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RESEARCH ARTICLE

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# An efficient cooperative sensing scheme with bandwidth-limited control channel



**Abstract** The conflict between scarcity of spectrum resources and low spectrum utilization motivates the concept of cognitive radio, which allows secondary unlicensed users to borrow temporally unused spectrum bands from primary licensed users. Spectrum sensing is one of the key functionalities that enable spectrum hole discovery and interference avoidance. As single user spectrum sensing may experience performance degradation in harsh wireless environment due to fading and shadowing, user cooperation is introduced to exploit spatial diversity for better sensing performance. However, local sensing results must be transmitted via a control channel. The advantage of cooperative sensing can be compromised by bandwidth limitation of the control channel. To overcome this, a benching cooperative sensing scheme is proposed in this paper. This scheme can reduce time overhead of sensing information exchange under a communication constraint. Analytical results of periodic sensing efficiency are then deduced while sensing parameters are optimized. Based on these, a recursive sensing algorithm exploiting prior channel state information is developed. Numerical results are presented to demonstrate the potential of our scheme.

**Keywords** cognitive radio, cooperative sensing, energy detection, data fusion

## 1 Introduction

During the last couple of decades, the world has witnessed the dramatic development of wireless communications. Along with such a rapid growth, the demand for radio frequency spectrum is continuously increasing. In conventional wireless communication systems, fixed spectrum allocation and exclusive usage pattern are deployed. This fixed allocation policy results in the scarcity of unallocated spectrum, which is likely to limit the future development of wireless services. On the other hand, recent surveys have revealed that most allocated frequency bands are under low spectrum utilization due to the exclusive spectrum usage mechanism. This conflict motivates the concept of cognitive radio which enables opportunistic spectrum sharing. In a cognitive radio network (CRN), secondary users (SUs) are allowed to reuse spectrum bands that are temporally unoccupied by primary users (PUs) and therefore increase spectrum utilization directly. The premise of opportunistic access for SUs is not to introduce interference to PUs, which is enabled by a key functionality called spectrum sensing. SUs are required to sense and monitor the state of the target frequency band. If the band is idle, SUs can make use of it. Once the band is occupied, SUs have to keep quiet or switch to another band.

As one of the most challenging problems of cognitive radio, spectrum sensing has been gaining much attention recently. Basic spectrum sensing algorithms include energy detection, matched filter and cyclostationary feature detection [1]. Energy detection requires no prior information about the property of transmitted signals of PUs and therefore becomes a general sensing method. Besides, as the spectrum sensing performance of a single SU is usually compromised by destructive channel conditions, such as deep fading and shadowing, cooperative spectrum sensing is introduced [2,3]. By combining sensing results of individual SUs, cooperative sensing can exploit spatial diversity among SUs and improve the sensing performance. A survey of cooperative sensing can be found in Ref. [4]. In Ref. [5], linear data fusion optimization is studied, while discussion about sensing time optimization can be found in Ref. [6].

In a CRN, the bandwidth constraint of the control channel is a negative factor for cooperative sensing. Sensing performance may suffer great degradation from

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the time overhead of sensing result exchange. To overcome this, optimization of decision fusion mechanism under the communication constraint is discussed in Ref. [7]. In this paper, we are proposing a more efficient cooperative sensing scheme. In the network level, linear data fusion is adopted to make a better decision. To mitigate the performance degradation caused by bandwidth limitation, a benching cooperative sensing scheme is proposed. Furthermore, sensing parameters are optimized, and a recursive sensing algorithm is developed to achieve higher sensing efficiency.

The remainder of this paper is organized as follows. Section 2 presents the system model of cooperative sensing and the framework of our sensing scheme. In Sect. 3, analytical results of sensing performance are derived. Optimization of sensing parameters and fusion rule is given in Sect. 4. Finally, numerical results and conclusion are presented in Sects. 5 and 6, respectively.

