Spectrum Sensing Algorithms for Cognitive Radio Applications

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Abstract— **The spectrum sensing problem has gained new aspects with cognitive radio and opportunistic spectrum access concepts. It is one of the most challenging issues in cognitive radio systems. In this paper, a survey of spectrum sensing methodologies for cognitive radio is presented. Various aspects of spectrum sensing problem are studied from a cognitive radio perspective and multi-dimensional spectrum sensing concept is introduced. Challenges associated with spectrum sensing are given and enabling spectrum sensing methods are reviewed. The paper explains the cooperative sensing concept and its various forms. External sensing algorithms and other alternative sensing methods are discussed. Furthermore, statistical modeling of network traffic and utilization of these models for prediction of primary user behavior is studied. Finally, sensing features of some current wireless standards are given.**

Index Terms— **Cognitive radio, spectrum sensing, dynamic spectrum access, multi-dimensional spectrum sensing, cooperative sensing, radio identification.**

I. Introduction

THE NEED for higher data rates is increasing as a result of the transition from voice-only communications to multimedia type applications. Given the limitations of the natural frequency spectrum, it becomes obvious that the current static frequency allocation schemes can not accommodate the requirements of an 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 the spectral congestion problem by introducing opportunistic usage of the frequency bands that are not heavily occupied by licensed users [1], [2]. 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 [3].In this paper, we use the definition adopted by Federal Communications Commission (FCC): "*Cognitive radio: A radio or system that senses its operational electromagnetic environment and can dynamically and autonomously adjust its radio operating parameters to modify system operation, such as maximize throughput, mitigate interference, facilitate interoperability, access secondary markets.*" [2]. Hence, one main aspect of cognitive radio is related to autonomously exploiting locally unused spectrum to provide new paths to spectrum access.

One of the most important components of the 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, 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 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 paper, spectrum sensing by far is the most important component for the establishment of cognitive radio. Spectrum sensing is the task of obtaining awareness about the spectrum usage and existence of primary users in a geographical area. This awareness can be obtained by using geolocation and database, by using beacons, or by local spectrum sensing at cognitive radios [4]–[6]. When beacons are used, the transmitted information can be occupancy of a spectrum as well as other advanced features such as channel quality. In this paper, we focus on spectrum sensing performed by cognitive radios because of its broader application areas and lower infrastructure requirement. Other sensing methods are referred when needed as well. Although spectrum sensing is traditionally understood as measuring the spectral content, or measuring the radio frequency energy over the spectrum; when 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 types 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.

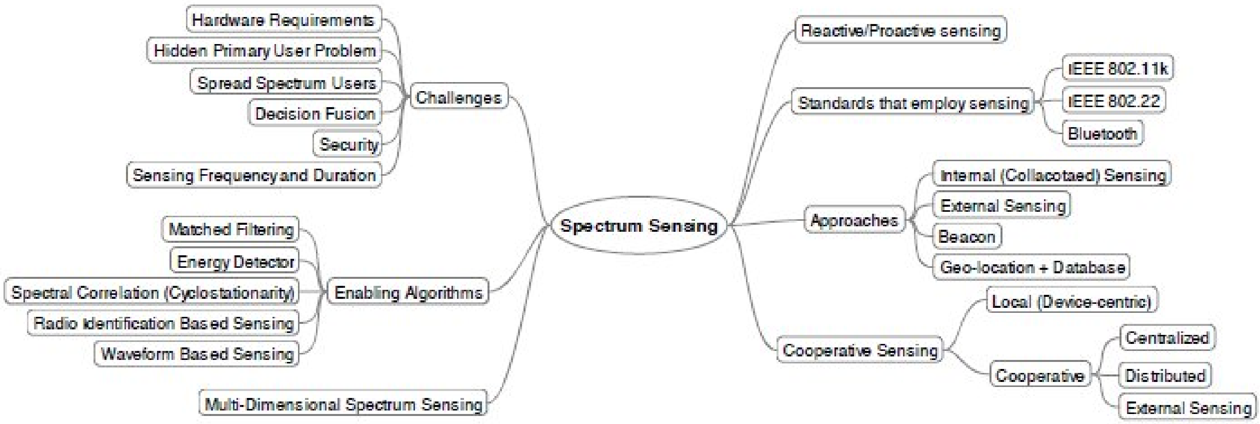


Fig. 1. Various aspects of spectrum sensing for cognitive radio.

