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Behavior Coordination of A Partner Robot based on Imitation

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Abstract

This paper proposes behavior coordination based on imitation of a partner robot interacting with a human. First of all, we discuss the role of imitation, and explain the method for imitative behavior generation. The robot searches for a human by using a CCD camera. A human hand motion pattern is extracted from a series of images taken from the CCD camera. Next, the position sequence of the extracted human hand is used as inputs to a spiking neural network to recognize it as a gesture. The trajectory for a behavior is generated and updated by a steady-state genetic algorithm based on human motions. Furthermore, a self-organizing map is used for clustering human hand motion patterns as gestures. Finally, we show experimental results of imitative behavior generation and behavior coordination through interaction with a human.

Keywords: Partner Robots, Imitative Learning, Spiking Neural Networks, Evolutionary Computation

1 Introduction

Recently, various types of human-friendly robots such as humanoid robots, personal robot, pet robots, entertainment robots, and partner robots have been developed as robots of the next generation. Such a robot requires the capabilities of perceiving, acting, communicating, learning, and surviving. Furthermore, we must consider the autonomy, adaptability, and embodiment in the robotic design. Especially, the concept of embodiment is very important for robots interacting with human. Embodiment means that an agent has not only a physical body, but also experience according to the study of phenomenology [15]. Accumulation of experience of a robot emphasizes the importance of the life-time learning for perceptual system, action system, and communication system interacting with its environment and humans. Therefore, a human-friendly robot must learn its behaviors. Especially, human-friendly physical expression using a robotic body is very important to realize social communication with a human. Therefore, we discuss a mechanism of obtaining and accumulating robotic behaviors through the interaction with human from the viewpoint of constructivism.

Imitation [8-11] is a powerful tool for gestural interaction between children and for teaching behaviors to children by parent. A robot also can obtain various actions using interactive learning based on imitation. We focus on behaviors generated by imitating the motion of a human hand. First of all, the robot detects a series of the movement of the human hand by image processing. Next, the motion is recognized as a gesture by using a spiking neural network [4] and a self-organizing map [7]. Furthermore, a steady-state genetic algorithm (SSGA) [6] is used for generating a trajectory similar to the motion of the human hand. Furthermore, the acquired motion patterns are incorporated into the behavior coordination of the robot according to the sensory inputs. We discuss the interactive learning of a human and a partner robot based on the proposed method through experiment results.

This paper is organized as follows. Section 2 explains the imitative behavior generation and the behavior coordination of a partner robot. Section 3 shows several experiment results of the partner robot based on the partner robot.

2 Imitation and Behavior Coordination

2.1 A Partner Robot; Hubot

We developed a human-like partner robot Hubot [14] in order to realize the social communication with a human (Fig.1). This robot is composed of a mobile base, a body, two arms with grippers, and head with pan-tilt structure. The robot has various sensors such as two CCD cameras, four line sensors (infrared sensors), microphone, ultrasonic sensors, touch sensors in order to perceive its environment. Furthermore, many encoders are equipped with the robot. Two CPUs are used for sensing, motion controlling, and communicating. Therefore, the robot can take various behaviors like a human. In previous researches, we proposed a human detection method using a series of images from the CCD camera and a simple trajectory planning method for a hand-to-hand behavior [14].

