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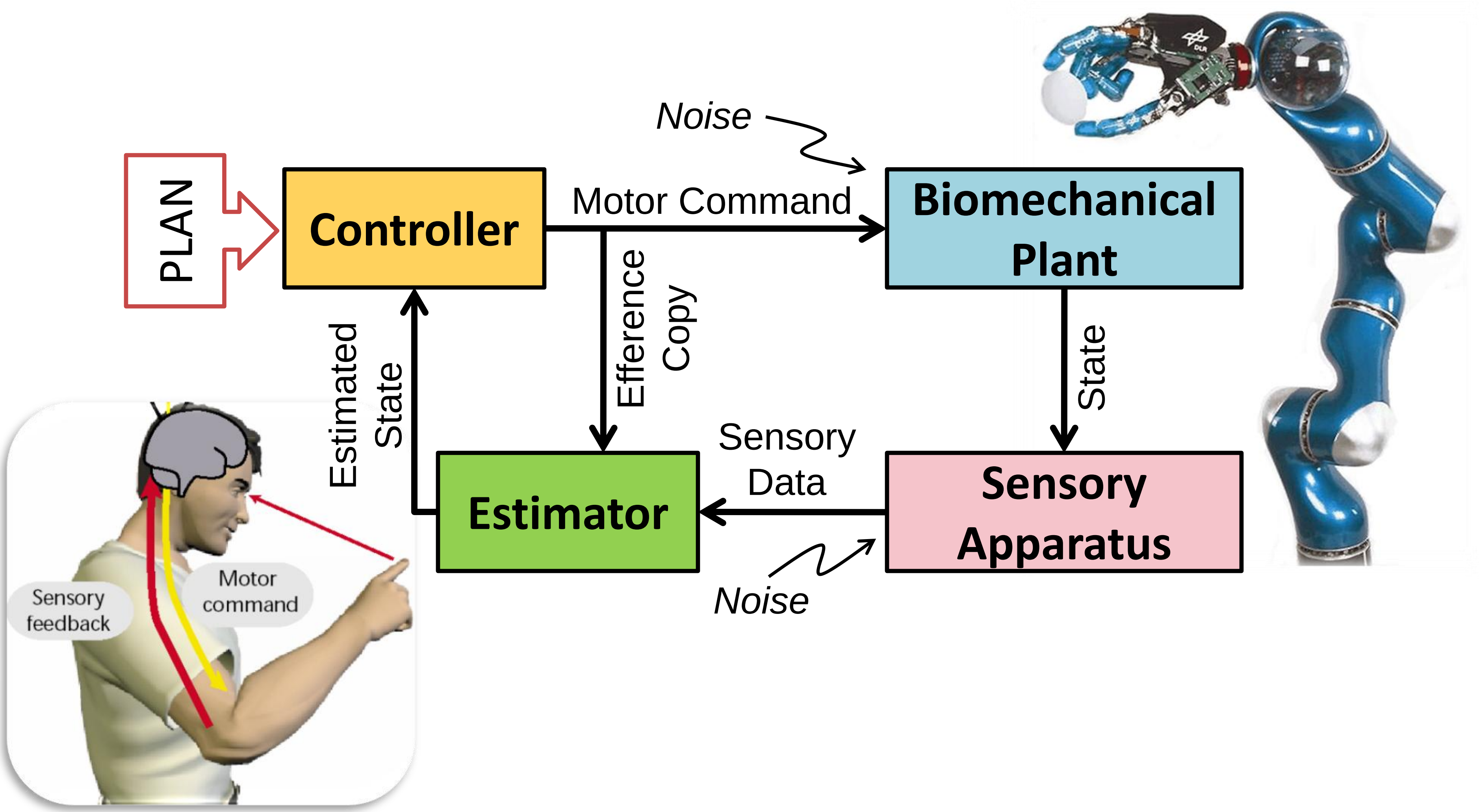
Machine Learning Challenges for Sensorimotor Control

