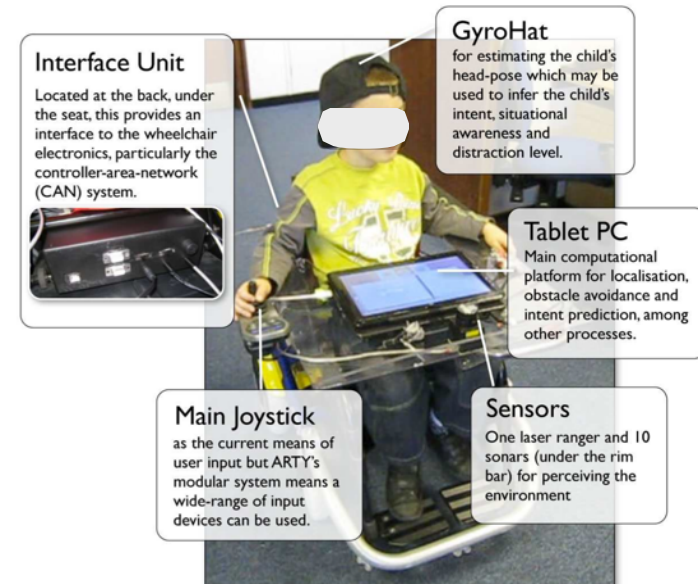


HUMAN-ROBOT COLLABORATION - PERSONALISATION AND DEVELOPMENTAL ISSUES

Yiannis Demiris

Personal Robotics Laboratory
Department of Electrical Engineering
Imperial College London

<http://www.imperial.ac.uk/PersonalRobotics>



Interface Unit
Located at the back, under the seat, this provides an interface to the wheelchair electronics, particularly the controller-area-network (CAN) system.

GyroHat
for estimating the child's head-pose which may be used to infer the child's intent, situational awareness and distraction level.

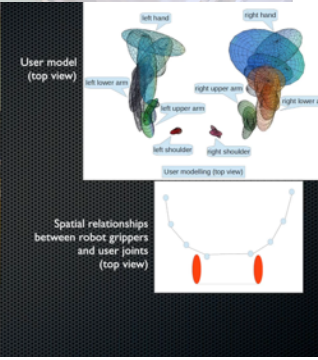
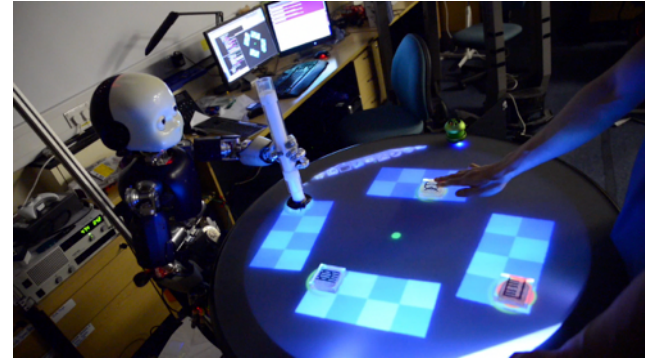
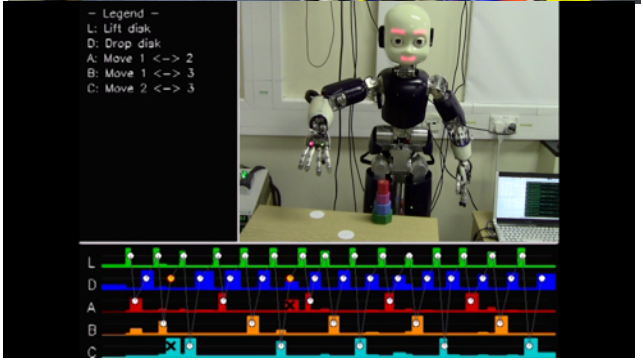
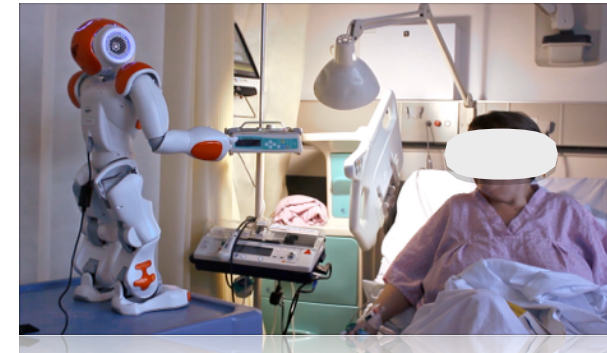
Tablet PC
Main computational platform for localisation, obstacle avoidance and intent prediction, among other processes.

Main Joystick
as the current means of user input but ARTY's modular system means a wide-range of input devices can be used.

Sensors
One laser ranger and 10 sonars (under the rim bar) for perceiving the environment

Cognitive Robot Systems that *learn to*:

- Perceive the world & **users** through sensors
- **Model** users, learn their skills and preferences, predict intentions
- **Collaborate** with the users to maximize learning outcomes
- Interaction over **extended** periods of time



Joint actions and tasks: key issues

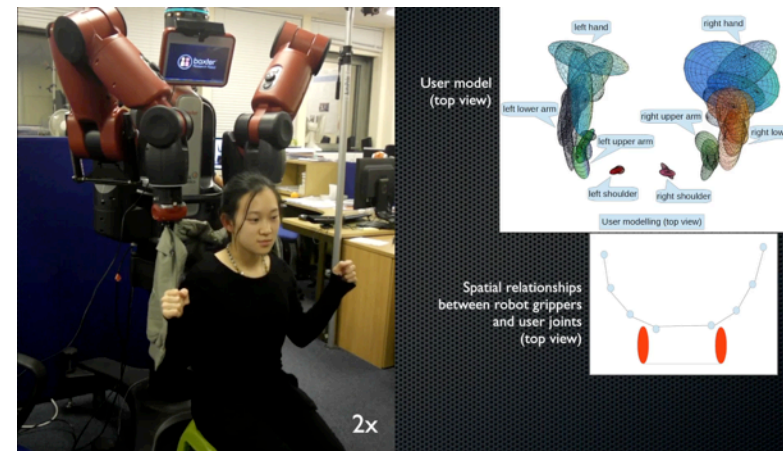
• Personalisation:

- Participants explicitly model their partner's parameters (skills, preferences, ...) and adjust their behaviour based on the internal models; prediction a key element
- Hierarchical partner modelling using ensembles of inverse and forward models at increasing levels of abstraction



• Lifelong joint action constraints:

- Includes developmental aspects: in our domain outcome is improvement of one or more of the partners, not only success of an external temporary goal

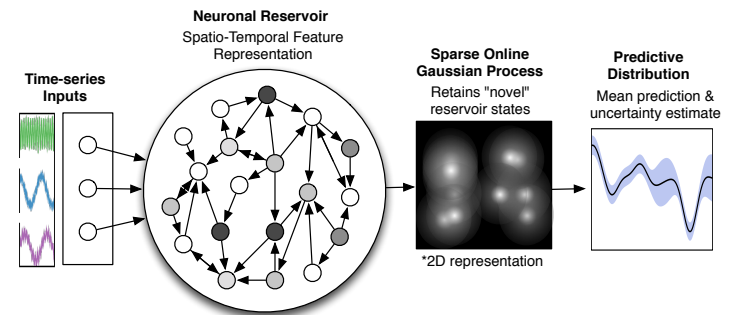


Continuous (lifelong) Interactive Learning Cycle

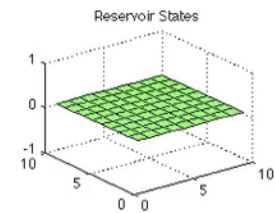
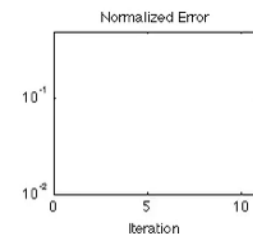
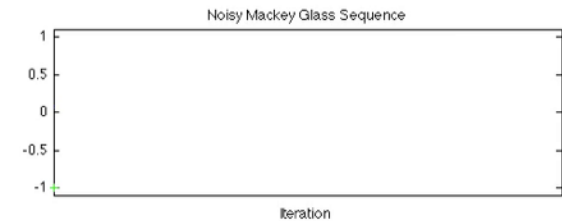
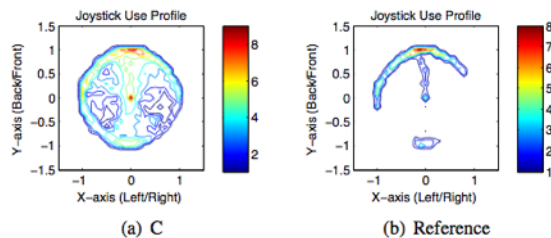
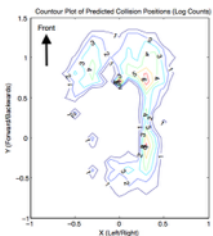
1. Perceive partner's actions



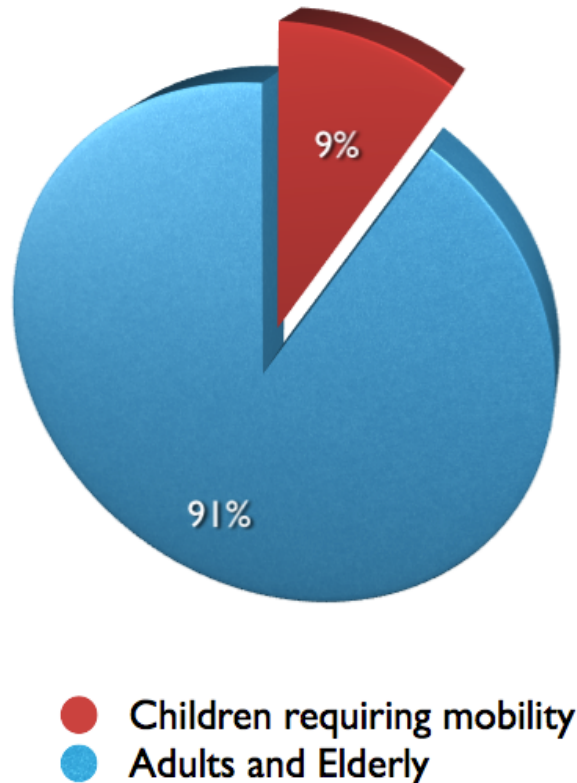
2. Use machine learning algorithms to build hierarchical user models



