Recent Advances on Sub-Nyquist Sampling-Based Wideband Spectrum Sensing

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Abstract—Cognitive radio (CR) is a promising technology enabling efficient utilization of the spectrum resource for future wireless systems. As future CR networks are envisioned to operate over a wide frequency range, advanced wideband spectrum sensing (WBSS) capable of quickly and reliably detecting idle spectrum bands across a wide frequency span is essential. In this article, we provide an overview of recent advances on sub-Nyquist sampling-based WBSS techniques, including compressed sensing-based methods and compressive covariance sensing-based methods. An elaborate discussion of the pros and cons of each approach is presented, along with some challenging issues for future research. A comparative study suggests that the compressive covariance sensing-based approach offers a more competitive solution for reliable real-time WBSS.

I. INTRODUCTION

The unprecedented progress of wireless communications has spurred an extensive deployment of wireless devices, through which a tremendous amount of wireless data needs to be transmitted at all times. It is predicted that mobile data traffic will grow by about 1000 times in the next decade. Such a proliferated increase magnifies the scarcity of radio spectrum resources. In the future networks, it is prospected that the wireless system should achieve a significant increase in capacity, spectrum efficiency, and energy efficiency by at least 10 times up to 1000 times [1]. To realize these grand visions, on one hand, new spectrum resources should be explored, while on the other hand, current spectrum entails to be more efficiently utilized. As such, a spectrum coordination system that is capable of easing the mobile traffic tension is imperatively required.

In traditional spectrum-management approaches, the frequency bands are exclusively allocated to primary users (PU) or licensed users. However, it has been reported by the Federal Communications Commission (FCC) that the spectrum localized in time and space is highly underutilized. Such an underutilization has propelled a considerable research interest in cognitive radio (CR) [2], which is a tempting paradigm that automatically senses a PU’s surrounding RF environment to provide opportunistic access to the idle spectrum. A key component in CR is spectrum sensing, which aims to detect the presence of incumbent signals and achieve interference avoidance, because PUs have no obligation to share or abaliente their spectrum. So far most studies are confined to perform sensing over a narrow band, which is also referred to as narrowband spectrum sensing (NBSS). Nevertheless, from a long-term perspective, it is of vital importance to perform sensing over a wide frequency range in order to provide more flexible dynamic access and achieve a higher opportunistic throughput. The need is evidenced in the 2012 report, “Realizing the Full Potential of Government-held Spectrum to Spur Economic Growth”, authored by the US President’s Council of Advisors on Science and Technology (PCAST), which advocated the concept of “shared-use spectrum superhighways” and recommended to share a 1 gigahertz (GHz) wide federal government spectrum ranging from 2.7 to 3.7 GHz with non-government entities for open access. Clearly, advanced WBSS techniques that can quickly detect idle spectrum over a wide frequency span is an enabling technology to realize the concept of shared-use spectrum superhighways. Analogously, applications like spectrum aggregation, which integrates intermittent spectrum slots to enhance user experiences, also need to oversee a wide spectrum range.

According to the classic Nyquist–Shannon theorem, one has to sample the signal at the Nyquist rate in order to realize real-time WBSS. When the spectrum to be sensed is very wide, this may bring a challenge to hardware implementation as high-speed analog-digital converters (ADCs) are energy-intensive and too costly for practical systems. Thus, sub-Nyquist sampling-based techniques which have the potential to accomplish real-time WBSS in a cost-effective and energy-efficient way are highly desirable and have received much attention recently [3].

In this article, we start with an introduction of the conventional NBSS. Then we provide an overview of recent advances on sub-Nyquist sampling-based WBSS methods, which can be classified into two broad categories: compressed sensing-based approach and compressive covariance sensing-based approach. We discuss the pros and cons of these two approaches, and review related state-of-the-art techniques. Future research challenges are subsequently highlighted, followed by concluding remarks.

