

Find out Unused Frequency Band and Allocated to Secondly User Base on Priority using Software

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Abstract: Cognitive radio (CR) technology could be a promising thanks to improve the information measure efficiency of underutilized radio-frequency spectrum. Spectrum sensing is a vital thought in psychological feature radio. During a real time spectrum sensing energy detection is simplest technique of user detection; however its performance degrades with increase in SNR. The Match Filter Detection needs previous info concerning User for its detection. Therefore to beat noise downside and security problems Cyclostationary Spectrum Sensing technique is employed. Cyclostationary Detection (CD) uses the cyclic property of the signal for the user detection. These cyclic property area unit time variables as there mean and autocorrelation changes with time. These signals area unit referred to as Cyclostationary Signal. The noise is non-cyclic in nature therefore at the time of detection noise is eliminated. To beat the one node sensing issue and hidden node downside that arises because of channel impediments, cooperative sensing is getting used. . This paper performs Cyclostationary spectrum sensing that is optimized by Frequency Accumulation technique.

Keywords: Cyclostationary Detection, Frequency Accumulation Method, Energy Detection, Probability of detection

I. INTRODUCTION

Due to the rapid growth of wireless communications, more and more spectrum resources are needed. Within the current spectrum framework, most of the spectrum bands are exclusively allocated to specific licensed services. However, a lot of licensed bands, such as those for TV broadcasting, are underutilized, resulting in spectrum wastage. This has promoted Federal Communications Commission (FCC) to open the licensed bands to unlicensed users through the use of cognitive radio (CR) technology. The IEEE 802.22 working group has been formed to develop the air interference for opportunistic secondary access to TV bands. Dynamic Spectrum Access is often used alongside Cognitive Radio. Dynamic Spectrum Access involves sharing of the spectrum between the primary and secondary users. The primary or licensed user is given priority as they hold the license. The secondary user is given permission to make use of the spectrum whenever the primary user is not active. The moment the primary user accesses the spectrum, the secondary user has to shift to an unused portion of the spectrum.

In practice, the unlicensed users, also called secondary users (SUs), need to continuously monitor the activities of the licensed users, also called primary users (PUs), to find the spectrum holes, which is defined as the spectrum bands that can be used by the SUs without interfering with the PUs. This procedure is called spectrum sensing. There are two types of Spectrum holes, namely temporal and spatial Spectrum holes, respectively. A temporal spectrum holes appears when there is no PU transmission during a certain time period and the SUs can use the spectrum for transmission. A spatial spectrum holes appears when the PU transmission is within an area and the SUs can use the spectrum outside that area. To determine the presence or absence of the PU transmission, different spectrum sensing techniques have been used, such as matched filtering detection, energy detection, and feature detection. However, the performance of spectrum sensing is limited by noise uncertainty, multipath fading, and shadowing, which are the fundamental characteristics of wireless channels. To address this problem, cooperative spectrum sensing (CSS) has been proposed by allowing the collaboration of SUs to make decisions.

Metrics for detection performance are the probability of detection and false alarms. The probability that a SU declares that a PU is present when the spectrum is idle is called the probability of a false alarm. Conversely, the probability that



the SU declares that the PU is present when the spectrum is occupied by the PU is called the probability of detection. The probability of misdetection indicates the probability that the SU declares that the PU is absent when the spectrum is occupied. CR should exhibit a low probability of false alarm and a high probability of detection. Misdetection leads to interference with the PUs, while false alarms decrease the efficiency of spectrum utilization.

The goal of this paper is to point out optimization of spectrum sensing by FAM Based Cyclostationary Detection. These methods are discussed in the rest of this paper. We start by introducing the local spectrum sensing model concept in Section II. Non-cooperative Spectrum Sensing Methods are explained in Section III. Section IV explains the cooperative spectrum sensing methods. The cooperative sensing concept and its various forms are introduced. Applications of the cognitive radio are given in Section V. And the conclusion of the work given in Section VI.

II. RELATED STUDY

Spectrum sensing plays a critical role for the efficient utilization of the radio spectrum. Researchers currently focus on two major aspects in spectrum sensing: how to improve local sensing results and cooperative spectrum sensing for better data fusion results.

