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Compressive Spectrum Sensing: An Overview

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Abstract: *Due to increasing number of wireless services spectrum congestion is a major concern in both military and commercial wireless networks. To support growing demand for omnipresent spectrum usage, Cognitive Radio is a new epitome in wireless communication that can be used to exploit unused part of the spectrum by dynamically adjusting its operating parameters. While cognitive radio technology is a promising solution to the spectral congestion problem, efficient methods for detecting white spaces in wideband radio spectrum remain a challenge in which secondary users reliably detect spectral opportunities across a wide frequency range. Conventional methods of detection are forced to use the high sampling rate requirement of Nyquist criterion. These are limited in their operational bandwidth by existing hardware devices, much of the extensive theoretical work on spectrum sensing is impossible to realize in practice over a wide frequency band. To lessen the sampling bottleneck, some researchers have begun to use a technique called Compressive Sensing (CS), which allows for the acquisition of sparse signals at sub-Nyquist rates, in conjunction with CRs. In this paper, various wideband spectrum sensing algorithms are discussed along with their merits and limitations and future challenges. Specially, the sub-Nyquist techniques, like compressive sensing and multi-channel sub-Nyquist sampling techniques are concentrated upon.*

1. INTRODUCTION

Efficient utilization of radio spectrum has received recent attention with the explosive growth in the number of wireless applications and services and the dearth of available spectrum for licensed allocation [13]. Recent spectrum measurements have shown that large portions of licensed spectrum, notably in the VHF-UHF bands licensed to television broadcasting, are under-utilized [8], [15]. This means that at a given spatial region and time, there are frequency bands with no signal occupancy. Such empty spectrum can be available for secondary access by means of cognitive radios.

Cognitive radio is an advanced software-defined radio that automatically detects its surrounding RF stimuli and intelligently adapts its operating parameters to network infrastructure while meeting user demands. Since cognitive radios are considered as secondary users for using the licensed spectrum, a crucial requirement of cognitive radio networks is that they must efficiently exploit under-utilized spectrum (denoted as spectral opportunities) without causing harmful interference to the PUs (Primary Users). Furthermore, PUs have no obligation to share and change their operating parameters for sharing spectrum with cognitive radio networks. Hence, cognitive radios should be able to independently detect spectral opportunities without any assistance from PUs; this ability is called spectrum sensing, which is considered as one of the most critical components in cognitive radio networks. [15] Cognitive radios employ spectrum sensing to determine frequency bands that are vacant of licensed transmissions and restrict their secondary transmissions to such empty portions to meet regulatory requirements of limiting harmful interference to licensed systems.

The motivation and techniques for spectrum agile Cognitive Radios (CR)s to efficiently utilize unoccupied licensed spectrum have been well documented in literature, like narrowband sensing techniques, such as matched-filtering, energy detection, cyclostationary detection, etc. While present narrow-band spectrum sensing algorithms are focusing on exploiting spectrum holes over narrow frequency range, CR networks will be required to exploit the spectrum opportunities over wide frequency range from some hundreds of megahertz (MHz) to several gigahertz (GHz) for better spectrum utilization and obtaining optimized throughput. This is considered on base of Shannon's formula, according to which, under certain conditions, the maximum theoretically achievable throughput or bit rate is directly proportional to the spectral bandwidth. Therefore, the wideband spectrum sensing can help us achieve more aggregate throughput by exploiting more available spectrum opportunities over a wide frequency range.

Due to hardware and sampling constraints, CRs in practice are often limited to a restricted frequency range, severely limiting their usefulness. As a result, most of the CR results derived in literature [1][2][3] are impossible to realize in practice over a wide frequency band.

In the remaining sections of the article, we first briefly discuss the traditional spectrum sensing techniques for narrowband sensing in next section. In the section after the next, we are discussing the issues related with implementation of wideband spectrum sensing. Then we will be discussing different advanced wideband spectrum sensing techniques for various categories. Then we will discuss the compressive spectrum sensing algorithms of different types that are being developed. After that, we will go face-to-face with future research challenges for implementation of wideband spectrum sensing, and specially, compressive spectrum sensing. At the end, we will be viewing the concluding remarks.

