A Classification of the Spectrum Sensing Techniques for Cognitive Radio

Faten Mashta, Wissam Altabban, Mohieddin wainakh

Abstract: Cognitive radio is a solution to the problem of radio spectrum scarcity. It gives the opportunity to a secondary user to exploit the spectrum allocated toa primary user. The main function of cognitive radio is spectrum sensing whichhas gained new aspects in the last decades to determine opportunistic spectrum holes. There are many spectrumsensing methods proposed in the literature. The Performance of thesetechniques may vary in different situations; it can be described by probability of detection, probability of false alarm, and sensing time. It is therefore important to compare and indicate the best scheme for a specified scenario. In this paper, we propose a classification of the main approaches of single user spectrum sensing based on its synchronization requirement into two main categories: coherent detection and non-coherent detection. The coherent detection needs some or full prior information about the primary user signal for detecting it, where the non-coherent detection does not need any prior information about the primary user signal for detecting it. In addition, we highlight the advantages and disadvantages of narrowband and wideband spectrum sensing procedures along with the challenges involved in their implementation.Furthermore, we introduce the concept and basics of cooperative sensing and interference based sensing.This paper helps the designer to be familiar with all the techniques used to achieve spectrum sensing.

Keywords: Cognitive radio, spectrum sensing, coherent detection,compressive sensing, cooperative sensing.

I. INTRODUCTION

Because of today'sfixed spectrum assignment policyof wireless networks [1], [2], the utilization of the licensed spectrumremains low in some areas. The geographically variations of the licensed spectrumare from 15% to 85% with a high variance in time[2]. Studies undertaken by The Office of Communications have explored the usage of the radio spectrum. These measurements seem to designate that there are many zones of the radio spectrum which are not fully utilized in different geographical spaces[3].Fig. 1 showsspectrum occupancy measurements from 50MHz to 1GHz in a rural area (top), near Heathrow airport (middle) and in central London (bottom).

Within, we see that the effective utilization of the spectrum in the different areas is mostly fewer than 16%.The limited accessible spectrum and the inefficiency of the licensed spectrum usage demand a novel communication pattern to abuse the present wireless spectrum opportunistically [1], [4], [5]. Cognitive radio firstly proposed by Mitola [6] suggestions a new solution to overcome the underutilization problem by allowing an opportunistic usage of the spectrum resources[7].

In cognitive radio system, *secondary users(SU)*(unlicensed users) exploit a specific part of the spectrum, which is allocated to *primary users(PU)*(licensed users),but they do not cause any interference to primary users [5]. Thus, secondary users must have cognitive radio abilities, such as sensing the spectrum availability to decide whether a primary user is using it and to modify the radio parameters to exploit the unused fragment of the spectrum[4].

The main tasks of cognitive radio can be summarized as [5]:

1) Radio-scene analysis, which has two main jobs: estimation of interference temperature of the radio environment, which is a measure of the RF power presented at a receiving antenna to be delivered to a receiver power generated by other emitters and noise sources [8], and recognition theholes of spectrum.

2) Channel identification, which deals with the estimation of channel-state information (CSI), and expectationthe channel capacity which can be used by the transmitter.

3) Transmit-power regulator and active spectrum administration.

We focus in this paper on the spectrum sensing task of cognitive radio since it is considered as the basic component of cognitive radioestablishing. By definition, spectrum sensing is the mission of obtaining awareness about the spectrum usage by primary users in a geographical area [4], [9]. In passively sensing we categorizethe radio scene into three generally defined types, as brief here [5]:

1) *Black spaces*, they areoften engaged by high-power "local" interferers.

2) *Grey spaces*, they are partially engaged by low-power interferers.

3) *White spaces*, there is no RF interferers not including ambient noise, made up of natural and artificial forms of noise.

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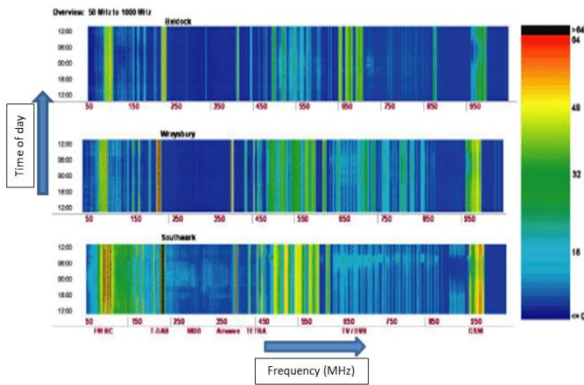# A Classification of the Spectrum Sensing Techniques for Cognitive Radio

Fig. 1. Spectrum occupancy measurements in a rural area (top), near Heathrow airport (middle) and in central London (bottom) [3].

