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Robotics and Autonomous Systems 29 (1999) 21–32

Robotics and Autonomous Systems

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Collision avoidance in multi-robot systems based on multi-layered reinforcement learning ☆

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Abstract

It is important for a robot to acquire adaptive behaviors for avoiding surrounding robots and obstacles in complicated environments. Although the introduction of a learning scheme is expected to be one of the solutions for this purpose, a large size of memory and a large calculation cost are required to handle useful information such as motions of robots. In this paper, we introduce the multi-layered reinforcement learning method. By dividing a learning curriculum into multiple layers, the number of expected situations can be reduced. It is shown that real robots can adaptively avoid collision with each other and to obstacles in a complicated situation. © 1999 Elsevier Science B.V. All right reserved.

Keywords: Collision avoidance; Reinforcement learning; Multi-layered learning; Local communication; Mobile robot

1. Introduction

To accomplish various and complicated tasks by multiple robots, Distributed Autonomous Robotic Systems (DARS) [1–3] have been studied actively. Collision avoidance is one of the most important functions of the mobile robots to carry out cooperative tasks in such systems. One of the most important abilities of the robots to realize robust collision avoidance is recognition of other robots. In the conventional works [4–6], collision avoidance behaviors are achieved in the form of planned paths on the basis of the information measured by ranging sensors. It is, however, difficult to recognize the moving objects only by those ranging data. In order to recognize the moving robots, the most effective way is to acquire their motion information by local communication. For this purpose, we have developed the local sensing device called "LOCISS (LOcally Communicable Infrared Sensory System)" [7]. By the LOCISS, each robot can recognize other robots and obstacles by communicating valuable information in the working environment. Based on this system, we can design and implement an algorithm for collision avoidance between two robots as predetermined behavioral rules [8]. For multi-robot systems, however, it is difficult to design appropriate rule sets by hand coding because complicated situations, in which three or more robots and obstacles exist in the short range, should be taken into account. In this paper, we introduce reinforcement learning as an adaptive behavior acquisition method in such complicated cases. We expand

☆ Extended version of a talk presented at the 4th International Symposium on Distributed Autonomous Robotic Systems (DARS'98) (Karlsruhe, May 1998).

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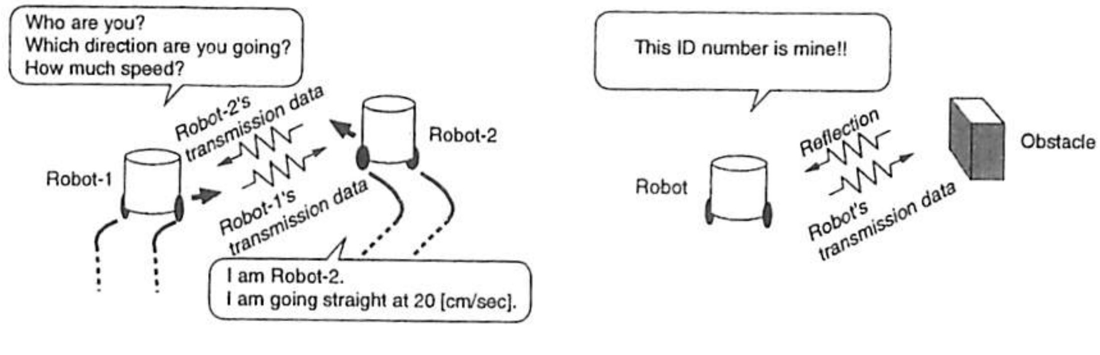
PII: S0921-8890(99)00035-4



(a) Recognition of robot (b) Detection of obstacle

Fig. 1. Concept of situation recognition around robot.

this method into the multi-layered learning method to reduce the size of required memory space and CPU power and implement it onto actual robots. This is a kind of structured process in which each situation for learning is rather simplified in intermediate steps. The concept and the detailed procedures of the adaptive behavior acquisition and multi-layered learning method are presented in this paper, after the description of the rule-based collision avoidance. Finally, the acquired behaviors are verified through collision avoidance experiments using actual robots.

2. Rule-based collision avoidance using LOCISS

Each robot should detect the surrounding objects to avoid collision with them. For avoidance of moving objects such as robots, it is particularly important to recognize their motion. The LOCISS is a device which accomplishes local communication among multiple robots using infrared light. Using the LOCISS, robots can recognize multiple moving objects simultaneously. Since the LOCISS transmits the robots' motion information, that is, moving direction and speed as well as unique ID number, each robot can recognize other robots' motion easily and discriminate other robots and obstacles by receiving these information. When Robot-1 receives the ID number of Robot-2, it can recognize Robot-2 as shown in Fig. 1(a). When a robot receives its own ID number, it can recognize that the object is an obstacle because the transmitted signal is reflected by the obstacle as shown in Fig. 1(b).

The omnidirectional mobile robot which was developed at RIKEN [9] is shown in Fig. 2. The LOCISS is

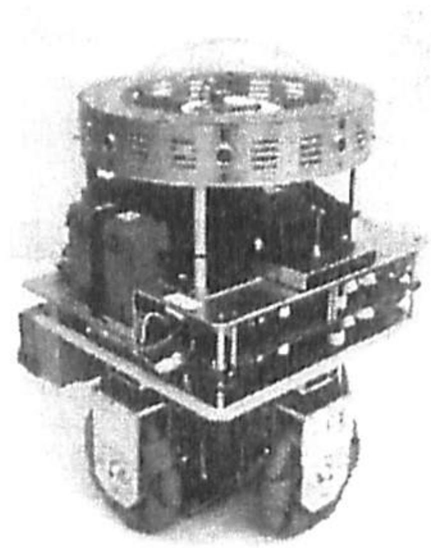


Fig. 2. Omnidirectional robot and LOCISS.

