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Advances on Spectrum Sensing for Cognitive Radio Networks: Theory and Applications

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***Abstract*—Due to the under-utilization problem of the allocated radio spectrum, Cognitive Radio (CR) communications have recently emerged as a reliable and effective solution. Among various network models, this survey paper focuses on the enabling techniques for interweave cognitive radio networks which have received great attention from standards perspective due to its reliability to achieve the required Quality-of-Service (QoS). Spectrum sensing provides the essential information to enable this interweave communications in which primary and secondary users are not allowed to access the medium concurrently. Several researchers have already considered various aspects to realize efficient techniques for spectrum sensing. In this direction, this survey paper provides a detailed review of the state-of-the-art related to the application of spectrum sensing in CR communications. Starting with the basic principles and the main features of interweave communications, the paper provides a classification of the main approaches based on the radio parameters. Subsequently, we review the existing spectrum sensing works applied to different categories such as narrowband sensing, narrowband spectrum monitoring, wideband sensing, cooperative sensing, practical implementation considerations for various techniques, and the recent standards that rely on the interweave network model. Furthermore, we present the latest advances related to the implementation of the legacy spectrum sensing approaches. Finally, we conclude this survey paper with some suggested open research challenges and future directions for the cognitive radio networks in next generation Internet-of-Things (IoT) applications.**

***Index Terms*—Cognitive radio, compressive sensing, narrowband sensing, spectrum sensing, spectrum monitoring, wideband sensing.**

I. Introduction

The electromagnetic radio frequency (RF) spectrum is a scarce natural resource, the use of which by transmitters and receivers is typically licensed by governments. Static spectrum access is the main policy for the current wireless communication technologies. Under this policy, fixed channels are assigned to licensed users or primary users (PUs) for exclusive use while unlicensed users or secondary users (SUs) are prohibited from accessing those channels even when they are unoccupied. Nowadays, it becomes obvious that this frequency allocation scheme cannot accommodate the constantly increasing demands of higher data rates. On the contrary, it has been reported that localized temporal and geographic spectrum utilization is extremely low [1]. Cognitive radio (CR) has emerged as an innovative technology to solve this spectrum under-utilization problem in the next generation networks [2]-[3]. Following its introduction, a great deal of effort has been expended to improve the efficiency of cognitive radio networks. These works have been dedicated to develop technologies that either exploit opportunities in time, frequency, and space domains or allow SUs to coexist with PUs in the same spectrum bands with minimal interference.

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Generally, there are three different models for the cognitive radio networks (CRN): the interweave, the underlay, and the overlay models. First, in the interweave network model, unlicensed or secondary users are not allowed to access an occupied band by the licensed or primary user. In fact, the Federal Communications Commission (FCC) is currently developing new spectrum policies that will allow SUs to opportunistically access a licensed band when the PU is absent [4]. In these networks, the CR has to identify the available sub-bands of the radio spectrum, or equivalently the spectrum holes, that are under-utilized (in part or in full) at a particular instant of time and specific geographic location. Therefore, the fundamental task for CR is to sense the spectrum in order to detect whether the PU is present or not. In other words, spectrum sensing is the main enabling feature for the interweave model. In that, spectrum sensing [5] is the process that is responsible for detecting the spectrum holes. Also, it is required for the SU to quickly vacate the channel once the PU reappears such that the harmful interference effect on the licensed users is reduced. In literature, spectrum sensing techniques can be classified based on the size of the band of interest. The problem of wideband (WB) spectrum sensing [6] consists of observing a wideband and identifying the portions of such band which are occupied by a signal and those which are free. On the other hand, narrowband (NB) sensing considers a single slice of the band to be either sensed or monitored [7].

Second, in the underlay network model, the coexistence of primary and secondary users is allowed and hence the network is also termed as a spectrum sharing network [8],[9],[10]. However, PUs are always allocated a higher priority to use the spectrum than SUs. Furthermore, the sharing must be maintained under the PU's predefined interference constraint (i.e., a predefined interference threshold which is also termed interference temperature). Usually, the SU spreads its signal over a bandwidth large enough to guarantee that the amount of interference caused to the PU is within the predefined limits. Due to this constraint, the underlay technique is mainly useful for short range communications. Third, in overlay cognitive networks, SUs and PUs are allowed to transmit concurrently. The defining assumption made in the current overlay models is that the primary message is known to the secondary transmitter in prior [9]. There are two main approaches to realize this model: (1) with the help of advanced coding techniques [11] such as dirty paper coding (a technique which completely mitigates a priori known interference over an input power

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constrained additive white Gaussian noise (AWGN) channel), where the secondary user can precode the transmitted stream in order to effectively null the interference at the secondary receiver. While this approach violates the cognitive radio principle of protecting the primary users, it provides a theoretical upper bound on the maximum throughput achievable by the secondary users. (2) The secondary user splits its own power into two parts, one used to raise the primary user power in order to mitigate the interference effect caused by the secondary user data and the other part is utilized to carry the secondary user data [12].

It is worth to mention that the FCC revealed that the radio spectrum utilization in the band below 3 GHz varies vastly where occupancy is found to be around 15%-85% [1]. Motivated by this practical percentage, industrial standardization bodies have preferred the interweave cognitive radio model not only due to its applicability for these low under-utilization usage of the radio spectrum, but also due to the fact that the interweave model can provide sufficient reliability and reasonable guaranteed QoS. As a consequence, standards such as IEEE 802.22, IEEE 802.11af, and Ecma-392 have been built to utilize the interweave network model. Due to the radical increase in applying interweave cognitive radio model, this paper is focused on one of the enabling techniques of this model. There are essential components to realize this model including spectrum sensing, spectrum analysis, and spectrum decision. However, in this paper, we are mainly interested in the most important feature of the interweave model which is spectrum sensing. The motivation and the contribution of this work are presented in sections I-A and I-B while the paper organization is considered in the following section.

A. Motivation

Since their introduction, researchers invested their effort in modelling cognitive radio networks, addressing various challenges to realize the main concepts of these models, and studying the issues that may appear from implementation perspectives. In fact, a countable number of survey papers exist in the literature in the context of cognitive radio communications covering a wide range of areas such as spectrum occupancy measurement [13], spectrum sensing [6][7][14][15], cognitive radio under practical imperfections [16], spectrum management [17], emerging applications for cognitive radios [18], spectrum decision [19], spectrum access strategies [20], and CR networks [21]. Due to the significant volume of available literature, it is likely to revise the presented problems and solutions every period of time. Investigation of realistic solutions towards combating various practical system implementations has become critical towards the actual system deployment.

Spectrum sensing is one of the topics that had many challenges to address and the research direction went from one phase to another during the past four to five years. As far as recent surveys are concerned, in [16], the authors provided a comprehensive review of the existing CR approaches considering practical imperfections including noise uncertainty, channel/interference uncertainty, CR transceiver imperfections, noise/channel correlation, signal uncertainty, ... etc. Despite the availability of many research efforts under ideal conditions, the work presents couple of solutions towards combating various practical imperfections. However, this work has a general scope to address imperfections for all CR models. For this reason and to maintain a balanced document, a thin contribution is provided towards the recent advances for spectrum sensing as an enabling technology for the interweave model. Indeed, only classical narrowband sensing approaches are highlighted without the introduction of the wideband sensing. On the other hand, an overview for the wideband sensing approaches and challenges have been presented in [6]. In this work, the state of the art for wideband sensing is introduced. However, practical implementation challenges were not the main focus and hence recent advances towards this front have not been covered. In all cases, neither standardization efforts nor recent advances for practical implementations have been considered.

Nowadays, we are mainly at the stage of investigating the practical implementation aspects of the conventional spectrum sensing approaches. Solutions have considered updating the existing techniques and/or providing new techniques. For example, some conventional sensing approaches provide high accuracy on the account of the complexity and sensing times such as a simple spectrum scanning. Others can efficiently utilize the time and resources but provide less accuracy such as the under sampling approaches with relatively low sampling frequency compared to the Nyquist rate. Enhancing the current algorithms to obtain near-optimum accuracy and reasonable complexity and sensing time is everyday tackled by research groups [22]. On the other hand, spectrum monitoring during reception is an issue that has been developed recently to optimize the secondary network throughput. Furthermore, from the industrial point of view, there are a couple of new standards such as IEEE 802.11af and IEEE 802.15.4m introduced for discussion. These standards rely on the interweave network model and they require not only the introduction of the basic concepts but also the challenges associated with the new specifications from implementation perspective. To the best of our knowledge, there has been no contributions reported in the direction of providing a comprehensive review of the advances of the spectrum sensing approaches and their applications in practical system implementation. Indeed, there are many recent solutions to the spectrum sensing problems in interweave network model that has changed the conventional classification of the solutions.

B. Key Contributions of the paper

In this paper, we provide a comprehensive, up-to-date survey of the advances provided to the key research works on spectrum sensing in interweave cognitive radio networks. We also identify and discuss some of the key open research challenges related to each aspect of the spectrum sensing framework. Our main contributions can be summarized as follow:

- A classification for spectrum sensing techniques based on the recent emerged approaches is presented. Since there are new solutions to the conventional problems in spectrum sensing, the emerged approaches have been

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Table I
DEFINITIONS OF ACRONYMS AND NOTATIONS

Acronym/Notation	Definition	Acronym/Notation	Definition
ADC	Analogue to Digital Converter	RSSI	Received Signal Strength Indicator
AGC	Automatic-Gain-Control	SFBC	Space-Frequency Block Code
AWGN	Additive White Gaussian Noise	SFO	Sampling Frequency Offset
BPF	Band-Pass Filter	SNR	Signal to Noise Ratio
CAF	Cyclic Autocorrelation Function	SPR	Secondary-to-Primary power Ratio
CFO	Carrier Frequency Offset	STBC	Space-Time Block Code
CP	Cyclic Prefix	SU	Secondary User
CR	Cognitive Radio	UHF	Ultra-High Frequency
CRN	Cognitive Radio Network	UWB	Ultra-Wideband
DFH	Dynamic Frequency Hopping	WB	Wide band
DSMF	Dynamic Spectrum Management Framework	$\mathcal{H}_0$	Null Hypothesis
ED	Energy Detector	$\mathcal{H}_1$	Alternative hypothesis
FC	Fusion Center	$\|\mathbf{x}\|_p$	p norm for vector $\mathbf{x}$, also called ℓ_p norm
FFT	Fast Fourier Transform	$\chi^2_N(\,)$	Chi-squared distribution of degree N
LDPC	Low Density Parity Check	$\mathcal{CN}$	Complex Symmetric Gaussian Distribution
LNA	Low Noise Amplifier	$*$	Conjugate operation
LO	Local Oscillator	$(\mathbf{x})^H$	Conjugate Transpose of vector $\mathbf{x}$
LS	Least Squares	$F(x)$	Cumulative distribution function
MF	Matched Filter	Λ	Decision statistic
MOF	Method Of Frames	$\delta(x)$	Delta function
NB	Narrow band	$\mathbb{E}$	Expectation operator
NBI	Narrow Band Interference	P_{FA}	False Alarm Probability
NLOS	Non-Line Of Sight	$(\mathbf{A})^{-1}$	Matrix inverse of matrix $\mathbf{A}$
OFDM	Orthogonal Frequency Division Multiplexing	min	Minimization
PLL	Phase-Locked-Loop	P_{MD}	Miss-detection Probability
PN	Phase Noise	$f(x)$	Probability density function
PSD	Power Spectral Density	Pr(a)	Probability of event a
PU	Primary User	$\mathbb{C}$	Set of complex numbers
QoS	Quality of Service	$\mathbb{R}$	Set of real numbers
QP	Quiet Period	$\sum$	Summation operation
RF	Radio Frequency	γ	Threshold
RIC	Restricted Isometry Constant	$(\mathbf{x})^T$	Transpose of vector $\mathbf{x}$
RIP	Restricted Isometry Property	σ^2_X	Variance of Gaussian distributed random variable X
ROC	Receiver Operating Characteristics	$\mathbf{x}$	Vector $\mathbf{x}$

classified based on the conventional bandwidth classification that divides the spectrum sensing techniques to narrowband sensing and wideband sensing.

- Due to the several challenges associated with traditional spectrum sensing techniques, many research papers have been presented during the past five years to provide sufficient solutions to these challenges. Therefore, similar to [16], the conventional approaches are briefly reviewed in this survey in order to prepare for introducing the recent research to tackle the original issues. In this front, various techniques from narrowband and wideband sensing are considered as well as the cooperative sensing.
- We present the advances on the practical system implementation side of the spectrum sensing framework. In this direction, complexity, power consumption, sensing interval, and system performance are considered as the potential aspects that affect practical system implementation. In all cases, there will be proposal to update the conventional techniques so that the parameter of interest is enhanced. On the other hand, novel approaches have been presented to tackle the practical implementation issues while preserving almost the same performance as conventional approaches. For each of the mentioned aspects, we introduce the most recent approaches in both directions.
- From the industrial perspective, there are a couple of innovative standards that employ interweave cognitive radio over the TV white space. In addition to the first cognitive standard, namely IEEE 802.22, recent standards such as IEEE 802.11af, IEEE 802.15.4m, and Ecma-392 have emerged to utilize the interweave cognition over TV white space. To address the associated challenges such as regulating the coexistence of these technologies, a review to the basic concepts of such standards is considered along with the efforts in the direction of addressing the challenges.
- In fact, CRNs not only solve the under-utilization problem in the current spectrum policies, but it can also be

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the solution for some other scenarios where the devices need to be smart enough to communicate. For example, we present the collaboration between cognitive radio networks and the next generation IoT network. Also, we address the advances in the direction of cognitive radio networks in general.

