

# Effective Usage of Available Spectrum Using Dispersion Detection Technique

Durga R<sup>a</sup> and Selvaraj D<sup>b</sup>

<sup>a</sup>PG Scholar, Dept of ECE, Panimalar Engineering College, Chennai

<sup>b</sup>Professor, Dept of ECE, Panimalar Engineering College, Chennai

**Abstract.** Spectrum sensing techniques are used for acquiring the frequency spectrum in cognitive radio. From research, the efficiency of the spectrum sensing technique increases only if its complexity is increased and if its complexity is decreased then its efficiency decreases. So, a new technique is proposed in this paper based on Dispersion Detection (DD) to balance both complexity and efficiency. Using this detection technique, the false alarm probability is derived for multiple antenna using test statistic distribution. The decision threshold is derived to provide accurate results. The derived values are verified with Monte Carlo simulation.

**Keywords.** Spectrum sensing, dispersion detection, false alarm, decision threshold

## 1. Introduction

Cognitive radio is defined as an upgrading technology for easing the spectrum shortage problem by utilizing the licensed band. There are various types of sensing techniques such as energy technique, matched filter technique, cyclostationary technique, Log-likelihood Ratio Test (LRT) techniques which contain both advantages and disadvantages. Some detection techniques require channel information and some techniques don't require channel information. The spectrum sensing using multiple antennas can improve the transmission rate and it can also increase the capacity of the channel. In [10] the multiple antenna case exploits covariance and achieves a low  $P_f$  detection rate by increasing the number of samples. The covariance detection method [9] provides the best signal strength from -6dB; the detection performance is increased with an enhanced SNR. In [8] the detection performance based on the noise signal is achieved at -10dB even in the existence of a noise signal. [7] the aim of this method is to separate the signal from its background noise. This method provides better results than energy detection by calculating different parameters for different numbers of antennas. [6] LRT is an optimal method but is quite complex and it requires channel information beforehand. [5]

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<sup>1</sup>Durga R PG Scholar, Department of ECE, Panimalar Engineering College, India  
Email: durga.1997r@gmail.com

The signal space analysis methodology is analyzed by capturing the data information from RF platform to analyze the robustness and to reduce the framework issues by providing better performance. [4] the analysis of test statistic id derived under signal absence hypothesis moment matching method is exploited to derive the distribution of gamma and by this, it provides better analysis for the given threshold.[1] the generalized order statistics and OR rule using a data fusion algorithm is analyzed to initialize protection due to non-homogenous signals. [2] the throughput maximization analysis is analyzed using local sensing optimization and fusion optimization. [3]The detection performance is not enhanced even when the samples are 50000.

**2. Dispersion detection method**

Dispersion is a measure that gives an idea about the scattering of the values. Some of the different measures of dispersion are Range, Mean, correlation, Variance and Coefficient of variance.

*2.1. The Signal Model*

Dispersion detection can differentiate the power and noise of the signal which is a drawback of interference feature detection and energy detection. The proposed technique is used for avoiding the uncertainty of noise power. The dispersion detection attempts on 1) noise samples are not dependent and hence not correlated 2) samples of reasonable information-carrying signals are correlated.Consider M antennas utilized. be the discrete-time sample received signal form the M<sup>th</sup> antenna. The statistical dispersion matrix of the discrete-time sample obtained signal with binary hypotheses are defined as (Eq. 1)

$$x(k) = \begin{cases} n(k), H_0 \\ s(k) + n(k), H_1 \end{cases} \tag{1}$$

i.e., the obtained signal  $x(k) = [x_1(k), x_2(k), \dots \dots x_n(k)]$  consists only of Independent and identically dessimated (IID) with zero mean additive white gaussian noise (AWGN)  $n(k) = [n_1(k), n_2(k) \dots \dots n_M(k)]$

$$n(k) = N(0, \sigma_n^2 I_M) \tag{2}$$

The dispersion detection of obtained signal is given by

$$R_x = E[x(k)x^T(k)] \tag{3}$$

Then,

$$R_x = \begin{cases} \sigma_n^2 I_M, H_0 \\ R_S + \sigma_n^2 I_M, H_1 \end{cases} \tag{4}$$

Then,  $x(k)$  is a multivariate random vector with general properties

$$x(k) \approx \begin{cases} N(0, \sigma_n^2 I_M), H_0 \\ N(0, R_S \sigma_n^2 I_M), H_1 \end{cases} \tag{5}$$

If the PU signal is not present  $R_x$  then the slanting values are zeros. If the PU signal is exists then the non-diagonal elements should be related to signal and power which should not be affected by correlation.

$$T = \frac{T_1}{T_2} \tag{6}$$

$T_1$  represents non-diagonal elements and  $T_2$  represents diagonal elements i.e. power signal where, and

$$T_2 = \sum_{p=1}^M |R_x(p, p)| \quad (7)$$

## 2.2. Statistical Dispersion Detection

The sample dispersion estimates  $R_x$  are calculated based on the obtained received signal (Eqs8 to 16)

$$\hat{R}_x = \frac{1}{k} \sum_{k=1}^k x(k)x^T(k) \quad (8)$$

The test dispersion is given by

$$\hat{T} = \frac{T_1}{T_2} \quad (9)$$

Where,

$$\hat{T}_1 = \sum_{p \neq q; p, q=1}^M |R_x(p, q)| \quad (10)$$

and

$$\hat{T}_2 = \sum_{p=1}^M |R_x(p, p)| \quad (11)$$

The decision threshold is given by

$$decision = \begin{cases} H_0, \hat{T} < \lambda \\ H_1, \hat{T} > \lambda \end{cases} \quad (12)$$

