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Comparative analysis of cooperative sensing techniques in cognitive radio

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Research Articles

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Abstract

Cognitive radio is an intelligent radio network that has the capability of recognizing when the spectrum is idle and unused by the licensed users to allot those frequencies to unlicensed users, thus increasing spectral efficiency. Spectrum sensing is a significant step in cognitive radio. Its senses the spectrum of interest to identify the presence or absence of a primary or a licensed user and detects spectrum holes. Cooperative spectrum sensing enhances spectrum sensing as it improves the spectrum efficiency by exploiting spatial diversity. In this paper, we have discussed the three most popular sensing techniques which are; energy detection, cyclo-stationary feature detection, and matched filter technique and performed a comparative analysis on parameters like sensing time, requirement of priori knowledge, and throughput.

Keywords: Cyclo-stationary feature detection, energy detection, matched filter, primary users, secondary users, spectrum sensing

I. Introduction

Cognitive radio is a smart radio network which employs dynamic spectrum access to ensure maximum utilization of the spectrum. An unoccupied spectrum, ready to be allotted to a secondary user (SU) is known as a spectrum hole. The licensed users or the primary users (PUs) are the first priority in the order of spectrum utilization. This spectrum can be allotted to unlicensed users or the PUs when the spectrum is not in use by any PU. If licensed users emerge again to use the spectrum, the SUs must vacate the occupied channels to avoid any interference with the PUs [1-4].

The performance of a cognitive radio is measured by two components: The probability of false alarm P_f and the probability of miss detection P_m [5]. The probability of false alarm dictates that the band is occupied by the PU when the spectrum is empty and can be used by a SU whereas; the P_m states that the spectrum is free when the PU is actually present. Since interference is caused when the presence of the PU in a spectrum is falsely detected, it is very important to minimize P_f and P_m and also increase the probability of detection Pd to increase spectral efficiency.

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A. Primary signal detection

The users in a cooperative cognitive radio network employ binary hypothesis for the purpose of primary signal detection. Each user senses the spectrum individually. This is known as local sensing. This hypothesis can lead to two decisions: The PU exists, represented by H0, or that the PU does not exist, represented by H1

$$x(t) = \begin{Bmatrix} n(t)\,,\ H0 \\ h(t) * s(t) + n(t)\,,\ H1 \end{Bmatrix} \tag{1}$$

where x(t) is the signal received by the cognitive radio user, s(t) is the transmitted PU signal, h(t) is the gain of the channel, n(t) is the additive white Gaussian noise (AWGN). H0 and H1 are the final outcomes or the decisions finalized by the users [6].

The receiver operating characteristics plot is an important metric for the evaluation of the performance of the sensing techniques in the

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cognitive radio. This curve is a plot of P_d versus P_m

$$P_d = P\{decision = H1|H1\} = P\{D > \lambda \mid H1\} \quad (2)$$

$$P_f = P\{decision = H1|H0\} = P\{D > \lambda \mid H0\} \quad (3)$$

Here, λ is the threshold decision and D is the decision statistic. The final decision is completely dependent on whether the decision statistic D falls above or below the decision threshold. If the decision falls above λ, the decision is H1 or else the decision is H0. Another important metric in sensing techniques is P_m which is defined as $P_m = 1 - P_d = P\{decision = H0|H1\}$.

II. Sensing techniques

The sensing techniques are mainly divided as coherent and non-coherent detection. A priori knowledge of the signal is required for a coherent detection which is opposite in case of the non-coherent detection. The three most commonly used sensing techniques are discussed below. The energy detection is the most popular sensing technique, which does not require any a priori knowledge of the signal. Whereas the cyclo-stationary detection technique and the matched filter technique require priori knowledge of the signal as depicted in Figure 1.

The cooperative sensing process begins with a local spectrum sensing of every user in the cooperating model. The goal of this sensing is the detection of the primary signal. We have considered the three most important techniques for sensing in a cooperative model. These are; energy detection, cyclo-stationary feature detection and matched filter.

