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Paper

Behavior Learning of Human-Friendly Robots by Symbolic Teaching*

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Abstract: This paper deals with behavior learning of human-friendly robots by human symbolic teaching. The mobile robot has an internal model for its behavior criteria and acquires human teaching model based on the behavior criteria. Outputs of human teaching model are used for learning reactive motions such as collision avoidance behavior. The feature of this method is to obtain suitable behaviors through the interaction with environment and symbolic teaching by human intuition. Experimental results show that the robot can acquire collision avoidance behaviors through the interaction with human symbolic teaching in a given environment.

Keywords: Human-Friendly Robot, Fuzzy Controller, Behavior Coordinate, Collision Avoidance

1. Introduction

HUMAN-FRIENDLY robots are required in various fields including service industry and welfare. Recently, various methodologies for robotic control have been discussed in subsumption architecture, behavior-based robotics, and evolutionary robotics [1]–[7]. These concepts are based on reactions that living creatures present. Robot's reactions can be described by production rules, neural networks, and fuzzy inference rules, which are acquired by learning in environments. However, a human-friendly robot should acquire its behaviors through interaction with human in a given environment. Furthermore, the evaluations of human concerning the robot's behaviors are different among human operators. This means that a human-friendly robot should acquire behaviors suitable to a certain human operator. In this study, we discuss a learning method for human-friendly robots. The learning methods can be classified into three types: supervised learning, unsupervised learning, and reinforcement learning only with the response of success or failure [8]–[12]. If a human operator can give exact teaching data, the robot can acquire a behavior suitable to the human operator. However, it is difficult for the human operator to represent exact numerical teaching data. Actually, symbolic communication such as "turn right," "go up," and "stop" is often used in teaching among human operators. In such a case, the robot must understand the meanings of symbolic teaching data. Therefore, the robot must build the human teaching model by itself. Here we use symbolic communication to share information between the robot and human operator. Therefore, the robot requires a mapping method from human symbolic information into numerical information for learning various behaviors based on human teaching. Consequently, we propose a behavior learning method based on the mapped information. As one of basic experiments, we focus on a collision-avoiding behavior of the human-friendly mobile robot in this paper. Generally, the robot should take into account various objectives simultaneously, such as collision avoiding and target tracing. Therefore, we propose a motion coordinate method for multi-objective behaviors of the robot.

This paper is organized as follows. Section 2 describes our developed robot hardware and control architecture. A motion coordinate method is proposed as a basic control architecture of the robot. Simplified fuzzy inference is used for describing robot's behaviors. Furthermore, a sensory network is applied as the perception mechanism of the robot. Section 3 proposes a behavior learning method for the mobile robot. Section 4 shows experimental results of the behavior coordinate and behavior learning of our developed robot.

2. A Mobile Robot with Fuzzy Controller

2.1 Hardware architecture of a mobile robot

We developed a mobile robot shown in **Fig. 1**. The diameter of the robot is 32.0 [cm]. The 32 bit CPU is built in the robot. **Figure 2** shows the sensing system of this robot. The robot has infrared proximity sensors which detect obstacles within 10.0 [cm] in each sensing direction. In addition, the robot has ultra sonic sensors that measure the distance to obstacles between 10.0 and 100.0 [cm]. Consequently, the degrees of danger based on distance is measured by the infrared proximity and ultra sonic sensors. In addition, CdS sensors are equipped to measure the degree of light surrounding the robot in 8 directions. Two stepping motors are used for the actuator. By using these motors, the robot can move forward and backward, and can turn right and left. The stepping motor can be controlled by the signal of a motor output level between 200 and 2000. A wireless communication is used for bidirectional communication between robot and host computer in order to download programs and to perform tele-operation by human operators. Furthermore, a wireless CCD camera system is built in the middle of the robot to perform tele-operation. The human can operate the robot by watching visual images

