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# Signal Preconditioning to Minimize Impulse Response Contribution

S. K. Lehman

July 7, 2021

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# Signal Preconditioning to Minimize Impulse Response Contribution

Sean K. Lehman

July 07, 2021

## Abstract

A study was performed to identify a method to minimize the effect of a linear time-invariant (LTI) system impulse response on an input. Three methods were studied: Wiener filter, the N4SID algorithm and transfer function estimation, the latter two using functions from MATLAB's System Identification Toolbox. Although all three methods were able estimate an unknown forward impulse response given an input/output time series pair, only the Wiener filter was able to estimate a system inverse which satisfactorily solved the problem using a cosine similarity measure.

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# 1 Introduction

All input/output systems have transfer functions which modify the input. For example, wave-based transducers emit the derivative (high-pass filtered version) of their inputs, at a minimum. A study was performed to identify a method to minimize the effect of a linear time-invariant (LTI) system impulse response on an input. That is, given the LTI system,

$$y = h * x, \quad (1)$$

where  $x_n$  is the input time series,  $y_n$  the output and  $h_n$  the forward system impulse response, determine a preconditioned input time series,  $x_{\text{pre}}$  such that

$$y \approx h * x_{\text{pre}}. \quad (2)$$

In theory,  $x_{\text{pre}} = h^{-1} * x$ . Only the input and output time series are available, the system impulse response,  $h$ , is unknown. Its inverse must be estimated.

Three algorithms were studied,

- The Wiener filter (see Appendix A);
- The MATLAB numerical algorithm for state-space identification function, `n4sid()`;
- The MATLAB transfer function estimation function, `tfest()`.

The latter two functions are from the System Identification Toolbox. Although determining an estimate of the impulse response,  $\hat{h}$ , is not required, the algorithms were used to identify it as a confirmation they functioned as expected on an input/output test set.

All three methods were successful at approximating the forward impulse response in proof-of-concept test using a 1–12 Hz chirp input and a single cycle 6.5 Hz sinusoid impulse response. However, only the Wiener filter estimation of the inverse was successful at compensating for the forward impulse response's effect on the input. The measure of success is the cosine similarity as described in Appendix B.

The next section presents an overview of signal preconditioning. Section 3 develops a proof-of-concept. Section 4 presents the empirical results using data from an electromechanical transducer system.

## 2 Signal Preconditioning

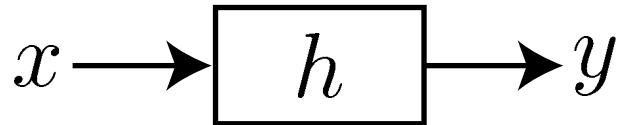
As shown in Figure 1, signal preconditioning involves convolving the input time series,  $x_n$ , with an approximation to the inverse impulse response,  $\hat{h}^{-1}$ , resulting in a preconditioned time series,  $x_{\text{pre}}$ , which minimizes the effect of the forward impulse response, resulting in a close approximation to the input signal at the output. This is more easily understood in the frequency domain where convolution transforms into a multiplication by the transfer function,

$$\hat{X} = H \left( H^{-1} X \right) = H X_{\text{pre}}, \quad (3)$$

where  $X_{\text{pre}} \equiv H^{-1} X$  is the preconditioned signal spectrum.

The inverse impulse response is estimated by swapping the input/output time series, as shown in Figure 2, in the impulse response estimation algorithms.

## Forward Problem



## Preconditioned Time Series



Figure 1: Preconditioned problem. Given an input/output time series,  $x$  and  $y$ , with unknown system impulse response,  $h$ , estimate the inverse impulse response,  $\hat{h}^{-1}$ . Then precondition the input so that when presented to the forward system, its output closely matches the original input. That is, convolve  $x$  with an approximation to the inverse impulse response,  $\hat{h}^{-1}$ , such that the effects of the impulse response,  $h$ , are minimized.

## Inverse Problem

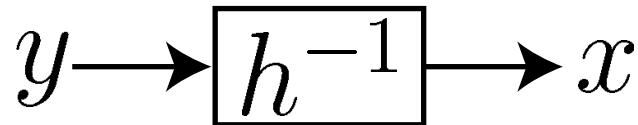


Figure 2: Inverse problem. The inverse impulse response may be estimated by swapping the input/output time series in the algorithms.

### 3 Proof-of-Concept

The proof-of-concept used a 1–12 Hz chirp as input and a 6.5 Hz single cycle sinusoid as forward impulse response. The time series are presented in Figure 3. The upper left plot presents the input,  $x$ . The upper right shows the output,  $y$ , with peak around 6.5 Hz. The middle left plot shows the true impulse response in red along with the Wiener, state-space (“SS”, `n4sid()`) and transfer function (“TF”, `tfest()`) estimates. The true impulse response is 24 samples. In a real situation where the impulse response length is unknown, a guess must be made of its length. In this example, 73 samples was selected. Similarly with the state-space and transfer function estimates. A value of 2 states was selected for the former, and 6 poles and 7 zeros for the latter.

The middle right plot presents the estimated inverse impulse response for the three methods where the number of Wiener taps remains 73 but the states were increased to 6 and the poles and zeros to 12 and 13, respectively. The state-space and transfer function numbers were selected in an attempt to maximize the cosine similarity between the chirp input and preconditioned output. However, given the poor inverse performance of the the `n4sid()` and `tfest()` functions, the task proved futile.

The bottom left graph shows the preconditioned input using the Wiener approach, the graph to its right overlays the chirp input and the preconditioned output. The similarity is 0.982 indicating a good match and the success of the Wiener algorithm.

Table 1 lists the simulation parameters and results. The similarity measures reflect the success in the forward problem for the three methods and the poor performance with the inverse with the state-space and transfer function methods.

For completeness, Figure 4 presents the state-space and transfer function inverse results. Evidently, for this proof-of-concept problem, the System Identification Toolbox functions perform well and as expected in the forward but not inverse case. When examining the spectra presented in the bottom plot of Figure 5, one observes good matches with the chirp input, yet their time domain equivalents have poor similarity measures. This indicates there is an issue with the phases. Perhaps, this may be explored at another time.

Table 1: Proof-of-concept parameters.