## 2 System model

### 2.1 Cognitive radio network architecture

Consider a CRN with $K$ secondary users and a fusion center. During spectrum sensing, each SU senses the state of a target channel independently and sends the local sensing result to the fusion center, as shown in Fig. 1. The fusion center then combines the local sensing results according to a certain fusion rule and makes a global decision. Let $S$ represent the actual channel state, where $S\in\{1(H_1), 0(H_0)\}$. $H_1$ denotes that the channel state is busy or PU is active, while $H_0$ denotes that the channel state is idle or PU is inactive. Let $\theta$ denote the decision of the fusion center. $\theta$ is sent back to SUs through broadcasting.

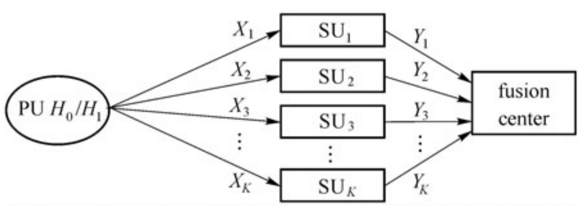


**Fig. 1** Cognitive radio network architecture

Detection of the channel state is a binary hypothetical test. Let $s(n)$ denote the transmitted signal of the PU and $h_k$ denote the channel gain from PU to the $k$th SU. We assume that $h_k$ is known and remains static during the sensing cycle. The signal received by the $k$th SU can be presented by

$$x_k(n)=\begin{cases}u_k(n), & H_0,\\ h_k s(n)+u_k(n), & H_1,\end{cases} \quad (1)$$

where $u_k$ is the additive white Gaussian noise (AWGN) of the $k$th SU. The noise power of $u_k$ is denoted by $\sigma_{uk}^2$.

### 2.2 Channel usage pattern and periodic sensing

For CRN, the channel state is always varying randomly. In this paper, we use the ON/OFF switch model to describe the channel usage pattern, which can be depicted by a two-state continuous Markov process. To avoid interference, CRN has to monitor the channel continuously. Unfortunately, SUs cannot transmit data and sense the channel simultaneously. A remedial approach is periodic sensing, as shown in Fig. 2. Each sensing cycle consists of two stages, spectrum sensing and data transmission. In the spectrum sensing stage, all SUs stop transmission and cooperate with others to sense the channel state. Once the channel is available, SUs can access the channel and transmit their own package. Otherwise, they shall wait for the next sensing cycle or switch to a new band. We assume the duration of a sensing period is fixed, but the sensing time is variable. Meanwhile, the sensing period is designed to be far less than the mean sojourn time of channel states. In this case, periodic sensing is equivalent to fixed period sampling of the channel state. We can use a two-state discrete Markov process to describe this random process, as shown in Fig. 3. Transitions between different states can be depicted by transition probability matrix

$$P=\begin{bmatrix}P_{00} & P_{01}\\ P_{10} & P_{11}\end{bmatrix}.$$

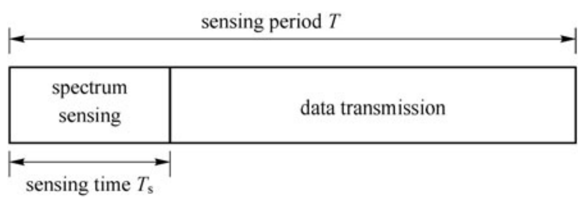


**Fig. 2** Two stages of periodic sensing

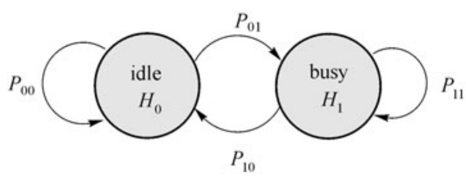


**Fig. 3** Channel usage pattern

### 2.3 Control channel bandwidth constraint and benching cooperative sensing scheme

In a CRN, SUs need to access a control channel to send local sensing results. For CRNs, a control channel can be an ultra-wideband (UWB) channel, an industrial, scientific and medical (ISM) channel, or part of an unused licensed channel. The design of a practical control channel is out of the concern in this paper. We assume there is a dedicated control channel independent from the target channel, and the bandwidth of the control channel is constrained. As a result, it is impossible for SUs to send all data samples to the fusion center for a centralized detection. SUs have to execute local sensing and then send the results only. We adopt energy detection as the local sensing algorithm. Each SU calculates its local sensing result by

$$Y_k = \frac{1}{\sigma_{uk}^2}\sum_{n=1}^{N_k}|x_k(n)|^2,\ k = 1,2,...,K, \tag{2}$$

where $N_k$ is the number of effective samples received by the $k$th SU; and $N_k = 2BT_{sk}$, $B$ is the bandwidth of the target channel, and $T_{sk}$ denotes the sensing time of the $k$th SU.

