Building Maps of Workspace for Autonomous Mobile Robots Using Self-Creating and Organizing Neural Network

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Building Maps of Workspace for Autonomous Mobile Robots Using Self-Creating and Organizing Neural Network

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This paper presents a method of building maps of the unknown workspace for autonomous mobile robots using self-creating and organizing neural network. By this method, the topological maps which roughly express the workspace can be self-organized from the relative distance data between robots and walls in the workspace only using ultrasonic distance sensors. However, when the shape of the workspace is complicated, an unsuitable map with dead nodes or dead links may be generated. In this paper, in order to cope with this problem, we propose a new building maps algorithm which consists of two learning stages.

Keywords: Autonomous Mobile Robot, Workspace Recognition, Building Map, Self-Creating and Organizing Neural Network

1 INTRODUCTION

For the unknown workspace recognition, the method of building maps of workspace for autonomous mobile robots using self-organizing neural network is proposed[1][2][3]. By this method, the topological maps of the workspace can be self-organized from the relative distance data between robots and walls in the workspace The relative distance data are collected only using ultrasonic distance sensors.

This method uses self-organizing neural networks called self-organizing feature map[4] or self-creating and organizing neural network[5] to learn maps of workspace. The inputs of the neural networks are the relative distance data between robot and wall at many places of the workspace. After a sufficient learning, a topological map of the workspace can be built on the self-organizing layer of these neural networks The topological map consists of nodes and links. The nodes on the map are the representative positions of the workspace and the links on the map are the relations of the representative positions. Thus, the topological map can roughly express the workspace.

However, when the shape of the workspace is complicated, some dead nodes and dead links may be generated on the maps. In this paper, in order to cope with this problem, we consider the problem of the workspace maps generated by the method, and we propose a new building maps algorithm which consists of two learning stages: the nodes learning and the links learning.

2 CONDITIONS OF ROBOTS AND WORKSPACE

In this study, the following three conditions are assumed about the workspace and the autonomous mobile robot. (1) The workspace is a closed space with obstacles. (2) The robot has no information about the workspace beforehand. (3) The robot has two or more ultrasonic distance sensors arranged in the uniform direction as in Fig. 1.

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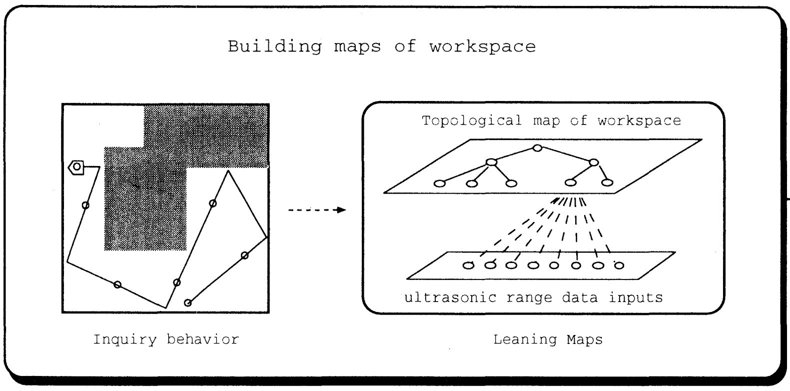

Fig. 2. Behavior procedure of autonomous mobile robot.

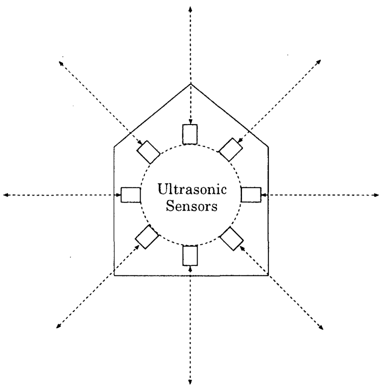

Fig. 1. Autonomous mobile robot.

And it is specified that this autonomous mobile robot behaves in the following procedure shown in Fig. 2.

