

# Fixed-Structure Discrete-Time $\mathcal{H}_\infty$ Controller Synthesis with HIFOO

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16.12.2010

49th IEEE Conference on Decision and Control

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- 1 Motivation
- 2 Discrete-time HIFOO
- 3 Active Suspension System
- 4 Conclusions

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# Motivation - 1: Simple Controllers

Fixed-structure controllers are

- + computationally efficient
- + economic/energy efficient
- + easy to implement and verify

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Fixed-structure controllers are

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- + economic/energy efficient
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But:

- generally a **non-convex** problem
- convex reformulation **only for SISO** systems  
(central polynomial approach) [Henrion, 2005], [Khatibi & Karimi, 2010]
- ~ variety of methods proposed for continuous-time problems

## Motivation - 2: Discrete-Time Synthesis

- + digital controllers
- + black-box identification
- + high performance requirements/large sampling times  $T$
- Performance is lost by continuous-time synthesis - shown in a moment

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Often: **bilinear** transformation + **continuous-time** synthesis

$$z = \frac{2 + Ts}{2 - Ts}, \quad \text{synthesis} \quad s = \frac{2}{T} \frac{z - 1}{z + 1}$$

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### Problems

- frequency warping
- performance loss by constrained sampling rate



## Motivation - 3: Gradient-Based Techniques

- Gradient-based fixed-structure  $\mathcal{H}_\infty$  synthesis [Burke et.al., 2006], [Apkarian & Noll, 2006]
- Offer
  - fast convergence
  - local optimum
  - good results [Gumussoy et.al., 2008]
- HIFOO is open source

# Problem Formulation

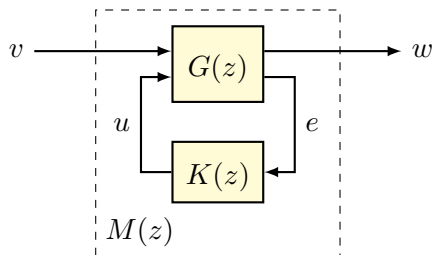
Given a generalized plant  $G(z)$   
find a controller  $K(z) \in \mathbf{K}(z)$   
such that

$$\|M(z)\|_{\infty}$$

is minimized,

where

$$M(z) = \mathcal{F}_L(G(z), K(z))$$



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# HIFOO Algorithm

1 Initialization - random controllers

2 Stabilization

find  $K(z) \in \mathbf{K}(z)$  s.t.  $M(z) = \mathcal{F}_L(G(z), K(z))$  is stable

3 Closed-loop  $\mathcal{H}_\infty$  norm minimization

$$\underset{K(z) \in \mathbf{K}(z)}{\text{minimize}} \|\mathcal{F}_L(G(z), K(z))\|_\infty$$

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# Stabilization

## Continuous-time

minimize  $\alpha(A)$   
 $K(z)$

until  $\alpha(A) < 0$

$\alpha$  - spectral abscissa

$A$  - closed-loop system matrix

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- 1 Given  $K(z)$ , compute  $\text{spec}(A)$  and find  $\lambda_k$  at which  $\alpha$  is attained
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# Gradient Computation

Let  $A(t) = A_0 + Pt$ ,  $A \in \mathbb{R}^{n \times n}$  and small  $t$ .

Let  $\lambda_k \in \text{spec}(A)$  has algebraic multiplicity one and eigenvectors  $y$  (left) and  $x$  (right).

$$\frac{d\lambda_k}{dt} = \frac{y^* P x}{y^* x} \quad [\text{Horn \& Johnson, 1985}]$$

Let  $\lambda_k = \mathcal{R} + j\mathcal{I}$ ;  $\ell_k = [\mathcal{R} \quad \mathcal{I}]$ .

$$\rho = |\lambda_k| = \sqrt{\mathcal{R}^2 + \mathcal{I}^2} = |\ell_k|$$

$$\frac{\partial \rho}{\partial \ell_k} = \left[ \frac{\mathcal{R}}{\sqrt{\mathcal{R}^2 + \mathcal{I}^2}} \quad \frac{\mathcal{I}}{\sqrt{\mathcal{R}^2 + \mathcal{I}^2}} \right] = \frac{\ell_k}{|\lambda_k|} \quad \Leftrightarrow \quad \frac{\partial \rho}{\partial \lambda_k} = \frac{\lambda_k}{|\lambda_k|}$$

