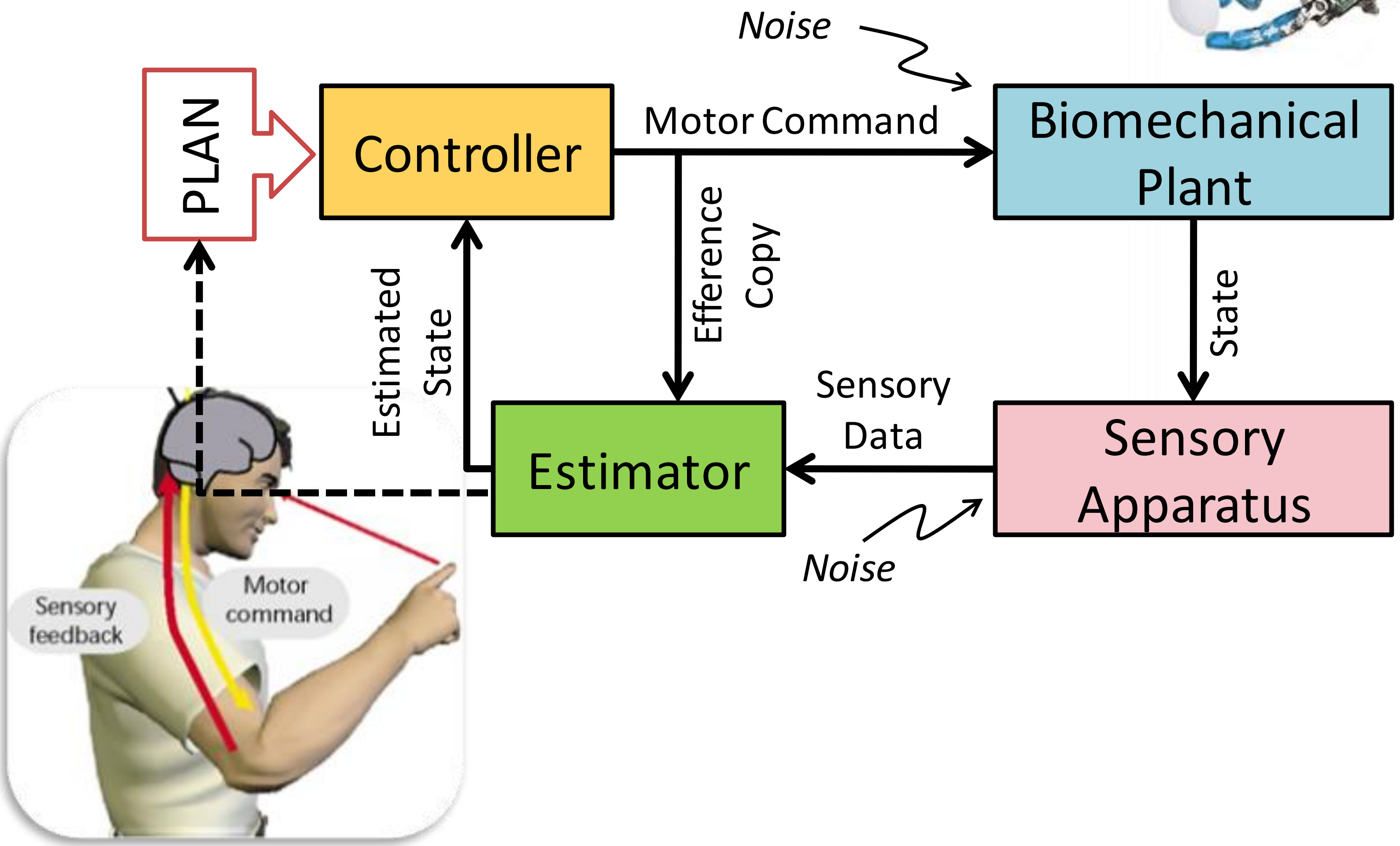
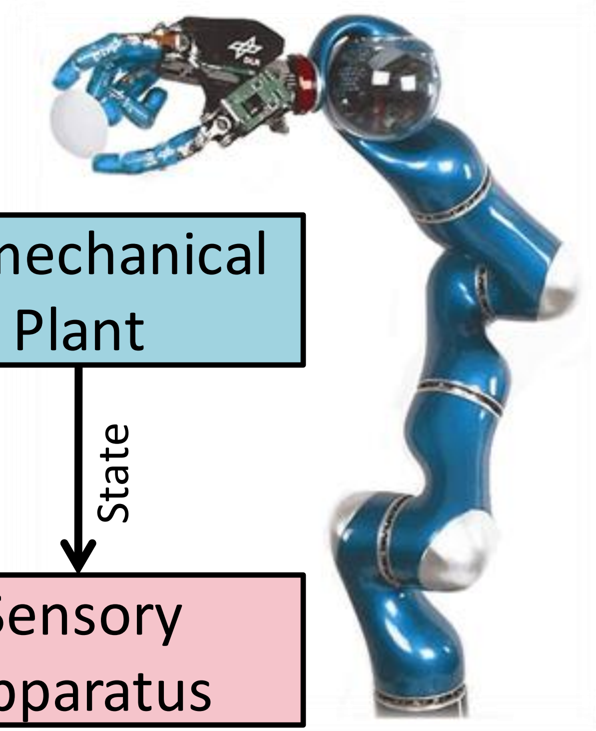
# Explaining and Exploiting Impedance Modulation in Motor Control

**Professor Sethu Vijayakumar** FRSE
Microsoft Research RAEng Chair in Robotics
**University of Edinburgh**, UK
http://homepages.inf.ed.ac.uk/svijayak

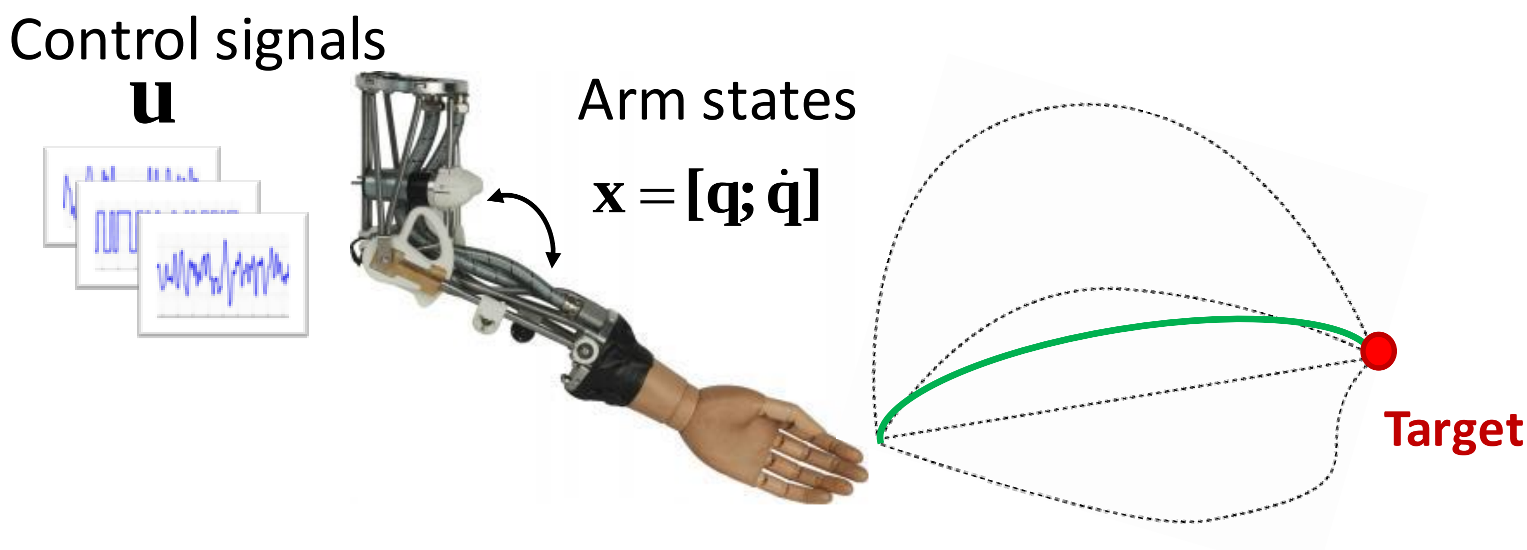
Director, **Edinburgh Centre for Robotics**
www.edinburgh-robotics.org

# Sensorimotor Control



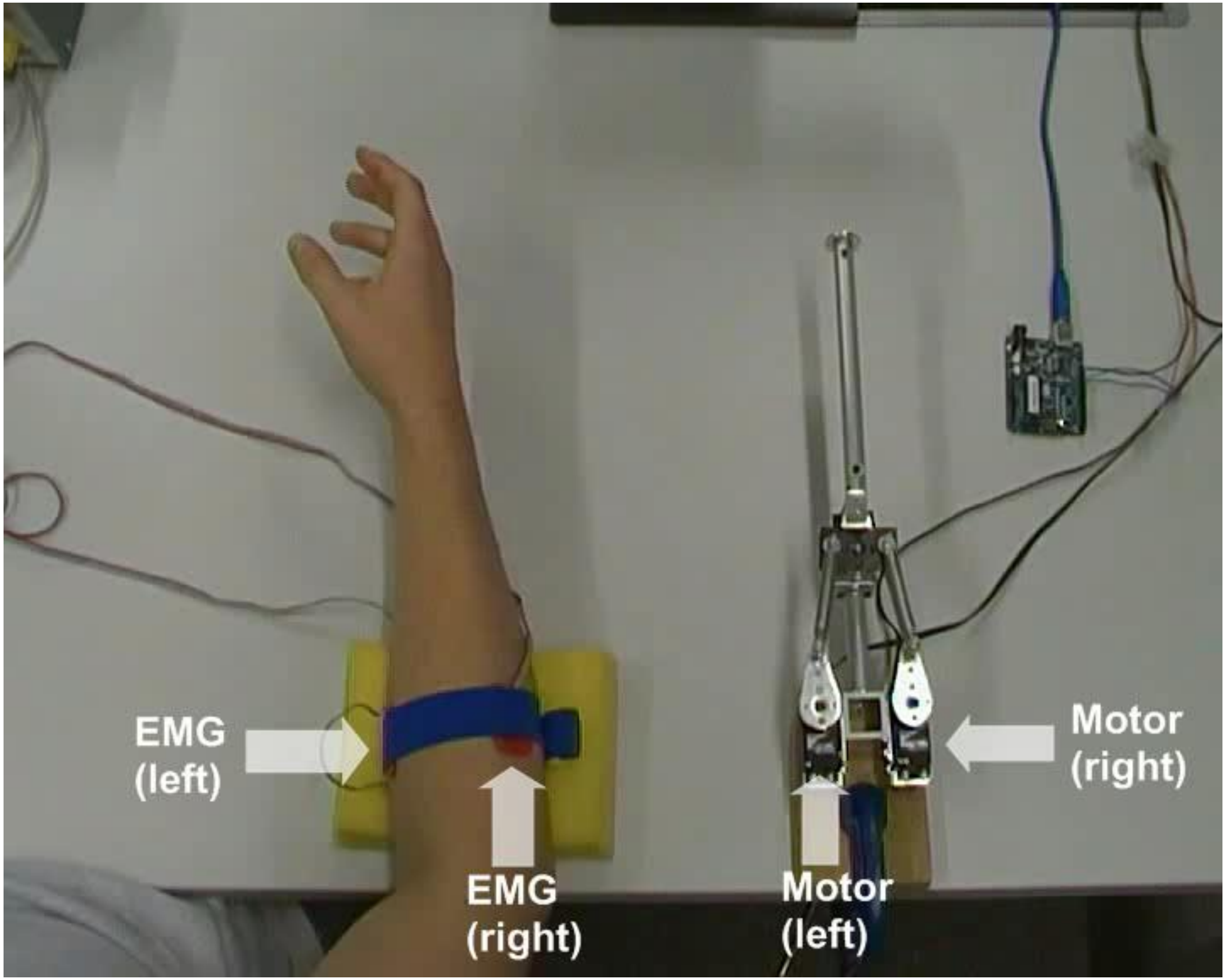
# Planning with Redundancy

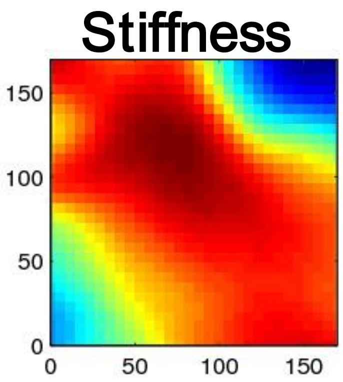



**Redundancy at various levels:**

- Task -> End Effector Trajectory *(Min. Jerk, Min. Energy etc.)*
- End Effector -> Joint Angles *(Inverse Kinematics)*
- Joint Angles -> Joint Torques *(Inverse Dynamics)*
- Joint Torques -> Joint Stiffness *(Variable Impedance)*

# Variable Stiffness Actuation

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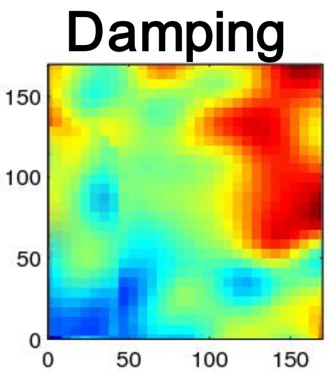



