Imitation faculty based on a simple visuo-motor mapping towards interaction rule learning with a human partner

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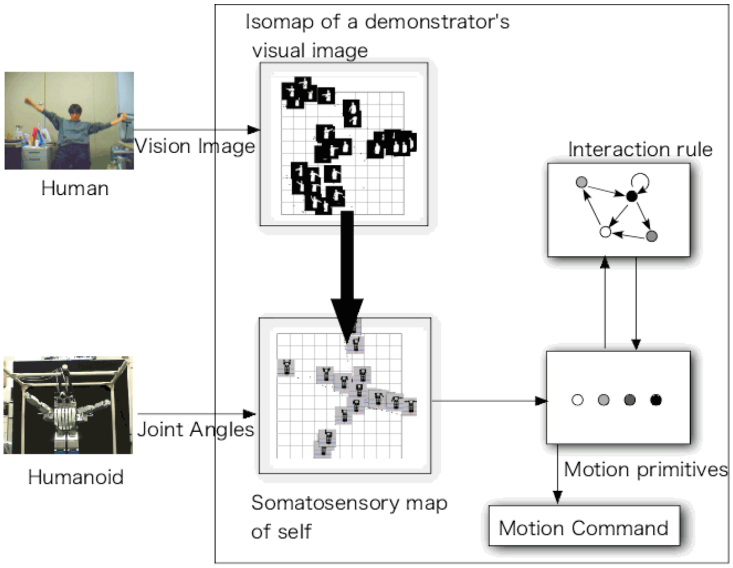
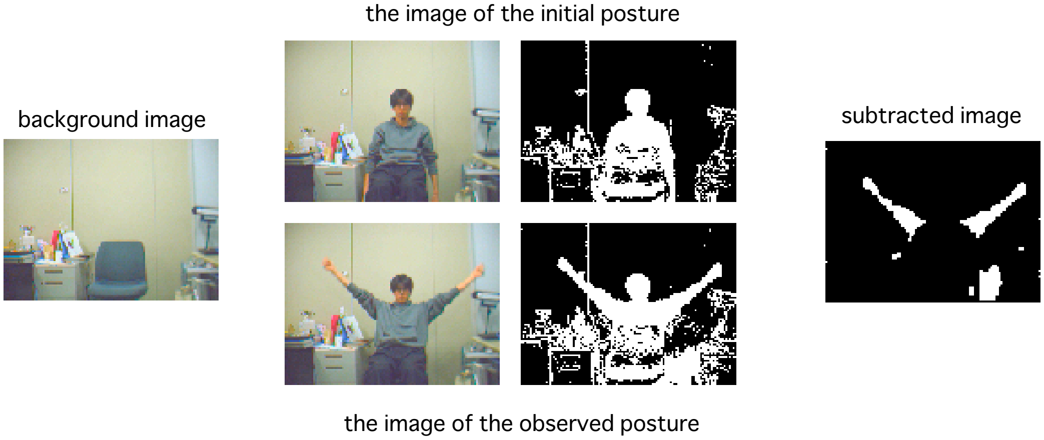
Supported by recent progresses in sensori-motor capabilities, humanoid robotics has been increasing its attention on natural communication between humans and robots. Imitation has been regarded as one of the key technologies indispensable for communication since mirror neuron [1] made a big sensation not only in physiology but also in other disciplines such as cognitive science, and even robotics as well. Unlike a simple copy of human motion trajectories, imitation may include more important role of human motion recognition. That is, observing other's behavior may recall the self motion through the mirror system, and this might be considered as the key component of the "recognition" system. A typical, artificial way of imitation is to use a motion capture system to obtain the trajectory information. However, it seems unnatural interaction between a human and a system with many cameras and artificial markers. More natural interactions are desirable towards human-robot communication.

