Arne Wahrburg[(*)], 2016-10-14

Cartesian Contact Force and Torque Estimation for Redundant Manipulators

IROS'16 Workshop: The Mechatronics behind Force/Torque Controlled Robot Actuation – Secrets & Challenges

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CCFE for Redundant Manipulators
Content

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- Estimating Cartesian Contact Forces and Torques
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- Applications of Force / Torque Estimation
  - Sensorless Null-Space Admittance
  - Sensorless Cartesian Admittance

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Joint Load Torque Estimation

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Straightforward Approach to Load Torque Estimation

- Rigid joint manipulator dynamics

$$M(q)\ddot{q} + C(q,\dot{q})\dot{q} + G(q) + \tau_{fric} + \tau_{ext} = \tau_{mot}$$

[Stolt et al. 2012],
[Stolt et al. 2015]

- Static approach: Solve dynamics for τ_{ext}

$$M\ddot{q} + C\dot{q} + G + \tau_{fric} + \tau_{ext} = \tau_{mot}$$

$$\Downarrow$$

$$\hat{\tau}_{ext} = \tau_{mot} - \tau_{fric} - M\ddot{q} - C\dot{q} - G$$

- Calculating $\ddot{q}$ → noise amplification
- Practical solution: Assume $\ddot{q} = 0$
  - Much less low-pass filtering needed…
  - …but acceleration spikes occur

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Generalized Momentum Observer Approach

- Generalized Momentum Observer approach: Reformulate manipulator dynamics in different coordinates to get rid of $\ddot{q}$

[De Luca and Mattone 2003], [De Luca et al. 2006],

- Introduce $p = M(q) \cdot \dot{q}$ and reformulate manipulator dynamics

$$\dot{p} = \tau_{mot} + C^T \dot{q} - G - \tau_{fric} - \tau_{ext}$$

- Choose diagonal L and implement

$$\dot{\hat{p}} = \tau_{mot} + C^T \dot{q} - G - \tau_{fric} + L(p - \hat{p})$$
$$\hat{\tau}_{ext} = -L(p - \hat{p})$$

- Diagonal matrix L results in $\hat{\tau}_{ext,i} = \frac{l_i}{s+l_i} \cdot \tau_{ext,i}$

Estimates are decoupled, can be shown to be a special case of Fault Isolation Observers, [Ding2013, Wahrburg et al. 2015]

+ Reduced acceleration spikes

– Higher demands on model quality & implementation effort

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General Remarks on Joint Load Torque Estimation

- Do not expect miracles – model quality matters a lot
  - Gravity, Friction, Inertia, Coriolis, other disturbances
- There is no such thing as “joint load torque sensing”
  - Even with joint torque sensors, you need a good model

- Desired results of joint level estimation
  - Joint load torque estimates (good)
  - Information about uncertainty in load torque estimates (even better)
    → How much to “trust” estimates in subsequent steps?

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Cartesian Contact Force (and Torque) Estimation

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General Remarks on CCFE

- Assumption: Contact at the TCP only
  - Results will be corrupted if assumption is not met
  - Alternative: Estimation of contact point

[Buondonno and De Luca 2016]

- For pure TCP contact

$$\tau_{ext} = J(q)^T \cdot f$$

Load torques induced by wrench applied to TCP

TCP-Jacobian w.r.t. base frame

Cartesian wrench, $f = \begin{bmatrix} f_x \\ f_y \\ f_z \\ \tau_x \\ \tau_y \\ \tau_z \end{bmatrix}$

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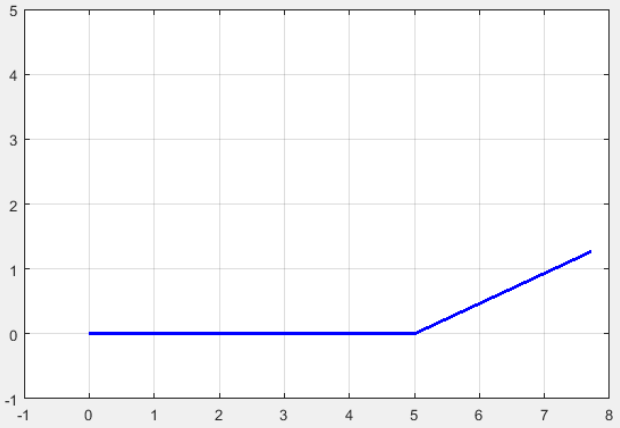
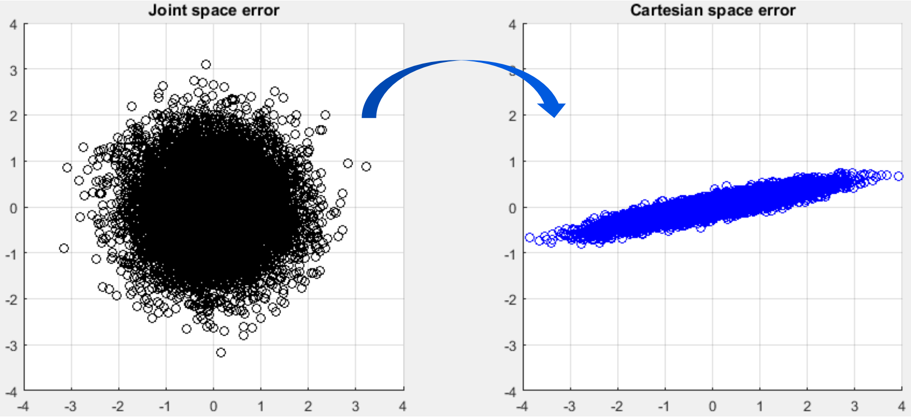
Mapping from Joint to Cartesian Space