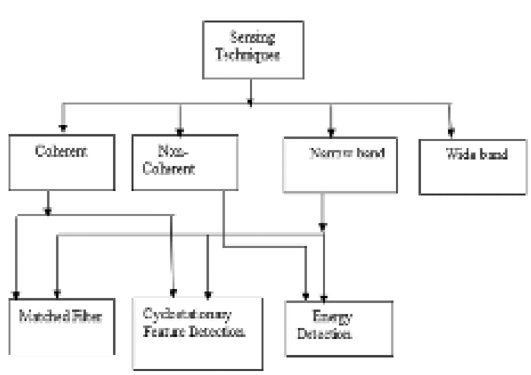

Figure 1: Classification of the three most popular sensing techniques

A. Energy detection

This is the least complex technique. It does not require a priori knowledge of the PU since it is not coherent [6]. The detection of the PU depends on the energy sensed [8]. The block diagram of energy detection is shown in Figure 2.

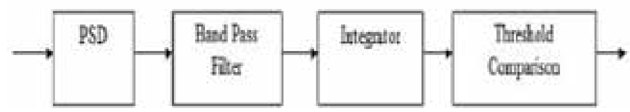

Figure 2: Block diagram showing energy detection method

The signal is passed through a band pass filter. It is sent through a squaring device. The band pass filter is used to reduce the noise bandwidth [9] [17]. Therefore, at the input of the squaring device the noise is band limited and has a flat spectral density. After this, it goes to an integrator. The output of the integrator is the decision statistic. This is compared with the threshold.

We have two hypotheses [7]: H_0 and H_1

$$\begin{aligned} y(t) &= n(t) && \ldots H_0 \\ y(t) &= h * s(t) + n(t) && \ldots H_1 \end{aligned} \quad (4)$$

H_0 refers to the primary signal being absent and H_1 refers to its presence. Here, s (t) gives the signal of the PU and $n\,(t)$ n (t) is noise, h h is channel gain [23].

The decision statistic is:

$$T = \frac{1}{N}\sum_{t=1}^{N} |y(t)|^2 \quad (5)$$

The conclusion regarding the spectrum being utilized by the PU is done by contrasting T (detection statistics) and λ (predetermined threshold) [7] [22]. There are two different probabilities to accomplish this technique [10]:

- Probability of detection (P_d): The primary signal is actually present and is declared present.
- Probability of false-alarm (P_f): The PU does not exist and is declared present.

$$Pf = P\,(T > \lambda | H0)$$
$$Pd = P\,(T < \lambda | H1) \quad (6)$$

A good detection method ensures a large P_d and a small P_f.

This method does have a few disadvantages as well [6].

They are:

- High sensing time is required for a particular probability of detection.
- Uncertainty of noise power is subjected on the performance of this process.
- Energy detection cannot distinguish CR user signals from PU signals. Therefore, the CR users have to be closely matched and restricted from transmitting in a period called the 'Quiet Period'.
- This technique is not useful for detecting the spread spectrum signals

B. Cyclo-stationary feature detection

This technique uses the periodic properties present in the primary signal to detect its presence [11, 7]. Some of these properties are in pulse trains, hopping sequences, etc. Due to this periodic property, the cyclo-stationary signals display the characteristics of periodic statistics and spectral correlation, which are not present in the noise and other interferences which make this technique robust to noise disturbances [14]. It also performs superior to the energy detection in regions of low SNR.

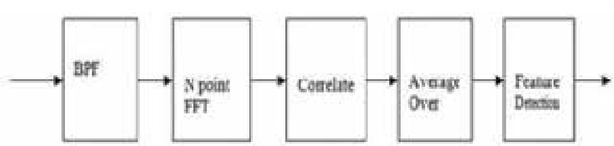

Figure 3: Block diagram showing cyclo-stationary feature detection

This technique is different from the previous techniques as its energy detector used time-domain signal, whereas this performs a transformation from the time domain into the frequency feature domain [15] [16].

In Figure 3, we can see that the input is first given to a band pass filter to calculate the energy of the band being used [10]. Then, this signal is fast Fourier transformed after which it is given to the correlator. The spectral correlation extracts the periodic properties of the primary signal [12]. This is then passed to an integrator. The final output is then compared with λ to detect the state of the PU. After the spectral correlation, the signals which are cyclo-stationary processes the property of periodicity.

