New Half-Voting Cooperative Sensing Algorithms in Cognitive Radio

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Abstract. In cognitive radio (CR) networks, hard fusion is widely applied for cooperative energy spectrum sensing, since it requires only one bit to transmit the decision results between sensing nodes and the sensing station. And half-voting is an effective algorithm in hard fusion. In this paper, two half-voting algorithms are proposed to enhance the sensing performance. In the first half-voting algorithm, we adopt linear data fusion with weights based on the SNR of each sensing node. In another algorithm, when the sensing station has no knowledge of each sensing node's SNR, the history decisions are utilized to estimate the weight factors. Analyses and numerical results show that the proposed new half-voting algorithms can significantly improve the sensing performance.

Keywords: cognitive radio, energy spectrum sensing, hard fusion, half-voting, linear data fusion.

1 Introduction

Recently, cognitive radio (CR) has emerged as a potential wireless communication technology to enhance spectrum usage efficienc by detecting and utilizing the spectrum holes [1]. And the first challenge of CR is spectrum sensing. Among the three main types of spectrum sensing: energy detection, matched filter detection and cyclostationary detection [2], energy detection has been widely applied since it doesn't require the priori knowledge of the primary users' signals..

However, the individual energy sensing performance suffers from the interference factors such as multi-path propagation and the shadow effect of the wireless channels. Therefor, many cooperative energy spectrum sensing algorithms have been proposed to tackle this problem. The cooperative sensing algorithms in CR networks can be mainly divided into soft fusion and hard fusion [3]. [4] studied the half-voting algorithm based twice cooperative spectrum sensing. [5] discussed the optimum number of sensing nodes in cooperative hard fusion spectrum sensing. [6] developed a partial spectrum sensing algorithm with decision result prediction and decision result modification techniques. [7] proposed a new decision combination scheme, in which the credibility of local spectrum sensing is taken into account to make the final decision. The linear cooperative algorithms with different weight factors were discussed in [8]$\sim$ [10]. These studies showed

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that although the soft fusion scheme could provide better sensing performance, the hard fusion scheme(requiring only one bit to transmit the decision result), especially the half-voting algorithm, is more practical with limited transmission resources.

In this paper, we propose two new half-voting algorithms for cooperative sensing which combine the advantages of linear soft fusion and traditional hard fusion algorithms. In the first algorithm, the SNR of each sensing node is used to obtain the weight factors for the linear fusion. When the sensing station has no knowledge of sensing nodes' SNRs, we propose another algorithm, which adopts the history decisions to estimate the weight factors.

The rest of this paper is organized as follows. In Section 2, the system model is introduced, then the cooperative sensing algorithms are discussed. In Section 3, we propose two half-voting algorithms for cooperative sensing and analyze their performance. Simulation results and analyses are given in Section 4. Conclusions are drawn in Section 5.

2 Energy Spectrum Sensing

2.1 Energy Sensing Model

In energy sensing, the sensing node detects M consecutive samples in the primary user's band each time:

$$Y[i] = \begin{cases} N[i], & H_0 \\ h * X[i] + N[i], & H_1 \end{cases} \tag{1}$$

where $N[i]$ is the noise of the i-th sample (here it is assumed that the noise is i.i.d. Gaussian white noise and $N[i] \sim \mathcal{N}(0, \sigma^2)$); $X[i]$ is the licensed user's signal at the i-th sample; $Y[i]$ is the signal detected by the cognitive sensing node; and h is the channel gain. Binary hypothesis is adopted here: H_0 indicates that there is no licensed user's signal, i.e. the band is idle; while H_1 indicates that the licensed user is using the band.

