Part 1

Report
Biomedical Signal Processing

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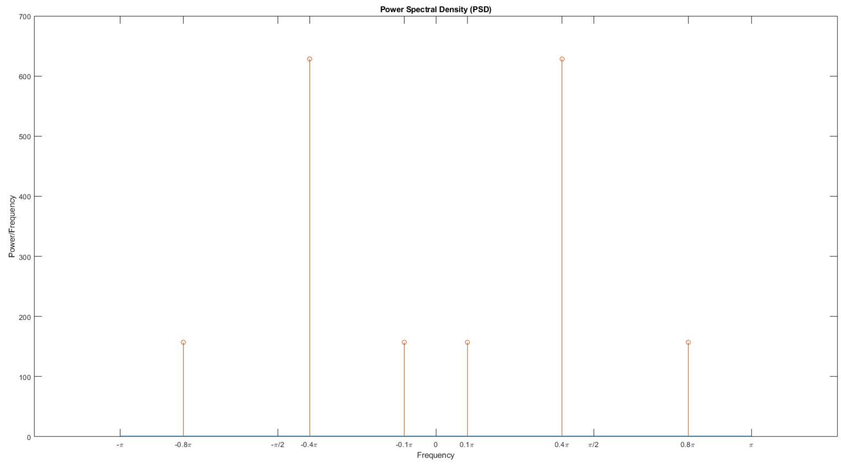
Contents

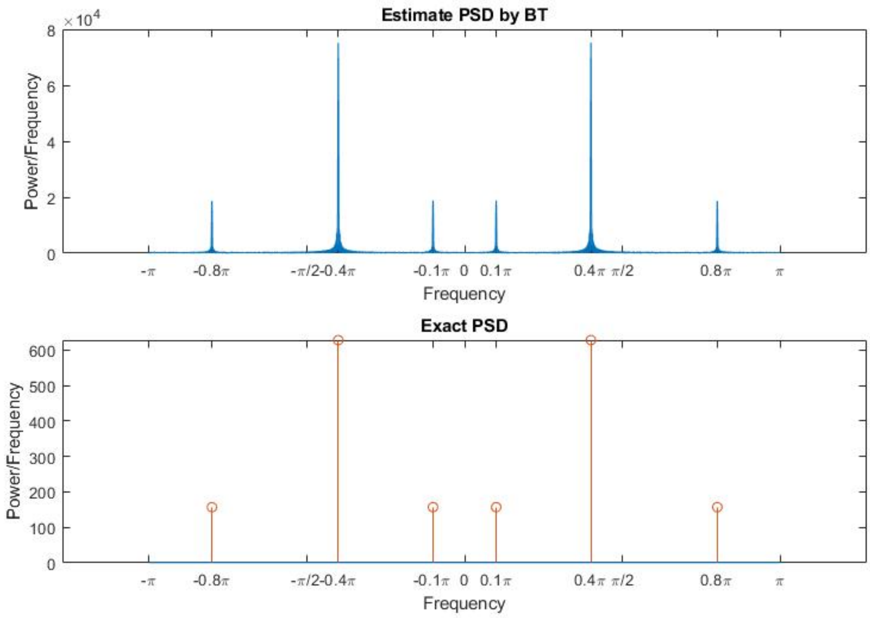
1 Question 1

1.1 part a

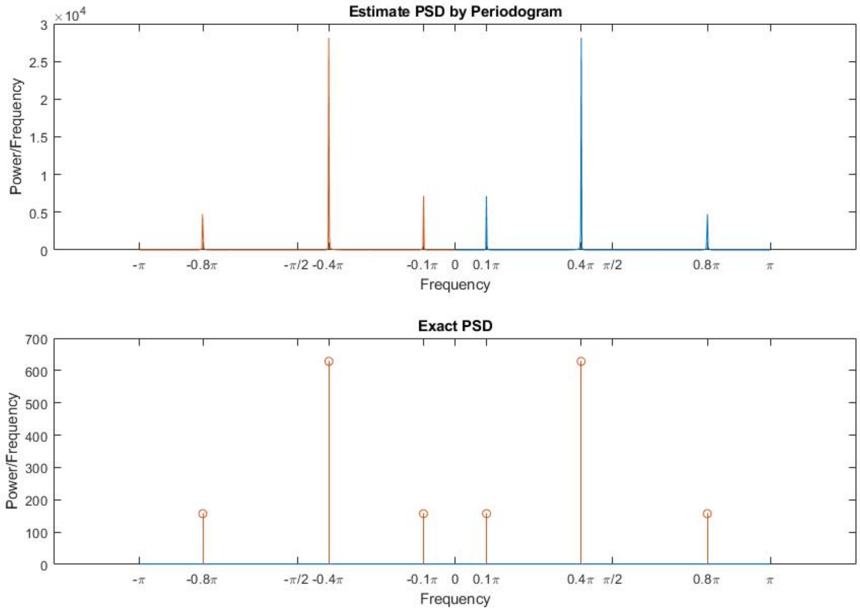
As we know for PSD of $Acos(\omega 0n + phi)$ is $A^2/2 * \pi(\delta(\omega - \omega 0) + \delta(\omega + \omega 0))$ and the PSD of white noise is σ^2.



