Cognitive Radio: A Survey on Spectrum Accessing and Sensing Schemes

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***Abstract*— Radio spectrum is a precious resource which is shrinking progressively due to inventions of many applications incorporating in wireless communication systems. Spectrum utilization efficiency can be improved by exploiting opportunistic radio, a promising candidate for the next generation wireless radio. In the emerging paradigm of opportunistic radio networks, unlicensed radio users are allowed to transmit opportunistically on a temporarily empty frequency band that is not currently being accessed by the licensee. Cognitive radio (CR) is considered as a promising solution to the spectrum scarcity problems that allows proficient use of radio resources through accessing spectrums opportunistically. In order to support spectrum accessing functionality, the CR users have the duty to sense the radio environment dynamically for being aware of the highly prioritized licensee while spectrum sensing is one of the most challenging tasks in the promising CR networks. In this paper, various aspects for dynamic spectrum access (DSA) schemes are presented, together with a brief discussion of the pros and cons of each algorithm of spectrum sensing methodologies from CR perspective. Additionally, the future challenges are investigated that are associated with DSA and spectrum sensing techniques. Special attention is paid to the challenges associated with wideband sensing.**

Index Terms*— Dynamic spectrum access; wideband spectrum sensing; compressive sampling; analog-to-information converter; spectral estimation.

I. INTRODUCTION

The demand for radio frequency (RF) spectrum is tremendously increased in time with the proliferation of various wireless services employing static frequency allocation planning, leading to spectrum scarcity and to cope up with this demand, cognitive radio (CR) is a solution of huge prospect. CR can be described as an intelligent and dynamically reconfigurable radio which itself can regulate its radio parameters in temporal and spatial domain according to modifications in the surrounding environment. The use of CR technology allows in principle flexible and agile access to the spectrum as well as improving spectrum efficiency substantially. It has been reported by the federal communications commission (FCC) that localized temporal and spatial spectrum utilization is very poor [1]. Currently, new spectrum policies are being developed by the Federal Communications Commission (FCC) that will allow CRs to opportunistically access a licensed primary user (PU) band, when the PU does not occupy a frequency band. The growing interest of dynamic spectrum access (DSA) in CR is specially related to the fact that it is considered as a possible solution of the static spectrum allocation policies and a number of DSA models are proposed in open literatures [2-6]. In order to dig up the benefit from DSA, knowledge about the PU vacant bands are necessary and CRs should be able to independently detect spectral opportunities without any assistance from PUs; this ability is called spectrum sensing, which is considered as one of the most challenging tasks in CR networks [7-8]. In particular, a CR should explore the information about inactive PU bands and geographical location which is then opportunistically utilized by the CRs, thus leads enhanced spectrum efficiency.

Several narrowband spectrum sensing algorithms have been studied in the literature [3], [6-9] and references therein, including matched-filtering, energy detection, and cyclostationary feature detection. To obtain higher opportunistic throughput for different multimedia data services wideband spectrum sensing [10-12] is necessary for future wireless networks as Shannon’s formula says that, under certain conditions, the maximum theoretically throughput is directly proportional to the spectral bandwidth. However, conventional wideband spectrum sensing techniques becomes challenging due to high sampling frequency functioning at or above Nyquist rates could lead implementation complexity [13]. There are several wideband sensing approaches exploiting sub-Nyquist sampling commonly known as compressive sensing (CS), thus employs relief of high-speed digital signal processing (DSP) units and is elaborately illustrated in [13-17].

This paper presents an introductory tutorial on DSA schemes and spectrum sensing for CR viewpoint featuring both noncooperative and cooperative sensing strategies and provides comparative analysis among various detection techniques. We begin with a short review of DSA management methodologies and point out the characteristic features of DSA in Section II. In Section III, we would like to deliver a comprehensive classification of narrowband and wideband spectrum sensing schemes. A variety of conventional and emerging spectrum sensing techniques based on recent advances in detection of narrowband and wideband signal at CR nodes are illustrated as long as with their performance comparisons. This is followed by a detailed discussion on the limitations associated with spectrum sensing at individual CR terminal. Section IV presents some open research issues in DSA and future research directions of spectrum sensing and finally some conclusions are drawn in Section V.

II. DYNAMIC SPECTRUM ACCESS IN CR NETWORKS

Nowadays, wireless communication is suffered from spectrum scarcity due to newly developed various wireless applications of them most of which are multimedia applications. FCC disclosed that the licensed frequency bands are poorly utilized most of the time and a particular geographic location mainly due to the conventional command and control type spectrum regulation (i.e., fixed spectrum allocation) policy that has prevailed for decades [1],[6]. In order to use the unused licensed spectrum holes or white spaces, effort is put on achieving DSA. CR can manage in order to mitigate the spectrum scarcity problem by enabling DSA scheme, which allows CRs to identify the unemployed portions of licensed band and utilize them opportunistically as long as the CRs do not interfere with the PUs communication. A taxonomy of the DSA scheme [6 and references therein] is illustrated in the following figure (Fig.1). In order to meet the massive demand of radio spectrum, the CR network has opened up flexible and agile access to the wireless radio resources, which in turn, improve spectrum utilization efficiency [2]. CR is a dynamically reconfigurable radio which can adjust its radio parameters in response to the surrounding environment. The state of art of DSA schemes will be discussed in this section.

