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Thinning-based Topological Exploration Using Position Probability of Topological Nodes

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***Abstract* - Exploration is the fundamental task of guiding a robot autonomously during mapping so that it covers the entire environment with its sensors. In the frontier-based exploration, a robot visits the unknown regions, but the sufficient information on the obstacles was not exploited. In the topological exploration, the robot was forced to visit all the topological nodes, but it was inefficient and time-consuming. In this paper, an efficient exploration called a thinning-based topological exploration (TTE) is proposed. This scheme is based on the position probability of the end nodes of a topological map built in real time. The robot then updates the position probability of each end node sustaining its position at the current location using the range data. By analyzing this position probability, the robot can determine whether or not it needs to visit the specific end node to examine the environment around this node. Various experiments show that the proposed TTE algorithm can perform exploration more accurately than the frontier-based exploration approach and more efficiently than the other topological exploration schemes, because in most cases, exploration for the entire environment can be completed without directly visiting everywhere.**

Index Terms* – *exploration; thinning-based topological exploration (TTE); position probability.

I. INTRODUCTION

Mapping 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. Two major paradigms have been used for mapping the indoor environment: an occupancy grid map and a topological map. The former can produce an accurate metric map in a relatively simple manner, but it requires large memory and is inefficient. The latter, on the other hand, provides more efficient and compact Voronoi graph-like map requiring much less memory, but it is not useful for accurate localization because of insufficient information [1].

In order to map an unknown environment, the robot requires some strategy which guides it autonomously to cover the environment, which is called *exploration*. The exploration scheme serves as a key element to SLAM (Simultaneous Localization And Mapping). The requirements for exploration are its completeness and efficiency. The completeness means that it should cover the entire environment without missing any portion of the environment. The efficiency means how fast the robot can finish the task of mapping by minimizing the travel distance to cover the entire environment.

Several exploration algorithms have been proposed so far. In a frontier-based exploration strategy [2], a robot detected the frontiers which were the regions on the boundary between the unexplored and open space. The robot then moved to the new frontiers to explore the unknown environment until the entire environment had been explored. This approach was integrated with the localizer and path planner to explore large-scale environments [3]. The frontier-based approach was also used to explore the environment using multiple robots [4] and adopted as part of the navigation system [5].

Although the frontier-based exploration generally showed good performance, this scheme has some drawbacks of not taking advantages of the obstacles which could serve as a guide for a robot's moves and for correcting its localization error, because in a free-space approach the robot was commanded to move to new places to collect the new environment information. To overcome this problem, an autonomous exploration method via regions of interest was proposed [6]. In this research the next best view was searched to get the next sensor data which could improve the quality of the map under construction. But little research has been done to improve the efficiency of exploration.

Another main strategy for exploration is a topological exploration based on the GVG representation. T-SLAM (Topological SLAM) was developed to explore the environment by tracing all GVG edges and visiting all meet points and boundary points [7]. This method worked very well in the unstructured and complex indoor environment. But it was inefficient and required a huge amount of operation time to generate a map because a robot should trace all the GVG edges to extract the topological information and to guarantee the quality of the map.

In this paper, an improved approach to building a thinning-based topological map (TTM) is briefly presented [8]. The TTM is built in real time by applying a thinning process to local occupancy grids constructed using the range data. This map could overcome some disadvantages of the GVG-based topological map which contained the boundary edges and weak meet points unnecessary in navigation. Based on the TTM, a thinning-based topological exploration (TTE) is proposed in this research.

In implementation of TTE, a position probability of each end node of TTM sustaining its position at the current location is computed in every sampling period. Since the higher position probability means that the environment around the corresponding node is more completely examined, exploration is conducted only for the end nodes whose position probability is below a certain threshold. By investigating the position probability of the end nodes, therefore, the robot is able to determine whether the environment around the nodes is sufficiently explored or not. As a result, the proposed TTE can be performed faster than the GVG-based exploration. At the same time, the robot can decide which end nodes should be explored more thoroughly. Thus the TTE scheme is more accurate than the frontier-based exploration. Consequently, the TTE can meet the requirements of completeness and efficiency of exploration.

This paper is organized as follows. Section 2 presents how to build a thinning-based topological map (TTM) and section 3 introduces the concept of position probability of an end node and deals with how to efficiently explore the unknown environment using the position probability. Experimental results are shown in section 4 and finally in section 5 conclusions are drawn.

