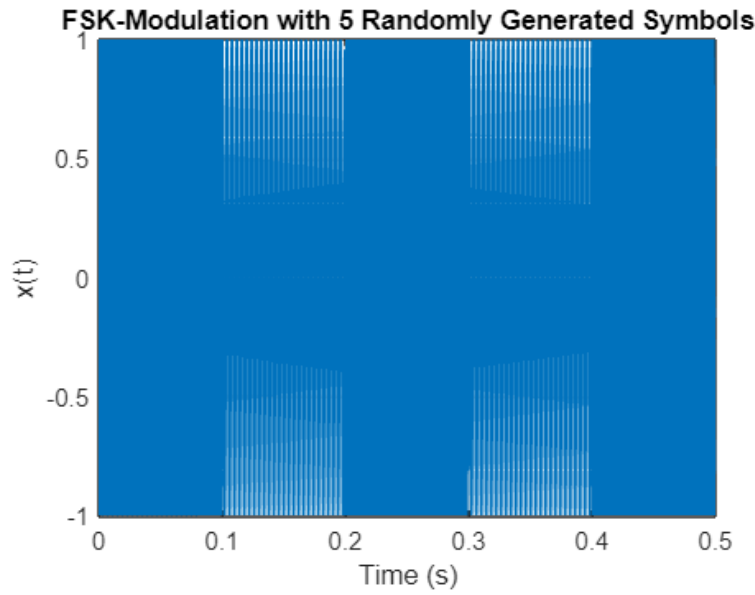


EEE431 Spring 2024/25 MATLAB Assignment 3

Question 1

In this question Frequency Shift Keying (FSK) is observed by using signal space concept, probability of error analysis and decision boundaries. In this question there are two defined signals which are modulated $h(t)$ signals with cosines. The bit assignment of four different symbols is given in the assignment.

- a) In this part it is desired to obtain a $x(t)$ which is random combination of the symbols. The decimal values for the randomly generated bits are 2, 0, 3, 0, 2. The duration of $x(t)$ is 0.5s since $x(t)$ is the random combination of 5 symbols each has duration of 0.1s. In Figure 1 $x(t)$ can be observed.

Figure 1 Demonstration of $x(t)$ in time

b) $s_1(t)$ and $s_2(t)$ are obtained with FSK modulation meaning that baseband signal is multiplied with cosines with different frequencies. From the Fourier transformation it is already known that cosines with different frequencies form an orthogonal basis. In this case it is only desired to normalize the cosine signals to find the orthogonal space. The inner product of a basis function with itself is expected to be 1 and cross inner product is expected to be 0. The found basis functions are verified with the previously mentioned inner product properties by using MATLAB.

$$E_i = \int_0^T \cos^2(2\pi f_i t) dt = \frac{T}{2}$$

$$\phi_1(t) = h(t)\cos(2\pi 250t) \sqrt{\frac{2}{T}}, \quad \phi_2(t) = h(t)\cos(2\pi 500t) \sqrt{\frac{2}{T}},$$

$\langle \phi_1, \phi_1 \rangle = 0.996$, $\langle \phi_2, \phi_2 \rangle = 0.997$, $\langle \phi_1, \phi_2 \rangle = -3.539e-03$

Figure 2 Inner product verification of obtained basis functions

Since there are 2 basis functions the signal space is a 2D space. The inner product of basis functions and symbols gives the constellation points (s_i) in the signal space in which every s_i has a magnitude of $\sqrt{\frac{T}{2}}$. The basis functions can be observed in Figure 3 and s_i 's can be observed in Figure 4.

