Robots that Learn

Machine Learning for smarter and efficient actuation

Professor Sethu Vijayakumar FRSE

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www.edinburgh-robotics.org

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University of Edinburgh
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ROBOTICS AND COMPUTER VISION

Institute of Perception, Action and Behaviour (IPAB)

Director: Sethu Vijayakumar

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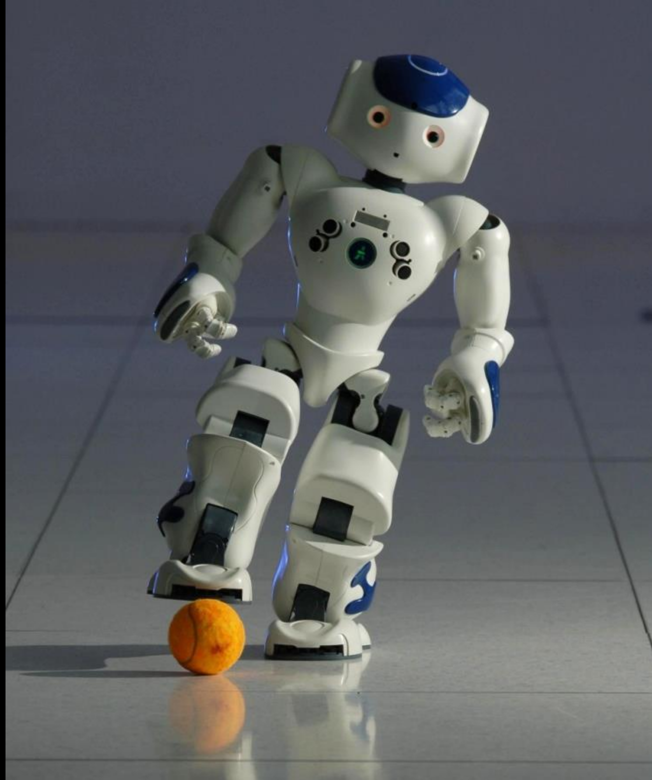
EDINBURGH CENTRE FOR ROBOTICS

ROYAL ACADEMY OF ENGINEERING

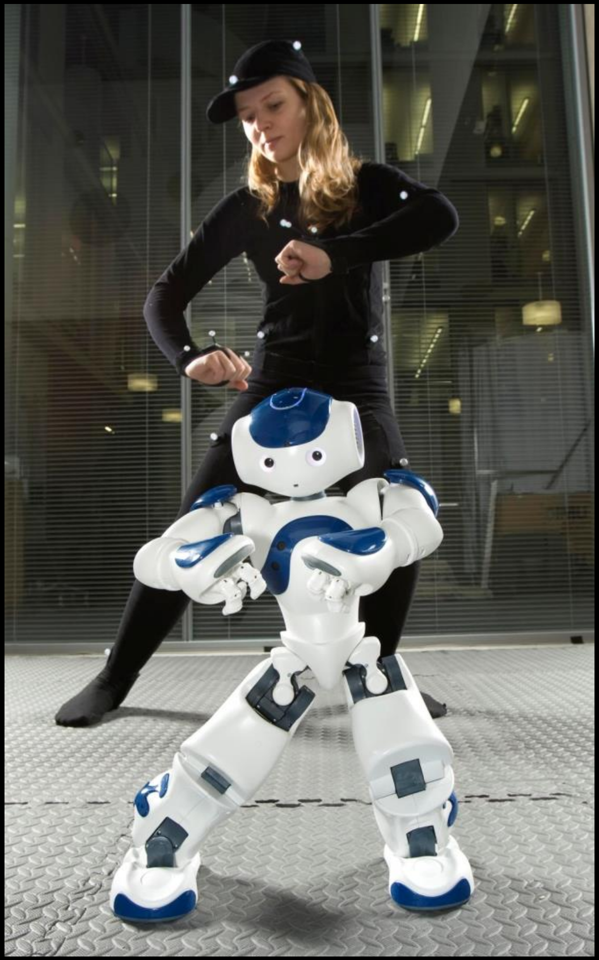
Microsoft® Research



Autonomous
Make decisions on its own
Adapt to changing world
React to unseen scenarios

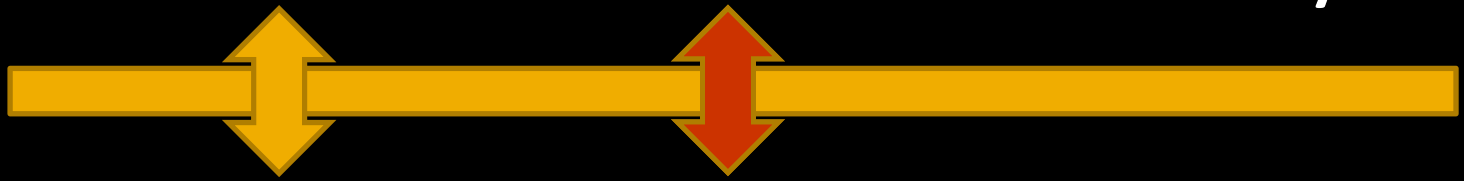
Autonomous?
Make decisions on its own: Game Playing Engine
~~Adapt to changing world~~
~~React to unseen scenarios~~

What is missing: Ability to Learn and Adapt?



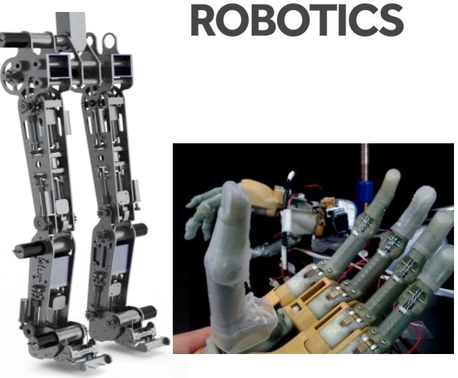
Teleoperation

Autonomy



Shared Autonomy

Robots That Interact



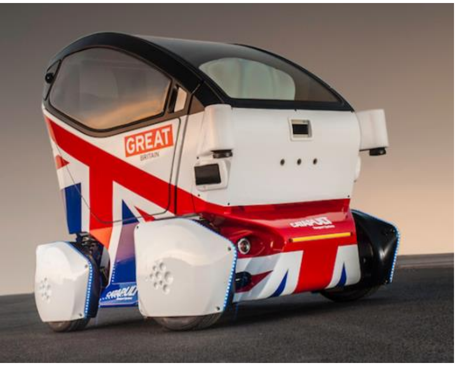
Prosthetics, Exoskeletons

Field Robots (Land)

Key challenges due to

1. Close interaction with multiple objects
2. Multiple contacts
3. Hard to model non-linear dynamics
4. Guarantees for safe operations
5. Highly constrained environment
6. Under significant autonomy
7. Noisy sensing with occlusions

...classical methods do not scale!