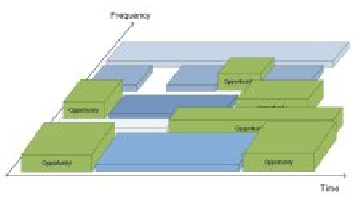
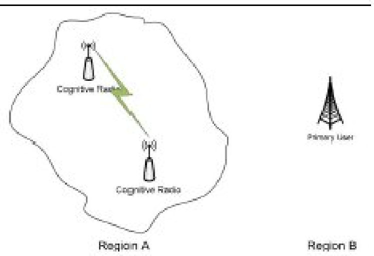
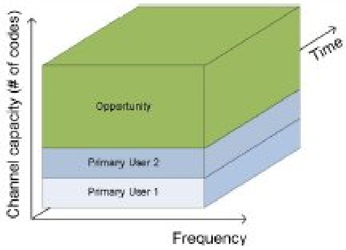
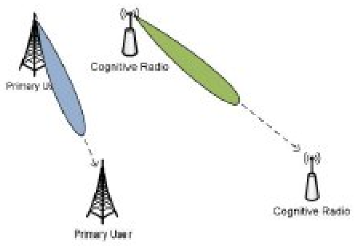
Various aspects of the spectrum sensing task are illustrated in Fig. 1. The goal of this paper is to point out several aspects of spectrum sensing as shown in this figure. These aspects are discussed in the rest of this paper. We start by introducing the multi-dimensional spectrum sensing concept in Section II. Challenges associated with spectrum sensing are explained in Section III. Section IV explains the enabling spectrum sensing methods. The cooperative sensing concept and its various forms are introduced in Section V. Statistical modeling of network traffic and utilization of these models for prediction of primary user behavior is studied in Section VI.Finally, sensing features of some modern wireless standards are explained in Section VII and our conclusions are presented in Section VIII.

II. 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 defined as "*a band of frequencies that are not being used by the primary user of that band at a particular time in a particular geographic area*" [7], only exploits three dimensions of the spectrum space: frequency, time, and space. Conventional sensing methods usually relate 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 as discussed in Section III-C.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 brings about 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 transmit 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 new dimension also creates new Opportunities for spectral estimation where not only the frequency spectrum but also the angle of arrivals (AoAs) needs to be estimated. Please note that angle dimension is different than geographical space dimension. In angle dimension, a primary and a secondary user can be in the same *geographical area* and share the same channel. However, geographical space dimension refers to physical separation of radios in distance.

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*" [8], [9]. 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 the radio environment can be shared among multiple (primary and/or secondary) systems [8]. Various dimensions of this space and corresponding measurement/sensing requirements are summarized in Table I along with some representative pictures. Each dimension has its own parameters that should be sensed for complete spectrum awareness as indicated in this 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. The idle periods between bursty transmissions of important as frequency dimension.

TABLE I
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 level. No interference means no primary user transmission in a local area. However, one needs to be careful because of hidden terminal problem.	
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.	

The idle periods between bursty transmissions of wireless local area network (WLAN) signals are, for example, exploited for opportunistic usage in [9]. This example can be extended to the other dimensions of spectrum space given in Table I. As a result of this requirement, advanced spectrum sensing algorithms that offer awareness in multiple dimensions of the spectrum space should be developed.

III. CHALLENGES

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

A. Hardware Requirements

Spectrum sensing for cognitive radio applications requires high sampling rate, high resolution analog to digital converters (ADCs) with large dynamic range, and high speed signal processors. Noise variance estimation techniques have been popularly used for optimal receiver designs like channel estimation, soft information generation *etc.*, as well as for improved handoff, power control, and channel allocation techniques [9]. 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 utilizing any opportunity. Hence, cognitive radio should be able to capture and analyze a relatively larger band for identifying spectrum opportunities. The large operating bandwidths impose additional requirements on the radio frequencies (RF) components such as antennas and power amplifiers as well. These components should be able to operate over a range of wide operating frequencies. Furthermore, high speed processing units (DSPs or FPGAs) are needed or performing computationally demanding signal processing tasks with relatively low delay. Sensing can be performed via two different architectures: single-radio and dual-radio [4], [5]. In the single-radio architecture, only a specific time slot is allocated for spectrum sensing. As a result of this limited sensing duration, only 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 [6], [7]. 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 [8], [9]. 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 [14]. A comparison of advantages and disadvantages of single and dual-radio architectures is given in Table II. One might prefer one architecture over the other depending on the available resources and performance and/or data rate requirements. There are already available hardware and software platforms for the cognitive radio. GNU Radio [20], Universal Software Radio Peripheral (USRP) [1] and Shared Spectrum's XG Radio [2] are some to name. Mostly energy detector based sensing is used in these platforms because of its simplicity. However, there is not much detail in literature on the exact implementation. Second generation hardware platforms will probably be equipped with more sophisticated techniques.

B. Hidden Primary User Problem

The hidden primary user problem is similar to the hidden node problem in Carrier Sense Multiple Accessing (CSMA). It can be caused by many factors including severe multipath fading or shadowing observed by secondary users while scanning for primary users' transmissions.Here, cognitive radio device causes unwanted interference to the primary user (receiver) as the primary transmitter's signal could not be detected because of the locations of devices. Cooperative sensing is proposed in the literature for handling hidden primary user problem. We elaborate on cooperative sensing in Section V.

