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Major Spectrum Sensing Techniques for Cognitive Radio Networks: A Survey

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***Abstract*— The limited available spectrum and the inefficiency in the spectrum usage results in a new communication technology, referred to as cognitive radio networks. Cognitive radio a promising technology which provides a novel way to improve utilization efficiency of available electromagnetic spectrum. Spectrum sensing is a key function of cognitive radio which helps to detect the spectrum holes (underutilized bands of the spectrum) providing high spectral resolution capability to prevent the harmful interference with licensed users and identify the available spectrum for improving the spectrum's utilization. Different spectrum sensing techniques including narrowband and wideband spectrum, single and cooperative spectrum sensing techniques are discussed. Challenges of spectrum sensing process is presented. Blind detector techniques and robust sensing algorithms are also explained and discussed in this paper.**

***Index Terms*—Spectrum Sensing, Cognitive Radio, Cooperative Sensing, Wideband Sensing.**

I. INTRODUCTION

A cognitive radio is designed to be aware of and sensitive to the changes in its surrounding. An important and essential function of Cognitive Radio (CR) networks is to sense the spectrum holes, unutilized band of the spectrum, which enables CR networks to adapt to its environment. The most effective way to detect spectrum holes is to detect the existence of active licensed users, also known as primary users (PUs) that are receiving data within the communication range of Next Generation (xG) networks. Figure (1) shows spectrum utilization in the frequency bands between 30 MHz and 3 GHz averaged over six different locations [1]. The relatively low utilization of the licensed spectrum suggests that spectrum scarcity, as perceived today, is largely due to inefficient fixed frequency allocations rather than any physical shortage of spectrum. This observation has prompted the regulatory bodies to investigate a radically different access paradigm where secondary (unlicensed) systems are allowed to opportunistically utilize the unused primary (licensed) bands, commonly referred to as white spaces. The fundamental task of each CR user in CR networks, in the most primitive sense, is to detect PUs if they are present and identify the available spectrum if they are absent. This is usually achieved by sensing the RF environment, a process called spectrum sensing [2-5]. The objectives of spectrum sensing are twofold: first, CR users should not cause harmful interference to PUs by either switching to an available band or limiting its interference with PUs at an acceptable level and, second, CR users should efficiently identify and exploit the spectrum holes for required throughput and Quality of Service (QoS). Thus, the detection performance in spectrum sensing is crucial to the performance of both primary and CR networks [6]. The detection performance can be primarily determined on the basis of two metrics: probability of false alarm, which denotes the probability of a CR user declaring that a PU is present when the spectrum is actually free, and probability of detection, which denotes the probability of a CR user declaring that a PU is present when the spectrum is indeed occupied by the PU. Since a miss in the detection will cause the interference with the PU and a false alarm will reduce the spectral efficiency, it is usually required for optimal detection performance that the probability of detection is maximized subject to the constraint of the probability of false alarm. In order to protect the primary systems from the adverse effects of secondary users' interference, white spaces across frequency, time and space should be reliably identified. Table 1 lists a variety of approaches that may be employed for this purpose [7]. The first two approaches charge the primary systems with the task of providing secondary users with current spectrum usage information by either registering the relevant data (e.g., the primary system's location and power as well as expected duration of usage) at a centralized database or broadcasting this information on regional beacons [8]. While leading to simplified secondary transceivers, these methods require some modifications to the current licensed systems and, as such, are incompatible with legacy primary users. Moreover, their deployment is costly and requires positioning information at the secondary users in addition to either a ubiquitous connection to the database or a dedicated standardized channel to broadcast the beacons. Spectrum sensing, on the other hand, solely relies on the secondary system to identify white spaces through direct sensing of the licensed bands. In this case the secondary system monitors a licensed frequency band and opportunistically transmits when it does not detect any primary signal. Thanks to its relatively low infrastructure cost and compatibility with legacy primary systems, spectrum sensing has received more attention than other candidates and is being considered for inclusion in the IEEE 802.22 standard. Due to their ability to autonomously detect and react to changes in spectrum usage, secondary users equipped with spectrum sensing capability may be considered a primitive form of cognitive radio [9]. Indeed, enabling dynamic spectrum access seems to be the first and

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foremost commercial application of cognitive radio [10].

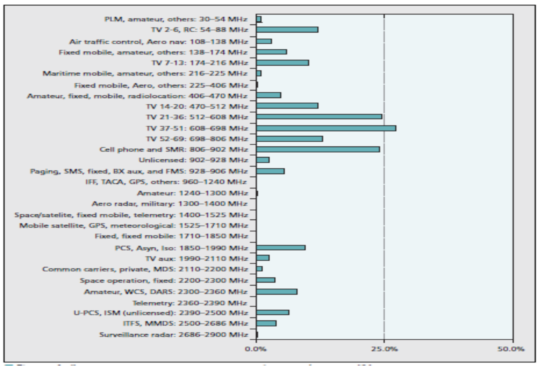

Fig 1. Spectrum usage measurements averaged over six locations [1]

II. CHALLENGES OF SPECTRUM SENSING PROCESS

Several sources of uncertainty such as channel uncertainty, noise uncertainty, sensing interference limit etc. need to be addressed while solving the issue of spectrum sensing in cognitive radio networks. These issues are discussed in details as follows.

A. Channel uncertainty

In wireless communication networks, uncertainties in received signal strength arises due to channel fading or shadowing which may wrongly interpret that the primary system is located out of the secondary user's interference range as the primary signal may be experiencing a deep fade or being heavily shadowed by obstacles. Therefore, cognitive radios have to be more sensitive to distinguish a faded or shadowed primary signal from a white space. Any uncertainty in the received power of the primary signal translates into a higher detection sensitivity requirement. Figure (2) shows the tradeoff between spectrum sensing time and user throughput.

Under severe fading, a single cognitive radio relying on local sensing may be unable to achieve this increased sensitivity since the required sensing time may exceed the sensing period. This issue may be handled by having a group of cognitive radios (cooperative Sensing), which share their local measurements and collectively decide on the occupancy state of a licensed band.

Table 1. Classification of white space identification methods [7].

	Infrastructure Cost	Legacy compatibility	Transceiver complexity	Positioning	Internet connection	Continuous monitoring	Standardized Channel
Database Registry	High		Low	X	X		
Beacon Signals	High		Low	X			X
Spectrum Sensing	Low	X	High			X	

B. Noise uncertainty

The detection sensitivity can be defined as the minimum SNR at which the primary signal can be accurately (e.g. with a probability of 0.99) detected by the cognitive radio and is given by Equation 1,

$$\gamma_{min} = \frac{P_p L\ (D+R)}{N} \tag{1}$$

Where N is the noise power, Pp is transmitted power of the primary user, D is the interference range of the secondary user, and R is maximum distance between primary transmitter and its corresponding receiver The above equation suggests that in order to calculate the required detection sensitivity, the noise power has to be known, which is not available in practice, and needs to be estimated by the receiver. However the noise power estimation is limited by calibration errors as well as changes in thermal noise caused by temperature variations. Since a cognitive radio may not satisfy the sensitivity requirement due to an underestimate of N, γ_{min} should be calculated with the worst case noise assumption, thereby necessitating a more sensitive detector [38].

