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CFDI-SS: CYCLOSTATIONARY FEATURE DETECTION WITH INVERSE COVARIANCE MATRIX BASED SPECTRUM SENSING IN COGNITIVE RADIO

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Abstract: Spectrum Sensing has been a major issue when dealing with the Cognitive Radio Networks. Predominantly we encounter situations where noise is falsely interpreted as primary user signal. Such false alarming signals are to be sensed by the detector by setting a threshold which determines the user's presence. A new method known as Cyclostationary Detection with inverse covariance matrix is proposed for spectrum sensing. Threshold is computed using Generalized Log Likelihood Ratio Test (GLRT). The simulation results of the proposed CFDI based Neyman Pearson observer approach shows a significant improvement when compared to previous methods of Cyclostationary Energy Detector (CED).

Keywords: Cognitive Radio, GLRT, Cyclostationary Feature Detector, 5G Technology, Receiver Operating Characteristics, Probability of False alarm, Probability of Detection.

1. INTRODUCTION

Communication system models assume a prevailing part in investigating new Communication Network [1]. In real time Mobile Communication spectrum wastage is a serious concern. If the spectrum is not used it remains idle and the cost of bandwidth overshoots. Through 5G technology CR emerged one of the preferred solutions to deal with spectrum wastage. CR Networks is an intelligent radio that changes spectral resources intellectually. Spectrum sensing is a serious issue in CR Networks. In CR Networks there are two types of users namely Licensed Users or Primary User (PU) and Unlicensed Users or Secondary User (SU). The key issue of these networks is that, the SU shall not interfere with primary transmitters. If SU detect primary's transmissions they are diverted to non interfering channels immediately. So that relinquish transmissions are possible [2]. The important task in CR networks is to identify the presence of PU in the spectrum slot. Two types of errors occur during identification of spectrum. Firstly, type-I error which is called false alarm and it occurs because the detector reflects the presence of PU, only noise appears in the spectrum. Secondly, type-II error which is called miss detection and it occurs because the detector reflects the absence of PU, even though user present in the spectrum [3]. In this paper, the researcher has proposed an algorithm to mitigate P_{fa} or Type-I error. There are two methods to sense the spectrum in CR Networks. They are Cooperative and Non cooperative Detection methods. Non Cooperative methods are Matched Filtering, Cyclostationary Feature Detector and Energy Detector. Out of these three detectors, Cyclostationary Feature Detector along with inverse covariance matrix is proposed and is framed as CFDI. From the less available literature it is found that, the scientists or researchers have conducted research only with GLRT but not introduced inverse covariance matrix condition. All the researchers or scientists had mentioned their work by analyzing the graphs drawn for Probability of False alarm (P_{fa}) versus Probability of Detection (P_D) with ROC or number of samples versus P_{fa}, P_D only. Some of them conducted their research on P_{fa} versus P_D using different detection algorithms at single power level. In this research letter, first proven that CFDI detection probability is higher than existed CED detection probability in Figure 2 and secondly by NP Observer approach the range of samples are identified and taking those samples we have verified with our proposed CFDI and measure P_{fa} occurrence. Finally, both P_{fa}'s and P_D's of NP Observer approach are compared with our proposed CFDI algorithm. It is proved that CFDI has better detection accuracy than NP Observer. The graphical plots are shown in Section III.

2. IMPLEMENTATION OF CFDI

In view of dynamic spectrum access Cyclostationary signal analysis produces many additional advantages. Coherent approaches like Matched Filter needs synchronization with signal of interest. But Cyclostationary analysis doesn't need any synchronization, it may be frequency or phase, this is a good approach to detect unknown signals in terms of frequency and symbol timing [4]. From the available little literature, earlier researchers could only propose their research with Cyclostationary detection method for randomly arriving or departing the signals. The earlier researchers explored that there is a relation between P_{fa} versus P_D and SNR versus P_D at various SNR levels [5]. Another researcher proposed his work on Cyclo energy detector for spectrum sensing in cognitive radio. The work is presented as, plotted ROC at different SNR levels using Cyclo energy detector. And also P_{fa} versus P_D graphs are plotted at different samples [6]. However the earlier researchers has conducted research in the same proposed area but based on accessed literature none of them has conducted their research to find for which samples, P_{fa} occurs. In this paper, ranges of samples that occur for P_{fa} are recognized using NP Observer approach. And also accuracy of detection is calculated. If these samples are applied to proposed algorithm CFDI, occurrences of P_{fa} samples can be identified and also accuracy can be calculated. An analysis has been carried to find which one among occurrences of P_{fa} samples by NP Observer and CFDI is optimal. This paper also covers analysis between accuracy detection of NP and CFDI. The proposed method is implemented as shown in Figure 1.

