Identification of Industrial Robots

Robot Modeling and Control

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Identification of Industrial Robots

Accurate robot models needed for:

- Control
- Mechanical design
- Performance simulation
- Diagnosis
- Supervision
- ...

System identification: Unknown model parameters are estimated from experimental data.

Types of Identification

- Kinematic model
- Dynamic rigid body model
- Mechanical elasticities
- Nonlinearities in actuators and transmission
- Load dynamics
- Sensor and actuator disturbances (ripple)
- Thermal models
- Mechanical stress
- ...

Outline

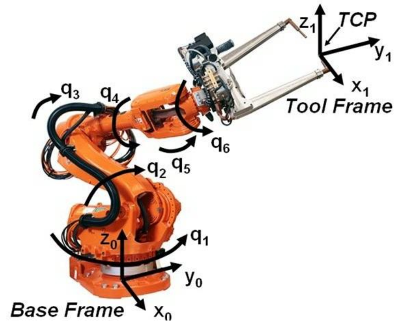
Recommended literature

- Sciavicco, L. and Siciliano, B. *Modeling and Control of Robotic Manipulators*. Springer, 2000, pages 131–181.
- Wernholt, E. *Multivariable Frequency-Domain Identification of Industrial Robots*, PhD thesis, LiTH, 2007, pages 61–72.
  `http://www.control.isy.liu.se/research/reports/Ph.D.Thesis/PhD1138.pdf`
- Olsson, R. *Identifiering av stelkroppsmodell för industrirobot*, Master's thesis, LiTH, 2005.
  `http://urn.kb.se/resolve?urn=urn:nbn:se:liu:diva-5535`

- Additional references can be found in the PhD thesis.

Identification of Kinematic Parameters

- Accuracy: Deviates a couple of milimeters with nominal kinematic model.



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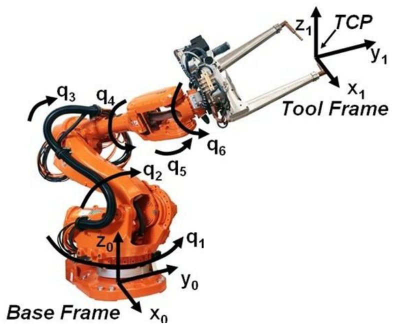
- Repeatability: 0.1 mm for ABB IRB6400, that can handle 200 kg.



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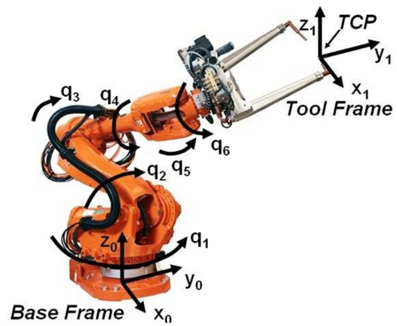
Identification of Kinematic Parameters

- Accuracy: Deviates a couple of milimeters with nominal kinematic model.
- Repeatability: 0.1 mm for ABB IRB6400, that can handle 200 kg.
- Can obtain volumetric accuracy of 0.5 mm for a large robot by calibration.



$$Z = \begin{bmatrix} \text{pos} \\ \text{ori} \end{bmatrix} = \Gamma_{kin}(q)$$

Identification of Kinematic Parameters, cont

- Taylor series expansion:

$$\Delta Z = Z - \Gamma_{kin}(q, \theta_{nom}) = \frac{\partial \Gamma_{kin}}{\partial \theta}(q, \theta_{nom})\Delta\theta$$

Identification of Kinematic Parameters, cont

7(29)

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Identification of Kinematic Parameters, cont

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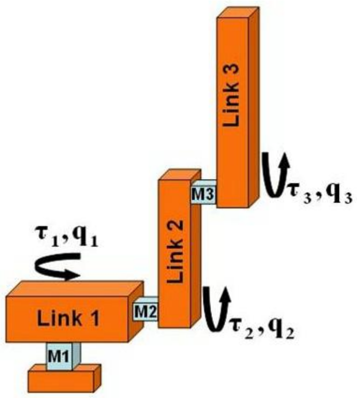
- Measure ΔZ in a number of locations, using e.g., a laser tracker, and solve for $\Delta\theta$ in least-squares sense.
- θ includes robot link parameters and parameters describing elastostatic effects (deflection due to gravity) and the mounting of the robot base and the end effector.

