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Incremental Topological Modeling using Sonar Gridmap in Home Environment

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Abstract— **This paper presents a method of topological modeling in home environments using only low-cost sonar sensors. The proposed method constructs a topological model using sonar gridmap by extracting subregions incrementally. A confidence for each occupied grid is evaluated to obtain reliable regions in a local gridmap, and a convexity measure is used to extract subregions automatically. Through these processes, the topological model is constructed without predefining the number of subregions in advance and the extracted subregions are guaranteed the convexity. Experimental results verify the performance of proposed method in real home environment.**

I. INTRODUCTION

An autonomous mobile robot needs to represent its environment as a map which can be recognized by robotic sensors such as range sensors or vision sensors. The map is used to execute self-localization and navigation to perform tasks in the environment. For this purpose, many researchers have developed various types of map representation during last two decades [1].

In general, robotic mapping methods can be classified into metric map and topological map. The metric map represents exact locations of geometric entities in the environment with respect to a reference frame. Occupancy gridmaps [2] and feature based maps [3] are typical examples of the metric map. The metric map would be helpful to perform elaborate tasks in the robot's workspace. On the other hand, topological maps [4], [5] represent the environment as a graphical model which consists of nodes and edges. The topological map has an advantage of compact and abstracted form of the environmental modeling and is useful for performing path planning because connectivity between places is represented well. Recently, by fusing metric and topological approaches, globally topological and locally metric maps are also proposed in some literatures [6], [7].

For the range sensor based map generation, laser sensors and sonar sensors are used popularly. A map generation using laser sensor is relatively easier than using sonar sensors because the sensory information of laser sensor is quite dense and accurate. In fact, successful results with laser sensor are reported by many researchers using the aforementioned mapping algorithms. However, use of the laser sensor is restricted by its expensive cost. On the other hand, sonar sensors which are cheap and give relatively accurate range readings can be an alternative. However, this cheap sensor suffers from significant angular uncertainty because of its large beam width.

The feature based approach using sonar sensor is not easy to obtain reliable mapping result especially in unstructured environment like home due to the difficulty of extracting robust features. On the other hand, occupancy gridmaps from sonar sensor can result in accurate environmental modeling by accumulating sensor information, and the topological map using sonar sensor can also give a reliable result due to the abstracted form of map model. However, using only gridmap is not sufficient for the autonomous mobile robot system because it gives only existence of obstacle for each locations. The topological approach using sonar sensor could not be an alternative because it is difficult to extract some meaningful points such as junctions in home environments. For these reasons, combining a topological map and a grid map can give a practical solution using sonar sensors in home environment. A global topological map which is extracted from a gridmap would be helpful for global path planning and a local gridmap corresponding to each node in topological map can be used to perform navigation and localization in local areas.

For this purpose, several researchers have tried to extract topological models from gridmaps. Thrun divided an occupancy gridmap into several subregions based on the voronoi diagram [8]. Similarly, graph partitioning methods are used to divide a gridmap into several nodes [9], [10]. Room-like spaces are extracted in gridmaps by using fuzzy morphological opening and watershed segmentation by Buschka and Saffiotti [11]. Even though those methods show successful topology extraction from gridmaps, they are not easy to apply directly in home environments because they are suitable for corridor environments or considers only narrow passages to extract topological model.

In this paper, incremental topological modeling using sonar gridmap is considered for home environments. In our previous work, a topological model was extracted from the gridmap by dividing the whole gridmap into several subregions using approximate cell decomposition and normalized graph cut [12]. However, the method can only be performed after generating gridmap over the entire environment, and the number of subregions should be given in advance. To overcome those limitations, a method which constructs a topological model incrementally while generating gridmap is proposed. The incremental extraction of the topological

