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Spectrum Sensing for Cognitive Radio Applications

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9.1 Introduction

The need for higher data rates is increasing as a result of the transition from voice-only communication to wireless multimedia and web type of applications. Given the limitations of natural frequency spectrum, it becomes obvious that current static frequency allocation schemes cannot accommodate these requirements of increasing number of higher data rate devices. As a result, innovative techniques that can offer new ways of exploiting the available spectrum are needed. *Cognitive radio* arises to be a tempting solution to spectral crowding problem by introducing the opportunistic usage of frequency bands that are not heavily occupied by licensed users [1]. While there is no agreement on the formal definition of cognitive radio as of now, the concept has evolved recently to include various meanings in several contexts [2]. One main aspect of cognitive radio is related to autonomously exploiting locally unused spectrum to provide new paths to spectrum access. Other aspects include interoperability across several networks; roaming across borders while being able to stay in compliance with local regulations; adapting the system, transmission, and reception parameters without user intervention; and having the ability to understand and follow actions and choices taken by their users to learn how to become more responsive over time.

One of the most important components of cognitive radio concept is the ability to measure, sense, learn, and be aware of the parameters related to the radio channel characteristics, availability of spectrum and power, interference and noise temperature, radio's operating environment, user requirements and applications, available networks (infrastructures) and nodes, local policies and other operating restrictions. In cognitive radio terminology, *primary users* can be defined as the users who have higher priority or legacy rights on the usage of a specific part of the spectrum. On the other hand, *secondary users*, which have lower priority, exploit this spectrum in such a way that they do not cause interference to primary users. Therefore, secondary users need to have cognitive radio capabilities, such as sensing the spectrum reliably to check

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whether it is being used by a primary user, and to change the radio parameters to exploit the unused part of the spectrum.

Being the focus of this chapter, spectrum sensing by far is the most important task among others for the establishment of cognitive radio. Spectrum sensing includes awareness about the interference temperature and existence of primary users. As an alternative to spectrum sensing, geolocation and database or beacons[1] can be used for determining the current status of the spectrum usage [3, 4]. In this chapter, we focus on spectrum sensing performed by cognitive radios because of its broader application areas while referring other methods as needed. Although spectrum sensing is traditionally understood as measuring the spectral content, or measuring the interference temperature over the spectrum; when the ultimate cognitive radio is considered, it is a more general term that involves obtaining the spectrum usage characteristics across multiple dimensions such as time, space, frequency, and code. It also involves determining what type of signals are occupying the spectrum (including the modulation, waveform, bandwidth, carrier frequency, etc.). However, this requires more powerful signal analysis techniques with additional computational complexity.

Various aspects of spectrum sensing task are illustrated in Figure 9.1. The goal of this chapter is to point out several aspects of spectrum sensing as shown in this figure. These aspects will be discussed in the rest of this chapter. We start by explaining some challenges associated with spectrum sensing in Section 9.2. Section 9.3 explains the main spectrum sensing methods. Cooperative sensing concept and its various forms are introduced in Section 9.4, followed by a discussion of external sensing algorithms in Section 9.5. Statistical modeling of network traffic and utilization of these models for prediction of primary user behavior is studied in Section 9.6. Section 9.7 explains the factors on deciding the frequency of spectrum sensing. Hardware perspective of sensing problem is discussed in Section 9.8. We introduce the multi-dimensional spectrum sensing concept in Section 9.9. Finally, sensing features of some current wireless standards are explained in Section 9.10 and our conclusions are given in Section 9.11.

9.2 Challenges

Before getting into the details of spectrum sensing techniques, some challenges associated with the spectrum sensing for cognitive radio is given in this section.

Hardware Requirements

Spectrum sensing for cognitive radio applications requires high sampling rate, high resolution Analog to Digital Converter (ADCs) with large dynamic range,

[1] When beacons are used, the transmitted information can be occupancy of a spectrum as well as other advanced features such as channel quality.

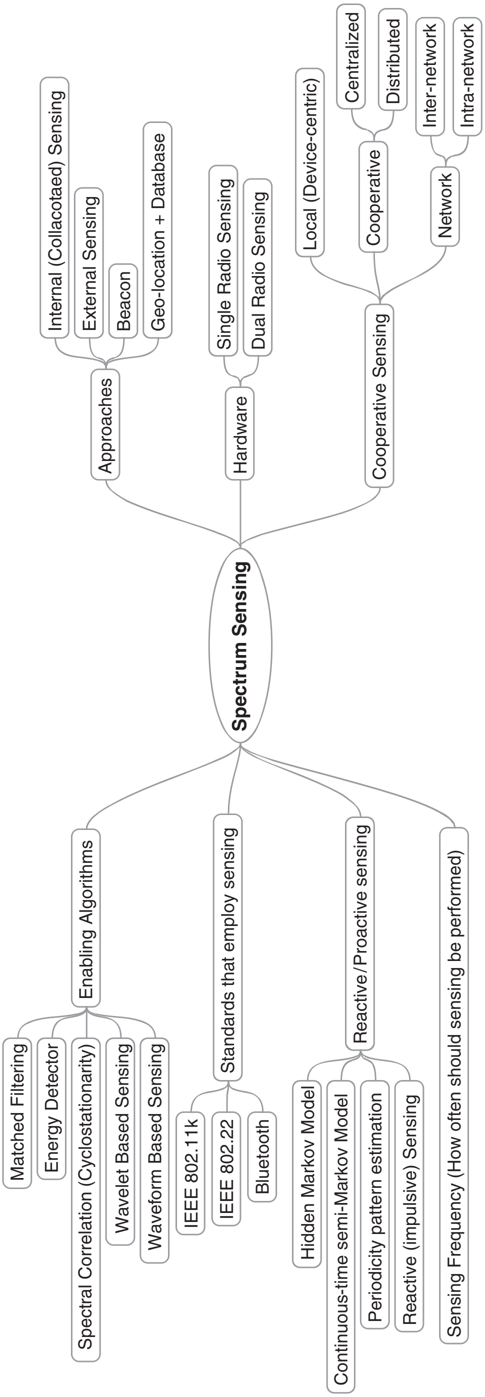


Fig. 9.1. Various aspects of spectrum sensing for cognitive radio.

multiple analog front end circuitry, and high speed signal processors. Estimating the noise variance or interference temperature over transmission of desired narrowband signals is not new. Such noise variance estimation techniques have been popularly used for optimal receiver designs like channel estimation, soft information generation, as well as for improved hand-off, power control, and channel allocation techniques. The noise/interference estimation problem is easier for these purposes as receivers are tuned to receive signals that are transmitted over a desired bandwidth. Moreover, receivers are capable of processing the narrowband baseband signals with reasonably low complexity and low power processors. However, in cognitive radio, terminals are required to process transmission over a much wider band for sensing any opportunity.

