iCub

a shared platform for research in robotics & AI

Genoa

June 25, 2015

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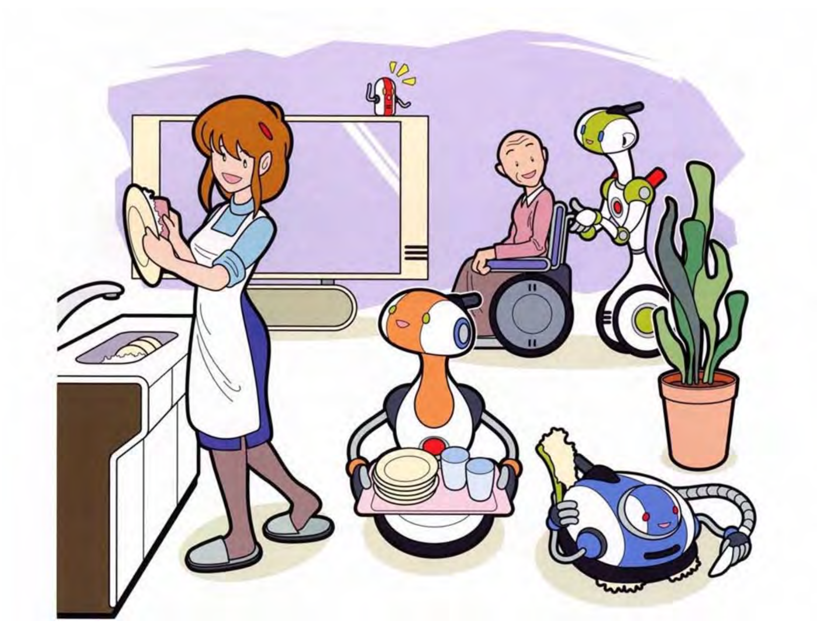
iit ISTITUTO ITALIANO DI TECNOLOGIA

we have a dream



the iCub

price: 250K€
30 iCub
distributed since 2008
about 3-4 iCub's/year

open hardware

why is the iCub special?

- hands: we started the design from the hands
  - 5 fingers, 9 degrees of freedom, 19 joints

- sensors: human-like, e.g. no lasers
  - cameras, microphones, gyros, encoders, force, tactile…

- electronics: flexibility for research
  - custom electronics, small, programmable (DSPs)

- reproducible platform: community designed
  - reproducible & maintainable yet evolvable platform
  - large software repository (~2M lines of code)

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why humanoids?

- scientific reasons
  - e.g. elephants don’t play chess

- natural human-robot interaction

- challenging mechatronics

- fun!

why open source?

- repeatable experiments

- benchmarking

- quality

this resonates with industry-grade R&D in robotics

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open source

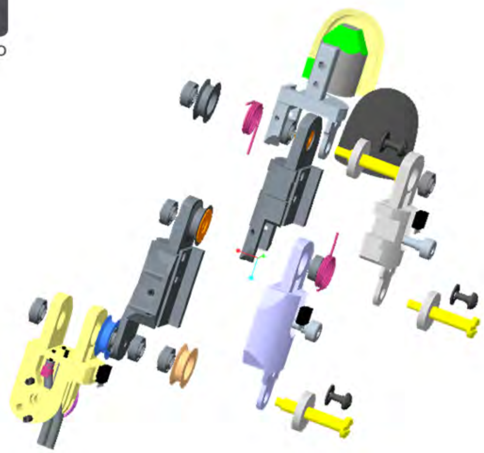
google and android

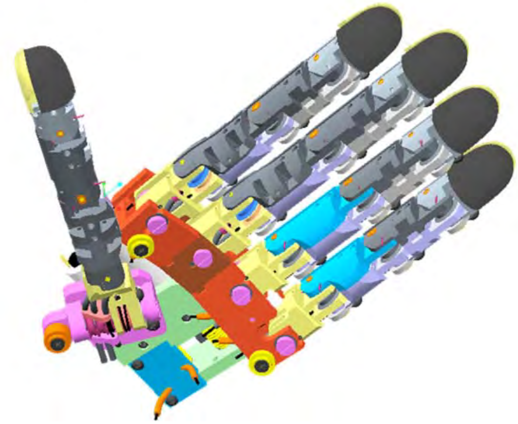
canonical, the ubuntu service provider company

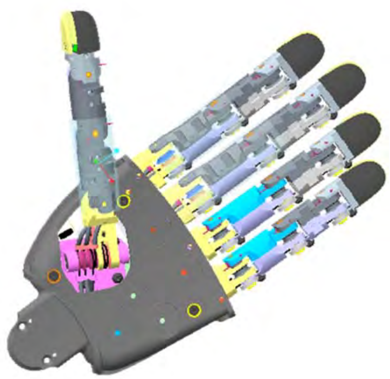
content manager built on open source

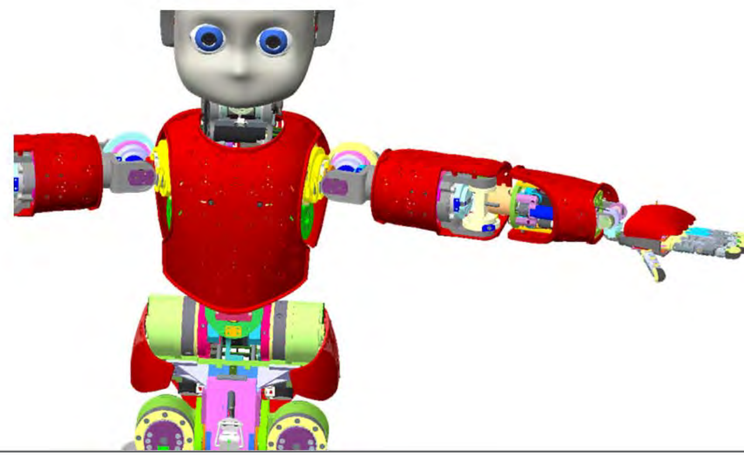
oracle and mysql

linux kernel development and redhat





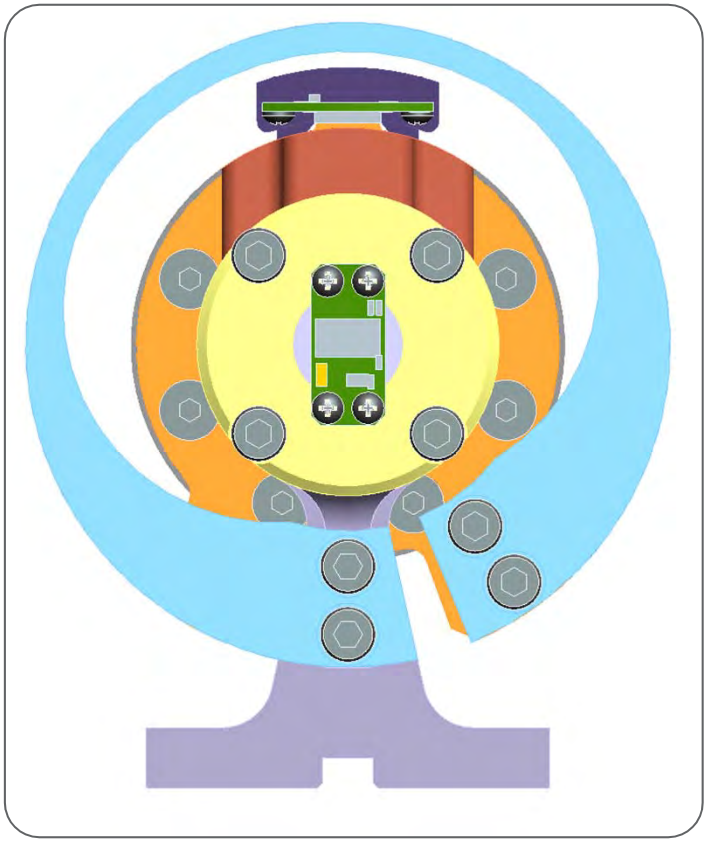




series-elastic actuators

- C spring design
- 320Nm/rad stiffness

- features:
  - stiffness by design
  - no preloading necessary (easy assembly)
  - requires only 4 custom mechanical parts
  - high resolution encoder for torque sensing



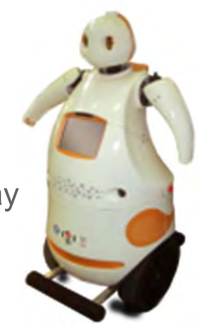
Yet Another Robot Platform

- YARP is an open-source (LGPL) middleware for humanoid robotics
- history
  - an MIT / Univ. of Genoa collaboration
  - born on Kismet, grew on COG, under QNX
  - with a major overhaul, now used by the iCub project
- C++ source code (some 400K lines)
- IPC & hardware interface
- portable across OSs and development platforms

2000-2001

2001-2002

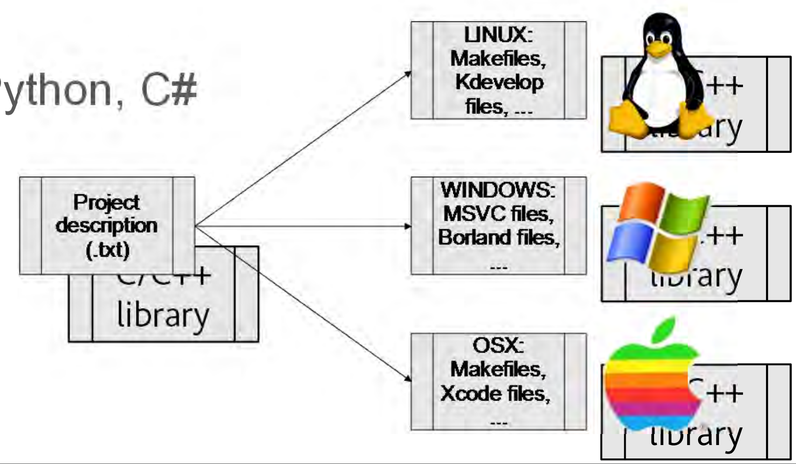
2003



2004-Today

exploit diversity: portability

- operating system portability:
  - Adaptive Communication Environment, C++ OS wrapper: e.g. threads, semaphores, sockets
- development environment portability:
  - CMake
- language portability:
  - via Swig: Java (Matlab), Perl, Python, C#



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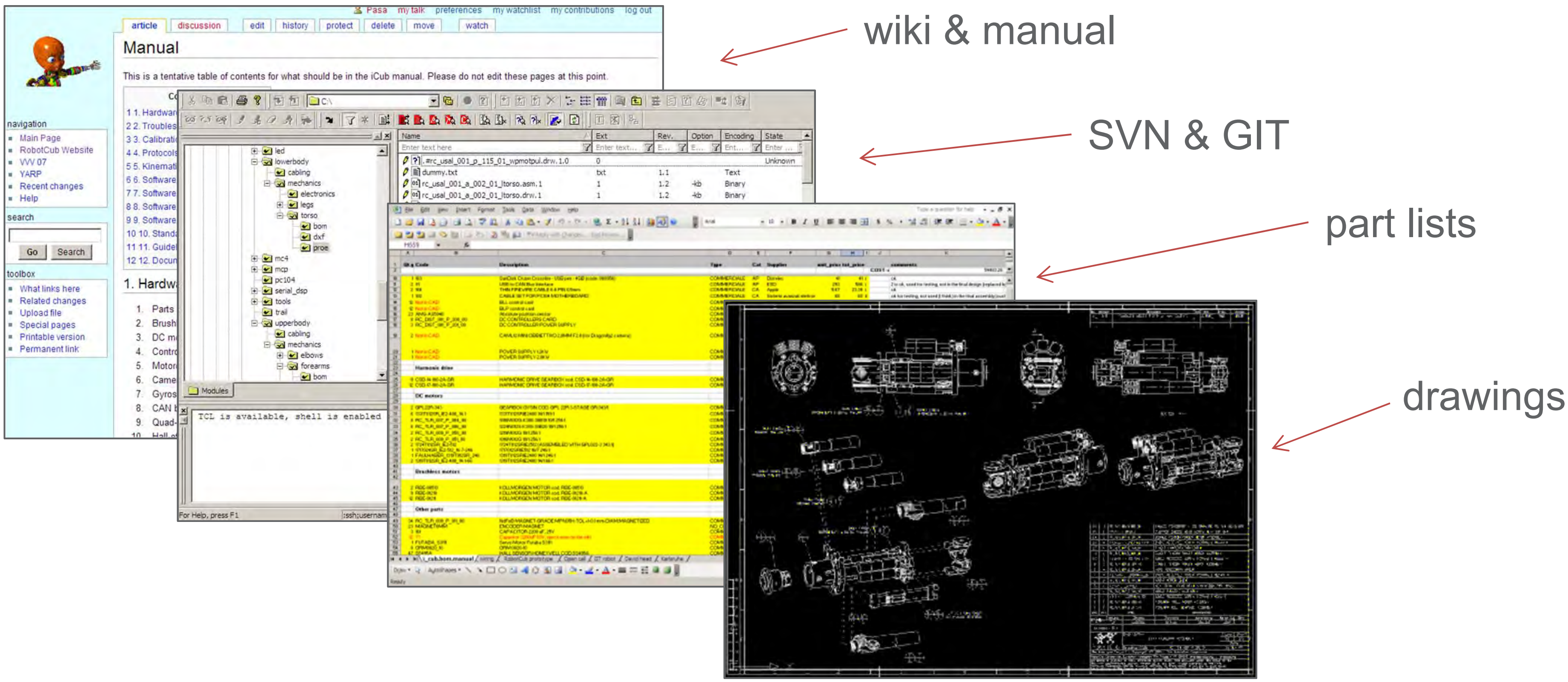
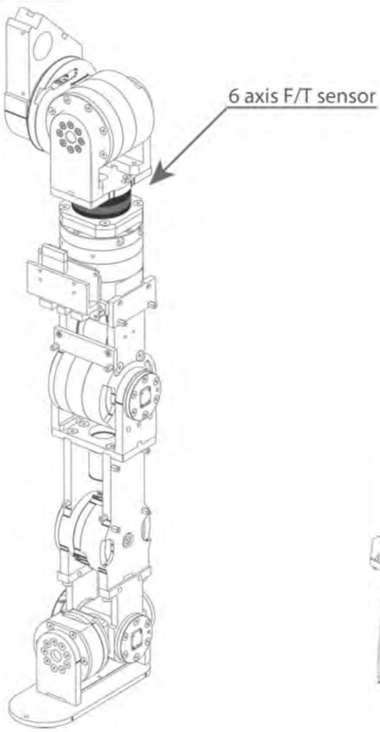
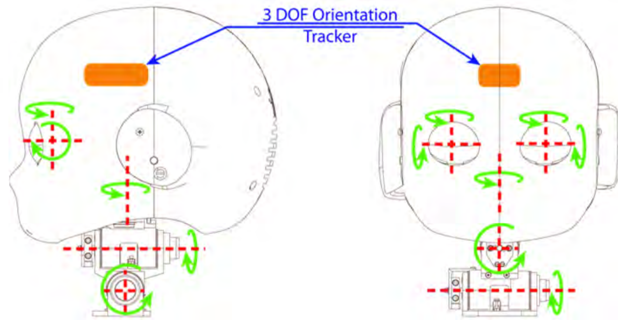
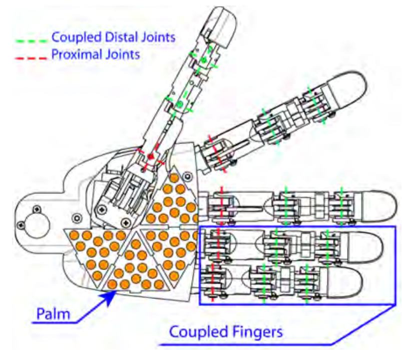
open source

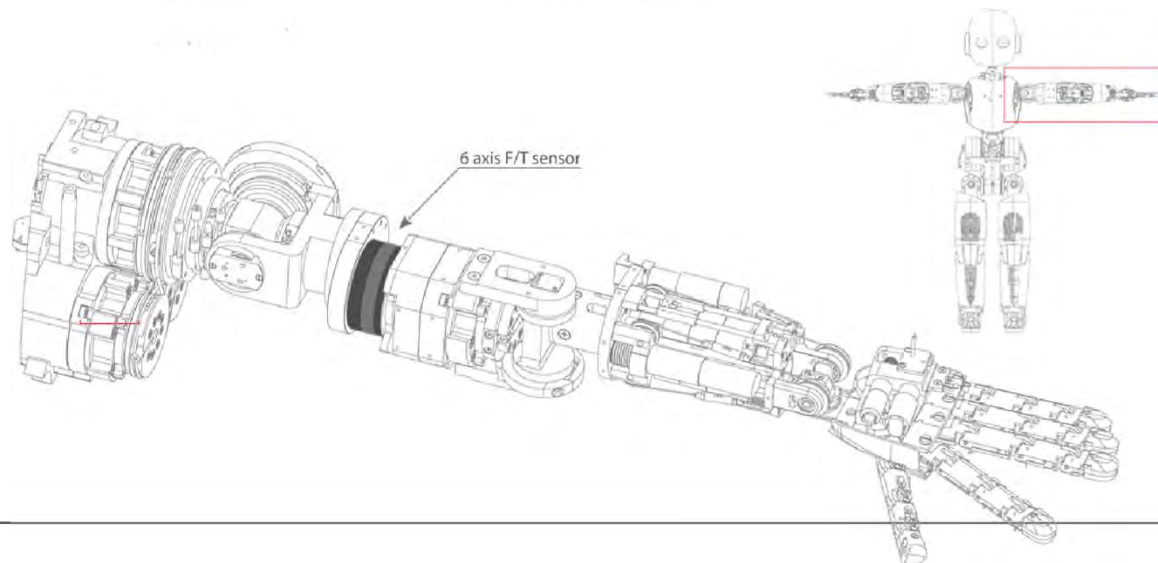


iCub sensors









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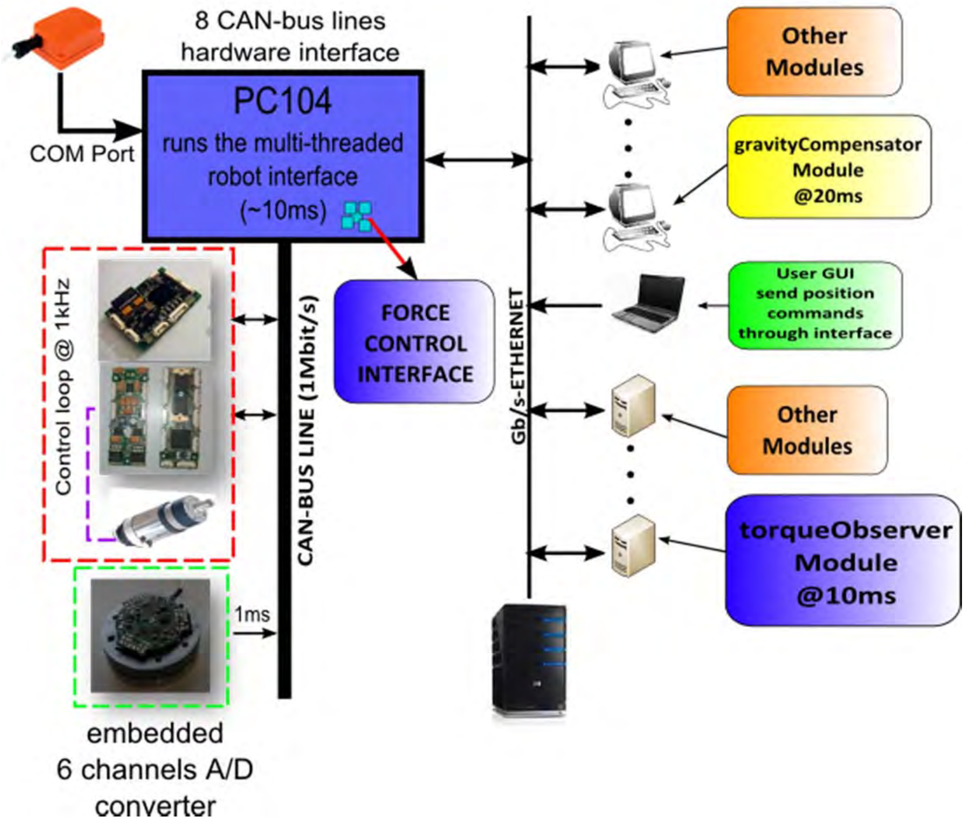
torque control



$$e = \tau - \tau_d$$

$$\widehat{w}_e = \begin{bmatrix} I & 0 \\ -[r_{se}]_\times & I \end{bmatrix} \cdot (w_s - w_i)$$

$$\hat{\tau}_e = J^T(q) \cdot \widehat{w}_e$$

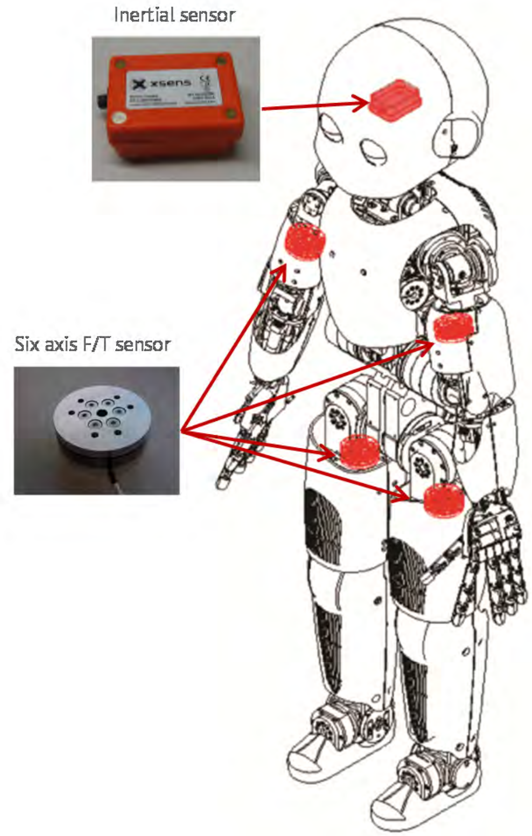
$$e = \hat{\tau}_e - \tau_d$$

$$u = k_p \cdot e + k_d \cdot \dot{e} + k_i \cdot \int e$$

$$\tau_d = K \cdot (q - q_d) + D \cdot (\dot{q} - \dot{q}_d)$$

learning dynamics

- learning body dynamics
  - compute external forces
  - implement compliant control



- so far we did it starting from e.g. the cad models
  - but we'd like to avoid it

our method in 4 easy steps

- regularized least square

$$f(x) = w^T x$$
$$\min_w J = \frac{\lambda}{2}\|w\|^2 + \frac{1}{2}\|y - Xw\|^2$$
$$w = (\lambda I + X^T X)^{-1} X^T y$$

- kernelized

$$f(x) = \sum_{i=1}^{m} c_i k(x, x_i)$$
$$c = (K + \lambda I)^{-1} y$$

- approximate kernel

$$k(x_i, x_j) = E\left[\frac{1}{D}\sum_{d=1}^{D} z_{w_d}(x_i)^T z_{w_d}(x_j)\right]$$
$$z_w(x) = [\cos(w^T x), \sin(w^T x)]$$

- make it incremental

$$w = (\lambda I + \Phi^T \Phi)^{-1} \Phi^T y$$

+ Cholesky rank-1 update

properties

- *O(1)* update complexity w.r.t. # training samples
- exact batch solution after each update
- dimensionality of feature mapping trades computation for approximation accuracy
- *$O(D^2)$* time and space complexity per update w.r.t. dimensionality of feature mapping
- easy to understand/implement (few lines of code)
- not exclusively for dynamics/robotics learning!