2. TRADITIONAL SPECTRUM SENSING TECHNIQUES

There are different spectrum sensing techniques already in use, like, energy detection, matched filter detection, and cyclostationary detection. These techniques detect the primary user in the frequency range that is sufficiently narrow enough that we can call the frequency response of the channel "flat". These lead us to actually the narrow-band spectrum sensing. The bandwidth of one's concern will be less than the coherence bandwidth of the channel. Each such techniques do require a specific condition for implementation and, therefore, their performances are also different based on detection outcome. The method of Energy Detection is a non-coherent technique for spectrum sensing. It does not require the prior knowledge of the signal to be sensed in the spectrum or the PU. It may be considered as the one of the simplest spectrum sensing techniques that does not require complicated hardware or algorithms for furnishing the task. This technique cannot give optimum results in presence of additive noise. Also, it cannot differentiate between signals from PUs and signals from other CR devices.

While Energy Detection seems to be less effective in presence of noise, Matched Filter can provide a better SNR for sensed signal in the above said scenario. In this method, the received signal is correlated with a pattern for detecting the known signal in the received signal [15]. However, it relies on prior knowledge of the PUs and requires cognitive radios to be equipped with carrier synchronization and timing devices, leading to increased implementation complexity.

One other such narrow-band coherent SS technique is Cyclostationary Feature Detection. It detects and discriminates between different types of primary signals by making use of their cyclostationary features. This method has the computational cost high as it has to calculate a two-dimensional function reliant on both frequency and cyclic frequency. [15]

3. WIDEBAND SPECTRUM SENSING

Wideband Spectrum Sensing is the technique which suggests the spectrum to be sensed will have the frequency bandwidth more than the coherent bandwidth of the channel. The typical narrowband sensing techniques are limited in the way that they make use of single binary decision and cannot detect individual spectrum opportunity available in the wideband spectrum.

Looking at the prevailing techniques nowadays, we can classify wideband spectrum sensing into two main classes: Nyquist (Rate based) spectrum sensing, and, Sub-Nyquist (Rate based) spectrum sensing. As the name suggests, the Nyquist (Rate based) spectrum sensing uses the sampling rate for spectral estimation at or more than the Nyquist rate. While the other one uses the rate of sampling below the Nyquist rate.

3.1. Nyquist Wideband Sensing

There are basically two methods adopted for Nyquist Wideband Sensing: Standard Analog-to-Digital Converter method, and, Sweep-tune/ Filter Bank Sampling [15].

3.2. Multiband Joint Detection for Nyquist Wideband Sensing

Quan *et al.* [6] proposed a multi-band joint detection algorithm that can sense the primary signal over multiple frequency bands. As shown in Fig. 1, the wideband signal x(t) was firstly sampled by a high sampling rate ADC, after which a serial to parallel conversion circuit (S/P) was used to divide sampled data into parallel data streams. Fast Fourier transform (FFT) was used to convert the wideband signals to the frequency domain. The wideband spectrum X(f) was then divided into a series of narrowband spectra $X_1(f), \cdots, X_v(f)$.

