Blind Spectrum Sensing Based on Cyclostationary Feature Detection

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Abstract. Cognitive Radio has emerged as a promising technology to improve the spectrum utilization efficiency, where spectrum sensing is the key functionality to enable its deployment. This study proposes a cyclostationary feature detection method for signals with unknown parameters. We develop a rule of automatic decision based on the resulting hypothesis test and without statistical knowledge of the communication channel. Performance analysis and simulation results indicate that the obtained algorithm outperforms reported solutions under low SNR regime.

Keywords: Cognitive radio · Cyclostationarity · Feature detection · Blind spectrum sensing

1 Introduction

A new paradigm for wireless communication devices called *Cognitive Radio* [1] has emerged to optimize the employment of the radio spectrum. Through the use of vacant channels it is possible to improve the spectrum utilization [2]. Several current technologies operate in this way, for example: *Bluetooth* (WPAN – IEEE 802.15.1) [3], WLAN – IEEE 802.11k [4], and WRAN – IEEE 802.22 [5]. In this regard, spectrum sensing techniques represent a key component of these systems.

From the perspective of signals detection, the spectrum sensing techniques can be classified as *coherent detection* or *non-coherent detection* [6]. In the former case, the signal of interest (SoI) is detected using a generated signal, this is conformed taking into account the modulation parameters like the carrier frequency and phase, order of the modulation, shape and duration of pulses, etc. Matched filter provides the optimal solution in terms of the output signal-to-noise-ratio (SNR). However, prior knowledge of the SoI is required [6]. On the other hand, non-coherent detection also referred as blind detection, does not require prior knowledge of the primary signals modulation parameters. Energy detection (ED) is the most widely used technique for blind detection [7]. Nevertheless, the incapability of distinguishing between different types of signals, the vulnerability to uncertainty in noise variance estimation, and the poor performance under low

A. Pardo and J. Kittler (Eds.): CIARP 2015, LNCS 9423, pp. 535–542, 2015.
DOI: 10.1007/978-3-319-25751-8_64

SNR regimes, represent an important limitation in practice [8]. On the other hand, the use of cyclostationarity detection (CD) is reported to mitigate the limitations of ED [9]. By means of CD, the performance in terms of reliability under low SNR and fading conditions overcomes the main disadvantages in regard to the ED [8,9]. Although this technique is considered by many authors as a coherent technique, there have been several attempts to use CD detectors in blind detection [10,11]. Jang in [11] gives a method to compute the cycle frequencies profile of the spectral correlation density (SCD). Using that method, the author proposes a threshold for automatically signal detection, which is the maximum estimated magnitude of SCD that rejects null hypothesis. The evaluation method used was Monte Carlo simulations, under multi-path fading and low SNR.

The rest of this paper is organized as follows. The CD model for blind detection is described in Section 2. In Section 3, the main results are discussed. Finally, the conclusions are drawn in Section 4.

2 Cyclostacionary Feature Detection

The spectrum sensing problem can be stated in terms of a binary hypothesis test, where $\mathcal{H}_0$ represents the hypothesis corresponding to the absence of the signal, and $\mathcal{H}_1$ to the presence of the signal. These hypotheses are given by:

$$\begin{aligned} \mathcal{H}_0 &: x[n] = \omega[n] \\ \mathcal{H}_1 &: x[n] = s[n] \otimes h[n] + \omega[n] \end{aligned} \qquad n = 0, 1, ..., N-1 \tag{1}$$

where $x[n]$ and $s[n]$ represent the received signal and the SoI, respectively. The impulse response of the channel ($h[n]$) is conformed taking into account fading conditions and it is modeled to be statistically independent from the additive white Gaussian noise (AWGN) of the channel ($w[n]$). The operation $\otimes$ indicates convolution product over N. The main difference between detection techniques is the statistic used to discriminate the hypotheses. The spectral correlation density function is the statistic used in cyclostationary feature detection.

2.1 Cyclostationary Processes

Cyclostacionarity[1] is an inherent property of the communication signals. This feature is present in sinusoidal carriers, train pulses, spreading codes, hopping sequences, cyclic prefixes and preambles, sampling and propagation phenomena [13]. For these signals, the autocorrelation function is periodic and can be obtained by a set of basis functions called *cyclic autocorrelation function* (CAF). The CAF is a generalization of the autocorrelation function, and allows to distinguish cyclic features from stationary noise. Extrapolating Wiener-Khinchin's

