Improved experiment design for closed-loop identification of industrial robots

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Introduction

Since the control system of an industrial robot often relies on models, the quality of the model is of high importance. Furthermore, a fast and easy-to-use process for finding the model parameters from a combination of pre-known information and experimental data is required.
This poster shows an approach for improving the experiment design by selecting the optimal combination of manipulator positions during the data collection. An optimization problem, which is based on the Fisher information matrix, is solved. It is shown that the parameter covariance is reduced by weighting the candidate positions.

Motivation

The identification of industrial robots is challenging, since a closed-loop system must be identified, and several nonlinearities are present. The experiment design problem aims to

- reduce the required experiment time,
- improve the model accuracy.

Nonlinear gray-box identification in frequency-domain[1]

1. Estimate non-parametric Frequency Response Functions (FRFs) $\hat{G}^{(i)}(l)$ in a number of robot positions.
2. Linearize the parametric gray-box robot model (see col. 2) in each of the robot positions, get parametric FRFs $\hat{G}^{(i)}(\theta)$.
3. Compute the error between $\hat{G}^{(i)}(l)$ and $\hat{G}^{(i)}(\theta)$, and optimize the parameter vector in order to minimize this error:

$$\hat{\theta} = \arg\min_{\theta} \sum_{i=1}^{Q_c} \sum_{l=1}^{m_i} \left[\mathcal{E}^{(i)}(l,\theta)\right]^T \left[\Lambda_0\right]^{-1} \mathcal{E}^{(i)}(l,\theta)$$

where $\mathcal{E}^{(i)}(l,\theta) = \hat{G}^{(i)}(l) - \hat{G}^{(i)}(\theta)$

Gray-box model:

- Known: rigid body parameters (dimensions, mass, inertia)
- Identified from measurements: elasticity, damping and friction parameters

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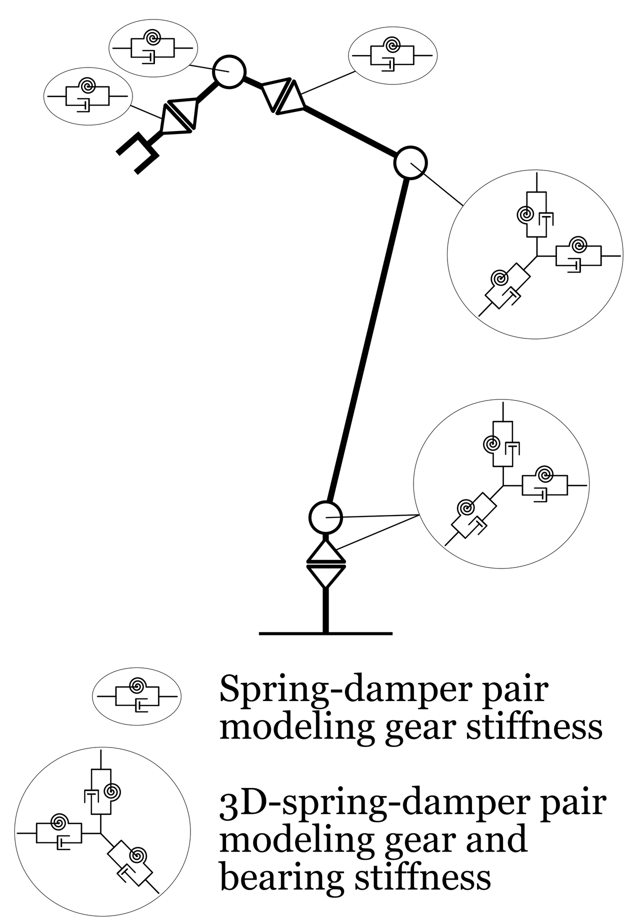
An industrial robot.



A lumped parameter robot model.

Idea of improved experiment design[2]

1. Choose a set of candidate positions Q_c
2. Perform experiments in each position i, estimate the FRF and the its total variance $\Lambda_0^{(i)}$ (avg. over different periods and realizations)
3. Estimate the information obtained from each position:

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

with the Jacobian $\left[\Psi^{(i)}(\theta_0)\right]^T = \frac{\delta \hat{G}^{(i)}(\theta_0)}{\delta\theta}$, where $\hat{G}^{(i)}(\theta_0)$ are the parametric model FRFs, and θ_0 the nominal parameters.

