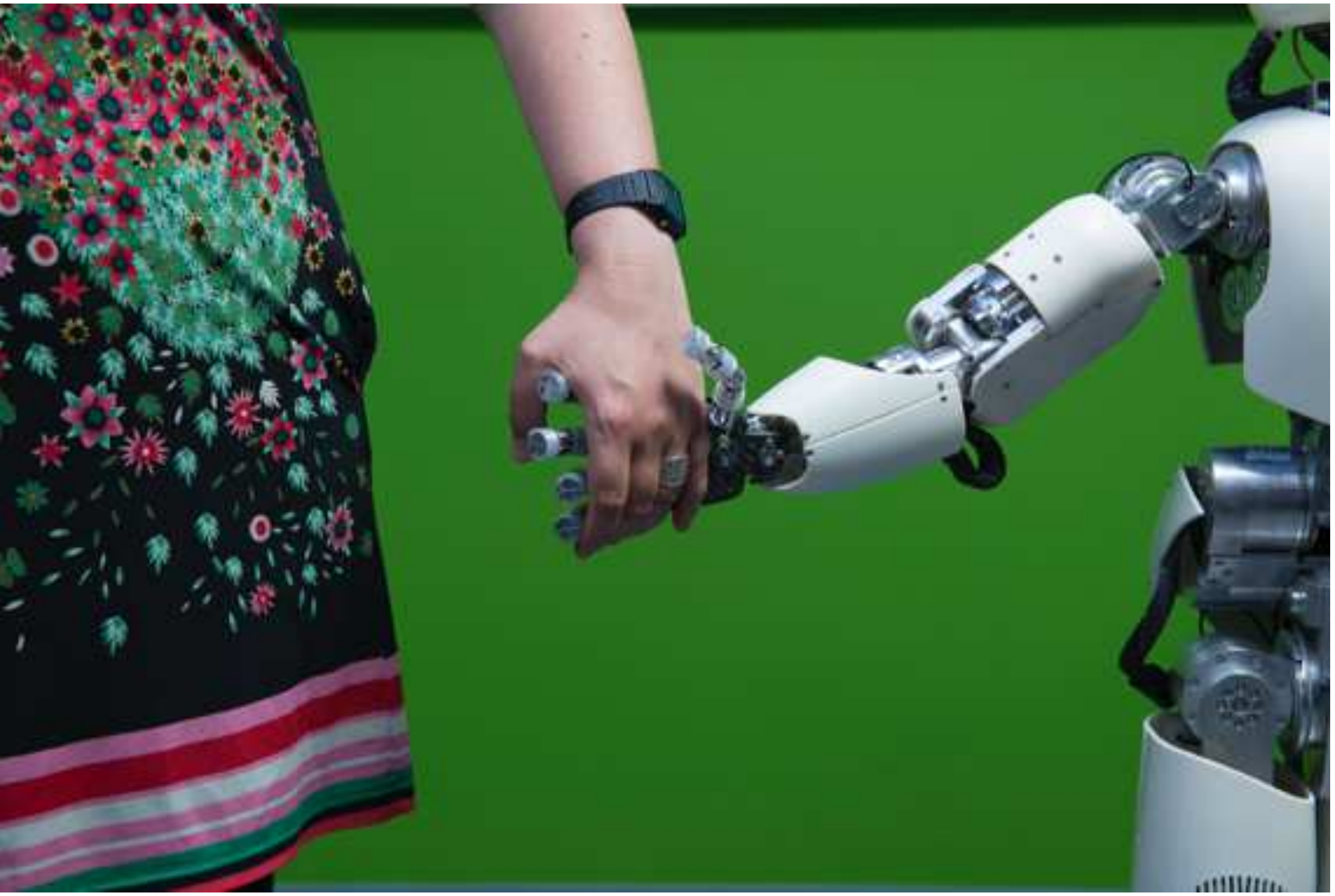
Exploiting tactile information for whole-body dynamics, learning and human-robot interaction



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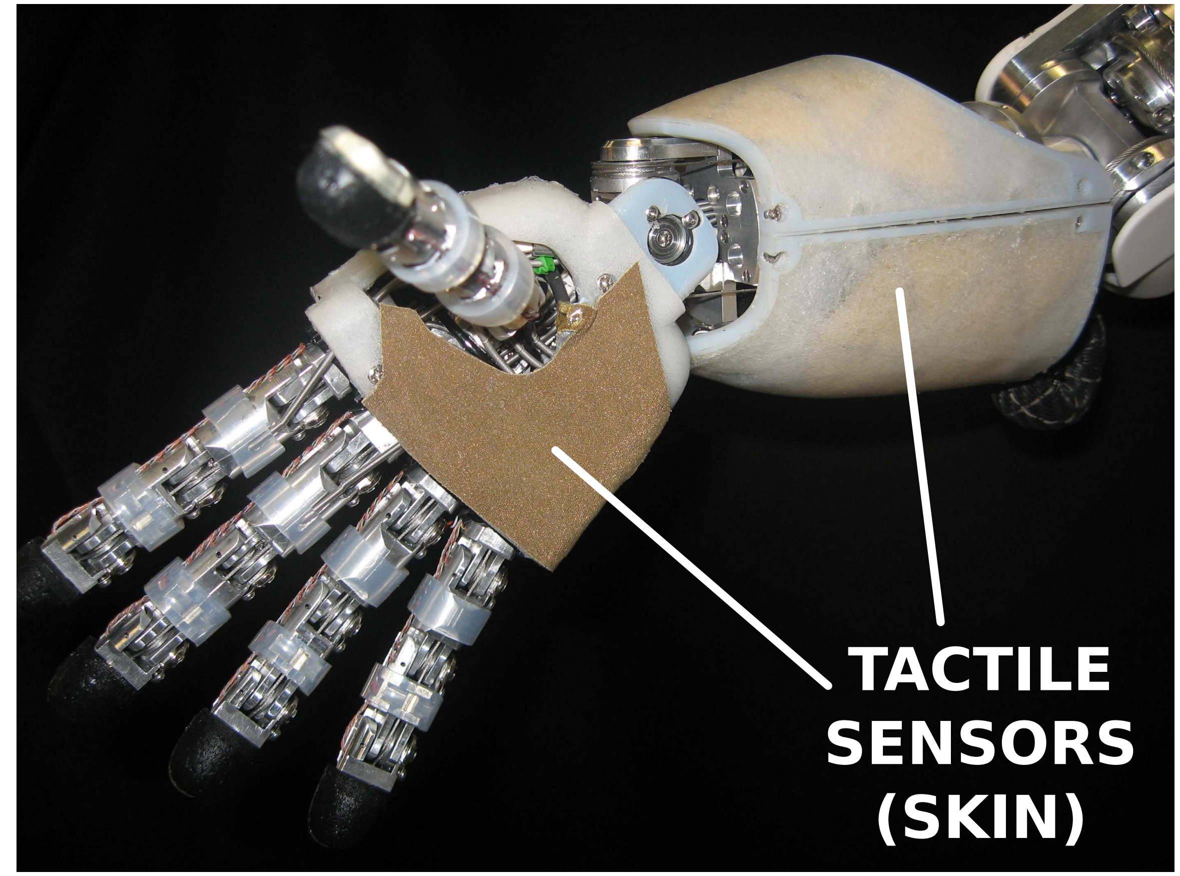
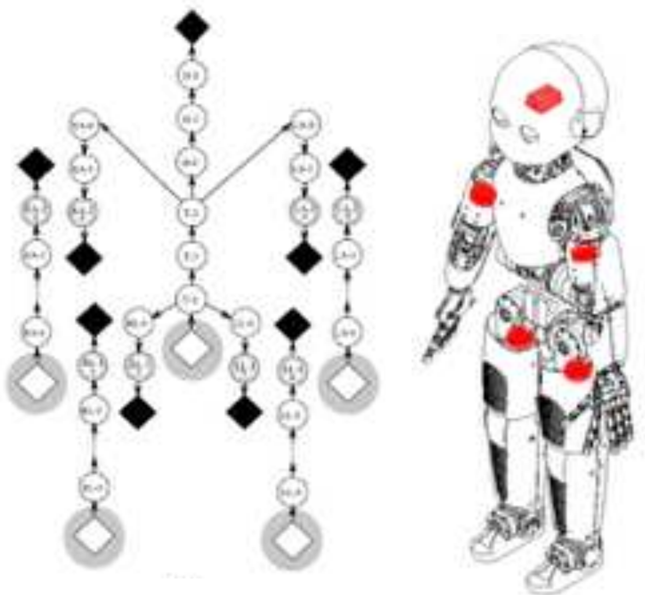
Pervasive tactile sensing in iCub

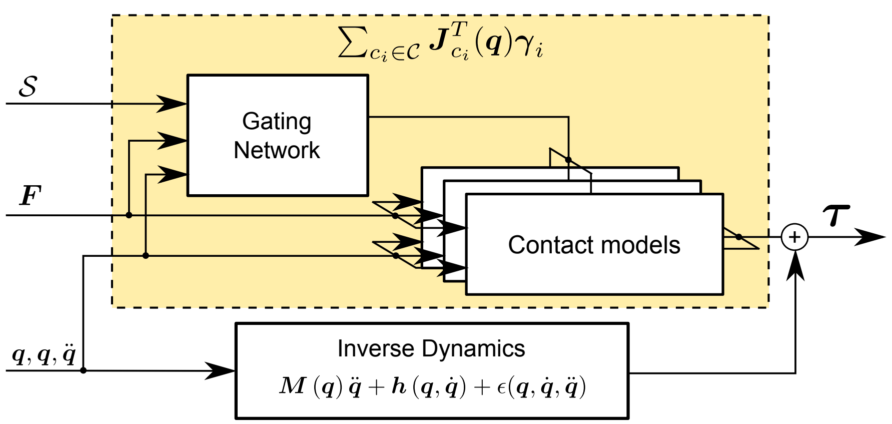


Credits: IIT
(F. Nori)

Outline of the talk



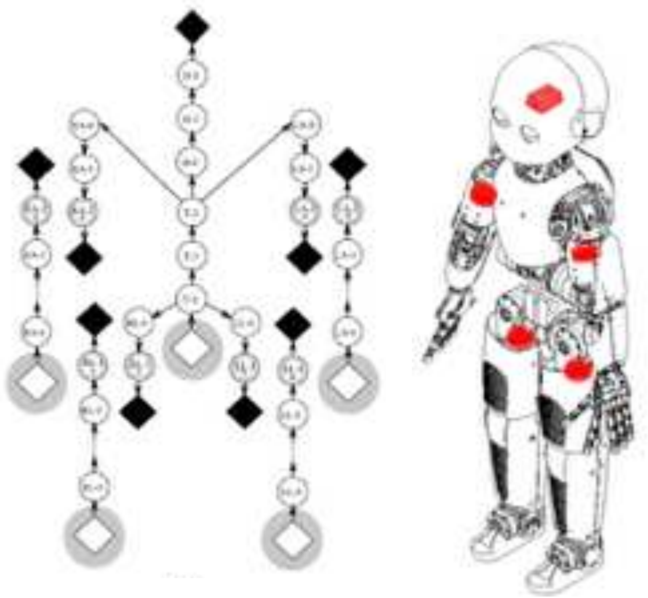
iDyn: computing whole-body dynamics thanks to inertial, force and tactile sensors



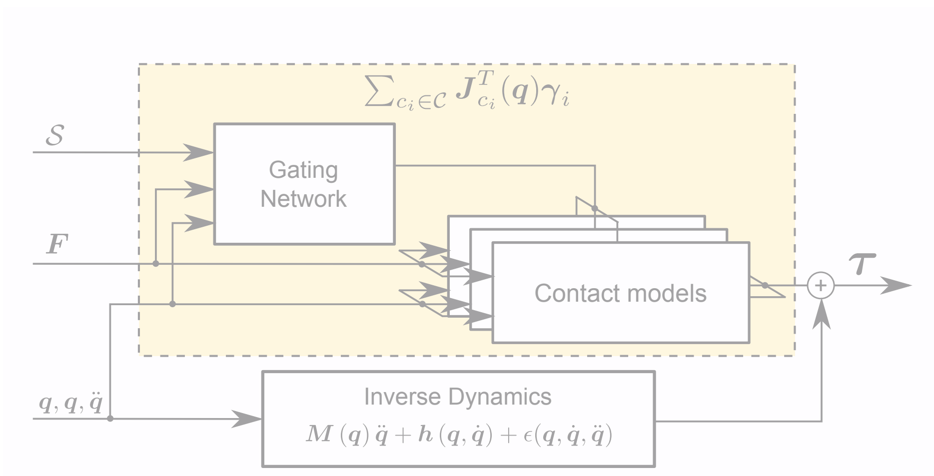
Learning the dynamics in presence of contacts thanks to the skin

Physical interaction: even non-experts can teach iCub how to assemble objects

Outline of the talk



iDyn: computing whole-body dynamics thanks to inertial, force and tactile sensors

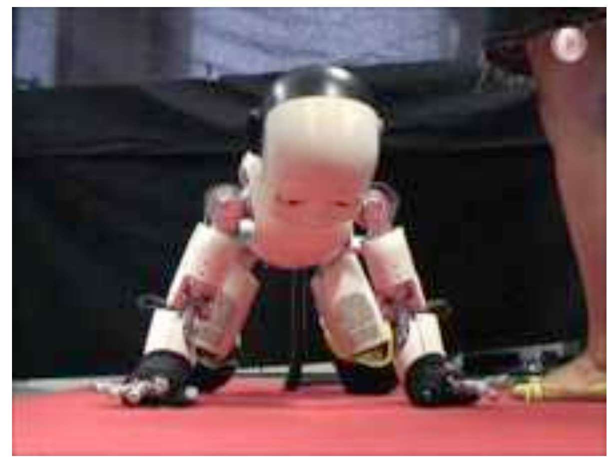


Learning the dynamics in presence of contacts thanks to the skin

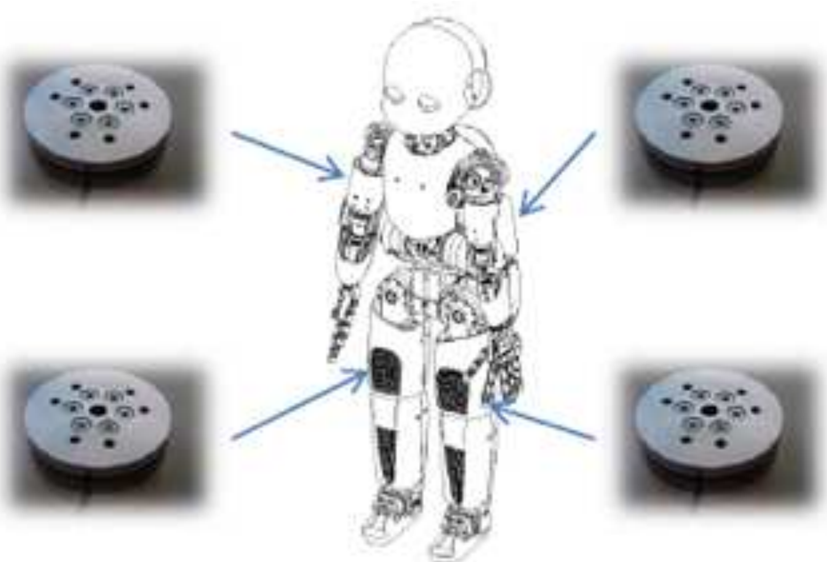
Physical interaction: even non-experts can teach iCub how to assemble objects

How to estimate the WB dynamics?

Estimate joint torques and external wrenches in case of multiple contacts, in changing locations and without dedicated sensors

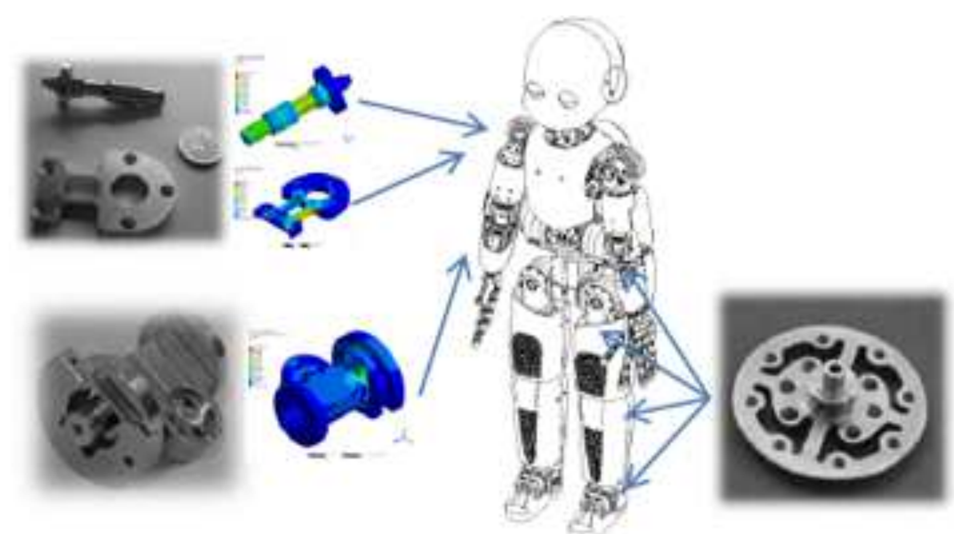


6 axis F/T sensors
(Fumagalli et al, 2009)



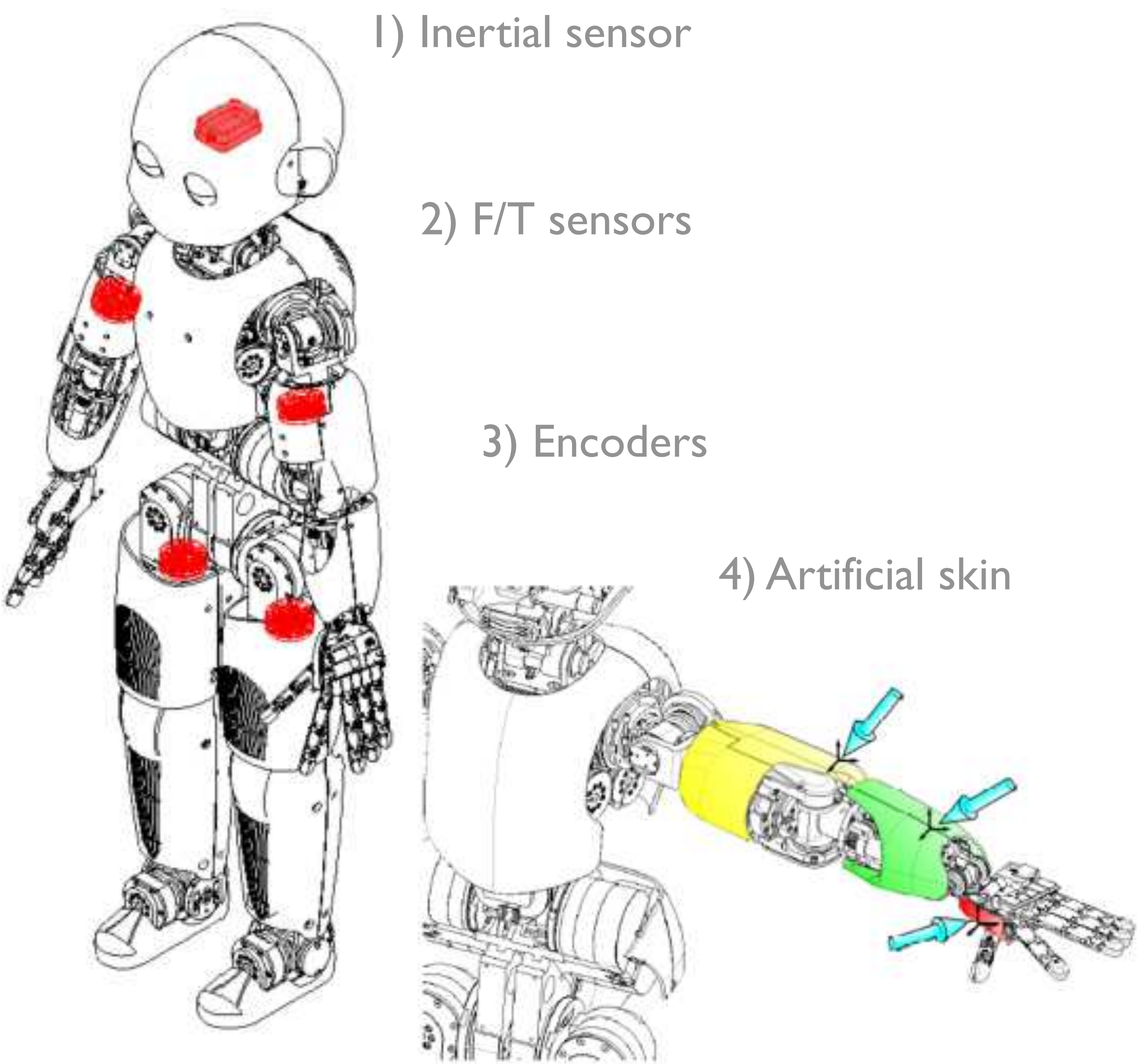
Pro: scalability, full perception
Cons: computational delays

Joint torque sensors
(Parmiggiani et al, 2009)



Pro: direct feedback loop
Cons: requires mechanical re-design

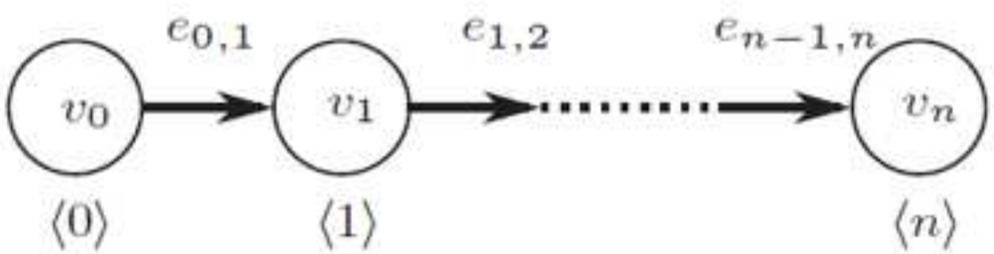
Idea: exploit available sensors



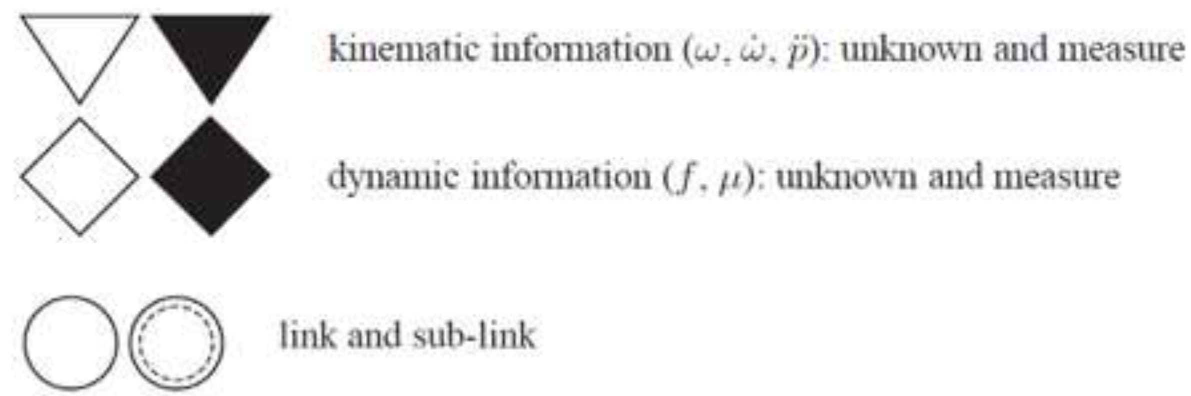
- What information (e.g. unknown external forces) can we retrieve?
- Given the number of F/T sensors, how many (external forces)?
- Given the distribution of F/T sensors, where can these external forces be located?
- What systematic procedure (i.e. algorithm) should we use?