The objective of energy sensing is to decide whether H_0 or H_1 is true by sensing the energy of signal Y. The output of the energy detector is:

$$T = \frac{1}{M} \sum_{i=1}^{M} |Y[i]|^2 \tag{2}$$

According to the central limit theorem, when M is large enough, T is approximately Gaussian distributed. The mean and variance of T are given as [11]:

$$E(T) = \begin{cases} \sigma^2, & H_0 \\ \sigma^2 + P, & H_1 \end{cases} \tag{3}$$

$$Var(T) = \begin{cases} \frac{1}{M} 2\sigma^4, & H_0 \\ \frac{1}{M} 2\sigma^4 + \frac{1}{M} 4\sigma^2 P, & H_1 \end{cases} \tag{4}$$

where $P = \frac{1}{M}\left|h^2\right|\sum_{i=1}^{M}\left|X[i]\right|^2$ is the signal energy detected by the cognitive sensing node; $E(\cdot)$ and $Var(\cdot)$ denote mean and variance, respectively.

In energy sensing, a threshold η is predefined. If $T \geq \eta$, H_1 is true, which indicates the primary user is using the current band. On the contrary, if $T < \eta$, H_0 is true, which implies the band is currently idle. The detection probability (P_d) and false alarm probability (P_f) can be obtained by the following formulae:

$$P_d = P(T \geq \eta \mid H_1) = Q(\frac{\eta - E(T \mid H_1)}{\sqrt{Var(T \mid H_1)}}) \tag{5}$$

$$P_f = P(T \geq \eta \mid H_0) = Q(\frac{\eta - E(T \mid H_0)}{\sqrt{Var(T \mid H_0)}}) \tag{6}$$

where $Q(\eta) = \frac{1}{\sqrt{2\pi}}\int_{\eta}^{\infty} e^{-x^2/2}dx$ is the cumulative distribution function of Gaussian distribution. And $1 - P_d$, which stands for the collision probability between the licensed user and cognitive user, cannot exceed a given threshold in the interweave CR networks.

2.2 Cooperative Spectrum Sensing

Due to the interference factors such as multi-path propagation and shadow effect in wireless channels, energy sensing conducted by single cognitive sensing node with low SNR of the received signal may be unreliable [3]. This problem can be eased by cooperative sensing strategies. Fig.1 illustrates the shadow effect and the advantage of cooperative sensing. Apparently, sensing node 2 suffers from severe shadow effect and is not able to detect the licensed user's signal individually. But if combining the data collected by sensing node 1 and 2, sensing station is able to identify that the spectrum is currently occupied by the licensed user.

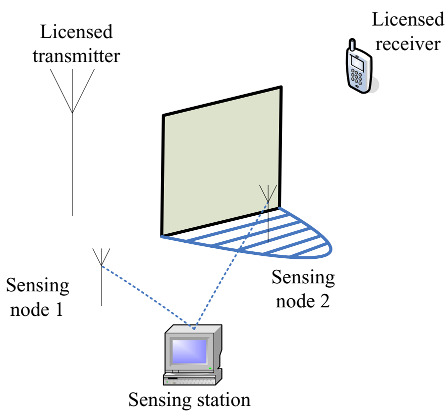

Fig. 1. The shadow effect and cooperative sensing [3]

In soft fusion algorithms, the sensing nodes send soft information (e.g. likelihood ratio or received signal power) to the sensing station. For hard fusion, the sensing nodes individually make binary decisions of whether the band is busy or idle by comparing the received power level to a threshold level. Then each binary decision will be transmitted to the sensing station with one bit. In both soft and hard schemes, the sensing station makes an overall decision based on the collected individual information under certain rules. In this paper we use half-voting rule [6] as our cooperative algorithm. That means the final decision is H_1 only when more than half of the total sensing nodes support H_1.

3 New Half-Voting Cooperative Sensing Algorithms

As discussed in Section 1, soft fusion cooperative algorithms can remarkably improve the sensing performance. In comparison, the hard fusion scheme requires only one bit to transmit the decision result between a sensing node and the sensing station. In this section, we propose two half-voting algorithms which contain the minimum transmission overhead and adopt the linear soft fusion scheme with weight factors to enhance the sensing performance.