2.2 Visual Perception

The robot takes an image from the CCD camera, and extracts a human (Fig.2). If the robot detects the human, the robot extracts the motion of the human hand. The sequence of the human hand is the inputs to the robot. The detailed procedure is explained in the following. The CCD camera is used for visual perception of a partner robot. The human wears a blue glove for performing a gesture displayed to a human in order to simplify the problem. Figure 3 (a) shows an example of an original image in the RGB color space. After the taken image is transformed into the HSV color space, color corresponding to the blue globe is extracted by using thresholds. Next, the blue globe is detected by using a steady-state genetic algorithm (SSGA) based on template matching. The SSGA simulates the continuous model of the generation [6]. Figure 4 shows a candidate solution of a template used for detecting a target where the jth point $P_{i,j}$ of the ith template is represented by ($g_{i,8}$,+$g_{i,j}$cos(jp/4), $g_{i,9}$+$g_{i,j}$sin(jp/4)), i=1, 2, ... , pn, j=0, 1, ... , 7; O (=($g_{i,8}$, $g_{i,9}$)) is the center of a template on the image. Therefore, a candidate solution (individual) is composed of numerical parameters of ($g_{i,0}$, $g_{i,1}$, ... , $g_{i,9}$) satisfying $0<g_{i,j}<g_{max}$ (j=0, 1, ... , 7), $0<g_{i,8}<X$, and $0<g_{i,9}<Y$. In this paper, the worst candidate solution and eliminated ("Delete least fitness" selection) and replaced with the candidate solution generated by the crossover and mutation. We use elitist crossover and adaptive mutation. Elitist crossover randomly selects one individual and generates an individual by incorporating genetic information from the selected individual and best individual. Next, the following adaptive mutation is performed to the generated individual,

$$g_{i,j} \leftarrow g_{i,j} + \left(\alpha_j^H \cdot \frac{f_{\max} - f_i}{f_{\max} - f_{\min}} + \beta_j^H \right) \cdot N(0,1) \tag{1}$$

where f_i is the fitness value of the ith individual, $f_{\max}$ and $f_{\min}$ are the maximum and minimum of fitness values in the population; α_j^H and β_j^H are the coefficient and offset; $N(0,1)$ is a Gaussian random variable with mean 0 and standard deviation 1, respectively. In the adaptive mutation, the variance of the normal random number is relatively changed according to the fitness values of the population. A fitness value is calculated

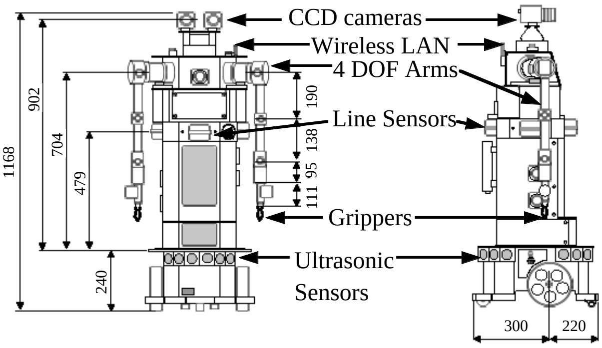


Figure 1: A human-like partner robot; Hubot

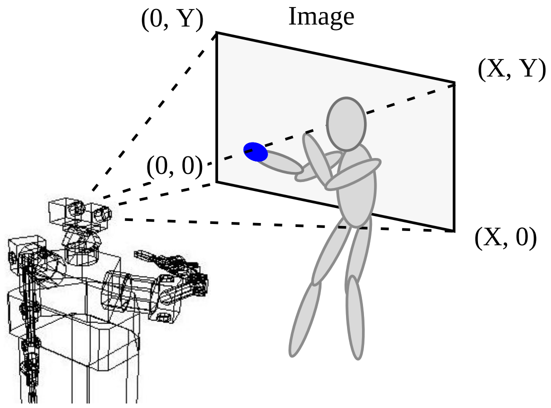
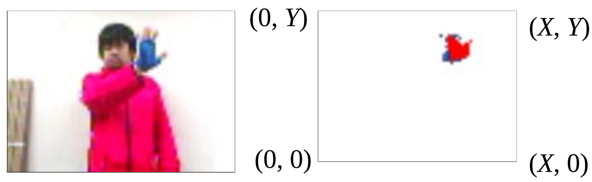


Figure 2: Visual system



(a) An original image (b) A detected globe

Figure 3: Image processing for detecting a human hand

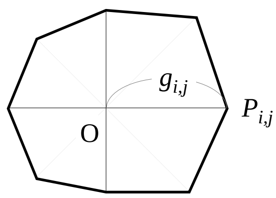


Figure 4: A candidate solution for detecting a target

by the following equation,

$$f_i = C_{Target} - \eta^H C_{Other} \tag{2}$$

where η^H is a coefficient for penalty; C_{Target} and C_{Other} indicate the number of pixels corresponding to a target and other colors, respectively. Therefore, this problem results in the maximization problem. The robot extracts motion of the human hand from images using SSGA where the maximal number of images is T. The sequence of the hand position is represented by $\mathbf{G}(t)$=($G_x(t)$, $G_y(t)$) where t=1, 2, ... , T.