Self Driving Cars

Nuclear Decommissioning

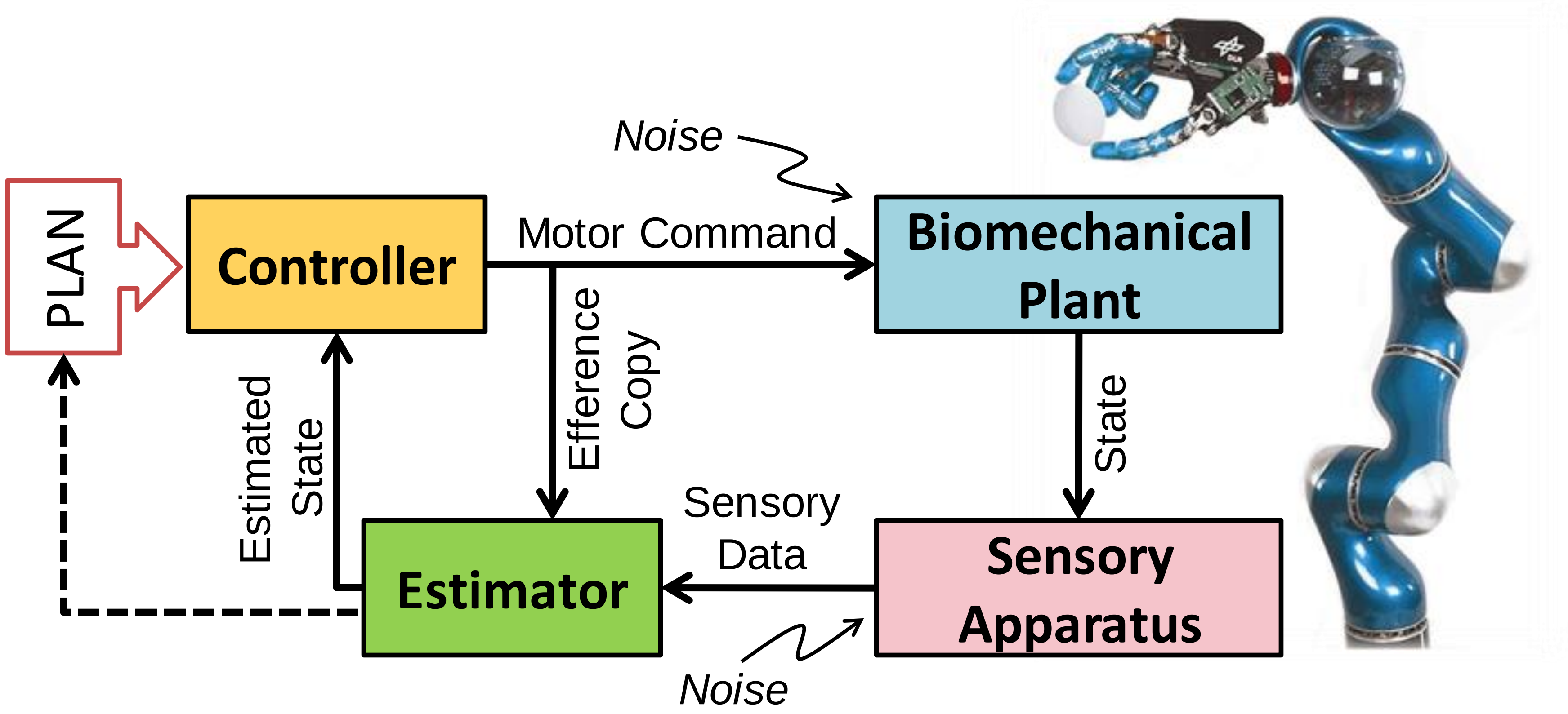
Field Robots (Marine)

Medical Robotics

Service Robots

Industrial/ Manufacturing

What does it take to control a robot?



Innovation 1

Making **sense** of the world around you

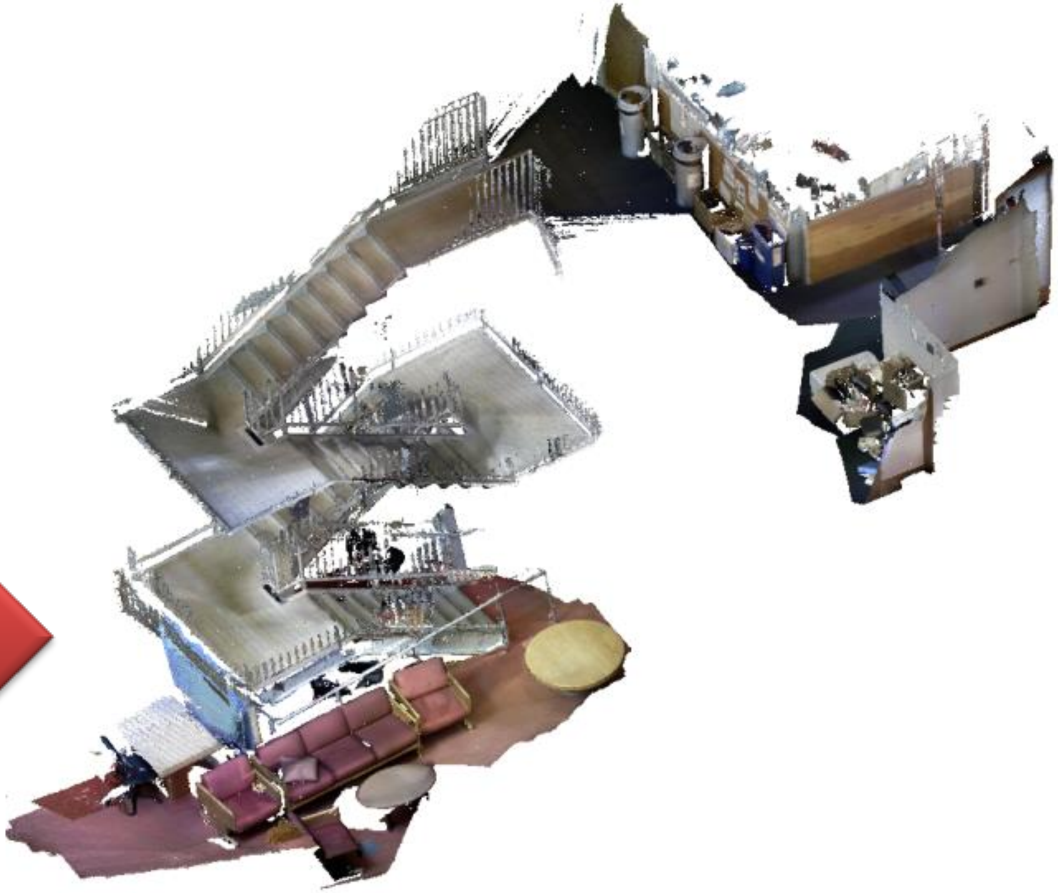
(Real-time pose estimation under **camera motion** and severe **occlusion**)

Innovation 1

Making **sense** of the world around you

(Tracking and Localisation)

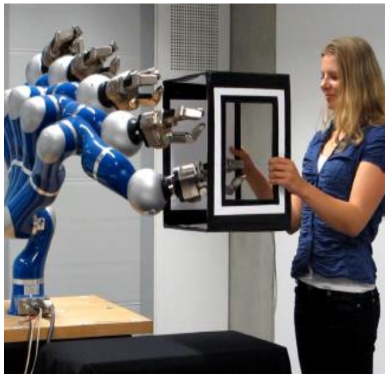
UEDIN-NASA
Valkyrie
Humanoid
Platform -2015



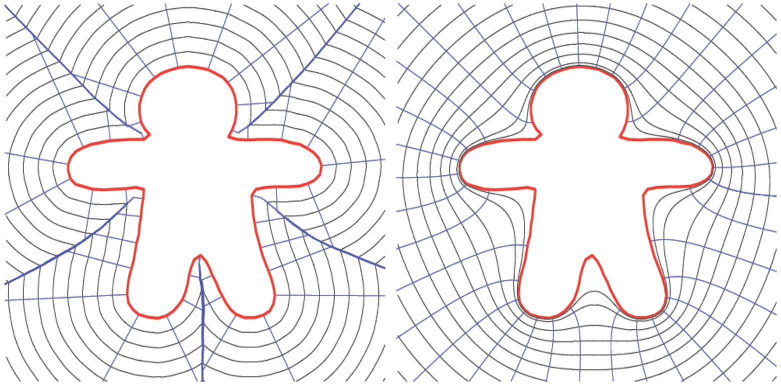
Wheelan, Fallon et.al, Kintinuous, IJRR 2014 (MIT DRC perception lead)

Innovation 2

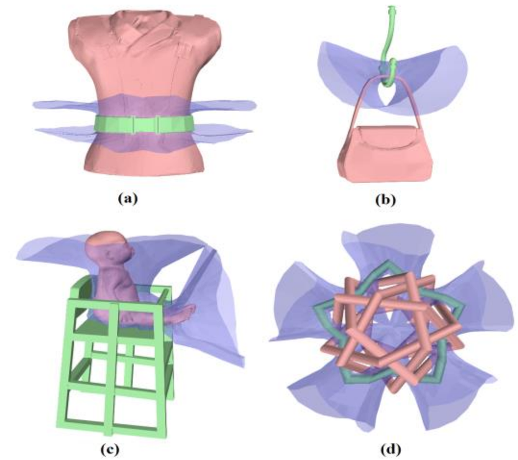
Scalable Context Aware Representations



Interaction Mesh



Electric field (right): harmonic as opposed distance based (non-harmonics)



