Cooperative Spectrum Sensing using Kalman Filter based Adaptive Fuzzy System for Cognitive Radio Networks

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Received October 7, 2011; revised December 14, 2011; accepted January 10, 2012; Published January 31, 2012

Abstract

Spectrum sensing is an important functionality for cognitive users to look for spectrum holes before taking transmission in dynamic spectrum access model. Unlike previous works that assume perfect knowledge of the SNR of the signal received from the primary user, in this paper we consider a realistic case where the SNR of the primary user's signal is unknown to both fusion center and cognitive radio terminals. A Kalman filter based adaptive Takagi and Sugeno's fuzzy system is designed to make the global spectrum sensing decision based on the observed energies from cognitive users. With the capacity of adapting system parameters, the fusion center can make a global sensing decision reliably without any requirement of channel state information, prior knowledge and prior probabilities of the primary user's signal. Numerical results prove that the sensing performance of the proposed scheme outperforms the performance of the equal gain combination based scheme, and matches the performance of the optimal soft combination scheme.

Keywords: CR, cooperative spectrum sensing, Kalman filter, adaptive fuzzy system, data fusion.

This work was supported by KRF funded by the MEST (Mid-Carrier Researcher Program 2011-0017922)

DOI: 10.3837/tiis.2012.01.016

1. Introduction

Cognitive radio (CR) has appeared as a new design paradigm for the next-generation wireless network that aims to enhance the utilization of scarce electromagnetic radio spectrum by enabling dynamic spectrum access. The motivation for the design of CR communication systems comes from the fact that many portions of licensed spectrum are underutilized or neglected by licensed users. As a secondary user (who is unlicensed user), CR user (CU) is allowed to access a spectrum band unoccupied by the primary user (PU, who is licensed user) at a particular time and specific geographic location [1]. The frequency band that has been assigned to a PU who is not currently using it is called *spectrum hole*. Spectrum sensing is a critical task for CR in order to detect spectrum holes and identify spectrum access opportunities. Furthermore, during CU data transmission, periodic spectrum sensing must be performed to detect the sudden return of the PU transmission signal. **Fig. 1** illustrates the process of using an idle channel (i. e., a spectrum hole) for data transmission in CR.

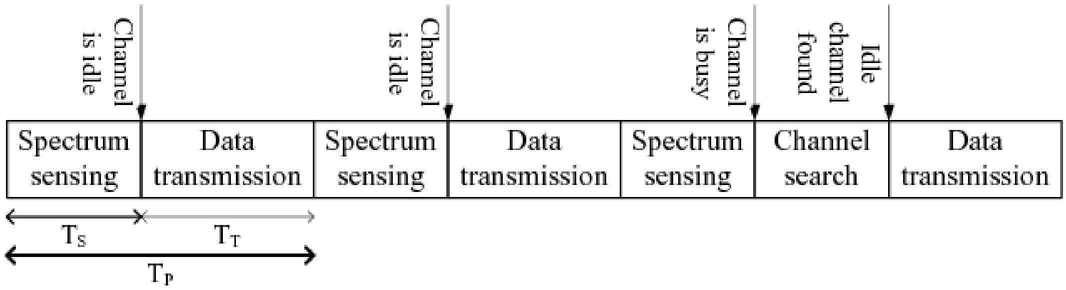

Fig. 1. The process of using an idle channel for data transmission in CR.

To avoid causing interference to the primary system, spectrum sensing must be efficient and reliable. Among spectrum sensing methods, energy detection is widely used to detect the present of the PU signal without any prior knowledge since it has very low implementation cost and admirable sensing performance [2][3][4]. However, when this method is applied to a standalone CU, due to time-varying natures of wireless channel (e.g., shadowing, fading), the CU may not be able to reliably distinguish between a spectrum hole and a deeply faded and shadowed PU signal [5]. To overcome this drawback, cooperative spectrum sensing has been proposed [6][7][8]. In cooperative spectrum sensing, the sensing information from different CUs are combined at the fusion center (FC) to make the global decision on the present status of PU signal. Consequently, the sensing accuracy is enhanced by the spatial diversity gain. Based on the Neyman-Pearson criterion, an optimal soft combination (OSC) scheme for cooperative spectrum sensing was derived in [6]. Results in the paper showed that the OSC reduces to the maximal-ratio combination (MRC) in low signal-to-noise ratio (SNR) regime, and reduces to the equal gain combination (EGC) in high SNR regime. In [7], an optimal linear cooperation framework for spectrum sensing was proposed. However, to implement algorithms in [7], the FC must have full knowledge of noise variance and SNR of the PU signal at all CUs to control the combining weights, which optimizes a modified deflection coefficient that characterizes the probability distribution function (*pdf*) of the global test statistic at the FC. A fuzzy inference system was proposed in [8] to make local soft spectrum sensing decision at CUs under the assumption that the SNR of the PU signal is known to CUs. Results in [8] showed that the sensing performance of the proposed scheme is comparable with the sensing performance of the MRC based scheme while does not require sending SNR of the PU signal from CUs to the FC.

It can be observed that most existing cooperative spectrum sensing schemes are based on the assumption that the SNR of the PU signal at the CU is perfectly known. However, in practice it is very difficult for a CU to exactly estimate SNR of the PU signal in a given spectrum band since there is no cooperation between the CU and the PU. Moreover, even if the CUs can estimate these parameters well, it is very expensive to transmit them along with local observations to the FC. To deal with these practical issues, in this paper an adaptive cooperative spectrum sensing scheme is proposed to detect spectrum holes accurately under the condition that the prior knowledge of the PU signal, the prior probability of the PU activity, and SNRs of the PU signal at CUs are not available. We consider the case that each CU in the CR network measures the energy of the received signal in the band of interest and then transmits its observation to the FC without any extra information. Data fusion at the FC is performed by using an adaptive Takagi and Sugeno's fuzzy system where fuzzification parameters are adapted from received data via a Kalman filter. It means that the detection problem and the estimation problem are solved at the FC simultaneously and cooperatively. Therefore, the FC can make a global decision based on local observed energies without the knowledge of the SNRs of the PU signal at CUs. Numerical results clearly prove that the proposed scheme is comparable with the OSC scheme and also outperforms the EGC based scheme in terms of sensing accuracy.

