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A comparative study of spectrum awareness techniques for cognitive radio oriented wireless networks

Raza Umar [a,b,*], Asrar U.H. Sheikh [a]

[a] Wireless Broadband Communication Research Group, Electrical Engineering Department, King Fahd University of Petroleum & Minerals, Dhahran, 31261, Saudi Arabia

[b] University of Engineering and Technology, Lahore 54890, Pakistan[1]

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ABSTRACT

Spectrum scarcity is impeding practical implementations of emerging wireless multimedia applications requiring significantly more frequency spectrum. Cognitive radio (CR) has emerged as a promising solution to the current spectral congestion problem by imparting intelligence to the conventional software defined radio that allows spectrum sharing through opportunistic spectrum access. The principal objective of CR is to optimize the use of under-utilized spectrum through robust and efficient spectrum sensing (SS). This paper introduces cognitive functionality and provides an in-depth comparative survey of various spectrum awareness techniques in terms of their sensing accuracy and computational complexities along with their merits and demerits. Specifically, key challenges in SS are highlighted and possible solutions are discussed. A classification of SS is presented to address the sensing method selection criterion. Both non-cooperative and cooperative sensing schemes are reviewed and open research problems are highlighted to identify future research directions.

1. Introduction

The emerging wireless multimedia applications are leading to an insatiable demand for radio spectrum. The current fixed frequency allocation strategy worked well in the past as it provided an optimal solution by avoiding interference between active wireless users. However, with steadily growing number of wireless subscribers and operators, fixed assignment of radio spectrum is proving to be a hurdle in the deployment of new wireless services. As a result, several spectrum regulatory authorities around the world carried out studies on current spectrum scarcity with an aim to optimally manage available radio spectrum. Interestingly, these studies revealed that a large portion of assigned spectrum is either not used at all or only sparsely utilized, for significant periods of time. According to Federal Communications Commission (FCC) [1], spectrum utilization varies from 15% to 85% with wide variance in time and space. It was concluded that the root cause of current spectrum scarcity is not the physical shortage of spectrum rather the inefficient fixed spectrum allocation. This finding opened doors to a new communication paradigm of sharing the under-utilized radio spectrum through dynamic and opportunistic spectrum access (DOSA) [2].

The technology that enables un-licensed users to dynamically and opportunistically access the licensed spectrum, without affecting the existing users with legacy rights to that spectrum, is the cognitive radio (CR) technology. The key component of CR technology is the ability to sense and ultimately adapt to the continuously changing radio's operating environment. In CR terminology, the incumbents of a frequency band are called primary users

* Corresponding author at: Wireless Broadband Communication Research Group, Electrical Engineering Department, King Fahd University of Petroleum & Minerals, Dhahran, 31261, Saudi Arabia.

E-mail addresses: raza.umar@gmail.com, razaumar@kfupm.edu.sa (R. Umar), asrarhaq@kfupm.edu.sa (A.U.H. Sheikh).

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(PU) while the term secondary users (SU) is reserved for low-priority un-licensed users equipped with a cognitive capability to exploit this spectrum without affecting the operation of PU. Therefore, the most crucial task of SU (also termed as simply CR in literature) is to reliably identify available frequency bands across multiple dimensions like time, space, frequency, angle and code etc., and efficiently exploit them by dynamically updating its transmission parameters under the stringent requirement of avoiding interference to the licensed users of that spectrum. To accomplish this, the secondary users rely on robust and efficient spectrum sensing (SS) to identify vacant frequency bands under uncertain radio frequency (RF) environment and to detect primary users with high probability of detection, as soon as the incumbents become active in the band of interest [3].

This paper presents an introductory tutorial on spectrum sensing for cognitive radio featuring both non-cooperative and cooperative sensing strategies and provides comparative analysis among various detection techniques in terms of required prior information about the source signal and propagation channel. Section 2 introduces cognitive functionality, identifies its objectives and highlights characteristic features of CR. Fundamental sensing approaches are outlined in Section 3 and a comprehensive classification of these schemes is provided. Section 4 presents a variety of conventional and emerging spectrum sensing techniques based on recent advances in local, non-cooperative detection of spectrum activity at CR and provides their performance comparison. This is followed by a detailed discussion on the limitations associated with single-user centric spectrum sensing, outlined in Section 5. Section 6 explains the cooperative sensing concept and discusses various elements of cooperative sensing including cooperation models, information fusion approaches, control channel and reporting concerns and user selection. An insight into the cooperation overhead as the cost of achievable cooperative gain is presented in Section 7 highlighting the key challenges in cooperative detection. Finally, open research problems and future research directions are provided in Section 8 and our conclusions are drawn in Section 9.

2. Cognitive radio

Cognitive radio is essentially an evolution of software defined radio (SDR) which is formally defined by FCC [4] as

A "Cognitive Radio" is a radio that can change its transmitter parameters based on interaction with the environment in which it operates.

The ultimate objective of CR is to utilize the unused spectrum. In essence, this means that CR introduces intelligence to conventional radio such that it searches for a *spectrum hole* defined as "a licensed frequency band not being used by an incumbent at that time within a selected area". As most of the spectrum is already assigned to PUs with legacy rights, the key task is to share licensed spectrum without producing harmful interference to PUs. Hence the main functionality of CR is to track the spectrum hole [5]. Spectrum usage opportunity is then exploited by CR as long as no spectrum activity is detected. If this band is re-acquired by PU, CR being low-priority secondary user must either vacate the band or adjust its transmission parameters to accommodate the PU or, if available/possible, shift to another spectrum hole.

2.1. Cognitive characteristics

Cognitive functionality described above is achieved by two main characteristics of CR namely, *cognitive capability* and *reconfigurability*. Cognitive capability refers to the ability of radio technology to interact with its radio environment in real time to identify and scavenge "un-occupied" licensed spectrum bands called *spectrum holes* or *white spaces* [6]. The observations published by FCC in [1], categorizes spectrum holes into two groups: temporal spectrum holes and spatial spectrum holes. This gives rise to two secondary communication schemes [7] of exploiting spectrum opportunity in time and space domain which are depicted in Fig. 1(a) and (b) respectively.

A *temporal spectrum hole* occurs when no primary transmission is detected over the scanned frequency band for a reasonable amount of time and hence this frequency band is available for secondary communication in current time slot. A *spatial spectrum hole* is generated when the primary transmissions are confined to a certain area as shown in Fig. 1(b) and hence this frequency band is available for secondary communication (may be in the same time slot) well outside the coverage area of PU to avoid any possible interference with primary communication. The secondary transmission over the spatially available licensed spectrum is allowed if and only if it remains transparent to presumably nearby primary receiver. This puts a stringent requirement on SU to be able to successfully detect PU at any place where secondary communication may cause interference to primary transmission. Therefore, a protection area of PU is defined wherein SU must be able to detect any PU activity to avoid harmful interference with primary receiver $D_{\min}$ apart from SU [8,9]. The cognitive capability is not limited to only monitoring power in some frequency band rather it demands multidimensional spectral awareness [10]. This requires that CR should be able to reconfigure its communication parameters on the fly in order to adapt to its dynamic radio environment, calling for the reconfigurability characteristic of CR.

2.2. Key to cognition: spectrum sensing

The key concept in CR is the provision of opportunistic and dynamic spectrum access of licensed frequency bands to unlicensed users. Hence, the main functionality of CR lies in efficient spectrum sensing so that whenever an opportunity of unused spectrum band is identified, CR may make use of it. This paper aims at exploring various dimensions of spectrum sensing with an aim to review ongoing and emerging trends in SS and compare different SS techniques to identify room for potential research opportunities in this field.

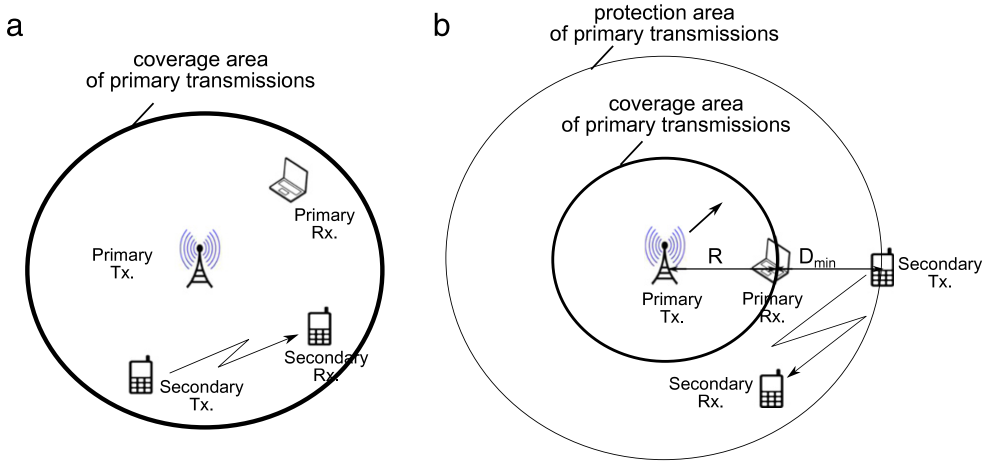

Fig. 1. (a) Temporal spectrum hole. (b) Spatial spectrum hole.

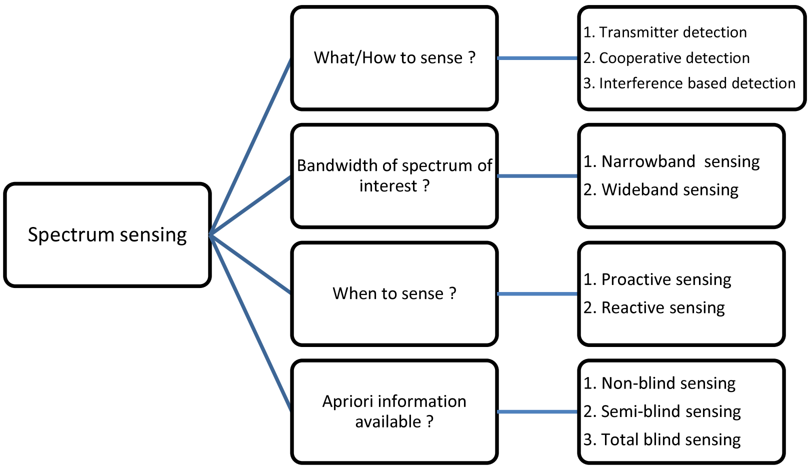

Fig. 2. Classification of spectrum sensing techniques.

3. Spectrum sensing: fundamental approaches and classification

SS is the task of obtaining spectrum occupancy information. Three main approaches can be adopted to obtain this spectrum occupancy knowledge. They are:

1. Spectrum sensing using geolocation and database [11,12].
2. Spectrum sensing by listening to cognitive pilot channel (CPC) or PU beacons [13,14].
3. Local spectrum sensing at CR [15,16].