Spiking neural networks (SNNs) have been applied for memorizing a spatial and temporal context [4]. We apply a SNN for memorizing several motion patterns of a human hand. A SNN is often called a pulse neural network and is considered as one of the artificial NNs imitating the dynamics introduced the ignition phenomenon of a cell, and the propagation mechanism of the pulse between cells. In this paper, we use a simple spike response model to reduce the computational cost. First of all, the internal potential $h_i(t)$ is calculated as follows;

$$h_i(t) = \tanh\left(h_i^{syn}(t) + h_i^{ext}(t) + h_i^{ref}(t)\right) \tag{3}$$

Here $h_i^{ext}(t)$ is the input to the ith neuron from the external environment and $h_i^{syn}(t)$ including the output pulses from other neurons is calculated by the following equation,

$$h_i^{syn}(t) = \gamma^{syn} \cdot h_i(t-1) + \sum_{j=1, j\neq i}^{N} w_{j,i} \cdot p_j(t-1) \tag{4}$$

Furthermore, $h_i^{ref}(t)$ indicates the refractoriness of the neuron; $w_{j,i}$ is a weight coefficient from the jth to ith neuron; $p_j(t)$ is the output of the jth neuron at the discrete time t; N is the number of neurons; γ^{syn} is a discount rate. When the neuron is fired, R is subtracted from the refractoriness value in the following,

$$h_i^{ref}(t) = \begin{cases} \gamma^{ref} \cdot h_i^{ref}(t-1) - R & if\ \ p_i(t-1) = 1 \\ \gamma^{ref} \cdot h_i^{ref}(t-1) & otherwise \end{cases} \tag{5}$$

where γ^{ref} is a discount rate. When the internal potential of the ith neuron is larger than the predefined threshold, a pulse is outputted as follows;

$$p_i(t) = \begin{cases} 1 & if\ \ h_i^{ref}(t) \geq q_i \\ 0 & otherwise \end{cases} \tag{6}$$

where q_i is a threshold for firing. Here spiking neurons are arranged on a planar grid (Fig.5) and N=25. By using the value of a human hand position, the input to the ith neuron is calculated by the radial basis function as follows;

$$h_i^{ext}(t) = \exp\left(-\frac{\left\|\mathbf{c}_i - \mathbf{G}(t)\right\|^2}{\sigma^2}\right) \tag{7}$$

where $\mathbf{c}_i=(c_{x,i}, c_{y,i})$ is the position of the ith neuron; σ is a standard deviation. The sequence of pulse outputs $p_i(t)$ is obtained by using the human hand positions $\mathbf{G}(t)$. The weight parameters are trained based on the Hebbian learning algorithm as follows,

$$w_{j,i} \leftarrow \tanh\left(\gamma^{wgt} \cdot w_{j,i} + \xi^{wgt} \cdot p_i(t) \cdot p_j(t-1)\right) \tag{8}$$

where γ^{wht} is a discount rate and ξ^{wgt} is a learning rate. Because the adjacent neurons along the trajectory of

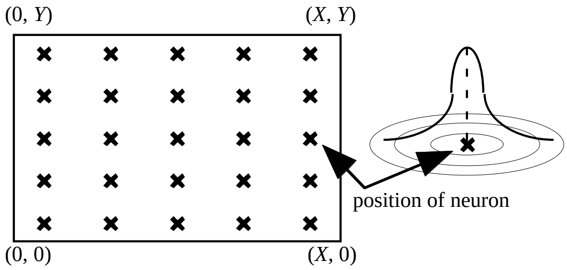


Figure 5: Spiking neurons arranged on the image

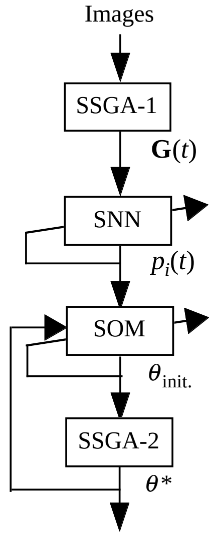


Figure 6: Procedure of imitative learning

the human hand position are easily fired by the Hebbian learning, the SNN can memorize the temporally firing patterns of various gestures.