Ry (t+ τ)=Ry (t+T_0,τ)

(7)

On performing the Fourier transform on the above equation, we get:

$$R_y^{\alpha}(\tau) = \lim_{T\to 0}\frac{1}{T}\int_T y\left(t+\frac{\tau}{2}\right) y\left(t-\frac{\tau}{2}\right)e^{-j2\pi\alpha t}\,dt \quad (8)$$

In (8), α is known as the "cyclic autocorrelation function" and is the fundamental cyclic frequency. "Spectrum correlation function" (SCF) is acquired by the "cyclic autocorrelation function" and it distinguishes the noise from the PU. Thus, SCF can be defined as below:

$$R_y^{\alpha}(\tau) = \lim_{T\to 0}\frac{1}{T}\int_T y\left(t+\frac{\tau}{2}\right) y\left(t-\frac{\tau}{2}\right)e^{-j2\pi\alpha t}\,dt \quad (8)$$

(9)

If the PU is available in the selected range of frequency, SCF will show a peak at the center. This peak would not be present when the PU signal is not available in the range of frequencies.

This technique has some demerits due to the increased computational complexity and high sensing time. As a result of problems like these, this technique is not as popular as energy detection.

C. Matched filter detection

Matched filter detection, similar to cyclo-stationary detection, uses priori information about the primary signal. This technique uses correlation of the observed signal with the known primary signal to sense the existence of the PU signal [13]. As a result of this, the SNR is maximized. It needs less number of samples and takes less time. However, the samples required increases as the received SNR decreases [7].

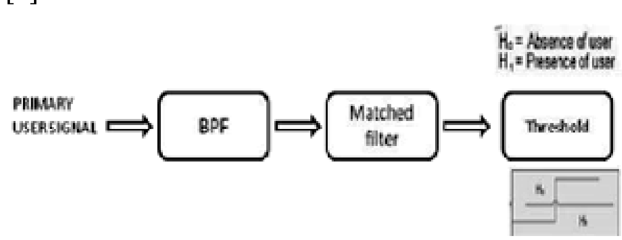

Figure 4: Block diagram showing matched filter detection

The transmitted signal, s (t) is passed through an AWGN channel where noise, n (t), is added to it. This received signal, x (t) is used as an input for the matched filter. In the filter, the cross correlation of the received signal x (t) is done with the transmitted signal s (t) [18-21]. The result from the matched filter is contrasted with a threshold to detect the presence of the primary signal.

Since matched filter needs receivers for various kinds of signals and algorithms corresponding to the receivers, the complexity as well as the power consumption of matched filter detection is very high.

III. Results

A. Energy detection simulations

If the energy detection is considered for spectrum sensing, the energy included over a spectrum band is first estimated and then contrasted with a certain threshold value. When the threshold is below the energy level, then the PU is present and if the level of energy is below the threshold, then the PU is absent, and the spectrum band is free to be used by SUs.

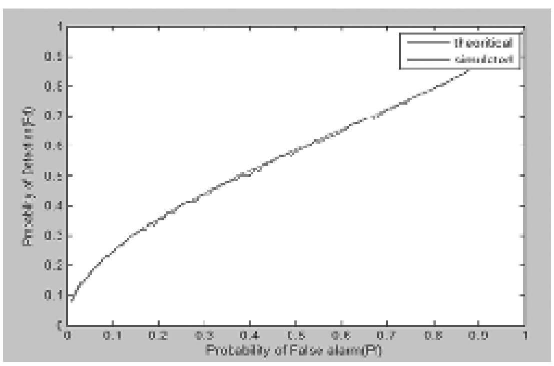

Figure 5: ROC curve in the presence of AWGN channel for -20dB

Here, in Figure 5, we simulated the Receiver Operating Characteristics curve (ROC) with the help of the MATLAB code. The ROC curve is a graphical representation that plots P_d versus P_f.