The most efficient and simple approach to identify spectrum opportunity with low infrastructure requirement is to detect primary receiver within operative range of CR. Practically, however, it is not feasible as CR cannot locate PU receiver, and hence, spectrum sensing techniques usually rely on primary transmitter detection. Before looking into the details of spectrum sensing methods, we summarize the typical grouping of SS schemes in Fig. 2 and highlight characteristic features of these sensing approaches in the following:

Typically, spectrum sensing is classified into three main detection approaches. In a *non-cooperative primary transmitter detection* approach, CR makes a decision about the presence or absence of PU on its local observations of primary transmitter signal. In comparison, *cooperative detection* refers to transmitter detection based SS methods where multiple CRs cooperate in a centralized or decentralized manner to decide about the spectrum hole. Each cooperating node in cognitive radio oriented wireless network (CROWN) may apply any sensing method locally, and then share its raw/refined sensing information with other node(s), depending on a selected cooperation strategy. Both of these approaches fall under the category of *spectrum overlay* wherein SUs only transmit over the licensed spectrum when PUs are not using that band. The third detection approach, based on *spectrum underlay*, wherein, SUs are allowed to transmit concurrently with PUs under the stringent interference avoidance constraint was analyzed and declared to be non-implementable [17] and thus not discussed in this paper.

Depending on the application at hand, CR can opt for either *narrowband* or *wideband* sensing. Thus, the focus of CR will be on identifying narrowband hole or free

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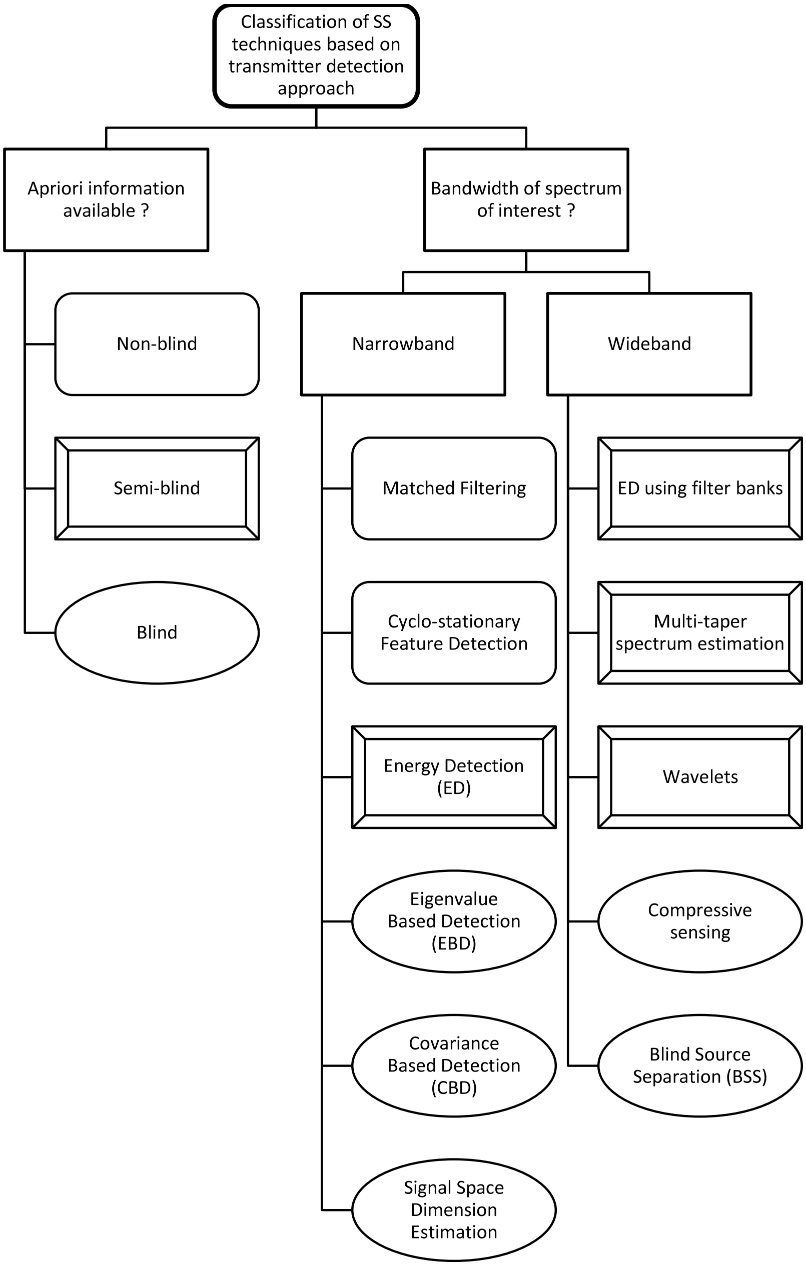

Fig. 3. Enabling spectrum sensing techniques based on primary Tx. detection.

wideband spectrum. To find spectrum opportunity, CR may adopt either a *proactive* (periodic) or *reactive* (on-demand) sensing strategy. Either of the two approaches may be employed in the absence or presence of cooperation among CRs.

A priori information required for PU detection is another important criterion upon which different SS methods are classified. In this category, different transmitter detection based sensing techniques are categorized as *non-blind, semi-blind* or *total blind*. Non-blind schemes require primary signal signatures as well as noise power estimation to reliably detect PU. Semi-blind schemes are relaxed in the sense that they need only noise variance estimate to detect a spectrum hole. However, most practical sensing techniques are generally total blind, requiring no information on source signal or noise power to determine PU activity.

Fundamental to all these classifications is to detect presence or absence of PU signal. Here, we focus on transmitter detection sensing based on a non-cooperative and cooperative approach. Fig. 3 illustrates the SS classification where different borders are used to group representative transmitter detection techniques as non-blind, semi-blind and blind schemes.

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4. SS: transmitter detection (non-cooperative sensing)

A variety of sensing methods are proposed in literature to identify spectrum holes [10,18]. In general, detection problem is analyzed as a binary hypothesis model, defined as:

$$x(t) = \begin{cases} n(t), & 0 < t \le T \quad H_0 \\ hs(t) + n(t), & 0 < t \le T \quad H_1 \end{cases} \tag{1}$$

where $x(t)$ is the signal received by CR during observation window T, $n(t)$ represents the additive white Gaussian noise (AWGN) with mean 0 and variance σ^2, $s(t)$ represents the transmitted signal from primary user which is to be detected and h is the channel gain. This is a classic binary signal detection problem in which CR has to decide between two hypotheses, H_0 and H_1. H_0 corresponds to the absence of primary signal in scanned frequency band while H_1 indicates that the spectrum is occupied. It is important to point out here that under H_1, spectrum may be occupied by an incumbent or a secondary user. Hence, a sensing scheme is generally required not only to detect but also to differentiate between the primary and secondary user signal. Conventionally, the performance of detection algorithm is gagged with its *sensitivity* and *specificity* [10] which are measured by probability of detection P_d and probability of false alarm P_f, respectively. P_d is the probability of correctly detecting the PU signal present in the considered frequency band. In terms of hypothesis, it is given as

$$P_d = \Pr(\text{signal is detected}|H_1). \tag{2}$$

P_f is the probability that the detection algorithm falsely decides that PU is present in the scanned frequency band when it actually is absent, and it is written as

$$P_f = \Pr(\text{signal is detected}|H_0). \tag{3}$$

Thus, we target at maximizing P_d while minimizing P_f. Another important parameter of interest is the probability of missed detection P_m which is the complement of P_d. P_m indicates the likelihood of not detecting the primary transmission when PU is active in the band of interest and can be formulated as

$$P_m = 1 - P_d = \Pr(\text{signal is not detected}|H_1). \tag{4}$$

Total probability of making a wrong decision on spectrum occupancy is given by the weighted sum of P_f and P_m. Hence the key challenge in transmitter detection approach is to keep both P_f and P_m under certain maxima as high P_f corresponds to poor spectrum utilization/exploitation by CR and high P_m may result in increased interference at primary receiver if the missed signal belongs to the incumbent.

A number of methods have been proposed for identifying any spectrum usage opportunity in the scanned frequency band ranging from very simple energy detection to quite advanced cyclostationary feature extraction and waveform based sensing. Recent work mainly focuses on further sophistication of these basic techniques with an aim to make sensing results more robust and accurate at the same time [16,18]. The following subsections provide a brief overview of principles of spectrum sensing techniques based on the observation of PU signal. This review provides a single unified reference guide to both classical and emerging trends in SS for CR in addition to providing reference to key publications for in-depth reading without going into the mathematical details of sensing methods.

4.1. Energy detection

Energy detection is a naive signal detection approach which is referred in classical literature as *radiometry*. In practice, energy detector (ED) is especially suitable for wideband SS when CR cannot gather sufficient information about the PU signal. First, received primary signal is prefiltered with a band pass filter (BPF) of bandwidth W to select the desired frequency band. Filtered signal is then squared and integrated over observation window of length T. This gives an estimated energy content of signal which is then compared with a threshold value depending on noise floor to decide about the presence of PU signal in scanned sub-band [19]. When the spectral environment is analyzed in frequency domain and power spectral density (PSD) of the observed signal is estimated, this approach is termed as *periodogram* [20].

General performance analysis of ED is outlined in [7] with some discussion on advanced power spectrum estimation techniques while its performance in fading environments is analyzed in [21]. Setting the right threshold value is of critical importance [22]. The key problem in this regard is illustrated in Fig. 4 which shows probability density functions of received signal with and without active PU. If Γ represents the test statistics in the form of energy content of the received signal, energy detection differentiates between the two hypotheses H_0 and H_1 by comparing Γ with threshold voltage V_t as:

$$\begin{aligned} \Gamma &\ge V_t \Rightarrow H_1 \\ \Gamma &< V_t \Rightarrow H_0. \end{aligned} \tag{5}$$

Hence if the selected V_t is too low, the false alarm probability ($P_f = \Pr(\Gamma \ge V_t|H_0)$) increases which results in low spectrum utilization.

On the other hand, if V_t is kept unnecessarily high, the probability of missed detection ($P_m = \Pr(\Gamma < V_t/H_1)$) is increased which may result in interference with an active PU.

Hence, a careful trade off is considered while setting the threshold for ED [23]. In practice, if a certain spectrum re-use probability of unused spectrum is targeted, P_f is fixed to a small value (e.g. $\le$5%) and P_d is maximized. This is referred to as constant false alarm rate (CFAR) detection principle. However, if in CROWN, it is required to guarantee a given non-interference probability, P_m is set at a minimum value (or equivalently P_d is fixed to a high value (e.g. $\ge$95%)) and P_f is minimized. This requirement is known as constant detection rate (CDR) principle. Recently, a weighted combination of P_m and P_f is proposed to define the spectrum sensing error which is minimized to get the optimum threshold using a gradient-based algorithm [24]. The authors have shown that the optimum threshold value adapts to changes in the radio operating

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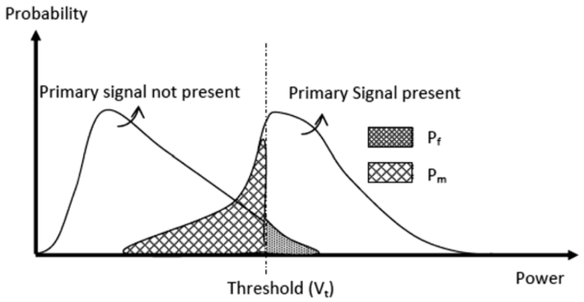

Fig. 4. Threshold setting in ED: trade off between missed detection and false alarm.

