

## System Identification

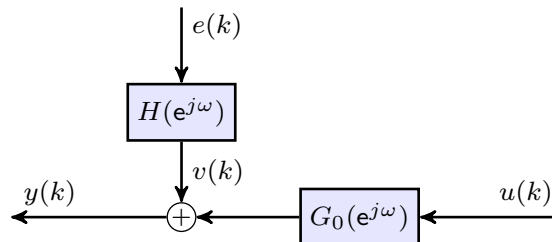
### Lecture 12: Closed-loop identification

Roy Smith

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### Open-loop identification methods



$$Y(e^{j\omega}) = G(e^{j\omega})U(e^{j\omega}) + \underbrace{V(e^{j\omega})}_{\text{noise}} + \underbrace{R(e^{j\omega})}_{\text{transient}}$$

Estimate:  $\hat{G}(e^{j\omega_n}) = \frac{\hat{Y}(e^{j\omega_n})}{\hat{U}(e^{j\omega_n})}$

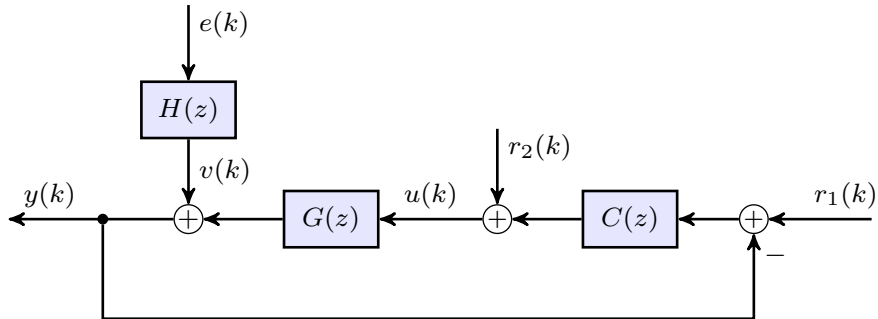
Bias:  $E\{\hat{G}(e^{j\omega_n}) - G(e^{j\omega_n})\} \rightarrow 0 \text{ as } N \rightarrow \infty$

Variance:  $E\left\{|\hat{G}(e^{j\omega_n}) - E\{\hat{G}(e^{j\omega_n})\}|^2\right\} \rightarrow \frac{\phi_v(e^{j\omega_n})}{\phi_u(e^{j\omega_n})} \text{ as } N \rightarrow \infty$

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## Closed-loop identification



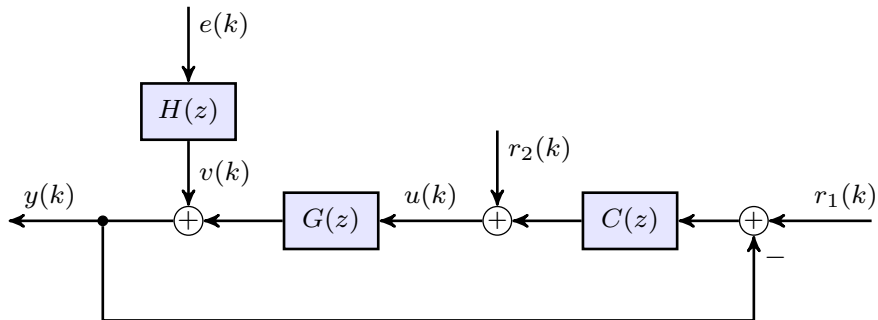
Excitation:

$r_2(k)$  and  $r_1(k)$

Measurements

$y(k), u(k), r_2(k)$  and  $r_1(k)$

## Closed-loop identification



For simplicity define:

$$r(k) = r_2(k) + C(z)r_1(k).$$

This generalises our excitation signal choices.

## Closed-loop identification

### Motivation for closed-loop identification

- ▶ Unstable systems must be operated in closed-loop.
- ▶ Operational constraints may require closed-loop.
- ▶ Closed-loop controller maintains the system close to the operating point of interest.
- ▶ Easier to focus identification on specific operating points.
- ▶ Will emphasize plant dynamics close to the cross-over frequency range.
- ▶ Closed-loop operation can remove a large-scale zero-frequency response.

