

ECE-S 632:  
Fundamentals of Stochastic DSP  
Prof. John Walsh

Zexi Liu  
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Electrical and Computer Engineering  
Drexel University

- 4.1** Project Proposal Write an abstract, complete with background references, on a statistical signal processing problem or problem area interesting to you and/or relevant to your job/research that you would like to investigate for your course project. The abstract is to ensure that your assignment matches your interests. Email me your abstract when it is ready. Over email, you and I will use the abstract to craft a specific mini-research problem of reasonable but limited scope.

The email was sent to Dr. Walsh on Mon 2/22/2010 9:55 PM.

- 4.2** Write a MATLAB program which calculates the order 20 forward linear prediction coefficients for a real valued wide sense stationary Gaussian process with mean zero and auto-correlation using the Levinson-Durbin algorithm. Also calculate the MSE of the order 20 linear predictor using the Levinson-Durbin algorithm, and compare it with an empirically observed MSE which you calculate by running the linear predictor on a length 10000 randomly generated sample from the given Gaussian random process and averaging the squared error.

The order 20 forward linear prediction coefficients:

Order	Coefficients
1	0.726636900430018
2	0.00626520788895617
3	0.00412685827773906
4	0.00271833907682490
5	0.00179055519325446
6	0.00117942905352016
7	0.000776883662657109
8	0.000511729304903103
9	0.000337073719683742
10	0.000222029256190734
11	0.000146250425834925
12	9.63358246606418e-05
13	6.34581095886934e-05
14	4.18028923690078e-05
15	2.75404713240350e-05
16	1.81485527615082e-05
17	1.19661860704105e-05
18	7.90002640694090e-06
19	5.23097784495583e-06
20	6.60879642726521e-06

The MSE of the order 20 linear predictor (theoretical value):

Order	Coefficients
0	0.8000000000000000
1	0.366957265248439
2	0.366903263616263
3	0.366879842199477
4	0.366869681793097
5	0.366865273720419
6	0.366863361210659
7	0.366862531424750
8	0.366862171400546
9	0.366862015194173
10	0.366861947419659
11	0.366861918013769
12	0.366861905255187
13	0.366861899719514
14	0.366861897317704
15	0.366861896275611
16	0.366861895823469
17	0.366861895627294
18	0.366861895542178
19	0.366861895505248
<b>20</b>	<b>0.366861895489225</b>

Empirically observed MSE:

**0.225752490827718**

```
% HW4-1
clc;
clear;

R = zeros( 20, 1 );
for i = 1 : 20
    R(i) = 0.2 * exp(-0.5*abs(i)) + 0.6 * exp(-0.25*abs(i));
end
R0 = 0.2 * exp(-0.5*0) + 0.6 * exp(-0.25*0);

f = zeros( 20, 20 );
MSE = zeros( 20, 1 );

MSE0 = R0;
MSE(1) = (1-(R(1)/R0)^2)*MSE0;
f(1,1) = R(1) / MSE0;
for P = 2 : 20
    SUM = 0;
    for i = 1:P-1
        SUM = SUM + f(P-1,i) * R(P-i);
    end
    f(P,P) = ( R(P) - SUM ) / MSE(P-1);
```

```

    for i = 1 : P-1
        f(P,i) = f(P-1,i) - f(P,P)* f(P-1,P-i);
    end
    MSE(P) = ( 1 - abs(f(P,P))^2 ) * MSE(P-1);
end

a = levinson( [R0; R], 20 )';

co = f( 20, : )';

X = normrnd( 0, R0, 10000, 1 );    % zero mean Gaussian noise with variance R0
N = numel(X);
Xp = zeros( N, 1 );

XX = conv( X, R );
for i = 21 : N
    Xp(i) = sum( co(1:20) .* XX( i-1:-1:i-20 ) );
end
Err = (XX(1:10000) - Xp).^2;

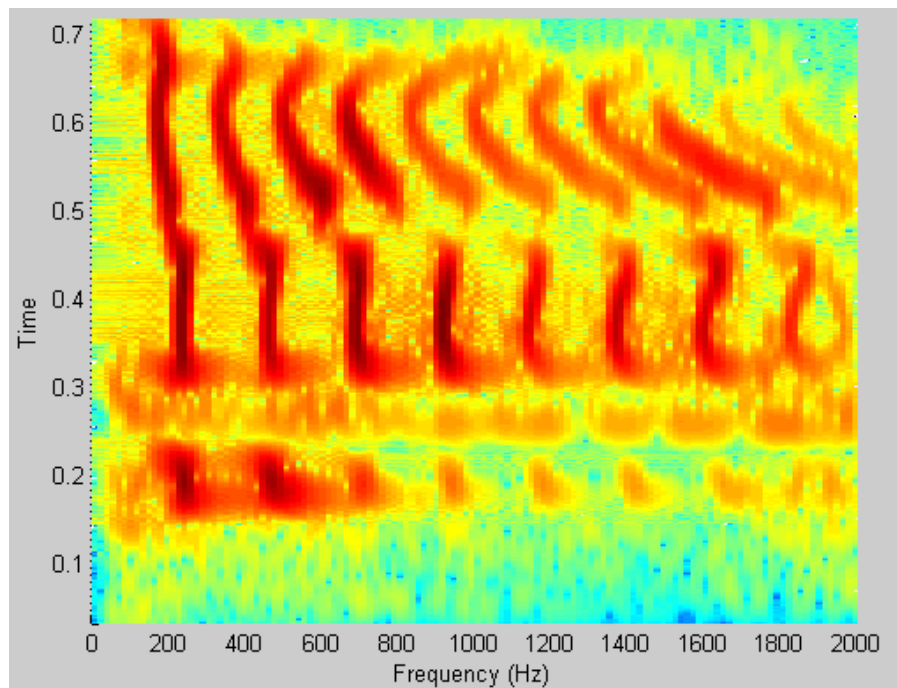
eMSE = sum(Err(21:10000))/numel(Err(21:10000));

