International Journal of Soft Computing and Engineering (IJSCE)
ISSN: 2231-2307, Volume-4, Issue-1, March 2014

An Adaptive Spectrum Sensing Model for Cognitive Radio Application

Wasim Arif , Dhrubjun Nath Saikia, S.Baishya

Abstract*—The problem of underutilization of spectrum may be solved by allowing the Secondary Users (SU) to use the spectrum allocated to the Primary Users(PU) (license holder of a spectrum band) when they are not using it, without causing any harmful interference to the PUs. Cognitive Radio (CR) technology promises to solve the problem of spectrum underutilization and spectrum crowding. The cognitive users employ their cognitive abilities, to adaptively change the radio parameters as per the radio environment, to communicate, without harming the primary users. In this paper Cyclostationary Feature Detection method has been taken as the detection method as it not only can detect the signal under low SNR but can also detect different features of the signal such as modulation type, carrier frequencies etc.. Energy Detection or radio meter can only detect presence or absence of the primary signal whereas a Matched Filter system requires extensive knowledge about the channel and the signals that are to be identified. The signals exhibiting cyclostationarity includes Spectral Correlation Function which is a data analysis algorithm that measures how the properties of a spectra varies, position to position, in a two dimensional spectral line map . We have proposed an adaptive sensing mechanism for an effective and efficient detection of spectrum hole. The signal SNR is determined in the first phase and appropriate sensing technique is adopted by the system based on the SNR level in the second phase confirming the radio parameters for CR.

Index terms*—Cycle Frequency, Cyclic Autocorrelation Function, Cyclostationarity, Spectral Correlation Function, Spectrum Sensing.

I. INTRODUCTION

The demand for new wireless services and applications are steadily increasing along with the number of users. But the growth is ultimately constrained by the amount of available radio frequency spectrum.

Since most of the prime radio frequency spectrum (i.e., less than 3 GHz) are exclusively assigned, the new wireless services is constrained to either overpopulated unlicensed bands ,such as the industrial, scientific, and medical (ISM) bands, or bands above 3 GHz. It seems that the command-and-control spectrum allocation approach has raised an "artificial scarcity" of usable spectrum. Closer spectral usage pattern measurement [1],[2] revealed that a large percentage of the prime radio frequency spectrum is significantly *underutilized.*

Manuscript Received March, 2014

Wasim Arif, Department of Electronics and Communication Engineering, National Institute of Technology Silchar, Assam, India.

Dhrubjun Nath Saikia, BEL India,India,

Dr. Srimanta Baishya,, Department of Electronics and Communication Engineering, National Institute of Technology Silchar, Assam, India.

Cognitive radio [3] promises to solve this problem and the complexity and heterogeneity characterizing the beyond 3G wireless scenario [4]-[7].

There are different signal processing techniques that can be used by a CU for spectrum sensing. The most popular methods among them are Matched Filter method, Energy Detection method and the Cyclostationary Feature Detection (CFD) method. Matched Filter method is the optimal method which requires prior knowledge of the incoming signal [9], where Energy Detection is a simple method with low complexity, but the performance is reduced at low Signal-to-Noise (SNR) environment. So in this work, we have used CFD as the detection method of the CUs, which is a data analysis algorithm that measures how the properties of a spectra varies position to position in a two dimensional spectral line-map [8] Apart from signal detection, CFD is also capable of determining the different features of the signal such as modulation type, carrier frequency etc. [9], [10].

II. CYCLOSTATIONARY FEATURE DETECTION

Many of the communication signals in use today are cyclostationary. The reason behind this is the coupling of stationary message signals with the periodic sinusoidal carriers, pulse trains or repeating code. So, these signals will exhibit periodicity in its autocorrelation. If the autocorrelation of a process is periodic, the autocorrelation will have its own frequency, called the cycle frequency(denoted by **α**).Since it is periodic with frequency, it can be described by Fourier series as follows:

$$R_x(t, \zeta)=\sum R_x(\zeta)e^{j2\pi\alpha t} \quad (1)$$

Where, $R_x(\tau)$ is the Cyclic Autocorrelation Function of process $x(t)$ with cycle frequency α, and also the Fourier coefficients of the autocorrelation of process(t)[11],[12].

