Cooperative Spectrum Sensing with a Progressive MAP Detection Algorithm

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Abstract— **In this paper, a new cooperative spectrum sensing algorithm is proposed for a cognitive radio network with multiple secondary users (SUs) sharing spectrum with one or more primary users (PUs). Unlike most previous spectrum sensing algorithms that do not consider the time domain traffic statistics of the PU, the algorithm in this paper is developed by exploiting the statistical properties of the PU's transmission pattern, which is modeled with a Markov chain with two states: busy (1) and idle (0). Each SU performs energy detection based on an observation of the Markov chain, and the detection results are forwarded to a fusion center (FC) through a noisy channel. The FC recovers the decisions of the SUs by using a new progressive maximum *a posteriori* (MAP) algorithm, where the *a priori* probability essential to the MAP detection is obtained by progressively estimating the transition probabilities of the Markov chain. Analytical expressions are derived for the probabilities of false alarm and missing detection, with both the majority data fusion rule and the OR data fusion rule. Both theoretical analysis and simulation results indicate that the proposed algorithm can provide reliable and efficient spectrum sensing over a large range of system configurations.**

I. Introduction

Cognitive radio, which provides flexible spectrum accesses by dynamically sensing and adapting to the surrounding radio environment, is quickly emerging as one of the most promising technologies for improving the utilization of the precious spectrum resources [1] - [3]. The proper operation of a cognitive radio network depends on the reliable and efficient spectrum sensing, with which a secondary user (SU) can detect the spectrum holes in the time-frequency plane and avoid interference to the licensed or primary users (PUs) [4].

Recently, there have been considerable efforts devoted to the development of spectrum sensing algorithms in cognitive radio networks [5] - [9]. It is shown in [5] that the energy detector is optimum in detecting weak unknown signals with zero-mean known constellations. The performance of spectrum sensing with energy detection can be significantly improved by allowing multiple SUs to cooperate with each other [6] - [9]. The cooperative spectrum sensing is usually performed in two steps: each SU performs energy detection individually, then a fusion center (FC) makes decision on the state of the channel by collecting detection results from the SUs. In [6], a noise-free channel is assumed between the SUs and the FC, and the noise-free assumption is not true in reality. Practical channel is considered in [7], where the FC detects the noisy signal from the SUs with a maximum *a posteriori* (MAP) decision rule. The MAP detector requires the knowledge of the *a priori* probability, which is estimated by assuming an infinite number of SUs. In [9], the SUs forward soft information, instead of binary hard decisions, to the FC. Soft information forwarding improves the sensing performance at the cost of significantly increased bandwidth requirement between the SUs and the FC. In addition, none of the above works consider the PUs' traffic patterns, which might be critical to the spectrum sensing performance.

In this paper, we propose a new cooperative spectrum sensing algorithm by exploiting the statistical traffic patterns of the PU. The transmission pattern of the PU is assumed to follow a Markov chain with two states: busy (1) and idle (0) [10]. Consequently, the binary energy detection results at the SUs, which can be considered as passing the two-state Markov chain through a binary symmetric channel, form a new Markov chain. The new algorithm is motivated by the time domain correlations of the Markov chain. The FC recovers the binary energy detection results of the SUs with a new progressive MAP algorithm, where the *a priori* probabilities are obtained by progressively estimating the transition probabilities of the Markov progress in the time domain. It is shown through simulations that the FC with the new algorithm can obtain a very accurate estimation of the SU detections. In most existing works [6], [7], the FC employs the OR data fusion rule over the estimated SU detections, and it is well known that the OR data fusion rule reduces missing detections at the cost of more false alarms. In this paper, the performance of the OR data fusion rule is compared to a majority data fusion rule. Exact analytical expressions of the probability of false alarm and the probability of missing detection are derived for the majority and OR data fusion rules, and their performances are compared through both analytical and simulation results.

II. System Model

Consider a cooperative spectrum sensing system in a cognitive radio network with one PU and N SUs. The traffic pattern of the PU is assumed to be a Markov chain with two states: idle (0) and busy (1), with the one-step transition probabilities being p_{00} and p_{10}.

