

MECH468 : Modern Control Engineering MECH509 : Controls

L30 : Steady-state Kalman filter Course summary

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Zoom lecture to be recorded and posted on Canvas

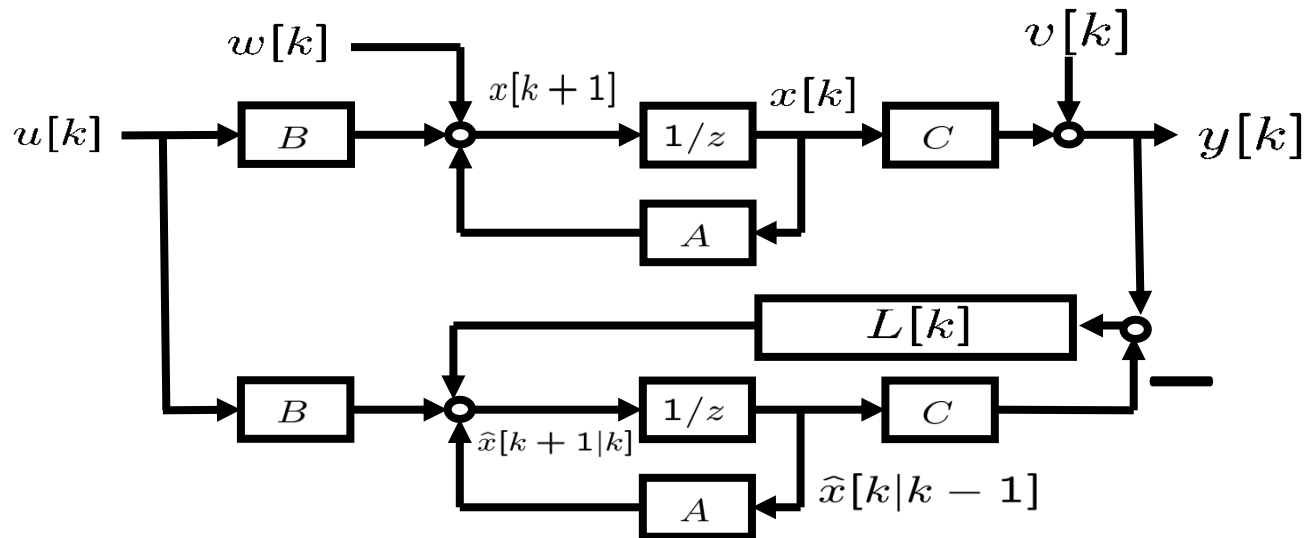


Outline

- Duality between LQR and Kalman filter
- Steady-state Kalman filter
- Linear Quadratic Gaussian (LQG)
- Summary of the course

One-step Kalman filter (review)

$$\hat{x}[k+1|k] = A\hat{x}[k|k-1] + Bu[k] + L[k](y[k] - C\hat{x}[k|k-1])$$



$$L[k] = AP[k|k]C^T R_v^{-1} = AP[k|k-1]C^T [R_v + CP[k|k-1]C^T]^{-1}$$

$$\begin{cases} P[k+1|k] = AP[k|k-1]A^T + R_w \\ \quad - AP[k|k-1]C^T [R_v + CP[k|k-1]C^T]^{-1} CP[k|k-1]A^T \\ P[0|-1] = P_0 \end{cases}$$

Duality between LQR and KF

- DT LQR** $K[k] = [R + B^T P[k+1]B]^{-1} B^T P[k+1]A$

LQR		KF
$K[k]$	\leftrightarrow	$L[k]^T$
A	\leftrightarrow	A^T
B	\leftrightarrow	C^T
R	\leftrightarrow	R_v
Q	\leftrightarrow	R_w

$$\begin{cases} P[k] &= A^T P[k+1]A + Q \\ &- A^T P[k+1]B [R + B^T P[k+1]B]^{-1} B^T P[k+1]A \\ P[k_f] &= S \end{cases}$$

Backward computation

- Kalman filter** $L[k] = AP[k|k-1]C^T [R_v + CP[k|k-1]C^T]^{-1}$

$$\begin{cases} P[k+1|k] &= AP[k|k-1]A^T + R_w \\ &- AP[k|k-1]C^T [R_v + CP[k|k-1]C^T]^{-1} CP[k|k-1]A^T \\ P[0|-1] &= P_0 \end{cases}$$

Forward computation

Mathematically dual!



