

# ANALYSIS OF SPECTRUM SENSING TECHNIQUES IN COGNITIVE RADIO

Abdul Razaq, Muhammad Riaz and Anas Bilal

School of Information Technology, University of Lahore, Islamabad Campus Islamabad, Pakistan.

[Razaq\\_a\\_h@hotmail.com](mailto:Razaq_a_h@hotmail.com), [mriaz77@gmail.com](mailto:mriaz77@gmail.com), and [chanasbilal@gmail.com](mailto:chanasbilal@gmail.com)

**ABSTRACT:** The problem of inefficient use of spectrum and concept of opportunistic spectrum access gives rise to the idea of designing cognitive radios. This report summarizes the concept of cognitive radio and why they are becoming a necessity. Some important characteristics and applications of CR are explained. Then the spectrum sensing is introduced as the most important function of cognitive radios. Further, the detection of primary user in spectrum sensing is discussed. A system model of spectrum sensing is explained and some key techniques for spectrum sensing are explained on an introduction level. In this research, the three spectrum sensing techniques, namely Matched Filter, Energy Detector and Cyclo-Stationary Feature Detector were simulated in Matlab. The process of Matlab implementation of these spectrum sensing techniques is explained. The Matlab design of a test QPSK signal is also discussed. Finally the simulation results of the three implemented sensing techniques are presented and explained with respect to their detection probabilities, performance under different SNR levels and their complexity.

**Keywords:** (SDR) Software Defined Radios, (RF) Radio Frequency, (ADC) Analog to Digital Conversions, (DAC) Digital to Analog Conversions, (DUC) Digital up Conversion, (DDC) Digital Down Conversion, (CR) Cognitive Radio, (CRN) Cognitive Radio Networks, (UWB) Ultra-wideband Communications, (PU) Primary User, (SU) secondary user, (SNR) Signal to Noise Ratio, (AWGN) Additive White Gaussian Noise, (PCM) Pulse Code Modulation, (FFT) Fast Fourier Transform, (MF) Match Filter.

## 1. INTRODUCTION

Cognitive Radio offers many potential benefits that current wireless communication technologies lack. For example, cognitive radios can be way more spectrum efficient than existing technologies. In order to start understanding how it works, we must discuss some pre-requisite knowledge.

### 1.1 Software Defined Radios

Before defining Software Defined Radios, we review the design of conventional digital radio. As shown in Fig 1, RF Front End transmits and receives radio frequency signals through Antenna. ADC/DAC section performs digital to analog and analog to digital conversions. Digital up-conversion (DUC) and Digital down-conversion (DDC) section performs modulation and demodulation of the signals on sending and receiving paths respectively. And the baseband processing using implements link layer protocols along with other functions such as connection setup, frequency hopping, equalization, coding/decoding, correlation etc[1].

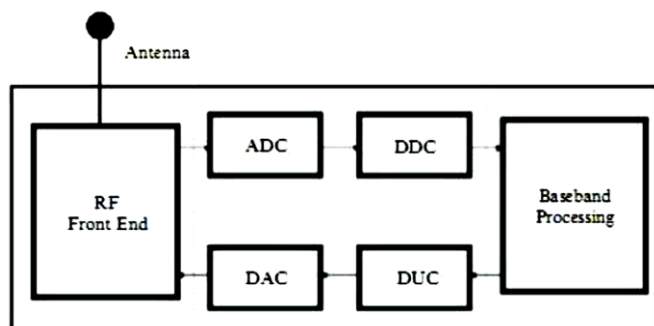


Fig 1: Schematic block diagram of a digital radio

In Software Defined Radios these functionalities are performed by software modules running on Digital Signal Processors (DSP), General Purpose processors (GPP), Field Programmable Gate Arrays (FPGAs) or a combination of

these platforms. This enables the programming of DDC, DUC and Baseband Processing sections. Hence the operational characteristics of radio such as modulation/demodulation, coding/decoding, frequency band etc can be changed at will through reprogramming. Currently SDRs are used to support multiple interface technologies (e.g. CDMA, GSM, WIFI) with a single modem by reconfiguring it in software. However there are number of drawbacks for making an ideal software radio such as, DDC/DUC and Baseband Processing must be done in software that increases power consumption and such devices cannot be portable, or the DAC/ADC part must be pushed into RF section in order to make it programmable as well. But this increases the amount of required sample rates making the transition from hardware to software more challenging[2].

### 1.2 Cognitive Radio

SDR technology offers re-configurability to the radio but this done on demand. In a number of earlier publications cognitive radio was envisioned as self-reconfiguring SDR. There have been a number of further definitions of CR since then: "A radio that employs model-based reasoning to achieve a specified level of competence in radio-related domains." "A radio (SDR) that can perform perception, reasoning, decision making through ongoing awareness of environment" FCC uses a narrower definition of CR: "A Cognitive Radio (CR) is a radio that can change its transmitter parameters based on interaction with the environment in which it operates. The majority of cognitive radios will probably be SDR but neither having software nor being field programmable is requirements of a cognitive radio." Despite these differences in scope and application focus of the CR concept, the following characteristics appear to be common in all the definitions.

- **Flexibility and Agility:**

Agility refers to the ability to change waveforms and other radio parameters, and flexibility refers to the concept of re-configurable antenna.

- **Sensing:**

The ability to observe and measure the state of the environment including spectral occupancy.

- **Learning and Adaptability:**

Ability to analyze sensory input, to recognize patterns and modify internal operational behavior based on the analysis of a new situation through both pre-coded algorithms and a learning mechanism.

### 1.3 Applications

CR devices have the potential to revolutionize how devices perform wireless networking through functions such as interoperability and dynamic spectrum access.

- **Interoperability:** Ability to rapidly assume any available radio configuration. This is done through automatic distinguishing between communication standards using artificial intelligence, in the absence of a centralized control.

- **Dynamic Spectrum Access:** Due to increasing demand of bandwidth to support existing and new services, both the policy makers and communication technologists are facing spectrum scarcity. Spectrum measurement studies indicate that there are always unused spectrum holes in both time and frequency. CR is proposed to have ability to detect these spectrum holes or gaps and use them for its own use increasing the overall spectrum efficiency. This feature is called dynamic spectrum access[3].