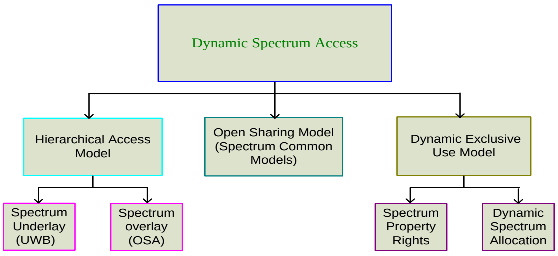

Fig.1: Fundamental classification of dynamic spectrum access

A. *Hierarchical Access Model*

In this model, a hierarchical access pattern for the PUs and CRs have been discussed. The fundamental concept is to open licensed spectrum to CRs while limiting the interference perceived by the PUs. This model can be categorized as two different approaches for sharing the spectrum, i.e., spectrum underlay and spectrum overlay. Spectrum underlay (Fig. 2a) exploits the spectrum by using it despite of a PU transmission, but by controlling the interference within a prescribed limits. This can be obtained by using spread spectrum techniques, resulting in a signal with large bandwidth but having low power spectral density (PSD), which can coexist with PUs. In an underlay system, regulated spectral masks impose stringent limits on radiated power as a function of frequency, and perhaps location [5]. Due to power limitation, underlay radios (URs) must spread their signals across large bandwidths with lower energy, and/or operate at relatively low rates. An advantage of such a system is that radios can be dumb, they do not need to sense the channel in order to defer to PUs. The underlying principle is that the PUs are either sufficiently narrowband or sufficiently high-powered or the URs are sufficiently fast frequency hopping with relatively narrow bandwidth usage in each dwell, so that there is little interference from the URs. As the signal is spread out over a large bandwidth, URs can use spread spectrum signalling systems, wideband orthogonal frequency division multiplexing (OFDM) or impulse radio. Because of the large front-end bandwidth, URs are susceptible to interference from a sort of co-existing sources, including relatively narrowband signals from PUs. In summary, URs tend to be complex in terms of hardware implementation, frontend interference suppression, high-fidelity low-power high-rate ADC circuit design, and estimation and equalization of long delay-spread channels. An UR could sense the spectrum as to shape its transmitted signal to avoid band congestion which requires reliable spectrum sensing like spectrum overlay systems.

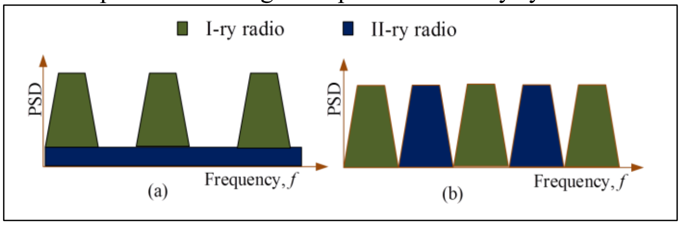

Fig. 2: (a) Spectrum Underlay, (b) Spectrum Overlay (e.g. Spectrum Pooling or OSA)

Spectrum overlay intends to use empty PU bands in an opportunistic way without interfering PUs, indicating that the spectrum should be monitored periodically by the CRs and seeking absence of PUs to utilize the unoccupied band. OSA can be applied in either temporal or spatial domain. For the first case, CRs exploit temporal spectrum opportunities resulting from the bursty traffic of PUs and in latter case, CRs aim to exploit frequency bands that are not being occupied by the PUs in a specific geographic location [5], e.g., the reuse of various TV white spaces that are very often used for TV broadcasting (e.g., digital TV transmission) in a particular geographic location. In the TV broadcasting system, TV-bands assigned to adjacent regions are different to avoid co-site interference. This results in unused frequency bands varying over space. Spectrum overlay mechanism is shown in Fig. 2b. OSA is also termed as interweaving of frequencies, is therefore done by doing some pre-coding at the transmitter to lessen the interference at the receiver. This technique is also known as dirty paper coding [5] and references therein. The majority of existing work on OSA focuses on the spatial domain where spectrum opportunities are considered static or slowly varying in time. As a consequence, real-time opportunity identification is not as critical a component in this class of applications, and the prevailing approach tackles network design in two separate steps: (i) opportunity identification assuming continuous full spectrum sensing; (ii) opportunity allocation among secondary users assuming perfect knowledge of spectrum opportunities at any location over the entire spectrum.

B. Dynamic Exclusive Use Model

In this model, the radio spectrum is licensed to a user or a service for exclusive usage under an agreement to enhance the spectrum efficiency and this model maintains the basic structure of spectrum regulation policy. Two schemes like *spectrum property rights* and *dynamic spectrum allocation* have been proposed under this model [6].

