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Hybrid Semantic Mapping using Door Information

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Abstract - We describe hybrid semantic mapping method with classified area information for home environments. The hybrid map contains two map types: a grid map, and a classified area information-in-grid (CAIG) map. The grid and CAIG maps can be used for intelligent navigation (e.g., localization and path planning) and motion selection, respectively. In home environments, a door can be used to divide an area into various sections such as a room or a kitchen. Therefore, we use a grid map of the home environment and door information as main clues to classify the area and to build the hybrid map. The proposed method is verified by various experiments. We show that the robot can build a hybrid semantic map autonomously in home environments.

Keywords – Area classification, semantic map, hybrid map, grid map, mobile robot

1. Introduction

In recent years, the simultaneous localization and mapping (SLAM) community has made tremendous progress in the development of efficient and highly accurate map building techniques [1]. Most of these techniques are focused on building metric or topological maps. However, other types of information are needed to intelligently perform various tasks. For example, a collision with dynamic obstacles can frequently occur in doorways due to blind spots. If a robot decreases its moving speed in doorways, it can reduce unexpected collisions. Thus, the robot needs to have some semantic information relating to the environment.

In [2], semantic map building based on supervised learning and geometrical features measured by a laser scanner is proposed.. Since this method is not sensitive to sensor noise occurring from static obstacles (e.g., desks and sofas) and dynamic obstacles (e.g., humans), it can classify environments more robustly than conventional area classification methods [3], [4]. However, it was difficult to gather a large quantity of learning data for supervised learning and apply it to learned environments and non-standardized environments with different geometric features.

In this paper, we propose an approach to allow a mobile robot to autonomously build a hybrid semantic map using door information in a home environment that is obtained by the door detection method described in our previous work [6]. The hybrid semantic map consists of two types of maps: grid and CAIG. The grid map can be used for basic navigation functions such as localization and path planning. For behavior selection of a robot in unexpected situations, a classified area information in the grid (CAIG) map can be used. To build the CAIG map, we used information from a door and from the modified wavefront algorithm proposed in this study. Semantic information relating to doorways and rooms is included in the CAIG map. We believe that proposed hybrid semantic map can improve the capabilities of a mobile robot in various domains including localization, path-planning, and human-robot interaction (HRI).

The remainder of this paper is organized as follows. Section 2 presents a method of hybrid semantic map building. Section 3 describes our experimental results. Our conclusions are given in Section 4.

2. Hybrid semantic mapping

The first step in area classification is to build a grid map of the environment, and create an initial CAIG map whose grid size is equal to that of the grip map. A grid whose occupancy probability is higher than 0.8 in the grid map has a value of 1 in the CAIG map. A grid lower than 0.8 has a value of 0. A grid with an occupancy probability of 0.5 in a grid map has a value of 2 in the CAIG map. The second step is to represent door information on the CAIG map. This procedure is illustrated in Fig. 1. Figure 1(a) is part of the CAD data, and Fig. 1(b) is the CAIG map of Fig. 1(a). Given the position and width of a detected door, a grid that corresponds to the door has a value of 3 in the CAIG map. The door grids are represented by slashed rectangles in Fig. 1(c). If all door grids are represented on the CAIG map, a dotted circle with the center of the door grids as its center can be generated by the ray casting method, as shown in Fig. 1(c). The diameter of the dotted circle is the width of the door. The area within the dotted circle, as shown in Fig. 1(d), is defined as the local area near the door. Then, a grid of the local area near the door has a value of 4, which is represented by yellow slashed rectangles in Fig. 1(d). The third step is to cluster grids that have a value of 0 in the CAIG map. In this study, we used a modified wavefront algorithm for clustering. All the grids with a value of 0 on the CAIG map are clustered, and each clustered grid is given its own unique clustering value.

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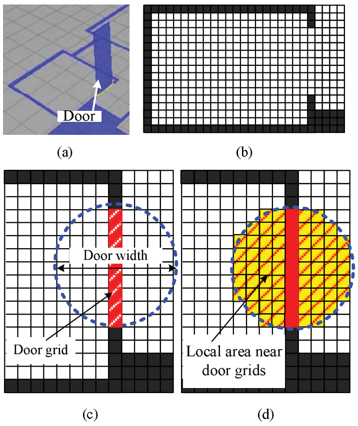

Fig. 1. Second step of area classification: (a) CAD data, (b) CAIG map, (c) door grids and (d) local area near door grids.

The fourth step is to extract a node representing each clustered area as shown in Fig. 2. The extracted nodes are used to find a relationship between nodes, and to classify clustered areas of each region. Nodes 0 to 4 in Fig. 2 are the mean points of the clustered areas and are included in the node set N_{CG} as follows:

$$N_{CG} = \{n_{CG,0}, n_{CG,1}, \ldots, n_{CG,m}\} \tag{1}$$

where $n_{CG,i}$ is the number of the node extracted from the clustered areas.

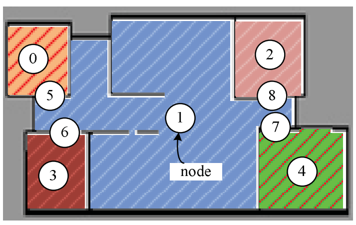

Fig. 2. Extracted nodes on clustered and door area.

