SPECTRUM SENSING TECHNIQUES AND THEIR PERFORMANCE METRICS AND PARAMETERS

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Abstract— Spectrum sensing is one of the major tasks in cognitive radio (CR). The main objective of spectrum sensing is to obtain the spectrum information and to determine the existence of primary users in a specific geographical location. There are several techniques for spectrum sensing have been discussed in the literature. This paper describes those techniques in detail. The quality of communication in CR-based networks depends on the performance of spectrum sensing. Various parameters influence the performance of spectrum sensing and are measured with various performance metrics. This paper discusses various relations and trade-offs among those sensing parameters and the performance metrics with the analysis of the results obtained by using MATLAB.

Keywords— Cognitive radio, spectrum sensing, sensing parameters, performance analysis.

I. INTRODUCTION

Some spectrum bands are going to be fully utilized in the coming days, such as DSRC (dedicated short-range communication, a standard for vehicular ad hoc network or VANET). On the other hand, some spectrum bands are under-utilized such as TV or military radio bands. Underutilization causes these bands to become idle and inactive [1]. These unused spectrums can be used by the secondary users (rather than primary users or licensed users of those spectrums). This will enhance the utilization efficiency of those spectrums and solve the spectrum scarcity issues. This is the concept of cognitive radio (CR) which was first coined by Mitola & Maguire in [2].

Spectrum sensing (SS) is one of the major parts of the CR process. SS is a technique by which a SU or the CR user senses the spectrum whether it is occupied by any PU or not. If it finds that there is no PU using that spectrum, SU can use that spectrum opportunistically and with some certain conditions. There are several techniques to perform SS, such as energy detection, cyclostationary feature detection, matched filter detection, centralized and decentralized detection and so on.

There are several performance metrics and parameters are available in the literature that can be used to measure the performance of the SS such as the probability of detection (of primary users or PU), probability of false alarm and misdetection, sensing time, throughput, value of SNR (signal to noise ratio), inter-arrival rate of PU and so on.

The authors in [3] provided a comprehensive survey on SS from its development to its current states with future challenges. They described the pros and cons of various types of SS techniques and the challenges associated with their implementation. They also provided the real application of the CR network (CRN) by taking the TV white spaces as the case study. They elaborated on the in-depth concept of SS, compressive sensing and usage of machine learning in SS. Other survey works are found in [1], [4]–[6].
Various measurement methods and the technologies used in SS especially in wideband SS were discussed in [7]. They classified the measurement methods into five main categories. They also did the analysis of main technologies related to wideband SS. Kadhim et. al. [8] did the throughput analysis for the CR system. They studied the tradeoff between sensing capability and mean throughput of the SUs, sensing time and throughput tradeoff. They presented their simulations' results with discussions. The authors in [9] discussed various performance metrics and their interrelationship at the node, network, and application levels of CR. They presented potential challenges in translating performance metrics into the utility functions that are required for the CR deployment.

Most of the articles mentioned above focused on the fundamental concepts of SS, but not did the performance analysis. In this paper, we have focused on the SS techniques used in CRN with their taxonomy and several parameters that are used to measure the performance of the SS performance.

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Some of the contributions of this paper are given below:

- Detail description of SS techniques and their taxonomy along with their pros and cons are discussed.
- Several performance metrics and the parameters used for the performance measurement of SS in CR are described.
- Performance analysis, trade-offs and the effect of several parameters in SS are presented with the results obtained from the MATLAB.

Table 1 includes the acronyms and their full forms used in the article.

The paper is organized as follows: Section 1 introduced the concept of CR, SS and their performance parameters and metrics. It also presents a few related works. Section 2 presents a few SS techniques in detail with their taxonomies. Section 3 describes the SS parameters and performance metrics. Section 4 presents the analysis of the results obtained from MATLAB simulation. Finally, section 5 concludes the paper.

Table 1 Acronyms and their full forms used in the article

Acronyms	Full form	Acronyms	Full form
BS	Base station	OOC	One order cyclostationary
CFD	Cyclostationary feature detection	PSD	Power spectral density
CNR	Cognitive radio network	PU	Primary user
CR	Cognitive radio	QoS	Quality of service
CSD	Cyclic spectral density	SNR	Signal to noise ratio
CSI	Channel state information	SS	Spectrum sensing
CSS	Cooperative spectrum sensing	SU	Secondary user
ED	Energy detection	VANET	Vehicular ad hoc network
FC	Fusion center	WD	Wavelet-based detection
MFD	Matched filtering detection		

II. Overview of CR and Spectrum Sensing (SS)

In this subsection, we are going to present the basic overview of CR and SS.

2.1 Cognitive Radio (CR)

CR is an intelligent wireless communication system in which a transceiver can intelligently cope up with the surrounding wireless environment. The scarce resource of the spectrum is efficiently utilized in CR. The basic concept of CR is to ensure the maximum usage of the limited frequency bands opportunistically by tuning the transmission parameters obtaining from the surrounding environment. CR learning process comprises obtaining communication parameters information and detecting any vacant channel by sensing the surrounded radio environment [10].

