A Survey on Spectrum Sensing Techniques in Cognitive Radio

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Abstract

The limited available spectrum and the inefficiency in the spectrum usage necessitate a new communication technology, referred to as cognitive radio (CR) networks. The key characteristic of CR system is that it senses the electromagnetic environment to adapt their operation and dynamically vary its radio operating parameters. A cognitive radio must detect the presence of primary user to avoid interference. Spectrum sensing helps to detect the spectrum holes (unutilized bands of the spectrum) providing high spectral resolution capability. Different spectrum sensing techniques for cognitive radio are discussed in this paper.

1. Introduction

Demand of radio spectrum is increasing day by day due to increase in wireless devices and applications. Current radio spectrum allocation is not efficient due to regulations that have limited spectrum access, spatial restriction on frequency usage. Peak traffic planning causes temporal under utilization since spectrum demand vary with time. A cognitive radio must detect the presence of primary user to avoid interference. The use of allocated spectrum varies at different times and over different geographical regions. In accordance to a report by Spectrum Policy Task Force of FCC, the spectrum is under or scarcely utilized and this situation is due to the static allocation of the spectrum rather than the physical shortage of the spectrum as shown in Figure 1 [1]. Thus, to overcome the spectrum deficiencies and the inefficient utilization of the allocated frequencies, it is necessary to introduce new communication models through which frequency spectrum can be utilized whenever the opening (hole) is available. Thus to resolve the spectrum inefficiency problem, the concept of dynamic spectrum access and cognitive radio is introduced. These dynamic techniques for spectrum access are known as Cognitive Radios (CR).

The concept of CR as proposed by Mitola in 1998 may also be defined as a radio that is aware of its environment and the internal state and with knowledge of these elements and any stored pre-defined objectives can make implement decisions about it.

2. Spectrum sensing

The important requirement of cognitive radio network is to sense the spectrum hole. Cognitive radio has an important property that it detects the unused spectrum and shares it without harmful interference to other users. It determines which portion of the spectrum is available and detects the presence of licensed users when a user operates in licensed band.

![Figure 1. Spectrum concentration](image_url)

<table>
<thead>
<tr>
<th>Spectrum Occupancy (%)</th>
<th>Opened Locations</th>
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<tbody>
<tr>
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The spectrum sensing enables the cognitive radio to detect the spectrum holes. Spectrum sensing techniques can be classified as frequency domain approach and time domain approach. In frequency domain method estimation is carried out directly from signal so this is also known as direct method. In time domain approach, estimation is performed using autocorrelation of the signal. Another way of categorizing the spectrum sensing and estimation methods is by making group into model based parametric method and periodogram based non-parametric method [2]. Another way of classification depends on the need of spectrum sensing as stated below [3]:

2.1. Spectrum sensing for spectrum opportunities
   a. Primary transmitter detection: In this approach, detection of a signal from a primary transmitter is based on the received signal at CR users whether it is present or not. It is also known as non-cooperative detection. This method includes matched filter based detection, energy based detection, cyclostationary based detection, and radio identification based detection.
   b. Cooperative or collaborative detection: It refers to spectrum sensing methods where information from multiple Cognitive radio users is incorporated for primary user detection. This approach includes either centralized access to the spectrum coordinated by a spectrum server or distributed approach.

2.2. Spectrum sensing for interference detection
   a. Interference temperature detection: In this method the secondary users are allowed to transmit with lower power then the primary users and restricted by interference temperature level so that there is no interference. Cognitive radio works in the ultra wide band (UWB) technology.
   b. Primary receiver detection: In this method, the interference and/or spectrum opportunities are detected based on primary receiver's local oscillator leakage power.

2.3. Classification of spectrum sensing techniques

![Diagram of spectrum sensing techniques](image)

Figure 2. Classification of spectrum sensing techniques [4]

Figure 2 shows the detailed classification of spectrum sensing techniques. They are broadly classified into three main types, transmitter detection or non cooperative sensing, cooperative sensing and interference based sensing. Transmitter detection technique is further classified into energy detection, matched filter detection and cyclostationary feature detection [5].

