

# Spectrum Monitoring and Interference Minimization Algorithm for OFDM-Based Cognitive Radio Networks

R. Swathi<sup>1</sup>, VVS. Murthy<sup>2</sup>

<sup>1</sup>Project Student, M.Tech (DECS),  
DVR & Dr. HS MIC College of Technology, Kanchikacherla

<sup>2</sup>Associate Professor, ECE department,  
DVR & Dr. HS MIC College of Technology, Kanchikacherla

**Abstract:** Cognitive radios network is programmable wireless devices to monitor spectrum used, and networking protocol as needed for better network and application performance. In Cognitive radio networks detection of licensed user reappearance during the non-licensed user transmission is very much required. This paper presents a spectrum monitoring algorithm in support of that purpose for OFDM based CR networks. The technique decreases the rate of spectrum monitoring and offers the chance of less time between primary transmission and its detection. Interference impact on proposed technique is studied and results are also presented.

**Keywords:** Cognitive radio network, OFDM, spectrum sensing/monitoring

## 1. Introduction

G. Marconi pioneered the world of wireless communications when he demonstrated his radio's ability to continuously contact ships sailing over the English Channel using an RF link. This historic event occurred in 1897 and triggered the rise of wireless technology. With improvements in RF technology, Wireless equipment has become portable and cheaper. The Figure 1.1 illustrates the occupancy of the spectrum and it shows that the spectrum is not prudently used and there are void spaces or holes in the spectrum. If the void spaces in the spectrum can be detected and used, then the problem of spectrum limitation can be solved to some extent. The race for occupying the increasing demand for bandwidth within a limited range of spectrum has given rise to a new technology known as **Cognitive Radio**.

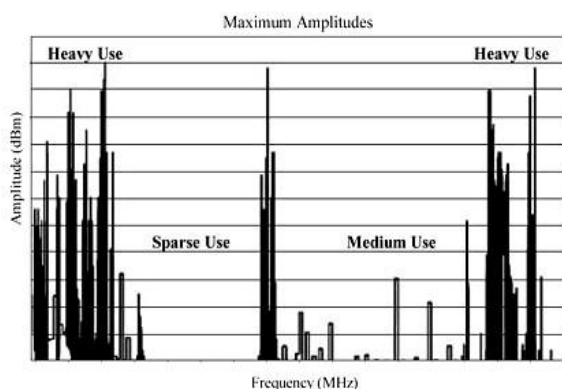


Figure 1.1: Occupancy of the spectrum

Present telecommunication technologies are facing difficulty to support large traffic growth, since wireless bands below 10 GHz are already flooded with users. In this situation, millimetre-wave (mm-wave) band is viewed as a solution with its 7 GHz unlicensed spectrum available for radio communication (57–64 GHz). Static spectrum access is the main policy for wireless communications. Primary User

(Licensed User) is the user who has an exclusive right to a certain spectrum band. In other words, the license holders are having no need to be aware of cognitive users. Secondary User (Unlicensed User) is known as Cognitive-radio enabled user and having lower priority than primary users. Under static spectrum access policy, fixed channels are assigned to licensed users or primary users (PUs) for exclusive use while unlicensed users or secondary users (SUs) are prohibited from accessing fixed channels even when they are vacant. The idea of a cognitive radio (CR) was proposed to achieve efficient utilization of the RF spectrum. Cognitive networks uses the overlay network model in which Secondary Users seeks to use the spectrum when the Primary User is idle. Primary and secondary users are not permitted to operate simultaneously. In this method, secondary users must monitor the spectrum whether it is available or not prior to communication. If the primary user (PU) is idle, the SU can then use the spectrum. Even SU must be able to sense very weak signals from the primary user otherwise Interference will be high at that time. If the SU must periodically stop communicating to detect the emergence of the PU, the following effects should be studied. For quite periods, the secondary user (SU) receiver may lose its synchronization to the secondary user transmitter which causes an overall degradation in the secondary network performance. The throughput of the secondary users network during sensing intervals is reduced to zero which degrading the Quality of Service (QoS) for those real-time applications like Voice over IP. **Spectrum sensing** is an important and a sensitive task in **Cognitive Radio** since interfering with other users is illegal. Spectrum holes are not stable and they migrate with frequency and time as shown in the Figure 1.2. The spectrum sensing algorithm should be fast enough to rapidly detect the moving holes in the spectrum in real time. Spectrum sensing is also computational expensive and requires special hardware to implement. Furthermore in the case of Low SNR scenario the noise power affects the operation of the spectrum Sensing algorithm thereby affecting the whole detection process. The spectrum sensing algorithm used must be

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sensitive enough to distinguish between the signal power and the noise power. The main objective of this paper is to simulate Energy Ratio Algorithm using MATLAB for the purpose of spectrum sensing in cognitive radio and to plot Receiver Operating Characteristics (ROC).