Sensorimotor Control



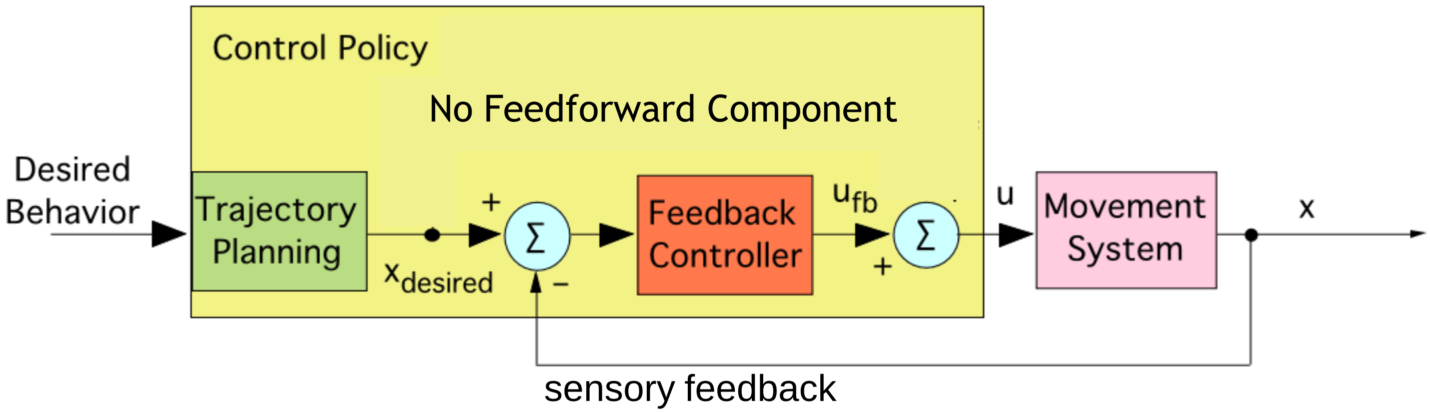
Sense, Plan, Move

Interesting **Machine Learning Challenges** in each domain

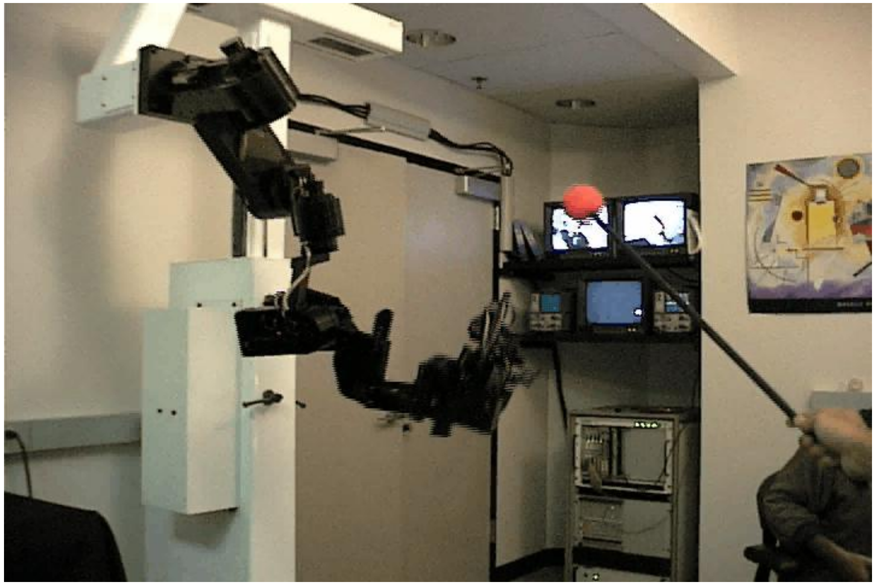
- **Sensing**
  - Incomplete state information
  - Unknown causal structure
  - Noise
- **Planning**
  - Redundancy resolution
  - Incomplete knowledge of appropriate optimization cost function
- **Moving**
  - Incomplete knowledge of (hard to model) nonlinear dynamics
  - Dynamically changing motor functions: wear and tear/loads