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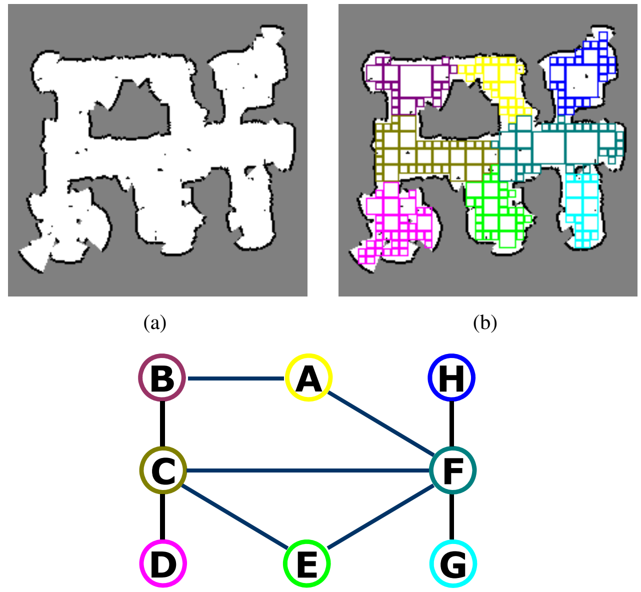
model from the sonar gridmap is performed in three steps : 1) apply approximate cell decomposition, 2) obtain reliable cells from noisy local gridmap, 3) extract new subregion. The extraction of a new subregion is performed to guarantee convexity of the extracted subregions because a convex region contains similar spatial characteristics generally.

The proposed method constructs a well-structured topological representation of the home environment using only sonar sensors. It has several benefits. Firstly, reliable cells are obtained by filtering out noisy data in local gridmap using a confidence value which can be calculated from the sound pressure function of sonar sensors. Secondly, a topological map can be constructed without predefining the number of subregions in advance. Lastly, the extracted subregions are similar to a spatial recognition of human by guaranteeing the convexity of subregions.

This paper is organized as follows. In Section II, our previous work is briefly summarized. Then, incremental topological modeling is described in Section III. Section IV presents experimental results and conclusion follows in Section V.



(a) (b)

(c)

Fig. 1. Offline Topological Modeling : (a) Generated gridmap, (b) Clustering as 8 subregions (Each cluster is represented as different color), and (c) Topological model.

II. Offline Topological Modeling using Sonar Gridmap

This section summarizes our previous work which performs offline topological modeling using sonar gridmap [12]. The topological modeling is achieved by partitioning navigable area in the gridmap into predefined number of subregions. The offline topological modeling is executed by the following processes.

A. *Offline topological modeling*

The first step for the offline topological modeling is generating occupancy gridmap using sonar sensors and odometry data. For this purpose, a grid mapping method in [13] is used. Fig. 1(a) shows an example of gridmap generation. The gridmap consists of empty grids, $m(x, y) = 0$, which represent free space and occupied grids, $m(x, y) = 1$, where obstacle exists.

After generating gridmap, approximate cell decomposition is applied to the gridmap. The approximate cell decomposition, also known as quadtree cell decomposition, divides a square cell into four smaller square cells of same size if the original cell is composed of both free and obstacle spaces [14]. This process is recursively executed until every cell gets decomposed into free and obstacle spaces separately. The approximate cell decomposition can extract empty regions in the gridmap effectively, and the empty regions can be modeled as various sizes of squares. A large empty region would be mainly modeled as a few large size of squares and the remaining parts are supplemented by relatively small squares. The result of the approximate cell decomposition provides an initial draft model of topological representation of the environment. Each extracted cell becomes node of the draft topological model, and the connecting edge is determined from the adjacency of two cells.

The constructed topological model from the approximate cell decomposition provides a connected graph structure for the empty regions of the environment. However, many small cells should be merged with large cells which could be considered as same region because the environment is divided into too many cells. For an effective clustering, normalized graph cut algorithm is applied to the draft topology model. Normalized graph cut algorithm is a clustering method using graph partitioning [15]. It uses a graph structure, $G(V, E)$, which is composed of a set of vertices (or nodes) $V = \{V_1, V_2, \cdots, V_n\}$ and a set of edges $E = \{E_1, E_2, \cdots, E_m\}$. Each edge has weight w_{ij} which represents a similarity between V_i and V_j. Then, normalized cut ($Ncut$) is defined to measure similarity between two clusters that should be partitioned. $Ncut$ between two clusters C_1 and C_2 is obtained as

$$Ncut = \frac{\sum_{i \in C_1, j \in C_2} w_{ij}}{\sum_{i \in C_1, j \in V} w_{ij}} + \frac{\sum_{i \in C_1, j \in C_2} w_{ij}}{\sum_{i \in C_2, j \in V} w_{ij}}. \quad (1)$$

