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Fast Cooperative Sensing with Low Overhead in Cognitive Radios

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Abstract

As is well known, cooperative sensing can significantly improve the sensing accuracy as compared to local sensing in cognitive radio networks (CRNs). However, a large number of cooperative secondary users (SUs) reporting their local detection results to the fusion center (FC) would cause much overhead, such as sensing delay and energy consumption. In this paper, we propose a fast cooperative sensing scheme, called *double threshold fusion* (DTF), to reduce the sensing overhead while satisfying a given sensing accuracy requirement. In DTF, FC respectively compares the number of successfully received local decisions and that of failed receptions with two different thresholds to make a final decision in each reporting sub-slot during a sensing process, where cooperative SUs sequentially report their local decisions in a selective fashion to reduce the reporting overhead. By jointly considering sequential detection and selective reporting techniques in DTF, the overhead of cooperative sensing can be significantly reduced. Besides, we study the performance optimization problems with different objectives for DTF and develop three optimum fusion rules accordingly. Simulation results reveal that DTF shows evident performance gains over an existing scheme.

Keywords: Cognitive radio, spectrum sensing, cooperation diversity, fusion rule, detection probability

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1. Introduction

In cognitive radio networks (CRNs), secondary users (SUs) should detect whether primary users (PUs) are present or not before they access the licensed spectrum [1-3]. If PU is detected, SU can send its messages with power control so as to ensure PU quality-of-service (QoS); otherwise, SU can access the spectrum directly [4]. The detection functionality is fulfilled by spectrum sensing in which both sensing accuracy and sensing delay are crucial to the performance of secondary transmissions. To improve the sensing accuracy, cooperative sensing is introduced, where SUs detect the states of PUs collaboratively coordinated by the fusion center (FC) [5]. However, a larger number of cooperative SUs would cause significant overhead, such as sensing delay and energy consumption.

In this paper, we propose a fast cooperative sensing scheme, called *double threshold fusion* (DTF), to reduce the sensing overhead while maintaining sensing accuracy. In DTF, sequential detection technique is naturally incorporated. More specifically, a final decision is attempted at the FC in each reporting sub-slot during a sensing process by comparing the numbers of successful and failed receptions of local decisions with two different thresholds. Specifically, once the number of successful decision receptions (or failed receptions) is equal to its predefined threshold in a sub-slot, FC will declare PU's presence (or absence) and stop spectrum sensing immediately. Besides, in the case of that the numbers of successful and failed decision receptions do not reach their thresholds at the end of a sensing phase, FC will declare PU's presence if the number of successful decision receptions is equal to or larger than that of failed receptions and declare PU's absence otherwise. Beisdes, similar to [6], the cooperative SUs in DTF report their local decisions in a selective fashion to reduce the reporting overhead, i.e., a SU will report only when it detects PU's presence.

Overall, our main contributions can be summarized as follows:

1) We investigate fast cooperative sensing for CRNs, and then propose a novel decision strategy called DTF to reduce the sensing times of detecting PU's presence and absence while maintaining a given sensing accuracy. Note that, the saved sensing time in detecting PU's presence can be used to improve the throughput of underlay transmissions while the saved sensing time in detecting PU's absence can be used to improve the throughput of interweave transmissions [7].
2) We analyze the performance of DTF in terms of false alarm probability, detection probability and sensing time, and also derive their closed-form expressions over Rayleigh fading channels with considering reporting errors. Besides, we study the performance optimization problems with different objectives for DTF, and then develop three optimum fusion rules accordingly.
3) We conduct extensive simulation studies to validate the effectiveness and efficiency of the proposed DTF scheme. It is shown that DTF can significantly reduce the sensing overhead without degrading the sensing accuracy compared to the traditional scheme.
4) Due to the use of decision fusion, DTF can be easily extended to many local detector cases, such as matched filter detection, feature detection, energy detection, and so on.

2. Related Work

Several strategies have been emerged in literature aiming at reducing the overhead of cooperative sensing. Recently, user selection is employed in cooperative sensing to reduce the sensing overhead. In [9], we proposed a user selection algorithm based on the correlations of trust functions for cooperative sensing to reduce the amount of fusion data collected at the FC. In [10], the authors investigated three methods to select the SUs with the best detection performance to participate in cooperative sensing. The authors showed that such cooperative sensing methods can effectively reduce the sensing overhead. In [9, 10], perfect reporting channels were assumed for ease of analysis. However, such assumption is not practical in real wireless environments. Unlike [9, 10], a selective reporting scheme was proposed with considering the reporting errors in [6]. In this scheme, a SU reports its local decision only when it does not detect the presence of PU, so as to reduce the reporting overhead as well as the induced interference to PU.

Although the user selection based cooperative sensing schemes [6, 9-10] can reduce the reporting overhead, they can not reduce the sensing delay. To reduce both the reporting overhead and sensing delay, sequential detection is utilized in cooperative sensing. In [11], the authors let cooperative SUs report in descending order of received signal-to-noise ratio (SNR) to reduce the sensing time. Unlike [11], cooperative SUs in [12] report their detection results in descending order of the magnitude of their local test statistics. The authors of [13] studied sequential detection under the constraints of limited sensing time and number of cooperative SUs, where local detectors reported their log likelihood ratio (LLR) in descending order of LLR magnitude.