3. Predict required levels of assistance / collaborative control



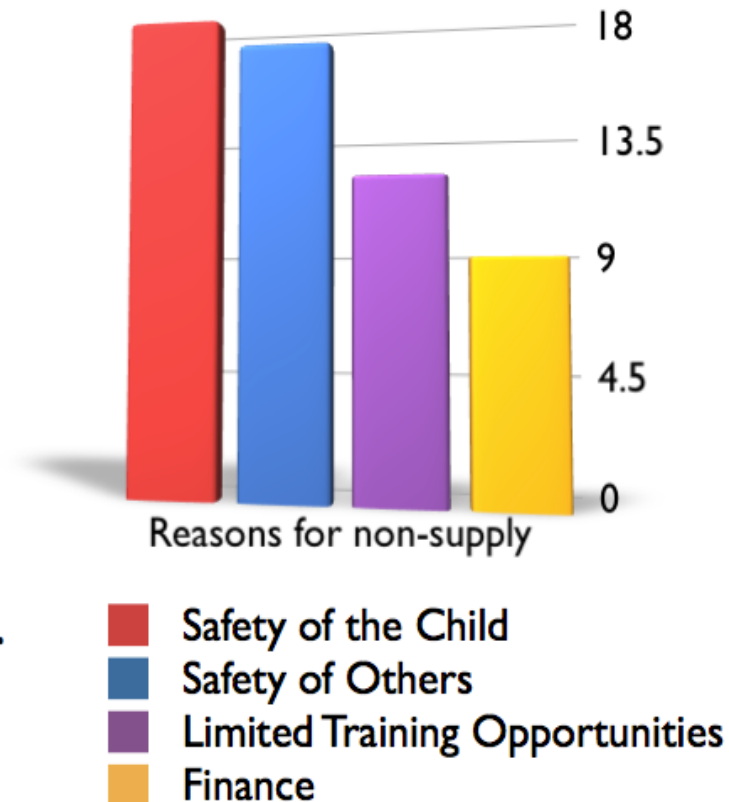
Disabled children in the UK



- **~54,000** children require wheelchairs [1,2]
- **33%** cannot navigate independently [3]
- **Safety** concerns **limits wheelchair provision** by NHS [4]

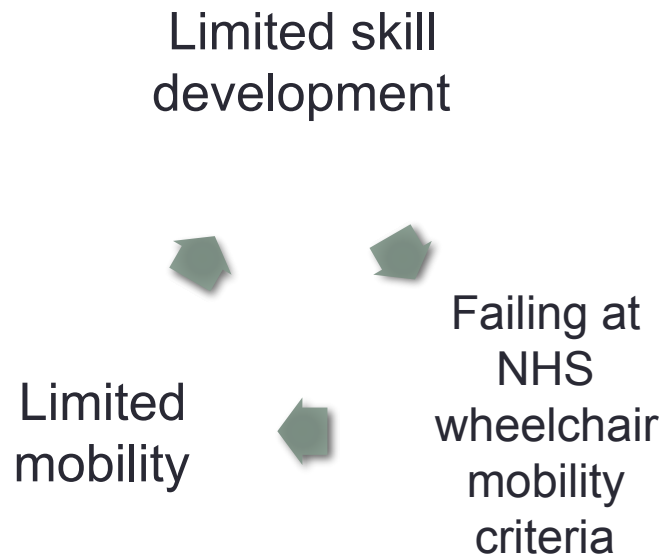
Limited Provision of Powered Wheelchairs

- Nicholson and Bonsall Survey of 139 NHS Wheelchair Services [4].
- Of 97 respondents, **50** (51%) did not supply wheelchairs for children (< 5 years).
- Why? **Safety concerns.**



Providing safe exploration opportunities

- In the development-critical years below 5, deprivation of movement leads to “learned helplessness”
- Vicious cycle:



Our approach: adaptive collaborative control with intelligent robotic wheelchairs
(and humanoid robot assistants)



Prediction of intention during collaborative task execution

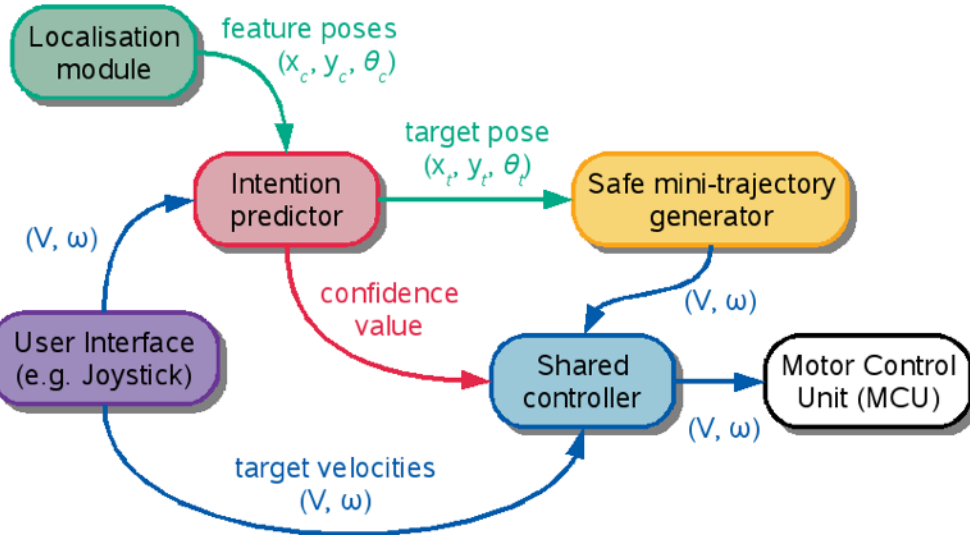
Assisting only when needed



Haptic Joystick based control



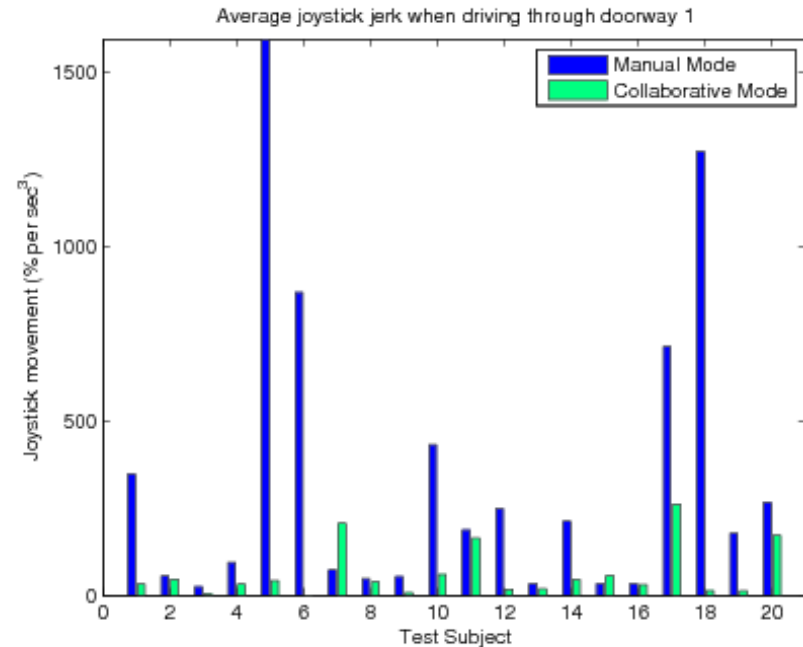
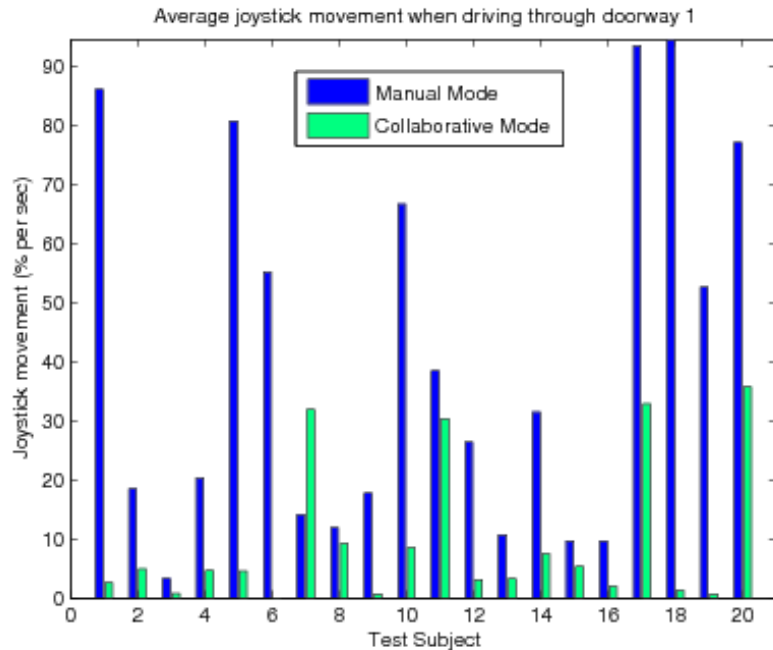
Electromyograph-based (EMG) control



- [T. Carlson and Y. Demiris, IEEE ICRA-2008 & IEEE Transactions SMC-B 2012, H Soh and Y Demiris, JHRI 2015]

Human evaluations

reduction of joystick movements and jerk



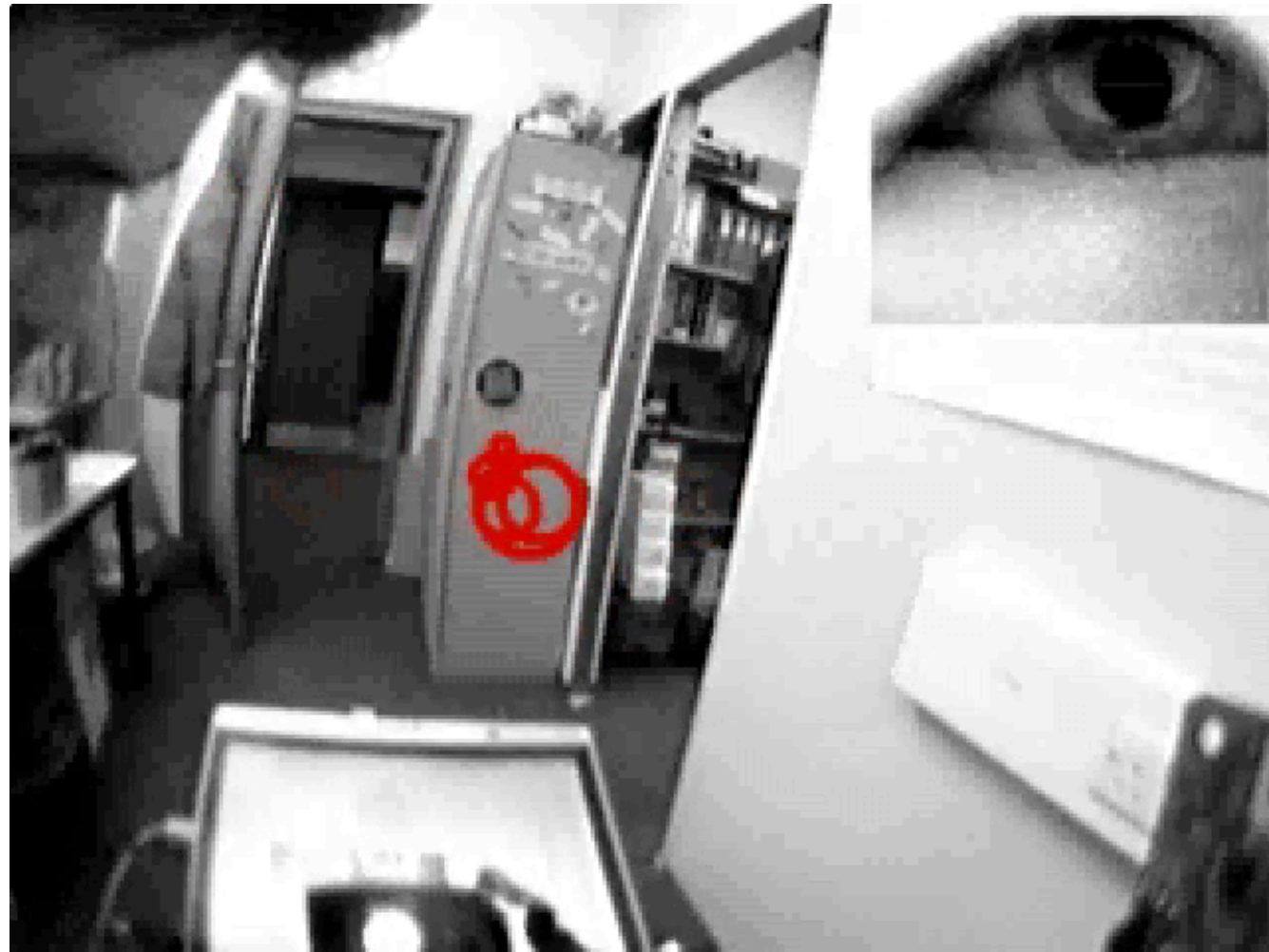
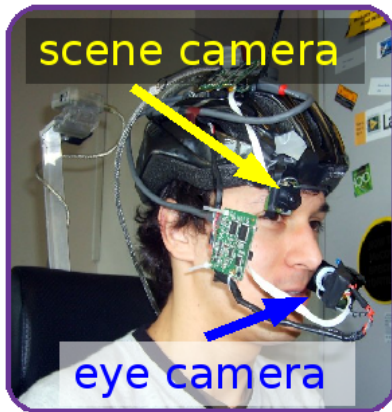
•81.7% reduction of joystick movements ($p < 0.001$)

