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Robots that Learn

Machine Learning for smarter and efficient actuation

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

EDINBURGH CENTRE FOR ROBOTICS

ROYAL ACADEMY OF ENGINEERING

Microsoft Research

Est. 1583

University of Edinburgh
www.ed.ac.uk

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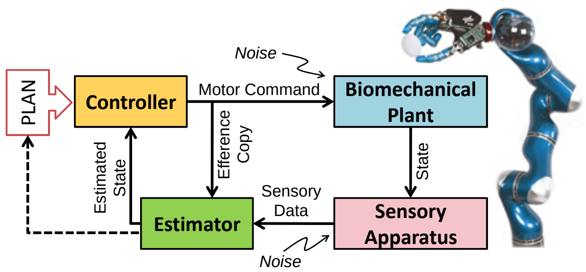
ROBOTICS AND COMPUTER VISION

Institute of Perception, Action and Behaviour (IPAB)

Director: Sethu Vijayakumar

What does it take to control a robot?

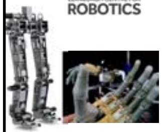


Teleoperation

Autonomy

Shared Autonomy

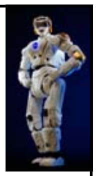
Robots That Interact



Prosthetics, Exoskeletons

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!



Field Robots (Land)

Nuclear Decommissioning

Self Driving Cars

Field Robots (Marine) | Medical Robotics | Service Robots | Industrial/ Manufacturing

Innovation 1

Making **sense** of the world around you

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

Real-time Object Pose Recognition and Tracking with an Imprecisely Calibrated Moving RGB-D Camera

Karl Pauwels*, Vladimir Ivan+, Eduardo Ros*, Sethu Vijayakumar+

*CITIC, University of Granada, Spain

+School of Informatics, University of Edinburgh, UK

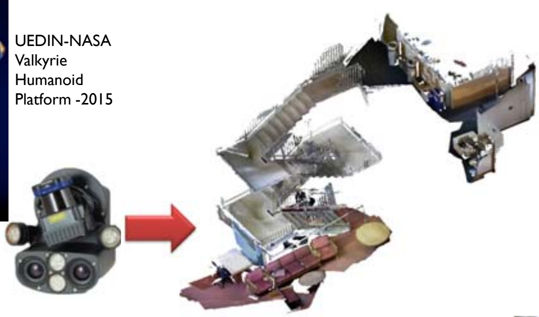
IROS 2014

Innovation 1

Making **sense** of the world around you

(Tracking and Localisation)

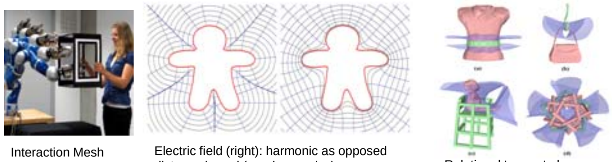
UEDIN-NASA Valkyrie Humanoid Platform -2015



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

Real-Time Motion Adaptation using Relative Distance Space Representation

Yiming Yang, Vladimir Ivan, Sethu Vijayakumar

School of Informatics, University of Edinburgh

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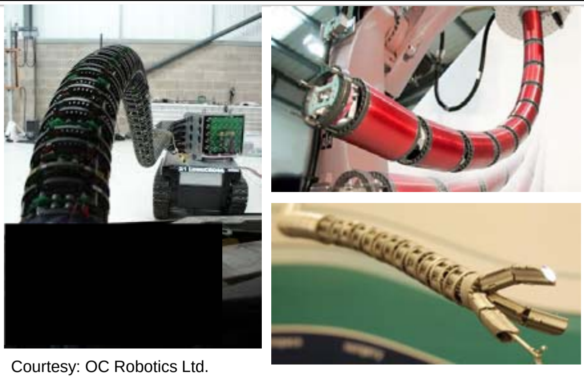
International Conference on Advanced Robotics 2015

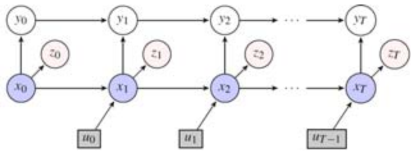
Robots for Confined Spaces



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:

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

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

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

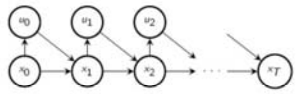
Graphical Model Representation

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

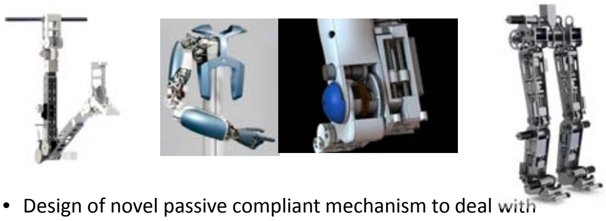
$$\mathcal{C}(\bar{x}, \bar{u}) = \sum_{t=0}^{T} \mathcal{C}_t(x_t, u_t) \qquad \mathcal{C}_t(\cdot,\cdot) \geq 0$$

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*]

