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Investigation of ROC parameters using Monte Carlo Simulation in Cyclostationary and Energy Detection Spectrum Sensing

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Abstract — Growing demand in the wireless world puts plenty of constraints on the usage of accessible spectrum. Static Spectrum Allocation (SSA) ends up in underutilization of spectrum. Much of the portion of Radio Frequency (RF) band is not effectively used. Cognitive feature Radio is upcoming technology to unravel spectrum deficiency. Various approaches have been developed to overcome this spectrum scarcity problem. In this work Cyclostationary feature detection (CFD) and Energy Detection Spectrum sensing techniques have been investigated using Monte Carlo simulation and compared on the basis of various ROC parameters. Spectrum sensing is the key that helps to sight the spectrum holes (underutilized band) providing high spectral resolution capability. Cyclostationary feature methodology out performs Energy detection in terms of detection likelihood Pd, likelihood of warning Pf and SNR. Both the algorithms are implemented using MATLAB. The result shows that for different SNR the CFD performs better than Ed. CFD also perform better in low signal to noise ratio as compare to ED.

Index Terms—Cyclostationary Feature Detection (CFD), Energy Detection (ED), PU, SU, Monte Carlo Simulation, Static Spectrum Allocation (SSA), Probability of Detection (Pd).

I. INTRODUCTION

Revolution in the wireless devices / network puts new dimensions in telecommunication area. To satisfy the necessity of spectrum, its maximum utilization and interference countability requires optimized methods. The radio frequency spectrum is a natural resource. Present Static Spectrum Allocation schemes (SSA) cannot accommodate increasing variety of wireless devices. The spectrum management policies answerable for the scarceness of the spectrum.

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As a result, innovative Opportunistic Spectrum Access (OSA) techniques suggested new ways in exploiting the offered spectrum. Spectrum band assignment is ruled by Centralized Government authorities, such as TRAI is in India. This organization assigns spectrum to commissioned holders, called primary users, on a long time duration basis for large geographical regions. A large portion of the allotted spectrum remains underutilized as steered in [1],[2],[3]. The inefficient usage of the restricted spectrum necessitates the Dynamic Spectrum Access techniques (DAS) [15]. In this method whenever secondary users (SU), who don't have any spectrum licenses are allowed to use the quickly unused accredited spectrum. Cognitive feature radio is the key sanctioning technology for the next generation communication networks, conjointly referred as Dynamic Spectrum Access networks [15]. Primary detection, sensing techniques will be classified into two broad categories, coherent and non-coherent detection [8]. In coherent detection the signal will be coherently detected by examine the received signal or the extracted signal characteristics with a priori data of primary signals. In non-coherent detection no priori data is needed for detection. Another way to classify sensing techniques relies on the information measure of the spectrum of interest for sensing, these are Narrow-band and Wideband [5-13],[29]. During this paper we have investigated CFD and ED techniques for Spectrum sensing using Monte Carlo simulation. It's a kind of simulation that depends on continual sampling and applied mathematics analysis to calculate the results. Spectrum sensing is the basic that helps to observe the spectrum holes which give the information to use the spectrum with high resolution capability. Cyclostationary feature methodology and ED spectrum sensing algorithms are analyzed using Monto Carlo simulation, both the methods are compared for Probability of detection, Probability of False Alarm for different SNR.

Rest of the paper is organized as follows. In Section II literature review is given and the downside statement is conferred. In Section III ED and CFD algorithmic is explained with the Monte Carlo simulation and analyzed using MATLAB. Section IV deals with estimation of Monte Carlo while in section V simulated results are explained followed by concluding remarks in Section VI , Acknowledgement to the authors are given in Section VII and references are given in VIII.

