Comparative study between cognitive radio techniques in FM broadcasting band

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Comparative study between cognitive radio techniques in FM broadcasting band

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Abstract. Optimum usage of the existing frequency spectrum is a major requirement due to the large increase in the number of subscribers at the same frequency. The cognitive radio scheme has become an important application used to optimize spectrum utilization, detects spectrum bands that are not occupied by primary users to create communication links between secondary users in the same band. These non-occupied bands are described as white space. In this paper, a spectrum sensing method that is an important stage in cognitive radio communications is discussed. Various spectrum sensing methods such as energy detection (ED) and cyclostationary feature detection (CFD) are used to sense the spectrum in the FM broadcasting band. A comparison of energy detection and cyclostationary feature detection spectrum sensing methods is made to determine the empty bands in the FM broadcasting band. This enables secondary users to transfer information in these empty bands without affecting the primary users of the FM broadcasting system.

1. Introduction

Recent years have witnessed an increase in the deployment of wireless devices and the need for a higher data rate transmission. Spectrum congestion and crowding have manifested as radio spectrum insufficiency. In most countries, national regulatory agencies such as the Federal Communications Commission (FCC) in the United State control the usage of the frequency spectrum. The FCC regulated the allocation of frequency bands and the granting of exclusive licenses to systems within a geographical region. At the same time, FFC prevents or at least coordinates other systems from working in these bands. According to the FCC report of the spectrum utilization, the utilization of licensed spectrum varies from 15% to 85% in the bands below 3 GHz [1]. FCC suggests that there is a substantial potential for improving the use of spectrum. Therefore, there is a need for new technologies to use empty spectrum bands and to increase the utilization of spectrum in dynamically changing environments.

Cognitive Radio (CR) [2] has emerged as the promising solution to the issue of spectrum crowding by allowing the opportunistic usage of frequency bands, which are not strongly used by licensed users. CR is an intelligent radio, which observes its surrounding environment and can learn and modify its actions and operation. It gives the best match between its surrounding environment and the needs of the users. CR can optimally adjust its operational parameters according to the surrounding radio environment activities. CR can identify white space holes in a frequency band that is not utilized by licensed users (primary users). It assigns these empty spectrum bands to a secondary user (SU) that uses them for transmitting its signal. However, when the primary user (PU) begins to reuse the spectrum, CR can recognize its activity via spectrum sensing techniques and hold the transmission produced by SU. There are various detection techniques available for spectrum sensing [3].

In this paper, two spectrum sensing techniques are used to scan the entire FM band (87.5 MHZ to 108 MHZ) and identify all unused spectrum holes. The first technique is energy detection, which is the most widely employed for spectrum sensing in CR systems because of its applicability and simplicity. The conventional energy detection approach [4] depends on a fixed threshold. It is sensitive to noise uncertainty that cannot be avoided in practical cases. In this paper, the calculation of the threshold of the energy-detection sensing method depends on some parameters that optimize the CR performance. The used method of threshold calculation optimizes the probability of detection and minimizes the probability of false alarms. Moreover, a cyclostationary feature detection based on a Fast Fourier Transform (FFT) filter with the spectral autocorrelation function is introduced [5]. Better detection of PU is accomplished through the use of the FFT filter in spectrum sensing at a very low value of SNR of the PU. It also allows the CR to track changes in the occupancy of the spectrum at a higher rate even at a low SNR value of PU and obtains more precise detection.

In this work, a proposed radio system is implemented based on the energy detection scheme and the cyclostationary feature detection. The proposed system detects the white space holes in the frequency band of the FM radio broadcasting. A simple adaptive method is also implemented to allocate the empty channels to the secondary user from the different holes identified by the previous two techniques.

2. Spectrum Sensing Techniques

Spectrum sensing allows CR to estimate, understand, and be aware of its operating environments like the availability of the spectrum and the state of the interference. If a frequency band is underused, by a PU at a specific time, a SU can use this frequency band in transmitting its signal. Spectrum sensing can also be carried out across the domains of frequency, time, and space. With the latest advancement of beam-forming technologies, several users can concurrently use the same channel/frequency in the same location [5], [3].