4. Solve optimization problem for finding the best combination of candidates:

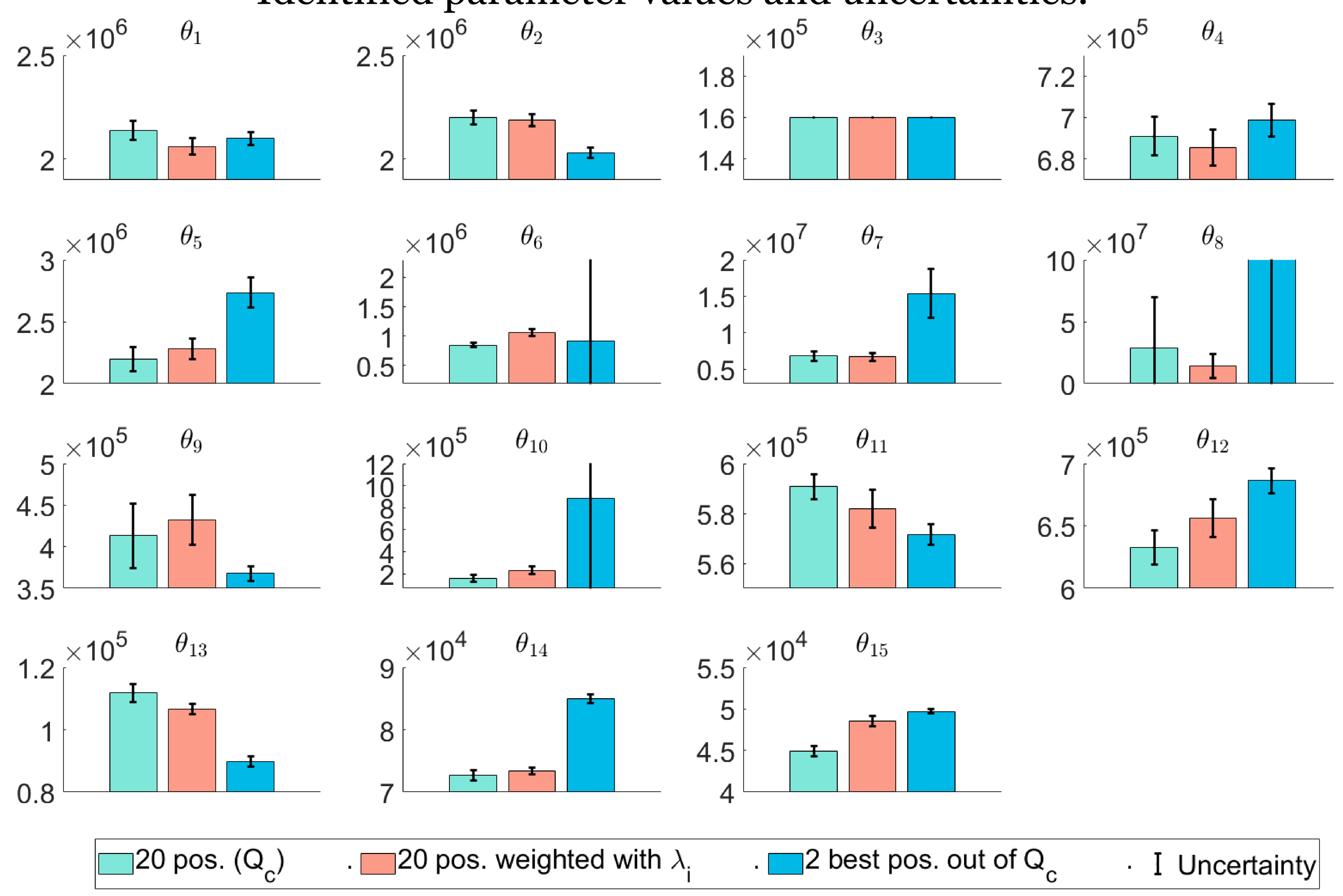
$$\begin{aligned} &\text{minimize} \quad \log\det\left[\sum_{i=1}^{Q_c}\lambda_i H_i\right] \\ &\text{subject to} \quad \lambda \geq 0, \;\; 1^T\lambda = 1 \end{aligned}$$

[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, ISSN 0005-1098, https://doi.org/10.1016/j.automatica.2011.01.021

[2] E. Wernholt and J. Lofberg, *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, doi: 10.1109/CDC.2007.4434059

Results

Identified parameter values and uncertainties.



- Uncertainty of the estimate θ_8 can be reduced if the positions Q_c are weighted according to the optimization result λ (orange bars).
- Reducing the number of positions leads to increased parameter uncertainty and physically unreasonable values for several parameters (turquoise bars).

Challenges

- How to get good initial parameters θ_0?
- Many experiments are needed for estimating the variance $\Lambda_0^{(i)}$ of the FRF estimate. Can simulated data be used?
- What if the information matrix is ill-conditioned (i.e. dominated by one parameter)?

Future work

- How to use the optimization result (i.e. λ)?
  → *Experiment time for each position vs. FRF-weighting*
- How to validate the method? What measure should be used for judging if the experiment design is improved?
  → *Parameter uncertainty vs. accuracy vs. experiment time*
- How can regularization be used for obtaining a sub-set of Q_c that contains the best positions (instead of considering all candidate positions according to λ)?