Learning to Move

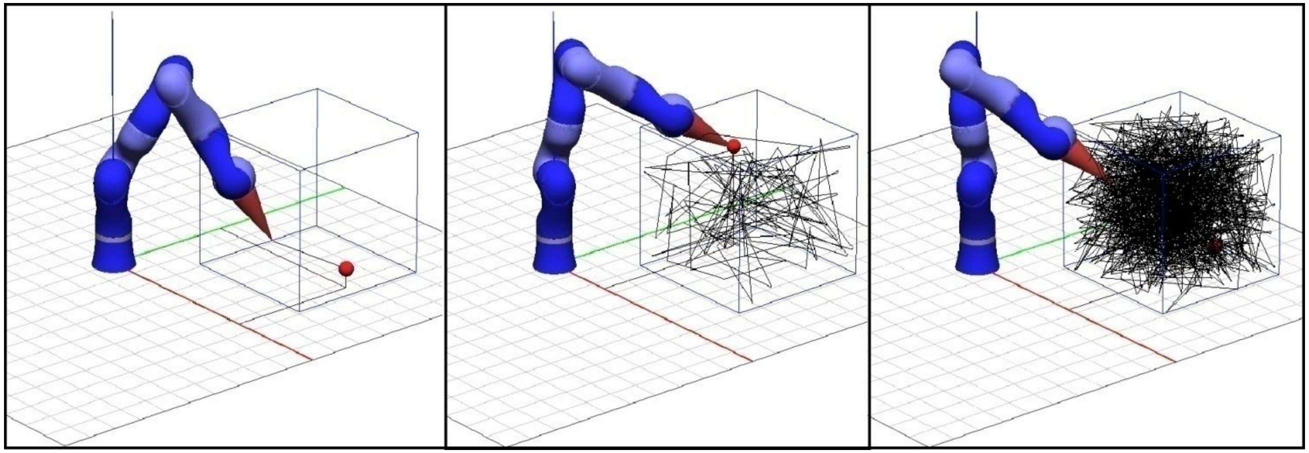
Feedforward Predictive Control



$$u_{fb} = k_p(x_{cur} - x_{des}) + k_d(\dot{x}_{cur} - \dot{x}_{des})$$



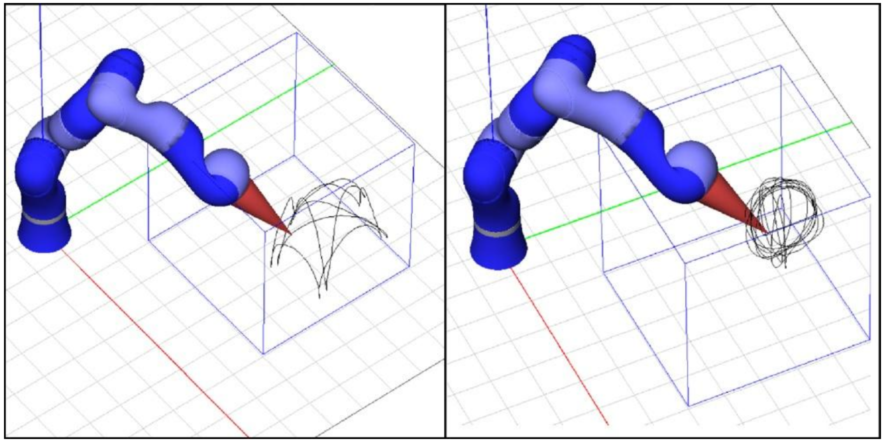
Data from Motor Babbling



Random motions in a specified work area

$$\tau = f(\theta, \dot{\theta}, \ddot{\theta})$$

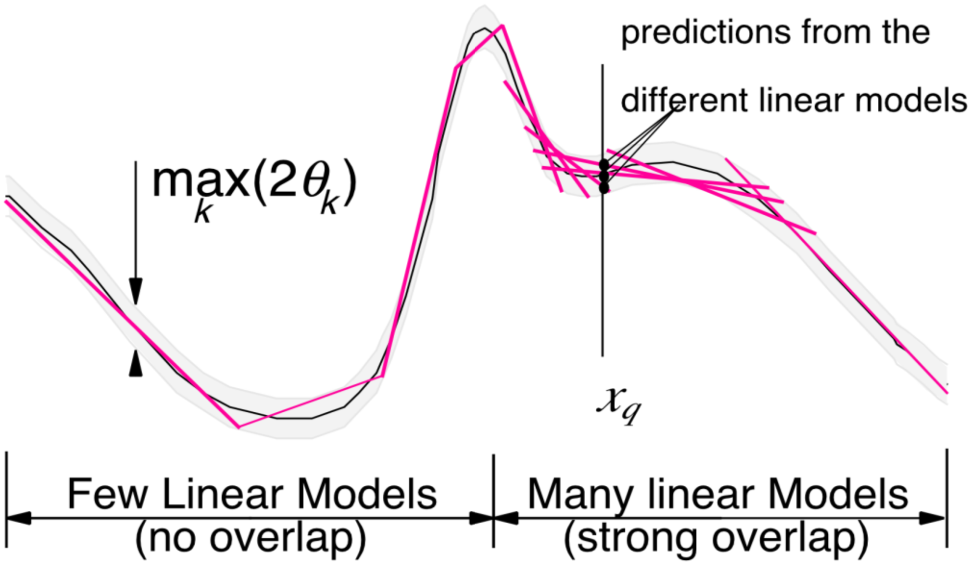
- High Dimensional
- Sampled at 500 Hz
- Need for real time results



Kinesthetic demo using a dynamic target

Local Weighted Learning

Approximate non-linear functions with a combination of multiple weighted linear models



$$w_{ii} = \exp\left(-\frac{1}{2}(\mathbf{x}_i - \mathbf{x}_q)^T \mathbf{D}_k (\mathbf{x}_i - \mathbf{x}_q)\right)$$

$$\boldsymbol{\beta}_k = (\mathbf{X}^T \mathbf{W}_k \mathbf{X})^{-1} \mathbf{X}^T \mathbf{W}_k \mathbf{Y}$$

$$\hat{\mathbf{y}}_k = \mathbf{x}_q^T \boldsymbol{\beta}_k$$

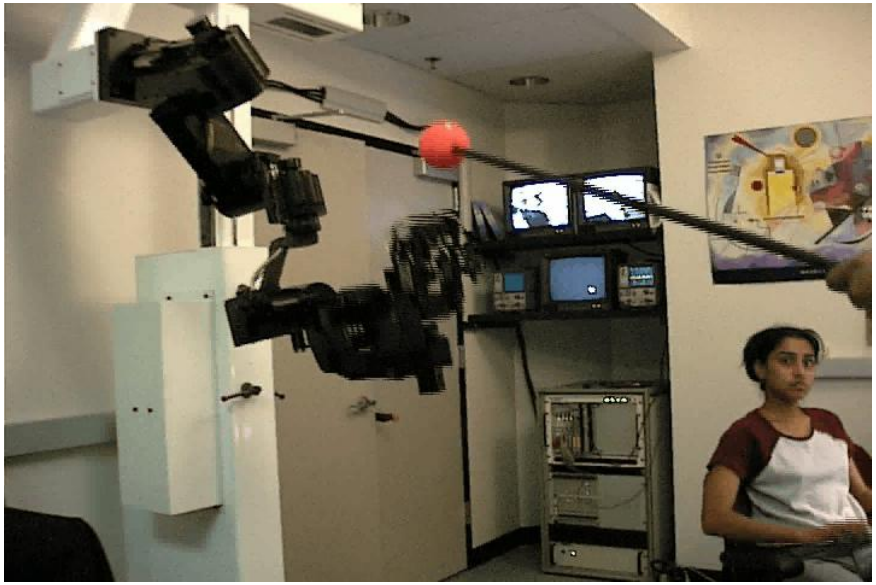
$$\hat{\mathbf{y}} = \sum_k w_k \hat{y}_k \,/\, \sum_k w_k$$

Solve this problem for high dimensional space: LWPR

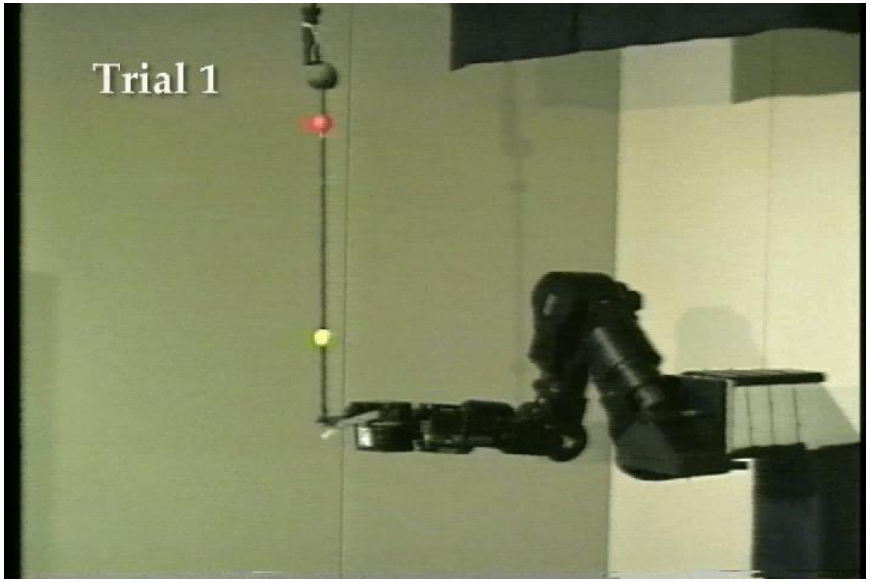
Sethu Vijayakumar, Aaron D'Souza and Stefan Schaal, Online Learning in High Dimensions, *Neural Computation,* vol. 17, pp. 2602-2634 (2005)