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Remarks on Kalman filter (KF)

- The gain $L[k]$ is time-varying, but it typically reaches the steady state quickly, because $P[k/k-1]$ reaches steady-state quickly.
- To simplify implementation of KF, it is often preferable to use a **constant-gain** KF.
- In many cases, this does not degrade the filter performance so much.
- How to obtain such **steady-state Kalman filter**?
 - We need an assumption “ (A,C) observable” for DARE in next slide to have a unique positive definite solution.

DARE for steady-state KF

- For time-varying gain $L[k]$, we solve an equation recursively to obtain the error covariance.

$$\begin{cases} P[k+1|k] = AP[k|k-1]A^T + R_w - AP[k|k-1]C^T [R_v + CP[k|k-1]C^T]^{-1} CP[k|k-1]A^T \\ P[0|-1] = P_0 \end{cases}$$

- To find the equation for steady-state, set

$$M = P[k+1|k] = P[k|k-1] > 0$$

$$\rightarrow AMA^T - M + R_w - AMC^T [R_v + CM C^T]^{-1} CMA^T = 0$$

Discrete Algebraic Riccati Equation (DARE)



Gain computation for KF in Matlab

- dare.m
 - Steady-state *a priori* error covariance
(Steady-state of $P[k+1/k]$) $M = \text{dare}(A^T, C^T, R_w, R_v)$
 - Steady-state *a posteriori* error covariance
(Steady-state of $P[k/k]$) $P = M - MC^T (CMC^T + R_v)^{-1} CM$
 - Observer gain $L = A \underbrace{PC^T R_v^{-1}}_{=:K \text{ Kalman gain}} = AMC^T (CMC^T + R_v)^{-1}$
- dlqe.m $[K, M, P] = \text{dlqe}(A, B_w, C, R_w, R_v)$
 ↘ (coefficient matrix of w)

Steady-state Kalman filter

- Initial conditions $\hat{x}[0| - 1]$

① Measurement update

$$\hat{x}[k|k] = \hat{x}[k|k-1] + \underbrace{P[k|k]C^T R_v^{-1}}_{\text{Kalman gain}} (y[k] - C\hat{x}[k|k-1])$$

$$P := P[k|k]$$

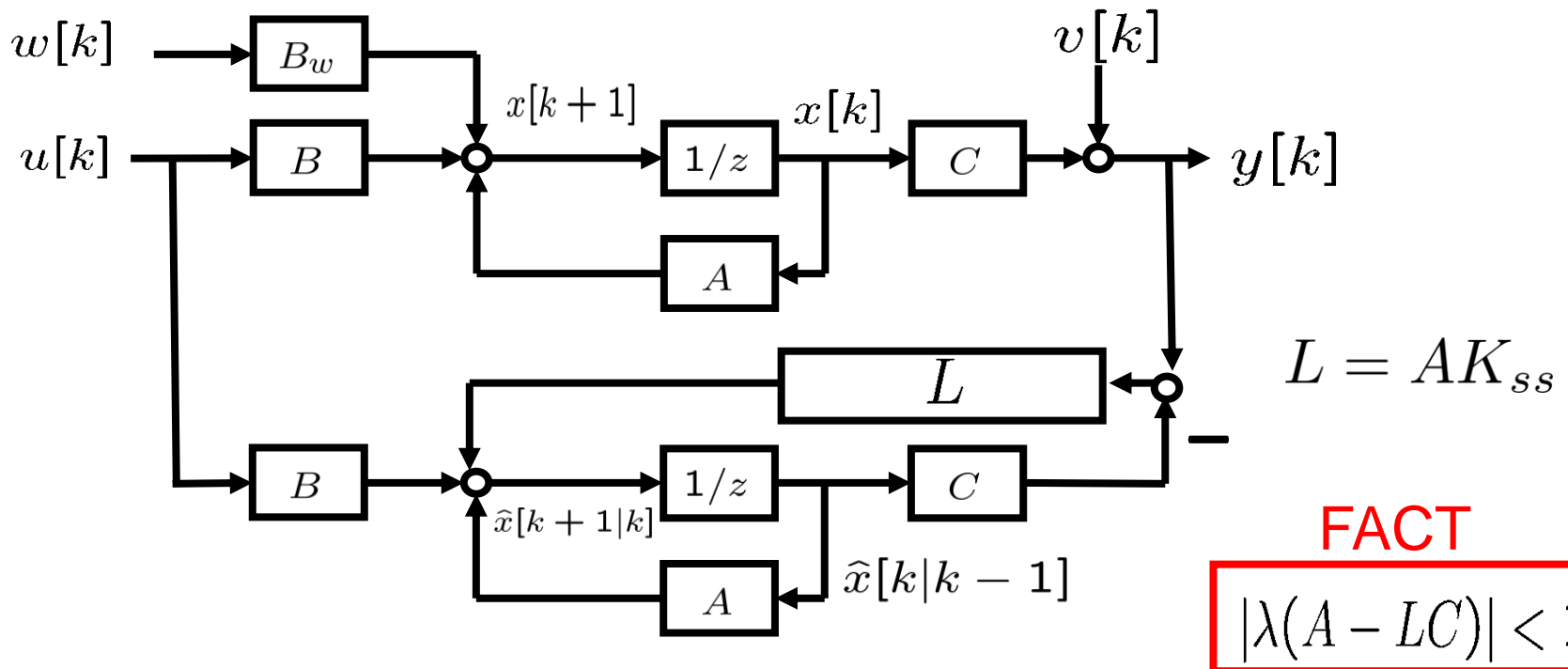
Kalman gain for steady-state Kalman filter

