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Full Length Research Paper

A review of cyclostationary feature detection based spectrum sensing technique in cognitive radio networks

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In wireless communications, the transmitted signals show very strong cyclostationary features based on the modulation type, carrier frequency, and data rate, especially when excess bandwidth is utilized. Therefore, identifying the unique set of features of a particular radio signal for a given wireless access system can be used to detect the system based on the cyclostationary analysis at the cognitive radio node. Cyclostationary feature detection based technique has been proposed by many researchers as a key solution for detecting these signals. This paper therefore, took a detail review of the proposals from different authors and pointed out the challenges faced by this method and concluded that it cannot be used to achieve optimality when detecting the presence and absence of primary user. The paper also went further to analyze the principle and model for cyclostationary feature based detection method.

Keywords: Cognitive radio, Cyclostationary feature detection, Spectrum sensing, cyclic power spectrum (CPS).

Introduction

The need for a flexible and robust wireless communication is becoming more evident in recent times. The future of wireless networks is thought of as a union of mobile communication systems and internet technologies to offer a wide variety of services to the users. Conventionally, the policy of spectrum licensing and its utilization lead to static and inefficient usage. The requirement of different technologies and market demand leads to spectrum scarcity and unbalanced utilization of frequencies. It has become essential to introduce new licensing policies and co-ordination infrastructure to enable dynamic and open way of utilizing the available spectrum efficiently. One promising solution to such problems is the Cognitive Radio. It is an intelligent wireless communication system that is aware of its surrounding environment and under a certain methodology is able to use the current available spectrum momentarily without interfering with the primary user who paid to be served in that area.

According to Federal Communication Commission (FCC), a cognitive radio is a radio or system that senses its operational electromagnetic environment and can dynamically and autonomously adjust its radio operating parameters to modify system operation, such as maximize throughput, mitigate interference, facilitate interoperability, access secondary markets The diagram in figure 1 according to Castro, 2011 shows a typical Cognitive Radio System.. Cabric *et. al*., (2004) and Haykin *et. al*., (2010) affirmed that one enabling technique for CR is spectrum sensing which is the ability to measure, sense and be aware of the parameters related to the radio channel characteristics, availability of spectrum and transmit power, interference and noise, radio's operating environment, user requirements and applications, available networks (infrastructures) and nodes, local policies and other operating restrictions. It is done across

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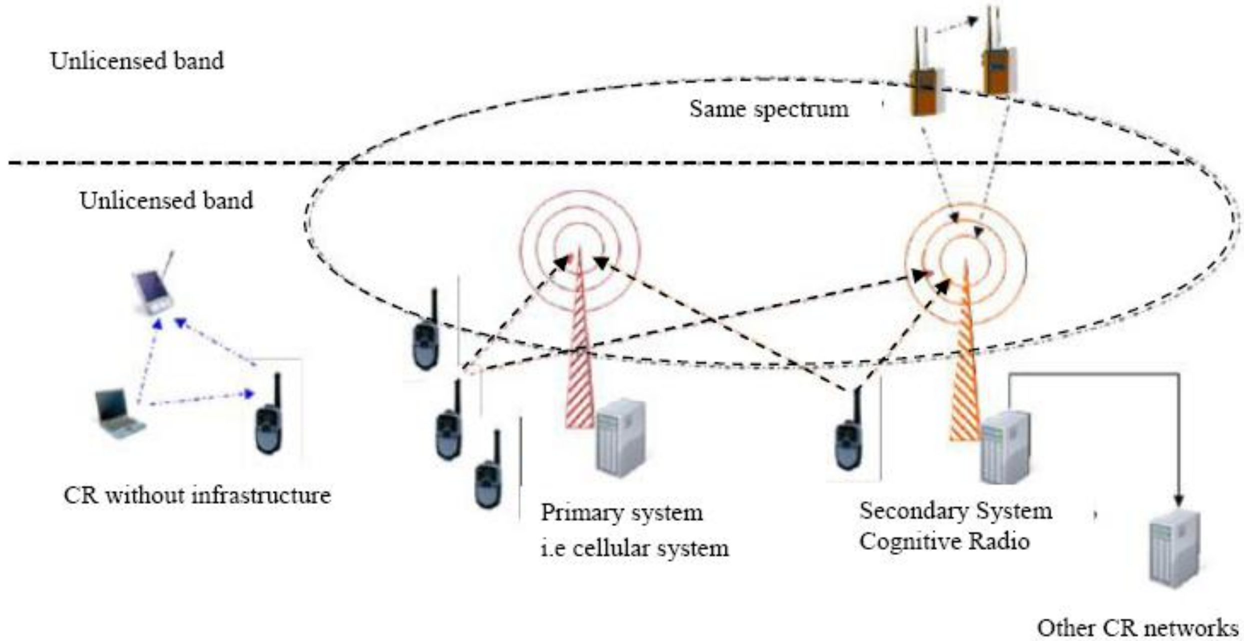