Thus, the Fourier coefficients can be expressed as [13]-

$$R_x^{\alpha}(\zeta)=\lim_{t\rightarrow \alpha T}\frac{1}{T}\int x(t+\alpha/2)\, x(t-\alpha/2)^*\, e^{j2\pi\alpha t}\, dt \quad (2)$$

When α=0, the Cyclic Autocorrelation will not be periodic but will be constant. In this case the Cyclic Autocorrelation function will be equal to simple autocorrelation. Thus Cyclic Autocorrelation includes normal autocorrelation.

Again according to Wiener relation, when we take Fourier Transform of a autocorrelation function then we get Power Spectral Density. Similarly in this case if we take Fourier Transform of Cyclic Autocorrelation, we will get Spectral Correlation Function while α≠0.

So, according to cyclic Wiener relation,

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

$$S_x^{\alpha}(f) = F\{R_x^{\alpha}(\tau)\} = \int_{-\alpha}^{\alpha} Rx(\tau)\, e^{-j2\pi f\tau} d\tau \qquad (3)$$

Where, $S_x^{\alpha}(f)$ is the Spectral Correlation Function and can be defined as the three dimensional complex transform on a support set (f, α).

Based on (2) and (3) the algorithm to find Spectral Correlation Function is modeled as shown.

III. RESULTS AND DISCUSSION

The Spectral Correlation Function represents the spectral components of a process are correlated with other spectral components of the process and thus it can be used for detection of a signal and different features of the signal. The model is designed on Intel Core i5,650 @ 3.20GHz,RAM size-4G,32 Bit Windows 7 OS. Based on the proposed algorithm the Spectral Correlation Function of the modulated signal is then derived from Cyclic Autocorrelation Function. The Spectral Correlation Function of the specific modulated (DSB-SC) signal found is shown in figure-1.

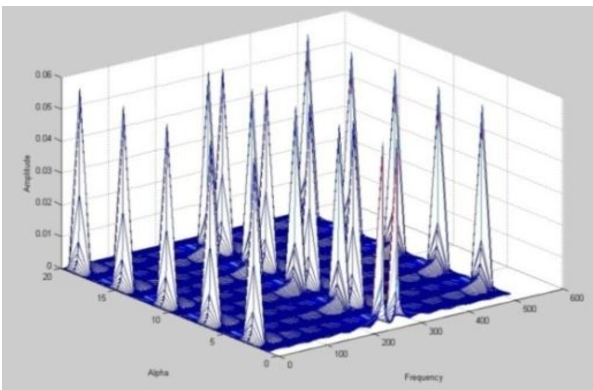
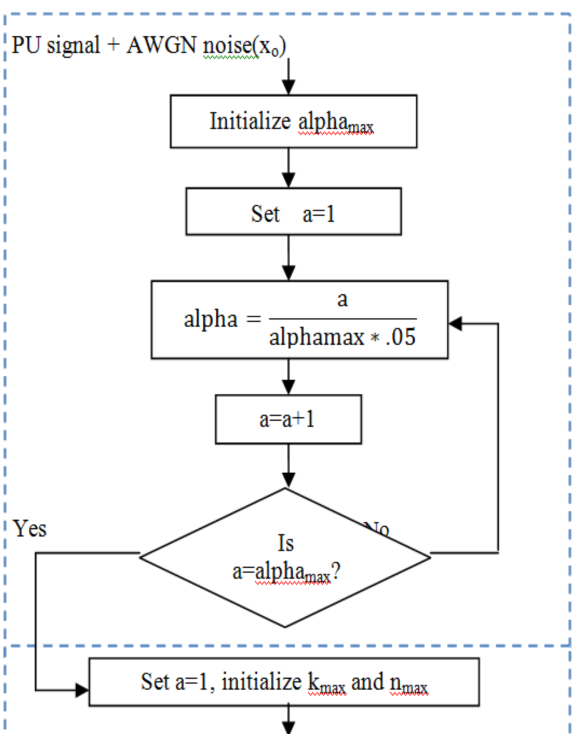
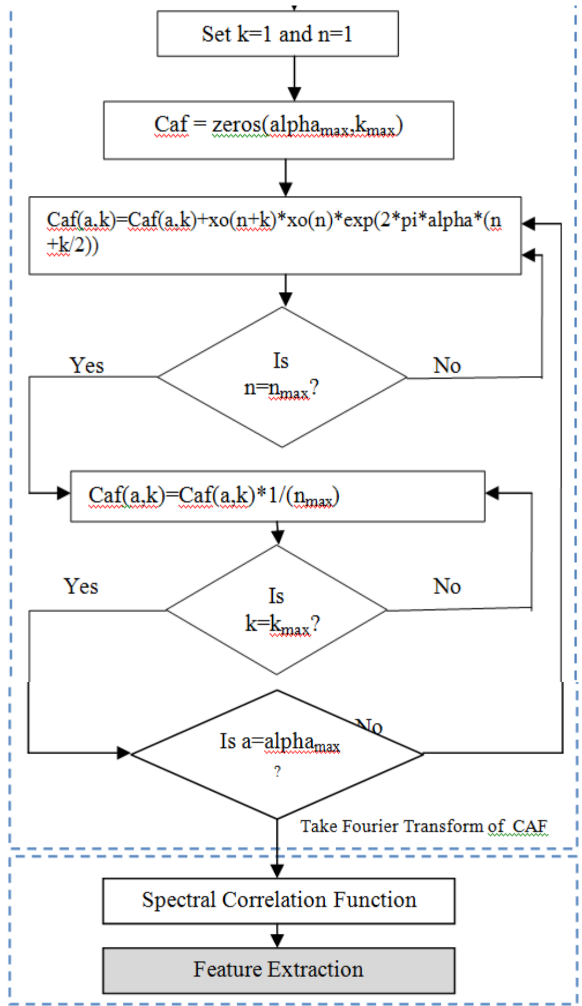