Hence

$$\frac{d\rho(A)}{dt} = \text{Re} \left\{ \frac{\bar{\lambda}_k}{|\lambda_k|} \frac{y^* P x}{y^* x} \right\}$$

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## Theorem

For a matrix  $A$  with  $\rho(A) = |\lambda_k|$  holds

$$\nabla_A \rho = \text{Re} \left\{ \frac{\lambda_k}{|\lambda_k|} \frac{y x^*}{y^* x} \right\}$$



# Gradient Steps

## Stabilization

- 1 Compute  $\text{spec}(A)$  and find  $\lambda_k$  at which  $\rho$  is attained
- 2 Compute gradient of  $\rho$  w.r.t.  $A$  ✓
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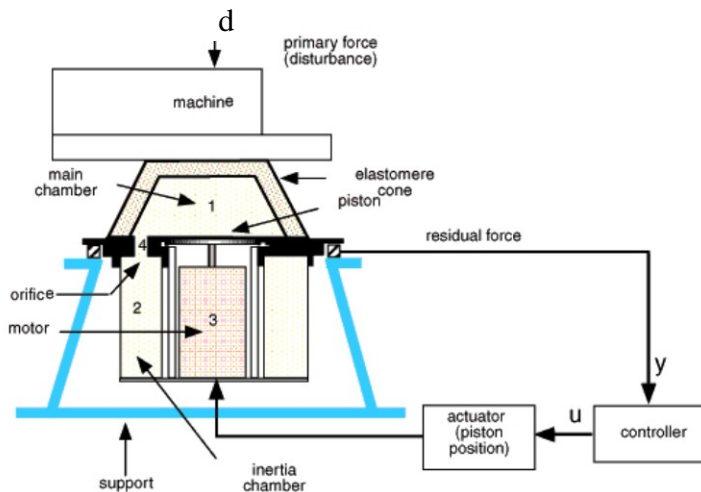
## $\mathcal{H}_\infty$ norm minimization

- 1 Compute  $f = \|M(z)\|_\infty = \bar{\sigma}(M_x)$   
where  $M_x = C (Ie^{j\omega_x} - A)^{-1} B + D$
- 2 Compute the gradient of  $f$  w.r.t.  $M_x$
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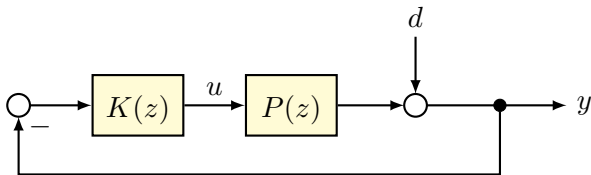
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# Active Suspension Benchmark System

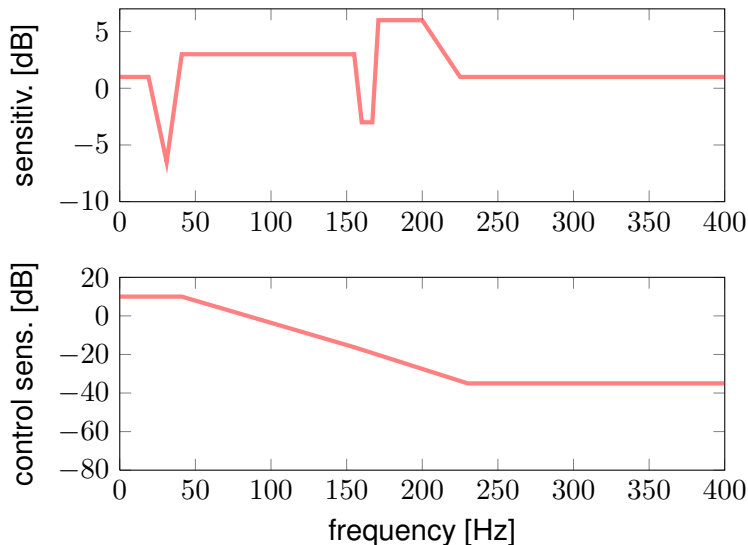


[Landau et.al. 2003]