We often define the spectrum sensing as the understood of the spectral content,or measuring the radio frequency energy over the spectrum; however, inthe cognitive radio, spectrum sensing is a more general task that includes finding the spectrum usage characteristicsacross multiple dimensions for example: time, space, frequency, and code. In addition, it should define the types of signals that areoccupying the spectrum plus the modulation type, waveform,bandwidth, carrier frequency, *etc.*In this situation, more requirements are necessary such as more powerful signal processing procedures with additional computationalcomplexity [4].In this paper, our goal is to offer a classification of the spectrum sensing techniquesin cognitive radio. Mainly, there are three types of spectrum sensing; single user sensing, cooperative sensing and interference based sensing. The main contribution of this work is to provide a classification of single user sensingtechniques based on the amount of information about primary signal needed by the SU to detect the presence of PU. In this context, we divide the spectrum sensing methods into twogroups: coherent detection and non-coherent detection techiniques.

- *Coherent detection* needs some or full prior information about the PU signal for detecting it. Using this knowledge, signal after reception is compared with the prior knowledge of PU signal.
- *Non-coherent detection* does not need any prior information about the PU signal for detecting it.

The coherent detection methodsdifferentiate if the received signal is a PU signal, a SU signal, noise, or an interfering signal. However, they are often sensitive to timing error and non-ideal channel. However, the non-coherent detection techniques have the ability to detect different PU waveforms without recognizing its type. The paper is organized as follows. Sections II address related works in the literature, Section III introduces a Top Down classification of the different spectrum sensingmethods. In Section IV, Single User Spectrum Sensing Techniques are demonstrated. Section V present cooperative sensing, interference based sensing is discussed in Section VI.In Section VII, the up-to-date standards such as IEEE 802.11af, IEEE 802.15.4m, IEEE 802.22, and Ecma-392 are presented. Finally, conclusions are drawn in Section VIII.Weoffer the descriptions of acronyms/notations in Table I.

II. RELATED WORKS

In fact, many surveys in the literature review the spectrum sensing techniques for cognitive radio.Most of which doesn't provide a classification of these techniques. We consider the classification of spectrum sensing techniques as a guide that determines the way to choose the best scheme for a given scenario.Reference [4] points out several aspects of spectrum sensing by introducing the concept of multi-dimensional spectrum sensing.Then, it explains challenges related to spectrum sensing, and the assisting spectrum sensing techniques. Also,it introduces cooperative sensing concept and its various forms.In[10], [11],the authors classify spectrum sensing techniques into three leadingcategories, transmitter detection, cooperative sensing and interference based sensing. They divide transmitter detection methodto three groups: energy detection, matched filter detection and cyclostationary detection.In [9], an overview of the wideband sensing approaches and challenges have been presented, the authorssort the wideband spectrum sensing procedures based on their implementation styles into two categories: Nyquist sensing and sub-Nyquist sensing.A classification for spectrum sensing techniques based on the conventional bandwidth is presented in [12]. Within, the spectrum sensing techniques is divided to narrowband sensing and wideband sensing. It presents also the advances on the practical system implementation side of the spectrum sensing framework.

According to [13], the spectrum sensing methods are divided to three types: total blind, semi-blind, and non-blindtechniques. As for total blind spectrum sensing does not need any prior information about a PU signal and noise, while in semi-blind method, the information of noise variance is important to be known. Non-blind methods need some prior information about the PU signal.

The following paragraph shows our classification of spectrum sensing techniques.

III. TOP DOWN CLASSIFICATION OF SPECTRUM SENSING

We present in Fig. 2 the top down classification of spectrum Sensing techniques. In the first level, they are classified into three main types: single user sensing, cooperative sensing, and interference-based sensing.Single user spectrum sensing mean that every CR performs independently spectrum sensing stage, and then decide whether the PU signal is present or not. In cooperative spectrum sensing, a group or network of cognitive radios exchange the sensing reports and one or more node of the network decide whether the primary user signal is present or not. Interference based spectrum sensing is defined widely in section VI.We propose to classify single user sensing into two types: coherent and non-coherent detection. Contrarily to non-coherent detection, coherent detection requires well-knownprior information about the PU signals. This is a requirement in Matched Filter and Feature detection. In the third level of classification, as we see in Fig. 2, we discriminate the non-coherent detection into narrow band and wide band detection.

In this context, Energy Detection and Eigenvalue detection are known as narrow band sensing, whilethe wideband spectrum sensing algorithms are categorized based on their implementation types into two types: Nyquistbased and Sub-Nyquistbased.In the next section, we review the most common spectrum sensing techniques for single cognitive radio.