II. LITERATURE REVIEW

Different Spectrum sensing ways are developed such as, Energy Detection (ED), Cyclostationary Feature Detection (CFD), Matched Filter (MF), Waveform based sensing and Cooperative sensing [5-14]. Energy Detection, Cyclostationary Feature Detection, Matched Filter Detection mostly referred to as transmitter detection based sensing techniques. These methods uses Signal to Noise Ratio (SNR) and threshold of the detected signal from transmitter seek out the presence of PUs. When the level of the SNR goes below the threshold level these techniques fail to work robustly [8],[11],[13]. The MF is known to be the optimum method for detection of primary users when the transmitted signal is known [16]. MF methods are optimal for stationary Gaussian noise scenarios as this maximize the received SNR [5-7]. The main advantage of MF is the short time to achieve a certain probability of false alarm or probability of miss detection [16] as compared to other methods. In fact the required number of samples grows as *O(1/SNR)* for a target probability of false alarm at low SNRs for matched filtering [5],[8]. However matched-filtering requires CR to demodulate received signals. It requires perfect knowledge of the PU signaling features such as BW, operating frequency, modulation type their order, pulse shaping, and frame format [5-7], [10-14] etc.

Energy detection is predicated on hypothesis check. The challenges with ED sensing embody choice of the threshold for PUs detection and its inability to differentiate interference from PUs and noise. The poor performance of this technique underneath low Signal to Noise (SNR) values [7],[24]. Moreover, energy detectors don´t work with efficiency for sleuthing unfolds spectrum signals [13]. An repetitious algorithmic program is projected to seek out the choice threshold in [21]. The brink is found iteratively to satisfy a given confidence level i.e. chance of warning [23]. The performance of energy detector degrades significantly underneath Rayleigh Fading [8].

Waveform-Based sensing uses patterns which are utilized for synchronization or for alternative functions [5]. These patterns embody preambles, mid ambles, frequently transmitted pilot patterns, spreading sequences etc. A preamble may be a famous sequence transmitted before every burst and a mid-amble is transmitted within the middle of a burst or slot [5], [11]. The presence of a famous pattern, sensing may be performed by correlating the received signal with a famous copy of itself [24, 25]. This methodology is just applicable to systems with known signal patterns, and it's considered waveform-based sensing or coherent sensing. In [26], waveform based sensing outperforms energy detector based sensing in reliability and convergence time.

Other spectrum sensing approach is Cyclostationary Based Sensing technique [5-7], [9], [27], [32]. Cyclostationary Feature Detection could be a technique for investigating primary user transmissions by exploiting the cyclostationarity options of the received signals [27],[31]. Cyclostationarity options are caused by the regularity within the signal or in its statistics like mean and autocorrelation [28]. Problems such as attenuation, shadowing and hidden primary user creates interference to primary users when Cognitive feature Radio devices using spectrum access [5], [8]. Cooperation Sensing is planned within the literature as an answer to the issues that arise in spectrum sensing attributable to noise uncertainty, multipath fading, and shadowing effect.

III. PROPOSED SCHEMES

In this work the ED and CFD is compared by using MC simulation methods. These methods are analyzed by using different SNR levels as well as Probability of False Alarm.

A. Energy detection

Energy Detection has lower complexity than other feature detection methods. It can be done in the time domain (TD) or frequency domain (FD). The basic principle is to compare the transmitted signal energy to a sensing threshold over a given BW within a specific sensing period. The TD model consists of a Band Pass filter, a squaring device and an integrator, the ED counterpart mainly requires a spectrum estimator. The performance of the Frequency Domain based energy detector is dependent on the variance of the spectrum estimate which is unique to the type of estimator used. The biggest challenge for spectrum sensing is in developing sensing techniques that is capable of detecting very weak PU signals while being sufficiently fast and low cost to implement [19,22]. The detection of the spectrum is occupied by a PU can be stated as a binary hypothesis test. Hypothesis testing is done when null H0 corresponds to the absence of a signal, and a hypothesis H1 corresponds to the presence of a signal. The signal received at the CR $u(t)$ is given by [17,18,29].