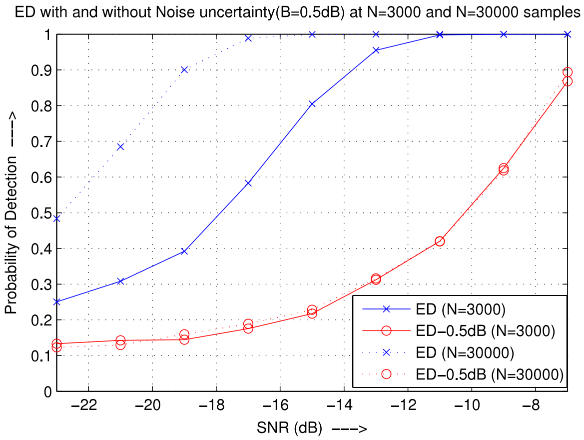

Fig. 5. Performance of energy detector based spectrum sensing under noise uncertainty.

environment and is suitable in dynamic scenarios, in which the active PU signal and/or the background noise variances change in time.

Favorable aspects of energy detection: The implementation simplicity and low computational complexity of ED are its key favorable aspects that have motivated most of the recent work in SS for CR towards enhanced energy detection algorithms and its combinations with other robust and accurate SS methods [25]. ED needs to estimate only the noise power to set its threshold and does not require any information on primary transmission characteristics. This makes energy detection based sensing a semi-blind technique. Furthermore, it is shown to be an optimal technique for detecting independent identically distributed (IID) primary transmissions especially when PU signal features are unknown to CR [8].

Limitations of energy detection: General limitations of ED are addressed in [8] and some hidden assumptions in conventional ED are unveiled more recently in [26]. The key limitation of ED based SS is uncertainty in threshold that produces optimal sensing results, since it strongly depends on the accurate estimation of the noise power which changes temporally and spatially. Fig. 5 shows the performance degradation of ED under noise uncertainty for different sample size and the presence of SNR wall [27]. The SNR wall defines the minimum SNR below which the performance of ED remains unreliable even for infinite sensing duration (unlimited sample size). Statistical performance of ED based on estimated noise variance is analyzed in [28].

Sensing results based on ED have limited reliability as energy observations are unable to differentiate between primary and secondary user signals which appears as a cost of semi-blind signal detection. This may result in false detection of PU signal triggered by other unintended signals. Also, disability to differentiate between signal types, causes difficulty in maintaining fair coexistence among competing secondary users in CROWN. Other limitations include its poor performance under deep signal fades resulting from shadowing and fading and inability to detect spread spectrum signals. All these factors characterize ED with less robustness and low accuracy/reliability.

4.1.1. *Applications of advanced power estimation techniques to ED*

Accurate power estimation is vital in determination of the presence and absence of PU signals. A number of sophisticated power estimation techniques are proposed in literature with an aim to improve over all sensing performance particularly while scanning a wide frequency band. The techniques include filter bank approach, multitaper spectrum estimation, wavelet based spectrum sensing and spectrum detection employing compressed sensing. In the following, we present a brief overview of these wideband sensing methods for ED.

ED using filter banks: In filter bank power spectrum estimation technique, a bank of N sub-filters is used to divide whole frequency band of interest into N sub-bands. The i-th sub-filter of the bank

$$h_i(n) = h(n)e^{j2\pi f_i n}, \quad (0 \le i \le N-1) \tag{6}$$

is used to extract spectral information from the i-th sub-band of interest with normalized center frequency $f_i = \frac{i}{N}$ where, $h(n)$ is termed as the *prototype filter* of the filter bank defined as the low pass filter used to realize *zero*-th sub-band. Frequency response of the prototype filter influences the quality of estimated power in the sub-band and it should be designed with low side lobes in spectral characteristics in order to minimize the power drain from the neighboring sub-bands to the sub-band of interest [29].

It is important to point out that the basic periodogram approach employs rectangular window in time as prototype filter which is characterized by large side lobes in frequency domain giving high power leakage. Improved results may be obtained by preprocessing the received signal before FFT operation with window functions that suppresses the side lobes i.e. by *tapering* the cut-off characteristics of the window. Prototype filters based on different window functions have been discussed in [30].

Multitaper spectrum estimation: Though *tapering* effectively improves the performance of conventional ED by minimizing the power leakage from the neighboring sub-bands to the sub-band of interest, however, it does so by truncating the time domain window which results in information loss. This information loss increases the variance of power spectrum estimate and hence severely degrades the accuracy and reliability of sensing results. In [31], authors have proposed to use multiple prototype filters or multiple tapers in power spectrum estimation to increase the accuracy of the estimate. The proposed algorithm is shown to be an approximation to maximum likelihood (ML) PSD estimator which behaves nearly optimal for wideband signals and at the same time it comes out to be computationally feasible. Because of this reason, Haykin [6] recommended this approach as a promising sensing technique for ED based wideband SS.

Wavelet based SS: The wavelet approach is based on detecting variations in the power level of the received wideband signal at CR. Wavelet based SS models the entire wide spectrum of interest as a train of consecutive frequency sub-bands exhibiting a discontinuous power level between adjacent sub-bands. In [32], the authors assumed PSD within each sub-band to be almost flat and treated changes in power spectral characteristics as irregularities. Wavelet transform was then employed to identify corner frequencies of each sub-band within scanned band of interest. Practically, the receiver noise introduces some spurious peaks in wavelet coefficients which makes it difficult to extract actual frequency boundaries. A novel PSD-whitening approach based on thresholding using the maximum noise wavelet coefficient is recently proposed in [33]. The effect of using different mother wavelets is investigated and comparison of multi-scale product and multi-scale sum on the detection performance revealed that median filtering of the received signal's PSD followed by single scale wavelet transform can reliably identify the corner frequencies of different sub-bands. Once the sub-bands are identified, power level within each sub-band is estimated by averaging the values inside each sub-band to decide about the spectrum hole. It is important to point out that under the assumption of zero mean additive white noise and *a priori* known fact that at least one frequency band is vacant in the scanned frequency range, the minimum power level in a frequency sub-band can be treated as noise variance. This noise floor is then subtracted from observed power level in each sub-band to get an estimate of signal power level in that sub-band. In this way, wavelet approach gives highly accurate sensing results even in low SNR (−5.22 dB corresponding to signal PSD = 3 and noise PSD = 10). This is evident from Fig. 6 which illustrates different steps of wavelet based SS and identify PSD values as [0, 24.0458, 2.9675, 29.9900, 0.1648, 36.3057, 0.0589] corresponding to the true PSD values [0, 24, 3, 30, 0, 36, 0] respectively, and noise PSD as 10.0804 corresponding to the true noise PSD value of 10.

Furthermore, wavelet based sensing also outperforms conventional wideband SS based on multiple narrowband BPFs, in terms of both implementation costs and flexibility in adapting to varying PSD structures over dynamic frequency sub-bands.

Spectrum detection based on compressed sampling: In [34], the authors have extended their approach of wavelets to wideband SS using sub-Nyquist sampling by exploiting the *sparse* nature of wireless signals in frequency domain. The sparsity results due to the low percentage of spectrum occupancy by PUs. This technique relies on the maximum sparsity order to determine the

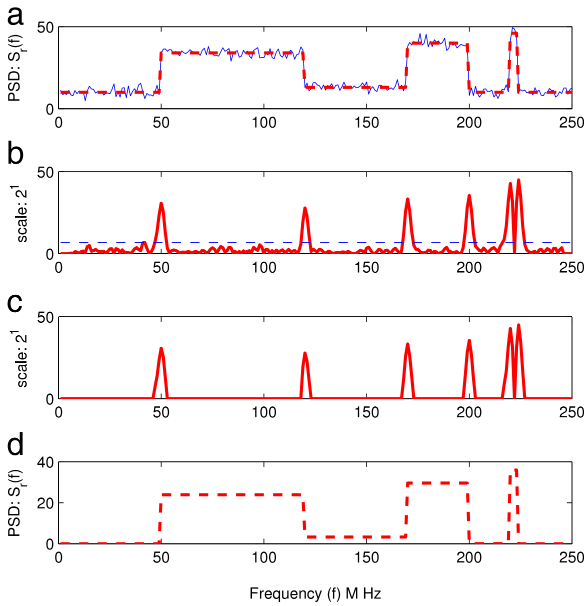

Fig. 6. Wavelet based spectrum sensing: (a) original PSD after Median filtering (b) wavelet transform modulus and noise threshold at scale 2^1 (c) wavelet transform modulus after thresholding (d) detected PU power levels over scanned band.

fundamental limit on the sampling rate which turns out to be unnecessarily high for the desired sensing performance and hence wasteful of sensing resources. To alleviate wasteful sampling, a two step compressed spectrum sensing (TS-CSS) scheme is proposed in [35]. The first step estimates the actual sparsity order, given by the number of non-zero elements in the received wideband primary signal vector at CR, using a small number of samples, and the second step uses the estimated sparsity order to adaptively decide about the number of additional samples required to accurately reconstruct the wideband spectrum and identify any spectrum hole. In this way, TS-CSS achieves the desired sensing accuracy at considerably lower average sampling rate. However, being based on random sampling, it requires complex clocking system which is practically not feasible for opportunistic spectrum hunting.

Compressed sampling for SS has also been reported in [36]. Authors have showed that linear compression with time shifted random pre-integration is equivalent to compressed sensing/sampling (CS) with Toeplitz matrices preserving the autocorrelation properties of PU signal. This allows for joint compressed spectrum estimation and compressed signal detection in an efficient manner.

4.2. Feature (cyclostationary) detection

The idea of feature detection is based on capturing a specific signature of PU signal. Wireless (digitally modulated) signals are in general coupled with sine wave carriers, pulse trains, repeating spreading or hopping sequences or cyclic prefixes, which induce periodicity in the signal making them cyclostationary. This periodicity may result from modulation or even be deliberately generated to assist channel estimation (regularly transmitted pilot sequences) and synchronization (preambles, mid-ambles etc.). Cyclostationary feature detection exploits built-in periodicity of received signal to detect primary transmissions in a background of noise and other modulated signals [37–43]. Features that can be extracted include RF carrier, symbol rate and modulation type etc. [44].

The inherent periodicity in cyclostationary signals causes key statistical characteristics of PU signal like mean and correlation to repeat after regular time intervals. This introduces correlation between widely separated frequency components of the received primary signal which is identified in cyclostationary detection by examining cyclic autocorrelation function (CAF) [45], or, equivalently in frequency domain by cyclic spectral density (CSD), also known as spectrum correlation function (SCF) [37]. Most of the cyclostationary-based feature detection algorithms rely on the detection of cyclic prefix (CP)-induced peaks in CAF whose location are known for standard signals like orthogonal frequency division multiplexing (OFDM). However, as SUs may also employ OFDM modulation with almost same useful symbol duration, this information can be unreliable in differentiating between PU and SU signals. This issue has been addressed in [46] wherein the authors have focused on the second-order cyclostationarity of the OFDM-based mobile worldwide interoperability for microwave access (WiMAX) and third-generation partnership project long term evolution (3GPP LTE) signals to develop a robust algorithm for their classification.

