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# **Dynamic System Estimation**

**Comparison between  
Kalman filter and  
Sequential Least  
Squares estimation**

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# Kalman filter vs. sequential LSQ

The table below compares the two algorithms

Kalman filter	sequential LSQ
state estimation	Est. of parameters, constant in time
<ul style="list-style-type: none"> <li>prediction</li> <li>correction/update</li> </ul>	
$\hat{\mathbf{x}}_{n n} = \hat{\mathbf{x}}_{n n-1} + \mathbf{K}_n \left( z_n - \mathbf{H}_n \hat{\mathbf{x}}_{n n-1} \right)$ $\mathbf{K}_n = \mathbf{P}_{n n-1} \mathbf{H}_n^T \left( \mathbf{H}_n \mathbf{P}_{n n-1} \mathbf{H}_n^T + \mathbf{R}_n \right)^{-1}$ $\mathbf{P}_{n n} = (\mathbf{I} - \mathbf{K}_n \mathbf{H}_n) \mathbf{P}_{n n-1}$ $\hat{\mathbf{x}}_{n n-1} = \Phi_{n-1 n-1} \cdot \hat{\mathbf{x}}_{n-1 n-1}$ $\mathbf{P}_{n n-1} = \Phi_{n-1 n-1} \mathbf{P}_{n-1 n-1} \Phi_{n-1 n-1}^T + \mathbf{Q}$	$\hat{\mathbf{x}}_n = \hat{\mathbf{x}}_{n-1} + \left[ \hat{\sigma}_{0n-1}^2 \Sigma(\hat{\mathbf{x}}_{n-1})^{-1} + \mathbf{A}_n^T \mathbf{P}_n \mathbf{A}_n \right]^{-1} \cdot \mathbf{A}_n^T \mathbf{P}_n [\mathbf{y}_n - \mathbf{A}_n \hat{\mathbf{x}}_{n-1}]$ $\Sigma(\hat{\mathbf{x}}_n) = \hat{\sigma}_{0n}^2 \left[ \hat{\sigma}_{0n-1}^2 \Sigma(\hat{\mathbf{x}}_{n-1})^{-1} + \mathbf{A}_n^T \mathbf{P}_n \mathbf{A}_n \right]^{-1}$

Question: Can we proof that the Kalman filter algorithm can be related to the sequential LSQ in case of time-invariant parameters?

## Kalman filter vs. sequential LSQ - cont'd

The Kalman filter degrades to the sequential LSQ estimation, if

- the state transition matrix  $\Phi_{n-1|n-1}$  is the identity matrix
- the process noise covariance matrix  $Q$  is zero

$$\Phi_{n-1|n-1} = I \Rightarrow \hat{x}_{n|n-1} = \hat{x}_{n-1|n-1}$$

$$Q = 0, \Phi_{n-1|n-1} = I \Rightarrow P_{n|n-1} = P_{n-1|n-1}$$

In other word the prediction step is not effective. Thus in the following we drop the notation  $n|n-1$  and just write

$$P_{n|n} = (I - K_n H_n) P_{n|n-1} \Rightarrow P_n = (I - K_n H_n) P_{n-1}$$

$$\begin{aligned} K_n &= P_{n|n-1} H_n^T (H_n P_{n|n-1} H_n^T + R_n)^{-1} \\ \Rightarrow K_n &= P_{n-1} H_n^T (H_n P_{n-1} H_n^T + R_n)^{-1} \end{aligned}$$

$$\begin{aligned} P_n &= P_{n-1} - K_n H_n P_{n-1} \\ \Rightarrow P_n &= P_{n-1} - P_{n-1} H_n^T (H_n P_{n-1} H_n^T + R_n)^{-1} H_n P_{n-1} \end{aligned}$$

Matrix inversion Lemma, for  $B, D$  being positive definite matrices

$$(B^{-1} - CD^{-1}C^T)^{-1} = B - BC(D + C^T BC)^{-1}C^T B$$

## Kalman filter vs. sequential LSQ - cont'd

We identify

$$B = P_{n-1}, \quad C = H_n^T, \quad D = R_n$$

and are able to write

$$P_n = \left( P_{n-1}^{-1} + H_n^T R_n H_n \right)^{-1}$$

which turns out to be equivalent to the covariance update for the sequential LSQ.

A similar derivation can be made for  $\hat{x}_n$ .