# Gesture Clustering and Imitative Behavior Generation for Partner Robots

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**Abstract**

This paper proposes a method for generating behaviors based on imitation of a partner robot interacting with a human. This method is constructed by a two-step procedure. At first, a gesture clustering is performed to classify a human hand motion. An evolutionary computation is applied for a pattern matching, and then a spiking neural network and a self-organizing map classify the motion as a gesture. Second, the robot take an imitative behavior which follows human hand motion generated by an evolutionary computation using the previous trajectory information identified by the clustered gesture. The goal of this study, by using these learning modules structurally, the robot and its user share various gestures for user friendly communication. Several experimental results show the effect of the proposed method.

## 1 Introduction

Recently, various partner robots have been developed by many companies and academic groups. Most of these robots can execute a number of given motions to communicate with its user. However their motions are designed based on the expert knowledge of the designer who is not an actual user. Thus, to take suitable actions for the user, the robot should acquire own behaviors through the interaction with the user. Moreover, the robot should accumulate obtained behaviors to reuse them at same situation. To realize the above functions, the robot needs a number of learning modules. In general, since the mechanism of the robot becomes complicated and large increasingly as intelligent capabilities are added gradually to the robot, we should consider the entire structure of intelligence for processing information flow over the hardware and software of the robot, not a single intelligent capability. Accordingly, we have proposed a concept of structured learning which emphasizes the importance of interactive learning of several learning modules through the interaction with its environment. We apply this concept to an imitative behavior learning for generating and accumulating behaviors of the partner robot. For human being, imitation is a powerful tool for gestural interaction with children and for teaching behaviors to children by adults. Partner robots should also obtain various behaviors by using an interactive learning based on the imitation. As the human imitation, there is an advantage that the imitative behavior learning performs without exact human instructions.

In this paper, we propose a method that the robot generates behaviors by imitating the motions of the human hand. Figure 1 shows the total architecture of the proposed method. First of all, the robot detects a series of human hand positions by processing images from CCD camera on the robot. We employ a steady-state genetic algorithm (SSGA) to this image processing in order to cope with environmental noise. We call this SSGA *SSGA-1* in this paper. Next, the motion is recognized as a gesture by using a spiking neural network (SNN), since SNN can learn the spatial and temporal pattern from a series of the human hand positions. Thereafter, a self-organizing map (SOM) is applied for clustering the motion to reuse previous behaviors as the initial trajectories of a SSGA for generating an imitative behavior. We call this SSGA *SSGA-2* in this paper. After generating the behavior, the robot accumulates the behavior by associating

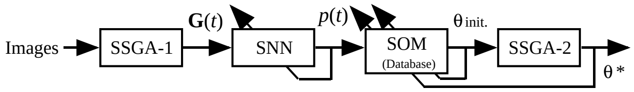



Figure 1: Total architecture for generating and accumulating behaviors.

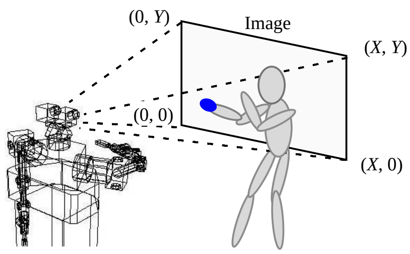



Figure 2: A coordinate system for image processing of a robot.

with the output of SOM. In this way, each learning module (i.e., two SSGAs, SNN, and SOM) relates with one another to achieve the generation and accumulation of imitative behaviors. Experimental results show that the robot can generate imitative behaviors faster by accumulating obtained behaviors.

# 2 Imitation for Partner Robots

## 2.1 Human Hand Detection

The robot takes an image from the CCD camera, and extracts a human hand (Fig.2). The human wears a blue glove for performing a gesture. The taken image from CCD camera is transformed into the HSV color space, and the color corresponding to the blue globe is extracted. Next, the blue globe is detected by using SSGA-1 based on template matching. We employ flexible templates to the candidate solutions in SSGA-1, since the robot must identify several hand shapes.