We aim at building a human-robot communication system and in this paper we propose an observation-to-motion mapping system as the first step towards the final goal. This system enables a humanoid platform to imitate the observed human motion, that is, a mapping from observed human motion data to the self motor commands. To realize this capability, we suppose a human partner who kindly imitates the robot motion, and the system associates both data of the robot somatosensory information (the set of joint angles) and observed human motions imitated from the robot motions, each of which is self-organized onto two dimensional maps using isometric feature mapping (ISOMAP) algorithm [2] for data reduction, respectively, beforehand. A neural network is utilized for this association based on which the humanoid can imitate human motions. This system is applied to interaction rule learning with a human partner who knows the rules and reacts to the humanoid action according to them. On the other hand, the humanoid does not know the rules at the beginning but gradually learns the rules by using its own reaction rule: to just imitate the observed human action if the corresponding reaction rule has not been learned, else to show a reaction to the human action according to the learned rules. Through these processes, the robot adaptively learns and updates the interaction rules with a human partner.



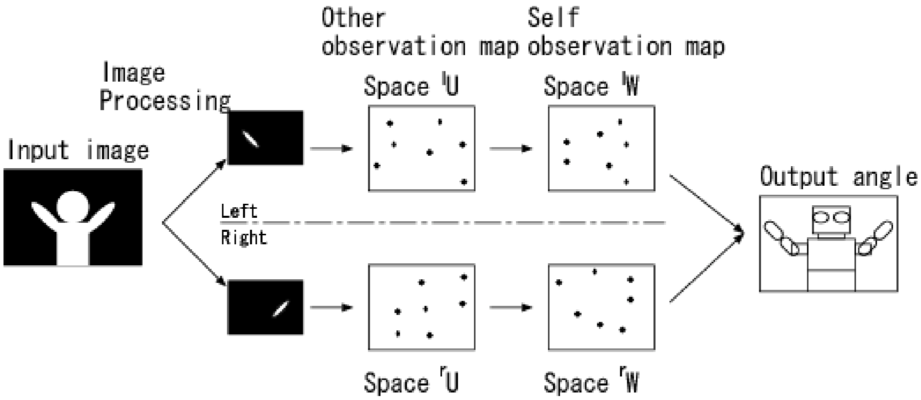
posture image and somato sensory map

The posture information of a person that a robot faces is acquired by the image processing and pattern matching of the posture of arms. Firstly, the silhouette image of the person is made by subtracting the background image from a camera image of a robot. Then the initial posture (both arms are down) image are subtracted from the silhouette image. Finally you can get the image that includes only arms. This image is divided into two images for acquiring right and left arm posture information, and input to the ISOMAP processing. The sensor information of a robot consists of two ISOMAPs that are organized by link angles of right and left arms, respectively.



Posture matching

A robot learns the correspondence between self and human posture based on the temporal relationship when the person imitates robot behaviors. That is, the angles of links of a robot and the images of a person that imitates robot's motion are stored and associated. The coordinates of the somatosensor information calculated based on the angles of links of a robot are associated with the coordinated of the posture image map that was calculated based on the images of a person that imitates robot's motions by the neural network. After learning, a new input image is described on the image posture map with weighting average of the stored images. Then, the data of the new input image is projected on the somatosensory map by the neural network, and can be recognized by self link angles, self posture.



Acquiring interaction rules through interaction

In this research, motion primitive is defined as the set of the initial and final points on the self posture space,

$$R_i = \{s_l^i, s_r^i, e_l^i, e_r^i\}, \quad (i = 1, 2, ..., N).$$

The self motion primitive, R_i, is updated by the observed motion primitive of others, R_x, as follows,

$$\Delta R_i = -\alpha \exp(-\beta \left\| R_x - R_i \right\|^2)\,(R_x - R_i), \quad (i = 1, 2, ..., N).$$

The motion of others is recognized as the self motion primitive that is nearest among self motion primitives.

$$R_s(t) = \arg \underset{i \in N}{min} (\left\| R_x - R_i \right\|)$$

The motion a robot takes when observing a human motion, R_a, is determined by the motion selection probability,

$$R_a(t) = \arg \max_{i \in N} P(R_i \mid R_s(t)) \ .$$

This probability is updated by both the prediction of motion of others and the reaction of others to self motion. The robot predicts the others' reaction, $\hat{R}_s(t+1)$, to its self motion, $R_a(t)$, based on its probability of the motion selection,

$$\hat{R}_s(t+1) = \arg \max_{i \in N} P(R_i \mid R_a(t)) \ .$$

Compared the predictive reaction of others, $\hat{R}_s(t+1)$, with the observed reaction, $R_s(t+1)$, the probability of the motion selection is updated as follows,

$$\Delta P(\hat{R}_s(t+1) \mid R_a(t)) = \begin{cases} -r & if \ \hat{R}_s(t+1) \neq R_s(t+1) \\ 0 & otherwise \end{cases} .$$