II. THINNING-BASED TOPOLOGICAL MAP (TTM)

A. Edge Generation of TTM

In the feature-based topological map, the environment is modeled by a set of geometric primitives such as edges and nodes. It has several advantages such as compactness, fast computation, natural expression to humans, and so on [1]. A topological map, however, is not appropriate for localization which requires comparison of the current map with the reference map because it has only limited feature information compared to a grip map.

To build a topological map using range sensors, a Voronoi graph is commonly used. But it is complex and difficult to apply to arbitrarily shaped objects. In building a topological map, therefore, a thinning method was proposed in [8], which needs simpler computation than the Voronoi graph, but can show similar performance.

A thinning method is one of the image processing algorithms which are used to detect the skeleton of images. Fig. 1 illustrates the concept of thinning. 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 with thin lines. In the case of mobile robots, the connected lines are used as paths on which a robot travels without colliding with other objects.

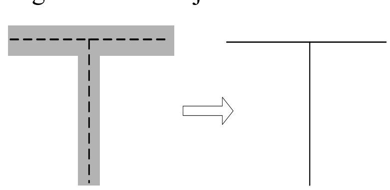


Fig. 1 Concept of thinning.

The detailed algorithm of the thinning process can be referred to [8]. As shown in Fig. 2, the free space to which the thinning process is applied is selected. Then the free space continues to be contracted from both the outside of the objects and the inside of the wall boundary. This process is repeated until the skeleton corresponding to the thinnest line for the free space is extracted.

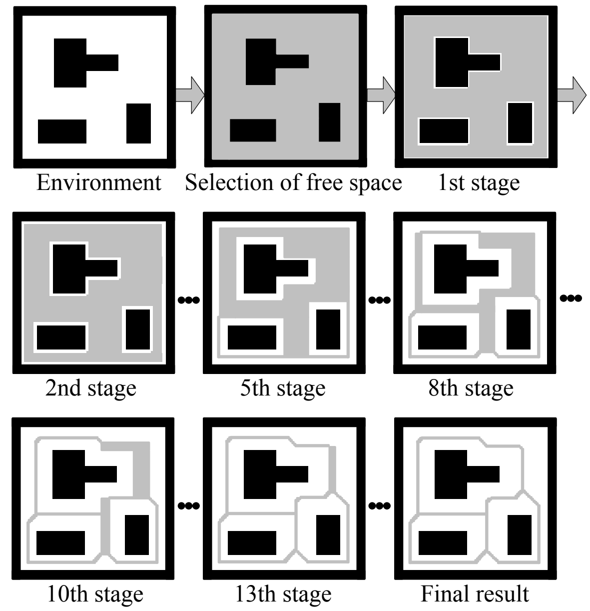


Fig. 2 Construction of a thinning-based topological map for given environment (Simulations).

The thinning-based topological map (TTM) is constructed as follows. The robot collects the range data by scanning the environment using a laser rangefinder. Since the scanning rate is about 5Hz and the robot navigates slowly, each cell is likely to be scanned several times. The occupancy probability for each cell is then updated based on the Bayesian update formula. This probabilistic approach to building a local occupancy grid enhances the confidence of the underlying grid map for a local topological map. At each sampling instant, based on the range data, the local grid map and the subsequent local topological map is built. The local topological map even for the same space is constantly changing as the underlying grid map is updated. The TTM is built in real time.

B. Node Generation of TTM

After the edges are extracted through the thinning process, three types of nodes can be extracted as shown in Fig. 3. An end node corresponding to the end of each edge represents the dead end of the environment (e.g., dead end of the corridor). A branch node at which more than three edges meet represents the junction (e.g., intersection of corridors). A corner node denotes the point at which the edge varies its slope significantly. For example, without introducing the corner node N_3 in Fig. 3, edge A that can detour the object cannot be reproduced from only the information on the connectivity of nodes N_1 and N_2. That is, the edge A can be roughly reconstructed by combining the edge between N_1 and N_3 and the edge between N_2 and N_3.

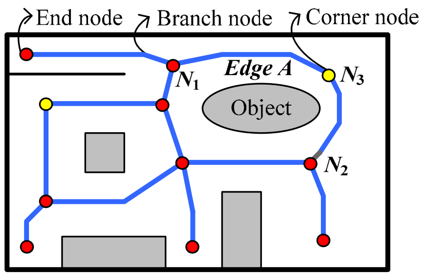


Fig.3 Three types of nodes in TTM.