Online Learning with LWPR

Learning the Internal Dynamics



Learning the Task Dynamics



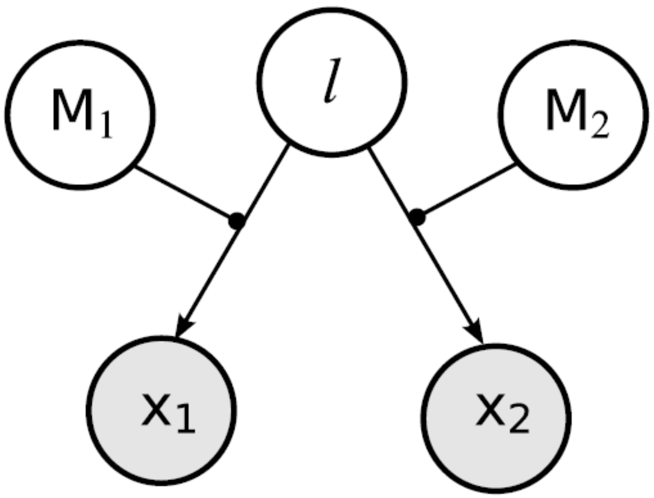
Stefan Klanke, Sethu Vijayakumar and Stefan Schaal, A Library for Locally Weighted Projection Regression, *Journal of Machine Learning Research (JMLR),* vol. 9. pp. 623--626 (2008).

Learning to Sense

Bayesian Structure Inference

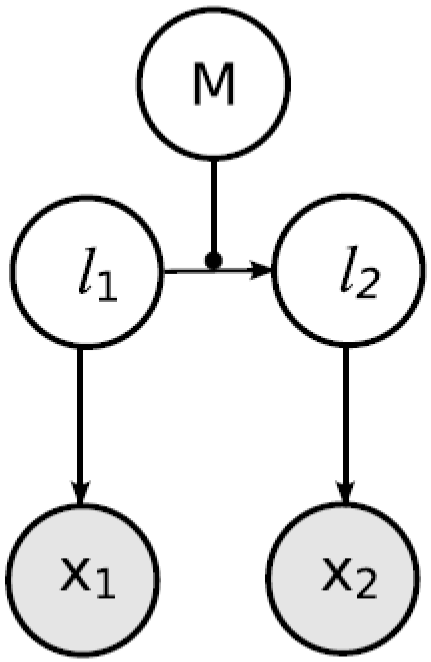
Cue integration under uncertain causal structure

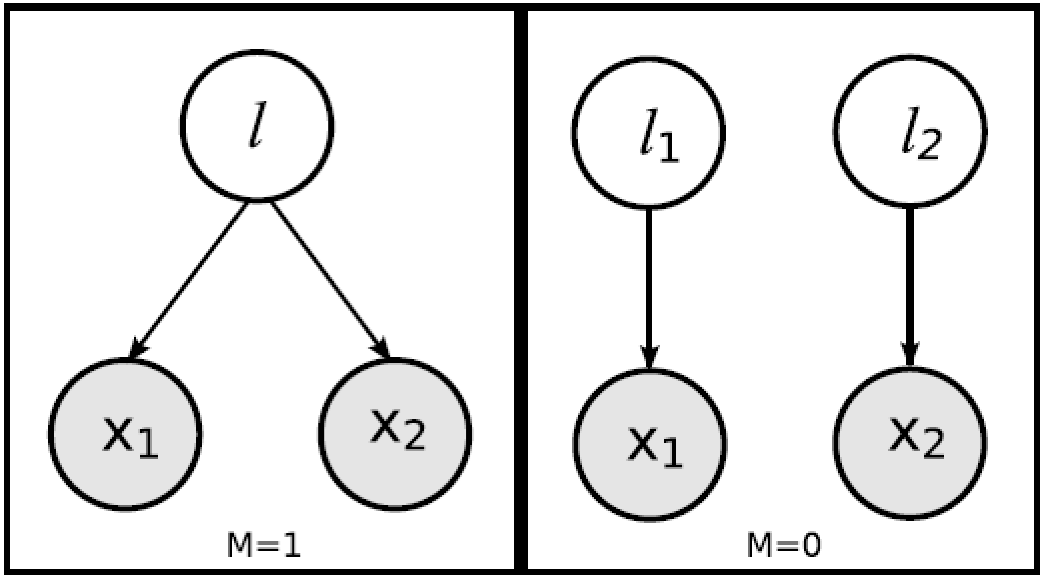
- Infer variables and structure
- e.g., AV localisation
  - Visible?
  - Audible?
  - Current state (Location)



Hospedales and Vijayakumar, Structure Inference for Bayesian Multi-sensory Scene Understanding, *IEEE Transactions on Pattern Analysis and Machine Intelligence (PAMI),* Vol. 99, No.1 (2008)