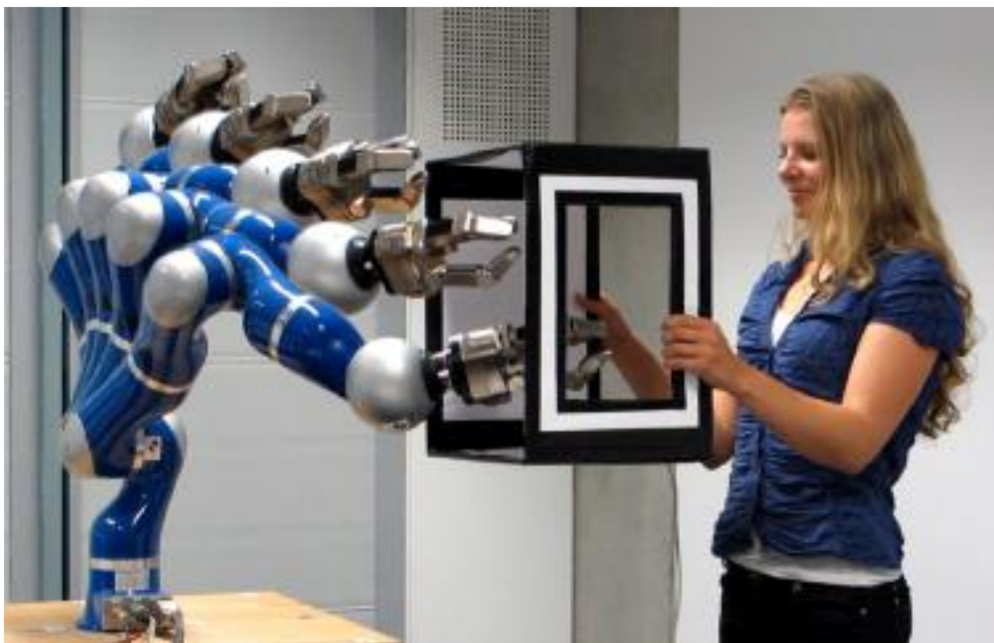
Relational tangent planes

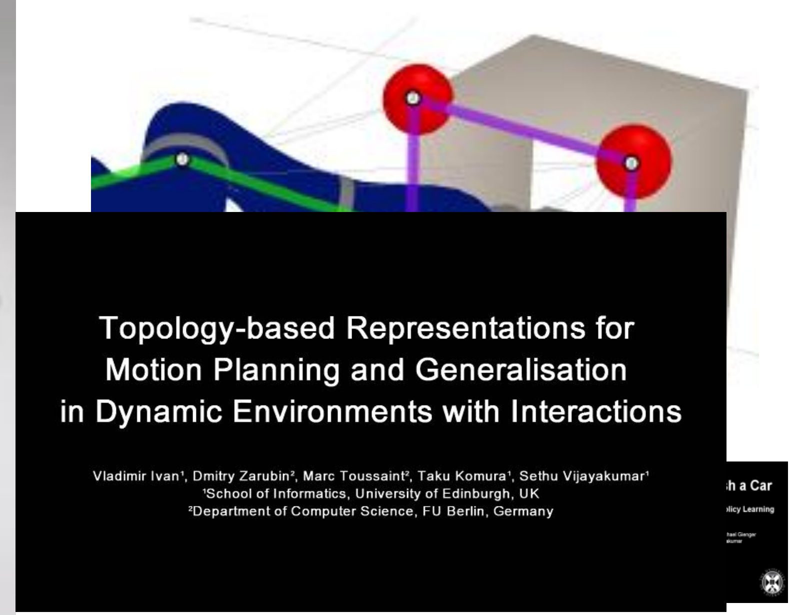
- Interaction with dynamic, articulated and flexible bodies
- Departure from purely metric spaces -- focus on relational metrics between active robot parts and objects/environment
- Enables use of simple motion priors to express complex motion

Ivan V, Zarubin D, Toussaint M, Komura T, Vijayakumar S. Topology-based Representations for Motion Planning and Generalisation in Dynamic Environments with Interactions. IJRR. 2013

Hierarchical Planning in Topology Spaces

- Generalize
- Scale and Re-plan
- Deal with Dynamic Constraints





Ivan V, Zarubin D, Toussaint M, Komura T, Vijayakumar S. Topology-based Representations for Motion Planning and Generalisation in Dynamic Environments with Interactions. IJRR. 2013

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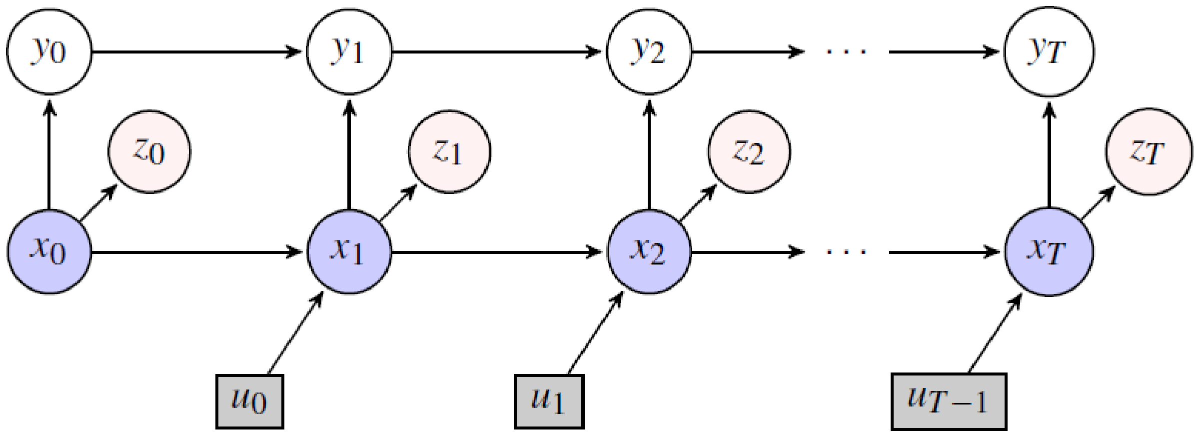
Real-time **Adaptation** using **Relational** Descriptors

Robots for Confined Spaces

Courtesy: OC Robotics Ltd.

Innovation 3

Multi-scale Planning by Inference



- Inference based techniques for working at multiple abstractions
- Planning that incorporates passive stiffness optimisation as well as virtual stiffness control induced by relational metrics
- Exploit novel (homotopy) equivalences in policy – to allow local remapping under dynamic changes
- Deal with contacts and context switching

Optimal Feedback Control (OFC)

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:

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

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

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

Graphical Model Representation

Given:

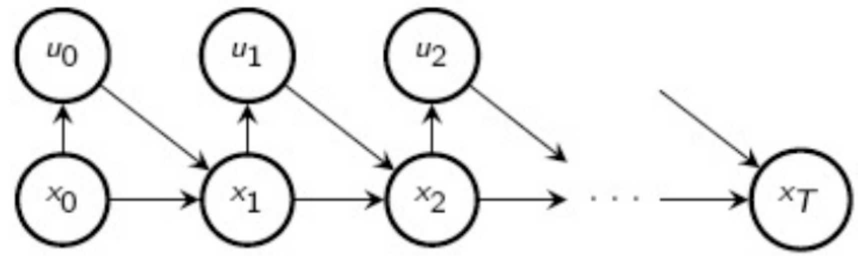
- Discrete time controlled stochastic process

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

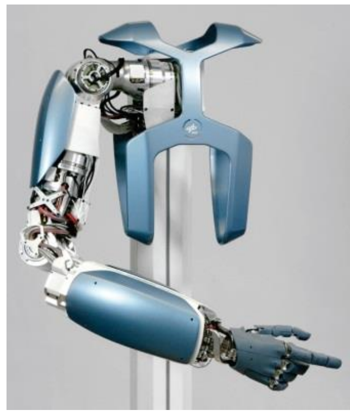
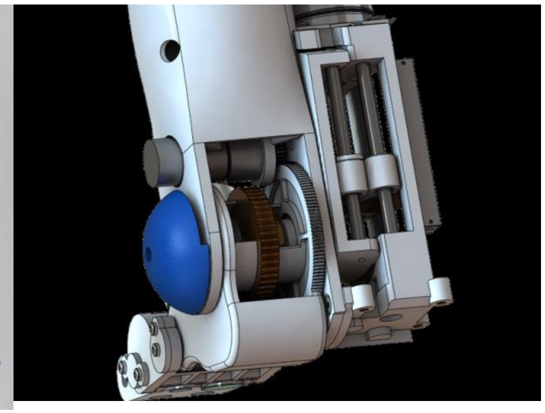
$$\mathcal{C}(\bar{x}, \bar{u}) = \sum_{t=0}^{T} \mathcal{C}_t(x_t, u_t) \qquad \mathcal{C}_t(\cdot, \cdot) \geq 0$$

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).

