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Topological Map Building Based on Thinning and Its Application to Localization

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Abstract

Map building and localization are essential to an autonomous mobile robot system. A global topological map is commonly constructed from a global grid map using a Voronoi diagram. In this hierarchical method, however, the advantage of a topological map such as compactness may not be fully utilized. In this paper sensor data are used to build a local grid map from which a local topological map is created using a thinning method. The thinning method is an alternative of the Voronoi diagram. The local topological map is then updated to the global one. Localization based on the topological map is usually difficult, but additional nodes created by the thinning method can improve localization performance. Various experiments with a laser scanner demonstrate validity and feasibility of the proposed algorithms for map building and localization.

1. Introduction

Map building is the task of modeling a robot's environment and localization is the process of determining the position and orientation of a robot with respect to the global reference frame. These are the key elements for an autonomous mobile robot system.

There are two major paradigms for mapping the indoor environment: a grid map and a topological map. The former can produce an accurate map in a relatively simple manner, but requires large memory, is inefficient, and time-consuming. The latter, on the other hand, provides more efficient and compact map requiring much less memory, but is difficult to apply to localization.

In most cases a global topological map is built from a global grid map. This hierarchical approach can utilize advantages of the grid and the topological maps, but still has the problem of large memory requirement involved in a grid map. Moreover, updating these hierarchical maps is very difficult[1]. As an alternative to this approach, the direct topological map building using the Voronoi diagram [2] was proposed by Zwynsvoorde [3]. The Voronoi diagram, however, has difficulty in applying to arbitrarily shaped objects and needs long computation time.

In this paper, an improved method for constructing a topological map is proposed. It can utilize the advantages of the topological map such as compactness. A local grid map from current sensor data is first constructed. From this map, a local topological map is then built using a thinning method which is the alternative to the Voronoi diagram. Finally, local topological maps are integrated and updated to the global one. Geometrical information of the nodes of the local topological maps enables the nodes to serve as landmarks in matching the local maps. This scheme is also used in localization based on the topological map.

In most research on localization, grid-based methods with detailed information are used. Probability-based methods for localization (e.g., Monte Carlo [4], Condensation [5], probability grids [6], etc.), therefore, are all based on grid maps. Localization using a topological map has been recently attempted in [7] and [8]. The problem with a topological map in localization, however, is that a robot may not recognize its state with momentary sensor information because geometric information in the topological map is ambiguous. To overcome this difficulty in applying the topological map to localization, additional nodes need to be added to the global topological map so that information of the topological map can be increased, which is possible with a thinning method.

Since the detailed model of the environment between nodes is not available in a topological map, the wave-front algorithm is used for navigating node to node. Using this method, a mobile robot can move to the next node optimally while avoiding the obstacles [9].

The paper is organized as follows. Chapter 2 presents local topological map building using a thinning method and the updating process to the global topological map. Chapter 3 deals with localization based on the topological map and the wave-front algorithm for node-to-node navigation. Various test results in the real environment are discussed in Chapter 4.

2. Topological Map Building

2.1 Local topological map building using thinning

A topological map is used as a main map for path

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planning and localization in this research. In the feature-based topological map, the environment is modeled by a set of geometric primitives such as nodes and arcs. It has several advantages such as compactness, fast computation, natural expression to human, and so on. Topological maps, however, are not appropriate for localization which requires comparison of the current map with the reference map because they have only limited feature information compared to grip maps. Localization performance can be improved by adding more node information through a thinning method (explained later on).

To build a topological map based on a grid map (binary map), a Voronoi diagram is commonly used. But it is complex and difficult to apply to arbitrarily shaped objects. In building a topological map, therefore, a thinning method is proposed in this paper, which needs simpler computation than the Voronoi diagram but can show similar performance.

A thinning method is one of the most popular image processing algorithms, which are used to detect the skeleton of images. In many image processing applications such as recognition of biological cell structure, thickness of the shapes does not contribute to the recognition process.