### 1.4 Cognitive Radio Networks (CRN)

In order to discuss cognitive radio networks, we redefine CR as: "Wireless communication system that intelligently utilizes any side information about activity, channel conditions, codebooks or messages of other nodes with which it shares spectrum." [5] An idea of making a CR based system or a CR network based on above definition of CR has caused much enthusiasm in several companies including the FCC. FCC have even allowed opportunistic use of the UHF/VHF TV bands based on the studies that indicate spectrum inefficiency in these bands to promote the concept of CRN[4]. There are three main proposed ways or paradigms to make CRN:

- **Underlay Paradigm:** It states that the concurrent non cognitive and cognitive transmissions may occur only if the interference caused by cognitive device at non cognitive end is less than a certain acceptable threshold. This can be achieved

by two methods, either using multiple antennas at non cognitive end to bounce back cognitive signals or by spreading cognitive signal below a certain noise floor and de-spread it at cognitive receiver. Later technique is basis for Spread Spectrum and Ultra-wideband (UWB) communications. This technique is most commonly used in bands that are licensed to non cognitive users.

- **Overlay Paradigm:** This system enhances the non cognitive signal by boosting its power or reducing its interference to make space for cognitive signal. This requires that the CR system must have a prerequisite knowledge of the non CR signal such as its codebooks, modulation schemes etc. This knowledge can either be transmitted by non CR system prior to the actual transmission or the CR system can be made to automatically detect the required information. Once the non cognitive signal is decoded and analyzed, either its signal power can be boosted or its interference can be

completely removed by using schemes such as Dirty Paper Coding.

- **Interweave Paradigm:** Interweave refers to the process of detecting spectrum holes in non cognitive signals and rapping the cognitive signal into those gaps. Opportunistic use of the spectrum was the original motivation for cognitive radios therefore interweave has prominent importance in the concept of CRN. The prerequisite for interweave is the knowledge of activity information of non CR users in the spectrum. The system also has to maintain minimum interference level during the process[5].

## 2. METHOD

Since our objective is the study, implementation and comparison of the spectrum sensing techniques, our method is not divided into discrete parts. We will first discuss the basic working of the spectrum sensing techniques and then in next phase we start Matlab coding where required and analysis of the results.

### 2.1 Spectrum Sensing

As discussed earlier, multiple spectrum measurement campaigns reveal that much of licensed spectrum remains unused in both time and frequency. Therefore CR must be able to sense those gaps accurately to be able to use those gaps for its own transmissions. In other words, Secondary user (CR) must be able to opportunistically use these time and frequency voids without interfering with primary user (non-CR). This approach reveals that a crucial component of Cognitive Radio Network is thus **Spectrum Sensing**[6].

There are two important tradeoffs associated with spectrum sensing:

- Throughput performance (CR's ability to transmit efficiently) VS interference Constraint

- Sensing accuracy VS sensing overhead We now discuss primary signal detection, which is not equivalent to spectrum opportunity detection but it can be translated into opportunity detection.

#### 2.1.1. Primary Signal Detection

As we know primary user (PU) is the one who is licensed to the band and CR intends to exploit its unused spectrum, therefore CR is secondary user (SU). A spectrum sensor's main function is detection of the PU signal in a particular channel. A spectrum can have two states, Idle and Busy. Ho (Idle) & Ho (Busy) In idle state, there is only ambient noise in the signal while in busy state the primary signal is also present with noise.

$$H_0: Y(k) = \mathcal{N}(k)$$

$$H_1: Y(k) = S(k) + \mathcal{N}(k)$$

Where  $y(k)$  is the received signal,  $\mathcal{N}(k)$  is noise,  $S(k)$  is the message signal or primary signal and  $k$  is the sample number.

We can make a few conclusions from above equations to form a basis for Spectrum Sensing Techniques:

- Busy signal will have more energy than idle signal, therefore, **Energy Detectors** can be used for PU detection

- Considering the periodicity feature of the modulated signal, techniques like

**Cyclo-stationary Feature Detection** can be used to determine structural characteristics of PU

• When PU's signal  $S(k)$  is completely known, a **Matched Filter** can be used to cancel the interference and signal enhancement. Two types of detection errors can occur:

- False Alarm (Type 1 error)
- Missed Detection (Type 2 error)

A False Alarm occurs when PU is detected while it's not there while Missed detection is when PU is detected absent while it is present. Type 1 error is less harmful than Type 2 because in case of a missed detection, both PU and SU signal can be lost completely. In order to make sensing more efficient both types of errors must be reduced.

### 2.1.2. System Model of Spectrum Sensing

According to the overlay design of the spectrum sharing, the existence of primary user must be detected before transmitting the secondary signal. Based on this principle, the transmission frame of a secondary user can be divided into sensing period and transmission period as shown in Fig 2.

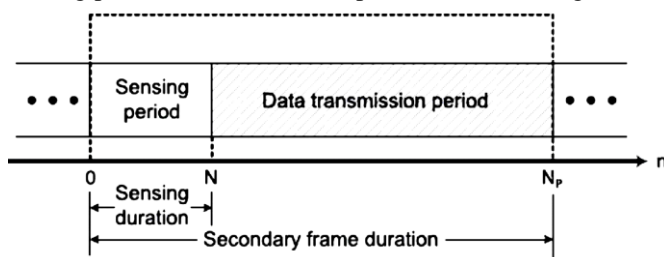


Fig 2: Sensing and transmission structure for energy detector [17]

If any primary user signal is detected during the sensing period, the secondary user stops the transmission until the primary user signal is again undetectable. Otherwise, if no primary user signal is detected, the secondary user continues transmission during the data transmission period. From this model of spectrum sensing it can be seen that the performance of a system can be increased by having longer sensing periods, however this will decrease the transmission period of the secondary signal. Therefore, there is a tradeoff between the sensing performance and throughput of the secondary user.

### 2.2. Spectrum Sensing Techniques

The spectrum sensing techniques 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. Fig 3 represents the classification.

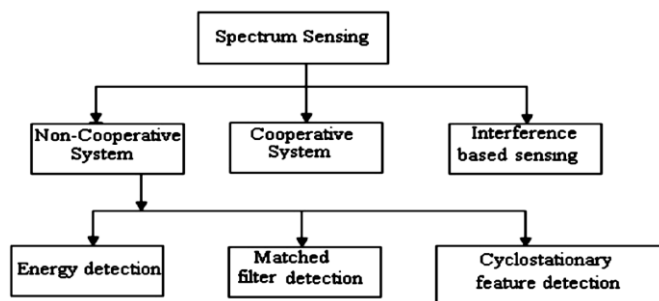


Fig 3: Classification of spectrum sensing techniques [18].

First we discuss the non-cooperative sensing techniques.

### 2.3. Energy Detector

The energy detector is a non-coherent system since no prior knowledge of the signal is required. Also it is quite simple. As shown in fig the signal is passed through band pass filter to select channel, then integrated over a certain period of time. Then the result is compared to a standard measurement of energy. This way the presence of the primary user can be guessed[7].