II. NARROWBAND SPECTRUM SENSING

The term narrowband means that the range of the frequency band is sufficiently small such that the whole frequency band is either occupied by the PU or available for opportunistic access. NBSS usually boils down to a binary hypothesis testing problem. When the PU’s signal waveform is known a priori, the matched filter detection (MFD), which correlates...
the received signal with the known waveform, is statistically optimal for this problem. The MFD, however, not only requires the knowledge of the PU’s waveform but also an accurate synchronization between the PU and the secondary user (SU), which limits its practical applications. When little is known about the PU’s signal, energy detection (ED) which distinguishes the PU’s presence and absence by measuring the energy of the received signal can be adopted for spectrum sensing. The energy detector is easy to implement and also computationally cheap. Nevertheless, it is sensitive to the noise uncertainty and does not provide satisfactory performance in the low signal-to-noise (SNR) regime.

Over the past decade, accompanying the development of the multiple-in-multiple-out (MIMO) technology, multi-antenna spectrum sensing has become the center of interest in the research of narrowband spectrum sensing. By exploiting the spatial correlation among different receive antennas, a variety of eigenvalue-based spectrum sensing algorithms were proposed. For example, the ratio of the maximum to the minimum eigenvalue of the receive sample covariance matrix is employed in [3] as the test statistic for spectrum sensing. More recently, the great success of deep learning in a variety of learning tasks has inspired researchers to use it as an effective tool to devise model-free spectrum sensing algorithms [5]. In contrast to traditional spectrum sensing algorithms that are model-based and perform detection based on the distribution of the received signal samples, deep learning-based methods are data-driven with the test statistics or features generated directly from signal samples. When sufficient training is available, deep learning-based algorithms can provide superior spectrum detection performance thanks to the powerful ability of neural networks in learning features out of signal samples [5].

III. WIDEBAND SPECTRUM SENSING

A straightforward approach for WBSS is to use a sufficiently high-speed ADC to meet the Nyquist–Shannon theorem. This approach, however, becomes prohibitively expensive or even infeasible when the frequency range is excessively wide, say, of a few GHz. With current hardware technologies, high-speed, high-precision ADCs are either not available, or too costly and power hungry. For example, some high-end ADCs like AD9213 can provide ultrafast sampling rates beyond 10 GSPS, but have a high power consumption up to a few Watts and cost about several thousands of US dollars. In addition, a high sampling rate generates a large amount of data and imposes a significant challenge on subsequent data storage, processing and transmission. To address these difficulties, an alternative method is to sequentially scan the frequency band of interest by resorting to the frequency mixing (superheterodyne) technique. The superheterodyne architecture, however, relies on high-quality RF components that need to be widely-tunable and thus can hardly be implemented on chip. Moreover, when the spectrum under monitoring reaches gigahertz, such a scanning scheme may incur a sensing latency from tens of milliseconds to the order of seconds, thus preventing the receiver from exploiting spectral opportunities in a more efficient way. Another solution is to uniformly divide the wideband signal into multi-narrowband signals by a number of parallel frequency-shifted bandpass filters, and each narrowband signal can be sensed at the Nyquist rate. Although the sensing latency is mitigated, the success of this approach comes at the expense of the complex structure of parallel filter banks as well as requiring a large number of RF components.

Recently, as a new paradigm for data sampling and acquisition, compressed sensing has inspired a wide interest in sub-Nyquist sampling-based WBSS. Many efforts have been made toward this direction and a plethora of sub-Nyquist-based spectrum sensing methods have been developed. These methods can be generally classified into two categories: compressed sensing-based approach and compressive covariance sensing-based approach, depending on what kind of information is extracted from sub-Nyquist data samples. In the sequel, we provide a review of each approach and discuss their respective pros and cons. Also, for clarity, a concise overview of some key aspects of existing WBSS techniques is summarized in Table I.

A. Compressed Sensing-Based Methods

Compressed sensing-based methods are motivated by the fact that the spectrum localized in time and space is in general severely underutilized. Utilizing the sparsity structure of the frequency domain, WBSS can be formulated as a compressed sensing problem, which aims to reconstruct the wideband analog signal from sub-Nyquist data samples. To bridge the analog and the digital domain, compressed sampling schemes including analog-to-information converter (AIC) [6], modulated wideband converter (MWC) [7], and multi-coset sampling (MCS), were proposed to convert the wideband analog signal into digital compressive measurements. Although different in hardware implementation, their common objective is to obtain linearly compressive measurements of the Nyquist data samples of the analog wideband signal.

