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Two-Stage Spectrum Sensing Scheme Using Fuzzy Logic for Cognitive Radio Networks

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Abstract

Spectrum sensing in cognitive radio networks allows secondary users to sense the unused spectrum without causing interference to primary users. Cognitive radio requires more accurate sensing results from unused portions of the spectrum. Accurate spectrum sensing techniques can reduce the probability of false alarms and misdetection. In this paper, a two-stage spectrum sensing scheme is proposed for cooperative spectrum sensing in cognitive radio networks. In the first stage, spectrum sensing is executed for each secondary user using energy detection based on double adaptive thresholds to determine the spectrum condition. If the energy value lies between two thresholds, a fuzzy logic scheme is applied to determine the channel conditions more accurately. In the second stage, a fusion center combines the results of each secondary user and uses a fuzzy logic scheme for combining all decisions. The simulation results show that the proposed scheme provides increased sensing accuracy by about 20% in some cases.

Index Terms: Cognitive radio, Cooperative spectrum sensing, Energy detection, Fuzzy logic

I. INTRODUCTION

Wireless networks are characterized by a fixed spectrum allocation policy. However, demand for the frequency spectrum is increasing, leading to spectrum scarcity. To overcome this scarcity in wireless communication, a cognitive radio network has been proposed. In this network, cognitive radio users, called secondary users (SU), are allowed to utilize the primary user (PU) bands when they are unoccupied but must avoid harmful interference with the primary users. To achieve this, spectrum sensing is an essential mechanism in cognitive radio networks [1]. Various techniques for spectrum sensing have been proposed in the literature, including the matched-filter technique, cyclostationary detection, and energy detection.

Energy detection is the most popular technique due to its simplicity. It does not require any prior information about the primary signal, and its sensing speed is fast. However, the performance of energy detection is limited by noise uncertainty. Furthermore, multipath fading, shadowing, and the hidden node problem degrade the performance of single-user spectrum-sensing techniques [2]. To overcome these problems, cooperative sensing was introduced as a solution. In this technique, secondary users collaborate to sense the unused spectrum and detect a PU signal. Then, with or without sharing information about the local decision, they forward the local decision results to the fusion center. The center then decides the final result according to the decision rules applied in the fusion center [3]. Various techniques have been proposed to mitigate noise uncertainty such as double threshold-based sensing. However, if all the energy lies between two thresholds, spectrum sensing will fail [4].

Due to the uncertainty in noise power, accurate detection becomes impossible, and choosing a suitable threshold in spectrum sensing becomes more difficult.

In this paper, a new two-stage spectrum sensing scheme using fuzzy logic for cognitive radio networks is proposed. In the first stage, spectrum sensing is executed at the local node based on a double adaptive threshold scheme. If the measured energy lies between the two thresholds, the actual channel condition is decided based on a fuzzy logic scheme to mitigate the sensing failure problem. After local spectrum sensing is performed, each secondary user sends their local decision results to the fusion center. In the second stage, this fusion center combines all the local decision results using fuzzy logic and gives the final decision.

II. RELATED WORK

The first energy detection technique was proposed by Urkowitz in 1967 [5]. He proved that energy detection is a simple technique and does not require complex computation. Despite its simplicity, the performance of energy detection is limited by noise uncertainty. In addition, the multipath, shadowing, and hidden node problems degrade the performance of single-user spectrum-sensing techniques. One possible technique to overcome these problems is cooperative sensing [3]. The main idea of this technique is that secondary users interact with each other to determine the availability of a channel after individual measurement of the channel. In contrast, the adaptive spectrum sensing technique, which is based on the dynamic selection threshold using the constant false alarm rate (CFAR) scheme, was proposed to enhance the spectrum sensing capability in a low signal to noise ratio (SNR) [6].

The two threshold sensing technique was introduced to mitigate noise uncertainty. However, the problem of a "confused region" remains in which all the detected energy values lie between two thresholds. Thus, the secondary users cannot decide whether the primary users are present or not. In this case, the spectrum sensing procedure will fail. In [7], the author proposed an "n-ratio" based logic with two thresholds. If all the detected values are between the two thresholds, the secondary user sends a "no decision" to the fusion center, and the fusion center helps the secondary users to determine the actual state of the spectrum. In [8], the author proposed hierarchical cooperative spectrum sensing based on double threshold energy detection. In this scheme, if the collected energy value lies between the two thresholds, it requires the fusion center to make a final decision. The fusion center quantizes the local value into four two-bit decisions and combines them to give the final decision. In contrast, because the performance degrades sharply as the noise uncertainty increases, a dynamic

threshold algorithm was proposed to combat noise uncertainty [9]. In [10], the author solved the sensing failure problem at a local node using two-bit quantization. The scheme is used to divide the confused region into four equal quantization intervals with the same weight. A three threshold scheme was proposed to mitigate the confused region based on the dynamic threshold factor [11].