The organization of the paper is as follows: In Section 2, the system model and the adaptive cooperative spectrum sensing problem are described. An overview of energy detection is given in Section 3. The Kalman filter for estimating mean under hypothesis H_1 of observed energy from local observation is derived in Section 4. We then propose an adaptive data fusion algorithm using Kalman filter and adaptive Takagi and Sugeno's fuzzy system in Section 5. Numerical results are presented in Section 6. Finally, in Section 7, we conclude the paper.

2. System Model

Spectrum sensing can be formulated as a binary hypothesis testing problem as follows:

$$\begin{cases} H_0: & PU\ signal\ is\ absent, \\ H_1: & PU\ signal\ is\ present. \end{cases} \tag{1}$$

In this paper, we consider a CR network with M distributed CUs and a FC. According to the status of the PU, the received signal at each CU is given as:

$$x_i(t) = \begin{cases} n_i(t), & H_0 \\ h_i(t)s(t) + n_i(t), & H_1 \end{cases} \tag{2}$$

where $x_i(t)$ represents the received signal at the i-th CU, $h_i(t)$ denotes the channel gain of the channel between the PU and the i-th CU, $s(t)$ represents the signal transmitted by the PU, and $n_i(t)$ is the additive white Gaussian noise (AWGN) at the i-th CU. Additionally, channel corresponding to different CUs are assumed to be independent, and further, all CUs and the PU share a common spectrum allocation.

The cooperative spectrum sensing is performed as shown in **Fig. 2**. For each sensing cycle, first, each CU calculates the energy of its received signal in the frequency band of interest. Local observed energies are then transmitted to the FC through a control channel. Finally, the FC combines local observations of individual CUs to make the global decision on the present status of the PU signal by an adaptive data fusion algorithm.

The main objective of this paper is to design an adaptive data fusion algorithm at the FC under the practical condition that the prior knowledge of the PU signal, the prior probability of the PU activity, and SNRs of the PU signal at CUs are not available.

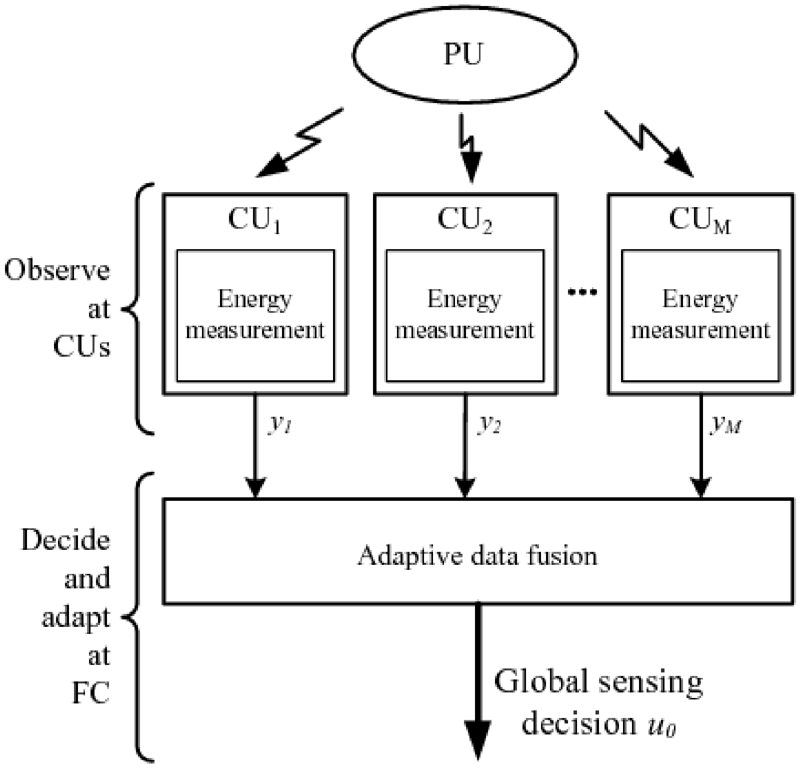

Fig. 2. The cooperative spectrum sensing scheme.

3. Overview of Energy Detection

The energy detection method is optimal for detecting signals when prior knowledge of the signal is unavailable [2][3][4]. The block diagram of the energy detection method in the time domain is shown in **Fig. 3**. To measure the energy of the signal in the frequency band of interest, a band-pass filter (BPF) is first applied to the received signal, which is then converted into discrete samples with an analog-to-digital converter (A/D).

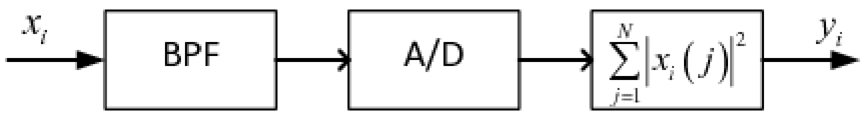

Fig. 3. The block diagram of energy detection.