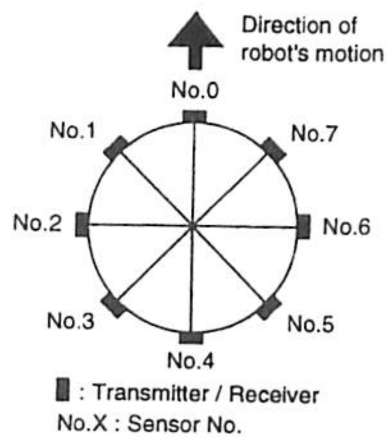


Fig. 3. Configuration of transmitters and receivers.

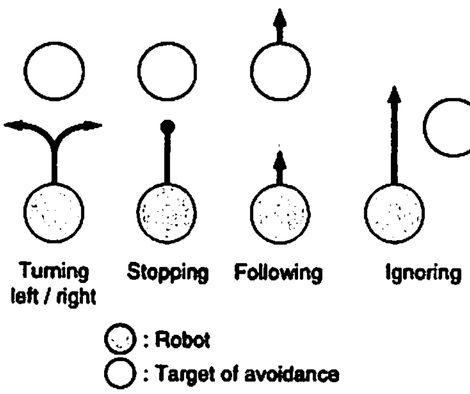


Fig. 4. Definition of avoiding behaviors.

mounted on the top of the robot. This system has eight transmitters and receivers located radially as shown in Fig. 3. The sensor number is assigned from 0 to 7 as starting from the heading of robot's motion. Every robot transmits these numbers as sensor codes by all transmitters to show its moving direction. Therefore, the robot can know the positional relation to surrounding objects as well as motion of robots by these information.

When surrounding objects are detected, robots should select appropriate behaviors to avoid them. In this section, a method selecting an avoiding behavior based on predefined rules between two objects is described. Behaviors are defined on the assumption that the robot moves at its maximum speed toward its goal when it detects no objects. Generally, a robot changes moving direction and speed to avoid objects which are on its path. The direction can be changed to the left or the right and the speed can be changed by accelerating, stopping and decelerating. However, the robot cannot avoid objects by acceleration because it moves at maximum speed according to the above assumption. Therefore, when two robots move in the same direction and one of them approaches behind another at faster speed, one has to adjust its own speed to another. This behavior is defined as "following". According to the above consideration, five kinds of behaviors, that is, "turning left/right", "stopping", "following" and "ignoring", are defined for the collision avoidance (Fig. 4). "Ignoring" behavior means to take no reaction even when collision warning is detected.

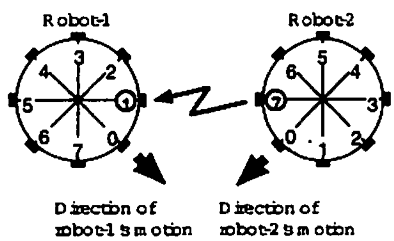
Two different sets of collision avoidance rules, i.e., for a robot and an obstacle, should be defined by using the above mentioned behaviors. The rule set for a moving robot is shown in Fig. 5(a). It is represented as a matrix for 64 patterns of situations which are defined by the combination of moving directions of two robots (8 × 8). The row S_n denotes the number of the sensor which received data from the surrounding robot and the column S_c denotes the sensor code which was transmitted from the other robot. When two robots approach each other into the communicable area of the LOCISS as shown in Fig. 5(b), Robot-1 receives the sensor code "7" of Robot-2 from sensor no. "1". In this case, Robot-1 refers to the row of "1" and the column of "7" in this rule matrix and applies "stopping" behavior. In the same manner, Robot-2 takes "ignoring" behavior on the row of "7" and the column of "1".

The rule set for a stationary obstacle is shown in Fig. 6(a). It is represented as a matrix for eight patterns of situations which are defined by the robot's moving direction. The row S_n shows the number of the sensor which received data from the surrounding obstacle. For example, when the robot approaches an obstacle

Sensor Code : S_c \ Sensor No. : S_n	0	1	2	3	4	5	6	7
0	T(l)	I	I	I	I	I	I	I
1	S	T(r)	I	I	I	I	I	I
2	S	I	I	I	I	I	I	S
3	F	I	I	I	I	I	I	F
4	F	I	I	I	I	I	I	I
5	F	F	I	I	I	I	I	I
6	S	S	I	I	I	I	I	I
7	S	S	I	I	I	I	I	T(l)

T(r) : Turning right
T(l) : Turning left
S : Stopping
F : Following
I : Ignoring

(a) Rule matrix



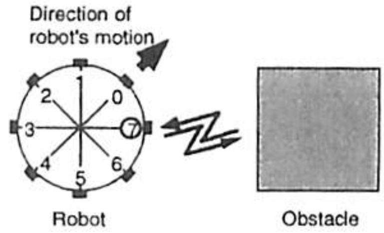
(b) Example of detection

Fig. 5. Collision avoidance rule for robot.

Sensor No.: S_n							
0	1	2	3	4	5	6	7
T(l)	T(r)	I	I	I	I	I	T(l)

T(r) : Turning right
T(l) : Turining left
I : Ignoring

(a) Rule matrix



(b) Example of detection

Fig. 6. Collision avoidance rule for obstacle.

as shown in Fig. 6(b), the robot receives its own data as well as its own ID number from sensor no. "7". In this case, the robot recognizes that the detected object is an obstacle and applies "turning left" behavior referring to the row of "7" in this rule matrix.

