ROBUST NAVIGATION TECHNIQUES FOR THE GVG-BASED SLAM IN UNSTRUCTURED ENVIRONMENT

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Abstract: The Generalized Voronoi Graph (GVG) has been effectively used for the SLAM and navigation of mobile robots. Since the mobile robot should perform the GVG-based SLAM and navigation in unstructured environments using inaccurate noisy sensors, it requires accurate data association and robust navigation techniques. In this paper, we suggest three techniques for a robust construction of the GVG. The first one is a robust node matching technique and the second one is an adaptable sensor area matching method for the robust exploration. Finally we propose a technique which is capable of distinguishing between closely located nodes. The simulation results show that the proposed algorithm can work successfully under 20% errors of odometry and range sensor in unstructured environment.

Keywords: Mobile robots, Topological localization, Generalized Voronoi Graph (GVG), Node matching.

1. INTRODUCTION

The Generalized Voronoi Graph (GVG) is an efficient tool for the SLAM (Simultaneous Localization and Mapping) because of its embedded navigation capability and computational efficiency. For that reason, several GVG-based SLAM algorithms have been successfully implemented (Choset and Nagatani, 2001; Nagatani and Choset, 1999; Doh *et al.*, 2003).

The GVG consists of nodes and edges. The nodes are topologically meaningful places such as junctions, corners, doors, etc., and the edges are connections between nodes. The GVG-based SLAM algorithms re-localize a robot on the node. Thus the key factor is a data association which matches a current node with a set of known nodes.

An ideal data association algorithm for the GVG-based SLAM should meet the following four conditions. First, the algorithm should use cheap sensors such as ultrasonic sensors, odometry for economical aspects. Second, the algorithm should work even in real unstructured environment. Third, the algorithm should reject a weak node efficiently. Here the weak node is a node that needs to be discriminated as edge but sometimes is falsely detected as a node because of its structural property as shown in Fig. 1(a). Fourth, the data association algorithm should be capable of distinguishing closely located nodes as shown in Fig. 1(b).

However, upon the author's knowledge, there seems to be no established result which satisfies above four necessities because of poor ability of sensors. In (Choset and Nagatani, 2001), an algorithm which covered about $230m^2$ using ultrasonic sensors and odometry is proposed. Their approach, however, was performed in well structured environment. And a Multi Layered

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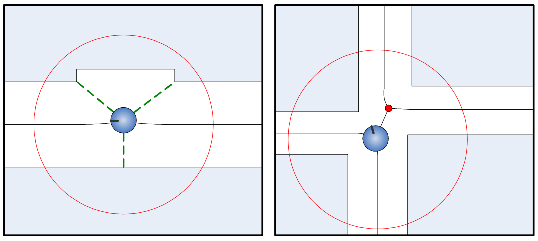


(a) (b)

Fig. 1. (a) A weak node and (b) Two nodes are located very closely. Data association with these nodes during the GVG navigation is very difficult.

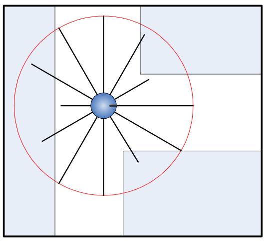


Fig. 2. Large uncertainty and low resolution of cheap sensors

Data Association (MLDA) for robust data association was suggested (Doh *et al.*, 2003), but they used a laser range finder which costs more than \$5,000 and the weak node rejection was not implemented.

In this paper, we propose three techniques that perform the data association that satisfies aforementioned necessities. First, we suggest a Local Occupancy Grid Map (LOGM) at the node. This is a fusion of metric and topological map. The LOGM is constructed by sensor scans on the node, and it can reject sensor noise coming from poor sensing ability of cheap sensors. The LOGM provides rich information of the node with less noise, and gives robustness to the data association algorithm, in return. The LOGM addresses the first necessity using cheap sensors.