75% of cases reduction of jerk (movement smoothness)

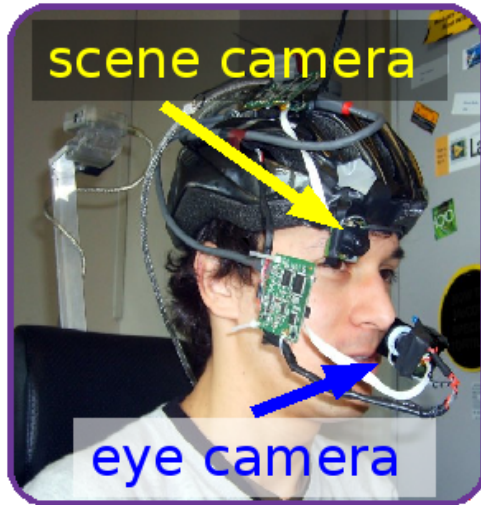
But not everyone benefited!

Evaluation II

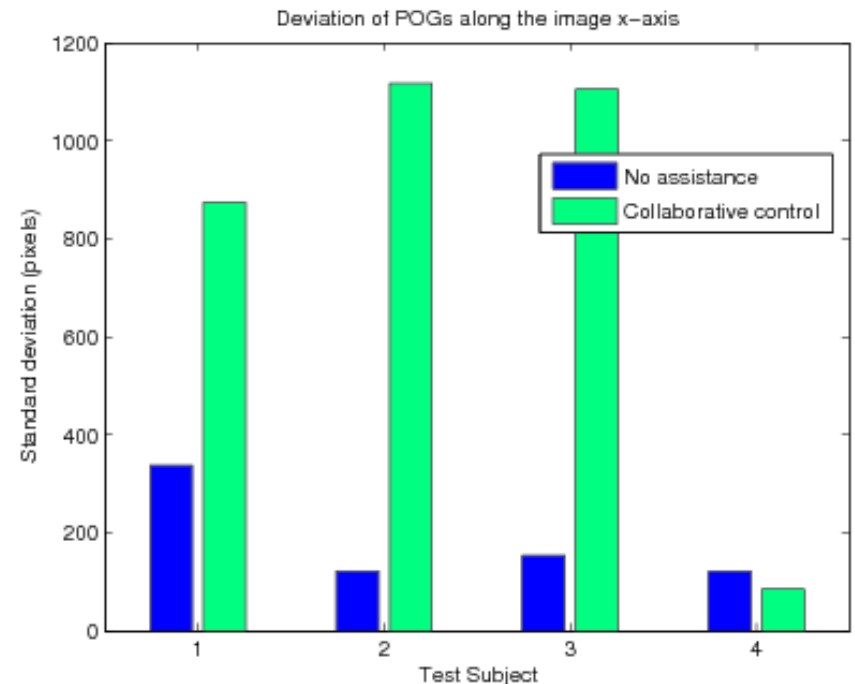
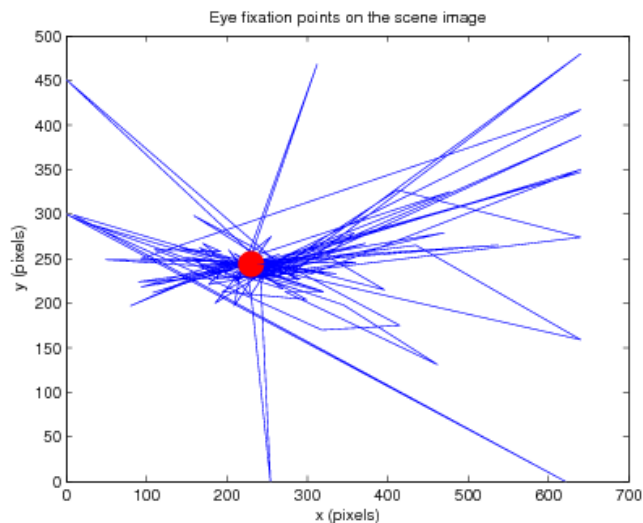
Gaze tracking



Evaluation II: Gaze Tracking [2]

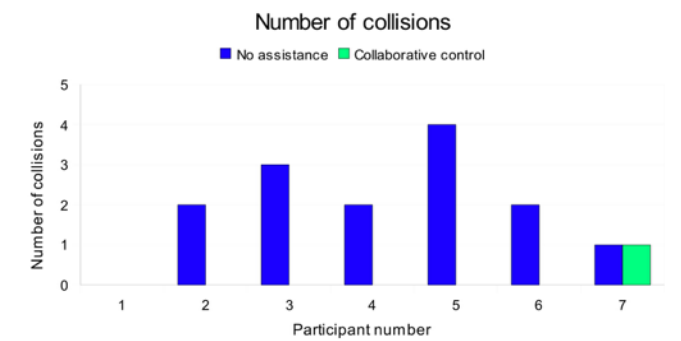
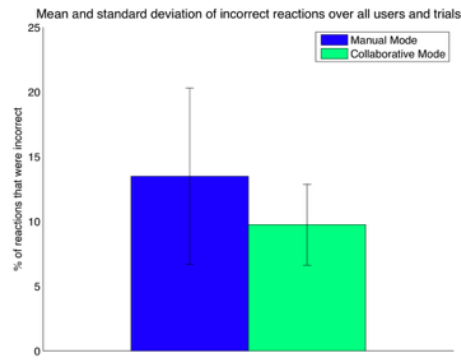
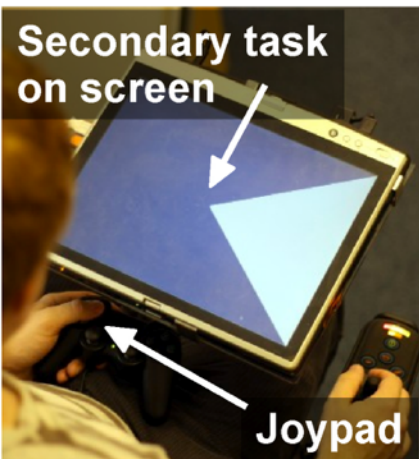


- For more experienced users, saccadic eye movements became more erratic when assisted
- Shared control disturbs the user's forward model



Evaluation III: Secondary task

Clear advantage for when the user is preoccupied with other activities



First conclusions: need for personalisation in human-robot collaboration

- One size does not fit all
- Assistance is not always needed/wanted
 - Must determine conditions under which joint action is desirable, and assistance is needed.
 - Need for lifelong user modeling of sensorimotor and cognitive skills
 - A decent amount of work in the fields of computer-aided learning, intelligent tutoring...
 - **Very little work in sensorimotor domains**

Designing for children



Children Robotic wheelchairs

Supporting the development of young disabled children

Interface Unit

Located at the back, under the seat, this provides an interface to the wheelchair electronics, particularly the controller-area-network (CAN) system.



GyroHat

for estimating the child's head-pose which may be used to infer the child's intent, situational awareness and distraction level.

Tablet PC

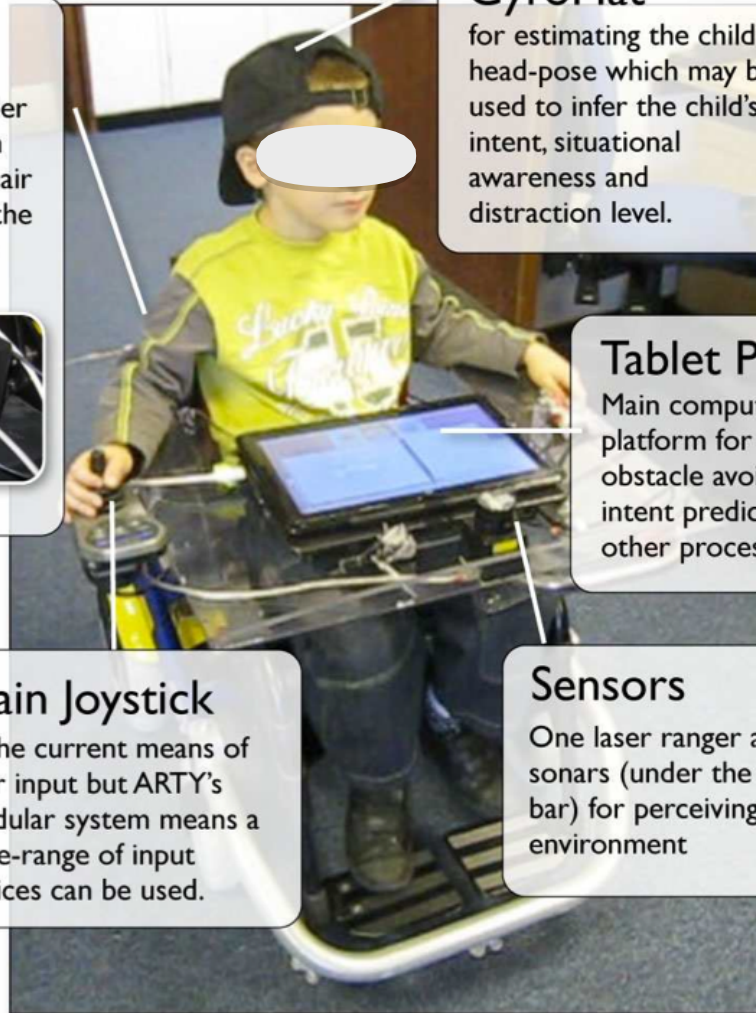
Main computational platform for localisation, obstacle avoidance and intent prediction, among other processes.