#### BPF Channel select Decide $H_0$ or $H_1$

However the drawbacks of energy detector are that it ignores the structure of the signal and also it has low performance in low SNR environments. If we consider the performance of an energy detector in terms of type 1 errors (false alarm) and type 2 errors (missed detection), the threshold level for deciding  $H_1$  and  $H_0$  must be adjusted carefully because, there is a tradeoff relationship between type 1 and 2 errors as long as the performance of the energy detector remains fixed.

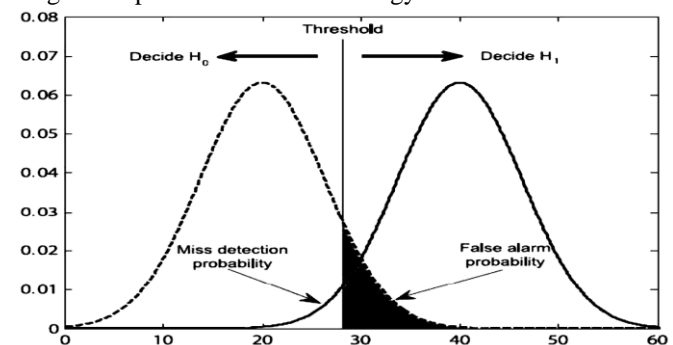


Fig 4: Threshold adjustment. [20]

Miss detection and false alarm cannot be reduced simultaneously.

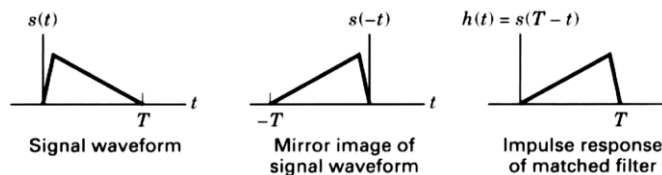
In order to enhance the performance of an energy detector, two methods can be used.

- 1) Enhancing the SNR of the received signal.
- 2) Increasing dimension or the degree of freedom of the received signal space. Intensifying the received SNR is very challenging within a practical situation, due to noise uncertainty, shadowing, and multi-path fading, whose effects are neither predictable nor can be compensated for. Thus, we focus upon increasing the degree-of-freedom of the received signal space. If the secondary user receives an increased number of observation samples, they are combined into an aggregated observation and the final decision can be made with more reliability. If the secondary user sums  $N$  samples of received energy within a sensing period, as depicted in Fig. 2, we obtain  $N$  degree-of-freedom in the time domain. However, as  $N$  increases, the time fraction that the secondary user can effectively use for data transmission decreases and, hence, restricts the increased use of the degree-of-freedom within the time domain. The increased degree-of-freedom basically refers to the usage of multiple antennas for energy detection to get more reliable results[8].

### 2.4. Matched Filter

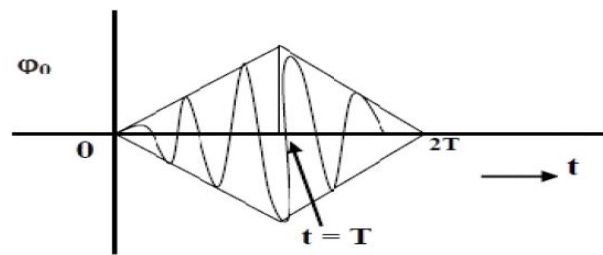
When the signal to be detected only has AWGN noise in it, the optimum filter for its detection is the Matched Filter. It is called a matched filter because it is the time-reversed and time-shifted version of the transmitted signal, hence the pre-

requisite information required to build a matched filter is a sample or a template of the signal which is to be detected. Matched Filters are commonly used in Radar Communications where a known signal is sent out and its reflection is received. Then Matched Filter is used to detect similarities between the transmitted and received signal and hence conclusions about the source of reflection are made. In the context of cognitive radios, the purpose of using a matched filter as a detection device is mainly to detect the presence of the primary user in the signal and there is less focus on reading or obtaining the contents of the message. Therefore, we discuss the introductory details of the matched filter operation and then move to its use as a primary signal detection device. Fig (5) shows the construction of a matched filter. As stated earlier, a matched filter is time-reversed and time-shifted version of the sample of a signal to be detected. If  $s(t)$  is a signal selected at random, then firstly, it is converted to  $s(-t)$  to time reverse it and then it is shifted to match the time interval of the original signal by making it  $s(T-t)$  where  $T$  is the time span of the signal  $s(t)$ . Thus the impulse response  $h(t)$  of the matched filter for  $s(t)$  is  $h(t) = s(T-t)$ .



**Fig 5: Construction of matched filter**

The fig (6) shows the block diagram of a matched filter receiver. Once we have matched filter built, it is fed with a signal containing AWGN and the output is sampled at  $t=T_b$  or  $t=T$  where  $T$  denotes the duration of the input signal. The reason for sampling the match filter output at  $t=T$  is that at  $T$  the maximum SNR is achieved according to [21]. The sample of an output of the matched filter is discussed in following section. Once the sampling is done, a decision device can be used to decide the transmitted bits according to a preset threshold. In case of primary user detection, the detection of bits is not important. Here only the presence of primary user must be identified which can be done by choosing a threshold that will represent the minimum value of output at  $T$  when the transmitted signal is detected. If the output falls below that threshold, the decision device would decide the absence of the primary user. *Matched Filter Decision device* PCM wave y Say 1 if  $y > \lambda$   $s(t)$  Sample at Say 0 if  $y < \lambda$  time  $t = T_b$  White Gaussian Threshold Noise  $w(t) \wedge$  The fig (8) shows the example of a matched filter output when the primary user was detected, or in other words, the transmitted signal was the one the matched filter was matched to.  $T$  denotes the duration of the input signal and it can be seen that the matched filter output extends to  $2T$ . The peak value is at  $t=T$  and denotes the output with maximum SNR. Thus, sampling at  $t=T$  will give the peak value of the output signal. The source of diagram is [9], where the reasons for sampling at  $T$  are discussed in further details.



**Fig 6: Match filter output**

Matched filters have a low detection time because of the fact that only 1 sample at  $t=T$  is needed for accurate detection. Also, another very important property of the matched filter comes from its proof [23] which gives following equation for maximum SNR.  $\text{Max (SNR)} = 2E_0 / N_0 (1)$

This means that the high SNR detection of matched filter depends only on the energy  $E_0$  and noise  $N_0$  values and the structure or waveform of the input signal doesn't have a role to play in matched filter detection, thus giving the freedom to choose an optimum waveform to the designer. This choice can have any basis for example, transmitting waveform with less bandwidth occupation. However a matched filter fails in situations where the primary signals are coming from multiple sources (as in case of cognitive radio networks). In such situations it is not possible to get the prior knowledge of the received signal. Even if the different primary systems are coordinating with the cognitive system in sharing the knowledge required for the operation of a matched filter, the receiving system must be prepared to suffer the demodulation complexity making the matched filter a costly solution for detection[9].