- How to find $\hat{f}$, given joint space estimates $\hat{\tau}_{ext}$?
- Intuitive approach: Invert $\tau_{ext} = J(q)^T \cdot f$

$$\Rightarrow \hat{f} = (J(q)^T)^{-1} \cdot \hat{\tau}_{ext} = W(q) \cdot \hat{\tau}_{ext}$$

- What's the effect of uncertainty?
  - $\hat{\tau}_{ext} = \tau_{ext} + e_j,\ \mathbb{E}[e_j] = 0, \mathrm{Var}[e_j] = \Sigma_j$





- Background: Transformation of covariance, $\Sigma_f(q) = W(q) \cdot \Sigma_j \cdot W(q)^T$

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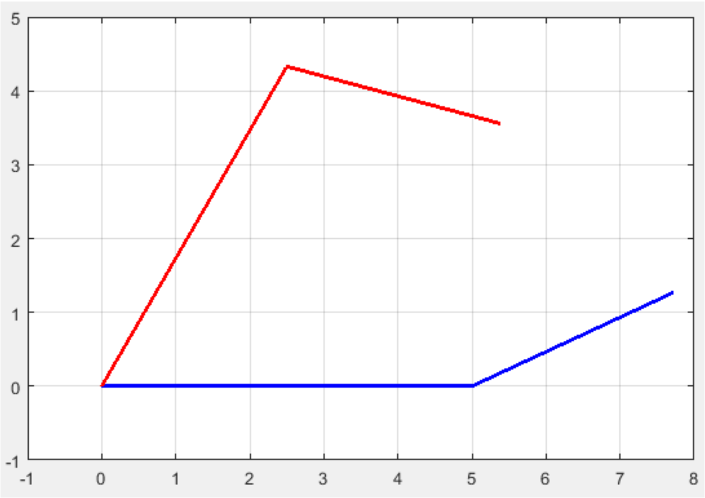
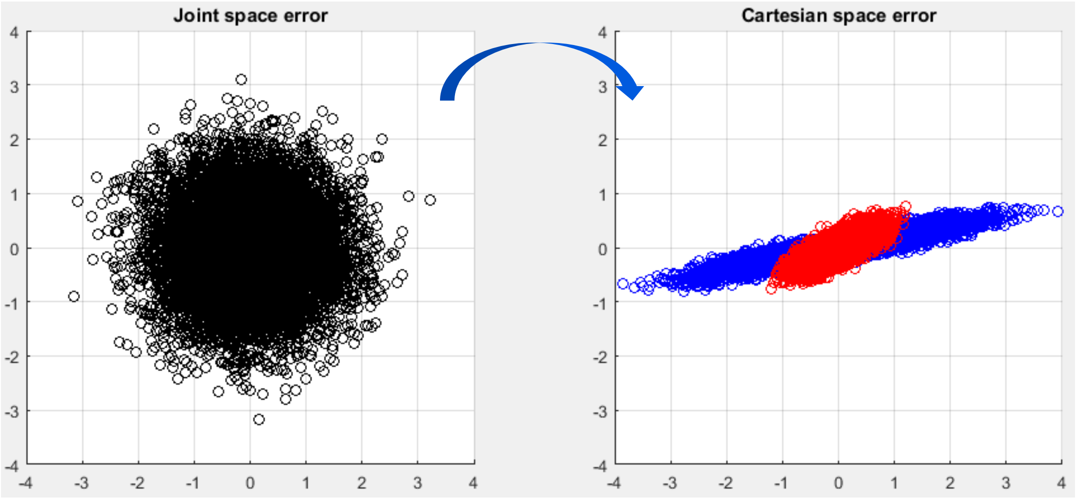
Configuration Dependency