<b>Simulation Parameters</b>	
Input, $x$ , & output, $y$ , size	1441 samples
Forward impulse response, $h$ , size	24 samples
Forward Wiener filter taps	73 samples
Inverse Wiener filter taps	73 samples
Forward state-space (SS) size	2
Forward transfer function (TF)	6 poles / 7 zeros
Inverse state-space (SS) size	6
Inverse transfer (TF)	12 poles / 13 zeros
Sample interval	6.94e-03 seconds
Regularization, alpha	1.00e-12
SNR	40 dB
Noise variance	6.11e-02
<b>Similarity Measure between Input &amp; Preconditioned Output</b>	
Input, $x$ , & output, $\hat{x}$	0.982
<b>Similarity Measures between Forward &amp; Estimated Impulse Responses</b>	
True & Wiener estimate	0.990
True & SS estimated	0.899
True & TF estimate	0.998
<b>Similarity Measures between Input and Preconditioned Output</b>	
Input & Wiener estimate	0.982
Input & SS estimate	-0.127
Input & TF estimate	0.676

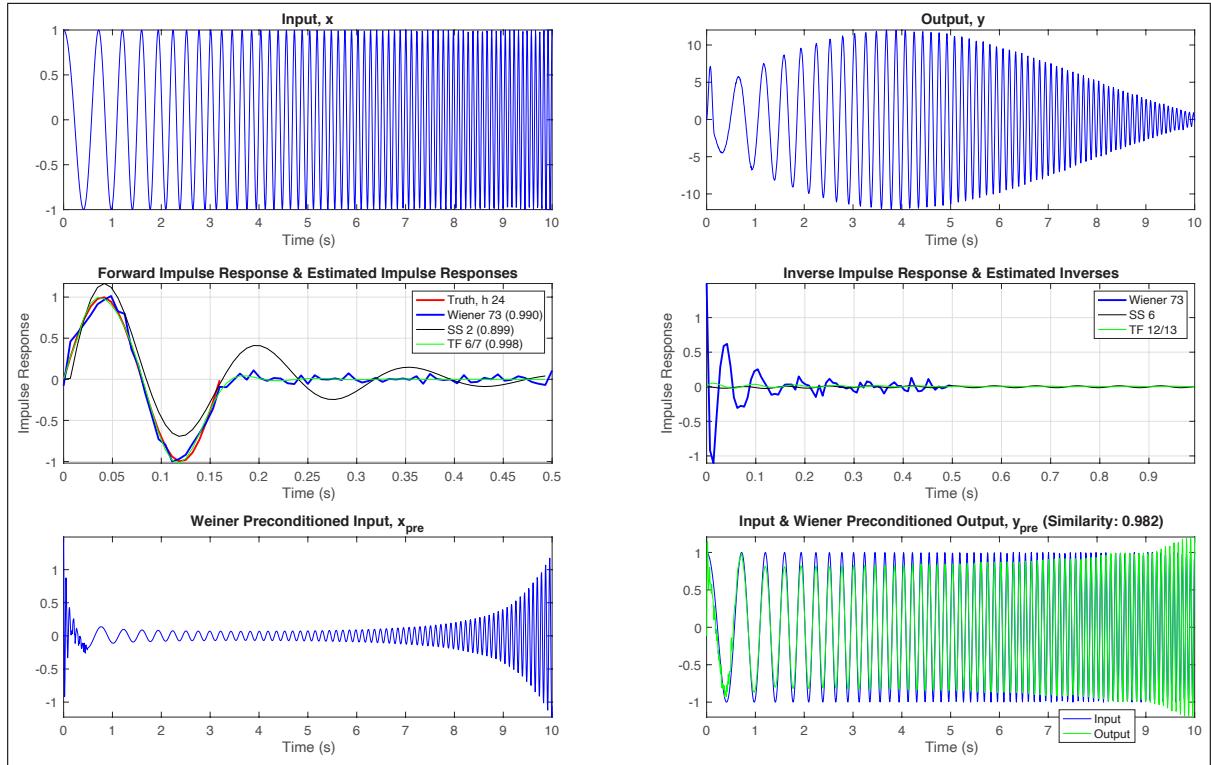


Figure 3: Proof-of-concept results with the Wiener filter algorithm.

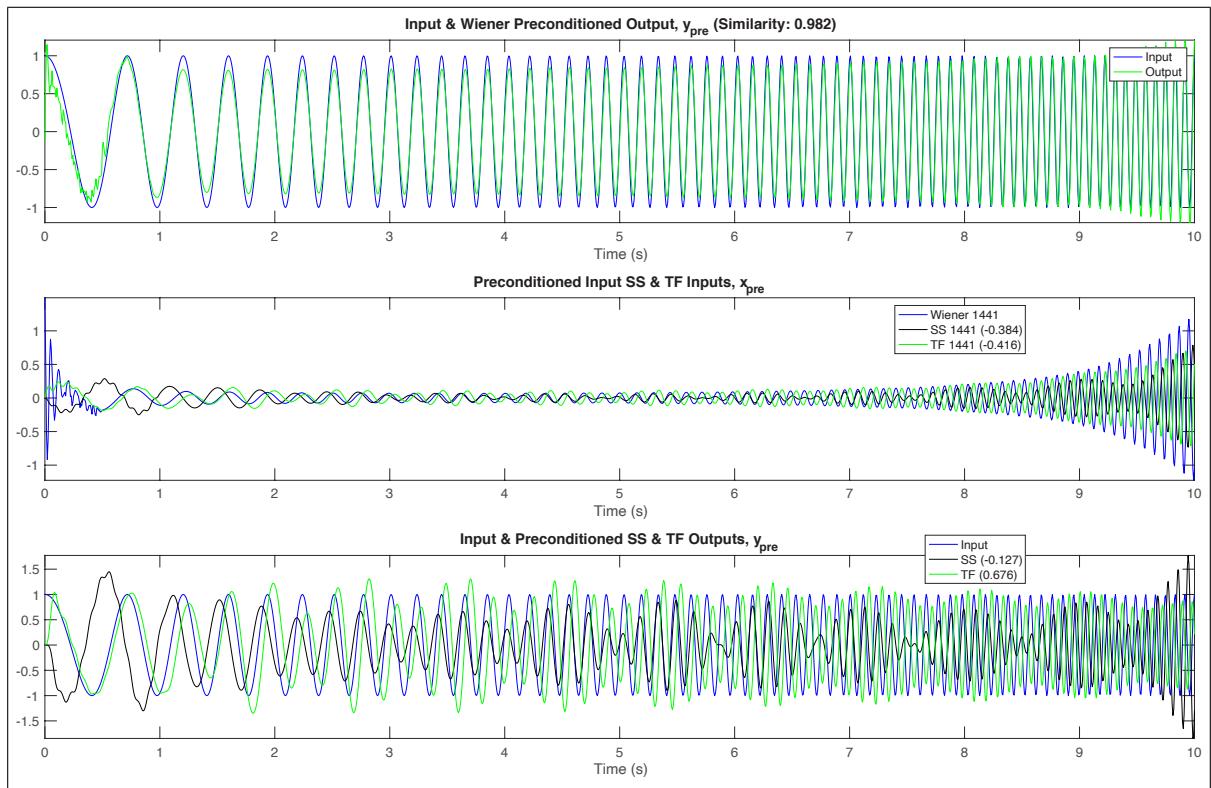


Figure 4: Proof-of-concept results with the state-space and transfer function algorithms.