C. Paper Organization

The paper is organized as follows. Section II introduces the fundamental concepts of the interweave network model and the corresponding dynamic spectrum management framework. The main objective of this section is to provide the essential background and the significant importance of the spectrum sensing which is the topic of interest. Based on the presented spectrum sensing classification, the narrowband spectrum sensing and monitoring are presented in Section III, where the recent approaches to tackle narrowband sensing and monitoring are considered in Sections III-A and III-B, respectively. The second item in this classification is the wideband sensing which is discussed in Section IV. The most important advances for the basic wideband sensing techniques are presented in Sections IV-A and IV-B. The impact of a single CR sensing is demonstrated in Section V, where the alternative approach of employing cooperative sensing is introduced. Recent advances in the direction of the cooperative sensing communication are presented in the same section. The up-to-date standards including IEEE 802.11af, IEEE 802.15.4m, IEEE 802.22, and Ecma-392 are considered in Section VII. The definitions of these standards are not only presented but the main differences among various standards are assumed as well in the scope of spectrum sensing. It is of great interest that cognitive radio networks could be a potential solution for the massive increase of devices in cellular based Internet-of-Things (IoT) network. Similar advances to cognitive radio networks and their applications in general are provided in Section VIII. Finally, conclusions are drawn in Section IX. In order to improve the flow of this paper, we provide the definitions of acronyms/notations in Table I.

II. Spectrum Sensing in Interweave Network Model

In this section, we present the fundamental concepts for the interweave cognitive radio model. Further, the enabling technology, namely spectrum sensing, for this model is defined, where its significant importance is discussed as an essential and most emerging part of the interweave system. The basic concept behind interweave cognitive radio is to exploit the available under-utilized spectral resources by reusing unused spectrum in an opportunistic manner [2][23][24]. Therefore, the process of realizing efficient spectrum utilization using the interweave cognitive radio technology requires a dynamic spectrum management framework (DSMF) which provides a complete architecture for the model with detailed functionalities. The DSMF proposed in [19] is adopted due to its clear functionality, well-defined interfaces among various blocks, and relevance to our discussion. This DSMF consists of four main blocks: spectrum sensing and monitoring, spectrum analysis, spectrum decision and spectrum mobility, as shown in Fig. 1. The tasks required for adaptive operation in one cognitive cycle can be briefly discussed as follows [2]:

- *Spectrum sensing and monitoring:* A cognitive radio senses the available spectrum, captures their information, and then detects the spectrum holes. Spectrum sensing is also able to capture the proper observations about the spectrum holes in order to assist the analysis stage for the spectrum characterization. If the CR is already camping on a spectrum slice for communication, then the occupied narrowband is monitored to determine whether the original licensed user reappears or not.
- *Spectrum analysis:* The characteristics of the spectrum holes that are detected through spectrum sensing are estimated. The primary user activity and the spectrum band information such as operating frequency and bandwidth have to be considered for individual holes. In fact, it is essential to define parameters such as interference level, channel error rate, path-loss, link layer delay, and holding time that can represent the quality of a particular spectrum band.
- *Spectrum decision:* A cognitive radio determines the data rate, the transmission mode, and the bandwidth of the transmission. Then, the appropriate spectrum band is chosen according to the spectrum characteristics and user requirements. Once spectrum holes are characterized, the next major step is to select the best available spectrum suitable for the user's specific QoS requirements. Due to dynamically changing topologies and varying propagation characteristics, spectrum selection techniques[19] can be closely coupled with routing protocols. In this front, spectrum prediction based on learning [25], game theory selection [26], and Graph theory [27] can provide enough details for the spectrum selection challenges. Since this topic is quite interesting while being out of the scope of this survey, the authors encourages the reader, if interested, to review the most recent comprehensive survey about spectrum selection in CRN found in [28].
- *Spectrum mobility:* is the ability of a CR to vacate the channel when a licensed user is detected. In other words, when a PU reclaims a licensed channel temporarily occupied by a SU, spectrum mobility suspends the transmission, vacates the channel, and resumes ongoing communication using another vacant channel. The hand-off strategies are the key element in this process, where reactive [29] and proactive [30] approaches are two main contributions in this direction. The first assumes that SU applies reactive spectrum sensing to find target backup channel, while the later considers a sufficient knowledge of PU traffic model so that SU is able to predict PU arrival and then SU evacuates the channel beforehand.

Spectrum sensing is the most important component for the establishment of interweave cognitive radio network. It is of significant importance as it detects the state of channel occupancy for opportunistic re-utilization. In other words, spectrum sensing is the task of obtaining awareness about the spectrum usage [6][14]. It provides the knowledge of the existence of

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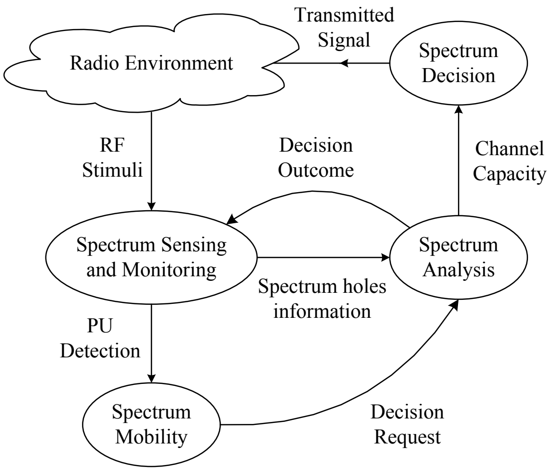

Fig. 1. Dynamic Spectrum Management Framework for interweave network model [23][19]

PUs temporally and geographically. Thus, having the spectrum characteristics at the CRs enables broader application areas and lower infrastructure requirement. The spectrum occupancy is commonly obtained by local spectrum sensing at the cognitive radios [5][14]. 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. With this concept in mind, one can clearly consider spectrum sensing as an enabling technology for interweave cognitive radios. In fact, there have been extensive research activities on spectrum sensing in CR networks due to its importance. However, the activities in this direction never stopped as more challenges and practical issues are introduced as long as implementation is concerned. For these reasons, we have selected the spectrum sensing to be the main focus of this paper whenever we consider the interweave network model.

It is worth to mention that geographical database is an alternative spectrum awareness approach to obtain the knowledge of the radio environment. In this scheme, spectrum usage parameters of the primary system such as the place, time, frequency, etc. are stored in a centralized database [31]. SUs can reuse the PU spectrum after requesting a channel from database system. Based on the availability of the unoccupied channels, the system can grant access to one of the channels. A CR can also use the database approach including history information and prediction methods to make the operation more efficient. This approach is based on maintaining a frequently updated and centrally located database with information about the regional spectrum usage [32]. It is a quite static method and the dynamics of this scheme depends on how fast the primary spectrum usage information is updated in the database. Several contributions in the literature have exploited this approach using the concept of a radio environment map [33][34]. In this paper, we focus more on the complete dynamic spectrum sensing approaches rather than the static database ones.

As stated before, spectrum sensing techniques can be classified based on the size of the band of interest. Narrowband sensing/monitoring [24][14] tackles the problem of deciding whether a particular slice of the spectrum is a hole or not. On the contrary, wideband spectrum sensing [6][35] is based on classifying individual slices of a wideband to be either occupied or vacant. As a matter of fact, both sensing procedures are required during the cognitive cycle. We have to emphasize that there are usually two distinct phases for the PU detection in interweave networks [36]. 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. Based on this classification, many spectrum sensing techniques are presented in literature. Fig. 2 shows the most important approaches followed by researches to tackle various challenges for spectrum sensing. In this paper, these methods are addressed from a practical implementation perspective in the scope of recent research.

III. Narrowband Sensing and Monitoring

In interweave networks, prior to communication, secondary user must sense the spectrum to detect whether it is available or not. To realize this functionality, two different architectures have been proposed as initial solutions to perform narrowband sensing: single-radio and dual-radio [37]. In the single-radio architecture, a single RF chain is utilized to process both CR features and data transmission. In that sense, only a specific time slot is allocated for spectrum sensing. Since the CR users do not access the spectrum during the sensing period, this period is called the quiet period (QP) [38]. As a result of this limited sensing duration, only a certain accuracy can be guaranteed for spectrum sensing results. Moreover, the spectrum efficiency is decreased as some portion of the available time slot is used for sensing instead of data transmission [39]. The obvious advantage of the single-radio architecture is its simplicity, low cost, and low power consumption. In the dual-radio sensing architecture, one radio chain is dedicated for data transmission and reception while the other chain is dedicated to spectrum monitoring [40]. The drawback of such an approach is the increased power consumption and hardware cost. Since the cognitive radio concept is currently in an advanced stage in which implementation issues are significantly considered, recent approaches attempt to optimize the single-radio architecture.

During communication, SU must be able to detect very weak signals generated by the primary user in order to quickly

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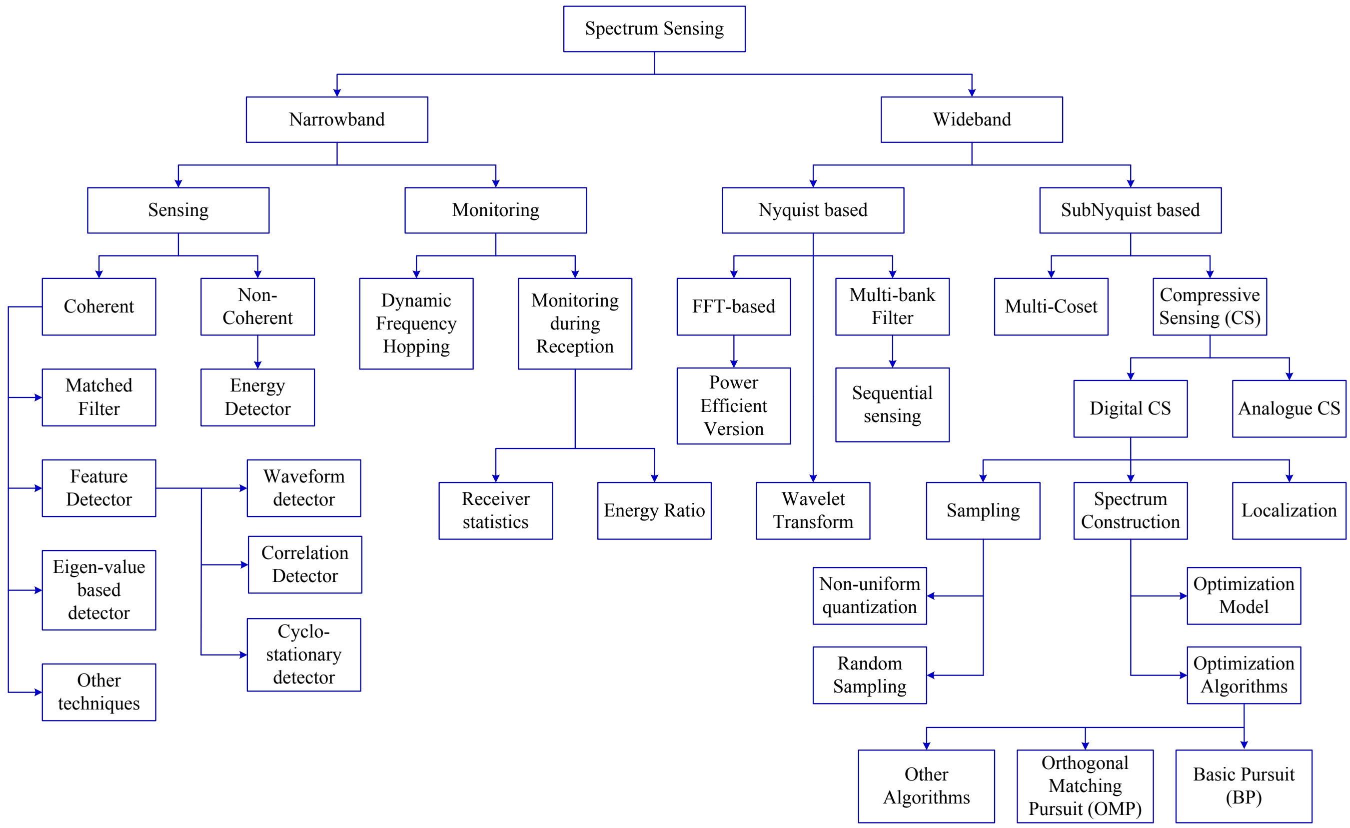

Fig. 2. Classification for the spectrum sensing approaches based on the bandwidth size.

vacate the occupied spectrum. Thus, primary user detection is essential by continuously monitoring the utilized spectrum to release the spectrum. Traditionally, spectrum monitoring techniques rely on the periodic spectrum sensing during quiet periods [41]. The processing is usually applied over the received signal at the SU to explore a specific feature to the primary user. This mechanism is repeated periodically to monitor the spectrum so that the SU can quickly abandon the spectrum for a finite period if the PU is detected. Then, SU chooses another valid spectrum band in the spectrum pool for communication. In reality, this monitoring procedure best suites the single-radio architecture since it employs QPs to re-sense the utilized band. However, we should emphasize that there is no distinction from the execution perspective between the initial sensing, that occurs in the first place to guarantee that this slice of the spectrum is available, and the monitoring procedure, which just confirms that the band is available and SU is still allowed to continue the communication.

Recent research efforts discriminate between the sensing and monitoring procedures so that monitoring is applied during reception without requiring any scheduling for QPs [42][43]. Another approach to reduce the wasted time in QPs and to realize higher throughput for the cognitive network is to employ Dynamic Frequency Hopping (DFH) which assumes that the SU is scheduled to switch from one band to another based on a prior knowledge of the hopping pattern [44][45]. There are other existing approaches that enable concurrent transmission and sensing by adding more resources to the system such as employing multiple receive paths, restructuring the frame format, relying on cooperation where inactive SUs perform sensing while the active SUs are transmitting [46][47].

Aside from DFH and in principle, narrowband spectrum sensing is applied once before the SU communication and is not be repeated again unless the monitoring algorithm indicates that a primary signal may be present in the band. If monitoring determines correctly that there is no primary signal in the band, then the time that would have been spent performing spectrum sensing is used to deliver packets in the secondary network. Therefore the spectrum efficiency of the secondary network is improved. If spectrum monitoring detects a primary signal in the band during a time period in which spectrum sensing would not have been scheduled, then the disruption to the primary user can be terminated more rapidly and hence the impact of secondary communications on the primary user is reduced. Based on this description, the SU receiver should follow two consecutive phases, namely sensing phase and monitoring phase, where the former is applied once for a predefined period. The approaches presented in this section are summarized by Table II which lists the algorithm, its classification, its limitation, and the relevant recent references. The comparative analysis are based on the classification presented in [48], where the exact expressions for the complexity, for example, are found. The reader is encourages to review also [49] for more details about the comparative study of classical narrowband sensing approaches.