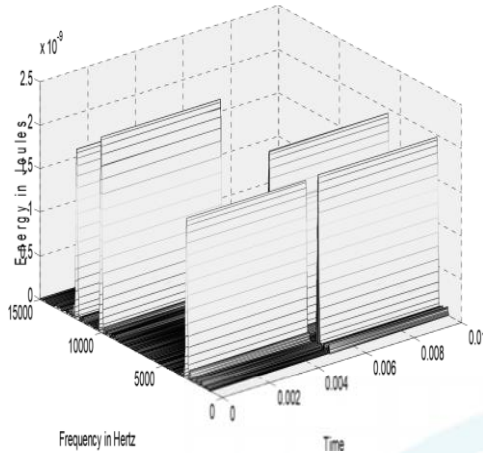


Figure 1.2: Migration of the holes in the spectrum

## 2. Spectrum Sensing Techniques

An important requirement of the CR is to sense the spectrum holes. It is designed to be aware of and sensitive to the changes its surrounding. The spectrum sensing function enables the cognitive radio to adapt to its environment by detecting the primary users that are receiving data within the communication range of CR user.

### 2.1 Classification of Spectrum Sensing:

The most efficient known method of detecting spectrum holes is to detect the Primary users that are transmitting data within the Communication range of a CR user. Generally, the spectrum sensing techniques can be classified as transmitter detection, cooperative detection, and interference-based detection.

#### 2.1.1 Transmitter Detection

In transmitter detection we have to find the primary transmitters that are transmitting at any given time. Hypothesis model for transmitter detection is defined in that is, the signal received (detected) by the CR (secondary) user is  $x(t) = n(t)H_0$ .

$$x(t) = h_s(t) + n(t)H_1$$

$x(t)$  is the signal received by the cognitive radio,  $s(t)$  is the signal transmitted by the primary user,  $h_s(t)$  is the amplitude gain,  $n(t)$  is the additive white Gaussian noise.

##### 2.1.1.1 Matched Filter Detection

A matched filter is a linear filter designed to provide the maximum signal-to noise ratio at its output for a given transmitted waveform. Figure 2.1 depicts the block diagram of matched filter. The signal received by CR is input to matched filter which is  $r(t) = s(t) + n(t)$ . The matched filter

convolves the  $r(t)$  with  $h(t)$  where  $h(t) = s(T-t + \tau)$ . Finally the output of matched filter is compared with a threshold  $\lambda$  to decide whether the primary user is present or not

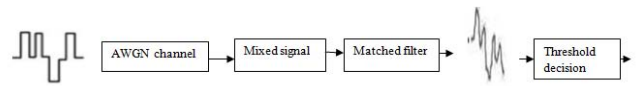


Figure 2.1: Block Diagram of Matched Filter

A Matched filter is an optimal detector in AWGN if the wave form of the primary user is previously known by CR. It means that CR should have knowledge about the waveform of primary user such as modulation type and order, the pulse shape and the packet format. CR may not detect primary user without that type of prior information. Advantage of matched filter is that it takes less time for high processing gain. However major drawback of Matched Filter is at a CR would need a dedicated receiver for every primary user class.

#### 2.1.1.2 Energy Detection

If CR can't have sufficient information about primary user's waveform, then the matched filter is not the optimal choice. However if it is aware of the power of the random Gaussian noise, then energy detector is optimal. In the authors proposed the energy detector as shown in Figure 2.2. The input band pass filter selects the center frequency  $f_s$  and bandwidth of interest  $\omega$ . The filter is followed by a squaring device to measure the received energy then the integrator determines the observation interval,  $T$ . Finally the output of the integrator,  $Y$  is compared with a threshold,  $\lambda$  to decide whether primary user is present or not.

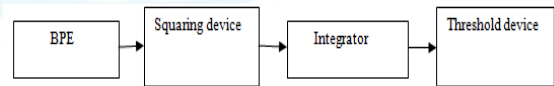


Figure 2.2: Block Diagram of energy detector

In a non fading environment where  $h$  is amplitude gain of the channel, probability of detection  $P_d$  and probability of false alarm  $P_f$  are given by following formulas

$$P_d = P(Y > \lambda / H_1) = Q_m(\sqrt{2\gamma}, \sqrt{\lambda})$$

$$P_f = P(Y > \lambda / H_0) = \Gamma(m, \lambda / 2) / \Gamma(m)$$

Where  $Y$  is the SNR,  $m = T\omega$  is the (observation/sensing) time bandwidth product  $\Gamma(\cdot)$  and  $\Gamma(\cdot, \cdot)$  are complete and incomplete gamma functions,  $Q_m(\cdot)$  is the generalized Marcum Q-function. In a fading environment  $h$  is the amplitude gain of the channel that varies due to the shadowing or fading effect which makes the SNR variable.  $P_f$  is the same as that of non fading case because  $P_f$  is independent of SNR.  $P_d$  gives the probability of detection conditioned on instantaneous SNR. In this case average probability of detection may be derived by averaging over fading statistics:

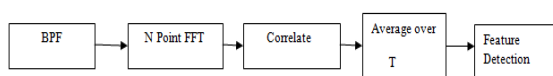
$$P_d = \int x Q_m(\sqrt{2\gamma}, \sqrt{\lambda}) f_\gamma(x) dx$$

where  $f_\gamma(x)$  is the probability distribution function of SNR

under fading. One of the main problems of energy detection is that performance is susceptible to uncertainty in noise power. It cannot differentiate between signal power and noise power rather it just tells us about absence or presence of the primary user.