The  $P_d$  and  $P_f$  is given by

$$P_f = P_r(\hat{T} > \lambda | H_0) \quad (13)$$

$$P_d = P_r(\hat{T} > \lambda | H_1) \quad (14)$$

The  $P_d$  and  $P_f$  is given by

$$P_d = 1 - F_{\hat{T}|H_1}(\lambda) \quad (15)$$

$$P_f = 1 - F_{\hat{T}|H_0}(\lambda) \quad (16)$$

## 2.3. The Decision Threshold

For a best detection technique, a high  $P_d$  and low  $P_f$  should be obtained. The threshold is undermined between  $P_d$  and  $P_f$ . The threshold is chosen such that a certain value of false alarm probability  $P_f$  is achieved. The threshold selection can be based on either theoretical derivation or computer simulation.

2.3.1 Threshold selection based on computer simulation

Initially,  $P_f$  value is set and a threshold 'I' is found to meet the required  $P_f$ . An AWGN is generated as the input signal and the threshold is adjusted to meet the required  $P_f$ .

3. Results

3.1  $P_f$  versus SNR

Fig. 1 shows the  $P_f$  versus SNR for a fixed number of antennas and different k(number of samples) and in fig. 2 the number of antennas is reduced. By reducing the number of antennas the result shows is for high SNR the  $P_f$  is low and for low SNR the  $P_f$  is high. By increasing the SNR values the false alarm probability can be reduced using dispersion detection.

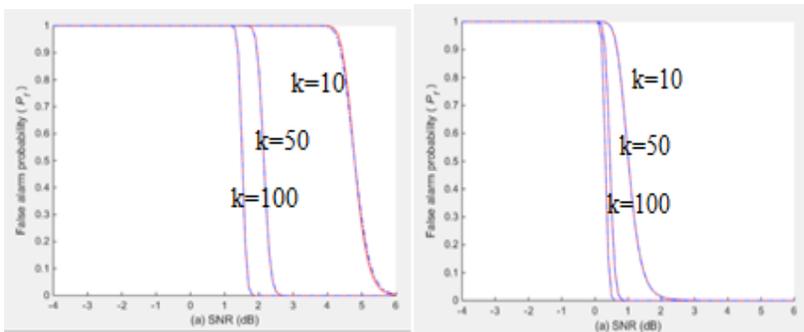


Figure 1.  $P_f$  versus SNR for k=10,50,100 (a) M=20 (b) M=5

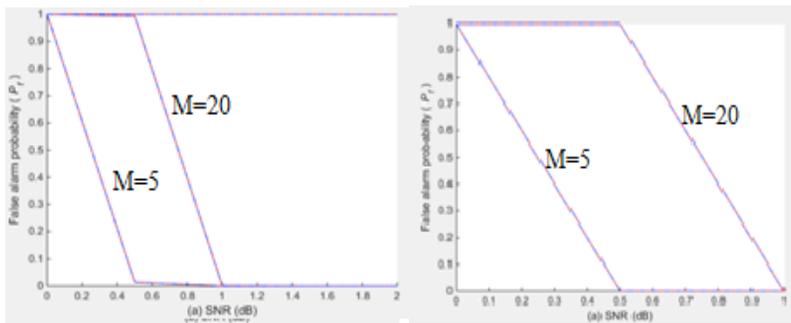


Figure 2.  $P_f$  versus SNR for M=5,20 (a)k=100 (b) k=1000

3.2.  $P_f$  versus  $\lambda$

The  $P_f$  versus threshold is calculated as fixed number of antennas with that of different samples is shown in the figure. for different ranges of k is simulated. The results are given for fixed M=5 in fig, and M=20 in fig, when the signal power and noise power is above the threshold there will be low false alarm probability.

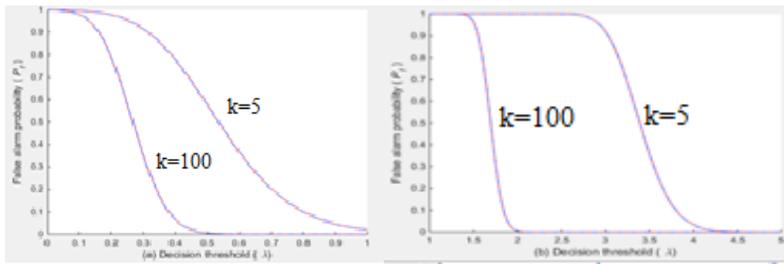


Figure 3.  $P_f$  versus  $\lambda$  for  $k=5,100$  (a)  $M=5$  (b)  $M=20$

#### 4. Conclusion

In this paper, the sensing algorithm of the dispersion detection is proposed. By receiving the number of samples, the received signal is exploited. The test statistics are provided for setting the threshold and obtain the probability of false alarm. Dispersion detection is doesn't require any signal information beforehand which is an advantage. The false alarm probability vs. SNR is calculated. This detection technique provides a low false alarm probability even under high SNR with the presence of noise.

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