A Cooperative Spectrum Sensing Scheme Using Fuzzy Logic for Cognitive Radio Networks

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Abstract

This paper proposes a novel scheme for cooperative spectrum sensing on distributed cognitive radio networks. A fuzzy logic rule - based inference system is proposed to estimate the presence possibility of the licensed user's signal based on the observed energy at each cognitive radio terminal. The estimated results are aggregated to make the final sensing decision at the fusion center. Simulation results show that significant improvement of the spectrum sensing accuracy is achieved by our schemes.

Keywords: Cognitive radio, cooperative spectrum sensing, data fusion, fuzzy logic inference system, presence possibility

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1. Introduction

Recently, cognitive radio (CR) has been proposed as a promising technology to improve spectrum utilization. In CR systems, CR users (CUs) are allowed to use the licensed bands opportunistically when such bands are not occupied, and must abandon its contemporary band to seek a new idle spectrum again when the frequency band is suddenly accessed by the licensed user (LU). Therefore spectrum sensing plays a key role in CR.

In general, spectrum sensing can be achieved by a single CU. Among various spectrum sensing techniques, energy detection is an engaging method due to its easy implementation and admirable performance. In [1], it is shown that the received signal strength could be seriously weakened at a particular geographical location due to multi-path fading and shadowing effect. In these circumstances, single sensing node is difficult to distinguish between an idle band and an occupied band that is deeply faded or shadowed. In order to overcome this problem, cooperative spectrum sensing has been considered [2][3][4][8]. A half-voting rule has been investigated in [2]. However, this rule only works well when the threshold of CUs is identical, which is an impractical condition. In [5], Z. Chair and P. K. Varshney proposed a optimal data fusion rule for the distributed sensing model. This rule gives a good performance but it needs local probabilities of detection and false alarm of sensing nodes and prior probabilities to determine weights of local decisions and the decision threshold. In [3], an adaptive cooperative spectrum sensing scheme has been proposed to implement the optimal data fusion rule by using a counting rule. Although it provides a good performance, it needs time to converge when the channel environment is changed. Reference [4] proposed a collaborative spectrum sensing scheme in which fuzzy theory is applied to evaluate the credibility of each CU based on its sensing performance matrix. This approach is reasonable since fuzzy theory can provide a framework for dealing with vagueness and ambiguity [7], and can be a powerful tool to model the system under uncertain conditions as the case of fast changing RF environment [8]. Nevertheless, this scheme based on the assumption that the sensing performance matrix of each CU is invariant and is determined in the training stage where the status of the LU is exactly known in advance, which is not regularly proper in practice. Additionally, this scheme only guarantees that it can outperform "OR" and "AND" combination rules. In [8], a new combining scheme for cognitive spectrum sensing based on fuzzy logic has been proposed. A simple fuzzy decision making algorithm for decision fusion has been constructed for the simple case of three cooperative CR nodes. This approach provides good sensing performance and high flexibility for the decision fusion process in comparison with "OR", "AND" and "Half-voting" combination rules. Nonetheless, when the number of cooperative CR nodes becomes larger, the number of inputs of this fuzzy decision making system increases. Subsequently, the number of inference rules increases exponentially, and the input of each rule must be adjusted. As a result, the decision fusion procedure at the fusion center must be upgraded.

In this paper, a fuzzy rule-based inference system is proposed to make a soft decision on the status of the LU's signal at each CU. Based on the observed energy the presence possibility of the LU's signal is estimated and transmitted to the fusion center. Furthermore, an appropriate data fusion rule is also proposed to make the final sensing decision from estimated results of CUs. By this approach, the sensing performance can be maximized.

The remainder of this paper is organized as follows: The problem of spectrum sensing and energy detection are briefly described in section 2. An overview of fuzzy logic and fuzzy logic inference is shown in section 3. Our proposed cooperative spectrum sensing scheme is explicitly described in section 4. The simulation results are shown and analyzed in section 5. Finally, we draw the conclusion in section 6.

2. Spectrum Sensing and Energy Detection

2.1 Spectrum Sensing

In a distributed scenario, each CU implements a local spectrum sensing to detect the LU's signal. Local spectrum sensing is essentially a binary hypotheses testing problem:

$$\begin{cases} H_0 : x(t) = n(t) \\ H_1 : x(t) = h(t)s(t) + n(t) \end{cases} \tag{1}$$

where H_0 and H_1 are respectively correspondent to hypotheses of absence and presence of the LU's signal, *x(t)* represents the received signal at the CU, *h(t)* denotes the amplitude gain of the channel, *s(t)* represents the signal transmitted by the LU and *n(t)* is the additive noise. Additionally, channels corresponding to different CUs are assumed be independent, and further, all CUs and LUs share common spectrum allocation.

