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Multi-Modal Cooperative Spectrum Sensing Based on Dempster-Shafer Fusion in 5G-Based Cognitive Radio

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ABSTRACT In 5G-based cognitive radio, the primary user signal is more active due to the broad frequency band. The traditional cooperative spectrum sensing only detects one characteristic of PU using one kind of detector, which may decrease the sensing performance when the wideband PU is in severe fading channel. In this paper, a multi-modal cooperative spectrum sensing is proposed to make an accurate decision through combining multi-modal sensing data of the PU signal, such as energy, power spectrum, and signal waveform. Each secondary user (SU) deploys multiple kinds of detectors, such as energy detector, spectral detector and waveform detector. The multi-modal sensing data from different detectors are sent to a fusion center. In the fusion center, the local decision is achieved through the Bayesian fusion, while the global decision is determined by the DS fusion. The sensing credibility of each detector can be fully considered in the DS fusion, in order to avoid the performance difference of different detectors. Weight DS fusion is also proposed to improve the decision performance through decreasing the sensing impact of malicious SU while increasing the fusion proportion of dominant SU. The simulation results have shown that the proposed multi-modal cooperative spectrum sensing can achieve better sensing performance in fading channel.

INDEX TERMS Cognitive radio, cooperative spectrum sensing, multi-modal data fusion, DS fusion, detection probability.

I. INTRODUCTIONS

With the rapid increasing of wireless communications, the traditional static spectrum allocation methodology has led to the shortage of the finite spectrum resource. However, the allocated spectrum has not been well-utilized in a specific time and space [1]. In order to improve the spectrum utilization, cognitive radio (CR) has been proposed, which allows a secondary user (SU) to occupy the idle spectrum licensed to a primary user (PU) [2]. To avoid causing any harmful interference to the PU, the SU has to detect the absence of the PU depending on spectrum sensing [3]. Energy detection, spectral detection and waveform detection are used as three effective spectrum sensing methods in CR. Energy detection can sense the PU without knowing any priori knowledge of the PU signal, while spectral detection is robust to the uncertain noise under low signal to noise ratio (SNR). Waveform detection can be the optimal sensing method with a fast sensing time when the priori knowledge of the PU signal is known [4]–[6].

The performance of single-user detection may be decreased when the PU is in the fading or shadow channel [7]. Cooperative spectrum sensing has been proposed to improve the sensing performance in fading channel, where a fusion center is used to make a global decision on the presence of the PU through combining local sensing information of multiple SUs [8]. In traditional cooperative spectrum sensing, each SU senses the PU independently using one kind of detector, such as energy detector, spectral detector or waveform detector, and reports the local sensing results to the fusion center. The fusion center fuses all the sensing results through data fusion, such as equal gain combining (EGC), maximal ratio combination (MRC) and Bayesian fusion, or decision fusion, such as AND fusion, OR fusion and K-OUT-N fusion [9]–[12]. In most of the literatures on cooperative spectrum sensing [13]–[16], SUs are assumed to achieve their local sensing results as to whether the PU signal is absent (such a process can be seen as 1-bit quantization or hard decision). A fusion center combines the 1-bit quantizations by simple decision fusion. The optimal K-OUT-N fusion rule can only be realized, when all the SUs are in an impractical condition (e.g. identical SNR and threshold) or when the number of SUs is infinite [17], [18]. In [15], the Chair-Varshney (CV) fusion rule [19], [20] is used for the fusion center, which may outperform the other fusion rules using hard decision through combining sensing information with a counting algorithm. However, it needs some time to converge when the channel is in fading environment. In [21], the CV fusion scheme is extended for the multibit local decision case, where an obvious improvement for cooperative spectrum sensing can be achieved. Nevertheless, it was unable to overcome the longer converging time of the counting method and the lower sensing performance in fading channel. In [22] and [23], the soft combination for cooperative spectrum sensing is proposed, which fuses the received signals based on MRC and EGC. The combination performance of the MRC-based fusion scheme is optimal in fading channel, while the EGC-based fusion scheme is considered as the best choice for a combination with the uncertain sensing information of SUs.

Recently, Dempster-Shafer (DS) fusion has been proposed to solve uncertain information fusion without any priori probability. In DS fusion, the sensing information can be combined using the basic credibility of the SU, which is measured by the basic probability assignment (BPA) [24], [25]. A data fusion scheme for a CR network based on the DS fusion is first proposed in [26], which achieves a significant improvement in detection probability as well as a considerable reduction in false alarm probability, without any priori knowledge of the PU signal.

However, in the traditional cooperative spectrum sensing, one SU only detects one characteristic of the PU signal and the single-modal sensing information cannot fully reflect the activity state of the PU signal [27]. Especially in fading channel, some sensing information such as energy and waveform may be very inaccurate due to the low SNR. Hence, the data fusion decision depending on one kind of detectors is not accurate and even contradictory to the real results. Through deploying a large number of independent multi-dimensional heterogeneous detectors, the multi-modal sensing data can be combined to make a more accurate decision through observing different characteristics of the detected signal [28], [29]. The contributions of this paper are listed as follows:

- Each SU deploys multiple kinds of detectors, such as energy detector, spectral detector and waveform detector, and achieves multi-modal sensing data of the PU signal. The multi-modal sensing data including energy, power spectrum and signal waveform are combined by the fusion center.
- Multi-modal cooperative spectrum sensing is proposed to combine the multi-modal sensing data from different SUs for getting a global decision. Since the detection data of multi-modal spectrum sensing are various, the accuracy of global decision can be improved through considering multiple characteristics of the PU signal.
- Multi-modal DS fusion decision has been proposed to combine the sensing information according to the basic credibility of each detector, in order to decrease the sensing uncertainty. Weight DS fusion is further proposed to improve the decision performance through decreasing the sensing impact of malicious SU while increasing the fusion proportion of predominant SU.

