Chapter 2
Spectrum Sensing in Cognitive Radio Networks: Potential Challenges and Future Perspective

2.1 Introduction

With the vast number and diversity of wireless devices and technologies, exponential increase in the number of wireless subscribers, the emergence of new applications, and the continuous demand for higher data rates, RF spectrum is becoming increasingly crowded. These developments in the communications market demand systems and devices which are aware of their RF environment and can facilitate flexible, efficient, and reliable operation and utilization of available spectral resources. Therefore, spectrum sensing and its ability to identify underutilized spectrum is becoming progressively more important to current and future wireless communication systems to identify underutilized spectrum with characterizing interference and consequently, achieving reliable and efficient operation. The cognitive radio is an intelligent radio that is aware of its surrounding environment, capable of learning and adapting its behaviour and operation to provide a better match to its surrounding environment as well as to the user's needs as extensively presented in Chap. 1. In order to exploit spectrum in a dynamic fashion, cognitive radios must have a sensing mechanism for identifying spectrum opportunities and avoiding interference with licensed primary users. In addition to dynamic spectrum access, spectrum sensing techniques are important for both civilian and military spectrum management operations [1].

The operation of a cognitive radio for dynamic spectrum access involves two main components: spectrum sensing and spectrum opportunity exploitation. Due to hardware limitations and energy constraints, a cognitive radio may be unable to sense the entire spectrum simultaneously. Hence, a sensing policy that defines when and which frequency band to sense must be implemented either individually or collaboratively. In addition, we must assume that the sensing periods have already been synchronized among different cognitive radios, because simultaneous transmission and sensing on the same frequency band is generally inefficient. Such a

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policy defines whether a cognitive radio performs sensing in a given period and, if so, which channel or channels it senses. Collaborative sensing policies are generally expected to offer benefits over individually selected policies. However, individual sensing policies have been proposed [2–4] that use a decision theory approach by formulating the design of an optimal sensing policy as a partially observable Markov decision process (POMDP). Myopic sensing policies that seek to maximize an immediate reward are analyzed in [5, 6]. Cognitive radios must also determine their access policy in order to exploit available spectral opportunities after they have been detected. An access policy addresses when and on which channels to transmit, or whether to transmit at all if conserving the energy of battery-operated terminals is necessary or channel quality is low. Access policy, like sensing policy, must be determined individually or collectively. Interference management is an integral part of spectrum exploitation. The cognitive radio system must ensure that its combined interference to the primary systems stays within the bounds set by regulatory authorities. Sensing and access policies are closely interwoven, and both are areas where cognition most naturally comes into play. In dynamic signal environment techniques such as reinforcement learning [7, 8], the potential for achieving the most efficient utilization of the available resources is significant [9, 10]. Feedback from past decisions and actions may be used to ascertain the state of the environment and thus enable better decisions in the future. Several other issues must also be resolved, including the modulation formats, transmit powers, and routing issues, as discussed in Chap. 1. Moreover, in addition to technological challenges, regulatory challenges must be met. Regulatory policies defining the rules for opportunistic spectrum access must be established to ensure that cognitive radios conform to the rules. An overview of spectrum sensing methods and algorithms for cognitive radios is presented in the following sections.

2.2 Spectrum Sensing Techniques

Spectrum sensing enables a cognitive radio to measure, learn, and be aware of its operating environment—for instance, spectrum availability and interference status. When a certain frequency band is detected as underutilized by the primary/licensed user at a particular time in a specific position, the secondary users can utilize the spectrum, i.e., a spectrum opportunity exists. Therefore, spectrum sensing can be performed across the domains of time, frequency, and space. With the recent development of beamforming technology, multiple users can utilize the same channel/frequency at the same time in the same geographical location. Thus, if a primary user (PU) is not transmitting in all directions, spectrum opportunities can be created for secondary users in the directions not in service, and spectrum sensing must also take into account the angle of arrivals [9]. The primary users can also use their assigned bands by means of spread-spectrum or frequency hopping, and secondary users can then transmit in the same band simultaneously without severe disruption to the primary users, provided they adopt an orthogonal code in relation to the codes adopted by the primary users [10]. This creates spectrum opportunities in code domain, but requires detection of the codes used by the primary users as well as multipath parameters. Because detecting primary users that are receiving data is generally very difficult, many studies on spectrum sensing have focused on primary transmitter detection based on the local measurements of secondary users Spectrum sensing and channel probing to acquire real-time spectrum/channel information required by the cognitive MAC layer are also critical components of cognitive radio networks. In general, spectrum sensing performs the following tasks [11]: (1) detection of spectrum holes, (2) determination of spectral resolution for each spectrum hole, (3) estimation of the spatial directions of an incoming interfering signal, and (4) signal classification. Among these, the detection of spectrum holes is probably the most important task, and is explored through a binary hypothesis-testing problem. Therefore, detection of spectrum holes on a narrow frequency band is usually referred to as spectrum sensing, which detects the presence or absence of primary users in the underlying band.

Spectrum sensing techniques can be divided into two main categories: non-cooperative/transmitter detection and cooperative detection (Fig. 2.1). Transmitter detection approaches are based on the detection of signals transmitted from a primary system through the local observations of cognitive radio users. Transmitter, or non-cooperative, detection techniques are generally based on the assumption that the location of the primary transmitter is unknown to the cognitive device. Therefore, cognitive users should rely only on the detection of weak primary transmitter signals and use only local observations to perform spectrum sensing. A cognitive device does not have complete knowledge of spectrum occupancy in its coverage area. As a consequence, it is not possible to completely avoid harmful interference with primary users. Moreover, transmitter detection cannot prevent a hidden terminal problem. Three schemes are usually employed for primary transmitter detection: matched filter detection, energy detection, and features detection. These schemes are discussed in detail in Sect. 2.3.

A cognitive user (CU) may have a good line of sight with a primary receiver, but may not be able to detect the presence of a primary transmitter (hidden terminal) as a result of the shadowing phenomenon, which is very common in urban/indoor

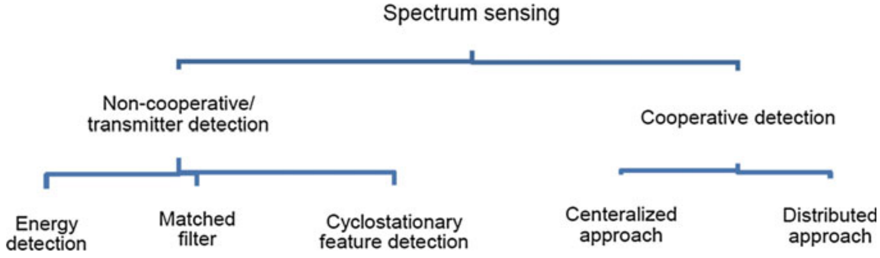

Fig. 2.1 Spectrum sensing techniques

environments. Cooperative detection strategies are implemented to mitigate this problem. Cooperative detection refers to spectrum sensing methods that enable multiple cognitive radios to share their local sensing information for more accurate primary transmitter detection [9, 12]. Cooperative detection can be implemented in either a centralized or a distributed manner. In the centralized method, a central unit collects sensing information from cognitive devices, identifies the available spectrum bands, and broadcasts this information to other cognitive radios [9]. In a distributed approach, there is no central node, and the sensing information is shared among the cognitive devices [9]. Distributed detection is easier to implement and does not require a backbone infrastructure, while centralized detection is more accurate and can effectively mitigate both multi-path fading and shadowing effects. The central node can also assign a specific weight to each spectrum sensing result to mitigate fading phenomena [13]. Cooperative detection techniques can be also classified as a soft or hard combination, according to the nature of the information shared among cognitive users. The soft combination refers to a cooperative strategy in which each node senses a certain frequency band and then sends the results of its measures—i.e., the energy of the received signal—to the central node [14–17]. Conversely, in hard combination strategies, each node decides whether a primary user is present, and then reports to the central node only the results of its decision [14–17]. Soft detection is usually more accurate and can implement macro-diversity techniques, as signals received from distant nodes tend to be uncorrelated. Hard detection is not as accurate but requires less information exchange between nodes. If a cognitive device is equipped with multiple antennas, sophisticated sensing strategies can be implemented, exploiting spatial, time, and/or frequency coding. Such cooperative spectrum sensing is discussed in detail in [18], and the authors demonstrate that the probability of false alarms can be reduced through the use of space, time, and frequency transmit diversity. Relay diversity can be further employed to compensate for the reduced sensing diversity order when some nodes in a cooperative spectrum sensing system cannot report directly to the central node (i.e., due to shadowing phenomenon).

Generally, spectrum sensing is performed using simple signal detection methods to detect unoccupied frequencies as quickly as possible. However, these simple techniques cannot achieve reliable and accurate sensing results in low-SNR and deep fading environments [9, 19]. Various methods have been proposed to enhance the reliability and accuracy of spectrum detection including fusion of multiple local detection decisions and cooperative spectrum sensing [20, 21]. The selection of the most suitable detection method for local spectrum sensing is a major challenge, because detection techniques differ in their performance. For example, the energy detector (ED) is unable to detect signals with low SNR. This can be achieved with the cyclostationary feature detector (CSFD), but with added time and complexity. The matched filter (MF) is the optimal detection technique if the PU's information is known. In contrast to the matched filter and cyclostationary feature detector, however, the energy detector requires no prior knowledge of the primary user signal. These observations raise the question of whether it would be possible to enhance sensing performance through collaboration among different detection techniques for local spectrum sensing, and if so, at what cost. Recent studies have proposed a two-stage spectrum sensing model, with a simple detection method is used in the first stage, and a more powerful one is used in the second stage [22, 23]. To achieve optimal performance, spectrum sensing techniques must be able to identify spectrum holes and any change in frequency-in-use status in a quick, secure, accurate, and reliable manner. Figure 2.2 shows potential requirements for spectrum sensing. However, developing a cognitive radio with spectrum sensing capability that meets all these requirements is impeded by several challenges. Detection results have a dramatic effect on the accuracy of the other cognitive radio components. Spectrum sensing is thus a critical issue in cognitive radio, and has recently received the attention of many researchers.

Cognitive radio can interact with its radio environment to acquire important information about its surroundings, including the presence of primary users and appearance of spectrum holes during spectrum sensing [1]. It is only with this information that it can adapt its transmitting and receiving parameters, such as transmission power, frequency, and modulation schemes, in order to achieve efficient spectrum utilization. Therefore, spectrum sensing and analysis is the first critical step toward dynamic spectrum management. In this chapter, we discuss three aspects of spectrum sensing: (1) spectrum hole detection, for determining additional available spectrum resources, including a comparison of several detection techniques; (2) cooperative sensing, which involves cooperation among

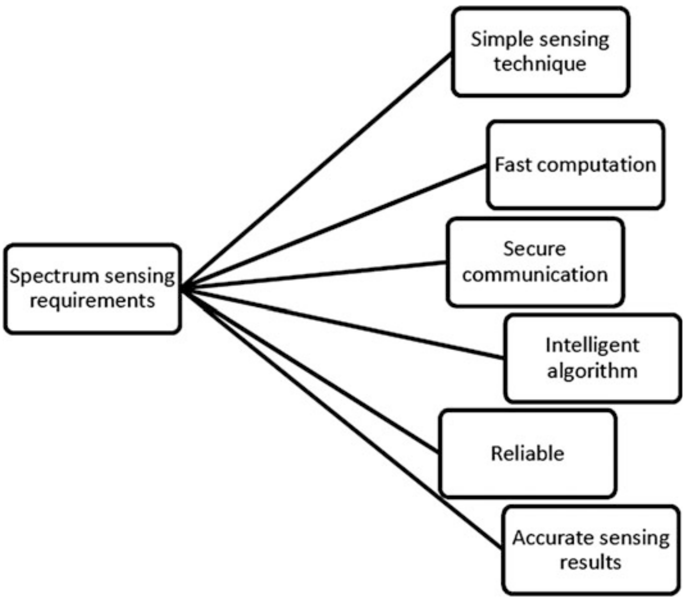

Fig. 2.2 Potential requirements of spectrum sensing

multiple cognitive users; and (3) interference temperature detection, which measures the interference level observed at a receiver and is used to protect licensed primary users from harmful interference due to unlicensed secondary users.