Impedance

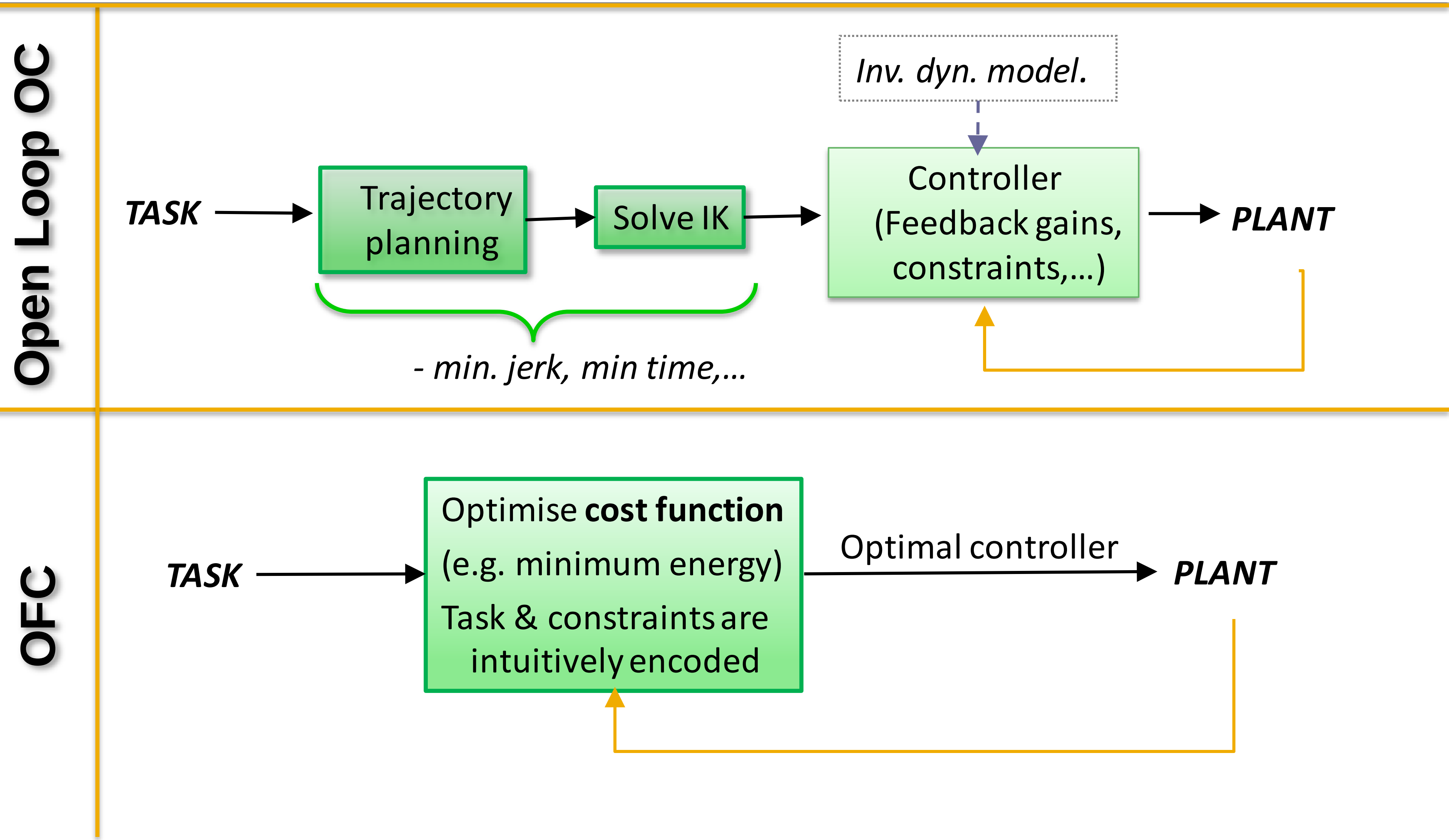
# Compliant Behaviour on a Complex Anthropomorphic Arm

This capability is crucial for **safe, yet precise** human robot interactions and **wearable exoskeletons**.

HAL Exoskeleton, Cyberdyne Inc., Japan

KUKA 7 DOF arm with Schunk 7 DOF hand @ Univ. of Edinburgh

# Plan Optimization and Control



# Optimal Feedback Control

Given:

- Start & end states,
- fixed-time horizon T and
- system dynamics $d\mathbf{x} = \mathbf{f}(\mathbf{x},\mathbf{u})dt + \mathbf{F}(\mathbf{x},\mathbf{u})d\boldsymbol{\omega}$

How the system reacts (Δx) to forces (u)

And assuming some cost function:

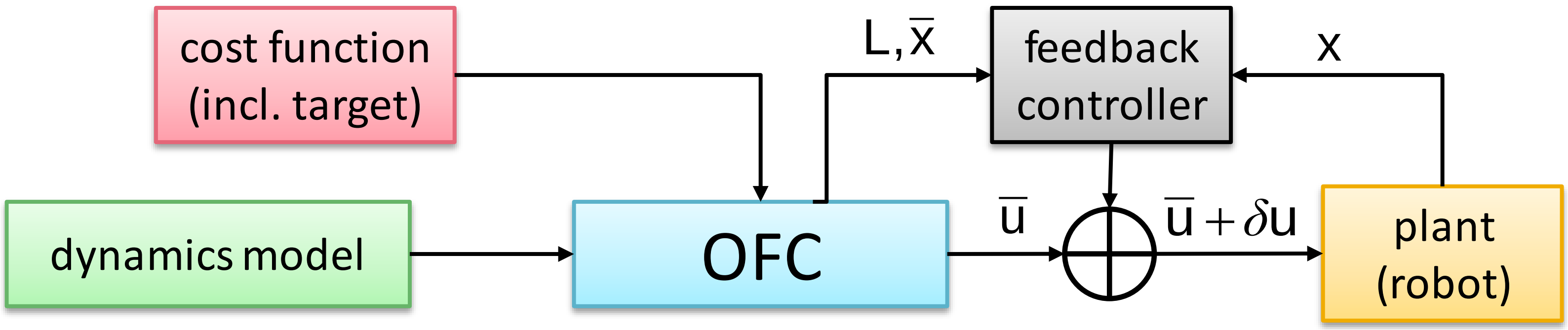
$$v^{\pi}(t,\mathbf{x}) \equiv E\left[ h(\mathbf{x}(T)) + \int_t^T l(\tau, \mathbf{x}(\tau), \boldsymbol{\pi}(\tau, \mathbf{x}(\tau)))d\tau \right]$$

Final Cost　　Running Cost

Apply **Statistical Optimization** techniques to find optimal **control commands**

Aim: find control law $\pi^*$ that minimizes $v^{\pi}(0, x_0)$.

# What does an OFC generate?




## OFC law

$$\mathbf{u}_k^{plant} = \bar{\mathbf{u}}_k + \delta\mathbf{u}_k$$

$$\delta\mathbf{u}_k = \mathbf{L}_k \cdot (\mathbf{x}_k - \bar{\mathbf{x}}_k)$$

# Choice of Optimization Methods

- Analytic Methods
  - Linear Quadratic Regulator (LQR)
  - Linear Quadratic Gaussian (LQG)
- Local Iterative Methods
  - iLQG, iLDP
- Dynamic Programming (DDP)
- Inference based methods
  - AICO, PI^2, ψ-Learning

# SOC through Approximate Inference

Given:

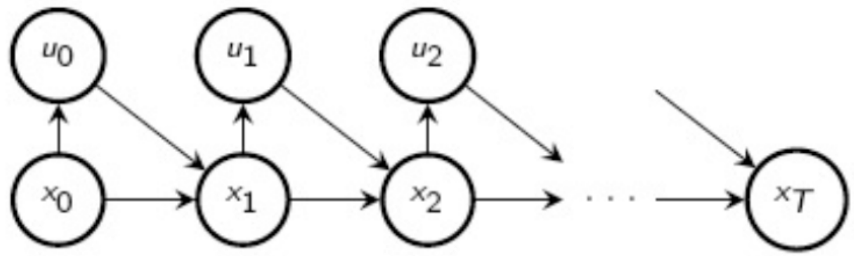
- Discrete time controlled stochastic process

*State:* $x_t \in \mathbb{X} = \mathbb{R}^n$

$\bar{x} = (x_0, \ldots, x_T)$

*Control:* $u_t \in \mathbb{U} = \mathbb{R}^m$

$\bar{u} = (u_0, \ldots, u_T)$




*Transition Probability:*

$P(x_{t+1}|x_t, u_t)$ (typically $P(x_{t+1}|x_t, u_t) = \mathcal{N}(x_{t+1}; f(x_t, u_t), \mathbf{Q})$)

- Cost function

$$\mathcal{C}(\bar{x}, \bar{u}) = \sum_{t=0}^{T} \mathcal{C}_t(x_t, u_t) \qquad \mathcal{C}_t(\cdot, \cdot) \geq 0$$

Solve: $\pi^* = \operatorname{argmin}_\pi \langle \mathcal{C}(\bar{x}, \bar{u}) \rangle_{\bar{x}, \bar{u} | x_0, \pi}$


Konrad Rawlik, Marc Toussaint and Sethu Vijayakumar, On Stochastic Optimal Control and Reinforcement Learning by Approximate Inference, *Proc. Robotics: Science and Systems (R:SS 2012),* Sydney, Australia (2012).

# Optimal Variable Impedance

- Explaining Human Impedance Modulation

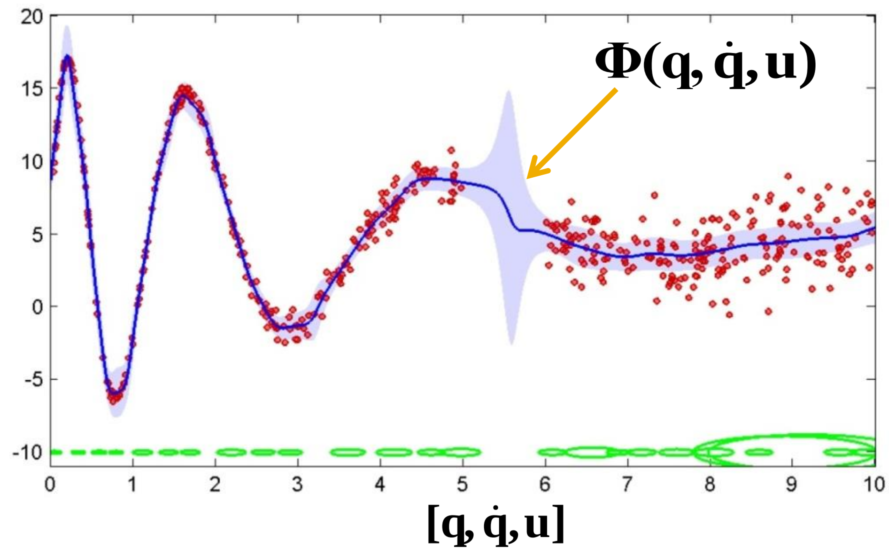
- Exploiting Impedance Modulation in Robots
  - Explosive Movement Tasks (e.g., throwing)
  - Periodic Movement Tasks and Temporal Optimization (e.g. walking, brachiation)

Djordje Mitrovic, Stefan Klanke, Rieko Osu, Mitsuo Kawato and Sethu Vijayakumar, A Computational Model of Limb Impedance Control based on Principles of Internal Model Uncertainty, *PLoS ONE* (2010).

# Dynamics Learning with LWPR

**Locally Weighted Projection Regression (LWPR) for dynamics learning (Vijayakumar et al., 2005).**

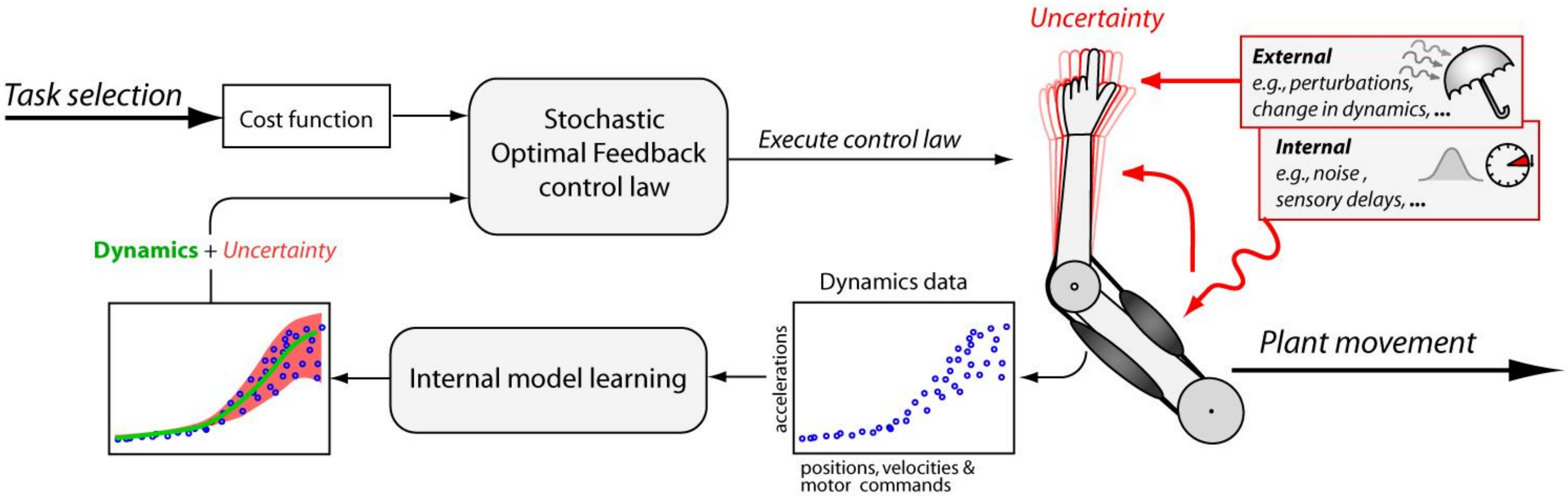
$$\tilde{\mathbf{f}}(\mathbf{q},\dot{\mathbf{q}},\mathbf{u}) = \ddot{\mathbf{q}}$$




$$d\mathbf{x} = \mathbf{f}(\mathbf{x},\mathbf{u})dt + \mathbf{F}(\mathbf{x},\mathbf{u})d\omega \quad \Rightarrow \quad d\mathbf{x} = \tilde{\mathbf{f}}(\mathbf{x},\mathbf{u})dt + \phi(\mathbf{x},\mathbf{u})d\omega$$

S. Vijayakumar, A. D'Souza and S. Schaal, Online Learning in High Dimensions, *Neural Computation,* vol. 17 (2005)

# OFC with Learned Dynamics (OFC-LD)




- OFC-LD uses LWPR learned dynamics for optimization (Mitrovic et al., 2010a)
- Key ingredient: Ability to learn both the dynamics and the **associated uncertainty** (Mitrovic et al., 2010b)

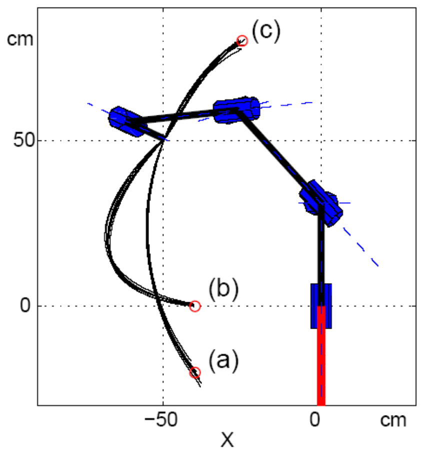
Djordje Mitrovic, Stefan Klanke and Sethu Vijayakumar, Adaptive Optimal Feedback Control with Learned Internal Dynamics Models, *From Motor Learning to Interaction Learning in Robots*, SCI 264, pp. 65-84, Springer-Verlag (2010).