Figure 1 illustrates of an example of a thinning process. The objects on the left can be described satisfactorily by the structure composed of connected lines (i.e., ‘T’ shape drawn with thin lines on the right). Note that connectivity of the structure is still preserved even for representation with thin lines. In the case of mobile robots, the connected lines are paths on which a robot navigates without colliding with other objects. In this paper, Suen’s thinning method [10] is adopted.

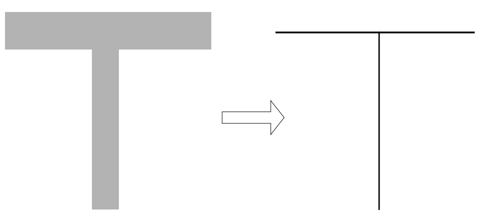


Fig. 1 Example of thinning.

The Suen’s method, which has been commonly used for years in the field of image processing, is fast and simple to implement when compared to other similar schemes. Figure 2 illustrates the center cell (p_1) under consideration and its neighboring cells (p_2 ~ p_9) called a mask for the thinning process. Note that ‘0’ denotes an empty cell and ‘1’ an occupied cell (assuming a binary map or image). The thinning procedure proceeds by eliminating the occupied cells until only the skeleton of the structure appears.

p_9	p_2	p_3
p_8	p_1	p_4
p_7	p_6	p_5

Fig. 2 Center cell p_1 and its thinning mask.

The thinning process is conducted by applying the following two steps for all the cells.

[Step 1]

① $2 \leq N(p_1) \leq 6$, ② $S(p_1) = 1$, ③ $p_2 \cdot p_4 \cdot p_6 = 0$,
④ $p_4 \cdot p_6 \cdot p_8 = 0$

$N(p_1)$: # of cells being not zero. (i.e., $N(p_1) = p_2 + p_3 + \cdots + p_8 + p_9$.)

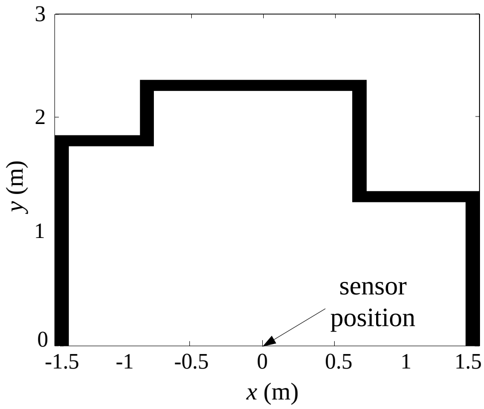
$S(p_1)$: # of changes from 0 to 1 in the sequence of p_2, p_3, $\cdots$, p_8, p_9

[Step 2]

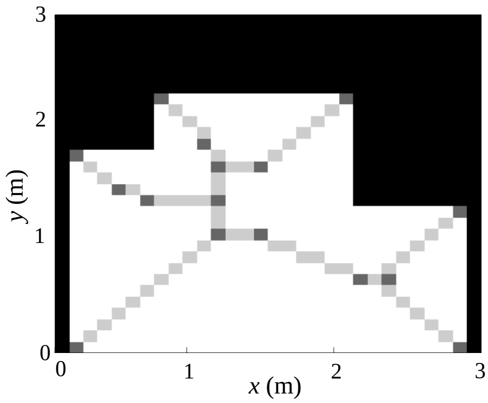
① and ② are the same as [step 1]
③ $p_2 \cdot p_4 \cdot p_8 = 0$, ④ $p_2 \cdot p_6 \cdot p_8 = 0$

Note that step 1 is conducted for the entire grid map and the corresponding grid cells are eliminated. Then step 2 is carried out for elimination of other cells meeting the conditions. The nodes, the representative points of the local environment, are extracted from the arcs (i.e., path) obtained above. Because the position and the number of nodes are related to accuracy and usefulness of a topological map, an appropriate selection rule of nodes is very important. In this paper, the nodes are selected at the end points of the arc, the corner points where the arc slope varies, and the branch points where more than three arcs intersect.

