Developing robot motions by simulated touch sensors

Fabio Dalla Libera[1],Takashi Minato[3], Hiroshi Ishiguro[2,3], Enrico Pagello[1] and Emanuele Menegatti[1]

[1] Intelligent Autonomous Systems Laboratory, DEI, University of Padua

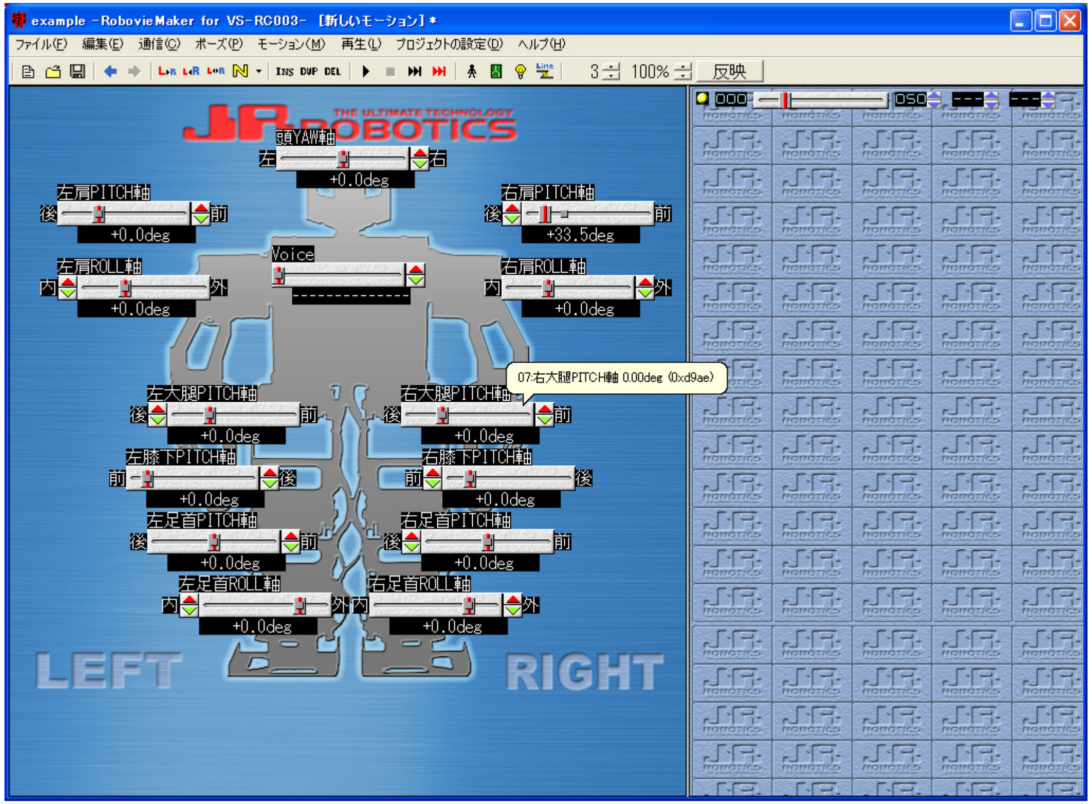
[2] Intelligent Robotics Laboratory, Department of Adaptive Machine Systems, Osaka University

[3] ERATO, Japan Science and Technology Agency, Osaka University

Generation of motions

- Many ways to generate motions:
  - ZMP, inverse pendulum based control, passive walkers (for walking)
  - Motion retargetting
  - Composition of motion primitives
  - CPGs
  - Genetic algorithms, reinforcement learning, policy gradient
  - Design from scratch (classical slider based motion editors)

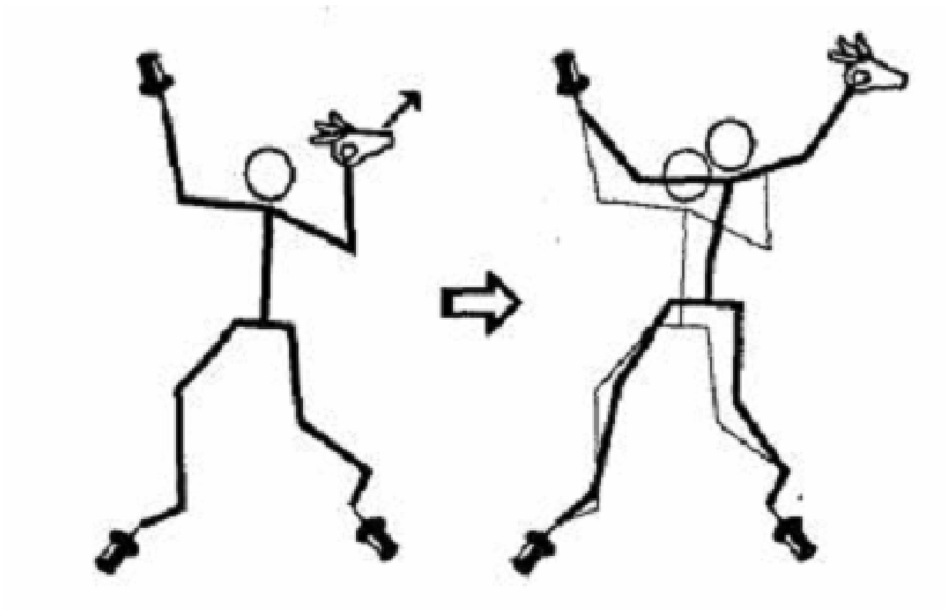
Current motion editor



- Movement defined by keyframes
- The user needs to set the position of each joint at each keyframe.
- *Time consuming* and *unintuitive*

Improving intuitiveness - CG

In the Computer Graphics field the pin-and-drag interface allows creating body motions of human and animal characters without reference motion.



