A Survey on Compressive Spectrum Sensing for Cognitive Radio Networks

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***Abstract*—Spectrum sensing aims at searching and finding the unused frequency bands in specific radio spectrum. It monitors the frequency bands to detect the activity of primary/licensed users and decide if secondary users can use these bands or not. In order to improve the efficiency of spectrum sensing in wideband cognitive radio networks, compressive sensing framework has been recommended and studied in many papers since it helps the system to get better and faster results using the sparse structure of the radio spectrum. Therefore, this paper represents an in-depth survey of the best requirements of compressive sensing and spectrum sensing techniques for robust combination and effective solution for wideband cognitive radio networks. It also provides examples of innovative applications of compressive spectrum sensing including IoT, smart city and 5th generation of mobile networks. To sum up some challenges and research directions related to compressive spectrum sensing technique are given at the end.**

Keywords— Cognitive radio; Spectrum sensing; Compressive sensing.

I. INTRODUCTION

Cognitive radio network (CRN) have been proposed as an attractive field of research and effective solution to improve the spectrum utilization in the next-generation of wireless networks. There exist two popular mode of spectrum access in CRN are underlay and interweave. In the first approach, the secondary user (SU) can transmit simultaneously with primary user (PU) over the same radio frequencies (RF) spectrum, while minimizing interferences with primary users , i.e., if the interference generated by SU at primary receiver is tolerable and controlled by an acceptable level [1][2]. In the second approach, the SU does not interfere with PU. It can intelligently detect unoccupied primary communication channel, named spectrum hole, and efficiently exploit them for data transmission. Indeed, the SU observes frequency bands and senses any activity of the PU, having license to use that particular part of the spectrum, to detect spectrum holes. This process is called spectrum sensing. Always transmit strategy combines spectrum underlay and spectrum interweave approaches [3][4]. In this strategy, the SU can transmit anytime and can do spectrum sensing and data transmission in parallel whether the primary band is occupied or is idle.

In this paper, we focus on the spectrum sensing, which plays a major role in the cognitive radio (CR) cycle for detecting a spectrum hole. There are several classification methods for spectrum sensing techniques according to the context of the need. One way among others to classify these techniques is based on the size of the bandwidth of the spectrum of interest: narrowband and wideband. Narrowband spectrum sensing techniques made a single binary decision about the presence of the PU traffic over narrow frequency range. While wideband spectrum sensing techniques attempt to detect the primary activity over a wide frequency band. Based on this classification, the most popular spectrum sensing algorithms for both types include: energy detection [5], matched filter detection [6], machine learning based sensing [7], wavelet-based detection [8],filter bank detection [9], and blind spectrum sensing [10].

The common challenge with these approaches is the high computational complexity associated with the extremely high sampling rates required. Thus, the approaches to perform wideband spectrum sensing based on sub-Nyquist techniques become increasingly important. These approaches are used to mitigate the sensing time and hardware cost used for high sample rates implementation. Based on the assumption of the scarcity of the wideband radio spectrum, compressive sensing has been become a promising solution to realize this sub-Nyquist approach. The mechanism of combining compressive sensing technique with spectrum sensing process is called compressive spectrum sensing.

There exist several methods and perspectives for representing and analyzing the concept of compressive spectrum sensing for CRN, which has engendered a numerous papers and surveys on this field of research. The authors of [11][12] provided an overview of compressive sensing theory, its implementation, and its applications. In [13-15], the authors discussed and detailed different spectrum sensing techniques, namely narrowband/wideband spectrum sensing techniques and compared the advantages and limitations of each type. In [16], the authors represented an overview of wideband spectrum sensing challenges and discussed compressive spectrum sensing approaches for CN. These approaches can be divided into two main categories: detection based sparse signal recovery and detection based compressed measurements. The authors of [17] described the existing approaches for performing the compressive estimation of various signal parameters such as SNR, and sparsity order.