From the above discussions, we know that DTF can make a final decision earlier before a sensing phase expires, which differs from [6, 9-10] where a final decision is always made at the end of a sensing phase. In this paper, the reporting errors are considered, which is more practical than [9, 10]. Different from [11-13] using data fusion, DTF employs decision fusion for implementation simplicity, which also implies that DTF is applicable for many local detector cases. Besides, unlike [6, 9-10, 11-13], we study the performance optimization problems for DTF and develop three optimum fusion rules with different objectives accordingly. DTF can not only improve secondary throughput but also reduce SU energy consumption due to less sensing delay and reporting overhead.

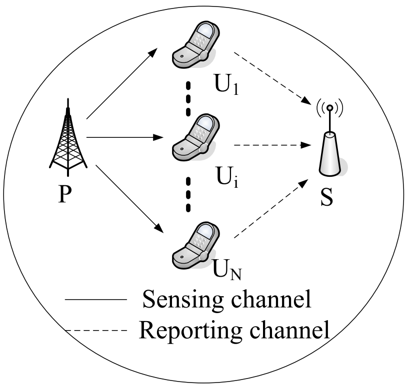

Fig. 1. The system model of cooperative sensing

3. System Model

As shown in **Fig. 1**, we consider a CRN consists of a source PU P, a FC S and N cooperative SUs $\Omega=\{U_1,\cdots$. In this CRN, P transmits the signal x_P ($E\{|x_P|^2\}=1$) to its destination with power E_P. The gain of link $I\to J$ ($I\in\{P,U_i\}$, $J\in\{S,U_i\}$, $I\neq J$), denoted as h_{IJ}, is Rayleigh fading with variance σ_{IJ}^2 [8]. We assume that n_J is the additive white Gaussian noise (AWGN) at J with zero mean and variance σ_n^2. Besides, like many existing works [9-13], a common control channel is assumed in this paper for the information exchange between U_i and S.

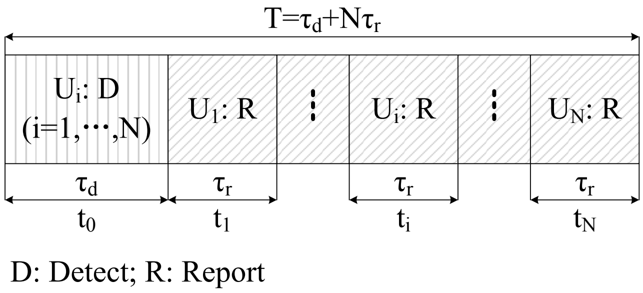

Fig. 2. The time slot structure of cooperative sensing

The time slot structure of cooperative sensing can be described by **Fig. 2**, where each sensing phase consists of a sub-slot t_0 with duration τ_d and N equal sub-slots $\{t_1,\cdots$, each of duration τ_r. Thus, the time duration of each sensing phase is $T=\tau_d+N\tau_r$. The sub-slot t_0 is used for local sensing while the sub-slot t_i ($1\le i\le N$) is used for the decision reporting of U_i.

4. Proposed Fast Cooperative Sensing

4.1 Traditional Sequential Detection Scheme

For the purpose of performance comparison, we will briefly introduce the *traditional sequential detection* (TSD) scheme as proposed in our previous work [15] in this subsection. In TSD, all cooperative SUs make local sensing in t_0 first, then report the local decisions during $\{t_1,\cdots$ sequentially. At the same time, S checks whether it successfully receives a local decision or not in each reporting sub-slot. Once S successfully recieves a local decision in a certain reporting sub-slot, it will make a final decision indicating P's presence and stop spectrum sensing immediately. If S does not receive any local decisions during $\{t_1,\cdots$, a final decision indicating P's absence is declared. In this process, a cooperative SU reports its local decision only when it detects P's presence in t_0 to reduce the reporting overhead.

Similar to [6], in this paper, the reported local decisions can be encoded by cyclic redundancy codes (CRCs), and then they will be sent to the FC where CRC checking is performed to retrieve the reported local decisions. It is noted that, to make fair comparison with the proposed DTF scheme and also for analysis simplicity, this paper does not consider the local detection of S and the optimization problem of cooperative SUs' number for TSD, which differs from [15]. Clearly, TSD can remarkably reduce the sensing time consumed for correctly detect P's presence when P is presnet. However, TSD can not reduce the sensing time consumed for finding spectrum hole when P is absence. To solve this issue, we propose the DTF scheme in Section 4.2.

4.2 Proposed DTF Scheme

In DTF, S maintains two counters, denoted as C_1 and C_2, used for counting the numbers of successful and failed decision receptions, respectively. Specifically, in t_i ($i=1,\cdots$), if S successfully receives a local decision from U_i, it will add C_1 by 1; otherwise, it will add C_2 by 1. Thus, the values of C_1 and C_2 in t_i, denoted by $C_{1,i}$ and $C_{2,i}$, are respectively given as

$$C_{1,i} = C_{1,i-1} + \hat{\theta}_{S,i} \tag{1}$$

$$C_{2,i} = C_{2,i-1} + 1 - \hat{\theta}_{S,i} \tag{2}$$

where $\hat{\theta}_{S,i} = 1$ denotes that S successfully receives a local decision from U_i while $\hat{\theta}_{S,i} = 0$ denotes the opposite.