$$K_{ss} := PC^T R_v^{-1}$$

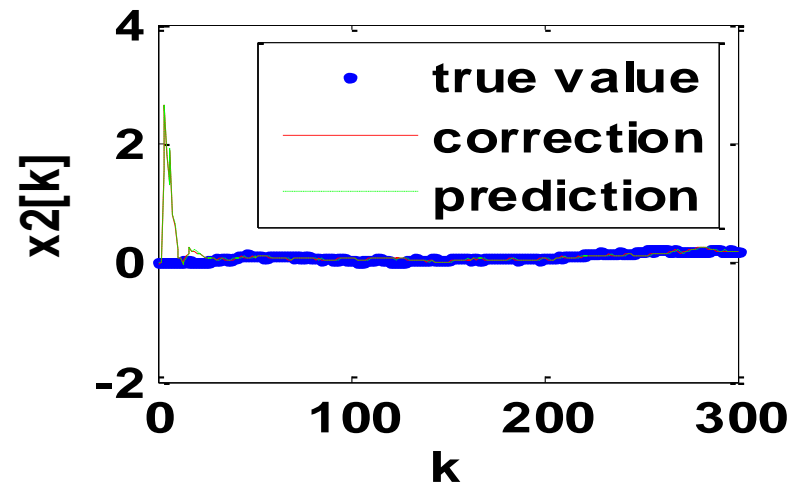
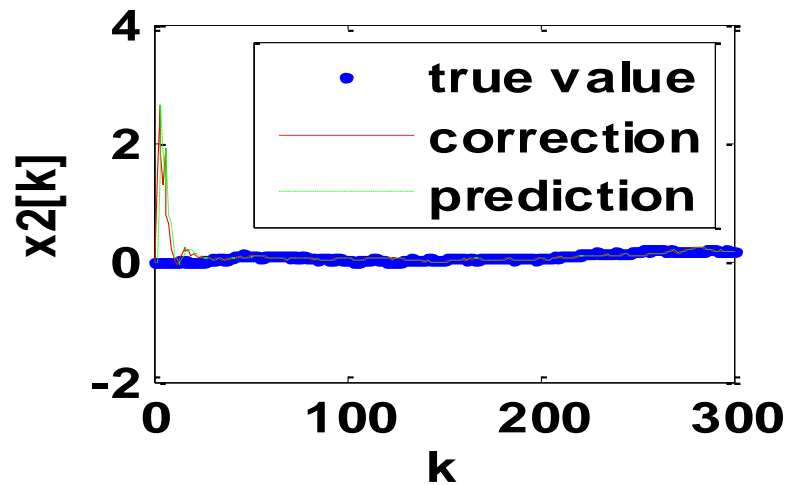
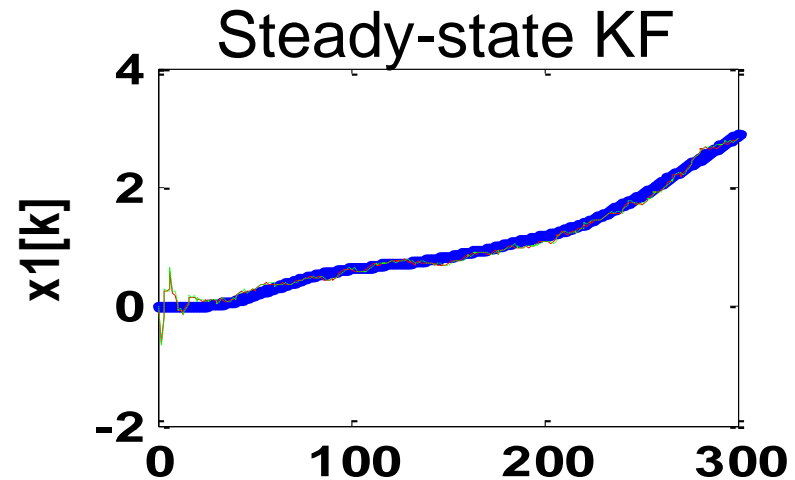
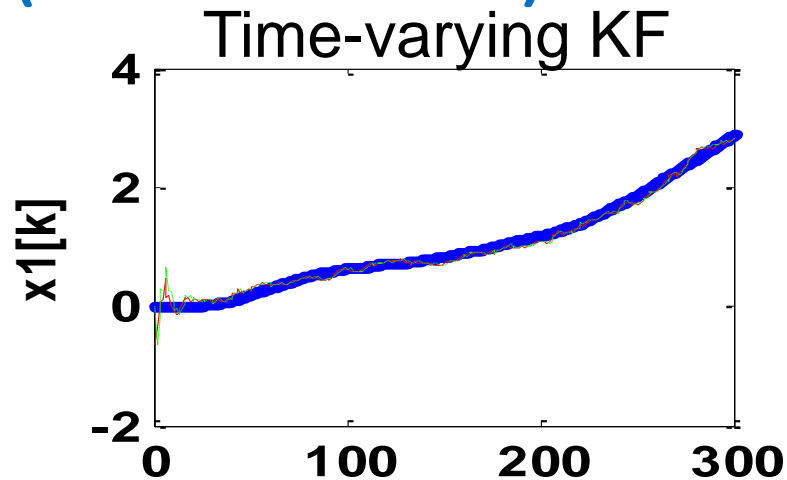
② Time update $\hat{x}[k+1|k] = A\hat{x}[k|k] + Bu[k]$