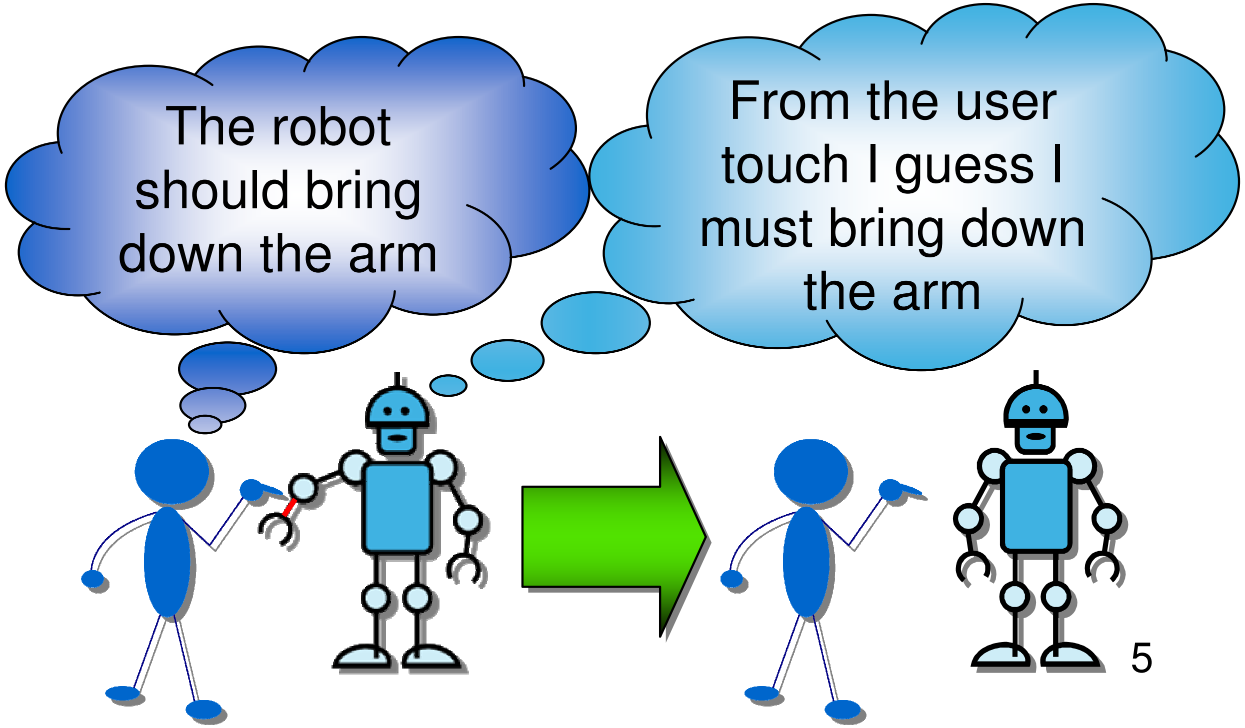
*K. Yamane and Y. Nakamura, ”Synergetic CG Choreography through Constraining and Deconstraining at Will”, ICRA 2002

Teaching by touching

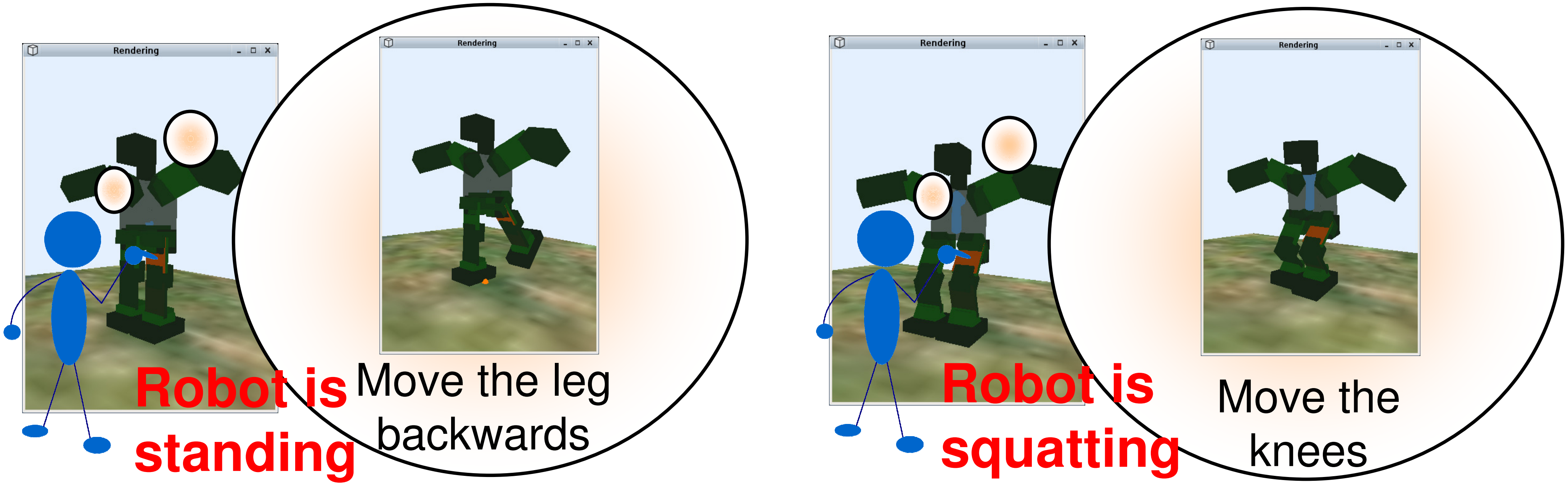
•Sport or dance instructors teach their students how to modify the motion by simple intuitive touches

•The idea is to allow the user do the same with humanoid robots,

•let the user **teach** a motion to the robot **by touching** the robot’s body parts.