Hidden Primary User Problem

Hidden primary user problem is similar to the hidden node problem in Carrier Sense Multiple Accessing (CSMA). This problem can be caused by many factors including severe multipath fading or shadowing that secondary users observe while scanning primary users' transmissions. Figure 9.2 shows an illustration of hidden node problem. Here, cognitive radio device causes unwanted interference to the primary user (receiver) as the primary transmitters signal could not be detected because of the positioning of devices in space.

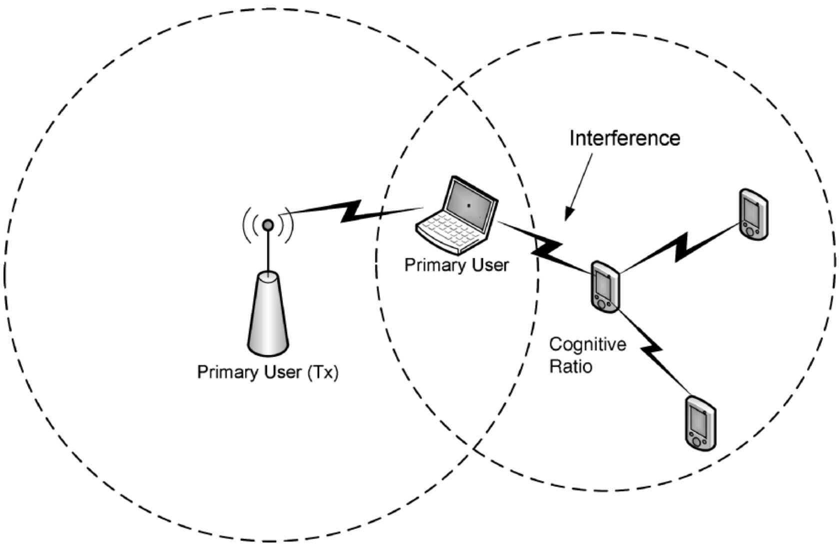


Fig. 9.2. Illustration of hidden primary user problem in cognitive radio systems.

Spread Spectrum Primary Users

Primary users that use frequency hopping or spread spectrum signaling, where the power of the primary user signal is distributed over a wider frequency even though the actual information bandwidth is much narrower, are difficult to detect. Especially, frequency hopping-based signaling creates significant problems regarding to spectrum sensing. This problem can be partially avoided if the hopping pattern is known and perfect synchronization to the signal can be achieved.

Sensing Time

Primary users can claim their frequency bands anytime while cognitive radio is operating at that band. In order to prevent interference to and from primary license owners, cognitive radio should be able to identify the presence of primary users as quickly as possible and should vacate the band immediately. Hence, sensing method should be able to identify the presence of primary user within a certain duration. This requirement possesses a limit on the performance of sensing algorithm and create a challenge for cognitive radio design.

Other Challenges

Some other challenges that need to be considered while designing effective spectrum sensing algorithm include implementation complexity, presence of multiple secondary users, coherence times, multipath and shadowing, cooperation, competition, robustness, heterogeneous propagation losses, and power consumption.

9.3 Spectrum Sensing Methods for Cognitive Radio

The present literature for spectrum sensing is still in its early stages of development. A number of different methods are proposed for identifying the presence of signal transmission. In some approaches, characteristics of the identified transmission are detected for deciding the signal transmission as well as identifying the signal type. In this section, some of the most common spectrum sensing techniques in the cognitive radio literature are explained.

9.3.1 Matched Filtering

Matched filtering is known as the optimum method for detection of primary users when the transmitted signal is known [5]. The main advantage of matched filtering is the short time[2] to achieve a certain probability of false

[2] The required number of samples grows as $O(1/SNR)$ for a target probability of false alarm or miss detection at low SNRs [6].

alarm or probability of miss detection [6] as compared to other methods that are discussed in this section. However, matched filtering requires the cognitive radio to demodulate received signals. Hence, it requires perfect knowledge of the primary users signaling features such as bandwidth, operating frequency, modulation type and order, pulse shaping, frame format, etc. Moreover, since cognitive radio needs receivers for all signal types, implementation complexity of sensing unit is impractically large [7]. Another disadvantage is large power consumption as various receiver algorithms need to be executed for detection.

9.3.2 Waveform-Based Sensing

Known patterns are usually utilized in wireless systems to assist synchronization or for other purposes. Such patterns include preambles, midambles, regularly transmitted pilot patterns, spreading sequences, etc. In the presence of a known pattern, sensing can be performed by correlating the received signal with a known copy of itself [8,9]. This method is only applicable to systems with known signal patterns, and it is termed as waveform-based sensing. In [8], it is shown that waveform-based sensing outperforms energy detector-based sensing in reliability and convergence time. Furthermore, it is shown that the performance of the sensing algorithm increases as the length of the known signal pattern increases. As one of the methods for analyzing the Wireless Local Area Network (WLAN) channel usage characteristics, packet preambles of IEEE 802.11b [10] signals are exploited in [11, 12]. Measurement results presented in [13] show that waveform-based sensing requires short measurements time, however, it is susceptible to synchronization errors.

Let us assume that the received signal has the following simple form:

$$y(n) = s(n) + w(n), \tag{9.1}$$

where $s(n)$ is the signal to be detected, $w(n)$ is the Additive White Gaussian Noise (AWGN) sample, and n is the sample index. Note that $s(n) = 0$ when there is no transmission by primary user. The waveform-based sensing metric[3] can be obtained as [8]

$$M = \mathrm{Re}\left[\sum_{n=1}^{N} y(n)s^*(n)\right], \tag{9.2}$$

where N is the length of known pattern. In the absence of the primary user, the metric value becomes

$$M = \mathrm{Re}\left[\sum_{n=1}^{N} w(n)s^*(n)\right]. \tag{9.3}$$

[3] In this chapter, time-domain sampling is explained as an example. Modified versions of the method explained in this chapter can be used in frequency domain as well. Likewise, the method given in this chapter can be modified depending on the available pattern.

