Universität des Saarlandes
Max-Planck-Institut für Informatik

Discriminating 4G and Broadcast Signals via Cyclostationary Feature Detection

Masterarbeit im Fach Informatik
Masters Thesis in Computer Science
von / by

Hossein Khoshnevis

angefertigt unter der Leitung von / supervised by

Prof. Dr.-Ing. Thorsten Herfet

begutachtet von / reviewers

Prof. Dr.-Ing. Thorsten Herfet
Prof. Dr. Bernt Schiele

Saarbrücken, April 26, 2012

Non-plagiarism Statement

Hereby I confirm that this thesis is my own work and that I have documented all sources used.

(Hossein Khoshnevis)

Saarbrücken, April 26, 2012

Abstract

According to the FCC, spectrum allocation will be one of the problems of future telecommunication systems. Indeed, the available parts of the spectrum have been assigned statically to some applications such as mobile networks and broadcasting systems and finding a proper operating band for new systems is difficult. These telecommunication systems are called *primary users*. However primary users do not always use their entire bandwidth and therefore a lot of spectrum holes can be detected. These spectrum holes can be utilized for undefined systems called *secondary users*. Federal communication commission (FCC) introduced *cognitive radio* which detects these holes and assigns them to secondary users.

There are several techniques for detention of signals such as energy based detection, matched filter detection and cyclostationary based feature detection. Cyclostationary based feature detection as one of the most sensitive methods for signal detection can be used for detection and classification of different systems. However, traditional multi-cycle and single-cycle detectors suffer from high complexity. Fortunately, using some priory knowledge about the signal, this shortcoming can be solved.

In this thesis, signals of DVB-T2 as a broadcasting system and 3GPP LTE and IEEE 802.16 (WiMAX) as mobile networks has been evaluated and two cyclostationary based algorithm for detection and classification of these signals are proposed.

Acknowledgements

I would like to show my sincere gratitude to Prof. Dr.-Ing. Thorsten Herfet for giving me an opportunity to work under their supervision. The extensive discussions with him were very helpful to understand the issues and solutions. I would like also appreciate his supports through personal issues.

I would like to thank International Max Planck Research School (IMPRS) for providing a friendly and proper work environment for the research and the financial support.

Last but not least, I am grateful to my parents for fusing in me the desire to learn and the will to achieve.

Chapter 1

Introduction

1.1 Motivation

The dramatic growth of communication services increases the demand for spectrum allocation. Today all part of the accessible spectrum has been statically assigned to licensed applications that are known as primary users (PU). According to the Federal Communications Commission (FCC), by increasing the data traffic, the spectrum allocation will be the problem of future telecommunication systems. Indeed, we are in danger of running out of spectrum. However, based on the FCC report on spectrum efficiency [20], a large amount of white space can be monitored in some applications.

In one of the researches on spectrum issues, the spectrum occupancy around Berkely is measured [4]. The interference map is shown in Fig. 1.1 and percentage of occupancy showed in Table 1.1. The table shows that the most parts of the spectrum is empty and can be utilized by secondary users (SU). Secondary users are users that are not defined in static spectrum allocation maps. The amazing observation relates even within the busiest part of the spectrum between 0-1 GHz, only about 50% of the spectrum is occupied by the primary user. The other parts of the spectrum have more free spaces e.g. within the 4-5 GHz, only 0.128 % of spectrum is occupied. Therefore a lot of white space can be detected and used by secondary users.

Table 1: Usage percentage of spectrum taken in downtown Berkeley

Band (Hz)	0-1G	1-2G	2-3G	3-4G	4-5G	5-6G
Percentage (%)	54.4	35.1	7.6	0.25	0.128	4.6

To utilize the spectrum holes, Federal Communications Commission introduced Cognitive Radio. The cognitive radio is a self-aware communication system that can detect free

