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SVFB Design via Gain Xformation & Pole Placement

- "Deadbeat" controller
- 2. Continuous-Discrete Gain Tranformation
 - Time response equivalence
 - Average gain method
 - Example-double integrator

3. Pole Placement via SVFB Design

- Direct approach
- Transformation approach
- Ackermann formula/algorithm
- Pole placement for MIMO systems
 - State feedback
 - output feedback (numerically not robust. So, won't discuss)

4. Example-Inverted Pendulum on a Cart

- Continuous-discrete transformation design
- Direct digital design
- 5. Implementation of High-Order Compensators
 - State prediction
 - Comparison with Smith compensator
 - Examples
- 6. Command Inputs to SVFB Systems
 - Integral feedback

Control in State-Space

What can be done with respect to controlling system states?

$$\underline{x}(k+1) = \Phi \underline{x}(k) + \Gamma u(k)$$

$$y(k) = C\underline{x}(k)$$

$$\underline{x}(0) = \text{known initial condition}$$

Equivalent discrete system matrices

$$\Phi = e^{Ah}, \qquad \Gamma = \int_0^h e^{A\sigma} d\sigma B$$

State response ٠

$$\underline{\mathbf{x}}(\mathbf{k}) = \Phi^{\mathbf{k}} \underline{\mathbf{x}}(0) + \sum_{i=0}^{k-1} \Phi^{k-1-i} \Gamma u(i)$$

Consider k = n•

- Can we find u(0), u(1), ..., u(n-1) so that $\underline{x}(n) = \xi$ = arbitrary vector, starting at any initial condition x(0)?

$$\underline{\xi} - \Phi^{n} \underline{x}(0) = \sum_{i=0}^{n-1} \Phi^{n-1-i} \Gamma u(i) = \Gamma u(n-1) + \Phi \Gamma u(n-2) + \dots + \Phi^{n-1} \Gamma u(0)$$
$$= \begin{bmatrix} | & | & | \\ \Gamma & \Phi \Gamma & \dots & \Phi^{n-1} \Gamma \\ | & | & | \end{bmatrix} \begin{bmatrix} u(n-1) \\ u(n-2) \\ \vdots \\ u(0) \end{bmatrix}$$

If H_c is invertible, it is possible to find the requisite {u(i)}.
Note: state may not necessarily stay at ξ for k > n.

H_c

Deadbeat Controller

- If system is cc the sequence {u(0), u(1), ..., u(n-1)} will drive $\underline{x}(0) \rightarrow \underline{x}(n) = \underline{\xi}$ where $\begin{bmatrix} u(n-1) \\ u(n-2) \\ \vdots \\ u(0) \end{bmatrix} = H_c^{-1} [\underline{\xi} - \Phi^n \underline{x}(0)]$
 - Open-loop control

$$\begin{array}{c}
 u(0) = \begin{bmatrix} 0 & 0 & \dots & 0 & 1 \end{bmatrix} H_{c}^{-1} \begin{bmatrix} \underline{\xi} & -\Phi^{n} \underline{x}(0) \end{bmatrix} \\
 u(1) = \begin{bmatrix} 0 & 0 & \dots & 1 & 0 \end{bmatrix} H_{c}^{-1} \begin{bmatrix} \underline{\xi} & -\Phi^{n} \underline{x}(0) \end{bmatrix} \\
 \vdots \\
 u(n-1) = \begin{bmatrix} 1 & 0 & 0 & \dots & 0 \end{bmatrix} H_{c}^{-1} \begin{bmatrix} \underline{\xi} & -\Phi^{n} \underline{x}(0) \end{bmatrix} \end{array} \xrightarrow{\underline{x}(0)} \underline{x}(0), \underline{not} \underline{x}(k) \text{ is used here}$$

- Closed-loop control via time-invariance
 - "turn system on" at time "k": $\underline{x}(0) \leq \underline{x}(k), u(0) \leq \underline{x}(k)$

$$= u(k) = [0 \ 0 \dots 1] H_c^{-1} [\underline{\xi} - \Phi^n \underline{x}(k)]$$

accomplishes same control sequence but via SVFB

• Special case $\underline{\xi} = \underline{0}$ $u(k) = -[0 \ 0 \ \dots \ 1] H_c^{-1} \Phi^n \underline{x}(k)$

is an SVFB control that reduces any (initial) state to $\underline{0}$ in n steps \rightarrow "deadbeat controller" (unique to discrete systems)

