Experimental evaluation of a method for improving experiment design in robot identification.

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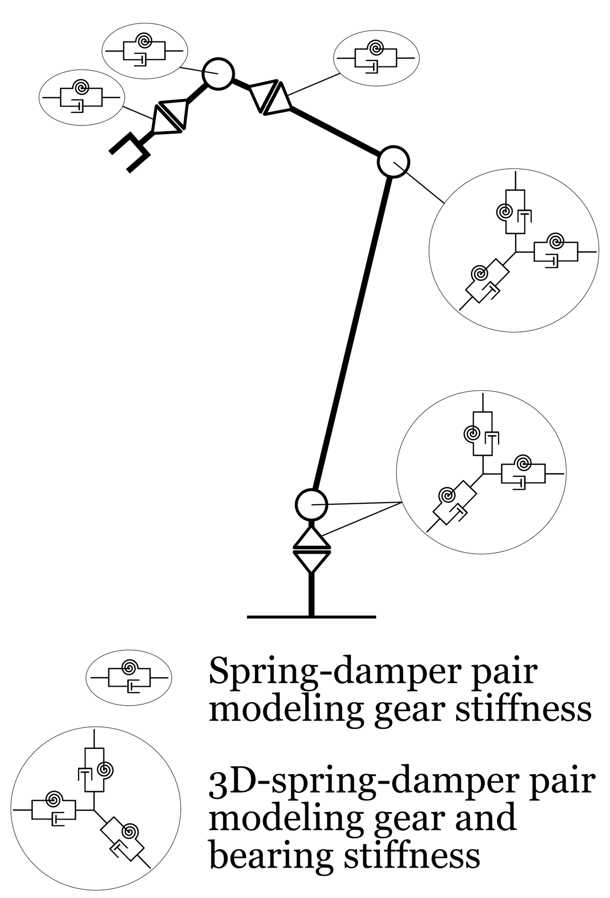
Introduction

In order to build a highly accurate robot model, parameters need to be estimated from a combination of prior knowledge and measurement data. It has been shown that the experiment design can be improved in terms of efficiency and accuracy by carefully selecting the robot configurations used for data collection. Estimates of the information matrix are generated from simulation for a number of candidate configurations, and an optimization problem is solved for finding the optimal combination of configurations.

This poster validates the method with data from a real manipulator. Both the experiment time and the average parameter standard deviation are reduced significantly.

Gray-box robot model

An industrial robot.



A lumped parameter robot model.

– Known: rigid body parameters (dimensions, mass, inertia)
– Assumed: damping and friction parameters
– Identified from data: elasticity parameters θ

Method

(M.1) Robot identification in frequency-domain[1]

Minimize the error between the estimated Frequency Response Functions (FRFs) $\hat{G}^{(i)}(\omega)$ and the model FRFs $G^{(i)}(\omega, \theta)$:

$$\hat{\theta} = \arg\min_{\theta} \mathcal{F}(\omega, \theta)$$

$$\mathcal{F}(\omega, \theta) = \sum_{i \in Q_c} \sum_{l=1}^{N_f} \left[\mathcal{E}^{(i)}(\omega_l, \theta)\right]^T W^{(i)}(\omega_l)\, \mathcal{E}^{(i)}(\omega_l, \theta)$$

$$\mathcal{E}^{(i)}(\omega_l, \theta) = \log \operatorname{vec}(\hat{G}^{(i)}(\omega_l)) - \log \operatorname{vec}(G^{(i)}(\omega_l, \theta))$$

– Estimate FRFs $\hat{G}^{(i)}(\omega)$ from multiple experiments in the robot configurations i.
– Linearize the gray-box robot model in each configuration, get parametric FRFs $G^{(i)}(\omega, \theta)$.
– Minimize the weighted ($W^{(i)}(\omega)$) error between $\hat{G}^{(i)}$ and $G^{(i)}$.