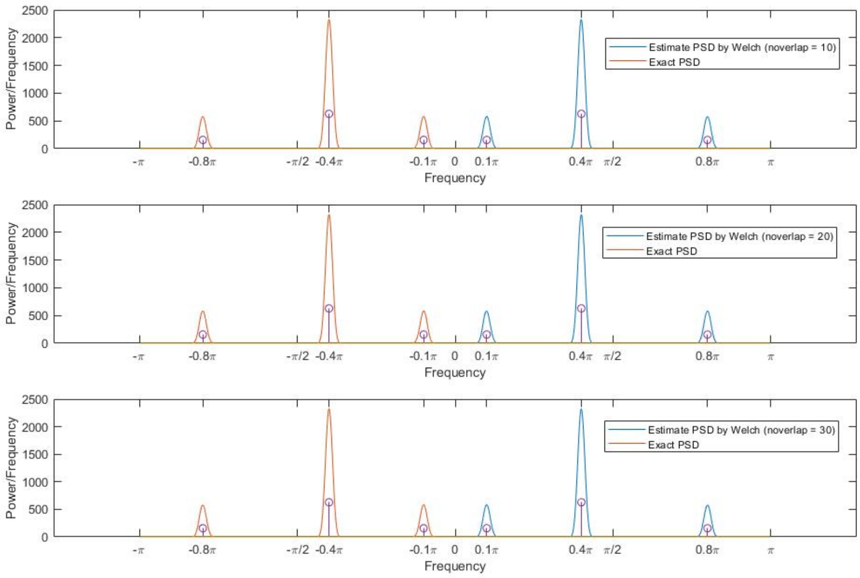
1.2 part b



1.3 part c

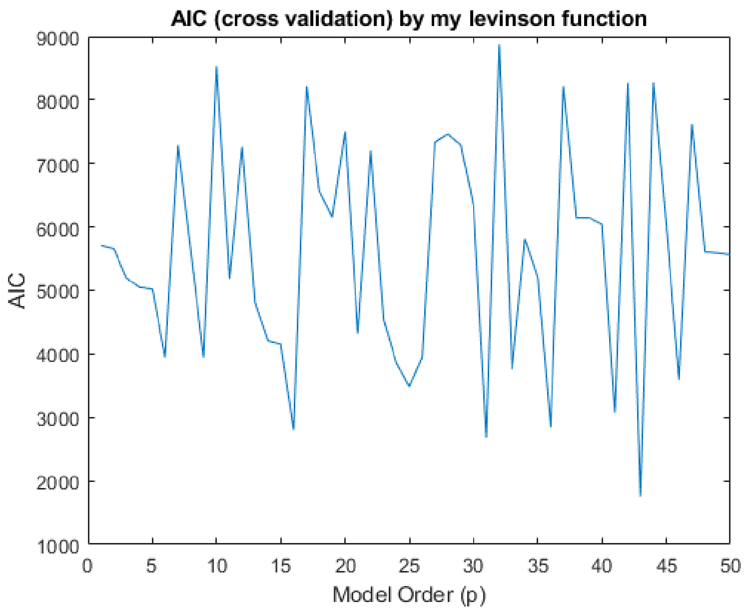


1.4 part d

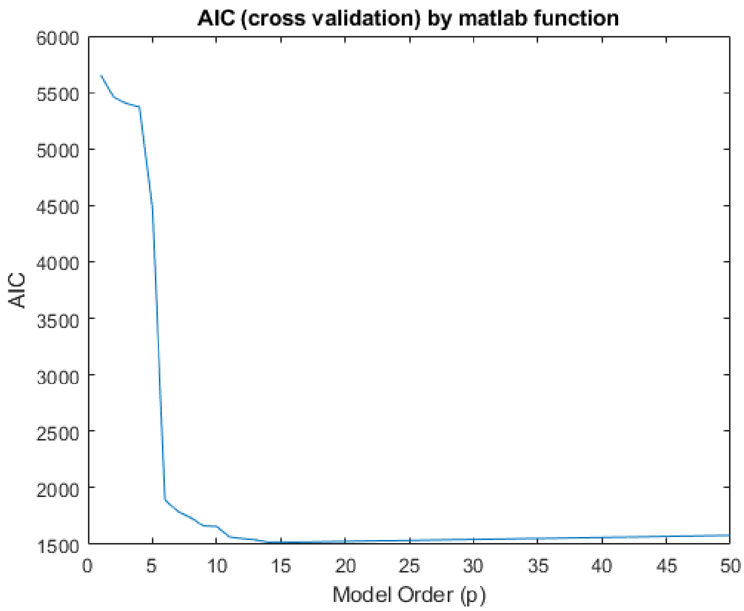


1.5 part e

- I have implemented my levonson function and matlab levin son and these are the results :
- By my function:



- By matlab function:



- optimal order:

```
Optimal AR coeffs:
   -0.1486
   -0.0970
    0.0584
   -0.1814
   -0.1533
    0.0999
   -0.0627
   -0.1252
    0.1621
    0.1041
   -0.0832
    0.1649
    0.1900
   -0.0650
    0.0728
   -0.8610
```

-coeffs for optimal order:

```
Optimal AR Order (p) by Levinson-Durbin:
    18
Optimal AR Order (p) by AIC:
    16
```

1.6 part f

1.7 part g

Matlab Code

```matlab
%% our information
samples = 1000;

alpha1 = 2*pi*rand;
alpha2 = 2*pi*rand;
alpha3 = 2*pi*rand;

n = 0:samples-1;
x = 10*cos(0.1*pi*n + alpha1) + 20*cos(0.4*pi*n + alpha2) + 10*cos(0.8*pi*n + alpha3) + randn(1, samples);


%% part a

f = linspace(-pi, pi, 1000);
PSD = ones(size(f));
add_delta = @(psd, freq, amp) psd + amp * (f == freq);
PSD = add_delta(PSD, 0.1*pi, pi * 50);
PSD = add_delta(PSD, -0.1*pi, pi * 50);
PSD = add_delta(PSD, 0.4 * pi, pi * 200);
PSD = add_delta(PSD, -0.4 * pi, pi * 200);
PSD = add_delta(PSD, 0.8 * pi, pi * 50);
PSD = add_delta(PSD, -0.8 * pi, pi * 50);
figure;
plot(f, PSD);
title('Power Spectral Density (PSD)');
xlabel('Frequency');
ylabel('Power/Frequency');
hold on;
```

```
stem([0.1*pi, -0.1*pi, 0.4 * pi, -0.4 * pi, 0.8 * pi, -0.8 * pi], ...
    [pi * 50, pi * 50, pi * 200, pi * 200, pi * 50, pi * 50]);
xticks([-pi -0.8*pi -pi/2 -0.4*pi -0.1*pi 0 0.1*pi 0.4*pi pi/2 0.8*pi pi]);
xticklabels({'-\pi', '-0.8\pi', '-\pi/2' , '-0.4\pi', '-0.1\pi', '0', '0.1\pi', '0.4\pi', '\pi/2', '0.8\pi', '\pi'});



%% part b

estimated_corr = zeros(1,samples/2);
BT_PSD = zeros(1, 20000);
f1 = linspace(-pi, pi, 20000);

for i=1:samples/2
    for j = 1:(samples-i)
        estimated_corr(i) = x(j)*x(j+i) + estimated_corr(i);
    end
    estimated_corr(i) = estimated_corr(i) / samples;
end
for w=1:20000
    temp = 0;
    for j=1:(samples/2)
        temp = estimated_corr(j) * exp(-1i*f1(w)*j) + temp;
    end
```

```
    BT_PSD(w) = estimated_corr(1) + 2 * real(temp);
end

figure;
subplot(2,1,1);
plot(f1,abs(BT_PSD))
title('Estimate PSD by BT');
xlabel('Frequency');
ylabel('Power/Frequency');
xticks([-pi -0.8*pi -pi/2 -0.4*pi -0.1*pi 0 0.1*pi
   0.4*pi pi/2 0.8*pi pi]);
xticklabels({'-\pi', '-0.8\pi', '-\pi/2' , '-0.4\pi',
   '-0.1\pi', '0', '0.1\pi', '0.4\pi', '\pi/2', '0.8\
   pi', '\pi'});

subplot(2,1,2);
plot(f, PSD);
hold on;
title('Exact PSD');
xlabel('Frequency');
ylabel('Power/Frequency');
stem([0.1*pi, -0.1*pi, 0.4 * pi, -0.4 * pi, 0.8 * pi,
   -0.8 * pi], ...
    [pi * 50, pi * 50, pi * 200, pi * 200, pi * 50, pi
        * 50]);
xticks([-pi -0.8*pi -pi/2 -0.4*pi -0.1*pi 0 0.1*pi
   0.4*pi pi/2 0.8*pi pi]);
xticklabels({'-\pi', '-0.8\pi', '-\pi/2' , '-0.4\pi',
   '-0.1\pi', '0', '0.1\pi', '0.4\pi', '\pi/2', '0.8\
   pi', '\pi'});