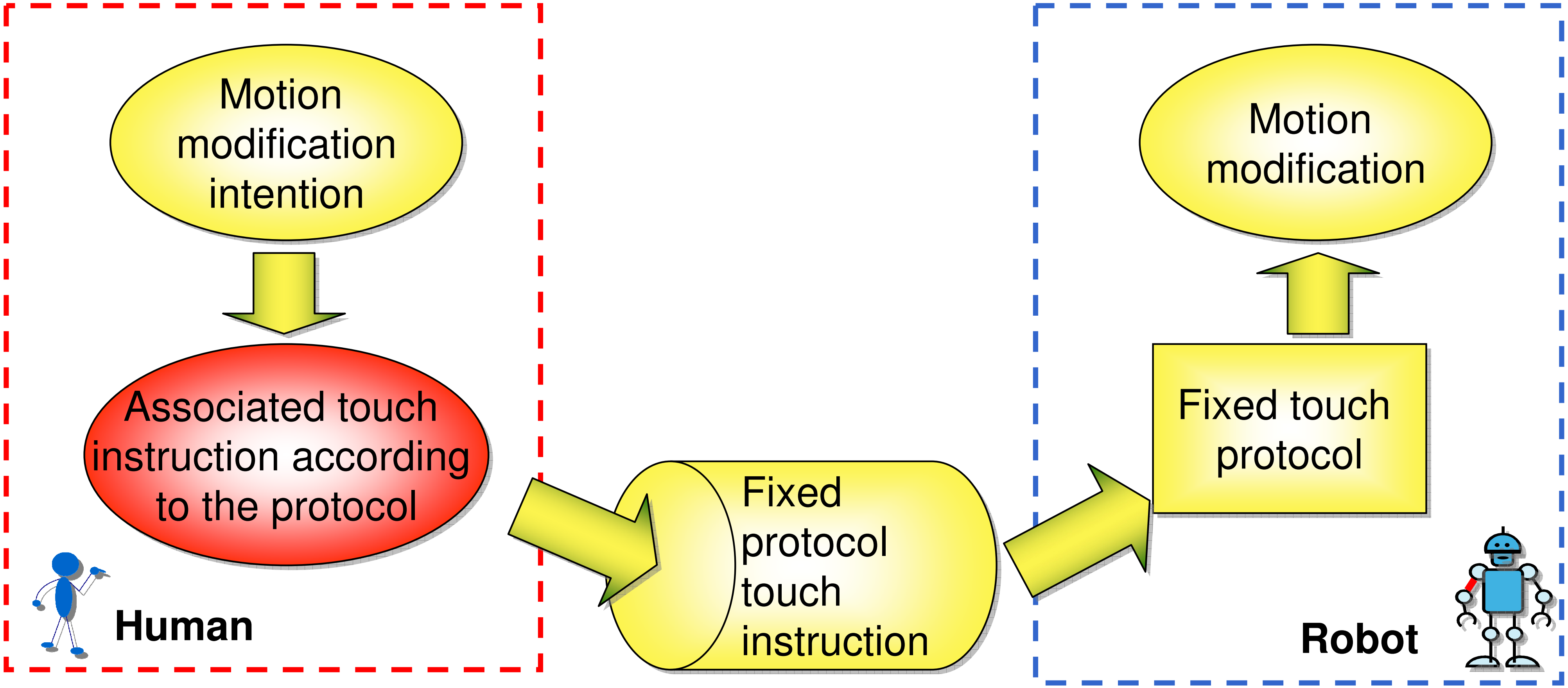
Context dependence



- Same touch, different meaning

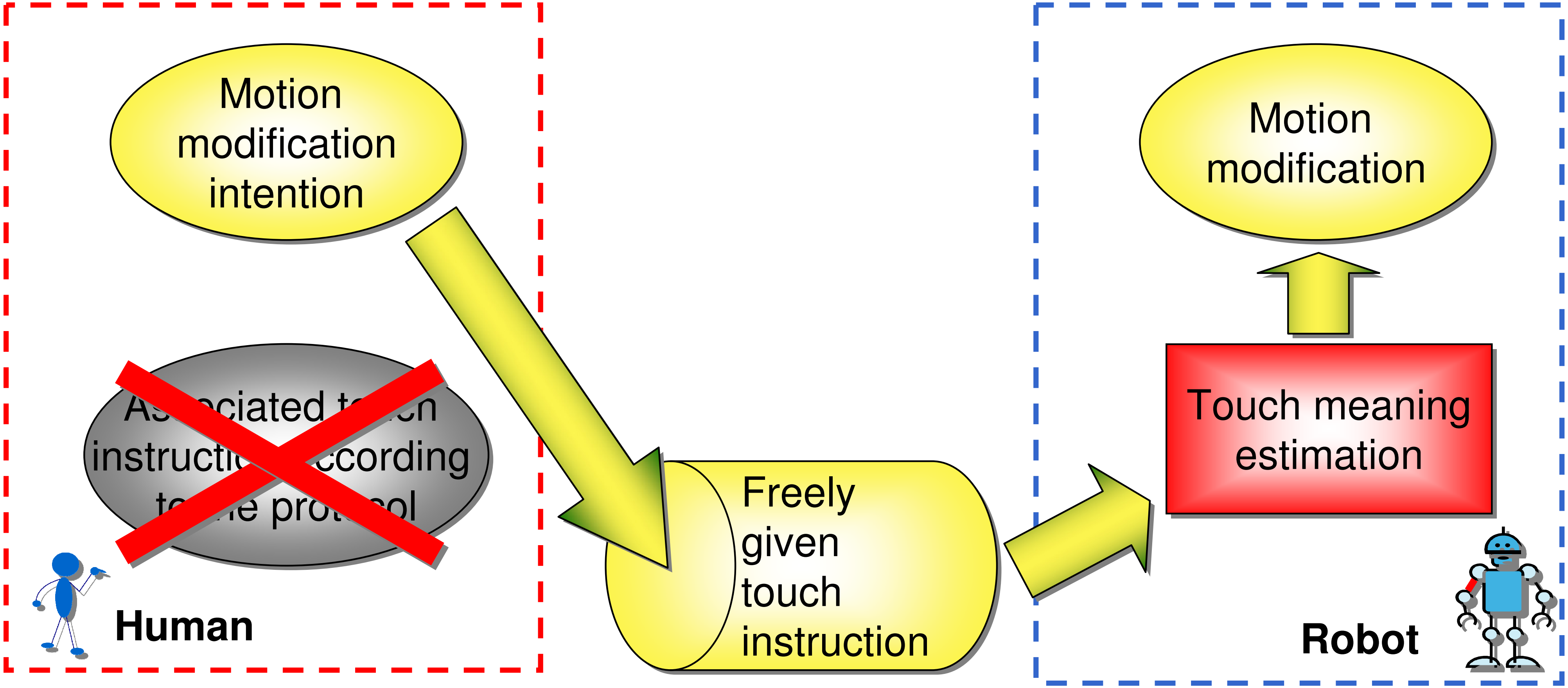
Removing the ambiguity

- One simple solution is to fix a protocol

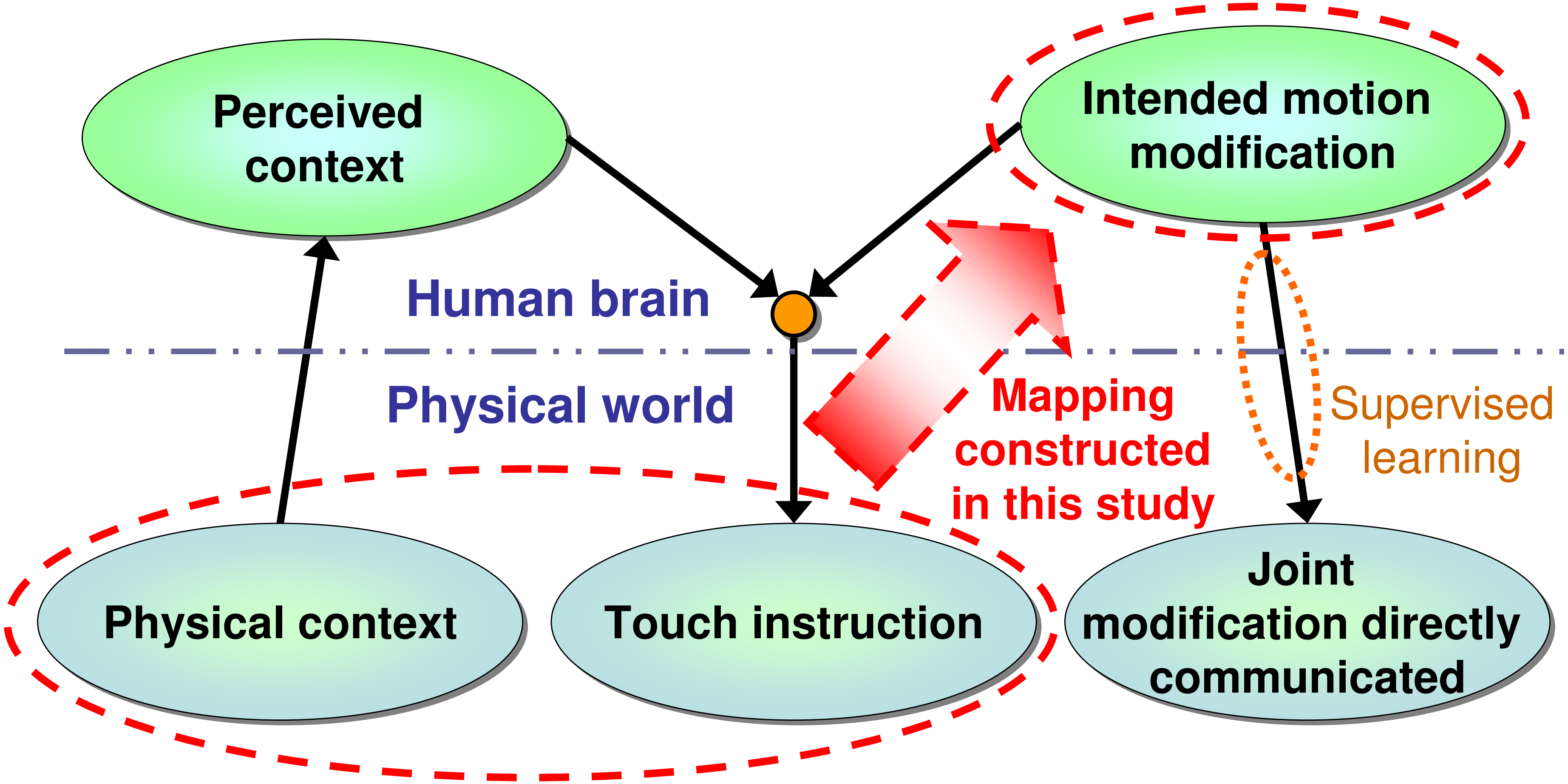


- This strongly reduces the intuitiveness

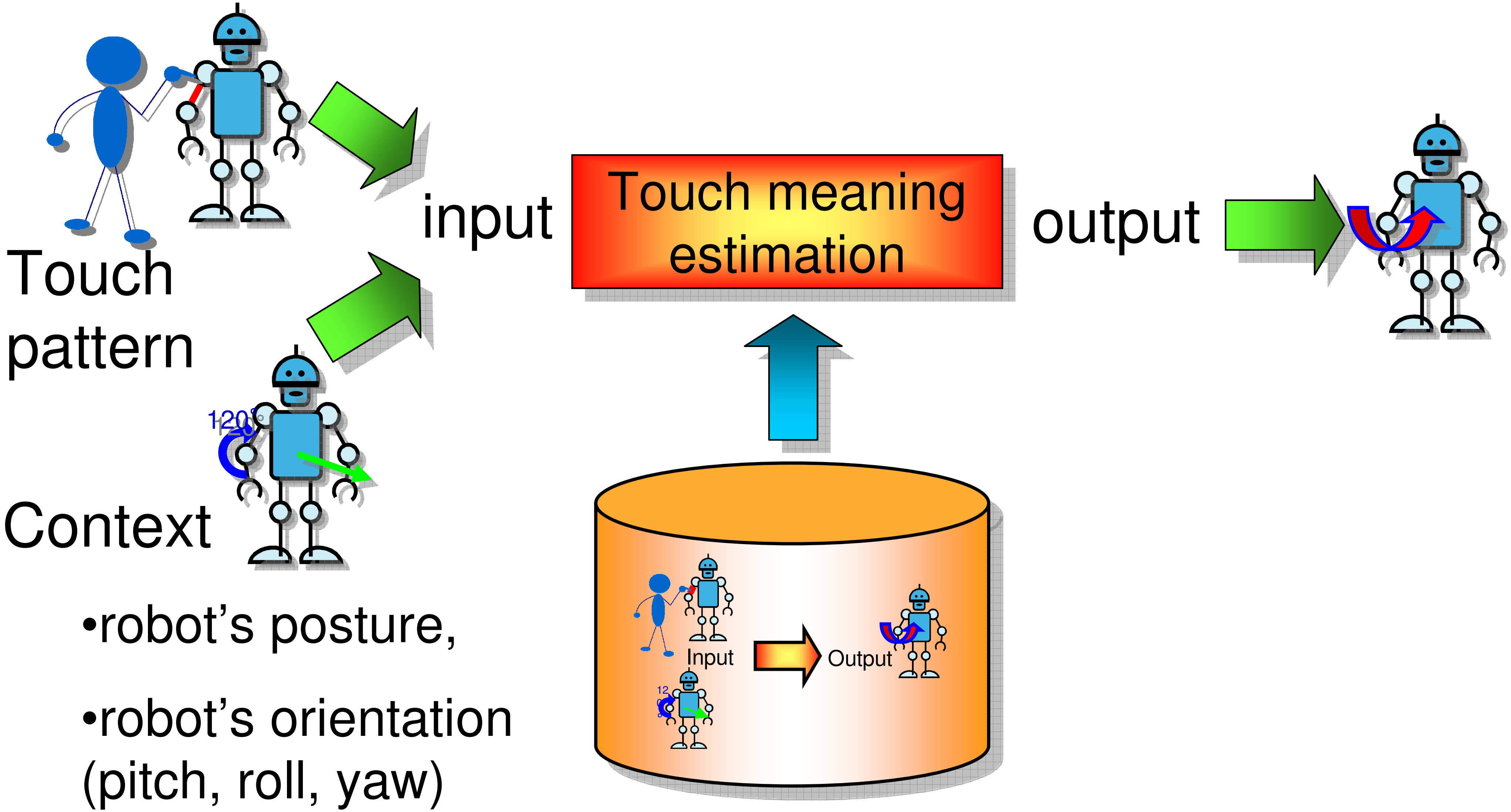
Touch meaning estimation



Conceptual schema