# OFC-LD: Advantages

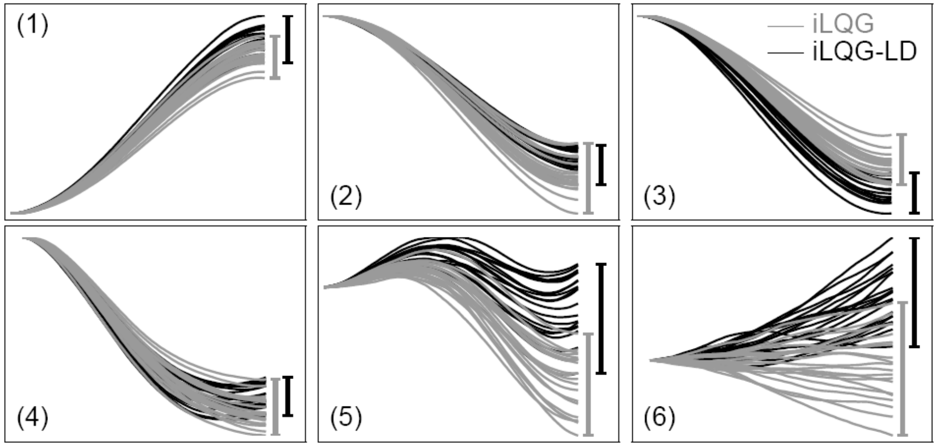
Reproduces the "trial-to-trial" variability in the uncontrolled manifold, i.e., exhibits the **minimum intervention principle** that is characteristic of human motor control.

KUKA LWR

Simulink Model



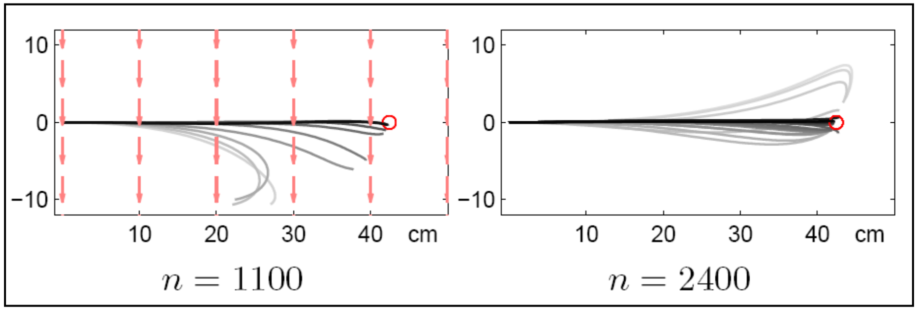

Minimum intervention principle



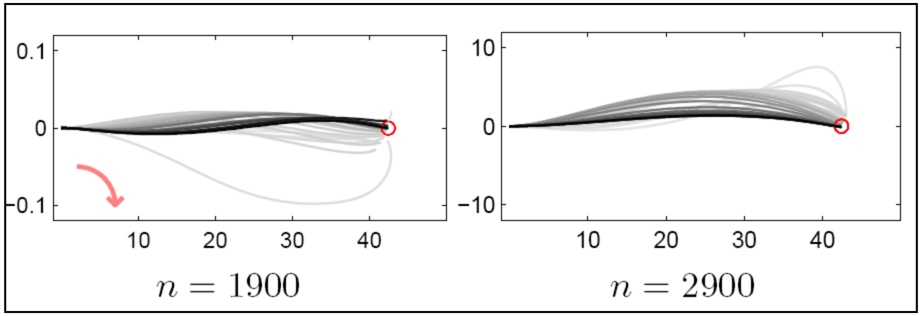
# OFC-LD: Explaining Motor Adaptation

Can predict the "ideal observer" adaptation behaviour under complex force fields due to the ability to work with adaptive dynamics

**Constant Unidirectional Force Field**




**Velocity-dependent Divergent Force Field**

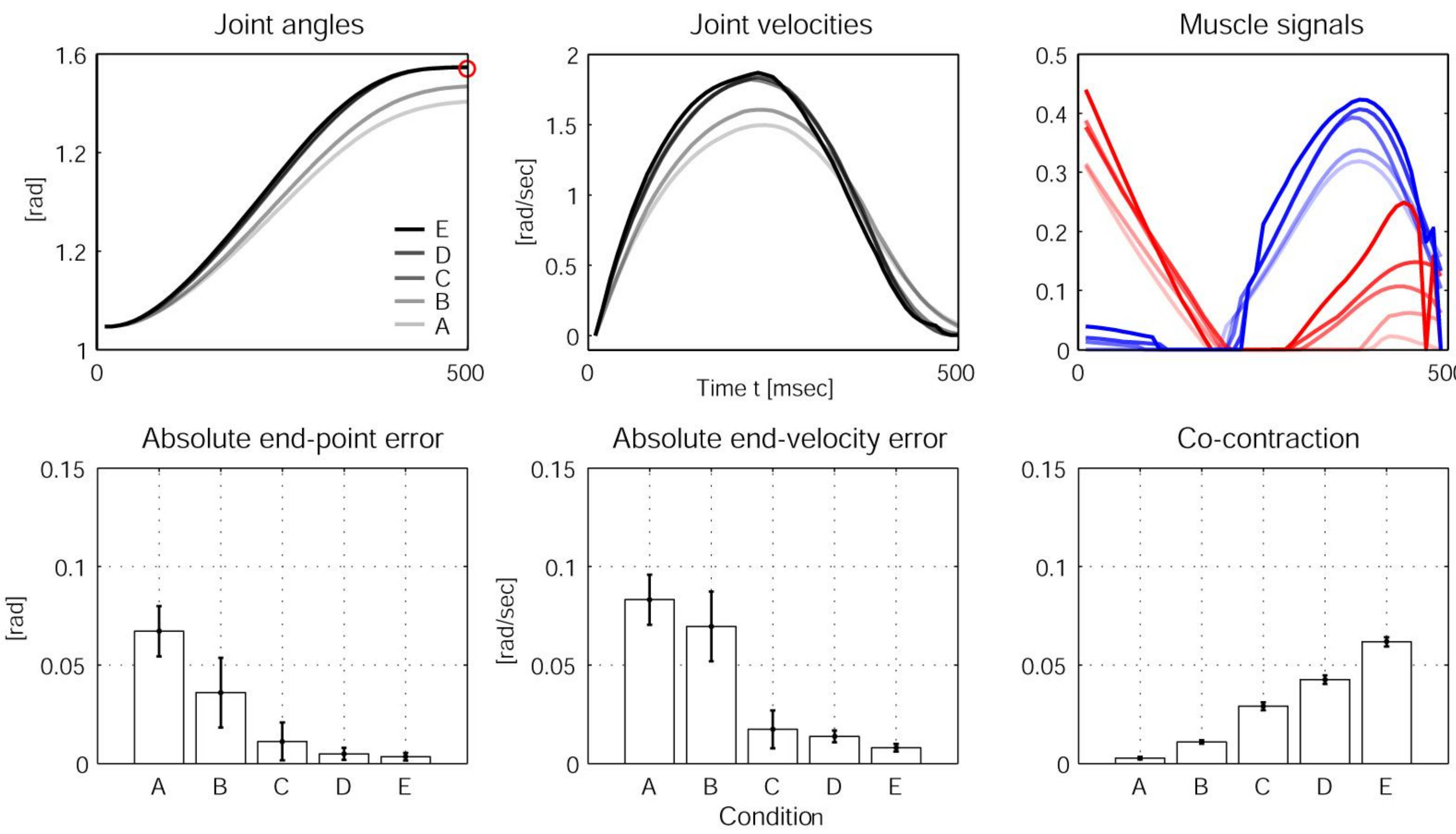



**Cost Function:**

$$v = w_p |\mathbf{q}_K - \mathbf{q}_{tar}|^2 + w_v |\dot{\mathbf{q}}_K|^2 + w_e \sum_{k=0}^{K} |\mathbf{u}_k|^2 \Delta t$$

Djordje Mitrovic, Stefan Klanke, Rieko Osu, Mitsuo Kawato and Sethu Vijayakumar, A Computational Model of Limb Impedance Control based on Principles of Internal Model Uncertainty, *PLoS ONE*, Vol. 5, No. 10 (2010).

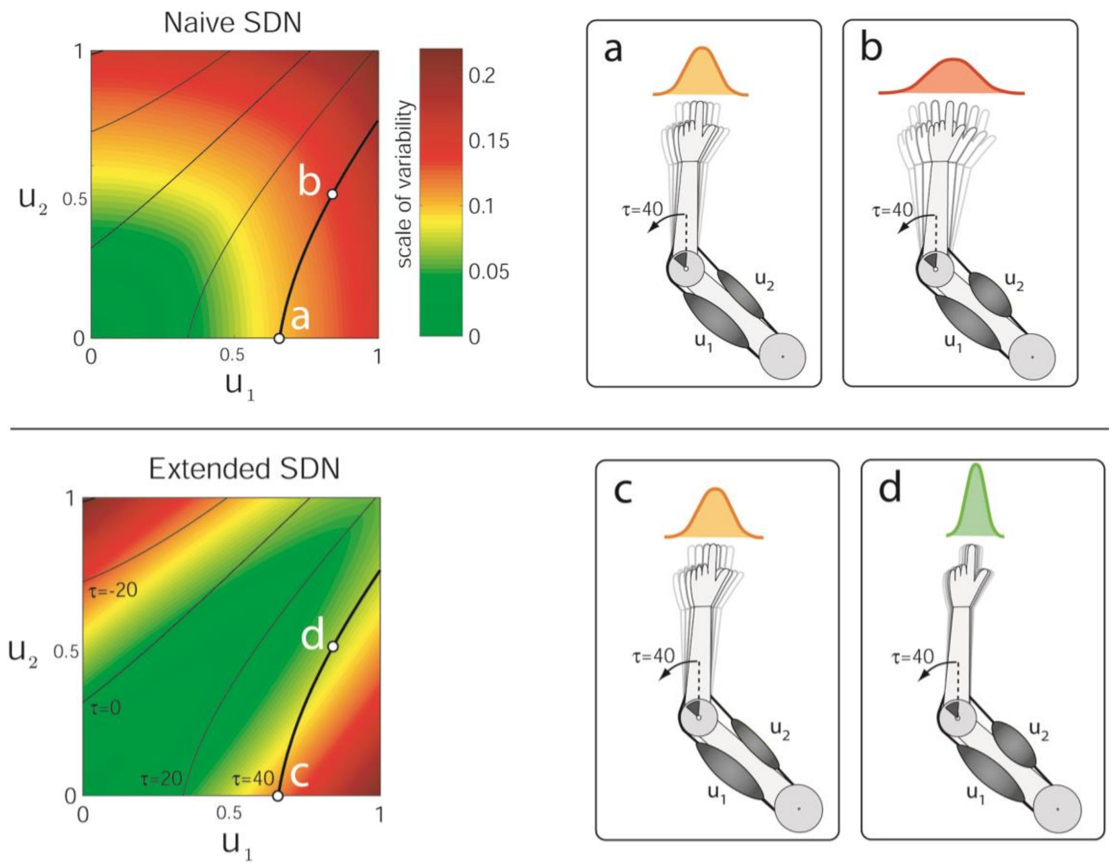
# Results: Higher accuracy demands




See: Osu et.al., 2004; Gribble et al., 2003

# Realistic kinematic variability

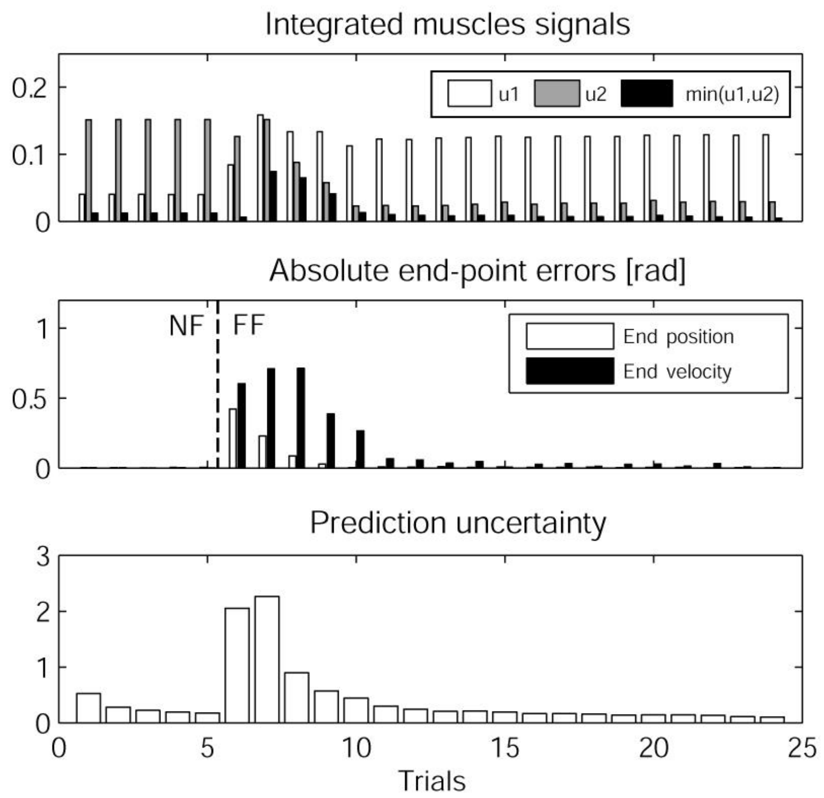
Focus: Signal Dependent Noise (SDN)




$$\sigma(\mathbf{u}) = \sigma_{isotonic}|u_1 - u_2|^n + \sigma_{isometric}|u_1 + u_2|^m, \quad \boldsymbol{\xi} \sim N(0, \mathbf{I}_2)$$