- Important to notice: $\Sigma_f(q) = W(q) \cdot \Sigma_j \cdot W(q)^T$





- Same uncertainty in joint space but
  varying uncertainty in Cartesian space

→ Cartesian estimation accuracy is configuration dependent

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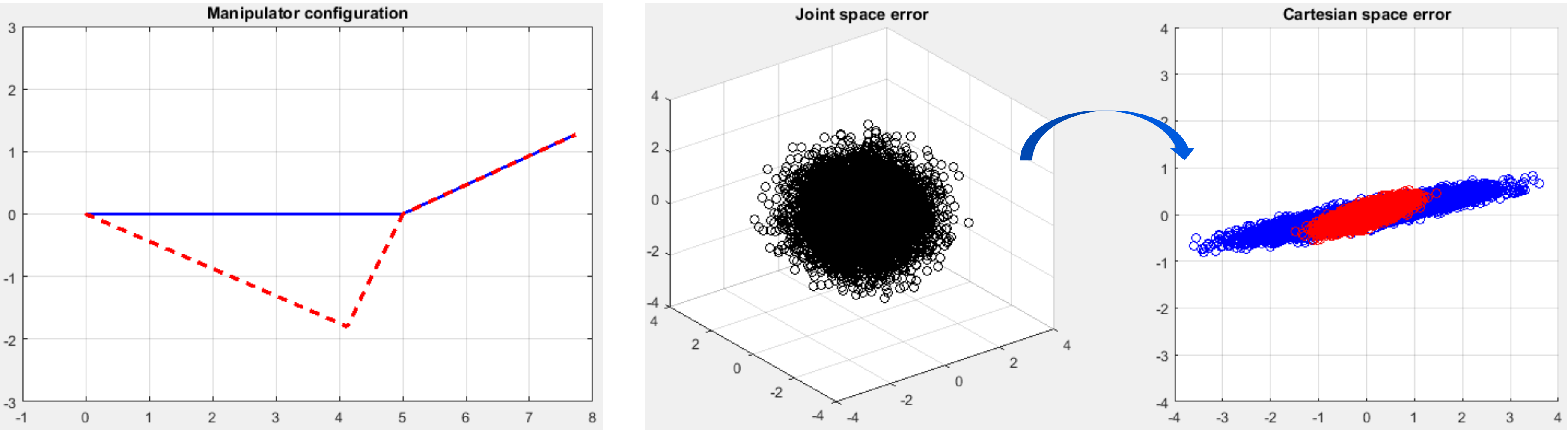
General Effect of Redundancy

- What about redundant manipulators?
- Intuitive approach: Use pseudo-inverse

$$\Rightarrow \hat{f} = (J(q)^T)^{+} \cdot \hat{\tau}_{ext} = W(q) \cdot \hat{\tau}_{ext}$$



- Reduced variance in Cartesian space

→ More information(*) ⇒ better results

(*)of the same quality

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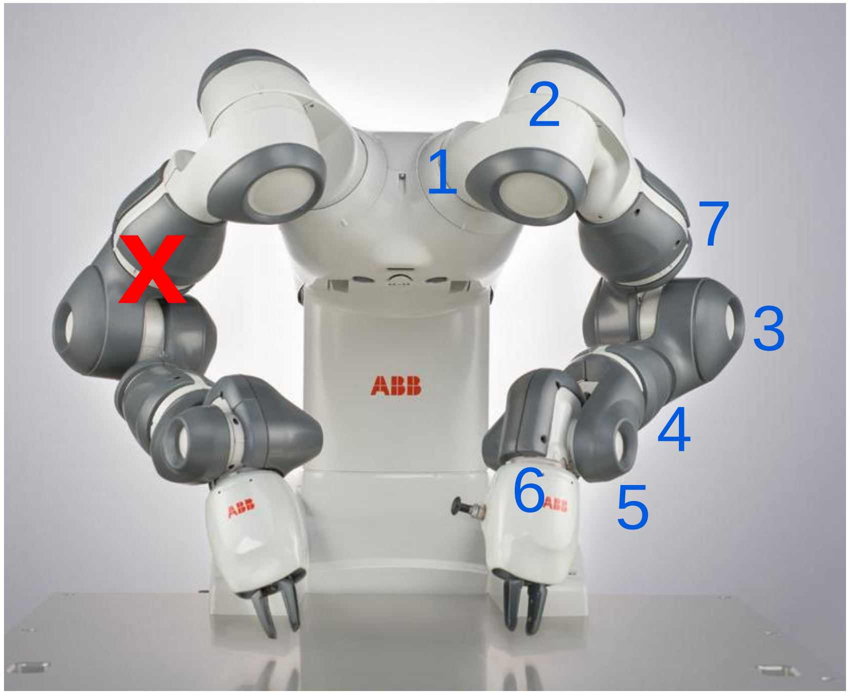
General Effect of Redundancy

- YuMi example
  Comparing the 7 DoF YuMi to a "virtually 6 DoF" YuMi

- Assuming $\Sigma_j = I$
  (all joints are the same)

Component	Change of variance (7 DoF compared to 6 DoF)
f_x	-5.09%
f_y	-49.22%
f_z	-13.17%
τ_x	-49.49%
τ_y	-0.18%
τ_z	-8.96%



- Significant reduction of variance for some components
  (but keep configuration dependency in mind!)