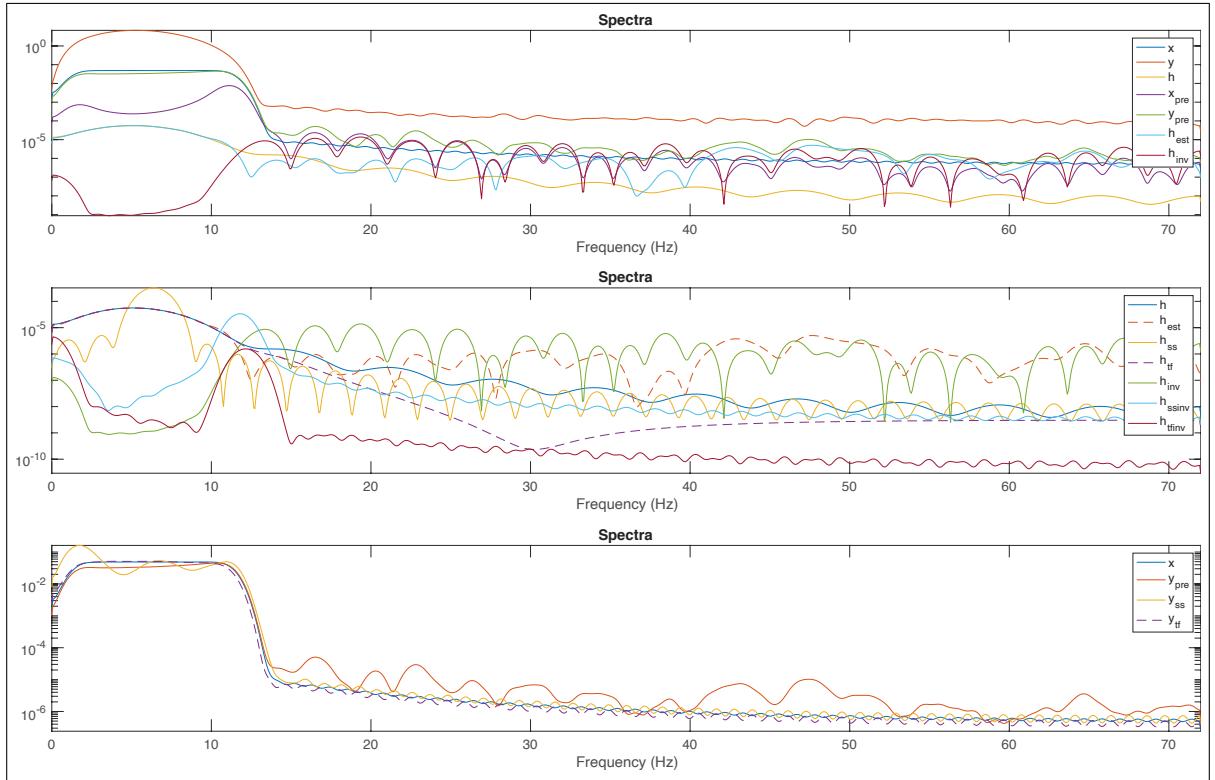


Figure 5: Proof-of-concept spectral results. The input, original output and impulse response are represented by  $x$ ,  $y$  and  $h$  respectively.  $x_{\text{pre}}$  and  $y_{\text{pre}}$  are the Wiener filter based preconditioned input and resulting output.  $h_{\text{est}}$  and  $h_{\text{inv}}$  are the Wiener based forward and inverse impulse responses.  $h_{\text{ss}}$  &  $h_{\text{tf}}$  are the state-space and transfer function estimates.  $h_{\text{ssinv}}$  &  $h_{\text{tfinv}}$  are the corresponding inverse estimates.  $y_{\text{ss}}$  &  $y_{\text{tf}}$  are the state-space and transfer function preconditioned outputs. It is curious their spectra are good matches with the chirp input, yet their time domain equivalents have poor similarity measures. This indicates there is an issue with the phases.

## 4 Empirical Results

The Wiener filter algorithm was applied to a real transducer system in which an input voltage signal drives an electromechanical transducer. The goal is to have the input signal match the output motion. Two data sets were collected. The first, presented in Figure 6, was subjectively quieter and required no regularization in the Wiener filter. A maximum similarity of 0.97 between the input and output time series was achieved by iterating over the number of filter taps. The result was 2500 points.

The second data set, shown in Figure 7, was noisier. It required a regularization constant of  $10^{-3}$ . A maximum similarity of 0.87 was achieved using 8192 filter points.

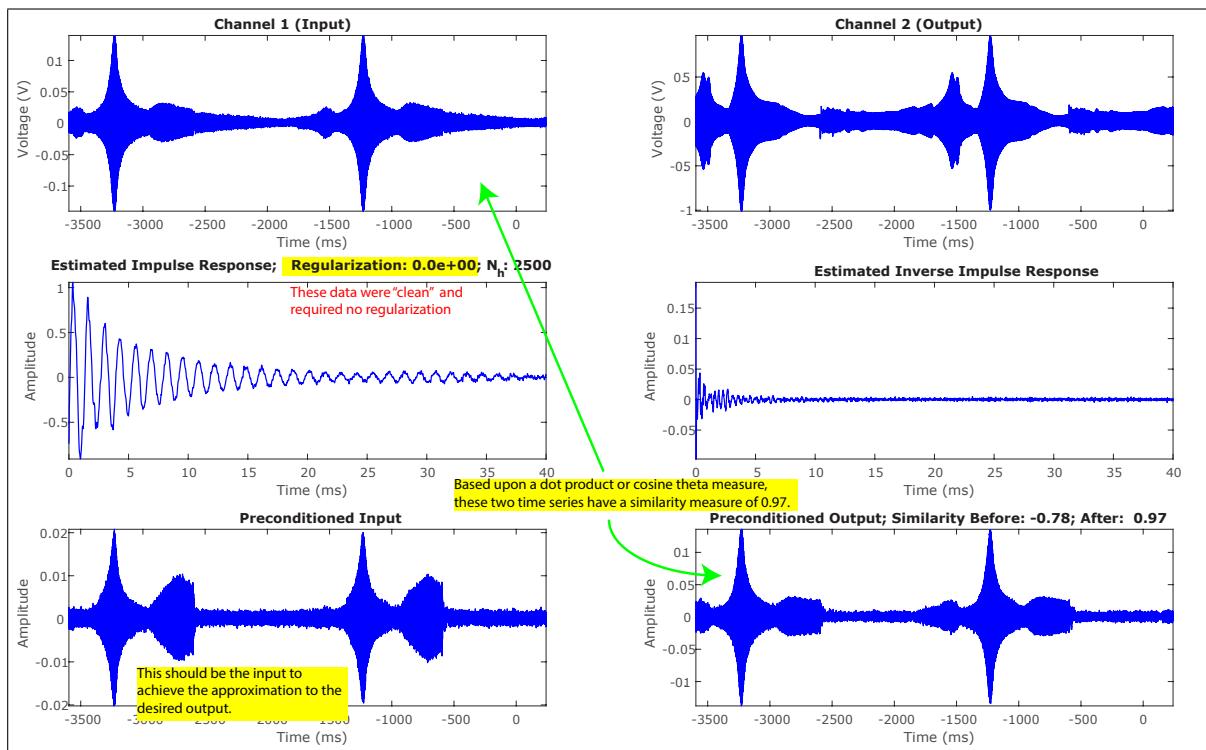


Figure 6: First input/output time series.