2.3.1. Non-cooperative detection
This technique is based on the detection of the weak signal from a primary transmitter. In primary transmitter based detection techniques, a cognitive user determines signal strength generated from the primary user. In this method, the location of the primary receivers are not known to the cognitive users because there is no signaling between the primary users and the cognitive users. Basic hypothesis model for transmitter detection can be defined as follows [6]

\[ x(t) = \begin{cases} n(t) & H_0, \\ h s(t) + n(t) & H_1, \end{cases} \]

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

2.3.1.1. Energy detection
This technique is suboptimal and can be applied to any signal. Conventional energy detector consists of a low pass filter to reject out of band noise and adjacent signals. Implementation with nyquist sampling A/D converter, square-law device and integrator as shown in Figure 3(a) [7] –[15]. An energy detector can be implemented similar to a spectrum analyzer by averaging frequency bins of a FFT.

Without loss of generality, we can consider a complex baseband equivalent of the energy detector. The detection is the test of the following two hypotheses: [15]

\[ H_0: Y[n] = W[n] \quad \text{signal absent} \]

\[ H_1: Y[n] = X[n] + W[n] \quad \text{signal present} \]

\( n=1,\ldots,N; \) where \( N \) is observation interval (2)

The noise samples \( W[n] \) are assumed to be additive white Gaussian (AWGN) with zero mean and variance \( \sigma_w^2 \). In the absence of coherent detection, the signal samples \( X[n] \) can also be modeled as Gaussian random process with variance \( \sigma_x^2 \). Note that over-sampling would correlate noise samples and in principle, the model could be always reduced into equation (2).
A decision statistic for energy detector is:

\[ T = \sum_{N} (Y[n])^2 \]  

Figure 3. (a) Implementation with analog pre-filter and square-law device (b) implementation using periodogram: FFT magnitude squared and averaging [15]

Note that for a given signal bandwidth \( B \), a prefilter-matched to the bandwidth of the signal needs to be applied. For narrowband signals and sinewaves this implementation is simple as shown in Figure 3 (a). An alternative approach could be proposed by using a periodogram to estimate the spectrum via squared magnitude of the FFT, as depicted in Figure 3(b). This architecture also provides the flexibility to process wider bandwidths and sense multiple signals simultaneously. As a consequence, an arbitrary band-width of the modulated signal could be processed by selecting corresponding frequency bins in the periodogram.

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

If the number of samples used in sensing is not limited, an energy detector can meet any desired \( P_d \) and \( P_f_a \) simultaneously. The minimum number of samples is a function of the signal to noise ratio \( SNR = \frac{\sigma_s^2}{\sigma_w^2} \):

\[ N = 2(Q^{-1}(P_f_a) - Q^{-1}(P_d) )SNR^{-1} - Q^{-1}(P_d) ]^2 \]  

(4)

In the low SNR \(< 1 \), number of samples required for the detection, that meets specified \( P_d \) and \( P_f_a \) scales as \( O(1/SNR^2) \). This inverse quadratic scaling is significantly inferior to the optimum matched filter detector whose sensing time scales as \( O(1/SNR) \).

Figure 4(a) shows how the sensing time scales with input signal level for QPSK signal sensing. Measurements also shows that when the signal becomes too weak then increasing the number of averages does not improve the detection. This result is expected and is explained by the SNR wall existence. The limit happens at -110dBm (SNRwall= -25dBm). From the theoretical analysis, we know that SNR wall=-25dB corresponds to less than 0.03 dB of noise uncertainty. Results for sinewave energy detection show interesting behavior as shown in Figure 4 (b). Slope of the scaling law is improved by increasing the FFT size. For 1024 pt. FFT. We obtained \( N \sim 1/SNR^{1.5} \). For 256 pt. FFT coherent gain is negligible and we observe scaling law of \( N \sim 1/SNR^2 \).

This technique has the advantages that it has low complexity, ease of implementation and faster decision making probability. In addition, energy detection is the optimum detection if the primary user signal is not known. It also have disadvantages:

1. The threshold used in energy selection depends on the noise variance.
2. Inability to differentiate the...
interference from other secondary users sharing the same channel and with the primary user. (3) It has poor performance under low SNR conditions. This is because the noise variance is not accurately known at the low SNR, and the noise uncertainty may render the energy detection useless. (4) It does not work for the spread spectrum techniques like direct sequence and frequency hopping.

2.3.1.2. Matched filter detection

Matched-filtering is known as the optimum method for detection of primary users when the transmitted signal is known [16]. The main advantage of matched filtering is the short time to achieve a certain probability of false alarm or probability of misdetection [17]. Block diagram of matched filter is shown in Figure 5.