When a robot applies a rule, the robot keeps taking the behavior while there are no changes of received data from the sensors. If received data are changed, it means a change of situation between the robot and the object. The robot takes the corresponding behavior based on the rule according to the change of received data. By repeating this procedure, the robot can go toward its goal by avoiding collisions.

3. Adaptive behavior acquisition

In the rule-based collision avoidance, it is difficult to give rules to robots when the number of robots increases, because the recognized situation becomes complicated and the combinatorial number of situations becomes very large. In order to avoid collision in such situations, it is necessary to introduce learning schemes to let the robot acquire adaptive behaviors by itself. We have introduced reinforcement learning for this purpose because it can execute without any teaching signals and large costs for calculation. The procedure of adaptive behavior acquisition based on reinforcement learning is shown in Fig. 7.

The avoiding behavior is defined as a combination of avoiding direction and speed. A score is introduced for each avoiding behavior in each situation specified by the input from the LOCISS as shown in Fig. 8.

Let S_{ij} be the score for an avoiding behavior which is defined by a combination of moving direction i and speed j. Then, the selecting ratio r_{ij} for the behavior is calculated by normalizing S_{ij} for scores of all the

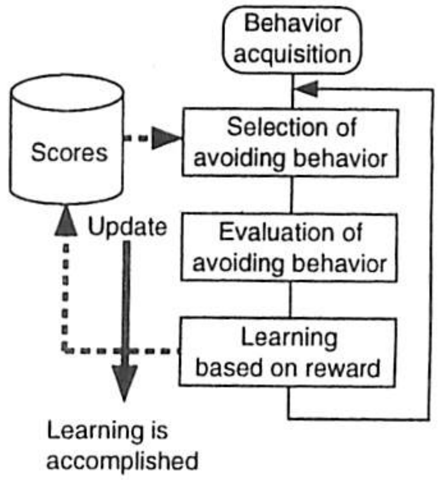


Fig. 7. Procedure of adaptive behavior acquisition.

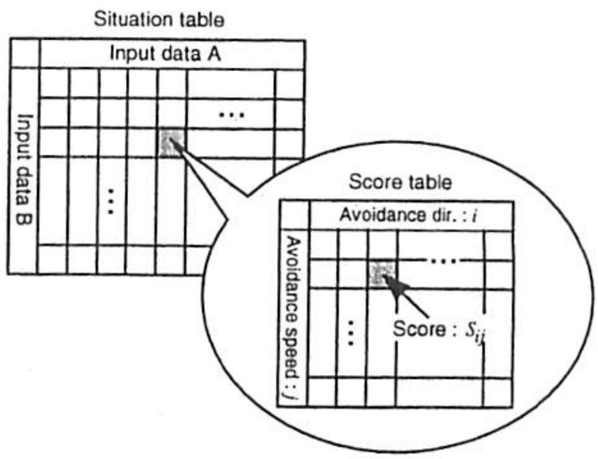


Fig. 8. Concept of score.

behaviors in the situation as

$$r_{ij} = \frac{S_{ij}}{\sum_m \sum_n S_{mn}}. \tag{1}$$

Using the selecting ratio, the robot selects the avoiding behavior in a probabilistic way. This means that the

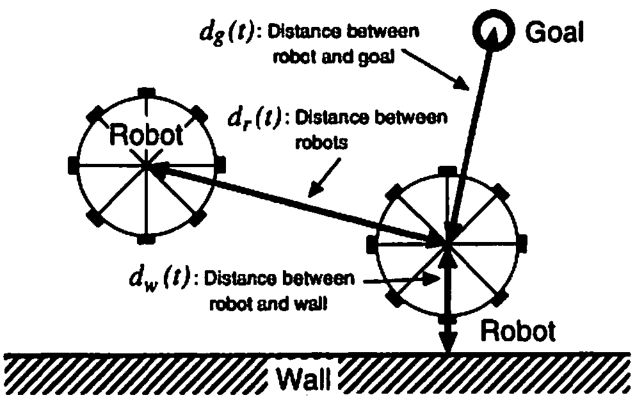


Fig. 9. Evaluation of avoidance behavior.

behavior which has larger score is selected with higher probability.

The robot executes the behavior and evaluates it based on the result of execution using the function $E(t)$. Whenever a behavior is selected and executed, the score for the behavior is calculated by adding the newest evaluation value $E(t)$ incrementally, as

$$S_{\text{new}} = S_{\text{old}} + E(t). \tag{2}$$

As shown in Fig. 9, the behaviors are evaluated based on three criteria at time t, i.e., the summation of the distances from the robot to stationary objects $d_w(t)$, the summation of the distances to other robots $d_r(t)$ and the distance to the goal $d_g(t)$. Here, it is assumed that the distance to the goal can be calculated by the position data based on the dead-reckoning. The total evaluation function $E(t)$ is expressed as:

$$E(t) = \alpha \Delta d_w(t) + \beta \Delta d_r(t) - \gamma \Delta d_g(t), \tag{3}$$

