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.

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. 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 \( \alpha \)). Since it is periodic with frequency, it can be described by Fourier series as follows:

\[
R_x(t, \zeta) = \sum \mathcal{R}_x(i\zeta)e^{j2\pi \zeta t}
\]

Where, \( R_x(t) \) is the Cyclic Autocorrelation Function of process \( x(t) \) with cycle frequency \( \alpha \), and also the Fourier coefficients of the autocorrelation of process \( x(t) \).[11],[12]. Thus, the Fourier coefficients can be expressed as [13]-

\[
R_x^f(\zeta) = \lim_{T \to \infty} \frac{1}{T} \int_{\alpha T}^{(\alpha+1)T} x(t+\alpha/2) x(t-\alpha/2) e^{j2\pi \zeta t} dt
\]

When \( \alpha = 0 \), 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 \( \alpha \neq 0 \).

So, according to cyclic Wiener relation,

\[
S_C^f(f) = F[R_x^f(\tau)] = \int_{-\alpha}^{\alpha} R_x(\tau)e^{-j2\pi ft}\, d\tau
\]
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Where, \( S_\alpha(f) \) is the Spectral Correlation Function and can be defined as the three dimensional complex transform on a support set \((f, \alpha)\).

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 (\(\alpha\))](image)

Algorithm to obtain SCF using Cyclostationary Detection.

![Fig 2: Contour Plot of Spectral Correlation Function of the DSB-SC modulated signal](image)

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 different magnitudes for various position of Alpha (\(\alpha\)) 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

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

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

If \( X[n] \) is the received signal, then the decision statistic for energy detection is:

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

Where, \( u \) denotes the number of sensing samples

If \( \zeta < \text{threshold} \) \( H_0 \)
If \( \zeta > \text{threshold} \) \( H_1 \)

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

\[
P_d = Q(\sqrt{2Y}, \sqrt{\lambda})
\]

\[
P_{fa} = \frac{\Gamma(u, \frac{\lambda}{2})}{\Gamma(u)}
\]

Where \( Y \) denotes signal-to-noise ratio and \( Q(\ldots) \) and \( \Gamma(\ldots) \) 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.

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.
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.

![Signal Detection Diagram](image)

**Fig 12:** Block diagram of Adaptive Spectrum Sensing model.

Where $\zeta_1$ and $\zeta_2$ 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 $\sigma_1$ and $\sigma_2$.
Where, $\sigma_1$ and $\sigma_2$ denote SNR wall for Energy Detection and Cyclostationary Feature Detection respectively.

**Step 2:** Determine SNR of the incoming signal.

**Step 3:** Estimate $\lambda$ keeping $P_{fa}$ constant.

**Step 4:** If $SNR > \sigma_1$, go to Step 5.
Else if $\sigma_2 < SNR \leq \sigma_1$, go to step 6.
Else go to END.

**Step 5:** If $\zeta_1 > \lambda$, set detect=1, go to END
Else go to Step 2.

**Step 6:** If $\zeta_2 > \lambda$, set detect=1, go to END
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**END**

<table>
<thead>
<tr>
<th>Table 1: Result showing the variation of $P_d$ of Energy detection, Cyclostationary detection and Adaptive model w.r.t SNR</th>
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<tbody>
<tr>
<td>SNR (dB)</td>
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![SNR vs. Probability of Detection(P_d) Curve](image)

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

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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.
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