Then, the sensing process of DTF is described as follows:

- In t_0, each cooperative SU attempts to detect the states of P by itself. Besides, S sets the initial values of C_1 and C_2 as $C_{1,0} = 0$ and $C_{2,0} = 0$, respectively.
- In t_i ($i=1,\cdots$), U_i reports its local decision to S in a selective fashion, i.e., U_i reports only when it detects P's presence in t_0. Meanwhile, S tries to decode the reported decision from U_i. Next, $C_{1,i}$ and $C_{2,i}$ are calculated by (1) and (2), then compared with the thresholds K_1 and K_2, respectively. If $C_{1,i} = K_1$, S claims P's presence and stops sensing immediately; if $C_{2,i} = K_2$, S declares P's absence and stops sensing immediately; if $C_{1,i} < K_1$ and $C_{2,i} < K_2$, the cooperative sensing will continue. Such sensing process will be sequentially performed from t_1 to t_N and not stop until a final decision is given or the current sensing phase expires. Note that, if $C_{1,N} < K_1$ and $C_{2,N} < K_2$ in t_N, the above fusion rule can not give a final decision. In this case, S will compare $C_{1,N}$ with $C_{2,N}$, then claims P's presence if $C_{1,N} \geq C_{2,N}$ and declares P's absence otherwise.

From the above discussions, we know that the decision strategy of DTF involves two basic fusion rules, denoted as D1 and D2, i.e.,

$$\text{D1:} \begin{cases} C_{1,i} = K_1, \text{ Declare H}_1 \\ C_{1,i} < K_1 \;\&\; C_{2,i} < K_2, \text{ Continue} \\ C_{2,i} = K_2, \text{ Declare H}_0 \end{cases} \tag{3}$$

$$\text{D2:} \begin{cases} C_{1,N} \geq C_{2,N}, \text{ Declare H}_1 \\ C_{1,N} < C_{2,N}, \text{ Declare H}_0 \end{cases} \tag{4}$$

where H_1 and H_0 are two hypotheses denoting P's presence and absence, respectively. Note that D2 is employed only when a final decision can not be made using D1.

Clearly, in traditional scheme, all cooperative SUs are used and the whole sensing phase is consumed, which would induce significant sensing delay and energy consumption. However, DTF is able to give a final decision before a sensing phase expires, which implies that it can reduce the sensing overhead. In DTF, since two fusion thresholds are used, both the times required for detecting PU's presence and that for finding spectrum holes can be reduced compared to traditional scheme as long as $K_1 < N$ and $K_2 < N$ holds. Actually, the saved sensing time can be used for possible secondary transmissions, which potentially promotes the secondary throughput.

5. Performance Analysis

In this section, we let Pf_{U_i} and Pd_{U_i} denote the local false alarm and detection probabilities of U_i, respectively. Besides, we suppose that all local false alarm probabilities are equal to the same value α and the overall false alarm probability is set as α_0 [14]. Without loss of generality, we use energy detecor to evaluate the performacne of proposed DTF scheme in this paper. Since we want to show the advantages of proposed DTF scheme, the choice of detector is not critical. Note that the results obtained in this paper can be easily extended into other local detector cases.

Here, we take an overview of energy detection first. For energy detection, a SU measures the received energy EY over a finite time interval and then compares it with a predefined threshold λ. The SU will claim P's presence if $EY \geq \lambda$ and P's absence otherwise. Note that false alarm occurs if $EY \geq \lambda$ under H_0 and miss detection occurs if $EY < \lambda$ under H_1. Following [3, 15-18], the false alarm probability and detection probability at U_i are respectively given as

$$Pf_{U_i} = \frac{\Gamma\left(m_{U_i}, \frac{\lambda_{U_i}}{2}\right)}{\Gamma\left(m_{U_i}\right)} \tag{5}$$

$$\begin{aligned} Pd_{U_i} = & \exp\left(-\frac{\lambda_{U_i}}{2}\right)\sum_{k=0}^{m_{U_i}-2}\frac{1}{k!}\left(\frac{\lambda_{U_i}}{2}\right)^k + \left(\frac{1+\bar{\gamma}_{U_i}}{\bar{\gamma}_{U_i}}\right)^{m_{U_i}-1} \\ & \times\left[\exp\left(-\frac{\lambda_{U_i}}{2\left(1+\bar{\gamma}_{U_i}\right)}\right) - \exp\left(-\frac{\lambda_{U_i}}{2}\right)\sum_{k=0}^{m_{U_i}-2}\frac{1}{k!}\left(\frac{\lambda_{U_i}\bar{\gamma}_{U_i}}{2\left(1+\bar{\gamma}_{U_i}\right)}\right)^k\right] \end{aligned} \tag{6}$$

where m_{U_i} is the time-bandwidth product of energy detector and $\bar{\gamma}_{U_i}$ is the average SNR received at U_i from P.

5.1 Detection Probability

Considering that U_i is allowed to report its local decision, the reported signal received at S in t_i is expressed as

$$y_S(i) = \sqrt{E_{U_i}}\, h_{U_i S} x_{U_i} + n_S(i) \tag{7}$$

where x_{U_i} is the reported signal from U_i and E_{U_i} is the corresponding transmit power. From (7) and following [6], the probability of that S successfully decodes the reported decision from U_i is

$$P_{U_i} = \Pr\left\{\log_2\left(1+\gamma_{U_i}\left|h_{U_i S}\right|^2\right) \geq \frac{1}{\tau_r B_r}\right\} = \mathrm{e}^{-\frac{\Delta_{U_i}}{\gamma_{U_i}\sigma^2_{U_i S}}} \tag{8}$$

where $\Delta_{U_i} = 2^{1/(\tau_r B_r)} - 1$ and B_r is the bandwidth of reporting channel.