Normalized graph cut algorithm considers a graph cut, which results in minimum $Ncut$, as an optimal solution of clustering. Unfortunately, finding the minimum $Ncut$ is NP-hard problem. So, spectral clustering is generally used as an approximate solution. Spectral clustering for the minimum $Ncut$ is performed by following procedures.

1) Construct a neighborhood graph with corresponding $n \times n$ affinity matrix $W(i, j) = w_{ij}$.
2) Compute the normalized graph Laplacian $L = D^{-1/2}(D - W)D^{-1/2}$ where $D = diag\{d_1, \cdots, d_n\}$ and $d_i = \sum_j W_{ij}$.
3) Find the k smallest eigenvectors $u_1, \cdots, u_k$ of L and form the matrix $U = [u_1 \cdots u_k] \in \mathbb{R}^{n \times k}$.

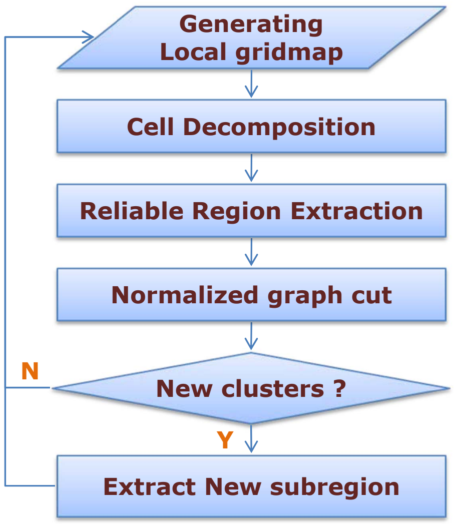


Fig. 2. Flowchart for the incremental topological modeling using sonar gridmap.

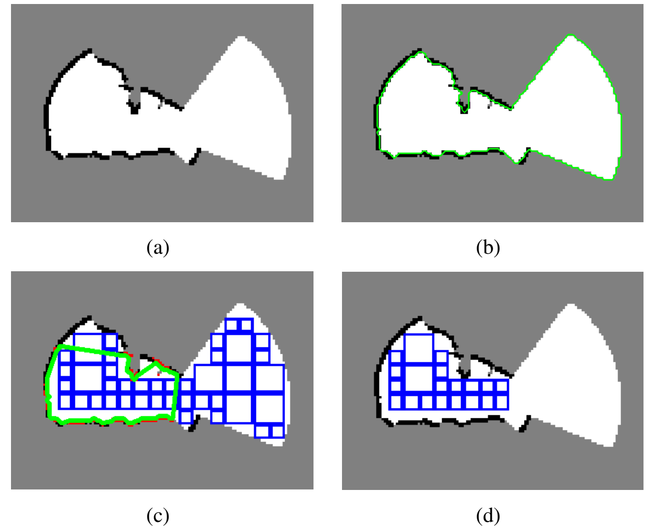


Fig. 3. Obtaining reliable region in local gridmap : (a) Noisy local gridmap, (b) Boundary tracing, (c) A contour for reliable region, and (d) Reliable cells.

4) Form matrix $\tilde{U}$ from U by re-normalizing each row of U to have unit norm, i.e, $\tilde{U}_{ij} = U_{ij}/(\sum_j U_{ij})^{1/2}$.
5) Treating each row of $\tilde{U}$ as a point in $\mathbb{R}^k$, segment them into k groups using k-means algorithm.
6) Assign V_i to cluster j if and only if row i of $\tilde{U}$ is assigned to cluster j.