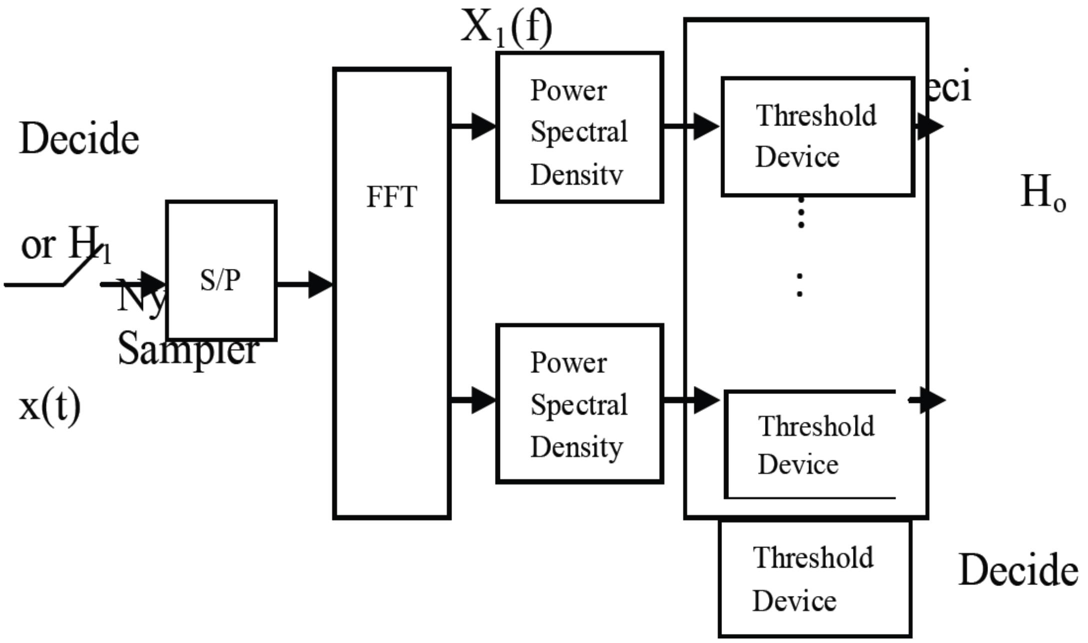

Fig1. *Block Diagram for Multiband Joint Detection for Nyquist Wideband Sensing*

Finally, spectral opportunities were detected using binary hypotheses tests, where H_0 denotes the absence of PUs and H_1 denotes the presence of PUs. The optimal detection threshold was jointly chosen by using optimization techniques. Such an algorithm can achieve better performance than the single band sensing case.

3.3. Wavelet Detection for Nyquist Wideband Sensing

By using a standard ADC, Tian and Giannakis proposed a wavelet-based spectrum sensing algorithm in [7]. In this algorithm, the power spectral density (PSD) of the wideband spectrum (denoted as S(f)) was modeled as a train of consecutive frequency subbands, where the PSD is smooth within each subband but exhibits discontinuities and irregularities on the border of two neighboring subbands. The wavelet transform was then used to locate the singularities of the wideband PSD, and the wideband spectrum sensing was formulated as a spectral edge detection problem as shown in Fig. 2.

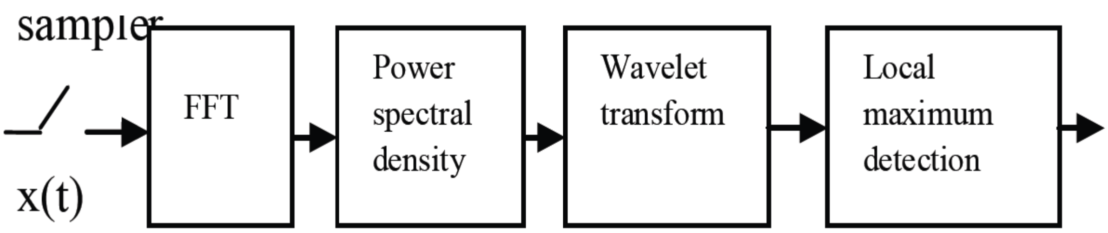

Fig2. *Block Diagram for Wavelet Detection for Nyquist Wideband Sensing*

In the above systems, the Shannon's Theorem is followed by the sampling signals. The sampling rate must be at least twice the maximum frequency present in the signal (known as Nyquist rate) in order to avoid spectral aliasing. Sensing wideband spectrum presents significant challenges on building sampling hardware that operates at a sufficiently high rate, and designing high-speed signal processing algorithms. With current hardware technologies, high-rate ADCs with high resolution and reasonable power consumption are difficult to implement. Even if it comes true, the real-time digital signal processing of sampled data could be very expensive. [15]

3.4. Sweep-Tune Detection for Nyquist Wideband Sensing

The super-heterodyne reception approach can also be used for Nyquist Wideband Sensing. Here, the frequency range of concern will be swept across by the system. A Local Oscillator (LO) will produce a sine wave that will mix with the wideband signal and will down-convert it to a lower frequency. The concept is shown in Fig. 3. The down-converted signal will then be filtered by a bandpass filter (BPF), after which existing narrowband spectrum sensing techniques can be applied. This sweep-tune approach can be realized by using either a tunable BPF or a tunable LO. However, this mechanism slows down the overall performance of the system. [15]

