

Kalman Filter Derivation

Leah Dickstein

June 16, 2014

Contents

1	Derivation/Proof	2
1.1	Problem Setup:	2
1.2	Goal:	2
1.3	Equations:	2
1.4	$\mathbb{E}[X[n+1] Y^{n-1}]$	2
1.5	$\mathbb{E}[Y[n] Y^{n-1}]$	3
1.6	$\mathbb{E}[X[n+1] Y[n] - C\hat{X}[n]]$	3
2	Simulation	4
2.1	Code	4
2.2	Plots	6
2.2.1	Example from the Book	6
2.2.2	Varying A	7
2.2.3	Varying C	9
2.2.4	Varying Noise	10
3	Predicting the Future	11
4	Dynamics	11
4.1	Without Memory	11
4.1.1	Problem Setup:	11
4.1.2	Simulation	11

1 Derivation/Proof

1.1 Problem Setup:

$$\begin{aligned}X[n] &= AX[n-1] + W[n-1] \\Y[n] &= CX[n] + V[n]\end{aligned}$$

$$\begin{aligned}\textcolor{red}{X} &\sim N(0, A^{2n} + \sigma_W^2 \Sigma_{i=0}^{n-1} A^{2i}) \\ \textcolor{red}{Y} &\sim N(0, C^2(A^{2n} + \sigma_W^2 \Sigma_{i=0}^{n-1} A^{2i}) + \sigma_V^2)\end{aligned}$$

$$\begin{aligned}X(0) &\sim N(0, 1) \\ W[n] &\sim N(0, \Sigma_W) \\ V[n] &\sim N(0, \Sigma_V)\end{aligned}$$

1.2 Goal:

$$\begin{aligned}\mathbb{E}[X[n+1]|Y^n] &= \hat{X}[n+1] \\ Y^n &= (Y[0] \dots Y[n]) \\ \mathbb{E}[X[n+1]|Y^n] &= \sqcup \mathbb{E}[X[n]|Y^{n-1}] + \sqcup (Y[n] - \mathbb{E}[Y[n]|Y^{n-1}])\end{aligned}$$

1.3 Equations:

$$\begin{aligned}(1) \quad & L[X|Y] = \mathbb{E}[X] + \frac{\text{cov}(X, Y)}{\text{cov}(Y)}(Y - \mathbb{E}[Y]) \\ (2) \quad & L[X|Y, Z] = L[X|Y] + L[X|Z - L[Z|Y]] \\ (3) \quad & \text{cov}(AX, CY) = A\text{cov}(X, Y)C' \\ (4) \quad & \text{if } V, W \perp \text{cov}(V + W) = \text{cov}(V) + \text{cov}(W)\end{aligned}$$

$$\mathbb{E}[X[n+1]|Y^n] = \mathbb{E}[X[n+1]|Y^{n-1}] + \mathbb{E}[X[n+1]|Y[n] - \mathbb{E}[Y[n]|Y^{n-1}]]$$

1.4 $\mathbb{E}[X[n+1]|Y^{n-1}]$

$$\begin{aligned}(1) \quad & \mathbb{E}[AX[n] + W[n]|Y^{n-1}] = \mathbb{E}[AX[n]|Y^{n-1}] + \mathbb{E}[W[n]|Y^{n-1}] \\ (2) \quad & = A\hat{X}[n] + \mathbb{E}[W[n]] \\ (3) \quad & = A\hat{X}[n]\end{aligned}$$

1.5 $\mathbb{E}[Y[n]|Y^{n-1}]$

$$\begin{aligned} (4) \quad & \mathbb{E}[CX[n] + V[n]|Y^{n-1}] = C\mathbb{E}[X[n]|Y^{n-1}] + \mathbb{E}[V[n]|Y^{n-1}] \\ (5) \quad & = C\hat{X}[n] \end{aligned}$$

1.6 $\mathbb{E}[X[n+1]|Y[n] - C\hat{X}[n]]$

$$\begin{aligned} (6) \quad & \mathbb{E}[X[n+1]|Y[n] - C\hat{X}[n]] = \mathbb{E}[AX[n] + W[n]|Y[n] - C\hat{X}[n]] \\ (7) \quad & = \mathbb{E}[AX[n]|Y[n] - C\hat{X}[n]] \\ (8) \quad & = \mathbb{E}[AX[n] - A\hat{X}[n]|Y[n] - C\hat{X}[n]] \end{aligned}$$

Lemma: $Y^{n-1} \perp Y[n] - \mathbb{E}[Y[n]|Y^{n-1}]$

Strong Induction!