At the first step, the robot behaves in inquiry in the unknown workspace, and collects the relative distance data between the robot and the wall at many places in the workspace for every fixed distance moving. This inquiry behavior consists of the combination of the straight-line moving and the random direction conversion carried out when the distance value from the wall becomes smaller than a fixed value. By inputting the collected relative distance data to a self-creating and organizing neural network and computing the learning algorithm described in the following chapter, a topological map which consists of nodes and links of the workspace can be generated on the self-organizing layer of the network. At the second step, the robot work out path-planning between the given destination with its present position using the map. At the third step, the given task (that is, moving to the destination) is achieved by moving along the planned path.

In this paper, we mainly discuss the first step: building maps of workspace.

3 SELF-CREATING AND ORGANIZING NEURAL NETWORK (SCONN)

3.1 NETWORK STRUCTURE

In order to implement the maps of the workspace, we use the self-creating and organizing neural network (SCONN) with the structure shown in Fig. 3.

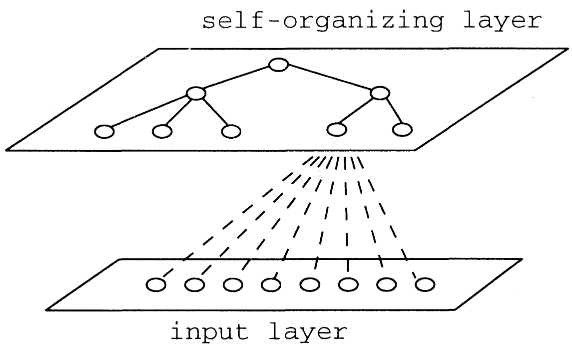

Fig. 3. The network structure of self-creating and organizing network (SCONN).

This SCONN consists of two layers. One layer is an input layer and another is a self-organizing layer.

Each neuron on the input layer and on the self-organizing layer has joined mutually. The learning of this network is carried out based on the competitive learning algorithm. Therefore, a neuron on the self-organizing layer which has the weight vector with the minimum distance from the input vector is selected as the winner neuron. At the initial state, there is only one neuron on the self-organizing layer. And the neurons on the network is self-created and organized, according to the change of the feature of input vectors, and then the topological map with a tree structure is generated on the self-organizing layer. Since the neurons on the

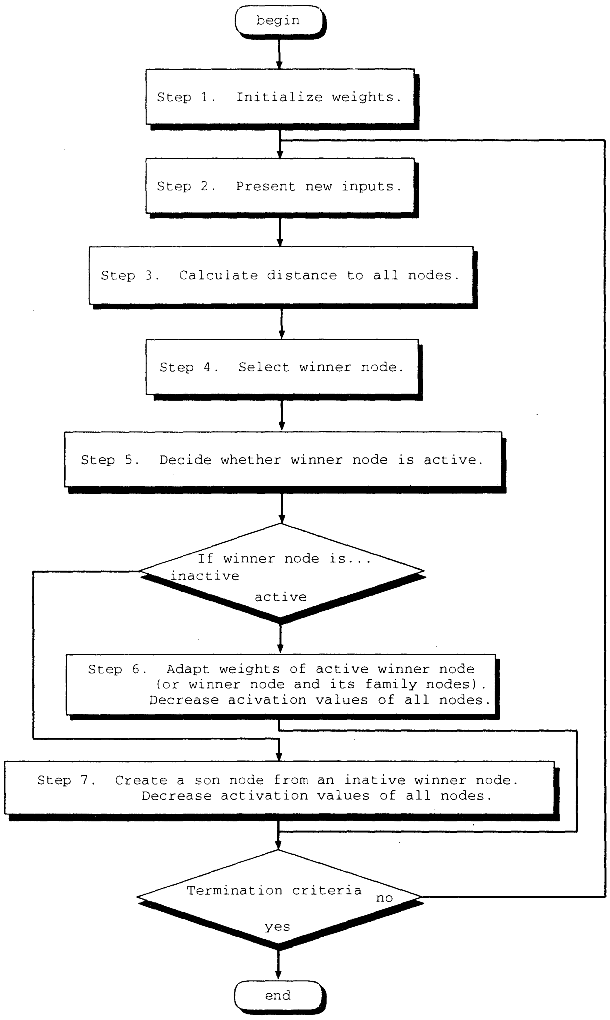

Fig. 4. A block diagram of the learning algorithm for the SCONN.

self-organizing layer express the nodes on the topological map, 'neuron' and 'node' are equivalent. Therefore, we describe uniformly 'neuron' as 'node' after this.