Figure 1: Cognitive Radio System (Castro 2011)

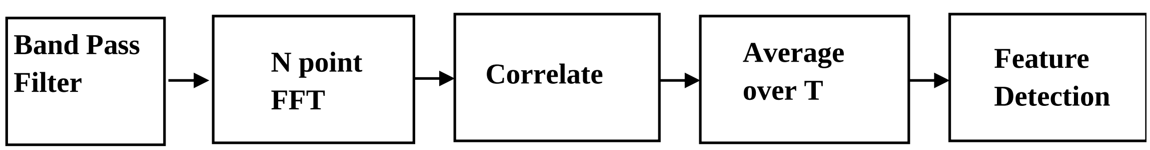

Figure 2: Block diagram of Cyclostationary feature (Shahzad 2010). detection

frequency, time, geographical space, code and phase. In summary, spectrum sensing refers to the identification of the most likely white spaces or spectrum holes in a specific moment. One of the key challenges of CR technology is to reliably detect the presence or absence of primary users at very low signal-to-noise ratio. There are various spectrum sensing techniques available such as the energy detector based sensing, waveform-based sensing, cyclostationarity based sensing and others Arslan and Yucek (2009) affirms. This paper therefore review the cyclostationarity based feature detection sensing methods as proposed by different authors and pointed out the prevailing challenges facing this method.
Cyclostationary feature detection is a method for detecting primary user transmissions by exploiting the cyclostationarity features of the received signals. It exploits the periodicity in the received primary signal to identify the presence of primary users (PU). The periodicity is commonly embedded in sinusoidal carriers, pulse trains, spreading code, hopping sequences or cyclic prefixes of the primary signals. Due to the periodicity, these cyclostationary signals exhibit the features of periodic statistics and spectral correlation, which is not found in stationary noise and interference Tkachenko *et. al*., (2007) affirmed. Cyclostationary features are caused by the periodicity in the signal or in its statistics like mean and autocorrelation or they can be intentionally induced to assist spectrum sensing.

Cyclostationary feature detection model

The block diagram for cyclostationary feature detection is presented in this section as shown in figure 2. The flow diagram presented in figure 3 according to Mishra *et al*., 2014 provides details of the entail process.