The receiver detection model of the SU uses a classical methodology known as binary hypothesis testing, where H0 is the null hypothesis (i.e., PU absence) and H1 is the alternative hypothesis (i.e., PU presence). Assume that the signal received by a cognitive radio user has a hypothesis model that is [3], [6].

$$y(t) = \begin{cases} x(t) + w(t) & for \quad H_1 \\ w(t) & for \quad H_0 \end{cases} \tag{1}$$

where y(t) is the received signal, x(t) is the transmitted signal of a PU, and w(t) represents the additive white Gaussian noise (AWGN). To differentiate between these two hypotheses, a binary hypothesis test is applied with a particular threshold calculated based on the probabilities of errors in the SU receiver. There are two error types in the binary hypothesis test that uses the model introduced in equation (1). The first error occurs when the receiver of the SU detects a PU signal while there is no PU signal is transmitted. The probability of this error is known as the false alarm probability (P_f). The false alarm probability in spectrum sensing is an important design parameter in specifying the threshold in the binary hypothesis test. The second error occurs when the receiver of the SU detects no PU signal while the PU signal exists. This probability of error is called the probability of missed detection (P_m) and it is equal to:

$$P_m = 1 - P_d \tag{2}$$

where P_d is the probability of detection. The missed detection results in collisions with primary user transmission. The error due to missed detection decreases the rates of data transmission for both the primary and secondary users. The probability of false alarm P_f (primary users exist in empty bands) and the probability of detection P_d (primary users exist in non-empty bands) defines the performance of the CR system. Generally, the constraints of the probability of false alarm as well as the probability of missed detection should be satisfied by a cognitive radio system. For the detection of the transmission of primary users, three schemes are typically used: matched filter detection, energy detection, and cyclostationary features detection.

2.1. Energy detection.

Energy detection [6] is a form of non-coherent detection technique which detects the primary signal depending on energy-sensing. Energy detection is considered to be the most common sensing technique in cooperative sensing since it's easy to use and doesn't need prior knowledge of PU signals. However, energy detection also comes by some drawbacks [7] such as:

- The sensing time needed to accomplish a given probability of detection can be high.
- The noise power uncertainties have an impact on the detection process efficiency.
- The differentiation between the PU and SU signals in the same CR system cannot be accomplished by energy detection technique.

Despite these drawbacks, in cooperative sensing, energy detection is the most common method of detection. Theoretical principle. Initially, the energy detector used a filter to remove the unwanted signals of the undesired frequency bands at the input of the energy detector. After that, the filter's output samples are squared. The summation of the squared samples is used to estimate the energy of the received signal. Finally, to compute whether a PU is present or not, the estimated energy is compared with a threshold value [3]. It is a difficult challenge to set the proper threshold since it must distinguish between the signal and noise.

It is important to have a priori knowledge of the amount of noise energy as its uncertainty degrades the performance of the detector. The probability of false alarm $\boldsymbol{P_f}$ and the probability of detection $\boldsymbol{P_d}$ must be measured in order to assess the energy detector's output. Moreover, the threshold value has to be specified to increase the probability of detection. The decision variable of an energy detector can be calculated as the mean of the energy of N samples as shown in equation (3) [8].

$$\mathbf{T} = \frac{\mathbf{1}}{\mathbf{N}} \sum_{n=1}^{\mathbf{N}} |y(n)|^2 \tag{3}$$

where N is the number of samples used in the calculation of the average energy. The decision variable T in equation (3) is a chi-square random variable because the received samples y(n) are Gaussian random variables. The decision variable T is compared with a predetermined threshold λ to decide whether the spectrum is occupied by PU or not. The energy detector model for the cognitive radio can be defined as the binary hypothesis test shown in equation (4) [8].

$$d_{ED} = \begin{cases} H_1 & \mathbf{T} \geq \lambda \\ H_0 & \mathbf{T} < \lambda \end{cases} \tag{4}$$

Gaussian distribution is used to approximate T for a substantial number of samples using the central limit theorem as indicated in equation (5) [8].