Fig 1: Spectral Correlation Function of the DSB-SC modulated signal showing different amplitudes for different positions of *Alpha* (α)





Algorithm to obtain SCF using Cyclostationary Detection.

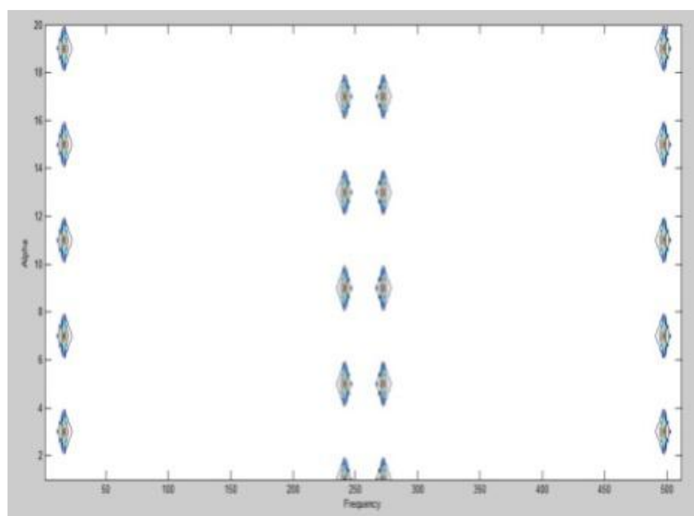


Fig 2: Contour Plot of Spectral Correlation Function of the DSB-SC modulated signal

If we modulate the above message signal with SSB (Single Side Band), then according to the above algorithm we will get different Spectral Correlation Function with

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

different magnitudes for various position of *Alpha* (α) as in figure-3.

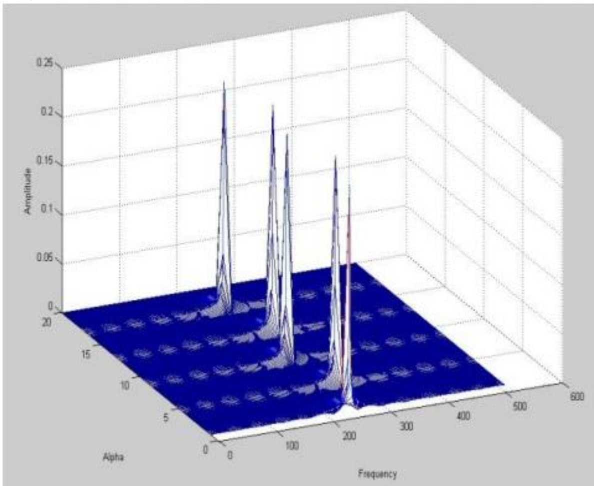


Fig 3: Spectral Correlation Function of the SSB modulated signal showing different amplitudes for different positions of *Alpha* (α) which different from the DSB-SC modulated signal.