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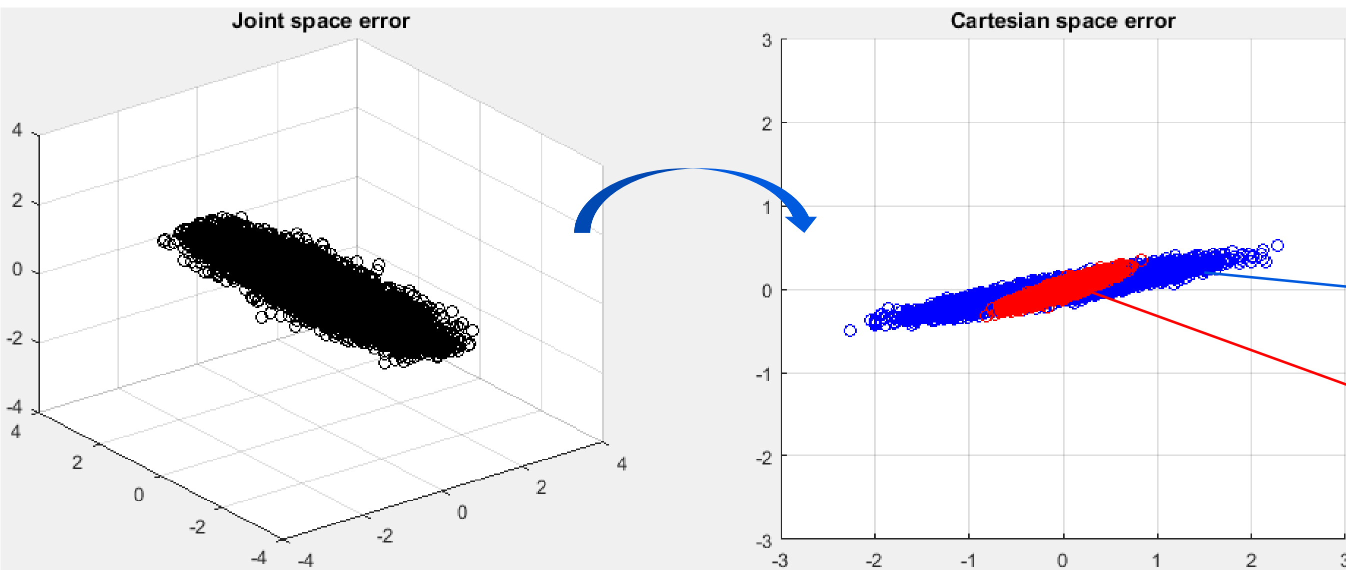
Exploiting Joint Space Prior Information

[Stolt et al. 2012], [Wahrburg et al. 2014]

- How to exploit prior knowledge in joint space?
  → joint-level estimation quality differs among joints ($\Sigma_j \neq I$)

- Maximum likelihood estimator $\hat{f} = \underbrace{\left(J(q) \cdot \Sigma_j^{-1} \cdot J(q)^T\right)^{-1} \cdot J(q) \cdot \Sigma_j^{-1}}_{W(q) = (J(q)^T)^{\#}_{\Sigma_j}} \cdot \hat{\tau}_{ext}$



Example:
$\Sigma_j = \mathrm{diag}(0.4; 1.6; 0.1)$

$(J(q)^T)^+$

$(J(q)^T)^{\#}_{\Sigma_j}$

→ Prior knowledge in joint space improves Cartesian estimation

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Exploiting Joint Space Prior Information