Similarly, in the presence of a primary user's signal, the sensing metric becomes

$$M = \sum_{n=1}^{N} |s(n)|^2 + \mathrm{Re}\left[\sum_{n=1}^{N} w(n)s^*(n)\right]. \tag{9.4}$$

The decision on the presence of a primary user signal can be made by comparing the decision metric M against a fixed threshold λ_W. This is equivalent to distinguishing between the following two hypotheses:

$$\mathcal{H}_0 : y(n) = w(n), \tag{9.5}$$

$$\mathcal{H}_1 : y(n) = s(n) + w(n). \tag{9.6}$$

The performance of the detection algorithm can be summarized with two probabilities: probability of detection P_D and probability of false alarm P_F. P_D is the probability of detecting a signal on the considered frequency when it truly is present, thus large detection probability is desired. It can be formulated as

$$P_D = \Pr\left(M > \lambda_W | \mathcal{H}_1\right), \tag{9.7}$$

where λ_W is the threshold value. P_F is the probability that the test incorrectly decides that the considered frequency is occupied when it actually is not, and it can be written as

$$P_F = \Pr\left(M > \lambda_W | \mathcal{H}_0\right). \tag{9.8}$$

P_F should be kept as small as possible. The decision threshold λ_W can be selected for finding an optimum balance between P_D and P_F. However, this requires the knowledge of noise and detected signal powers. The noise power can be estimated, but the signal power is difficult to estimate as it changes depending on ongoing transmission characteristics and the distance between the cognitive radio and primary user. In practice, the threshold is chosen to obtain a certain false alarm rate. Hence, the knowledge of noise variance is enough for selection of a threshold.

9.3.3 Cyclostationarity-Based Sensing

Cyclostationarity feature detection is a method for detecting primary user transmissions by exploiting the cyclostationarity features of the received signals [7, 14–19]. Cyclostationary features are caused by the periodicity in the signal or in its statistics like mean and autocorrelation. Instead of Power Spectral Density (PSD), cyclic correlation function is used for detecting signals present in a given spectrum. The cyclostationarity-based detection algorithms can differentiate noise from primary users' signals. This is a result of the fact that noise is wide-sense stationary Wide-Sense Stationary (WSS) with no correlation while modulated signals are cyclostationary with spectral correlation due to the redundancy of signal periodicities [16].

The Cyclic Spectral Density (CSD) function of received signal (9.1) can be calculated as [20]

$$S(f,\alpha) = \sum_{\tau=-\infty}^{\infty} R_y^\alpha(\tau) e^{-j2\pi f\tau}, \tag{9.9}$$

where

$$R_y^\alpha(\tau) = E\left[y(n+\tau)y^*(n-\tau)e^{j2\pi\alpha n}\right] \tag{9.10}$$

is the Cyclic Autocorrelation Function (CAF), and α is the cyclic frequency. The CSD function outputs peak values when the cyclic frequency is equal to the fundamental frequencies of transmitted signal $x(n)$. Cyclic frequencies can be assumed to be known [14,19] or they can be extracted and used as features for identifying transmitted signals [17].

9.3.4 Energy Detector-Based Sensing

Energy detector-based approaches, also known as radiometry or periodogram, are the most common ways of spectrum sensing because of their low computational and implementation complexities [7–9,11,12,18,22–28,28–30]. Moreover, they are more generic as receivers do not need any knowledge on the primary users' signals. The signal is detected by comparing the output of energy detector with a threshold which depends on the noise floor [31]. Some of the challenges with energy detector-based sensing include selection of the threshold for detecting primary users, inability to differentiate interference from primary users and noise, and poor performance under low Signal-to-Noise-Ratio (SNR) values [8]. Moreover, the energy detector does not work efficiently for detecting spread spectrum signals [7].

Using the same model given in (9.1), decision metric for energy detector can be written as

$$M = \sum_{n=0}^{N} |y(n)|^2. \tag{9.11}$$

The white noise can be modeled as a zero-mean Gaussian random variable with variance σ_w^2, i.e. $w(n) = \mathcal{N}(0, \sigma_w^2)$. For a simplified analysis, let us model the signal term as a zero-mean Gaussian variable as well,[4] i.e. $s(n) = \mathcal{N}(0, \sigma_s^2)$. Because of these assumptions, the decision metric M follows chi-square distribution with $2N$ degrees freedom χ_{2N}^2 and hence, it can be modeled as

$$M = \begin{cases} \frac{\sigma_w^2}{2}\chi_{2N}^2 & \mathcal{H}_0, \\ \frac{\sigma_w^2+\sigma_s^2}{2}\chi_{2N}^2 & \mathcal{H}_1. \end{cases} \tag{9.12}$$

For energy detector, the probabilities P_F and P_D can be calculated as [22][5]

$$P_F = 1 - \Gamma\left(L_f L_t, \frac{\lambda_E}{\sigma_w^2}\right), \tag{9.13}$$

$$P_D = 1 - \Gamma\left(L_f L_t, \frac{\lambda_E}{\sigma_w^2 + \sigma_s^2}\right), \tag{9.14}$$

[4] In fact, the model for $s(n)$ is more complicated as fading should also be considered.

[5] Please note that the notation used in [22] is slightly different. Moreover, the noise power is normalized before it is fed into the threshold device in [22].

