

## UEC1728 - Cognitive Radio Assignment

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### 1 Energy Detection

#### Aim:

To detect the unknown PU (Primary user) signal based on energy of the received signal. The Energy detector is optimal to detect the unknown signal if the noise power is known. In the energy detection, CR users sense the presence/absence of the PUs based on the energy of the received signals. As above, the measured signal  $r(t)$  is squared and integrated over the observation interval  $T$ . Finally, the output of the integrator's compared with a threshold  $k$  to decide if a PU is present. Since the energy detection depends only on the SNR of the received signal, its performance is susceptible to uncertainty in noise power. If the noise power is uncertain, the energy detector will not be able to detect the signal reliably as the SNR is less than a certain threshold, called an SNR wall. In addition, the energy detector can only determine the presence of the signal but cannot differentiate signal types.

i) Code for performance of detector (pd) under various values of probability of false alarm (pfa) for SNR = 6dB

```
1 % energy_detection_pfa.m
2 clc;
3 close all;
4 m = 10;
5 N = 2 * m;
6 pf = logspace(-5,0,20);
7 snr_avgdB = 4;
8 snr_avg = power(10, snr_avgdB / 10);
9 for i = 1:length(pf)
10     over_num = 0;
11     th(i) = gammaincinv(1 - pf(i), 2 * m);
12     for kk = 1:1000
13         t = 1:N;
14         x = sin(pi * t);
15         noise = randn(1, N);
16         pn = mean(noise.^2);
17         amp = sqrt(noise.^2 * snr_avg);
18         x = amp .* x ./ abs(x);
```

```

19     SNRdB_Sample = 10 * log10(x.^2 ./ (noise.^2));
20     signal = x(1:N);
21     ps = mean(abs(signal).^2);
22     Rev_sig = signal + noise;
23     accum_power(i) = sum(abs(Rev_sig)) / pn;
24     if accum_power(i) > th(i)
25         over_num = over_num + 1;
26     end
27 end
28 pd_sim(i) = over_num / kk;
29 end
30 figure;
31 s = semilogy(pf, pd_sim, 'r-*');
32 set(s, 'linewidth', 1);
33 title('Nonfluctuating Coherent ROC');
34 grid on;
35 xlabel('Probability of Falsed Alarm (pfa)');
36 ylabel('Probability of Detection (pd)');
37 legend(['SNR=' num2str(snr_avgdB) 'dB']);

```

ii) Code for performance of detector under various values of signal to noise ratio (SNR)

```

1 % energy_detection_snr.m
2 clc;
3 close all;
4 m = 10;
5 N = 2 * m;
6 pd_sim = [];
7 pf = 0.5;
8 for snr_avgdB = 0:1:30
9     snr_avg = power(10, snr_avgdB / 10);
10    for i = 1:length(pf)
11        over_num = 0;
12        th(i) = gammaincinv(1 - pf(i), 2 * m);
13        for kk = 1:1000
14            t = 1:N;
15            x = sin(pi * t);
16            noise = randn(1, N);
17            pn = mean(noise.^2);
18            amp = sqrt(noise.^2 * snr_avg);
19            x = amp .* x ./ abs(x);
20            SNRdB_Sample = 10 * log10(x.^2 ./ (noise.^2));
21            signal = x(1:N);
22            ps = mean(abs(signal).^2);
23            Rev_sig = signal + noise;
24            accum_power(i) = sum(abs(Rev_sig)) / pn;
25            if accum_power(i) > th(i)
26                over_num = over_num + 1;

```

```

27         end
28     end
29     pd_sim = [pd_sim over_num / kk];
30 end
31 end
32 figure;
33 SNR = 0:1:30;
34 s = plot(SNR, pd_sim, 'r-*');
35 set(s, 'linewidth', 1);
36 title('Energy detection method');
37 grid on;
38 xlabel('Signal-to-noise ratio (dB)');
39 ylabel('Probability of Detection (pd)');
40 legend(['PFA=' num2str(pf)]);

```

Results and Inference:

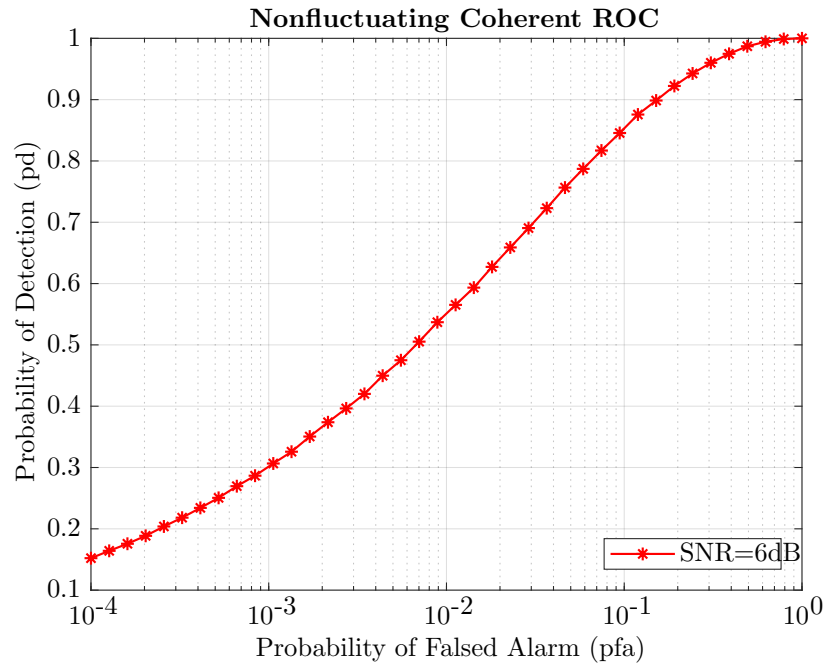


Figure 1.1: Pd vs Pfa for Energy Detection (SNR = 6dB)

From Figure 1.1, we can infer the fact that there is an trade-off/inverse relationship between Pd and Pfa. Since we want Pd value to be high (greater than 0.5), we see that the corresponding Pfa values range from 0.01 to 0.8. After that the detection probability Pd is approximately 1 for SNR = 6 db.