$$\mathbf{T} \approx \begin{cases} \mathcal{N}\left(\mathbf{N}(\sigma_\omega^2 + \sigma_s^2), 2\mathbf{N}(\sigma_\omega^2 + \sigma_s^2)^2\right) & for \quad H_1 \\ \mathcal{N}\left(\mathbf{N}\sigma_\omega^2, 2\mathbf{N}\sigma_\omega^4\right) & for \quad H_0 \end{cases} \tag{5}$$

where $\boldsymbol{\sigma_s^2}$ denotes the primary user signal variance, $\boldsymbol{\sigma_\omega^2}$ denotes the noise variance, and $\mathcal{N}$ denotes the normal distribution. For the binary hypothesis test in equation (4), the probability of detection $\boldsymbol{P_d}$ and the probability of false alarm $\boldsymbol{P_f}$ can be as shown in equations (6) and (7) [9].

$$P_d = \mathbf{Q}\left(\frac{\lambda - \mathbf{N}(\sigma_s^2 + \sigma_\omega^2)}{\sqrt{2\mathbf{N}(\sigma_s^2 + \sigma_\omega^2)^2}}\right) \tag{6}$$

$$P_f = \mathbf{Q}\left(\frac{\lambda - \mathbf{N}\sigma_\omega^2}{\sqrt{2\mathbf{N}\sigma_\omega^4}}\right) \tag{7}$$

where Q(.) is the Gaussian tail probability Q-function [10] and λ denotes the testing threshold. This threshold depends on the noise power and it is expressed from the probability of false alarm $\boldsymbol{P_f}$ as shown in equation (8).

$$\lambda = \left(\mathbf{Q}^{-1}(P_f)\sqrt{2\mathbf{N}} + \mathbf{N}\right)\sigma_\omega^2 \tag{8}$$

2.1.1. Implementation. In this work, an effective energy detector for FM broadcasting-band is introduced. In the used detector, some parameters are calculated and used to determine the system threshold λ. The FM broadcast band in Egypt is starting from 88 MHz to 108 MHz. This band is divided into 5 sub-bands. Five band-pass filters (PBFs) are used to filter the FM signal in these 5 sub-bands. One digital BPF has been used with a bandwidth of 5 MHz. The center frequency of this filter is changed according to the working sub-band. The working sub-bands and the center frequency of used BPF are shown in table (1).

Table 1. The frequencies of the used FM sub-bands

FM sub-band	Center frequency of the BPF
88 MHz – 92 MHz	90 MHz
92 MHz – 96 MHz	94 MHz
96 MHz – 100 MHz	98 MHz
100 MHz – 104 MHz	102 MHz
104 MHz – 108 MHz	106 MHz

The used digital BPF is a finite-impulse-response (FIR) filter whose coefficients are calculated according to the operation band. The filter coefficients for the different bands are stored in a look-up table (LUT) memory and they are recalled according to the working band. In the beginning, the detector selects the working FM band by selecting the coefficients of the corresponding BPF. The output signal from the BPF is sampled according to the second Nyquist theorem (under-sampling theory). The used sampling frequency is 20 MHz, which is 4 times the bandwidth of the used BPF. A squaring device is used to square the samples after the BPF. An accumulator is used to accumulate N samples from the output of the squaring device. The output of the accumulator is divided by N to get an estimate of the average energy of the received samples. The estimated average energy represents the decision variable to the threshold detector. This decision variable is compared with the appropriate threshold. The threshold value is set according to the number of samples N, the variance of the noise floor σ_{ω}^2, and the required probability of false alarm P_f as shown in equation (8). Finally, the energy detector decides whether the PU is present or not according to equation (4). The block diagram and the flowchart that illustrate the proposed technique are introduced in figure.1 and 2 respectively.

Figure 1. The block diagram of the energy detection scheme.