Main Joystick

as the current means of user input but ARTY's modular system means a wide-range of input devices can be used.

Sensors

One laser ranger and 10 sonars (under the rim bar) for perceiving the environment



Case study: Children Robotic wheelchairs

Supporting the development of young disabled children



Case study⁽²⁾: Children Robotic wheelchairs

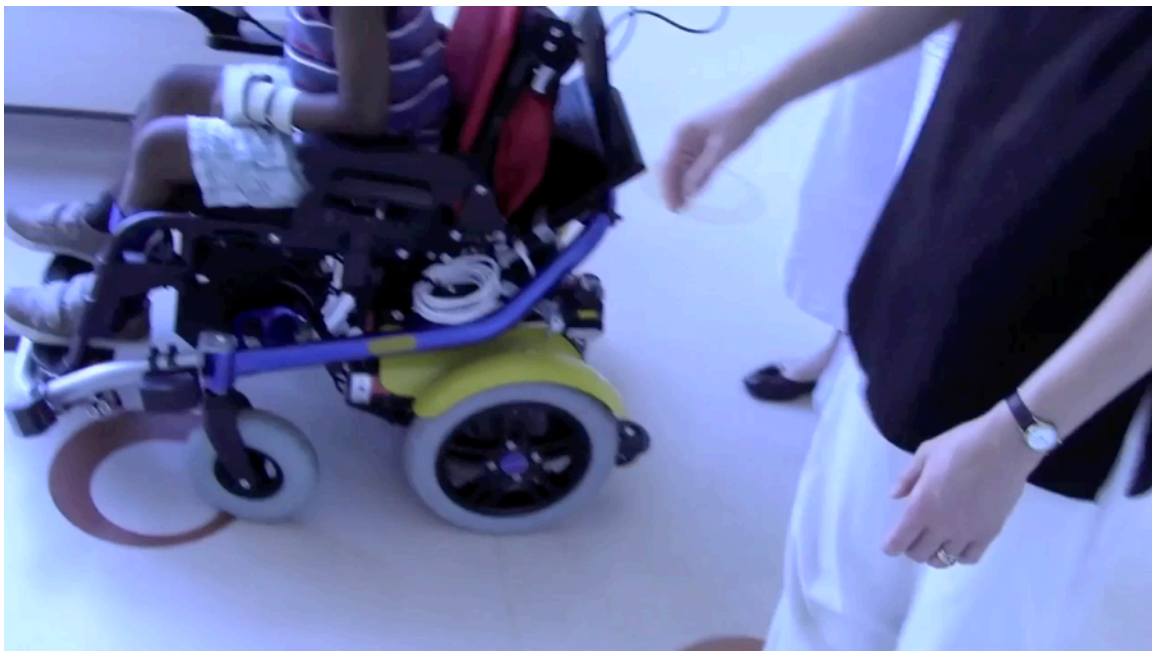
Supporting the development of young disabled children



Follow the Leader

Hospital trials

User trials with brain injured children



Doubled training time tolerance

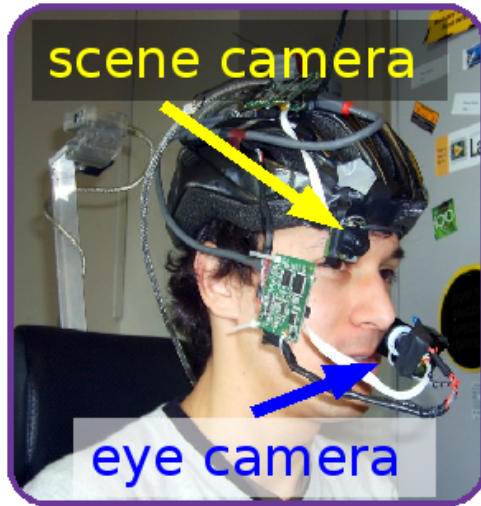
Improved accessibility to new environments (eg. the hospital's gardens)



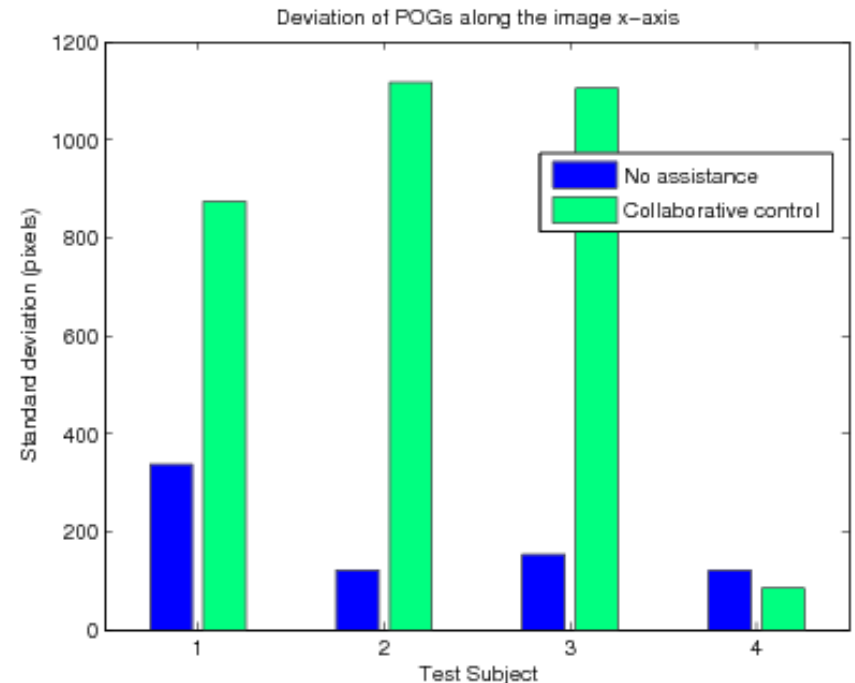
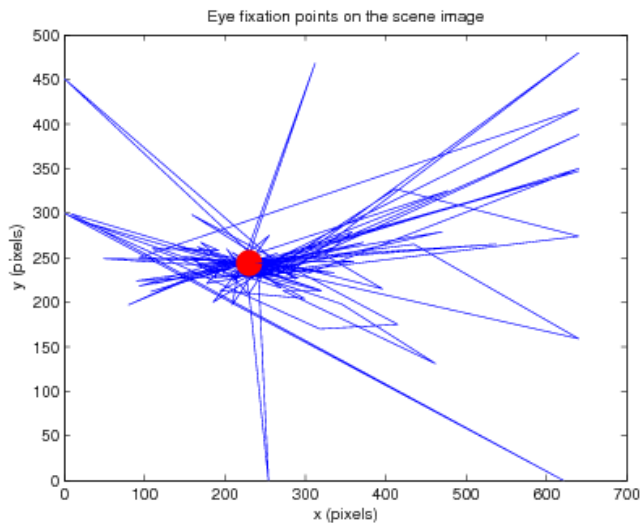
Time: 153.4

Assistance Level: 3.0%

Recall importance for participants for understanding why a partner's action was performed in a certain way



- For more experience users, saccadic eye movement became more erratic when assisted
- Shared control disturbs the user's forward model



Robotic companion for disabled children

Humanoid Companion for a Paediatric Wheelchair

Miguel Sarabia
Yiannis Demiris

Personal Robotics Lab



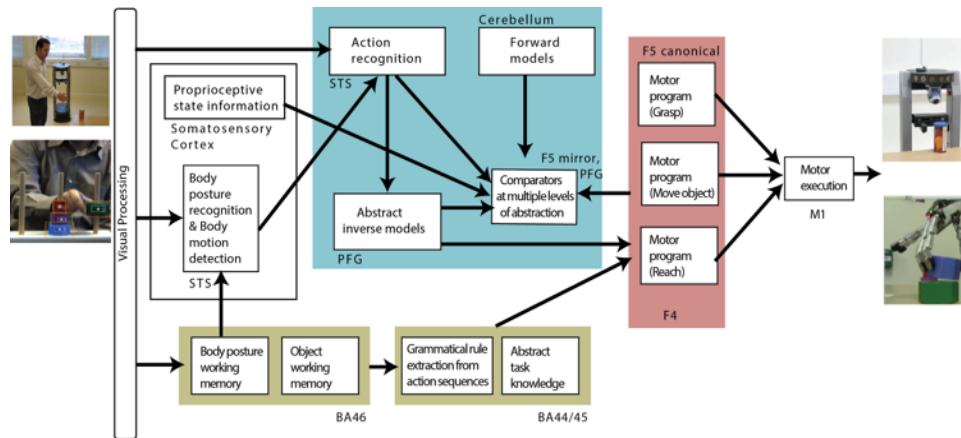
Robotic companion for disabled children

A robotic companion for mobility impaired children

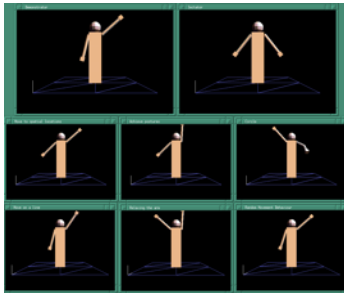
Miguel Sarabia
Yiannis Demiris

Personal Robotics Lab

HIERARCHICAL ATTENTIVE MULTIPLE MODELS FOR EXECUTION AND RECOGNITION (HAMMER)