Base Case: $\text{cov}(Y[0], Y[1] - \mathbb{E}[Y[1]|Y[0]]) = 0$

$$\begin{aligned} (1) \quad & \mathbb{E}[y[0](cax[0] + cw[0] + v[1] - \frac{ac^2\Sigma_{x[0]}}{\Sigma_{y[0]}}y[0])] = \mathbb{E}[y[0](cax[0] - \frac{ac^2\Sigma_{x[0]}}{\Sigma_{y[0]}}y[0])] \\ (2) \quad & = \mathbb{E}[(cx[0] + v[0])cax[0] - \frac{ac^2\Sigma_{x[0]}}{\Sigma_{y[0]}}y^2[0]] \\ (3) \quad & = \mathbb{E}[c^2ax^2[0] - \frac{ac^2\Sigma_{x[0]}}{\Sigma_{y[0]}}y^2[0]] \\ (4) \quad & = c^2a\Sigma_{x[0]} - \frac{ac^2\Sigma_{x[0]}}{\Sigma_{y[0]}}\Sigma_{y[0]} \\ (5) \quad & = c^2a\Sigma_{x[0]} - ac^2\Sigma_{x[0]} = 0 \end{aligned}$$

Inductive Hypothesis: $\text{cov}(Y[n-1], Y[n] - \mathbb{E}[Y[n]|Y[n-1]]) = 0 \wedge \dots \wedge \text{cov}(Y[0], Y[n] - \mathbb{E}[Y[n]|Y[0]]) = 0$

Inductive Step: $\text{cov}(Y[n], Y[n+1] - \mathbb{E}[Y[n+1]|Y[n]]) = 0$

$$\mathbb{E}[y[n](cax[n] - \frac{c^2a\Sigma_{x[n]}}{\Sigma_{y[n]}}y[n])] = c^2a\Sigma_{x[n]} - \frac{c^2a\Sigma_{x[n]}}{\Sigma_{y[n]}}\Sigma_{y[n]} = 0$$

In addition,

$$\begin{aligned} (6) \quad & \forall t \leq n, \quad \text{cov}(y[t], y[n+1] - \mathbb{E}[y[n+1]|y[t]]) = 0 \\ (7) \quad & = \mathbb{E}[y[t](ca^{n+1-t}x[t] - \frac{c^2a^{n+1-t}\Sigma_{x[t]}}{\Sigma_{y[t]}}y[t])] \\ (8) \quad & = \mathbb{E}[c^2a^{n+1-t}x^2[t] - \frac{c^2a^{n+1-t}\Sigma_{x[t]}}{\Sigma_{y[t]}}y^2[t]] = c^2a^{n+1-t}\Sigma_{x[t]} - \frac{c^2a^{n+1-t}\Sigma_{x[t]}}{\Sigma_{y[t]}}\Sigma_{y[t]} = 0 \end{aligned}$$

If $t = n+1$, $\text{cov}(y[n+1], y[n+1] - \mathbb{E}[y[n+1]|y[n+1]]) = \text{cov}(y[n+1], y[n+1] - y[n+1]) = \text{cov}(y[n+1], 0) = 0$.
The answer is trivial.

$$\text{cov}(Y^{n-1}, Y[n] - \mathbb{E}[Y[n]|Y^{n-1}]) = \mathbb{E} \left[[Y[0] \dots Y[n-1]] \left[Y[n] - \frac{\text{cov}(Y[n], Y^{n-1})}{\text{cov}(Y^{n-1})} \begin{bmatrix} Y[0] \\ \vdots \\ Y[n-1] \end{bmatrix} \right] \right]$$

We have proved for $\forall t < n$ this = 0, therefore the answer is the 0 vector and we prove the Lemma. Since $\hat{X}[n] = \mathbb{E}[X[n]|Y^{n-1}]$, it is the projection of X onto Y^{n-1} . If $Y^{n-1} \perp \tilde{Y}$, $\hat{X}[n] \perp \tilde{Y}$. We can add if inside the cov() since it's equivalent to adding 0.