The rest of the paper is organized as follows. The spectrum sensing modality and the system model of multi-modal cooperative spectrum sensing are described in Section 2; the data fusion decisions of multi-modal cooperative spectrum sensing including local Bayesian fusion decision and global multi-modal DS fusion decision are presented in Section 3; the simulation results are presented and discussed in Section 4; the conclusions are finally drawn in Section 5.

II. MULTI-MODAL COOPERATIVE SPECTRUM SENSING

A. SPECTRUM SENSING MODALITY

In spectrum sensing of CR, the status of the PU signal only includes absence and presence, thus the detected signal of a single SU follows a binary hypothesis as follow

$$y(m) = \begin{cases} n(m), & H_0 \\ s(m)h(m) + n(m), & H_1 \end{cases} \quad m = 1, 2, \ldots, M \quad (1)$$

where $y(m)$ denotes the sensing signal, H_0 and H_1 denote the idle and busy status of the PU, respectively, $s(m)$ is the PU signal, $n(m)$ is the Gaussian noise, $h(m)$ is the channel gain from the PU transmitter to the SU receiver, and M is the number of the observation nodes. We can detect the different characteristics of the sensing signal, such as energy, power spectrum and signal waveform using the corresponding energy detector, spectral detector and waveform detector. These three kinds of detectors have been widely used in spectrum sensing of CR, which can achieve different modal data of the PU signal [30]. The common spectrum sensing modalities are described as follows

- Energy detection modality: energy detector is used to sense the energy of the PU signal, which can be seen as the optimal detector when the detected signal and the noise are unknown. Energy detector can sense the signals with any modulations and waveforms by collecting the energy of the received signal. As shown in Fig. 1, the detected signal $y(m)$ is squared and integrated over the observation interval M. Finally, the output of the integrator is compared with a threshold to decide if the PU is present or not. Sometimes the noise power may be large, and we can use a filter to decrease the noise power

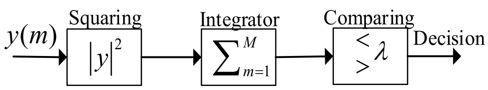


FIGURE 1. Energy detector.

before energy detection. Though the energy detector is easy to implement, it has several shortcomings, such as longer detection time and lower detection performance under low SNR.

- Spectral detection modality: spectral detector senses the presence of the PU by analyzing a spectral correlation function. Similar to energy detection, the spectral correlation of the detected signal $y(m)$ is averaged over the interval M and compared with the test statistic to determine the presence of PU signals, as shown in Fig. 2. The main advantage of the spectral detection is its robustness to the uncertain noise power and higher detection performance in low SNR. Furthermore, it can distinguish the signals from different communication systems. However, spectral detection has a high complexity and sometimes consumes longer calculation time.

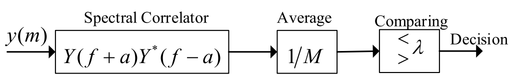


FIGURE 2. Spectral detector.

- Waveform detection modality: the matched filter is adopted as the linear optimal filter for detecting the waveform of the PU signal. The presence of the PU can be determined through using coherent signal detection to maximize the signal-to-noise ratio (SNR) in the presence of additive noise. As shown in Fig. 3, the known PU signal $s(m)$ is correlated with the detected signal $y(m)$ within observation interval M. Then the output of the matched filter is sampled at the synchronized timing. The sampled value is finally compared with a threshold to determine the presence of the PU. Waveform detector shows a fast sensing time but needs priori knowledge of the PU signal.

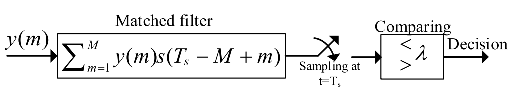


FIGURE 3. Waveform detector.

Traditional spectrum sensing only senses one characteristic of the PU signal using one kind of detectors, which cannot make a comprehensive decision on the presence of the PU using the multiple presence features of the detected signal. However, using multi-modal sensing data fusion, a multi-dimensional signal description can be obtained to improve the detection accuracy greatly.

B. MULTI-MODAL COOPERATIVE SPECTRUM SENSING

Cooperative spectrum sensing has been proposed to improve sensing performance through letting multiple SUs sense the PU collaboratively, when the sensing path from the PU transmitter to the SU receiver is in fading [31], [32]. In cooperative spectrum sensing, a fusion center is adopted to manage the SUs and exchange their sensing information. The fusion center functions as a base station in a centralized CR network, which can collect and store the local sensing information of each SU. The fusion center will make a final decision through combining the sensing information from all the SUs and broadcast the decision to all the SUs. There is a control channel between the SUs and the fusion center. The SUs send their sensing information and status information to the fusion center periodically through the uplink of the control channel, while the fusion center sends its control information and decision results to the SUs using the downlink of the control channel.

In the traditional cooperative spectrum sensing, each SU senses the PU signal using only one detector and obtains the single-modal sensing data of the PU signal; then the fusion center combines the sensing data from all the SUs for getting a global decision on the presence of the PU, as shown in Fig. 4.

