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Topological Localization using Sonar Gridmap Matching in Home Environment

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Abstract— **This paper presents a method of topological localization in a home environment using only low-cost sonar sensors. The proposed method utilizes a relative motion model to obtain a prior information of node probability. Moreover, the size of a local gridmap used for gridmap matching is determined adaptively by an entropy test of node probability. The proposed method results in a reliable and convergent localization result even under the uncertainty and sparsity of sonar sensros. Experimental results verify performance of the proposed topological localization in a real home environment.**

I. INTRODUCTION

One of the most important ability for an autonomous mobile robot is self-localization. The mobile robot should recognize its current location by comparing current sensor data with a known environmental map data to perform various tasks such as navigation to a goal position. For this purpose, many researchers have developed various localization solutions during last two decades.

In general, localization methods can be classified into geometric and topological approaches. The geometric localization represents the location of the mobile robot as exact locations, (x, y, θ), in the environmental model with respect to a reference frame. Monte Carlo Localization (MCL) [1] and extended Kalman filter (EKF) based localization [2] are typical examples of geometric localization method. Besides, scan matching methods [3] using laser range finder is also developed for geometric localization.

On the other hand, the topological localization recognizes the location of the mobile robot as a node of an adjacency graph structure which represents spatial relations of the environment. To achieve the node classification, the topological localization extracts salient characteristics for each node. In corridor environment, geometric characteristics for junctions and corners are used to classify the current node such as Generalized Voronoi Graph (GVG) [4], [5]. Moreover, appearance based image matching [6], [7] and machine learning techniques using laser range finders [8] are also used for the topological localization.

In this paper, we focus on the topological localization problem using only sonar sensors in home environment. Sonar sensors which give relatively accurate range readings are one of the most popularly used range sensor. It is cost effective and useful for the mobile robot applications such as obstacle avoidance. However, the sonar sensor suffers from a significant angular uncertainty because of its large beam width. Due to these defects, the above localization methods are not easy to apply to sonar sensors in home environment directly. Even though several geometric localization methods show successful results using range and vision sensors, the geometric localization using sonar sensor always has a potential possibility of failure due to the high uncertainty of the sonar sensor. In addition, the previous topological approach cannot be an alternative because sonar sensor data is too sparse and node classification is not easy in home environment than the corridor environment.

This paper presents a novel topological localization method based on a local gridmap matching. In our previous work [9], a topological model was extracted from the gridmap by dividing the whole gridmap into several subregions using approximate cell decomposition and normalized graph cut. A gridmap matching method was also proposed by using Ring Projection Transformation (RPT) and a distance vector. However, the previous method is just a node classification using the gridmap matching and doesn't consider any prior information. Moreover, it doesn't give any criterion for the size of the local gridmap. To overcome those limitations, a sequential topological localization method considering the mobile robot motion is proposed. The proposed sequential topological localization is composed of two parts : 1) obtaining node probability considering the robot motion, 2) determining the size of the local gridmap according to an entropy of node probability.

Here, as a robot motion model, a relative distance and a relative angle are used to calculate a prior information of node probability. Moreover, the entropy of the node probability is used to determine whether the current local gridmap should be expanded by accumulating more sensor data or not. Through these processes, the proposed method provides a successful topological localization result in a home environment using only sonar sensors and it has several benefits. First, the odometry error is not accumulated by using only temporary relative robot motion model to calculate the node probability. Second, the size of the local gridmap can be determined adaptively to guarantee robust localization. Third, the proposed method results in a convergent node probability by using the effective prior information and robust gridmap matching.

