# 무선인지시스템을 위한 선택적 협력 스펙트럼 검출 기법

## Selection Based Cooperative Spectrum Sensing in Cognitive Radio

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요 약

본 논문에서는 무선인지시스템에서 스펙트럼 센싱을 효율적으로 수행하기 위한 선택적 협력 스펙트럼 검출 기법을 제안한다. 제안된 알고리즘에서는 각 무선인지 사용자가 자신의 유도비(likelihood ratio)를 기반으로 자신의 센싱 신뢰도를 평가하고, 센싱 신뢰도에 따른 타이머를 활용하는 경쟁기반의 센싱 결과 보고 메커니즘을 활용한다. 이를 통해, 제안된 선택적 협력 스펙트럼 기법에서는 가장 높은 센싱 신뢰도를 갖는 무선인지 사용자만이 국부 스펙트럼 센싱값을 융합센터로 전송함으로써, 스펙트럼 센싱의 성능을 일정한 레벨로 유지하고, 협력 스펙트럼 센싱의 단점인 제어 트래픽 및 협력 센싱 시간을 줄이는 이점을 갖는다.

ABSTRACT

In this paper, we propose an effective method for cooperative spectrum sensing in cognitive radios where cognitive user(CR) with the highest reliability sensing data is only selected and allowed to report its local decision to FC as only decision making node. The proposed scheme enables CR users to implicitly compare their sensing data reliabilities based on their likelihood ratio, without any collaboration among cognitive radio users. Due to the mechanism, the proposed cooperative scheme can achieves a high spectrum sensing performance while only requiring extremely low cooperation resources such as signaling overhead and cooperative time in comparison with other existing methods such as maximum ratio combination (MRC) based, equal gain combination (EGC) based and conventional hard combination based cooperative sensing methods.

☞ keyword : Cognitive radio, cooperative spectrum sensing, data fusion, 인지 무선, 협력 스펙트럼 센싱, 데이터 융합

## 1. Introduction

Recently, Cognitive Radio (CR) which enables opportunistic access to unused licensed bands has been proposed as a promising technology to improve spectrum utilization. A prerequisite of secondary access is no interference to primary system which makes spectrum sensing a key role for cognitive radio. Among various spectrum sensing techniques, energy detection is an engaging method due to its simplicity and efficiency. However, the major disadvantage of energy detection is the hidden node problem in which the sensing node cannot distinguish between an idle and a deep faded or shadowed band[1]. The cooperative spectrum sensing which uses a distributed detection model has been considered to overcome that problem in many literatures[2-8].

Cooperation among CR Users (CUs) is usually coordinated by a fusion center. There are two main methods in cooperative spectrum sensing techniques for combining sensing data; one is the hard decision fusion and the other is the soft data fusion. Obviously, the soft data fusion is superior to hard decision fusion since it imposes a larger control

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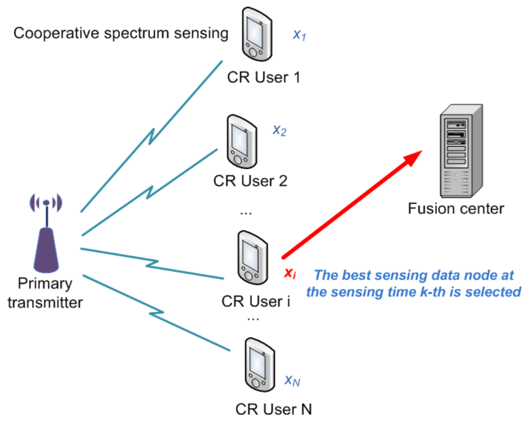
channel bandwidth for transferring the sensing data from different sensing nodes to the fusion center. For hard fusion, an optimal data fusion rule, firstly mentioned by *Z. Chair and P.K. Varshney*[2], was applied by combining with a counting rule in [3]. Despite of good performance it needs convergence time when the channel environment changes. In the reference [4], *Wei* et al. propose an optimal "half-voting" rule which only works well under impractical condition - identical threshold for all CUs.