IV. SINGLE USER SPECTRUM SENSING TECHNIQUES

We defined Single user spectrum sensing in section III that every CR performs independently spectrum sensing stage, and then decide by itself whether the PU signal is existing or not. In other words, the cognitive radio has toelect whether a specificpart of the spectrum is "available" or not. That is, to discriminate between the two hypotheses [14]:

$$\begin{cases} H_0: y(n) = w(n) & n = 1, \ldots, N \\ H_1: y(n) = x(n) + w(n) & n = 1, \ldots, N \end{cases} \quad (1)$$

where $x(n)$ represents a PU's signalsamples, $y(n)$is the received signalsample,$w(n)$ present the additive white Gaussian noisesample(AWGN), and$N$is number of samples[14].In spectrum sensing, it should decide whether the received signal y was generated under H_0 or H_1. Usually, this isdone bymaking a test statistic $\Lambda(y)$from the received observation y, and then comparing $\Lambda(y)$ with a preset threshold η [14].

$$\Lambda(y) = \lessgtr_{H_1}^{H_0} \eta \quad (2)$$

The performance of the detection process is described with two probabilities: the probability of detection P_d and the probability of false alarmP_{fa}.By definition, P_d is defined by the following equation:

$$P_d = \Pr(\Lambda(y) > \eta | H_1) \quad (3)$$

On the other hand, P_{fa} is the probability that the test wronglyindicates that the PU signal is existing when in factit is not, it is defined by:

$$P_{fa} = \Pr(\Lambda(y) > \eta | H_0) \quad (4)$$

For the benefit of spectrum efficiency,P_{fa}has to be kept as small as possible [14]. On the other hand, for the benefit of the primary user and preventing any kind of interferenceP_d should be high enough.The designof detection algorithm depend on choosing the value of the test statistic$\Lambda(y)$, and the decision threshold η to realize good probability of detection. Detection processes are either considered in the context of classical statistics, or in the context of Bayesian statistics. In the classical context, either H_0 or H_1 is deterministically true, and the objective is to choose $\Lambda(y)$ and η so as to maximize P_d subject to a constraint on P_{fa}: $P_{fa} < \alpha$; this is known as the Neyman-Pearson criterion. In the Bayesian context, the source chooses the true hypothesis, in keeping with some a priori probabilities $\Pr(H_0)$ and $\Pr(H_1)$to minimize the Bayesian cost [12], [15].As mentioned before, detection algorithmsare classified according to its dependence or not on the prior information ofthe primary user. We describe foreword each coherent and non-coherent techniques of spectrum sensing according to this classification.

A. Coherent Techniques

Coherent techniques of cognitive radios need prior information of primary signal user. In this context, matched filter is considered as coherent technique because it requires a prior full information about the PU signal which are used for channel estimation and synchronization like the preamble,pilot and training sequence. In addition, feature detection method that captures a specific signature of the PU signal, like the cyclostationary, the correlation, or signal patterns is a coherent technique as well. In the following paragraph we present these methods in details.

1) Matched Filter Detection (MFD):

Matched filter is an optimal detection technique when the transmitted PU signal in AWGN environment is known by the SU [16], [17]. In this case, the test statistic can be written as [17]:

$$\Lambda_{MFD} = S^H C_w^{-1} Y \quad (5)$$

TABLE I. Definitions of Acronyms and Notations

Acronyms/Notations	Definitions	Acronyms/Notations	Definitions				
ADC	Analogue to Digital Converter	SU	Secondary User	FC	Fusion Center	H_0	Null Hypothesis
AWGN	Additive White Gaussian Noise	UHF	Ultra-High Frequency	FCC	Federal Communications Commission	H_1	Alternative hypothesis
CFD	Cyclostationary Feature Detection	WB	Wide Band	FFT	Fast Fourier Transform	P_d	Detection Probability
CR	Cognitive Radio	WS	White Spaces	MF	Matched Filter	P_{fa}	False Alarm Probability
CSD	cyclic spectral density	Y	Vector Y				
ED	Energy Detector	w	AWGN				

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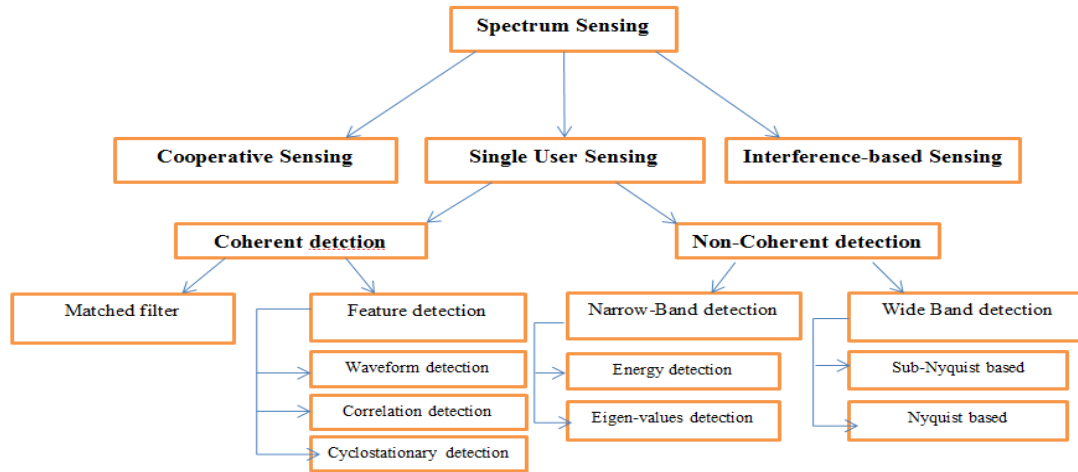| NB	Narrow band	$\Lambda(y)$	The test statistic		SNR	Signal to Noise Ratio	x	The PU's signal
PSD	Power Spectral Density	η	Threshold		SS	Spectrum Sensing	C_w	The noise covariance matrix
PU	Primary User	Pr (a)	Probability of event a					

Fig. 2. Classification for the spectrum sensing techniques based on its synchronization specifications.

where Y is the observation vector, S is the known deterministic signal to be detected, and C_w is the noise covariance matrix.