Demiris, Aziz-Zadeh and Bonaiuto, Neuronformatics 2014

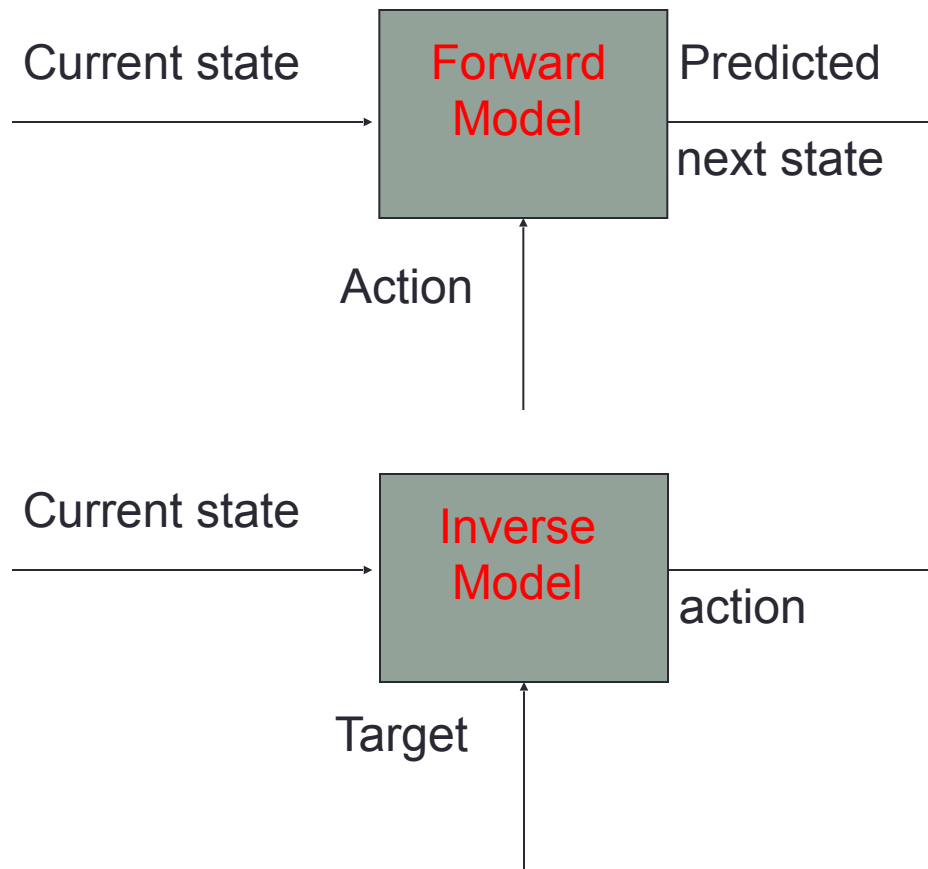


Several learning algorithms working at multiple levels :

- Learning human representations
- Learning at trajectory level [*Gaussian Processes, Quantum Mixtures, Recurrent Neural Nets*]
- Learning at action sequence and symbolic level [*Context-free stochastic grammars*]
- Auto- and hetero-biographical memory for storing and revisiting memories

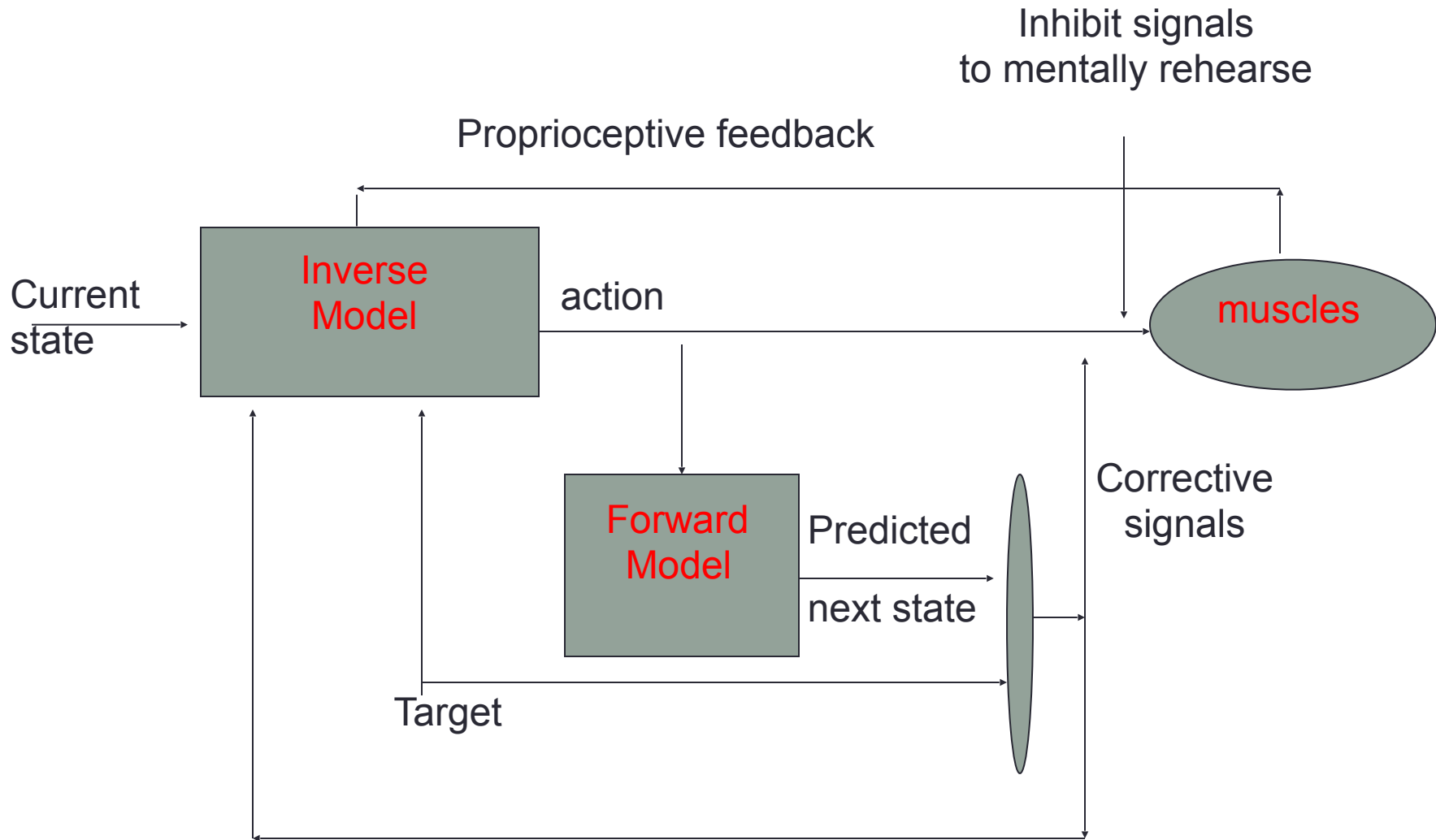
HAMMER Architecture (1)

The Basic Building Blocks



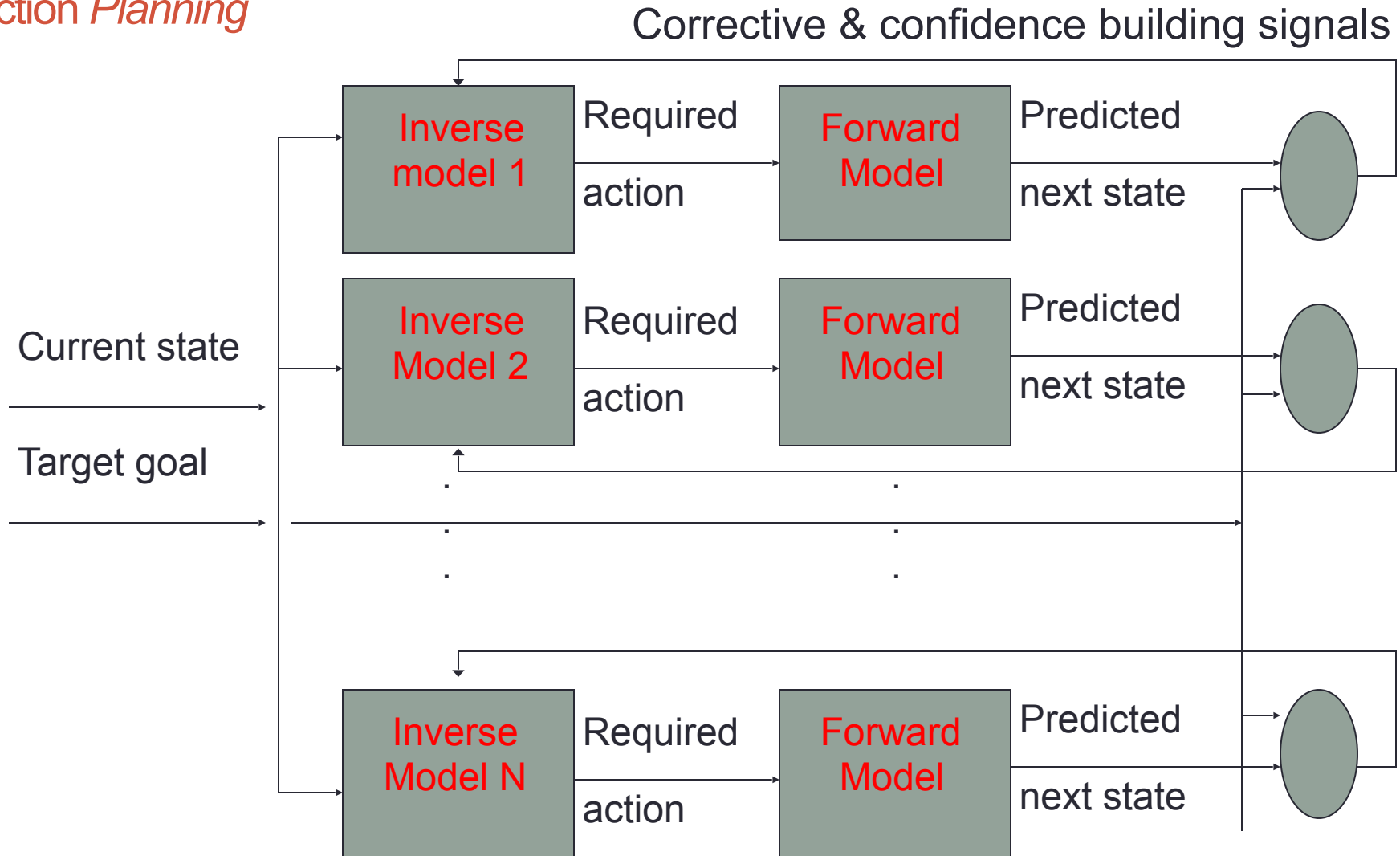
HAMMER Architecture (2)