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

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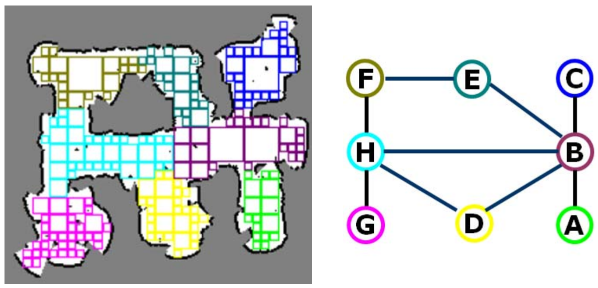
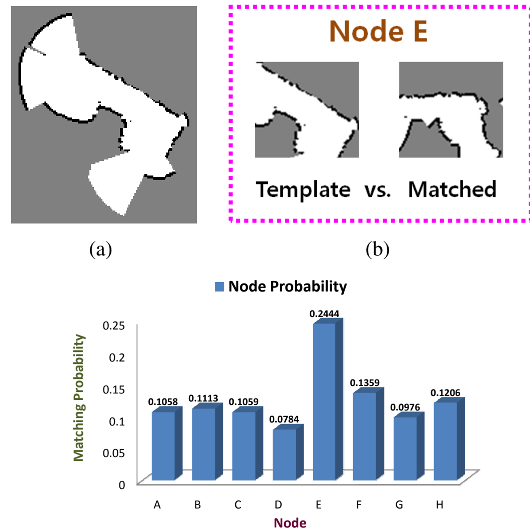


(a) (b)

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



(a) (b) (c)

Fig. 2. Node Classification : (a) A local grimap, (b) Template gridmap and matching result, and (c) Matching probability.

Section V.

II. Topological Modeling and Global gridmap matching using Sonar gridmap

This section summarizes our previous work which performs a topological modeling and a node classification using sonar gridmap [9]. The topological modeling is achieved by partitioning navigable area in a gridmap into several subregions and the node classification is performed by comparing a current local gridmap with the original gridmap.

A. Topological modeling using sonar gridmap

The first step for the topological modeling is generating an occupancy gridmap using sonar sensors and odometry data. After generating gridmap, approximate cell decomposition is applied to the gridmap. The approximate 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 [10]. The result of the approximate cell decomposition provides an initial draft model of topological representation of the environment. Each extracted cell corresponding to empty region becomes node of the draft topological model, and the connecting edge is determined from the adjacency of two cells.

Finally, normalized graph cut algorithm is applied to the draft topology model [11]. Using the draft model and an affinity matrix W, k number of 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 the topological model (Fig. 1(b)).

B. Node classification using gridmap matching

After the modeling procedure, the node classification is achieved by comparing a local gridmap around current robot location with the original gridmap of the entire environment.

For the local gridmap matching, we firstly extract a template gridmap from the noisy local gridmap by filtering out uncertain data. Using a sonar sensing model [12], a confidence rate for each occupied grid $m(x,y)$ in the local gridmap is evaluated, and the template gridmap is extracted by removing the grids which have less confidence. Fig. 2(a) shows an example of the local gridmap and the corresponding template gridmap is acquired as shown in Fig. 2(b).

Then, a candidate location for each node is obtained by applying a rotation invariant template matching method to the extracted template gridmap. The rotation invariant gridmap matching is performed by Ring Projection Transformation (RPT) [13] which transforms 2D image data into 1D vector $P(r)$. By calculating normalized correlation between the RPT vectors of the template gridmap ($P_T(r)$) and the original gridmap ($P_O(r)$), the most probable location within the node can be obtained (1).

$$\rho = \frac{\sum_{r=0}^{R}\{P_T(r)-\mu_T\}\{P_O(r)-\mu_O\}}{\left(\sum_{r=0}^{R}\{P_T(r)-\mu_T\}^2\cdot\sum_{r=0}^{R}\{P_O(r)-\mu_O\}^2\right)^{1/2}}, \tag{1}$$

where $\mu_L = \frac{1}{1+R}\sum_{r=0}^{R}P_T(r)$, and $\mu_O = \frac{1}{1+R}\sum_{r=0}^{R}P_O(r)$.