#### • Cyclo-stationary features Detection

This method exploits the existence of inherent periodicity of modulated signals. The modulated signal is generally coupled with sinusoidal carriers resulting in a built in periodicity. If a cognitive system is able to detect this periodicity, then the presence of primary user can be detected. The periodicity can be present in sinusoidal carriers, pulse trains, hopping sequences and cyclic prefixes of the primary signal. And thus these periodic signals have features of periodic statistics and spectral correlation which are absent in the noise only signals [10]. Thus the cyclic features are a difference between noise signals and modulated signal and cyclic detection should have better performance even in low SNR environments. This method also does not require perfect synchronization which other techniques may require and also it's not necessary for the cognitive user to remain silent during the cooperative sensing process.

However, this method has its own drawbacks such as its high computational complexity and longer sensing durations due to which this method is less popular than others such as energy detection. While considering the practical implementation of cyclo-stationary feature detection, following features can be listed that are to be detected



- Double Sided Sinewave carriers
- Data rate (symbol period)
- Modulation type

For our simulation, we focus on detection of double sided sinewave carriers.

$$x(t) = \sum_{k=-\infty}^{\infty} a_k e^{jkw_0 t}$$

As we know the periodic signals can be represented with the Fourier series coefficients.

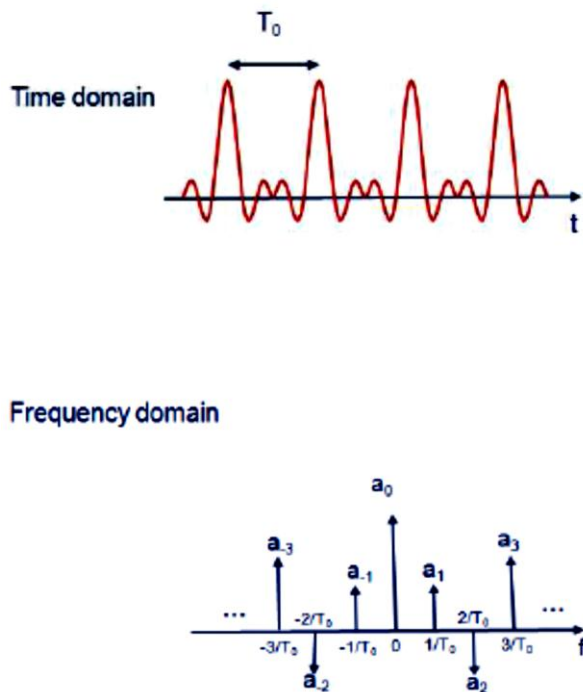
$$w_0 = \frac{2\pi}{T_0}$$

With fundamental frequency

$$a_k = \frac{1}{T_0} \int_{T_0} X(t) e^{jkw_0 t} dt$$

Fourier coefficient:

Obtained by projecting onto complex sinewave basis  $e^{jkw_0 t}$   
The following figure shows how the Fourier series expansion extracts the periodic features of the sinusoidal signal.



**Fig 7: Time domain and Frequency domain**

Thus, when extracting the double sided features of sinusoidal signals, we can use the Fourier series expansion[10].

## 2.6. Interference Bases Sensing:

We will not be simulating this type of detection but it must be defined to give the reader a better idea of various approaches to spectrum sensing. Till now we have been following the hypothesis of whether primary user is present or not bases on thresholds. This hypothesis falls victim to the SNR wall when the SNR value is very low. In [11] a new aspect of diversity is explored which is called event bases detection. Here the hypothesis is detection of energy edges. If we can detect the event when energy values suddenly change, we can assume

facts about entrance or exit of the PU from the spectrum. Thus, even in very low SNR situations, the sudden changes in energy values can be detected and thus the performance of detection can be improved. Since this scheme works on the ongoing monitoring of noise in the spectrum, it is called Interference Based Sensing or Event Based Sensing[11].

## 2.7. Co-operative Sensing:

The performance of all the non cooperative sensing techniques can be improved by combining the results from individual techniques for a collective analysis better decision making. This creates collaboration between individual techniques and becomes Cooperative Sensing. In [12] the practical implementation of such a cooperative sensing scheme called Fuzzy Logic Detection (FLD) is discussed. In this scheme the normalized outputs of matched filter, energy detector and cyclo-stationary feature detector are fed to a Fuzzy logic controller, which then ranks the decision as strong or weak and thus a very good improvement in final result occurs. Thus while discussing the practical use of spectrum sensing, considering the option of cooperative sensing is very important as it can practically improve the output without adding much computational cost or time.

## 3.RESULTS AND DISCRIPTIONS

As the main objective of this project is to implement the spectrum sensing techniques in Matlab and then evaluate their performance under similar conditions and provide detailed results that can give an insight on how a certain technique can be better than others with respect to certain parameters, we now discuss the implementation in detail keeping the previously discussed knowledge in mind. The main objective is to make a Matlab script file that generates a signal, adds AWGN noise to it and then implements spectrum sensing techniques to it to gather results. Thus we start with the first objective that is the generation of a random signal. We choose

QPSK as the modulation technique for our test signal. The theory of QPSK is discussed in the following section.

### 3.1. Quadrature Phase-Shift Keying (QPSK)

QPSK is a form of phase shift keying where the phase of the carrier signal is changed to represent bit changes. When the phase has only 2 variations, the modulation is called Binary-PSK or BPSK. In this modulation only 1 bit per symbol will be transmitted as only 1 phase variation can be transmitted for a symbol duration that represent either 0 or 1. The phase shift is of 180o in BPSK. A better way to add more information to this signal is splitting it into I (In-Phase) and Q (Quadrature) components. There is a 90o shift between the I and Q components and are in Quadrature or orthogonal to each other. Thus, if a signal is split into I and Q components and both components are simultaneously given 1 bit to modulate, these components become a BPSK each. This way the signal can now carry 2 bits per symbol. This adds up to make a total of 4 phase variations possibilities for a signal. And there is a 90o phase change in each subsequent variation. Fig (8) shows a symbol mapping for QPSK and Fig (9) shows the constellation for QPSK.