- YuMi example: $J(q) \in \mathbb{R}^{6\times 7}$
- Artificial joint space covariance: $\Sigma_j = \mathrm{diag}(1,1,1,1,1,1,100)$
  → all joints are the same except for J7

$$(J^T)^+ = \begin{bmatrix} 2.35 & 1.63 & -5.73 & 0.01 & 3.12 & 0.44 & 0.63 \\ 2.78 & -0.15 & -1.80 & -0.88 & -0.77 & -0.86 & -1.46 \\ 0.28 & 1.53 & 1.52 & 0.45 & -2.27 & 1.46 & 0.52 \\ 0.26 & -0.48 & -0.02 & 0.32 & 0.38 & -0.36 & 0.34 \\ -0.01 & -0.08 & 0.14 & 0.33 & -0.72 & 0.52 & -0.02 \\ -0.02 & 0.18 & -0.21 & 0.22 & 0.85 & 0.52 & -0.13 \end{bmatrix}$$

$$(J^T)^{\#}_{\Sigma_j} = \begin{bmatrix} 2.04 & 2.28 & -5.86 & 1.12 & 3.04 & -0.31 & 0.00 \\ 3.51 & -1.51 & -1.51 & -3.47 & -0.54 & 0.88 & -0.00 \\ 0.02 & 2.07 & 1.42 & 1.37 & -2.35 & 0.84 & 0.00 \\ 0.09 & -0.13 & -0.09 & 0.92 & 0.33 & -0.76 & 0.00 \\ -0.01 & -0.09 & 0.15 & 0.31 & -0.72 & 0.54 & -0.00 \\ 0.04 & 0.05 & -0.19 & -0.01 & 0.87 & 0.67 & -0.00 \end{bmatrix}$$

Result (e.g.)

$$\sigma^2_{f_x}\Big|_{+} = 4050$$

$$\sigma^2_{f_x}\Big|_{\#} = 54.28$$

Information from J7 not used because it's known to be "bad"

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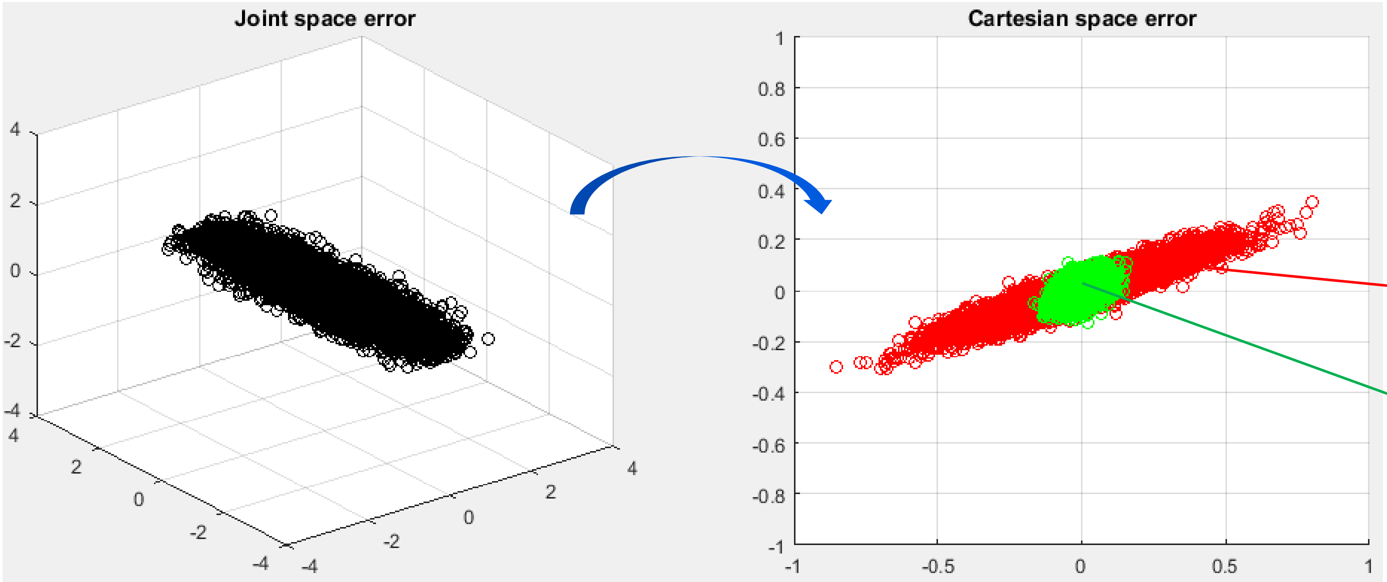
Exploiting Cartesian Space Prior Information

[Stolt et al. 2012], [Wahrburg et al. 2014]

- How to exploit prior knowledge in Cartesian space? $(\bar{\Sigma}_f^{-1} \neq 0)$
- Maximum a-posteriori estimator

$$\hat{f} = \underbrace{\left(J(q)\cdot\Sigma_j^{-1}\cdot J(q)^T + \bar{\Sigma}_f^{-1}\right)^{-1}\cdot J(q)\cdot\Sigma_j^{-1}}_{W(q) = (J(q)^T)^{\#}_{\Sigma_j,\Sigma_f}}\cdot\hat{\tau}_{ext}$$