C. Detecting Spread Spectrum Primary Users

For commercially available devices, there are two main types of technologies: fixed frequency and spread spectrum. The two major spread spectrum technologies are frequency hopping spread-spectrum (FHSS) and direct-sequence spread spectrum (DSSS). Fixed frequency devices operate at a single frequency or *channel*. An example to such systems is IEEE 802.11a/g based WLAN. FHSS devices change their operational frequencies dynamically to multiple narrowband channels. This is known as *hopping* and performed according to a sequence that is known by both transmitter and receiver. DSSS devices are similar to FHSS devices; however, they use a single band to *spread* their energy. Primary users that use spread spectrum signaling are difficult to detect as the power of the primary user is distributed over a wide frequency range even though the actual information bandwidth is much narrower [6]. This problem can be partially avoided if the hopping pattern is known and perfect synchronization to the signal can be achieved as discussed in Section II. However, it is not straightforward to design algorithms that can do the estimation in code dimension.

TABLE II
COMPARISON OF SINGLE-RADIO AND DUAL-RADIO SENSING ALGORITHMS.

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

D. Sensing Duration and Frequency

Primary users can claim their frequency bands anytime while cognitive radio is operating on their bands. 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 methods should be able to identify the presence of primary users within certain duration. This requirement poses a limit on the performance of sensing algorithm and creates a challenge for cognitive radio design. Selection of sensing parameters brings about a tradeoff between the speed (sensing time) and reliability of sensing. 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 the temporal characteristics of primary users in the environment [7]. If the statuses of primary users are known to change slowly, sensing frequency requirements can be relaxed. A good example for such a scenario is the detection of TV channels. The presence of a TV station usually does not change frequently in a geographical area unless a new station starts broadcasting or an existing station goes offline. In the IEEE 802.22 draft standard (see Section VII), for example, the sensing period is selected as 30 seconds. In addition to sensing frequency, the channel detection time, channel move time and some other timing related parameters are also defined in the standard [8]. Another factor that affects the sensing frequency is the interference tolerance of primary license owners. For example, when a cognitive radio is exploiting opportunities in public safety bands, sensing should be done as frequently as possible in order to prevent any interference. Furthermore, cognitive radio should immediately vacate the band if it is needed by public safety units. The effect of sensing time on the performance of secondary users is investigated in [9]. Optimum sensing durations to search for an available channel and to monitor a used channel are obtained. The goal is to maximize the average throughput of secondary users while protecting primary users from interference. Similarly, detection time is obtained using numerical optimization in [6]. Channel efficiency is maximized for a given detection probability. Another method is given in [3] where the guard interval between orthogonal frequency division multiplexing

(OFDM) symbols is replaced by quiet periods and sensing is performed during these quiet periods. Hence, sensing can be performed without losing useful bandwidth. Sensing time can be decreased by sensing only changing parts of the spectrum instead of the entire target spectrum. A sensing method is developed in [3] that adapts the sweeping parameters according to the estimated model of channel occupancy. This way, a better sensing efficiency is obtained and sensing duration is reduced over non-adaptive sensing methods. A channel that is being used by secondary users can not be used for sensing. Hence, secondary users must interrupt their data transmission for spectrum sensing [3]. This, however, decreases the spectrum efficiency of the overall system [7]. To mitigate this problem, a method termed as dynamic frequency hopping (DFH) is proposed in [3]. DFH method is based on the assumption of having more than a single channel. During operation on a working channel, the intended channel is sensed in parallel. If there is an available channel, channel switching takes place and one of the intended channels becomes the working channel. The access point (AP) decides the channel-hopping pattern and broadcasts this information to connected stations.

E. Decision Fusion in Cooperative Sensing

In the case of cooperative sensing (see Section V), sharing information among cognitive radios and combining results from various measurements is a challenging task. The shared information can be soft or hard decisions made by each cognitive device [3]. The results presented in [3], [4] show that soft information-combining outperforms hard information-combining method in terms of the probability of missed opportunity. On the other hand, hard-decisions are found to perform as good as soft decisions when the number of cooperating users is high in [5]. The optimum fusion rule for combining sensing information is the Chair-Varshney rule which is based on log-likelihood ratio test [6]. Likelihood ratio test are used for making classification using decisions from secondary users in [3]–[5]. Various, simpler, techniques for combining sensing results are employed in [4]. The performances of equal gain combining (EGC), selection combining (SC), and switch and stay combining (SSC) are investigated for energy detector based spectrum sensing under Rayleigh fading. The EGC method is found to have a gain of approximately two orders of magnitude while SC and SSC having one order of magnitude gain. When hard decisions are used; AND, OR or M-out-of-N methods can be used for combining information from different cognitive radios [2]. In AND-rule, all sensing results should be H_1 for deciding H_1, here H_1 is the alternate hypothesis,*i.e.* the hypothesis that the observed band is occupied by a primary user. In OR-rule, a secondary user decides H_1 if any of the received decisions plus its own is H_1. M-out of- N rule outputs H_1 when the number of H_1 decisions is equal to or larger then *M*. Combination of information from different secondary users is done by Dempster-Shafer's theory of evidence [3]. Results presented in [4] shows better performance than AND and OR-rules. The reliability of spectrum sensing at each secondary user is taken into account in [4]. The information fusion at the AP is made by considering the decisions of each cognitive radio and their credibility which is transmitted by cognitive radios along with their decisions. The credibility of cognitive radios depends on the channel conditions and their distance from a licensed user. Required number of nodes for satisfying a probability of false alarm rate is investigated in [4].

