A Novel Cooperative Spectrum Sensing Algorithm in Cognitive Radio Systems

Xueqiang Zheng, Jinlong Wang, Qihui Wu, and Liang Shen

Abstract: **In cognitive radio (CR) systems, cognitive users can use the frequency bands when the primary users are not present. Hence, reliable detection of available spectrum is foundation of cognitive radio technology. To ensure unimpaired operation of primary users, cooperative spectrum sensing is needed. To reduce the network overhead of cooperative spectrum sensing, a novel cooperative spectrum sensing algorithm based on credibility is proposed. In particular, the close-form expressions for probability of detection and false-alarm are derived for the novel algorithm, and expression for the average overhead used for cooperation is given. The thresholds design method for the algorithm is also discussed. The conclusion is proved by computer simulations.**

Index Terms: **Cognitive radio (CR), credibility, network overhead, spectrum sensing.**

I. INTRODUCTION

Wireless networks are characterized by a fixed spectrum assignment policy in most countries. However, the allocated spectrums are vastly underutilized sporadically and geographically with a high variance in time [1]. There are increasing interests in increasing the spectrum efficiency. Cognitive radio (CR) enables much higher spectrum efficiency by dynamic spectrum access [2]. Therefore, it is a potential technique for future wireless communications to mitigate the spectrum scarcity issue.

In cognitive radio systems, cognitive users need to have cognitive radio capabilities, such as sensing the spectrum reliably to check whether it is being used by a primary user. A number of different methods are proposed for identifying the presence of signal transmission, such as matched filter detection, energy detection, feature detection techniques, and wavelet approach [3]. However, due to fading and shadowing effects, the sensing performance for one cognitive user will be degraded. To enhance the sensing performance, cooperative spectrum sensing has been discussed [4]–[6]. It has been shown that cooperative spectrum sensing needs reporting channel for cognitive users to report their sensing results and the reporting channel is usually bandwidth limited. In [7], both soft information-combining strategy and hard information-combining strategy are introduced to detect the primary user. The soft information-combining strategy has better sensing performance but it needs more bits for reporting to the common receiver (base station). In [8], a censoring method is given to decrease the average number of reporting bits to the base station. But the fail sensing problem can not be eliminated.

Some previous work [9] have been done based on [8], we considered the potential of using the reliability of cognitive users for cooperative spectrum sensing over AWGN channels. It was shown that by proper combination of decisions and some observations, the fail sensing problem can be eliminated. And it is possible to achieve higher probability of detection than the censoring method in [8]. Other independent and similar contributions were made in [10], which appeared in roughly the same time period. The performance of [9] and [10] were both better than hard information-combining strategy, but less than soft information-combining strategy.

The previous work in [9] is only a basic idea using the credibility of some cognitive users, there are some unsolved problems. In this paper, we address some further work to approach the soft information-combining strategy, and present a novel credible cooperative spectrum sensing (CCSS) algorithm. Firstly, the thresholds design method is not given in both [9] and [10]. The thresholds determine how to define the credibility and whether the cognitive users makes a decision or not. So the thresholds design is the core of the algorithm. We propose a threshold design method which maximizes the sensing performance of CCSS algorithm. Secondly, the expression for average number of reporting bits is deduced. This can be used to evaluate the tradeoff between sensing performance and the network overhead, which is not given in [10]. Furthermore, the close-form expressions for the probability of the detection and the false-alarm are only derived over AWGN channels in the previous work, the uniform expressions for AWGN channels and fading channels are given in this paper, which are used for algorithm design.

The paper is organized as follows. In Section II, the system model and the local sensing algorithm are briefly introduced. In Section III, CCSS algorithm is given. In Section IV, the performance of the novel algorithm and the average overhead for cooperation are analyzed. The simulation results are shown in Section V. Finally, the conclusion is given in Section VI.

II. SYSTEM MODEL AND LOCAL SENSING

A. System Model

The cognitive radio system model is illustrated in Fig. 1, which includes one primary user, one base station and some cognitive users. The primary user and the base station among cognitive users are far apart and the cognitive users are randomly distributed within the coverage radius of the base station. In cognitive radio system, when cognitive users are sensing the channel, the sampled received signal of cognitive users has two

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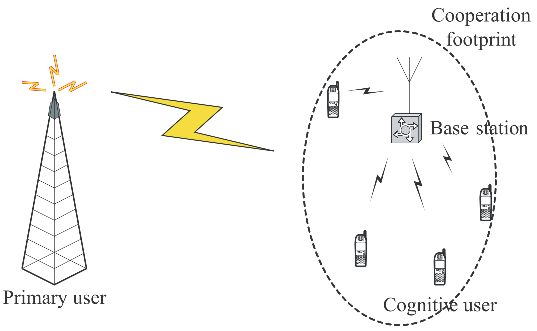

Fig. 1. Cooperative spectrum sensing system model.

hypotheses.