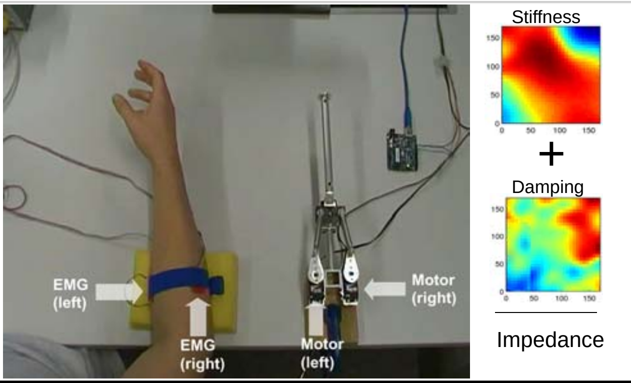
The need for compliant actuation

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



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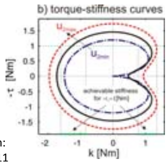
Compliant Actuators

- VARIABLE JOINT STIFFNESS


MACCEPA: Van Ham et.al, 2007


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

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



Torque/Stiffness Opt.

- Model of the system dynamics:

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

- Control objective:

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

- 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)

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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

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

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

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

- 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)

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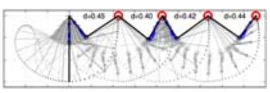
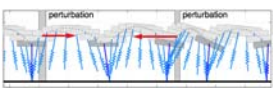
Multi Contact, Multi Dynamics, Time Optimal

- 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

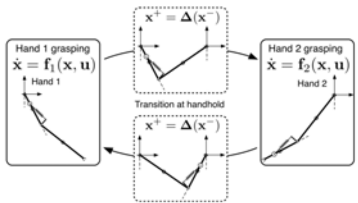
$$\dot{\mathbf{x}} = \mathbf{f}_i(\mathbf{x}, \mathbf{u}) \ (i = 1, 2)$$

(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).

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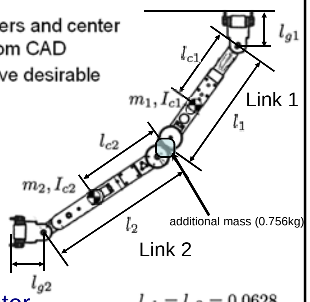
Identification of Physical Parameters

- 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

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

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

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Multi-phase Movement Optimization

- Task encoding of movement with multi-phases

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

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 $T_1, \cdots, T_k$

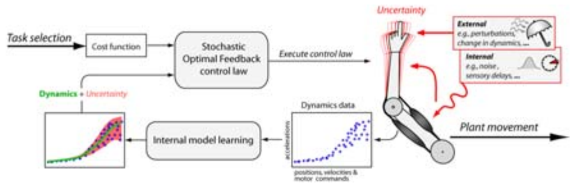
(3) final time (total movement duration) T_f

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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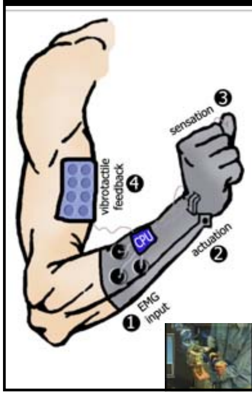
Online Adaptive Machine Learning

Learning the Internal Dynamics — Learning the Task Dynamics

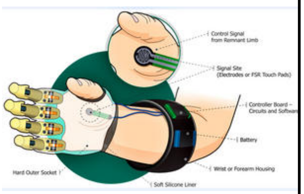
Stefan Klanke, Sethu Vijayakumar and Stefan Schaal, A Library for Locally Weighted Projection Regression, *Journal of Machine Learning Research (JMLR)*, vol. 9. pp. 623--626 (2008).

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

Haptic Feedback + Shared (EMG) Autonomous Control for Prosthetics



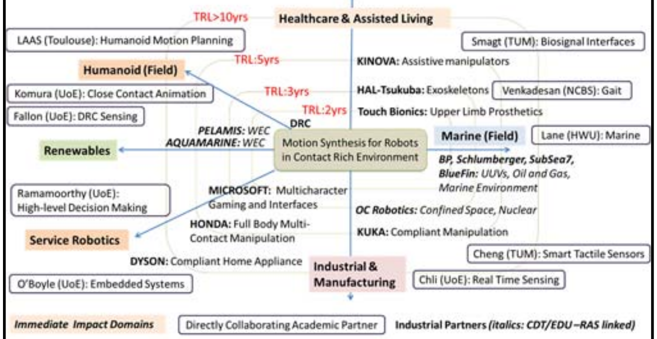
Touch Bionics – U.Edinburgh Partnership



touch bionics

Translation and Impact

Example: for Prof. Vijayakumar (2013)



- Translation through Industrial & Scientific Collaborations and Skilled People

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

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 …

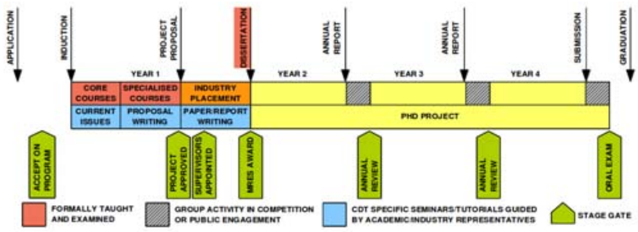
www.edinburgh-robotics.org

EPSRC

CDT Structure

EDINBURGH CENTRE FOR ROBOTICS

- 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

Acknowledgement

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- RIKEN Brain Science Institute
- Touch Bionics
- DLR