```

```
%% part c

[pxx, f2] = periodogram(x,[],[],2*pi);

figure;
subplot(2,1,1);
plot(f2 , pxx); % Adjust frequency range to [-pi, pi]
hold on;
plot(-f2,pxx)
title('Estimate PSD by Periodogram');
xlabel('Frequency');
ylabel('Power/Frequency');
xticks([-pi -0.8*pi -pi/2 -0.4*pi -0.1*pi 0 0.1*pi
    0.4*pi pi/2 0.8*pi pi]);
xticklabels({'-\pi', '-0.8\pi', '-\pi/2' , '-0.4\pi',
    '-0.1\pi', '0', '0.1\pi', '0.4\pi', '\pi/2', '0.8\
    pi', '\pi'});

subplot(2,1,2);
plot(f, PSD);
hold on;
stem([0.1*pi, -0.1*pi, 0.4 * pi, -0.4 * pi, 0.8 * pi,
    -0.8 * pi], ...
     [pi * 50, pi * 50, pi * 200, pi * 200, pi * 50, pi
         * 50]);
title('Exact PSD');
xlabel('Frequency');
ylabel('Power/Frequency');
xticks([-pi -0.8*pi -pi/2 -0.4*pi -0.1*pi 0 0.1*pi
    0.4*pi pi/2 0.8*pi pi]);
xticklabels({'-\pi', '-0.8\pi', '-\pi/2' , '-0.4\pi',
```

```
    '-0.1\pi', '0', '0.1\pi', '0.4\pi', '\pi/2', '0.8\pi', '\pi'});





%% part d


[pxx_welch_10, f3] = pwelch(x, 100, 10, samples, 2*pi);
[pxx_welch_20, f4] = pwelch(x, 100, 20, samples, 2*pi);
[pxx_welch_30, f5] = pwelch(x, 100, 30, samples, 2*pi);

figure;
subplot(3,1,1);
plot(f3, pxx_welch_10);
hold on;
plot(-f3,pxx_welch_10)
hold on;
plot(f, PSD);
hold on;
stem([0.1*pi, -0.1*pi, 0.4 * pi, -0.4 * pi, 0.8 * pi, -0.8 * pi], ...
    [pi * 50, pi * 50, pi * 200, pi * 200, pi * 50, pi * 50]);
xlabel('Frequency');
ylabel('Power/Frequency');
```

```
legend('Estimate PSD by Welch (noverlap = 10)','Exact PSD')
xticks([-pi -0.8*pi -pi/2 -0.4*pi -0.1*pi 0 0.1*pi 0.4*pi pi/2 0.8*pi pi]);
xticklabels({'-\pi', '-0.8\pi', '-\pi/2' , '-0.4\pi', '-0.1\pi', '0', '0.1\pi', '0.4\pi', '\pi/2', '0.8\pi', '\pi'});

%%%%

subplot(3,1,2);
plot(f4 , pxx_welch_20);
hold on;
plot(-f4,pxx_welch_20)
hold on;
plot(f, PSD);
hold on;
stem([0.1*pi, -0.1*pi, 0.4 * pi, -0.4 * pi, 0.8 * pi, -0.8 * pi], ...
    [pi * 50, pi * 50, pi * 200, pi * 200, pi * 50, pi * 50]);
xlabel('Frequency');
ylabel('Power/Frequency');
legend('Estimate PSD by Welch (noverlap = 20)','Exact PSD')
xticks([-pi -0.8*pi -pi/2 -0.4*pi -0.1*pi 0 0.1*pi 0.4*pi pi/2 0.8*pi pi]);
xticklabels({'-\pi', '-0.8\pi', '-\pi/2' , '-0.4\pi', '-0.1\pi', '0', '0.1\pi', '0.4\pi', '\pi/2', '0.8\pi', '\pi'});

```

```
%%%%%


subplot(3,1,3);
plot(f5, pxx_welch_30);
hold on;
plot(-f5,pxx_welch_30)
hold on;
plot(f, PSD);
hold on;
stem([0.1*pi, -0.1*pi, 0.4 * pi, -0.4 * pi, 0.8 * pi,
    -0.8 * pi], ...
     [pi * 50, pi * 50, pi * 200, pi * 200, pi * 50, pi
         * 50]);
xlabel('Frequency');
ylabel('Power/Frequency');
legend('Estimate PSD by Welch (noverlap = 30)','Exact
    PSD')
xticks([-pi -0.8*pi -pi/2 -0.4*pi -0.1*pi 0 0.1*pi
    0.4*pi pi/2 0.8*pi pi]);
xticklabels({'-\pi', '-0.8\pi', '-\pi/2' , '-0.4\pi',
    '-0.1\pi', '0', '0.1\pi', '0.4\pi', '\pi/2', '0.8\
    pi', '\pi'});





%% part e