3.2 LEARNING ALGORITHM

Fig. 4 shows a block diagram of the learning algorithm for the SCONN, and the detailed steps of the learning algorithm are as follows:

At the first step, there is only one node on the self-organizing layer with small random weight at the primitive stage and its activation level is set large enough to respond to any input stimuli. At the second step, new input vector is presented randomly or sequentially. At the third step, distances d_j between the input and each output node j are calculated using (1).

$$d_j{}^2 = \sum_{i=1}^{N} \{x_i(t) - w_{ij}(t)\}^2 \qquad (1)$$

where $x_i(t)$ is the input to node i at time t and N is the demension of the input and $w_{ij}(t)$ is the weight from input node i to output node j at time t. At the fourth step, an output node with the minimum distance is selected as the winner node. At the fifth step, it is decided using (2) whether the winner node is active or inactive.

$$y_{wj} = \begin{cases} \text{is active,} & \text{if } d_{wj} < \theta(t) \\ \text{is inactive,} & \text{otherwise} \end{cases} \qquad (2)$$

where y_{wj} is the output of the winner node, d_{wj} is the distance between the inputs and the winner node, and $\theta(t)$ is an activation level that is sufficiently wide at a primitive stage and decreases with time. In this study, we use (3) as the activation level.

$$\theta(t) = c_1 \exp(-c_2 t) + c_3 \qquad (3)$$

where c_1, c_2, c_3 are constant. At the sixth step, the weights of an active winner node is adapted using (4).

$$\begin{aligned} w_{i,wj}(t+1) &= w_{i,wj}(t) \\ &+ \alpha(t)\{x_i(t) - w_{i,wj}(t)\} \end{aligned} \qquad (4)$$

where $w_{i,wj}(t)$ are the weights from the inputs to an active winner node and $\alpha(t)$ is the gain term that can be constant or decrease with time. At the seventh step, a son node is created from a mother node (an inactive winner node) using (5) and (6). and the son node is linked the mother node.

$$sj = sj + 1 \qquad (5)$$

$$\begin{aligned} w_{i,sj}(t+1) &= w_{i,sj}(t) \\ &+ \beta(t)\{x_i(t) - w_{i,wj}(t)\} \end{aligned} \qquad (6)$$

where sj is the current number of total output nodes, $w_{i,sj}(t)$ are the weights from the inputs to a son node created from a mother node, and $\beta(t)$ is the resemblance factor that varies from 0 to 1.

In this algorithm, there can be three criteria to stop the program. Those criteria are iterations t, number of output nodes sj and activation level $\theta(t)$.

4 BUILDING MAPS OF WORKSPACE USING SCONN

There are some problems on the maps of workspace built using directly the above-mentioned learning algorithm of SCONN. In this section, through a simulation case study, we consider the problems and propose a new improved learning algorithm.

4.1 SIMULATION CASE STUDY

We use the workspace shown in Fig. 5 as the unknown workspace in this simulation case study. The robot behaves in inquiry in the unknown workspace and measures the relative distance data from walls as shown in Fig. 6, and then the topological map of the workspace is built by the learning algorithm of SCONN.