$$u(t) = n_o(t) \qquad \text{H0 } \textit{is Ture} \tag{1}$$

$$= Km(t) + n_o(t) \qquad \text{H1 } \textit{is True} \tag{2}$$

Where $m(t)$ is the PU signal, K is the amplitude gain of the channel, and $n_o(t)$ is the additive white Gaussian noise (AWGN) with zero mean and variance σn.

$$Pd = E[Pr(H1|H1)] = Pr(d > d_{th}|H1) \tag{3}$$

$$Pf = E[Pr(H1|H0)] = \Pr(d > d_{th}|H0) \tag{4}$$

$$Pm = E[Pr(H0|H1)] = 1 - Pd \tag{5}$$

These parameters are calculated using Monto Carlo Simulation methods, given a decision statistic d_{th}, the probabilities of detection Pd, false alarm Pf, and missed alarm Pm respectively. Where d_{th} may be a threshold level, which might be calculated from a fixed Pf [27]. Pf is independent than the SNR, when no PU signal present the H0 hypothesis is true.

Pd is dependent on the SNR of the received signal and also on channel conditions. From the incumbent protection point of view higher Pf is more tolerable than a lower Pd. ED does not require the Knowledge about the PU as it consider PU signal as noise this is the advantage in this method. The false alarm probability can be defined as follows

$$Pf = (Base)^2 \quad (6)$$

Where Base is range of Pf i.e.0.001:0.001:1 And the threshold can be calculated as

$$\lambda = gamin\ (1 - Pf,\ m,\ 1) * 2 \quad (7)$$

Where m is time band width factor.

B. Cyclostationary Feature detection and Spectrum Sensing

The cyclostationary feature detection algorithm performs better for the spectrum sensing. Most of the communication signals are modulated with sine wave carrier and treated as cyclostationary random signals. Let a zero mean discrete time signal *u(t)* is cyclostationary with periodic T then its autocorrelation function *Rx(n,k)* is also periodic in T, as shown in Equation.

$$R_x(n; k) = Rx(n + T; k + T) \quad (8)$$

Autocorrelation function is expressed as

$$Rx(n, + \tfrac{T}{2}, n - \tfrac{T}{2}) = Rx(n + T + \tfrac{T}{2}, k + T - \tfrac{T}{2}) \quad (9)$$

Where $Rx(n, + \frac{T}{2}, n - \frac{T}{2})$ a function of two independent variable n and T is, is periodic in n with T for each value of *T*.

C. Cyclostationary Spectrum Sensing

The signal received by the Secondary user *u(t)* is the input primary user signal and it is scalar waveform. If we exploiting the cyclostationary property then spectrum sensing done such a hypotheses testing for received signal *u(t)*. The Hypothesis H0 true as *u(t)* is (wide-sense) stationary so the band is treated as vacant, and Hypothesis H1 is true as u(t) is cyclostationary and the band is declared as occupied [30].

The cyclic autocorrelation of the *u(t)* obtained as

$$R_{xx}^{\propto}\ (\tau) = \mu(t)\mu^{*} e^{-j2\pi\propto t} \quad (10)$$

Where α is Conjugate cyclic frequency and t is time shift. The spectral correlation density (SCD) as the spectral resolution Δf = 1/W becomes infinitesimal as shown Eqn.11.

$$S_{xx}^{\propto}(f) = \lim_{W\to\infty} \lim_{Z\to\infty} \frac{1}{Z} \int_{-Z/2}^{Z/2} \frac{1}{W}\, E\ \left(X_W\left(n, f + \frac{\propto}{2}\right) X_W\left(n, f + \frac{\propto}{2}\right)^{*}\right) dn \quad (11)$$