```

```
R_x = xcorr(x,'biased');

% implementing levinson by myself and AIC cross
    valiadation
E = [];
K=[];
AIC = zeros(50,1);
temp = 0;
R_xx = R_x(1000:1999);
for i = 1:50
    if i == 1
        E(i) = R_xx(i);
    elseif i == 2
        k(i) = -R_xx(i) / E(i-1);
        a(i,i) = k(i);
        E(i) = (1 - k(i)^2) * E(i-1);
    else
        for j = 1:i-1
            temp = temp + a(j,i-1) * R_xx(i-j);
        end
        k(i) = -(R_xx(i) + temp) / E(i-1);
        a(i,i) = k(i);
        for j = 1:i-1
            a(j,i) = a(j,i-1) + k(i) * a(i-j,i-1);
        end
        E(i) = (1 - k(i)^2) * E(i-1);
    end
    AIC(i) = samples * log(E(i)) + 2 * (i);
    temp = 0;
end
[~, p_opt_AIC] = min(AIC);
```

```
p_opt_LD = 1;
disp('Optimal AR Order (p) by Levinson-Durbin:');
disp(p_opt_LD);
disp('Optimal AR Order (p) by AIC:');
disp(p_opt_AIC);
figure;
plot(1:50, AIC);
title('AIC (cross validation)');
xlabel('Model Order (p)');
ylabel('AIC');
disp('Optimal AR coeffs (p) by Levinson-Durbin:');
disp(a(:,p_opt_LD));
disp('Optimal AR coeffs (p) by AIC:');
disp(a(:,p_opt_AIC));
% implementing levinson by matlab function and AIC
    cross valiadation

e = zeros(51,1);
aic = zeros(50,1);
[al, e(1)] = levinson(R_xx, 0); % Order 0 model
for p = 1:50
    [al, e(p+1)] = levinson(R_xx, p);
    aic(p) = p*log(e(p+1))+2*p;
end
[~, p_opt_aic] = min(AIC);
p_opt_LD_m = 1;
disp('Optimal AR Order (p) by Levinson-Durbin:');
disp(a(:,p_opt_LD_m));
disp('Optimal AR Order (p) by AIC:');
disp(a(:,p_opt_aic));
figure;
```

```
plot(1:50, AIC);
title('AIC (cross validation)');
xlabel('Model Order (p)');
ylabel('AIC');



%% part f


% Maximum MA order to consider
max_q = 20;

% Preallocate arrays for criteria
aic = zeros(max_q, 1);
bic = zeros(max_q, 1);
fpe = zeros(max_q, 1);

% Loop through different MA orders
for q = 1:max_q
    try
        % Estimate MA model of order q
        model = arima('Constant', 0, 'MA', q, 'Variance', 1);
        fit = estimate(model, x, 'Display', 'off', 'EnforceInvertibility', true);

        % Get the log-likelihood, number of parameters, and variance of residuals
        logL = loglikelihood(fit);
        numParams = q + 1; % q MA parameters + 1
```

```
            variance parameter
        variance = fit.Variance;

        % Calculate criteria
        aic(q) = -2 * logL + 2 * numParams;
        bic(q) = -2 * logL + log(N) * numParams;
        fpe(q) = variance * (1 + 2 * numParams / N) /
            (1 - 2 * numParams / N);
    catch ME
        % If estimation fails, set criteria to Inf
        aic(q) = Inf;
        bic(q) = Inf;
        fpe(q) = Inf;
        disp(['Order ', num2str(q), ' estimation
            failed: ', ME.message]);
    end
end

% Find the order with minimum AIC, BIC, and FPE
[~, min_aic_order] = min(aic);
[~, min_bic_order] = min(bic);
[~, min_fpe_order] = min(fpe);

% Display results
disp(['Optimal order by AIC: ', num2str(min_aic_order)
    ]);
disp(['Optimal order by BIC: ', num2str(min_bic_order)
    ]);
disp(['Optimal order by FPE: ', num2str(min_fpe_order)
    ]);
```

```
% Plot AIC, BIC, and FPE
figure;
subplot(2,3,1);
plot(1:max_q, aic, 'LineWidth', 2);
title('AIC for Different MA Model Orders');
xlabel('MA Order');
ylabel('AIC');
legend('AIC');
grid on;

subplot(2,3,2);
plot(1:max_q, bic, 'LineWidth', 2);
title('BIC for Different MA Model Orders');
xlabel('MA Order');
ylabel('BIC');
legend('BIC');
grid on;

subplot(2,3,3);
plot(1:max_q, fpe, 'LineWidth', 2);
title('FPE for Different MA Model Orders');
xlabel('MA Order');
ylabel('FPE');
legend('FPE');
grid on;
```

```
%% part g
```

```
%% part h
```

2 Question 2

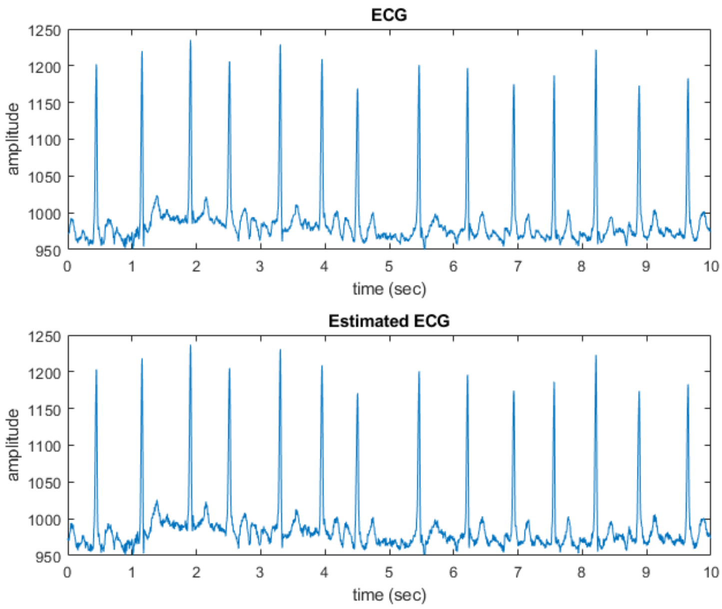
2.1 part a

```
%% a
ECG_dataset = load('test.mat');
fs = 360;
s = ECG_dataset.val;
t = 0:1/fs:(length(s)-1)/fs;
phi1 = 2*pi*rand;
phi2 = 2*pi*rand;
N1 = 2*cos(100*pi*t+phi1);
```