2.2. Energy Detection

To measure the energy of the received signal in a particular frequency region, a band-pass filter is applied to the received signal. The test static is equivalent to an estimation of the received signal energy which is given at each CU by:

$$x_E = \sum_{j=1}^{N} \left| x_j \right|^2 \tag{2}$$

where x_j is the *j*-th sample of received signal and N is the number of samples, $N = 2TW$ where T and W are correspondent to detection time and signal bandwidth, respectively.
Without loss of generality, we assume that the noise at each sample is a Gaussian random variable with zero mean and unit power. If LU's signal is absent, x_E follows a central chi-square distribution with N degree of freedom; otherwise, x_E follows a non-central chi-square distribution with N degree of freedom and a non-centrality parameter $N\gamma$ [6]:

$$x_E \sim \begin{cases} \chi_N^2, & H_0 \\ \chi_N^2(N\gamma), & H_1 \end{cases} \tag{3}$$

where γ is the signal to noise ratio (SNR) of the LU's signal at the CU. When N is relatively large (e.g. $N > 200$), x_E can be well approximated as a Gaussian random variable under both hypotheses H_0 and H_1 with mean μ_0, μ_1 and variance σ_0^2, σ_1^2 respectively [6]

$$\begin{cases} \mu_0 = N; \sigma_0^2 = 2N & , H_0 \\ \mu_1 = N(1+\gamma); \sigma_1^2 = 2N(1+2\gamma) & , H_1 \end{cases} \tag{4}$$

A local hard decision of the CU can be made as follows:

$$u = \begin{cases} H_1 : & x_E \ge \lambda \\ H_0 : & otherwise \end{cases} \tag{5}$$

where λ is the decision threshold of the CU.
The false alarm probability and detection probability of the CU are calculated as follows:

$$p_f = P[u = H_1 \mid H_0] = P[x_E \ge \lambda \mid H_0] \tag{6}$$

$$p_d = P[u = H_1 \mid H_1] = P[x_E \geq \lambda \mid H_1] \tag{7}$$

where $P[.]$ stands for the probability.
From equation (4), p_f and p_d can be given as

$$p_f = Q\left(\frac{\lambda - N}{\sqrt{2N}}\right) \tag{8}$$

$$p_d = Q\left(\frac{\lambda - N(1+\gamma)}{\sqrt{2N(1+2\gamma)}}\right) \tag{9}$$

where $Q(.)$ is the complementary cumulative Gaussian distribution function,

$$Q(x) = \frac{1}{\sqrt{2\pi}} \int_x^{+\infty} e^{-\frac{t^2}{2}} dt. \tag{10}$$

3. Brief Overview of Fuzzy Logic

3.1 Fuzzy Set

Traditional set theory has a crisp concept of membership: an element either belongs to a set or it does not. Fuzzy set theory differs from traditional set theory in that partial membership is allowed. This degree of membership is commonly referred to as the membership value and is represented using a real value in [0, 1], where 0 and 1 correspond to full non-membership and membership, respectively. Formally, a fuzzy set A in a universe U is defined by the membership function

$$\mu_A : U \rightarrow [0,1] \tag{11}$$

so that for each u in U, its grade of membership to A is given by $\mu_A(u)$.

3.2 Fuzzy Logic

Fuzzy logic was proposed as a method to extend binary logic to cover the problem of reasoning under uncertainty. Fuzzy logic can be used to make decisions by using incomplete, approximate, and vague information. In short, instead of using complicated mathematical formulations, fuzzy logic uses human-understandable fuzzy sets and inference rules (e.g. IF, THEN, ELSE, AND, OR, NOT) to obtain the solution that satisfies the desired system objectives.

Predicates in fuzzy logic can have partial degrees of truth, in the same way as elements can have partial membership in fuzzy set theory. The grade of truth of a predicate is represented using a real number in [0, 1]. The grade of truth of a generic predicate P in the form "x is A" is given by $\mu_P = \mu_A(x)$. The traditional logic operators ¬ (NOT), v (OR), and ^ (AND) are redefined in terms of how they modify the truth value of the predicate(s) to which they are applied in order to produce the truth value of the final statement:

$$\mu_{\neg P} = 1 - \mu_P \tag{12}$$

$$\mu_{P_1 \wedge P_2} = min\left(\mu_{P_1}, \mu_{P_2}\right) \tag{13}$$

$$\mu_{P_1 \vee P_2} = max\left(\mu_{P_1}, \mu_{P_2}\right) \tag{14}$$

These operators provide basic support for qualitative reasoning in decision making systems.

3.3 Fuzzy Logic Inference System

The architecture of a fuzzy logic inference system is depicted in **Fig. 1**. The modules composing a fuzzy logic inference system are described in the rest of this subsection.

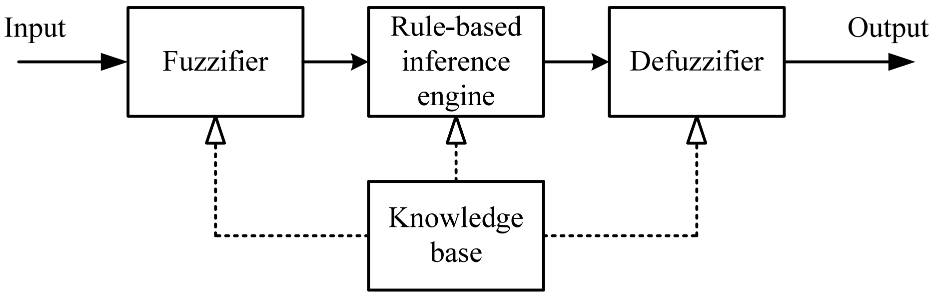

Fig. 1. The basic architecture of a fuzzy logic inference system.