Outline

Rigid Body Dynamics



$$M(q)\ddot{q} + c(q,\dot{q}) + g(q) + \tau_f(\dot{q}) = \tau$$

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- It is common to use a friction model

$$\tau_f(\dot{q}) = F_v\dot{q} + F_c\,\mathrm{sign}(\dot{q})$$

which gives two additional parameters for each link, but still an expression that is linear in the parameters.

Linear in Parameters, cont.

The robot dynamic model can then be rewritten as

$$H_{rb}(q,\dot{q},\ddot{q})\theta_{rb} = \tau$$

or as the energy difference model

$$\Delta h_{rb}(q,\dot{q})\theta_{rb} = \Delta\mathcal{H}_{rb} = \mathcal{H}_{rb}(t_b) - \mathcal{H}_{rb}(t_a) = \int_{t_a}^{t_b} \tau^T \dot{q}\,dt$$

where $\theta_{rb} \in \mathbb{R}^{12n}$ is the parameter vector and n is the number of links. $\mathcal{H}_{rb}$ is the total energy of the system.

Base Parameters

Consider N samples of data,
$Z^N = \{q(t_i), \dot{q}(t_i), \ddot{q}(t_i), \tau(t_i),\ i = 1, 2, \dots, N\}$:

$$\underbrace{\begin{bmatrix} H_{rb}(q(t_1),\dot{q}(t_1),\ddot{q}(t_1)) \\ H_{rb}(q(t_2),\dot{q}(t_2),\ddot{q}(t_2)) \\ \vdots \\ H_{rb}(q(t_N),\dot{q}(t_N),\ddot{q}(t_N)) \end{bmatrix}}_{\Phi} \theta_{rb} = \underbrace{\begin{bmatrix} \tau(t_1) \\ \tau(t_2) \\ \vdots \\ \tau(t_N) \end{bmatrix}}_{Y}$$

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- For a particular robot, a number of the parameters are zero or linearly dependent.
- *Base parameters* θ_b – minimum number of parameters that characterize the dynamic model.
- Different approaches can be found in the literature. Most basic distinction is if the problem is solved using a numerical (SVD or QR factorization of Φ) or an analytical method.
- $H_{rb}\theta_{rb} = \tau$ is replaced by

$$H_b(q, \dot{q}, \ddot{q})\theta_b = \tau$$

- The robot is moved along a trajectory and joint motion and torque are measured.

Estimator 14(29)

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- Finally the base parameters can be estimated, for example, by a *weighted least squares (WLS)* method

$$\hat{\theta}_b = \arg\min_{\theta_b} \frac{1}{2}(Y - \Phi_b\theta_b)^T W (Y - \Phi_b\theta_b) = (\Phi_b^T W \Phi_b)^{-1}\Phi_b^T W Y$$

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- To obtain good results, experiment design is important, e.g., path as sum of sinusoids and maximize $\log\det(\Phi_b^T W \Phi_b)$. See, e.g., (Olsson, 2005).

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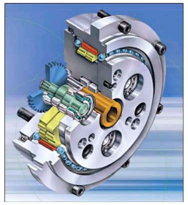
Sources of Elasticity

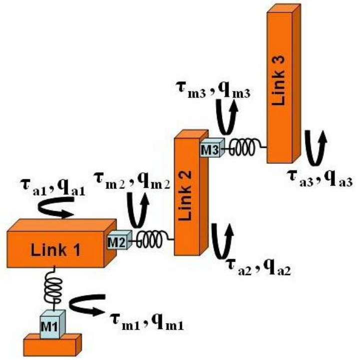


- Transmission
- New structure (single bearings, etc.)
- Reduced weight ⇒ Increased elastic effects
- Mounting and equipment

Flexible Joint Model

For many (traditional) robots, the joint flexibility is dominant, which motivates the **Flexible joint model:**

$$
\begin{aligned}
M_m\ddot{q}_m + \tau_{fm}(\dot{q}_m) + r_g\tau_g &= \tau,\\
M_a(q_a)\ddot{q}_a + c_a(q_a,\dot{q}_a) + g_a(q_a) &= \tau_g,\\
k_g(r_g q_m - q_a) + d_g(r_g\dot{q}_m - \dot{q}_a) &= \tau_g,
\end{aligned}
$$

