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Interaction rule learning with a human partner based on an imitation faculty with a simple visuo-motor mapping

Masaki Ogino[a,*], Hideki Toichi[a], Yuichiro Yoshikawa[a], Minoru Asada[a,b]

[a] Department of Adaptive Machine Systems, Graduate School of Engineering, Osaka University, 2-1 YamadaOka, Suita, Osaka, 565-0871, Japan
[b] HANDAI Frontier Research Center, Graduate School of Engineering, Osaka University, 2-1 YamadaOka, Suita, Osaka, 565-0871, Japan

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Abstract

Imitation has been receiving increasing attention from the viewpoint of not simply generating new motions but also the emergence of communication. This paper proposes a system for a humanoid who obtains new motions through learning the interaction rules with a human partner based on the assumption of the mirror system. First, a humanoid learns the correspondence between its own posture and the partner's one on the ISOMAPs supposing that a human partner imitates the robot motions. Based on this correspondence, the robot can easily transfer the observed partner's gestures to its own motion. Then, this correspondence enables a robot to acquire the new motion primitive for the interaction. Furthermore, through this process, the humanoid learns an interaction rule that control gesture turn-taking. The preliminary results and future issues are given.

Keywords: Imitation learning; Communication; Humanoid; ISOMAP

1. Introduction

Studies on human–robot interaction are roughly classified into two categories. The first one is related to physical task accomplishment by cooperation (e.g. [3] for table carrying) or tele-operation (e.g. [2] for spaceship inspection/repairing), and sensor feedback and/or latency are main issues. The second one is related to communication with verbal or nonverbal aids, and language communication is typical for the former, and gesture for the latter. Since language acquisition is one of the most formidable issues in general, robotic approaches have been showing very limited capabilities. Gesture recognition systems usually prepare a fixed set of gesture patterns for matching the observed movements with them [5].

Imitation has been receiving increasing attention from the viewpoint of not simply generating new motions [1] but also the emergence of communication owing to recent findings in physiology such as the mirror neuron [6]. Inspired by these findings, there has been study of how the mirror system is developed without explicit knowledge given by a designer [4].

Working towards the emergence of communication under such a mirror system, we focus on how a humanoid robot obtains new motions through learning interaction rules that control gesture turn-taking with a human partner who knows the rules and reacts (shows his/her gesture) to the robot motion. In this paper, we propose a system that has two learning phases: in the first phase, a robot makes the mapping between the human posture and the robot one supposing that the human partner imitates the robot posture, and in the second phase, the robot learns the interaction rule by using the prediction error between the predicted motion and the observed human gesture based on this mapping result. The preliminary results are shown and future issues are discussed.

2. A system overview

The proposed system consists of three modules as shown in Fig. 1. The first one learns the posture matching between the human (other) image and the joint angles of a humanoid (self). This module enables the robot to correspond to the observed

* Corresponding author.
E-mail address: ogino@er.ams.eng.osaka-u.ac.jp (M. Ogino).
URL: http://www.er.ams.eng.osaka-u.ac.jp/ (M. Ogino).

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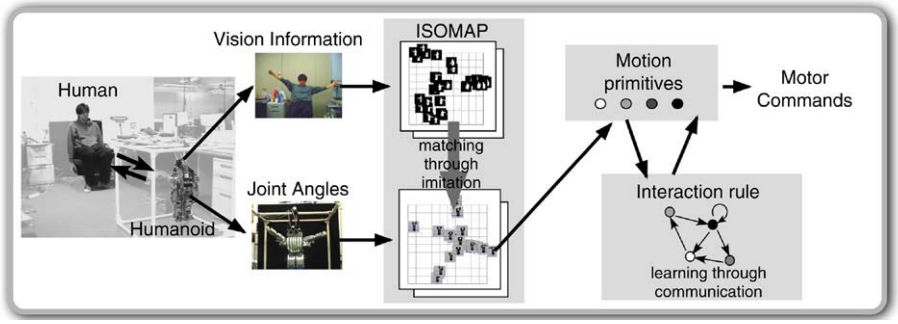

Fig. 1. An overview of the proposed system.

human gestures with self-motions. The second one learns the motion primitives from the observation of the human gesture. This module compares the observed gesture with the self-motion primitive and acquires it as a new motion primitive if it is novel for the robot. The third one learns an interaction rule that controls gesture turn-taking between a human partner and the robot expected to show a motion primitive to be taken when a certain human gesture is observed. The humanoid updates the interaction rule by comparing the human gesture with one that is predicted using the current interaction rule the robot has.