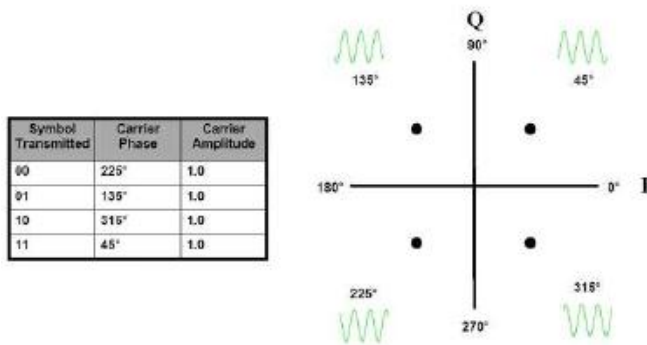


Fig 8: Constellation of QPSK

Fig (12) shows the waveform of the carrier signal and the modulated signal. The phase differences can be observed clearly.

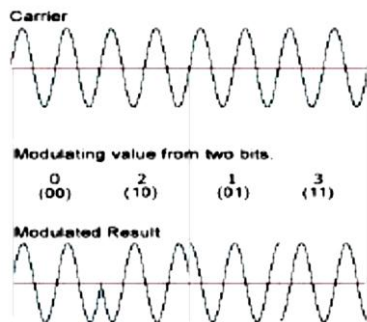


Fig 9: Carrier signal and Modulated signal

### 3.2. Random QPSK in Matlab:

The first step in the generation of a random QPSK signal is the generation of a random sequence of bits to be modulated. This was done by the use of a custom made function called *random\_binary(bits,samples)* which creates a random sequence of 1's and -1's. The input argument "bits" is the number of bits to be generated and "samples" is the number of samples to be generated for each bit. In our case we keep the sample argument equal to 1. The length of bits was kept equal to twice the number of QPSK symbols to be made as one QPSK symbol carries 2 bits of information. The second step is to split the bit stream into even and odd bits so that they can be modulated separately with sine and Cos carries respectively. This was done by a loop that saves odd and even bits in separate arrays, each having length equal to the number of symbols to be generated. These are the bits that will eventually become the In Phase and Quadrature components of the modulated signal. Next step is the modulation with carriers. This was done by multiplying the even bits with sine carrier and odd bits with Cos carrier. The carrier parameters are following.

$Amp = \text{Constant Amplitude by formula with } E \text{ symbol energy and } T \text{ symbol duration}$

$F = \text{carrier frequency}$

$F_s = \text{sampling frequency}$

$t = \text{time vector with length equal to } T \text{ the symbol duration}$

Both the bit sequences are multiplied with their respective carriers. This way if the bit value is 1, the carrier becomes

positive and if it is -1 the carrier becomes negative, thus inducing a 180 carrier phase difference in +1 and -1. Also the carriers are 90 apart from each other, thus satisfying the QPSK mapping of Fig (9). Next the In Phase and Quadrature parts are added together and concatenated into a vector *signal*. This whole modulation process is performed in a loop that runs a number of symbol times. Thus in the end the *signal* vector has a modulated QPSK signal having multiple symbols. Fig (10) shows the plot of *signal* vector and Fig (11) shows the scatter plot obtained from Matlab.

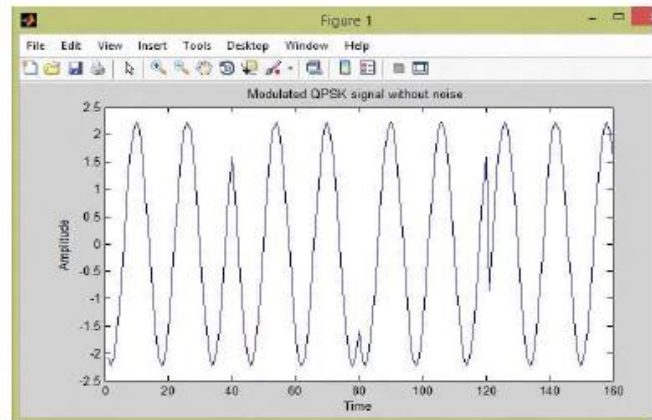


Fig10: Modulated QPSK having 4 symbols with symbol duration 40

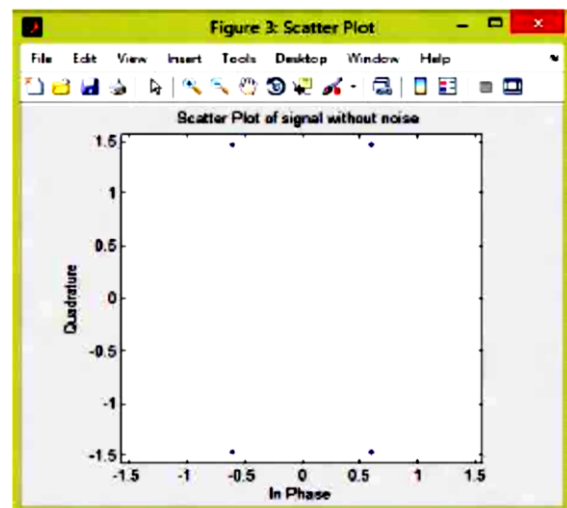


Fig 11: Scatter plot of signal without noise

The next step is addition of AWGN noise into the signal vector using *awgn(signal,snrdb,power)* command. Also some symbols are removed at random and replaced with noise only to simulate the situations where the primary user was not transmitting data. This was done by the use of a *trigger* variable which is assigned a random number from 0 and 1 at each loop iteration. And if the *trigger* value is 1, noise is added to that symbol and if it was 0, the symbol is replaced with zeros and then noise is added to it. This way we have a noisy signal saved in vector *signalnoisy*. Fig (12) shows the plot of *signalnoisy* with some symbols replaced with noise only and the *snrdb* value given to *awgn* function was 10.