3.3.1 Knowledge Base

The knowledge base characterizes the relationship between crisp input/output parameters and their fuzzy representation understood by the fuzzy logic inference system. Each input/output variable is characterized by the following items in the knowledge base:

- Its universe
- The set of linguistic attributes ("labels") that compose its qualitative representation
- For each label, the membership function defining it

Furthermore, the knowledge base provides a set of inference rules for the inference engine. These rules is constructed in form of "IF – THEN" statement based on the experience of experts.

3.3.2 Fuzzifier

Fuzzification is the process of translating crisp input measurements into their fuzzy representation. This process is carried out for each input variable at every inference cycle, by evaluating the membership value of each attribute characterizing it.

3.3.3 Rule-based Inference Engine

The heart of a fuzzy logic inference system is composed of a set of IF-THEN rules used to determine the value of the output variables. IF conditions are composed using the predicates and logic operators, while THEN statements are commonly predicates indicating the fuzzy attribute that is more appropriate for the output variables involved.
The process of rule evaluation is easier to explain by an example. Let A, B be input variables, and C be an output variable. Let A, B and C be represented by the linguistic attributes A_1 and A_2, B_1 and B_2, and C_1 and C_2, respectively. Suppose we have the following rule set:

- Rule 1: IF (A is A_1) and (B is B_1) THEN (C is C_1).
- Rule 2: IF (A is A_2) or (B is B_2) THEN (C is C_2).

Finally, let a and b be the current crisp values for A and B. First of all, the truth value for each rule is calculated as follows:

$$\alpha_1 = \mu_{A_1}(a) \wedge \mu_{B_1}(b) \tag{15}$$

$$\alpha_2 = \mu_{A_2}(a) \vee \mu_{B2}(b) \tag{16}$$

Then a modified membership function is calculated for the inference output recommended by each rule by taking the minimum (fuzzy ^ operator) of its membership function and the truth value of the IF clause:

$$\mu'_{C_1} = \alpha_1 \wedge \mu_{C_1} \tag{17}$$

$$\mu'_{C_2} = \alpha_2 \wedge \mu_{C_2} \tag{18}$$

Finally, the membership function for the decision output of variable C is calculated by taking the maximum (fuzzy v operator) of the modified membership of all decision actions referring to C:

$$\mu_C = \mu'_{C_1} \vee \mu'_{C_2} \tag{19}$$

The above inference method is called max-min inference method [7].

3.3.4 Defuzzifier

The rule evaluation and decision making process has produced, for each output variable, a membership function $\mu_C(c)$ representing the appropriateness of each output value c. Defuzzification is the process of determining an appropriate crisp value to be used as the actual output. One of the most commonly used techniques for this purpose is the center of area method, in which the output is determined from the center of gravity of the membership function from the outcome of the set of rules. Let $\Theta = \{c \mid \mu_C(c) > 0\}$ denote a set of outputs c with membership value larger than zero, the appropriate crisp value at the output of the fuzzy logic inference system is derived as follows:

$$\hat{c} = \frac{\int_{\Theta} c\mu_C(c)\,dc}{\int_{\Theta} \mu_C(c)\,dc}. \tag{20}$$

4. Proposed Cooperative Spectrum Sensing Scheme

For LU's signal detection, we consider a cooperative spectrum sensing scheme like **Fig. 2**. Each CU conducts its local estimation of LU signal presence possibility based on its observed energy, and then transmits its estimation result to the fusion center (FC) where the final decision is made.

4.1 Local Estimation of the LU's Signal Presence Possibility

To make the soft decision about the presence of the LU's signal, each CU measures the received signal energy following equation (2) and estimates the SNR of the LU's signal [10][11][12]. From equation (4), we have the estimated means and variances corresponding to hypotheses H_0 and H_1 as follows:

$$\begin{cases} \hat{\mu}_0 = N; \sigma_0^2 = 2N & , H_0 \\ \hat{\mu}_1 = N(1+\gamma); \sigma_1^2 = 2N(1+2\hat{\gamma}), H_1 \end{cases} \tag{21}$$

where $\hat{\gamma}_i$ is the estimated SNR of the LU's signal at the i-th CU.