3. Human posture image and robot's posture map

The human posture information is acquired by the image processing and pattern matching of the posture of arms. First, the silhouette image (120×160 pixel) of the human is obtained by subtracting the background image from a camera image of the human partner taken from the robot. Then, the initial posture (both arms are down) image is subtracted from the silhouette image. Finally the image that includes only both arms is obtained. This image is reduced into a 40×30 pixel one, divided into two images to acquire right and left arm posture information separately, and input to the ISOMAP processing [7] for data compression.

The robot posture information consists of eight joint angles (four in each arm). Using ISOMAP, we map the data for each arm to a two-dimensional space.

The coordinates on the ISOMAP of the human posture image are associated with ones on the ISOMAP of robot joint angles by the neural network, which is trained by the pairs of corresponding data when the human imitates the robot motions (Fig. 2).

After learning, a new input image of the human's posture is projected on the robot posture map by the neural network, and the robot can recognize the human posture based on its own joint angles.

4. Acquiring interaction rules through interaction

Fig. 3 shows examples of human gestures (human motion primitives) and interaction rules used in the experiment. For example, the human partner shows the gesture A, and the robot is expected to show gesture B, but at the beginning, it does not have any motion primitives, therefore the robot acquires gesture A as a new motion primitive and imitates gesture A, then the human partner shows the gesture B reacting to the robot gesture A, and this process continues. The task of the robot is to acquire the same motion primitives and the same interaction rule as the human in order to play gesture turn-taking. In the following, the details of the system are explained.

(a) *Motion primitive*

A motion primitive is defined as a set of the initial and final points on the self-posture ISOMAP,

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

where s_l, s_r are the coordinates of the starting points on the robot posture ISOMAP for the left and right arm, and e_l, e_r are those of the end points, and N is the number of motion primitives (Fig. 4).

(b) *Motion recognition and selection*

The motion of the human is recognized as the self-motion primitive, R_s, that is the nearest among the self-motion primitives,

$$R_s(t) = \arg\min_{i \in N}(\|R_x - R_i\|), \tag{2}$$

where R_x is the observed human gesture projected on the posture map, and R_i is the motion primitive that the robot has. The motion the robot makes when observing a human motion, $R_a(t)$, is determined by the motion selection probability,

$$R_a(t) = \arg\max_{i \in N} P(R_i | R_s(t)). \tag{3}$$

(c) *Updating the interaction rule*

The motion selection probability is updated by both the prediction of motion of the human and the reaction of the human to the self-motion every pair of turns as shown in Fig. 5. The robot predicts the human's reaction, $\hat{R}_s(t+1)$, to its self-motion, $R_a(t)$, based on its probability of motion selection,

$$\hat{R}_s(t+1) = \arg\max_{i \in N} P(R_i | R_a(t)). \tag{4}$$

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

$$\Delta P(\hat{R}_s(t+1) | R_a(t)) = \begin{cases} -r & \text{if } \hat{R}_s \neq R_s \\ 0 & \text{otherwise.} \end{cases} \tag{5}$$

On the other hand, the robot can update the interaction rule based on the reaction of the human because the robot presumes

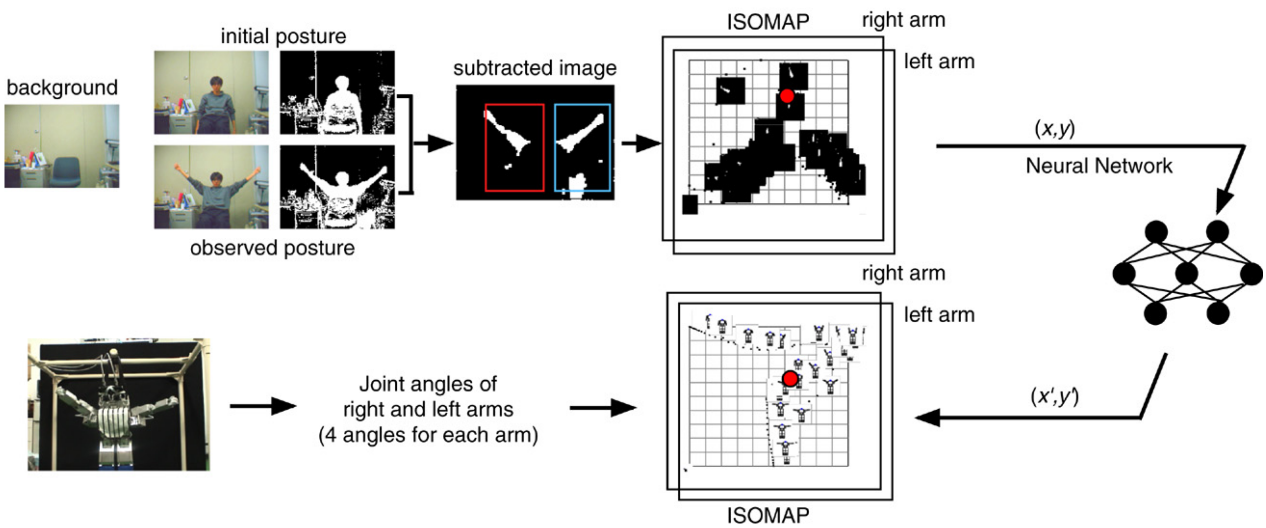

Fig. 2. Human and robot posture ISOMAP.

