A Comprehensive Survey on Effective Spectrum Sensing in 5G Wireless Networks through Cognitive Radio Networks

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Abstract: Spectrum sensing is a challenging issue in cognitive radio network. In particular, wideband spectrum sensing gains more attention due to emerging 5G wireless networks characterized by high data rates in the order of hundreds of Gbps. Conventional sensing techniques use samples for its observations based on Nyquist rate. Due to hardware cost and sampling rate limitations those techniques can sense only one band at a time. In spite of this issue secondary users have to sense multiple frequency bands using frontend technologies which leads into increased cost, time and complexity. Considering the facts and issues, compressive sensing was introduced to minimize the computation time by improving the sensing process even for high dimensional resources. Holding the essential information and reduces the sample size which is related to high dimensional data acquisition is performed in compressive sensing. In the last decade various researchers paid more attention to improve the performance of compressive sensing in cognitive radio networks based on sensing matrix, sparse representation and recovery process. This survey paper provides an in-depth analysis of conventional models and its sensing strategies in cognitive radio networks along with its merits and demerits to obtain a detailed insight about compressive sensing.

Keywords: Cognitive radio network, compressive sensing, spectrum sensing, channel estimation, Nyquist theorem.

1. Introduction

The demand towards radio spectrum resources increases due to the advancement in wireless communications. Federal communications commission has set up regulations to access this limited spectrum resource. Using specific wireless services, the spectrum is allocated to the licensed users based on spectrum allocation policy which is defined by FCC [1]. Licensed users are allowed to transmit and receive data through allocated spectrum while, the unlicensed users are prohibited to utilize the resource. Due to this reason, some of the channels are heavily used and other channels are not used properly which leads into spectrum underutilization. The licensed users are the primary users and the unlicensed users are considered as secondary users. Primary users will not utilize the resource all the times which creates a spectrum hole [2]. These holes are not utilized and the spectrum remains unused by licensed user leads into inefficiency as the other users cannot utilize the spectrum which results into spectrum scarcity. To reduce spectrum scarcity dynamic spectrum management is introduced to utilize the unused spectrum without affecting the performance to primary users. Secondary users are allowed to utilize the spectrum if it is unused by PUs. Cognitive radio network [3] performs spectrum utilization in this manner. It detects the available channel and allocates the resources to secondary users to reduce the inefficiency in spectrum. Figure 1 gives an illustration of dynamic spectrum access in cognitive radio network.
Various spectrum sensing models [4] such as coherent, Non-coherent, narrowband and wideband sensing are evolved in cognitive radio network. In this compressive sensing gains more attention to sense the wideband radio spectrum [5]. Generally, the utilization of multiple radio frequencies in communication systems leads into high hardware cost, implementation cost, system complexity and computation cost. To resolve this issues, efficient spectrum sensing techniques are evolved [6]. Compressive sensing is one among them which is proposed as low-cost wideband spectrum sensing technique in cognitive radio network. It minimizes the hardware cost in cognitive radio network and increases the acquisition speed in the network.

In digital systems, data acquisition and sampling are considered as an important aspect. Compressive sensing is an acquisition and reconstruction algorithm [7] which combines sampling and sensing. Initially it was introduced to sample the signals based on the Nyquist rate where the conventional sensing models are performed sensing using Shannon- Nyquist theorem [8]. The signal recovery in conventional models forces the receiver to change its sampling rate similar to Nyquist rate to recover the information. The limitation of Nyquist theorem-based sampling is present in its bandwidth specification. Minimum two times of signal bandwidth is required to recover a signal in Nyquist sampling which leads into numerous samples and makes the acquisition process as cost expensive in large communication networks. Instead compressive sensing recovers the signals with few samples and measurement values which is far better than conventional models [9]. Based on three process such as spare representation, encoding and decoding, compressive sensing is performed. In this sparse representation is used to identify and reconstruct the signals as much as possible. Based on measurement matrix, the sparse signals are sampled and then compressed. Using suitable recovery algorithm, the compressed signals has been recovered in the receiver end.
Fig3 Compressive sensing scheme

In conventional sampling process, single point sampling is performed before data compression [10]. In detail, compression is mainly classified into two types as lossless compression and lossy compression. Conventional sampling, discards and reduces the data in order to increase the bit storage. Whereas in compressive sensing each sample is selected based on its linear functions and then compression is performed in data acquisition time itself [12]. CS doesn’t compress the sample data separately as like conventional compression models. Compressive sensing handles large amount of data in a simpler way of transform codes to process the input signals. These input signals are sampled in terms of sparsity based on the transform domain which has samples with weighted coefficients. The difference between conventional sampling and data compression is depicted in figure 2 and figure 3 depicts an illustration of compressing sensing process.