Favorable aspects of feature detection: The salient property of cyclostationary detection is its ability to differentiate PU signal from interference and noise and even distinguish among different types of PUs. This stems from the fact that noise is in general (white) uncorrelated while every PU signal has a specific cyclostationary feature. Another important advantage is robustness to noise uncertainty which allows cyclostationary detector to identify primary transmissions more than 30 dB below the noise floor. Therefore, feature detector outperforms ED especially in low SNR regime. Hidden PU problem occur much less likely than with ED because of its high Probability of detection.

Limitations of feature detection: High accuracy of cyclostationary detection comes at the cost of increased implementation complexity in terms of high processing requirements which results in large sensing time. Specifically, this processing is required to extract cyclic frequencies (if not known *a priori*) from received primary transmissions which in turn also makes this approach non-blind. Also, short duration spectral opportunities cannot be exploited efficiently using this approach because of large observation time requirements.

Recent work [25] has reported to combine ED with feature detection to benefit from complementary advantages of both the schemes by doing coarse detection using ED which is then made more reliable by fine detection employing cyclostationary detection.

4.3. *Coherent sensing: pilot based detection*

Coherent sensing makes use of known patterns in PU signal to coherently detect the presence of active PU. These known patterns, sometimes termed as *pilot signals*, are usually transmitted periodically by PU to assist channel estimation and achieve time and frequency synchronization at primary receiver. When CR has *a priori* knowledge of these known signal patterns in primary transmission, it can detect the PU signal by either passing the received signal at CR through a filter (matched filter: MF) having impulse response matched to the incoming signal or correlating it with a known copy of itself. Thus there are two main approaches of coherent sensing namely: Matched filtering and correlation (waveform-based) detection.

4.3.1. *Matched filtering*

Matched filtering is an optimal detection approach as it maximizes the output SNR. The output of MF is compared with a threshold to decide about the presence or absence of PU signal. More details on SS based on matched filtering can be found in [7].

4.3.2. *Waveform based sensing*

Waveform based approach is less complex as compared to MF and consists of a correlator which exploits the known patterns in PU signal by correlating the received primary signal at CR with its own copy. Similar to MF, correlator output is compared with a fixed threshold to pick out spectrum hole [47].

Favorable aspects of pilot based detection: The main advantage of pilot based sensing lies in its high processing gain which is achieved in comparatively very short time because of coherent detection [48]. As is the case of cyclostationary feature detection, coherent detection exploits *a priori* knowledge about PU signals to be able to distinguish them from interference and noise and thus detecting PU in very low SNR. Moreover, it is computationally less complex as compared to cyclostationary detection. It is shown in [47] that performance of waveform based sensing is better than ED in terms of reliability and convergence time and improves further with increasing length of known signal patterns.

Limitations of pilot based detection: Pilot based detection requires CR to demodulate the signal prior to detection. As a result, it requires perfect knowledge of PU transmission parameters like carrier frequency, bandwidth, modulation type and order, frame format, pulse shaping etc. This makes this scheme non-blind and detection performance degrades dramatically in case of inaccurate PU signal information or synchronization errors. A significant drawback of MF is its stringent requirement of dedicated receivers for all possible primary signal forms which makes this scheme unpractical [49]. MF also suffers from high power consumption because of its computational complexity. Waveform based detector has been shown to be very sensitive to synchronization errors [47].

4.4. *Covariance based detection*

Covariance based detection exploits the inherent correlation in received PU signal samples resulting from the time dispersive nature of wireless channel and oversampling of received signal [50]. If CR uses multiple antennas,

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received signal samples are also spatially correlated as they originate from the same source (primary) signals.

In multi-antenna CR, multiple copies of the received PU signal can be coherently combined to maximize the SNR of received (combined) signal. The diversity combining approaches of maximum ratio combining (MRC) and selection combining (SC) are analyzed for ED in [51]. Although, MRC gives optimal detection performance but is difficult to implement as it requires channel between transmitter (primary) and receiver (secondary) to be known at the receiver. In comparison, blind detection calls for equal gain combining (EGC) or blind combining (BC). In [52], authors revisited the combining strategies for PU signal samples received at different CR antennas during different time intervals. An optimal combining approach (MRC), requires *a priori* information about the primary signal and channel in the form of eigenvector corresponding to maximum eigenvalue of the received source (primary) signal covariance matrix. However, this eigenvector can be estimated using the received signal samples only without requiring any information of primary transmitted signal. In this way, temporal spatial combining of received samples may be achieved blindly. After combining, ED is used to identify any vacant spectrum band in the received wideband signal. The authors have named MRC based ED as optimally combined energy detection (OCED) and BC based ED as blindly combined energy detection (BCED) in [52].

There are other possible ways to utilize eigenvalues of received sample covariance matrix for SS. In [53], authors have indicated that number of significant eigenvalues is directly related to presence/absence of data in received signal and may be exploited to identify vacant spectrum bands. The ratio of maximum eigenvalue to minimum eigenvalue (MME) and the ratio of average eigenvalue (energy of received signal) to minimum eigenvalue (EME) are used in [54] to detect the presence of primary signal. Figs. 7 and 8 provide a comparison of semi-blind ED with variety of blind eigenvalue based detection (EBD) algorithms under no noise uncertainty and 0.5 dB noise uncertainty case respectively. It is evident that EBD not only outperforms ED for correlated PU signals by capturing the inherent correlation in source signals but is also robust to noise uncertainty. However, it is important to point out here that EBD relies on the distribution of ratio of extreme eigenvalues of received covariance matrix whose closed form expressions are still mathematically untractable and asymptotic assumptions are usually employed to set the detection threshold [55,56]. More recently, an upper bound on the joint probability density function of the largest and smallest eigenvalues of the received covariance matrix is used to derive analytically simple expression for the required distribution of the ratio of extreme eigenvalues as reported in [57,58]. Eigenvalue based detection is discussed in detail in [59–61].

If the signals exhibit time correlation as well, the concept of EBD can be extended to incorporate joint space–time processing. This approach is generally known as covariance based detection, EBD being its one special case where the eigenvalues of received signal sample covariance matrix are used for PU signal detection. Covariance based detection has been addressed in [62–64].

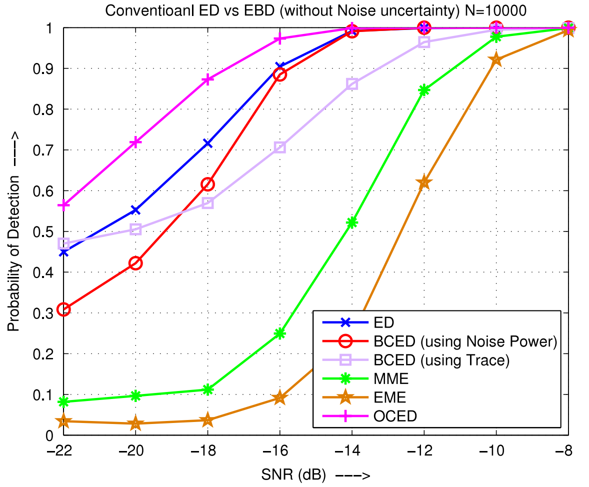

Fig. 7. Performance comparison of the conventional energy detector with eigenvalue based detection under no noise uncertainty.

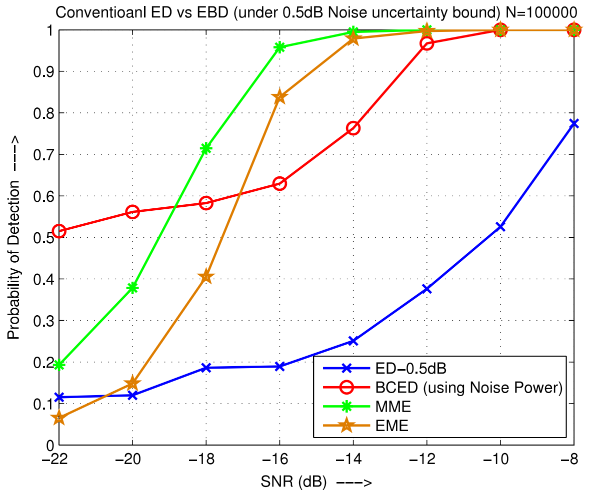

Fig. 8. Performance comparison of the conventional energy detector with eigenvalue based detection under 0.5 dB noise uncertainty factor.

Favorable aspects of covariance based detection: Generally covariance based detection does not require any information about the primary signal or noise. However, if some *a priori* information about primary signal correlation becomes available, this may assist in choosing corresponding elements in sample covariance matrix making the decision test statistic more efficient. Most importantly, covariance based detection does not need noise power estimation as the threshold is related to P_f and sample size N of the received signal at CR only thereby, it achieves better performance for highly correlated signals.

Limitations of covariance based detection: Performance of covariance based detection strongly depends on statistics of received primary signal which degrades if primary signal tends to be uncorrelated.

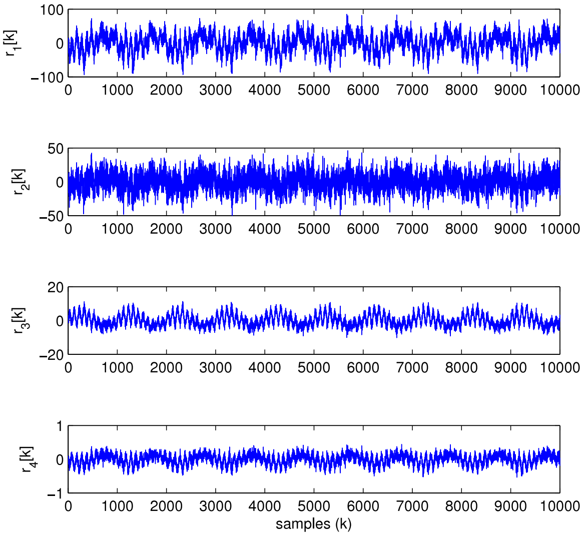

Fig. 9. SS using BSS: observed noisy mixed signals at four antennas of CR.

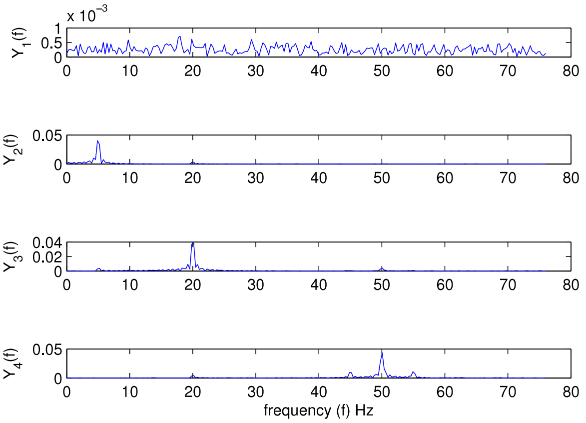

Fig. 10. SS using BSS: frequency spectrum of noisy recovered signals after pre-whitening.