Enhanced Oriented Graphs (EOG)

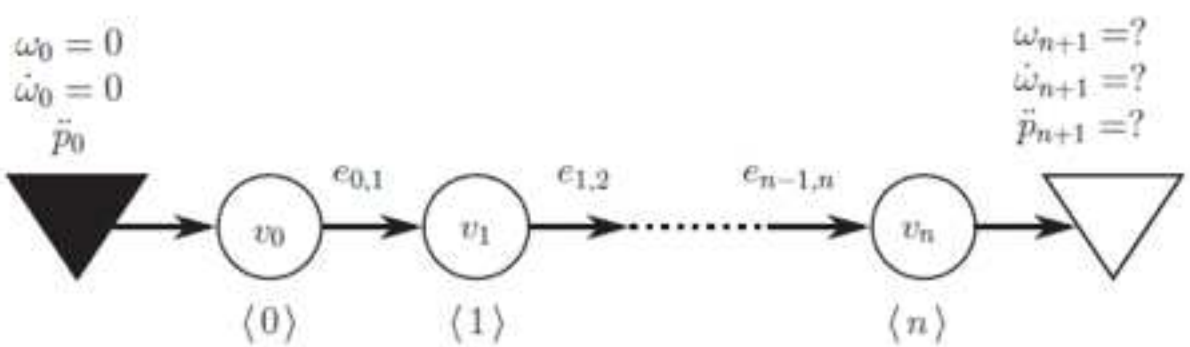
An open chain as a graph

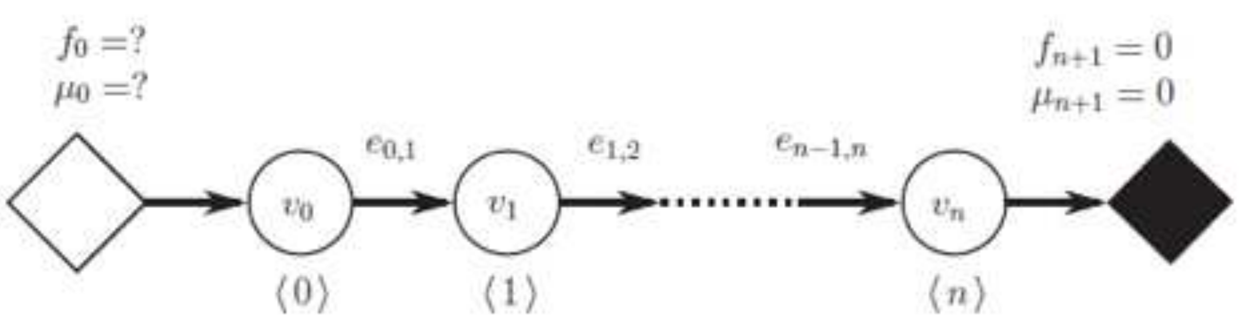


Enhance a Graph



Classical Recursive Newton-Euler



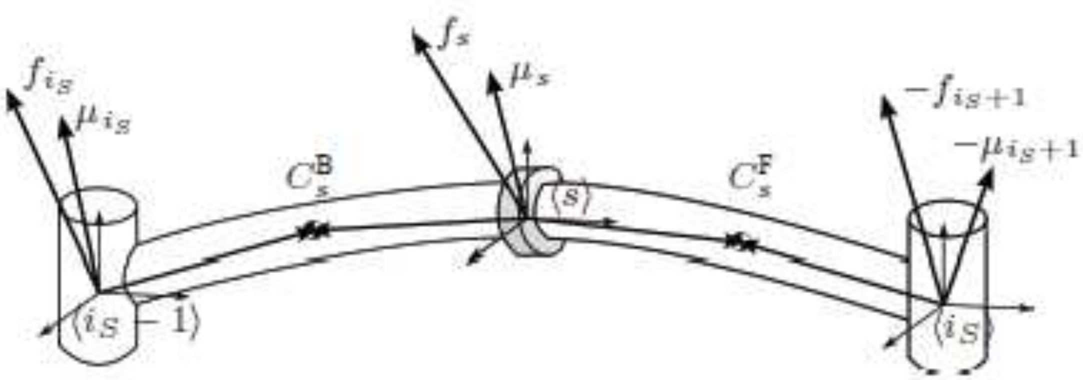


$$\omega_{i+1} = \omega_i + \dot{\theta}_{i+1} z_i,$$
$$\dot{\omega}_{i+1} = \dot{\omega}_i + \ddot{\theta}_{i+1} z_i + \dot{\theta}_{i+1} \omega_i \times z_i,$$
$$\ddot{p}_{i+1} = \ddot{p}_i + \dot{\omega}_i \times r_{i,i+1} + \omega_{i+1} \times (\omega_{i+1} \times r_{i,i+1})$$
$$\ddot{p}_{C_i} = \ddot{p}_i + \dot{\omega}_i \times r_{i,C_i} + \omega_i \times (\omega_i \times r_{i,C_i})$$

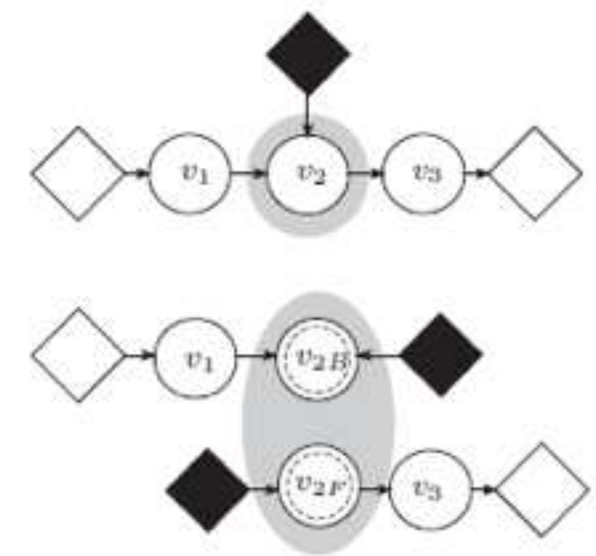
$$f_i = f_{i+1} + m_i \ddot{p}_{C_i},$$
$$\mu_i = \mu_{i+1} - f_i \times r_{i-1,C_i} + f_{i+1} \times r_{i,C_i} + \bar{I}_i \dot{\omega}_i + + \omega_i \times (\bar{I}_i \omega_i)$$

Enhanced Oriented Graphs (EOG)

Proximal Force/Torque sensor measurements can be inserted in the graph



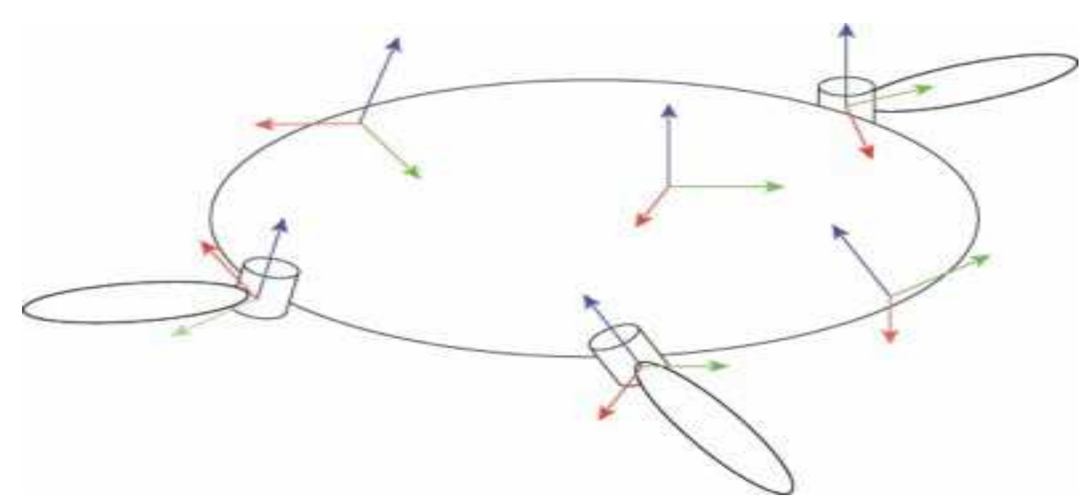
For each FTS, the graph is split into two subgraphs



Generalized forces are found with basic RNEA

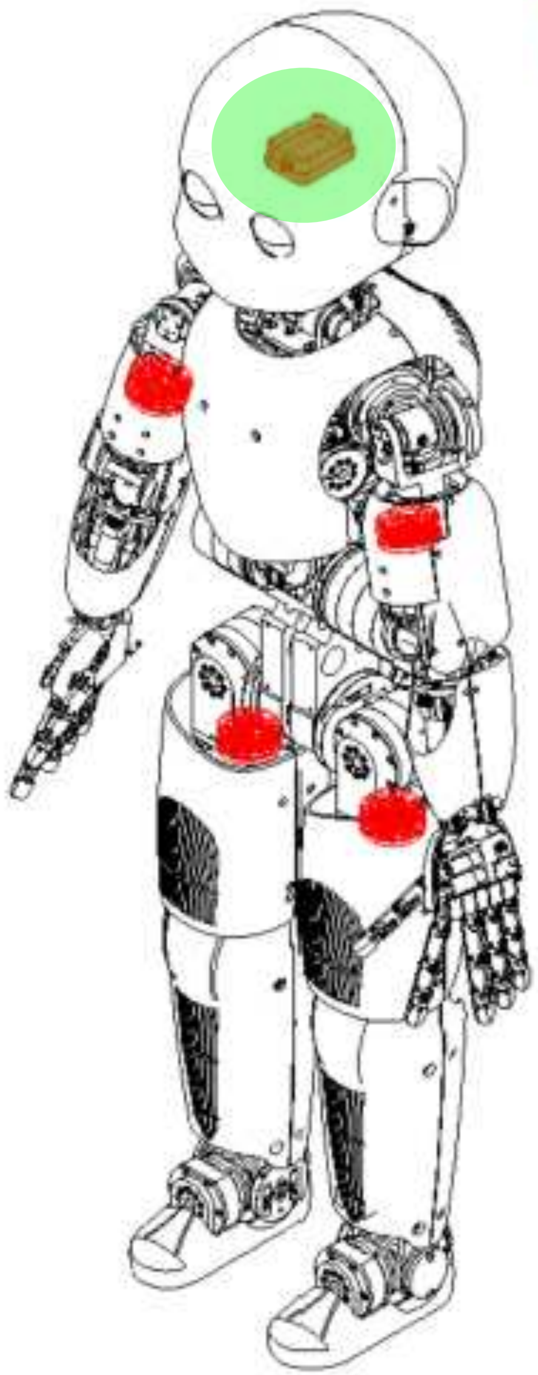
$$f_i = -\sum_{\substack{e_I \in \mathscr{E}_I(v) \\ e_I \neq i}} f_{e_I} + \sum_{e_O \in \mathscr{E}_O(v)} f_{e_O} + m_v \ddot{p}_{C_v},$$

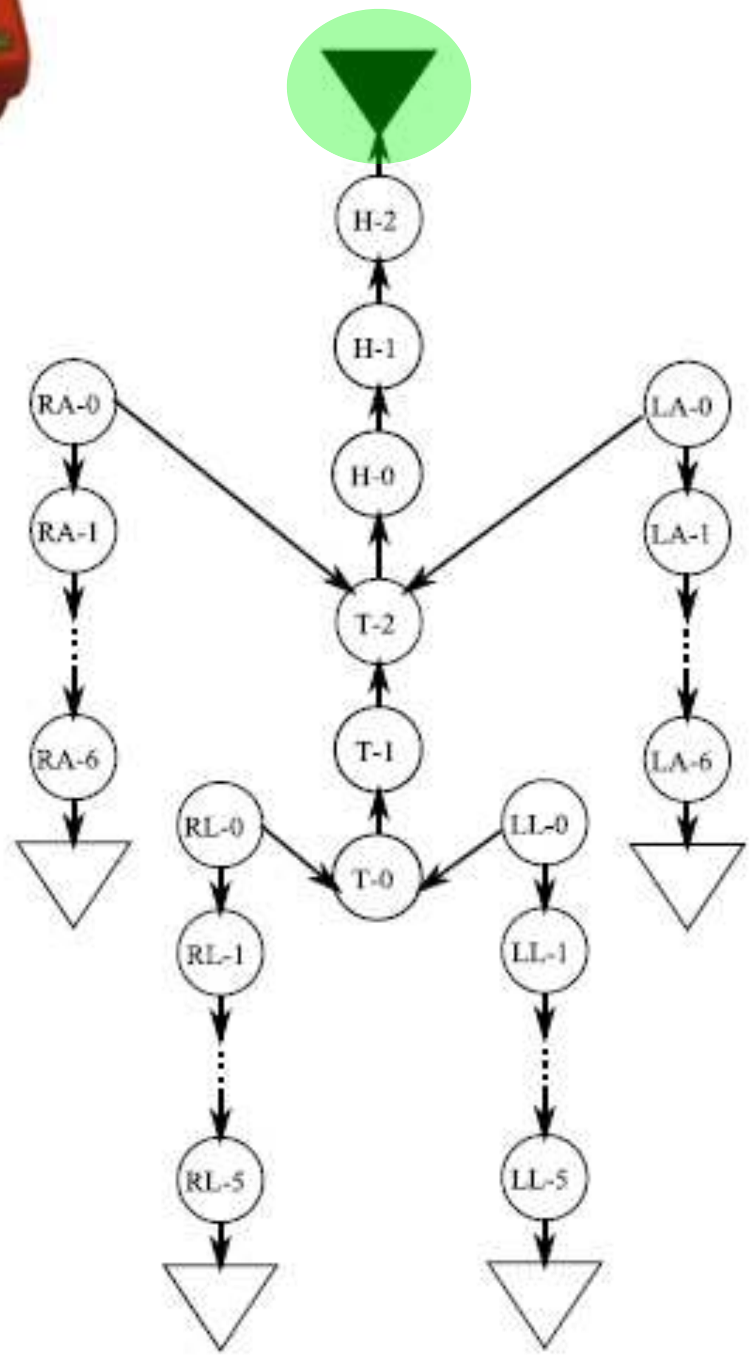
$$\mu_i = -f_i \times r_{i,C_v} - \sum_{\substack{e_I \in \mathscr{E}_I(v) \\ e_I \neq i}} (\mu_{e_I} + f_{e_I} \times r_{e_I,C_v})$$
$$+ \sum_{e_O \in \mathscr{E}_O(v)} (\mu_{e_O} + f_{e_O} \times r_{e_O,C_v}) + \bar{I}_i \dot{\omega}_i + \omega_i \times (\bar{I}_i \omega_i)$$

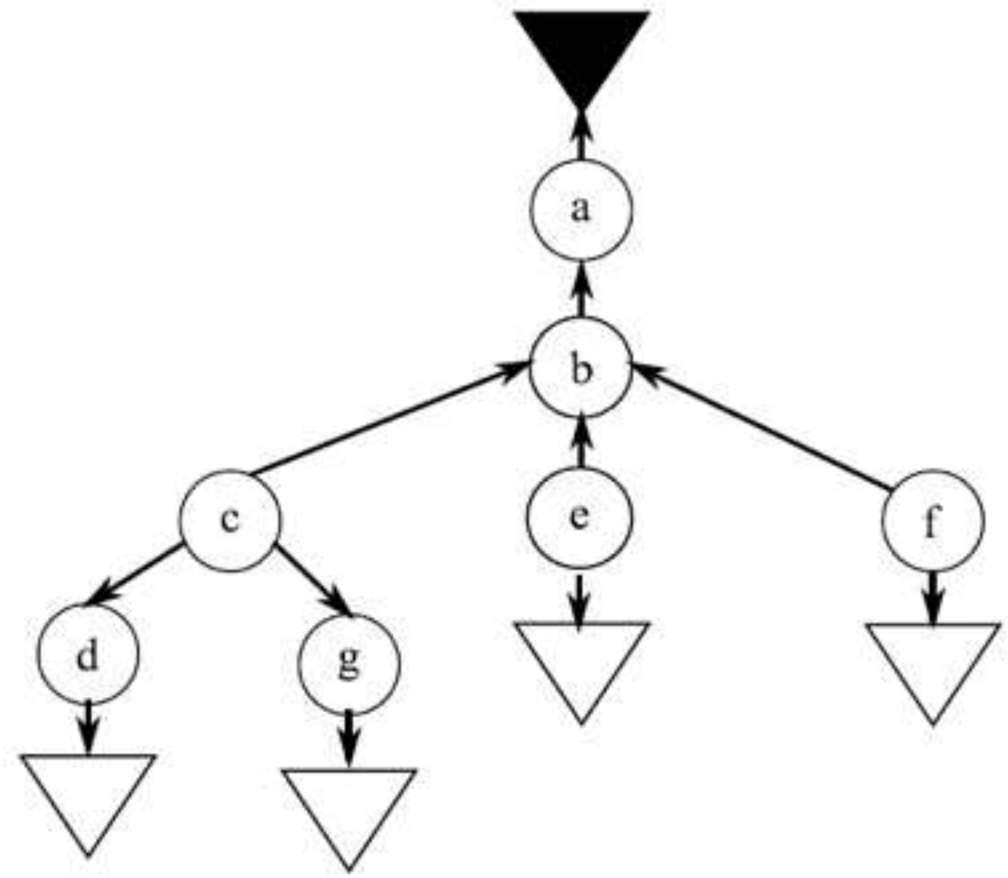


Kinematics EOG

Inertial sensor



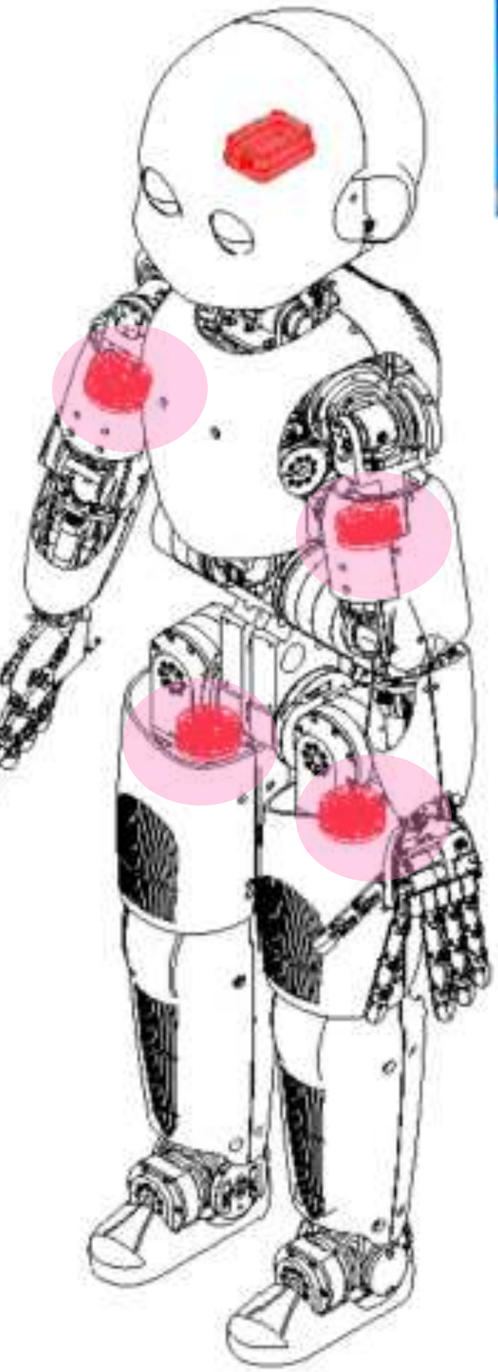




(pre-order traversal of the tree: a,b,c,d,g,e,f)

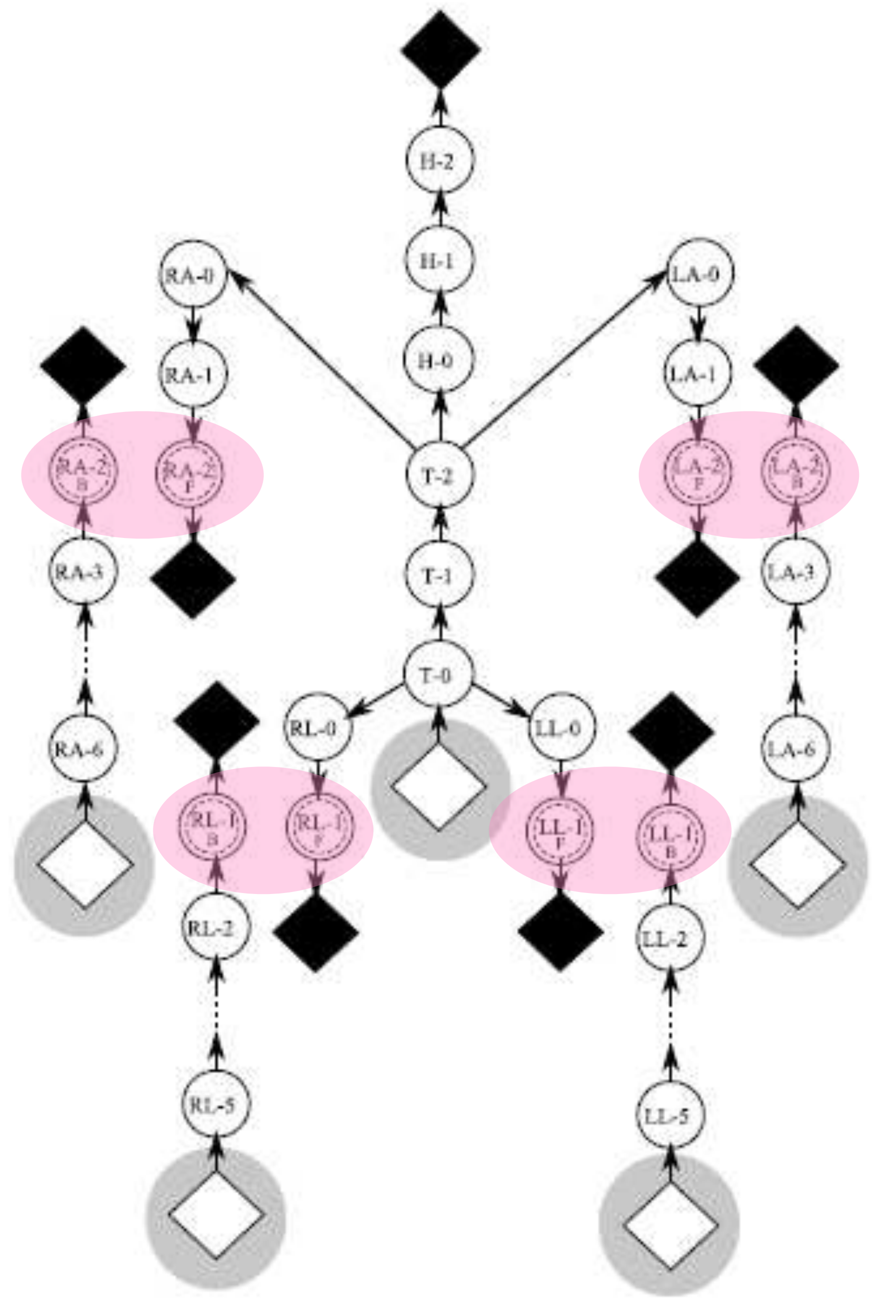
Ivaldi et al. HUMANOIDS 2011

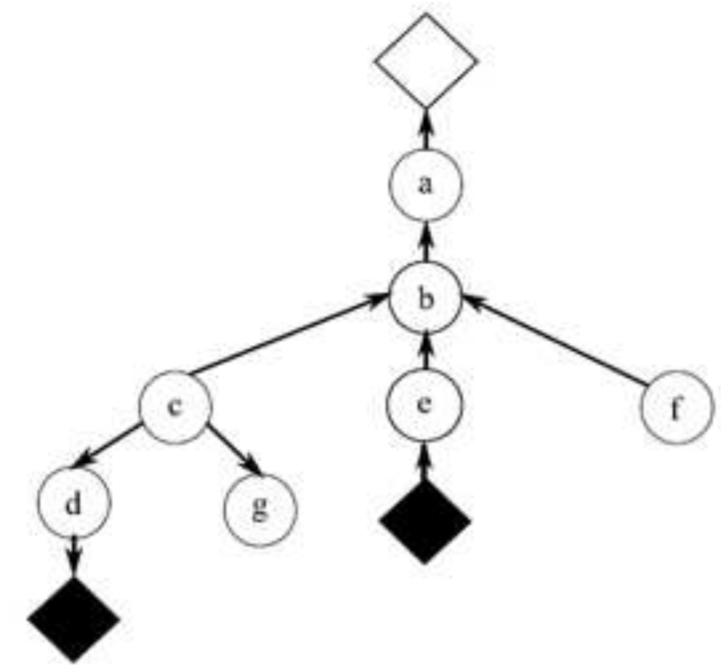
Dynamics EOG



contacts
by skin

F/T sensor



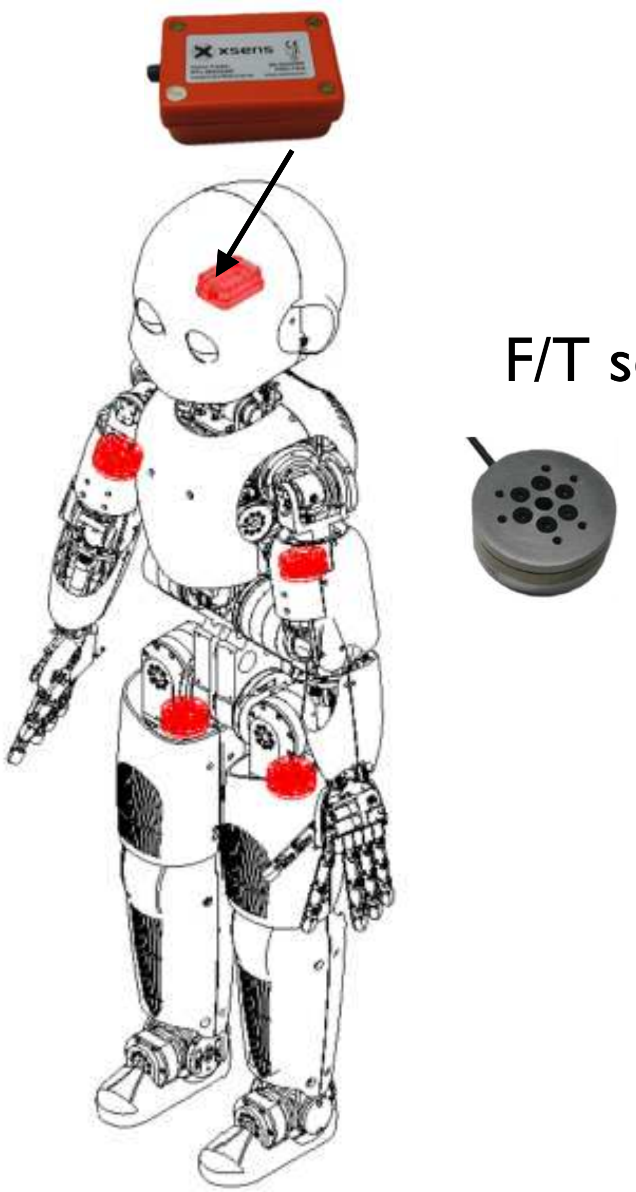


(post-order traversal of the tree: d,g,c,e,f,b,a)

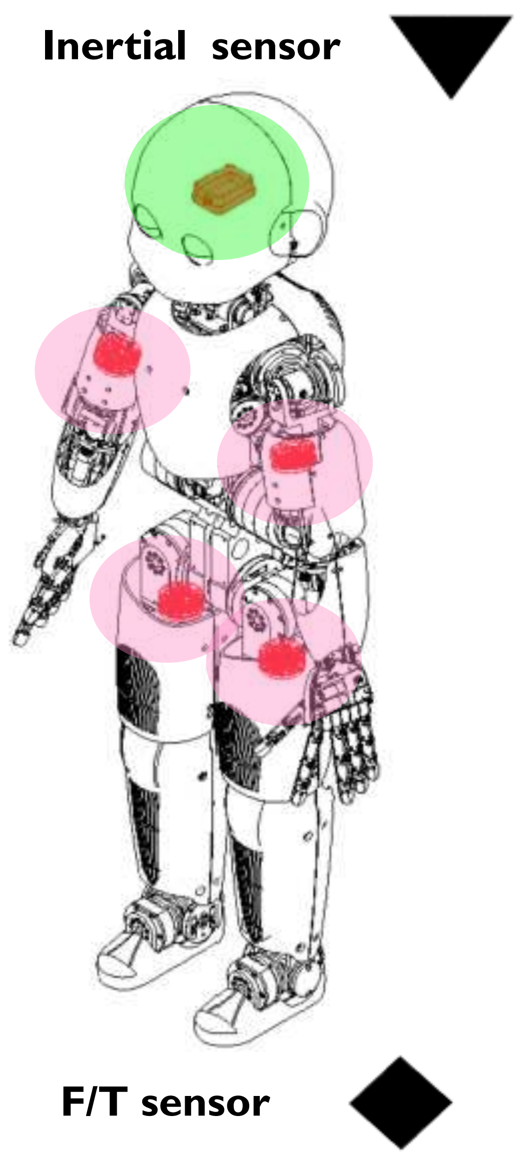
Ivaldi et al. HUMANOIDS 2011

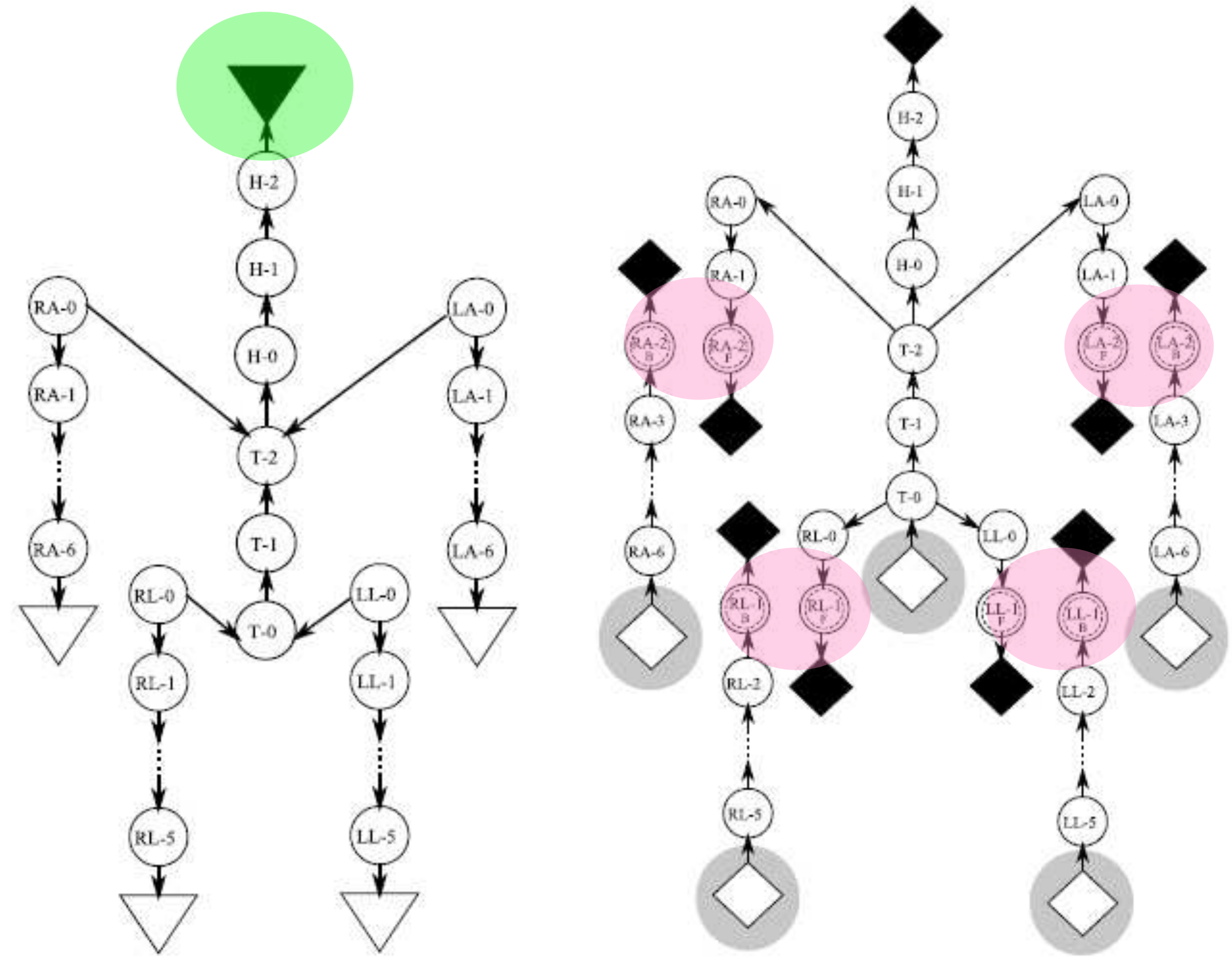
Computing whole-body dynamics with iDyn

Inertial sensor



F/T sensor





(a) (b)