For soft data fusion, *Quan* et al. [5] use a non-linear optimization to formulate the cooperative spectrum sensing problem which might be difficult to implement. In [6], an optimal soft combination scheme is proposed, based on some approximation in the target optimality function and the assumption that cooperative CUs in the network experience independently and identically distributed (i.i.d.) fading effects. It is thereby proved to be identical to a maximal ratio combination (MRC) strategy. *Nhan* et al. [7] propose an enhanced method for combining all nodes' self-assessed credibility of decision via *Dempter-Shafer* theory of evidence , which provides a high sensing performance. Nevertheless, similarly to other soft combination methods in [5, 6], this method requires extremely overhead for signaling and sensing data collaboration.

In this paper, we propose a selection based cooperative spectrum sensing scheme which utilizes the reliability of the sensing data to implicitly select the node with the highest sensing reliability at each sensing interval without any extra collaboration among cognitive radio users. According to the sensing data from the node with the highest sensing reliability, the final decision will be made. By this way, the cooperative sensing will be performed with an extremely low cooperation resource requirement while ensuring the utilization of sensing diversity of the distributed model.




(Fig.1) System model

The rest of this paper is organized as follows. In section 2, the system model is described. In section 3, we propose the selection based cooperative spectrum sensing scheme. Simulations are carried out in section 4, and conclusions are drawn in section 5.

## 2. System Description

For Primary User (PU) detection, we consider the cooperative spectrum sensing scheme like Fig.1. Each CU conducts its local sensing process, calculates and estimates some necessary information that will be transmitted to the fusion center where the final decision will be made. Generally, the whole process of the scheme includes two steps:

- Local spectrum sensing at CU
- Data fusion at fusion center

### 2.1 Local spectrum sensing at CU

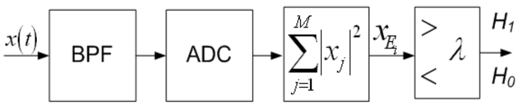
The $i$-th cognitive user ($CU_i$) conducts a spectrum sensing process, which is called local spectrum sensing in distributed scenario for detecting PU signal. Local spectrum sensing is essentially a binary hypotheses testing problem:

$$\begin{cases} H_0 : x_i(t) = n_t(t) \\ H_1 : x_i(t) = h_i \cdot s(t) + n_t(t) \end{cases} \quad (1)$$

where $H_0$ and $H_1$ are respectively correspondent to hypotheses of absence and presence of PU's signal, $x_i(t)$ represents the received data at $CU_i$, $h_i$ denotes the gain of the channel between the PU and the $CU_i$, $s(t)$ is the signal transmitted from the primary user and $n(t)$ is the additive white Gaussian noise. Additionally, channels corresponding to different CUs are assumed to be independent, and further, all CUs and PUs share common spectrum allocation.

Among various methods for spectrum sensing, energy detection has shown that it is quite simple, quick and possible to detect primary signal - even if the feature is unknown. Here we consider the energy detection for local spectrum sensing. Fig.2 shows the block diagram of energy detection scheme. To measure the signal power in particular frequency region in time domain, a band-pass filter (BPF) is applied to the received signal and the power of signal samples is then measured at CU. The estimation of received signal power is given at $CU_i$ by following equation:

$$x_{E_i} = \sum_{j=1}^{M} |x_j|^2 \quad (2)$$




(Fig.2) Block diagram of energy detection scheme

where $x_j$ is the $j$-th sample of the received signal and $M = 2TW$ in which $T$ and $W$ are correspondent to detection time and signal bandwidth in Hz, respectively.

If primary signal is absent, $x_{E_i}$ follows a central chi-square distribution with $M$ degrees of freedom; otherwise, $x_{E_i}$ follows a non-central chi-square distribution with M degrees of freedom and a non-centrality parameter $\theta_i = M\gamma_i$, i.e.,

$$x_{E_i} \sim \begin{cases} \chi_M^2 & H_0, \\ \chi_M^2(\theta_i), & H_1, \end{cases} \quad (3)$$

When $M$ is relatively large (e.g. $M > 200$)[9], $x_E$ can be well approximated as a Gaussian random variable under both hypotheses $H_1$ and $H_0$, according to Central Limit Theorem such that we have

$$x_{E_i} \sim \begin{cases} N(M, 2M), & H_0, \\ N(M(1+\gamma_i), 2M(1+2\gamma_i)), & H_1, \end{cases} \quad (4)$$

where $\gamma_i$ is the signal to noise ratio (SNR) of the primary signal at the CU.