```

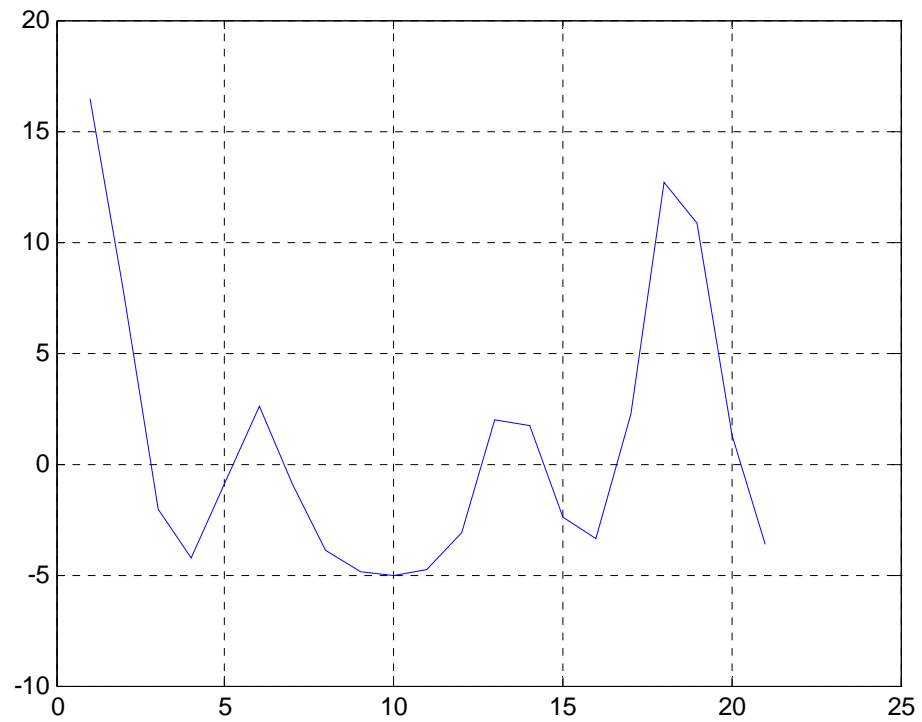
**4.3** Select an audio wav file of your choice that contains speech and load it into Matlab. Speech is a quasi-stationary signal: on short segments (e.g. 32 millisecond blocks) it appears stationary, but it is in its changing spectrum across different such blocks in which carries its information.

- (a) Using a spectrogram, find a temporal region of the \_le over which the spectrum appears to be constant. Select the portion of the audio \_le associated with this temporal region and build an autocorrelation estimate for this region. Generate a linear predictor from this autocorrelation estimate using Levinson Durbin. Record the performance you achieve with this.