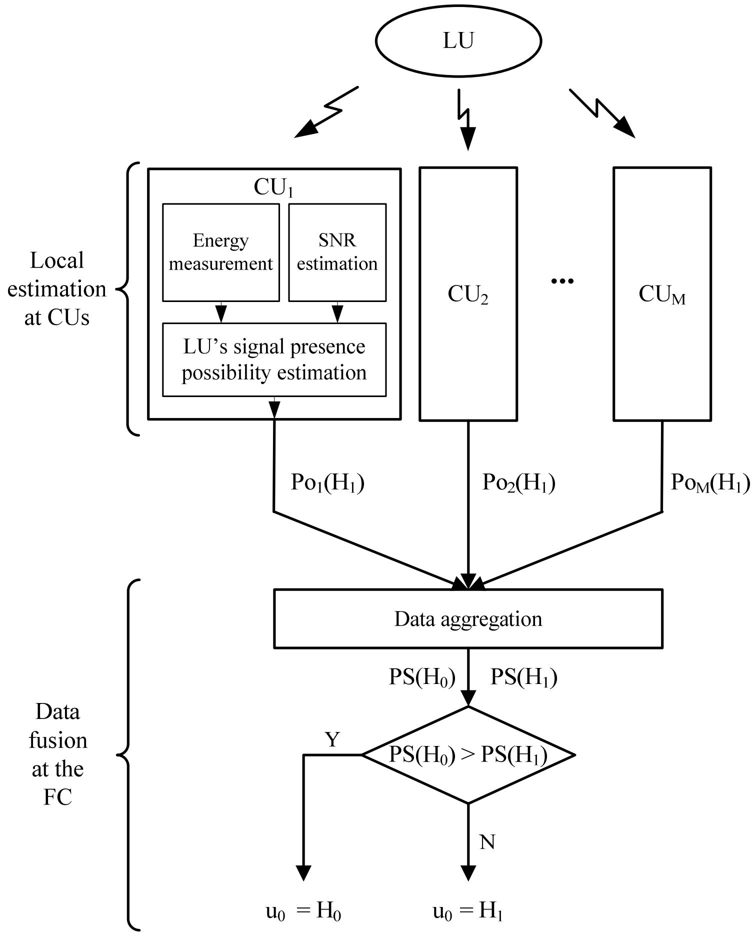

Fig. 2. The fuzzy logic-based cooperative spectrum sensing scheme.

In order to apply fuzzy logic to estimate the presence possibility of the LU's signal at each CU, we propose a simple fuzzification strategy as follows:

- The observed energy, denoted by x_{Ei}, is represented by the two linguistic attributes, *Weak* and *Strong*, with their membership functions respectively given as follows:

$$\mu_{Weak}\left(x_{E_i}\right)=\begin{cases}1 & ,\, if\ x_{E_i}\le \hat{\mu}_{0i}\\ e^{-\frac{(x_{Ei}-\hat{\mu}_{0i})^2}{2\hat{\sigma}_{0i}^2}} & ,\, otherwise\end{cases} \quad (22)$$

$$\mu_{Strong}\left(x_{E_i}\right)=\begin{cases}1 & ,\, if\ x_{E}\ge \hat{\mu}_{1i}\\ e^{-\frac{(x_{Ei}-\hat{\mu}_{1i})^2}{2\hat{\sigma}_{1i}^2}} & ,\, otherwise\end{cases} \quad (23)$$

These membership functions are illustrated in **Fig. 3**.

- The presence possibility of the LU's signal, denoted by *PP*, is represented by the two linguistic attributes, *Low* and *High*, with their membership functions illustrated in **Fig. 4**.

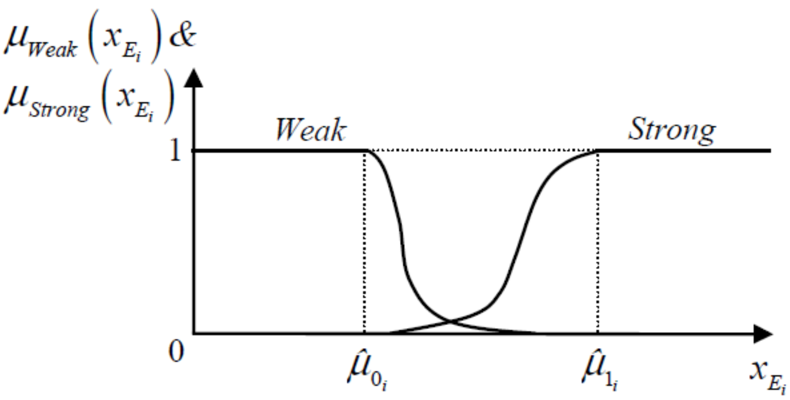

Fig. 3. The membership functions of the input parameter.

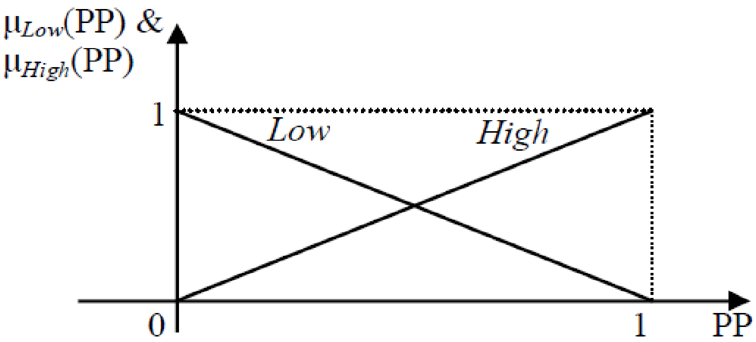

Fig. 4. The membership functions of the output parameter.

