secondary user $\aleph_\gamma$ initially enters a primary user network, it possesses no spatiotemporal information about the primary user network upon which it can rely on for spectrum sensing. Therefore, $\aleph_\gamma$ sends a request on a dedicated control channel CH_0 to its ρ neighboring secondary users $\aleph_1, \aleph_2, ..., \aleph_\rho$ for their respective long-term statistics when data transmission is required. During the waiting period in which statistical information is being received from $\aleph_1, \aleph_2, ..., \aleph_\rho$, fast sensing is performed to scan the spectrum to obtain an initial set of instantaneous probabilities $P_{inst}(CH_1, \zeta), P_{inst}(CH_2, \zeta), ..., P_{inst}(CH_K, \zeta)$ at a instance in time ζ regarding channel availability that can be used to aid in obtaining the channel priority for fine sensing. Along with the instantaneous probabilities $P_{inst}(CH_1, \zeta), P_{inst}(CH_2, \zeta), ..., P_{inst}(CH_K, \zeta)$, local statistical analysis is performed over time τ to obtain a set of short-term probabilities $P_s(CH_1), P_s(CH_2), ..., P_s(CH_K)$. Based on the local instantaneous and short-term probabilities obtained at $\aleph_\gamma$ and the long-term probabilities $P_L^{(j)}(CH_1)_\zeta, P_L^{(j)}(CH_2)_\zeta, ..., P_L^{(j)}(CH_K)_\zeta$ obtained from each neighboring secondary user $\aleph_j$, weighted based on their associated received signal strength (RSS), $\aleph_\gamma$ can then quantify channel availability using adaptive statistical fusion and prioritize the channels accordingly for the fine sensing process using a stochastic prioritization scheme.

Upon the request of data transmission, fine sensing is performed based on the sensing priority of each channel $CH_{(1)}, CH_{(2)}, ..., CH_{(K)}$, until the required number of available channels n_{req} is obtained. The required number of available channels can be fixed or adaptively chosen based on the situation and is not the focus of this present work. The four types of channel statistics used in the proposed algorithm are further elaborated in the following paragraphs.

A. Instantaneous statistics

Let $P_{inst}(CH_i, \zeta)$ represent the likelihood of channel CH_i being available at time instant ζ based on the on-demand fast sensing process. According to the system model, there are two hypotheses H_1 and H_0, which represent signal presence and signal absence for the primary network respectively. Therefore, the probability of detection of the presence of primary user is defined as $p_d = prob(u_i > \lambda | H_1)$ and the probability of false alarm is defined as $p_f = prob(u_i > \lambda | H_0)$. By comparing u_i to a threshold λ, the secondary users can estimate the likelihood of primary user presence. Generally, the threshold λ determines how sensitive the energy detection is in a fading channel environment. In other words, given a certain probability of false alarm $p_f = \phi$., the decision threshold λ can be defined as,

$$\lambda = \{\lambda | prob(u_i > \lambda | H_0) = \phi\}. \quad (4)$$

Given λ and the probability density function of the test statistics u_i from Eq. (3), for a given noise PSD model N_0, the probability of detection p_d can be evaluated as

$$p_{d|N_0} = prob(u_i > \lambda | H_1, N_0) = \int_{\lambda}^{\infty} f(u_i) du_i. \quad (5)$$

In a Rayleigh fading channel model, the average detection probability, i.e. the aforementioned instantaneous statistics $P_{inst}(CH_i, \zeta)$ can be evaluated as

$$P_{inst}(CH_i, \zeta) = p_d = \frac{1}{\bar{\mu}} \int_0^{\infty} \int_{\lambda}^{\infty} f(u_i) \exp(-\frac{\mu}{\bar{\mu}}) du_i d\mu, \quad (6)$$

where $\bar{\mu}$ is the average SNR. This result is consistent with that obtained in [12].

