

A Review of Spectrum Sensing Techniques for Cognitive Radio Environment

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Abstract – This paper focuses on the physical layer of cognitive radio networks (CR), that is, techniques that are used to detect the presence or absence of licensed users in different bands of the electromagnetic spectrum. The techniques presented, with their advantages and disadvantages, are organized hierarchically as: fundamental techniques (energy detection, adapted filter and cyclostationary characteristics), techniques based on fundamentals or evolution (waveform detection, identification of radio transmitter, detection of the leakage power at the receiver) and typical alternative techniques of image analysis (Hough and Wavelet transform). Additionally, the main challenges in the detection of licensed users are described along with the different dimensions in which opportunities for efficient spectral use by cognitive radio devices can be found.

Keywords – CR, WiFi, WLAN, WSN.

I. INTRODUCTION

Currently, wireless networks, such as the cellular telephone network or WiFi networks, communicate to almost all the inhabitants of the planet, providing services such as conventional telephone calls, Internet access, geolocation, etc. The main advantage of this type of networks is their mobility, which makes them very attractive for users who need a portable network. However, this fundamental strength of wireless connections is overshadowed by the reduction in bandwidth when compared to the transmission capacity of the wired networks. To increase the bandwidth of wireless networks, it is necessary to change the static allocation paradigm of the electromagnetic spectrum. It is suggested that much of the spectrum allocated under current policies is used sporadically, indicating that spectrum is being underutilized to a large extent [1]. In this scenario, CR concepts are seen as a solution that will allow mobile users large bandwidths using heterogeneous wireless architectures. Of course, this interaction between architectures imposes important

challenges, ranging from the estimation of frequency bands that are in an idle state to the development of routing protocols of a dynamic allocation of network resources.

The suggested framework for structuring the study of CR networks [2] establishes the functionality that these systems must offer and proposes three fundamental aspects of design related to the prevention of interference, the permanent sense of quality of service and connection Transparent from the unlicensed user or CR, when it transmits opportunistically in licensed regions of the spectrum that are not being used. Responding to these design conditions, the literature divides a successful CR communication into four steps, Detection, Decision, Sharing, and Mobility.

This paper focuses on the Spectrum Detection stage for CR. The first part discusses basic concepts of detection and gives some examples of the multiple dimensions of the electromagnetic spectrum. The main section, followed by the conclusions, describes in a hierarchical way a considerable number of techniques for estimating and detecting primary users with their advantages and disadvantages.\

II. BASIC CONCEPT OF SPECTRUM SENSING

Spectrum Sensing has been briefly defined as the task of obtaining a sense of available spectrum, determining the existence of licensed users within a defined geographical region. This sense is obtained in several ways within which the local detection of the spectrum in CR [3-5] is found. A CR user may transmit only at frequencies not being used in the surrounding spectrum. Therefore, such user must monitor the available bands and capture their information to finally detect what are known as spectral gaps [6].

Although spectrum detection is traditionally understood as the measure of the energy of radio frequencies along the spectrum, when it is CR the detection becomes a broader term that involves obtaining usage characteristics Spectral in multiple dimensions such as time, space, frequency and code [7]. The detection comprises a variety of aspects associated with determining the type of signal that a band occupies; however, this requires more robust techniques for the analysis of signals, which are more complex from the computational point of view. The following are the concepts associated with the possible dimensions in which the spectrum can be exploited for its opportunistic use by CR systems.

Considering the Multiple Dimensions of the Spectrum

The basic dimensions of Figure 1 were the initial model to analyze the underutilization of the spectrum in early cognitive radio studies [8]. However, in subsequent studies new dimensions were proposed that make possible an even more efficient use of the spectrum, taking into account aspects such as coding schemes and the use of intelligent antennas. These two aspects can be interpreted as two new dimensions for the opportunistic use of the spectrum. Thus, in addition to the basic dimensions already mentioned, an available spectrum detection is proposed where code and angle dimensions [7] are included.

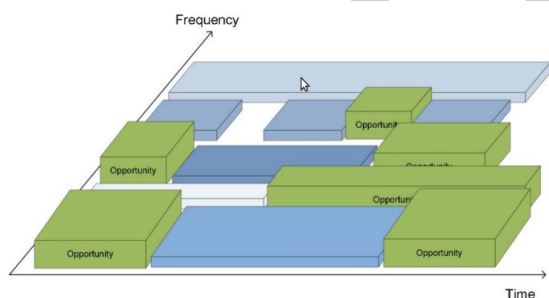


Figure 1: Time and frequency dimensions

Below are provided comments that clarify the different spectral usage opportunities associated with the five dimensions discussed in this section.

Frequency and Time

In this two-dimensional space we look for opportunities in the frequency domain.

The different bands of available spectrum are divided into narrower portions where spectral opportunities appear, since not all bands are used simultaneously, Figure 1. Each spectral gap in this diagram represents a transmission opportunity for

CR devices in the dimensions of Frequency and time. In [11], for example, the idle periods between the burst transmissions of the signals are exploited in a WLAN (Wireless Local Area Network).

Geographical Space

Here opportunities are sought for location (latitude, longitude, and elevation) and distance from primary users. The spectrum may be available in certain parts of a geographic area while being occupied elsewhere at the same time. This dimension takes advantage of the losses by propagation in the space. These propagation measures can be avoided simply by observing interference levels. The fact that there is no interference means that there are no transmissions of primary users in the local context of the specific area. However, in this dimension care must be taken with the hidden terminal problem.

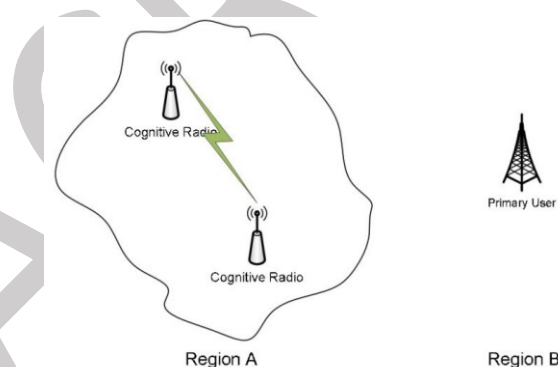


Figure 2: Geographic space dimension

Code

In this dimension it is sought to detect the sequences of the spread spectrum codes, both of the time jumps (TH) and the frequency jumps (FH) that are used by the licensed users. Synchronization information is also sought for CR users to coordinate their transmissions with respect to licensed users. Synchronization estimation can be avoided by using extensive random codes. However, partial interference in this case is inevitable.

