ISSN (Online) : 2319 - 8753
ISSN (Print) : 2347 - 6710

International Journal of Innovative Research in Science, Engineering and Technology

Volume 3, Special Issue 3, March 2014

2014 International Conference on Innovations in Engineering and Technology (ICIET'14)

On 21st & 22nd March Organized by

K.L.N. College of Engineering, Madurai, Tamil Nadu, India

Cooperative Spectrum Sensing and Decision Making Rules for Cognitive Radio

R.Karthickeyan, R.Vadivelu

P.G Scholar, Department Of ECE, Sri Krishna college of Technology, Coimbatore, India

Asst.Professor, Department Of ECE, Sri Krishna college of Technology, Coimbatore. Tamilnadu, India

ABSTRACT: Cognitive radios are proposed to be the technology that will alleviate the problem of spectrum scarcity by using the underutilized radio frequency on non-interfering basis. So the cognitive radio user must be able detect the available spectrum opportunity reliably and efficiently. Spectrum sensing is an important functionality for cognitive users to look for spectrum holes before taking transmission in dynamic spectrum access model. 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. Adaptive 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. Simulation 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.

I. INTRODUCTION

Entire spectrum bands are already been allocated to different services, most often requiring licenses for operation, a fundamental problem facing future wireless systems is to find suitable carrier frequencies and bandwidths to meet the predicted demand for future services. However, studies by the FCCs reported vast temporal and geographic variations in the usage of allocated spectrum with utilization ranging from 15% to 85% [1]. This has forced researchers to explore new technologies to efficiently utilize this underutilized spectrum. One of such technologies that are actively under research to increase the capacity of wireless system is cognitive radio which aims at improving the utilization of crowded otherwise underutilized spectrum in time, frequency and space. The first and foremost requirement of cognitive radio (CR) for capitalizing the unused spectrum is to efficiently detect the availability of spectrum hole or white spaces, where there is no active primary user (PU). Since cognitive radio user have low priority in the licensed band, they must detect the spectrum hole efficiently to avoid interfering with primary user and exploit the spectrum holes to increase the data rate and increase the spectrum efficiency. For this purpose many signal detection techniques can be used in spectrum sensing ranging from feature detection [2] to energy level measurements [3]. The energy detection approach is optimal for detecting any unknown deterministic signal [4] and widely investigated as it is fast and offers low complexity. However, performance of the energy detector is susceptible to uncertainty in noise power [5]. Many factors in practice such as multipath fading, shadowing, and the receiver uncertainty problem may significantly reduce the detection performance in spectrum sensing. This is the reason why cooperative spectrum sensing (CSS) [6] is an attractive and effective approach to combat multipath fading and shadowing and mitigate the receiver uncertainty problem by exploiting spatial diversity.

The organization of the paper is as follows: In Section 2, the system model and the Section 3, Cooperative spectrum sensing 4.overview of energy detection, 5.Fusion rules, 6.simulation results 7.conclusion.

II. SYSTEM MODEL

Spectrum sensing can be formulated as binary hypothesis as follows,

H_0=Primary signal absent.

H_1= Primary signal present. (2.1)

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:

$$X_i(t) = \begin{cases} n_i(t), & H_0 \\ n_i(t)+h_i(t)s(t), & H_1 \end{cases} \quad (2.2)$$

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.

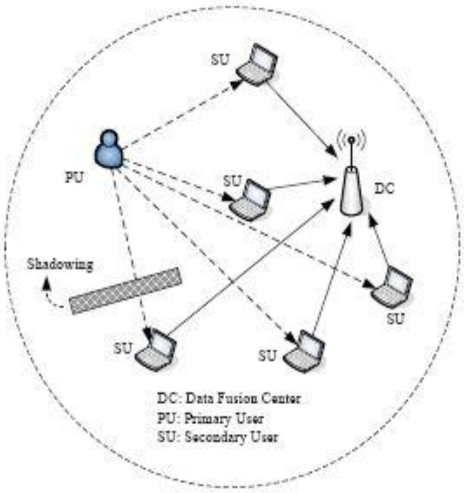

Fig 1: -system model

III. CO-OPERATIVE SPECTRUM SENSING

Cooperative spectrum sensing can be implemented in two methods.

A. *Centralized sensing*

In this approach to CR cooperative spectrum sensing, there is a central CR called fusion centre (FC) within the network that collects the sensing information from all the sense CRs within the network. For data cooperative, all CRs are tuned to a control channel where a physical point-to-point link between each cooperating CR and the FC for sending the sensing results is called a reporting channel as shown in Figure (2). FC then analyses the information and determines the bands that can and cannot be used.