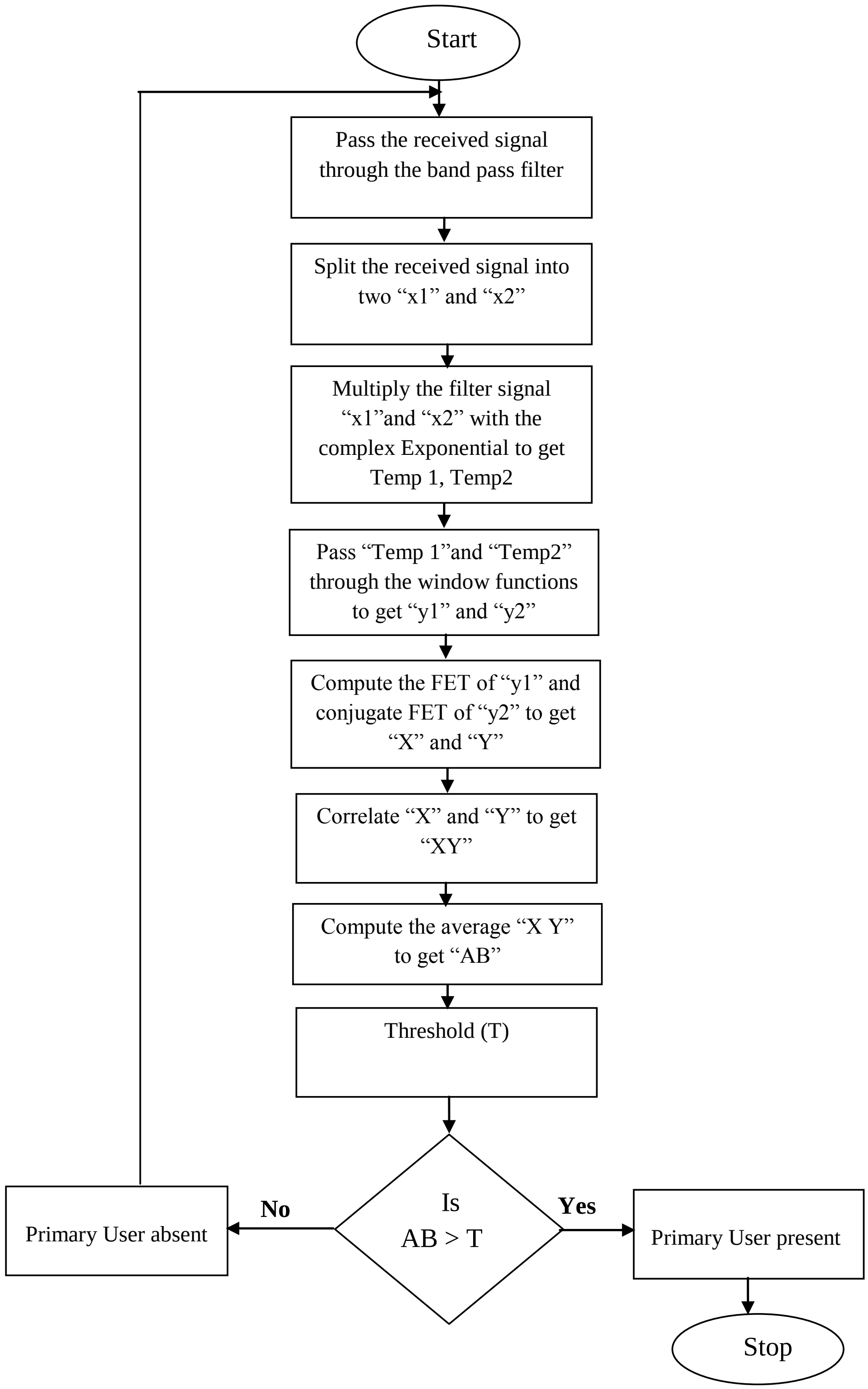

Figure 3: Process Flow diagram of Cyclostationary feature Detection (Mishra et al., 2014)

Principle of Cyclostationarity

A signal is said to be stationary if its frequency or spectral contents are not changing with respect to time. This is because when sine waves are generated using either a function generator or software, the frequency values are selected and kept constant forever. Thus the frequency content of the sine wave will not change with time and hence is an example for stationary signal. Suppose if you change the frequency, then it altogether becomes a new sine wave. Stationarity is linked to the behaviour of the frequency contents of the signal with respect to time and nothing else. A cyclostationary process is a signal having statistical properties that vary cyclically with time. According to Dave (2012), a cyclostationary process can be viewed as multiple interleaved stationary processes. These processes are not periodic function of time but their statistical features indicate periodicities. The following conditions are essential to be filled by a process for it to be wide sense cyclostationary. According to Baldini *et. al*., (2012), a random process $x(t)$ is classified as a wide sense cyclostationary process if the mean and

$$E_x(t) = E_x(t+mT) = E[x(t)] \qquad (3.1)$$

some period T,

and

$$R_x(t,\tau) = R_x(t+mT,\tau) = E[x(t)x(t+\tau)] \qquad (3.2)$$

where, t is the time variable, t is the lag associated with the autocorrelation function, $\tilde{x}(t)$ is the complex conjugate of $x(t)$, and m is an integer. The periodic autocorrelation function can be expressed in terms of the Fourier series given by

$$R_x(t,\tau) = \sum_{\alpha=-\infty}^{\infty} R_X^{\alpha}(\tau)\exp(2 = \pi j\alpha t) \qquad (3.3)$$

when

$$R_X^{\alpha}(\tau) = \lim_{T\to\infty}\frac{1}{T}\int_T x(t+\frac{\tau}{2})\tilde{x}(t-\frac{\tau}{2})\exp(-2\pi j\alpha t)dt \qquad (3.4)$$

