Implementation of Eigenvalue Based Cooperative Spectrum Sensing in Cognitive Radio

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Abstract - Wireless communication services have been growing in recent years because of easy implementation and evidence of connectivity in remote areas. With this evolution, high-quality connectivity to the wireless frequency spectrum has led to large-spectrum use. Therefore the available radio spectrum is in great demand. Radio spectrum is a finite resource and hard to assign spectrum frequency for new applications. Cognitive radio (CR) is an effective technology which makes it possible to use it effectively.The aim is to introduce cooperative spectrum sensing based on eigenvalue using NI-USRP hardware platform and achieve good efficiency. In this article, a transmitter is used as primary user and implemented in hardwareby using two cognitive radio users. The implementation is achieved with LABVIEW and detection performance is evaluated.

Keywords – Wireless networks, Cognitive radio, Spectrum, Fusion center.

1. Introduction

Cognitive Radio (CR) users utilize the available radio spectrum, even though Primary Users (PUs) not prefer licensed user to optimize spectrum usage. The principal role of spectrum sensing by cognitive radio is to identify the presence or absence in a particular geographic area of primary consumer spectrum use over a given duration.It is done by continuously monitoring the radio system parameters. It ensures that the licensed users should not be interfered while utilizing the channel. As it is a secondary user CR user needs to omit the spectrum at the retransmitting of PU again. Collects the data from the environment to operate and can adjust its transmission parameters. Cognitive radio technique is Dynamic Spectrum Access (DSA) and a spectrum sensing method is cooperative spectrum senses the task of recognizing the primary users in a frequency band. Noise power can be detected by eigenvalue, at low SNR values of noise signal can be separatedin PU. It is possible to estimate the sensing efficiency based on two metrics, they are false alarm probability (P_{fa}) and probability of detection (P_d).

The P_{fa} likelihood found at a CR user by assuming at the presence of PU at the time of spectrum not in use. The probability of detection is when the presence of the PU is calculated correctly by the CR user. Cognitive radio consumer interference occurs when PU detection is removed.A new method with more effective is said to be Cooperative Spectrum Sensing(CSS)which detects spectrum holes. The result can be easily taken by multiple CR as sensing information. By using the proposed method performance is sensed accurately.

2. Literature Survey

CR technology is unutilized in sensing frequency bandsknowns as white spaces or spectrum holes and allocate unlicensed user with nointrusion to the licensed user. The appearance of PU is sensed and spectrum bands are notaccessible. Sothe SU requeststo make the band free and allocate primary user by [1]. Energy detection method is straightforward and works only in low SNR region. Matched filter detection is more difficult**.**

CSS involving in NI-USRP hardware platform by the detection of energy implemented. Energy detector performs fine in high SNR region and a new detection of eigenvalue is better with low SNR region. Energy detector detectsignal with 10dBexpressedby [2].The new technique is the probabilitydetection with OR fusion rule performs well as compared with AND fusion rule.

Centralized spectrum sensing is performed by [3], where all cognitive radio users regularly monitor the frequency band and send identified information to fusion centre. Cognitive radio users are tuned to a particular frequency band for sensing the channel. For reporting data to fusion centre CR users are assigned with different frequency called control channel. Different fusion methods that can be incorporated are OR, AND and MAJORITY rules.

Sensing time and count of cognitive radio users in cooperative spectrum sensing is to be limited to increase probability of detection as suggested by [4-5]. Incorporating CR users in the network and utilizing full length frame size do not attain the finest detection probability. With changes in network size, throughput and frame duration the detection probability would be improved. [6] presented centralized sensing for different fusion schemes. In this paper And rule is incorporated with small threshold, Or rule is done with high threshold and Majority rule with average threshold value. It is found OR rule provide improved decision in comparison with other two fusion schemes.

The accuracy of detector depends on selection threshold. Root finding algorithm for the numerical

derivation of threshold by [7]. Analytical detection probability based on combination of OR and AND rules.

3. Cognitive Radio Testbed

Category

The architecture of the Cognitive Radio network can be divided into two categories, the main network and cognitive radio network. It includes recognized framework like mobile and broadcast networks [8]. Primary Users and primary base-station are the elements of the major networks. Registered users are the main users and the PUs should not be affected by CR users operations. The primary base station is a licenced base station that has a fixed framework component [9]. The CR network has no licence to control in a licenced band, and access to its spectrum is opportunistically permitted. Cognitive radio user and cognitive radio base-station are the representatives of the networks [10].

If there is no licence in the spectrum of CR user can only access spectrum opportunistically leave the channel when the PU is identified. Cognitive radio consisting of CR capable fixed framework that provides with a single-hop link. The CR base-station also acts as a fusion centre for cooperative spectrum sensing in order to obtain input from cooperative users and make the final decision on spectrum sensing [11].