To apply the normalized graph cut to the draft graph model, the weight value between two cells needs to be defined to calculate the affinity matrix W. Therefore, the weight value for arbitrary two cells are defined as follows :

$$w_{ij} = \begin{cases} \sharp \text{ of adjacent grids} & \text{if } V_i \text{ and } V_j \text{ are adjacent} \\ 0 & \text{otherwise.} \end{cases} \tag{2}$$

Using the draft model and affinity matrix W, k clusters are extracted with a predefined variable k. Fig. 1 shows results of segmenting the whole gridmap into 8 subregions. The topological modeling for the entire environment could be achieved successfully by considering the obtained subregions as nodes in topological model (Fig. 1(c)).

B. Limitations of offline topological modeling

The offline topological modeling method can extract topological representation from the gridmap successfully. However, the offline method has two limitations.

1) The number of cluster k should be predefined manually.
2) Topological model can be extracted after generating gridmap over the entire environment.

Using the same gridmap, the extracted topological model gives different results for the different predefined number of cluster. Furthermore, the topological model can be extracted when the gridmap generation is finished over the entire environment. If the robot navigates unexplored areas after extracting topological model, the topological model should be extracted totally again. To overcome those limitations, an incremental topological modeling will be proposed in the following section.

III. Incremental Topological Modeling using Sonar Gridmap

The incremental topological modeling performs subregion extraction and gridmap generation simultaneously. As a robot navigates an environment, a local gridmap is generated around the robot and the subregions are extracted using the local gridmap. During this process, the subregion can be extracted without predefining the number of subregions. In other words, the robot performs the incremental topological modeling using sonar gridmap autonomously. For this purpose, this paper concentrates on the extraction of topological model and assumes that robot poses are given.

Fig. 2 shows flowchart for the incremental topological modeling. Most processes are similar to the offline topological modeling. The major differences are a reliable region extraction in local gridmap and determining extraction of new subregion. The following subsections describe these different processes of the proposed incremental topological modeling in detail.

A. Obtaining Reliable Region in Local gridmap

The local gridmap contains noisy data inevitably because sensor data couldn't be accumulated sufficiently to filter out spurious sonar data (Fig. 3(a)). For this reason, obtaining reliable region in the local gridmap should be performed by filtering out the noisy data.

As a first step of obtaining reliable region, a boundary tracing technique is applied to find boundaries between occupied and empty regions (Fig. 3(b)). The boundary tracing method finds a contour which encloses the empty regions in the local gridmap. Then, a sonar sensor model is used to measure a confidence for each occupied grid. A sonar beam

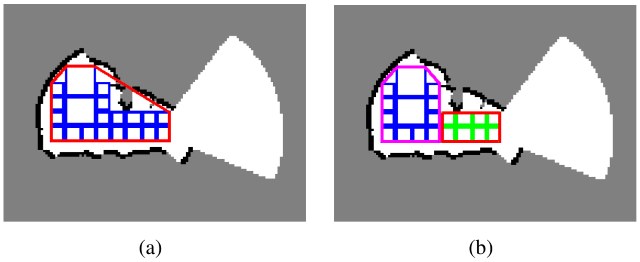


Fig. 4. Convex hulls for (a) 1 cluster, and (b) 2 clusters. (Blue and green cells represent two different clusters obtained from normalized graph cut)

(S) fired from a transmitter has a sound pressure function, $P_S(r, \theta)$, as follows:

$$P_S(r, \theta) = \frac{\beta f a^4}{r^2} \left(\frac{2J_1(kasin\theta)}{kasin\theta} \right)^2, \tag{3}$$

where r is a distance from the transmitter, and θ is an angle with respect to direction of the transmitter. Detail explanations for other variables can be found in [16].

The sound pressure function can be used to measure the amount of sensor information. So, by using the sensor model, the confidence for each occupied grid $m(x, y)$ is evaluated as

$$Conf(x, y) = \sum_{m(x,y) \in Occ.(S)} P_S(r, \theta), \tag{4}$$

where $Occ.(S)$ is a set of grids which are determined as occupied by sensor data S.

Then, occupied grids which have high confidence value are regarded as confident grids (5),

$$Conf(x, y) > avg(Conf), \tag{5}$$

and the reliable region can be found by obtaining a contour which connects those confident grids (Fig. 3(c)).