From Figure 1.2, we can infer that the relation is between Pd and SNR is linear for a certain range after which Pd saturates for higher values of SNR (for Pfa = 0.5). For lower values of SNR the detection probability is almost 0 and

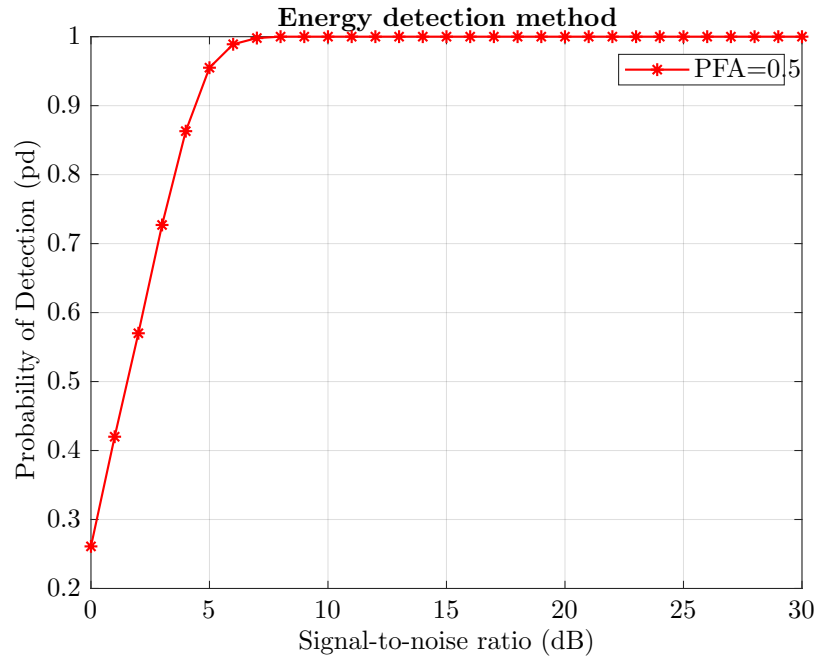


Figure 1.2: Pd vs SNR for Energy Detection ( $P_{fa} = 0.5$ )

increasing at a constant slope for every dB increase in SNR. Above 5 db the detection probability Pd saturates 1.

## 2 Matched Filter Detection

### Aim:

To detect the unknown PU (Primary user) signal based on Prior knowledge (bandwidth, operating frequency, modulation type etc) and to maximize the SNR. When the user has information on the primary user signal, the optimal detector in stationary Gaussian noise happens to be the matched filter as it maximizes the received signal-to-noise ratio (SNR). The palpable advantage of matched filter lies in its requirement of smaller time for achieving high processing gain for the reason of coherence and of a prior knowledge of the basic user signal like the modulation type and order, the shape of the pulse and the packet format. The performance of the matched filter will be poor if this information has no accuracy.

**i) Code for performance of detector (pd) under various values of probability of false alarm (pfa) for SNR = 6dB**

```

1 % matched_filter_detection_pfa.m
2 clc;
3 close all;
```

```

4  rstream = RandStream.create('mt19937ar', 'seed', 2009);
5  Ntrial = 1e5; % number of Monte-Carlo trials
6  spower = 1; % signal power is 1
7  pd_graph = [];
8  for snrdb = 6 % SNR in dB
9      snr = db2pow(snrdb); % SNR in linear scale
10     npower = spower / snr; % noise power
11     namp = sqrt(npower / 2); % noise amplitude in each channel
12     s = ones(1, Ntrial); % signal
13     n = namp * (randn(rstream, 1, Ntrial) + 1i...
14         * randn(rstream, 1, Ntrial)); % noise
15     x = s + n;
16     mf = 1;
17     y = mf' * x;
18     z = real(y);
19     Pfa = 1e-3;
20     snrthreshold = npwgnthresh(Pfa, 1, 'coherent');
21     mfgain = mf' * mf;
22     % To match the equation in the text above
23     % npower - N
24     % mfgain - M
25     % snrthreshold - SNR
26     threshold = sqrt(npower * mfgain * snrthreshold);
27     Pd = sum(z > threshold) / Ntrial;
28     x = n;
29     y = mf' * x;
30     z = real(y);
31     Pfa = sum(z > threshold) / Ntrial;
32     [Y, X] = rocsnr(snrdb, 'SignalType', ...
33         'Nonfluctuatingcoherent', 'MinPfa', 1e-4);
34     pd_graph = [pd_graph; Y'];
35 end
36 figure;
37 s=semilogx(X,pd_graph(1,:), 'r-*');
38 set(s, 'linewidth', 1);
39 title('Nonfluctuating Coherent ROC - Matched Filter');
40 grid on;
41 xlabel('probability of falsed alarm(pfa)');
42 ylabel('probability of detection(pd)');
43 snr_avgdB = 6;
44 legend(['SNR=' num2str(snr_avgdB(1)) 'dB'])

```

ii) Code for performance of detector under various values of signal to noise ratio (SNR)

```

1  % matched_filter_detection_snr.m
2  clc;
3  close all;
4  rstream = RandStream.create('mt19937ar', 'seed', 2009);