The cooperative spectrum sensing is performed with a two-step protocol as shown in Fig. 1. In the first step, each SU performs energy detection to sense the state of the PU, and makes a binary decision (busy or idle) based on the local sensing result. In the second step, the SUs forward their

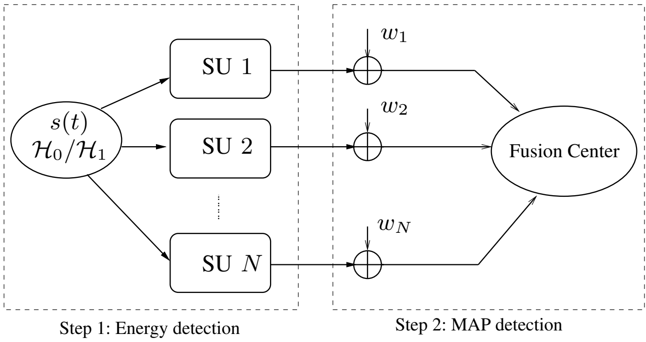

Fig. 1. Block diagram of a cooperative spectrum sensing in cognitive radio networks.

individually obtained sensing results to a FC, which will make a final decision on the state of the PU by performing data fusion over the noisy observations of the decisions from all the SUs.

In the first step, the hypothesis test of the energy detection performed by the n-th SU can be represented as [11], [12],

$$\begin{aligned} \mathcal{H}_0 : r_n(t) &= v_n(t), \\ \mathcal{H}_1 : r_n(t) &= s(t) + v_n(t), \end{aligned} \tag{1}$$

where $s(t)$ is a bandlimited signal from the PU with an one-sided bandwidth W, $v_n(t)$ is the additive white Gaussian noise (AWGN) with one-sided power spectral density N_{0v}, and $r_n(t)$ is the signal observed by the n-th SU.

The energy detection is performed by using signals observed during an interval of duration T. It is assumed that the state of the channel does not change within T. This assumption can be easily met by choosing a small enough T. The test statistic used by the n-th SU during the k-th detection interval, $R_n(k)$, is obtained by passing the received signal, $r_n(t)$, through an energy detector as shown in Fig. 2. The low pass filter (LPF) in the energy detector has a cut off frequency of W, and it is used to limit the bandwidth of the white noise. After a s square law device and a finite time integrator, the output of the energy detector can be expressed as [11],

$$R_n(k) = \frac{1}{N_{0v}} \int_{(k-1)T}^{kT} |r_n(t)|^2 dt = \sum_{i=1}^{2u} \left(\frac{s_i + v_{ni}}{\sqrt{N_{0v} W}} \right)^2, \tag{2}$$

where $u = TW$ denotes the time bandwidth product, with W being the one-sided bandwidth of the signal, $v_{ni} = v_n(\frac{i}{2W})$ and $s_i = s(\frac{i}{2W})$ are the noise sample and signal sample, respectively. The noise sample, v_{ni}, is a zero mean Gaussian random variable with variance, $N_{0v}W$, i,e, $v_{ni} \sim N(0, N_{0v}W)$.

The test statistic, $R_n(k)$, has the following distributions [11], [12],

$$R_n(k) \sim \begin{cases} \chi^2_{2u}, & \mathcal{H}_0, \\ \chi^2_{2u}(2\gamma_s), & \mathcal{H}_1, \end{cases} \tag{3}$$

where χ^2_{2u} denotes the central chi-square distribution with $2u$-degree of freedom, $\chi^2_{2u}(2\gamma_s)$ is the non-central chi-square distribution with $2u$-degree of freedom and a non-centrality parameter $2\gamma_s$, $\gamma_s = \frac{E_0}{N_{0v}}$ is the signal-to-noise ratio (SNR), and $E_0 = \int_0^T s^2(t)dt$ is the signal energy.

