Applied Mathematics & Information Sciences
An International Journal

http://dx.doi.org/10.18576/amis/110326

Spectrum Sensing for Cognitive Radio Systems Using Modulation Classification: A Review

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Received: 6 Mar. 2016, Revised: 24 Feb. 2017, Accepted: 26 Feb. 2017
Published online: 1 May 2017

Abstract: Spectrum sensing is the most important procedure for the operation of cognitive radio systems. To overcome the shortcomings of the conventional spectrum sensing techniques, considerable attention has been recently focused on the use of Modulation Classification (MC) for spectrum sensing. It relies on the fact that all primary users employ one modulation scheme or another for the transmission over the wireless channel; therefore, detecting any modulation scheme would be enough to confirm the presence of the primary user's signal in the wireless channel. This paper discusses the spectrum sensing for cognitive radio systems using modulation classification and provides a critical review of the existing methods; where gaps in the knowledge base are highlighted and directions for future research are suggested.

Keywords: Cognitive radio, modulation classification, spectrum detection, spectrum holes, spectrum sensing.

1 Introduction

With the tremendous development of wireless communication systems and services, the need for wireless spectrum is anticipated to grow very fast in the coming years. However, since most of the available frequency bands are already statically allocated to dedicated wireless communication systems and services for exclusive use, the radio spectrum is already very crowded. It appears that it is very hard to hold additional systems and services within this scarce resource. In contrast, most of the allocated wireless spectrum can be under-utilized due to inflexibility and ineffectiveness of the static spectrum allocation policy; just a portion of the licensed wireless spectrum can be utilized in a certain time and area. This viewpoint is reinforced by several studies of the Federal Communications Commission (FCC); the United States' spectrum regulatory agency. These studies revealed that, in some sites or at some times of day, around seventy percent of the licensed wireless spectrum in the US can possibly be sitting idle, despite the fact that it is officially spoken for [1]. Thus, the spectrum scarcity is not because of fundamental lack of spectrum, but largely because of the conventional static spectrum allocation policy.

Cognitive Radio (CR) technology, which allows dynamic access of the under-utilized licensed spectrums, has been lately proposed as a novel and efficient solution to the current inefficient usage of the scarce spectrum. It allows unlicensed users, also called secondary users (SUs) or cognitive radio users, to opportunistically use locally and temporarily licensed bands unoccupied by licensed users, also called primary users (PUs), at the right place and time. This can greatly enhance the overall spectrum utilization and reduce the spectrum white spaces; the unused spectrum bands in the temporal and/or spatial domain [2].

One of the most fundamental requirements for the cognitive radio systems is to try avoiding interference for potential primary users in their vicinity. To guarantee that the cognitive radio users (i.e., secondary users) will not interfere with the primary users, they need to detect the primary user's signal existence in the wireless environments. This detection process is achieved by

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sensing the wireless environment, and it is known as spectrum sensing [3].

As the main concept of cognitive radio relies on sensing the activity of the primary users, spectrum sensing is the most important procedure for the operation of cognitive radio systems. However, it imposes a great challenge which is the ability to detect the primary user's presence with a high level of reliability and speed. This is because the primary user signals often experience significant impairments before reaching the cognitive radio sides. Furthermore, the computational capability of cognitive radios is highly limited. As a result, carrying out reliable and fast spectrum sensing is a challenging task for cognitive radio systems; especially in the low signal-to-noise ratio (SNR) environments [4].

Various conventional spectrum sensing techniques have been proposed so far (e.g., [5, 6, 7, 8, 9, 10, 11]) These techniques have various shortcomings that can highly hinder their practical use in cognitive radio environments. To overcome these drawbacks, considerable attention has been recently paid to the use of Modulation Classification (MC) for spectrum sensing in cognitive radio systems [12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26]. This technique enables cognitive radio devices to reliably sense and detect all forms of primary radio signals in the spectrum environment and enhance the overall performance of cognitive radio systems [22].

The rest of this paper is organized as follows. Section 2 formulates the spectrum sensing problem for cognitive radio systems. Section 3 discusses the conventional spectrum sensing methods for cognitive radio systems. Section 4 discusses the spectrum sensing for cognitive radio systems using modulation classification. Section 5 presents a critical review of existing spectrum sensing methods for cognitive radios using modulation classification, and Section 6 presents observations from this review. Finally, Section 7 concludes this paper.