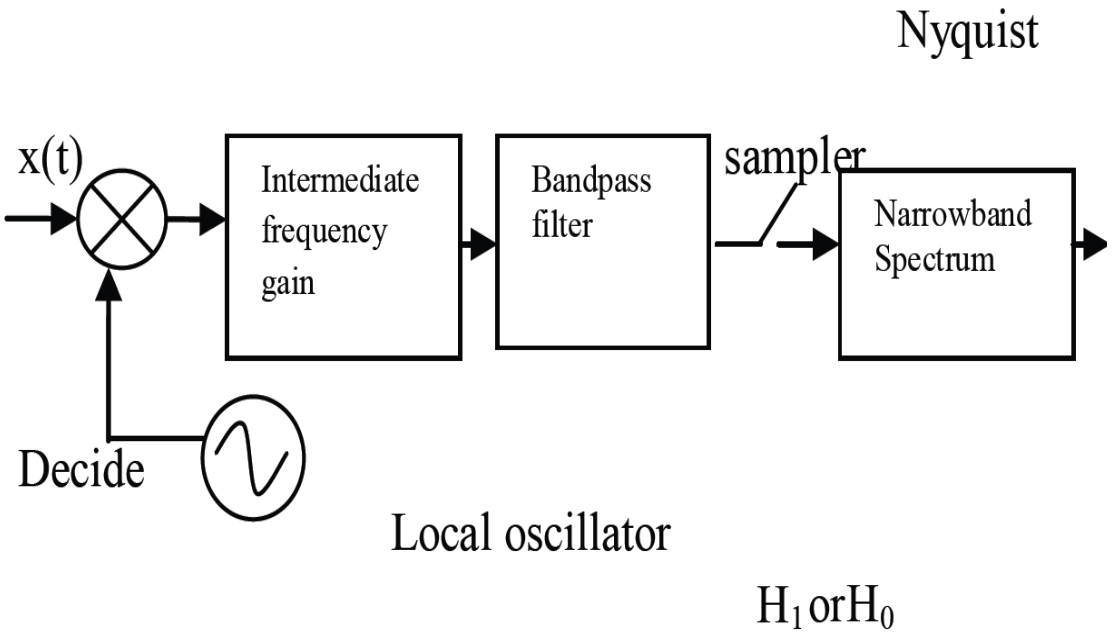

Fig3. *Block Diagram for Sweep-tune Detection for Nyquist Wideband Sensing*

3.5. Filter Bank Sampling Detection for Nyquist Wideband Sensing

Farhang-Boroujeny [4] suggested filter bank algorithm as a possible solution for WBSS for cognitive radio at Nyquist rate. As shown in Fig. 4, a bank of prototype filters (with different shifted central frequencies) was used to process the wideband signal. The base-band can be directly estimated by using a prototype filter, and other bands can be obtained through modulating the prototype filter. In each band, the corresponding portion of the spectrum for the wideband signal was down-converted to base-band and then low-pass filtered. This algorithm can therefore capture the dynamic nature of wideband spectrum by using low sampling rates. [15]

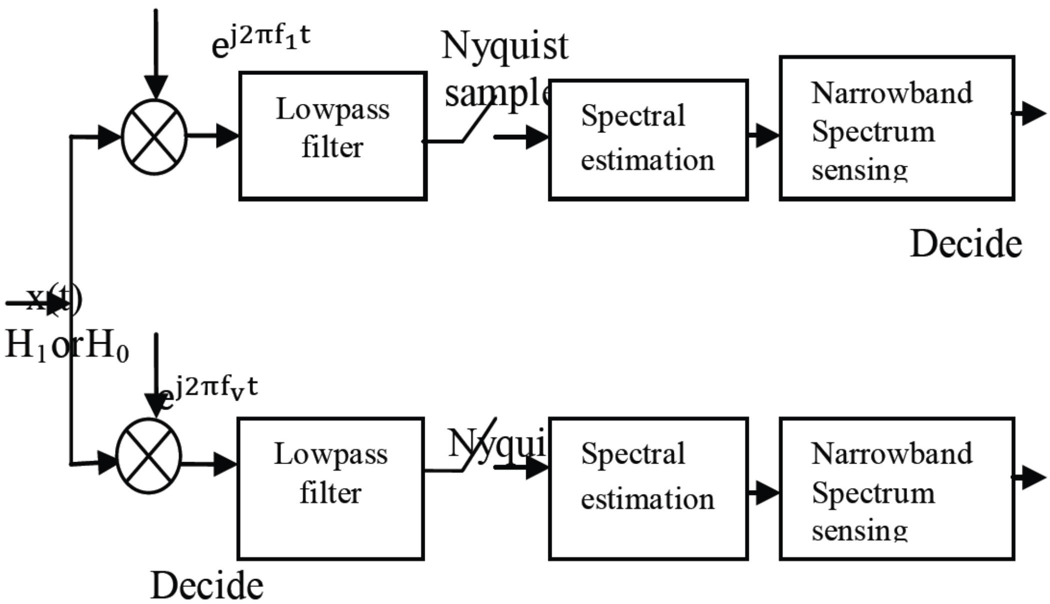

Fig4. *Block Diagram for Filter-Bank Detection for Nyquist Wideband Sensing*

But, due to the parallel structure of the filter bank, the implementation of this algorithm requires a large number of RF components, that can be practically less feasible for real implementation.