## Closed-loop identification

### Methods

- ▶ Direct (open-loop) methods:

$$\hat{G} = \hat{Y}_N / \hat{U}_N \quad \text{or} \quad \hat{G} = \hat{\phi}_{yu} / \hat{\phi}_u.$$

- ▶ Indirect methods:

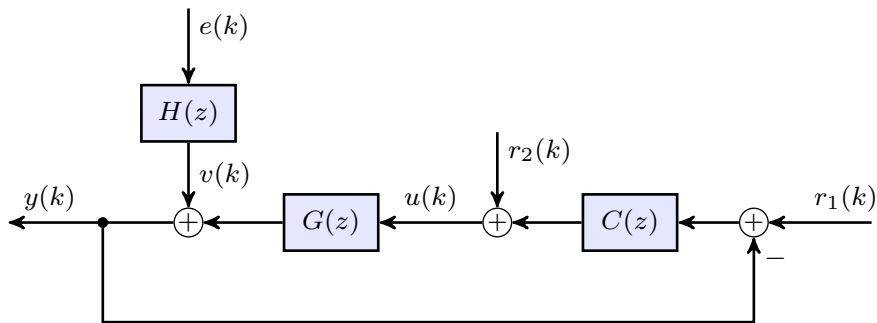
$$y = \frac{G(z)}{(1 + G(z)C(z))} r.$$

- ▶ Input-output methods:

$$y = \frac{G(z)}{(1 + G(z)C(z))} r, \quad \text{and} \quad u = \frac{1}{(1 + G(z)C(z))} r.$$

- ▶ Dual-Youla methods.

## Direct methods: closed-loop identification with open loop methods



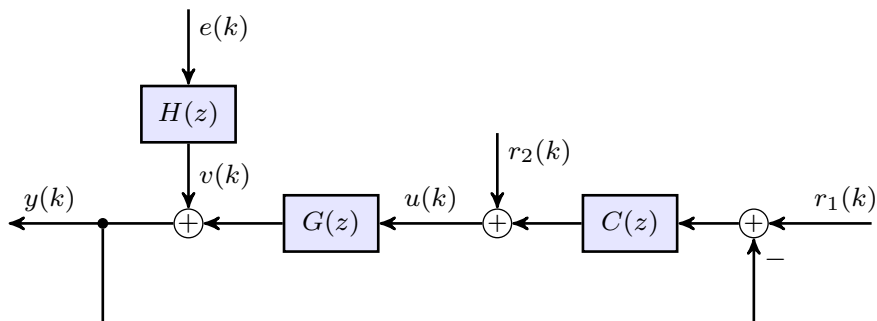
### Open-loop spectral estimation methods:

$$\hat{\phi}_{yu}(e^{j\omega_n}) = \frac{1}{N} Y_N(e^{j\omega_n}) \overline{U_N(e^{j\omega_n})}$$

$$\hat{\phi}_u(e^{j\omega_n}) = \frac{1}{N} |U_N(e^{j\omega_n})|^2$$

$$\hat{G}(e^{j\omega_n}) = \frac{\hat{\phi}_{yu}(e^{j\omega_n})}{\hat{\phi}_u(e^{j\omega_n})}$$

## Direct closed-loop identification methods



### Closed-loop transfer functions:

$$y = SGr_2 + SGCr_1 + Sv = SGr + Sv$$

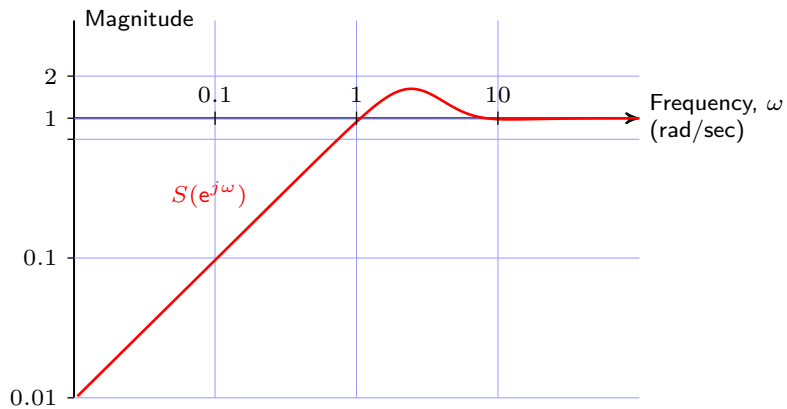
$$u = Sr_2 + SCr_1 - SCv = Sr - SCv.$$

where,  $S(e^{j\omega}) = \frac{1}{1 + C(e^{j\omega})G(e^{j\omega})}$  (assumed stable)

## Sensitivity function weighting

Closed-loop transfer functions:

$$\begin{aligned} y &= SGr + Sv \\ u &= Sr - SCv \end{aligned} \quad S = \frac{1}{1 + CG}$$



## Direct closed-loop identification methods

### Spectral analysis

Assume that  $\phi_{rv} = 0$ .