![Figure 5. Block diagram of matched filter [18]](image)

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

The operation of matched filter detection is expressed as [1]:

\[ Y[n] = \sum_{k=-\infty}^{\infty} h[n - k] x[k] \]  

(5)

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

This technique has the advantage that it requires less detection time because it requires less time for higher processing gain. The required number of samples grows as \( O(1/\text{SNR}) \) for a target probability of false alarm at low SNRs for matched-filtering [17]. However, matched-filtering requires cognitive radio to demodulate received signals. Hence, it requires perfect knowledge of the primary users signaling features such as bandwidth, operating frequency, modulation type and order, pulse shaping, and frame format. Moreover, since cognitive radio needs receivers for all signal types, the implementation complexity of sensing unit is impractically large [19]. Another disadvantage of match filtering is large power consumption as various receiver algorithms need to be executed for detection. Further, this technique is feasible only when licensed users are cooperating. Even in the best possible conditions, the results of matched filter technique are bound by the theoretical bound.

2.3.1.3. Cyclostationary feature detection

It has been introduced as a complex two dimensional signal processing technique for recognition of modulated signals in the presence of noise and interference [19]. To identify the received primary signal in the presence of primary users it exploits periodicity of modulated signals couple with sine wave carriers, hopping sequences, cyclic prefixes etc. Due to the periodicity, these cyclostationary signals exhibit the features of periodic statistics and spectral correlation, which is not found in stationary noise and interference [20] – [28]. Block diagram is shown in Figure 6.

![Figure 6. Cyclostationary feature detector block diagram [18]](image)

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

\[ y(n) = s(n) + w(n) \]  

(6)

The cyclic spectral density (CSD) function of a received signal (6) can be calculated as [29]

\[ S(f, \alpha) = \sum_{\tau=-\infty}^{\infty} R_y^\alpha(\tau) e^{-j2\pi\tau f} \]  

(7)

where \( R_y^\alpha(\tau) = E[y(n + \tau) y^*(n - \tau) e^{-j2\pi\alpha n}] \)  

(8)

is the cyclic autocorrelation function (CAF) and \( \alpha \) is the cyclic frequency. The CSD function outputs peak values when the cyclic frequency is equal to the fundamental frequencies of transmitted signal \( x(n) \). Cyclic frequencies can be assumed to be known [23], [25] or they can be extracted and used as features for identifying transmitted signals [24].

The main advantage of the feature detection is that it can discriminate the noise energy from the modulated signal energy. Furthermore, cyclostationary feature detection can detect the signals with low SNR. This technique also have disadvantages that the detection requires long observation time and higher computational
complexity [20], [30]. In addition, feature detection needs the prior knowledge of the primary users.

2.3.2. Cooperative or collaborative detection In this technique cognitive radio users are incorporated, for this two methods Gains and Group Intelligence are discussed.

2.3.2.1. Gains The performance of spectrum sensing is limited by noise uncertainty, shadowing, and multi-path fading effect. When the received primary SNR is too low, there exists a SNR wall, below which reliable spectrum detection is impossible even with a very long sensing time. If secondary users cannot detect the primary transmitter, while the primary receiver is within the secondary user’s transmission range, a hidden primary user problem will occur, and the primary user’s transmission will be interfered. Cooperative sensing decreases the probabilities of misdetection and false alarm. In addition, cooperation can solve hidden primary user problem and also decreases sensing problem [9]-[10],[15]. This also provides higher spectrum capacity gains then local sensing. In this pilot channel (control channel) can be implemented using different methodologies such as dedicated band, an unlicensed band such as ISM (Industrial Scientific and Management) , UWB(Ultra Wide Band ) i.e. under lay system [32].

Collaborative spectrum sensing is most effective when collaborating cognitive radios observe independent fading or shadowing [15], [33]. The performance degradation due to correlated shadowing is investigated in [14], [34] in terms of missing the opportunities. This technique is more beneficial when some amount of users collaborating over a large area then over a small area. To, overcome the effect of shadowing, beam forming and directional antenna is used [15].

Figure 8 (a) and (b) shows collaborative gain as a function of the number of collaborative radios for sine wave and QPSK signals.

For a given probability of false alarm for the cooperating system, an estimated threshold was computed for each location based on the idle spectrum data. Then, these thresholds were used to compute the probability of detection for each location.