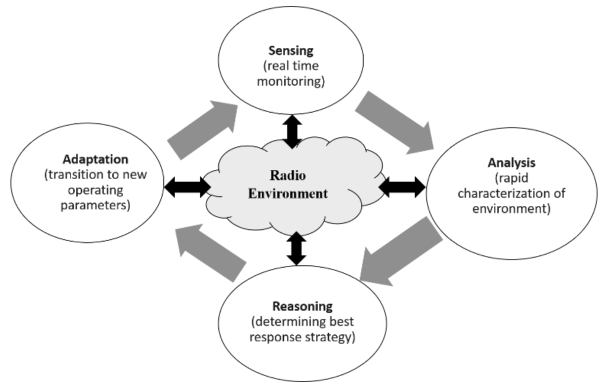


Fig. 1. CR Cycle (Redrawn from [24])

Spectrum hole, an important concept of CR, is a vacant band of frequencies allocated to the authorized and the licensed users (known as PUs or primary users). However, at a certain time and in a specific location, this band may not be used by PUs. In CR, the users (known as SUs or secondary users) who use unlicensed bands and temporarily unused licensed bands can utilize the spectrum hole. The SUs must vacant that used channel whenever any PU wants back. SUs sense the spectrum holes or vacant channel, select the best available one, coordinate with other SUs and the spectrum condition, and release the channel when PUs reclaim it (this is known as “spectrum mobility.”). Then, the SU must sense for other vacant channels, and the process goes on. This CR cycle is illustrated in Figure 1.

SS is a method of gaining spectrum occupancy information in a specific location, time, and frequency by perceiving the surrounding wireless environment. The core objective of SS is to select the free channel and PU occupancy of that channel. There are several ways of performing SS [11]. They are described as follows:

2.2 Spectrum sensing techniques:

There are several types of SS techniques, each of these techniques has own features, advantages, and drawbacks. From the taxonomy given below, we can say that there are mainly 3 types of spectrum sensing [11] [12].

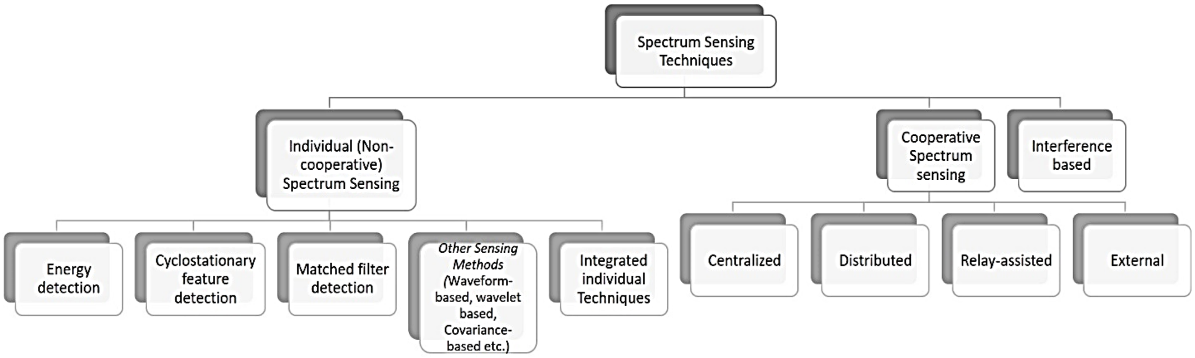


Fig. 2. Taxonomy of the types of SS techniques

2.2.a Non-cooperative SS:

This type of SS is also known as individual SS. In this technique, SU or CR users sense the spectrum individually and take spectrum decisions on their own. There are various detection techniques under this type of SS. They are described below:

2.2.a.i Energy detection (ED)

ED is one of the most usage SS techniques used in CRN. This is because of its simplicity and faster sensing capability. Another advantage of ED is that no prior information about PU characteristics and CSI (channel state information) is needed. Due to these, most of the researchers choose ED over other SS techniques for the CRN [13].

Here in ED, it detects the presence of PU by the measurement of received signal power or the value of SNR (signal to noise ratio) of the PU transmitter. Then the value is compared with the fixed threshold value that is predefined. If the received signal power (SNR) is higher than the threshold value, the presence of PU is declared. This simple strategy makes the ED faster, which means it can do faster sensing or PU detection.

For the employment of ED, the ON/OFF PU activity model is used. There is a hypothesis known as the Neyman-Pearson Lemma binary hypothesis that is used to determine the PU's presence or absence [14].

The overall process of ED can be represented in the block diagram illustrated in Figure. 3. The details are described below.

Let us consider, y is a signal sampled at the receiving SU, and then we can write as:

$$y(x) = \begin{cases} n(x) \rightarrow H_0 \\ n(x) + hs(x) \rightarrow H_1 \end{cases} \tag{1}$$

Here, x →represents the x^{th} sample whose value ranges from 1 to N.

$y(x)$ → signal sample received by SU.

$n(x)$ → it is a noise signal which follows Gaussian distribution which has zero mean and variance of σ_n^2 (i.e. $n(x) \sim \mathrm{N}(0, \sigma_n^2)$)

$h \rightarrow$ signal gain.

N →number of sensing samples.

The presence of PU is denoted by H_1 and the absence of PU by H_0. For H_1, signal and noise both are received but in the case of H_0, the only noise is received.

The energy test statistics (e_d) can be written as:

$$e_d = \sum_{i=1}^{N} |y(x)|^2 \tag{2}$$

The performance of ED is measured by the value of P_d and P_f for some SNR value and the threshold value (λ) *(described in next section)*.

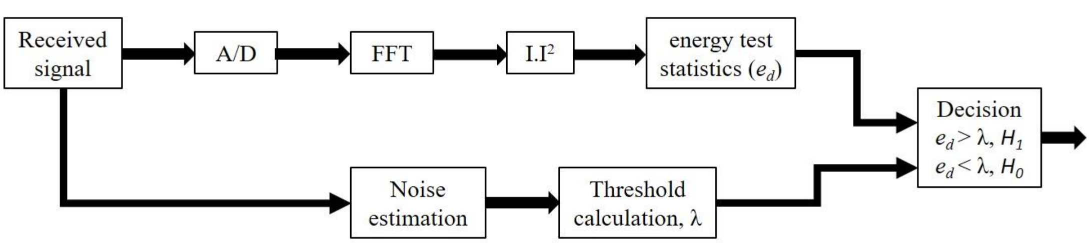


Fig. 3. Block diagram for the energy detection spectrum sensing process *(redrawn and modified from* [15]*)*