1) *Spectrum Property Rights:* Generally, when PUs do not utilize their spectrum the PUs can sub-lease those underutilized spectrum to third party thus can do spectrum trading. This type of spectrum trading can be given the right to exclusively use those resources without being mandated by a regulation authority. This approach is called spectrum property rights, as the license or the right is based on the three spectrum properties as fixed frequency band, time and a geographic location and detailed can be found in [6]. One of the most important difficulties in applying this scheme lies in the unpredictability of radio wave propagation in both frequency and space. Spectral and spatial spillover is unavoidable, unpredictable, and depending on the characteristics of both transmitters and receivers.

2) *Dynamic Spectrum Allocation:* The temporal and spatial traffic statistics are explored, which is valuable for sub-leasing long-period of applications. Sub-leasing based on traffic statistics leads to a much more flexible spectrum allocation than in the previous fixed spectrum allocation scheme. As an example, the spectrum assigned to UMTS and DVB-T can differ over temporal basis and geographic location. DSA opens new possibilities of multiple radio communications infrastructures when optimized interworking is considered. *Firstly*, to access every service operators can allocate spectrums inside a radio network according to local and temporal needs. *Secondly*, users on the move are provided with the benefit of accessing enhanced IP based mobile services on the fly and wherever they are in a cost efficient way [3]. Multiple networks regulation policy and issues in the context of temporal and spatial DSA algorithms are pointed out in [3]. The typical operational steps in temporal DSA algorithm include: a) periodic triggering of DSA algorithm, b) management of the traffic on the carriers, c) prediction of the loads on the networks and d) access decision while the goal of spatial DSA is to allocate spectrum to radio access networks (RANs) according to the traffic requirements in each location using DSA scheme. Still, the spectrum allocations of different RANs belong to adjacent DSA areas should not overlap in the same portion of spectrum to avoid interference. A guard band of suitable size guarantees the coexistence of the different radio systems. The structure of an usual spatial DSA scheme can be summarized in three main steps: a) calculating the spectrum overlap, b) performing initial assignment and c) optimize the spectrum usage.

C. Open Sharing Model

The two models addressed in dynamic exclusive model deals with the opportunistic usage of the license band, while open sharing model accepts an empty band focused only peer users. Mostly, technical features of this model are close to the traditional medium access control (MAC) issues and this model can be categorised as centralized and distributed modes. In a *centralized model*, there is one cognitive manager (CM) presents controlling the entire CR environment. The CM can be an intelligent system and the problem can be seen as an optimization problem. The centralized approach considers that there is a reliable pilot channel connecting each CRs to the CM. In fact, the CM has great influence on the proficient spectrum usage, as well as reconfigure other transmission parameters e.g., transmit-power, SNR, modulation scheme, etc. In this model, coordination between pairs or coalitions of pairs can facilitate the spectrum sensing, competent use of radio resources and enhance the quality of the information by which the pairs can rely to make their decisions. Centralized dynamic spectrum access can be studied in two ways as optimization approach and auction-based approach [7]. With an optimization-based approach, different types of optimization problems can be formulated (e.g., convex optimization, assignment problem, linear programming, and graph theory). While auction based spectrum access mainly states the spectrum trading in a business oriented viewpoint. Here, every CR offers price for a specific band of interest to the spectrum owner or broker and the highest bidder will then get access to utilize it for a certain time period. Though, in most of practical scenarios e.g., in ad-hoc CR networks, incorporating a CM is problematic [7] while distributed DSA suits well in such networks. As there is no CM present, every CR user has to gather, exchange, and process the information about the surrounding environment independently. Further, independent decisions would be taken by the CRs based on available radio environment information thus, the CRs obtain its performance objective under interference constraints. In the following we will present methodologies where a CM is absent in the collaborative environment and how the learning capability can be employed in such cooperative scenario.

1) *Cooperative or Non-cooperative Behavior:* due to the absence of a CM, a CR user can adopt either cooperative or non-cooperative behavior. When a CR operating in cooperative mode will make a decision on spectrum access concerning the performance of the overall network (i.e., a collective objective), however, this decision may not result in the highest individual benefit of individual CR user. On the other hand, a CR user with non-cooperative behavior will make a decision that is opposite to cooperative behavior i.e. it wants to maximize the individual performance while without concerning about the network performance. This behavior is also known as selfish behavior of a CR terminal. In [5], it is discussed that game theory and iterative water filling approach can be used for the distributed DSA. To pertain game theory to the process of decision making in a CR, the decision making process needs to be modelled as a game. First of all, it should be checked whether it is a centralized or a distributed DSA model (i.e., the centralized or the distributed open sharing model). Secondly, it must be decided which performance metric (i.e., the throughput or the latency) is to be

optimized. Thirdly, all information about any CR in the environment of the decision maker needs to be collected (i.e., the possible actions and the preferred strategy).