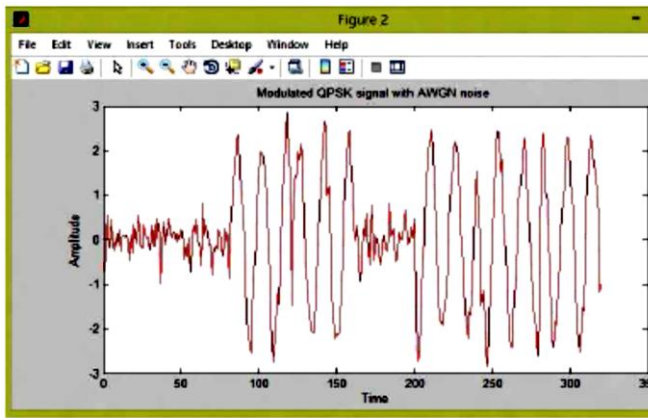


Fig 12: Modulated QPSK signal with AWGN noise

### 3.3. Energy Detector in Matlab:

In Energy Detection, the energy of each symbol duration is to be calculated and compared with a fixed threshold value and a decision is to be made. This was done by squaring all the values of a given symbol duration for both real and imaginary parts and then all the values added together. Once energy is calculated, the threshold testing can be applied by a simple if/else condition. As we know the energy detection has a low complexity and is quite simple. The important part of this method is setting a threshold that gives best performance as shown graphically in Fig (5). Therefore we performed test runs of energy detector to gather probabilities of false alarms and missed detections for different threshold values. Then those probabilities are plotted on the same plot to view the tradeoff relationship and then an optimum threshold value is set. The plot of false alarm and missed detection probabilities is shown in Fig (5) of the results section.

### 3.4. Matched Filtering in Matlab:

The first step for matched filter detection is the making of matched filter. As we can see in Fig (6) that a matched filter is a flipped and shifted version of the original signal. This is done in Matlab using the following statements:

```
matchedfilter1= signal (1: length
(signal));
matchedfilter= matchedfilter1(end:-1:1);
```

Where *signal* vector is the signal without noise and *signal* has a length equal to the length of a symbol. The fact that the signal without noise cannot be obtained at receivers end, dictates that a sample or a template of the original signal must be provided by the PU as prior knowledge. Now the vector *matchedfilter* has a length equal to length of each symbol. Matched filtering is performed by convolving each symbol with *matchedfilter* and the result is saved and plotted. Also the result is ready to be applied a threshold to. The threshold can be obtained using equation (1) as a guideline which states that the maximum value of matched filter output is a function of Symbol energy and the noise variance. We know the symbol energy value and noise variance is a constant for which we assumed a value. Thus the maximum of each symbol output of the matched filter is compared with the threshold value and decision is made. This whole process was performed in a loop so that all the symbols get convolved with matched filter one by one and the presence of primary

user is decided. Fig (13) shows the examples of matched filter outputs for different symbols. If the user was present, the resulting plot was in agreement with Fig (5) and had a peak value greater than threshold. If user was not present, the output did not look like Fig (5) and maximum value was also very low then the threshold verifying that matched filter was applied correctly.

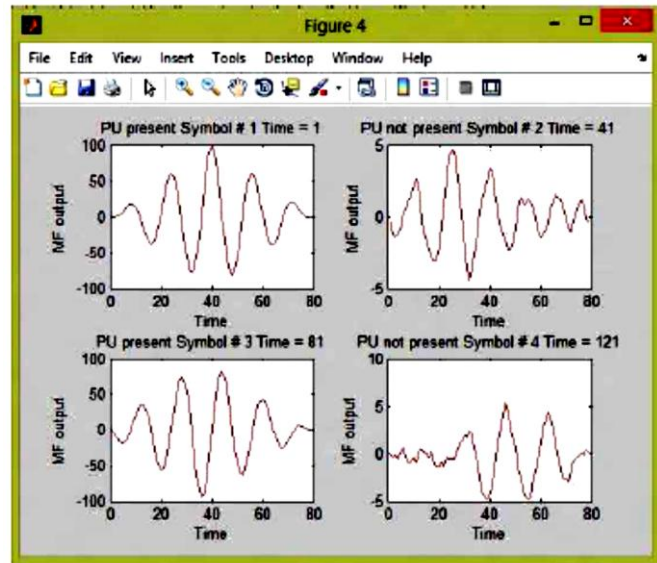


Fig 13: Matched Filtering in Matlab

### 3.5. Cyclo-stationary Feature Detection in Matlab:

In our simulation of the Cyclo-stationary Feature detection, we use the fact, that there are double sided sine wave carriers present in periodic signal, as a detection method. Therefore to be able to perform the detection, we first needed to plot the Fourier transform of the signal to be able to notice the presence of double sided sine wave carrier frequency. Theoretically if we plot the single sided amplitude spectrum of the signal, we

should get a peak exactly at the carrier frequency value of modulated signal. First a proper frequency scale is defined to represent the horizontal frequency axis. Then T point FFT of each symbol is taken using `fft(signal,T)` command and stored in variable *X*. Here *T* is symbol time and *signal* is the noisy signal. Then magnitude of *X* is calculated using `abs(X)` command. Then the values of magnitude are plotted against the frequency values and the presence of single peak can be seen at the signal frequency if the symbol had a periodic PU signal present. To define the decision method, we extract the index of signal frequency from the vector that defines the frequency axis for plotting magnitude. `ind= find(fx==f)` command was used for this where *fx* is the vector containing frequency axis values, *f* is the variable containing signal frequency value and *ind* is the variable that stores index for that frequency. Next the presence of maximum value in magnitude vector at *ind* index is checked. If condition is true, the signal is periodic and PU is present. Otherwise PU is decided absent. Fig (14) shows the plots of various symbols with and without PU. It is obvious that there are peak values at the carrier frequency if the PU is present. The carrier frequency used here is 1000Hz and SNR is 10db.



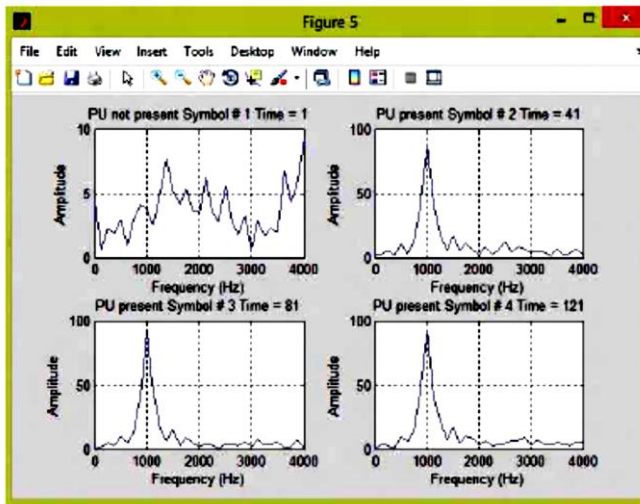


Fig 14: Cyclo-stationary Feature Detection in Matlab

### 3.6 Results:

The results gathered from the extensive simulations of the three spectrum sensing techniques provide useful insight on the performance of these techniques under different SNR conditions. The results for each technique are discussed on the basis of following metrics.