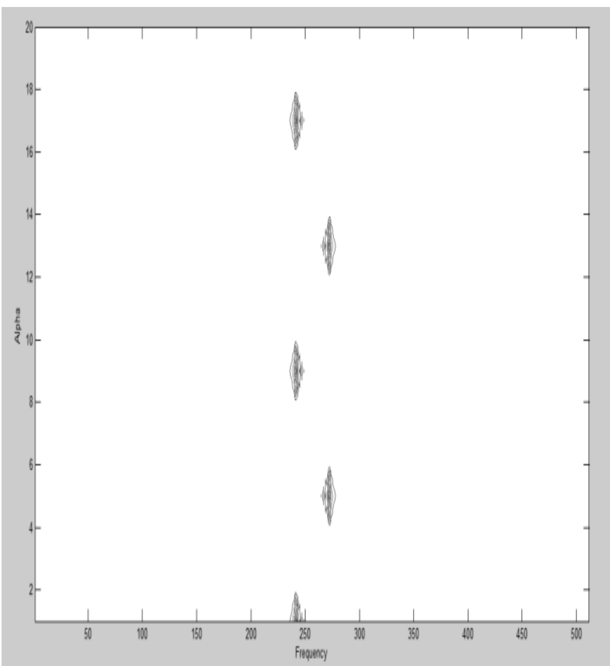


Fig 4: Contour Plot of Spectral Correlation Function of the SSB modulated signal

By inspecting the locations and relative magnitudes of the peaks at α≠0 from the diagram of Spectral Correlation Function, we can determine the modulation type as different modulation type will have different Spectral Correlation Function. Amplitudes of SCF for different modulation at α=1 is shown in figure-5.

From the figure-6 it is seen that at **α**=0, the Spectral Correlation Function will be same as Power Spectral Density. Hence through Spectral Correlation Function, Power Spectral Density of the received signal may be obtained.

The another advantage of Spectral Correlation Function is that it will have different unique features for same modulation type with different number of possible symbols,

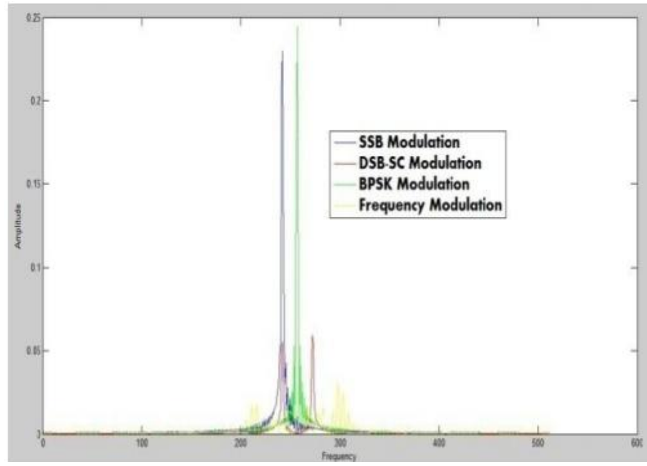


Fig 5: Plot of SCF for different modulation at α=1

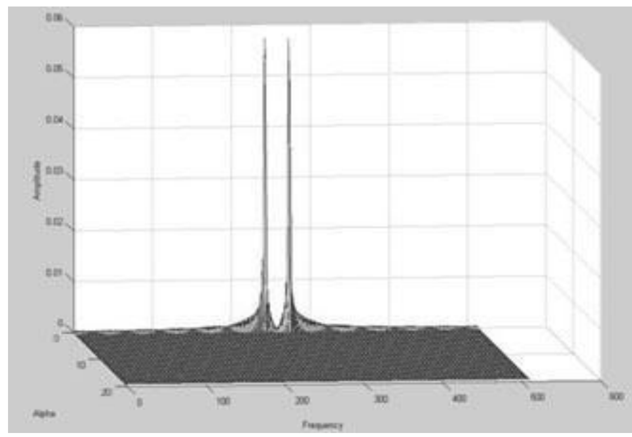


Fig 6: Spectral Correlation Function of the DSB-SC modulated signal at α=0which is same as Power Spectral Density of the modulated signal.

such as BPSK and QPSK. Whereas the *power spectral density (PSD)* shows almost identical feature for the same modulation type. The signals BPSK and QPSK differ only in their phase shifts and pulse timing and, as a result they have identical PSDs. However these difference in phase and timing results in substantially different *SCF*s. In fig-9 and fig-10, we can see the difference between the graphs if both are split into four quadrants and evaluate magnitude of maximum peak in each quadrant separately.