Finally, a matching probability is obtained by comparing detail distance information between the template gridmap and the obtained candidate locations in the original gridmap. A distance vector for the candidate location for i^{th} node ,$L(x_i,y_i)$, can be obtained as follows :

$$D_i(\theta) = \min.\ \text{Dist}\ (L(x_i,y_i)\ \text{to}\ Occ(x,y)\ \text{in}\ \theta\ \text{direction}), \tag{2}$$

where θ is an integer from 1 to 360, and $Occ(x,y)$ is occupied grid in the gridmap. Then, a measure of dissimilarity between distance vectors, D_i for i^{th} node and D_T for the template gridmap.

$$\triangle D_i = \arg\min_{\theta_c}\sum_{\theta=1}^{360}|D_T(\theta)-D_k(\theta-\theta_c)|, \tag{3}$$

where $D(\theta)=D(\theta+360)$ for $\theta<0$.

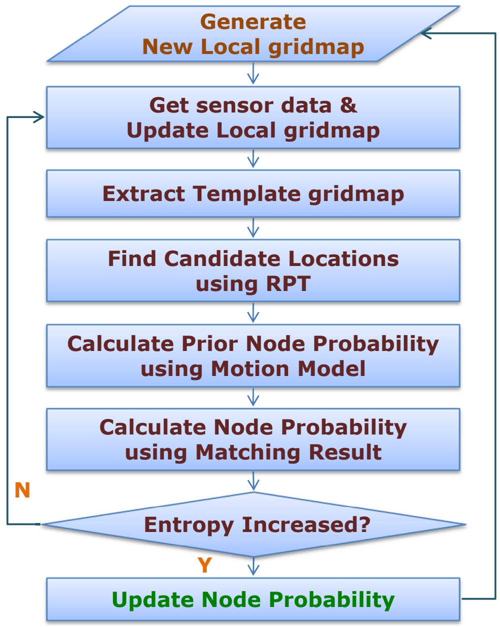


Fig. 3. Flowchart of the proposed sequential topological localization using sonar gridmap.

After calculating $\triangle D$ for every node, the similarity of distance vector for i^{th} candidate location is obtained as follows:

$$P_D(i) = \frac{1/\triangle D_i}{\sum_{j=1}^{k} 1/\triangle D_j} \tag{4}$$

By using this similarity measure, we obtain the final matching probability for each node like Fig. 2(c) by multiplying with the normalized correlation calculated from RPT vectors.

$$P_{match}(i) = P_D(i) \times \rho(x_i, y_i) \tag{5}$$

C. Limitations of node classification

The node classification method can provide a successful classification result using the local gridmap matching. However, it has two limitations.

1) A prior information is not considered.
2) A criterion for the size of the local gridmap cannot change.

The previous method doesn't considers the robot motion model and it should perform the node classification process without any prior information. Furthermore, the size of the local gridmap should be predefined as a constant time or a constant traveling distance. The criterion can not change after it is predefined at the first time. To overcome those limitations, a sequential topological localization will be proposed in the following section.

III. Sequential Topological Localization

This section describes the proposed sequential topological localization method. The sequential topological localization performs the node classification considering a robot motion model. By using the robot motion model, the mobile robot can obtain node probability using not only the gridmap matching probability but also a prior information of node probability. For the robot motion model, a relative distance and a relative angle are used. Moreover, to generate the local gridmap, an entropy test of node probability is used. Using the entropy test of node probability, the size of the local gridmap could be determined adaptively.

Fig. 3 shows a flowchart for the sequential topological localization. Finding candidate locations and obtaining matching probability are adopted from the previous node classification algorithm. The major differences are calculating the prior node probability using robot motion model and the entropy test to determine the size of the local gridmap. The following subsections describe these different processes of the proposed sequential topological localization in detail.

A. Basic equations

The node probability using robot motion models and observations can be calculated as follows :

$$\begin{aligned} &P(N_t = N_i | u_{1:t}, z_{1:t}) \\ &= \eta_1 P(z_t | N_t = N_i, u_{1:t}, z_{1:t-1})\ P(N_t = N_i | u_{1:t}, z_{1:t-1}) \\ &= \eta_1 P(z_t | N_t = N_i)\ P(N_t = N_i | u_{1:t}, z_{1:t-1}) \end{aligned} \tag{6}$$

where η_1 is a normalizing factor, N_t denotes a node where the mobile robot located at t, N_i is i^{th} node, and $u_{1:t}, z_{1:t}$ are robot motions and observations from 1 to t, respectively.