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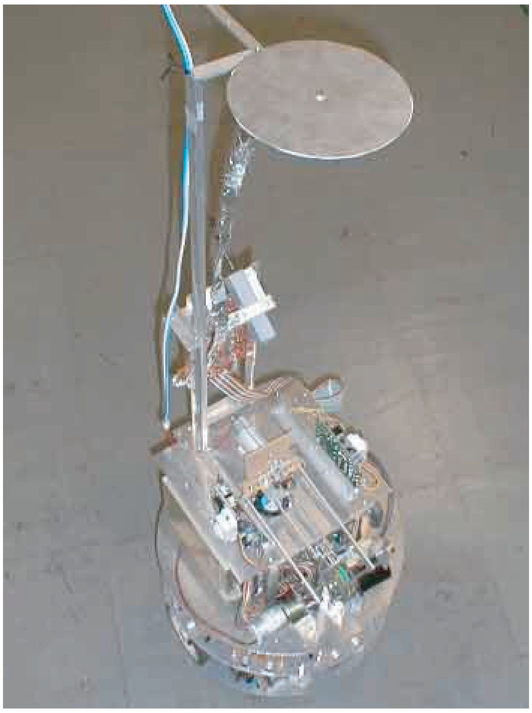


Fig. 1 A developed mobile robot

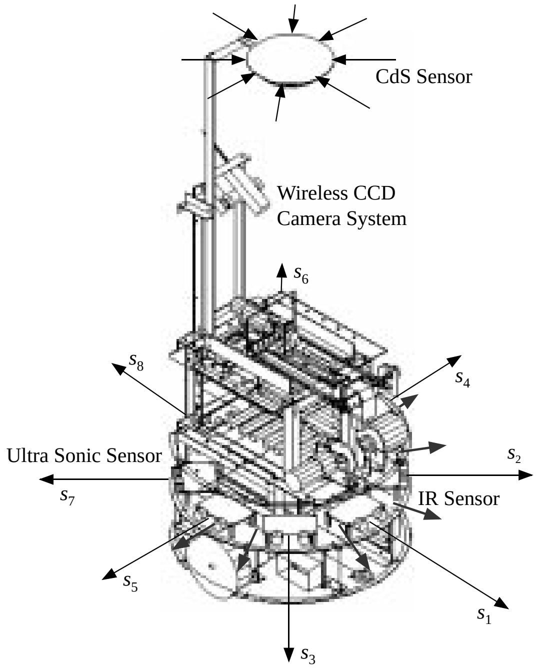


Fig. 2 Sensing system of a mobile robot using ultra sonic sensors and IR sensors

sent from the wireless CCD camera system, but the robot does not process visual images in the decision making.

2. 2 Motion coordinate of the mobile robot

We propose a motion coordinate mechanism for multi-objective behaviors (**Fig. 3**). The mobile robot has a set of several behaviors such as collision avoiding, wall following, target tracing, and random running. A behavior weight is assigned to each behavior. By updating these behavior weights dynamically, the robot can take a multi-objective behavior. In this paper, each behavior is described by a fuzzy controller.

A simplified fuzzy inference is used for the fuzzy control because of the simple architecture and low computational cost [12], [13]. In general, a fuzzy if-then rule is described as follows,

$$\begin{aligned}&\text{if } x_1 \text{ is } A_{i,1} \text{ and } x_2 \text{ is } A_{i,2} \text{ and} \cdots \text{and } x_n \text{ is } A_{i,n}\\ &\text{then } y_1 \text{ is } w_{i,1} \text{ and} \cdots \text{and } y_o \text{ is } w_{i,o}\end{aligned}$$

where $A_{i,j}$ is a membership function for the j-th input of the i-th rule, $w_{i,j}$ is a singleton for the j-th output of the i-th rule, and n and o are the numbers of inputs and outputs, respectively. Here we use a triangular membership function in order to reduce the setting parameters for the fuzzy controller. A triangular membership function is generally described as,

$$\mu_{A_{i,j}}(x_j) = \begin{cases} 1 - \frac{|x_j - a_{i,j}|}{b_{i,j}} & \text{if } |x_j - a_{i,j}| \le b_{i,j} \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

where $a_{i,j}$ and $b_{i,j}$ are the central value and the width of the membership function $A_{i,j}$. Consequently, the firing strength of the i-th rule $(i = 1, \cdots, r)$ is calculated by,

$$\mu_i = \prod_{j=1}^{r} \mu_{A_{i,j}}(x_j). \tag{2}$$

Next, we obtain the j-th resulting output $(j = 1, \cdots, o)$ by weighted average as follows,

$$y_i = \frac{\sum_{j=1}^{r} \mu_i \cdot w_{i,j}}{\sum_{j=1}^{r} \mu_i} \tag{3}$$