B. Short-term statistics

The short-term statistics present a microscopic view of channel usage of primary users, and are used to compensate for inaccuracies made in the long-term, macroscopic view of channel usage. The short-term statistics $P_s(CH_1), P_s(CH_2), ..., P_s(CH_K)$ are determined at $\aleph_\gamma$ based on the estimated probability distribution $\hat{f}_s(\mathbf{CH})$ over a short time scale τ (e.g., 10ms) prior to ζ. For a channel CH_i, $\Omega_i^\tau = \{\omega_i(\tau_1), \omega_i(\tau_2), ..., \omega_i(\tau_n)\}$ represents the observations of primary user channel occupancy as successfully identified by $\aleph_\gamma$,

$$\omega_i(t) = \begin{cases} 1 & \text{if } u_i{<}\lambda, \text{ given } H_0 \\ 0 & \text{otherwise} \end{cases} \quad (7)$$

.

Based on Ω_i^τ, assuming that the observations are i.i.d. with a Poisson distribution during τ, the arrival rate of primary users Λ can be estimated as

$$\hat{\Lambda}_i = \sum_{t=\tau_1}^{\tau_n} \omega_i(t)/\tau. \quad (8)$$

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

$$\hat{P}_s(\mathbf{CH}) = 1 - \int_0^{\tau} \hat{\Lambda} e^{-\hat{\Lambda} t} dt. \quad (9)$$

It can be seen that the estimation reliability of $\hat{P}_s(\mathbf{CH})$ is highly dependent on the frequency of fine sensing, i.e., the data arrival rate of $\aleph_\gamma$. Secondary users with high traffic volume have more channel usage information with regards of the primary users. Under such a scenario, the estimation of $\hat{P}_s(\mathbf{CH})$ using Eq. (9) can more practically model the real-world situation. However, this is not always the case, as traffic volume may fluctuate over time. Therefore, this partial observation over a short period makes the estimation very hard and challenging. This issue will be addressed in Section III-E.

C. Long-term statistics

The local long-term statistics for channel usage at $\aleph_\gamma$ are represented by a spatiotemporal probability distribution $\hat{f}_L^{(\gamma)}(\mathbf{CH}, t)$, which is based on local observations of primary user channel occupancy for a longer period of time T_{cycle} (e.g., 24 hours). Furthermore, in the case where $T_{cycle} = 24h$, long-term observations of channel availability can be made cyclically over a larger periods of time (e.g., days, weeks). For a channel CH_i, the observations of primary user channel occupancy $\Omega_i = \{\omega_i(t_1), \omega_i(t_2), ..., \omega_i(t_n)\}$ as successfully identified by $\aleph_\gamma$ are used to estimate the probability distribution, $\hat{f}_L(CH_i, t)$, which indicates channel availability across the time axis. The set of observations Ω_i, which are assumed to be i.i.d., are subdivided into ϵ sampling time slots $B_1, B_2, ..., B_\epsilon$, and v_m denotes the number of observations indicating an absence of primary users that corresponding to time slot B_m. Therefore, the probability of v_m (of $V_i = \sum_{m=1}^{\epsilon} v_m$) learning observations corresponding to B_m is given by the binomial density [11],

$$P_{B_m} = \begin{pmatrix} V_i \\ v_m \end{pmatrix} P^{v_m} (1-P)^{V_i - v_m}. \quad (10)$$

The expected value of v_m is therefore

$$E[v_m] = \sum\nolimits_{m=0}^{\epsilon} v_m P_{B_m} = V_i P. \quad (11)$$

Therefore, the estimation of $E[v_m]$ by observed v_m leads to estimated probabilities of channel availability of CH_i by $\aleph_\gamma$ across the time axis as

$$P \approx \hat{P}_L^\gamma(CH_i, t) = v_i / V_i. \quad (12)$$

While the above formulation provides probability estimations at fixed intervals of time, we are interested in obtaining probability estimations at specific instances of time. To address this issue, a Parzen window density estimator is used. The Parzen estimate of the probability distribution $\hat{f}_L^\gamma(CH_i, t)$ at time t can be expressed as

$$\hat{f}_L^\gamma(CH_i, t) = \frac{1}{nh} \sum_{j=1}^{n} G(\frac{\omega_i(t) - \omega_i(t_j)}{h}), \quad (13)$$