Example:
$\bar{\Sigma}_f = \mathrm{diag}(0.1; 1.0)$

$(J(q)^T)^{\#}_{\Sigma_j}$

$(J(q)^T)^{\#}_{\Sigma_j,\Sigma_f}$

→ Prior on Cartesian estimates can substantially reduce variance

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Direct Estimation in Cartesian Space

[Wahrburg et al. 2015]

- Improved Cartesian estimation: Kalman filter approach
- Formulating an augmented system

$$\begin{bmatrix} \dot{p} \\ \dot{f} \end{bmatrix} = \begin{bmatrix} 0 & -J^T \\ 0 & 0 \end{bmatrix} \begin{bmatrix} p \\ f \end{bmatrix} + \begin{bmatrix} I \\ 0 \end{bmatrix} \bar{\tau} + \begin{bmatrix} w_p \\ w_f \end{bmatrix},$$

$$p_{meas} = \begin{bmatrix} I & 0 \end{bmatrix} \begin{bmatrix} p \\ f \end{bmatrix} + v$$

  - $\bar{\tau} = \tau_{mot} + C^T \dot{q} - G - \tau_{fric}$
  - Standard disturbance observer assumption: $\dot{\mathrm{f}} = 0$
  - Estimate obtained from $\hat{\mathrm{f}} = \begin{bmatrix} 0 & I \end{bmatrix} \hat{x}$
- No inversion of $J(q)^T$
- Joint space prior taken into account by $w_p \sim \mathcal{N}(0, \Sigma_j)$
- Superior performance compared to „joint-space detour“

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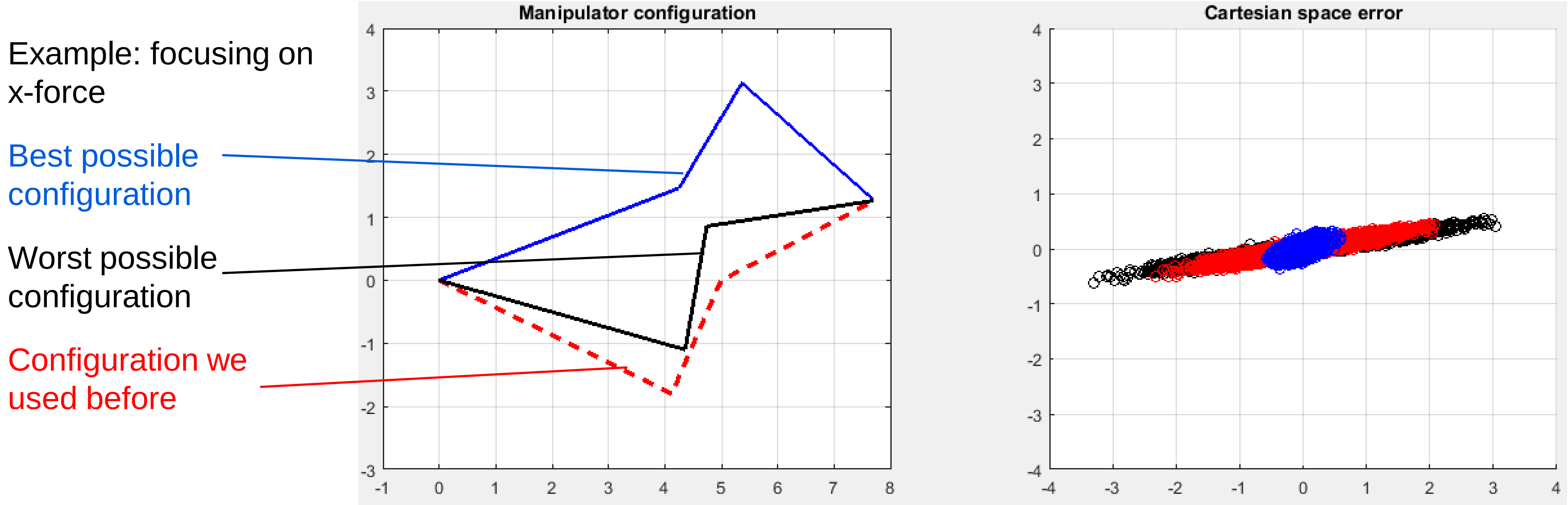
CCFE for Redundant Manipulators
Actively Exploiting Redundancy w.r.t. CCFE

[Wahrburg et al. 2016]

- How to actively exploit redundancy w.r.t. CCFE?
  → For a given TCP pose, there are infinitely many configurations…which one is the best for CCFE?
- Solve optimization problem $\underset{q \in \{\mathcal{N}(x_{TCP}) \cap \mathcal{A}\}}{\text{minimize}} \; \text{tr}\left(\Lambda\left(J(q)\Sigma_j^{-1}J^T(q) + \bar{\Sigma}_f^{-1}\right)^{-1}\right)$