From Figure 5, we can see that P_f increases with an increase in P_d. At high signal-to-noise ratio SNR, P_d of PU signal increases. P_f is inversely proportional to SNR; but, we observe that P_f is directly proportional to $P_{d,}$ though the rate of increase of P_d is less compared to P_f with increase in SNR level. In Figure 6, we can see that with increase in SNR, probability of miss (P_m) reduces, where P_m = 1-P_d.

B. Cyclo-stationary feature detection simulation

The Simulink model used for detecting the PU is represented in Figure 7. Firstly, the noise is added to the input signal after passing it through a channel. This is followed by filtering, taking FFT of the signal and windowing. Thereafter, the absolute value is taken which when compared to the constant value with the help of a relational operator, generates the end result.

The end result, which is the final output in Figure 8 and Figure 9, depicts the absence and presence of PU. The peak value depicts the presence of PU. The use of autocorrelation function here helps in efficiently detecting the presence of PU through a comparison with a threshold value.

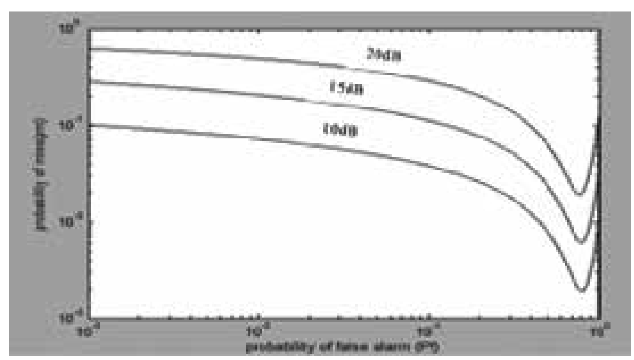

Figure 6: ROC curve in the presence of Rayleigh fading channel

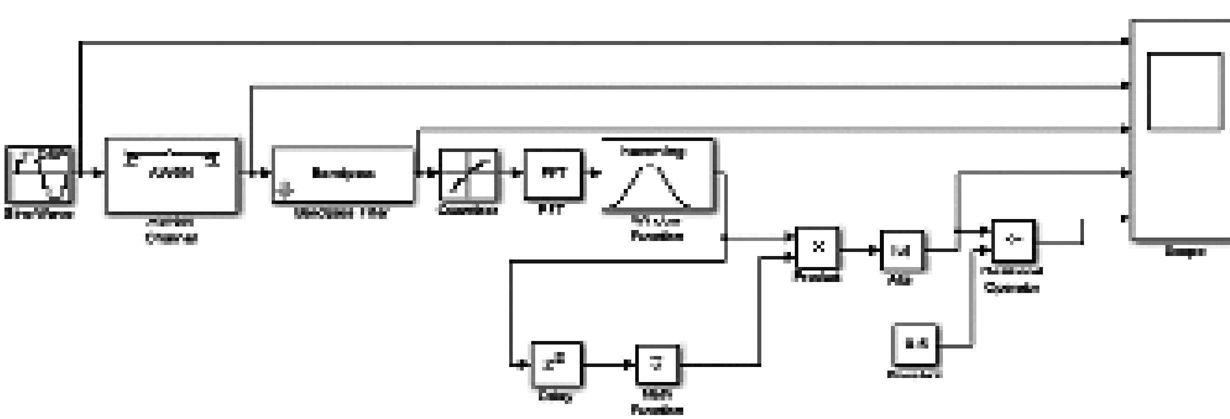

Figure 7: Simulink model for cyclo-stationary feature detection

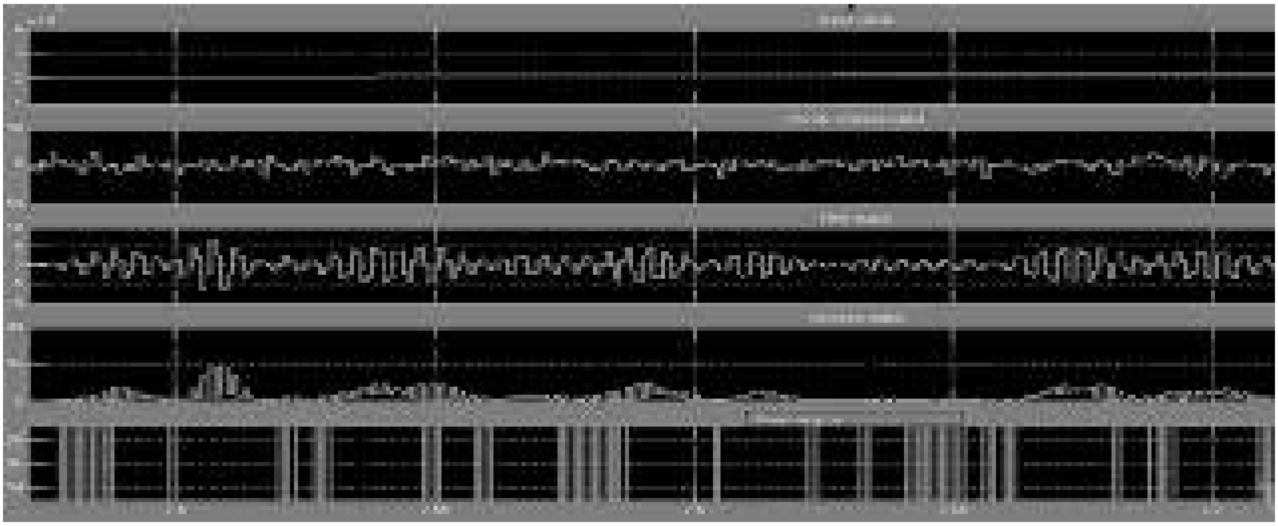

Figure 8: Simulation results for 20 kHz frequency (Input signal, AWGN channel output, filter output, absolute output and final output - from top to bottom)

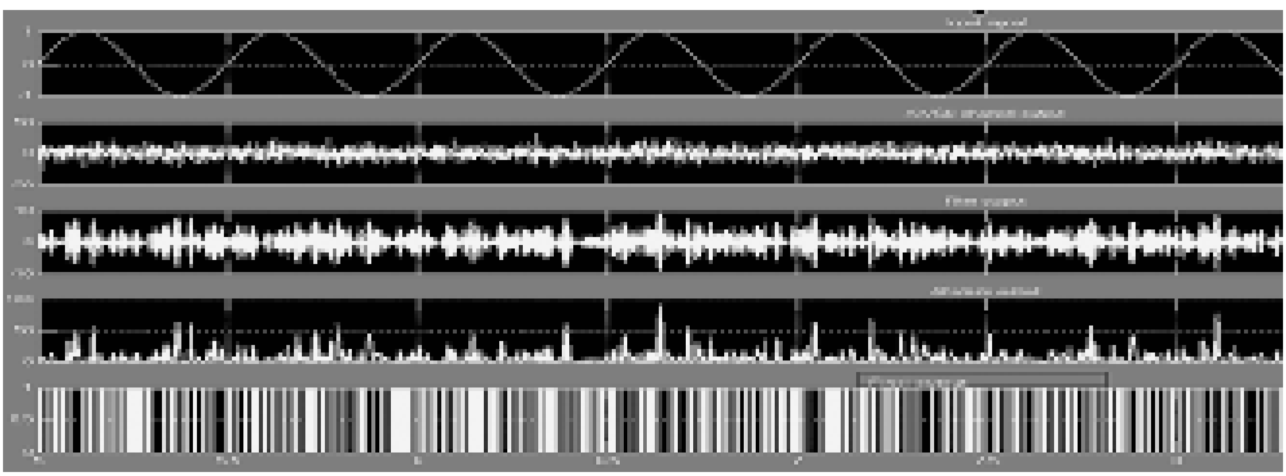

Figure 9: Simulation results for 2 kHz frequency (Input signal, AWGN channel output, filter output, absolute output and final output - from top to bottom)

The previous results were for only one user. In Figure 10, the simulation results of the hard decision fusion method are shown where we have considered four users of varying frequencies.