where r is the number of rules. Because the output of each behavior is calculated independently, the output is regarded as the reasonable output of each behavior in the multi-objective behavior. Accordingly, the motion coordinate is performed as follows;

$$M_j = \frac{\sum_{k=1}^{z} wgt_k(t) \cdot y_{k,j}(t)}{\sum_{k=1}^{z} wgt_k(t)} \tag{4}$$

where $M_j(t)$, $wgt_k(t)$, $y_{k,j}(t)$, and z are the coordinated j-th output, a behavior weight of the k-th behavior, the inference result (the above output y_j) of the k-th behavior over the discrete time step t, and the number of behaviors, respectively. The behavior weights are updated by simple rules according to the perceptual information.

$$wgt_k(t+1) = G_k(wgt_k(t), x) \tag{5}$$

where x is a set of sensed information and G_k is a weight updating function for the k-th behavior. Therefore, the selection and integration of behaviors depend on the time-series of the sensed information. Here the updating rules are decided experimentally. The inputs in the collision avoiding, target tracing, and wall following behaviors are

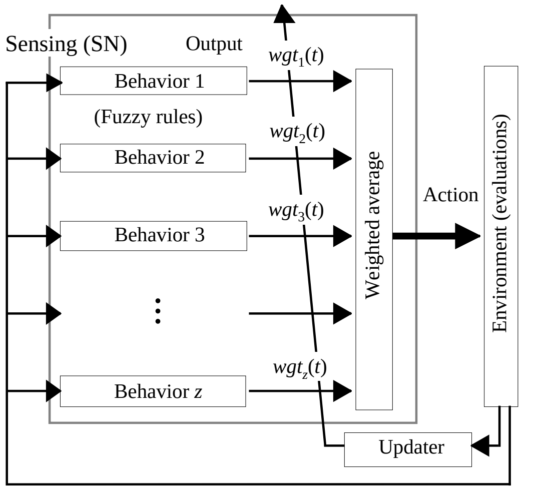


Fig. 3 Motion coordinate mechanism based on the weighted average

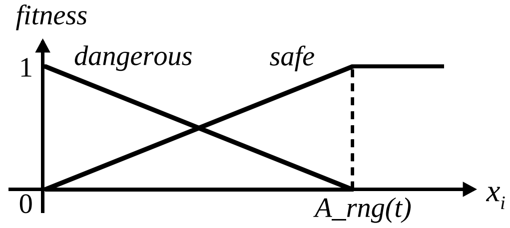


Fig. 4 Triangular membership functions

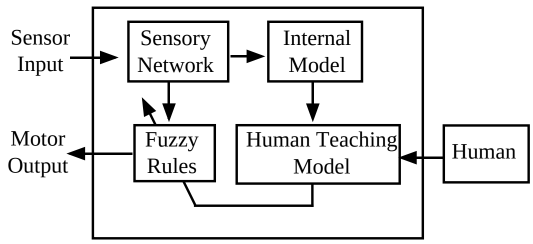


Fig. 5 Total architecture including learning mechanism based on human teaching model

the distances measured by infrared proximity and ultra sonic sensors, the degree of brightness measured by CdS sensors, and the distance measured by ultra sonic sensors, respectively. The output levels of the stepping motors are used as the outputs in all behaviors.

2. 3 Sensory network for the mobile robot

Fuzzy controllers can be tuned or optimized by delta rules and evolutionary methods [14]–[17]. The fuzzy rules working well under various environmental conditions can be exactly described, but the number and structure of fuzzy rules are very large and complicated. On the other hand, the collision avoidance behavior has a close relationship with the environmental condition. For example, if there are many obstacles in the environment, the robot should move slowly to the target point, while avoiding collision. On the contrary, if there are few obstacles, the robot can move easily to the target point without slowdown. The robot should dynamically update the attention range according to the facing environment. Therefore, we have proposed a sensory network with scalable attention ranges, which adjusts the shape of membership functions [16], [17]. When we assume the scalability of control rules, the sensory network changes the output of fuzzy controller according to the time-series of sensed information. The attention range corresponds to $a_{i,j}$ in the membership function of the fuzzy controller. The attention range $A\_rng(t)$ is updated as follows,