3.1 Half-Voting Algorithm with Weights Based on SNRs

Denoting the individual decision of the i-th sensing node as d_i, where $d_i = 0$ (individual decision supports H_0) or 1 (individual decision supports H_1), the set of decision results received by the sensing station is $\{d_1, d_2, \cdots, d_N\}$(N is the sensing nodes' number). The final cooperative decision result is denoted as $\bar{H}_1$ and $\bar{H}_0$. The traditional hard fusion scheme of half-voting can be written as:

$$D = \begin{cases} \sum_{i=1}^{N} d_i < \frac{N}{2}, \bar{H}_0 \\ \sum_{i=1}^{N} d_i \geq \frac{N}{2}, \bar{H}_1 \end{cases} \tag{7}$$

In fact, (7) can be regarded as a linear average weighted cooperative sensing algorithm since each weight factor of d_i is 1. It can be proved that that accounting for higher received SNRs and increasing weight factors accordingly can remarkably improve the cooperative sensing performance. Thereby, we propose a new half-voting algorithm whose weight factors are based on SNRs:

$$\bar{D} = \begin{cases} \sum_{i=1}^{N} \omega_i d_i < \frac{1}{2}, \bar{H}_0 \\ \sum_{i=1}^{N} \omega_i d_i \geq \frac{1}{2}, \bar{H}_1 \end{cases} \tag{8}$$

where $\omega_i = \frac{SNR_i}{\sum_{i=1}^{N} SNR_i}$. Here we assume the sensing station has full knowledge of the SNR information of the sensing nodes. The essence of (8) is that the sensing nodes with higher SNRs have greater impacts on the final decision.

Obviously $d_i, i = 1, 2, \ldots, N$, satisfies Bernoulli distribution and the probability is

$$P(d_i = 1) = \begin{cases} P_{f,i}, H_0 \\ P_{d,i}, H_1 \end{cases} \tag{9}$$

$$P(d_i = 0) = \begin{cases} 1 - P_{f,i}, \; H_0 \\ 1 - P_{d,i}, \; H_1 \end{cases} \tag{10}$$

where $P_{d,i}$ and $P_{f,i}$ are the detection probability and false alarm probability of the i-th sensing node. When N is large enough, $\bar{D}$ is approximately Gaussian distributed. The mean and variance of $\bar{D}$ are given as:

$$E(\bar{D}) = \begin{cases} \sum_{i=1}^{N} \omega_i P_{f,i}, \; H_0 \\ \sum_{i=1}^{N} \omega_i P_{d,i}, \; H_1 \end{cases} \tag{11}$$

$$Var(\bar{D}) = \begin{cases} \sum_{i=1}^{N} \omega_i^2 (P_{f,i} - P_{f,i}^2), \; H_0 \\ \sum_{i=1}^{N} \omega_i^2 (P_{d,i} - P_{d,i}^2), \; H_1 \end{cases} \tag{12}$$

So the cooperative detection probability $\bar{P}_d$ and false alarm probability $\bar{P}_f$ can be obtained in the same way as (5) and (6).

From (3) and (4), each T_i has the same mean and variance under H_0, so each node's false alarm probability $P_{f,i}$ determined by (6) is the same with the given threshold η. Here we denote $P_{f,i} = \alpha$ and (11) can be rewritten as

$$E(\bar{D}) = \begin{cases} \alpha, & H_0 \\ \sum_{i=1}^{N} \omega_i P_{d,i}, & H_1 \end{cases} \tag{13}$$

It's mathematically prohibitive to strictly prove that the proposed weighted half-voting algorithm (8) provides better performance than the traditional one (7). However, this advantage offered by (8) can be analyzed intuitively by (13). Under H_0, $E(\bar{D})$ is a constant despite of the choice of ω_i. Moreover, from (3), (4), (5), and the properties of $Q(\cdot)$, the sensing node with higher SNR will accordingly have higher $P_{d,i}$ with the fixed threshold η under H_1. Thereby, with sensing nodes of higher SNR allocated with greater weight factors, the $E(\bar{D})$ under H_1 could be greatly increased, which results in significant improvement of $\bar{P}_d$ but slightly increasing of $\bar{P}_f$.