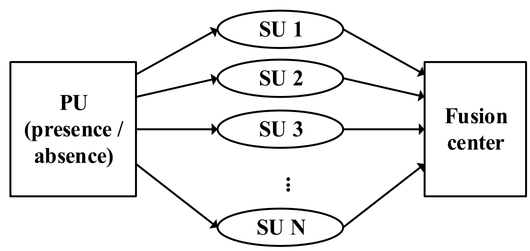


FIGURE 4. Traditional cooperative spectrum sensing.

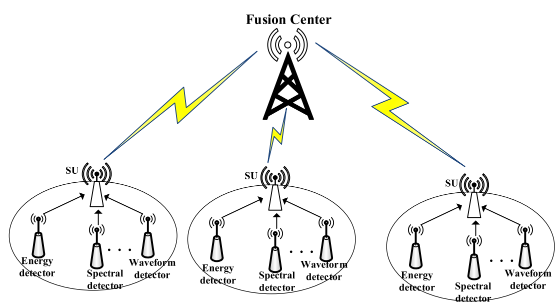


FIGURE 5. Multi-modal cooperative spectrum sensing.

In multi-modal cooperative spectrum sensing, each SU applies multiple kinds of detectors to sense different characteristics of the PU, such as energy, power spectral and signal waveform, in order to obtain multi-modal sensing data for giving an integrated decision, as shown in Fig. 5. In this model, each SU deploys energy detector, spectral detector and waveform detector, while the fusion center installs corresponding energy combiner, spectral combiner and waveform combiner. To achieve a local sensing decision, each combiner fuses the sensing data from the same kind of detectors of all the SUs. The fusion center will make a global sensing decision through combining the local sensing decisions from all the combiners.

Each combiner fuses the sensing information of the detectors with the Bayesian fusion, because the Bayesian fusion may deal with the uncertain detection information, thus improving the reliability and accuracy of spectrum sensing greatly [33]. However, the detection results of multi-modal cooperative spectrum sensing are various. For example, energy detector may achieve better sensing performance when the power strength of the detected signal is high, while spectral detector may decrease the accuracy when the power of the received noise is large. Hence, the DS fusion is used to combine the local sensing decisions from multiple independent modal information. DS fusion can improve the confidence level of decision accuracy through deducing with uncertain sensing information, as shown in Fig. 6.

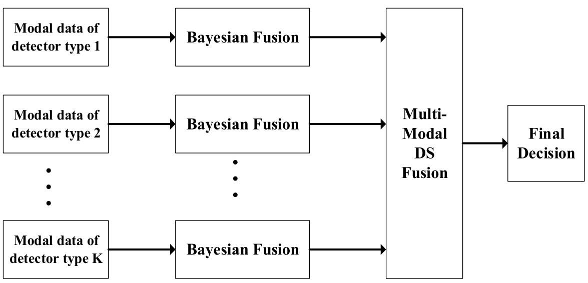


FIGURE 6. Multi-modal sensing data fusion.

III. MULTI-MODAL DATA FUSION DECISION

A. LOCAL BAYESIAN FUSION DECISION

We suppose that there are N SUs in the CR network, each of which deploys K kinds of detectors. In the Bayesian fusion, by allocating corresponding cost value to each decision result, the average aggregate cost can be achieved based on the hypothesis probability. We select the sensing strategy to minimize the average aggregate cost. We suppose that η_{ij} denotes the sensing cost of deciding H_i when H_j is actually existed, where $\eta_{ij} \leq 0$ indicates the accurate decision while $\eta_{ij} > 0$ denotes the wrong decision. Supposing that the sensing cost of accurate decision is larger than that of the wrong decision, we can get $\eta_{i,j\neq i} > \eta_{jj}$ for any i and j. Then the average aggregate cost of one SU can be obtained by

$$\eta = P(H_0)\left[\eta_{00}P(H_0|H_0) + \eta_{10}P(H_1|H_0)\right] + P(H_1)\left[\eta_{01}P(H_0|H_1) + \eta_{11}P(H_1|H_1)\right] \quad (2)$$

Then the error detection probability is given by

$$P_e = P(H_0) \cdot P(H_1|H_0) + P(H_1) \cdot P(H_0|H_1) \quad (3)$$

where η_{00} and η_{11} denote the accurate detection costs, while η_{10} and η_{01} denote the false alarm cost and miss detection cost, respectively; $P(H_1|H_0)$ and $P(H_0|H_1)$ indicate false alarm probability and miss detection probability denoted by P_f and P_m, respectively. The detection probability is given by $P_d = 1 - P_m$. The decision threshold of each detector is obtained to make P_e achieve the minimum [34], as follows

$$\lambda_s = \arg\min\left(P(H_0) \cdot P_f(\lambda_s) + P(H_1) \cdot P_m(\lambda_s)\right) \quad (4)$$

If $y \geq \lambda_s$, H_1 denoted as $u = 1$ is decided by the detector, otherwise H_0 denoted as $u = 0$ is decided by the detector. The Bayesian fusion decision is given by

$$\frac{P(u_1, u_2, \ldots, u_N|H_1)}{P(u_1, u_2, \ldots, u_N|H_0)} \underset{<}{>} \frac{P(H_0)(\eta_{10} - \eta_{00})}{P(H_1)(\eta_{01} - \eta_{11})} \quad (5)$$

where H_1 is determined if the left value is larger than the right value, otherwise H_0 is determined. Thus, the local decision threshold of combiner is given by

$$\lambda_g = \frac{P(H_0)(\eta_{10} - \eta_{00})}{P(H_1)(\eta_{01} - \eta_{11})} \quad (6)$$