For the case of local sensing or hard decision fusion, the CUs will make the local sensing decision based on a energy threshold $\lambda_i$ as follows:

$$D_i = \begin{cases} H_1, & x_{E_i} > \lambda_i, \\ H_0, & otherwise. \end{cases} \quad (5)$$

The local probability of detection and local probability of false alarm can be determined by

$$p_f = P(x_{E_i} > \lambda_i | H_0) = Q\left(\frac{\lambda_i - M}{\sqrt{2M}}\right) \quad (6)$$

and

$$p_d = P(x_{E_i} > \lambda_i | H_1) = Q\left(\frac{\lambda_i - M(1+\gamma_i)}{\sqrt{2M(1+2\gamma_i)}}\right) \quad (7)$$

respectively, where $Q(.)$ is the Marcum-Q function, i.e. $Q(x)=\frac{1}{\sqrt{2\pi}}\int_x^\infty e^{-\frac{t^2}{2}}dt$.

The threshold $\lambda_i$ can be determined by Neyman-Pearson criterion or Bayes's criterion. For Neyman-Pearson criterion, the threshold $\lambda_i$ is chosen such that the false-alarm probability is kept according to a predefined value. For Bayes' criterion, the threshold is selected such that the risk function $\mathrm{R}$ is minimized. The risk function $\mathrm{R}$ is defined as follows.

$$\begin{aligned} R= & C_{00}\cdot \Pr(H_0)\cdot \Pr(H_0|H_0) \\ & + C_{10}\cdot \Pr(H_0)\cdot \Pr(H_1|H_0) \\ & + C_{11}\cdot \Pr(H_1)\cdot \Pr(H_1|H_1) \\ & + C_{01}\cdot \Pr(H_1)\cdot \Pr(H_0|H_1) \end{aligned} \tag{8}$$

where $C_{00}$, $C_{10}$, $C_{11}$ and $C_{01}$ denote the cost for four cases which can happen in a simple binary hypothesis test, i.e. ($H_0$ true; choose $H_0$), ($H_1$ true; choose $H_0$), ($H_1$ true; choose $H_1$) and ($H_1$ true; choose $H_0$), respectively.

For simplicity, in a CR network, we can assign that $C_{00}=C_{11}=0$ and $C_{10}=C_{01}=1$. As a result, the risk function is now equivalent to the probability of error as follows:

$$\begin{aligned} R &= \Pr(H_0)\Pr(H_1|H_0)+\Pr(H_1)\Pr(H_0|H_1) \\ &= \Pr(H_0)p_f+\Pr(H_1)p_m \\ &= \Pr(H_0)\int_{\lambda_i}^{\infty} p(x_{E_i}|H_0)dx_{E_i} \\ &\quad +\Pr(H_1)\int_{\infty}^{\lambda_i} p(x_{E_i}|H_1)dx_{E_i} \end{aligned} \tag{9}$$

where $p_m$ is the miss detection probability. Consequently, the Bayes' criterion is similar to the minimum probability of error criterion. From the Eqn.(9), the Bayes test is minimizing the total probability of error. The test will be

$$\frac{p(x_{E_i}|H_0)}{p(x_{E_i}|H_1)} \underset{H_0}{\overset{H_1}{\lessgtr}} \frac{\Pr(H_0)}{\Pr(H_1)} \tag{10}$$

The quantity on the left of Eqn.(10) is called *likelihood ratio* and is denoted by $\Gamma(x_{E_i})$. The quantity on the right of Eqn.(10) is the threshold of the test and is denoted by $\eta$. Thus the Bayes criterion is equivalent to the following Likelihood Ratio Test (LRT).

$$\Gamma(x_{E_i}) \underset{H_0}{\overset{H_1}{\lessgtr}} \frac{\Pr(H_0)}{\Pr(H_1)} \tag{11}$$

From Eqn.(4) and (10), the optimal energy threshold can be calculated by

$$\lambda_i^{opt}=\frac{2\sigma_0^2\sigma_1^2}{\sigma_1^2-\sigma_0^2}ln\frac{\eta\sigma_0}{\sigma_1} \tag{12}$$

where the $\sigma_0^2$ and $\sigma_1^2$ are the variance values, defined in Eqn. (4), of hypothesis $H_0$ and $H_1$ distribution, respectively.