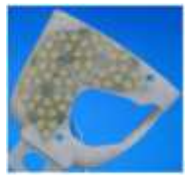
Joint torques are easily computed once we know the link wrenches

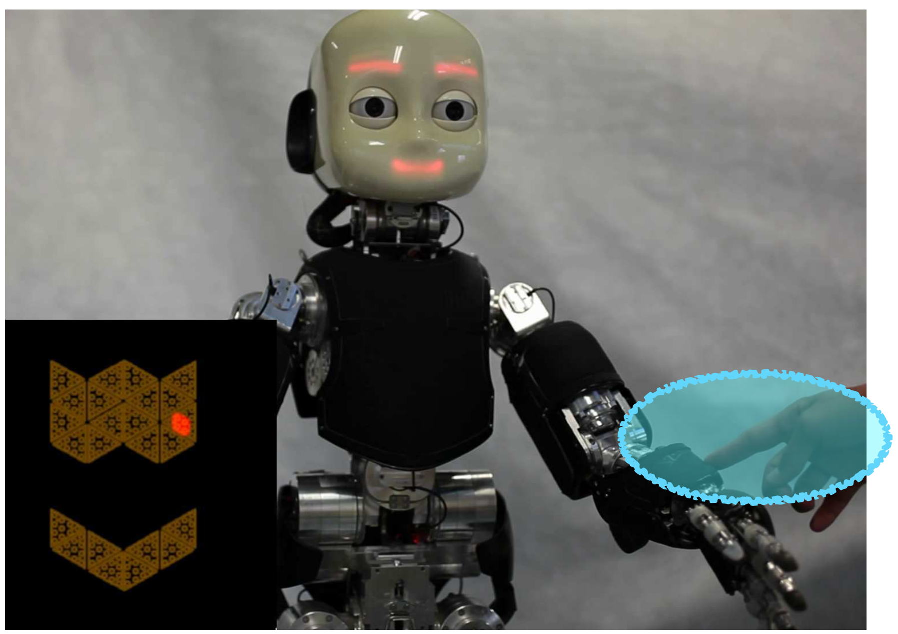
$$\tau_i = \mu_i^\top z_{i-1}$$

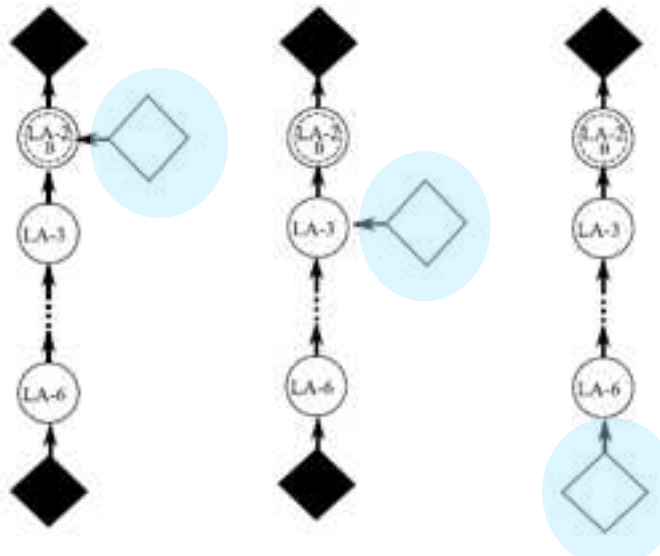
Ivaldi et al. HUMANOIDS 2011

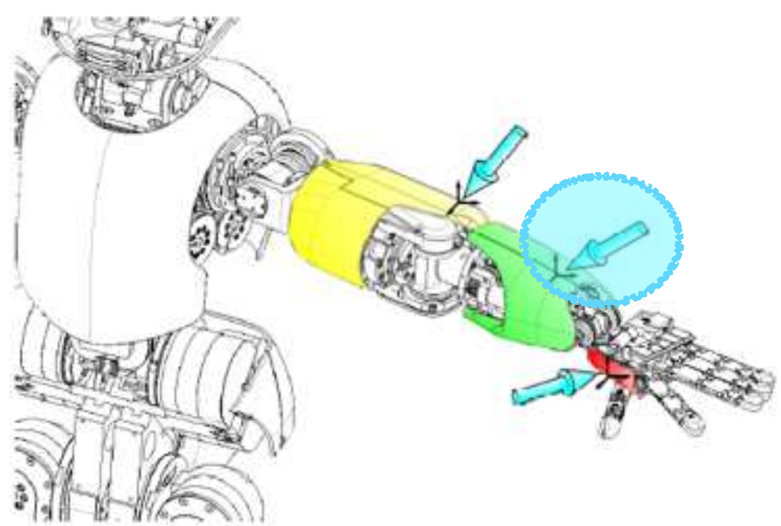
Using tactile information in iDyn

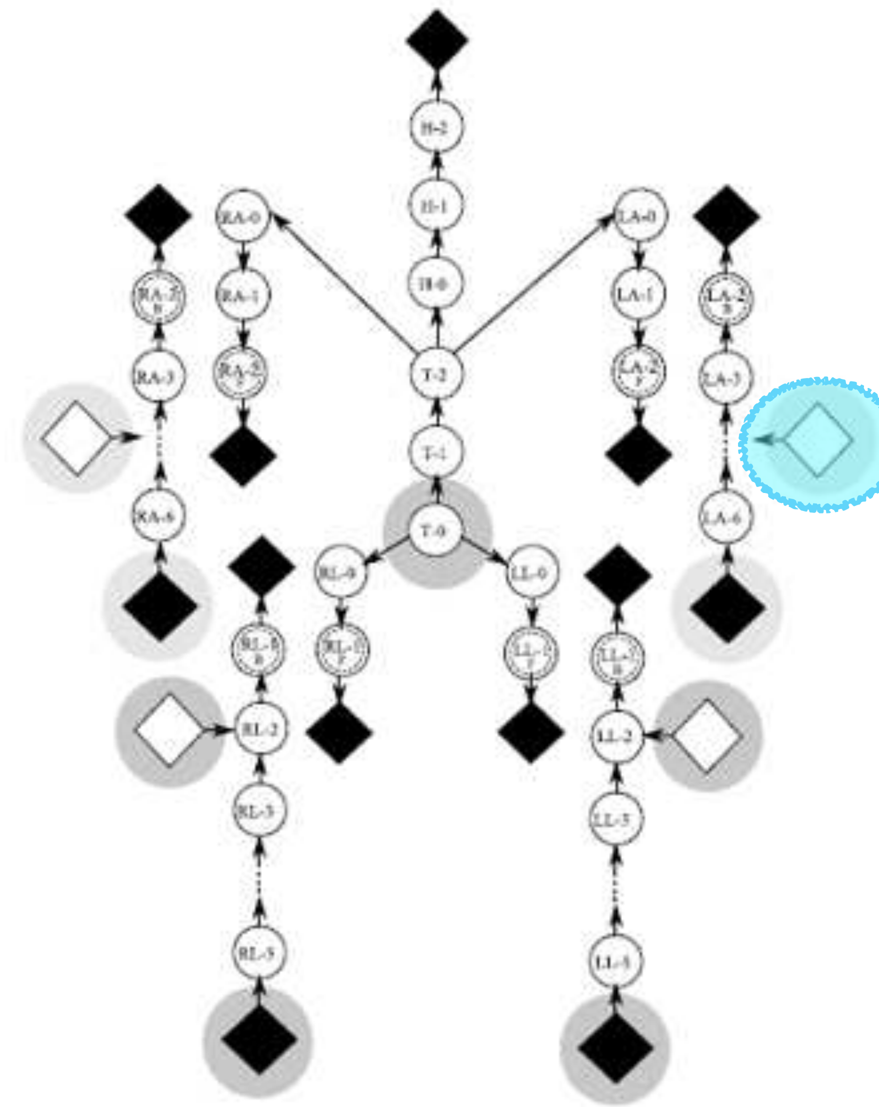
skin





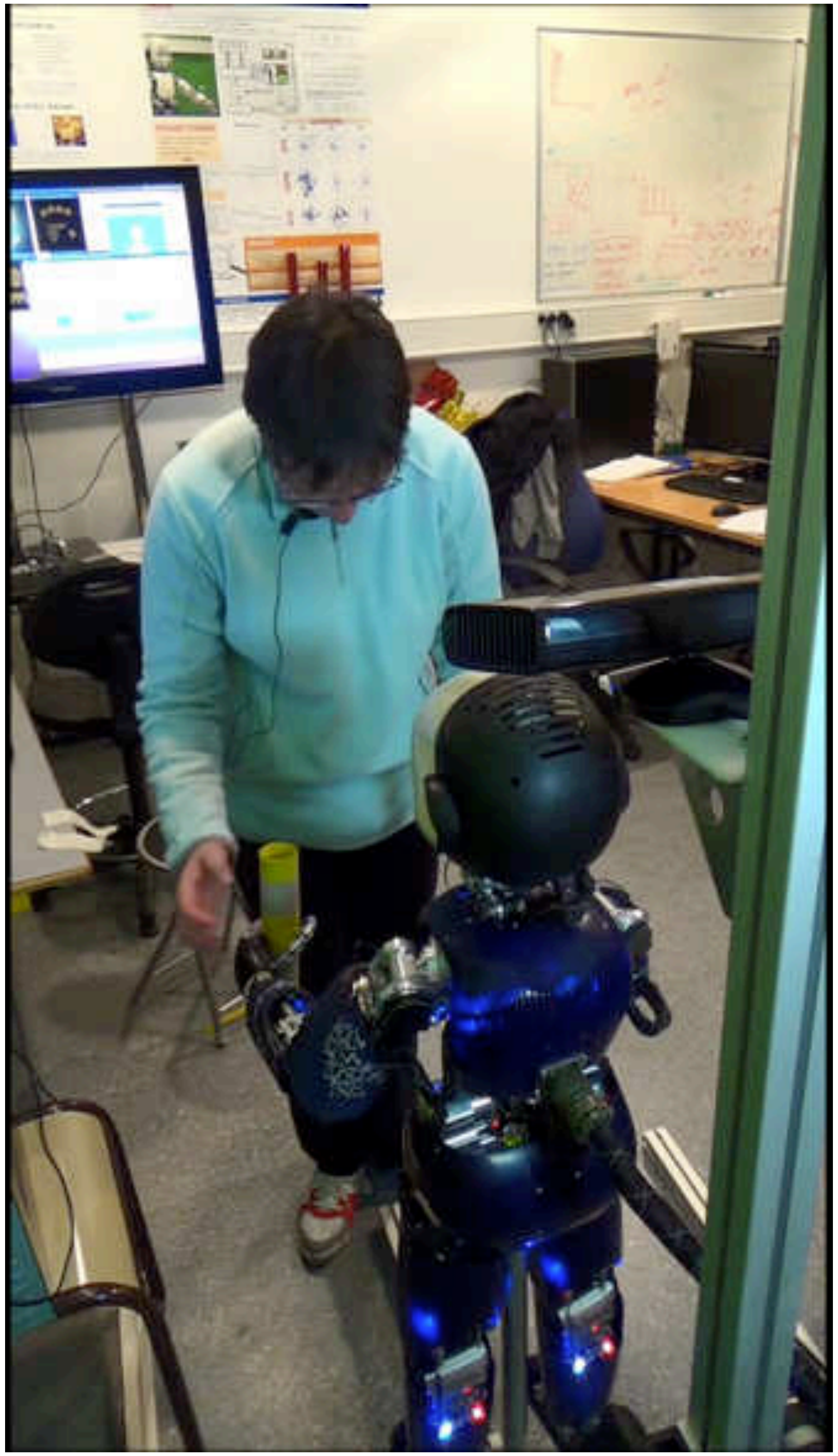






HUMANOIDS 2011, Autonomous Robots 2012

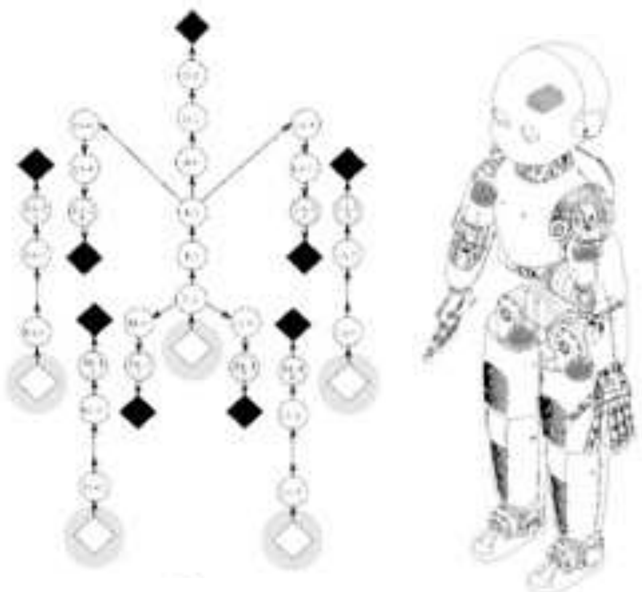
Physical interaction thanks to iDyn



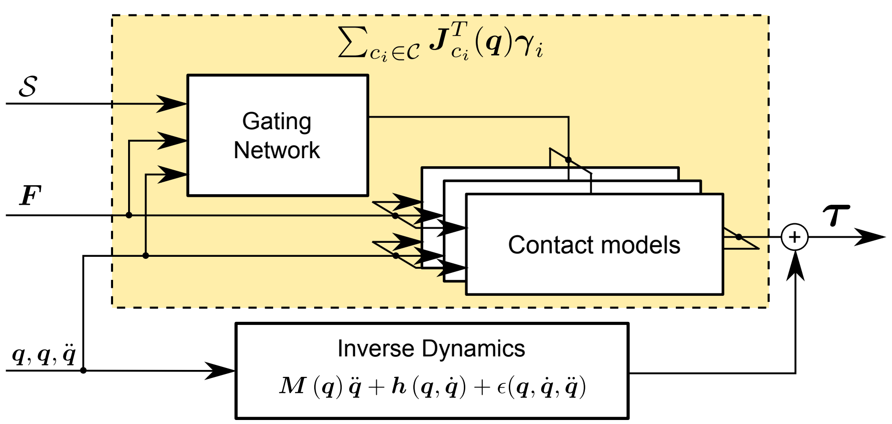
Droniou et al, RAS 2015, Stulp et al, HUMANOIDS 2013

Ivaldi, et al. IJSR 2016

Outline of the talk



iDyn: computing whole-body dynamics thanks to inertial, force and tactile sensors



Learning the dynamics in presence of contacts thanks to the skin

Physical interaction: even non-experts can teach iCub how to assemble objects

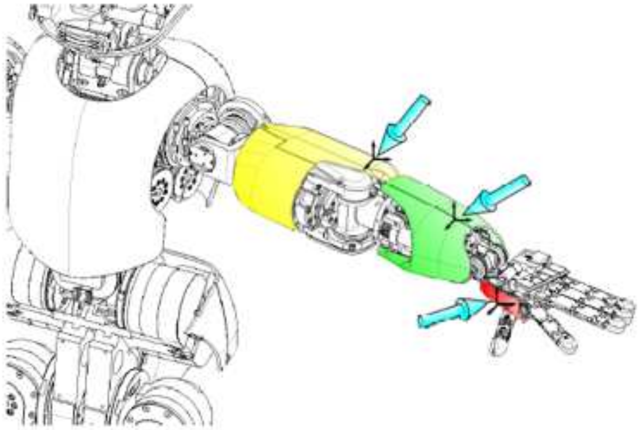
Limits of model-based approaches

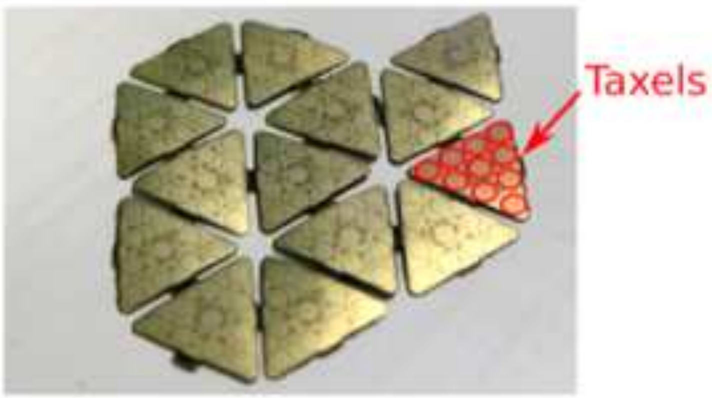
Inaccurate contact forces and joint torque estimation can deteriorate performances in tracking of desired trajectories… but:

- Impossible to put force/torque sensors in each possible contact location
- Joint torque sensors are expensive!
- Better models?

$$\tau = \underbrace{M(q)\ddot{q} + h(q,\dot{q}) + \epsilon(q,\dot{q},\ddot{q})}_{\tau_{\mathrm{ID}}} + \underbrace{\sum_{c_i \in C} J_{c_i}^T(q)\gamma_i}_{\tau_{\mathrm{ext}}}$$

$$h(q,\dot{q}) = C(q,\dot{q})\dot{q} + g(q) + F_v\dot{q} + F_s\,\mathrm{sgn}(\dot{q})$$

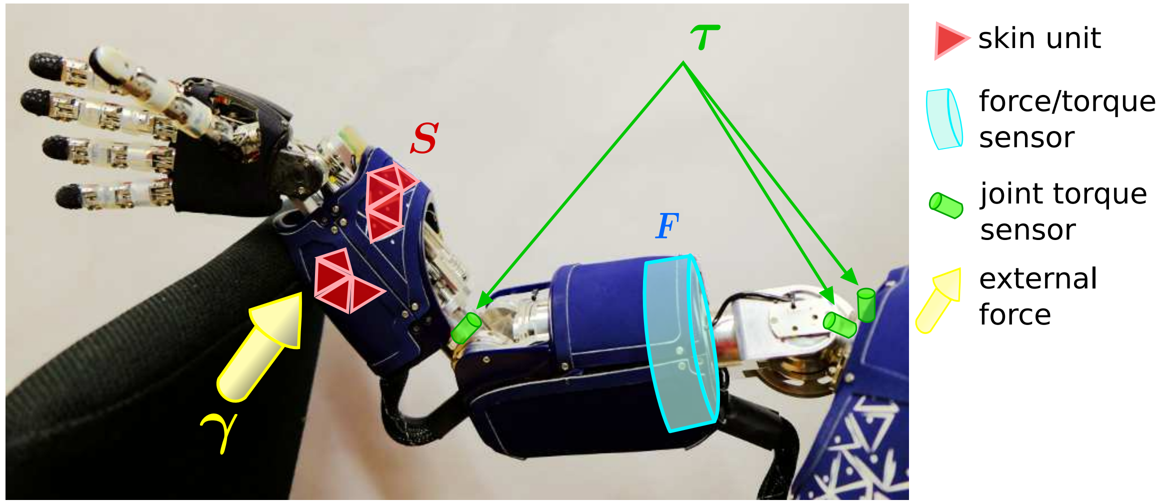




- Models are never perfect
- Identification of dynamic parameters for floating base robots and multiple contacts is very challenging (cf. Yamane 2011)
- Using the skin requires the <u>spatial calibration of each taxel</u> (difficult to automatize, prone to errors - see Del Prete et al, 2012)

Learning the joint torques with contacts

$$\boldsymbol{\tau} = \underbrace{\boldsymbol{M}(\boldsymbol{q})\ddot{\boldsymbol{q}} + \boldsymbol{h}(\boldsymbol{q},\dot{\boldsymbol{q}}) + \epsilon(\boldsymbol{q},\dot{\boldsymbol{q}},\ddot{\boldsymbol{q}})}_{\boldsymbol{\tau}_{\mathrm{ID}}} + \underbrace{\sum_{c_i \in \mathcal{C}} \boldsymbol{J}_{c_i}^T(\boldsymbol{q})\boldsymbol{\gamma}_i}_{\boldsymbol{\tau}_{\mathrm{ext}}}$$



Predicting contact torques is formalised as a regression problem:

$$\boldsymbol{\tau}_{\mathrm{ext}} = \sum_{i \in \mathcal{C}} \boldsymbol{J}_i(\boldsymbol{q})^T \boldsymbol{\gamma}_i = f([\boldsymbol{q}, \boldsymbol{s}, \boldsymbol{F}]) + \epsilon\,,$$

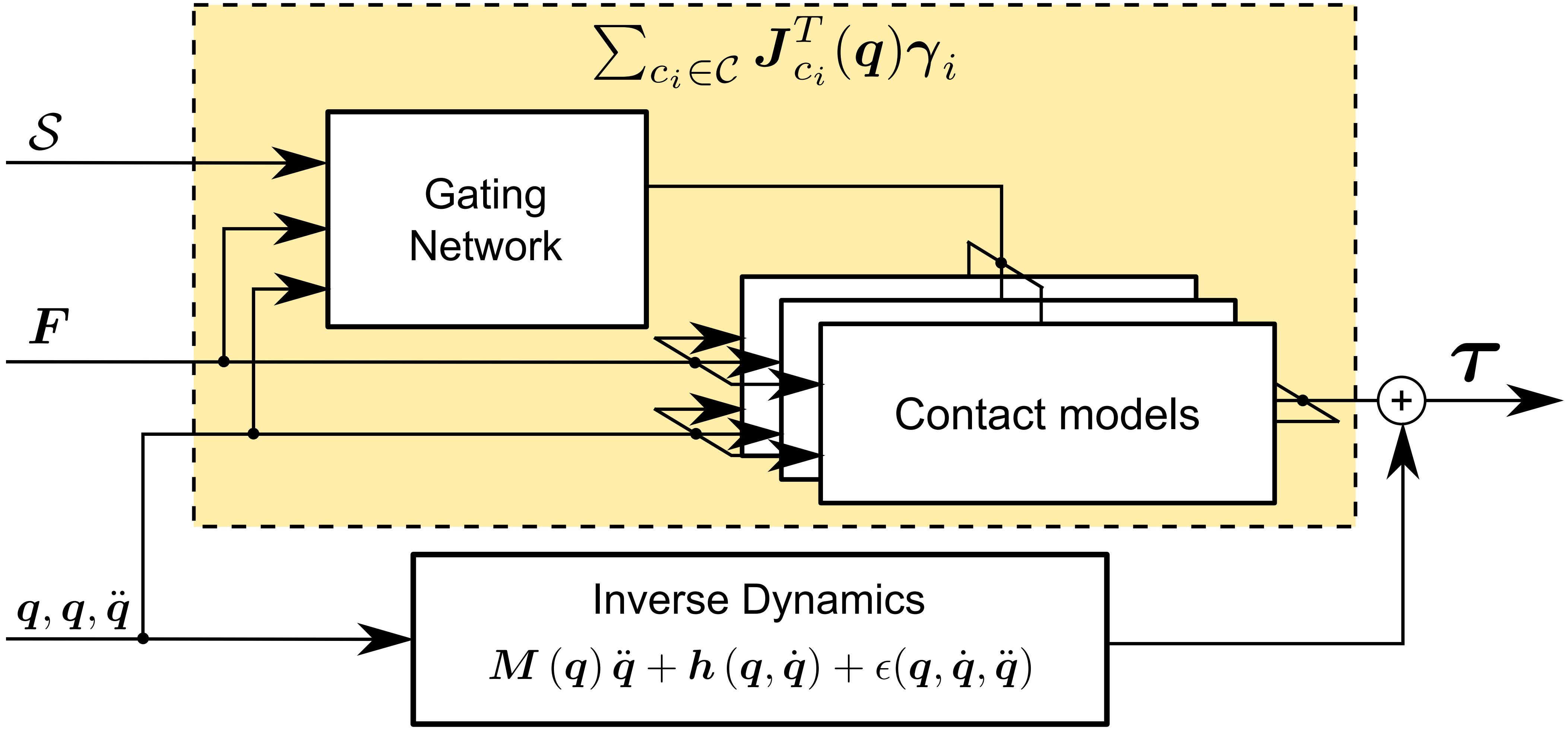
We rephrase this as a "mixture of experts" learning problem:

$$\boldsymbol{\tau}_{\mathrm{ext}} = \sum_{i \in \mathcal{C}} \boldsymbol{J}_i(\boldsymbol{q})^T \boldsymbol{\gamma}_i = \sum_{j \in \mathcal{J}} f_j([\boldsymbol{q}, \boldsymbol{F}]) + \epsilon\,,$$

We can exploit the skin to identify which contact model is currently active => select an "expert" through a gating network.