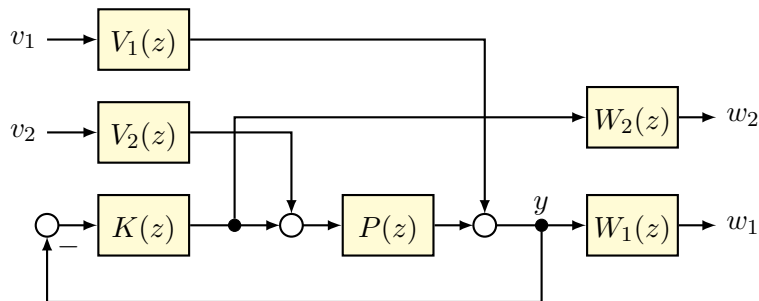
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# Design Requirements

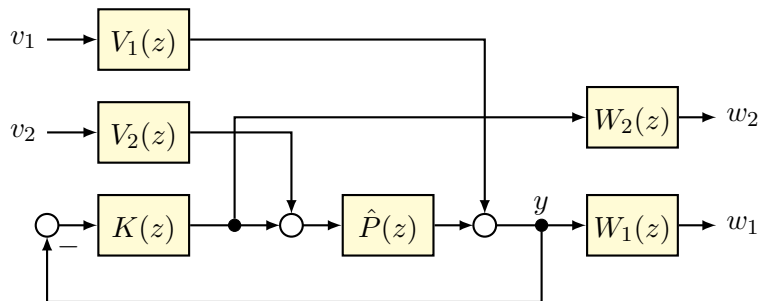


# Active Suspension System - 4-Block Design



[Hol et. al. 2003]

# Active Suspension System - 4-Block Design



[Hol et. al. 2003]

Cont. gain of zero at  $0.5F_s \Rightarrow \hat{P}(z) = P(z) \frac{z+1}{z}$



# Comparison

Controller design approach	$k$	$\gamma$	Computation	
			time	load
Full order	27	2.476	11.9 s	1
Balanced reduction	5	3.405	12.8 s	1.07
Curved line search	5	2.506	4h23m45s	1329.00
Cone complement.	5	2.630	14m33s	73.36
Hybrid Evol.-Algebr.	5	2.589	2m42s	13.61
Hybrid Evol.-Algebr.	2	2.596	1m25s	7.16
HIFOO - continuous	5	2.611	22.3 s	11.69
	2	2.473	41.4 s	21.68
	1	2.611	20.6 s	10.82
HIFOO - discrete	5	2.466	1m33s	51.87
	2	2.470	28.2 s	14.75
	1	2.611	7.7 s	4.17