The local test static of the *i*-th CU using energy detection is:

$$y_i = \sum_{j=1}^{N} \left| x_i(j) \right|^2, \tag{3}$$

where $x_i(j)$ is the *j*-th sample of received signal at the *i*-th CU and N is the number of samples, $N = 2TW$ where T and W are 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 variance. If the PU signal is absent, y_i follows a central chi-square distribution with N degree of freedom; otherwise, y_i follows a non-central chi-square distribution with N degree of freedom and a non-centrality parameter $N\gamma_i$ [2]:

$$y_i \sim \begin{cases} \chi_N^2, & H_0 \\ \chi_N^2(N\gamma_i), & H_1 \end{cases} \tag{4}$$

where

$$\gamma_i = \frac{E_s |h_i|^2}{N} \tag{5}$$

is the SNR of the PU signal at the *i*-th CU and the quantity

$$E_s = \sum_{k=1}^{N} \left| s(k) \right|^2 \tag{6}$$

represents the transmitted signal energy over a sequence of N samples during each detection interval.

When N is relatively large (e.g. $N > 250$), y_i can be well approximated as a Gaussian random variable under both hypothesis H_0 and H_1 with a mean of m_{0_i} and m_{1_i}, and a variance of v_{0_i} and v_{1_i} respectively, which are given as follows [2]:

$$\begin{cases} m_{0_i} = N, v_{0_i} = 2N;\ H_0 \\ m_{1_i} = N(1+\gamma_i), v_{1_i} = 2N(1+2\gamma_i);\ H_1. \end{cases} \tag{7}$$

An example of observed energy and its conditional means is shown in **Fig. 4**. In this example, the PU signal is binary phase shift keying (BPSK) signal [13], number of samples is $N = 5$, and SNR of the PU signal at the CU is $\gamma = 10$ dB.

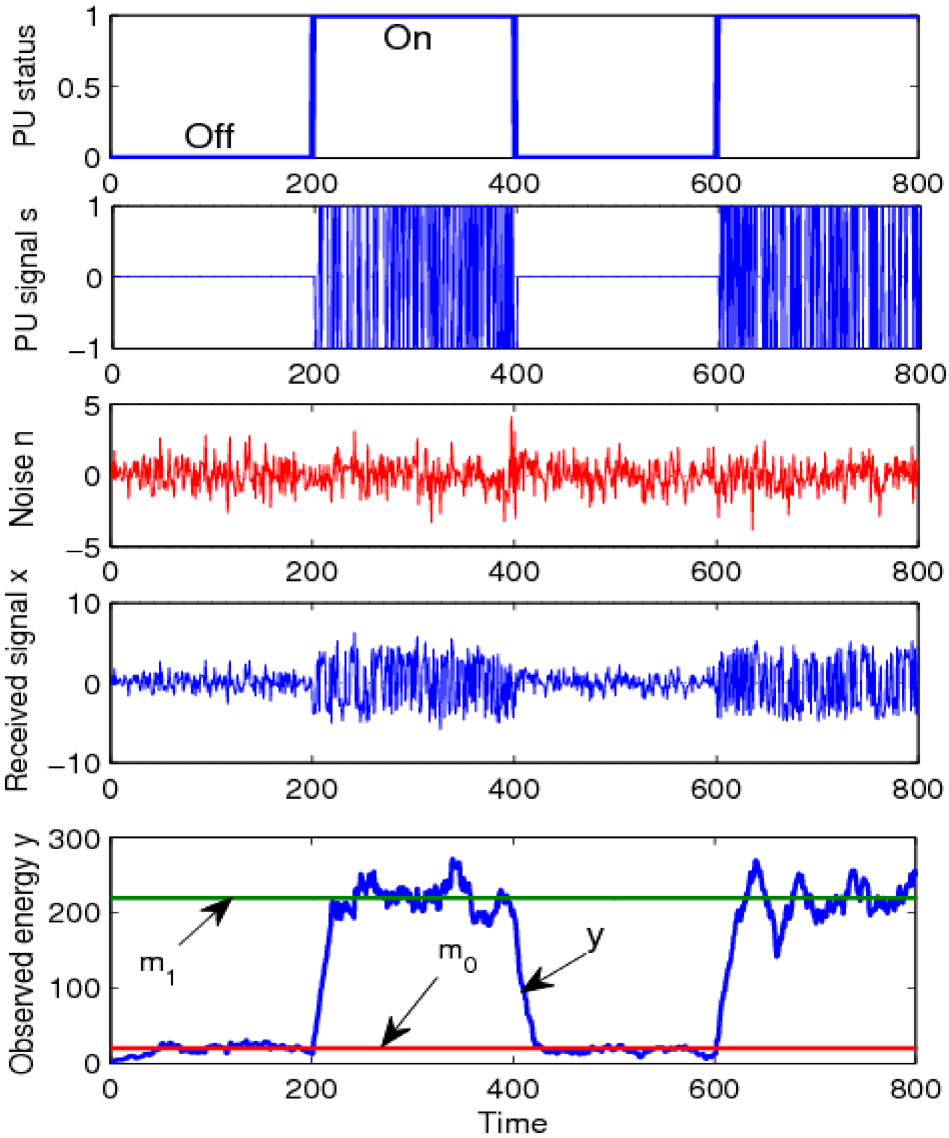

Fig. 4. An example of the observed energy and its conditional means at a CU when the PU signal is BPSK signal, number of samples is N = 5, and SNR of the PU signal at the CU is γ = 10 dB.

4. Derivation of Kalman Filter

Kalman filter is a recursive algorithm which is used to obtain the optimal estimate of a random process from its measurement so that the mean-square estimation error is minimized [9][10]. Assume that the PU is taking transmission, and the SNR of the PU signal at each CU is changed slowly over time, hence the mean under hypothesis H_1 of the observed energy at the arbitrary i-th CU is almost unchanged between two adjacent sensing cycles:

$$m_{1_i}(k+1) = m_{1_i}(k). \tag{8}$$

Recall that when the PU signal is present, the observed energy y_i follows a Gaussian distribution with mean $m_{1_i} = N(1+\gamma_i)$ and variance $v_{1_i} = 2N(1+2\gamma_i)$. Therefore, the observed energy y_i can be considered as a noisy measurement of the mean m_{1_i} as follows:

$$y_i(k) = m_{1_i}(k) + w_i(k), \tag{9}$$

where w_i is the measurement noise, w_i follows a Gaussian distribution with mean zero and variance $R_i(k) = v_{1_i}(k)$.

