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Developmental Cognitive Map Learning and Behavior Acquisition by a Mobile Robot Through a Self-Organizing Incremental Neural Network

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***Abstract*— Needs for making of the robot intelligence have risen. The acquisition of the symbol is one of the most important tasks in the process of making of the robot intelligence. A lot of methods of the intelligent robot's using the neural network in the process of an autonomous problem solving through the interaction with environment are proposed. In the method based on these functional approximations, a huge computational complexity is required to learning a higher dimension input like the image sensor. Moreover, it doesn't correspond to an additional input. Self-organizing incremental neural network (SOINN) is robust in a higher dimension and additional input. e propose the model by which the change in the action and the perception input is learned based on SOINN in the form of the if-then rule as a symbol. We confirmed the effectiveness of the proposed method by the navigation experiment which human specified the state of the goal. The outcome of an experiment showed the possibility of the achievement of the mobile robot based on the pattern base reasoning.**

Index Terms:SOINN,Behavior Acquisition,Reasoning,mobile robot,Symbol Grounding

I. INTRODUCTION

RECENTRY, needs for making of the robot intelligence have risen. The presumptio of the self-position and the state of the robot is one of the most important tasks in the process of making to intelligence. In this self-position estimation, it is necessary to maintain the position and the state as a symbol. It is thought that intellectual behavior is achieved by the operation of the system of the symbol in the robot. Therefore, how an internal symbol system ties to physical information on a real environment becomes a problem. In the navigation, the gap between the internal symbol and information of the environment proves fatal. [1]

In this self-position estimation, the method using the landmark, the method of giving the location information, and the method of giving the visual information is enumerated.

According to the literature [6], it is made as finite state machine (FSM) by which a symbolic model of the environment makes the landmark a node. It is necessary to set up the landmark in the environment in the method of giving the landmark. Moreover, it is necessary to associate the system of the symbol input information on the landmark of the image etc. and in the robot beforehand. According to the literature [4],The navigation is done by making the model of the place cell by using Neural Gas network(NG) [5].This method acquires the symbol by learning positional coordinates and the image in the surrounding to NG. In addition, because this technique uses the reinforcement learning to search, a huge trial and error is required.

The method based on the location information, method of dependence on positional coordinates that use overhead camera and GPS, doesn't function appropriately in the situation in which global information on the environment cannot be obtained accurately. Therefore, estimating the position and the state from local information like the image sensor becomes important. It is necessary to understand how scenery changes to estimate the position from limited part information when the robot moves. In this study, the causal relation between the action and perception is learned as an internal symbol system.

According to the literature [12], recurrent neural network does a positional estimate by self-organizing the function that forecasts a local perception input after the action. According to the literature [2], the symbol system is acquired by treating the node of SOM as a time series forecasting model. In the method based on these functional approximations, a huge computational complexity is required to learning a higher dimension input like the image sensor.

Moreover, it doesn't correspond to an additional input. Then, we propose the model by which the change in the action and the perception input is learned based on SOINN in the form of the if-then rule as a symbol.

The proposed model combines acquired if-then rules and makes the cognitive map of the environment. The robot can plan the problem solving method by making the cognitive map a problem space and searching for the solution. The solution can be led autonomous only by inputting the state of the target and the initial state to the robot by not the sign but higher dimension pattern information. In the experiment, it was confirmed that the navigation task when man specified the state of the start and the goal had made autonomous action generation possible based on the image input.

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II. PROPOSED METHOD

A. Overview of SOINN and SOINN-AM

In this section, we describe SOINN and SOINN-AM that became basic of the proposed method.

At first, the outline of Self-organizing incremental neural network (SOINN) is described. This model can learn the real number value and is similar to competitive learning models such as Self-Organizing Map (SOM) [9] and Growing Neural Gas (GNG)[10]. Similar competitive learning models such as SOM need decide the structure of the network like uniting the edges and the number of nodes etc. beforehand. On the other hand, SOINN need not decide the structure of the network beforehand. SOINN is a neural network model that the number of nodes that maintain the weight vector increases autonomously. SOINN not only generates new nodes but also eliminates unnecessary nodes. This property renders SOINN immune to noise. When the number of nodes increases, nodes are united by the edge if necessary. The edge has the parameter of age, and when becoming more than the specified age, the edge is deleted. Whether the perception input data is an input from the unknown region is judged by using the criterion of similarity threshold Ti when a competitive layer is inserted in the node.