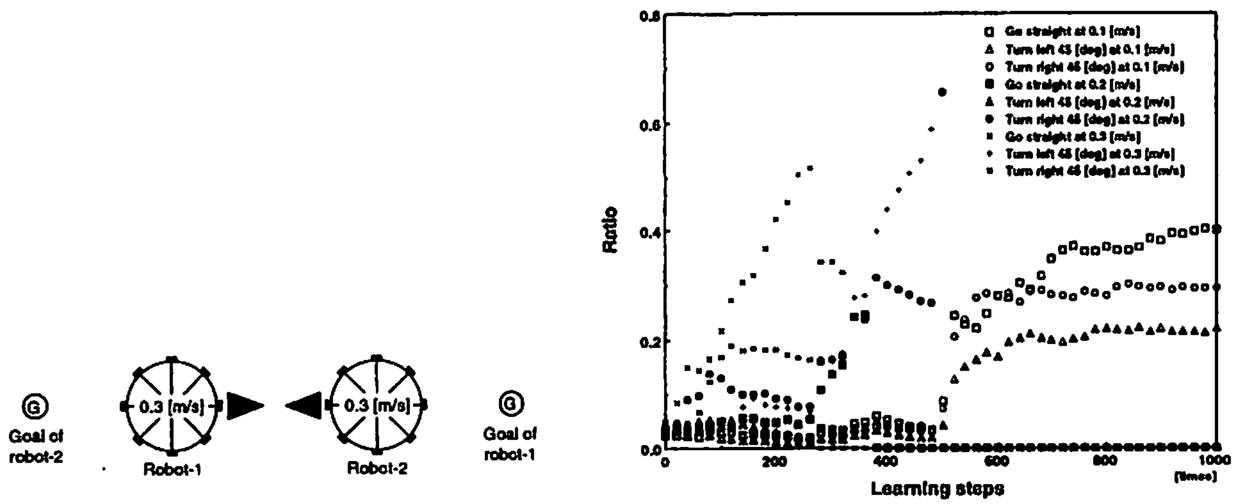
where

$$\Delta d_w(t) = d_w(t) - d_w(t - \Delta t),$$
$$\Delta d_r(t) = d_r(t) - d_r(t - \Delta t),$$
$$\Delta d_g(t) = d_g(t) - d_g(t - \Delta t),$$

where $\Delta d_w(t)$, $\Delta d_r(t)$ and $\Delta d_g(t)$ are differences of the distances for Δt. α, β and γ are weighting coefficients for each criterion. Hence, the reward means the positive evaluation value, and the punishment means the negative value in the context of the reinforcement learning methodology.

In case the robot collides with surrounding objects by executing selected behavior, the score of the selected behavior is set to zero unconditionally for disabling the behavior. By repeating this procedure, the scores for suitable behaviors in the situation become large and the learning is proceeded.

To show the validity of the proposed method, a learning experiment was conducted in a simulation environment, which is shown in Fig. 10(a). There are two robots in the environment and the goal of each robot exists on the other side of each. The robot can move in eight directions in every 45° at discrete speed, that is, from 0 to 30 cm/s by every 10 cm/s, keeping its orientation constant. The robots approach each other



(a) Environment of simulation experiment

(b) Transition of selecting ratio

Fig. 10. Covergence of learning.

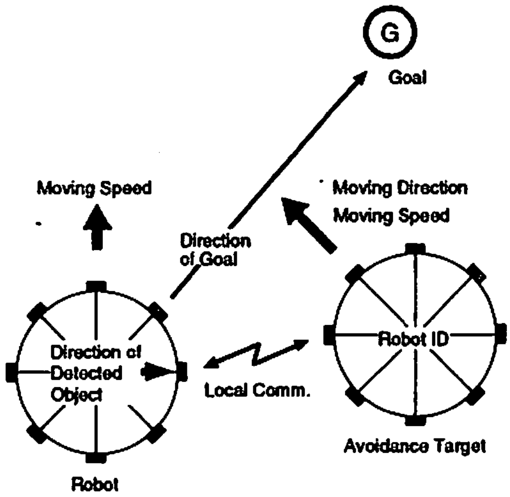


Fig. 11. Parameters for learning.

face to face to go toward their goals. Initial score values are set to be equal for the behaviors to all the directions on a speed and to be proportional to the speeds. α, β and γ are set to 50, 50 and 100, respectively.

Fig. 10(b) shows the transition of the ratios of selected avoidance behaviors. As a result, at about 800 learning steps, the behaviors converged into the following three behaviors, which had the largest three probabilities:

- Go straight at 10 cm/s.
- Turn right 45° at 10 cm/s.
- Turn left 45° at 10 cm/s.

In the learning steps from 0 to 500, ratios of three behaviors were very small because ratios of other behaviors with faster movement were large in this region. Although ratios of some behaviors grew drastically, these behaviors led to collision and their ratios were reduced to zero in order not to repeat collision. It is reasonable that behaviors with slower movement are learned to avoid the robots.

4. Multi-layered learning

To implement the proposed learning scheme onto a real robot, a memory large size is required for the storage of the score set because the number of situations is very large and the number of scores is in proportion to it. Fig. 11 shows the parameters used to accomplish adaptive behavior acquisition in this paper. The robot ID is used to discriminate robots and obstacles. If the recognized object is a robot, the behavior of the robot, that is, the moving direction and the moving speed should be considered. The direction of the detected object and the robot's own moving speed are used to recognize the relation between the object and the robot. The relative direction of the goal is important to show the direction in which the robots should go. The number of scores is represented by the product of the ranges of these parameters and is about 1.8×10^{15}. When the score is represented by 1 byte, the size of the score sets becomes unaffordable amounts, i.e., about 1.8×10^9 Mb. To reduce the size of the required memory and to make the learning process more structured, the concept of the multi-layered learning is introduced.