The spectrum over a broadband may be being used in a time given by spread spectrum signals or by signals using frequency hopping. This does not mean that there is no spectral availability in that band. It must be possible to carry out simultaneous transmissions without interfering with licensed users if codes that are orthogonal to the codes of the corresponding licensed users are used. These implementations require the proper use of frequency bands in the code dimension, and possibly determine the selective fading parameters in frequency with the aim of minimizing interference [53]. Figure 3 shows

a stack of possible transmission codes on a single band where spread spectrum signals exist.

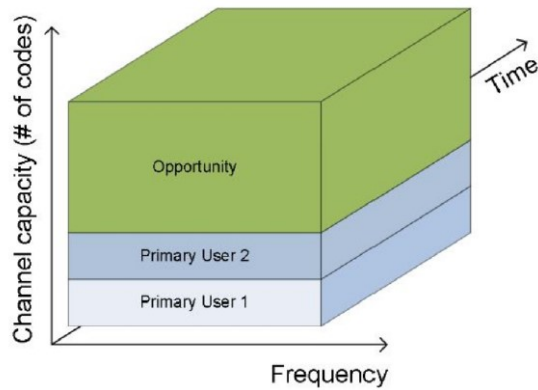


Figure 3: Representation of spectral use opportunities in the code dimension

Angle

In this dimension the directions of the electromagnetic radiation lobes (azimuth and elevation angle) and the location of the licensed users are detected. The knowledge of the position or direction of the licensed users is what generates the opportunities (gaps) in the angle dimension. Figure 4 shows different simultaneous transmissions that can use the same frequency band within the same range. Since the transmissions are directional, the level of interference is significantly reduced.

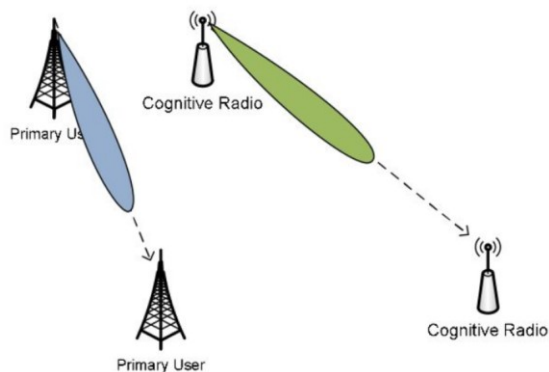


Figure 4: Angle dimension

Taking into account the dimensions mentioned above, the radio wave space can be defined as a theoretical hyperspace, occupied by radio signals, which has dimensions of physical position, angle of arrival, frequency, time and possibly other more [9-10].

Researchers at CR suggest the development of advanced algorithms for spectrum detection that

include estimation of unlicensed spectral usage opportunities in multiple dimensions.

III. DETECTION CHALLENGES

Requirements for Physical Devices

It is possible to detect the spectrum through two architectures: unique radio architecture and dual radio architecture [12-13]. In the unique radio architecture the efficiency in the use of the spectrum is not ideal because part of the transmission time must be used for detection and not for sending the data [14-15]. The single radio constantly allocates a time interval to monitor the spectrum. Due to this restriction in detection time, it is not possible to guarantee high levels of accuracy when estimating the absence of licensed users.

On the other hand, in the dual radio architecture there is a dedicated link for the transmission and reception of the data. Another link is responsible for the monitoring of the available spectrum [16-17]. The disadvantages of this architecture are: the increase in energy consumption and the cost of equipment. It is pertinent to mention that a single antenna would be sufficient for the connection of both links [12].

Hidden Licensed User Problem

This problem is similar to the hidden node problem of CSMA (Carrier Detection Multiple Access) systems. This situation can be caused by several factors, among which are the multi-stream fading (or shadowing) experienced by CR users when detecting licensed users that are transmitting. In Figure 5, the CR device causes undesired interference on the licensed user (the receiver) because the transmitter signal (licensed station) could not be detected given its distance from CR users.

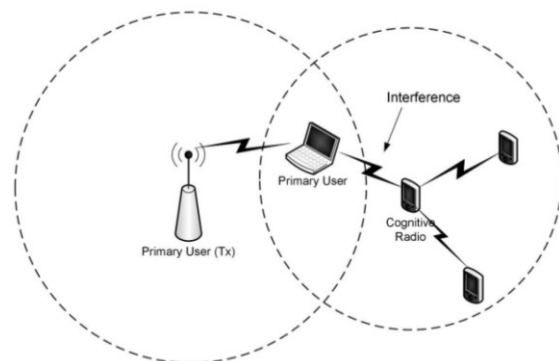


Figure 5: Hidden user problem in Cognitive Radio

To overcome this problem, cooperative detection schemes have been proposed [18-20].



Detection of Licensed Users of Spread Spectrum

Wireless transmission technologies for commercial devices can be classified in two ways: fixed frequency technologies and spread spectrum technologies. In spread spectrum technologies, such as FHSS (Frequency Hopping Spread Spectrum), devices dynamically change their operating frequencies by occupying multiple narrowband channels. These frequency changes are known as jumps and are performed according to a sequence that must be known by both the transmitter and the receiver.

Licensed users using spread spectrum signaling are difficult to detect because their transmission power is distributed across a wide range of frequencies, even though their actual information bandwidth is much narrower [21]. This problem can be partially avoided if the skip pattern is known and a perfect synchronization of the signals is achieved. However, designing algorithms that can make an appropriate estimate in this code space (dimension) is not easily achievable.