The model for transmitter detection can be described as a classical hypothesis testing approach, where H_0 is the null hypothesis, which states that there is no primary signal in a certain band, and H_1 is the alternative hypothesis (i.e., presence of the primary user). A testing variable is compared with a specific threshold to discriminate between the two hypotheses. System performance is evaluated in terms of probability of detection P_d (the probability of detecting the presence of a primary user) and probability of false alarm P_f (the probability of declaring the presence of a primary user in bands that are actually empty). Let us assume that the hypothesis model of the signal received at a cognitive radio user is:

$$y(t) = \begin{cases} h.s(t) + w(t) & H_1 : if\ PU\ is\, present \\ w(t) & H_0 : if\ PU\ is\, absent \end{cases} \tag{2.1}$$

where $y(t)$ is the received signal, h and $s(t)$ are the channel gain and primary user's signal to be detected at the secondary user (SU), which is assumed to be a Gaussian random process with variance σ_s^2, and $w(t)$ is the additive white Gaussian noise (AWGN) with zero-mean and variance σ_n^2. H_0 is a null hypothesis, meaning there is no primary user present in the band, while H_1 indicates the primary user's presence.

In the above-mentioned binary hypothesis test, there are two types of errors: type I and type II. A type I error, often called the probability of false alarm, is made if H_1 is accepted when H_0 is true. In spectrum sensing, the probability of a false alarm is an important design parameter for a detector, because it causes spectral opportunities to be overlooked. A type II error, on the other hand, occurs if H_0 is accepted when H_1 is true, known as a missed detection, which leads to collisions with primary user transmission and reduced data rates for both the primary and secondary user systems. In general, a cognitive radio system should satisfy the constraints of both the probability of false alarm and the probability of missed detection. However, the detection rule presents a trade-off between these two probabilities. From an implementation point of view, it is desirable to have algorithms whose threshold may be set and performance evaluated analytically.

2.3 Non-cooperative/Transmitter Detection

Spectrum sensing techniques requiring prior knowledge about the primary user's signal for comparing particular signal features to the cognitive user's received signal are called coherent signal detection techniques. Non-coherent detection techniques compare the received signal to a threshold defined on the basis of features that are independent of primary signal knowledge. Alternatively, spectrum sensing techniques can also be classified from a bandwidth perspective into wideband and narrowband detection techniques. Non-cooperative/transmitter detection is so named because cognitive radio sensing only detects a transmitted signal from a primary user transmitter [19]. Transmitter detection is classified as follows:

2.3.1 Energy Detection

Energy detection is the most commonly used spectrum sensing technique for determining the presence or absence of a primary user signal without requiring any information regarding the nature of the primary user signal. Energy detection is robust to the variation in the primary signal because it does not need any a priori knowledge of the primary signal. In the energy detection technique, shown in Fig. 2.3, the energy of a received signal is used to detect a primary user signal, and the presence of a signal in the channel is detected if the energy present is significantly greater than only noise [23]. Initially, the energy detector filters out the undesired signal from the unwanted frequency band [24]. The resulting output samples from the filter are then squared and summed, basically computing the signal energy. Finally, the output is compared with a threshold λ [25] to determine whether a licensed user is present or not as shown in Fig. 2.3. Setting the proper threshold is a challenging task, as it must differentiate between the signal and noise. Energy detection is the simplest method of detection. However, a priori knowledge of noise energy level is necessary, as its uncertainty degrades detector performance [26].

In addition, energy detection does not involve complicated signal processing and has low complexity that is especially suitable for wideband spectrum sensing. In this case, the simultaneous sensing of a number of sub-bands can be realized by simply scanning the power spectral density (PSD) of the received wideband signal. However, it is preferable to complete wideband spectrum sensing via the following two stages:

(1) Low-complexity energy detection is applied to search for possible idle sub-bands.
(2) More advanced spectrum sensing techniques with a higher detection sensitivity, and therefore higher complexity, are applied for accurate idle band detection.

Further, in a cognitive radio network, sensing time and periodic sensing intervals are optimized to maximize sensing accuracy or cognitive user throughput. In the energy detector, sensing time influences detector performance in terms of the probability of false alarm and the probability of missed detection. Moreover, when

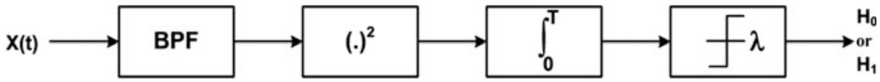

Fig. 2.3 The energy detection technique [9]

periodic sensing [9, 11, 12] is adopted, the periodic sensing interval affects the ability of the detector to grasp the spectrum opportunities and utilize them. If we consider optimizing the sensing time and the periodic sensing interval for each channel in the PU spectrum, then the objective would be to achieve the highest possible detector performance and opportunity utilization in that channel. For a multichannel system, this objective will still hold true, with a different interpretation of opportunity utilization, reflecting the utilization for all available opportunities in all channels rather than each channel individually.

However, energy detection is limited, as follows: (1) the energy detector cannot distinguish among the primary user signals, secondary user signals, and interference; (2) energy detection is susceptible to uncertainty in noise power; (3) prior knowledge of noise power or a reliable estimate of it is needed to obtain best performance; and (4) noise level uncertainty renders robust detection below a certain SNR impossible [20, 23]. To constrain the resulting false alarm rate, the detection threshold has to be set based on the worst case noise level uncertainty. As a result, energy detector performance depends heavily on the accuracy and reliability of the noise level estimate. The noise level may be estimated from guard bands or the detection may be performed in the frequency domain using a channelized radiometer [27, 28], which divides the total frequency band into smaller channels and then integrates energy from each channel separately using a radiometer. If the noise bandwidth is significantly larger than the signal bandwidth, a reasonably accurate noise level estimate may be obtained. In addition, collaboration among secondary users that employ energy detection mitigates the effects of noise uncertainty when users are experiencing independent and identically distributed (i.i.d.) fading or shadowing [29–31]. A review of the literature on energy-based detection is provided in [28]. Constant false alarm rate (CFAR) strategies for the channelized radiometer, such as cell averaging as discussed in [32], are considered in [28], and recent performance analyses of energy detection in fading channels are carried out in [21, 29, 33–37]. Experimental measurements of energy detection performance with noise uncertainty have been provided [36, 37]. If the signal power is below a certain threshold, called the SNR wall, the energy detector cannot distinguish the signal from a slightly larger noise power, regardless of the detection time [26]. Further, energy detection is suitable for random signal detection, and it does not require any assumptions about the primary signal. Unfortunately, this also means that energy detection cannot distinguish among different signals or interference. Ultimately, therefore, energy detection is not a suitable sensing approach if efficient spectral opportunity utilization is desired.

In the given flow diagram (Fig. 2.4), the probability of detection (P_d) and the probability of false alarm (P_f) are computed in order to analyze the effect of the fading channels on the performance metrics for detection. Further, in order to maximize the probability of detection, the threshold value is lowered. The detection statistics of an energy detector can be defined as the average (or total) energy of N observed samples. The energy of the received signal, which is the decision statistic, is given by [38]:

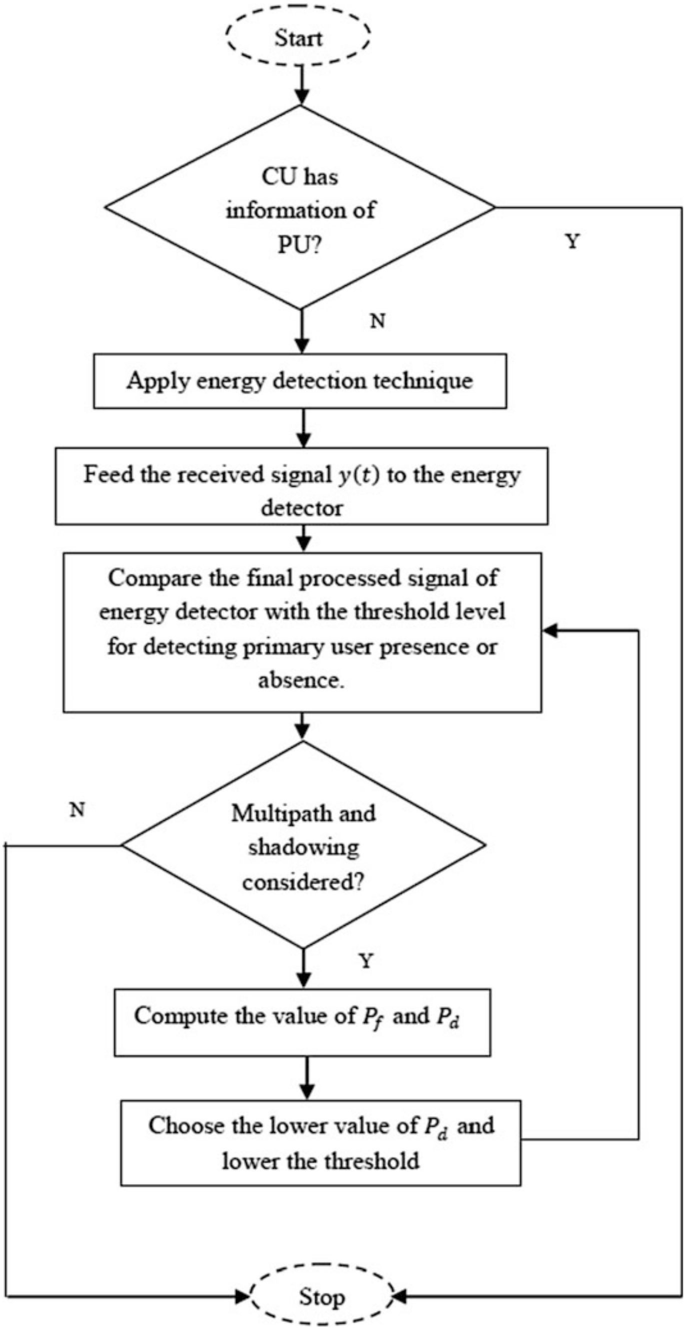

Fig. 2.4 Flow sequence of the energy detection technique

$$T = \frac{1}{N}\sum_{t=1}^{N} y^2(t) \tag{2.2}$$

where N is the number of samples considered. The energy detector model for cognitive radio can be formulated as the following binary hypothesis [38]:

$$d_{ED} = \begin{cases} +1 & if\ H_1\ is\ declaired\ (T \geq \lambda) \\ -1 & if\ H_0\ is\ declaired\ (T < \lambda) \end{cases} \tag{2.3}$$

