CODYCO Whole-body Compliant Dynamical Contacts in Cognitive Humanoids

Whole-body Compliant Dynamical Contacts in Cognitive Humanoids

proj. no. 600716

WP1: Systems Integration, Standardization and Evaluation on the iCub robot

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Outline

* T4.1 Improved Models from Real-Time Regression with Latent Contact Type Inference.
  - Parametric identification with arbitrary choices of the base link for accurate and computationally efficient torque and external-force estimation.
  - Maximum-a-posteriori dynamics

Whole-body dynamics identification for enhanced torque control

Premises

* On the iCub joint torques AND external-forces are estimated from embedded force/torque sensors.
* The algorithm is consists of reordering the recursive Newton-Euler algorithm. Specifically, the base link is chosen to coincide with the perceived location of external forces (requires skin sensor).

Problem

* Improving the above procedure by identifying the dynamic model.

Whole-body dynamics identification for enhanced torque control

Previous results

* Parameters estimated from base-force can be used to compute joint-torques.
  * With base-force sensing the so called base parameters can be identified.
  * With joint-torque sensing only a subset of the base parameters can be identified (Ayusawa et al., 2013) .

Problem (reformulated)

* Parameters estimated from base-force can be used to compute joint-torques AND external forces?

SEVENTH FRAMEWORK PROGRAMME

Identification with torque@joints

$$\begin{bmatrix} \mathbf{I}^c & \mathbf{F} \\ \mathbf{F}^\top & \mathbf{H} \end{bmatrix} \begin{bmatrix} {}^b\mathbf{a}_b \\ \ddot{\mathbf{q}} \end{bmatrix} + \begin{bmatrix} \mathbf{p}^c \\ \mathbf{n} \end{bmatrix} = \begin{bmatrix} \mathbf{0} \\ \boldsymbol{\tau} \end{bmatrix} + \sum_{l \in L} \begin{bmatrix} {}^b\mathbf{X}_l^* \\ \mathbf{J}_l^\top \end{bmatrix} \mathbf{f}_l$$

Articulated rigid body dynamics

$$\begin{bmatrix} \mathbf{I}^c & \mathbf{F} \\ \mathbf{F}^\top & \mathbf{H} \end{bmatrix} \begin{bmatrix} {}^b\mathbf{a}_b \\ \ddot{\mathbf{q}} \end{bmatrix} + \begin{bmatrix} \mathbf{p}^c \\ \mathbf{n} \end{bmatrix} = \begin{bmatrix} \mathbf{0} \\ \boldsymbol{\tau} \end{bmatrix} + \sum_{l \in L} \begin{bmatrix} {}^b\mathbf{X}_l^* \\ \mathbf{J}_l^\top \end{bmatrix} \mathbf{f}_l$$

Joint space dynamics

$$\boldsymbol{\tau} = \mathbf{F}^\top \mathbf{a}_b + \mathbf{H}(\mathbf{q})\ddot{\mathbf{q}} + \mathbf{n}(\mathbf{q}, \dot{\mathbf{q}}) - \sum_{l \in L} \mathbf{J}_l^\top \mathbf{f}_l$$

Assumption: known forces and base accelerations

$$\begin{aligned} \boldsymbol{\tau} &= \mathbf{F}^\top \mathbf{a}_b + \mathbf{Y}_{\boldsymbol{\tau}}(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}})\boldsymbol{\phi} - \sum_{l \in L} \mathbf{J}_l^\top \mathbf{f}_l \\ \boldsymbol{\phi}_l^\top &= \begin{bmatrix} m_l & m_l \mathbf{c}_l^\top & \mathrm{vech}(\bar{\mathbf{I}}_l)^\top \end{bmatrix}^\top \in \mathbb{R}^{10}, \end{aligned}$$

Parametric representation

$$\boldsymbol{\tau} = \mathbf{F}^\top \mathbf{a}_b + \mathbf{Y}_{\boldsymbol{\tau}}(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}}) \boldsymbol{B}_{\boldsymbol{\tau}} \boldsymbol{\phi}_{\boldsymbol{\tau}} - \sum_{l \in L} \mathbf{J}_l^\top \mathbf{f}_l$$