This method has the shortest detection time, with a good detection performance and easy implementation. However, the SU requires receivers for different PU signals so the complexity of MFD is very high [18]. The detection performance of the matched filters is degraded when the channel is non-line-of-sight frequency selective, and synchronization errors may change the pilot structure[17].

2) Feature detection:

Feature detection captures a specific signature of the PU signal. This feature is added intentionally for synchronization or signaling purposes such as preambles, pilots, beacon frames cyclic prefix (CP), hopping sequence, etc. Other features are originated by having a modulated digital PU signal. In this context, the second-order statistics, or even a general cyclostationary of the modulated PU signal exhibit an observable grade of periodicity that can be explored for sensing purposes [12].

In fact, feature detection includes a wide class of spectrum sensing algorithms. These techniques are coherent methods because they share the concept that knowing partial or full information about the PU signal features enables the construction of detectors that exploit this characteristic. In the flowing, we present the most common examples for feature detection.

a) Cyclostationary feature detection (CFD):

This method exploits the cyclostationary properties that are added to the modulated signals on purpose, or they are caused by the periodicity in the signal or in its statistics, such as mean and autocorrelation to detect the PU signal. CFD can differentiate PU signals from noise where the noise is wide-sense stationary (WSS) with no correlation while the

PU signals are cyclostationary with spectral correlation. Other advantages of CFD are the distinction between various kinds of PU signals, and the good detection performance at very low SNR values [18]. However, the computational complexity of the CFD is high, and it needs long time to provide detection.

The cyclic spectral density (CSD) function of a received signal is defined as [4]

$$S(f, \alpha) = \sum_{\tau=-\infty}^{\tau=+\infty} R_y^\alpha(\tau) e^{-j2\pi f \tau} \qquad (6)$$

where

$$R_y^\alpha(\tau) = E(y(n+\tau)y^*(n-\tau)) e^{-j2\pi\alpha n} \qquad (7)$$

$R_y^\alpha(\tau)$ is the cyclic autocorrelation function (CAF), and α is the cyclic frequency. When α is equal to the fundamental frequencies of transmitted signal The CSD function outputs peak values [4].

b) Correlation detection:

Additional method to feature detection is to estimate the second-order statistics of the received signals. In this approach, we may differentiate a perfectly white signal from a colored one. Typically, the transmitted signal has a redundancy added data that results in its samples becoming correlated.

Since $cov(Ax) = A cov(x) A^H$ for any A and x, redundancy is usually added at the transmitter to explore if the transmit processing lies of a linear procedure. Also, we can entirely determine the distribution of a Gaussian signals by its first and second-order statistics, if the transmitted signals sufficiently close to Gaussian, and enough samples are collected. Then, estimation the first- and second-order statistics are enough to detect the PU signal.

Moreover, as the transmitted signals are often zero-mean signals, then observingthe second-order moment is sufficient [14]. Thus, we can design near-optimal signal detectionprocedures by estimating second-order statistics [14].

c) Waveform detection:

Itrelies on a prior knowledge of the PU signal construction. For synchronization issues, preambles, pilot carrier, spreading sequences are usually added to the PU signal. Waveform detection is a coherent sensing method that makes use of the known signal patterns. In this case, the test statistic is made by correlating the received signal to a known pattern. Then,making decision by comparing the result with a threshold value [19].

3) Comparison of coherent techniques

The matched filter is considered to have the shortest detection time with optimal probability of detection, it is an optimal method for SS in AWGN environment,it is easy to implement.However, it requires full information about the PU signals such as bandwidth, pilot frequency, the type and order of modulation, pulse shaping, and frame format. Furthermore, since cognitive radio needs receivers for all signal types, the implementation complexity of sensing component is very high.

The feature detection can differentiate the PU signal from thenoise, SU signal, and interference. Moreover, cyclostationary detection has a good detection performance with low SNR. However, these techniques require long observation time and higher computational complexity. In addition, feature detection needs prior information about the PU signals [10].