2 Spectrum Sensing Problem

As mentioned previously, it is a fundamental requirement in cognitive radio systems that secondary users must be able to reliably detect the presence of the primary user signal in the radio environments. This can be achieved by performing the spectrum sensing, which is regarded as a detection problem. Secondary users have to scan a wide range of frequencies in order to find available spectrum white spaces, also referred to as holes, that are spatially and temporarily out of service. In practice, this process (i.e., the spectrum sensing) can be generally formulated as a binary detection problem, where the goal is to decide between the following two binary hypotheses [27]

$$\begin{aligned} H_0 &: r(t) = n(t) \,(\text{PU is absent}) \\ H_1 &: r(t) = hs(t) + n(t) \,(\text{PU is absent}), \end{aligned} \tag{1}$$

where H_0 denotes the hypothesis that the primary user is absent in the frequency channel under consideration; H_1 denotes the hypothesis that the primary user is present in the frequency channel under consideration; $r(t)$ is the received signal at the secondary user; $s(t)$ is the signal transmitted from the primary user; $n(t)$ is the additive background noise and h is the channel gain between the primary and the secondary users.

3 Spectrum Sensing Techniques

Due to the significant importance of spectrum sensing in cognitive radio technology, it has grown to become a very active research topic over the last few years. Various spectrum sensing techniques have been proposed including the Energy Detection (ED) (e.g., [5]), Matched-Filter Detection (MFD) (e.g., [6]), Cyclostationary Feature Detection (CFD) (e.g., [7]), Covariance-Based Detection (CBD) (e.g., [8]), Wavelet-Based Detection (WBD) (e.g., [9]), Compressed Sensing Detection (CSD) (e.g., [10]) as well as some newly introduced techniques stated in [11]. These techniques have different implementation requirements, and accordingly can be categorized into four main classes:

– Techniques that require a priori information of the primary user's signals (e.g., MFD and CFD).
– Techniques that require no a priori information of the primary user's signals (e.g., ED, WBD and CSD).
– Techniques that can sense the narrowband primary user's signals (e.g., MF, CFD and ED).
– Techniques that can sense the broadband primary user's signals (e.g., ED, WBD and CSD).

The advantages and disadvantages of these techniques are listed in Table 1, which shows that the use of the energy detection for spectrum sensing is limited due to its poor performance in low SNR environments. Similarly, the use of the matched filter detection for spectrum sensing can be also highly limited since it requires a priori information of the primary user's signals which may not be available at the cognitive radio side in real wireless communication scenarios. Also, because the cyclostationary feature detection for spectrum sensing requires a high computational complexity and a priori information of the primary user's signals, its practical use is also limited. Other spectrum sensing methods also suffer from various drawbacks that can greatly limit their practical applications in cognitive radio environments [28, 29].

4 Spectrum Sensing Using Modulation Classification

Due to the significant drawbacks of the conventional spectrum sensing techniques for cognitive radio systems,

Table 1: Advantages and disadvantages of conventional spectrum sensing techniques.

Technique	Advantages	Disadvantages
Energy Detection (ED) (e.g., [5])	- It does not require any a priori information of primary users' signals - It requires a low computational complexity - It can be used for sensing wide-band signals	- Its performance is poor in low SNR environments
Matched Filter Detection (MFD) (e.g., [6])	- It is the optimal spectrum sensing method since it maximizes the SNR of received signal - It requires a shorter sensing time to achieve a given performance as compared to other sensing methods	- It requires a priori information of primary users' signals to perform well, such as the modulation scheme and the pulse shape - Its computational complexity will be very high if a variety of primary user signal types must be received; a dedicated receiver is needed for each signal type - It requires coherency with primary users' signals
Cyclostationary Feature Detection (CFD) (e.g., [7])	- It can distinguish between primary user and noise - It can differentiate between different types of signals - It performs well in low SNR environments - It is capable of estimating accurately the carrier frequency and symbol rate	- It requires a high computational complexity - It requires a priori information of primary user's signals to perform well; which are the cyclic frequencies of primary users' signals
Covariance-Based Detection (CBD) (e.g., [8])	- It does not require any a priori information of primary users' signals - It performs well in low SNR environments	- It requires a high computational complexity - Its performance degrades if primary user's signals, received at the secondary users, tend to be uncorrelated
Wavelet-Based Detection (WBD) (e.g., [9])	- It does not require any a priori information of primary users' signals - It is effective for sensing wide-band signals	- It requires a high computational complexity - It may require high sampling rates for characterizing the entire bandwidth
Compressed Sensing Detection (CSD) (e.g., [10])	- It has a reasonable computational complexity - It is effective for sensing wide-band signals	- It may not be able to properly detect weak primary user signals