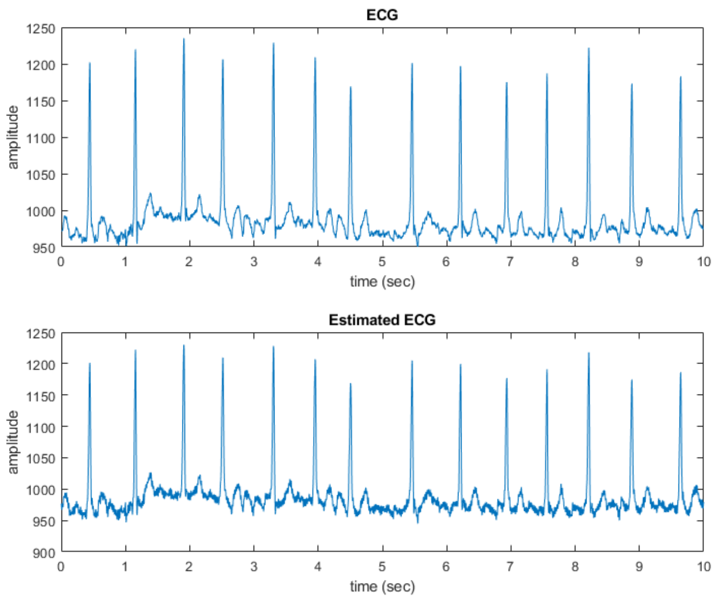
```
N2 = 2*cos(100*pi*t+phi2);
reference_signal = N1;
primary_signal = s + N2;
w = zeros(length(s),1);
y = zeros(length(s),1);
e = zeros(length(s),1);
mu = 0.000001;
p = y-w;
[e,y] = adaptivefilter(w,reference_signal,
    primary_signal,mu);
```

2.2 part b

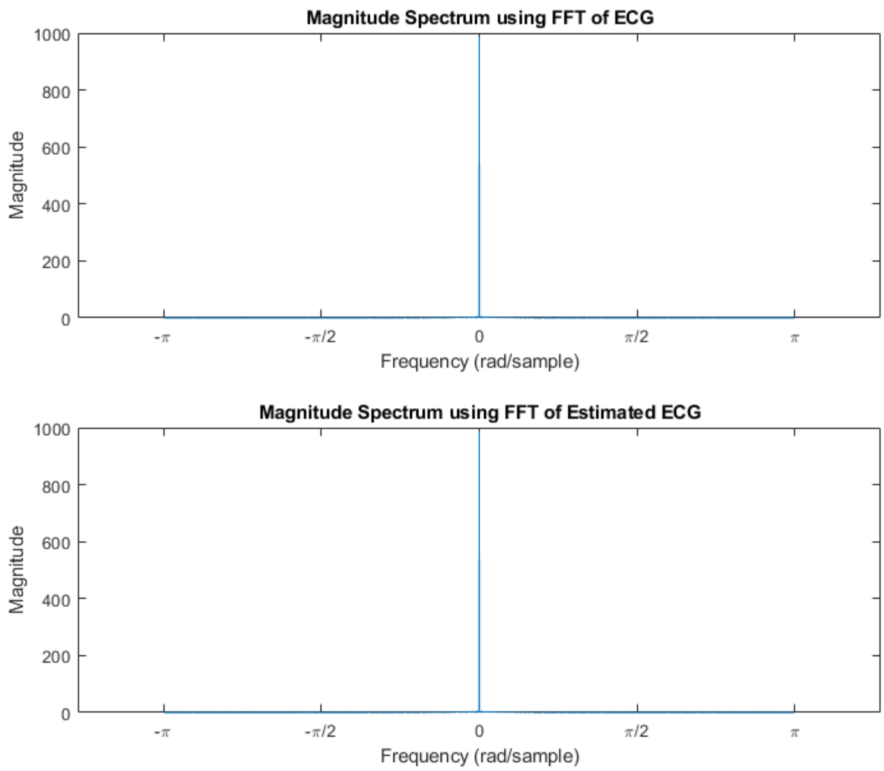
with Amplitude = 5 for noises :



with Amplitude = 20 for noises :



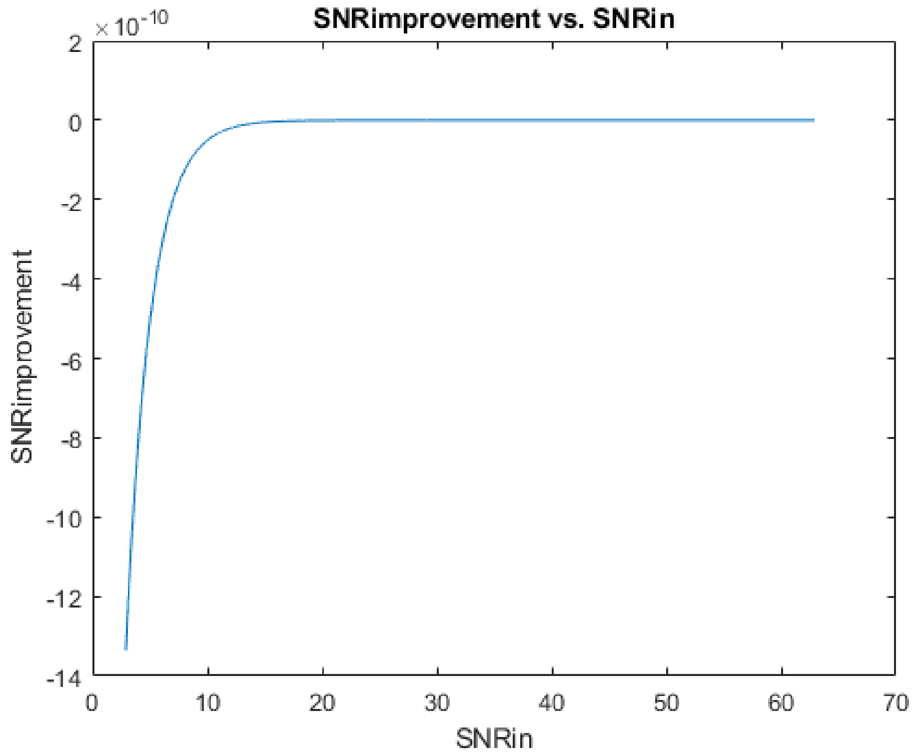
* As we can see still we have a little amount of effect from the noise , which added to the ECG signal, but we have estimated the ECG signal properly. Also we have to say that the effect of noise relate to the amplitude directly.