## 2.2 Data fusion - Conventional schemes

### 2.2.1 Hard decision combination

For hard decision fusion, each CU, after conducting sensing process, will make a local decision and send to the fusion center. These local decisions will be combined by a fusion rule which can be OR-rule (i.e., 1-out-of-N) or AND-rule (i.e., N-out-of-N) or Half-voting-rule (i.e., k-out-of-N). Unless the fusion center has adequate information of all CUs, such as PU signal's SNR, local threshold $\lambda_i$, it can not make an optimal fusion rule.

### 2.2.2 Data fusion - Conventional schemes

For soft combination scheme, the received energies from difference CUs are combined with weight factor corresponding to each CR node. The weighted summation is given by

$$Y=\sum_{i=1}^{N} w_i x_{E_i} \tag{13}$$

where $w_i$ denotes the weight of $CU_i$. According to Eqn. (4), $Y$ is Gaussian with

$$Y \sim \begin{cases} N(M\sum_{i=1}^{N} w_i, 2M\sum_{i=1}^{N} w_i^2), & H_0, \\ N(M\sum_{i=1}^{N} w_i(1+\gamma_i), 2M\sum_{i=1}^{N} w_i^2(1+2\gamma_i)), & H_1. \end{cases} \tag{14}$$

Let $\Lambda$ be the decision threshold. Then, the global false alarm probability and detection probability can be calculated by

$$P_F = P(Y>\Lambda|H_0) = Q\left(\frac{\Lambda - M\sum_{i=1}^{N} w_i}{\sqrt{2M\sum_{i=1}^{N} w_i^2}}\right) \tag{15}$$

and

$$P_D = P(Y>\Lambda|H_1) = Q\left(\frac{\Lambda - M\sum_{i=1}^{N} w_i(1+\gamma_i)}{\sqrt{2M\sum_{i=1}^{N} w_i^2(1+2\gamma_i)}}\right), \tag{16}$$

respectively. Likewise in cooperative systems with relay nodes, we can apply equal gain combination (EGC) scheme with the corresponding weight coefficients

$$w_{EGC_i} = \frac{1}{\sqrt{N}}, 1 \le i \le N \tag{17}$$

According to the reference[5] the optimal weight coefficients is identical to the Maximal Ratio Combination (MRC) weight, i.e.,

$$w_{MRC_i} = \frac{\gamma_i}{\sqrt{\sum_{i=1}^{N} \gamma_i^2}} \tag{18}$$

# 3. Selection based cooperative spectrum sensing scheme

As mentioned before, for both the hard and the soft fusions, the large overhead signaling and control channel bandwidth requirements are compulsory. Besides, the time to collaborate sensing data is also constrained by the channel throughput efficiency. In other words, if the time for collaboration gets larger the total sensing time will be larger. Therefore the channel utilization will be decreased. For the purpose of reducing overhead signaling, control bandwidth and total sensing time, in the paper the selection based cooperative spectrum sensing scheme is proposed. The main idea of the proposed scheme is that at each sensing time, the final decision will be made, based on the sensing data from the best CR node among CUs. The problem now is to determine a mechanism that enable CUs to compare the reliability of their sensing data each other.

Keeping in mind the purpose, firstly, we propose the self reliability evaluation method based on the Bayes criterion. From LRT Eqn.(11), the reliability $\rho_i$ of sensing data $x_{E_i}$ of a $CU_i$ can be determined as the distance between the likelihood ratio $\Gamma(x_{E_i})$ and the threshold $\eta$ by following equation:

$$\rho_i = |\log\Gamma(x_{E_i}) - \log\eta| \tag{19}$$

Indeed, in comparison among CUs' sensing data, the CU with the larger value of $\rho_i$ has the higher reliability when it makes the decision based on the LRT. Therefore, in our selection based cooperative spectrum sensing scheme, the final decision will be made based on the sensing data from CR node with the highest reliability. This scheme will be useful under the realistic condition where CUs suffer from different condition of sensing channel, and thus can utilize the diversity of sensing environment.

Secondly, in order to implicitly compare the sensing data reliability without any data collaboration among CUs, the offset time, which a CU will need to wait before sending the sensing data to the fusion center if it does not receive any report from other CU before, is proposed as follows

$$t_{offset} = e^{-c \cdot \rho_i} \tag{20}$$

where $c$ is a pre-defined constant such that the offset time is sufficient for avoiding collision.

Consequently, the whole process for the selection based cooperative spectrum sensing scheme includes four following steps:

Local energy sensing is performed at each CU.