Innovation 4

Novel Compliant Actuation Design & Stiffness Control


- Design of novel passive compliant mechanism to deal with unexpected disturbances and uncertainty in general
- Algorithmically treat stiffness control under real world constraints
- Exploit natural dynamics by modulating variable impedance
- **Benefits:** Efficiency, Safety and Robustness

Braun, Vijayakumar, et. al., Robots Driven by Compliant Actuators: Optimal Control under Actuation Constraints, *IEEE T-RO*), 29(5) (2013). [*IEEE Transactions on Robotics Best Paper Award*]

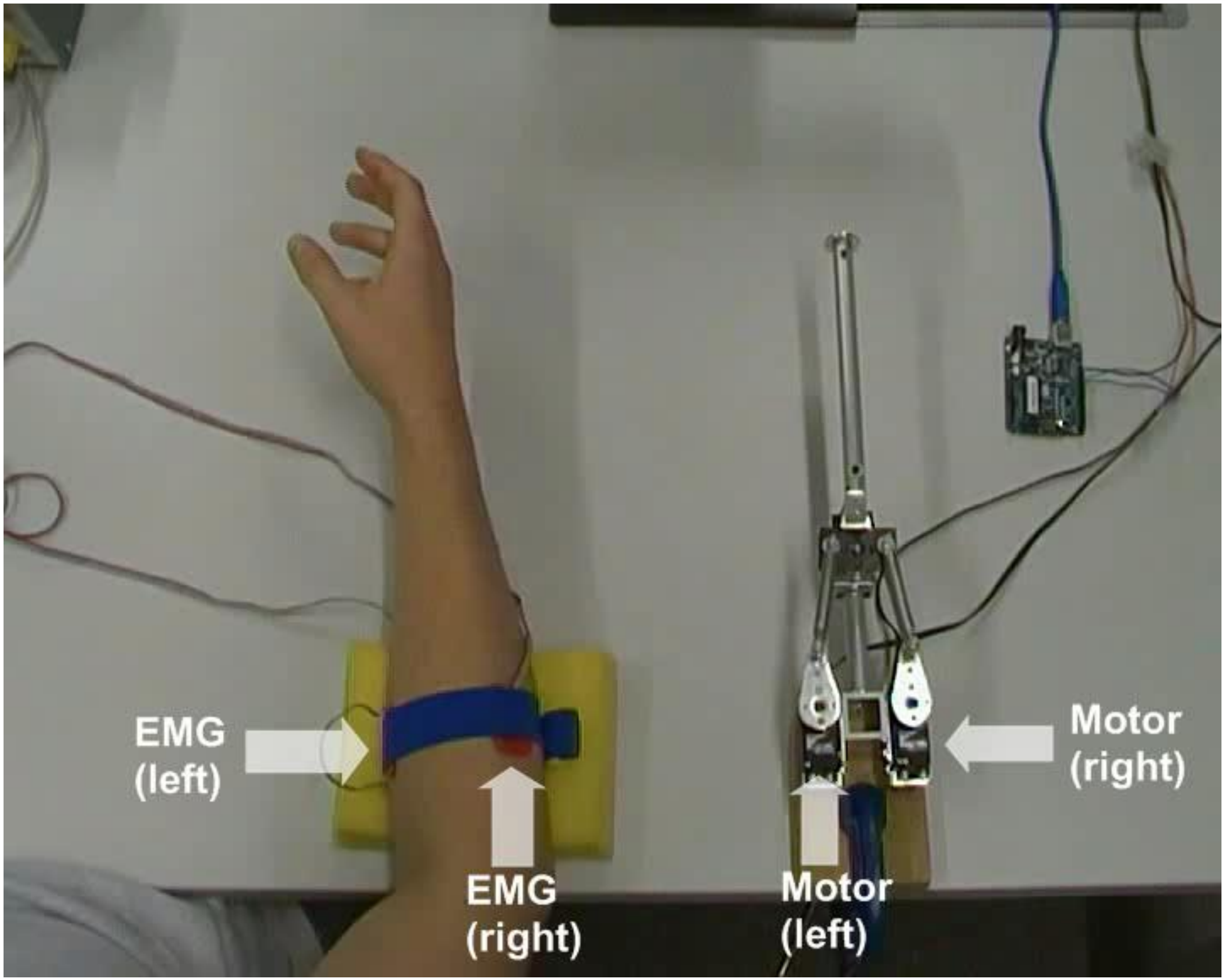
The need for compliant actuation

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

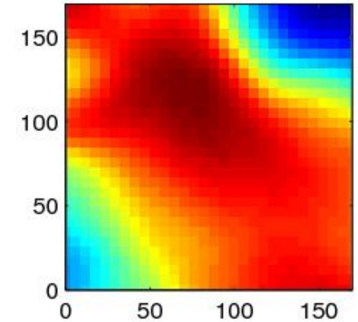
HAL Exoskeleton, Cyberdyne Inc., Japan

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

Variable Stiffness Actuation

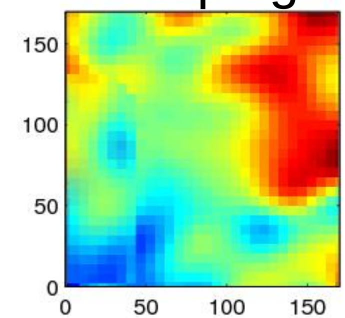


Stiffness



+

Damping



Impedance

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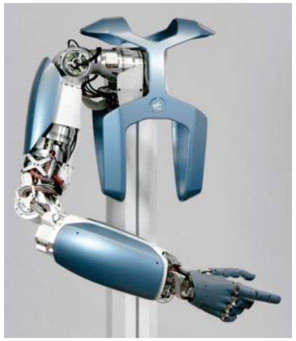
Compliant Actuators

- VARIABLE JOINT STIFFNESS

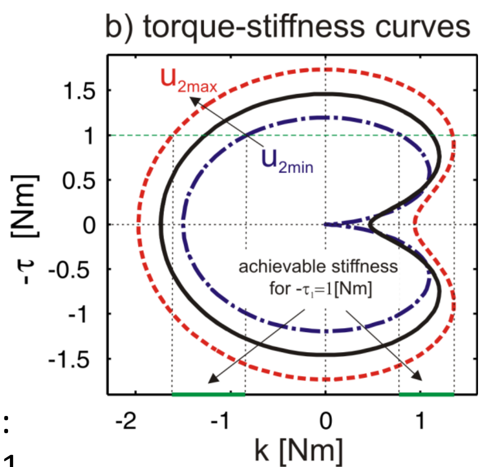
MACCEPA:
Van Ham et.al, 2007

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

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



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

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

Optimizing **Spatiotemporal** Impedance Profiles

Plant dynamics

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

Note: Here 'u' refers to motor dynamics of passive VIA elements

Reference trajectory

$$y(t) = r\ \boldsymbol{\psi}^T(\phi)\boldsymbol{\theta} + y_{offset}$$

$$\dot{\phi} = \omega$$

Optimization criterion

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

Optimal feedback controller

$$\mathbf{u}^*(\mathbf{x}, t) = \mathrm{argmin}_{\mathbf{u}} J$$

EM-like iterative procedure to obtain $\mathbf{u}^*$ and ω^*

Temporal optimization

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

- optimize β to yield optimal T or ω

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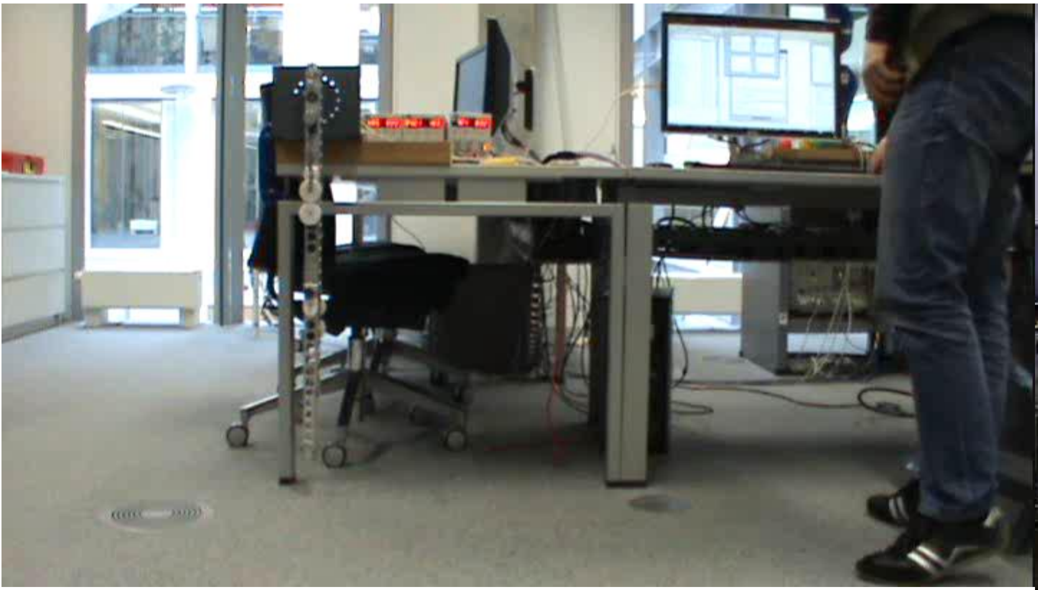
Highly **dynamic** tasks, explosive movements