Duration and Frequency of Detections

The number of times spectrum availability is to be detected over a time interval is a design parameter that should be carefully considered. The optimal value of the time between detections depends on the capabilities of the CR device and the temporal characteristics of users licensed in a given scenario [22]. In [23] the impact of time between detections on the performance of unlicensed users has been investigated. With a similar approach, in [14], the detection time is obtained using numerical optimization, in this study the channel efficiency is maximized for a given detection probability. Another method is proposed in [24] where the guard interval between Orthogonal Frequency Division Multiplexing (OFDM) symbols is replaced by periods of inactivity and the detections are performed in these inactive periods.

Detection times can be reduced by detecting only those parts of the spectrum that exhibit changes. A detection method that adapts spectral scanning parameters according to an estimated model of channel occupancy is developed in [25].

A channel occupied by unlicensed users cannot be used simultaneously to make detections. This is why unlicensed users should disrupt their data transmissions to perform spectrum detections [24]. These interruptions reduce the spectral efficiency of the entire system [22]. To minimize this problem we propose a method called dynamic frequency hopping (DFH) [26].

These challenges have led to the development of different techniques and schemes for the detection of licensed users, which are increasingly elaborated; However, it is important to mention that some of the more robust techniques suggest computational complexity and energy consumption that would involve high costs in constructing the devices or would simply be very difficult to put into practice. The concepts that support the existing techniques are explained below.

IV. SPECTRUM DETECTION TECHNIQUES FOR COGNITIVE RADIO

Fundamental Techniques

The metrics and principals involved in these three models represent the fundamental information that subsequently serves as a basis for developing more elaborate detection algorithms.

Power Detection

The detection of energy in frequency bands is the most common way to detect opportunities in the spectrum, due to its low level of complexity in terms of computation and implementation [13, 17-21, 23, 25, 27-46].

Considering that the signal to be received is of the form:

$$y(n) = x(n) + r(n) \quad (1)$$

In equation (1), $x(n)$ is the target signal, $r(n)$ is the white Gaussian noise, and n is the sample index (in the time domain) or symbol index frequency). For simplicity, it will be assumed that the different samples of $x(n)$ are independent. The correlation between the $x(n)$ samples will improve detection performance. Because the noise samples $r(n)$ are also independent, the samples and (n) received will be independent.

The energy detection metric M will correspond to the sum of the samples detected in a particular spectrum band as follows:

$$M = \sum_{n=1}^N |y(n)|^2 \quad (2)$$

In equation (2), N is the size of the sample vector or number of signal samples that will fit into the buffer of the licensed user detector. It should be noted that $|y(n)|^2$ is a sequence of independent random variables and distributed identically with mean μ and variance σ^2 .

When N is large, using the central limit theorem, the detection metric M can be approximated as a Gaussian random variable with mean $\mu_M = N \cdot \mu$ and variance $\sigma_M^2 = N \sigma^2$.

Note that $x(n) = 0$ when there are no transmissions by licensed users. According to this technique, it will be determined that there exists a licensed user transmitting in a given band when the metric M

exceeds a specific threshold λ . This is the same as making a decision regarding the following binary hypothesis:

$$H_0: y(n) = r(n) \quad (3)$$

$$H_1: y(n) = x(n) + r(n) \quad (4)$$

According to the decision between these two hypotheses, the most relevant indexes for this type of detection are the probabilities of correct detection P_d and the probability of false alarm P_f . The probability P_d is equivalent to deciding aptly that a user exists, that is:

$$P_d = P(M > \lambda | H_1) \quad (5)$$

The probability of false alarm P_f is the probability of losing opportunities of spectral use, since the metric M exceeds the threshold λ , when there are no licensed user transmissions, that is:

$$P_f = P(M > \lambda | H_0) \quad (6)$$

What is sought is an adequate balance between PF and P_d to obtain an optimal λ threshold.

The main advantage of this technique is that Cognitive Radio receivers do not require any knowledge of the primary user's signal. The signals are detected by comparing the output level of an energy detector with respect to a noise-dependent threshold [47, 57]. However, the selection of this threshold is one of the weaknesses of this technique. Another failure of energy detection is the lack of precision in differentiating the noise from the interference produced by other licensed users. Additionally, this technique has limited performance when applied under low signal-to-noise ratio conditions and when it is desired to detect spread spectrum signals [21, 42].

The threshold that is used in the energy detection algorithms depends on the variance of the noise, for this reason, a small error in the estimation of the power of the noise produces a significant low in the performance [48]. To solve this problem, the noise level is estimated dynamically by the use of multiple signal classification algorithms (MUSIC) [49]. In [45] an iterative algorithm is proposed to find the threshold. This threshold must satisfy a certain level of confidence, for example a certain false alarm probability. Other more recent methodologies based on energy detection are studied under conditions of unknown noise power [37], where it is proposed to estimate noise levels adaptively.

Adaptive Filter Detection

Basically a tailored filter suits its impulse response so that when sampling the signal at a specific time, the output of the filter is equivalent to the output of a correlation receiver. This technique is recognized

for its optimal performance in detecting licensed users when transmitted signals are known [50]. This type of filtering achieves certain probabilities of false alarm and erroneous detection in considerably short times [51]. However, adapted filtering requires that the CR receiver demodulate the received signals, which requires a very high knowledge of the characteristics of the licensed user signals (bandwidth, operating frequency, type and order of Modulation, formed of the pulses and format of the waveforms). The complexity of implementing a detection unit with these characteristics is too high to be implemented [21].