- CL dynamics $\underline{x}(k+1) = (\Phi - \Gamma K) \underline{x}(k)$ $\underline{x}(n) = (\Phi - \Gamma K)^n \underline{x}(0) = \underline{0}$ ==> $\Phi - \Gamma K$ has all eigenvalues at z = 0



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Discrete SVFB Design Methods

Continuous → discrete equivalence methods
 Given a <u>continuous</u> FB control law

 $\mathbf{u}(t) = \mathbf{K}_{\mathbf{r}} \mathbf{r}(t) - \mathbf{K} \, \underline{\mathbf{x}}(t)$

develop from K_r, K an "equivalent" discrete control

 $u(k) = \widetilde{K}_r r(k) - \widetilde{K} \underline{x}(k)$

- Idea: capitalize on earlier design for $\underline{\dot{x}} = A \underline{x} + B u$
- Compare continuous vs. discrete time response, phase margin, closed-loop poles, etc.
- Direct digital controller design

Find $u(k) = K_r r(k) - K \underline{x}(k)$ directly to place poles at $z = z_1, z_2, ..., z_n$

(1) select $z_i = e^{s_i h}$ i = 1, 2, ..., n;

 s_i = desired pole location in s-plane

or, (2) select $z_1, z_2, ..., z_n$ directly

- Evaluation
 - Time response via simulation
 - Phase margin via Bode/Nyquist plot of

$$LG(j\omega) = K(zI - \Phi)^{-1} \Gamma \Big|_{z = e^{j\omega}}$$

- Sensitivity to parameters, RD, etc.



B) Average Gain Method

(Kleinman, Automatica, 1978)

Consider C over (0, h] with $\underline{\mathbf{x}}(0)$, and $\mathbf{r}(t) = \mathbf{r}_0$ •

$$\underline{\mathbf{x}}(t) = e^{(\mathbf{A} - \mathbf{B}\mathbf{K})t} \ \underline{\mathbf{x}}(0) + \int_0^t e^{(\mathbf{A} - \mathbf{B}\mathbf{K})\sigma} \mathbf{K}_r \mathbf{B} d\sigma \cdot \mathbf{r}_0$$

• Control, u_c(t) over (0, h], in continuous system

$$u_{c}(t) = K_{r}r_{0} - K \underline{x}(t)$$
$$u_{c}(t) = \left[1 - K \int_{0}^{t} e^{(A - BK)\sigma} B d\sigma\right] K_{r}r_{0} - K e^{(A - BK)t} \underline{x}(0)$$

• Discrete control over (0, h] = u(0)

$$u(0) = \tilde{K}_{r} r_{0} - \tilde{K} \underline{x}(0)$$

=> Pick \tilde{K} , \tilde{K}_{r} so that $u(0) = \overline{u}_{c} = \frac{1}{h} \int_{0}^{h} u_{c}(t) dt$

$$\overline{u}_{c} = \left[1 - \frac{K}{h} \int_{0}^{h} \int_{0}^{t} e^{(A - BK)\sigma} d\sigma dt B\right] K_{r} r_{0} - \frac{K}{h} \int_{0}^{h} e^{(A - BK)t} dt \underline{x} (0)$$

• Discrete equivalent gains

(1) $\tilde{\mathbf{r}}$ K \mathbf{f}^{h} (A-BK)t 1

$$= \left[1 - \frac{K}{h} \int_{0}^{h} \int_{0}^{t} e^{(A - BK)\sigma} d\sigma dt B\right] K_{r} r_{0} - \frac{K}{h} \int_{0}^{h} e^{(A - BK)t} dt \underline{x}(0) \qquad \frac{K}{h} \int_{0}^{h} \int_{0}^{t} e^{(A - BK)\sigma} d\sigma dt = \frac{K}{h} \int_{0}^{h} \overline{\Psi}(t) dt \\ = \frac{K}{h} \int_{0}^{h} \int_{0}^{h} e^{(A - BK)t} dt \qquad = \frac{K}{h} \int_{0}^{h} (\overline{\Phi}(t) - I) dt \left[(A - BK)^{-1} \right] \\ = (\widetilde{K} - K)(A - BK)^{-1} \\ = (\widetilde{K} - K)(A - BK)^{-1}$$

$$(2) \quad \widetilde{K}_{r} = \left[1 - \frac{K}{h} \int_{0}^{h} \int_{0}^{t} e^{(A - BK)\sigma} d\sigma dt B\right] K_{r} = \left[1 + \left(K - \widetilde{K}\right) \left(A - BK\right)^{-1} B\right] K_{r}$$