As for cognitive radio networks, a sensing information exchange stage is needed for SUs to access the control channel and send their sensing results, as shown in Fig. 4. However, the bandwidth constraint of the control channel results in queuing time. Especially when there are many SUs, time overhead of information exchange may cause serious sensing performance degradation.

To overcome this, we propose a benching cooperative sensing scheme in this paper. This scheme combines the two stages of local sensing and information exchange into one single stage. First, we simplify the access of the control channel as a slotted system. SUs can access and send their sensing results in each timeslot. Second, a time division multiple access (TDMA) mechanism along with benching sensing is deployed. An illustration of a CRN with three SUs is shown in Fig. 5. In this scheme, SUs send their sensing results sequentially. Since the control channel is independent from the target channel, when an SU is transmitting, others can keep sensing until their own turn. Thus, the sensing time for each SU is different. The later an SU sends its result, the longer it can sense. Then the issue of sensing information exchange can be simplified as how to arrange the access order. In a CRN, the access order can be decided by the fusion center according to the sensing performance — specifically, the receiver signal-to-noise ratio (SNR) of each SU, and notified to SUs through broadcasting.

Let $T_{slot}$ denote the duration of a timeslot. Sensing period is of $M_0$ slots, and sensing time is of $M_1$ slots. Suppose the $k$th SU sends its result at slot $m_k$. Then the actual sensing time for it is

$$T_{sk} = T_{slot}(m_k - 1),$$

and the number of effective samples is

$$N_k = 2BT_{slot}(m_k - 1).$$

On the other hand, suppose the sensing result of each SU is quantified into $l$ bits. Then the bandwidth of the control channel is

$$B_c = \frac{l}{T_{slot}}.$$

In the fusion center, sensing results from SUs are fused to make a global decision. Linear data fusion is adopted in our sensing scheme.

$$Y = \sum_{k=1}^{K} w_k Y_k, \tag{3}$$

where $w_k$ is the weight coefficient of the $k$th SU. $Y$ is compared with a threshold $\gamma$. If $Y \geqslant \gamma$, the target channel is considered to be busy. Otherwise, the target channel is available.

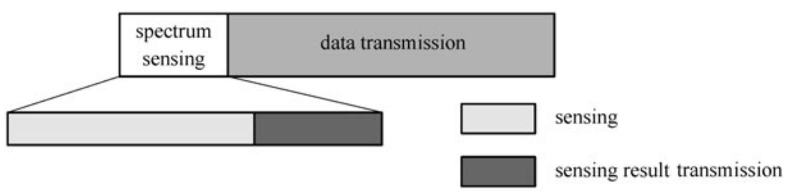


**Fig. 4** Periodic sensing with stage of sensing result exchange

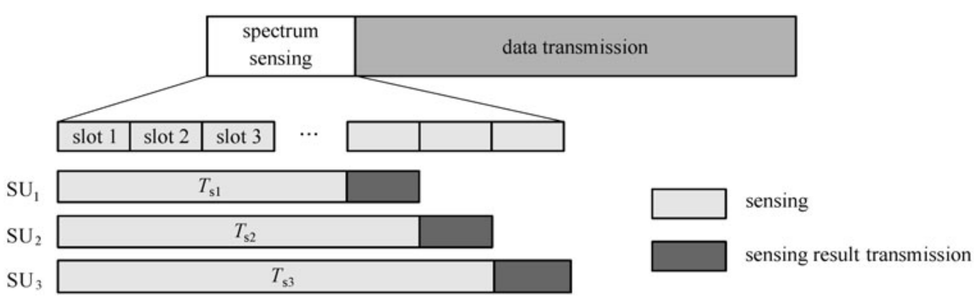


**Fig. 5** Benching cooperative sensing in a CRN with three SUs

## 3 Sensing performance analysis

According to Ref. [8], $Y_k$ in Eq. (2) follows a central chi-square distribution with $N_k$ degrees of freedom under the hypothesis of $H_0$. Otherwise, $Y_k$ follows a non-central chi-square distribution with $N_k$ degrees of freedom and a non-central parameter of $N_k\lambda_k$, where