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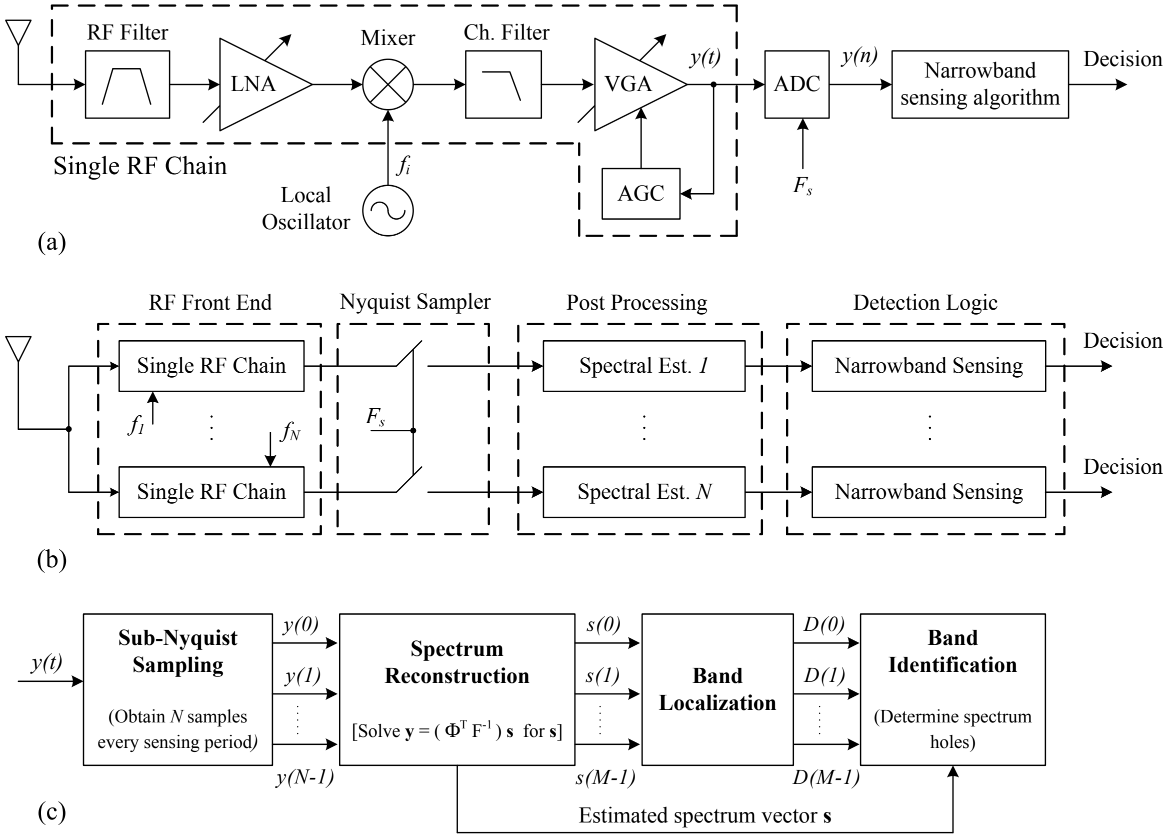

Fig. 3. Basic block diagrams for various spectrum sensing techniques: (a) Block diagram for the narrowband sensing architecture at the SU receiver. (b) General block diagram for the Nyquist-based wideband sensing techniques. (c) Block diagram for the digital logic of the wideband compressive sensing approach.

A. Advances on Narrowband Sensing Approaches

In general, the problem of narrowband spectrum sensing is to decide whether a particular slice of the spectrum is "available" or not. That is, in its simplest form, it is required to discriminate between the two hypotheses defined by (1), where $x(n)$ represents a primary user's signal observed at the SU receiver, $w(n)$ is a complex symmetric Additive White Gaussian Noise (AWGN) with zero-mean and variance σ_w^2 such that $w(n) \sim \mathcal{CN}(0, \sigma_w^2)$, and n represents time. The received signal $y(n)$ can be vectorized to probably represent the received signal at different antenna ports in case of multi-receive antenna systems.

$$\begin{cases} \mathcal{H}_0 : \; y(n) \; = \; w(n) \\ \mathcal{H}_1 : \; y(n) \; = \; x(n) + w(n) \end{cases} \tag{1}$$

The performance of the detection algorithm can be summarized with two probabilities: the probability of miss-detection P_{MD} and the probability of false alarm P_{FA} [5][7]. P_{MD} is the probability of miss-detecting a primary signal when it is truly present. For a given decision statistic Λ, the miss-detection probability can be defined by $P_{MD} = \Pr\left[\Lambda < \gamma \,|\, \mathcal{H}_1\right]$ where γ is a threshold that should be determined. On the other hand, P_{FA} is the probability that the test incorrectly decides that the primary user is present when it is actually not. The false alarm probability can be defined by $P_{FA} = \Pr\left[\Lambda > \gamma \,|\, \mathcal{H}_0\right]$. Generally, P_{FA} should be kept as small as possible in order to prevent under-utilization of transmission opportunities while P_{MD} needs to be minimized.

Clearly, the fundamental problem of detector design is to choose detection criteria, and to set the decision threshold γ to achieve good detection performance. These matters are treated in detail in the literature of detection theory. Detection algorithms are either designed in the framework of classical statistics, or in the framework of Bayesian statistics [80]. In the classical approach, either $\mathcal{H}_0$ or $\mathcal{H}_1$ is deterministically true, and the objective is to minimize P_{MD} subject to a constraint on P_{FA}; this is known as the Neyman-Pearson (NP) criterion. In the Bayesian framework, by contrast, it is assumed that the source selects the true hypothesis at random, according to some priori probabilities. The objective is to minimize the so-called Bayesian cost. In this section, we will be focusing on the most popular narrowband sensing techniques to which most of the recent research activities have been directed. Thus, matched filter detection, energy detection, and cyclostationary feature detection will be considered. A general block diagram for these approached is shown in Fig. 3-(a).

1) Energy Detector: Energy detection (ED) algorithm is a popular non-coherent detection method that is widely employed in the literature. ED does not require prior information about PU signals and it provides relatively low computational complexity [7][14]. In reality, when sensing is addressed, ED will be the first approach to come to mind since sensing is significantly related to PU signal power detection. Actually,

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Table II
SUMMARY FOR VARIOUS NARROWBAND SENSING AND MONITORING TECHNIQUES IN INTERWEAVE COGNITIVE RADIO NETWORK

Sensing/Monitoring Technique	Class	Advantages	Limitations	Relevant recent references
Energy Detector	Sensing	• Non-coherent and does not require prior knowledge about the primary network. • Simple to design and implement, less complexity.	• Can't discriminate between primary signal and noise • can't perform well for low SNR • vulnerable to noise uncertainty	[50][51][52][53][54] [55][56][57][58] [59][60][61][62][63]
Matched Filter	Sensing	• Optimal sensing performance, maximizes the received SNR. • less time needed to achieve high processing gain	• Prior knowledge of the primary network. • Computational complexity depends on the primary network. • dedicated sensing receiver required for synchronization at each SU.	[64][65][62]
Feature Detection	Sensing	• Fast sensing as compared to energy detection • Sensing performance is highly reliable, can detect signals with low SNR. • Robust to noise uncertainty	• Require prior knowledge to the primary network • Higher accuracy requires a longer length of known sequences that results in lower efficiency of the spectrum. • Slower sensing compared to energy detection.	[66][67][68][69][70] [71][72][73]
Eigenvalue-based Detector	Sensing	• Non-coherent • Sensing performance is highly reliable, can detect signals with low SNR. • Robust to noise uncertainty	• High Computational complexity.	[74][75][76]
Receiver Statistics	Monitoring	• Monitoring during reception • Reliable for flat fading	• Sensitive to receiver impairments. • Computational complexity.	[42][77][78]
Energy Ratio	Monitoring	• Insensitive to receiver impalements • Reliable for flat and selective fading	• Only for OFDM • May require long monitoring cycle.	[43][79]

the availability of ED enables many sensing approaches to operate in various environments and implementation conditions [50][51][52][53][54]. Due to these promising advantages, research offers extensive activities to significantly study ED in various channel conditions [55][56][57]. Practical implementation perspectives have been the focus of recent research efforts [58][59][60]. Real measurements are considered to evaluate the ED and to investigate the validity of the underlying assumptions [61][62]. Therefore, the assumptions beyond applying ED have been listed and carefully investigated [63]. It has been shown that a major drawback for ED is that it has poor detection performance under low SNR scenarios, and cannot differentiate between the signals from PUs and the interference from other cognitive radios. In this section, we will focus on a brief background of the ED but we will elaborate more on those recent research activities and their associated problems and solutions.

In energy detection based sensing, the absolute square of the received signal $y(n)$ is computed and averaged over a period of time, say N samples, in order to obtain more reliable decision statistic. Following the classical detection theory, the energy detector is studied and analysed [14]. The analysis assumes that the channel is assumed to be the typical AWGN channel with a known noise power. Also, the SU receiver is a perfect one, where no distortion is introduced due to any non-linear frequency mixing, amplification, and IQ imbalance. These assumptions are carefully studied and compared to the practical scenarios in [63], where noise uncertainty, receiver non-linearities, and practical fading channels show the most degradation factors for energy detectors. Therefore, researchers have been encouraged to investigate those issues.

Multipath fading and shadowing phenomena result in power fluctuations of received PU signals and the need to operate under very low PU SNR is unavoidable. To achieve sustainable performance in these scenarios, the noise uncertainty and the channel effect have to be carefully studied. In fact, noise uncertainty has been extensively explored and studied [7][81]. The main issue is that ED performance relies on a well-known noise power and signal-to-noise ratio. However, it is always assumed that no noise estimation or SNR estimation are applied at the SU receiver before utilizing the detection mechanism. It has been shown that noise uncertainty will result in the SNR-wall problem [81] in which an infinite number of samples is not enough to guarantee the required false alarm and detection rates when there is uncertainty about the noise level. Analytical results for the SNR-wall problem is provided by [82]. In fact, many recent approaches are presented to overcome the noise uncertainty problem such as [83] which cooperatively estimates the noise level to reduce the uncertainty to its minimal level.

Similar to the noise uncertainty issue, various research activities have investigated the ED performance under different

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fading conditions [84] to study the limits of the detector with respect to different fading environments. However, more sophisticated channel models such as the cascaded Rayleigh fading [56], Hyper-Rayleigh fading [57], and $\kappa - \mu$ extreme fading [85] have been recently analyzed for the ED approach. In [58][59], the effect of the IQ imbalance has been analyzed and the impact of the introduced image signal due to IQ imbalance is quantified. Further, the solutions to this problem consider either employing multi-threshold detector [58] or utilizing an interference cancellation approach with an optimized cancellation coefficient [59]. The non-linear behaviour of the receiver is considered by [60], where the intermodulation of the Low Noise Amplifier (LNA) at the RF front-end is analyzed and its performance reduction effect is clearly shown. Estimation and compensation techniques are presented on the signal processing level to mitigate the amplifier non-linearities.

2) Matched Filter Detector: In communication theory, a matched filter (MF) aims at maximizing the received signal-to-noise ratio for AWGN channels. Therefore, it is known to be an optimal coherent detector in nature [86]. Being coherent, this technique can be used only when the SU has prior information not only about the various parameters of the physical implementation of the primary user, but also the physical structure of the primary signal. In this case, MF can be implemented by employing cross-correlation between the known sequence and the received signal. Whenever a true correlation peak appears, the detector assumes that a primary signal is present. Otherwise, a vacant band is claimed [87]. In fact, most wireless network systems have pilots, preambles, synchronization signals, or certain spreading codes which enable coherent detection.

Due to its robust performance in low SNR regime, MF detection has been selected to assist the basic energy detector for observing very weak signals [64] where the performance of the later is significantly degraded. Aside from the high computational complexity of this approach, the matched filter has been applied at SU receiver to identify the mistaken transmissions during a silent period. In [65], MF detector is not only used to detect the presence of the PU, but it also recognizes the power level of such a PU. The issue is that practical systems provide flexibility to PU to change its transmit power level based on the situation of the environment. If the SU can really measure the power level of the PU, SU will be able to adjust its transmit power to meet the interference requirement for different PU power levels. Recently, as a step towards practical system implementation, the MF detector performance has been simulated and experimentally evaluated in comparison to the energy detector [62]. As expected, the experimental results show that MF has a lower SNR tolerance by about 7dBs when compared to the energy detector. However, it has been noticed that the efficiency and sensitivity for MF detector rapidly decrease with rising in average fluctuation of noise power and become even worst in low SNR. This happens only for a fixed threshold but the performance can be improved by adjusting the threshold factor.

Although MF detector seems to provide the superior performance, this requires the SU to be fully aware of the primary network. In some scenarios such as the spectrum trading in which the secondary network is in full coordination with the primary network since the former rents the spectrum while it is not in use [88], this is possible but indeed it is not the main principle of being cognitive radios. Furthermore, it is not always easy to obtain this good performance by employing the matched filter detector due to the practical implementation issues which degrade its performance. For instance, without any knowledge about a possible frequency offset, fading channel, or proper timing, the correlation becomes poor and the detection accuracy is degraded.

3) Feature Detection: Feature detection captures a specific signature of the PU signal. In general, practical communication systems include distinctive features by definition, where some features are added for synchronization or signalling purposes such as preambles, pilots, beacon frames, cyclic prefix (CP), hopping sequence, etc. Other features are originated by having a modulated digital PU signal. That is the second-order statistics, or even a general cyclostationarity of the modulated PU signal exhibit an observable grade of periodicity [7] that can be explored for sensing purposes. In fact, feature detection includes a wide class of spectrum sensing algorithms. These techniques share the concept that knowing partial or full information about the PU signal features enables the construction of detectors that exploit this characteristic. Here, we will present the most common examples for feature detection that dominate in the recent research topics about narrowband sensing.