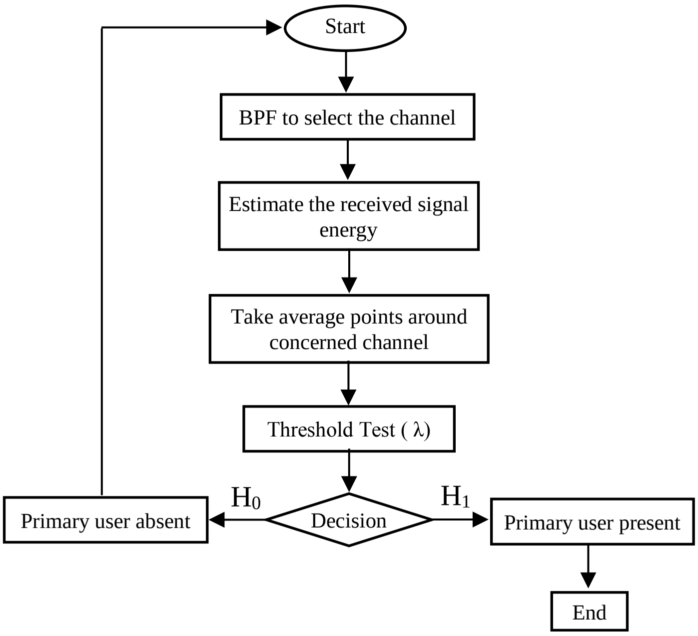

Figure 2. The flow chart of the proposed energy detection scheme.

2.2. *Cyclostationary feature detection.*

Cyclostationary feature detection [11] takes advantage of the periodicity feature in the received primary signal to detect the primary user presence. The periodicity is usually embedded in pulse trains, hopping sequences, sinusoidal carriers, or cyclic primary signals prefixes. The periodicity feature and the spectral correlation are only present in the useful signal and not in interferences signals and stationary noise. Therefore, the detection of cyclostationary features is immune to noise uncertainties and outperforms energy detection in low SNR regions. A signal is called cyclostationary if its autocorrelation and mean are periodic functions. Feature detection means obtaining features from the received signal and employing the detection task on the obtained features. This technique can differentiate PU noise and PU signal [12]. This technique is less common than energy detection due to some drawbacks such as:

- It is mandatory a priori awareness about the primary user.
- The observation time is long.
- The computational complexity is high.

2.2.1. Theoretical principle. This principle depends on the information extracted from the cyclic Spectral Correlation Function (SCF) and the PU signal periodicity. When the PU exists, this will generate a high value of the peak cyclic spectral correlation at the output. To obtain a more accurate decision about the correlation value, it is mandatory to use a large number of samples. The autocorrelation function for the signal x(t) is shown in equation (9) [13].

$$R_x(\mathrm{t},\tau) = \mathrm{E}\left\{\chi\left(\mathrm{t}+\frac{\tau}{2}\right)\chi^*\left(\mathrm{t}-\frac{\tau}{2}\right)\right\} \tag{9}$$

Since the correlation function in equation (9) is periodic, it can be decomposed into Fourier series as.

$$R_x(\mathrm{t},\tau) = \sum_{k=1}^{M} R_x^{k\alpha_0}(\tau)e^{j2\pi k\alpha_0 t} \tag{10}$$

The fundamental cyclic frequency is $\alpha_0 = 1/T_0$, where T_0 is the hidden period and M represents the rank of the last harmonic. The Fourier coefficients of $R_x(\mathrm{t},\tau)$ are called the Cyclic Autocorrelation Function (CAF).

$$R_x^{k\alpha_0}(\tau) = lim_{T\to\infty}\frac{1}{T}\int_{-T/2}^{+T/2} R_x(t,\tau)e^{-j2\pi\alpha_0 t}\ dt \tag{11}$$

where T is the time duration that can be used to calculate the CAF. The Spectral Correlation Density function (SCD) is the Fourier transform of the CAF.

$$S_x^{\alpha}(f) = \int_{-\infty}^{+\infty} R_x^{\alpha}(\tau) e^{-j2\pi f\tau}\, d\tau \tag{12}$$

Equation (11) can be approximated as:

$$R_x^{\alpha}(\tau) = lim_{T\to\infty} \frac{1}{T}\int_{-T/2}^{T/2} x(t+\frac{\tau}{2})x^*(t-\frac{\tau}{2})\, e^{-j2\pi\alpha t} dt$$

$$R_x^{\alpha}(\tau) = lim_{T\to\infty} \frac{1}{T}\int_{-T/2}^{T/2} x\left(t+\frac{\tau}{2}\right) e^{-j2\pi\frac{\alpha}{2}(t+\frac{\tau}{2})}\ \ x^*(t-\frac{\tau}{2})\, e^{-j2\pi\frac{\alpha}{2}(t-\frac{\tau}{2})} dt \tag{13}$$