* As we can see there is almost no difference in spectrum of the ECG and estimated ECG.

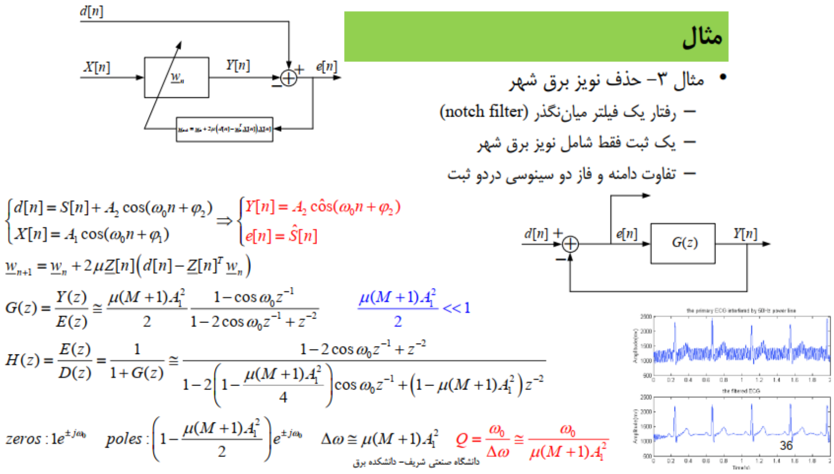
2.3 part c

- For different values of amplitude we have below figure, As we can see after some amplitudes the SNRimprovement will be constant even by increasing SNRin and converge.

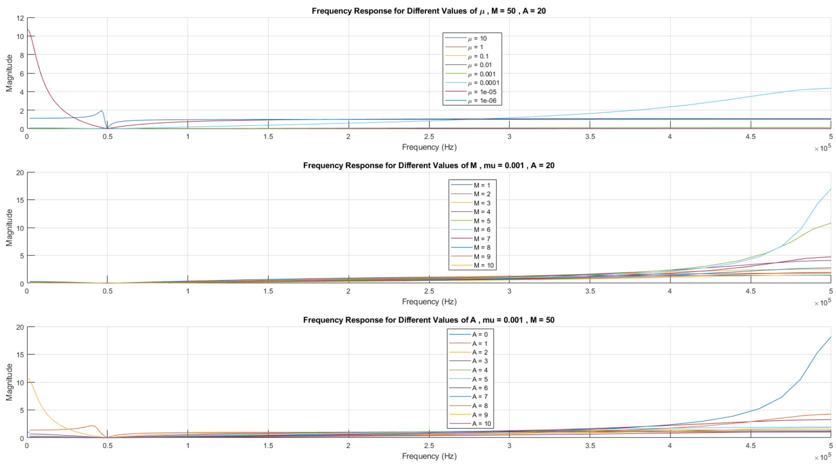


2.4 part d

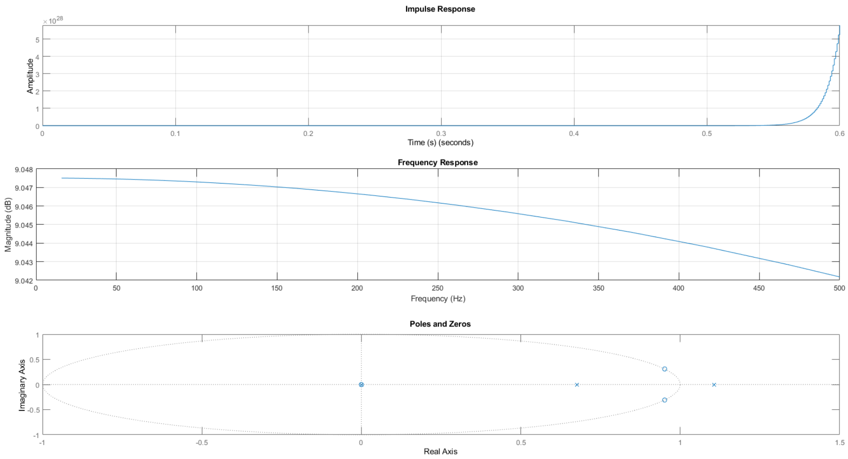
* As we had in slides :



- Now for different values of mu,A and M I've plotted frequency responses:

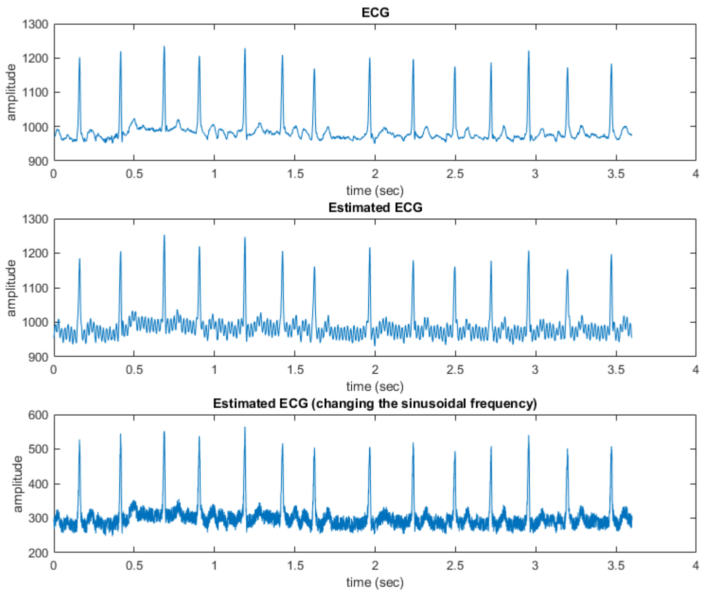


* Now for mu = 0.0001 , A = 5 , M = 100 :