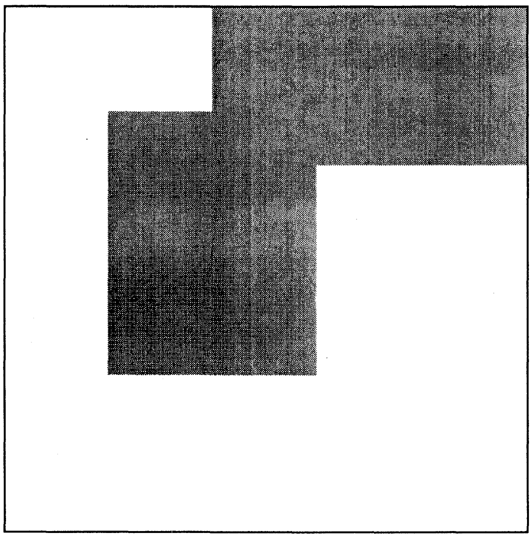

Fig. 5. The shape of the unknown workspace used in the simulation case study.

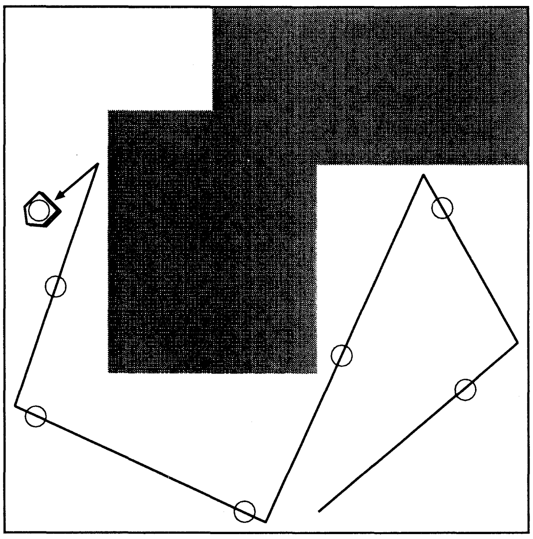

Fig. 6. Inquiry behavior of autonomous mobile robot.

Fig. 7 shows an example of simulation results of an autonomous mobile robot with eight sonar sensors($N = 8$) by the conventional learning algorithm of SCONN. This map is projected the topological map on the real (2D) space. Simulation parameters are $\alpha = 0.085, \beta = 0.85, c_1 = 450000, c_2 = 0.001, c_3 = 50000$. It is confirmed by Fig. 7 that the workspace has been divided roughly.

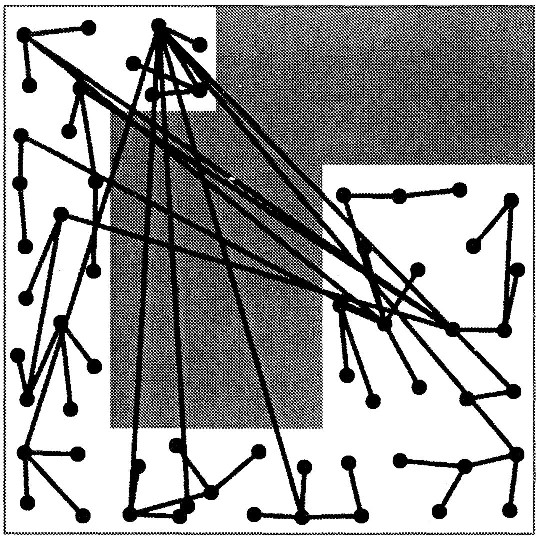

Fig. 7. The map generated by the conventional learning algorithm of SCONN.

However, there are two problems on this map. The first problem is that the links have the thin tree structure and there is no link between the nodes that can actually move in the workspace, that is, there are some dead nodes on the map. The second problem is that there are some dead links that can not actually move in the workspace.

4.2 DISCUSSION ABOUT THE PROBLEMS

In the first place, we try to solve the former problem that there are few links on the map by changing the structure of the map into graph structure from tree structure. And if the distance between the inputs and the winner node is smaller than the activation level (that is, if $d_{wj} < \theta(t)$), we not only adapt the weights of the network but link to the winner node and the previous winner node.

The total number of links could increase by these improvements, but number of dead links also increase on the other hand. A simulation result by this improved learning algorithm is shown in Fig. 8. Therefore, the algorithm which decreases the number of dead links is needed.