3.5.1. Sub-Nyquist Wideband Sensing

Due to the drawbacks of high sampling rate or high implementation-complexity of Nyquist systems, Sub-Nyquist Wideband Sensing systems prefer to acquire wideband signals using lower sampling rates (compared to Nyquist rate) and detect spectrum opportunities using these partial measurements of the spectrum. Two main systems are proposed for Sub-Nyquist Wideband Sensing, (i) Compressive Sensing based Wideband Sensing, and, (ii) Multi-Channel Sub-Nyquist Wideband Sensing.

3.6. Compressive Sensing-Based Wideband Sensing

Compressive Sensing-Based Wideband Sensing is a technique that can efficiently acquire a signal using relatively few measurements, by which unique representation of the signal can be found based on the signal's sparseness or compressibility in some domain. This technique used fewer samples closer to the information rate, rather than the inverse of the bandwidth, to perform wideband spectrum sensing. After reconstruction of the wideband spectrum, wavelet-based edge detection was used to detect spectral opportunities across wideband spectrum. [9] Furthermore, to improve the robustness against noise uncertainty, Tian et al. [18] studied a cyclic feature detection-based compressive sensing algorithm for wideband spectrum sensing.It is the two dimensional cyclic spectrum(spectral correlation function) of a wideband signal can be directly reconstructed from the compressive measurements.

For further reducing the data acquisition cost, Zeng *et al.* [11] proposed a distributed compressive sensing-based wideband sensing algorithm for cooperative multi-hop cognitive radio networks. By enforcing consensus among local spectral estimates, such a collaborative approach can benefit from spatial diversity to mitigate the effects of wireless fading. In addition, decentralized consensus optimization approach was proposed that aims to achieve high sensing performance at a reasonable computational cost.

3.7. AIC Converter Sub-Nyquist Wideband Sensing

As compressive sensing has concentrated on finite-length and discrete-time signals, innovative technologies are required to extend the compressive sensing to continuous time signal acquisition, i.e., implementing compressive sensing in analog domain. To realize the analog compressive sensing, Tropp *et al.* [12] proposed an analog-to-information converter (AIC), which could be a good basis for the above-mentioned algorithms.

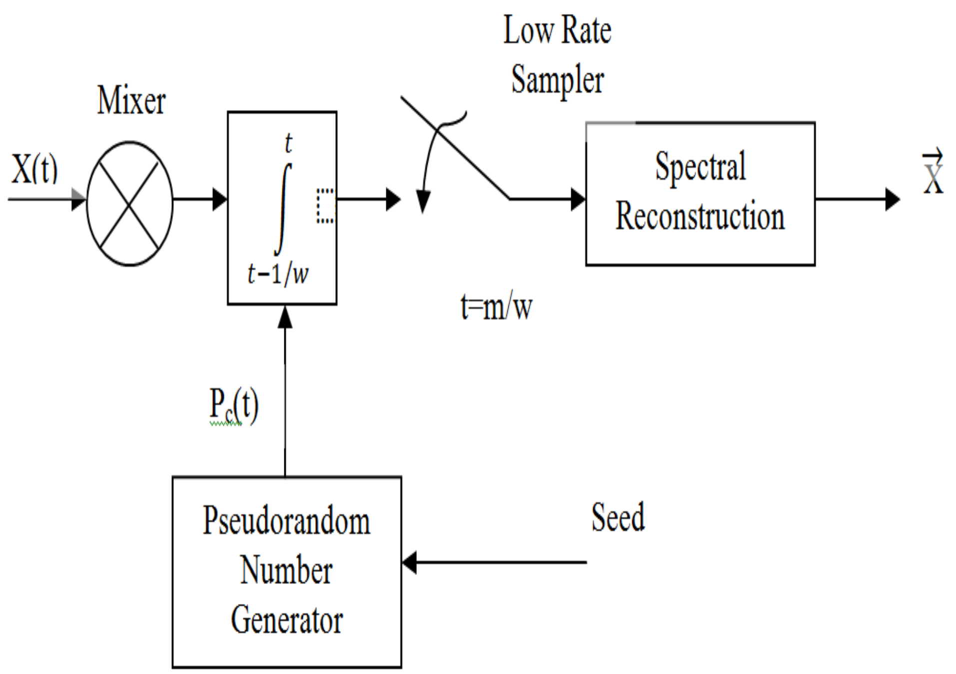

Fig5. *Block diagram of AIC converter Sub-Nyquist wideband sensing*

As shown in Fig. 5, the AIC-based model consists of a pseudo-random number generator, a mixer, an accumulator, and a low-rate sampler. The pseudo-random number generator produces a discrete time sequence that demodulates the signal x(t) by a mixer. The accumulator is used to sum the demodulated signal for '1/w' seconds, while its output signal is sampled using a low sampling rate. After that, the sparse signal can be directly reconstructed from partial measurements using compressive sensing algorithms.