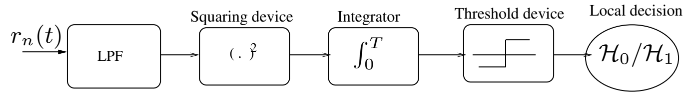

Fig. 2. Block diagram of the energy detector employed at the SU.

During the k-th detection interval, the SU makes decision on the state of the PU by comparing $R_n(k)$ to a predefined threshold, λ, as $b_n(k) = 1$ if $R_n(k) > \lambda$, and $b_n(k) = 0$ otherwise.

Define the probability of false alarm, P_{f_n}, as the probability that a PU is detected by the n-th SU while the PU is idle. The probability of missing, P_{m_n}, is defined vice versa. With the hypotheses test defined in (1), we have [12]

$$\begin{aligned} P_{f_n} &= P_r(R_n > \lambda|\mathcal{H}_0) = \frac{\Gamma(u, \frac{\lambda}{2})}{\Gamma(u)}, \\ P_{m_n} &= P_r(R_n < \lambda|\mathcal{H}_1) = 1 - Q_u(\sqrt{2\gamma_s}, \sqrt{\lambda}), \end{aligned} \tag{4}$$

where $\Gamma(a, b)$ is the incomplete gamma function, $Q_u(a, b)$ is the generalized Marcum Q-function. The decision threshold, λ, can be chosen to meet the requirements on P_{f_n} and P_{m_n}.

The local decisions from the SUs are transmitted to the FC through an orthogonal media access control (MAC) scheme, such as frequency division multiplexing access (FDMA), to achieve a collision free communication at the FC. The signal received by the FC from the n-th SU can be represented as

$$y_n(k) = \sqrt{E_s} x_n(k) + w_n(k), \tag{5}$$

where $x_n(k) = 2b_n(k) - 1$, E_s is the transmission energy of one symbol, and $w_n(k)$ is the AWGN with one-sided power spectral density N_{0w}. The models in (1) and (5) can be extended to systems with flat fading channels. The FC will make a decision on the state of the PU by collecting the information from all the SUs.

III. A New Cooperative Spectrum Sensing Algorithm

A new data fusion algorithm at the FC is proposed in this section to improve the performance of the cooperative spectrum sensing.

A. MAP detection with Progressively Updated A Priori Information

In this subsection, a new MAP decision rule with progressively updated *a priori* information is proposed to improve the detection performance at the FC.

The FC detects the information transmitted by the n-th SU with the MAP detection rule as

$$\hat{x}_n(k) = \underset{b \in \mathcal{B}}{\operatorname{argmax}}\, p(y_n(k)|x_n(k) = b) P(x_n(k) = b), \tag{6}$$

where $\mathcal{B} = \{-1, 1\}$, and $p(y_n(k)|x_n(k) = b) = \frac{1}{\sqrt{\pi N_{0w}}} \exp\left\{-\frac{1}{N_{0w}} \left|y_n(k) - \sqrt{E_s} b\right|^2\right\}$. The above detection rule can be alternatively represented as $\hat{x}_n(k) = 1$, if $y_n(k) \geq \tau_n(k)$, and $\hat{x}_n(k) = -1$ otherwise, where the threshold, $\tau_n(k)$, is

$$\tau_n(k) = \frac{N_{0w} \ln\left(\frac{1-P_n(k)}{P_n(k)}\right)}{4\sqrt{E_s}}, \tag{7}$$

with $P_n(k) = P(x_n(k) = 1) = P(b_n(k) = 1)$ being the probability that a PU is detected by the n-th SU.

The MAP decision rule requires the knowledge of the *a priori* probability, $P_n(k)$, which is usually not available at the receiver. We propose to progressively estimate the *a priori* probability by using a sliding window that contains the received signal and decisions from the previous K detection intervals, as well as the statistical properties of the Markov chain.