Supposing that the sensing results of N detectors are independently and identically distributed, eq. (5) is rewritten as follows

$$\prod_{i=1}^{N} \frac{P(u_i|H_1)}{P(u_i|H_0)} \underset{<}{>} \lambda_g \quad (7)$$

which is calculated by

$$\sum_{i=1}^{N} \theta(i) \underset{<}{>} \log \lambda_g \quad (8)$$

where

$$\theta(i) = \begin{cases} \log \dfrac{P_d^i(\lambda_s)}{P_f^i(\lambda_s)}, & u_i = 1 \\ \log \dfrac{1 - P_d^i(\lambda_s)}{1 - P_f^i(\lambda_s)}, & u_i = 0 \end{cases} \quad (9)$$

B. GLOBAL MULTI-MODAL DS FUSION DECISION

Since the sensing differences may cause the uncertainty of the final decision, the DS fusion has been proposed to cope with this problem. We suppose that Θ is the identification framework of DS theory, which includes limited mutual-exclusion hypothesis. The BPA function $m(A)$, $A \in \Theta$ where $2^{\Theta} \in [0, 1]$ satisfies the following equation

$$\begin{cases} m(\Phi) = 0 \\ \sum_{A\subset\Theta} m(\mathrm{A}) = 1 \end{cases} \quad (10)$$

where Φ is an empty set and $m(\mathrm{A})$ denotes the basic credibility of the assumption A. Defining the belief function as $Bel(\mathrm{A})$ for any $A \subset \Theta$, we have

$$Bel(A) = \sum_{B\subset A} m(B) \quad (11)$$

where $Bel(A)$ denotes the aggregate basic credibility of all the subsets in A. We define m_1 and m_2 as two BPA functions within the same identification framework Θ, which include corresponding elements $A_1, A_2, \ldots, A_k$ and $B_1, B_2, \ldots, B_r$, respectively. Then the fused BPA of m_1 and m_2 is given by

$$m(C) = m_1(A_i) \oplus m_2(B_j) = \frac{\sum\limits_{A_i \cap B_j = C} m_1(A_i) m_2(B_j)}{1 - \sum\limits_{A_i \cap B_j = \emptyset} m_1(A_i) m_2(B_j)} \tag{12}$$

where $i = 1, 2, \ldots, k$ and $j = 1, 2, \ldots, r$. With (12), multiple independent BPA functions can be combined with exchangeable and binding operations.

Each combiner gets a local decision through Bayesian fusion, then all the local decisions are combined through the DS fusion at the fusion center. Supposing the decision data vector of each combiner is $\boldsymbol{\theta}_\mathbf{k} = \{\theta_k(1), \theta_k(2), \ldots, \theta_k(N)\}$ for $k = 1, 2, \ldots, K$, where θ_k is achieved from (9) and $(\theta_1(0), \theta_2(0), \ldots, \theta_K(0))$ is the referencing vector of the K modalities, the decision matrix is denoted by

$$\begin{bmatrix} \theta_1(0) & \theta_1(1) & \theta_1(2) & \ldots & \theta_1(N) \\ \theta_2(0) & \theta_2(1) & \theta_2(2) & \ldots & \theta_2(N) \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \theta_K(0) & \theta_K(1) & \theta_K(2) & \ldots & \theta_K(N) \end{bmatrix} \tag{13}$$

where we can calculate the correlation coefficient of N sensing vectors as follows

$$\varepsilon_k(n) = \frac{\min\limits_k \min\limits_n |\theta_k(0) - \theta_k(n)| + \rho \cdot \max\limits_k \max\limits_n |\theta_k(0) - \theta_k(n)|}{(1+\rho)\ |\theta_k(0) - \theta_k(n)|}, \quad n = 1, 2, \ldots, N \tag{14}$$

where $\rho \in [0, 1]$ is the resolution coefficient, which is often selected by $\rho = 0.5$. The average correlation coefficient of each kind of detectors is given by

$$\gamma_k = \frac{1}{N} \sum_{n=1}^{N} \varepsilon_k(n), \quad k = 1, 2, \ldots, K \tag{15}$$

Define $\Theta = \{H_0, H_1, \Omega\}$, where Ω denotes any of H_0 and H_1 to be true, and $u_{n,k}$ as the sensing information of detector k in SU n. Substituting (15) into (7), the BPA function of each SU is described as follows

$$\begin{aligned} m_n(H_0) &= \prod_{k=1}^{K} P(u_{n,k}|H_1)^{\gamma_k} \\ m_n(H_1) &= \prod_{k=1}^{K} P(u_{n,k}|H_0)^{\gamma_k} \\ m_n(\Omega) &= 1 - m_n(H_0) - m_n(H_0) \end{aligned} \tag{16}$$

The fusion center achieves $\{m_n(H_0),\ m_n(H_1),\ m_n(\Omega)\}$ for $n = 1, 2, \ldots, N$. According to the DC fusion rule, the fusion center gets the aggregate BPA function by combining the BPA

