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Visual Perception and Reproduction for Imitative Learning of A Partner Robot

NAOYUKI KUBOTA
Dept. of System Design
Tokyo Metropolitan University
1-1 Minami-Osawa, Hachioji, Tokyo 192-0397
Japan
SORST, Japan Science and Technology Agency
http://www.eng.metro-u.ac.jp/prec/SEKKEI/eng/index.html

Abstract: - This paper proposes visual perception and model reproduction based on imitation of a partner robot interacting with a human. First of all, we discuss the role of imitation, and propose the method for imitative behavior generation. After the robot searches for a human by using a CCD camera, human hand positions are 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 fuzzy spiking neural network to recognize the position sequence as a motion pattern. The trajectory for the robot behavior is generated and updated by a steady-state genetic algorithm based on the human motions pattern. Furthermore, a self-organizing map is used for clustering human hand motion patterns. Finally, we show experimental results of imitative behavior generation through interaction with a human.

Key-words: - Visual Perception, Partner Robots, Spiking Neural Network, Genetic Algorithm

1 Introduction

Natural communication with a human is required for various types of human-friendly robots such as humanoid robots, personal robots, pet robots, and entertainment robots [1-9]. The main methods for natural communication are natural languages and gestures. The theory of relevance emphasizes the importance of mutual cognitive environments for communication [10]. This indicates the high level of perceptual capability is required for natural communication. One of important roles in perception is to specify or extract an object from its background. This is deeply related with the figure-ground problem [12]. According to the theory of relevance, an object can be specified by natural language and gestures. And also, Zadeh discusses the relationship between perception and natural language in his work on computing with words [11]. The meaning of an object depends on the environment as a background and the physical embodiment treating the object, *i.e.*, how to use it considered as possible actions. Therefore, we must take into account all of natural language, gestures, perception, and action to realize natural communication. In this paper, we focus on the gesture imitation as a basic level of human-friendly communication, and propose a total mechanism of behavior acquisition and behavior accumulation through the interaction with human from the viewpoint of constructivism.

Imitation is a powerful tool for gestural interaction between children [6] and for teaching behaviors to children by parents. Imitation is defined as the ability to recognize and reproduce others' action, and imitation has been also discussed in the research of social learning theory. In general, the social learning is classified into two levels: observational learning and imitative learning [12]. The concept of imitative learning has been applied to robotics [1-6]. Basically, in the traditional researches of learning by observation, a motion trajectory of a human arm assembling or handling objects is measured, and the obtained data are analyzed and transformed for the motion control of a robotic manipulator. Furthermore, various biologically-inspired neural systems have been applied to imitative learning for robots [1-3]. Especially, the discovery of mirror neurons is very important [1]. Each mirror neuron activates not only in performing a task, but also in observing that somebody performs the same task. In this way, imitation has been applied for learning robotic behaviors. Rao and Meltzoff classified imitative abilities into four stage progression: (i) body babbling, (ii) imitation of body movements, (iii) imitation of actions on objects, and (iv) imitation based on inferring intentions of others [6]. The third stage of imitation was realized in the previous research. If the robot can perform the fourth stage of imitation, the robot might develop in the same way as humans. Actually, we should discuss how to reproduce the behaviors acquired by the robot, before discussing the fourth stage of imitation. Therefore, we focus on behavior coordination based on imitation. For this, the robot should have three modes of human search, interaction with human, and imitative learning motions at least. First of all, the robot detects a human, and extracts his or her hand motion by image processing. Next, the hand motion is recognized as a gesture by using a spiking neural network [13] and a self-organizing map [14]. Furthermore, a steady-state genetic algorithm (SSGA) [15] is used for generating a trajectory similar to the motion of the human hand. Finally, the acquired motion patterns are incorporated into the behavior coordination of the robot according to the sensory inputs. We discuss the interactive learning between 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 imitative learning.

2 Imitation and Behavior Coordination

2.1 A Partner Robot and Visual Perception

We developed a human-like partner robot Hubot [9] in order to realize the natural communication with a human (Fig.1). This robot is composed of a mobile base, a body, two arms with grippers, and s 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 and internal states. Each CCD camera can capture

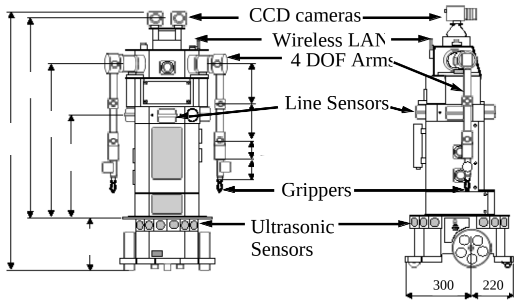

Fig.1: A human-like partner robot; Hubot

an image with the range of -30° and 30° in front of the robot. 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 an interactive trajectory planning method for a hand-to-hand behavior [8,9].