4.5. *Other blind spectrum sensing techniques*

A variety of promising blind sensing techniques are reported in recent literature. In [65], moments of received PU signal are investigated to identify spectral opportunity. Model selection tools such as Akaike information criterion (AIC) and Akaike weights [66] are applied to SS in [67] where authors have analyzed Akaike weights under AWGN to decide if the distribution of received signal at CR fits the noise distribution or not. Blind SS algorithm based on oversampling the received signal or employing multiple antennas at CR is proposed in [68]. In this approach, linear prediction is used in conjunction with QR decomposition of the received signal matrix to compute two signal statistics whose ratio indicates the presence/absence of primary signal in the scanned frequency band.

Blind source separation (BSS) technique is discussed for the CR system model with multiple antennas in [69] to simultaneously detect active PUs in the scanned spectrum. For the sake of illustration, four channels/PU signals are analyzed in [70] and performance of BSS in CROWN is simulated using simple PU signal models. In this setup, channel one and two are occupied by pure tones of 5 Hz and 20 Hz, respectively, channel three is amplitude modulated (AM) with carrier centered at 50 Hz while channel four is kept idle and hence contains only noise. These four primary signals are observed at four antennas/sensors and appear to be noisy linear mixture of active PU signal samples, represented by $r_i[k]$ $(i = 1, 2, 3, 4)$ in Fig. 9. These mixed observed samples are then passed through a whitening filter before applying a low complexity, non-iterative BSS approach for multiuser detection. Finally, the inherent channel sequence uncertainty in BSS is resolved by looking at the frequency spectrum of separated signal samples shown by $Y_i(f)$ $(i = 1, 2, 3, 4)$ in Fig. 10.

Recently, Kurtosis metric is used inside BSS algorithm based on independent component analysis (ICA). A new framework for SS is proposed that combines BSS based SS with conventional blind SS techniques employing EBD [71]. In this approach, sensing accuracy is significantly increased as SS can be performed even when the cognitive transmitter is in operation.

4.6. *Emerging sensing schemes*

A glimpse of recent advances in spectrum sensing is given below:

4.6.1. *Quickest detection*

The key requirement in *spectrum overlay* is that the SU must vacate the spectrum as quickly as possible when the primary user resumes its transmissions in that band. The theory of quickest detection [72] has been applied to spectrum sensing problem in order to promptly detect the change of distribution in spectrum occupancy observations and combine generalized likelihood ratio test (GLRT) with parallel cumulative sum (CUMSUM) test to estimate the amplitude of the discovered PU signal [73]. More recently, collaborative quickest detection has also been explored in [74].

4.6.2. *Learning/reasoning-based sensing*

In learning-based sensing, CR updates its sensing decision based on previous sensing results while reasoning-based sensing improves its sensing decision through deductive inference. A reinforcement learning based artificial intelligence approach is proposed in [75] to estimate the available resources in multiple frequency bands. This facilitates the CR to switch to another frequency band in case of shortage of resources in the active band. The same idea is investigated for a group of cooperating CRs under different conditions in [76–78] for the case of cognitive radio ad hoc networks. Medium access layer (MAC) sensing scheme using knowledge-based reasoning is analyzed in [79] and an optimal data transmission and rate selection strategy is developed to maximize the CR throughput. More recently, the extended version of the scheme is discussed in [80] to improve the fine sensing accuracy by jointly considering network states and environmental statistics.

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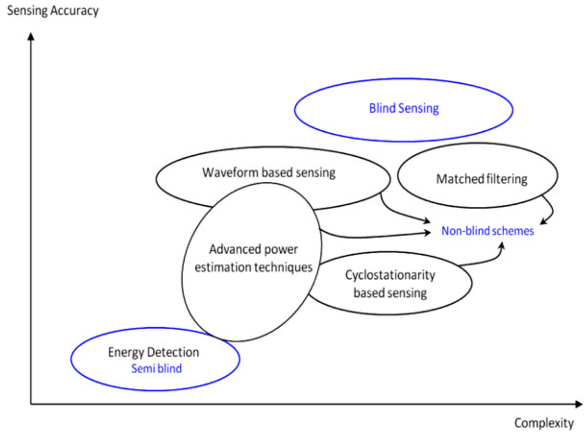

Fig. 11. Comparison of spectrum sensing methods.

4.6.3. *Joint spectrum sensing and resource allocation*

In the hunt for empty frequency band in the scanned spectrum with multiple bands, the availability probability of each radio channel is unknown to CR. As a result, efficient spectrum sharing policy must maintain a balance between exploring new white spaces and exploiting the available free channels in a competitive environment where multiple secondary users compete for available radio resources. This leads to cross-layer optimization problem solved by merging spectrum sensing with resource allocation which translates into multi-armed bandit problem [81]. Such problems are usually NP-hard. A low complexity asymptotically optimal medium access strategy is developed recently in [82] and a generic case of simultaneously sensing and accessing multiple channels is analyzed.

4.7. *Comparison of sensing methods*

The selection of a sensing method comes with a tradeoff between accuracy and complexity. A concluding comparison of spectrum sensing techniques is presented in Table 1 to identify key factors in deciding on a sensing strategy.

Fig. 11 compares different SS methods in terms of their implementation, computational complexities and sensing accuracies. When nothing is known about the PU signal, ED happens to be most simple approach but it fails in the presence of fading and noise uncertainties. Advanced power spectrum estimation techniques achieve accuracy while sacrificing the simplicity of energy detection. As a matter of fact, some *a priori* knowledge about primary transmissions is necessary to distinguish primary signal from secondary signal and interference/noise. Processing of this known information achieves reliability in detection at the cost of additional computational complexities. Such schemes are classified as non-blind and the type of the detection approach depends on the available information about primary signal. In particular, cyclostationary detector is suitable when cyclic frequencies associated with primary transmissions are known while coherent detector is preferred when pilot transmissions of primary system are known. Blind sensing, based on received signal covariance matrix and other approaches achieves high accuracy with its computational complexity dependent on sensing algorithm used.

It is important to note that, practically, there are number of factors that may significantly compromise the promised sensing accuracy/reliability of these schemes [83]. The following section highlights such limiting factors that are common to all transmitter detection based non-cooperative spectrum sensing techniques.

5. Challenges in non-cooperative detection

In the following, we discuss some of the key challenges associated with single-user centric transmitter detection schemes that impede them to achieve promised sensing performance under practical conditions.

5.1. *Restricted sensing ability*

CRs need to sense their multidimensional radio environment with limited sensing ability. In general, CRs have no information regarding the possible primary communication over a licensed band. This makes spectrum sensing for cognitive radio a very challenging task.

5.2. *High detection sensitivity requirements*

Detection of low-power primary signals in itself is an arduous job which becomes challenging under uncertain channel conditions. In a typical wireless environment, severe multipath fading and shadowing cause high attenuation of primary transmitted signal such that the SNR at CR for even high power digital TV signal may be practically as low as −21 dB. Poor CR sensitivity in this case results in missed detection of PU (transmitter), ending up in secondary transmissions offering unacceptable interference to PU receiver. It is important to point out here that, in practice, these sensitivity requirements are more demanding and must be raised by additional 30–40 dB [49]. SS is further challenged by noise/interference power variations which are dependent on both time and space [84,85].

5.3. *Vulnerability of primary receivers to secondary transmissions*

The locations of PUs are unknown; the SU may lie outside the PU coverage area or it may be located within the PU's transmission range but primary signal is obscured due to deep fading or shadowing. These practical scenarios are referred to as *primary receiver uncertainty problem* (Fig. 12(a)) and *hidden primary transmitter problem* (Fig. 12(b)), respectively. In both cases, primary receiver may become vulnerable to harmful interference by secondary communications as such situations make CR incapable of picking up ongoing primary transmissions.

5.4. *SS in multiuser environment*

Usually, CRs reside in a multiuser environment consisting of users with and without exclusive rights for frequency spectrum. In addition, CRs can be co-located with

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Table 1
Comparison of spectrum sensing methods.

SS approach	Advantages	Disadvantages	Comments
Energy detection	+ Implementation simplicity	– Non robust • Threshold strongly depends on noise uncertainties • Threshold strongly depends on noise uncertainties	Advanced power estimation techniques become feasible for wideband spectrum sensing • Multitapering [31] • Wavelets [32] • Compressive sensing [34]
	+ Low computational complexity	– Low accuracy/reliability • Unable to differentiate interference from PU signal and noise • Poor performance under low SNR (due to shadowing and multipath fading) • Inability to detect spread spectrum signals	
	+ Optimal for detecting IID primary signals	– Inefficient for detecting correlated primary signals	
	+ Semi-blind (No *a priori* PU signal information required)	– More susceptible to hidden terminal problem	
Feature detection	+Robust to noise uncertainty + High accuracy/reliability • Able to differentiate PU signal from interference and noise • Able to differentiate among PU signals	– Implementation complexity – Non-blind	Hybrid schemes employing coarse detection using ED and fine sensing using feature detection give complementary advantages of both ED and feature detection
	+ High prob. of detection	– High prob. of miss-detection resulting from large observation time	
	+Less susceptible to hidden terminal problem		
Pilot based detection	+ Less complex than cyclostationary feature detection	– (Matched filtering) High complexity and high sensitivity to inaccurate PU signal information	Benefits from all advantages of feature detection at reasonable complexity cost but susceptible to errors in *a priori* information
	+ Higher agility than cyclostationary feature detection	– (Waveform based sensing) High sensitivity to synchronization errors	
	+ Less susceptible to hidden terminal problem	– Non-blind	
Covariance based detection	+High accuracy + Low computational complexity + Blind	– Performance degrades for uncorrelated PU signals	• Detection accuracy can further be increased by making use of available *a priori* information about PU signal correlation • Computational complexity depends on blind detection algorithm • Hidden terminal problem points to cooperation among CRs for sensing performance improvement

other secondary networks in the hunt for same spectrum resource. The presence of a second secondary network affects the detection capability of a CR in two ways:

- A secondary signal may be detected as a primary signal.
- A secondary signal may mask the primary signal thus deteriorating the PU detection capability of CR.

The above discussed limitations of conventional spectrum sensing can be overcome by sharing the sensing information among spatially distributed CRs in the CROWN which leads to the concept of cooperative detection. In the following section, we explore various aspects of cooperative spectrum sensing and analyze how it can guarantee improved sensing performance with minimum incurred cost.

6. Cooperative detection

The most serious limitation of transmitter detection approach is its degraded performance in the presence of multi-path fading and shadowing. This problem can be solved by exploiting the inherent spatial diversity in a multi-user environment resulting from the fact that if some SUs are in deep fade or observe severe shadowing, as shown in Fig. 13, there might be other SUs, in the network, with relatively strong signal from primary transmitter. Consequently, combining the sensing information from different CRs gives a more reliable spectrum awareness. This leads to the concept of cooperative spectrum sensing (CSS) wherein CRs employing different technologies, exchange information about the time and frequency usage of spectrum to avail more efficiently any vacant spectrum opportunity [86,87].