(M.2) Improved experiment design[2, 3]

Select the best combination of robot configurations from a set of candidates Q_c by solving

$$\begin{aligned} &\text{minimize} && \log\det\left[\sum_{i=1}^{Q_c} \lambda_i H_i\right] \\ &\text{subject to} && \lambda \geq 0,\ \ 1^T\lambda = 1 \end{aligned}$$

– Compute the information content of each configuration:

$$H_i = 2Re\left\{\overline{\Psi^{(i)}(\theta_0)}\left[\Lambda_0^{(i)}\right]^{-1}\left[\Psi^{(i)}(\theta_0)\right]^T\right\}$$

– Get the Jacobian $\left[\Psi^{(i)}(\theta_0)\right]^T = \frac{\partial G^{(i)}(\theta_0)}{\partial \theta}$ from the nominal model FRFs $G^{(i)}(\theta_0)$.
– Obtain the total variance $\Lambda_0^{(i)}$ of the FRF estimate $\hat{G}^{(i)}$ from simulation.

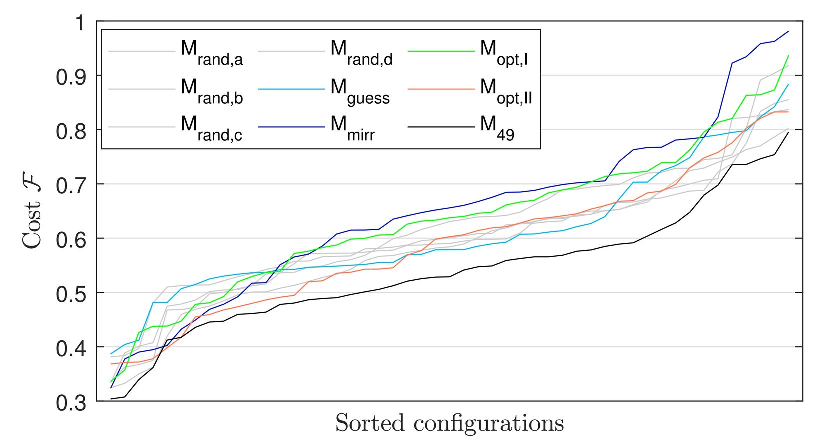
[1] E. Wernholt, S. Moberg, *Nonlinear gray-box identification using local models applied to industrial robots*, Automatica, Volume 47, Issue 4, 2011, Pages 650-660.
[2] E. Wernholt and J. Löfberg, *Experiment design for identification of nonlinear gray-box models with application to industrial robots*, 46th IEEE Conference on Decision and Control, 2007, pp. 5110-5116.
[3] S.A. Zimmermann, M. Enqvist, S. Gunnarson, S. Moberg and M. Norrlöf, *Improving experiment design for frequency-domain identification of industrial robots*, In 2022 Modeling, Estimation and Control Conference, IFAC online, accepted for publication.