# Results: Adaptation to external force fields

## Stochastic OFC-LD

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David Braun, Matthew Howard and Sethu Vijayakumar, Exploiting Variable Stiffness for Explosive Movement Tasks, *Proc. Robotics: Science and Systems (R:SS), Los Angeles* (2011)

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# Highly **dynamic** tasks, explosive movements

David Braun, Matthew Howard and Sethu Vijayakumar, Exploiting Variable Stiffness for Explosive Movement Tasks, *Proc. Robotics: Science and Systems (R:SS), Los Angeles* (2011)

# The two main ingredients:

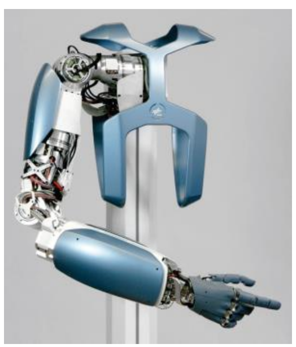
## Compliant Actuators

- VARIABLE JOINT STIFFNESS

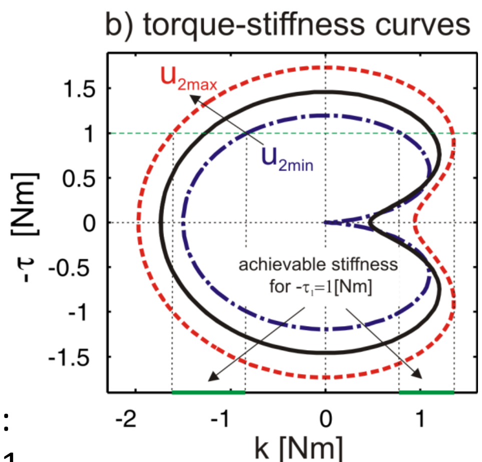
MACCEPA:
Van Ham et.al, 2007

$$\boldsymbol{\tau} = \boldsymbol{\tau}(\mathbf{q}, \mathbf{u})$$

$$\mathbf{K} = \mathbf{K}(\mathbf{q}, \mathbf{u})$$



DLR Hand Arm System:
Grebenstein et.al., 2011




## Torque/Stiffness Opt.

- Model of the system dynamics:

$$\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}, \mathbf{u}) \quad \mathbf{u} \in \Omega$$

- Control objective:

$$J = -d + w\frac{1}{2}\int_0^T \|\mathbf{F}\|^2 dt \rightarrow \min.$$

- Optimal control solution:

$$\mathbf{u}(t, \mathbf{x}) = \mathbf{u}^*(t) + \mathbf{L}^*(t)(\mathbf{x} - \mathbf{x}^*(t))$$

iLQG: Li & Todorov 2007
DDP: Jacobson & Mayne 1970

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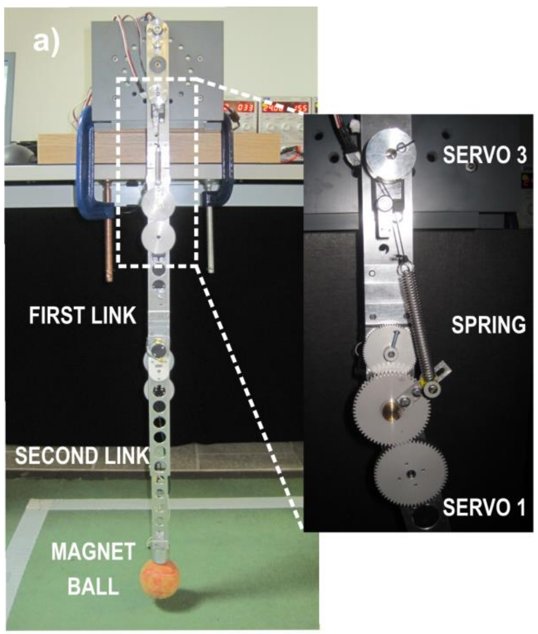
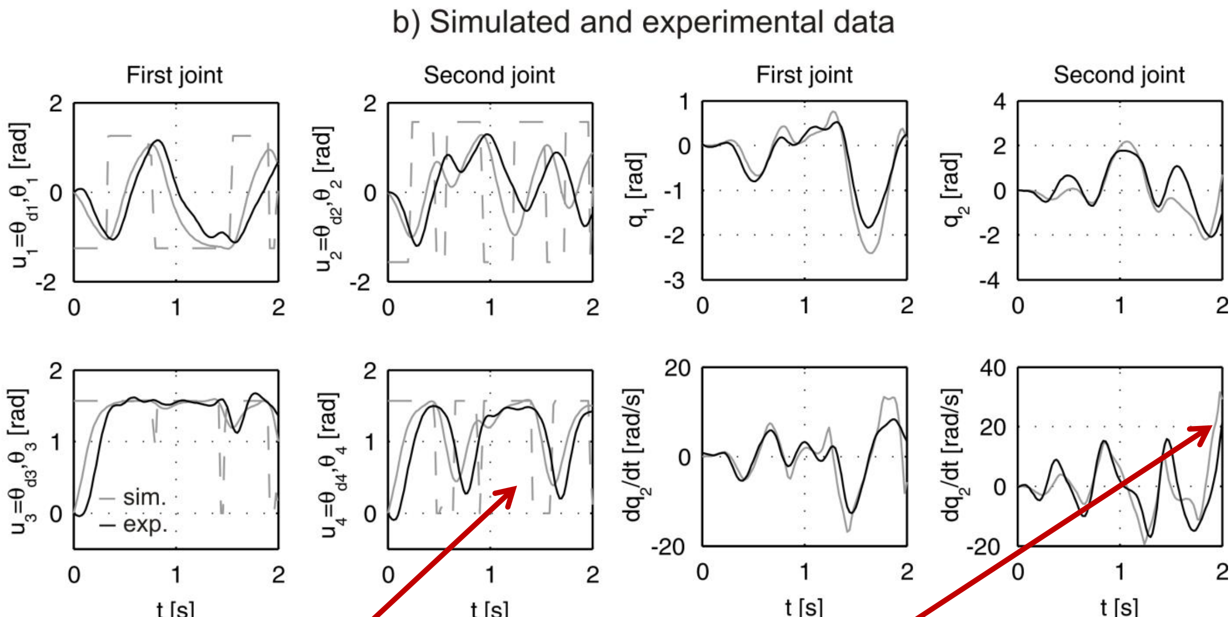
# 2-link ball throwing - MACCEPA



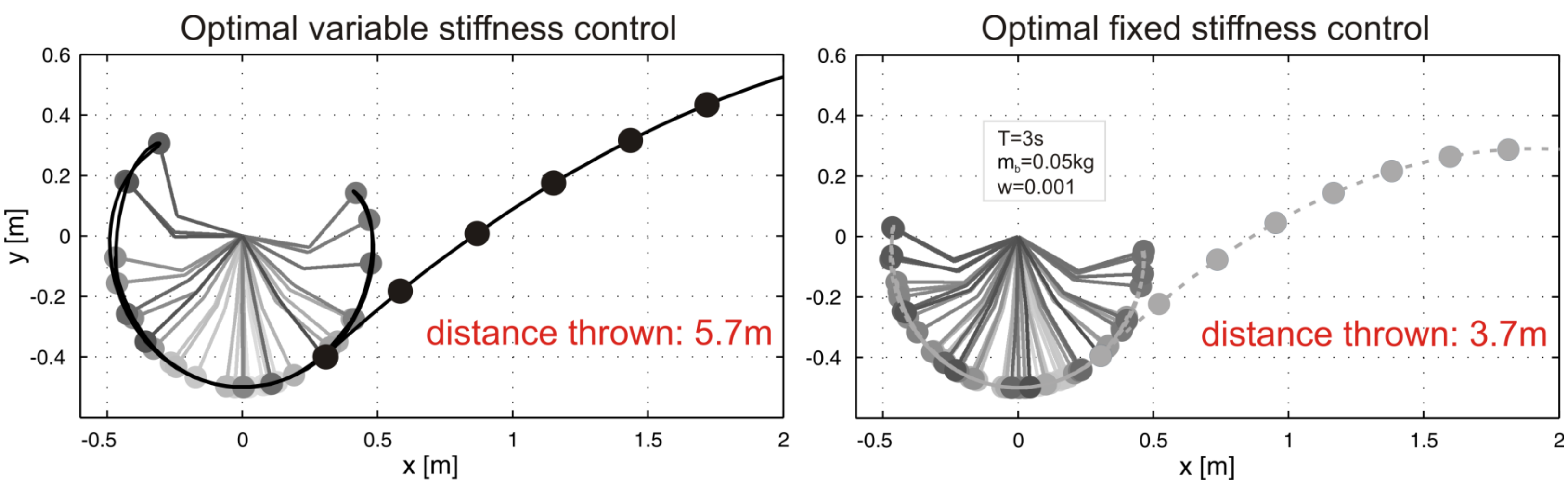




stiffness modulation

speed: 20 rad/s
distance thrown: 5.2m

# Benefits of Stiffness Modulation:

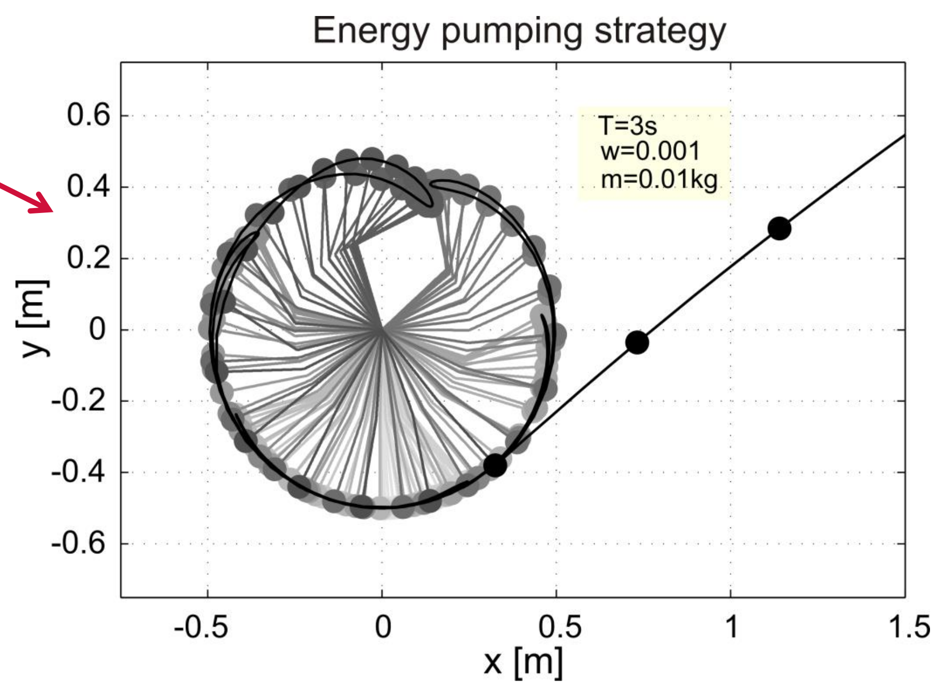
Quantitative evidence of improved task performance (distance thrown) with temporal **stiffness modulation** as opposed to **fixed** (optimal) stiffness control

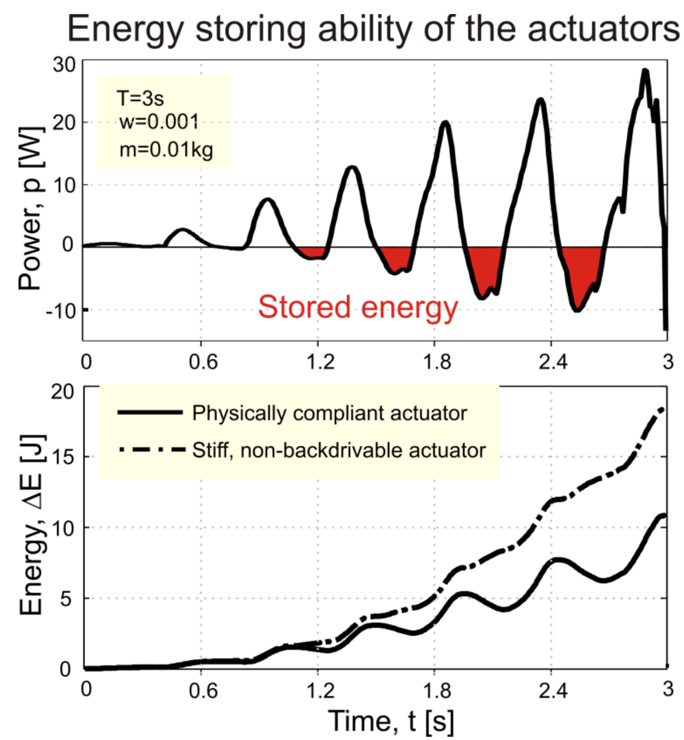



David Braun, Matthew Howard and Sethu Vijayakumar, Exploiting Variable Stiffness for Explosive Movement Tasks, *Proc. Robotics: Science and Systems (R:SS), Los Angeles* (2011)

# Exploiting Natural Dynamics:

a) **optimization suggests power amplification through pumping energy**
b) **benefit of passive stiffness vs. active stiffness control**




David Braun, Matthew Howard and Sethu Vijayakumar, Exploiting Variable Stiffness for Explosive Movement Tasks, *Proc. Robotics: Science and Systems (R:SS), Los Angeles* (2011)

# Behaviour Optimization:

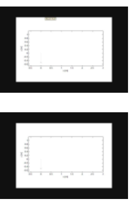
Simultaneous stiffness and torque optimization of a VIA actuator that reflects strategies used in human explosive movement tasks:

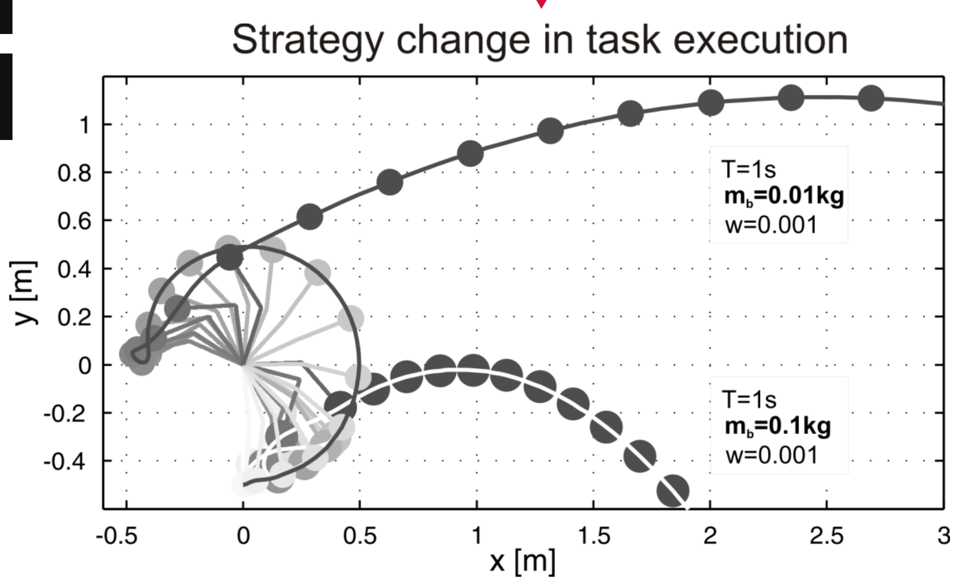
a) performance-effort trade-off

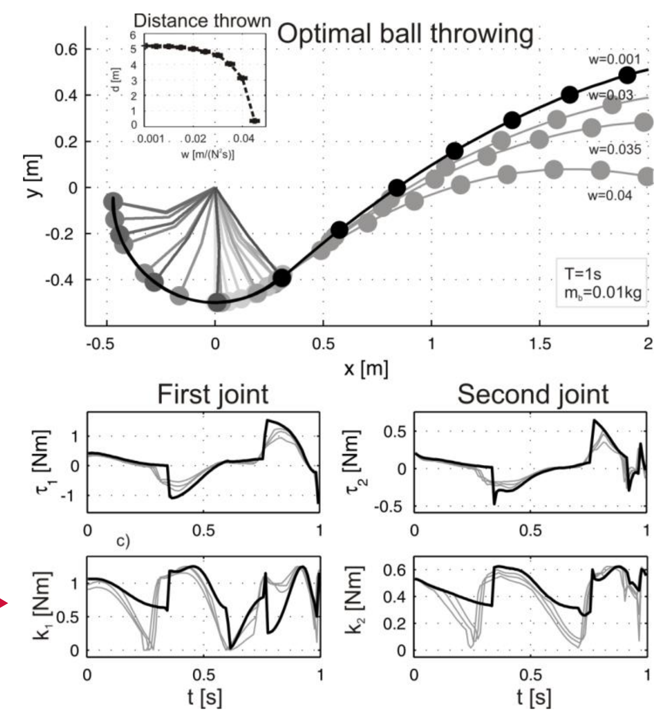
b) qualitatively similar stiffness pattern

c) strategy change in task execution

$$J = -d + w\frac{1}{2}\int_0^T \|\mathbf{F}\|^2 \, dt$$



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# Scalability to More Complex Hardware

**DLR HASY:**

State-of-the-art research platform for variable stiffness control.

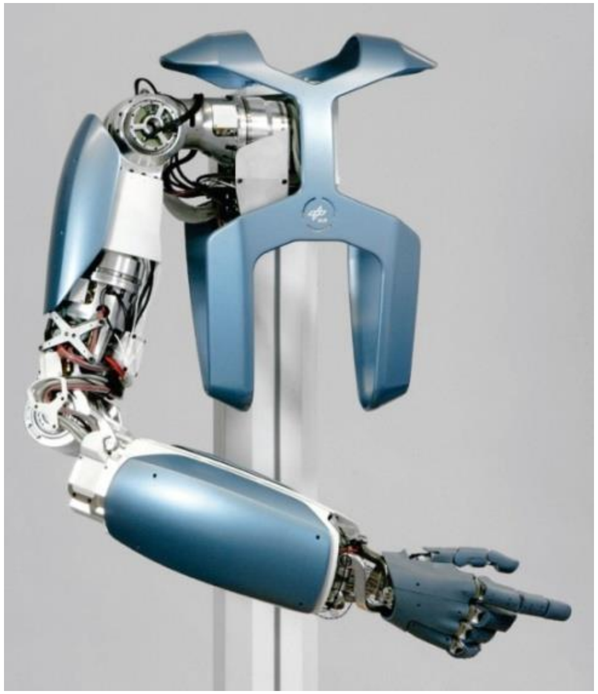
Restricted to a 2-dof system (shoulder and elbow rotation)

Max motor side speed: 8 rad/s

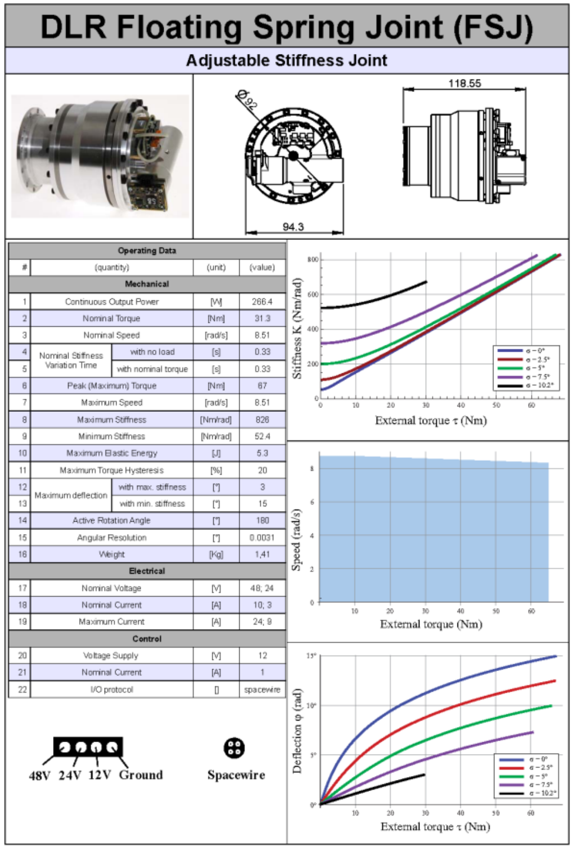
Max torque: 67Nm

Stiffness range: 50 – 800 Nm/rad

Speed for stiffness change: 0.33 s/range

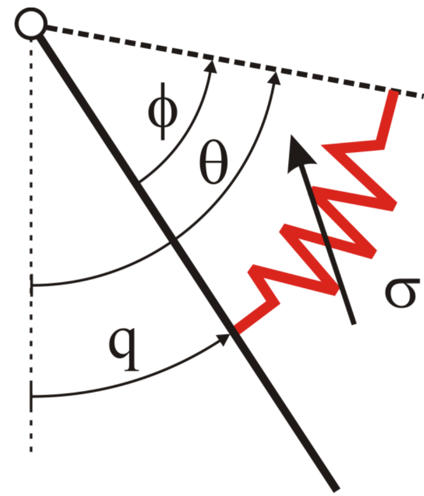


# DLR - FSJ




| Operating Data | | | | |
|---|---|---|---|---|
| # | (quantity) | | (unit) | (value) |
| **Mechanical** | | | | |
| 1 | Continuous Output Power | | [W] | 266.4 |
| 2 | Nominal Torque | | [Nm] | 31.3 |
| 3 | Nominal Speed | | [rad/s] | 8.51 |
| 4 | Nominal Stiffness Variation Time | with no load | [s] | 0.33 |
| 5 | | with nominal torque | [s] | 0.33 |
| 6 | Peak (Maximum) Torque | | [Nm] | 67 |
| 7 | Maximum Speed | | [rad/s] | 8.51 |
| 8 | Maximum Stiffness | | [Nm/rad] | 826 |
| 9 | Minimum Stiffness | | [Nm/rad] | 52.4 |
| 10 | Maximum Elastic Energy | | [J] | 5.3 |
| 11 | Maximum Torque Hysteresis | | [%] | 20 |
| 12 | Maximum deflection | with max. stiffness | [°] | 3 |
| 13 | | with min. stiffness | [°] | 15 |
| 14 | Active Rotation Angle | | [°] | 180 |
| 15 | Angular Resolution | | [°] | 0.0031 |
| 16 | Weight | | [Kg] | 1,41 |
| **Electrical** | | | | |
| 17 | Nominal Voltage | | [V] | 48; 24 |
| 18 | Nominal Current | | [A] | 10; 3 |
| 19 | Maximum Current | | [A] | 24; 9 |
| **Control** | | | | |
| 20 | Voltage Supply | | [V] | 12 |
| 21 | Nominal Current | | [A] | 1 |
| 22 | I/O protocol | | [] | spacewire |

Schematic representation of the DLR-FSJ




Motor-side positions:

$$\mathbf{q}_2 = [\boldsymbol{\theta}, \boldsymbol{\sigma}]^T \in \Re^4$$

Constraint:

$$\phi_{\min}(\sigma) \le \phi \le \phi_{\max}(\sigma)$$

# Dealing with Complex Constraints

$$\mathbf{M}_{11}(\mathbf{q}_1)\ddot{\mathbf{q}}_1 + \mathbf{C}_{11}(\mathbf{q}_1, \dot{\mathbf{q}}_1)\dot{\mathbf{q}}_1 + \mathbf{G}_1(\mathbf{q}_1) = \boldsymbol{\tau}_1(\mathbf{q}_1, \mathbf{q}_2)$$

$$\ddot{\mathbf{q}}_2 + 2\boldsymbol{\beta}\dot{\mathbf{q}}_2 + \boldsymbol{\kappa}^2\mathbf{q}_2 = \boldsymbol{\kappa}^2\mathbf{u}$$

Incorporating the constraints:

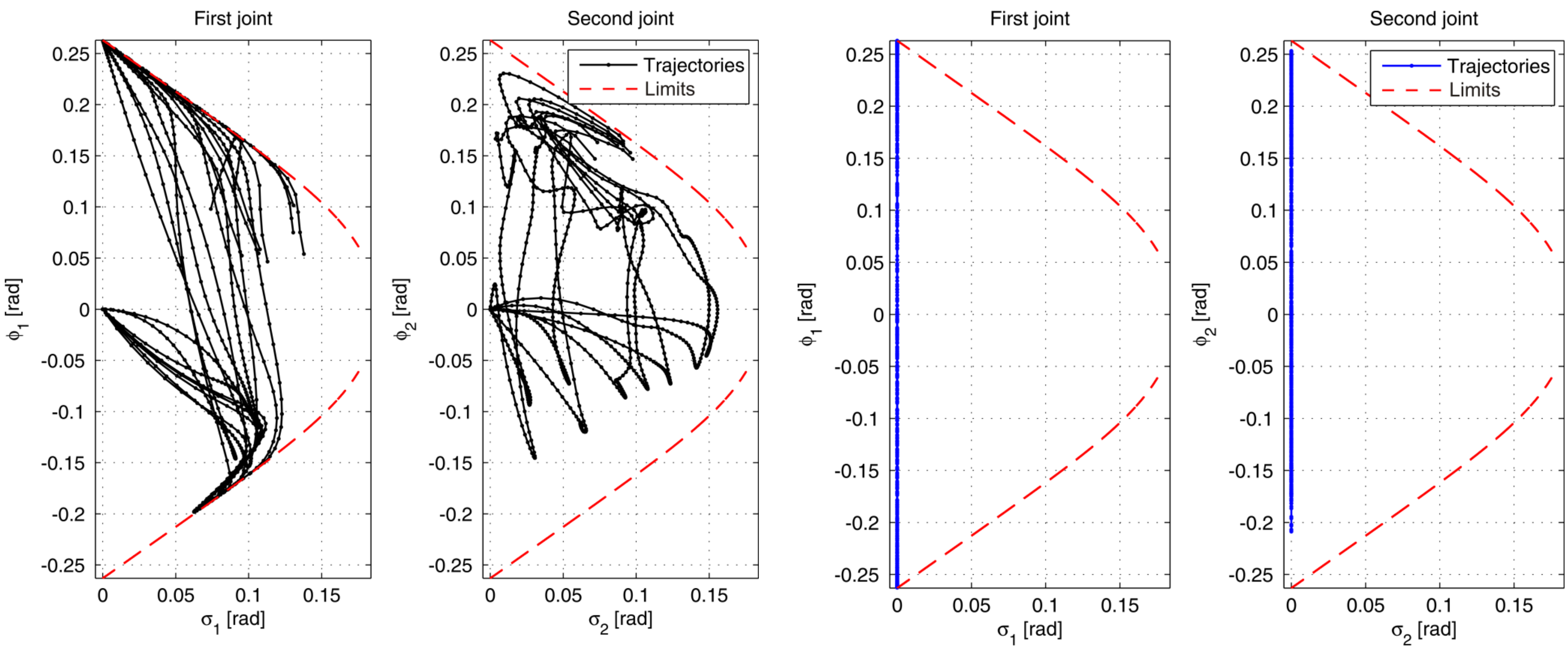
1. Range constraints: $\boldsymbol{\Phi}(\mathbf{q}_1, \mathbf{q}_2) \in \Omega = [\boldsymbol{\Phi}_{\min}(\mathbf{q}_2), \boldsymbol{\Phi}_{\max}(\mathbf{q}_2)]$

$$\mathbf{u} \in [\mathbf{u}_{\mathbf{min}}, \mathbf{u}_{\mathbf{max}}] \Rightarrow \boldsymbol{\Phi}(\mathbf{q}_1, \mathbf{q}_2) \in \Omega$$