```

```

5  spower = 1; % signal power is 1
6  Ntrial = 1e5; % number of Monte-Carlo trials
7  s = ones(1, Ntrial); % signal
8  mf = 1;
9  Pfa = 0.5;
10 Pd = [];
11 for snrdb = 0:1:30 % SNR in dB
12     snr = db2pow(snrdb); % SNR in linear scale
13     npower = spower / snr; % noise power
14     namp = sqrt(npower / 2); % noise amplitude in each channel
15     n = namp * (randn(rstream, 1, Ntrial) + 1i ...
16         * randn(rstream, 1, Ntrial)); % noise
17     x = s + n;
18     y = mf' * x; % apply the matched filter
19     z = real(y);
20     snrthreshold = npwgntthresh(Pfa, 1, 'coherent');
21     mfgain = mf' * mf;
22     threshold = sqrt(npower * mfgain * snrthreshold);
23     Pd = [Pd sum(z > threshold) / Ntrial];
24 end
25 figure;
26 SNR = 0:1:30;
27 s = plot(SNR, Pd, 'r-*');
28 set(s, 'linewidth', 1);
29 title('Matched Filter');
30 grid on;
31 xlabel('Signal-to-noise ratio (dB)');
32 ylabel('probability of detection(pd)');
33 legend(['PFA=' num2str(Pfa)]);

```

## Results and Inference:

From Figure 2.1 we can infer the fact that there is an trade-off/inverse relationship between  $P_d$  and  $P_{fa}$ , similar to Energy Detection. Since we want over  $P_d$  value to be high (greater than 0.5), we see that the corresponding  $P_{fa}$  values range from 0.005 to 0.6. After that the detection probability  $P_d$  is approximately 1 for  $\text{SNR} = 6$  db. For the same value of SNR, Matched Filter detection provides better  $P_d$  vs  $P_{fa}$  characteristics when compared to Energy Detection.

From Figure 2.2, we can infer that the relation is between  $P_d$  and SNR is linear with saturation at a threshold, similar to Energy Detection (for  $P_{fa} = 0.5$ ). However, it can be clearly seen that the characteristics of  $P_d$  vs SNR for Matched Filter Detection is much better than that of Energy Detection. The detection probability is high even for very low values of SNR. As expected it saturates to maximum probability around 5 dB.

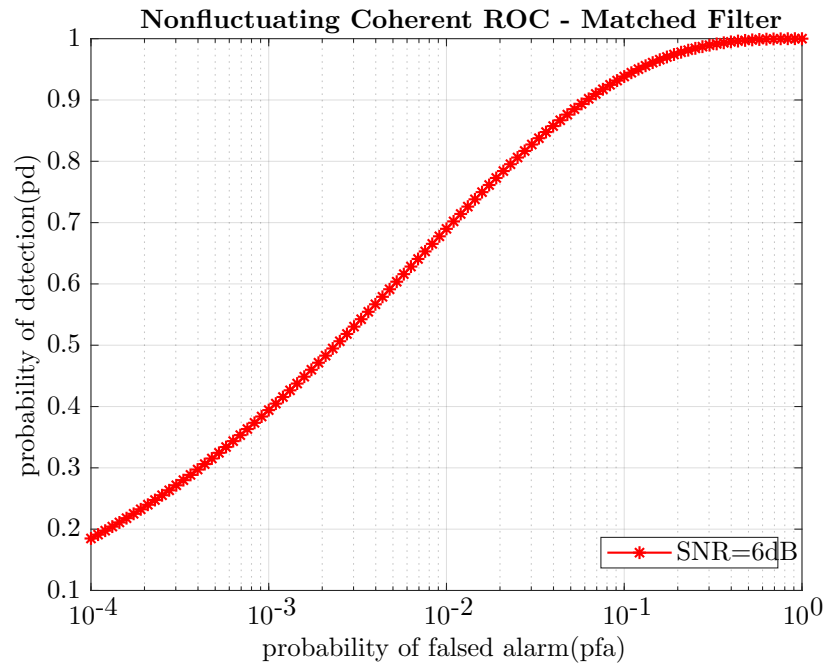


Figure 2.1: Pd vs Pfa for Matched Filter Detection (SNR = 6dB)

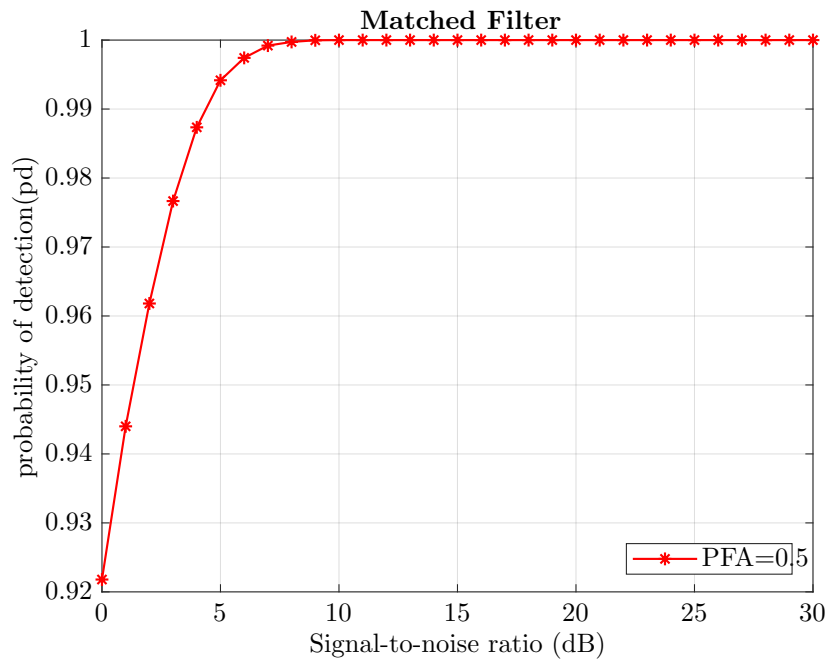


Figure 2.2: Pd vs SNR for Matched Filter Detection (Pfa = 0.5)