The SCD is will be expressed after denoting $y(t) = x^*(t-\frac{\tau}{2})e^{-2j\pi\frac{\alpha}{2}(t-\frac{\tau}{2})}$as shown in equations (14 -16).

$$S_x^{\alpha}(f) = \mathbb{FT}\{S_x^{\alpha}(\tau)\}, \tag{14}$$

$$S_x^{\alpha}(f) = lim_{T\to\infty} \frac{1}{T}\mathbb{FT}\{y(\tau) * y^*(-\tau)\}, \tag{15}$$

$$S_x^{\alpha}(f) = lim_{T\to\infty}\{\frac{1}{T} X_T\left(f+\frac{\alpha}{2}\right) X_T^*\left(f-\frac{\alpha}{2}\right)\}, \tag{16}$$

In equation (16), $X_T(f)$ is the Fourier transform of the product of $x(t)$ and a rectangular window of width T.

$$X_T(f) = \int_{-T/2}^{T/2} x(t)\, e^{-j2\pi f t}\, dt \tag{17}$$

In this method, it's important to have advanced knowledge of the primary user. The probability of false alarm P_f and the probability of detection P_d must be calculated to evaluate the performance of the cyclostationary feature detection. It is common knowledge that to increase the probability of detection, the threshold value has to be specified. The probability of false alarm of cyclostationary feature detection (P_f) can be calculated from equation (18).

$$P_f = \mathrm{P_r}(\mathrm{H1/H0}) = \exp\left(\frac{-\lambda^2}{2\sigma_A^2}\right) \tag{18}$$

where λ is the threshold value, exp(.) denotes the exponential function. $\sigma_A^2 = \frac{\sigma_\omega^2}{(2N+1)}$, and N is the number of received signal samples. The probability of detection ($\mathrm{P_d}$) for cyclostationary feature detection can calculate from equation (19).

$$P_d = \mathrm{P_r}(\mathrm{H1/H1}) = \mathrm{Q}\left(\frac{\sqrt{2\gamma}}{\sigma_\omega}, \frac{\lambda}{\sigma_A}\right) \tag{19}$$

where γ is a signal-to-noise ratio, Q(.) is Generalized Marcum Q-function, and σ_ω^2 is noise variance. The threshold can be expressed from the probability of false alarm P_f as shown in equation (20).

$$\lambda = \sqrt{((-\log P_f) * 2 * \sigma_A^2)} \tag{20}$$

2.2.2. Implementation. In this section, the cyclostationary feature detection technique is implemented. The received signal is applied to digital BPF then the autocorrelation function is calculated. The autocorrelation function is calculated by multiplying the signal by shift versions of itself and averaging the result of the multiplication. The result is a function of the amount of shift. We then calculate the received signal's power spectrum density by getting the Fourier transform of the autocorrelation function. Finally, the cyclostationary detector determines the presence of the PU by comparing the PSD at the specified FM bands with a predetermined threshold for determining whether a signal is present or not. The block diagram and the flowchart that illustrate the proposed technique are introduced in figure.3 and 4 respectively.

Figure 3. The block diagram of the proposed cyclostationary feature detection scheme.

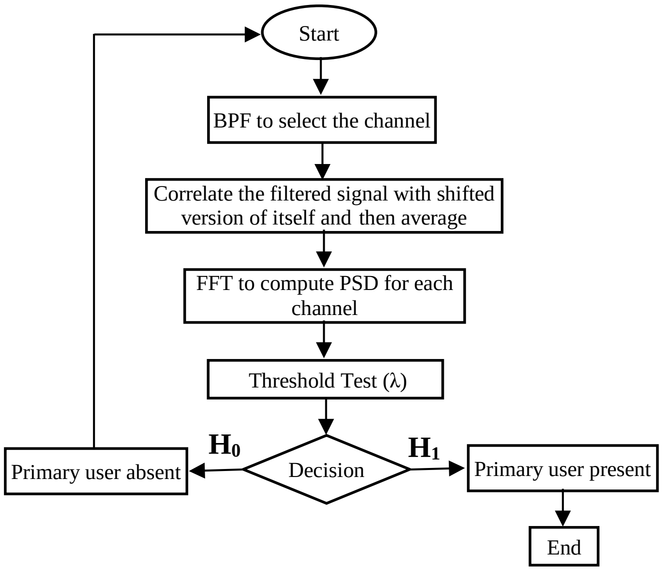

Figure 4. Flow diagram of the proposed cyclostationary feature detection scheme.