Second, we suggest the weak node (Fig. 1(a)) rejection algorithm via sensor area matching method. And the algorithm can be adaptively performed for various environments. The sensor area matching algorithm can reject various weak nodes induced in unstructured environment. And its adaptiveness gives robustness, and this enhancement addresses the second and third necessities improving robustness in the unstructured environment and adaptive weak node rejection.

Third, we provide a discriminant technique for the closely located nodes (Fig. 1(b)). Those closely located nodes are distinguished by using the constructed LOGM image and the MLDA (Doh *et al.*, 2003). This technique addresses the final condition that the closely related nodes should be distinguished.

Simulations were performed for a robot with 36 range sensors in unstructured environment. A Gaussian error, $\mathcal{N}(0,\sigma^2)$, whose 2σ corresponds to 20% of the odometry and the range errors, is added to the real odometry and the real range sensor data.

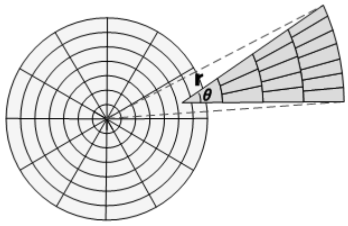


Fig. 3. Circular occupancy grid

This paper is organized as follows. In section 2, we present robust node matching technique. And adaptive sensor area matching method is explained in section 3. Then section 4 presents a technique about closely located nodes detection. In section 5 we show simulation results and conclusion follows in section 6.

2. ROBUST NODE MATCHING TECHNIQUE

If we use cheap sensors, its characteristic of low resolution and noisy signal is shown as Fig. 2. In this section, we describe a Local Occupancy Grid Map (LOGM) scheme for the robust data association of the GVG-based SLAM. Here the LOGM performs to cover the defects coming from cheap sensors such as low resolution and noise.

2.1 Local Occupancy Grid Map (LOGM)

To describe node information and to apply it to data association, we use the most common mapping technique based on the occupancy grid map (Elfes, 1989). Instead of building metric grid map for entire space, we adopt it only at the node. Moreover we newly propose a circular grid to construct the LOGM. The circular grid is divided by cells ($r = 10cm,\ \theta = 30°$) as shown in Fig. 3. The areal size of each cell is equivalent and the center of the circular grid is located on the node position.

The proposed circular grid can describe environmental information in two different scales: sparse grid near the robot and dense grid around obstacles. The property of the different grid scale is appropriate for the description of information on the GVG node. And the circular grid can be constructed intuitively and directly from range sensor data.

Then, we choose a probabilistic sensor model as the shape of an arc in (Konolige, 1997). When the robot arrives at a new node, the sensor model is applied and the LOGM at that node is created by the Bayesian procedure as follows (Elfes, 1989):

$$\begin{aligned} P(s(C_i) = OCC|\{r\}_{t+1}) \\ = \frac{p[r_{t+1}|s(C_i) = OCC]P[s(C_i) = OCC|\{r\}_t]}{\Sigma_{s(C_i)}p[r_{t+1}|s(C_i)]P[s(C_i)|\{r\}_t]}, \end{aligned} \quad (1)$$

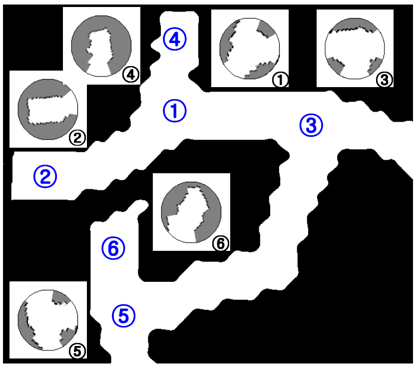


Fig. 4. Local Occupancy Grid Map (LOGM) on the GVG nodes

where $s(C_i)$ is state of i_{th} cell of the LOGM (Occupied or Empty) and $\{r\}_t$ is range data at time t.