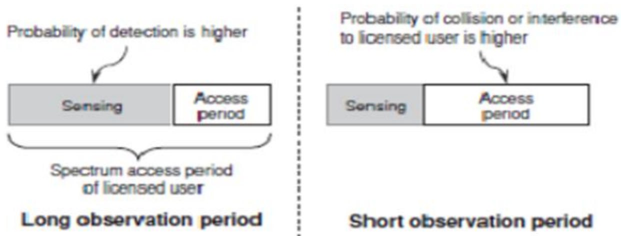

Fig. Tradeoff between spectrum sensing time and user throughput [37]

C. Aggregate interference uncertainty

In future, due to the widespread deployment of secondary systems, there will be increased possibility of multiple cognitive radio networks operating over the same licensed band. As a result, spectrum sensing will be affected by uncertainty in aggregate interference (e.g. due to the unknown number of secondary systems and their locations). Though, a primary system is out of interference range of a secondary system, the aggregate interference may lead to wrong detection. This uncertainty creates a need for more sensitive detector, as a secondary system may harmfully interfere with primary system located beyond its interference range, and hence it should be able to detect them.

D. Sensing interference limit

Primary goal of spectrum sensing is to detect the spectrum status i.e. whether it is idle or occupied, so that it can be

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accessed by an unlicensed user. The challenge lies in the interference measurement at the licensed receiver caused by transmissions from unlicensed users. First, an unlicensed user may not know exactly the location of the licensed receiver which is required to compute interference caused due to its transmission. Second, if a licensed receiver is a passive device, the transmitter may not be aware of the receiver. So these factors need attention while calculating the sensing interference limit.

III. SPECTRUM SENSING TECHNIQUES

There are many ways of classification for spectrum sensing in cognitive radio. One of these classifications based on frequency domain approach and time domain approach. In frequency domain method estimation is carried out directly from signal so this is also known as direct method. In time domain approach, estimation is performed using autocorrelation of the signal. Another classification is by making group into model based parametric method and period gram based non-parametric method [11]. Another way of classification is based on the need of spectrum sensing [12].

A. Spectrum sensing for spectrum opportunities

a) **Primary transmitter detection**: In this approach, detection of a signal from a primary transmitter is based on the received signal at CR users whether it is present or not. It is also known as non-cooperative detection. This method includes matched filter based detection, energy based detection, cyclostationary based detection, radio identification based detection [13], wavelet detection and compressed sensing detection.

b) **Cooperative or collaborative detection**: It refers to spectrum sensing methods where information from multiple Cognitive radio users is incorporated for primary user detection. This approach includes either centralized access to the spectrum coordinated by a spectrum server or distributed approach.

B. Spectrum sensing for interference detection

a) **Interference temperature detection**: In this method the secondary users are allowed to transmit with lower power then the primary users and restricted by interference temperature level so that there is no interference. Cognitive radio works in the Ultra Wide band (UWB) technology.

b) **Primary receiver detection:** In this method, the interference and/or spectrum opportunities are detected based on primary receiver's local oscillator leakage power [13].

C. Classification of spectrum sensing techniques

From the perspective of signal detection, sensing techniques can be classified into two broad categories: coherent and non-coherent detection. In coherent detection, the primary signal can be coherently detected by comparing the received signal or the extracted signal characteristics with a priori knowledge of primary signals. In non-coherent detection, no a priori knowledge is required for detection. Another way to classify sensing techniques is based on the bandwidth of the spectrum of interest for sensing: narrowband and wideband. The classification of sensing techniques [6] is shown in Figure (3). In this article, we will discuss in a quite details spectrum sensing techniques related to wide band and narrowband signals which are the base of wireless communication specially, mobile communications and most of data transmission signals.

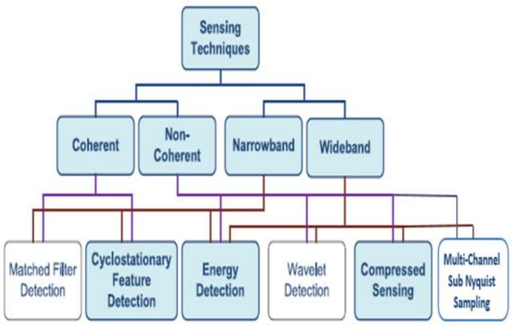

Fig 3. Classification of spectrum sensing techniques

IV. NARROW BAND SPECTRUM SENSING TECHNIQUES

There are different techniques to achieve spectrum sensing within narrow bands. The most effective and practical techniques are energy detection, matched filter detection and cyclostationary feature detection. Each technique has its advantages and drawbacks according to the followings.

A. Energy Detection

Energy detection [14, 15] is a non-coherent detection method that detects the primary signal based on the sensed energy. Energy detection is a sub-optional signal detection technique which has been extensively used in radiometry.

The detection process can be performed in both time domain and frequency domain. To measure the signal power in a particular frequency band in time domain, a band-pass filter is applied to the target signal and the power of the signal samples is measured. To measure the signal power in frequency domain, the time domain signal is transformed to frequency domain using FFT and the combined signal power over all frequency bins in the target frequency band is then measured [16]. Time domain energy detector consists of a low pass filter to reject out of band noise and adjacent signals. Implementation with Nyquist sampling A/D converter, square-law device and integrator as shown in Figure 4(a). Frequency domain energy detector can be implemented similar to a spectrum analyzer by averaging frequency bins of a FFT as shown in Figure 4(b). In energy detection method, the locations of the primary receivers are not known to the cognitive users because there is no signaling between the primary users and the cognitive users.

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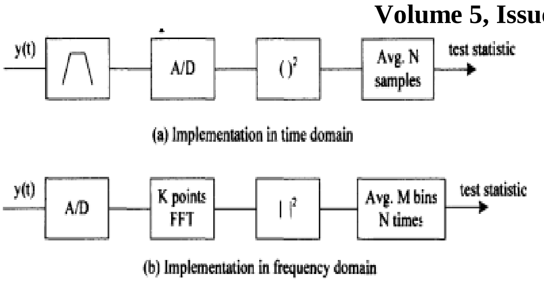


Fig 4. Implementation of Energy Detector

Basic hypothesis model for energy detection can be defined as follows [17]

$$x(t) = \begin{cases} n(t) & H_0 \\ hs(t) + n(t) & H_1 \end{cases} \qquad \textbf{(2)}$$

Where, x(t) is the signal received by the cognitive user, s(t) is the transmitted signal of the primary user, n(t)is the AWGN(Additive White Gaussian Noise) and h is the amplitude gain of the channel. (H_0) is a null hypothesis, (H_1) is an alternative hypothesis.