4.1. *Concept of multi-layered learning*

In the multi-layered learning method, the learning curriculum is divided into multiple layers. By limiting the number of parameters minimum for each layer, the number of situations in each layer is reduced drastically and the number of situations in whole layers is represented not as the product but as the summation of numbers in every layer. In this method, the result of the precedent learning layer must be reflected in the layers downstream because the learning has to be represented by an accumulation of experiences in situations which become complicated layer by layer. Therefore, the avoiding behavior which is selected in the precedent layer should be used as one of the inputs to the next layer.

4.2. *Configuration of controller*

Fig. 12 shows the flow of multi-layered learning. In this paper, the curriculum is divided into four layers, that is, movement toward goal, avoidance of a single object, avoidance with sensor groups and avoidance of multiple objects. In this figure, selectors of behaviors are represented as controllers in each layer. Namely, the aim of the learning is to construct these controllers.

The aim of the first layer is to acquire the behavior to go toward goal. There are no objects around the robot. The robot can go toward its goal without any interferences, recognizing the direction in which the goal exists.

The aim of the second layer is to avoid a single object. Only one object, that is, an obstacle or a moving

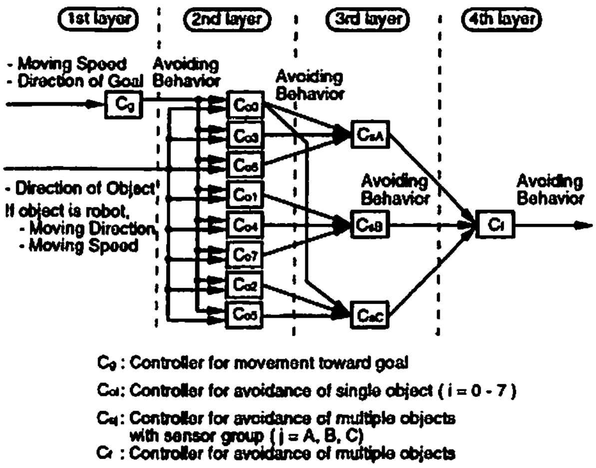


Fig. 12. Flow of multi-layered learning.

robot, exists around the robot. In this layer, there are eight controllers from C_{o0} to C_{o7} for each channel of sensors. Moreover, these controllers C_{oi} are divided into three flows based on the ID detection as shown in Fig. 13. They are for avoiding one robot C^{r}_{oi}, avoiding one obstacle C^{o}_{oi} and through. Inputs used for each controller in this layer are as follows:

- the avoiding behavior from the controller C_g in the first layer;
- moving direction and speed of the robot, if a robot is detected.

The aim of the third layer is to avoid multiple objects detected by each sensor group. The configuration of the sensor group is shown in Fig. 14. Eight channels of sensors are divided into three groups based on the direction of robot's motion. The sensor on the moving direction belongs to two groups, that is, sensor group A and C, because the robot collides easily with the object which exists in this direction. With this configuration,

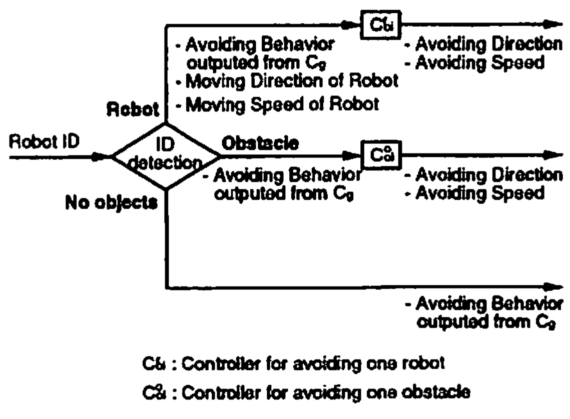


Fig. 13. Flow of learning for avoidance of single object.

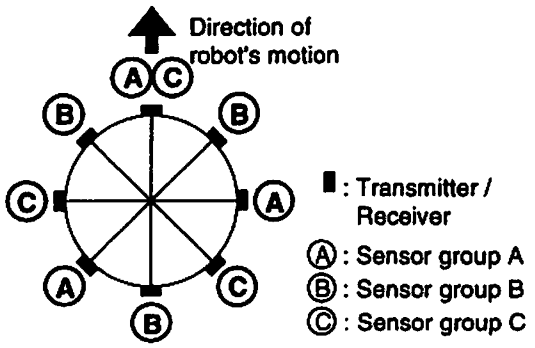


Fig. 14. Configration of sensor group.

it is possible to reflect information from the sensor in this direction strongly on the result of learning in this layer. Inputs to this layer are three pairs of avoiding behaviors selected by controllers C_{oi} for three sensor groups.

The fourth layer is the final layer. The aim of the fourth layer is avoiding multiple objects with all the sensing information. Inputs to this layer are three avoiding behaviors selected by controllers C_{sj} for each sensor group in the third layer.