the attention of researchers over the past few years has been drawn to the use of MC for spectrum sensing; where we define the spectrum sensing as the combination of signal detection and modulation classification. This technique enables cognitive radio devices to sense and detect the primary radio signals in a way that can overcome the shortcomings of the conventional methods and improve the overall performance of the cognitive radio system [29]. It is based on the fact that all primary users employ one modulation scheme or another for the transmission over the frequency channel; therefore, the detection of any modulation scheme employed by a primary user would be enough to ensure the existence of the primary user's signal in the frequency channel. Thus, when applying this technique and detecting a modulation scheme, the frequency channel will be noted as a busy channel (i.e., an occupied channel) and consequently unsafe to be used by a secondary user; otherwise it will be noted as a free channel (i.e., an idle channel) and consequently safe to be used by a secondary user [28].

In general, spectrum sensing methods using modulation classification have three main stages: pre-processing, feature extraction and classification. Any work performed prior to the feature extraction stage is usually regarded as data pre-processing. Thus, pre-processing tasks may include data sampling, pulse shaping, noise reduction, etc. After preprocessing the received signal, a set of discriminating features for modulation classification are extracted. Based on the extracted features, the classification stage is then performed to detect the modulation type of the received signal.

Actually, when using modulation classification to sense and identify the spectrum, many other benefits can also be reaped, such as:

– The secondary users will be able to set their transmission parameters according to the modulation schemes employed for the transmission over the adjacent channels, such that the interference can be kept at a non-harmful levels [30, 31].
– The cognitive radio networks can have a protection against serval possible security attacks that may severely influence their performance. Due to the lack of global information about the usage of the spectrum resource, cognitive radio networks are susceptible to various security attacks, such as Primary User Emulation Attack (PUEA), illegal use of the radio spectrum, and selfish misbehavior [32, 33]. However, when the cognitive radio user analyzes the primary signals' characteristics for spectrum detection, the user's identity can be verified and the effects of these security attacks can be highly mitigated [34].

For the evaluation of the detection performance of the spectrum sensing methods using modulation classification, the average probability of correct classification P_{cc} is usually measured. Let $P(m_i|m_i)$ denote the probability of correct classification for the modulation scheme m_i, P_{cc} can be then given by [35, 36]

$$P_{cc} = \sum_{i=1}^{m} P(m_i|m_i)\, P(m_i), \tag{2}$$

where m is the number of the considered modulation schemes, and $P(m_i)$ is the transmission probability of the modulation scheme m_i [37, 38]. A desirable spectrum sensing method for cognitive radio systems using modulation classification should be able to give a high probability of correct classification, especially in the low SNR regions, while exhibiting low computational complexity [39].

5 Studies on Spectrum Sensing Using Modulation Classification

Considerable research work has been carried out over the past few years on spectrum sensing for cognitive radio systems using modulation classification. Several methods are found in the literature [12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26].

In [12, 13, 14, 15] spectrum sensing methods for cognitive radio systems using modulation classification are proposed, for different modulation sets under various transmission conditions, by employing cyclostationary signatures of the received signals as key features for modulation classification and multiclass Support Vector Machines (SVMs) as classification systems. It was shown that these methods can achieve a good performance in the low SNR scenarios. However, the computational complexity of the features used in these methods is quite high; accordingly, these methods are not suitable for the practical and real-time applications. It is also worth mentioning here that the cyclostationary signatures of the modulated signals cannot classify the quadrature amplitude modulation (QAM) schemes unless a complex higher order cyclostationary analysis is performed. This is due to the fact that high-order QAM schemes do not show periodicity of second order, or in some cases, they may show characteristics similar to that for the Quadrature Phase-Shift Keying (QPSK) schemes [22].

In [16], a spectrum sensing method using modulation classification is proposed by employing the cyclostationary signatures of the received signals as key features for modulation classification and a hybrid classifier combining Hidden Markov Model (HMM) and SVM as a classification system. It was shown that using a hybrid classifier combining HMM and SVM as a classification system slightly increases the classification accuracy compared to using simple SVM or Artificial Neural Network (ANN) classifier as a classification system. However, in addition to the computational complexity of the employed features, the performance of the classification system employed in this method depends highly on the prior statistical knowledge of the pre-experimentation [24].