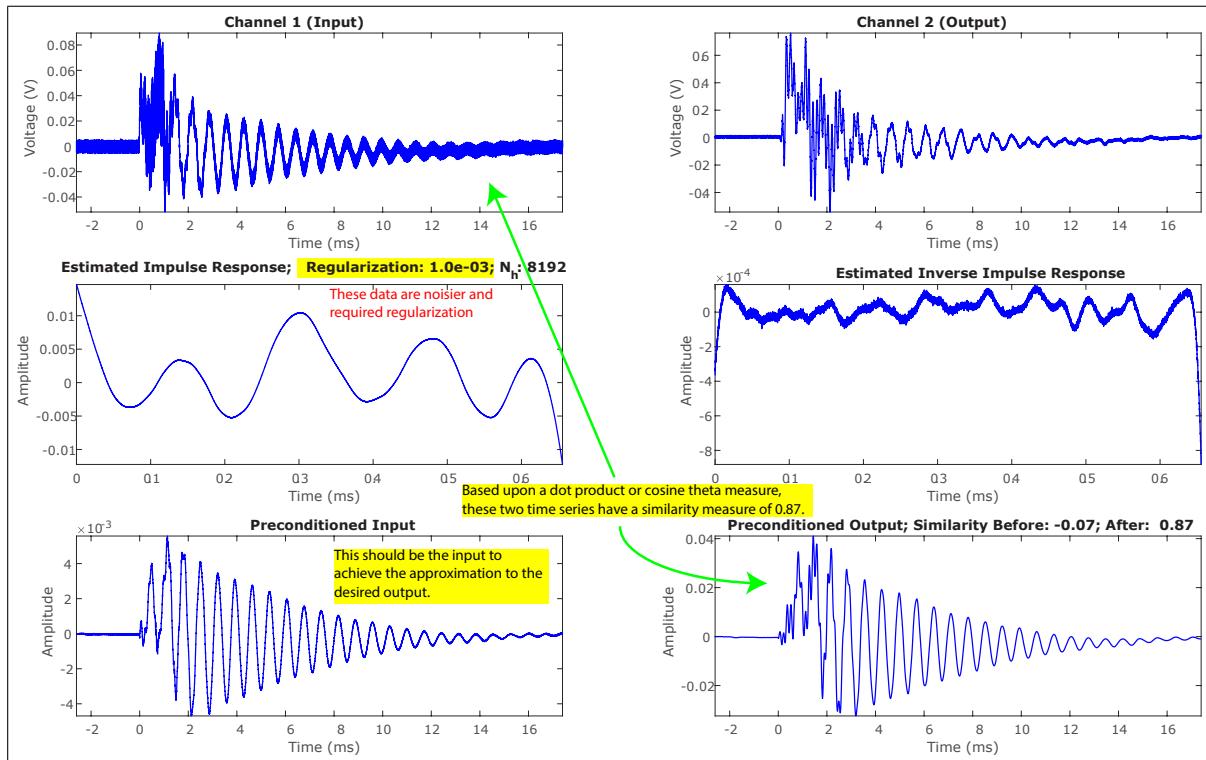


Figure 7: Second input/output time series.

## 5 Conclusion

Three methods were evaluated to solve a signal preconditioning problem:

- The Wiener filter (see Appendix A),
- The MATLAB numerical algorithm for state-space identification function, `n4sid()`,
- The MATLAB transfer function estimation function, `tfest()`,

the latter two functions having been taken from the MATLAB System Identification Toolbox.

Although all three algorithms solved the forward problem, only the Wiener filter successfully solved the inverse and preconditioning problem. Further investigation is required to determine why the state-space and transfer function methods failed at the inverse problem.

## A Wiener Filter

There are multiple interpretations of the Wiener filter. A deconvolution interpretation is used here.

Consider a linear time-invariant system, shown in Figure 8, described by

$$y_n = h_n * x_n, \quad (4)$$

$$y_n = \sum_{m=0}^{N-1} h_m x_{n-m} \quad (5)$$

where  $x_n$  is the input,  $y_n$  is the output and  $h_n$  is the unknown system impulse response. The Wiener solution is to find  $h_n$  such that

$$h_n = \underset{h_n}{\operatorname{argmin}} \mathbb{E} \{e_n^2\}, \quad (6)$$

where

$$e_n \equiv y_n - \sum_{m=0}^{N-1} h_m x_{n-m}. \quad (7)$$

Expand  $\mathbb{E} \{e_n^2\}$ ,

$$\mathbb{E} \{e_n^2\} = \mathbb{E} \left\{ \left( y_n - \sum_{m=0}^{N-1} h_m x_{n-m} \right)^2 \right\}, \quad (8)$$

$$= \mathbb{E} \{y_n^2\} + \mathbb{E} \left\{ \left( \sum_{m=0}^{N-1} h_m x_{n-m} \right)^2 \right\} - 2\mathbb{E} \left\{ \sum_{m=0}^{N-1} h_m x_{n-m} y_n \right\}. \quad (9)$$

Minimize with respect to  $h_k$ ,

$$\frac{\partial}{\partial h_k} \mathbb{E} \{e_n^2\} = 2\mathbb{E} \left\{ \sum_{m=0}^{N-1} h_m x_{n-m} x_{n-k} \right\} - 2\mathbb{E} \{x_{n-k} y_n\}, \quad (10)$$

$$= 2 \sum_{m=0}^{N-1} h_m \mathbb{E} \{x_{n-m} x_{n-k}\} - 2\mathbb{E} \{x_{n-k} y_n\}, \quad (11)$$

$$= 2 \sum_{m=0}^{N-1} h_m R_{xx}(m-k) - 2R_{yx}(k) \equiv 0, \quad (12)$$

where the correlations are defined as

$$R_{xx}(m) = \mathbb{E} \{x_n x_{n-m}\}, \quad (13)$$

$$R_{yx}(k) = \mathbb{E} \{x_{n-k} y_n\}. \quad (14)$$

Eqn. (12) is a matrix equation,

$$R_{xx}(m-k) \cdot \mathbf{h}(m) = R_{yx}(k) \quad (15)$$

with solution,

$$\mathbf{h}(m) = \mathbf{R}_{xx}^{-1}(m - k) \cdot \mathbf{R}_{yx}(k). \quad (16)$$

When the data are noisy, a regularization may be included with the inverse as,

$$\mathbf{h}(m) = (\mathbf{R}_{xx}(m - k) + \alpha)^{-1} \cdot \mathbf{R}_{yx}(k), \quad (17)$$

where  $\alpha$  is a positive constant.

Given input,  $x_n$ , and output,  $y_n$ , time series, Eqn. (16) is used to identify the *forward* impulse response,  $h_n$ .

## B Similarity Measure

An inner product or  $\cos \theta$  test is used to determine the similarity between to functions or time series in particular,

$$m = \frac{y \cdot x}{\|y\| \|x\|}. \quad (18)$$

Using this measure, identical time series yield  $m \equiv 1$ , time series which are 180 degrees out of phase have  $m \equiv -1$  and those which are completely dissimilar result in  $m \equiv 0$ .

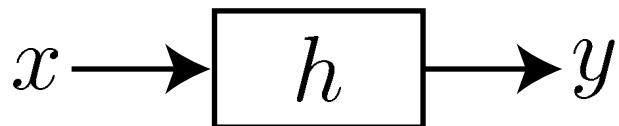


Figure 8: Forward linear time-invariant problem.