Hypothesis H_1 denotes the primary user is active, and hypothesis H_0 denotes the primary user is inactive.

$$\begin{array}{ll} H_1 : y_i(k) = h_i * s(k) + n_i(k) & i = 1, 2, \cdots, N, \\ H_0 : y_i(k) = n_i(k), & i = 1, 2, \cdots, N \end{array} \tag{1}$$

where $y_i(k)$ is the signal received by the ith cognitive user, $s(k)$ is the transmitted signal of the primary user, N is the number of cognitive users. The signal $s(k)$ is distorted by the channel gain h_i, which is assumed to be constant during the detection interval, and is further corrupted by the zero-mean additive white Gaussian noise $n_i(k)$ with the variance σ_i^2 . Without loss of generality, $s(k)$ and $n_i(k)$ are assumed to be independent of each other. $r_i = |h_i|^2 E_s / {\sigma_i}^2$ denotes the signal-to-noise ratio, where E_s is the signal energy of primary user.

B. Local Sensing

Assume that cognitive users do not know any prior knowledge of the primary user. We use energy detector for cognitive users as the channel sensing scheme to present our results. The test statistic for energy detector is $\theta = \sum_{k=1}^{2u} |y(k)|^2$, where u is the time-bandwidth product.

Note that given an instantaneous r, θ follows the distribution [11]

$$f(\theta \mid r) \sim \begin{cases} \chi^2_{2u}, & H_0, \\ \chi^2_{2u}(2r), & H_1 \end{cases} \tag{2}$$

where r is exponentially distributed with the mean value $\bar{r}$, u is the time-bandwidth product of the energy detector, χ^2_{2u} represents a central chi-square distribution with $2u$ degrees of freedom, and $\chi^2_{2u}(2r)$represents a non-central chi-square distribution with $2u$ degrees of freedom and a non-centrality parameter $2r$.

Let $F_{awgn}(\lambda)$ and $F_{Ray}(\lambda)$ denote the cumulative distribution function (CDF) of the local test statistic θ under the hypothesis H_0 over AWGN and Rayleigh channels, $G_{awgn}(\lambda)$ and $G_{Ray}(\lambda)$ denote the CDF of the local test statistic θ under the hypothesis H_1 over AWGN and Rayleigh channels. According to [11]

$$F_{awgn}(\lambda) = F_{Ray}(\lambda) = \int_0^\lambda f(\theta \mid H_0) d\theta = 1 - \frac{\Gamma\left(u, \frac{\lambda}{2}\right)}{\Gamma(u)}, \tag{3}$$

$$G_{awgn}(\lambda) = \int_0^\lambda f(\theta \mid H_1) d\theta = 1 - Q_u\left(\sqrt{\frac{2r}{\sigma^2}}, \sqrt{\frac{\lambda}{\sigma^2}}\right), \tag{4}$$

$$\begin{aligned} G_{Ray}(\lambda) &= \int_0^\lambda f(\theta \mid H_1) d\theta = 1 - e^{-\frac{\lambda}{2\sigma^2}} \sum_{n=0}^{u-2} \frac{\left(\frac{\lambda}{2\sigma^2}\right)^n}{n!} \\ &+ \left(\frac{\sigma^2 + \bar{r}}{\bar{r}}\right)^{u-1} \left[e^{-\frac{\lambda}{2\sigma^2 + 2\bar{r}}} - e^{-\frac{\lambda}{2\sigma^2}} \sum_{n=0}^{u-2} \frac{\left(\frac{\lambda \bar{r}}{2\sigma^2\left(\sigma^2 + \bar{r}\right)}\right)^n}{n!} \right] \end{aligned} \tag{5}$$

where $\Gamma(\cdot, \cdot)$ is the gamma function and $Q_u(\cdot, \cdot)$ is the generalized Marcum-function.

III. THE CCSS ALGORITHM

In order to effectively use the reliability of cognitive users under bandwidth constraints, CCSS algorithm contains two steps: Local sensing and decision, base station fusion, as in Fig. 2.

A. Local Sensing and Decision

In the local sensing and decision step, every cognitive user conducts spectrum sensing and collects energy individually. Then, two thresholds λ_1 and λ_2 are used to measure the reliability of the collected energy of cognitive user, as in Fig. 3. "Decision H_0" and "decision H_1" represent the absence and the presence of primary user, respectively. "Calculating credibility" means that the observation is not reliable enough to make a decision, cognitive user will calculate credibility of the observation as the decision result.