Then, the probability of the case $\hat{\theta}_{S,i} = 1$ under H_0, i.e., S successfully receives a false alarm from U_i, is derived as

$$Pf_{S,U_i} = Pf_{U_i} P_{U_i} = aP_{U_i} \tag{9}$$

Besides, the probability of the case $\hat{\theta}_{S,i} = 1$ under H_1, i.e., S successfully receives a detection from U_i, is given as

$$Pd_{S,U_i} = Pd_{U_i} P_{U_i} \tag{10}$$

As shown in Section 3.3, the decision strategy of DTF involves two fusion rules, i.e., D1 and D2. Consequently, the calculations of overall false alarm and detection probabilities for DTF can be given as follows:

Case 1 (D1): In this case, a final decision is made by D1, where D2 is not required. Clearly, using D1, a final decision indicating PU's presence could not be given before t_{K_1} or after $\tilde{I}$ $K_1 + K_2 - 1, N)$. We let Φ_i denote the set of $\{U_1, \cdots$ and $\Phi_{i,j}$ denote its jth non-empty sub-collection. Besides, we let A_i represent a set of sub-collections $\{\Phi_{i,j} \mid |\Phi_{i,j}| = K_1 - 1, j \in \{1, \cdots$ $\}$ and $A_{i,n}$ represent A_i's nth element, where $|\bullet|$ is the number of the elements in a set. Then, the probabilities of that S declares P's presence under H_0 and H_1 using D1 in t_i ($K_1 \leq i \leq \tilde{I}$) are respectively calculated as

$$\begin{aligned}&\Pr\left\{C_{1,i} = K_1 \mid H_0, \mathrm{D1}\right\}\\ &= Pf_{U_i S}\sum_{n=1}^{|A_{i-1}|}\left[\prod_{U_j \in A_{i-1,n}} Pf_{S,U_j}\right]\left[\prod_{U_k \in \Phi_{i-1} - A_{i-1,n}}\left(1 - Pf_{S,U_k}\right)\right]\end{aligned} \tag{11}$$

$$\begin{aligned}&\Pr\left\{C_{1,i} = K_1 \mid H_1, \mathrm{D1}\right\}\\ &= Pd_{U_i S}\sum_{n=1}^{|A_{i-1}|}\left[\prod_{U_j \in A_{i-1,n}} Pd_{S,U_j}\right]\left[\prod_{U_k \in \Phi_{i-1} - A_{i-1,n}}\left(1 - Pd_{S,U_k}\right)\right]\end{aligned} \tag{12}$$

In (11) and (12), $\prod_{g \in G} f(g)$ is equal to 1 if the set G is empty. Then, the false alarm and detection probabilities for DTF under D1 are respectively given by

$$Pf^{Pro}_{\mathrm{D1}} = \sum_{i=K_1}^{\tilde{I}} \Pr\left\{C_{1,i} = K_1 \mid H_0, \mathrm{D1}\right\} \tag{13}$$

$$Pd^{Pro}_{\mathrm{D1}} = \sum_{i=K_1}^{\tilde{I}} \Pr\left\{C_{1,i} = K_1 \mid H_1, \mathrm{D1}\right\} \tag{14}$$

Case 2 (D2): If a final decision can not be given by D1 at the end of t_N, D2 is employed. First, we let Ω_i denote the ith non-empty sub-collection of Ω. Besides, we define

$$B=\{\Omega_i \mid 0\le|\Omega_i|<K_1, 0\le|\Omega-\Omega_i|<K_2, |\Omega_i|\ge|\Omega-\Omega_i|\} \tag{15}$$

Then, the false alarm and detection probabilities for DTF under D2 are respectively derived as

$$Pf_{\mathrm{D2}}^{Pro}=\sum_{n=1}^{|B|}\left[\prod_{U_j\in B_i} Pf_{S,U_j}\right]\left[\prod_{U_k\in\Omega-B_i}\left(1-Pf_{S,U_k}\right)\right] \tag{16}$$

$$Pd_{\mathrm{D2}}^{Pro}=\sum_{n=1}^{|B|}\left[\prod_{U_j\in B_i} Pd_{S,U_j}\right]\left[\prod_{U_k\in\Omega-B_i}\left(1-Pd_{S,U_k}\right)\right] \tag{17}$$

where B_i is the ith element of B.

Finally, from (13), (14), (15) and (17), the overall false alarm and detection probabilities of DTF are respectively calculated as

$$Pf^{Pro}=Pf_{\mathrm{D1}}^{Pro}+Pf_{\mathrm{D2}}^{Pro} \tag{18}$$

$$Pd^{Pro}=Pd_{\mathrm{D1}}^{Pro}+Pd_{\mathrm{D2}}^{Pro} \tag{19}$$

We define $\phi(\alpha)=Pf^{Pro}$ as a function of α. Since $Pf^{Pro}=\alpha_0$ is assumed, we have $\alpha=\phi^{-1}(\alpha_0)$, where ϕ^{-1} is the inverse function of ϕ.

5.2 Sensing Time

In this paper, we will examine the sensing overhead in terms of sensing time. Here, we define the average sensing time required for S to declare P's presence under H_1 as *presence sensing time* (PST) and that required for S to declare P's absence under H_0 as *absence sensing time* (AST), respectively. Note that PST is the sensing time consumed by S for correctly detecting P's presence while AST is that for correctly finding the spectrum hole.