where h is the smoothing parameter, $G(\cdot)$ is a Gaussian function with mean of zero and variance of 1 ($G(\cdot) \sim N(0,1)$). So far, we have only discussed the temporal statistics of channel availability across the time axis of by taking look at estimated probability distribution, $\hat{f}_L^\gamma(\mathbf{CH}, t)$, of the set of channels $\mathbf{CH}$. Since the goal of the proposed cooperative channel prioritization algorithm is to order the channels for fine sensing based on their likelihood of availability, we must also take into account their likelihoods with respect to other channels. Therefore, beside the temporal statistics, the likelihood of CH_i being available compared with the other channels are taken into consideration by taking a cross-section of the above spatiotemporal probability distribution $\hat{f}_L^{\gamma}(\mathbf{CH}, t)$ at time instance ζ. The probability of channel availability with respect to other channels $P_L^{\gamma}(CH_i)_{\zeta}$ is given by

$$P_L^{\gamma}(CH_i)_{\zeta} = \frac{\hat{f}_L^{\gamma}(CH_i, \zeta)}{\sum_{j=1}^{K} \hat{f}_L^{\gamma}(CH_j, \zeta)}. \tag{14}$$

D. Cooperative Statistical Fusion

Each secondary user can obtain long-term statistical information from its own spatiotemporal probability distribution at any time according to Eq. (14). The proposed algorithm, as a complimentary technique to existing cooperative spectrum sensing techniques, takes advantage of this capability by allowing for the exchange of long-term statistical information between secondary users. The channel prioritization process can then utilize the statistical information obtained from neighboring secondary users to obtain an improved estimate of the likelihood of channel availability.

There are several advantages to this cooperative approach to channel prioritization. First, when a secondary user $\aleph_{\gamma}$ initially enters the primary user network, it can request statistical information of the channel usage from its neighboring secondary users for a particular time of interest, $P_L^{(j)}(CH_i)_t$, and use the information directly without an initial learning period to improve its estimation of channel availability. Second, in the situation where there are insufficient active neighboring secondary users to perform cooperative sensing at the same instance in time, $\aleph_{\gamma}$ is still able to make use of statistical information from neighboring secondary users to perform improved channel prioritization. Finally, the exchange of long-term statistical information allows the knowledge gained by neighboring secondary users to be retained in the secondary user network even when neighboring secondary users leave the network.

The cooperative statistical fusion process can be described as follows. Suppose that a secondary user $\aleph_{\gamma}$ requests long-term statistics for channel CH_i for time instance ζ from neighboring secondary users $\aleph_1, \aleph_2, ..., \aleph_J$ over a common channel CH_0. The neighboring second users return the requested information $P_L^{(1)}(CH_i)_{\zeta}, P_L^{(2)}(CH_i)_{\zeta}, ..., P_L^{(J)}(CH_i)_{\zeta}$ to $\aleph_{\gamma}$. The secondary user $\aleph_{\gamma}$ can then estimate the likelihood of channel availability $P_L^{(\Sigma)}(CH_i)_{\zeta}$ based on neighboring secondary user statistics as well as the local long-term statistics $P_L^{(\gamma)}(CH_i)_{\zeta}$ by aggregate all the retrieved information as a weighted sum for a particular channel CH_i,

$$P_L^{(\Sigma)}(CH_i)_{\zeta} = W_i^{(\gamma)} P_L^{(\gamma)}(CH_i)_{\zeta} + \sum_{j=1}^{J} W_i^{(j)} P_L^{(j)}(CH_i)_{\zeta}, \tag{15}$$

where $W_i^{(\gamma)} + \sum_{j=1}^{J} W_i^{(j)} = 1$, $W_i^{(j)}$ is a weight associated with the received signal strength (RSS) on the dedicated control channel and the resident time of neighboring secondary user $\aleph_j$. A strong RSS indicates a higher probability that $\aleph_j$ is close to $\aleph_{\gamma}$, while the resident time indicates the credibility of the statistics of $\aleph_j$.