Identifiable parameters

Identification with force@base

$$\begin{bmatrix} \mathbf{I}^c & \mathbf{F} \\ \mathbf{F}^\top & \mathbf{H} \end{bmatrix} \begin{bmatrix} {}^b\mathbf{a}_b \\ \ddot{\mathbf{q}} \end{bmatrix} + \begin{bmatrix} \mathbf{p}^c \\ \mathbf{n} \end{bmatrix} = \begin{bmatrix} \mathbf{0} \\ \boldsymbol{\tau} \end{bmatrix} + \sum_{l \in L} \begin{bmatrix} {}^b\mathbf{X}_l^* \\ \mathbf{J}_l^\top \end{bmatrix} \mathbf{f}_l$$

Articulated rigid body dynamics

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Base dynamics

$$\mathbf{I}^c \mathbf{a}_b + \mathbf{F}\ddot{\mathbf{q}} + \mathbf{p}^c = \mathbf{f}_b + \sum_{\substack{l \in L \\ l \neq b}} {}^b\mathbf{X}_l^* \mathbf{f}_l$$

Assumption: known forces

$$\mathbf{Y}_b(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}})\boldsymbol{\phi} = \mathbf{f}_b + \sum_{\substack{l \in L \\ l \neq b}} {}^b\mathbf{X}_l^* \mathbf{f}_l$$

Parametric representation

$$\mathbf{Y}_b(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}})\boldsymbol{B}_b\boldsymbol{\phi}_b = \mathbf{f}_b + \sum_{\substack{l \in L \\ l \neq b}} {}^b\mathbf{X}_l^* \mathbf{f}_l$$

Base parameters

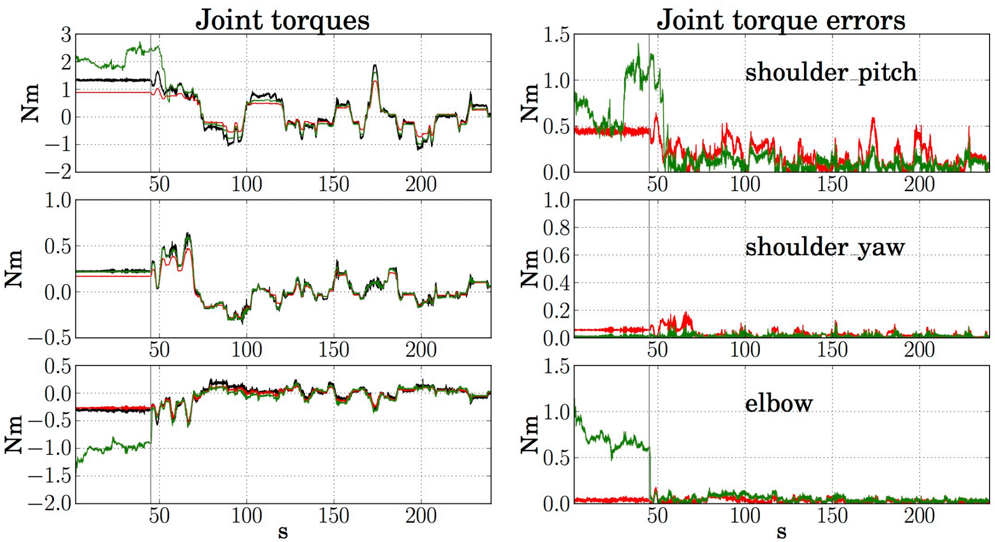
Identification with force@base

Proposition (Ayusawa et al., 2013)

The indefinable parameters subspace associated to joint torque measurements is a subspace of the one associated to base force measurements. In other terms, the parameters estimated with base forces can be used to predict joint torques.