The first part of (6) is a likelihood and the last part is a prior information. Here, the likelihood can be obtained from the local gridmap matching which is described in II-B (5). The prior information can be derived from the previous node probability and the robot motion model like (7).

$$\begin{aligned} &P(N_t = N_i | u_{1:t}, z_{1:t-1}) \\ &\quad = \sum_j P(N_t = N_i | N_{t-1} = N_j, u_{1:t}, z_{1:t-1}) \\ &\qquad \times P(N_{t-1} = N_j | u_{1:t-1}, z_{1:t-1}) \end{aligned} \tag{7}$$

B. Sequential Node Classification using Motion Model

As aforementioned, the prior node probability can be obtained from the robot motion model and the node probability of previous time step. In this paper, the robot motion model is used as a relative distance and a relative angle.

1) Effective Distance (ED) as a motion model: For the node classification using the local gridmap matching, the mobile robot should generate a local gridmap by accumulating sensor data along a certain length of path. Therefore, the motion model should be determined from the robot path corresponding to the current local gridmap.

For this purpose, we used a distance in a straight line between start and end points of the path, even though the robot doesn't move in a straight line. The distance in a straight line is denoted as Effective Distance (ED) in the proposed localization method. For example, consider a robot motion shown in Fig. 4(a). Even though the real robot moved along the dashed line, ED considers only a straight line like

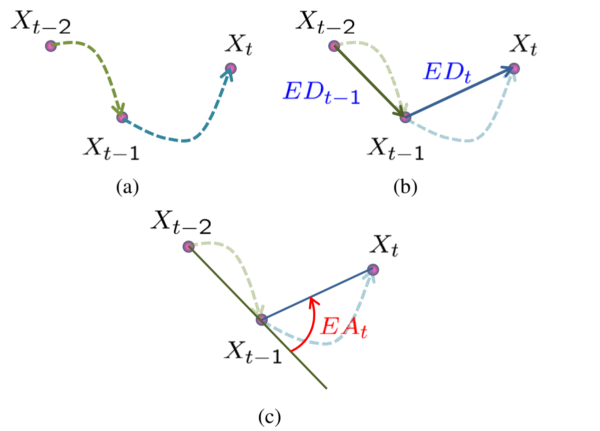


Fig. 4. Robot Motion Model : (a) Real robot motion, (b) Effective Distance (ED), and (c) Effective Angle (EA).

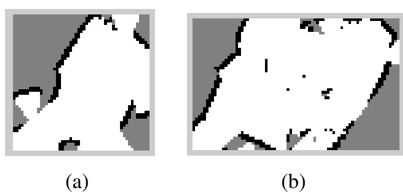


Fig. 5. Template gridmaps from node C : (a) Insufficient template gridmap to perform the reliable gridmap matching, and (b) Expanded template gridmap by accumulating more sensor data.

Fig. 4(b). Therefore, the ED for the robot path in Fig. 4(a) is obtained as a length of straight line in Fig. 4(b).

Using the ED, the prior node probability is calculated by the following procedures. Firstly, ED for the real robot motion, $\hat{d}$, is obtained from odometry. Then, estimated EDs are acquired by calculating distances between candidate locations for previous and current local gridmaps. In other words, an estimated ED, d_{ij} is determined as a distance between a candidate location $L_{t-1}(x_j, y_j)$ for j^{th} node at time $t-1$ and another candidate location $L_t(x_i, y_i)$ for i^{th} node at time t. Finally, the first part of the prior node probability (7) is calculated as follows:

$$\begin{aligned} &P(N_t = N_i | N_{t-1} = N_j, ED_{1:t}, z_{1:t-1}) \\ &\quad = P(N_t = N_i | N_{t-1} = N_j, ED_t) \\ &\quad = \mathcal{N}(ED; \hat{d}, \sigma_d^2)|_{ED=d_{ij}} \end{aligned} \tag{8}$$

where $\mathcal{N}(\cdot)$ is normal distribution function. Using this motion model, calculating node probabilities for every nodes can be achieved.