Since $x_n(k)$ is obtained through independent observations of a Markov chain, it is easy to show that $x_n(k)$ is also a Markov chain with two states: 0 ($x_n(k) = -1$) and 1 ($x_n(k) = 1$). Define the transition probabilities of $x_n(k)$ as $q_{n00} = P(x_n(k) = -1|x_n(k-1) = -1)$ and $q_{n10} = P(x_n(k) = 1|x_n(k-1) = -1)$. When the Markov chain enters the stable state, the *a priori* probability can be expressed as [14]

$$\lim_{k\to\infty} P_n(k) = \frac{1-q_{n00}}{1+q_{n10}-q_{n00}}. \tag{8}$$

We propose to estimate the value of $P_n(k)$ by using the above relationship. Consider a sliding window with a size K, with $\{y_n(i)\}_{i=k-K}^{k-1}$ and $\{\hat{x}_n(i)\}_{i=k-K}^{K-1}$. When the Markov chain enters the stable state, the transition probability, q_{n00}, can be approximated by

$$\hat{q}_{n00}(k) = \frac{\sum_{i=k-K}^{k-2} I(\hat{x}_n(i+1) = 0 \& \hat{x}_n(i) = 0)}{\sum_{i=k-K}^{k-2} I(\hat{x}_n(i) = 0)}, \tag{9}$$

where $a \& b$ is the AND operation between two logic expressions a and b, and $I(a) = 1$ if the logical expression a is true, and 0 otherwise. The probability $\hat{q}_{n10}$ can be obtained similarly.

The transition probabilities are estimated by using the previous hard decisions. In order to get a better estimate, we propose to also use the soft information, $\{y_n(i)\}_{i=k-K}^{k-1}$. Define $\Delta_k = \frac{1}{K}\sum_{i=k-K}^{k-1} y_n(i)$. Then based on the strong law of large numbers, we have

$$P_n(k) = \frac{1}{2}\left(\frac{1}{\sqrt{E_s}} \lim_{K\to\infty} \Delta_k + 1\right). \tag{10}$$

Combining (8) with (10), we have an over-determined system with two independent equations and one unknown variable, $P_n(k)$. The system can be solved with the least squares (LS) method, and the solution is

$$\hat{P}_n(k) = \frac{1}{4}\left[\frac{\Delta_k}{\sqrt{E_s}} + \frac{2(1-\hat{q}_{n00})}{1+\hat{q}_{n10}-\hat{q}_{n00}} + 1\right]. \tag{11}$$

The estimated *a priori* probability, $\hat{P}_n(k)$, can then be used in (6) to obtain a decision on $x_n(k)$. The simulation results show that the *a priori* probability estimated by using the progressive estimation method described in (11) is very close to its true value.

With this new progressive MAP detection algorithm performed at the FC, define two error probabilities between the n-th SU and the PU as, $e_{n01} = P\{\hat{x}_n(k) = 1|x_n(k) = -1\}$, $e_{n10} = P\{\hat{x}_n(k) = -1|x_n(k) = 1\}$. The values of e_{n01} and e_{n10} will be analyzed in the next subsection.

Once the FC obtains the estimates of the decisions from all the SUs, the results will be combined to estimate the state of the PU. Many existing cooperative spectrum sensing algorithms employ the OR data fusion rule, where the logic OR operation is performed on all the binary decisions [6], [7]. The OR data fusion rule will minimize the probability of missing at the cost of a higher probability of false alarm.

To achieve a better tradeoff between false alarm and missing detection, we will compare the performance of the OR data fusion rule with that of a majority data fusion rule, where the FC will decide in favor of the state that has the most votes from the SUs. In case there is a draw, the FC will decide in favor of the state 1 (busy) to reduce the probability of missing. Based on the above description, the FC with the majority decision rule will decide that the PU is busy during the k-th detection interval if and only if the following condition is met

$$\sum_{n=1}^{N} I(\hat{x}_n(k) = 1) \geq \lfloor N/2 \rfloor, \tag{12}$$

where $\lfloor a \rfloor$ returns the largest integer that is smaller than or equal to a.

B. Performance Analysis

The performance of the proposed cognitive sensing algorithm is analyzed in this subsection.

Given the noisy channel between the SU and the FC, the FC might make decision errors on the information transmitted by the SU. The following lemma gives the error probabilities at the FC during the SU signal detection.