We assume that we have an initial estimate of m_{1_i} at time slot *k*. This prior estimate is denoted as $\hat{m}_{1_i}^-(k)$. The estimation error is defined as

$$e_i^-(k) = m_{1_i}(k) - \hat{m}_{1_i}^-(k) \tag{10}$$

and the associated error variance is:

$$P_i^-(k) = E\left[\left(m_{1_i}(k) - \hat{m}_{1_i}^-(k)\right)^2\right]. \tag{11}$$

A linear combination of the noisy measurement y_i and the prior estimate $\hat{m}_{1_i}^-$ is used to obtain the posterior estimate of m_{1_i} in accordance with the equation

$$\hat{m}_{1_i}(k) = K_i(k)\,y_i(k) + \left(1-K_i(k)\right)m_{1_i}^-(k), \tag{12}$$

where $K_i(k)$ is combination factor, $K_i(k) > 0$.
The error variance associated with this estimate is

$$P_i(k) = E[(m_{1_i}(k) - \hat{m}_{1_i}(k))^2] \tag{13}$$

By substituting (12) into (13), we have

$$\begin{aligned} P_i(k) &= E\left[\left(m_{1_i}(k) - \{K_i(k)\,y_i(k) + \left(1-K_i(k)\right)\hat{m}_{1_i}^-(k)\}\right)^2\right] \\ &= E\left[\left(m_{1_i}(k) - \{K_i(k)\left(m_{1_i}(k) + w_i(k)\right) + \left(1-K_i(k)\right)\hat{m}_{1_i}^-(k)\}\right)^2\right] \\ &= E\left[\left(\left(1-K_i(k)\right)\left(m_{1_i}(k) - \hat{m}_{1_i}^-(k)\right) - K_i(k)\,w_i(k)\right)^2\right] \\ &= \left(1-K_i(k)\right)^2 P_i^-(k) + K_i(k)^2 R_i(k) \end{aligned} \tag{14}$$

To find the particular $K_i(k)$ that minimizes the mean-square estimation error, we differentiate $P_i(k)$ with respect to $K_i(k)$. The result is:

$$\begin{aligned}\frac{dP_i(k)}{dK_i(k)} &= -2\left(1-K_i(k)\right)P_i^-(k)+2K_i(k)R_i(k)\\ &= 2K_i(k)\left(R_i(k)+P_i^-(k)\right)-2P_i^-(k)\end{aligned} \tag{15}$$

By setting the derivate equal to zero, we get optimal combination factor called *Kalman gain*

$$K_i(k)=\frac{P_i^-(k)}{R_i(k)+P_i^-(k)}. \tag{16}$$

Substitution of the Kalman gain into (14) leads to

$$P_i(k)=\left(1-K_i(k)\right)P_i^-(k). \tag{17}$$

The updated estimate of m_{1_i} is projected ahead via the transition equation (8). Thus, we have

$$\hat{m}_{1_i}^-(k+1)=m_{1_i}(k). \tag{18}$$

The prior error variance associated with the prior estimate $\hat{m}_{1_i}^-(k+1)$ is obtained as

$$\begin{aligned}P_i^-(k+1) &= E\left[\left(m_{1_i}(k+1)-\hat{m}_{1_i}^-(k+1)\right)^2\right]\\ &= E\left[\left(m_{1_i}(k)-\hat{m}_{1_i}^-(k)\right)^2\right]\\ &= P_i(k).\end{aligned} \tag{19}$$

Equations (16), (12), (17), (18), and (19) bring us a Kalman filter recursive algorithm for estimating the mean under hypothesis H_1 of the observed energy at each CU. Operation principle of this algorithm is summarized in **Fig. 5**.

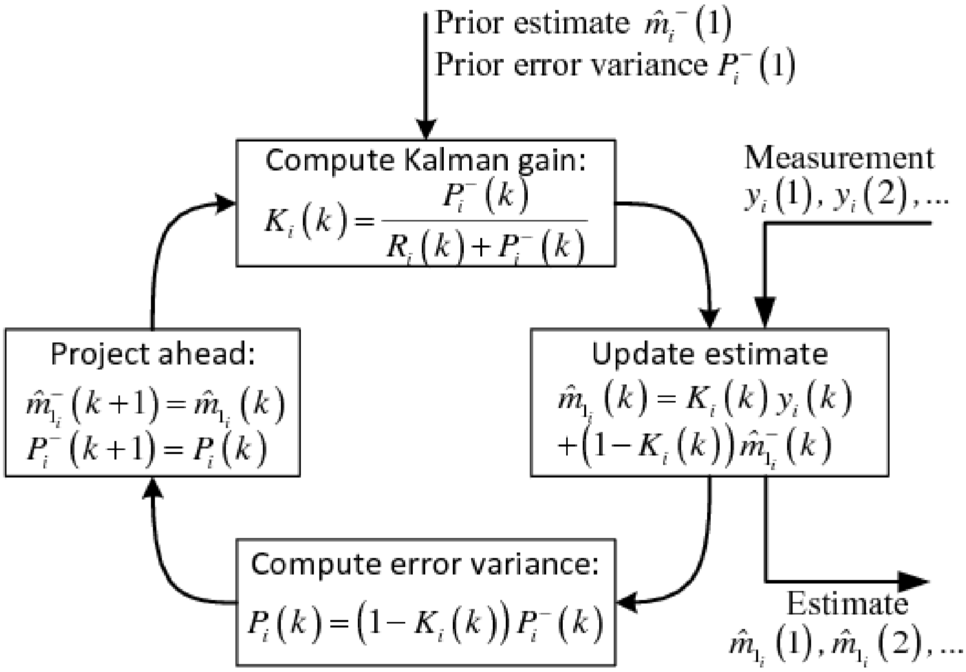

Fig. 5. Kalman filter loop for estimating mean under hypothesis H_1 of observed energy.