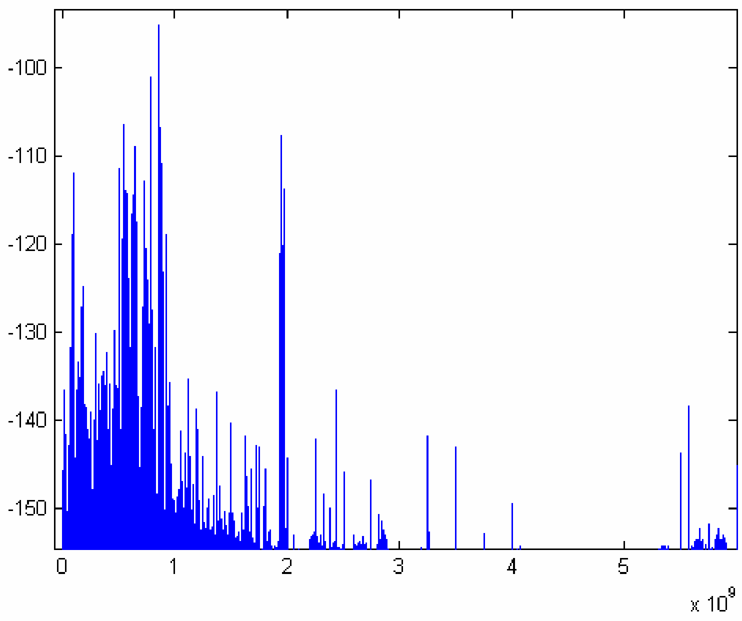

FIGURE 1.1: Interference map between 0-6GHz

spectrum spaces and can assign them to other purposes. Haykin presented a complete definition for cognitive radio in [22]:

"Cognitive radio is an intelligent wireless communication system that is aware of its surrounding environment (i.e., outside world), and uses the methodology of understanding-by-building to learn from the environment and adapt its internal states to statistical variations in the incoming radio frequency stimuli by making corresponding changes in certain operating parameters (e.g. transmit power, carrier frequency and modulation strategy) in real-time, with two primary objectives in mind: (i.) highly reliable communication whenever and wherever needed and (ii.) efficient utilization of the radio spectrum."

Broadcasting systems and mobile networks form the dominant part of communications and occupy a considerable portion of the spectrum. Therefore utilizing their spectrum for cognitive radio is subject of several studies. DVB as a well-known standard for broadcasting has been implemented in several countries and is widely used. Forth generation of mobile networks (4G) provides modern and flexible systems for user and operators. Two well known standards defined in frame work of 4G are WiMAX and 3GPP LTE. WiMAX is a global standard for broadband networks and provides affordable long-range data and high quality communications. The next step in 3G services is 3GPP long term evolution (LTE) that provides higher data rates, better coverage, better multipath, mobility, and power performance as well as the higher level of security.

For each of these three systems, special operating frequency band has been assigned statically. However allocated frequency bands of DVB, WiMAX and 3GPP LTE has partial interference and the coexistence issue is the subject of some researches as discussed in [39]. Therefore cognitive radio system should be able to discriminate between these signals and find the spectrum holes. Furthermore, it is important that the cognitive radio can detect the desired primary users without considering the spectrum map.

The spectrum detection is the first step in a cognitive radio system. The detection can be done based on the signal features such as energy, shape and periodicity. There are different techniques for spectrum sensing in CR systems such as energy detection, matched filter detection, covariance based detection, cyclostationary feature detection and wavelet based detection. These methods are partially discussed in [6, 48, 49, 50].

The simplest method is energy detection that has been widely used in different telecommunication systems. In energy detection, the existence of a signal can be evaluated without priori knowledge about the signal. Usually for implementation, the energy of the received signal in special interval is compared with a threshold. The disadvantage of this method is sensitivity of threshold to changing the noise and interference which results in wrong detection.

The second approach is matched filter detection that maximizes the signal to noise ratio (SNR) to detect the desired signal using the priori knowledge about the signal. In this method that is usually used in radar, the input signal is correlated with a known signal to discriminate between the input signal and the noise or interference. The performance of this method is dramatically decreased when the parameters of the desired signal are not previously known. This method also needs timing, synchronization and equalization before detection.

The third type of spectrum sensing methods is covariance based detection. This method differentiates between signal and noise based on this fact that signal generates more correlations than the noise. For implementation, the received signal covariance matrix should be calculated and the decision should be made based on some thresholds. [48] The advantage of this method is working under low SNR without priori knowledge about the signal however the detection of type of the signal is an issue.

The forth method for signal detection is cyclostationary based feature detection. In this method, periodic features of signals are determined by calculating cyclic autocorrelation function (CAF) and spectral correlation function (SCF). The well-known cyclostationary based detector is multi-cycle detector [15]. The cyclostationary features are computed and summed for all cyclic frequencies in CAF or SCF. This method differentiates between signal, noise and interference. Unfortunately, despite its high sensitivity, this detector suffers from high complexity. However, it is possible to reduce the complexity of this method by computing some special lags or lines of CAF or SCF that include the dominant features.