A Simulation and analysis of cognitive radio in MATLAB projected in [2]. During this the Energy detection method of spectrum sensing is used. The periodogram MATLAB function is used to compute the Energy of the received signal for its detection. In the low SNR the performance of the system degrades as the amplitude is does below threshold.

In [5], a two-stage fuzzy logic-based detection (FLD) scheme is proposed. In the first stage, each CR performs existing spectrum sensing techniques, i.e., energy detection, matched filter detection, and Cyclostationary detection. While in the second stage, the output from each technique employed in the first stage is combined using fuzzy logic to ultimately decide about the presence or absence of a PU.

A low power discrete Fourier transform (DFT) filter bank-based two-stage spectrum sensing is proposed in [6]. Energy detector is used for the first stage coarse sensing and then in the second stage fine sensing it is complemented by the Cyclostationary detection. Authors exploited the fact that power of sensing operation depends on the sampling rate. Therefore, poly phase DFT filter bank is used to choose appropriate sampling rate.

SNR-based two-stage adaptive spectrum sensing is proposed in [7]. In the first stage, the SNR is estimated in advance for available channels. The SU then performs either energy detection or Cyclostationary detection based on the SNR estimated in the first stage of PU detection.

A novel high-speed two-stage detector is proposed in [8] that effectively decreased the sensing time by satisfying the required detection capabilities. Energy detector is used in the coarse sensing stage and if the measured energy is greater than threshold then it declares PU present, else it computes the SNR of device. If the computed SNR is greater than theoretical SNR, then the result of energy detector is reliable. If computed SNR is less than theoretical SNR then second stage for fine sensing is performed in which covariance absolute value is used.

In [7] proposed Cyclostationary Spectrum Sensing method. This method use the cyclic property of the received signal as all the First User signals are modulated by Carrier. The Mean and autocorrelation property are used for the User detection. Also the synchronization does not require which overcome match filter spectrum sensing drawback. Also this method correctly identify primary user signal due to the noise rejection ability.

In [6] proposed Cooperative Spectrum Sensing under Mobile Cognitive Radio. The system is implemented by energy detection and different fading channels. The Energy detection has low Probability of detection due to noise power consideration as compare to other methods. The system performance matrixes are increased due to cooperative communication.

III. SPECTRUM SENSING METHODS

To identify the Spectrum holes and protect PU transmission, different local spectrum sensing techniques have been proposed for individual SUs by applying the hypothesis testing criteria. Cooperative sensing starts with spectrum sensing performed individually at each CR. Typically, local sensing for primary signal detection is formulated as a binary hypothesis problem as follows:



$$x(t) = \begin{cases} n(t) \dots \dots \dots H_0 \dots \text{True} \\ s(t) + n(t) \dots \dots \dots H_1 \dots \text{True} \end{cases}$$

Where $n(t)$ is the additive white Gaussian noise (AWGN), $x(t)$ signal received by secondary user, $s(t)$ is signal of the Primary User. H_0 and H_1 denote the hypothesis of the absence and the presence, respectively, of the PU signal in the frequency band of interest. For the evaluation of the detection performance, the probabilities of detection P_d and false alarm P_f are defined as [3],

$$P_d = P\{\text{decision} = H_1 \mid H_1\} = P\{T > \lambda \mid H_1\}$$

$$P_f = P\{\text{decision} = H_1 \mid H_0\} = P\{T > \lambda \mid H_0\}$$

Where T is the decision statistic and λ is the decision threshold. The value of λ is set depending on the requirements of detection performance. Probability of false alarm, P_f is the probability of a CR user declaring that a PU is present when the spectrum is actually free. Probability of detection, P_d is the probability of a CR user declaring that a PU is present when the spectrum is indeed occupied by the PU. A miss in the detection will cause the interference with the PU and a false alarm will reduce the spectral efficiency.