III. THINNING-BASED TOPOLOGICAL EXPLORATION (TTE)

A. Position Change of End Nodes

The nodes of TTM have their own characteristics. For example, the position of a branch node at which more than three edges meet is relatively robust to a change in environment and the sensing methodologies, so it can be used as a reliable landmark for localization [8]. On the other hand, the position of an end node representing the end of an edge is likely to change according to the degree to which the environment is sensed by the range sensor mounted on the robot. That is, it is related to visibility of the sensor. Therefore, the observation of the end node position may indicate how much of the environment is explored.

Fig. 4 shows the topological map constructed in real time when the robot navigated through the unknown environment. In the figure, the circle with the red mark denotes a mobile robot with the red mark pointing to the robot's heading. In Fig. 4(a), the robot scanned the unexplored frontal area using the laser scanner capable of providing 181 range readings with a resolution of 1°. Based on these range data, the local grid map and then the local TTM were constructed as shown in the figure. In this initial TTM shown in Fig. 4(a), 1 branch node, 3 end nodes, and 1 corner node were created. Consider node A in the figure for instance. No information on the area to the left of node A was available with the current sensor location. However, as the robot traversed towards node A and the unseen area around node A was exposed to the range sensor, node A continued to change its position (through (b) and (c)) until the robot thoroughly detected the region around the dead end of the hallway. Note that the branch nodes maintained their position unlike the end nodes.

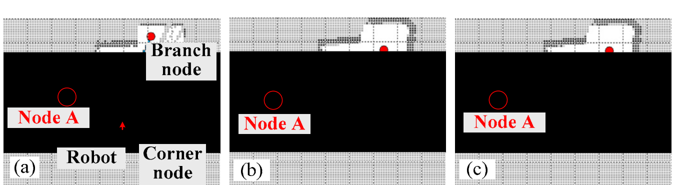


Fig. 4 Change in end node position during exploration of dead end of hallway.

Fig. 5 shows the situation different from Fig. 4. Since the newly sensed area was not the dead end of a hallway and a new hallway was found, the end node sprawled out into this hallway as the robot approached this end node. Consequently, if the position of the end node varies no longer as the robot approaches the end node, we can determine that the environment around the end node is fully explored.

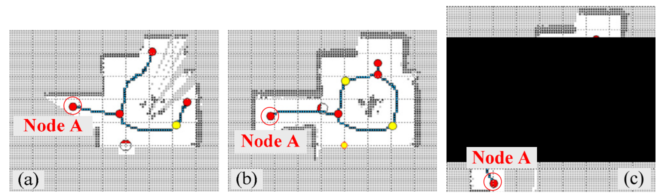


Fig. 5 Change in end node position during exploration of connecting area of two hallways.

B. Position Probability Based Exploration

Two commonly used exploration methods are a frontier-based exploration approach and a GVG-based exploration approach. But as described in Section 1, the frontier-based approach has little emphasis on gaining the information about the obstacles and the GVG-based exploration is not very efficient [2][6][7]. To enhance the efficiency and accuracy of exploration, this paper proposes a thinning-based topological exploration (TTE) method to efficiently explore the environment using the information on the topological nodes updated in real time.

Thorough examination of the environment from the node under consideration guarantees accurate modeling of the environment, but it often leads to inefficient and time-consuming exploration. If the mobile robot can model the environment around the end node from a distance without closely approaching the node, the exploration time can be significantly reduced. However, it is not easy to determine whether the complete examination has been conducted or not. To this end, we introduce the *position probability* that indicates how much of the environment around the end node under consideration is explored by investigating the node behavior.

In this context, the reliable node position with high position probability means that the end node under consideration will persist at the current location after the exploration around this node is completed. For example, if the end node position does not alter even after scanning the environment around the end node, then the position probability of the end node staying at this current position is regarded as 1.

The first type of position probability is associated with the distance between the end node and the robot. Obviously, the closer the robot approaches the end node, the more thorough exploration can be conducted, thereby resulting in an increase in the position probability of the node. The *distance-based position probability* (DPP) for end node n is represented by $D_{n,t}(\mathbf{X}_{node,t}\ ,\ \mathbf{X}_{robot,t})$, where $\mathbf{X}_{node,t}$ and $\mathbf{X}_{robot,t}$ are the absolute positions of end node n and the robot at time t relative to the global reference frame, respectively. It is assumed that the DPP of the end node is 1 when the distance between the robot center and the end node is less than 0.5m (i.e., the distance between the node and the laser scanner is about 0.3m in consideration of the robot radius of 0.2m in this research), because the environment is highly likely to be closely examined at this distance. If the distance is greater than a certain threshold (in this case, 4.5m), then it is assumed that the robot is on the verge of reasonable modeling of the environment, thus assigning the DPP of 0.5. Between these two limits, the DPP tends to decrease inversely proportional to the distance between the node and the robot. In summary, the DPP for end node n, $D_{n,t}$, is defined as