First, a subclass of feature detectors, known as waveform detector, relies on a prior knowledge of the PU signal construction. Usually, preambles, mid-ambles, pilot carrier, and/or spreading sequences are intentionally added to the PU signal to help synchronization process [14]. Waveform detection is a coherent sensing method that makes use of the known signal patterns. In the presence of known signals, the decision statistic is formed by correlating the received signal to a true-copy of the know pattern. The output is then compared to a threshold value in order to detect the presence or absence of a PU [66].

Second, another subclass of feature detectors depends on the second order statistics of the received signal. In some cases such as the Orthogonal-Frequency-Division Multiplexing (OFDM), the feature is attached to the periodicity of the PU signal itself and second order statistics such as autocorrelation can reveal the explicit correlation structure imposed by the insertion of CP at the PU transmitter. Due to the popularity of OFDM in advanced communication systems nowadays, a special attention has been made to design good decision statistic that provides good detection performance and requires the minimum set of known information about the OFDM signal [67][68].

Third, since PU signals are typically digitally modulated, the second order periodicity inherited in these signals exploit a cyclostationary feature. In reality, most man-made signals show periodic patterns related to symbol rate, chip rate, or channel code. Cyclostationary feature detection method deals with the inherent cyclostationary properties that cannot be found in any interference signal or stationary noise [14]. Mainly, the detector utilizes cyclic correlation periodicity in the received primary signal to identify the presence of primary

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users, and that is why the cyclostationary feature detection method is reliable method of spectrum sensing at low SNR as it possesses higher noise immunity than any other spectrum sensing method [69][70]. Since cyclostationary signals exhibit second order periodicity, the Cyclic Autocorrelation Function (CAF) at a cyclic frequency α is defined by (2) where τ is the lag value, $\mathbb{E}$ denotes expectation, and $(*)$ refers to the conjugate operation. From the implementation perspective, the CAF is estimated based on the received samples and prior knowledge to α and/or τ [89]. It acts as a decision statistic which is compared to a threshold to decide whether a PU is present or not.

$$R_y(\alpha,\tau) = \frac{1}{N}\sum_{n=0}^{N-1}\mathbb{E}\Big[y(n)y^*(n+\tau)\Big]e^{-j\alpha n} \qquad (2)$$

Recently, in [69], the authors studied cyclostationary detection of PU signals and investigated its performance via simulation, since the derivation of the false alarm and detection probabilities for cyclostationary detectors for complex modulation schemes are known to be mathematically intractable. The noise uncertainty demonstrates a negligible effect on the cyclo-stationary detection approach [70]. The effect of the receiver impairments on the cyclostationary detectors is considered in [71], where the promising performance results encourage the authors to propose the cyclostationary detection as not only a narrowband sensing approach, but also as a wideband sensing technique. Further, the implementation effort of the cyclostationary detectors focuses on reducing the complexity [72][73], which is the main disadvantage for having practical cyclostationary detectors. Furthermore, the sensing interval for this type of detectors is known to be high [89].

4) Other Detection Approaches: Due to the limitations of practical system implementation and coherent detection for the conventional narrowband sensing techniques, more investigations and innovative solutions have been recently presented. Among those methods, the eigenvalue based detection [74][75] has been proposed. Some communication signals impart a specific known structure to the covariance matrix which can be obtained based on the correlation among the received signal samples. The max to min eigenvalue of covariance matrix serves as the test statistics which is then compared to a threshold to form decisions. Based on random matrix theory, decision threshold expression can be derived. No priori information of PU signals and/or the transmission channel is required. Thus, it overcomes problematic noise uncertainty encountered by other detectors [74]. Based on test statistics, this method can be classified into [76]: (1) Max-min eigenvalue detection in which the test statistic is defined as ratio of Max and Min eigenvalue of covariance matrix. (2) Energy with min eigenvalue in which the test statistics is defined as ratio of average power of received signal to min eigenvalue. (3) Max eigenvalue detection in which test statistics is given by the maximum eigenvalue.

Some of the characteristics of the primary transmitted signal can be obtained from the regulatory bodies such as FCC which usually assigns pulse shaping for realistic signals. Based on this piece of information, the authors of [90] presents a Max-Min SNR based signal detection approach by exploiting the pulse shaping filter of the primary users. This technique is a non-coherent approach with robust behaviour for noise uncertainty. Furthermore, another approach relies on the differentiation between the noise and signal covariances. In [91], analytical expressions for the performance of the covariance based detectors are demonstrated. The test statistic is considered to be the covariance absolute value. In addition to the robust performance, this technique does not require any prior knowledge for the primary signal. In general, advanced communication systems, that include digital modulation, multiple antenna system, Space-Time Block Code (STBC), Space-Frequency Block Code (SFBC), or OFDM, impose specific structure to the primary signal characteristics. Research efforts are directed to design detectors for each of these properties to explore the spectrum occupancy of the primary signal. Several approaches have been presented already and some are still expected. For example, measuring the ratio of the fourth absolute moment to the square of second absolute moment of a modulated signal is a presented detector that makes use of a modulated signal [92].

B. Narrowband Spectrum Monitoring Approaches

In this section, we present the basic concepts for the spectrum monitoring procedures. This includes the dynamic frequency hopping and the monitoring during reception.

1) Dynamic Frequency Hopping: In dynamic frequency hopping approach, the SU uses the working (in-band) channel for data transmission and performs spectrum sensing on out-of-band channels simultaneously. Based on this spectrum awareness, the SU dynamically selects one of the channels validated in a previous operation period for data transmission in the next operation period [44][45]. To realize this concept, DFH assumes that a super power module is always present to coordinate the system, check the band availability, apply the scheduling, and monitor every individual spectrum hole to ensure the possible hopping sequence. DFH is justified only if the channel switching can be executed quickly enough. In practice, there are many issues with this approach to realize a reliable transmission that guarantees a known Quality-of-Service (QoS) for the CRs. For example, to prevent scheduling deadlock, there has to be one unassigned spectrum hole every time slot and the whole idea breaks up if this condition is not satisfied. Further, imperfect spectrum sensing significantly limits the capacity of this approach as pointed out in [93]. In this paper, we will consider the non-frequency hopping mode with the two sensing phases, to which we present the recent research directions and the practical issues associated with various solutions.

2) Monitoring During Reception: Due to the introduction of quite periods, the cognitive radios must stop communicating in order to detect the emergence of the primary signal. As a result, there will be a trade-off between the performance of the secondary network and the performance of the primary network. During sensing intervals (i.e: the time intervals during which the secondary transmitters are silent while the

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frequency band is examined), the secondary network achieves no throughput. If the frequency or duration of the sensing intervals is too large, then the secondary network's average throughput is low and its average delay is high. Between consecutive sensing intervals, traditional spectrum sensing provides no information about the status of the frequency band. Thus, if the frequency or duration of the sensing intervals is too small, then the interference to the primary users is excessive.

To avoid this trade-off, the cognitive radios can monitor the frequency band without interrupting their communications. Such methods can detect the reappearance of the primary user during the secondary user transmission. This may supplement traditional spectrum sensing and provide enhanced communications efficiency. If spectrum monitoring determines correctly that there is no primary signal in the band, then the time that would have been spent performing spectrum sensing is used to deliver packets in the secondary network. If spectrum monitoring detects a primary signal in the band during a time period in which spectrum sensing would not have been scheduled, then the disruption to the primary user can be terminated more rapidly. Thus the spectrum efficiency of the secondary network is improved and the impact of secondary communications on the primary user is lessened. Different techniques are presented to monitor the spectrum by the CR receiver during reception. These techniques are not replacements for traditional spectrum sensing. Instead, they are supplemental techniques that reduce the frequency with which spectrum sensing must be performed and decrease the elapsed time between the start of a primary transmission and its detection by the secondary network. If single RF path is utilized with no cooperation, then two solutions are presented to realize narrowband spectrum monitoring, namely the receiver statistics approach [42] and the energy ratio approach [43].

a) Receiver Statistics Approach: One of the techniques is presented in [42][77] where the spectrum is monitored by the CR receiver during reception and without any quiet periods. The idea is to compare the bit error count, that is produced by a strong channel code like Low Density Parity Check (LDPC) code, for each received packet by a threshold. If the number of detected errors is above certain value, the monitoring algorithm reports the primary user activity. The threshold is obtained by considering the hypothesis test between the receiver statistics when the primary signal is absent and the receiver statistics for the desired Secondary-to-Primary power Ratio (SPR). Although this technique is simple and adds almost no complexity to the system, the receiver statistics are subject to change by varying the system settings [78]. In real systems, there are many parameters that can disturb the receiver error count such as RF impairments including phase noise (PN), Carrier Frequency Offset (CFO), Sampling Frequency Offset (SFO), and Narrowband Interference (NBI). That is the error count will depend not only on the presence of a primary signal but it will also depend on the parameters for those impairments. The receiver statistics may change from one receiver to the other based on the residual errors generated from estimating and compensating different impairments.

b) Energy Ratio Approach: To overcome the above mentioned issues, another spectrum monitoring algorithm is presented in [79]. This algorithm is designed for OFDM-based cognitive radios. At the transmitter side, couple of sub-carriers are reserved for monitoring purposes, where these sub-carriers are left unmodulated. At the receiver side, an energy ratio is utilized between two consecutive equal-sized sliding windows which are passed over the frequency domain reserved tone sequence. The algorithm aims to check the change in variance on the reserved tones over time. If the ratio exceeds a certain threshold, the secondary user assumes that there is a power change on the reserved tones which is due to the primary user appearance and it is time to vacate the band. Otherwise, the secondary user can continue transmission. Moreover, the OFDM impairments such as power leakage, NBI, and Inter-Carrier Interference (ICI) as well as the multi-path channel are investigated and their impact on the presented technique are studied [43]. Due to the amount of overhead introduced due to allocating the reserved tones, the spectral efficiency of the system is reduced. Despite the fact that most of the recent wireless communication systems are built on OFDM systems, still the presented approach is limited to only one type of systems and does not provide solutions to single carrier systems.

IV. Wideband Spectrum Sensing

Wideband spectrum sensing techniques aim to sense a frequency bandwidth that exceeds the coherence bandwidth of the channel. For example, to exploit spectral opportunities in the whole ultra-high frequency (UHF) TV band (between 300 MHz and 3 GHz), wideband spectrum sensing techniques should be employed. It is worth to mention that narrowband sensing techniques cannot be directly employed to perform wideband spectrum sensing as they make a single binary decision for the whole spectrum and thus cannot identify individual spectral opportunities that lie within the wideband spectrum.

Based on the sampling frequency, two main classes of solutions are available to deal with the wideband sensing problem. The first approach to realize wideband sensing assumes that it is feasible to sample the desired spectrum by the ordinary Nyquist rate [6]. 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 an edge detection. The common challenge in these approaches is the high computational complexity attached to the required ultra high sampling rates, the high computational complexity of the solutions, and the required sensing time especially when practical considerations are taken into account such as the Automatic-Gain-Control (AGC) settling time, the switching time for the Phase-Locked-Loop (PLL), and the processing delay.

The second approach to perform wideband sensing is based on the sub-Nyquist techniques. These approaches [116] are utilized to relax the long sensing delay or the higher computational complexity and hardware cost resulted from the

Table III
SUMMARY FOR VARIOUS WIDEBAND SENSING TECHNIQUES IN INTERWEAVE COGNITIVE RADIO NETWORK

Sensing Technique	Class	Description and Advantages	Limitations	Relevant recent references
FFT-based Detector	Nyquist WB	• Non-coherent • Reasonable complexity	• Require high sampling rate	[94][95]
Wavelet-based Detector	Nyquist WB	• Non-coherent • Edge detector	• High Computational complexity.	[96][97][98][99]
Filter-bank Detector	Nyquist WB	• Non-coherent • High performance	• High Computational complexity.	[100][101][102]
Compressive Sensing	Sub-Nyquist WB	• Non-coherent • Low power • Low sampling rate	• High Computational complexity. • Sparsity assumption • Dynamic behaviours for sparsity level	[103][104][105][106][107][108][109][110][111][112][113]
Multi-coset Sensing	Sub-Nyquist WB	• Non-uniform sampler • Can reconstruct the spectrum	• Require synchronization circuits	[114] [115]

high sampling rate implementations. Compressive sensing [6] becomes a promising candidate to realize this sub-Nyquist approach. Here, a signal can be efficiently acquired using relatively few measurements by which unique representation of the signal can be found based on the signal's sparsity or compressibility in some domain. Other techniques such as multi-cosets can also be used to reconstruct the spectrum from fewer samples. The idea here is to chose a sampling sequence that enables this reconstruction. In this section, we introduce the basic concepts for the conventional approaches to perform wideband sensing. Also, we include the recent research advances introduced for each approach to enhance its feasibility. The techniques presented in this section are summarized by Table III which lists the algorithm, its classification, its brief description and limitation, and the relevant recent references.

A. Nyquist Approaches and Their Advances

A simple approach of wideband spectrum sensing is to directly acquire the wideband signal using a standard ADC and then employ digital signal processing techniques to detect spectral opportunities. However, special attention should be paid to the signal sampling procedure. In these algorithms, sampling signals should follow Shannon's celebrated theorem: the sampling rate must be at least twice the maximum frequency present in the signal (known as Nyquist rate) in order to avoid spectral aliasing. Thus, using these approaches for wideband sensing either causes long sensing delay or incurs higher computational complexity and hardware cost. In fact, there are many techniques to address this approach and there are also numerous solutions to address the challenges. For example, in [117], a wideband sensing approach is realized by appropriately taking the observations in all sub-bands into account for sensing a single sub-band. This technique is originally motivated by the recent eigenvalue based narrowband sensing. However, there are basic approaches that are reliable enough to encourage researchers to continue improving them. We present the multiband approach, the wavelet-based approach, and the filter-bank approach. Each is accompanied by its advances. A general block diagram for these approached is shown in Fig. 3-(b). We present the most common approaches along with their recent enhancements.