Calandra, Ivaldi, Deisenroth, Rueckert, Peters (2015) Learning Inverse Dynamics Models with Contacts. ICRA 2015

Learning the joint torques with contacts



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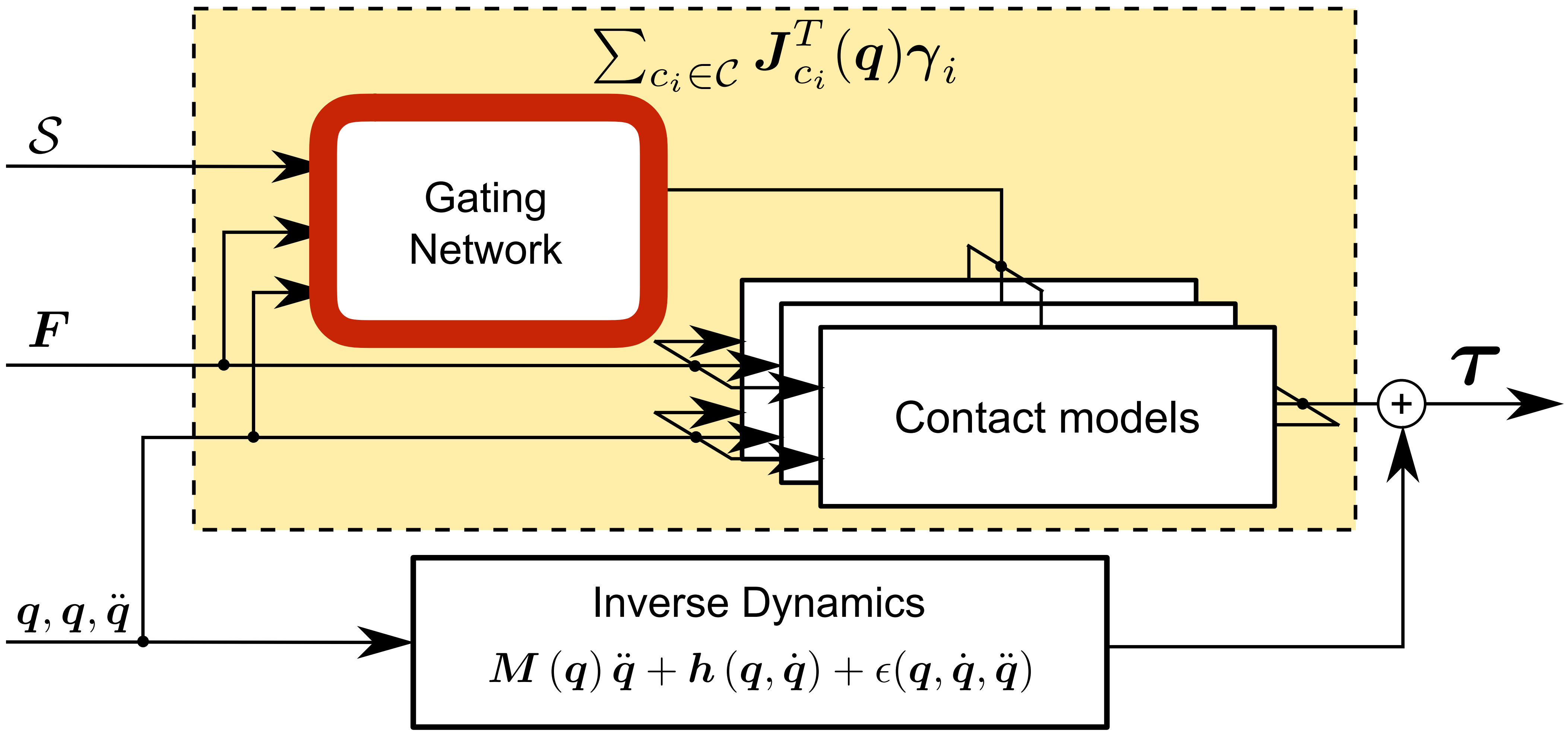
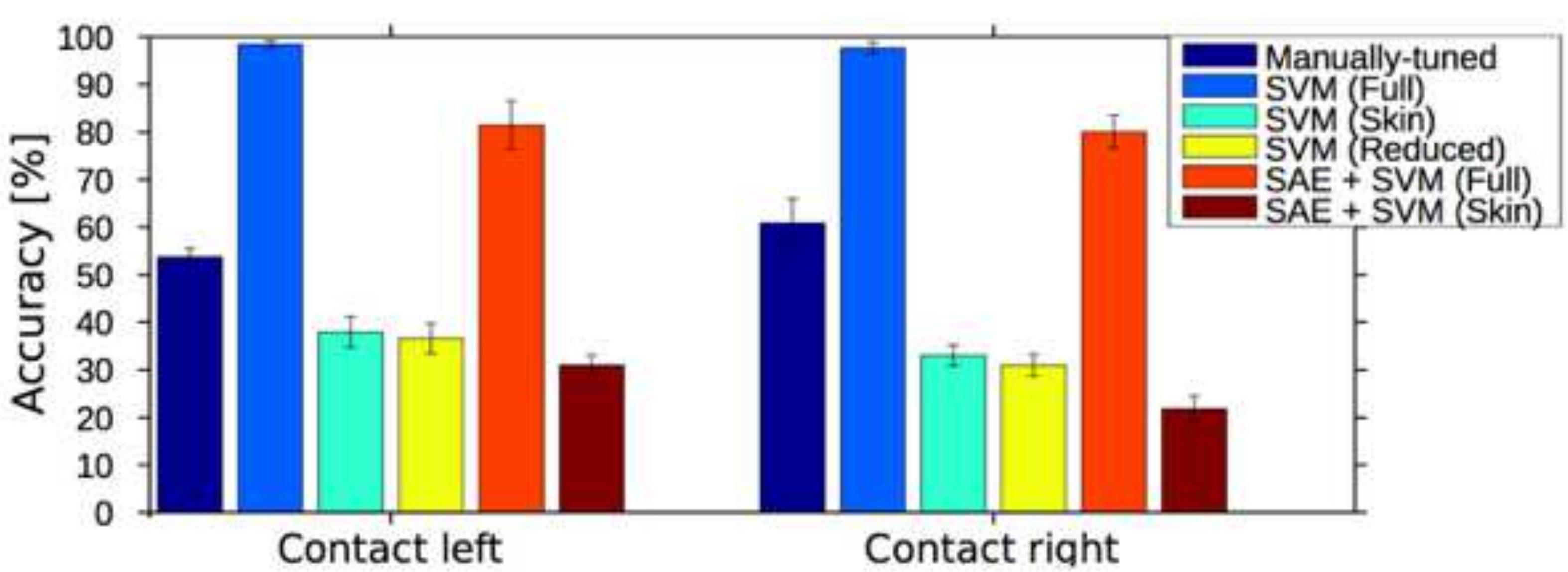
Learning the joint torques with contacts

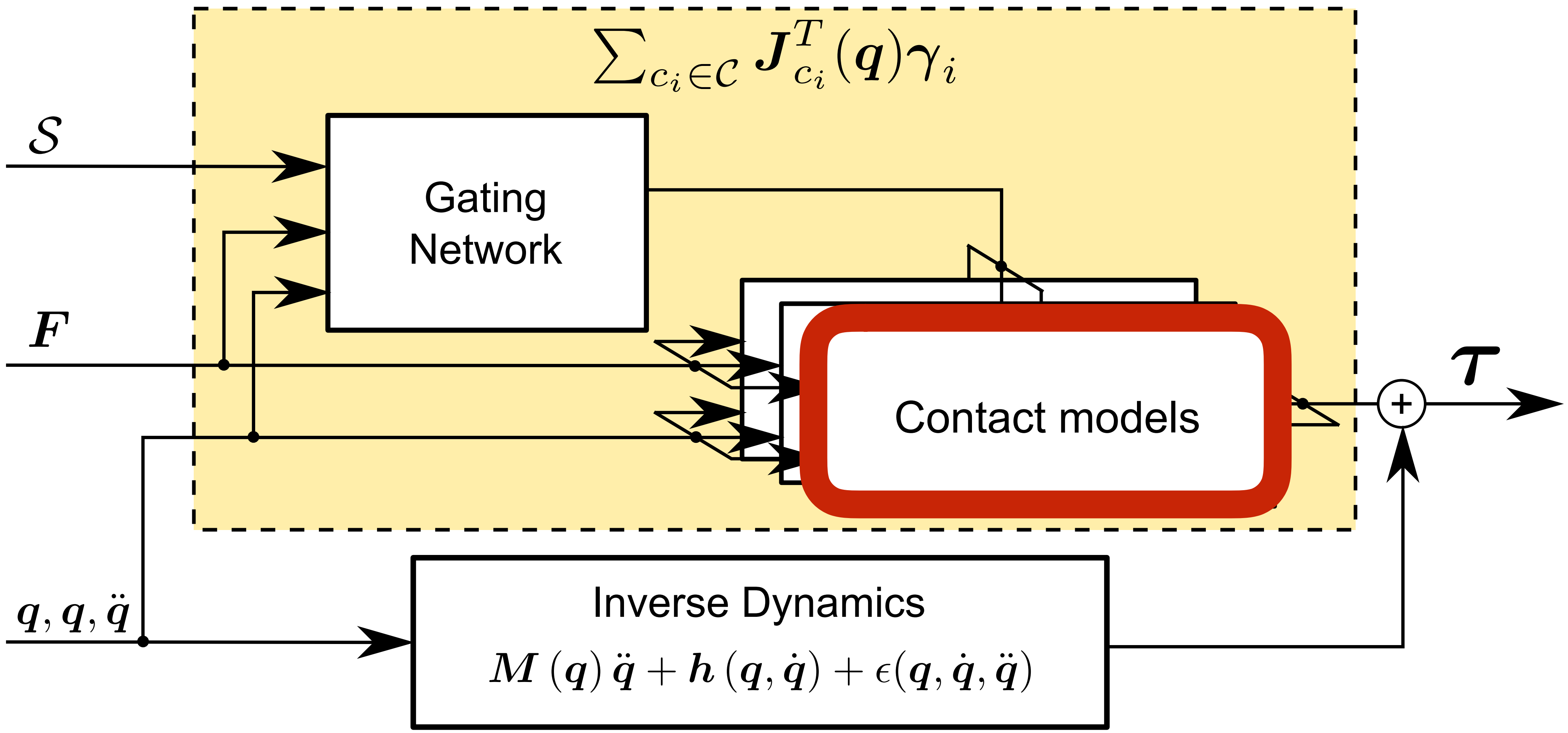


The gating network is a classifier:

$$\mathcal{J} = g(\boldsymbol{q}, \boldsymbol{s}, \boldsymbol{F})$$



Learning the joint torques with contacts

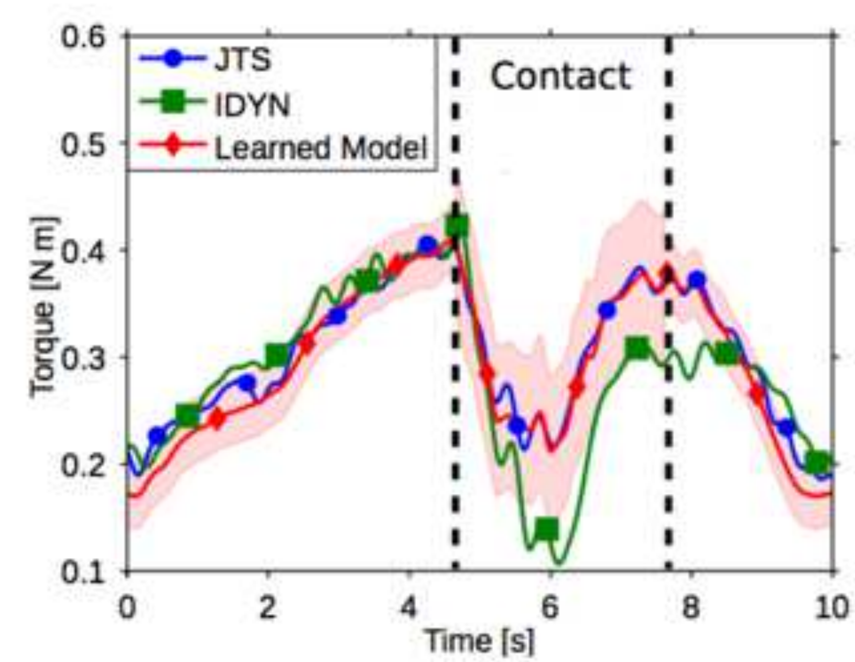


The expert models predict the torque contribution for the ongoing contact.

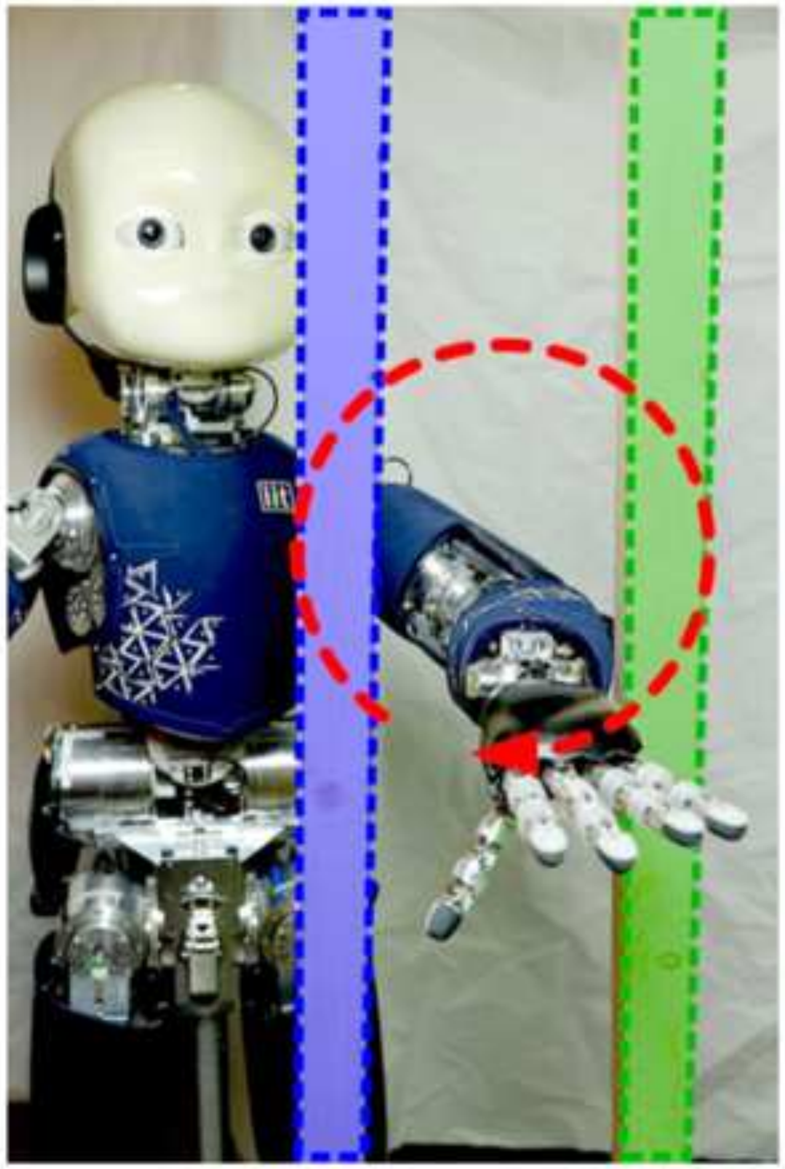
We use Gaussian Processes as a probability distribution over inverse dynamics models:

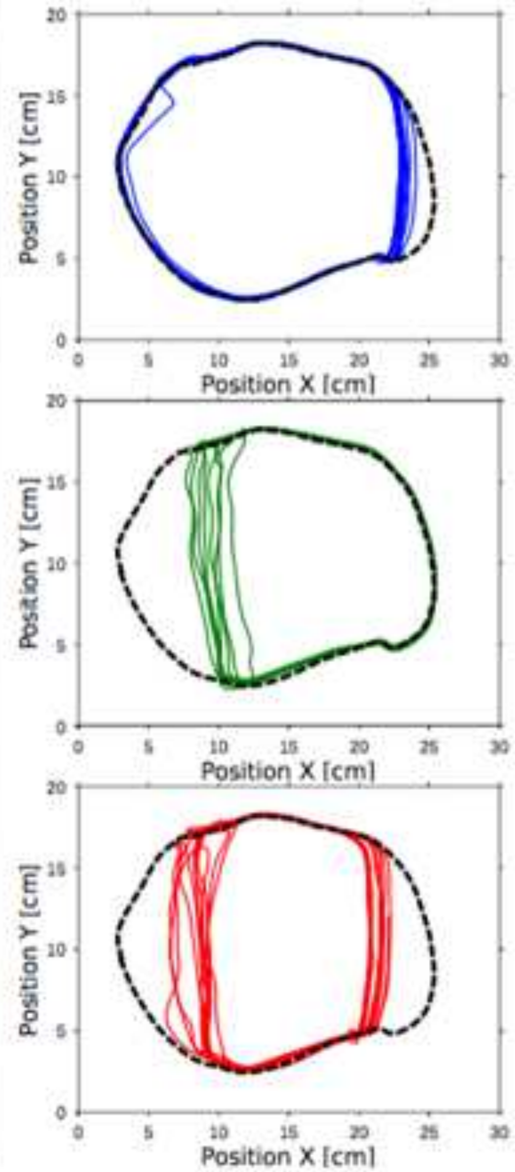
$$f \sim \mathcal{GP}(m_f, k_f)$$

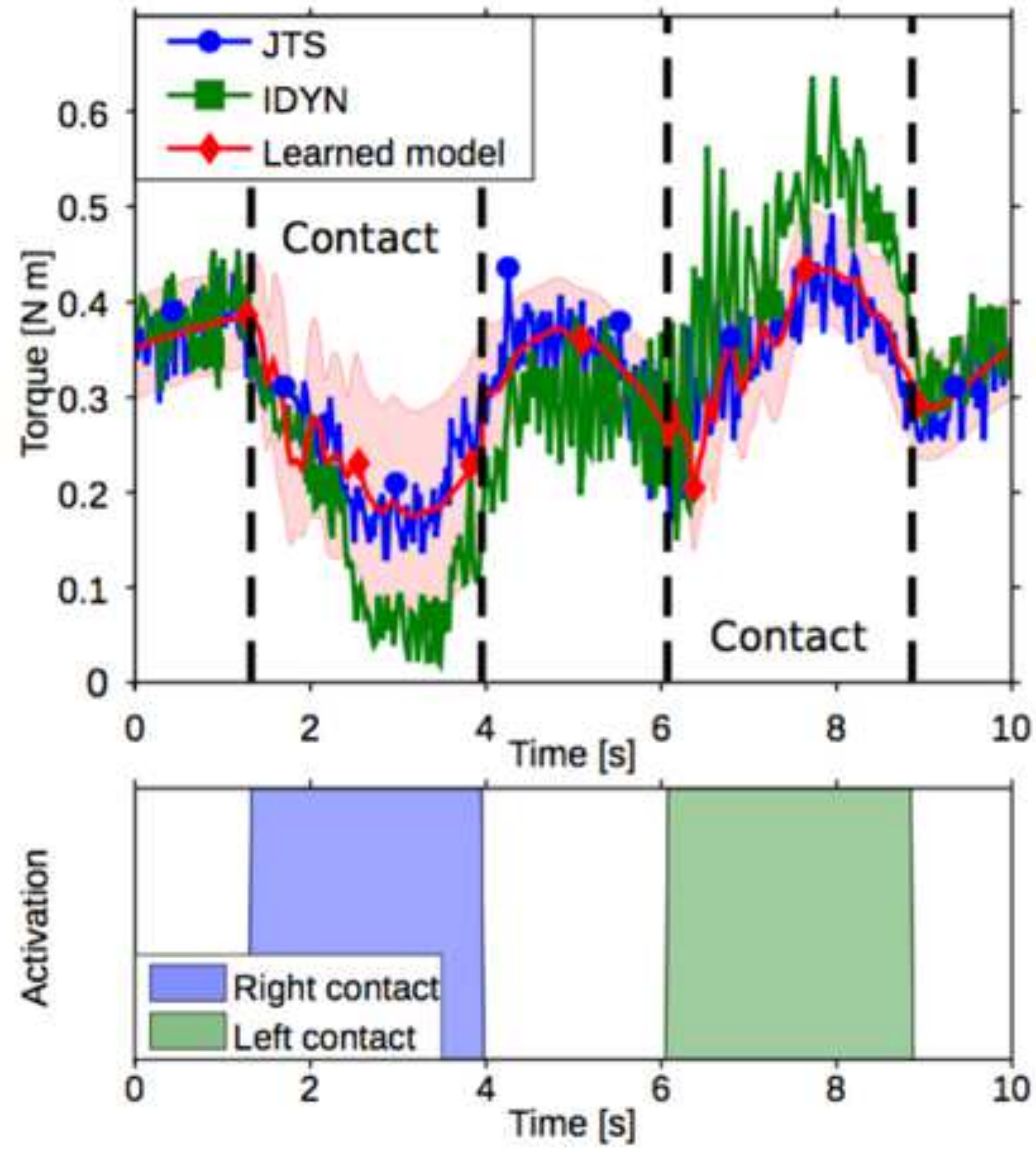
$$m_f \equiv \boldsymbol{\tau}_{\mathrm{ID}}$$



Learning with multiple contacts



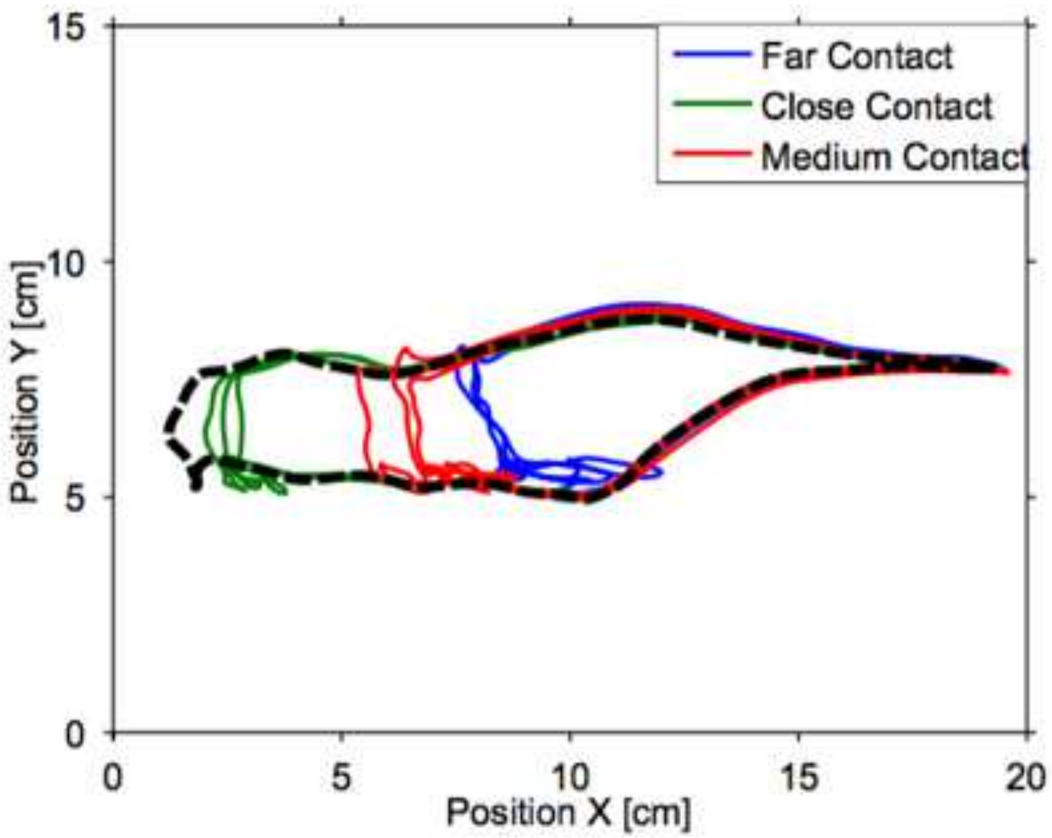




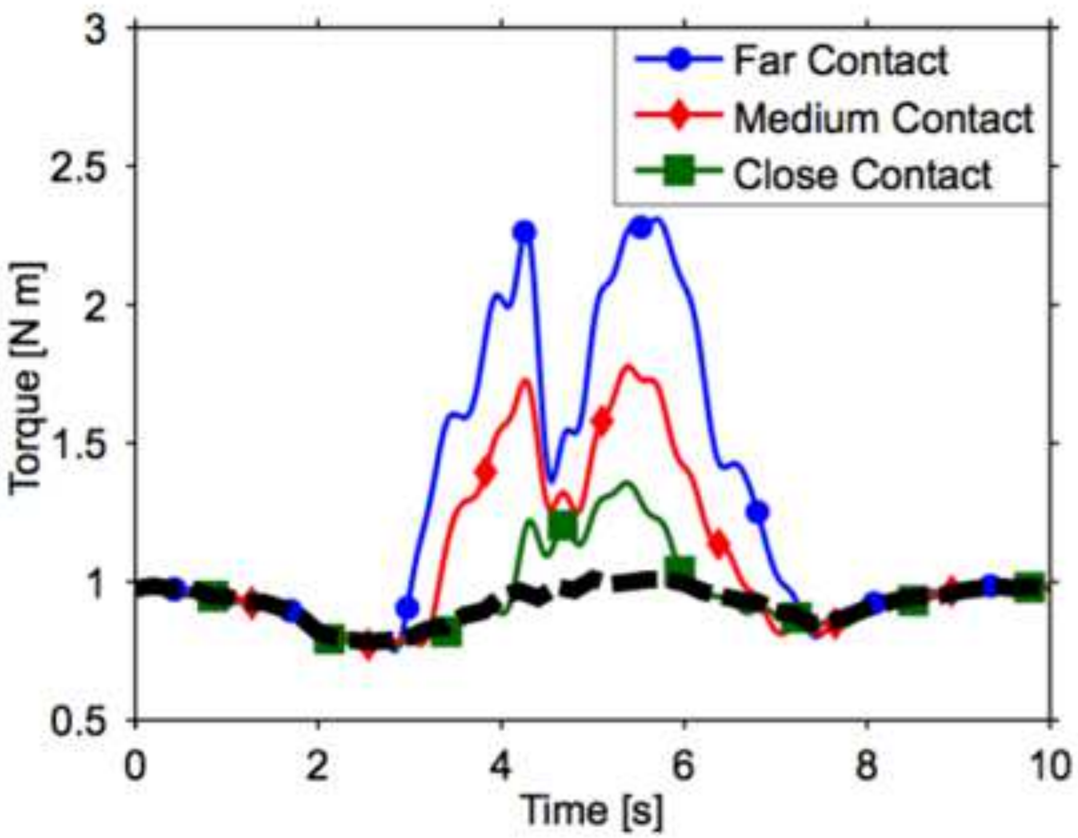
	Method	Shoulder 1 [Nm]	Shoulder 2 [Nm]	Elbow [Nm]
Right contact	*IDYN*	$0.10 \pm 1.3 \times 10^{-3}$	$0.13 \pm 1.6 \times 10^{-3}$	$0.06 \pm 8.1 \times 10^{-4}$
	Our model	$\mathbf{0.04 \pm 6.3 \times 10^{-4}}$	$\mathbf{0.07 \pm 1.2 \times 10^{-3}}$	$\mathbf{0.02 \pm 2.7 \times 10^{-4}}$
Left contact	*IDYN*	$0.08 \pm 1.2 \times 10^{-3}$	$0.16 \pm 2.0 \times 10^{-3}$	$0.05 \pm 8.2 \times 10^{-4}$
	Our model	$\mathbf{0.03 \pm 5.7 \times 10^{-4}}$	$\mathbf{0.07 \pm 9.6 \times 10^{-4}}$	$\mathbf{0.02 \pm 2.8 \times 10^{-4}}$
Both contacts	*IDYN*	$0.10 \pm 1.3 \times 10^{-3}$	$0.11 \pm 1.4 \times 10^{-3}$	$0.07 \pm 8.4 \times 10^{-4}$
	Our model	$\mathbf{0.05 \pm 8.3 \times 10^{-4}}$	$\mathbf{0.10 \pm 1.6 \times 10^{-3}}$	$\mathbf{0.03 \pm 4.0 \times 10^{-4}}$