$$D_{n,t}(\mathbf{X}_{node,t}, \mathbf{X}_{robot,t}) = \frac{4.0}{r+3.5} \tag{1}$$

where

$$r = \begin{cases} 0.5\text{, if } (\min\limits_i \left\| \mathbf{X}_{node,i} - \mathbf{X}_{robot,i} \right\| < 0.5) \\ \min\limits_i \left\| \mathbf{X}_{node,i} - \mathbf{X}_{robot,i} \right\|\text{, else} \end{cases} \quad (i = 1, \ldots, t) \tag{2}$$

In (2), r represents the minimum of the distances experienced during exploration up to time t. It is also noted that the end node out of the scanning range (180^o) or blocked by obstacles is excluded in computation of (2).

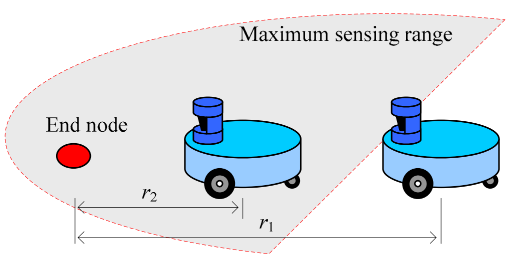


Fig. 6 A robot can scan the environment around the node at different distances.

The second type of position probability is associated with the angle between sensing positions. It can be easily understood that more information on the environment around the end node can be collected when the node of interest is scanned from various angles. Let us define the angle difference α as

$$\alpha_{\max} = \max_{i,j} \left| \angle(\mathbf{X}_{node,i} - \mathbf{X}_{robot,i}) - \angle(\mathbf{X}_{node,j} - \mathbf{X}_{robot,j}) \right| \\ (i, j = 1, ..., t) \tag{3}$$

where $\angle(\mathbf{X}_{node,i}\text{-}\mathbf{X}_{robot,i})$ is the angle of the vector from the robot center to the end node measured counterclockwise relative to the X axis of the global reference frame as shown in Fig. 7. It is also noted that the end node out of the scanning range (180^o) or blocked by obstacles is excluded in computation of (3). Note that the angle difference α_{max} is the maximum of the angle differences $|\alpha_1 - \alpha_2|$, $|\alpha_2 - \alpha_3|$, and $|\alpha_3 - \alpha_1|$ in the case of Fig. 7, so $\alpha_{max} = |\alpha_3 - \alpha_1|$.

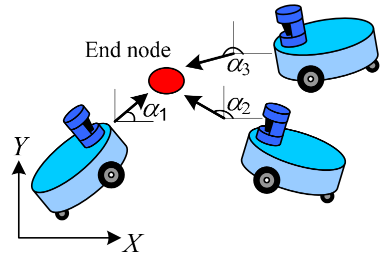


Fig. 7 A robot can scan the environment around the node from different angles.

It is likely that the *angle-based position probability* (APP) of the end node persisting at the current location gets higher when the robot sees the end node from various angles. Therefore, the APP for end node n, $A_{n,t}$, is defined by

$$A_{n,t}(\mathbf{X}_{node,t}, \mathbf{X}_{robot,t}) = \begin{cases} \dfrac{\alpha_{\max}}{90} (\alpha_{\max} \le 90^\circ) \\ 1 \ (\alpha_{\max} > 90^\circ) \end{cases} \tag{4}$$

Note that the APP of (4) is so designed that $A_{n,t} = 1$ when $\alpha \geq 90^o$ and $A_{n,t} = 0$ when $\alpha = 0°$. Since the laser scanner has a scanning range of 180°, α_{max}=180° means that the neighboring environment of the end node in the range of 360° is scanned. However, the end nodes are usually placed in a corner as shown in Fig. 8, the position of the end node can be determined even when α_{max} = 90°.

The end nodes can be generated in two cases as shown in Fig. 8. In (a), the end node is generated at a corner where two walls meet. In this case, the robot does not need to visit the end node because examining the environment around the node from various angles (even at a great distance) is sufficient to thoroughly model it. In (b), the end node is generated at the dead end of a narrow hallway. It is difficult to scan the environment from various angles, so the robot needs to approach the end node sufficiently closely. In conclusion, the APP is more preferable in case (a), while the DPP in case (b).