Optimising and Planning with Redundancy: **Stiffness** and **Movement** Parameters

Scale to High Dimensional Problems

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

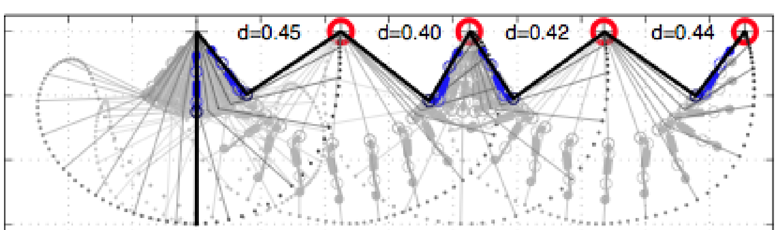
Multi Contact, Multi Dynamics, Time Optimal

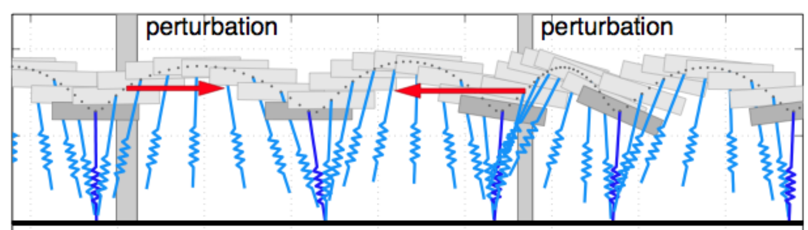
- Development of a systematic methodology for spatio-temporal optimization for movements including
    - multiple phases
    - switching dynamics
    - contacts/impacts

Hybrid dynamics

$$\begin{cases} \dot{\mathbf{x}} = \mathbf{f}_i(\mathbf{x}, \mathbf{u}) \\ \mathbf{x}^+ = \boldsymbol{\Delta}(\mathbf{x}^-) \end{cases}$$

- Simultaneous optimization of stiffness, control commands, and movement duration
- Application to multiple swings of brachiation, hopping





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Multi Contact, Multi Dynamics, Time Optimal

Plant dynamics

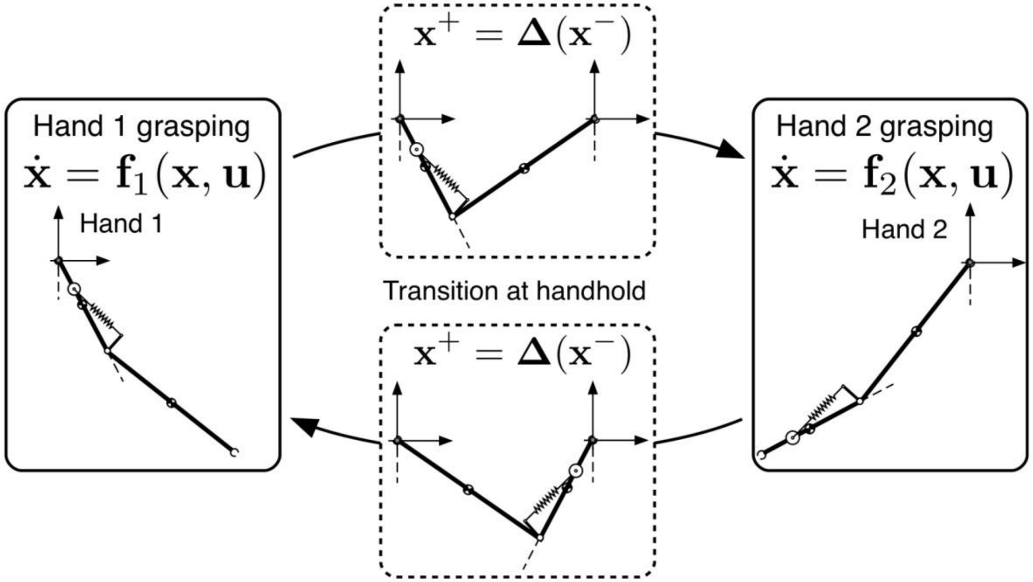
$$\dot{\mathbf{x}} = \mathbf{f}_i(\mathbf{x}, \mathbf{u}) \ (i = 1, 2)$$

(asymmetric configuration)

Discrete state transition

$$\mathbf{x}^+ = \boldsymbol{\Gamma}(\mathbf{x}^-)$$

(switching at handhold)

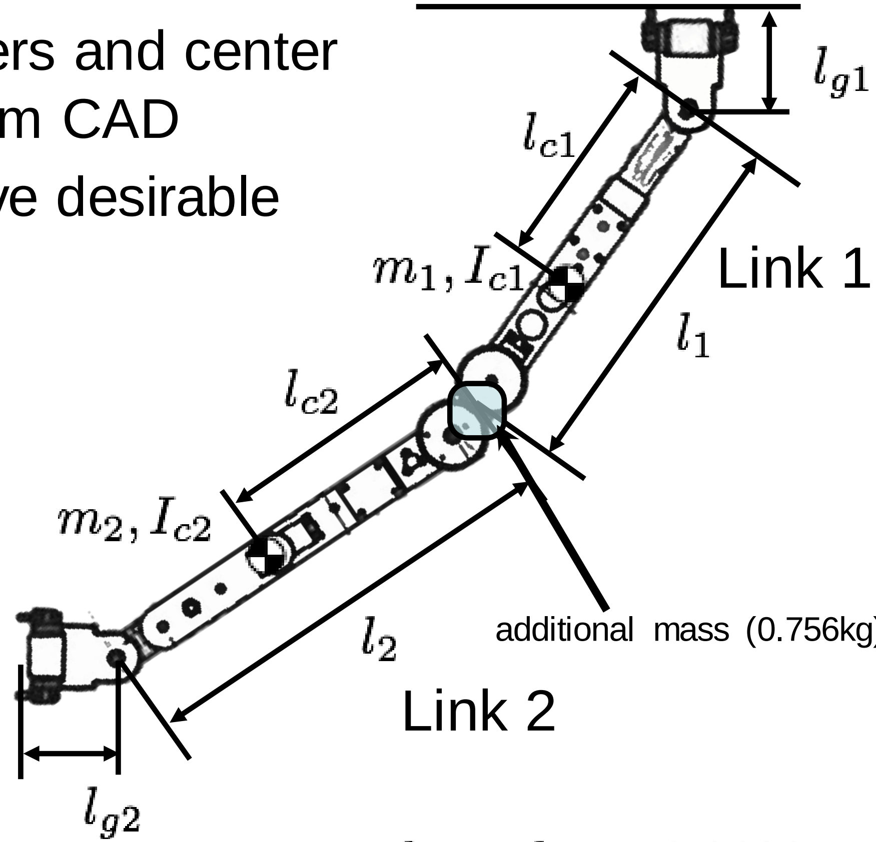


- Hybrid dynamics modeling of swing dynamics and transition at handhold
- Composite cost for task representation
- Simultaneous stiffness and temporal optimization

J. Nakanishi, A. Radulescu and S. Vijayakumar, **Spatiotemporal Optimisation of Multi-phase Movements: Dealing with Contacts and Switching Dynamics**, *Proc. IROS*, Tokyo (2013).

Identification of Physical Parameters

- estimate moment of inertia parameters and center of mass location of each element from CAD
- added mass at the elbow joint to have desirable mass distribution between two links



Link parameters

Link 1 (w/o gripper, magnet)

$$m_1 = 0.279, I_{c1} = 0.0018$$
$$l_{c1} = 0.1737, l_1 = 0.290$$

Link 2 (incl. gripper, magnet, add. mass)

$$m_2 = 1.311, I_{c2} = 0.0203$$
$$l_{c2} = 0.0774, l_2 = 0.290$$

$$l_{g1} = l_{g2} = 0.0628$$
$$m_{gripper} = 0.168$$
$$m_{magnet} = 0.108$$

Servo motor dynamics parameter

$$\ddot{\mathbf{q}}_m + 2\boldsymbol{\alpha}\dot{\mathbf{q}}_m + \boldsymbol{\alpha}^2(\mathbf{q}_m - \mathbf{u}) = 0$$

$\alpha \approx 25$ with maximum range $-\frac{\pi}{2} \leq q_m \leq \frac{\pi}{2}$

Multi-phase Movement Optimization

- Task encoding of movement with multi-phases

$$J = \phi(\mathbf{x}\underbrace{(T_f)}_{(3)}) + \sum_{j=1}^{K} \psi^j(\mathbf{x}\underbrace{(T_j^-)}_{(2)}) + \int_{T_0}^{\overbrace{T_f}^{(3)}} h(\mathbf{x}, \underbrace{\mathbf{u}}_{(1)})dt$$