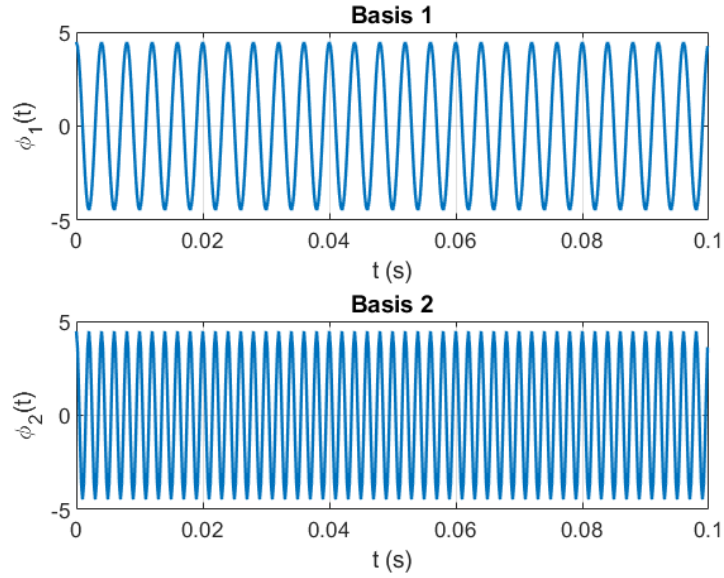


Figure 3 Basis functions in time

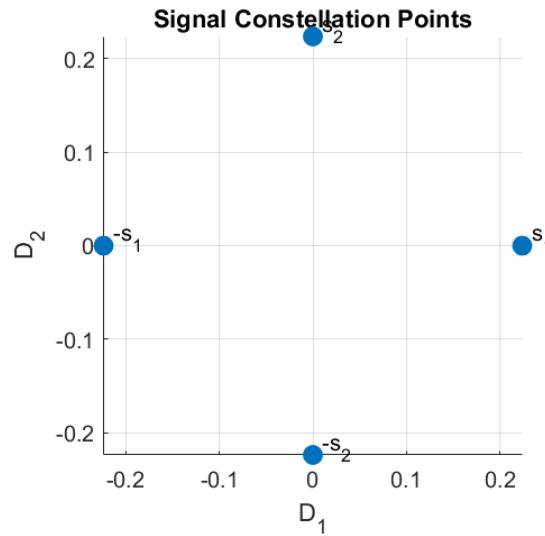


Figure 4 Demonstration of signal constellation points

c) In this part noise is added to $x(t)$ with variances 10^{-4} , 10^{-2} and, 1. Before plotting the noise added signals influence of the samples per symbol on the SNR will be discussed. The number of samples per sample is related to the sampling frequency hence the relation between sampling frequency and SNR is investigated.

$$SNR = \frac{E_s}{N_0}$$

$$E_s = \frac{1}{M} \sum_{i=0}^{M-1} |s_i|^2$$

In this case variance of noise does not change, and E_s is also constant since the inner product between the symbols and basis functions does not change hence SNR is not influenced from changes in sampling frequency in other words, the number of samples for each symbol. The noise added signals can be observed in the following figure.

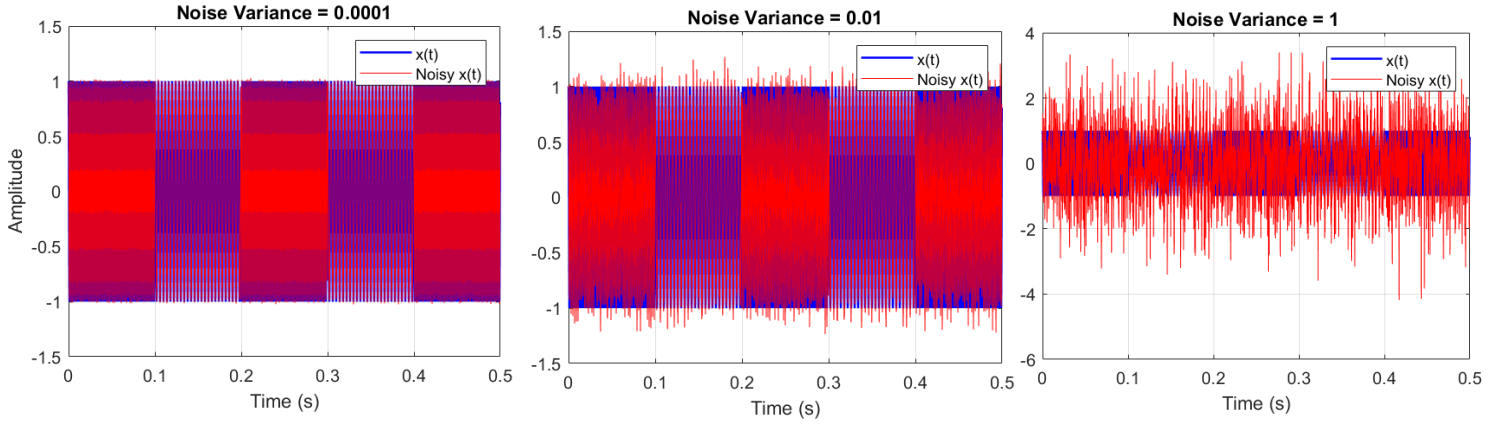
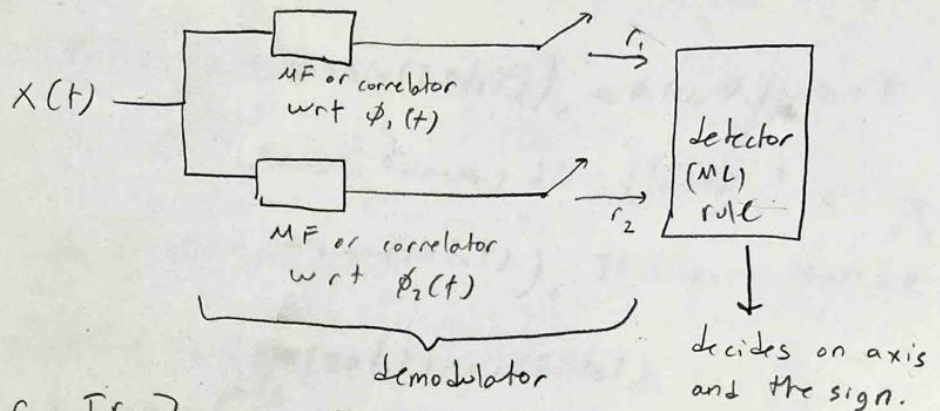


Figure 5 Noise added $x(t)$ signals with different noise variances

(d)



$$\underline{r} = \begin{bmatrix} r_1 \\ r_2 \end{bmatrix} = \underline{s}_i + \begin{bmatrix} n_1 \\ n_2 \end{bmatrix}$$

$$ML \text{ rule} \rightarrow \underset{i \in \{1,2,3,4\}}{\operatorname{argmin}} \|\underline{r} - \underline{s}_i\|^2 = \underset{i \in \{1,2,3,4\}}{\operatorname{argmin}} -2 \underline{r} \cdot \underline{s}_i = \underset{i \in \{1,2,3,4\}}{\operatorname{argmax}} \underline{r} \cdot \underline{s}_i$$