The fuzzy inference rule set is proposed as follows:

- Rule 1: IF (x_{Ei} is *Weak*) THEN (*PP* is *Low*),
- Rule 2: IF (x_{Ei} is *Strong*) THEN (*PP* is *High*).

To obtain a low computation cost, the max-min inference method [7] was used. If we denote e_i be the value of the observed energy measured by the i-th CU, then the truth value for each rule is calculated as below:

$$\alpha_{1_i} = \mu_{Weak}\left(e_i\right) \tag{24}$$

$$\alpha_{2_i} = \mu_{Strong}\left(e_i\right) \tag{25}$$

The modified membership function of each rule is derived by taking the minimum of its membership function and the corresponding truth value of the IF clause:

$$\mu'_{R_{1i}}(PP) = min\left(\alpha_{1_i}, \mu_{Low}(PP)\right), \tag{26}$$

$$\mu'_{R_{2i}}(PP) = min\left(\alpha_{2_i}, \mu_{High}(PP)\right). \tag{27}$$

The final output membership function of the estimation process at the i-th CU is

$$\mu_{Ri}(PP) = max\left(\mu_{R_{1i}}(PP), \mu_{R_{2i}}(PP)\right). \tag{28}$$

By using the center of area defuzzification method, the crisp value of the LU's signal presence possibility evaluated by the i-th CU, denoted by $Po_i(H_1)$, is obtained as follows:

$$Po_i(H_1) = \frac{\int_0^1 PP\mu_{Ri}(PP)dPP}{\int_0^1 \mu_R(PP)dPP}. \tag{29}$$

4.2 Data Fusion at the FC

Let $PS(H_1)$ and $PS(H_0)$ be respectively the summation of the local LU's signal presence possibility values and the summation of the local LU's signal absence possibility values. Then we have

$$PS(H_1) = \sum_{i=1}^{M} Po_i(H_1) \tag{30}$$

$$PS(H_0) = \sum_{i=1}^{M}(1 - Po_i(H_1)) = M - PS(H_1). \tag{31}$$

where M is the number of CUs in the CR network.

The FC makes the final decision upon the following strategy:

$$u_0 = \begin{cases} H_1 : & if \quad PS(H_1) \geq PS(H_0) \\ H_0 : & otherwise. \end{cases} \tag{32}$$

It means that the final decision is made based on the sum of local soft decisions. Intuitively, the proposed fusion rule is more simple than the combining rule proposed in [8]. In [8], local decisions are firstly fuzzified into three linguitic attributes. For the case of M CUs, there are 3^M inference rules must be evaluated, and each rule contains M predicates. After aggregating modified membership functions of 3^M inference rules, the final decision is made by comparing the output of defuzzification procedure with a certain threshold. Therefore, when M increases, the number of rules as well as predicates of each rule must be changed correspondingly. On the other hand, in the proposed rule, the FC can make the final decision after summing received local soft decisions.

5. Simulation Results and Analysis

To evaluate the performance of the proposed spectrum sensing scheme, Monte-Carlo simulations are carried out with 20,000 samples under following conditions:

- The number of CUs is 5.
- The LU signal is DTV signal as in [9].
- The bandwidth of LU signal is 6 MHz, and both the non-fading and fading additive white Gaussian noise (AWGN) channel are considered.
- The identical number of samples N is 300.

For sensing performance comparison, we consider “AND”, “OR”, “Half-voting” and “Chair-Varshney” hard decision fusion rules, and equal gain combination (EGC) based and maximal-ratio combination (MRC) based soft decision rules.

In **Table 1**, some differences between the proposed scheme and other comparison schemes are briefly analyzed.

Table 1. The comparison of proposed scheme and other comparison schemes

Scheme	Local decision making procedure at CUs	Final decision making procedure at the FC
AND/OR based scheme	Binary decision is made using (5) with optimal decision threshold.	The final decision is made upon AND/OR rule.
Half-voting rule based scheme	Binary decision is made using (5) with optimal decision threshold.	The final decision is made upon majority rule.
Chair-Varshney (Optimal data fusion) rule based scheme	Binary decision is made using (5) with optimal decision threshold.	- The final decision is made based on the assumption that the FC has fully knowledge about local sensing performance and prior probabilities of LU's signal. - The final decision is made by comparing the weighted summation of local decisions with a decision threshold. - The decision threshold is a function of prior probabilities, namely $P[H_0]$ and $P[H_1]$. - The weight of each local decision is a function of local sensing performance, namely local miss detection probability and local false alarm probability.
Equal gain combination (EGC) based scheme	Local observed energy x_{Ei} is transmitted directly to the FC.	- Local observed energies are combined equally to make a summation. - The final decision is made by comparing the summation with a decision threshold. - The decision threshold is determined based on the desired global false alarm probability [13].
Maximal-ratio combination (MRC) based scheme	Local observed energy x_{Ei} and SNR of LU'signal γ_i are transmitted directly to the FC.	- Local observed energies are combined to make a weighted summation. - The weight of each local observation is determined by normalizing the SNR of LU's signal at the corresponding CU. - The final decision is made by comparing the weighted summation with a decision threshold. - The decision threshold is determined based on the desired global false alarm probability [13].