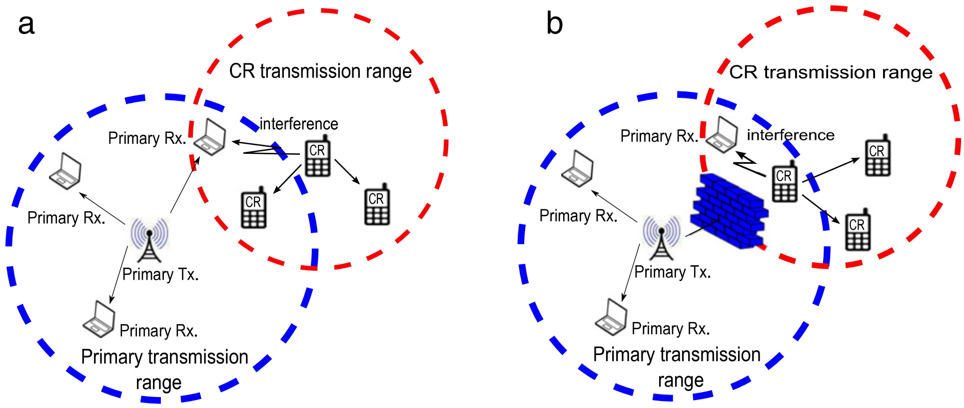

Fig. 12. Vulnerability of primary receivers to secondary transmissions. (a) Receiver uncertainty. (b) Hidden primary transmitter.

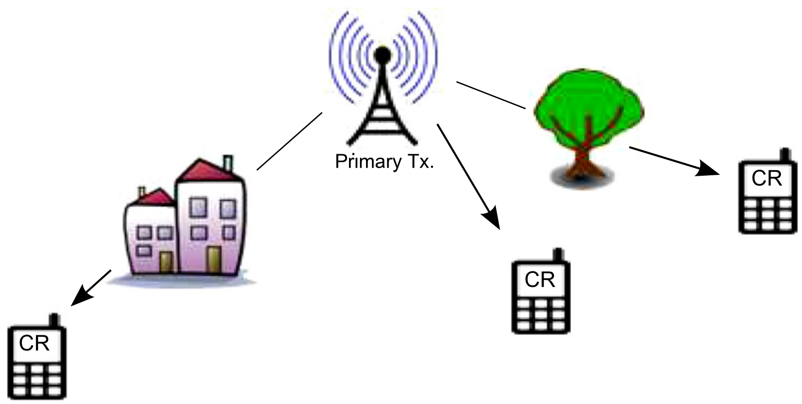

Fig. 13. Cooperative SS in a shadowed environment.

6.1. *Classification of cooperative sensing*

Cooperative sensing can be classified based on different criteria. The key questions in this regard include: who performs sensing, who makes the final decision about spectrum opportunity, how the sensing information is shared and what information is shared among the cooperating SUs. Classification of cooperative spectrum sensing based on these questions is depicted in Fig. 14.

A very comprehensive survey on CSS is provided in [88]. In essence cooperative spectrum sensing is a series of actions involving *Local Sensing, Reporting* and *Information Fusion*. The following subsections highlight the distinguishing features of cooperation strategies.

6.1.1. *Centralized and distributed sensing*

The conventional cooperation strategy completes the three above mentioned steps based on centralized approach which is the most popular cooperation scheme. In *centralized cooperation*, a central unit, also called the *fusion center* (FC), decides about the spectrum hole after collecting local sensing information from cooperating SUs [89,90]. This spectrum opportunity is then either broadcast to all CRs or central unit itself controls the CR traffic by managing the detected spectrum usage opportunity in an optimum fashion. This central node is an access point (AP) in a wireless local area network (WLAN) or a base station (BS) in a cellular network while in CR ad hoc networks, any CR can act as a master node to coordinate CSS. Hence, centralized cooperation can take place in both centralized and distributed network architectures. On the other hand, in *distributed cooperation*, CRs do not rely on a FC to make a cooperative decision. Instead, CRs communicate among themselves and converge to a joint global decision on the presence or absence of PU in an iterative manner [91–93]. This is accomplished in three basic steps defined by a distributed algorithm as follows:

- Each cooperating CR sends its local sensing data to other CR users in its neighborhood (defined by transmission range of CR user).
- Each cooperating CR combines its data with received sensing information from other users to decide on presence or absence of PU based on its local criterion. The shared spectrum observations are usually in the form of *soft* sensing results or quantized (binary/*hard*) version of local decisions about spectrum hole availability.
- If spectrum hole is not identified, CRs send their combined sensing information to other secondary users in

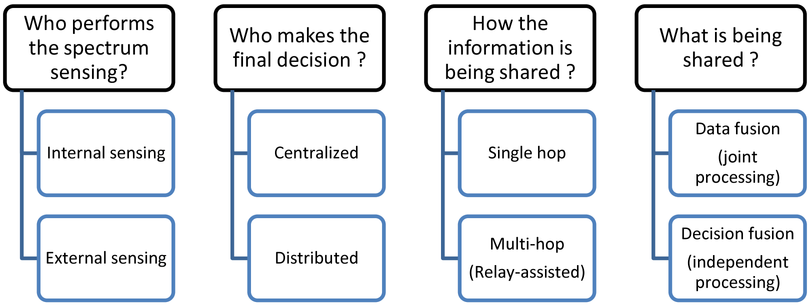

Fig. 14. Classification of cooperative spectrum sensing.

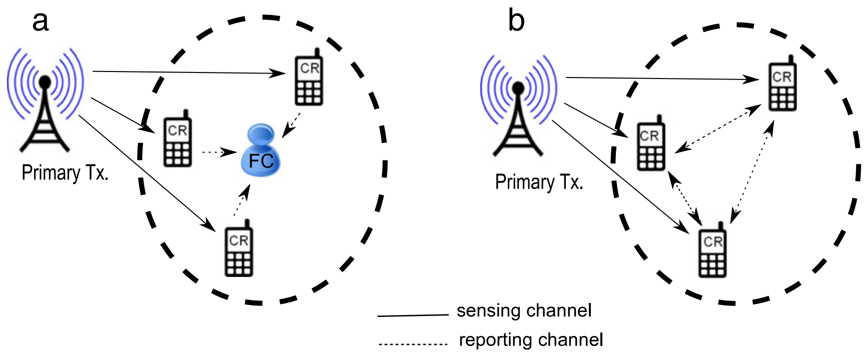

Fig. 15. Cooperative SS (a) centralized approach (b) distributed approach.

Table 2
Comparison of centralized and distributed spectrum sensing.

CSS approach	Advantages	Disadvantages
Centralized sensing	+ Bandwidth efficient for same number of cooperating CRs as compared to distributed cooperation	– One CR i.e. FC becomes very critical as well as complex to carry the burden of all cooperating CRs
Distributed sensing	+ No need of backbone infrastructure resulting in low implementation cost	– Large control bandwidth required for information exchange among all cooperating CRs – Finding neighbors in itself is a challenging task for CRs – Large sensing duration resulting from iterative nature of distributed algorithm

next iteration. The process continues until the scheme converges and a final unanimous opinion on spectrum availability is achieved.

In this way, each CR in distributed cooperation partially plays the role of FC. The significant features of centralized and distributed cooperation are highlighted in Table 2.

The working principle of centralized and distributed cooperation is shown in Fig. 15(a) and (b) respectively.

As shown in Fig. 15, CRs make use of sensing and reporting channels to arrive at a cooperative decision. At first, CRs establish a link with primary Tx. to perform local sensing over the selected licensed frequency band. This physical channel between primary Tx. and each cooperating CR is termed as *sensing channel*. During the reporting phase, CRs need a control channel, also known as *reporting channel* to share local spectrum sensing data with FC or each other. This control channel, depending upon system requirements, can be implemented using a dedicated spectrum, an un-licensed band such as ISM or an underlay approach such as ultra-wide band (UWB) [94]. Usually, a medium access protocol governs the shift between the sensing and control channel.

6.1.2. *Data and decision fusion*

In both centralized and distributed sensing, a control channel is required for sharing sensing information within CROWN to reach a cooperative decision on spectrum hole availability. The bandwidth of the control channel limits the amount of sensing information that can be reported to FC or shared among cooperating CRs. If the entire local sensing data or the complete local test statistics are shared, joint processing of the raw sensing data offers the best detection performance at the cost of control channel communication overhead. This fundamental component of cooperative sensing is termed as *data fusion*. Variety of signal combining techniques are reported in literature to implement *data fusion* based on optimally combining the weighted local observations. In [95], authors have proposed a generalized *soft combining* scheme that reduces to equal gain combining (EGC) at high SNR and boils down to maximal ratio combining (MRC) at low SNR. Furthermore, a two-bit *quantized soft combining* scheme is also presented in the same work to overcome the computational complexity of data fusion scheme and

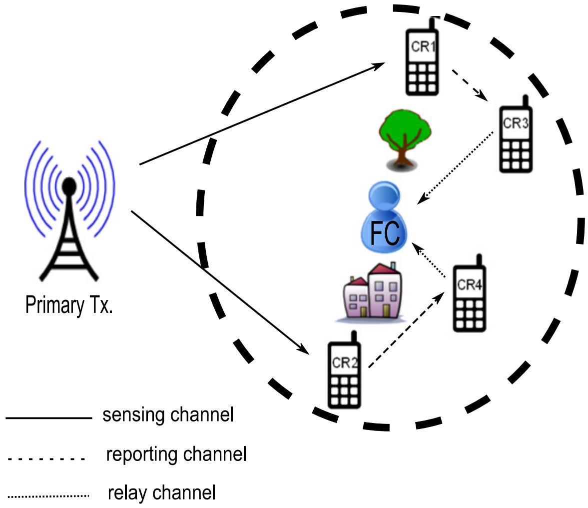

Fig. 16. Relay-assisted cooperative SS.

relax the control channel bandwidth requirement. In comparison to quantized soft combining, *hard combining* is another alternative to perform cooperation under control channel bandwidth constraint. In this approach, sensing data is processed locally before transmitting it over the control channel and the one-bit local decision from each of the cooperating secondary users is combined using linear fusion rules. This leads to *decision fusion* based cooperative detection which requires much less control channel bandwidth at the cost of depreciated sensing performance when compared with data fusion based CSS. Typically, *OR*, *AND*, and *MAJORITY* rules are used for decision fusion which can be considered as special instances of generalized k out of N rule. It has been shown in [96] that *OR* ($k = 1$) rule outperforms when number of cooperating secondary users is large while *AND* ($k = N$) rule gives optimal performance for small number of CRs. In general, *half-voting* rule ($k = N/2$) in comparison to *majority* ($k \geq N/2$) is shown to offer optimal or near-optimal performance by achieving minimum total error probability in identifying vacant spectrum opportunity. More advanced data fusion and decision fusion techniques are discussed in [97,98], respectively.