Then,

$$\phi_{yu} = |S|^2 G\phi_r - |S|^2 \bar{C}\phi_v$$

$$\phi_u = |S|^2 \phi_r + |S|^2 |C|^2 \phi_v$$

$$\begin{aligned} \hat{G} &= \frac{\hat{\phi}_{yu}}{\hat{\phi}_u} \approx \frac{|S|^2 G\hat{\phi}_r - |S|^2 \bar{C}\hat{\phi}_v}{|S|^2 \hat{\phi}_r + |S|^2 |C|^2 \hat{\phi}_v} \\ &\approx \frac{G\hat{\phi}_r - \bar{C}\hat{\phi}_v}{\hat{\phi}_r + |C|^2 \hat{\phi}_v} \end{aligned}$$

## Indirect closed-loop identification methods

Closed-loop transfer functions:

$$\begin{aligned}y &= SGr + Sv & \text{define: } T_{yr} &= SG, \\ &= T_{yr}r + Sv.\end{aligned}$$

### Identification problem (open-loop)

If  $\phi_{vr} = 0$ ,

$$\hat{T}_{yr}(e^{j\omega_n}) = \frac{Y_N(e^{j\omega_n})}{R_N(e^{j\omega_n})} \quad (\text{asymptotically unbiased}).$$

### Solving for $\hat{G}(e^{j\omega_n})$

$$\begin{aligned}T_{yr}(z) &= \frac{G(z)}{1 + C(z)G(z)} & \implies & G(z) = \frac{T_{yr}}{1 - T_{yr}(z)C(z)} \\ & & \rightsquigarrow & \hat{G}(e^{j\omega_n}) = \frac{\hat{T}_{yr}(e^{j\omega_n})}{1 - \hat{T}_{yr}(e^{j\omega_n})C(e^{j\omega_n})}\end{aligned}$$

## Joint input-output methods

Closed-loop transfer functions:

$$\begin{aligned}y &= SGr + Sv & \text{define: } T_{yr} &= SG, \\ u &= Sr - SCv & T_{ur} &= S\end{aligned}$$

### Identification problems

If  $\phi_{vr} = 0$ ,

$$\hat{T}_{yr}(e^{j\omega_n}) = \frac{Y_N(e^{j\omega_n})}{R_N(e^{j\omega_n})} \quad (\text{asymptotically unbiased}).$$

Similarly, if  $\phi_{vr} = 0$ ,

$$\hat{T}_{ur}(e^{j\omega_n}) = \frac{U_N(e^{j\omega_n})}{R_N(e^{j\omega_n})} \quad (\text{asymptotically unbiased}).$$

## Joint input-output methods

### Closed-loop identification approach

$$\frac{T_{yr}}{T_{ur}} = \frac{SG}{S} = G \quad \rightsquigarrow \quad \hat{G}(e^{j\omega_n}) = \frac{\hat{T}_{yr}(e^{j\omega_n})}{\hat{T}_{ur}(e^{j\omega_n})}$$

#### Key points:

- ▶ The estimates,  $\hat{T}_{yr}$  and  $\hat{T}_{ur}$  may be unbiased. Their ratio is not.
- ▶ The estimated spectra are weighted by  $S(e^{j\omega})$  or  $S(e^{j\omega})C(e^{j\omega})$ .
- ▶ The noise enters in a complicated manner.

## Ratio distributions

### Mean of a ratio of stochastic variables

## Ratio distributions

### Probability density function of a ratio of stochastic variables

Suppose we have two normal distributions,  $v \in \mathcal{N}(0, 1)$  and  $w \in \mathcal{N}(0, 1)$ .

$$f_v(v) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}v^2}, \quad f_w(w) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}w^2}.$$

The ratio,  $z = v/w$ , is a stochastic variable with PDF:

$$f_z(z) = \frac{1}{\pi} \frac{1}{1+z^2} \quad \text{Cauchy distribution.}$$

The mean and variance of a Cauchy distribution are undefined.

## Youla parametrisations

### Coprime factorisations

$$G_0(s) = \frac{N_0(s)}{D_0(s)},$$

with  $N_0(s), D_0(s)$  stable and coprime (no common zeros).