The fifth method is wavelet detection and is used for wideband signals. Wavelet detection employs the wavelet transform of the power spectral density (PSD) of input signal. The search algorithm in this technique finds the singularities of PSD to find the white space. This method is computationally expensive.

1.2 Thesis overview

The main contribution of this thesis is to find a solution for discrimination and classification of broadcast and 4G signals. For case of broadcast signal, DVB-T2 and for case of 4G signals, WiMAX and 3GPP LTE are studied. The method used for detection of signals is cyclostationary based feature detection since it benefits from high sensitivity and by considering priori knowledge about the signal, the complexity can be reduced.

The cyclostationary based approach for detection of signals is explained in Chapter 2. In Chapter 2, the system model of DVB-T2, WiMAX and 3GPP LTE has been elaborated. Discrimination of mentioned signals based on cyclic prefix has been mentioned in Chapter 4. Discrimination based on the pilot structure is discussed in Chapter 5. Finally, this thesis ends with *Conclusion* and *Future work* in Chapter **??**.

Chapter 2

Cyclostationary Based Signal Detection

Several of natural signals can be modeled as stationary. Stationary processes are stochastic processes whose statistics does not change with time. However in some signals, the statistics are changed periodically. They can be modeled as cyclostationary processes. Wide-sense cyclostationary processes are defined as processes whose mean and autocorrelation vary periodically in time. Many of natural and manmade processes generate cyclostationary such as revolution and rotation of planets and on pulsation of stars [47] and gear rotation [10]. In telecommunication even though the raw data is a stationary process, signals modulated with carriers, pulse train, mapping or cyclic prefix exhibits wide-sense cyclostationary process.

Cyclostationary feature detection has been extensively studied in [13, 16] and its performance is evaluated in [17]. In this chapter a brief review on necessary aspects and definitions of this topic is presented. Fundamentals of cyclostationary feature detection are explained in section 2.1. Spectrum estimation based on cyclostationary is discussed in section 2.2 and low complexity cyclostationary detection briefly mentioned in section 2.3.

2.1 Fundamentals of Cyclostationary Feature Detection

One of the features of signals that can be used for detection is periodicity. A lot of signals have first order periodicity such as simple sine wave. First order periodicity can be defined as:

$$x(t) = x(t+T). \tag{2.1}$$

where $x(t)$ is the periodic signal and T is the period of the signal. Any first order periodic signal can be represented in terms of Fourier coefficients in frequency domain:

$$X(t) = \sum_{\alpha} a_{\alpha}.e^{j2\pi\alpha t} \tag{2.2}$$

where α shows the frequency and is integer multiple of fundamental frequency $\alpha_0 = 1/T$, a_α is Fourier coefficient corresponding to frequency α and t shows the time. Fig. 2.1 illustrates the Fourier coefficients.

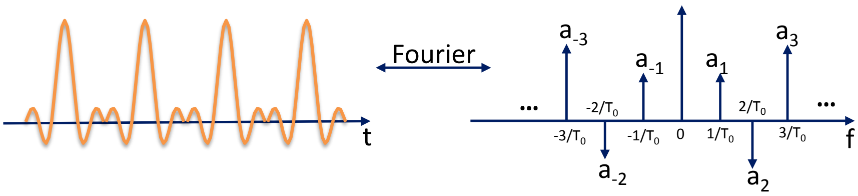

FIGURE 2.1: Fourier coefficients for first order periodic signal, from [38]

Although carrier signals are usually periodic, the messages are not periodic and therefore modulated signals do not show the first order periodicity. For example by considering $x(t) = a(t)cos(2\pi ft)$ where $a(t)$ is the message and $cos(.)$ is the modulating signal, we simply observe that $x(t)$ is not first order periodic signal. A well designed example is shown in Fig. 2.2. In this figure, a sample of a modulated signal is shown.