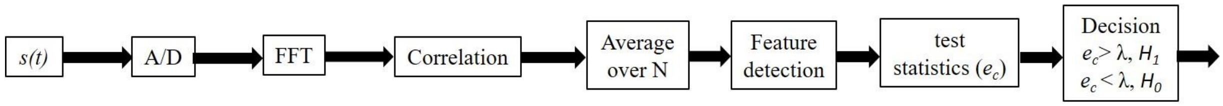


Fig. 4. Block diagram of Cyclostationary feature detection sensing technique *[redrawn and modified from* [3]*]*

λ must be chosen in such a way so that it can compensate for the noise variance. There are three causes for the performance measurement of ED. They are:

$$\begin{aligned} P_d &= P\left(e_d > \lambda \mid H_1\right) \\ P_f &= P\left(e_d < \lambda \mid H_0\right) \\ P_{md} &= 1 - P_d = P\left(e_d < \lambda \mid H_1\right) \end{aligned} \tag{3}$$

According to [15], the above equations can be expressed as:

$$\begin{aligned} P_d &= Q\left(\frac{\lambda - N\left(\sigma_n^2 + \sigma_x^2\right)}{\left(\sigma_n^2 + \sigma_x^2\right)\sqrt{2N}}\right) \\ P_d &= Q\left(\frac{\lambda - N\sigma_n^2}{\sigma_n^2\sqrt{2N}}\right) \end{aligned} \tag{4}$$

Where, σ_n and σ_s are the standard deviation of noise and PU signal respectively and Q(..) is the generalized Marcum Q function and can be written as:

$$Q(x) = \frac{1}{2\pi}\int_x^\infty \exp\left(\frac{-u^2}{2}\right)du \tag{5}$$

The threshold value can be expressed as [16]:

$$\lambda = \sigma_n^2\left(Q^{-1}\left(P_f\right)\sqrt{2N} + N\right) \tag{6}$$

Where, Q^{-1} is the inverse Q function.

Though ED is simple and faster in nature, it has some own drawbacks. One of them is that it performs very poor in noisy radio environment or in a very low SNR value. Another drawback is that it cannot differentiate between the PU signals, noise signals, and SU signals. It only measures the received signal power, it does not know the source of the signal (whether it comes from PU, or noise source or from other SUs). Therefore, sometimes, SUs might detect H_1 after receiving other SU's signals (assuming the signal comes from PU). This leads to the false alarm and hence lessen the spectral opportunity to SUs. Another challenge of ED is to figure out the value of the threshold (λ). Because λ depends on the PU activity model that is very dynamic and sometimes is not known by SUs. Some researchers have considered certain P_f values such as 0.1 to select the λ. Nevertheless, for the dynamic environment such as in CR based VANET or CR-VANET, it is a complex task to fix the λ's value.

2.2.a.ii Cyclostationary feature detection (CFD) sensing technique

Another important sensing technique used in CR is CFD sensing technique. A signal is known as cyclostationary when it consists of autocorrelation function with periodic changing features. CFD depends on some received signals' specific features such as modulation rate, carrier frequency, and periodicity. CFD can differentiate between the PU signal and noise signal as the noise signal is stationary with no correlation [3].

The overall process of CFD is given in Figure 4 and also the details are given below:

The PU signal *s(t)* is cyclostationary if the autocorrelation of the signal and the mean of the signal are periodic. That means,

$$\begin{aligned} m_s(t) &= E\left[s(t)\right] = m_s\left(t + \mathrm{T}_0\right) \\ R_s(t,\tau) &= R_s\left(t + \mathrm{T}_0, \tau\right) \end{aligned} \tag{7}$$

Here, T_0 is the period of the PU signal *s(t)*, τ is the time offset, E is the expectation operator and R_s is the autocorrelation of *s(t)*. The cyclic autocorrelation function (CAF), R_s can be expressed further as:

$$R_s(\tau) = E\left[s(t+\tau)s^*(t-\tau)\exp(j2\pi\alpha t)\right] \tag{8}$$

Here, α denotes the cyclic frequency, * denotes a complex conjugate and *E[.]* denotes as the expectation operator. The cyclic spectral density (CSD) function of the PU signal can be expressed as:

$$S_{CSD}(f) = \int_{\tau=-\infty}^{\infty} R_s^\alpha(\tau)\exp(-j2\pi f\tau)d\tau \tag{9}$$

The CSD value will be at the peak when PU transmits a signal on the same channel that is sensed by SU (in case of H_1) and there will be no peak value when PU does not transmit signal on that channel (in case of H_0).

The test statistic ($e_c(\alpha)$) of the feature detector is calculated from the CSD of the PU signal. The aggregative CSD of *s(t)* is given by:

$$e_c\left(\alpha_i\right) = \max\left(S_{CSD}(f,\alpha)\right) \tag{10}$$

The $e_c(\alpha)$ is then compared to the threshold λ to determine the presence or absence of the PU signal.

$$\begin{aligned} P_d &= P\left(e_c(\alpha) > \lambda \mid H_1\right) \\ P_f &= P\left(e_c(\alpha) < \lambda \mid H_0\right) \\ P_{md} &= 1 - P_d = P\left(e_c(\alpha) < \lambda \mid H_1\right) \end{aligned} \quad (11)$$

CFD is a very effective SS technique, especially in the low SNR situation. It can distinguish between the PU signal, noise signal, and the SU signal. This reduces the false alarm probability. However, its implementation is more complex than the ED. Moreover, SU needs a long sensing or observation period to collect enough sensing samples to improve its detection performance. That means CFD performs poor while the number of samples is low. It needs longer sensing for the optimal performance. The dynamic network for example in CR-VANET, SU does not get more time for sense. Therefore, SU might miss the spectral opportunity because of using the CFD technique, Nevertheless, CFD should be further developed so that it can provide robust performance but doing shorter sensing.