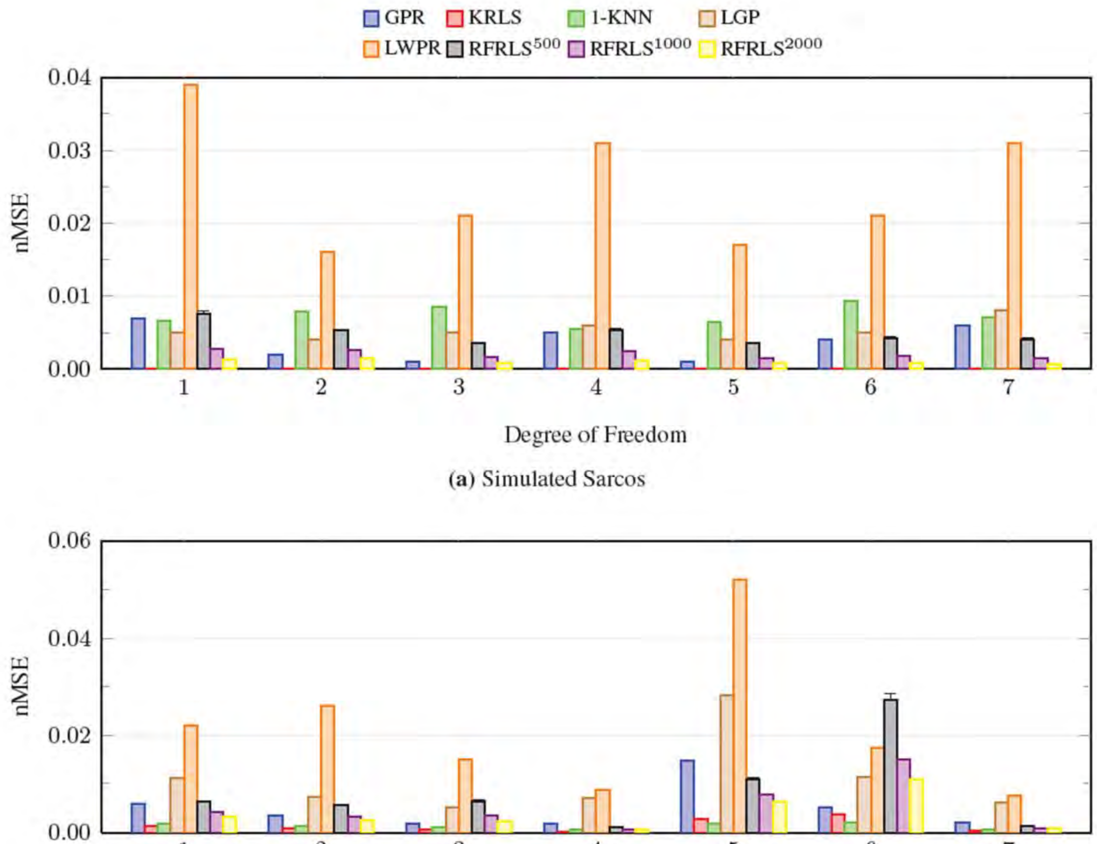
batch experiments

- 3 inverse dynamics datasets: Sarcos, Simulated Sarcos, Barrett [Nguyen-Tuong et al., 2009]
- approximately 15k training and 5k test samples
- comparison with LWPR, GPR, LGP, Kernel RR
- RFRR with 500, 1000, 2000 random features
- hyperparameter optimization by exploiting functional similarity with GPR (log marginal likelihood optimization)

datasets

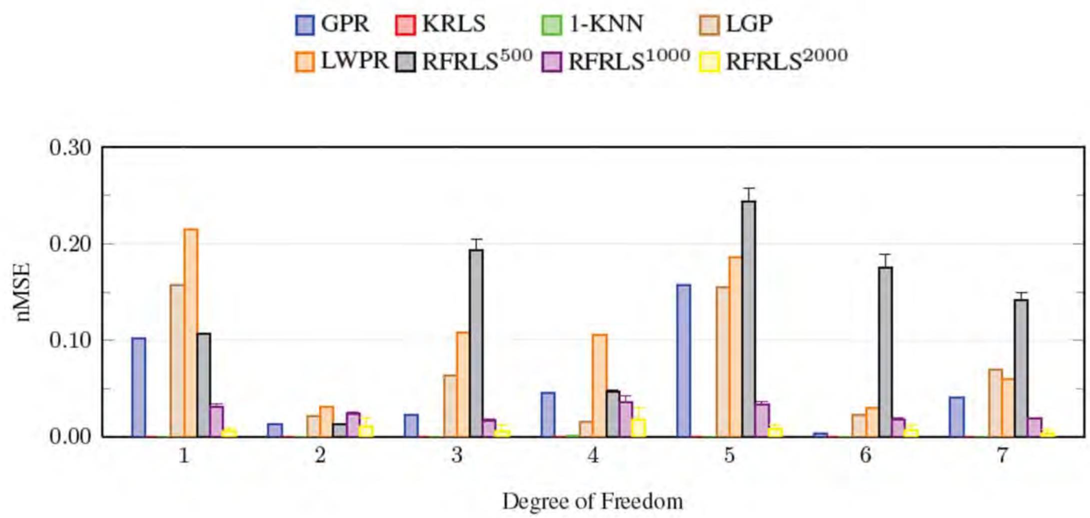
Table 5.1: Datasets used for the batch dynamics experiments.

	#joints	output	#train	#test
Simulated Sarcos	7	$\tau \times 7$	14904	5520
Sarcos	7	$\tau \times 7$	13922	5569
Barrett	7	$\tau \times 7$	13572	5000

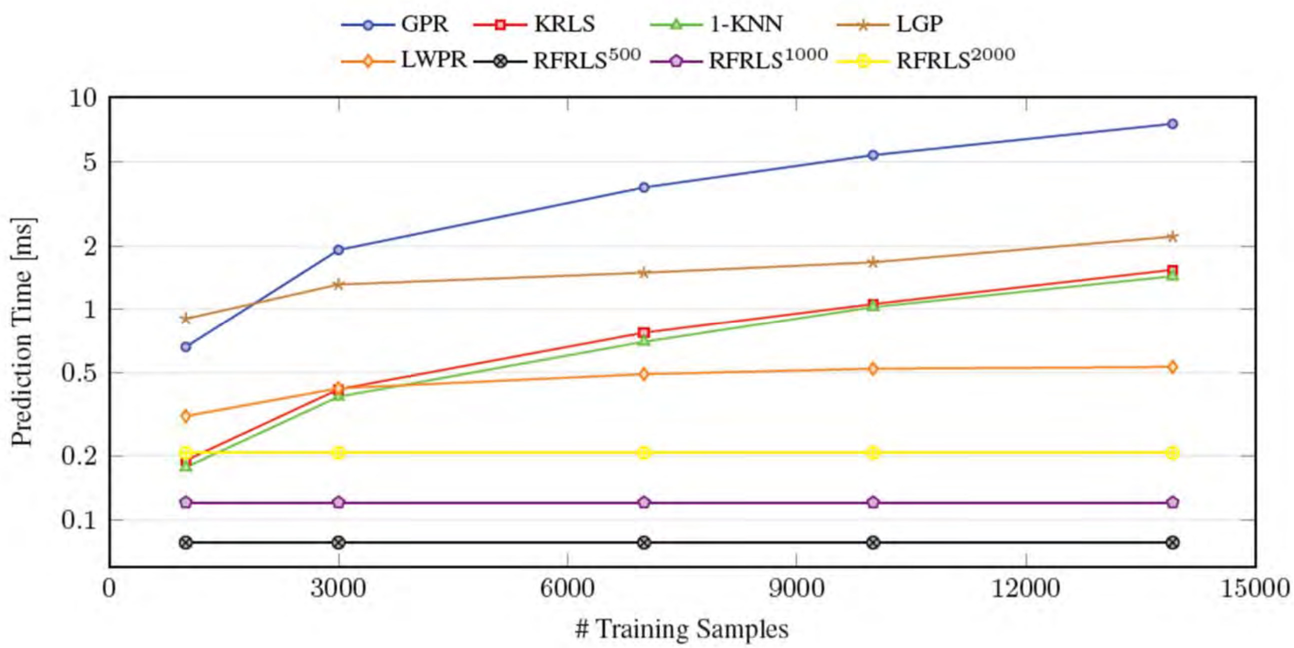


(a) Simulated Sarcos

(b) Sarcos


GPR
KRLS
1-KNN
LGP
LWPR
RFRLS500
RFRLS1000
RFRLS2000
0.30
0.20
0.10
0.00
nMSE
1
2
3
4
5
6
7
Degree of Freedom

(c) Barrett


GPR
KRLS
1-KNN
LGP
LWPR
RFRLS500
RFRLS1000
RFRLS2000
Prediction Time [ms]
10
5
2
1
0.5
0.2
0.1
0
3000
6000
9000
12000
15000
Training Samples

incremental experiments

Table 5.2: Datasets used for the incremental dynamics experiments.

	#joints	output	#train	#test
Sarcos	7	$\tau \times 7$	4449	44484
James	4	$[F, \tau]_{x,y,z}$	15000	195977
iCub	4	$[F, \tau]_{x,y,z}$	15000	72850

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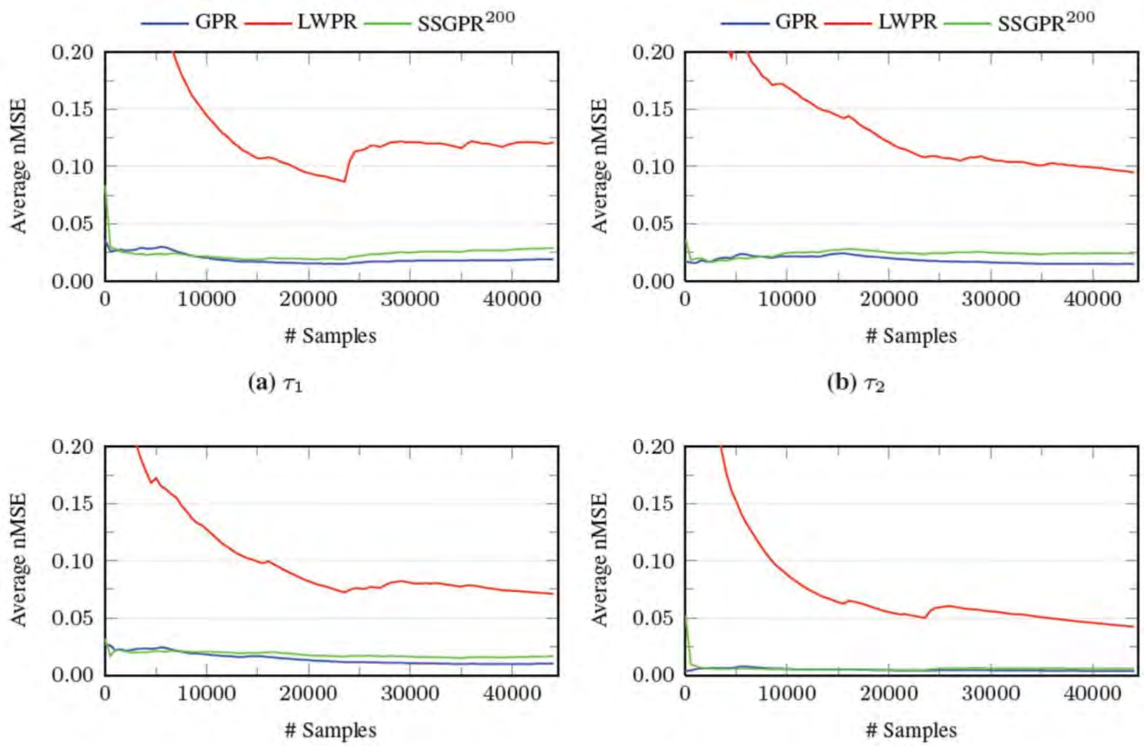
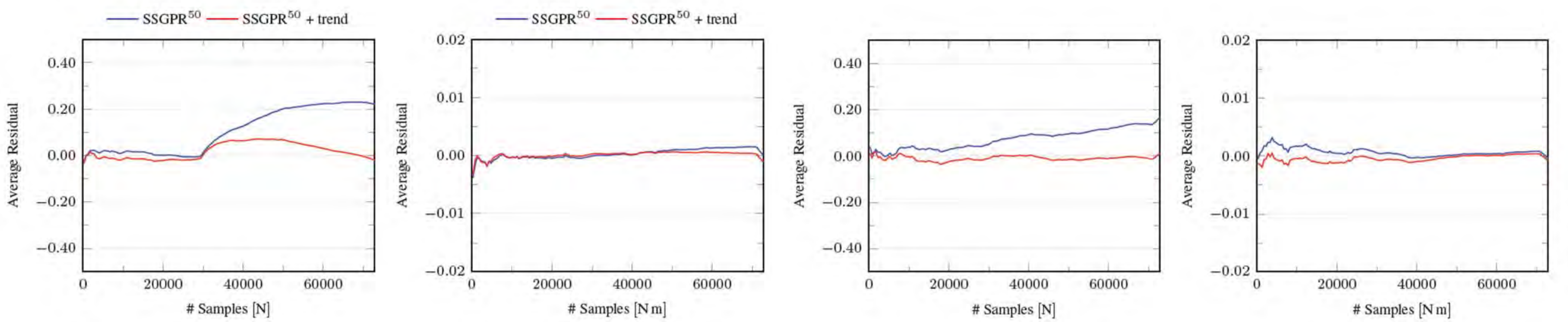
incremental experiments



(a) τ_1 (b) τ_2 (c) τ_3 (d) τ_4

temperature compensation

$$\phi(\boldsymbol{x}) = \frac{\sigma_f}{\sqrt{D}} \left[\sin\left(\langle \boldsymbol{\omega}_1^{\mathrm{T}}, \boldsymbol{x}\rangle\right), \cos\left(\langle \boldsymbol{\omega}_1^{\mathrm{T}}, \boldsymbol{x}\rangle\right), \cdots, \sin\left(\langle \boldsymbol{\omega}_D^{\mathrm{T}}, \boldsymbol{x}\rangle\right), \cos\left(\langle \boldsymbol{\omega}_D^{\mathrm{T}}, \boldsymbol{x}\rangle\right), t\right]^{\mathrm{T}}$$



(a) F_x (b) τ_x (c) F_y (d) τ_y

summary

- Fast prediction and model update of RFRR
  - 200RF: 400μs
  - 500RF: 2ms
  - 1000RF: 7ms
- Non-stationary: thermal sensor drift in force components
- Rapid convergence of RFRR
- No further gain by using additional random features (problem specific)

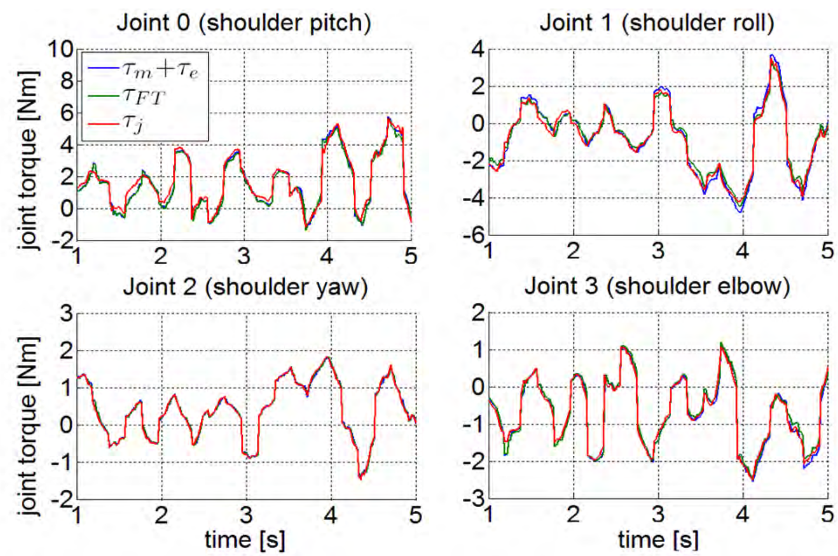
experiments & model validation

static configuration:

an additional six axis F/T sensor is placed at the end effector to measures the external wrenches w_e

in this experiment we consider the following quantities:

- joint torques measured by the joint torque sensors: t_j
- joint torques computed from the arm F/T sensor: t_{FT}
- joint torques estimated thought the additional F/T sensor located at the end effector: $t_e = J^T w_e$
- joint torques predicted by the arm model (no external forces): t_m



additional F/T sensor at the end-effector

	Joint 0	Joint 1	Joint 2	Joint 3
E $(\tau_j-\tau_{ft})$	0.127 Nm	-0.049 Nm	-0.002 Nm	-0.032 Nm
σ $(\tau_j-\tau_{ft})$	0.186 Nm	0.131 Nm	0.013 Nm	0.042 Nm
E $(\tau_j-(\tau_m+\tau_e))$	0.075 Nm	-0.098 Nm	-0.006 Nm	0.006 Nm
σ $(\tau_j-(\tau_m+\tau_e))$	0.191 Nm	0.173 Nm	0.020 Nm	0.032 Nm

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the robot skin

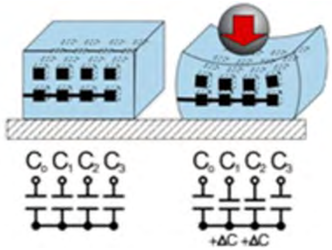
capacitor

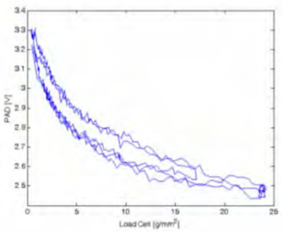
ground plane: e.g. conductive fabric
parameters: mechanical properties, impedance, etc.

soft material: e.g. silicone
parameters: dielectric constant, mechanical stiffness, etc.

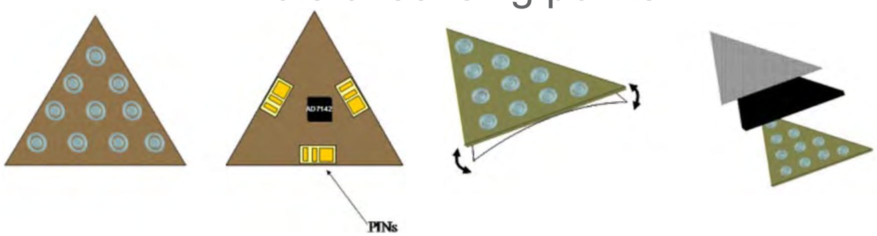
electrodes: etched on a flexible PCB
parameters: shape, folding, etc.

principle

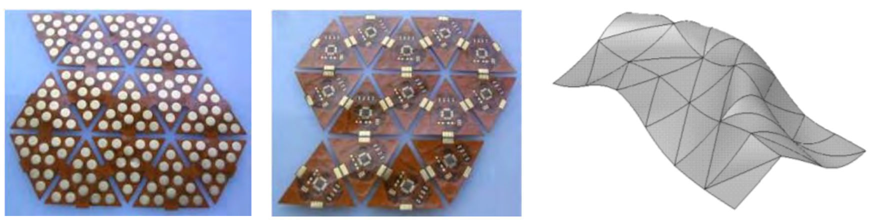


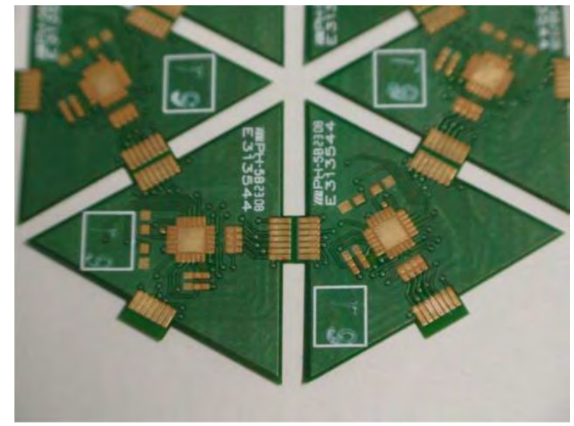


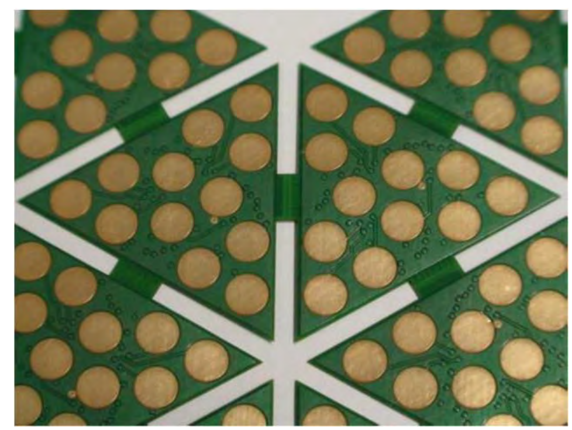
lots of sensing points



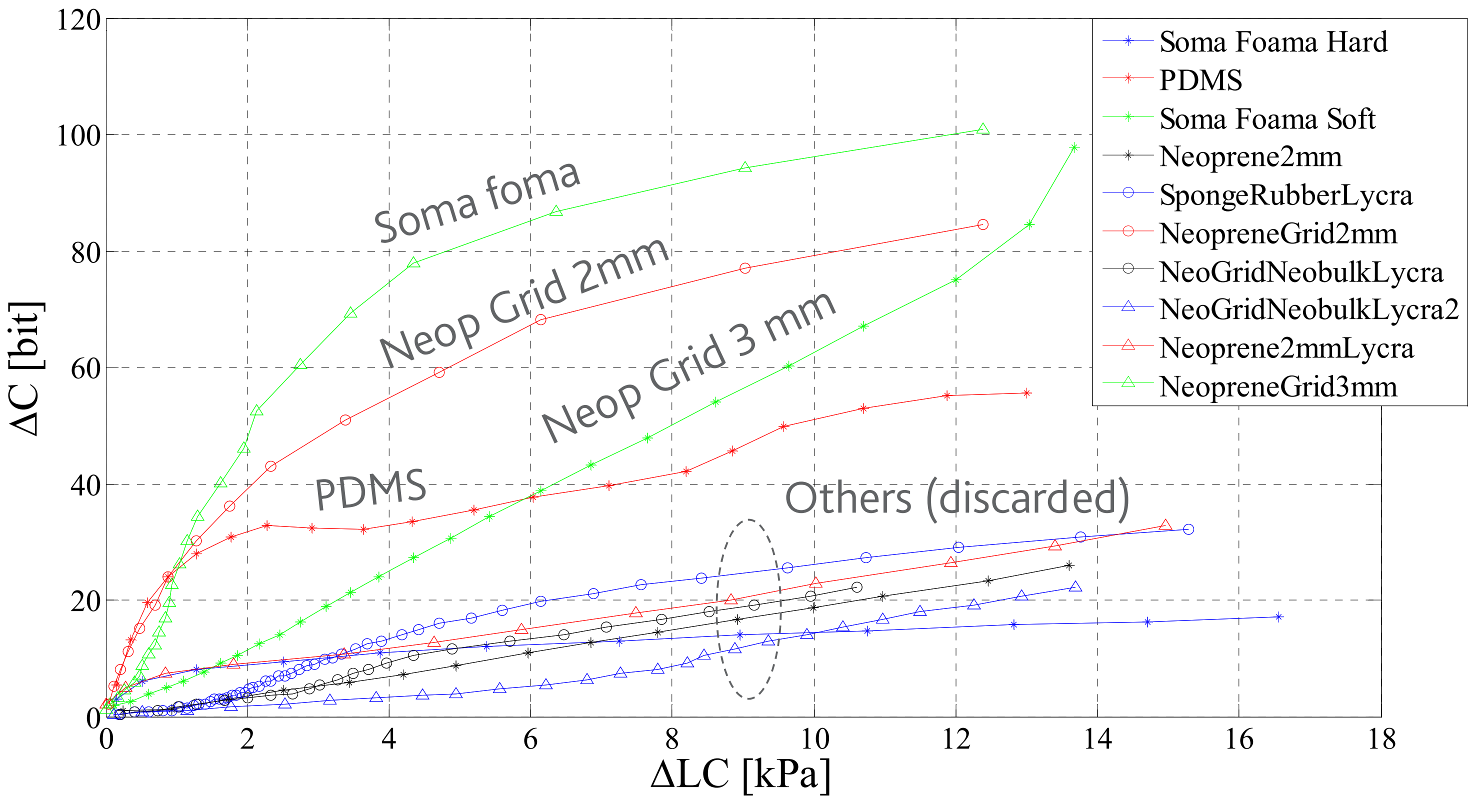
structure of the skin



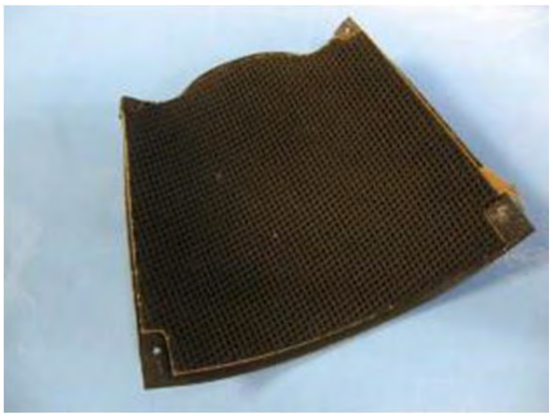




tests of various materials



latest implementation



advantages:

- good performance: gluing is made with industrial machines, no hysteresis due to glue
- production: automatic and reliable
- mounting and replacing is easy, easy ground connection
- protective layer can be of different materials → increase reliability
- customizations: surface can be printed

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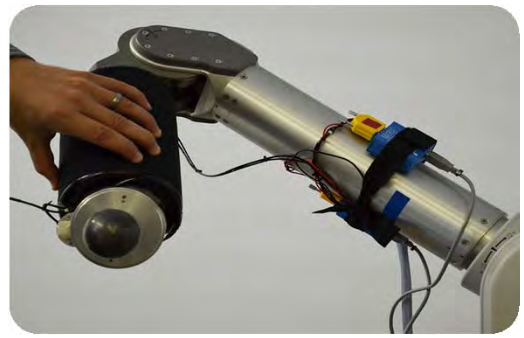
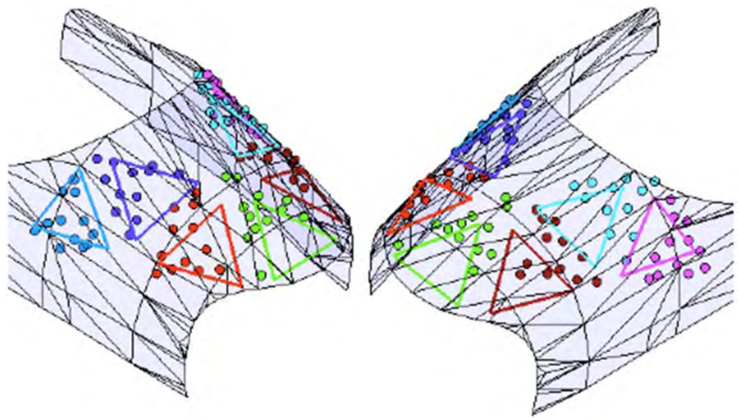
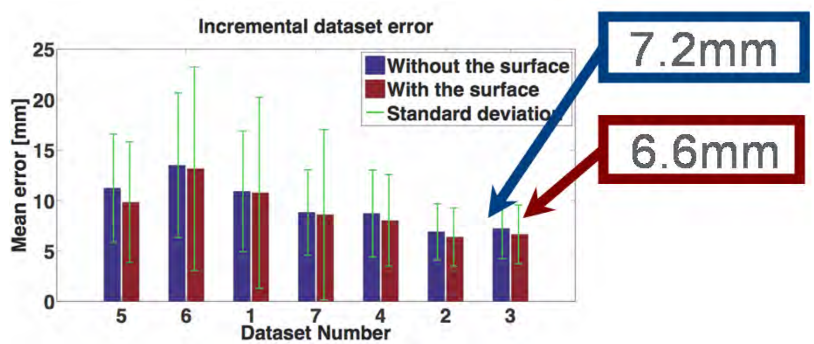


skin calibration





performed manually by poking the robot with a tool

works iteratively with different datasets taken in different robot positions

A. Del Prete, S. Denei, L. Natale, F. Mastrogiovanni, F. Nori, G. Cannata, and G. Metta. "Skin spatial calibration using force/torque measurements", in Intelligent Robots and Systems (IROS), 2011

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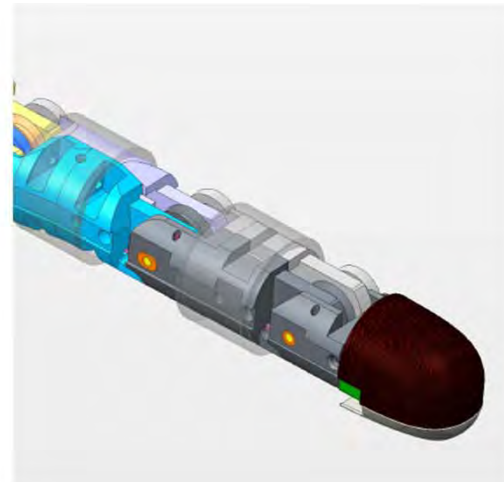
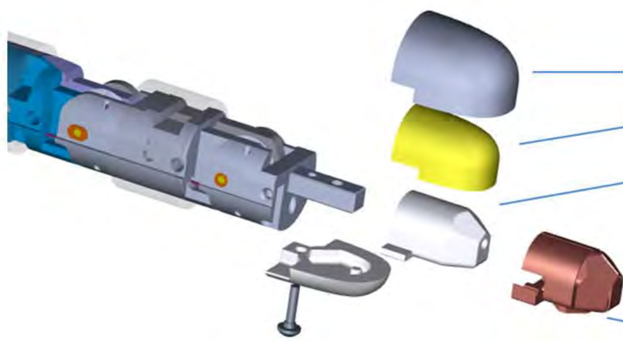
12 sensors
14.5 x 13 mm





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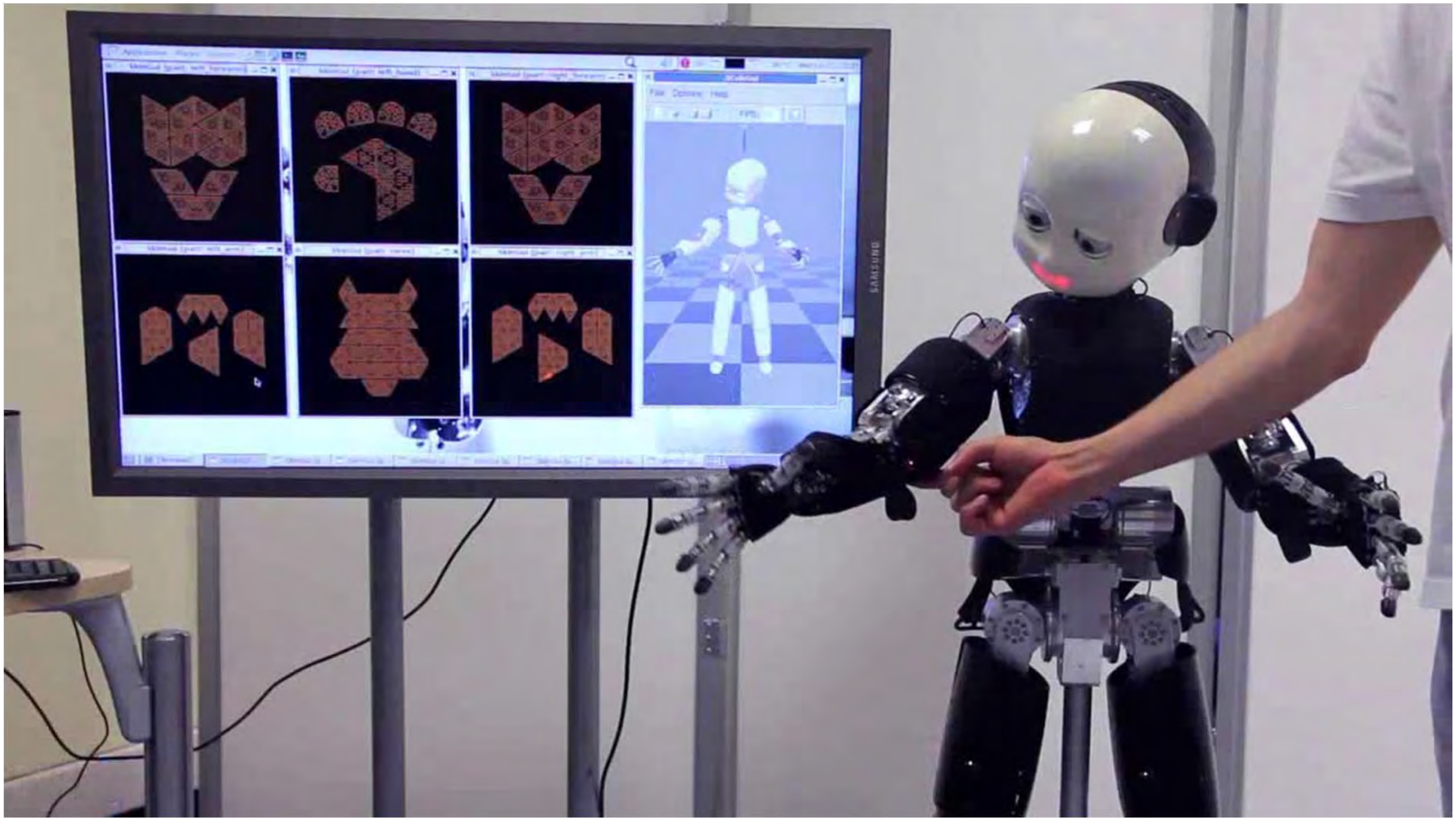


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RBCS

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project CoDyCo, Nori et al.

Scenario 1.	Scenario 2.	Scenario 3.	Scenario 4.
Balancing with multiple rigid contacts.	Goal directed actions involving contacts.	Learning non-rigid contacts.	Human assistive contacts.

floating base robots

$$\begin{bmatrix} \mathbf{I}^c & \mathbf{F} \\ \mathbf{F}^\top & \mathbf{H} \end{bmatrix} \begin{bmatrix} {}^b\mathbf{a}_b \\ \ddot{\mathbf{q}} \end{bmatrix} + \begin{bmatrix} \mathbf{p}^c \\ \mathbf{n} \end{bmatrix} = \begin{bmatrix} \mathbf{0} \\ \boldsymbol{\tau} \end{bmatrix} + \sum_{l \in L} \begin{bmatrix} {}^b\mathbf{X}_l^* \\ \mathbf{J}_l^\top \end{bmatrix} \mathbf{f}_l$$

$\mathbf{a}_b$ spatial acceleration of the floating base

$\mathbf{q}$ joint positions

$\mathbf{I}^c$ composite rigid body inertia of the tree

$\mathbf{p}^c$ spatial bias force of the composite tree

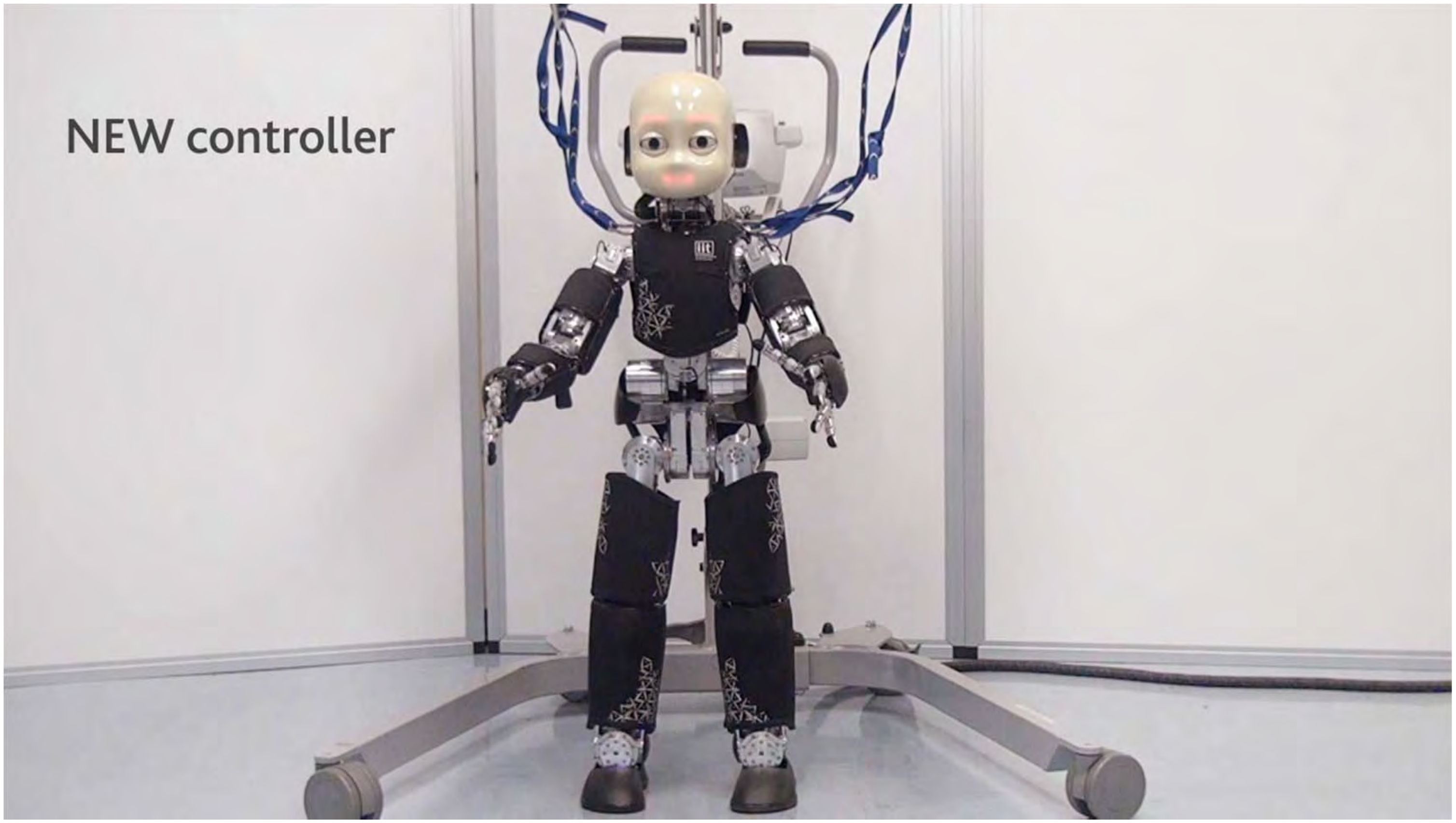
$\boldsymbol{\tau}$ joint torques

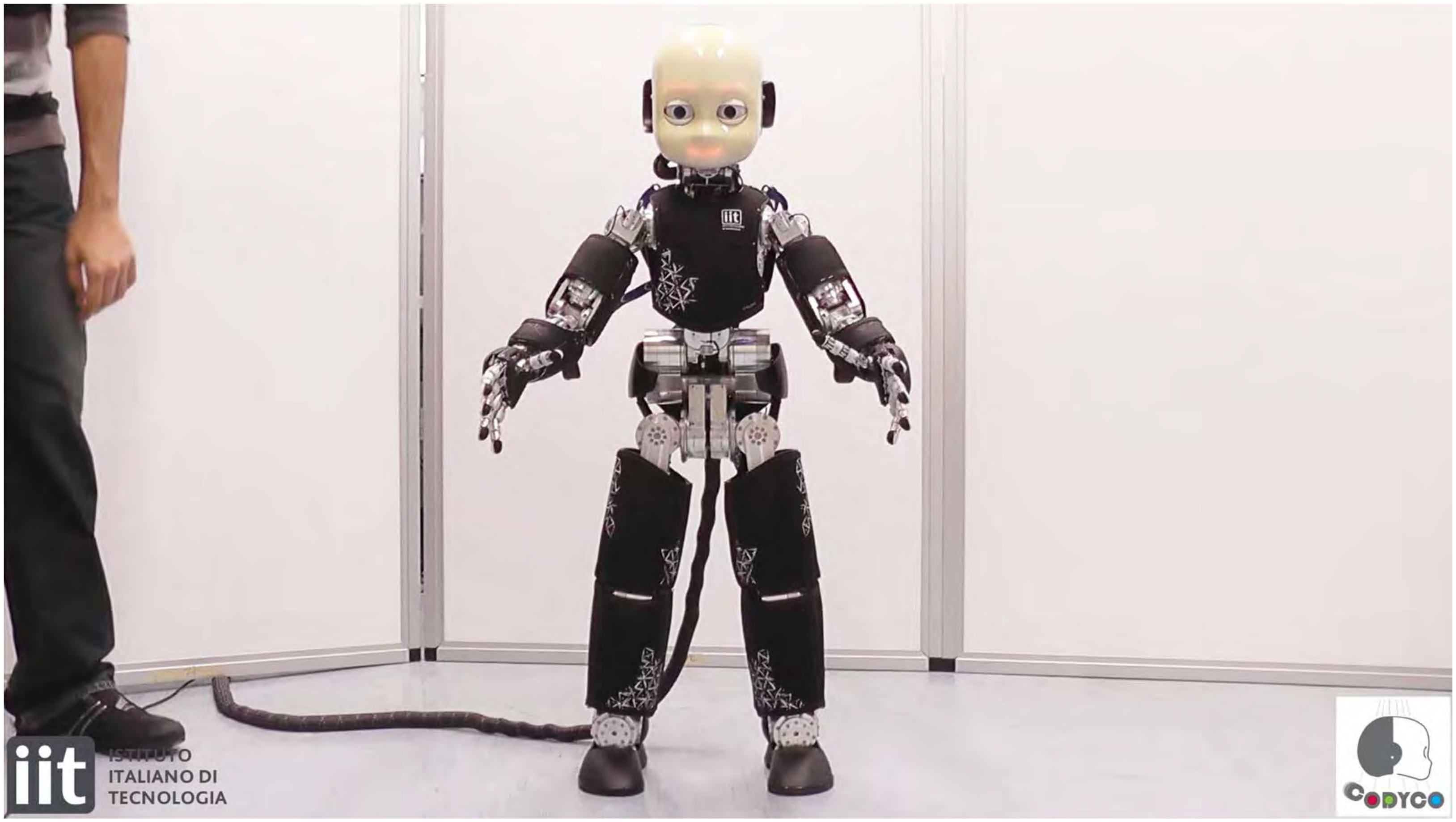
$\mathbf{f}_l$ the external wrench acting on link l

$\mathbf{H}$ joint inertia matrix

$\mathbf{n}$ the bias torques

$\mathbf{J}_l$ the Jacobian for link l


NEW controller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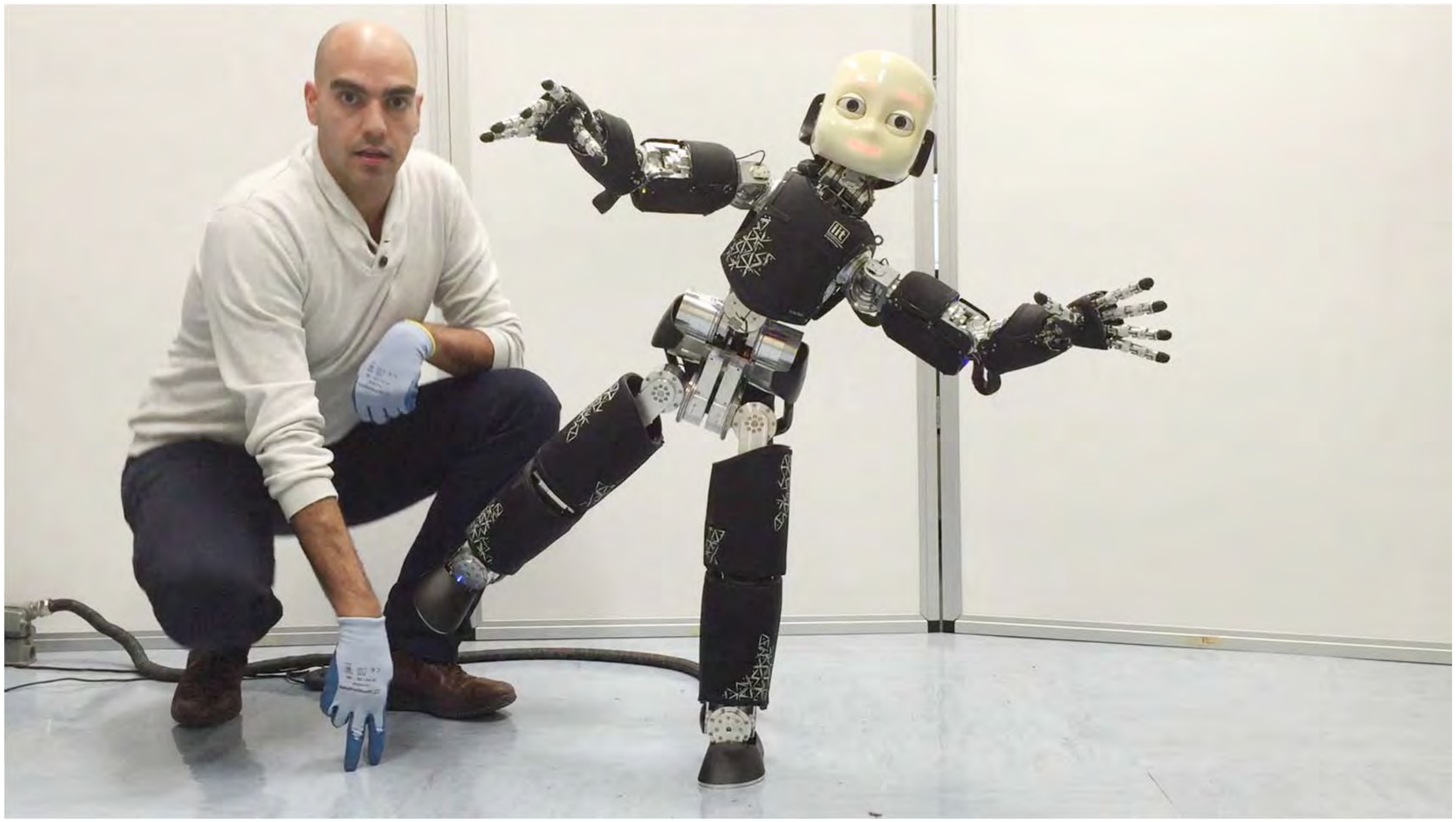

