Spectrum Sensing Techniques for Low Noise Uncertainty environment in Cognitive Radio Networks

R.Harikrishnan, Dr.V.Padmathilgam

Abstract: It is an age of communication era, an exponential growth of wireless accessing services and devices has been observed in nowadays .But when new devices opting for communication relay on new spectrum as a path to communication process. It is also observed that all frequency spectrum meant for wireless services are already allocated to those devices only .this create spectrum scarcity for new user ,unable to establish new communication .To handle this situation cognitive radio is an emerging solution for spectrum scarcity. It is an idea of searching of ideal spectrum which not utilized by licensed users. Among all the parameters of cognitive radio, the spectrum sensing is paid more attention for initial step to indentify the free spectrum band. In this work, the detection performance was evaluated for Absolute Covariance detection (CAV), Maximum to Minimum Eigen value (MME) detection, Minimum Eigen value detection (EME), Energy detection (ED) and Matched filter method. The detection performance was carried out on the basis of probability of detection (p_d) and False alarm probability (p_{fa}). The low noise SNR up to -25 db is tested for effectiveness for detection techniques carried out in this paper. The MME technique shows good detection performance than other methods under noise uncertainty as shown in the simulated results.

Index terms: cognitive radio, spectrum sensing, sample covariance matrix based detection, Eigen value based detection, noise uncertainty.

1 INTRODUCTION

By using cognitive radio technology, the shortage of wireless spectrum can be easily eliminated. In cognitive radio, the existing free spectrum is identified by the process of spectrum sensing methods. The unused spectrum is allocated to cognitive user for well-organized usage of spectrum. As a existing scenario, numerous spectrum sensing techniques have been analyzed like matched filter detection, cyclostationary detection, Energy Detection (ED), covariance based detection and Eigen value detection (EBD), [2] [3].Among, above said detection method Energy detection is most preferable technique for its less complexity and easy for implementation. However, they show less performance on low noise uncertainty scenario. Moreover, to perform the detection process under noise uncertain channel it is necessary to estimate the noise variance. The covariance and Eigen value based method is better known for better detection performance in low noise uncertainty channel, in which other detection method performance found to be low. In this paper, the simulation of covariance based method, Eigen value methods, matched filter and energy detection is carried out and the detection performance of above said method compared in MATLAB tool under noise uncertainty channel.The paper is structured as follows: The system model is briefly discussed in section II. The detail theory about covariance and Eigen value based methods is presented in section III. The explanation about simulation setup utilizing MATLAB tool and the brief view about obtained results discussed are in section IV. Finally, conclusion of this work is presented in section V.

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2 SYSTEM MODEL

The received signal can be a mixture of the primary signal and noise from the communication channel. Then, the received signal is put forward as

$$y(n) = hx[n] + w(n) \quad (1)$$

Where, x[n] implies signal is transmitted by Primary User (PU) and w[n] is noise encountered in communication channel and h stands for the channel in which communication takes place. Also, considering that the flat fading channels by means of unity gain. The binary hypothesis can be characterized for the obtained signal for the same is represented as

$$H_0 : y[n] = w(n) \quad (2)$$

Equation (2) denotes the hypotheses when primary users are absent

$$H_1 : y[n] = x(n) + w(n) \quad (3)$$

Equation (3) represents the hypotheses when primary users are present.

Based on the statistical covariance matrix, the subsequent vector form is put forward as

$$Y[n] = [y[n] \quad y[n-1] \ldots\ldots\ldots . y[n-(L+1)]]$$
$$X[n] = [x[n] \quad x[n-1] \ldots\ldots\ldots . x[n-(L+1)]]$$
$$W[n] = [w[n] \quad w[n-1] \ldots\ldots\ldots . w[n-(L+1)]]$$

Where, L denotes smoothing factor for consecutive sample. The received signal with covariance matrix in statistical form is put forward as

$$R_Y = E[Y(n)\, Y^H(n)\,] \quad (4)$$

Similarly, the transmitted signal with the covariance matrix in statistical form is put forward as

$$R_X = E[X(n)\, X^H(n)] \quad (5)$$

Then, the transmitted signal with statistical covariance matrix can be represented as $R_Y = R_X + \sigma_W^2 I_i$

The statistical covariance matrix may be estimated by means of inadequate number of samples. Originally, the auto correlation of the received signal is formulated by mathematical equation

$$\lambda(l) = \frac{\sum_{n=0}^{N_s-1} y(n)y(n-l)}{N_s} \qquad (6)$$

Where, l = 1, 2, 3 . . . L − 1 and Ns is numbers of sampling matrix. Following equation (6) the sampling covariance matrix is formulated by matrix form as

$$\hat{R}_Y = \begin{bmatrix} \lambda(0) & \lambda(1) & \cdots & \lambda(L-1) \\ \lambda(1) & \lambda(2) & \cdots & \lambda(L-2) \\ \vdots & \vdots & \ddots & \vdots \\ \lambda(L-1) & \lambda(L-2) & \cdots & \lambda(0) \end{bmatrix}$$