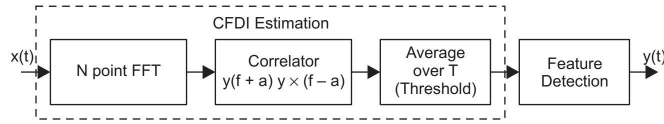

Figure 1: CFDI Block Diagram

From Figure 1, the sensed signal information is connected to N-Point Fast Fourier Transform (FFT). These computed samples are fed to the correlator [7], which correlates new samples with existing samples. These new samples that are correlated with existing samples are assigned with existing decision. The remaining uncorrelated samples are sent for threshold comparison. If instant sample power is higher than threshold sample power we consider as the presence of user, if not no user is present in the spectrum. In addition to this, Cyclo Autocorrelation Function (CAF) is utilized for better results. The binary hypotheses test values are expected [5] [8] as shown in equation (4)

$$\begin{aligned} H_0 &= y(t) = n(t) \\ H_1 &= y(t) = s(t) + n(t) \end{aligned} \tag{1}$$

H_0 represents only the noise signal presented at input $y(t)$. H_1 represents signal along with noise signal at the input of $y(t)$. The Joint density of n-jointly Gaussian Random variables is given as [9]

$$f_{y1,\, y2,\, \dots,\, yn}(y1, y2, \dots, yn) = \frac{1}{(2\pi)^{N/2} \det^{1/2}(C)} \exp\left[-\frac{1}{2}(y - H)^T C^{-1}(y - H)\right] \tag{2}$$

Where C is a known positive definite covariance matrix. H is equivalent to either H_0 or H_1 The basic equation of GLRT is [7]

$$\gamma = \frac{P(y; H_1)}{P(y; H_0)} \tag{3}$$

γ is the predetermined threshold and it is assumed to be equivalent to T in our proposed scheme. The GLRT for the CAF of initial threshold is [8]

$$R^{\alpha}_{yy^*} = \frac{\sum_{n=0}^{N-1} \exp\left[-\frac{1}{2}(y_n - H_1)^T C^{-1}(y_n - H_1)\right] \exp(-j2\pi\alpha n f_s)]}{\sum_{n=0}^{N-1} \exp\left[-\frac{1}{2}(y_n - H_0)^T C^{-1}(y_n - H_0)\right] \exp(-j2\pi\alpha n f_s)]} \underset{< H_0}{\overset{\geq H_1}{}} \approx T \tag{4}$$

where, α is the cyclic frequency and R_{yy*} is the auto correlation function for the input samples. The exponential function represents the Fast Fourier Transform (FFT). The above equation(4) is simplified as

$$\frac{-1}{2}(y - H_1)^T C^{-1}(y - H_1) + \frac{1}{2}(y - H_0)^T C^{-1}(y - H_0) \gtrless \ln(T) \quad (5)$$

On simplifying the above equation (5), we get

$$= (H_1 - H_0)^T C^{-1}\left[y - \frac{1}{2}(H_0 + H_1)\right] \gtrless \ln(T) \quad (6)$$

Expanding the above equation (6) and comparing with initial threshold. The threshold ln(T) is equal to predetermine threshold γ.

$$= (H_1 - H_0)^T C^{-1} y - \frac{1}{2}(H_1 - H_0)^T C^{-1}(H_0 + H_1) \gtrless \ln(T) \quad (7)$$

The negative term is moved to right hand side and the remaining term will equalize to the $T(x)$. Then

$$T(x) = (X_1 - X_0)^T C^{-1} y \quad (8)$$

The simplified equation is equalized to threshold of the CFDI threshold and cyclic auto correlation function, then the threshold value equates to:

$$R^{\alpha}_{yy*} = T(x) \gtrless \ln(T) + \frac{1}{2}(H_1 - H_0)^T C^{-1}(H_1 + H_0) \quad (9)$$