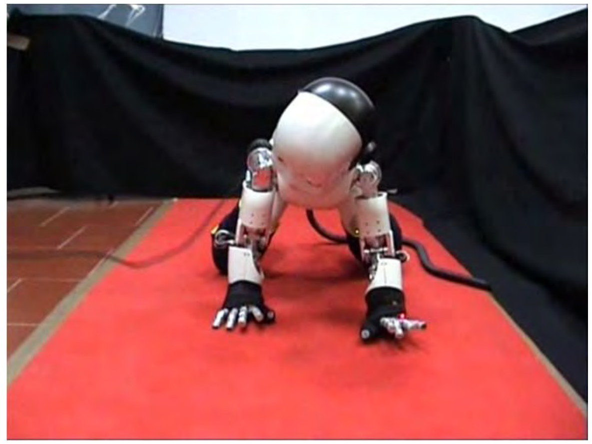

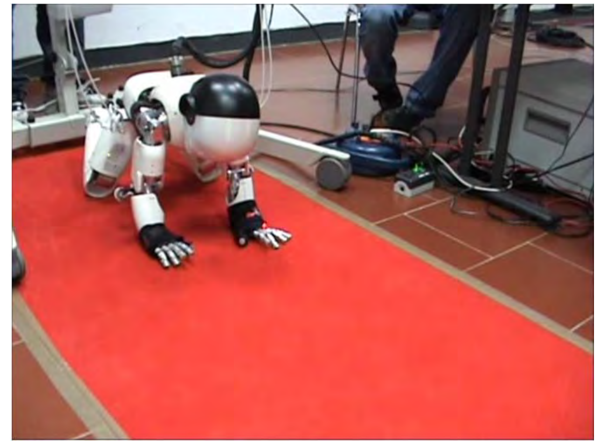
x1.0

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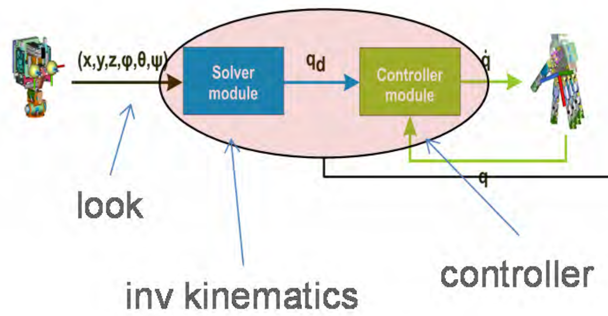
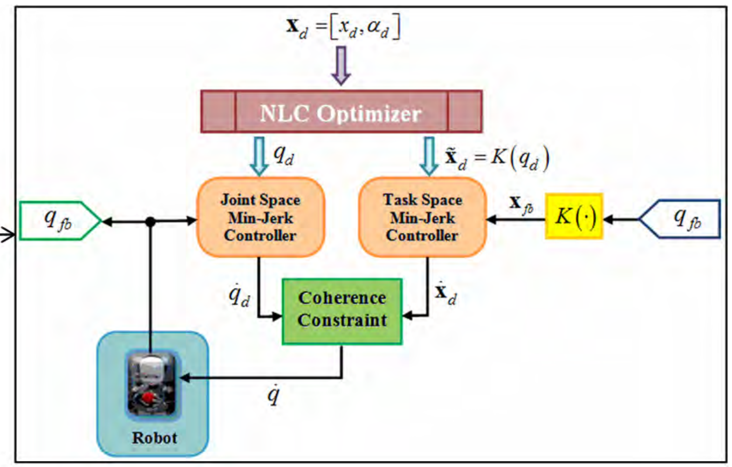
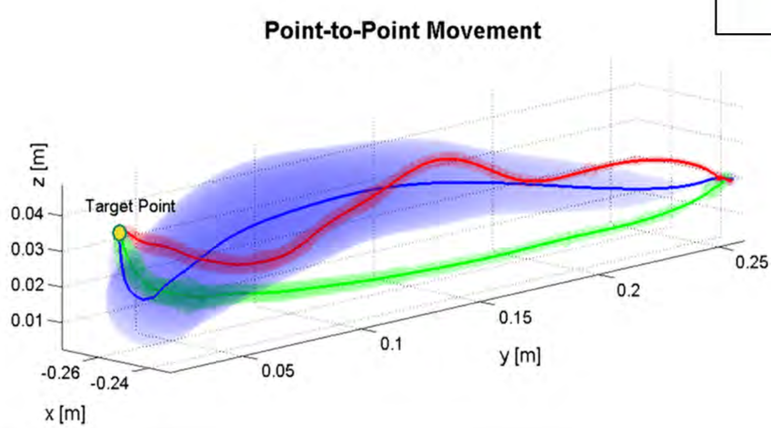
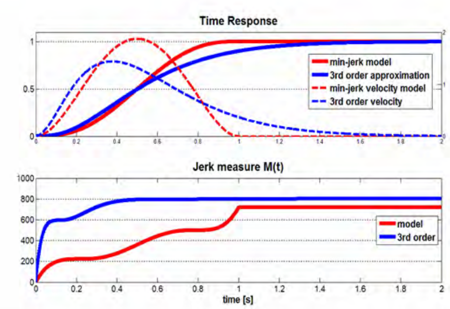
point to point movements









ipopt

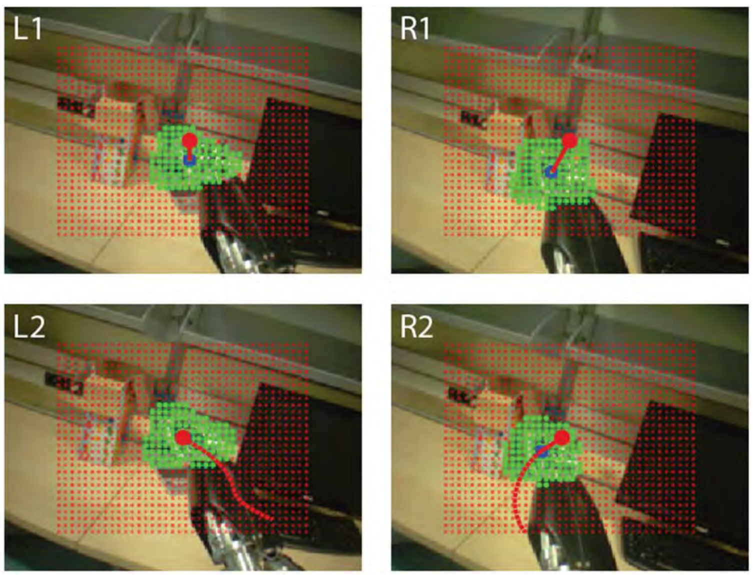
$$\begin{cases} q_d = argmin_{q \in R^n}(\|\alpha_d - K_\alpha(q)\|^2 + \beta(q_{res} - q)^T W(q_{res} - q)) \\ s.t. \begin{cases} \|x_d - K_x(q)\|^2 < \varepsilon \\ q_L < q < q_U \end{cases} \end{cases}$$

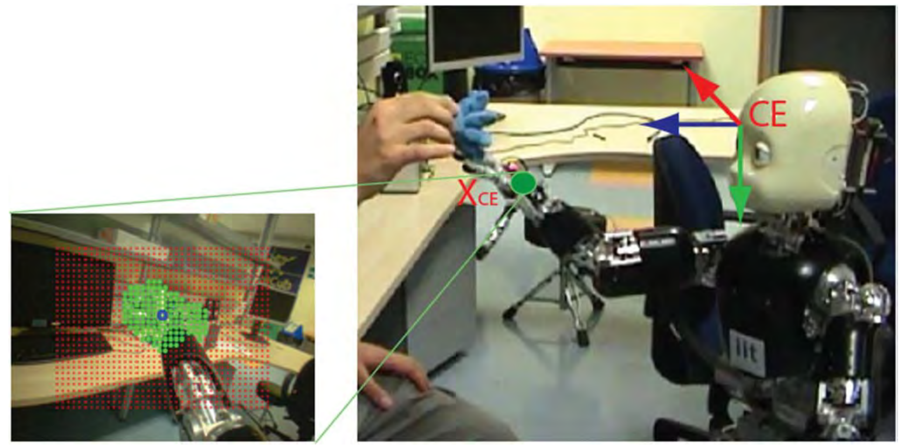
- quick convergence (<20ms)
- scalability
- singularities and joints bound handling
- tasks hierarchy
- complex constraints

$$\begin{cases} \min_{\dot{q},\dot{x}} \frac{1}{2}\left((\dot{q} - \dot{q}_d)^T W_q (\dot{q} - \dot{q}_d) + (\dot{x} - \dot{x}_d)^T W_x (\dot{x} - \dot{x}_d)\right) \\ s.t.\ \ \dot{x} = J \cdot \dot{q} \end{cases}$$

- merges joint and Cartesian space trajectories

$$\dot{q} = \dot{q}^d + W_q^{-1} J^T \left(W_x^{-1} + J W_q^{-1} J^T\right)^{-1} \left(\dot{x}^d - J\dot{q}^d\right)$$

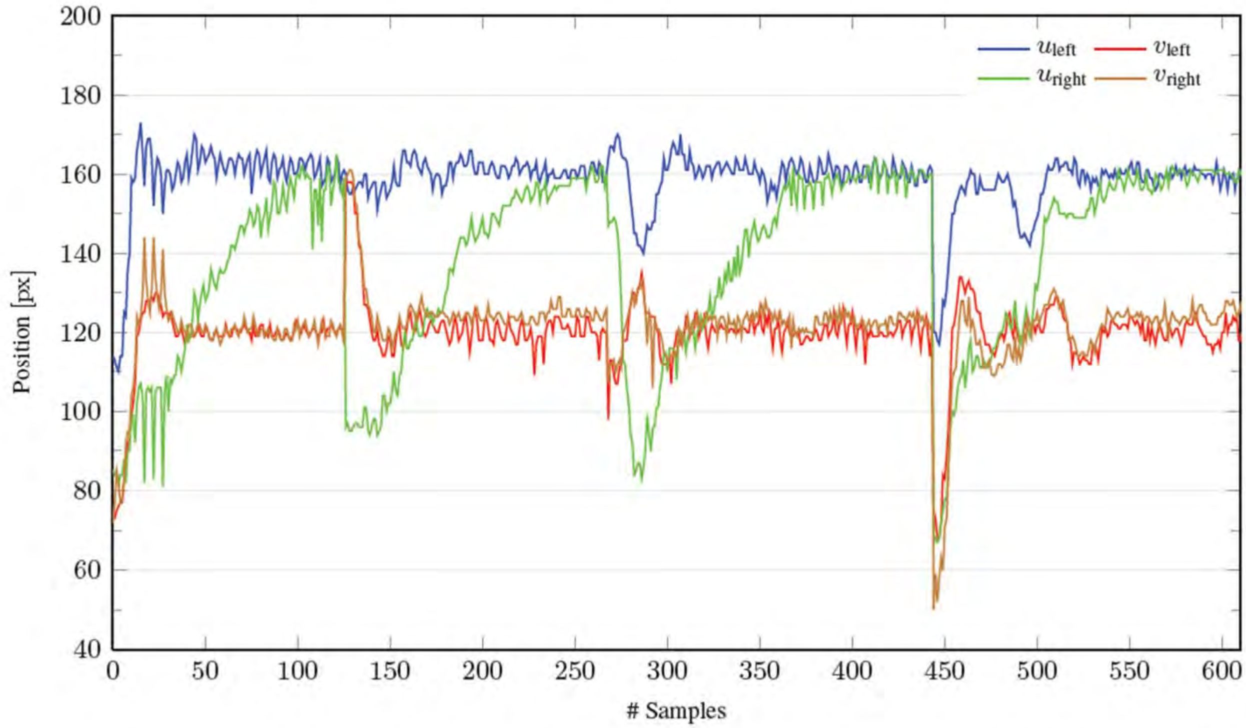




$$f : \{\boldsymbol{q}_{\text{arm}}, \boldsymbol{q}_{\text{head}}\} \mapsto \mathcal{I}$$

$$\mathcal{I} = \{u_{\text{left}}, v_{\text{left}}, u_{\text{right}}, v_{\text{right}}\} \in \mathbb{N}^4$$

$$\boldsymbol{q}_{\text{arm}} \in \mathbb{R}^7 \quad \boldsymbol{q}_{\text{head}} \in \mathbb{R}^6$$



200
180
160
140
120
100
80
60
40
0
50
100
150
200
250
300
350
400
450
500
550
600
u_{left}
v_{left}
u_{right}
v_{right}
Position [px]
Samples

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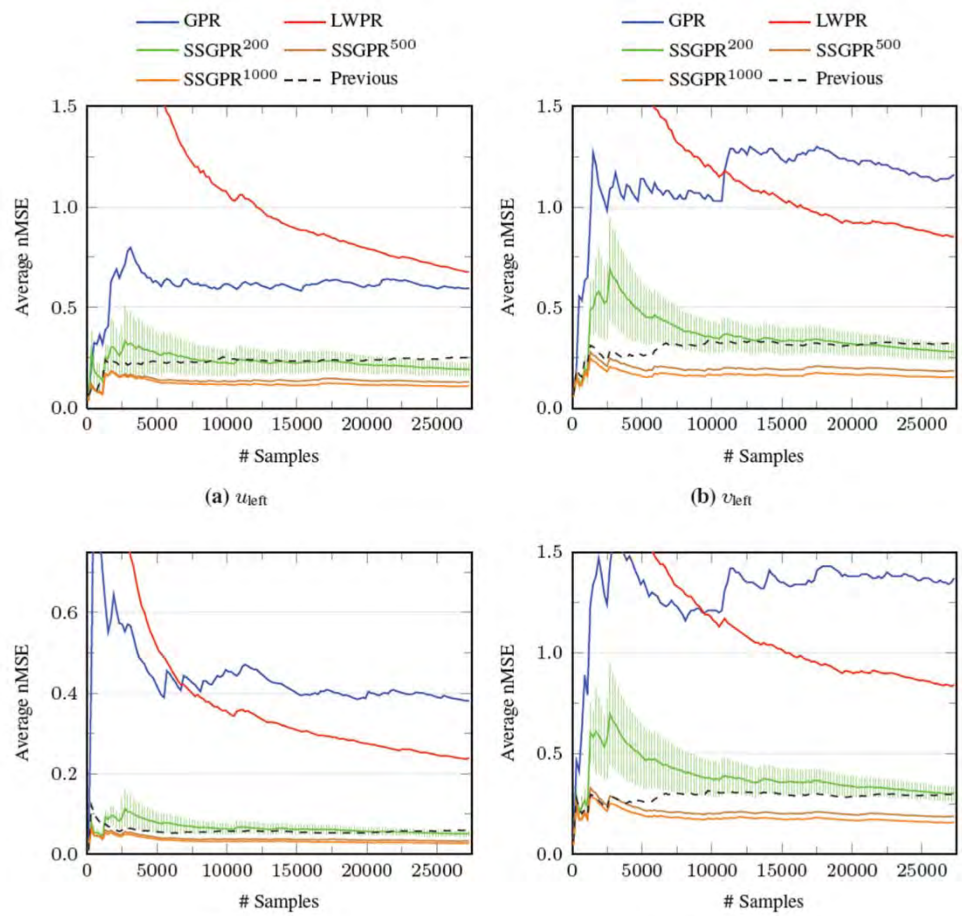
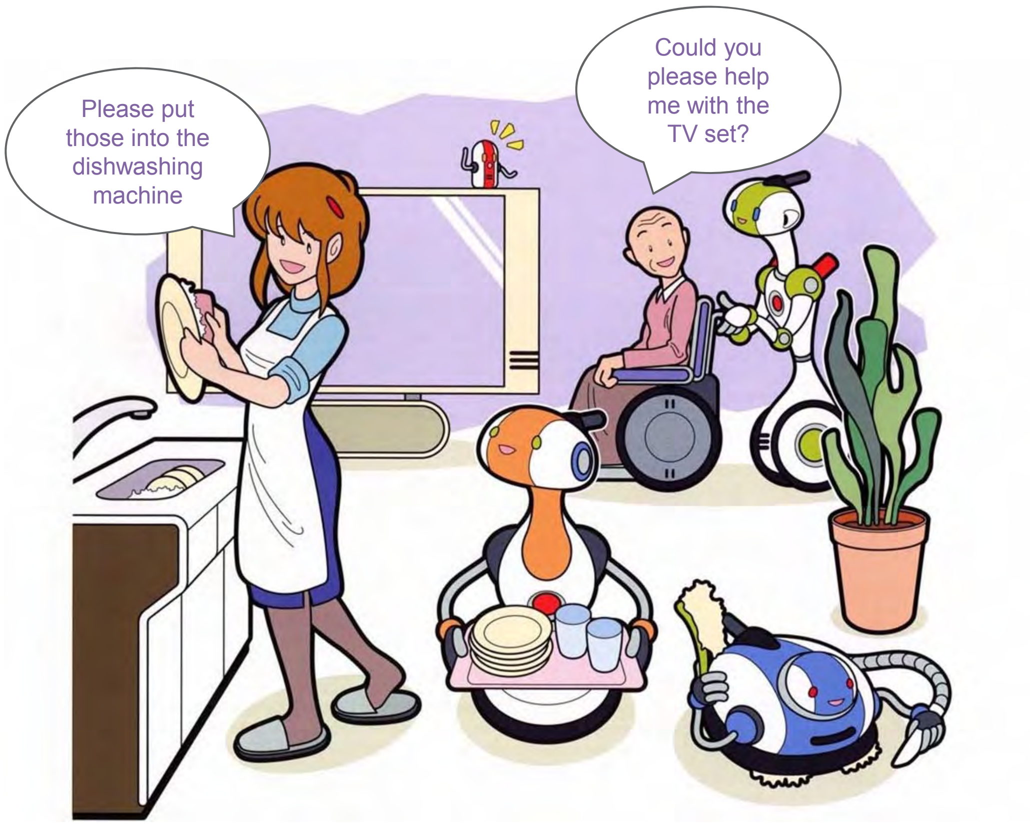
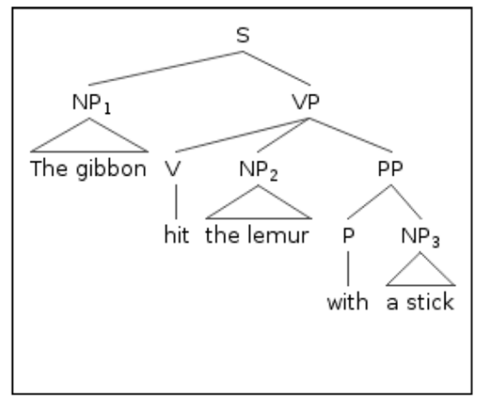


(a) u_{left} **(b)** v_{left} **(c)** u_{right} **(d)** v_{right}





The iCub puts the plates into
the dishwashing machine

Trueswell, J. C., & Gleitman, L. R. (2007) Learning to parse and its implications for language acquisition, in G. Gaskell (ed.) *Oxford Handbook of Psycholing.* Oxford: Oxford Univ. Press.

The iCub puts the plates into the dishwashing machine

actions objects tools

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actions | objects | tools

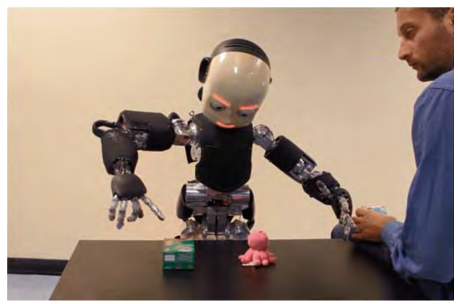
learning actions

learning objects

learning tools

learn

recognizing actions



recognizing objects

using tools

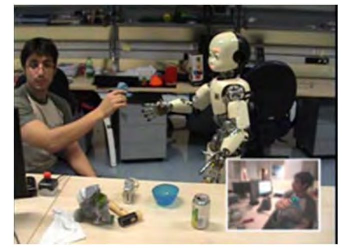
use

Ranked 2nd at Microsoft Kinect Demonstration Competition, CVPR 2012 Providence, Rhode Island

object recognition

self-supervised strategies

kinematics



motion

Human Robot Interaction is a **new** and **natural** application for visual recognition

In robotics settings strong cues are often available, therefore object detectors can be avoided

Recognition as tool for complex tasks: grasp, manipulation, affordances, pose

S.R. Fanello, C. Ciliberto, L. Natale, G. Metta – Weakly Supervised Strategies for Natural Object Recognition in Robotics, ICRA 2013

C. Ciliberto, S.R. Fanello, M. Santoro, L. Natale, G. Metta, L. Rosasco - On the Impact of Learning Hierarchical Representations for Visual Recognition in Robotics, IROS 2013

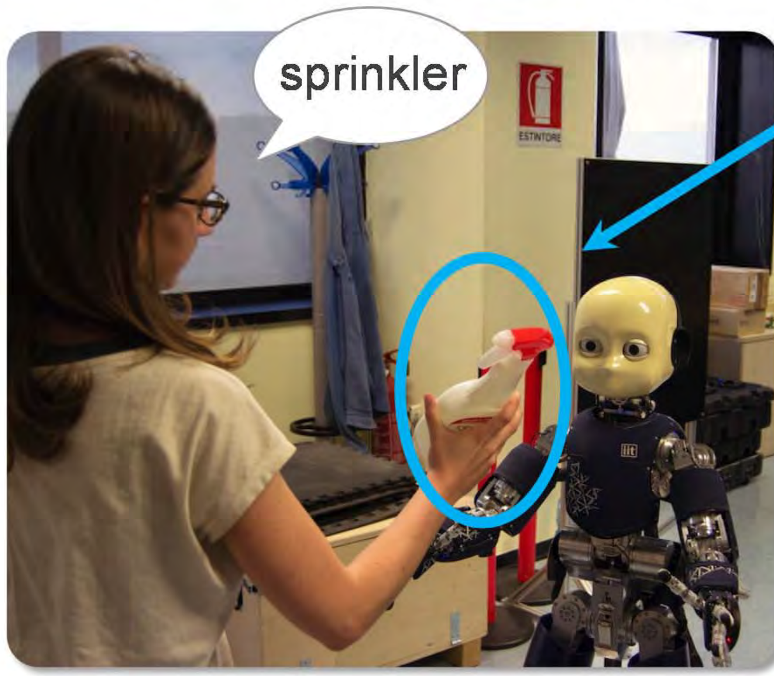

Operator: What is this?

dataset

Verbal (weak) Supervision

Motion Detection

Human “Teacher”