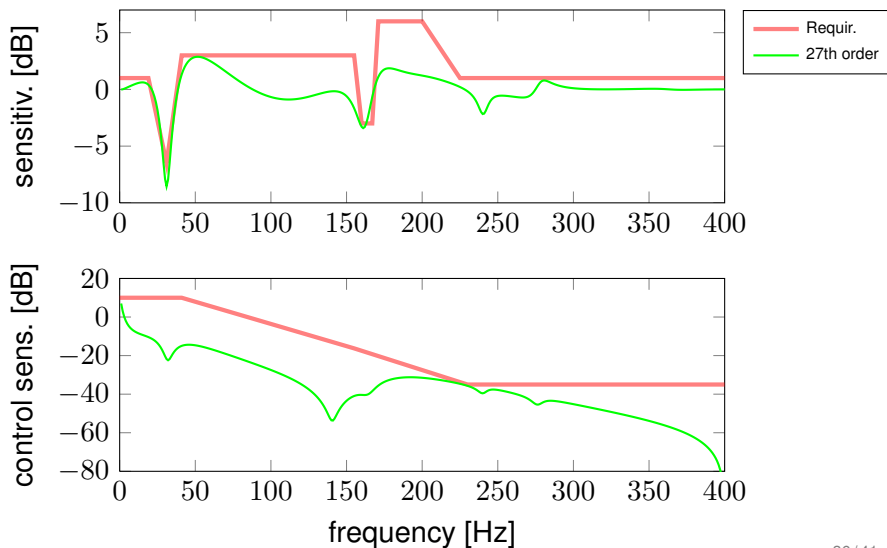
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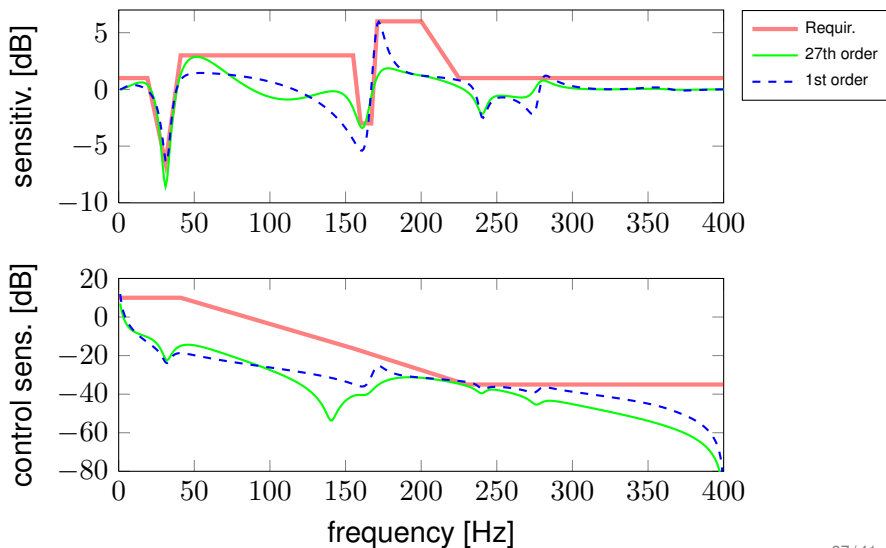
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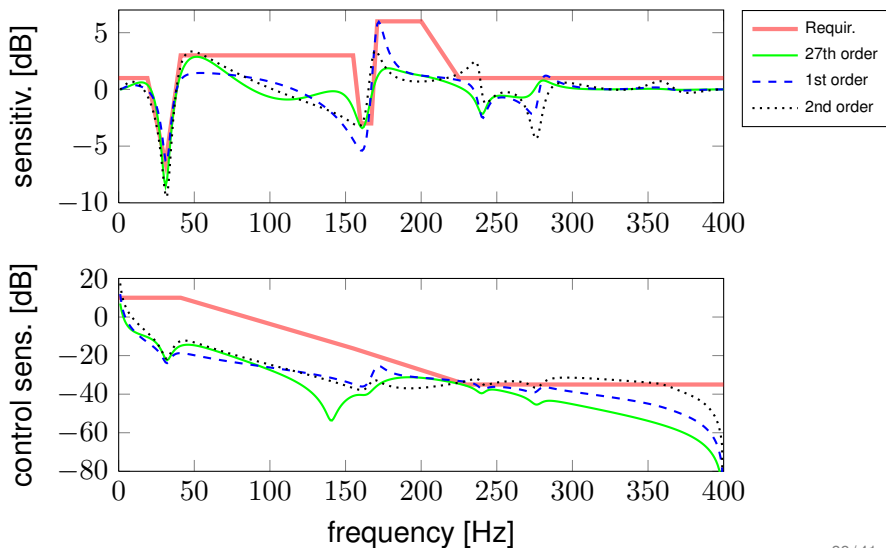
# Performance



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# Conclusions

- Discrete-time fixed-structure  $\mathcal{H}_\infty$  synthesis
- Allows direct structural restrictions
- Better results than previous techniques



# Software

## HIFOO+d

- <http://bitbucket.org/andrey.popov/hifoo-d>

- **Discrete-time**

- **Replicated/repeated** controller blocks:

$$K(z) \in \begin{bmatrix} \mathbf{K}_1(z) & & \mathbf{K}_1(z) \\ & \mathbf{K}_2(z) & \\ & & \mathbf{K}_2(z) \end{bmatrix}$$

- redundant elements
  - symmetric systems
  - multi-agent systems [Popov & Werner, 2010]
  - $\mu$ -synthesis [Apkarian, 2010]
- 
- features, **not available in MATLAB 2010b or HIFOO 3.0**
  - GPL