One-step steady-state KF

- One-step steady-state Kalman filter design can be seen as a special way of designing observer gain L .



Satellite attitude estimation (KFsatellite.m)

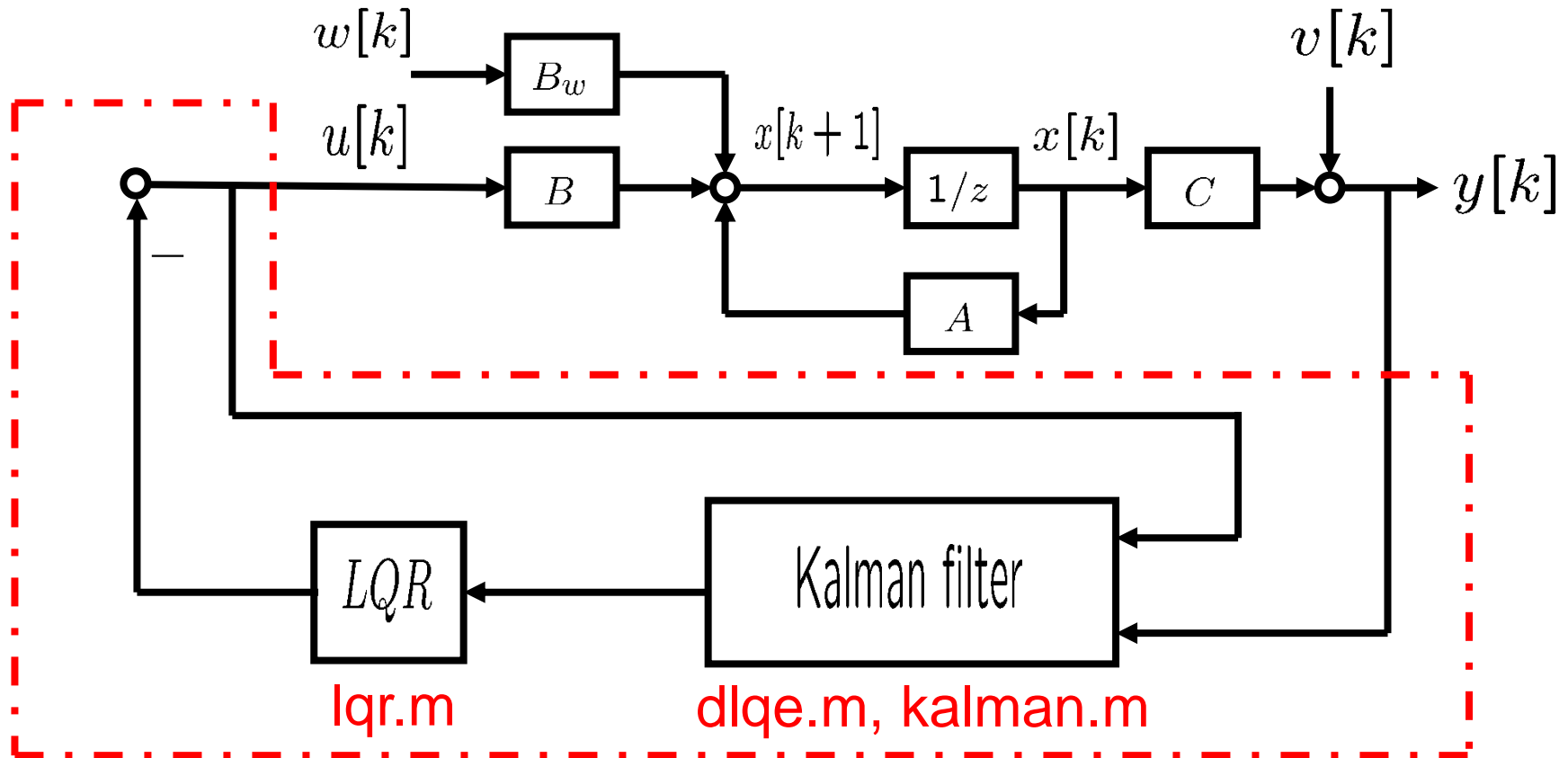




Outline

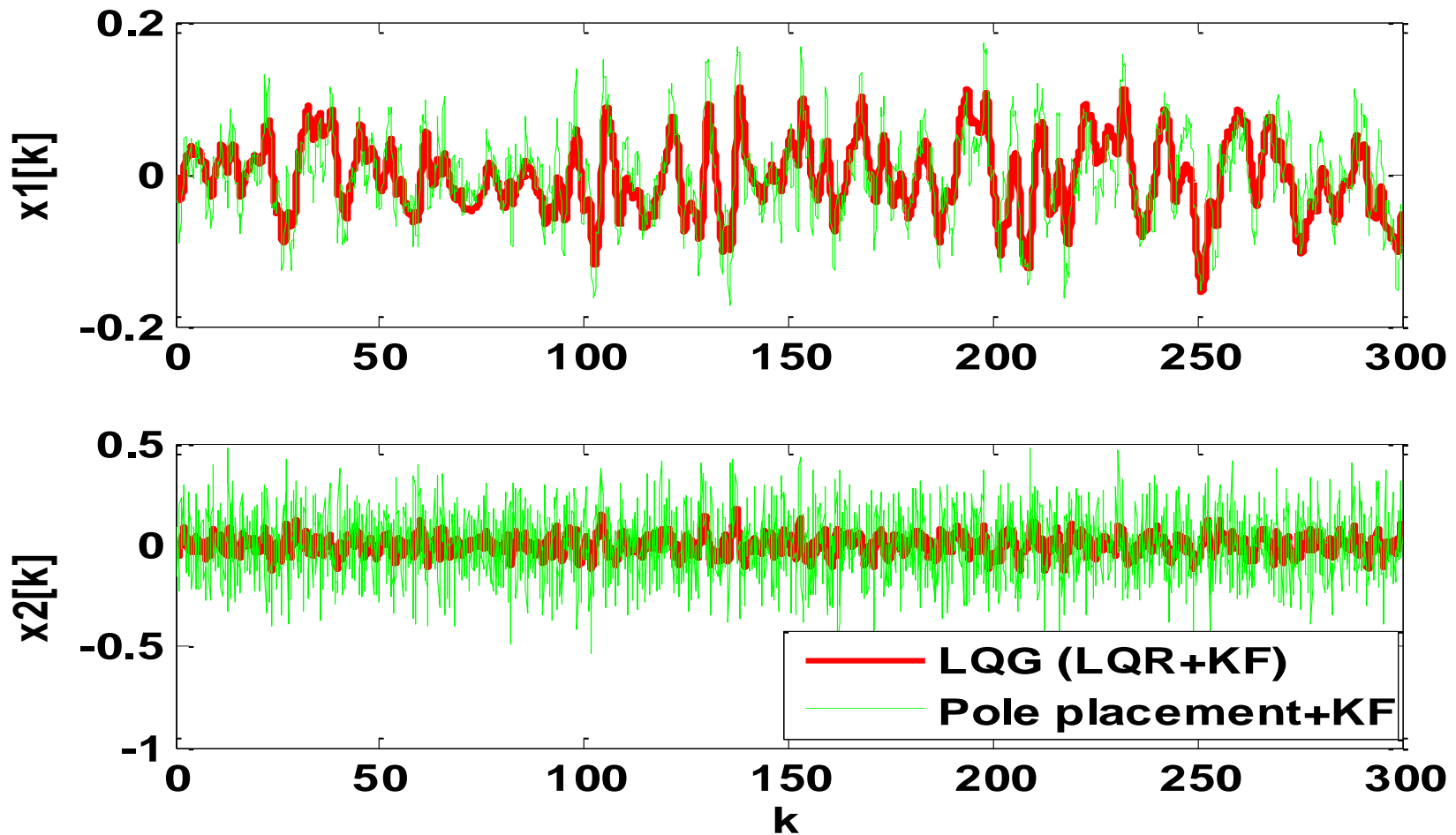
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LQG control (LQR + Kalman filter)