- Obtain \tilde{K} using c2d, then compute K_r
- Approximation for small h

$$\tilde{\mathbf{K}} \approx \mathbf{K} \left[\mathbf{I} + \left(\mathbf{A} - \mathbf{B}\mathbf{K} \right) \frac{\mathbf{h}}{2} + \left(\mathbf{A} - \mathbf{B}\mathbf{K} \right)^2 \frac{\mathbf{h}^2}{3!} + \cdots \right]$$

$$\tilde{K}_{r} \approx \left\{ 1 - K \left[\frac{h}{2} + (A - BK) \frac{h^{2}}{3!} + \cdots \right] B \right\} K_{r}$$

• Average gain scheme is "good" provided

$$h \leq \frac{1.0}{|\lambda_{max} (A - B K)|} \sim \frac{1.0}{||A - BK||}$$

Closed-loop system matrix

- Generally requires a smaller h than does the usual criterion

 $h~\leq~(0.5~\rightarrow 1.0)\,/\mid\lambda_{max}(A)\mid$

- Using average gain \tilde{K} is always better than just using K
 - but $\widetilde{K}_r \;$ may not maintain same $\underline{DC \; gain}$ as in continuous case
- Inverse procedure: given a discrete K_d, find continuous gain K.
 Solve

$$\mathbf{K} = \mathbf{K}_{\mathrm{d}} \mathbf{h} \left[\int_{0}^{h} \mathbf{e}^{(\mathrm{A} - \mathrm{B}\mathrm{K})\mathrm{t}} \mathrm{d}\mathrm{t} \right]$$

iteratively:

$$K_{i+1} = K_{d}h \left[\int_{0}^{h} e^{(A-BK_{i})t} dt \right]^{-1}$$
 with $K_{0} = K_{d}$.

- Generally converges in 2 3 iterations.
- Useful when h is subject to change, e.g., $K_d(h_1) \rightarrow K \rightarrow K_d(h_2)$









- Unconverted discrete system (K = $[1 \ 1]$) becomes unstable as h increase.
- CL system with average gains still hanging in, with noticeable slow-down in step response.

Summary of Equivalent Gain Method

• Average gain is best method to convert

If h ~ small (
$$< \frac{1.0}{|\lambda_{max} (A - B K)|}$$
) use \tilde{K}, \tilde{K}_r

- Do not simply use $\tilde{K} = K$, $\tilde{K}_r = K_r$ (instability as h increases).
- Useful if need to change h on-line frequently
 - Store K, K_r from continuous design
 - Use series approximation to obtain $\tilde{K},\,\tilde{K}_r$ for current value of h
- Generally
 - \tilde{K}_i will be smaller in magnitude than K_i .
 - Gains \tilde{K} will yield discrete CL poles with a slightly smaller ω_n than original continuous system (i.e., slower response).
 - Eigenvalues of $\Phi \Gamma \widetilde{K} \approx exp$ (h \cdot eigenvalues of A BK).
 - Phase margin of discrete system with average gain \approx phase margin of a discrete system with poles placed at exp [h $\cdot \lambda_i(A BK)$].
 - DC gain $(r \rightarrow y)$ of equivalent system not always same as C.
 - ==> may wish to pick \tilde{K}_r so that DC gain of discrete CL system = DC gain of original continuous CL design, i.e., so that

 $\tilde{K}_r C [I - \Phi + \Gamma \tilde{K}]^{-1}\Gamma = -K_r C [A - B K]^{-1}B$

• If $h \neq$ small, design K, K_r directly for discrete system.





- Same scheme should work for either continuous or discrete problems, $\Phi \iff A$, $\Gamma \iff B$ $\Phi - \Gamma K \iff A - BK$
- Direct approach

- Expand
$$|zI - \Phi + \Gamma K| = z^n + f_1(K)z^{n-1} + \dots + f_n(K)$$

[each f_i will be linear in $K_1, K_2, ..., K_n$]

- Expand
$$p_d(z) = (z - z_1) (z - z_2) \cdots (z - z_n) = z^n + d_1 z^{n-1} + \dots + d_n$$