The temporally firing pattern of pulses from SNN is used as an input for the clustering by a self-organizing map (SOM) in order to detect a spatial pattern of a human gesture. SOM is often applied for extracting a relationship among inputs data, since SOM can learn the hidden topological structure from the learning data [7]. The inputs to SOM is the sum of pulse outputs from neurons. The selected output unit is the nearest pattern among the previously learned gestures.

2.3 Imitative Learning

A trajectory planning problem for a behavior can result in a path planning problem from an initial configuration to a final configuration corresponding to the motion of the detected human hand. Here a configuration $\boldsymbol{\theta}$ is expressed by a set of joint angles, because all joints are revolute,

$$\boldsymbol{\theta} = (\theta_1, \theta_2, \ldots, \theta_n)^{\mathrm{T}} \in R^n \tag{9}$$

where n denotes the DOF of a robot arm. The number of DOF of the partner robot shown in Fig.1 is 4 (n =

4). In addition, the position of the end-effector (robot hand or gripper) is expressed as $\boldsymbol{P}=(p_x\ p_y\ p_z)^{\mathrm{T}}$ on the base frame. Because a trajectory can be represented by a series of *m* intermediate configurations, the trajectory planning problem is to generate a trajectory combining several intermediate configurations corresponding to $\mathbf{G}(t)$. SSGA is applied to generate a trajectory for an imitative behavior corresponding to a human hand motion. Here the SSGA for detecting a human hand is called SSGA-1, while the SSGA for generating a trajectory is called SSGA-2.

Figure 6 shows a total architecture of generating a trajectory for a robot behavior. First of all, the robot detects the human hand position by SSGA-1, and then, SOM selects a node according to the human hand motion as inputs, and its corresponding trajectory is selected by referring to the knowledge database stored. The trajectory is used for generating initial trajectory candidates (θ_{init}) as an initial population of SSGA-2. Next, SSGA-2 outputs the best trajectory, and the robot displays it to the human. And finally, the generated best trajectory is stored in the behavior knowledge database linking with SOM.

A trajectory candidate is composed of all joint variables of intermediate configurations (Fig.7). Initialization generates an initial population based on the previous best trajectory stored in the knowledge database linked with SOM. The *j*th joint angle of the *k*th intermediate configuration in the *i*th trajectory candidate $\theta_{i,j,k}$, which is represented as a real number, is generated as follows (i=1, 2, ... , gn),

$$\theta_{i,j,k} \leftarrow \theta^*_{j,k} + \beta^I_j \cdot N(0,1) \tag{10}$$

where $\theta^*_{j,k}$ is the previous best trajectory referred from the knowledge base; β_j^I is a coefficient for the *j*th joint angle. A fitness value is assigned to each trajectory candidate. The objective is to generate a trajectory realizing the possibly short distance from the initial configuration to the final configuration while realizing good evaluation. To achieve the objectives, we use a following fitness function,

$$f_i = f_p + \eta^T f_d \tag{11}$$

where η^T is a weight coefficient. The first term, f_p, denotes the distance between the hand position and the target point. The second term, f_d, denotes the sum of squares of the difference between each joint angle between two configurations of t and t-1.