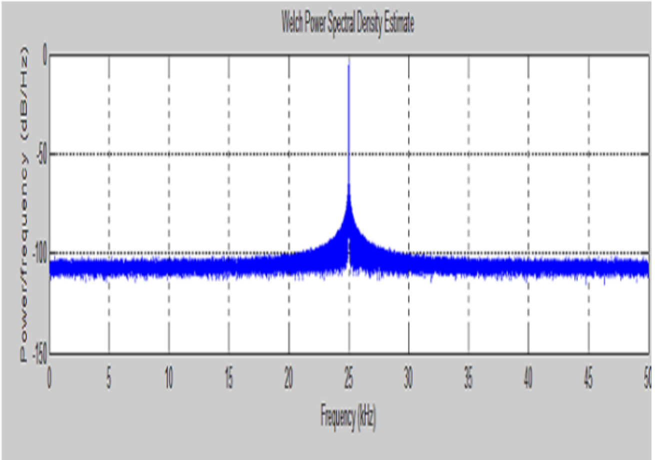


Fig 7: Power Spectral Density of the BPSK –modulated signal.

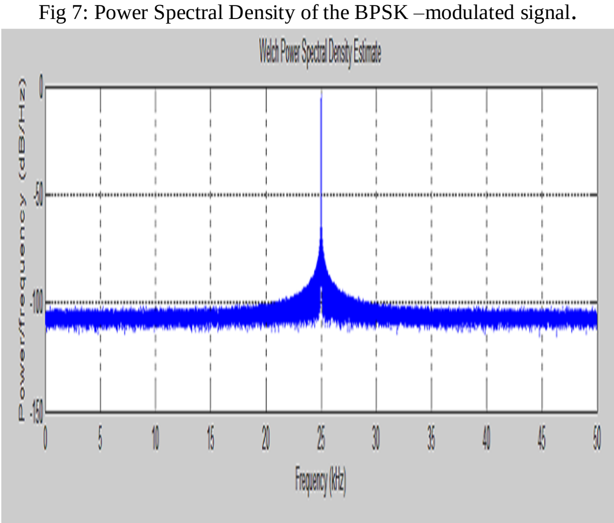


Fig 8: Power Spectral Density of the 4-PSK –modulated signal which is exactly same as the Power Spectral Density of the BPSK –modulated signal.