The local decision of cognitive user is

$$x_i = \Phi(\theta_i) = \begin{cases} 0, & 0 \le \theta_i \le \lambda_1, & H_0, \\ 1, & \theta_i \ge \lambda_2, & H_1, \\ \alpha_i, & \lambda_1 < \theta_i < \lambda_2, & \text{otherwise} \end{cases} \tag{6}$$

where $\alpha_i = (\theta_i - \lambda_1)/(\lambda_2 - \lambda_1)$ is the credibility of the test statistic when $\lambda_1 < \theta_i < \lambda_2$, and $\alpha_i \in [0, 1]$. In order to further decrease the number of reporting bits, let $\alpha_i = quantize((\theta_i - \lambda_1)/(\lambda_2 - \lambda_1), M)$ denote the quantization of the credibility, where $quantize\,(X, M)$ denotes the quantization of X using M bits. It was shown that two or three bits quantization was most appropriate without noticeable loss in the performance [12]. There are two thresholds as the bounds of the quantization. So the number of average reporting bits will be largely reduced. After local sensing and decision of the cognitive user, the result x_i is sent to the base station through the reporting channel.

B. Base Station Fusion

Assume that the number of 1-bit local decisions and M-bits decisions which the base station receives are K and $N - K$ out of N cognitive users. Among the decisions received by the base station, $\boldsymbol{\beta} = [\ \beta_1, \beta_2, \cdots, \beta_K\ ]^T$ is defined as the 1-bits decisions, and $\boldsymbol{\alpha} = [\ \alpha_1, \alpha_2, \cdots, \alpha_{N-K}\ ]^T$ is defined as the M-bits decisions. The base station makes a fusion $\omega = \Upsilon(\boldsymbol{\alpha})$ based on $\boldsymbol{\alpha}$, which fusion method is the soft information-combining strategy [7]. Assume that we do not have any prior information, such as channel fading gains and the energy sent by primary user, so

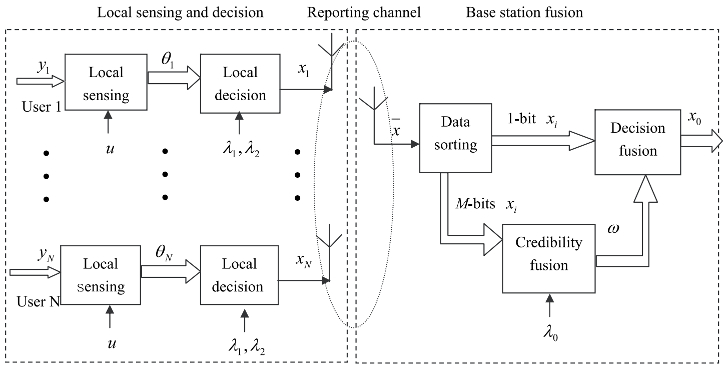

Fig. 2. Scheme of CCSS algorithm.

Table 1. Summary of CCSS algorithm.

Parameters: targeted probability of false farm Q_f^C, number of cognitive users N, quantization bits M , time-bandwidth product u
Data: $\mathbf{y}$ = received data of cognitive users
Calculation: (1) $\theta_i = \sum_{k=1}^{2u} \lvert y_i(k)\rvert^2,\ i = 1, 2, \cdots, N$ (2) $x_i = \Phi(\theta_i) = \begin{cases} 0 & 0 \le \theta_i \le \lambda_1 \\ 1 & \theta_i \ge \lambda_2 \\ \alpha_i & \lambda_1 < \theta_i < \lambda_2 \end{cases}$ where $\alpha_i = quantize\left(\frac{\theta_i - \lambda_1}{\lambda_2 - \lambda_1}, M\right)$, if $\lambda_1 < \theta_i < \lambda_2$, (3) $\omega = \Upsilon(\boldsymbol{\alpha}) = \begin{cases} 0 & \frac{\mathbf{1}^T \Sigma^{-1} \boldsymbol{\theta}'}{\mathbf{1}^T \Sigma^{-1} \mathbf{1}} \le \lambda_0 \\ 1 & \frac{\mathbf{1}^T \Sigma^{-1} \boldsymbol{\theta}'}{\mathbf{1}^T \Sigma^{-1} \mathbf{1}} > \lambda_0 \end{cases}$ where $\boldsymbol{\theta}' = \lambda_1 + (\lambda_2 - \lambda_1)\,\boldsymbol{\alpha}$ (4) $x_0 = \Omega(\omega, \boldsymbol{\beta})$.

the following fusion rule is optimal.

$$\omega = \Upsilon(\boldsymbol{\alpha}) = \begin{cases} 0, & \frac{\mathbf{1}^T \Sigma^{-1} \boldsymbol{\theta}'}{\mathbf{1}^T \Sigma^{-1} \mathbf{1}} \le \lambda_0, \\ 1, & \frac{\mathbf{1}^T \Sigma^{-1} \boldsymbol{\theta}'}{\mathbf{1}^T \Sigma^{-1} \mathbf{1}} > \lambda_0 \end{cases} \tag{7}$$

where $\boldsymbol{\theta}' = \lambda_1 + (\lambda_2 - \lambda_1)\,\boldsymbol{\alpha}$, λ_0 is the threshold for credibility fusion, $\Sigma = eyes\left(\sigma_1^2, \sigma_2^2, \cdots, \sigma_N^2\right)$ is the noise covariance matrix since cognitive users are statistically independent. The calculating method for the thresholds will be discussed in the next section.