And, insertion in the cluster and insertion in the outside are distinguished. The similarity threshold Ti is as follows:

$$T_i = \begin{cases} \max_{c \in N_i} \| \boldsymbol{W}_i - \boldsymbol{W}_c \| & if(N_i \neq \phi) \\ \min_{c \in A \setminus \{i\}} \| \boldsymbol{W}_i - \boldsymbol{W}_c \| & otherwise \end{cases} \quad (1)$$

Here, N_i shows sets of neighborhood nodes of i-th node.The neigh-borhood node with i-th node is a node that is united by the edge and exists in the contiguity. A shows sets of all nodes.W_i is a weight vector of i-th node, and $\boldsymbol{W}_c$ is a weight vector of the winner node. T_i is calculated based on Euclidean distance of $\boldsymbol{W}_i$ and $\boldsymbol{W}_c$ .Because an unnecessary node and the edge disappear, SOINN is robust for the noise and, flexibly learns additional inputs.

Next, we describe associative memory with SOINN (SOINN-AM). SOINN-AM is a model to enhance SOINN to the associative memory (see figure 1). SOINN-AM need not build in the amount of knowledge that should be learned and the structure of the network so that the number of nodes may increase autonomous as well as SOINN.

SOINN-AM not only generates new nodes but also eliminates unne-cessary nodes. Features of SOINN-AM are not only incremental learning, learning of continuous value and the noise robust learning but also association of 1-to-many. The point where SOINNAM is the most different from SOINN is that one node has two kinds of vectors. Two phases of training and the recollection exist in the processing of SOINN-AM. In the recall phase, the vector of the association pair corresponding to the input vector is output. In this method, two or more association outputs became possible for one input because it was able to decide two or more winner nodes.

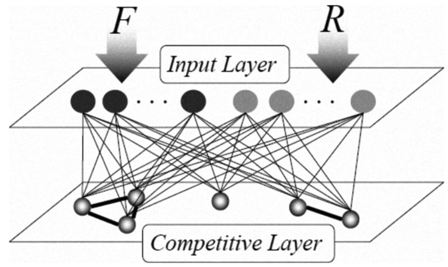

Fig. 1. Schematic diagram of the SOINN-AM

B. Overview of Proposed Model

This neural network model is a model that the number of nodes increases like SOINN-AM. The point where this model is different from SOINN-AM is the structure of the network and representation of data. The proposed model is a trilaminar structure of the input layer, the memory layer, and the reasoning layer. Because the role of each layer was clearly divided, pattern information learned once need not even be learned again. Therefore, knowledge can be efficiently acquired. Figure 2 shows a whole image structural of the proposed model. Two kinds of input vectors with a different dimension are treated in the input layer. These data is composed of the image and the motor output. The perception data and the action data are separately memorized in the memory layer. (see Figure 2)

Figure 3 shows details of the memory layer. It is divided into the temporary memory, the short-term memory, and the long-term memory internally in the memory layer. SOINN is used for the short-term memory and the long-term memory. When a constant frequency is observed to the input data with temporary memory, data is saved in the short-term memory. Data is shifted from the short-term memory to the long-term memory when the error margin of the intermediate data storage and the short-term memory is smaller than that of a constant value. (see figure3)

Figure 4 shows details of the memory reasoning layer. The relation between the action output and the perception input is saved as if-then rules in the reasoning layer. The transition rule of this perception input is given by:

$$\boldsymbol{Q}_t \wedge \boldsymbol{A}_t \Rightarrow \boldsymbol{Q}_{t+1} \quad (2)$$

where $\boldsymbol{Q}_t$ and $\boldsymbol{A}_t$ denote the perception vector at time t and the action vector at time t, respectively. $\boldsymbol{Q}_t$ and $\boldsymbol{A}_t$ used in the reasoning layer are generated from information acquired from the long-term memory of the memory layer.