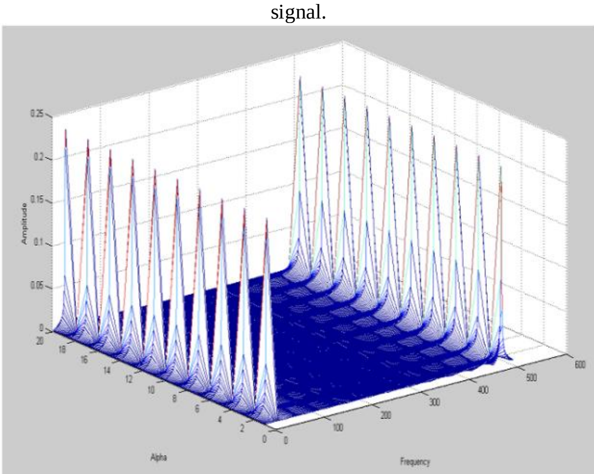


Fig 9: Spectral Correlation Function of the BPSK –modulated signal

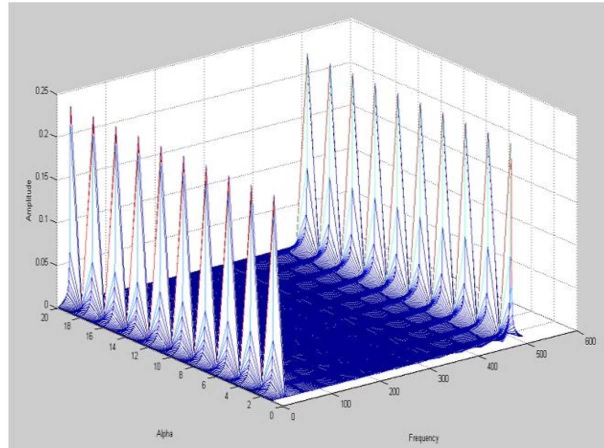


Fig 10: Spectral Correlation Function of the 4-PSK –modulated signal which is different from the Spectral Correlation Function of the BPSK –modulated signal.

Through training and testing of different processes and studying the sensing environment of the cognitive radios we can make a database of Spectral Correlation Function of different types of modulations for different carrier frequencies. On comparing the SCF of the incoming modulated signal with that already saved database we can get the different features of the signal as different database determines different modulation type, different carrier frequency etc.

IV. ADAPTIVE SPECTRUM SENSING MODEL

Energy Detector is the another well-known and simple spectrum sensing technique which uses Power Spectral Density. It is based on the principle that, at the reception, the energy of the signal to be detected is always higher than the energy of the noise. It estimates the presence of a signal by comparing the energy received with a known threshold, λ.

If X[n] is the received signal, then the decision statistic for energy detection is-

$$\zeta = \sum (X[n]^2) \text{ for } n=1 \text{ to } u \qquad (4)$$

Where, u denotes the number of sensing samples

If $\zeta <$ threshold $\quad H_0$

If $\zeta >$threshold $\quad H_1$

Where H_0 and H_1 represent hypothesis corresponding to the absence and presence of primary user's signal respectively [16].

The probability of false-alarm (P_{fa}) and probability of detection (P_d) can be described as

$$P_d = Q(\sqrt{2\Upsilon}, \sqrt{\lambda}) \qquad (5)$$

$$P_{fa} = \frac{\Gamma(u, \frac{\lambda}{2})}{\Gamma(u)} \qquad (6)$$

WhereΥ denotes signal-to-noise ratio and $Q(.,.)$ and $\Gamma(.,.)$ are the Marcum Q-function and incomplete gamma function respectively.

Now, considering both Cyclostationary and Energy Detection and varying the SNR with P_d, keeping P_{fa} constant, the obtained result using Monte-Carlo Simulations is shown in figure-11.

From figure-11, it is seen that when the SNR is very low Energy Detection fails to detect the incoming signal, but Cyclostationary Detection still have the ability to detect it and extract different features of it.

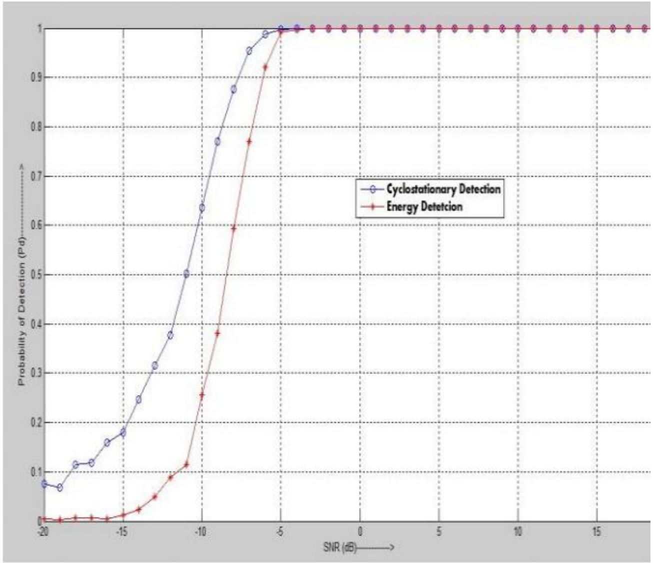


Fig 11: SNR vs Probability of Detection(P_d)curve for both Cyclostationary and Energy detection taking probability of false-alarm (P_{fa}) as .001

Again computational complexity of Cyclostationary Feature Detection (O (N^2 + $N/2$ $\log_2 N$)) is much more complicated as compared to Energy Detection method (O ($N/2$ $\log_2 N$)) [14],[15]. To meet the time and sensitivity requirements, we have proposed an efficient model for spectrum sensing where Cyclostationary Feature Detection will be used as a complimentary option when energy detection fails. Both the detection technique will have its own specific SNR wall below which it cannot detect the signal. So according to this model, when the SNR level is very low (SNR wall($\sigma 2$) for CFD< SNR≤SNR wall($\sigma 1$)) for ED) then it will use Cyclostationary Feature Detection as spectrum sensing technique. Otherwise it will use Energy Detector for spectrum sensing.