Detection based on Cyclostationary Characteristics

In this case, in order to detect the presence of licensed users, the periodic nature of the modulated signals is exploited, i.e., unlike what happens in the detection of energy, a signal carrying information will be very different from noise and Interference due to consecutive changes occurring in equal periods of time, e.g. The rate at which the symbols change or the intrinsic periodicity of the carriers themselves. From the formal point of view, a stochastic process $X(t)$ representing a signal modulated linearly with respect to a sequence of symbols (or bits) can be represented as:

$$X(t) = \sum_{n=-\infty}^{\infty} a_n g(t - nT) \quad (7)$$

In equation (7), (a_n) is a sequence of random variables (in discrete time) with mean $\mu_a = E[a_n]$ for all n and the autocorrelation sequence $C_{aa}(k) = E[a_n a_{n+k}^*]$. The signal $g(t)$ is deterministic (i.e. the carriers). The sequence (a_n) represents the sequence of digital symbols transmitted by the channel, whose transmission rate is $1/T$. Given this period T for the change from one symbol to another, it can be easily demonstrated that the correlation sequence of the whole stochastic process, i.e. $C_{xx}(t, t + \tau)$, is periodic:

$$\begin{aligned} C_{xx}(t, t + \tau) &= E[X(t)X^*(t + \tau)] \\ &= C_{xx}(t + kT, t + \tau + kT) \end{aligned} \quad (8)$$

Being periodic, C_{xx} can be represented by a Fourier series with fundamental frequency of the following form:

$$C_{xx}(t, t + \tau) = \sum_{\alpha} C_{xx}^{\alpha}(\tau) e^{j2\pi\alpha t} \quad (9)$$

This summation runs through the integer multiples of the fundamental frequency α . The coefficients of this series, which depend on the delay τ , can be calculated as:

$$C_{xx}^{\alpha}(\tau) = \lim_{T \rightarrow \infty} \frac{1}{T} \int_{-T/2}^{T/2} C_{xx}(t, t + \tau) e^{-j2\pi\alpha t} dt \quad (10)$$

The $C_{xx}^{\alpha}(\tau)$ function is known as the cyclic autocorrelation function. The spectral correlation



density $S_{xx}^{\alpha}(f)$ is defined as the Fourier transform of $C_{xx}^{\alpha}(\tau)$:

$$S_{xx}^{\alpha}(\tau) = \int_{-\infty}^{\infty} C_{xx}^{\alpha}(\tau) e^{-j2\pi\alpha\tau} d\tau \quad (11)$$

This expression can be seen as a generalization of the conventional power spectral density function. A very useful modification of the $C_{xx}^{\alpha}(\tau)$ function of equation (10) is its conjugate function, defined as:

$$C_{xx}^{\alpha*}(\tau) = \lim_{T \rightarrow \infty} \frac{1}{T} \int_{-T/2}^{T/2} C_{xx}^{\alpha}(t, t + \tau) e^{-j2\pi\alpha t} dt \quad (12)$$

In equation (12) $C_{xx}^{\alpha*}(t, t + \tau) = E[X(t)X(t + \tau)]$. As in the non-conjugated case, the conjugated spectral correlation density function $S_{xx}^{\alpha*}(f)$ is the Fourier transform of $C_{xx}^{\alpha*}(\tau)$. The $C_{xx}^{\alpha}(\tau)$ and $C_{xx}^{\alpha*}(\tau)$ functions are discrete with respect to the fundamental frequency α and continuous with respect to τ . In a signal that does not have cyclostationary characteristics $C_{xx}^{\alpha}(\tau) = 0$ and $C_{xx}^{\alpha*}(\tau) = 0 \forall \alpha \neq 0$. The values of α , for which these two functions are different from zero, are found in the hidden periodicities of the stochastic process $X(t)$ of Eq. (7). These values of α represent cyclic marks inherent to the detected signal. Therefore, for a CR device there is greater certainty in differentiating a true information signal from the interference produced by the signals of other licensed users and the noise variance.

Cyclostationary characteristics can also be intentionally induced to contribute to spectrum detection [61-63]. The algorithms used in this technique differentiate the noise of the licensed user signals. The above is achieved because the noise is stationary (WSS) and no correlation at all, while the modulated signals are cyclostationary [54]. Additionally, the cyclostationary characteristics can be used to distinguish between different types of modulation and licensed users [58], [60]. It can be assumed that the cyclic frequencies are known [52, 56]; Otherwise, they can be extracted and used as characteristics to identify transmitted signals [55]. The waveform of the OFDM signals is altered before being transmitted [61-63] in order to generate specific system marks in certain bands. These marks are used to provide an effective signal classification mechanism. In [63], the number of characteristics generated in the signal is raised to make the system more robust to multichannel fading. The disadvantage in this case is the loss of bandwidth, due to the increase of bits that do not carry information of the signal in the transmission. Although the methods in [61] and [62] have been proposed specifically for OFDM, similar techniques can be developed for any type of signal [64]. In [65]

a hardware implementation is presented for a detector of cyclostationary characteristics.

Evolution of Fundamental Techniques

In most cases, the basic principle is the detection of energy, followed by the extraction of cyclostationary characteristics. In other examples, without using a matched filter, what is sought is to have as much signal information as possible to perform signal and / or vector correlation processes.

Waveform Detection (Coherent Detection)

The use of patterns is usually implemented in wireless systems for different purposes, e.g. synchronization. Such patterns include the use of preambles, half-wave patterns, regularly transmitted pilot patterns, spread spectrum sequences, among others. Whenever a known pattern occurs, a detection can be made by correlating the received signal with a known copy of itself [31, 41, 46]. With respect to the metric used to decide whether or not a licensed user exists when receiving the signal from equation (1), a waveform detector will calculate the product of the vectors $y(n)$, $x(n)$ as it's shown in the following:

$$\begin{aligned} M &= \text{Re} \left[\sum_{n=1}^N y(n)x^*(n) \right] \\ &= \sum_{n=1}^N |x(n)|^2 + \text{Re} \left[\sum_{n=1}^N r(n)x^*(n) \right] \end{aligned} \quad (13)$$

This makes the threshold λ at which M is compared is easier to determine than in the case of energy detection. This method is only applicable to systems involving signals with known patterns. In [31] it is shown that this type of detection has better performance than the detection of energy in terms of reliability and time of convergence. In [38, 39] the packet preambles of the IEEE 802.11b signals [66] are exploited to analyze the usage characteristics of a WLAN channel. The results of the measurements presented in [20] show how the waveform-based detection uses very short measurement times. The disadvantage of this type of detection is in the synchronization errors that may occur. Packet preambles are also exploited to detect WiMAX signals [46].