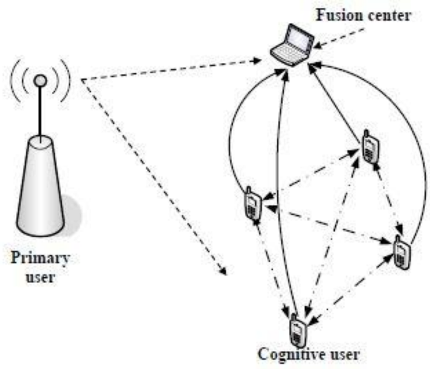

Fig 2: Centralized sensing.

B. *Distributed sensing*

Unlike centralized approach, distributed cooperative sensing does not depend on a FC for making the cooperative decision. Using the distributed approach for CR cooperative spectrum sensing, no one CR takes control. Each CR sends its specific data of sensing to other CRs, merges its data with the received data of sensing, and decides whether or not the PU is present by using a local condition as shown in Figure(3). However this approach requires for the individual CRs to have a much higher level of independence, and possibly setting themselves up as an ad-hoc network.

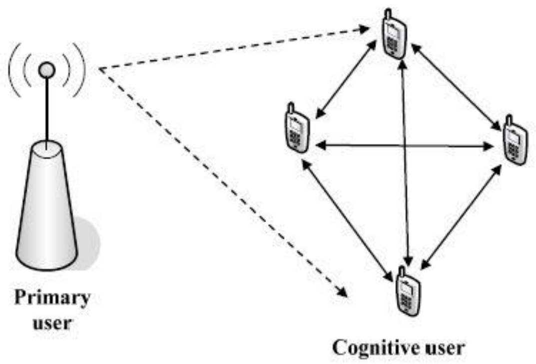

Fig 3 -Distributed sensing.

IV. OVERVIEW OF ENERGY DETECTION

Energy detection uses the energy spectra of the received signal in order to identify the frequency locations of the transmitted signal. Energy detection approach relies only on the energy present in the channel. Since the energy of a signal needs, no phase information. The underlying assumption is that with the presence of a signal in the channel, there would be significantly more energy than if there was no signal present. Therefore, energy detection involves the *application* of a threshold in the frequency domain, which is used to decide whether a transmission is present a specific frequency. Any portion of the frequency band where the energy exceeds the threshold is considered to be occupied by a transmission. Energy detector measures the energy received from primary user during the observation interval. If energy is less then certain threshold value then it declares it as spectrum hole. Let r(t) is the received signal which we have to pass from energy detector.

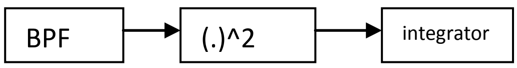

Figure 4. Energy Detector

The output signal V from the integrator is

$$\mathbf{V=1/T}\int_{t}^{t-T} |y(r)|^{2} dr \qquad \textbf{(4.1)}$$

Finally, this output signal V is compared to the threshold n in order to decide whether a signal is present or not. The threshold is set according to statistical properties of the output V when only noise is present. The probability of detection Pd and false alarm Pf are given as follows.

$$\mathbf{Pd=p}\{y > \lambda | H_1\}$$

$$\mathbf{Pf=p}\{y > \lambda | H_0\} \qquad \textbf{(4.2)}$$

From the above functions, while a low Pd would result in missing the presence of the primary user with high probability which in turn increases the interference to the primary user, a high Pf would result in low spectrum utilization since false alarm increase the number of missed opportunities.