- Equate coefficients and solve n linear equations, n unknowns

 $f_i(K) = d_i; i = 1, 2, ..., n$

- Useful in simple problems, some structured ones

• Example:
$$z_1 = 0.5 + j0.3$$
, $z_2 = 0.5 - j0.3$

$$\Phi = \begin{bmatrix} 1.0 & 0.2 \\ 0.2 & 1.0 \end{bmatrix} \quad \Gamma = \begin{bmatrix} 1.0 \\ 0.5 \end{bmatrix} \quad K = \begin{bmatrix} K_1 & K_2 \end{bmatrix}$$

$$\bar{\Phi} = \Phi - \Gamma K = \begin{bmatrix} 1.0 - K_1 & 0.2 - K_2 \\ 0.2 - 0.5 K_1 & 1.0 - 0.5 K_2 \end{bmatrix} \quad p_d = (z - z_1) (z - z_2) = z^2 - 1.0z + 0.34$$

$$| z I - \bar{\Phi} | = z^2 + (-2 + K_1 + 0.5 K_2)z + (0.96 - 0.3 K_2 - 0.9 K_1)$$

$$f_1 \qquad f_2 \qquad f_2 \qquad f_2 \qquad f_2 \qquad f_2 = 1.867$$

$$-2 + K_1 + 0.5 K_2 = -1$$

$$0.96 - 0.9 K_1 - 0.3 K_2 = 0.34 \qquad \Rightarrow K_1 = 0.067, \quad K_2 = 1.867$$

$$- \text{ Select } K_r (e.g. \text{ so that DC gain = 1})$$



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Ackermann Formula

• Circumvents requirement to compute a_i

 $p_d(z) = (z - z_1) (z - z_2) \cdots (z - z_n) = z^n + d_1 z^{n-1} + \cdots + d_{\overline{n}}$ desired CL characteristic polynomial

$$K = \begin{bmatrix} 0 & 0 & \dots & 1 \end{bmatrix} H_c^{-1} p_d(\Phi)$$
$$H_c = \begin{bmatrix} | & | & | & | \\ \Gamma & \Phi \Gamma & \cdots & \Phi^{n-1} \\ | & | & | & | \end{bmatrix} = Controllability matrix$$

 $p_{d}(\Phi) = (\Phi - z_{1}I) (\Phi - z_{2}I) \cdots (\Phi - z_{n}I)$

 $(z_i = desired poles, must be in complex conjugate pairs)$

• Algorithm

2. Solve

1. Set up H_c matrix one column at a time. Transpose $H_c \rightarrow H_c'$.

c ¹c

Numerically unstable

$$H_{c}' \underline{q} = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 1 \end{bmatrix} \text{ for n-vector } \underline{q}$$

- Use any available routine for solving $A \underline{x} = \underline{b}$.
- If solution fails, stop. System is not completely controllable.
- 3. Evaluate $p_d(\Phi) = X$.
- 4. Obtain gains $K = \underline{q}' X = [K_1, K_2, ..., K_n]$
- 5. Compute K_r if needed.



- Develop as a Subroutine GAINS
 - Can be used for continuous or discrete models
- Generally pick z_i via $e^{s_i h}$
- No restriction on h other than usual $\frac{(0.5 \rightarrow 1.0)}{|\lambda_{max}(A)|}$
- Deadbeat response: all $z_i = 0 \implies p_d(z) = z^n$; also $p_d(\Phi) = \Phi^n$

$$K = [0 \ 0 \ \cdots \ 1] H_c^{-1} \Phi^n$$

- deadbeat gains $K_i \to \infty$ as $h \to 0$

Example – Satellite Control/Pointing

$$\underline{\mathbf{x}}(\mathbf{k}+1) = \begin{bmatrix} 1 & \mathbf{h} \\ 0 & 1 \end{bmatrix} \underline{\mathbf{x}}(\mathbf{k}) + \begin{bmatrix} \mathbf{h}^{2}/2 \\ \mathbf{h} \end{bmatrix} \mathbf{u}(\mathbf{k})$$

• Desired CL characteristic polynomial:

$$z^{2} + d_{1}z + d_{2} = p_{d}(z)$$

- if $s_{i} = -\zeta \omega_{n} \pm j\omega_{n}\sqrt{1-\zeta^{2}}$: $d_{1} = -2e^{-\zeta \omega_{n}h} \cos\left(\omega_{n}h\sqrt{1-\zeta^{2}}\right)$; $d_{2} = e^{-2\zeta \omega_{n}h}$