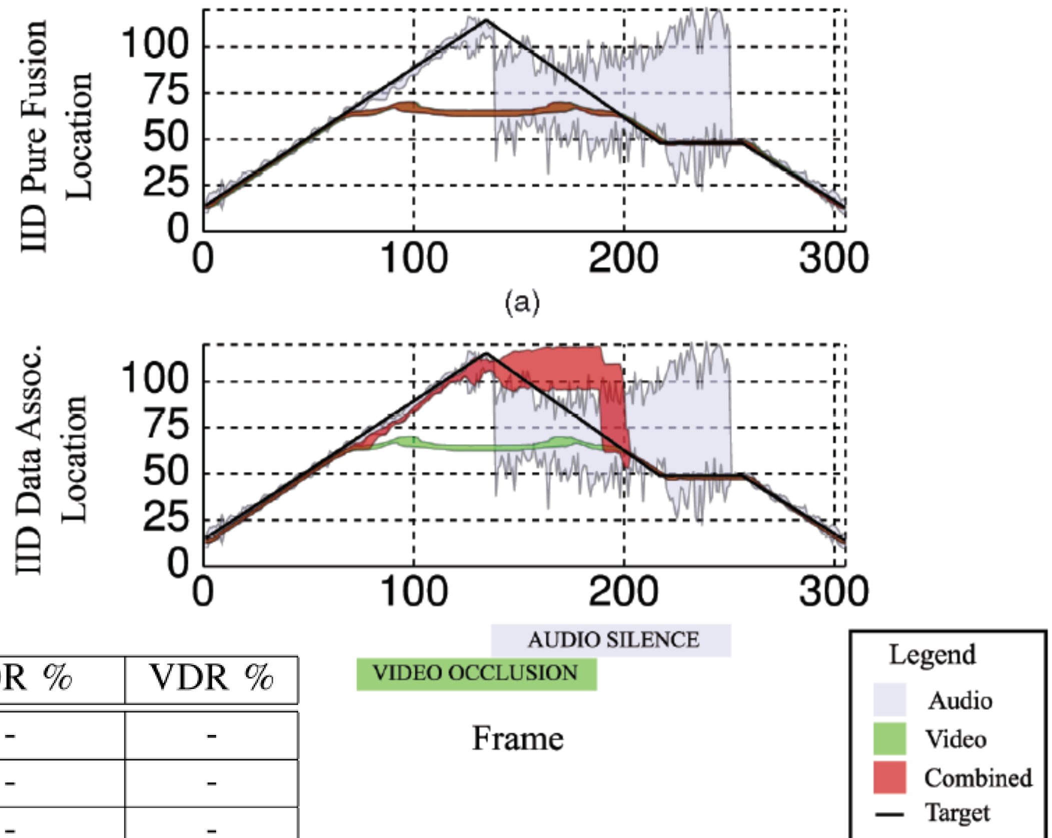
Multi-object Inference





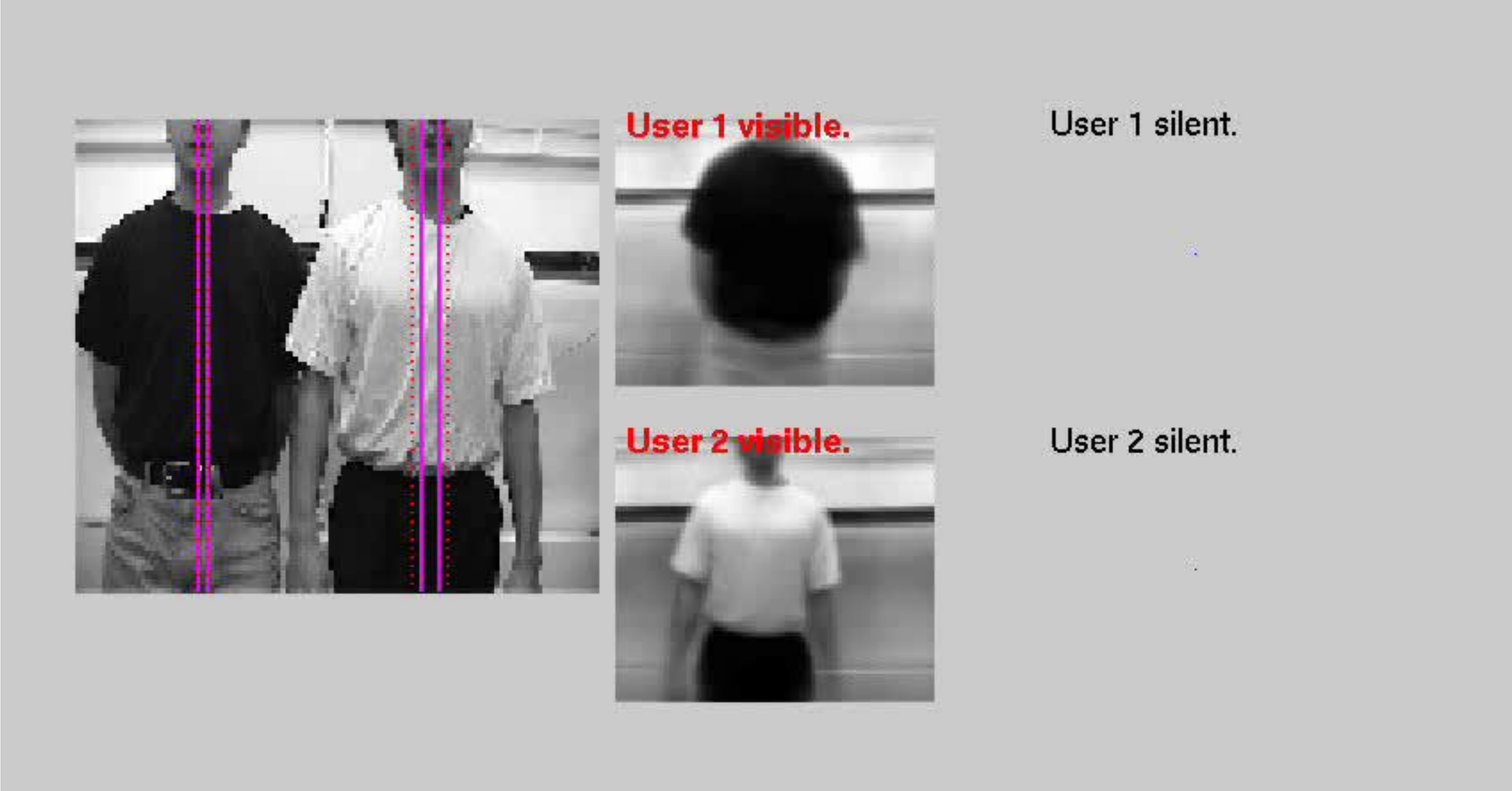
Hospedales and Vijayakumar, Structure Inference for Bayesian Multi-sensory Scene Understanding, *IEEE Transactions on Pattern Analysis and Machine Intelligence (PAMI),* Vol. 99, No.1 (2008)