$$\lambda_k = \frac{E_s|h_k|^2}{N_k\sigma_{uk}^2}$$

is the receiver SNR of the $k$th SU, and

$$E_s = \sum_{n=1}^{N_k}|s(n)|^2$$

is the energy of the PU signal during sensing time $T_k$. For a large $N_k$, the asymptotical distribution of $Y_k$ is

$$Y_k \sim \begin{cases} N(N_k, 2N_k), & H_0, \\ N\Big(N_k(1+\lambda_k), 2N_k(1+2\lambda_k)\Big), & H_1, \end{cases} \quad (4)$$

where $N(a, b)$ is a Gaussian distribution with expectation of $a$ and variance of $b$.

From Eqs. (3) and (4), we can deduce the probability distributions of $Y$ under $H_0$ and $H_1$:

$$\begin{cases} H_0 : N\left(\sum_{k=1}^{K} w_k N_k, 2\sum_{k=1}^{K} w_k^2 N_k\right), \\ H_1 : N\left(\sum_{k=1}^{K} w_k (1+\lambda_k) N_k, 2\sum_{k=1}^{K} w_k^2 (1+2\lambda_k) N_k\right). \end{cases} \quad (5)$$

Detection probability $P_\mathrm{d}$ and false alarm probability $P_\mathrm{f}$ can be derived by comparing $Y$ and the threshold $\gamma$:

$$P_\mathrm{d} = \Pr[Y \geqslant \gamma | H_1] = Q\left(\frac{\gamma - \sum_{k=1}^{K} w_k(1+\lambda_k)N_k}{\sqrt{2\sum_{k=1}^{K} w_k^2(1+2\lambda_k)N_k}}\right), \quad (6)$$

$$P_\mathrm{f} = \Pr[Y \geqslant \gamma | H_0] = Q\left(\frac{\gamma - \sum_{k=1}^{K} w_k N_k}{\sqrt{2\sum_{k=1}^{K} w_k^2 N_k}}\right). \quad (7)$$

Note that the ultimate goal of cognitive radio networks is to improve spectrum utilization while limiting potential interference to PUs. Here we define sensing efficiency $\eta$ to be the efficiency of discover and exploiting spectrum opportunities. In the case of periodic sensing, $\eta$ can be expressed by

$$\eta = p_0(1-P_\mathrm{f})\left(1-\frac{T_\mathrm{s}}{T}\right), \quad (8)$$

with $p_0$ denoting the prior probability that the target channel is idle.

On the other hand, interference to PUs is mainly caused by miss detection and inappropriate access. Thus, we can use the probability of miss detection when PU is active as the metric of interference, which can be denoted by

$$P_\mathrm{I} = p_1(1-P_\mathrm{d}),$$

where $p_1$ denotes the prior probability that the target channel is occupied. By introducing a constraint

$$p_1(1-P_\mathrm{d}) \leqslant \overline{P}_\mathrm{I}, \quad (9)$$

potential interference can be limited.

Now the optimization problem of sensing efficiency can be concluded as follows:

$$\begin{aligned} &\max_{w,m,\gamma} \eta = p_0(1-P_\mathrm{f})\left(1-\frac{T_\mathrm{s}}{T}\right), \\ &\text{s.t.} \quad P_\mathrm{I} = p_1(1-P_\mathrm{d}) \leqslant \overline{P}_\mathrm{I}. \end{aligned} \quad (10)$$

## 4 Sensing performance optimization

Searching for the optimal solution of Eq. (10) is too complicated for online operation. In this section, we will use some approximation to simplify the problem and derive a simple, but near-optimal solution.