Coprime factorisations are not unique.

For example:  $G(s) = \frac{(s-2)}{(s+5)(s-5)}$ , (unstable, non-minimum phase)

$$N_0(s) = \frac{(s-2)}{(s+5)(s+\alpha)},$$

$$D_0(s) = \frac{(s-5)}{(s+\alpha)}, \quad \alpha > 0.$$



## Youla parametrisations

### Bezout identity

The transfer functions  $N_0(s)$  and  $D_0(s)$  are coprime  
iff there exists  $U(s)$  and  $V(s)$  such that,

$$U(s)N_0(s) + V(s)D_0(s) = I.$$

### Normalised coprime factorisations

A coprime factorisation is “normalised” if,

$$D_0^*(s)D_0(s) + N_0^*(s)N_0(s) = I.$$

**MATLAB:** `sncfbal`

## Youla parametrisations

### All stabilising controllers

If we have a controller,  $C_0$ , which stabilises  $G_0$ , with

$$C_0 = \frac{X_0}{Y_0}, \quad (X_0, Y_0 \text{ a coprime factorisation})$$

then, all controllers,  $C$ , stabilising  $G_0 = N_0/D_0$ , have the form,

$$C_Q = \frac{X_0 + QD_0}{Y_0 - QN_0}, \quad \text{with } Q \text{ stable.}$$

## Dual-Youla methods

### Control design

Given a particular plant,  $G(s)$ ,  
select  $C(s)$  from the set of all controllers stabilising  $G(s)$ .

### Closed-loop identification

Given a particular controller,  $C(s)$ ,  
select  $G(s)$  from the set of all plants stabilised by  $C(s)$ .

Both problems can be formulated as a search over stable  $Q(s)$ .

## Dual-Youla methods

### Usual identification formulation:

$$y = Gu + He, \quad e \in \mathcal{N}(0, 1).$$

Find  $G$  (and possibly  $H$ ) from the data. We assume that  $H$  is stable and stably invertible.

### Dual-Youla formulation:

$$Dy = Nu + Fe, \quad e \in \mathcal{N}(0, 1) \quad D, N, \text{ and } F \text{ stable.}$$

Find  $D, N$  (and possibly  $F$ ) from the data.

Plant is stabilised by  $C_0 = X_0/Y_0$ .

## Dual-Youla methods

Parameterisation with  $R$  and  $F$ :

$$G_R = \frac{N}{D} = \frac{N_0 + RY_0}{D_0 - RX_0}, \quad R \text{ is stable.}$$

$$H_{R,F} = \frac{F}{D} = \frac{F}{D_0 - RX_0}, \quad F \text{ is stable and stably invertible.}$$

Equivalent open-loop ID experiment:

$$(D_0 - RX_0)y = (N_0 + RY_0)u + Fe$$

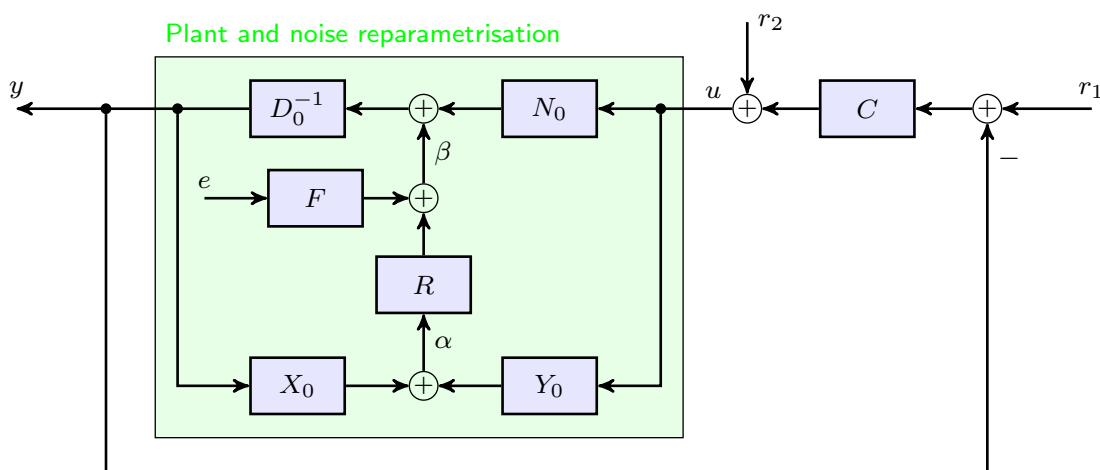
and rearranging gives,

$$\underbrace{D_0y - N_0u}_{=: \beta} = R \underbrace{(X_0y + Y_0u)}_{=: \alpha} + Fe$$

“Open-loop” system:  $\beta = R\alpha + Fe$  with  $R$  and  $F$  stable.