Contacts on the same link are discriminated

(a) Far contact (b) Medium contact (c) Close contact



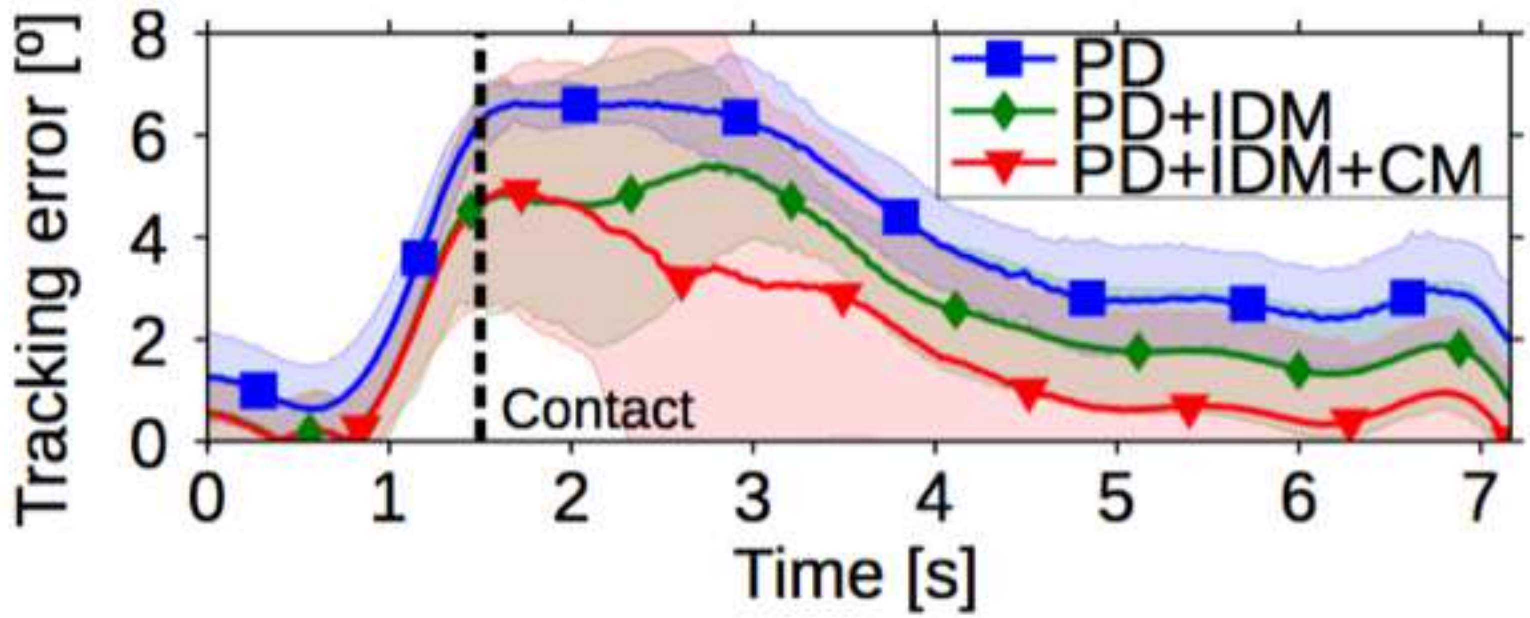
(a) Task space



(b) Torque

Calandra, Ivaldi, Deisenroth, Rueckert, Peters (2015) Learning Inverse Dynamics Models with Contacts. ICRA 2015

Learned models improve control performance



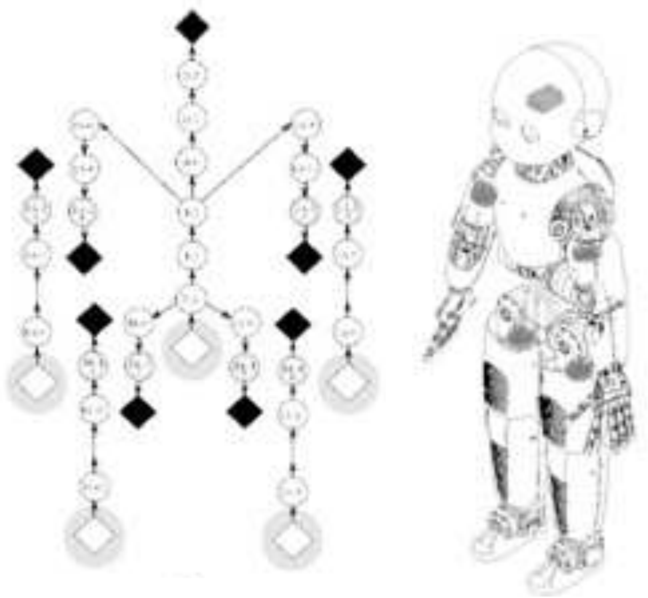
- Without contacts and a perfect model: $\boldsymbol{u} = \boldsymbol{\tau}_{\text{ID}}$
- To compensate for inaccuracies: $\boldsymbol{u} = \boldsymbol{\tau}_{\text{ID}} + \underbrace{\boldsymbol{K}_P\left(\boldsymbol{q}^{\text{des}} - \boldsymbol{q}\right) + \boldsymbol{K}_D\left(\dot{\boldsymbol{q}}^{\text{des}} - \dot{\boldsymbol{q}}\right)}_{\boldsymbol{\tau}_{\text{PD}}}$
- With contacts: $\boldsymbol{u} = \boldsymbol{\tau}_{\text{ID}} + \boldsymbol{\tau}_{\text{PD}} + \boldsymbol{\tau}_{\text{ext}}$

Controller	Shoulder Pitch	Shoulder Roll	Shoulder Jaw	Elbow
PD	0.50 ± 0.40	4.67 ± 2.52	3.78 ± 1.91	2.04 ± 0.11
PD + IDM	0.49 ± 0.38	3.96 ± 2.28	2.63 ± 1.65	$\mathbf{0.25 \pm 0.18}$
PD + IDM + CM	$\mathbf{0.46 \pm 0.31}$	$\mathbf{3.34 \pm 1.68}$	$\mathbf{1.81 \pm 1.55}$	0.46 ± 0.19

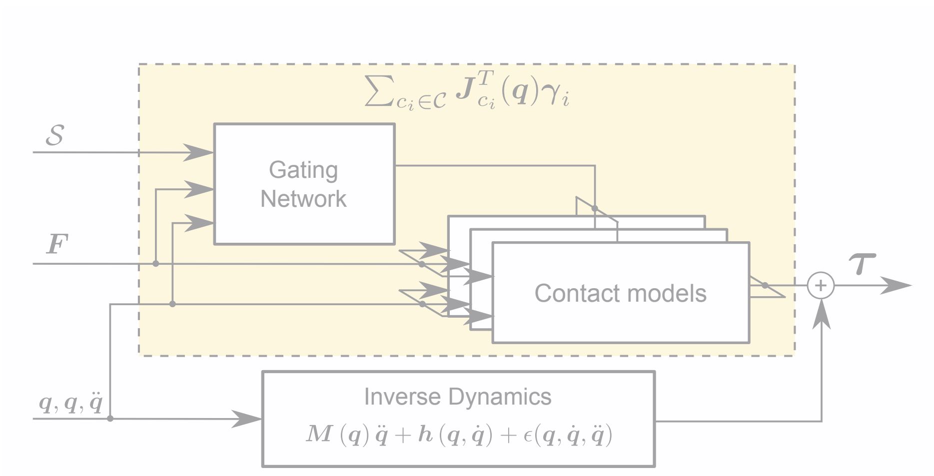
- The tracking error is smaller with the learned inverse dynamics!

Calandra, Ivaldi, Deisenroth, Peters (2015) Learning Torque Control in Presence of Contacts using Tactile Sensing from Robot Skin. HUMANOIDS 2015

Outline of the talk



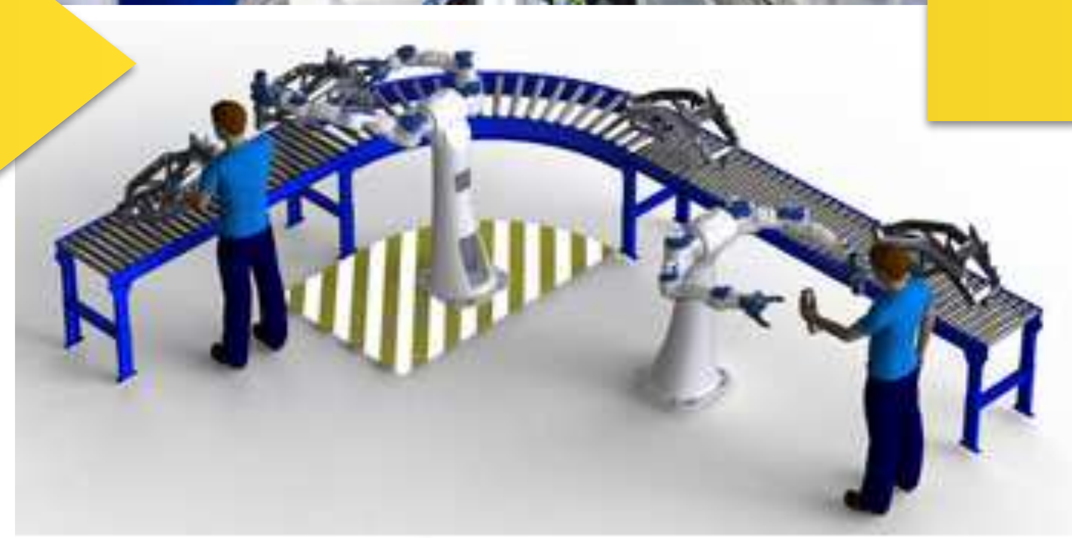
iDyn: computing whole-body dynamics thanks to inertial, force and tactile sensors



Learning the dynamics in presence of contacts thanks to the skin

Physical interaction: even non-experts can teach iCub how to assemble objects

Motivation: more and more collaboration



An assembly line model of collaborative robots working with human coworkers (Courtesy of Yaskawa Motoman Robotics, Miamisburg, Ohio)

Skilled operator	Ordinary people
Robots ~ machines	Robots ~ agents

Human-human collaboration

Individual factors appear in the interaction

Ivaldi, S.; Lefort, S.; Peters, J.; Chetouani, M.; Provasi, J.; Zibetti, E. (2016) Towards engagement models that consider individual factors in HRI: on the relation of extroversion and negative attitude towards robots to gaze and speech during a human-robot assembly task. Int. Journal Social Robotics

Personality, attitudes

- "*Attitudes and personality traits are latent, hypothetical dispositions that must be inferred from observable responses*" (Ajzen, 1986)

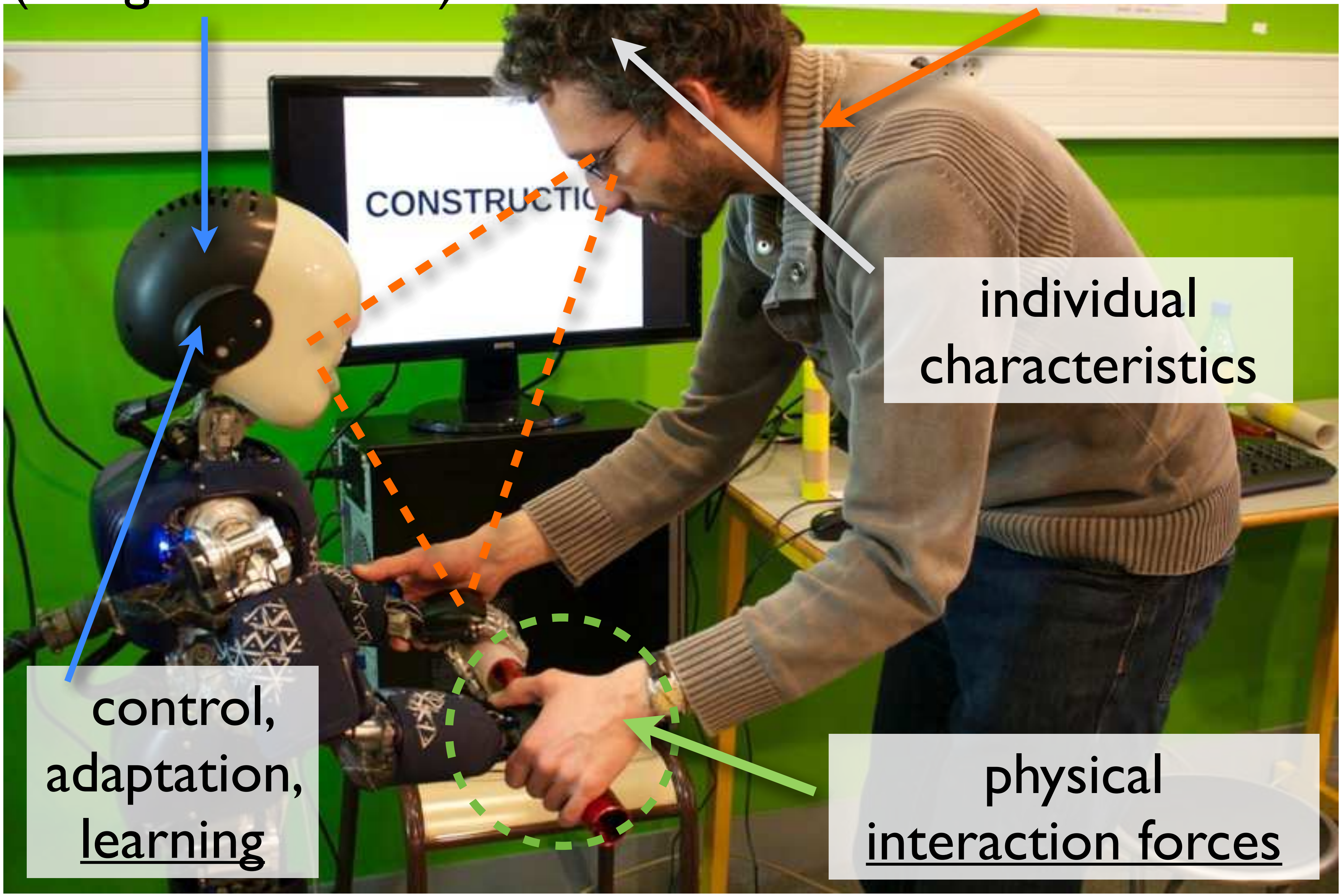
- The effect of personality and attitudes is observable on the <u>overt</u> actions of the individual.

- **Both attitudes and personality traits influence our actions and behaviors, together with other social, contextual and individual factors.**

Human-robot collaboration

multimodal “behavior” control
(use/give feedback)

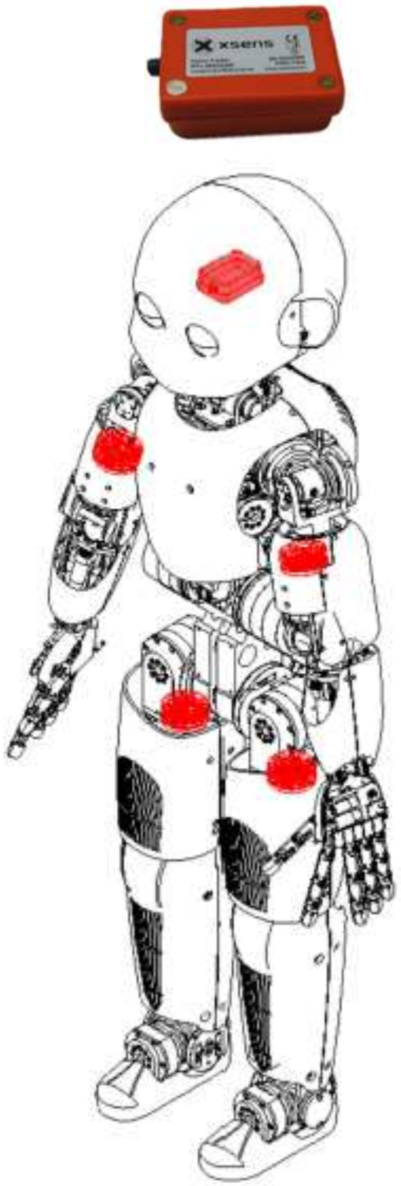
verbal/non-verbal signals



Physical interaction

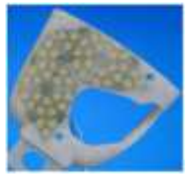
Physical interaction thanks to iDyn

Inertial sensor

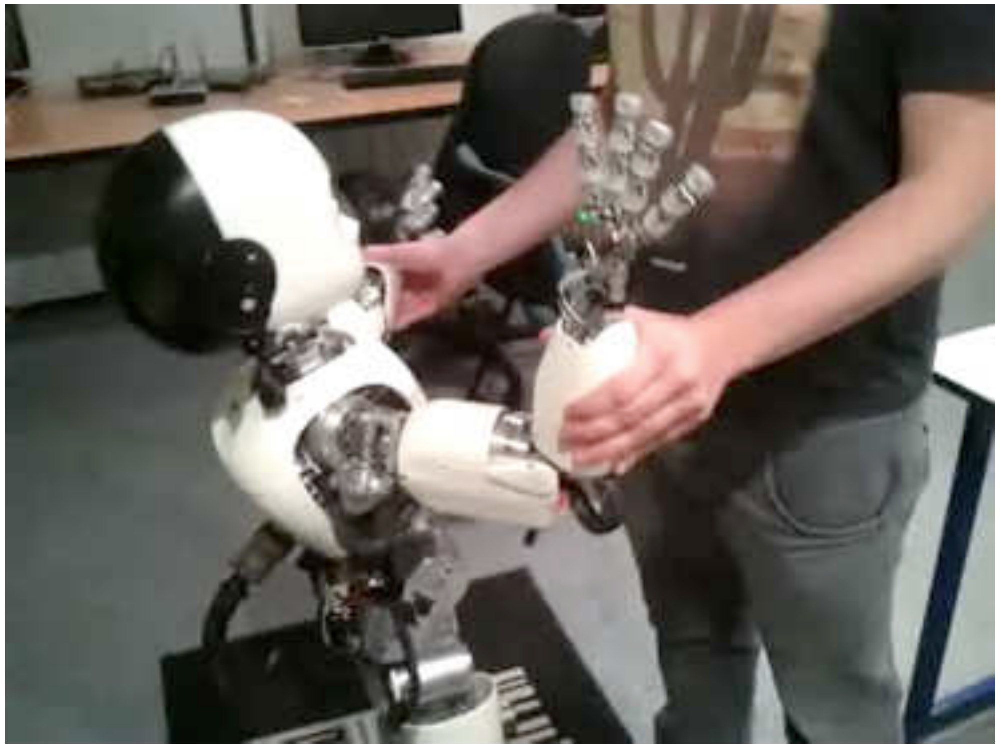


F/T sensor

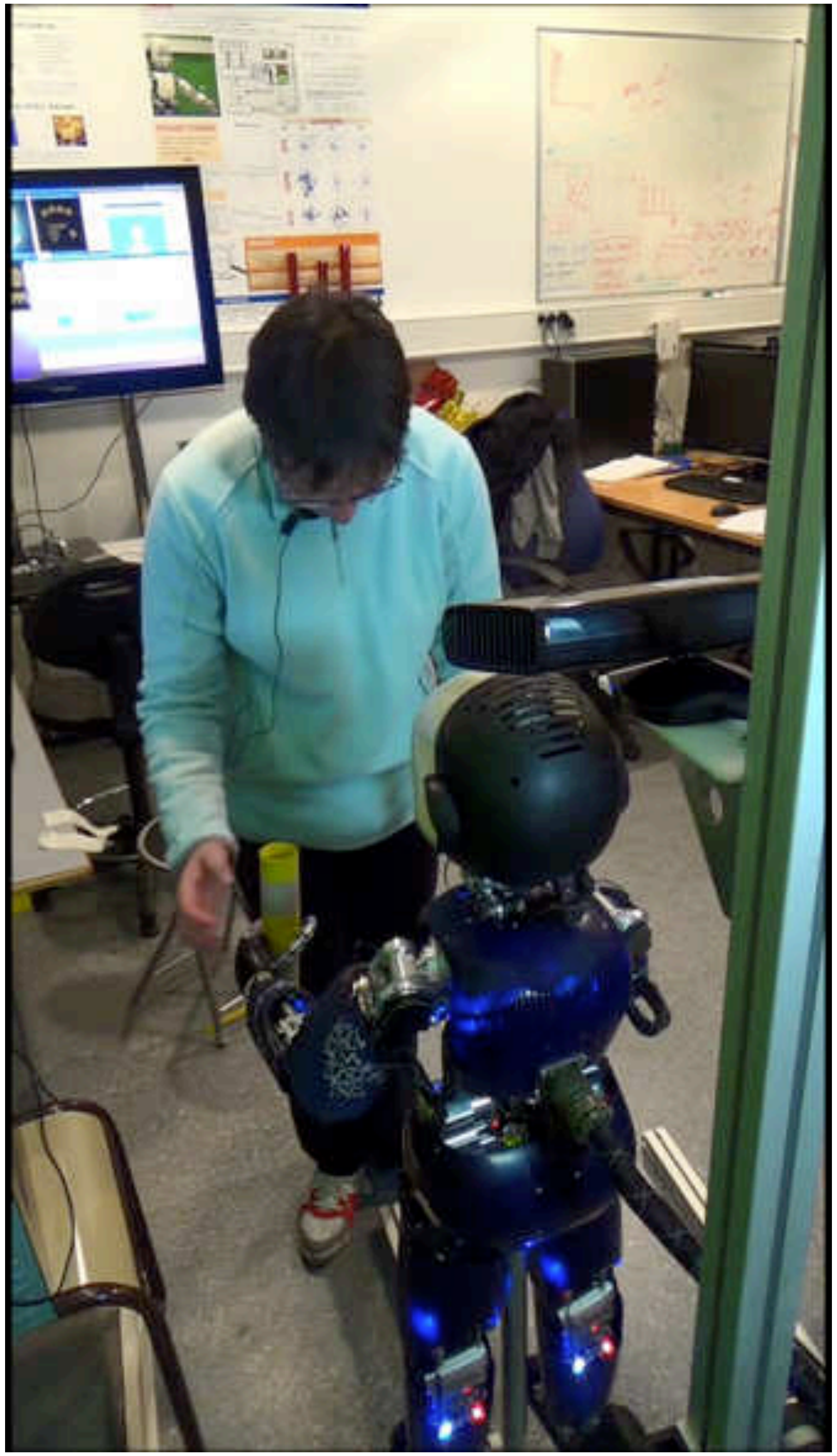
skin



Ivaldi, et al. HUMANOIDS 2011



Droniou et al, RAS 2015, Stulp et al, HUMANOIDS 2013



Ivaldi, et al. IJSR 2016

Social interaction

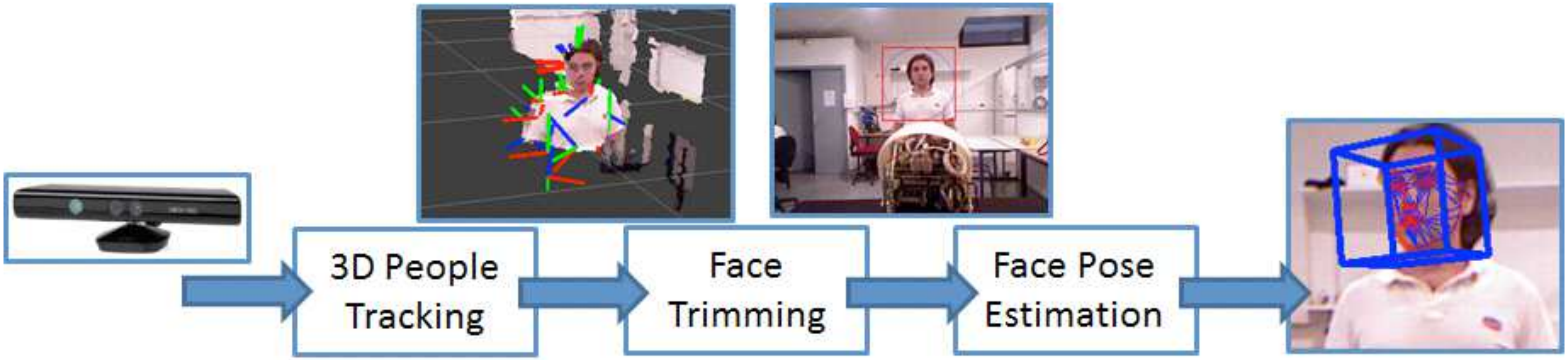
<u>verbal/non-verbal signals</u>

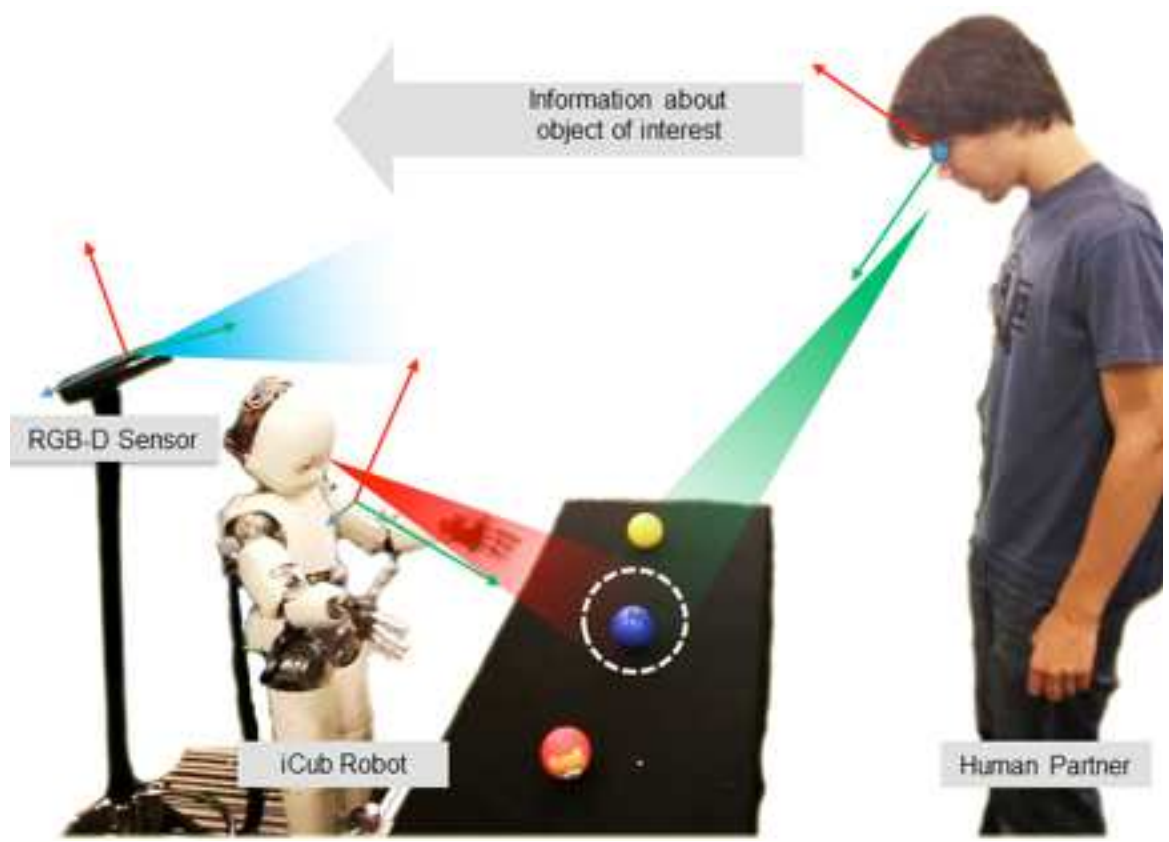
Social signals

Study	Ref	Social signals used to assess the engagement
Castellano et al., 2009	[9]	Gazes towards the robot Smiles
Ishii et al., 2011	[25]	Gazes Towards the object the agent is talking about Gazes Towards the agent's head Gazes Towards anything else
Ivaldi et al., 2014	[26]	Reaction time to the robot attention utterance stimulus Time between two consecutive interactions
Le Maitre and Chetouani, 2013	[28]	Utterance directed to the robot Utterance directed to self
Rich et al., 2010	[41]	Gazes Focused (man and robot are looking at the same object Gazes Mutual (man and robot look at each other) Utterance Adjacent (two successive locutions, produced one by the robot, the other by the human, separated by a maximum interval) Utterance Responses (the subject responds to the robot through a gesture or a very short verbal intervention)
Sanghvi et al., 2011	[42]	Postures (curve and inclination of the back)
Sidner et al., 2004	[45]	Gazes Shared (mutual or directed) Gazes Directed towards the robot without the latter looking at the human
Sidner et al., 2005	[46]	Gazes Shared (mutual or directed) Gazes Directed towards the robot without the latter looking at the human

Table 1 Social signals used in literature as metrics for the assessment of engagement.