2. Rate/effort limitations: $\boldsymbol{\kappa} \in [\mathbf{0}, \boldsymbol{\kappa}_{\max}]$

# DLR – FSJ: optimisation with state constraints

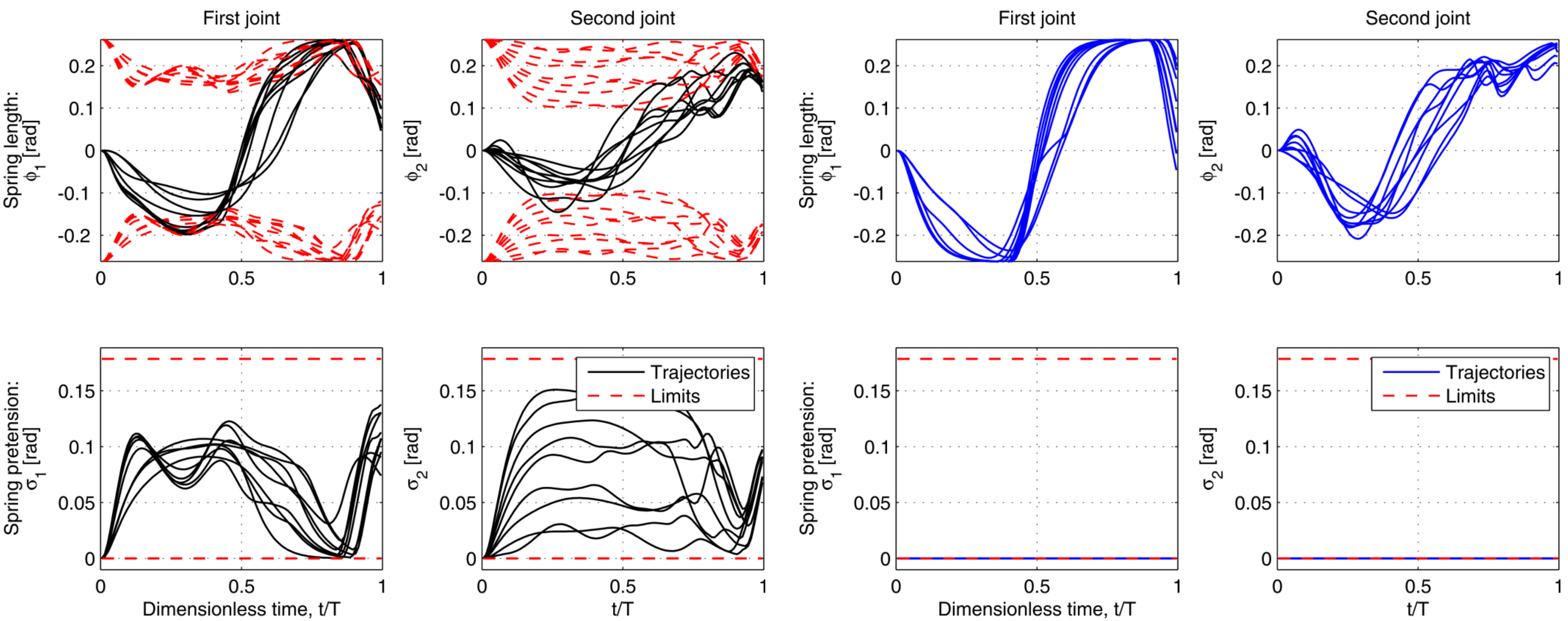
variable stiffness | fixed stiffness




Spring Length vs Stiffness Modulation

# DLR – FSJ: optimisation with state constraints

variable stiffness | fixed stiffness




Spring Length and Stiffness Modulation (plotted against time)

# Ball throwing with DLR HASy

motor velocity limited to: 2rad/s, 3rad/s

# Optimal Variable Impedance

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Jun Nakanishi, Konrad Rawlik and Sethu Vijayakumar, Stiffness and Temporal Optimization in Periodic Movements: An Optimal Control Approach , *Proc. IEEE Intl Conf on Intelligent Robots and Systems (IROS '11) , San Francisco* (2011).

# Periodic Movement Control: Issues

Representation

- what is a suitable representation of periodic movement (trajectories, goal)?

Choice of cost function

- how to design a cost function for periodic movement?

Exploitation of natural dynamics

- how to exploit resonance for energy efficient control?
  - optimize frequency (temporal aspect)
  - stiffness tuning

# Cost Function for Periodic Movements

## Optimization criterion

$$\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}, \mathbf{u})$$

$$J = \Phi(\mathbf{x}_0, \mathbf{x}_T) + \int_0^T r(\mathbf{x}, \mathbf{u}, t) dt$$

## Terminal cost

- ensures periodicity of the trajectory

$$\Phi(\mathbf{x}_0, \mathbf{x}_T) = (\mathbf{x}_T - \mathbf{x}_0)^T \mathbf{Q}_T (\mathbf{x}_T - \mathbf{x}_0)$$

## Running cost

- tracking performance and control cost

$$r(\mathbf{x}, \mathbf{u}, t) = (\mathbf{x} - \mathbf{x}_{ref})^T \mathbf{Q} (\mathbf{x} - \mathbf{x}_{ref}) + \mathbf{u}^T \mathbf{R} \mathbf{u}$$

$$\mathbf{x} = [\, y, \; \dot{y} \,]^T$$

$$y_{ref}(t) = a_0 + \sum_{n=1}^{N} (a_n \cos n\omega t + b_n \sin n\omega t)$$

Jun Nakanishi, Konrad Rawlik and Sethu Vijayakumar, Stiffness and Temporal Optimization in Periodic Movements: An Optimal Control Approach , *Proc. IEEE Intl Conf on Intelligent Robots and Systems (IROS '11) , San Francisco* (2011).

# Another View of Cost Function

- Running cost: tracking performance and control cost

$$r(\mathbf{x}, \mathbf{u}, t) = (\mathbf{x} - \mathbf{x}_{ref})^T \mathbf{Q} (\mathbf{x} - \mathbf{x}_{ref}) + \mathbf{u}^T \mathbf{R} \mathbf{u}$$

- Augmented plant dynamics with Fourier series based DMPs

$$\begin{cases} \dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}, \mathbf{u}) & (1) \\ y = r\ \boldsymbol{\psi}^T(\phi)\boldsymbol{\theta} + y_{\mathit{offset}} & (2) \\ \dot{\phi} = \omega & (3) \\ \mathbf{z} = \mathbf{x} - \mathbf{y},\ \text{where } \mathbf{y} = [y,\ \dot{y}] & (4) \end{cases}$$

- Reformulated running cost

$$r(\mathbf{z}, \mathbf{u}) = \mathbf{z}^T \mathbf{Q} \mathbf{z} + \mathbf{u}^T \mathbf{R} \mathbf{u}$$

- Find control $\mathbf{u}$ and parameter $\omega$ such that plant dynamics (1) should behave like (2) and (3) while min. control cost

Jun Nakanishi, Konrad Rawlik and Sethu Vijayakumar, Stiffness and Temporal Optimization in Periodic Movements: An Optimal Control Approach , *Proc. IEEE Intl Conf on Intelligent Robots and Systems (IROS '11) , San Francisco* (2011).

# Temporal Optimization

How do we find the right **temporal duration** in which to optimize a movement ?

**Solutions:**

- Fix temporal parameters
  ... not optimal
- Time stationary cost
  ... cannot deal with sequential tasks, e.g. via points
- Chain *'first exit time'* controllers
  ... Linear duration cost, not optimal
- Canonical Time Formulation

# Canonical Time Formulation

**Dynamics:** $d\mathbf{x} = f(\mathbf{x},\mathbf{u})\beta dt + g(\mathbf{x},\mathbf{u})d\eta$

**Cost:** $J = \sum_{i=1}^{N} \Phi_i(\mathbf{x}(t_i)) \quad + \int_0^{t_N} \left[ r(\mathbf{x}(t)) + \mathbf{u}(t)^T \mathbf{H}\mathbf{u}(t) \right] dt$

n.b. $t_i$ represent *real* time

Introduce change of time $t' = \int_0^t \frac{1}{\beta(s)} ds$

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# Canonical Time Formulation

**Dynamics:** $d\mathbf{x} = f(\mathbf{x}, \mathbf{u})\beta dt' + g(\mathbf{x}, \mathbf{u})d\eta'$

**Cost:** $J = \sum_{i=1}^{N} \Phi_i\left(\mathbf{x}(\tau^{-1}(t'_i))\right) + \int_0^{\tau^{-1}(t'_N)} \left[r\left(\mathbf{x}(t)\right) + \mathbf{u}(t)^T \mathbf{H}\mathbf{u}(t)\right] dt$

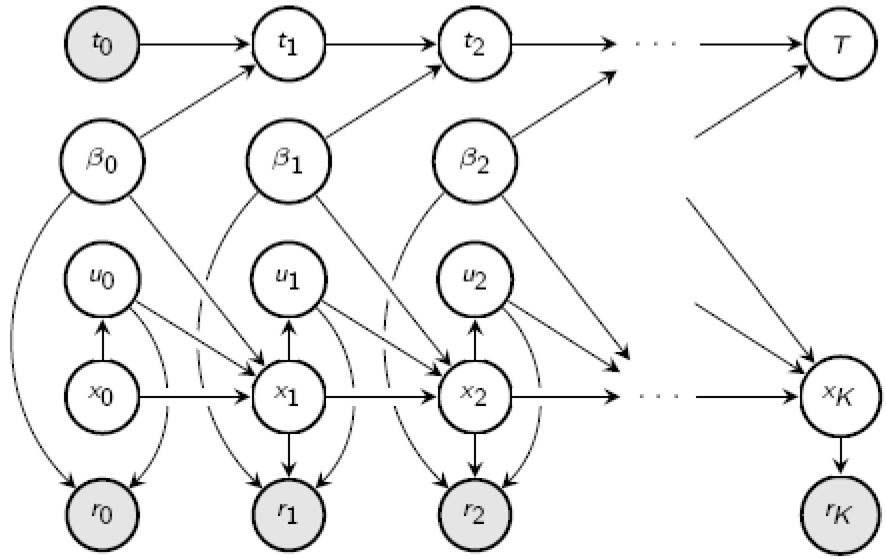
$$+ \int_0^{t'_N} c(\beta(s))ds$$

n.b. $t'_i$ now represents *canonical* time

Introduce change of time $t' = \int_0^t \frac{1}{\beta(s)} ds$

Konrad Rawlik, Marc Toussaint and Sethu Vijayakumar, An Approximate Inference Approach to Temporal Optimization in Optimal Control, *Proc. Advances in Neural Information Processing Systems (NIPS '10)*, Vancouver, Canada (2010).

# AICO-T algorithm

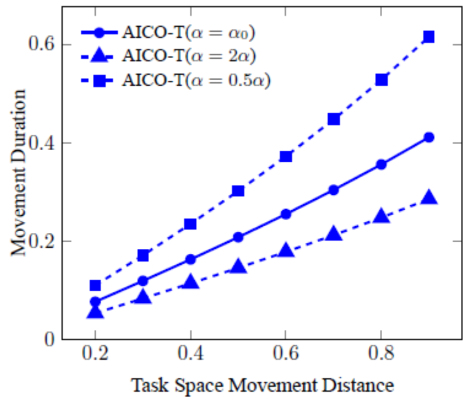


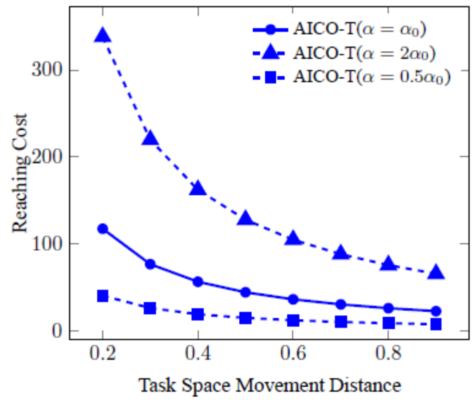

- Use approximate inference methods
- EM algorithm
  - **E-Step:** solve OC problem with fixed β
  - **M-Step:** optimise β with fixed controls

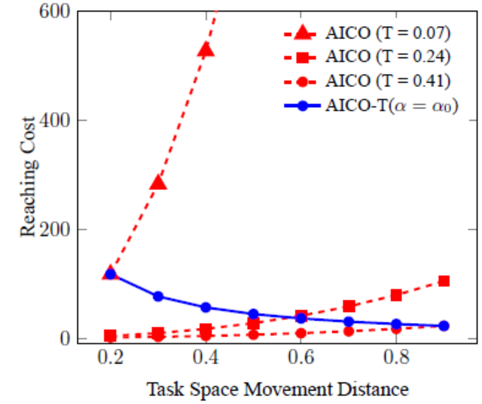
Konrad Rawlik, Marc Toussaint and Sethu Vijayakumar, An Approximate Inference Approach to Temporal Optimization in Optimal Control, *Proc. Advances in Neural Information Processing Systems (NIPS '10)*, Vancouver, Canada (2010).