B. Non-Coherent Techniques

We divide the non-coherent spectrum sensing techniques to narrowband sensing and wideband sensing.By definition, NarrowbandSensing deals with the problem of deciding whether a specificpart of the spectrum is buzy or not. On the contrary, wideband spectrum sensing is basedon classifying individual slices of a wideband to be eitheroccupied or vacant. In fact, both sensing proceduresare required during the cognitive cycle.In [20] it is proposed that PU detection is necessarily effectuated through two distinct phases. During the initial sensing phase, wideband sensing is required to detect the available spectrum holes. After detecting and analyzing the spectrum holes, the spectrum decision (or spectrum selection) selects the best available band according to some criteria. Once a suitable operating frequency has been selected, the communication can be started, but due to the high dynamics of the mobile environment, after a while the selected narrowband may become occupied by a PU. Therefore, prior to communication, SU narrowband sensing is executed for the selected band as a second phase of sensing to confirm that no PU is present. Once the band is utilized, continuous spectrum sensing/monitoring is required to validate the assumption that the utilized band is still unoccupied and CR can continue its communication on the same band [20]. We present forewords the narrow and wideband approaches.

1) Narrow Band Approaches:

The narrowband approachindicates that it can be considered that the channel frequency response is flat, or the sensing bandwidth is less than the coherence bandwidth of the channel. These techniques make a single binary decision for the whole spectrum. In the flowing, we will discuss two narrow band approaches: energy detection and eigen-value detection.

a) Energy detection (ED):

Energy detector is widely explained in the literature [13], [21], [16], [18],[22]. Within, we compare the energy of the received signal with a predefined threshold value to decide whether the PU signal is existing or not. The ED is a non-coherent detection technique, where the SU receiver does not require any priorinformation about the PU signals.It is also with low implementation complexity, and it has the applicability for various signals. However, ED cannot differentiatebetween different types of signals. Furthermore, ED is susceptible to the uncertainty of noise power, which makes it challenging to determine the detection threshold.Also, it is not able to detect spread spectrum signals, and it is not a suitable method for selective fading channel[21].

In ED technique, to measure the energy of received signal, the output of band pass filter with bandwidth W is squared and integrated over the observation interval T. Then, we compare the output of the integrator Y with a predefined threshold valueη to make the decision whether a PU signal is existing or not.

Considering non-fading environment, the probability of detection and false alarm of the ED are definedby the following equations[22]:

$$P_d = \Pr(Y > \eta | H_1) = Q_m\left(\sqrt{2Y}, \sqrt{\eta}\right) \qquad (8)$$

$$P_{fa} = \Pr(Y > \eta | H_0) = \frac{\Gamma(m, \eta/2)}{\Gamma(m)} \qquad (9)$$

where: $m = N/2$is the number of samples per either I (In phase) or Q (In Quadrature) components,Y is the SNR, u = TW is the time bandwidth product, $\Gamma(.)$ and $\Gamma(.,.)$ are complete and incomplete gamma functions and $Q_m(.)$ is the generalized Marcum Q-function. Thus, when $P_d$is high that will decrease the interference to the license user. Alternatively, when$P_{fa}$is high that will increase the number of missed opportunities [22].

Because of the easy implementation, many works on spectrum sensing of the license user haveassumed the energy detection technique and working to improve their performance or combined with other techniques.

b) Eigen-values detection:

These techniques depend on the eigenvalues of the covariance matrix of the received signals at the SU receiver. Wherein, the test statistic is formed using the ratio of the maximum or average eigenvalue to the minimum eigenvalue, and it is compared with predefined threshold value to decide whether the PU is present or not. The threshold value is set using the result of Random Matrix Theories (RMT).Moreover,the probability of false alarm and probability of detection are derivative using the RMT[23].

There are other procedures based on eigenvalues to reveal the primary user signal:Maximum Eigenvalue Detection (MED), Minimum Eigenvalue Detection, Generalized Likelihood Ratio Test (GLRT), Energy with Minimum Eigenvalue (EME), Roy's Largest Root Test (RLRT), and Difference of Means of Eigenvalue (DME) [24], [25], [26]. This methodof detection is non-coherent, it does not need any prior information about the PU signal, the channel and noise power. Itis better than ED method for many reasons such as it overcomes the noise uncertainty problem and ithas betterdetection performance when the PU signals are highly correlated. In addition, the proposed method does not require accurate synchronization [26].

2) Wide Band Approaches:

Wideband sensing termpoint to sensing a frequency bandwidth that exceeds the coherence bandwidth of the channel. Such as, to exploit spectral holes in the entire TV band, wideband sensing should be engaged. It is worth to mention that we cannot use narrowband sensing techniques to achievewideband sensing, because they make a single binary decision for the entire sensing band, and thus they cannot presentvarious spectral opportunities that lie within the wideband spectrum [9].Based on the sampling frequency, two main classes of solutions are available to deal with the wideband sensing problem. The first approach assumes that it is feasible to sample the desired spectrum by the Nyquist rate. In this case, some approaches assume that the problem can be converted into multiple narrowband detection problems. Others try to distinguish between the occupied segments and the vacant ones by just identifying edge detection. The common challenge in these approaches is the high computational complexity attached to the required ultra-high sampling rates [9].The second approach is based on the sub-Nyquist techniques. These approaches are used to reduce the long detectiontime and hardware cost resulted from the high sampling rate implementations [12].