The decision on whether the spectrum is being occupied by the primary user is made by comparing the detection statistics T (chi-square distribution) with a predetermined threshold λ. For a large number of samples, T can be approximated to Gaussian distribution using the central limit theorem, with test statistics as follows [38]:

$$T \sim \begin{cases} N(L\sigma_n^2, 2L\sigma_n^4) & if\ T \geq \lambda \\ N(L\sigma_t^2, 2L\sigma_t^4) & if\ T < \lambda \end{cases} \tag{2.4}$$

where $\sigma_t^2 = \sigma_n^2 + \sigma_s^2$. The probability of false alarm, detection, and missed detection (P_m) are given in [38]. The performance of the detector is characterized by two probabilities: the probability of false alarm P_f and the probability of detection P_d. P_f denotes the probability that the hypothesis test determines H_1 while it is actually H_0 that is [38, 39]:

$$P_f(ED) = P(T > \lambda/H_0) = \Gamma(u, \lambda/2)/\Gamma(u) = Q\left(\frac{\lambda - \sigma_n^2}{\sqrt{2L\sigma_n^4}}\right) \tag{2.5}$$

and P_d denotes the probability that the test correctly decides H_1.

$$P_d(ED) = P(T > \lambda/H_1) = Q_u\left(\sqrt{2SNR}, \sqrt{\lambda}\right) = Q\left(\frac{\lambda - \sigma_t^2}{\sqrt{2L\sigma_t^4}}\right) \tag{2.6}$$

where $\Gamma(.)$ is the incomplete gamma function, $Q_u(.)$ is the generalized Marcum Q-function, and u is the time-bandwidth product,

and

$$P_m(ED) = P(T > \lambda/H_1) = (1 - P_d) \tag{2.7}$$

A robust detector should ensure a high detection probability P_d and a low false alarm probability P_f, or it should optimize the spectrum usage efficiency while guaranteeing a certain level of primary user protection. To this end, various approaches have been proposed to improve energy detector efficiency for spectrum sensing. As detection performance is very sensitive to the noise power estimation error [40], an adaptive noise level estimation approach is proposed [41] in which the multiple signal classification algorithms are used to decouple the noise and signal subspaces and estimate the noise floor. A well-chosen detection threshold can minimize spectrum sensing error, provide the primary user with adequate protection, and fully enhance spectrum utilization. In [42], the detection threshold is optimized iteratively to satisfy the requirement on false alarm probability. Threshold optimization subject to spectrum sensing constraints is investigated in [43], where an optimal adaptive threshold level is developed by utilizing the spectrum sensing error function. Forward methods for energy detection have been proposed [44], where the noise power is unknown and is adaptively estimated. A localization algorithm based on double-thresholding (LAD) has been proposed [45] for finding and localizing narrowband signals, where the use of two thresholds can provide signal separation and localization. The LAD method with normalized thresholds can reduce computational complexity without performance loss by combining adjacent clusters, enabling more accurate estimation of the number of narrowband signals. The sensing throughput trade-off of energy detection is studied in [46], where the sensing period duration in a time slot is optimized to maximize the achievable throughput for the secondary users under the constraint that the primary users are sufficiently protected. A novel wideband spectrum sensing technique based on energy detection has been introduced in [47], in which joint detection of signal energy levels over multiple frequency bands improves the opportunistic throughput of CRs and reduces their interference with the primary systems. Analysis in [48] shows that detection of narrowband transmission using energy detection over multiband orthogonal frequency-division multiplexing (OFDM) is feasible, and can be further extended to cover more complex systems. Further, with the noise power level constantly changing over time, the determination of a detection threshold becomes challenging. Even if the threshold is set adaptively, the presence of any in-band interference would confuse the energy detector. In addition, in frequency-selective fading, it is not clear how the threshold is set with respect to channel notches. Because the energy detector cannot recognize the interference, it cannot benefit from adaptive signal processing for canceling the interferer. Furthermore, the spectrum policy for use of the band is limited to primary users, so a cognitive user should treat noise and other secondary users differently. Lastly, an energy detector is not effective for spread-spectrum signals—direct sequence and frequency hopping signals—for which more sophisticated signal processing algorithms must to be devised.

2.3.2 Matched Filter Detection

The matched filter is a coherent detection technique that employs a correlator matched to the signal of interest or to specific parts of it such as pilot and training sequences. Coherent detection processing provides very good performance under nominal conditions. With this technique, the received signal is matched with the PU signal, and the presence or absence of PU can thus be determined. Matched filter detection assumes that Gaussian noise exists, for which matched filtering is the optimal detection technique [49]. However, with the matched filter detection, the cognitive user needs to be fully synchronized with the PU, a capability that is not possible in most cases, particularly with low SNRs. The matched filter method detects a signal by computing the correlation between the received signal and a known copy of the signal. As the optimal detection technique, however, it requires perfect information regarding the primary user's signal, such as the operating frequency, bandwidth, modulation type and order, pulse shape, and packet format. In addition, if incorrect information is used for matched filtering, detection performance will be degraded. On the other hand, most wireless communication systems exhibit certain patterns, such as pilot tones, preambles, midambles, and spreading codes, which are used for purposes of control, equalization, synchronization, continuity, or reference. Even when perfect knowledge of a primary user's signal is not attainable, if a certain pattern is known from the received signals, coherent detection can be used to determine whether a primary user is transmitting [50] (Fig. 2.5).

Matched filter is the optimal detection method [51, 52] when the secondary user has a priori information on the primary user's signal. A matched filter can correlate a previously identified primary signal with the received signal to detect the presence of the primary user, maximizing the SNR in the presence of additive stochastic noise. An advantage of a matched filter, which needs fewer received signal samples, is the short time it requires to achieve acceptable detection performance such as a low probability of missed detection or false alarm [53]. However, the required number of signal samples also grows as the received SNR decreases, so there also exists a SNR wall [26] for a matched filter. Further, the matched filter needs receivers for all types of signals and corresponding receiver algorithms to be executed, resulting in excessive implementation complexity and power consumption [54]. There are two hypotheses in coherent detection:

$$y(t) = \begin{cases} \sqrt{\varepsilon}x_p(t) + \sqrt{1-\varepsilon}x(t) + w(t) & H_1 : \mathit{if\ PU\ is\ present} \\ w(t) & H_0 : \mathit{if\ PU\ is\ absent} \end{cases} \tag{2.8}$$

where $x_p(t)$ is a known pilot tone, ε is the fraction of energy allocated to the pilot tone, and $x(t)$ is the desired signals assumed to be orthogonal to the pilot tone. The

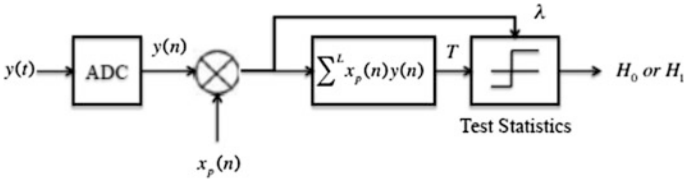

Fig. 2.5 Schematic of matched filter [50]

test statistics of the coherent detection are defined as the projected received signal in the pilot direction that is:

$$T = \frac{1}{N}\sum_{t=1}^{N} y(t)\hat{x}_p(t) \tag{2.9}$$

with $\hat{x}_p(t)$ representing a normalized unit vector in the direction of the pilot tone. As N increases, test statistics T under hypothesis H_1 are much greater than those under H_0. By comparing T with a predetermined detection threshold, one can determine the presence of a primary user. Coherent detection can also be performed in the frequency domain [55]. One can express the binary hypothesis test using the power spectrum density of the received signal $S_Y(\omega)$, and distinguish between H_0 and H_1 by exploiting the unique spectral signature exhibited in $S_X(\omega)$. Coherent detection is robust to noise uncertainty and not limited by the SNR wall [56], as N is large enough. Moreover, coherent detection outperforms energy detection in sensing convergence time [57, 58], because the sensing time of energy detection increases quadratically with SNR reduction, while that of coherent detection increases only linearly [58]. However, information about waveform patterns is a prerequisite for implementing coherent detection; the more precise the information that a coherent detector has, the better the sensing performance will be. The matched filter is Gaussian in nature and works on the principle of maximizing the received SNR. However, the main advantage of matched filter detection is that, because of coherency, it requires less time to achieve high processing gain. The flow sequence of matched filter detection, beginning with the hypothesis model, is demonstrated in Fig. 2.6.

The CU receives the signal $y(t)$. In order to apply the matched filter technique, the CU must have the PU signal information. The main advantage of the matched filter is that, because of coherency, it requires less time to achieve high processing gain, since only $O(1/\mathrm{SNR})$ samples are needed to meet a given probability of detection constraint. However, a significant drawback of the technique is that the cognitive radio would need a dedicated receiver for every primary user class.

2.3.3 Cyclostationary Feature Detection

Feature detection relies on identification of primary signals based on their deterministic or statistical properties. Since feature detection is based on extracted signal features, it can distinguish signals with different features. In general, feature detection has higher computational complexity than energy detection or matched filtering. One important subclass of feature detectors is the cyclostationarity-based detectors, which is more robust against noise uncertainty than that of the energy based detection because the noise is typically not cyclostationary. However, cyclostationarity-based detection can be very sensitive to synchronization errors,