Proposition (Traversaro et al., 2015)

The indefinable parameters subspace associated with different choices of the base link coincides with the subspace associated to a specific choice of the base link. In other terms, the parameters estimated with base forces can be used to predict joint torques and external-forces.



Open-source code:
https://github.com/robotology-playground/idyntree
S. Traversaro et al. (*ICRA 2015*)

Maximum-a-posteriori dynamics

Motivations:

* Cons: classical dynamics computations (e.g. inverse dynamics) rely on a subset of available sensors (e.g. inverse dynamics).
* Pros: classical computations are computationally efficient, e.g. RNEA is O(n).

Problem:

* Efficiently compute the dynamics by exploiting all available sensors, including force/torque sensors, gyros and accelerometers.

SEVENTH FRAMEWORK PROGRAMME

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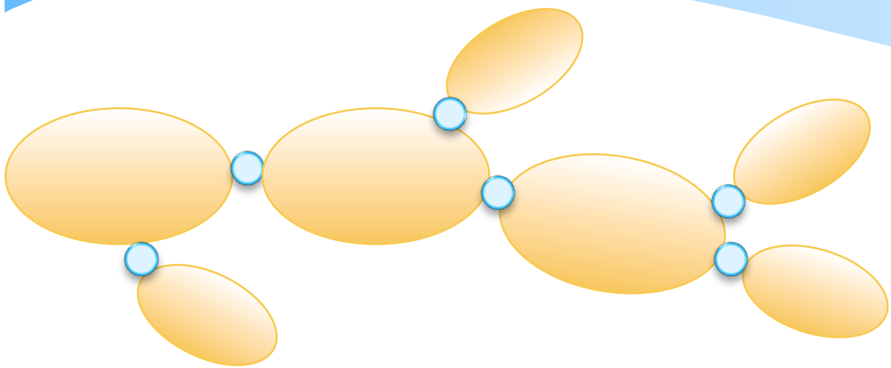
Notation



N_B: number of links

Joint quantities

$\boldsymbol{q}_i$: the joint i position,

$\dot{\boldsymbol{q}}_i$: the joint i velocity,

$\ddot{\boldsymbol{q}}_i$: the joint i acceleration,

$\boldsymbol{\tau}_i$: the joint i torque.

Link quantities

$\boldsymbol{v}_i$: the link spatial velocity,

$\boldsymbol{a}_i$: the link spatial accelerations,

$\boldsymbol{f}_i$: the spatial force transmitted to body i from $\lambda(i)$,

$\boldsymbol{f}_i^x$: external forces acting on body i.

Dynamic variables

$$\boldsymbol{d}_i = \begin{bmatrix} \boldsymbol{a}_i \\ \boldsymbol{f}_i \\ \boldsymbol{\tau}_i \\ \boldsymbol{f}_i^x \\ \ddot{\boldsymbol{q}}_i \end{bmatrix}, \quad \boldsymbol{d} = \begin{bmatrix} \boldsymbol{d}_1 \\ \vdots \\ \boldsymbol{d}_{N_B} \end{bmatrix}$$

Joint positions

$$\boldsymbol{q} = \begin{bmatrix} \boldsymbol{q}_1 \\ \vdots \\ \boldsymbol{q}_{N_B} \end{bmatrix}$$

Joint velocities

$$\dot{\boldsymbol{q}} = \begin{bmatrix} \dot{\boldsymbol{q}}_1 \\ \vdots \\ \dot{\boldsymbol{q}}_{N_B} \end{bmatrix}$$