In this section, we introduce the basic concepts for these approaches to performwide band sensing.

a) Nyquist based:

These methods acquire the wideband signalusing a standard ADC, and then they identify all spectral opportunities using digital signalprocessing techniques. In the following, we will address some of these techniques.

▪ *Multiband Joint Detection:*

In this approach, the main idea is to consider the detection of PU signals jointly across a bank of narrow bands instead of considering single narrow band at a time [27].

The wideband signal is sampled by a conventional ADC at a high sampling rate. The samples are then divided into segments, where the discrete Fourier transform is obtained for each segment individually by applying a Fast Fourier Transform (FFT) algorithm. The wideband spectrum from various segments is utilized to obtain an estimate for the power spectral density (PSD) which is then divided into a series of narrowband spectra. Spectral opportunities are detected using binary hypotheses tests for various narrow bands,as shown in Fig. 3a.Although, this technique is non-coherent, and it provides reasonable complexity, it suffers

from the practical issues such as power consumption, and feasibility of ultra-high sampling ADCs [27].

▪ *Wavelet-based Sensing:*

A wavelet-based spectrum sensingalgorithm is non-coherenttechnique, it was proposed in [28], [29]. In this algorithm, the power PSD of the wideband spectrum was modeled as a train of consecutive frequency sub-bands,as shown in Fig. 3b,within individually sub-band the PSD is flat but revealsirregularities and discontinuities on the transitions of two neighboring sub-bands. Unlike conventional Fourier transform, wavelet transform has been used as it provides information about exact location of frequency transition locations and spectral densities. Therefore, the wavelet transform is utilized to discover the singularities of the wideband PSD. Detection of the irregularities can be treated as edge detection problem. The identified spectrum bands have been classified as occupied or vacant depending on the PSD level of each channel[28].

▪ *Filter-bank Sensing:*

The other benefit of filter banks thatit can be used for multicarrier transmission in CR systems, and that is mean there is no computational cost for the spectrum sensing procedure. Itjustrequire to amount the signal power at the outputs of subcarrier channels at the receiver (i.e., demodulator) outputs [30].As shown in Fig. 3c,Filter banks are regularlyrealized based on low pass filtercalled prototype filter which is utilized to implement the zero band of the filter bank. Other bands are recognizedby modulation of the prototype filter [30]. This method is non-coherent technique with high performance, but it requires high computational complexity.

b) Sub-Nyquist based:

Interest in sub-Nyquist techniques is increasingdramatically in both academia and industry, due to the problems of high sampling rate or high implementation complexity in Nyquist approaches.The basic idea in Sub-Nyquist techniques is to acquire the wideband signals using sampling rates lower than the Nyquist rate and identifying spectral opportunities depending on these incomplete measurements. In this context, we can use the compressed sensing to estimated and recover the sensed spectrum based on the assumption that the spectrum is under-utilized. Therefore, the detection of sparse primary signals in wideband spectrum is facilitated by applying compressed sensing techniques with reasonable computational complexity. On the other hand, if the sparse signal spectrum can be reconstructed from the few measurements by introducing the proper sampling and reconstruction, then this procedure can be utilized to perform sub-Nyquist wideband sensing [12].

3) Comparison of non-coherent techniques

Non-coherent detection techniques do not need any information about the primary signal to detect the presence of PU, and they have the ability to sensevarious PU signals, but they cannot distinguish between different waveforms.
We categorize these techniques into two types: narrow band and wide band sensing.

The narrowband techniques make a single binary decision for the whole spectrum. While the wideband techniques recognizeddifferent spectral opportunities that lie within the wideband spectrum.