E. Stochastic Channel Prioritization

Given the instantaneous statistics,$P_{inst}(CH_i, \zeta)$, cooperative long-term statistics $P_L^{(\Sigma)}(CH_i)_{\zeta}$, and the short-term statistics $\hat{P}_s(CH_i)$, one can now estimate the overall likelihood of channel availability based on all of the above statistical information. This can be viewed as the importance of each channel to the channel prioritization process, as channels that are more likely to be available are treated with greater importance when considering the priority of channels to be finely sensed. One possible formulation for determining channel importance at time instance ζ can be expressed as

$$\begin{aligned} \widehat{I}(\mathbf{CH}, \zeta) = \quad & (1 - W_{\alpha} - W_{\beta}) \cdot P_L^{(\Sigma)}(\mathbf{CH})_{\zeta} + \\ & W_{\beta} \hat{P}_s(\mathbf{CH}) + W_{\alpha} P_{inst}(\mathbf{CH}, \zeta), \end{aligned} \tag{16}$$

where $\mathbf{CH}$ denotes the set of channels $\{\mathbf{CH}|CH_i, i = 1, 2, ..., K\}$, W_{α} is a weighting factor that weighs the impact of long-term statistics $P_L^{(\Sigma)}(\mathbf{CH})_{\zeta}$ and the instantaneous statistics $P_{inst}(\mathbf{CH}, \zeta)$, and W_{β} is a dynamic weighting factor that weights the impact of short-term statistics $\hat{P}_s(\mathbf{CH})$ based on the quantity of observations n_{Ω} learned during τ.

$$W_{\beta} = \frac{\breve{W}_{\beta} n_{\Omega}}{n_{\max}} \tag{17}$$

where $\breve{W}_{\beta}$ is the base weight and $n_{\max}$ is the maximum number of observations that can be stored within the observation period. As such, the impact of $\hat{P}_s(\mathbf{CH})$ is reduced in situations characterized by insufficient observations. The above formulation of channel importance has low computational complexity and can be performed in an efficient manner.

Due to the uncertainties associated with spectrum availability, it is difficult to perform channel prioritization in a purely deterministic fashion. However, each observation of spectrum availability follows a certain probability distribution. Therefore, a stochastic approach to channel prioritization may be more appropriate. The proposed stochastic channel prioritization scheme can be described as follows. First, a biasing density $q_*(i)$ is defined as the normalized channel importance function $\widehat{I}(\mathbf{CH}, \zeta)$,

$$q_*(i) = \frac{\widehat{I}(CH_i, \zeta)}{\sum_{i=1}^{K} \widehat{I}(CH_i, \zeta)}. \tag{18}$$

Given the fact that $q_*(i)$ is a probability density function, its cumulative density function $Q_*(i)$ is given by

$$Q_*(i) = q_*(X \leq i) = \sum_{j=1}^{i} q_*(j) \tag{19}$$

Given the biasing density $q_*(i)$ and its associated cumulative density function $Q_*(i)$, the CR system generates non-repeated random samples $s_1, s_2, ..., s_K$ based on the biasing density and determines sequence of prioritized channels as

$$\Theta = \{CH_{s_1}, CH_{s_2}, ..., CH_{s_K}\}\,. \tag{20}$$

IV. Numerical Results

The numerical results of proposed cooperative stochastic channel prioritization algorithm is presented as follows. Consider $K = 40$ channels over a licensed spectrum in a primary user network. Each of the secondary users independently sense the targeted spectrum band in a Rayleigh fading environment. For simplicity, the transmission power of the primary users is assumed at the same power level. We analyze the performance of the proposed algorithm via the following parameters:

Percentage of missed opportunities (p_m): This is defined as the ratio of the number of missed available channels n^* to the number of actual available channels n,

$$p_m = \frac{n^*}{n}, \tag{21}$$

under the condition of no limitations on the number of channels to finely sense. If there is a time constraint on the process of fine sensing, and the time constraint can be interpreted as a fixed number of fine sensing $\mathscr{N}$ with an assumption that each fine sensing consumes the same amount of time, the above performance metrics can be rewritten as

$$p'_m = \begin{cases} \frac{n^*}{\mathscr{N}}, & \mathscr{N} \leq n \\ \frac{n^*}{n}, & \mathscr{N} > n. \end{cases} \tag{22}$$

The percentage of missed opportunities p'_m captures the quality of a sensing algorithm within a limited time window. For an efficient sensing algorithm, it would be desirable to have p'_m as low as possible.