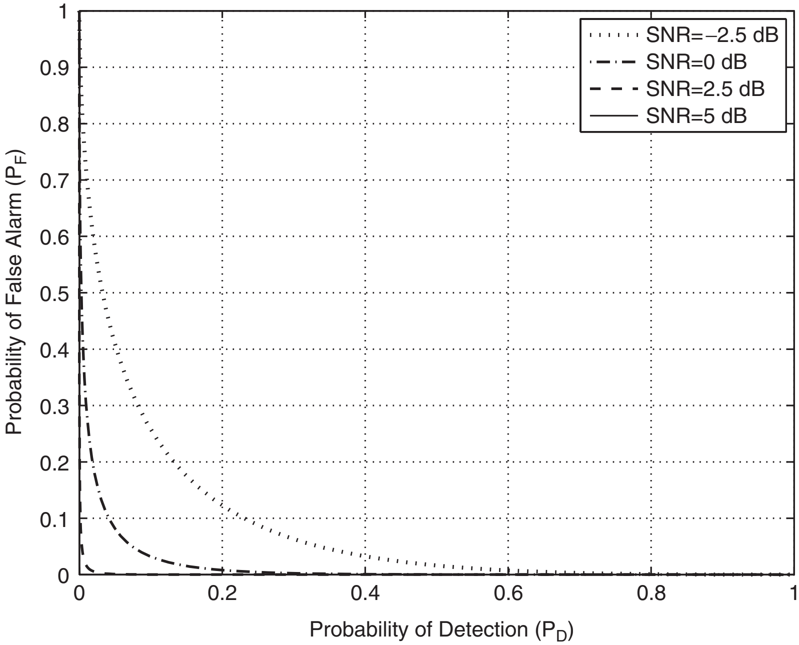


Fig. 9.3. ROC curves for energy detector-based spectrum sensing under different SNR values.

where λ_E is the decision threshold, and $\Gamma(a, x)$ is the incomplete gamma function as given in [32] (see Equation 6.5.1). Figure 9.3 shows the Receiver Operating Characteristics (ROCs) for different SNR values. SNR is defined as the ratio of the primary user's signal power to noise power, i.e. SNR $= \sigma_s^2/\sigma_w^2$. The averaging size is set to 15 in this figure, $N = 15$. As this figure clearly shows, the performance of the threshold detector increases at high SNR values.

The threshold used in energy detector-based sensing algorithms depends on the noise variance. Consequently, small noise power estimation errors causes significant performance loss [33]. As a solution to this problem, in [34], noise level is estimated dynamically by applying a reduced-rank eigenvalue decomposition to incoming signal's autocorrelation. Then, the estimated value is used to choose the threshold for satisfying a constant false alarm rate.

Measurement results are analyzed in [11,12] using energy detector to identify the idle and busy periods of WLAN channels. Energy level for each Global System for Mobile (GSM) slot is measured and compared in [25] for identifying the idle slots for exploitation. The sensing task in this work is different in the sense that the cognitive radio has to be synchronized to the primary user network and the sensing time is limited to slot duration. A similar approach is used in [35] as well for opportunistic exploitation of unused cellular slots. In [26], power at the output of Fast Fourier Transform (FFT) of incoming signal is compared with a threshold value in order to identify the number of used TV channels. FFT is performed on the data sampled at 45 kHz around the centered TV carrier frequency for each TV channel. The performance of energy detector-based sensing over various fading channels is investigated in [22]. Closed-form expressions for probability of detection under AWGN and fading (Rayleigh, Nakagami, and Ricean) channels are derived. Average probability of detection for energy detector-based sensing algorithms under log-normal shadowing and Rayleigh fading channels is derived in [8]. It is observed that the performance of energy-detector degrades considerably under Rayleigh fading. Forward methods based on energy measurements are studied for unknown noise power scenarios in [37]. The proposed method adaptively estimates the noise level, hence suitable for practical cases where noise variance is not known.

9.3.5 Radio Identification

A better knowledge about the spectrum characteristics can be obtained by identifying the transmission technology used by primary users. Such an identification enables cognitive radio with a higher dimensional knowledge as well as providing higher accuracy [30]. For example, assume that the primary users technology is identified as a Bluetooth signal. Cognitive radio can use this information for extracting some useful information in space dimension as the range of Bluetooth signal is known to be around 10 m.[6] Furthermore, cognitive radio may want to communicate with the identified communication systems in some applications. For radio identification, feature extraction and classification techniques are used in the context of European Transparent Ubiquitous Terminal (TRUST) project [38]. The goal is to identify the presence of some known transmission technologies and achieve communication through them. The two main tasks are Initial Mode Identification (IMI) and Alternative Mode Monitoring (AMM). In IMI, the cognitive device searches for a possible transmission mode (network) following the power on. AMM is the task of monitoring other modes while cognitive device is having communication in a certain mode. Some of the proposed methods for blind radio identification are shown in Table 9.1. Several features are extracted from the received signal and they are used for selecting the most probable primary user technology by employing various classification methods.

9.3.6 Other Sensing Methods

Other alternative spectrum sensing methods include multitaper spectral estimation, wavelet transform-based estimation, Hough transform, and time-frequency analysis. Multitaper spectrum estimation is proposed in [43]. The proposed algorithm is shown to be an approximation to maximum likelihood PSD estimator, and for wideband signals, it is nearly optimal. Although the

[6] Please see Section 9.9 for more examples.

Table 9.1. Blind radio identification algorithms.

Article	Used Features	Classification Method
Mehta [39], Vardoulias [40]	Amount of energy detected, its distribution across the spectrum, and its correlation with some predefined functions (Briefly mentioned, not explained in detail)	–
Palicot [41]	Channel bandwidth and its shape: this feature is found to be the most discriminating parameter using tables and cross-tables, i.e. by comparing with other parameters	Radial Basis Function (RBF) neural networks
Gandetto [42]	The standard deviation of the instantaneous frequency and the maximum duration of a signal (time–frequency analysis)	Feed Forward Back-Propagation Neural Networks (FFBPNNs) and Support Vector Machines (SVMs) with RBF
Fehske [17]	Spectral Correlation Density (SCD) and Spectral Coherence Function (SCF)	Multilayer Linear Perception Network (MLPN) neural networks
Oner [14]	Spectral Correlation Density (SCD) and Spectral Coherence Function (SCF)	Statistical tests for identifying the presence of cyclostationarity

complexity of this method is less than the maximum likelihood estimator, it is still computationally demanding. Random Hough transform of received signal is used in [44] for identifying the presence of radar pulses in the operating channels of IEEE 802.11 systems. This method can be used to detect any type of signals with periodic patterns as well. In [45], wavelets are used for detecting edges in the PSD of a wideband channel. Once the edges, which correspond to transitions from occupied band to empty band or vice versa, are detected, the power within bands between two edges are estimated. Using this information and edge positions, the PSD can be characterized as occupied or empty in a binary fashion. The assumptions made in [45], however, need to be relaxed for building a practical sensing algorithm.