Systematic Testing



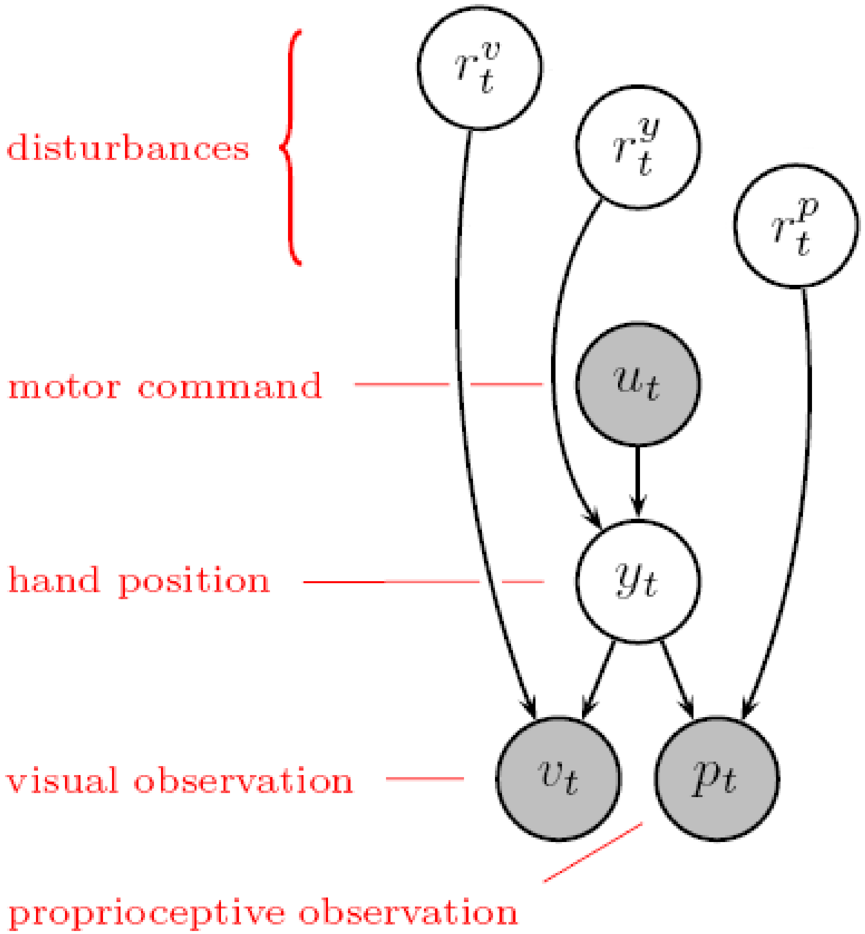
	Track %	Accuracy	ADR %	VDR %
Aud Only	72.3 ± 2.5	2.57 ± 0.08	-	-
Vid Only	65.6 ± 1.1	2.52 ± 0.01	-	-
PF IID	$\mathbf{65.6} \pm 1.1$	2.52 ± 0.01	-	-
PF Filt	65.6 ± 1.1	2.52 ± 0.01	-	-
DA IID	81.5 ± 2.4	2.67 ± 0.01	96.7 ± 10.2	100 ± 0
DA Filt	$\mathbf{86.3} \pm 2.6$	2.70 ± 0.01	96.7 ± 10.2	100 ± 0

Who said what?



Hospedales and Vijayakumar, Structure Inference for Bayesian Multi-sensory Scene Understanding, *IEEE Transactions on Pattern Analysis and Machine Intelligence (PAMI),* Vol. 99, No.1 (2008)

Unifying the Sensory & Motor Components of Adaptation



- Motor disturbance affects hand position

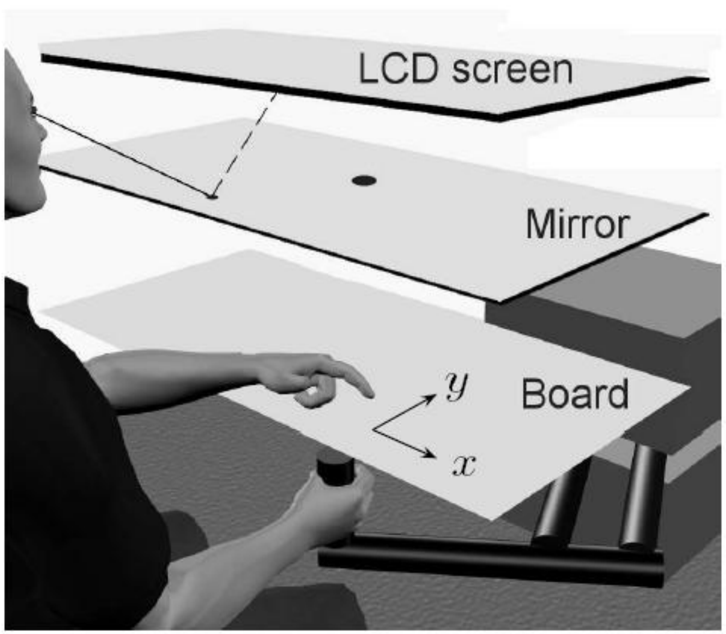
$$y_t = u_t + r_t + \epsilon_t$$

- Sensory disturbances affect observations

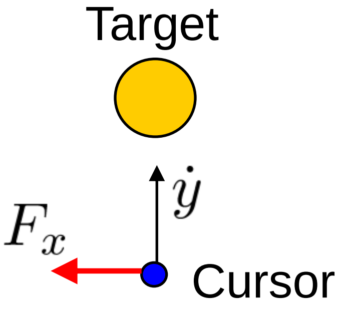
$$v_t = y_t + r_t^v + \epsilon_t^v$$
$$p_t = y_t + r_t^p + \epsilon_t^p$$

Theory driven 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



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

Some interesting results

- Sensory and motor adaptation are **NOT** independent
  - Motor adaptation leads to sensory recalibration (after-effects) even without introducing any sensory discrepancy

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 '08),* Vancouver, Canada (2008).