Another approach to research has been to apply fuzzy logic to cognitive radio networks. This technique can provide a framework to handle ambiguity and vagueness. A fuzzy decision chooses the most appropriate access opportunity by using cross-layer information, past history, and shared knowledge among different devices through a knowledge base. Cognitive spectrum sensing based on fuzzy logic was presented in [12]. This approach provides good sensing performance and high flexibility for decision combining at the fusion center. In [13], the author proposed a spectrum sensing scheme with fuzzy logic that is applied in the local node. In this scheme, the author performs three different spectrum sensing techniques simultaneously in the local node. Then, the probability of detection (P_d) of each technique is used as the input values for a fuzzy inference system (FIS). This scheme increases the hardware system requirements for the secondary user in order to perform three different spectrum sensing techniques. In this paper, we propose a new scheme to mitigate the sensing failure problem in a confused region by applying fuzzy logic. By using this approach, we can improve local spectrum sensing without increasing system requirements. In order to achieve high accuracy detection, all the local decisions collaborate in a cooperative sensing scheme using fuzzy logic for decision combining.

III. PROPOSED SPECTRUM SENSING SCHEME

The spectrum sensing scheme used in this paper is based on the double adaptive threshold scheme. The consideration for using energy detection with double adaptive thresholds is that this scheme can mitigate uncertainty in noise power. In the conventional single threshold case, the false alarm probability (P_f) and P_d can be expressed as

$$P_f = Q\left(\frac{\lambda - N\sigma_\omega^2}{\sqrt{2N\sigma_\omega^4}}\right),\tag{1}$$

$$P_d = Q\left(\frac{\lambda - N(\sigma_s^2 + \sigma_\omega^2)}{\sqrt{2N(\sigma_s^2 + \sigma_\omega^2)^2}}\right),\tag{2}$$

where $Q(.)$ denotes the Gaussian tail probability Q-function, and σ_ω^2, and σ_s^2 are the noise variance and the

average signal power, respectively. Based on the given target false alarm probability, the threshold (λ) can be determined as

$$\lambda = Q^{-1}(P_f) \times \sqrt{2N\sigma_\omega^4} + N\sigma_\omega^2. \qquad (3)$$

According to the single threshold, we can derive two different thresholds, the lower threshold (λ_1) and the higher threshold (λ_2) by applying min-max noise variance ($\sigma^2 \in [\frac{1}{\rho}\sigma_\omega^2, \rho\sigma_\omega^2]$). Two thresholds can be determined as

$$\lambda_1 = Q^{-1}(P_f) \times \sqrt{2N/\rho\, \sigma_\omega^4} + N/\rho\, \sigma_\omega^2, \qquad (4)$$

$$\lambda_2 = Q^{-1}(P_f) \times \sqrt{2N\rho\sigma_\omega^4} + N\rho\sigma_\omega^2, \qquad (5)$$

where $\rho > 1$ is the parameter that determines the amount of noise uncertainty.

The overall procedure of the proposed scheme is shown in Fig. 1. Each process in Fig. 1 is described below.

A. First Stage (Local Decision)

(a) Each secondary user senses the primary user's signal and decides based on a double adaptive threshold. If the energy is larger than λ_2, it will be decided as H_1 (Spectrum Occupied). If it is lower than λ_1, it will be decided as H_0 (Spectrum Free).
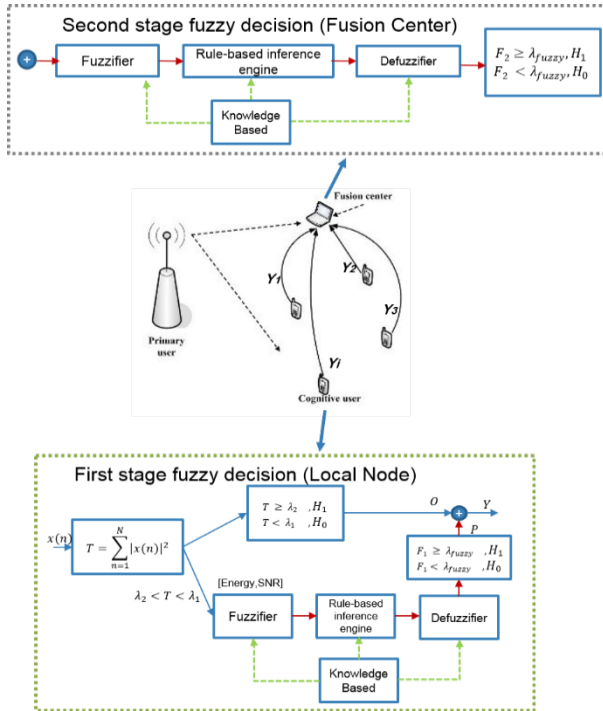