6.1.3. Relay-assisted cooperative sensing

It is noteworthy that under realistic transmission conditions, both sensing and reporting channel are not ideal. Such a scenario is illustrated in Fig. 16 where CR1 and CR2 observe strong sensing channels but weak reporting channels (to FC) due to possible shadowing or multipath effect. In this case, sensing data from these CRs is forwarded to CR3 and CR4 who suffer from shadowed sensing channels but strong reporting channels. Hence, CR3 and CR4 act as relays to transmit sensing information from CR1 and CR2 to FC through them and thus the reporting channels between CR3, CR4 and FC are termed as *relay channels*. This scheme is popularly known as *Relay-assisted cooperative sensing* and has been discussed in [99].

6.1.4. Single hop and multi-hop cooperative sensing

It is important to point out that Fig. 16 shows a centralized network for sake of simplicity, however, relay-assisted cooperation is equally applicable in distributed sensing where each cooperating CR plays the role of FC. In fact, when sensing data reaches the intended secondary user through multiple hops, all the intermediate hops act as relays. Hence, centralized and distributed sensing schemes depicted in Fig. 15 are classified as *single hop cooperative sensing* while relay-assisted cooperation shown in Fig. 16 falls under the category of *multi-hop cooperative sensing*.

6.1.5. Internal and external sensing

From the network perspective, both centralized and distributed sensing, involving either single hop or multi-hop (relay-assisted), fall under the category of *internal sensing*, which results in suboptimal utilization of spectrum opportunity as both the spectrum sensing and subsequent data transmission on the detected frequency band are collocated at a single CR. In [100], CR network architecture based on two distinct networks i.e. the *sensor network* and an *operational network* has been proposed as a third approach for cooperative PU detection, known as *External sensing*. In *external sensing*, a dedicated network composed of only sensing nodes is employed to scan the targeted frequency band continuously or periodically. The sensing results are then passed on to the master sensor in this external network which optimally combines the sensing data and shares the PU activity information in the sensed area with *operational network*. In this way, CRs in the *operational network*, do not spend time for spectrum sensing rather simply use the data from (external) *sensor network* for selecting the appropriate spectrum and time duration for secondary transmissions. As a result, external sensing not only solves the shadowing/fading and hidden PU problems but also increases spectrum efficiency by allowing CRs to acquire available spectrum usage opportunity with minimum delay.

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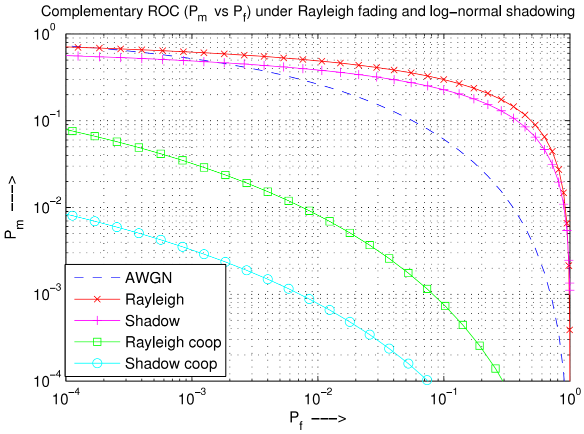

Fig. 17. Sensing performance enhancement through cooperation.

6.2. *Favorable aspects of cooperative detection*

Cooperative detection mitigates the multipath fading and shadowing effects which are the key issues in spectrum sensing. In this way, cooperative detection results in much improved sensing performance of CR network by improving the detection probability while simultaneously decreasing the probabilities of mis-detection and false alarms. Performance enhancement through CSS involving cooperation among 10 CRs is depicted in Fig. 17. The figure shows the complementary receiver operating characteristics (ROC) (plot of P_m vs. P_f) of ED under Rayleigh fading and Log-normal shadowing (with 6 dB spread) for time-bandwidth product = 5 and average received SNR of 10 dB [101].

In addition, cooperative detection solves the hidden PU problem. This results in improved agility with decreased sensitivity requirements [102].

6.3. *Limitations of cooperative detection*

While cooperative sensing provides high sensing accuracy, these are not feasible on resource-limited networks due to the need for additional infrastructure, increased computational complexity, overhead control traffic and operations. Furthermore, CSS is based on exploiting inherent spatial diversity in the local observations of cooperating CRs resulting in enormous *cooperation gain* as indicated in Fig. 17. However, the practically achievable cooperation gain may diminish when cooperating CRs are obstructed by the same blockade resulting in correlated shadowing. Sensing performance degrades further when more and more spatially correlated CRs participate in reaching a cooperative decision [90,101]. In addition to gain-limiting elements, CSS can incur *cooperation overhead* in terms of cooperative sensing delay, increased energy requirements and more vulnerability to security attacks.

7. Challenges in cooperative detection

Key challenge in cooperative sensing is to achieve optimal cooperation gain without being compromised by the associated cost. Open problems in this regard are devising efficient information sharing approach with minimum control channel overhead (e.g. short-listing reliable CRs to cooperate, minimizing information to share etc.) and information fusion criteria. In a comparative analysis, the spectrum efficiency may be impacted how much resources have been used in sensing and spectrum utilization for actual data. In the following, we discuss some of the fundamental challenges in CSS and present possible solutions to meet these challenges.

7.1. *Cooperative sensing delay*

As opposed to non-cooperative spectrum sensing, CSS involves sharing local sensing information to achieve a unified global cooperative decision. As a result, the total sensing time in cooperative detection must include reporting time along with the conventional local sensing time. Following three factors play a critical role in deciding about the overall reporting time:

- amount of reporting data,
- number of cooperating secondary users and
- reporting channel access scheme.

Synchronization among the cooperating CRs is also taken as an underlined assumption in many typical cooperative sensing schemes such as ED based CSS. Such schemes, being blind or semi-blind suffer from the lack of the capability to distinguish between primary and secondary transmissions and hence require all CRs to halt their transmissions for simultaneous sensing operations. Also, most of the cooperative sensing techniques assume that the sensing results become available for combining not only instantly but also concurrently. In such cases, the delay for synchronization also needs to be taken into account while analyzing the cooperative sensing delay.

Moreover, the cooperative decision results from an iterative process in distributed cooperation and thus *convergence rate* of distributed cooperation algorithm also affects the overall sensing time in CSS.

Therefore, it is evident that cooperative sensing delay is influenced by multiple factors which must be carefully analyzed in order to determine practically achievable throughput of CROWN employing cooperative detection. Many approaches have been discussed in literature to keep cooperative sensing delay overhead within acceptable limits. In [103], authors proposed to decrease the cooperative sensing delay by optimizing the local sensing results both in terms of size and reliability. In this approach, only reliable CRs are involved in making cooperative decision and their local sensing results are shared in the form of one bit hard decision. They have used two thresholds in conventional energy detector to reliably detect a spectrum hole and have also considered reporting over bandwidth limited and imperfect control channel. To avoid synchronization induced delays in CSS, variety of asynchronous sensing methods are proposed. In [104], a sliding window algorithm is devised to sequentially detect the change point in received sensing reports while a probability based combination approach is studied to combine the sensing results arriving at different times in [105]. Increased reporting overhead for cognitive radio ad hoc wireless networks with large number of secondary users is addressed in [106]. It is further shown that the overall throughput of CROWN can been significantly improved by employing fast physical layer signaling to save temporal resources for secondary data transmission. An interesting cooperation-processing tradeoff between the sensing time and reporting delay is reported in [107].

7.2. Spatially correlated shadowing and optimal user (CR) selection

Cooperative sensing is most efficacious when cooperating nodes witness independent fading and shadowing [108,109]. Correlated shadowing results in increased probability of missed detection, degrading the overall sensing performance of CROWN which has been analyzed in [110]. In this paper, it is shown that spread out locations of cooperating CRs result in better defense against fading and shadowing. Hence, the key challenge to mitigate correlated shadowing lies in *optimal user (CR) selection* ensuring that all cooperating CRs experience independent observations under practical fading and shadowing conditions. Careful CR selection in CSS not only improves the reliability and security of CROWN but also increases the overall network efficiency both in terms of throughput and energy requirements. CR selection, usually termed as user selection, schemes based on centralized and decentralized approach are discussed in literature [111,112]. In *centralized user selection*, FC selects independent CRs for cooperation based on location estimates of CRs sharing information with this FC. Empirical results [113] show that spatial correlation between two CRs is a decaying exponential function of the inter-user distance and hence there exists a *decorrelation distance* beyond which the cooperating radios can be considered to experience uncorrelated shadowing. When large number of CRs are involved in cooperative detection, centralized user selection suffer from prohibitively large control channel bandwidth and much increased reporting delay. Hence, a *distributed selection* technique needs to be adopted for optimal user selection particularly for large networks. For such scenarios, variety of clustering methods are proposed in [114]. These clustering techniques rely on the availability of location information of primary and secondary users in CROWN and can be either statistical, random, reference-based or distance-based. Similarly, optimally choosing the number of cooperating CRs is another challenge which has been studied in [115]. It has been shown that CRs with high PU's SNR give optimum sensing performance rather employing all SUs in CROWN to cooperate. A classic heuristic algorithm based on the binary particle swarm optimization (BPSO) approach to find suitable cooperative nodes is applied in [116] to show improved sensing performance when compared with the case that all neighboring nodes participate in sensing.

7.3. Information fusion criterion

Finding an efficient information sharing approach is another challenge in CSS. This problem in itself is manifold and becomes very critical when the number of CRs in CROWN become large, requiring prohibitively large control channel band width along with added computational complexity and reporting delay [117]. Optimum decision combining approach is analyzed for both soft and hard combining at FC in [118] and a genetic-based soft combining algorithm is proposed to improve cooperative decision provided SNRs of all cooperating CRs and channel conditions are known while combining. More recently, in [119], the optimal value of cooperating nodes (k) for k out of N (where, N stands for total number of nodes) decision fusion rule is derived using completely blind, learning automata based, voting rule optimization approach.

7.4. Energy efficiency

The energy consumption in CSS is proportional to number of cooperating CRs and amount of sensing information that is shared among CRs. Optimal user selection and decision fusion approaches are generally invoked to deal with the increased energy consumption overhead in CSS. The key challenge in this regard is to let only those CRs sense and report (i.e. consume energy) which participate in final cooperation. In this regard, a combination of *censoring* and *sleeping* policies is proposed for the cases of known and unknown PU activity in [120]. Authors have shown that applying this technique in large sensor networks results in almost constant number of active nodes out of total operating nodes in any given time slot. Hence, overall energy consumption of the network becomes independent of the number of cooperating nodes.

7.5. PU and CR mobility

Mobility of primary and/or secondary users in CROWN is a unique challenge for cooperative detection as it may boost or diminish the achievable cooperative gain in CSS. For example, if we consider stationary PU, moving CRs may observe independent or correlated shadowing at different times depending on their direction and speed. In this way, cooperation throughput changes with the movement of cooperating CRs. Problem analysis becomes more challenging if PU also starts to move simultaneously with secondary users in CROWN. Impact of mobility on sensing is addressed in [121] though such studies are still in their infancy phase and need detailed analysis for the actual deployment of CROWN.