First, the optimization problem of Eq. (10) can be decomposed into two optimization problems:

$$\begin{aligned} &\min_{w,m,\gamma} P_\mathrm{f}(M_1), \\ &\text{s.t.} \begin{cases} p_1(1-P_\mathrm{d}) \leqslant \overline{P}_\mathrm{I}, \\ m_k \leqslant M_1, \ k = 1,2,\ldots,K, \end{cases} \end{aligned} \quad (11)$$

and

$$\begin{aligned} &\max_{M_1} \eta = p_0\Big(1-P_\mathrm{f}^*(M_1)\Big)\left(1-\frac{M_1}{M_0}\right), \\ &\text{s.t.} \quad 0 \leqslant M_1 \leqslant M_0, \end{aligned} \quad (12)$$

where $P_\mathrm{f}^*(M_1)$ is the optimized false alarm probability of Eq. (11).

### 4.1 Suboptimal weight coefficient and access order

As for optimization problem Eq. (11), using the first constraint, we can get the optimal threshold as

$$\gamma^* = Q^{-1}\left[\left(1-\frac{\overline{P}_\mathrm{I}}{p_1}\right)^+\right]\mathrm{Var}(Y|H_1) + E(Y|H_1), \quad (13)$$

where $(a)^+$ denotes $\max\{a,0\}$. Equation (10) can be simplified as

$$\min_{w,m} P_{\mathrm{f}}(M_1),$$
$$\text{s.t. } m_k \leqslant M_1,\ k = 1,2,...,K. \tag{14}$$

This optimization problem has a complicated expression and is a non-convex optimization problem. Therefore, in this paper, we introduce the following approach to find suboptimal weight coefficients and transmission order:

$$\max_{w,m} \frac{E(Y|H_1)-E(Y|H_0)}{\sqrt{\mathrm{Var}(Y|H_0)}}. \tag{15}$$

Constraints are the same as Eq. (11). By substituting Eq. (5), Eq. (13) can be represented by

$$\max_{w,m} \frac{\sum_{k=1}^{K} w_k\lambda_k(m_k-1)}{\sqrt{\sum_{k=1}^{K} w_k^2(m_k-1)}}. \tag{16}$$

Optimal weight coefficients of Eq. (14) can be obtained by applying the Cauchy-Schwartz inequality.

$$\frac{\sum_{k=1}^{K} w_k\lambda_k(m_k-1)}{\sqrt{\sum_{k=1}^{K} w_k^2(m_k-1)}} \leqslant \sqrt{\sum_{k=1}^{K} \lambda_k^2(m_k-1)}. \tag{17}$$

The equivalence case stands if and only if

$$w_k\sqrt{m_k-1} = \alpha\lambda_k\sqrt{m_k-1}, \quad k = 1,2,...,K. \tag{18}$$

Without loss of generality, let $\alpha = 1$. Then

$$w_k^* = \lambda_k, \quad k = 1,2,...,K, \tag{19}$$

are the suboptimal weight coefficients of linear data fusion. And Eq. (14) can be simplified as

$$\max_{m} \sum_{k=1}^{K} \lambda_k^2(m_k-1). \tag{20}$$

Suppose $\lambda_1 \leqslant \lambda_2 \leqslant \cdots \leqslant \lambda_K$. The suboptimal access order can be derived:

$$m_k^* = (M_1 - K + k)^+, \quad k = 1,2,...,K. \tag{21}$$

This result reveals that SUs with a relatively high SNR should send their sensing results later, and those with a low SNR should send earlier. If sensing time slots are not enough for all SUs to transmit their results, then SUs with the lowest SNR do not have to run spectrum sensing.

### 4.2 Asymptotic optimality of linear data fusion in a low SNR

In the former data fusion part, we adopt linear data fusion without explanation; based on that, we obtain a suboptimal solution. In this subsection, we will explain why linear fusion is deployed. We shall prove that linear data fusion with the suboptimal weight coefficients in Eq. (17) is actually an asymptotically optimal fusion rule in the low SNR case.