In [17, 18], spectrum sensing methods using modulation classification are proposed, for different modulation sets under various transmission conditions, by employing the constellation shapes of the received signals as key features for modulation classification and K-means classifiers as classification systems. These methods are computationally efficient, and therefore suitable for real time applications. However, the features utilized in these methods are very sensitive to synchronization errors, and capable of characterizing the linear digital modulations schemes only [40]. Furthermore, the employed classification systems (i.e., K-means classifiers) are sensitive to the initialization conditions (i.e., the initial selection of the cluster centers) and prone to get stuck in local optima [41]. Moreover, since K-means classifiers are fully unsupervised clustering techniques, they are highly vulnerable to signal classification attacks and can be easily fooled into misclassification. If a malicious secondary user has the ability to manipulate the learning process, even in the simplest manner, he can be misclassified as a primary user, giving him unfettered and free access to the radio spectrum [42].

In [19], a spectrum sensing method using modulation classification is proposed by employing a Gaussianity test statistic, the signal bandwidth, the cyclic prefix, and the number of subcarriers estimates as key features for modulation classification and the K-Nearest Neighbor (KNN) classifier as a classification system. It was shown that this method can achieve a good performance even for a very small number of observation samples. However, the performance of this method has not been investigated in the low SNR regions, where the cognitive radio receiver generally operates. Furthermore, the employed classification system can suffer from many drawbacks such as high computational costs, large memory consumption and poor classifications performance in multidimensional datasets [43].

In [20], a low-complexity spectrum sensing method using modulation classification is proposed by employing fractional lower order statistics of the received signals as key features for modulation classification and the conventional Euclidean distance classifier as a classification system. This method is efficient and simple to implement. However, the features employed in this method require a high number of observation samples to yield good estimates [44].

In [21], a spectrum sensing method using modulation classification is proposed by employing characteristic parameters derived from the instantaneous information of the received signals as key features for modulation classification and multi-class SVM as a classification system. The authors developed a new instantaneous characteristics parameter which the average value of the absolute value of the zero-center normalized instantaneous energy to improve the detection performance. However, although the features used in this method are very easy to implement and highly suitable for real-time operation, they can easily be affected by noise or fading (i.e., very sensitive to noise effects), especially in low and medium SNR regions [45].

In [22], a spectrum sensing method using modulation classification is proposed by employing characteristic parameters derived from the instantaneous information and the Higher Order Moments (HOMs) of the received signals as key features for the modulation classification and ANN as a classification system. This method is quite general and considers a wide variety of analog and digital modulations. However, the employed classification system (i.e., ANN) has several shortcomings, such as slow learning speed and local minima problem [46].

In [23], a spectrum sensing method based on the combination of energy detection and modulation classification techniques is proposed, where modulation classification is performed by employing spectral characteristics of the received signals as key features and ANN as a classification system. This method has been tested offline using real signals and it has shown a good performance. However, besides the shortcomings of the employed classification system [45], the features employed in this method need a large number of samples to give good estimates [47]. Furthermore, this method considers a very small set of modulation schemes.

In [24], a spectrum sensing method using modulation classification is proposed by employing characteristic parameters derived from the instantaneous information and the Higher Order Cumulants (HOCs) of the received signals as key features for modulation classification, and the Kernel- based Generalized Discriminant Analysis (KGDA) as a classification system. It was shown that this method can provide a good performance, particularly in low SNR regimes. However, this method has a high overall computational complexity as it employs a large set of features, specifically eighteen features, to characterize the modulation schemes.

In [25], a spectrum sensing method using modulation classification is proposed by employing cyclostationary signatures of the received signals as key features for modulation classification and an improved random forest classifier as a classification system. It was shown that the method can provide an excellent classification performance in low SNR environments. However, this method, as in [23], covers a very small set of modulation schemes.

In [26], a spectrum sensing method using modulation classification is proposed by employing time-frequency features derived from the Pseudo Wigner–Ville Distribution (PWVD) of the received signals as key features for modulation classification and the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) approach as a classification system. It was shown that the method performs well within the investigated range of SNRs. However, the features employed in this method require a significantly high number of observation samples to yield good estimates [44].

Table 2 lists the spectrum sensing methods for cognitive radio systems using modulation classification proposed in the literature, emphasising the feature types, the classification system types, the transmission conditions, the considered range of SNRs, and the modulation sets.