## C MATLAB Levinson-Wiggins-Robinson Algorithm, lwr.m

The Levinson-Wiggins-Robinson (lwr) algorithm is the core of the Wiener filter. It solves Eqn. (16) or generally Eqn. (17) when there is a need for a regularization constant.

```

1  function [h,varargout] = lwr( x , y , Norder , varargin )
2  %*****%
3  %
4  % TITLE:      lwr.m
5  % AUTHOR:     Sean K. Lehman
6  % DATE:       April 08, 2021
7  % FUNCTION:   This is the Levinson-Wiggins-Robinson algorithm to compute the
8  %               FIR Wiener solution.
9  %               This is based upon JVC's original lwr.m code.
10 %
11 %
12 % SYNTAX:
13 %
14 %           h = lwr( x , y , Norder );
15 %           [h,Rxx] = lwr( x , y , Norder );
16 %           [h,Rxx,Ryx] = lwr( x , y , Norder );
17 %           ... = lwr( x , y , Norder , alpha );
18 %
19 %           x  is the input.
20 %           y  is the output.
21 %           h  is the impulse response to be estimated.
22 %           Norder is the number of FIR taps or filter order.
23 %           alpha is an optional regularization parameter.
24 %
25 %
26 % MODIFICATIONS:
27 %
28 %
29 %*****%
30 alpha = 0;
31 switch nargin
32     case 4
33         if ~isempty(varargin{1}); alpha = varargin{1}; end
34 end
35
36 %%%%%%
37 % JVC's lwr() code returns a result which matches MATLAB's firwiender()
38 % code.  His code uses FD_Xcorr() which normalizes by,
39 %
40 %     N      = max( Nx , Ny );
41 %     Nfft = 2^nextpow2(N);
42 %     if Nfft/2 < N; Nfft = 2*Nfft; end
43 %     Apply the same normalization here
44 %     % Normalization

```

```

45  %%%%%%
46  N          = max([ length(x) length(y) ]);
47  Nfft       = 2^nextpow2( N );
48  if Nfft/2 < N; Nfft = 2*Nfft; end
49  %%%%%%
50 % Correlations
51 %%%%%%
52 [Rxx,lags] = xcorr(x(:), Norder);
53 Ryx        = xcorr(y(:),x(:),Norder);
54 Rxx        = Rxx / Nfft;
55 Ryx        = Ryx / Nfft;
56 n          = find( lags==0 );
57 ndx        = (0:Norder)';
58 Rxx        = Rxx(n+ndx);
59 Ryx        = Ryx(n+ndx);
60 Rxx(1)     = Rxx(1) + alpha;
61 a          = zeros([Norder 1]);
62 k          = zeros([Norder 1]);
63 kstar      = k;
64 h          = zeros([Norder+1 1]);
65 a(1)       = 1;
66 Δ          = Rxx(2);
67 p          = Rxx(1);
68 kstar(1)   = Δ/p;
69 a(2)       = -kstar(1);
70 h(1)       = Ryx(1)/p;
71 del        = h(1)*Rxx(2);
72 p          = p - kstar(1)*Δ;
73 k(1)       = (del-Ryx(2))/p;
74 h(1)       = h(1) - k(1)*a(2);
75 h(2)       = -k(1);
76 if Norder+1 ≥ 3
77   for n = 3:Norder+1
78     Δ      = a(1:n-1)'*Rxx(n:-1:2);
79     kstar(n-1) = Δ/p;
80     at     = [a(1:n-1); 0];
81     a      = at-kstar(n-1)*flipud(at);
82     del    = h(1:n-1)'*Rxx(n:-1:2);
83     p      = p-kstar(n-1)*Δ;
84     k(n-1) = (del-Ryx(n))/p;
85     h(1:n) = [h(1:n-1); 0] - k(n-1)*a(n:-1:1);
86   end
87 end
88
89 switch nargout
90   case 2
91     varargout{1} = Rxx;
92   case 3
93     varargout{1} = Rxx;
94     varargout{2} = Ryx;
95 end

```

---

## D MATLAB Wiener-Based Signal Preconditioner Algorithm

### Precondition.m

```
1 function [xpre,varargout] = Precondition(x,y,varargin)
2 %*****%
3 %
4 % TITLE: Precondition.m
5 % AUTHOR: Sean K. Lehman
6 % DATE: April 19, 2021
7 % FUNCTION: Use a Wiener filter to attempt to precondition an input to
8 % minimize the effects of a transfer function
9 % SYNTAX:
10 % xpre = Precondition(x,y)
11 % xpre = Precondition(x,y,N)
12 % xpre = Precondition(x,y,N,alpha)
13 % [xpre,hinv] = Precondition(...)
14 % [xpre,hinv,h] = Precondition(...)
15 %
16 % method is either 'lwr' or 'firwiener'
17 % CALLS:
18 %
19 % MODIFICATIONS:
20 %
21 %
22 %*****%
23 x = reshape( x , [] , 1 );
24 y = reshape( y , [] , 1 );
25 Nx = length( x );
26 alpha = 0;
27 Method = 'lwr';
28 if Nx ~= length(y)
29     error('Inputs must have the same lengths');
30 end
31 Nh = fix( Nx/2 );
32
33 switch nargin
34     case 3
35         if ~isempty(varargin{1}); Nh = varargin{1}; end
36     case 4
37         if ~isempty(varargin{1}); Nh = varargin{1}; end
38         if ~isempty(varargin{2}); alpha = varargin{2}; end
39     case 5
40         if ~isempty(varargin{1}); Nh = varargin{1}; end
41         if ~isempty(varargin{2}); alpha = varargin{2}; end
42         Method = varargin{3};
43 end
44
45 switch Method
```

```

46     case 'lwr'
47         hinv = lwr( y , x , Nh , alpha );
48     case 'firwiener'
49         hinv = firwiener( Nh , y , x )';
50     otherwise
51         error('%s: Method is either ''lwr'' or ''firwiener''',Method);
52 end
53
54 xpre = conv( hinv , x ) ;
55 xpre = xpre(1:Nx);
56
57 %          [xpre,hinv] = Precondition(...)
58 %          [xpre,hinv,h] = Precondition(...)
59 switch nargout
60     case 2
61         varargout{1} = hinv;
62     case 3
63         varargout{1} = hinv;
64         switch Method
65             case 'lwr'
66                 varargout{2} = lwr( x , y , Nh , alpha );
67             case 'firwiener'
68                 varargout{2} = firwiener( Nh , x , y )';
69         end
70 end