2) Effective Angle (EA) as a motion model: As a secondary motion model, a relative angle of robot motion is used to complement the ED motion model. The relative angle is defined similarly as the ED. Because an angle should be defined with respect to a reference, we used the direction of ED_{t-1} as a reference angle for the relative angle at time t. As shown in Fig. 4(c), Effective Angle(EA) at time t is defined as a relative angle of ED_t with respect to the direction of ED_{t-1}.

Using the EA, the prior node probability can be calculated similarly as (8). However, the EA is related to not only the state of time step $t-1$ but also that of time step $t-2$. So, the equation for the prior node probability should be expanded to the time step $t-2$. For derivation, we assumed that ED and EA are independent.

$$\begin{aligned} &P(N_t = N_i | N_{t-1} = N_j, ED_{1:t}, EA_{1:t}, z_{1:t-1}) \\ &= \eta_2 \; P(N_t = N_i | N_{t-1} = N_j, ED_{1:t}, EA_{1:t-1}, z_{1:t-1}) \\ &\quad \times P(N_t = N_i | N_{t-1} = N_j, ED_{1:t-1}, EA_{1:t}, z_{1:t-1}) \\ &= \eta_2 \; P(N_t = N_i | N_{t-1} = N_j, ED_t) \; \times \\ &\sum_k P(N_t = N_i | N_{t-1} = N_j, N_{t-2} = N_k, ED_{1:t-1}, EA_{1:t}, z_{1:t-1}) \\ &\quad \times P(N_{t-2} = N_k | N_{t-1} = N_j, ED_{1:t-1}, DA_{1:t}, z_{1:t-1}) \\ &= \eta_2 \; P(N_t = N_i | N_{t-1} = N_j, ED_t) \\ &\quad \times \sum_k P(N_t = N_i | N_{t-1} = N_j, N_{t-2} = N_k, EA_t) \\ &\quad \times P(N_{t-2} = N_k | N_{t-1} = N_j, u_{1:t-1}, z_{1:t-1}) \end{aligned} \tag{9}$$

In (9), the first part is same as (8) and the last part can be obtained from the previous motion model. The second part of (9) can be calculated as follows:

$$\begin{aligned} &P(N_t = N_i | N_{t-1} = N_j, N_{t-2} = N_k, EA_t) \\ &\quad = \mathcal{N}(EA; \hat{a}, \sigma_a^2)|_{ED=a_{ijk}} \end{aligned} \tag{10}$$

where $\hat{a}$ is EA obtained from odometry and a_{ijk} is an estimated EA calculated from candidate locations $L_{t-2}(x_k, y_k)$, $L_{t-1}(x_j, y_j)$ and $L_t(x_i, y_i)$.

By using the ED and EA simultaneously, the prior node probability can be obtained efficiently. Moreover, the proposed method has an advantage that the accumulation of the odometry error is bounded within 2 time steps because it utilizes relative motion models.

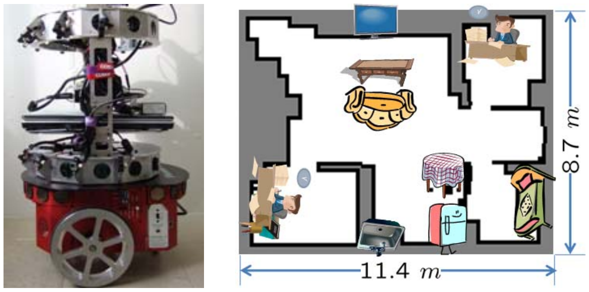
C. Entropy test of Node probability

In general, the size of the local gridmap might be determined by a constant time or a constant traveling distance. Unfortunately, the constant time and traveling distance criterions might be insufficient for the sparse sonar gridmap. Two template gridmaps in Fig. 5 are obtained from node C of Fig. 1. A template gridmap in Fig. 5(a) is difficult to match with the original gridmap due to insufficient information. Then, the candidate locations using the local gridmap in Fig. 5(a) might be acquired as wrong positions. In this case, the template gridmap should be regenerated by accumulating more sensor data like Fig. 5(b). Even though the template gridmap in Fig. 5(b) also contains noisy data, this template gridmap could be matched with the original gridmap to find reliable candidate locations.