Example: focusing on x-force



- Real-world example: s. IROS'16 paper

Applications

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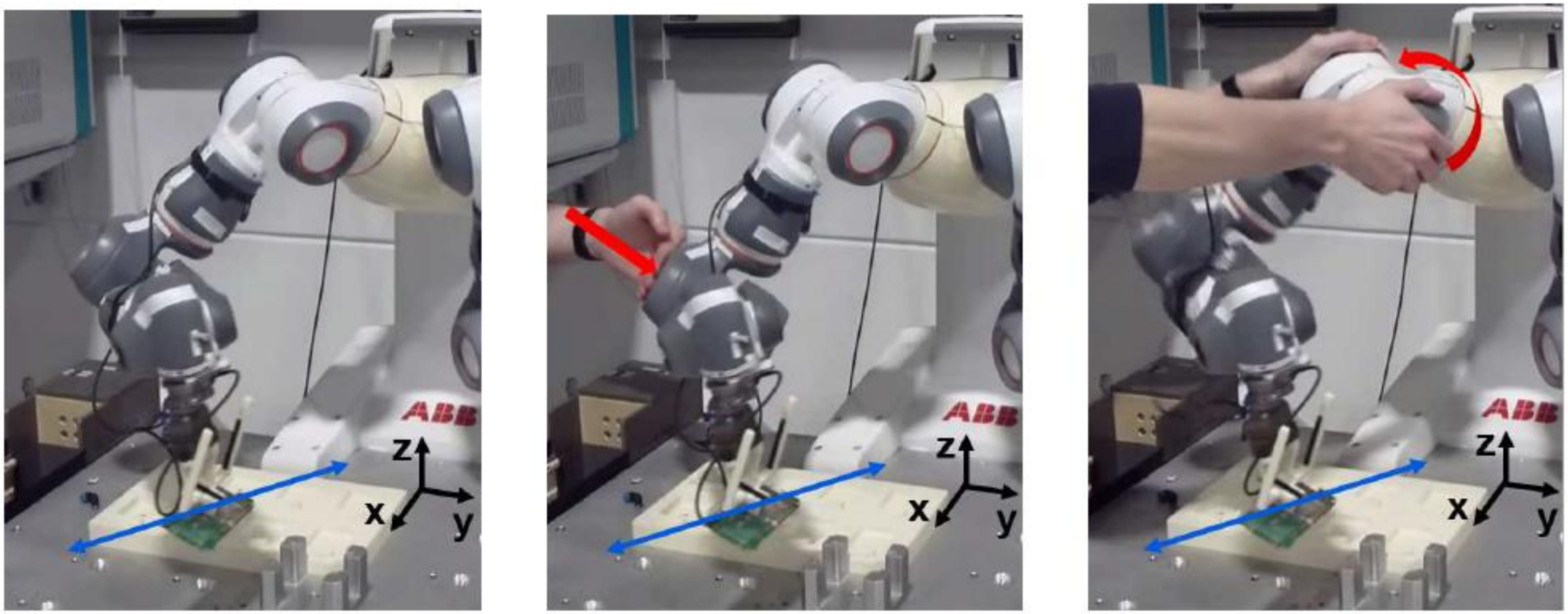
CCFE for Redundant Manipulators
Sensorless Null-Space Admittance Control

[Wahrburg et al. 2016]

- Joint space admittance control with null-space projection
- High TCP accuracy due to admittance control
- Also works at high speeds