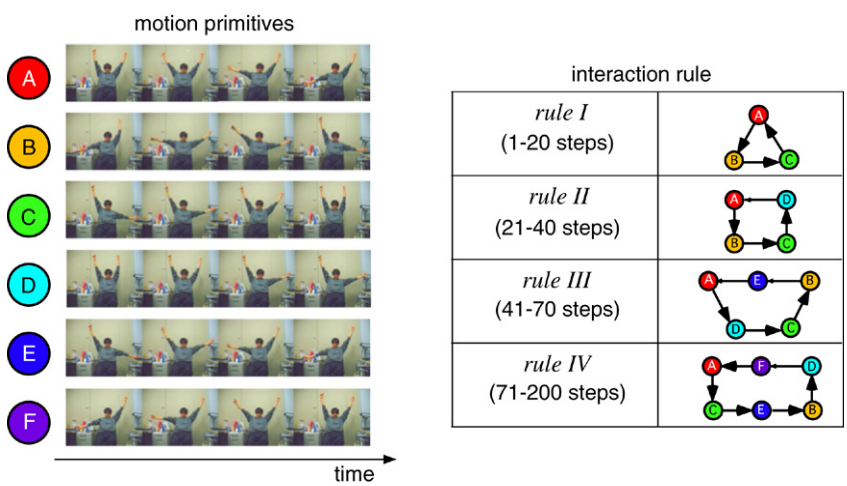

Fig. 3. Motion primitives and interaction rules of the human.

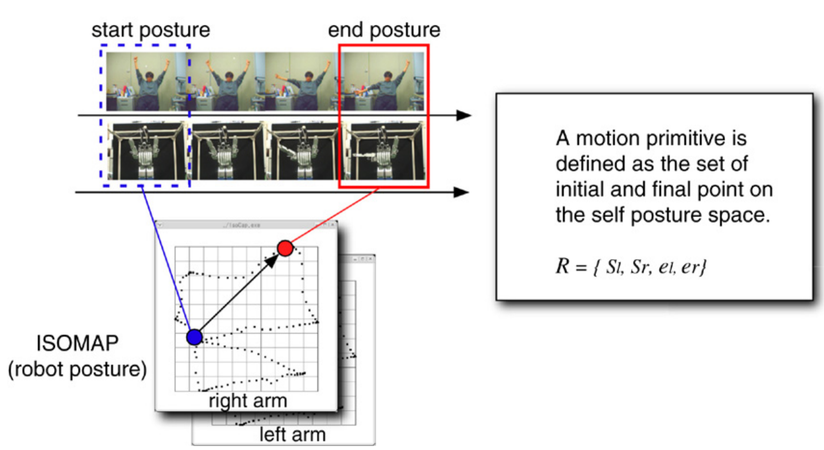

Fig. 4. Motion primitive.

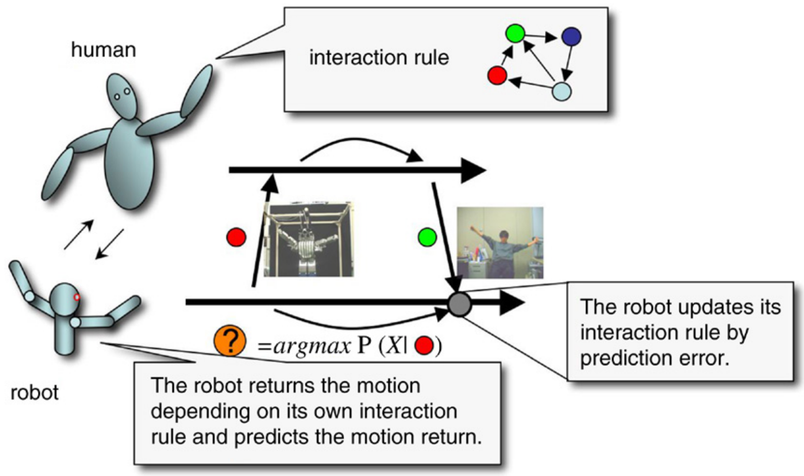

Fig. 5. Learning an interaction rule via prediction error.