### 2.1.1.3 Cyclostationary Feature Detection

Cyclostationary feature detection based on introduction of periodic redundancy into a signal by sampling and modulation. The periodicity in the received primary signal to identify the presence of Primary Users (PU) is exploited by Cyclostationary feature detector. Cyclostationary feature detector implementation can differentiate the modulated signal from the additive noise, distinguish Primary User signal from noise. It is used at very low SNR detection by using the information embedded in the Primary User signal which does not exist in the noise.



**Figure 2.3:** Block diagram of Cyclostationary Detection

This technique is robust to noise discrimination and it performs better than energy detector. It has disadvantage of more computational complexity and longer time observation.

### 2.1.2 Receiver Detection

Now we need such spectrum sensing techniques which are able to remove the problems in transmitter detection. To remove receiver's uncertainty, we have to design techniques which we have some information about primary receiver. The makers of transmitter detection techniques state that we have available the information of primary receiver. The detection of weak signals from primary transmitter where it was shown that the problems becomes very difficult when there is uncertainty in the receiver noise variance. Then new spectrum sensing techniques are introduced in which we will get information about receiver from its own architecture.

### 2.1.3 Interference Temperature Management

Interference is typically regulated in a transmitter centric way. Interference can be controlled at the transmitter through radiated power, out-of-band emissions, location of individual transmitters and frequencies used by specific type of radio operations. These interference management techniques served well in the past but do not take into account the interference from the receiver point of view, as most of interferences occur at the receiver. Moreover, the dramatic increase in the overall demand for spectrum based services, rapid technical advancements in radio systems; in particular the introduction of new robust modulation techniques demands a new technique that focuses on actual RF environment and interaction between transmitter and receiver.

This demand moves us towards new interference management technique known as Interference Temperature Management. We can define interference temperature as measure of the RF power generated by undesired (CR) emitters plus noise that is

present in the receiver system per unit of bandwidth. The emissions from undesired (CR) transmitters could include out of band emission from transmitters operating on adjacent frequencies as well as from transmitters operating on the same frequency as a desired transmitter. In principle, the interference temperature measurements would be taken at various receiver locations and these measurements would be combined to estimate real time condition of RF environment. The interference temperature model shown below explains the signal of a radio designed to operate in a range at which the received power approaches the level of the noise floor. As additional interfering signals appear, the noise floor increases at various points within the service area, as indicated by the peaks above the original noise floor. This model manages the interference at the receiver through the interference temperature limit, which is represented by the amount of new interference that the receiver can tolerate.

## 3. Methodology

For reducing the effect of Inter-Symbol Interference (ISI) in frequency domain OFDM system, the last  $N_g$  samples of the time domain OFDM symbol is copy to the beginning of the symbol to form a guard time or cyclic prefix. Therefore, the OFDM block has a period of  $T_s = (N_s + N_g)/F_s$  where  $F_s$  is the sampling frequency. At the receiver, the inverse block is applied. After time synchronization (frame detection, start of symbol timing, and SFO estimation and compensation) and frequency synchronization (CFO estimation and correction), the cyclic prefix is removed. Then, the received OFDM symbol are transformed into the frequency domain through an  $N_s$  point DFT. The channel is then estimated and the received data is equalized. The complex data output is then mapped to bits again through the De-mapper. De-interleaving, decoding, and randomization is applied later to the received block to recover the original source bits. From the network point of view, we consider a cognitive radio network of  $K$  SUs and one PU. The PU occupies a spectrum of a certain bandwidth for its transmission, while the same sensed spectrum is shared by the SUs. In fact, the spectrum is totally utilized by one SU (the master node or the fusion node) to send different data to the other  $K - 1$  SUs (the slave nodes). In our model, the fusion node constructs OFDM frames in the downlink path such that the same pilots are transmitted to all slaves but the data sub-carriers are allocated in time and frequency for different users based on a predefined scheduling technique. For the return path, Orthogonal Frequency Division Multiple Access (OFDMA) is assumed to divide the spectrum and the time into distinct and non-overlapping channels for different slaves, so that interferences between the slaves is avoided. The fusion node fully controls the timing of each slave, possibly by letting the slave know the required time advance or delay, so that the combined signal from all slaves seem to be synchronized at the fusion node receiver. In this case, the fusion node can convert the signal back to the frequency domain to extract the data and control information from different slaves.