1) Multiband Sensing or FFT-based Sensing: An FFT-based technique is originally proposed in [94]. In this approach, 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 are utilized to obtain an estimate for the power spectral density which is then divided into a series of narrowband spectra. Spectral opportunities are detected using binary hypotheses tests for various narrowbands. The optimal detection threshold is jointly chosen by using optimization techniques. Although, this technique provides reasonable complexity, it suffers from the practical issues such as power consumption and feasibility of ultra high sampling ADCs. As a recent extension, an adaptive multiband spectrum sensing procedure is developed in [95]. The procedure consists of two phases, the exploration phase and the detection phase. In the exploration phase, several iterations are carried out and a substantial portion of the available channels are progressively eliminated according to the accumulated statistic of each channel. In the detection phase, multiple spectrum holes are finally identified among the surviving channels.

2) Wavelet-based Sensing: A wavelet-based spectrum sensing algorithm is proposed in [96][97]. In this algorithm, the power spectral density (PSD) of the wideband spectrum was modelled as a train of consecutive frequency sub-bands, where the PSD is smooth within each sub-band but exhibits discontinuities and irregularities on the transitions of two neighbouring 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 used to locate 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. This conventional approach is usually termed as Wavelet Transform Modulus Maxima (WTMM) algorithm. Recently, this technique has been studied in fading environment [98]. Furthermore, various versions of the algorithm have been presented such as Wavelet

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Transform Multiscale Sum (WTMS) and Wavelet Transform Multiscale Product (WTMP) to define new decision statistic [99]. The trade-off is usually the performance versus the sensing time and complexity.

3) Filter-bank Sensing: A bank of prototype filters (with different shifted central frequencies) is presented in [100] to process the received wideband signal. The baseband can be directly estimated by using a prototype filter. Other bands can be obtained by modulating the prototype filter so that its center frequency is adjusted to select the desired band. In each band, the corresponding portion of the spectrum for the wideband signal is down-converted and filtered to form a baseband version to which a narrowband sensing algorithm is applied. This algorithm can therefore capture the dynamic nature of wideband spectrum by using low sampling rates. Unfortunately, due to the parallel structure of the filter bank, the implementation of this algorithm requires a large number of RF components. An extension to this idea is presented in [101], where the authors presented a framework of multi-channel sensing architecture based on polyphase discrete Fourier transform filter bank followed by energy detector in order to reduce the complexity. Another extension is presented in [102], where a progressive decimation filter bank is designed to provide variable sensing resolution and adapt to different detection bandwidths.

B. Sub-Nyquist Approaches and Their Advances

Due to the drawbacks of high sampling rate or high implementation complexity in Nyquist systems, sub-Nyquist approaches are drawing more and more attention in both academia and industry. Sub-Nyquist wideband sensing refers to the procedure of acquiring wideband signals using sampling rates lower than the Nyquist rate and detecting spectral opportunities using these partial measurements. In this context, compressed sensing can be utilized to approximate 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 that provide promising solutions to promptly recover wideband signals and facilitate wideband sensing at the 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. On top of these approaches, the multi-coset approach is employed. In this section, we present an overview of the conventional sub-Nyquist sensing approaches with their corresponding advances.

1) Compressed Sensing: Compressed sensing theory [116] attempts to recover the exact or very accurate version of the original sparse signal $\mathbf{s}$ from few measurements $\mathbf{y}$ by solving the linear set of equations $\mathbf{y} = \Phi^T \Psi \mathbf{s} = A\mathbf{s}$, where A is the sensing matrix, Ψ is an $M \times M$ transform matrix (i.e. $\Psi \in \mathbb{C}^{M\times M}$), and Φ is the projection matrix or the measurement matrix (i.e. $\Phi \in \mathbb{R}^{M\times N}$). Based on linear set of equations, the signal $\mathbf{s}$ can be reconstructed from few measurements represented by the signal $\mathbf{y}$. In fact, the classical theory of linear algebra has some basic rules to solve this linear system of equations. If there are fewer measurements than unknowns $(N < M)$ which is the case, then the problem is under-determined even when A has full rank. Knowledge of $A\mathbf{s} = \mathbf{y}$ restricts $\mathbf{s}$ to an affine subspace of $\mathbb{C}^M$, but does not determine $\mathbf{s}$ completely. In order to have an accurate and guaranteed solution to the under-determined system, the sensing matrix should be properly selected to satisfy some constraints. A large number of algorithms that attempt to solve the linear system within the broader field of compressed sensing have been studied using the restricted isometry property (RIP) for the matrix A [118]. This property characterizes matrices which are nearly orthonormal, at least when operating on sparse vectors.

Compressive sensing theory was firstly introduced to sense wideband spectrum in [103]. This technique used fewer samples closer to the information rate, rather than the Nyquist rate, to perform wideband spectrum sensing. To implement compressive sensing in cognitive networks, [103] shows the detailed procedure which is shown in Fig. 3-(c). First, a sub-Nyquist sampler is required to obtain the few measurements. Second, the spectrum is reconstructed from the measured samples. Third, a localization and identification for the occupied sub-bands are explored to finalize the wideband sensing decisions.

a) Sub-Nyquist Sampling: Let the received signal $y(t)$ be sampled by the conventional Nyquist rate. After conversion, the discrete time signal can be denoted by $y(n) = y(t)|_{t=nT_0}$ where T_0 is the Nyquist sampling period. Assume that the sensing period $T_{sensing} = MT_0$, therefore we have traditionally M digital samples from the signal $y(t)$ within the time period $T_{sensing}$. Instead, the digital receiver converts the continuous-domain signal $y(t)$ to a discrete sequence $\mathbf{y} \in \mathbb{C}^N$ of length N such that $N \ll M$. This process is defined as the sub-Nyquist-rate sampling process. One solution is the recurrent and non-uniform sampling that is equivalent to choosing some samples from a uniform grid, which can be obtained using a sampling rate F_s that is higher than the Nyquist rate. The uniform grid is then divided into blocks of M consecutive samples, and in each block N samples are retained such that $N \leq M$ while the rest of samples are skipped. The process is repeated periodically to continuously achieve sub-Nyquist sampling.

Another realization for non-uniform sampling is the random sampler which is the class of non-recurrent sampling. The sampling process does not show any periodicity and can only be described statistically. The theoretical framework is based on the random sampling theory. Unlike uniform sampling, the Nyquist rate is no longer the barrier under a random sampling scheme [104] [105]. It is possible to unambiguously reconstruct a class of spectrally sparse signals that is sampled randomly below the Nyquist rate.

b) Spectrum Reconstruction: The main challenge for compressive sensing is the spectrum reconstruction part. It is required to accurately reconstruct the signal spectrum $\mathbf{s}$ represented by M frequency samples at the Nyquist rate from the available measurement set $\mathbf{y}$ which has a reduced size of $N(< M)$ elements. Since $\mathbf{y} = \Phi^T\ \mathbf{x}$ and $\mathbf{x} = \Psi\ \mathbf{s}$, then simply $\mathbf{y} = \Phi^T \ \Psi \ \mathbf{s}$. If $\mathbf{s}$ represents the spectrum of the Nyquist rate samples $\mathbf{x}$, then the transform matrix Ψ represents the inverse discrete Fourier transform matrix such that $\Psi = F^{-1}$ where $F \in \mathbb{C}^{M \times M}$ is the discrete Fourier transform matrix. Then, we have a linear set of equations $\mathbf{y} = \left(\Phi^T F^{-1}\right) \mathbf{s} = A \, \mathbf{s}$ where A is the sensing matrix. Assuming that the sensing matrix $A_{N \times M}$ is known, of course with some constraints, one can minimize the error between the measurements $\mathbf{y}$ and the linear system of equations $A \, \mathbf{s}$ in order to find the best guess for $\mathbf{s}$. Intuitively, if a signal is K sparse, then it should only have K degrees of freedom rather than M. In principle, one should now only need K measurements or so to reconstruct $\mathbf{s}$, rather than M. *In fact, this is the underlying philosophy of compressed sensing; that is, one only needs a number of measurements proportional to the compressed size of the signal, rather than the uncompressed size*. There are essentially two methods to recover a K sparse signal in compressed sensing after fully utilizing the sparsity of the signal.

The pioneering works of [116] [104] make full use of sparsity so that a sparse signal can be reconstructed from very few measurements. Suppose that any K columns of the $N \times M$ matrix A are linearly independent which is a reasonable assumption since $N \geq K$. Then, any K sparse signal $\mathbf{s} \in \mathbb{C}^M$ can be reconstructed uniquely from $A \, \mathbf{s}$. In fact, this concept shows that the reconstruction of a K sparse signal $\mathbf{s}$ from the measurements $\mathbf{y}$ is the unique sparsest solution. The reconstruction of sparse signals can be reduced to an optimization problem with efficient algorithms. One of them is the orthogonal matching pursuit which formulates the problem as finding the sparsest solution of linear equations $\mathbf{y} = A \, \mathbf{s}$ such that the linear programming is used to find the solution based on the optimization problem given by (3). Notice that the sparsest solution means the solution which has fewest non-zero entries and this is the reason for using ℓ_0 norm as a count of the non-zero elements in the vector $\mathbf{x}$. The orthogonal matching Pursuit (OMP) is a method that pursues greedy algorithm for this ℓ_0 minimization. OMP assumes that A represents an over-complete dictionary for the signal space so that K sparse signal can be reconstructed using this dictionary. The columns of the matrix refer to the atoms by which the sparse signal is constructed. The dictionary should be selected properly such that this assumption holds all the time.

$$\hat{\mathbf{s}} = \arg\min_{\mathbf{s}} \|\mathbf{s}\|_0 , \ \text{s.t.} \ \mathbf{y} = A \, \mathbf{s} \tag{3}$$

Despite the considerable attention that has been paid to both OMP, analysis of OMP using the RIP has been relatively elusive to date. However, several alternative greedy algorithms have been proposed, all essentially modifications of OMP, that are apparently much more amenable to RIP-based analysis. These ca be listed as the regularized orthogonal matching pursuit (ROMP) [119], the compressive sampling matching pursuit (CoSaMP) [110], subspace pursuit (SP) [112], the tree-based orthogonal matching pursuit (TOMP) [111]. Unfortunately, ℓ_0 minimisation is computationally intractable. In fact, in complexity theory, ℓ_0 minimisation can be classified as an NP-hard problem in general [120]. An NP-hard (or Non-deterministic Polynomial hard) is at least as hard as the NP-Complete problems which is the problem of solving all possible set of NP problems. In part, this is because ℓ_0 minimisation is not a convex optimisation problem. To summarise, when solving an under-determined problem $\mathbf{y} = \Phi^T F^{-1} \mathbf{s} = A \, \mathbf{s}$, ℓ_2 minimisation is easy to compute, but often wrong. When $\mathbf{s}$ is sparse, ℓ_0 minimisation is often correct, but very difficult to compute. The basis pursuit [121] method considers a convex relaxation of (3). Under certain RIP conditions, we can exactly recover via the ℓ_1 minimization which is given by (4). In fact, basis pursuit was introduced empirically in the sciences and then studied mathematically.

$$\hat{\mathbf{s}} = \arg\min_{\mathbf{s}} \|\mathbf{s}\|_1 , \ \text{s.t.} \ \mathbf{y} = A \, \mathbf{s} \tag{4}$$

c) Localization and Identification: After the reconstruction of the wideband spectrum, the spectrum holes are localized and identified so that the SU can decide which band is suitable for its transmission. The spectrum is assumed to be K sparse. The typical approach here is to obtain the wavelet transform for the estimated spectrum and hence the spectrum discontinuities can be obtained. The locations of those discontinuities determine the boundaries for the occupied and vacant bands. Now, the bands are localized by having proper corner frequencies for both vacant and occupied bands. The last step is to distinguish which band is vacant and which is occupied. In fact, this reduces the problem of wideband sensing into a narrowband one in which the spectrum is known. Therefore, a simple energy detection can do the job of identifying the band type of being whether a spectrum hole or not.

d) Analogue Compressed Sensing: In fact, compressive sensing has concentrated on finite-length and discrete-time signals. Thus, innovative technologies are required to extend the compressive sensing to continuous-time signal acquisition, i.e., implementing compressive sensing in analogue domain. To realize the analogue compressive sensing, an analogue-to-information converter (AIC), which could be a good basis for the above-mentioned algorithms, is proposed in [113]. For sparse input signals, AIC promises greatly reduced digital data rates (matching the information rate of the signal). The AIC-based model consists of a pseudo-random number generator, a mixer, an accumulator, and a low-rate sampler. The pseudo-random number generator produces a discrete-time sequence that demodulates the signal $x(t)$ by a mixer. The accumulator is used to sum the demodulated signal for T_s seconds, while its output signal is sampled using a low sampling rate. After that, the sparse signal can be directly reconstructed from partial measurements using compressive sensing algorithms. Unfortunately, it has been identified that the performance of AIC model can be easily affected by design imperfections or model mismatches. The idea is that the input signal $x(t)$ can be expressed by a linear combination of the atoms $\psi_m(t)$ such that $x(t) = \sum_{m=1}^{M} \alpha_m \psi_m(t)$ where α_m are the linear coefficients. When this signal is multiplied by a chip sequence $p_c(t)$ and then applied to a filter whose impulse response is $h(t)$, the resulting sampled signal can be obtained as given by (5). If we define the discrete elements of the matrix $\Phi_{n,m}$ as given by (6), then we can reduce the relation of the sub-

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Nyquist samples $y[n]$ and the atoms gains vector Γ to the linear relation such that $\mathbf{y}_{N\times 1} = \Phi_{N\times M}\ \Gamma_{M\times 1}$.

$$y[n] = \sum_{m=1}^{M} \gamma_m \int_{-\infty}^{\infty} \psi_m(\tau) p_c(\tau) h(nT_s - \tau) \mathrm{d}\tau \quad (5)$$

$$\Phi_{n,m} = \int_{-\infty}^{\infty} \psi_m(\tau) p_c(\tau) h(nT_s - \tau) \mathrm{d}\tau \quad (6)$$

2) Multi-Coset Approach: Multi-coset sampling (MC) is a special case of the general periodic non-uniform sub-Nyquist sampling technique for acquiring sparse multi-band signals [114] [115]. For a fixed time interval T_s that is less than or equal to the Nyquist period and for a suitable positive integer M, MC samplers sample $y(t)$ at the time instants $t = (kM + c_i)T_s$ for $1 \le i \le N$, $k = 0,\ 1,\ \ldots$. The time offsets c_i are distinct, positive real numbers less than M and are known collectively as the multi-coset sampling pattern.