The output from each of the four users are shown. The combination of the signals at the Fusion Center (FC) before any decision were applied is also shown and in the end is the output after the AND fusion decision is applied. The Simulink model used for the hard fusion rule is given in Figure 11.

It shows four users of frequencies 2MHz, 4MHz, 6MHz, and 8MHz sending their signals to the 'Fusion Center' where AND rule is applied to get the final result which is displayed on the scope as seen in Figure 10.

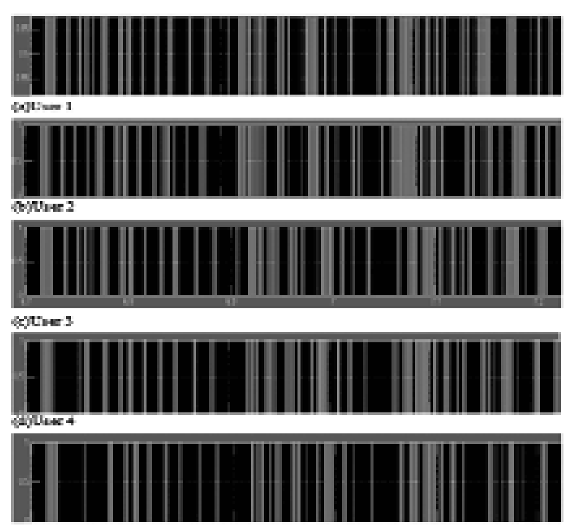

Figure 10: Hard fusion decision simulation results considering 4 users- user 1, user2, user3, user4 and final output simulation showing the AND decision output (from top to bottom)

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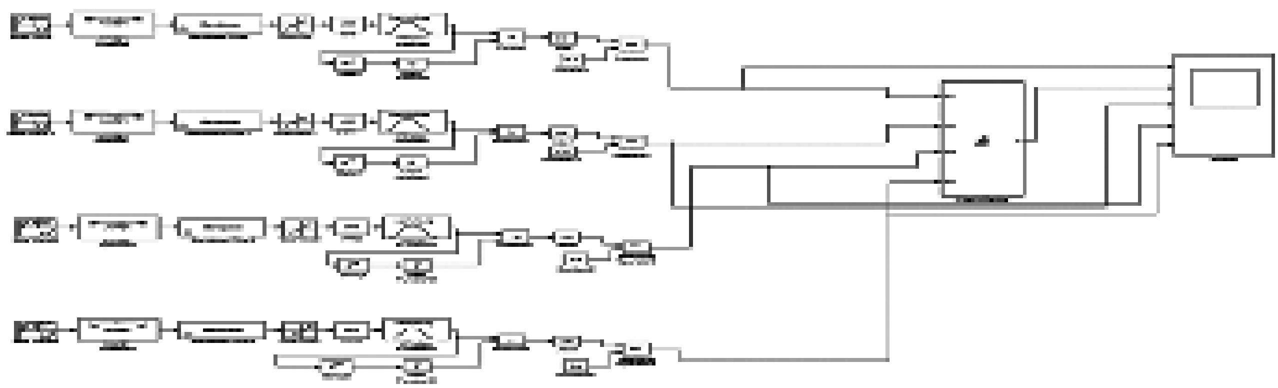

Figure 11: Simulink model for hard fusion rule of cyclo-stationary based detection method for four users

C. Matched filter simulations

When we have priori information about the PU signal (for example, the modulation scheme used), then a matched filter tends to become the preferred option for detection. This means that if the priori knowledge of modulation scheme is not correct, the matched filter will perform poorly. So, correct priori information is important for matched filters to give the desired results.

The plot shown in Figure 12 was drawn with the help of the MATLAB code.