• Use Ackermann algorithm: $K = [0 \ 1] H_c^{-1} p_d(\Phi)$

$$\begin{split} H_{c} &= \begin{bmatrix} | & | & | \\ \Gamma & \Phi \\ | & | \end{bmatrix} = \begin{bmatrix} h^{2}/2 & 3h^{2}/2 \\ h & h \end{bmatrix}; \text{ solve } \begin{bmatrix} h^{2}/2 & h \\ 3h^{2}/2 & h \end{bmatrix} \begin{bmatrix} q_{1} \\ q_{2} \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \end{bmatrix} => \underline{q} = \begin{bmatrix} 1/h^{2} \\ -0.5/h \end{bmatrix} \\ p_{d}(\Phi) &= \begin{bmatrix} 1+d_{1}+d_{2} & 2h+d_{1}h \\ 0 & 1+d_{1}+d_{2} \end{bmatrix} = \Phi^{2} + d_{1}\Phi + d_{2}I \\ K &= \underline{q}'p_{d}(\Phi) = \begin{bmatrix} 1+d_{1}+d_{2} & 3+d_{1}-d_{2} \\ h^{2} & 2h \end{bmatrix} \end{split}$$

• Deadbeat controller: $d_1 = d_2 = 0 == K = [1/h^2 3/2h]$

- as $h \rightarrow 0$, require excessive control energy
- good control scheme when h is large

• For
$$\zeta = 0.707$$
, $\omega_n = 0.707$, $h = 0.5$
 $s_i = -0.5 \pm j0.5 \rightarrow z_i = e^{s_i h} = 0.53 \pm j0.29$
 $d_1 = -1.5092$, $d_2 = 0.6065 \rightarrow K = [0.3894 \ 0.8843]$

RQ Implementation

Transform (Φ, Γ) to controller Hessenberg form, $H_p = Q^T \Phi Q$; $\Gamma_p = Q^T \Gamma = \beta \underline{e}_1$ Perform RQ factorization of Hessenberg as follows Set $H_1 = H_p$ For i=1,2,...,n Do Algorithm 1. Set $H_1 = H_p$, $\alpha = \left(\prod_{i=1}^{n-1} [H_p]_{i+1,i}\right)$ $R_i O_i = H_i - \lambda_i I$ 2. For i = 1, 2, ..., n DO $H_{i+1} = Q_i R_i + \lambda_i I$ $R_i Q_i = H_i - \lambda_i I$ End $H_{i+1} = Q_i R_i + \lambda_i I$ Note $H_{i+1} = Q_i H_i Q_i^T \Longrightarrow H_{n+1} = Q_n Q_{n-1} \dots Q_2 Q_1 H_n Q_1^T Q_2^T \dots Q_{n-1}^T Q_n^T$ $\alpha \rightarrow \alpha [R_i]_{m}$ $\Rightarrow P_d(H_p) = \prod^n (H_p - \lambda_i I) = R_1 R_2 \dots R_n Q_n Q_{n-1} \dots Q_2 Q_1$ End 3. Obtain gains $\Rightarrow P_d(\Phi) = QP_d(H_p)Q^T$ $K = \alpha e_{\pi}^{T} O_{\pi} O_{\pi} \dots O_{2} O_{1} O_{1}^{T}$ Controllability matrix: $H_c = Q \begin{bmatrix} \Gamma_p & H_p \Gamma_p \end{bmatrix}$. $H_p^{n-1} \Gamma_p \begin{bmatrix} \Gamma_p & \Gamma_p \end{bmatrix}$ $K = \underline{e}_{n}^{T} H_{c}^{-1} P_{d}(\Phi) = \underline{e}_{n}^{T} \left[\Gamma_{p} \quad H_{p} \Gamma_{p} \quad . \quad H_{p}^{n-1} \Gamma_{p} \right]^{-1} R_{1} R_{2} \dots R_{n} Q_{n} Q_{n-1} \dots Q_{2} Q_{1} Q^{T}$ $= \alpha' \prod_{n=1}^{n} [R_i]_{nn} e_n^T Q_n Q_{n-1} \dots Q_2 Q_1 Q^T; \alpha' = 1 / \prod_{i=1}^{n-1} [H_p]_{i+1,i}$ Numerically stable Implementation of 'place' command Copyright ©2006-2012 by K. Pattipati













 First design SVFB u(k) = - K<u>x</u>(k) assuming τ = 0. Case 1: M > 0, ε = 0

$$\underline{\mathbf{x}}(\mathbf{k}+1) = \Phi \ \underline{\mathbf{x}}(\mathbf{k}) + \Gamma \ \mathbf{u}(\mathbf{k}-\mathbf{M})$$