3.8. Multichannel Modulated Sub-Nyquist Wideband Sensing

To circumvent model mismatches, Mishali and Eldar proposed a modulated wideband converter (MWC) model in [13] by modifying the AIC model. The main difference between MWC and AIC is that MWC has multiple sampling channels, with the accumulator in each channel replaced by a general low-pass filter.

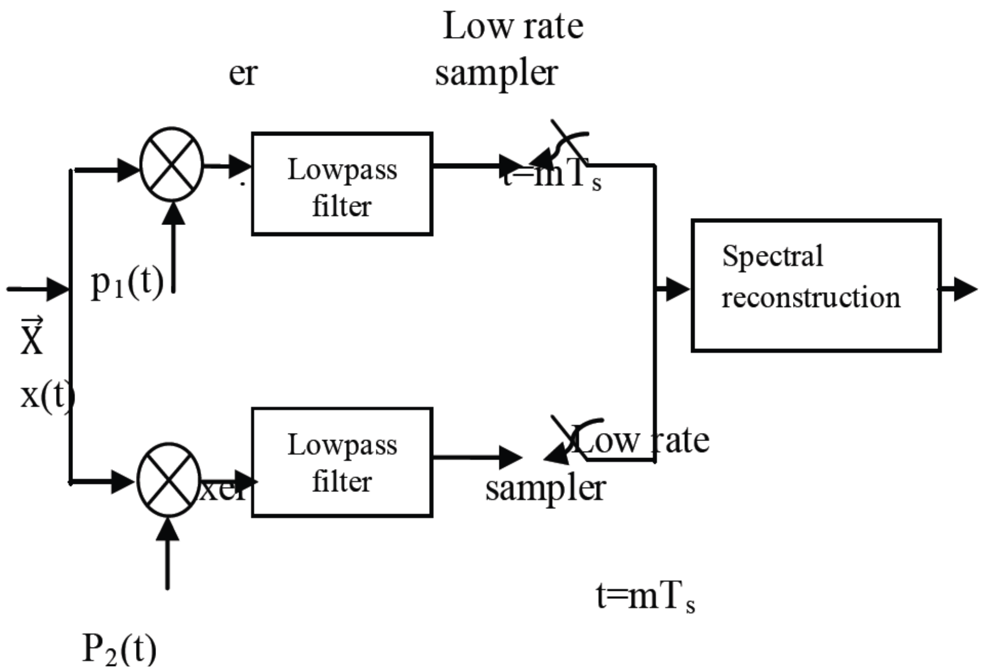

Fig6. *Block Diagram for Multichannel Modulated Sub-Nyquist Wideband Sensing*

One significant benefit of introducing parallel channel structure in Fig. 6 is that it provides robustness against the noise and model mismatches. In addition, the dimension of the measurement matrix is reduced, making the spectral reconstruction more computationally efficient. [15]