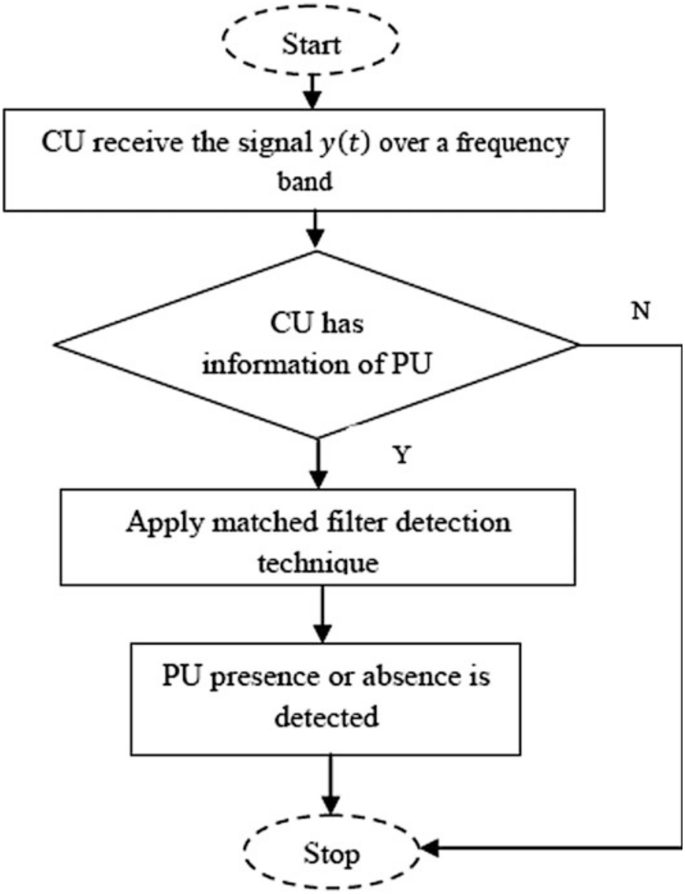

Fig. 2.6 Flow sequence of matched filter detection

resulting in carrier frequency and sampling clock frequency offsets. The cyclostationary feature detection technique used in cognitive radio is a very attractive spectrum sensing scheme because it is capable of differentiating the primary signal from interference and noise [59]. This spectrum sensing technique relies on periodic redundancy introduced into the signal by modulation and sampling because modulated signals are, in general, coupled with sine wave carriers, pulse trains, spreading sequences, or cyclic prefixes, causing periodicity in the transmitted signal [60, 61]. The cyclostationary feature detector uses these non-random periodic statistics of signals for detection by observing the mean and autocorrelation of the received signal. If the mean and autocorrelation vary periodically in time, then the received signal is associated with the primary user, otherwise it is noise, which lacks periodicity. As a result, cyclostationary feature detectors can operate successfully in extremely low-SNR environments and can differentiate between the primary user signal and noise [61]. This detector has demonstrated enhanced detection capability, especially in the presence of noise power uncertainty, and is suitable when the pilot signal of the primary user is known. However, a matched filter detector is more suitable when the period of the primary signal is known. Probability-based spectrum sensing techniques have recently been proposed, utilizing statistical information on primary user activity. The more a cognitive user knows about the primary signal, the better the detector works. These types of detectors exploit certain PU signal properties, such as pilots or cyclostationary features to perform the detection. However, this type of detection requires a very accurate synchronization which is difficult to maintain under low-SNR conditions [62]. A schematic of cyclostationary feature detection is shown in Fig. 2.7.

There are specific features associated with the information transmission of a primary user. For instance, the statistics of transmitted signals in many communication paradigms are periodic because of inherent periodicities such as the modulation rate and carrier frequency. Such features are typically viewed as cyclostationary, based upon which a detector can distinguish cyclostationary signals from stationary noise. In a more general sense, the features can refer to any intrinsic characteristics associated with a primary user's transmission, as well as cyclostationary features. For example, center frequencies and bandwidths [63] extracted from energy detection can also serve as reference features for classification and determining a primary user's presence. As in most communication systems, transmitted signals are modulated signals coupled with sine wave carriers, pulse trains, hopping sequences, or cyclic prefixes, while additive noise is generally wide-sense stationary (WSS) with no correlation. Therefore, cyclostationary feature detectors can differentiate noise from primary users' signals [57, 64, 65] and can distinguish among different types of transmissions and primary systems [66]. A cyclostationary feature detector differs from an energy detector, which uses time-domain signal energy as test statistics however cyclostationary feature detector perform a transformation from the time-domain into the frequency feature domain, followed by conducting a hypothesis test in the new domain. Specifically, the cyclic autocorrelation function (CAF) of the received signal is defined as:

$$R_y^\alpha = E[Y(t+\tau)Y^*(t-\tau)e^{j2\pi\alpha t}] \tag{2.10}$$

where $E[.]$ is the expectation operation, * denotes the complex conjugation, and α is the cyclic frequency. Given that periodicity is a common property of wireless modulated signals, while noise is WSS, the received signal's CAF also demon-

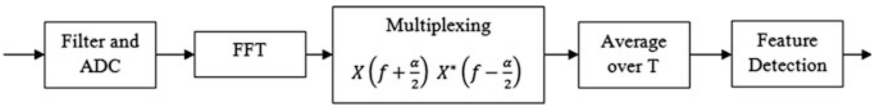

Fig. 2.7 Schematic of cyclostationary feature detection

strates periodicity when the primary signal is present. Thus, we can represent CAF using its Fourier series expansion, called the cyclic spectrum density (CSD) function, expressed as [54]:

$$S(f,\alpha) = \sum_{\tau=-\infty}^{\infty} R_Y^{\alpha}(\tau)e^{-j2\pi f\tau} \tag{2.11}$$

The CSD function has peaks when the cyclic frequency α equals the fundamental frequencies of the transmitted signal $x(t)$, i.e., $\alpha = (k/T_x)$ with T_x being the period of $x(t)$. Under the hypothesis H_0, the CSD function does not have any peaks, as the noise comprises non-cyclostationary signals. A peak detector [67] or a generalized likelihood ratio test [57] can be further used to distinguish between the two hypotheses. Different primary communication systems using different air interfaces (modulation, multiplexing, coding, etc.) can also be differentiated by their different cyclostationarity properties. Indeed, in comparison to energy detectors, which are prone to high false alarm risk due to noise uncertainty and are unable to detect weak signals in noise, cyclostationary detectors represent an attractive alternative, as they can differentiate noise from the primary user's signal and have more robust detection in a low-SNR regime. A spectrum sensing method based on maximum cyclic autocorrelation selection was proposed in [55] in which the peak and non-peak values of the cyclic autocorrelation function were compared to determine whether the primary signal was present. This method does not require noise variance estimation, and is robust against noise uncertainty and interference signals. Frequency-selective fading and uncertain noise impair the robustness of cyclostationary signal detection in low SNR environments. Run time noise calibration has been considered in [9, 56] in order to improve detector robustness. The method exploits in-band measurements at frequencies where a pilot is absent in order to calibrate the noise statistics at the pilot frequencies. Generalized feature detection refers to a detection and classification process that extracts feature information other than the cyclostationarity due to the modulated primary signals, such as the transmission technologies used by a primary user, the amount of energy and its distribution across different frequencies [68, 69], channel bandwidth and its shape [45, 48], power spectrum density [45], center frequency [48], and fast Fourier transform (FFT)-type features [60]. Primary users can be identified by matching the features extracted from the received signal to a priori information on primary user transmission characteristics. Information on the location of the primary signal is also an important feature that can be used to distinguish a primary user from other signal sources. Under a primary user emulation attack, a malicious secondary user transmits signals whose characteristics emulate those of the primary signals. A transmitter verification scheme is proposed in [70] to secure trustworthy spectrum sensing based on verification of primary user location.

In conclusion, the cyclostationary technique is implemented in order to differentiate between the primary user signal and noise signal by exploiting the unique nature of the received signal $y(t)$. This is performed by the modulation of the received signal using periodic sequences and then computing the spectral correlation function to detect the correlation. If a correlation exists, then the primary user signal is assumed to be present; otherwise, it is noise, and further action is required according the detection results, as shown in Fig. 2.8. These modulated signals are characterized as cyclostationary [22], since their mean and autocorrelation exhibit periodicity. Such features are detected by analyzing a spectral correlation function. The main advantage of this function is its ability to differentiate noise energy from modulated signal energy, which is a primary need. As a result, since the noise is a wide-sense stationary signal with no correlation [23], modulated signals are cyclostationary, with spectral correlation due to the embedded redundancy of signal periodicity. Therefore, a cyclostationary feature detector can perform better than an energy detector in discriminating against noise because of its robustness to the uncertainty in noise power. The flow sequence of a cyclostationary detection technique with the hypothesis model is demonstrated in Fig. 2.8.

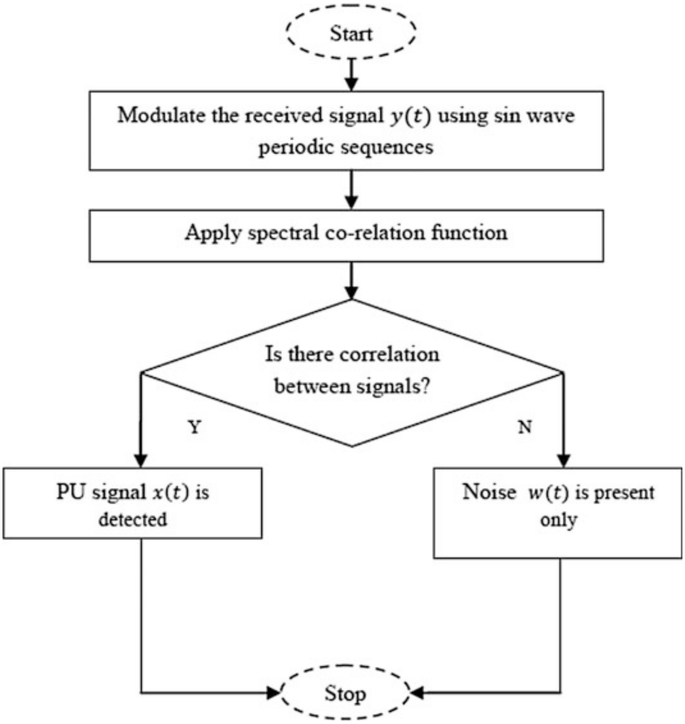

Fig. 2.8 Flow sequence of the cyclostationary technique

2.4 Cooperative Detection

The hidden terminal problem is a critical issue in spectrum sensing. It occurs when cognitive radio is shadowed and, because of the very low SNR of the received signal, cannot reliably sense the presence of the primary user. This cognitive radio assumes that the observed channel is vacant, and begins to access the channel while the primary user is still in operation, resulting in interference. As discussed in the preceding sections, several challenges are inherent in spectrum sensing which can negatively impact sensing reliability. In addition, each of the local spectrum sensing techniques has its own strengths and limitations, and no any optimal scheme exists for all applications and scenarios. Various spectrum sensing studies have proposed that cooperation among several spatially distributed cognitive users is needed to mitigate the issues with local spectrum sensing techniques. Therefore, multiple cognitive radios can perform spectrum sensing in a coordinated and cooperative manner. Several recent works have shown that cooperative spectrum sensing can greatly increase the probability of detection in fading channels [21]. Cooperative sensing in cognitive radio networks is analogous to distributed decision making in wireless sensor networks, where each sensor makes a local decision, and those decision results are reported to a fusion center (FC) to produce a final decision according to a certain fusion rule [71]. The main difference between these two applications lies in the wireless environment. Compared to wireless sensor networks, cognitive radios and the FC (or common receiver) are distributed over a larger geographic area. This creates a much greater challenge for cooperative spectrum sensing, because sensing channels (from the primary user to cognitive radios) and reporting channels (from cognitive radios to the FC or common receiver) are normally subject to fading or heavy shadowing. Therefore, cooperative spectrum sensing aims to utilize the variation in cognitive user locations to ultimately produce one global decision for all cognitive users [72]. Based on the methods used by cognitive users to share their sensing information, cooperative spectrum sensing techniques can be categorized into two main classes: centralized and distributed [73].

- Centralized Cooperative Spectrum Sensing

In this class, all cognitive users sense a band of interest using the same or different sensing techniques, and ultimately send their local decisions, either hard or soft, through a control channel to a central unit. Subsequently, all received data are fused to arrive at one final or global decision regarding the PU's current status [73, 74]. Interestingly, centralized cooperative spectrum sensing can be organized into both centralized and distributed types. If the fusion process is performed at a central base station, the cooperative system is recognized as a centralized model. In cognitive radio ad hoc networks (CRAHNs), on the other hand there is no base station and one of the cooperating nodes coordinates the synchronization and fusion processes [21, 75]. Several fusion models that rely on various factors to make their final decision have been suggested in the literature.