7.6. Data falsification and security attacks

Security plays a critical role in CSS. The risk of involving malfunctioning and malicious secondary users increases proportionally with the increasing number of cooperating CRs. Such unwanted secondary users may intentionally corrupt or send unreliable sensing information to influence the cooperative decision in their favor. PU emulation attacks and control channel jamming are examples of security attacks where legitimate CRs are forced to vacate the acquired frequency band for attackers. To

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address security problems, all cooperating users are authenticated [122] which puts additional overhead in cooperative detection. The open research challenge in this regard is to ensure security during cooperation under the constraint of minimum incurred overhead.

8. Open problems and future research directions

The cognitive radio research has witnessed immense growth in the past few years after the FCC legalized the secondary access to TV white spaces for broadband wireless networks in November, 2008 [123]. There are, however, number of concerns that need critical investigations before the actual deployment of cognitive radio networks. Most importantly, practical operating conditions need to be incorporated while evaluating the performance of proposed sensing algorithms and required sensing accuracy needs to be carefully examined against the implementation complexity of these schemes. In the following, we present open issues in this regard that have not been explored much and require substantial research efforts in the field of spectrum sensing:

8.1. Dynamic scenarios

Spectrum sensing techniques discussed in this paper have been developed and analyzed under static scenarios, where the spectrum usage and noise statistics do not vary in time. However, in the real-world, the number of active transmissions and/or their transmission parameters change and the background noise varies due to temperature fluctuations. In [124], authors have examined noise samples from a reference channel to estimate noise power and dynamically adapt the energy detection threshold accordingly. More recently, it has been shown that dynamic selection of detection threshold based on the present noise level increases the detection probability for moderate SNR in the range −12 dB and above [125]. However both of these work target simple energy detectors while there is plenty of research opportunities in analyzing the sensing performance of other more robust and accurate sensing schemes under dynamic scenarios, where SNR changes during sensing.

8.2. Fair coexistence

Non-blind sensing schemes usually exploit some known features of the primary signal. For example, typical TV whitespace network designs rely on cyclostationary-based feature detectors tuned for digital TV signals. As pointed out in [126], such a signal-specific approach may offer desired performance under assumed conditions but completely fails to detect any activity when the scanned spectrum is occupied by another secondary user who does not transmit a digital TV signal over that band. Similarly, blind schemes inherently cannot classify active transmissions as primary or secondary and hence can trigger false alarm much frequently. Such limitations pose open challenges in achieving fair division of opportunistic spectrum resources among secondary users.

8.3. Frequency selective fading

The effect of channel uncertainties on spectrum sensing has been studied focusing on flat fading and log-normal shadowing with very little attention given to multipath fading. Some of the recent works [127,128] show simulation results under frequency selective fading but they have limited scope in the sense that they target OFDM signals and do not give the mathematical analysis of the problem. Performance analysis of variety of sensing techniques discuss in this review paper remains an open challenge which needs thorough investigations in order to compare the sensing performance of available detectors in actual multipath-rich radio environment.

8.4. Sensing performance metric

The traditional sensing problem is mathematically casted as a binary hypothesis testing problem giving probability of missed detection and probability of false alarm as key performance evaluation metrics. However, such a formulation focuses on the temporal dimension of the possible spectrum hole while missing the possible opportunity in the spatial dimension. In [129], it was emphasized that CR can reuse the spectrum not only when PU signal is truly absent but also when PU is active but lies far away from the CR. In this regard, the degree of required detector *sensitivity* was investigated and a joint space–time perspective of the sensing problem was put forward as composite hypothesis test. This hypothesis-testing framework led to two new sensing performance metrics namely, *fear of harmful interference* (FHI), capturing the PU safety and *weighted probability of area recovered* (WPAR) capturing the sensing performance of CRs across different spatial locations, as discussed in [130]. The comparison of different sensing schemes based on these new performance metrics is an interesting open problem that can reveal the true tradeoffs between PU safety and SU performance.

8.5. Practical wideband sensing

Recent advances in compressed sensing has relaxed much of the stringent requirements on RF front-end of cognitive radio to accomplish wideband sensing. However, due to limited number of samples resulting from sub-Nyquist rate sampling, a weak PU signal with a nearby strong secondary signal may not be properly reconstructed for detection. This poses a typical near-far problem making it practically very difficult to achieve desired detection sensitivity in wideband sensing.

8.6. Sensing duration and sensing frequency

The key to efficient spectrum utilization is rapid and reliable spectrum sensing. However, sensing time reduction is always traded off with sensing reliability. An important thing to note is that a channel that is being used by SU cannot be used for sensing. This requires SU to interrupt their data transmission for possible PU identification on that channel [131]. As a result, spectrum utilization of secondary network is compromised. To combat this situation, a method known as dynamic frequency hopping (DFH) has been reported in [132] which assumes availability of multiple channels. During transmission over a *working channel*, *intended channel* is sensed simultaneously and if its availability is reported, the *intended channel* becomes the *working channel*. In this way, spectrum efficiency can be improved to some extent though some of the time would still be wasted in sensing the *intended channel* which can otherwise be used for secondary transmissions. However, multiple users operating in DFH must coordinate their hopping pattern to avoid mutual blocking/interference which in itself is a non-trivial task and requires further investigations to reach practically viable solution. Similarly, sensing frequency (i.e. how often spectrum sensing is performed) is another design parameter that must be selected very carefully. Finding an optimum value of sensing frequency depends on CR capabilities and PU temporal characteristics in the radio environment [133] and poses an open challenge in achieving desired sensing performance.

8.7. Detecting spread spectrum primary signals

PUs employing spread spectrum signaling spread their transmitted power over wide frequency range. This may be a single band in the case of direct sequence spread spectrum (DSSS) or multiple bands for frequency hopping spread spectrum (FHSS). In both the cases, SS becomes difficult and needs some *a priori* information regarding frequency hopping patterns and synchronization pulses to successfully detect such primary transmissions [49]. It is important to highlight here that a spectrum usage opportunity might exist in code dimension of the spectrum space and hence advanced SS techniques need to be devised that can detect both the frequency and used code for primary transmissions. In this way, secondary users can coexist with primary users by employing orthogonal or near orthogonal codes as compared to primary signals. Detection of this new opportunity is an open research challenge and has not been well explored in the literature.

8.8. Exploiting spectrum usage opportunity in angle dimension of spectrum space

With the recent advances in multiple input multiple output (MIMO) technology and signal processing, PUs instead of emitting radio waves over air interface in all directions may confine their transmissions within an angle targeting particular primary receivers present in specific direction. In such cases, different users can transmit over the same frequency band, at the same time in the same geographical area using the same codes. Such users employ highly directional antennas or use signal processing techniques like beamforming to avoid interference with neighboring users. In CR technology, this means that primary and secondary users can share the same frequency band in the same time slot and in same area if the secondary transmissions can be directed in directions other than the primary transmission directions. To benefit from this new dimension of spectrum space, CR must estimate the angle of arrivals (AoAs) of the primary transmissions along with the occupied frequency band which is a challenging task and needs yet to be explored in depth for its practical feasibility.

8.9. Efficient remote knowledge base access

With the recent FCC ruling [134], the cognitive use of TV white spaces is proposed to be based on database architecture only rather than spectrum sensing capabilities. As part of that ruling, TV white space devices must download all the information about the RF environment such as traffic patterns, location, transmit power etc. from a remote database, known as *knowledge base*. Though knowledge base enhances the detection performance of CR by utilizing the accumulated knowledge and learned experience from the history yet it raises new challenges in efficiently accessing the remote knowledge base. Recently, cognitive radio cloud network (CRCN) is proposed for cooperative sensing in TV bands [135], however, significant research efforts are required to achieve fast, secure, scalable and energy efficient access to knowledge base.

8.10. Other challenges

For the sake of completeness of topic, some of the other challenges hindering the actual deployment of state-of-the-art wireless networks with cognitive capabilities are indicated below.

(a) Spectrum sharing solutions typically assume a common control channel (CCCH) for information sharing. However, when a PU becomes active this control channel also needs to be vacated. This requires that local CCCHs should be exploited for clusters of nodes.
(b) In CROWN, legitimacy of PU is an important aspect to consider. The proposed security measures are limited in their scope and devising a universal security scheme is an open research avenue to explore.
(c) Keeping track of interference level enhancement by secondary transmissions of opportunistic unlicensed users is another research challenge which requires substantial analysis before the actual deployment of cognitive networks.

9. Conclusions

In this paper, we examined various aspects of cognitive radio and identified spectrum sensing as the prerequisite requirement for the deployment of cognitive radio oriented wireless networks. Variety of detection techniques were studied, compared and classified. We found that blind transmitter detection sensing techniques are most generic in their application and are robust to all kinds of channel/system uncertainties. Moreover, they provide highly accurate results at realizable complexity. However, performance of all single-user centric sensing schemes degrades drastically in multipath fading environment which is unavoidable in wireless communication. Hence, for practical scenarios, CROWN must be equipped with cooperative sensing ability. The intrinsic features of cognitive technology impose stringent requirements on the spectrum awareness strategies. Comparison of sensing algorithms revealed wide variability in their computational complexity for the targeted detection performance. As a result, future research is envisioned to be focused more on implementation-friendly, low-complexity sensing algorithms that are robust enough to provide required sensing performance with demanded reliability in minimum time.

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Raza Umar received his B.Sc. degree in Electrical Engineering from the University of Engineering and Technology (UET), Lahore, Pakistan in 2000. He received his M.Sc. degree from the University of Stuttgart, Germany in 2005. He is an Assistant Professor in the Department of Electrical Engineering, UET Lahore, Pakistan.

Before joining academia, he was with Alcatel Germany where he was involved in the evaluation of MIMO schemes for 3.5 G (HSDPA) during 2004–2005. He worked as a Senior Design Engineer in DSP Software Optimization Group at Avaz Networks, formerly Communications Enabling Technologies, a leading R&D company based in Islamabad, Pakistan from 2000 to 2003. Currently he is pursuing his Ph.D. degree under the supervision of Prof. Asrar U.H. Sheikh at KFUPM, Dhahran Saudi Arabia. His current research interests include next generation wireless systems, signal processing for optimum detection and estimation and game theoretic approaches for cooperative spectrum sensing in cognitive radio networks.

Asrar U.H. Sheikh graduated from the University of Engineering and Technology (UET), Lahore, Pakistan in 1964 and received his M.Sc. and Ph.D. degrees from the University of Birmingham, England, in 1966 and 1969 respectively. He held positions in Pakistan, Iran, UK, Libya, Canada and Hong Kong before joining KFUPM as Bugshan/Bell Lab Chair in Telecommunications in 2000.

Dr. Sheikh is the author of a book, Wireless Communications—Theory & Techniques published by Springer, USA in 2004. He also contributed several chapters on number of books on wireless communications. He has been an editor of IEEE Transaction on Wireless Communications (2003–05), and was a Technical Associate Editor of IEEE Communication Magazine (2000–01). He is currently on the Editorial Board of several technical journals. Dr. Sheikh is listed in Marquis's Who's Who in the World and Who's Who in Science and Engineering. He is a Fellow of the IEEE and a Fellow of the IET (London).

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