The procedure of the Energy Detector is as follows

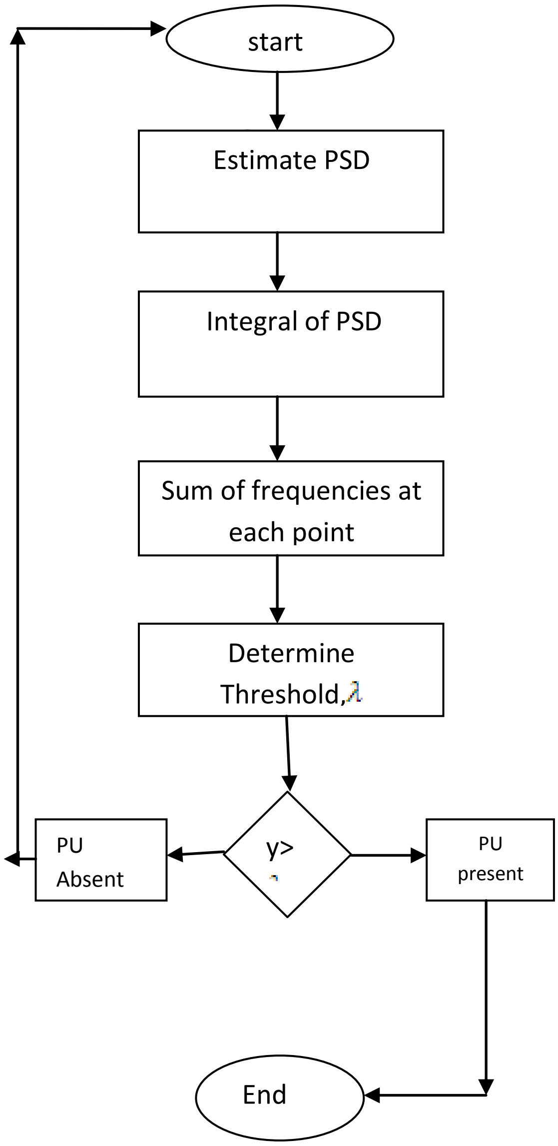

Fig 5: Flow Chart of Energy Detection

Step 1: First estimate Power Spectral Density (PSD) by using periodogram function in MATLAB. Pxx =Periodogram(r)

Step 2: The power spectral density (PSD) is intended for continuous spectra. The integral of the PSD over a given frequency band computes the average power in the signal over that frequency band. Hpsd=Dspdata.psd (Pxx)

Step 3: Now one frequency component takes almost 20 points in MATLAB. So for each frequency there points are summed and get the result.

Step 4: On experimental basis when results at low and high SNR are compared then threshold λ.
Step 5: Finally the output of the integrator, Y is compared with a threshold value λ to decide whether primary user is present or not.

V. FUSION RULES

A. Hard decision Rules:

In this scheme, each user decides on the presence or absence of the primary user and sends a one bit decision to the data fusion center. The main advantage of this method is the easiness the fact that it needs limited bandwidth [7]. When binary decisions are reported to the common node, two rules of decision can be used, the "and" and "or". Assume that the individual statistics Δ*k* are quantized to one bit with Δk=0, 1; is the hard decision from the kth CR user. 1 means that the signal is present, and 0 means that the signal is absent.

A.1. OR LOGIC

The **OR** rule decides that a signal is present if ***any*** of the users detect a signal.

$$P_{OR-D} = 1-\prod_{i=1}^{N}(1-P_{Di})$$

$$P_{OR-F} = 1-\prod_{i=1}^{N}(1-P_{Fi}) \qquad (5.1)$$

A.2.AND LOGIC

The **AND** rule decides that a signal is present if ***all*** users have detected a signal.

$$P_{AND-D} = \prod_{i=1}^{N} P_{Di}$$

$$P_{AND-F} = \prod_{i=1}^{N} P_{Fi} \qquad (5.2)$$

A.3 Majority rule:

A majority decision is a special case of the voting rule for M=K/2, the same as the AND and the OR rule which are also special cases of the voting rule for M=K and M=1 respectively.Cooperative detection probability *Pd* and cooperative false alarm probability *Pf* are defined as:

$$P_D = P\{\Delta = 1|H_1\}$$

$$P_F = P\{\Delta = 1|H_0\} \qquad (5.3)$$

B. Soft decision rules:

In soft data fusion, CR users forward the entire sensing result Ek to the center fusion without performing any local decision and the decision is made by combining these results at the fusion center by using appropriate combining rules such as square law combining (SLC), maximal ratio combining (MRC) and selection combining (SC). Soft combination provides better performance than hard combination, but it requires a larger bandwidth for the control channel [8]. It also generates more overhead than the hard combination scheme [7].

B.1. Square Law Combining (SLC):

SLC is one of the simplest linear soft combining schemes. In this method the estimated energy in each node is sent to the center fusion where they will be added together. Then this summation is compared to a threshold to decide on the existence or absence of the PU and a decision statistic is given by [9]

$$E_{slc} = \sum_{K=1}^{K} E_k \qquad (5.4)$$

B.2 Maximum Ratio Combining (MRC):