Identification Detection of the Radio Transmitter

It is possible to obtain a complete knowledge of spectrum characteristics by identifying the transmission technology being used by licensed users. This type of identification allows greater accuracy [42]. In addition, CR systems could

communicate with technologies identified for specific applications. In the context of the European project called TRUST (Transparent Ubiquitous Terminal) [67], classification and extraction techniques are used to perform spectrum detections using radio identification.

The procedure in these techniques is basically the extraction of a significant number of characteristics of the signals received, followed by the implementation of several classification methods. The characteristics obtained from the energy detection are used to perform the corresponding classification [12, 68]. Such extraction includes the amount of energy detected and its spectral distribution. The channel bandwidth and its shape are also used as reference characteristics [69], in this study the classification was done with neural networks. In [42], the operating bandwidth and the central frequency of the received signal are extracted using methods based on energy detection. These two characteristics are processed by a Bayesian classifier to determine the active licensed users. The standard deviation of the instantaneous frequency and the maximum duration of the signal are extracted using time-frequency analysis to later use neural networks in the identification of active transmissions [70-73]. In [74], the cycle characteristics of the signals are used to obtain the information of the vacant channels of GSM technology of a licensed user. In [59] the cyclic frequencies of the input signals are used for both the detection and the classification of the signals, here the identification of the signals is effected by the processing of the cyclo-stationary characteristics using Hidden Markov Models (HMM). Another method based on cyclo-stationary features is implemented in [52, 55], where the spectral correlation density and the spectral coherence function are used as characteristics. In the classification stage, we used neural networks in [55] and statistical tests in [52].

Hough Transform-based Detection

The Hough Random transform of the received signal is used to identify the presence of radar pulses [79] in the IEEE 802.11 systems' operating channels. This method can also be used to detect any type of signal with a periodic pattern. It is known that the statistical covariance of noise and signal are different. This property is used to develop algorithms [80] that identify the existence of a communications signal. This study shows that the proposed methods are effective in the detection of digital television signals.

Multitaper Spectral Detection

This type of detection is an approximation of the maximum likelihood estimator for Spectral Power Density [6]. The algorithm is very close to an optimal solution for spread spectrum signals. Although the complexity of this method is smaller than that of the maximum likelihood estimator, this method is still demanding in terms of computational load.

Detection based on Wavelet Transform

In this case, Wavelets are used to detect the edges of the power spectral density of a wideband channel [75], the frequency spectrum can be characterized as occupied or empty (in binary form) using the power information found and Of the edges. In [76] the method proposed in [75] is extended using a sampling similar to that of Nyquist. The analogous implementation of Wavelet transform-based detection is suggested in [16, 77-78], to make non-detailed detections. The detection of Spectrum with Multiresolution is achieved by changing the base functions without needing to modify the detection circuits [16]. The base functions are changed by adjusting the pulse width of the Wavelets and the carrier frequency. In this way it is possible to perform a rapid detection by focusing on frequencies with active transmissions after a superficial sweep. In [78] the implementation of a test bench for this algorithm is explained.

This architecture converts the RF signal into an intermediate frequency (IF) signal, allowing to replace an adjustable RF filter with a low Q factor by a less expensive intermediate frequency filter that has a much higher Q factor. To convert the RF signal to the intermediate frequency (IF) a Local Oscillator must be used, whose power is reflected towards the antenna and therefore is radiated. This minimum radiation emitted by these local oscillators can be used to detect the receivers of the licensed frequencies.

Unlike other detection techniques that focus on the search of licensed transmitters, in this case spectrum opportunities are detected by looking for licensed users who are receiving the signals within the communication range of a CR user. In [81] the power emitted by the local oscillators is exploited. Although this technique allows to identify the licensed receivers, the reference power is so low that the implementation of a reliable detector is not simple. At present, this method has only been implemented to detect television receivers.



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V. CONCLUSION

This paper describes the techniques used to detect licensed users from CR devices. In addition, the [5] concept of multidimensional spectrum was clarified. The techniques exposed are being studied to guarantee minimal interference on licensed users, offering efficient use of channels that support current application bandwidths (quality of service for data and multimedia). Adequate detection is the starting point for correct functioning of the other stages of the cognitive cycle in CR (decision, sharing and mobility) systems. At present, most studies are using energy-based detection [7] and cyclostationary features. Many of the challenges associated with aspects such as uncertainty regarding noise, fading and hidden terminals can be solved [8] using cooperative detection schemes. Cooperative detections greatly reduce [9] the probability of false detection and false alarms. In addition, the cooperation between CR nodes can solve the hidden terminal problem and reduce detection times [18-20]. In general, the dimensions of the exploited spectrum are mostly limited to space, frequency and range. Future studies should focus on the analysis of other techniques (or hybrid techniques). In this sense, new opportunities for efficient spectrum use that involve more actively the spectral dimensions associated with the codes of [11] the signals and their angles of arrival must be studied.