- Distributed Cooperative Spectrum Sensing

Instead of relying on a central FC, cognitive nodes exchange sensing information and eventually converge to make one global decision after trading information several times. Distributed cooperative spectrum sensing systems might cost less than other models because their establishment does not require any infrastructure. Several algorithms have been employed in cooperative spectrum sensing to coordinate the sensed data at different cognitive nodes. A discrete time gossip protocol has been employed in which a secondary user senses a band of interest during a certain time slot, and later sends its observations to a set of neighboring cognitive users selected at random [76]. Similarly, a dissemination strategy for sensing information among cognitive users has also been proposed [77], where a small group of cooperating cognitive users exchange their local decisions during a particular time slot, after which a cognitive user within this group sends all received data to a randomly selected neighbor that serves as the designated user in the next time slot, and so on, until all cognitive users receive the sensing information.

However, for traditional cooperative spectrum sensing algorithms such as AND, OR, and majority fusion rules, if most or all of the cognitive nodes are located in low-SNR environments, the cooperation between these nodes provides no advantage, and can even degrade the overall sensing accuracy. This is largely because those cooperative spectrum sensing techniques involve sensing information acquired blindly by different unlicensed users, without specific consideration for the surrounding contexts (e.g., SNR values) of these secondary users. In this study, the SNR value of every secondary user is considered within the contextual data in the fusion process. In fact, the value of the SNR for each cognitive node implicitly works as a weighting factor for the SU's local detection information.

The entire centralized cooperative spectrum sensing process consists of three steps: local spectrum sensing, transmission of the results of local spectrum sensing, and information fusion. We will now briefly describe these three steps of cooperative spectrum sensing and highlight the problems we have considered in each of these.

Step 1: Local spectrum sensing
Every cognitive radio performs local spectrum measurements independently, utilizing detection algorithms such as energy detection, matched filter detection or cyclostationary detection, and then makes a binary decision. Because energy detection is a simple and facile method, as discussed in the previous section, many studies have used this technique to assess local spectrum sensing performance [78–80]. When this method is used in local spectrum sensing, each cognitive user transmits the detected energy signal or decision results to the destination node.

Step 2: Transmission of the results of local spectrum sensing
In centralized cooperative spectrum sensing, each cognitive user sends detected signals to the FC through the reporting channel. Many researchers have studied cooperative spectrum sensing performance when the reporting channels (the channels from the SUs to the FC) are additive white Gaussian noise (AWGN) [29,

73, 74, 81, 82]. The hidden terminal problem also exists in the reporting channels—for example, shadowing between the cognitive user and FC. Thus the data transmitted from the cognitive user to the FC will be impacted by channel fading, which may result in transmission error. The literature [83, 84] has shown that fading of the reporting channel will also affect the performance of cooperative spectrum sensing. At present, research on the performance of cooperative spectrum sensing under both imperfect sensing and reporting channels is still in the initial stages. Further, cognitive radios forward their binary decisions to a common receiver, which is an access point in a wireless LAN or a base station in a cellular network.

Step 3: Information fusion at the FC
In centralized cooperative spectrum sensing, the FC combines all of the information from each cognitive user and makes a final decision to infer the presence or absence of the cognitive user in the observed channels. There are different procedures for information fusion, and a variety of methods have been studied in the literature [15–17, 85]. We can conclude that the major fusion methods include a soft and hard combination. In the soft combination method, the cognitive user is weighted before sending information to the FC, so that the channel state information can be used to improve the accuracy of the combined information, whereas with the hard combination, the cognitive user sends the information directly to the FC with no preprocessing. Fusion methods can also be divided into data fusion and decision fusion according to the data format transmitted by the cognitive user. From step 1 to step 2, when each cognitive user performs local spectrum sensing, it can either send the detected primary user information directly to the FC or make a judgment first and then send the result to the FC—the former constituting data fusion and the latter decision fusion. Afterwards, the common receiver combines those binary decisions and makes a final decision to infer the absence or presence of the primary user in the observed band.

Cooperative spectrum sensing uses two successive channels: the sensing channel (from the primary user to cognitive radios) and the reporting channel (from cognitive radios to the common receiver). A simple decision fusion method is typically used to conserve the control channel bandwidth. Each cognitive user makes a binary decision based on its local observation, indicating the presence of the primary user if the local decision result is 1, and the absence of the primary user if the decision is 0. The benefit of cooperative spectrum sensing lies primarily in the achievable space diversity afforded by the independent sensing channels, or sensing diversity gain, provided by multiple cognitive radios. Even if one cognitive radio fails to detect the signal of the primary user, many detection opportunities remain for other cognitive radios. With the increased number of cooperative cognitive radios, the probability of missed detection for all users is extremely small. As the number of cooperating cognitive users participating in cooperative spectrum sensing increases, so does sensing diversity order and sensing performance. Another merit of cooperative spectrum sensing is the mutual benefit of communicating with each other to improve sensing performance [86]. When a cognitive radio is far removed from the primary user, the received signal may be too weak to detect. However, by employing a cognitive radio located near the primary user, as a relay, the signal of the primary user can be detected reliably by a distant user.

Improved cognitive user performance through user collaboration was investigated [73, 74] in the case of AWGN sensing channels, which presented methods of cooperation between two users as well as multiple users based on periodic spectrum sensing. Others studies have investigated the effect of sensing diversity order on cooperative spectrum sensing performance when the sensing channel experienced AWGN and fading channel, respectively [29, 81]. The results illustrate significantly improved performance by cooperative spectrum sensing with an increase in sensing diversity. Furthermore, it has been theoretically proven that cooperative spectrum sensing can reduce the demand of the average SNR of sensing channels compared with single user spectrum sensing. However, these investigations are based on periodic spectrum sensing, in which the sensing time and sensing performance are contradictory: a longer sensing duration can improve sensing performance, but results in a longer waiting time for the SUs to access the channel, causing serious interference for the PU [84]. Therefore, studies have been undertaken to determine optimal sensing duration to improve the system performance [87–90].

In decision based cooperative spectrum sensing, the control bandwidth can be greatly reduced by one-bit quantization compared with data fusion and multiple bits quantization method. However, when the number of sensing users is very large, the total number of sensing bits transmitted to the FC remains significant, and use of the larger control bandwidth also creates a potential problem. Further, the influence of reporting channel fading on sensing performance is related to sensing diversity order [83]. Therefore, establishing an appropriate trade-off between reporting channel fading and sensing diversity order must be further considered. System performance can be effectively improved through the soft combination method versus the hard combination in cooperative spectrum sensing. At present, research on soft combination-based cooperative spectrum sensing is largely focused on the data fusion method, in which the SU can provide relatively detailed and effective local detection information for the FC. In [14], the authors proposed an optimal soft combination scheme, demonstrating that cooperative spectrum sensing performance increased as the number of sensing users grew. However, infinite bits are required, and this will result in a large communication bandwidth for many cognitive users, leading to substantial waste of communication bandwidth.

The elements of cooperative spectrum sensing are shown in Fig. 2.9 and are briefly described as follows:

- Cooperation models consider how cognitive users cooperate to perform spectrum sensing. The popular parallel fusion network models [71] and the recently developed game theory models [91, 92] have been considered for achieving optimal detection performance. Most existing models for cooperative spectrum sensing are centered on detection performance in terms of cooperative gain, and the modeling of cooperation overhead is still an open issue.
- Sensing techniques are used for the RF environment, taking observation samples and employing signal processing techniques for detecting a primary user signal

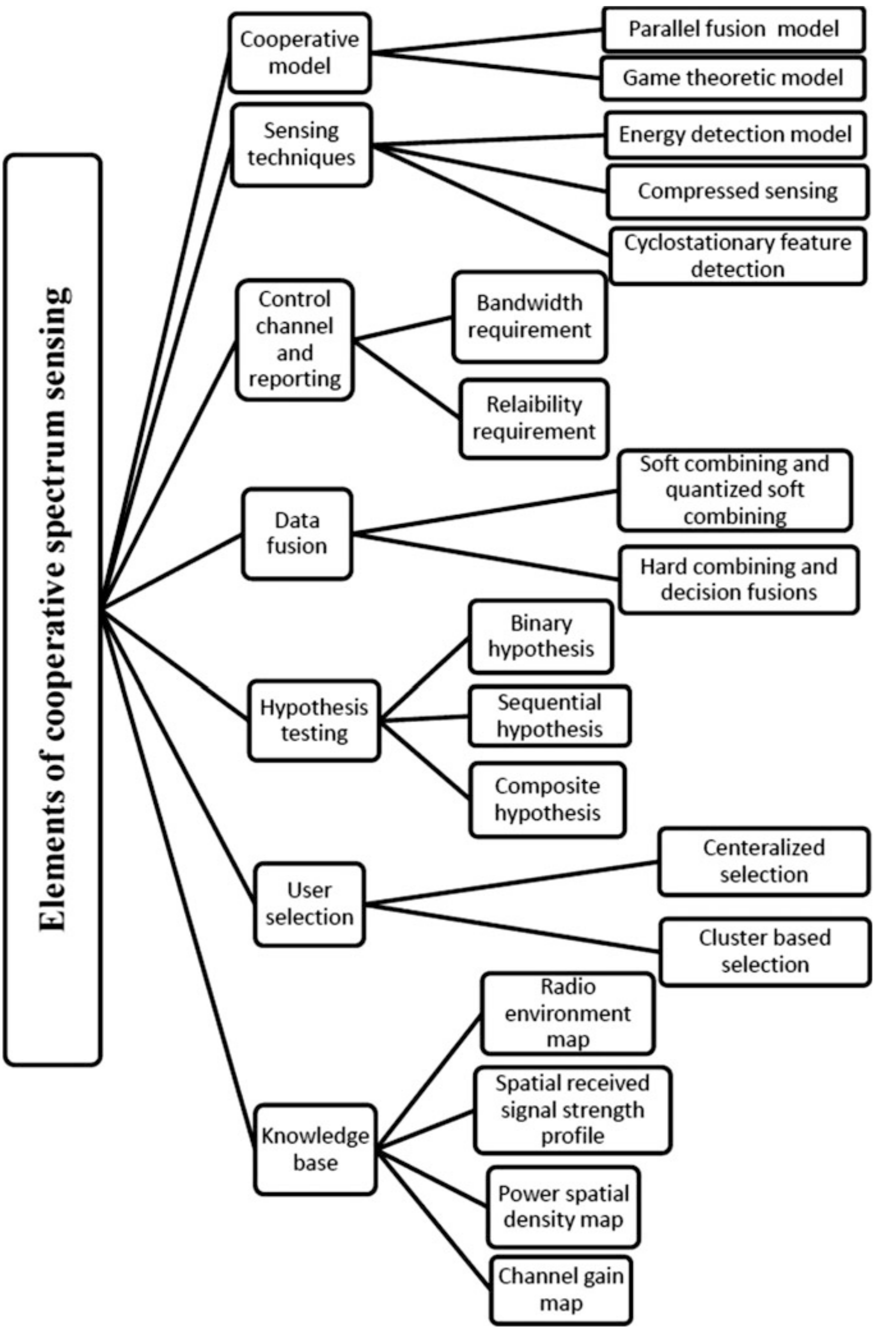

Fig. 2.9 Potential elements of the cooperative spectrum sensing technique

or available spectrum. The choice of sensing technique influences how cognitive radio users cooperate with each other. The process of cooperative spectrum sensing begins with local spectrum sensing at each cooperating cognitive user. Sensing techniques are crucial in cooperative spectrum systems, because the sensing, sampling, and processing of primary signals is strongly dependent on cognitive user cooperation. However, due to sub-Nyquist rate sampling and insufficient number of samples, a weak primary user signal with a nearby strong signal may not be properly reconstructed for detection in a wideband spectrum. In such a scenario, it may be challenging to achieve detection sensitivity by compressed sensing in a wideband spectrum.