3 COVARIANCE BASED DETECTION

Covariance based detection (CAV) method is highly preferable, when the detector has no information regarding received signal and channel with low noise uncertainity.Therefore, these method said to be call a blind detection method. The positive feature of covariance based detection is there is no details about the primary user signal are required like other detector. The noise power estimation is also not necessary to perform detection process. The threshold can be computed using false alarm probability (p_{fa}) and received signal's sample size. The sampling covariance matrix of the primary signal is calculated supported on the obtained signal samples. The Two test statistics is obtained from the sampling covariance matrix. Lastly, a conclusion on the occurrence or non occurrence of the primary signal is done by contrasting the ratio of the two assessment statistics by predefined threshold [8]. The sampling and filtering is done at the initial stage to perform detection process in absolute covariance detection. Then the estimated sample covariance matrix ($\hat{R}_Y$) is calculated as discussed in the previous session. Two assessment statistics are characterized as T1 and T2 as of the statistical covariance matrix$\hat{R}_Y$, where,

$$T_1 = \frac{\sum_{i=1}^{L}\sum_{j=1}^{L}|(R_Y)|}{L} \qquad (7)$$

$$T_2 = \frac{\sum_{i=1}^{L}|(R_Y)|}{L} \qquad (8)$$

i and j denotes the rows and columns of the obtained matrix $\hat{R}_Y$. The ratio of T1 and T2 afford information concerning the occurrence and non occurrence of the primary signals. If T1/T2 < λ1, the signal is absent and if T1/T2 ≥ λ1, the signal is present. The ratio of T1/T2 is referred as Tcov.

$$T_{COV} = \frac{T_1}{T_2} \qquad (9)$$

The threshold λ1 for detection process is selected to organize the necessity with false alarm probability (Pfa) and computed as

$$\lambda_1 = \frac{1 + (L-1)\sqrt{\frac{2}{N_S\pi}}}{1 - Q^{-1}(p_{fa})\sqrt{\frac{2}{N_S\pi}}} \qquad (10)$$

where Q denotes Marcum-Q function, Ns represents to total samples in the obtained signal, and L stands for smoothing factor[8] [11].

4 EIGENVALUE BASED DETECTION

When compared to covariance based detection, Eigen value Based Detection (EBD) method also surmounts the low noise power uncertainty. The Eigen value method highly depends on the Eigen value from the sampling covariance matrix [6].

4.1 Maximum to Minimum Eigen value detection

The ratio of the maximum Eigen value to the minimum Eigen value of the sampling covariance matrix is utilized to detect the signal presence. The MME technique surmounts the problem of low SNR scenario. The sampling and filtering is done at the initial stage to perform detection process in maximum to minimum Eigen value method like covariance based detection. The sample covariance matrix is computed as conferred prior. The maximum Eigen value λmax and minimum Eigen value λmin are computed from the sampling covariance matrix . The ratio of λmax and λmin afford information concerning the occurrence or non occurrences of the signal.

$$\lambda_{mme} = \frac{\lambda_{max}}{\lambda_{min}} \qquad (11)$$

The ratio of λmax/λmin is referred as λmme. If λmax/λmin < λ2, the signal is absent and if λmax / λmin ≥ λ2, the signal is present. The threshold λ2, for process of detection is formulated equation follows as

$$\lambda_2 = \frac{1 + Q^{-1}(P_{fa})\sqrt{\frac{2}{MN_S\pi}}}{\frac{\sqrt{N_S}}{\left(\sqrt{N_S - \sqrt{ML}}\right)}} \qquad (12)$$

Where, M = 1 since just one receiver is preferred, L and Ns symbolize smoothing factor and the total sample numbers correspondingly [5] [6].

4.2. Energy with Minimum Eigen Value Detection (EME)

The energy with minimum Eigen value detection (EME) technique utilizes the idea of inspecting the minimum Eigen value to averaging signal energy's ratio and compared with predefined the threshold. This is techniques also doesn't need any information about received signals.

At the initial stage of this technique, the Computation and averaging the energy of the received signal as

$$T(N_S) = \frac{\sum_{n=1}^{N_s}|(y(n))|}{N_s} \qquad (13)$$

From equation (13), the notation y[n] is the signal obtained with sample numbers (Ns). The sampling covariance matrix (ˆRY) of the received signal y[n] is obtained. The threshold for EME detection is similar as the threshold of MME method as revealed in equation (11).The presences and absences of primary user is decided by computing the ratio of the average energy T(Ns) to minimum Eigen value λmin .The ratio of T(Ns)/λmin is referred as λeme, then

$$\lambda_{eme} = \frac{T(N_s)}{\lambda_{min}} \qquad (14)$$

If T(Ns)/λmin < λ2, the signal is absent and for T(Ns)/λmin ≥ λ2, the signal is present.

4.3 Computational complexity

The computational complexity of MME and EME methods can be evaluated from the estimation of covariance matrix and the Eigen value decomposition of the covariance matrix. The covariance matrix is an block Toeplitz matrix and Hermitian, simply to estimate its first block row. Hence M2LNs multiplications and M2L (Ns−1) additions are essential. For computing computational complexity ((ML)3) multiplications as well as additions are enough. The total complexity are denoted as M2LNs + O(M3L3). Therefore, the energy detection wants MNs multiplications and M(Ns−1) additions. Consequently, the complexity of Eigen value based methods is in relation to ML times to the energy detection.