To help researchers to be up to date with the evolution of the concept of compressive spectrum sensing, recent surveys and detailed reviews are needed on a regular basis to provide the latest developments and updates in this field. Therefore, this paper provides an in depth-survey on the combination of compressive sensing and spectrum sensing to improve and speed up the detection of available channels in CRN. Most recent works focused on either compressive sensing or spectrum sensing part of the model. However, in this paper, we aim at providing a study of the best requirements of each technique to make robust solution. The rest of this paper is structured as follows: Section II represents the state of the art of compressive sensing and spectrum sensing. Section III describes and analyses the different approaches of compressive spectrum sensing. Section IV represents the applications of CN compressive spectrum sensing . Section V highlights the main challenges and limitations of compressive spectrum sensing approaches. To sum up a conclusion is given at the end.

II. COMPRESSIVE SPECTRUM SENSING THEORY

Fig. 1 represents the basic model system of compressive spectrum sensing. The main purpose of this technique is to recover the original sparse signal x from only few measurements y and then perform spectrum sensing using the recovered signal x' [18]. The sensing decision about the primary signal presence performs by choosing between binary hypotheses, H1 (occupied) and H0 (not occupied). A detection threshold, denoted by λ, is chosen according to the sensing technique used and then compared with the output signal. As shown in Fig. 1, the performance of compressive spectrum sensing depends on several factors, in particular: the sparsity level, the choice of measurement matrix, the recovery algorithm, and the used spectrum sensing technique. Thus, an appropriate selection of these factors is the key of success of compressive spectrum sensing.

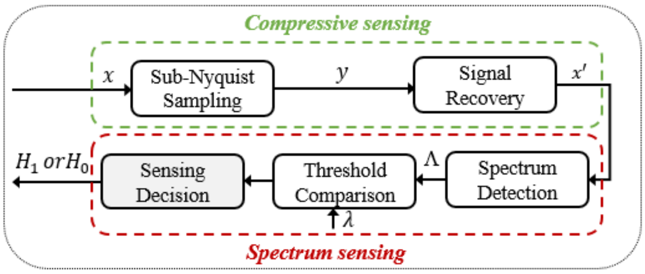

Fig. 1. Diagram of compressive spectrum sensing.

For an efficient analysis of compressive spectrum sensing mechanism, it is required to overview the theoretical basis of each stage of this technique. Thus, in this section we will formally study and define the detailed model of each process.

A. *Compressive sensing theory*

The aim of signal processing is the ability to reconstruct a signal from a sequence of sampling measurements. The conventional approach used is the famous Shannon-Nyquist theorem. However, for some wideband applications such as radar, wireless communications, and CR, the application of Shannon's theorem requires sampling frequencies that exceed the hardware limitations of analog-to-digital converters. In addition, data compression is essential for an appropriate use of available bandwidth and minimization of storage memory and energy consumption.

In order to overcome these problems, compressive sensing concept was first introduced by Donoho, Candès, Romberg, and Tao, as a new approach to sample signals with a lower rate than Shannon-Nyquist. The aim of this technique is an accurate and robust reconstruction of a signal from a minimum of linear measurements through the resolution of underdetermined linear systems. Compressive sensing mechanism involves two main operations: acquisition process and reconstruction algorithm. In the first process, a sparse input signal and the measurement matrix are multiplied to generate compressive measurements. Then, using a reconstruction algorithm the compressed signal is recovered in the second process getting an estimation of the original signal at the output of the system.

1) *Acquisition model*

The acquisition model contains two main stages; the first is presenting the input signal by a number of projections on an appropriate sparse basis. Some examples of these algorithms include the wavelet transform, the Fourier transform, and the discrete cosine transform. In mathematical form, the sparse signal can be formulated as

$$X = \Psi \times S \tag{1}$$

Where X is a signal with a number of samples N, its sparsity level D satisfies D << N and S is the sparse projection of the signal X on the sparse base Ψ. The second stages of the acquisition process is compression that can be described mathematically by

$$Y = \Theta \times X \tag{2}$$

Where Θ is an M x N measurement matrix multiplied by the input signal X to generate the compressed measurements vector Y, which selects only M samples from X (N,1).