With non-collaborative behavior, all network information is gathered and processed locally by each CR nodes while without interactions among the CRs. In contrary to collaborative behavior, the CR users can exchange network information with each other. Typically, collaboration among CR users to exchange network information is required to achieve collective goal. In fact, if the CRs are collaborative, they could be either cooperative or non-cooperative as the CRs may agree to reveal some information (e.g., the chosen spectrum access action), but they make a decision to achieve their own objectives (non-cooperative), rather than a group objective (cooperative). A protocol will be needed to exchange network information for the collaboration among CRs.

However, when a CR node possesses non-cooperative behavior, the network information has to be observed and learned individually. Therefore, learning ability plays an important role for sorting out intelligent decisions concerning radio parameters in the CR distributed DSA management systems. The learning process can be either non-collaborative or collaborative. In the case of non-collaborative learning, the knowledge about the system is produced by each individual CRs without interaction with other nodes. On the other hand, the CRs can exchange network information as well as to process and produce overall system knowledge and based on this a CR can make the decision whether to achieve the group objective or its individual objective.

III. Spectrum Sensing Techniques for CRs

Radio spectrum is classified as *black spaces*, *grey spaces* and *white spaces* based on the usage of it [3]. CRs take the advantages from grey and white spaces by opportunistic use. To reuse the spectrum, spectrum sensing is necessary and there are different approaches for CR to grasp the spectrum sensing issues. Based on the band of interest, spectrum sensing techniques can be classified as narrowband and wideband. The CR is liable to identify the presence of PU transmission hence it is called transmitter based detection or stand-alone detection [3] which is addressed for military and many civilian applications for signal detection, automatic modulation classification, to locate radio source and to perform the jamming activities in communication networks. As, no collaboration is apparent among the CRs hence this method cannot identify hidden PUs. In this section, some of the most common transmitter based sensing schemes are addressed.

A. Narrowband Sensing

The most efficient way to sense spectral opportunities is to detect active primary transmitters in the vicinity of CRs. Here, the term "narrowband" implies that the bandwidth of interest is less than the coherence bandwidth of the channel. We would like to address a number of narrowband spectrum sensing methods (Fig. 3) in the following:

1) Energy Detection: A well-known method for spectrum sensing is based on energy detection (ED) where received PU signal energy is measured in a specific time period of a particular frequency band of interest. This technique comprises low computational and implementation complexities, thus leads to its popularity. In addition, the notable advantage of this scheme is that it does not require any prior information about the PUs transmission [8]. While the signal received at CR node, the PU status is determined by comparing the output of the ED with a threshold which depends on the noise floor. The performance of the detection algorithm can be determined by two probabilities as the probability of detection P_d and probability of false alarm P_f. ED is considered a non-coherent detection method where knowledge of noise variance is adequate for choosing threshold to obtain a predetermined false alarm rate. Meanwhile, to design a standard CR system higher value of detection probability P_d as well as lower value of false alarm probability P_f is anticipated. The decision threshold λ_E can be selected for finding an optimum balance between P_d and P_f however this requires knowledge of noise and detected signal powers. The noise power can be estimated, while the signal power is difficult to predict as it changes depending on the transmission characteristics and the distance between the CR and PU [8]. A major drawback 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.

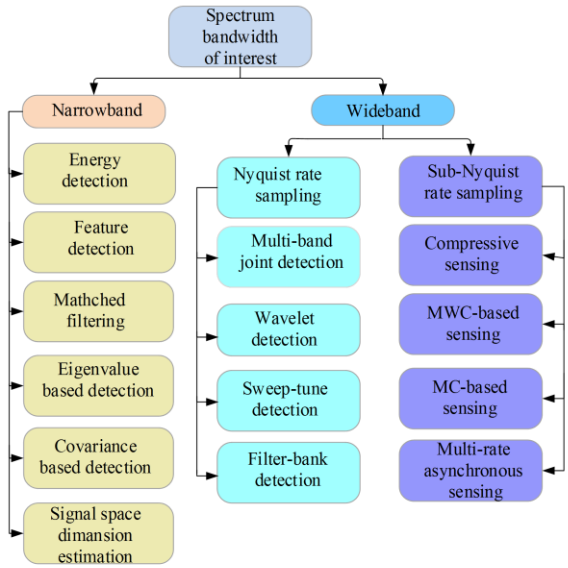

Fig. 3. Hierarchy of spectrum sensing in cognitive radio

2) Feature Detection: Another promising spectrum sensing technique is based on feature detection. A feature is unique and inherent characteristics of the PUs signal and it is drawn as pilot signal, segment sync, field sync, and also the instantaneous amplitude, phase and frequency [9]. In practice, these features are commonly perceived many signals employed in wireless communication and radar systems [8]. Cyclostationary feature detection method detects and distinguishes between different types of PU signals by exploiting their cyclostationary features. Nowadays, analog to digital conversion has made the use of signal transformation practical in order to discover a specific feature. The fundamental and promising feature detection technique is based on the cyclic feature [8]. Cyclic-feature detection approaches are based on the fact that modulated signal are usually coupled with sinusoidal carriers, hopping sequences, cyclic prefixes, spreading codes, or pulse trains, which result in a built-in periodicity [9]. Cyclostationary features are originated by the periodicity in the signal in statistical manner like mean and autocorrelation or they can be intentionally used in order to sustain the spectrum sensing by analyzing a spectral correlation function (SCF) or cyclic spectrum [9]. This detection algorithms can differentiate noise from the signals as the noise is wide-sense stationary (WSS) with no correlation while modulated signals are cyclostationary with spectral correlation due to the redundancy of signal periodicities. Cyclostationary feature detector can overcome the energy detector limits in detecting signals in low SNR environments [4]. In fact, signals with overlapping features in the power spectrum, can have non-overlapping features in the cyclic spectrum [8].