Terminal cost Via-point cost Running cost

- cf. individual cost J_i for each phase $T_{j-1} \leq t < T_j$
- total cost by sequential optimization could be suboptimal

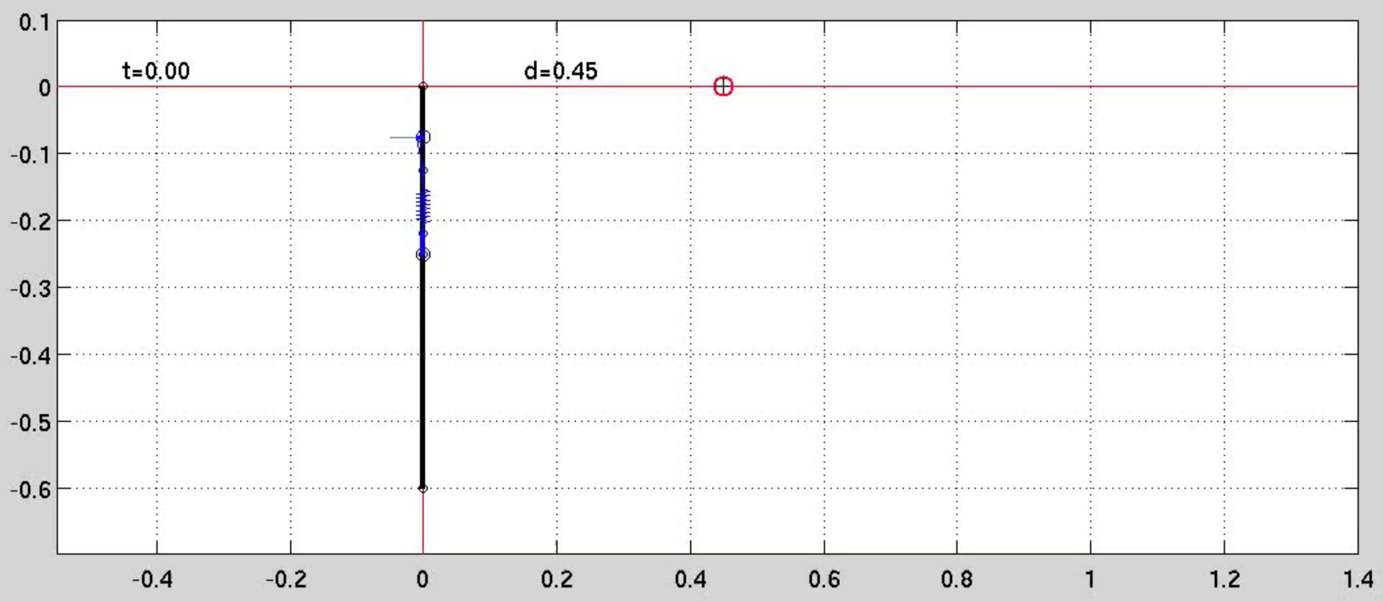
Optimization problem

(1) optimal feedback control law $\mathbf{u} = \mathbf{u}(\mathbf{x}, t)$ to minimize J

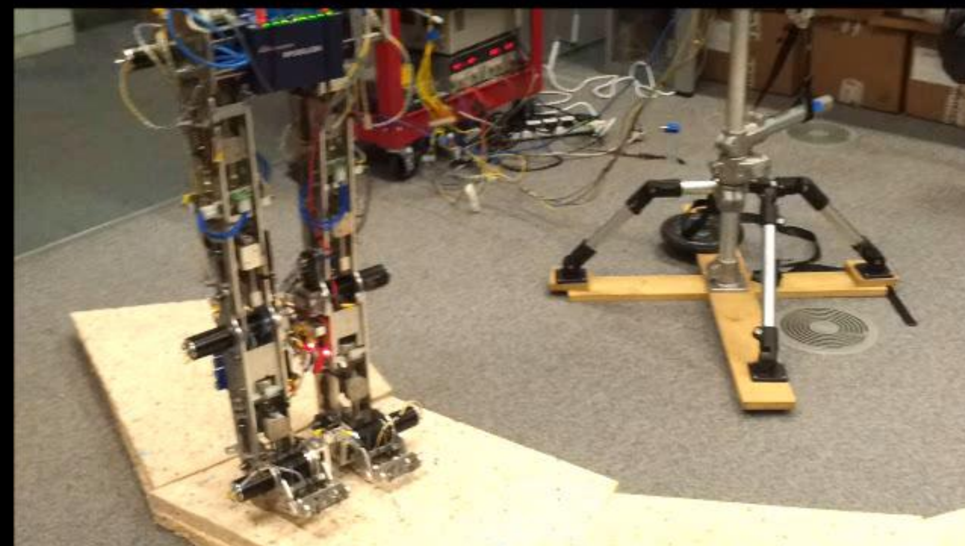
(2) switching instances $T_1, \cdots, T_k$

(3) final time (total movement duration) T_f

Brachiation with Stiffness Modulation



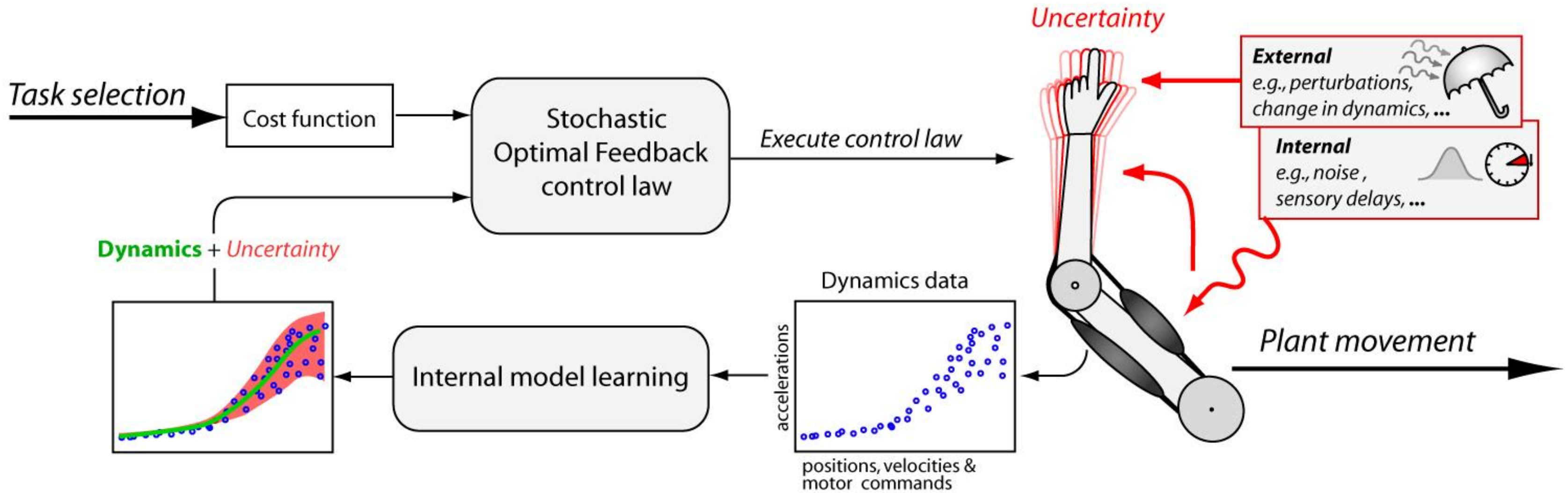
Variable Impedance Bipeds:
Towards Smart Lower Limb Prosthetics



Robust Bipedal Walking with Variable Impedance
- To make robots more energy efficient
- To develop robots that can adapt to the terrain
- To develop advanced lower limb prosthetics

Innovation 5

On-the-fly adaptation at Any Scale



- Fast dynamics online learning for adaptation
- Fast (re) planning methods that incorporate dynamics adaptation
- Efficient Any Scale (embedded, cloud, tethered) implementation