1. Energy Detection

Energy detector is the most common spectrum sensing method. When it is difficult for the SU to bring adequate information about the PU waveform, matched filter detection is not a favorable choice. However, if the SU is given the power of random Gaussian noise, energy detection becomes a better alternative for spectrum sensing. Figure 1 depicts the block diagram for energy detection. The elementary approach behind energy detection is the estimation of the power of the received signal $y(n)$. To evaluate the power of the received signal, the output of a band pass filter of bandwidth W is squared and integrated over an interval T . Finally, the integrated value is compared with a threshold λ in order to decide whether the PU is present or not. The decision statistics of the energy detector are defined as the average energy of the observed samples as given by eqn.6.

$$E = \sum_{n=0}^N |y(n)|^2 \dots \dots \dots 6$$

If $E > \lambda$ then Hypothesis H_1 True and PU present, similarly if $E < \lambda$ then Hypothesis H_0 True the PU absent. The performance matrix Probability of Detection and Probability of False alarm given by eqn 7 and 8 respectively.



Fig.1 Block Diagram of Energy Detection

$$P_d = P(Y > \lambda \mid H_1) = Q_m(\sqrt{2\gamma}, \sqrt{\lambda}) \dots \dots \dots 7$$

$$P_f = P(Y > \lambda \mid H_0) = \frac{\Gamma(m, \lambda/2)}{\Gamma(m)} \dots \dots \dots 8$$

Where Y is the Energy of PU signal, m is time bandwidth product, $\Gamma(.)$ And $\Gamma(.)$ are complete and incomplete gamma functions, $Q_m(.)$ is the generalized Marcum Q-function. A low value of P_d indicates an absence of primary user with high probability; it means that the CR use spectrum. One of the main problems of Energy Detection is that performance



is susceptible to uncertainty in noise power. It cannot differentiate between signal power and noise power rather it just tells us about absence or presence of the primary user.

2. Cyclostationary Spectrum Sensing

Cyclostationary feature detection is a method for detecting primary user transmissions by exploiting the Cyclostationary features of the received signals. Cyclostationary features are caused by the periodicity in the signal statistics like mean and autocorrelation or they can be intentionally induced to assist spectrum sensing. Instead of power spectral density (PSD), cyclic correlation function is used for detecting signals present in a given spectrum. The Cyclostationary based detection algorithms can differentiate noise from primary users' signals. This is a result of the fact that noise is wide-sense stationary (WSS) with no correlation while modulated signals are Cyclostationary with spectral correlation due to the redundancy of signal periodicities. Furthermore, Cyclostationary can be used for distinguishing among different types of transmissions and primary users. Fig below shows the block diagram for Cyclostationary Detection.

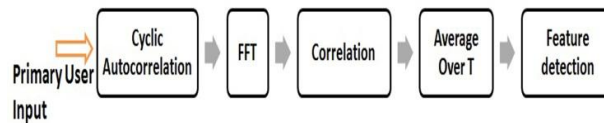


Fig.2 Block Diagram of Cyclostationary Detection

Commonly the primary modulated waveforms are coupled with patterns also characterized as Cyclostationary features like sine wave carriers, pulse trains, repeating spreading, hopping sequences, and cyclic prefixes inducing periodicity. SU can detect a random signal with a specific modulation type in the presence of random stochastic noise by exploiting periodic statistics like the mean and the autocorrelation of the PU waveform. Features like autocorrelation and mean are estimated by analyzing spectral correlation functions (SCFs). SCF, also called a cyclic spectrum, is a two-dimensional function with a cyclic frequency α . Power spectral density is a special case of a SCF with $\alpha = 0$. The features detected are the number of signals, their modulation types, symbol rates, and presence of interferers. Using the computed SCF and a hypothesis model for spectrum sensing, we can determine whether a signal of a specific cyclic frequency of interest is present or not. The signal received by the Secondary user $x(t)$ is the input primary user signal and it is scalar waveform, then the cyclic autocorrelation of the $u(t)$ obtained as

$$R(\tau) = x(t) \cdot x^*(t) e^{-j2\pi\alpha\tau}$$

Where $*$ is a conjugate of scalar waveform, $(.)$ Is infinite time average; α is cycle or conjugate frequency. Although the cyclic spectrum has been defined to be the Fourier transform of the cyclic autocorrelation, it can be given an alternative equivalent definition that derives from its interpretation in terms of spectral correlation.