F. Security

In cognitive radio, a selfish or malicious user can modify its air interface to mimic a primary user. Hence, it can mislead the spectrum sensing performed by legitimate primary users. Such a behavior or attack is investigated in [4] and it is termed as primary user emulation (PUE) attack. Its harmful effects on the cognitive radio network are investigated. The position of the transmitter is used for identifying an attacker in [46]. A more challenging problem is to develop effective countermeasures once an attack is identified. Public key encryption based primary user identification is proposed in [7] to prevent secondary users masquerading as primary users. Legitimate primary users are required to transmit an encrypted value (signature) along with their transmissions which is generated using a private key. This signature is, then, used for validating the primary user. This method, however, can only be used with digital modulations. Furthermore, secondary users should have the capability to synchronize and demodulate primary users' signal.

IV. 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 transmissions. 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.

A. Energy Detector Based Sensing

Energy detector based approach, also known as radiometry or periodogram, is the most common way of spectrum sensing because of its low computational and implementation complexities [8]. In addition, it is more generic (as compared to methods given in this section) as receivers do not need any knowledge on the primary users' signal. The signal is detected by comparing the output of the energy detector with a threshold which depends on the noise floor [6]. 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, energy detectors do not work efficiently for detecting spread spectrum signals. Let us assume that the received signal has the following simple form

$$y(n) = s(n) + w(n) \tag{1}$$

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 decision metric for the energy detector can be written as

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

Where N is the size of the observation vector. The decision on the occupancy of a band can be obtained by comparing the decision metric M against a fixed threshold λ_E. This is equivalent to distinguishing between the following two hypotheses:

$$H_0 : y(n) = w(n), \quad (3)$$

$$H_1 : y(n) = s(n) + w(n). \quad (4)$$

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, a large detection probability is desired. It can be formulated as

$$P_D = \Pr(M > \lambda_E | H1). \quad (5)$$

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

$$P_F = \Pr(M > \lambda_E | H0). \quad (6)$$

P_F should be kept as small as possible in order to prevent underutilization of transmission opportunities. The decision threshold λ_E can be selected for finding an optimum balance between P_D and P_F . However, this requires 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 [65]. Hence, knowledge of noise variance is sufficient for selection of a threshold. The white noise can be modeled as a zero-mean Gaussian random variable with variance σ^2_w , *i.e.* $w(n) = \mathcal{N}(0, \sigma^2_w)$.

For a simplified analysis, let us model the signal term as a zero-mean Gaussian variable as well, *i.e.* $s(n) = \mathcal{N}(0, \sigma^2_s)$. The model for s (n) is more complicated as fading should also be considered. Because of these assumptions, the decision metric (2) follows chi-square distribution with $2N$ degrees of freedom χ^2_{2N} and hence, it can be modeled as

$$M = \begin{cases} \frac{\sigma_w^2}{2}\chi^2_{2N} & \mathcal{H}_0, \\ \frac{\sigma_w^2+\sigma_s^2}{2}\chi^2_{2N} & \mathcal{H}_1. \end{cases} \quad (7)$$

For energy detector, the probabilities P_F and P_D can be calculated as

$$P_F = 1 - \Gamma\left(L_f L_t, \frac{\lambda_E}{\sigma_w^2}\right), \quad (8)$$

$$P_D = 1 - \Gamma\left(L_f L_t, \frac{\lambda_E}{\sigma_w^2 + \sigma_s^2}\right), \quad (9)$$

where λ_E is the decision threshold, and Γ (a, x) is the incomplete gamma function as given in [6]. In order to compare the performances for different threshold values, receiver operating characteristic (ROC) curves can be used. ROC curves allow us to explore the relationship between the sensitivity (probability of detection) and specificity (false alarm rate) of a sensing method for a variety of different thresholds, thus allowing the determination of an optimal threshold. SNR is defined as the ratio of the primary user's signal power to noise power, *i.e.* SNR=σ^2_s/σ^2_w. The number of used samples is set to 15 in this figure, *i.e.* N = 15 in (2). 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, a small noise power estimation error causes significant performance loss [7]. As a solution to this problem, noise level is estimated dynamically by separating the noise and signal subspaces using multiple signal classification (MUSIC) algorithm [8]. Noise variance is obtained as the smallest eigenvalue of the incoming signal's autocorrelation. Then, the estimated value is used to choose the threshold for satisfying a constant false alarm rate. An iterative algorithm is proposed to find the decision threshold in [6]. The threshold is found iteratively to satisfy a given confidence level, *i.e.* probability of false alarm. Forward methods based on energy measurements are studied for unknown noise power scenarios in [5]. The proposed method adaptively estimates the noise level. Therefore, it is suitable for practical cases where noise variance is not known. Measurement results are analyzed in [6] using energy detector to identify the idle and busy periods of WLAN channels. The energy level for each global system for mobile communications (GSM) slot is measured and compared in [5] for identifying the idle slots for exploitation. The sensing task in this work is different in the sense that 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 [9] as well for opportunistic exploitation of unused cellular slots. In [5], the power level at the output of fast Fourier transform (FFT) of an incoming signal is compared with a threshold value in order to identify the 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 [1]. 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 Rayleigh fading channels is derived in [7]. The effect of log-normal shadowing is obtained via numerical evaluation in the same paper. It is observed that the performance of energy-detector degrades considerably under Rayleigh fading.