EPSRC Grant: Anyscale Applications (EP/L000725/1): 2013-2017

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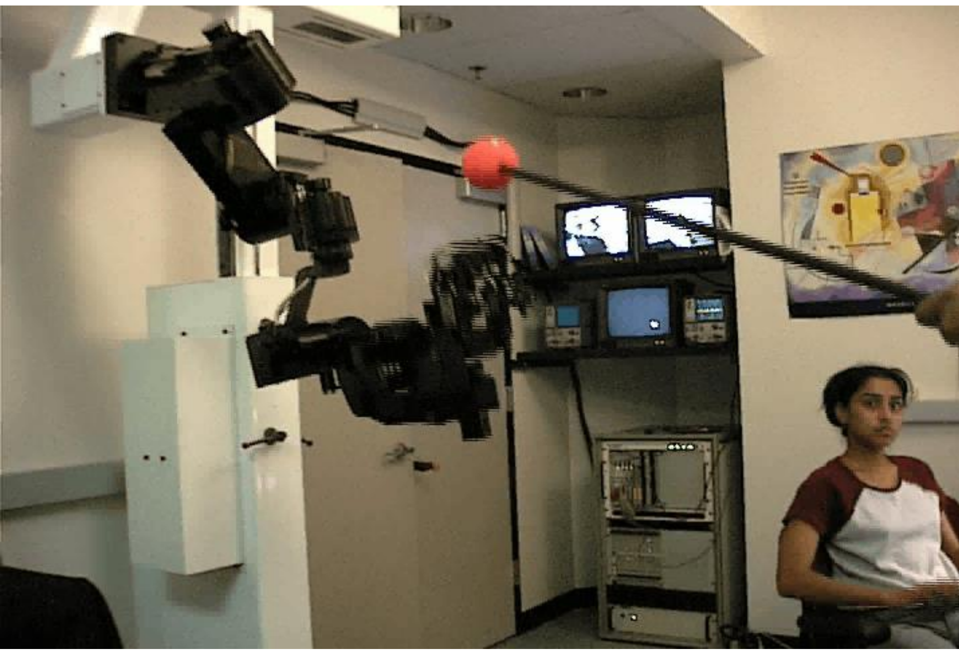
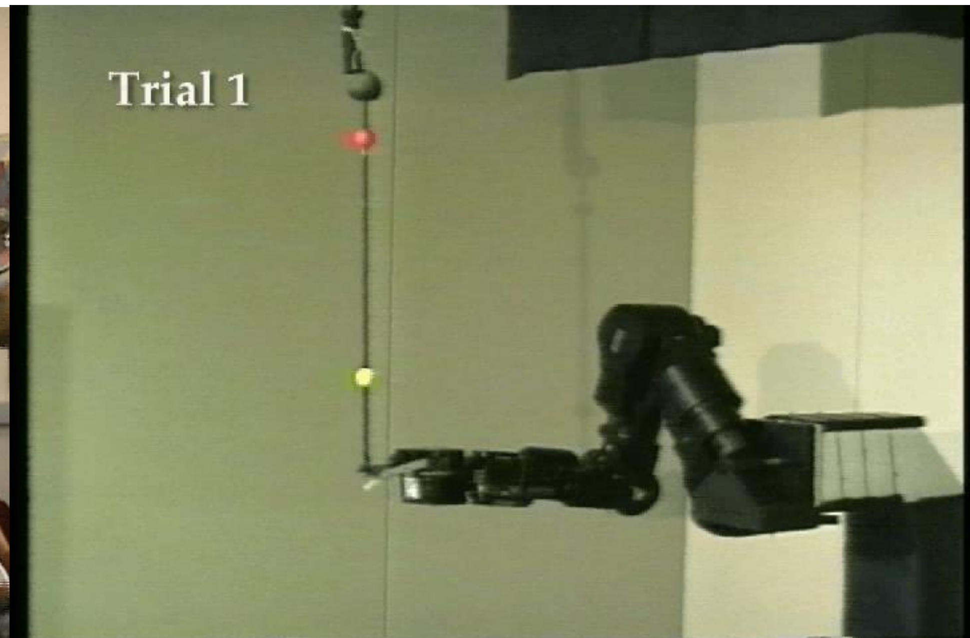
Online Adaptive Machine Learning

Learning the Internal Dynamics



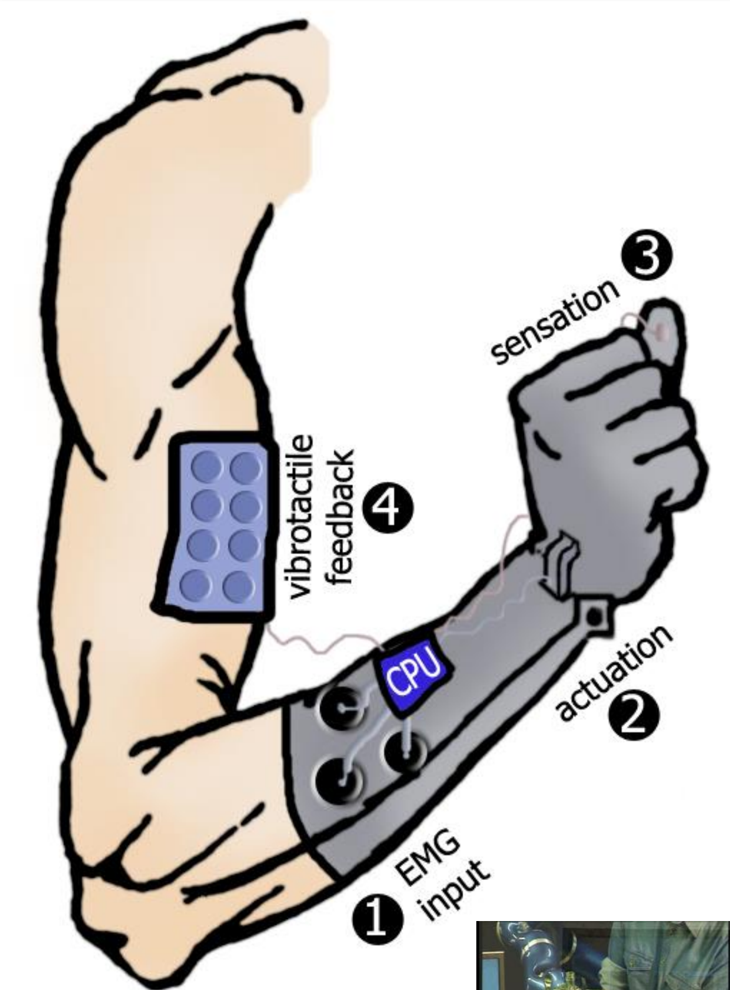
Learning the Task Dynamics



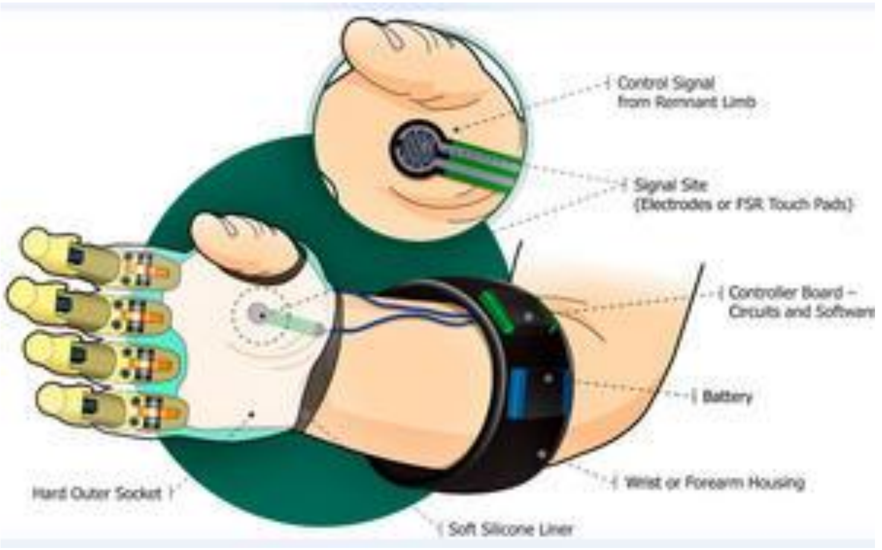
Stefan Klanke, Sethu Vijayakumar and Stefan Schaal, A Library for Locally Weighted Projection Regression, *Journal of Machine Learning Research (JMLR),* vol. 9. pp. 623--626 (2008).