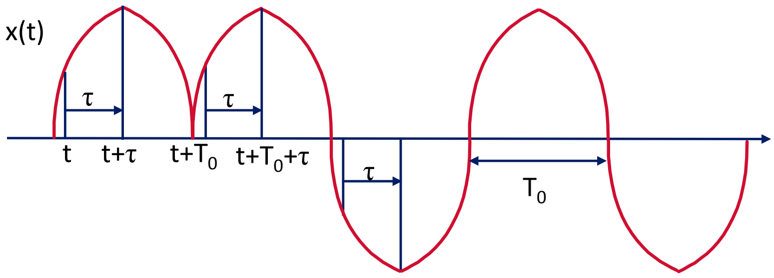

FIGURE 2.2: Modulated signals usually show second order periodicity, from [38]

However in most of these signals, mean and autocorrelation vary periodically. When the autocorrelation of one signal varies periodically with time, the process is called wide-sense cyclostationary. Since in these processes, the autocorrelation is a periodic functions, it can be written as

$$R_{xx}(t, \tau) = R_{xx}(t + T_0, \tau). \tag{2.3}$$

where

$$R_{xx}(t,\tau) = E[x(t+\frac{\tau}{2})x^*(t-\frac{\tau}{2})] \tag{2.4}$$

is called the autocorrelation function. Like first order periodic signals, periodic autocorrelation can be represented in terms of Fourier series

$$R_{xx}(t,\tau) = \sum_{\alpha} R_x^{\alpha}(\tau).e^{j2\pi\alpha t} \tag{2.5}$$

where

$$R_{xx}^{\alpha}(\tau) = \lim_{T\to\infty} \frac{1}{T}\int_{-T/2}^{T/2} R_{xx}(t,\tau).e^{-j2\pi\alpha t}\,dt \tag{2.6}$$

is the cyclic autocorrelation function (CAF) of $x(t)$ and α is called cycle frequency and equals to n$/T_0$, $n = 0, \pm1, \pm2, ..., \pm\infty$. CAF shows cyclic features for harmonics of fundamental frequency $1/T_0$. The conventional limit autocorrelation can be achieved by substitution of $\alpha = 0$. The conjugate autocorrelation function of $x(t)$ is defined as

$$R_{xx^*}(t,\tau) = E[x(t+\frac{\tau}{2})x(t-\frac{\tau}{2})] \tag{2.7}$$

and the conjugate cyclic autocorrelation would be

$$R_{xx^*}^{\alpha}(\tau) = \lim_{T\to\infty} \frac{1}{T}\int_{-T/2}^{T/2} R_{xx^*}(t,\tau).e^{-j2\pi\alpha t}\,dt \tag{2.8}$$

The Wiener-Khinchin theorem states that the Fourier transform of autocorrelation function is the power spectral density (PSD) of corresponding signal which is

$$S_{xx}(f) = \int_{-\infty}^{\infty} R_{xx}(\tau).e^{-j2\pi f\tau}\,d\tau \tag{2.9}$$

where $R_{xx}(\tau)$ is the special case of $R_{xx}^{\alpha}(\tau)$ when $\alpha = 0$. The general case of above relation which shows the spectral correlation function (SCF) of $x(t)$ and named spectral correlation function (SCF) is given by

$$S_{xx}^{\alpha}(f) = \int_{-\infty}^{\infty} R_{xx}^{\alpha}(\tau).e^{-j2\pi f\tau}\,d\tau \tag{2.10}$$

that is also called cyclic Wiener relation. The conjugate cyclic Winer relation is defined as

$$S_{xx^*}^{\alpha}(f) = \int_{-\infty}^{\infty} R_{xx^*}^{\alpha}(\tau).e^{-j2\pi f\tau}\,d\tau \tag{2.11}$$

Above relations clearly show that each line of SCF is the Fourier transform of corresponding line of CAF with the same α. CAF and its Fourier transform SCF, are two dimensional transforms depending on α and τ or f which show the cyclic features of a signals based on their cyclostationary class. The type of process depends on $R^{\alpha}_{xx}(\tau)$ for different values of α. When only for $\alpha = 0$, $R^{\alpha}_{xx}(\tau) \neq 0$, the process is called purely stationary while when only for all integer/T_0, $R^{\alpha}_{xx}(\tau) \neq 0$ the process is purely cyclostationary [14].

Cyclostationary features overlap in PSD. The overlapping features in PSD, can be detected in cycle frequencies that are non-overlapping [15]. Generally, non-cyclostationary noises do not generate any component in cyclic frequencies except $\alpha = 0$ which is PSD while different types of modulation based on modulating carrier, show cyclic features in different cyclic frequencies which originates from preservation of the phase and frequency information in cyclostationary analysis.

2.2 Spectrum Estimation

Most of processes in new telecommunication systems should be done in discrete domain. Reduction of complexity is the key point in designing system in this domain. In order to estimate the cyclic spectrum, different methods has been discussed in [3, 12, 35]. The sensitivity of different cyclostationary based spectrum sensing methods has been evaluated in [29].