- Control and reporting channels are concerned with how the sensing results obtained by cooperating cognitive users can be efficiently and reliably reported to the FC or shared with other cognitive users via the bandwidth-limited and fading-susceptible control channel. In cooperative spectrum sensing, a common control channel (CCC) [93, 94] is generally used by cognitive users to report local sensing data to the FC or for sharing sensing results with neighboring nodes. A MAC scheme is generally used by all cooperating cognitive users to access the control channel. From the perspective of the physical layer, a physical point-to-point link from a cooperating cognitive user to the FC is called a reporting channel. The availability of a perfect control channel in cooperative sensing is unrealistic, but recent studies suggest that imperfect control channels for influencing cooperative sensing performance should be considered as reasonable alternatives. However, the design of a control channel that is resilient to channel impairments, robust to primary user activity, and bandwidth-efficient for delivering sensing data is not a trivial task. Most existing cooperative sensing schemes assume a dedicated control channel for data reporting. In certain applications where the control channel must be dynamic allocated according to primary user activity, channel availability, and network topology, this allocation scheme significantly increases the difficulty for cognitive user cooperation and data reporting in cooperative sensing.
- Data fusion is the process of combining the reported or shared sensing results for making a cooperative decision. Depending on their data type, sensing results can be combined by signal combining techniques or decision fusion rules. In cooperative sensing, data fusion is a process for combining local sensing data for hypothesis testing. Depending on the control channel bandwidth requirement, reported sensing results may be of different forms, types, and sizes. In general, sensing results reported to the FC or shared with neighboring users can be combined in three different ways in descending order of control channel bandwidth performance: (1) soft combining, where cognitive users can transmit all local sensing samples or the complete local test statistics for a soft decision; (2) quantized soft combining, in which cognitive users can quantize local sensing results and send only the quantized data for soft combining in order to alleviate control channel communication overhead; and (3) hard combining, where cognitive users make a local decision and transmit the one-bit decision for hard combining. The use of soft combining at the FC clearly achieves the best

detection performance among the three, at a cost of greater control channel overhead, while quantized soft and hard combinations require much less control channel bandwidth, although degradation of performance is possible due to the loss of information from quantization.

- Hypothesis testing is a statistical test to determine the presence or absence of a primary user. This test can be performed individually by each cooperating user for local decisions or performed by the FC for a cooperative decision. However, large numbers of samples are needed to reach a decision during extended sensing time, which is a challenging task [95].
- User selection facilitates optimal selection of the cooperating cognitive users and determines the proper cooperation footprint/range to maximize cooperative gain and minimize cooperation overhead. The selection of cognitive users for cooperative sensing plays a key role in determining the performance of cooperative sensing because it can improve cooperative gain and address the overhead issues. For example, when cooperating cognitive users experience correlated shadowing, selecting independent cognitive users for cooperation can improve the robustness of sensing results, indicating that user selection is a critical issue for cooperation performance [20]. Potential challenges are summarized as follows:

  (1) Cooperation footprint [20] is the area where cognitive users cooperate with one another. As cooperative gain is obtained from spatial diversity, the cooperation footprint is an important parameter for evaluating performance and overhead in cooperative sensing. Thus, in addition to the distance between CR users, the selection of user schemes should consider the distribution of cognitive users and the area covered by their cooperation. However, deriving the exact footprint of cooperation from user selection is a challenge.
  (2) User selection and overhead: User selection is strongly related to every type of cooperative sensing overhead ranging from control channel bandwidth to energy efficiency, to security issues, among others. A trade-off exists between detection performance and the various types of overhead. Because attempting to address all overhead issues within the user selection scheme is challenging, most user selection schemes target one or two of these issues to address.

- The knowledge base stores information and facilitates the cooperative sensing process to improve detection performance. The stored information is either a priori knowledge or knowledge accumulated through user experience. The knowledge may include PU and CR user locations, PU activity models, and received signal strength profiles. The performance of cooperative sensing schemes largely depends on the knowledge of PU characteristics such as traffic patterns, location, and transmission power. PU information, if available in a database, can facilitate PU detection. The knowledge base is an indispensable element of cooperative sensing, because it can be utilized to assist, complement, or even replace cooperative sensing for detecting PU signals and identifying available spectrum. In addition, it serves two roles in cooperative sensing: (1) enhancing detection performance by utilizing the accumulated knowledge and learned experience, such as statistical models, in the database; and (2) alleviating the burden of cooperative sensing by retrieving spectrum information (e.g., a list of PU-occupied channels) from the database. To address security issues in cooperative sensing, the database should include other types of knowledge such as the behavior model of CR users and the model for jammer identification. Although cooperatively establish accurate statistical models for security purposes is challenging, the knowledge derived from these models can significantly improve security in cooperative sensing. In addition, because a recent U.S. Federal Communications Commission (FCC) ruling [96] has removed spectrum sensing requirement in TV white space, CR devices are able to access PU activity and spectrum information from a remote spectrum database. This ruling gives rise to new challenges for on-demand and web-based processing applications such as cloud computing [97, 98] in providing CR users with fast, secure, scalable, and energy-efficient access to a remote knowledge base.

2.5 Interference Temperature

The interference temperature limit is defined as the amount of additional interference that a receiver could tolerate [99], but a potential issue with this approach is the calibration of the limit itself. However, the conventional approach is based on the worst-case assumption of various primary users transmitting simultaneously. Severe constraints are imposed on the transmission power of cognitive users that should operate below the noise floor of primary systems. Various spectrum sensing methods based on interference level are reported in the literature [99, 100]. In dynamic spectrum access, cognitive users need to detect the primary user's appearance and decide, according to different metrics, which portion of the spectrum is available. The traditional approach is to limit the transmitter power of interfering devices such that the transmitted power should be no higher than a prescribed noise floor at a certain distance from the transmitter. However, constraints on transmitter power become more problematic as the mobility and variability of RF emitters increases, potentially revealing new, unpredictable sources of interference. The FCC Spectrum Policy Task Force [101] proposed a new metric on interference assessment, the interference temperature, to enforce an interference limit perceived by receivers. The interference temperature is a measure of the RF power available at a receiving antenna that is then to be delivered to a receiver, reflecting the power generated by other emitters and noise sources [102]. The purpose of the metric was to expose and remove the subjectivity that regulatory agencies might use to analyze interference. The development of an interference metric is critical if more intensive, dynamic use of the spectrum is desired. Interference-based detection is an underlay approach based on an estimation of the interference level at the primary receiver. Although interference is regulated by the transmitter, it actually occurs at the receivers. In interference-based approaches, a cognitive user transmits only if the new interference introduced by its own transmission is below a specific threshold, or the interference temperature limit. Using the interference temperature parameter, two crucial controls can be defined: (1) the upper threshold, above which the channel is declared to be occupied, and (2) the lower threshold, below which the channel can be declared empty or available for another user.

More specifically, it is defined as the temperature equivalent to the RF power available at a receiving antenna per unit bandwidth [103]: $T_I(f_c, B) = (P_I(f_c, B)/kB)$, where $P_I(f_c, B)$ is the average interference power in watts centered at f_c, covering bandwidth B measured in Hertz, and Boltzmann's constant is $k = 1.38 \times 10^{-23}$ J/K. Any unlicensed secondary transmitter using the licensed band must ensure that their transmission, plus the existing noise and interference, does not exceed the interference temperature limit at a licensed receiver. Any transmission in the licensed band is viewed as harmful if it increases the noise floor above the interference temperature limit. Thus, the receiver needs a reliable spectral estimate of the interference temperature. This requirement can be met by using the multi-taper method to estimate the power spectrum of the interference temperature with a large number of sensors [15]. If a regulatory body sets an interference temperature limit for a particular frequency band, then the secondary transmitters must keep the average interference below this level. Thus the interference temperature serves as a cap placed on potential RF energy that could appear on that band. Previous efforts have shown how to implement efficient spectrum allocation within the interference temperature limit. Spectrum shaping has been proposed as a method to improve spectrum efficiency [104] in cognitive radio networks. More specifically, using interference fitting, a cognitive radio senses the shape of the interference power spectrum and creates spectra inversely shaped to the current interference environment to take advantage of gaps between the noise floor and the cap on the interference temperature limit. A comprehensive analysis is presented in [25], which quantifies how interference temperature limits should be selected and how those choices affect the range of licensed signals. The FCC received input from external parties commenting that the interference temperature approach is not workable, as it would increase interference in the frequency bands where it would be used. Therefore, in May 2007, the FCC terminated the rule making process for implementing the interference temperature model.

2.6 The Spectrum Sensing Hybrid Model

The hybrid model for non-cooperative spectrum detection is the combination of all three techniques: matched filter, energy detection, and cyclostationary feature detection. Under this approach, the proper channelization of these techniques and add-on functionalities are used for opportunistic detection of idle spectrum bands. Let us now consider an area where spectrum sensing through a non-cooperative technique must be implemented, as shown in Fig. 2.10.

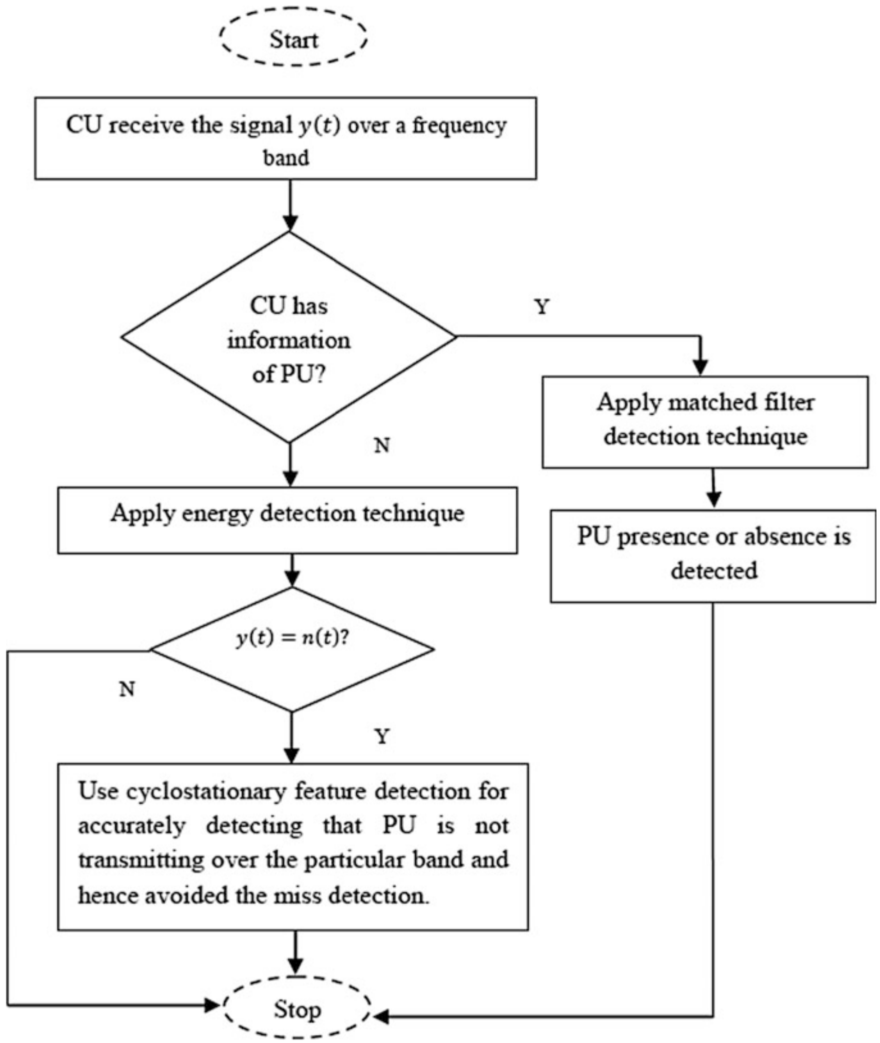

Fig. 2.10 Flowchart of the hybrid model for transmitter sensing

Step 1: The cognitive user receives the signal from the designated frequency band. The receiver will then determine whether the PU signal characteristics are present at the CU. If the signal is present, then directly matched filter detection is used for locating the licensed user on that band at that particular moment.