$$S_{xx}^{\alpha}(f) = \lim_{W \rightarrow \infty} \lim_{Z \rightarrow \infty} \frac{1}{Z} \int_{-Z/2}^{Z/2} \frac{1}{W} E(X_W(n, f + \frac{\alpha}{2})) \cdot X_W(n, f - \frac{\alpha}{2})^* dn \quad \dots\dots\dots 9$$

$$S_{xx}^{\alpha}(f) = \int_{-\infty}^{+\infty} \frac{1}{W} \int_{-(W-|\tau|/2)}^{(W-|\tau|/2)} \lim_{z \rightarrow \infty} \int_{-Z/2}^{+Z/2} R_x(n+T+\frac{\tau}{2}, n+T-\frac{\tau}{2})^* e^{-2\pi\alpha(n+T)} dt d\tau e^{-j2\pi f t} dt \quad \dots\dots 10$$

From the Eqn.4.14, Operation of Fourier Transformation, Expectation & Time averaging Eqn.4.16 modified as



$$S_{xx}^{\alpha}(f) = \lim_{W \rightarrow \infty} \int_{-\infty}^{+\infty} \frac{1}{W} \int_{-(W-|\tau|/2)}^{(W-|\tau|/2)} R_{xx}^{\alpha}(\tau) e^{-j2\pi f\tau} d\tau dT \quad \dots\dots\dots 11$$

$$S_{xx}^{\alpha}(f) = \lim_{W \rightarrow \infty} \int_{-\infty}^{\infty} \left(1 - \frac{|\tau|}{W}\right) R_{xx}^{\alpha}(\tau) e^{-j2\pi f\tau} d\tau dT \quad \dots\dots\dots 12$$

By convolution Theorem Eqn.14 becomes

$$S_{xx}^{\alpha}(f) = \lim_{W \rightarrow \infty} V_{1/W}(f) \otimes \int_{-\infty}^{\infty} R_{xx}^{\alpha}(\tau) e^{-j2\pi f\tau} d\tau dT \quad \dots\dots\dots 13$$

Where

$$V_{1/W}(f) = W \left[\frac{\sin(\pi W f)}{\pi W f} \right]^2 \quad \dots\dots\dots 14$$

Now since from above equation

$$\lim_{W \rightarrow \infty} V_{1/W}(f) = \delta(f) \quad \dots\dots\dots 15$$

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

$$S_{xx}^{\alpha}(f) = \int_{-\infty}^{\infty} R_{xx}^{\alpha}(\tau) \exp^{-j2\pi f\tau} d\tau \quad \dots\dots\dots 16$$

But for the N sample the SCD is called as SCF and is can be implemented as conjugate of eqn 4.22. The SCF is given by

$$SCF_{xx}^{\alpha}(f) = \frac{1}{NT} \sum_{n=0}^{N-1} S_{xx}^{\alpha}(f) c(f) \quad \dots\dots\dots 17$$

Where $c(f)$ is conjugate of SCD. The SCF function causes peak at the cyclic frequency. The SCF function causes peak at the cyclic frequency. If the maximum value of SCF is greater than threshold then hypothesis H_1 true. And Primary User present else the Hypothesis H_0 true and Primary User absent.

IV. FAM BASED CYCLOSTATIONARY DETECTION

The performance of spectrum sensing is limited by noise uncertainty, multipath fading, and shadowing, which are the fundamental characteristics of wireless channels. The performance parameter such as probability detection is shall high in cognitive radio and probability of False alarm and Miss-detection is should low. Usually, the Cyclostationary detection requires high computation complexity and can't meet the real-time operation that required by spectrum sensing for cognitive radio.

In this paper, we assume that the characteristics of licensed user's signals are known and detect these signals under specific points. We use time-domain averaging and frequency-domain smoothing to obtain SCF as follows

- 1) Determine points of cycle frequency and carrier frequency that we need to analyze.
- 2) Get Mgroups of data with length of N; compute FFT for each group of data.



V. SIMULATION RESULTS

Figure 3 illustrate that SCF of signal is different from SCF of Gaussian white noise and Cyclostationary feature can be used for signal detection under low SNR environment. Fig 3 shows the detection of Primary User in low SNR region.