For Probability of Error analysis let $T/2 = A$, assume s_1 is sent.

$$\underline{s}_1 = \begin{bmatrix} \sqrt{A} \\ 0 \end{bmatrix}, \underline{s}_2 = \begin{bmatrix} 0 \\ \sqrt{A} \end{bmatrix}, \underline{s}_3 = \begin{bmatrix} -\sqrt{A} \\ 0 \end{bmatrix}, \underline{s}_4 = \begin{bmatrix} 0 \\ -\sqrt{A} \end{bmatrix}, \underline{r} = \begin{bmatrix} \sqrt{A} + n_1 \\ n_2 \end{bmatrix}$$

$$P_{e,2} = P(\underline{r} \cdot \underline{s}_2 > \underline{r} \cdot \underline{s}_1) = P(\sqrt{A} n_2 > A + n_1 \sqrt{A}) = P(n_2 - n_1 > \sqrt{A})$$

$$P_{e,3} = P(\underline{r} \cdot \underline{s}_3 > \underline{r} \cdot \underline{s}_1) = P(-A - n_1 \sqrt{A} > A + n_1 \sqrt{A}) = P(n_1 < -\sqrt{A})$$

$$P_{e,4} = P(\underline{r} \cdot \underline{s}_4 > \underline{r} \cdot \underline{s}_1) = P(-\sqrt{A} n_2 > A + n_1 \sqrt{A}) = P(n_1 + n_2 < -\sqrt{A})$$

Decision Region $|r_2| > r_1 \cup r_1 < 0$

$$P_e = 1 - P_c, \quad P_c = P(r_1 > |r_2|)$$

$$P_c = \int_0^\infty P(n_1 > x - \sqrt{A}) \cdot f_{n_2}(x) \cdot dx$$

$$P_c = \int_0^\infty Q\left(\frac{x - \sqrt{A}}{\sqrt{N_0/2}}\right) \cdot \frac{\sqrt{2}}{\sqrt{2\pi N_0}} \cdot e^{-\frac{x^2}{2N_0/2}} \cdot dx \quad \text{zero mean } n_2$$

$$P_e = 1 - P_c$$

e) In this part the relation between SNR and probability of symbol error is observed. Both theoretical curve and simulation curve are observed. Theoretical curve is obtained by the closed form expression of 4-ary orthogonal FSK. The probability of error is implemented according to the found decision boundaries in part d). Figure 6 demonstrates the Probability of symbol error vs SNR plots.

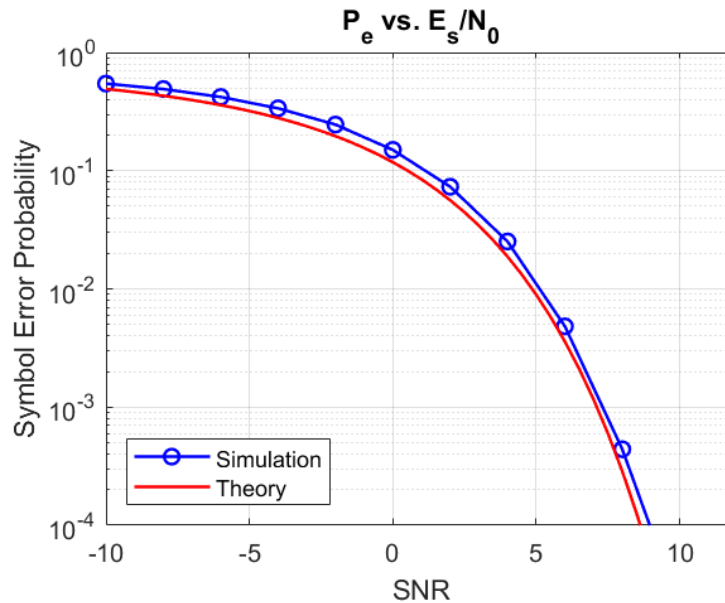


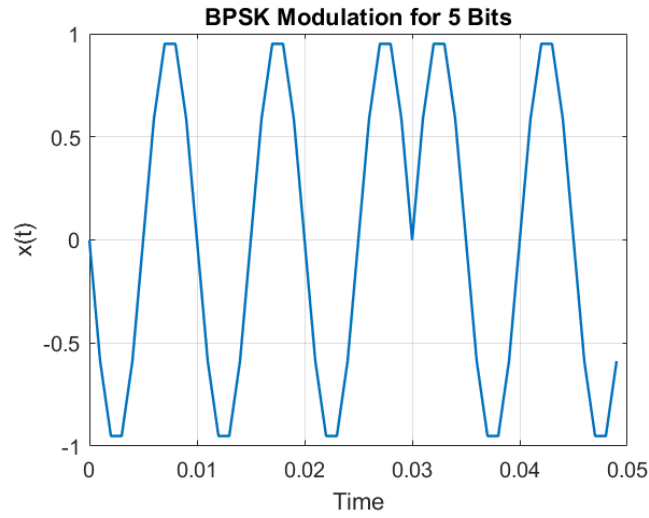
Figure 6 Probability of symbol error vs SNR plots regarding simulation and theory

The behaviour of the plot does fit to logical reasoning. As signal to noise ratio increases, signal supresses the noise hence chances of making an error diminishes. Therefore in the plot it can be observed that as SNR increases symbol error probability decreases. Also plot verifies that the decision boundaries found in part d) are precise since simulation curve tightly follows the theory curve with insignificant error.