In SSGA-1, only a few existing solutions are replaced by new candidate solutions generated by genetic operators in each generation. The worst candidate solution is eliminated (delete least fitness selection) and replaced with an offspring solution generated by the crossover and mutation. We use elitist crossover and adaptive mutation. Elitist crossover randomly selects one solution and generates an individual by incorporating genetic information from the selected solution and best solution. In the adaptive mutation, the variance of the normal random number

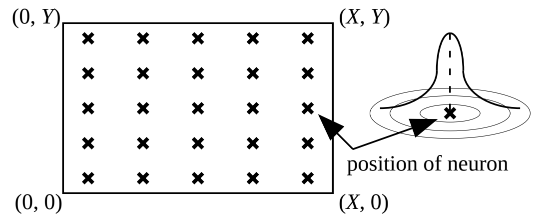



Figure 3: Spiking neurons arranged on the image.

is relatively changed according to the fitness values of the population. A fitness value is calculated by the following equation,

$$f_i = C_{Target} - \eta C_{Other} \tag{1}$$

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

## 2.2 Gesture Recognition and Clustering

We apply a SNN ([1]) for memorizing several motion patterns of a human hand. SNN is often called a pulse neural network and considered as one of the artificial NNs based on the dynamics introduced the ignition phenomenon of a cell, and the propagation mechanism of the pulse between cells.

In this paper, spiking neurons are arranged on a planar grid (Fig.3) and $N = 25$. By using the value of a human hand position, the input to the $i$th neuron is calculated by the radial basis. The weight parameters are trained based on the Hebbian learning algorithm. Because the adjacent neurons along the trajectory of 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 SNN is used as an input for the clustering by SOM in order to detect a spatial pattern of a human gesture. SOMs is often applied for extracting a relationship among inputs data, since SOMs can learn the hidden topological structure from the learning data. The inputs to our SOM is the sum of pulse outputs from SNN. The output node is selected by comparing the Euclidean distance with each reference vector. Moreover, the reference vectors are updated for classifying several gestures. That is, the

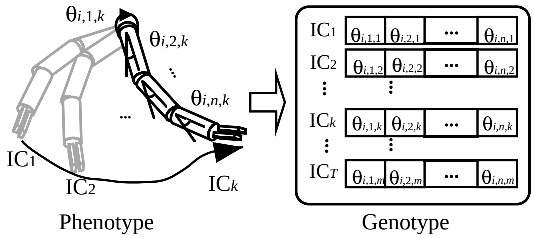



Figure 4: The representation of the $i$th trajectory candidate composed of $m$ intermediate configurations.

selected output unit means the nearest gesture among the previously learned gestures.

### 2.3 Trajectory Generation based on Imitation

A trajectory planning problem for a behavior can result in a path planning problem from an initial human hand position to a final human hand position. Here a configuration $q$ is expressed by a set of joint angles, because all joints are revolute,

$$q = (\theta_1, \theta_2, \cdots, \theta_n) \in R^n \tag{2}$$

where $n$ denotes the degree of freedom (DOF) of a robot arm. Because a trajectory can be represented by a series of $T$ intermediate configurations (i.e., $IC_k$ in Fig. 4), the trajectory planning problem is to generate a trajectory combining several intermediate configurations corresponding to $\mathbf{G}(t) = (G_x(t), G_y(t))$, $t = 1, 2, ..., T$. SSGA-2 is applied to generate a trajectory for an imitative behavior corresponding to a human hand motion.

A trajectory candidate is composed of all joint variables of intermediate configurations (Fig.4). 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 $q_{i,j,k}$, which is represented as a real number, is generated as follows $(i = 1, 2, ..., gn)$,

$$\theta_{i,j,k} \leftarrow \theta^*_{j,k} + \beta^I_j \cdot N(0,1) \tag{3}$$

where $\theta^*_{j,k}$ is the previous best trajectory referred from the knowledge database; $\beta^I_j$ is a coefficient for the $j$th joint angle; $N(0, 1)$ is a Gaussian random variable with mean 0 and standard deviation 1. 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,

$$f_i = f_p + \mu f_d \tag{4}$$

where $\mu$ is a weight coefficient. The first term, $f_p$, denotes the distance between the human hand position and the position of robot end-effector. 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. After SSGA-2, the best trajectory obtained is stored in the knowledge database.

Table 1: Parameters used in SSGA-1 and SSGA-2.

| Parameter | SSGA-1 | SSGA-2 |
|---|---|---|
| Chromosome length | 10 | $4T$ |
| Population size $(gn)$ | 120 | 200 |
| Number of evaluations | 300 | $1000T$ |
| Crossover rate | 0.2 | 0.2 |
| Mutation rate | 1.0 | 0.2 |

## 3 Experiments

This section shows an experimental result using a humanoid-type robot. The size $(X, Y)$ of an image is $(160, 120)$. Here a trial is defined as one cycle from human hand detection by SSGA-1, spatial and temporal pattern generation by SNN, gesture clustering by SOM, and behavior generation by SSGA-2 (Fig. 1). Table 1 show the parameters used in SSGA-1 and SSGA-2. $T$ is the maximum number of human hand positions detected by SSGA-1. According to $T$, the number of intermediate configurations is changed in this experiment.