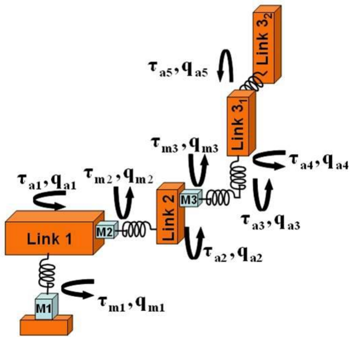


Extended Flexible Joint Model

Modern robots require additional elastic effects to be modeled (due to weight reduction, single bearings, non-symmetric), e.g., by using the **Extended Flexible joint model:**

$$
\begin{aligned}
M_m\ddot{q}_m + \tau_{fm}(\dot{q}_m) + r_g\tau_g &= \tau,\\
M_{ae}(q_a,q_e)\begin{bmatrix}\ddot{q}_a\\ \ddot{q}_e\end{bmatrix} + c_{ae}(q_a,q_e,\dot{q}_a,\dot{q}_e) + g_{ae}(q_a,q_e) &= \begin{bmatrix}\tau_g\\ \tau_e\end{bmatrix}\\
k_g(r_g q_m - q_a) + d_g(r_g\dot{q}_m - \dot{q}_a) &= \tau_g,\\
-k_e q_e - d_e\dot{q}_e &= \tau_e,
\end{aligned}
$$

(Moberg and Hanssen, 2007)



Rigid vs. Elastic Body Dynamics Id.

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- Main reason: only a subset of the state variables are typically measured and linear regression can therefore not be used.
- (This could partly be solved by adding expensive sensors.)

Given: Kinematic and rigid body models from a priori knowledge or previous identification experiments.

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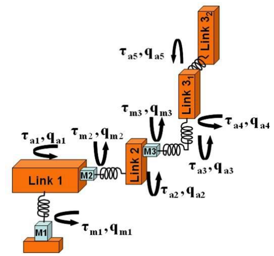
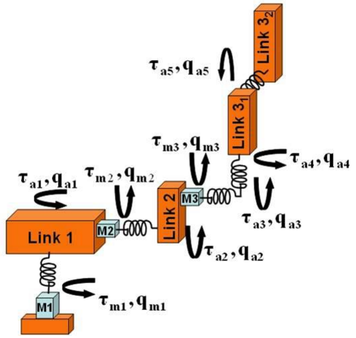
Aim: Identify springs and dampers



Challenge for System Identification



- Accurate models are needed
- Multivariable
- Nonlinear
- Unstable
- Highly resonant
- Data collected in closed loop
- Normally only motor angle measurements available
- Difficult disturbance properties

$$\dot{x}(t) = f(x(t), u(t), \theta),$$
$$y(t) = h(x(t), u(t), \theta),$$

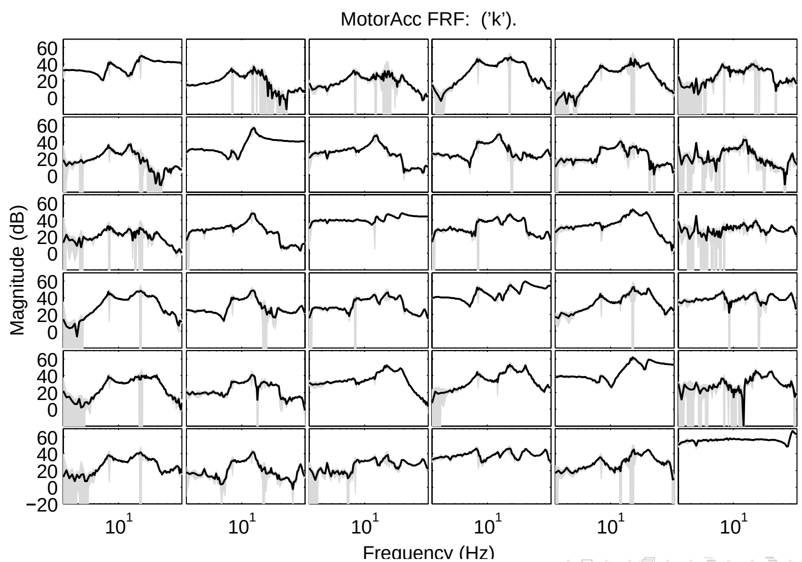
Identification Procedure

1. Estimate nonparametric FRFs in Q operating points

$$\widehat{G}^{(i)}(\omega_k), \quad i = 1, \dots, Q$$

Pros & Cons

FRF Example



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3. Obtain $\hat{\theta}$ by minimizing the discrepancy between the parametric and nonparametric FRFs.