Fig. 1. Two-stage spectrum sensing scheme using fuzzy logic for cognitive radio networks.
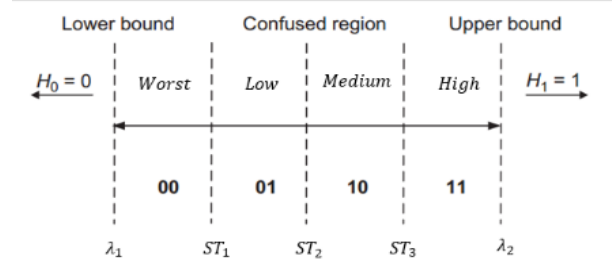

Fig. 2. Two-bit quantization in a confused region with a linguistic variable.
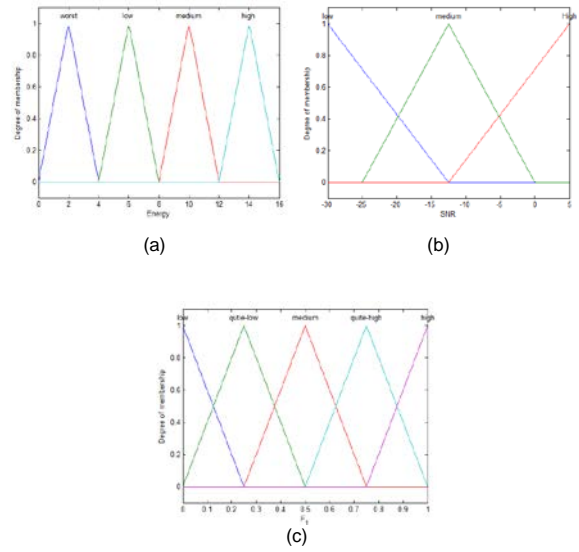

Fig. 3. Membership function for the first stage. (a) MF of the 1st antecedent for the first stage (energy). (b) MF of the 2nd antecedent for the first stage (SNR). (c) MF of consequent for the first stage (possible of present PU).

(b) If the energy lies in a confused region, the secondary users will use a fuzzy logic scheme to decide the actual conditions. Inside the FIS, the confused region is divided into four equal regions using two-bit quantization ($\lambda_1 \sim ST_1,\ ST_1 \sim ST_2,\ ST_2 \sim ST_3,\ ST_3 \sim \lambda_2$), as shown in Fig. 2, where ST_1, ST_2, ST_3 are the sub-thresholds (ST), and these values can be obtained as

$$\text{Range} = \frac{\lambda_2 - \lambda_1}{4}, \qquad (6)$$

$$\text{ST} = \begin{cases} ST_1 = \lambda_1 + \text{Range} \\ ST_2 = ST_1 + \text{Range} \\ ST_3 = ST_2 + \text{Range} \end{cases}. \qquad (7)$$

The membership functions (MF) for two-bit quantization, SNR and F_1, are shown in Fig. 3. In Table 1, we present the fuzzy rule-based system used for rule evaluation in the first stage.

Table 1. Rule-based system for the first stage

SNR	Energy	F_1
Low	Worst	Low
Low	Low	Quite-low
Low	Medium	Quite-low
Low	High	Medium
Medium	Worst	Quite-low
Medium	Low	Quite-low
Medium	Medium	Medium
Medium	High	Quite-high
High	Worst	Quite-low
High	Low	Medium
High	Medium	Quite-high
High	High	High

(c) According to the process for FIS in the first stage, shown in Fig. 1, the fuzzifier converts each crisp input value to a linguistic variable using the membership function. The output for the fuzzification process is the fuzzy input values. Using the If-Then type, fuzzy rules convert the fuzzy input to fuzzy output and the defuzzifier converts the degrees of membership of the output linguistic variables (fuzzy output) into numerical values using the centroid of area (COA) as the defuzzification method [14]. The range value of the energy in the membership function is an assumed value because it is recalculated when the measured energy lies in a confused region. A detailed description of the decision making process with the fuzzy logic scheme for the first stage is described as follows:

- First, the crisp value is input to the fuzzy inference system.
- The ranges of the energy membership function are recalculated using Eqs. (6) and (7).
- The crisp value is converted to a fuzzy input value by the fuzzifier using the membership function. In this process, the two values (degree of membership (μ) and linguistic value) for each crisp input are obtained.
- Each fuzzy input is evaluated in the rule inference engine using a fuzzy rule-based system. Suppose we have two input variables X, Y and one output variable Z, and their respective linguistic attributes are X1, X2 for X; Y1, Y2 for Y; and Z1, Z2 for Z. Then the two defining rules (for example) are

> If X is X1 AND Y is Y1, then Z is Z1.
> If X is X2 OR Y is Y2, then Z is Z2.

Also, let x, y be the exact values of X, Y. The first step is to calculate the truth value (α_i) for each of the given rules:

$$\alpha_1 = \mu_{X_1}(x) \wedge \mu_{Y_1}(y), \tag{8}$$

$$\alpha_2 = \mu_{X_2}(x) \vee \mu_{Y_2}(y). \tag{9}$$

- Before performing the defuzzification process, the implication process for the two degrees of membership value from the previous step is needed. In this step, the max-min composition method for the implication process is used. The first step is to calculate the modified membership function (μ') for the conclusion output recommended by each rule by taking the minimum of its membership function and the truth value of the IF clause as follows:

$$\mu'_{Z_1} = \alpha_1 \wedge \mu_{Z_1}, \tag{10}$$

$$\mu'_{Z_2} = \alpha_2 \wedge \mu_{Z_2}. \tag{11}$$

Finally, the membership function μ_z for the final output of variable Z is calculated by taking the maximum value of the modified membership μ' of all the conclusion output by referring to Z:

$$\mu_z = \mu'_{Z_1} \vee \mu'_{Z_2}. \tag{12}$$

After the implication process, all the values of Z are aggregated by summing all of the values.

- The last process for the fuzzy inference system is defuzzification. By using the COA method [14], the actual output for the fuzzy inference system can be derived.

$$COA = \frac{\sum_{i=1}^{K} \mu_{z,i}(z) z_i}{\sum_{i=1}^{K} \mu_{z,i}(z)} . \tag{13}$$

- The output value is the possibility of a present PU (F_1). If the F_1 value is larger than λ_{fuzzy}, it is decided as H_1; otherwise, it is decided as H_0.

(d) After performing local spectrum sensing, each secondary user sends their local decision results (P_d) to the fusion center. In our simulation, it is assumed that there are three secondary users collaborating in the cooperative sensing scheme.

B. Second Stage (Fusion Center)

The fusion center combines all the local decisions using the fuzzy logic scheme. Thus, there are three local decision values as crisp input for the fuzzification process. The next process also uses the same procedure as point (c) in the first stage for the decision combining process. However,

for FIS in the second stage, we used the max-product implication method as the implication method and the middle of maximum (MOM) method as the defuzzification method. The defuzzification method for MOM can be expressed as

$$MOM = \frac{\sum_i LocalMax_i^x LocalMax_i^y}{\sum_i LocalMax_i^y} \qquad (14)$$

where $LocalMax_i^y$ is the y-axis value of the local maximum; $LocalMax_i^x$ is the x-axis value of the local maximum point; and $LocalMax$ is the vector of the local maximum points in the output shape for the defuzzification method [15]. Eq. (14) is used to obtain the high output probability. The output value of the second stage is the final possibility of a present PU (F_2). If the F_2 value is larger than λ_{fuzzy}, it is decided as H_1, otherwise as H_0. The membership functions for the second stage are shown in Fig. 4. In Table 2, we present an example fuzzy rule-based system that is used for rule evaluation in the second stage where there are actually 27 rules in our scheme.