### 3.1 Energy Ratio Algorithm

The overall algorithm is illustrated by Figure 3.1 It is assumed that the primary signal appears after some time

during the monitoring phase. At the secondary receiver, after CP removal and frequency domain processing on the received signal, the reserved tones from different OFDM symbols are combined to form one sequence of complex samples. Two consecutive equal-sized sliding windows are passed over the reserved tone sequence in the time direction. The energy of the samples that fall in one window is evaluated and the ratio of the two energies is taken as the decision making variable and hence the name energy ratio. The algorithm aims to check the change in variance on the reserved tones over time. In a mathematical form, let  $Z_i$  be the  $i^{\text{th}}$  sample of the reserved tone sequence. The decision making variable,  $X_k$ , can be defined as given by (1) where  $N$  is the number of samples per window,  $U_k$  is the energy of the second window,  $V_k$  is the energy of the first window, and  $k$  is an integer such that  $k = 1, 2, 3, \dots$

$$X_k = \frac{U_k}{V_k} = \frac{\sum_{i=N+k}^{2N+k-1} |Z_i|^2}{\sum_{i=k}^{N-1} |Z_i|^2}$$

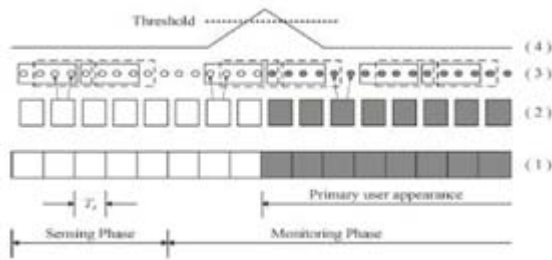


Fig 3.1: Energy ratio processing details (1) the time domain sequence for the OFDM blocks (2) frequency domain sample (3) reserved tones processing with two sliding windows for  $NRT = 2$  &  $N = 4$ . (4) Decision making variable  $X_k$ .

It is mentioned that the reserved tones processing done by the energy ratio algorithm starts from the beginning of the sensing phase. Meaning that, the decision making variable is evaluated during both sensing and monitoring phases. However, it provides decisions only during monitoring phase. During the sensing phase, if the decision from the spectrum sensing algorithm is that the PU is inactive, then the energy ratio algorithm has been properly calibrated to be able to detect the appearance of the PU during monitoring phase. Calibration means that both sliding windows are filled with pure unwanted signals. During the monitoring phase, the receiver monitors the reserved tones by evaluating the parameter,  $X_k$ . If it exceeds a certain threshold, then the secondary user assumes that there is a power change on the reserved tones which perhaps due to the primary user appearance and it is time to vacate the band. If not the secondary user can continue transmission. Indeed, if there is no primary user in band, then the energy of each window still involves only the strength of the unwanted signals including the noise, the leakage from the neighboring sub-carriers, and the effects of ICI produced by the residual synchronization

errors. Therefore, if  $N$  is large enough, the ratio will be very close to unity since the strength of the unwanted signals does not offer significant changes over time. Once the primary user appears, the second window will have two types of signaling which are the primary user interference and the unwanted signals. Meanwhile, the first window will only maintain the unwanted signals without the primary user interference. The ratio of the two energies will result in much higher values when compared to one. The value will of course depend on the primary user power. When the two windows slide again, the primary signal plus the unwanted signals will be observed by the two windows and the decision making variable returns to the initial state in which the ratio is close to unity. Thus, we can expect that the decision variable produces a spike when the primary user is detected. Otherwise, it changes very slowly maintaining the energy ratio close to one as shown in Figure 3.1 part (4). This approach can resist the different impairments involved in the received signal on the account of reducing the throughput of the secondary user by the ratio of the number of reserved tones to the number of useful tones. However, this reduction can be easily overcome since OFDM systems allow adaptive modulation where good conditioned sub-carriers are loaded with higher modulation order.

For the previous discussion, it is assumed that the primary user should appear at the boundaries of the OFDM blocks. Therefore, the reserved tones should have the full power, which is supposed to be for those sub-carrier indices, of the primary user when it is active. In reality, the primary user may appear any time within any OFDM block in the monitoring phase. In this case, we have to consider two effects. (1) The FFT window applied by the SU receiver will have a time-shifted version of the PU signal which involves a phase rotation to the PU sub-carriers. Since the energy is the useful parameter for our algorithm, the phase shift is acceptable to happen with no effect on the algorithm. (2) The power on the reserved tones will not have the full power transmitted by the primary user on those sub-carriers since part of the signal is truncated. However, the next OFDM symbol will have that full power. Similar to the near-far problem, if the PU power is large enough, then the reserved tones form the first OFDM symbol, in which PU signal appears, are considered to be full. Otherwise, the reserved tones from this OFDM symbol are considered as noise if  $N \gg NRT$ .