$$A\_rng(t) = sprs(t) \cdot S\_rng \tag{6}$$

$$sprs(t) = \begin{cases} \gamma^{-1} \cdot sprs(t) & \text{if all } x_i \geq A\_rng(t) \\ \gamma \cdot sprs(t) & \text{otherwise} \end{cases} \tag{7}$$

where $sprs(t)$ is the degree of sparseness of obstacles satisfying $0 < sprs_{\min} \leq sprs(t) \leq 1.0$, S_rng is the maximal sensing range, and γ is a perceptual coefficient. **Figure 4** shows the membership functions corresponding to linguistic variables of “dangerous” and “safe.” In the simplified fuzzy inference, x_i is regarded as $A\_rng(t)$ if x_i is larger than $A\_rng(t)$. Furthermore, the motor output is also scaled by the internal state of the perception,

$$V_j(t) = sprs(t) \cdot M_j(t) \tag{8}$$

$V_j(t)$ is used for the speed control of the mobile robot. In this way, the sensory network adjusts the sensing range and motor outputs from the meta-level.

3. Reinforcement Learning by Human Teaching Model

This section proposes a reinforcement learning method based on a human teaching model. Generally the learning based on human teaching data is categorized as one of supervised learning methods. However, because this paper assumes that a human operator gives only symbolic information, the robot must infer and build the meanings of symbolic information by itself. Consequently, this learning method can be regarded as one of reinforcement learning, since the teaching information is not exactly given to the robot. In the following, we consider a collision-avoiding behavior of the mobile robot.

In order to build a human teaching model, the robot requires internal criteria to evaluate human teaching data. **Figure 5** shows the total architecture of the robot. In the figure, the sensory network plays a role of perceptual mechanism that translates the sensed data into the membership grade of linguistic variables for fuzzy controllers. The internal model is composed of internal criteria to evaluate the state of the robot. Based on the evaluation results, the robot generates the human teaching model. Here we use keyboard input as an interface between the robot and the human operator. Consequently, the robot translates the symbolic data into numerical data of the teaching model, that is, the robot uses a mapping method from the symbolic information into numerical information. This mapping is statistically performed as follows;

$$T_j(t,c) = \frac{T_j(t-1,c) \cdot cnt(c) + S_j(i)}{cnt(c)+1} \tag{9}$$

where c is an input symbol given by the human operator, t is the discrete time step, $cnt(c)$ is the number of the input of symbol c, and $S_j(i)$ is the generated teaching signal for the

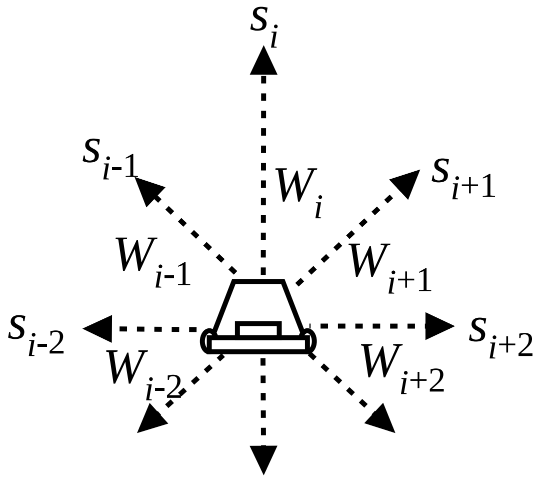


Fig. 6 State evaluation for generating teaching signal in the internal model. $W_i = \{0.1, 0.3, 1.0, 0.3, 0.1\}$

j-th output. After that, $cnt(c)$ is incremented. Each symbol corresponds to numerical teaching signal for learning a fuzzy controller. Consequently, a reinforcement signal $d_j(t)$ for the j-th output is calculated by

$$d_j(t) = T_j(t, c) - y_j(t) \tag{10}$$

where $y_j(t)$ is the output of fuzzy inference and the singleton $w_{i,j}(t+1)$ of the j-th output in the i-th rule is reinforced by

$$w_{i,j}(t+1) = w_{i,j}(t) + \tau \cdot \mu_i \cdot d_j(t) \tag{11}$$

where τ and μ_i are learning rate and the firing strength of the i-th rule, respectively. This learning is performed only when the human operator inputs the symbolic data from the keyboard.