9.4 Cooperative Sensing

The estimation of traffic in a specific geographic area can be done locally (by one cognitive radio only) or information from different cognitive radios can be combined. In the literature, cooperation is discussed as a solution to problems that arise in spectrum sensing due to noise uncertainty, fading, and shadowing. Cooperative sensing decreases the probability of mis-detections and the probability of false alarms considerably. In addition, cooperation can solve the hidden primary user problem and can decrease sensing time [13, 27, 28].

The interference to primary users caused by cognitive radio devices employing spectrum access mechanisms based on simple Listen-Before-Talk (LBT) scheme is investigated in [29] via analysis and computer simulations. Results show that even simple local sensing can be used to explore the unused spectrum without causing interference to existing users. On the other hand, it is shown analytically and through numerical results that collaborative sensing provides significantly higher spectrum capacity gains than local sensing. The fact that cognitive radio acts without any knowledge about the location of the primary users in local sensing degrades the performance.

The challenges of cooperative sensing include developing efficient information sharing algorithms and increased complexity [46]. The advantages and disadvantages of local and cooperative (or collaborative) sensing methods are tabulated in Table 9.2.

In cooperative sensing architectures, the control channel can be implemented using different methodologies. These include a dedicated band, unlicensed band such as ISM, and underlay Ultra Wideband (UWB) system [47]. Depending on the system requirements, one of these methods can be selected. The shared information can be soft or hard decisions made by each cognitive device [48]. Furthermore, various techniques for combining sensing results can be employed. The performances of Equal Gain-Combining (EGC), Selection Combining (SC), and Switch and Stay Combining (SSC) are investigated in [22] for energy detector-based spectrum sensing under Rayleigh fading. The EGC method is found to have a gain of approximately two

Table 9.2. Local versus cooperative sensing.

Sensing Method	**Advantages**	**Disadvantages**
Non-cooperative sensing (Local sensing)	Computational & implementation simplicity	Hidden node problem Multipath and shadowing
Cooperative sensing	Higher accuracy (close to optimal) Reduced sensing time [27] Shadowing effect and hidden node problems can be prevented	Complexity (complexity of sensor, complexity of within-system cooperation, complexity of among-system cooperation) Traffic overhead The need for a control channel

orders of magnitude while SC and SSC having one order of magnitude gain. As far as the networking is concerned, the coordination algorithm should have reduced protocol overhead and it should be robust to changes and failures in the network. Moreover, the coordination algorithm should introduce minimum amount of delay.

Cooperative sensing can be implemented in two fashions: centralized or distributed [49]. These two methods will be explained in the following sections.

Centralized Sensing

In centralized sensing, a central unit collects sensing information from cognitive devices, identifies the available spectrum, and broadcasts this information to other cognitive radios or directly controls the cognitive radio traffic.

The hard (binary) sensing results are gathered at a central place which is known as Access Point (AP) in [28]. The goal is to mitigate the fading effects of the channel and increase detection performance. Resulting detection and false alarm rates are given in [50] for the sensing algorithm used in [28]. In [48], the sensing results are combined in a central node, termed as master node, for detecting TV channels. Hard and soft information combining methods are investigated for reducing the probability of missed opportunity. The results presented in [28, 48] show that soft information-combining outperforms hard information-combining method in terms of the probability of missed opportunity.

Distributed Sensing

In the case of distributed sensing, cognitive nodes share information among each other but they make their own decisions as to which part of the spectrum they can use. Distributed sensing is more advantageous in the sense that there is no need for a backbone infrastructure.

An incremental gossiping approach termed as GUESS (Gossiping Updates for Efficient Spectrum Sensing) is proposed in [51] for performing efficient coordination between cognitive radios in distributed collaborative sensing. The proposed algorithm is shown to have low-complexity with reduced protocol overhead. The GUESS algorithm has fast convergence and robust to network changes as it does not require a setup phase to generate the clusters. Incremental aggregation and randomized gossiping algorithms are also studied in [51] for efficient coordination within a cognitive radio network. A distributed collaboration algorithm is proposed in [28]. The collaboration is performed between two secondary users. The user closer to primary transmitter, which has a better change of detecting the primary user transmission, cooperates with a far away user. An algorithm for pairing secondary users without a centralized mechanism is also proposed. A distributed sensing method is proposed in [8] where secondary users share their sensing information among themselves. Only final decisions are shared in order to minimize the network overhead due to collaboration. A secondary user receives decisions from other users and decides $\mathcal{H}_1$ if any of the received decisions plus its own is $\mathcal{H}_1$, a fusion rule known as OR-rule. The results presented in [8] clearly show the performance improvements achieved through collaborative sensing.

9.5 External Sensing

Another technique for obtaining spectrum information is external sensing. In external sensing, an external agent performs the sensing and broadcasts the channel occupancy information to cognitive radios. External sensing algorithms solve some problems associated with the internal sensing, which is termed as collocated sensing in [18]. The main advantages are overcoming hidden primary user problem as well as the uncertainty due to shadowing and fading. Furthermore, as the cognitive radios do not spend time for sensing, spectrum efficiency is increased. The sensing network does not need to be mobile and not necessarily powered by batteries. Hence, power consumption problem of internal sensing can also be addressed.

A sensor node detector architecture is used in [52]. The presence of passive receivers, viz. television receivers, is detected by measuring the Local Oscillator (LO) power leakage. Once a receiver and the channel is detected, the sensor node notifies cognitive radios in the region of passive primary user via a control channel. Similar to [52], a sensor network-based sensing architecture is proposed in [18]. A dedicated network composed of only spectrum sensing units is used to sense the spectrum continuously or periodically. The results are communicated to a sink (central) node which further processes the sensing data and shares the information about the spectrum occupancy in the sensed area with opportunistic radios. These opportunistic radios use the information obtained from sensing network for selecting the bands (and time durations) of their data transmissions. The sensing results can also be shared via a pilot channel similar to Network Access And Connectivity Channel (NACCH) [53]. External sensing is one of the methods proposed for identifying primary users in IEEE 802.22 standard as well (see Section 9.10).