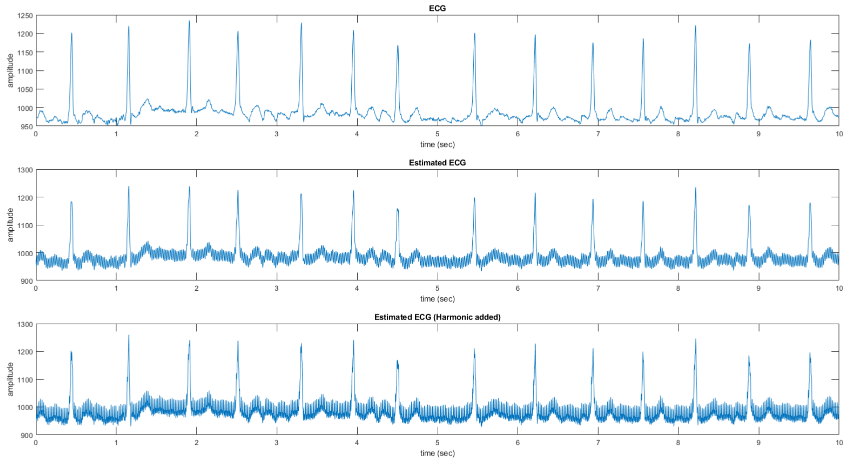
2.5 part e

- For analysis the effect of a little change in sinusoidal frequencies, I have added noise to the frequency and we will have :



* As we can see the output of Adaptive filter would be noisier than previous estimated ECG.

2.6 part f



* As we can see by adding the first harmonic component Adaptive filter can remove less noise from primary signal but still estimation works almost properly.

Matlab Code

```
%% a
ECG_dataset = load('test.mat');
fs = 360;
s = ECG_dataset.val;
t = 0:1/fs:(length(s)-1)/fs;
phi1 = 2*pi*rand;
phi2 = 2*pi*rand;
N1 = 20*cos(100*pi*t+phi1);
N2 = 20*cos(100*pi*t+phi2);
reference_signal = N1;
primary_signal = s + N2;
w = zeros(length(s),1);
y = zeros(length(s),1);
e = zeros(length(s),1);
```

```
mu = 0.000001;
p = y-w;
[e,y] = adaptivefilter(w,reference_signal,
    primary_signal,mu);
%% b
figure;

subplot(2,1,1)
plot(t,s)
title('ECG');
xlabel('time (sec)');
ylabel('amplitude');

subplot(2,1,2)
plot(t,e)
title('Estimated ECG');
xlabel('time (sec)');
ylabel('amplitude');

f = (-length(s)/2:length(s)/2-1)*(2*pi/length(s));
figure;
subplot(2,1,1)
plot(f, abs(fftshift(fft(s)))/length(s));
title('Magnitude Spectrum using FFT of ECG');
xlabel('Frequency (rad/sample)');
ylabel('Magnitude');
xticks([-pi -pi/2 0 pi/2 pi]);
xticklabels({'-\pi', '-\pi/2', '0', '\pi/2', '\pi'})
    ;

subplot(2,1,2)
```

```
plot(f, abs(fftshift(fft(e)))/length(e))
title('Magnitude Spectrum using FFT of Estimated ECG');
xlabel('Frequency (rad/sample)');
ylabel('Magnitude');
xticks([-pi -pi/2 0 pi/2 pi]);
xticklabels({'-\pi', '-\pi/2' , '0', '\pi/2', '\pi'});

%% c

for i = 0:1000
    N1 = i*cos(100*pi*t+phi1);
    N2 = i*cos(100*pi*t+phi2);
    reference_signal = N1;
    primary_signal = s + N2;
    w = zeros(length(s),1);
    y = zeros(length(s),1);
    e = zeros(length(s),1);
    mu = 0.000001;
    [e,y] = adaptivefilter(w,reference_signal,
        primary_signal,mu);
    SNRin(i+1) = 10*log10(norm(s)^2/norm(N2)^2);
    SNRout(i+1) = 10*log10(norm(s)^2/(norm(e-s)^2));
    SNRimprovement(i+1) = SNRout(i+1) - SNRin(i+1);
end

figure;
plot(SNRin,SNRimprovement)
title('SNRimprovement vs. SNRin');
xlabel('SNRin');
```

```
ylabel('SNRimprovement');


%% part d


f = 50;
z = tf('z', 1/fs);
figure;
mu_values = [10 1 0.1 0.01 0.001 0.0001 0.00001
    0.000001];
M = 50;
A = 20;
for i = 1:length(mu_values)
     mu = mu_values(i);
     H = (1 - 2*cos(2*pi*f/fs)*z^(-1)+z^(-2)) / ...
          (1 - 2*(1 - (mu*(M+1)*A^2)/4)*cos(2*pi*f/fs)*z
              ^(-1) + (1 - mu*(M+1)*A^2)*z^(-2));
     subplot(3, 1, 1);
     hold on;
     [mag, phase, w] = bode(H);
     plot(w*fs/(2*pi), mag(:));
end
title('Frequency Response for Different Values of \mu'
    );
xlabel('Frequency (Hz)');
ylabel('Magnitude');
legend(arrayfun(@(x) ['\mu = ' num2str(x)], mu_values,
      'UniformOutput', false));
grid on;