Proposed scheme	Soft decision is made by exploiting an identical fuzzy inference system as follows: - Measured energy is fuzzified into 2 linguistic attributes. - The modified membership function of each rule is calculated (there are 2 rules and each rule has 1 predicate). - The membership function of the output decision is calculated by taking maximum of the modified membership function of 2 rules. - The output decision is obtained by defuzification procedure.	The final decision is simply made by comparing summation of presence possibilities with summation of absence possibilities: $u_0 = \begin{cases} H_1: & \text{if} \quad PS(H_1) \ge PS(H_0) \\ H_0: & \text{otherwise.} \end{cases}$

Firstly, the sensing performance of the proposed scheme is compared with the sensing performance of hard decision based schemes like "AND", "OR", "Half-voting" [2] and "Chair-Varshney" [5] decision fusion rules in AWGN and Rayleigh fading channels. In these comparision schemes, CUs make local hard decision based on the equation (5) with optimal local decision thresholds. The local decision threshold is chosen to balance the tradeoff between minimizing local false alarm probability and maximizing local detection probability. With the full knowledge of LU's signal at each CU, its optimal local decision threshold is selected at the intersection between *p.d.f* curves of the measured energy under H_0 hypothesis and H_1 hypothesis.

In the first simulation, our proposed algorithm have been experienced under condition that the CU_1, CU_2, CU_3 and CU_4 have same AWGN channel with SNR = -12dB, and the SNR at the fifth CU is changed from -24 to -6 dB, which is reasonable for the spectrum sensing problem in CR context. Under such condition, the global detection probability p_D and the global false alarm probability p_F of our proposed scheme and reference schemes are shown on **Fig. 5**. The detection probability of "OR" rule is always largest but its probability of false alarm also is always largest. The false alarm probability of "AND" rule is always smallest but its probability of detection is similar too. It can be said that both "AND" rule and "OR" rule have bad performance. For our proposed scheme, both detection probability and false alarm probability always give a remarkable improvement, compared to "AND" rule, "OR" rule, "Half-voting" rule and even to "Chair – Varshney" rule, which is mainly due to the selection of effective membership functions and reasonable inference rules. In the comparison schemes, each CU makes a local hard decision by using equation (5) as mentioned above. However, this hard decision can not convey complete information to the FC. The "Chair – Varshney" scheme, which has been known as an optimal fusion rule [5] in the case of hard decision, compensates for this information loss by weighting local hard decisions according to their reliability, that is, the weights are functions of local probability of false alarm and local probability of miss detection. These local probabilities are transmitted from CUs to the FC to calculate weights. As a result, "Chair – Varshney" scheme outperforms "AND", "OR", and "Half-voting" scheme. On the other hand, in our proposed scheme, each CU makes a soft decision on the status of the LU's signal by utilizing a fuzzy logic inference system. Each soft decision contains complete information about the status of LU's signal as well as the realibility of the decision since the proposed membership functions fully reflect characteristics of the probability distributions under both hypotheses H_0 and H_1 as well as the relationship between observed energy and its statistic parameters. Consequently, the proposed scheme is superior to comparison schemes.

The second simulation was conducted under condition that all the CUs in the CR network are affected by Rayleigh fading. When a signal experiences a Non-Line-of-Sight multipath, the signal amplitude follows a Rayleigh ditribution, and the SNR of the LU's signal at the CU follows an exponential distribution whose *p.d.f* is given by

$$f_\gamma(\gamma) = \frac{1}{\bar{\gamma}} e^{\frac{-\gamma}{\bar{\gamma}}}, \quad \gamma > 0 \tag{33}$$

where $\bar{\gamma}$ is the mean SNR value.

We assume that all CUs suffer independent and identically distribution fading channel with $\bar{\gamma} = -12$ dB. The fading is assumed to be slow compared to the observed interval of the sensing method. Thus, the channel is assumed to remain constant during data block but it varies randomly between consecutive blocks. The sensing performance is assessed based on the receiver operating characteristics (ROC) curves of the proposed scheme and comparison schemes. As shown in **Fig. 6**, the fading degrades the sensing performance of "Chair – Varshney" rule and our proposed rule. Although the "Half-voting" rule is not degraded by fading, but its performance is quite low. Intuitively, it can be seen that our proposed scheme has the outstanding sensing performance compared with comparison schemes under both non-fading and fading condition.