Consider the AIC as an example to illustrate the basic idea of the compressed sensing-based WBSS methods. The AIC sampling scheme encompasses a set of parallel sampling branches. In each branch, the wideband analog signal is modulated by a periodic pseudo-noise (PN) sequence which takes constant values within each Nyquist interval. Specifically, the period of the PN sequence is an integer multiple of the Nyquist interval, and the ratio of the PN sequence’s period to the Nyquist interval is called as the downsampling factor, which is a positive integer of user’s choice. After the PN sequence modulation, the signal is then passed through an integrate-and-dump device whose period is the same as that of the PN sequence. At last, the analog signal is sampled by an ADC whose sampling rate is equal to the Nyquist rate divided by the downsampling factor. Note that multiple branches are sampled synchronously. Let $y$ be a sub-Nyquist sample vector obtained by stacking the sampled signals of all branches. The signal acquisition process can thus be described as an underdetermined system of linear equations (see Fig. 1):

$$y = Cx$$  \hspace{1cm} (1)
where $C$ is a matrix constructed by PN sequences, and $x$ consists of Nyquist samples collected within a period of the PN sequence. Since the spectrum under monitoring is under-utilized, it has a sparse representation in the DFT domain. Thus the Nyquist data sample vector can be reconstructed from sub-Nyquist samples via compressed sensing techniques, provided that the restricted isometric property is satisfied [8].

Some encouraging results have been reported on hardware implementation of compressed sensing-based wideband signal receivers. The first compressed sampling hardware was reported in [7], where a wideband receiver prototype based on the MWC sampling scheme was developed, which can deal with 2GHz Nyquist-rate input signals with a total sampling rate of 280 megahertz (MHz). Later in [9], a WBSS detector was developed based on a quadrature AIC (QAIC). The detector, implemented in 65 nm CMOS, is capable of quickly detecting the presence of strong interference signals over the PCAST Band.

Although these compressed sensing-based approaches are of theoretical and practical values, they suffer several severe drawbacks. Firstly, sparse signal recovery via optimization methods or other heuristic methods incurs a high computational complexity that grows quadratically with the problem size. Table II provides a summary of the computational complexities of both compressed sensing-based and compressive covariance sensing-based WBSS methods, which shows that compressed sensing-based methods generally have a higher complexity than compressive covariance sensing-based methods. Secondly, a practical system is inevitably subject to measurement noise. Sparse signal recovery algorithms, however, usually require a moderately high SNR to achieve satisfactory performance. It was reported in [7] that to ensure correct recovery of the spectrum support, an SNR above 15dB is needed. Such a high SNR requirement results in a low receiver sensitivity, which could potentially lead to a miss of some strong signals that should have been detected for interference avoidance/management.

In [10], a multirate sub-Nyquist sampling scheme was proposed to realize WBSS. The proposed approach does not intend to recover the wideband analog signal. The rationale behind the work is to employ multiple sub-Nyquist sampling rates to sample a wideband analog signal. When the spectral occupancy rate is sufficiently low and these sub-Nyquist sampling rates satisfy a certain condition, the probability that different sub-Nyquist samplers have aliased frequencies on the same frequency bin is small. Thus the spectral occupancy can be estimated by fusing detection results from different sub-Nyquist samplers. Although not aiming to directly reconstruct

![Table I](image-url)

| Algorithms | Features | Sampling architectures | Advantages | Limitations |
|------------|----------|------------------------|------------|------------|
| Nyquist methods | Direct sampling | Standard ADC sampling | Simple structure | High sampling rate, High energy cost |
| Sweeping scanner | Standard ADC sampling | Low sampling rate | High latency |
| Filter bank methods | Filter bank sampling | Low sampling rate | Complicated structure |
| Sub-Nyquist methods | Compressive sensing-based methods | Analog-to-information converter | Low sampling rate | Sparsity requirement, Sensitive to noise, High computational complexity |
| | Modulated wideband converter | Large instantaneous bandwidth |
| | Multi-coset sampling | |
| | Compressive covariance sensing-based methods | Analog-to-information converter | Low sampling rate, No sparsity requirement, Large instantaneous bandwidth, Robust to noise |
| | Modulated wideband converter | Suitable for only wide-sense stationary/cyclostationary signals |

Fig. 1. Compressed sampling architecture: AIC, where $M$ denotes the number of sampling branches, $N$ represents the downsampling factor, $T$ is the Nyquist sampling interval, and $p_m(t)$ denotes the PN sequence.
the wideband signal, this method can still be considered as a compressed sensing-based approach with the objective of recovering the support set of a sparse signal.