### 3.2 Energy ratio Algorithm for MIMO System

To evaluate the energy ratio from complexity point of view, we propose architecture for the algorithm and then analyze the corresponding complexity and compare it to the traditional energy detectors. The proposed architecture is shown in Figure 3.2 First; the reserved tone sequence is injected to be squared. Next, two first-In first-Out (FIFO) memories are used to store the squared outputs to manage the energy evaluation for the two windows. The idea depends on the sliding concept for the windows where the total energy enclosed by one window can be evaluated by only adding the absolute squared of the new sample and subtracting the absolute squared of the last sample in the previous window as given

$$V(k) = \sum_{i=k}^{N+k-1} |Z_i|^2$$

$$V(k) = V(k-1) + |Z_{N+k-1}|^2 - |Z_{k-1}|^2$$

The ratio may not be evaluated directly, instead we can multiply the energy of the first window by the threshold and the multiplication output is then compared to the energy of the second window

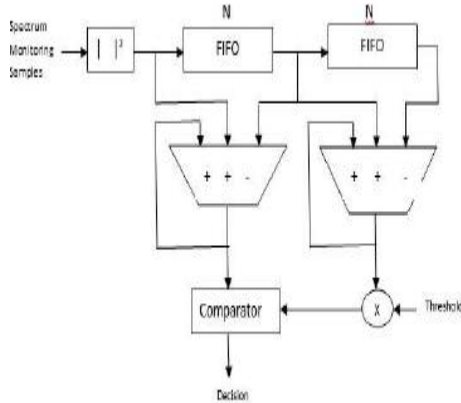


Figure 3.2: Proposed architecture for the energy ratio the algorithm

3.3 Algorithm to implement the algorithm

STEP 1. We are clearing the Command window, Clearing the workspace and closing the previous figures in the tool MATLAB.

STEP 2. Considering the input parameter of Cognitive radio Network such as time bandwidth Factor, no of samples, pathloss exponent, no. of cognitive users, probability of false alarm etc.

STEP 3: Initially we are going to calculate lambda value for threshold and further calculation of load spectrum sensing.

STEP 4: We are considering random distance and initial pathloss, which are going to update in the further operation.

STEP 5: We are considering Monticalro Simulation for ten to hundred noise realization.

STEP 6: We are considering the Additive White Gaussian Noise as the channel medium.

STEP 7: After passing into the medium we collect the signal at the receiver end and calculate generalized Marcum Q function for the energy of detection process.

STEP 8: For the detection of energy we are considering the variable PDSIM by using which we are going to find the probability of MISS detection.

STEP 9: Now we are considering the CFO(Carrier frequency Offset operation)and SFO operation for estimating and calculating the receiver characteristics.

1. We are considering no. of data sub carriers and the size of prefix which is going to apply the receiver processing looping operation of CFO, where we are going to calculate detection probability bit error rate.
2. We are going to consider total sub carriers, over sampling index, count Index for SFO, in which we are going to calculate the detection probability.

STEP 10: We are considering SISO and MIMO models for antenna configuration by which we are getting the detection probability (MIMO2\*2, 4\*4)

Now we are considering the main for loop of mean square error by using

1. Random channel taps
2. Generation of symbols(BPSK)
3. Channel convolution and AWGN
4. Receiver Processing
5. Frequency domain channel estimation
6. Frequency domain mean square error estimation.
7. Time Domain mean square error estimation
8. Neglecting channel Covariance.
9. Neglecting Smoothing Matrix.
10. Calculation final square error and detection probability of all methods collectively.

Steps to implement the Sub channel activity Index algorithm:

STEP 1: Subchannel activity index method in Novel Inter cell power allocation, for multicarrier Cognitive cellular network.

STEP 2: We are considering 2 User's and 4 data sub carriers for which they are considering ten thousand as the number of processing bits.

Steps to processing:

1. Generation of User data.
2. Spreading the data into blocks
3. Applying IFFT.
4. Adding cyclic prefix.

The above points we will implement for the 2 user's model. We will consider channel as Rayleigh Fading which contains Four different power tapings and gain factor. We are calculating different time delay for different tapping. We are generating a unique data channel for 4 different tapings. We are considering AWGN for transmitting data in the Receiver section. Initially we are removing the cyclic prefix. We are applying the FFT. We are applying the channel equalization and calculating the means Square error of two users.