# Spatiotemporal Optimization

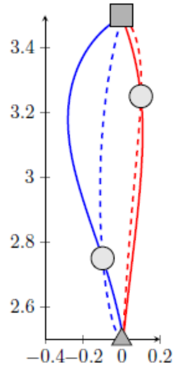
- 2 DoF arm, reaching task

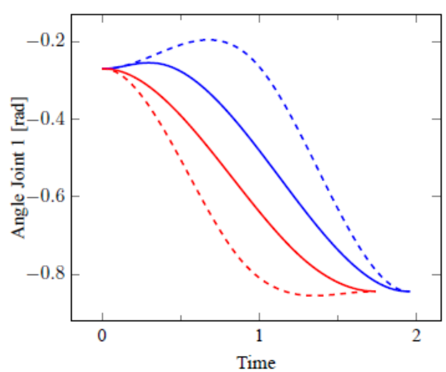


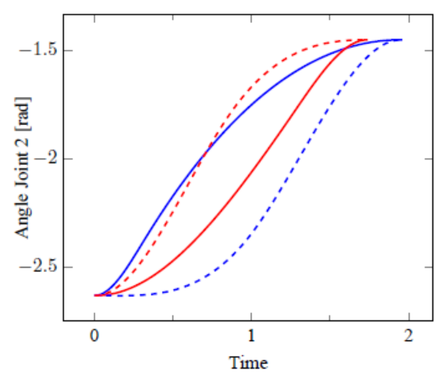



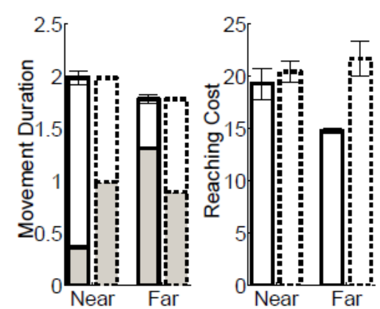




- 2 DoF arm, via point task





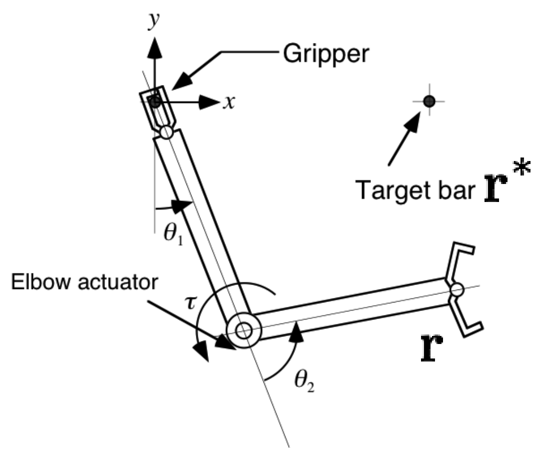
# Temporal Optimization in Brachiation

- Optimize the joint torque and movement duration
- Cost function

$$J = (\mathbf{y} - \mathbf{y}^*)^T \mathbf{P}_T (\mathbf{y} - \mathbf{y}^*) + \int_0^T Ru^2 dt$$

$\mathbf{y} = [\, \mathbf{r}, \ \dot{\mathbf{r}} \,]^T \in \mathbb{R}^4$ $\mathbf{r}$ : gripper position

$u = \tau$




- Time-scaling

$$t' = \int_0^t \frac{1}{\beta(s)} ds$$

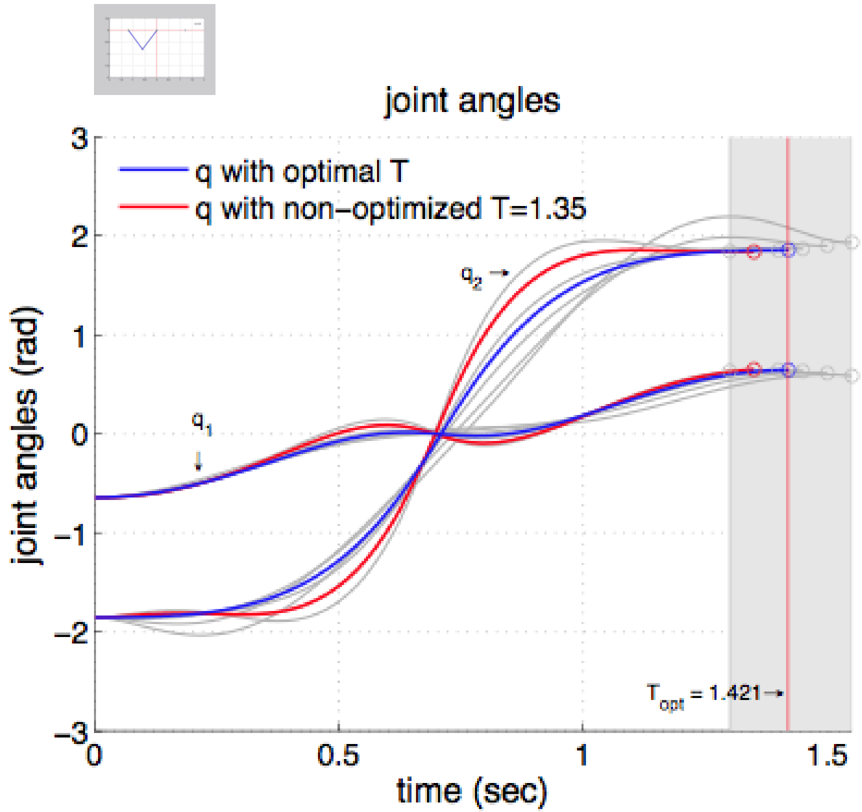
$t'$ : canonical time

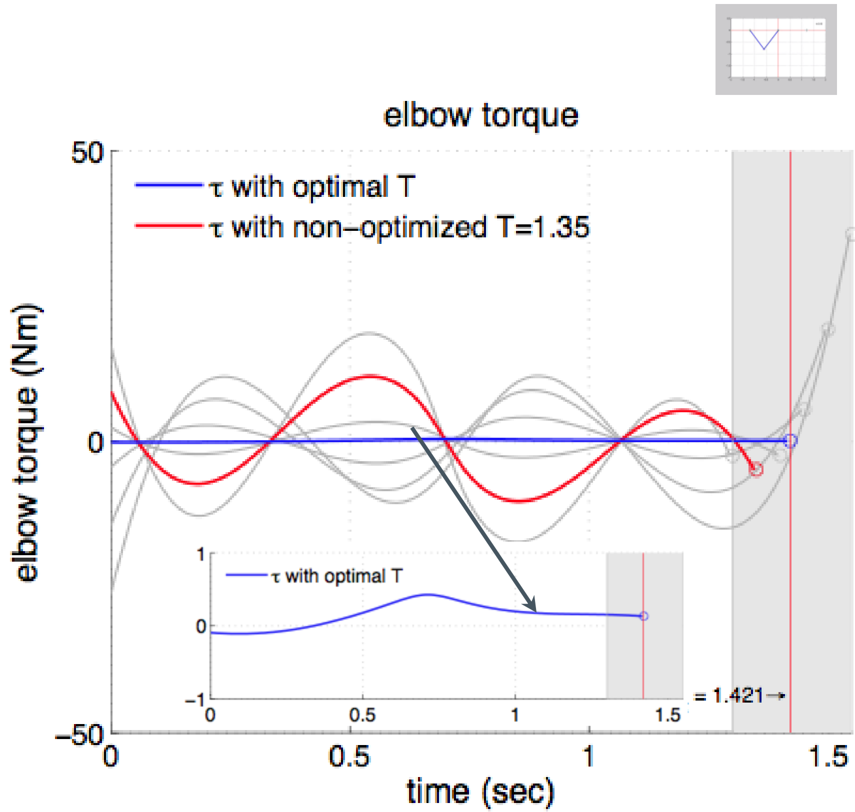
- Find optimal $\mathbf{u}^*$ using iLQG and update $\beta$ in turn until convergence [Rawlik, Toussaint and Vijayakumar, 2010]

Jun Nakanishi, Konrad Rawlik and Sethu Vijayakumar, Stiffness and Temporal Optimization in Periodic Movements: An Optimal Control Approach , *Proc. IEEE Intl Conf on Intelligent Robots and Systems (IROS '11) , San Francisco* (2011).

# Temporal Optimization of Swing Locomotion

- vary T=1.3~1.55 (sec) and compare required joint torque
- significant reduction of joint torque with $T_{opt} = 1.421$



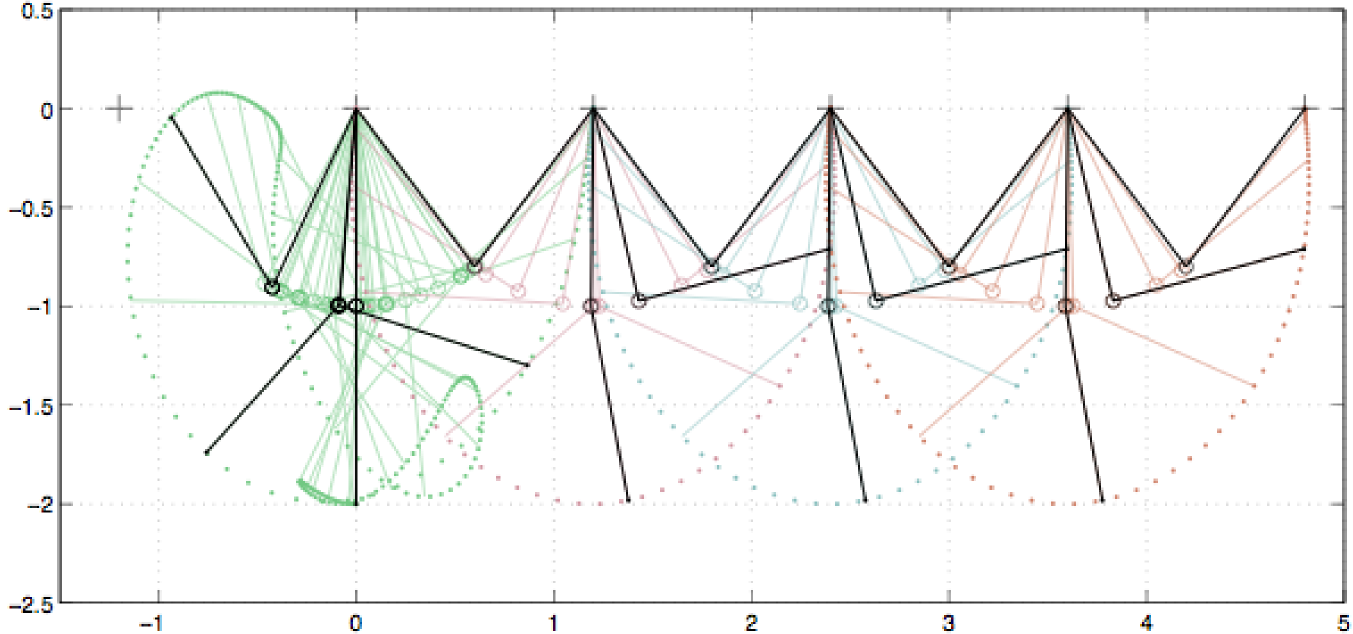



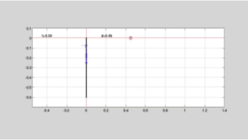


Jun Nakanishi, Konrad Rawlik and Sethu Vijayakumar, Stiffness and Temporal Optimization in Periodic Movements: An Optimal Control Approach , *Proc. IEEE Intl Conf on Intelligent Robots and Systems (IROS '11) , San Francisco* (2011).

# Optimized Brachiating Manoeuvre

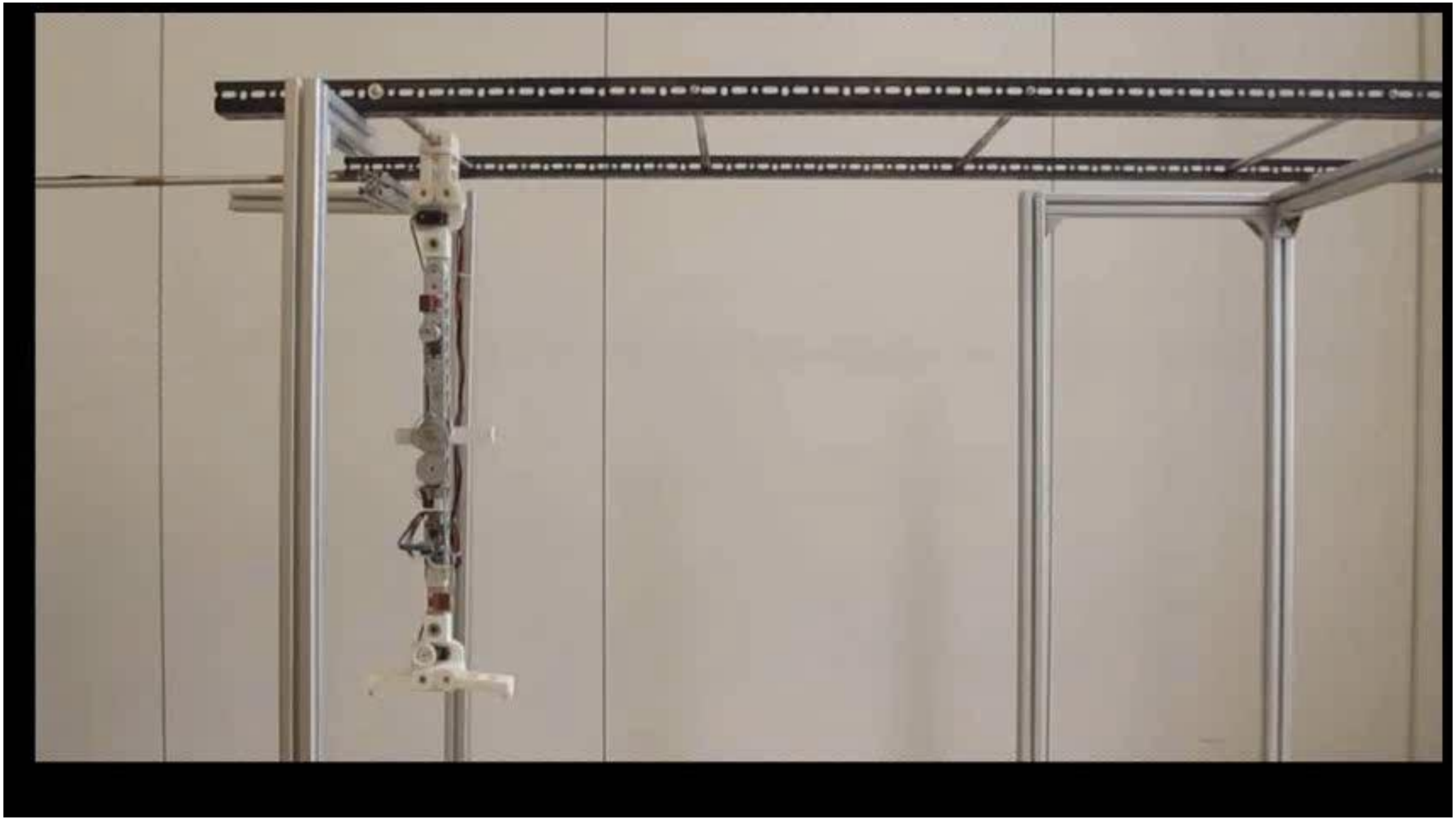
## Swing-up and locomotion



Jun Nakanishi, Konrad Rawlik and Sethu Vijayakumar, Stiffness and Temporal Optimization in Periodic Movements: An Optimal Control Approach , *Proc. IEEE Intl Conf on Intelligent Robots and Systems (IROS '11) , San Francisco* (2011).