From [15], we know that althrough TSD scheme can significantly reduce the PST, its AST can not be shortened, which is equal to $T=\tau_d+N\tau_r$. However, in DTF, if S claims P's presence or absence in t_i, the consumed sensing time is $\rho_i=\tau_d+i\tau_r$. As shown in Section 4.1, the probability of that S claims P's presence under H_1 in t_i ($K_1\le i\le \tilde{I}$) can be easily calculated by (12) or (17). Thus, the PST of DTF is given as

$$PST=\sum_{i=K_1}^{\tilde{I}}\rho_i \Pr\{C_{1,i}=K_1 \mid H_1,\mathrm{D1}\}+\rho_N Pd_{\mathrm{D2}}^{Pro} \tag{20}$$

We let X_i represent a set of sub-collections $\{\Phi_{i,j} \mid |\Phi_{i,j}|=K_2-1, j\in\{1,\cdots \quad\}$ and $X_{i,n}$ represent X_i's nth element. Besides, we define

$$Y=\{\Omega_i \mid 0\le|\Omega_i|<K_1, 0\le|\Omega-\Omega_i|<K_2, |\Omega_i|<|\Omega-\Omega_i|\} \tag{21}$$

In a similar way, the probability of that S claims P's absence under H_0 in t_i ($K_2\le i\le \tilde{I}$) using D1 is

$$\begin{aligned}&\Pr\left\{C_{2,i}=K_2 \mid H_0,\mathrm{D1}\right\}\\&=Pf_{U_iS}\sum_{n=1}^{|X_{i-1}|}\left[\prod_{U_j\in X_{i-1,n}}\left(1-Pf_{S,U_j}\right)\right]\left[\prod_{U_k\in\Phi_{i-1}-X_{i-1,n}}Pf_{S,U_k}\right]\end{aligned} \tag{22}$$

On the other hand, the probability of that S claims P's absence under H_0 in t_N using D2 is

$$Pa_{\mathrm{D2}}^{Pro}=\sum_{n=1}^{|Y|}\left[\prod_{U_j\in Y_i}Pf_{S,U_j}\right]\left[\prod_{U_k\in\Omega-Y_i}\left(1-Pf_{S,U_k}\right)\right] \tag{23}$$

where Y_i is the ith element of Y. From (22) and (23), the AST of DTF can be easily derived as

$$AST=\sum_{i=K_2}^{\tilde{I}}\rho_i\Pr\left\{C_{2,i}=K_2 \mid H_1,\mathrm{D1}\right\}+\rho_N Pa_{\mathrm{D2}}^{Pro} \tag{24}$$

6. Optimization Problems in DTF

In CRNs, reducing the sensing time can not only lower the energy consumption but also improve the secondary throughout. Thus, in this paper, we will focus on minimizing the sensing time while satisfying a given detection probability requirement Pd_0 under a reasonable false alarm probability α_0, which is very important for secondary spectrum access. On the other hand, to reduce the induced interference to PUs, the detection probability is usually required to be maximized.

According to different objectives, we develop three efficient rules to obtain the optimum fusion thresholds of K_1 and K_2 for DTF, which are respectively described as follows:

Min-PST-plus-AST (MPA) rule: If the SUs are allowed to use the spectrum with power control when the PU is present, it is necessary to minimize the *overall sensing time* (OST) for given α_0 and Pd_0. Here, the OST is defined as $\mu PST+(1-\mu)AST$, where μ is equal to the probability of that the PU is present. Thus, the optimization problem is given by

$$\begin{aligned}&\underset{K_1,K_2}{\text{minimize}}\ OST\\&\text{subject to } Pd^{Pro}\le Pd_0,\ Pf^{Pro}=\alpha_0\end{aligned} \tag{25}$$

Min-AST (MA) rule: When the PUs are highly sensitive to the interference from SUs, secondary access is not allowed if the spectrum is detected busy. In this case, it is appropriate to minimize AST to improve the secondary throughput for given α_0 and Pd_0. In fact, by setting $\mu=0$, the optimization problem of (25) evolves into the MA rule case.

Max-Detection-Probability (MDP) rule: If PUs are sensitive to the interference induced by SUs, in addition to forbiding secondary access when PU is present, the detection probability should be maximized for given α_0. Such optimization problem can be described as follows:

$$\begin{aligned}&\underset{K_1,K_2}{\text{maximize}}\ Pd^{Pro}\\&\text{subject to } Pf^{Pro}=\alpha_0\end{aligned} \tag{26}$$

From Section 5, we know that the closed-form expressions of detection probability and AST are derived for DTF. In addition, the calculations of detection probability and AST for DTF only need average channel gains instead of instantaneous ones. Thus, the detection probability and AST of DTF can be estimated in prior. When the number of cooperative SUs is not very large, the optimization problems of (25) and (26) can be easily solved by exhaustion search methods. More convenient mathematical methods for solving (25) and (26) will be studied in our future works.

7. Simulation Results

Without loss of generality, we use the energy detector shown in [3] to evaluate the performance of DTF, which is also compared with the traditional case. In these examples, we set the PU appearance probability as $\mu=0.5$, the time duration of local sensing as $\tau_d=4$ms, the time duration of each decision reporting as $\tau_r=2$ms, the bandwidth of energy detector as $B_e=10^3$ Hz, the bandwidth of reporting channel as $B_r=10^4$ Hz.

