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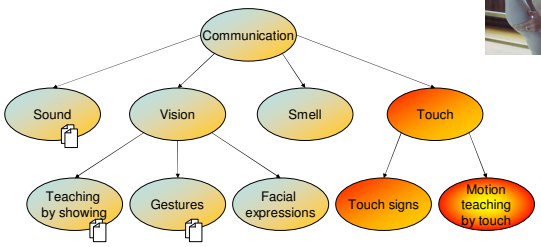
Teaching by touching: an intuitive method for development of humanoid robot motions

Fabio Dalla Libera•, Takashi Minato♦, Ian Fasel•◊,
presenter
Hiroshi Ishiguro ♦○, Emanuele Menegatti• and Enrico Pagello•

• Department of Information Engineering (DEI), University of Padova
♦ ERATO, Japan Science and Technology Agency, Osaka University
○ Department of Adaptive Machine Systems, Osaka University
◊ Department of Computer Sciences, The University of Texas at Austin

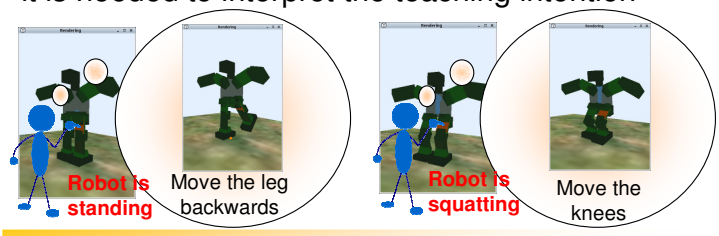
Background

Touch is a powerful mean of communication, for example in motion teaching, but it has received very little attention.



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

Touch interpretation is strongly context dependent, it is needed to interpret the teaching intention



If the robot is standing, touching the upper part of one leg could mean that the leg should bend further backwards, however if the robot is squatting the same touch could mean that the robot should move lower to the ground by bending its knees.

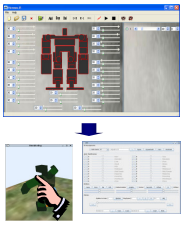
Purpose

•Realize an intuitive interface for motion development

In most mostion editors the movement is defined by keyframes. In each keyframe the position of each motor is set by sliders

Scarce intuitiveness

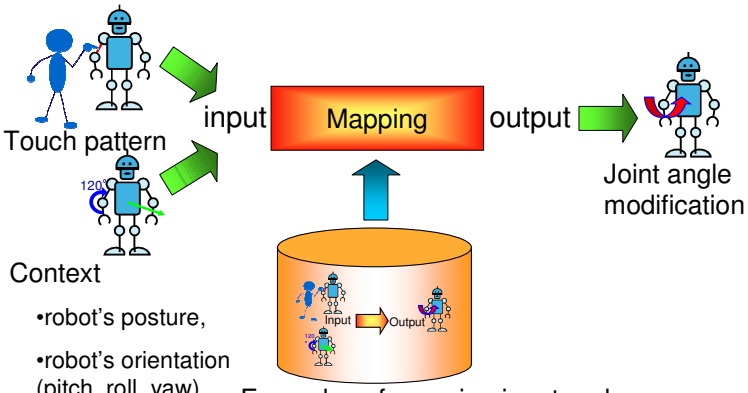
Using touch it is possible to change multiple joints simultaneously



•Study the way humans communicate through touch.

A teaching by touching interface

•The mapping from the touch instructions and the context in which they are given to the robot's joint angle modification is build online from examples provided by the user: great intuitiveness, no need to learn protocols.



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

Examples of mapping input and corresponding output given by the user

•Current implementation uses the k-Nearest Neighbor algorithm with a specifically devised weighting schema

The output is a weighted sum of the example outputs

$$m' = \sum_{i=1}^{n_E} g(x', x^i) m^i$$

The weight is null for examples where sensors not pushed in the input were pushed.

$$g(x', x^i) = \alpha_i \beta_i \prod_{s:t'_s=0} (1 - \delta(t^i_s))$$

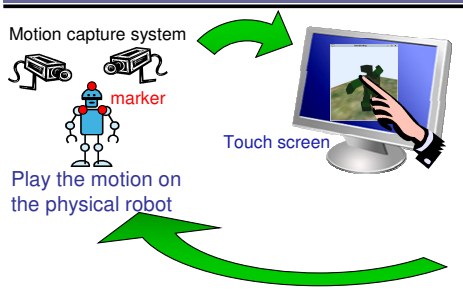
The weight increases increasing the pushing time and decreasing the differences between the system input and the example input

$$\alpha_i = \prod_{s:t'_s>0} \frac{t'_s}{t^i_s} \qquad \beta_i = \frac{1}{1+d_i}$$

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

t_s	pushing time of s-th sensor
p	posture (vector of joint angles)
o	orientation (pitch, roll, yaw)
v	CoG velocity vector
m	output (joint angles)
x	concatenation of t, p, o and v
$*^i$	element of the i-th example
$*'$	element of the I/O of the mapping

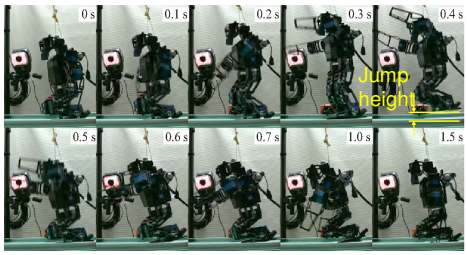
Experiment



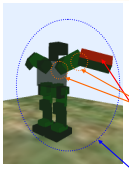
Replay the recorded evolution on its 3D representation

Modify the motion touching the virtual touch sensors on the robot's model (pushing time=intensity). If the system misunderstands the touch instruction the user can provide the intended modification by direct manipulation of the physical robot and by a slider-based interface.

On the employed robot no touch sensors are available and due to the small size it's difficult to interact in real time with the physical robot, so virtualization of the sensors and offline motion modification were used



Two motions were developed, a jumping and walking.



Example of collected data: the user required to move both these joints when this sensor pushed and this is the posture.

Development time of a jumping motion with classical interface 44 minutes, with more intuitive developed touch interface 17 minutes.

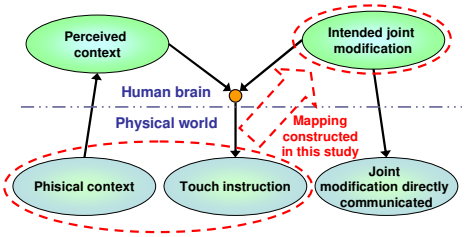
Studying touch instructions

Apply Linear regression to the the datasets collected in the experiment and to their union.
→ Linear model is not sufficiently rich to describe the touch instructions

Define classes for the examples
Each example is associated to a class telling for each joint if it should be increased/decreased/kept constant
→ Constuct a decision tree
Using Quinlan's C4.5 Algorithm, for each of the datasets acquired in the data section and on their union

Observe the features of the context appearing in the higher levels of the tree
These features are the most important
→ The angles of the joint near the trunk (determining the global orientation of the limbs) are important features of the context

Touch instruction model



Users have an intended joint modification. The way they express this depends on the perceived context. When they provide examples users actually specify directly their intention.