Figure 9. Small scale collaborative gain and benefit of multiple antennas[15]
Figure 9(a) shows that it is beneficial to space the antennas at distances larger than $\lambda/2$ to maximize the gain. Figure 9(b) shows that performance improves with the number of antennas; 2 antennas improve $Q_D$ by 4% and 4 antennas maximize it by 25% gain.

### 2.3.2.2. Group intelligence

A spectrum sensing technique using group intelligence is proposed where multiple users, each with incomplete information, can learn from the group's wisdom to reach a supposedly correct conclusion. He proposed adaptive threshold based on group intelligence accuracy of the spectral occupancy has improved by training the Secondary User (SU). This training is done with the help of the global decision derived from other SUs in the network. This approach is suitable in two ways. (1) To indicate the presence or absence of the PU separate training signal are not required. Training can be done continuously, not limited to the training signal. (2) Training signal derived from spatially diverse SUs should be robust and less sensitive to local channel fading. Together the SUs are expected to reach a unanimous decision, which should be correct in all situations [35].

Group Intelligence emerges from the collaboration and competition among many individuals, enhancing the social pool of existing knowledge. The concept of Group Intelligence obtains prominence in the context of Multi Agent scenarios where in the global decision made is an essence of the all the individual local decisions. In the Cognitive Adhoc Network (CAN) scenario, the group intelligence in terms of the accuracy of the spectral information learned by the group of SUs. In other words lesser the number of decision errors, wiser is the network [36].

![Figure 10](image1.png)

**Figure 10.** $P_m$ vs. SNR with SNR estimate error=5dB, mean SNR of group=5dB [35]

Figure 10 shows the simulation result using 10(N) SUs. The mean operating SNR for the SUs is 5 dB with a variance of 5 dB. The SNR estimate error at the SUs is 5 dB. In the first case, it assumed that each SU broadcasts its hard decision (PU present or absent). The training signal for each SU is obtained by fusing these decisions using majority logic decision. In the second case, knowledge of $(P_d, P_f)$ for each SU is assumed and training signal is obtained using Log Likelihood Ratio Test (LLRT).

![Figure 11](image2.png)

**Figure 11.** $P_m$ vs. SNR with SNR Estimate Error=1dB, mean SNR of group=5dB [35]

Figure 11 shows the simulation result under same conditions as before, except here the error in SNR estimation is smaller 1 dB. It can be see that the method is relatively insensitive to SNR estimation error and continues to perform better than the distributed sensing methods. Thus the decision margin is an indicator of the confidence we have in our final decision and can also be interpreted as reliability of the result. Figure 12 represents this scenario.

![Figure 12](image3.png)

**Figure 12.** Reliability vs. number of SUs [35]

### 2.3.3. Advantages of cooperation

Advantages of Cooperation technique are given below.

#### 2.3.3.1. Plummets sensitivity requirements

Channel distortions like multipath fading, shadowing and building penetration losses impose high sensitivity requirements on cognitive radios. Sensitivity in cognitive radio is limited by cost and power requirement, power is limited by statistical uncertainties in noise and signal characteristics, a CR can detect this minimum power called SNR walls. If there is cooperation between them sensitivity
requirement decreases. Figure 13 shows the sensitivity benefits obtained from a partially cooperative coordinated centralized scheme considered by [37]. This also shows a -25 dBm reduction in sensitivity threshold obtained by this scheme [38].

Figure 13. Reduction in sensitivity threshold [38]

2.3.3.2. Agility improvement using totally cooperative centralized coordinated scheme

The major challenge in CR is reduction in overall detection time. Totally cooperative centralized scheme is highly agile of all cooperative schemes. They have been shown to be over 35 percent more agile compared to the partially cooperative schemes. Totally cooperative schemes achieve high agility by pairing up “weak users” with “strong ones”. Figure 14 shows the benefits of total cooperation over partial cooperation. Cooperative sensing has to be performed frequently and small benefits too will have a large impact on system performance [39].