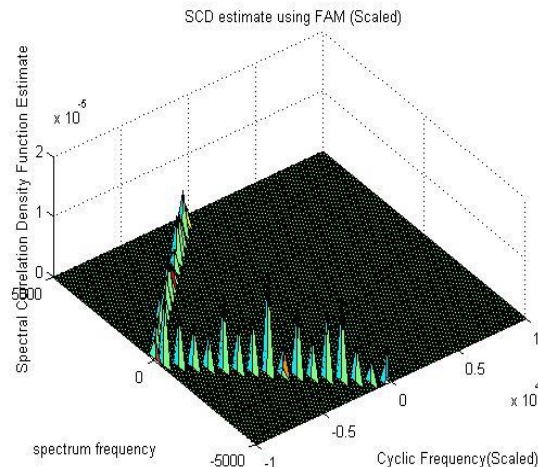


Fig.3 SCD estimation Using FAM

Figure 4 ROC curve for probability of false alarm versus probability of detection .It shows that probability of detection is also varies based on SNR and SNR -5dB,-10dB,-13dB SNR are used for simulation. From simulation result we see that when SNR -5dB and $P_{fa}=0.2$, the detection of probability is about 100%.When SNR is -13dB and $P_{fa}=0.4$,the detection is about 80%,but after $P_{fa}=0.6$ to 0.97 detection is good. For -10dB SNR at $P_{fa}=0.1$ the detection is 88% but after that detection is approximately good (above 90%)and it is 100%for P_{fa} above 0.65 . For different SNR shows that under low SNR (-10 db) condition false alarm rate is less than 10% and probability of detection is greater than 90%.

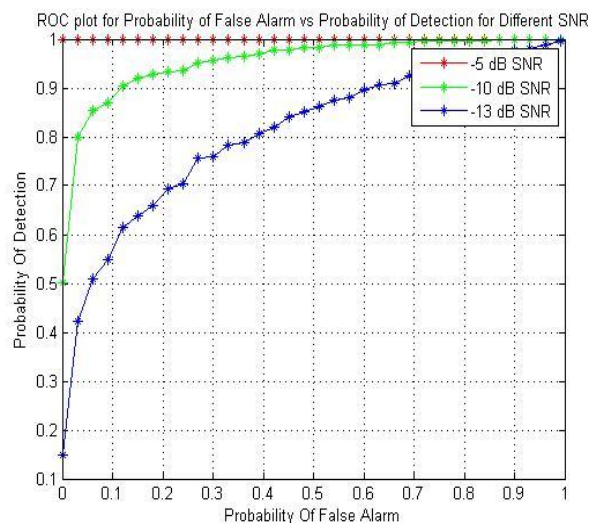


Fig.4 Pd vs Pf in different SNR by FAM Method

Figure 5 ROC plot for probability of False alarm Vs. Probability of Miss-detection for different SNR shows that probability of miss detection varies based on SNR and SNR(-8dB, -11dB, -13dB) probability of false alarm decreases with increase in probability of miss detection.



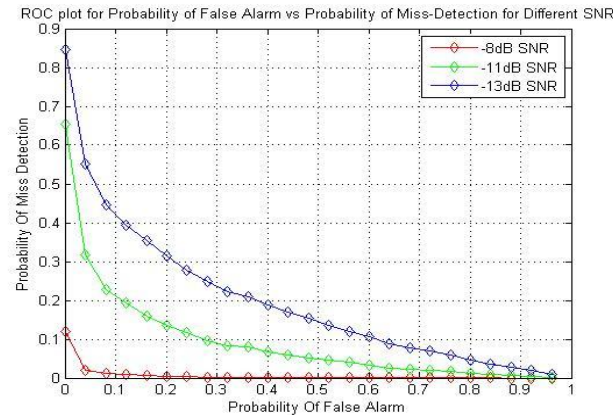


Fig 5 P_f vs Probability of miss detection

Figure 6 ROC curve for SNR Vs. probability of detection for different value of P_f (1, 10, 20) at -5dB SNR shows that probability of detection is 100%. Performance of detection based on SNR. It also shows that with increase of SNR (-30dB to 5dB) the detection also increased. Probability of detection is 100% above -8dB SNR and detection probability was less before -10db SNR. Detection of probability increased after -25dB and significantly increased after -18 dB and finally we get detection of probability 1 when SNR is -8dB.

