System identification and end-effector force estimation of an open-chain robotic manipulator using a multibody formulation

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EXTENDED ABSTRACT

1 Introduction

Digitalized industrial processes require enhanced data collection techniques for process control and optimization. Kalman filters have been extensively proposed in literature to produce virtual measurements for a multibody system [1] such as input forces [2]. Kalman filters in general are based on a dynamic model of the system, which is commonly considered to be known including only small modeling inaccuracies. However, in complex systems, such as robots, the model parameters may not be directly derived from design information of the device but can only be obtained through system identification.

This study investigates a practical implementation of virtual force measurements of an open-chain robot. The study starts by defining an identifiable set of unknown inertia and friction parameters. The system model is formed using a semi-recursive multibody formulation [3] and is identified using linear regression approach [4], while the force estimator is build using discrete extended Kalman filter [2]. The approach is verified with artificial measurements. The results show good agreement both in parameter identification and in force estimation.

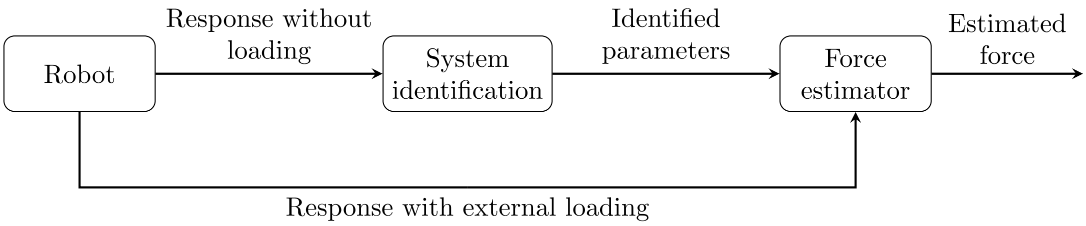


Figure 1: Simplified process description of system identification and force estimation

2 System identification

This study utilizes the property of linearity of actuator torques with respect to a specific parameter set, named *Standard parameters*. To acquire an identification problem with a unique solution, a subset of linearly independent *Base parameters*, $\mathbf{K_B}$ is formed. Consequently, the parameter estimation can be written as a linear regression:

$$\bar{\mathbf{Q}}^{\Sigma}_{act} = \frac{\partial\left(\bar{\mathbf{M}}^{\Sigma}\ddot{\mathbf{z}} - \bar{\mathbf{Q}}^{\Sigma} - \bar{\mathbf{Q}}^{\Sigma}_{fric}\right)}{\partial \mathbf{K}_B}\mathbf{K}_B \equiv \Phi(\mathbf{z},\dot{\mathbf{z}},\ddot{\mathbf{z}})\mathbf{K}_B, \tag{1}$$

where $\bar{\mathbf{Q}}^{\Sigma}_{act}$ and $\bar{\mathbf{Q}}^{\Sigma}_{fric}$ are actuation torques and friction torques, respectively, $\bar{\mathbf{M}}^{\Sigma}$ is the mass matrix in joint space, $\bar{\mathbf{Q}}^{\Sigma}$ is a composite external force vector through gravity, Coriolis and centripetal forces and unknown external forces. The friction is modelled by Coulomb and viscous friction where the sign function is replaced by an hyperbolic tangent. This produces a friction model that is both continuously differentiable, a requirement for extended Kalman filter, but is also linear with respect to identified friction coefficients. In Eq. (1), $\Phi(\mathbf{z},\dot{\mathbf{z}},\ddot{\mathbf{z}})$ is a regression matrix of a single observation being a function of joint positions $\mathbf{z}$, velocities $\dot{\mathbf{z}}$ and accelerations $\ddot{\mathbf{z}}$.