First, we plot the AST of MA rule and OST of MPA rule versus the PU transmit SNR γ_P for DTF in **Fig. 3** and **Fig. 4**, respectively, which are also compared with the method in [15]. We set the simulation parameters as $N=20$, $\alpha_0=10^{-3}$, $\gamma_{U_i}=5$ and $\sigma^2_{PU_i}=\sigma^2_{U_iS}=1$. From [15], we know that the AST of TSD scheme is equal to $\tau_d+N\tau_r=44$ ms as illustrated in **Fig. 3**. **Fig. 3** and **Fig. 4** show that the optimum DTF rules significantly reduce the sensing time compared to the method in [15].

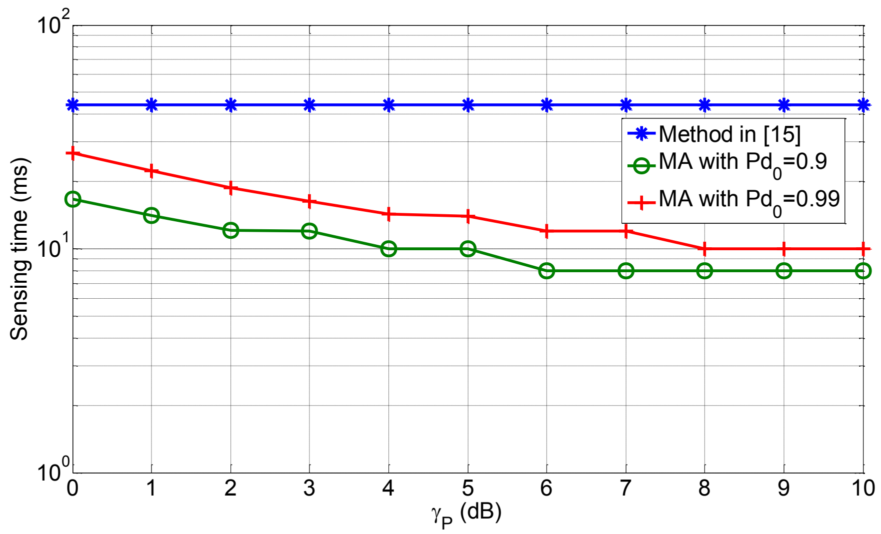

Fig. 3. The AST of MA rule versus γ_P

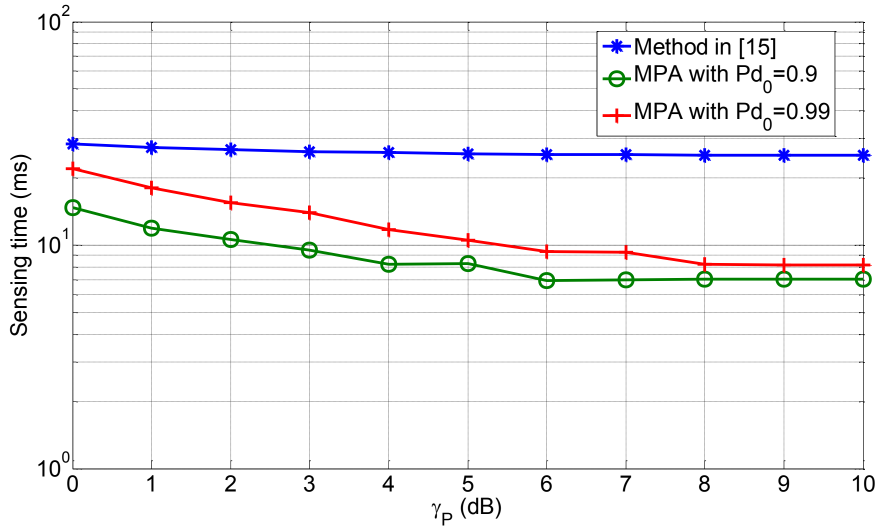

Fig. 4. The OST of MPA rule versus γ_P

Clearly, both the AST of MA rule and the OST of MPA rule decrease as γ_P increases. That is because, on one hand, the local detection probabilities of cooperative SUs will be improved with increasing γ_P, which implies that S can make a final decision on P's presence faster. As a result, the PST of DTF is reduced. On the other hand, for a given Pd_0, the fusion threshold K_2 can be reduced as γ_P increases due to an increased overall detection probability, resulting in a reduction of the AST in DTF. Besides, the sensing time can be cut by loosening the detection probability constraint Pd_0 for both MA and MPA rules since the fusion thresholds are decreased in this case.