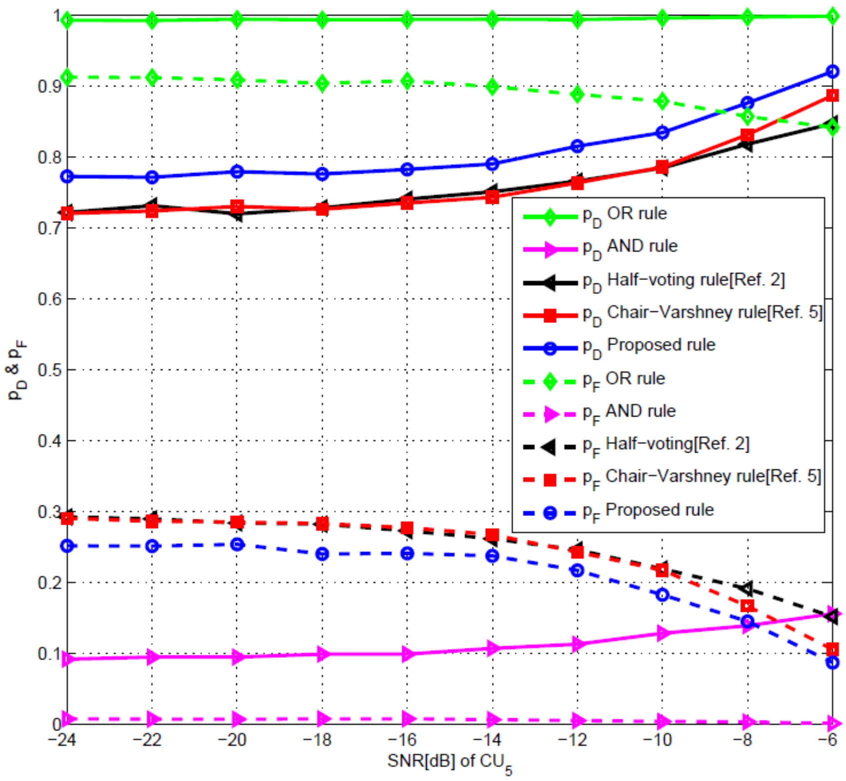

Fig. 5. The comparison of global detection and global false alarm probability between proposed scheme and other combination rules under the condition that all channels are AWGN and SNR of CU_1 - CU_4 are -12dB and SNR of CU_5 changes from -24dB to -6dB.

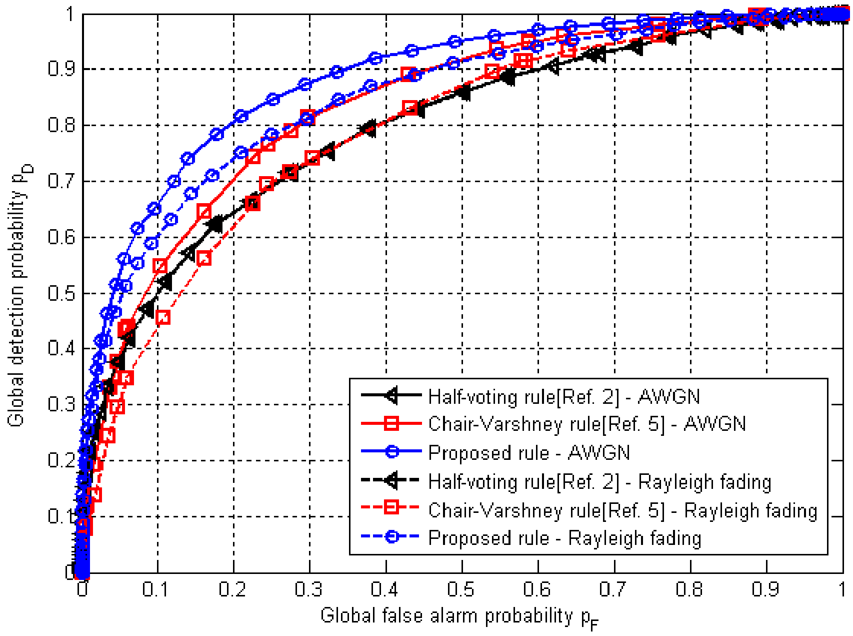

Fig. 6. ROC curves of our proposed scheme vs. other combination schemes under the condition that all channels are AWGN and mean SNR of five CUs is -12dB.