The robot calculates teaching signal $S_j(i)$ for collision avoidance by a heuristic rule [16], [17]. The heuristic rule is to select a move direction toward the collision-free space based on the distances to obstacles. Consequently, the robot searches a relatively safe space. The state of the sensing direction s_i is evaluated by the following equation,

$$state_i = \sum_{j=i-2}^{i+2} W_j \cdot x_j \tag{12}$$

where W_i is a weight coefficient (**Fig. 6**). This evaluation value for the direction s_i becomes high, when the robot is far away from the obstacles. The i-th direction with the highest evaluation is selected and then the corresponding signal $S_j(i)$ is selected from the look-up table of the motor outputs.

4. Experimental Results of Mobile Robot

4.1 Motion coordinate experiment

We conducted motion coordinate experiments in two different environmental conditions. In the experiments, we use a light source as a goal point. Consequently, the robot takes a target-tracing behavior by using CdS sensors. The behavior coordinate is performed by target tracing, collision avoiding, and wall following. **Figures 7** and **8** show an

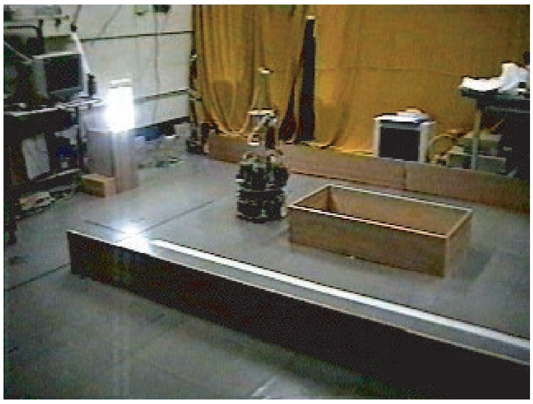


Fig. 7 An experimental environment (case 1)

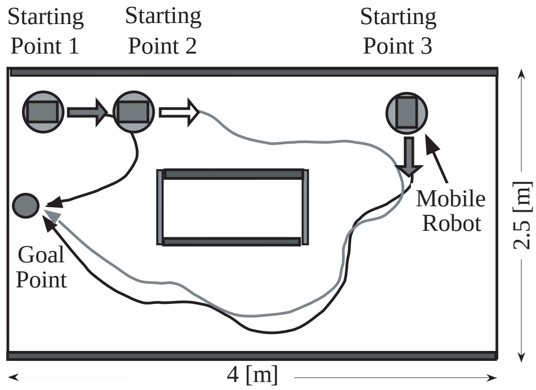


Fig. 8 Experimental results using three different starting points (case 1)

experimental environment (case 1) and the experimental results using three different starting points, respectively. **Figure 9** shows the change of behavior weights of each case where $wgt_1(t)$, $wgt_2(t)$, and $wgt_3(t)$ indicate the behavior weights of target tracing, collision avoiding, and wall following, respectively. In the experiment of the first starting point (Figs. 8 and 9(a)), the robot takes the collision avoiding behaviors, and then takes the target tracing behaviors. The robot reaches the target point in the experiments using other starting points (Figs. 8 and 9).

Figure 10 shows an experimental result (case 2). The environment includes several obstacles. **Figure 11** shows the snapshots of a motion coordinate experiment. The mobile robot reaches the goal point with avoiding obstacles. **Figure 12** shows the experimental results of the measured distance, behavior weights, and motor outputs, respectively. In the figures, $x_1 \sim x_5$ indicate the distances measured by the ultra sonic sensors shown in Fig. 2 and $wgt_1(t)$, $wgt_2(t)$, and $wgt_3(t)$ indicate the behavior weights of target tracing, collision avoiding, and wall following, respectively. Figure 12(a) indicates that the robot updates the behavior weights according to the time-series of density information of obstacles in the environment. The attention range in Fig. 12(b) is reduced by the sensory network as the robot detects obstacles in the environment. As a result, the motor outputs are also reduced by the sensory network (Fig. 12(c)). Afterward, the robot extends the attention range and speeds up toward the goal (light source). These experimental results indicate that the motion coordinate method can select and integrate suitable behaviors