REFERENCE

- [1] Federal Communications Commission. "Notice of proposed rule making and order". ET Docket N° 03-322. 2003.
- [2] I.F. Akyildiz, W.-Y. Lee, M. C. Vuran and Sh. Mohanty. "A survey on spectrum management in cognitive radio networks". IEEE Communications Magazine. 2008.
- [3] Federal Communications Commission. "Notice of proposed rule making: Unlicensed operation in the tv broadcast bands". ET Docket No. 04-186 (FCC 04-113). 2004.
- [4] M. Marcus. Unlicensed cognitive sharing of tv spectrum: "The controversy at the federal communications commission". IEEE Commun. Mag. Vol. 43, Issue 5, pp. 24-25. 2005.
- [5] Y. Zhao, L. Morales, J. Gaeddeert, K.K. Bae, J.-S. Um and J.H Reed. "Applying radio environment maps to cognitive wireless regional area networks". Proc. IEEE Int. Symposium on New Frontiers in Dynamic Spectrum Access Network, pp. 115-118. 2007.
- [6] S. Haykin. "Cognitive radio: Brain-empowered wireless communications". IEEE J. Select. Areas Commun. Vol. 23, Issue 2, pp. 201-220. February, 2005.
- [7] T. Yucek and H. Arslan. "A survey of spectrum sensing algorithms for cognitive radio applications". IEEE Communications survey & tutorials. Vol. 11, Issue 1. 2009.
- [8] P. Kolodzy. "Next generation communications: Kickoff meeting". In Proc. DARPA. 2001.
- [9] R. Matheson. "The electrospace model as a frequency management tool". In Int. Symposium on Advanced Radio Technologies, pp. 126-132. 2003.
- [10] A.L. Drozd, I.P. Kasperovich, C.E. Carroll and A.C. Blackburn. "Computational electromagnetics applied to analyzing the efficient utilization of the rf transmission hyperspace". In Proc. IEEE/ACES Int. Conf. on Wireless Communications and Applied Computational Electromagnetics, pp. 1077-1085. 2005.
- [11] S. Geirhofer, L. Tong and B. Sadler. "Dynamic spectrum access in the time domain: Modeling and exploiting white space". IEEE Commun. Mag. Vol. 45, Issue 5, pp. 66-72. 2007.
- [12] G. Vardoulas, J. Faroughi-Esfahani, G. Clemo and R. Haines. "Blind radio access technology discovery and monitoring for software defined radio communication systems: problems and techniques". In Proc. Int. Conf. 3G Mobile Communication Technologie, pp. 306-310. 2001.
- [13] S. Shankar, C. Cordeiro and K. Challapali. "Spectrum agile radios: utilization and sensing architectures". In Proc. IEEE Int. Symposium 206 on New Frontiers in Dynamic Spectrum Access Networks, pp. 160-169. 2005.
- [14] P. Wang, L. Xiao, S. Zhou and J. Wang. "Optimization of detection time for channel efficiency in cognitive radio systems". In Proc. IEEE Wireless Commun. and Networking Conf., pp. 111-115. 2007.
- [15] Q. Zhao, S. Geirhofer, L. Tong and B.M. Sadler. "Optimal dynamic spectrum access via periodic channel sensing". In Proc. IEEE Wireless Commun. and Networking Conf., pp. 33-37. 2007.
- [16] Y. Hur, J. Park, W. Woo, K. Lim, C. Lee, H. Kim and J. Laskar. "A wideband analog multi-resolution spectrum sensing (MRSS) technique for cognitive radio (CR) systems". In Proc. IEEE Int. Symp. Circuits and Systems, pp. 4090-4093. 2006.
- [17] Y. Yuan, P. Bahl, R. Chandra, P. A. Chou, J. I. Ferrell, T. Moscibroda, S. Narlanka and Y. Wu. "Knows: Cognitive radio networks over white spaces". Symposium on New Frontiers in Dynamic Spectrum Access Networks, pp. 416-427. 2007.
- [18] G. Ganesan and Y. Li. "Agility improvement through cooperative diversity in cognitive radio". In Proc. IEEE Global Telecomm. Conf. (Globecom). Vol. 5, pp. 2505-2509. 2005.
- [19] G. Ganesan and Y. Li. "Cooperative spectrum sensing in cognitive radio networks". Proc. IEEE Int. Symposium on New Frontiers in Dynamic Spectrum Access Networks, pp. 137-143. 2005.
- [20] D. Cabric, A. Tkachenko and R. Brodersen. "Spectrum sensing measurements of pilot, energy, and collaborative detection". In Proc. IEEE Military Commun. Conf., pp. 1-7. 2006.
- [21] D. Cabric, S. Mishra and R. Brodersen. "Implementation issues in spectrum sensing for cognitive radios". In Proc. Asilomar Conf. on Signals, Systems and Computers. Vol. 1, pp. 772-776. 2004.
- [22] S.D. Jones, E. Jung, X. Liu, N. Merheb and I.-J. Wang. "Characterization of spectrum activities in the u.s. public safety band for opportunistic spectrum access". In Proc. IEEE Int. Symposium on New Frontiers in Dynamic Spectrum Access Networks, pp. 137-146. 2007.
- [23] A. Ghasemi and E. Sousa. "Optimization of spectrum sensing for opportunistic spectrum access in cognitive