When frequency domain analysis is obtained for the signals $z_i(k)$, it was shown in [115] that $Z_i(e^{j\omega M})$ is a linear combination of a particular (finite) set of spectral segments of $y(t)$ as given by (14). In fact, if we define $z_i(\omega) = e^{-jc_i\omega}\ Z_i(e^{j\omega M})$, $y_l(\omega) = Y\big(\omega - \frac{2\pi}{M} m_l\big)$, and $\Upsilon_{i,l} = \frac{1}{M} e^{-j\frac{2\pi}{M} m_l c_i}$, then $\mathbf{z} = \Upsilon\ \mathbf{y}$ from (14) where $1 \le i \le N$, $1 \le l \le M$, and $m_l = -\lfloor (M+1)/2 \rfloor + l$. The authors guarantee signal reconstruction when the linear combinations are properly selected along with the parameters N, M, and $\{c_i\}$. In this case, this method cannot only be used as a method to sub-Nyquist sampling for the compressed sensing reconstruction, but also it has its own reconstruction technique with which the reconstructed spectrum can be directly applied to the wavelet transform. In [115], some sampling patterns were proved to be valid for unique signal reconstruction. The advantage of the multi-coset approach is that the sampling rate in each channel is M times lower than the Nyquist rate. One drawback of the MC approach is that the channel synchronization should be met such that accurate time offsets between sampling channels are required to satisfy a specific sampling pattern for a robust spectral reconstruction.

3) Recent Advances: In terms of having practical assumptions and performance characteristics, the authors in [122] have presented an adaptive compressive sensing approach that does not require sparsity estimation while sensing the wideband by using an appropriate number of measurements from consecutive time slots. Unlike the traditional sub-Nyquist approaches which concentrate on spectral estimation and aim at perfectly reconstructing the original signal to realize sufficient detection capabilities, a power spectrum estimation method is introduced for compressive sensing in [123]. The authors in [124] presented new performance metrics such as the probability of insufficient spectrum opportunity and the probability of excessive interference opportunity to evaluate the spectrum sensing approached. In response to these metrics, a study to various uniform sampling approaches are presented to reduce the complexity of the conventional compressive sensing implementation. In [125], a spectrum sensing technique based on spectral correlation for detection of television broadcasting signals is presented. The interesting point is that this technique has been extended for compressive sensing in [126] in which a compressive sensing-based feature detection on correlation matching is presented. Another approach to realize compressive sensing based on the covariance to select the proper measurements is presented in [127].

There is an implementation and architectural design effort that can be summarized here. Comparisons of various architectures in compressive sensing are presented in [128]. A new compressive spectrum sensing architecture based on the principle of under-sampling is employed in [129], where a bandpass filter is utilized with a homodyne receiver to enable fast detection with low ADC rate. The multi-coset sub-Nyquist sampling has been carefully analysed in [130]. The complexity and the power consumption of the presented implementation are considered in details. The implementation of a cooperative compressive sensing approach is addressed in [131]. In this technique, the implementation of the conventional architecture that relies on FFT engine has been adopted and modified to include the multi-coset sampling. Similarly, a non-uniform sampling approach has been implemented in [132].

In the direction of analogue compressive sensing, a novel scheme with only a single processing chain instead of the parallel chains is presented to reduce the modulated wideband converter complexity without increasing the sampling rate in wideband spectrum sensing [133]. A special periodic waveform in the time domain in the presented scheme is introduced to the model. Another design with its respective analysis is considered in [134]. Furthermore, a quadrature analogue-to-information converter is introduced in [135] to rapidly sense the spectrum of interest ranging from bandpass fashion and an energy efficient way.

V. Cooperative Sensing

Due to non line of sight (NLOS) communication and hidden terminal issues in the medium, single node sensing performance is unreliable and increases the miss-detection rate. The CR receiver will be imposed on a strict sensitivity requirement greatly increasing the implementation complexity since receiver sensitivity indicates the capability of detecting weak signals. More importantly, the detection performance cannot be improved by increasing the sensitivity, when the SNR of PU signals is below a certain level known as a SNR wall [81][83][136]. To mitigate the impact of these issues, cooperative sensing [137] is utilized. The basic concept is to enhance the sensing performance by exploiting the spatial diversity in the observations of spatially located CR users. Cooperative sensing model can be classified as either centralized or distributed [138][139][140]. In centralized cooperative sensing, a central identity called fusion center (FC) or a master node controls the three-step process of cooperative sensing [141]: (1) the FC selects a frequency band of interest for sensing and instructs all cooperating CR users to individually perform local sensing. (2) All cooperating CR users report their sensing results via a defined control channel. (3) The FC combines the received local sensing information, determines the presence of PUs, and diffuses the decision back to cooperating CR users. Distributed cooperative sensing

$$Z_i(e^{j\omega M})\Big|_{\left[\frac{-\pi}{M},\frac{\pi}{M}\right)} = \frac{e^{jc_i\omega}}{M}\sum_{m=-\lfloor(M+1)/2\rfloor+1}^{\lfloor(M+1)/2\rfloor} e^{-j\frac{2\pi}{M}mc_i}\,Y\left(\omega-\frac{2\pi}{M}m\right)\Big|_{\left[\frac{-\pi}{M},\frac{\pi}{M}\right)} \tag{14}$$

is another model [142] where SUs exchange data with one another instead of reporting to a common FC.

Originally, conventional cooperative sensing focuses on one frequency band during each round of cooperation (i.e., narrowband sensing). However, this process can incur significant switching delay and synchronization overhead if an ultra wideband spectrum is required to be sensed. If wideband sensing is required, CR users can cooperate to sense multiple narrow bands instead of focusing on one band at a time in order to reduce the total sensing time for all users. One way is to sense K bands from M spatially distributed CR users and then the statistics are combined at the FC [143] which makes a cooperative decision on each band. Also, a parallel cooperative sensing scheme [144] is proposed to enable the multi-channel sensing by optimally selected cooperating CR users. Here, each of cooperating CR users senses a different channel whose maximum detection rate can be achieved by the coordinated CR user. Indeed, using multi-band sensing can reduce the sensing time and channel switching overhead of narrowband sensing. However, additional hardware cost or overhead is required to facilitate simultaneous detection in multiple bands.

As mentioned above, cooperative sensing is just one of numerous cooperative communication schemes and is only applicable to interweave cognitive networks to improve the sensing precision, including detection probability and false alarm probability, which may not be satisfactory with any single-user sensing method [145]. However, an interweave CR working in a passive mode is sensitive to the activities of primary users. In the case with a low idle probability of licensed spectrum, a cognitive network can hardly get a chance to access the spectrum for its own communications. Indeed, despite the performance improvement to sensing precision brought by cooperation, there are some limitations that may discourage the use of cooperative sensing. First, cooperative techniques require the information exchange between the nodes, resulting in the increase of signalling overheads. Second, there may be some attacking nodes to destruct the cooperation and hence the reliability of cooperation would be significantly reduced. Third, cooperation gain may be affected by different impairments accompanying various SU nodes. For example, various SUs may have different channel conditions, SNR values, and RF imperfections so that the expected decisions from various nodes are generally random.

In order to follow with the practical implementation advances in the direction of cooperative sensing, the basics of the cooperation process are considered. In fact, up to the best of our knowledge, the cooperative sensing challenges have been introduced a long time ago. What really remains is how to address and solve the issues related to cooperative sensing. Towards this objective, most of the advances in cooperative sensing are related to the practical system consideration and implementation aspects which will be considered in Section VI. Therefore, in this section, we will introduce the fundamental elements for cooperative sensing. This includes the control channel and reporting, data fusion, and user selection.

A. *Control Channel and Reporting*

A common control channel is commonly used by CR users to report local sensing data to the FC or share the sensing results with neighbouring nodes [146]. The control channel can be implemented as a dedicated channel in licensed or unlicensed bands [147]. A full communication model including medium access control and physical requirements is required to realize this channel. However, there are many challenges and trade-offs in this design problem. First, the control channel bandwidth will limit the level and quality of cooperation [148][149]. Second, the reliability of the control channel will also affect the overall performance of the cooperative sensing[150][151]. Third, the control channel has to be secure enough in order to provide robustness against jamming signals [147].

As a cooperative wideband sensing, the "frugal sensing" has been recently presented in [152] to reduce the bandwidth requirements for the control channel. In this technique, each sensor node applies Nyquist sampling to the same wideband signal by an ordinary ADC after passing over AGC. The sensor then employs a broadband filter to somehow provide independent complementary views of the underlying power spectrum. The sensor node would compute the average power after the filter and just reports a single bit to a fusion center to provide the information of whether the power exceeds the threshold or not. The authors have extended the frugal sensing approach in [153] by introducing a more accurate model for the soft power measured at the sensor node prior to quantization. In addition, selective fading has been modelled and its impact was captured in the average power evaluation at each sensor node.

B. *Data Fusion*

Data fusion is a process of combining local sensing data for hypothesis testing. The sensing results reported to the FC or shared with neighbouring users can be combined in two different ways in descending order of demanding control channel bandwidth. First, soft combining [154], in which CR users can transmit the entire local sensing samples or the complete local test statistics for soft decision, can utilize the conventional combining techniques such as equal gain combining (EGC) and maximal ratio combining (MRC). Due to the overhead of the soft combining, a quantized version of the decision statistics can be utilized instead of the full precision value. In this case, CR users can quantize the local sensing

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results and send only the quantized data for soft combining to alleviate control channel communication overhead [155]. Second, hard combining [156][157], in which CR users make a local decision and transmit the one-bit decision for hard combining, applies linear fusion rules to obtain the cooperative decision. The main rules that can be applied by hard decision combining are the OR, AND, Majority, and K-out-of-N rule. Obviously, using soft combining at the FC can achieve the best detection performance among all three at the cost of control channel overhead while the quantized soft combining and hard combining require much less control channel bandwidth with possible degraded performance.

C. User Selection

Due to various channel conditions for various CRs, it might be wise to select the users that can contribute to the overall decision[147]. In reality, if a CR user suffers from deep fading or correlated shadowing, the reliability for its decision statistic is reduced. There are various techniques to best select the cooperative users. First, a centralized selection is applied at the FC. The FC can select independent CRs to report based on a priori knowledge about their correlation distribution, their locations, or transmit power levels [138]. Second, cluster-based selection can be used in which cooperative users are grouped into clusters to reduce the overhead over the control channel. Also the division to clusters can be random, position-based, or statistical-based [158][159].

VI. Practical Implementation Considerations

Since cognitive radios come to the implementation phase already, we have to address the implementation considerations that have been recently investigated. The main factors that enable efficient and optimized implementation is to provide the smallest power consumption, the highest network throughput which is mainly affected by the sensing cycles, a feasible complexity for the target technology. While all these factors are optimized, the system performance has been carefully investigated to measure the loss in performance due to the implementation challenges. In very specific scenarios, there may be additional considerations for the system to be realized. For example, if cooperative sensing is employed, the control channel parameters have to be optimized as well. In fact, comparisons between conventional sensing approaches have been presented in more than one research activity [48][160]. However, these efforts have not considered the recent advances to spectrum sensing with the presented deep classifications. In this section, we present the most important considerations including the power consumption, the sensing interval, the complexity, the impact of implementation on performance, and some other system specific considerations.

A. Complexity and Processing Capabilities

The complexity and computational power is the most sensitive aspect from implementation perspective. The reason is that complex algorithms many not be feasible for implementation or they might be feasible but not efficient from power consumption and delay perspectives. In this regard, massive proposals from research have been recently presented to tackle the complexity issues. The proposals either present enhancements to existing algorithms or new techniques that reduce the complexity when compared to conventional ones. In this section, we present the most interesting proposals in both directions to highlight the complexity issue.

Due to the well-known detection performance limitations for energy detectors, an improved version of the energy detection algorithm is presented and evaluated in [161]. Results show that this technique is able to outperform the classical energy detection scheme while preserving a similar level of complexity. In [162], a max-min approach is presented to detect signal energy under selective fading and uncertainty conditions. A justified complexity reduction by 78% is the main objective of this proposed approach. Under timing misalignment from various PUs at the CR receiver, a generalized likelihood ratio test is utilized in [163] along with energy detection to not only estimate the time differences but also to sense the presence of the PUs.

Due to the drawbacks of high implementation complexity in Nyquist wideband sensing, a new class, namely sequential sensing, is introduced [164][165][166]. In its simplest forms, the high complexity requirements by either FFT-based or filter-bank approaches can be relaxed by using super-heterodyne (frequency mixing) techniques that "sweep" across the frequency range of interest. Down-conversion is utilized and the signal is then filtered by a band-pass filter (BPF), after which existing narrowband spectrum sensing techniques can be applied. This sweep-tune approach can be realized by using either a tunable BPF or a tunable Local Oscillator (LO). The main issue with this simple approach is that it is often slow and inflexible due to the sweep-tune operation. However, the idea never stopped at this simple realization. In [167], a novel sequential sensing scheme based on suprathreshold stochastic resonance is presented to achieve reasonable performance for non-Gaussian noise and to provide less sensing time. In [168], a sequential shifted chi-square test has been employed as a new approach for sequential sensing to provide non-coherent low complexity technique. In multi-user environment, an optimization technique is studied in [169] to sequentially sense the PU channels taking into account the effect of data traffics of offload users. The objective is not only to sense the presence of the PUs but also to capture the characteristics of practical network traffic.

As mentioned earlier, one of the fundamental limitations for compressive sensing is the complexity. Extensive research work has been developed in this direction. In [170], a hybrid framework has been presented to combine compressive spectrum sensing with geolocation database to find spectrum holes. The main motivation for this data assisted approach is to significantly reduce the complexity which has been modelled analytically. Another approach found in [171], where compressed sampling for PU's signal acquisition is presented to reduce the implementation complexity of ADC when wavelet transform is utilized for wideband sensing. In [172], a Bayesian compressive sensing has been demonstrated to achieve the sampling reduction advantage of the conventional compressive

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sensing with significantly less computational complexity. A high-order statistics based wideband spectrum sensing scheme is presented in [173] with compressive measurements to skip the signal recovery stage of the conventional compressive sensing and hence to provide lower computational complexity.