The difference between this method and the SLC is that in this method the energy received in the center fusion from each user is ponderated with a normalized weight and then added. The weight depends on the received SNR of the different CR user. The statistical test for this scheme is given by:

$$E_{mrc} = \sum_{K=1}^{K} wE_k \qquad (5.5)$$

VI. SIMULATION RESULT

In this section we study the detection performance of our scheme through simulations, and compare its performances with soft and hard fusion schemes. First, we present the performance of the hard combining schemes as depicted in Figure 6. Secondly, we will compare the performance of the different fusion rules in case of soft combining. For the hard decision, we present in Fig.6 the ROC curves of the 'AND' and the 'OR' rule, and compare it to the detection performance of a single CR user. For the simulations, we consider 3 CR users. Each user has a SNR of -2db. As shown in Fig.7, the OR rule has better detection performance than the AND rule, which provides slightly better performance at low Pf than the OR, because the data fusion center decide in favor of H1 when at least one CR user detects the PU signal. However in the AND rule, to decide of the presence of a primary user, all CR users must detect the PU signal. Figure 7, shows the ROC curves of different soft combination schemes discussed under AWGN channel. For the simulations, each CR user sees a different SNR. We observe from this figure that the MRC scheme exhibits the best detection performance, but it requires channel state information. The SLC scheme does not require any channel state information. The SLC scheme does not require any channel state information and still present better performance than SC. When no channel information is available, the best scheme is SLC.

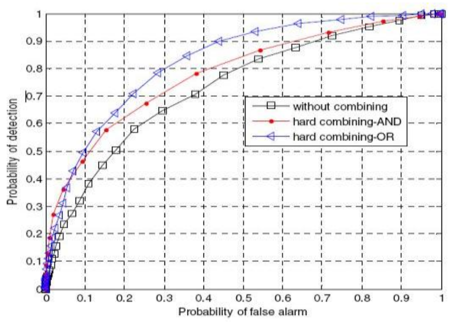

Fig 6: ROC of Hard decision rule

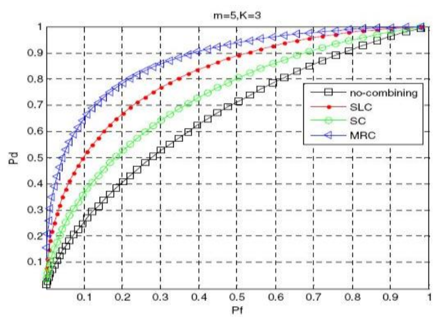

Fig 7: ROC of Soft decision rule

VII. CONCLUSION

In this paper, the effect of fusion rules for cooperative spectrum sensing using energy detection is investigated. It is shown that the soft fusion rules outperform the hard fusion rules. However, these benefits are obtained at the cost of a larger bandwidth for the control channel. The hard fusion rules occur with less complexity, but also with a lower detection performance than soft combination schemes. In practical application, we can select an appropriate method of data fusion and decision algorithms according to the requirement of detection performance and the requirement of the available bandwidth for the reporting channel.

REFERENCE

[1] "Spectrum policy task force report," in Federal Communications Commission, Tech. Rep. 02-155, Nov 2002.

[2] J. Lunnden, V. Koivunen, A. Huttunen, and H. V. Poor, "Spectrum sensing in cognitive radios based on multiple cyclic frequencies," Proc. CrownCom'07, August 2007.

[3] F. F. Digham, M. S. Alouini, and M. K. Simon, "On the energy detection of unknown signals over fading channels," *IEEE International Conference* on Communications (ICC'03), vol. 5, pp. 3575–3579, May 2003.

[4] U. Urkowitz, "Energy detection of unknown deterministic signals," IEEE Proceedings, vol. 55, no. 4, pp. 523–531, April 1967.

[5] A. Sonnenschein and P. M. Fishman, "Radiometric detection of spread spectrum signals in noise of uncertain power," IEEE Transactions on Aerospace and Electronic Systems, vol. 28, no. 3, pp. 654–660, July 1992.

[6] A. Ghasemi, E. Sousa, Collaborative spectrum sensing for opportunistic access in fading environments, in: Proc. of IEEE DySPAN 2005, pp. 131–136.J. Ma and Y. Li, "Soft combination and detection for cooperative spectrum sensing in cognitive radio networks," in Proc. IEEE Global Telecomm.Conf., 2007, pp. 3139–3143.

[7] J. Ma and Y. Li, "Soft combination and detection for cooperative spectrum sensing in cognitive radio networks," in Proc. IEEE Global Telecomm. Conf., 2007, pp. 3139–3143.

[8] Zhi Quan, Shuguang Cui, H. Vincent Poor, and Ali H. Sayed,"Collaborative wideband sensing for cognitive radios," IEEE Signal Processing Magazine, Vol. 25, No. 6, pp. 63–70, 2008.

[9]Zhengquan Li, Peng Shi, Wanpei Chen, Yan Yan, "Square Law Combining Double threshold Energy Detection in Nakagami Channel", Internation Journal of Digital Content Technology and its Application, volume5,Number 12, December 2011.

[10] M. K. Simon and M.-S. Alouini, Digital communication over fading channels. John Wiley & Sons, Inc., 2 ed., Dec. 2004.