```

```
% Frequency response for different values of M
mu = 0.001;
M_values = 1:10;
A = 20;

for M = M_values
    H = (1 - 2*cos(2*pi*f/fs)*z^(-1)+z^(-2)) / ...
        (1 - 2*(1 - (mu*(M+1)*A^2)/4)*cos(2*pi*f/fs)*z
        ^(-1) + (1 - mu*(M+1)*A^2)*z^(-2));
    subplot(3, 1, 2);
    hold on;
    [mag, phase, w] = bode(H);
    plot(w*fs/(2*pi), mag(:));
end
title('Frequency Response for Different Values of M');
xlabel('Frequency (Hz)');
ylabel('Magnitude');
legend(arrayfun(@(x) ['M = ' num2str(x)], M_values, '
   UniformOutput', false));
grid on;
mu = 0.001;
M = 50;
A_values = 0:10;
for A = A_values
    H = (1 - 2*cos(2*pi*f/fs)*z^(-1)+z^(-2)) / ...
        (1 - 2*(1 - (mu*(M+1)*A^2)/4)*cos(2*pi*f/fs)*z
        ^(-1) + (1 - mu*(M+1)*A^2)*z^(-2));
    subplot(3, 1, 3);
    hold on;
    [mag, phase, w] = bode(H);
    plot(w*fs/(2*pi), mag(:));
```

```
end
title('Frequency Response for Different Values of A');
xlabel('Frequency (Hz)');
ylabel('Magnitude');
legend(arrayfun(@(x) ['A = ' num2str(x)], A_values, '
    UniformOutput', false));
grid on;
hold off;

%%%%

mu = 0.0001;
A = 5;
M = 100;
figure;
subplot(3, 1, 1);
impulse(H);
title('Impulse Response');
xlabel('Time (s)');
ylabel('Amplitude');
grid on;
subplot(3, 1, 2);
[mag, phase, w] = bode(H, {0, pi});
mag = squeeze(mag);
w = squeeze(w);
plot(w*fs/(2*pi), 20*log10(mag));
title('Frequency Response');
xlabel('Frequency (Hz)');
ylabel('Magnitude (dB)');
grid on;
subplot(3, 1, 3);
```

```
pzmap(H);
title('Poles and Zeros');


%% part e




%% part f
phi1 = 2*pi*rand;
phi2 = 2*pi*rand;
phi3 = 2*pi*rand;
N1 = 20*cos(100*pi*t+phi1);
N2 = 20*cos(100*pi*t+phi2);
first_harmonic = 20*cos(2*100*pi*t+phi3);
reference_signal = N1+first_harmonic;
primary_signal = s + N2+first_harmonic;
w = zeros(length(s),1);
y = zeros(length(s),1);
e = zeros(length(s),1);
mu = 0.000001;
[eh,yh] = adaptivefilter(w,reference_signal,
    primary_signal,mu);
[ewh,ywh] = adaptivefilter(w,reference_signal-
    first_harmonic,primary_signal-first_harmonic,mu);
figure;

subplot(3,1,1)
plot(t,s)
```

```
title('ECG');
xlabel('time (sec)');
ylabel('amplitude');

subplot(3,1,2)
plot(t,ewh)
title('Estimated ECG');
xlabel('time (sec)');
ylabel('amplitude');

subplot(3,1,3)
plot(t,eh)
title('Estimated ECG (Harmonic added)');
xlabel('time (sec)');
ylabel('amplitude');



%% part g


phi1 = 2*pi*rand;
N2 = 20*cos(100*pi*t+phi2);
primary_signal = s + N2;
w = zeros(length(s),1);
mu = 0.000001;
for i = 1:15
    [eal(i), yal(i)] = ALEfilter(w, primary_signal,
       primary_signal, mu, i);
    SNRinal(i) = 10*log10(norm(s)^2/norm(N2)^2);
    SNRoutal(i) = 10*log10(norm(s)^2/(norm(e(i)-s)^2))
```

```
    ;
    SNRimprovemental(i) = SNRoutal(i) - SNRinal(i);
end
figure;
plot(SNRin,SNRimprovement)
title('SNRimprovement');
xlabel('sample');
ylabel('SNRimprovement');
%% Adaptive filter function :

function [e,y] = adaptivefilter(w,reference_signal,
    primary_signal,mu)
    for i=1:length(reference_signal)
        y = reference_signal*w;
        e = primary_signal - y;
        w = w + 2*mu*e*reference_signal';
    end
end


%% Adaptive Line Enhancer (ALE)

function [e, y] = ALEfilter(w, reference_signal,
    primary_signal, mu, delay)
    % Initialize variables
    N = length(primary_signal);
    y = zeros(1, N); % Filter output
    e = zeros(1, N); % Error signal

    % Apply delay to the primary signal
    delayed_primary_signal = [zeros(1, delay),
```

```
        primary_signal(1:end-delay)];

    % Adaptive filtering
    for i = 1:N
        % Ensure the reference signal is properly
            indexed to avoid overflow
        if i > delay
            ref_signal_segment = reference_signal(i-
                delay:i-1)'; % Delayed segment for
                filter input
            primary_segment = delayed_primary_signal(i
                -delay:i-1); % Delayed primary segment
            y(i) = ref_signal_segment * w; % Filter
                output
            e(i) = primary_signal(i) - y(i); % Error
                signal
            w = w + 2 * mu * e(i) * ref_signal_segment
                '; % Update filter coefficients
        end
    end
end
```

3 Question 3

3.1 part a

Article: "Model-based Prediction of Heart Rate Variability"

Summary: This study focuses on the use of parametric models for predicting heart rate variability (HRV) in clinical settings. The authors utilize autoregressive models to forecast HRV based on historical data, helping in the early detection of cardiac conditions. The approach allows for real-time monitoring and prediction of heart anomalies, providing valuable insights for preventive healthcare. By leveraging parametric modeling, the system adapts to individual patient data, enhancing the accuracy and reliability of predictions.

3.2 part b

Article: ”Super-resolution spectral estimation in short-time
non-contact vital sign measurement” Summary: This study applies non-parametric spectral estimation methods to non-contact vital sign measurement using Doppler radar. Techniques such as short-time Fourier transform are employed to analyze the spectral content of radar signals reflected from the body. This allows for accurate extraction of vital signs like heart rate and respiratory rate in real-time, proving beneficial for remote patient monitoring and emergency medical applications.

3.3 part c

Article: ”Parametric Spectral Estimation for Sleep Apnea Detection”
Summary: The research discusses the use of parametric spectral estimation techniques, specifically autoregressive (AR) modeling, to detect sleep apnea events from respiratory signals. By estimating the power spectral density of the respiratory signal, the method identifies characteristic patterns associated with apnea episodes. The parametric approach allows for high-resolution spectral analysis, making it possible to detect subtle changes in the signal that are indicative of apnea, thus aiding in the accurate diagnosis and monitoring of sleep disorders.

3.4 part d

Article: ”Adaptive Filtering by Non-Invasive Vital Signals Monitoring and Diseases Diagnosis” Summary: The paper examines the use of adaptive filters, particularly LMS and RLS algorithms, in processing ECG and PPG signals. These filters dynamically adjust to varying noise conditions, effectively removing artifacts and enhancing signal quality. This facilitates accurate measurement of vital parameters such as heart rate and oxygen saturation, improving the reliability of non-invasive monitoring systems in clinical and home settings.