Without loss of generality, we can consider a complex baseband equivalent of the energy detector. The detection is the test of the following two hypo-theses:

$$\begin{matrix} H_0 : Y[n] = W[n] & \text{Signal absent} \\ H_1 : Y[n] = X[n] + W[n] & \text{Signal present} \end{matrix} \quad , n = 1, \ldots, N$$

Where, (N) is observation interval, the noise samples W[n] are assumed to be additive white Gaussian (AWGN) with zero mean and variance σ_ω. In the absence of coherent detection, the signal samples X[n] can also be modeled as Gaussian random process with variance σ_x. The model could be always reduced into Equation (3).

A decision statistic for energy detector is shown in Equation (4).

$$T = \sum_N (Y[n])^2 \qquad (4)$$

In this architecture, to improve signal detection we have two degrees of freedom. The frequency resolution of the FFT increases with the number of points K (equivalent to changing the analog pre-filter), which effectively increases the sensing time. As the number of averages N increases, estimation of signal energy also increases. In practice, to meet the desire resolution with a moderate complexity and low latency, fixed size FFT is chosen. Then, the number of spectral averages becomes the parameter used to meet the detector performance goal.

If the number of samples used in sensing is not limited, an energy detector can meet any desired probability of detection (P_d) and probability of false alarm (P_{fa}) simultaneously. The minimum number of samples is a function of the signal to noise ratio

$$SNR = \frac{\sigma_x^2}{\sigma_\omega^2} \qquad (5)$$

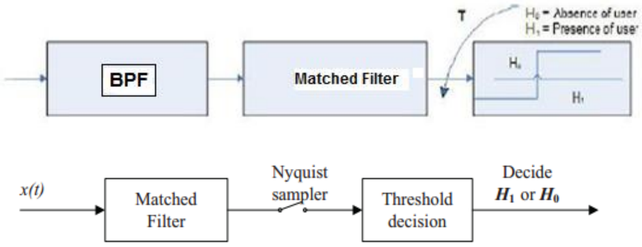
$$N = 2[Q^{-1}(P_{fa}) - Q^{-1}(P_d)\, SNR^{-1} - Q^{-1}(P_d)]^2 \qquad (6)$$

Due to its simplicity and no requirement on a priori knowledge of PU signals, energy detection is the most popular sensing technique. However, energy detection is often accompanied by a number of disadvantages.

i. The sensing time taken to achieve a given probability of detection may be high.
ii. The detection performance is subject to the uncertainty of noise power.
iii. Energy detection cannot be used to distinguish primary signals from CR user signals. As a result, CR users need to be tightly synchronized and refrained from transmissions during an interval called Quiet Period in cooperative sensing.
iv. Energy detection cannot be used to detect spread spectrum signals.

B. Matched Filter

Matched-filtering is known as the optimum method for detection of primary users when the transmitted signal is known [19]. The main advantage of matched filtering is the short time to achieve a certain probability of false alarm or probability of misdetection [20]. Block diagram of matched filter is shown in Figure (5).



(a)
(b)

Fig 5. Block diagram of matched filter. (a) Implementation technique based on [21], (b) Implementation technique based on [23].

Initially the input signal passes through a band-pass filter; this will measure the energy around the related band, then output signal of BPF is convolved with the match filter whose impulse response is same as the reference signal. Finally the matched filter out value is compared to a threshold for detecting the existence or absence of primary user. The operation of matched filter detection is expressed in Equation (7)

$$Y[n] = \sum_{k=-\infty}^{\infty} h[n-k]X[k] \qquad (7)$$

Where (X[k]) is the unknown signal (vector) and is convolved with the (h), the impulse response of matched filter that is matched to the reference signal for maximizing the SNR. Detection by using matched filter is useful only in cases where the information from the primary users is known to the cognitive users [13].

This technique has the advantage that it requires less detection time because it requires less time for higher processing gain. However, matched-filtering requires cognitive radio to demodulate received signals. Hence, it requires perfect knowledge of the primary users signaling features such as bandwidth, operating frequency, modulation

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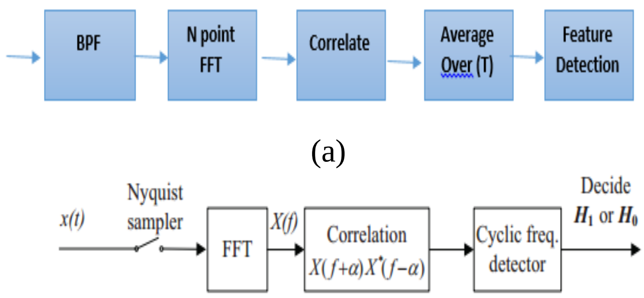
type and order, pulse shaping, and frame format. Moreover, since cognitive radio needs receivers for all signal types, the implementation complexity of sensing unit is impractically large [22]. Another disadvantage of match filtering is large power consumption as various receiver algorithms need to be executed for detection. Further this technique is feasible only when licensed users are cooperating. Even in the best possible conditions, the results of matched filter technique are bound by the theoretical bound [13].

C. Cyclostationary Feature Detection

It has been introduced as a complex two dimensional signal processing technique for recognition of modulated signals in the presence of noise and interference [22]. Cyclostationary feature detection exploits the periodicity in the received primary signal to identify the presence of PUs. The periodicity is commonly embedded in sinusoidal carriers, pulse trains, spreading code, hopping sequences, or cyclic prefixes of the primary signals. Due to the periodicity, these cyclostationary signals exhibit the features of periodic statistics and spectral correlation, which is not found in stationary noise and interference. Thus, cyclostationary feature detection is robust to noise uncertainties and performs better than energy detection in low SNR regions. Although it requires a priori knowledge of the signal characteristics, cyclostationary feature detection is capable of distinguishing the CR transmissions from various types of PU signals.

This eliminates the synchronization requirement of energy detection in cooperative sensing. Moreover, CR users may not be required to keep silent during cooperative sensing and thus improving the overall CR throughput. This method has its own shortcomings owing to its high computational complexity and long sensing time. Due to these issues, this detection method is less common than energy detection in cooperative sensing. Block diagram of cyclostationary feature detection technique is shown in Figure (6).



(a)

(b)

Fig 6. Cyclostationary feature detector block diagram. (a) Implementation technique based on [21], (b) Implementation technique based on [23].