Waveform based or coherent sensing is another promising feature detection scheme which uses patterns like preambles, repeatedly transmitted pilot patterns, spreading sequences, etc. in wireless systems. In the presence of a known pattern, sensing can be performed by correlating the received PU signal with a known copy of itself [8] which provides a barrier of this type of sensing. It is shown that waveform based sensing outperforms energy detector based sensing in terms of reliability and convergence time. Likewise, the performance of the sensing algorithm increases if the length of the known signal pattern increases. The OFDM waveform is altered before transmission to generate cycle-frequencies at different frequencies which is effective to categorize the signals [8]. Again if the number of features generated in the signal is increased, the robustness against multipath fading is improved considerably at a cost of bigger overhead and bandwidth loss. The main advantage of the feature detection is easily distinguishable the signals from the noise (even under low SNR value). In contrast, feature detection requires long observation time and higher computationally complexity as it requires to calculate a two-dimensional function dependent on both frequency and cyclic frequency and also this scheme needs a priori information of the PUs.

3) Matched Filtering: The advantage is achieved by correlating the received signal with a template for detecting the presence of a known signal in the received signal. However, it requires apriori knowledge of the PUs and requires CRs to be equipped with carrier synchronization and timing devices that leads enhanced implementation complexity. At a CR node, to maximize the output SNR for a certain input signal a matched filter is designed which belongs to the linear filter [6]. Matched filter detection is applied if a CR has apriori knowledge of PUs transmitted signal. Therefore, matched-filtering is known as the optimal strategy for detection of PUs in the presence of stationary Gaussian noise. The main advantage of matched filtering is the short time as it requires only $O(1/SNR)$ samples to meet a given probability of detection constraint as compared to other detection schemes. As matched filtering requires a CR node to demodulate received PU signals and thus, it requires a priori information of the PUs transmission features such as bandwidth, operating frequency, modulation type and order, pulse shaping, and frame format [9]. Further, if the CRs want to process a variety of signals, the implementation complexity of sensing unit is impractically large. In addition, this scheme consumes large power as various receiver algorithms require to be executed for detection and a priori knowledge requirement of PU signals place it in challenging to implement in CR networks [6].

4) Covariance Based Detection: Another narrowband spectrum sensing is based on covariance based detection which exploits the inherent correlation in received signals at the CR terminal ensuing from the time dispersive nature of wireless channel and oversampling of received signal [9]. Usually covariance based detection does not require any prior information about the PU signal or noise. Conversely, if some a priori knowledge concerning the correlation of PU signal becomes available, this helps to develop sample covariance matrix making the decision test statistic more reliable. In particular, received PU signal samples in MIMO-CR systems are spatially correlated as they originated from the same PU signals. Another significant feature of this detection scheme is that the noise power estimation is not a requisite here as the threshold is related to false alarm probability and number of samples of the received signal at CR. The better performance would possibly be achieved for highly correlated PU signals while the performance of this detection degrades with the uncorrelated PU signal. In multi-antenna CR systems, multiple copies of the received PU signal can be coherently combined to maximize the SNR of received signal. The diversity combining approaches of maximum ratio combining (MRC) and selection combining (SC) are analyzed for ED in [9] and the references therein. Although, MRC gives optimal detection performance but is difficult to implement as it necessitates a priori knowledge of PU signal and channel in the form of eigenvector corresponding to maximum eigenvalue of the received PU signal covariance matrix and the eigenvector can be estimated using the received PU signal samples.

5) Eigenvalue Based Detection (EBD): If the received signals exhibit time correlation as well, the concept of EBD can be extended to incorporate joint space–time processing [9]. This approach is generally known as covariance based detection, EBD being its one special case where the eigenvalues of received signal sample covariance matrix are used for PU signal detection. In [9], authors have indicated that number of significant eigenvalues is directly related to presence/absence of data in received PU signal and may be exploited to identify the PU occupancy status.

B. Wideband Sensing

Wideband spectrum sensing techniques aim to sense a frequency bandwidth that exceeds the coherence bandwidth of the channel (e.g., 300 MHz - 3 GHz). In the wideband regime, traditional narrowband sensing methods cannot be casted off directly for performing wideband spectrum sensing, as of making a single binary decision (PU present or absent) in the entire wideband signal, thus cannot locate individual spectral opportunities that lie within the wideband spectrum. As shown in Fig. 3, wideband spectrum sensing can be broadly categorized into two types; Nyquist rate wideband sensing and sub-Nyquist wideband sensing. The former type processes digital signals taken at or above the Nyquist rate, while the latter acquires signals using sampling rate lower than the Nyquist rate. In the rest of this paper, an overview of the state-of-the-art wideband spectrum sensing algorithms will be provided.