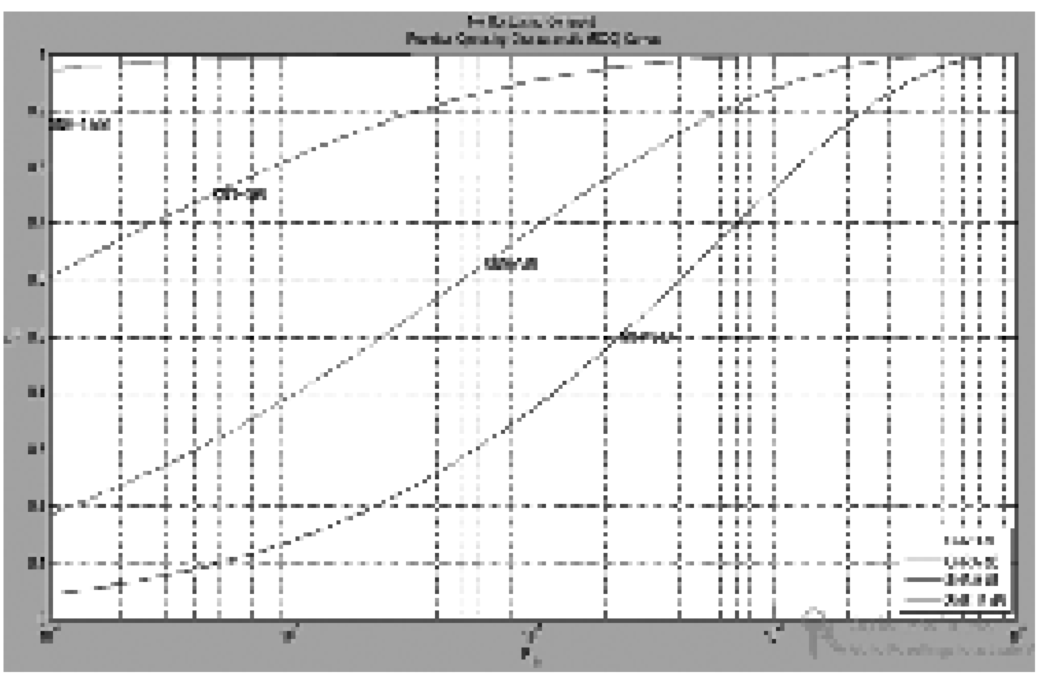

Figure 12: ROC curve for matched filter (12dB, 9dB, 6dB, 3dB - from top to bottom)

From Figure 12, we can see that P_f increases with an increase in P_d. At high SNR, probability of detection of PU signal increases. The probability of false alarm is inversely proportional to SNR. But, we observe that the probability of false alarm is directly proportional to probability of detection, though the rate of increase of Pd is less compared to P_f, with increase in SNR level.

In Table 1, the comparisons of the three techniques are displayed. Each of the sensing techniques can be used for spectrum sensing but each of them have varying pros and cons. Based on the requirement needed, any of the three techniques can be used to get satisfactory results.

Table 1: Summary comparison of the three sensing techniques

Sensing Type	Test Statistics	Advantages	Disadvantages
Energy detection	Energy of the received signal samples	• Easy to implement • No a priori knowledge required about primary signals	• High sensing time. • Detection performance is subject to the uncertainty of noise power • Difficult to distinguish primary signals from the CR user signals • Unreliable in low SNR regions
Cyclo-stationary feature detection	Cyclic spectrum density function of the received signal	• Robustness to the uncertainty in noise power • Improves the overall CR throughput • Better detection in low SNR regions than ED method • Can distinguish between different types of transmissions	• High computational complexity • Specific cyclo-stationary features must be associated with the primary signal • Poor performance when a user experiences shadowing or fading effects • Long sensing time
Matched Filter	Projected received signal in the direction of the already known primary signal	• Optimum performance • More robust to noise uncertainty and better detection in low SNR regions than feature detection • Requires less time to achieve high processing gain due to coherent detection	• Requires full primary signal knowledge • High power consumption • Uneconomical to implement • High complexity

IV. Conclusion

In this paper, the basic concepts about cognitive radio features functions were explored. Spectrum sensing is the first step in cognitive radio technology. The cooperative sensing is an effective technique to increase detection performance by exploring spatial diversity at the expense of the cooperation overhead. The cognitive capability and configurability of cognitive radio enhances the performance by providing the ability to gather and sense information from the surrounding environment and efficiently adapts to the parameters of operation. Thus, cognitive radio increases spectral efficiency and reduces interference with the licensed user.

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