▸ Pros & Cons

Weighted Logarithmic Least Squares

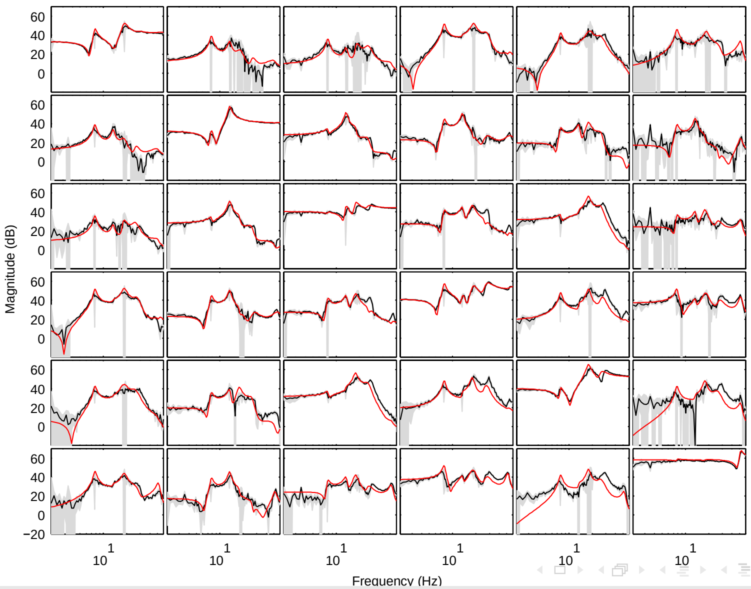
$$\hat{\theta} = \arg\min_{\theta} \sum_{i=1}^{Q} \sum_{k=1}^{N_f} [\mathcal{E}^{(i)}(k,\theta)]^H [\Lambda^{(i)}(k)]^{-1} \mathcal{E}^{(i)}(k,\theta)$$

with

$$\mathcal{E}^{(i)}(k,\theta) = \log \operatorname{vec}(\widehat{G}^{(i)}(\omega_k)) - \log \operatorname{vec}(G^{(i)}(\omega_k,\theta))$$

and $\Lambda^{(i)}(k)$ a Hermitian weighting matrix.

Parametric and Nonparametric FRF



Conclusions

- Identification of industrial robots varies depending on the model (kinematic, rigid body dynamics, elasticities, . . .)
- Rigid body dynamics can be identified using linear regression techniques.
- Identification of elastic effects is quite challenging due to: multivariable, nonlinear, unstable, resonant, high accuracy required, ...

Frequency-domain

+ Data compression
+ Unstable systems ok
+ Easy to validate that resonances are captured
+ Frequency-domain requirements easily handled
- Biased estimates due to nonlinearities and closed loop
- Linear approximations might be inaccurate, e.g., for Coulomb friction.

Time-domain

+ No approximations
- Large data sets
- Numerical problems
- Stable predictor (nonlinear observer)

Return

For each operating point i and θ value do:

1. Calculate the stationary point $(x_0^{(i)}(\theta), u_0^{(i)}(\theta))$.
2. Linearize the nonlinear system.
3. Obtain the continuous-time transfer function as

$$G_c^{(i)}(s,\theta) = C^{(i)}(\theta)(sI - A^{(i)}(\theta))^{-1}B^{(i)}(\theta) + D^{(i)}(\theta).$$

4. Convert the continuous-time FRF $G_c^{(i)}(j\omega,\theta)$ to discrete time (assuming zero-order hold):

$$G_{T_s}^{(i)}(e^{j\omega T_s},\theta) \approx \frac{1 - e^{-j\omega T_s}}{j\omega T_s} G_c^{(i)}(j\omega,\theta).$$

($G^{(i)}(\omega,\theta)$ is a short notation for $G_{T_s}^{(i)}(e^{j\omega T_s},\theta)$)

Id. Proc.