On the other hand, the robot can update the interaction rule based on the reaction of others because the robot presumes that the other person determines the next motion based on the same interaction rule (the probability of motion selection) as its own rule,

$$\Delta P(R_s(t+1) \mid R_a(t)) = r' \ .$$

When the observed motion cannot be recognized as any of self motions because the shortest distance between the observed and self primitive exceeds certain threshold and the presumable nearest motion primitive resulted in wrong prediction, the observed motion primitive is registered as the new self motion primitive. At this time, a robot returns the new motion primitive in the next step instead of using the motion selection probability.

Experimental results

To validate the effectiveness of the proposed system, we examine a robot endowed with our proposed system can acquire the interaction rule in the environment in which a human takes motions under an artificial interaction rule. The interaction rule by which a human plays interactions changes at the 20th, 40th and 70th steps. In each step of them, new motions are added and the interaction rule is changed.

A

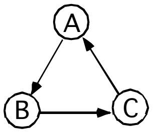

B


C

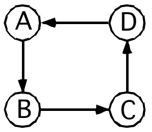

D


E

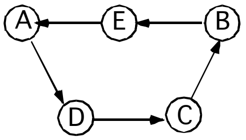

F

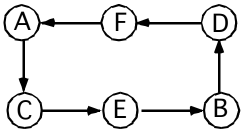
(a) Interaction rule in the first stage
(1-20 steps)



(b) Interaction rule in the second stage
(21-40 steps)

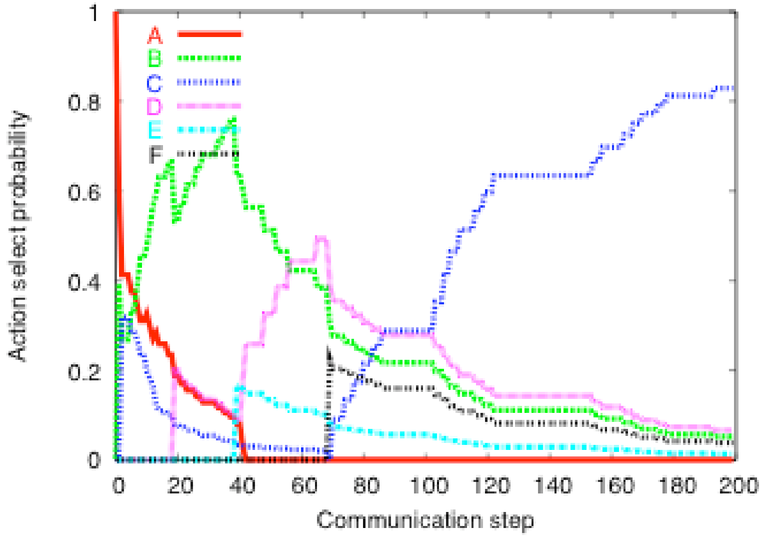


(c) Interaction rule in the third stage
(41-70 steps)



(d) Interaction rule in the fourth stage
(71- steps)

The figure below shows that the temporal transition of the probability of motion selection when a robot observes the motion A. The graph shows that firstly the motion B is selected until 55 steps, then the motion D until 85 steps, and finally the probability for the motion C goes up highest. This corresponds to the interaction rule in each stage, although it takes certain time to adapt to the updated interaction rule.



[1] G. Rizzolatti and L. Craighero, “The Mirror-Neuron System”, Annu. Rev. Neurosci. 27, pp. 169-192, 2004.

[2] J.B.Tenenbaum, V.deSilva, and J.C.Langford. “A global geometric framework for nonlinear dimensionality reduction”, Science, 290(5500) pp. 2319–2323, 2000.