A novel cooperative spectrum sensing technique based on matrix rank minimization has been developed in [174] to jointly collect both diversity gain and complexity gain. In [175], a suboptimal detector with much lower complexity has been designed for a cooperative sensing procedure which addresses the multi-bit quantized information transmitted from various SUs to the fusion center. In dynamically varying noise levels environment, a reduced complexity cooperative sensing is presented in [176]. The approach introduces the concept of a cooperative power spectral density split cancellation in which various SUs assist each others to cancel the dynamic noise behaviour from the decision statistic. An optimization procedure is followed in [177] to jointly apply cooperative spectrum sensing and power allocation in interweave cognitive networks, two heuristic approaches are introduced to significantly reduce the complexity of the presented optimization solution.

B. Power Consumption

Although the Nyquist approach exploits traditional ways to treat the tradeoff between performance and complexity, new implementation challenges are introduced to process the wideband spectrum. One major issue is the power consumption associated with the RF front end, ADCs, and even the digital processing part that typically operates by a very high sampling rate. Actually, low power consumption makes wideband sensing possible even at the secondary user equipments. These devices typically operate through batteries which have strict lifetime constraints.

First, the RF chain power consumption relies on the fabrication process, the operating center frequency, the operating bandwidth, and the architecture. Mainly, the RF power dissipation is distributed almost equally between amplification, mixing, and filtering/control. For example, it has been reported that 33% of the power consumption for the RF processing is dissipated by various gain amplifiers [178] for the currently available ultra-wideband (UWB) systems operating at 500MHz bandwidth. Second, the power consumption for the digital processing depends on the system architecture, the complexity, the operating clock frequency, the word length of various variables, and the fabrication technology. Third, ADC power consumption depends on ageing parameters such as the fabrication technology, the internal architecture, the operating frequency, and the resolution. In this regard, it has been shown that ADC power consumes a significant portion of the total power dissipation, and it requires a special treatment [179]. For these reasons, research efforts focus on producing innovative solutions for quantization process.

In reality, reducing the power consumption generally has three axes: the sensing performance which typically relies on the sensing algorithm and the quantization effect, the operating sampling/carrier frequency, and the resolution which influences the system complexity as well. First, the sensing performance based on the conventional Nyquist approaches assumes infinite precision of the acquired measurements in order to evaluate the presented algorithmic effort. For this reason, the quantization impact on the spectrum sensing detection performance has been considered [180]. However, the influence of the quantization on the power consumption was not the main focus of this research effort. Second, wideband Nyquist approaches assume the availability of an ultra high sampling rate. However, it should be emphasized that all results presented by previous research work including [6][181], consider relatively small band (order of 300MHz) which is somehow in the order of a medium-sized band when compared to the practical wideband in the order of GHz. Third, low resolution will impact the sensing performance, which may result in a degradation in secondary network throughput.

In fact, aggressive quantization strategies which compress real-valued measurements into one or only a few bits of data are preferred in such scenarios if performance constrains are met. Another benefit brought by low-rate quantization is that it can significantly reduce the hardware complexity and cost of the ADC. As pointed out in [182], low-resolution quantizer can operate at a much higher sampling rate than high-resolution quantizer. This merit may lead to a new data acquisition paradigm which enables reliable wideband sensing from high speed but low-resolution measurements. In [183], a survey for the state of the art ADC designs is introduced for various ADC sampling rates and resolutions. Furthermore, an optimization technique is developed for sequential sensing approach to choose the proper ADC resolution that achieves the required performance at the minimum power consumption. This has been quantified only for the FFT-based wideband sensing approach [184]. However, the effort in this direction always relaxes the requirements on the sensing time to provide a room of improved performance at very low power consumption. Unfortunately, high-speed (e.g., 1 GSamples/s and more), high-resolution ADCs are costly and power-hungry. The commercially available ADCs with these specifications consume power on the order of several Watts [185]. One of the most direct solutions to the power consumption and complexity bottlenecks is to reduce the quantization resolution of ADCs and to be able to live with ultra low precision ADCs (1-3 bits), which reduces power consumption and cost.

To reduce the power consumption of the FFT-based wideband sensing approach [184], a one-bit quantizer is employed [186]. The system architecture has been updated so that the RF processing assists the digital processor by providing a power estimate through the Received Signal Strength Indicator (RSSI) block. The digital processor utilizes this power measurements to properly set an optimized threshold value to distinguish between vacant and occupied narrow bands. The quantization effect is analyzed and the amount of power leakage is quantified, where the constant of proportionality to the PU power is obtained by computer simulations. Also imperfect power measurement and it contribution have been considered and analytically modelled. Following the same theme, an autocorrelation based wideband sensing technique is presented in [187], where again a single bit quantizer is employed. An analytical model is used to show that the spectrum occupancy is preserved when the 1-bit quantized signal is utilized for PSD estimation provided that the spectrum is sparse. A sub-optimal detector is designed to provide the detection rate for a given false alarm.

C. Sensing Interval

In fact, increasing the sensing period has the impact of reducing the overall cognitive network throughput. Therefore, this parameter has to be carefully considered with the same importance as the power budget. There have been research efforts which attempt to minimize the time duration for spectrum sensing by jointly optimizing the sensing time with the detection threshold [188]. The PU throughput statistics are considered to protect the PU while the sensing time is minimized. Motivated by the fact that high false alarm rates require the sensing cycle to be more frequent, an enhanced quiet-period management scheme has been presented in [189] to reduce the sensing interval. The technique utilizes multiple sensing approaches to reduce the sensing interval. The idea is that a feature detector is employed if an energy detector constantly issues false alarms for a predefined number of times.

Recently, an analytical model has been presented in [190] to optimize the sensing interval based on a satisfactory measure which accounts for the missed transmission opportunities if the current state is busy, the transmission collisions to the PU if the current state is idle, the decreased or increased throughput and possible interference to the PU caused by the delayed spectrum sensing. The effect of imperfect sensing performance on the optimized sensing interval is investigated in [191]. From the primary user perspective, the effect of sensing time and interval on the interference ratio (equivalently, the probability of collision) has been studied in [192]. The optimal sensing time and interval achieving maximum throughput for secondary users while satisfying the required interference ratio are also derived. Following this study, several proposals to realize this protection have been presented [193]. Other efforts try to coordinate between the primary user requirements and the optimized sensing interval. For example, in [194], the authors divide the PU band into two sub-bands, one for opportunistic SU data transmission, and the other for continuous spectrum sensing. Based on the PU band division, a delay oriented continuous spectrum sensing scheme is presented for delay sensitive SU services.

D. Performance Aspect

As mentioned earlier, the performance of a spectrum sensing algorithm is typically measured in terms of the false alarm probability and detection probability. In this section, we present the performance of some selective algorithms to show the practical implementation effects including imperfections and settings that discriminate between various algorithms. We tried to be fair in presenting various approaches for spectrum sensing. Due to the numerous number of algorithms and their enhancements, performance comparisons are also considered. However, the reader is encouraged to revise the original references for more details about the performance comparisons.

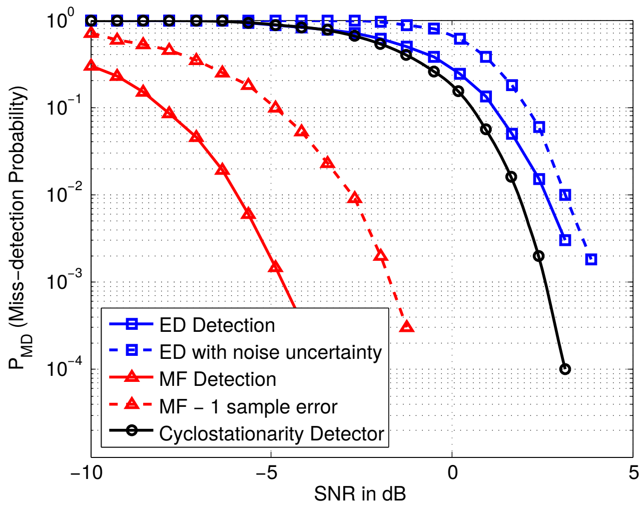

Fig. 4. These curves are plotted for a false alarm rate of 1%. The window size for the energy detector is the same as the matched filter length. Both agree with the cyclostationary detector period which is 32 samples. The noise uncertainty error is ± 0.5 dBs for the energy detection case [196].

Fig. 4 shows the probability of miss-detection for various narrowband sensing techniques against SNR. Effects of timing errors, noise uncertainty, and hard decision cooperative sensing have been included. The performance results show that any uncertainty of the noise level will significantly alter the performance of the energy detector. Furthermore, matched-filter detection is very sensitive to timing errors. However, these results assume an ideal channel (i.e., no fading environment) between PU and SU receiver. The conclusion is that, improvements and/or new sensing techniques are needed to provide less-complex, non-coherent, and robust practical algorithms.

When it comes to the monitoring algorithms during reception, the energy ratio algorithm [43] is compared to the receiver statistics technique found in [42]. The OFDM system for the energy ratio is simulated such that the system parameters match the simulation environment followed by [42]. The simulation is run for SNR = 6dB, P_{FA}=0.04, and an averaging window size of 128. Fig. 5 shows the simulation results for the detection probability for both algorithms. In addition of having fast detection, it is noted that ER shows a better performance than the receiver statistics algorithm. The OFDM system is then simulated to consider the synchronization errors and Rayleigh fading channel. The channel taps are scaled to fit the exponential power delay profile (PDP) [195].

For Nyquist-based wideband sensing, various algorithms are compared for the same settings as shown in Fig. 6. A total band of 1.024GHz that is divided into 1024 non-overlapped sub-bands, 100 of which are occupied by primary signals that uniformly spread over the entire band. For simplicity, the PUs are assumed to have the same power level. This assumption certainly holds only when primary radios deploy uniform power transmission strategies given no channel knowledge at the transmitter side which is justified in [197][94]. For the wavelet approach, the edge detection is achieved by comparing

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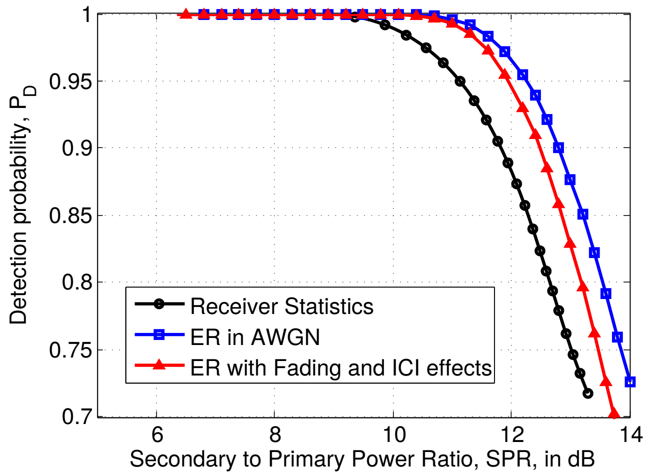

Fig. 5. Comparison between energy ratio and receiver statistics algorithms in case of QPSK, SNR = 6dB, P_{FA} = 0.04, and averaging window size of 128 [43].

the transformed spectral density to a known threshold that is a function of the noise level. For the filter-bank detection technique [100], 1024 bandpass filters have been designed to disjoint the sub-bands and hence narrowband energy detector can be applied to each sub-band. Each energy detector computes the average energy of the time domain samples presented by the corresponding filter. Averaging is applied over 100 samples. This technique shows better performance when compared to the FFT based. The performance of the one-bit quantizer algorithm presented in [186] is also compared to non-quantized systems.

For the basic concept of CS, Fig. 7 shows the detection performance as a function of the ratio of non-uniform sampling frequency to the typical Nyquist rate. The sparsity level in this simulation is $K = 4$ out of the available 16 sub-bands. The spectrum is reconstructed based on the OMP technique where the resampling is applied using a non-uniform sampler. It is clear that CS is able to detect the spectrum occupancy by a ratio of 1/10 of the Nyquist rate at high SNRs. Although compressive sensing is very promising in this context, many challenges exist due to the current algorithmic complexity as well as the basic assumptions. For example, the spectrum is dynamically loaded and the *sparse* assumption may not be valid which results in performance degradation. In Fig. 7, an imperfect estimation to the sparsity level (shown as $K = 7$) introduces significant degradations to the detection rate.

VII. Advances from Standards Perspective

With several conditions and limitations, the FCC offered the opportunity to utilize the unused TV bands in the very high frequency and ultra high frequency bands. The opening of these TV frequencies is a catalyst to encouraging more innovative and opportunistic applications of wireless communication systems, while the terms and conditions imposed on accessing TV white spaces show a "no pain no gain" type of wisdom. The new regulations offer opportunities for additional spectrum utilization. In response, industry and standardization initiatives have mobilized efforts to specify cognitive radio technologies to effectively take advantage of these newly available spectra. Due to its reliability and reasonable implementation cost, many standards have employed the interweave network model to enable cognition. Although the IEEE 802.22 is known to be the first cognitive standard [198]. There are new standards such as IEEE 802.11af, IEEE 802.15.4m, and ECMA 392 that rely on the interweave cognitive model in part or in full as the cognitive feature [199][200][201]. In this section, we cover the fundamentals for each of the new standards and we also provide the recent advances from the research perspective to various challenges introduced by deploying these technologies.

It is worth to mention that the above standards share the fact that they have been designed to be deployed in the TV white space. Once the new standards and compatible products are developed, one can envision scenarios, where multiple cognitive wireless networks will likely overlap with each other, creating a need for coexistence mechanisms. The main model assumed in this scenario is that various cognitive wireless networks form a general heterogeneous network where cognitive devices take advantage of the TV white space to achieve higher capacity and/or larger transmission ranges. Research activities are still open to regulate the medium access in order to enable the coexistence of various technologies [202][203][204][205]. Understanding the need to provide coexistence solutions for different cognitive radio systems operating in white space frequency bands, the IEEE 802 Executive Committee initiated project P802.19.1 to develop a standard for "TV White Space Coexistence Methods" [206][207][208]. This standard specifies radio technology independent methods for coexistence among dissimilar or independently operated TV band networks, and it defines services and mechanisms to enable coexistence between different cognitive radio systems operating in the TV white space frequency bands. In addition to this standard, the IEEE Dynamic Spectrum Access Network Standards Committee (DySPAN SC) has created the working group 1900.7 to specify technologies for dynamic spectrum access particularly in TV white spaces [209][210]. The scope of 1900.7 includes the specification of radio interface in the Medium Access Control (MAC) and Physical (PHY) layers for a dynamic spectrum access system operating in TV white spaces. The project supports communications for both fixed and mobile terminals, while avoiding harmful interference to incumbent services.