We see that in order to obtain optimal estimate $\hat{m}_{1_i}$ of the conditional mean m_{1_i} from the observed energy y_i, we firstly give the Kalman filter algorithm our prior estimate $\hat{m}_{1_i}^-(1)$ and its error $P_i^-(1)$ based on our knowledge about the systems. Kalman filter loop will output estimate $\hat{m}_{1_i}$ by an optimal linear combination of the prior estimate $\hat{m}_{1_i}^-$ and the noisy measurement y_i.

5. Adaptive Data Fusion at the FC

Based on local observations received from CUs, the FC makes the global spectrum sensing decision by using a Kalman filter based adaptive fuzzy system as illustrated in **Fig. 6**.

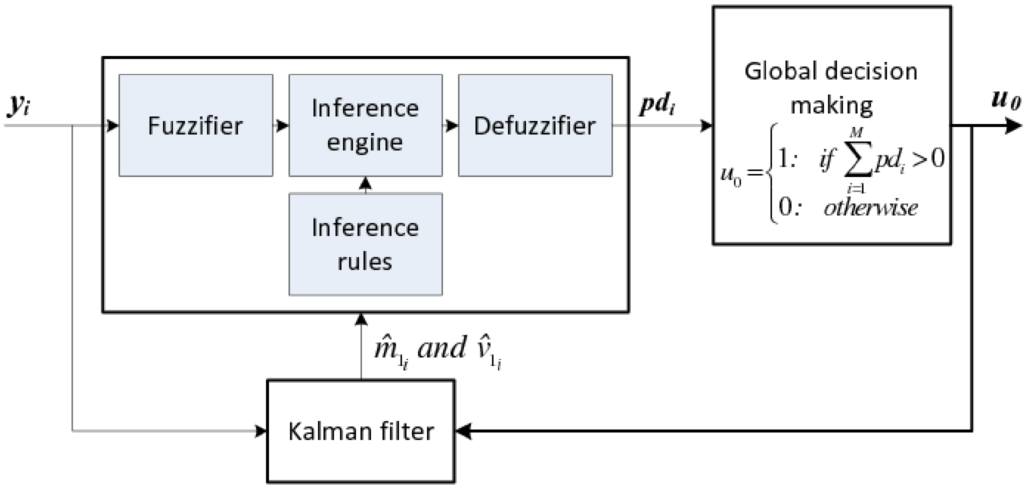

Fig. 6. Adaptive data fusion at the FC.

5.1 Making Global Decision

Fuzzy logic is known as a simple way to obtain the solution to a problem based on imprecise, noisy, and incomplete input information. To capture dynamic system behavior with low computation complexity, adaptive Takagi and Sugeno's fuzzy logic system is used due to its adaptability to the changing environment so that the desired performance can be achieved [11]. Takagi and Sugeno's fuzzy logic system was proposed by Takagi and Sugeno [12] to obtain a compact system equation. Instead of considering fuzzy IF-THEN rules whose IF and THEN parts are fuzzy, Takagi and Sugeno proposed to use the fuzzy IF-THEN rules whose IF part is fuzzy, but whose THEN part is crisp. As a result, the output of Takagi and Sugeno's fuzzy system is just a weighted average over all rules, and the computation cost is reduced significantly.

Let $\hat{m}_{1_i}$ and $\hat{v}_{1_i}$ be the estimate of m_{1_i} and v_{1_i}, respectively. Each observed energy is fuzzified by two fuzzy sets, namely *Low* and *High*. The membership functions recommended in [8] are applied for fuzzy sets *Low* and *High* as follows:

$$\mu_{Low}(y_i) = \begin{cases} 1 & , if\ \ y_i \le m_{0_i} \\ e^{-\frac{(y_i - m_{0_i})^2}{2v_{0_i}}} & , otherwise \end{cases} \tag{20}$$

$$\mu_{High}(y_i) = \begin{cases} 1 & , if\ \ y_i \ge \hat{m}_{1_i} \\ e^{-\frac{(y_i - \hat{m}_{1_i})^2}{2\hat{v}_{1_i}}} & , otherwise \end{cases}. \tag{21}$$

The shapes of these functions are illustrated in **Fig. 7**.

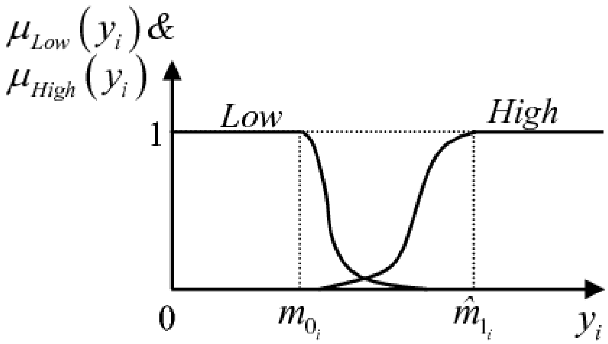

Fig. 7. Membership functions of fuzzy sets.