1) Nyquist Rate Wideband Sensing: A conventional approach of wideband multicarrier signal sensing is to directly acquire the entire signal using a standard ADC and then use DSP algorithms to detect spectral opportunities to CRs. A promising solution for the multicarrier wideband sensing would be the filter bank schemes as presented in [10]. A special class of filter banks (prototype filters) was proposed to detect the opportunity in the wideband spectrum. Besides, those filter banks can be used for the multicarrier communications for the CR nodes. The baseband can be directly estimated through using a prototype filter, and other bands can be obtained through modulating the prototype filter [10]. From a filter bank point of view, in each subcarrier, the corresponding portion of the input wideband signal was down-converted to base-band, low-pass filtered, and then decimated. Later, this technique finds the correlation properties of the low rate samples comes from each subcarrier band. Therefore, the same filter bank can be used demodulation as well as signal analysis. In fact, this scheme offers parallel arrangement of the filter banks demanding a large number of RF modules, which put limit to implement it in economy CR systems design.

Moreover, a wavelet approach to efficient spectrum sensing algorithm is proposed by using a standard ADC in [11]. There, the wideband spectrum has decomposed into a train of consecutive subbands, where the power spectral property is regular within each subband but exhibits discontinuities and irregularities between adjacent subbands. In order to locate the singularities and irregular structures of the wideband PSD, the wavelet transform is an attractive mathematical tool, chosen for this scheme. This algorithm works well for the wide range of bandwidth to simultaneously identify all piecewise smooth subbands, without having prior information about the number of subbands within the band of interest. Furthermore, it leads more benefit than multiple narrowband band-pass filters, in terms of implementation costs and flexibility in adapting to dynamic PSD structures.

Furthermore, a novel multiband joint spectrum detection was introduced in [12], which jointly detects the PU occupancy status over multiple frequency bands rather than over one band at a time where the spectrum sensing problem was considered as a class of optimization problems. Here, the wideband signal was firstly sampled at Nyquist rate, after which a serial to parallel conversion circuit was introduced to divide sampled data into parallel data streams. Time domain wideband signal was converted to frequency domain spectrum by using standard FFT transformation. The whole wideband spectrum was then divided into successive sequences of narrowband spectra. Lastly, binary hypotheses tests was been performed at the bank of multiple narrowband detectors to find the empty PU bands for opportunistic usage by the CRs. By using proper optimization technique the detection threshold was chosen mutually as to maximize the aggregate opportunistic throughput in an interference-limited CR network. This strategy allows CRs to take maximum advantage of the unused spectra and limit the subsequent interference.

2) Sub-Nyquist rate Wideband sensing: The high sampling rate as well as obligation of diverge DSP utensils in Nyquist systems set limit to explore in wideband sensing hence, sub-Nyquist approaches are drawing more and more attention in both academia and industry [13-17]. Sub-Nyquist wideband sensing refers to the procedure of acquiring wideband signals/spectrums using sampling rates lower than the Nyquist rate and detecting spectral opportunities in the wideband. Two important types of sub-Nyquist wideband sensing are illustrated so far in the open literatures; wideband CS and wideband multi-channel sub-Nyquist sensing. In the subsequent paragraphs, we will deliver some discussions and comparisons regarding these wideband sensing algorithms.

a) Compressive Sensing: As wideband spectrum is inherently sparse due to its low utilization and capitalizing the sparseness, CS becomes a promising approach to recover the wideband signal (or data) expending only partial measurements. In the CS framework [14] a real-valued, finite-length, one-dimensional time-variant signal $x(t), 0 \leq t \leq x$, can be denoted as a finite weighted sum of orthonormal basis functions (e.g., discrete cosine transform, discrete Fourier transform (DFT), etc.) as follows:

$$x(t) = \sum_{i=1}^{N} b_i \psi_i(t) = \psi b \quad (1)$$

where only a small number of basis coefficients b_i signifying the sparsity of wideband signal $x(t)$. Let the acquisition of an $\mathrm{N} \times 1$ vector $\mathbf{x} = \boldsymbol{\psi}\mathbf{b}$ where $\boldsymbol{\psi}$ is the sparsity basis matrix of size $\mathrm{N} \times \mathrm{N}$ and $\mathbf{b}$ an $\mathrm{N} \times 1$ vector with S, the number non-zero entries in b_i. In case of sparse signals, an S-sparse depiction of x can be realized as a linear combination of S orthonormal basis functions, with $S \ll N$ and it can be obtained by considering only S of the b_i coefficients in (1) those are significant number of non-zero (NNZ) elements, while the rest $(\mathrm{N} - \mathrm{S})$ of values representing less significant elements or zeros leads to the basis of the transform coding [15]. It is confirmed that the original signal x can be reconstructed by using $M = S\mathcal{O}(\log N)$ non-adaptive linear projection measurements against a measurement matrix $\boldsymbol{\Phi}$ of size $\mathrm{M} \times \mathrm{N}$ which is incoherent with sparsifying basis, $\boldsymbol{\psi}$ [15]. The formation of measurement matrix $\boldsymbol{\Phi}$ is given by choosing elements that are drawn independently from a random distribution functions, e.g. Bernoulli, Gaussian, etc. thus the measuring expression, $\mathbf{y}$ can be written as