Then, considering a generation factor of a dead link, we found out that the link which generated at the begin-

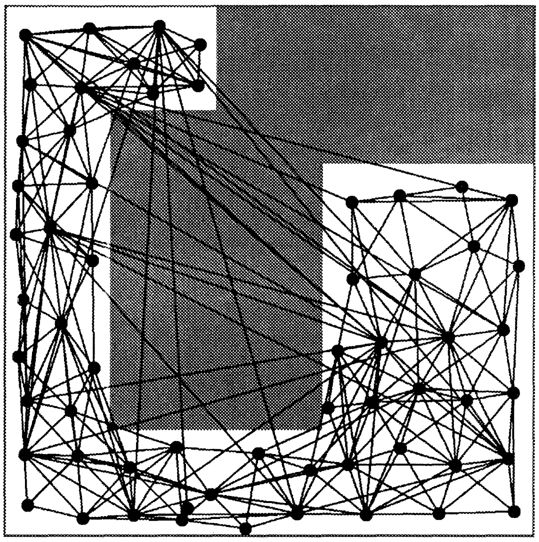

Fig. 8. The map with graph structure.

ning of learning becomes a dead link in many cases. The basic function of the SCONN is generating representative nodes from input vectors and determining weights of the representative nodes. As the weights is not stabilized at the initial learning stage, the links which is generated at the time will extend by movement of the nodes and tend to grow into the links over an obstacle of the workspace as shown in Fig. 9.

4.3 IMPROVED LEARNING ALGORITHM

Based on the above-mentioned consideration, we propose a new improved algorithm as follows. In this algorithm, at the beginning of leaning, only determination of representative nodes of the workspace (so-called vector quantization) is carried out. That is, at the first leaning stage, the movement of the representative nodes can converge and the rough division of the workspace can be done. And after this, at the second leaning stage, we generate the links on the map in the same way of the above-mentioned method. A Block diagram of this new improved learning algorithm is shown in Fig. 10.

Fig. 11 shows a simulation result by this new improved learning algorithm. And Fig. 12 shows a simulation result with the limitation of number of links which one node has. It is confirmed by Fig. 12 that the dead links can be completely eliminated with the limitation of the number of links.

5 CONCLUSIONS

In this paper, it is confirmed that there are two problems on the topological maps built using directly self-creating and organizing neural network, when the shape of the workspace is complicated. In order to cope with