Initially 0.5 (likely to be occupied or free) is equally assigned to the probability of occupancy grid cell. When the robot revisits a node through navigation, the LOGM is updated sequentially by (1). Consequently we can obtain a circular gray-scale image via the probability of the LOGM as shown in Fig. 4.

2.2 Maximum Likelihood LOGM Matching

As mentioned previously, we can think that the robot captures LOGM images on every node of the given environment. Here we want to know a degree of difference between two given LOGM images.

For robust node matching, the robot compares a current node image with node images obtained from prior navigation. For that purpose, we use an image matching method in terms of Maximum Likelihood (ML) estimation (Olson, 2002). It can be implemented by both edge template matching and gray-level image matching.

From edge and gray-level information, we seek the template LOGM image j in a way that maximizes the likelihood of the difference measurement given all available data as follows:

$$j = \arg\max_j p(j|E_j, G_j, \mathit{Current\ LOGM}) \qquad (2)$$

where E_j and G_j means the edge and gray-level difference between *Current LOGM* and template LOGM j, respectively. This comparison will take place with finite number, since we adopt the LOGM only at the possible nodes.

For the data association using the LOGM, we adopt the Multi Layered Data Association (MLDA) scheme (Doh *et al.*, 2003) which uses as many reliable data as possible for data association. The MLDA handles not only deterministic data of essential graph structure but also probabilistic data of accurate odometry and sensor scan.

From a set of constructed LOGMs, we can find that each of them represents local information at the node.

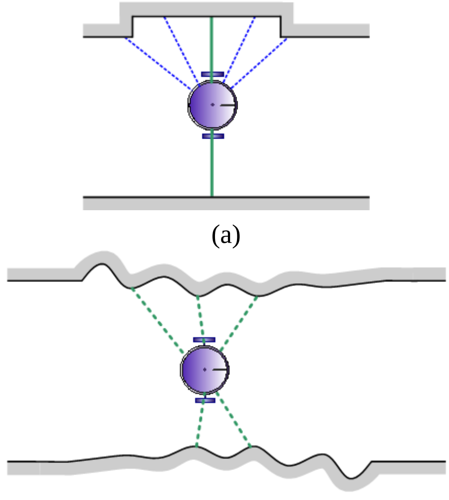


Fig. 5. Problematic nodes in an unstructured environment : (a) a weak node and (b) a node with meaningless local minima

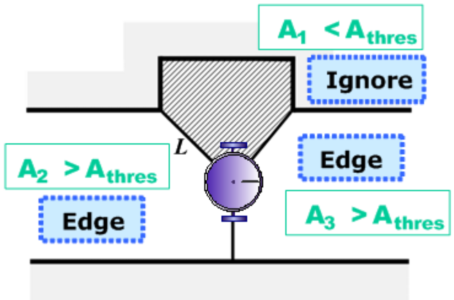


Fig. 6. Sensor area matching method based on threshold area, A_{thres}

Because there exists no consistency between the local grids (Duckett and Saffiotti, 2000), we can use the LOGMs on-line by the robot for self node matching. Therefore, by using this ML and a Multi Layered Data Association (MLDA) (Doh *et al.*, 2003), we can effectively perform data association for node points. The results will be shown in section 5.

3. ADAPTIVE SENSOR AREA MATCHING METHOD

In this section, we provide a weak node rejection algorithm via the adaptive sensor area matching method.

3.1 Accounting for Sensor Area Matching Method

When a robot navigates an unstructured environment, the weak node, which is essentially an edge but sometimes detected as node (Fig. 5(a)), and meaningless local minima (Fig. 5(b)) will increase ambiguities of data association.