B. 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*. A preamble is a known sequence transmitted before each burst and a midamble is transmitted in the middle of a burst or slot. In the presence of a known pattern, sensing can be performed by correlating the received signal with a known copy of itself [3]. This method is only applicable to systems with known signal patterns, and it is termed as waveform-based sensing or coherent 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. Using the same model given in (1), the waveform-based sensing metric can be obtained as [8]

$$M = \mathcal{R}e\left[\sum_{n=1}^{N} y(n)s^*(n)\right] , \tag{10}$$

where * represents the conjugation operation. In the absence of the primary user, the metric value becomes

$$M = \mathcal{R}e\left[\sum_{n=1}^{N} w(n)s^*(n)\right] . \tag{11}$$

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

$$M = \sum_{n=1}^{N} |s(n)|^2 + \mathcal{R}e\left[\sum_{n=1}^{N} w(n)s^*(n)\right] . \tag{12}$$

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. For analyzing the WLAN channel usage characteristics, packet preambles of IEEE 802.11b [71] signals are exploited in [5]. Measurement results presented in [5] show that waveform-based sensing requires short measurement time; however, it is susceptible to synchronization errors. Uplink packet preambles are exploited for detecting Worldwide Interoperability for Microwave Access (WiMAX) signals in [6].

C. Cyclostationarity-Based Sensing

Cyclostationarity feature detection is a method for detecting primary user transmissions by exploiting the cyclostationarity features of the received signals [9]. Cyclostationary features are caused by the periodicity in the signal or in its statistics like mean and autocorrelation [8] or they can be intentionally induced to assist spectrum sensing [8]. 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 (WSS) with no correlation while modulated signals are cyclostationary with spectral correlation due to the redundancy of signal periodicities [7]. Furthermore, cyclostationarity can be used for distinguishing among different types of transmissions and primary users [8]. The cyclic spectral density (CSD) function of a received signal (1) can be calculated as

$$S(f,\alpha) = \sum_{\tau=-\infty}^{\infty} R_y^{\alpha}(\tau)e^{-j2\pi f\tau} , \tag{13}$$

where

$$R_y^{\alpha}(\tau) = E\left[y(n+\tau)y^*(n-\tau)e^{j2\pi\alpha n}\right] \tag{14}$$

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 [7] or they can be extracted and used as features for identifying transmitted signals [5]. The OFDM waveform is altered before transmission in [3] in order to generate system specific signatures or cycle-frequencies at certain frequencies. These signatures are then used to provide an effective signal classification mechanism. In [8], the number of features generated in the signal is increased in order to increase the robustness against multipath fading. However, this comes at the expense of increased overhead and bandwidth loss. Even though the methods given in [1] are OFDM specific, similar techniques can be developed for any type of signal [4]. Hardware implementation of a cyclostationary feature detector is presented in [8].

D. Radio Identification Based Sensing

A complete knowledge about the spectrum characteristics can be obtained by identifying the transmission technologies used by primary users. Such an identification enables cognitive radio with a higher dimensional knowledge as well as providing higher accuracy [9]. For example, assume that a primary user's 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 meters. 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 [8]. 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 the cognitive device is communicating in a certain mode. In radio identification based sensing, 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. In [7], features obtained by energy detector based methods are used for classification. These features include amount of energy detected and its distribution across the spectrum. Channel bandwidth and its shape are used in [4] as reference features. Channel bandwidth is found to be the most discriminating parameter among others. For classification, radial basis function (RBF) neural network is employed. Operation bandwidth and center frequency of a received signal are extracted using energy detector based methods in [5]. These two features are fed to a Bayesian classifier for determining the active primary user and for identifying spectrum opportunities. The standard deviation of the instantaneous frequency and the maximum duration of a signal are extracted using time-frequency analysis in [9] and neural networks are used for dentification of active transmissions using these features. Cycle frequencies of the incoming signal are used for detection and signal classification in [7]. Signal identification is performed by processing the (cyclostationary) signal features using hidden Markov model (HMM). Another cyclostationarity based method is used in [5] where spectral correlation density (SCD) and spectral coherence function (SCF) are used as features. Neural network are utilized for classification in [7] while statistical tests are used in [2].

