# Subspace identification with constraints on the impulse response 

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## Aims of this talk

identification from a "few" data points
regularize the problem by prior knowledge
use practically meaningful prior knowledge

## Motivation: "small data" is also challenging and relevant problem

| $T$ | $\left[0, T_{\min }\right)$ | $\left[T_{\min }, 2 \sim 5 T_{\min }\right)$ | $\left(5 T_{\min }, \infty\right)$ |
| :---: | :---: | :---: | :---: |
| problem | ill-posed | ill-conditioned | well-conditioned |
| cost fun. | - | local minima | $\rightarrow$ convex |
| solution | non-unique | sensitive | robust |
| analysis | - | few results | many results |

$T$ — number of data points
surprising often we are dealing with "small" $T$

## We are in the "small data" case when doing

nonparameteric identification
\# parameters $\approx$ \# samples $\Longrightarrow$ ill-posed problem
nonlinear identification
large number of parameters $\quad \Longrightarrow \quad$ large $T_{\text {min }}$
fault detection
needs fast real-time identification $\quad \Longrightarrow \quad$ small $T$

## Solution by prior knowledge on parameters

estimation problem:

$$
\min _{\theta} \underbrace{e(u, y, \theta)}_{\text {model error }}
$$

regularized problem: $\min _{\theta} e(u, y, \theta)+\underbrace{\gamma p(\theta)}_{\text {regularizer }}$

$$
\text { (e.g., } p(\theta)=\left\|\theta_{0}-\theta\right\| \text { ) }
$$

alternative problem:

$$
\min _{\theta \in \Theta} e(u, y, \theta)
$$

$$
\text { (e.g., } \Theta:=\left\{\theta \mid\left\|\theta_{0}-\theta\right\| \leq \rho\right\} \text { ) }
$$

$\theta$ may not be unique!

## Prior knowledge on the model behavior

examples of prior:
DC gain =1
rise time $<5 \mathrm{sec}$
overshoot $<10 \%$
prior is often specified on model trajectories
$\left.\mathscr{B}\right|_{L}$ - set of all L-samples long trajectories

## Two-stage identification method

1. $(u, y) \mapsto h$ - impulse response estimation
2. $h \mapsto \mathscr{B}$ - realization of $h$

## Plan

Impulse response estimation

Adding constraints

Numerical examples

## Model behavior = image of Hankel matrix

$\mathscr{H}_{L}(w):=\left[\begin{array}{ccccc}w(1) & w(2) & w(3) & \cdots & w(T-L+1) \\ w(2) & w(3) & w(4) & \cdots & w(T-L+2) \\ w(3) & w(4) & w(5) & \cdots & w(T-L+3) \\ \vdots & \vdots & \vdots & & \vdots \\ w(L) & w(L+1) & w(L+2) & \cdots & w(T)\end{array}\right]$
for exact data $w_{d}=\left(u_{\mathrm{d}}, y_{\mathrm{d}}\right)$ and persistently exciting $u_{\mathrm{d}}$

$$
\operatorname{image}\left(\mathscr{H}_{L}\left(w_{\mathrm{d}}\right)\right)=\left.\mathscr{B}\right|_{L}
$$

therefore, for any $\left.w \in \mathscr{B}\right|_{L}$, there is $g$, such that

$$
\mathscr{H}_{L}\left(w_{\mathrm{d}}\right) g=w
$$

## Computing impulse response is linear prob.

 impulse response$$
W=(\underbrace{0, \ldots, 0}_{\text {zero ini. cond. }},\left[\begin{array}{c}
\prime \\
h(0)
\end{array}\right],\left[\begin{array}{c}
0 \\
h(1)
\end{array}\right], \ldots,\left[\begin{array}{c}
0 \\
h(t)
\end{array}\right])
$$

define

$$
\mathscr{H}_{\ell+t}\left(u_{\mathrm{d}}\right)=:\left[\begin{array}{l}
U_{\mathrm{p}} \\
U_{\mathrm{f}}
\end{array}\right] \quad \text { and } \quad \mathscr{H}_{\ell+t}\left(y_{\mathrm{d}}\right)=:\left[\begin{array}{l}
Y_{\mathrm{p}} \\
Y_{\mathrm{f}}
\end{array}\right]
$$

we have

$$
\left.\left[\begin{array}{l}
U_{p} \\
Y_{p} \\
U_{f}
\end{array}\right] g=\left[\begin{array}{c}
0 \\
0 \\
1 \\
1 \\
0
\end{array}\right]\right\} \begin{gathered}
\text { zero ini. conditions } \\
\text { impulse input }
\end{gathered}
$$