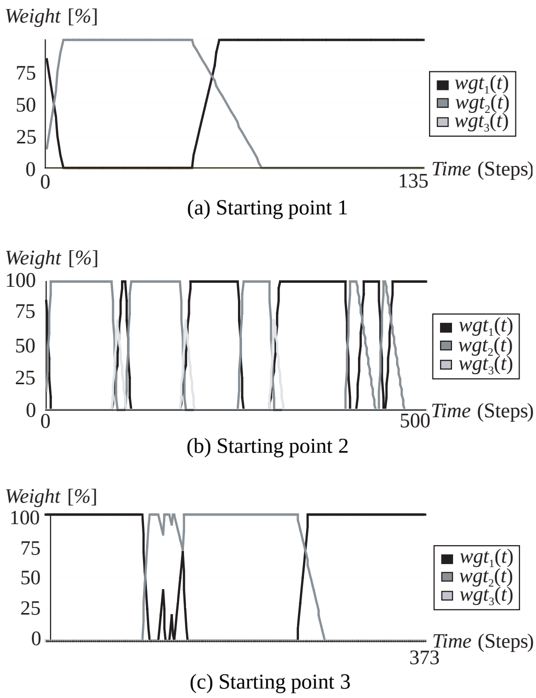


Fig. 9 Change of behavior weights in simulation case 1, where $wgt_1(t)$, $wgt_2(t)$, and $wgt_3(t)$ indicate the behavior weights of target tracing, collision avoiding, wall following

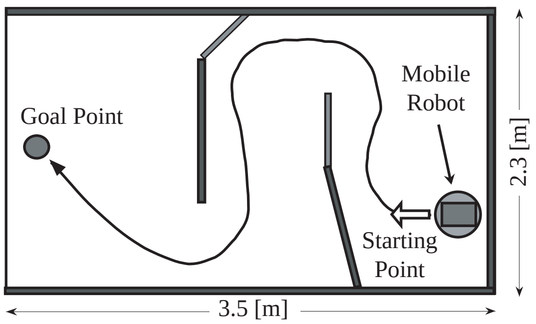


Fig. 10 An experimental result of motion coordinate (case 2)

according to the time-series of sensed information.

4. 2 Human teaching experiment

We conducted human teaching experiments to the mobile robot. Collision avoiding behavior is trained by human teaching model in the experiments. The set of input symbols from the keyboard is "4," "6," and "8," which correspond basically to "turn left," "turn right," and "go straight," respectively. The number of human teaching trials is 10. **Figure 13** shows a visual image from CCD camera of the robot. A human operator (h_1) inputs a symbol by watching this kind of visual image. **Figure 14** shows the changes of maximal degree of danger, average motor outputs, and consumed discrete time steps over trials in human teaching, respectively. Furthermore, **Tables 1** and **2** show the modeling result of human teaching data and learning result of the fuzzy controller. The robot learns the collision-avoiding behavior by using the teaching signals (human teaching model) in Table 1. These results show that the robot can build the human teaching model and can acquire the collision-avoiding behavior by the delta rule based on