In this algorithm, it's not necessary to calculate the cyclic autocorrelation function of signal. Instead, we add a factor of exponential, which is related to cyclic frequency α, to the received signal [12] .That exponential function, is applied to threshold as FFT. The FFT is applied to the initial threshold, and then the equation will be:

$$T(x) = R^{\alpha}_{yy*} = (\ln(T)) + \text{FFT}\left[\frac{1}{2}(H_1 - H_0)^T C^{-1}(H_1 + H_0)\right] \quad (10)$$

The sampled signal is applied to Average threshold level then the resultant equation is:

$$T(x) = R^{\alpha}_{yy*} = \left(\ln(T) + \text{FFT}\left[\frac{1}{2}(H_1 - H_0)^T C^{-1}(H_1 + H_0)\right]\right)^{\frac{1}{2}} \quad (11)$$

The above equation is the final threshold $T(x)$ for the Cyclostationary feature Detector. From this the Probability of False Alarm is estimated as

$$P_{fa} = erfc\left(\frac{[T(x) - [(H_1 - H_0)^T C^{-1}(H_0)]]}{\sqrt{[(H_1 - H_0)^T C^{-1}(H_1 - H_0)]}}\right) \quad (12)$$

And the Probability of Detection is

$$P_D = 1 - P_{fa} \quad (13)$$

For estimation of P_{fa} occurrences, initially NP Observer approach applied to below equation

$$P_{D1} = Q\left[Q^{-1}(P_{fa}) - \sqrt{(H_1 - H_0)^T C^{-1}(H_1 + H_0)}\right] \quad (14)$$

where, $\sqrt{(H_1 - H_0)^T C^{-1}(H_1 + H_0)}$ is the Deflection Coefficient, P_{D1} is the Probability of Detection for NP Observer. For identification of false alarm effected samples and improvement estimation of MDI detection, NP observer approach is taken as reference only.

3. RESULTS AND DISCUSSIONS

In this paper, the threshold estimation of CFDI is calculated based on GLRT Condition. The Inverse Covariance matrix ($1/\sigma^2$) is expected to be unity. 100 Monte Carlo trials with AWGN are generated for estimation of threshold. The input power measured in decibels (dB) and rests of parameters are measured in Watts, because the power loss in communications is measured in watts. For estimation of threshold of proposed algorithm, primarily based on the data that resulted from spectrum scanning, the presence of PU is estimated. Using the input power a Real Receiver Operating Characteristics (ROC) curve is plotted in Figure 2. The ROC is plotted for P_{fa} versus P_D. Proposed CFDI P_D is compared with the research of Y.Lee [5] who proposed P_D and P_{fa} at SNR = −5dB power level. Proposed CFDI P_D is better than the reference P_D (in Figure 6(c)) of ROC. The proposed algorithm by Y.Lee of ROC contains the P_D is less than 0.1at 10^{-2} of $P_{fa,}$ but in our proposed ROC the P_D is above 0.1 at 10^{-2} of P_{fa}. Hence the detection of accuracy of CFDI gives better result at low SNR than proposed CED.