Nodes 5 to 8 in Fig. 2 are extracted from the doors and are included in the node set N_{DG}:

$$N_{DG} = \{n_{DG,m+1}, n_{DG,2}, \ldots n_{DG,m+q}\} \tag{2}$$

where $n_{DG,i}$ is the number of the node extracted at the door areas. Each node in the node sets (i.e., N_{CG} and N_{DG}) has the information on all the grids that are included in its representing area. To find a relationship between nodes, we extracted the paths between nodes using the gradient path planning method. The path between nodes is defined as edge E as follows:

$$E_{jk} = \{e_1, e_2, \ldots e_h\} \tag{3}$$

where j and k are the numbers of the nodes that are linked by an edge e_i that represents the (x, y) coordinates of each grid constituting an edge, and h is the total number of grids.

The relationship between nodes that are included in N_{CG} can be described by the edge. Then, d_{CE}, the node number of the door connected by the edge E_{jk}, is given by

$$\begin{aligned} &d_{CE} = n_{DG,l} \quad \text{if } E_{jk}(i) \in G(n_{DG,l}) \\ &\text{where } i = 1 \cdots h,\ l = m+1, \cdots, m+q \end{aligned} \tag{4}$$

where $E_{jk}(i)$ is the number of the grids constituting an edge E_{jk}, and $G(n_{DG,l})$ is the grid set of door node l. Equation (4) is applied to all nodes in N_{CG}, and thus the relationship between N_{CG} and N_{DG} is found. After the relationship between N_{CG} and N_{DG} is found, all the nodes in N_{CG} can be classified into a room and a living room. If the robot moves from node 0 to node 1, the robot must visit door node 5. Similarly, if the robot moves from node 0 to nodes 2, 3, and 4, the robot must visit door nodes (5, 7), (5, 6), and (5, 8), respectively.

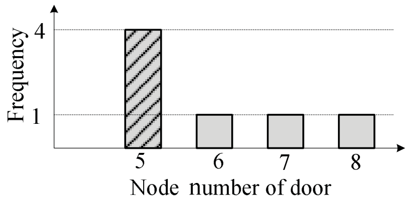

Fig. 3. Example of histogram construction with the total number of door nodes visited by the robot.

Figure 3 shows the histogram constructed by the total number of door nodes visited by the robot. The slashed rectangle in the histogram of Fig. 3 represents the frequency of visiting the same door node when a robot moves from node 0 to other nodes. This could be decisive evidence with which to classify the space as a room and a living room. From this result, to classify the space, the following relation is defined:

If $M_{histo} = m$, then we define a room.
If $M_{histo} \neq m$, then we define a living room. (5)

where M_{histo} represents the highest frequency in a histogram, and m is the number of other nodes of the set N_{CG}. When such a process is performed for all nodes of N_{CG}, the information for each region is represented on a CAIG map as shown in Fig. 4.

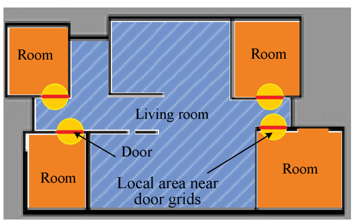

Fig. 4. Result of area classification: (a) CAIG map, and (b) topological map.

3. Experimental results

(a) (b)

Fig. 5. Experimental environment and mobile robot platform.

To verify the method of classifying home environments, we used a pioneer P3-DX robot equipped with one laser scanner and Kinect sensor as shown in Fig. 5(a). The experimental environment consisted of one living room, two rooms, and two doors, as shown in Fig. 5(b). The process of area classification is shown in Fig. 6. Figure 6(a) shows the CAIG map built by the grid map and door information. To segment the whole area into rooms and living rooms, the modified wavefront algorithm was executed. Figure 6(b) shows the nodes (represented by a circle) extracted from each segmented region and the door nodes (represented by a slashed circle). To find the relationship between nodes, the path generation procedure was executed at each node in $N_{CG.}$ If all paths between nodes in N_{CG} are generated as shown in Fig. 6(c), the relationship between N_{CG} and N_{DG} can be found as shown in Fig. 6(d). After finding the relationship between nodes, the area can be classified as two rooms, one living room, two doors, and a local area near the door, as shown in Fig. 7.

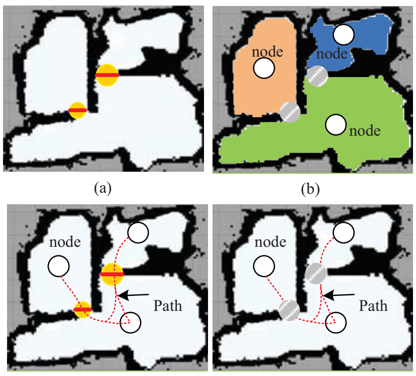

Fig. 6. Process of area classification with CAIG map.

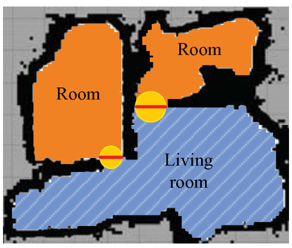

Fig. 7. Final results of area classification.

4. Conclusion

We presented an approach to build a hybrid semantic map that was successfully tested in a real environment. The hybrid semantic map consists of two types of maps: grid and CAIG. The grid map was built by an autonomous map building method and was used as a basis for building the CAIG map. To store various information in a classified area such as doorways and rooms in the CAIG map, we used the door information and a modified wavefront algorithm. The proposed method can build the hybrid semantic map without human intervention such as supervised learning. We believe that the proposed semantic map can improve the capabilities of a mobile robot in various domains including localization, path-planning, and human-robot interaction (HRI). In the future, we plan to use the object recognition system in order to classify the environments accurately.

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