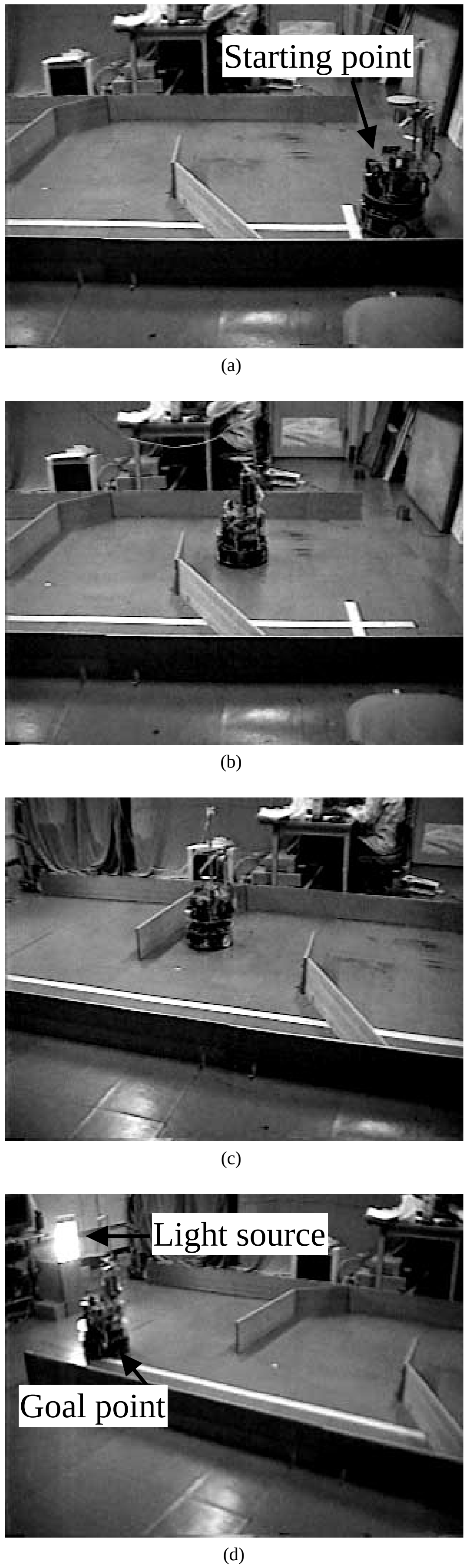
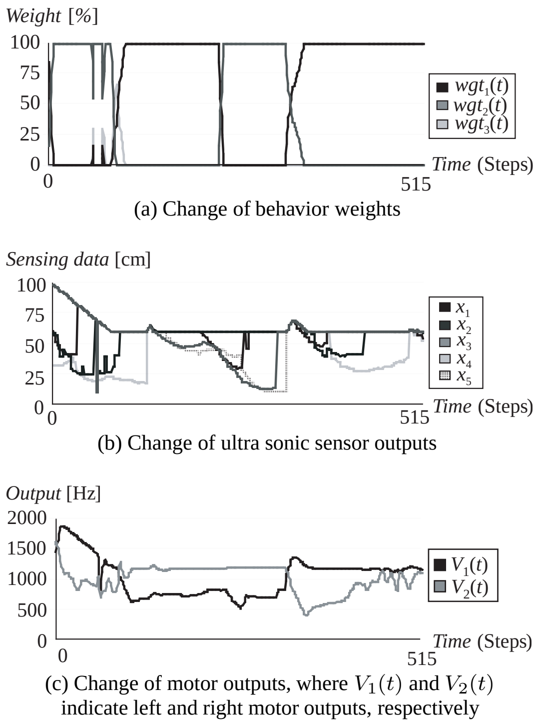


Fig. 11 Snapshots of the motion coordinate experiment



(a) Change of behavior weights

(b) Change of ultra sonic sensor outputs

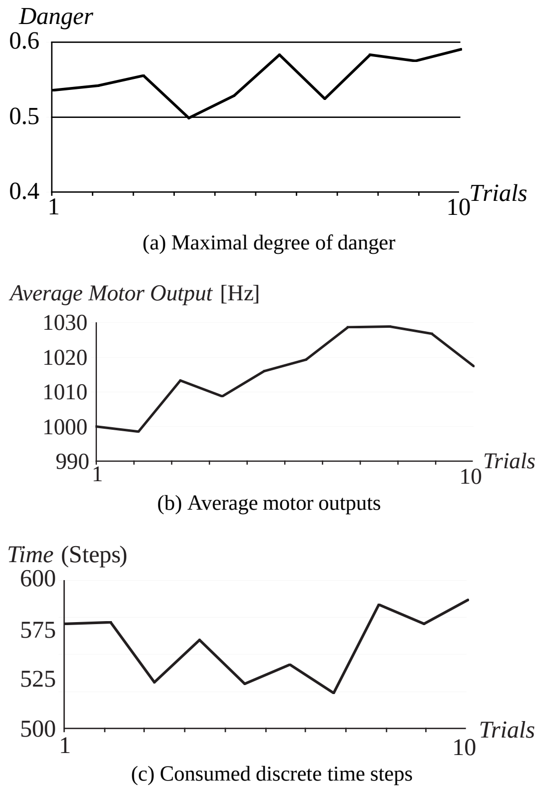
(c) Change of motor outputs, where $V_1(t)$ and $V_2(t)$ indicate left and right motor outputs, respectively

Fig. 12 Experimental result of case 2

Fig. 13 Visual image from the CCD camera system

Table 1 Symbolic translation in human teaching model (h_1)

c	$T_1(t,c)$	$T_2(t,c)$	$cnt(c)$
4	767	2000	35
6	2000	937	46
8	1883	1864	89



(a) Maximal degree of danger

(b) Average motor outputs

(c) Consumed discrete time steps

Fig. 14 Experimental result of h_1

Table 2 Change of fuzzy rules (h_1), where membership functions "dangerous" and "safe" are represented as 0 and 1, respectively