B. Compressive Covariance Sensing-Based Methods

To overcome the difficulties of compressed sensing-based methods, some recent works, e.g. [11], proposed to reconstruct the covariance matrix (equivalently, power spectrum) of the wideband signal, instead of the signal itself, from sub-Nyquist data samples. This class of methods are referred to as the compressive covariance sensing-based or the compressed power spectrum estimation approach. Compressive covariance sensing-based approaches use the same compressed sampling architectures as those of compressed sensing-based methods. Note that WBSS can be accomplished simply based on the power spectrum of a wideband signal. Also, recovering the power spectrum can bring in some noteworthy advantages.

Firstly, compressive covariance sensing-based methods can reconstruct the power spectrum reliably even in a low SNR environment, since the white noise is averaged out or effectively suppressed in the second-order statistics. Empirical results reported later in this section show that compressed power spectrum estimation methods can achieve reliable spectrum sensing performance even when the SNR is below 0dB. Secondly, compressive covariance sensing-based methods are in general computationally more efficient than compressed sensing-based methods as they do not require solving a computationally costly sparse recovery problem. For example, the fast Fourier transform (FFT)-based method proposed in [12] requires several FFTs to reconstruct the power spectrum from sub-Nyquist data samples, making it possible to perform real-time WBSS using highly mature commercial solutions such as field-programmable gate array (FPGA). Lastly, unlike compressed sensing-based methods, compressive covariance sensing-based methods do not need to impose any sparsity requirement on the frequency domain. This is because the covariance matrix to be recovered has a Toeplitz structure, which can be utilized to significantly reduce the number of unknowns and ensure an overdetermined linear system without requiring the sparsity of the wideband signal. Such a merit enables the CR to efficiently utilize spectrum fragments in a crowded frequency band.

We now provide an overview of state-of-the-art compressive covariance sensing-based WBSS methods. There are two different approaches to compressive covariance sensing-based WBSS, namely, a time-domain approach and a frequency-domain approach. The time-domain approach tackles the power spectrum estimation problem from a time-domain perspective, and aims to reconstruct the autocorrelation of a wide-sense stationary signal. Again, let us take the AIC as an example. Based on the linear relationship [1], it is clear that the covariance matrix of the sub-Nyquist sample vector can be expressed in terms of the covariance matrix of the Nyquist sample vector as:

\[ R_y = C R_x C^T \]  

(2)

Due to the wide-sense stationarity, the covariance matrix of the Nyquist sample vector is a Toeplitz matrix, whose intrinsic degree of freedom is much smaller than its natural dimension. For this reason, reconstruction of the autocorrelation of the wide-sense stationary signal from the autocorrelation of the sub-Nyquist samples reduces to solving an over-determined linear system of equations, as long as the PN sequences are properly designed and a sufficient number of sampling channels are deployed [6].

For the MCS scheme, the linear relationship between the sub-Nyquist sample vector’s covariance matrix and the Nyquist sample vector’s covariance matrix can be similarly established, except that \( C \) is a selection matrix obtained via extracting a portion of rows from an identity matrix (see Fig. 2). The indices of those nonzero elements in rows of \( C \) correspond to the time delays incurred by different sampling branches. The condition for recovering the autocorrelation of the wide-sense stationary signal from the sub-Nyquist sample vector’s covariance matrix was thoroughly investigated in [6]. [12], where it is shown that the recoverability is guaranteed if the time delay set is a circular sparse ruler of a particular length. A circular sparse ruler of length-\( Q \) is a set of integer marks \( \{ a_m \} \ (0 \leq a_m \leq Q) \) such that it can measure all integers from 0 to \( Q \) in a modular fashion. The problem of finding a smallest number of marks (i.e. branches) such that we can construct a circular sparse ruler of a specified length, also referred to as minimal circular sparse ruler, is a combinatorial problem that has attracted much attention in the field of sensor array processing [11].

