Floating Base Rigid Body Dynamics Estimation

Francesco Nori, Jorhabib Eljaik

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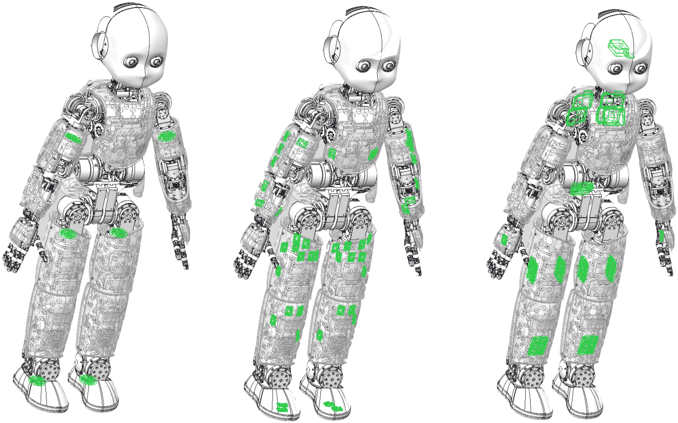
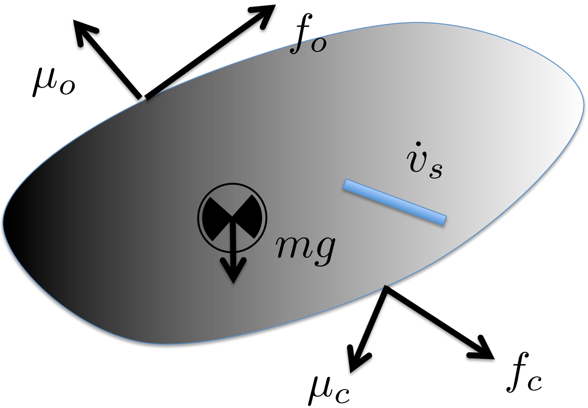
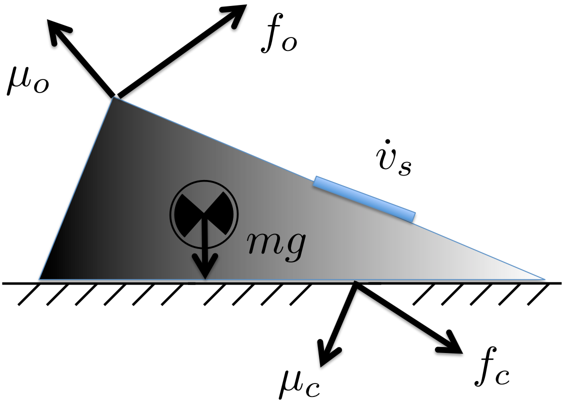
Sensor fusion on the iCub



Sensor fusion on the iCub



Sensor fusion on the iCub



Sensor fusion on the iCub

$$
\begin{aligned}
m\dot{v}^B + \omega^B \times (mv^B) &= f_1^B + ... + f_n^B + mg^B \\
I^B\dot{\omega}^B + \omega^B \times (I^B\omega^B) &= \mu_1^B + ... + \mu_n^B
\end{aligned}
$$

- I^B : inertia in the body reference frame
- m : mass of the rigid body
- f_i^B : i-th force expressed in the body reference frame
- μ_i^B : i-th torque expressed in the body reference frame
- ω^B: angular velocity expressed in the body reference frame
- v^B : linear velocity in the body reference frame
- q : quaternion representing the rigid body orientation

Sensor fusion on the iCub

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I^B \dot{\omega}^B + \omega^B \times (I^B \omega^B) &= \mu_1^B + \ldots + \mu_n^B
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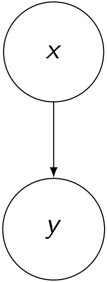
- ω^B: angular velocity expressed in the body reference frame
- $\dot{v}^B$: linear acceleration in the body reference frame
- q : quaternion representing the rigid body orientation

Bayesian Network for a Floating Base Rigid Body System



$$x = \begin{bmatrix} v^B & \omega^B & f_o & \mu_o & f_c & \mu_c \end{bmatrix}^T$$

$$y = \begin{bmatrix} f_o & \mu_o & f_c & \mu_c & \dot{v}^B \end{bmatrix}^T$$

The Extended Kalman Filter

Given a nonlinear system:

$$y_k = h(x) + \rho_m \tag{1}$$

$$x_k = f(x_{k-1}) + \rho_p \tag{2}$$

Where y, the measurement vector and x, the state vector have gaussian uncertainties.

After linearizing our dynamical system about an estimate of the current state $x_{k|k-1}$, the corresponding Extended Kalman Filter can be obtained following a **prediction** and **update** steps.

Prediction

$$\mathbf{x}_{k|k-1} = f(\mathbf{x}_{k-1|k-1})$$

Update

$$\mathbf{x}_{k|k} = x_{k|k-1} + K_k(y_k - h(\mathbf{x}_{k|k-1}))$$

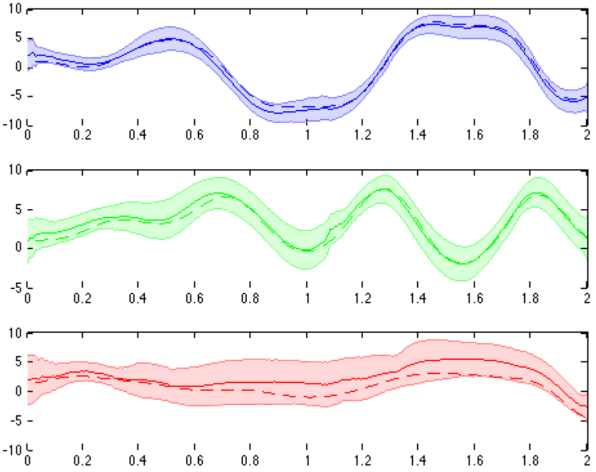
The Extended Kalman Filter

Linearized measurement model: $y = Cx + e$ where:

$$
\mathrm{y} = \begin{pmatrix} 0 & 0 & \mathbf{I} & 0 & 0 & 0 \\ 0 & 0 & 0 & \mathbf{I} & 0 & 0 \\ 0 & 0 & 0 & 0 & \mathbf{I} & 0 \\ 0 & 0 & 0 & 0 & 0 & \mathbf{I} \\ S(\bar{\omega}_B) & -S(\bar{V}_B) & \mathbf{I} & 0 & \mathbf{I} & 0 \end{pmatrix} \mathrm{x} + \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ S(\bar{V}^B)\bar{\omega}^B \end{pmatrix}
$$

Extended Kalman Filter results

Linear Velocities smoothing



Extended Kalman Filter results

Angular velocities smoothing