Using the fusion result ω and $\boldsymbol{\beta}$, the base station will make a final decision $x_0 = \Omega(\boldsymbol{\beta}, \omega)$. To maximize the detection probability, the OR-rule is used for final decision in the base station. Because of using the sensing result of all cognitive users in the CR system, the fail sensing problem in [8] can be eliminated in CCSS algorithm.

As defined in local decision section, when cognitive user's observation is very informative, that cognitive user simply transmits a 1-bit local decision to base station; otherwise, the cognitive user will send the quantization of the credibility to base station. After the credibility fusion of unreliable observations in base station, the result ω and $\boldsymbol{\beta}$ are both reliable, so the OR-rule is optimal for final decision.

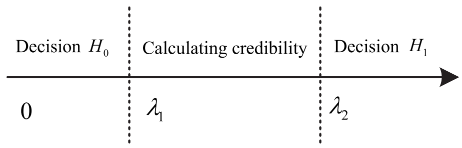

Fig. 3. The decision method based on θ for cognitive users.

The summary of CCSS algorithm is illustrated in Table 1.

IV. THE PERFORMANCE ANALYSIS OF CCSS ALGORITHM

A. Sensing Performance

Assume that the reporting channels between the base station and cognitive users are perfect, the local decisions are reported without any error. Let $F(\lambda)$ and $G(\lambda)$ denote the CDF of the local test statistic θ under hypothesis H_0 and H_1 [11]. We define (8) and (9), where λ_0 is the threshold for credibility fusion. We further assume that $\sigma_1^2 = \sigma_2^2 = \cdots = \sigma_N^2$ here.

$$\begin{aligned} p &= P(\theta_i > \lambda_2 \mid H_1) = 1 - G(\lambda_2) \\ p_1 &= P(\theta_i < \lambda_1 \mid H_1) = G(\lambda_1) \\ q &= P(\theta_i > \lambda_2 \mid H_0) = 1 - F(\lambda_2) \\ q_1 &= P(\theta_i < \lambda_1 \mid H_0) = F(\lambda_1) \end{aligned} \tag{8}$$

The detection probability of CCSS algorithm can be calculated as (10). The false alarm probability of CCSS algorithm can be calculated as (11).

B. Network Overhead

Let T_K and T'_{N-K} represent the event that there are K cognitive users reporting 1-bit local decision and $N - K$ users reporting M

$$\begin{cases} a(K) = \displaystyle\iiint\limits_{\sum_{i=1}^{N-K}\theta_i>\lambda_0,\lambda_1<\theta_i<\lambda_2} f(\theta_1 \mid H_1) f(\theta_2 \mid H_1)\cdots f(\theta_{N-K} \mid H_1)\, d\theta_1 d\theta_2\cdots d\theta_{N-K} \\ b(K) = \displaystyle\iiint\limits_{\sum_{i=1}^{N-K}\theta_i>\lambda_0,\lambda_1<\theta_i<\lambda_2} f(\theta_1 \mid H_0) f(\theta_2 \mid H_0)\cdots f(\theta_{N-K} \mid H_0)\, d\theta_1 d\theta_2\cdots d\theta_{N-K} \end{cases} \tag{9}$$

$$\begin{aligned} Q_d &= P\{x_0 = 1 \mid H_1\} \\ &= P\left\{\text{any of cognitive users claims } H_1 \text{ or the result of fusing credibility is } H_1 \mid H_1\right\} \\ &= P\{\max(\theta_1,\theta_2,\cdots,\theta_N) \ge \lambda_2 \mid H_1\} \\ &+ \sum_{K=0}^{N-1} P\{\theta_1 \le \lambda_1,\cdots,\ \theta_K \le \lambda_1,\ \lambda_1 < \theta_{K+1} < \lambda_2,\cdots,\lambda_1 < \theta_N < \lambda_2 \mid H_1\}\, P\left\{\sum_{i=1}^{N-K}\theta_i > \lambda_0 \mid \lambda_1 < \theta_i < \lambda_2,\ i=1,2,\cdots,\ N-K; H_1\right\} \\ &= 1-(G(\lambda_2))^N + \sum_{K=0}^{N-1}\binom{N}{K}(G(\lambda_2)-G(\lambda_1))^{N-K}(G(\lambda_1))^K P\left\{\sum_{i=1}^{N-K}\theta_i > \lambda_0 \mid \lambda_1 < \theta_i < \lambda_2,\ i=1,2,\cdots,\ N-K; H_1\right\} \\ &= 1-(1-p)^N + \sum_{K=0}^{N-1}\binom{N}{K} {p_1}^K a(K) \end{aligned} \tag{10}$$