$$\mathbf{y} = \boldsymbol{\Phi}\mathbf{x} = \boldsymbol{\Phi}\boldsymbol{\psi}\mathbf{b} = \boldsymbol{\Theta}\mathbf{b} \quad (2)$$

where $\boldsymbol{\Theta} = \boldsymbol{\Phi}\boldsymbol{\psi}$ is a matrix of size $\mathrm{M} \times \mathrm{N}$. As $\mathrm{M} \ll \mathrm{N}$, the dimension of $\mathbf{y}$ in (2) is much lower than that of $\mathbf{x}$, thus there are theoretically infinite solutions to the equation. However, if the condition that $\mathbf{x}$ is S-sparse is satisfied and with a proper condition of measurement matrix, $\mathbf{\Phi}$ and the recovery of $\mathbf{x}$ can be achieved with only $\mathbf{y}$ measurements by solving the l_1-norm minimization problem [14-15] as follows

$$\hat{\mathbf{b}} = \arg \min_{\mathbf{b}} \|\mathbf{b}\|_1 \quad \text{such that } \mathbf{\Theta b} = \mathbf{y} \tag{3}$$

This is a convex optimization problem solved as a linear program celebrated as basis pursuit (BP), iterative greedy algorithms, etc.

Though, CS scheme has concentrated on finite-length and discrete-time signals and to acquire sparse, band limited signals an analog to information converter (AIC) was introduced in [16] which is also entitled as random demodulator (RD). An AIC is theoretically similar to an ADC operating at Nyquist rate followed by the above mentioned CS procedure. The AIC-based model consists of a pseudo-random number generator, a mixer, an accumulator, and a low-rate sampler. To decline design time, behavioral models of AIC yield the same results as the costly circuit models, but reduce the complexity of simulation [16]. Usually, sub-Nyquist rate samples are employed for wideband spectral reconstruction and classify the frequency bands via PSD, wavelet-based edge detector tailored to the coarse sensing task of vacant spectrum identification. The advantage of this scheme is robust to noise and can afford less number of samples.

b) Multi-channel Sub-Nyquist Wideband Sensing: Conventional CS scheme for analog signals require prior information about the signal sparsity pattern. The spectral estimation becomes more challenging without having the spectral support i.e., blind sub-Nyquist sampling of multiband signals. The authors in [13] presented a mixed analog-digital spectrum sensing method also known as modulated wideband converter (MWC) that has multiple sampling channels, with the accumulator in each channel replaced by a general low-pass filter. A unified digital architecture for spectrum-blind reconstruction was introduced in that scheme and the architecture consists of an analog back-end and digital support recovery, the crucial part in this technique. Very few number of measurements are required for the digital operations in support recovery, thus introducing a short delay and making computationally efficient. When the signal support set is identified, numerous real-time computations are possible with this scheme. The multi-channel structure in MWC provides robustness against the noise.

Another multi-channel sub-Nyquist sampling approach employs multi-coset (MC) sampling which incorporates the advantages of CS when the frequency power distribution is sparse, but applies to both sparse and non-sparse power spectra [17]. An innovative PSD estimator was presented in their works for continuous wide-sense stationary (WSS) random processes producing both compressive and non-compressive estimates at finite resolutions. The method estimates the average PSD within specific sub-bands of a WSS random process. Hence, it produces piecewise constant estimates that are in contrast to those supported on a discrete frequency grid, while the DFT has been employed to sort the periodogram. Through proper estimating the PSD, the estimator minimized the spectral aliasing effects that occurs in each channel to underpin the formation of a linear system of equations. Therefore, MC sampling is often implemented by using multiple channels with different sub-sampling rates while each sampling channels having unlike time offsets. In order to obtain a unique solution for the WSS random process from the compressive measurements, the sampling pattern should be carefully designed in [17] as a result MC sampling approach requires the channel synchronization for a robust spectral reconstruction.

An alternative sub-Nyquist sampling scheme also accredited as multi-rate asynchronous wideband sub-Nyquist sampling (MASS) scheme was presented in [18] to perform wideband spectrum sensing. In that scheme, the sampling of the wideband signals was performed by the parallel low-rate samples. Consequently, spectral aliasing generated by the sub-Nyquist samples is persuaded in each sampling branch to wrap the sparse spectrum occupancy map onto itself, as of the low utilization factor of the spectrum. Specifically, in the same observation time, the numbers of samples in multiple sampling channels are selected as different consecutive prime numbers [18]. Additionally, this scheme only acknowledge the amplitudes of sub-Nyquist spectra are of interest, such a multi-rate wideband sensing approach was perceived robust against lack of time synchronization between multiple sampling channels, leading to lower implementation complexity, better data compression capability, to have excellent performance in realistic wireless channels, and is more suitable to implement in CR networks.