4.3. Improvement for size of memory space

The number of situations recognized in each layer using this method is as shown in Table 1. In the first layer, the number of recognized situations is defined by the robot's own moving direction (8) and speed (4), and should be 3.2×10^1. In the second layer, a motion of the detected robot which is recognized by its moving direction (8) and speed (4), or an existence of detected obstacle (1) is considered to recognize the surrounding situation. The number of situations recognized by each sensor is defined by this kind of consideration for the detected object and avoiding behaviors from the controller in the first

Table 1
The number of recognized situations in each layer

	The number of situations	
First layer	8×4	$= 3.2 \times 10^1$
Second layer	$(8 \times 4 + 1) \times 32 \times 8$	$\doteq 8.4 \times 10^3$
Third layer	$32 \times 32 \times 32 \times 3$	$= 9.8 \times 10^4$
Fourth layer	$32 \times 32 \times 32$	$= 3.3 \times 10^4$
Total		1.4×10^5

layer (32). Consequently, the number of situations recognized in this layer should be 8.4×10^3 because the system has eight sensors (8). In the third layer, the number of situations recognized by each sensor group is 32^3 based on avoiding behaviors acquired from three controllers in the second layer ($32 \times 32 \times 32$). Therefore, the total number of situations recognized by all sensor groups (3) is three times as large as itself and becomes 9.8×10^4. In the fourth layer, the number of recognized situations is about 3.3×10^4 based on avoiding behaviors from three controllers in the third layer ($32 \times 32 \times 32$).

Consequently, the total number of situations for the whole system is about 1.4×10^5. The total number of scores is about 4.5×10^6 increasing the number of situations by 32 because 32 patterns of scores, that is, combinations of eight avoiding directions and four avoiding speeds, are assigned to each situation. The size of required memory space for the score set is about 4.5 Mb when the required memory space for a score is assumed to be 1 byte. It seems possible to mount this size of memory to the real robot.

5. Experiment

To show the validity of the proposed method, the collision avoidance experiment using real robots was conducted. In the case that a learning is processed along the proposed procedure, it is not realistic to use real robots because a long time is needed for repetitive trials and there are many risks of breakdown due to collisions. Here, we implement the score set which has been constructed in the simulation environment onto an actual robot to verify the performance of the proposed learning method and acquired collision avoidance behaviors.

5.1. Construction of score set

In this section, simulation experiments to construct a score set are described. The sampling cycle of a robot is set to 200 ms adjusting to the characteristics of the robot. If the cycle is too short, the robot cannot move because the next behavior is selected before the previous behavior is executed for a certain time period. If it is too long, the robot cannot accomplish collision avoidance in real time because a selected behavior continues too long. The number of learning steps in each layer is set to 1000 considering the characteristics of the convergence of this learning procedure. The robot can move toward eight directions discretized in every 45° at discrete speed, that is, from 0 to 30 every 10 cm keeping its orientation constant. Some examples of collision avoidance after the learning is completed are shown in Fig. 15.

Fig. 15(a) shows an example of avoidance based on the learning to go toward the goal in the first layer. In this situation, there are no objects on the path of the robot. The robot moved directly toward its goal.

Fig. 15(b) shows an example of avoidance for an obstacle in the second layer. At first, the robot moved just like the above mentioned example reflecting the learning in the first layer. When it detected an obstacle, it avoided the obstacle by changing its path left. After that, it moved toward its goal directly again.

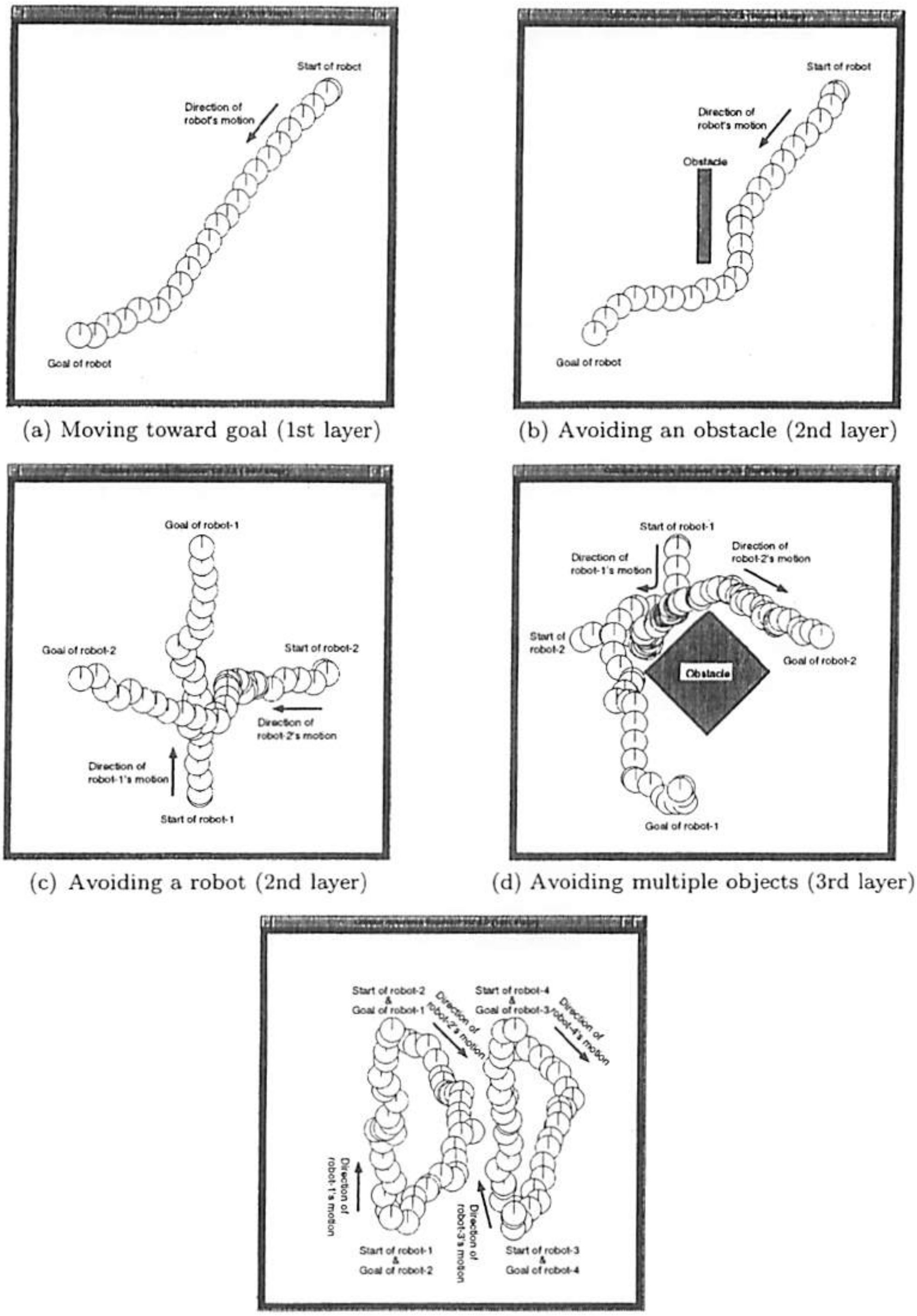
Fig. 15(c) shows an example of avoidance for a robot in the second layer. In the same way as in the previous example, two robots moved toward their goals before they encountered in the center of environment. When they recognized each other as a robot, collision avoidance to each other was accomplished. Robot-1 continued its movement toward the goal and Robot-2 stopped and waited until Robot-1 passed by.