From the Eqn.9 we can modify Eqn.11 as

$$S_{xx}^{\propto}(f) = \int_{-\infty}^{+\infty} \frac{1}{W} \int_{-(W-|\tau|)/2}^{(W-|\tau|)/2} \lim_{Z\to\infty} \int_{-z/2}^{+z/2} R_x\left(n + T + \frac{\tau}{2}\right) * e^{-j2\pi\alpha(n+T)}\, dt dT e^{-j2\pi f\tau} d\tau \quad (12)$$

From the Eqn.10, Operation of Fourier Transformation, Expectation & Time Averaging Eqn.12 modified as

$$S_{xx}^{\alpha}(f) = \lim_{W\to\infty} \int_{-\infty}^{\infty} \frac{1}{W} \int_{-(W-|\tau|)/2}^{(W-|\tau|)/2} R_{xx}^{\alpha}\ (\tau) e^{-j2\pi f\tau} d\tau dT \quad (13)$$

$$S_{xx}^{\alpha}(f) = \lim_{W\to\infty} \left(1 - \frac{|\tau|}{W}\right)\ R_{xx}^{\alpha}\ (\tau) e^{-j2\pi f\tau} d\tau dT \quad (14)$$

By convolution Theorem Eqn.14 becomes

$$S_{xx}^{\alpha} = \lim_{W\to\infty} V_{\frac{1}{W}}(f) \otimes \int_{-\infty}^{\infty} R_{xx}^{\alpha}\ (\tau) e^{-j2\pi f\tau} d\tau dT \quad (15)$$

Where

$$V_{1/W}\ (f) = W\ \left(\frac{\sin(\pi W f)}{\pi W f}\right)^2 \quad (16)$$

From Eqn.16

$$\lim_{W\to\infty} V_{1/W}\ (f) = \delta(f) \quad (17)$$

As the limit of spectral resolution Δf = 1/W so the Spectral correlation density given by

$$S_{xx}^{\alpha}\ (f) = \int_{-\infty}^{\infty} R_{xx}^{\alpha}(\tau) exp^{-j2\pi f t} d\tau \quad (18)$$

But for the N sample the Spectral Correlation Density is called as Spectral Correlation Function (SCF) and is can be implemented as conjugate of eqn. 18. The SCF is given by

$$SCF_{xx}^{\alpha}\ (f) = \frac{1}{NT} \sum_{n=0}^{N-1} S_{xx}^{\alpha}\ (f) c(f) \quad (19)$$

Where c(f) is conjugate of SCD. The probability of False alarm can be calculated the following expression,

$$Pf = \exp\frac{-(2N+1)\lambda^2}{2\delta^4} \quad (20)$$

Modified equation as

$$\lambda = \sqrt{\frac{2\ln(Pf)\delta^4}{-(2N+1)}} \quad (21)$$

IV. USE OF MONTE CARLO SIMULATION

Monte Carlo simulation area unit a broad category of procedure algorithms that think about recurrent sampling to obtain numerical results. Typically employed in physical and mathematical issues and are most helpful once it's troublesome or not possible to use different mathematical strategies. Monte Carlo simulation is area unit principally employed in three distinct downside classes are improvement, numerical integration, and generation of attracts from a probability distribution. The following steps area unit generally performed for the Monte Carlo simulation of a physical method.

- Static Model Generation
- Input Distribution Identification
- Random Variable Generation
- Analysis and deciding

Cognitive radio spectrum sensing is also a complex and dynamic system. For determining the characteristics of this system we considered a loop with the number of Monte Carlo simulation for the statistical analysis of the system performance matrix *Pd, Pf, Pmd*.

V. RESULTS

These spectrum sensing methods CFD and ED are implemented using MATLAB by taking different iteration in Monte Carlo Simulation. In Part-A Information Separation between Primary and Secondary User can be seen. Part B is investigated performance of power spectral density at various SNR for CFD and ED. The performance measures for ROC parameters (Pf, Pd, Pm) are verified in succeeding sections.

A. Separation in spectrum band between PU and SU

PU is not share its information with the SU for the security purpose so band is present at carrier frequency, and for the SU the CR will share information from all SU using CR network. The LHS figure is for PU and the RHS figure is of SU showing the shift of allocated frequency in second RHS graph.