The robot takes an image from the CCD camera, and extracts a human (Fig.2). In this paper, a long-term memory based on differential extraction is used to detect a human considered as a moving object. Figure 3 shows an example of the visual tracking based on the human extraction. If the robot detects a 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. A human wears a blue glove for performing a gesture displayed to the robot in order to simplify the problem. After the taken image is transformed into the HSV color space, color corresponding to the blue glove is extracted by using thresholds. Next, the blue glove is detected by using template matching based on a steady-state genetic algorithm (SSGA). The SSGA simulates the continuous model of the generation, which eliminates and generates a few individuals in a generation (iteration) [15]. The sequence of the hand position is represented by $\mathbf{G}(t)=(G_x(t), G_y(t))$ where t=1, 2, ... , T; the maximal number of images is T.

2.2 A Fuzzy Spiking Neural Network for Human Motion Extraction

We apply a fuzzy spiking neural network (FSNN) for memorizing several motion patterns of a human hand, because the human hand motion has specific dynamics. A SNN [13] is often called a pulsed neural network and is considered as one of the artificial NNs imitating the dynamics introduced the ignition phenomenon of a cell with the propagation mechanism of the pulse between cells. In this paper, we use a modified simple spike response model to reduce the computational cost. First of all, the action potential $h_i(t)$ used as an internal state is calculated as follows;

$$h_i(t) = \tanh\left(h_i^{syn}(t) + h_i^{ext}(t) + h_i^{ref}(t)\right) \tag{1}$$

Here $h_i^{syn}(t)$ including the output pulses from other neurons and $h_i^{ext}(t)$ is the input to the ith neuron from the external environment. Furthermore, $h_i^{ref}(t)$ is used for representing the refractoriness of the neuron. When the internal state of the ith neuron is larger than the predefined threshold, a spike or an impulse is outputted as follows;

$$p_i(t) = \begin{cases} 1 & if\ \ h_i^{ref}(t) \geq q_i \\ 0 & otherwise \end{cases} \tag{2}$$

where q_i is a threshold predefined for firing. Here spiking neurons are arranged on a planar grid (Fig.4) and the number of the neuron (N) is set at 25. By using the values of a human hand position, the input to the ith neuron is calculated by the Gaussian membership function as follows;

$$h_i^{ext}(t) = \exp\left(-\frac{\left\|\mathbf{c}_i - \mathbf{G}(t)\right\|^2}{\sigma^2}\right) \tag{3}$$

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

$$w_{j,i} \leftarrow \tanh\left(\gamma^{wgt} \cdot w_{j,i} + \xi^{wgt} \cdot p_i(t) \cdot p_j(t-1)\right) \tag{4}$$

where γ^{wht} is a discount rate and ξ^{wgt} is a learning rate. Because the adjacent neurons along the trajectory of the human hand position are easily fired by the Hebbian learning, the FSNN can memorize the temporal spike patterns based on various gestures. Next, the sequence of the fired spiking neurons are as an input for clustering by a self-organizing map (SOM) based on the competitive learning in order to memorize and detect a spatial pattern of a human gesture.

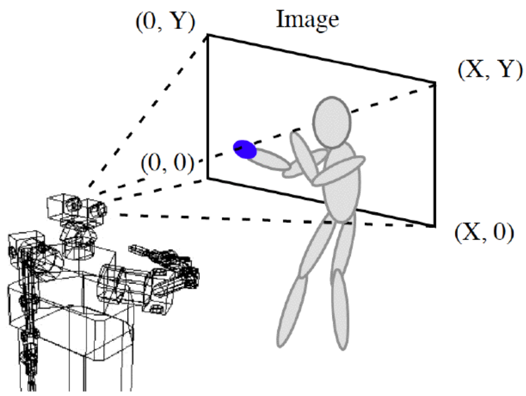

Fig.2: A visual system of the robot in imitation

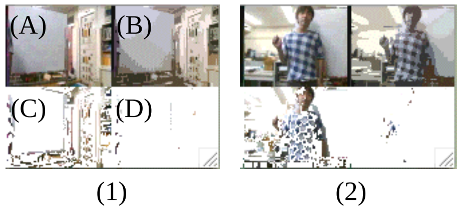

Fig.3: An example of visual tracking: (A) An original image, (B) Reduced colors image, (C) difference between two images, and (D) The result of differential filter.

