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Identification of Inverse Models for Feedforward Control:

Non-Causal Basis Functions & Optimal IV Approach

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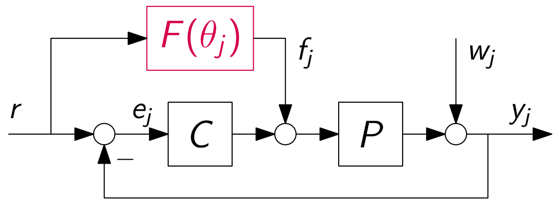
Estimation of Inverse Systems

Identification for feedforward

- Identify model of $P \rightarrow$ invert
- Identify inverse model P^{-1} directly



Thus, aim for: $F(q,\theta^*) = P^{-1}(q) = \frac{A(q)}{B(q)}$

- Measurements in closed-loop configuration
  $\Rightarrow$ Instrumental Variable approach [1]
- Stability/causality of F?

Identification Approach

Model structure:

- Linear: $F(q,\theta) = \sum_i \psi_i(q)\theta[i] = \Psi(q)\theta$ (1)
- Nonlinear (rational): $F(q,\theta) = \frac{\Psi_A(q)\theta_A}{1+\Psi_B(q)\theta_B}$ (2)

IV criterion:

$$V(\theta_{j+1}) = \left\| \frac{1}{N}\sum_{t=1}^{N} z^\top(t) L(q) \hat{e}_{j+1}(t,\theta_{j+1}) \right\|_W^2$$

with predicted error in next experiment

$$\hat{e}_{j+1}(t,\theta_{j+1}) = e_j(t) - \varphi^\top(t)\theta_{j+1}$$

and $\varphi(t) = \Psi(q)\left(C(q)+F_j(q)\right)^{-1} y_j(t)$

Key questions:

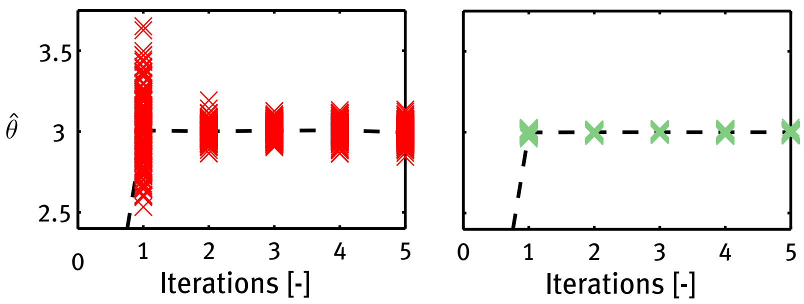
1. How to determine $z(t)$ and $L(q)$ for optimal accuracy?
2. How to select basis functions for inverse model ID?

Optimal IV for Feedforward

Design of $z(t)$ and $L(q)$ for optimal accuracy of $\hat{\theta}_{j+1}$ [1]?

Lower bound covariance matrix: $P_{IV}^{opt} = \lambda_\epsilon^2[\bar{\mathbb{E}}\varphi_r(t)\varphi_r^\top(t)]^{-1}$

Approach: iteratively refine IVs to improve accuracy [2,3]



Parameters θ using suboptimal IV (left) and optimal IV approach (right) as a function of iterations for $m = 200$ realizations

Non-Causal Basis Functions in $\mathcal{L}_2$

IV-based approach can handle:

- Polynomial models (e.g. FIR)
- Rational models
  - Optimize the poles in (2): non-convex [3]
  - Prespecify the poles in (1): convex [4]

What about stability of F? Well: non-causality!
$\Rightarrow$ No problem for feedforward!

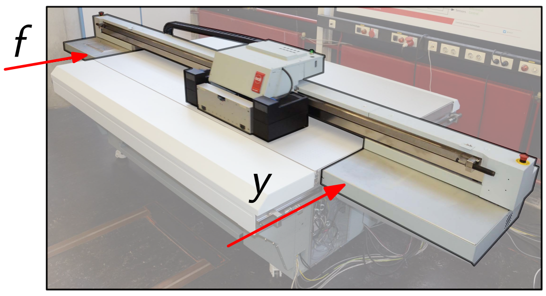
Selection of basis functions $\Psi(q)$ for inverse model ID

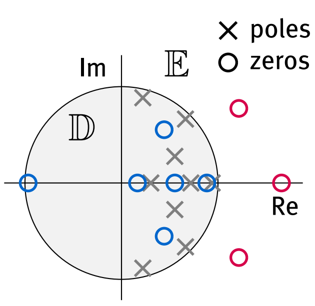
Key point: if P has NMP zeros, then P^{-1} has poles in $\mathbb{E}$

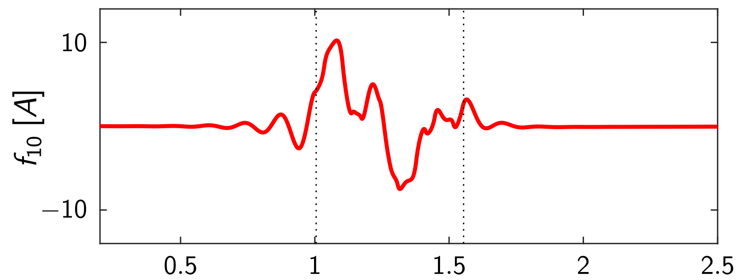
Approach: rational orthonormal basis functions (ROBFs)

- Well known in system identification [5,6]
  Aim: identification of causal models, i.e., $P \in \mathcal{RH}_2$
- Feedforward aim: estimation of $P^{-1} \in \mathcal{RL}_2$
  $\Rightarrow$ Use ROBFs in $\mathcal{L}_2$ for non-causal control actions [4]
  Implementation: stable inversion

Experimental Results







Using ROBFs in $\mathcal{RL}_2$, non-causal feedforward can be generated for NMP systems. The motion task starts at the dashed black line. [4]

References

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