$$\begin{aligned} Q_f &= P\{x_0 = 1 \mid H_0\} \\ &= P\left\{\text{any of cognitive users claims } H_1 \text{ or the result of fusing credibility is } H_1 \mid H_0\right\} \\ &= P\{\max(\theta_1,\theta_2,\cdots,\theta_N) \ge \lambda_2 \mid H_0\} \\ &+ \sum_{K=0}^{N-1} P\{\theta_1 \le \lambda_1,\cdots,\ \theta_K \le \lambda_1,\ \lambda_1 < \theta_{K+1} < \lambda_2,\cdots,\ \lambda_1 < \theta_N < \lambda_2 \mid H_0\} P\left\{\sum_{i=1}^{N-K}\theta_i > \lambda_0 \mid \lambda_1 < \theta_i < \lambda_2,\ i=1,2,\cdots,\ N-K; H_0\right\} \\ &= 1-(F(\lambda_2))^N + \sum_{K=0}^{N-1}\binom{N}{K}(F(\lambda_2)-F(\lambda_1))^{N-K}(F(\lambda_1))^K P\left\{\sum_{i=1}^{N-K}\theta_i > \lambda_0 \mid \lambda_1 < \theta_i < \lambda_2,\ i=1,2,\cdots,\ N-K; H_0\right\} \\ &= 1-(1-q)^N + \sum_{K=0}^{N-1}\binom{N}{K} {q_1}^K b(K) \end{aligned} \tag{11}$$

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bits credibility to the base station respectively. Then,

$$\begin{cases} P(T_K) = [1-P(\lambda_1<\theta_i<\lambda_2)]^K, \\ P\left(T'_{N-K}\right) = [P(\lambda_1<\theta_i<\lambda_2)]^{N-K} \end{cases} \tag{12}$$

where $P\{\cdot\}$ stands for the probability. Further let $P_0 = P\{H_0\}$ and $P_1 = P\{H_1\}$ denote probability of the primary user is not present or present respectively, and then the average number of reporting bits for CCSS algorithm can be calculated as

$$\begin{aligned} K_{avg} = P_0 &\sum_{K=0}^{N}(K+M(N-K))\binom{N}{K}P\{T_K \mid H_0\}P\left\{T'_{N-K} \mid H_0\right\} \\ +P_1 &\sum_{K=0}^{N}(K+M(N-K))\binom{N}{K}P\{T_K \mid H_1\}P\left\{T'_{N-K} \mid H_1\right\}. \end{aligned} \tag{13}$$

We define

$$\begin{cases} z = P(\lambda_1<\theta_i<\lambda_2 \mid H_0) = F(\lambda_2) - F(\lambda_1), \\ y = P(\lambda_1<\theta_i<\lambda_2 \mid H_1) = G(\lambda_2) - G(\lambda_1), \end{cases} \tag{14}$$

then

$$\begin{aligned} K_{avg} = P_0 &\sum_{K=0}^{N}[K+M(N-K)]\binom{N}{K}(1-z)^K z^{N-K} \\ +P_1 &\sum_{K=0}^{N}[K+M(N-K)]\binom{N}{K}(1-y)^K y^{N-K}. \end{aligned} \tag{15}$$

Let network overhead W denote the normalized average number of reporting bits, then

$$\begin{aligned} W &= \frac{K_{avg}}{N} \\ &= P_0\sum_{K=0}^{N}\left[(1-M)\frac{K}{N}+M\right]\binom{N}{K}(1-z)^K z^{N-K} \\ &\quad +P_1\sum_{K=0}^{N}\left[(1-M)\frac{K}{N}+M\right]\binom{N}{K}(1-y)^K y^{N-K} \end{aligned} \tag{16}$$

where $\sum_{K=0}^{N}\left[(1-M)\frac{K}{N}+M\right]\binom{N}{K}(1-z)^K z^{N-K}$ can be derived as in (17).

Consequently, the normalized average number of reporting bits used for CCSS algorithm can be calculated

$$W = \frac{K_{avg}}{N} = 1 + (M-1)(P_0 z + P_1 y). \tag{18}$$

C. Calculating the Thresholds

Because cognitive users do not know any prior information of primary user, CCSS algorithm uses same thresholds over cognitive users. Let Q_f and Q_d denote probability of false alarm and detection of CCSS algorithm respectively. According to (10) and (11), Q_d is influenced by system parameters (N, u), signal noise ratio γ, thresholds λ_1, λ_2, and λ_0. Q_f is influenced by system parameters (N, u), thresholds λ_1, λ_2, and λ_0.