$$\text{cov}(AX[n] - A\hat{X}[n], CX[n] - C\hat{X}[n]) = A\text{cov}(X[n] - \hat{X}[n])C'$$

$$S_n = \text{cov}(X[n] - \hat{X}[n])$$

$$\text{cov}(Y[n] - C\hat{X}[n]) = \text{cov}(CX[n] + V[n] - C\hat{X}[n]) = \text{cov}(C(X[n] - \hat{X}[n])) + \text{cov}(V[n]) = CS_nC' + \sigma_v^2$$

$$K_n = \frac{AS_nC'}{CS_nC' + \sigma_v^2}$$

$$\hat{X}[n+1] = \mathbb{E}[X[n+1]|Y^n] = A\hat{X}[n] + \frac{A\text{cov}(X[n] - \hat{X}[n])C'}{C\text{cov}(X[n] - \hat{X}[n])C' + \sigma_v^2} (Y[n] - C\hat{X}[n])$$

2 Simulation

2.1 Code

```
%% Kalman Filter (Prediction of Present)
clc
clear all

a = 1; %Test 2,0.5,10
c = 1;
varv = 0.09; %channel noise
varw = 0.04;
n = 50;

%initialize
x = normrnd(0,1,[1,1]); %x[0]
y = c*x+normrnd(0,varv);
xhat = y*c*1/(c^2+varv);
xhatmem = y*c/(c^2+varv);
varx = 1;
vary = c^2+varv;

sigman = varx - 2*c*varx^2/vary + c^2*varx^2/vary^2*(c^2*varx+varv);

%sn = a^2+varw - 2*a^2*c^2/(c^2+varv) + a^2*c^4/(c^2+varv)^2 + a^2*c^2/(c^2+varv)^2*varv;
```

```

%time passing
for t=1:(n-1)
    w = normrnd(0,varw);
    x = [x a*x(1,t)+w];
    v = normrnd(0,varv);