A sensor area matching method can effectively reduce above two problems in the unstructured environment. To describe the method briefly, let us assume that an

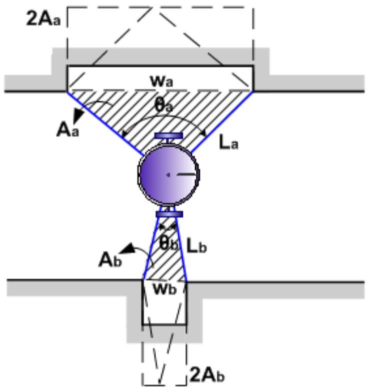


Fig. 7. Adaptable sensor area matching method

equidistant local minimum of range data is L. Then we can define sensor area as the shaded area between two local minima L as shown in Fig. 6. We can filter weak nodes and meaningless local minima whose sensor area between the local minima pair is smaller than a preset threshold, A_{thres} as shown in Fig. 6.

3.2 *Adaptive Sensor Area Matching Method*

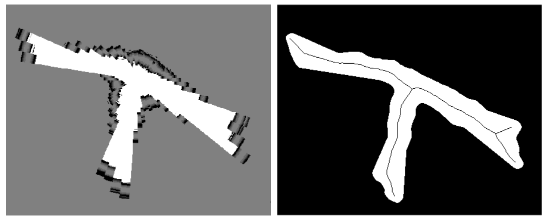
However, the sensor area matching method is very sensitive to A_{thres}. Accordingly two undesirable cases can be induced by the sensitivity. First, if a map consists of weak nodes whose sensor area is close to the preset threshold, A_{thres}, the sensor area matching method won't work. Second, if we set unreasonable A_{thres} (too high or small), the sensor area matching won't be successful.

Therefore, for highly robust data association, sensor area threshold should be adaptively selected. For that reason, we propose a technique named an *adaptive sensor area matching method*.

To explain this technique, firstly, we denote the distance of the equidistant local minimum of range sensor data as L_i. Also we denote the angle and the width between local minimum pair as θ_i and w_i, respectively. Then, we can obtain an *unit sensor area threshold*, A_i (shaded area in Fig. 7) from L_i and θ_i of the local minimum pairs. After that, we can define the sensor area threshold as $A_{thres} = nA_i$ where n is the number of unit sensor area threshold. Upon the various trials via simulation, we found that $n = 3$ shows the best performance.

As aforementioned, the unit sensor area, A_i is a function of local minimum distance of current sensor data. When the robot meets an environmental change (i.e. a width change of the corridor, etc.), the unit sensor area is adaptively selected by the current sensor data.

By applying this technique, the robot can adaptively choose threshold value for sensor area matching method based on the current sensor data. And it makes the robot to navigate an unstructured environment robustly and consistently.



(a) (b)

Fig. 8. Extraction of the GVG edges and nodes (a) acquired local occupancy grid map (b) extracted edges and nodes after image processing

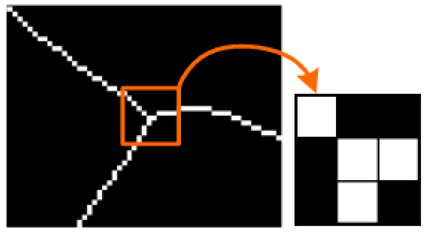


Fig. 9. Detecting the GVG nodes by checking 8 neighbor of pixels on the LVD edge

4. DISCRIMINATING TECHNIQUE BETWEEN CLOSELY LOCATED NODES

Different nodes were associated in section 2 and weak node was rejected in the previous section. However, if two nodes are closely located, it is not easy to discriminate these nodes. In this section, we suggest a technique to distinguish between neighbor nodes located closely for the robust GVG navigation.

4.1 *LVD Extraction from the LOGM image*

A Local Voronoi Diagram (LVD) is a locally generated Voronoi Diagram which is the locus of points equidistant to two or more obstacles. Two closely located nodes can be closed distinguished in the LVD, and the Local Occupancy Grid Map (LOGM in section 2) provides good information for the LVD extraction.