6 Observations Based on the Review

In the previous section, we have carried out a critical review of existing spectrum sensing methods for cognitive radio systems using modulation classification and highlighted their benefits and drawbacks. Based on this review, we can see that:

– The cyclostationary signatures of the received signals are the frequently used features to characterize the modulation schemes in the existing spectrum sensing methods for cognitive radio systems using modulation classification. However, these features are highly complex and difficult to be performed in real time, especially on cognitive radio devices where the computational capability is limited.
– Most existing spectrum sensing methods for cognitive radio systems using modulation classification consider Additive White Gaussian Noise (AWGN) in the performance analysis. However, in general, the interference in the radio channels, especially when man-made noise is involved, exhibit impulsive behavior, and therefore its distribution is highly non-Gaussian. In practice, detection methods optimized for operating in Gaussian noise environments show significantly degraded performance when operating in non-Gaussian noise environments.
– Most existing spectrum sensing methods for cognitive radio systems using modulation classification are evaluated only by simulation under the assumption of perfect synchronization at the secondary user sides. Hence, implementation of such methods on real-time hardware is needed in order to evaluate their practical performance in real wireless communication scenarios; where the computational capability is limited and severe realistic impairments, such as phase jitter and frequency offsets, are present.

7 Conclusion

In this paper, we provided an overview on spectrum sensing for cognitive radio networks using modulation classification. We presented the conventional spectrum sensing methods for cognitive radio systems. We also presented a critical review of the existing spectrum sensing methods for cognitive radio systems using modulation classification, presenting their merits and drawbacks. It has been shown that the research in the field is quite active and rapidly growing. In practice, developing reliable and fast spectrum sensing method for cognitive radio systems using modulation classification is still a great challenge, especially over multipath fading channel and in the presence non-Gaussian impulsive noise, where the received signal experiences a very deep fade.

Table 2: Summary of the existing spectrum sensing methods for cognitive radio systems using modulation classification.

Author(s) and Date	Key Features	Classification system	Transmission conditions	SNR (dB) min: x : max	Modulation Set
Liu et al. [12], 2008	Cyclostationary signatures	SVM	AWGN	-5:2:14	AM, BPSK, FSK, MSK, QPSK
Hu et al. [13], 2008	Cyclostationary signatures	SVM	Rayleigh	0:2:20	AM, ASK, FSK, PSK, MSK, QPSK
Ramon et al. [14], 2009	Cyclostationary signatures	SVM	AWGN / Impulse Noise	0:1:7	BPSK, QPSK, FSK, MSK
Dan and Jian Liu [15], 2010	Cyclostationary signatures	SVM	AWGN	0:2:14	BPSK, QPSK, 2-FSK, 4-FSK, 16-QAM
He et al. [16], 2009	Cyclostationary signatures	HMM/SVM	AWGN	-5:2.5:5	AM, BPSK, FSK, MSK, QPSK
Zamanian et al. [17], 2011	Constellation shape	K-means	AWGN / Rayleigh	5:5:30	BPSK, QPSK, 8-PSK, Rectangular 8-QAM, Square 8-QAM, Circular 8-QAM, 16-QAM
Azarmanesh and Bilen [18], 2013	Gaussianity test statistic and Constellation shape	K-means	AWGN	2:2:16	OFDM, 4-QAM, 8-QAM, 16-QAM, 64-QAM, 8-PSK, 16-PSK
Sichelschmidt and Brückmann [19], 2012	Gaussianity test statistic, signal bandwidth, cyclic prefix, number of subcarriers	KNN	AWGN/ Rayleigh/ Rician	Not mentioned	BPSK, QPSK, GMSK, 16-QAM, 64-QAM,
Madhavan et al. [20], 2013	Fractional lower order statistics	Euclidian distance	AWGN/ Impulse Noise	0:2:20	BPSK, QPSK, 16-QAM, 32-QAM, 64-QAM
Yibing et al. [21], 2013	Derived from the instantaneous information	SVM	AWGN	-5:5:20	2-ASK, 4-ASK, 2-FSK, 4-FSK, BPSK, 4-PSK
Popoola and Olst [22], 2013	Derived from the instantaneous information and higher order moments	ANN	AWGN	-5:5:20	2-ASK, 4-ASK, 2-FSK, BPSK, QPSK, AM, DSB, SSB, FM, 16-QAM, 64-QAM, OFDM
Elrharras et al. [23], 2014	Amplitudes in the frequency domain	ANN	AWGN	Not mentioned	AM, FM, FSK
Zare and Abouei [24], 2014	Derived from the instantaneous information and higher order cumulants	KGDA	AWGN/ Rayleigh	-25:5:15	BPSK, QPSK, 2-FSK, 4-FSK, 16-QAM, 64-QAM
Wang et al. [25], 2016	Cyclostationary signatures	Improved random forest	AWGN/ Rayleigh	-15:5:0	BPSK, 2-FSK, OFDM
Zhu and Fujii [26], 2016	Derived from the PWVD coefficients	DBSCAN	AWGN	0:2:10	BPSK, QPSK, 8-PSK, 16-QAM, 64-QAM

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