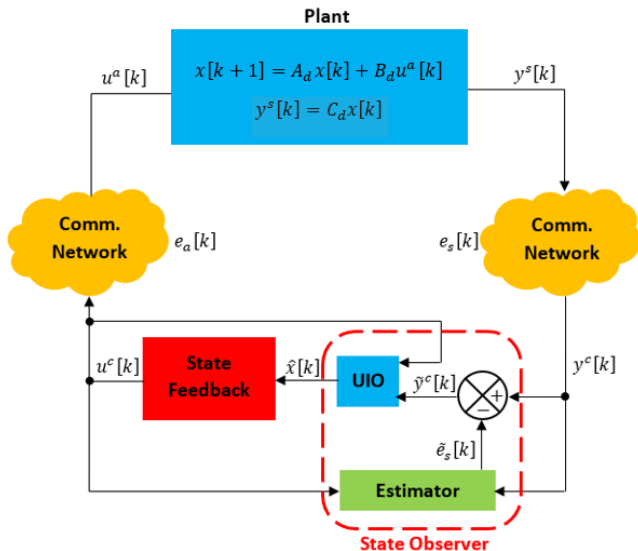


# **ECE 68000: MODERN AUTOMATIC CONTROL**

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Recovering Corrupting Errors Using a Combined  
Observer Controller Compensator

# State Observer = UIO + Output Sensor Error Estimator



# Combined output sensor error estimator and UIO

- Construct an estimator of output sensor error  $\mathbf{e}_s[k]$  to obtain its estimate denoted  $\tilde{\mathbf{e}}_s[k]$
- Subtract  $\tilde{\mathbf{e}}_s[k]$  from  $\mathbf{y}^c[k]$  to obtain

$$\begin{aligned}\tilde{\mathbf{y}}^c[k] &= \mathbf{y}^c[k] - \tilde{\mathbf{e}}_s[k] \\ &= \mathbf{y}^s[k] + \mathbf{e}_s[k] - \tilde{\mathbf{e}}_s[k]\end{aligned}$$

- To proceed, assume  $\tilde{\mathbf{y}}^c[k] = \mathbf{y}^s[k]$
- We obtain

$$\left. \begin{aligned}\mathbf{x}[k+1] &= \mathbf{A}\mathbf{x}[k] + \mathbf{B}(\mathbf{u}^c[k] + \mathbf{e}_a[k]) \\ \tilde{\mathbf{y}}^c[k] &= \mathbf{C}\mathbf{x}[k]\end{aligned}\right\}$$

# Constructing UIO

- First decompose the state  $\mathbf{x}[k]$  as

$$\begin{aligned}\mathbf{x}[k] &= \mathbf{x}[k] - \mathbf{M}\tilde{\mathbf{y}}^c[k] + \mathbf{M}\tilde{\mathbf{y}}^c[k] \\ &= \mathbf{x}[k] - \mathbf{MC}\mathbf{x}[k] + \mathbf{MC}\mathbf{x}[k] \\ &= (\mathbf{I} - \mathbf{MC})\mathbf{x}[k] + \mathbf{M}\tilde{\mathbf{y}}^c[k]\end{aligned}$$

where  $\mathbf{M} \in \mathbb{R}^{n \times p}$  is a parameter matrix to be constructed

- Let  $\mathbf{z}[k] = (\mathbf{I} - \mathbf{MC})\mathbf{x}[k]$
- Then

$$\begin{aligned}\mathbf{z}[k+1] &= (\mathbf{I} - \mathbf{MC})\mathbf{x}[k+1] \\ &= (\mathbf{I} - \mathbf{MC})(\mathbf{Ax}[k] + \mathbf{Bu}^c[k] + \mathbf{Be}_a[k]) \\ &= (\mathbf{I} - \mathbf{MC})(\mathbf{Ax}[k] + \mathbf{Bu}^c[k]) + (\mathbf{I} - \mathbf{MC})\mathbf{Be}_a[k]\end{aligned}$$

# Open-Loop UIO

- We have

$$\mathbf{z}[k+1] = (\mathbf{I} - \mathbf{MC})(\mathbf{Ax}[k] + \mathbf{Bu}^c[k]) + (\mathbf{I} - \mathbf{MC})\mathbf{Be}_a[k]$$

- Select  $\mathbf{M}$  such that  $(\mathbf{I} - \mathbf{MC})\mathbf{B} = \mathbf{O}$
- Then,  $\mathbf{z}[k+1] = (\mathbf{I} - \mathbf{MC})(\mathbf{Ax}[k] + \mathbf{Bu}^c[k])$
- Substituting  $\mathbf{x}[k] = \mathbf{z}[k] + \mathbf{M}\tilde{\mathbf{y}}^c[k]$  gives

$$\mathbf{z}[k+1] = (\mathbf{I} - \mathbf{MC})(\mathbf{Az}[k] + \mathbf{AM}\tilde{\mathbf{y}}^c[k] + \mathbf{Bu}^c[k])$$