    y = [y c*x(1,(t+1))+v];

    sn = a^2*sigman+varw; %generating sn for this iteration
    kn = sn*c/(c^2*sn+varv);
    xhatmem = [xhatmem a*xhatmem(1,t)+kn*(y(1,t+1)-c*a*xhatmem(1,t))];
    sigman = (1-kn*c)*sn; %generate new sigma_n for next iteration
    %sn = a^2*sigman+varw;

    varx = a^2*varx + varw;
    vary = c^2*varx + varv;
    xhat = [xhat y(1,t+1)*c*varx/vary];
end

%hold all
subplot(1,2,1), stem(0:t,x,'k','filled')
%subplot(1,2,1), hold on, stem(0:t,y,'b','filled')
subplot(1,2,1), hold on, stem(0:t,xhat,'r')
subplot(1,2,1), hold on, stem(0:t, xhatmem, 'g','filled')
xlabel('n=time')
legend1 = legend('x','y','xhat','Location','Best');

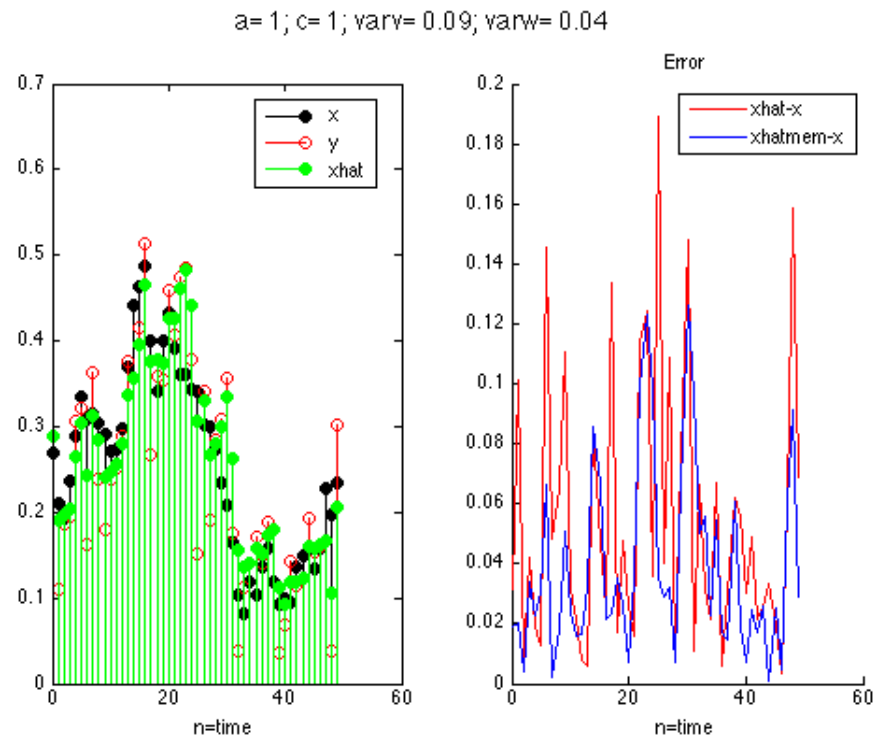
%subplot(1,2,2), plot(0:t,abs(y/c-x),'g')
subplot(1,2,2), hold on, plot(0:t,abs(xhat-x),'r')
subplot(1,2,2), hold on, plot(0:t,abs(xhatmem-x),'b')
xlabel('n=time')
legend2 = legend('xhat-x','xhatmem-x');
subplot(1,2,2), title('Error')

suptitle(['a= ' num2str(a) '; c= ' num2str(c) '; varv= ' num2str(varv) '; varw= ' num2str(varw)])

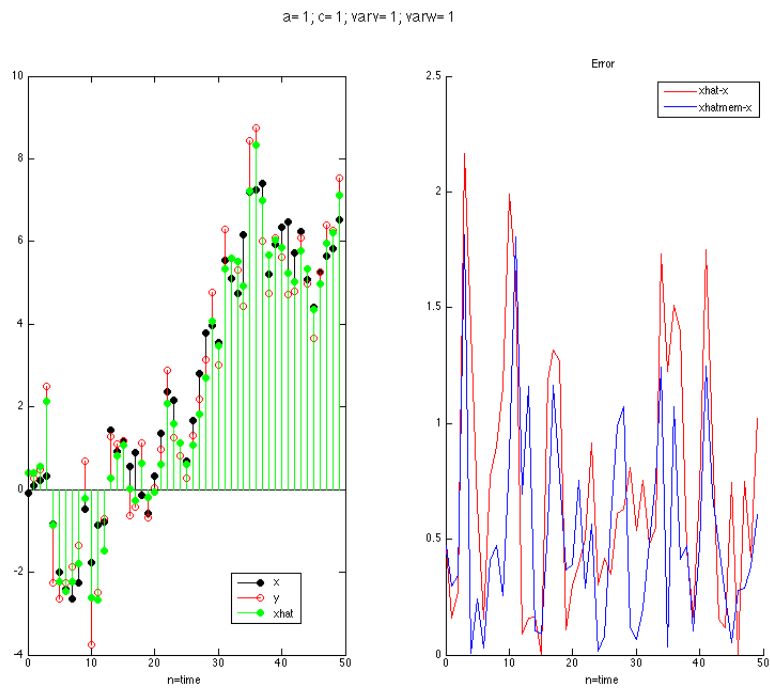
```