Question 2

In this question, upto part f same analysis in Question 1 is performed for BPSK modulation. Afterwards the case in which probability of transmitted signals are different is investigated

a) The randomly selected bit sequence is 1, 1, 1, 0, 0 and the duration of the signal is 0.05s. The sampling frequency is given as 1kHz in this question. The period of the sine wave is 0.01s meaning that for each period of a sine wave 10 samples are acquired hence a perfect smooth waveform can not be obtained. In Figure 7 $x(t)$ can be observed.

Figure 7 Demonstration of $x(t)$ in time

b)The orthonormal basis function is derived as following. Since there is one basis function the signal lives in 1D space. Basis function can be observed from Figure 8 and the constellation points can be observed in Figure 9.

$$E = \int_0^T \sin^2(2\pi ft) dt = \frac{T}{2}$$

$$\phi(t) = h(t)\sin(2\pi 100t) \sqrt{\frac{2}{T}}$$

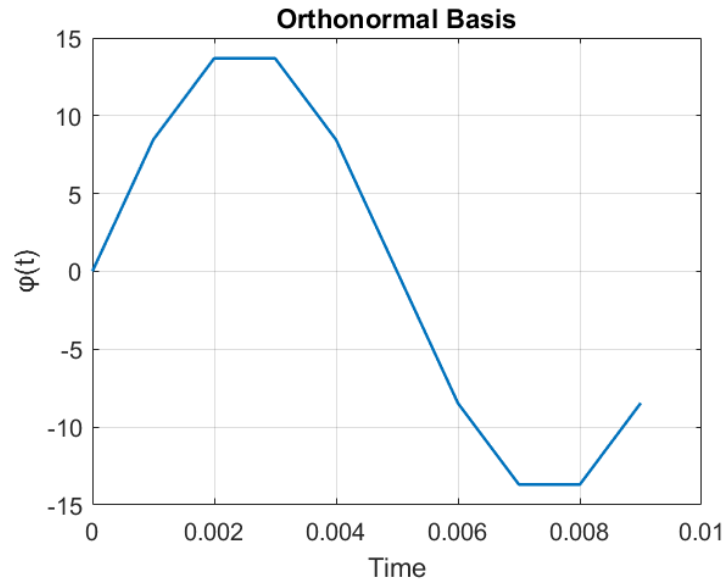


Figure 8 Basis function in time

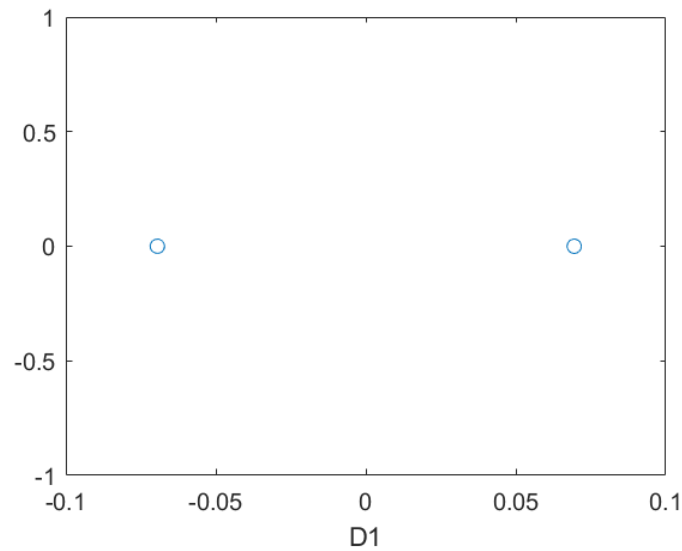
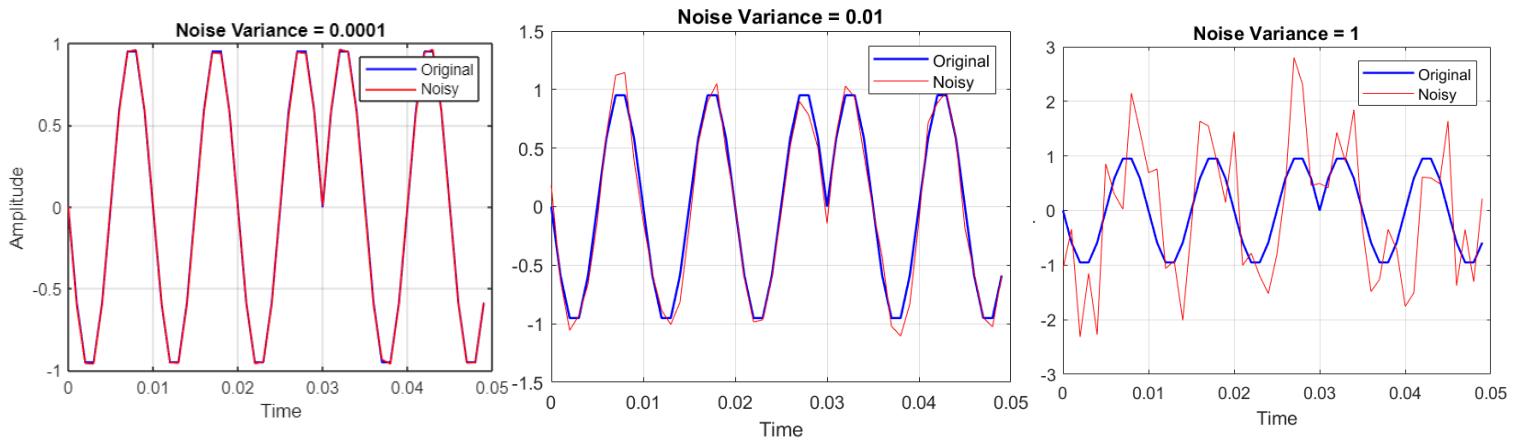
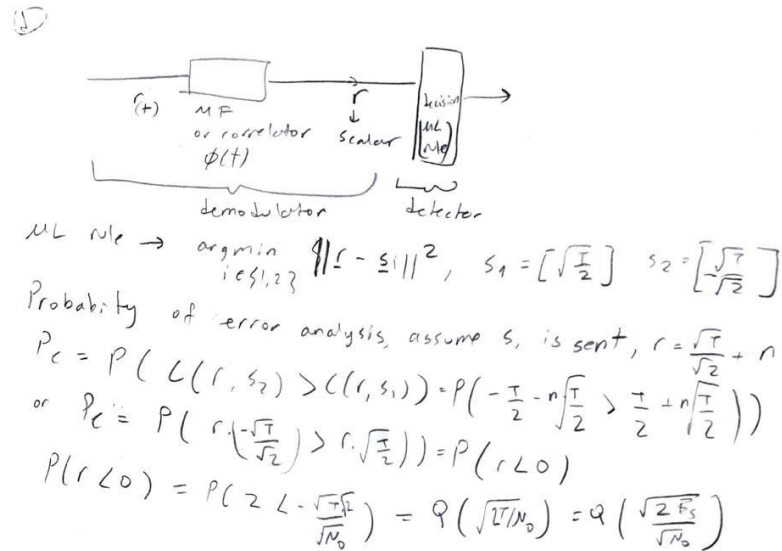