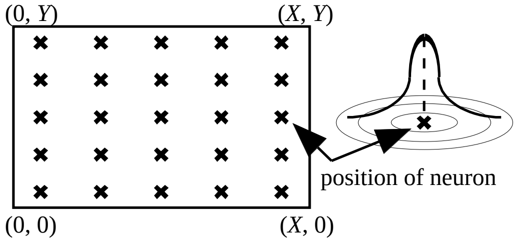

Fig.4: Fuzzy spiking neurons arranged on the image

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.3 Imitative Behavior Generation

The essential of an imitative learning in this method is to acquire a behavior according to a human physical motion. After behavior acquisition, a behavior similar to the human motion can be used as a communication signal, *i.e.*, a gesture. The robot can acquire a behavior by incorporating some action segment from the human gesture. 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 θ is expressed by a set of joint angles, because all joints are revolute,

$$\theta = (\theta_1, \theta_2, \cdots, \theta_n)^{\mathrm{T}} \in R^n \tag{5}$$

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), $\boldsymbol{P}=(p_x\ p_y\ p_z)^T$ 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 5 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.

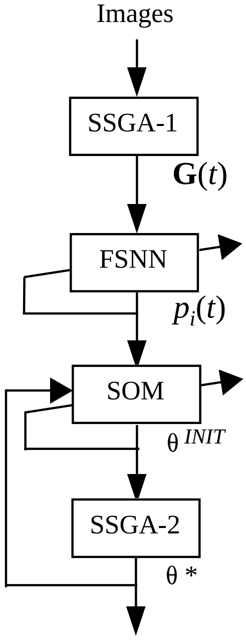


Fig.5: Total architecture of the imitative learning

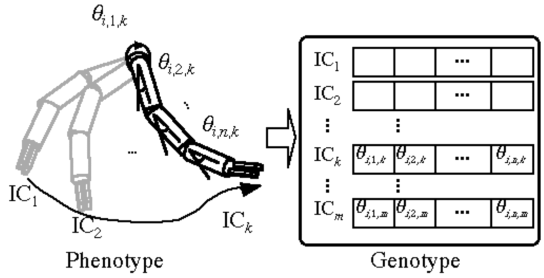


Fig.6: The representation of the ith trajectory candidate composed of m intermediate configurations

A trajectory candidate is composed of all joint variables of intermediate configurations (Fig.6). Initialization generates an initial population based on the previous best trajectory stored in the knowledge database linked with SOM. The jth joint angle of the kth intermediate configuration in the ith trajectory candidate $\theta_{i,j,k}$, which is represented as a real number, is generated as follows (i=1, 2, ... , g),

$$\theta_{i,j,k} \leftarrow \theta^{INIT}_{j,k} + \beta^{I}_{j} \cdot N(0,1) \tag{6}$$

where $\theta^{INIT}{}_{j,k}$ is the previous best trajectory referred from the knowledge base; β_j^I is a coefficient for the jth 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,

$$f_i = f_p + \eta^T f_d \tag{7}$$

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. Therefore, this trajectory planning problem can result in a minimization problem. A selection removes the worst individual from the current population. Next, an elite crossover is performed. The elite crossover generates an individual by incorporating several genes from the best individual in the population. Consequently, the worst individual is replaced with the individual generated by the elite crossover. Furthermore, we use the adaptive mutation based on the fitness vault. 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 the termination condition.

The robot can simply extend the acquired motions into duplication in a same phase, duplication in a different phase, and combination of different motions to realize the motion using both arms. These motion reproduction is performs in the mode of interaction with human.

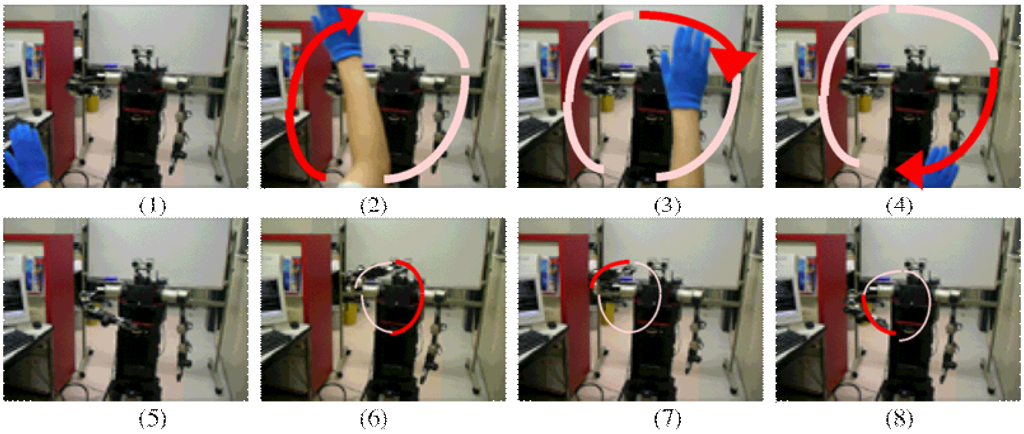


Fig.7: The experimental result of imitative learning

3 Experiments

This section shows experimental results of the partner robot Hubot. First, we show the imitative learning. 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 learning of human hand motion by FSNN, gesture clustering by SOM, and behavior generation by SSGA (SSGA-2). The number of spiking neurons (N) is 25, and the number of nodes in SOM is 10. The population sizes of SSGA-1 and SSGA-2 are 120 and 200, respectively. The number of evaluations in SSGA-1 and SSGA-2 are 300 and 5000, respectively. Furthermore, local hill-climbing search is used in SSGA-2.