Action Execution



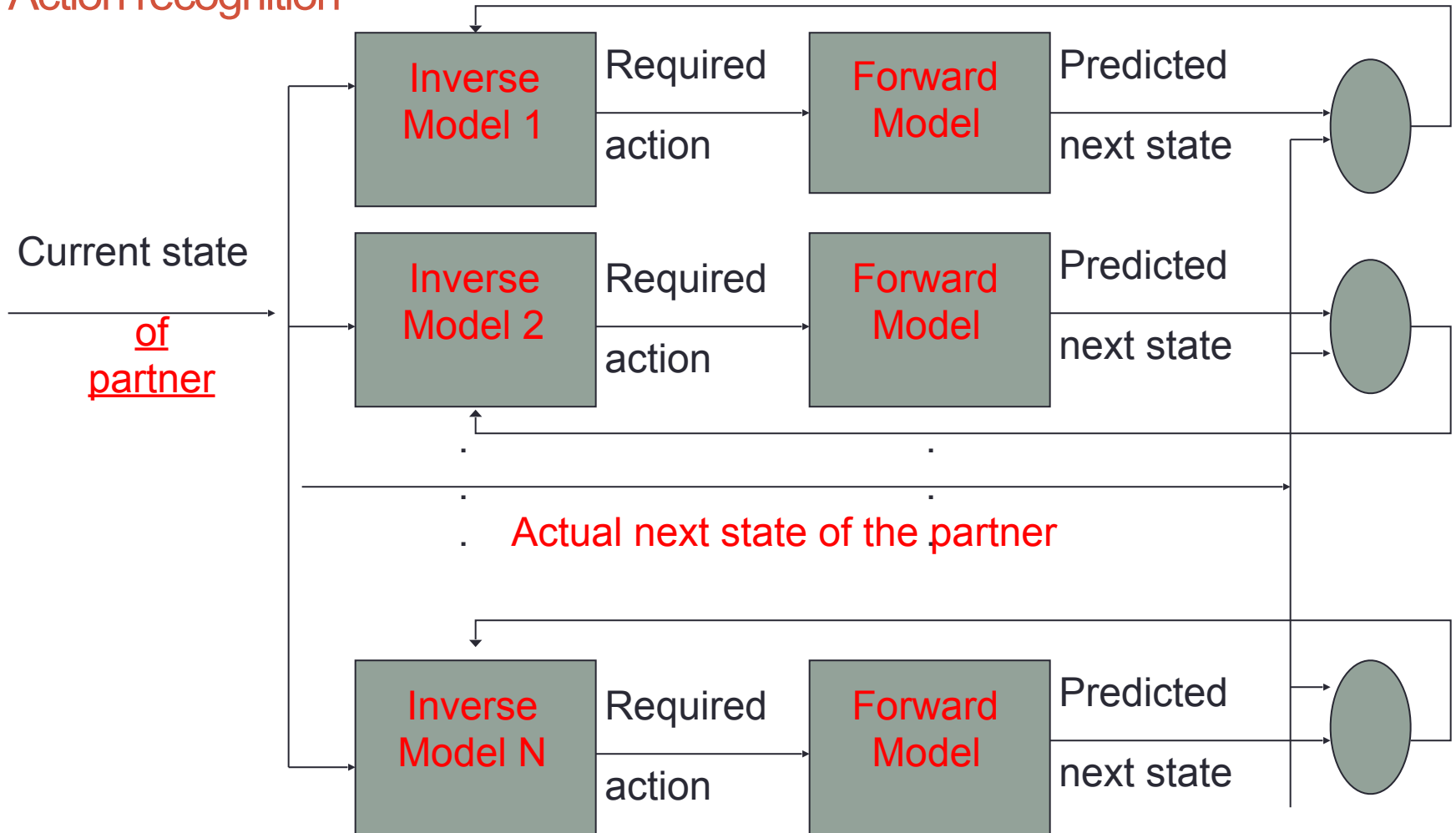
HAMMER Architecture (3)

Action Planning



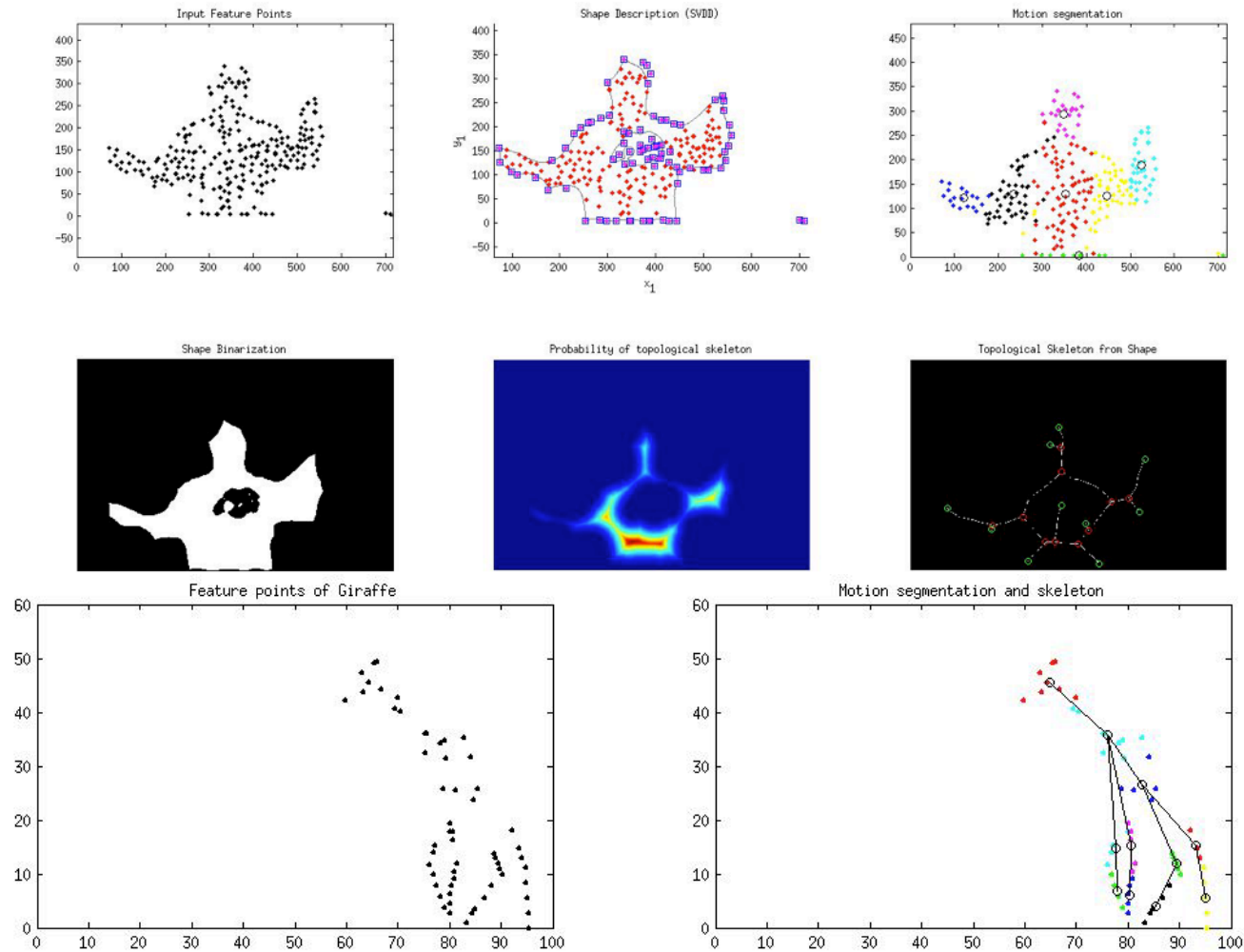
HAMMER Architecture (4)

Action recognition



Learning Human Representations

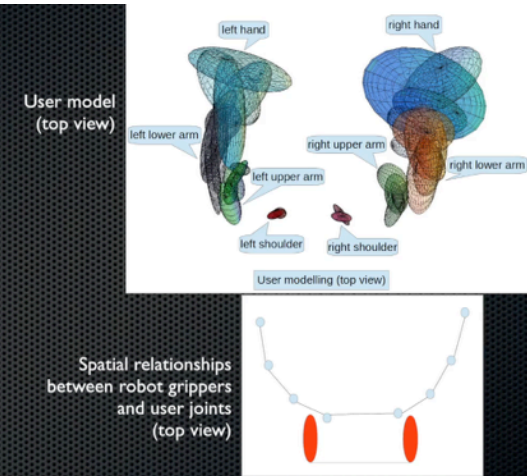
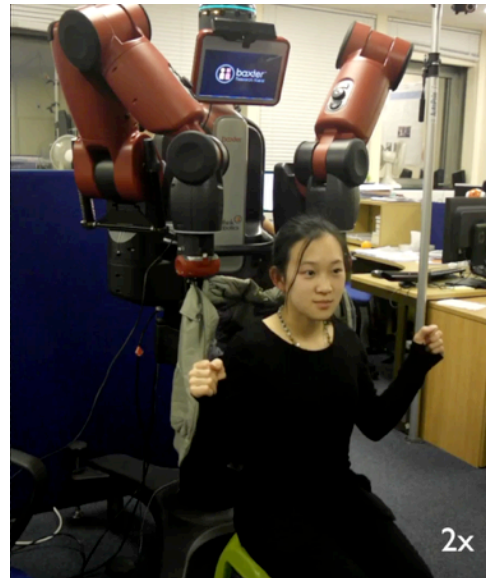
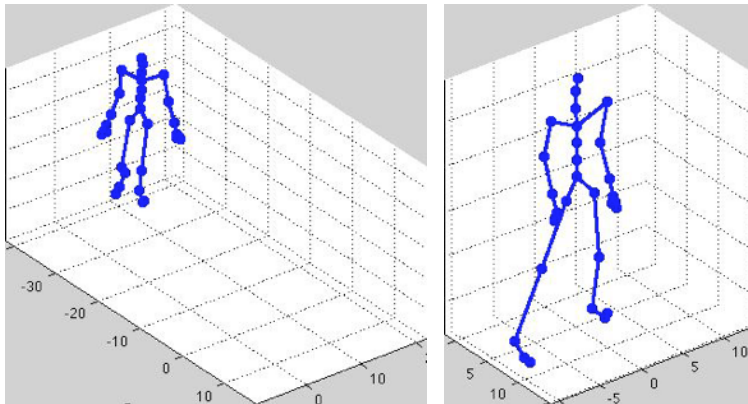
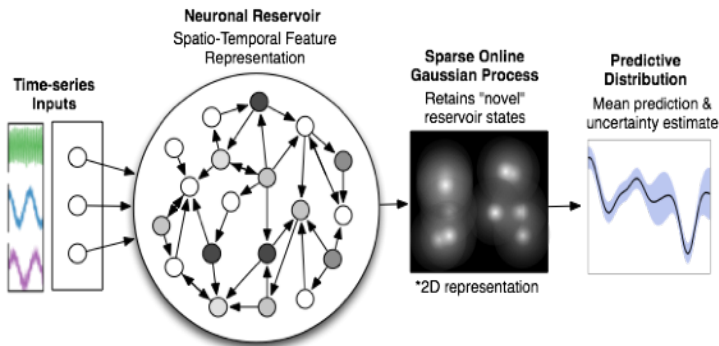
- **Using computer vision for Latent kinematic structure estimation (combining appearance and movement)**



Learning complex spatiotemporal data

Echo-State Neural Network + Sparse Online Gaussian Process

- Sequential data learning merging **reservoir computing** approaches, and **Bayesian inference** techniques.



Y. Gao, HJ Chang, and Y Demiris, “User Modelling for Personalised Dressing Assistance by Humanoid Robots”, IROS 2015, Hamburg, Germany.