Lemma 1: If the FC has ideal knowledge of the *a priori* probability, $P_n(k)$, then the error probabilities, e_{n01} and e_{n10}, can be calculated as

$$e_{n01} = Q\left(\frac{4E_s - \eta}{\sqrt{8N_{0w}E_s^2}}\right),$$
$$e_{n10} = Q\left(\frac{4E_s + \eta}{\sqrt{8N_{0w}E_s^2}}\right), \tag{13}$$

where $Q(x) = \frac{1}{\sqrt{2\pi}}\int_x^\infty \exp\left(-\frac{u^2}{2}\right) du$ is the Gaussian-Q function, and $\eta = N_{0w} \cdot \ln\left(\frac{P_n(k)}{1-P_n(k)}\right)$.

Proof: The MAP decision rule in (6) will decide on $\hat{x}_n(k) = \hat{b}$ if

$$\left|y_n(k) - \sqrt{E_s}\hat{b}\right|^2 - \left|y_n(k) - \sqrt{E_s}b\right|^2 < \eta, \tag{14}$$

where $\eta = N_{0w} \cdot \ln\left(\frac{P(x_n(k)=\hat{b})}{P(x_n(k)=b)}\right)$, $b, \hat{b} \in \mathcal{B}$, and $b \neq \hat{b}$.

If $x_n(k) = b$ is transmitted, the above decision rule can be alternatively represented as

$$\mathbf{Z} < \eta - E_s|d|^2, \tag{15}$$

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where $\mathbf{Z} = 2d\sqrt{E_s}\Re\{w_n(k)\}$, and $d = b - \hat{b} \in \{-2, 2\}$. The decision variable, $\mathbf{Z}$, is a Gaussian random variable, with mean $\mathbb{E}(\mathbf{Z}) = 0$, and variance $\sigma_{\mathbf{Z}}^2 = 2N_{0w}{E_s}^2|d|^2$. The error probabilities can then be calculated by using $e_{nb\hat{b}} = P\left(\mathbf{Z} < \eta - E_s|d|^2\right)$, and this leads to (13). ∎

After the detection at the FC, the probabilities of false alarm and missing at the FC for the n-th SU can be expressed as follows

$$\begin{aligned}\hat{P}_{f_n} &= {P_f}_n(1 - e_{n10}) + (1 - {P_f}_n)e_{n01}, \\ \hat{P}_{m_n} &= {P_m}_n(1 - e_{n01}) + (1 - {P_m}_n)e_{n10}, \end{aligned} \quad (16)$$

where ${P_f}_n$ and ${P_m}_n$ are defined in (4), and e_{n01} and e_{n10} are given in Lemma 1.

With the above results, we can derive the global probabilities of false alarm and missing for a system with the majority decision rule. The results are stated in the following proposition.

Proposition 1: If the SUs experience independent and identical channels, then the global false alarm probability, P_f, and the global missing probability, P_m, of the proposed cooperative spectrum sensing system with the majority decision rule can be calculated as

$${P_f}^{(MJ)} = \sum_{M=\lfloor N/2 \rfloor}^{N} \binom{N}{M} \hat{P}_{f_n}^{M}(1 - \hat{P}_{f_n})^{N-M}, \quad (17)$$

$${P_m}^{(MJ)} = 1 - \sum_{M=\lfloor N/2 \rfloor}^{N} \binom{N}{M} \hat{P}_{m_n}^{N-M}(1 - \hat{P}_{m_n})^{M}, \quad (18)$$

where $\binom{N}{M}$ is the binomial coefficients, $\hat{P}_{f_n}$ and $\hat{P}_{m_n}$ are given in (16).