Measuring gaze in dyadic HRI

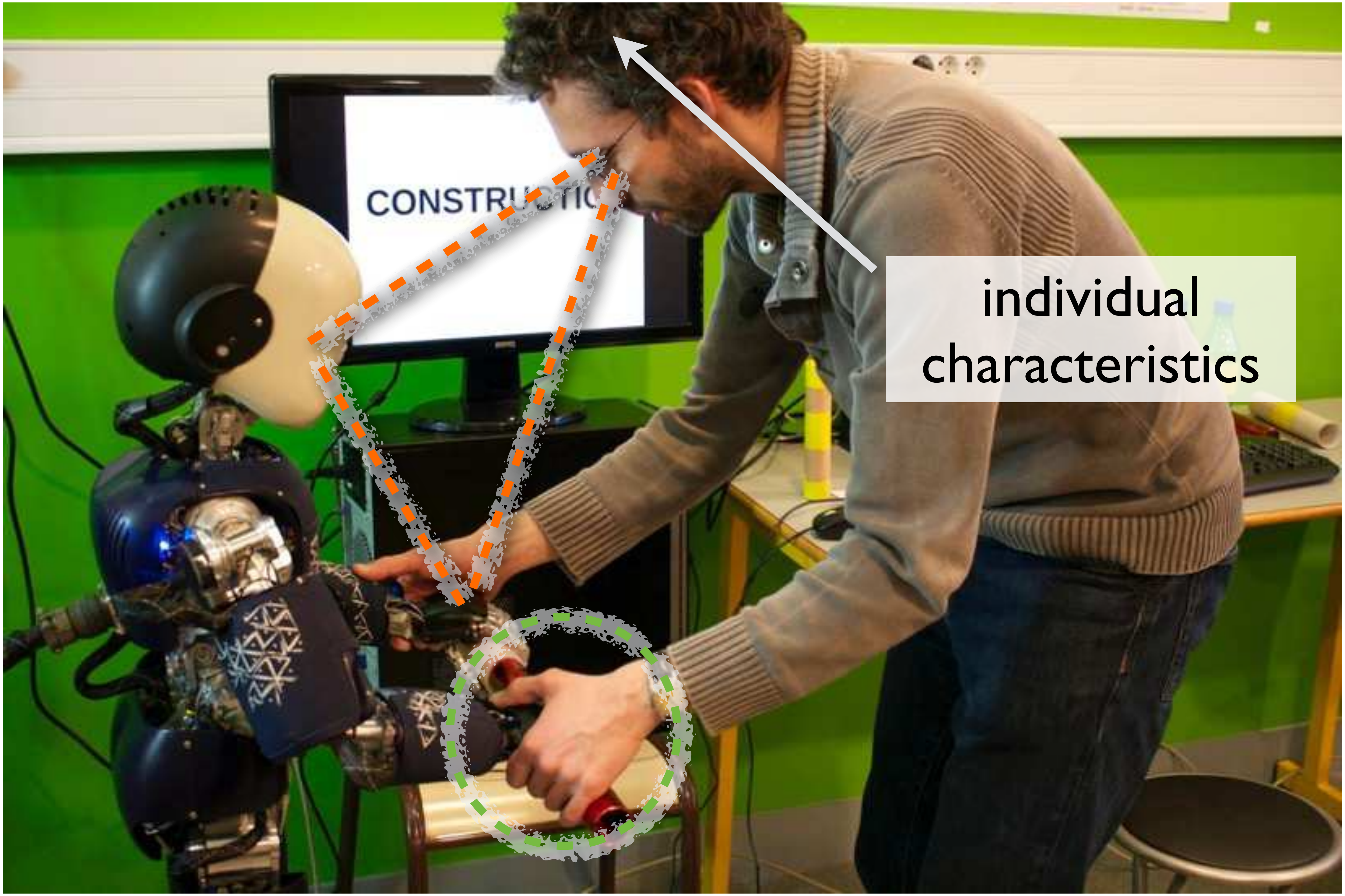




Ivaldi et al, Frontiers in Neurorobotics, 2014

Individual factors influence our behavior

individual factors, contexts,
personality traits & attitudes



Personality traits vs attitudes

- <u>Personality</u> traits : characteristic of the human personality that leads to consistent patterns of behaviors.
  - Assumed to be almost invariant for an adult.
  - Stable over time.
  - Different theories to explain where they come from.

The <u>personality</u> of an individual consists of several characteristics and dispositions, each being described as a "gathering of attitudes obviously linked to each other, or as patterns of cognitive treatment of the information or underlying psycho-physiological mechanisms generating specific dispositions towards some behaviors" (Scherer, 1981, p.116).

- An <u>attitude</u> is a behavior tendency, directed towards people, objects, situations, and is generally determined by the social context, the background and experiences of the individual.
  - More contingent.
  - Can change through time because of subjective experiences.

<u>Attitudes</u> are mental dispositions matured through experience, that might impact the reactions (behavioral, verbal, emotional) of the individual towards objects and situations (Gaudiello et al., 2015).

Personality: Big 5 Factor Model

	Factor	Low Scorers	High Scorers
1	Openness	Down-to-earth Uncreative Conventional Uncurious	Imaginative Creative Original Curious
2	Conscientiousness	Negligent Lazy Disorganized Late	Conscientious Hard-working Well-organized Punctual
3	Extroversion	Loner Quiet Passive Reserved	Joiner Talkative Active Affectionate
4	Agreeableness	Suspicious Critical Ruthless Irritable	Trusting Lenient Soft-hearted Good-natured
5	Neuroticism	Calm Even-tempered Comfortable Unemotional	Worried Temperamental Self-conscious Emotional

McCrae, R. R., & Costa, P.T. (2003). Personality in Adulthood: A Five-Factor Theory Perspective. New York: Guilford Press

Attitude: Negative attitude towards robots (NARS)

N.	Questionnaire Item in English	Questionnaire Item in French	Subscale
1	I would feel uneasy if robots really had emotions.	Je me sentirais mal à l'aise si les robots avaient réellement des émotions.	**S2**
2	beings.	Quelque chose de mauvais pourrait se produire si les robots devenaient des êtres vivants.	**S2**
3	I would feel relaxed talking with robots.	Je serais détendu(e) si je parlais avec des robots.	S3*
4	I would feel uneasy if I was given a job where I had to use robots.	Je me sentirais mal à l'aise dans un travail où je devrais utiliser des robots.	S1
5	If robots had emotions, I would be able to make friends with them.	Si les robots avaient des émotions, je serai capable de devenir ami(e) avec eux.	S3
6	I feel comforted being with robots that have emotions.	Je me sens réconforté(e) par le fait d'être avec des robots qui ont des émotions.	S3*
7	The word <u>"robot"</u> means nothing to me.	Le mot ''robot'' ne signifie rien pour moi.	S1
8	I would feel nervous operating a robot in front of other people.	Je me sentirais nerveux/nerveuse de manœuvrer un robot devant d'autres personnes.	S1
9	I would hate the idea that robots or artificial <u>intelligences</u> were	Je détesterais que les robots ou les intelligences artificielles fassent des jugements sur des choses.	S1
10	I would feel very nervous just standing in front of a robot.	Le simple fait de me tenir face à un robot me rendrait très nerveux/ nerveuse.	S1
11	I feel that if I depend on robots too much, something bad might	Je pense que si je dépendais trop fortement des robots, quelque chose de mauvais pourrait arriver.	**S2**
12	I would feel paranoid talking with a robot.	Je me sentirais paranoïaque de parler avec un robot.	S1
13	I am concerned that robots would be a bad influence on children.	Je suis préoccupé(e) par le fait que les robots puissent avoir une mauvaise influence sur les enfants.	**S2**
14	I feel that in the future society will be dominated by robots.	Je pense que dans le futur la société sera dominée par les robots.	**S2**

Original (Japanese/English): Nomura et al, 2004. French translation: Ivaldi et al., 2015.

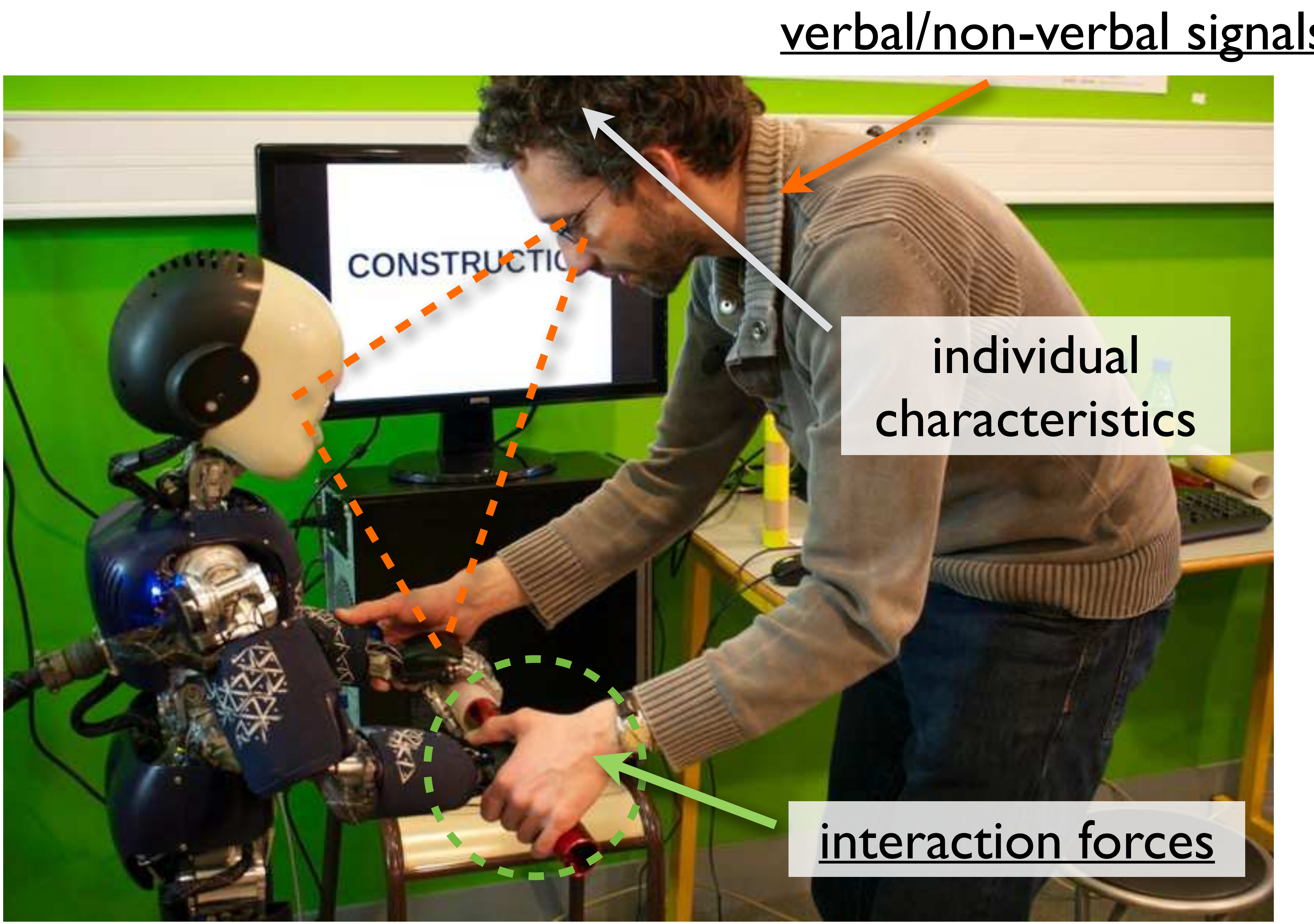
Why personality is useful in HRI

- Personality traits influence people acceptance of robots (Fischer, 2011; Looije et al., 2010; Weiss et al. 2008), and the way we behave with robots
  - extroverts tend to trust robots more than introverts (McBride & Morgan, 2010)
  - proactive people keep higher distance from the robot than others (Walters et al, 2005)
  - people with negative attitude towards robots respond slower to the robot's speech (Nomura et al, 2006)

- Personality traits may correlate with task performances
  - extroversion influence tasks that do not enforce very short time constraints, while agreeableness is important in tasks with high level of collaboration (Mc Givney et al, 2008)
  - the more people are extrovert, the more they talk to the robot (Ivaldi et al, 2015)

=> we need a parametrised model

Studying human-robot collaborative assembly



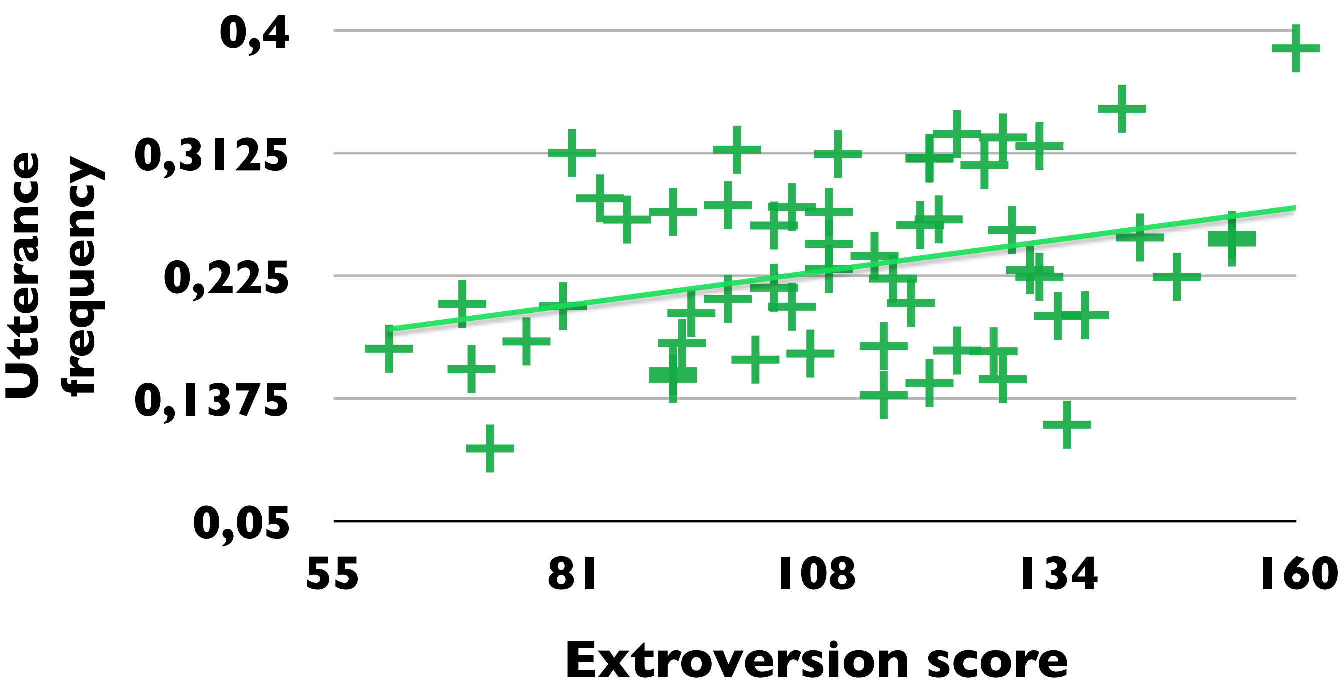
Ordinary people teach iCub how to assembly an object

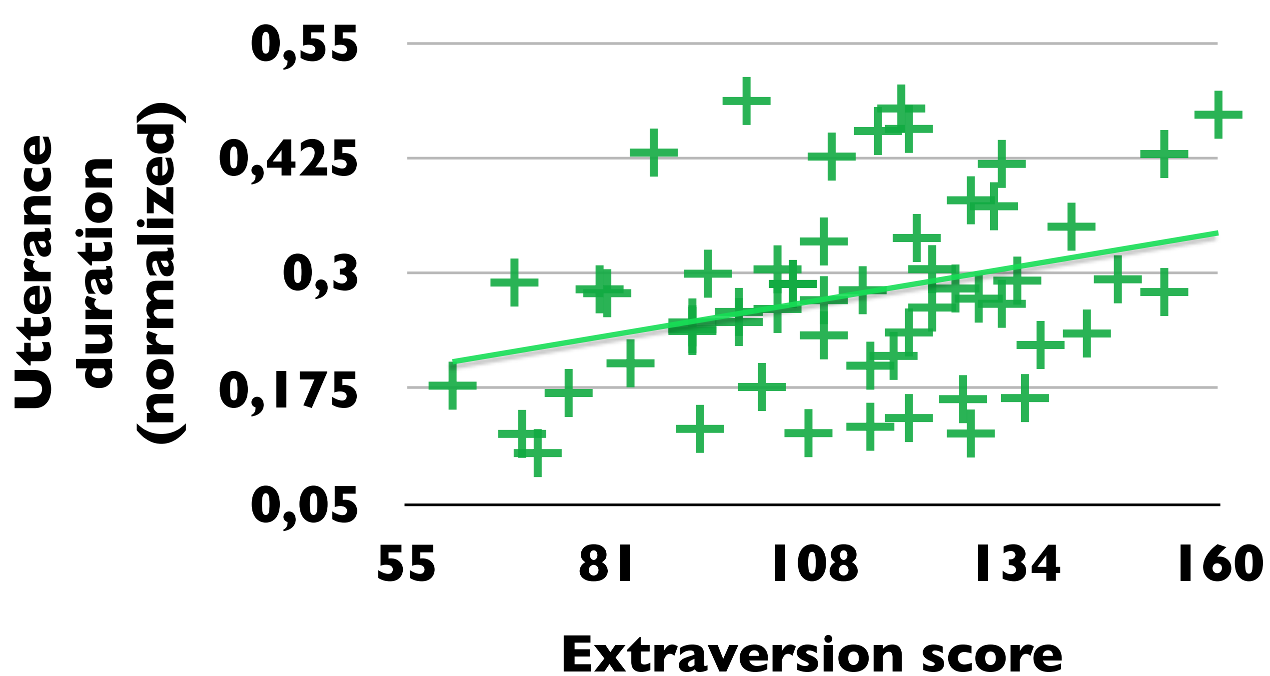
56 participants (19 M, 37 F), aged 36,95±14,32 (min 19, max 65)

Assembly: personality effects on speech

Extroverts talk more to the robot

Variable	Extroversion score
Utterance frequency	r^2= 0,318 ; p=0.017 <0.05
Utterance duration	r^2= 0,321 ; p=0.016<0.05



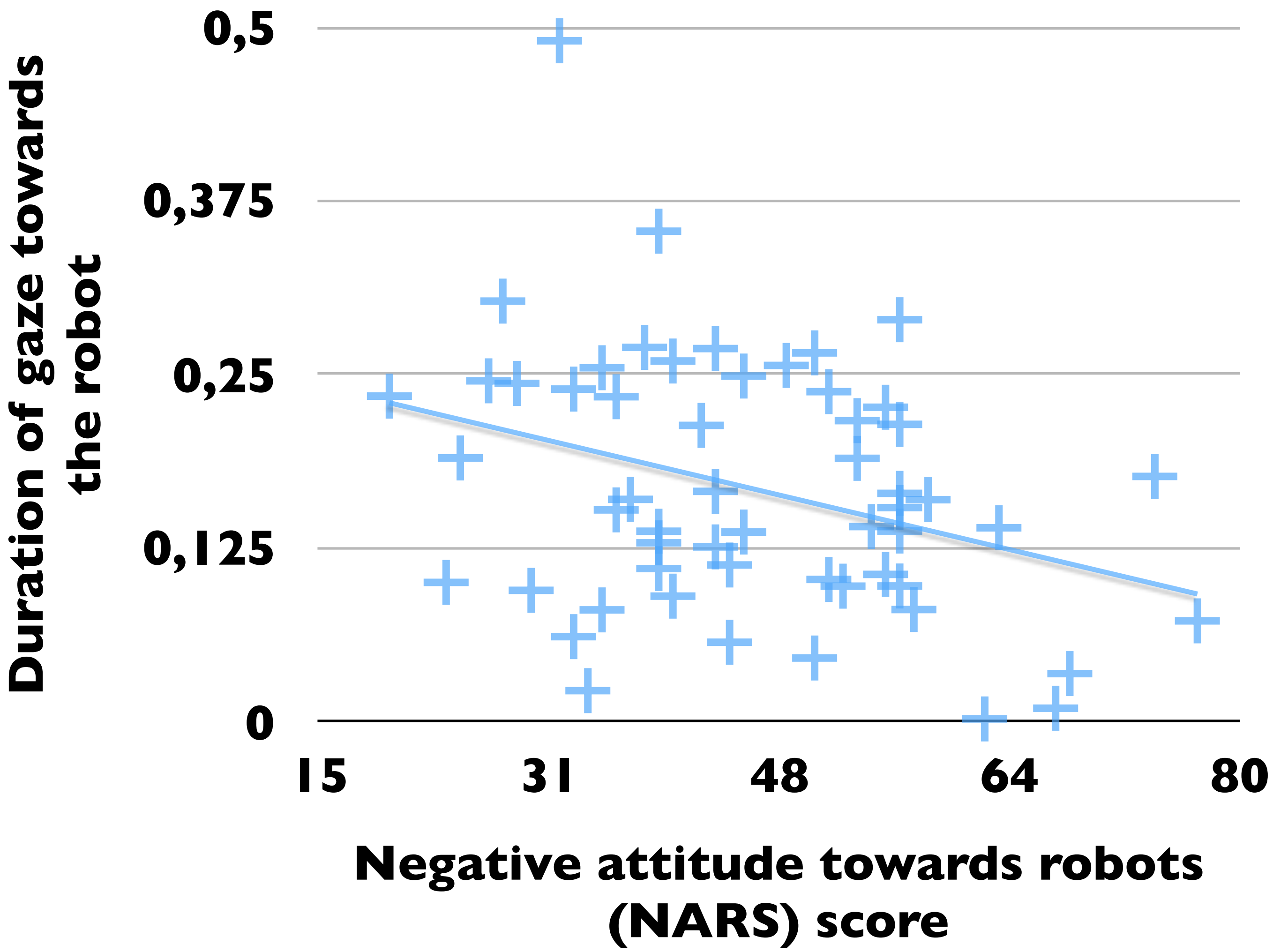


Ivaldi, S.; Lefort, S.; Peters, J.; Chetouani, M.; Provasi, J.; Zibetti, E. (2016) Towards engagement models that consider individual factors in HRI: on the relation of extroversion and negative attitude towards robots to gaze and speech during a human-robot assembly task. Int. Journal Social Robotics

Assembly: personality effects on gaze

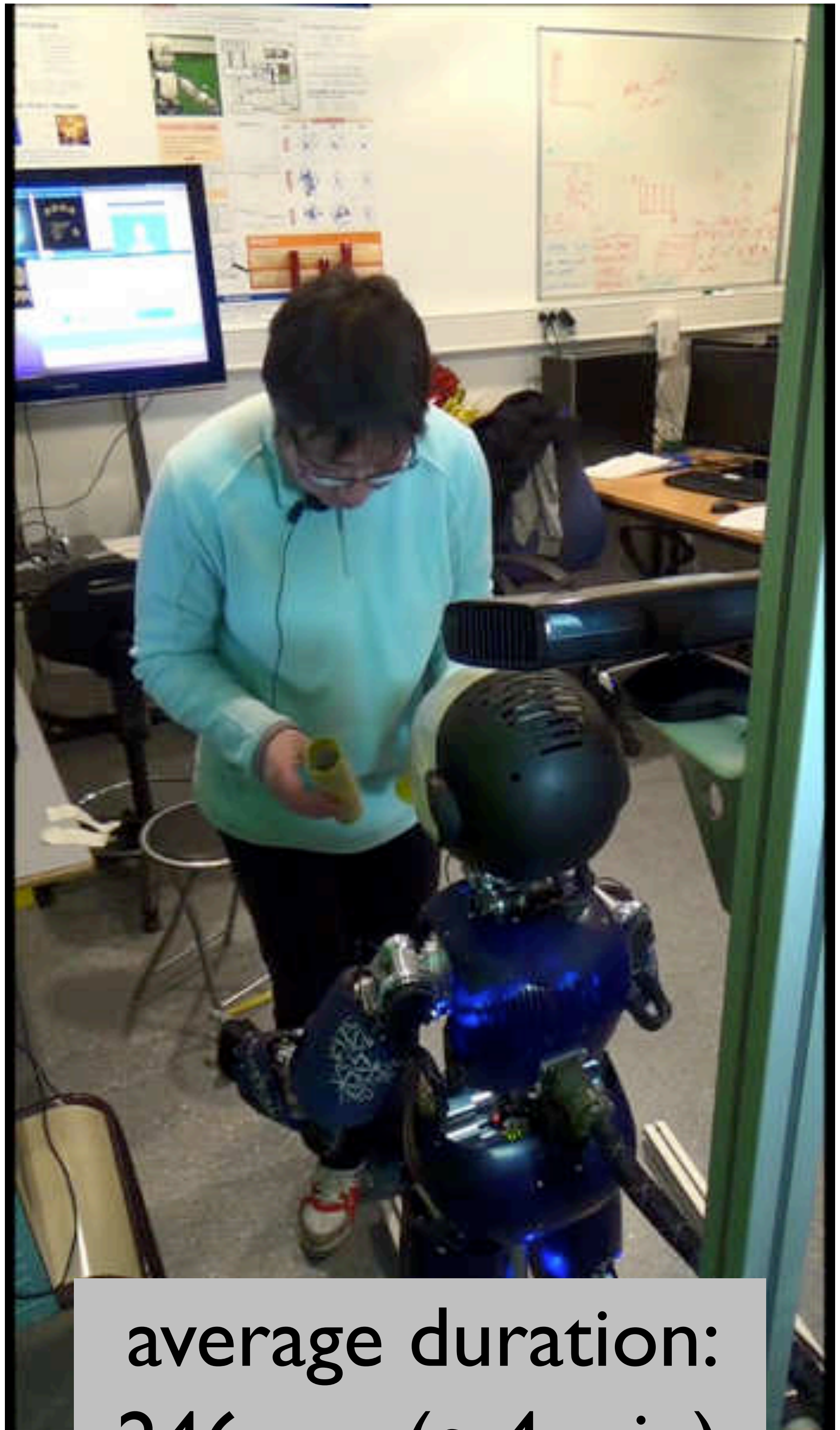
People with negative attitude towards robots look at the robot face for shorter time, and more at the hands where the physical interaction occurs.