- State estimate:  $\hat{\mathbf{x}}[k] = \mathbf{z}[k] + \mathbf{M}\tilde{\mathbf{y}}^c[k]$
- State observation error:

$$\mathbf{e}[k+1] = \mathbf{x}[k+1] - \hat{\mathbf{x}}[k+1] = (\mathbf{I} - \mathbf{MC})\mathbf{Ae}[k]$$

# Open-Loop Observer Error Analysis

- UIO observer

$$\begin{aligned} \mathbf{z}[k+1] &= (\mathbf{I} - \mathbf{MC})(\mathbf{A}\mathbf{z}[k] + \mathbf{AM}\tilde{\mathbf{y}}^c[k] + \mathbf{B}\mathbf{u}^c[k]) \\ \hat{\mathbf{x}}[k] &= \mathbf{z}[k] + \mathbf{M}\tilde{\mathbf{y}}^c[k] \end{aligned}$$

- Observation error dynamics

$$\begin{aligned} \mathbf{e}[k+1] &= \mathbf{x}[k+1] - \hat{\mathbf{x}}[k+1] \\ &= \mathbf{Ax}[k] + \mathbf{B}(\mathbf{u}^c[k] + \mathbf{e}_a[k]) - \mathbf{z}[k+1] \\ &\quad - \mathbf{M}\tilde{\mathbf{y}}^c[k+1] \\ &= \mathbf{Ax}[k] + \mathbf{B}(\mathbf{u}^c[k] + \mathbf{e}_a[k]) - \mathbf{z}[k+1] \\ &\quad - \mathbf{MCx}[k+1] \\ &= \mathbf{Ax}[k] + \mathbf{B}(\mathbf{u}^c[k] + \mathbf{e}_a[k]) - \mathbf{z}[k+1] \\ &\quad - \mathbf{MCAx}[k] - \mathbf{MCBu}^c[k] - \mathbf{MCBe}_a[k] \end{aligned}$$

# Open-Loop Observation Error

- Select  $\mathbf{M}$  so that  $(\mathbf{I} - \mathbf{MC})\mathbf{B} = \mathbf{O}$  gives

$$\begin{aligned} \mathbf{e}[k+1] &= \mathbf{Ax}[k] + \mathbf{B}(\mathbf{u}^c[k] + \mathbf{e}_a[k]) - \mathbf{z}[k+1] \\ &\quad - \mathbf{MCAx}[k] - \mathbf{MCBu}^c[k] - \mathbf{MCBe}_a[k] \\ &= (\mathbf{I} - \mathbf{MC})(\mathbf{Ax}[k] + \mathbf{Bu}^c[k]) \\ &\quad + (\mathbf{I} - \mathbf{MC})\mathbf{Be}_a[k] \\ &\quad - \mathbf{z}[k+1] \\ &= (\mathbf{I} - \mathbf{MC})(\mathbf{Ax}[k] + \mathbf{Bu}^c[k]) \\ &\quad - (\mathbf{I} - \mathbf{MC})(\mathbf{A}\hat{\mathbf{x}}[k] + \mathbf{Bu}^c[k]) \\ &= (\mathbf{I} - \mathbf{MC})\mathbf{Ae}[k] \end{aligned}$$

- Open-loop UIO impractical—no control of the observation error dynamics

# Closed-Loop UIO Error Dynamics

- Close the loop by adding the term  $\mathbf{L}(\tilde{\mathbf{y}}^c[k] - \hat{\mathbf{y}})$  to the UIO, where  $\hat{\mathbf{y}} = \mathbf{C}\hat{\mathbf{x}}$  is the UIO output
- Closed-loop UIO observation error

$$\begin{aligned} \mathbf{e}[k+1] &= (\mathbf{I} - \mathbf{MC})\mathbf{A}\mathbf{e}[k] - \mathbf{L}(\tilde{\mathbf{y}}^c[k] - \hat{\mathbf{y}}) \\ &= (\mathbf{I} - \mathbf{MC})\mathbf{A}\mathbf{e}[k] - \mathbf{L}(\mathbf{C}\mathbf{x}[k] - \mathbf{C}\hat{\mathbf{x}}) \\ &= (\mathbf{I} - \mathbf{MC})\mathbf{A}\mathbf{e}[k] - \mathbf{LC}\mathbf{e}[k] \end{aligned}$$

- Let  $\mathbf{A}_1 = (\mathbf{I} - \mathbf{MC})\mathbf{A}$ , then we have

$$\mathbf{e}[k+1] = (\mathbf{A}_1 - \mathbf{LC})\mathbf{e}[k]$$

- Closed-loop UIO—use the observer gain  $\mathbf{L}$  to control the observation error dynamics