2.2.a.iii Matched filter detection (MFD) sensing technique

MFD is another kind of popular SS technique. It is known as the optimum PU detection method when the transmitted signal is known [17]. The key benefit of MFD is that by doing short sensing, it can provide maximum performance as compared to other detection methods [18].

MFD technique compares the received signal with the pre-defined and pilot samples obtained from the same transmitter. These samples are used to calculate the test statistic, which is then compared to the threshold value. If the test statistic value is greater than the pre-defined threshold value (λ), the presence of PU is declared.

The overall process has been illustrated in Figure 5.

The test statistic for the MFD can be expressed as follows:

$$e_m = \frac{1}{N}\sum_{n=1}^{N} s(n) x_p^*(n) \quad (12)$$

Where N is the number of the samples, s is the signal envelope received at the SU and x_p are the pilot samples. Now, e_m will be compared with λ. Following decisions will be taken after the comparison:

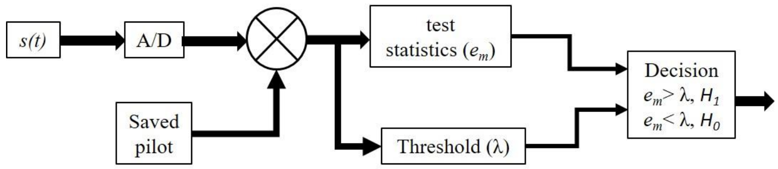


Fig. 5. Block diagram of Matched filter detection SS technique *[redrawn and modified from* [3]*]*

$$\begin{aligned} P_d &= P\left(e_m(\alpha) > \lambda \mid H_1\right) \\ P_f &= P\left(e_m(\alpha) < \lambda \mid H_0\right) \\ P_{md} &= 1 - P_d = P\left(e_m(\alpha) < \lambda \mid H_1\right) \end{aligned} \quad (13)$$

As we have discussed, MFD has some advantages such as it needs shorter sensing time to achieve better sensing performance. However, it has some drawbacks too. MFD requires CR to demodulate the received signals. Therefore, it needs perfect PU signaling features such as bandwidth, carrier frequency, modulation type and order, pulse shaping, frame format, and so on. For example, in the VANET scenario, it is not feasible for the vehicles (SUs) to have the perfect knowledge of PU signaling in advance. Moreover, the implementation complexity for the sensing unit is very large, as CR needs receivers for all types of signals. That means the CR users have to be equipped with multiple antennas to detect each licensed spectrum. Another drawback of MFD is it needs large power consumption for its operation [3].

2.2.a.iv Other Sensing Methods

Waveform-based Sensing

Waveform-based sensing or coherent sensing is another type of sensing technique. Here, the sensing user has to have the knowledge of the pattern such as preambles, midambles, pilot patterns, spreading sequences and so on [19]. SU correlates the received signal with the known copy of itself. This technique is only feasible for systems where the signal pattern is known. Though it outperforms other sensing techniques and less complex compared to MFD, the implementation of this technique will be very complex especially for the dynamic changing networks. Because it is very difficult for the CR devices to know the PU signal patterns in advance.

Covariance-based detection

Covariance-based detection is another sensing technique used in CR. To detect a PU signal, it uses a sample covariance matrix of the received signal and singular value decomposition [20]. This technique provides high accuracy but its implementation is quite complex especially to calculate the sample covariance matrix and its singular value decomposition. This complexity makes this technique not suitable for the network where real-time communications happen.

Wavelet-based detection (WD)

Another approach is WD. Here, SUs scan over a wide bandwidth simultaneously. In WD, SU exploits the wavelet theory-based wavelet transform to detect PU's presence by doing time-frequency analysis. This method is applied to find out the irregularities in power spectral density (PSD) of a wideband signal by taking its multi-scale wavelet transform and calculate its edges [11].

Table 2 Comparative analysis of different non-cooperative detection techniques

Sensing technique	Accuracy in a noisy environment	Sensing time	Prior knowledge Requirement	Complexity
Energy detection	Low	Short	No	Low
Cyclostationary feature detection	High	Long	No	High
Matched filter detection	High	Short	Yes	Very high
Waveform based detection	High	Moderate	Yes	Moderate
Covariance based detection	High	Moderate	Yes	Very high

From above Table 2, we can see that every technique has its own advantages and disadvantages. ED is easy to implement and takes a shorter time for sensing but very poor accuracy in the noisy radio environment. Another technique has higher accuracy but some need prior signal information, some need multiple antennas and some are very much complex especially for real-time applications such as VANET. In short, for choosing the optimal sensing technique for a network, it has to consider some issues such as sensing accuracy and timing requirements, computational complexity, and network requirements and so on. Some tradeoffs have to be considered while choosing the sensing technique.

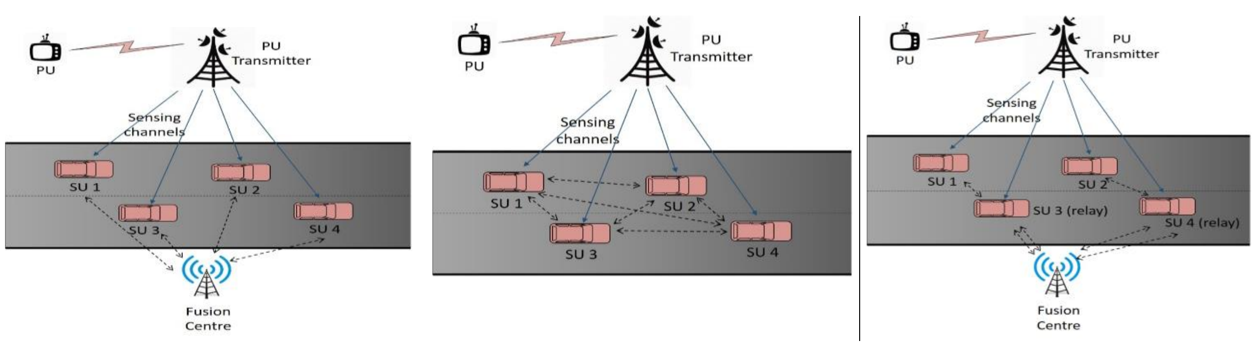
2.2.a.v Integrated individual Techniques for spectrum sensing