2.2 Plots

2.2.1 Example from the Book

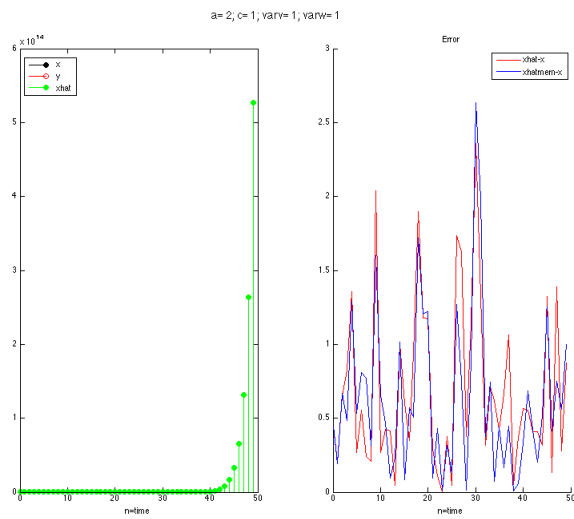


I know this is correct because my $\Sigma_n = 0.0432$, which perfectly matches the result in the textbook.

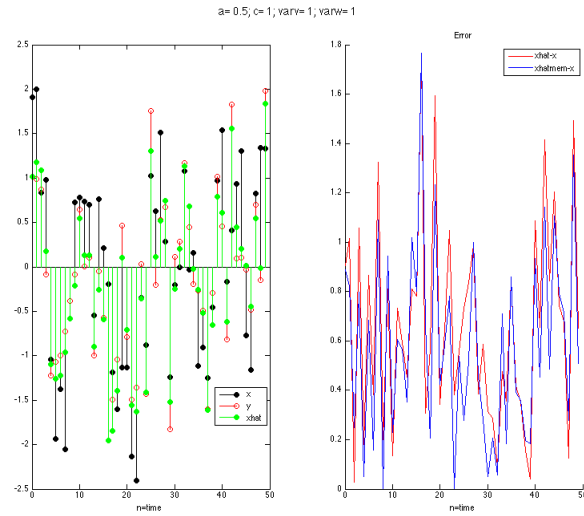


Average $\hat{X}-X = 0.7338$; Average $\hat{X}_{\text{atmem}}-X = 0.5278$

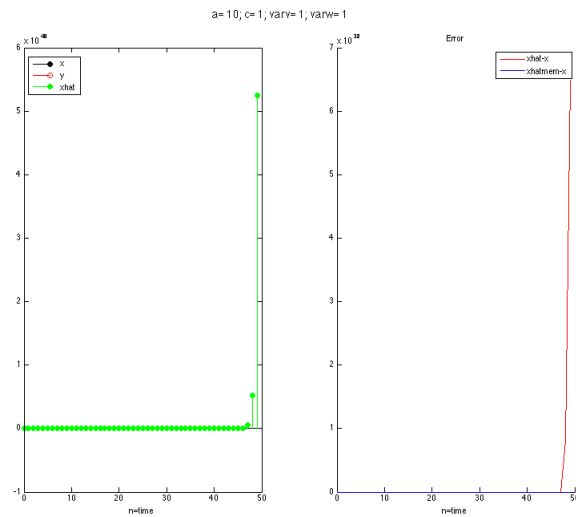
2.2.2 Varying A



Average Xhat - X = 0.6997; Average Xhatmem - X = 0.6376



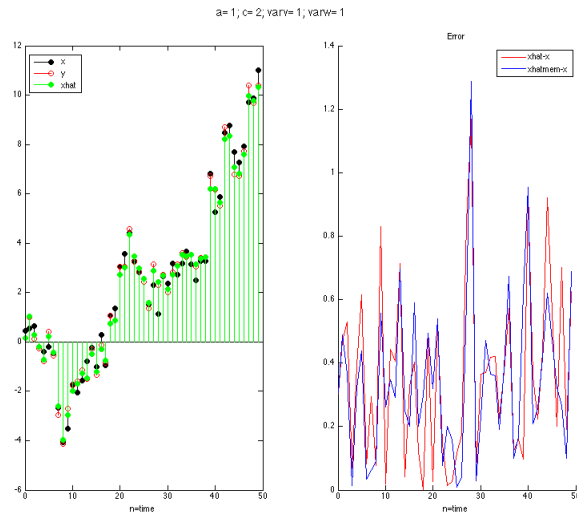
Average Xhat - X = 0.6645; Average Xhatmem - X = 0.5791



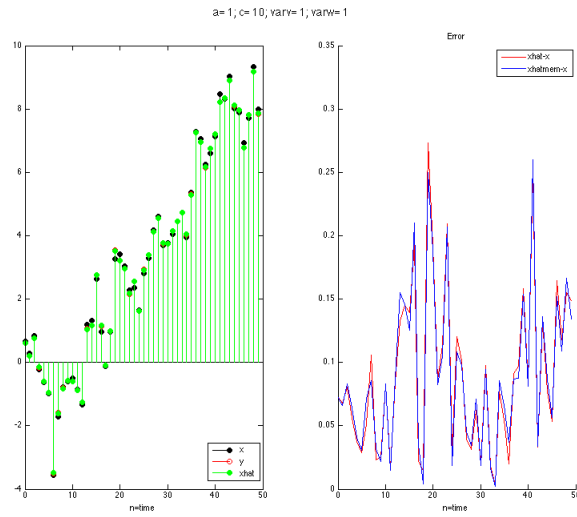
Average Xhat - X = 1.4603×10^{31} ; Average Xhatmem - X = 0.2476

These results indicate that when scaling A larger, Xhat works less efficiently. However, the Kalman Filter (Xhat with Memory) continues to work at around the same level of accuracy.