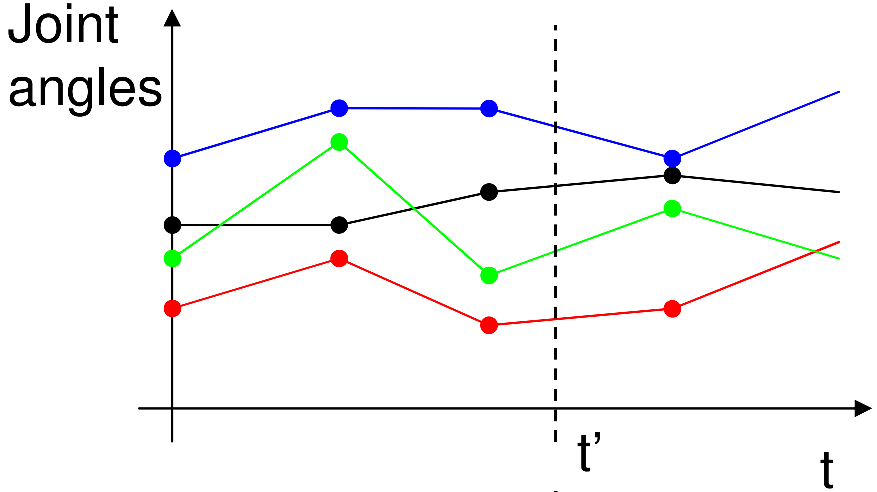
Supervised learning of touch

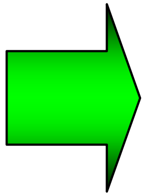


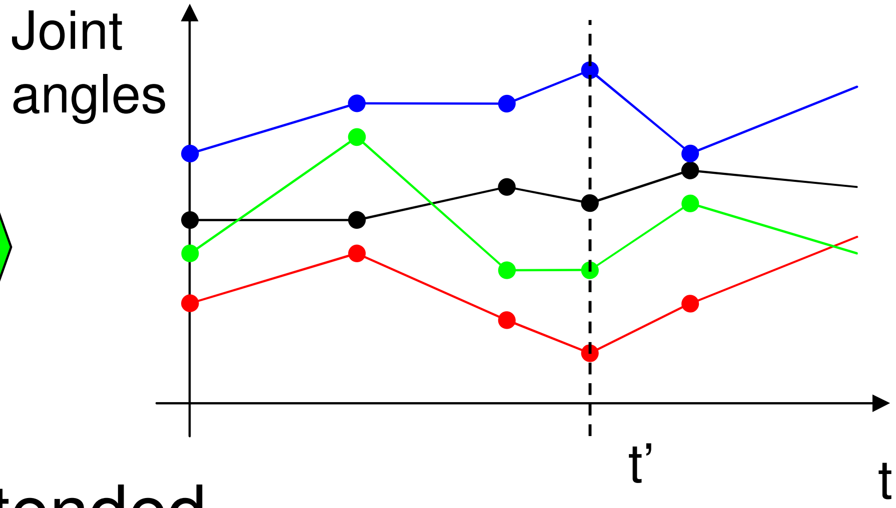
- robot’s posture,
- robot’s orientation (pitch, roll, yaw)
- center of gravity velocity vector

Examples of (input, output) couples given by the user

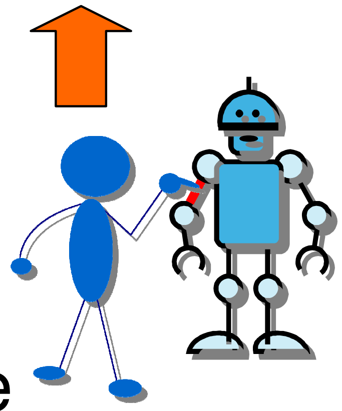
Motion development







The user
- •chooses an instant in time
- •Touches the robot



The intended joint modification is estimated

A new keyframe is inserted

Simulating touch sensors

Real touch sensors:

✓ Intuitive Interaction

✗Difficult wiring for small robots

✗cost

T. Yoshikai, M. Hayashi, Y. Ishizaka, T. Sagisaka and M. Inaba, Behavior Integration for Whole-body Close Interactions by a Humanoid with Soft Sensor Flesh, Humanoids 07

Simulated sensors:

✓Safe interaction

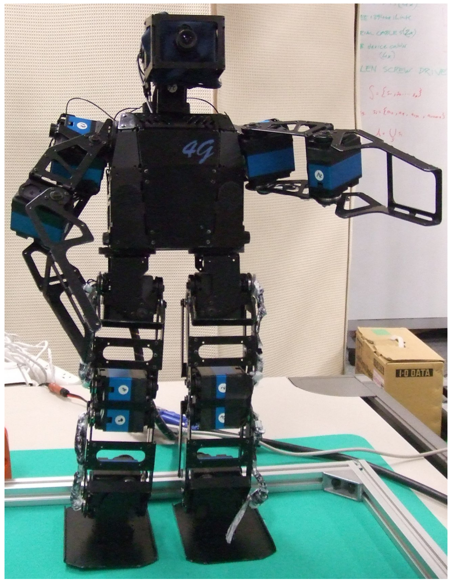
✓Can be applied to any robot

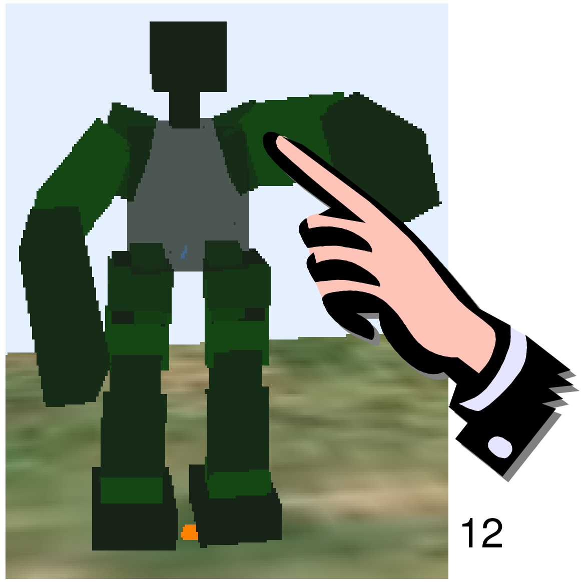
✓Cheap

✓Distinguish between gravity and user touch

✗Interaction is less direct

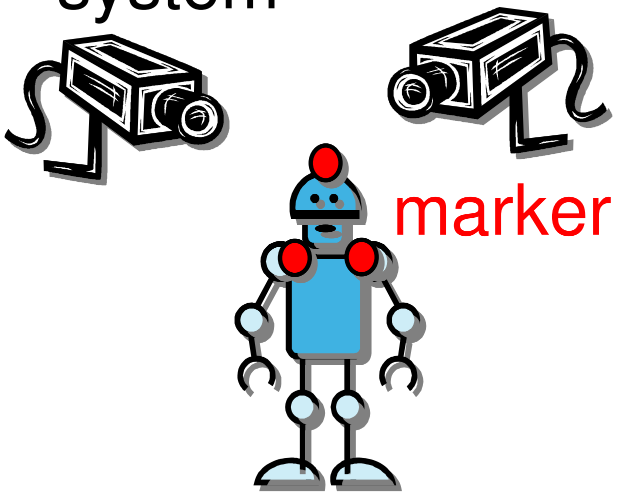
✗Just pushing time can be sensed (mice)





Motion development cycle

Motion capture system



Play the motion on the physical robot

Replay the recorded evolution on its 3D representation

Touch screen

Modify the motion touching the virtual touch sensors on the robot's model (pushing time=intensity).

Learning algorithm

- A weighted NN- Algorithm

$$\omega_i = \alpha_i \beta_i \prod_{s:t_s^*=0} \left(1-\delta(t_s^i)\right)$$

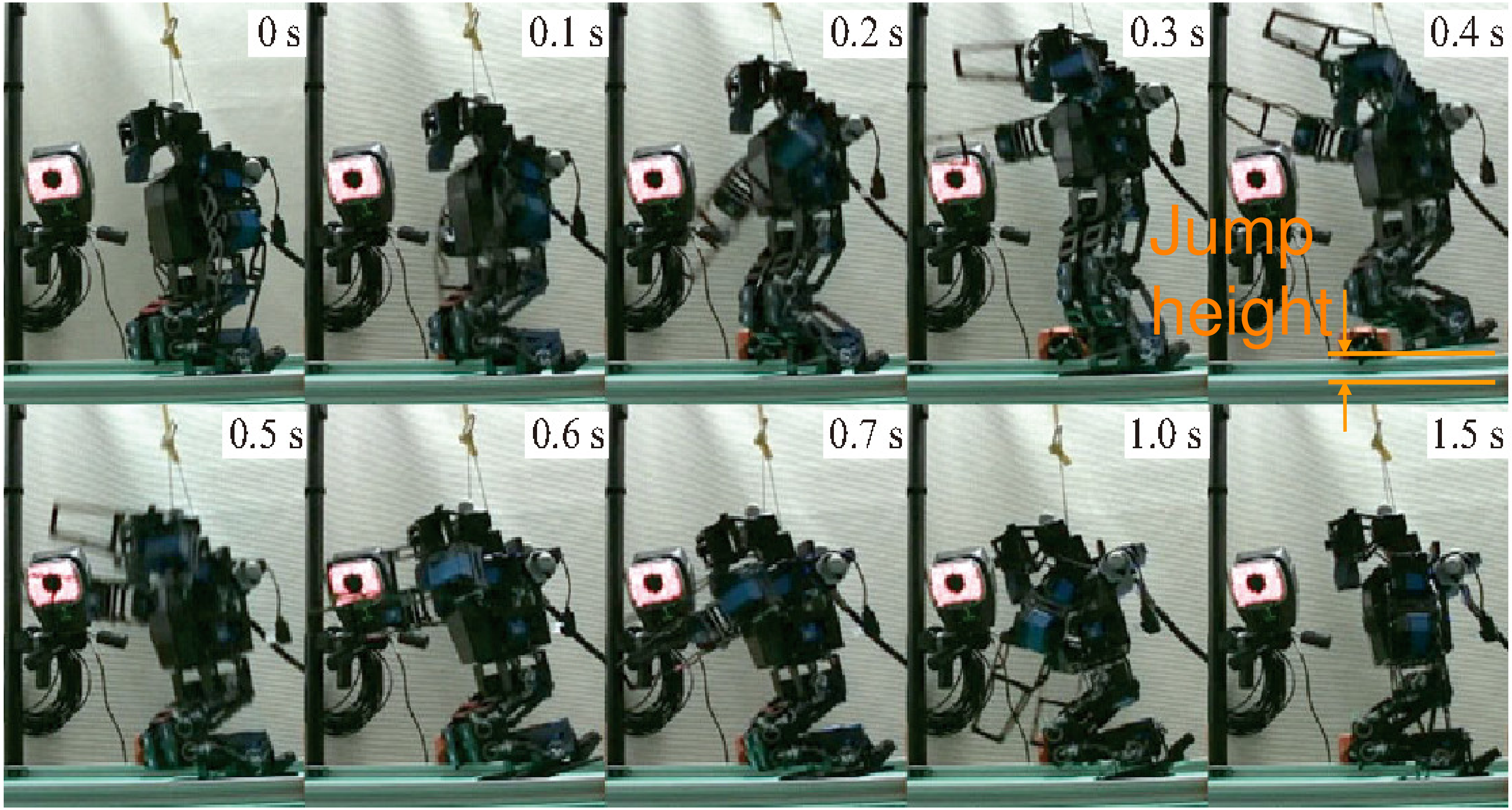
$$\alpha_i = \prod_{s:t_s^i>0} \frac{t_s^*}{t_s^i}$$

$$d_i = \sqrt{\sum_{s:t'_s=0} t'^2_s + \left\|p^* - p^i\right\|^2 + \left\|o^* - o^i\right\|^2 + \left\|v^* - v^i\right\|^2}$$

$$\beta_i = \frac{1}{1+d_i}$$

- Examples of the mapping are provided during motion development
  - No special training sessions
  - The mapping is refined where the system fails to predict the user will
- Examples can be studied