Table 2. Example rule-based system for the second stage

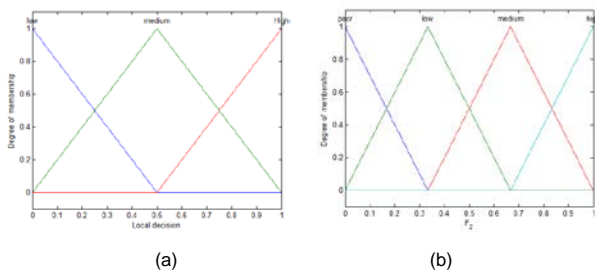| 1st SU	2nd SU	3rd SU	F_2
Low	Low	Low	Poor
Medium	Low	Low	Low
High	Low	Low	Low
Low	Medium	Low	Low
Medium	Medium	Low	Medium
High	Medium	Low	Medium
Low	High	High	Medium
Medium	High	High	High
High	High	High	High

SU: secondary user.

(a)   (b)

Fig. 4. Membership function for the second stage. (a) MF of the 1st, 2nd, and 3rd antecedent for the second stage. (b) MF of consequent for the second stage (final possibility of present PU).

IV. SIMULATION RESULTS AND ANALYSIS

A. Experimental Setup

The simulation was implemented using MATLAB. The parameters used for our simulation were total samples (N) of 1,000, SNR range from -30 dB to 5 dB, and three secondary users. For deriving a double adaptive threshold, we used the following parameters: $P_f = 0.1$, noise uncertainty factor (ρ) = 1.05, dynamic threshold factor (ρ') = 1.09, and QPSK modulation in the AWGN channel.

The performance results of our proposed scheme were evaluated and compared with other schemes that have a different number of thresholds. These are the CFAR (single threshold) scheme, double adaptive thresholds scheme, and three thresholds scheme. We applied the AND rule and the OR rule as the decision rules in the fusion center. The AND rule decides that a signal is present if all users have detected a signal [16]. The cooperative probability of detection (Q_d) and the cooperative probability false alarm (Q_f) cooperative sensing based for the AND rule can be expressed as

$$Q_d(M) = \prod_{i=1}^{M}(P_{d,i}) \ , \qquad (15)$$

$$Q_f(M) = \prod_{i=1}^{M}(P_{f,i}) \ . \qquad (16)$$

In the opposite way, if at least one of the secondary users decides that a primary user signal is present at the local decision, the fusion center decides whether a primary user is present. This fusion rule is known as the OR rule [16]. The cooperative probability of detection (Q_d) and the cooperative probability false alarm (Q_f) for the OR rule can be expressed as

$$Q_d(M) = 1 - \prod_{i=1}^{M}(1 - P_{d,i}) , \qquad (17)$$

$$Q_f(M) = 1 - \prod_{i=1}^{M}(1 - P_{f,i}) . \qquad (18)$$

where M is the number of secondary users subscribing cooperation, and $P_{d,i}$ and $P_{f,i}$ are the probability of detection and probability of false alarm for each secondary user, respectively.

B. Results and Analysis

Fig. 5 shows a comparison of the cooperative detection probability as a function of the SNR value. As the SNR value decreases in the local node, the cooperative probability of detection (Q_d) also decreases dramatically. Moreover, the result shows that by applying fuzzy logic at the node level,

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the sensing accuracy can be greatly improved compared to other schemes. Using fuzzy logic in a local node also helps to mitigate sensing failure in the confused region. When SNR = -20 dB, our scheme can outperform the three thresholds cooperative scheme by 21%.

Fig. 6 shows a comparison of the cooperative false alarm probability when the signal is noise only or the primary user is almost absent. Spectrum sensing is performed with a variant of the SNR value or a variant in the noise power. As shown in Fig. 6, the cooperative probability of a false alarm (Q_f) starts to increase when SNR = 0 dB. This is particularly likely in cases where a CFAR scheme with OR rules is Q_f = 0.3, while the other schemes have a lower value than 0.1. At SNR > 0 dB, all of the schemes have a high false alarm rate because the energy detection scheme cannot distinguish the primary signal from the noise. However, according to the spectrum sensing requirement for the probability of a false alarm [17], the maximum of the false alarm value is 0.1. Thus, our proposed scheme meets the spectrum sensing requirement because when the thresholds are derived using P_f = 0.1 and SNR = 0 dB, the cooperative false alarm probability is still lower than 0.1.
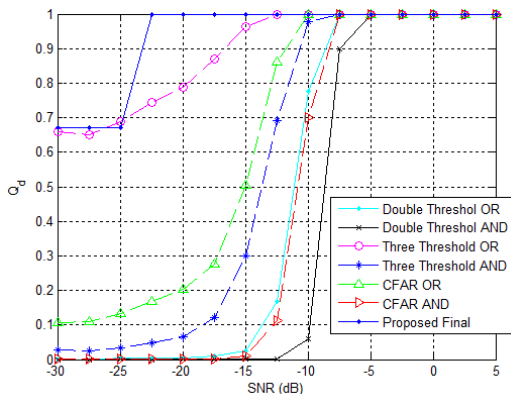