A selection removes the worst individual from the current population. Next, an elitist crossover is performed. Consequently, the worst individual is

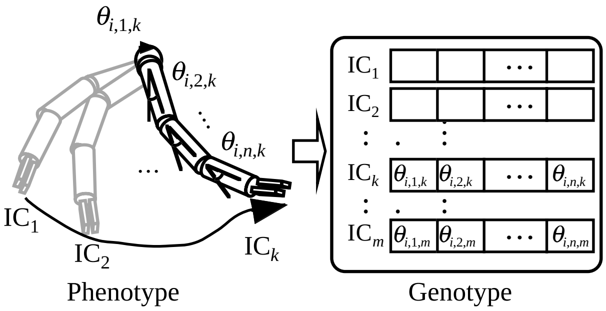


Figure 7: The representation of the ith trajectory candidate composed of m intermediate configurations

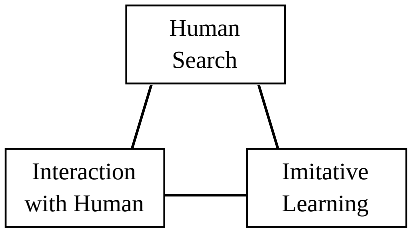


Figure 8: Behavior modes of the robot

replaced with the individual generated by the elitist crossover. Furthermore, we use the adaptive mutation. The searching processes using the internal simulator are repeated until the termination condition is satisfied. Here we use the maximal times of internal evaluations as a termination condition. And finally, the best trajectory obtained is stored in the knowledge database.

2.4 Behavior Coordination

The acquired behaviors are incorporated into the behavior coordination mechanism for the robot. The total architecture of the behavior coordination is shown in Fig.8. We use three basic modes of human search, interaction with human, and imitative learning. First of all, the robot searches for a human by visual tracking. The visual tracking is performed by body movement and CCD-camera's pan-tilt movement. Figure 9 shows an example of visual tracking to move the CCD camera to the suitable direction for imitative learning. The differential extraction based on three images is used for the human detection. After the robot detects human, the behavior mode is transited to the interaction with the human or the imitative learning according to the predefined selection probabilities. If the interaction mode is selected, the robot selects a behavior from the behavior knowledge according to the perceptual information. If the imitative learning mode is selected, the robot stops in the front of the human, and starts human hand detections.

(1) (2) (3) (4)

Figure 9: An example of visual tracking: (A) an original image, (B) reduced color image, (C) difference between two images, and (D) moving objects by the differential extraction.

3 Experiments

This section shows an experimental result of behavior generation using the partner robot Hubot. The size (X,Y) of an image is (160, 120). Here a trial is defined as one cycle from human hand detection by SSGA (SSGA-1), spatial and temporal pattern generation by SNN, gesture clustering by SOM, and behavior generation by SSGA (SSGA-2). Tables 1 and 2 show the parameters used in SSGA-1 and SSGA-2.

Figure 10 shows the snapshots of imitative learning (Case 1). The person moved his right hand from right to left (Fig.10 (1)-(4)), and the robot moved the right hand according to the hand motions (Fig.10 (5)-(8)). Figure 11 shows another result (Case 2). This time the person moved his right hand from top to bottom (Fig.11 (1)-(4)), and the robot moved the right hand according to the hand motions (Fig.11 (5)-(8)). In this way, the robot can acquire behaviors by imitative learning. Figure 12 shows the interaction with the human. The human moved his hands from the top to bottom (Fig.12 (1)-(3)), and the robot took similar motions. Afterward, the behavior mode of the robot was transited to the human search, and the robot started the human search (Fig.12 (4)-(7)), and the robot detected another human (Fig.12 (4)-(7)).

4 Summary

This paper proposed imitative learning and behavior coordination for a partner robot. We applied a spiking neural network for extracting spatial and temporal patterns of gestures, a self-organizing map for clustering gestures, and a steady-state genetic algorithm for generating trajectory to perform a behavior similar to the human motion pattern. Experimental results show that the robot acquires various motion patterns by imitating human hand motions. However, it is difficult for the human to understand the robot behavior mode, because the robot does not use utterance and voice recognition.

As a future work, we intend to incorporate voice recognition for verbal communication with a human.