In order to have a robust solution that guarantees the system performance, the sensing matrix, Θ must be properly selected to satisfy some definite properties. The first property to be considered is called the *Restricted Isometry Property* (RIP), which can be described as follows

$$\exists \varepsilon \in (0, 1) / (1 - \varepsilon_D) \, ||X||^2_2 \le ||\Theta X||^2_2 \le (1 + \varepsilon_D) \, ||X||^2_2 \tag{3}$$

Where ε is the restricted isometry constant (RIC) of the matrix Θ ,$||.||^2$ is the l_2-norm and X is D-sparse signal. The second property is the coherence, that consists in calculating the maximum correlation between the elements of Θ and Ψ, which must be incoherent from each other to guarantee a stable solution and a recovery with low error. The relation for finding the coherence between two matrices is given by

$$\mu(\Theta, \Psi) = \sqrt{N} \max |< \Theta_i | \ \Psi_j >| \tag{4}$$

Choosing a suitable sensing matrix is very important in the cycle of success of compressive sensing. Thus, a careful selection of this matrix is necessary. Sensing matrices proposed in literature are generally classified in two categories: random and deterministic. Random matrices are matrices in which some or all elements are random variables including Gaussian, Bernoulli, and uniform matrices. Those matrices are easy to construct and satisfy the RIP. In the second category, deterministic matrices are structured matrices that allow faster acquisition with less memory storage. Some examples of those matrices are Toeplitz and Circulant.

2) Reconstruction model

The sparse input signal can be recovered from compressed measurements by solving (2), which is an under-determined system and has an infinite number of possible solutions. This process can be formulated as a l_0-minimisation problem to find the sparest and unique solution of the system as follows

$$min\ ||X||_0 \quad subject\ to\ \ Y = \Theta \times X \qquad (5)$$

Where $||.||_0$ is the l_0-norm, which represents the number of non-zero elements of a vector. Unfortunately, in the theory of complexity, the l_0-minimization has been classified as NP-hard problem. To overcome the complexity of standard l_0, methods based on convex relaxation, such as Basis Pursuit, relax the problem by replacing l_0-norm by l_1-nom presented by the following

$$min\ ||X||_1 \quad subject\ to\ Y = \Theta \times X \qquad (6)$$

Where $||.||_1$ is the absolute sum of elements of a vector.

The compressive sensing reconstruction algorithms proposed in the literature to solve this problem can be mainly classified into six approaches: convex optimization, Greedy, thresholding, Bayesian, non-convex, and combinatorial. Their main objective is to find the sparse estimate solution of the original signal from few measurements taking into account a number of factors such as noise, speed, complexity, and performance guarantees.

B. Spectrum Sensing theory

The aim of spectrum sensing process is to decide about the spectrum status (occupied / unoccupied), so that the SU can use the radio spectrum without interfering with the PU. It refers to choosing between the two binary hypotheses H1 (presence of the PU) and H0 (absence of PU).

$$\begin{aligned} H_0 &: y(n) = v(n) \\ H_1 &: y(n) = x(n) + v(n) \end{aligned} \qquad (7)$$

Where *n* denotes sensing time, *y (n)* is the SU received signal, *x (n)* is the PU signal, and *v (n)* is the additive white Gaussian noise (AWGN) with zero mean and variance δ^2.

To analyze the received signal *y(n),* one of the spectrum sensing techniques previously mentioned can be used including energy detection, machine learning based detection, and matched filter. Finally, to make the sensing decision about the primary signal presence, a detection threshold, denoted by λ, is chosen according to the adopted sensing technique and then compared to the output signal Λ ,called the test statistic, as follows

$$\begin{aligned} H_0 &: \Lambda(y) < \lambda \\ H_1 &: \Lambda(y) > \lambda \end{aligned} \qquad (8)$$

The performance of a spectrum sensing technique can be quantified using a number of evaluation metrics such as:

- Probability of detection P_d: is the probability that the SU decides the presence of the PU signal when the spectrum is in fact occupied. It is expressed as

$$P_d = Prob\ (H_1/H_1) \qquad (9)$$

- Probability of false alarm $P_{fd:}$ is the probability that the SU decides the presence of the PU signal when the spectrum is actually free. It is expressed as

$$P_{fd} = Prob\ (H_1/H_0) \qquad (10)$$

- Probability of miss detection P_{md}: is the probability that the SU decides the absence of a PU signal when the spectrum is occupied. It is expressed as

$$P_{md} = Prob\ (H_0/H_1) \qquad (11)$$

Therefore, to design a robust spectrum sensing technique, these three metrics must be considered as success requirements of this technique.

III. ANALYSIS AND COMPARISON OF SEVERAL COMPRESSIVE SPECTRUM SENSING APPROACHES

The implementation of compressive spectrum sensing technique in CRN was first presented by Tian and Giannakis [19] as a novel solution to identify spectrum holes using reduced sampling rates. The detailed procedure is shown in Fig. 2.

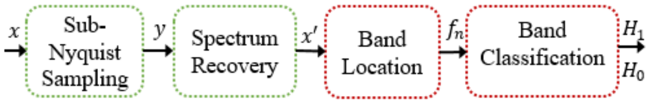

Fig. 2. Concept of compressive spectrum sensing [19].

Firstly, to ensure perfect recovery of the received signal, random sampling or universal non-uniform sampling are used to obtain the compressive measurements. Secondly, an estimate of the frequency response of the received signal is recovered based on a reconstruction algorithm such as Basis Pursuit (BP), Orthogonal Matching Pursuit (OMP), or Tree-based OMP. Then a wavelet-based edge detector method is applied to detect frequency locations of spectrum holes by selecting the local maxima of the wavelet modulus of recovered signal. Finally, a boundaries estimator is used to classify the detected bands into occupied or vacant [19].

Following this introduction, several works and papers were published to detail and improve this technique. In this paper, we gathered a review of recent advances and classified them into four categories based on the model presented on Fig. 1: Contribution based on sparsity level, acquisition model, and reconstruction algorithm or spectrum detection.

A. Approaches based on sparsity level

The sparsity order τ of a signal *x* is defined as follows

$$\tau = D/N \qquad (12)$$

Where *D* and *N* respectively denotes the number of non-zero elements and the dimension of *x*. It measures the degree of compressibility.

The sparsity of a signal is a property that plays an essential role in compressive sensing cycle. It is used to identify the number of measurements required to perform an efficient recovery of the signal, which leads to two different approaches to develop the concept of compressive spectrum sensing. The first one is based on the need to estimate the sparsity level of a signal before measurements process to reduce the sampling rate and the recovery error. This method is referred to as non-blind compressive spectrum sensing. The second approach does not require any prior knowledge of the sparsity level, to avoid more complexity in sensing process and it is called blind compressive spectrum sensing.

Example of non-blind techniques is presented in [20], where the authors suggested an adaptive method to determinate the sparsity of the estimated vector that reduces the error of the estimation, based on two new variations of the Least Mean Squares (LMS) algorithm. Another example is proposed in [21] where the authors developed a two-step compressive spectrum sensing algorithm for wideband CRs. In the first step, they used a small number of samples to estimate the sparsity order τ of the unknown spectrum. In the second step, they exploited the estimate of τ' to determine the number of samples that must be added and used. Finally, the wideband spectrum is reconstructed and the sensing decision of the state of the spectrum is taken using the samples collected from the two previous steps.

A number of blind compressive spectrum sensing techniques have been proposed in [22-24]. In [22][23], the authors proposed a blind algorithm referred to as Residual corrElation mAtrix Detection (READ). This algorithm finds efficiently the location of non-zero elements of a noisy multiband signal without prior knowledge of the signal parameters. Then, it uses energy ratios of adjacent frequencies of the Modulated Wideband Converter (MWC) sub-Nyquist sampling framework as the test statistics to make the sensing decision. In [24], the authors suggested a novel method that does not require an estimation of the PU signal sparsity. This algorithm is called DCT-based compressive spectrum sensing and it exploits the performance of energy concentration in the discrete cosine transform domain compared to the discrete Fourier transform to improve the signal detection.