When $\lambda_1 = 0, \lambda_2 \to \infty$, CCSS algorithm is equivalent to soft information-combining strategy, let λ_s denote the threshold of soft information-combining strategy, i.e., $\lambda_0 = \lambda_s$. According

$$\begin{aligned}
&\sum_{K=0}^{N}\left[(1-M)\frac{K}{N}+M\right]\binom{N}{K}(1-z)^{K}z^{N-K}\\
&= Mz^{N}+\sum_{K=1}^{N}(1-M)\frac{K}{N}\binom{N}{K}(1-z)^{K}z^{N-K}+\sum_{K=1}^{N}M\binom{N}{K}(1-z)^{K}z^{N-K}\\
&= Mz^{N}+M\sum_{K=1}^{N}\binom{N}{K}(1-z)^{K}z^{N-K}+(1-M)\sum_{K=1}^{N}\binom{N-1}{K-1}(1-z)^{K-1}z^{N-K}(1-z)\\
&= M\sum_{K=0}^{N}\binom{N}{K}(1-z)^{K}z^{N-K}+(1-M)(1-z)\sum_{K'=0}^{N'}\binom{N'}{K'}(1-z)^{K'}z^{N'-K'}\\
&= M+(1-M)(1-z)\\
&= 1+(M-1)z
\end{aligned} \tag{17}$$

to [7], the false farm probability of soft information-combining strategy Q_f^{soft} is

$$Q_f^{soft}=P\{\Delta=\sum_{i=1}^{N}\theta_i>\lambda_s\mid H_0\}=\frac{\Gamma(Nu,\lambda_s/2)}{\Gamma(Nu)}. \tag{19}$$

As system parameters (N,u) are predefined, Q_f^{soft} is only influenced by λ_s and can be simplified as $Q_f^{soft}=g(\lambda_s)$. When $\lambda_1=\lambda_2$, CCSS algorithm is equivalent to OR-rule hard information-combining strategy, i.e., $\lambda_0=0$. The false farm probability of OR-rule is

$$Q_f^{OR}=1-\prod_{i=1}^{N}(1-F(\lambda_1))=1-\left[\frac{\Gamma(u,\lambda_1/2)}{\Gamma(u)}\right]^{N}. \tag{20}$$

To compare conveniently and simplify calculation, we define $\overline{\lambda}=\lambda_s/N=(\lambda_1+\lambda_2)/2, \Delta\lambda=\overline{\lambda}-\lambda_1, \lambda_0=(N-K)\lambda_s/N$, then λ_1,λ_2, and λ_0 can be calculated by λ_0 and $\Delta\lambda$,

$$\begin{cases}\lambda_2=\dfrac{\lambda_s}{N}+\Delta\lambda,\\ \lambda_1=\dfrac{\lambda_s}{N}-\Delta\lambda,\\ \lambda_0=\dfrac{N-K}{N}\lambda_s,\end{cases} \tag{21}$$

and Q_f is only influenced by the thresholds λ_s and $\Delta\lambda$. When λ_s is defined, we have

$$\begin{cases}\Delta\lambda\to\infty, & Q_f\to Q_f^{soft}(\lambda_s),\\ \Delta\lambda\to 0, & Q_f\to Q_f^{OR}\left(\dfrac{\lambda_s}{N}\right).\end{cases} \tag{22}$$

If we choose a temp false farm probability Q_f^S of soft information-combining strategy to calculate λ_s, the thresholds of CCSS algorithm can be calculated according to the false farm probability Q_f^C of CCSS algorithm. The temp false farm probability of soft information-combining strategy Q_f^S should satisfy the following constrains:

$$\begin{cases}Q_f^S<Q_f^C,\\ Q_f^{OR}\left(\dfrac{g^{-1}\left(Q_f^S\right)}{N}\right)>Q_f^C.\end{cases} \tag{23}$$

According to Q_f^S and (19), λ_s can be calculated, then, $\Delta\lambda$ can be calculated according to Q_f^C and (11) by numerical methods.

V. SIMULATION RESULTS

In this section we present some simulation results to demonstrate the sensing performance and overhead of CCSS algorithm. The results of soft information-combining strategy and hard information-combining strategy are also shown for a comparison. The parameters used in our simulations of cognitive radio system shown in Fig. 1 are as follows.

There is one primary user, one base station among $N=20$ cognitive users. The cognitive users are randomly distributed within the coverage radius of the base station. The primary user and the base station are far apart. Either the signal to the noise ratio received at each cognitive user or the distance between primary user and cognitive user is assumed to be unknown. We use $P_0=P_1=0.5$.

A. Sensing Performance of CCSS Algorithm

In this section we present some simulation results to demonstrate the performance of CCSS algorithm. For CCSS algorithm, λ_1,λ_2, and λ_0 were adjusted to achieve the targeted probability of false farm satisfies $Q_f^C=10^{-2}$ and $Q_f^C=10^{-3}$. For other spectrum sensing methods displayed in Fig. 4 and Fig. 5, the detection thresholds at cognitive users or base station were adjusted to achieve the constant targeted probability of false farm satisfies $Q_f^C=10^{-2}$ and $Q_f^C=10^{-3}$.

Figs. 4 and 5 show the sensing performance (Q_d vs. SNR) over Rayleigh channels. During the sensing time, the number of received signal samples at each cognitive user is set to 100. To validate the analytical results, we assume that there is no quantization on the credibility, i.e., $M=\infty$.