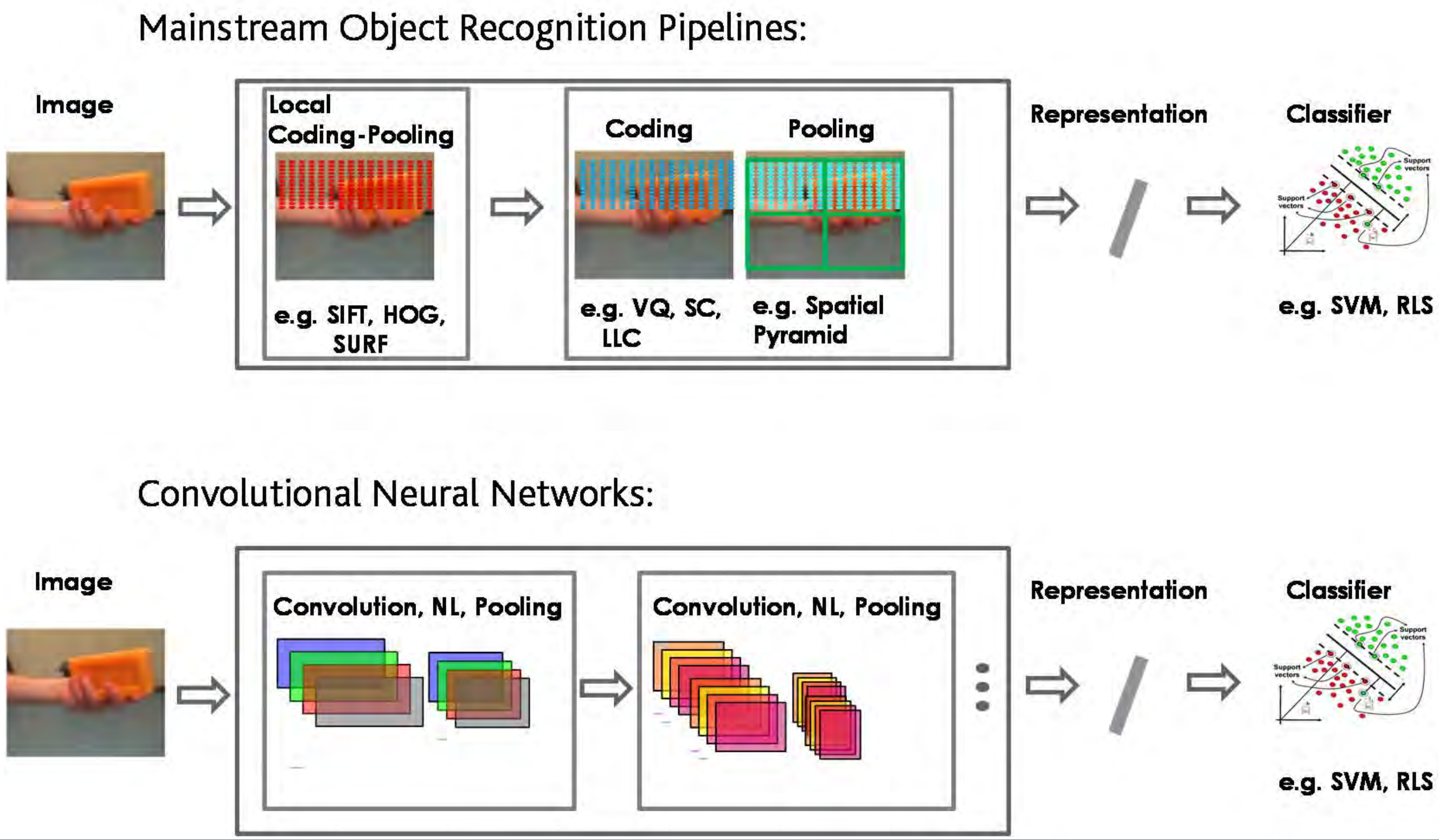


iCubWorld dataset (2.0)

- Growing **dataset** collecting images from a real robotic setting
- Provide the community with a tool for **benchmarking** visual recognition systems in robotics
- 28 Objects, 7 categories, 4 sessions of acquisition (four different **days**)
- 11Hz acquisition frequency.
- ~50K Images

http://www.iit.it/en/projects/data-sets.html

methods


Mainstream Object Recognition Pipelines:
Image
Local Coding-Pooling
e.g. SIFT, HOG, SURF
Coding
Pooling
e.g. VQ, SC, LLC
e.g. Spatial Pyramid
Representation
Classifier
e.g. SVM, RLS
Convolutional Neural Networks:
Image
Convolution, NL, Pooling
Convolution, NL, Pooling
Representation
Classifier
e.g. SVM, RLS

methods

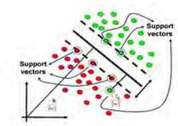
Mainstream Object Recognition Pipelines:

Image

Sparse Coding [yang et al. ’09]
Learned on iCubWorld

Representation

Classifier



e.g. SVM, RLS

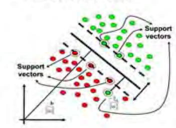
Convolutional Neural Networks:

Image

Overfeat [sermanet et al. ’14]
Learned on Imagenet

Representation

Classifier



e.g. SVM, RLS

some questions

- Scalability. How do iCub recognition capability decrease as we add more objects to distinguish?
- Can we use assumptions on physical continuity to make recognition more stable?
- Incremental Learning. How does learning during multiple sessions affect the system recognition skills?
- Generalization. How well does the system recognize objects “seen” under different settings?

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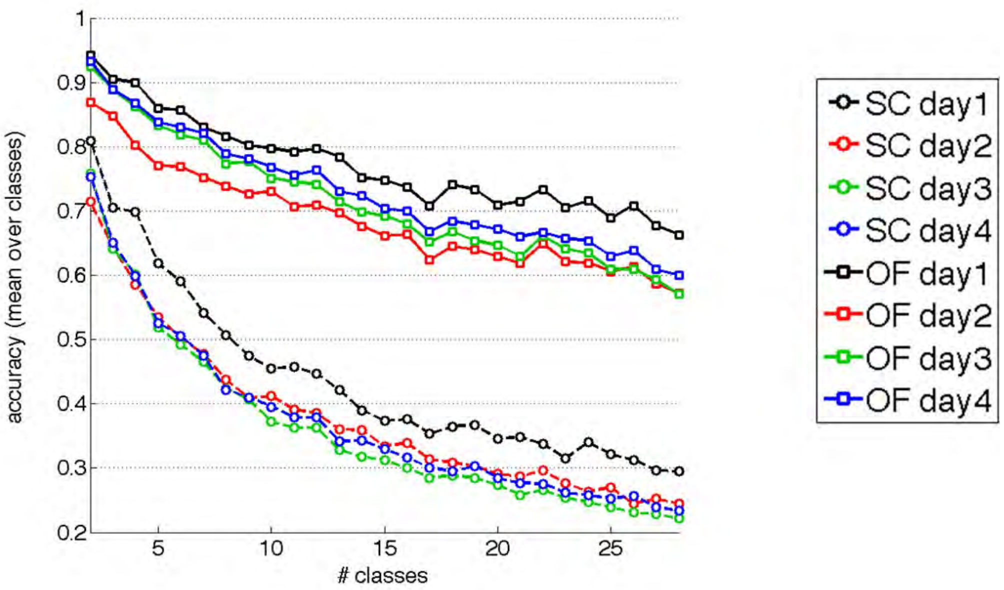
first results

We started by addressing **instance recognition**

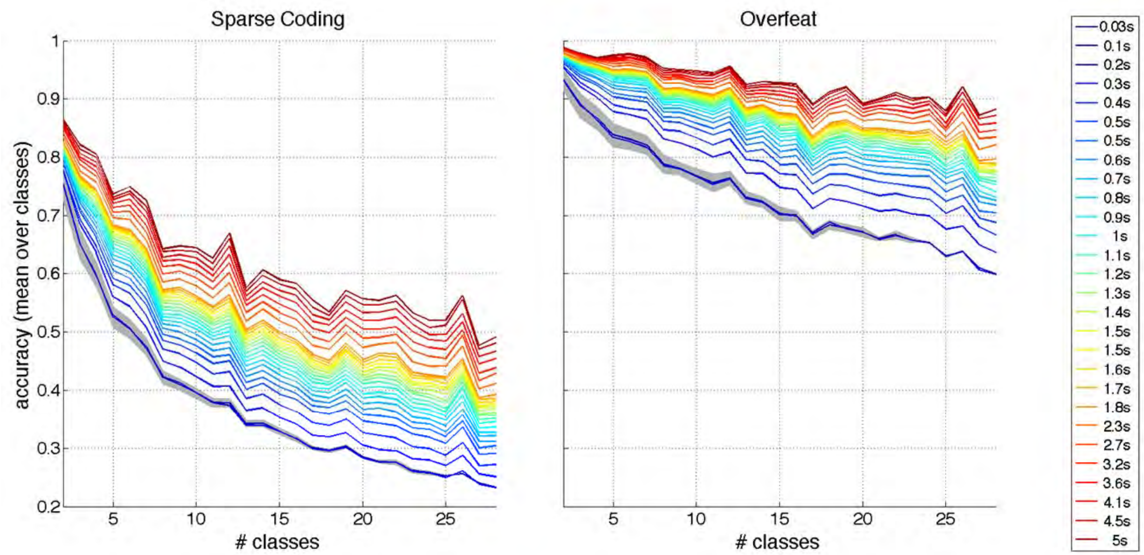
Instance Recognition

Category recognition

performance wrt # of objects



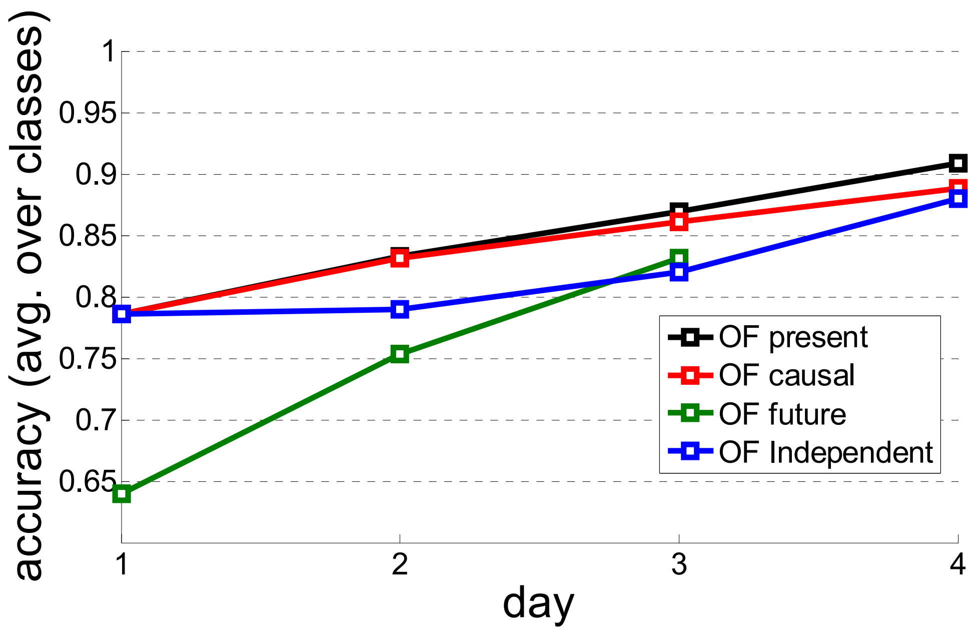
exploiting continuity in time



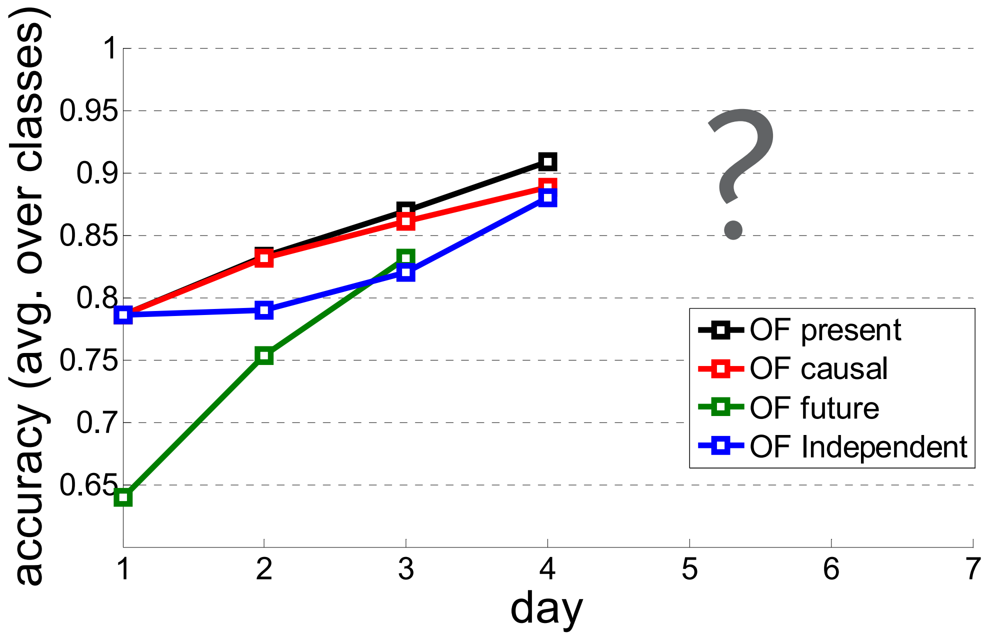
incremental learning

Cumulative learning on the 4 days of acquisition. Tested on:

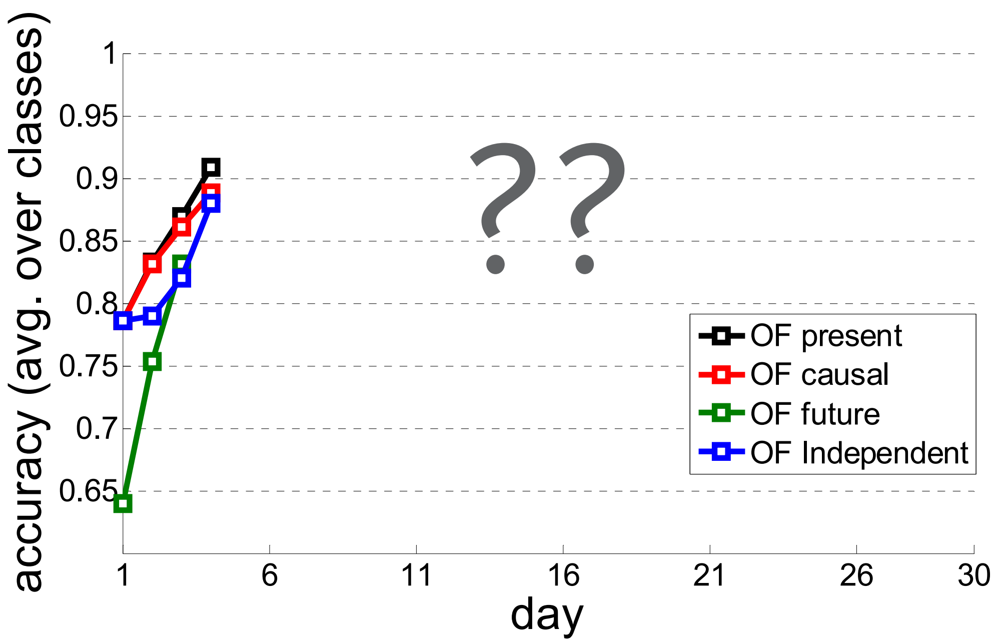
- **Present**: test on current day
- **Causal**: test on current and past days
- **Future**: test on future days (current not included)
- **Independent**: train & test on current day only

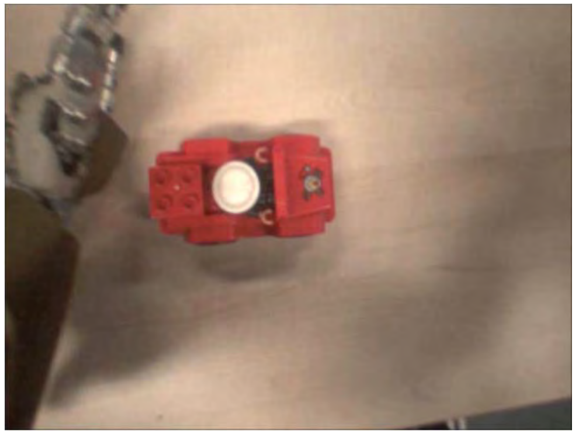


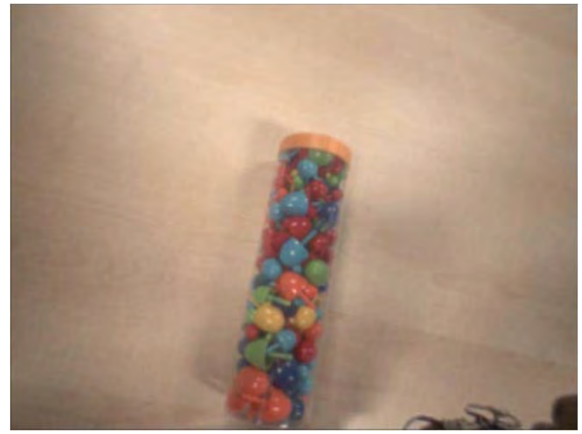
what about a week?

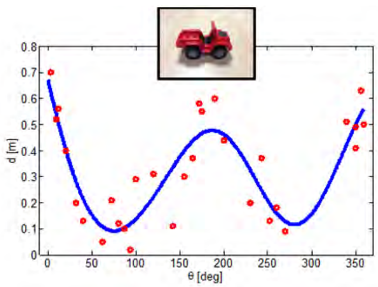


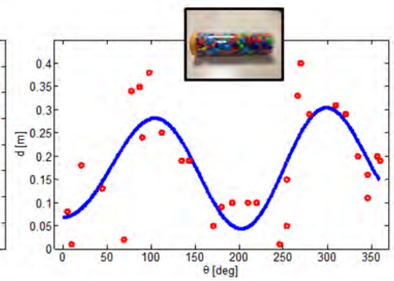
… or a month?

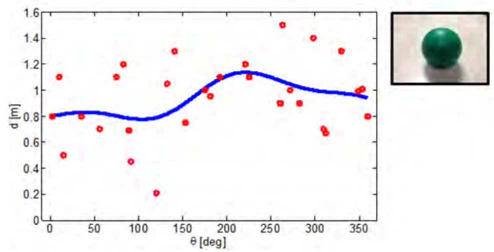

??
accuracy (avg. over classes)
1
0.95
0.9
0.85
0.8
0.75
0.7
0.65
1
6
11
16
21
26
30
day
OF present
OF causal
OF future
OF Independent





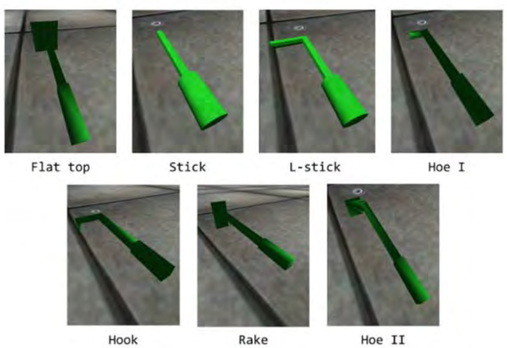

d [m]
θ [deg]


d [m]
θ [deg]


d [m]
θ [deg]

Experiments on affordances

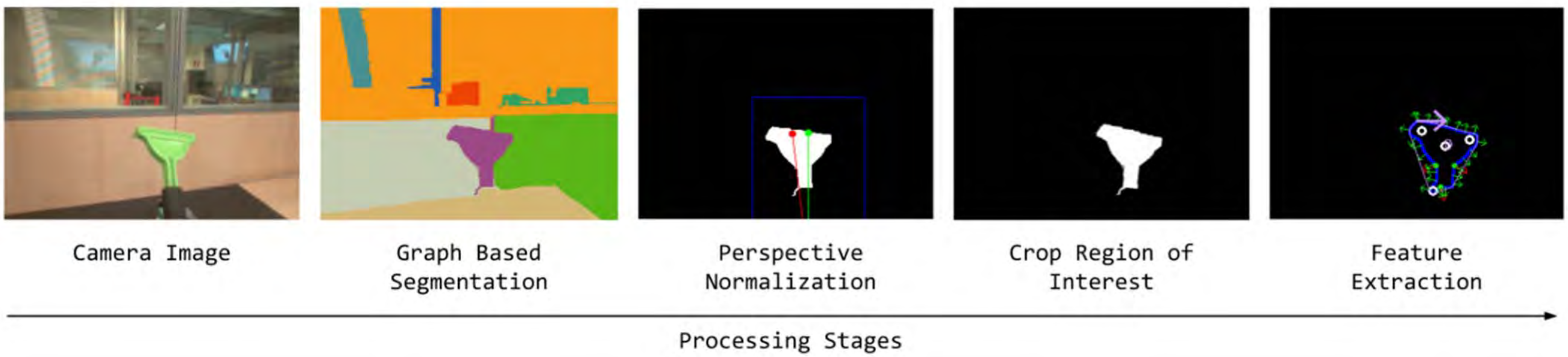
(a) Real Tools.



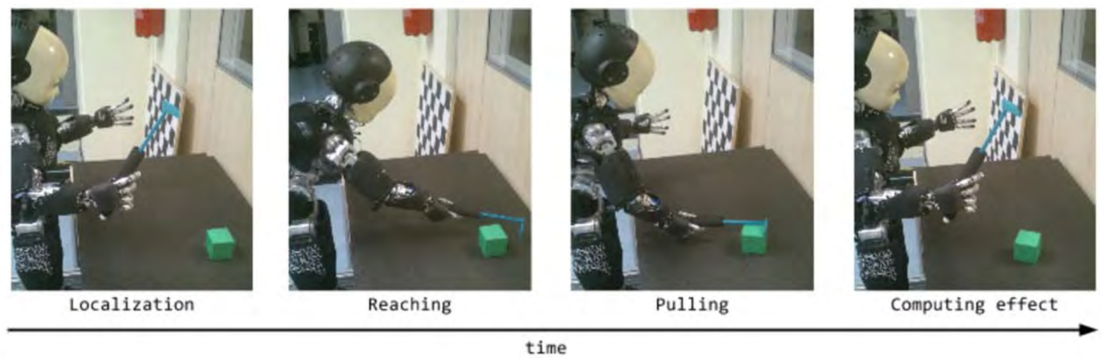
(b) Simulated Tools.