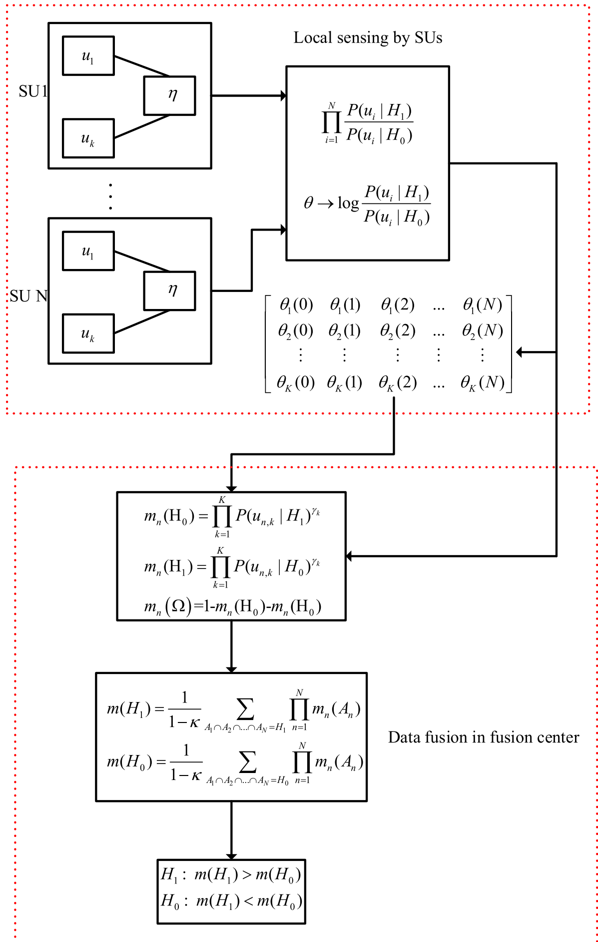


FIGURE 7. Overall framework of multi-modal DS fusion decision.

of each SU, as follows

$$\begin{aligned} m(H_1) &= \frac{1}{1-\kappa} \sum_{A_1 \cap A_2 \cap \ldots \cap A_N = H_1} \prod_{n=1}^{N} m_n(A_n) \\ m(H_0) &= \frac{1}{1-\kappa} \sum_{A_1 \cap A_2 \cap \ldots \cap A_N = H_0} \prod_{n=1}^{N} m_n(A_n) \end{aligned} \tag{17}$$

where $\kappa = \sum\limits_{A_1 \cap A_2 \cap \ldots \cap A_N = \emptyset} \prod\limits_{n=1}^{N} m_n(A_n)$ and $A_1, A_2, \ldots, A_N \in \{H_0, H_1, \Omega\}$. The global decision is achieved through comparing $m(H_1)$ with $m(H_0)$ as follows

$$\begin{aligned} H_1 &: m(H_1) \geq m(H_0) \\ H_0 &: m(H_1) < m(H_0) \end{aligned} \tag{18}$$

The overall framework of multi-modal DS fusion decision is shown in Fig. 7. The multi-modal cooperative spectrum sensing consists of three main parts: local sensing in SUs, data fusion in combiner and final processing for global decision in fusion center. In local sensing stage, spectrum sensing is performed by multiple kinds of detectors, where multi-modal data are sensed together instead of one modality. These multi-modal data are sent to the fusion center in ordered sequential manner for making final decision. Upon obtaining the target detection and false alarm, the fusion center manages to report decision information to all the SUs.

The multi-modal DS fusion decision is shown in Algorithm 1. The calculation of the Algorithm 1 includes two main stages. In the first stage, γ_k for $k = 1, 2, \ldots, K$ are calculated with the computing cost of $(2N + 1)K$, while in the second stage, BPA functions are calculated with the computing cost of N^2K. Hence, the total computing cost of the Algorithm 1 is given by $(2N + 1)N^2K^2$.

Algorithm 1 Multi-Modal DS Fusion Decision

1. Each SU detects the energy, power spectrum and signal waveform of the PU signal using energy detector, spectral detector and waveform detector, respectively;
2. The multi-modal sensing data of all the SUs are sent to the fusion center;
3. Each combiner of the fusion center fuses the detected data from the corresponding kind of detectors by the Bayesian fusion using the decision threshold obtained by (4);
4. Obtain $\theta_k(n)$ according to (9) and build the decision matrix according to (13);
5. Obtain the correlation coefficient of each kind of detectors γ_k;
6. Fusion center calculates the BPA functions of each SU under H_0 and H_1 according to (16), respectively, and achieves $\{m_n(H_0),\ m_n(H_1),\ m_n(\Omega)\}$ for $n = 1, 2, \ldots, N$;
7. Obtain the aggregate BPA function by combining the BPA of each SU as $m(H_1)$ and $m(H_0)$ according to (17);
8. Make the global decision according to (18).

The key issues of the Algorithm 1 in practical implementations are listed as follows:

- Since the spectrum sensing requires lower false alarm probability and higher detection probability, the local sensing threshold should be chosen reasonably.
- In order to use the reliability of each SU effectively, the multi-modal cooperative spectrum sensing contains two main stages: local sensing and data fusion.
- The DS fusion is adopted for data fusion to decrease the impact of malicious SU. The BPA function is obtained through estimating the correlation coefficient of each kind of detectors.