### 3 Cyclostationary Feature Detection

#### Aim:

To detect the PU (Primary user) signal exploiting the cyclostationary features (spreading code, cyclic prefixes etc). Cyclostationary feature detection is an alternative detection method. Modulated signals are combined with sine wave carriers, pulse trains, repeating spreading, hopping sequences or cyclic prefixes which end up in built in periodicity. These modulated for the reason that their mean and autocorrelation display periodicity feature. Analysis of the spectral correlation function helps detection of such periodicity feature. The spectral correlation function can distinguish between noise energy and modulated signal energy. This arises from the feature of noise as a wide-sense stationary signal and no correlation. On the other hand, modulated signals have the feature of being cyclostationary with special correlation in view of the embedded redundancy of signal periodicity. Therefore, it is possible for a detector of cyclostationary feature to perform better than the energy detector for discrimination against noise. This is because of its robustness to uncertainty seen in noise power. But, there is the computational complexity entailing a long duration for observation.

#### Code for Cyclostationary Feature Detection

```

1  % cyclostationary_feature_detection.m
2  clc;
3  close all;
4  r = randi([0 1], 100, 1);
5  stem(r, 'DisplayName', 'r');
6  hold on;
7  l = length(r);
8  r(l + 1) = 0;
9  n = 1;
10 L = 1000;
11 fs = 1000;
12 T = 1 / fs;
13 fc = 3 / T;
14 t1 = (0:L);
15 while n <= L
16     t = (n - 1) : .001 : n;
17     if r(n) == 1
18         if r(n + 1) == r(n)
19             y = (t <= n);
20         else
21             y = (t < n);
22         end
23     else
24         if r(n + 1) == r(n)
25             y = (t > n);
26         else
27             y = (t >= n);

```



```

28         end
29     end
30     plot(t, y, 'r');
31     title('NRZ encoding');
32     grid on;
33     xlabel('time');
34     ylabel('amplitude');
35     hold on;
36     axis([0 100 -1.5 1.5]);
37     n = n + 1;
38 end
39 b = (2 * 3.142 * fc * t1) + (3.142 * (1 - y));
40 s = sqrt(2) * cos(b);
41 figure;
42 plot(t1, s, 'r');
43 axis([0 1000 -1.5 1.5]);
44 title('BPSK - Transmitted');
45 xlabel('Time');
46 ylabel('Amplitude');
47 axis([0 1000 -1.5 1.5])
48 hold on;
49 noise = awgn(s, 20, 'measured');
50 snr_db = 10 * log10(s.^2 / (noise.^2));
51 snr_avg = power(10, snr_db / 10);
52 rs1 = (s + noise)/2;
53 vr = var(rs1);
54 figure;
55 plot(t1, rs1, 'r');
56 axis([0 100 -1.5 1.5]);
57 title('BPSK - Received');
58 xlabel('Time');
59 ylabel('Amplitude');
60 axis([0 1000 -1.5 1.5])
61 hold on;
62 nfft = 2^nextpow2(L);
63 f1 = fft(rs1, nfft) / L;
64 fs1 = fs / 2 * linspace(0, 1, nfft / 2 + 1);
65 figure;
66 plot(fs1, 2 * abs(f1(1:nfft / 2 + 1)), 'r');
67 title('FFT of received signal');
68 xlabel('Frequency (HZ)');
69 ylabel('|rs1|');
70 grid on;
71 hold on;
72 fc=1:3/T;
73 s1=cos(2*3.14*fc*T);
74 l1=length(s1);
75 sc=s1+sin(2*3.14*fc*T);
76 l2=length(sc);

```

```

77  cr1=xcorr2(rs1,s1);
78  figure;
79  plot(cr1, 'r');
80  title('Cross Correlation of Rx signal with cos');
81  xlabel('Frequency (Hz)');
82  ylabel('Amplitude');
83  axis([0 500 -5.5 5.5]);
84  hold on;
85  cr2=xcorr2(rs1,sc);
86  l2=length(cr2);
87  figure;
88  plot(cr2,'r');
89  title('Cross Correlation of Rx signal with with sin+cos');
90  xlabel('Frequency (Hz)');
91  ylabel('Amplitude');
92  axis([0 500 -5.5 5.5]);
93  hold on;
94  for i = 1:500
95      if s1(i) > 0.5 || sc(i) > 0.5
96          disp('PU PRESENT');
97      end
98  end
99  L = 2:1:30;
100  snr1 = 2:1:30;
101  q1 = (2 * L + 1) * (0.5)^2;
102  Pf = exp(-q1);
103  del = (2 * snr1 + 1) * vr / (2 * L + 1);
104  q2 = sqrt(2 * snr1 / vr);
105  q3 = 0.5 / del;
106  Pd = marcumq(q1, q2);
107  figure;
108  P = plot(snr1, Pd, 'r-*');
109  set(P, 'linewidth', 1);
110  title('Pd Vs SNR');
111  xlabel('SNR');
112  ylabel('Probability of detection');
113  hold on;
114  grid on;
115  figure;
116  P2 = semilogx(Pf, Pd, 'r-*');
117  set(P2, 'linewidth', 1);
118  title('Pfa Vs Pd');
119  xlabel('Probability of false alarm');
120  ylabel('Probability of detection');
121  hold on;
122  grid on;