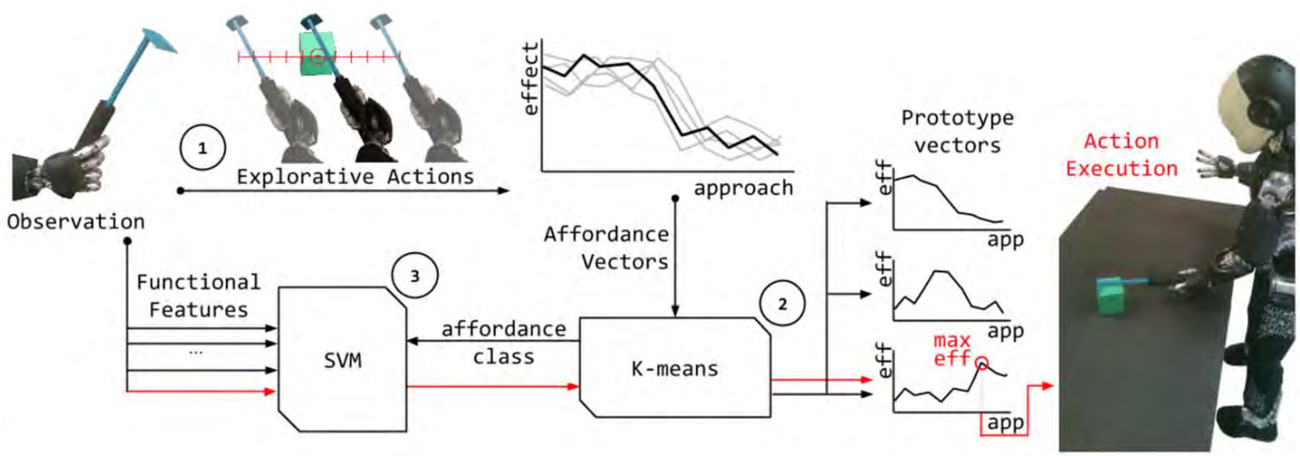
- Detailed list of extracted features
  - Based on convex hull
    - Depth of the 5 larger convexity defects
    - Histogram of bisector angles at convexity defects
    - Area of the convex hull
    - Solidity
  - Based on thinning
    - Number of skeleton bifurcations to the left, right, under and above
    - Number of skeleton endings to the left, right, under and above the blob's center of mass
  - Based on Moments
    - Normalized central moments
  - Shape descriptors
    - Area, perimeter, compactness
    - Major principal axis (length), Minor principal axis (width)
    - Aspect ratio, Extension, Elongation, Rectangularity
  - From the angle signature
    - Bending energy (sum of squares of the angle variation along the contour), divided by the number of points in the contour.)
    - Angle signature histogram
  - Domain transformation from the distance to the centroid signature
    - Fourier coefficients
    - Wavelet coefficient

Experiments on affordances

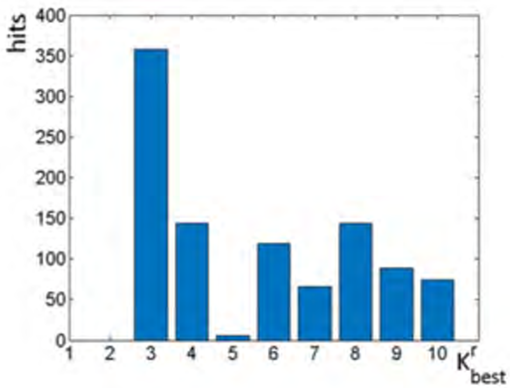


Experiments on affordances

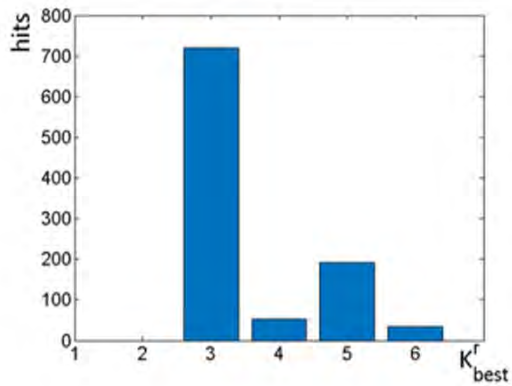




Experiments on affordances

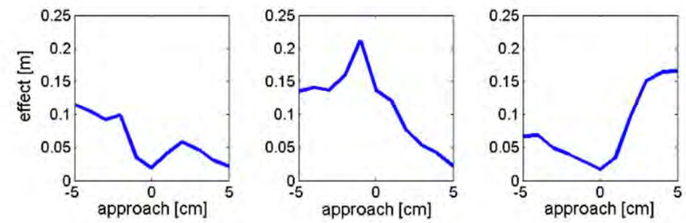


(a) Simulated data

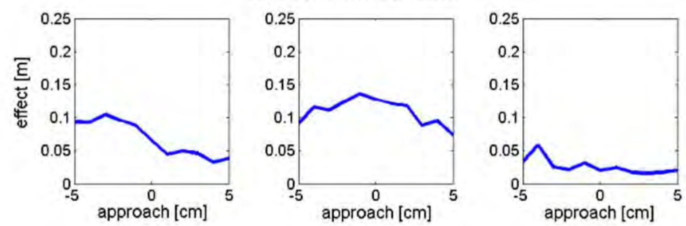


(b) Robot data

Environment	Goal Acc. (%)	Avg. Diff [m]
Simulation	86.51 %	0.064
Robot	86.11 %	0.056



(a) Simulated data



(b) Robot data

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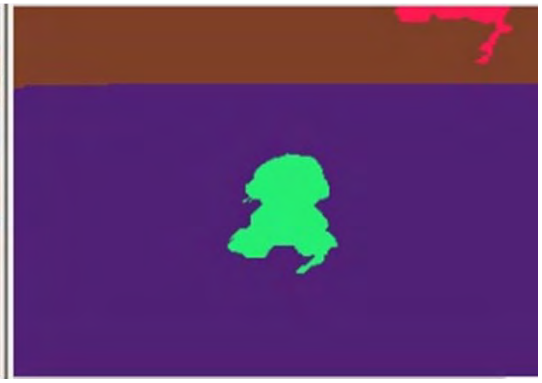
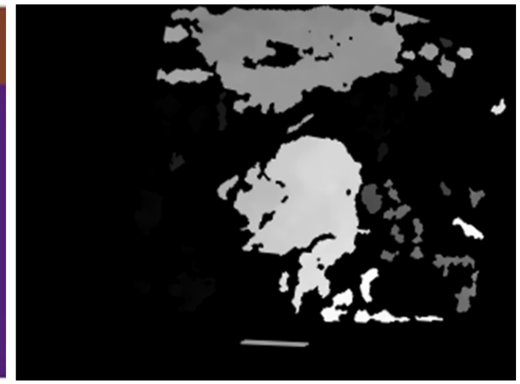
3D vision for grasping

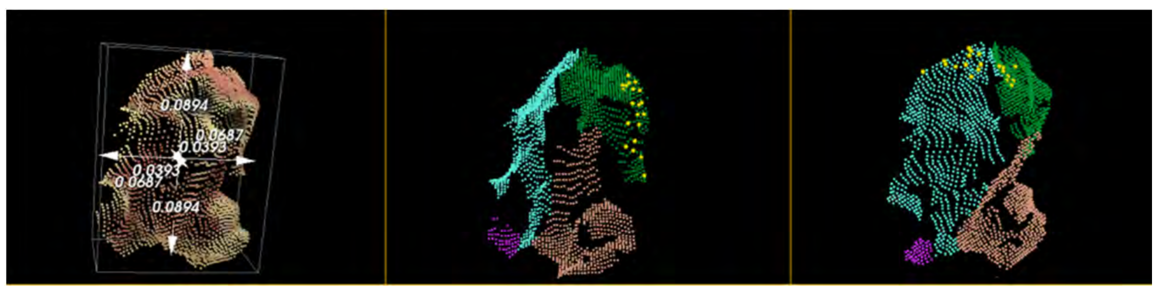
Input



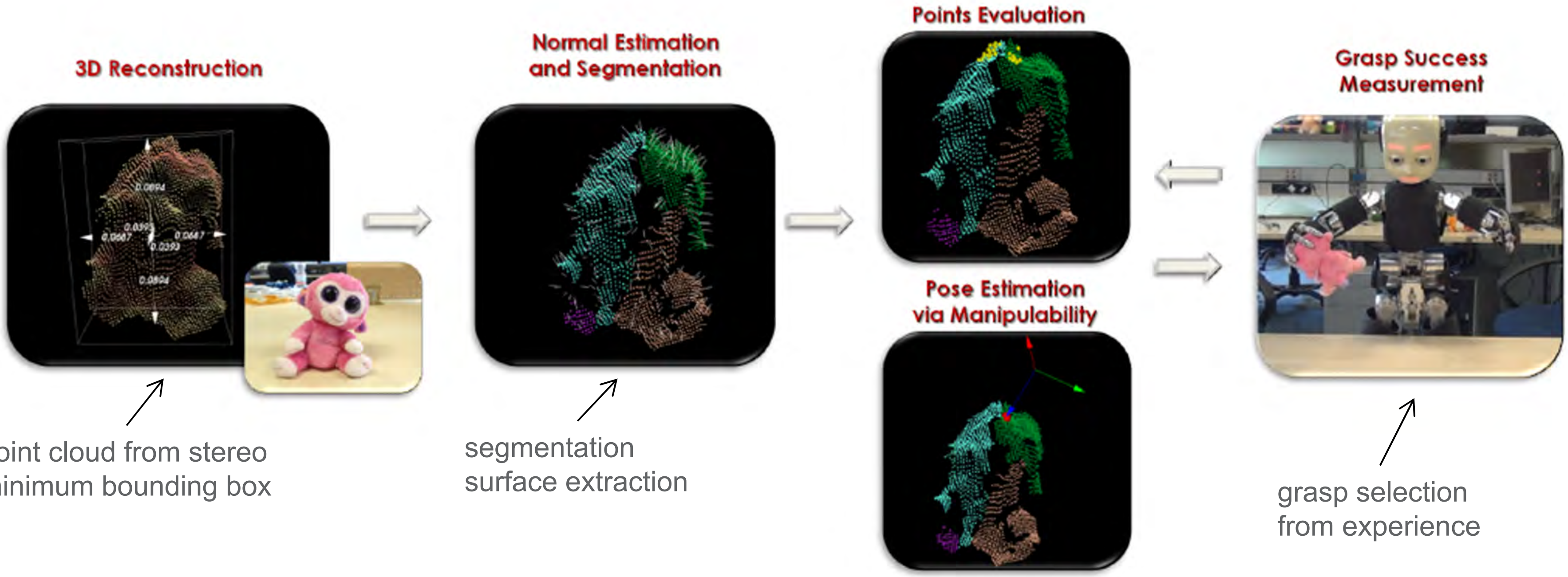
Segmentation



Disparity



grasping



point cloud from stereo
minimum bounding box

segmentation
surface extraction

grasp selection
from experience

grasp points from curvature
+ bias (task dependent)

Gori,I; Pattacini, U; Tikhanoff, V; Metta G; (submitted 2013) Ranking the Good Points: A Comprehensive Method for Humanoid Robots to Grasp Unknown Objects 2013 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS 2013)

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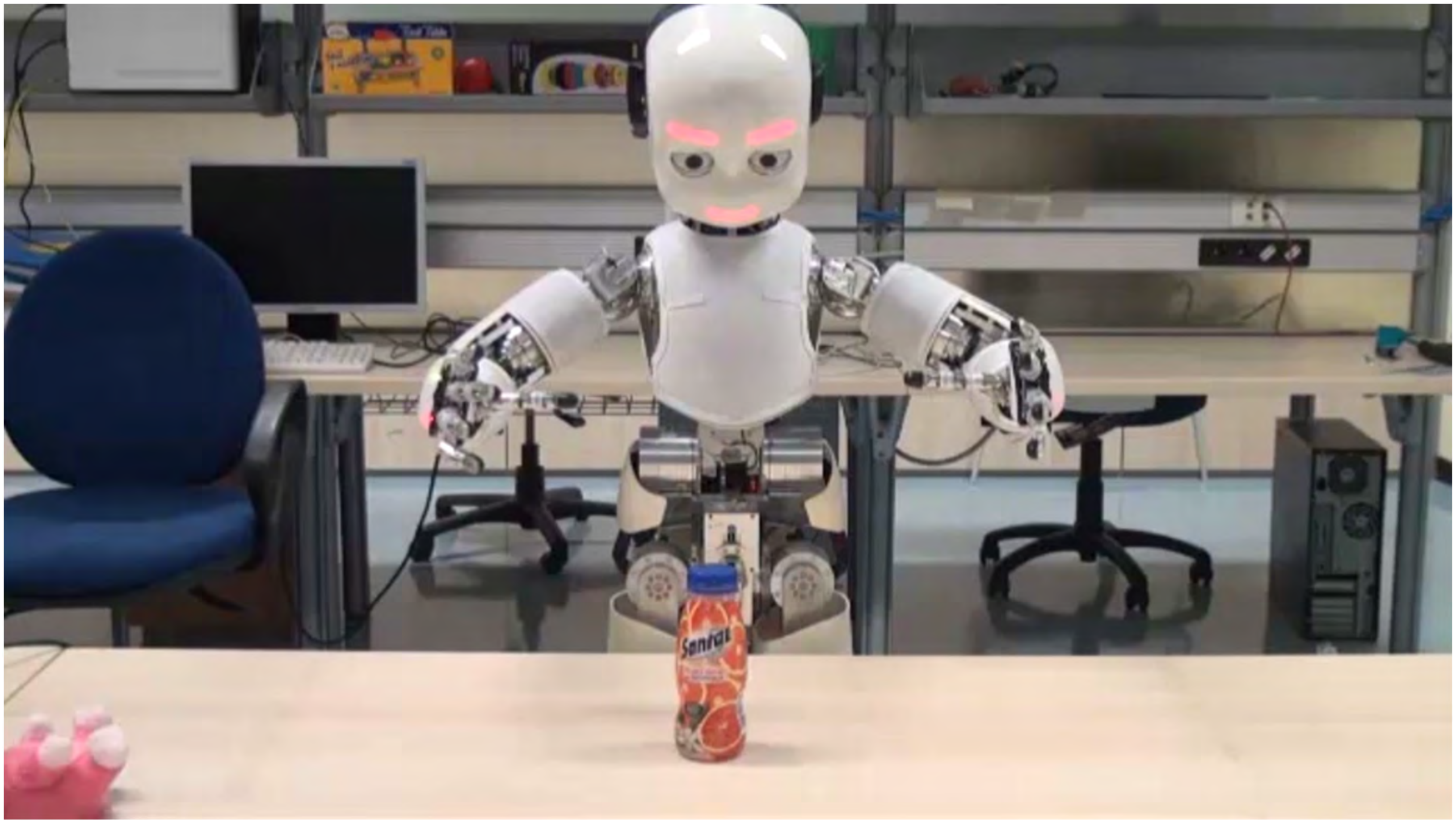
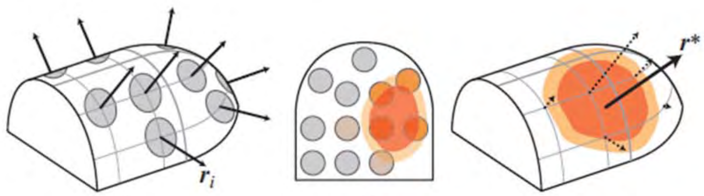
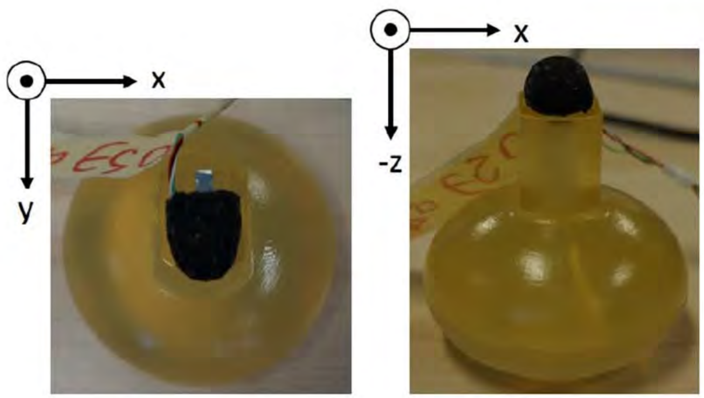
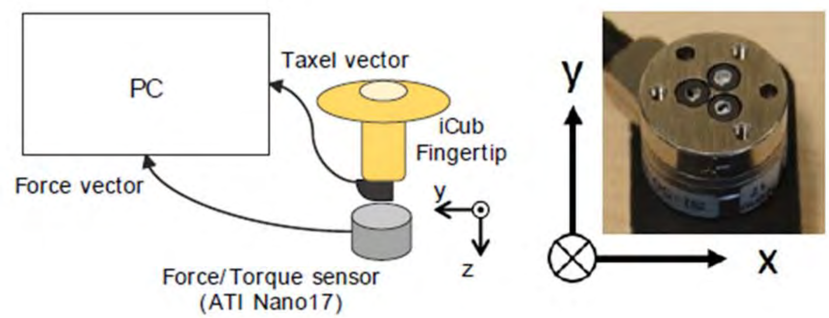


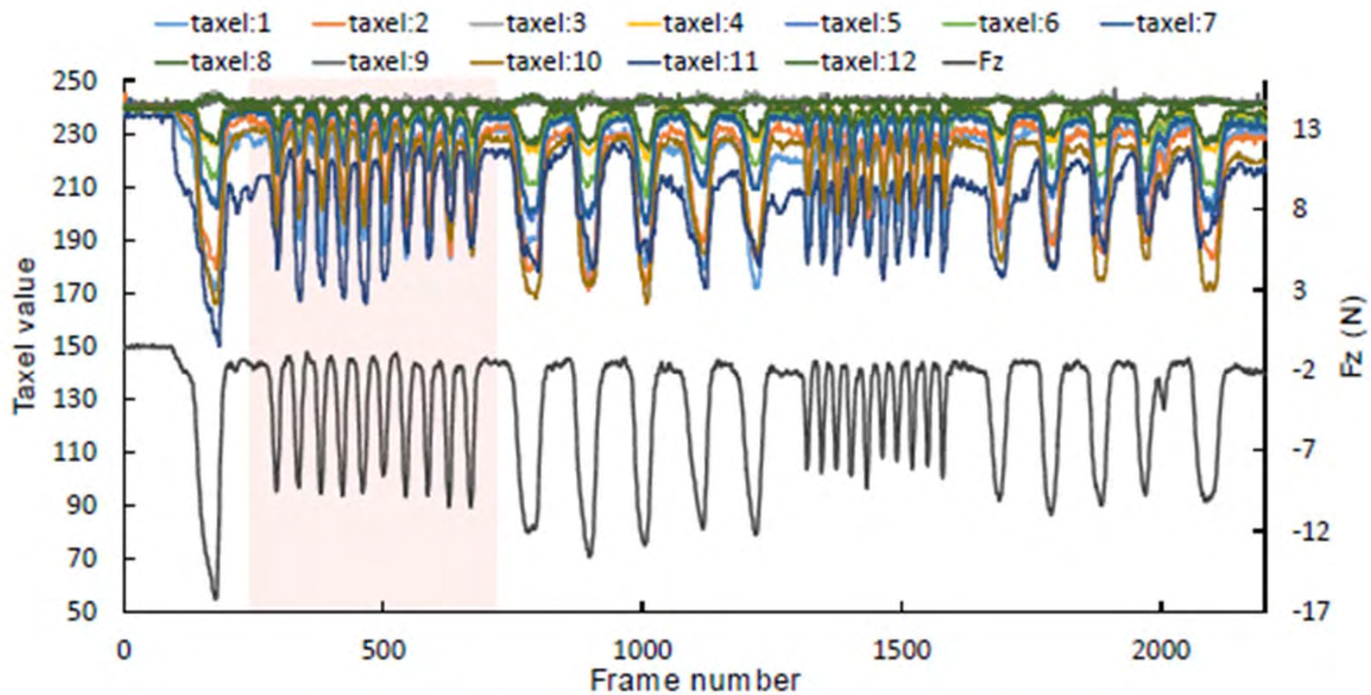
force reconstruction





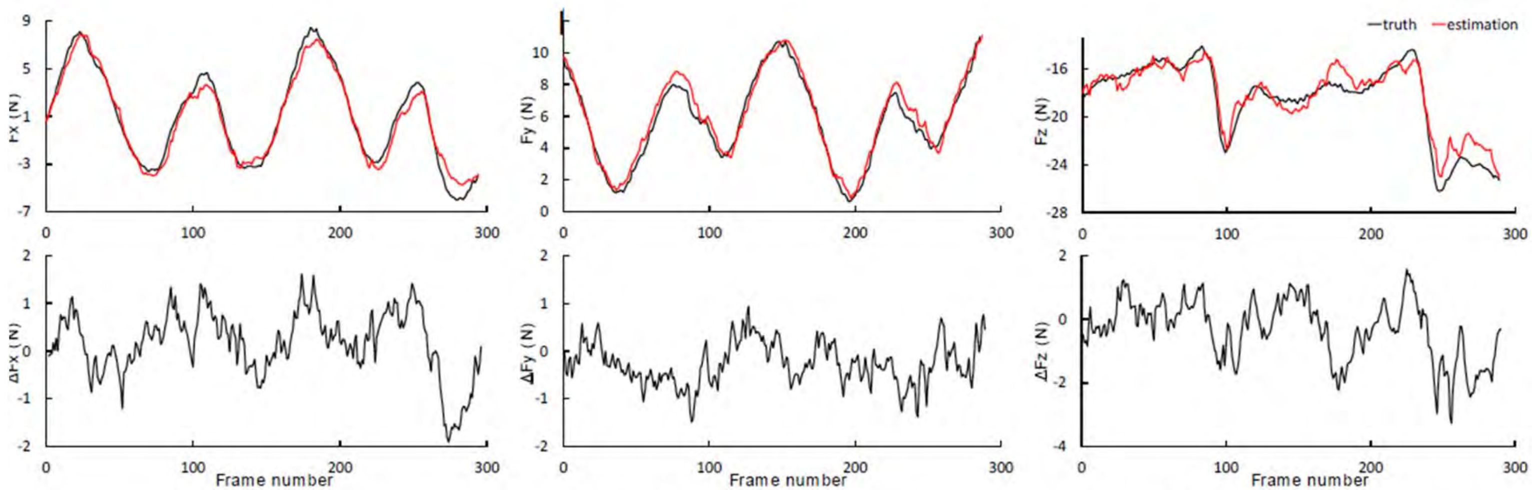


raw data



(a) One-dimensional force condition (Z axis)

GP approximation

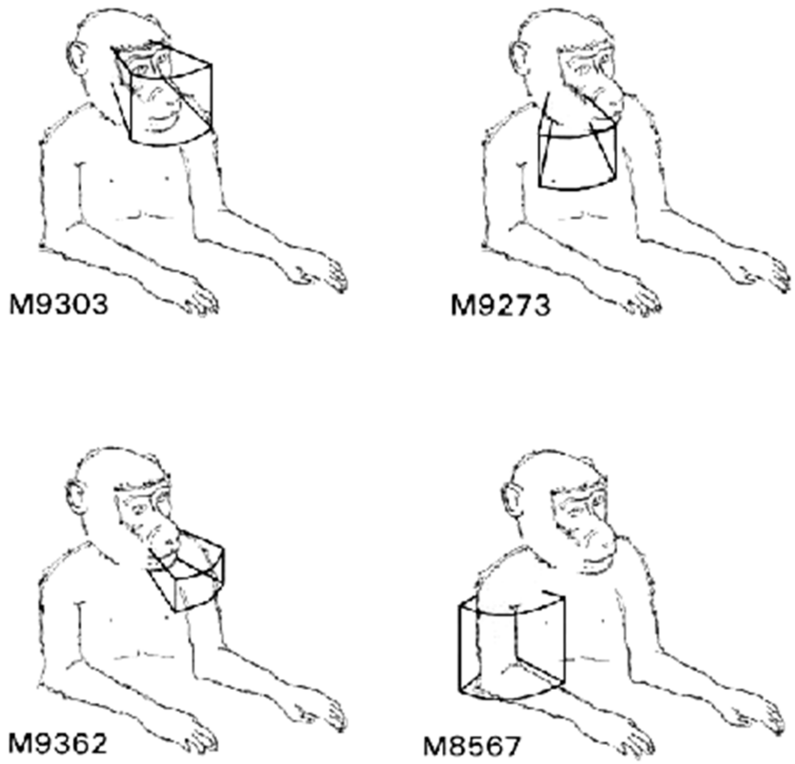


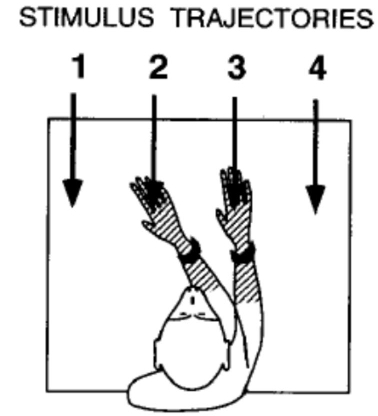
(a) In the X axis direction (b) In the Y axis direction (c) In the Z axis direction