9.6 Statistical Approaches and Prediction

For minimizing interference to primary users while making the most out of the opportunities, cognitive radios should keep track of the variations in spectrum and should make predictions. Stemming from the fact that cognitive radio senses the spectrum steadily and has the ability of learning, the history of the spectrum usage information can be used for predicting the future profile of the spectrum. Towards this goal, knowledge about currently active devices or prediction algorithms based on statistical analysis can be used.

Channel access patterns of primary users are identified and used for predicting spectrum usage in [54]. Assuming a TDMA transmission, periodicity pattern of channel occupancy is extracted using cyclostationary detection. This parameter is then used to forecast the channel idle probability for a given channel. Furthermore, [54] proposes to use Hidden Markov Models (HMMs) in order to model the channel usage patterns of primary users. A multivariate time series approach is taken in [55] to be able to learn the primary user characteristics and predict the future occupancy of neighboring channels. A binary scheme (*empty* or *occupied*) is used to reduce the complexity and storage requirements as shown in Figure 9.4. It is noted in [11] that the statistical model of primary users behavior should be kept simple enough to be able to design optimal higher order protocols. On the other hand, it will be useless if the primary user's behavior could not be predicted well. In order to strike a balance between complexity and effectiveness, continuous-time semi-Markov process model is used to describe the statistical characteristics of WLAN channels that can be used by cognitive radio to predict transmission opportunities. The investigation of VoIP and FTP-type traffic scenarios for semi-Markov model is performed in [12]. Pareto, phase-type (hyper-Erlang) and mixture distributions are used for fitting to the empirical data. Statistics of spectrum availability is employed in [24] for dynamically selecting the operating frequency, i.e. for identifying the spectrum holes. The statistics of the spectral occupancy of a bin (FFT output) is assumed to be at least piecewise stationary over the time at which they are observed in order to guarantee that these statistics are still reliable when a spectrum access request is received. Using the statistics, the likelihood that the spectral opportunity will remain available for at least the requested time duration is calculated for each bin. Then, these likelihood values are used to identify the range of frequencies which can be used for transmission.

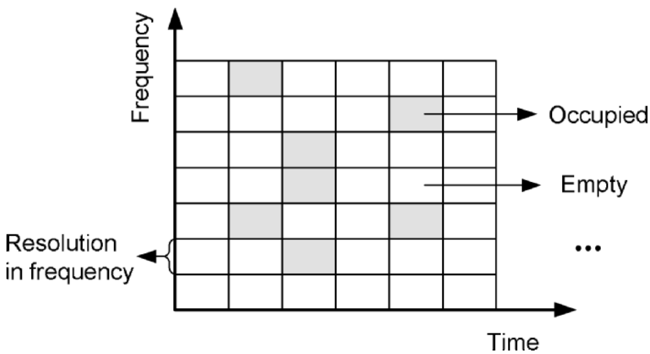


Fig. 9.4. Binary scheme used for modeling spectrum occupation in [55].

9.7 Sensing Frequency

Sensing frequency, i.e. how often cognitive radio should perform spectrum sensing, is a design parameter that needs to be chosen carefully. The optimum value depends on the capabilities of cognitive radio itself and temporal characteristics of primary users in the environment. If the status of primary users are known to change slowly, sensing frequency can be relaxed. A good example for such a scenario is detection of TV channels. The presence of a TV station usually do not change frequently in a geographical area unless a new station starts broadcasting or an existing station goes offline. Another factor that affects the sensing frequency is the interference tolerance of primary license owners. For example, when the cognitive radio is exploiting opportunities in public safety bands, sensing should be done as frequently as possible in order to prevent any interference. Cognitive radio should immediately vacate the band if it is needed by public safety units. In the IEEE 802.22 draft standard (see Section 9.10), the sensing period is defined as 30 seconds. In addition to these, the channel detection time, channel move time and some other timing related parameters are also defined [56].

9.8 Hardware Requirements and Approaches

In this section, several aspects of spectrum sensing from hardware perspective are investigated. As explained before, one of the main challenges lies on the requirements of high sampling rate, high resolution ADCs with large dynamic range. This requirement is a result of the need for a wideband sensing. Cognitive radio should be able to capture and analyze a relatively large band for identifying spectrum opportunities. Moreover, high speed processing units (Digital Signal Processors (DSPs) or Field Programmable Gate Arrays (FPGAs)) are needed for performing computationally demanding signal processing tasks with relatively low delay.

Sensing can be performed via two different architectures: single-radio and dual-radio [18, 40]. In the single-radio architecture, only a specific time slot is allocated for spectrum sensing. As a result of this, only a certain accuracy can be guaranteed for spectrum sensing results. Moreover, the spectrum efficiency is decreased as some portion of the available time slot is used for sensing instead of data transmission. The obvious advantage of single-radio architecture is its simplicity and lower cost. In the dual-radio sensing architecture, one radio chain is dedicated for data transmission and reception while the other chain is dedicated for spectrum monitoring. The drawback of such an approach is the increased power consumption and hardware cost. Note that only one antenna would be sufficient for both chains as suggested in [40]. A comparison of advantages and disadvantages of single and dual-radio architectures is given in Table 9.3. In conclusion, one might prefer one architecture over the other depending on the available resources, and performance and/or data rate requirements.

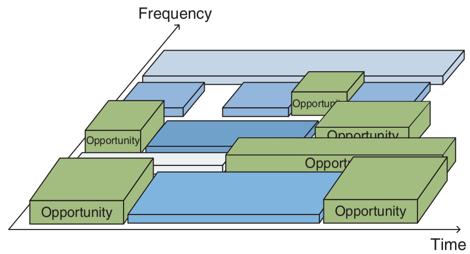
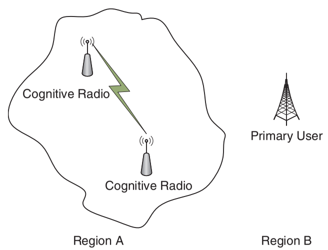
Table 9.3. Comparison of single-radio and dual-radio sensing algorithms.