B. Approaches based on acquisition model

In the acquisition process, the received signal is subsampled and then compressed. This operation is performed in practice by numerous acquisition techniques including Random demodulator (RD), MWC, Compressive multiplexer, Random convolution, and Random filtering. Details of these strategies are presented in [12].

In the context of compressive spectrum sensing technique, several contributions based on these acquisition strategies are developed. For instance, the authors of [25] designed a high speed chipping sequence architecture for RD. It works at 2.27 GHz clock frequency to improve the performance of wideband sub-Nyquist spectrum sensing. In [26], the authors proposed a simplified structure of the MWC. They removed the continuous-to-finite block and pseudo inversion operation of the MWC to reduce the computational complexity and then used sparse Bayesian learning as a recovery algorithm.

Other techniques have been proposed in the same context, but they focused mainly on the compression process of the acquisition model. This process is based on the measurements matrices. The authors of [27] introduced a modified Regular Parity Check (RPC) matrix to enhance the compressive sensing performance in CR. They defined a new algorithm based on the gradient descent method to convert the basic RPC matrix to a semi-orthogonal one. Another example of these approaches is presented in [28] where the authors proposed chaotic matrices as sensing matrices, which are easy to design using few parameters and safe with inherent security to secondary users.

C. Approaches based on reconstruction model

The reconstruction process is one of the key success factors for the compressive spectrum sensing solution. Several techniques based on reconstruction algorithms have been widely recommended and proposed in the literature [29-32]. For instance, in [29][30], the authors presented the Wavelet Packet Adaptive Reduced-set Matching Pursuit (WP-ARMP) as a new approach and suitable Greedy recovery algorithm for compressive spectrum sensing. The basic idea of this technique is based on a developed Fast Matching Pursuit (FMP) algorithm that practically allows a recovery rate of the input signal at 25% of the Nyquist rate. The authors of [31] also adopted Greedy algorithms and chose to develop the OMP algorithm. As a result, a three different algorithm was introduced namely, Stage wise Orthogonal Matching Pursuit (StOMP), Regularized Orthogonal Matching Pursuit (ROMP) and Compressive Sampling Matching Pursuit (CoSaMP) which guarantees better performance for the recovery of the wideband signals compared to original OMP. Thus, the detection based signal recovery improves the detection accuracy, but the interactive algorithms leads to a high system complexity.

To overcome the complexity challenge, other approaches were introduced. In [32], the authors presented a Non-Reconstructed Sequential Compressed Wideband Spectrum Sensing (NSCWSS) algorithm. The innovation in this algorithm is the use of an efficient sequential sensing process based on historical data gathering. Then, the algorithm is applied without the reconstruction process to simplify and reduce the hardware cost and implementation.

Another strategy to guarantee the performance of compressive spectrum sensing in terms of speed, robustness, and error recovery rate is based on the combination of acquisition and reconstruction techniques. An example of model proposed in this perspective is detailed in [33][34] where the authors evaluated the efficiency of Bayesian recovery algorithm with the advantages of Toeplitz and Circulant measurements matrices respectively.

D. Approaches based on spectrum detection

Recently, several research papers have proposed to improve spectrum sensing techniques. Among those techniques, energy detection method was commonly discussed and reviewed as the most used spectrum sensing approach. It is performed by comparing the received signal energy with a predetermined threshold. However, this technique is very sensitive to the noise uncertainty because the noise statistics (for example variance) are typically unknown at the receiver.

Thus, to enhance the performance of energy detection in the context of compressive spectrum sensing. the authors of [35], based on the assumption that the signal energy statistics in compressive spectrum sensing is different from that in traditional non-compressive spectrum sensing, suggested the use of a new algorithm based on Mixture Model (MM) and Expectation-Maximization (EM) methods combined with a threshold adaption scheme. The first step aims at identifying the channel energy statistics of recovered signal and the second step uses the model identified in the previous one to adapt the threshold and keep the false alarm rate constant.