H. Soh and Y. Demiris, “Spatiotemporal learning with the online finite and infinite echo-state Gaussian Process”, IEEE Transactions on Neural Networks and Learning Systems, 2015

Stochastic context free grammars for task representations

Using “linguistic” representations for task descriptions – Towers of Hanoi

ACTION GRAMMAR RULES RELATED TO DROP BRANCH

* Naming conventions: OBJ=object, BOX=box, A=approach, L=leave
 HGONE=hand invisibility, OGONE=object invisibility
 CONTACT=hand in contact with an object, SKIP=(See Sec.II-D.2)

BEGIN	⇒	NEXTBOX	[0.33]
		DROP	[0.33]
		PLACE	[0.33]
DROP	⇒	AOBJ CONTACT ABOX LOBJ OGONE	[1.0]
AOBJ	⇒	AOBJ aobj	[0.5]
		aobj	[0.4]
		SKIP aobj	[0.1]
ABOX	⇒	ABOX abox	[0.5]
		abox	[0.4]
		SKIP abox	[0.1]
CONTACT	⇒	CONTACT contact	[0.5]
		contact	[0.4]
		SKIP contact	[0.1]
LOBJ	⇒	LOBJ lobj	[0.5]
		lobj	[0.4]
		SKIP lobj	[0.1]
OGONE	⇒	OGONE ogone	[0.5]
		ogone	[0.4]
		SKIP ogone	[0.1]

— Legend —

L: Lift disk

D: Drop disk

A: Move 1 <-> 2

B: Move 1 <-> 3

C: Move 2 <-> 3

Frame 34

0: 549,3

1: 551,4

2: 534,407

L _____

D _____

A **The height of each bar represents certainty level**

B _____

C _____

— Legend —

L: Lift disk

D: Drop disk

A: Move 1 <-> 2

B: Move 1 <-> 3

C: Move 2 <-> 3

L _____

D _____

A _____

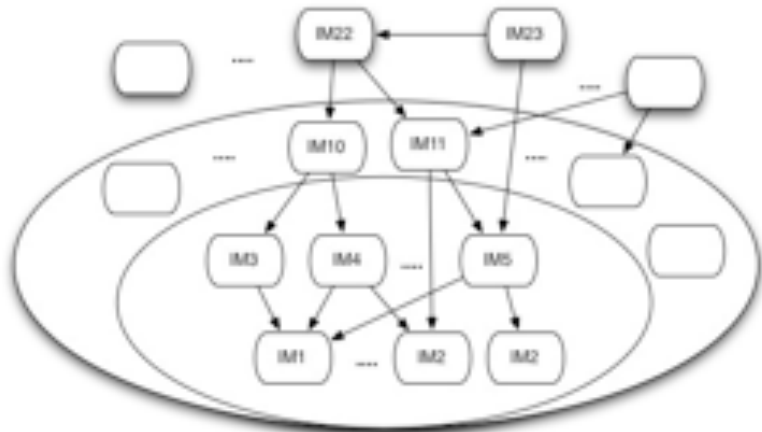
B _____

C _____

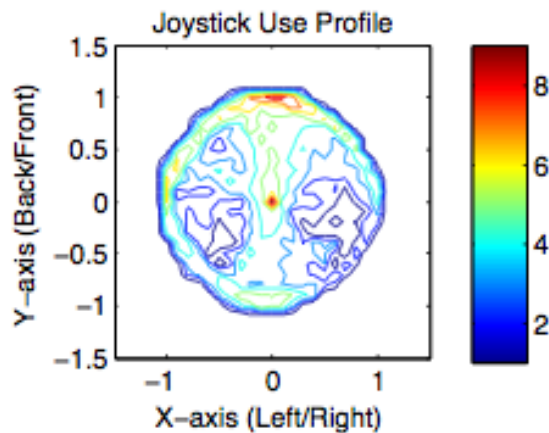
Lee, Su, Kim & Demiris, A syntactic approach to robot imitation learning using probabilistic activity grammars, Robotics & Autonomous Systems, 2013.

Representing human skills (1)

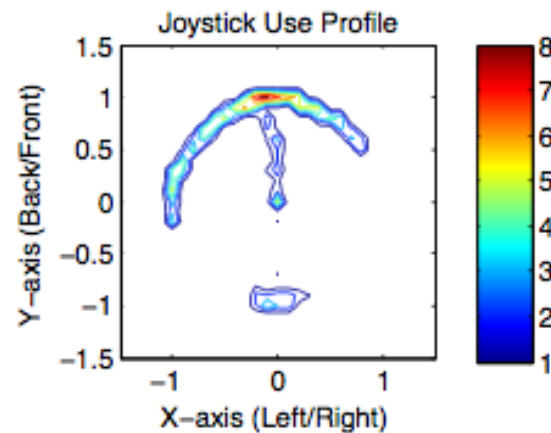
Hierarchical Representations - building the Zone of Proximal Development



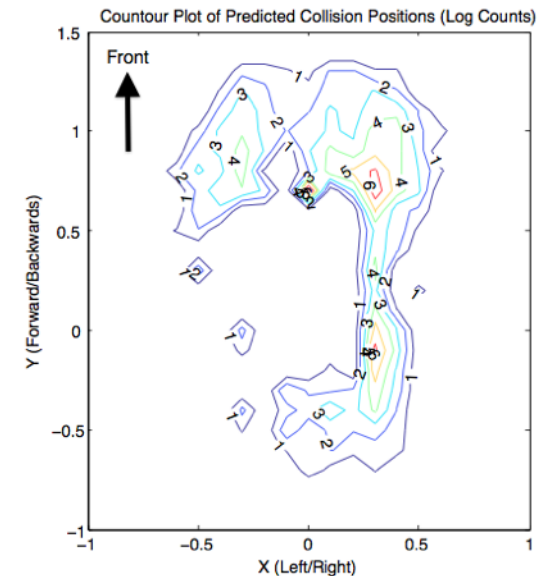
- Collect user data for each component inverse model and propagate uncertainties in the hierarchical model
- Predict level of shared control required
 - Attentional and sensorimotor load calculations (Demiris and Khadhouri, Interaction Studies, 2008)



(a) C

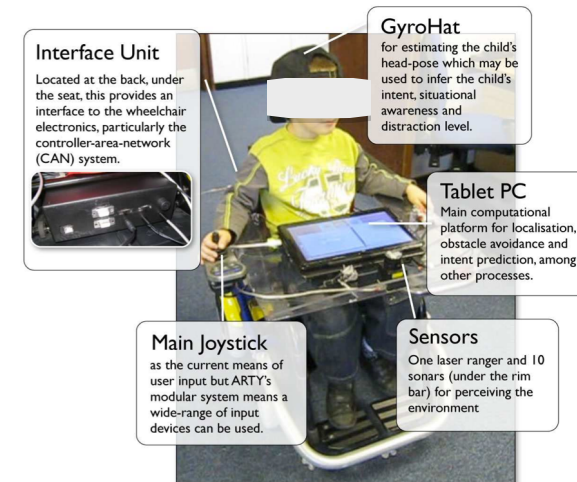
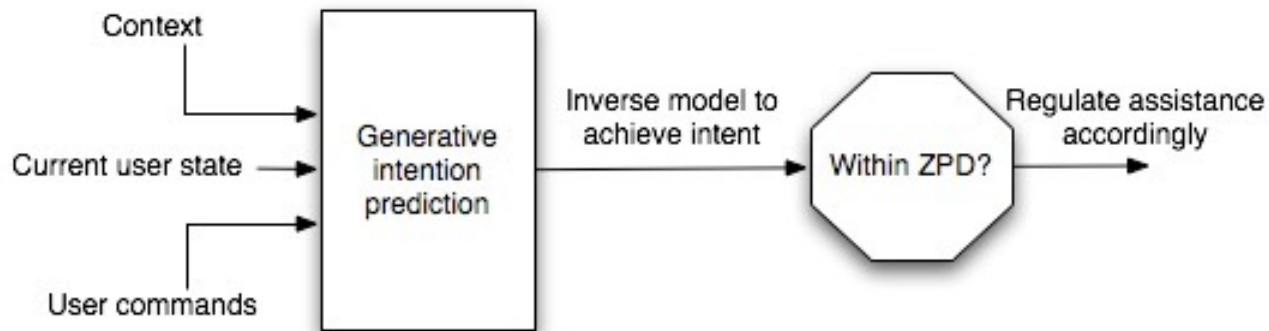


(b) Reference



Representing human skills (2)

Hierarchical Representations - building the ZPD



- Research challenge – principled methods for determining whether we should help
 - Balancing short and long term benefits

Demiris 2009, "Knowing when to assist: Developmental issues in lifelong assistive robots", IEEE EMBC 2009

Rehabilitation settings ₂

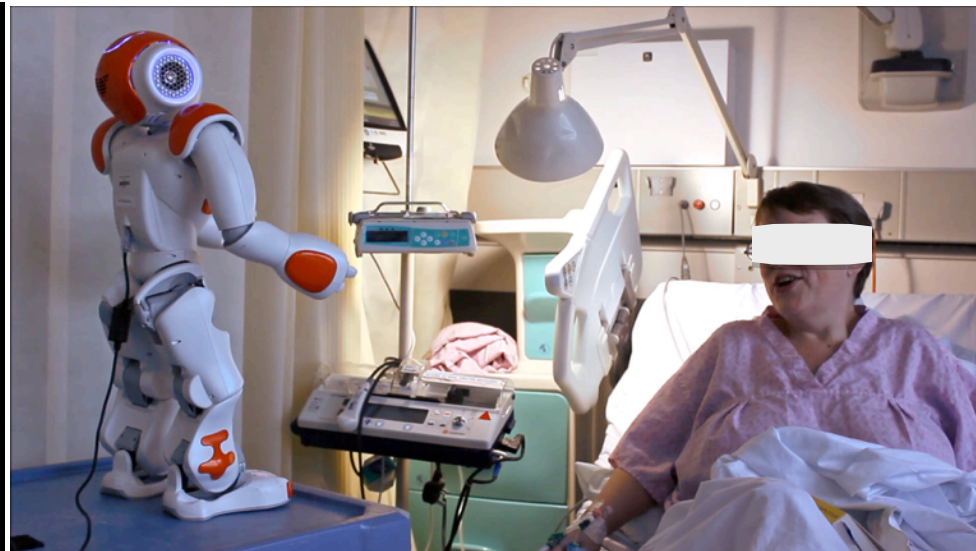
Technology challenges

- Lifelong modelling of the *sensorimotor and cognitive* states of a human user
- Formulating a user-specific joint action plan
- Short- and long-term robot response adaptation to a developing system [Demiris, IEEE EBMC 2009]

Towards a
dance robot teacher

Imperial College

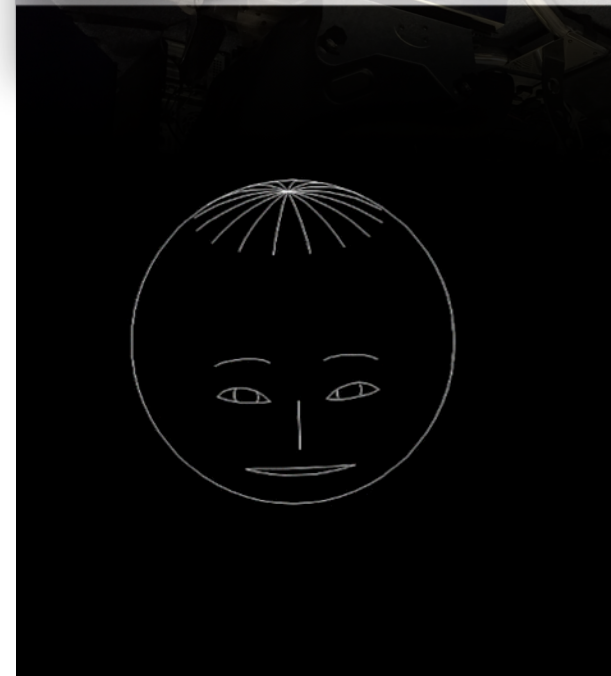
Fondazione Centro San Raffaele del Monte Tabor