The received signal is assumed to be of the following simple form

$$\mathbf{Y(n) = S(n) + W(n)}$$

The cyclic spectral density (CSD) function of a received signal in Equation (7) can be calculated as

$$S(f,\alpha) = \sum_{\tau=-\infty}^{\infty} R_y^\alpha(\tau) e^{-j2\pi t} \quad (9)$$

Where, $R_y^\alpha(\tau)$ is the cyclic autocorrelation function (CAF) as in Equation (9) and α is the cyclic frequency?

$$R_y^\alpha(\tau) = E\left[y(n+\tau)\, y(n-\tau)\, e^{-j2\pi f n}\right] \quad (10)$$

The CSD function outputs peak values when the cyclic frequency is equal to the fundamental frequencies of transmitted signal x(n).Cyclic frequencies can be assumed to be known [24], [25] or they can be extracted and used as features for identifying transmitted signals.

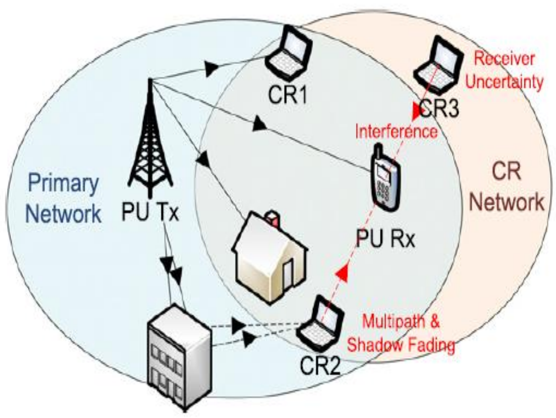


Fig 7. Receiver uncertainty and multipath/shadow fading [6].

The main advantage of the feature detection is that it can discriminate the noise energy from the modulated signal energy. Furthermore, cyclostationary feature detection can detect the signals with low SNR. This technique also have disadvantages that the detection requires long observation time and higher computational complexity [26]. In addition, feature detection needs the prior knowledge of the primary users. Table (2) summarizes the advantages and drawbacks of narrowband sensing techniques.

Table 2. SUMMARY OF ADVANTAGES AND DISADVANTAGES OF NARROWBAND SPECTRUM SENSING ALGORITHMS.

Narrow band Spectrum sensing algorithm	Advantages	Disadvantages
Energy Detection	Low computational complexity. Don't require a priori knowledge of PU signals	Bad performance at Low SNR. Cannot detect spread spectrum signals. Cannot differentiate between PUs and SUs.
Matched-filter detection	Optimum method for detection. Low computational cost. Low sensing time.	Requires perfect knowledge of the primary users signaling features. Large power consumption Large implementation

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		complexity
Cyclostationary Feature Detection	Detect the signals with low SNR. Robust against interference	It needs the prior knowledge of the primary users. long observation time Higher computational complexity

V. COOPERATIVE SENSING TECHNIQUE

In this technique cognitive radio users are cooperated. Many factors in practice such as multipath fading, shadowing, and the receiver uncertainty problem [2] may significantly compromise the detection performance in spectrum sensing. In Figure (7), multipath fading, shadowing and receiver uncertainty are illustrated. As shown in Figure (7), CR1 and CR2 are located inside the transmission range of primary transmitter (PU TX) while CR3 is outside the range. Due to multiple attenuated copies of the PU signal and the blocking of a house, CR2 experiences multipath and shadow fading such that the PU's signal may not be correctly detected. Moreover, CR3 suffers from the receiver uncertainty problem because it is unaware of the PU's transmission and the existence of primary receiver (PU RX). As a result, the transmission from CR3 may interfere with the reception at PU RX. However, due to spatial diversity, it is unlikely for all spatially distributed CR users in a CR network to concurrently experience the fading or receiver uncertainty problem. The main idea of cooperative sensing is to enhance the sensing performance by exploiting the spatial diversity in the observations of spatially located CR users. By cooperation, CR users can share their sensing information for making a combined decision more accurate than the individual decisions [6]. The performance improvement due to spatial diversity is called cooperative gain. The cooperative gain can be also viewed from the perspective of sensing hardware. Owing to multipath fading and shadowing, the signal-to-noise ratio (SNR) of the received primary signal can be extremely small and the detection of which becomes a difficult task. Since receiver sensitivity indicates the capability of detecting weak signals, the receiver will be imposed on a strict sensitivity requirement greatly increasing the implementation complexity and the associated hardware cost. The detection performance cannot be improved by increasing the sensitivity, when the SNR of PU signals is below a certain level known as a SNR wall [8]. Fortunately, the sensitivity requirement and the hardware limitation issues can be considerably relieved by cooperative sensing. As shown in Figure (8), the performance degradation due to multipath fading and shadowing can be overcome by cooperative sensing such that the receiver's sensitivity can be approximately set to the same level of nominal path loss without increasing the implementation cost of CR devices [27]. Fig 8. Improvement of sensitivity with cooperative sensing [27]. However, cooperative gain is not limited to improved detection performance and relaxed sensitivity requirement. For example, if the sensing time can be reduced due to cooperation, CR users will have more time for data transmission so as to improve their throughput. In this case, the improved throughput is also a part of cooperative gain. Thus, a well-designed cooperation mechanism for cooperative sensing can significantly contribute to a variety of achievable cooperative gain. Although cooperative gain can be achieved in cooperative sensing as previously discussed, the achievable cooperative gain can be limited by many factors. For example, when CR users blocked by the same obstacle are in spatially correlated shadowing, their observations are correlated. More spatially correlated CR users participating in cooperation can be detrimental to the detection performance [27].

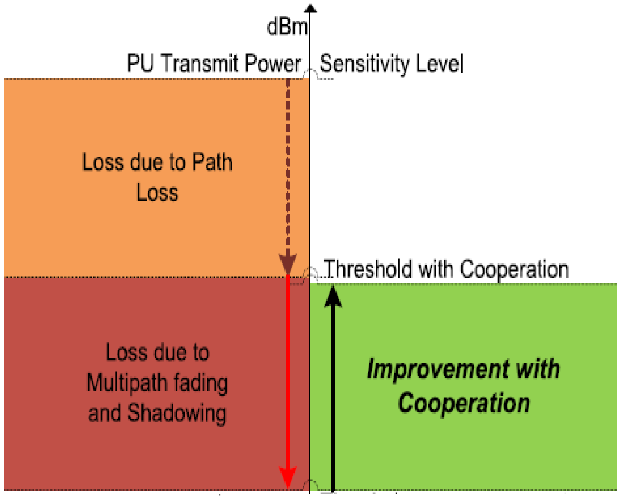

Fig 8. Improvement of sensitivity with cooperative sensing [27].