Fig. 15(d) shows an example of collision avoidance for multiple objects in the third layer. In this environment, there were two robots and an obstacle. When the robots approached the obstacle, Robot-1 avoided the obstacle while Robot-2 stopped and waited. After that, Robot-2 also avoided the obstacle.

Fig. 15(e) shows an example of collision avoidance for multiple objects in the fourth layer. In this environment, there were four robots and they mutually avoided each other. Here three avoidance sequences were accomplished simultaneously. This means that the proposed method is effective in this kind of complicated situation.

5.2. Collision avoidance

To verify the performance of the proposed learning method, the collision avoidance experiment using real robots was conducted by implementing the score set which is constructed in the simulation environment. General assumptions for the experiment using



(a) Moving toward goal (1st layer)

(b) Avoiding an obstacle (2nd layer)

(c) Avoiding a robot (2nd layer)

(d) Avoiding multiple objects (3rd layer)

(e) Avoiding multiple objects (4th layer)

Fig. 15. Results of collision avoidance in the simulation environment.

real robots are the same as for the simulation environment described in the previous section.

In the environment for the experiment (shown in Fig. 16), there were four robots and a wall as an obstacle. Two pairs of robots were set face to face at a distance of 4.0 m. The lateral distance between two pairs was 2.0 m. The distance between a wall and Robot-3,4 was 1.5 m. Goals of the robots were set at the start position of the counterpart robot in each pair.

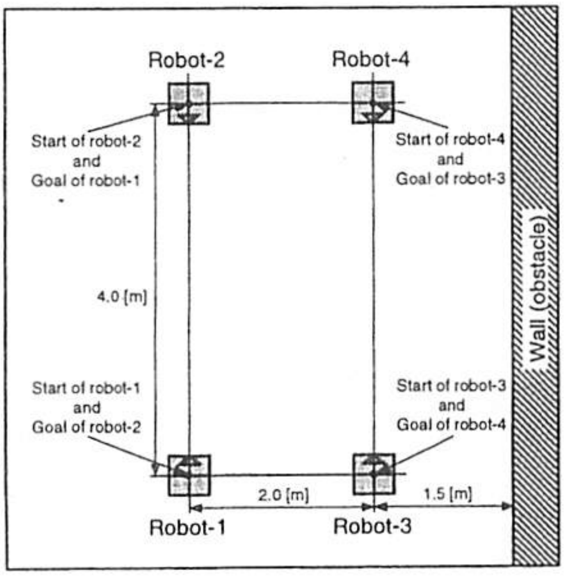


Fig. 16. Environment of collision avoidance using a real robot.

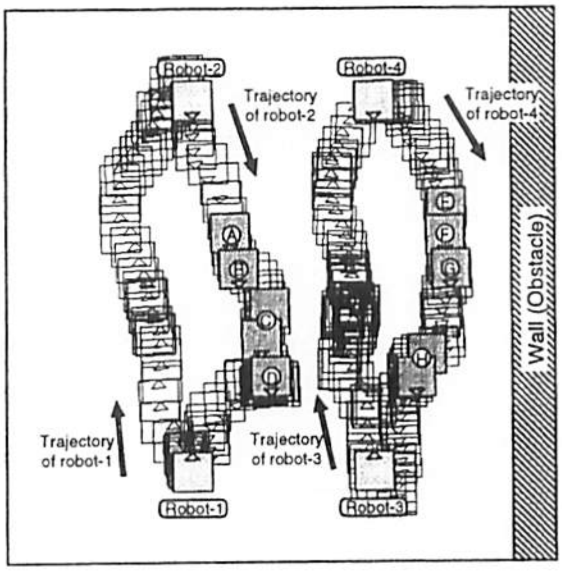


Fig. 17. Experimental result.