```

## E MATLAB M-File Which Demonstrates the Preconditioner

### tst\_Precondition.m

```
1 function tst_Precondition(varargin)
2 %*****%
3 %
4 % TITLE:      tst_Precondition.m
5 % AUTHOR:     Sean K. Lehman
6 % DATE:       June 14, 2021
7 % FUNCTION:   Test the Precondition.m function
8 % SYNTAX:
9 % CALLS:      Precondition()
10 %             fetchrigure()
11 %             Similarity()
12 %
13 %
14 % QUESTION:
15 % Given an LTI of the form,
16 %         y = conv( h , x )
17 %
18 % Seek a preconditioned input, x_{pre}, to minimize the difference
19 % between y_{pre} and x based upon a cosine similarity measure.
20 %
21 % That is, seek an input such that
22 %         m = y_{pre}' * x / (norm(y_{pre}) * norm(x))
23 % is maximized, where
24 %         y_{pre} = conv( h , x_{pre} )
25 % and
26 %         x_{pre} = conv( h^{-1} , x )
27 % and h^{-1} is an estimate of the inverse of h.
28 %
29 % As demonstrated in this M-file, a Wiener approach using MATLAB's
30 % firwiener() function yielded the best results.
31 %
32 % However, an approach using the System Identification Toolbox functions,
33 % n4sid() and tfest() is also tried.
34 %
35 % Although they estimate the forward impulse response well, they failed
36 % miserably at estimating the inverses for preconditioning.
37 %
38 %
39 %
40 %*****%
41 Print = 'no';
42 switch nargin
43     case 1
44         Print = varargin{ 1 };
45 end
```

```

46 %%%%%%
47 % Define the figure aspect ratio.
48 %%%%%%
49 AspectRatio = [11 8.5]/4;
50 %%%%%%
51 % Form a chirp input signal, x.
52 %%%%%%
53 flim = [ 1 12 ];
54 tend = 10;
55 dt = 1/(12*max(flim));
56 t = (0:dt:tend)';
57 x = chirp(t,flim(1),tend,flim(2));
58 %%%%%%
59 % Get the signal length.
60 %%%%%%
61 Nt = length( t );
62 %%%%%%
63 % Create a single cycle sine impulse response.
64 %%%%%%
65 Fc = 6.25;
66 th = (0:dt:1/Fc)';
67 Nhimp = length( th );
68 h = sin( 2*pi*Fc*th );
69 %%%%%%
70 % Filter the input.
71 %%%%%%
72 y = conv( h , x );
73 Y = y( 1:Nt );
74 %%%%%%
75 % Add noise.
76 %%%%%%
77 SNR = 40; % dB
78 SigmaNoise = std(y) * 10^(-SNR/20);
79 noise = SigmaNoise * randn([Nt 1]);
80 y = y + noise;
81 %%%%%%
82 % Given the input/output data, determine the filter using the Wiener
83 % approach.
84 % Guess at Nid since, in practice, the length of the impulse response, h,
85 % is unknown.
86 %%%%%%
87 Nid = 3 * Nhimp;
88 % hest = firwiener( Nid , x , y )';
89 %%%%%%
90 % Determine the inverse.
91 %%%%%%
92 % hinv = firwiener( Nid , y , x )';
93 %%%%%%
94 % Compute the predistored input signal.
95 %%%%%%
96 % xpre = conv( hinv , x ) ;

```

```

97 % xpre = xpre( 1:Nt );
98 %%%%%%
99 % Compute the preconditioned input signal using the Precondition() function
100 % which implements all of the above steps.
101 %%%%%%
102 alpha = 1e-12;
103 [xpre,hinv,hest] = Precondition(x,y,Nid,alpha,'lwr');
104 %%%%%%
105 % Compute the output using the predistored signal.
106 % This should be a close match to the input.
107 %%%%%%
108 ypre = conv( hest , xpre ) ;
109 ypre = ypre( 1:Nt );
110 %%%%%%
111 %%%%%%
112 %%%%%%
113 % Use the ID Toolbox.
114 % Put the time series into ID toolbox format.
115 %%%%%%
116 dforward = iddata( y , x , dt ); % For the forward estimate
117 dinverse = iddata( x , y , dt ); % For the inverse estimate
118 %%%%%%
119 % Estimate the forward SS & TF models using the ID toolbox.
120 %%%%%%
121 Nss = 2;
122 Ntf = 6;
123 ssopt = n4sidOptions( 'EnforceStability' , true );
124 ssforward = n4sid( dforward , Nss , ssopt );
125 tfforward = tfest( dforward , Ntf );
126 %%%%%%
127 % Estimate the inverse models.
128 %%%%%%
129 Nssinv = 3 * Nss;
130 Ntfinv = 2 * Ntf;
131 ssinverse = n4sid( dinverse , Nssinv , ssopt );
132 tfinverse = tfest( dinverse , Ntfinv );
133 %%%%%%
134 % Create impulse for impulse responses.
135 %%%%%%
136 u = zeros([2*Nid 1]);
137 u(1) = 1;
138 u = iddata( [] , u , dt );
139 %%%%%%
140 % Compute the forward impulse responses.
141 %%%%%%
142 ipssforward = sim( ssforward , u(1:Nid) );
143 iptffforward = sim( tfforward , u(1:Nid) );
144 %%%%%%
145 % Compute the inverse impulse responses.
146 %%%%%%
147 ipssinverse = sim( ssinverse , u );

```

```

148 iptfinverse = sim( tfinverse , u );
149 % Get the estimated impulse response time series.
150 % Get the estimated impulse response time series.
151 hss = get(ipssforward, 'y');
152 htf = get(iptffforward, 'y');
153 hssinv = get(ipssinverse, 'y');
154 htfinv = get(iptfinverse, 'y');
155 htfinv = get(iptfinverse, 'y');

156 % hss = impulse( ssforward );
157 % htf = impulse( tfforward );
158 % hssinv = impulse( ssinverse );
159 % htfinv = impulse( tfinverse );
160 % Compute the predistored input signals.
161 % Compute the predistored input signals.
162 % Compute the predistored input signals.
163 % Compute the predistored input signals.
164 xpress = conv( hssinv , x ) ;
165 xpress = xpress( 1:Nt );
166 xpretf = conv( htfinv , x ) ;
167 xpretf = xpretf( 1:Nt );
168 % Compute the output using the predistored signals.
169 % Compute the output using the predistored signals.
170 % This should be a close match to the input.
171 % This should be a close match to the input.
172 ypress = conv( hss , xpress ) ;
173 ypress = ypress( 1:Nt );
174 ypretf = conv( htf , xpretf ) ;
175 ypretf = ypretf( 1:Nt );
176 % Determine the similarity between the Wiener predistored output and the
177 % desired output.
178 % Determine the similarity between the Wiener predistored output and the
179 % desired output.
180 similarity = Similarity( ypre , x );
181 % Determine the similarity of the forward impulse response estimates.
182 % Determine the similarity of the forward impulse response estimates.
183 %hpadded = zeros( [Nid+1 1] );
184 hpadded = zeros( [Nid+1 1] );
185 hpadded(1:Nhimp) = h;
186 hsimilarity = [ ...
187     Similarity( hpadded , hest )
188     Similarity( hpadded(1:Nid) , hss )
189     Similarity( hpadded(1:Nid) , htf )
190 ];
191 % Save the figure handles.
192 % Save the figure handles.
193 %figureList = [0;0;0];
194 figureList = [0;0;0];
195 % Fetch the figure.
196 % Fetch the figure.
197 %figureList(1) = fetchfigure( 'Signal Preconditioning I' , AspectRatio );
198 figureList(1) = fetchfigure( 'Signal Preconditioning I' , AspectRatio );clf