The expression in (3.4) is known as the cycle autocorrelation. Using the Wiener relationship, cyclic power spectrum (CPS) or the spectral correlation function can be defined as:

$$S_X^{\alpha}(f) = \int_{-\infty}^{\infty} R_X^{\alpha}(\tau)\exp(-j2\pi f\tau)d\tau \qquad (3.5)$$

The CPS in (3.5) is a function of the frequency f and the cycle frequency α and any cyclostationary features can be detected in the cyclic frequency domain a property that is exploited to be used as a spectrum sensing technique. An alternative expression for (3.4) for the ease of computing the CPS is given by

$$S_X^{\alpha}(f) = \lim_{T_0\to\infty}\lim_{T\to\infty}\frac{1}{T_0 T}\int_{-T_0/2}^{T_0/2} X_T(t, f+\frac{1}{\alpha})\tilde{X}_T(t, f-\frac{1}{\alpha})dt \qquad (3.6)$$

Where $\tilde{X}_T(t, u)$ is the conjugate of $X_T(t, u)$, and $X_T(t, u)$ given by

$$X_T(t,u) = \int_{t-T/2}^{t+T/2} x(v)\exp(-2j\pi uv)dv \qquad (3.7)$$

Expression in (3.6) is also known as the time-averaged CPS, which achieves the theoretical CPS when computed over a sufficient number of samples. In order to use the cyclostationary features to perform spectrum sensing in wireless communications, the hypothesis equation for the presence of a primary user signal can be re-written considering the CPS as

$$H_0: S_r^{\alpha}(f) = S_v^{\alpha}(f)$$

$$H_1: S_r^{\alpha}(f) = S_s^{\alpha}(f) + S_v^{\alpha}(f) \qquad (3.8)$$

Where, $S_v^{\alpha}(f)$ is the CPS of the additive noise $u(t)$, and $S_s^{\alpha}(f)$ is the CPS of the primary user signal $s(t)$. Since $v(t)$ is not a cyclostationary process, the CPS of v for $\alpha \neq 0$ is zero.

Review of works on Cyclostationary feature based detection

Cyclostationary feature detection is a method that has been proposed by several authors for sensing the presence and absence of primary users. From the initial work by Gardner (1991) which highlighted that most of the communication signals can be modeled as cyclostationary that exhibits underlying periodicities in their signal structures. Oner and Jondral (2004), proposed Cyclostationarity based air interface recognition for software radio systems. In their work they showed that wireless transmissions in general show very strong cyclostationarity features depending on their modulation type, data rate and carrier frequency etc., especially when excess bandwidth is utilized. Therefore the identification of the unique set of features of a particular radio signal for a given wireless access system can be used to detect the system based on its cyclostationarity features. They claimed that Spectrum sensing based on cyclostationarity performs very well with very low signal-to-noise ratio. Sutton *et. al*., (2008), proposed an alternative approach to feature detection using signatures embedded in a signal to solve a number of challenges associated with dynamic spectrum access applications; especially receiver complexity. Using a flexible cognitive radio platform, implementation of a full Orthogonal Frequency Division Multiplexing (OFDM) based transceiver using cyclostationary signatures is presented and the system performance is examined from experimental results. Although, methods presented therein are OFDM specific, similar techniques can be developed for any type of signal. In the work of Cabricand Broderson (2005), Fehske *et. al*., (2005), Ghozzi *et. al*., (2006), Khambekar *et. al*., (2007), they showed that cyclostationarity feature detection was a method for detecting primary user transmissions by exploiting the cyclostationarity features of the received signals. In the work of Hou-Shin *et. al*., (2007), the authors study spectrum detection in a low SNR environment applying the noise rejection property of the cyclostationary spectrum. This is computed by measuring the cyclic spectrum of the received signal. Statistics concerning the spectrum of the stationary white Gaussian process were fully analyzed. An application to the IEEE 802.22 WRAN1, alongside analytic derivation of the probability of false alarm is also presented. Since the stationary Gaussian process has a zero-valued spectral correlation density function (SCD) at nonzero frequencies, the desired signal is detected by computing the SCD - provided the signal is cyclostationary - such that its cyclic spectrum is not identically zero at some nonzero cyclic frequency.