Based on the fuzzified energy, the inference rules are used to gain information on the present status of the PU signal. Let denote pd_i be the private decision which reflects the presence possibility of the PU signal based on the observation of the *i*-th CU. Then, the fuzzy inference rule set can be proposed as follows:

- Rule 1: IF (y_i is *Low*) THEN ($pd_i = pd_{\min}$),
- Rule 2: IF (y_i is *High*) THEN ($pd_i = pd_{\max}$).

where $pd_{\min}$ and $pd_{\max}$ are lower and upper bounds of private decisions, for $1 \le i \le M$.
The defuzification procedure is taken by weighted average [11] as follows:

$$pd_i = \frac{\mu_{Low}(y_i)\, pd_{\min} + \mu_{High}(y_i)\, pd_{\max}}{\mu_{Low}(y_i) + \mu_{High}(y_i)}. \tag{22}$$

To ensure that the private decision pd_i takes values in a symmetric domain [-1, 1], we set $pd_{min} = -1$ and $pd_{max} = 1$, where $pd_i = -1$ indicates that the PU signal is certainly absent and $pd_i = 1$ indicates that the PU signal is certainly present. Hence, the private decisions are simplified as:

$$pd_i = \frac{-\mu_{Low}(y_i) + \mu_{High}(y_i)}{\mu_{Low}(y_i) + \mu_{High}(y_i)}. \tag{23}$$

The global spectrum sensing decision is defined as:

$$u_0 = \begin{cases} 1, \, if \;\; H_1 \;\; is \; declared, \\ 0, \, if \;\; H_0 \;\; is \; declared. \end{cases} \tag{24}$$

Based on private decisions obtained from the defuzification procedure, the global decision is then made by applying a majority rule as follows:

$$u_0 = \begin{cases} 1, if \ \sum_{i=1}^{M} pd_i > 0 \\ 0, otherwise. \end{cases} \tag{25}$$

5.2 Adapting Parameters

At each sensing cycle, the Kalman filter algorithm derived in Section 4 will be performed to adjust fuzzification parameters for the next sensing cycle if the PU signal is declared to be present. In the first sensing cycle, the data fusion algorithm is performed with initial values set for these parameters: $\hat{m}_{1_i}(1) = N(1+\gamma_{min})$ and $\hat{v}_{1_i}(1) = N(1+2\gamma_{min})$, for $1 \le i \le M$, where γ_{min} is a pre-determined parameter denoting minimal SNR of the PU signal at CUs. The prior estimates and their associated error for Kalman filter are initialized as: $\hat{m}_{1_i}^{-}(1) = N(1+\gamma_{min})$, $P_i^{-}(1) = N(\gamma_{\max} - \gamma_{\min})^2$, for $1 \le i \le M$, where γ_{max} is a pre-determined parameter denoting the maximal SNR of the PU signal at CUs.

After that, in each sensing cycle, if current global decision $u_0 = 1$, the Kalman filter algorithm is implemented to update $\hat{m}_{1_i}$'s from current observed energies y_i's, for $1 \le i \le M$, using equations (16), (12), (17), (18), and (19). Estimated SNR of PU signal at each CU is then calculated according to the estimated mean under hypothesis H_1 as:

$$\hat{\gamma}_i = \frac{\hat{m}_{1_i}}{N} - 1. \tag{26}$$

Hence, the estimate of conditional variance under hypothesis H_1 of observed energy at each CU is obtained as follows:

$$\hat{v}_{1_i} = 2\left(2m_{1_i} - N\right). \tag{27}$$

The variance of measurement error is adapted accordingly as:

$$R_i = \hat{v}_{1_i}. \tag{28}$$

In conclusion, the adaptive data fusion algorithm at the FC can be summarized as follows:

Step 1: Initialize $m_{0_i} = N$, $v_{0_i} = 2N$, $\hat{m}_{1_i} = N(1+\gamma_{min})$, $R_i = \hat{v}_{1_i} = N(1+2\gamma_{min})$, $\hat{m}_{1_i}^{-} = N(1+\gamma_{min})$, $P_i^{-} = N(\gamma_{\max} - \gamma_{\min})^2$, for $1 \le i \le M$.

Step 2: Poll local observations y_i, for $1 \le i \le M$

Step 3: Calculate private decisions pd_i's

$$pd_i = \frac{-\mu_{Low}(y_i) + \mu_{High}(y_i)}{\mu_{Low}(y_i) + \mu_{High}(y_i)}, \text{ for } 1 \le i \le M$$

Where

$$\mu_{Low}(y_i) = \begin{cases} 1 & , if \;\; y_i \le m_{0_i} \\ e^{-\frac{(y_i - m_{0_i})^2}{2v_{0_i}}} & , otherwise \end{cases}$$

$$\mu_{High}(y_i) = \begin{cases} 1 & , if \;\; y_i \ge \hat{m}_{1_i} \\ e^{-\frac{(y_i - \hat{m}_{1_i})^2}{2\hat{v}_{1_i}}} & , otherwise \end{cases} .$$

Step 4: Make global decision u_0:

$$u_0 = \begin{cases} 1, if \; \sum_{i=1}^{M} pd_i > 0 \\ 0, otherwise. \end{cases}$$

Step 5: If $u_0 = 1$ then perform Kalman filter to update fuzzification parameters:

$$\begin{aligned} & K_i = \frac{P_i^-}{R_i + P_i^-}, \\ & \hat{m}_{1_i} = K_i y_i + (1 - K_i) m_{1_i}^-, \\ & P_i = (1 - K_i) P_i^-, \\ & \hat{m}_{1_i}^- = m_{1_i}, \\ & P_i^- = P_i, \\ & \hat{v}_{1_i} = 2(2m_{1_i} - N), \\ & R_i = \hat{v}_{1_i}, \end{aligned}$$

for $1 \le i \le M$.

Step 6: Go to step 2 for the next sensing cycle.

6. Simulation Results

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

- The number of CUs is $M = 5$.
- The PU signal is likely-equally BPSK signal [13] with prior probabilities $\Pr\{H_0\} = \Pr\{H_1\} = 0.5$.
- The noises at CUs are Gaussian with zero mean and unit variance.
- The number of samples N is 300.

The proposed adaptive data fusion algorithm is implemented with following initial values for pre-determined parameters:

- γ_{min} = -30 dB.

- $\gamma_{\max}$ = 20 dB.