In compressive sensing, high dimensional signal with large number of samples are assumed to be in some domain sparse. This sparse representation is used to represent the signal into numerous projections referred as dictionary of projection. Generally spare includes Fourier transform, wavelet transform and discrete cosine transform. Then these sparse signals are compressed using sensing matrix with \( \times \) values which has necessary information about the high dimensional signal. These compressed signals are recovered using recovery matrix based on the isometric property and then the signal is reconstructed. Due to this sparsity assumption [13] compressive sensing can estimate high dimensional signals and solve the undetermined system issues in an optimal way.

2. Literature Review

Research towards compressive sensing in cognitive radio networks is increased in last decade and numerous research works are evolved to improve the sensing performance and other parameters. This section provides a detailed analysis of existing research models in detail to obtain the issues in compressive sensing methods. On view of analysing the compressive sensing, detailed classification is presented in figure 4. Generally compressive sensing is classified into distributed sensing and jointly compressive sensing [14]. In distributed compressive sensing the sampling is performed in separate manner where the recovery is performed in joint manner. In this data acquired from each node and sampling is performed based on sensing matrix to obtain signal measurements. Also, the same reconstruction is used jointly to recover the signal. Reduced data storage and measurement rates are the advantages of this distributed compressive sensing. Using the same sensing matrix, the measurements and reconstruction of the signals are performed in jointly compressive sensing process.
Wide-band compressive spectrum sensing

Wide band compressive spectrum sensing is used to realize wideband spectrum based on sampling frequency. In particular, it is classified based on Nyquist [14] and sub Nyquist [15] approaches. In this Nyquist based approach, Nyquist sampling rate is used to obtain the desired spectrum. It is a cost-efficient model which easily identifies the spectrum state. In Nyquist based approach, the unused spectrums are identified using conventional digital signal processors followed by analog to digital converter. In this, the sampling spectrum follows the Shannon sampling theorem which reduces the aliasing effect which makes the sensing process suitable for multiband sensing operations. Edge detection [16] is a simple approach which progress based on this model, it differentiates the spectrum status as occupied or unused spectrum through its simple sampling rate. The performance of edge detection lags in its increased sensing time and complexity. To reduce the limitations in Nyquist sampling-based models, Sub-Nyquist approaches are evolved.

Based on compression ability of signals and its measurements the spectrum status is efficiently acquired in the Sub-Nyquist approach using less sampling rate than Nyquist rate approach. This type of spectrum sensing is suitable for frequency bands where the spectrum is underutilized so that it could be reconstructed using compressive sensing. It improves the reconstruction performance in wide band signals and reduces the complexity level. Wide band compressive spectrum sensing approach is introduced to obtain the unused band status in cognitive radio network [17]. It is a four-stage process and in the first stage, Sub-Nyquist sampler is used and in the second stage the reconstruction is performed based on the samples. In the third stage, the sub bands are examined based on frequency band localization process. In the last stage, the spectrum holes are identified as a sensing process. Later adaptive compressive spectrum sensing [18] is implemented to reconstruct the spectrum using compressed samples.

Compressive sensing based wideband spectrum is classified into two types such as one-bit compressive sensing and multi-bit compressive sensing. Generally, quantization step used in signal processing systems
results into multi-level quantization errors. To minimize the quantization errors one-bit compressive sensing is introduced [19]. Using a quantizer it performs one-bit quantization. Mostly comparator is used as quantizer and considered as zero level to attain quantization results. One-bit compressive sensing reduces the hardware cost and preserves the measurement information. One-bit compressive sensing recovery algorithms are categorized into regularized, Bayesian and penalty-based algorithms [20]. In the regularized techniques, an optimization model is used to validate the sign violations and adds a regularization term. In Bayesian approach, probability distribution function and noise function are related to sparse signal to maximize the function and obtains the necessary parameters which helps to recover the signal. In penalty-based approaches a penalty function is used to obtain the sparse signal.

Multi-bit compressive sensing [21] is used to obtain wideband signal sparse in frequency domain. It recovers the sparse signal using few measurements by involving three process such as sparse representation, measurement and recovery. In sparse representation the signals are projected as sparse signals using representation techniques such as Fourier transform (FFT and DFT) and discrete cosine transform to process in compressive sensing applications. Since compressive sensing could be applied only to sparse signals and this representation is essential in multi-bit compressive sensing process. In sparse measurement, few values are selected to recover the original sparse signal. For this process the measurement matrix values are multiplied with sparse signals represented in first step is used. This measurement matrix is classified into two categories as random and deterministic. Based on the identical distributions which includes gaussian, uniform and Bernoulli matrices, random matrix are generated [22]. Using circulant, chirp and Toeplitz sensing the deterministic matrices are generated to recover the original information.