IV. OPEN RESEARCH ISSUEES IN SPECTRUM SENSING

In this section, we would like to focus some research challenges that outstretched while implementing the CR scenario in practical cases. Especially, attention is paid to the issues related to the wideband sensing for future CR networks.

A. Cooperative Wideband Sensing

Research is still carried out for deploying the dynamic spectrum management; the received PU signal (either narrowband or wideband) at a single CR terminal may be severely degraded, basically due to hidden terminal problems, multipath fading or shadowing problems, lead to sensing performances in a challenge. Such a scenario can be employed with cooperative sensing strategies to obtain highly reliable detection performance while the computational complexity and hardware constraints push those schemes into challenge. Cooperative spectrum sensing is considered as a solution to some common problems. Several approaches of this kind was proposed in [8] and the references therein. Usually, control channels can be employed using suitable methodologies schemes to share common spectrum sensing outcomes. When considering centralized and distributed sensing, optimization technique could be a good choice to implement in both data and decision fusion. There are several fusion schemes presented in [19] with their performances wireless network which could be explored in cooperative CR environment. In fact, in a distributed CR network, the wideband signal is observed by different CRs, while each CRs sense a precise spectral components with compressive measurements. Those compressed data from different CR nodes are fused together at the fusion center and exploit the spectral opportunities in entire wideband in order to save the total number of measurements at CR node leads to computationally efficient. As the data transmission burden is too high for control channels in such a data fusion method, thus, to lessen the data load, decision fusioning is introduced when each CR is able to detect wideband spectrum independently and at the global decision is originated from fusing the local decisions. When the CR nodes perceive fading or shadowing independently, in such a scenario cooperative sensing performs better. *Flexible radio*, will possibility be employed for future wireless network; which will be increasingly complex and certainly heterogeneous in nature and the idea of flexible radio will play a vital role in the future wireless communications that must satisfy the scalability, adaptability, reconfigurability, modularity, and many more.

B. Sparsity Basis and Level Selection

Practically most of the CS techniques assume that the signal is sparse in some suitable basis functions (frequency domain) i.e., the sparsity basis is a Fourier matrix while estimating wideband spectrum. The theory of CS states that the more the sparsity the better would be the signal estimation which directs to better detection performance [21] at the CR node as shown in Fig. 4. In future, the spectrum usage improves in cellular networks and the sparsity in Fourier domain shrinks while sparsity may exist in other domain (e.g., sparsity based on mathematical functions). Therefore, forthcoming CR receiver exploiting CS will have the capability to find the effective basis functions which will computationally efficient to estimate dynamic-sparse spectrum and thus minimizes prohibitive energy cost.

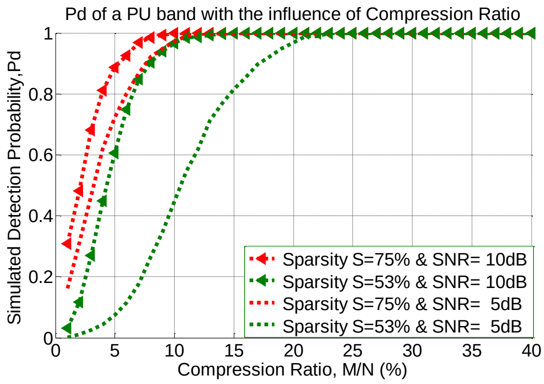

Fig. 4. Detection performance as a function of compressive samples

Hence, one possibility for future CR would be to perform the sparsity pattern recovery [20] based on the PU received signal. Another promising candidate will be exploiting spectrum "blind" sub-Nyquist wideband sensing, where a priori information of sparsity pattern is insignificant for the spectral estimation. In most of CS schemes, the required number of compressive measurements will proportionally varies with the sparsity level of wideband signal. Therefore, to calculate the exact number of compressive measurement for doing wideband spectral estimation sparsity level estimation is often required. Yet, due to the dynamic behavior of the PUs and time variant fading channels, the sparsity level of wideband signal is often time-varying and difficult to estimate. This type of uncertainty in sparsity level will be studied in future CR networks for the minimum number of compressive measurements which will also be energy efficient.

V. Conclusion

In this paper, various aspects and issues of DSA and spectrum sensing in CR networks have presented. A variety of detection techniques have been briefly studied, compared and classified in this article. We found that spectrum blind detection methods are most generic in their application and are robust to all kinds of channel/system uncertainties. Moreover, they provide highly accurate results at reliable complexity. However, if a CR functions independently lead to drastic sensing performance degradation in multipath fading or shadowing environment which occurs in practical wireless networks. Hence, cooperative spectrum sensing could provide a mature solution of this type of problems. In summary, future research is envisioned to be focused more on implementation-friendly, low-complexity sensing algorithms that are robust enough to timely provide requisite sensing performance with demanded reliability.

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