Experiment 1 – feasibility

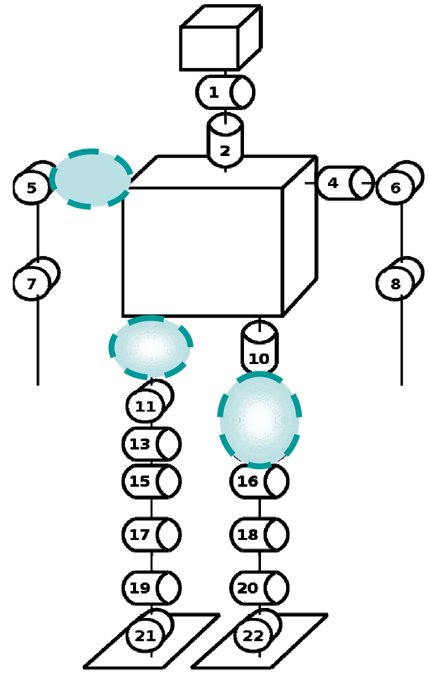


Experiment 1 - Data analysis

- Linear regression: A linear model is not suited to explain the mapping

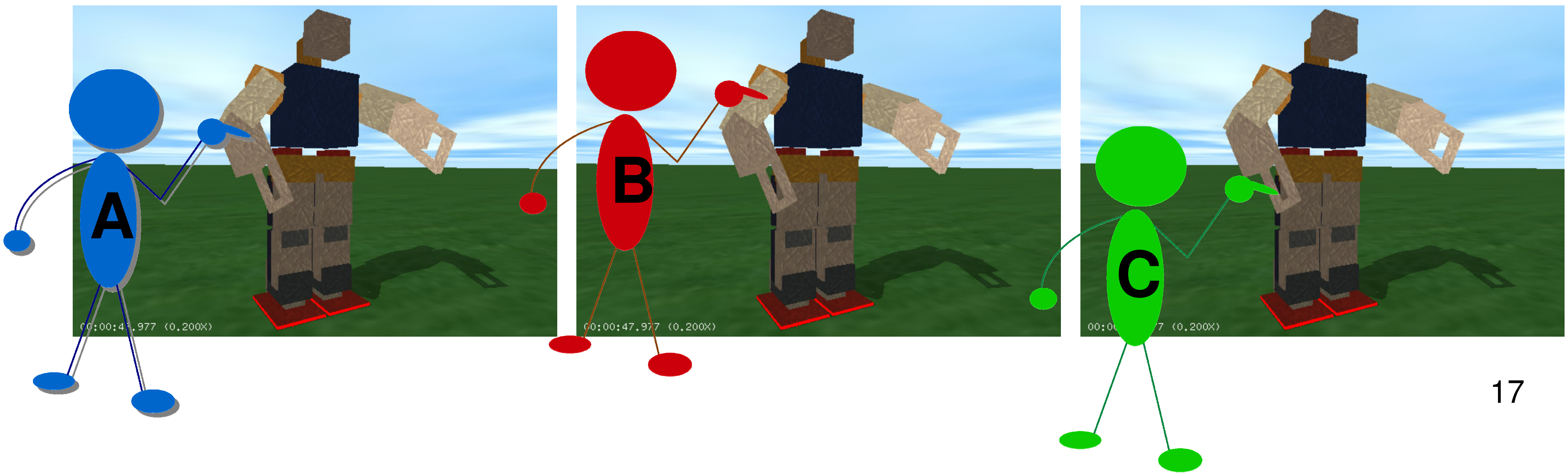
Training data	Test data	Average relative error	
		linear regression	K-NN
JUMP	JUMP	0. 1872	0. 1863
JUMP	WALK	715. 0779	1. 0325
WALK	JUMP	2. 6658	0. 9569
WALK	WALK	3. 98E-06	0. 1022