Figure 9 Demonstration of signal constellation points

c) In this part noise is added to $x(t)$ with variances 10^{-4} , 10^{-2} and, 1. Before plotting the noise added signals influence of the samples per symbol on the SNR will be discussed. The definition of SNR does not change for different modulation schemes hence the previous argument in question 1 part c also holds for this part. The noise added signals can be observed in the following figure.

Figure 11 Noise added $x(t)$ signals with different noise variances

e) In this part the relation between SNR and probability of symbol error is observed. Both theoretical curve and simulation curve is observed. Theoretical curve is obtained by the closed form expression of BPSK modulation which is given below. The probability of error (simulation) is implemented according to the found decision boundaries in part d). Figure 12 demonstrates the Probability of symbol error vs SNR plots.

$$P_e = Q\left(\sqrt{\frac{2E_s}{N_0}}\right)$$

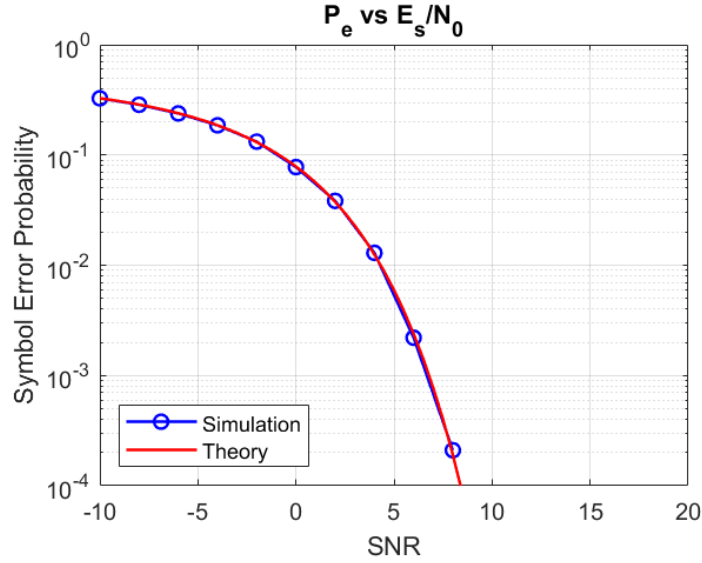


Figure 12 Probability of symbol error vs SNR plots regarding simulation and theory

The behaviour of the curve again suits the logic described in question 1 part 2. The plot also verifies that obtained decision boundary is accurate since the simulation curve tightly follow the theory curve. The 10^{-4} probability crossing of BPSK and FSK require very close SNR. Meaning that both modulation scheme gives approximately same probability of error at fixed SNR value. Check Figure 6 and Figure 12

f) Now the transmission probability of bits differ. In this case MAP rule is observed. The expressions and final decision value is obtained as following. The receiver in part d is not optimal any more since bit transmission probabilities are considered.

$$\frac{p(r|0)}{p(r|1)} > \frac{P(1)}{P(0)}$$

$$\exp\left(-\frac{(r - \sqrt{E})^2}{2\sigma^2} + \frac{(r + \sqrt{E})^2}{2\sigma^2}\right) > \frac{P(1)}{P(0)}$$

$$r > \frac{\sigma^2}{2\sqrt{E}} \ln\left(\frac{P(1)}{P(0)}\right)$$

g) In this part various probability of error as a function of different values of bit transmission probability is observed. The relation can be observed from the Figure 13.