Spatial transformations

Spatial transformations

${}^{j}\boldsymbol{X}_i$: motion-vector transform from link i to j,

${}^{j}\boldsymbol{X}_i^*$: force-vector transform from link i to j,

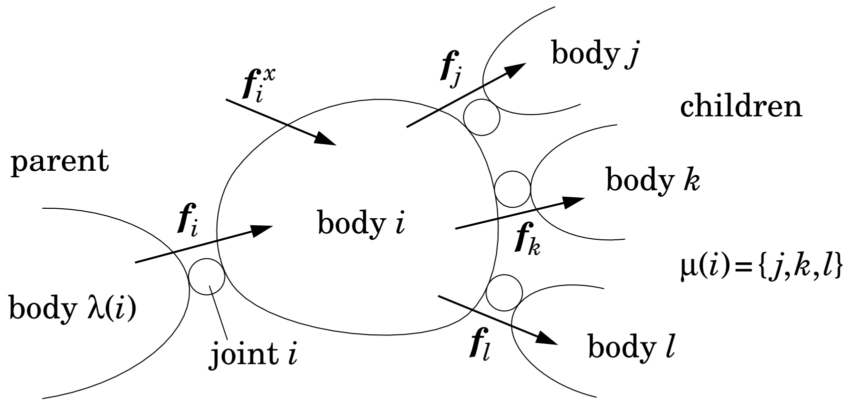
$\boldsymbol{I}_i$: spatial inertia tensor link i,

$(\boldsymbol{v})_l$: linear component,

$(\boldsymbol{v})_a$: angular component,

$\times$: cross product on spatial motions,

$\times^*$: cross product on spatial forces.



Link velocities

$$\boxed{\boldsymbol{v}_i = {}^{i}\boldsymbol{X}_{\lambda(i)}\boldsymbol{v}_{\lambda(i)} + \boldsymbol{S}_i\dot{\boldsymbol{q}}_i,} \Rightarrow \boxed{\boldsymbol{v}_i(\boldsymbol{q},\dot{\boldsymbol{q}})}$$

SEVENTH FRAMEWORK PROGRAMME

Measurement equation and dynamical consistency

Dynamic and kinematic constraints

$$\begin{aligned}
\boldsymbol{\tau}_i &= \boldsymbol{S}_i^\top \boldsymbol{f}_i, \\
\boldsymbol{a}_i &= {}^i\boldsymbol{X}_{\lambda(i)}(\boldsymbol{q}_i)\boldsymbol{a}_{\lambda(i)} + \boldsymbol{S}_i\ddot{\boldsymbol{q}}_i + \boldsymbol{v}_i \times \boldsymbol{S}_i\dot{\boldsymbol{q}}_i, \\
\boldsymbol{f}_i &= \boldsymbol{I}_i\boldsymbol{a}_i - \boldsymbol{f}_i^x + \sum_{j\in\mu(i)} {}^i\boldsymbol{X}_j^*(\boldsymbol{q}_j)\boldsymbol{f}_j + \boldsymbol{v}_i \times^* \boldsymbol{I}_i\boldsymbol{v}_i
\end{aligned}$$

$$\boxed{\boldsymbol{D}(\boldsymbol{q})\boldsymbol{d} + \boldsymbol{b}_D(\boldsymbol{q},\dot{\boldsymbol{q}}) = \boldsymbol{0}}$$

Measurement equations

$$\begin{aligned}
\boldsymbol{y}_{acc} &= ({}^s\boldsymbol{X}_i\boldsymbol{a}_i)_l + ({}^s\boldsymbol{X}_i\boldsymbol{v}_i)_a \times ({}^s\boldsymbol{X}_i\boldsymbol{v}_i)_l, \\
\boldsymbol{y}_{gyr} &= {}^sR_i(\boldsymbol{v}_i)_a, \\
\boldsymbol{y}_{fts} &= {}^s\boldsymbol{X}_i^*(\boldsymbol{f}_i - \boldsymbol{I}_{im}\boldsymbol{a}_i - \boldsymbol{v}_i \times^* \boldsymbol{I}_{im}\boldsymbol{v}_i), \\
\boldsymbol{y}_{skn} &= {}^s\boldsymbol{X}_i^*\boldsymbol{P}_\perp^s\boldsymbol{f}_i^x.
\end{aligned}$$

$$\boxed{\boldsymbol{Y}(\boldsymbol{q},\dot{\boldsymbol{q}})\boldsymbol{d} + \boldsymbol{b}_Y(\boldsymbol{q},\dot{\boldsymbol{q}}) = \boldsymbol{y}.}$$