The compressed power spectrum estimation problem was also addressed from the frequency-domain perspective. In [13], authors proposed a frequency-domain approach based on the MWC sampling scheme. The MWC architecture resembles the AIC architecture except that the integrate-and-dump device is replaced by a low-pass filter. Since the analog signal is multiplied by a periodic PN sequence, the spectrum of the PN modulated signal at each branch is a convolution of the spectrum of the original signal and a train of impulses, in other words, it is a weighted superposition of the original spectrum and its frequency-shifted versions. After going through the low-pass filter, the resulting spectrum is a superposition of a number of equal-width segments of the spectrum of the original signal. To facilitate readers’ understanding, an illustrative example of this linear relationship is provided in Fig. 3. In summary, this sub-Nyquist sampling process can be expressed as an underdetermined system of linear equations which characterize the relationship between the Fourier transform of the low-pass filtered signal and that of the original analog signal. As the Fourier transform of a wide-sense stationary process is white noise, the autocorrelation of the Fourier transform of the original signal exhibits a diagonal structure. Thus reconstructing the power spectrum of the original signal from the autocorrelation of the Fourier transform of the low-pass filtered signal can be cast into an over-determined inverse problem and readily solved.

Many man-made signals such as digital communication signals are cyclostationary instead of wide-sense stationary because their covariance function is periodic. In fact, wide-sense stationarity is a special case of cyclostationarity since the former can be regarded as a cyclostationary signal with a
TABLE II
Summary of computational complexity of existing WBSS techniques, where $M$ denotes the number of sampling branches, $N$ represents the downsampling factor, $L$ is the number of samples (in time) chosen to attain a specified spectrum resolution, $K$ denotes the sparsity level in an $N$-dimensional sparse signal, $T$ stands for the number of iterations required for the convex method, and $P$ represents the number of samples used to calculate the correlation matrix of sub-Nyquist signals. The number of floating-point operations is calculated based on the following setup: Suppose we aim to sense a frequency band of 1GHz with a spectrum resolution of 100kHz. The spectrum occupancy ratio is assumed to be 10%. The sensing system has 25 sampling channels and the downsampling factor is set to 100. We choose $L$ to be 100 to achieve the desired spectrum resolution, and $P$ and $T$ are respectively set as 10 and 100.

Fig. 2. Compressed sampling architecture: MCS.

cyclic period of one. It was shown in [12] that when it comes to the cyclostationary signal, compressive covariance sensing methods based on the wide-sense stationarity assumption render an estimate of the average power spectrum, i.e. the cyclic spectrum of the cyclostationary signal at the zeroth cyclic frequency. To explicitly accommodate cyclostationary signals, Tian and Tafesse [14] presented the first attempt to reconstruct the cyclic spectrum from sub-Nyquist data samples. As opposed to the stationary case, the Nyquist sample vector’s covariance matrix is no longer a Toeplitz matrix. Thus the linear relationship between the Nyquist sample vector’s covariance matrix and the sub-Nyquist sample vector’s covariance matrix is usually under-determined. However, it is observed that the cyclic spectrum of a cyclostationary signal is sparse. Such a prior knowledge can be incorporated to convert cyclic spectrum recovery into a sparse recovery problem [14]. From another point of view, although the Nyquist sample vector’s covariance matrix is non-Toeplitz, it is block-Toeplitz because of the periodicity of the covariance function. Inspired by this, [15] proposed to divide the vector of Nyquist samples into a number of block vectors, where the length of each block is an integer multiple of the cyclic period. Each block is then sampled by an individual multi-coset sampling module to collect its associated sub-Nyquist samples. By utilizing the block-Toeplitz structure, the linear relationship between the autocorrelation of the wideband signal and that of sub-Nyquist samples becomes over-determined, which helps avoid the computationally costly sparse recovery process.