This raises the issue of user selection for cooperation in cooperative sensing. In addition to gain-limiting factors, cooperative sensing can incur cooperation overhead. The overhead refers to any extra sensing time, delay, energy, and operations devoted to cooperative sensing compared to the individual (non-cooperative) spectrum sensing case. Moreover, any performance degradation in correlated shadowing or the vulnerability to security attacks is also a part of the cooperation overhead. Thus, we are motivated to explore the idea of cooperation in spectrum sensing and provide an insight on how cooperative sensing can be effectively leveraged to achieve the optimal cooperative gain without being compromised by the incurred cooperation overhead.

A. Classification of Cooperative Sensing

Cooperative spectrum sensing can be classified into three categories based on how cooperating CR users share the sensing data in the network: centralized [28], distributed [29], and relay-assisted [30]. These three types of cooperative sensing are illustrated in Figure (9). In centralized

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cooperative sensing, a central identity called fusion center (FC) controls the three-step process of cooperative sensing. First, the FC selects a channel or a frequency band of interest for sensing and instructs all cooperating CR users to individually perform local sensing. Second, all cooperating CR users report their sensing results via the control channel. Then the FC combines the received local sensing information, determines the presence of PUs, and diffuses the decision back to cooperating CR users. As shown in Figure 9(a), CR0 is the FC and CR1–CR5 are cooperating CR users performing local sensing and reporting the results back to CR0. For local sensing, all CR users are tuned to the selected licensed channel or frequency band where a physical point-to-point link between the PU transmitter and each cooperating CR user for observing the primary signal is called a sensing channel. For data reporting, all CR users are tuned to a control channel where a physical point-to-point link between each cooperating CR user and the FC for sending the sensing results is called a reporting channel. Note that centralized cooperative sensing can occur in either centralized or distributed CR networks. In centralized CR networks, a CR base station (BS) is naturally the FC. Alternatively, in CR ad hoc networks (CRAHNs) where a CR BS is not present, any CR user can act as a FC to coordinate cooperative sensing and combine the sensing information from the cooperating neighbors. Unlike centralized cooperative sensing, distributed cooperative sensing does not rely on a FC for making the cooperative decision. In this case, CR users communicate among themselves and converge to a unified decision on the presence or absence of PUs by iterations. Figure 9(b) illustrates the cooperation in the distributed manner. After local sensing, CR1–CR5 share the local sensing results with other users within their transmission range. Based on a distributed algorithm, each CR user sends its own sensing data to other users, combines its data with the received sensing data, and decides whether or not the PU is present by using a local criterion. If the criterion is not satisfied, CR users send their combined results to other users again and repeat this process until the algorithm is converged and a decision is reached. In this manner, this distributed scheme may take several iterations to reach the unanimous cooperative decision. The third scheme is relay-assisted cooperative sensing. Since both sensing channel and report channel are not perfect, a CR user observing a weak sensing channel and a strong report channel and a CR user with a strong sensing channel and a weak report channel, for example, can cooperate with each other to improve the performance of cooperative sensing. In Figure (9c), CR1, CR4 and CR5, who observe strong PU signals, may suffer from a weak report channel. CR2 and CR3, who have a strong report channel, can serve as relays to assist in forwarding the sensing results from CR1, CR4, and CR5 to the FC.

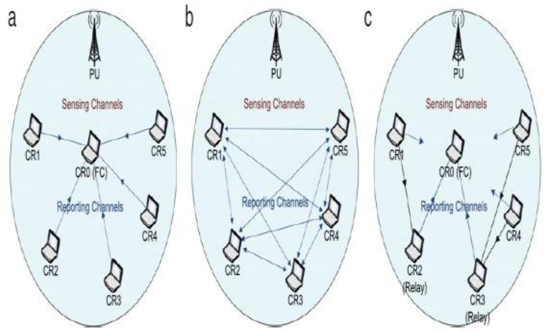

Fig 9. Classification of cooperative sensing: (a) centralized, (b) distributed, and (c) relay-assisted.

In this case, the report channels from CR2 and CR to the FC can also be called relay channels. Note that although Figure (9c) shows a centralized structure, the relay-assisted cooperative sensing can exist in distributed scheme. In fact, when the sensing results need to be forwarded by multiple hops to reach the intended receive node, all the intermediate hops are relays. Thus, if both centralized and distributed structures are one-hop cooperative sensing, the relay-assisted structure can be considered as multi-hop cooperative sensing. In addition, the relay for cooperative sensing here serves a different purpose from the relays in cooperative communications [31], where the CR relays are used for forwarding the PU traffic.

VI. WIDEBAND SPECTRUM SENSING

In wideband sensing, the entire band of interest is processed at once to find a free channel, with either a single Nyquist rate Analog-to-Digital Converter (ADC) or a bank of sub-Nyquist rate ADCs, both followed by digital processing. These typically consume a lot of power and radios with limited power budget cannot afford it [32]. Wideband scanning could be performed via the following two different methods.

(1) By using a filter bank formed by preset multiple narrowband pass filters BPFs [42].This hardware-based solution requires more hardware components, thus increasing the cost and the RF impairments harmful effect, and limiting the flexibility of the radio by fixing the number of filters. After each filter, a narrowband state-of-the-art technique is implemented.

(2) By using sophisticated signal processing techniques. In fact, narrowband sensing techniques cannot be directly applied to scan a wideband since they are based on single binary decision for the whole spectrum. Thus, they cannot simultaneously identify vacant channels that lie within the wideband spectrum. Recently proposed wideband spectrum sensing can be broadly categorized into two types:

(i) **Nyquist wideband sensing** processes digital signals taken at or above the Nyquist rate, for example, Multiband joint detection, Wavelet detection, Sweep-tune detection, and Filter-bank detection as

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shown in Figure (10).

(ii) **Sub-Nyquist wideband sensing** acquires signals using a sampling rate lower than the Nyquist rate, for example, Analog to information converter-based wideband sensing, Modulated wideband converter-based wideband sensing, Multi coset sampling-based wideband sensing, and Multi-rate sub-Nyquist sampling-based wideband sensing as shown in Figure (12).

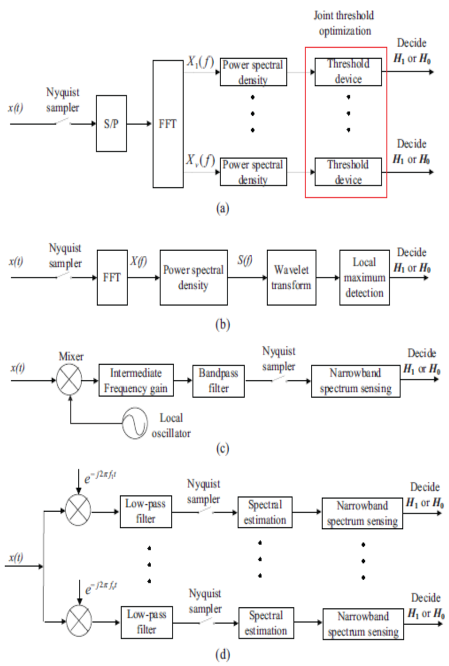
A. Nyquist Wideband Sensing

A simple approach of wideband spectrum sensing is to directly acquire the wideband signal using a standard ADC and then use digital signal processing techniques to detect spectral opportunities. There are many algorithms are proposed to achieve wideband spectrum sensing as discussed below.