Proof: With the majority decision rule, a false alarm happens if $\lfloor N/2 \rfloor$ or more SUs have false alarm after the FC detection. The number of SUs with false alarm at the FC can be modeled with a binomial distribution with parameters N and $\hat{P}_{f_n}$. Based on the probability mass function (PMF) of a binomial random variable, we can get the global false alarm probability as in (17). The probability of missing can be calculated in a similar manner. ∎

The probabilities for the OR decision rule can be obtained by replacing $\lfloor N/2 \rfloor$ in (17) with 1, since a single $\hat{x}_n(k)$ is sufficient for the FC to make a decision in favor of 1. The results are summarized as follows.

Corollary 1: If the SUs experience independent and identical channels, then the probabilities of global false alarm, P_f, and missing, P_m, of the proposed cooperative spectrum sensing system with the OR data fusion rule can be calculated as

$${P_f}^{(OR)} = 1 - (1 - \hat{P}_{f_n})^N, \quad (19)$$

$${P_m}^{(OR)} = \hat{P}_{m_n}^{N}, \quad (20)$$

where $\binom{N}{M}$ is the binomial coefficients, $\hat{P}_{f_n}$ and $\hat{P}_{m_n}$ are given in (16).

IV. Numerical Results

Numerical results are presented in this section to evaluate the performance of the proposed cooperative sensing algorithm.

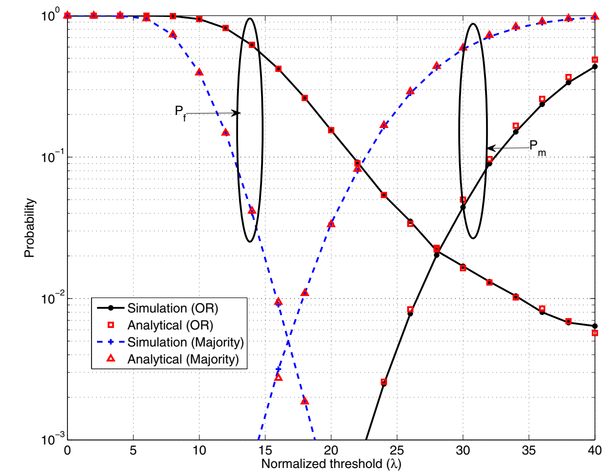

Fig. 3. Comparison between the analytical and simulated P_f and P_m.

In the simulation, the time-bandwidth product is $u = 5$. The traffic pattern of the PU follows a two-state Markov chain with transition probabilities $p_{00} = 0.8$ and $p_{10} = 0.3$. The SNR between the PU and the SU is assumed to be $\gamma_s = 10$ dB. The SNR between the SU and the FC, γ_T, varies for different examples. In the progressive MAP decision rule, the size of the sliding window is $K = 100$.

Fig. 3 shows the global P_f and P_m as a function of the normalized threshold. There are $N = 5$ SUs in the network. The SNR between the SU and the FC is $\gamma_T = 5$ dB. The FC performs detection of the signals from the SUs with the new progressive MAP algorithm. Both the OR and majority data fusion rules are applied to the detection results. Excellent agreement is observed between the analytical and simulation results. It should be noted that the analytical results are obtained under the assumption of perfect *a priori* information. The results indicate the newly proposed progressive algorithm can obtain a very accurate estimation of the *a priori* probabilities. In addition, as expected, the majority rule is better than the OR rule in terms of P_f, and the relationship is reversed for P_m.

Fig. 4 compares the performance of the newly proposed progressive MAP algorithm, with the algorithm presented in [7], where the *a priori* probability is estimated by averaging the signals from all the SUs in the spatial domain. The algorithm in [7] is denoted as spatial MAP in this paper. The results are presented in Fig. 4 in the form of receiver operating characteristics (ROC). There are two SUs in the network, thus the OR fusion rule and the majority fusion rule are the same. The SNR at the second step, γ_T, varies from -10 dB to 10 dB. When the second step SNR is less than or equal to 0 dB, the newly proposed progressive MAP algorithm outperforms the spatial MAP in most of the P_m/P_f regions, except the region with $P_m \approx P_f$, where the spatial MAP slightly outperforms the progressive MAP. As γ_T increases, the differences between the two algorithms gradually diminishes. In order to reduce the interference to the PU, the SUs usually have a very low transmission power. Therefore, the second step SNR is usually low. The proposed progressive MAP algorithm can achieve a better P_m/P_f tradeoff in most of the operation regions.