A combination of two or more detection techniques can enhance the sensing performance. That means energy detector, cyclostationary detector, matched filter detector or waveform detector techniques can be combined for the spectrum sensing issue. This combination can help to overcome individual technique's drawbacks. In [21], the authors combined energy detector, feature detector and matched filter detector and the authors in [22] combined energy detector and one order cyclostationary (OOC) detection techniques. They showed that they got better performance compared to the individual sensing technique. However, the sensing time and complexity are increased if two or more sensing techniques are combined.

2.2.b Cooperative Spectrum sensing (CSS)

The SS techniques described in the previous subsection are based on the individual CR users' detection. Here, CR users themselves sense the spectrum for the vacant channels and detect the PUs' occupancy without involving other CR users. Those techniques face some severe challenges such as hidden node problems, the uncertainty of noise, multipath fading, and shadowing, etc. To solve these issues, CSS decision techniques have been proposed in the literature. It can also decrease the overall sensing time requirement and decreases the probability of misdetection. In CSS, several CR users or SUs involve themselves for the spectrum sensing for better performance.

That means instead of taking own individual decision,



(a) (b) (c)

Fig. 6. a) Centralized CSS, b) decentralized CSS and c) Relay-assisted CSS

they cooperate with each other to take optimal decisions. [12]. The main concept of CSS is to improve sensing performance by exploiting the spatial diversity and temporal diversity [12].

Based on how CR users share the sensing data among themselves, CSS can be categorized into four: centralized, distributed, relay-assisted and external sensing [18], [12]. They are briefly described below:

2.2.b.i Centralized CSS:

In centralized CSS, a central unit called a fusion center (FC) controls the spectrum decision. For the infrastructure-based network, a CR base station (BS) is used as an FC and for the ad hoc based network; any CR user can be used as an FC. In this CSS technique, FC chooses the frequency band or the channels for sensing. FC tells nearby CR users to provide the individual sensing information to it. After doing the local individual sensing, all the participating CR users send their sensing information to that FC by using the 'control channel'. At this stage, FC combines all the received sensing information, determines the vacancy or occupancy of the channel and sends back the decision to those participating CR users by using the 'reporting channel' [12]. There are several variations in combining techniques such as hard fusion rules, soft combining method, renewal process method, blind detection method and so on [1].

In Figure 6 (a), according to the directions of the FC, SU1-SU4 senses the spectrum and send the information to the FC, in return, FC detects the PU occupancy and send back the decision to these SUs. Here, the decision is taken by the FC with the help of the participating SUs or CR users.

2.2.b.ii Distributed CSS:

Distributed CSS does need any central point like FC. It does not need the fixed network infrastructure, it can be applied in the ad hoc based network. In this CSS, CR users share their own sensing information among themselves. After gathering all participating SUs' information, they go for convergence to a combined decision on the presence or absence of PUs by iterations. Here, the decision taker is the CR user itself but with the help of other users' information. This CSS is advantageous compared to centralized CSS is that it does not need any predefined infrastructure. However, the disadvantage of this CSS is that it needs to exchange excessive network overheads [23].

In Figure 6(b), the distribute CSS has been illustrated. Here, SU1-SU4 sense the channels and then share their individual information with everyone (SU1-SU4). Each SU combines its information with other SUs' sensing information and then it decides the presence or absence of PU on that particular channel by following local criteria. Until the criterion is satisfied, the process of sensing and sharing continues in an iteration. That means the same process of sensing and sharing information is repeated until the algorithm is converged and the decision is taken. Some examples of the algorithm used in distributed CSS are a consensus-based algorithm, belief propagation algorithm, weighted algorithms, historical spectrum sensing, data mining approach and so on [1].

2.2.b.iii Relay-assisted CSS:

There is another type of CSS is found in literature is relay-assisted CSS, though it is slightly a variation from the above two types of CSS. Sensing channels and report channels are not perfect in nature. Some SUs might experience weak sensing channels and strong report channels, while some others might experience the opposite. In this case, relay-assisted CSS is found very useful. Here, the SUs pair and cooperate with each other to enhance the performance of CSS. In Figure 6(c), SU1 and SU2 might experience strong PU signals but might suffer from a weak report channel. On the other hand, SU3 and SU4 might have a strong report channel. Therefore, in this case, SU3 and SU4 can serve as relays for SU1 a SU2 to assist in forwarding the sensing results to the FC. The report channels of SU3 and SU4 to the FC are also known as relay channels. The example given here is considered as the centralized structure, but it can be used in the distributed CSS also. The main difference between relay-assisted CSS with other two is that relay-assisted is kind of multi-hop (SU1>SU3>FC from Figure 6(c)) CSS and other two are kind of one-hop (SU1>FC from Figure 6(a) or SU>SU3 from Figure 6(b)) CSS [12].

This CSS solves a kind of near-far problem. However, the SU, which involves relaying, has to sacrifice its own energy and bandwidth to help the other SUs. This creates another problematic issue.

