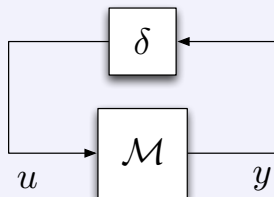


Structured Stochastic Uncertainty

Bassam Bamieh

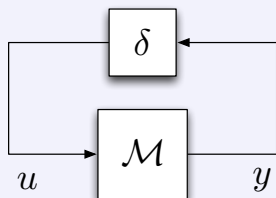
Mechanical Engineering, UNIVERSITY OF CALIFORNIA AT SANTA BARBARA

Stochastic Perturbations



- Perturbations are iid gains: $u(k) = \delta(k) y(k)$
- \mathcal{M} is LTI
- nec & suff condition is the H^2 norm $\|\mathcal{M}\|_2^2 < \frac{1}{\sigma_\delta}$

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- LMI proof (S. Boyd, '84)

$$x(k+1) = (A + BC \delta(k)) x(k)$$

$$P(k) := \mathcal{E} \{x(k)x(k)^T\}$$

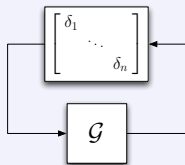
$$\Rightarrow P(k+1) = A P(k) A^T + \sigma_\delta BC P(k) C^T B^T$$

$$\text{LMI cond. for } P(K) \xrightarrow{k \rightarrow \infty} 0 = \text{LMI cond. for } \|\mathcal{M}\|_2^2 < \frac{1}{\sigma_\delta}$$

Linear System w Mult. Noise

Structured Stochastic Perturbations

Perturbations $\delta_1(t), \dots, \delta_n(t)$
are iid



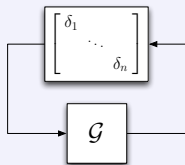
nec & suff cond. for **Mean Square Stability** given by *matrix of H^2 norms* !

$$\rho \left(\begin{bmatrix} \|g_{11}\|_2^2 & \cdots & \|g_{1n}\|_2^2 \\ \vdots & \ddots & \vdots \\ \|g_{n1}\|_2^2 & \cdots & \|g_{nn}\|_2^2 \end{bmatrix} \right) < \frac{1}{\sigma_\delta}$$

(Hinrichsen&Pritchard '95, Lu&Skelton '02, Elia '04)

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(Hinrichsen&Pritchard '95, Lu&Skelton '02, Elia '04)

- Proof involves LMIs and scalings
cf. time-varying L^2 and L^∞ -norm bounded perturbations
- Not clear how to generalize to correlated δ s

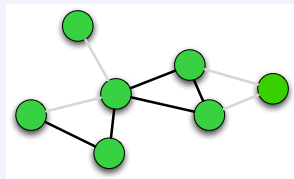
Applications of Structured Stochastic Perturbations

- Network dynamics with link/node failures, etc.

(Elia, Patterson & Bamieh)

$$x(t+1) = A x(t) + \left(\sum_{i=1}^M \mu_i(t) b_i b_i^* \right) x(t)$$

Linear system w. multiplicative noise



Applications of Structured Stochastic Perturbations

- Network dynamics with link/node failures, etc.

(Elia, Patterson & Bamieh)

(“discrete space”)

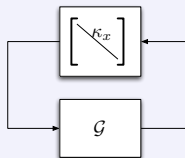
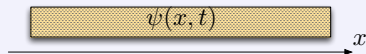
- PDEs with random coefficients

(“continuous space”)

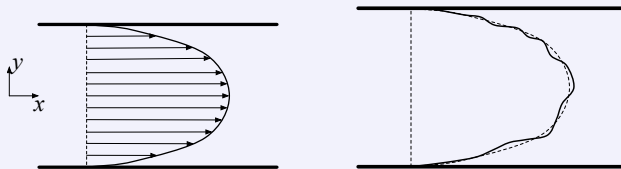
$$\frac{\partial}{\partial t} \psi(x, t) = (\mathcal{A} + \mathcal{B} \delta(x, t) \mathcal{C}) \psi(x, t)$$

- ▶ e.g. problems from random materials

$$\frac{\partial}{\partial t} \psi(x, t) = (\bar{\kappa} + \kappa(x, t)) \frac{\partial^2}{\partial x^2} \psi(x, t)$$



Stochastic Hydrodynamic Stability and Turbulence



Uncertain base flow

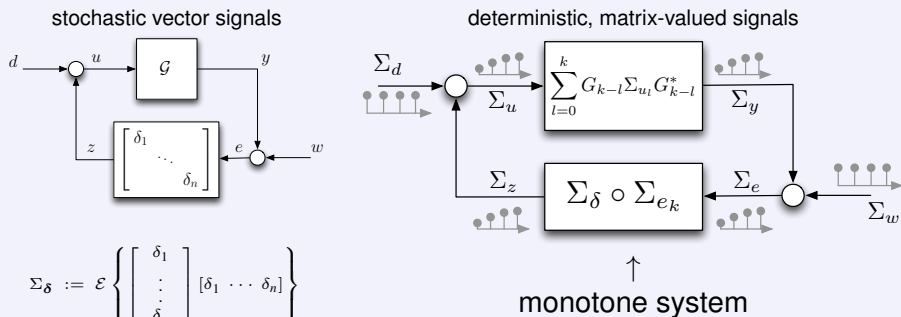
$$U(x, y, t) = \bar{U}(y, t) + \delta(x, y, t)$$

spatiotemporal correlations of δ should be “dialed into” the model

AN INPUT-OUTPUT APPROACH TO STRUCTURED STOCHASTIC PERTURBATIONS

An IO Approach to Stochastic Stability

Look at the dynamics of the *correlation matrix sequences* Σ_{u_k} , etc.