We compare the performance of the proposed cooperative channel prioritization algorithm against the conventional spectrum sensing approach where long-term statistics are not exchanged amongst secondary users. The percentage of missed opportunities of each sensing event are shown in Fig. 1. It is observed that the percentage of missed opportunities p'_m of the proposed algorithm is lower than the conventional spectrum sensing approach. Although some results of the proposed algorithm are lower or equivalent to that obtained using the conventional approach due to the randomness introduced in the simulation process, the overall average percentage of missed opportunities of the proposed algorithm is $\bar{p'_m} = 0.4872$ as compared to $\bar{p'_m} = 0.6882$ for the conventional approach, resulting in a 20% reduction in missed opportunities.

Sensing overhead ($\boldsymbol{o}$): This is defined as the amount of additional fine sensing necessary to detect the required number of available channels n_{req},

$$\boldsymbol{o} = n_{\Sigma} - n_{req}, \quad n_{req} \neq 0, \tag{23}$$

where n_{Σ} is total number of fine sensing. This metric represents the cost of a sensing algorithm in obtaining the required number of available channels given unlimited time. The reason for removing the time constraint for this metric is to provide a better visualization of how fast n_{req} channels can be obtained in its entirety by adopting a sensing algorithm. If performed under the time constraint, only part of n_{req} channels may be obtained. Therefore, the use of time constraints in this case would not provide a good visualization of the efficiency of a sensing algorithm. For an efficient sensing algorithm, it would be desirable to have $\boldsymbol{o}$ as small as possible.

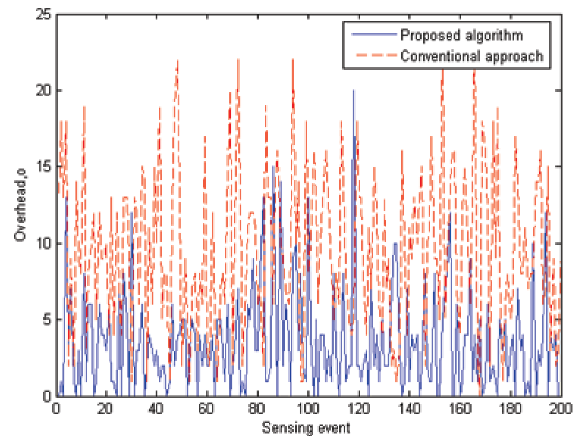

Fig. 2. Sensing overhead of each sensing event of the proposed algorithm and the conventional spectrum sensing approach

In Fig. 2, the sensing overhead $\boldsymbol{o}$ of each sensing event to obtain $n_{req} = 1$ required available channel for both the proposed algorithm and the conventional approach are plotted in the case that there are $n = 5$ actual available channels among $K = 40$ channels. It can be observed that the sensing overhead of the proposed algorithm is significantly lower than the latter. The average sensing overhead $\bar{\boldsymbol{o}}$ associated with different numbers n of actual available channels are depicted in Fig. 3 to further measure the performance of the proposed algorithm. It is seen that the average sensing overhead $\bar{\boldsymbol{o}}$ decreases with the increase of the number of actual available channels, n, and it also decreases with the increase of the number of required available channels, n_{req}. Moreover, as expected, the average sensing overhead of the proposed algorithm shown in Fig. 3.a) is lower than that of the conventional approach shown in Fig. 3.b).