C. Learningning Phase

In this section we explain details of learning phase in proposed method.(see figure 3) The following notations are used to describe the proposal method:

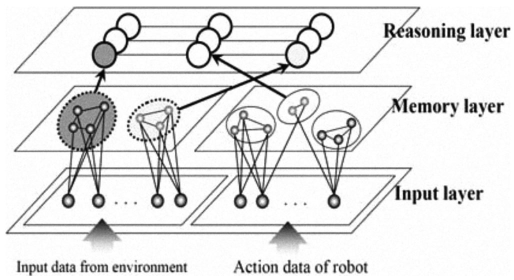

Fig. 2. Schematic diagram of the SOINN-AM

A	set of generated nodes
λ	frequency of node removal
E_i	set of neighbors of the i-th node
$\boldsymbol{W}_f$	weight vector of the first winner node
$\boldsymbol{W}_s$	weight vector of the second winner node
$\parallel \boldsymbol{a} - \boldsymbol{b} \parallel$	Euclidean distance between $\boldsymbol{a}$ and $\boldsymbol{b}$
$\boldsymbol{W}_i$	weight vector of the i-th node
W_ij	j-th element of vector $\boldsymbol{W}_i$
$\boldsymbol{Input}$	input vector

Figure.5 shows the flow chart in the learning phase of theproposal method. The distance between input data and the node in long-term memory are calculated by the next equation.In Eq.(4)σ_r denotes the threshold.

$$D(\boldsymbol{W}_i, \boldsymbol{W}_m) = \sum_{j=1}^{M} \frac{||\boldsymbol{W}_{i,j} - \boldsymbol{W}_{m,j}||}{M} \tag{3}$$

$$Unknown : \sigma_r < \min_{m \in A} D(\boldsymbol{W}_i, \boldsymbol{W}_m) \tag{4}$$

The distance from all nodes to the input value is calculated. this model judges that it obtained an unknown input from the environment when the minimum value is larger than threshold σ_r.When λ piece input data judged to be unknown is continuously save, the data is input to SOINN of the short-term memory. D_i is calculated by the following equations. In SOINN of the short-term memory, the winner node f and second-nearest (second winner) node s searched by $D(\boldsymbol{Input}, \boldsymbol{W}_i)$.When the number of nodes in short-term memory is less than two, the node of which the uniting weight is $\boldsymbol{Input} is generated$. When becoming $D(\boldsymbol{Input}, \boldsymbol{W}_f) < d_f$ and $D(\boldsymbol{Input}, \boldsymbol{W}_s) < d_s$, the edge that newly connects node f and node s is generated.

$$\parallel \boldsymbol{I}_c - \boldsymbol{W}_f \parallel < d_f, \parallel \boldsymbol{I}_c - \boldsymbol{W}_s \parallel < d_s \tag{5}$$

$$d_i = \begin{cases} \max_{c \in E_i} \parallel \boldsymbol{W}_i - \boldsymbol{W}_k \parallel & if(N_i \neq \phi) \\ \min_{c \in A \setminus \{i\}} \parallel \boldsymbol{W}_i - \boldsymbol{W}_k \parallel & otherwise \end{cases} \tag{6}$$

Age of the edge that exists between node $\boldsymbol{W}_f$ and other nodes is increased. And, the edge that the age exceed DeadEge is removed. And the connection weight vectors of the winner neuron and the neurons in its neighborhood is updated by next equations.

$$\boldsymbol{W}_f \leftarrow \boldsymbol{W}_f + \frac{1}{\mu_f}(\boldsymbol{I}_c - \boldsymbol{W}_f) \tag{7}$$

$$\boldsymbol{W}_i \leftarrow \boldsymbol{W}_i + \frac{1}{100\mu_i}(\boldsymbol{I}_c - \boldsymbol{W}_i)(i \in E_r) \tag{8}$$

The node made from learning two or more times in short-term storage temporarily calculates the distance with input data in temporally memory according to timing (removeNodeTime) that the input of SOINN deletes the noise whenever a constant frequency is given. When the minimum value of distance between the input data in temporary memory and the nodes in the cluster are thresholds smaller than σ_r,All nodes in the cluster are moved to the long-term memory. When it is judged that all the entire data in temporary memory can be recollected with learning of an enough frequency, all nodes included in the cluster moved to the long-term memory are treated as same fact $\boldsymbol{Q}_t$. In a similar algorithm, the behavior data of the robot is brought together as fact $\boldsymbol{A}_t$. In the reasoning layer, new if-then rule is made by using fact $\boldsymbol{Q}_t$ and $\boldsymbol{A}_t$ acquired here and it is added to the rule set. Thus, because the if-then rules are preserved only with the cluster label of pattern information brought together in the reasoning layer, pattern information can be treated just like the reasoning of the symbol base.