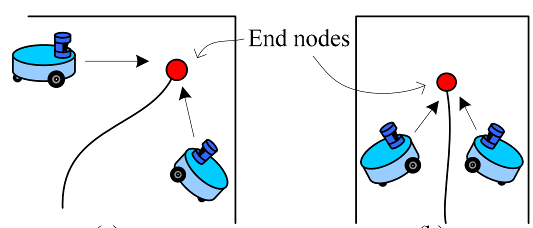


Fig. 8 Two cases in which end nodes are generated.

In order to cover both cases shown in Fig. 8, the overall position probability, $P_{n,t}$, is defined as

$$P_{n,t}(\mathbf{X}_{node,\,t}, \mathbf{X}_{robot,\,t}) = \max(D_{n,i}, A_{n,i}) \quad (i = 1, \ldots, t) \tag{5}$$

where n is the node number. Using (5), the position probability for every end node of a topological map can be obtained. The position probability means the possibility of the end node sustaining its position at the current location after completion of the exploration. The exploration task is executed in the unknown environment, so the nodes and edges of a topological map continue to change their positions and shapes, respectively. In some cases, the nodes and edges appear or disappear as the exploration progresses. Therefore, the position probability of end node n should be calculated continuously and updated during exploration up to time t.

During exploration, the position probabilities of the end nodes within the scanning range of the laser scanner at the current time are computed by (5). The robot visits only the end nodes whose position probability is lower than a certain threshold (e.g., 0.9 in this research) until all end nodes have the position probability higher than the threshold. If the edges of a topological map are chosen as an exploration path, the robot can safely navigate the unknown area while avoiding static obstacles without additional path planning.

In this research, the breadth first search algorithm was used to determine the target end node to visit next. Once the target node is selected, the robot explores the environment along the topological edge on which the end node is placed. As mentioned before, during navigation to the target node the robot sees other end nodes within its scanning range, and the overall position probability of all these nodes are updated although these are not the current target nodes. Using this exploration strategy based on the position probability of the end nodes, the robot can explore the unknown environment more efficiently and rapidly than the previous topological exploration methods like the GVG-based exploration and more accurately than the frontier-based exploration methods.

IV. Experiments

The proposed exploration scheme in this research is called a thinning-based topological exploration (TTE), since the topological edges are used as a navigational path and the topological end nodes are exploited as an indicator showing the progress of exploration. The proposed TTE has been tested on various environments using Pioneer DX2. One laser scanner (SICK LMS200) with a scan range of 180° was installed with the scanning area facing forward. Fig. 9 shows the exploration process. In the figure, each cell of the grid map is 10cmx10cm in size and the environment is 10mx10m in size. The figures beside each end node denote the end node number and its position probability computed by (5) at the current time. For example, 1(0.92) means that the position probability of end node 1 persisting at the current location after complete exploration is 0.92.

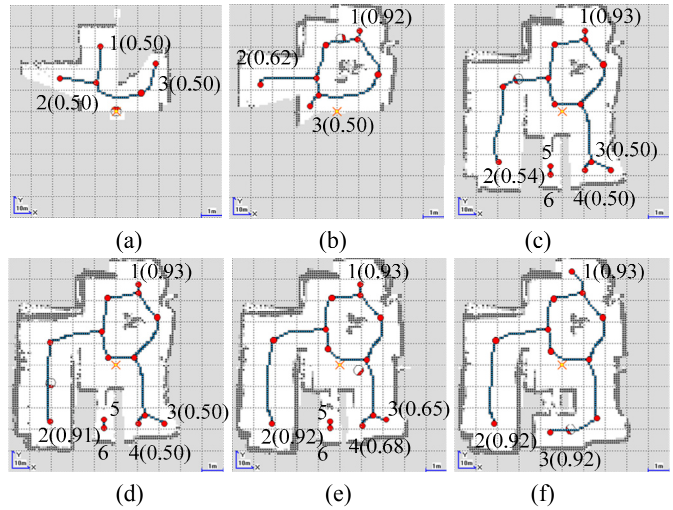
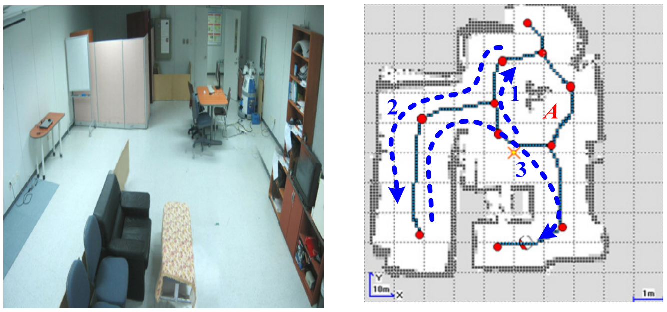


Fig. 9 Changes in end nodes and their probabilities during exploration.