- Probability of detection in different SNR conditions
- Probability of false alarms in different SNR conditions
- Code complexity for each technique
- Estimated sensing speed as compared to other techniques
- Amount of prior information required for detection

#### 3.6.1. Energy Detector Performance:

As we already know, the matched filter doesn't have any requirements of pre requisite knowledge of the primary signal. Also its complexity is very low since it only involves addition of all the signal values and comparison with threshold. Therefore the detection time required for energy detection would also be very low. Thus the only metrics left to analyze for energy detection are probabilities of detection and false alarms.

#### 3.6.2. Probability of Detection:

The probability of detection for energy detection always stays 1 on all SNR values. The reason for it is matched filters compares the computed energy with a fixed threshold value and the decision can never be wrong when the PU is present as the computed value will always stay above the threshold. The negative values of SNR will only add more energy to the signal and hence the detection probability stays 1.

#### 3.6.3. Probability of False Alarms:

The false alarm probability of matched filter increases as the SNR decreases since the lower SNR values will add more energy to the signal and there comes a point such that the noise value alone becomes higher than the selected threshold. Fig (15) shows the plot of false alarm probabilities against SNR values. We can see that SNR values lower than 0 have a very high probability of false alarms. Thus it can be concluded that energy detector can only be used when SNR is higher than 0 and it has a very poor performance in low SNR

scenarios.

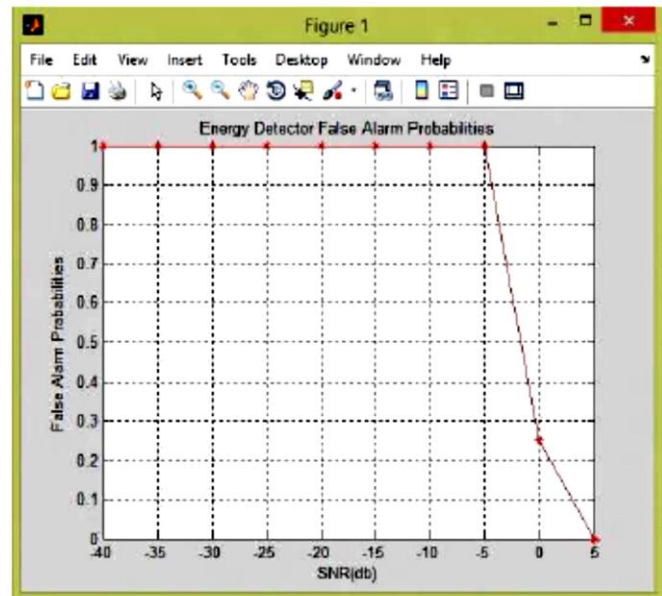


Fig 15: Energy Detector False Alarm Probabilities

#### 3.6.4 Threshold Adjustment:

While designing energy detector, we assume that we will have no prior knowledge of the primary user. Thus we assume that slight variance in transmitted energy from the PU can be possible although QPSK scheme has fixed energy in symbols. Reasons for which can be difference in transmission sources or in accuracy of transmission equipment. And in such cases, the false alarm probability and missed detection probability can overlap at certain threshold values when the SNR stays fixed. This creates a tradeoff situation between type 1 and type 2 errors as discussed in section 3.3. Therefore and adjustment

according to requirements may be needed. Fig (16) shows the plot of false alarm and missed detection probabilities when the SNR was fixed at -1 db and energy value was slightly varied. If it is desired to suffer lesser missed detections, one must chose a threshold that will have slightly higher probability of false alarms.

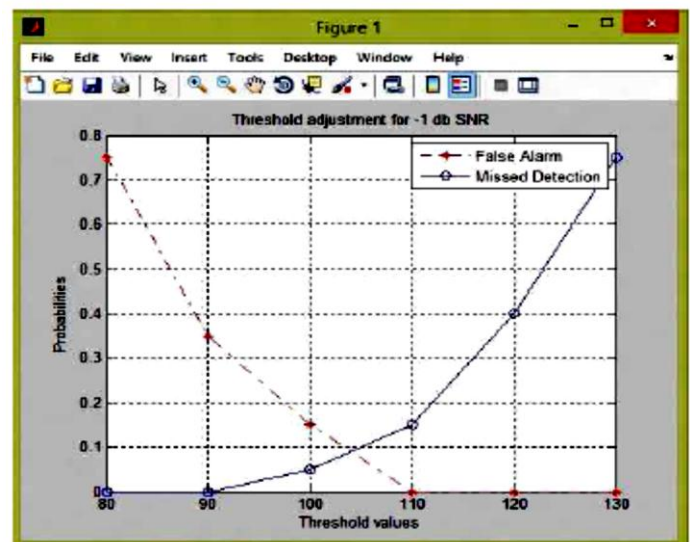


Fig 16: False alarm and missed detection probabilities



### 5.3. Matched Filter Performance:

The matched filter requires complete knowledge of the PU prior to detection process. In case of our simulation, the prior knowledge required is a sample of the modulated message signal to create a matched filter from, the energy of the signal to create threshold (which can be calculated from the sample) and also perfect synchronization of received symbols with the transmitted symbols. The complexity of the detection code is low but slightly higher than the energy detector. The code involves convolution of each symbol with the matched filter and then the maximum value of the output is computed. This value is then compared to a threshold. The comparison checks whether the output is between two decided values of threshold or not. The lower threshold value is  $2E-x$  and higher is  $2E+x$  where  $E$  is energy and  $x$  is any number which increases or decreases the false alarm probability.

#### 5.3.1 Detection Probability:

Fig (17) shows the detection probability plot against SNR values. It can be seen that matched filter has a better detection probability as long as the SNR stay above -10db. And below that it suddenly falls. The output of the matched filter comes from convolution of received signal with the matched filter response. Thus the maximum of output is slightly higher than  $2E$  because of the noise component which is also being convolved with the filter. And when the output becomes higher than the upper threshold limit, it is discarded as a false alarm. For this reason matched filter has a low detection probability in SNR that is lower than -10 db.