	Single-Radio Architecture	**Double-Radio Architecture**
Advantages	Simplicity Lower cost	Higher spectrum efficiency Better sensing accuracy
Disadvantages	Lower spectrum efficiency Poor sensing accuracy	Higher cost Higher power consumption Higher complexity

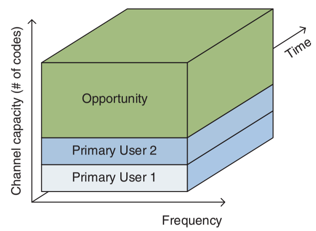
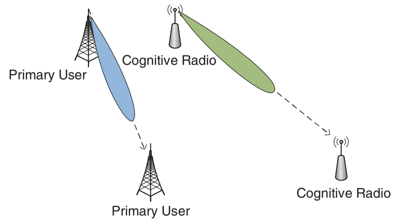
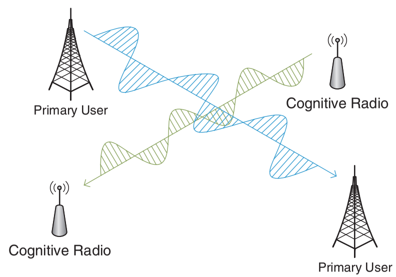
9.9 Multi-dimensional Spectrum Awareness

The definition of opportunity determines the ways of measuring and exploiting the spectrum space. The conventional definition of the spectrum opportunity which is often referred as "*band of frequencies that are not being used by the primary user of that band at a particular time in a particular geographic area*" [57] only exploits three dimensions of the spectrum space: frequency, time, and space. The problems stated in the previous section also relates to sensing the spectrum in these three dimensions. However, there are other dimensions that need to be explored further for spectrum opportunity. For example, the code dimension of the spectrum space has not been explored well in the literature. Therefore, the conventional spectrum sensing algorithms do not know how to deal with signals that use spread spectrum, time or frequency hopping codes. As a result, these types of signals constitute a major problem in sensing the spectrum. If the code dimension is interpreted as part of the spectrum space, this problem can be avoided, and new opportunities for spectrum usage can be created. Naturally, this will bring about other new challenges for detection and estimation of this new opportunity. Similarly, the angle dimension has not been exploited well enough for spectrum opportunity. It is assumed that the primary users and/or the secondary users are transmitting in all the directions. However, with the recent advances in multi-antenna technologies, e.g. beam forming, multiple users can be multiplexed into the same channel at the same time in the same geographical area. In other words, an additional dimension of spectral space can be created as opportunity. This will also create new opportunities for spectral estimation, where not only the frequency spectrum but also the angle of arrivals might need to be estimated. With these new dimensions, sensing only the frequency spectrum usage falls short. The radio space with the introduced dimensions can be defined as "*a theoretical hyperspace occupied by radio signals, which has dimensions of location, angle-of-arrival, frequency, time, and possibly others*" [58]. This hyperspace is called electrospace, transmission hyperspace, radio spectrum space, or simply spectrum space by various authors, and it can be used to describe how radio environment can be shared among multiple (primary and/or secondary) systems [59]. Various dimensions of this space and the corresponding measurement/sensing requirements are summarized in Table 9.4 along

Table 9.4. Multi-dimensional radio spectrum space and transmission opportunities.

Dimension	What needs to be sensed?	Comments	Illustrations
Frequency	Opportunity in the frequency domain.	Availability in part of the frequency spectrum. The available spectrum is divided into narrower chunks of bands. Spectrum opportunity in this dimension means that all the bands are not used simultaneously at the same time, i.e. some bands might be available for opportunistic usage.	
Time	Opportunity of a specific band in time.	This involves the availability of a specific part of the spectrum in time. In other words, the band is not continuously used. There will be times where it will be available for opportunistic usage.	
Geographical space	Location (latitude, longitude, and elevation) and distance of primary users.	The spectrum can be available in some parts of the geographical area while it is occupied in some other parts at a given time. This takes advantage of the propagation loss (path loss) in space. These measurements can be avoided by simply looking at the interference temperature. No interference means no primary user transmission in a local area. However, one needs to be careful because of hidden terminal problem.	

Continued on next page.

Dimension	What needs to be sensed?	Comments	Illustrations
Code	The spreading code, time hopping (TH), or frequency hopping (FH) sequences used by the primary users. Also, the timing information is needed so that secondary users can synchronize their transmissions w.r.t. primary users. The synchronization estimation can be avoided with long and random code usage. However, partial interference in this case is unavoidable.	The spectrum over a wideband might be used at a given time through spread spectrum or frequency hopping. This does not mean that there is no availability over this band. Simultaneous transmission without interfering with primary users would be possible in code domain with an orthogonal code with respect to codes that primary users are using. This requires the opportunity in code domain, i.e. not only detecting the usage of the spectrum, but also determining the used codes, and possibly multipath parameters as well.	
Angle	Directions of primary users' beam (azimuth and elevation angle) and locations of primary users.	Along with the knowledge of the location/position or direction of primary users, spectrum opportunities in angle dimension can be created. For example, if a primary user is transmitting in a specific direction, the secondary user can transmit in other directions without creating interference on the primary user.	
Signal	Signal polarization and waveforms of primary users.	Primary users and secondary users might be transmitting a waveform at a specific band for a given time in a geographical area in all the directions but secondary users can exploit the signal dimension to transmit an orthogonal waveform so that it does not create interference with primary users. This requires not only spectrum estimation but also waveform identification.	

with some representative pictures. Each dimension has its own parameters that should be sensed for a complete spectrum awareness as indicated in the Table.

It is of crucial importance to define such an n-dimensional space for spectrum sensing. Spectrum sensing should include the process of identifying occupancy in all dimensions of the spectrum space and finding spectrum holes, or more precisely spectrum space holes. For example, a certain frequency can be occupied for a given time, but it might be empty in another time. Hence, temporal dimension is as important as frequency dimension. This example can be extended to the other dimensions of spectrum space given in Table 9.4. As a result of this requirement, advanced spectrum sensing algorithms that offer awareness in multiple dimensions of the spectrum space should be developed.