# Brachiating Hardware with Constraints



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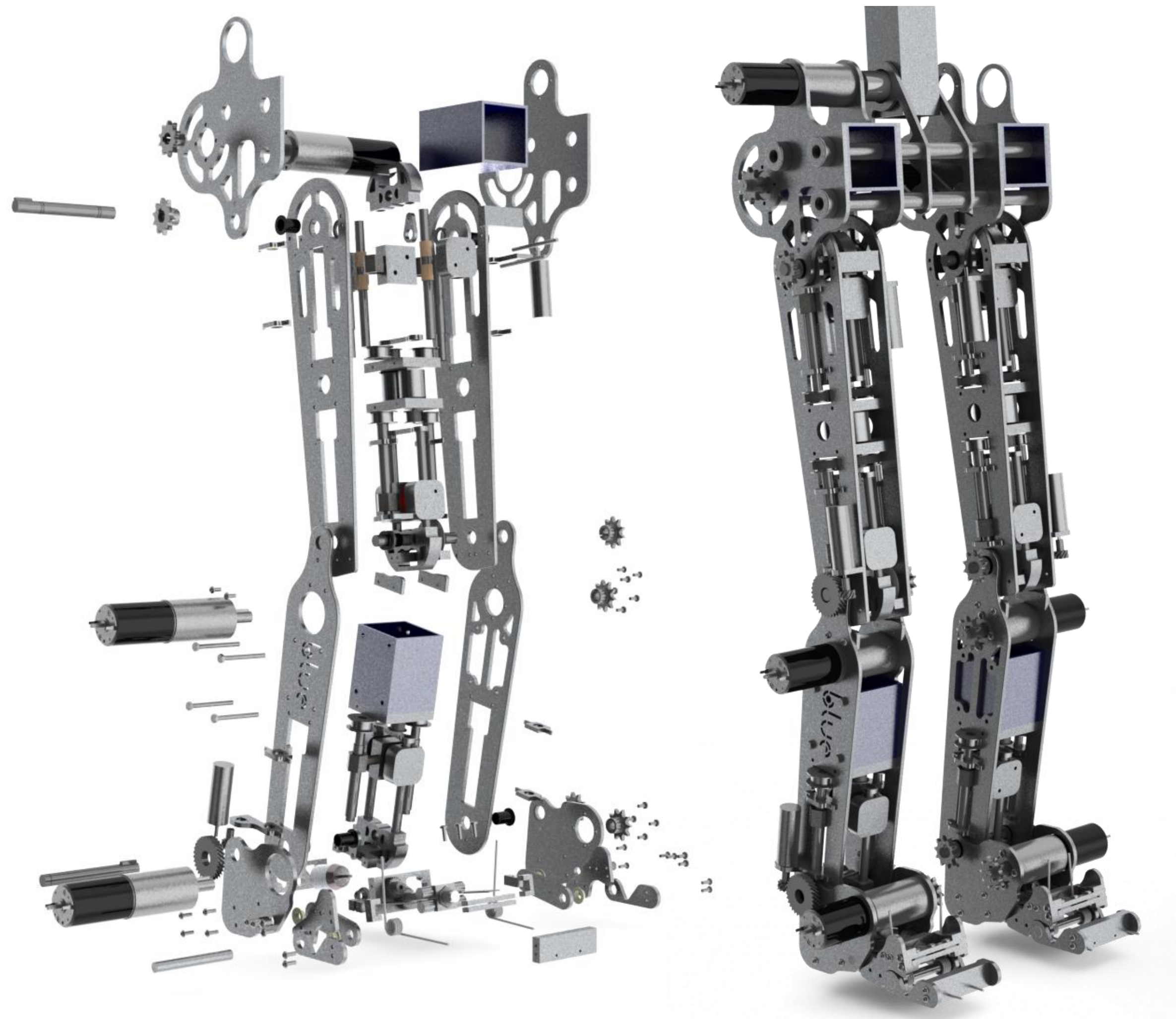
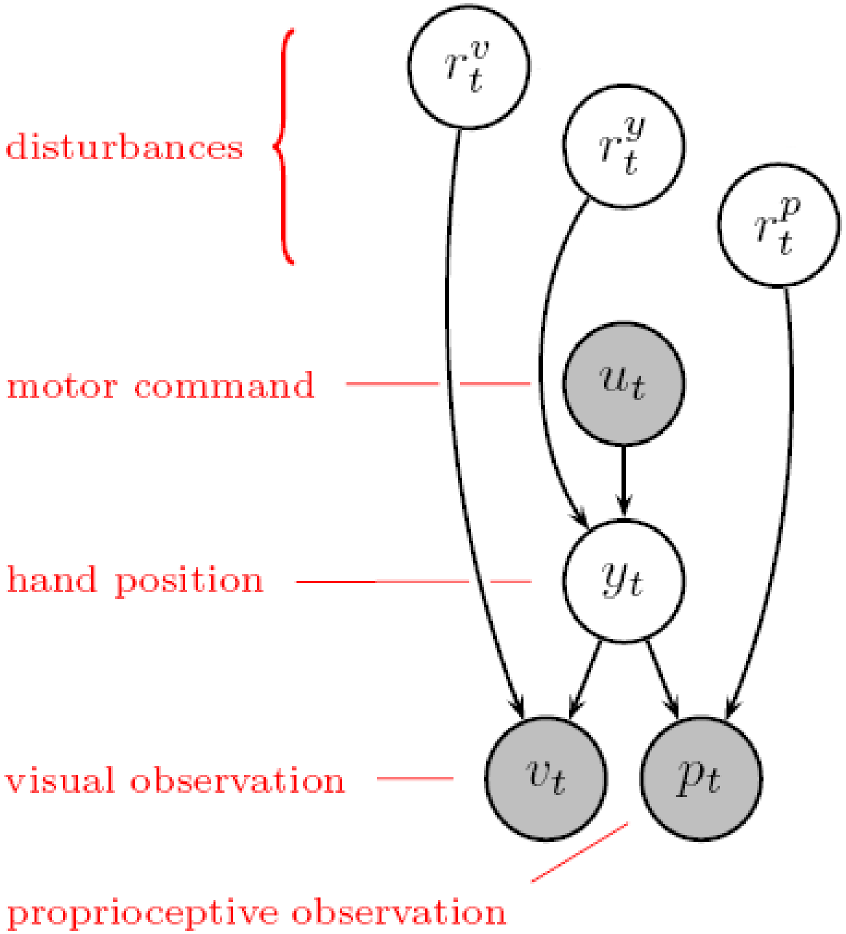
# Variable Impedance Biped
(BLUE: Bipedal Locomotion @ UoE)



# Case Study 1:
# Causal Modeling of Motor Adaptation

## Cue integration under **uncertain** causal structure




- Motor disturbance affects arm position

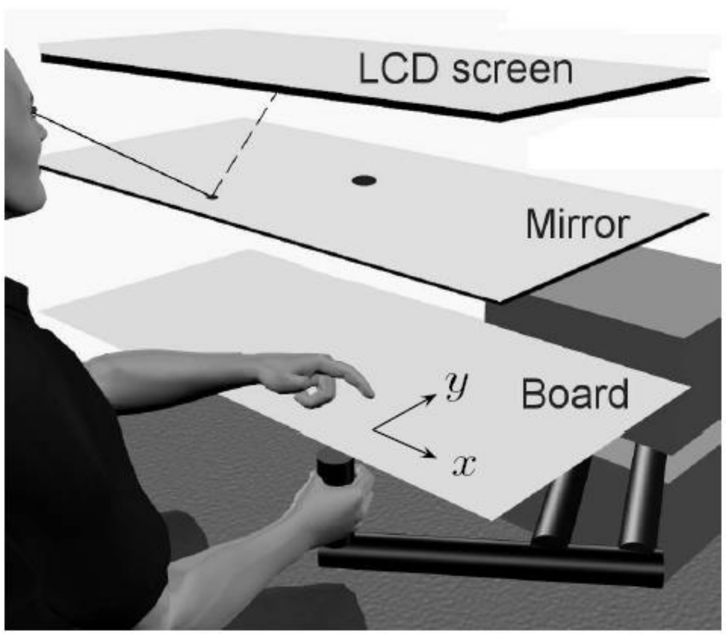
$$y_t = u_t + r_t + \epsilon_t$$

- Sensory disturbances affect observations

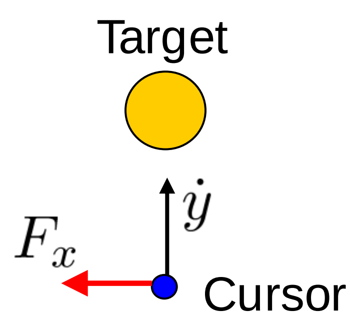
$$v_t = y_t + r_t^v + \epsilon_t^v$$
$$p_t = y_t + r_t^p + \epsilon_t^p$$

# Theory Driving Novel Experiments

- Test whether force field exposure leads to sensory adaptation
  - Experimental setup and design:



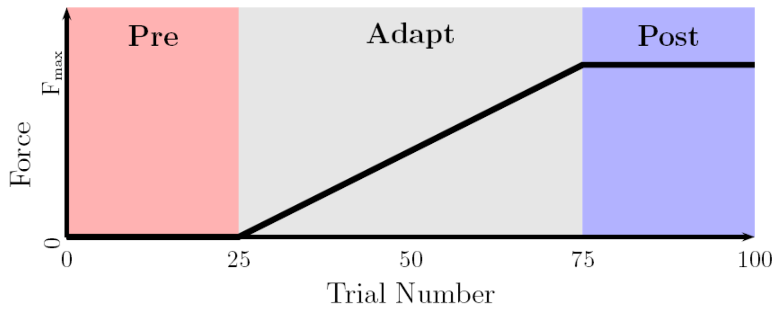

- Reaches in a single direction
- Lateral force applied to hand
  - Forward velocity-dependent

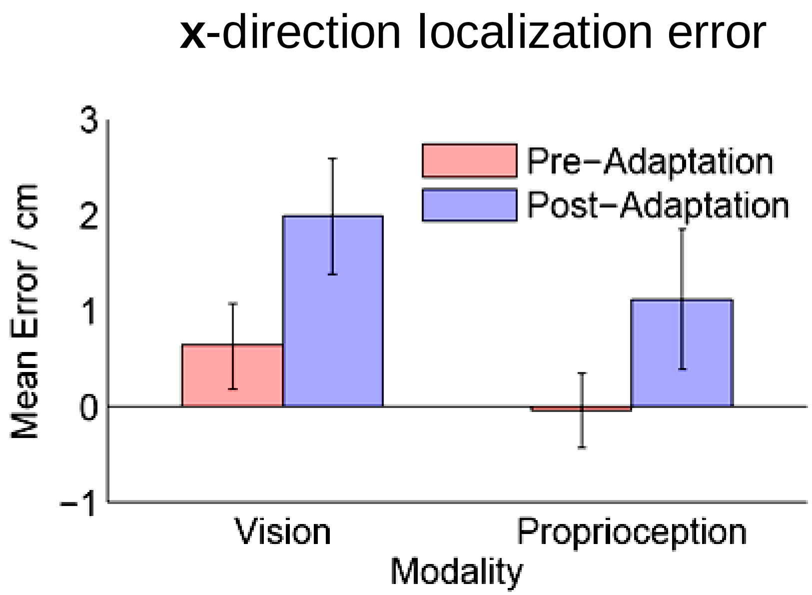



$$F_x = -a\dot{y}$$

# Results

- Compare Pre vs Post-adaptation alignment errors



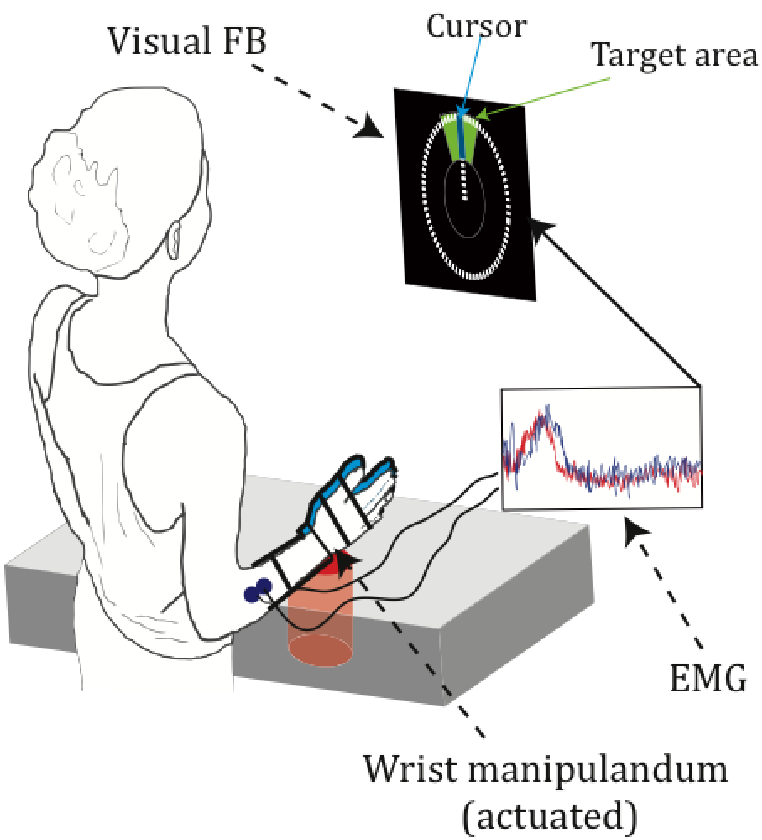

- Significant shifts following adaptation
  - $p < 0.05$ (2-tailed T) for both modalities

# Sensory vs Motor Adaptation

- Proves that sensory and motor adaptation are **NOT** independent
  - systematic *motor* perturbation elicits *sensory* recalibration
- Evidence that brain resolves sensorimotor adaptation in a **unified** and **principled** manner
- We should revisit human motor adaptation results/paradigm with this new insight!

Adrian Haith, Carl Jackson, Chris Miall and Sethu Vijayakumar, Unifying the Sensory and Motor Components of Sensorimotor Adaptation, *Proc. Advances in Neural Information Processing Systems (NIPS ),* Canada (2009).

# Case Study 2: Sensory vs. Motor Noise




- **Does visual perturbation provoke impedance control?**
- Closing the control loop with EMG feedback
- Manipulating visual and proprioceptive feedback
- On-line impedance adaptation and data driven stiffness/visual displacement model

# Credits

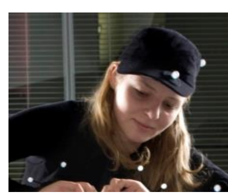
The Royal Academy of Engineering

- Dr. Matthew Howard
- Dr. David Braun
- Dr. Jun Nakanishi
- Konrad Rawlik
- Dr. Takeshi Mori
- Dr. Djordje Mitrovic

- Evelina Overling
- Alexander Enoch



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# More details at

- My webpage and relevant publications:
  - http://homepages.inf.ed.ac.uk/svijayak
- Our group webpage:
  - http://ipab.inf.ed.ac.uk/slmc