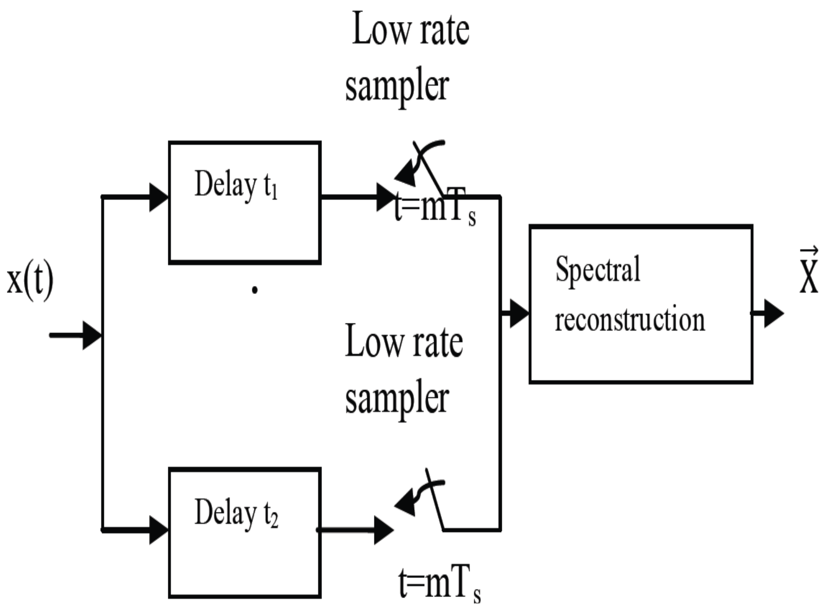

Fig7. *Block diagram of Multicoset sampling Sub-Nyquist wideband sensing*

An alternative multi-channel sub-Nyquist sampling approach is the multi-coset sampling as shown in Fig. 7. The multi-coset sampling is equivalent to choosing some samples from a uniform grid, which can be obtained using a sampling rate f_s higher than the Nyquist rate. The uniform grid is then divided into blocks of m consecutive samples, and in each block v (v < m) samples are retained while the rest of samples are skipped. Thus, the multi-coset sampling is often implemented by using v sampling channels with sampling rate of f_x/m, with different sampling channels having different time offsets. To obtain a unique solution for the wideband spectrum from these partial measurements, the sampling pattern should be carefully designed.

In [14], some sampling patterns were proved to be valid for unique signal reconstruction. The advantage of multi-coset approach is that the sampling rate in each channel is m times lower than

the Nyquist rate. Moreover, the number of measurements is only v-mth of that in the Nyquist sampling case. One drawback of the multi-coset approach is that the channel synchronization should be met such that accurate time offsets between sampling channels are required to satisfy a specific sampling pattern for a robust spectral reconstruction.

3.9. Multirate Sampling Sub-Nyquist Wideband Sensing

To relax the multi-channel synchronization requirement, asynchronous multi-rate wideband sensing approach was studied in [15]. In this approach, sub-Nyquist sampling was induced in each sampling channel to wrap the sparse spectrum occupancy map onto itself; the sampling rate can therefore be significantly reduced.

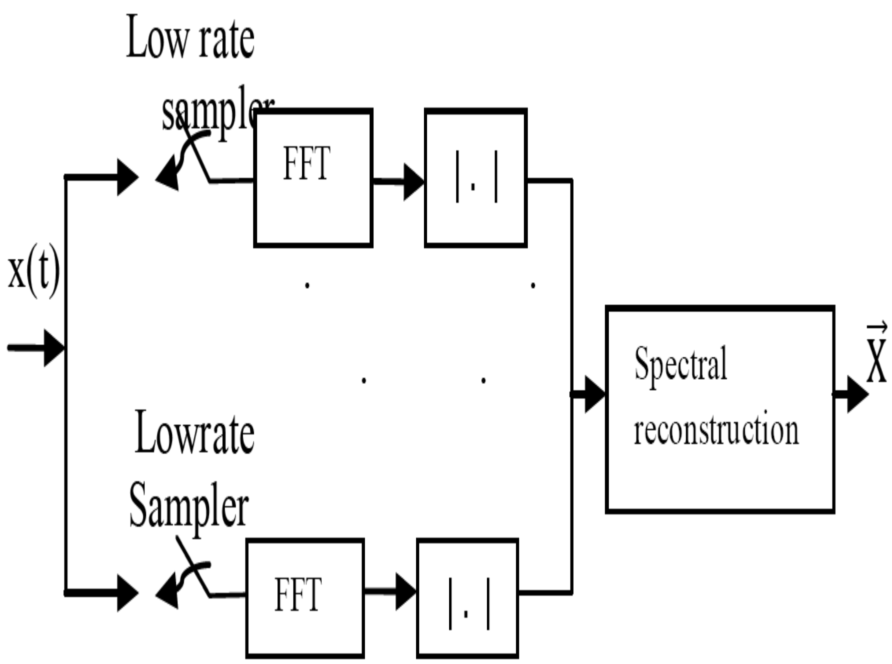

Fig8. *Block Diagram of Multirate Sampling Sub-Nyquist Wideband Sensing*

By using different sampling rates in different sampling channels as shown in Fig. 8, the performance of wideband spectrum sensing can be improved. Specifically, in the same observation time, the numbers of samples in multiple sampling channels are chosen as different consecutive prime numbers. Furthermore, as only the magnitudes of sub-Nyquist spectra are of interest, such a multi-rate wideband sensing approach does not require perfect synchronization between multiple sampling channels, leading to easier implementation.

Also, [17] proposes an analog/ mixed signal topology for wideband spectrum sensing that replaces the conventional Nyquist ADCs and digital Fast Fourier Transform (FFT) core with a bank of Sample and Hold (S/H) circuits, each operating at sub-Nyquist rate, and an all-analog FFT processor.

4. RESEARCH CHALLENGES

The following research challenges are there that need to be addressed for implementing a feasible wideband spectrum sensing device for future cognitive radio networks.