$$\begin{bmatrix}\boldsymbol{D}(\boldsymbol{q}) \\ \boldsymbol{Y}(\boldsymbol{q},\dot{\boldsymbol{q}})\end{bmatrix}\boldsymbol{d} + \begin{bmatrix}\boldsymbol{b}_D(\boldsymbol{q},\dot{\boldsymbol{q}}) \\ \boldsymbol{b}_Y(\boldsymbol{q},\dot{\boldsymbol{q}})\end{bmatrix} = \begin{bmatrix}\boldsymbol{0} \\ \boldsymbol{y}\end{bmatrix}, \quad \begin{bmatrix}\boldsymbol{D}(\boldsymbol{q}) \\ \boldsymbol{Y}(\boldsymbol{q},\dot{\boldsymbol{q}})\end{bmatrix} \text{ will be assumed full column rank,}$$

Problem 1: estimation

$\boxed{\text{ESTIMATION: estimate } \boldsymbol{d} \text{ given } \boldsymbol{y}.}$

$$p(\boldsymbol{d},\boldsymbol{y}) = p(\boldsymbol{d})p(\boldsymbol{y}|\boldsymbol{d})$$

$$\boxed{\boldsymbol{D}(\boldsymbol{q})\boldsymbol{d} + \boldsymbol{b}_D(\boldsymbol{q},\dot{\boldsymbol{q}}) = \boldsymbol{0}}$$

$$\boxed{\boldsymbol{Y}(\boldsymbol{q},\dot{\boldsymbol{q}})\boldsymbol{d} + \boldsymbol{b}_Y(\boldsymbol{q},\dot{\boldsymbol{q}}) = \boldsymbol{y}.}$$

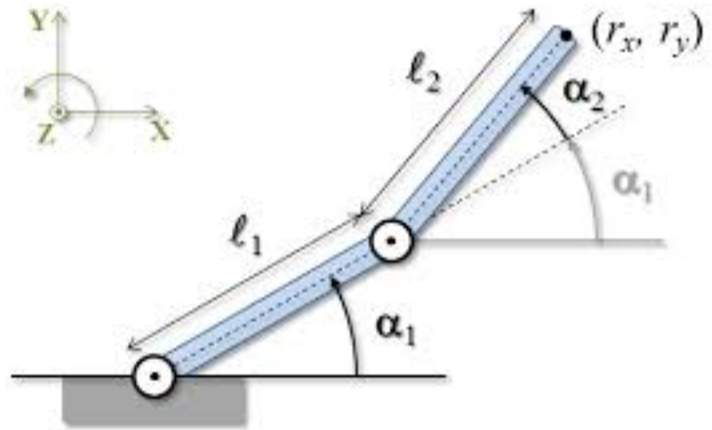
$$\boxed{\begin{aligned} p(\boldsymbol{d}) &\propto \exp\left\{\boldsymbol{e}(\boldsymbol{d})^\top \boldsymbol{\Sigma}_D^{-1}\boldsymbol{e}(\boldsymbol{d})\right\}, \\ \boldsymbol{e}(\boldsymbol{d}) &= \boldsymbol{D}(\boldsymbol{q})\boldsymbol{d} + \boldsymbol{b}_D(\boldsymbol{q},\dot{\boldsymbol{q}}), \end{aligned}}$$