5 SIMULATION SETUP AND RESULTS

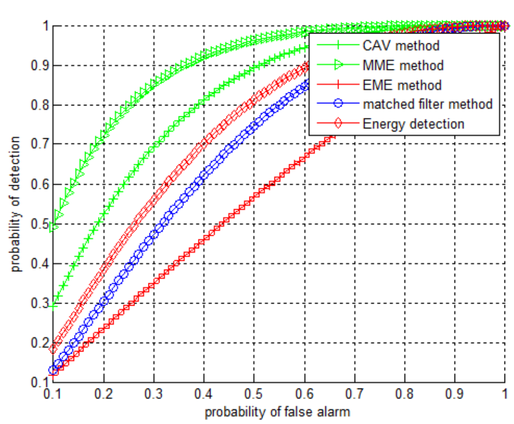
The detection of the Binary phase shift keying (BPSK) signal was carried out by the help of Maximum to Minimum Eigen Value detection (MME), Energy with Minimum Eigen Value detection (EME), Absolute Covariance Method (CAV), Energy Detection (ED) and matched filter detection method. The detection performance was contrasted and assed in the degree of detection probability (Pd) , false alarm probability (Pfa) for altering SNR rate.

Table.1 *Simulation Parameters*

Simulation Parameters	
Monte Carlo Simulations	1000
Signal type	BPSK
SNR	-40 - 5db
Probability of False alarm	0.01
Number of samples	1500

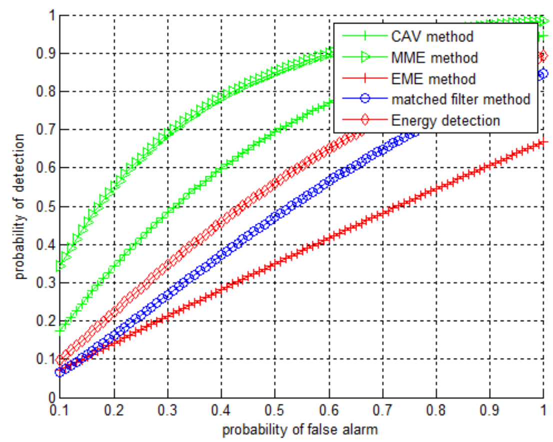
The simulations were performed for up to 1000 Monte Carlo simulations. The primary signal is set be BPSK signal and SNR range are used from -40 to 5 db .The number of samples for simulation are taken is about 1500 and false alarm probability is put as 0.01.

Fig. 1.*ROC curve of Pd vs. Pfa for SNR of -15dB*



The results of ROC (Receiver operating curve) of pd vs. Pfa are shown in Fig.1. The obtained results show the influence of false alarm probability vs. Pd. From figure, it is notice that max-min based Eigen value method provides good performance than other method such as energy with Minimum Eigen value, energy detection and matched filter detection. The reason for good detection performance of max-min based Eigen value method is having high correlation of signal samples and hence it shows better performances in noise uncertainty SNR up to -15 db

Fig.2. *ROC curve for Pd vs. Pfa for SNR of -20dB*



The results ROC curve of Pd vs. Pfa are shown in Fig.2, This figure indicates that the false alarm probability increases with the raise of Pd.It is observed that max-min based Eigen value method provides good performance than other methods under noise uncertainty SNR up to -20 db. Since, max-min Eigen value signal samples are used are highly correlated so they offer good detection performance; when compared to other method under noise uncertainty.

Fig.3. *Pd vs. SNR for Pfa of 0.01*

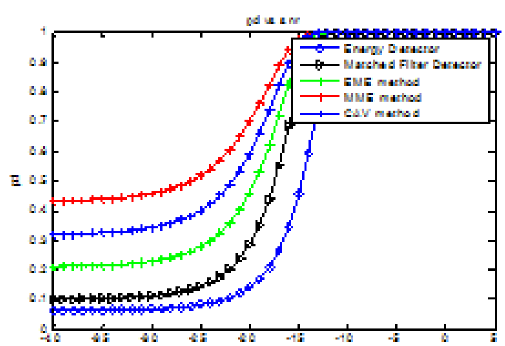


Fig.3 illustrates the effect of SNR on the detection probability (Pd) for different detection scheme. From figure it is reveals that max-min based method attain good detection rate about Pd=0.95 at SNR=-15 db for given pfa=0.01, when compared to other detection methods.

6 CONCLUSION

Detection technique can be utilized by signal detection purpose without knowledge of the signal, noise power and channel are Eigen value based and covariance based detection technique is well suitable. When considering noise uncertainty channel these techniques are very useful.

From the evaluation of simulated output of conventional and Eigen value based technique it is shown that the maximum to minimum Eigen value detection (MME) method shows better performance than other detection schemes . The benefit of Eigen value based technique in realistic sensing situation is that no need of any prior information for licensed user signals. This technique also provide good detection rate attained for very low SNR values up to -20 dB when compared to other detection technique.

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