3 Force estimator

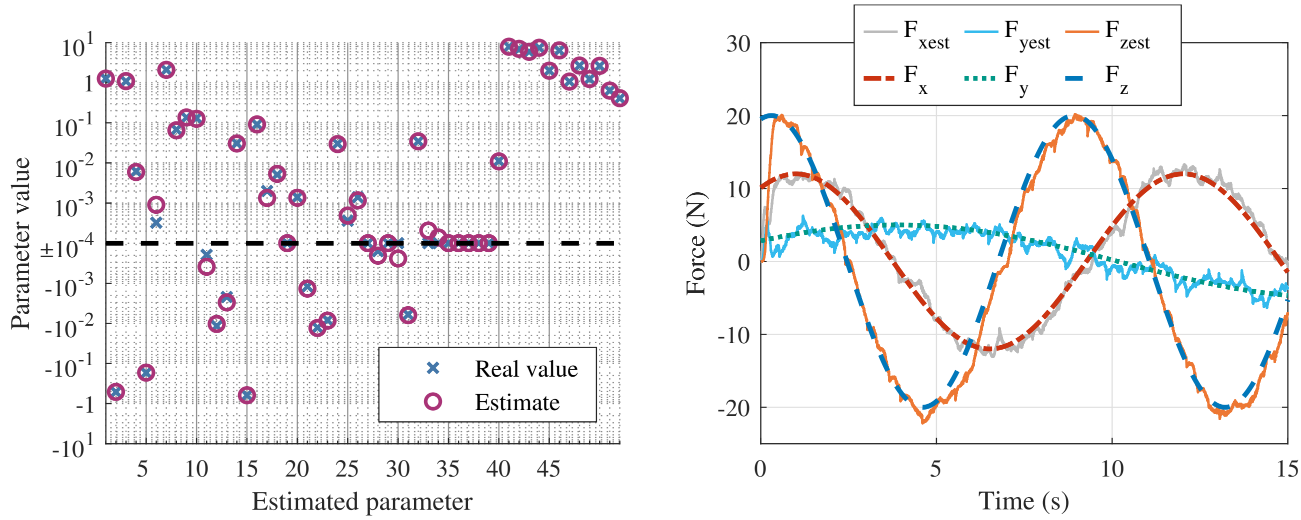
The force estimator is being build using discrete extended Kalman filtering, where the unknown forces $\mathbf{f}$ are considered as additional states with random walk behavior. The continuous time stochastic model of the system can be constituted as:

$$\dot{\mathbf{X}} = \frac{\mathrm{d}}{\mathrm{d}t}\begin{bmatrix}\mathbf{z}\\ \dot{\mathbf{z}}\\ \mathbf{f}\end{bmatrix} = \begin{bmatrix}\dot{\mathbf{z}}\\ \left(\bar{\mathbf{M}}^{\Sigma}\right)^{-1}\left(\bar{\mathbf{Q}}^{\Sigma} + \bar{\mathbf{Q}}^{\Sigma}_{fric} + \bar{\mathbf{Q}}^{\Sigma}_{act}\right)\\ \mathbf{0}\end{bmatrix} + \mathbf{w} \equiv \mathcal{F}(\mathbf{X}) + \mathbf{w}, \tag{2}$$

where $\mathbf{w}$ is Gaussian zero mean white noise. The continuous time model is discretized using exponential integration resulting in a discrete time system model that can be directly applied to discrete extended Kalman filter framework.

4 Results and conclusion

Parameter identification and force estimation framework was tested with a numerical example based on Stäubli TX40 robot, of which inertia parameters can be found from the literature [5]. However, the coupling between last two joints, characteristic for this robot, was neglected for simplicity. Figure 2a presents the system identification results with artificially created measurements. Actuation torques and positions were considered as measurements and both were augmented with noise. In the figure, x-axis represents a minimum set of inertia parameters, given that the other inertia parameters are assumed to be zeros. In the figure, I refers to a component of body inertia tensor, J_a is an actuator inertia, mX, mY and mZ refer to first moments of mass with respect to a joint, σ is a viscous friction coefficient, and F_c is a Coulomb friction coefficient. It should be noted that the physical inconsistency of some of the inertia parameters in the figure (*e.g.* negative moments of inertia) is because of grouping effects of total set of standard parameters being reduced to a set of base parameters. Correspondingly, Fig. 2b shows the comparison between the applied external force and the estimated force.



(a) Identified base parameters*

(b) Estimated forces

Figure 2: System identification and force estimation results

*Key for Fig. 2a x-axis: 1:I_{1zz}, 2:I_{2xx}, 3:I_{2zz}, 4:I_{2xy}, 5:I_{2zx}, 6:I_{2yz}, 7:m_2X_2, 8:m_2Y_2, 9:I_{3xx}, 10:I_{3zz}, 11:I_{3xy}, 12:I_{3zx}, 13:I_{3yz}, 14:m_3X_3, 15:m_3Y_3, 16:J_{a3}, 17:I_{4xx}, 18:I_{4zz}, 19:I_{4xy}, 20:I_{4zx}, 21:I_{4yz}, 22:m_4X_4, 23:m_4Y_4, 24:J_{a4}, 25:I_{5xx}, 26:I_{5zz}, 27:I_{5xy}, 28:I_{5zx}, 29:I_{5yz}, 30:m_5X_5, 31:m_5Y_5, 32:J_{a5}, 33:I_{6xx}, 34:I_{6zz}, 35:I_{6xy}, 36:I_{6zx}, 37:I_{6yz}, 38:m_6X_6, 39:m_6Y_6, 40:J_{a6}, 41:σ_1, 42:F_{c1}, 43:σ_2, 44:F_{c2}, 45:σ_3, 46:F_{c3}, 47:σ_4, 48:F_{c4}, 49:σ_5, 50:F_{c5}, 51:σ_6, 52:F_{c6}.

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