C. WEIGHED MULTI-MODAL DS FUSION

Since the data acquisition accuracy and data processing ability of each detector is different, even under the same conditions, the quality of multi-modal data produced by different detectors are also different. Therefore, we assign a weight to the modal data fusion of each SU. We use the information error to measure the quality of modal data as follows

$$L_n = \frac{\sum_{n\in[1,N]} |\theta(n) - \theta(0)|}{M\,|\max\{\theta(n)\} - \min\{\theta(n)\}|} \tag{19}$$

where large L_n denotes great information error. Then the iterative expression of the weight is given by

$$w_n(t+1) = \frac{w_n(t)L_n}{\frac{1}{N}\sum\limits_{n=1}^{N} w_n(t)L_n} \tag{20}$$

where $w_n(t)$ is the fusion weight of SU n in sensing time t, which satisfies $\sum_{n=1}^{N} w_n(t) = N$. Thus, the weighed BPA function is given from (17) as follows

$$\begin{aligned} m(H_1) &= \frac{1}{1-\kappa} \sum_{A_1\cap A_2\cap\ldots\cap A_N=H_1} \prod_{n=1}^{N} w_n m_n(A_n) \\ m(H_0) &= \frac{1}{1-\kappa} \sum_{A_1\cap A_2\cap\ldots\cap A_N=H_0} \prod_{n=1}^{N} w_n m_n(A_n) \end{aligned} \tag{21}$$

The weight allocation algorithm is described in Algorithm 2.

Algorithm 2 Weight Allocation Algorithm

1. Initialize: $t = 1$, the fusion weight of each SU as $w_n(t) = 1$ for $n = 1, 2, \ldots, N$ and the calculation accuracy δ;
2. Get $w_n(t+1)$ from (20) and set $m_1(A_n) = w_n(t)/N$ and $m_2(B_n) = w_n(t+1)/N$;
3. Obtain $m(C)$ from (12) and calculate $\xi_n(t+1) = m(C_n) - (m_1(A_n) + m_1(B_n))\,/2$;
4. Set $t = t + 1$;
5. Repeat (2) to (4) until $\|\xi\| \leq \delta$;
6. Output $w_n^* = N \cdot m(C_n)$ for $n = 1, 2, \ldots, N$.

The strengths and weaknesses of energy detection, spectral detection, waveform detection and multi-modal cooperative spectrum sensing are listed in Table 1.

TABLE 1. Strengths and weaknesses of different sensing method.

sensing methods	strengths	weaknesses
energy detection	without knowing any priori information of the detected signal	sensitive to noise and fading channel
spectral detection	robustness to the uncertain noise power and high detection performance	high complexity and long detection time
waveform detection	linear optimal spectrum sensing with fast sensing time	needing the priori information of the detected signal
multi-modal cooperative sensing	Accurate detection in fading channel without priori information	high complexity and long detection time

IV. SIMULATIONS AND DISCUSSIONS

In the simulations, each SU deploys three kinds of detectors including energy detector, spectral detector and waveform detector, i.e. $K = 3$; the PU signal is QPSK modulation and the sensing signal to noise ratio is -10dB; the actual presence probability of the PU is $P(H_1) = 0.5$; the number of SUs is $N = 10$; the reporting channel between the SU transmitter and the fusion center is perfect. As shown in Fig. 8,

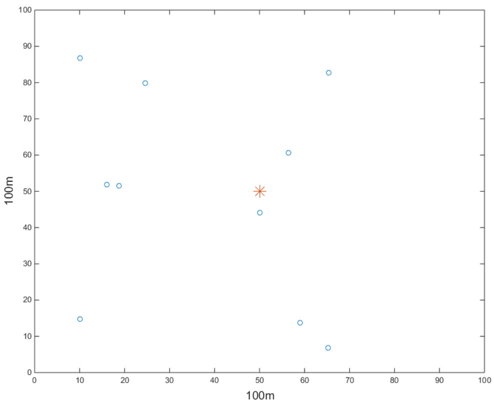
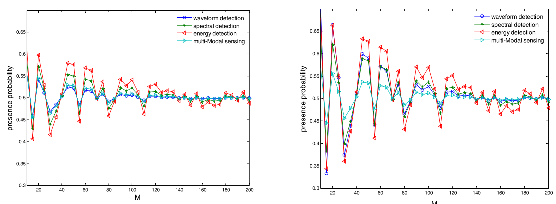


FIGURE 8. SU and PU locations.

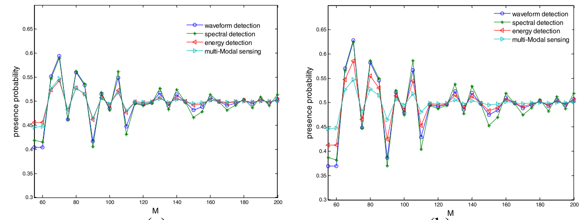
we assume that N SUs locate in a 100m$\times$100m area randomly as marked by 'o' and one PU locates in the center of the area as marked by '$*$'.



(a) (b)

FIGURE 9. Detection comparison of presence probability when priori knowledge of PU is known. (a) AWGN channel; (b) Rayleigh fading channel.

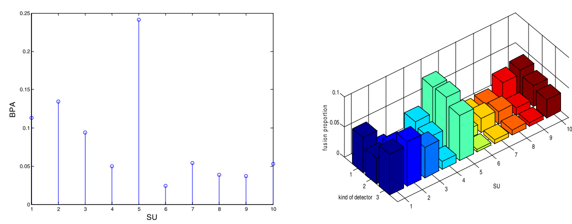
Fig. 9 (a) and (b) compare the presence probabilities of the PU in AWGN channel and Rayleigh fading channel detected by waveform detection, spectral detection, energy detection and multi-modal cooperative spectrum sensing, respectively, when the priori knowledge of the PU is known. It is seen that the waveform detection can achieve better performance with less detection time, because the priori knowledge can be used as the correlated signal of the matched filter; while energy detection has the worst performance, because the noise power may impact the threshold selection. However, the detection performance of multi-modal cooperative spectrum sensing approaches to the waveform detection, because the waveform detector of each SU can achieve accurate sensing information and the waveform data fusion may occupy the major proportion in the DS fusion. In Rayleigh fading channel, the performance of all the single-modal detection decreases due to the weak strength of the detected signal. However, the multi-modal sensing can guarantee the sensing performance because of the multi-modal data fusion, by which the detected presence probability can reach 0.5 when $M \geq 120$. Fig. 10 (a) and (b) compare the detected presence probability of the PU in AWGN channel and Rayleigh fading channel, respectively, when the priori knowledge of the PU is unknown. It is seen that energy detector can achieve better performance without priori knowledge, and the performance



