Kalman-filter smoothing



■ Smoothing is the estimation of the system state at a time m amid the data interval. That is (where m < N),

$$\hat{x}_{m|N}^+ = \mathbb{E}[x_m \mid \mathbb{Z}_N].$$

- There are three different smoothing scenarios:
 - \Box <u>Fixed-point smoothing</u>: Find $\hat{x}_{m|k}^+$ where m is fixed, but k is changing as more data becomes available;
 - $\ \ \Box$ <u>Fixed-lag smoothing</u>: Find $\hat{x}_{k-L|k}^-$ where L is a fixed lag time;
 - \Box <u>Fixed-interval smoothing</u>: Find $\hat{x}_{m|N}^+$ where k is fixed, but m can take on multiple past values.
- We will discuss all three in this lesson but focus on fixed-interval smoothing; the others use a variation of this idea.

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University of Colorado Colorado Springs

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2.3.4: Using the Kalman filter for smoothin

Fixed-interval smoothing: State estimate



- The fixed-interval-smoothing algorithm consists of a forward recursive pass followed by a backward pass.
- The forward pass uses a Kalman filter and saves the intermediate results \hat{x}_k^- , \hat{x}_k^+ , $\Sigma_{\tilde{x},k}^-$, and $\Sigma_{\tilde{x},k}^+$.
- lacktriangle The backward pass starts at time N of the last measurement, and computes the smoothed state estimate using the results obtained from the forward pass.
- The recursive equations of the backward sweep for estimating the state are:

$$\hat{x}_{m|N}^{+} = \hat{x}_{m}^{+} + \lambda_{m} \left(\hat{x}_{m+1|N}^{+} - \hat{x}_{m+1}^{-} \right)$$
$$\lambda_{m} = \sum_{\tilde{x},m}^{+} A_{m}^{T} \left(\sum_{\tilde{x},m+1}^{-} \right)^{-1}$$

where $m=N-1,N-2,\ldots,0.$ Note, $\hat{x}_{N|N}^+=\hat{x}_N^+$ to start backward pass.

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2.3.4: Using the Kalman filter for smoothing

Fixed-interval smoothing: Covariance estimate



- We can also compute the smoothed estimation-error covariance matrix (for developing confidence bounds).
- The error covariance matrix for the smoothed estimate is

$$\Sigma_{\tilde{x},m|N}^{+} = \Sigma_{\tilde{x},m}^{+} + \lambda_m \left[\Sigma_{\tilde{x},m+1|N}^{+} - \Sigma_{\tilde{x},m+1}^{-} \right] \lambda_m^T.$$

- Notice (from the prior equations) that we are not required to compute this quantity to be able to perform the backward pass.
- Also note that the term in the square brackets is negative semi-definite, so the covariance of the smoothed estimate is "smaller" than for the filtered estimate only.

Fixed point smoothing



 \blacksquare Here, m is fixed, and the final point k keeps increasing.

$$\hat{x}_{m|k}^{+} = \hat{x}_{m|k-1}^{+} + \mu_k \left(\hat{x}_k^{+} - \hat{x}_k^{-} \right)$$
 where $\mu_k = \prod_{i=m}^{k-1} \lambda_i$,

where the product multiplies on the left as i increases.

 \Box For example, for k = m + 1,

$$\hat{x}_{m|m+1}^{+} = \hat{x}_{m}^{+} + \mu_{m+1} \left(\hat{x}_{m+1}^{+} - \hat{x}_{m+1}^{-} \right)$$
$$\mu_{m+1} = \lambda_{m} = \sum_{\tilde{x},m}^{+} A_{m}^{T} \left(\sum_{\tilde{x},m+1}^{-} \right)^{-1}.$$

 \Box Then, for k=m+2, (and so forth for k>m+2)

$$\hat{x}_{m|m+2}^{+} = \hat{x}_{m|m+1}^{+} + \mu_{m+2} \left(\hat{x}_{m+2}^{+} - \hat{x}_{m+2}^{-} \right)$$
$$\mu_{m+2} = \sum_{\tilde{x},m+1}^{+} A_{m+1}^{T} \left(\sum_{\tilde{x},m+2}^{-} \right)^{-1} \mu_{k+1}.$$

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2.3.4: Using the Kalman filter for smoothing

Fixed-lag smoothing



- Here, we seek to estimate the state vector at a fixed time interval lagging the time of the current measurement.
 - ☐ This type of smoothing trades off estimation latency for more accuracy.
 - The fixed interval smoothing algorithm could be used to perform fixed-lag smoothing when the number of backward steps equals the time lag
 - □ This is fine as long as the number of backward steps is small.
 - □ Fixed-lag smoothing algorithm has a startup problem: Cannot run until enough data are available.