2.2.3 Varying C



Average \hat{x} - $X = 0.3592$; Average \hat{x}_{mem} - $X = 0.3486$

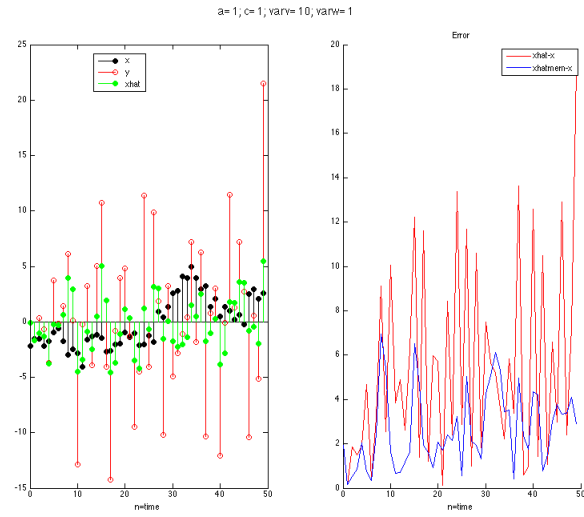


Average \hat{x} - $X = 0.0899$; Average \hat{x}_{mem} - $X = 0.0900$

These results indicate changing C decreases error for both \hat{x} and \hat{x}_{mem} . In addition, \hat{x} works just as well if not better as \hat{x}_{mem} , indicating increasing the power of the signal decreases the benefit of memory.

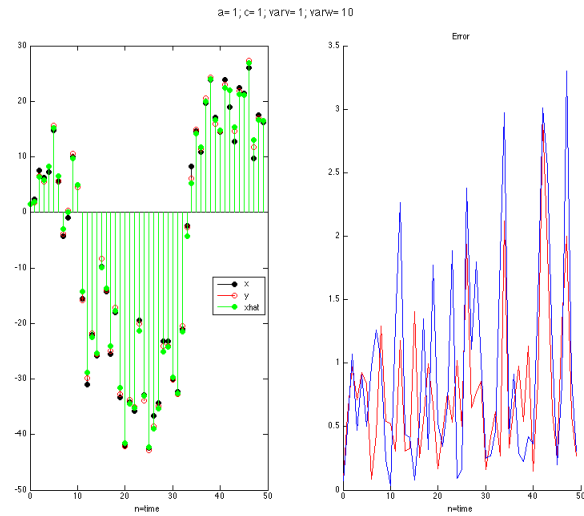
2.2.4 Varying Noise

Increasing Channel Noise:



Average \hat{x} - $X = 5.4140$; Average \hat{x}_{hatmem} - $X = 2.6805$

Increasing System Noise:



Average \hat{x} - $X = 0.7729$; Average \hat{x}_{hatmem} - $X = 0.9512$

Increasing Channel Noise increases the accuracy gap between \hat{X} and \hat{X}_{atmem} , with \hat{X}_{atmem} doing better. Increasing System Noise has a larger effect on \hat{X}_{atmem} (the Kalman Filter) than just \hat{X} , with \hat{X}_{atmem} doing worse.

For better results, repeat the experiment $m = 100, 10,000$ and calculate/compare average error over m trials.

3 Predicting the Future

See KF5_140614 for the code.

4 Dynamics

4.1 Without Memory

4.1.1 Problem Setup:

$$\begin{aligned} X_1[n] &\sim N(0, 2^{2n}) \\ X_2[n] &\sim N(0, 3^{2n}) \\ Y[n] &\sim N(0, 2^{2n} + 32n) \end{aligned}$$

Similar to just $\hat{X}[n]$, $\mathbb{E}[X_1[n]|Y[n]] = \frac{\text{cov}(X_1[n])}{\text{cov}(Y[n])} Y[n]$.