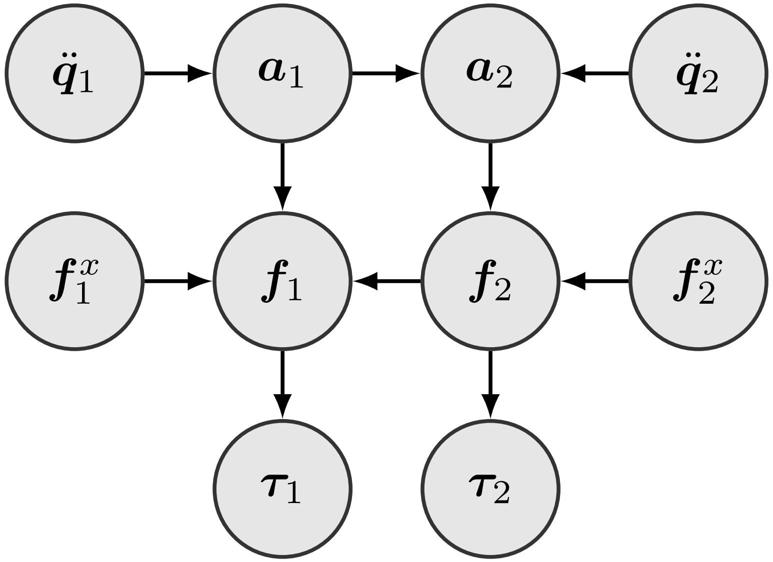
$$\boxed{\begin{aligned} p(\boldsymbol{y}|\boldsymbol{d}) &\sim \mathcal{N}\left(\boldsymbol{\mu}_y, \boldsymbol{\Sigma}_y\right), \\ \boldsymbol{\mu}_y &= Y(\boldsymbol{q},\dot{\boldsymbol{q}})\boldsymbol{d} + \boldsymbol{b}_Y(\boldsymbol{q},\dot{\boldsymbol{q}}), \end{aligned}}$$

$$\boldsymbol{d}_{map} = \arg\max_d p(\boldsymbol{d}|\boldsymbol{y}),$$

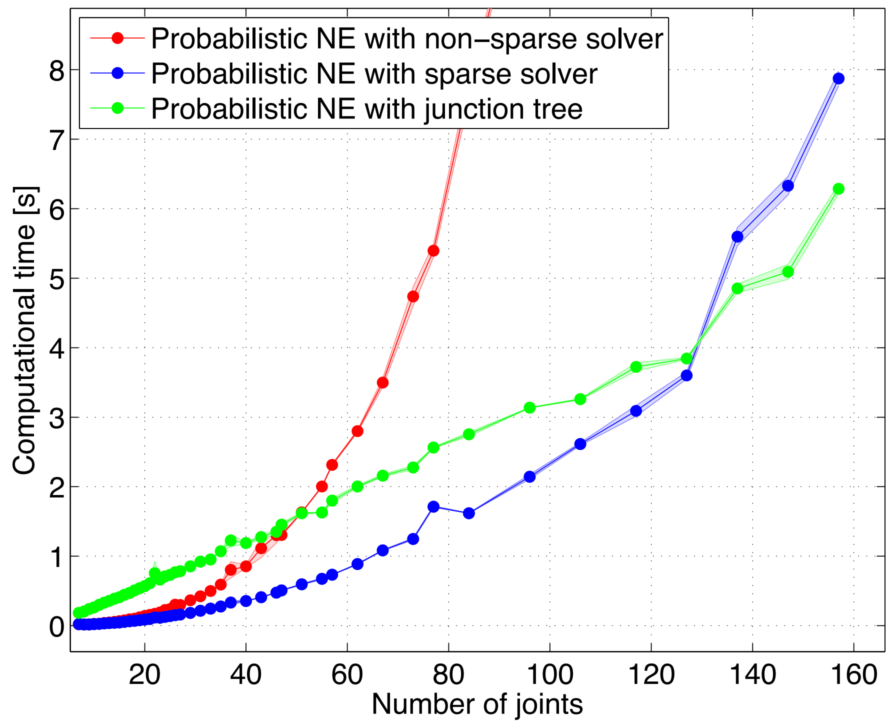
$$\boldsymbol{d}_{map} = \left(\boldsymbol{D}^\top\boldsymbol{\Sigma}_D^{-1}\boldsymbol{D} + \boldsymbol{Y}^\top\boldsymbol{\Sigma}_y^{-1}\boldsymbol{Y}\right)^{-1} \cdot \left(\boldsymbol{Y}^\top\boldsymbol{\Sigma}_y^{-1}(\boldsymbol{y} - \boldsymbol{b}_Y) - \boldsymbol{D}^\top\boldsymbol{\Sigma}_D^{-1}\boldsymbol{b}_D\right).$$

Computational efficiency





Computations have been optimized by exploiting the matrices sparsity.