LQG satellite attitude control

(KFsatellite.m & LQGsatellite.slx)



More on Kalman filter

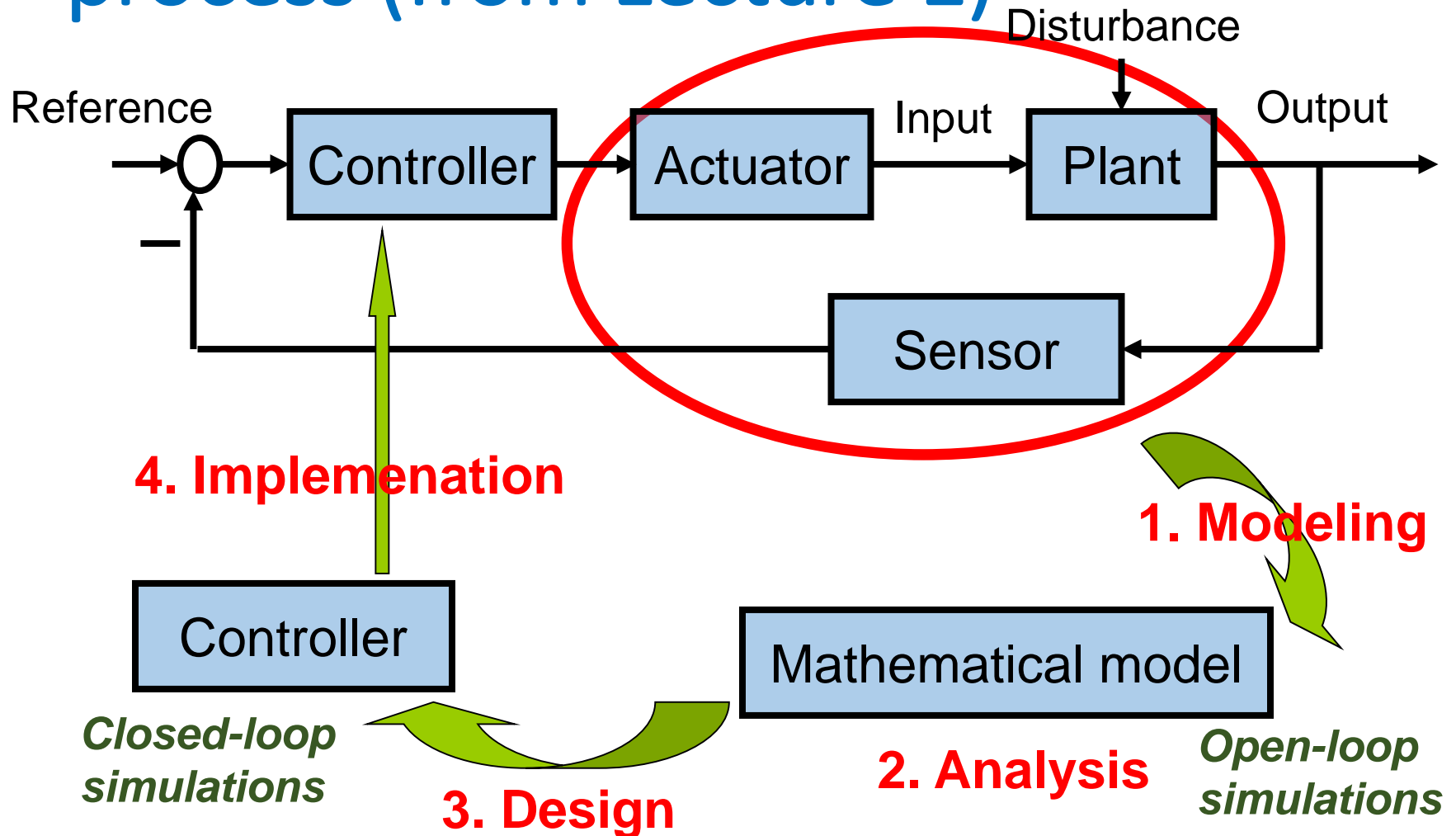
- Books
 - D. Simon, “*Optimal State Estimation*”, John Wiley & Sons, 2006
 - R. F. Stengel, “*Optimal Control and Estimation*”, Dover Publications, 1994
 - B. D. O. Anderson and J. Moore, “*Optimal Filtering*”, Dover Publications, 2005
 - F. Lewis, L. Xie and D. Popa, “*Optimal and Robust Estimation*”, 2nd ed., CRC Press, 2007
- Websites
 - Greg Welch and Gary Bishop
<http://www.cs.unc.edu/~welch/kalman/index.html>