Fig. 3(a) shows the raw range data obtained by a laser scanner. The laser scanner is assumed to be placed at the origin. Fig. 3(b) shows the binary map with range data, its arcs and nodes are obtained by the thinning method. It is assumed that the back of the points sensed by the laser scanner is filled with the obstacles. In the global topological map, geometric information of the node (x, y) with respect to the reference (global) frame and connectivity between two nodes are stored.



(a) Laser scanner range data.



(b) Collision-free path obtained by thinning and its nodes.

Fig. 3 Thinning and local topological map building.

A thinning method can provide additional nodes to the local topological map. Fig. 4 demonstrates the comparison of the topological map using a Voronoi diagram (left figure) with that using a thinning method (right figure). Four more nodes are created when the thinning method is employed. More geometrical information due to these additional nodes improves performance of localization.

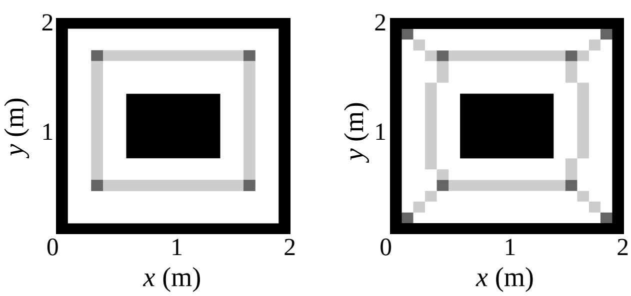
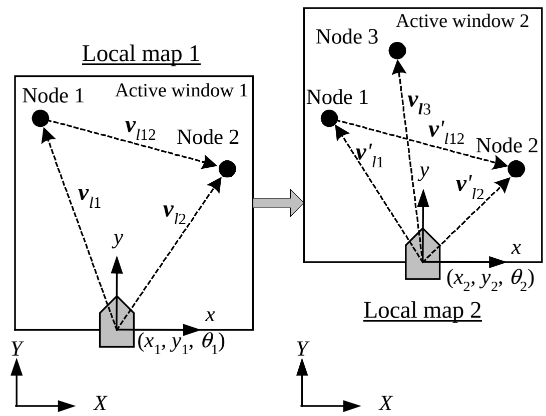


Fig. 4 Topological map using Voronoi diagram (left) and thinning method (right).

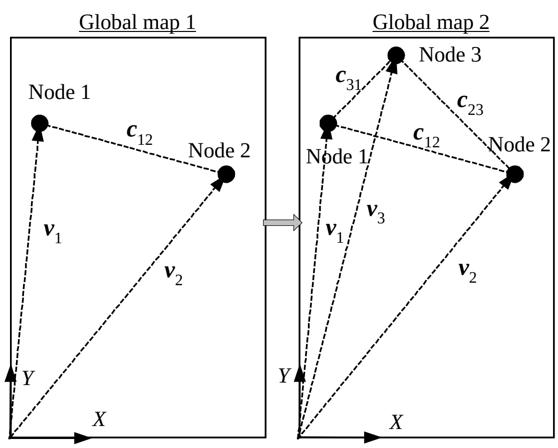
2.2 Global topological map building

A method for updating a local topological map to the global one is presented below. The local topological map contains geometrical information of the nodes and connectivity between the nodes. The update process of a global topological map is basically performed by matching the nodes of the local topological maps to those of the global topological map.

Figure 5 illustrates the local and global topological maps at the instants t_1 and t_2. Suppose that the robot detected node 1 and node 2 at the position (x_1, y_1, θ_1) at t_1 within the active window 1. This local topological map 1 is updated to form the global map 1. The robot then moves to the next position (x_2, y_2, θ_2) and detected node 1, node 2 and node 3 within the active window 2 at t_2. Since node 1 and node 2 are common to both global maps, only node 3 is updated to form the global map 2. The updating process will repeat until the entire region of the environment is covered.



(a) Local topological map at each instant.



(b) Global topological updating at each instant.