Cognitive Radio cycle

CR network allows to sense the information from its RF atmosphere. This task is functioned in three steps which are referred as the cognitive cycle as shown in Fig 1.
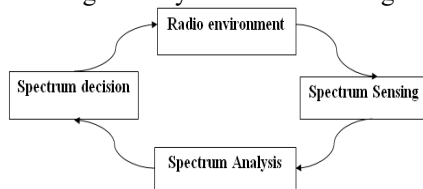

Fig 1. Cognitive Radio cycle

As a first step the CR user needs to sense the radio environment once it wants to access the spectrum. The information is captured by spectrum sensing and the spectrum holes are detected. Spectrum analysis is the approach in which the features of the holes in the spectrum are estimated.

CR then specifies the characteristics, such as data rate, broadcast mode and broadcast bandwidth, for spectrum decision.If CR consumer begins working in defined spectrum band, since radio atmosphere can change over time and space, it can keep trail of changes in the radio atmosphere.

When existing spectrum is inaccessible, CR users must immediately avoid using that channel to prevent interference with the PU. In many applications, such as emergency communications systems, broadband wireless networking, multimedia wireless networking, vehicular networks, health vehicles, cognitive radio can be used.In these situations, in order to increase quality of service, cognitive radio system may make decisions about its own actions and activities due to its operating context [12].

For the modern age of digital media, CR is a very critical technology and its advancement is a key to ensuring the effective usage of the radio spectrum, as well as leading to economic and social gains.

4. Implementation Of Cooperative Spectrum Sensing

Algorithm for Maximum-Minimum Eigenvalue (MME) Based Detection

Eigen value-based detection can be done in two ways MME detection andEME detection. The value of maximum to minimum is obtained by signal samples in the MME detection ratio is compared to a predefined threshold. Identification of average energy and value in EME then MME identification is being applied in this article. Eigen values are calculated by the covariance matrix estimation of the signal samples obtained [13]. Measures concerned with MME dependent detection are as follows [17].

Step1: Calculation of matrix for sample covariance of the signal obtained in equ 1.

$$R_r(N_s) = \sum_{n=L}^{N_s-L+1}(r(n) * [r(n)]^H) \qquad (1)$$

Step2:matrix maximum and minimum eigenvalues can be denoted as $R_r(N_s)$,(i.e) λmax and λmin. Second stage of sensing method is to evaluate sample covariance matrix's maximum and minimum eigenvalues depending on magnitude [14].

Step3: Decision: if λmax / λmin>threshold of MME. The threshold estimation and decision making is last step of sensing algorithm. In this step, maximum to minimum own value ratio is compared with the fixed decision-making threshold where the MME threshold is always greater than 1 [15].

Flowchart of MME

The flow chart Fig 2 for MME based detection where the received signals are sampled to calculate the covariance matrix. From the covariance matrix, the eigenvalues are collected. The maximum to minimum value ratio is measured and a predefined threshold via primary users can be calculated using detection based on MME [18].

Threshold calculation

The threshold calculation for both detection algorithms are based on Random matrix theories (RMT). Here, Tracy Widom distribution is used as a limiting law to determine The highest Wishart Random matrix value or for large matrices. Wishart Random matrix is one of the class of Random matrices. Here, threshold calculation of both the algorithms are based on P_{fa}, Ns, L as it doesn't require any precedingdata about signal, noise and channel. Here, threshold can be evaluated easily as P_{fa}, Ns, L values are given by user inputs only. The threshold of MME is given by the following equation
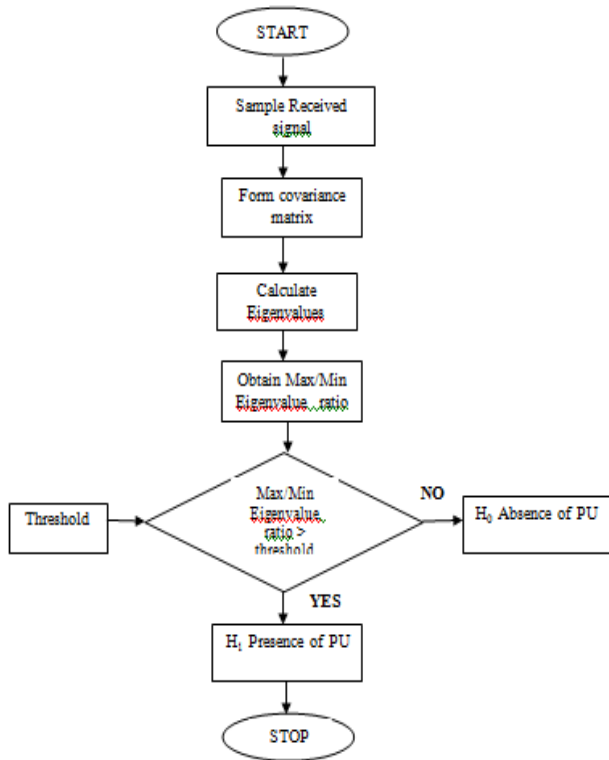
Fig 2. Flowchart of MME

$$r1 = (\sqrt{Ns} + \sqrt{L})^2 / (\sqrt{Ns} - \sqrt{L})^2$$
$$r2 = 1 + ((\sqrt{Ns} + \sqrt{L})^{-2/3} / (Ns*L)^{1/6}) * F_1^{-1}(Pfa)$$
$$\text{threshold\_MME} = r_1 * r_2 \quad (2)$$