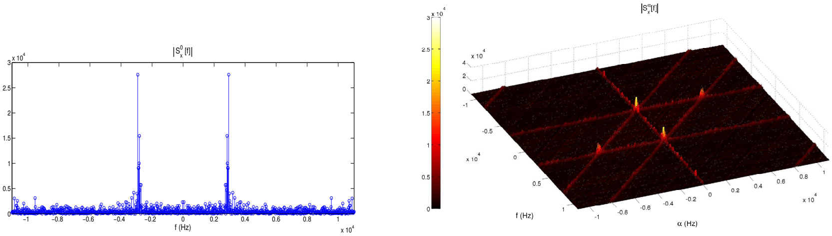
[1] In the proposed model, only *wide sense cyclostationary processes* are considered. Further mathematical details can be found in [12].

theorem [14] to cyclostationary signals, the Fourier transform of the CAF stands for the *cyclic spectrum*, also referred as *spectral correlation density function* (SCD). The SCD can be estimated for each cyclic frequency α by the *cyclic periodogram* as:

$$I^{\alpha}[n,f] \triangleq \frac{1}{N} X_N[n,f] X_N^*[n,f-\lfloor \alpha N \rfloor] \equiv S_{x_N}^{\alpha}[n,f] \tag{2}$$

where $X_N[n,f]$ indicates the short-time Fourier transform (STFT) of $x[n]$ at n over N samples, and $\lfloor \cdot \rfloor$ stands for the integer part of the number. The symbol $(^*)$ indicates complex conjugate. From (2) a classical spectral analysis could be made setting $\alpha = 0$ (no periodicities at all). This particular case corresponds to the power spectral density function (PSD), derived from the wide sense stationary processes theory.

Figures 1(a) and 1(b) show[2] the PSD and the SCD, respectively, of a BPSK signal contaminated with AWGN. From the PSD, it is difficult to distinguish the set of spectral frequencies corresponding to a SoI, due to the overlapping between signal and noise. On the other hand, the cyclic spectral analysis avoids this effect, since the SoI exhibits periodicities and the noise does not. For example, it is easier to detect a peak in the cycle frequency at $\alpha = 2f_c$ (where there is not overlapping noise) than in $\alpha = 0$, that corresponds to the traditional PSD. It should be noted that, for every $\alpha \neq 0$, the SCD of noise ($S_{\omega}^{\alpha}[f]$) is zero due to it's stationarity.



(a) (b)

Fig. 1. Spectral analysis of a BPSK signal ($f_c = 2886$ Hz, $R_b = 260$ bits/s, $N = 1024$ samples) contaminated with AWGN (SNR = 3 dB). (a) Power spectral density (PSD), $S_x^0[f]$. (b) Spectral correlation density (SCD), $S_x^{\alpha}[f]$.

2.2 Impact of Channel Fading and Doppler Shift on the Cyclostationary Features

According to the results presented by Bkassiny [15], cyclostationary features in communication signals are preserved even in the presence of channel fading. The

[2] Cyclic and spectral frequencies are specified in *Hz*, it is easily done from the sampling frequency, $f_s = 22050$ Hz in this example.

channel can be considered as wide sense stationary as long as the mobile device covers a distance about a few tens of the wavelength of the carrier signal, this in an observation period. An acceptable approximation is to consider the channel as wide sense stationary with uncorrelated scattering (WSSUS), a commonly used model for dealing frequency selective channels [15]. In this case, the autocorrelation function of the received signal is also periodic with the same period than the SoI. Hence, the received signal is also cyclostationary with the same cycle components than the transmitted signal. As a result, when fading channels are considered as general linear time-variant systems, the cyclostationary features of the SoI are not modified. This is why the blind detection technique presented in this work is robust under practical scenarios.

If the channel is also characterized by Doppler effect, the cyclic spectrum of the SoI is convolved by the Doppler power spectral density. Let f_{max} be the maximum Doppler shift, the convolution causes the cyclic spectrum to spread at most $\pm f_{max}$ for every cycle frequency. However, Doppler shifting is irrelevant in blind spectrum sensing performance, given that the parameters of the signal are not used in the detection procedure. The cyclic features do not vanish, so it is still possible to perform detection.

2.3 Detection Statistic

In case of cyclostationary signals in AWGN, an approximate sufficient statistic for the *maximum likelihood detector* [16], called *multicycle detector*, is given by:

$$Y_{ML} = \sum_{\alpha \in A} \sum_{f} S_s^{\alpha}[f] S_{x_N}^{*\alpha}[f] \tag{3}$$

where $S_s^{\alpha}[f]$ and $S_{x_N}^{\alpha}[f]$ are the SCD[3] of the SoI and the received signal, respectively, and A is the set of cycle frequencies for which the SCD is not zero. If only cycle frequencies different from zero are considered in equation (3), then $S_x^{\alpha}[f] = S_s^{\alpha}[f]$, and

$$Y_{ML} = \sum_{\alpha \in A, (\alpha \neq 0)} \sum_{f} |S_{x_N}^{\alpha}[f]|^2 \tag{4}$$