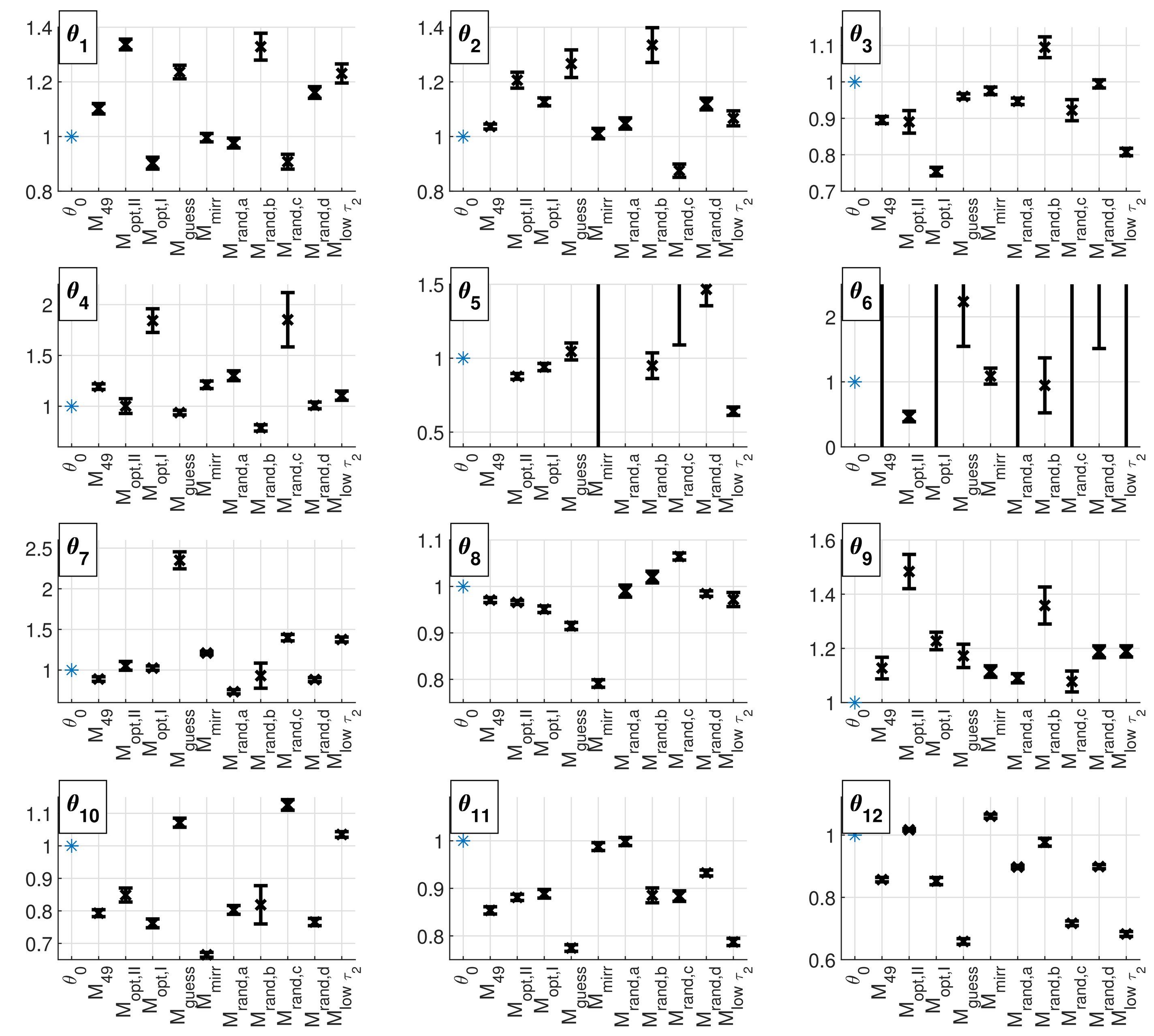
Results

If the optimal configurations $Q_{opt,II}$ are used for collecting estimation data (instead of Q_c),

- the experiment time is reduced (only 7 configs),
- the average standard deviation of $\hat{\theta}$ is reduced (see θ_6),
- the avg. cost $\mathcal{F}(\omega, \theta)$ is comparable low.

Model	Worst-case cost	Average cost	Average std θ
M_{49}	0.7956	0.5391	>10 %
$M_{opt,I}$	0.9369	0.6339	>10 %
$M_{opt,II}$	0.8326	0.5892	3.971 %
M_{guess}	0.8842	0.6074	4.826 %
M_{mirr}	0.9814	0.6477	>10 %
M_{low,τ_2}	1.0114	0.6135	>10 %
$M_{rand,a}$	0.8369	0.5979	>10 %
$M_{rand,b}$	0.9181	0.6208	8.496 %
$M_{rand,c}$	0.8024	0.6053	>10 %
$M_{rand,d}$	0.8552	0.5864	6.486 %





Model parameters estimated with different data sets.

Challenges and future work

- What if the information matrix is badly conditioned (i.e. dominated by one parameter)?
- How to include nonlinear transmission stiffnesses in the model structure and the experiment design problem?
- Can the design be improved further by optimizing the excitation signal?