No.	Membership function	$w_{i,1}(t), w_{i,2}(t)$	
	$A_1, A_2, A_3, A_4, A_5, A_6, A_7, A_8$	Initial	Final
1	0, 0, 0, 1, 0, 0, 0, 0	2000, 1500	2000, 1824
2	0, 0, 0, 0, 1, 0, 0, 0	1500, 2000	1849, 1998
3	0, 1, 0, 1, 0, 0, 0, 0	2000, 800	2000, 726
4	0, 0, 1, 0, 1, 0, 0, 0	800, 2000	981, 2000
5	1, 1, 0, 0, 0, 0, 0, 0	2000, 200	2000, 211
6	1, 0, 1, 0, 0, 0, 0, 0	200, 2000	277, 2000
7	0, 0, 0, 0, 0, 0, 0, 0	2000, 2000	2000, 2000

Table 3 Symbolic translation in human teaching model (h_2)

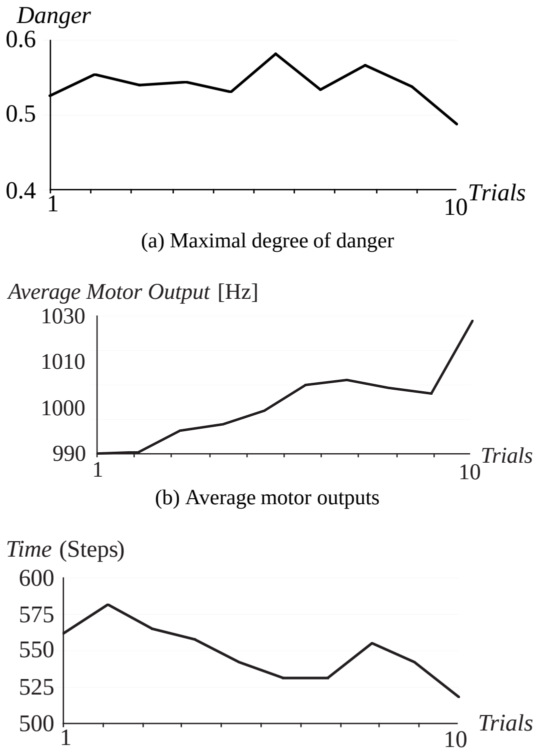
c	$T_1(t,c)$	$T_2(t,c)$	$cnt(c)$
4	1888	1322	72
6	870	1958	82
8	1595	1692	121

the human teaching model. Thus, the robot can understand human teaching data based on the internal criteria.

Figures 15 shows experimental results of the other human operator (h_2). **Table 3** shows the modeling result of h_2. The value of $T_1(t,4)$ is larger than that of $T_2(t,4)$ in Table 3, i.e., the tendency of values of "4" and "6" is opposite to the modeling result of Table 1. This means that the h_2 gives the dangerous direction, not the avoiding direction. However, the robot can correctly learn the collision avoiding behavior, since the h_2 inputs "4" when the robot approaches to the left obstacles. This teaching is generally considered as mistake, but this modeling method is independent on the correctness of the teaching method. Thus, the robot can build the human teaching model dependent on a human operator.

5. Conclusion

Human-friendly robots are required more and more in the future. In this paper, we discussed a learning method for robots based on symbolic communication with human operator. First, this paper proposes a motion coordinate method for mobile robots based on the time-series of sensed information. By using this method, the robot can coordinate various behaviors according to a given environ-



(a) Maximal degree of danger

(b) Average motor outputs

(c) Consumed discrete time steps

Fig. 15 Experimental result of h_2

ment. Furthermore, this paper proposes a reinforcement learning method for collision avoiding behavior. Using this learning method, the robot can acquire a behavior by generating a human teaching model through the symbolic communication with a human operator. This modeling method dynamically gives a particular meaning to a symbol used in symbolic communication. The translation of symbol is different among operators. Therefore, the symbolic translation is very important for robots coexisting with human operators.

A statistical mapping method is simply applied in human teaching model. Therefore, we must discuss how to generate human teaching model in detail. Furthermore, we must discuss how to distinguish a human operator from other human operator by using input symbols based on human teaching models.

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