Figure 7 shows an example of imitative learning and Fig.8 shows the history of the node selected in SOM in the learning. The person tries to display various motions in order to know the reactive motion patterns of the robot. Therefore, several nodes are selected at first, but gradually, similar nodes are selected repeatedly. Finally, the aim of the human trial is to teach a circular hand motion. The person moved his right hand like a circle (Fig.7 (1)-(4)), and then, the robot moved the right hand in the same way as the person did (Fig.7 (5)-(8)). In this way, the robot memorizes various human hand motion patterns.

Figures 9 and 10 shows more complicated gestures and their corresponding motion patterns generated by SSGA-2. The circle indicates the detected hand positions corresponding to motion patterns. The robot extracts human motion patterns and reproduces them in the internal representation of the robotic configuration space. Figures 11 shows the history of the best fitness value of SSGA-2 in the imitation shown in Fig.9.

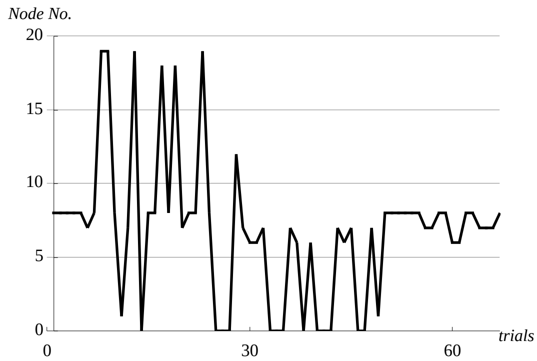
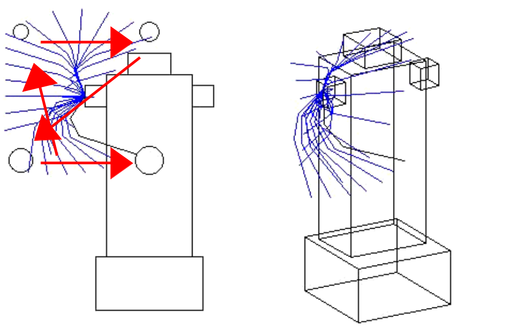


Fig.8: The change of the node selected in the SOM according to human hand motion patterns.

4 Summary

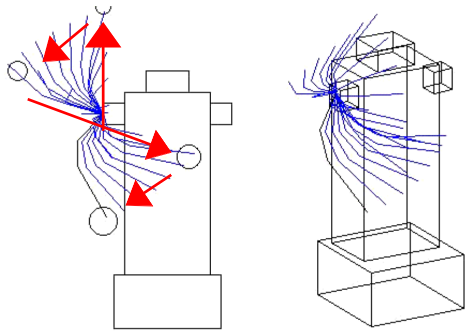
This paper proposed imitative learning for a partner robot. We must realize the high level of signal processing and system integration in order to deal with human factors. We applied a fuzzy spiking neural network for extracting spatial and temporal patterns of human gestures, a self-organizing map for clustering gestures, and a steady-state genetic algorithm for generating a 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, the voice recognition is required for natural communication.

In our other research, we integrated voice recognition and gesture recognition for mobile partner robots [16], and furthermore, we used multilayer perceptron as behavior learning. Therefore as a future work, we intend to incorporate the behavior learning method instead of knowledge database used in SOM.



(A) Front view (B) Oblique view

Fig.9: An experimental result 1 of imitative learning



(A) Front view (B) Oblique view

Fig.10: An experimental result 2 of imitative learning

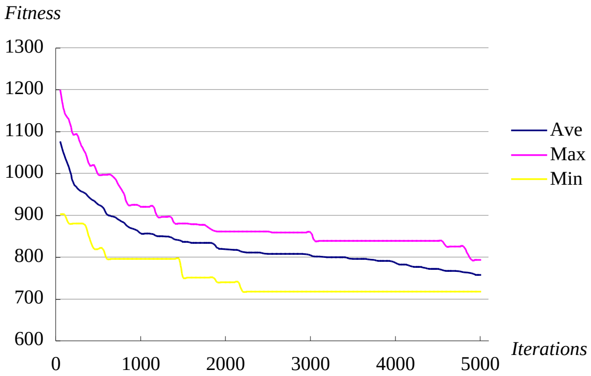


Fig.11: History of fitness value of SSGA-2

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