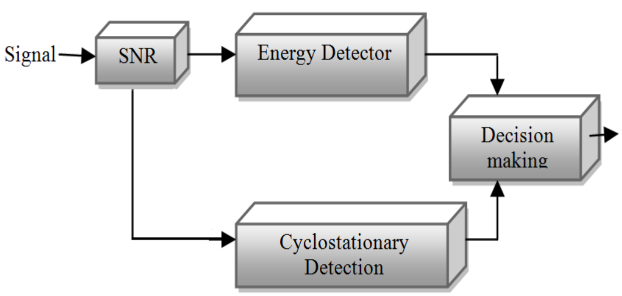


Fig 12: Block diagram of Adaptive Spectrum Sensing model.

Where ζ_1 and ζ_2 denotes test statistics for Energy Detection and Cyclostationary Feature Detection respectively. The different P_d according to SNR for Energy Detection, Cyclostationary Detection and the proposed Adaptive Model are listed in table-1. In the proposed model the SNR hard decision threshold for Energy Detection is set at -10 dB(worse case) and above it automatically Cyclostationary Feature Detection starts sensing the channel. The result shows the model is detecting the presence of Primary user upto -20dB where the Pd is around 0.1

The algorithm for our proposed sensing model is as follows-

Step 1: Initialize u (number of sensing samples)
Determine σ_1 and σ_2.
Where, σ_1 and σ_2 denote SNR wall for Energy Detection and Cyclostationary Feature Detection respectively.
Step 2: Determine SNR of the incoming signal.
Step 3: Estimate λ keeping P_{fa} constant.
Step 4: If SNR >σ_1,go to Step 5.
Else if σ_2< SNR ≤ σ_1, go to step 6.
Else go to END.
Step 5: Ifζ_1> λ, set detect=1, go to END
Else go to Step 2.
Step 6: If ζ_2> λ, set detect=1, go to END
Else go to Step 2.
END

V. CONCLUSION

Spectrum sensing is a key element in cognitive radio which enables the cognitive radio to share the licensed bands by detecting temporarily unused spectral resources. In this paper, we have studied the Cyclostationary based signal feature extraction .

Table - 1*: Result showing the variation of P_d of Energy detection, Cyclostationary detection and Adaptive model w.r.t SNR*

SNR (dB)	$(P_d)_{Energy}$	$(P_d)_{Cyclo}$	$(P_d)_{Adap}$
20	1	1	1
19	1	1	1
18	1	1	1
17	1	1	1
16	1	1	1
15	1	1	1
:	:	:	:
5	1	1	1
3	1	1	1
2	1	1	1
1	1	1	1
0	1	1	1
-1	1	1	1
-2	1	1	1
-3	1	1	1
-4	0.998	1	0.998
-5	0.992	0.998	0.992
-6	0.920	0.988	0.920
-7	0.770	0.954	0.770
-8	0.594	0.876	0.594
-9	0.380	0.770	0.380
-10	0.256	0.636	0.256
-11	0.114	0.502	0.502
-12	0.088	0.378	0.378
-13	0.050	0.316	0.316
-14	0.024	0.246	0.246
-15	0.012	0.180	0.180
-16	0.004	0.160	0.160
-17	0.003	0.118	0.118
-18	0.001	0.114	0.114
-19	0.000	0.068	0.068
-20	0.000	0.076	0.076