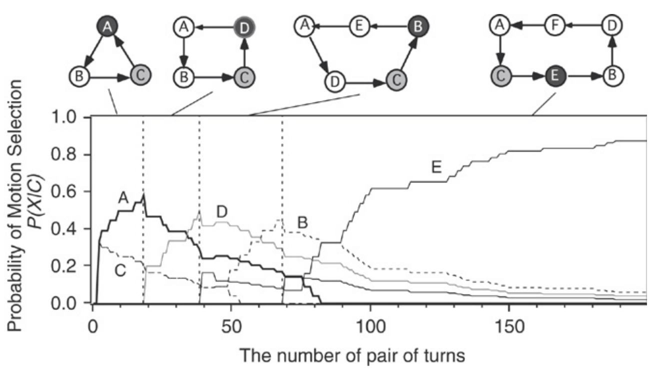

Fig. 6. The time course of the probabilities of motion selection of the robot.

that the human determines the next motion based on an interaction rule (the probability of motion selection) that is the same as its own rule,

$$\Delta P(R_s(t+1)|R_a(t)) = r'. \tag{6}$$

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

(d) *Experimental result*

Fig. 6 shows the time course of the probability of motion selection of the robot when the robot observes the motion C. The graph shows that the appropriate motion selection probability goes up highest in each phase corresponding to the human interaction rule. The probabilities of motion selection when observing other gestures also correspond to the interaction rules of humans (not shown).

5. Discussion

There are several issues left unsolved. First is how to represent postures and motions appropriately. ISOMAPs used in this paper have an advantage in complementary mapping because similar data are mapped to similar positions on the map. However, it is not apparent how many samples should be stored. Moreover, there is no assurance that the topology of the mapped data is appropriate for binding by a neural network.

The second problem is how to segment an appropriate motion primitive from the observed motions. In our experiments, the motion primitive is defined in advance as the set of start and end postures of the motion. In a human, however, it seems that an appropriate motion primitive type is dynamically selected among many types depending on the communication context.

The third problem is turn-taking. In this paper, the phase during which the human shows his/her motion to the robot and the phase during which the robot shows a motion to the human are switched by the human (experimenter). Apparently, in a human, people autonomously take turns.

In future, we will attack these problems to realize more natural communication.

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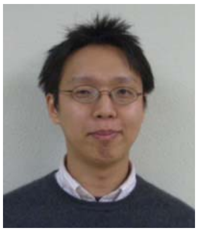

Masaki Ogino received the BS, MS and Ph.D. degrees from Osaka University, Osaka, Japan, in 1996, 1998 and 2005 respectively. He is currently a research associate in the Department of Adaptive Machine Systems, Graduate School of Engineering, Osaka University. His research interests are humanoid robot control, biped walking and cognitive issues involved with humanoid robots.

Hideki Toichi received the B.E. and M.E. degrees from Osaka University, Osaka, Japan, in 2003 and 2005, respectively. He works for Canon Inc. He is interested in applying pattern recognition to humanoid robots.

Yuichiro Yoshikawa received the Ph.D. degree in engineering from Osaka University, Japan in 2005. From April 2003 to March 2005, he was a research fellow of the Japan Society for the Promotion of Science. Since April 2005, he has been a researcher of Intelligent Robotics and Communication Laboratories, Advanced Telecommunications Research Institute International.

Minoru Asada received the B.E., M.E., and Ph.D., degrees in control engineering from Osaka University, Osaka, Japan, in 1977, 1979, and 1982, respectively. From 1982 to 1988, he was a Research Associate of Control Engineering, Osaka University, Toyonaka, Osaka, Japan. In April 1989, he became an Associate Professor of Mechanical Engineering for Computer-Controlled Machinery, Osaka University, Suita, Osaka, Japan. In April 1995 he became a Professor in the same department. Since April 1997, he has been a Professor in the Department of Adaptive Machine Systems at the same university. From August 1986 to October 1987, he was a visiting researcher at the Center for Automation Research, University of Maryland, College Park, MD. He received the 1992 best paper award of the IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS92), and the 1996 best paper award of the RSJ (Robotics Society of Japan). Also, his paper was one of the ten finalists for the IEEE Robotics and Automation Society 1995 Best Conference Paper Award. He was a general chair of IEEE/RSJ 1996 International Conference on Intelligent Robots and Systems (IROS96). Since early 1990, he has been involved in RoboCup activities and his team was the first champion team with the USC team in the middle size league of the first RoboCup held in conjunction with IJCAI-97, Nagoya, Japan. In 2001, he received the Commendation of the Minister of Education, Culture, Sports, Science and Technology, Japanese Government, for Persons of distinguished service to enlightening people on science and technology. Since 2002, he has been the president of the International RoboCup Federation. From September 2005, he has been a leader of JST ERATO Asada Synergistic Intelligence Project. He has been an IEEE Fellow since 2005.