**Proof** In the low SNR case, in Eq. (5), $1 + 2\lambda_k \approx 1$. Then the log-likelihood ratio of all the sensing results received can be derived:

$$\ln\frac{f(Y_1,Y_2,...,Y_K|H_1)}{f(Y_1,Y_2,...,Y_K|H_0)} = \sum_{k=1}^{K}\ln\frac{f(Y_K|H_1)}{f(Y_K|H_0)} = \frac{1}{2}\sum_{k=1}^{K} Y_k\lambda_k - \frac{1}{4}\sum_{k=1}^{K} N_k\lambda_k(2+\lambda_k). \tag{22}$$

Therefore, the best global fusion statistic is

$$Y = \sum_{k=1}^{K} \lambda_k Y_k,$$

which is the same as linear data fusion with suboptimal weight coefficients.

Note that a low SNR caused by deep fading and shadowing is the main motivation of cooperative sensing. Therefore, our suboptimal solution can achieve near-optimal performance in most cases.

### 4.3 Sensing time optimization

As for optimization problem Eq. (12), we can see that $P_{\mathrm{f}}^*(M_1)$ is a monotonically decreasing function in the interval of $0 \leqslant M_1 \leqslant M_0$. Thus, $1 - P_{\mathrm{f}}^*(M_1)$ is a monotonically increasing function in the same interval, and $0 \leqslant 1 - P_{\mathrm{f}}^*(M_1) < 1$. On the other hand, $1 - M_1/M_0$ is a monotonically decreasing function of $M_1$, and $0 \leqslant 1 - M_1/M_0 \leqslant 1$. Therefore, there exists a unique maximum of $\eta = \left(1 - P_{\mathrm{f}}^*(M_1)\right)(1 - M_1/M_0)$ in the interval of $0 \leqslant M_1 \leqslant M_0$. The optimal sensing time slots $M_1^*$ and the corresponding sensing efficiency $\eta^*$ can be found by Algorithm 1.

**Algorithm 1** Optimal sensing time searching

Solve

$$\eta(m+1) - \eta(m) = 0,$$

where $m$ is a continuous variable, and $0 \leqslant m < M_0$.

**if** a solution $m^*$ is found, **then**

$$\eta^* = \max\{\eta(\lfloor m^* \rfloor), \eta(\lfloor m^* \rfloor + 1)\}$$

**else**

$$\eta^* = \eta(0)$$

**end if**

$$M_1^* = \arg\ \eta^*$$

### 4.4 Prior probability acquisition

With the assumption of a Morkovian channel usage pattern, the prior probability of the channel state can be obtained through two ways. One is the steady-state distribution. The other is to calculate it dynamically with the state of last sensing cycle and the transition probability matrix $P$. Obviously, the second approach can get a closer result to the actual channel state. However, knowledge of the state of the last sensing cycle can be wrong due to potential miss detection and false alarm. What we can exploit is the posterior probability of the channel state in the last sensing cycle, which is determined by the sensing parameters of the last cycle. This motivates a recursive approach for periodic sensing.

The prior probability of the $n$th sensing cycle can be derived from

$$\pi[n|n-1] = \pi[n-1|n-1]P, \tag{23}$$

where

$$\pi[n-1|n-1] = (p_0[n-1|n-1], p_1[n-1|n-1])$$

is the posterior probability distribution of the last sensing cycle.

$$p_i[n|n] = \frac{p_i[n|n-1]p(\theta|S)}{\sum_{S=0}^{1} p_i[n|n-1]p(\theta|S)}, \quad i = 0,1, \tag{24}$$

where $p(\theta|S)$ represents the sensing performance. $p(0|0) = 1-P_{\mathrm{f}}$, $p(1|0) = P_{\mathrm{f}}$, $p(0|1) = 1-P_{\mathrm{d}}$, and $p(1|1) = P_{\mathrm{d}}$.

### 4.5 Section summary

Now, a high efficiency cooperative sensing algorithm can be developed as follows.

**Algorithm 2** High efficiency cooperative sensing algorithm

1) (Initialization) Let the steady-state distribution be the prior probability of the channel state.