Other works focused on improving the spectrum detection performance by reducing the false alarm rate and the processing time, which leads to increasing the compressive spectrum sensing accuracy in a smaller time period. This approach was discussed by the authors of [36] as an efficient approach to achieve more transmission throughput for the SU. The authors proposed a novel Likelihood Ratio Test (LRT) applied on the learned feature information of Primary User's signal (eigenvalues and eigenvectors) since this signal is position dependent but time invariant. Compared to existing spectrum detection techniques that use non-blind feature detections, the proposed Feature-Based technique is more efficient since is uses Primary User's signal localized features to improve the spectrum sensing accuracy.

Another approach of improving the spectrum detection was introduced in [37] by the combination of machine learning and compressive sampling techniques. On one hand, compressive sensing was used to decrease the number of required measurements. On the other hand, based on some activity statistics of both the Primary and Secondary users, a prediction technique was then applied to decide if the spectrum is occupied or vacant. This step uses one of the following regression models: Linear regression using batch gradient descent or support vector regression.

E. Comparison of Compressive Spectrum Sensing approaches

Table I, reviews the advantages and limitations of the related compressive spectrum sensing approaches in terms of complexity, number of measurements, and sensing time. As shown in this table, the approaches based on sparsity level (Non-Blind compressive spectrum sensing) and on reconstruction model (with recovery) are more hardware complex but require low number of measurements. On the other hand, the approaches based on acquisition model, reconstruction model (without recovery), and spectrum detection are fast and easy to implement (hardware cost). To sum up, the choice of the solution to implement depends on the system requirements (cost, speed, and performance).

IV. COMPRESSIVE SPECTRUM SENSING APPLICATIONS

A. Internet of Things (IoT)

With the rise of IoT technologies to enable large-scale connectivity of physical devices and objects, the traditional static frequency allocation strategies are becoming inefficient and wasteful. Therefore, researchers recommended new allocation policies based on dynamic frequency allocation and CR benefits. For that reason, the implementation of compressive spectrum sensing in large IoT networks is proposed to enable CR capabilities in wireless sensors and connected objects and make those networks more cost-effective in terms of spectrum occupancy and performance. In [38], a practical case of this implementation was detailed by presenting a blind compressive spectrum sensing algorithm adapted to IoT networks to dynamically adjust the sensing time and the sampling rate based on the fact that IoT devices uses the spectrum randomly. In addition, a distributed sensing scheme was proposed enabling the neighboring devices to jointly sense the spectrum using the multi-coset sampling theory.

B. Fifth generation of mobile networks (5G)

Another attractive area of compressive spectrum sensing application is presented in [39] aiming to enable spectrum sharing and spectrum aggregation to improve the capabilities of 5G mobile networks. The Enhanced 5G Cognitive Radio Networks (ECRN) uses the licensed bands shared with the primary users (TV white space and LTE TDD Bands) and aggregates from Wi-Fi unlicensed spectrum bands.

C. Smart city

Due to rapid growth in data acquisition for smart city applications, robust approaches are increasingly needed to well exploit all spectrum resources. As result, CR has been

TABLE I. ADVANTAGES AND LIMITATIONS OF COMPRESSIVE SPECTRUM SENSING APPROACHES

Compressive Spectrum Sensing approaches		**Advantages**	**Limitations**
Based on sparsity level [20-24]	**Non-Blind compressive spectrum sensing**	-Reduces the number of measurements to be used based on the estimation of sparsity of the received signal. -Minimizes the recovery error	-More complexity because of the estimation process
	Blind compressive spectrum sensing	-The estimation of the sparsity level is not required, which reduces the computational complexity of the system -Accelerates the detection process	-Reduced quality of reconstruction compared to non-blind compressive spectrum sensing
Based on acquisition model [25-28]		-Reduces the sensing time -Easy to implement -Low complexity -Ensures security	-Reduced detection performance under low SNR -Low detection probability with random locations
Based on reconstruction model [29-32]	**With recovery**	-Low number of samples -Fast algorithms	-High complexity due to interactive algorithm
	Without recovery	-Simplifies and reduces the hardware cost and implementation. -Detection based on compressed measurements only without recovery -Low sensing time	-Requires more measurements to improve the detection performance
Based on spectrum detection [35-37]		-Low number of measurements needed -Adaptive process -Reduces the false alarm rate -Low processing time	-Estimates of sparsity level is required