Step 2: If the cognitive user does not have any knowledge of the PU signal characteristics, an energy detection technique is employed. However, energy detection is not a highly accurate detection method and may result in sensing error, causing interference to licensed users. Therefore, hybrid model energy detection can be used as a fast sensing method. The idle channel sensed by the energy detector is again sensed by the cyclostationary feature detector to avoid missed detection. Cyclostationary feature detection provides higher sensing accuracy than the energy detector, but at the cost of greater processing time. The hybrid sensing method thus provides a shorter sensing time and accurate sensing results.

2.7 Threshold Setting

Setting an optimal threshold—the value needed to meet detection performance requirements—is one of the most important challenges to implementing detection techniques. Under optimal conditions, the probability of false alarm must be as low as possible, and the probability of detection as high as possible. A low probability of false alarm increases spectrum utilization, while a high probability of detection ensures the presence or absence of a primary user and reduces the probability of interference. The threshold can be set as either fixed or dynamic; two principles can be used to set a fixed threshold: constant false alarm rate (CFAR) and (2) constant detection rate (CDR) [105]. In CFAR, the threshold is set to meet a target P_f, and the obtained threshold is then used to compute the corresponding P_d, whereas in CDR, a certain P_d is used to set the threshold. For energy detection, the threshold can be computed based on these two principles [105]:

$$\lambda_f = \sigma_n^2\left(L + Q(P_f)\sqrt{2L}\right) \tag{2.12}$$

where λ_f is the threshold based on CFAR.

$$\lambda_d = \sigma_t^2\left(L + Q(P_d)\sqrt{2L}\right) \tag{2.13}$$

where λ_d is the threshold based on CDR. From Eqs. (2.12) and (2.13), in contrast to CDR, CFAR does not need the signal power of a PU to set the threshold; therefore, CFAR is more commonly used. However, constantly setting P_f to a small value such as 0.1 means that the corresponding threshold will be high. Consequently, it is difficult to detect low-power signals, and interference may occur. Therefore, a fixed threshold based on CFAR is not optimal. An optimal threshold setting can be archived if each cognitive user dynamically sets its threshold according to its channel states. In this context, the concept of constant false alarm is utilized to compute the energy detection threshold, and that value is then compared to the decision statistic to identify the primary user's current status (active/idle). The CFAR is used to compute the threshold value. The false alarm probability (P_f) is swept through a set of values in the range [0, 1], and the corresponding threshold is simultaneously computed using Monte Carlo simulations for each threshold value. Noise variance, as a significant parameter used to compute the threshold, is also varied. For each value of noise variance, the false alarm probability is updated through different values to observe the impact of this variation on the energy detection threshold. A low probability of missed detection and false alarm must always be jointly maintained to optimize detection performance in an SNR-varying environment. Minimizing the probability of missed detection affords greater protection to the PU against potential cognitive user transmissions, whereas minimizing the false alarm probability allows cognitive users to efficiently utilize the unused bands of spectrum. Therefore, the decision threshold must be adaptively adjusted to satisfy these two conflicting requirements for various channel conditions. The overall performance objective of the entire CRN can also be put into a single optimization problem of minimizing the total sensing error, which is discussed in detail in [106].

In cooperative spectrum sensing, local decisions are obtained by an energy detector based on CFAR. The authors in [107] proposed an optimal threshold method based on minimizing the total error rate, which is the summation of the probability of false alarm and missed detection, as follows:

$$P_e = P_m + P_f \tag{2.14}$$

By substituting Eqs. (2.5) and (2.7) in Eq. (2.14), the total error of energy detection is:

$$P_{e(ED)} = 1 - Q\left(\frac{\lambda - \sigma_t^2}{\sqrt{2L\sigma_t^4}}\right) + Q\left(\frac{\lambda - \sigma_n^2}{\sqrt{2L\sigma_n^4}}\right) \tag{2.15}$$

The optimal threshold (λ_{opt}) is the value that gives the minimum total error rate, which is obtained by solving the next optimization problem:

$$\lambda_{opt} = \arg \lambda \min P_e \tag{2.16}$$

The solution to this problem is as follows [107]:

$$\lambda_{opt} = \frac{-B - \sqrt{B^2 - 4AC}}{2A} \tag{2.17}$$

where $A = \frac{-1}{2L}\left(\frac{1}{\sigma_t^2} + \frac{1}{\sigma_n^2}\right)$, $B = \left(\frac{\sigma_s^2}{\sigma_t^2 \sigma_n^2}\right)$ and $C = -2\ln\left(\frac{\sigma_n^2}{\sigma_t^2}\right)$

This threshold setting approach is employed for the energy detector in [107]. However, this method can be applied to both the matched filter and cyclostationary feature detector. Further, for the dynamic threshold setting for the matched filter, the total error is [108]:

$$P_{e(MF)} = 1 - Q\left(\frac{\lambda - \varepsilon}{\sqrt{\varepsilon\sigma_n^2}}\right) + Q\left(\frac{\lambda}{\sqrt{\varepsilon\sigma_n^2}}\right) \tag{2.18}$$

where $\varepsilon = \sum_1^L x_p^2$. Using the dynamic threshold setting scheme [107], the optimal threshold is:

$$\lambda_{opt(MF)} = \arg\lambda\min\left[1 - Q\left(\frac{\lambda - \sigma_t^2}{\sqrt{2L\sigma_t^4}}\right) + Q\left(\frac{\lambda - \sigma_n^2}{\sqrt{2L\sigma_n^4}}\right)\right] \tag{2.19}$$

The solution to this minimization problem is the threshold value that makes the derivative of the total error equal to zero.

$$\frac{\partial P_{e(MF)}}{\partial\lambda} = 0 = -\frac{\partial}{\partial\lambda}\int\limits_{\frac{\lambda-\varepsilon}{\sqrt{\varepsilon\sigma_n^2}}}^{\infty} e^{-t^2/2}dt + \frac{\partial}{\partial\lambda}\int\limits_{\frac{\lambda}{\sqrt{\varepsilon\sigma_n^2}}}^{\infty} e^{-t^2/2}dt = 0 \tag{2.20}$$

Using Leibniz's integral rule, the above Equation becomes:

$$\frac{e^{-\frac{(\lambda-\varepsilon)^2}{\varepsilon\sigma_n^2}}}{\sqrt{\varepsilon\sigma_n^2}} - \frac{e^{-\frac{\lambda^2}{\varepsilon\sigma_n^2}}}{\sqrt{\varepsilon\sigma_n^2}} = 0 \tag{2.21}$$

$$(\lambda - \varepsilon)^2 = \lambda^2 \tag{2.22}$$

The optimal threshold of the matched filter is: $\lambda_{opt(MF)} = \varepsilon/2$. Similarly, in dynamic threshold setting for cyclostationary feature detection, the total error is given by [108]:

$$P_{e(CSFD)} = 1 - Q_1\left(\frac{S}{\sigma_1}, \frac{\lambda}{\sigma_1}\right) + e^{-\frac{\lambda^2}{\sigma_0^2}} = 1 - \int\limits_{\frac{\lambda}{\sigma_1}}^{\infty} xe^{\left(-\frac{\left(x^2 + \frac{s^2}{\sigma_1^2}\right)}{2}\right)} I_0\left(\frac{S.x}{\sigma_1}\right).dx + e^{\frac{-\lambda^2}{\sigma_0^2}} \tag{2.23}$$

The objective function is to find the optimal threshold that minimizes $P_{e(CSFD)}$. This problem is defined as: $\lambda_{opt(CSFD)} = \arg\lambda\min P_{e(CSFD)}$. The solution to this minimization problem is the threshold value that makes the derivative of the total error equal to zero; thus the solution lies in finding the value of λ that solves Eq. (2.24).

$$\frac{\partial P_{e(CSFD)}}{\partial \lambda} = \lambda^2 \left(\frac{1}{\sigma_0^2} - \frac{1}{2\sigma_0^2} \right) + \ln\left(I_0 \left(\frac{S_{xN'}^{\alpha_0}(n, k_0) N \lambda}{\sigma_1^2} \right) - \ln(2\sigma 1) \right) - \frac{\left(S_{xN'}^{\alpha_0}(n, k_0) N \right)^2}{\sigma_1^2} = 0 \tag{2.24}$$

Using a numerical methods such as the Newton-Raphson method, Eq. (2.24) can be solved with respect to λ. The detection and false alarm probabilities depend on the threshold λ, and hence it is necessary to choose an appropriate value that meets specific requirements. Detection probability also depends on signal power and the time-bandwidth product, whereas the false alarm probability depends only on the time-bandwidth product apart from the threshold. Therefore, one approach to choosing the threshold for a given time-bandwidth product is to select λ to meet the desired false alarm probability.