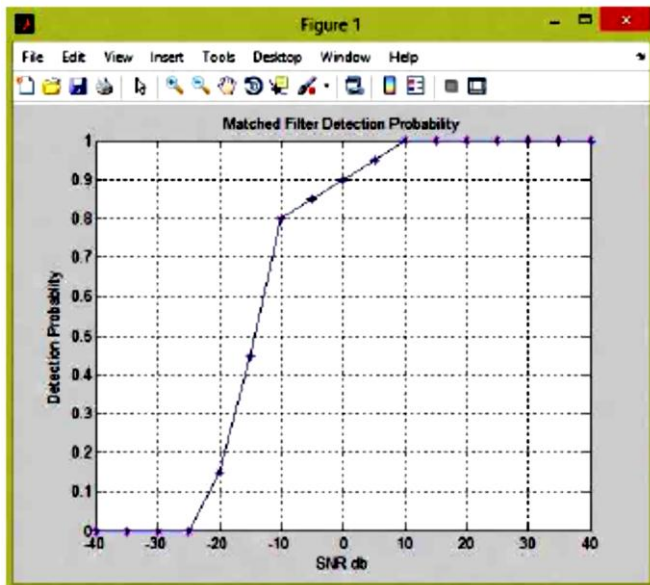


Fig 17: Matched Filter Detection Probabilities

### 5.4. Cyclo-Stationary Feature Detector Performance:

The prior knowledge required for CFD detection is the knowledge of carrier frequency of the transmitted signal. Symbol duration of the modulated signal will also be required so that the presence of double sided sine wave carriers can be detected in 1 or multiple symbols duration. The complexity of CFD is higher than both matched filter and energy detector techniques since it involves computation of Fourier transform for each symbol. Thus it has a higher detection time.

### 5.4.1 Detection probabilities:

Fig (18) shows the detection probability of CFD plotted against SNR values. It can be seen that CFD performs better than matched filter as its detection probability starts rising from -30db SNR and reaches 1 between -10db and 0db SNR. The reason is it doesn't use threshold and detects the presence of maximum amplitude value at the carrier frequency from the amplitude spectrum of the signal. Thus as long as the PU is present in the signal, the maximum amplitude value will be at the carrier frequency. And also the probability of false alarms will stay close to zero as the chances of getting a peak at the carrier frequency in the absence of PU are very low. And similarly if PU is present then the SNR value of less than -20 will cause the frequent occurrence of peaks at points other than the carrier frequency point. However in our simulation, we tested only the presence of sine wave carriers in the signals while a variety of more detailed CFD schemes are being developed which test the presence of other more reliable cyclic feature such as data rate and modulation type of the signal. Such techniques or more accurate and better performing in lower SNR regions but come at the price of greater computational complexity and cost with higher detection times.

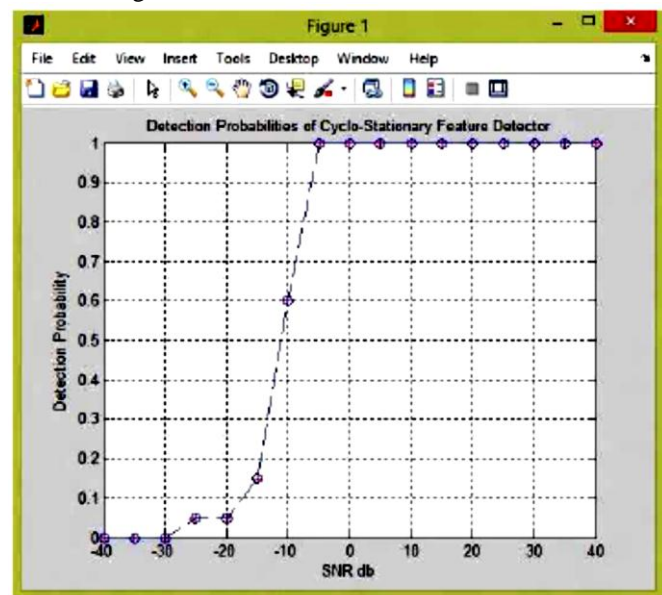


Fig 18: Detection probability of Cyclo-stationary Feature Detector

### 5.5. Compared Performance:

Fig (19) shows the detection probabilities of all three detection techniques from our simulation. From this it can be concluded that while operating in higher SNR, energy detector tends to be the best with very fast detection time and simplest and least complex implementation. And for lower SNRs, either of matched filter or CFD can be used from which CFD is better but has higher computational complexity and detection time than matched filter.

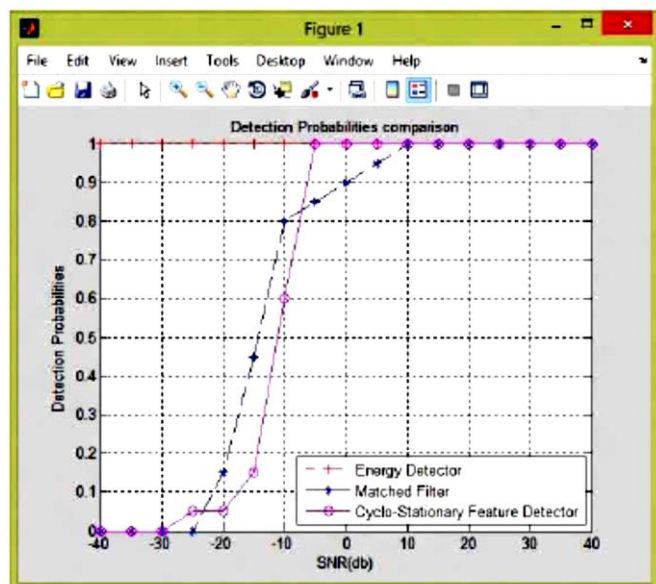


Fig 19: Detection probabilities Comparison

### 6.1. CONCLUSION:

Spectrum is a limited and very useful resource for wireless communications. The spectrum allocation charts suggest a considerable inefficient use of the available spectrum and possible spectrum shortage in near future. The idea of opportunistic spectrum use via cognitive radios is one of the answers for this problem. The most important and challenging function of cognitive radios is spectrum sensing. Steps to ensure the improvement of spectrum sensing techniques are already being taken by the FCC as they have allowed opportunistic use of various TV frequencies. In this research

we have discussed in detail the process of Matlab simulations for three most common spectrum sensing techniques, Energy Detector, Matched Filter and Cyclo-Stationary Feature Detector. Since the test signal we used was QPSK modulated, the Matlab design process for QPSK is also discussed. From the simulations it is shown that Energy Detection is a very less complicated and least costly solution for spectrum sensing. This scheme is non-coherent detection and having knowledge of the primary user before detection is not required. However its performance degrades drastically in SNRs lower than 5db as it cannot distinguish between noise and primary signal as the noise values rise and probability of false alarms start increasing. Matched Filtering gives better results in lower SNRs and has significantly better detection as compared to Energy Detection but in turn it requires a lot of prior knowledge of the primary signal as it performs coherent detection. Cyclo-stationary detection performs even better than both previous techniques as it can achieve 1 detection probability and 0 false alarm probabilities at -10db SNR. It

requires low amount of prior knowledge than Matched Filtering but it has a higher complexity and design cost than both the previous techniques. Therefore in scenarios when cost can be sacrificed over detection accuracy, Cyclo-Stationary Feature Detection is the best option to use.

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