• Predictor controller

$$u(k) = -K \underbrace{\hat{x}(k+M)}_{\mathbf{x}(k+1)} \qquad \text{prediction of state at time } (k + M)h \\ \text{from } \underline{x}(k) \text{ and } u(k-1), \dots, u(k-M) \\ \underline{\hat{x}}(k+2) = \Phi \underbrace{\hat{x}(k+1)}_{\mathbf{x}(k+1)} + \Gamma u(k-M+1) \\ \vdots \qquad = \Phi^2 \underbrace{x}(k) + \Phi \Gamma u(k-M) + \Gamma u(k-M+1) \\ \underline{\hat{x}}(k+M) = \Phi^M \underbrace{x}(k) + \sum_{i=1}^{M} \Phi^{i-1} \Gamma u(k-i)$$

- Present control u(k) will have its first effect on $\underline{x}(k+1+M)$
- Need to store past controls in a pushdown stack

- Requires a good knowledge of Φ , Γ to perform accurate propagation of $\underline{x}(k)$ <u>Case 2</u>: M = 0, $\epsilon > 0$ ($0 \le \epsilon < h$)

• Use

 $u(k) = -K \underline{\hat{x}}(kh + \varepsilon)$

$$\hat{\mathbf{x}}(\mathbf{k}\mathbf{h}+\mathbf{\varepsilon}) = \mathbf{e}^{\mathbf{A}\mathbf{\varepsilon}} \, \underline{\mathbf{x}}(\mathbf{k}) + \int_{0}^{\mathbf{\varepsilon}} \mathbf{e}^{\mathbf{A}\sigma} d\sigma \mathbf{B}\mathbf{u} \left(\mathbf{k}-\mathbf{1}\right)$$
$$=> \mathbf{u}(\mathbf{k}) = -\mathbf{K}_{\mathbf{x}} \, \underline{\mathbf{x}}(\mathbf{k}) - \mathbf{K}_{\mathbf{u}} \, \mathbf{u}(\mathbf{k}-\mathbf{1})$$

- Modification to structure only, propagation "hidden"
- Identical to earlier equations when $\varepsilon = h^-$ (corresp to M = 1)





Example – Inverted Pendulum

h = 0.18 sec K = [-43.8 -13.2 -6.67 -5.91] (gains obtained via pole placement) $\omega_c = 6.7, \ \phi_m = 19.3^\circ \implies \tau_{max} = \phi_m / \omega_c \approx 0.05 \text{ sec}$

- Select $\tau = 0.18$ (corresponds to M = 1, $\epsilon = 0$). System is highly unstable unless delay is compensated.
- Simulation $\underline{x}(0) = [0.1 \ 0 \ 1.0 \ 0] = [\theta, \dot{\theta}, d, \dot{d}]$ compare with response of system with no delay



- System "drifts" for first τ sec, then is controlled to zero.
- In ideal case, state response for k > M is identical to an undelayed response with an initial condition $\underline{x}(M) = \Phi^M \underline{x}(0)$, and shifted by Mh sec.
 - => from k \geq M, predictor control is "perfect" (assuming you know Φ and Γ).

Robust MIMO Pole Placement : State Feedback - 1

- Kautsky's Algorithm
- In MIMO, we have *mn* degrees of freedom, but only *n* pole locations. Use the remaining degrees of freedom to *minimize the conditioning of the closed-loop eigen vector matrix*.

Recall Eigen value conditioning:

$$s_{j} = \frac{d\lambda_{j}}{d\varepsilon} = \frac{\|\underline{y}_{j}\|_{2} \|\underline{x}_{j}\|_{2}}{|\underline{y}_{j}^{T}\underline{x}_{j}|}; \varepsilon = parameter in \Phi, \Gamma, K$$

$$\underline{x}_{j} = \text{Right eigen vector of } \Phi - \Gamma K; \ \underline{y}_{j} = \text{Left eigen vector of } \Phi - \Gamma K$$

$$Metrics: (i) J = \min_{K} \max_{j} s_{j}; (ii) J = \min_{K} \left(\sum_{i=1}^{n} s_{j}^{2}\right)^{1/2}; (iii) \kappa_{2}(T) = \|T\|_{2} \|T^{-1}\|_{2}$$