1. Multi-band Joint Detection Algorithm

It can sense the primary signal over multiple frequency bands. As shown in Figure 10(a), 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 X1(f), · · · ,Xv(f). 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 [43].

2. Wavelet Transform-Based Algorithm



In this method, the SU transceiver scans a wideband without using a bank of narrow BPFs. Alternatively, a wideband receiver will be based on high-speed digital signal processing to search over multiple frequency bands in an adaptive manner. The obtained digital signal will be modeled as a train of consecutive narrow frequency bands as illustrated in Figure (11). To identify these bands and search for potential spectrum holes, the wavelet transform will be used to locate edges between different narrow sub bands [43]. The corresponding block diagram is depicted in Figure 10 (b). Wavelet transform is used in mathematics to locate irregularities [44]. Consequently, it will be a good candidate to differentiate between the narrow sub-bands of wideband signal [45].A wavelet edge detector is able to identify the average power level within each identified sub-band which will lead to the localization of the spectrum holes. Figure 10. Block diagrams for Nyquist wideband sensing algorithms: (a) Multiband joint detection, (b) Wavelet detection, (c) Sweep-tune detection, and (d) Filter-bank detection [43]. The analysis using wavelet transform is based on a function known as the principal wavelet ψ which has a finite energy. Wavelets are used to transform a given signal into another representation that models the information related to the signal in a more utile way. Wavelets could be manipulated in two different ways: moved along the frequency axis or stretched with a variable energy. A Wavelet transform, obtained by summing the product of the signal multiplied by the wavelet, is calculated at different spots of the signal and for different combinations of the wavelet. This calculation could be monitored to detect the irregularities of the signal by observing the different values of the wavelet transform.

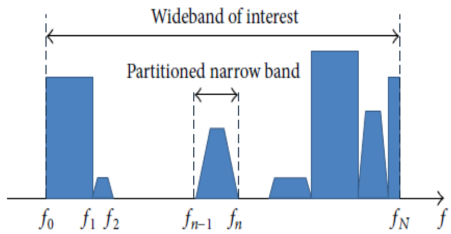


Fig 11. A wideband spectrum seen as a train of narrowband signals and presenting frequency irregularities.

3. Sweep-Tune Detection Algorithm

It could relax the high sampling rate requirement using super heterodyne (frequency mixing) techniques that “sweep” across the frequency range of interest as shown in Figure 10(c). A local oscillator (LO) produces a sine wave that mixes with the wideband signal and down-converts it to a lower frequency. The down-converted signal is then 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 approach is often slow and inflexible due to the sweep-tune operation.

4. Filter Bank Algorithm

A bank of prototype filters (with different shifted central frequencies) was used to process the wideband signal as

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shown in Figure 10(d). 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. Unfortunately, due to the parallel structure of the filter bank, the implementation of this algorithm requires a large number of RF components [43].Table (3) summarizes various Nyquist wideband sensing algorithms.

B. Sub-Nyquist Wideband Sensing

Due to the drawbacks of high sampling rate or high implementation complexity in Nyquist systems, sub-Nyquist approaches are drawing more and more attention in both academia and industry. Sub-Nyquist wideband sensing refers to the procedure of acquiring wideband signals using sampling rates lower than the Nyquist rate and detecting spectral opportunities using these partial measurements. Two important types of sub-Nyquist wideband sensing are compressive sensing-based wideband sensing and multi-channel sub-Nyquist wideband sensing [43].

Table. 3 Comparison between Nyquist wideband sensing algorithms

Algorithm	Multi-band Joint Detection	Wavelet Transform-Based	Sweep-Tune Detection	Filter Bank
Advantages	Good performance	Based on Edge detection using wavelet Simple structure	low sampling rate, high dynamic range	low sampling rate, high dynamic range
Disadvantages	Optimization techniques for detection threshold High sampling rate & Energy cost High implementation complexity	High sampling rate & Energy cost Bad performance at low SNR	Long sensing time. High implementation complexity.	High implementation complexity.

1. Compressive Sensing Algorithm

Compressive Sensing, Compressed Sampling or Compressed Sensing (CS) is a method in which signals are acquired through a set of a few non-adaptive, means the measurement process does not depend on the signal being measured, linear measurements and reconstructed efficiently from this incomplete set of measurements [32]. It is a recently emerging approach for wideband sensing [35], which samples the signal at the information rate rather than at the Nyquist rate. CS requires knowledge of the sparsity level (ratio of the number of busy channels to the total number of channels). Usually, detection with CS is preceded by a coarse or a fine spectrum estimation. Estimating the spectrum using CS generally requires ℓ1-norm optimization and is usually carried out using high-complexity recursive algorithms (e.g., the interior point linear program solver of [36]). let **X** be a sparse (that has a very few non-zero coefficients) vector of length N, we are going to reconstruct **X** using an M<<N measurement by solving the underdetermined linear system **Y=AX**. **Y** belongs to $\mathbf{R}^{Mx1}$ and is called the measurement vector and **A**∈ (MxN) is the CS matrix or the reconstruction matrix. In other words, we are sensing a length N samples signal by only using M (which is very small comparing to N) measurements. The reconstruction algorithm does solving the underdetermined linear system described above. Basically, the challenge of the CS theory includes two main problems. First, the proper design of the CS matrix that establishes the underdetermined linear system and second, choosing the right reconstruction algorithm so as to solve that system. Figure 12. Block diagrams for sub-Nyquist wideband sensing algorithms: (a) Analog-to-information converter-based wideband sensing, (b) Modulated wideband converter-based wideband sensing, (c) Multi-coset sampling-based wideband sensing, and (d) Multi-rate sub-Nyquist sampling-based wideband sensing [43]. Figure (13) shows the basic CS framework, it demonstrates the general stages that the sparse vector will go through. It shows the technique in general, how and why it can be applied to different acquisition systems. Compressed Sensing is a rapidly growing field that has attracted researchers and developers in many fields and applications, such as in general coding and information theory, high dimensional geometry, statistical signal processing, machine learning, compressive imaging, medical imaging, analog to information conversion, radars, digital communication, and computer engineering. In Digital Communication, researchers have been and have tried applying this technique to many general and specific applications such as sparse channel estimation, equalization, sparse multipath channel modeling, UWB-based compressed sensing, cognitive radios, OFDM, sparse codes of multi-antenna systems [39].