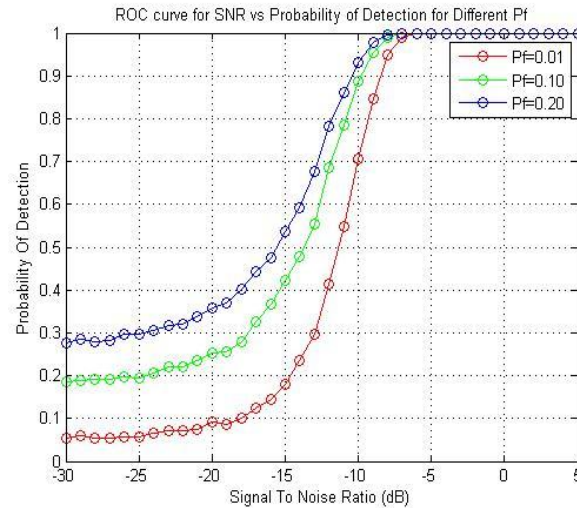


Figure 6 SNR Vs. probability of detection

Figure 7 shows that Probability of miss detection is above 75% for lower value of SNR(-30db). If SNR increases probability of detection decreases .



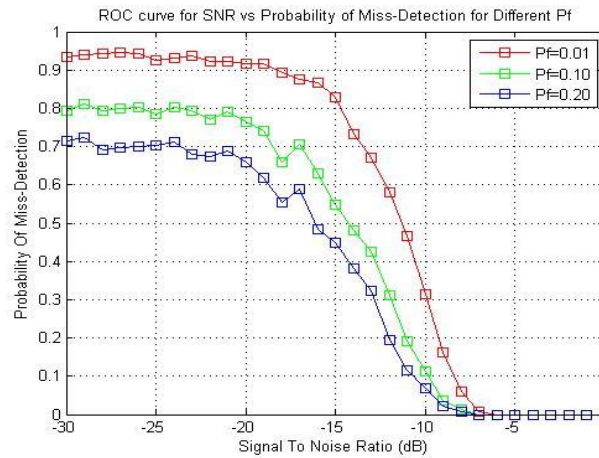


Figure 7 SNR vs Probability of miss-detection

Figure 8 A random signal is taken and modulated using FSK ,BPSK,QPSK,8-PSK techniques. The operating frequency chosen is 5000Hz.Noise is added in the signal and then signal passes through AWGN channel.The received signal is demodulated and fed to the Cyclostationary Feature Detection (CFD) block. Modulation schemes like QPSK,8-PSK , FSK are almost similar to BPSK modulation scheme.The difference is only that the modulator and demodulator block have to replace as per required modulation scheme. The output obtained is the cyclic SCF. The feature of cyclic SCF is that it contains peak at the center if primary user is present in spectrum. If primary user will not present in spectrum, SCF will not show any peak. Thus the output of cyclic feature detector is obtained with and without primary user. Figure 8 ROC curve for SNR vs. Probability of detection for different modulation method with $p_f = 0.01$ shows that proposed detector is not sensitive to number and modulation technique of primary user.

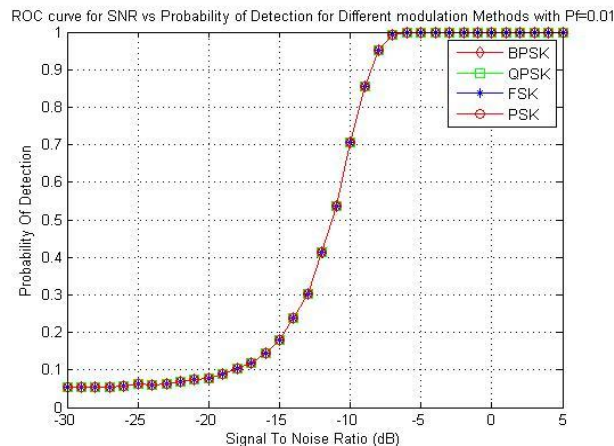


Figure 8 SNR vs. Probability of detection for different modulation method

Figure 9 depicts “probability of primary user detection” as a function of SNR for three cases (i) Cyclostationary detection (ii) Energy detection (iii) FAM based cyclostationary detection .It observed that for Cyclostationary detection and Energy detection, much higher SNR required to obtain performance comparable to FAM based cyclostationary detection. For Energy detection at -15 dB SNR with $P_f = 0.3$ produce 10% probability of detection whereas cyclostationary detection achieve 92% probability of detection. For FAM based cyclostationary detection 100% of probability of detection is attained at -15db.We compare the conventional energy detection and Cyclostationary method with FAM Based Cyclostationary detection and seen that FAM based Cyclostationary detection gives better result in low SNR as compare to Energy Detection and Cyclostationary Detection due to noise rejection ability.