The spectrogram of input speech signal.



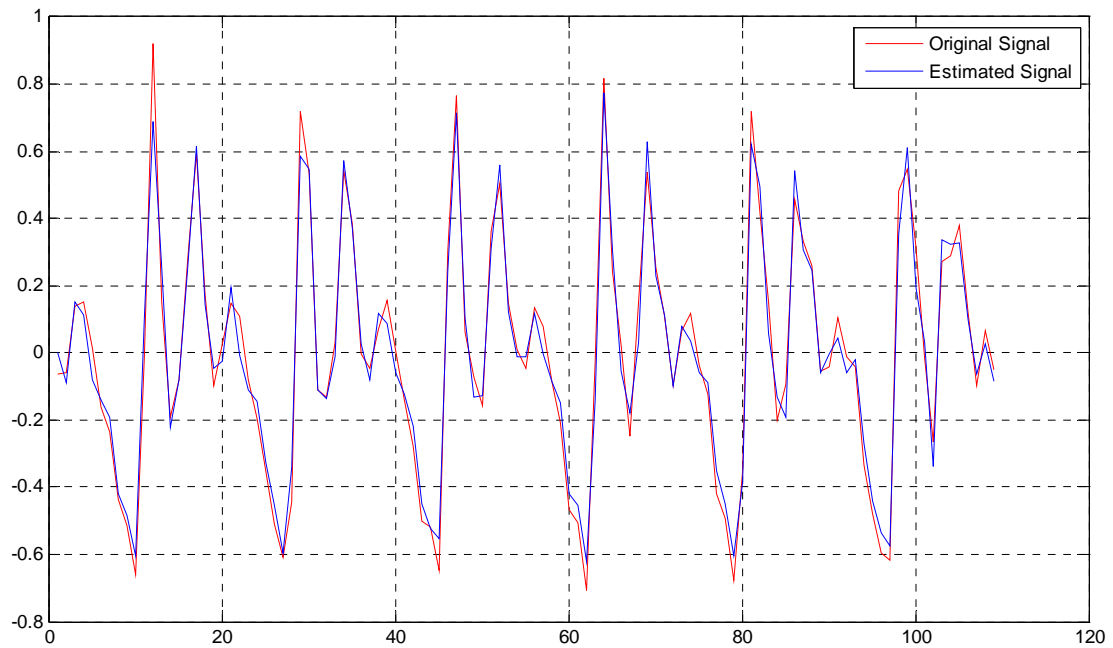
Auto-correlation of the chosen temporal region:



The order 20 forward linear prediction coefficients:

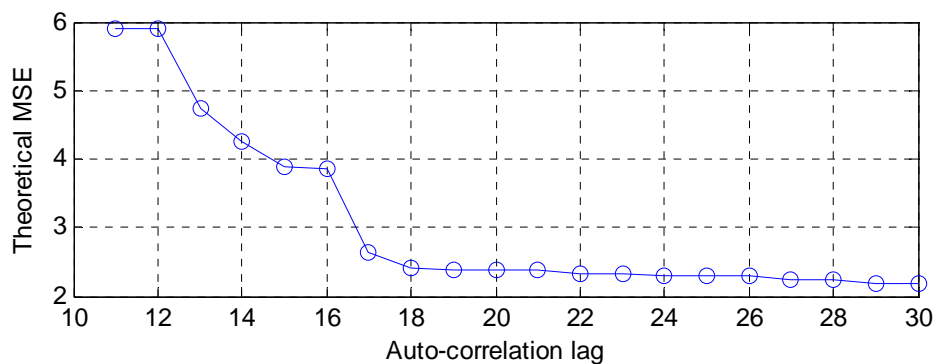
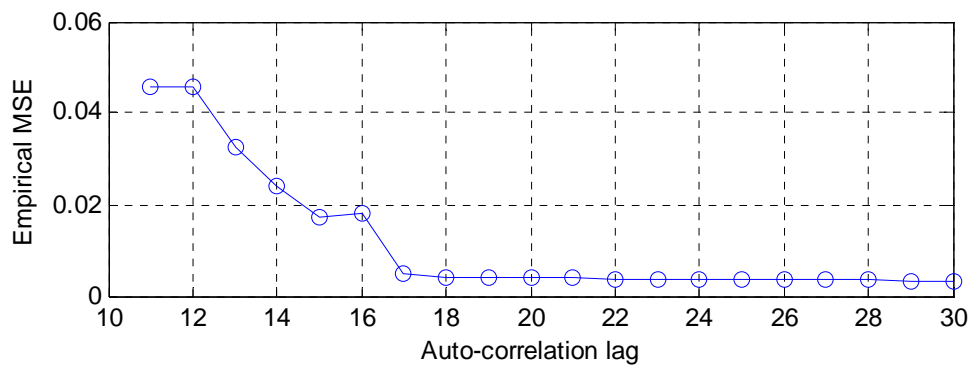
Order	Coefficients
1	0.661028210250749
2	-0.596467931594581
3	0.189793085195174
4	-0.398600394902704
5	0.247440532874425
6	-0.384625222492282
7	0.136756443330365
8	-0.354829424009870
9	0.167945542621277
10	-0.370210092367595
11	0.0360700626582739
12	-0.175716001727205
13	0.0455643928929486
14	-0.277896122026717
15	0.116536461547976
16	-0.370036261793053
17	0.758057349156431
18	-0.365226131399721
19	0.120926824176675
20	-0.0149783145425018