- C4.5: The position of the joints near the torso are important context elements

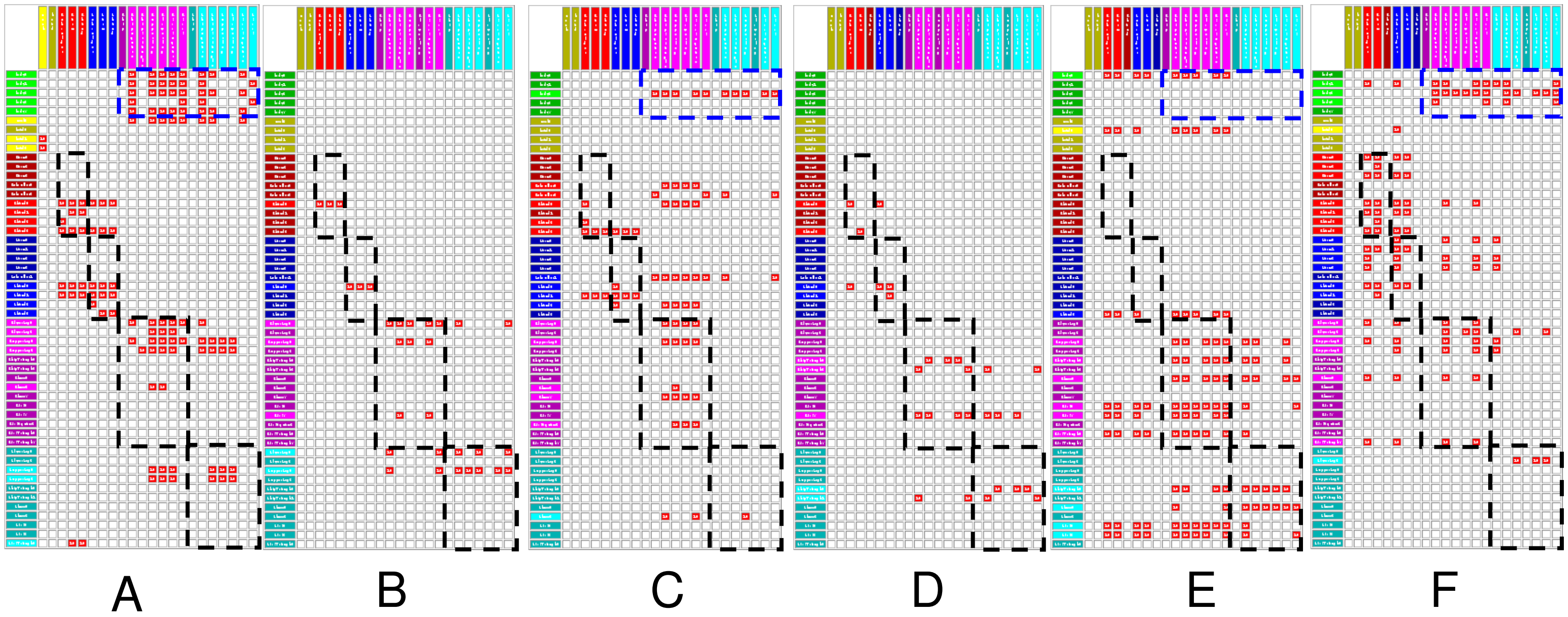


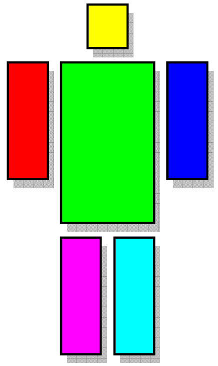
Assuring identical conditions

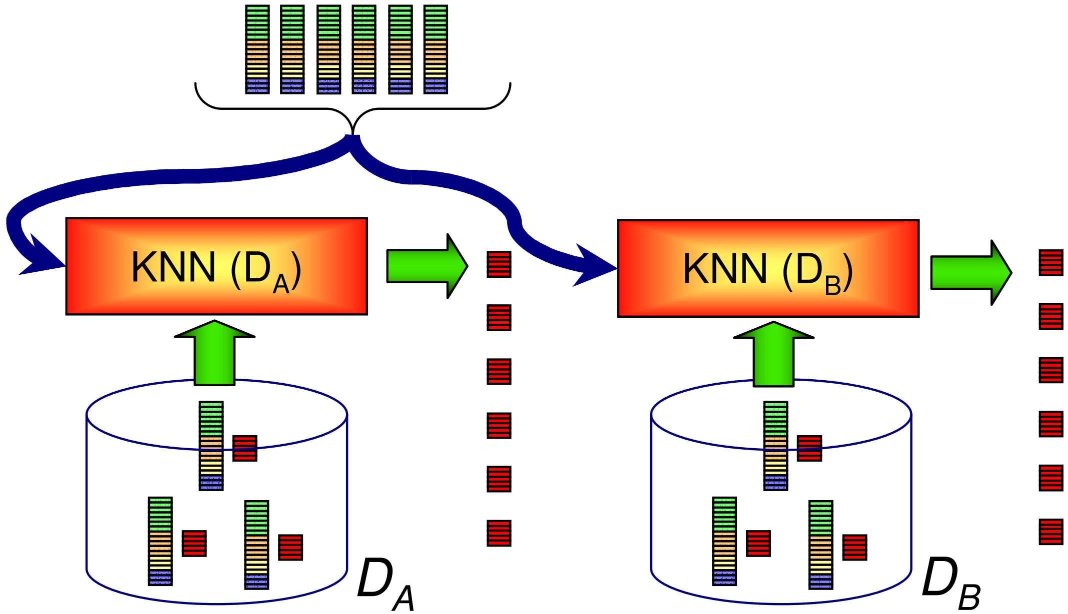
- To study user dependence of touch-instructions we need to assure the same conditions for all user
- This can be done by simulation



Experiment 2 – user dependence





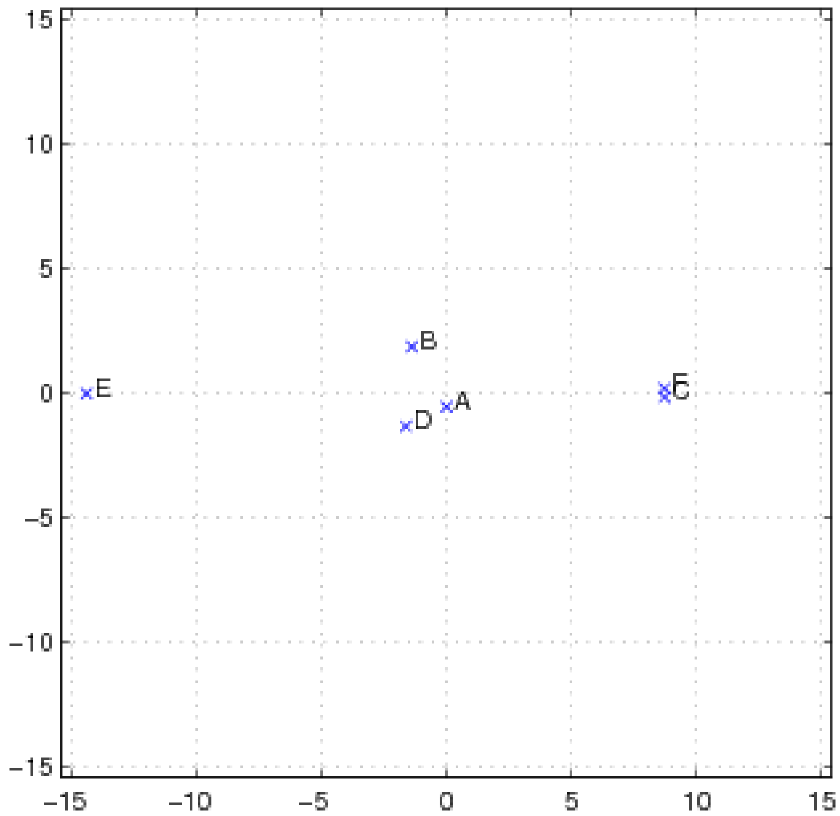


$$corr(u_1,u_2)=\begin{cases} 1 & \text{if } u_1 = u_2 \\ \underset{i}{avg}\left(\dfrac{M_{i,u_1}\cdot M_{i,u_2}}{\left\|M_{i,u_1}\cdot M_{i,u_2}\right\|}\right) & \text{if } u_1 \neq u_2 \end{cases}$$

$$dist(u_1,u_2) = -\log\left(\left\|corr(u_1,u_2)\right\|\right)$$

Data analysis

- MDS: users use much different levels of abstraction
  - B,D: strict association sensor – joint
  - A: apply force, elastic joints
  - C,F: several sensors for the same joints
  - Motion primitives (user E)



Future works

- Extend the context features
- Increase the number of subjects for statistical significance
- Study automatic discrimination between self touch, user touch and pressure due to gravity (using the gyro information)
  - Use a simulated robot as "shadow-robot" Seiichiro Katsura and Kouhei Ohnishi and Kiyoshi Ohishi, Transmission of Force Sensation by Environment Quarrier Based on Multilateral Control, IEEE Transactions on Industrial Electronics