Open-source code: https://github.com/iron76/bnt_time_varying

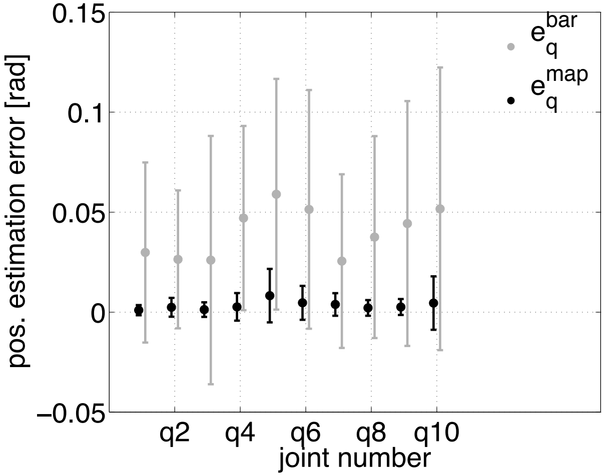
Problem 2: state estimation

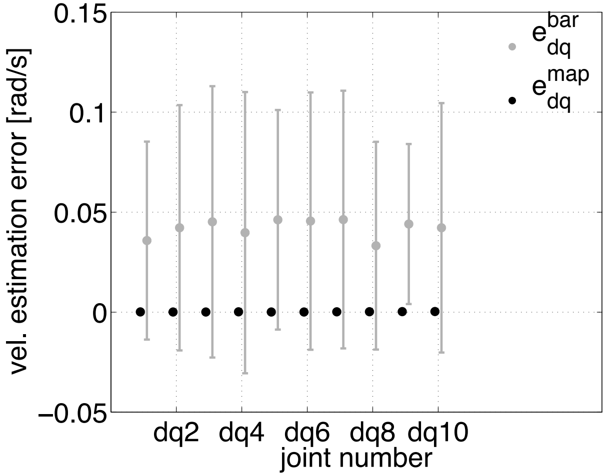
STATE ESTIMATION: estimate $\boldsymbol{q}$, $\dot{\boldsymbol{q}}$ given $\boldsymbol{y}$.

$$\begin{bmatrix} \boldsymbol{D}(\boldsymbol{q}) \\ \boldsymbol{Y}(\boldsymbol{q}, \dot{\boldsymbol{q}}) \end{bmatrix} \boldsymbol{d} + \begin{bmatrix} \boldsymbol{b}_D(\boldsymbol{q}, \dot{\boldsymbol{q}}) \\ \boldsymbol{b}_Y(\boldsymbol{q}, \dot{\boldsymbol{q}}) \end{bmatrix} = \begin{bmatrix} \boldsymbol{0} \\ \boldsymbol{y} \end{bmatrix}, \qquad \boldsymbol{x} = \begin{bmatrix} \boldsymbol{q} \\ \dot{\boldsymbol{q}} \end{bmatrix}$$

First order approximation around $\bar{\boldsymbol{d}}$, $\bar{\boldsymbol{x}}$

$$\begin{bmatrix} \boldsymbol{D}(\bar{\boldsymbol{x}}) & \partial \boldsymbol{b}_D(\bar{\boldsymbol{d}}, \bar{\boldsymbol{x}}) \\ \boldsymbol{Y}(\bar{\boldsymbol{x}}) & \partial \boldsymbol{b}_Y(\bar{\boldsymbol{d}}, \bar{\boldsymbol{x}}) \end{bmatrix} \begin{bmatrix} \boldsymbol{d} \\ \boldsymbol{x} \end{bmatrix} + \begin{bmatrix} \boldsymbol{b}_D(\bar{\boldsymbol{x}}) - \partial \boldsymbol{b}_D(\bar{\boldsymbol{d}}, \bar{\boldsymbol{x}})\bar{\boldsymbol{x}} \\ \boldsymbol{b}_Y(\bar{\boldsymbol{x}}) - \partial \boldsymbol{b}_Y(\bar{\boldsymbol{d}}, \bar{\boldsymbol{x}})\bar{\boldsymbol{x}} \end{bmatrix} = \begin{bmatrix} \boldsymbol{0} \\ \boldsymbol{y} \end{bmatrix}$$