Under blind conditions, the set A of cycle frequencies is unknown. The *radiometer*, or energy detector, is a common solution of blind detection, and it is a particular case of equation (3) when $\alpha = 0$ is considered:

$$Y^0 = \sum_{f} |S_{x_N}^0[f]|^2 \tag{5}$$

Let $Y^{\alpha} = \sum_{\alpha \in A} \sum_{f} |S_{x_N}^{\alpha}[f]|^2$, then the maximum likelihood detection criterion in equation (4) can be stated in term of Y^0 and Y^{α} by:

$$Y_{ML} = Y^{\alpha} - Y^0 \tag{6}$$

[3] From now on, the time parameter in the SCD is omitted for simplicity. Hence, $S_{x_N}^{\alpha}[f] \equiv S_{x_N}^{\alpha}[n, f]$ is always treated as the SCD estimated using equation (2).

From the interpretation of the cyclic spectrum as a spectral correlation function [11], Y^α is also given by:

$$Y^\alpha = \lim_{N\to\infty} \frac{1}{2N+1} \sum_{\alpha\in A} Y[\lfloor \alpha N \rfloor] \otimes Y^*[-\lfloor \alpha N \rfloor] \tag{7}$$

where $Y[f] = X_N[f]X_N^*[f]$.

Given the statistic $Z[\lfloor \alpha N \rfloor] = Y[\lfloor \alpha N \rfloor] \otimes Y^*[-\lfloor \alpha N \rfloor]$, it is easy to verify that Z is an estimator of $|S_{x_N}^\alpha[f]|^2$ for every cycle frequency [11]. Besides, $Z[\lfloor \alpha N \rfloor] = \mathcal{F}\{y[n]y^*[n]\}$, and $y[n] = x_N[n] \otimes x_N[-n]$. The sequence $y[n]$, can be obtained applying the inverse DFT to $|X_N[f]|^2$, in order to avoid the convolution. This can be performed in a very efficient way if an FFT (Fast Fourier Transform) algorithm is used.

As Jang proposed in [11], the accumulative value of Z can be used to avoid missing features due to the lack of cycle frequency resolution.

$$G[\lfloor \alpha N \rfloor] = \sum_{\beta=0}^{\lfloor \alpha N \rfloor} Z[\beta] \tag{8}$$

An equivalent and more efficient way to obtain this magnitude is attainable through the following convolution:

$$\begin{aligned} G[\lfloor \alpha N \rfloor] &= Y[\lfloor \alpha N \rfloor] \otimes Y^*[-\lfloor \alpha N \rfloor] \otimes u[\lfloor \alpha N \rfloor] \\ &= \mathcal{F}\left\{y[n]y^*[n] \times \mathcal{F}^{-1}\{u[\lfloor \alpha N \rfloor]\}\right\} \end{aligned} \tag{9}$$

where the notation $u[\cdot]$ indicates a unit step sequence. Hence, the statistic Z can be efficiently computed by the following difference equation:

$$Z[\lfloor \alpha N \rfloor] = G[\lfloor \alpha N \rfloor] - G[\lfloor \alpha N \rfloor - 1] \tag{10}$$

for every $\alpha \in A$. The resulting set of values correspond to the cycle frequencies profile of the SCD [11]. The block diagram of the proposed algoritm for obtaining the cylic profile is shown in Figure 2.

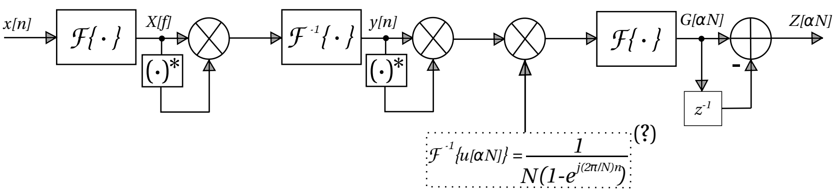
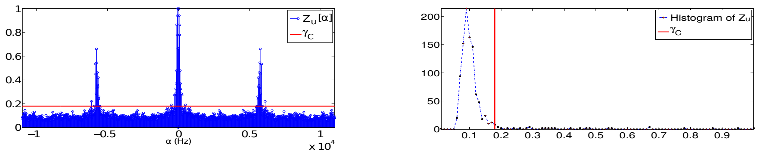


Fig. 2. Block diagram of the proposed algoritm for obtaining the cylic profile. The inverse DFT of unit step is not computed during the procedure, it's assumed to be previously caculated.