For this purpose, an entropy test is used to determine whether more sensor data should be accumulated or not.

$$H(P) = \sum_{i=1}^{n} -P(i) \log_n P(i) \tag{11}$$

where n is the number of nodes and $P(i)$ is a node probability for i^{th} node. Without loss of generality, we can say that a successful observation should result in a convergent node probability. A convergent result would make the entropy



(a) (b)

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

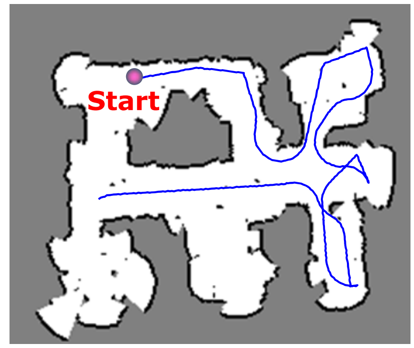


Fig. 7. Real Robot Path

value of node probability decrease. Therefore, an increasing entropy means that the template gridmap is not sufficient to update node probability reliably. In the proposed entropy test, we used the increasing entropy of node probability as a criterion of accumulating more sensor data for the local gridmap. In other words, when the entropy measure is increased, node probability is not updated and the robot continue to generate the local gridmap by accumulating more sensor data. This entropy test is applied in real experiment with some heuristics. The entropy test is applied to the localization process if a maximum node probability is less than a threshold value.

By using the entropy test, the size of the local gridmap can be determined adaptively. Then, the obtained local gridmap could be used to update node probability reliably.

IV. Experimental Results

This section shows experimental results of the proposed topological localization in a 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 [14] in the home environment (Fig. 6(b)).

The 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 an arbitrary path manually with an average speed of about $0.15m/s$ and acquired sensor data in $4Hz$ frequency.

For the experiments of sequential topological localization, an environmental model in Fig. 1 is used. Fig. 7 shows a real robot path for the localization experiment. Moving along the path, the robot generated local gridmaps and performed localization using the proposed method.

The experimental results of topological localization are presented in Fig. 8. Fig. 8(a)-Fig. 8(d) show four template gridmaps and matching results. The matched gridmaps are obtained from the candidate locations which have maximum node probability. For those cases, gridmap matching probabilities are shown in Fig. 8(e)-Fig8(h). Using the matching probability and the motion model, the localization results are obtained like Fig. 8(i)-Fig8(l). As shown, the proposed method results in a reliable gridmap matching even under the noisy data in the local gridmaps. Moreover, the results show that the node probability becomes more convergent as the mobile robot updates the node probability.

Fig. 9 shows maximum node probabilities for each time step. The maximum node probability also shows that the proposed localization method results in a convergent node probability. A few times of decreasing maximum node probability might be caused by noisy sensor data in the local gridmap. As a whole, even though the maximum probability decreased a few times, the maximum probability increased as the time goes.

The experimental results in Fig. 8 and 9 show that the proposed method provides a reliable gridmap matching and satisfactory node probability.

V. Conclusions

This paper addressed a topological localization using low-cost sonar sensor in a home environment. First, a relative motion model is applied to obtain a prior information of node probability. By using only relative motion, the proposed method is not affected by the accumulated odometry errors. Second, the size of the local gridmap is determined by considering the entropy of node probability. The entropy test determines the local gridmap size adaptively.

As a result, the proposed topological localization could obtain the prior node probability efficiently and the entropy test guarantees a reliable gridmap matching.

Experimental results verified that the proposed method can be applied to a real home environment and the proposed topological localization resulted in a convergent and successful node probability.