Firstly, the sensing performance of the proposed scheme, in terms of its receiver operating characteristic (ROC), is evaluated under non-fading, Rayleigh fading, and Log-normal shadow fading channels. Rayleigh fading occurs when the PU signal experiences a Non-Line-of-Sight multi-path channel. Under Rayleigh fading environment, the received signal amplitude follows a Rayleigh distribution, and hence the SNR of the PU signal at the CU follows an exponential distribution whose *pdf* is given by:

$$f(\gamma_i) = \frac{1}{\bar{\gamma}_i} e^{\frac{-\gamma_i}{\bar{\gamma}_i}}, \quad \gamma_i > 0 \tag{29}$$

where $\bar{\gamma}_i$ is mean SNR value at the *i*-th CU [14][15].

Under log-normal shadow fading environment [16], the SNR of the PU signal at CUs follows a Log-normal distribution whose *pdf* is given by:

$$f(\gamma_i) = \frac{1}{\sqrt{2\pi}\sigma_i \gamma_i} \mathrm{e}^{-\frac{(\ln \gamma_i - \bar{\gamma}_i)}{2\sigma_i^2}} \tag{30}$$

where σ_i is standard deviation of the SNR at the *i*-th CU.

In this simulation, we assume that all CUs suffer independent and identically distribution Rayleigh/Log-normal shadow fading channel with mean SNRs of PU signal at CUs are -16, -14, -12, -10 and -8 dB, respectively, and 6 dB of standard deviation. The fading is assumed to be slow compared to the observed interval of the sensing method. Thus, the channel gain is assumed to remain constant during observed interval but it varies randomly between consecutive observed intervals.

Under these circumstances, furthermore, the ROC of the proposed scheme is compared with the two schemes from [6], namely the EGC based scheme and the OSC scheme. In the OSC scheme, the global spectrum sensing decision is made based on the weighted sum of the observed energies as follows:

$$u_0 = \begin{cases} 1, if \ \sum_{i=1}^{M} \frac{\gamma_i}{\gamma_i + 1} y_i > \tau \\ 0, otherwise \end{cases} \tag{31}$$

where τ is the decision threshold. The OSC scheme has an optimal sensing performance but it exhibits a significant transmission overhead as all CUs are requested to send their observed energies along with SNRs to the FC.

On the other hand, the EGC based scheme makes the global spectrum sensing decision by comparing the sum of the observed energies with the decision threshold:

$$u_0 = \begin{cases} 1, if \ \sum_{i=1}^{M} y_i > \tau \\ 0, otherwise. \end{cases} \tag{32}$$

Compared with the OSC scheme, the EGC based scheme has lower communication cost since in the EGC based scheme, each CU needs sending only its observed energy to the FC. Nonetheless, the sensing performance of the EGC based scheme is lower than that of the OSC scheme.

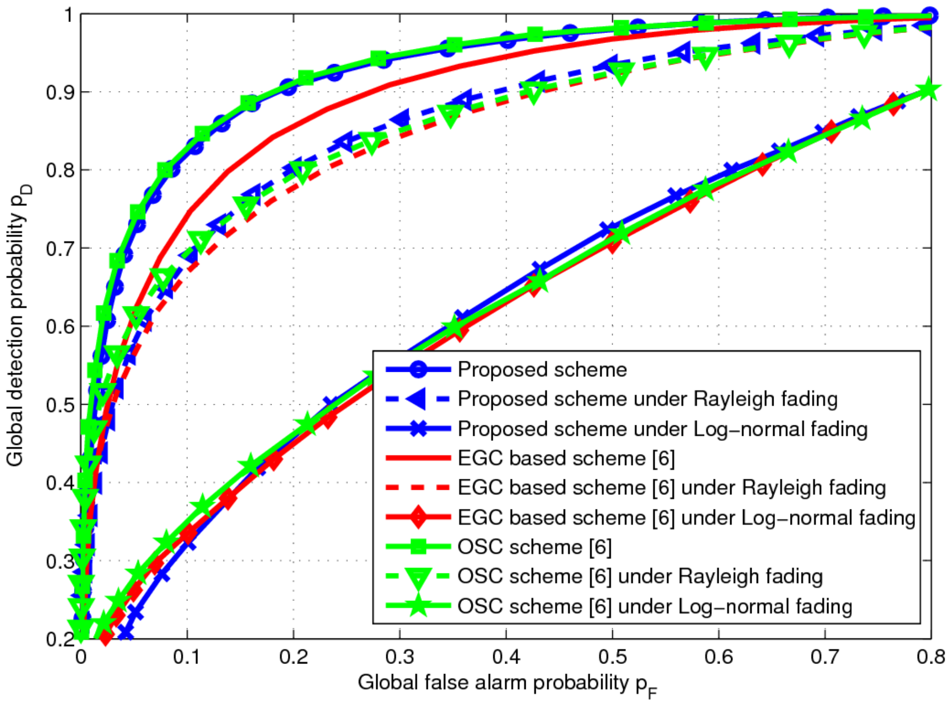

Fig. 8. ROC curves of the proposed scheme and comparison schemes.

A comparison of these results is presented in **Fig. 8**. Under non-fading conditions, the proposed scheme outperforms the EGC based scheme and has almost the same performance as the OSC scheme. However, note that to implement the proposed scheme, only the observed energies are needed. Yet in the case of the OSC scheme, each CU must also send the SNR of the PU signal to the FC. Under both Rayleigh fading and Log-normal shadow fading conditions, the sensing performance of the proposed scheme and the OSC scheme are almost similar to the one of the EGC based scheme.