9.10 Spectrum Sensing in Current Wireless Standards

Recently developed wireless standards has started to include cognitive features. Even though it is difficult to expect a wireless standard that is based on wideband spectrum sensing and opportunistic exploitation of spectrum, the trend is in this direction. In this section, wireless technologies that require some sort of spectrum sensing for adaptation or for Dynamic Frequency Selection (DFS) will be discussed. However, the spectrum knowledge can also be used to initiate advanced receiver algorithms such as adaptive interference cancellation [60].

9.10.1 IEEE 802.11k

A proposed extension to IEEE 802.11 specification is IEEE 802.11k which defines several types of measurements [61]. Some of the measurements include channel load report, noise histogram report and station statistic report. The noise histogram report provides methods to measure interference levels that display all non-802.11 energy on a channel as received by the subscriber unit. The access point (AP) collects channel information from each mobile unit and makes its own measurements. This data is then used by the AP to regulate access to a given channel.

The sensing (or measurement) information is used to improve the traffic distribution within a network as well. WLAN devices usually connects to the AP that has the strongest signal level. Sometimes, such an arrangement might not be the optimum and can cause overloading on one AP and underutilization of others. In 802.11k, when an AP with the strongest signal power is loaded to its full capacity, new subscriber units are assigned to one of the underutilized APs. Despite the fact that the received signal level is weaker, the overall system throughput is better thanks to more efficient utilization of network resources.

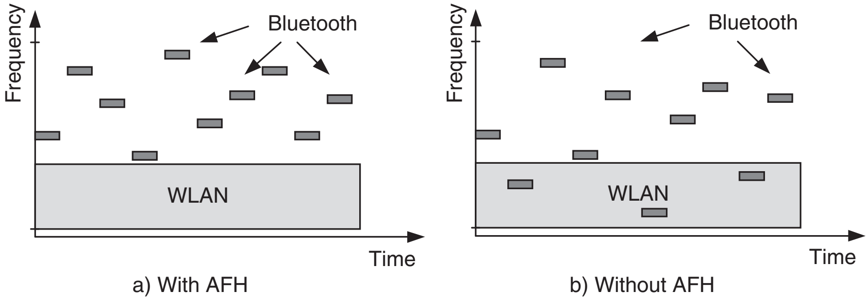


Fig. 9.5. Bluetooth transmission with and without adaptive frequency hopping (AFH). AFH prevents collusions between WLAN and Bluetooth transmissions.

9.10.2 Bluetooth

A new feature, namely Adaptive Frequency Hopping (AFH), is introduced to Bluetooth standard to reduce interference between wireless technologies sharing the 2.4 GHz unlicensed radio spectrum [62]. In this band IEEE 802.11b/g devices, cordless telephones, microwave ovens use the same wireless frequencies as Bluetooth. AFH identifies the transmissions in the ISM band and avoids their frequencies. Hence, narrow-band interference can be avoided and better Bit-Error-Rate (BER) performance can be achieved as well as reducing the transmit power. Figure 9.5 shows an illustrative Bluetooth transmission with and without AFH. By employing AFH, collusions with Wireless Local Area Network (WLAN) signals are avoided in this example.

AFH requires a sensing algorithm for determining whether there are other devices present in the ISM band and whether or not to avoid them. The sensing algorithm is based on statistics gathered to determine which channels are occupied and which channels are not occupied. Channel statistics can be packet-error rate, BER, Received Signal Strength Indicator (RSSI), Carrier-To-Interference Noise Ratio (CINR) or other metrics [63]. The statistics are used to classify the channel as *good*, *bad*, or *unknown* [62].

9.10.3 IEEE 802.22

IEEE 802.22 standard is known as *cognitive radio standard* because of the cognitive features that it has. The standard is still in the development stage. One of the most distinctive feature of 802.22 standard is its sensing requirements [40]. IEEE 802.22-based wireless rural area network (WRAN) devices sense the TV channels and identify transmission opportunities.

The sensing is envisioned to be based on two stages: fast and fine sensing [56]. In the fast sensing stage, a fast sensing algorithm is employed, e.g. energy detector. The fine sensing stage is initiated based on the fast sensing results. Fine sensing involves a more detailed sensing where more powerful methods are used. Several techniques that have been proposed and included in the draft standard include energy detection, waveform-based sensing (PN511 or PN63 sequence detection and/or segment sync detection), cyclostationary feature detection, and matched filtering. A Base Station (BS) can distribute the sensing load among Subscriber Stations (SSs). The results are returned to BS which uses these results for managing the transmissions. Hence, it is a practical example of centralized collaborative sensing explained in Section 9.4.

Another approach for managing the spectrum in IEEE 802.22 devices is based on a centralized method for available spectrum discovery. The BSs would be equipped with a Global Positioning System (GPS) receiver which would allow its position to be reported. The location information would then be used to obtain the information about available TV channels through a central server. For low-power devices[7] operating in the TV bands, external sensing is proposed as an alternative technique. These devices periodically transmit beacons with a higher power level. These beacons are monitored by IEEE 802.22 devices to detect the presence of such low-power devices which are otherwise difficult to detect due to the low-power transmission.

9.11 Conclusions

Spectrum is a very valuable resource in wireless communication systems, and it has been a focal point for research and development efforts over the last several decades. Cognitive radio, which is one of the efforts in utilization of the available spectrum more efficiently through opportunistic spectrum usage, become an exciting and promising concept. One of the important elements of the cognitive radio is sensing the available spectrum opportunities. In this chapter, various aspects of spectrum sensing task is explained in detail. Several sensing methods are studied and collaborative sensing is considered as a solution to some common problems in spectrum sensing. Hardware aspects of spectrum sensing and pro-active approaches are given and sensing methods employed in current wireless systems are discussed. Furthermore, the spectrum opportunity and spectrum sensing concepts are re-evaluated by considering different dimensions of the spectrum space. The new interpretation of spectrum space will create new opportunities and challenges for spectrum sensing while it will solve some of the traditional problems. Estimating real levels of usage of the spectrum in multiple dimensions including time, frequency, space, angle, and code; identifying for opportunities in multiple dimensions including prediction into the future using past information and making reasoning can be considered some of these challenges for future research.

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