Learning to Plan

Optimal Feedback Control (OFC) for planning

Known: Start & end states, fixed-time horizon T and system dynamics

$$d\mathbf{x} = \mathbf{f}(\mathbf{x},\mathbf{u})dt + \mathbf{F}(\mathbf{x},\mathbf{u})d\boldsymbol{\omega}.$$

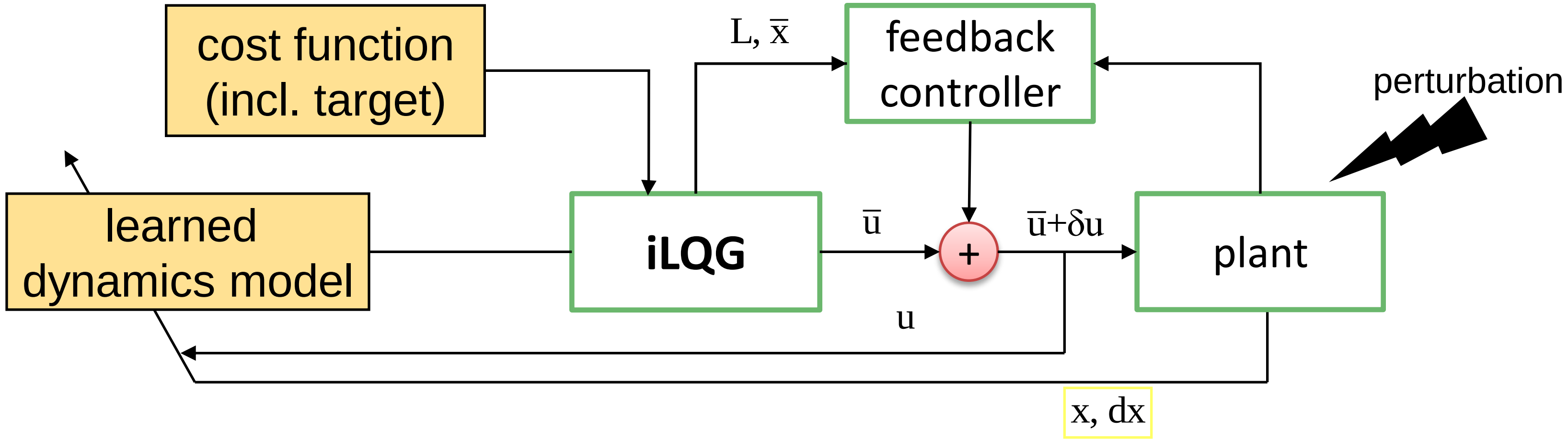
Control as a result of an optimisation process of some cost function.

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

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

iLQG-L(earned) D(ynamics)

iLQG-LD uses a LWPR-learned forward dynamic model of the plant.

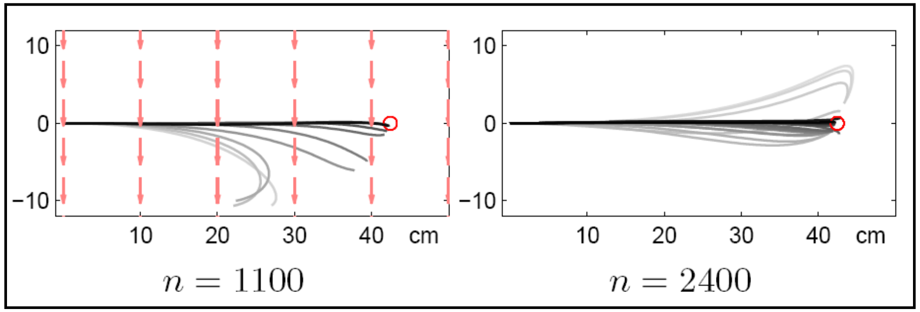


Djordje Mitrovic, Stefan Klanke and Sethu Vijayakumar, **Optimal control with adaptive internal dynamics models**, In: Robotics Challenges for Machine Learning, *Neural Information Processing Systems (NIPS 2007),* Whistler, Canada (2007).

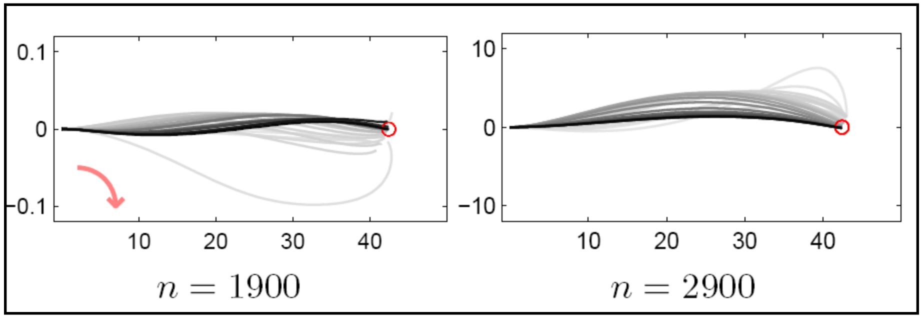
iLQG-LD: Advantages

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:

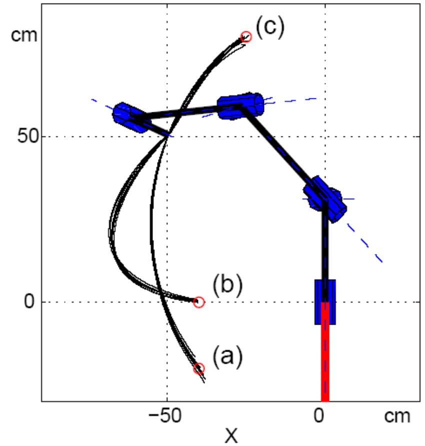
$$v = w_p \left| \mathbf{q}_K - \mathbf{q}_{tar} \right|^2 + w_v \left| \dot{\mathbf{q}}_K \right|^2 + w_e \sum_{k=0}^{K} \left| \mathbf{u}_k \right|^2 \Delta t$$

iLQG-LD: Advantages

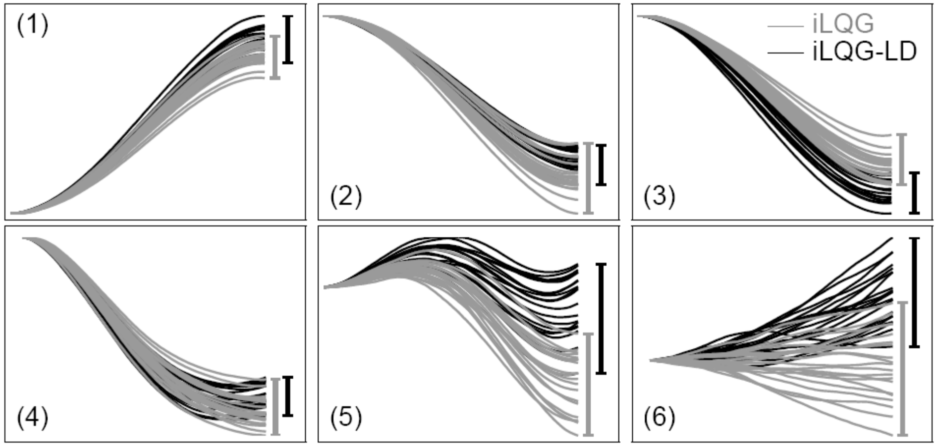
Reproduces the “trial-to-trial” variability in the uncontrolled manifold, i.e., exhibits the minimum intervention principle that is characteristic of human motor control.

DLR LWR III

Simulink Model

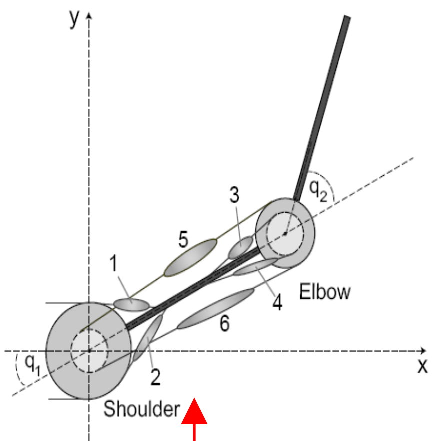


Minimum intervention principle

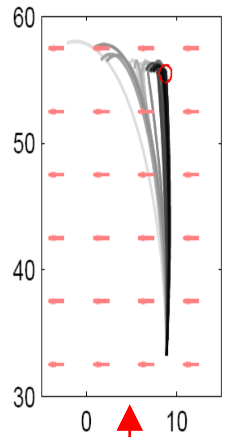


iLQG-LD in Variable Impedance Actuators

Preliminary results suggest iLQG-LD can be used as an effective control strategy in redundant, co-actuated, variable stiffness actuators.

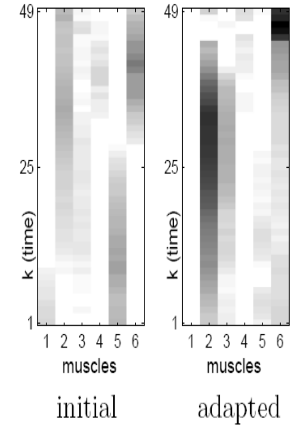


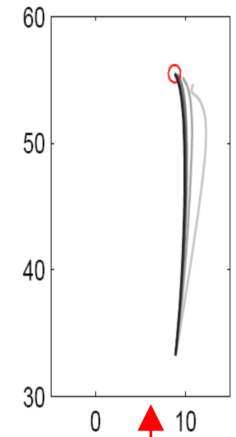
2 joint and
6 antagonistic muscles



Constant force field
→Online adaptation!

Muscle plots:
Minimal co-contraction remains





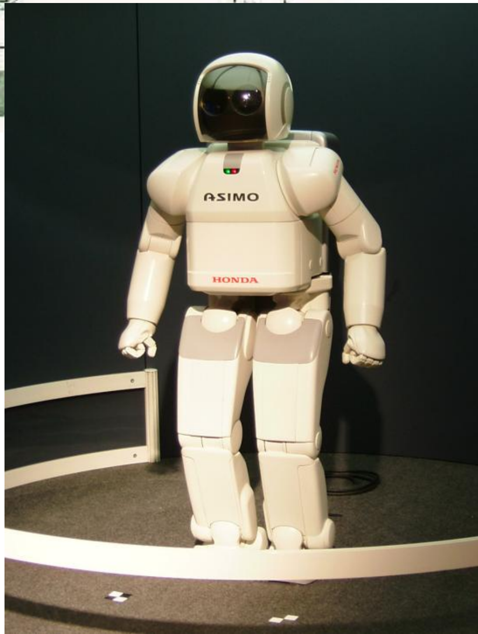
Overshoot
→ Online re-anneal

Djordje Mitrovic, Stefan Klanke, Sethu Vijayakumar, **Adaptive Optimal Control for Redundantly Actuated Arms**, *Proc. Tenth International Conference on the Simulation of Adaptive Behavior (SAB '08), Osaka, Japan* (2008)

Learning from demonstration

Why do we care?

- Rehabilitation Robotics
- Entertainment Robotics
- Exoskeletons



… involve much closer human-robot interactions !!

Sense, Plan, Move

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  - Dynamically changing motor functions: wear and tear/loads

The SLMC research group (Statistical Learning & Motor Control)

- Dr. Stefan Klanke
- Narayanan Edakunni
- Matthew Howard
- Adrian Haith
- Sebastian Bitzer
- Djordje Mitrovic
- Chris Towell
- Konrad Rawlik

- Alumni: Dr. Graham McNeill, Dr. Timothy Hospedales, Dr. Giorgos Petkos