A detector for OFDM signals based on cyclostationary features is presented by Axell and Larsson (2011), their work exploits the inherent correlation of Orthogonal Frequency Division Multiplexing (OFDM) signals obtained by data repetition in the cyclic prefix; i.e. using knowledge of the length of the cyclic prefix and length of the OFDM symbol. The authors demonstrated that detection performance improves by 5dB in applicable cases. Choi *et. al*., (2007), proposed cyclostationarity based collaborative detection where binary decisions of the secondary users using cyclic detectors are combined. Optimal test thresholds at the fusion center (FC) and the secondary users are determined using an iterative algorithm. However, due to the iterative nature of the algorithm, multiple expensive transmissions between the FC and the secondary users are required. Koivunen *et. al*., (2009), proposed a collaborative cyclostationary spectrum sensing for cognitive radio systems. In their work, cyclostationary spectrum sensing of primary users in a cognitive radio system was considered. They proposed single user multicycle detectors and extended them to accommodate user collaboration. They also proposed a censoring technique for reducing energy consumption and the number of transmissions of local test statistics during collaboration. They claimed that combining cyclostationary detection and user collaboration with censoring provides a powerful energy efficient approach for spectrum sensing in cognitive radio systems and that their approach is able to distinguish among primary users, secondary users, and interference. Chakravarthy and Wu (2007), propose cyclostationary spectrum sensing method which was used to detect spectral correlation peaks of a PU signal, in their work they first estimated the spectral correlation function (SCF), which was a two dimensional spectral map showing the spectral correlation peaks. Mishali and Eldar (2010), also proposed sub-Nyquist cyclostationary feature detection. In their work they used Modulated Wideband Converter (MWC) as a front-end. Cohen *et. al*., (2011), showed that one approach to perform sub-Nyquist cyclostationary feature detection is to first recover the Nyquist samples, then estimate the SCF, and perform feature detection. Tian (2011), considered cyclostationary detection using sub-Nyquist samples, the spectral correlation function (SCF), reconstruction was performed blindly with no a priori knowledge of the carriers and bandwidths of the signals to be detected. Rebeiz *et. al*., (2011), proposed cyclostationarity-based low complexity wideband spectrum sensing using compressive sampling. In their work they exploit the sparsity of the two-dimensional spectral correlation function (SCF), and propose a reduced complexity reconstruction method of the sub-Nyquist SCF from the sub-Nyquist samples. They analyzed the trade-off between compression ratio and sensing time, and showed that the SCF reconstruction, and concluded that signal detection, is feasible as long as the compression ratio is above the compression wall. Cyclostationary spectrum sensing was also investigated in the work of Hosseini *et. al*., (2010), which addressed the problem in many applications, for a specific signal, the statistical characteristics were not the same in two adjacent periods, but they change smoothly. So, the periodicity which appears in the aforementioned processes, does not necessarily lead to a pure cyclostationary process, but leads to an almost cyclostationarity which causes limitation on using cyclostationary features. The authors suggested a new estimator for almost cyclostationary signals. In the work of Thamizharasan *et. al*., (2013), cyclostationary spectrum sensing method for identifying the presence of primary user was introduced which uses the concept of periodicity in OFDM signals. They claimed that the proposed scheme was robust for the detection of primary user signal with guard interval insertion in the OFDM signals which use the concept of periodicity. Cyclostationary based spectrum sensing in cognitive radio: windowing approach was proposed by Mishra *et. al*., (2014)**,** in their work they studied how to sense a particular spectrum by using cyclostationary detection method. The received signal was passed in the output side into different windows and they found out the autocorrelation of different signals from each window and verified the channels occupied by the primary users as well as the channels not occupied by the primary users. The channels that are not occupied by the primary users were assigned to the secondary users. Their work shows that very fewer variations occurred during the evaluation of no. of frequency components to detect presence of PU and absence of PU by taking multiple iterations. They claimed that the best performance can be achieved by passing the signal through the “Rectangular window” and “Kaiser window”.