Since standardization bodies always put QoS among the highest priorities while the specifications are discussed, the addressed standards assumes the TV white spaces as the underutilized bands of interest. Furthermore, in the system design, geolocation awareness functionalities are supported, and the interface to the incumbent database is also defined. To guarantee QoS, spectrum sensing employed for incumbent discovery is typically divided into the faster (coarse) sensing and the more accurate (fine) sensing, which utilizes the outcome of the former. To elaborate, in IEEE 802.22 system, the quiet period consists of a series of consecutive spectrum sensing using energy detections followed by feature detection [211]. Since the energy detection checks only the energy level of the channel, it requires relatively short time but cannot identify the source of energy among primary users and noise. If the

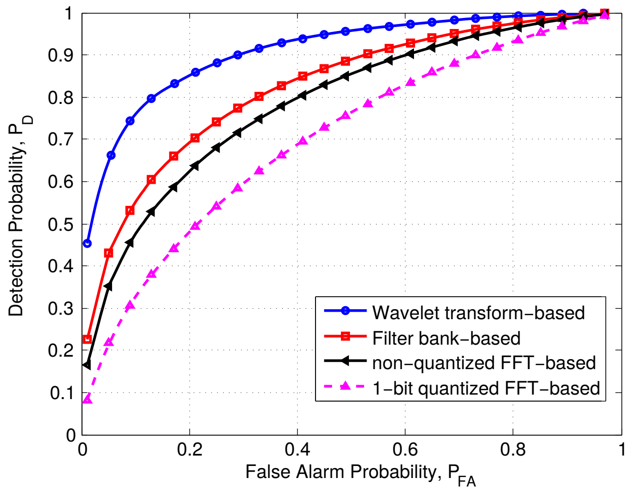

Fig. 6. Performance comparison between Nyquist-based wideband sensing approaches for SNR = -3dB, number of sub-bands of 1024 [186].

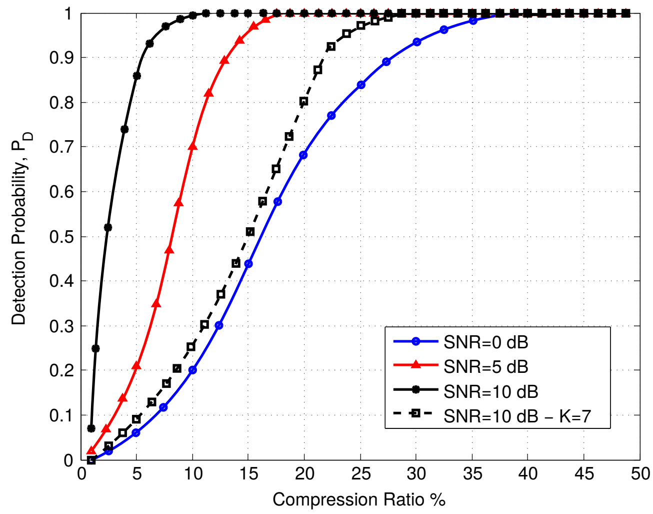

Fig. 7. Effect of SNR and sparsity level on compressed sensing detection versus the compression ratio [196].

CR system detects the energy level higher than the predefined value, that is, it is alarmed by the energy detection, the system performs the feature detection that is able to discern the source of signal by finding the unique feature of each signal but the feature detection spends long time when compared to energy detection [212]. Additionally, a channel selection algorithm and spectrum etiquette are specified to provide guidelines for occupying a TV channel [203][204].

A. IEEE 802.11af

IEEE 802.11 is a well-known set of standards specifying Wireless Local Area Network (WLAN) communication systems. IEEE 802.11af is a new version of the WLAN standard that enables WLAN to operate in the TV white space based on its cognition capabilities. IEEE 802.11af is commonly seen as a regulatory-driven standard, indicating that the majority of the technical amendments in the specification are intended to enable legacy IEEE 802.11 WLAN system to legally operate in the TV white spaces. This highlights the necessity for IEEE 802.11af to flexibly accommodate the regulatory requirements of different regions [199].

One major fraction of the regulatory requirements is the architectural design of the incumbent service detection and protection mechanism, namely the geolocation White Space Database (WSDB) mechanism [213][214][215]. The IEEE 802.11af has specified a common framework to address various WSDB spectrum management methods. For instance, this framework allows the white space devices to access the WSDB directly which is a required behaviour for FCC. On the other hand, in regulatory domains requiring the white space devices to access the WSDB through an intelligence entity that provides receiver-based information on the operating parameters for the white space devices, the IEEE 802.11af has introduced the Registered Location Secure Server (RLSS). This RLSS can be a simple computer located between the WSDB and the white space devices, that performs calculation for the information exchange when necessary. With this flexible framework, IEEE 802.11af is capable of addressing multiple regulatory-specific requirements.

The other design consideration to be noted is the suitability of existing system design to be applied in TV white space communications [216][217]. Since WLAN systems commonly operate in the GHz-band of the radio spectrum, mainly 2.4 GHz, 5 GHz, and 3.6 GHz. Correspondingly, various network layers are optimized for transmission in these frequency ranges. In order to migrate to the TV band, modifications to existing system design are essential to ensure that the system is capable of delivering the promised performance. For example, when IEEE 802.11y in the 3.6 GHz band was specified, modifications were conducted in the enhanced contention-based protocol to support the first kilometer-order transmission range for WLANs.

B. IEEE 802.15.4m

The IEEE 802.15.4m is a regulatory-driven standard to enable legacy ZigBee systems to operate in TV white spaces [200]. The targeted applications are low-power low-complexity devices for smart grid/utility, advanced sensor networks, and machine-to-machine networks. The IEEE 802.15.4m PHY design inherits the two PHY layers specified in the IEEE 802.15.4g smart utility networks standard, frequency shift keying PHY and OFDM PHY, with the addition of a narrow-band OFDM PHY, forming a multi-PHY-layer architecture [218][219]. The rationale of specifying several PHY layer choices under one unified access control mechanism is to address different market segments with respective application demands. The trade-off for such an architecture is the potential interference among the homogeneous systems within IEEE 802.15.4m. Again, effective coexistence mechanisms should be specified to manage or mitigate the inter-PHY-layer interference.

Another design consideration for IEEE 802.15.4m system operating in TV white spaces is network architecture [200][220]. The proposed network architecture in TV

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white space regulations are primarily based on a master-slave formation. On the other hand, for legacy IEEE 802.15.4 applications, a popular network topology is the peer-to-peer mesh network, allowing range extension and increased network reliability. Hence, it is important to specify a flexible IEEE 802.15.4m network topology capable of operating within the allowable context of TV white space regulations while fulfilling the performance of the legacy systems.

C. ECMA 392

The ECMA-392 is an international standard for the communication between personal/portable devices on TV white space [201][221]. Similar to IEEE 802.11af, a white band device usually obtains an available channel list from TV white space database, which has information of unused TV channels geometrically. This list is a starting point to reduce the search space for suitable channels. In addition, the standard supports spectrum sensing functionality to periodically check the existence of incumbent signals on the current operating channel. Ecma-392 has specified the operation in only single TV channel which can be one of three channel bandwidths of 6 MHz, 7 MHz, or 8 MHz according to regulatory domain. The objective is that the secondary user can utilize the full band on which the primary user operates. On the other hand, the channel bandwidths in IEEE 802.11af can be adaptively changed when several adjacent TV channels are available [216]. The fusion node (the access point) utilizes the whole primary user band to broadcast the downlink signal to all slaves. The main design consideration here is the traditional challenge to realize coexistence between various standards that share the same spectrum[222]. However, ECMA 392 does not assume this issue as a significant problem since it applies the "win-win" business model.

D. IEEE 802.22

Compared to its younger standard counterparts, IEEE 802.22 has gone through a long process of design improvement and refining. Thus, many of the design issues have been either resolved or addressed [198]. The MAC layer provides a set of cognitive functionalities for relatively superior incumbent service protection. IEEE 802.22 applies the design approach of employing systems and hardware that are relatively more sophisticated to achieve superior incumbent detection, security, and the promised communication performance [223]. This design philosophy is expected to have an impact on cost effectiveness of the system implementation, and in turn the industry adoption for actual consumer products. There has been noticeable research effort to evaluate the performance of this standard under different channel conditions, different scenarios, and for different cognitive devices [224][225] and even different sensing methodologies [226]. Also, there is another direction of exploring the challenges in different deployment scenarios such as broadcasting transmission [227]. However, most of the effort is directed towards the implementation challenges and optimizations including the physical layer aspects such as channel estimation [228] or even a complete modem implementation for the cognitive radio [229][230].

VIII. Future Developments and Open Issues

A. CRN Assistance and Spectrum Scarcity for M2M Communications

The current network protocols and infrastructure are optimized for human-oriented traffic characteristics. Lately, an entirely different paradigm of communication has emerged with the inclusion of "machines" in the communications landscape. In that sense, machines/devices are able to communicate with each other exchanging information and data without human intervention. Since the number of connected devices/machines is expected to surpass the human-centric communication devices by tenfold, machine-to-machine (M2M) communication is expected to be a key element in future networks [231]. With the introduction of M2M, the next generation Internet or the Internet-of-Things (IoT) has to offer the facilities to connect different objects together whether they belong to humans or not. The ultimate objective of M2M communications is to construct comprehensive connections among all machines distributed over an extensive coverage area. Due to the radical change in the number of users, the network has to carefully utilize the available resources in order to maintain reasonable quality-of-service (QoS). Generally, one of the most important resources in wireless communications is the frequency spectrum. To support larger number of connected devices in the future IoT, it is likely to add more degrees of freedom represented in more operating frequency bands. However, the frequency spectrum is currently scarce and requiring additional frequency resources makes the problem of supporting this massive number of devices even harder to solve. In fact, this issue is extremely important especially for the cellular architecture since the spectrum scarcity problem directly influences the reliability and the QoS offered by the network.

The idea of cognitive radios was originally proposed to offer more efficient utilization for the RF spectrum. In this context, there are two approaches to apply the CR concept in wireless M2M networks. The first approach [232] assumes that there can be two types of base stations, one for typical user equipments and other for M2M devices coexisting with each other, to relax signalling congestion and management burden. In this case, M2M devices seek to opportunistically use the spectrum when other devices are idle. This can be done through coordination between the corresponding base stations. Once a radio resource is occupied by M2M communications, this radio resource is regarded as suffering from server interference and will not be utilized by legacy communication. Even though this approach is simple to apply, it can degrade the QoS of legacy applications especially when the number of MTC devices is very large. A second approach assumes that the network will sense unlicensed bands to find extra vacant bands [196][233]. If complexity permits, more than one unlicensed band per cell can be utilized by a smart base station to further increase the number of devices. This can be implemented by introducing a new layer for spectrum management to support cognition over the unlicensed bands. In that sense, CRN does not only provide solutions to the under-utilization problem of the frequency spectrum, but it

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also becomes essential to enable the realization of the next generation internet.

B. Cooperative Sensing Challenges

Device level decision is the basic unit for better performance when cooperative sensing is utilized. Indeed, the requirement of the signaling links is hindering its actual realization. Cooperative sensing techniques require a large number of cooperating devices in order to reduce the probability of false alarms to acceptable levels. This in turn increases the excessive latency. For example, by the time a decision is made, the spectrum availability and network conditions might already have changed. In this context, future research should focus on investigating suitable decision/data fusion schemes which can reduce the cooperation burden as well as the delay and at the same time can achieve the desired performance targets. Furthermore, existing cooperative sensing literature mostly considers homogeneous nodes which behave identically as they have the same capabilities. However, in practice, the cooperating nodes are much likely to be heterogeneous such that the nodes may not have the same SNR requirements, the same number of antennas, sampling rates ... etc. In this font, it is a real challenge for researchers to study suitable cooperative schemes which can combine sensed information from heterogeneous nodes to provide reliable decision with less overhead.

C. Compressive Sensing Challenges

Most existing compressed sensing techniques assume system models contaminated with either Guassian noise with the known variance or the bounded noise. Furthermore, most compressed sensing based works in the context of CR communications assume ideal operating conditions in terms of noise, channel and transceiver hardware components and there exist only a few works investigating compressed sensing based techniques with practical imperfections such as noise uncertainty [234]. In practice, various imperfections can happen such as noise uncertainty, channel correlation, noise correlation, and quantization noise, RF impairments, RF non-linearities. These imperfections may lead to significant performance degradation of a compressed sensing based techniques in practical CR communications. Therefore, an important future step is to study the compressed sensing based approaches in the presence of practical imperfections.

IX. Conclusion

This paper has provided the recent advances in the spectrum sensing framework as the main enabling technology for the interweave cognitive radio model. In addition to presenting an overview for the conventional narrowband and wideband spectrum sensing approaches, the advances in each direction are addressed as well. An overview for the new approaches to tackle the trade-off between system performance and practical system implementations for both narrowband and wideband spectrum sensing branches are provided. Furthermore, the up-to-date effort in the direction of cooperative sensing is introduced for each of the cooperative communication element including hypothesis testing, control channel and reporting, data fusion, and knowledge base. The practical system considerations with respect to implementation have been presented. The advances for different aspects for the implementation side such as complexity, power consumption, throughput, and performance are considered. The recent industrial effort in terms of standard specifications is addressed while presenting the main concepts for the recent cognitive radio standards. The next generation cognitive radio networks such as the heterogeneous model and the cooperation with IoT is demonstrated as part of the advances to cognitive radio networks.

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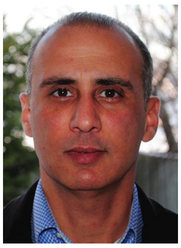

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