E. Matched-Filtering

Matched-filtering is known as the optimum method for detection of primary users when the transmitted signal is known [9]. The main advantage of matched filtering is the short time to achieve a certain probability of false alarm or probability of miss-detection [9] as compared to other methods that are discussed in this section. In fact, the required number of samples grows as $O(1/SNR)$ for a target probability of false alarm at low SNRs for matchedfiltering [9]. However, matched-filtering requires 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, and frame format. Moreover, since cognitive radio needs receivers for all signal types, the implementation complexity of sensing unit is impractically large [6]. Another disadvantage of match filtering is large power consumption as various receiver algorithms need to be executed for detection.

F. 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 [3]. The proposed algorithm is shown to be an approximation to maximum likelihood PSD estimator, and for wideband signals, it is nearly optimal. Although the complexity of this method is smaller than the maximum likelihood estimator, it is still computationally demanding. Random Hough transform of received signal is used in [4] 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 signal with a periodic pattern as well. Statistical covariance of noise and signal are known to be different. This fact is used in [5] to develop algorithms for identifying the existence of a communication signal. Proposed methods are shown to be effective to detect digital television (DTV) signals. In [6], wavelets are used for detecting edges in the PSD of a wideband channel. Once the edges, which correspond to transitions from an occupied band to an empty band or vice versa, are detected, the powers within bands between two edges are estimated. Using this information and edge positions, the frequency spectrum can be characterized as occupied or empty in a binary fashion. The assumptions made in [6], however, need to be relaxed for building a practical sensing algorithm. The method proposed in [9] is extended in [7] by using sub-Nyquist sampling. Assuming that the signal spectrum is sparse, sub-Nyquist sampling is used to obtain a coarse spectrum knowledge in an efficient way. Analog implementation of wavelet-transform based sensing is proposed in [8] for coarse sensing. Analog implementation yields low power consumption and enables real-time operation. Multi-resolution spectrum sensing is achieved by changing the basis functions without any modification to sensing circuitry in [1]. Basis function is changed by adjusting the wavelet's pulse width and carrier frequency. Hence, fast sensing is possible by focusing on the frequencies with active transmissions after an initial rough scanning. A testbed implementation of this algorithm is explained in [4].

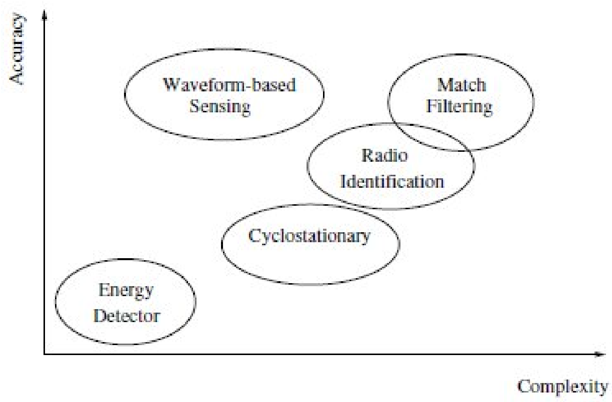


Fig. 2. Main sensing methods in terms of their sensing accuracies and complexities.

G. Comparison of Various Sensing Methods

A basic comparison of the sensing methods given in this section is presented in Fig. 2. Waveform-based sensing is more robust than energy detector and cyclostationarity based methods because of the coherent processing that comes from using deterministic signal component [7]. However, there should be a priori information about the primary user's characteristics and primary users should transmit known patterns or pilots. The performance of energy detector based sensing is limited when two common assumptions do not hold [5]. The noise may not be stationary and its variance may not be known. Other problems with the energy detector include baseband filter effects and spurious tones [3]. It is stated in literature that cyclostationary-based methods perform worse than energy detector based sensing methods when the noise is stationary. However, in the presence of co-channel or adjacent channel interferers, noise becomes non-stationary. Hence, energy detector based schemes fail while cyclostationarity-based algorithms are not affected [5]. On the other hand, cyclostationary features may be completely lost due to channel fading [1]. It is shown in [1] that model uncertainties cause an SNR wall for cyclostationary based feature detectors similar to energy detectors [9]. Furthermore, cyclostationarity-based sensing is known to be vulnerable to sampling clock offsets [8]. While selecting a sensing method, some tradeoffs should be considered. The characteristics of primary users are the main factor in selecting a method. Cyclostationary features contained in the waveform, existence of regularly transmitted pilots, and timing/frequency characteristics are all important. Other factors include required accuracy, sensing duration requirements, computational complexity, and network requirements. Estimation of traffic in a specific geographic area can be done locally (by one cognitive radio only) using one of the algorithms given in this section. However, information from different cognitive radios can be combined to obtain a more accurate spectrum awareness. In the following section, we present the concept of cooperative sensing where multiple cognitive radios work together for performing spectrum sensing task collaboratively.