3. Results and Discussion

In this section, simulation results of the proposed system are represented. The proposed system is simulated using Matlab m-files. The primary users in the simulated system are 8 FM broadcasting channels that work in the FM band (88 MHz to 108 MHz). Two different detection methods are used to detect primary user's activity. The first detection method is the energy detection criterion represented in section (2.1), and the second detection method is the cyclostationary detection criterion represented in section (2.2). In the simulated system, 2 channels (users) out of the simulated 8 FM channels (users) are empty. These two channels are selected randomly each time the experiment is conducted.

In the simulated system, the channel output is sampled using an analog-to-digital (ADC) converter. The number of samples that are used as an input to the proposed detectors is equal to 10^6 samples. The received SNR at the input of the detector is changed from -20dB to 15dB. The simulated system's output is assessed by determining the obtained SNR value at which the detector can detect both empty and busy primary users with a probability of detection of 1.Three different probabilities of false alarms are used to calculate the threshold value in each detector according to equations (8) and (20), respectively. The used values of the probability of false alarm are $P_f = 0.1$, $P_f = 0.01$ and $P_f = 0.2$.

The decision variable at the output of each detector is calculated once for each received 10^6 samples from the ADC. The threshold in equations (8) and (20) is compared with this decision variable. If the decision variable is larger than the threshold, the detector will decide that the channel is busy and vice versa. The threshold may be compared with one decision variable or the average of more than one decision variable. The number “n” is the number of the samples of the decision variable that are used to calculate the average, which is compared with the threshold value.

Table 2a shows the SNR value at which the detector discriminates between the empty channel and the busy channel (primary user exists or not) with a probability of detection equal to 1. In our simulation, the detector indicator is the value of the SNR at which the detector can sense the primary user's presence with a probability of 1. Table 2b shows the SNR at which the detector discriminates between the empty channel and the busy channel when the threshold is compared with the average of 5 decision variables.

Table 2a. The threshold is compared with one decision variable (n=1)

Probability of false alarm	0.1	0.01	0.2
Cyclostationary Indicator	5dB	6dB	4dB
Energy Detection Indicator	10dB	12dB	9dB

Table 2b. The threshold is compared with the average of 5 decision variables (n=5)

Probability of false alarm	0.1	0.01	0.2
Cyclostationary Indicator	2dB	3dB	1dB
Energy Detection Indicator	8dB	9dB	7dB

Figure (5.a) and (5.b) show the probability of detection at the output of the energy detection detector (ED) and the cyclostationary feature detector (CFD) at different input SNR values. The probability of detection in figure (5.a) is calculated based on one value of the decision variable, however, the probability of detection in figure (5.b) is calculated based on the average of 5 values of the decision variable. The figures illustrate that the performance of the CFD detector is better than the performance of the ED detector. The CFD detector can detect the status of the channel (empty/busy) at lower received SNR than the ED detector. Moreover, using the average value of (n>1) samples of the decision variable gives better and accurate performance than using one sample of the decision variable.