TABLE I

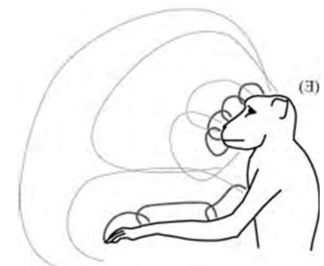
PERFORMANCE OF ALL MODELS AND CONDITIONS

Condition	Model	F_x			F_y			F_z		
		RMSE	CC	AME (N)	RMSE	CC	AME (N)	RMSE	CC	AME (N)
One-dimensional force condition	Normal GP model	0.955	0.959	2.847	0.645	0.979	3.055	1.035	0.933	3.625
	Proposed model	**0.718**	**0.977**	**2.000**	**0.447**	**0.989**	**2.014**	**0.561**	**0.981**	**1.944**
	Markov order		$n = 6$			$n = 6$			$n = 3$	
Three-dimensional force condition	Normal GP model	0.792	0.979	2.115	0.549	0.980	1.654	1.493	0.879	3.941
	Proposed model	**0.714**	**0.983**	**1.932**	**0.518**	**0.981**	**1.503**	**1.006**	**0.948**	**3.210**
	Markov order		$n = 5$			$n = 11$			$n = 10$	
Cross learning condition	Normal GP model	1.664	0.870	4.218	**1.505**	**0.877**	2.813	1.963	0.734	4.943
	Proposed model	**1.472**	**0.901**	**3.210**	1.530	0.873	**2.740**	**1.739**	**0.798**	**4.785**
	Markov order		$n = 7$			$n = 1$			$n = 2$	





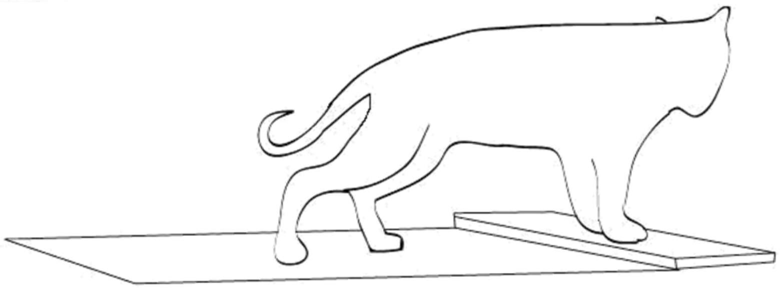
From: Graziano 1999



From: Graziano et al. 2006

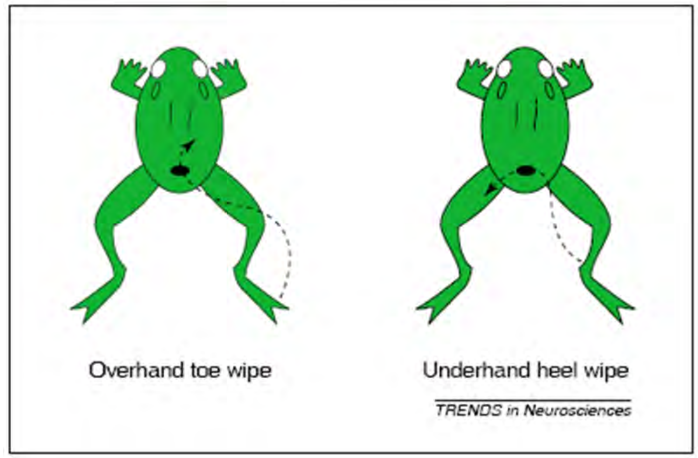
from: Fogassi L., Gallese V., Fadiga L., Luppino G., Matelli M., Rizzolatti G. *Coding of peripersonal space in inferior premotor cortex (area F4)*. Journal of Neurophysiology **76** (1) 1996.

spinal reflexes



walking behavior: cat rehabilitated to walk after complete spinal cord transection

wiping reflex: an irritating stimulus elicits a wiping movement precisely directed at the stimulus location



from: Poppele, R., & Bosco, G. (2003). Sophisticated spinal contributions to motor control. *Trends in Neurosciences, 26*(5), 269-276.

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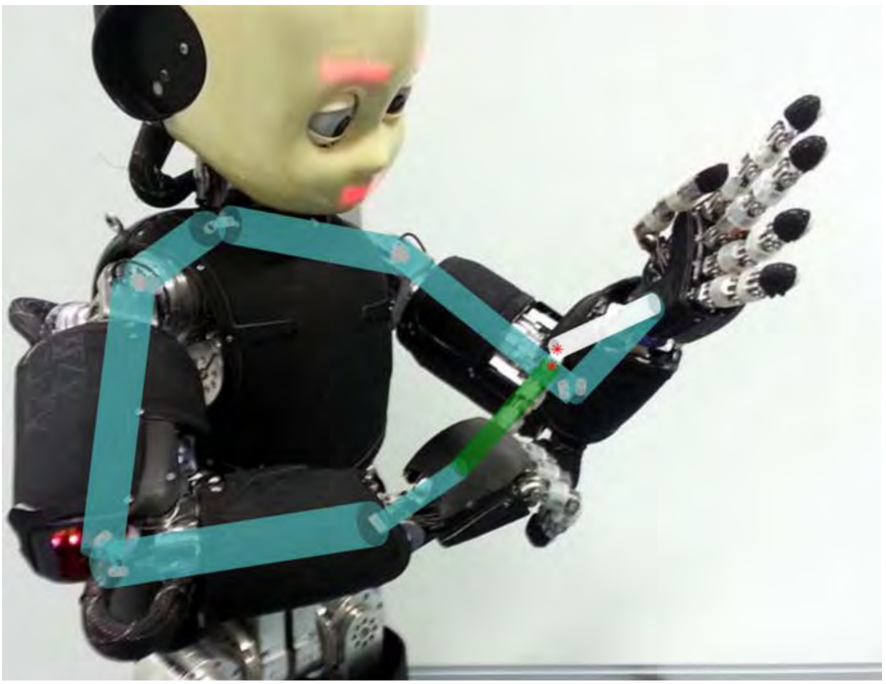
visuo-tactile fusion

Photos by Laura Taverna

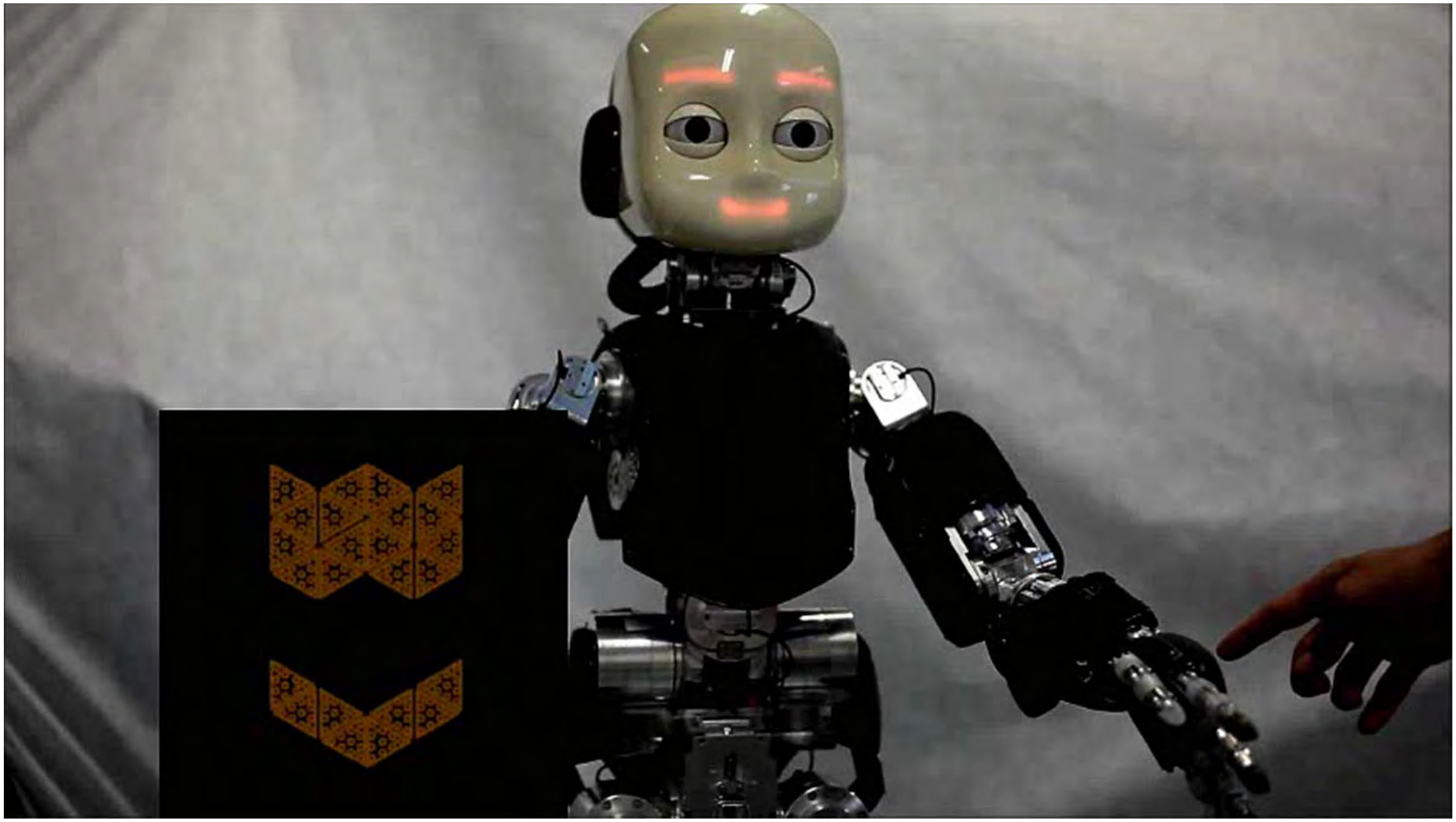
double touch

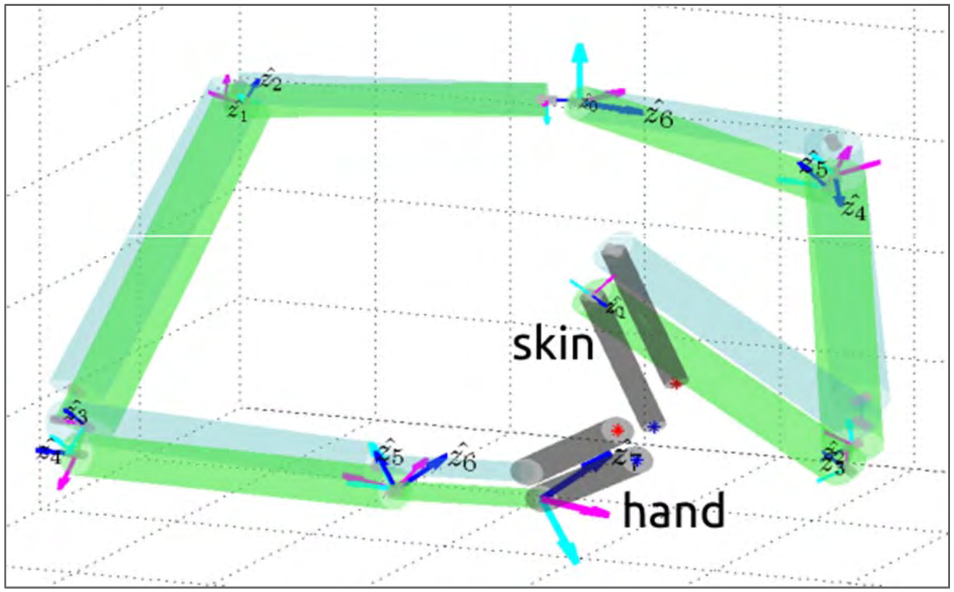


From two fixed-base chain to a single floating-base serial chain $\rightarrow$ 12 dof

$$q^* = arg \min_{q \in \mathbb{R}^n} (n_O \cdot y_{ee})$$

$$s.t. \begin{cases} \|K_x(q) - O\|^2 < \epsilon \\ q_l < q < q_u \end{cases}$$





	Initial (m)	**Optimized (m)**
Exp 1	0.0226	0.0208
Exp 2 (10% noise)	0.0819 ± 0.0299	0.0377 ± 0.0139
Exp 3 (30% noise)	0.1919 ± 0.0301	0.0664 ± 0.0175

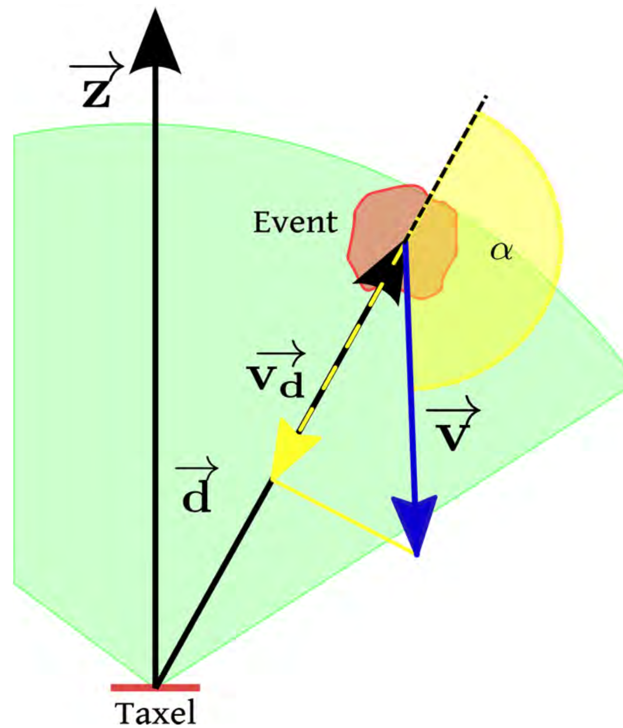
receptive fields

- Receptive field: a cone that extends up to 0.2m and angle of 40°

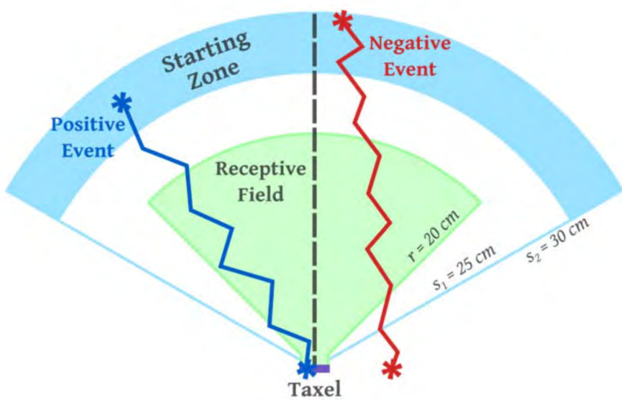
$$\begin{cases} \mathbf{D} = sgn(\overrightarrow{\mathbf{d}} \cdot \overrightarrow{\mathbf{z}})||\overrightarrow{\mathbf{d}}|| \\ \mathbf{TTC} = \dfrac{||\overrightarrow{\mathbf{d}}||}{||\overrightarrow{\mathbf{v}}|| \cdot cos(\alpha)} \end{cases}$$

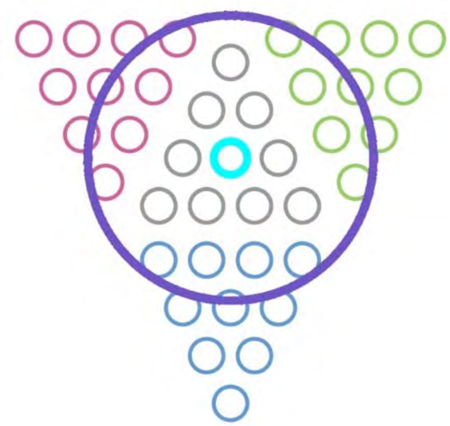
$$p(\mathbf{x}) = \frac{1}{n}\sum_{i=1}^{n}\frac{1}{\sqrt{2\pi}\sigma}exp\left(-\frac{(\mathbf{x}_i - \mathbf{x})^2}{2\sigma^2}\right)$$

$$\mathbf{x} : \{\mathbf{D}, \mathbf{TTC}\}$$

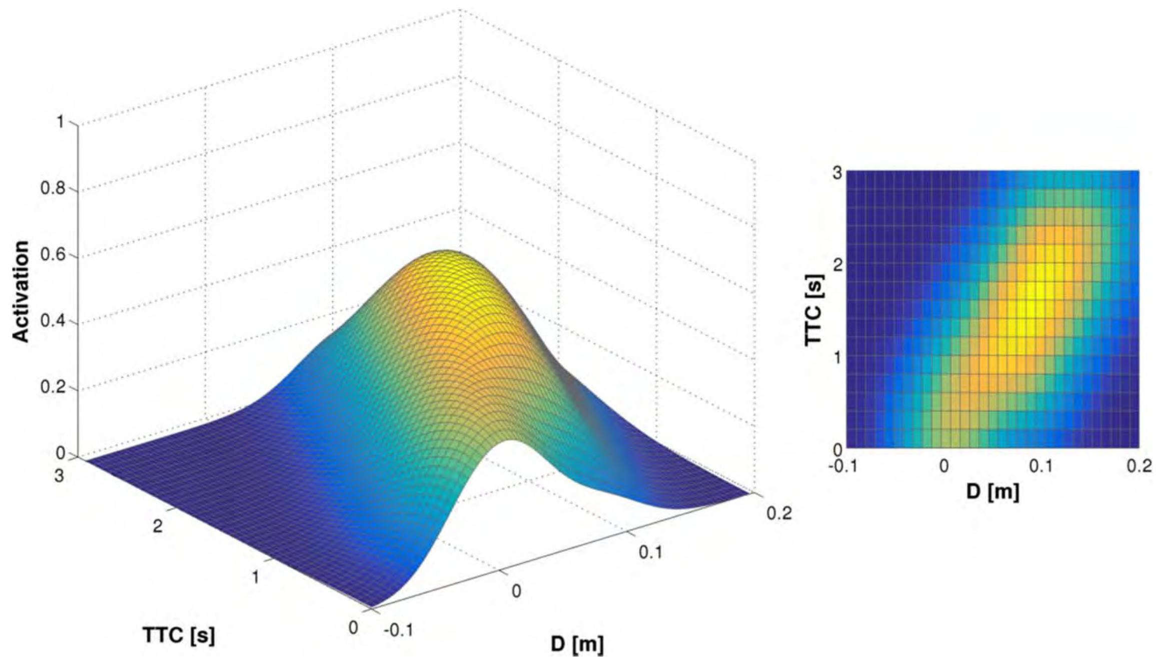


single taxel model

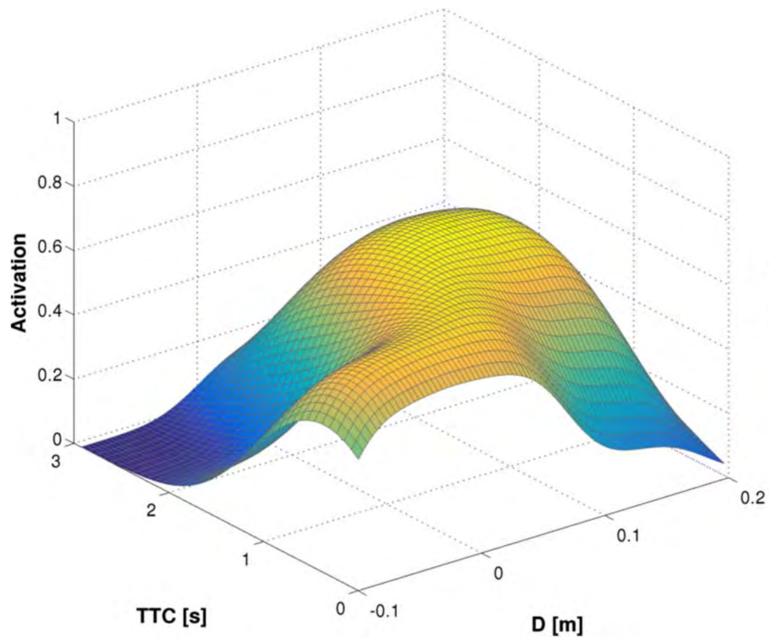




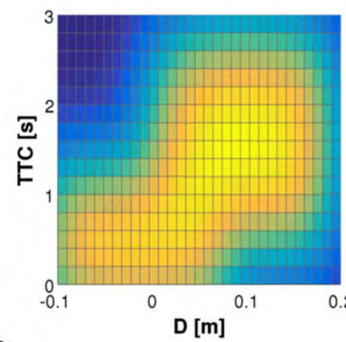
no noise


Activation
1
0.8
0.6
0.4
0.2
0
3
2
1
0
TTC [s]
-0.1
0
0.1
0.2
D [m]
TTC [s]
3
2
1
0
-0.1
0
0.1
0.2
D [m]

noisy data

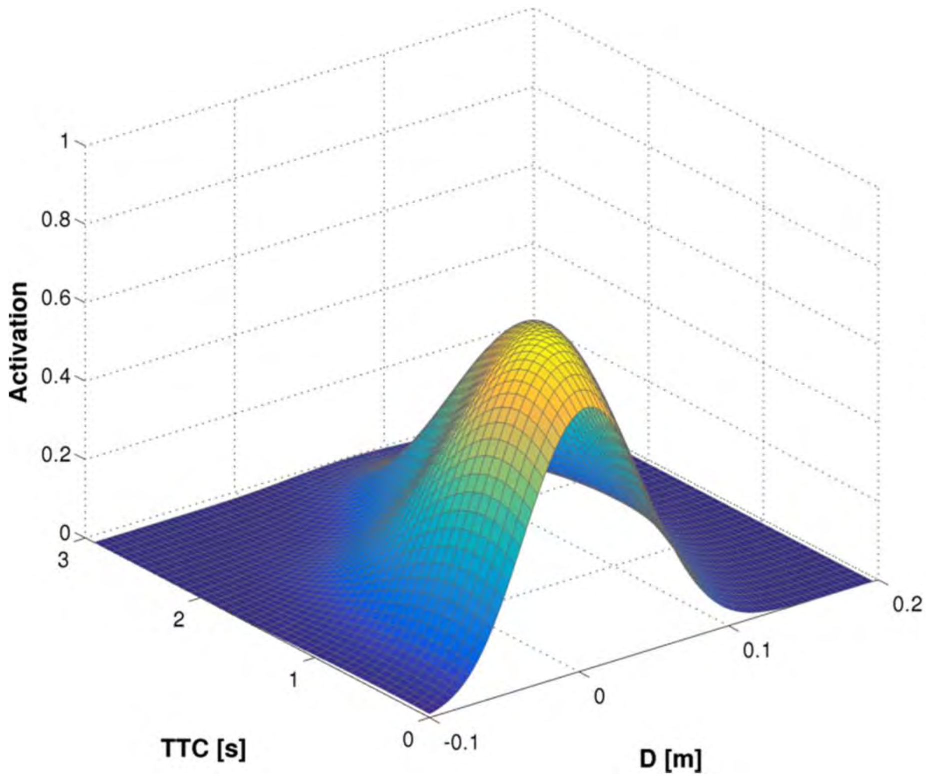


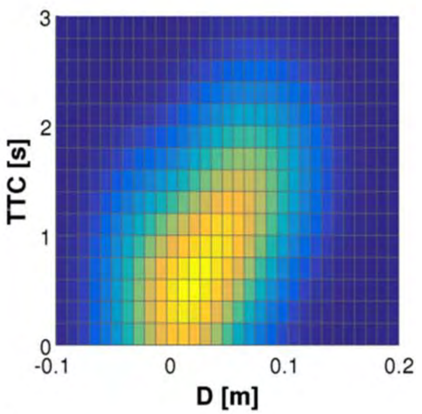
Activation
1
0.8
0.6
0.4
0.2
0
3
2
1
0
TTC [s]
-0.1
0
0.1
0.2
D [m]