Some papers presented CS as an alternative to Nyquist sampling theorem; they claim that, if we have an analog signal which its spectrum contains a very high center frequency with small bandwidth, and we want to sample using the conventional Nyquist theorem, we don’t have to use the regular ADC which cannot support a very high oscillators, and if they could, they consume high power. Instead they are proposing that compressed sensing techniques can perform these tasks with a much lower sampling rate and with less power consumption.

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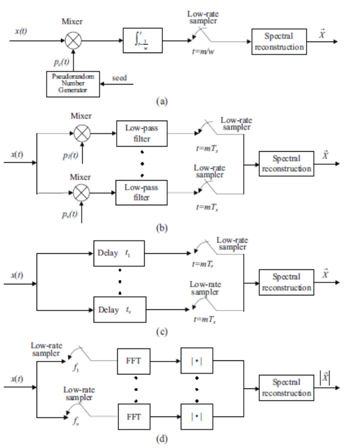

Fig 12.

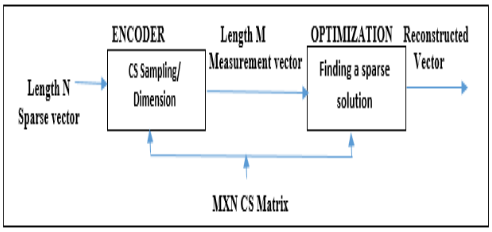

Fig 13. CS framework.

2 Multi-Channel Sub-Nyquist Spectrum Sensing Algorithm

There are many algorithms are proposed to achieve multi-channel sub-Nyquist technique in wideband spectrum sensing each has its advantages and drawbacks as follow.

- A modulated wideband converter (MWC) model has multiple sampling channels, with the accumulator in each channel replaced by a general low-pass filter. One significant benefit of introducing parallel channel structure in Figure 12(b) 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.
- Multi-coset sampling-based wideband sensing which is equivalent to choose 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 [43]. Thus, the multi-coset sampling is often implemented by using v sampling channels with sampling rate ($\frac{Fs}{m}$), with different sampling channels having different time offsets. The block diagram of multi-coset algorithm is shown in Figure (12). To obtain a unique solution for the wideband spectrum from these partial measurements, the sampling pattern should be carefully designed [43]. 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-m th 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 [43].
- Asynchronous multi-rate wideband sensing approach which is designed to relax synchronization problem in multi-coset algorithm. 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. By using different sampling rates in different sampling channels as shown in Figure 12(d), 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. Table (4) presents advantages, disadvantages and challenges of sub-nyquist spectrum sensing techniques [43].

C. Challenges in Wideband Spectrum Sensing

In order to find a free channel quickly, the secondary radios should be able to process the entire band of interest all at once, which a paradigm needs shift from conventional narrowband sensing engines to wideband architectures. Then, challenges of wideband sensing can be analyzed in the following steps.

1. Latency and Complexity

In order to minimize the latency, the radios should adopt wideband architectures to search over multiple frequency channels all at once. It is also necessary for the secondary radios to be aware of the PU retransmission. Hence, sensing has to be repeated at certain intervals, which also demands for low-complexity techniques, which in turn will result in power saving. Realizing low-complexity wideband sensing techniques that can be afforded by sensor nodes is a challenging task.

2. Reliable Detection

Even though spectrum sharing radios allow secondary spectrum usage and co-existence with other technologies, protection of the PU from the harmful interference and minimizing degradation of the PU's performance due to this secondary radio link, always has the top priority. The interference to the PU due to the secondary radio link is often measured in terms of miss-detection probability (to detect a channel as free, when the channel is actually busy). The receiver that performs sensing could be affected due to multipath, fading and shadowing in the channel, or the PU could be hidden to the sensing receiver [33]. These effects limit the detection performance and interfere with the PU. In addition to this, the receiver sensitivity plays a key role for a reliable detection. This becomes important especially while detecting nodes with lower transmit power. Receiver sensitivity decreases with an increase in the receiver bandwidth, as the receiver noise increases with the bandwidth (**$N_0 = -174 + 10 \log B + N_F$**, where **$N_0$** is the receiver noise power in dB, **N_F** is the Noise Figure and **B** is the bandwidth in Hz). Achieving good receiver sensitivity with wideband architectures is relatively difficult.

3. Wideband RF Front-End

Designing a low-complexity wideband RF front-end is a challenging task and different approaches have been proposed in the literature. Multiple narrowband Band-Pass Filters (BFPs) could be employed to realize a filter bank, followed by a decision device to perform wideband sensing [34], but this architecture would require a large number of bulky components and the filter bandwidth of the BPFs (usually determined by the bank of capacitors) is preset. An alternative approach is to use a wideband Nyquist rate ADC, followed by digital processing. In order to achieve better sensitivity, the ADCs should have a higher dynamic range, which means a larger number of bits. Thus, wideband sensing requires high-rate and high resolution ADCs, which typically consume a lot of power. In case of sparse signals, the sampling rate can be relaxed and the acquisition can be done at a sub-Nyquist rate (significantly lower than the Nyquist rate). Later optimization algorithms can be used to recovery the signal without forgoing perfect reconstruction in the noiseless case. This is often referred to as a CS problem. However, current techniques demand signal recovery before detection.

VII. BLIND DETECTORS

Blind detectors were recently proposed to elude the model uncertainty problem relying on advanced digital signal processing techniques. In a cognitive receiver, RF impairments could harm the performance of the spectrum sensing algorithm by inducing unwanted frequency components in the collected signal spectrum. To mitigate the effects of such impairments, "Dirty RF" is applied on the SU receiver inducing a post processing of the signal, thus compensating analog imperfections [46]. A robust detector, based on smart digital signal processing, should be able to digitally lower the effects of RF impairments and guarantee a high sensing accuracy. The selection of signal processing algorithms and their parameters reflects the speed and sensing time of the cognitive receiver. A complex signal processing algorithm should respect an optimum sensing value depending on the capabilities of the radio and its temporal characteristics in the environment. On the other hand, the ADC is considered as the primary bottleneck of the DSP architecture since it forces the clock speed of the system. Moreover, the selection of the digital signal processing platform affects the speed of the front end. All these parameters influence the sensing frequency and speed of cognitive radio receivers. For that, researchers focus on implementing sensing algorithms with low complexity, high speed, and flexibility in order to conceive an adaptive CR terminal. As per regulation specifications, secondary users are required to detect very weak licensed users in order to protect primary transmissions. Any missed detection will enable an unlicensed transmission on a busy channel harming the incumbent primary signal. Unfortunately, many detectors reveal performance degradation at low SNR due to inappropriate estimation of the signal or noise models. This phenomenon is known as SNR wall. For the ED, an estimation of the noise variance is required to select a suitable threshold. Imperfect knowledge of the noise model, especially in low SNR scenarios, will consequently deteriorate the efficiency of this algorithm. The SNR wall phenomenon also harms any detector based on the received signal's moments. Using cooperative spectrum sensing techniques or relying on calibration and compensation algorithms are possible solutions to the model uncertainty problem [47]. However, using totally blind detectors, which detect the presence of a signal without any knowledge of signal or noise parameters, is considered the ideal alternative. Two recently proposed blind detectors are described below.