Utilizing the matrices in recovery of signal increases the system complexity. To reduce the complexity in recovery process, convex and relaxation, Bayesian and greedy models are evolved. In this convex and relaxation models reduces the issues in sparse recovery through optimization algorithms. whereas greedy models are used to reduce the computation time as an iterative approach. Bayesian models gains more attention in sparse signal and its optimal solution finding process.Various models such as first Laplace prior [23], relevance vector machine [24], relief propagation is evolved based on Bayesian approach [25]. In Bayesian spectrum sensing model single fusion center [45] is used along with multiple secondary users and the secondary users senses the channel state and shares the information to fusion center. Based on the sensing information the fusion center takes the decision by processing the information and confirms the presence of primary user. This reduces the probability of false alarm and improves the spectrum utilization. So that the secondary user can use the spectrum when primary user is not present in the network.

Compressive sensing is further analysed based on the following factors
- Sparsity Model
- Acquisition Model
- Reconstruction model

2.1 Sparsity-based models

In this, sparsity-based models use its sparsity order to define the signal with number of non-zero elements by measuring the compressibility degree [26]. Since sparsity plays an important role in compressive sensing, it helps to identify the necessary measurements which is required to perform recovery of the signal. Based on these numerous research models are evolved. Depends upon the recovery error and sampling rate the sparsity is estimated in nonblind compressive spectrum sensing [27]. Where as in blind spectrum sensing the complexity of sensing process is reduced as it doesn’t need prior knowledge about the sparsity level [28]. Based on these two categories researchers introduced various implementation
models. In literature [29] Least Mean square algorithm is used to estimate the error function which reduces the cost of estimation function. Later an adaptive method is introduced to reduce the estimation complexity and improves the performance.

Two step compressive spectrum sensing for wideband cognitive radio network is reported in[30] to estimate the sparsity order and the number of samples. Using small number of samples, the first step is used to estimate the unknown spectrum where as in second step the number of samples which requires is added and then used in network. Based on the two steps and the sample values the spectrum is reconstructed and sensing decision is taken in the network. Under blind compressive spectrum sensing, residual correlation matrix detection is proposed in literature [31] which effectively obtains the non-zero elements location over a multiband signal without any signal parameter knowledge. Based on the adjacent frequency’s energy ratios and sub Nyquist sampling values the sensing process is formulated. Later discrete cosine transform based compressive spectrum sensing is evolved to estimate the sparsity of the primary user signal [32]. Based on energy concentration the performance is compared with discrete Fourier transform which greatly improves the signal detection in cognitive radio network. The advantages of non-blind compressive sensing model are present in its utilization of reduced number of measurements to estimate the signal sparsity and minimized recovery error. The estimation process makes the sparsity into more complex is considered as the limitation. In blind compressive spectrum sensing [33], estimation of sparsity level is not required which greatly reduces the computation complexity and accelerates the detection process. The limitation of blind compressive spectrum sensing is present in its reduced quality of signal reconstruction. Detailed analysis of sparsity models is listed in table 1.

Table 1 Merits and Demerits of existing sparsity models

| S.No. | Algorithms                                      | Merits                                           | Demerits                                          |
|-------|-------------------------------------------------|--------------------------------------------------|--------------------------------------------------|
| 1     | Wavelet model [34]-[37]                         | Reduced latency                                 | High energy consumption                           |
|       |                                                 |                                                 | High complexity                                   |
| 2     | Two step compressive sensing [38]              | Better estimation of wideband signal sparsity    | Complex due to estimation characteristics         |
|       |                                                 | Minimum number of samples                       |                                                  |
| 3     | Adaptive compressive sensing [18] [40]          | Predefined number of samples                    | High computation complexity                       |
|       |                                                 | Controlled recovery error                       |                                                  |
| 4     | DCT without recovery [41]                       | Reduced complexity                              | Reduced performance in detection probability    |
|       |                                                 | Sparsity estimation not required                 | Increased false alarm rate                       |
|       |                                                 | Measurement based direct recovery               |                                                  |
| 5     | One-bit compressive sensing [20] [39]           | Robust to noise                                 | Less reliable                                     |
|       |                                                 | Low complexity and computation cost             |                                                  |
|       |                                                 | Fast sampling                                   |                                                  |
| 6     | Multi-bit compressive sensing [21]             | Suitable for wide range of applications         | Increased hardware cost and computation time.    |
2.2 Acquisition-Based Models