C. Comparison of Various Sensing Methods

In fact, differences between the above described spectrum sensing methods is appropriate, because each situation of the secondary user has its own properties and responds to different requirements. Differences between these methods in latency, complexity, and reliability give the designers an opportunity to make a decision that have to take into account the system requirements. For example, the fast and low complex energy detector is paid by its low performance in low SNR values. In addition, other methods provide high sensitivity performance that is paid by high complexity and long detection times. One method could be suitable for one scenario more than other; energy detector is considered as a good choice when no information about the primary signal is provided. However, if a prioriinformation such as the cyclo-stationary feature is known, the matched filter is more suitable.
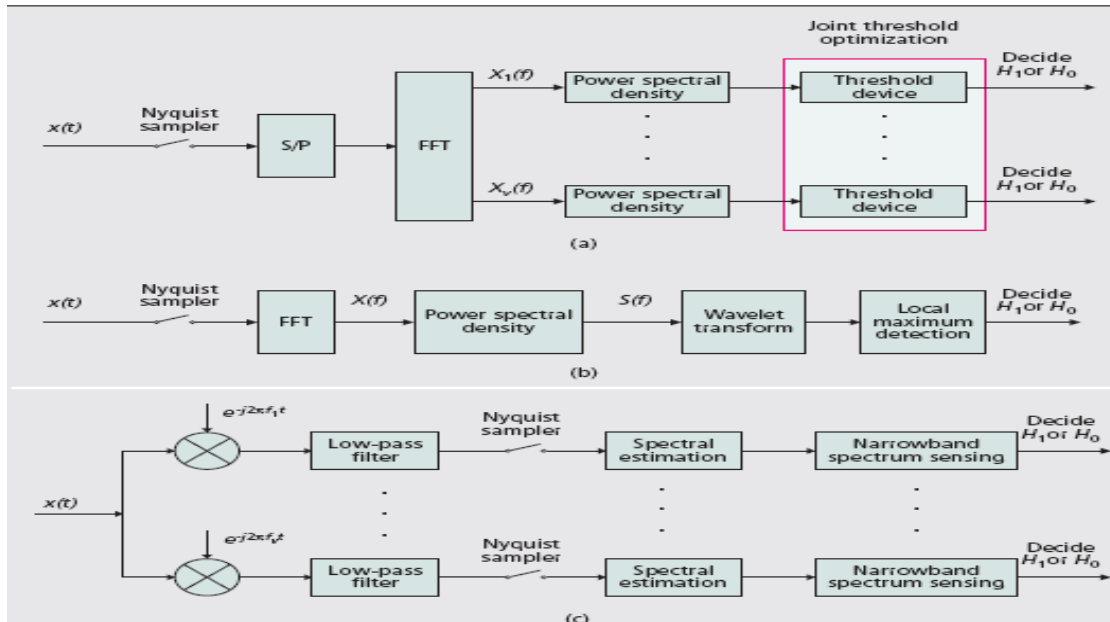

Fig. 3. Block diagrams for Nyquist wideband sensing algorithms: a) multiband joint detection; b) waveletdetection; c) filter-bank detection[9].

V. COOPERATIVE SPECTRUM SENSING

Cooperative spectrum sensing is defined in cognitive radio as the sharing of multiple nods (secondary users) their sensing information.Choosing cooperative sensing to replace single user spectrum sensing has many reasons. Energy constraints are the first limitation of single user spectrum sensing. In addition, the fading phenomena that might affect the secondary user and results in deteriorated SNR ratio and a miss detection situation, is probably not affecting another one. Another reason is the hidden problem that happens when the primary signal is not detected buy the secondary user and it is the neighborhood of the primary receiver, in this case, the spectrum use of the secondary user will definitely interfere the primary receiver [14]. Thus, an improvement of the sensitivity information between multiple secondary users could resolve the hidden problem and get over the fading situation of secondary user. Studies done by [31] present a great increase of probability of detection in fading channels.Challenges of cooperative sensing include developing efficient information sharing altgorithms and increased complexity [4]. It have toprovide a number of requirements such as:

▪ *Control channel:*

A control channel is required to communicate the different nodes in a cooperative spectrum sensing network. Obviously, this channel occupies a proportion of the system bandwidth. It cannot be considered as a waste of spectrum, because this channel is used in handshake operation, base station communication and of course sharing sensing information [1].

▪ *System synchronization:*

The synchronization between cooperative nodes in cognitive radio network is necessary.For a CR node, it is not beneficial to transmit while other node is sensing the spectrum. The sensing time has to be minimized without negatively affecting the sensing performance. Because accurate spectrum sensing has generally long sensing periods to see that a primary user is back, using adaptive time sensing is beneficial in terms of channel throughput maximization, while not forgetting the problem of cooperating nodes synchronization [1].

▪ *Geographical spread of cooperating nodes:*

It is necessary to have the best geographical spread of cooperating nodes to make the optimum sensing. In this

case, the effect of hidden problems and fading channel is minimized [1].

Cooperation can be implemented either internally, using the cognitive radios or externally using sensor network. There are three methods to make the sensing cooperation in a CR network: centralized, distributed, or external [1]. Next, we discuss these methods.

A. Centralized Sensing

The frequency band is determined by a central unit named fusion center (FC), then, the cooperative CR nodes are informed by the FC to make their local sensing, and report their sensing results back to the FC via the control channel.After the collection of all nodes sensing information's, the FC decides the presence or absence of PUs and diffuses back its decision [32].

B. Distributed Sensing

In this network, every CR node makes its own decisions about which part of the spectrum it can use while sharingthe sensing information. Distributed sensing is less cost than centralized networks because it has no infrastructure, and it is suitable for ad-hoc networks [33].

C. External Sensing

An external agent is used to perform spectrum sensing and to diffuse its report about the channel occupationto CR nodes. This sensing network type gets over some problems of the internal sensing such as spectrum efficiency because CRs do not have to spend time for sensing. In addition, the external sensors may be fixe and powered separately, thus conserving the CR power for communication only [4].

VI. INTERFERENCE BASED SPECTRUM SENSING

In this section, we introduce two approaches for interference based spectrum sensing.