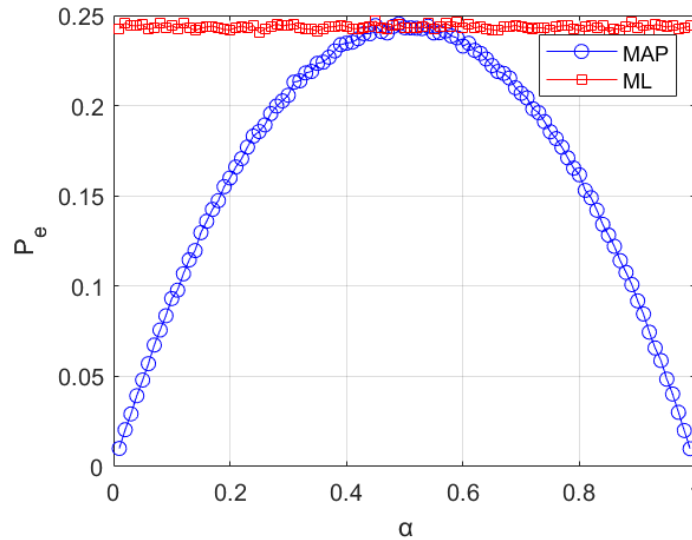


Figure 13 Probability of error as a function of bit transmission probability for ML and MAP receiver

As it can be observed the ML receiver is not able to capture the differences in probabilities since it takes only L2 norm into consideration by assuming equal probabilities. However MAP receiver outputs a new decision boundary by taking bit transmission probabilities into consideration. The MAP receiver converges to ML receiver when $\alpha=0.5$ which is the case where transmission probability is the same for 2 bit modulation. Therefore the experiment supports the argument.

h) As it can be observed from Figure 13 the MAP receiver probability error converges to ML receiver probability error when probability of the two bits are equal. Meaning that MAP adapts to different transmission probabilities and at the worst case converges to ML receiver. So MAP receiver is more preferable. However in a case where transmission probabilities can not be defined strictly then using ML receiver is more appropriate to overcome any unexpected behaviour.

Question 3

(a) $\phi_1(t) = c \cdot (\cos(2\pi f_0 t) + \sin(2\pi f_0 t))$, $\langle \phi_1(t), \phi_1(t) \rangle = 1$

$$\int_0^{T_s} \phi_1(t)^2 dt = c^2 \int_0^{T_s} (\cos^2 + \sin^2 + 2\sin\cos) dt = (T_s + 0) c^2, \quad c = \frac{1}{\sqrt{T_s}}$$

$\phi_1(t) = \frac{1}{\sqrt{T_s}} \cdot (\cos(2\pi f_0 t) + \sin(2\pi f_0 t))$, It is desired that $\langle \phi_1, \phi_2 \rangle = 0$

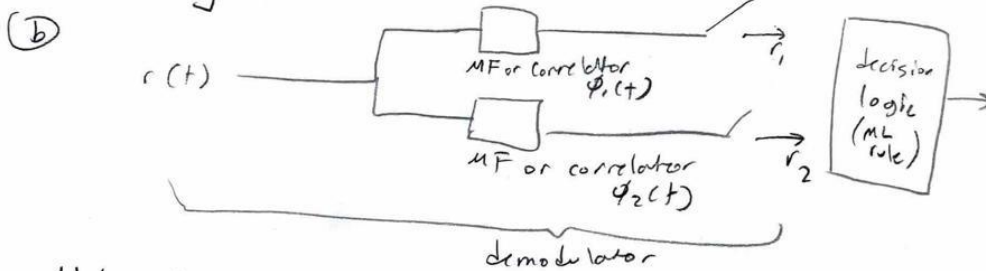
Let $\phi_2(t) = c_2 \cdot (\cos(2\pi f_0 t) - \sin(2\pi f_0 t))$, $c_2 = \frac{1}{\sqrt{T_s}}$

$$\langle \phi_1(t), \phi_2(t) \rangle = \frac{1}{T_s} \int_0^{T_s} (\cos^2 - \sin^2) dt = \frac{1}{T_s} \int_0^{T_s} \cos(2\pi \cdot 2f_0 t) dt = 0$$

Hence $\phi_2(t) = \frac{1}{\sqrt{T_s}} \cdot (\cos(2\pi f_0 t) - \sin(2\pi f_0 t))$

$s_1 = \langle s_1(t), \phi(t) \rangle$, $s_2 = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$, $s_2 = \begin{bmatrix} -\frac{\sqrt{T}}{2} \\ -\frac{\sqrt{T}}{2} \end{bmatrix}$, $s_3 = \begin{bmatrix} \sqrt{T}/2 \\ -\sqrt{T}/2 \end{bmatrix}$

$s_4 = \begin{bmatrix} \sqrt{T}/2 \\ \sqrt{T}/2 \end{bmatrix}$



ML rule $\rightarrow \arg \min_{i \in \{1,2,3,4\}} \|r - s_i\|^2$. ML rule is determined so that L2 norm, euclidian distance is minimized in signal space.