2.8 Potential Spectrum Sensing Challenges

Designing an efficient spectrum-sensing technique is the most fundamental yet problematic functionality in the cognitive radio paradigm because the levels of complexity, accuracy, reliability, computational cost, and sensing time of spectrum sensing fluctuate. Indeed, it is difficult for any given spectrum sensing technique to achieve high performance for all these spectrum sensing requirements; thus a trade-off among these requirements is necessary to achieve overall satisfactory spectrum-sensing results. Several potential challenges that make spectrum sensing an exigent task are shown in Fig. 2.11. Wideband spectrum sensing for cognitive radio applications requires a high sampling rate, high-resolution analog-to-digital converter (ADC) with a large dynamic range, multiple analog front-end circuitry, and high speed signal processors [109], all of which demand potential hardware, software, or algorithms/approaches. In traditional receiver design, noise variance or interference temperature estimation over the transmission of desired narrowband signals has been commonly used for optimal receiver designs such as channel estimation and soft information generation, as well as for improved handoff, power control, and channel allocation techniques. The noise/interference estimation problem is easier for these purposes, as receivers are tuned to receive signals that are transmitted over a desired bandwidth. Moreover, receivers are generally capable of processing the narrowband baseband signals with reasonably low complexity and low-power processors. However, in cognitive radio, the terminals are required to process transmission over a much wider band to sense an opportunity. Cognitive radio should thus be able to capture and analyze a relatively large band for

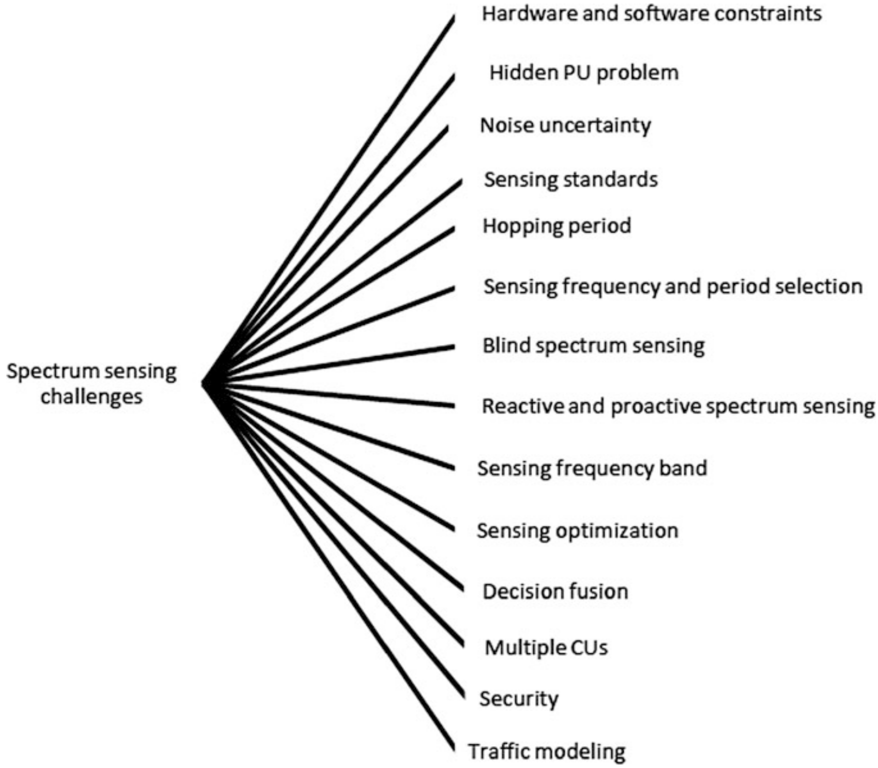

Fig. 2.11 Potential spectrum sensing challenges

identifying spectrum opportunities. Further, the high-speed processing units or field-programmable gate arrays (FPGAs) are needed for performing computationally demanding signal processing tasks with relatively short delay. The sensing can be performed via two architectures: single-radio and dual-radio [109, 110]. A specific time slot is allocated for spectrum sensing in the single radio architecture, and minimum accuracy can be guaranteed for spectrum sensing results. Moreover, spectrum efficiency decreases as some portion of the available time slot is used for sensing instead of data transmission. The obvious advantage of single-radio architecture is its simplicity and lower cost. However, in the dual-radio sensing architecture, one radio chain is dedicated to data transmission and reception, while the other chain is dedicated to spectrum monitoring. The potential limitation of such an approach is increased power consumption and hardware cost.

The level of noise power is required to estimate SNR, but it is difficult to measure the exact level of the noise power that is the noise uncertainty. In several studies, noise power is assumed to be known and fixed, but in fact it varies in time, requiring real-time measurements to determine its exact value. By considering noise uncertainty in performing spectrum sensing, it was shown that primary users' signals could not be detected under a certain a SNR value even over an extended sensing period [26]. This value is called the SNR wall, and its exact value depends on the detection technique used. The SNR wall is expressed as [31] $SNR_{wall} = 10\log_{10}\left[10^{x/10} - 1\right]$, where x is noise uncertainty in dB. In addition, in order to provide a promising security level and low probability of detection and interference, the wireless communication systems uses a spread spectrum technique or frequency hopping that utilizes spread frequencies with a wide bandwidth. Due to these characteristics, hopping is one of the main concerns in PU detection, requiring prior knowledge of PU hopping patterns [9]. Another crucial design element in cognitive radio spectrum sensing is the identification of the sensing period and how often it should be performed (sensing frequency). During the sensing period, data transmission is suspended, thus reducing network throughput and increasing end-to-end delay. Thus the sensing time chosen should be as short as possible. However, short sensing times may negatively affect detection performance, and sensing must be repeated frequently to ensure that the channel usage status for primary users is accurate. In other words, sensing must be active most of the time, which affects network performance. Hence, the selection of a suitable detection time must weigh these considerations.

Another fundamental design parameter of spectrum sensing is related to the frequency bands. Sensing a wide frequency band guarantees identification of more frequency opportunities, at the expense of time and hardware cost. A parallel sensing mechanism has been proposed [111] whereby cognitive users sense different frequencies simultaneously, and subsequently send their estimations to a FC, an approach that could enable rapid sensing of wider frequency bands. Another potential issue is determining the most effective frequency bands for a given cognitive radio environments to provide high QoS for both primary and cognitive users. Cognitive radio not only inherits the security concerns of wireless communication, but also raises new security concerns, such as primary user emulation and belief manipulation attacks [112, 113]. These malicious actions may degrade the performance of spectrum sensing and other cognitive radio functionalities. However, most proposed spectrum sensing techniques have not adequately addressed such security concerns [112, 114], and thus this important issue in cognitive radio will require significant attention. Furthermore, there is a high possibility that multiple secondary user networks competing for the same licensed bands will increase the likelihood of interference; thus coordination among SUs will be necessary [59].

An additional important consideration for cognitive radio networks aimed at maximizing performance is a sensing policy that addresses decisions about when, how long, and which frequency bands to sense. Sensing policies should be coordinated among cognitive users, and sensing periods must be synchronized among cognitive radios. Ideally, a cognitive radio user wants to minimize the amount of time required for identifying spectral opportunities in order to maximize the time available for transmission. Opportunistic spectrum access and/dynamic spectrum access are still in their infancy, and several complex technical, economical, and regulatory issues must be addressed before its potential can be fully assessed and realized. Potential research efforts within the signal processing community are particularly important in providing technical data for crafting of spectrum regulatory policies.

Moreover, the potential importance and challenges of spectrum sensing have been presented, however the present study has been emphasized to explore the possibilities to enhance the local sensing results in low-SNR environments. Further, experimental investigations are also needed to assess the effects of fading/shadowing (composite fading) on sensing results. However, an important initial step is determining whether collaboration between different detection techniques can significantly enhance sensing performance. A collaborative spectrum sensing model must be able to utilize various detection techniques to support reliable detection decisions. Much of the recent research in this area has focused on multistage spectrum sensing [83, 84, 115]. All detection techniques require an estimate of the noise power to compute SNR, but measuring noise uncertainty is problematic because this parameter changes with time. Therefore, it is important to evaluate spectrum sensing under certain noise uncertainty scenarios. MAC layer sensing schemes in cognitive radio networks generally consider both reactive and proactive sensing. In proactive sensing, adapted and non-adapted sensing period schemes are also assessed, via two performance metrics: available spectrum utilization and idle channel search delay. Simulation results show that the best performance is achieved with proactive sensing and adapted periods, but with observable overhead computational tasks to be performed by the network nodes.

2.9 Summary

In this chapter, we have provided a comprehensive survey on the fundamentals of cognitive radio spectrum sensing and the major research challenges, focusing on non-cooperative and cooperative spectrum sensing perspectives. The fundamental tasks of cognitive radio include spectral estimation of a radio frequency (RF) spectrum, hole identification, extraction of channel state estimation, and transmitter power control. Efficient utilization of radio spectrum by the cognitive radio transmitter can be achieved only with spectral information of the radio environment and spectrum hole identification in the neighborhood of a receiver, as well as information on the evolution of spectrum holes This information can be used by cognitive radio transmitter, for example, to select the appropriate modulation and coding format and transmission power level. The basic objective of the transmit power control function problem is to determine the transmit power levels for cognitive radio transmitters so that their data transmission rates can be maximized under the constrained interference limits in the frequency bands.

We have presented system models for selected detection techniques—the energy detector, matched filter, and cyclostationary feature detector, and compared them with fixed and dynamic threshold setting methods. Hybrid spectrum sensing techniques were also used to improve sensing performance through the proper channelization of detection techniques in a non-cooperative environment. However, as discussed, a first step in the spectrum sensing process could use energy detection or spectral estimation to provide a quick, coarse sensing in order to narrow the set of potentially available frequency bands, which would then be checked using more computationally complex feature detectors or matched filters. The main purpose of this initial step is to determine whether the power level at a given frequency band is below a specified threshold to enable secondary user transmissions. Regardless of the spectrum sensing algorithm employed, each algorithm provides a trade-off between the probability of false alarm and the probability of missed detection. These probabilities further depend on the number of collaborating users, the fusion rule employed, and the number of samples. However, selection of a proper detection threshold is a cross-layer optimization problem. The MAC layer protocols define the bounds for the physical layer algorithms for obtaining a desired trade-off between false alarms and missed detections. Physical layer algorithms whose thresholds can be set analytically to obtain a desired trade-off are preferred for their simplicity and predictability. For a multiuser distributed cognitive radio network, self-organization can be achieved with the help of two basic mechanisms—cooperation and competition. With cooperation (via either a distributed or centralized approach), the cognitive nodes can share network information among one another to achieve coordinated and efficient spectrum management. However, synchronization among the nodes may be required, resulting in a more complex network design. Conversely, a competitive (or non-cooperative) approach may simplify the network design, but at the expense of network performance. However, cooperative spectrum sensing techniques, with their advantages and limitations, have also been presented. Various parameters required for the design of cognitive radio models were explored, including hardware, spectrum sensing techniques, reasoning agent, and spectrum model.

In order to ensure low-interference operation for primary users, the detection sensitivity of cognitive users must be very high. However, spectrum sensing that relies on opportunistic access is not possible without tolerance of significant interference. The sensing problem is typically formulated to detect the primary transmitters instead of primary receivers. In practice, this is the only feasible option if the primary receivers are passive. There are multiple means of improving the detection sensitivity of a cognitive radio network. These include RF front-end sensitivity, designing and employing powerful signal processing algorithms well-suited to the task, and exploiting spatial diversity through collaborative sensing among multiple cognitive radios.

In summary, each of the two major classes of spectrum sensing (non-cooperative and cooperative) has its advantages and disadvantages. The selection and design of a proper detection algorithm is highly dependent on the application and primary user system. An algorithm best suited for every application may not exist. Hence, the use of a library of different sensing algorithm—for example, both energy and feature detectors—may be the most viable strategy. The spectrum sensing approach should be primarily system-oriented in order to maximize the probability of spectral opportunity detection. Therefore, feature detection or matched filter methods should be used whenever a desired performance must be achieved, with the aid of a computationally feasible algorithm; alternatively, energy detection may be used.

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