## Dual-Youla methods

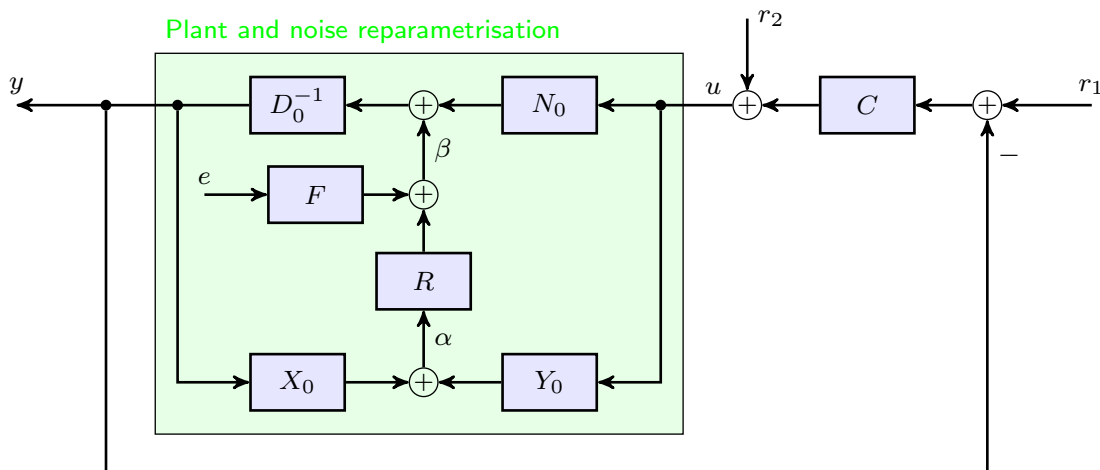
Reparametrised plant and noise structure



## Dual-Youla methods

### Key feature

The transfer function from  $\beta$  to  $\alpha$  is zero.

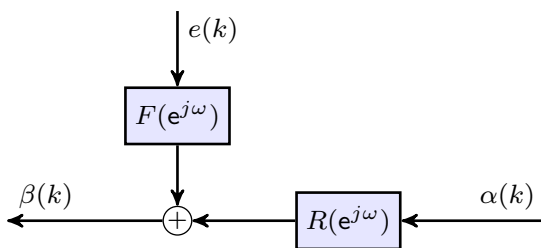


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## Dual-Youla methods

### Equivalent open-loop ID problem



$$\beta = D_0 y - N_0 u \quad (\text{filtered input and output signals})$$

$$\alpha = X_0 y + Y_0 u$$

$$= X_0 y + Y_0 \left( r_2 + \frac{X_0}{Y_0} (r_1 - y) \right) = X_0 y + Y_0 \left( r - \frac{X_0}{Y_0} y \right)$$

$$= Y_0 r \quad (\text{filtered excitation signal})$$

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## Dual-Youla methods

### Procedure

Given a stabilizing controller,  $C_0$ ,

1. Factorise:  $C_0 = X_0/Y_0$ .
2. Choose excitation,  $r$ . (Note  $\alpha = Y_0 r$  filtering).
3. Run closed-loop experiments with  $C_0$ , measuring  $y$  and  $u$ .
4. Choose an initial model,  $G_0 = N_0/D_0$  (must be stabilised by  $C_0$ ).
5. Filter measurements,  $\beta = D_0 y - N_0 u$  (time or frequency domain).
6. Filter excitation,  $\alpha = Y_0 r$ .
7. Estimate  $\hat{R}$  (and  $\hat{F}$ ) from  $\beta = R\alpha + Fe$ .
8. Calculate plant estimate,  $\hat{G} = (N_0 + \hat{R}Y_0)/(D_0 - \hat{R}X_0)$ .

## Bibliography

### Indirect methods

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### Coprime factorisations

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### Dual Youla identification formulation

Fred Hansen, Gene Franklin & Robert Kosut, "Closed-loop identification via the fractional representation: experiment design," *Proc. ACC*, pp. 1422–1427, 1989.