The robot was placed in the unknown environment at the beginning and it scanned its neighboring environment to construct an occupancy grid with the range data. The topological map was then created by the thinning process as explained before. An initial value of 0.5 was assigned to each end node as its initial position probability. In Fig. 9(a), end node 1 was selected as a target node because the robot's heading happened to be directed toward this node. Note that choice of an initial target node does not affect the exploration results. As the robot traversed toward end node 1 along the topological edge created as a result of TTM building, the position probability of end node 1 continued to increase. If it exceeded 0.9, then the end node would be believed to sustain its position with confidence sufficient to guarantee that the robot does not need to visit this node to complete the modeling of the neighboring environment. In Fig. 9(b), since the position probability was found to be 0.92, the robot started to head for another end node nearby without directly visiting end node 1. End node 3 appeared temporarily and disappeared soon in Fig. 9(c).

In Fig. 9(c), the robot was heading for end node 2. As the robot approached this node, the new environment which had not been visible in Fig. 9(b) was now detected, thereby causing the target node to move into a hallway as shown in Fig. 9(c). Note that most environment of the room could be roughly modeled even at the time of Fig. 9(c) and the topological map continued to be updated in real time. Through Fig. 9(b) and (c), the position probability of end node 2 was less than the threshold of 0.9, but as the robot followed this node, it finally reached the threshold in Fig. 9(d), thus indicating completion of the exploration around the neighborhood of end node 2. Then the new target (i.e., end node 3 in Fig. 9(e) in this case) was set for further exploration on the unknown environment. As the robot approached end node 3, this node disappeared in Fig. 9(f) and the robot headed for another end node 3 (i.e., a newly numbered node which was different from the old node 3) and stopped exploration after the position probability of end node 3 was found to be 0.92.



(a) (b)

Fig. 10 (a) Experimental environment, and (b) grid and topological maps created using the TTE algorithm and robot paths during exploration.

In Fig. 10, paths 1, 2 and 3 illustrates the actual paths along which the robot traveled in succession during TTE. As can be seen in the figure, the robot did not explore every nook and corner of the environment, but could obtain the relatively accurate environment model. In the figure, the topological loop was formed around region *A* which consisted of desks and chairs. The exact shapes of the objects were not reflected in the grid map because the laser sensor could scan only the legs of the desks and chairs.

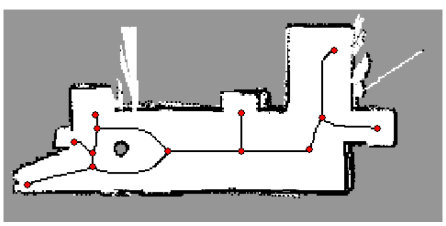


Fig. 11 Another example of grid and topological maps created by means of TTE in large-scale environment

Fig. 11 shows the map constructed by applying the proposed TTE method for large-scale environments. This sparse environment was 25m x12m in size and consisted of a hallway, doors and a column. This demonstrates that the TTE method can also effectively explore large-scale environments.

V. Conclusions

In this paper, an efficient exploration scheme called a thinning-based topological exploration (TTE) was proposed. It is based on the position probability of the end nodes of a topological map. The position probability was introduced to determine the level of thoroughness of exploration for the specific region of the environment. With TTE, the robot does not have to visit the entire environment to accurately model the unknown environment. The validity of this exploration strategy has been verified by a series of experiments. From this research, the following conclusions have been drawn.

1. The thinning-based approach can provide a simple but robust way of constructing a topological map in real-time.
2. The edge of a topological map can serve as a navigation path which is free of static obstacles and does not require additional path planning for exploration of the unknown environment.
3. The position probability was useful to determine the level of thoroughness of exploration for the specific region of the environment.
4. The proposed TTE based on the position probability can efficiently model the environment because the robot does not have to visit all end nodes directly to complete exploration.

Currently, research on more efficient exploration strategy for the large-scale environment is under way.

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