2.2.b.iv External CSS:

Another kind of CSS found in the literature is external sensing [18]. Here, an external agent does all the sensing activities and delivers the sensing information to SUs. This CSS solves some problems associated with the above-mentioned CSS such as it can solve hidden PU problems, shadowing and fading problems. Moreover, as the SUs do not have to allocate time for the SS, the spectrum efficiency and the throughput (get more time for the data transfer instead of allocating more time in sensing). Another advantage is that external agents can be mobile or stationary and can be powered by battery or the main power grid (that means power consumption issue is not an issue here) [18].

2.2.c Interference based SS

FCC (Federal Communications Commission) set a threshold value of interference for the PUs. The SUs are allowed to use the transmission power provided that it (in addition to the noise power) will not go beyond that threshold value of interference temperature level [4]. However, the main drawback of this SS is, it is very hard to measure the interference temperature in real-life. This SS has not fully explored in the literature and therefore further comprehensive research is much needed in this field.

III. PERFORMANCE METRICS AND PARAMETERS FOR SPECTRUM SENSING

PU activities have two states: ON and OFF. The active or ON state is denoted by H_1 and the idle state or OFF state is denoted by H_0.

$$i.e.\quad \begin{array}{l} H_0 \rightarrow PU \text{ is idle / absent} \\ H_1 \rightarrow PU \text{ is active / present} \end{array}$$

SUs are only allowed to use the licensed channel when PU is absent on in OFF state (H_0).

There are few metrics available to measure the SS performance. They are described below:

3.1.1 Probability of detection (P_d):

It is defined as the probability to detect the presence of the PU signal given H_1 and some threshold value (λ) of the signal (here, threshold refers to the certain level of the power set by network). Probability of detection, P_d can be expressed as follows:

$$P_d = P\left(H_1 \mid \lambda\right) \tag{14}$$

That means it is the probability that the PU is transmitting on the licensed channel being true and SU detects that PU signal correctly (detects the presence of PU). SS performance depends on the accuracy of the detection. If SU spends more time on sensing, the detection accuracy is increased. There is a tradeoff between the shortening the sensing time and the increasing the detection accuracy. In CRN, the higher accuracy value of P_d minimizes interference and improves network performance.

3.1.2 Probability of false alarm (P_f):

It is the probability in which a SU mistakenly detects the presence of PU, but in reality, there is no PU presents at that time. That means a SU detects H_1 as true but in reality, H_0 is true.

$$\therefore P_f = P\left(H_1 \mid H_0\right) \tag{15}$$

If this incorrect detection happens, SUs are deprived to use that licensed channel, as a result, overall performance degrades. Therefore, for better SS performance, P_f should be kept low.

From the above discussion, it can be said that the sensing performance increases when the value of P_f is lower and the P_d is higher.

3.1.3 Probability of missed detection (P_{md}):

It is the opposite of the false alarm. It is the probability where SU senses the channel as idle (absence of PU) but in reality, the channel is not idle (occupied by the PU). It can be written as:

$$P_{md} = P\left(H_0 \mid H_1\right) \tag{16}$$

This value should be kept low for better sensing performance. P_{md} causes interference while P_f causes the losses of spectral opportunities.

For the best performance, P_{md} and P_f should be at a minimum level while P_d should be at the maximum level. In general, to get the improved P_d, either P_f or P_{md} has to make as a fixed value.

3.1.4 Sensing time and throughput:

As we have discussed earlier, if SU goes for a longer sensing period, it will get a better SS performance but it has to sacrifice the throughput as it would get less time for transmission. One the other hand, shorter sensing time will lead to miss detection. In short, to increase the throughput, SU needs quick spectrum sensing (i.e. spending less time for the sensing) with high P_d and low P_f and P_{md}.

3.2 Parameters for SS performance

There are several parameters that affect the performance of SS. To meet certain QoS, the values of these parameters have to be chosen accordingly. A brief description of these parameters has been given in Table 3.

Table 3 Brief descriptions of the parameters and their notations

No.	Parameters	Description	Unit	Notation (in this article)
1	SNR	Signal to noise ratio or SNR is the ratio between the power of the desired signal and the power of the unwanted background noise. It is usually measured in decibels (dB). Generally, the good sensing needs high SNR value (say for example, 15~20 dB), the poor value of SNR degrades the overall SS performance.	dB or dBm	---
2	Operating frequency	The performance of SS depends on the operating frequency or the carrier frequency of the network. Though this parameter does not vary too much, that means, the operating frequency range is somehow fixed for the particular network of interest. It also depends on the rules and regulations set by the authority such as the FCC.	Hz	f
3	Duration of the frame of secondary networks	Frame length for the SUs. Frame duration includes the sensing and transmission of data. Sensing time and the transmission time should be optimal. If more time is allocated for sensing, the overall throughput is reduced, while for less time of sensing, spectrum opportunity will be lessened.	msec (millisecond)	T_F
4	Duration of communication frame of PU	The time length for the PU for data transmission.	msec	T_{PU}
5	Modulation type	It depends on the network type. For example, if CR users are going to access LTE (Long Term Evolution), the modulation type might be QPSK, 16QAM, and 64QAM, while for other networks, it might be OFDM or BPSK for example. For simplicity, we have used the BPSK modulation scheme in our simulation.	---	---
6	Number of samples in an observation period	It defines how many samples in a unit time is required to detect a signal. In general, in low SNR, more sample value is needed and vice-versa. However, for the larger sampling size, more sensing time is required. Detecting the PU signal by using a low number of samples is desirable in the CR system.	integer number	L
7	Mean interval between two starting times of PU	It defines the mean duration between PU's one ON status to another ON status. That means the duration of PU being idle or inactive.	msec	*beta* (β)
8	Threshold value	This value is used to determine the presence of PUs. If a SU receives an SNR value that is greater than the threshold value, the presence of PU is declared (PU detected) and vice versa.	dB	λ
9	Number of SU and PU	It affects the performance of SS. The performance of SS degrades as the number of users is increased.	integer number	---
10	Sensing time	The time a SU needs to detect the spectrum hole or the presence of PU.	msec	T_S

IV. Simulation, Results, and Discussions

For the performance analysis of the SS and to explore the effects of the several parameters, MATLAB R2018b is used. Various parameters' value has been varied and some are kept fixed. Table 4 shows some values of the parameters have been considered for the simulation. Modulation type 'BPSK' is considered due to its simplicity. In general, IEEE 802.11 and IEEE 802.22 standards permit the maximum value of P_f is 0.1 while for the P_d is 0.9.