Fig. 17 shows the trajectory in the experiment. This figure is drawn by plotting positions of each robot at intervals of 1 s. It is confirmed that four robots take left directions to avoid other robots. The symbols from A to H are added to explain situations of avoidance with the log of communication as shown in Fig. 18. In this figure, arrows mean the flow of received information by the robot from other robots. The filled area in the axis means that the robot receives its own ID, that is, the robot detects an obstacle. Results of two avoidance sequences are explained as examples. The former is the sequence from A to D (Fig. 17). The latter is the sequence from E to H (Fig. 17).

Fig. 19(a) shows an enlarged view of the trajectory from A to D in Fig. 17. At point A, Robot-2 moves in the left forward direction by receiving information from Robot-1 (Fig. 19(a) A). At point B, it is confirmed that Robot-2 moves approximately along the center line between the Robot-1 and Robot-3; Robot-2 detects these robots by receiving information from both (Fig. 19(a) B). At point C, Robot-2 avoids Robot-3 by moving along a parallel path based on communication from Robot-3 because Robot-1 has already gone away (Fig. 19(a) C). At point D, Robot-2 goes toward its goal because no robots are detected at all (Fig. 19(a) D).

Fig. 19(b) shows an enlarged view of the trajectory from E to H in Fig. 17. In this figure, it is confirmed that Robot-4 detects an obstacle by receiving its own ID at points E, F and G. At point E, Robot-4 can avoid Robot-3 without collision with the wall (Fig. 19(b) E). At point H, Robot-4 goes toward its goal ignoring detection of Robot-3 because there are no risks of collidsion at this moment (Fig. 19(b) H).

Consequently, the collision avoidance using real robots is successfully accomplished by the proposed

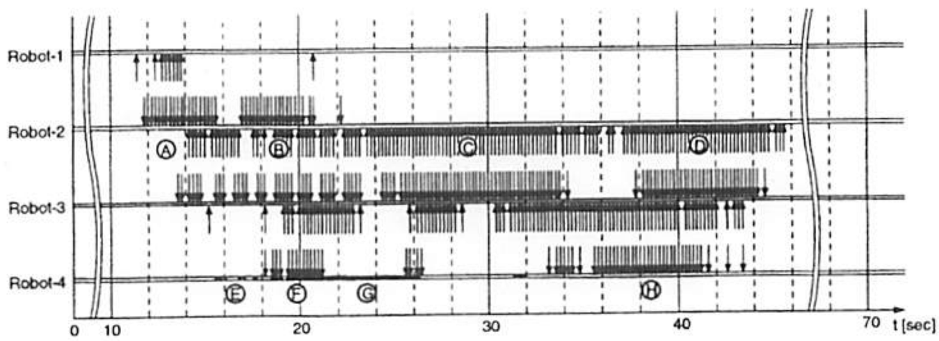
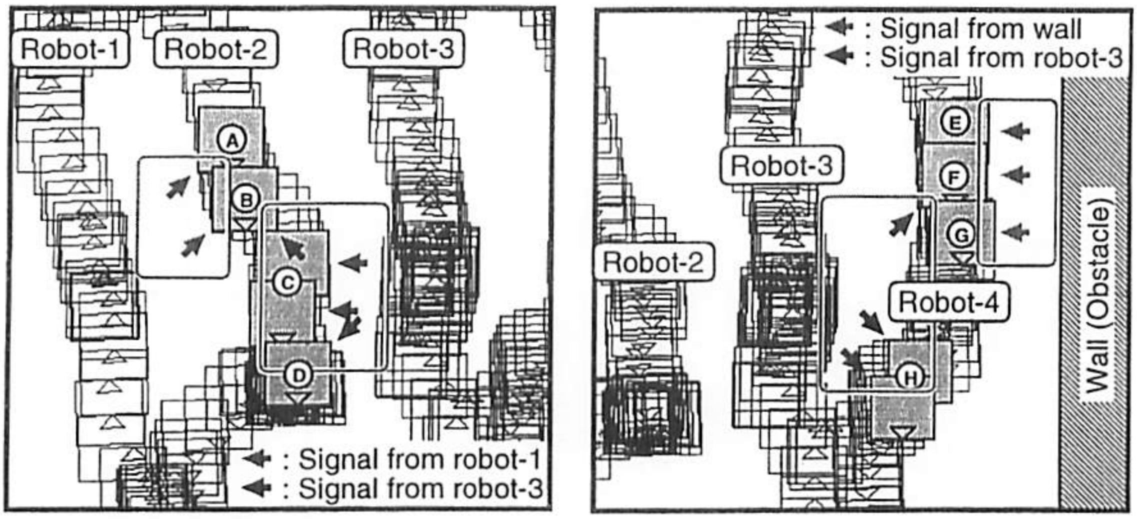


Fig. 18. Log of communication between robots.



(a) Collision avoidance for robots (b) Collision avoidance for multiple objects

Fig. 19. Trajectory of robots avoiding each other.

method. It is confirmed that the proposed method is useful in multi-robot system.

6. Conclusion

We propose a new collision avoidance method for actual multiple robots based on reinforcement learning. The robot can reflect many information acquired by local communication on a behavior selection and select adaptive behaviors in a complicated situation. By dividing the learning curriculum into multiple layers, it is possible to reduce the required size of memory space and to implement the learning scheme for collision avoidance to actual robots. It is shown that a robot can avoid collision with surrounding robots and obstacles in a realistic environment through the experiment with four robots and a wall. For future work, the combination of the method with global path planning should be discussed to solve deadlock problems which could frequently occur when the robots work in an environment with complicated topography.

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