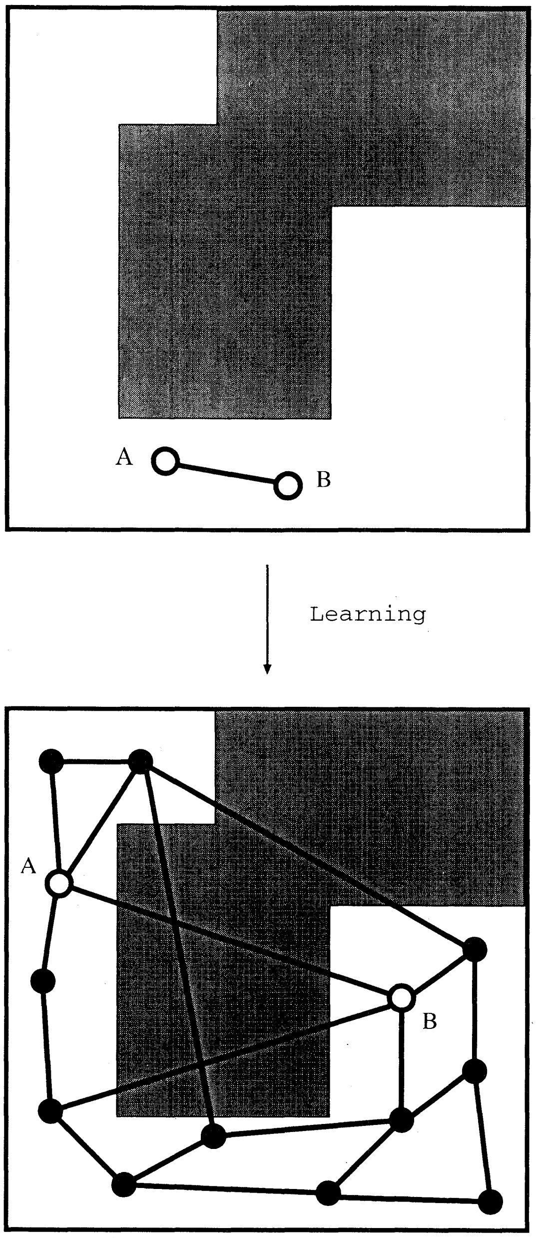

Fig. 9. A generation factor of a dead link.

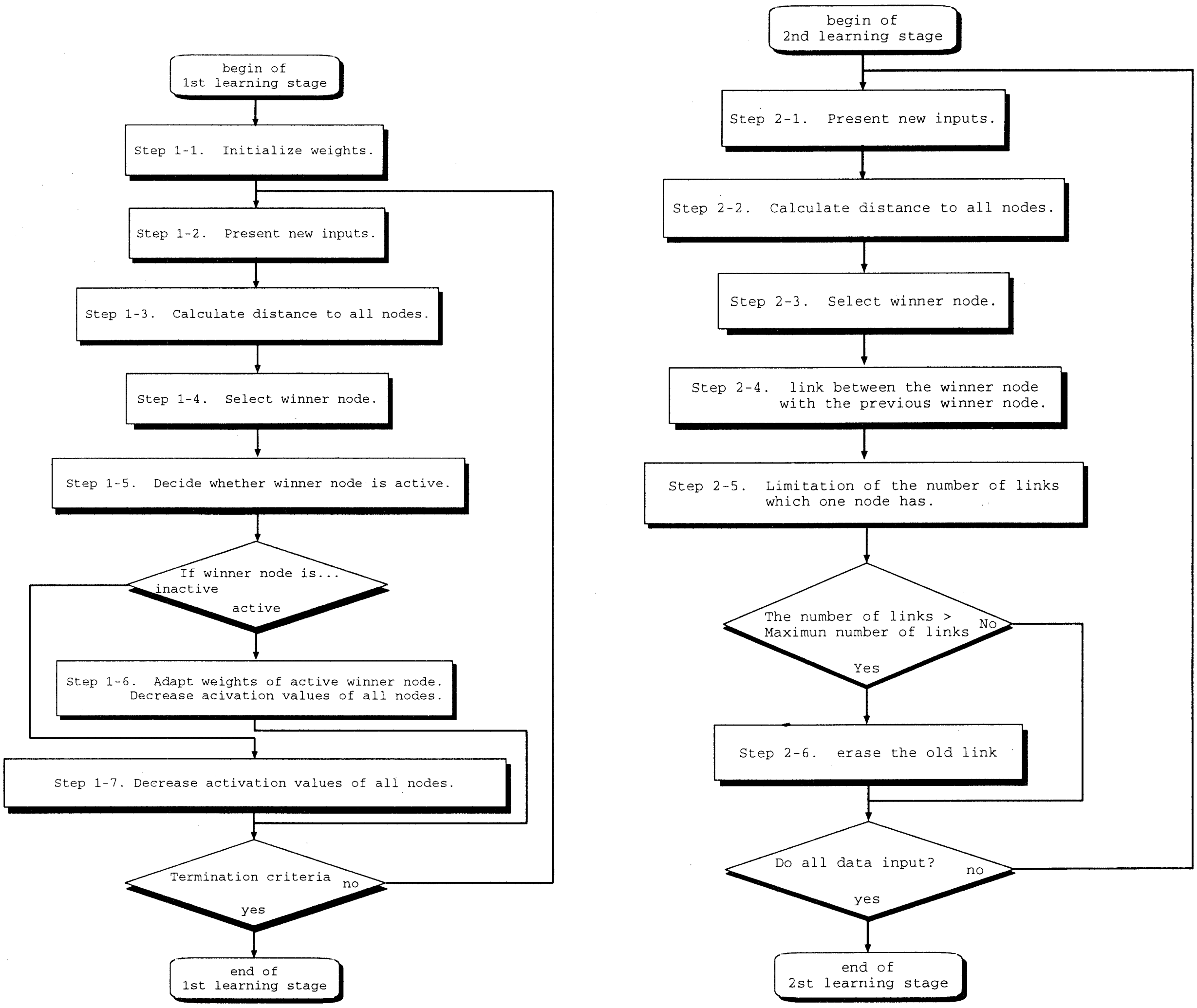

Fig. 10. A block diagram of the improved learning algorithm.