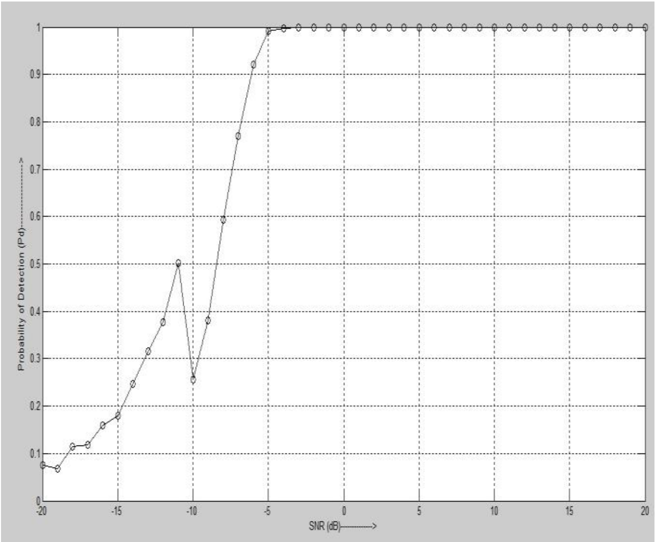


Fig 12: SNR vs. Probability of Detection(P_d)curve for the proposed Adaptive sensing model.

Technique and implement an adaptive model which effectively enhances the detection probability even in low SNR. The comparison between SCF and PSD has been studied by using different properties and the result shows SCF as more efficient than PSD under low SNR condition which validates today's wireless environment. The different signature parameters of the signals may also be extracted from the SCF model and may be used for advanced reliable spectrum sensing technique. Our aim is to create a knowledge base at the cognitive network nodes supported by an adaptive and fast spectrum sensing technique for wideband co-operative cognitive radio network.

REFERENCES

1. FCC, B Spectrum Policy Task Force, ET Docket 02-135, Nov. 2002.
2. M. McHenry, E. Livsics, T. Nguyen, and N. Majumdar, BXG dynamic spectrum access field test results, IEEE Commun. Mag.,vol. 45, pp. 51–57, Jun. 2007.
3. J. Mitola and G. Q. Maguire, "Cognitive radio: Making software radios more personal," IEEE Pers. Commun. , vol. 6, Aug. 1999, pp. 13–18.
4. S. Haykin, "Cognitive radio: brain-empowered wireless communications," IEEE J. Select. Areas Commun., vol. 23, Feb. 2005, pp. 201-220.
5. Paul D. Sutton. "Cyclostationary signature inpractical cognitive radio application". IEEE journalon Selected Areas In Communications, VOL. 26, NO.1, January 2008.
6. J. Mitola III, "Cognitive radio an integrated agent architecture for software defined radio", KTH Royal Institute of Technology, Stockholm, Sweden, 2000.
7. Qiwei Zhang, Andre B.J. Kokkeler and Gerard J.M.Smit, "A reconfigurable radio architecture for cognitive radio in emergency network", Proceedings of 9th European Conference on Wireless Technology.
8. K. Kim, I.A. Akbar, K. K. Bae, J. S. Um, C. M. Spooner, and J. H. Reed, "Cyclostationary approaches to signal detection and classification in cognitive radio," in Proc. IEEE DySpan, 2007, pp. 212–215.
9. W. A. Gardner, Statistical Spectral Analysis: A Non probabilistic Theory. Englewood Cliffs, NJ: Prentice-Hall, 1988.
10. G. K. Yeung and W. A. Gardner, "Search efficient methods of detection of cyclostationary signals," IEEE Trans. Signal Processing , vol. 44, no. 5, pp. 1214–1223, May 1996.
11. Paul D. Sutton. "Cyclostationary signature inpractical cognitive radio application". IEEE journalon Selected Areas In Communications, VOL. 26, NO.1, January 2008
12. William A. Gardner, "Spectral Correlation of Modulated Signals-Part-I-Digital Modulation", IEEETrans. on Commun. ,Vol.35,no.6, pp-595-601.
13. ArtemT kachenko, DanijelaCabric, and Robert W.Brodersen, "Cyclostationary Feature Detector Experiments using Reconfigurable BEE2", in 2ndIEEE International Symposium on New Frontiers in Dynamic Spectrum Access Networks ,2007
14. Dong-Chan Oh and Yong-Hwan Lee, "Energy detection based spectrum sensing for sensing error minimization in Cognitive Radio networks" International journal of Communication Networks and Information Security, vol. 1, no. 1, April 2009.
15. W. M. Gardner, "Measurement of Spectral Correlation," IEEE Trans. Acoustics, Speech, and Signal Processing, vol. ASSP-34, No. 5, Oct. 1986.