4.1. Sparse Basis Selection

Nearly all sub-Nyquist wideband sensing techniques require that the wideband signal should be sparse in a suitable basis. Given the low spectrum utilization, most of existing wideband sensing techniques assumed that the wideband signal is sparse in the frequency domain, i.e., the sparsity basis is a Fourier matrix. However, as the spectrum utilization improves, e.g., due to the use of cognitive radio techniques in future cellular networks, the wideband signal may not be sparse in the frequency domain any more. Thus, a significant challenge in future cognitive radio networks is how to perform wideband sensing using partial measurements, if the wideband signal is not sparse in the frequency domain. It will be essential to study appropriate wideband sensing techniques that are capable of exploiting sparsity in any known sparsity basis. Furthermore, in practice, it may be difficult to acquire sufficient knowledge about the sparsity basis in cognitive radio networks, e.g., when we cannot obtain enough prior knowledge about the primary signals.

Hence, future cognitive radio networks will be required to perform wideband sensing when the sparsity basis is not known. In this context, a challenging issue is to study “blind” sub-Nyquist wideband sensing algorithms, where we do not require prior knowledge about the sparsity basis for the sub-Nyquist sampling or the spectral reconstruction. [15]

4.2. Adaptive Wideband Sensing

In most of sub-Nyquist wideband sensing systems, the required number of measurements will proportionally change when the sparsity level of wideband signal varies. Therefore, sparsity level estimation is often required for choosing an appropriate number of measurements in cognitive radio networks. However, in practice, the sparsity level of wideband signal is often time-varying and difficult to estimate, because of either the dynamic activities of PUs or the time varying fading channels between PUs and cognitive radios. Due to this sparsity level uncertainty, most of sub-Nyquist wideband sensing systems should pessimistically choose the number of measurements, leading to more energy consumption in cellular networks.

Hence, future cognitive radio networks should be capable of performing wideband sensing, given the unknown or time varying sparsity level. In such a scenario, it is very challenging to develop adaptive wideband sensing techniques that can intelligently/quickly choose an appropriate number of compressive measurements without the prior knowledge of the sparsity level. [15]

4.3. Cooperative Wideband Sensing

The wideband spectrum sensing reliability may be compromised due to the wireless channel fluctuations and fading effects. It is possible to improve the sensing accuracy through cooperative approaches significantly.

In a multipath or shadow fading environment, the primary signal as received at cognitive radios may be severely degraded, leading to unreliable wideband sensing results in each cognitive radio. In this situation, future cognitive radio networks should employ cooperative strategies for improving the reliability of wideband sensing by exploiting spatial diversity. Actually, in a cluster-based cognitive radio network, the wideband spectra as observed by different cognitive radios could share some common spectral components, while each cognitive radio may observe some innovative spectral components. Thus, it is possible to fuse compressive measurements from different nodes and exploit the spectral correlations among cognitive radios in order to save the total number of measurements and thus the energy consumption in cellular networks.

Such a data fusion-based cooperative technique, however, will lead to heavy data transmission burden in the common control channels. It is therefore challenging to develop data fusion-based cooperative wideband sensing techniques subject to relaxed data transmission burden.

An alternative is to develop decision fusion-based wideband sensing techniques, if each cognitive radio is able to detect wideband spectrum independently. Due to the limited computational resource in cellular networks, the challenge that remains in the decision fusion-based cooperative approach is how to appropriately combine information in real time. [15]

Furthermore, one of the problems in cooperation is in combining the results of various users which may have different sensitivities and sensing times. Some form of weighted combining needs to be performed in order to take this into account.

Also, the design of control channels is also a major task in Cooperative Spectrum Sensing. A control channel can either be implemented as a dedicated frequency channel or as an underlay UWB channel. Wideband RF frontend tuners/filters can be shared between the UWB control channel and normal cognitive radio reception/transmission.

Furthermore, with multiple cognitive radio groups active simultaneously, the control channel bandwidth needs to be shared. With a dedicated frequency band, a CSMA scheme may be desirable.

For a spread spectrum UWB control channel, different spreading sequencing could be allocated to different groups of users; thus imposing the challenge of defining the spreading sequences for an underlay spread spectrum UWB control channel.

5. Conclusion

In this article, we have addressed typical problems that conventional narrow-band spectrum sensing techniques do face. In context of these, we have discussed various Wideband Spectrum Sensing algorithms. We have reviewed these techniques briefly along with their merits and demerits here. Also, the designing issues and the challenges obligatory to them are also discussed in this article, that is still open research issues in the field of spectrum sensing.

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