Figure 14. The benefits of total cooperation over partial cooperation [38]

2.3.3.3 Cognitive relaying

It is the fact that 80 percent of the spectrum remains unused at any point of time [37]. As the number of CR users increases, probability of finding spectrum hole decrease with time. CR users would have to scan a wider range of spectrum to find a hole resulting in undesirable overhead and system requirements. An alternate solution to this is cognitive relaying proposed by [39] shown in Figure 15. In cognitive relaying the secondary user selflessly relays the primary users transmission thereby decreasing the primary users transmission time. Thus cognitive relaying in effect creates “spectrum holes”.

This method is not practical because of (1). The primary user don’t have any information about secondary user decode its transmission due to security related issues. (2). The cognitive users are generally ad hoc energy constrained devices, they might not relay primary users transmission. This technique is a very good way of creating transmission opportunities when spectrum gets scarce.

Figure 15. Illustration of cognitive relaying [38]

2.3.4. Disadvantages of cooperation

Cooperative sensing schemes are not beneficial due to following reasons [38].

2.3.4.1. Scalability

Even though cooperation has its benefits, too many users cooperating have reverse effects. It was shown in [37] as the number of users increases that cooperative centralized coordinated schemes follows the law of diminishing returns. However a totally cooperative centralized coordinated scheme was considered in [40] where with the number of nodes participating benefits of cooperation increased.

2.3.4.2. Limited Bandwidth

CR users might not have dedicated hardware for cooperation because of low cost low power devices. So data and cooperation information would have to be multiplexed, there is degradation of throughput for the cognitive users.

2.3.4.3. Short Timescale

The CR user would have to do sensing at periodic intervals as sensed information will become stale fast due to factors like mobility, channel impairments etc. This increases the over-head.
2.3.4.4. Large Sensory Data  Cognitive radio have the ability to use any unused spectrum hole so it will have to scan wide range of spectrum, resulting in large amount of data.

2.4. Interference based sensing  For interference based spectrum sensing techniques there are two methods proposed. (a) Interference Temperature Management (b) Primary Receiver Detection.

2.4.1. Interference temperature management  Interference is actually happen at receivers, it is regulated in trans-centric way and is controlled at the transmitter through the radiated power and location of individual transmitters. Interference temperature model is shown in Figure 16. The interference temperature is a measure of the RF power available at a receiving antenna to be delivered to a receiver, reflecting the power generated by other emitters and noise sources [39]. Specifically, it is defined as the temperature equivalent to the RF power available at a receiving antenna per unit bandwidth [41], i.e.,

$$T_I(f_c, B) = \frac{P_I(f_c, B)}{kB}$$  \hspace{1cm} (9)

where $P_I(f_c, B)$ is the average interference power in Watts centered at $f_c$ covering bandwidth $B$ measured in Hertz.

Figure 16. Interference temperature model [16]

FCC established an interference temperature limit, which provides a maximum amount of average tolerable interference for a particular frequency band.

2.4.2. Primary receiver detection  Advantage of Local Oscillator (LO) leakage power is that all RF receivers emit to allow cognitive radios to locate these receivers. Block diagram of superheterodyne receiver is shown in Figure 17. Detection approach can detect the LO leakage with very high probability and takes on the order of milliseconds to make a decision. In this architecture RF signal to be converted down to a fixed lower intermediate frequency (IF), replacing a low Q tunable RF filter with a low-cost high-Q IF filter. A local oscillator (LO) is used to downconvert an RF band to IF. This local oscillator is tuned to a frequency such that when mixed with the incoming RF signal, the desired RF band is downconverted to the fixed IF band. In all of these receivers, there is inevitable reverse leakage, and therefore some of the local oscillator power actually couples back through the input port and radiates out of the antenna [42].

Figure 17. Superheterodyne receiver [42]

Figure 18. TV LO leakage versus model year [42]

Figure 18 shows the leakage power of television receivers versus model year. Detecting this leakage power directly with a CR would be impractical for two reasons. First, it is difficult for the receive circuit of the CR to detect the LO leakage over larger distances. The second reason that it would be impractical to detect the LO leakage directly is that the LO leakage power is variable, depending on the receiver model and year.

3. Conclusion  The growing demand of wireless applications has put a lot of constraints on the usage of available radio spectrum which is limited and precious resource. In wireless communication system spectrum is a very important resource. In cognitive radio (CR) systems, reliable spectrum sensing techniques are required in order to avoid interference to the primary users. In this paper, different spectrum sensing techniques are
discussed that basically involves non cooperative, cooperative and interference based detection. For cooperative detection group intelligence technique is also discussed.

4. References