Fig. 5 Detected nodes and their vectors and connectivity between the nodes at each instant.

3. Localization Using Topological Map and Optimal Path Planning

3.1 Localization using topological maps

To determine the position (x, y) and orientation (θ) of a robot based on the topological map, the modified probability method and the Bayesian updating rule are employed. The entire region covered by the global topological map is decomposed into the evenly-spaced grids whose centers correspond to the robot position. Since the robot has different orientations for each grid, a large number of robot states (x, y, θ) can exist. Thus, it is very time-consuming to perform localization for all these states. Hence samples are randomly chosen among all possible states, and localization for these samples is conducted.

This procedure is carried out in the following steps.

1) n samples are randomly chosen in the x-y-θ space in which a robot can be placed.
2) A uniform probability of $1/n$ is assigned to all the samples.
3) Obtain all the nodes by considering the size of the active window and the sensor range specified for each sample.
4) Compute the distances to the nodes and the angles between nodes for both samples and current range data (i.e., actual sensing using a laser scanner).
5) Compare the computed data (i.e., distances and angles) for samples with the current range data. Whenever these two values are not identical, this sample is discarded and a new probability of $1/(n\text{-}1)$ is assigned to the remaining samples.
6) Update probability with a Bayesian updating rule.

3.2 Optimal path planning

To obtain all possible paths, connectivity information is used. The minimum cost (i.e., minimum distance in this case) path is found using an A* search algorithm in which the distance between two nodes is taken as the cost of a path. On the other hand, to reach the goal through the global optimal path, the wave front algorithm proposed by Konolige is adopted, in which a robot can navigate on an optimal path while avoiding collision.

The cost of the wave front algorithm consists of the intrinsic cost (I) and the adjacency (A) cost as follows:

$$F(P) = \sum_i I(P) + \sum_i A(P_i, P_{i+1}) \qquad (1)$$

The intrinsic cost involves the requirements given by the user (e.g., avoid slippery road, go far from the object, etc). The adjacency cost is proportional to the moving distance of a robot. It enables the robot to navigate without being trapped in local minima and is applicable to both static and dynamic environments. Furthermore, a robot can reach the goal with minimum cost and path planning can be performed without accurate information on the environment.

4. Experimental Results and Discussions

To verify validity of the proposed algorithm, various tests on topological map building and global localization have been conducted. The Pioneer II DX mobile robot equipped with a Sick laser scanner was used for the test.

4.1 Experiments on topological map building

The environment for the test is about 20*10m large. The laser range data are gathered manually by placing the robot at the specified locations. Fig. 6 is a laser-based global grid map of the environment under consideration. Note that this global grid map is shown only for better understanding of the environment, and is not used to construct the global topological map.

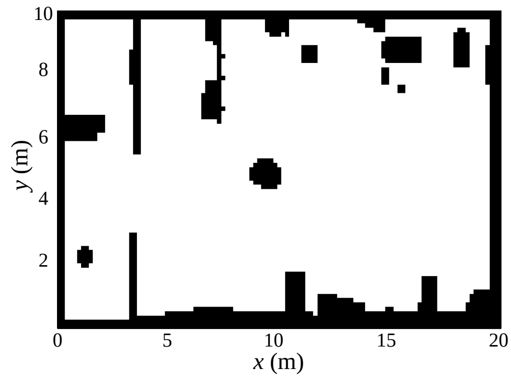
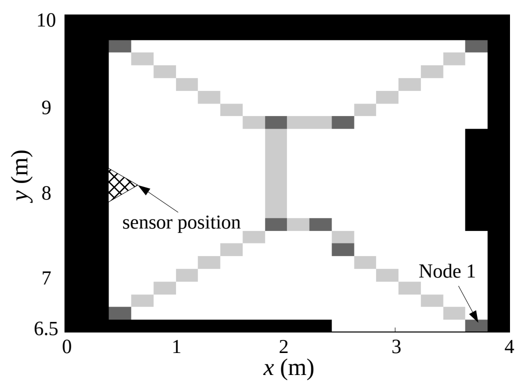
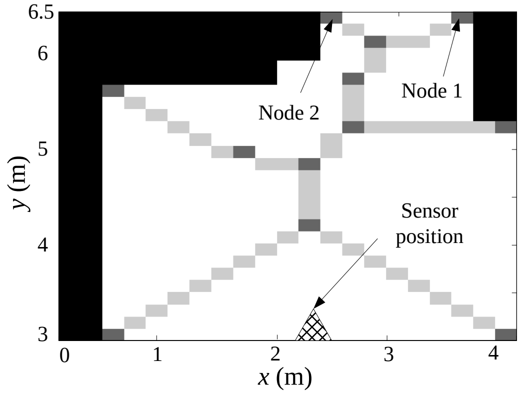