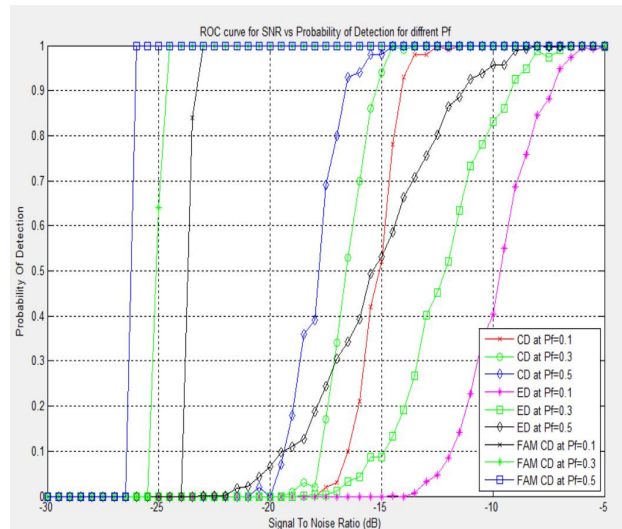


Figure 9 Comparison of CD,ED FAM based CD

A. TV white spaces

The main regulatory agencies for the unlicensed use of TV white spaces are the FCC in the United States, the Office of Communications (Ofcom) in the United Kingdom, and the Electronic Communications Committee (ECC) of the conference of European Post and Telecommunications in Europe. After many years of effort in this area, FCC released the final rules for using the TV white space in September 2010, which led to the culmination of this field. Meanwhile, other agencies have also been getting progress. This is based on the idea of having an accessible database (centralize-fashion) of free TV bands, otherwise called TV white space, or to sense and obtain Spectrum holes (distributed-fashion) within TV bands to utilize for SUs communication.

B. Cellular networks

The applications of CR in cellular networks are emerging in recent years. To overcome the indoor coverage problem and adapt to traffic growth, the concept of small cells, such as femtocells, has been proposed in 3GPP LTE-Advanced (LTE-A) and IEEE 802.16m, and companies like PicoChip driving femtocell revolution. The femtocell unit has the function of the typical BS (eNodeB in LTE). However, the self-deployment property of the femtocells makes the centralized interference management impractical. With CR, the femtocells can search and estimate the available spectrum bands in order to maintain the coverage and avoid the interference to other femtocells and macro cells.

C. Military usage

CR is a must-have technique for military usage. With CR, the users can recognize the enemies' communications and protect their owns. Moreover, the users can search for more transmission opportunities. The US department of defense (DoD) has already established programs such as SPEAKEasy radio system and next Generation (XG) to exploit the benefits of CR techniques.

VI. CONCLUSION

CR technology has been studied to increase the spectrum utilization efficiency. With spectrum sensing techniques, the SUs are able to monitor the activities of the PUs. To address the limitations of the spectrum sensing techniques by a single SU, CSS schemes have been discussed. Based on the spectrum sensing results, the SUs can access the spectrum bands under the interference limit to the PUs. Different spectrum sharing and allocation schemes have been considered to increase the spectrum efficiency. Even though many critical issues in CR have been addressed in the past decade, there are still some challenges. Nevertheless, we believe the CR technology will be applied to many real systems in the near future.