In the first method explained in [12, 33], to measure the power spectral density (PSD), we can pass the signal through several narrow band filters and then we measure the average power using moving average filter. Therefore for any special part of the spectrum we have

$$S_{xx}(f) = \lim_{W \to 0} \frac{1}{W} \int_{-\infty}^{\infty} |h^f_W(t) \otimes x(t)|^2 dt \tag{2.12}$$

where $h^f_W(t)$ is the impulse response of band pass filter with central frequency of f and bandwidth W. For case of spectral correlation (SCF), we can use the frequency translated signals in equation (2.13). This method is illustrated in Fig. 2.3. In this method we use a set of filters with different central frequency to measure the SCF.

$$S_{xx}(f) = \lim_{W \to 0} \frac{1}{W} \int_{-\infty}^{\infty} (h^f_W(t) \otimes x(t).e^{-j\pi\alpha t}).(h^f_W(t) \otimes x(t).e^{+j\pi\alpha t})^* dt \tag{2.13}$$

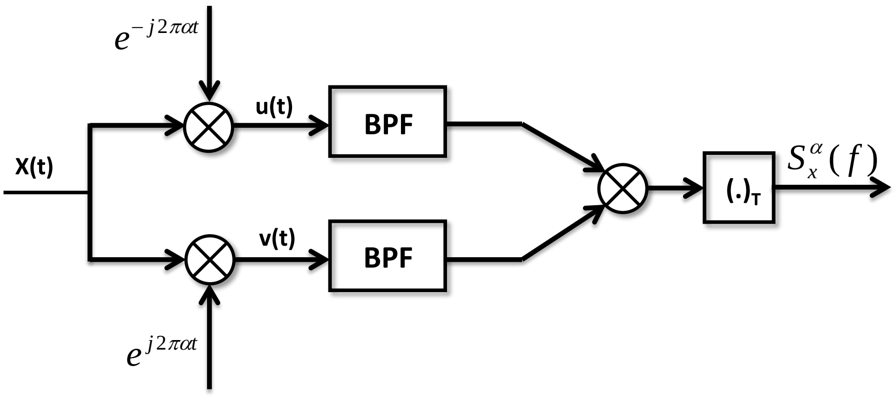

FIGURE 2.3: The first method for measurement of the spectral correlation

In the second method explained in [12, 33], we use a special interpretation of CAF that is

$$S_{xx}^{\alpha}(f) = \lim_{\Delta f \to 0} \lim_{\Delta t \to \infty} \frac{1}{\Delta t} \int_{-\Delta t/2}^{\Delta t/2} \Delta f X_{1/\Delta f}(t, f + \alpha/2).X_{1/\Delta f}^{*}(t, f - \alpha/2) dt \tag{2.14}$$

where $X_{1/\Delta f}(t, v)$ is called the short time Fourier transform for signal $x(t)$ and can be written as

$$X_{1/\Delta f}(t, v) = \int_{t-1/\Delta f}^{t+1/\Delta f} x(u).e^{-j2\pi vu} du \tag{2.15}$$

Since implementation of equation (2.14) is difficult, we can evaluate cyclic periodogram as

$$S_{xx1/\Delta f}^{\alpha}(f) = \Delta f X_{1/\Delta f}(t, f + \alpha/2).X_{1/\Delta f}^{*}(t, f - \alpha/2) \tag{2.16}$$

where Δf is a dummy parameter and can be considered as $T = 1/\Delta f$. Equation (2.16) is the Fourier transform of the cyclic correlogram that can be driven as

$$R_{xxT}^{\alpha}(t, \tau) = \frac{1}{T} \int_{t-(T-|\tau|)/2}^{t+(T+|\tau|)/2} x(u + \tau/2).x(u - \tau/2).e^{-j2\pi\alpha u} du \tag{2.17}$$

A well-known method for implementation of SCF is the spectrally smoothed cyclic periodogram that can be written as

$$S^{\alpha}_{xx\Delta t}(t,f)_{\Delta f} = \frac{1}{\Delta f}\int_{f-\Delta f/2}^{f+\Delta f/2} S^{\alpha}_{x\Delta t}(t,v)dv \tag{2.18}$$

It should be notified that to achieve a better estimation of SCF, the observation interval Δt should be increased and the size of smoothing window Δf should be decreased.