Comparing the MSE result with previous results

4. Results

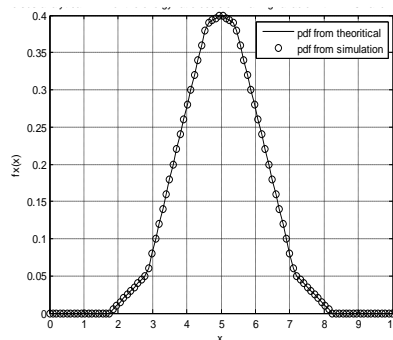


Figure 4.1: Simulated PDF versus analytical PDF for the energy ratio algorithm making variable with N=32 and 10(σ²u/σ²v)=5db

Figure 4.1 shows a comparison between the PDF given by (4-1)

$$= \frac{\sigma_v^2 \Gamma(2N) (\sigma_v^2 x / \sigma_u^2)^{N-1}}{\sigma_u^2 \Gamma^2(N) (1 + \sigma_v^2 x / \sigma_u^2)^{2N}}, \quad x \geq 0 \quad \text{-----(4-1)}$$

and the one obtained from simulation where we have used  $10\log_{10}(\sigma^2_u/\sigma^2_v)=5$  dB and an energy ratio window  $N = 32$ . To obtain the simulated PDF, circularly symmetric Gaussian distributed samples are generated and scaled properly for both windows. The samples are then applied to the energy ratio algorithm and the PDF is obtained by considering the histogram of the decision making variable. It is obvious that the analytical results are in excellent agreement with the simulated ones.

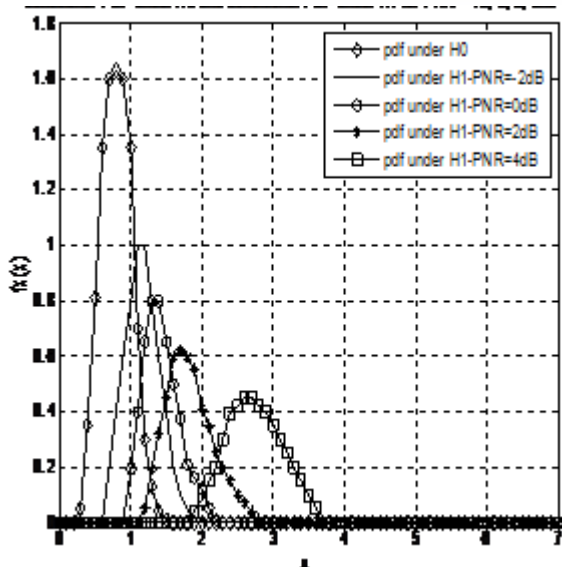


Figure 4.2: Conditional PDF under H0 and conditional PDF under H1 for PNR= -2, 0, 2 and 4db.

The hypothesis test is to be verified by exploring the conditional PDF under both H0 and H1. In fact, when there is no primary user in band, the decision variable follows only one unique PDF that is shown in Figure 4.2 under H1, the conditional PDF depends on the PNR ratio. Four additional curves are also shown in Figure 4.2 for the conditional PDF under H1 with four different PNR values (-2, 0, 2, and 4 dB). It is clear that the decision variable can distinguish between no primary user case and primary user presence based on the PNR.

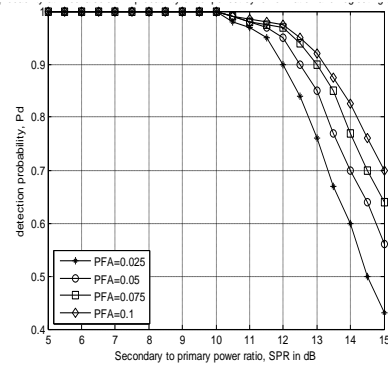


Figure 4.3: The detection probability for four different false alarm probabilities under perfect synchronization and neglecting the power leakage effect

Receiver characteristics:

The detection probability for four different false alarm probabilities is shown in Figure 4.3 The horizontal axis denotes the secondary to primary power ratio (SPR) which is related to the primary to secondary noise ratio (PNR) such that  $PNR|_{dB} = SNR|_{dB} - SPR|_{dB}$ , where SNR is the secondary power to noise power ratio. It is to be noticed that, PNR is the ratio that determines the performance of the energy ratio algorithm.

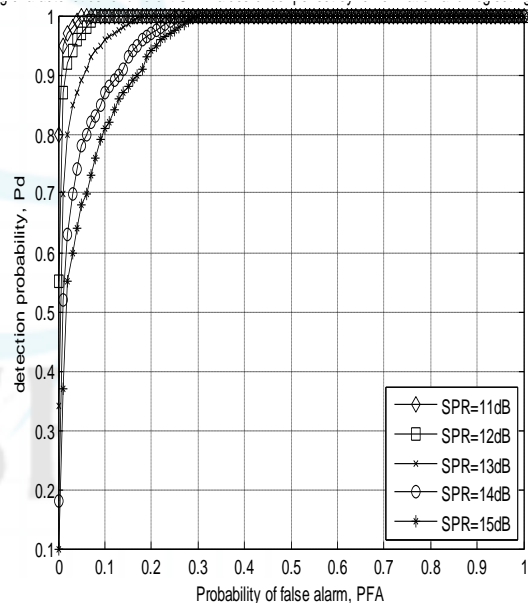
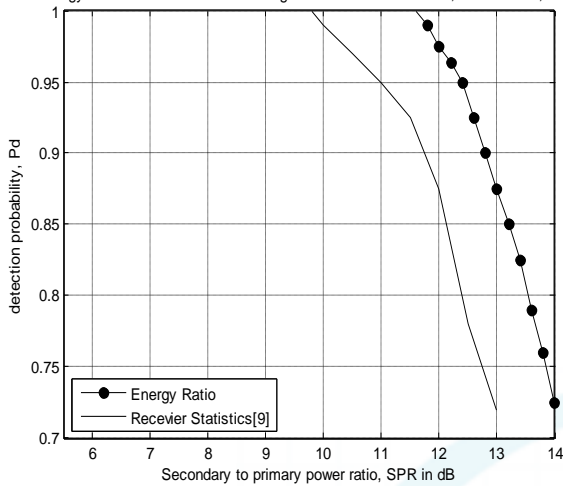