- radio networks". In Proc. IEEE Consumer Commun. and Networking Conf., pp. 1022-1026. 2007.
- [24] N. Khambekar, L. Dong and V. Chaudhary. "Utilizing ofdm guard interval for spectrum sensing". In Proc. IEEE Wireless Commun. and Networking Conf., pp. 38-42. 2007.
- [25] D. Datla, R. Rajbanshi, A.M. Wyglinski and G.J. Minden. "Parametric adaptive spectrum sensing framework for dynamic spectrum access networks". In Proc. IEEE Int. Symposium on New Frontiers in Dynamic Spectrum Access Networks, pp. 482-485. 2007.
- [26] W. Hu, D. Willkomm, M. Abusubaih, J. Gross, G. Vlantis, M. Gerla and A. Wolisz. "Dynamic frequency hopping communities for efficient IEEE 802.22 operation". IEEE Commun. Mag. Vol. 45, Issue 5, pp. 80-87. 2007.
- [27] T. Weiss, J. Hillenbrand and F. Jondral. "A diversity approach for the detection of idle spectral resources in spectrum pooling systems". In Scientific Colloquium, pp. 37-38. 2003.
- [28] F. Digham, M. Alouini and M. Simon. "On the energy detection of unknown signals over fading channels". In Proc. IEEE Int. Conf. Commun. Vol. 5, pp. 3575-3579. 2003.
- [29] P. Qihang, Z. Kun, W. Jun and L. Shaoqian. "A distributed spectrum sensing scheme based on credibility and evidence theory in cognitive radio context". In Proc. IEEE Int. Symposium on Personal, Indoor and Mobile Radio Commun, pp. 1-5. 2006.
- [30] P. Pawelczak, G.J. Janssen and R.V. Prasad. "Performance measures of dynamic spectrum access networks". In Proc. IEEE Global Telecomm. Conf. (GlobeCom). 2006.
- [31] H. Tang. "Some physical layer issues of wide-band cognitive radio systems". In Proc. IEEE Int. Symposium on New Frontiers in Dynamic Spectrum Access Networks, pp. 151-159. 2005.
- [32] M. Wylie-Green. "Dynamic spectrum sensing by multiband ofdm radio for interference mitigation". In Proc. IEEE Int. Symposium on New Frontiers in Dynamic Spectrum Access Networks, pp. 619-625. 2005.
- [33] S. Jones and N. Wang. "An experiment for sensing-based opportunistic spectrum access in csma/ca networks". In Proc. IEEE Int. Symposium on New Frontiers in Dynamic Spectrum Access Networks, pp. 593-596. 2005.
- [34] P. Papadimitratos, S. Sankaranarayanan and A. Mishra. "A bandwidth sharing approach to improve licensed spectrum utilization". IEEE Commun. Mag. Vol. 43, Issue 12, pp. 10-14. 2005.
- [35] A. Leu, K. Steadman, M. McHenry and J. Bates. "Ultra-sensitive TV detector measurements". In Proc. IEEE Int. Symposium on New Frontiers in Dynamic Spectrum Access Networks, pp. 30-36. 2005.
- [36] J. Lehtomäki. "Analysis of energy based signal detection". PhD thesis. University of Oulu. 2005.
- [37] J. Lehtomäki, J. Vartiainen, M. Juntti and H. Saarnisaari. "Spectrum sensing with forward methods". In Proc. IEEE Military Commun. Conf., pp. 1-7. 2006.
- [38] S. Geirhofer, L. Tong and B. Sadler. "A measurement-based model for dynamic spectrum access in WLAN channels". In Proc. IEEE Military Commun. Conf. 2006.
- [39] S. Geirhofer, B. Sadler and L. Tong. "Dynamic spectrum access in WLAN channels: Empirical model and its stochastic analysis". In Proc. of Int. Workshop on Technology and Policy for Accessing Spectrum. 2006.
- [40] A.E. Leu, M. McHenry and B.L. Mark. "Modeling and analysis of interference in listen-before-talk spectrum access schemes". Int. Journal of Network Management. Vol. 16, Issue 2, pp. 131-147. 2006.
- [41] A. Sahai, R. Tandra, S.M. Mishra and N. Hoven. "Fundamental design tradeoffs in cognitive radio systems". In Proc. of Int. Workshop on Technology and Policy for Accessing Spectrum. 2006.
- [42] T. Y. Cek and H. Arslan. "Spectrum characterization for opportunistic cognitive radio systems". In Proc. IEEE Military Commun. Conf., pp. 1-6. 2006.
- [43] P. Pawelczak, C. Guo, R. Prasad and R. Hekmat. "Cluster-based spectrum sensing architecture for opportunistic spectrum access networks". Tech. Rep. IRCTR-S-004-07. 2007.
- [44] X. Liu and S. Shankar. "Sensing-based opportunistic channel access". Mobile Networks and Applications. Vol. 11, Issue 4, pp. 577-591. 2006.
- [45] F. Weidling, D. Datla, V. Petty, P. Krishnan and G. Minden. "A framework for RF spectrum measurements and analysis". In Proc. IEEE Int. Symposium on New Frontiers in Dynamic Spectrum Access Networks. Vol. 1, pp. 573-576. 2005.
- [46] Sh. M. Mishra, S.T. Brink, R. Mahadevappa and R.W. Brodersen. "Cognitive technology for ultra-wideband/wimax coexistence". In Proc. IEEE Int. Symposium on New Frontiers in Dynamic Spectrum Access Networks, pp. 179-186. 2007.
- [47] H. Urkowitz. "Energy detection of unknown deterministic signals". Proc. IEEE. Vol. 55, pp. 523-531. 1967.
- [48] N. Hoven, A. Sahai and R. Tandra. "Some fundamental limits on cognitive radio". In Proc. Allerton Conf. on Commun. Control, and Computing. 2004.
- [49] M.P. Olivieri, G. Barnett, A. Lackpour and A. Davis. "A scalable dynamic spectrum allocation system with interference mitigation for teams of spectrally agile software defined radios". In Proc. IEEE Int. Symposium on New Frontiers in Dynamic Spectrum Access Networks, pp. 170-179. 2005.
- [50] J.G. Proakis. "Digital Communications" McGraw-Hill (editorial), 4th edition. 2001.
- [51] R. Tandra and A. Sahai. "Fundamental limits on detection in low snr under noise uncertainty". In Proc. IEEE Int. Conf. Wireless Networks, Commun. and Mobile Computing. Vol. 1, pp. 464-469. 2005.
- [52] M. Oner and F. Jondral. "Cyclostationarity based air interface recognition for software radio systems". In Proc. IEEE Radio and Wireless Conf., pp. 263-266. 2004.
- [53] Borah, D.K. and Hart, B.T., 1999. Frequency-selective fading channel estimation with a polynomial time-varying channel model. IEEE Transactions on Communications, 47(6), pp.862-873.
- [54] D. Cabric and R.W. Brodersen. "Physical layer design issues unique to cognitive radio systems". In Proc. IEEE Int. Symposium on Personal, Indoor and Mobile Radio Commun. Vol. 2, pp. 759-763. 2005.
- [55] A. Fehske, J. Gaedert and J. Reed. "A new approach to signal classification using spectral correlation and neural networks". In Proc. IEEE Int. Symposium on New Frontiers in Dynamic Spectrum Access Networks, pp. 144-150. 2005.
- [56] M. Ghoszi, F. Marx, M. Dohler and J. Palicot. "Cyclostationarity-based test for detection of vacant frequency bands". In Proc. IEEE Int. Conf. Cognitive