```

```

199 %%%%%%
200 % Plot the input.
201 %%%%%%
202 subplot(321)
203 plot( t , x , 'b' );
204 xlabel( 'Time (s)' );
205 title( 'Input, x' );
206 set(gca,'fontsize',14);
207 %%%%%%
208 % Plot the output.
209 %%%%%%
210 subplot(322)
211 plot( t , y , 'b' );
212 xlabel( 'Time (s)' );
213 title( 'Output, y' );
214 axis tight
215 set(gca,'fontsize',14);
216 %%%%%%
217 % Plot the forward impulse responses.
218 %%%%%%
219 subplot(323)
220 hp = plot( ...
221     t(1:size(h)) , h , 'r' , ...
222     t(1:Nid+1) , hest , 'b' , ...
223     t(1:Nid) , hss , 'k' , ...
224     t(1:Nid) , htf , 'g' , ...
225     'linewidth' , 1);
226 set( hp(1:2) , 'linewidth' , 2 );
227 axis tight
228 grid on
229 xlabel('Time (s)');
230 ylabel('Impulse Response');
231 title('Forward Impulse Response & Estimated Impulse Responses');
232 legend( ...
233     sprintf('Truth, h %d',Nhimp) , ...
234     sprintf('Wiener %d (%.3f)',Nid+1,hsimilarity(1)) , ...
235     sprintf('SS %d (%.3f)',Nss,hsimilarity(2)) , ...
236     sprintf('TF %d/%d (%.3f)',Ntf+[0 1],hsimilarity(3)) );
237 set(gca,'fontsize',14);
238 %%%%%%
239 % Plot the inverse impulse responses.
240 %%%%%%
241 subplot(324)
242 % hp = plot( ...
243 %     t(1:Nid+1) , hinv , 'b' , ...
244 %     t(1:Nid) , hssinv , 'k' , ...
245 %     t(1:Nid) , htfinv , 'g' , ...
246 %     'linewidth' , 1);
247 hp = plot( ...
248     t(1:Nid+1) , hinv , 'b' , ...
249     (0:length(hssinv)-1)*dt , hssinv , 'k' , ...

```

```

250      (0:length(htfinv)-1)*dt , htfinv , 'g' , ...
251      'linewidth' , 1);
252 set( hp(1) , 'linewidth' , 2 );
253 axis tight
254 grid on
255 xlabel('Time (s)');
256 ylabel('Impulse Response');
257 title('Inverse Impulse Response & Estimated Inverses');
258 legend( ...
259     sprintf('Wiener %d',Nid+1), ...
260     sprintf('SS %d',Nssinv), ...
261     sprintf('TF %d/%d',Ntfinv+[0 1]));
262 set(gca,'fontsize',14);
263 %%%%%%%%%%%%%%
264 % Plot the Wiener predistorted input.
265 %%%%%%%%%%%%%%
266 subplot(325)
267 plot( ...
268     t , xpre , 'b' , ...
269     'linewidth' , 1);
270 axis tight
271 xlabel('Time (s)');
272 title('Wiener Preconditioned Input, x_{pre}');
273 set(gca,'fontsize',14);
274 %%%%%%%%%%%%%%
275 % Plot the Wiener predistorted output.
276 %%%%%%%%%%%%%%
277 subplot(326)
278 plot( ...
279     t , x , 'b' , ...
280     t , ypre , 'g' , ...
281     'linewidth' , 1);
282 axis tight
283 xlabel('Time (s)');
284 title( sprintf('Input & Wiener Preconditioned Output, y_{pre} ...
285     (Similarity: %.3f)',similarity) )
286 legend('Input','Output','Location','NorthEast')
287 set(gca,'fontsize',14);
288 % Fetch the figure.
289 %%%%%%%%%%%%%%
290 figureList(2) = fetchfigure( 'Signal Preconditioning II' , AspectRatio ...
291     );clf
292 % Re-plot the Wiener predistorted output.
293 %%%%%%%%%%%%%%
294 subplot(311)
295 plot( ...
296     t , x , 'b' , ...
297     t , ypre , 'g' , ...
298     'linewidth' , 1);

```

```

299 axis tight
300 xlabel('Time (s)');
301 title( sprintf('Input & Wiener Preconditioned Output, y_{pre} ... ...
302 (Similarity: %.3f)',similarity) )
302 legend('Input','Output','Location','NorthEast')
303 set(gca,'fontsize',14);
304 %%%%%%%%%%%%%%%%
305 % Plot the SS & TF predistorted inputs.
306 %%%%%%%%%%%%%%%%
307 subplot(312)
308 plot( ...
309     t , xpre , 'b' , ...
310     t , xpress , 'k' , ...
311     t , xpretf , 'g' , ...
312     'linewidth' , 1);
313 axis tight
314 xlabel('Time (s)');
315 title('Preconditioned Input SS & TF Inputs, x_{pre}'); 
316 legend(...
317     sprintf('Wiener %d',length(xpre)) , ...
318     sprintf('SS %d (%.3f)',length(xpress),Similarity(xpre,xpress)) , ...
319     sprintf('TF %d (%.3f)',length(xpretf),Similarity(xpre,xpretf)) );
320 set(gca,'fontsize',14);
321 %%%%%%%%%%%%%%%%
322 % Plot the SS & TF predistorted outputs.
323 %%%%%%%%%%%%%%%%
324 subplot(313)
325 plot( ...
326     t , x , 'b' , ...
327     t , ypress , 'k' , ...
328     t , ypretf , 'g' , ...
329     'linewidth' , 1);
330 axis tight
331 xlabel('Time (s)');
332 title( 'Input & Preconditioned SS & TF Outputs, y_{pre}' );
333 legend(...
334     'Input',...
335     sprintf('SS (%.3f)',Similarity(xpress,x)),...
336     sprintf('TF (%.3f)',Similarity(xpretf,x)));
337 set(gca,'fontsize',14);
338 %%%%%%%%%%%%%%%%
339 % Compute spectra
340 %%%%%%%%%%%%%%%%
341 %%
342 Nwindow = 128;
343 Noverlap = Nwindow / 2;
344 Nfft = 2^nextpow2( Nt );
345 [X,freq] = pwelch( x , Nwindow , Noverlap , Nfft , 1/dt );
346 Y = pwelch( y , Nwindow , Noverlap , Nfft , 1/dt );
347 H = pwelch( [h;zeros([Nt-Nhimp 1])] , Nwindow , Noverlap , Nfft ...
348 , 1/dt );