VI. Acknowledgments

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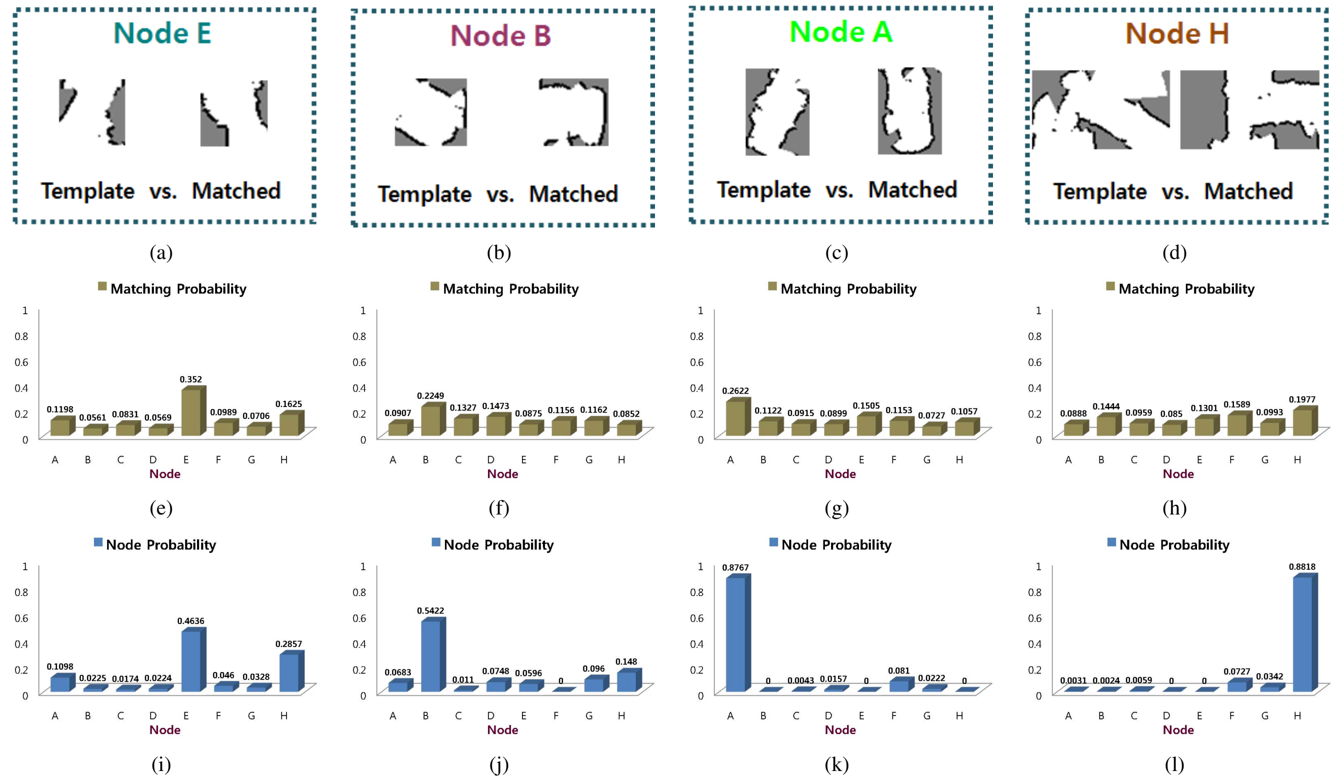

Fig. 8. Experimental results of topological localization (arranged in time sequence). (a)-(d) Template gridmaps and matching results, (e)-(h) corresponding matching probability P_{match} (5), and (i)-(l) corresponding node probabilities.

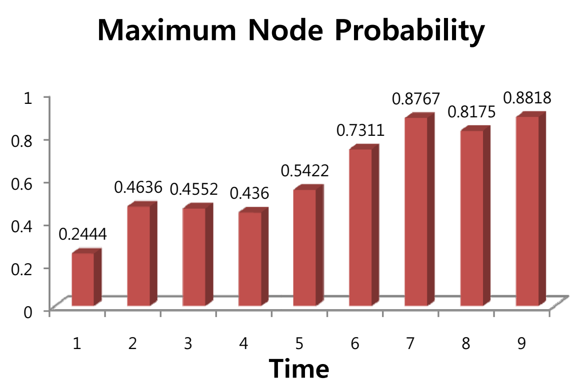

Fig. 9. Maximum Node Probability

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