Figure 5 shows the history of the selected node in SOM and the history of the gesture pattern displayed to the robot. First of all, the human tried to show various patterns to the robot, because the human wanted to know the reaction of the robot. At the time, various nodes in SOM were selected. After 11 trials, the human tried to teach the hand motions like clockwise and counterclockwise circles. The robot classifies the motions by using the $12th$ and $18th$ nodes mainly. And then, the human tried to show various motion again, in order to search for better motions that the robot can follow them well. Based on this searching process, the human tried to teach the hand motions like a

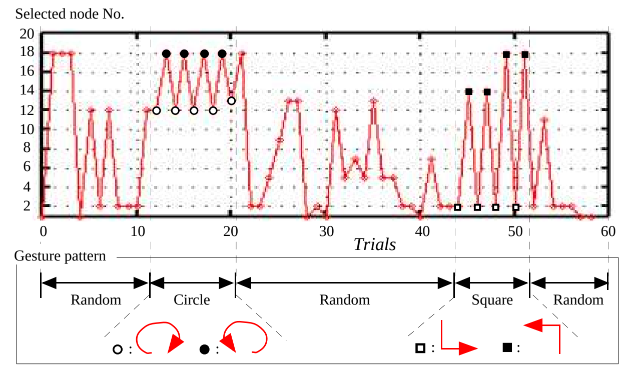



Figure 5: Change of selected nodes in SOM and human motions.

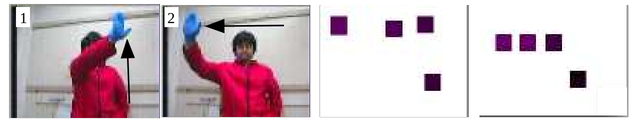
square from $44th$ to $51st$ trial. The robot classifies the motions by using $2nd$, $14th$, and $18th$ nodes mainly. In this way, SOM classifies the human hand motions as specific gestures.

Figure 6 shows the result of image processing at the $51st$ trial. Figures 6 (a), (b), and (c) show the human hand motion, the detected result of the human hand positions, and the outputs of the SNN, respectively. The light and shade of the boxels indicate the time sequence where the lighter boxel indicates the later hand position. Although the detected hand positions were separate, SNN interpolated the detected hand positions and made a sequence as a result of temporal firing. Figure 7 shows the Robot could generate a motion following the human hand motion. That is, it shows that the robot recognized the human hand motion by SNN and SOM, and reproduced the behavior based on imitative behavior generation.

Figure 8 shows the change in fitness value on $2nd$, $14th$, and $18th$ nodes. In each node, the fitness in SSGA-2 decreased trial by trial. This shows the effectiveness of the SOM clustering and the database.

## 4 Summary

This paper proposed a method for imitative behavior generation of a partner robot. We applied SNN for extracting spatial and temporal patterns of gestures, SOM for clustering gestures, and SSGA for generating trajectory to perform a behavior following to the human hand motion. Experimental results show that the robot learns various motion patterns by imitating human hand motions. Furthermore the robot could reuse obtained trajectories for generating better imitative behaviors at the same situations.



(a) Human motion (b) Detected human hand position (c) SNN Output

Figure 6: The results of image processing at the $51st$ trial.

(a) (b) (c) (d)

Figure 7: The snapshots at the $51st$ trial.

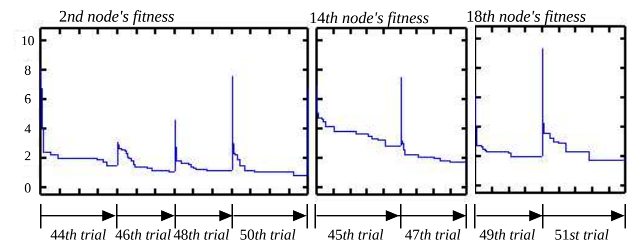



Figure 8: Change in fitness value on $2nd$, $14th$, and $18th$ nodes. A scale interval of the horizontal axis is 1000 iterations.

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