From Figs. 4 and 5, it can be observed that for a fixed targeted probability of false farm Q_f^C, the sensing performance of soft information-combining strategy is better than hard information-combining strategy, the sensing performance of CCSS algorithm is very close to soft information-combining strategy.

B. The Overhead of CCSS Algorithm

In this section we present some simulation results to demonstrate the overhead of CCSS algorithm. For CCSS algorithm, λ_1,λ_2, and λ_0 were adjusted to achieve the targeted probability of false farm satisfies $Q_f^C=10^{-2}$ and $Q_f^C=10^{-3}$. For other spectrum sensing methods, the detection thresholds at cognitive users or base station were adjusted to achieve the targeted probability of false farm satisfies $Q_f^C=10^{-2}$ and $Q_f^C=10^{-3}$. During

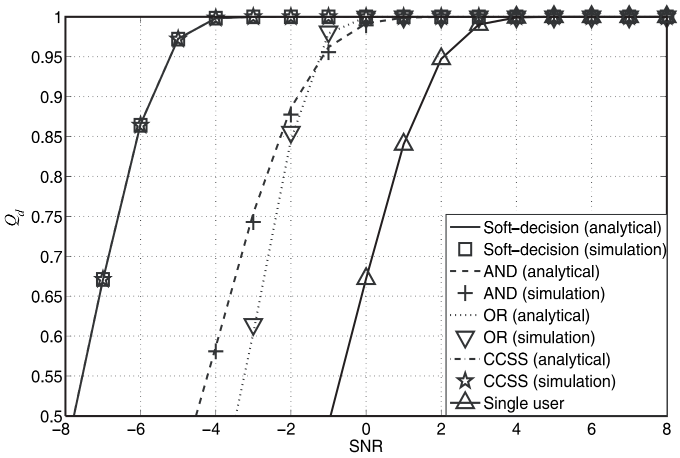

Fig. 4. The sensing performance of CCSS algorithm ($Q_f^C = 10^{-2}$).

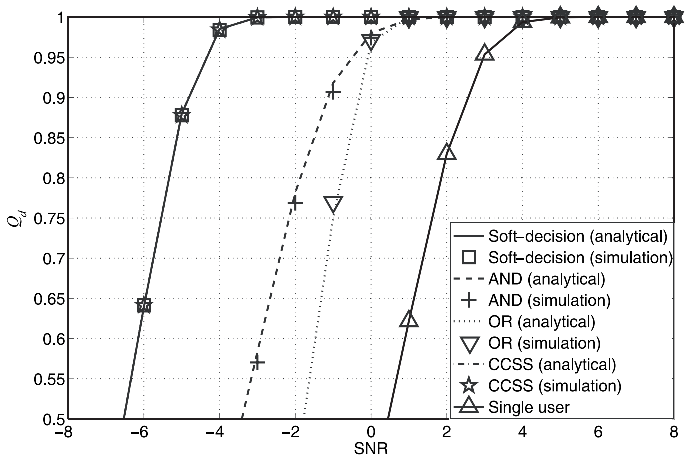

Fig. 5. The sensing performance of CCSS algorithm ($Q_f^C = 10^{-3}$).

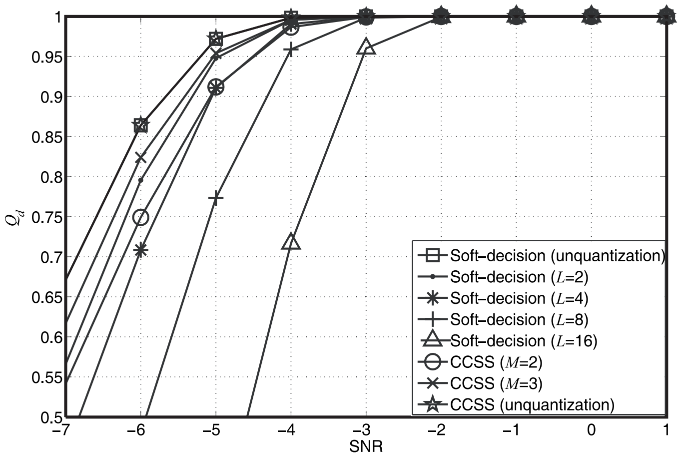

Fig. 6. The sensing performance of CCSS algorithm ($Q_f^C = 10^{-2}$).

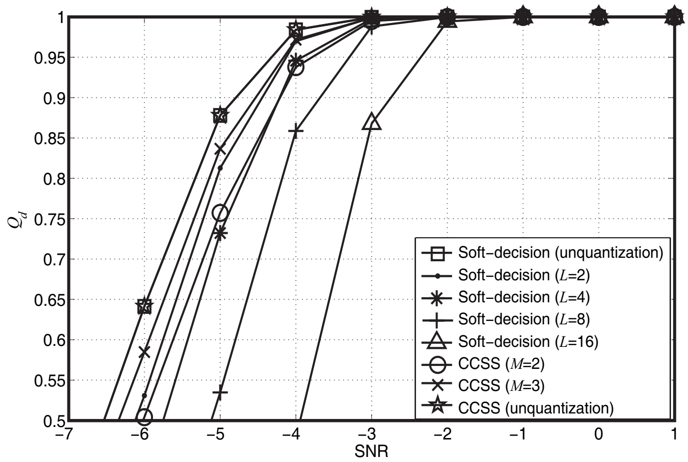

Fig. 7. The sensing performance of CCSS algorithm ($Q_f^C = 10^{-3}$).

the sensing time, the number of received signal samples at each cognitive user is set to 100. To evaluate the overhead of CCSS algorithm, the normalized average number of reporting bits is calculated.