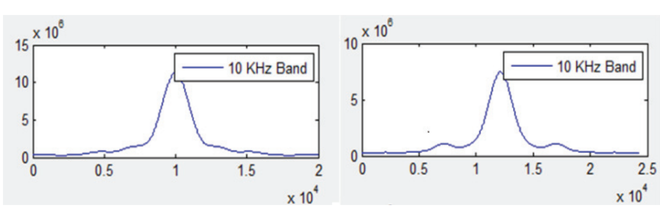


Fig. 1: PU and SU separation in spectrum band

B. Detection User at the Low SNR

Cyclostationary Detection gives PSD at 10Khz which is shown on top right in figure-2. Whereas the Energy Detection PSD for SNR -10 dB negligible in the second graph of right side as well as it is very low when SNR is -30 dB which is shown in bottom right plot. The energy detection outperform when SNR increases as compare to CFD.

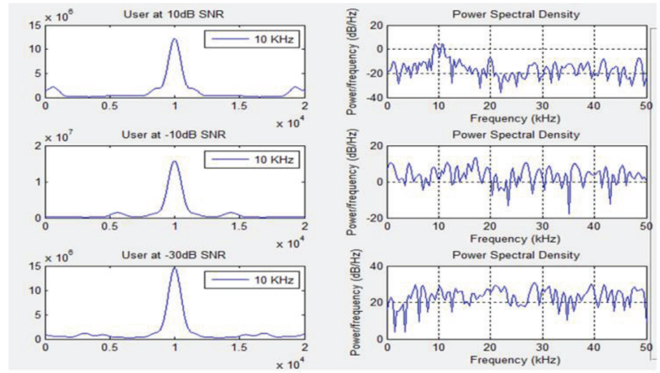


Fig. 2: SCF for CD and PSD for ED at different SNR levels

C. Pd vs Pf Comparison at low Pf i.e. Pf=20%

These two methods are compares for Pd and Pf. Monte Carlo simulation is used and the 100 iteration taken for the simulation. The probability of false Pf and detection Probability Pd is detected, the Comparison is done at low Pf i.e. Pf = 20%.

TABLE I: Pd in % at Different SNR for CD and ED

SNR	Pd for ED in %	Pd for CD in %
-10	93	100
-15	52	100
-27	28	95

The graph in Fig.3 shows that the Pd in energy detection decreases with increase in SNR. But in Cyclostationary Detection at the worst case of -27 dB SNR, Pd is 95% whereas in ED it is 28%. If here the Monte Carlo Iteration value is changed to 1000 i.e. the number of sample will be more and resulting in more processing time. The Monte Carlo simulation gives optimum performance it the iteration value is taken around 750.

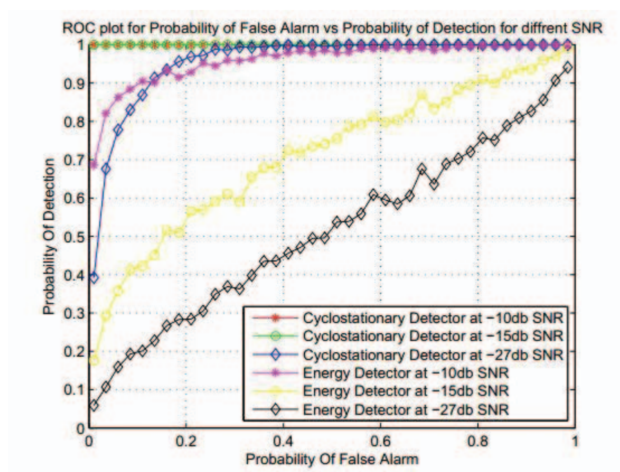
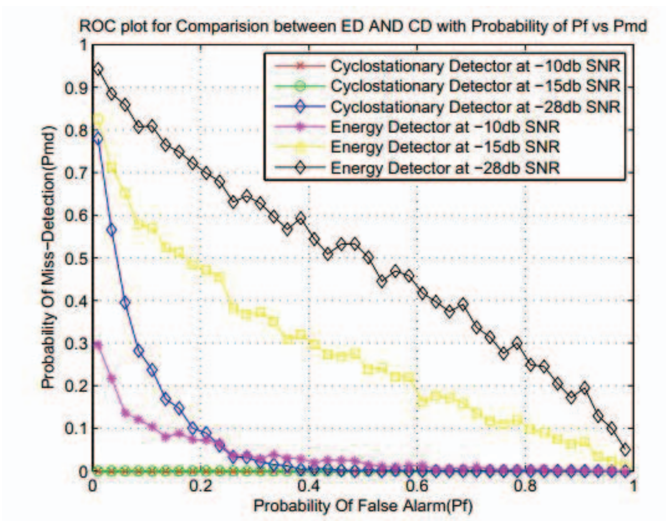