Figure 4.4: Receiver operating characteristics for different SPR values under perfect synchronization and neglecting the power leakage effect

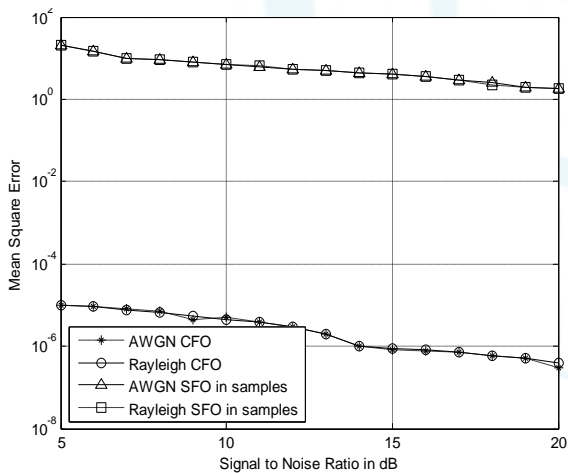
The ROC for the energy ratio for different values of SPR is shown in Figure 4.4 These results are obtained by simulating the OFDM system twice, one when primary signal is present and the second when it is absent. The system is run over 106 realizations and the probability of detection or false alarm is evaluated. The threshold is set based on the theoretical value given by (4-2). In order to compare the proposed monitoring algorithm with the receiver statistics technique the OFDM system is simulated such that the system parameters match the simulation environment. The simulation is run for 4-QAM under SNR = 6 dB, PFA = 0.04, and N = 128.

$$\gamma = \frac{I_{1-P_{FA}}^{-1}(N, N)}{1 - I_{1-P_{FA}}^{-1}(N, N)} \quad \text{-----(4-2)}$$



**Figure 4.5:** Comparison between energy ratio and receiver statistics algorithms in case of QPSK, SNR = 6 dB, PFA = 0.04, and N = 128

Figure 4.5 shows the simulation results for the detection probability of the energy ratio algorithm in comparison with the results obtained in receiver statistics. In addition of having fast detection, it is noted that the energy ratio shows a better performance than the receiver statistics algorithm.



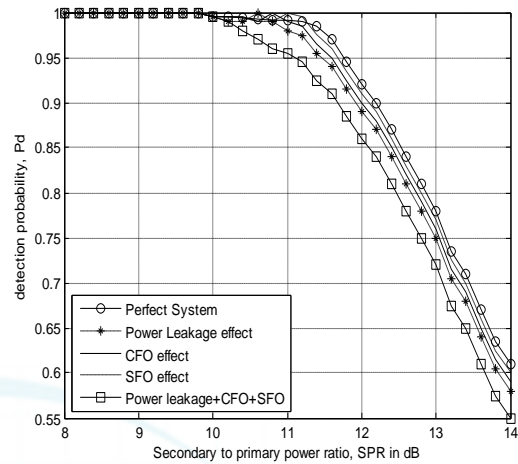
**Figure 4.6:** MSE for both CFO and SFO estimation under AWGN and frequency selective fading channels. The MSE for SFO is measured in samples

Figure 4.6 shows the mean square error for the estimated CFO and SFO. From these results, we can see that the residual fractional CFO and SFO at 9 dB are  $9 \times 10^{-3}$  and  $5 \times 10^{-6}$ , respectively. This implies SNR degradation of  $\text{SNR}_{\text{DCFO}} = 0.0092$  dB for CFO, and  $\text{SNR}_{\text{DSFO}}(1023) = 0.003$  dB for SFO at the last sub-carrier, based on (4-3) and (4-4), respectively.

$$\text{SNR}_{\text{DCFO}} \Big|_{\text{dB}} = \frac{10}{3 \ln(10)} (\pi \epsilon_r)^2 \text{SNR} \quad \text{-----(4-3)}$$