```

### Results and Inference:

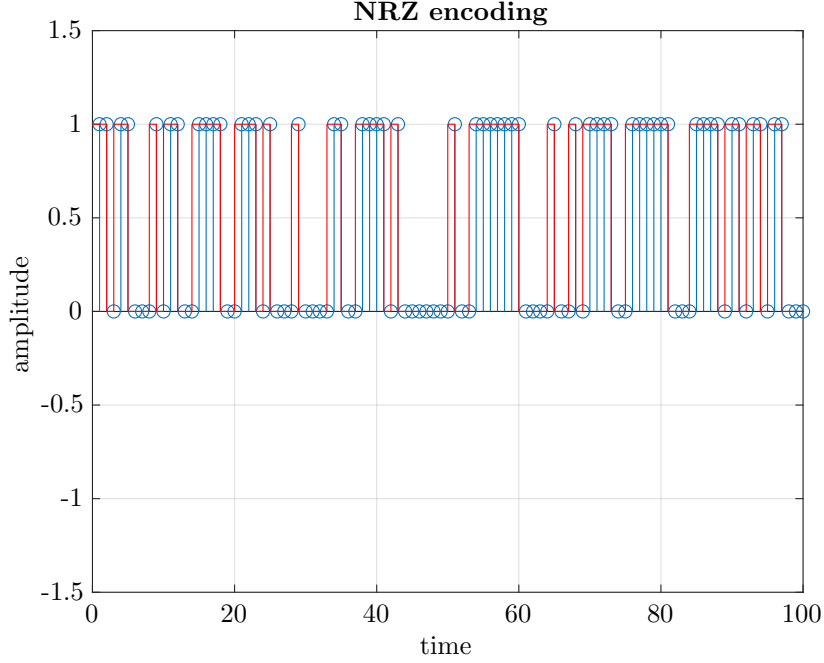


Figure 3.1: NRZ Encoding of input data

The figures 3.1, 3.2, 3.3 and 3.4 show the type of line coding (NRZ), signal with modulation type (BPSK) transmitted and received with AWGN noise, and the spectrum of the received signal respectively. Figures 3.5 and 3.6 show the cross correlation of the received signal with cosine signal and sine+cosine signal respectively. The amplitude of cross-correlated output signal is a measure of how much the received signal resembles the target signal. The correlation peak specifies the location of the target.

The main inference from figure 3.7 is the presence of decreasing relation between  $P_d$  and  $P_{fa}$ , contrary to what was seen in Energy Detection and Matched Filter Detection. For the lower values of  $P_f$  up to 0.0001, probability of detection is nearly 1 and after that, detection of PU is less for more probability of false alarm.

From figure 3.8, we can infer the presence of a linear increase in the probability of detection  $P_d$  for increasing values of SNR. For  $SNR = 2$  dB, probability of detection is increased compared to other methods of detection. Finally, is that the detection probability reaches 1 at  $SNR = 15$  dB.