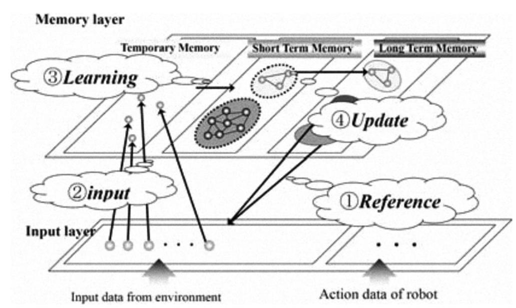

Fig. 3. Schematic diagram of the memory layer.

D. Reasoning Phase

In this section we explain details of reasoning phase in proposed method.(see figure.4). Figure.6 shows the flow chart in the reasoning phase of the proposal method. In the reasoning phase, first of all, pattern information in the ambient environment is input to the system as a associative key. Distance $D(\boldsymbol{W}_i, \boldsymbol{W}_m)$ of node $\boldsymbol{W}_m$ preserved in the long-term memory by the learning phase and input data $\boldsymbol{W}_i$ is calculated. In all nodes preserved in long-term memory, the distance makes the node of minimum and threshold σ_r or less a winner node. At this time, it is judged that input data is already-known. When the winner node doesn't exist it is judged that input data is unknown. When both starts and goals were already-known input, if-then rules saved in the reasoning layer are combined and the structured graph of cognitive map is made. The shortest route between the start goals in storage is planned by using Dijkstra's Algorithm. Finally, the prototype of the if-then rule used for the shortest route is output. The prototype is decided through the following equation.

$$\boldsymbol{W}_{prototype} = \boldsymbol{W}_{\delta} \tag{9}$$

$$\delta = \min_{m \in A} D(\boldsymbol{W}_i, \boldsymbol{W}_m) \tag{10}$$

The prototype was defined as the node that the distance of data is the shortest to vector $\boldsymbol{W}_{m}ean$ in which the weight of all nodes in same cluster C was averaged.

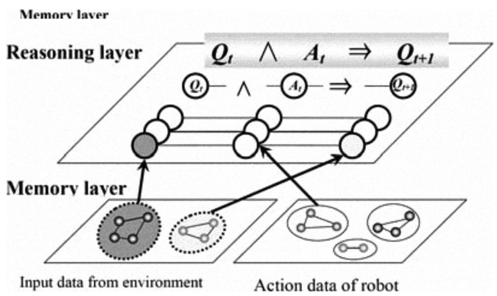

Fig. 4. Schematic diagram of the reasoning layer.

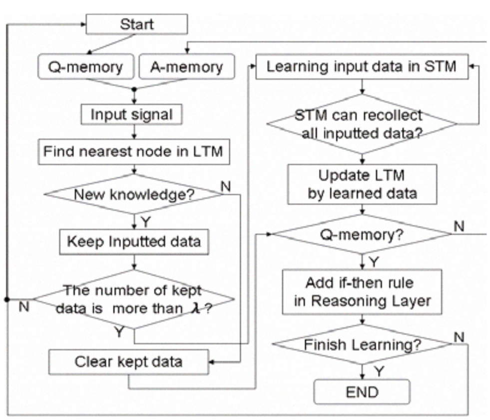

Fig. 5. Flow chart of learning phase.