Fig. 6 Global grid map of the environment.

Local topological maps have been built at the 10 –15 predetermined locations in the environment with a laser scanner. These maps are continuously updated to the global topological map as explained in Section 2.2.



(a) Local map 1 for sensor position at (30, 80, 0˚)



(b) Local map 2 for sensor position at (23, 30, 90˚)

Fig. 7 Binary map and its local topological maps.

The process of building the global topological map is show in Fig. 7 and 8. Fig. 7 represents the local topological map built at each sensor location. Since the position is expressed by the grid number and the grid size is 10cm*10cm, Fig. 7(a) represents the map at the location (3m, 8m, 0˚) and Fig. 7(b) the map at (2.3m, 3m, 90˚).

Fig. 8 shows the process of updating each local topological map to the global one. In this map, node 1 is common to both local maps 1 and 2, so the geometrical information of this node makes matching of two local maps easy. Node 2, which is shown only in map 2, is a redundant node which should be deleted after update. This node is formed because it is around the edge of the active window in local map 2, but is not necessary in the global map since it is no longer the edge of the active window and part of empty space in the global map. Fig. 9 shows the final global topological map and it has only the geometrical information of nodes and connectivity between two nodes.

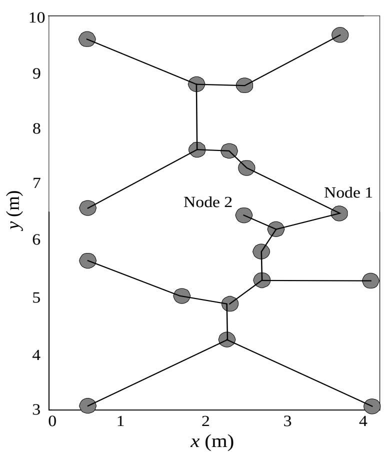


Fig. 8 Intermediate topological map obtained by matching two local maps 1 and 2.

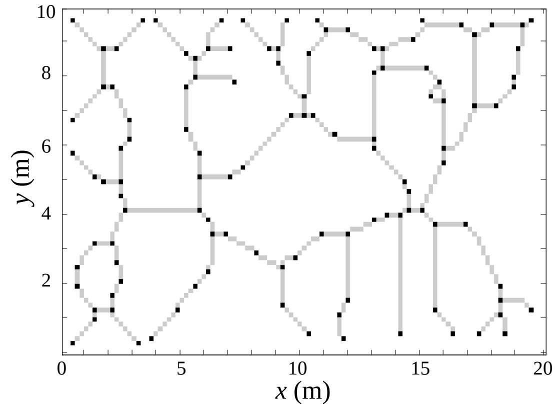


Fig. 9 Final global topological map.