Chelsea and Westminster Hospital **NHS**

NHS Foundation Trust

Adaptive Training in high performance scenarios



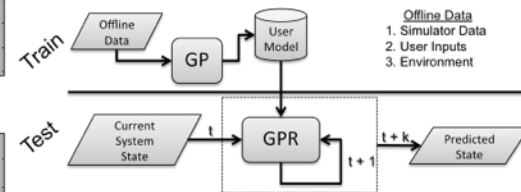
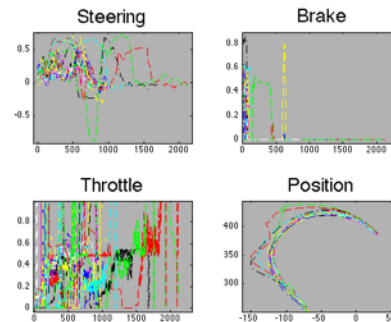
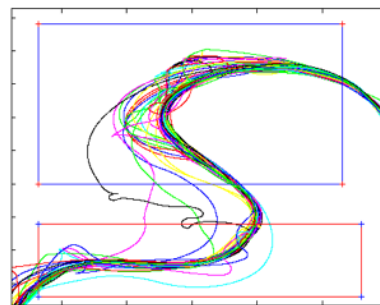
Georgiou and Demiris,
“Predicting Car States
through Learned Models of
Vehicle Dynamics and User
Behaviours”, **IEEE Intelligent
Vehicles 2015, Seoul, Korea.**



- **Racing Simulator**
User races for a certain period on one specific track

- **Personalised User Models**
User, EEG, Simulator and Environment data are being captured while the user is driving

- **Model Creation**
Model encapsulates user's habits and behaviour on road paths



Georgiou and Demiris, "Predicting Car States through Learned Models of Vehicle Dynamics and User Behaviours", IEEE Intelligent Vehicles 2015, Seoul, Korea.

Scaling to high number of inverse models

Attention during action perception

Multi-objective optimisation examining the content of the requests of the multiple models

Saliency of request is a function of the confidence of inverse model

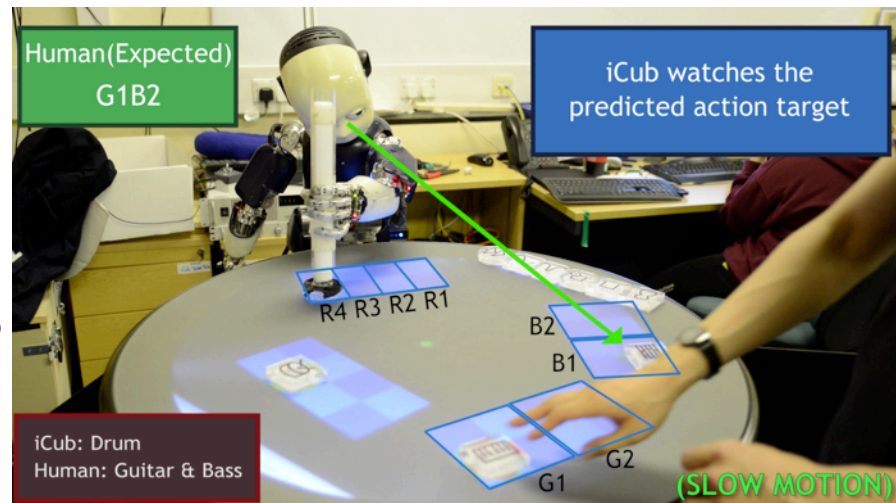
Multiple additional criteria:

- **Utility of the request**

(how many behaviours will be served if this request is serviced?)

- **Cost of request** (e.g. saccades)

- **Current reliability** of requested information

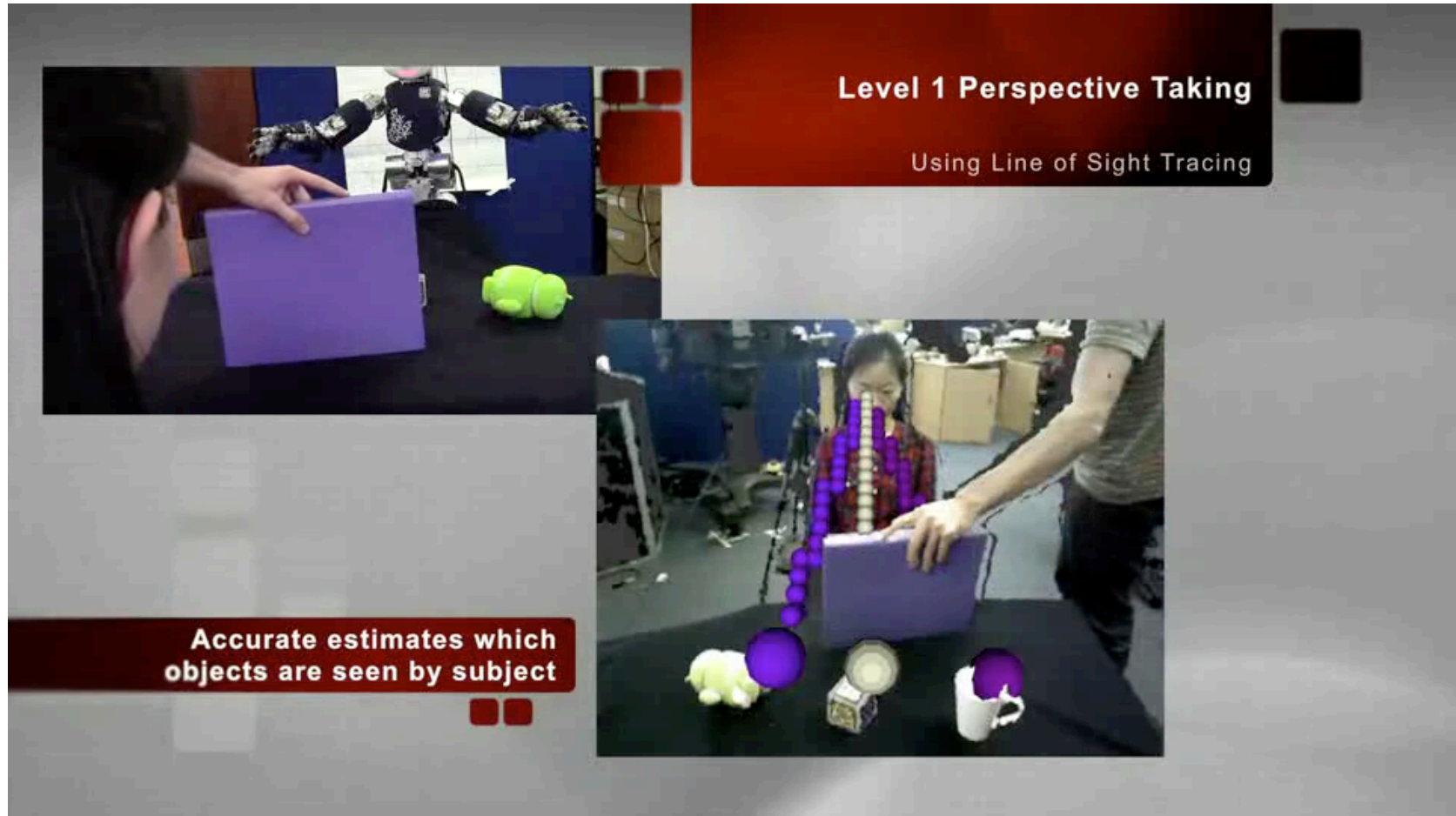


Demiris & Khadhoury, Interaction Studies, 2008

Ognibene & Demiris, IJCAI 2013

EU FP7 project WYSIWYD

Perspective Taking

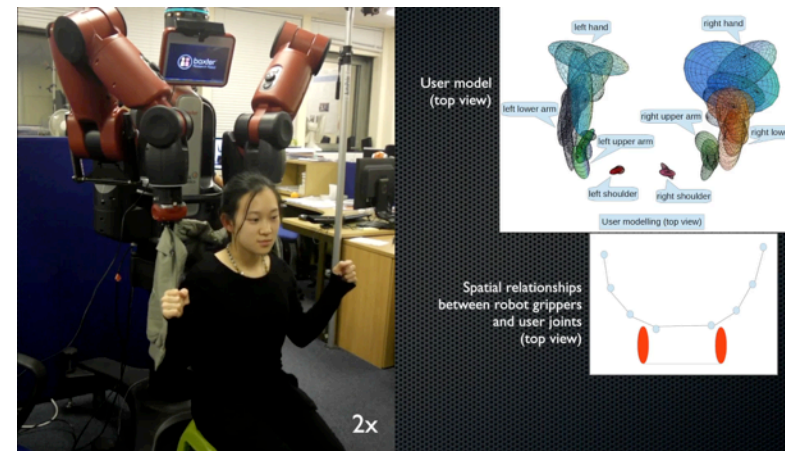


M. Johnson and Y. Demiris, “[Perceptual Perspective Taking and Action Recognition](#)”, International Journal of Advanced Robotic Systems, 2:4, pp. 301-308, Dec. 2005.

Fischer T, Demiris Y, Markerless Perspective Taking for Humanoid Robots in Unconstrained Environments, IEEE International Conference on Robotics and Automation, IEEE ICRA 2016

Conclusions

- **Personalisation:**
 - Participants explicitly model their partner's parameters (skills, preferences, ...) and adjust their behaviour; prediction a key element
 - Hierarchical partner modelling using ensembles of inverse and forward models
- **Lifelong joint action constraints:**
 - Has to include developmental aspects: in our domain outcome is improvement of one or more of the partners, not only success of an external temporary goal



THANKS TO MY TEAM



Yiannis Demiris



Hyung Jin Chang



Antoine Cully



Maxime Petit



Martina Zambelli



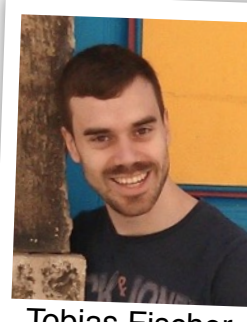
Miguel Sarabia



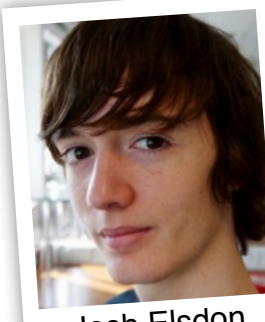
Theo Georgiou



Yixing Gao



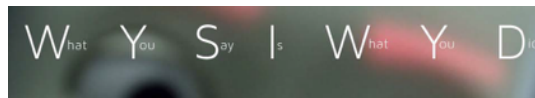
Tobias Fischer



Josh Elsdon



Regina Lio



Papers & videos at:
imperial.ac.uk/PersonalRobotics

Yiannis Demiris
www.demiris.info