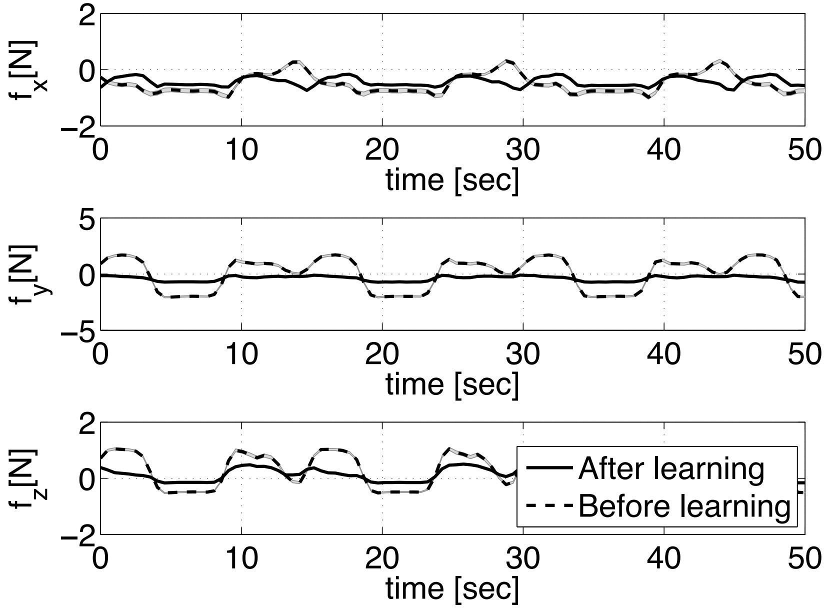
Problem 3: hyper-parameter estimation

HYPERPARAMETER ESTIMATION: estimate $\boldsymbol{\Sigma}_y$ and $\boldsymbol{\Sigma}_d$ given $\boldsymbol{y}$.

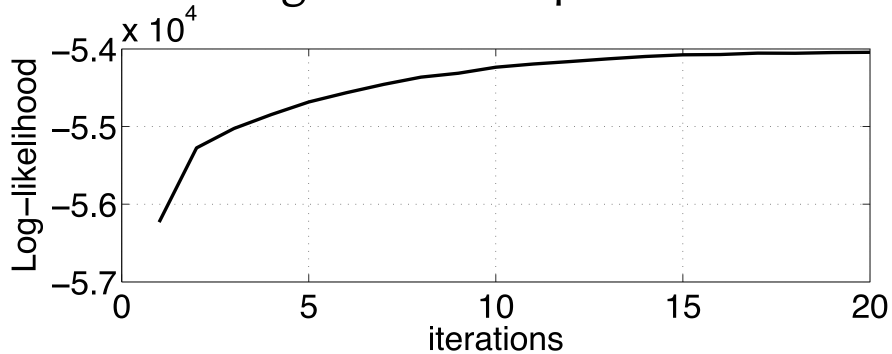
E-step $\quad Q(\boldsymbol{\theta}|\boldsymbol{\theta}^t) = \sum_t E_{\boldsymbol{d}|\boldsymbol{y}^t;\boldsymbol{\theta}^t}\left[\log p(\boldsymbol{d}, \boldsymbol{y}^t; \boldsymbol{\theta}, t)\right],$

M-step $\quad \boldsymbol{\theta}^{t+1} = \arg\max_{\boldsymbol{\theta}} Q(\boldsymbol{\theta}|\boldsymbol{\theta}^t).$

External force estimation



Log-likelihood optimization



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