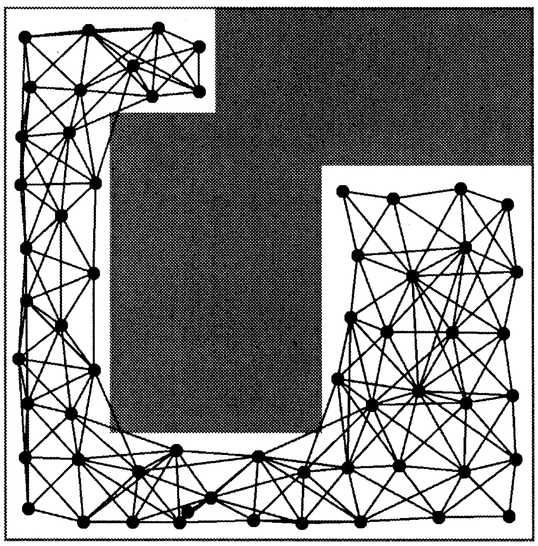

Fig. 11. The map generated by the improved learning algorithm.

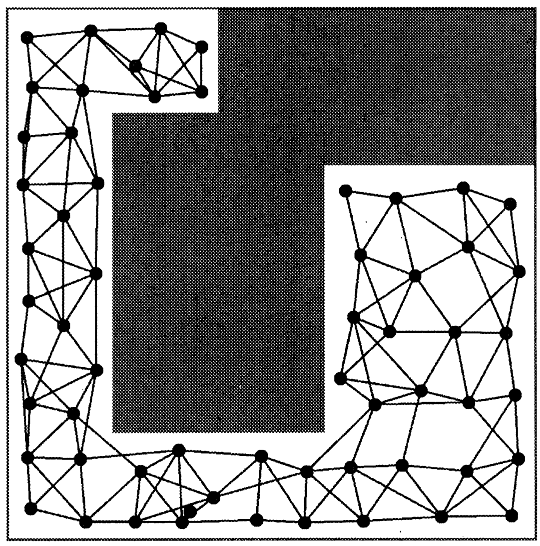

Fig. 12. The map generated by the improved learning algorithm with the limitation of the number of links which one node has.

these problems, we propose a new learning algorithm divided into the two learning stages. At the first stage, only representative nodes are learned, and at the second stage, links between the nodes are generated. As a result, the proper maps are built in these two stages. This algorithm was tested by the simulation for an autonomous mobile robot with eight ultrasonic distance sensors, and it was demonstrated that the algorithm is useful for the purpose.

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自己生成・自己組織化ニューラルネットワークを用いた自律移動ロボットの作業環境マップの自動生成

堀 勝博 *、橋本 幸男 **

概要

本論文では、自律移動ロボットの未知作業環境認識のための、作業環境マップの自動生成手法について論ずる。本手法では、自己生成・自己組織化ニューラルネットワークによる自己組織化学習を行うことにより、超音波センサにより得られるロボットと障害物間の相対的な距離情報のみから、作業環境を大まかに表した位相マップを自己組織的に獲得可能である。しかし、作業環境の形状によっては、到達不可能なデッドリンクやデッドノードを持つ不適切なマップが生成される場合がある。本報告では、その問題点に対処した、新しいマップ自動生成アルゴリズムを提案する。

キーワード: 自律移動ロボット、作業環境認識、マップ生成、自己生成・自己組織化ニューラルネットワーク

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