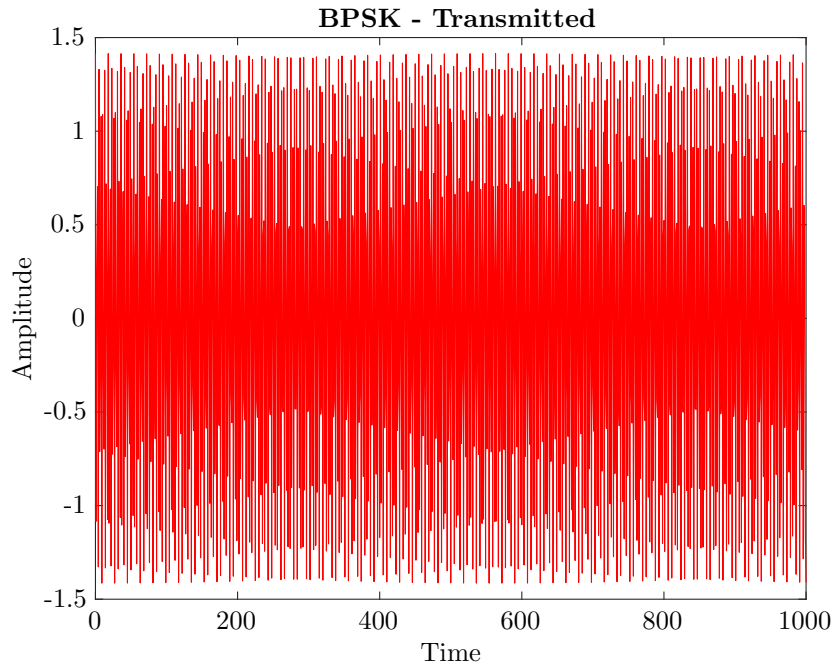


Figure 3.2: BPSK - Transmitted signal

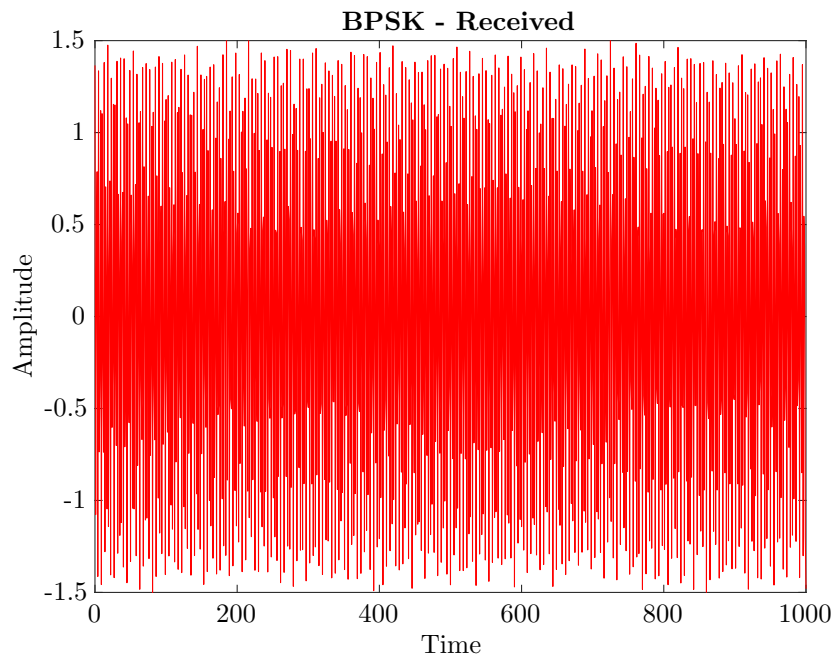


Figure 3.3: BPSK - Received signal with AWGN noise

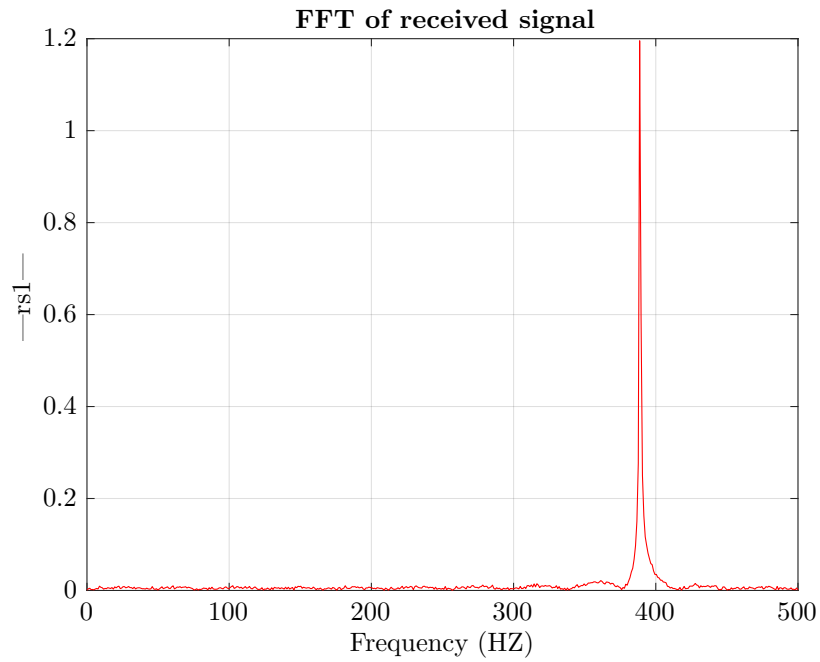


Figure 3.4: FFT of Received signal showing main frequency component

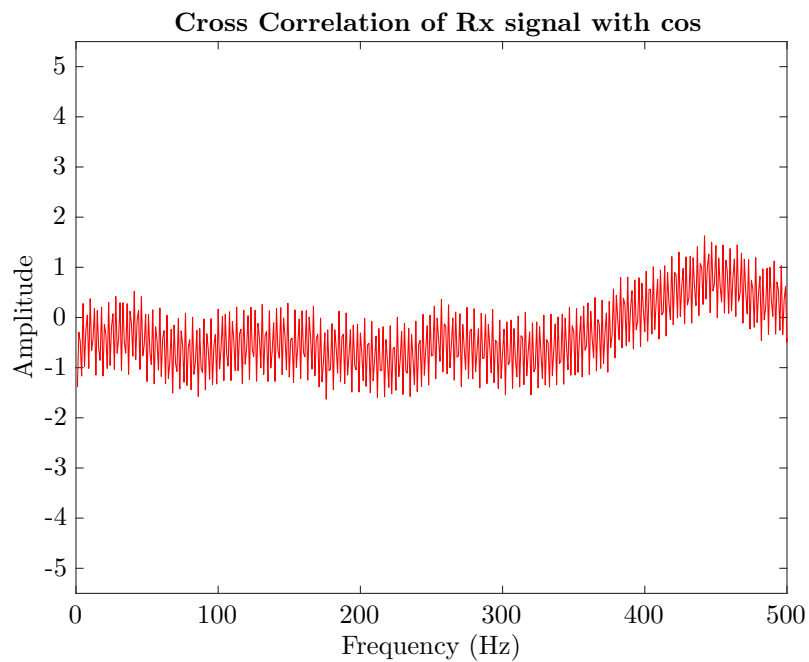


Figure 3.5: Cross Correlation of received signal with cosine

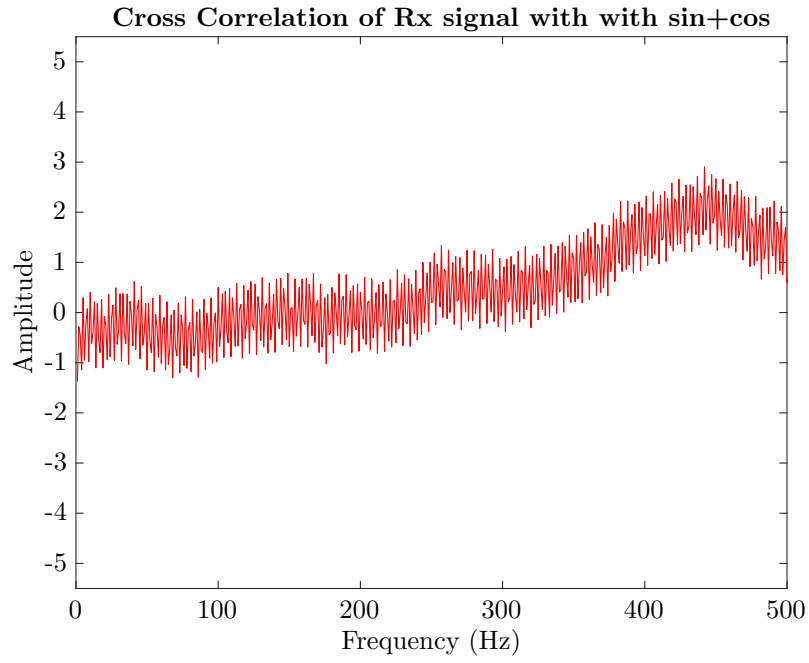


Figure 3.6: Cross Correlation of received signal with sine + cosine

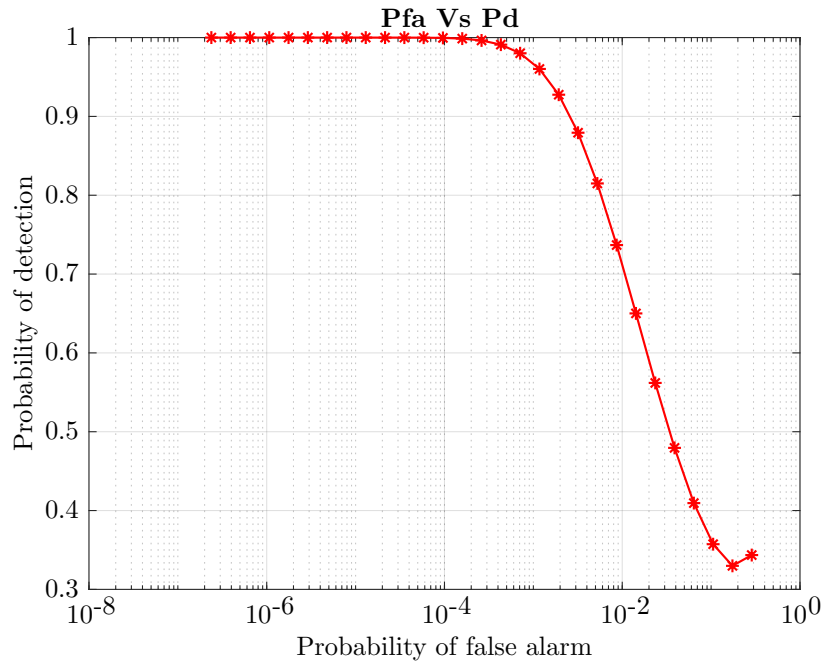


Figure 3.7: Pd Vs Pfa for Cyclostationary Feature Detection

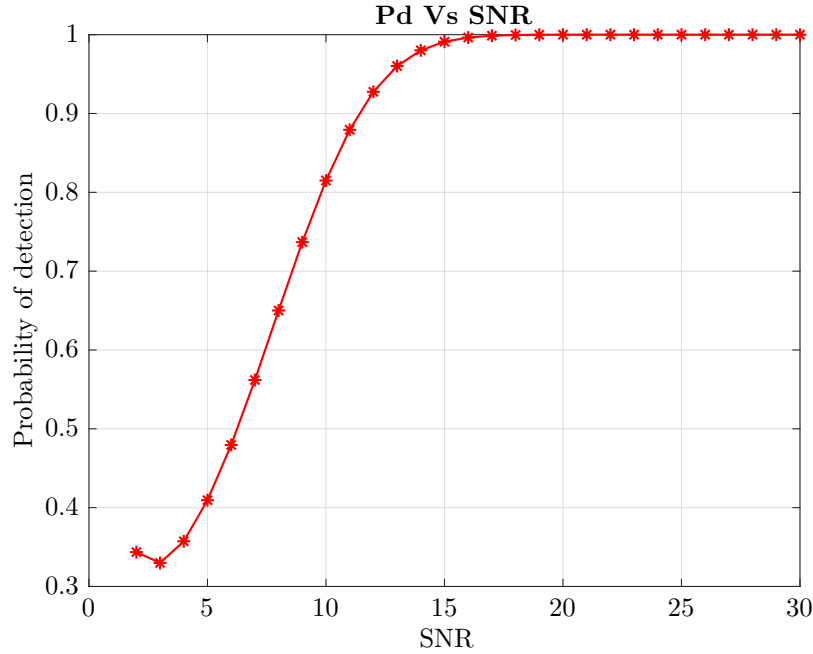


Figure 3.8: Pd Vs SNR for Cyclostationary Feature Detection

## 4 Co-Operative Spectrum Sensing

### Aim:

To enhance the sensing performance by exploiting the spatial diversity in the observations of spatially located CR users. Theoretically, there is greater accuracy seen in cooperative detection among unlicensed users with the possibility of uncertainty in a single user's detection getting minimized. The features of multipath fading and shadowing effect undermine the performance of primary user detection methods. However, cooperative detection schemes permit mitigation of multipath fading and shadowing effects, thereby improving the detection probability in a heavily shadowed ambience.