2) Use the optimal sensing time searching algorithm to find the optimal sensing time.

3) Use Eqs. (17) and (19) to obtain the suboptimal weight coefficients, access order and decision threshold.

4) Run benching cooperative sensing.

5) If the target channel is busy, switch to another channel and return to 1). Otherwise, SUs can utilize the channel.

6) Calculate the posterior probability of the channel state by Eq. (22).

7) Calculate the prior probability of the next sensing cycle by Eq. (21) and return to 2).

## 5 Numerical results

In this section, we will present numerical results to demonstrate the potential of our sensing scheme. Throughout this section, we use the following settings. The number of SUs is 5. Signal-to-noise ratios are −19 dB, −17 dB, −15 dB, −13 dB, and −11 dB, respectively. The sensing period is 10 ms. The sampling frequency is 1 MHz, corresponding to a target channel bandwidth of $B = 500$ kHz.

In Fig. 6, receiver operating characteristic (ROC) curves of benching cooperative sensing algorithms under different control channel bandwidth constraints are given. The

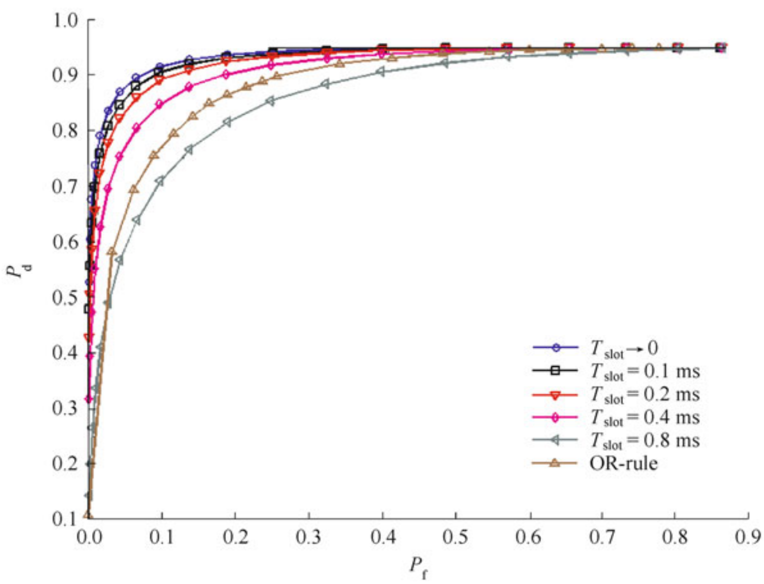


**Fig. 6** ROC curves of benching sensing with different timeslots

sensing time $T_s$ is 2 ms. Variation of the control channel bandwidth results in different $T_{slot}$. $T_{slot} \to 0$ denotes the ideal case that the bandwidth is infinity. $T_{slot} = 0.1$ ms, 0.2 ms. 0.4 ms, 0.8 ms correspond to different bandwidth constraints. Suppose each local sensing result is quantified with 8 bit; data transmission rates of the control channel are 80 kbit/s, 40 kbit/s, 20 kbit/s, and 10 kbit/s respectively. The ROC curve of the OR-rule sensing scheme without communication constraint is also presented to make a comparison. As we can see, cases of $T_{slot} = 0.1$ ms and $T_{slot} = 0.2$ ms have close sensing performance as the ideal case $T_{slot} \to 0$. Only when the bandwidth of the control channel is strictly constrained that most SUs have no chance to send their results, sensing performance is degraded to worse than the OR-rule scheme.

When sensing time increases, sensing performance of linear data fusion can be rapidly improved. Figure 7 shows how $P_f$ decreases when sensing time increases. $T_{slot}$ is set as 0.2 ms, and $P_d$ is set as 0.9. We can see that, in the case control, the channel bandwidth is constrained; sensing performance of the OR-rule is better when sensing time is less than 0.4 ms, or 2 slots. However, when sensing time increases, $P_f$ of the data fusion scheme decreases to 0 much faster than the OR-rule scheme.