Figure 7 shows the relation between the P_d and P_f and the impact of the signal power (SNR values). From the figure, it is shown that the value of P_d increases when the value of SNR is increased as the value of P_f is increased. The figure has been drawn under the energy detection technique as the SS technique. The figure also shows the impact of the L (sample) values on the

Table 4 Some parameters and their values used in the simulation

Parameters	Value
Frequency	96 kHz
Probability of false alarm, P_f	0.1
Probability of detection, P_d	0.9
Modulation type	BPSK
Duration of the frame of secondary networks, T_F	100 msec
Duration of communication frame of PU, T_{PU}	150 msec
SNR	-10 to -20 dB
Number of samples in an observation period, L	500, 1000
Mean interval between two starting times of PU, *beta* (β)	300, 400, 500 msec

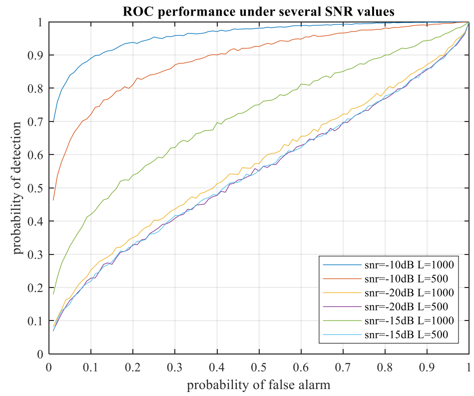


Fig. 7. Probability of detection vs probability of false alarm under various values of SNR based on Energy detection technique.

spectrum performance. For -10dB case, the effect of *L* shows a significant variation. For -15 dB and -20dB cases, both give around the same values for the *L*=500 but quite different for *L*=1000. Therefore, it can be said the value of *L* has an impact on the spectrum sensing performance. Taking large number of samples would provide better results of SS. But in reality, sometimes large number of samples can not be taken into consideration. Similarly, the higher value of SNR would provide better results. Therefore, we have to ensure the good quality of the signals for the better performance of SS.

As a summary, the SS performance highly depends on the value of SNR and *L*.

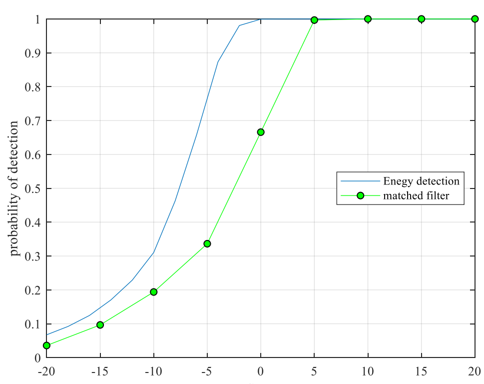


Fig. 8. Comparative analysis of energy detection vs matched filter

From the above Figure 8, it is shown that ED performs better than the MFD in our simulation scenario. After SNR=5 dB, they both reach the highest level. When the value of SNR is high, ED is a good choice as the SS technique due to its simplicity. However, for poor SNR, ED does not perform satisfactorily. Therefore, for the noisy region, ED is not a good choice.

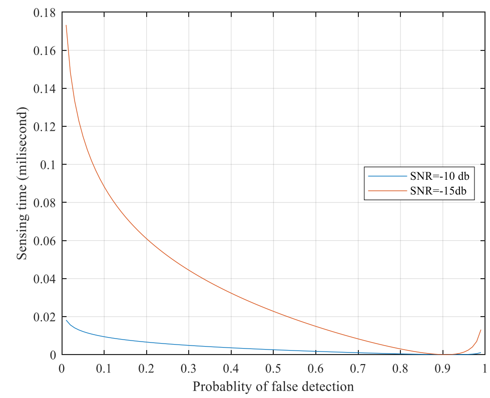


Fig. 9. Sensing time vs P_f for various SNR value

Figure 9 shows the performance of ED in terms of sensing time and the probability of false detection based on SNR's value. It can be said that if the SNR is high, it takes less time for the SS and vice versa. It can be also noticed that if less time is allocated for the SS, the probability of false detection is increased. In summary, to get better results in terms of PU detection, SS needs more sensing time. However, for the dynamic network such as in CR-VANET, a vehicle would not get much time for the sensing and that degrades the quality of SS. Moreover, increasing sensing time would lessen the data transmission time, that means if sensing time is increased, less number of data can be transferred.

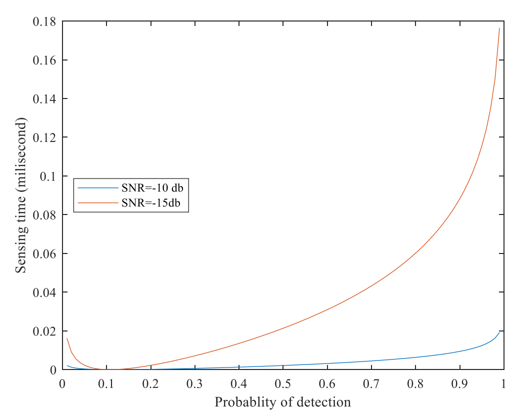


Fig. 10. Sensing time vs P_d for various SNR value

The above illustration (Figure 10) shows the sensing time vs the probability of detection for two SNR values for the ED technique. It is shown that sensing time might be reduced if the SNR value is increased. That means, in the good SNR value, it needs less time for the detection and for the poor SNR, it needs more time for the sensing for the detection.