TABLE 1 Parameters used in SSGA-1 for human detection

Chromosome length	10
Population size (pn)	120
Number of evaluations	300
Crossover rate	0.2
Mutation rate	1.0

TABLE 2 Parameters used in SSGA-2 for trajectory planning

Chromosome length (n DOF $\times$ m IC)	16 (4×4)
Population size (gn)	200
Number of evaluations	1000
Crossover rate	0.2
Mutation rate	1.0

Furthermore, we will discuss a method for solving the symbol grounding problem by learning through interaction with a human.

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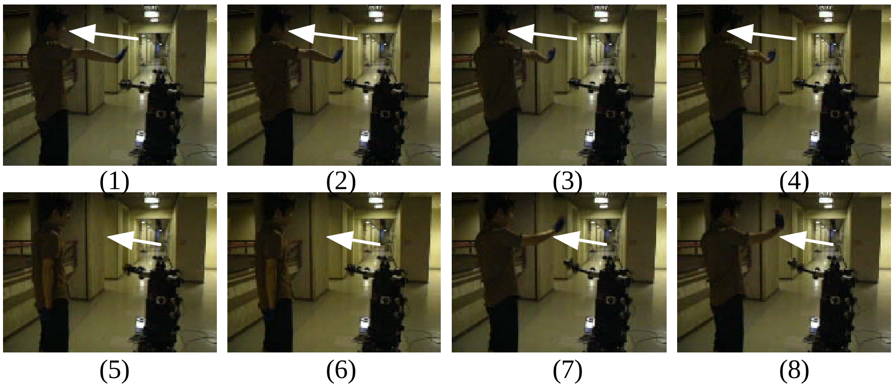

Figure 10: The experimental result of imitative learning (Case 1)

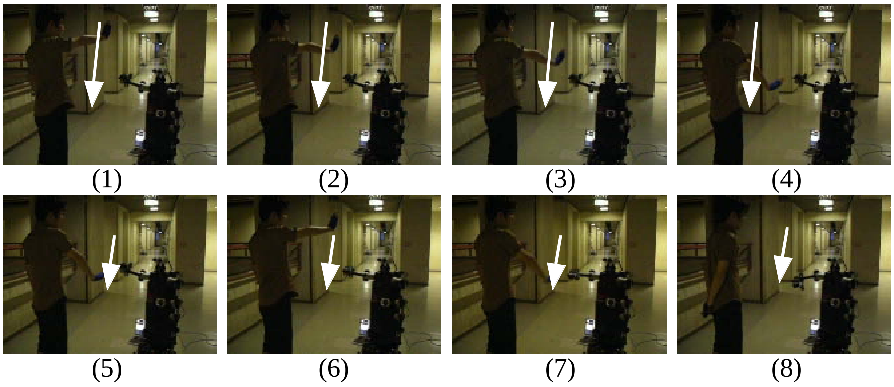

Figure 11: The experimental result of imitative learning (Case 2)

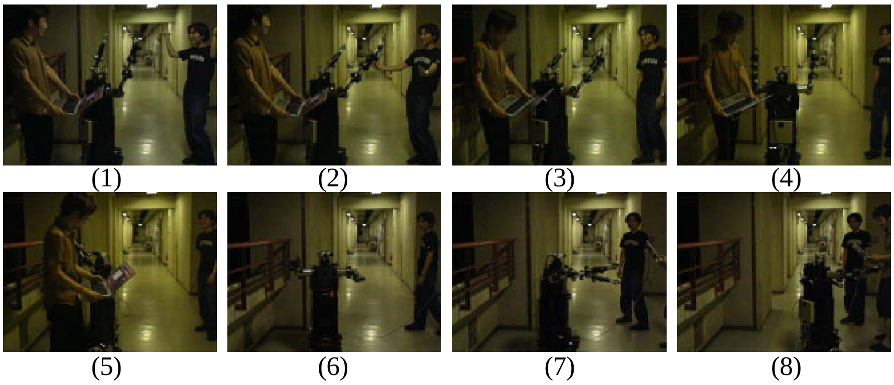

Figure 12: The behavior transition of the robot through interaction with the humans

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