### Code for Co-Operative Spectrum Sensing

```

1  % cooperative_spectrum_sensing.m
2  clc;
3  close all;
4  u = 1000; % time bandwidth factor
5  N = 2 * u; % samples
6  a = 2; % path loss exponent
7  C = 2; % constant losses
8  Crs = 10; % Number of cognitive radio users
9  PdAnd = 0;
10 % -----Pfa-----%
```

```

11 Pf = 0:0.005:1;
12 Pfa = Pf.^2;
13 % -----signal-----%
14 t = 1:N;
15 s1 = cos(pi * t);
16 % s1power=var(s1);
17 % ----- SNR -----%
18 % Snrdb=-15:1:15;
19 Snrdb = 15;
20 Snreal = power(10, Snrdb / 10); % Linear Snr
21 % while Snrdb<15
22 for i = 1:length(Pfa)
23     lamda(i) = gammaincinv(1 - Pfa(i), u) * 2; % thershold
24     % lamdadB=10*log10(lamda);
25     % -----Local spectrum sensing-----%
26     for j = 1:Crs % for each node
27         detect = 0;
28         % d(j)=7+1.1*rand(); %random distanse
29         d = 7:0.1:8;
30         PL = C * (d(j)^-a); % path loss
31         for sim = 1:10
32             % Monte Carlo Simulation for 100 noise realisation
33             % -----AWGN channel-----%
34             noise = randn(1, N);
35             % Noise production with zero mean and s^2 var
36             noise_power = mean(noise.^2); % noise average power
37             amp = sqrt(noise.^2 * Snreal);
38             s1 = amp .* s1 ./ abs(s1);
39             % SNRdB_Sample=10*log10(s1.^2./(noise.^2));
40             Rec_signal = s1 + noise; % received signal
41             localSNR(j) = mean(abs(s1).^2) * PL / noise_power;
42             Pdth(j, i) = marcumq(sqrt(2 * localSNR(j))...
43                 , sqrt(lamda(i)), u); % Pd for j node
44             % Computation of Test statistic for energy detection
45             Sum = abs(Rec_signal) * PL;
46             Test(j, sim) = sum(Sum);
47             if Test(j, sim) > lamda(i)
48                 detect = detect + 1;
49             end
50         end % END Monte Carlo
51         Pdsim(j) = detect / sim;
52         % Pd of simulation for the j-th CRuser
53     end
54     PdAND(i) = prod(Pdsim);
55     PdOR(i) = 1 - prod(1 - Pdsim);
56 end
57 PdAND5 = (Pdth(5, :)).^5;
58 Pmd5 = 1 - PdAND5;
59 PdANDth = (Pdth(Crs, :)).^Crs;

```



```

60 PmdANDth = 1 - PdANDth; % Probability of miss detection
61 Pmdsim = 1 - PdAND;
62 figure(1);
63 semilogy(Pfa, Pmdsim, 'r-x', ...
64     Pfa, PmdANDth, 'k-o', Pfa, Pmd5, 'g-*');
65 title('Complementary ROC Cooperative sensing - AND rule (AWGN)');
66 grid on;
67 ylim([0,1]);
68 xlabel('Probability of False alarm (Pfa)');
69 ylabel('Probability of Missed Detection (Pmd)');
70 legend('Simulation', 'Theory n=10', 'Theory n=5');

```

### Results and Inference:

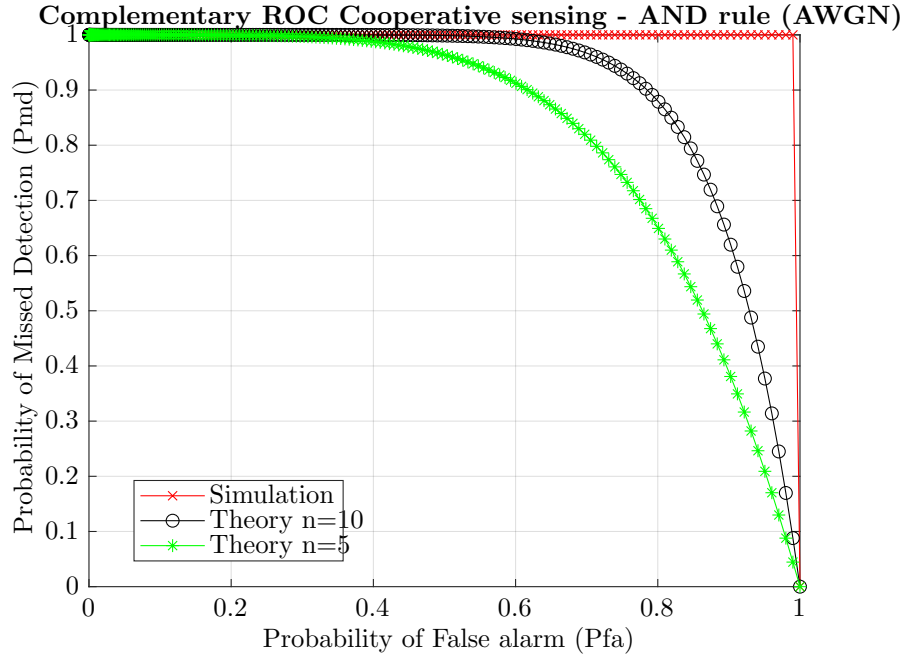


Figure 4.1: Complementary ROC of Cooperative sensing - AND rule under AWGN channel

From Figure 4.1 we can infer that for lower values of Pfa, probability of missed detection (Pmd) is almost 1 and as the value of Pfa increases, Pmd value gradually decreases.

When the number of users in the cognitive radio system is increased from 5 to 10, the performance of missed detection is increased. In simulation results, Pmd value remains 1 for Pfa values close to 1 ( 0.99) and later suddenly reaches 0 when Pfa = 1.