Finally, obtaining reliable region in the local gridmap can be achieved by removing the decomposed cells which are outside of the contour (Fig. 3(d)). Through the aforementioned processes, a reliable region can be extracted from the noisy local gridmap and the remaining reliable cells are applied to the normalized graph cut to extract subregions.

B. Extracting New Subregion

The aforementioned processes give a successful result of obtaining reliable cells which correspond to the reliable regions in the local gridmap. Then, the incremental topological modeling is performed by extracting new subregion from the obtained reliable cells. To extract new subregion, the proposed method determines whether the obtained cells should be divided into 2 clusters or not. If the obtained cells should be divided into 2 clusters, one of the 2 divided clusters is extracted as new subregion. Otherwise, the robot continues to generate a gridmap.

For this purpose, a convexity of the subregion is used as a criterion of extracting new subregion. In other words, a new subregion is extracted if the obtained reliable region couldn't be regarded as a convex region. The measure of evaluating convexity is obtained as follows. At first, a convex hull of all the obtained cells is acquired to measure the convexity when the cells are considered as 1 cluster (Fig. 4(a)). Then, a convexity measure for the case of 1 cluster is evaluated as,

$$\mathcal{C}_{\text{1cluster}} = \frac{\sharp \text{ of } occ. \text{ grids} \in CH1}{\sum \text{size of Cell}}, \tag{6}$$

where $CH1$ is convex hull for 1 cluster. The convexity measure, $\mathcal{C}_{\text{1cluster}}$ represents a ratio of occupied grids in the convex hull $CH1$ with respect to total size of reliable cells.

Similarly, the convexity measure for the case of 2 clusters is also evaluated. Normalized graph cut is applied to the obtained reliable cells with the number of cluster 2 to segment the reliable region into 2 subregions. Then, two convex hulls for the segmented two clusters are acquired like Fig. 4(b), and the convexity measure for the case of 2 clusters is obtained as

$$\mathcal{C}_{\text{2clusters}} = \frac{\sum_{i=1}^{2} \sharp \text{ of } occ. \text{ grids} \in CH2(i)}{\sum \text{size of Cell}}, \tag{7}$$

where $CH2(i)$ represents a convex hull for i^{th} cluster.

Using the convexity measures, $\mathcal{C}_{\text{1cluster}}$ and $\mathcal{C}_{\text{2clusters}}$, a new subregion is extracted if the following conditions are satisfied (8).

$$\mathcal{C}_{\text{1cluster}} > c_t \quad \& \quad \mathcal{C}_{\text{2clusters}} < 0.5 \times \mathcal{C}_{\text{1cluster}} \tag{8}$$

where c_t is a threshold value. The threshold value is used as 0.2 in the proposed method by determining experimentally. In other words, 20% of occupied grids in the subregion are allowed to regard the subregion as same space.

If the conditions in (8) are satisfied, one of the 2 divided clusters, whichever one is older, is extracted as a new subregion. Then, such extracted subregion is not considered