III. EXPERIMENT

A. Experiment Setting

We carry out a mobile robot simulation, and we confirm the performance of the model and the validity of the learning by investiga-tion of the knowledge acquired by the learning. This simulator models the well-known desktop robot e-pack. The robot navigation task aims at moving of a mobile

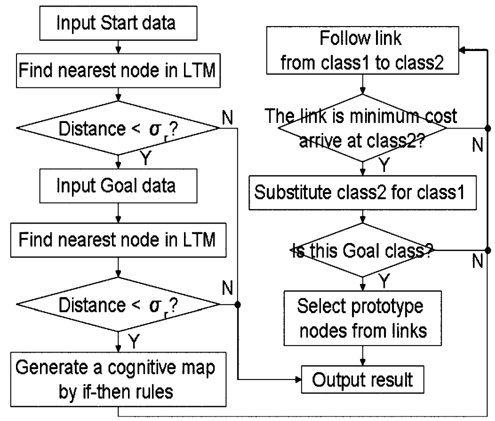

Fig. 6. Flow chart of reasoning phase.

robot from start to goal without a detour. The outline of the robot that uses it to experiment is as shown in figure 7(a). It acts based on the Subsumption Architecture[11] at the learninphase(figure.7(b)). Each action is executed by specifying the corresponding rotation angle It is also assumed that this robot can obtain 2 kinds of sensor information of the left and right wheels.One is the camera vision sensor and the other is the motor sensor.

The former is used for observing the scenery around and inputted grey scale image of 40 × 40 pixels. On the other hand, the latter is used for observing the robot own behavior and inputted value of rotation of right and left wheels.

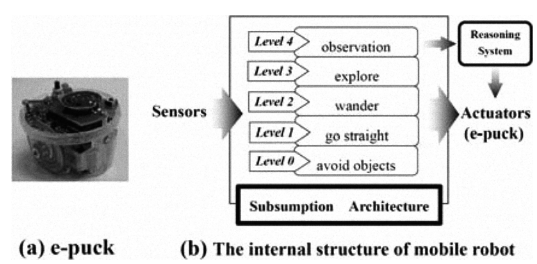

Fig. 7. The robot that used it to experiment.

B. Experiment1

The target of the experiment is to acquire the shortest route until reaching a goal with the pattern base. Here, it is confirmed for the proposed model to be able to construct the internal symbol model of the environment with a little number of trials, and to plan the action based on a higher dimension pattern input. The experiment is carried out by using the maze as shown in fig.8. First of all, whether the cognitive map can be made from pattern information to which the proposal system is input from this environment is confirmed. The texture shown in figure 9 was stuck on the wall of the experimental environment. The movement that went straight after having made about 5/4 rotations from the

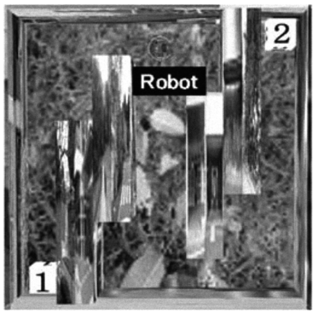

Fig. 8. Experimental Environment.

Fig. 9. The texture that was stuck on the wall of the experimental environment.

Fig. 10. Sets of vectors of representative of each cluster.

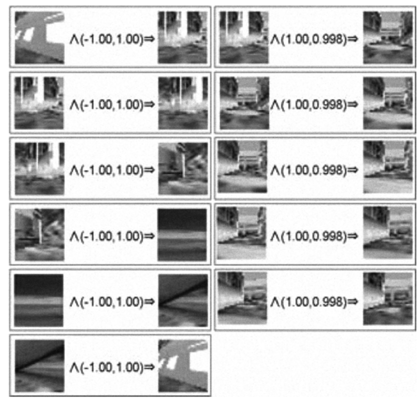

Fig. 11. Sets of acquired symbolic rules.

position of the robot of Figure 11 to the left for 100 steps was done. The data that had been perceived at that time was input to the proposal system. Consequently, the robot acquired 11 cluster groups with the image of Figure 10 as the representative. The If-Then rule of Figure 11 was acquired, it was combined, and the cognitive map was made. Figure 13 shows the one that the structure of the cognitive map was made visible. Several characters of figure 13 for each show the number of nodes of SOINN that composes the cluster. A gray line where the figure ties shows action (Left,Right) = (-1.00,1.00) corresponding to a left rotation. And, a white line shows action (Left,Right) = (0.998,1.00) corresponding to straight advancement. A network size necessary to compose each cluster of the feature of SOINN has been decided automatically. From this experiment, It can be confirmed that the proposed model can leave 1-to-many association and the noise robustness and the incremental learning that is the feature of SOINN-AM. It can be confirmed to be able to acquire the cognitive map as a model of the environment. The parameters in the first experiment are set as $\sigma_r = 0.04$,$\lambda = 3$.