V. COOPERATIVE SENSING

Cooperation is proposed in the literature as a solution to problems that arise in spectrum sensing due to noise uncertainty, fading, and shadowing. Cooperative sensing decreases the probabilities of miss-detection and false alarm considerably. In addition, cooperation can solve hidden primary user problem and it can decrease sensing time [2]. The interference to primary users caused by cognitive radio devices employing spectrum access mechanisms based on a simple listen-before-talk (LBT) scheme is investigated in [5] 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 sensing performance. Challenges of cooperative sensing include developing efficient information sharing algorithms and increased complexity [4]. In cooperative sensing architectures, the control channel (pilot channel) can be implemented using different methodologies. These include a dedicated band, an unlicensed band such as ISM, and an underlay system such as ultra wide band (UWB).Depending on the system requirements, one of these methods can be selected. Control channel can be used for sharing spectrum sensing results among cognitive users as well as for sharing channel allocation information. Various architectures for control channels are proposed in the cognitive radio literature. A time division multiple access (TDMA)-based protocol for exchange of sensing data is proposed in [6]. Cognitive radios are divided into clusters and scanning data is sent to the cluster head in slots of frames assigned to a particular cluster. 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 a minimum amount of delay. Collaborative spectrum sensing is most effective when collaborating cognitive radios observe independent fading or shadowing. The performance degradation due to correlated shadowing is investigated in [5] in terms of missing the opportunities. It is found that it is more advantageous to have the same amount of users collaborating over a large area than over a small area. In order to combat shadowing, beam forming and directional antennas can also be used .In [4], it is shown that cooperating with all users in the network does not necessarily achieve the optimum performance and cognitive users with highest primary user's signal to noise ratio are chosen for collaboration. In [4], constant detection rate and constant false alarm rate are used for optimally selecting the users for collaborative sensing. Cooperation can be among cognitive radios or external sensors can be used to build a cooperative sensing network. In the former case, cooperation can be implemented in two fashions: centralized or distributed .These two methods and external sensing are discussed in the following sections.

A. 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 AP in [3]. The goal is to mitigate the fading effects of the channel and increase detection performance. Resulting detection and false alarm rates are given in [108] for the sensing algorithm used in [3]. In [3], 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. In [8], users send a quantized version of their local decisions to central unit (fusion center). Then, a likelihood ratio test over the received local likelihood ratios is applied. In the case of a large number of users, the bandwidth required for reporting becomes huge. In order to reduce the sharing bandwidth, local observations of cognitive radios are quantized to one bit (hard decisions) in [9]. Furthermore, only the cognitive radios with reliable information are allowed to report their decisions to the central unit. Hence, some sensors are censored. Censoring can be implemented by simply using two threshold values instead of one. Analytical performance of this method is studied for both perfect and imperfect reporting channels.

B. 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 than centralized sensing in the sense that there is no need for a backbone infrastructure and it has reduced cost. An incremental gossiping approach termed as GUESS (gossiping updates for efficient spectrum sensing) is proposed in [7] for performing efficient coordination between cognitive radios in distributed collaborative sensing. The proposed algorithm is shown to have low-complexity with reduced protocol overhead. Incremental aggregation and randomized gossiping algorithms are also studied in [7] for efficient coordination within a cognitive radio network. A distributed collaboration algorithm is proposed in [4]. Collaboration is performed between two secondary users. The user closer to a primary transmitter, which has a better chance of detecting the primary user transmission, cooperates with far away users. An algorithm for pairing secondary users without a centralized mechanism is proposed. A distributed sensing method where secondary users share their sensing information among themselves is proposed in [7]. Only final decisions are shared in order to minimize the network overhead due to collaboration. The results presented in [7] clearly show the performance improvements achieved through collaborative sensing. A distributed cognitive radio architecture for spectrum sensing is given in [4]. Features obtained at different radios are shared among cognitive users to improve the detection capability of the system.

C. 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 where sensing is performed by the cognitive transceivers internally. Internal sensing is termed as collocated sensing in [5]. The main advantages of external sensing are overcoming hidden primary user problem and 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, the power consumption problem of internal sensing can also be addressed. A sensor node detector architecture is used in [7]. The presence of passive receivers, *viz.* television receivers, is detected by measuring the local oscillator (LO) power leakage. Once a receiver and the used channel are detected, sensor node notifies cognitive radios in the region of passive primary users via a control channel. Similar to [7], a sensor network based sensing architecture is proposed in [5]. 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 spectrum occupancy in the sensed area with opportunistic radios. These opportunistic radios use the information obtained from the sensing network for selecting the bands (and time durations) for their data transmission. Sensing results can also be shared via a pilot channel similar to network access and connectivity channel (NACCH) [7]. External sensing is one of the methods proposed for identifying primary users in IEEE 802.22 standard as well (See Section VII).