In Fig. 4, we plot the ROC curves for both the compressed sensing-based methods and compressive covariance sensing-based methods, where the SNR is set to -10dB. We consider sensing a frequency range of [0,1]GHz using a multicoset sampling scheme with 8 sampling channels. The sampling rate for each channel is 80MHz. We see that compressive covariance sensing-based methods can render reliable spectrum sensing performance in the low SNR regime, whereas the compressed sensing-based methods which aim to recover the wideband analog signal suffer a considerable amount of performance degradation.

IV. OPEN RESEARCH CHALLENGES
The research on sub-Nyquist sampling-based WBSS has witnessed enormous progress over the past few years. Nevertheless, extensive work is needed to obtain a more com-
A. Innovative Sub-Nyquist Sampling Architectures

Existing sub-Nyquist sampling architectures have some drawbacks. A major difficulty of the AIC and MWC sampling schemes lies in that the flipping rate of each PN sequence should be at least the same as the Nyquist rate. However, the high rate PN sequence generator is expensive and also is the most power hungry block of AIC and MWC. Moreover, a timing synchronization module is required to synchronize different PN sequences. Although the MCS architecture is simpler than the AIC and MWC, a precise timing control is required to ensure that the time delays are exactly integer multiples of the Nyquist interval. Unfortunately, maintaining precise time delays is rather difficult due to time shift inaccuracies, particularly when the time delays are at the order of the Nyquist interval. Also, since MCS needs to sample the analog wideband signal directly, the ADCs used to implement the MCS require a high analog bandwidth to ensure that the analog wideband signal is not severely distorted before being sampled. In this regard, there is a need to quantify and provide an in-depth understanding of the impact of the hardware imperfections on the performance of practical systems. In addition, innovative sub-Nyquist sampling architectures that can overcome those drawbacks are highly desirable.

B. Cooperative Wideband Spectrum Sensing

Currently, the research on WBSS mainly focuses on the single CR scenario. Due to shadowing or multipath fading, the received signal at the CR may suffer severe degradation, leading to an unreliable detection result. It is therefore necessary to study cooperative schemes that encompass a networked system of CRs. In such a cooperative system, a number of CRs that spread over a large area are connected to a data center. If different nodes can be well synchronized, then cooperation can be performed at a bottom level, where raw sub-Nyquist data samples are pulled together at the date center for joint WBSS. Specifically, since different nodes could share some common spectral components, this spatial correlation may be utilized to devise a cooperative sub-Nyquist sampling scheme to reduce the overall sampling rate required for WBSS. Nevertheless, such a bottom-level fusion scheme may involve a large amount of communication overhead, especially when there is a large number of CRs. To address this issue, cooperation can be performed at a higher level, i.e. nodes report their initial detection results or signal statistics to the data center, where signal processing techniques can be developed to fuse these high-level information by incorporating the data correlation.
observed by different nodes as well as node’s location information.

C. Multi-Antenna-Assisted Wideband Spectrum Sensing

Recently, there is a growing interest in sub-Nyquist sampling-based algorithms for joint WBSS and direction-of-arrival (DoA) estimation in a phased-array framework. Due to the emergence of massive MIMO beamforming techniques, future electromagnetic environments could exhibit directionality in a local area. In particular, a beamformed signal is significant in only a limited number of directions. This fact potentially enables a same frequency band to be reused in the spatial domain. In this perspective, joint WBSS and DoA estimation would allow the spectrum resource to be more efficiently utilized. Moreover, compared with the single-antenna receiver, multiple antennas which exploit spatial diversity can effectively mitigate multipath fading, thereby improving the reliability of spectrum sensing. In the multi-antenna context, new sub-Nyquist sampling architectures as well as methods for WBSS are worthy of future investigation.

V. CONCLUDING REMARKS

This article presented a survey of recent developments on WBSS. In particular, our survey is emphasized on sub-Nyquist sampling-based WBSS methods, as these methods have the potential to realize real-time WBSS in a cost-effective and energy-efficient way. Based on the underlying principles, we classified sub-Nyquist sampling-based methods into two categories, namely, a compressed sensing-based approach and a compressive covariance sensing-based approach. State-of-the-art techniques in each category were reviewed, along with an extensive discussion on the pros and cons of these two different kinds of approaches. Finally, several open research issues for sub-Nyquist sampling-based WBSS were presented.

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