4.2 Experiments on Global Localization

Based on the global topological map obtained in the previous section, global localization can be conducted. It is assumed that the initial position of the robot is unknown. The entire region covered by the global topological map is decomposed into the squares whose size is 10cm*10cm. In this test, 5,000 samples are randomly extracted. Figure 10 shows 5,000 samples in the x-y-θ space initially. The robot has position and orientation at each point

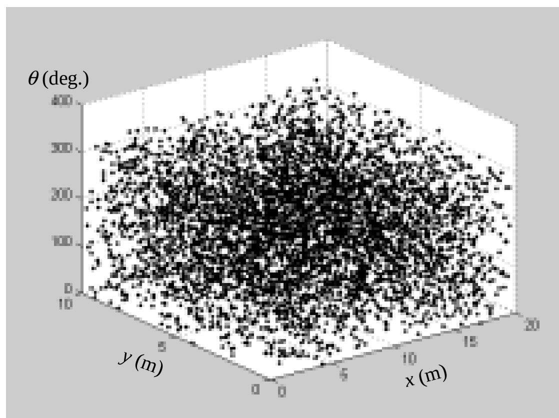
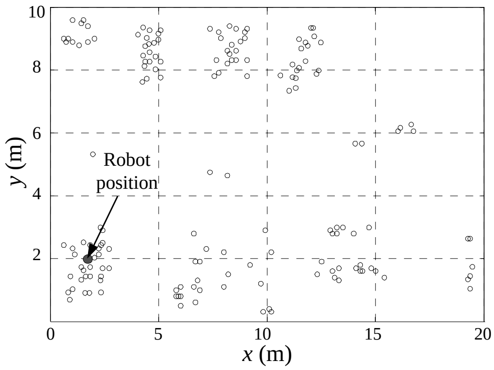
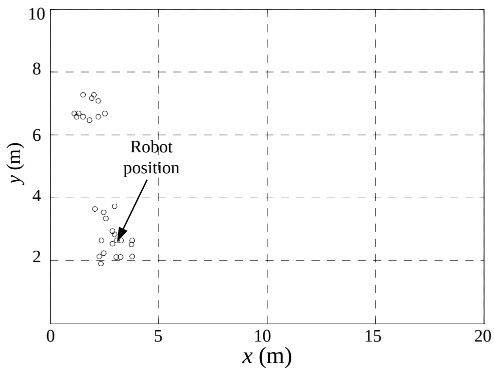


Fig. 10 Initial position and orientation of the robot in the x-y-θ space.

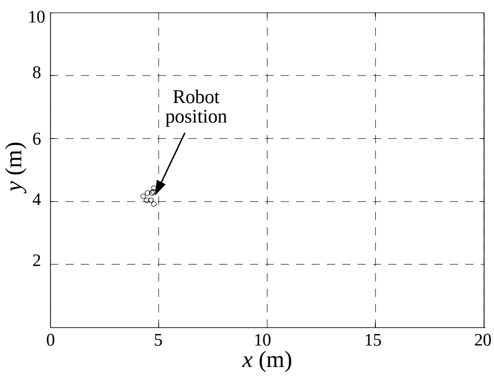
Fig. 11 illustrates convergence of the robot position. Initially, the robot is located at (20, 20, 270˚), and moves continuously. During the robot movement, localization process continues with new sensor data and thus probability of the robot position is updated by a Bayesian rule. For efficiency, after the number of candidates is reduced to 2 positions (from 5,000 samples), localization process takes place only within the boundaries of a circle centered at these 2 positions. Even thought the initially assumed position of the robot is arbitrary, the robot position converges to a point as localization continues over time. Once localization is carried out successfully, the subsequent localization is easy to accomplish because the initial position of the robot is approximately known.



(a) After 2 time steps.



(b) After 7 time steps.



(c) After 11 time step.

Fig. 11 Convergence of the robot position with time.

5. Conclusions

In this research fast and simple approaches to map building and localization are proposed for a mobile robot equipped with a laser scanner. A robot collects sensor data at the predetermined positions and builds the binary grid map from which a local topological map is constructed using a thinning method. The global topological map is then built from the local topological maps. The following conclusions are drawn.

1. The global topological map using a thinning method needs much simpler computation than that using a Voronoi diagram.
2. A thinning method can create additional nodes in the resulting topological map, thus providing more information on the environment when compared to the topological map based on a Voronoi diagram.
3. Localization based on the topological map can be significantly improved with the additional nodes created by the thinning method.

Acknowledgement

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