(c) $d_{\min} = \sqrt{T_s}$, the loose bound $\rightarrow P_e \leq \frac{(M-1)}{M} Q\left(\frac{\sqrt{T_s}}{\sqrt{2N_0}}\right)$

The exact union bound is $\rightarrow P_e \leq \frac{1}{4} \sum_{i=1}^4 \sum_{j=1, j \neq i}^4 Q\left(\frac{d_{ij}}{\sqrt{2N_0}}\right)$

$$P_e \leq \frac{1}{4} \left(\underbrace{3Q\left(\frac{\sqrt{T_s}}{\sqrt{2N_0}}\right)}_{\text{from } s_1} + \underbrace{2Q\left(\frac{\sqrt{T_s}}{\sqrt{2N_0}}\right) + Q\left(\frac{\sqrt{T_s}}{\sqrt{2N_0}}\right)}_{\text{from } s_2 \text{ and } s_3} + \underbrace{3Q\left(\frac{\sqrt{T_s}}{\sqrt{2N_0}}\right)}_{\text{from } s_4} \right)$$

$$\textcircled{1} \quad s_1 = \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \quad s_2 = \begin{bmatrix} -\sqrt{T}/2 \\ -\sqrt{T}/2 \end{bmatrix}, \quad s_3 = \begin{bmatrix} \sqrt{T}/2 \\ -\sqrt{T}/2 \end{bmatrix}, \quad s_4 = \begin{bmatrix} \sqrt{T}/2 \\ \sqrt{T}/2 \end{bmatrix}$$

$$\underline{r} = \begin{bmatrix} r_1 \\ r_2 \end{bmatrix} = \begin{bmatrix} r_1 + 0 \\ r_2 + 0 \end{bmatrix}, \quad \begin{aligned} \|r - s_1\|^2 &< \|r - s_2\|^2 \\ -\frac{\sqrt{T}}{2} r_1 - \frac{\sqrt{T}}{2} r_2 &> 0 \\ 0 &> r_1 + r_2 \end{aligned} \quad \textcircled{1}$$

$$\begin{aligned} \|r - s_1\|^2 &< \|r - s_3\|^2 \quad \textcircled{2} \\ r_1 - r_2 &> 0 \\ \|r - s_4\|^2 &> \|r - s_1\|^2 \\ r_1 + r_2 &> 0 \quad \textcircled{3} \end{aligned}$$

Hence, $P_e | s_i = P(\{r_1 + r_2 > 0\} \cup \{r_1 - r_2 > 0\} \cup \{r_1 + r_2 < 0\})$

Note that $\{r_1 + r_2 > 0\} \cup \{r_1 + r_2 < 0\} = \mathbb{R}^2$ and $P(r_1 + r_2 > 0) = \frac{1}{2}$

$P(r_1 + r_2 < 0) = \frac{1}{2}$. As a result, $P(\text{error} | s_i) = 1$.

APPENDIX

MATLAB Codes for Q1

```

Fs = 5000;
T = 0.1;
Ts = 1/Fs;
N = T*Fs
time_vect = (0:N-1)*Ts;
s1 = cos(2*pi*250*time_vect);
s2 = cos(2*pi*500*time_vect);
symbols = [2, 0, 3, 0, 2];
x_t= zeros(1,5*N);
%disp(x_t);
disp(symbols)
for k = 1:5
    idx = symbols(k);
    switch idx
        case 0
            segment = s1;
        case 1
            segment = -s1;
        case 2
            segment = s2;
        case 3
            segment = -s2;
    end
    first_idx=(k-1)*N + 1;
    last_idx =k*N;
    x(first_idx:last_idx)=segment;
end
t_plot = (0:length(x_t)-1)*Ts;
figure;
plot(t_plot, x, 'LineWidth', 1.2);
xlabel('Time (s)');
ylabel('x(t)');
title('FSK-Modulation with 5 Randomly Generated Symbols');
grid on;
%%part b
t_demo = (0:N-1)*Ts;
basis1 = sqrt(2/T)*cos(2*pi*250*t_demo);
basis2 = sqrt(2/T)*cos(2*pi*500*t_demo);
inner1 = trapz(t_demo, basis1.*basis1);
inner2 = trapz(t_demo, basis2.*basis2);
inner3 = trapz(t_demo, basis1.*basis2);
fprintf('<phi1,phi1>=%.3f, <phi2,phi2>=%.3f, <phi1,phi2>=%.3e\n', inner1,
inner2, inner3);
figure;
subplot(2,1,1);
plot(t_demo, phi1, 'LineWidth',1.2);
xlabel('t (s)'); ylabel('\phi_1(t)');
title('Basis 1');

```

```

grid on;
subplot(2,1,2);
plot(t_demo, phi2, 'LineWidth',1.2);
xlabel('t (s)'); ylabel('\phi_2(t)');
title('Basis 2');
grid on;
%%constellation points in 2D space
E = sqrt(T/2);
constellation = [ E,  0;
                 -E,  0;
                   0,  E;
                   0, -E ];
labels = {'s_1', '-s_1', 's_2', '-s_2'};

figure; hold on;
scatter(constellation(:,1), constellation(:,2), 80, 'filled');
for i=1:4
    text(constellation(i,1)+0.01,constellation(i,2)+0.01, labels{i});
end
xlabel('D_1'); ylabel('D_2');
title('Signal Constellation Points');
axis equal tight; grid on;
%%part c
noise_vars = [1e-4, 1e-2, 1];

for i = 1:length(noise_vars)
    var_n = noise_vars(i);
    noise_gauss = sqrt(var_n)*randn(size(x));
    x_noisy = x + noise_gauss;
    figure;
    plot(t_plot, x, 'b', 'LineWidth',1.2); hold on;
    plot(t_plot, x_noisy, 'r');
    xlabel('Time (s)');
    ylabel('Amplitude');
    title(sprintf('Noise Variance = %g', var_n));
    legend('x(t)', 'Noisy x(t)');
    grid on;
end

SNR_db = -10:2:12;
SNR_sim = 10.^(SNR_db/10);
SNR_db_theo = -10:0.5:20;
SNR_th = 10.^(SNR_db_theo/10);
number_symbols = 1e5;
Es = T/2;
Eb = Es/2;

sig_space = [ E,  0;