Challenges of Cyclostationary feature based detection

In the above reviewed cyclostationary based detection methods, though the signals which are used in several applications are generally coupled with sinusoid carriers, cyclic prefix, spreading codes, pulse trains etc. which result in periodicity of their statistics like mean and auto-correlation. Such periodicities can be easily highlighted when cyclic spectral density (CSD) for such signals is found out. Primary user signals which have these periodicities can be easily detected by taking their correlation which tends to enhance their similarity. Fourier transform of the correlated signal results in peaks at frequencies which are specific to a signal and searching for these peaks helps in determining the presence of the primary user. Noise is random in nature and as such there are no such periodicities in it and thus it doesn't get highlighted on taking the correlation. The challenges faced by this method are highlighted thus:
High computational complexity since all the cycle frequencies are calculated.It is characterize with long sensing time which is not favourable for situation under consideration.

Though the number of features generated in the signal is increased in order to increase the robustness against multipath fading. However, this comes at the expense of increased overhead and bandwidth loss. Requires a priori knowledge of specific transmitted signal parameters and characteristics

DISCUSSION AND RESULT

Nature has its way in such a manner that many of its processes arise due to periodic phenomenon. Examples include fields like radio astronomy wherein the periodicity is due to the rotation and revolution of the planets, weather of the earth due to periodic variation of seasons. In telecommunication, radar and sonar fields it arises due to modulation, coding etc. It might be that all the processes are not periodic function of time but their statistical features indicate periodicities and such processes are called cyclostationary process. For a process that is wide sense stationary and exhibits cyclostationarity has an auto-correlation function which is periodic in time domain. Now when the auto-correlation function is expanded in term of the Fourier series co-efficient it comes out that the function is only dependent on the lag parameter which is nothing but frequency. The spectral components of a wide sense cyclostationary process are completely uncorrelated from each other. The Fourier series expansion is known as cyclic auto-correlation function (CAF) and the lag parameter i.e. the frequencies is given the name of cyclic frequencies. The cyclic frequencies are multiples of the reciprocal of period of cyclostationarity. The cyclic spectrum density (CSD) which is obtained by taking the Fourier transform of the cyclic auto-correlation function (CAF) represents the density of the correlation between two spectral components that are separated by a quantity equal to the cyclic frequency. However, this has much usefulness in spectrum sensing because the signals which are used in several applications are generally coupled with sinusoid carriers, cyclic prefix, spreading codes, pulse trains etc. which result in periodicity of their statistics like mean and auto-correlation. Such periodicities can be easily highlighted when cyclic spectral density (CSD) for such signals is found out. Primary user signals which have these periodicities can be easily detected by taking their correlation which tends to enhance their similarity. Fourier transform of the correlated signal results in peaks at frequencies which are specific to a signal and searching for these peaks helps in determining the presence of the primary user. Noise is random in nature and as such there are no such periodicities in it and thus it doesn't get highlighted on taking the correlation. Result from review of this method show that it works well for signal to noise ratio (SNR) conditions and it has the capability to distinguish between primary user and noise and also can differentiate between different types of signals

Conclusion

In this paper, the basic analysis of cyclostationary feature detection was presented alongside its model. The paper also analyzed different authors and their proposed cyclostationary feature detection techniques. From the analysis, it was concluded that the signals which are used in several applications are generally coupled with sinusoid carriers, cyclic prefix, spreading codes, pulse trains etc, which result in periodicity of their statistics like mean and auto-correlation. Such periodicities can be easily highlighted when cyclic spectral density (CSD) for such signals is found out. Primary user signals which have these periodicities can be easily detected by taking their correlation which tends to enhance their similarity. Finally the challenges faced by this method were pointed out and this makes it not suitable for enhancing the sensing capability of cognitive radio.

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