REFERENCES

- [1]. Yucek and H. Arslan, "A survey of spectrum sensing algorithms for cognitive radio applications," IEEE Communication Surveys Tutorials, vol. 11, no. 1, pp. 116-130, First Quarter, 2009.
- [2]. Beibei Wang And K. J. Ray Liu, "Advances In Cognitive Radio Networks: A Survey," IEEE Journal Of Selected Topics In Signal Process, Vol. 5, No. 1, Feb 2011, pp. 5-19.
- [3]. Lu Lu, Xiangwei Zhou, Uzoma Onunkwo and Geoffrey Ye Li, "Ten years of research in spectrum sensing and sharing in cognitive radio," EURASIP Journal on Wireless Communications and Networking , pp.1-16, 2012.
- [4]. Waleed Ejaz, Najamul Hasan, Muhammad Awais Azam and HyungSeok Kim, "Improved local spectrum sensing for cognitive radio networks," EURASIP Journal on Wireless Communications and Networking, pp.1-12, 2012.
- [5]. Sai kiranpudi, T. Syama Sundara, "Performance Analysis of Cognitive Radio based on Cooperative Spectrum Sensing," International Journal of Engineering Trends and Technology (IJETT) - Volume 4, Issue 4, pp. 821-827, April 2013.
- [6]. Mohammad Alamgir Hossain, Md. Shamir Husain, and Md. Ibrahim Abdullah, "Performance Analysis of Cooperative Spectrum Sensing in Cognitive Radio," International Journal of Innovation and Applied Studies, Vol. 1 No. 2 Dec. 2012, pp. 236-245.
- [7]. Y-L Zou, Y-D Yao, BY Zheng, Outage probability analysis of cognitive Transmissions: Impact of spectrum sensing overhead. IEEE Trans Wireless Communication, Vol. 9, pp. 2676-2688, Jan-2010.
- [8]. Mr. Pradeep Kumar Verma, Prof. Rajeshwar Lal Dua, "A Survey on Cyclostationary Feature Spectrum Sensing Technique," International Journal of Advanced Research in Computer Engineering & Technology (IJARCET), Volume 1, Issue 7, pp. 300-303, September 2012.
- [9]. R. Gill, A. Kansal, "Comparative Analysis of the Spectrum Sensing Techniques Energy Detection and Cyclostationary Feature Detection," International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering, Vol. 3, Issue 7, pp. 10601-10608, July 2014.
- [10]. Omkar S. Vaidya, Vijaya M. Kulkarni, "Analysis of Energy Detection based Spectrum Sensing over Wireless Fading Channels in Cognitive Radio Network," International Journal of Emerging Technology and Advanced Engineering Journal, Volume 3, Issue 3, pp. 645-653, March 2013.
- [11]. V. Sri Lakshmi, Dr. S. Sri Gowri, "Performance of Energy Detection based Spectrum Sensing using Diversity Techniques over Rayleigh Fading Channel," International Journal of Scientific Engineering and Volume No. 2, Issue No. 9, pp. 840-845, Sep 2013.
- [12]. Marko Kosunen, Vesa Turunen, "Survey and Analysis of Cyclostationary Signal Detector Implementations on FPGA," IEEE journal on emerging and selected topics in circuits and systems, vol. 3, no. 4, pp. 541-551, December 2013.
- [13]. Waleed Ejaz, Najamul Hasan "I3S: Intelligent spectrum sensing scheme for cognitive radio networks," EURASIP Journal on Wireless Communications and Networking, pp.1-10, 2013.
- [14]. Ikram Ilyas, Niger Fatema, Dr. Md. Abdur Rahman, "Simulink based Cooperative (Hard Decision Fusion Method) and Non-Cooperative Spectrum Sensing in Cognitive Radio using Energy Detection Technique," International Journal of Scientific & Engineering Research, Volume 5, Issue 8, pp. 359-363, August-2014.
- [15]. F. Yu, H. Tang, M. Huang, Z. Li, P. Mason, Defense against spectrum sensing data falsification attacks in mobile ad hoc networks with cognitive radios, in: Proc. of IEEE MILCOM 2009, 2009, pp. 1-7.
- [16]. L. Lazos, S. Liu, M. Krunz, Mitigating control-channel jamming attacks in multi-channel ad hoc networks, in: Proc. of the Second ACM Conf. on Wireless Network Security, WiSec, 2009, 2009, pp. 169-180.
- [17]. S. Appadwedula, V. Veeravalli, D. Jones, Robust and locally optimum decentralized detection with censoring sensors, in: Proc. of the Fifth Int'l Conf. on Information Fusion, 2002, vol. 1, 2002, pp. 56-63.
- [18]. S-J Kim, GB Giannakis, Sequential and cooperative sensing for multi-channel cognitive radios. IEEE Trans Signal Process. Vol. 58, pp. 4239-4253, Jan 2010.