4.1.2 Simulation

Code:

```
clc;
clear all;
set(0,'DefaultAxesFontSize', 14);

a1 = 2; %Test 2,0.5,10
a2 = 3;
c1 = 1;
c2 = 1;
n = 10;

%initialize
x1 = normrnd(0,1,[1,1]); %x[0]
x2 = normrnd(0,1,[1,1]);
y = c1*x1+c2*x2;

varx1 = 1;
varx2 = 1;
vary = c1^2+c2^2;
```

```

xhat1 = y*c1*varx1/vary;
xhat2 = y*c2*varx2/vary;
sigman1 = (1-c1*varx1/vary)^2*varx1+(c2*varx1/vary)^2*varx2;

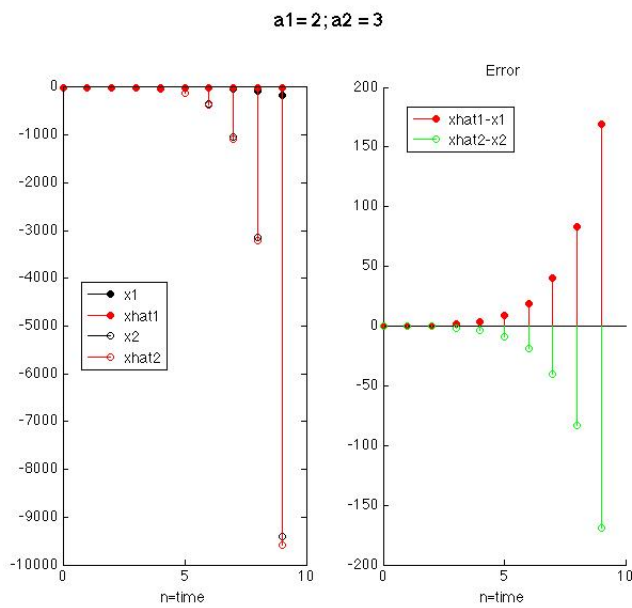
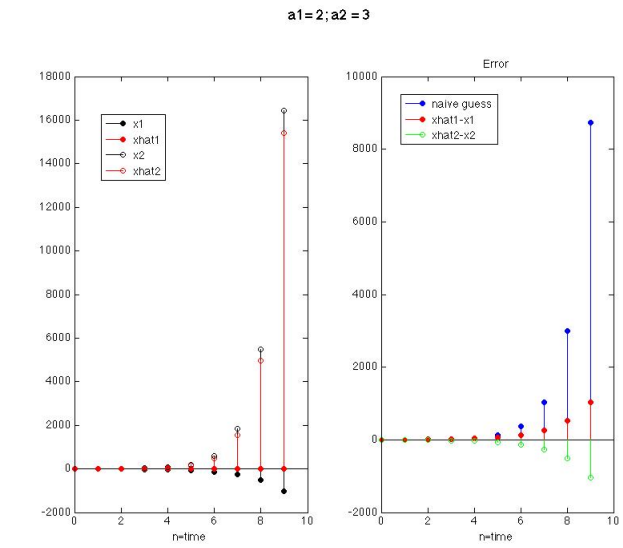
%time passing
for t=1:(n-1)
    x1 = [x1 a1*x1(1,t)];
    x2 = [x2 a2*x2(1,t)];
    y = [y c1*x1(1,t+1)+c2*x2(1,t+1)];
    varx1 = a1^2*varx1;
    varx2 = a2^2*varx2;
    vary = c1^2*varx1 + c2^2*varx2;
    xhat1 = [xhat1 y(1,t+1)*c1*varx1/vary];
    xhat2 = [xhat2 y(1,t+1)*c2*varx2/vary];
    sigman1 = [sigman1 (1-c1*varx1/vary)^2*varx1+(c2*varx1/vary)^2*varx2];
end

%hold all
subplot(1,2,1), stem(0:t,x1,'k','filled')
%subplot(1,2,1), hold on, stem(0:t,y,'b','filled')
subplot(1,2,1), hold on, stem(0:t,xhat1,'r','filled')
subplot(1,2,1), hold on, stem(0:t, x2, 'k')
subplot(1,2,1), hold on, stem(0:t, xhat2, 'r')
xlabel('n=time')
legend1 = legend('x1','xhat1','x2','xhat2','Location','Best');

%subplot(1,2,2), stem(0:t,abs(y*c1/(c1+c2)-x1),'b','filled')
subplot(1,2,2), hold on, stem(0:t,xhat1-x1,'r','filled')
%subplot(1,2,2), hold on, stem(0:t, sqrt(sigman1), 'k')
subplot(1,2,2), hold on, stem(0:t,xhat2-x2,'g')
%subplot(1,2,2), hold on, stem(0:t, abs(xhat1-x1+xhat2-x2), 'k', 'filled')
xlabel('n=time')
legend2 = legend('xhat1-x1','xhat2-x2');
subplot(1,2,2), title('Error')

suptitle(['a1= ' num2str(a1) '; a2 = ' num2str(a2)])

```



Here, the error appears to be a concave up, increasing curve. However, if I change the parameters to $a_1=1$, $a_2 > 1$, the curve changes shape.

$a_1=1; a_2=5$