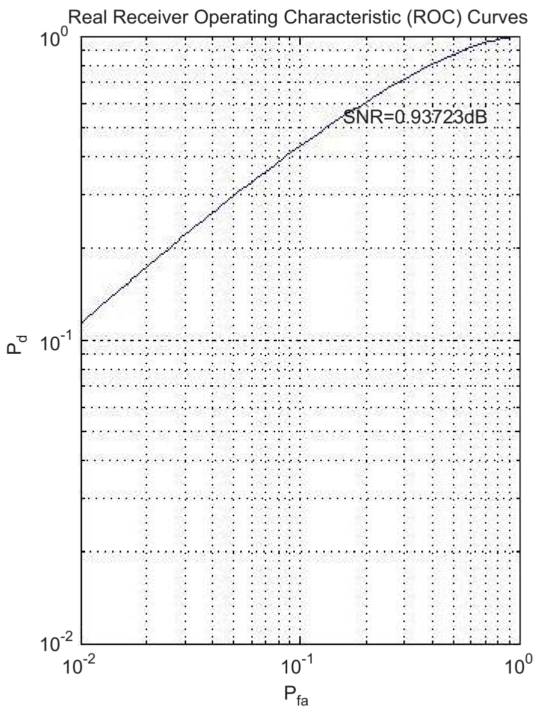

Figure 2: ROC curve

In real time mobile communication the power radiated from cell towers is 20, 40 and 60 watts. Now a day's power radiating is 40 watts, which is represented as 46 dBm or 16dB. Hence for our analysis we considered the power from –6dB (24dBm) to 15dB (44dBm). The mobile phone receives the power of a few Pico Watts to 1 milli Watt without adding Effective Radiated Power (ERP), antenna gain and Low Noise Amplifier (LNA).

Initially, the drawn samples of signals are applied to NP Observer approach. The samples that are transmitted using NP observer approach are shown in Figure 4. where *x*-axis represents the number of samples and y-axis represents the threshold power of NP Observer. Threshold power at 2dBW input SNR is 0.8962 Watts, P_D = 0.4587 and P_{fa} = 0.5413. The same input power 2dB signal applied to our CFDI is represented in Figure 3. The axis notations are similar to Figure 4. Threshold power at 2dB input is 1.1310 Watts, P_D = 0.5521 and P_{fa} = 0.4479 when both Figure 3 & 4 are compared, it is found that in Figure 4 few samples between 20 to 40 range are above the threshold line. But in Figure 3, the same samples below the threshold line. These are called as P_{fa} affected samples. The false alarm of those signals fallen above the threshold line (P_{fa} = 0.5413) in Figure 4 are due to loud noise power than signal power. But Figure 3 reveals that though the signal of noise is dominated the CFDI algorithm of P_{fa} is shown only 0.4479. Hence it is understood that the P_{fa} CFDI has less P_{fa} but detection accuracy is high comparatively to NP Observer approach detection accuracy. In further comparison of both the figures, a similar trend is observed between 40 to 60 and 60 to 80 ranges of samples.

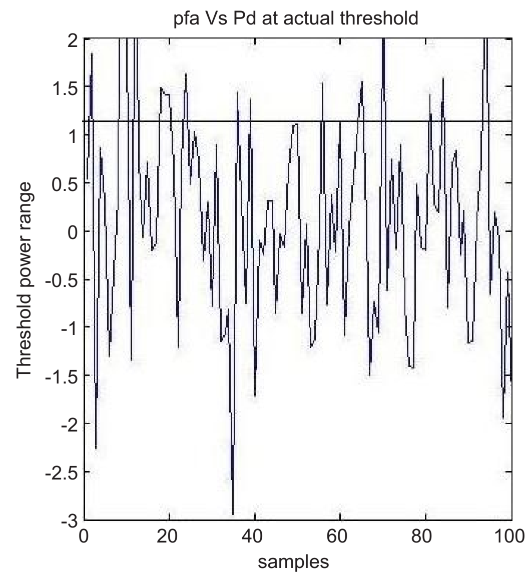

Figure 3: CFDI threshold at SNR = 2dB

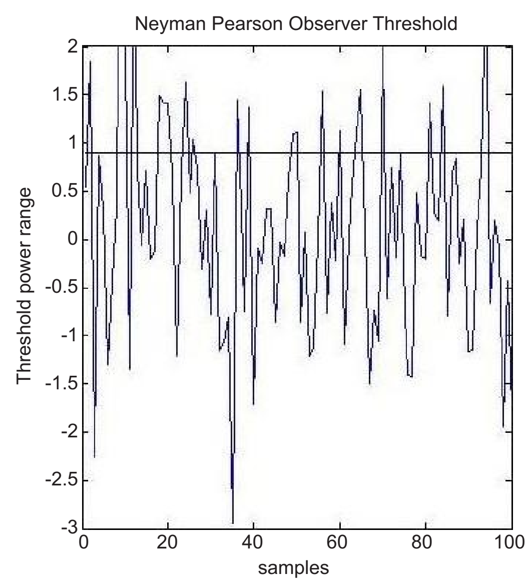

Figure 4: NP Observer threshold at SNR=2dB

If the user's presence is not identified in the spectrum, detector gives a busy signal. In such case the user cannot consume the bandwidth of our spectrum. Hence the spectrum remains idle and it will be costlier to the customers. This problem can be rectified in 5G technology by using CFDI algorithm at low SNR.