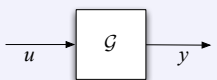
- The “loop gain” operator plays a central role

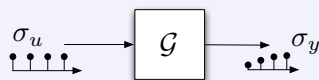
$$\mathcal{L}(X) := \Sigma_{\delta} \circ \left(\sum_{l=0}^{\infty} G_l X G_l^* \right)$$

complexity of \mathcal{L} scales w # of perturbations, *not state space dimension*

IO notion of Mean Square Stability

- **Def:** \mathcal{G} is *Mean-Square Stable* (MSS) if for white input process u , output process y has uniformly bounded variance

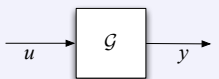
$$y_k = \sum_l g_{k-l} u_l$$


$$\sigma_{y_k} = \sum_l g_{k-l}^2 \sigma_l$$


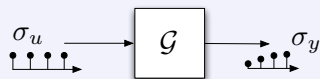
$$\begin{aligned} \sigma_{y_k} &:= \mathcal{E} \{y_k^* y_k\} \leq \underbrace{\left(\sum_k g_k^2 \right)}_{\|\mathcal{G}\|_2^2} \left(\sup_k \sigma_{u_k} \right) && k \in \mathbb{Z}^+ \\ &= \|\mathcal{G}\|_2^2 \|\sigma_u\|_\infty \end{aligned}$$

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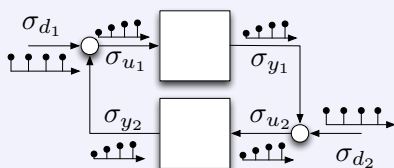
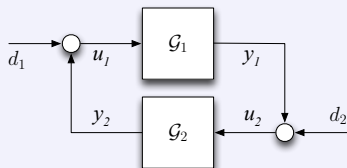
$$y_k = \sum_l g_{k-l} u_l$$


A block diagram showing a system \mathcal{G} with an input u and an output y .

$$\sigma_{y_k} = \sum_l g_{k-l}^2 \sigma_l$$


A block diagram showing a system \mathcal{G} with an input variance σ_u and an output variance σ_y . The input and output are represented by sequences of dots with arrows pointing into and out of the system block.

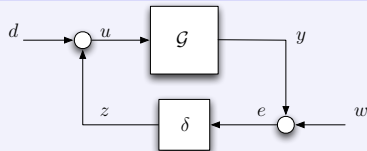
- MSS of feedback systems (insert disturbances, d_1, d_2 white)



MSS Feedback Stability

\Leftrightarrow All internal signals have uniformly bounded variance sequences

nec & suff Small Gain Condition (SISO)



- δ iid $\Rightarrow z$ is white (δ “whiten’s” e)

- u is also white

- y is colored, but uncorrelated with w

- go around the loop with the *variance sequences*

$$\Rightarrow \sigma_{z_k} = \sigma_\delta \sigma_{e_k}$$

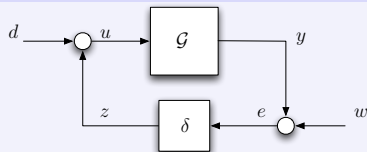
$$\Rightarrow \sigma_{y_k} \leq \|\mathcal{G}\|_2^2 \sigma_{u_k}$$

$$\Rightarrow \sigma_{e_k} = \sigma_{y_k} + \sigma_w$$

$$(1 - \sigma_\delta \|\mathcal{G}\|_2^2) \|\sigma_u\|_\infty \leq \sigma_\delta \sigma_w + \sigma_d$$

suff

nec & suff Small Gain Condition (SISO)



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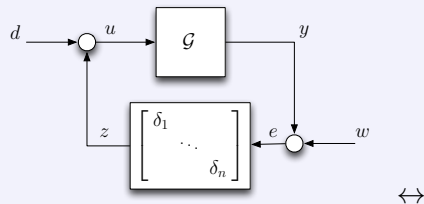
$$(1 - \sigma_\delta \|\mathcal{G}\|_2^2) \|\sigma_u\|_\infty \leq \sigma_\delta \sigma_w + \sigma_d \quad \text{suff}$$

$$\sigma_\delta \|\mathcal{G}\|_2^2 \geq 1 \Rightarrow \sigma_{u_k} \text{ unbounded as } k \rightarrow \infty \quad \text{nec}$$

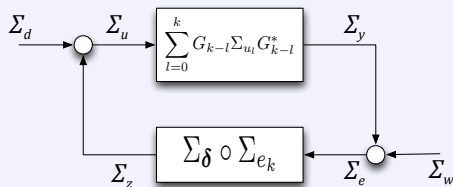
don't need to construct “destabilizing” δ s!

nec & suff Structured Small Gain Condition

Look at the dynamics of the *correlation matrix sequences* Σ_{u_k} , etc.