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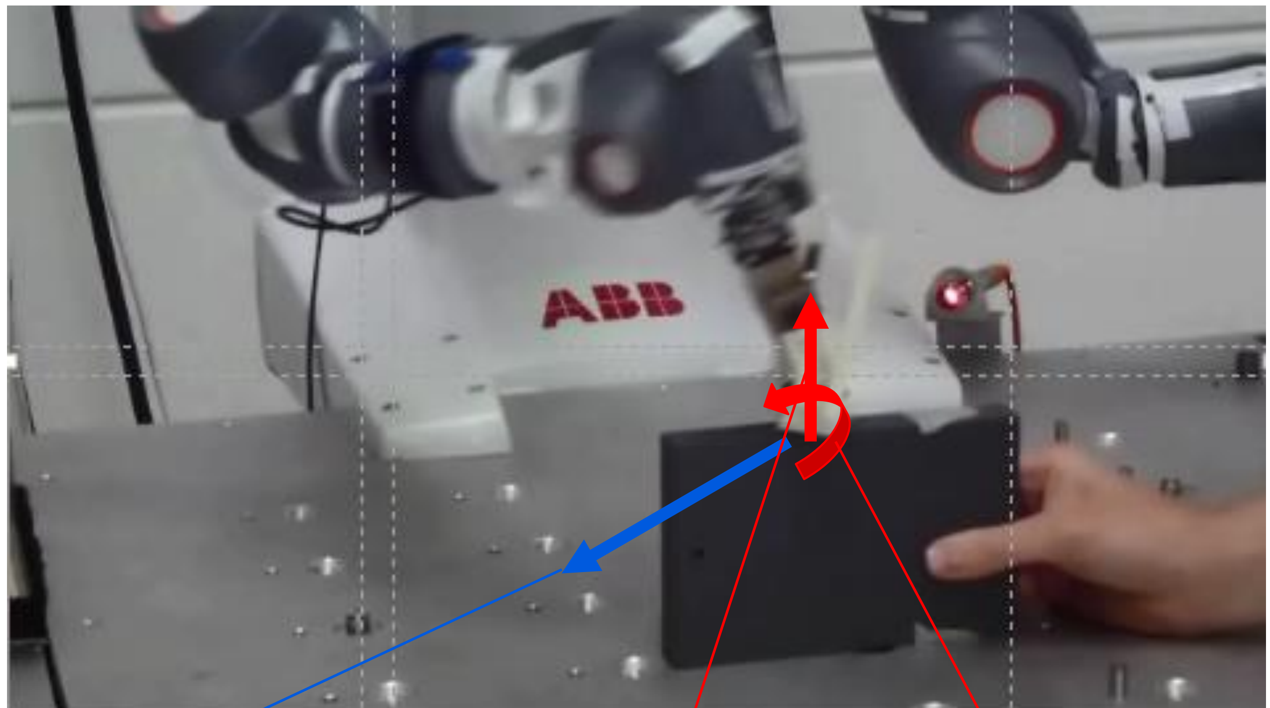
Sensorless Cartesian Admittance Control

- Estimation accuracy and lag are sufficient for admittance control
- CCFE using motor currents and joint angles only
- Contact stability even in stiff contact situations
- Rotational admittance control possible



Rotational admittance about x

Originally commanded motion

Translational admittance in z

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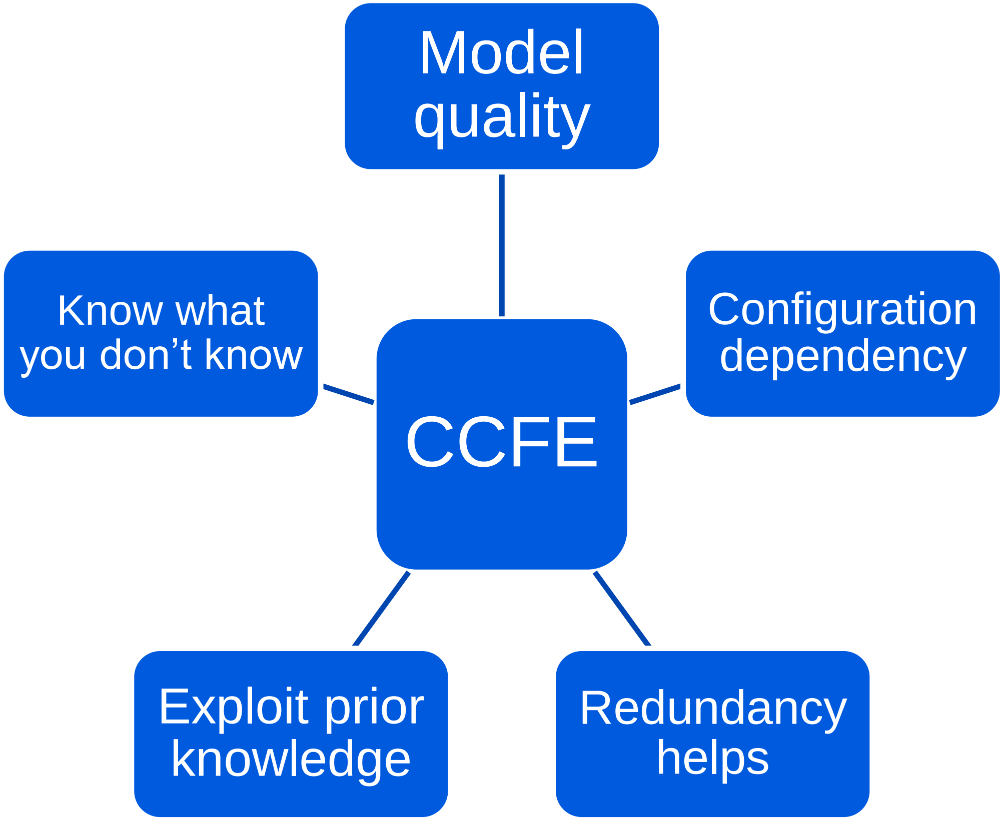
Summary



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…just to name a few – check out the references for more literature

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