(a) (b)

FIGURE 10. Comparison of detected presence probability when priori knowledge of PU is unknown. (a) AWGN channel; (b) Rayleigh fading channel.

of the multi-modal sensing approaches to energy detection in AWGN channel. However, the advantage of multi-modal sensing is obviously in Rayleigh fading channel. Thus, without the priori information of the PU signal, the multi-modal cooperative spectrum sensing can achieve better performance both in AWGN channel and Rayleigh fading channel. This is because waveform detection becomes the primary factor in AWGN channel, while energy detection and spectral detection are the leading factors in Rayleigh fading channel. Fig. 11 (a) and (b) show the BPA value of each SU and the fusion proportion of each detector, respectively. It is seen that the larger fusion proportion is allocated to the SU closer to the PU with a higher BPA.



(a) (b)

FIGURE 11. BAP value and fusion proportion of multi-modal sensing fusion. (a) BAP value of SU (b) fusion proportion of detector.

Fig. 12 compares the detected presence ranges of the PU in AWGN channel, using different sensing methods including multi-modal cooperative spectrum sensing, waveform detection, spectral detection and energy detection. The observation range is x$\times$y=20m$\times$20m with the center of the PU. It is seen that the multi-modal cooperative spectrum sensing can detect the presence of the PU in a small range from the center, which indicates that the presence position of the PU can be detected more accurately. However, the presence range of the PU is detected to be large by the other sensing methods. Fig. 13 compares the detected presence ranges of the PU in Rayleigh fading channel. It is seen that the multi-modal cooperative spectrum sensing can also detect the presence of the PU more accurately. However, all the other sensing methods detect multiple presence ranges of the PU, which indicates that false alarm detection has been produced.

Fig. 14 shows the detected PU signal using waveform detection and multi-modal sensing in AWGN channel and Rayleigh fading channel, respectively. It is seen that the

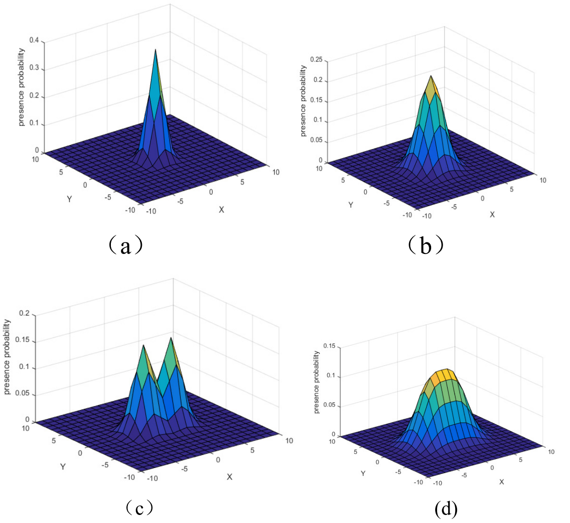


FIGURE 12. Detected presence range of PU in AWGN channel. (a) multi-modal cooperative spectrum sensing (b) waveform detection (c) spectral detection (d) energy detection.

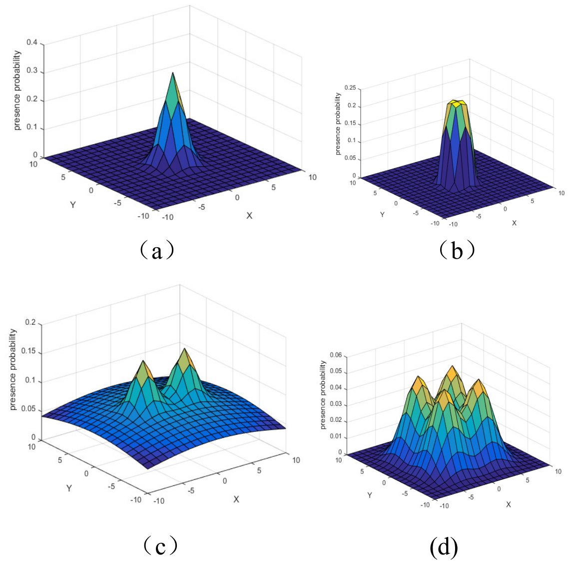


FIGURE 13. Detected presence range of PU in Rayleigh fading channel. (a) multi-modal cooperative spectrum sensing (b) waveform detection (c) spectral detection (d) energy detection.