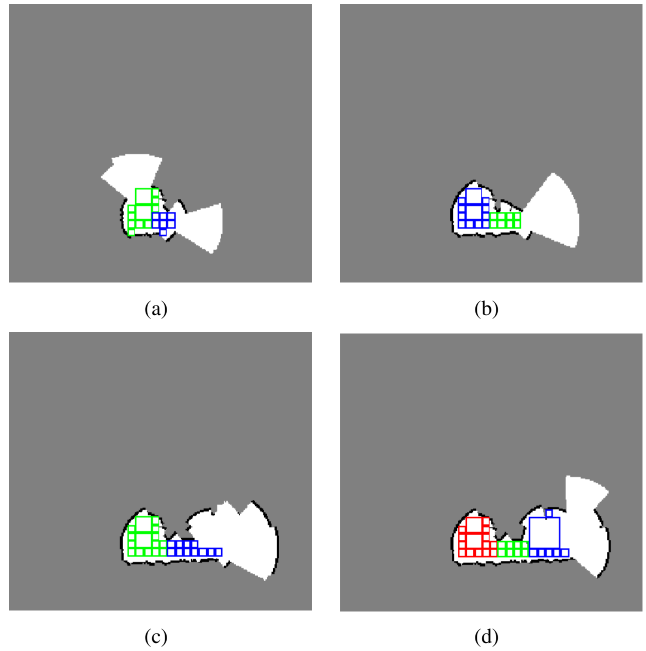
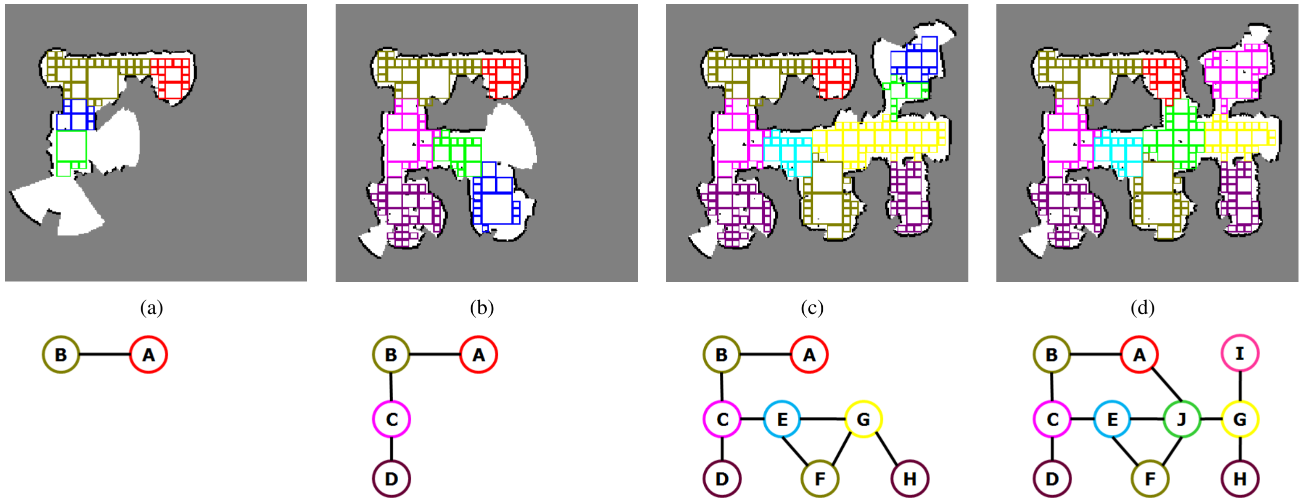


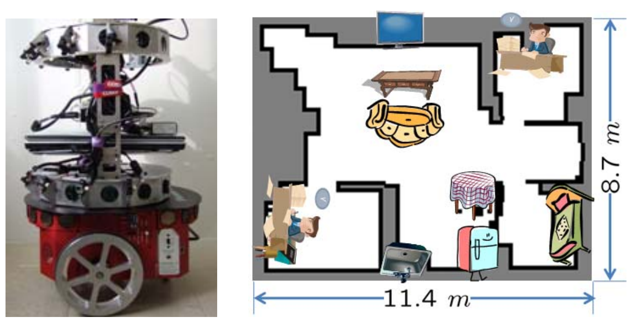
Fig. 5. Example of incremental topological modeling using sonar gridmap.



(a) (b) (c) (d)

(e) (f) (g) (h)

Fig. 7. Experimental results of incremental topological modeling. (a)-(d) Incremental subregion extraction (Each subregion is represented as different color), and (e)-(h) Corresponding topological model (Blue and green cells in (a)-(c) are not included in topological model because they are not extracted as new subregion yet).



(a) (b)

Fig. 6. Experimental Setup : (a) PIONEER3-DX with 12 MURATA sonar sensors, and (b) Experimental environment.