```

```

348 HEST      = pwelch( [hest;zeros([Nt-length(hest) 1])], Nwindow , ...
349           Noverlap , Nfft , 1/dt );
350 XPRE      = pwelch( xpre , Nwindow , Noverlap , Nfft , 1/dt );
351 YPRE      = pwelch( ypre , Nwindow , Noverlap , Nfft , 1/dt );
352 YPRESS    = pwelch( ypress , Nwindow , Noverlap , Nfft , 1/dt );
353 YPRETF   = pwelch( ypretf , Nwindow , Noverlap , Nfft , 1/dt );
354 HSS       = pwelch( [hss;zeros([Nt-length(hss) 1])], Nwindow , Noverlap ...
355           , Nfft , 1/dt );
356 HTF       = pwelch( [htf;zeros([Nt-length(hss) 1])], Nwindow , Noverlap ...
357           , Nfft , 1/dt );
358 HINV      = pwelch( [hinv;zeros([Nt-length(hinv) 1])], Nwindow , ...
359           Noverlap , Nfft , 1/dt );
360 HSSINV   = pwelch( [hssinv;zeros([Nt-length(hssinv) 1])], Nwindow , ...
361           Noverlap , Nfft , 1/dt );
362 HTFINV   = pwelch( [htfinv;zeros([Nt-length(htfinv) 1])], Nwindow , ...
363           Noverlap , Nfft , 1/dt );
364 % S = [ X Y H HEST XPRE YPRE YPRESS YPRETF HSS HTF HINV HSSINV HTFINV ];
365 %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
366 % Fetch the spectra figure.
367 %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
368 figureList(3) = fetchfigure( 'Signal Preconditioning III' , AspectRatio ...
369                           );clf
370 subplot(311)
371 semilogy( ...
372           freq , [ X Y H XPRE YPRE HEST HINV ], ...
373           'linewidth' , 1 );
374 xlabel( 'Frequency (Hz)' );
375 title( 'Spectra' );
376 legend('x','y','h','x_{pre}','y_{pre}','h_{est}','h_{inv}');
377 axis tight
378 set( gca , 'fontsize' , 14 );
379 subplot(312)
380 hp = semilogy( ...
381           freq , [ H HEST HSS HTF HINV HSSINV HTFINV ] , 'linewidth' , 1 );
382 set( hp([2 4]) , 'linestyle' , '--' );
383 xlabel( 'Frequency (Hz)' );
384 title( 'Spectra' );
385 legend('h','h_{est}','h_{ss}','h_{tf}','h_{inv}','h_{ssinv}','h_{tfinv}');
386 axis tight
387 set( gca , 'fontsize' , 14 );
388 subplot(313)
389 hp = semilogy( ...
390           freq , [ X YPRE YPRESS YPRETF ] , 'linewidth' , 1 );
391 set( hp(4) , 'linestyle' , '--' );
392 xlabel( 'Frequency (Hz)' );
393 title( 'Spectra' );
394 legend('x','y_{pre}','y_{ss}','y_{tf}');
395 axis tight
396 set( gca , 'fontsize' , 14 );

```

```

392 %%%%%%%%%%%%%%%%
393 % Print useful information
394 %%%%%%%%%%%%%%%%
395 fprintf(1, '%25s : %6d\n', 'x & y size', Nt);
396 fprintf(1, '%25s : %6d\n', 'h size', Nhimp',Nhimp);
397 fprintf(1, '%25s : %6d\n', 'Wiener size, Nid',Nid);
398 fprintf(1, '%25s : %6d\n', 'hest size, Nid+1',Nid+1);
399 fprintf(1, '%25s : %6d\n', 'hinv size, Nid+1',length(hinv));
400 fprintf(1, '%25s : %6d\n', 'Forward SS size',Nss);
401 fprintf(1, '%25s : %6d/%d\n', 'Forward TF size',Ntf+[0 1]);
402 fprintf(1, '%25s : %6d\n', 'Inverse SS size',Nssinv);
403 fprintf(1, '%25s : %6d/%d\n', 'Inverse TF size',Ntfinv+[0 1]);
404 fprintf(1, '%25s : % .3f\n', 'x, Wiener similarity',similarity);
405 fprintf(1, '%25s : % .3f\n', 'x, SS similarity',Similarity(xpress,x));
406 fprintf(1, '%25s : % .3f\n', 'x, TF similarity',Similarity(xpretf,x));
407 fprintf(1, '%25s : % .3f\n', 'h, Wiener similarity',hsimilarity(1));
408 fprintf(1, '%25s : % .3f\n', 'h, SS similarity',hsimilarity(2));
409 fprintf(1, '%25s : % .3f\n', 'h, TF similarity',hsimilarity(3));
410 fprintf(1, '%25s : %.2e seconds\n', 'Sample interval, dt',dt);
411 fprintf(1, '%25s : %.2e\n', 'Regularization, alpha',alpha);
412 fprintf(1, '%25s : %g dB\n', 'SNR',SNR);
413 fprintf(1, '%25s : %.2e\n', 'Noise variance',SigmaNoise);
414 %%%%%%%%%%%%%%%%
415 % Print figures
416 %%%%%%%%%%%%%%%%
417 if strcmp( Print , 'yes' )
418     fprintf(1, ' Printing figures ... ');
419     for n = 1:length(figureList)
420         EPSFile = sprintf('Signal_Precondition-%d.eps',n);
421         fprintf(1, '%s ... ',EPSFile);
422         figure( figureList(n) );
423         orient landscape;
424         print( EPSFile , '-depsc2' );
425     end
426     fprintf(1,'done.\n');
427 end
428
429
430
431 end % function tst_Precondition()
432
433 function s = Similarity(x,y,varargin)
434 %*****%
435 %
436 % TITLE: Similarity.m
437 % AUTHOR: Sean K. Lehman
438 % DATE: April 19, 2021
439 % FUNCTION: Measure the similarity between two time series
440 % SYNTAX:
441 %           s = Similarity(x,y)
442 %           s = Similarity(x,y,Measure)

```

```

443 %
444 % Measure is 'cosine' (default)
445 % 'numsim'
446 % where the similarity between two numbers, 'numsim' is
447 % numsim(a,b) = 1 - abs( a - b ) / (abs(a)+abs(b))
448 % CALLS:
449 %
450 % MODIFICATIONS:
451 %
452 %
453 %*****
454 Measure = 'cosine';
455 switch nargin
456 case 3, Measure = varargin{ 1 };
457 end
458
459 x = reshape( x , [ ] , 1 );
460 y = reshape( y , [ ] , 1 );
461
462 if length(x) ~= length(y)
463 error('Inputs must have the same lengths');
464 end
465
466 switch Measure
467 case 'numsim'
468 s = mean( 1 - abs( x-y ) ./ (abs(x) + abs(y)) );
469 otherwise % cosine measure
470 s = y' * x / (norm(y) * norm(x));
471 end
472 end % s = Similarity(x,y,varargin)
473
474
475 function fig = fetchfigure( FigureName , varargin )
476 %*****
477 %
478 % TITLE: fetchfigure.m
479 % AUTHOR: Sean K. Lehman
480 % DATE: July 08, 2004
481 % FUNCTION: Fetch a figure by name
482 %
483 % SYNTAX: fig = fetchfigure( FigureName )
484 % fig = fetchfigure( FigureName , scale )
485 %
486 % MODIFICATIONS: Philip Top 11/24/09 modified function to use findobj
487 % method, should be slightly faster than previous methodology
488 %
489 %
490 %*****
491
492 fig = findobj(get(0,'Children'),'Name',FigureName);
493 if isempty(fig) % Create new window

```

```

494 scrnsize = get( 0 , 'screenSize' );
495 fig = figure('Name',FigureName,'visible','off');
496 pos = get( fig , 'position' );
497
498 switch length(varargin)
499 case 1
500     scale = varargin{1};
501     if length(scale)==1; scale = scale*[1 1]; end
502 otherwise
503     scale = [1 1];
504 end
505
506 % Center on screen
507 pos(1) = (scrnsize(3)-scale(1)*pos(3))/2;
508 % Because the Windows OS is a cluster f**k, one must correct for the
509 % vertical mis-position.
510
511 if ispc
512     pos(2) = (scrnsize(4)-scale(2)*pos(4))/2;
513 end
514
515 % Set the figure position
516 set( fig , 'position' , [pos(1) pos(2) scale(1)*pos(3) ...
517 scale(2)*pos(4)] );
518
519 end % fig = fetchfigure( FigureName , varargin )

```