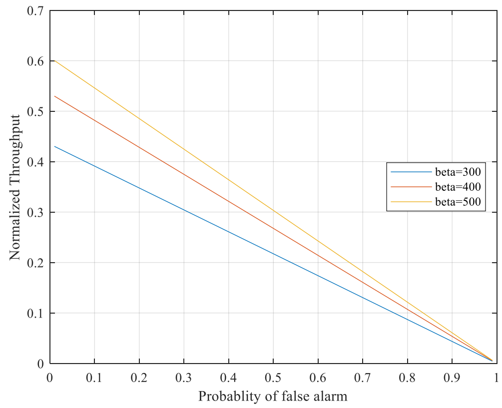


Fig. 11. P_f vs throughput for various values of β (beta)

Figure 11 shows the probability of false alarm vs normalized throughput for various values of β (beta). The value of β denotes the mean interval between two starting times of PU communications and is generally measured in msec (millisecond). From the figure, it can be shown that, if the β's value is increased, it gives better throughput. That means, if the duration of PU's inactivity is higher, the SU gets more time for the data transfer and as a result, higher throughput is achieved. Therefore, knowing or predicting PU's activity is very much important for the SU to ensure the good quality of SS.

From the figure, it is also shown that an increase in the probability of false alarm, throughput is decreased. The reason is, if SU detects PU wrongly, it faces interference from the PUs and then have to switch to another frequency to avoid such interference. Switching from one channel to another, SU takes more time for the sensing and therefore it gets less time for the data transmission. As a result, the throughput is decreased.

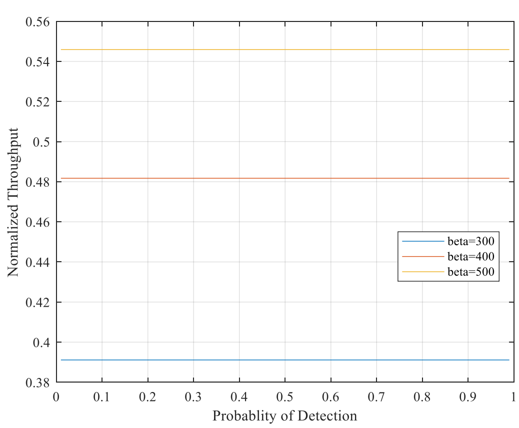


Fig. 12. Throughput vs P_d for various values of β (beta)

Figure 12 shows the analysis of throughput with the probability of detection with the several values of β. For the higher values of beta, more throughput is achieved as we discussed earlier. It is also being noticed that the normalized throughput is not dependent on the value of P_d (it remains constant). This is the opposite of the previous case (throughput vs P_f).

Figure 13 explains the relation between the threshold values for the detection with the probability of false alarm. If the threshold value is increased, the value of the probability of false alarm is decreased. That means, increasing the threshold increases the SS performance. However, the problem is if the value of the threshold is increased, the SU might be deprived of the spectrum opportunity. That means if the threshold value is higher than the SNR value of SU, it always assumes that there is any PU is present nearby.

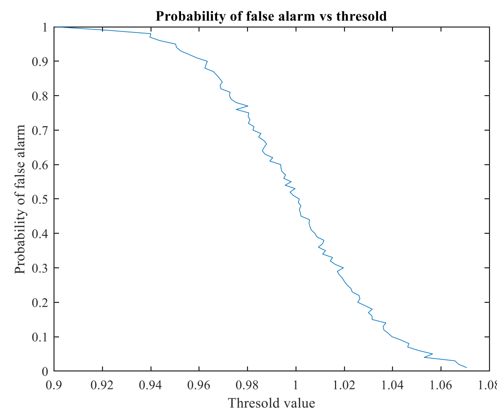


Fig. 13. Probability of false alarm vs threshold values

In general, the value of λ is considered by fixing the value of either P_d or P_f and optimizing the other parameter. However, there are several other ways to determine the value of λ [13].

Table 5 Summary of the results

Parameters/metrics (if the value is increased ↑)	P_d	P_{md}	P_f	Sensing time	Normalized throughput
SNR	↑	↓	↓	↓	↑
L	↑	↓	↓	↑	↓
β (beta)	--	--	--	↓	↑
λ	↑	↓	↓	--	--
P_d	--	↓	↓	↑	--
P_f	↑	↑	--	↓	↓

↑ means 'increase', ↓ means 'decrease'

Table 5 summarizes the results obtained in this section. There are several tradeoffs are found from the table. For example, the tradeoff between sensing time vs throughput, number of sample and detection accuracy vs the sensing time, detection accuracy vs throughput, threshold value vs spectrum opportunity vs probability of false alarm.

V. CONCLUSION

In this paper, spectrum sensing (SS), one of the major stages of cognitive radio (CR), has been described in detail. Firstly, the basics of SS and its taxonomy have been presented. Details descriptions of the types of SS have been discussed elaborately especially individual SS techniques such as energy detection, cyclostationary detection, matched filter detection and so on. Various types of cooperative SS have also been discussed. Secondly, various types of performance metrics that have been used to measure the performance of SS have been described. The parameters that affect the performance of SS have also been discussed. Finally, simulation has been performed by using MATLAB to analyze the SS with those performance metrics and the parameters. It has found that tuning the values of the parameters is very important to obtain the best SS performance. Optimal values of these parameters have to be chosen by considering several tradeoffs between them.

In the future, more analysis would be done with other SS techniques and with other performance metrics and parameters. The analysis will also be done in some real-time CR based networks such as in vehicular ad hoc network (VANET).

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