In Fig. 8, sensing efficiency of the benching sensing scheme with limited potential interference is presented.

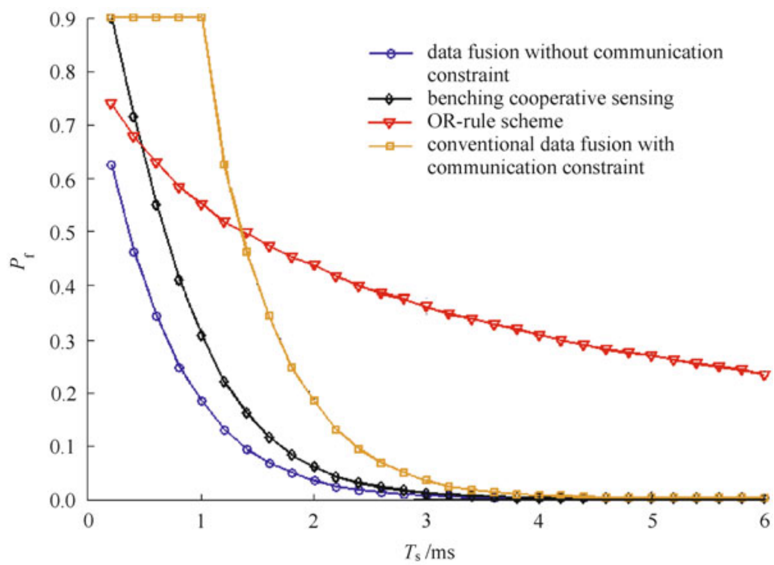


**Fig. 7** Comparison of different sensing schemes

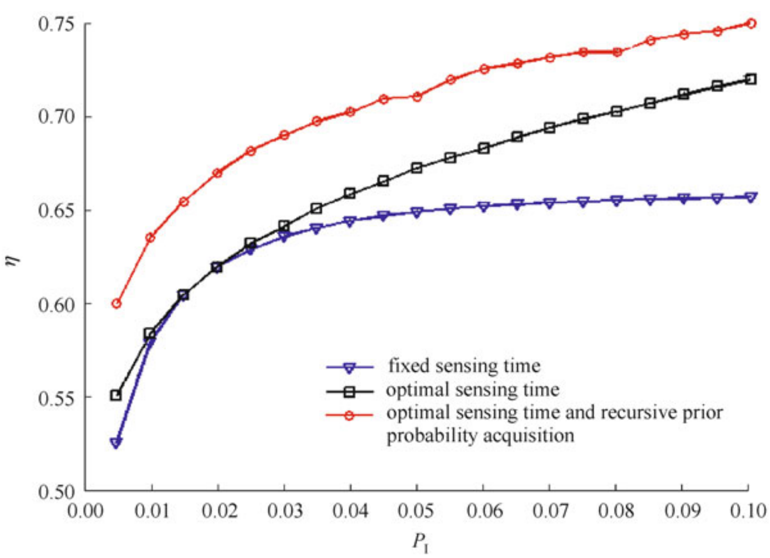


**Fig. 8** Performance improvement with sensing time optimization and prior channel state information

Transition probability matrix is set as

$$P = \begin{bmatrix} 0.95 & 0.05 \\ 0.2 & 0.8 \end{bmatrix}.$$

Thus, the steady-state probability distribution is

$$\pi^* = [p_0^* \ p_1^*] = [0.8 \ 0.2].$$

As one can see, sensing efficiency $\eta$ with given interference limitation $P_{\mathrm{I}}$ is notably improved by optimizing sensing and exploiting the prior probability of the channel state. Because sensing time is usually a small part of a sensing period, the improvement of sensing efficiency indicated remarkably reduction of the actual sensing time.

## 6 Conclusion

In this paper, a benching cooperative spectrum sensing scheme is proposed to reduce time overhead introduced by the control bandwidth constraint. Linear data fusion is deployed. Near-optimal weight coefficients and access order are derived. Sensing time optimization and prior channel state information are also exploited to achieve the best performance. Through simulation, the advantage of our sensing scheme is testified.

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