In the acquisition-based models, the received signal is first subsampled and then it is compressed for further process [42]. Using various acquisition techniques like Random convolution, Random demodulator, Random filtering and compressive multiplexer this operation are performed in acquisition models [43]. To improve the performance of sub Nyquist spectrum sensing sequence architecture-based application is developed. In few research works are summarized in literature [44] for spectrum acquisition in which continuous to finite block is replaced with pseudo inversion process which reduces the complexity in computation. Later using Bayesian learning [46] based recovery algorithms are implemented using sparse which further reduces the computation complexity. Similarly, various methodologies are introduced in the same line by focusing compression in the acquisition process. This helps to improve the compression parameter but lags in other cost functions of the network.

Regular parity check [47] matrix is used in compressive spectrum sensing to improve the sensing performance. It uses basic RPC matrix to evaluate the functions related to sensing process in the network. Though, the performance metrics are noteworthy, modified regular parity checker matrix is introduced by replacing basic matrix into semi orthogonal matrix which improves the sensing process in cognitive radio network [48]. The advantages of acquisition-based models are, reduced sensing time, low complexity, secure and easy implementation. The limitation of acquisition-based models is, low detection probability and reduced detection performance. Table 2 gives a comparison of few acquisition models with its merits and demerits in detail.

| S.No. | Algorithms                        | Merits                                                                 | Demerits                                               |
|-------|-----------------------------------|------------------------------------------------------------------------|--------------------------------------------------------|
| 1     | Random Filtering                  | (i) Applicable to various compressive signal applications              | (i) Nonlinear reconstruction algorithm                 |
|       |                                   | (ii) Efficient measurement operator                                    | (ii) Prior knowledge about filters                     |
|       |                                   | (iii) Simple and easy implementation                                   |                                                       |
| 2     | Random Convolution                | (i) Implicit algorithm based on fast Fourier transform                 | (i) Unknown pulse structure which makes the application not suitable for sparse signals |
|       |                                   | (ii) Suitable for various physical systems                             |                                                       |
| 3     | Random Demodulator                | (i) High rate ADC is not required                                      | (i) Slow reconstruction of signals                     |
|       |                                   | (ii) Reduced noise and quantization errors                             | (ii) High sampling delay                               |
|       |                                   |                                                                        | (iii) Suitable for finite set of signals               |
| 4     | Modulated Wideband Converter      | (i) Suitable for Analog Multiband signals                              | (i) Needs low pass filter for effective reconstruction |
|       |                                   | (ii) Flexible sampling rate control                                   | (ii) Applicable for limited number of bands and bandwidth |
|       |                                   | (iii) Insensitive to parameter choice                                  | (iii) Inadequacy of non-ideal low pass filter           |
Reconstruction models gains more importance in compressive spectrum sensing which is widely used in various application related to cognitive radio network. Various reconstruction models [49] [50] are evolved in last decade. Nonlinear algorithm used in compressive sensing to reconstruct the signal at receiver end based on the knowledge of actual representation of signal sparse. Similarly, $l_1$ norm minimization is introduced to recover the signal from measurement values. In few research models $\theta$ minimization is used to reconstruct the signal. It solves the simple convex optimization problems through its nonlinear programming. Later $l_2$ minimization method is evolved but this reconstruction model lags in performance with non-sparse signals and provides substandard results. Though $\theta$ minimization [51] model gives accurate results but is lags in performance in terms of computation time and complexity. To overcome this issue $l_1$ norm minimization is preferred in most of the applications to obtain similar results as $\theta$ minimization with minimum computation complexity. To improve the performance of $l_1$ minimization, Bregman iterative algorithms are evolved. Based on the iteration sequence it provides solutions to the constrained issues in $l_1$ minimization based compressive sensing. Minimum of four to six iterations Bregman models regularize the issues and reconstruct the signal. Compared to minimization algorithms, the computational time is less in this iterative algorithm.

To solve the convex optimization issues in reconstruction algorithms using linear programming [52] convex relaxation-based models are evolved. Based on the measurements the signals are reconstructed as similar to original signal. Basic pursuit, basic pursuit de-noising, least absolute shrinkage and selection operator, least angle regression [53] are some of the familiar models under convex relaxation category. Though these methods are simple and reconstruction ability is better compared to minimization algorithms, the computation ability is bit complex. Similarly, iterative approaches are introduced to reduce the convex optimization issue in compressive sensing. These iterative models are much faster in resolving the issues by using exact measurement values to recover the signal. The thresholding function is defined in the algorithms based on the iteration and issue characteristics. Expander matching pursuit, sequential sparse matching pursuit, sparse matching pursuit [54] and belief propagation [55] are some of the familiar models comes under this iterative based approach.