2.4 Detection Threshold Setting

The main parameters that characterize any detector's performance are: the probability of detection (P_d) and the probability of false alarm (P_{fa}) [17]. The value of γ that maximizes the P_d for a fixed P_{fa}, can be obtained from the Neyman-Pearson's Theorem, also known as *likelihood ratio test* [17]. However, it is required to know the probability density functions of the detection statistic under both hypotheses $\mathcal{H}_0$ and $\mathcal{H}_1$. Therefore, under blind conditions, an empirical criteria for establishing a detection threshold is demanded.

Figure 3(a) shows the normalized Z statistic (Z_u), obtained using the method described in Figure 2, corresponding to the same signal of Figure 1. The histogram of Z_u is shown in Figure 3(b). When the SoI is present, most of the samples of Z_u are related with noise[4]. In order to select a threshold, a confidence criteria C must be defined. The detection threshold for a confidence C, denoted by γ_c, corresponds to the magnitude of Z_u for which the $C*100$ percent of samples are lower than γ_c. However, the proposed criteria is valid only under the hypothesis $\mathcal{H}_1$. If there is not a signal present (and γ_c is close to 1), there will always be samples above this value. Hence, both the probability of detection and the probability of false alarm would be one, and this detector would not be useful.



(a) (b)

Fig. 3. Establishing the detection threshold (C = 0.95). (a) Normalized detection statistic for the BPSK signal of Figure 1. (b) Histogram corresponding to (a).

Another parameter is defined for avoiding this problem: the *tolerance level* (T), defined as the maximum value of γ_c for which $\mathcal{H}_0$ is rejected. Every threshold below T indicates detected signal. Finally, the normalized threshold for blind cyclostationary feature detection can be stated as follows:

$$\gamma = \begin{cases} \gamma_c \ , & \text{if } \gamma_c \leq T \\ 1 \ , & \text{otherwise.} \end{cases} \tag{11}$$

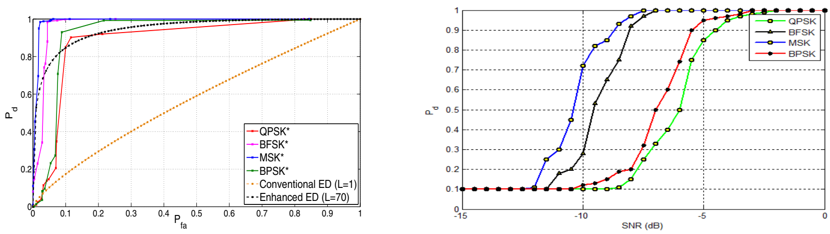
If $\gamma_c > T$ ($\gamma = 1$), then hypothesis $\mathcal{H}_0$ will never be rejected.

[4] This noise is not channel noise properly, but estimation error from the periodogram in equation (2). According to the *central limit theorem* [17], this error can be modeled as a normally distributed random variable.

3 Results

The proposed detector was verified through Monte Carlo simulations, as suggested by Kay [17]. For each hypothesis, 2000 iterations were conducted in order to obtain reliable results. BPSK, QPSK, BFSK and MSK signals with length $N = 1024$ samples were analyzed. As an additional condition, fading and Doppler effects were considered, which parameters were randomly selected from trial to trial.

Receiver Operating Characteristics (ROC). An effective way to summarize the detector performance is to represent P_d versus P_{fa} [17]. A set of ROCs curves corresponding to the detection of different signals are showed in Figure 4(a). In Figure 4(b) another representation of the simulations results are shown for several types of signals. Similar representations are shown for the conventional ED and the enhanced version using sliding window, obtained from their analytical expressions presented in [10]. Note that the performance of the ED is independent of the modulation detected. Although the performance of the classical ED is poor under low SNR regimes, about 10 dB gain can be obtained if a sliding window of length 70 samples is used. However, the complexity of the detector is increased. Even using this enhanced version, the proposed CD method overcomes the ED for all the signals analyzed and $P_d = 0.9$.



(a) (b)

Fig. 4. Comparison between the ED and the proposed technique. (a) ROC curves for SNR = -5 dB. (b) Curves of P_d vs. SNR for P_{fa} = 0.1. * Results obtained by simulations using the proposed technique.

4 Conclusions

The method proposed in this paper takes advantage of the cyclic features commonly presented in communication signals, in order to perform spectrum sensing. Conventional cyclostationary feature detection techniques are not well posed if the signal parameters are unknown. Under these conditions, a decision criteria for blind detection of primary signals is proposed based on practical assumptions.

Considering the trade-off between implementation complexity and performance, our proposed method stands as a good compromised solution for blind spectrum sensing. Low SNR regimes, presence of a fading channel and Doppler effect were considered in simulations. It was shown that the proposed method has a better performance than other solutions based on energy detection.

The proposed solution represents a useful technique for cognitive radio devices that operate as secondary users. It allows to detect idle channels for increasing spectrum utilization efficiency.

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