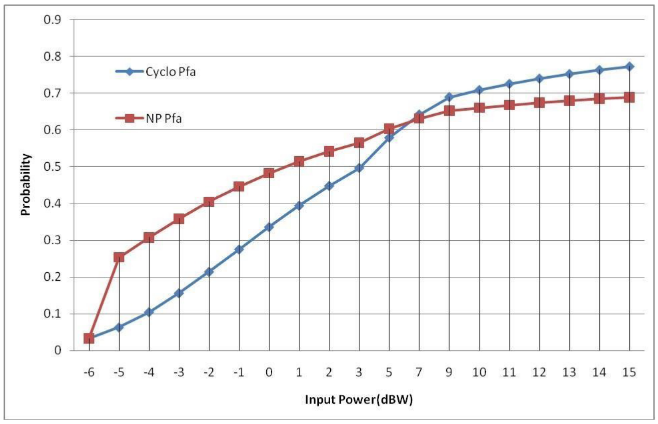

Figure 5: Comparison of CFDI P_{fa} Vs NP Observer P_{fa}

From Figure 5, –6dB to 7dB CFDI P_{fa} is lower than NP Observer P_{fa}. Hence at low SNR ranges our proposed algorithm gives fewer false alarms than NP Observer.

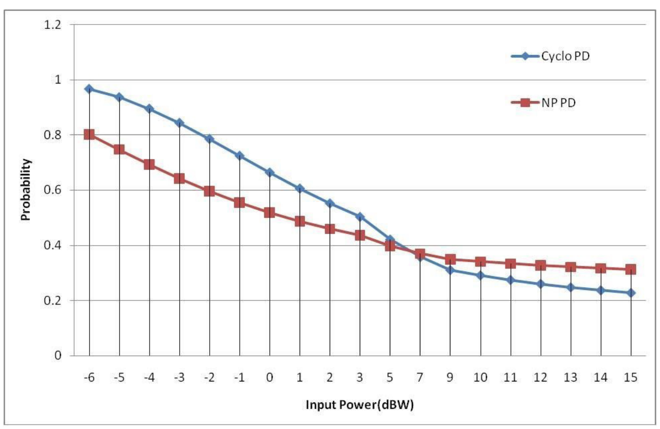

Figure 6: Comparison of CFDI P_D Vs NP Observer P_D

From Figure 6, The P_D is analyzed from the input power levels of –6dB to 14dB.From -6dB to 7dB CFDI P_D is higher than NP Observer P_D. Hence at low SNR ranges our proposed algorithm gives good accuracy than NP Observer.

Figure 7 represent the comparison between the thresholds of CFDI and the NP Observer thresholds. From power levels –6dB to7dB proposed algorithm threshold level is slightly higher than NP Observer

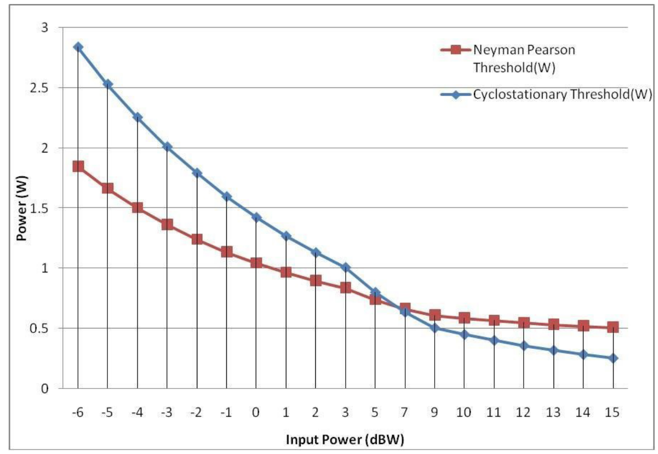

Figure 7: Comparison of CFDI Threshold Vs NP Observer Threshold

threshold even though the accuracy of detection is more for proposed algorithm at low SNR. In mobile communication the power is required for initiation of calls at base station is in between –6dB to 7 dB only. So to do analysis for we took the power values in that range only. Above of 7dB power values are not considered and those are negligible. Hence at low SNR level our proposed CFDI gives better result than existed NP Observer.