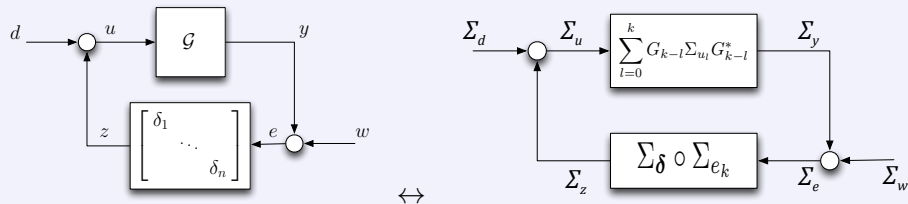
$$\Sigma_{\delta} := \mathcal{E} \left\{ \begin{bmatrix} \delta_1 \\ \vdots \\ \delta_n \end{bmatrix} \begin{bmatrix} \delta_1 & \cdots & \delta_n \end{bmatrix} \right\}$$



↑
monotone system

nec & suff Structured Small Gain Condition

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- going around the loop

↑
monotone system

$$(I - \mathcal{L})(\Sigma_{u_k}) \leq \Sigma_d + \Sigma_\delta \circ \Sigma_w$$

$$\mathcal{L}(X) := \Sigma_\delta \circ \left(\sum_{l=0}^{\infty} G_l X G_l^* \right) \quad \leftarrow \text{“loop gain”}$$

Properties of the “Loop Operator” \mathcal{L}

$$\mathcal{L}(X) := \Sigma_{\delta} \circ \left(\sum_{l=0}^{\infty} G_l X G_l^* \right)$$

- \mathcal{L} maps pos. s. def. matrices to pos. s. def. matrices
- It is thus “cone invariant” for the cone of pos. s. def. matrices
& \exists a Perron eigenvalue and corresponding pos. s def. *eigenmatrix*
(Parrilo & Khatri '00)

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these properties imply

$$(1 - \rho(\mathcal{L})) \Sigma_{u_k} \leq (I - \mathcal{L})(\Sigma_{u_k}) \leq \Sigma_d + \Sigma_{\delta} \circ \Sigma_w$$

MSS stability condition (nec & suff)

$$\rho(\mathcal{L}) < 1$$

Special Case of iid δ s

- δ s iid $\rightarrow \Sigma_\delta = I$



$$\mathcal{L}(X) := I \circ \left(\sum_{l=0}^{\infty} G_l X G_l^* \right) = \text{diag} \left(\sum_{l=0}^{\infty} G_l X G_l^* \right)$$

- The “eigen-matrices” of \mathcal{L} must be diagonal matrices !

$$\mathcal{L}(X) = \lambda X$$

- How does \mathcal{L} act on diagonal matrices?

$$\begin{bmatrix} w_1 & & \\ & \ddots & \\ & & w_n \end{bmatrix} = \mathcal{L} \left(\begin{bmatrix} v_1 & & \\ & \ddots & \\ & & v_n \end{bmatrix} \right) \Leftrightarrow \begin{bmatrix} w_1 \\ \vdots \\ w_n \end{bmatrix} = \begin{bmatrix} \|g_{11}\|_2^2 & \cdots & \|g_{1n}\|_2^2 \\ \vdots & \ddots & \vdots \\ \|g_{n1}\|_2^2 & \cdots & \|g_{nn}\|_2^2 \end{bmatrix} \begin{bmatrix} v_1 \\ \vdots \\ v_n \end{bmatrix}$$

Therefore

$$\text{eigs}(\mathcal{L}) = \text{eigs} \left(\begin{bmatrix} \|g_{ij}\|_2^2 \end{bmatrix} \right)$$

Mutually Correlated δ s (but temporally white)

$$\mathcal{L}(\mathbf{X}) := \Sigma_{\delta} \circ \left(\sum_{l=0}^{\infty} G_l \mathbf{X} G_l^* \right)$$

- $\mathcal{L} : \mathbb{R}^{n \times n} \rightarrow \mathbb{R}^{n \times n}$

In general, it involves terms like

$$\sum_{k=0}^{\infty} g_{ij}(k) g_{lm}(k)$$

inner products between subsystems' impulse responses

- At worst: \mathcal{L} represented as an $n^2 \times n^2$ matrix

Further Work

- Robust Performance and Correlations
- Spatial correlations in δs and \mathcal{G} have special structure
e.g. spatial invariance \Rightarrow simpler conditions
useful for applications to large-scale systems
- Partial Differential Equations
 \mathcal{L} is a map on pos. s. spatial operators
- Temporal correlations in δs ??? probably involves other
aggregates of the impulse response sequence $\{g_k\}$