Greedy recovery algorithms [56] [57] provide solution to reconstruction issue in an iterative manner. In each iteration the column values are correlated and selected to minimize the least square error. Greedy recovery algorithm is considered as base for various models of compressive spectrum sensing. Later fast matching algorithms are developed which has a better recovery rate than conventional models. Evolution of orthogonal matching pursuit-based algorithms [58] such as regularized orthogonal matching pursuit [59], compressive sampling matching pursuit [60] and stage wise orthogonal matching pursuit [61] provides better performance over wideband signal recovery. Though the signal recovery based on detection improves the accuracy, simultaneously it increases the complexity of the system. To reduce the complexity non reconstructed models are evolved.

Non-reconstructive algorithm uses sequential sensing process based on data history and performs the recovery function which greatly reduces the hardware implementation cost. Recently various parameters
like speed, error recovery rate and robustness-based models are evolved as a combined acquisition and reconstruction model to improve the compressive sensing performance. Bayesian recovery algorithm with Toeplitz [62] [63], circulant measurement matrix [64] [65] are the few related models which improves the efficiency of the system. Reconstruction models with recovery process has advantages due to its utilization of less number of samples and fast processing characteristics. Interactive algorithm makes the process into more complex in reconstruction models with recovery. In case of reconstruction without recovery model has advantages as reduced hardware implementation cost and minimized sensing time. The limitation of reconstruction without recovery model is present in its more measurement requirements to improve the detection performance. From the analysis it is observed that convex algorithms are efficient for reconstructing the signal but it consumes more time. While the greedy algorithms are easy to implement but the results are not reliable. Bayesian algorithms are much faster than other and provides better results with minimal errors. Table 3 gives a summary of reconstruction algorithms overview in terms of complexity, recovery time and recovery error.

Table 3 comparison of reconstruction algorithms

| S.No. | Algorithms | Merits | Demerits |
|-------|------------|--------|----------|
| 1     | Convex and Relaxation [52][53][54][55] | • Noise robustness | • High complexity  
  • Difficult to implement |
| 2     | Greedy [56]-[59] | • Less complex  
  • Fast computation time  
  • Noise robustness | • High convergence issue  
  • Requires more measurements  
  • Prior knowledge about signal sparsity |
| 3     | Thresholding Approach [60] [61] | • Less complex  
  • Fast computation time  
  • Multiple entries per iteration | • High convergence issue  
  • High complexity  
  • High adaptive step size |
| 4     | Combinational Approach [65]-[68] | • Fast computation time  
  • Simple implementation | • System requires noiseless and specific measurements |
| 5     | Non-Convex Approaches [69] | • Less measurement values | • Slower computation time  
  • High complexity |
| 6     | Bayesian Approaches [70]-[74] | • Fast sparse solution  
  • Estimation of signal parameters without intervention | • Results are difficult to select  
  • High computation time  
  • High complexity |

3 Findings from the survey

Based on the survey made on compressive spectrum sensing approaches in cognitive radio network, the below findings are observed and listed as follows.
Sparsity based compressive sensing algorithms are processed based on measurement values to obtain the signal status, which is considered as simple and efficient method.

High computation cost and complexity are the limitation of sparsity-based models.

Most of the research work focuses on complexity reduction and not considered the implementation cost.

Spectrum acquisition-based models are better and suitable for various compressive sensing applications.

Slow reconstruction and high sampling delay are some of the limitation of acquisition models. Research works are listed based on reconstruction and flexible sample rates.

Acquisition models performs better if the research focus is directed towards under sampling characteristics and filter performances.

Most of the reconstruction algorithms are progressed based on greedy and Bayesian approaches. Few research models are evaluated using convex and relaxation algorithms.

Reconstruction based research works are focused only on measurement values and computation time. Due to this the system complexity is increased and selection of parameters from the results becomes complex.

4 Conclusion

A systematic survey is presented in this research work to identify the challenges and issues in existing compressive spectrum sensing approaches in cognitive radio networks. Analysing the conventional spectrum sensing process and its difficulties this research is forwarded to compressive spectrum sensing approaches based on three factors such as sparsity-based models, acquisition-based models and reconstruction-based models. Various research works are analysed in each section and observed the merits and demerits. Based on the observation the issues in compressive spectrum sensing is summarized. The further progress in this research could be developing an efficient spectrum sensing and reconstruction algorithm using hybrid models to obtain better performance with reduced system complexity.

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