Let $\Lambda = diag(\lambda_1, \lambda_2, ..., \lambda_n)$ be pole locations If T is the matrix of eigen vectors: $(\Phi - \Gamma K)T = T\Lambda \Rightarrow \Gamma K = \Phi - T\Lambda T^{-1}$ Suppose we do QR decomposition of $\Gamma : \Gamma = Q_1 R_1 = \begin{bmatrix} Q_1 & Q_2 \end{bmatrix} \begin{bmatrix} R_1 \\ 0 \end{bmatrix}$ so, $R_1 K = Q_1^T (\Phi - T\Lambda T^{-1}) \Rightarrow K = R_1^{-1} Q_1^T (\Phi - T\Lambda T^{-1})$. Also, $Q_2^T \Gamma K = 0 = Q_2^T (\Phi - T\Lambda T^{-1})$ One way of picking T is find $N \begin{bmatrix} (\Phi - \lambda_j I)^T Q_2 \end{bmatrix}$; j = 1, 2, ..., n and pick directions from these. So, $(\Phi - \lambda_j I)^T Q_2 = \begin{bmatrix} L_j & V_j \end{bmatrix} \begin{bmatrix} \Delta_j \\ 0 \end{bmatrix} = L_j \Delta_j \Rightarrow V_j \in N \begin{bmatrix} (\Phi - \lambda_j I)^T Q_2 \end{bmatrix}$ One approach: Form an arbitray T. Replace column $\underline{t}_j \Rightarrow new \underline{t}_j = \frac{V_j V_j^T \underline{u}_j}{\|V^T u_j\|}$ where $\underline{u}_j \perp R[\underline{t}_1, \underline{t}_2, ..., \underline{t}_{j-1}, \underline{t}_{j+1}, ..., \underline{t}_n]$

Robust Pole Placement Algorithm

- Kautsky's Algorithm
 - Step 1: Do QR decomposition of $\Gamma = Q_1 R_1 = \begin{bmatrix} Q_1 & Q_2 \end{bmatrix} \begin{bmatrix} R_1 \\ 0 \end{bmatrix}$
 - Step 2: For j=1,2,..,n Do

Compute V_j by doing QR decomposition of $\begin{bmatrix} \left(\Phi - \lambda_j I \right)^T Q_2 \end{bmatrix} = \begin{bmatrix} L_j & V_j \end{bmatrix} \begin{bmatrix} \Delta_j \\ 0 \end{bmatrix}$ End

Step 3: Select from {V_j}ⁿ_{j=1} one from each an independent vector set to form *T*.
 Now iterate until k₂(*T*) stabilizes.

$$\begin{bmatrix} \underline{t}_1, \underline{t}_2, \dots, \underline{t}_{j-1}, \underline{t}_{j+1}, \dots, \underline{t}_n \end{bmatrix} = \begin{bmatrix} U_j & \underline{u}_j \end{bmatrix} \begin{bmatrix} Z_j \\ 0 \end{bmatrix} \Longrightarrow new \, \underline{t}_j = \frac{V_j V_j^T \underline{u}_j}{\|V_j^T \underline{u}_j\|_2}$$

$$Note: s_j = \frac{1}{|\underline{u}_j^T \underline{t}_j|} = \frac{1}{\|V_j^T \underline{u}_j\|_2}$$

MATLAB **place** implements this

• Compute gains:

$$K = R_1^{-1} Q_1^T \left(\Phi - T \Lambda T^{-1} \right)$$





- Valid for continuous or discrete design
 - Ackermann formula to find K
 - Transform $K \rightarrow \tilde{K}$ if design developed on C and $h \sim$ small
 - Need to select all n pole locations
- SVFB does not modify system zeros
 - Can combine compensator H(z) and SVFB to adjust/move zeros
- => <u>Advantages</u>
 - Straightforward design methodology
 - Direct control over CL pole locations
 - Uses all available information in the feedback
 - Ability to design deadbeat control
 - Possible to extend to MIMO systems, but cumbersome
- =><u>Disadvantages</u>
 - Need to measure or estimate all states
 - More complex design than series compensation
 - No direct control over CL time response (still requires trial and error with CL simulation)
 - Not always clear where to place all n poles
 - No direct control over $\phi_{\rm m}$, $\omega_{\rm c}$