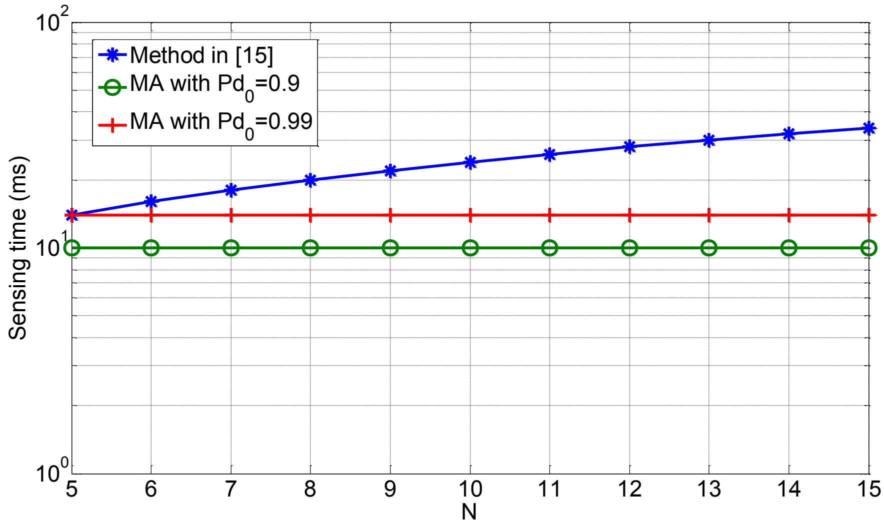

Fig. 5. The AST of MA rule versus N

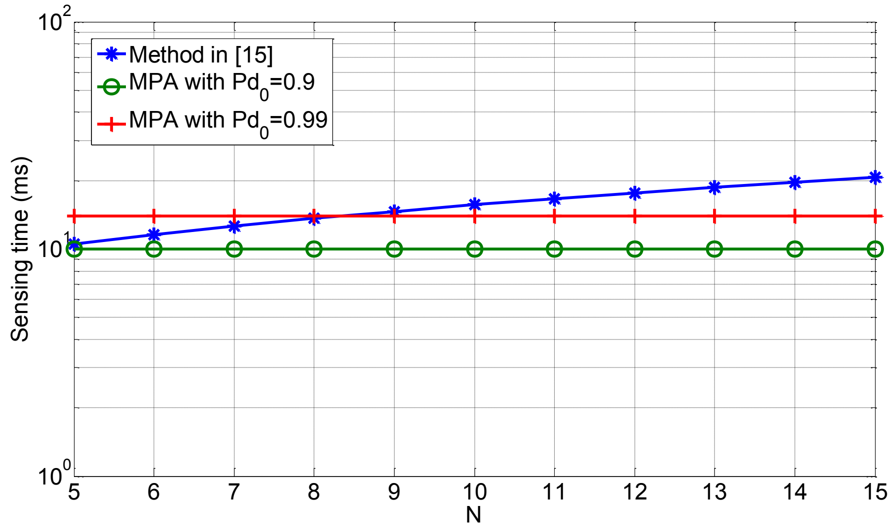

Fig. 6. The OST of MPA rule versus N

Second, we illustrate the AST of MA rule and OST of MPA rule versus N in **Fig. 5** and **Fig. 6** for DTF, respectively. The simualtion parameters are chosen as $\alpha_0 = 10^{-3}$, $\gamma_P = 5$ dB, $\gamma_{U_i} = 5$ dB and $\sigma^2_{PU_i} = \sigma^2_{U_iS} = 1$. From **Fig. 5** and **Fig. 6**, it is observed that the sensing time of the method in [15] increases remarkably as the number of cooperative SUs grows. However, the sensing time in optimum DTF rules is always able to keep at a low level. This evidently confirms the advantages of proposed fusion rules. Besides, as expected, the sensing time of DTF is lower when the detection probability requirement becomes looser. As shown in **Fig. 6**, it is clear that the method in [15] consumes less sensing time than proposed MPA rule when the detection probability requirement is stringent and the number of cooperative SUs is small.

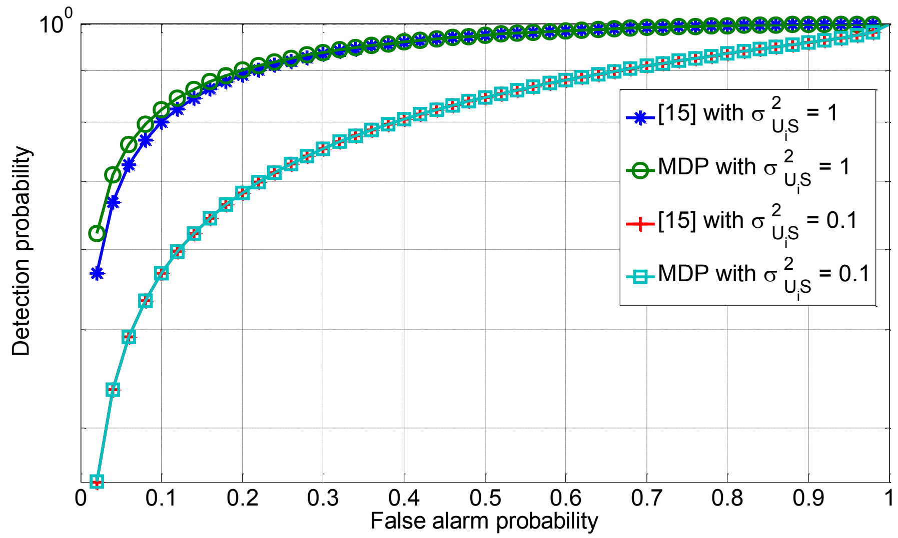

Fig. 7. The detection probability versus the false alarm probability for MDP rule

Third, we depict the detection probability versus the false alarm probability in **Fig. 7** for MDP rule and the method in [15], respectively. In this case, we set $N = 10$ and

$\gamma_P = \gamma_{U_i} = -5$ dB. Then, under the same simulation settings, we compare the sensing time of MDP with that of the method of [15] in **Fig. 8** and **Fig. 9**, respectively. From **Fig. 7**, we know that the sensing accuracy of MDP rule is no lower than that of the method in [15], and even higher when the quality of reporting channel is good. Besides, the sensing accuracy will be improved as the quality of reporting channels goes high.