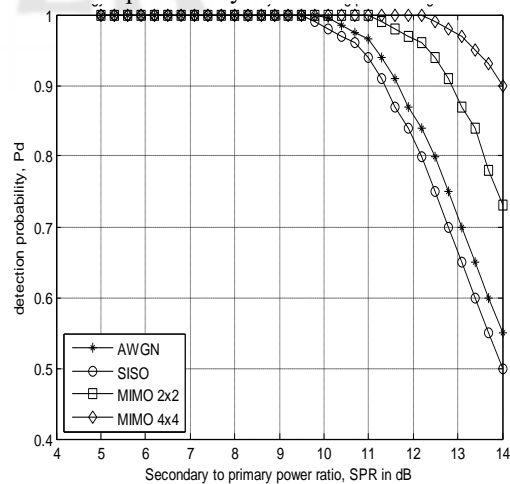
$$\text{SNR}_{\text{DSFO}}(k) \Big|_{\text{dB}} = 10 \log_{10} \left( 1 + \frac{1}{3} (\pi \delta_r k)^2 \text{SNR} \right) \quad \text{-----(4-4)}$$

This shows the advantages of the powerful estimation techniques we have chosen for the OFDM synchronization engine.



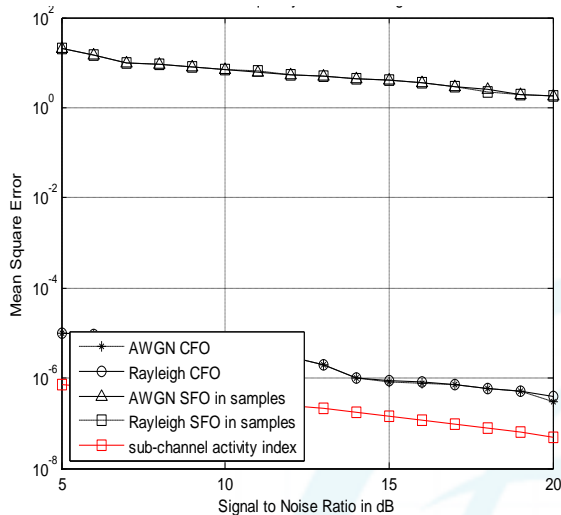
**Figure 4.7:** Power leakage, CFO and SFO effects on the energy ratio algorithm at PFA=0.025.

To examine the combined effects of OFDM impairments, the detection probability for the energy ratio is simulated in the presence of power leakage, CFO, and SFO as shown in Figure 4.7. The signal is oversampled four times by applying 4096 points DFT at the receiver to allow the emulation of the continuous spectrum. The sub-carriers are then selected by sampling this spectrum every four samples. Since the sub-carrier shape becomes narrower because of the Hanning window, the introduced ICI by the residual CFO and SFO errors has a very small noticed degradation. Therefore, if windowing, CFO and SFO estimations and compensations are applied, the power leakage to neighboring sub-carriers does not introduce severe degradation to the PU detection. As we claimed earlier, the energy ratio is shown to be robust to OFDM challenges as only minor degradation in detection performance is noted compared to the perfect case. For instance, the overall loss due to all impairments is only 0.4 dB at a detection probability PD = 0.9.



**Figure 4.8:** frequency selective fading channel effect on energy ratio for SISO and MIMO systems Taking power leakage and ICI into consideration. PFA=0.025 and n=128.

The OFDM system is simulated in frequency selective channel for different SPR. In Figure 4.8, we show the effect of frequency selective fading channel on the energy ratio performance for SISO,  $2 \times 2$  MIMO, and  $4 \times 4$  MIMO systems. The fading channel effect is compared with the AWGN channel where a minor degradation is noticed due to the narrow band problem. From these results, it is clear that having more receive antennas will offer great enhancement to the detection accuracy of the energy ratio detector.



**Figure 4.9:** MSE for both CFO and SFO estimation under AWGN and frequency selective fading channels. The MSE for SFO is measured in samples.

By using the sub channel activity algorithm the Mean square error is reduced. The OFDM offset can be degraded.

## 5. Conclusion and Future Scope

We proposed a spectrum monitoring algorithm that can sense the reappearance of the primary user during the secondary user transmission. This algorithm, named “energy ratio” is designed for OFDM systems such as Ecma-392 and IEEE 802.11af systems. We also derived the detection probability and the probability of false alarm for AWGN channels to analyze the performance of the proposed algorithm. Simulation results indicate that the detection performance is superior to the receiver statistics method. For computational complexity, the energy ratio architecture is investigated where it was shown that it requires only about double the complexity of the conventional energy detector. When frequency-selective fading is studied, the energy ratio algorithm is shown to achieve good performance that is enhanced by involving SIMO or MIMO systems. We have proven that the multiple receive antenna system will further result in a better detection accuracy by emulating the increase in sliding window size. Therefore, our proposed spectrum monitoring algorithm can greatly enhance the performance of OFDM-based cognitive networks by improving the detection performance with a very limited reduction in the secondary network throughput.

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