Fig. 5. Comparison of cooperative detection probability as a function of the SNR values when a primary user is present.
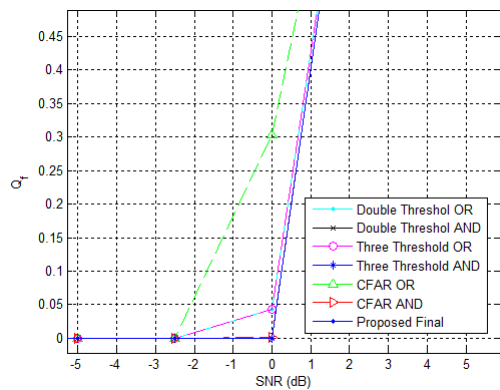

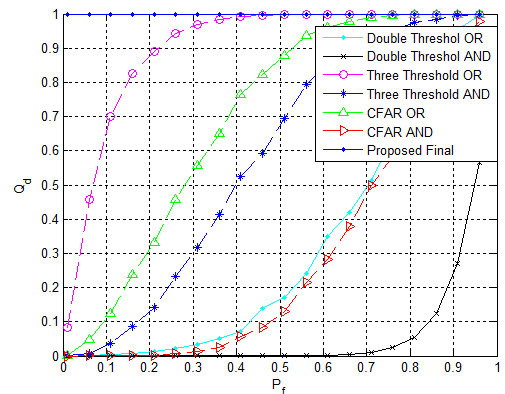**Fig. 6.** Comparison of cooperative FA probability as a function of the SNR values when a primary user is absent.

Fig. 7. Comparison of cooperative detection probability as a function of P_f when a primary user is present.
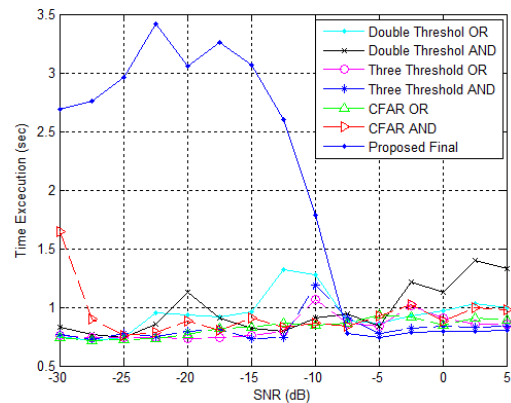

Fig. 8. Comparison of the time execution when a primary user is present.

Fig. 7 shows a comparison of the cooperative detection probability (Q_d) as a function of the probability of false alarm (P_f). It is assumed that the SNR value is -20 dB, and P_f varies between 0.01 and 1. When P_f = 0.01, our scheme provides Q_d = 1 whereas in other schemes Q_d is lower than 0.1. Therefore, our scheme does not produce any negative effects associated with changes in the probability of false alarm in determining the threshold. According to the spectrum sensing standard, the minimum requirement of probability detection is 0.9 [17]. Thus, when P_f varies between 0.01 and 1, our scheme successfully decides the true condition of the presence of a primary user with Q_d = 1. This result was the best among all of the schemes that were considered.

Fig. 8 shows a comparison of the executed time as a function of SNR when a primary user is present. The overall results of the average executed time for determining the channel status are below one second. When a secondary user faces worse SNR, the proposed scheme can enhance the accuracy of detection better than the other schemes. However, when SNR = -30 dB to -15 dB, the proposed scheme requires around three seconds for time execution.

This indicates that in order to achieve high accuracy, execution time must be slightly sacrificed.

V. CONCLUSION

The aim of this paper is to enhance the performance of spectrum sensing schemes, particularly energy detection. Although our energy detection scheme is simple to implement, it is not robust at low SNR conditions, and the performance of the energy detection is limited by noise uncertainty. Furthermore, multipath fading, shadowing, and the hidden node problem degrade the performance of single-user spectrum-sensing techniques. Thus, a fuzzy logic scheme is applied to enhance the performance of energy detection based on double thresholds as well as to achieve high flexibility for decision making. By using a fuzzy logic scheme, vagueness and unclear decisions are mitigated in a confused region. Based on the simulation results, our scheme successfully enhances the performance of energy detection at low SNR and reduces the effect of noise uncertainty.

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