Secondly, the estimation performance of the proposed scheme is tested in terms of estimation error and stability. **Fig. 9** shows the observed energy at CU_5, its mean under hypothesis H_1 and the estimate of its mean under hypothesis H_1 by the FC. We observe that although the observed energy of the 5-th CU varies strongly due to effect of the additive noise and the change of the PU signal status, but the estimated conditional mean $\hat{m}_{1_5}$ quickly catches the realal one m_{1_5}, and the gap between them is very small. The stability of the proposed detection and estimation algorithm is verified through estimation error variance. The error variance of the estimated mean $\hat{m}_{1_5}$, namely P_5, is plotted in **Fig. 10**. This result proves that the proposed algorithm reaches steady state in just only about 60 iterations.

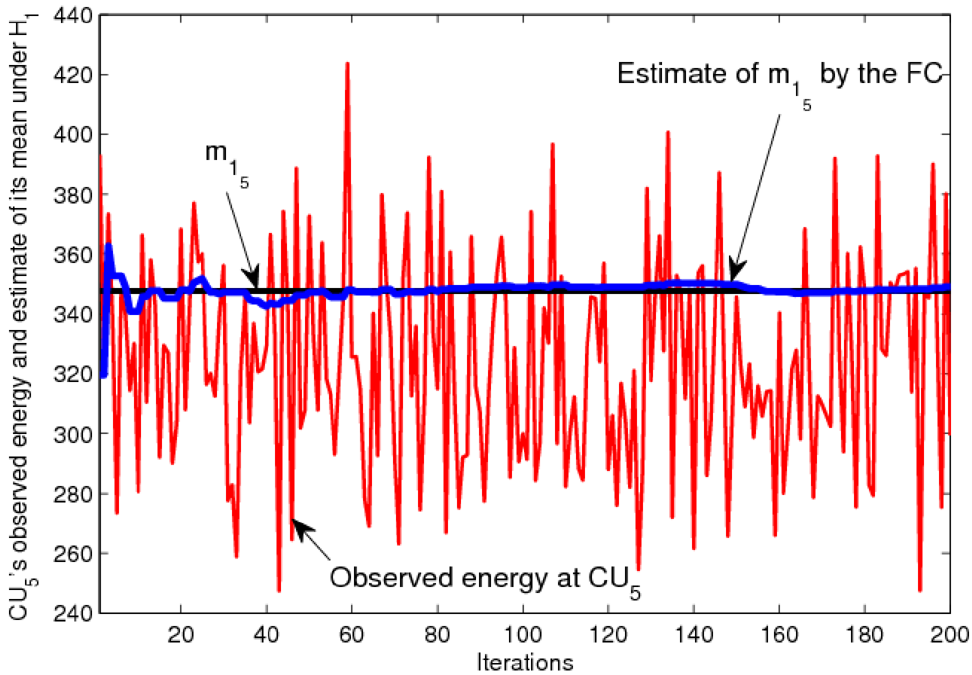

Fig. 9. Estimate of mean under H_1 of CU_5's observed energy.

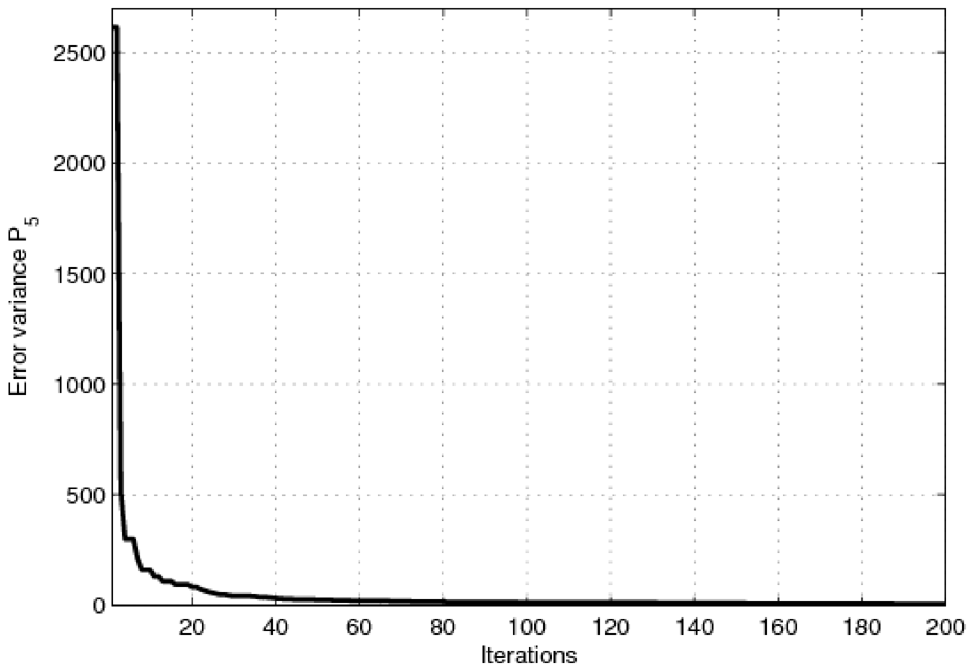

Fig. 10. Error variance of $\hat{m}_{1_5}$.

7. Conclusions

In order to detect spectrum holes reliably and efficiently, in this paper we propose an adaptive fuzzy based data fusion algorithm for cooperative spectrum sensing in CR networks. The advantage of the proposed scheme comes from the fact that it can work without any requirements about the knowledge of the PU signal, the prior probability of the PU activity, and SNRs of the PU signal at cognitive radio terminals. Simulation results showed that the sensing performance of the proposed scheme outperforms the performance of equal gain combination based scheme, and matches the performance of the optimal soft combination scheme.

One limitation of the proposed scheme is the choice of the pre-determined parameters, namely γ_{min} and $\gamma_{\max}$, since the convergent speed of the proposed estimation algorithm depends on this choice. Consequently, finding lower bound of γ_{min} and upper bound of $\gamma_{\max}$ is still an open issue. Future work is in progress in this direction.

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