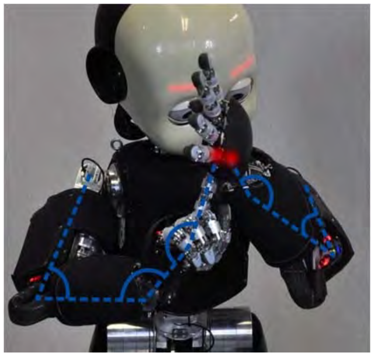


TTC [s]
3
2
1
0
-0.1
0
0.1
0.2
D [m]

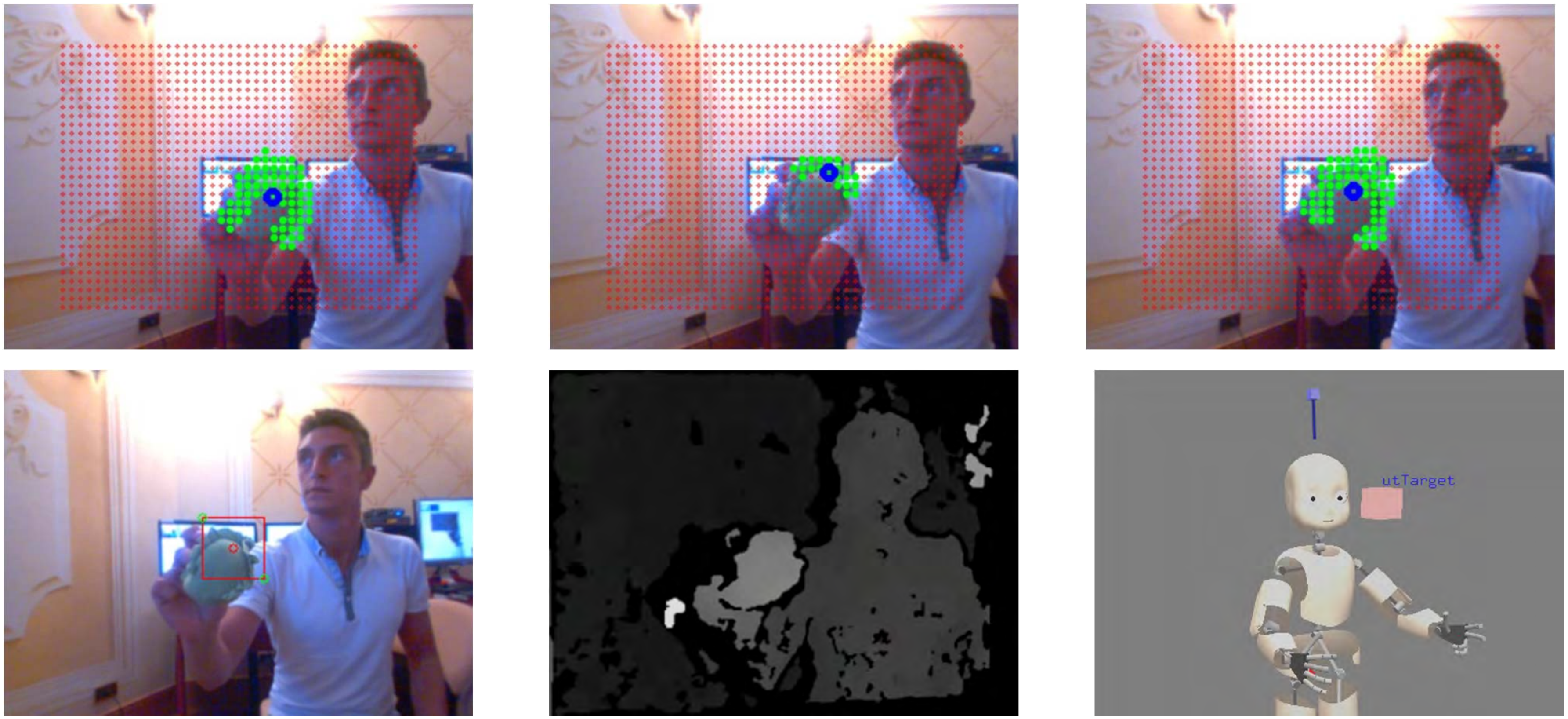
with double touch



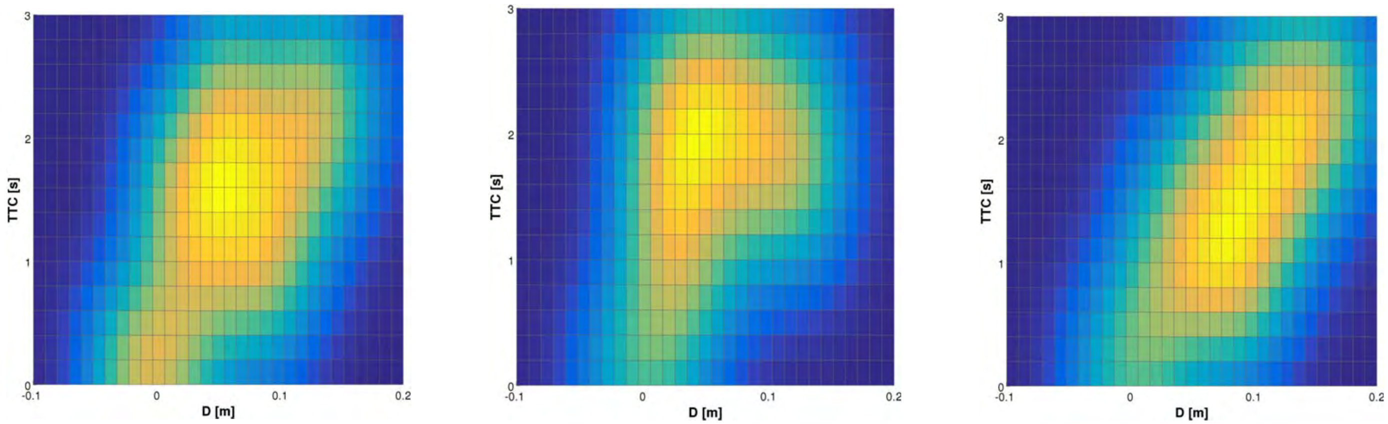


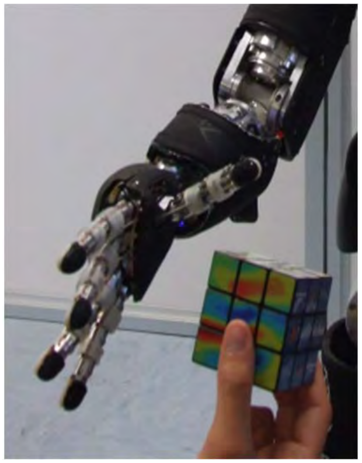


visual tracker



external stimulation

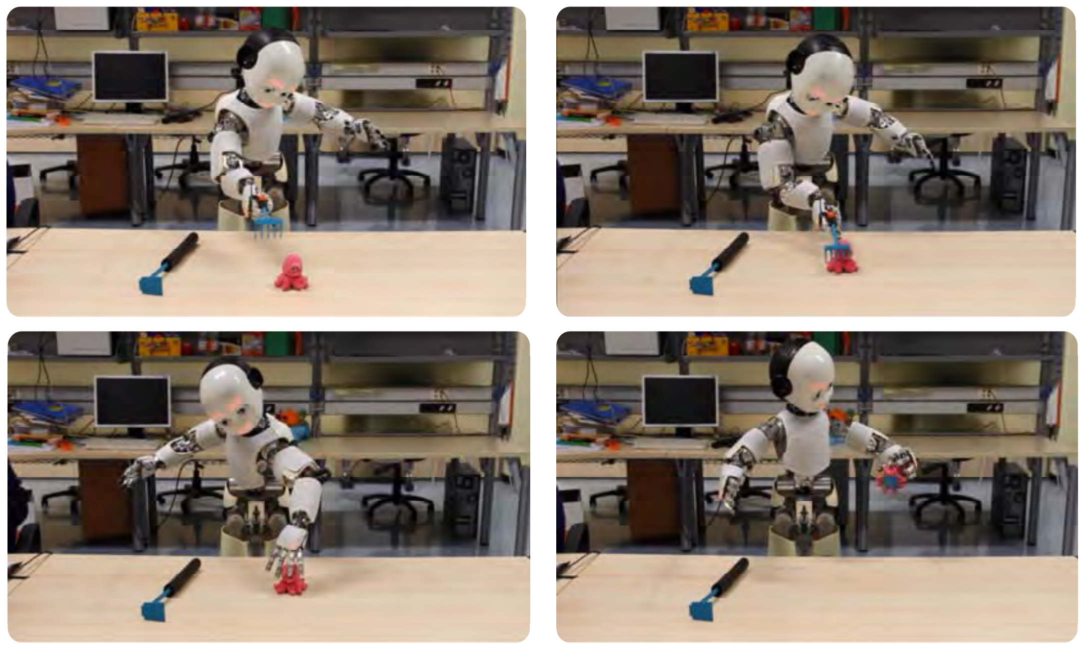




2. Learning peripersonal space representation

distributed representation of nearby space
through visuo-tactile associations

extending peripersonal space



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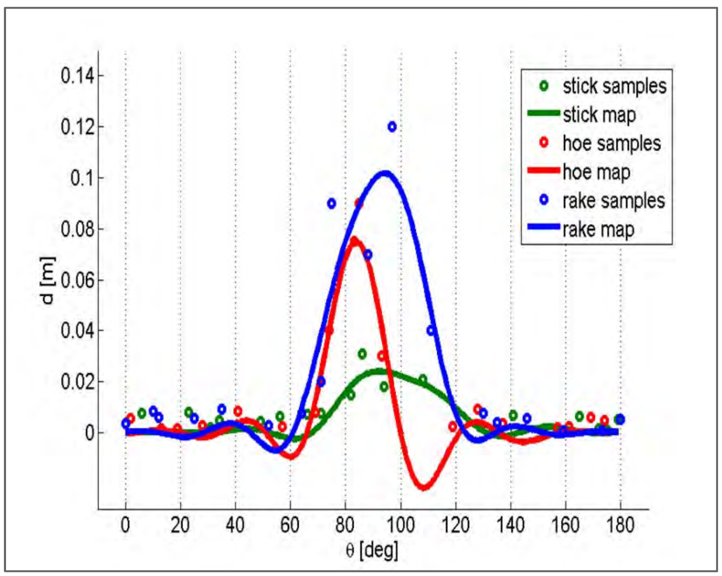
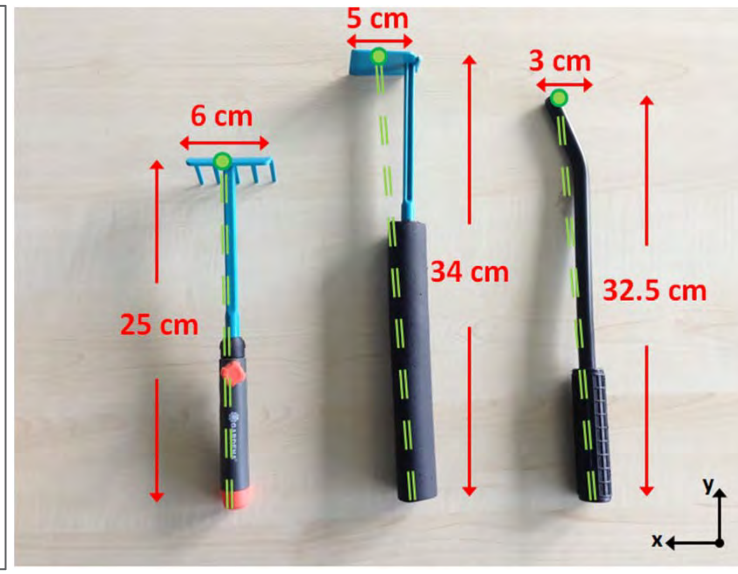
DI TECNOLOGIA





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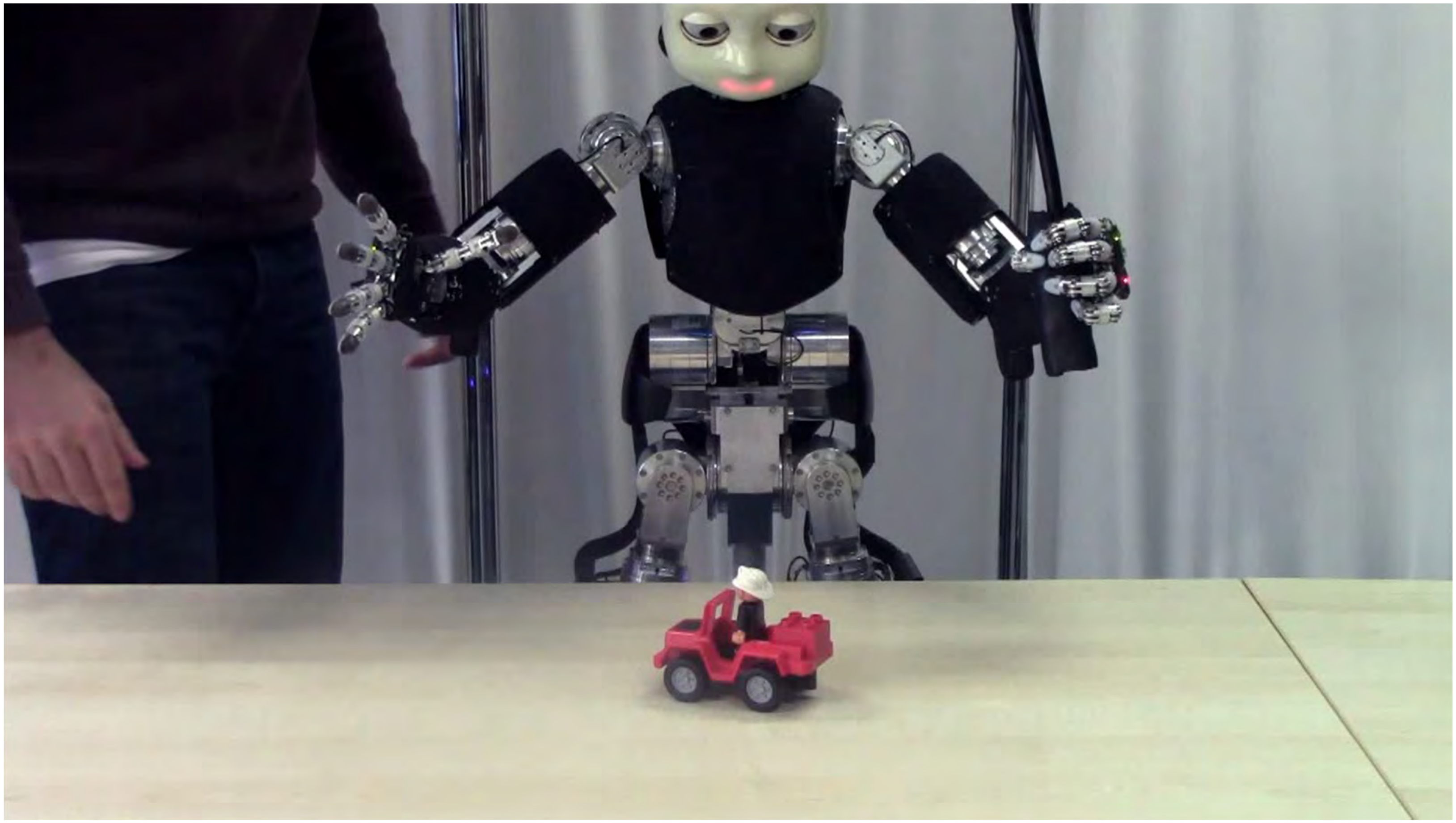
DI TECNOLOGIA



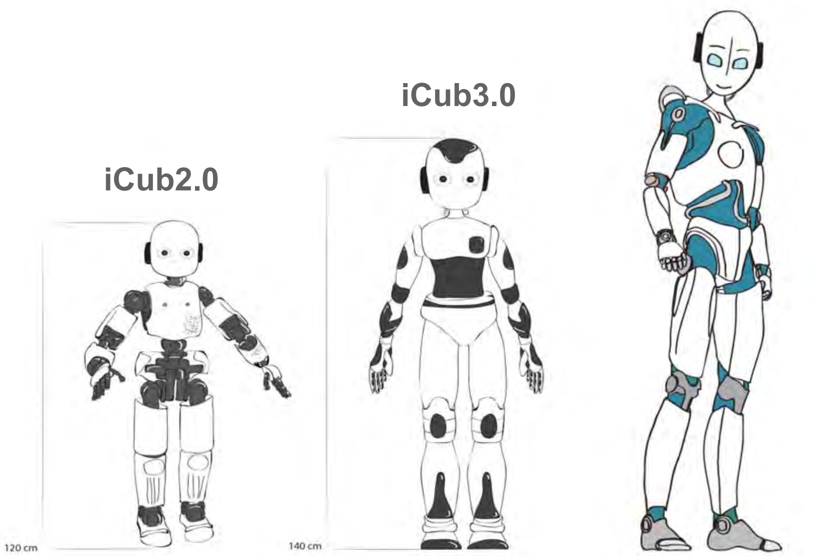

Task:
Clear the table

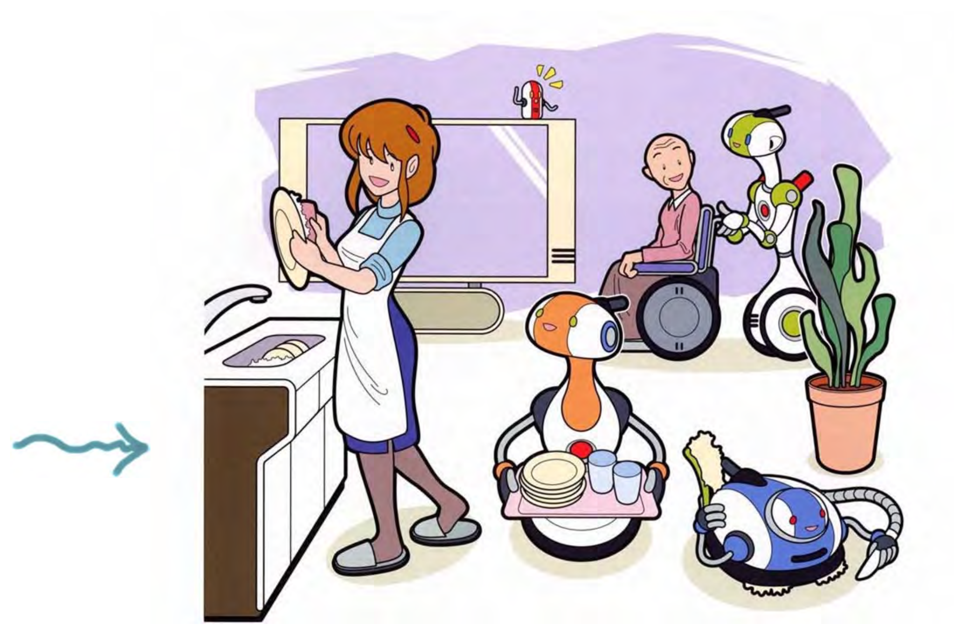
what future?

iCub new tech

iCub3.0

iCub2.0





now

the future?

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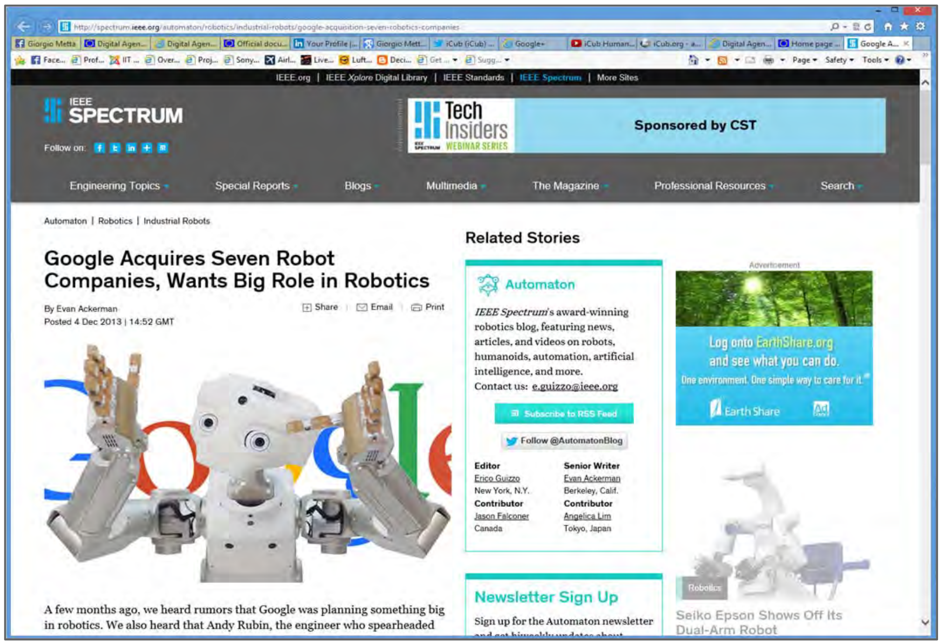


iit
iCub
ISTITUTO ITALIANO DI TECNOLOGIA
iCUB PROJECT
iCub Meeting December 2014

"How old are you?" she wanted to know.

"Thirty-two," I said.

"Then you don't remember a world without robots. There was a time when humanity faced the universe alone and without a friend. Now he has creatures to help him; stronger creatures than himself, more faithful, more useful, and absolutely devoted to him. Mankind is no longer alone. Have you ever thought of it that way?"

external funding

completed projects

- RobotCub, grant FP6-004370, http://www.robotcub.org
- CHRIS, grant FP7-215805, http://www.chrisfp7.eu
- ITALK, grant FP7-214668, http://italkproject.org
- Robotdoc, grant FP7-ITN-235065 http://www.robotdoc.org
- Roboskin, grant FP7-231500 http://www.roboskin.eu
- eMorph, grant FP7-231467 http://www.emorph.eu
- Poeticon, grant FP7-215843 http://www.poeticon.eu

- more information: http://www.iCub.org

- Poeticon++, grant FP7-288382 http://www.poeticon.eu
- Xperience, grant FP7-270273 http://www.xperience.org
- EFAA, grant FP7-270490 http://efaa.upf.edu/
- Codyco, grant FP7-600716 http://www.codyco.eu

new projects

- Tacman, grant FP7-610967
- Wysiwyd, grant FP7-612139
- Walk-man, grant FP7-611832
- Koroibot, grant FP7-611909