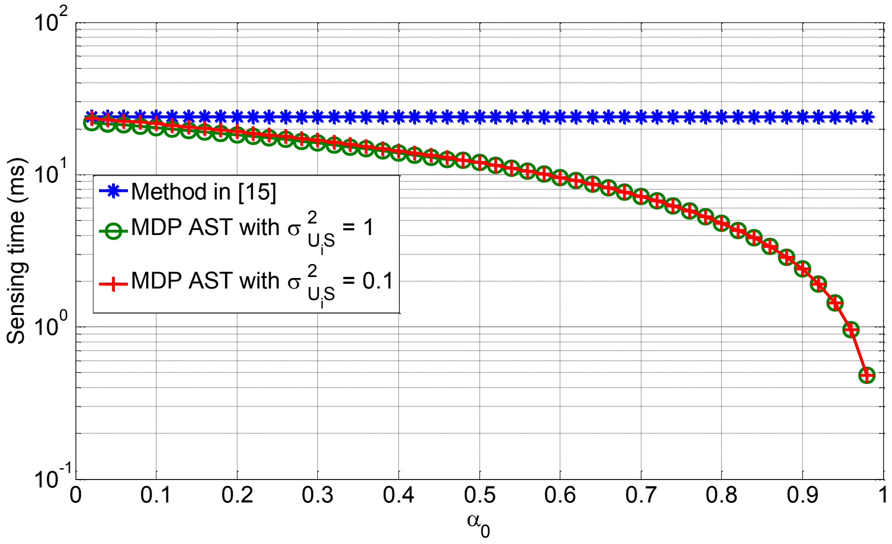

Fig. 8. The AST versus α_0 for MDP rule

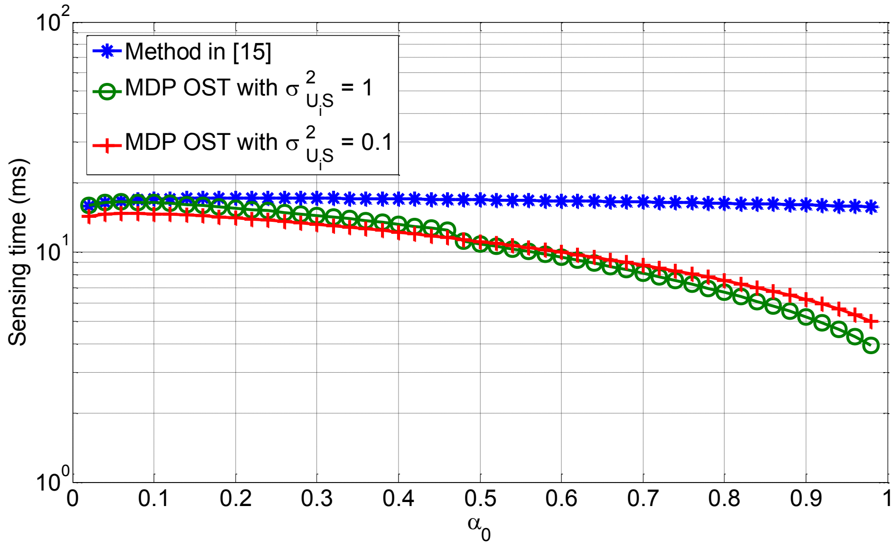

Fig. 9. The OST versus α_0 for MDP rule

On the other hand, we can easily observe from **Fig. 8** and **Fig. 9** that MDP rule can remarkably reduce the sensing time as compared to the method in [15] while maintaining the sensing accuracy. When α_0 is low, the AST of MDP rule is higher under $\sigma^2_{U_i S} = 0.1$ than under $\sigma^2_{U_i S} = 1$ due to the lower probability of detecting PU's absence in each reporting sub-slot. However, the OST is higher under $\sigma_{U_iS}^2 = 1$ than under $\sigma_{U_iS}^2 = 0.1$ since the sensing time in detecting PU's presence is longer in this case. When α_0 is high, the AST of MDP rule under $\sigma_{U_iS}^2 = 0.1$ will approach to that under $\sigma_{U_iS}^2 = 1$ because the probablities of detecting PU's absence in each reporting sub-slot under these two cases will get close to each other. But, the OST of MDP rule under $\sigma_{U_iS}^2 = 0.1$ becomes higher than that under $\sigma_{U_iS}^2 = 1$, which is due to the fact that the probability of detecting PU's presence in each reporting sub-slot is lower under $\sigma_{U_iS}^2 = 0.1$ than under $\sigma_{U_iS}^2 = 1$. Besides, the AST and OST of MDP rule will decrease as α_0 is improved eventually due to an improved local sensing reliability.

8. Conclusion

In this paper, we propose a fast cooperative sensing scheme, called DTF, to reduce the sensing overhead while maintaining the sensing accuracy for CRNs. DTF uses two fusion thresholds to make a final decision sequentially at the FC in each reporting sub-lot, which has been shown as a promising method to reduce both the time for correctly detecting the presence of PU and that for finding the spectrum holes under the detection probability constraints. Besides, we develop three novel rules, i.e., MA, MPA and MDP, to obtain the optimum fusion thresholds with different objectives for DTF. Finally, simulation results are provided to confirm the effectiveness of proposed fusion rules and also make performance comparisons between DTF and existing schemes. Note that DTF can be easily extended to other local detector cases, such as matched filter detection, feature detection, etc.

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