To extract the LVD, we choose a skeletonization algorithm based on the Zhang Suen-Stentiford-Holt combined algorithm (Parker, 1997). Firstly, we apply binary transformation and Stentiford's boundary smoothing method to the LOGM image as a preprocess. Then Zhang-Suen thinning algorithm using Holt's variation makes a skeletonized image as a LVD from the original LOGM image (Fig. 8).

After that, the image is post-processed by staircase removal algorithm. Then, to find nodes of the processed LVD image, we should check 8 neighbor of all pixels which are located on the LVD as shown in Fig. 9. Consequently, we can exactly find all nodes contained in the given LOGM image by using the proposed technique.

4.2 *Modified Multi Layered Data Association*

The Multi Layered Data Association (MLDA) scheme in (Doh *et al.*, 2003) conducts a data association process into two step: deterministic and probabilistic data process. If we modify the probabilistic data process in the MLDA slightly, it can cope with a situation to distinguish between closely located nodes.

To modify the MLDA scheme, we induce the Mahalanobis distance between two nodes by using mean node position and its covariance from odometry. The procedure of the probabilistic test parts for the modified MLDA is as follows:

Modified MLDA Algorithm

for all the nodes {

- The deterministic test as follows:
  - · Checking the number of edge of the nodes.
  - · Checking the relative angles between the edges.
  - · Checking the types of nodes (boundary, junction, etc.).
- The probabilistic test as follows:
  - · Calculate the Mahalanobis distance, L_M from N_{cur}
  - · If $L_M < L_{thres}$,
    then using the probability of reliable odometry
    else using the probability of reliable sensor scan

}

Algorithm end

Here, N_{cur} and L_{thres} represent current node and distance threshold, respectively.

5. SIMULATION RESULTS

In previous 3 sections, we proposed three robust navigation techniques for the robust data association of the GVG-based SLAM in unstructured environment. We evaluated the performance of the proposed algorithms through the following simulations in unstructured and corridor-like environments. All the simulations were performed for a robot with 36 range sensors (10° angular resolution) in unstructured environments. A Gaussian error, $\mathcal{N}(0,\sigma^2)$, whose 2σ corresponds to 20% of the odometry and the range, is added to the real odometry and the real range sensor data.

5.1 *Unstructured Environment*

Firstly, we applied the proposed algorithm to an unstructured symmetric environment as shown in Fig. 10. The map is given by a bitmap image representing a $3.7km \times 3.7km$ environment with 240 GVG nodes. The unstructured environment has many candidates that match to the current node because every place looks similar and has less topological features.

In Fig. 11, the plot shows a simulation result of robust data association using cheap sensors in the given environment (Fig. 10). It presents the percentage of successfully matched node versus odometry uncertainty.

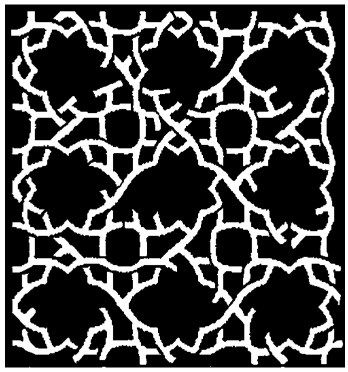


Fig. 10. An unstructured environment

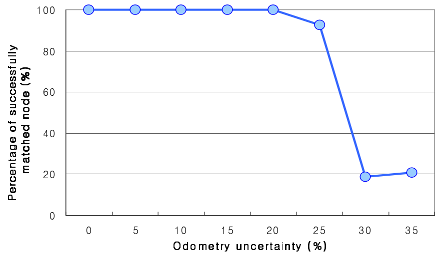


Fig. 11. The percentage of successfully matched node versus odometry uncertainty under 20% range sensor error within 2σ bounded uncertainty in unstructured environment(Fig. 10).

This result indicates that the robot can successfully navigate the unstructured environment under 20% uncertainties of odometry and range sensor.