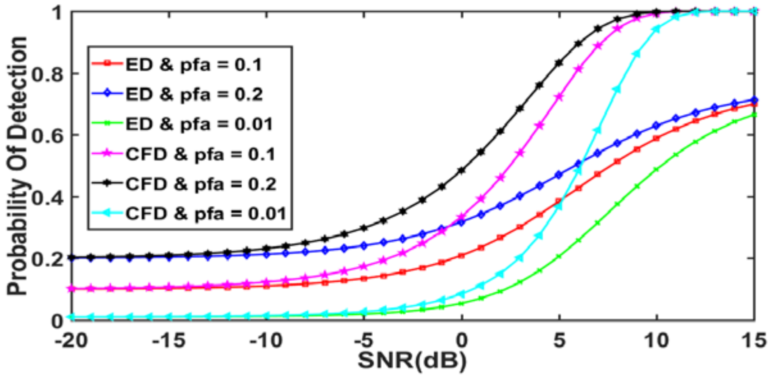

Figure 5a. performance of ED and CFD at n =1

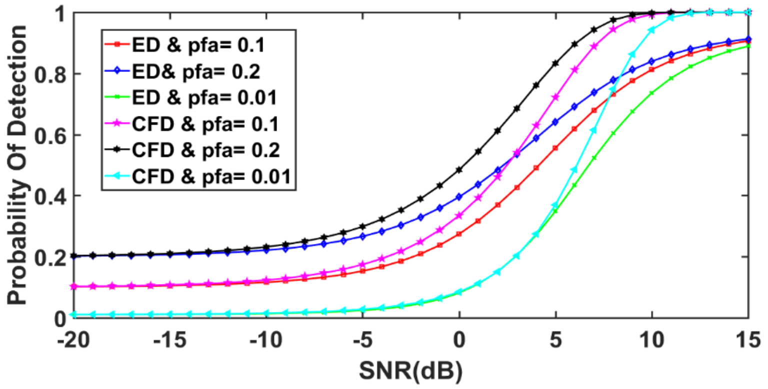

Figure 5b. performance of ED and CFD at n=5

Figures (6.a) and (6.b) show the channel indicator at the output of the energy detection detector (ED) and the cyclostationary feature detector (CFD) at different received SNR values. The figures illustrate that the channel indicator of the CFD detector will rise earlier at a lower SNR value than the channel indicator of the ED detector.

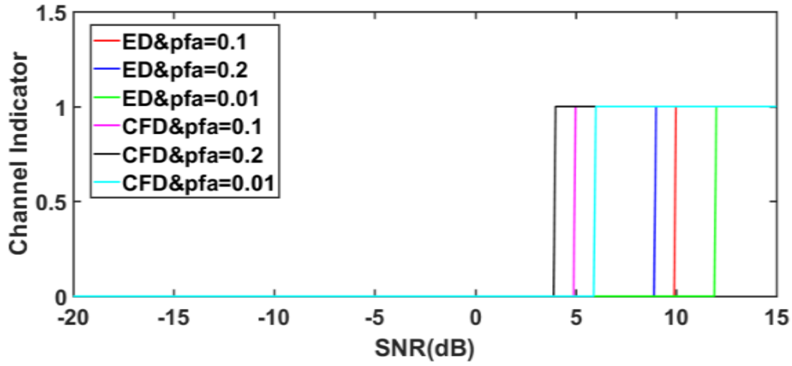

Figure 6a. Channel indicator for ED and CFD at n=1

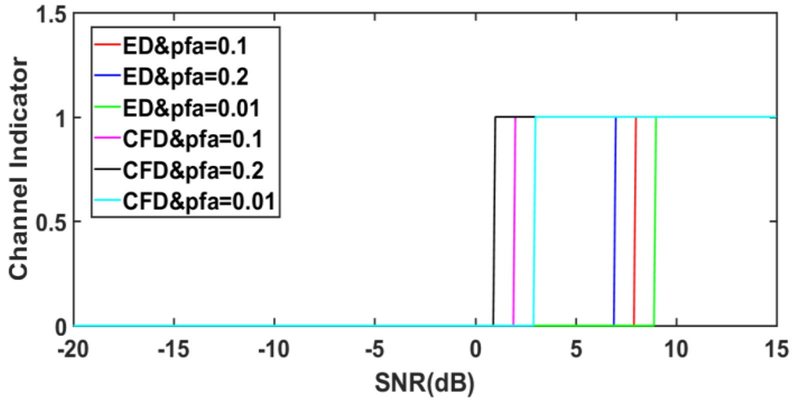

Figure 6b. Channel indicator for ED and CFD at n=5

4. Conclusion

In this paper, we use the energy detection method and the cyclostationary detection method for sensing spectrum in the FM broadcasting band. Each sensing technique has its own set of benefits and drawbacks. Energy Detection is the simplest technology and it is not necessary to have any prior knowledge about primary users. However, it performs poorly at low SNR. Cyclostationary detection technology is preferable to energy detection technology. It performs well at a low signal-to-noise ratio (SNR) as illustrated in all results, but it is a complex technique and needs prior knowledge of the primary users.

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