Original signal compare with estimated signal:



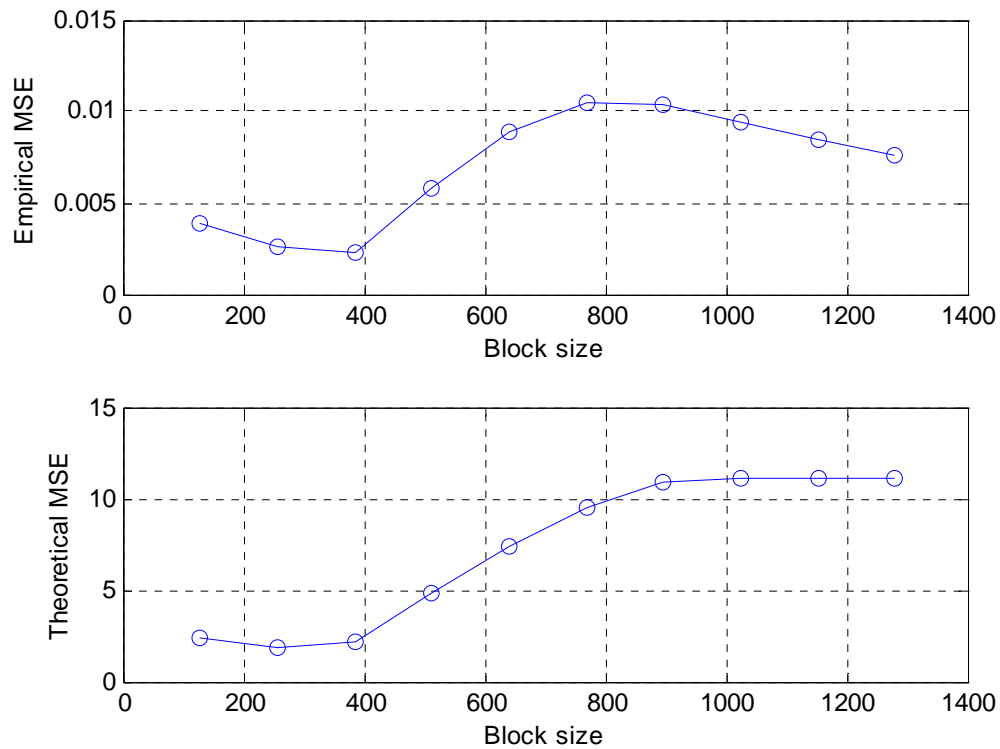
- (b) Compare the empirical average squared prediction error over the block you used to calculate the auto-correlation estimate with the theoretical MSE given by Levinson Durbin. Make a plot of these two values as a function of the maximal auto-correlation lag estimated. Why are these two numbers different from one another?

Empirical MSE vs. Theoretical MSE



- (c) Repeat this experiment, but by measuring the average squared prediction error over a larger block than the one you used to calculate the auto-correlation estimate. Choose the size of this block to be one over which you can see that spectral properties of the data changing in the spectrogram. How do your estimated squared prediction errors compare now with the ones you obtained with the smaller (original) block? Why?