The performances of the majority and OR data fusion rules are compared in Fig. 5. There are three SUs in the network. The FC employs the new progressive MAP algorithm to detect the signals from the SUs. For a given value of the second step SNR γ_T, when the P_f is smaller than a certain threshold (or P_m is larger than a certain threshold), the majority decision rule is better than the OR decision rule. The relationship is reversed when P_f is larger than the threshold. Therefore, the choice between the OR and the majority fusion rules depends on the targeted P_f (or P_m). If the targeted P_f is small, then the majority fusion rule is preferred. The OR fusion rule is preferred when the targeted P_m is small. In addition, the P_f threshold decreases as γ_T increases. At $\gamma_T = 10$ dB, the majority fusion rule outperforms the OR fusion rule over all the operation ranges shown in the figure. Therefore, when the second step SNR is high, the majority decision rule can usually lead to a better performance.

V. Conclusions

A new cooperative spectrum sensing algorithm was proposed for a cognitive radio network. The algorithm was developed by exploiting the PU's statistical transmission pattern, which was modeled with a two-state Markov chain. With the new algorithm, the *a priori* probabilities of the information from the SUs were obtained at the FC by progressively estimating the transition probabilities of a Markov chain, and this led to a progressive MAP detection algorithm. Analytical expressions were derived for the error probabilities of the progressive MAP detection, and the global probabilities of false alarm and missing detection with the majority and OR data fusion rules. It was observed through numerical results that the new progressive MAP detection improved the performance of existing spectrum sensing algorithms. In addition, when the SNR at the FC was high, the majority data fusion rule outperformed the OR data fusion in terms of both probabilities of false alarm and missing.

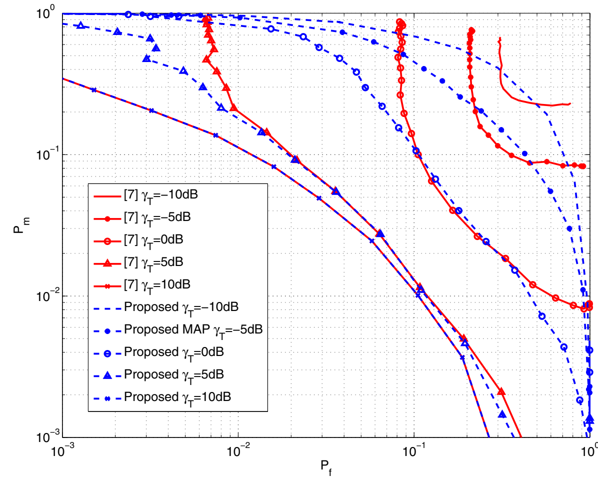

Fig. 4. ROC performance of the systems with the progressive MAP algorithm.

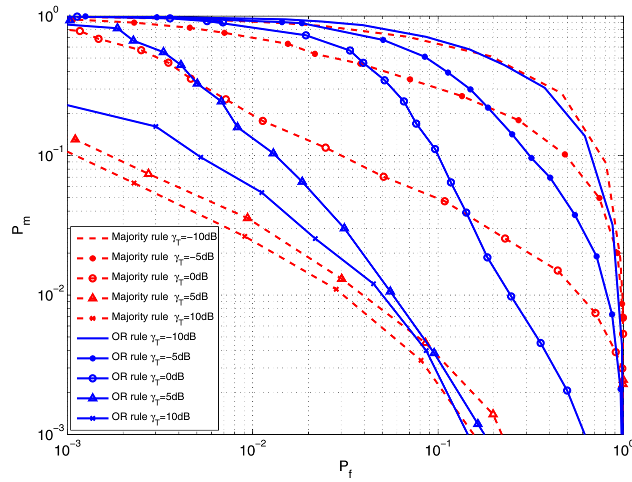

Fig. 5. ROC performances of the systems with the OR data fusion rule and the majority data fusion rule.

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