V. Conclusion

In this paper, we introduced a novel cooperative stochastic approach to channel prioritization for cooperative cognitive radio systems. Channel priority was determined in a stochastic manner based on both local statistics of the CR as well as long-term statistics obtained from neighboring secondary users to improve the probability of each CR obtaining the required available channels. The proposed algorithm facilitates the exchange of learned statistics between secondary users so that knowledge is retained in the secondary user network even when secondary users leave the network. Simulation results the effectiveness of the proposed channel prioritization algorithm in reducing both percentage of missed opportunities and sensing overhead.

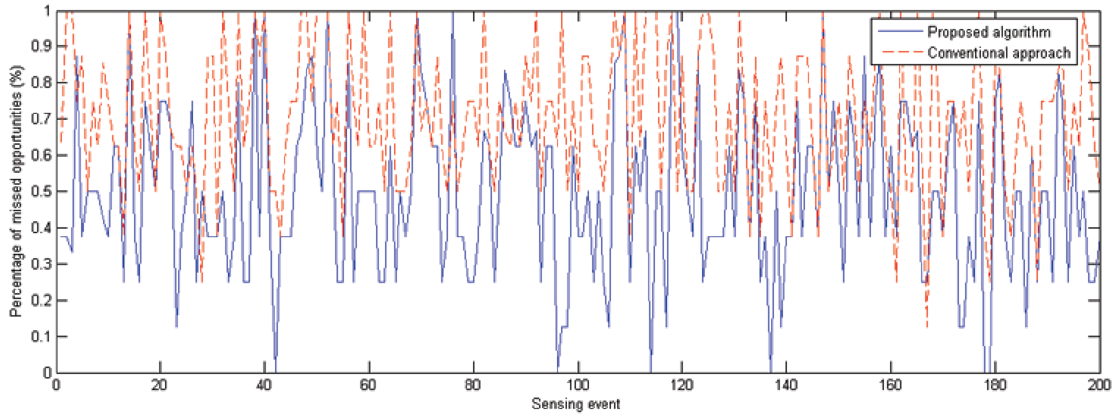

Fig. 1. Percentage of missed opportunities of the proposed algorithm and that of the conventional approach

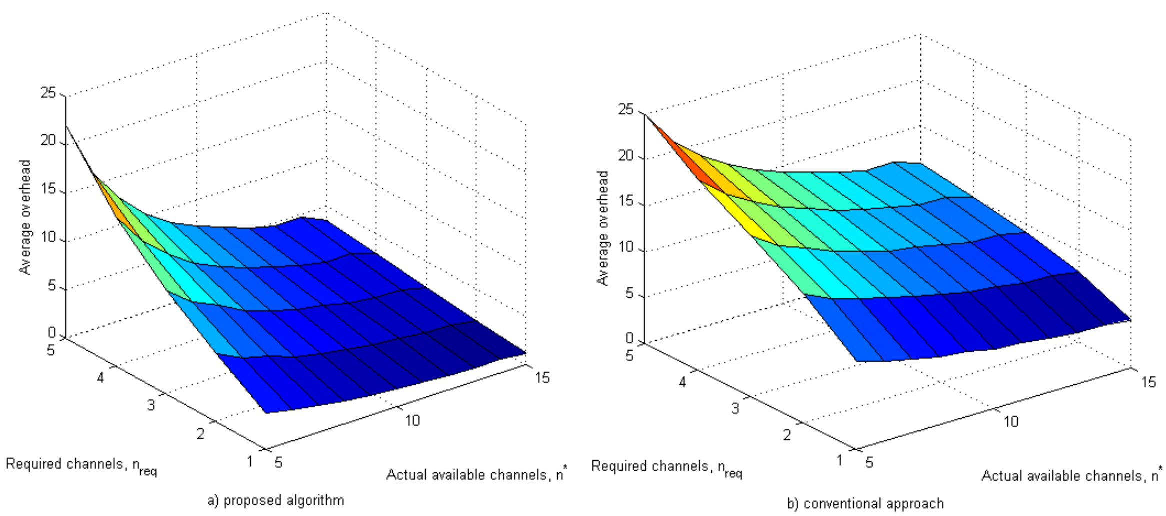

Fig. 3. Average overhead $\bar{\boldsymbol{o}}$ to obtain different number of required channels n_{req} with different number of actual available channels n

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