5. Results and Discussion

In the test bed, cooperative spectrum sensing is applied and energy values are gained. Eigenvalue-based detection is done by taking into account the likelihood of false alert, probability of detection, signal-to-noise ratio, number of samples and smoothing factor. The estimation of frequency of identification by sample values and thenP_{fa}. The graphs of Roc were plotted by using the characteristics features of various parameters [16].

NS vs Probability of Detection (P_d)

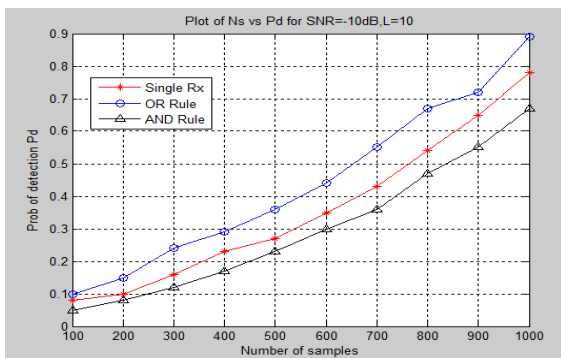Eigenvalue detection are analyzed by varying a samples, SNR then P_f. in Fig 3.
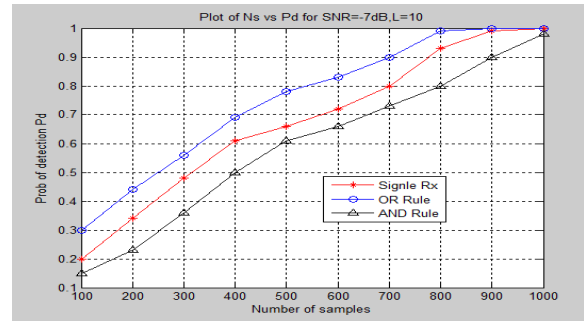

Fig 3. NS VS $P_d$for SNR=-10dB and L=10

Fig 4. NS VS $P_d$for SNR=-7dB and L=10

The above Fig 4. shows signal to noise at a constant rate of -7dB and smoothing factor L as 10. It is found that the increase in probability detection with a number of samples and an increasing signal to noise ratio. Efficiency would be higher as SNR increases and so the chance of identification also increases.

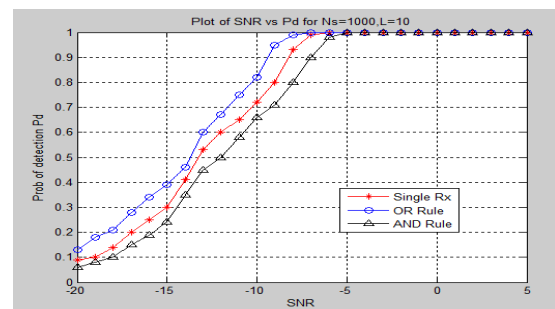*SNR VS Probability of Detection (P_d)*

Fig 5. SNR VS P_d

A plot Fig 5. of SNR vs. probability of detection by a number of samples as 1000 and is held constant. False warning odds range from 0.01, 0.05 and 0.1. It is found from the above graphs that the probability detection increases by an increase in SNR and P_{fa}.
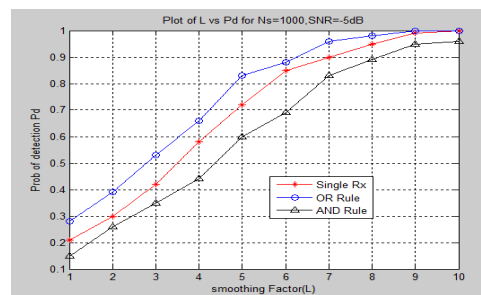

Fig 6. Plot of smoothing factor vs. P_d

Smoothing Fig 6. factor vs. probability of detection gives the constant value of samples is at a range of 1000 and a constant SNR is at -5dB. It is found from the graphs that the detection likelihood increases with smoothing factor increasing.

The chance of identification is greater than the AND law and the single receiver with the OR Cooperative rule with the number of samples and SNR level, likelihood of detection increases.

6. Conclusion

The Cooperative spectrum sensing was applied by a method of eigenvalue. Eigenvalue-based identification with a low SNR region works well. The signal is fully detected by the eigenvalue detector at ratio of -9dB. From the result observation collection and a performance is carried out on a possible of identification. For different criteria, the ROC characteristics graphs are plotted. Cooperative spectrum sensing is found to perform better relative to detect a reducing probability of missed non-cooperative sensing. It is also identified that the chance of OR fusion detection is higher than the AND fusion law.

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