proposed as new form of wireless communication to examine spectrum accessibility via spectrum sensing techniques. In this context, an interesting methodology was presented in [40], the authors propose a dynamic spectrum sensing approach based on multiple antenna and energy detection techniques, to improve detection performance of primary users. In further research work, compressive spectrum sensing can be studied as a better technique to implement CR in smart city context.

V. CHALLENGES AND FUTURE SCOPE

With the fast evolution of wireless technology, each proposed solution needs to be continually improved to keep up with the latest developments. Thus, there are always some challenges to face and opening doors to new future directions to mitigate. In this section, we are highlighting some of the challenges of the two major techniques: compressed sensing and spectrum sensing. Examples of these challenges and future directions are:

- *Practical limitations:*

The signal acquisition is the most critical step in the compressive spectrum sensing process because it is the stage where the measurements are taken. Due to several invariants including multipath fading, shadowing, hardware anomalies, and channel noise correlation, uncertainty can affect this first process [41]. Then, sometimes the wrong actions are taken by using these affected and uncertain measurements. Because of this limitation, most papers assume simple operating conditions in terms of noise and channel. Few works exploit the compressive spectrum sensing techniques in the presence of practical imperfections as in [41][42]. Thus, there is a great need for detailed papers that performs compressive spectrum sensing in real and complex scenarios.

- *Security issues:*

The security aspect is a key factor in evaluation of new techniques. In CR, compressive spectrum sensing with multiple secondary users is vulnerable to attacks, which requires secure communication between the networks' users. Therefore, approaches based on the SU security are required at the signal detection stage. Examples of components introduced to improve the compressive spectrum sensing security is the use of structured sensing matrices. In [28], the authors proposed the chaotic matrices as sensing matrices to ensure and provide inherent security to secondary users.

- *Hardware requirements:*

To implement compressive spectrum sensing technique in real applications, the solution must be cost-effective in terms of processing time, speed, and hardware cost. For this purpose, some papers recommended the use of wideband antennas with reconfigurable characteristics as in [43]. Other works focused on the acquisition strategy such as random demodulator and modulated wideband converter as introduced in [25][26]. Hence, more research and real-world tests need to be done to develop a universal and efficient compressive spectrum sensing architecture to simplify and standardize the hardware design.

- *Blind compressive spectrum sensing:*

Most of the proposed compressive spectrum sensing techniques require prior knowledge of the sparsity level of the received signal to reduce the recovery error rate. Relating to practical scenarios, especially in the next generation of wireless networks, it is difficult to estimate the sparsity of the signal. In addition, estimation process can add more complexity to the system in term of sensing time. Thus, future compressive spectrum sensing systems will have to be able to operate without any prior knowledge of sparsity order, which lead to another attractive challenge that needs more detailed work.

CONCLUSION

The introduction of compressive sensing in signal processing has a revolutionary effect in several areas including CR. Compressive spectrum sensing is the result of the combination of compressive sensing with spectrum sensing that represents an essential block of the radio cognitive cycle. In order to exploit the advantages of compressive spectrum sensing, a number of approaches have been proposed in the literature. In this paper, we firstly presented a detailed review of compressive sensing and spectrum sensing theory. Secondly, we introduced a study and comparison of the four compressive spectrum sensing approaches (based on the sparsity, based on the acquisition model, based on the reconstruction algorithm, and based on the spectrum detection). Finally, applications and challenges of compressive spectrum sensing technique were reviewed.

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