Outline

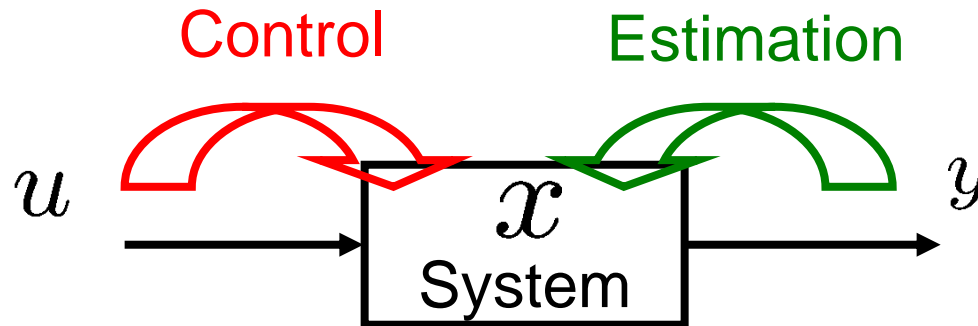
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Model-based controller design process (from Lecture 1)



Control and estimation of states

- **State** has been the key concept in this course!



- **Controllability** & **Observability**
- **State feedback** & **Observer**
- **Linear quadratic regulator** & **Kalman filter**
- Mathematical duality between **control** and **estimation**

Goal of this course (from Lec. 1)

To learn control theory with linear state-space models

- **Modeling** as a **state-space model**
 - Differential or difference equation (instead of TF)
 - Linear algebra (instead of Laplace transform)
- **Analysis**
 - Stability, controllability, observability
 - Realization, minimality
- **Design**
 - State feedback, observer
 - Linear Quadratic Regulator (LQR), Kalman Filter
- **Matlab simulation**



Course plan

Topics	CT	DT
Modeling	✓	✓
Stability	✓	✓
Controllability/observability	✓	✓
Realization	✓	✓
State feedback/observer	✓	✓
LQR/Kalman filter	✓	✓



Brief history of control engineering (from Lecture 1)

- Classical control (-1950)
 - Transfer function
 - Frequency domain
- Modern control (1960-) (contents in this course)
 - State-space model
 - Time domain
 - Optimality
- Post-modern control (1980-)
 - Robust control
 - Hybrid control, etc.



What is next?

- Advanced control theory
 - Nonlinear control
 - Robust and optimal control
 - Adaptive control
 - Digital control, sampled-data control
 - Hybrid control
 - System identification
- In this course, you learned basic control theory:
 - not only for its immediate engineering applications,
 - but also for further study on control engineering.

Summary

Control engineering supports various disciplines!