# Closed-Loop UIO

- Compute  $\mathbf{M}$  such that

$$(\mathbf{I} - \mathbf{MC})\mathbf{B} = \mathbf{O}$$

- The UIO

$$\begin{aligned} \mathbf{z}[k+1] &= (\mathbf{I} - \mathbf{MC})(\mathbf{A}\mathbf{z}[k] + \mathbf{AM}\tilde{\mathbf{y}}^c[k] + \mathbf{B}\mathbf{u}^c[k]) \\ &\quad + \mathbf{L}(\tilde{\mathbf{y}}^c[k] - \hat{\mathbf{y}}[k]) \\ \hat{\mathbf{x}}[k] &= \mathbf{z}[k] + \mathbf{M}\tilde{\mathbf{y}}^c[k] \end{aligned}$$

where

$$\hat{\mathbf{y}}[k] = \mathbf{C}\hat{\mathbf{x}}[k]$$

Solving  $(\mathbf{I} - \mathbf{MC})\mathbf{B} = \mathbf{O}$  for  $\mathbf{M}$

- $(\mathbf{I} - \mathbf{MC})\mathbf{B} = \mathbf{O} \iff \mathbf{MCB} = \mathbf{B}$
- $\mathbf{MCB} = \mathbf{B}$  implies

$$\text{rank}(\mathbf{MCB}) = \text{rank}\mathbf{B}$$

- On the other hand,

$$\text{rank}(\mathbf{MCB}) \leq \text{rank}(\mathbf{CB}) \leq \text{rank}(\mathbf{B})$$

- Hence, a necessary and sufficient condition for solvability of  $(\mathbf{I} - \mathbf{MC})\mathbf{B} = \mathbf{O}$  is

$$\text{rank}(\mathbf{CB}) = \text{rank}(\mathbf{B})$$

# Summary of UIO Construction

## Theorem

Let  $\mathbf{A}_1 = (\mathbf{I} - \mathbf{MC})\mathbf{A}$  and  $\mathbf{T} = \mathbf{PL}$ . If

- ①  $(\mathbf{I} - \mathbf{MC})\mathbf{B} = \mathbf{O}$ ,
- ② there exists  $\mathbf{P} = \mathbf{P}^\top \succ 0$  such that

$$\begin{bmatrix} -\mathbf{P} & \mathbf{A}_1^\top \mathbf{P} - \mathbf{C}^\top \mathbf{T}^\top \\ \mathbf{P}\mathbf{A}_1 - \mathbf{T}\mathbf{C} & -\mathbf{P} \end{bmatrix} \prec 0,$$

then the UIO exists

# Theorem Discussion

- $(\mathbf{A}_1 - \mathbf{LC})$  Schur stable  $\iff$  there exists  $\mathbf{P} = \mathbf{P}^\top \succ 0$  such that

$$(\mathbf{A}_1 - \mathbf{LC})^\top \mathbf{P} (\mathbf{A}_1 - \mathbf{LC}) - \mathbf{P} \prec 0$$

- Substitute  $\mathbf{P} = \mathbf{P} \mathbf{P}^{-1} \mathbf{P}$  into the Lyapunov matrix inequality to obtain

$$(\mathbf{A}_1 - \mathbf{LC})^\top \mathbf{P} \mathbf{P}^{-1} \mathbf{P} (\mathbf{A}_1 - \mathbf{LC}) - \mathbf{P} \prec 0$$

which is equivalent to the LMI condition of the Theorem by taking the Schur complement

# Combined Estimator-UIO Design

- ① Design an estimator  $\tilde{\mathbf{e}}_s[k]$  of  $\mathbf{e}_s[k]$
- ② Design the UIO performing the following steps:
  - ▶ Check if  $\text{rank}(\mathbf{CB}) = \text{rank}(\mathbf{B})$  is satisfied. If the condition is not satisfied, STOP
  - ▶ Solve  $(\mathbf{I} - \mathbf{MC})\mathbf{B} = \mathbf{O}$  to obtain

$$\mathbf{M} = \mathbf{B} \left( (\mathbf{CB})^\dagger + \mathbf{H}_0(\mathbf{I}_p - (\mathbf{CB})(\mathbf{CB})^\dagger) \right),$$

where the superscript  $\dagger$  denotes the Moore-Penrose pseudo-inverse and  $\mathbf{H}_0$  is a design parameter matrix

- ▶ Solve for  $\mathbf{P}$  and  $\mathbf{T}$
- ▶ If  $\mathbf{P} = \mathbf{P}^\top \succ 0$ , UIO exists
- ▶ Compute  $\mathbf{L}_1 = \mathbf{P}^{-1}\mathbf{T}$