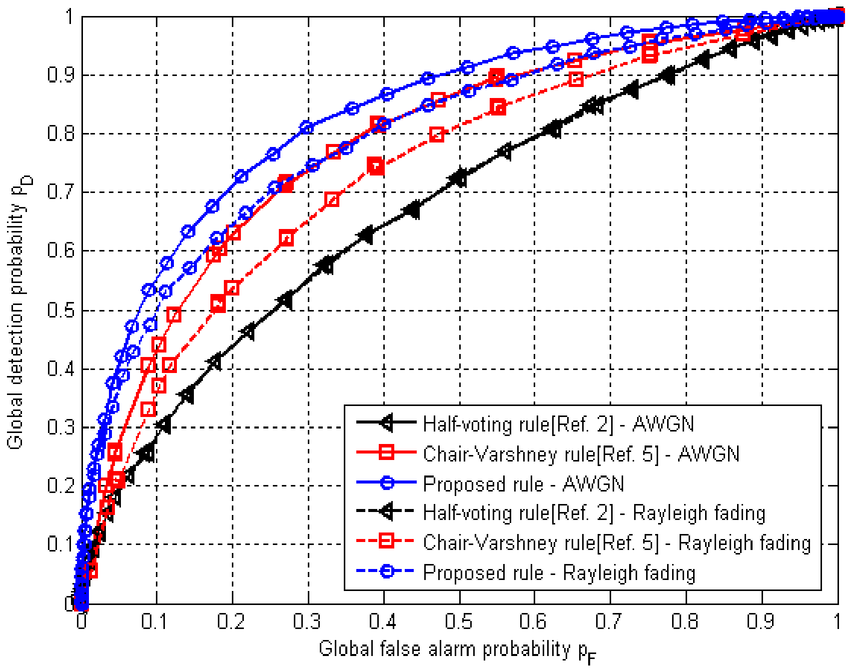

Fig. 7. ROC curves of our proposed scheme vs. other combination schemes when non-fading and fading AWGN channels are considered with mean SNR of five CUs' SNR are -22, -19, -16, -13, and -10dB, respectively.

In order to evaluate our proposed scheme with the fading channel corresponding to more realistic operational environments where distributed CUs suffer difference channel condition, we consider the situation that the mean SNR value at five CUs are respectively -22dB, -19dB,

-16dB, -13dB, -10 dB. Under such condition, the ROC curves, illustrated on **Fig. 7**, shows that among five combination rules "Half-voting" combination rule has lowest sensing performance whereas our proposed rules has highest sensing performance under both non-fading and fading AWGN channel.

Secondly, the sensing accuracy of the proposed scheme is compared with that of two soft decision based schemes including equal gain combination (EGC) based scheme and maximal-ratio combination (MRC) based scheme. In the EGC based scheme, each CU sends its observed energy to the FC, and then the final decision is made by comparing the summation of local observed energies with a decision threshold that is determined based on the desired global false alarm probability. In the other hand, in the MRC based scheme, each CU sends its observed energy and SNR of LU's signal to the FC. At the FC, the final decision is made by comparing the weighted summation of local observed energies with a decision threshold, in which the weight of a local observed energy is determined by normalizing the corresponding SNR. As a result, the MRC based scheme has a good sensing accuracy. In low SNR regime, i.e. $\gamma < 1$, the MRC is identical to the optimal soft combination as proved in [13].

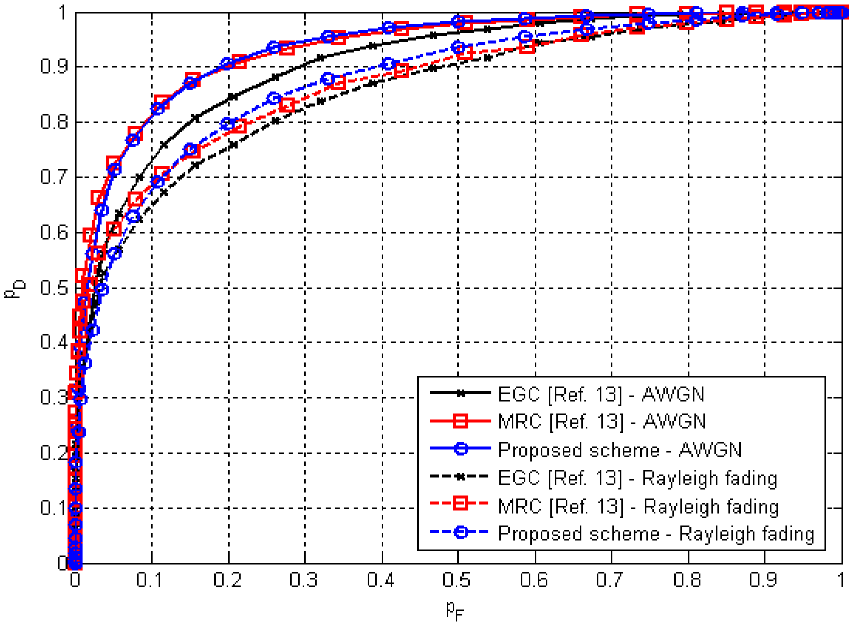

Fig. 8. ROC curves of our proposed scheme vs. other soft decision based schemes when non-fading and fading AWGN channels are considered with mean SNR of five CUs' SNR are -18, -16, -14, -12, and -10dB, respectively.

Fig. 8 shows the simulation results under the condition that the mean SNR values for five CUs are respectively -18dB, -16dB, -14dB, -12dB, -10 dB. It can be observed that under both non-fading and fading conditions, our proposed scheme outperforms the EGC based scheme, and has as a good sensing performance as the MRC based scheme does. However, it is noteworthy that the MRC based scheme requires more control channel bandwidth than the proposed scheme since all CUs have to send their local observed energy as well as SNR of LU's signal to the FC in the case of MRC based scheme.

Admittedly, the simulation results in this section prove that the proposed scheme has the ability to significantly improve the sensing performance in CR networks.

6. Conclusions

Spectrum sensing is a fundamental problem in CR networks. In this paper, we have proposed a cooperative spectrum sensing scheme using fuzzy logic to estimate the presence possibility of the LU's signal at CUs. At the fusion center, the final sensing decision is made based on local estimated results of the CUs. Simulation results have shown that the proposed scheme achieves a good sensing performance in comparison with other cooperative spectrum sensing schemes.

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