Variable	Score "negative attitude towards robots"
Gaze towards face duration	r^2= -0,331 ; p=0.013<0,05
Gaze towards hands duration	r^2= 0.355 ; p=0.007 < 0.05



Ivaldi, S.; Lefort, S.; Peters, J.; Chetouani, M.; Provasi, J.; Zibetti, E. (2016) Towards engagement models that consider individual factors in HRI: on the relation of extroversion and negative attitude towards robots to gaze and speech during a human-robot assembly task. Int. Journal Social Robotics

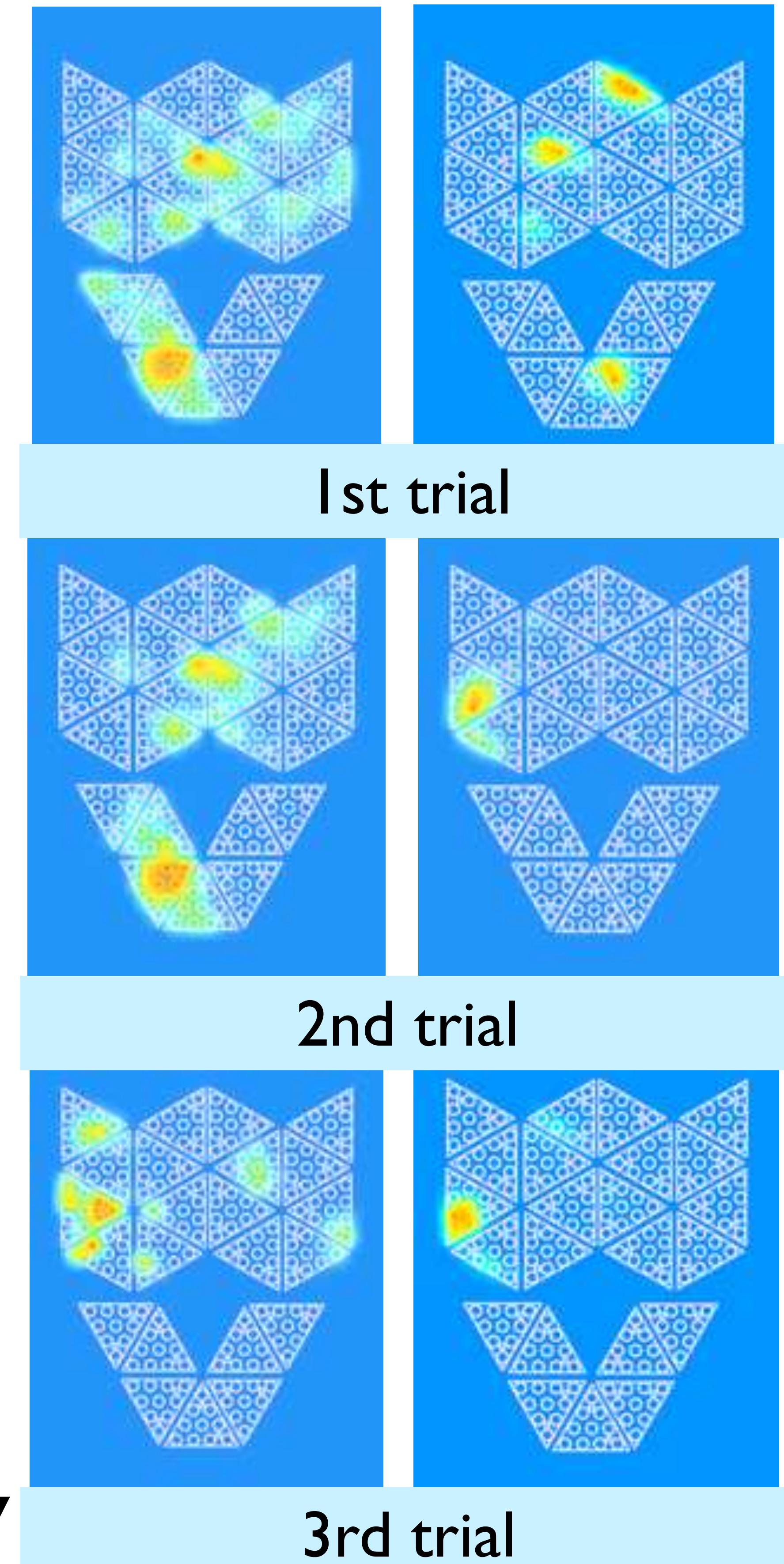
Tactile signatures during teaching



average duration:
246 sec (≈4 min)

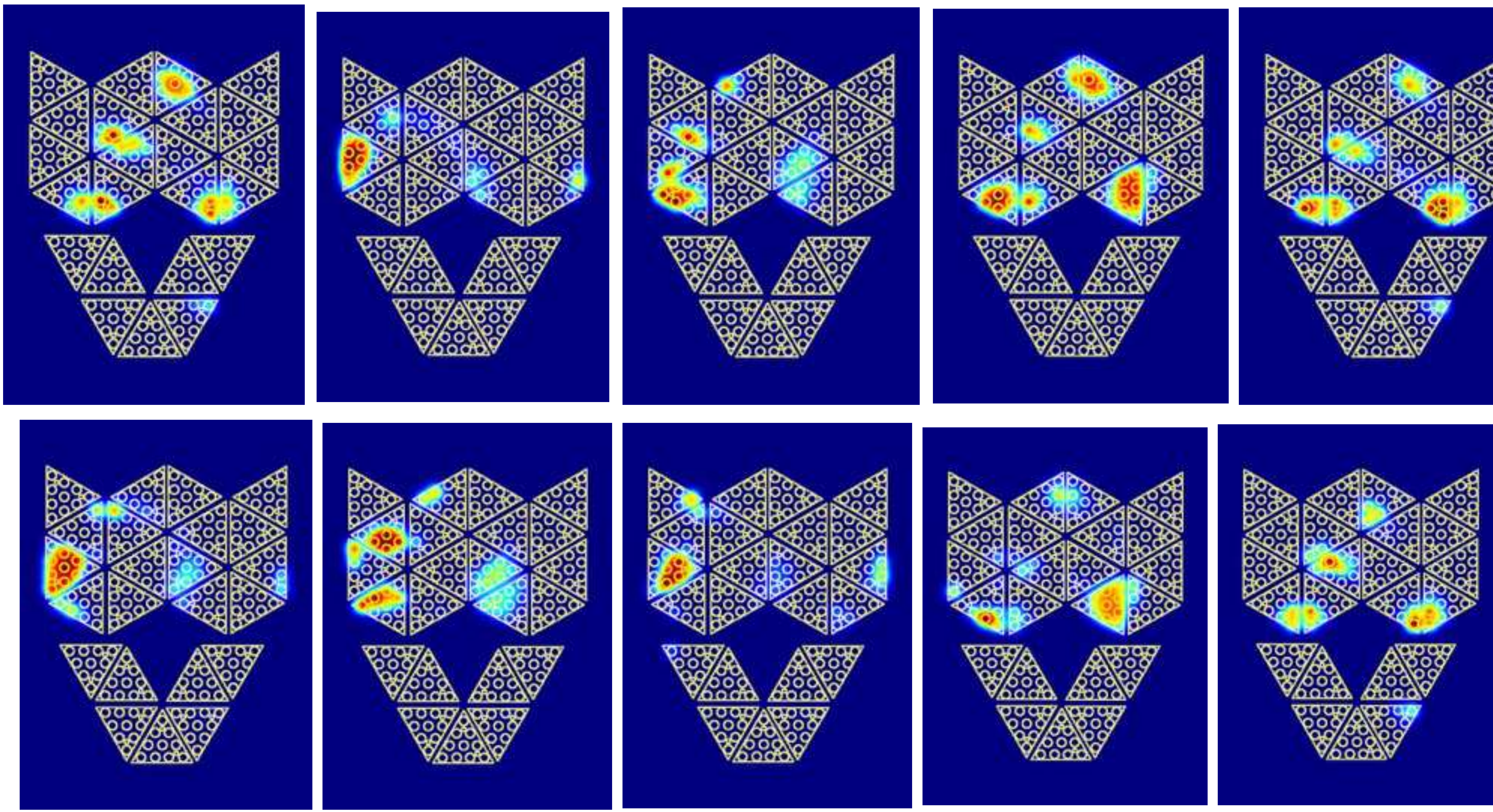
faster
less force

Learning effect

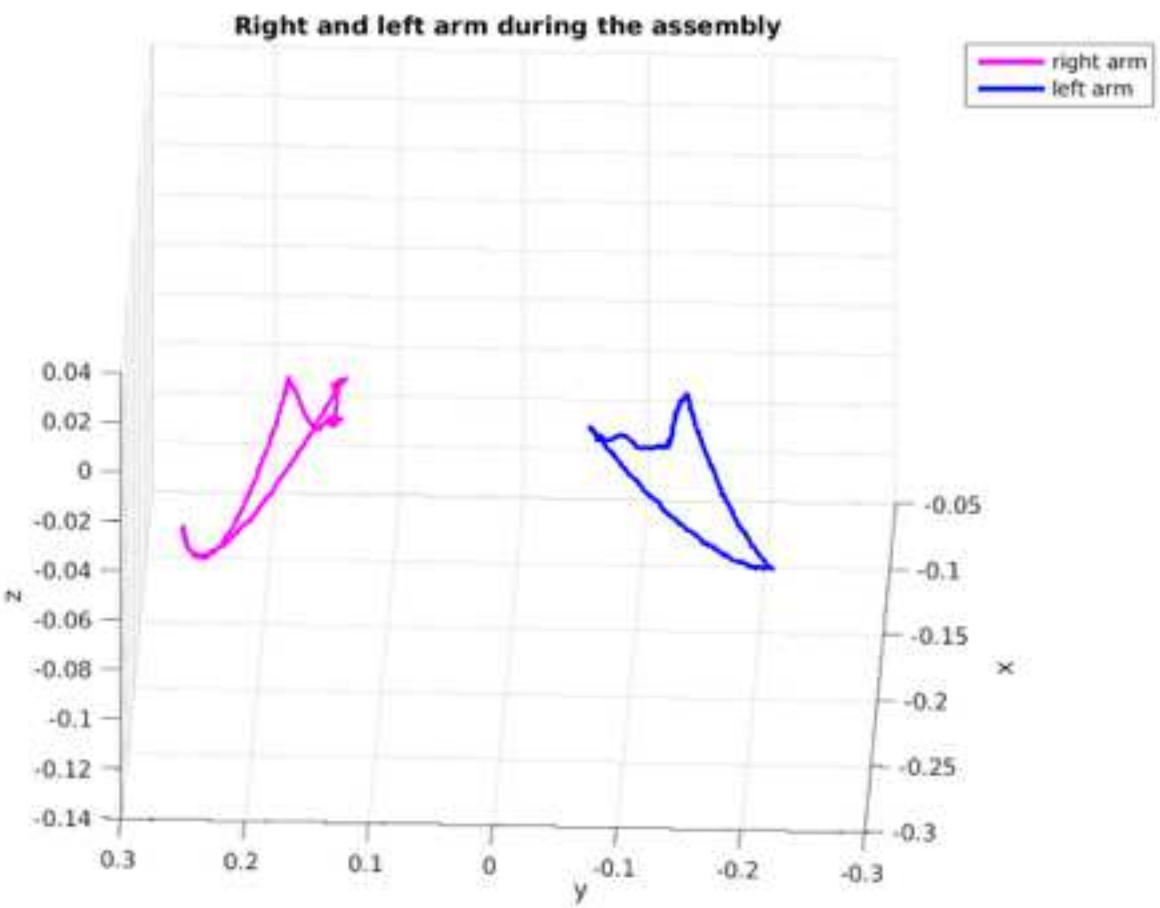


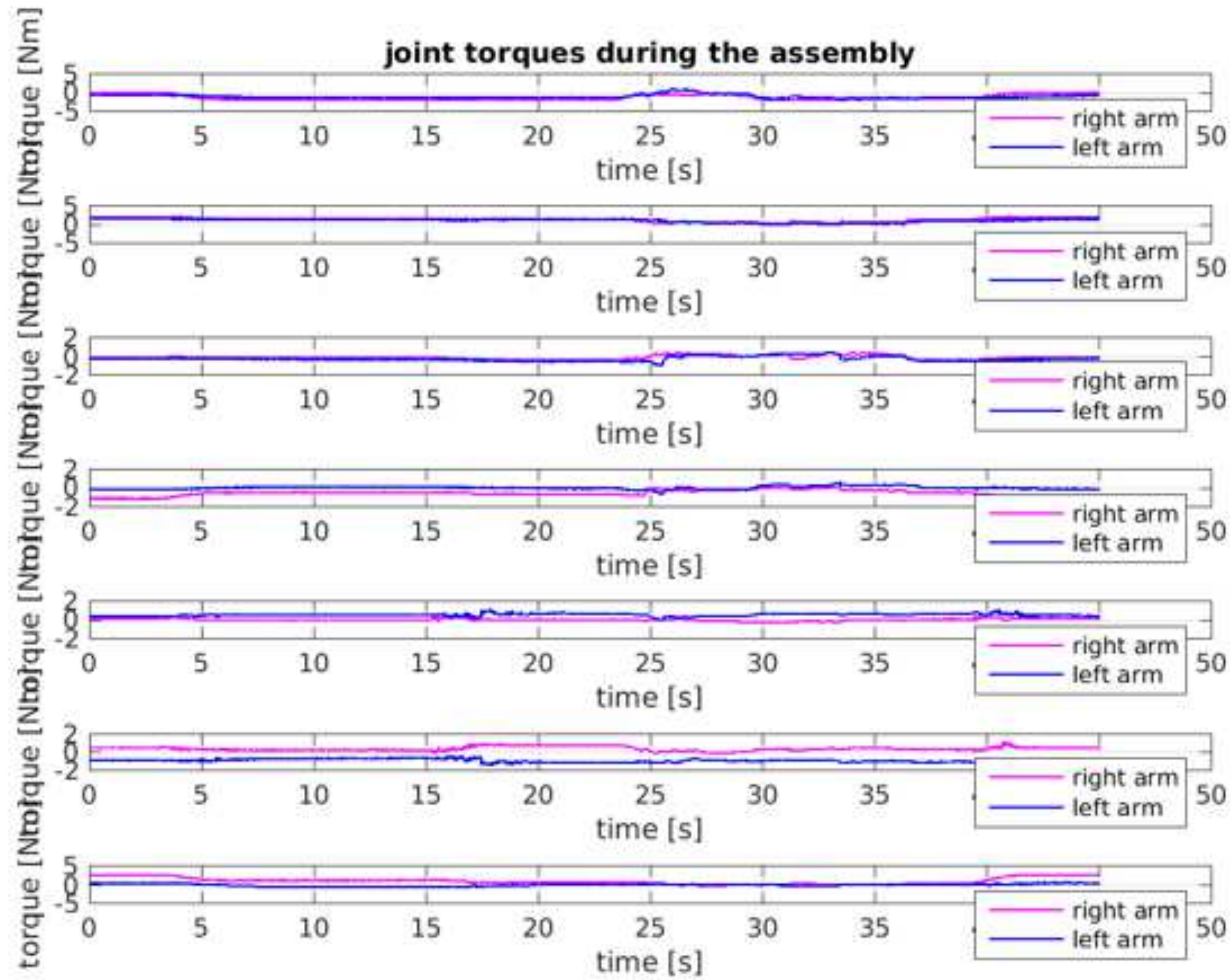
Tactile signatures

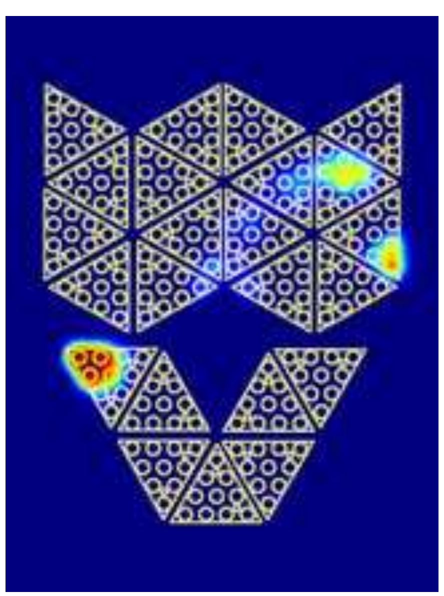
You can almost always recognise the fingers if people have a firm grasp!