Command Inputs to SVFB Systems

Consider continuous case for simplicity $\dot{\mathbf{x}}(t) = \mathbf{A} \mathbf{x}(t) + \mathbf{B} \mathbf{u}(t)$ u(t) = -Kx(t)- Closed-loop A–BK has poles at desired locations • Desire $x_m = m$ -th component of $\underline{x}(t) \rightarrow x_m^*$ in steady-state • Idea: Use control $u(t) = -K_1 x_1(t) - \dots - K_m [x_m(t) - x_m^*] - \dots - K_n x_n(t)$ $\mathbf{u}(\mathbf{t}) = \mathbf{K}_{\mathbf{m}} \mathbf{X}_{\mathbf{m}}^* - \mathbf{K} \mathbf{X}(\mathbf{t})$ like $K_r r(t)$ with r(t) = constantSystem $\dot{\mathbf{x}}(t) = (\mathbf{A} - \mathbf{B}\mathbf{K}) \mathbf{x}(t) + \mathbf{B}\mathbf{K}_{m}\mathbf{x}_{m}^{*}$ X_1 X_m u · X_* m-th element • Steady-state $\underline{\mathbf{x}}$: $\underline{\mathbf{x}}_{ss} = -(\mathbf{A} - \mathbf{B}\mathbf{K})^{-1} \mathbf{B} \mathbf{K}_m \mathbf{x}_m^*$ $\underline{\mathbf{x}}_{m ss} = -\underline{\mathbf{e}}_{m}' (\mathbf{A} - \mathbf{B}\mathbf{K})^{-1} \mathbf{B} \mathbf{K}_{m} \mathbf{x}_{m}^{*}; \ \underline{\mathbf{e}}_{m}' = [0 \ 0 \ \dots \ 1 \ \dots \ 0]$ - Generally $x_{mss} \neq x_m^*$ \Rightarrow Adjust $x_m^* \rightarrow \beta x_m^*$ and pick β so that $x_{mss} = x_m^*$ or consider use of integral control $u(t) = -Kx_1(t) - \dots - K_m [x_m(t) - x_m^*] - \dots - K_n x_n(t) - K_{n+1} \int_0^t [x_m(\sigma) - x_m^*] d\sigma$

Integral Control in SVFB

Define $x_m(t)|_{new} = x_m(t)|_{old} - x_m^* \triangleq error in state x_m \Rightarrow \underline{\dot{x}}(t) = A \underline{x}(t) + \underline{a}_m x_m^* + Bu(t)$ \underline{a}_{m} = m-th column of A, (often $\underline{a}_{m} = \underline{0}$, especially if x_{m} is a position variable) $x_{n+1}(t) = \int_0^t x_m(\sigma) d\sigma = \begin{cases} \text{ integral of error in } x_m \\ \text{ from desired ss value} \end{cases}$ • Define $\dot{\mathbf{x}}_{n+1}(t) = \mathbf{x}_{m}(t); \quad \mathbf{x}_{n+1}(0) = 0$ • Augmented (n +1)-st order system, $\underline{x}_a = [\underline{x}, x_{n+1}]'$ $\begin{vmatrix} \dot{\mathbf{x}} \\ \dot{\mathbf{x}}_{n+1} \end{vmatrix} = \begin{vmatrix} \mathbf{A} & \mathbf{0} \\ \mathbf{e}_{m}' & \mathbf{0} \end{vmatrix} \begin{vmatrix} \mathbf{x} \\ \mathbf{x}_{m} \end{vmatrix} + \begin{bmatrix} \underline{\mathbf{a}}_{m} \\ \mathbf{0} \end{vmatrix} \mathbf{x}_{m}^{*} + \begin{bmatrix} \mathbf{B} \\ \mathbf{0} \end{bmatrix} \mathbf{u}$ $\dot{\mathbf{x}}_{a}(t) = \mathbf{A}_{a}\mathbf{x}_{a}(t) + \mathbf{B}_{a}\mathbf{u}(t) + \tilde{\mathbf{a}}_{m}\mathbf{x}_{m}^{*}$ • Augmented system may not be controllable. Examine $\begin{bmatrix} B_a & A_a B_a & \cdots & A_a B_a \end{bmatrix} = \begin{bmatrix} B & AB & \cdots & A^nB \\ 0 & \underline{e_m}'B & \cdots & \underline{e_m}'A^{n-1}B \end{bmatrix} = (n+1) \times (n+1)$ Controllability matrix • Selection of $u(t) = -K_a \underline{x}_a(t) = -K \underline{x}(t) - K_{n+1} x_{n+1}(t)$ - Design K as before, to place poles of A-BK = A- $K_{n+1} \sim$ small gain on integral error • CL characteristic polynomial, $| sI - A_a + B_a K_a$ $\begin{vmatrix} sI - \bar{A} & BK_{n+1} \\ -\underline{e}_{m'} & s \end{vmatrix} = |sI - \bar{A}| \underbrace{\cdot |s + \underline{e}_{m'} (sI - \bar{A})^{-1} B}_{\bullet} K_{n+1} | = |sI - \bar{A}_{a}|$ ~ $(s - \underline{e}_{m}'A^{-1}BK_{n+1})$ for small K_{n+1} - Select K_{n+1} so that pole is in LHP.