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2.3.4: Using the Kalman filter for smoothing

Octave code for fixed-interval smoothing



Octave code for fixed-interval smoothing



■ The main program loop begins:

```
% KF Step 1a: State prediction time update
xhat = Ad*xhat + Bd*u(:,k-1); % use prior value of "u"
\mbox{\ensuremath{\it \%}} KF Step 1b: Prediction-error covariance time update
SigmaX = Ad*SigmaX*Ad' + SigmaW;
% Store prediction data for smoothing
xhatMstore(:,k) = xhat;
                             % store xhat-minus
SigmaXMstore(:,:,k) = SigmaX; % store sigma-minus
% KF Step 1c: Estimate system output
zhat = Cd*xhat + Dd*u(k);
% KF Step 2a: Compute Kalman gain matrix
L = SigmaX*Cd'/(Cd*SigmaX*Cd' + SigmaV);
% KF Step 2b: State estimate measurement update
xhat = xhat + L*(z(k) - zhat);
% KF Step 2c: Estimation-error covariance measurement update
SigmaX = SigmaX - L*Cd*SigmaX;
```

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2.3.4: Using the Kalman filter for smoothing

Octave code for fixed-interval smoothing



```
% Store estimate data for smoothing and KF output
 SigmaXstore(:,:,k) = SigmaX; % store sigma-plus
 xhatstore(:,k) = xhat;
                          % store xhat (i.e., xhat-plus)
 boundstore(:,k) = 3*sqrt(diag(SigmaX)); % store xhat bounds
end
% % Now, do backward pass...
SigmaXSstore = SigmaXstore; % smoothed covariance
for k = nt-1:-1:1
 Sp = SigmaXstore(:,:,k); Sm = SigmaXMstore(:,:,k+1);
 lambda = Sp*Ad'/Sm;
 xhatSstore(:,k) = xhatstore(:,k) + ... % compute smoothed estimate
   lambda*(xhatSstore(:,k+1) - xhatMstore(:,k+1)); % and store it
 Spp = SigmaXSstore(:,:,k+1);
 SigmaXSstore(:,:,k) = Sp;
                                  % store smoothed covariance
 boundSstore(:,k) = 3*sqrt(diag(Sp)); % store smoothed estimate bounds
end
```

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2.3.4: Using the Kalman filter for smoothing

Octave code for fixed-interval smoothing



Plot states, estimates, and smoothed estimates:

```
CL = lines;
figure(1); clf;
t2 = [t fliplr(t)]; % Prepare for plotting bounds via "fill"
x2 = [xhatstore-boundstore fliplr(xhatstore+boundstore)];
x3 = [xhatSstore-boundSstore fliplr(xhatSstore+boundSstore)];
h1 = fill(t2,x2,CL(1,:),'FaceAlpha',0.15,'LineStyle','none'); hold on; grid on
h3 = fill(t2,x3,CL(5,:),'FaceAlpha',0.20,'LineStyle','none');
set(gca,'ColorOrderIndex',1);
h2 = plot(t,x(1:2,:)',t,xhatstore(1:2,:)','--');
h4 = plot(t,xhatSstore(1:2,:)','--');
legend([h2;h4;h1(1);h3(1)],{'True posn.','True vel.','Posn. est.',...
   Vel. est.', 'Posn. smooth', 'Vel. smooth', 'KF bounds', 'Smooth bounds'},...
    'NumColumns',3);
title('KF state estimates with smoothing');
xlabel('Time (s)'); ylabel('State (m or m/s)');
```

Octave code for fixed-interval smoothing



Plot estimation errors and smoothed-estimate errors:

```
xerr = x - xhatstore; xSerr = x - xhatSstore;
subplot(2,1,1);
fill([t fliplr(t)],[-boundstore(1,:) fliplr(boundstore(1,:))],CL(1,:),...
  'FaceAlpha', 0.15, 'LineStyle', 'none'); hold on; grid on;
fill([t fliplr(t)],[-boundSstore(1,:) fliplr(boundSstore(1,:))],CL(5,:),...
  'FaceAlpha',0.20,'LineStyle','none');
plot(t,xerr(1,:),'Color',CL(1,:)); plot(t,xSerr(1,:),'Color',CL(5,:));
title('Position estimation error with bounds'); ylabel('Error (m)');
subplot (2,1,2);
fill([t fliplr(t)],[-boundstore(2,:) fliplr(boundstore(2,:))],CL(1,:),...
  'FaceAlpha',0.15,'LineStyle','none'); hold on; grid on;
fill([t fliplr(t)],[-boundSstore(2,:) fliplr(boundSstore(2,:))],CL(5,:),...
  'FaceAlpha',0.20,'LineStyle','none');
plot(t,xerr(2,:),'Color',CL(1,:)); plot(t,xSerr(2,:),'Color',CL(5,:));
title('Velocity estimation error with bounds');
xlabel('Time (s)'); ylabel('Error (m/s)');
```

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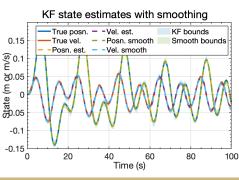
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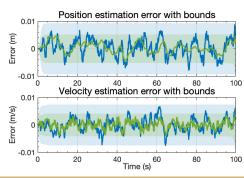
2.3.4: Using the Kalman filter for smoothing

Results from the Kalman smoother



- The figures show results of running the smoother.
- The improvement is most noticeable in the error plots where the blue lines (and shading) display the forward estimation error (and bounds) and the green lines (and shading) display the backward smoothed error (and bounds).





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2.3.4: Using the Kalman filter for smoothing

Summary



- The Kalman filter can be extended to use "future" data to compute an improved estimate of a "past" state.
- Three common scenarios: Fixed-point smoothing, fixed-lag smoothing, fixed-interval smoothing.
- We focused here on fixed-interval smoothing:
 - A standard KF is run in the "forward" direction and signals are saved.
 - A backward pass is made to refine the KF's state estimates and bounds.
- You learned how to implement a fixed-interval Kalman smoother in Octave code.
- An example showed that errors are smaller and bounds are tighter using the smoother than simply using a standard Kalman filter.