4. CONCLUSION

Sensing of the channel is a primary aspect in Cognitive Radio Networks (CRN). As per the available literature, different sensing algorithms has been explored, in extension of those studies this work made an attempt to apply CFDI concept to get better results of false alarm signals. This CFDI technology provides an extended benefit of receiving signals even though there is no priori information. In Cognitive Users how much ever the noise presents the signal is received and it gives proper accuracy at low SNR. Hence at the low SNR region the CFDI algorithm gives better detection results comparatively to existing method of NP Observer approach.

References

[1] P. Trinatha Rao, "Performance of non-homogeneous communication networks with Poisson arrivals and dynamic bandwidth allocation", IJSCC, Vol. 4, No. 3, 2012.

[2] Saptarshi Debroy, "Spectrum Map and Its *Application in Resource Management in Cognitive Radio Networks", IEEE transactions on Cognitive Communications and Networking*, Vol. 1, No. 4, December 2015.

[3] Clayton Scott, "A Neyman-Pearson Approach to Statistical Learning", *IEEE Transactions on Information Theory*, Vol. 51, No. 11, November 2005.

[4] Paul D. Sutton, "Cyclostationary Signatures in Practical Cognitive Radio Applications", *IEEE Journal on Selected Areas in Communications,* Vol. 26, No. 1, January 2008.

[5] Y. Lee, " Cyclostationarity-Based Detection of Randomly Arriving or Departing Signals", *ELSEVIER Journal on Applied Research and Technology*, Vol. 12, pp. 1083-1091, December 2014.

[6] Lei Yang, "Cyclo-energy detector for spectrum sensing in cognitive radio", *ELSEVIER Article Letter on International Journal of Electronics and Communication*, pp. 89-92, 2012.

[7] Shital Vachhani, "Cyclostationary Based Detection Method of Spectrum Sensing for Cognitive Radio", IJPPT, Vol. 7, pp. 26-28, April 2014.

[8] Stefan Tertinek, "Optimal Detection of Deterministic and Random Signals", Advanced Signal Processing, 1SE, 2002.

[9] P. Srihari, "Probability Theory and Stochastic Processing" 3rd Edition, pp. 63-65, 2010.

[10] Yang Mingchuan, "Cyclostationary Feature Detection Based Spectrum Sensing Algorithm under Complicated Electromagnetic Environment in Cognitive Radio Networks", *China Communications*, September 2015.

[11] Merrill I. Skolink, "Introduction to Radar Principles", *Tata McGraw Hill Third Edition*, pp. 284-285, 2008.

[12] Hemant Saggar, "Cyclostationary Spectrum Sensing in Cognitive Radios Using FRESH Filters", *Indian institute of Technology*, Roorky, pp. 1-6.

[13] Danijela Cabric, "Implementation Issues in Spectrum Sensing for Cognitive Radios", White Paper.

[14] Navid Tadayon, "A Multichannel Spectrum Sensing Fusion Mechanism for Cognitive Radio Networks: Design and Application to IEEE 802.22 WRANs", *IEEE Transactions on Cognitive Communications and Networking*, Vol. 1, No. 4, December 2015.

[15] Ashok patel, "Optimal Noise Benefits in Neyman-Pearson and Inequality-Constrained Statistical signal Detection", *IEEE Transactions on Signal Processing,* Vol. 57, No. 5, May 2009.

[16] J. Derek Tucker, "Neyman Pearson Detection of K-Distributed Random Variables", *Approved for public release*, 110 Vernon Ave Panama City, FL, USA 32407.

[17] E.L. Lehmann, "The Fisher, Neyman Pearson Theories of Testing Hypotheses: One Hypotheses or Two?", *Journal of the American statistical Association*, Vol. 8, pp. 1242-1249, December 1993.

[18] Clayton Scott, "A Neyman Pearson Approach to Statistical Learning", *IEEE Transactions on Information Hypotheses*,Vol. 51, No. 11, pp. 3806-3819, November 2005.

[19] http://www.dot.gov.in/sites/default/files/ Annexures/ Hand book.pdf