C. Experiment2

Next, it was confirmed to be able to plan the action by combining if-then rules of the result of the separate search. Figure 12 shows the environment used for the navigation experiment. Figure 12(a) partitions the experimental environment with the wall, and shows the one that the robot was made not to be able to invade 1/3 in the left. Figure 12(b) partitions the experimental environment with the wall, and shows the one that the robot was made not to be able to invade 1/3 in the right. Processing of the learning phase is done twice by using experimental environment (a) and (b) of Figure 12. It learned respectively by 6000 steps by experimental environment (A)and (B) of Figure 12. The navigation of the mobile robot is done in the environment that removes the wall after the learning phase. Images of the goal state and the initial sate are inputted to the proposed system (see figure 15). And, the robot is made to hold the action plan from the initial state to the state of the target. Figure 14 shows the result of the action plan. This shows

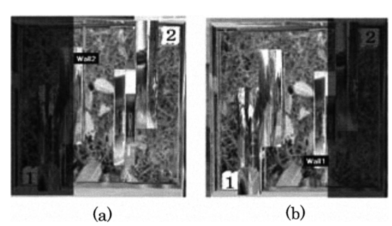

Fig. 12. Experimental Environment. (a) shows the environment to make it not enter 1/3 in the left. (b) shows the environment to make it not enter 1/3 in the left.

the change of the scenery of the shortest route until reaching a goal of the inside plan of the robot. The robot was able to combine if-then rules by the learning phase though it has not been from the start to the goal even once, and to do the action plan from the start to the goal by the search. The rule and the node were acquired even if human did not design the cognitive map structure beforehand and only the number of targets was able to be acquired.

The parameters in the second experiment are set as $\sigma_r = 0.002, \lambda = 8$. The parameter used in SOINN used remove $NodeTime = 120$ and $deadAge = 120$

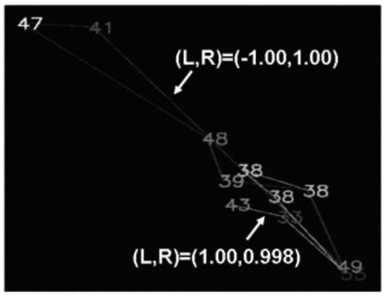

Fig. 13. Acquired cognitive map.

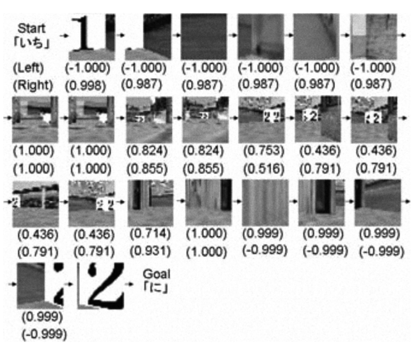

Fig. 14. Output result of action plan.

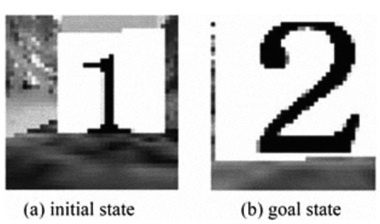

Fig. 15. Input vector of initial state and goal state.

IV. CONCLUSION

In this paper, we proposed a new method of action acquisition based on the SOINN-AM for intelligent robots. Proposed method plays an important role in the acquisition of the symbols from pattern information that is necessary for coexistence of man and robot.

The effectiveness of the proposal technique is shown with the following points:

1) The symbols can be appropriately acquired even by the higher dimension real number value vector.
2) It is possible to learn robustly even in the environment including the noise.
3) Because this method can symbolic search by using the pattern based reasoning, the behavior acquisition can be done by a little number of trials.
4) Because the structure and the size of the network can be decided automatically, and incremental learning can be done, it is not necessary to build in knowledge beforehand.

The effectiveness of the proposed method was verified using the simulation task from which the state of the target is given by human after the robot learns and the simulation task where two or more goals exist together. A further direction of this study will be that we adapt the model to an environment which changes.

V. ACKNOWLEDGMENTS

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