VI. USING HISTORY FOR PREDICTION

For minimizing interference to primary users while making the most out of the opportunities, cognitive radios should keep track of variations in spectrum availability and should make predictions. Stemming from the fact that a 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 [4]. Assuming a TDMA transmission, the periodic pattern of channel occupancy is extracted using cyclostationary detection. This parameter is then used to forecast the channel idle probability for a given channel. In order to model the channel usage patterns of primary users, HMMs are proposed in [4]. A multivariate time series approach is taken in [5] 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. It is noted in [2] that the statistical model of a primary user's behavior should be kept simple enough to be able to design optimal higher order protocols. On the other hand, the model would be useless if the primary user's behavior could not be predicted well. In order to strike a balance between complexity and effectiveness, a 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 voice over Internet protocol (VoIP) and file transfer protocol (FTP) traffic scenarios for a semi-Markov model is performed in [6]. Pareto, phase-type (hyper-Erlang) and mixture distributions are used for fitting to the empirical data. Statistics of spectrum availability is employed in [5] for dynamically selecting the operating frequency, *i.e.* for identifying the spectrum holes. Statistics of the spectral occupancy of an FFT output bin are 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 a 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. When observation history is used optimally, the throughput of the secondary user can be increased approximately 40%. A predictive model is proposed in [7] which is based on long and short-term usage statistics of TV channels. The usability characteristics of a channel are based on these statistics and it is used for selection of a channel for transmission. Channels with frequent and heavy appearance of primary users are filtered out using a threshold mechanism.

VII. SPECTRUM SENSING IN CURRENT WIRELESS STANDARDS

Recently developed wireless standards have 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 the 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 access (DFA) are discussed. However, the spectrum knowledge can be used to initiate advanced receiver algorithms as well as adaptive interference cancellation.

A. IEEE 802.11k

A proposed extension to IEEE 802.11 specification is IEEE 802.11k which defines several types of measurements [8]. 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. 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 connect to the AP that has the strongest signal level. Sometimes, such an arrangement might not be 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.

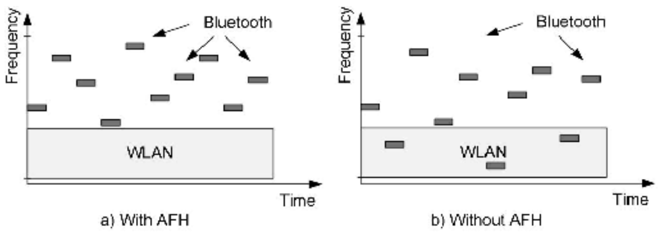


Fig. 3. Bluetooth transmission with and without adaptive frequency hopping (AFH). AFH prevents collusions between WLAN and Bluetooth transmissions.

B. Bluetooth

A new feature, namely adaptive frequency hopping (AFH), is introduced to the Bluetooth standard to reduce interference between wireless technologies sharing the 2.4GHz unlicensed radio spectrum [4]. In this band, IEEE 802.11b/g devices, cordless telephones, and microwave ovens use the same wireless frequencies as Bluetooth. AFH identifies the transmissions in the industrial, scientific and medical (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. Fig. 3 shows an illustrative Bluetooth transmission with and without AFH. By employing AFH, collisions with 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 empty. Channel statistics can be packet-error rate, BER, received signal strength indicator (RSSI), carrier-to-interference-plus-noise ratio (CINR) or other metrics. The statistics are used to classify channels as *good*, *bad*, or *unknown.*

C. IEEE 802.22

IEEE 802.22 standard is known as *cognitive radio standard* because of the cognitive features it contains. The standard is still in the development stage. One of the most distinctive features of the IEEE 802.22 standard is its spectrum sensing requirement. IEEE 802.22 based wireless regional area network (WRAN) devices sense TV channels and identify transmission opportunities. The functional requirements of the standard require at least 90% probability of detection and at most 10% probability of false alarm for TV signals with - 116 dBm power level or above. The sensing is envisioned to be based on two stages: fast and fine sensing .In the fast sensing stage, a coarse 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 the BS which uses these results for managing the transmissions. Hence, it is a practical example of centralized collaborative sensing explained in Section V-A. 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 operating in the TV bands, *e.g.* wireless microphone and wireless camera, 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.

VIII. 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 to utilize the available spectrum more efficiently through opportunistic spectrum usage, has become an exciting and promising concept. One of the important elements of cognitive radio is sensing the available spectrum opportunities. In this paper, the spectrum opportunity and spectrum sensing concepts are reevaluated by considering different dimensions of the spectrum space. The new interpretation of spectrum space creates new opportunities and challenges for spectrum sensing while solving some of the traditional problems. Various aspects of the spectrum sensing task are explained in detail. Several sensing methods are studied and collaborative sensing is considered as a solution to some common problems in spectrum sensing. Pro-active approaches are given and sensing methods employed in current wireless systems are discussed. Estimation of spectrum usage in multiple dimensions including time, frequency, space, angle, and code; identifying opportunities in these dimensions; and developing algorithms for prediction into the future using past information can be considered as some of the open research areas.

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