To calculate CCSS algorithm's network overhead W, the local decisions must be quantized. We use the equal quantization levels to quantize the local decision. The quantization level for CCSS algorithm is $L_0 = (\lambda_2 - \lambda_1)/2^M$ and the quantization level L for soft information-combining strategy is from 2 to 16.

Fig. 6 and Fig. 7 show the sensing performance (Q_d vs. SNR) over Rayleigh channels when the local decisions are quantized.

From Figs. 6 and 7, we can see that when the quantization level of soft information-combining strategy $L = 2$, the performance loss is least. When the number of quantization bits $M = 3$, the performance loss of CCSS algorithm is little. Fig. 8 and Fig. 9 show the normalized average number of reporting bits W vs. SNR of CCSS algorithm when $L = 2$ and $M = 3$.

From Figs. 8 and 9, we can see that when SNR is lower, the overhead of CCSS algorithm is only half of soft information-combining strategy; when SNR is higher, the overhead of CCSS algorithm decreases with SNR increasing, and the overhead of soft information-combining strategy increases with SNR increasing.

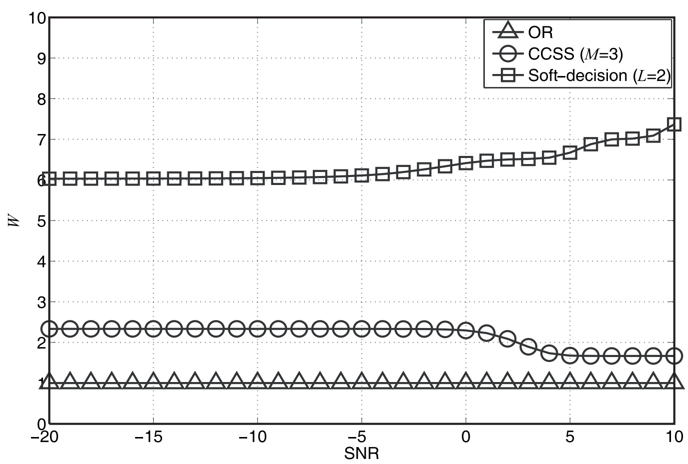

Fig. 8. The overhead of CCSS algorithm ($Q_f^C = 10^{-2}$).

For a fixed targeted probability of false farm Q_f^C, compared with soft information-combining strategy, CCSS algorithm can achieve a large reduction of number of reporting bits at a very little expense of performance loss.

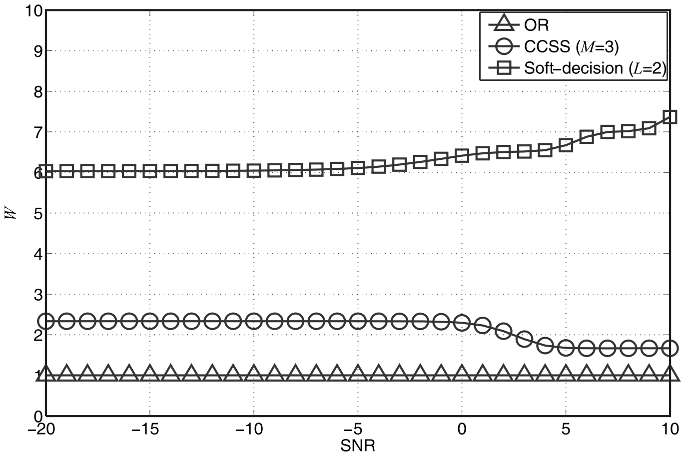

Fig. 9. The overhead of CCSS algorithm ($Q_f^C = 10^{-3}$).

VI. CONCLUSION

To reduce the network overhead of soft information-combining strategy with little expense of performance loss, a novel credible cooperative spectrum sensing (CCSS) algorithm was given. We considered the potential of using the reliability of cognitive users for cooperative spectrum sensing. Analysis showed that it is possible to achieve high probability of detection as soft information-combining strategy by proper fusion of the cognitive users' decisions. In particular, the close-form expressions for the probability of the detection and the false-alarm were derived for the novel algorithm, and the expression for the average overhead used for cooperation was given. The thresholds design method for the algorithm was also discussed. The simulation results show that the novel algorithm can perform as well as soft information-combining strategy and its overhead is much less than soft information-combining strategy.

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