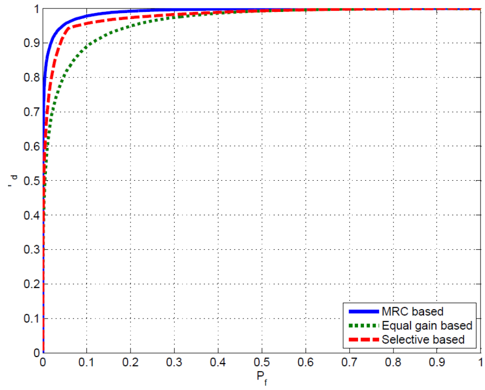
Each CR node self-estimates the sensing data reliability and the offset time.

The CR node with the smallest offset time will send sensing data to the fusion center.

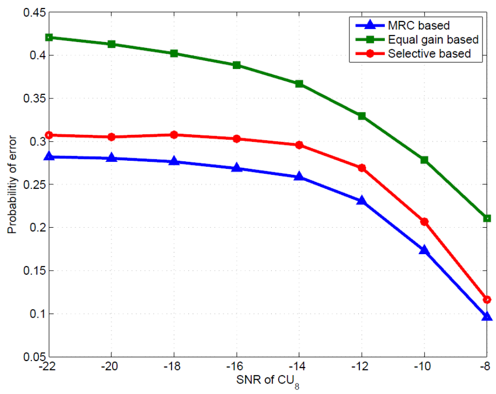
The fusion center broadcasts the final decision to all CUs.

# 4. Simulation Results

For our simulation, we assume the PU signal is DTV signal as in [10], and the probability of presence and absence PU signal is 0.5, respectively. The bandwidth of PU signal is 6 MHz, and AWGN channel is considered. Eight sensing nodes are spread in the network to perform local sensing. The local sensing time is 50 $\mu$s.




(Fig.3) ROC curves of the proposed scheme vs. "MRC based fusion", and "EGC based fusion" when eight CUs' SNR are -22dB, -20dB, -18dB, -16dB, -14dB, -12dB, -10dB, and -8dB, respectively.




(Fig.4) Probability of error comparison between the proposed scheme and other combination rule under condition that SNR of $CU_1$ -$CU_7$ are -22, -20, -18, -16, -14, -12, and -10dB respectively, and SNR of $CU_8$ is changed from -22dB to -8dB.

Our scheme of data fusion has been tested with many cases of CUs' SNR. In order to evaluate the proposed scheme in a practical situation, where distributed CUs endure difference channel condition, we consider the condition that the received signal of all eight CUs are respectively -22dB, -20dB, -18dB, -16dB, -14dB, -12dB, -10dB, and -8dB. Under such condition, the ROC curves, illustrated on Fig. 3, show that our selection based cooperative spectrum sensing scheme outperforms the EGC and can approximate the performance of the optimal combination - MRC scheme.

For further evaluation, in Fig.4, the proposed scheme has been experienced under condition that SNR of $CU_1$ - $CU_7$ are -22dB, -20dB, -18dB, -16dB, -14dB, -12dB, and -10dB, respectively, and SNR of $CU_8$ is changed from -22dB to -8dB, which is reasonable for spectrum sensing problem in CR context. In this simulation the global threshold is chosen by the optimal global threshold for each scheme, i.e.,

$$\begin{aligned} \Lambda^{opt} &= \arg\min(P_E(\Lambda)) \\ &= \arg\min(P_F(\Lambda) + (1 - P_D(\Lambda))) \end{aligned}$$

As shown in the Fig.4, the proposed scheme can achieve lower error probability, compared with equal gain combination method and has a small gap compared with the optimal combination MRC. This result is fully significant if we note that the proposed scheme only requires a very small control bandwidth as well as sensing time in comparison with other methods.

Numerous other situations have also been tested and the proposed scheme has given similar results.

## 5. Conclusions

In this paper, we have proposed a selection based cooperative spectrum sensing scheme which utilizes the likelihood ratio information to evaluate the reliability of the sensing data. With the advantage of the mechanism that utilizes implicitly comparing sensing data reliability among CR users without any collaboration, the control channel bandwidth as well as the cooperative time can be reduced. Simulation results have shown that the proposed scheme can achieve a high sensing performance while only requiring extremely low cooperation resources.

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