Algorithm	**Compressive Sensing**	**Multi-Channel Sub-Nyquist Sampling**
Advantages	low sampling rate, signal acquisition cost	low sampling rate, robust to model mismatch
Disadvantages	Sensitive to design imperfections	Require multiple sampling channels
Challenges	improve robustness to design imperfections	Relax synchronization requirement

Table. 4 Comparison between Sub-Nyquist wideband sensing algorithms [43].

A. Blind Eigen value-Based Detector

Zeng et al. devised a blind detector based on the computation of the minimum and maximum eigenvalues λmin and λmax of the sample covariance matrix R(NS) defined in [48]. The test statistics of this maximum-minimum eigenvalue (MME) detection is simply given by

$$\frac{\lambda_{max}}{\lambda_{min}} \underset{H_0}{\overset{H_1}{\gtrless}} v \qquad (11)$$

Where, v is the threshold calculated by using the number of acquired samples, the smoothing factor used for the calculation of **R**(NS), and a selected probability of false alarm. It is expected that noise produces small eigenvalues, whereas the correlation inherited in modulated signals increases the eigenvalues. The proposed test statistic does not depend on any knowledge of noise, signal, or channel models; thus it is not sensitive to the model uncertainty problem. The

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detailed computational steps of this scheme are described in Algorithm 1.

B. The Cyclic Autocorrelation Function (CAF) Symmetry-Based Detector

This blind spectrum sensing detector is based on the symmetry property of the cyclic autocorrelation function (CAF). Benefiting from the sparsity property of CAF, the compressed sensing tool is adopted in this algorithm. A test statistic is defined, without the computation of any threshold, by checking if the estimated CAF exhibits symmetry or not. As demonstrated in [49], a positive symmetry check affirms the presence of a primary signal. The estimation of the cyclic autocorrelation vector is computed using an iterative optimization technique, called the Orthogonal Matching Pursuit (OMP) [50]. The computational complexity of this algorithm is reduced by limiting the number of acquired samples and the number of needed iterations to ensure its practical feasibility. Algorithm 2 summarizes the main steps of this detector.

VIII. CONCLUSION

This paper presented a review of spectrum sensing techniques with different classifications and performed the comparison in terms of operation, accuracies, complexities and implementations. Narrowband and wideband spectrum sensing techniques are discussed with appropriate details that enable researchers to choose a suitable sensing technique to study and develop. Cooperative spectrum sensing types and classifications are explained with examples. Challenges of spectrum sensing are generally discussed and those of wideband spectrum sensing are specifically concentrated. Blind detectors with their characteristics and algorithms are discussed.

Initialize: Acquire L consecutive data samples and assume that there are $(M \geq 1)$ receivers (antennas), and (N_S) is the total number of collected samples.

(a) Define the received vector x_n given by:

$$\mathbf{x}(n) = [x_1(n), x_2(n), \ldots, x_M(n)]^T$$

(b) The collection of L consecutive outputs $\hat{\mathbf{x}}_n$ is defined as:

$$\hat{\mathbf{x}}_n = \left[\mathbf{x}^T(n), \mathbf{x}^T(n-1), \ldots, \mathbf{x}^T(n-L+1)\right]^T$$

(c) Compute the sample covariance matrix $\mathrm{R}(N_S)$:

$$\mathrm{R}(N_S) = \frac{1}{N_S} \sum_{n=L}^{L-1+N_S} \hat{\mathbf{x}}_n \hat{\mathbf{x}}_n^H$$

(d) Compute λ_{max} and λ_{min} the maximum and minimum eigenvalues of the matrix $\mathrm{R}(N_S)$.

(e) Compute the threshold ν for the test statistics:

$$\nu = \frac{\left(\sqrt{N_S} + \sqrt{ML}\right)^2}{\left(\sqrt{N_S} - \sqrt{ML}\right)^2} \left(1 + \frac{\left(\sqrt{N_S} + \sqrt{ML}\right)^{-2/3}}{(N_S ML)^{1/6}} F_1^{-1}(1 - P_{FA})\right),$$

where F_1 is the Tracy-Widom distribution of order 1 [102].

The decision test:

(f) Decide on H_0 or H_1 by computing the ratio between λ_{max} and λ_{min}:

$$\frac{\lambda_{max}}{\lambda_{min}} \gtrless_{H_0}^{H_1} \nu$$

Algorithm (1) Steps of MME blind detectors

Initialize: Acquire n data samples from the spectrum sensing interval formed by N samples and set $(l+1)$ the number of OMP iterations, and (M) the number of delays τs

For M different values of τ,

(a) Calculate the autocorrelation vector $\mathbf{f}_{\tau_0}$ given by:

$$\mathbf{f}_\tau = [f_\tau(0), f_\tau(1), \ldots, f_\tau(N-1)]^T,$$

where $f_\tau(t) = y(t)y(t+\tau)$.

(b) Calculate the elements of the matrix A performing the IDFT transform:

$$a_{(p,q)} e^{2i\pi(p-1)(q-1)/N}$$

The OMP algorithm

(c) Estimate the cyclic autocorrelation vector by solving the following system of equations: $A\mathbf{r}_\tau = \mathbf{f}_\tau$ by using an iterative optimization technique called Orthogonal Matching Pursuit (OMP) that delivers an approximated solution $\hat{\mathbf{r}}_\tau$.

Symmetry check

(d) Calculate the symmetry index for this value of τ, by ignoring the first amplitude that corresponds to the first iteration of OMP, and measuring the mean value of the abscissa of the remaining $(l-1)$ non zero elements in $\hat{\mathbf{r}}_\tau$. The symmetry index is given by:

$$\mathrm{IND}_{\mathrm{sym}}^{(\tau)} = \frac{1}{l} \sum_{i=1}^{l} \hat{\mathbf{r}}_{\tau_i}.$$

End For

Equivalent symmetry check:

$$\mathrm{IND}_{\mathrm{sym}}^{(\mathrm{equ})} = \frac{1}{M} \sum_{i=1}^{M} \left|\mathrm{IND}_{\mathrm{sym}}^{(\tau_i)}\right| < 0.$$

Algorithm (2) Steps of the CAF symmetry-based detector.

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