## Plan

## Impulse response estimation

Adding constraints

Numerical examples

## Prior $E h=f \leadsto$ analytical solution

adding the constraint

$$
E h=f
$$

to

$$
\underbrace{\left[\begin{array}{c}
U_{p} \\
Y_{p} \\
U_{f}
\end{array}\right]}_{\mathscr{A}} g=\underbrace{\left[\begin{array}{c}
0 \\
0 \\
{[1]}
\end{array}\right]}_{V}
$$

leads to

$$
h=Y_{\mathrm{f}}\left(\left(E Y_{\mathrm{f}}\right)^{+} f+N(\mathscr{A} N)^{+}\left(v-\mathscr{A}\left(E Y_{\mathrm{f}}\right)^{+} f\right)\right)
$$

## Prior $E^{\prime} h \leq f^{\prime} \leadsto$ quadratic program

minimize over $g\|\mathscr{A} g-v\|$<br>subject to $E Y_{\mathrm{f}} g=f$ and $E^{\prime} Y_{\mathrm{f}} g \leq f^{\prime}$

convex problem
solved by active-set methods

## Plan

## Impulse response estimation

## Adding constraints

Numerical examples

## Simulation setup

mass-spring-damper system

$$
m \frac{\mathrm{~d}^{2}}{\mathrm{~d} t^{2}} y+d \frac{\mathrm{~d}}{\mathrm{~d} t} y+k y=u
$$

errors-in-variables setup

$$
w_{\mathrm{d}}=\bar{w}+\widetilde{w}, \quad \bar{w} \in \overline{\mathscr{B}} \quad \text { and } \quad \widetilde{w} \sim \mathrm{~N}\left(0, s^{2} I\right)
$$

$T=50$ samples

## Methods compared

uy2ss_pk - two-stage method with prior knowledge
uy2ss — two-stage method without prior knowledge
n4sid-N4SID method (with default parameters)

## Validation criteria

$$
\begin{aligned}
& e_{\mathscr{B}}=\frac{1}{N} \sum_{k=1}^{N} \frac{\left\|\overline{\mathscr{B}}-\widehat{\mathscr{B}}^{(k)}\right\|}{\|\overline{\mathscr{B}}\|}-\quad \text { model error } \\
& e_{h}=\frac{1}{N} \sum_{k=1}^{N} \frac{\left\|\bar{h}-\widehat{h}^{(k)}\right\|}{\|\bar{h}\|}-\quad \text { impulse response error }
\end{aligned}
$$

## A single equality constraint

$$
E=\left[\begin{array}{lll}
1 & \cdots & 1
\end{array}\right] \quad f=E \bar{h}
$$

|  | uh2ss_pk | uh2ss | n4sid |
| :--- | :---: | :---: | :---: |
| $\boldsymbol{e}_{\mathscr{B}}$ | 0.1925 | 0.2218 | 0.1597 |
| $\boldsymbol{e}_{h}$ | 0.1828 | 0.2137 | - |

## Multiple equality constraints



## Multiple equality constraints



## Inequality constraints

|  | uh2ss_pk | uh2ss | n4sid |
| :--- | :---: | :---: | :---: |
| $\boldsymbol{e}_{\mathscr{B}}$ | 0.2291 | 0.2611 | 1.4984 |
| $\boldsymbol{e}_{h}$ | 0.2022 | 0.3235 | - |

## Inequality constraints



## Inequality constraints

impulse response of $\mathscr{\mathscr { B }}$


## Conclusions

prior knowledge makes the problem well conditioned
classical approach: Bayesian prior on the parameters
alternative approach: constraints on the model behavior