3.2 Half-Voting Algorithm with Estimated Weights

(8) assumes that the sensing station accurately knows the SNR of each sensing node. However, this assumption may not be satisfied for two reasons: first, it's difficult to obtain the SNRs, since the sensing node has no priori information of the licensed user's signals and also there is not any cooperation between the sensing nodes and primary user; second, there may not be sufficient channels between the sensing nodes and sensing station for transmitting the information of SNRs in real-time. Therefore, we propose another half-voting algorithm whose weight factors are estimated by the history decision results.

To simplify the discussion, we suppose that the licensed user's state H has constant probability of busy (H_1) or idle (H_0). Denoting $P(H = H_1) = \varepsilon$, we obtain

$$\begin{aligned} P(\bar{H}_1) = P(\bar{H}_1 \mid H = H_1)P(H = H_1) \\ +P(\bar{H}_1 \mid H = H_0)P(H = H_0) \\ = \bar{P}_d\varepsilon + \bar{P}_f(1-\varepsilon) \end{aligned} \tag{14}$$

The bayesian posteriori probability of the licensed user's state $H = H_1$ under the final cooperative decision $\bar{H}_1$ is:

$$\begin{aligned} P(H = H_1 \mid \bar{H}_1) = \frac{P(\bar{H}_1 \mid H = H_1)P(H = H_1)}{P(\bar{H}_1)} \\ = \frac{\bar{P}_d\varepsilon}{\bar{P}_d\varepsilon + \bar{P}_f(1-\varepsilon)} \end{aligned} \tag{15}$$

Similarly,we have

$$P(H = H_0 \mid \bar{H}_1) = \frac{\bar{P}_f(1-\varepsilon)}{\bar{P}_d\varepsilon + \bar{P}_f(1-\varepsilon)} \tag{16}$$

Hence conditioned on the final cooperative decision $\bar{H}_1$, the i-th sensing node's probability of individual decision $d_i = 1$ is

$$\begin{aligned} P(d_i = 1 \mid \bar{H}_1) = \frac{\bar{P}_d\varepsilon}{\bar{P}_d\varepsilon + \bar{P}_f(1-\varepsilon)}P_{d,i} \\ + \frac{\bar{P}_f(1-\varepsilon)}{\bar{P}_d\varepsilon + \bar{P}_f(1-\varepsilon)}\alpha \end{aligned} \tag{17}$$

For each sensing node, $\bar{P}_d$, $\bar{P}_f$, ε and α are the same. Since higher SNR_i corresponds to higher $P_{d,i}$, (17) indicates the probability of $d_i = 1$ will be larger if and only if the i-th sensing node has higher SNR compared with other sensing nodes. So this probability can be applied to estimate weight factors. Here we construct the weight factors of (8) as:

$$\omega_i = \frac{P(d_i = 1 \mid \bar{H}_1)}{\sum_{i=1}^{N} P(d_i = 1 \mid \bar{H}_1)} \tag{18}$$

Under the assumption that the received signal powers or SNRs do not change over a number of sensing slots (which is reasonable when the sensing slot is quite short or the channel between sensing nodes and primary user changes slowly), we can approximately calculate the probability of $d_i = 1$ under the final cooperative decision $\bar{H}_1$ by using history decision results. Set $S = \{s_1, s_2, ..., s_N\}$ to record history decision results. At the beginning $s_i = 1$ and when the final cooperative decision is $\bar{H}_1$, $s_i = s_i + d_i$. Then the weight factors in (18) can be approximately calculated as follow:

$$\omega_i = \frac{s_i}{\sum_{i=1}^{N} s_i} \tag{19}$$

4 Simulation Result and Analyses

To evaluate the proposed half-voting algorithms for cooperative sensing in CR networks, numerical simulations are conducted and the results are shown in Fig.2-Fig.3. In our simulation, $\sigma^2 = 1$, $M = 64$.