A. Interference Temperature Management

There are two main interference sources in a typical radio. In the transmitter side of CR, the out band signals are radiated with the interested signal. These signals are viewed as interference at the receiver side of primary user. In addition, this interference is cumulative, means that multiple CR transmitters that use different radio channels might have out band signals that are collected at the same channel of PU thus increasing the noise floor and deteriorating the receiver sensitivity. The interference is measured by interference temperature model shown in Fig. 4, which represents the amount of cumulative out band signals that are produced by different transmitters and compare it to a threshold/limit that is defined by the receiver. The secondary users are permitted to use the spectrum if the temperature level is under this limit [1].

B. Primary Receiver Detection

The problem of hidden primary receiver is mentioned previously and is well known in CR. A way to get over it can be made when one of CR nodes is close to the primary user. In this case, the CR can detect the leakage signal of the local oscillator diffused by the primary user antenna and

inform the CR nodes. Another method that has lower cost is to mount a sensor close to the primary user to detect the LO leakage power.Then, the local sensor sends its report about the sensing information to the CR users to identify the spectrum occupancy [11].
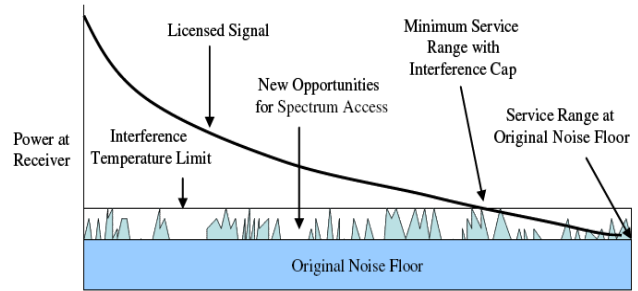

Fig. 4. Interference temperature model [1].

VII. STANDARDS OF COGNITIVE RADIO

We present in this section some information provided by some standards concerning requirements, rules, and guide lines, for the design of cognitive radio. The goalof the standards is to achieve the optimum design for a given situation and to provide starting points for research and development for further improvements.

- ECMA 392:

This is the first CR standard that describes the physical and medium access control layers in the TV band. It defines the rules that allow cognitive users to occupy frequency band. Dynamic channel occupancy is presented using sensing, geo-location, and database approaches. It is expected to implement many new applications with wide wireless coverage by ECMA 392[35].

- IEEE SCC41:

This standard ispresented by five working group. Each group works with a standard that describes specific topics for dynamic spectrum access. The IEEE 1900.1 standard describes the system functionality, spectrum management and dynamic spectrum access. IEEE 1900.2 standard presents the rules to analyze the coexistence and interference between radio systems [35].

- IEEE 802.11:

IEEE 802.11 standards are published between 2007 and 2010. It includes IEEE 802.11h, IEEE 802.11y, and IEEE 802.11af. IEEE 802.11h standard presents the dynamic selection of spectrum band and control band in the radar band. IEEE 802.11h is extended to IEEE 802.11y standard in order to include the frequency band of satellite communications. IEEE 802.11af standard is deals with the TV white spaces and it is interested by the increase of data rate and coverage range of the conventional Wi-Fi [36].

- IEEE 802.15:

It includes IEEE 802.15.4 and IEEE 802.15.2 which are published in 2003. IEEE 802.15.4 depicts the mechanisms of dynamic frequency selectionin the TV white spaces whereas the IEEE 802.15.2 presents the guidelines of this application [35].

Retrieval Number: D8811118419/2019©BEIESP
DOI:10.35940/ijrte.D8811.118419
Journal Website: www.ijrte.org

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

11593

▪ IEEE 802.16:

It includes IEEE 802.16.2, IEEE 802.16a, and IEEE 802.16h. IEEE 802.16.2 standard recommends practices to mitigate interference in fixed broadband wireless networks. The IEEE 802.16a standard describes the interface of the wireless medium access network in unlicensed frequency bands [35].

▪ IEEE 802.19:

It provides the metrics of the coexistence of all IEEE 802 systems; for example, the coexistence between IEEE 802.16h and IEEE 802.11y [35].

▪ IEEE 802.22:

It is the first international cognitive radio standard that specifies the wireless network operating in TV white spaces. It is called IEEE 802.22 Wireless Regional Area Network (WRAN) standard. IEEE 802.22 WRAN standard deals with wider frequency range than that of IEEE 802.11 standard [34]. In addition, its physical and medium access control layers are similar to the layers of IEEE 802.16. However, some reforms concerning the power levels are investigated in order toprevent the interference between adjacent bands and identify the primary users [35].

VIII. CONCLUSIONS

In this paper, we introduced a classification of the spectrum sensing techniques; we divided the single user sensing algorithms into coherent or non-coherent sensing. Each technique was described in details about basic principal, advantages and disadvantages. In addition, we compared between narrowband and wideband spectrum sensing procedures, and we counted the challenges involved in their implementation. Furthermore, we presented the basic concepts of the cooperative sensing, and the interference based sensing. Finally, the recent industrial effort in terms of standard specifications is addressed while presenting the recent cognitive radio standards.

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