Fig. 4: Pf vs Pmd comparison at 20% Pf

TABLE II: Pmd in % at Different SNR for CD and ED

SNR	Pmd for ED in %	Pmd for CD in %
-10	8	0
-15	45	0
-28	70	8

The graph in Fig.4 shows that Pmd in energy detection increases with increase in SNR. At worst case of SNR i.e. -28 dB Pmd in Energy Detection is 70% where as in Cyclostationary detection is 8% only. The performance behavior can be seen from the figure.4.



E. Comparison of Pd vs SNR for various Pf

Here Monte Carlo simulation is carried for 1000 iterations. The listed table III is showing the *Pd Vs SNR* for different values of false alarm.

TABLE III: Pd in % at Different Pf for CD and ED

Pf	Pd for ED in %	Pd for CD in %
0.1	42	100
0.3	82	100
0.5	97	100

The graph in Fig.5 shows that the Pd in energy detection is increases with increase in Pf. But in Cyclostationary Detection Pf does not affect the Pd it is 100% at -10 db SNR. A performance gain of 20 dB SNR is obtained for between CFD and Ed.

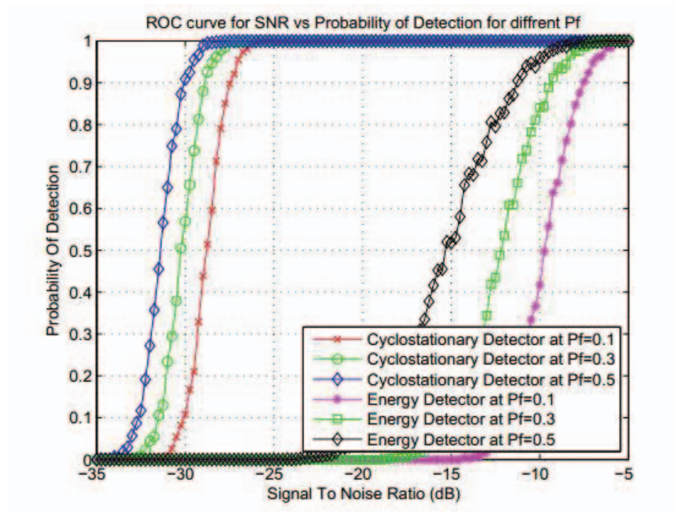


Fig. 5: Pd vs SNR comparison for different Pf

VI. CONCLUSION

In this paper we investigated the Energy Detection and Cyclostationary Feature Detection spectrum sensing techniques by using Monte Carlo Simulation. Cyclostationary Feature Detection is better than Energy Detection techniques since it produces better results as at low SNR. The Performance of CFD in terms of Pmd with respect to Pf at different values of SNR has observed to be far better than ED. Also the Cyclostationary feature detection has shown a performance gain of almost 20dB SNR in the probability of detection as compare to Energy Detection method.

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