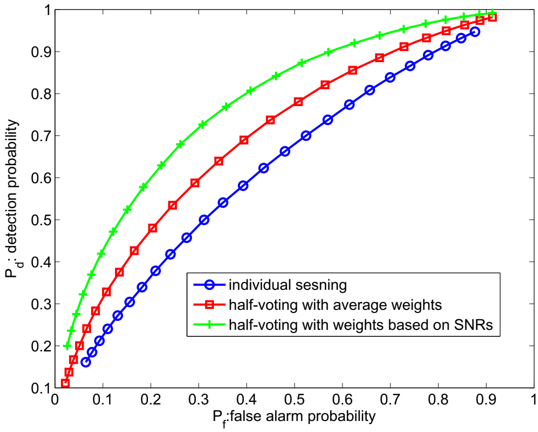

Fig. 2. P_d vs. P_f with different sensing algorithms, the number of the sensing nodes N is 10, and sensing nodes' received SNRs are set to be {-10.38, -14.77, -6.81, -16.89, -18.75, -13.80, -16.99, -14.16, -13.80, -12.22} in dB

Fig.2 depicts the relationship between P_d and P_f with different hard fusion schemes. This figure shows that compared with the individual sensing and the traditional half-voting algorithm, the proposed half-voting algorithm with weight factors based on SNRs provides better performance. Hence performance-wise, when the sensing station has the knowledge of each sensing node's SNR, the proposed half-voting algorithm would be the best choice for the cooperation. It is worth noting that the bigger the gaps of sensing nodes' SNRs are, more performance gains can be obtained since in the new algorithm the sensing node with higher SNR will have much greater impact on the final decision.

Fig.3 portrays the relationship between P_d and P_f of different half-voting algorithms. These curves illustrate that the proposed algorithm with estimated weights can evidently improve the cooperative sensing performance compared with the traditional half-voting algorithm with average weights. And the simulation result also indicates that there is an obvious performance gap between the algorithm with weights based on SNRs and the one with estimated weights. This gap can be explained by the difference between the $P(d_i = 1 \mid \bar{H}_1)$ and the received SNR_i, especially when $\bar{P}_f$ is high in (17). So the sensing performance with weight factors based on SNRs is always better than that based on estimation.

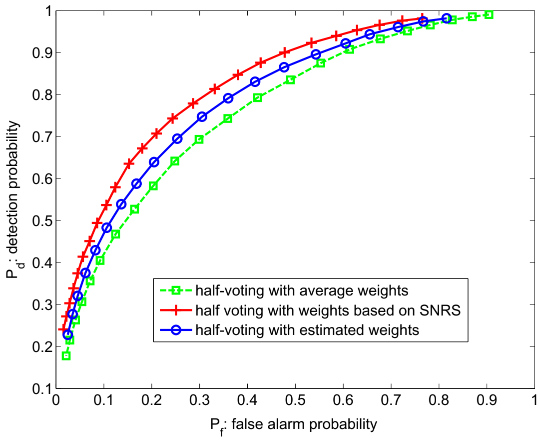

Fig. 3. P_d vs. P_f of different half-voting algorithms, the number of the sensing nodes N is 8, and sensing nodes' received SNRs are set to be {-12.73, -13.56, -7.78, -13.97, -17.44, -12.73, -10.96, -6.19} in dB

5 Conclusion

In this paper, we propose two half-voting algorithms for cooperative sensing in CR networks. In the first algorithm, the linear soft fusion scheme is adopt with weights based on the SNR of each sensing node. In another half-voting algorithm, when the sensing station has no knowledge of each sensing node's SNR, we calculate the weight factors with estimators which are consistent with the SNRs. These estimators can be obtained by the history decision results. We analyze and demonstrate the proposed half-voting algorithms can considerably improve sensing performances . Simulation results show that the performance of the algorithm with weights based on SNRs can offer significant performance gains compared with the traditional one. And when the sensing station has difficulty to obtain the information of the sensing nodes' SNRs, the half-voting algorithm with estimated weights can be adopted to improve the sensing performance.

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