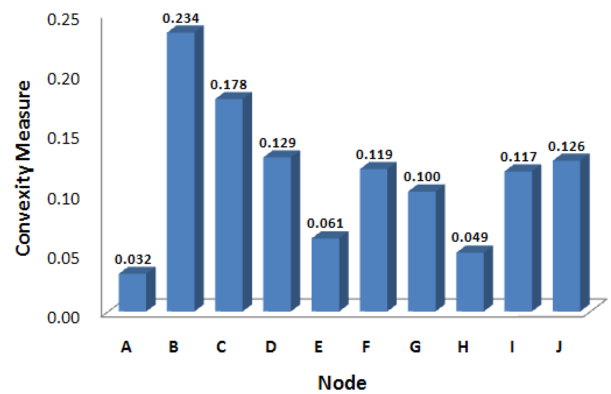


Fig. 8. Convexity measure for extracted subregions.

for any subsequent segmentation unless the robot navigates back to the same subregion again.

Fig. 5 shows the process of extracting a new subregion incrementally. During the first two steps (Fig. 5(a)–5(b)), the obtained cells are considered as the same subregion because they couldn't satisfy the dividing conditions (8). Then the dividing conditions are satisfied in Fig.5(c) and as a result, green cells, which are older than blue cells, are extracted as a new subregion. These cells are represented as red cells in Fig. 5(d), and they are not reconsidered for the subsequent extraction of a new subregions. In other words, remaining spaces (blue and green cells) except the extracted new subregion are used to extract another subregion in Fig. 5(d). Through these processes, a successful topological modeling can be achieved incrementally from a sonar gridmap.

IV. Experimental Results

This section shows experimental results of the proposed incremental topological modeling in home environment. Experiments were carried out using a differential drive robot PIONEER-DX (Fig. 6(a)) equipped with 12 MA40B8 sonar sensors from MURATA company [17] in home environment (Fig. 6(b)).

The home environment, which is composed of several rooms and contains a few pieces of furniture and electronics, covers an area of $11.4m \times 8.7m$. The mobile robot was driven a wall following path manually with an average speed of about $0.15m/s$ and acquired sonar sensor data in $4Hz$ frequency.

The experimental results of incremental topological modeling using sonar gridmap are presented in Fig. 7. The results of extracting subregions are shown in Fig. 7(a)-(d), and the corresponding topological models are shown in Fig. 7(e)-(h). The experimental results show that the reliable cells within the reliable region are obtained successfully by filtering out the noisy data and the topological models are constructed effectively by extracting subregions from the gridmap as the robot moves.

As a result, the entire environment is partitioned into 10 subregions (Fig. 7(d)) and the subregions are constructed as a topological model successfully as shown in Fig. 7(h). The constructed topological model represents the environment properly. Three rooms are classified into three different subregions (D, H, and I) and a kitchen is extracted as node F. In a living room, the areas are segmented into several subregions because a sofa and a table are located in the center of the living room.

The proposed method extracted subregions with guaranteeing the convexity well. To evaluate the convexity of extracted subregion, a measure similar to (6) is calculated for each node. Because this measure evaluates convexity of each subregion, both empty grids which belong to other subregions and occupied grid are considered to obtain the convexity measure. The convexity measure for each grid is shown in Fig. 8. As shown in the result, most subregions have convexity measure under the threshold value ($c_t = 0.2$). Only node B has convexity measure larger than the threshold value due to the upper left corner area of the environment.

Consequently, the proposed method provides a successful topological modeling result using sonar gridmap by extracting subregions incrementally.

V. CONCLUSIONS

This paper addressed incremental topological modeling using low-cost sonar sensor in home environment. Firstly, a reliable region is obtained from local gridmap. The confidence of each occupied grid is evaluated using sonar sensor model and the reliable region is obtained by effective filtering of noisy data using the confidence value. Secondly, subregion extraction is performed by using normalized graph cut and convexity measure of the extracted subregion. The subregion extraction is executed incrementally with guaranteeing the convexity of the extracted subregion.

As a result, the topological model could be constructed without predefining the number of subregions in advance by performing the topological modeling and gridmap generation simultaneously.

Experimental results verified that the proposed method can be applied to home environment. The topological model is constructed from sonar gridmap successfully and the extracted subregions are guaranteed the convexity.

VI. ACKNOWLEDGMENTS

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