http://www.ipab.inf.ed.ac.uk/slmc/software/lwpr

Haptic Feedback + Shared (EMG) Autonomous Control for Prosthetics



Touch Bionics – U.Edinburgh Partnership



touch
bionics

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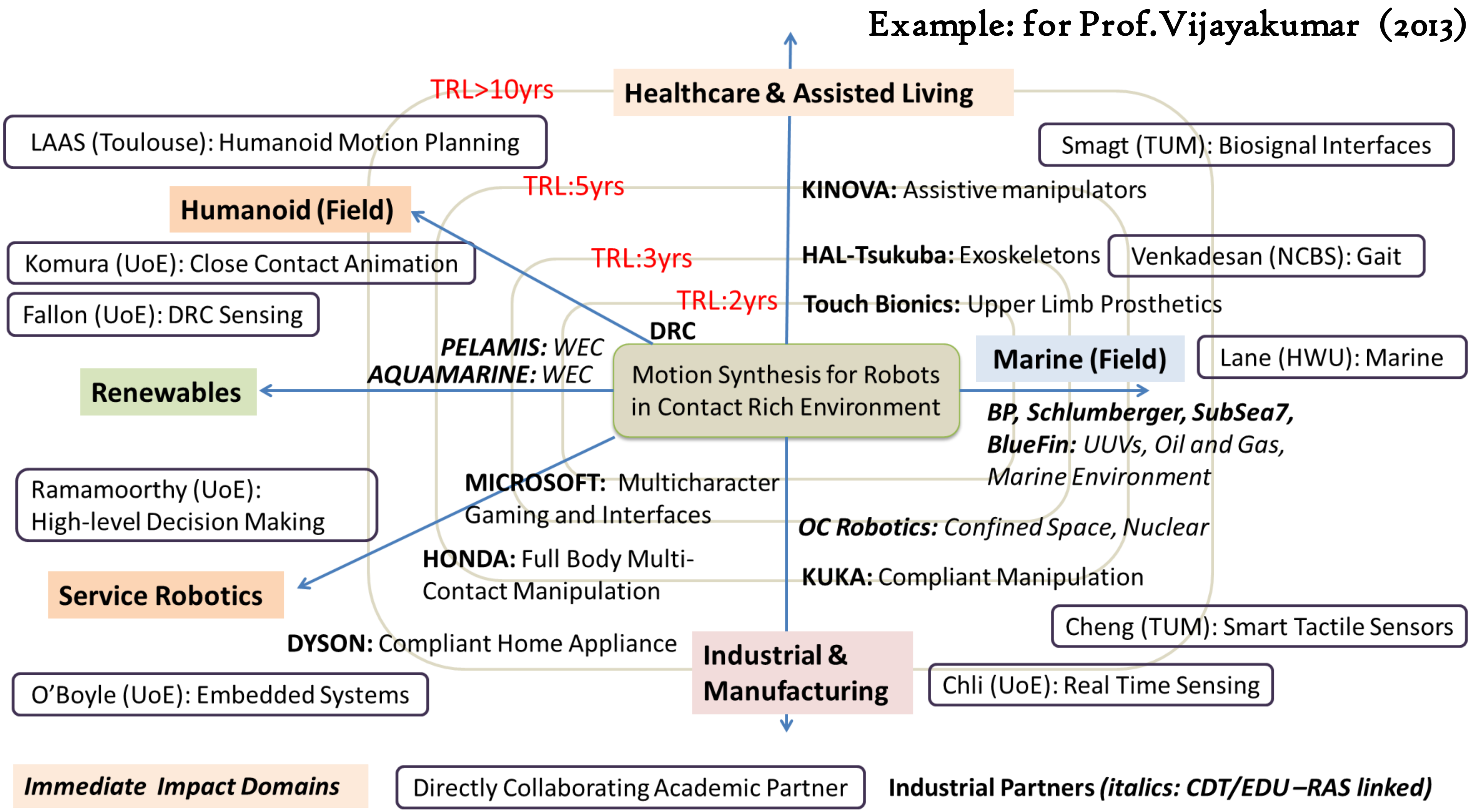
Translation and Impact



- Translation through Industrial & Scientific Collaborations and Skilled People

UoE contact: Professor Sethu Vijayakumar (CDT Director)
sethu.vijayakumar@ed.ac.uk

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EPSRC CDT-RAS

The EPSRC Center for Doctoral Training in Robotics & Autonomous Systems

- Multidisciplinary ecosystem – 65 PhD graduates over 8.5 years, 50 PIs across Engineering and Informatics disciplines

  Control, actuation, Machine learning, AI, neural computation, photonics, decision making, language cognition, human-robot interaction, image processing, manufacture research, ocean systems …
- Technical focus – 'Interaction' in Robotic Systems

  Environment: Multi-Robot: People: Self: Enablers
- 'Innovation Ready' postgraduates

  Populate the innovation pipeline. Create new businesses and models.
- Cross sector exploitation

  Offshore energy, search & rescue, medical, rehabilitation, ageing, manufacturing, space, nuclear, defence, aerospace, environment monitoring, transport, education, entertainment ..
- Total Award Value (> £14M): CDT £7M, Robotarium £7.1M

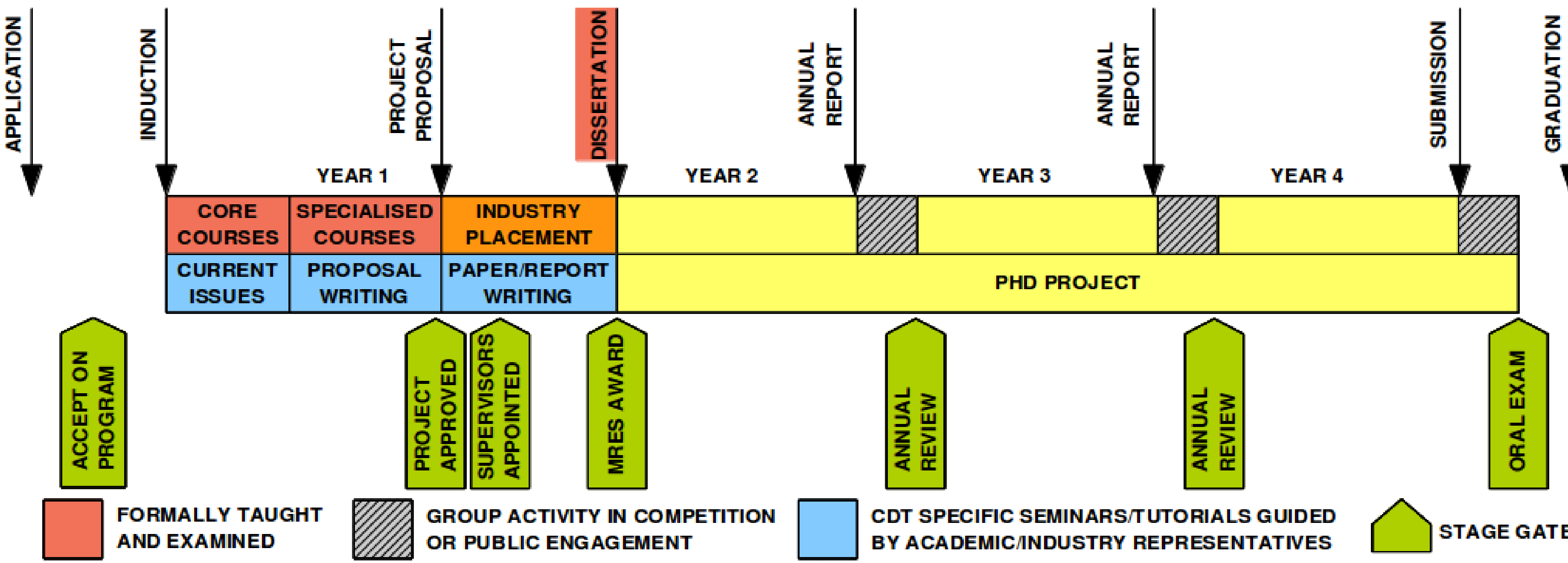
  38 company sponsors, £2M cash, £6.5M in-kind (so far ..)

  Schlumberger, Baker Hughes,, Renishaw, Honda, Network Rail, Selex, Thales, BAe, BP, Pelamis, Aquamarine Power, SciSys, Shadow Robot, SeeByte, Touch Bionics, Marza, OC Robotics, KUKA, Dyson, Agilent …

www.edinburgh-**robotics**.org

CDT Structure

- MRes in the first year
- PhD starting in Year 2 after Project Proposal approval
- Yearly reports and reviews
- Thesis submission



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ROBOTARIUM

A National UK Facility for Research into the Interactions amongst Robots, Environments, People and Autonomous Systems

www.edinburgh-robotics.org

EPSRC

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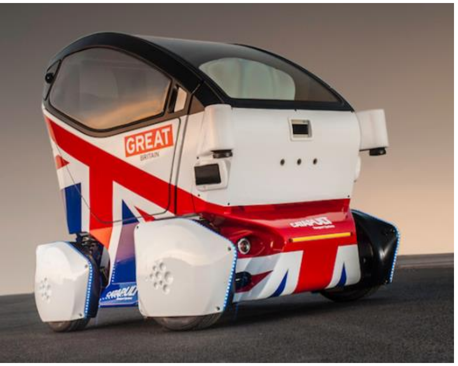
Robots That Interact

Prosthetics, Exoskeletons



Self Driving Cars

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Field Robots (Land)

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Industrial/ Manufacturing

Acknowledgement

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Robots that Learn

Machine Learning for smarter and efficient actuation

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Thank You!

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