#### Block size vs. MSE



```
% HW4-2
eMSE = zeros( 20, 1 );
tMSE = zeros( 20, 1 );
for i = 1 : 20
    [eMSE(i) tMSE(i)] = HW42(i+10, 128);
end
x = 11 : 30;
figure(1);
subplot(2,1,1);
plot( x, eMSE, '-o' );
xlabel('Auto-correlation lag');
ylabel('Empirical MSE');
grid on
subplot(2,1,2);
plot( x, tMSE, '-o' );
xlabel('Auto-correlation lag');
ylabel('Theoretical MSE');
grid on;
```

```

% HW4-2
eMSE = zeros( 8, 1 );
tMSE = zeros( 8, 1 );
k = 1;
for i = 128 : 128 :1280
    [eMSE(k) tMSE(k)] = HW42( 20, i );
    k = k + 1;
end
x = 128 : 128 :1280;
figure(1);
subplot(2,1,1);
plot( x, eMSE, '-o' );
xlabel('Block size');
ylabel('Empirical MSE');
grid on
subplot(2,1,2);
plot( x, tMSE, '-o' );
xlabel('Block size');
ylabel('Theoretical MSE');
grid on;

function [eMSE tMSE]= HW42(lag)

Female = wavread('d.wav');
% figure(1);
% spectrogram(Female,256,250,256,4e3);

R = xcorr( Female(1600:1600+128), lag );
R0 = R(lag+1);
R = R(lag+2: numel(R));

f = zeros( lag, lag );
MSE = zeros( lag, 1 );

MSE0 = R0;
MSE(1) = (1-(R(1)/R0)^2)*MSE0;
f(1,1) = R(1) / MSE0;
for P = 2 : lag
    SUM = 0;
    for i = 1:P-1
        SUM = SUM + f(P-1,i) * R(P-i);
    end
    f(P,P) = ( R(P) - SUM ) / MSE(P-1);
    for i = 1 : P-1
        f(P,i) = f(P-1,i) - f(P,P)* f(P-1,P-i);
    end
    MSE(P) = ( 1 - abs(f(P,P))^2 ) * MSE(P-1);
end

R = [R0; R];
a = levinson( R, lag );

co = f( lag, : );

X = Female(1600:1600+128);
N = numel(X);

```



```

Xp = zeros( N, 1 );
for i = lag+1 : N
    Xp(i) = sum( co(1:lag) .* X( i-1:-1:i-lag ) );
end
Err = (X(lag+1:129) - Xp(lag+1:129)).^2;

eMSE = sum(Err)/numel(Err);
tMSE = MSE(numel(MSE));

```

- 4.4** Write a MATLAB function which implements the root-MUSIC frequency estimation method. Test it out on a length 1000 signal containing a sinusoid with frequency  $f_1 = 3\pi/8$  and phase 0 with amplitude 0.6, and a sinusoid at frequency  $f_2 = \pi/17$  with phase  $\pi/16$  and amplitude 0.2 observed through complex Gaussian white noise with variance  $\sigma^2 = 1$  and mean 0. Try other lengths and observe how the performance of the estimate varies with different lengths and different Monte Carlo trials.

Different lengths and different Monte Carlo trials:

Length	Trials	Est. frequencies	True frequencies
10	10	-1.3704 1.2929	0.1848 1.1781
	100	-1.3160 1.3906	
	1000	-1.3121 1.3250	
100	10	-0.6402 1.1813	
	100	-0.7394 1.2539	
	1000	-0.6690 1.2889	
1000	10	0.2598 1.1900	
	100	0.1417 1.2514	
	1000	0.1705 1.2157	
10000	10	0.1884 1.1751	
	100	0.1749 1.1763	
	1000	0.1833 1.1779	

% HW4-3

```

clc;
clear;

```

```

N = 10000;
T = 1000;
% randn( 'state', 1 );
W = zeros( T, 2 );
P = zeros( T, 2 );
n = 0:N-1;

for i = 1:T
    s = 0.6 * exp(1i*3*pi/8*n) + 0.2 * exp(1i*pi/17*n+pi/16) + normrnd( 0, 1, N, 1 )';
    % Hs = spectrum.music( 2, 20 );
    % pseudospectrum( Hs, s );
    [W(i,:) ~] = sort( rootmusic( s, 2 ) );
end
mean(W)
[ pi/17 3*pi/8 ]

```