5.2 *Corridor-like Environment*

We applied the same algorithm to a corridor-like environment which has closely located nodes and places with similar sensor scan. Fig. 12 represents a result of complete mapping of the given environment. The proposed algorithm identified 69 nodes accurately and the path navigated by the robot is about $1,600m$. In Fig. 12 and 13, the points with number mean the acquired nodes of the Reduced GVG (Nagatani and Choset, 1999).

From the simulation result of complete exploration, we can confirm that one of the proposed schemes, adaptive sensor area matching method is useful for the incremental construction of the GVG in the unstructured environment like a corridor. It makes the robot to navigate robustly the given environment without suffering problematic landmarks like weak nodes.

Also we can verify the performance of the suggested data association using Local Occupancy Grid Map (LOGM) matching and it can solve the problem of closely located nodes through robust data association as shown in Fig. 13. It means that node match can be accomplished efficiently and robustly in unstructured environmental situations using the proposed method. Finally, Fig. 14 shows a histogram of the matching er-

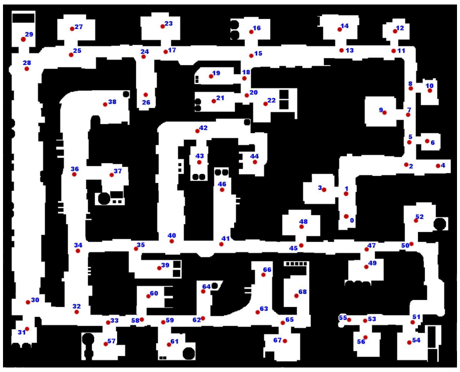


Fig. 12. Simulation result of a unstructured corridor-like environment

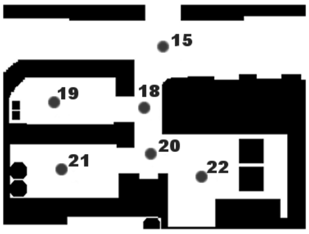


Fig. 13. A partially magnified map of Fig. 12 to show discriminant ability between closely located nodes

ror rate between two LOGMs and the decision boundary for probabilistic data association using LOGMs.

6. CONCLUSION

This paper addressed a robust data association and navigation techniques for the GVG-based SLAM in unstructured environment.

For that purpose, we suggested three techniques: (1) Robust node matching technique using Local Occupancy Grid Map (LOGM) (2) Adaptive sensor area matching method for robust GVG-based navigation (3) Discriminating technique between closely located nodes.

These three techniques can achieve robust data association and navigation in a way that the robot navigates an unstructured environment using cheap sensor as follows.

First, we adopted metric grid map only at the node point to enhance the data association capability. This algorithm makes data association more robust. Second, we enhanced the weak node rejection algorithm via the adaptive sensor area matching method. It perceives the environmental changes and improves robustness in the unstructured environment. Third, we provided a discriminant technique for the closely located nodes. Those closely located nodes are distinguished by using the constructed LOGM image and the modified MLDA.

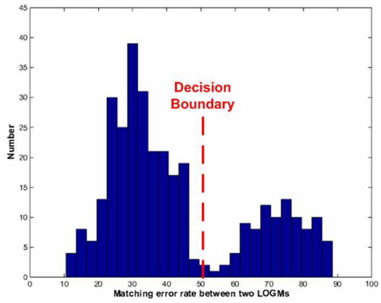


Fig. 14. A histogram of matching error rate between two LOGMs when the robot navigates the given environment (Fig. 12). It shows that the capability of the maximum likelihood matching process.

We integrated these techniques and were able to evaluate their robustness on the data association and navigation through simulations. From the simulation results, we can confirm that the proposed algorithm is suitable to the efficient navigation with robustness. In simulation, the robot successfully mapped an unstructured and a corridor-like environments under a condition that a Gaussian error, $\mathcal{N}(0, \sigma^2)$, whose 2σ corresponds to 20% of the odometry and the range, is added to the real odometry and the real range sensor data.

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