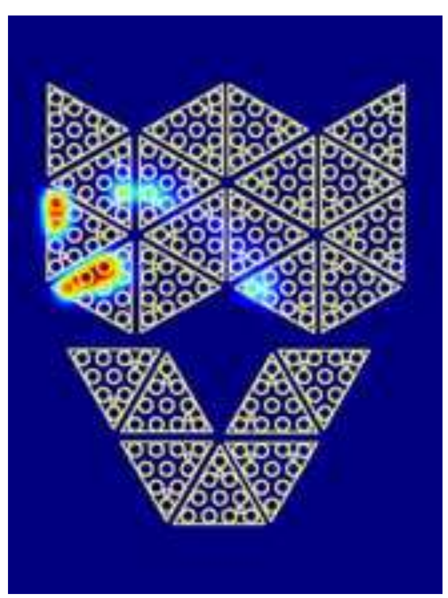
Demonstration from the expert







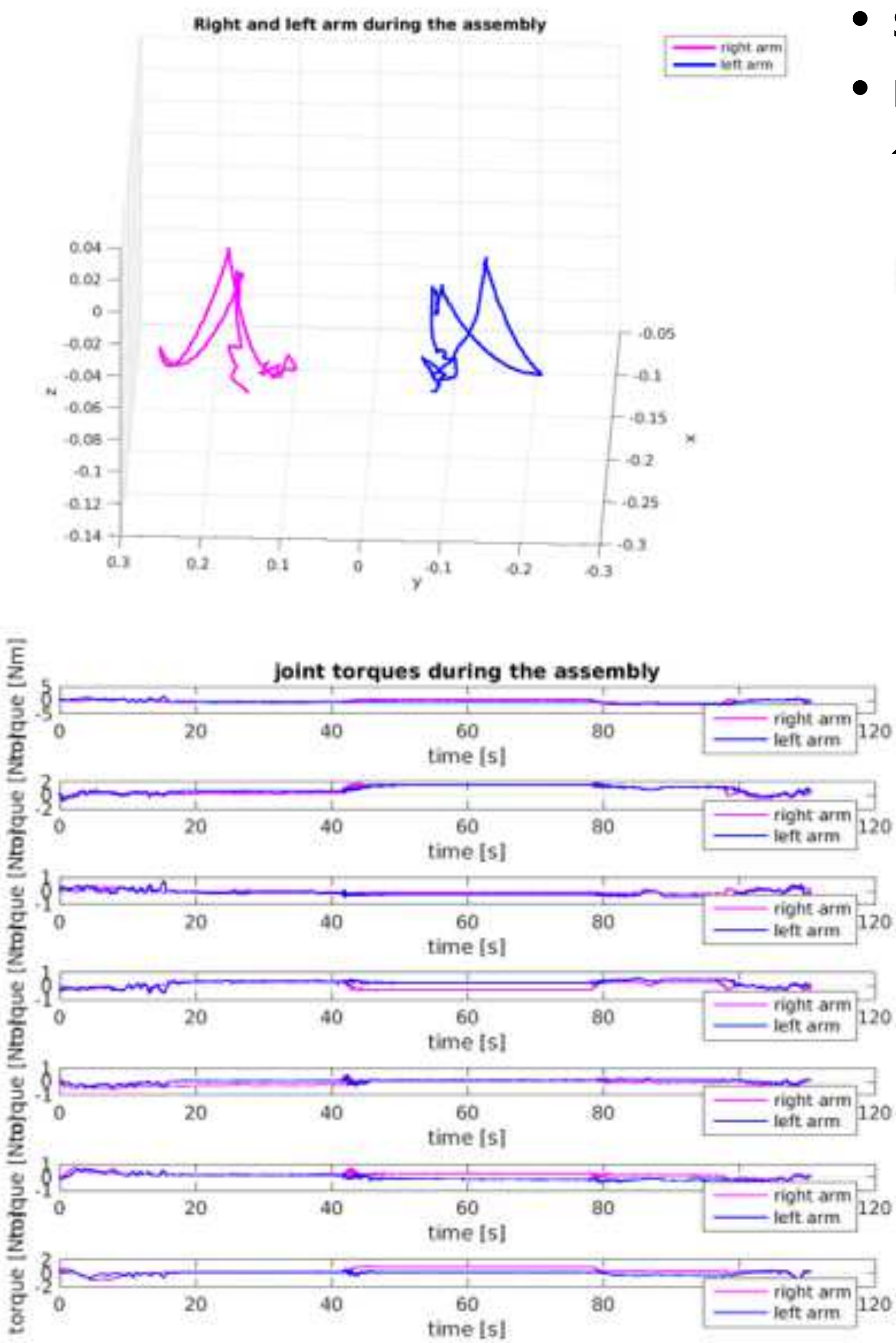
Right Forearm



Left Forearm

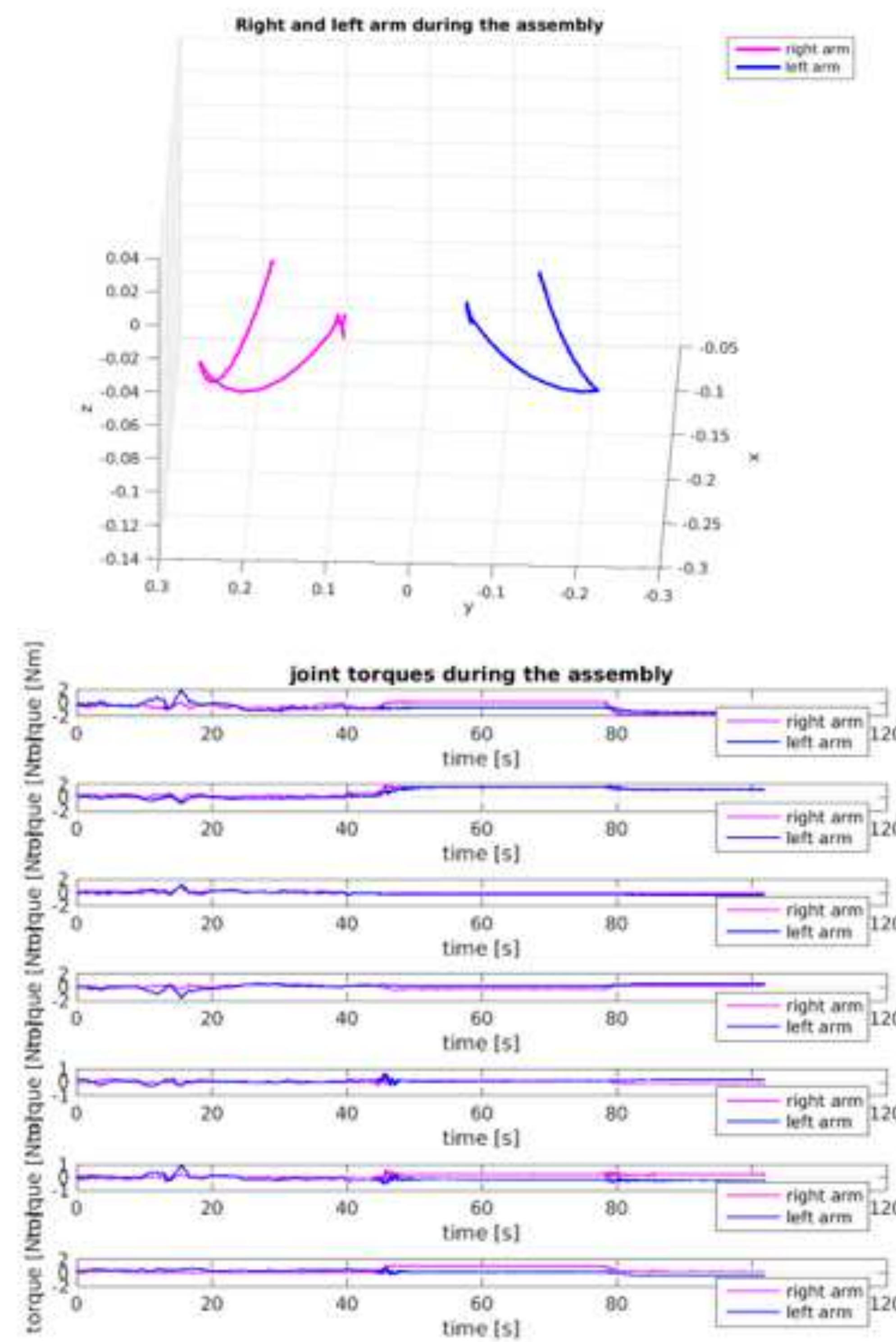
Trials of the non-expert #62

Trial #2



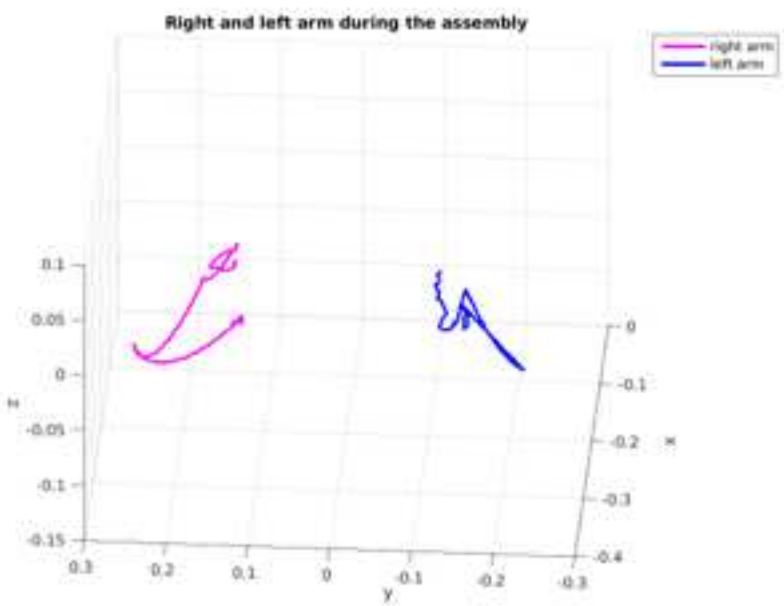
- smoother
- more precise trajectory

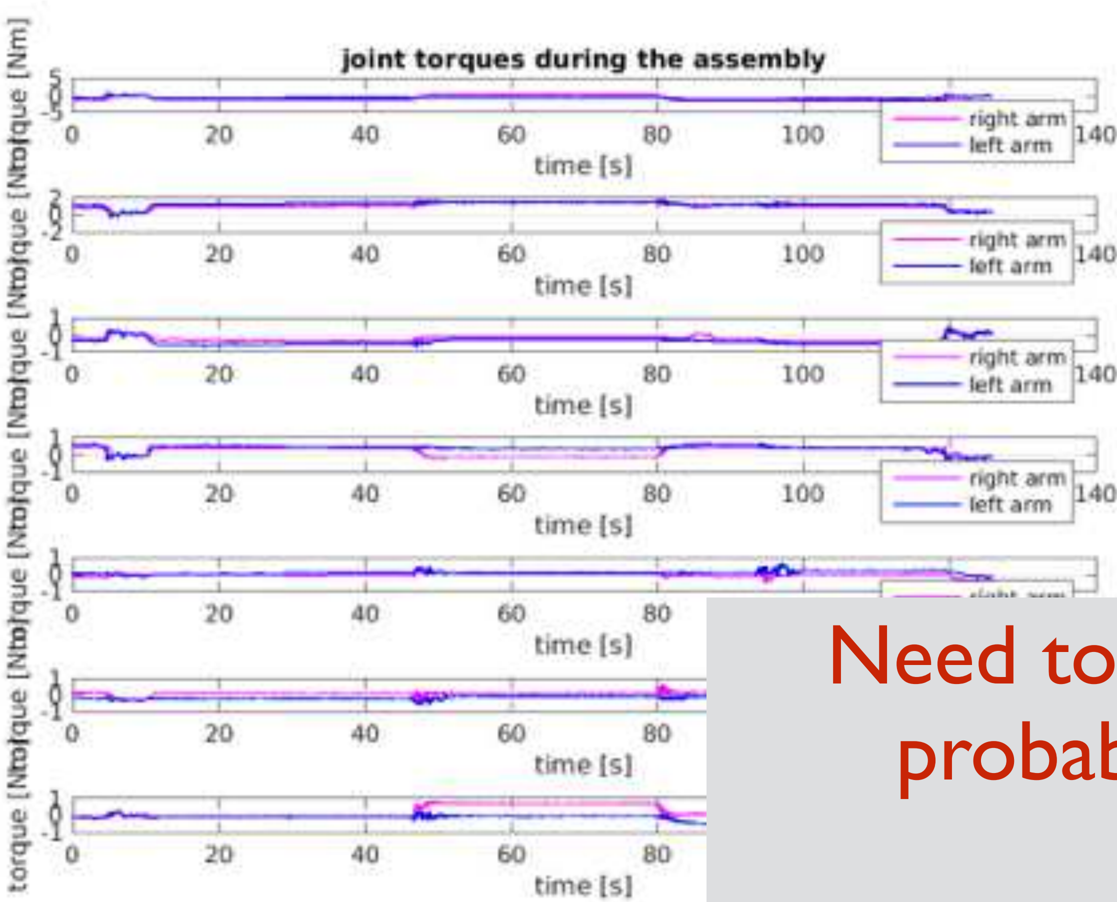
Trial #3



Trials of the non-expert #58

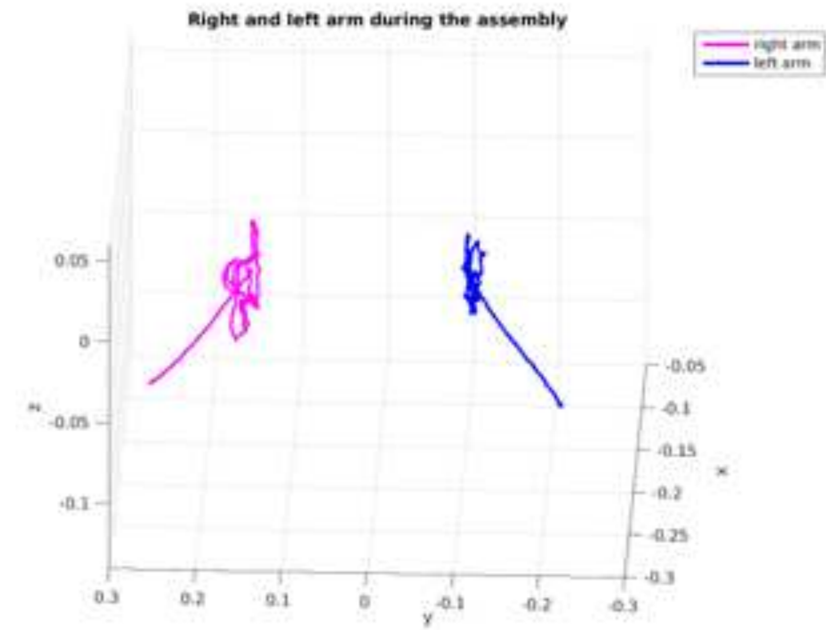
Trial #2

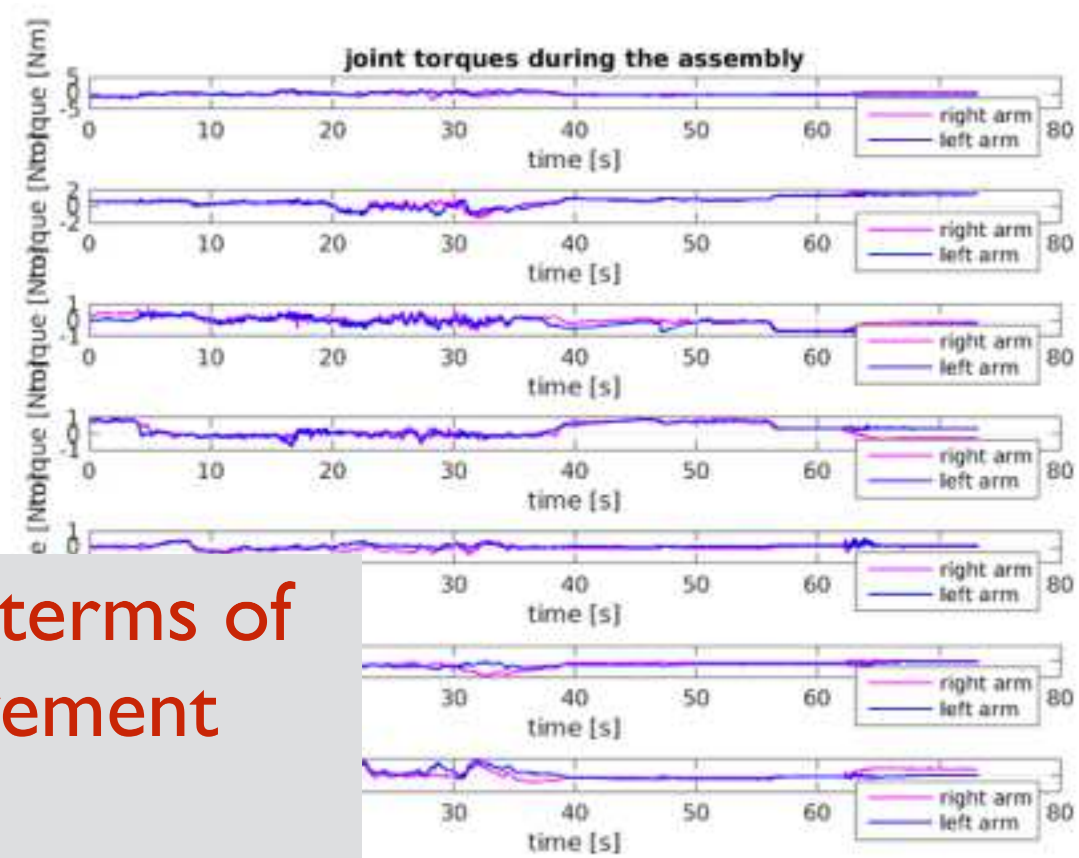




- faster
- precise alignment of the cylinders

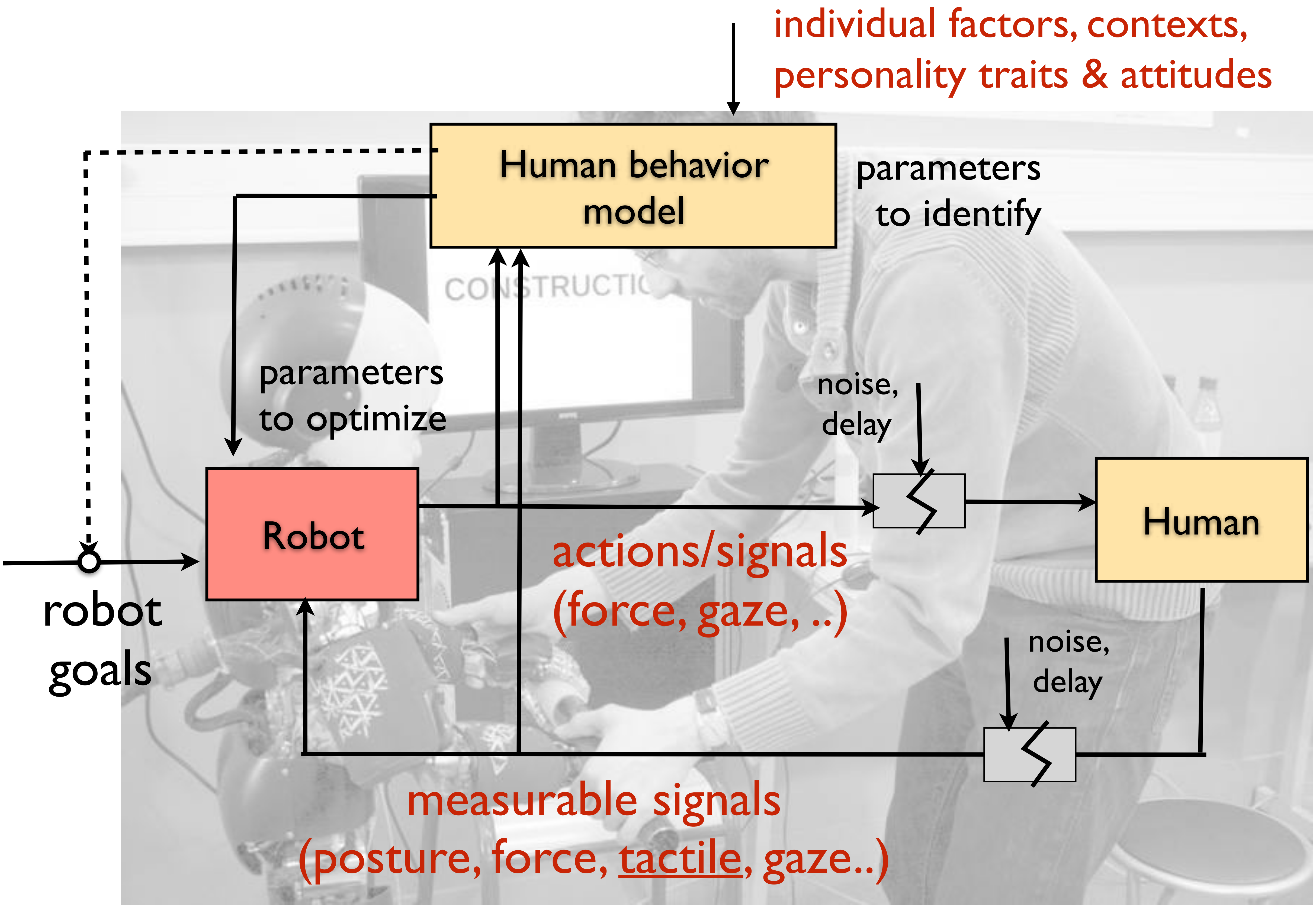
Trial #3





Need to reason in terms of probabilistic movement primitives.

Human behavior model to improve collaboration

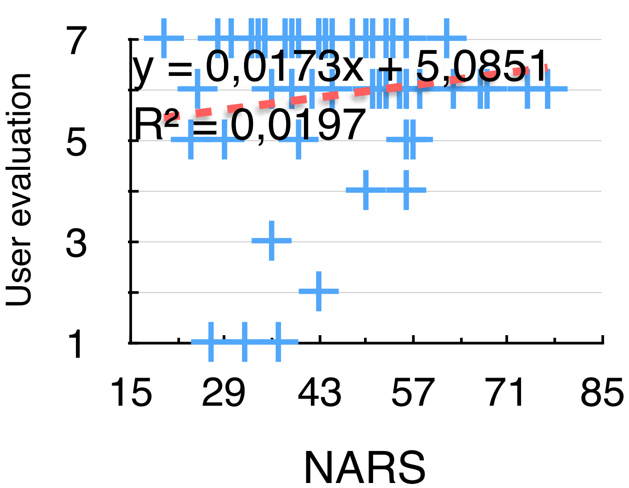


Subjective evaluation - questionnaires

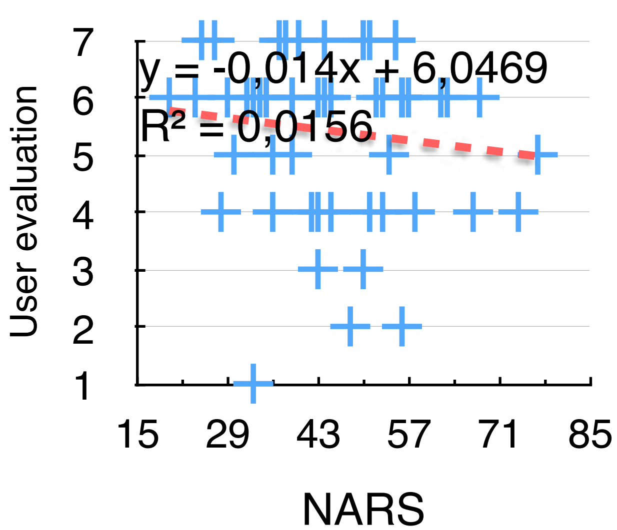
- Subjects with negative attitude towards robots are more anxious/afraid to touch the robot and its hands.
- The age of the participants and their extroversion/introversion do not influence this anxiety.

=> the NARS seems a good scale to catch the anxiety of the participants having to interact physically with the robot.

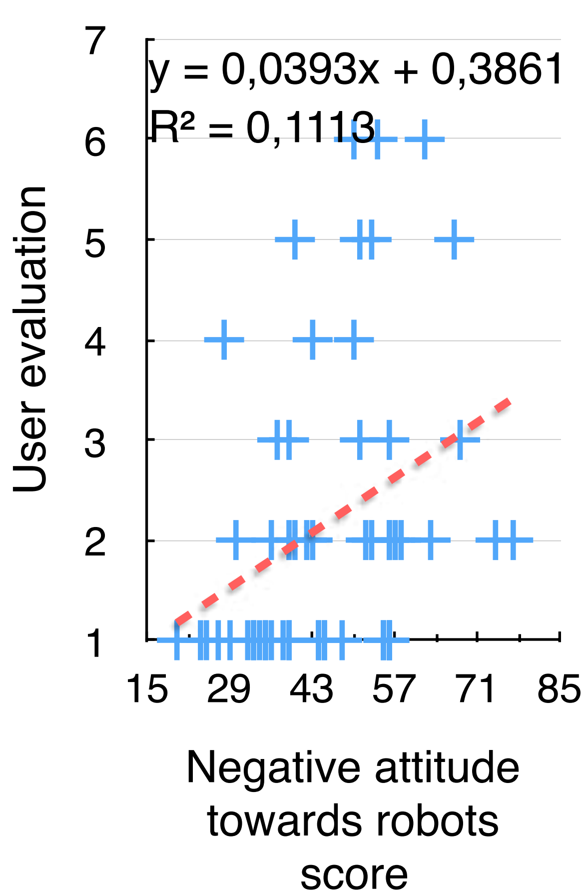
The assembly task was interesting



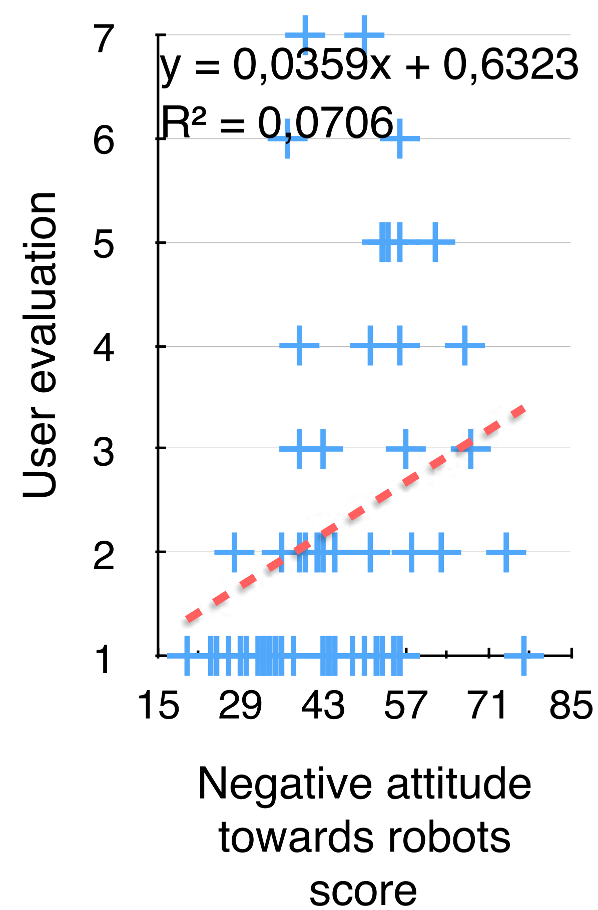
The assembly task was easy to do



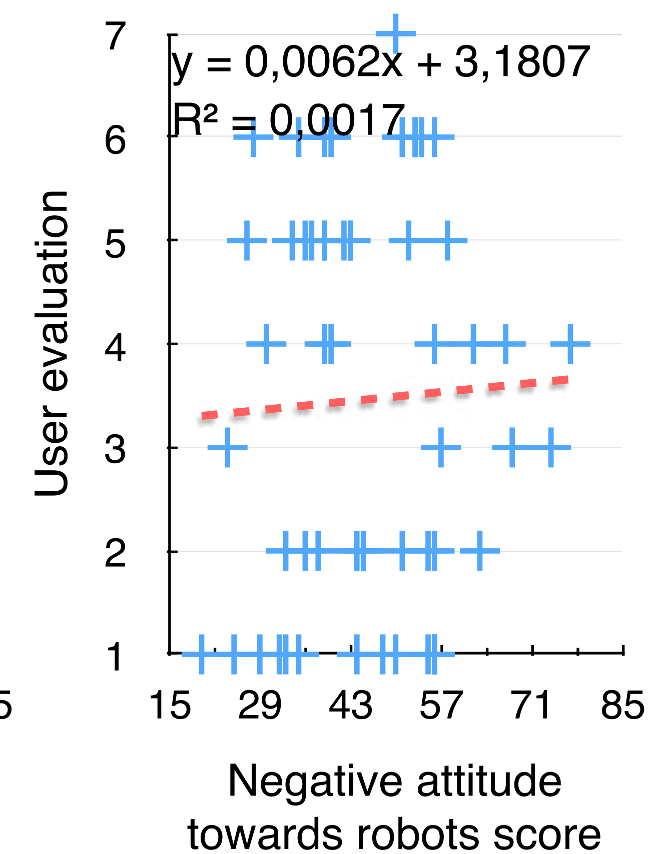
I was anxious that I had to touch the robot to build the objects



I was afraid to touch the hands of the robot



I was afraid to damage the robot

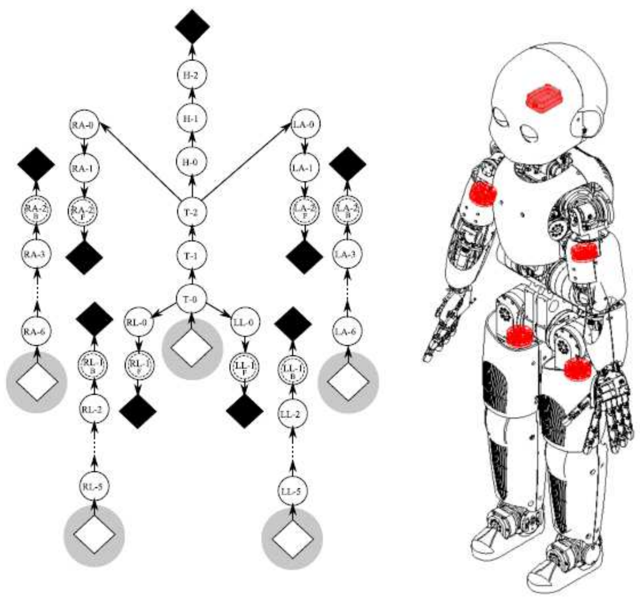


Subjective evaluation - interviews

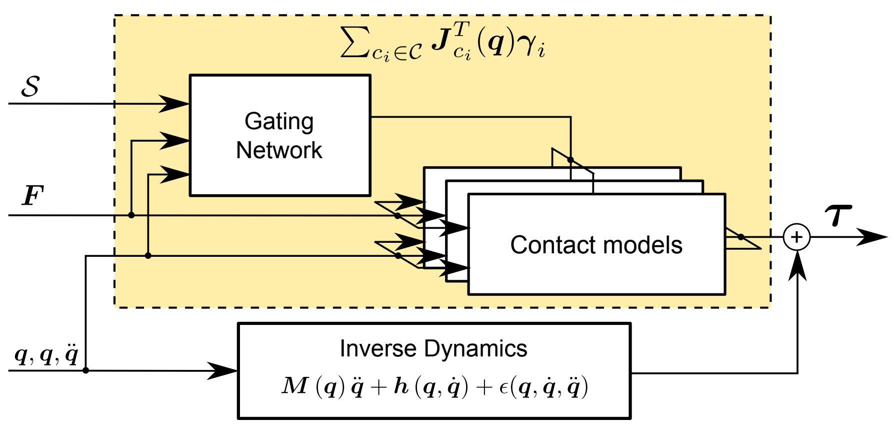
- “I didn’t like the cables and the metallic parts” (cf. hands)
- “I had no problem touching the blue skin”
- “I was not afraid to interact with it”
- “It seems “safe” and follows the mouvement I want”
- “Could it become coloured in the areas that I touch? To show the touch, but also if it gets hurt”
- “The skin was not cold as I expected”

… thanks to the skin and the soft covers!

Take home messages



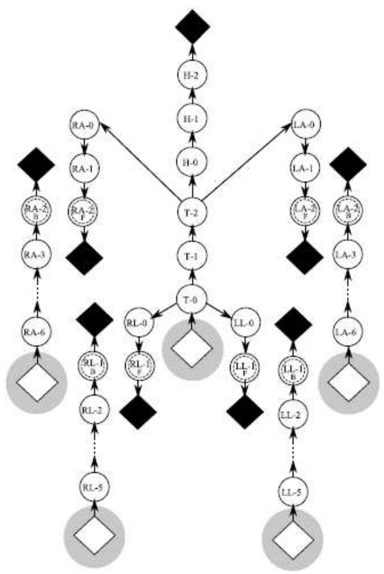
Tactile skin fundamental to compute contact forces occurring not exclusively at the end-effectors but on the whole body.

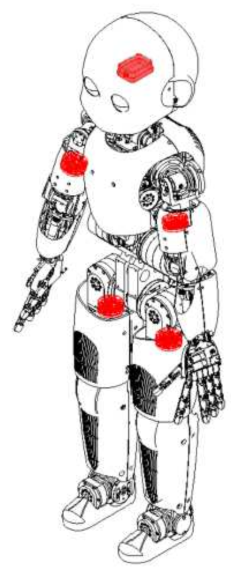


Tactile information can be used to discriminate contact types without having to estimate the contact location or accurately modelling the contact.

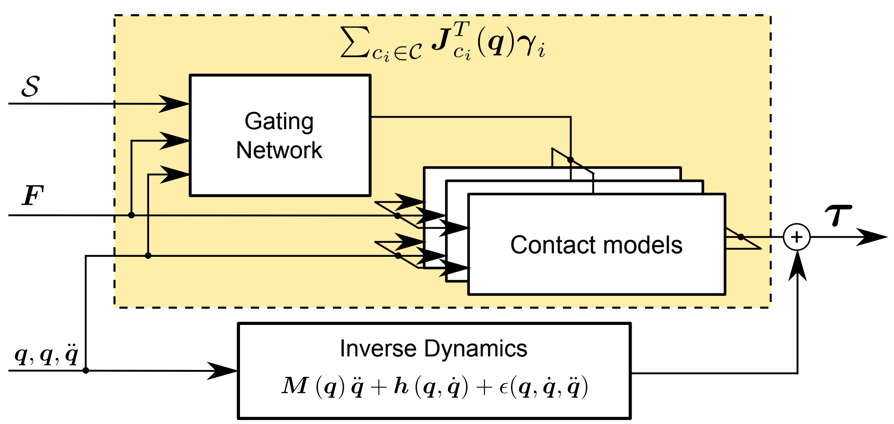
Ordinary people can physically grab the robot without being scared: this enables a social collaboration.

Thank you to my team mates





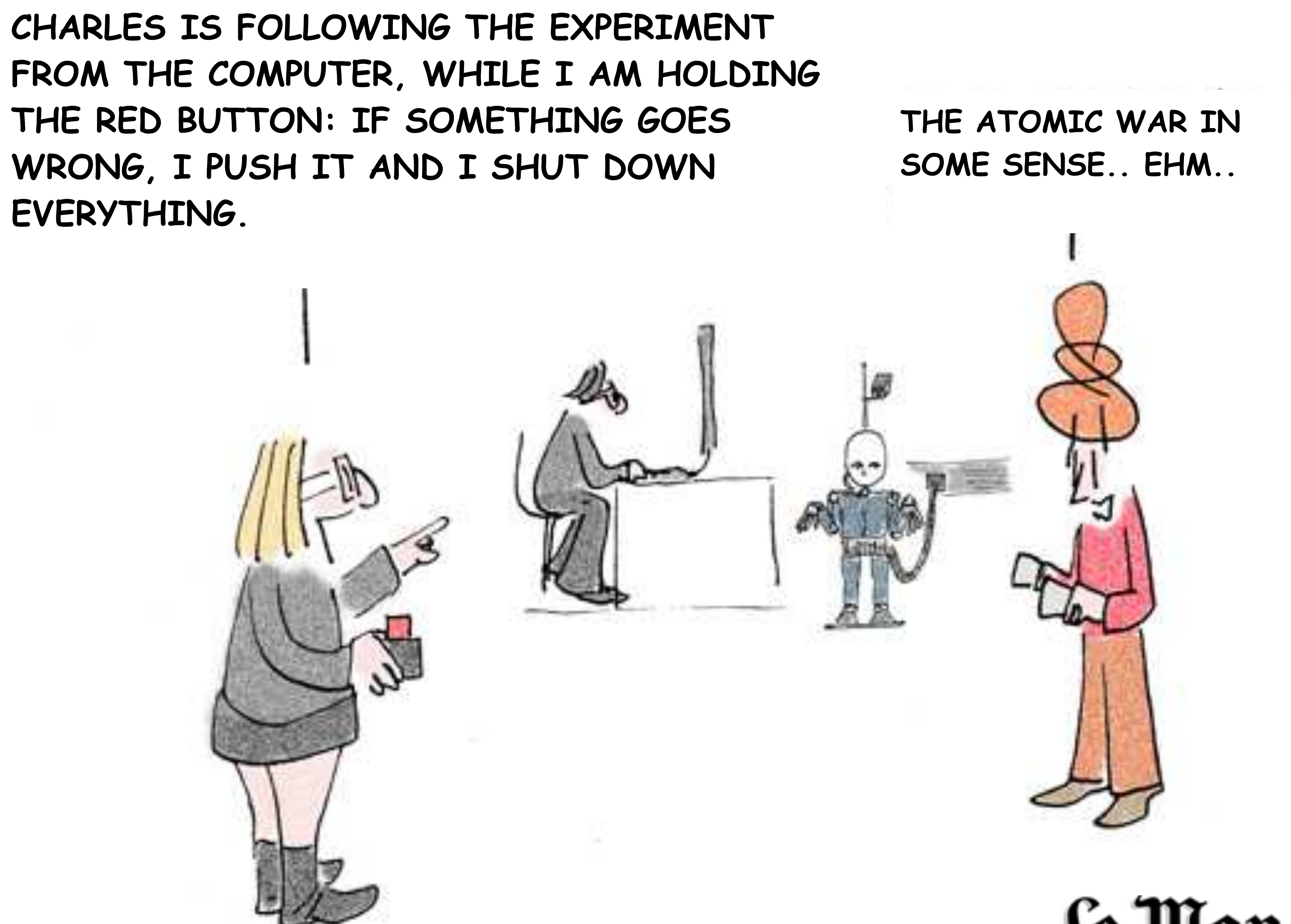
F. Nori, M. Fumagalli, L. Natale
(IIT)



R. Calandra, M.P. Deisenroth, J. Peters
(TU Darmstadt)

E. Zibetti
(UPMC/INRIA)

Thank you!
Questions ?



Le Monde

Comics by Fiamma Luzzati - Le Monde - April 2014