- Radio Oriented Wireless Networks and Commun. 2006.
- [57] Atapattu, S., Tellambura, C. and Jiang, H., 2011. Energy detection based cooperative spectrum sensing in cognitive radio networks. *IEEE Transactions on wireless communications*, 10(4), pp.1232-1241.
- [58] J. Lundn, V. Koivunen, A. Huttunen and H.V. Poor. "Spectrum sensing in cognitive radios based on multiple cyclic frequencies". In *Proc. IEEE Int. Conf. Cognitive Radio Oriented Wireless Networks and Commun.* 2007.
- [59] K. Kim, I.A. Akbar, K.K. Bae, J.-S. Um, C.M. Spooner and J.H. Reed. "Cyclostationary approaches to signal detection and classification in cognitive radio". In *Proc. IEEE Int. Symposium on New Frontiers in Dynamic Spectrum Access Networks*, pp. 212-215. 2007.
- [60] W.A. Gardner. "Exploitation of spectral redundancy in cyclostationary signals". *IEEE Signal Processing Mag.* Vol. 8, Issue 2, pp. 14-36. 1991.
- [61] K. Maeda, A. Benjebbour, T. Asai, T. Furuno and T. Ohya. "Recognition among ofdm-based systems utilizing cyclostationarity-inducing transmission". In *Proc. IEEE Int. Symposium on New Frontiers in Dynamic Spectrum Access Networks*, pp. 516-523. 2007.
- [62] P.D. Sutton, K.E. Nolan and L.E. Doyle. "Cyclostationary signatures for rendezvous in ofdm-based dynamic spectrum access networks". In *Proc. IEEE Int. Symposium on New Frontiers in Dynamic Spectrum Access Networks*, pp. 220-231. 2001.
- [63] P.D. Sutton, J. Lotze, K.E. Nolan and L.E. Doyle. "Cyclostationary signature detection in multipath rayleigh fading environments". In *Proc. IEEE Int. Conf. Cognitive Radio Oriented Wireless Networks and Commun.* 2007.
- [64] M.K. Tsatsanis and G.B. Giannakis. "Transmitter induced cyclostationarity for blind channel equalization". *IEEE Trans. Signal Processing.* Vol. 45, Issue 7, pp. 785-794. 1997.
- [65] A. Tkachenko, D. Cabric and R.W. Brodersen. "Cyclostationary feature detector experiments using reconfigurable BEE2". In *Proc. IEEE Int. Symposium on New Frontiers in Dynamic Spectrum Access Networks*, pp. 216-219. 2007.
- [66] Inc. Std. IEEE 802.11b. "Supplement to IEEE standard for information technology telecommunications and information exchange between systems - local and metropolitan area networks specific requirements part 11: wireless lan medium access control (mac) and physical layer (phy) specifications: high-speed physical layer extension in the 2.4 GHz band". The institute of electrical and electronics engineering. Technical report, IEEE. 1999.
- [67] T. Farnham, G. Clemo, R. Haines, E. Seidel, A. Benamar, S. Billington, N. Greco, N. Drew, T. Le, B. Arram and P. Mangold. "Ist-trust: A perspective on the reconfiguration of future mobile terminals using software download". In *Proc. IEEE Int. Symposium on Personal, Indoor and Mobile Radio Commun.*, pp. 1054-1059. 2000.
- [68] M. Mehta, N. Drew, G. Vardoulas, N. Greco and C. Niedermeier. "Reconfigurable terminals: an overview of architectural solutions". *IEEE Commun. Mag.* Vol. 39, Issue 8, pp. 82-89. 2001.
- [69] J. Palicot and C. Roland. "A new concept for wireless reconfigurable receivers". *IEEE Commun. Mag.* Vol. 41, Issue 7, pp. 124-132. 2003.
- [70] A.F. Cattoni, I. Minetti, M. Gandetto, R. Niu, P.K. Varshney and C.S. Regazzoni. "A spectrum sensing algorithm based on distributed cognitive models". In *Proc. SDR Forum Technical Conference.* 2006.
- [71] M. Gandetto and C. Regazzoni. "Spectrum sensing: A distributed approach for cognitive terminals". *IEEE J. Select. Areas Commun.* Vol. 25, Issue 3, pp. 546-557. 2007.
- [72] M. Gandetto, M. Guainazzo and C.S. Regazzoni. "Use of time-frequency analysis and neural networks for mode identification in 209 a wireless software-defined radio approach". *EURASIP Journal on Applied Signal Processing*, pp. 1778-1790. 2004.
- [73] M. Gandetto, M. Guainazzo, F. Pantisano and C.S. Regazzoni. "A mode identification system for a reconfigurable terminal using wigner distribution and non-parametric classifiers". In *Proc. IEEE Global Telecomm. Conf.* Vol. 4, pp. 2424-2428. 2004.
- [74] M. Oner and F. Jondral. "Cyclostationarity-based methods for the extraction of the channel allocation information in a spectrum pooling system". In *Proc. IEEE Radio and Wireless Conf.*, pp. 279-282. 2004.
- [75] Z. Tian and G.B. Giannakis. "A wavelet approach to wideband spectrum sensing for cognitive radios". In *Proc. IEEE Int. Conf. Cognitive Radio Oriented Wireless Networks and Commun.* 2006.
- [76] Z. Tian and G. Giannakis. "Compressed sensing for wideband cognitive radios". In *Proc. IEEE Int. Conf. on Acoustics, Speech, and Signal Processing.* Vol. 4, pp. 1357-1360. 2007.
- [77] Y. Youn, H. Jeon, J. Choi and H. Lee. "Fast spectrum sensing algorithm for 802.22 wran systems". In *Proc. IEEE Int. Symp. Commun. and Information Techn.*, pp. 960-964. 2006.
- [78] Y. Hur, J. Park, K. Kim, J. Lee, K. Lim, C. Lee, H. Kim and J. Laskar. "A cognitive radio (CR) testbed system employing a wideband multiresolution spectrum sensing (MRSS) technique". In *Proc. IEEE Veh. Technol. Conf.*, pp. 1-5. 2006.
- [79] K. Challapali, S. Mangold and Z. Zhong. "Spectrum agile radio: Detecting spectrum opportunities". In *Proc. Int. Symposium on Advanced Radio Technologies.* 2004.
- [80] Y. Zeng and Y.-C. Liang. "Covariance based signal detections for cognitive radio". In *Proc. IEEE Int. Symposium on New Frontiers in Dynamic Spectrum Access Networks*, pp. 202-207. 2007.
- [81] B. Wild and K. Ramchandran. "Detecting primary receivers for cognitive radio applications". In *Proc. IEEE Int. Symposium on New Frontiers in Dynamic Spectrum Access Networks*, pp. 124-130. 2005.