```

```

        -E, 0;
        0, E;
        0, -E];

sim_Pe = zeros(size(SNR_sim));
theory_Pe = (4-1)/4 * erfc(sqrt(SNR_th));
for ii = 1:length(SNR_sim)
    N0 = Eb / SNR_sim(ii);
    sigma = sqrt(N0/2);
    tx = randi([0 3],1,number_symbols);
    rx = zeros(size(tx));
    for k = 1:number_symbols
        a = sig_space(tx(k)+1,:);
        r_vect = a + sigma*randn(1,2);
        if abs(r_vect(2)) < abs(r_vect(1))
            if 0<r_vect(1), rx(k)=0; else rx(k)=1; end
        else
            if r_vect(2)>0, rx(k)=2; else rx(k)=3; end
        end
    end
    sim_Pe(ii) = mean(rx~=tx);
end
sim_Pe(sim_Pe==0) = 1/number_symbols;
figure;
semilogy(SNR_db, sim_Pe, 'bo-','LineWidth',1.2); hold on;
semilogy(SNR_db_theo, theory_Pe, 'r-','LineWidth',1.2);
xlabel('SNR');
ylabel('Symbol Error Probability');
legend('Simulation','Theory','Location','southwest');
grid on;
title('P_e vs. E_s/N_0');
ylim([1e-4 1]);
xlim([SNR_db(1), SNR_db(end)]);

```

MATLAB Codes for Q2

```

Fs=1000;
T=0.01;
Ts=1/Fs;
N=T*Fs;
time_vect=(0:N-1)*Ts;
signal1=sin(2*pi*100*time_vect);
bits=randi([0 1],1,5);
disp(bits)
%bits=[1,1,1,0,0];
x=zeros(1,5*N);
for k=1:5
    if bits(k)==0
        segment=signal1;
    else

```

```

        segment=-signal1;
    end
    start_idx=(k-1)*N+1;
    end_idx=k*N;
    x(start_idx:end_idx)=segment;
end

t_plot=(0:length(x)-1)*Ts;
figure;
plot(t_plot,x,'LineWidth',1.2);
xlabel('Time');
ylabel('x(t)');
title('BPSK Modulation for 5 Bits');
grid on;
E=trapz(time_vect,s.^2);
basis_func=signal1/sqrt(E);
figure;
plot(time_vect,phi,'LineWidth',1.2);
xlabel('Time');
ylabel('ϕ(t)');
title('Orthonormal Basis');
grid on;
constellation=[sqrt(E), -sqrt(E)];
figure;
plot(constellation,0*constellation,'o');
xlabel('D1');
ylabel('');
noise_vars=[1e-4,1e-2,1];
for i=1:length(noise_vars)
    current_var=noise_vars(i);
    noise_gaussian=sqrt(current_var)*randn(size(x));
    x_noisy=x+noise_gaussian;
    figure;
    plot(t_plot,x,'b','LineWidth',1.2);
    hold on;
    plot(t_plot,x_noisy,'r');
    xlabel('Time');
    ylabel('Amplitude');
    title(sprintf('Noise Variance = %g',current_var));
    legend('Original','Noisy');
    grid on;
end
SNRdb_sim=-10:2:20;
SNR_sim=10.^(EbN0_dB_sim/10);
SNRdb_th=-10:0.5:20;
SNR_th=10.^(EbN0_dB_th/10);
numBits=1e5;
simulation_error=zeros(size(SNR_sim));
for ii=1:length(SNR_sim)
    N0=E/SNR_sim(ii);
    var_noise=sqrt(N0/2);

```



```

    tx=randi([0 1],1,numBits);
    a=(1-2*tx)*sqrt(E);
    received_vect=a+var_noise*randn(size(a));
    rx=received_vect<0;
    simulation_error(ii)=mean(rx~=tx);
end
theoretical_error=0.5 * erfc( sqrt(SNR_th) );
figure;
semilogy(SNRdb_sim,simulation_error,'bo-','LineWidth',1.2);
hold on;
semilogy(SNRdb_th,theoretical_error,'r-','LineWidth',1.2);
xlabel('SNR');
ylabel('Symbol Error Probability');
legend('Simulation','Theory','Location','southwest');
grid on;
title('P_e vs E_s/N_0');
ylim([1e-4 1]);
xlim([SNRdb_sim(1),SNRdb_sim(end)]);
E=trapz(t,s.^2);
var_n=1e-2;std=sqrt(var_n);
alpha=0.01:0.01:0.99;
symbol_num=1e5;
map_rule=zeros(size(alpha));
ml_rule=zeros(size(alpha));
for i=1:length(alpha)
    prob=rand(1,symbol_num)<alpha(i);
    tx=(1-2*prob)*sqrt(E);
    received_vector=tx+std*randn(1,symbol_num);
    boundry=(var_n/(2*sqrt(E)))*log(alpha(i)/(1-alpha(i)));
    map_received=received_vector<=boundry;
    map_rule(i)=mean(map_received~=prob);
    ml_received=received_vector<0;
    ml_rule(i)=mean(ml_received~=prob);
end
figure
plot(alpha,map_rule,'b-o',alpha,ml_rule,'r-s')
xlabel('α');ylabel('P_e');legend('MAP','ML')
grid on

```