$$S^{\alpha}_{xx}(f) = \lim_{\Delta f\to 0}\lim_{\Delta t\to\infty} S^{\alpha}_{xx\Delta t}(t,f)_{\Delta f} \tag{2.19}$$

Using Fast Fourier Transform (FFT) algorithms, equation (2.19) can be efficiently implemented.

$$\begin{aligned}\tilde{S}^{\alpha}_{x\Delta t}(t,f)_{\Delta f} \quad &= \quad \frac{1}{M}\sum_{v=-(M-1)/2}^{v=(M-1)/2}\frac{1}{\Delta t}\tilde{X}_{\Delta t}(t,f+\alpha/2+vF_s) \\ &\quad .\tilde{X}^{*}_{\Delta t}(t,f-\alpha/2+vF_s)\end{aligned} \tag{2.20}$$

where

$$\tilde{X}(t,f) = \sum_{k=0}^{N-1} a_{\Delta t}(kT_s).x(t-kT_s).e^{-j2\pi f(t-kT_s)} \tag{2.21}$$

$\tilde{X}(t,f)$ is the sliding DFT, $a_{\Delta t}(kT_s)$ is the data tapering window, $\Delta f = Mf_s$ is the smoothing interval and f_s is sampling frequency. The FFT based spectral smoothing method has been illustrated in Fig. 2.4.

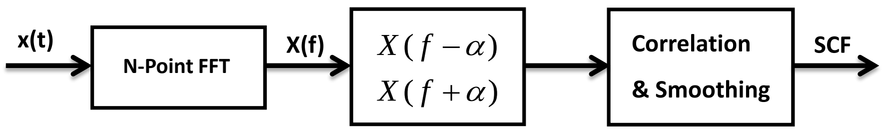

FIGURE 2.4: FFT based spectral smoothing for measurement of spectral correlation

It is obvious that when the observation interval increases, the better estimation of cyclic features is generated. The Matlab pseudocode for estimation of SCF and CAF based on the equation (2.16) and (2.17) are presented in Table 2.2 and Table 2.2, respectively.

Table 1: Matlab pseudocode for estimation of SCF

Step 1: Dividing the signal into N frames. The number of frames (N) is the length of signal diving over window size.
Step 2: Taking the FFT of each frame that is X_T
Step 3: Computing conjugate of X_T that is X_T^*
Step 4: Shifting X_T to $+\alpha/2$ and X_T^* to $-\alpha/2$ using circular shift
Step 5: Computing $S_{xT}^{\alpha}(f)_{\Delta f \Delta t} = \Delta f X_T(f+\alpha/2).X_T^*(f-\alpha/2)$
Step 6: Taking the average value of N frames to achieve $S_{xT}^{\alpha}(f)_{\Delta f}$
Step 7: Passing the signal into the moving average filter to achieve $S_{xT}^{\alpha}(f)$
Step 8: Returning to step 4 and repeating the whole process for all cyclic frequencies α

Table 2: Matlab pseudocode for estimation of CAF

Step 1: Dividing the signal into N frames. The number of frames (N) is the length of signal diving over window size.
Step 2: Computing $a(t) = \langle x(t).e^{-j2\pi\alpha t}\rangle$ where $x(t)$ includes one frame.
Step 3: Computing the correlation of $a(t)$ and $x(t)$ to achieve $R_{xx}^{\alpha}(\tau)_{\Delta t \Delta \tau}$
Step 4: Taking the average value of N frames to achieve $R_{xx}^{\alpha}(\tau)_{\Delta \tau}$
Step 5: Taking the moving average filter to achieve $R_{xx}^{\alpha}(\tau)$
Step 6: Returning to step 2 and repeating the whole process for all cyclic frequencies α.

2.3 Complexity Reduction

By achieving some priori knowledge about the signal, the complexity of cyclostationary based feature detection method can be reduced. For example, in case that the position of dominant and viable peaks of a signal are known, we can compute just these special positions to check the presence of the signal. In Chapter 4, detection of OFDM signal based on the peak which lies in useful time of an OFDM symbol is discussed. The position of dominate peaks for different signals and modulations are dissimilar. Therefore, it is possible to discriminate between signals based on the position and hight of peaks. In this case, cyclostationary feature detection plays the role of a classifier and cyclostationary feature space is the classification medium. Some of efforts for designing low complexity cyclostationary based detector are mentioned in [1, 19].