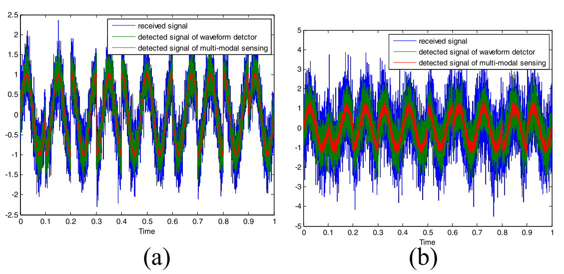


FIGURE 14. Detected PU signal. (a) AWGN channel; (b) Rayleigh fading channel.

multi-modal sensing can achieve more accurate signal waveform. Fig. 15 compares the number of the observation nodes M of different sensing methods, where M reflects the spectrum sensing time. It is seen that the multi-modal sensing can use less observation nodes to achieve the same detection performance compared with spectral detection and energy detection, and the sensing time of multi-modal sensing is close to the waveform detection with the fastest sensing speed.

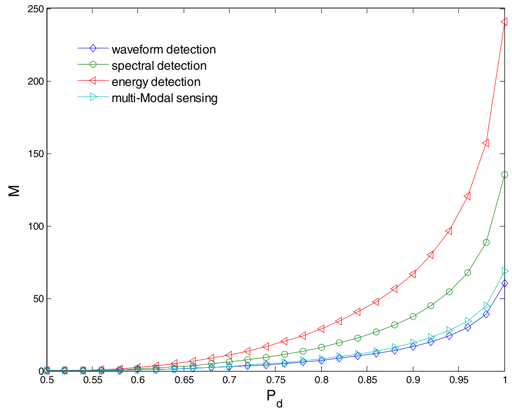


FIGURE 15. The number of observation nodes.

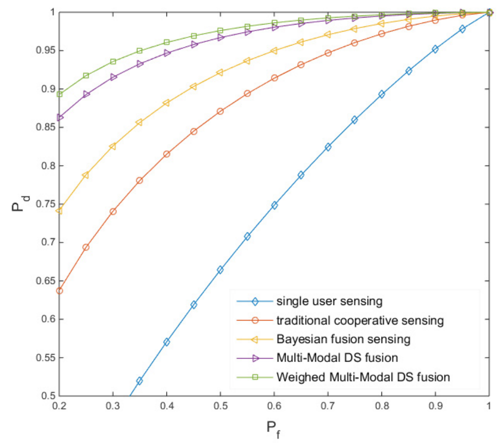


FIGURE 16. Detection probability in AWGN channel.

Fig. 16 compares the detection probabilities of single-use sensing, traditional cooperative sensing with energy detection, Bayesian fusion sensing, multi-modal DS fusion sensing and weighed multi-modal DS fusion sensing. It is seen that the multi-modal DS fusion sensing and weighed multi-modal DS fusion sensing can achieve higher detection probability, because three kinds of sensing information including energy, power spectrum and signal waveform are considered comprehensively in the proposed method, thus improving the overall detection performance. The weighed multi-modal DS fusion sensing can obtain the best sensing performance, because the weight allocation can decrease the sensing impact of malicious SU while increasing the sensing proportion of predominant SU. Fig. 17 compares the miss detection probability in Rayleigh fading channel. It is seen that multi-modal DS fusion sensing can also achieve lower miss detection

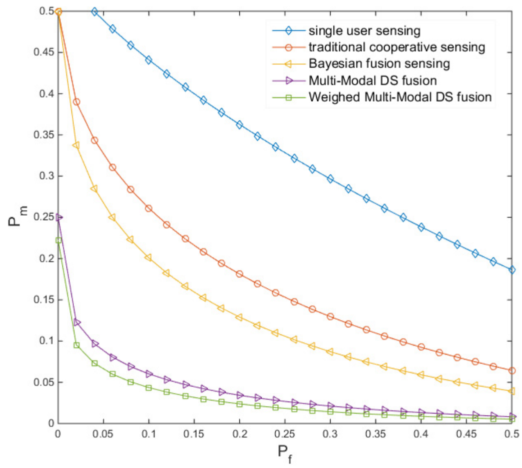


FIGURE 17. Miss detection probability in Rayleigh fading channel.

probability, which reflects the predominance of multi-modal sensing fusion in fading channel.

V. CONCLUSIONS

In this paper, a multi-modal cooperative spectrum sensing has been proposed to make a decision on the presence of the PU through combing multi-modal sensing data of the PU signal, such as energy, power spectrum and signal waveform. In the fusion center, each combiner makes a local decision through fusing the sensing data from the same kind of detectors with the Bayesian fusion, and the multi-modal data from all the combiners are finally fused by the DS fusion for getting the global decision. A weight DS fusion is also proposed to improve the decision performance by resisting the inaccurate detection of malicious SU. We have got the following conclusions:

- The multi-modal cooperative spectrum sensing can guarantee the sensing performance in fading channel through fusing the multi-modal data and considering the different present characteristics of the PU.
- The larger fusion proportion is allocated to the SU closer to the PU with a higher BPA, which indicates that the sensing credibility is fully considered in the DS fusion.
- The multi-modal DS fusion and weighed multi-modal DS fusion can achieve higher detection probability, because multiple kinds of sensing information including energy, power spectrum and signal waveform are combined to improve the overall detection performance.

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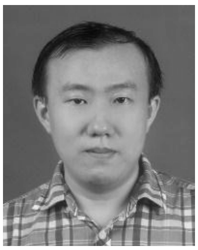

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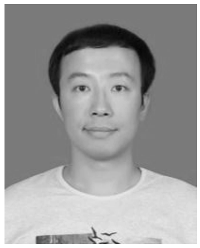

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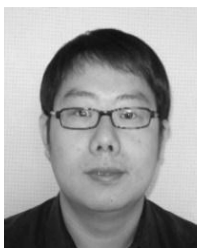

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