Proceedings of 2004 IEEE/RSJ International Conference on Intelligent Robots and Systems
September 28 - October 2, 2004, Sendai, Japan

Real-Time Building of a Thinning-Based Topological Map with Metric Features

Bang-Yun Ko, Jae-Bok Song
Dept. of Mechanical Engineering
Korea University
Seoul, Korea
{bangyun_ko, jbsong}@korea.ac.kr

Sooyong Lee
Dept. of Mechanical and System Design Engineering
Hongik University
Seoul, Korea
sooyong@hongik.ac.kr

***Abstract*—An accurate and compact map is essential to an autonomous mobile robot system. A topological map represents the environment in terms of the discrete nodes with edges connecting them. It is usually constructed by the Voronoi-like graphs. In this paper the topological map is incrementally built based on the local grid map using the thinning algorithm. This thinning-based topological map does not create the boundary edges and weak meet points which are found in the generalized Voronoi graph. Furthermore, the map can be built in real-time and is robust to the environment change. Since lack of metric data in the topological map poses difficulty in localization, the metric features such as corners are incorporated into the topological map, thus leading to the hybrid map. In this paper the detailed procedure to obtain this hybrid map is discussed and the experimental results are shown to verify the validity of the proposed algorithm.**

Key words – thinning-based topological map; hybrid map; feature extraction

I. INTRODUCTION

Map building 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: a grid map and a topological map. The former can produce an accurate map in a relatively simple manner, but requires large memory, is inefficient, and time-consuming. The latter, on the other hand, provides more efficient and compact map requiring much less memory, but is difficult to apply to localization [1].

A topological map is an abstraction of the environment in terms of the nodes representing discrete places and the edges connecting them together. The topological map can be built in various ways. It can be constructed off-line after the global grid map is made [2]. This hierarchical approach can gain the advantages of both grid and topological maps, but still suffers from the problem of large memory requirement of the grid map. Furthermore, updating of a map is generally difficult.

On the other hand, the topological map can be built by means of the GVG (Generalized Voronoi Graph) [3]. The GVG-based topological map is robust to various environments and can be extended to the higher-dimensional space. However, the map creates the boundary edges and weak meet points which are unnecessary in navigation [4][5].

In this paper, an improved method for constructing a topological map is proposed. It can utilize the advantages of the topological map such as compactness. A local grid map using the range data is first constructed. From this map, a local topological map is then built using the thinning method [6], which is the alternative to the Voronoi diagram. Finally, the local topological map is incrementally updated to the global one. This thinning-based topological map can be constructed in real-time and does not create the boundary edges or weak meet points found in GVG.

The disadvantage of the typical topological map is the lack of metric information which is very useful in localization. In this research, therefore, metric features added to the topological map to form a hybrid map. Feature extraction can be performed using the same scan data as used in building the topological map. Particularly, corners are selected as a main feature since they are frequently found in the indoor environment [7]. These features can serve as landmarks in the localization and SLAM. In the hybrid map found in [8], the hallway was represented by the topological map, whereas the room by the feature map alone and switching between the two maps were executed. However, in the hybrid map proposed in this research, both the topological and feature map are fused together at all times and thus no switching is necessary.

This paper is organized as follows. Section 2 presents building of a thinning-based topological map. Section 3 deals with how to extract the corners from the range data. A hybrid map based on the thinning-based topological map with metric features is discussed in Section 4. Various experimental results are shown in Section 5 and finally conclusions are drawn and future work is outlined in Section 6.

II. Topological Map Building

A. Local topological map based on thinning

In the feature-based topological map, the environment is modeled by a set of geometric primitives such as nodes and edges. It has several advantages such as compactness, fast computation, natural expression to human, 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. Localization performance can be improved by adding more features by the hybrid approach.

To build a topological map based on a grid map, a Voronoi diagram is commonly used. But it is complex and difficult to apply to arbitrarily shaped objects. In building a topological map, therefore, a thinning method is proposed in this paper, which needs simpler computation than the Voronoi diagram, but can show similar performance.

A thinning method is one of the popular image processing algorithms, which have been used to detect the skeleton of images. Figure 1 illustrates of 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 for representation with thin lines. In the case of mobile robots, the connected lines are used as paths on which a robot navigates without colliding with other objects.

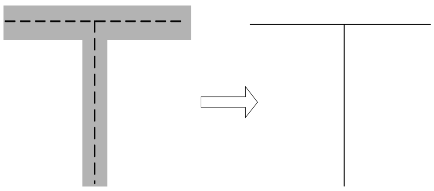

Figure 1. Concept of thinning.

Figure 2 illustrates the center cell (p_1) under consideration and its 8 neighboring cells (p_2~p_9). Note that ‘0’ denotes an empty cell and ‘1’ an occupied cell. For the occupied cell p_1, if its 8 neighboring cells satisfy the following thinning conditions, it is converted into an empty cell because it is not a part of skeleton.

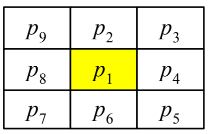

Figure 2. Center cell p_1 and its 8 neighboring cells.

[Step 1]

① $2 \le N(p_1) \le 6$, ② $S(p_1) = 1$,

③ $p_2 \cdot p_4 \cdot p_6 = 0$, ④ $p_4 \cdot p_6 \cdot p_8 = 0$

where $N(p_1)$ is the number of cells being not zero (i.e., $N(p_1) = p_2 + p_3 + \cdots + p_8 + p_9$) and $S(p_1)$ is the number of changes from 0 to 1 in the sequence of $p_2, p_3, \cdots, p_8, p_9$.

[Step 2]

① and ② are the same as [step 1].

③ $p_2 \cdot p_4 \cdot p_8 = 0$, ④ $p_2 \cdot p_6 \cdot p_8 = 0$

Figure 3 illustrates some examples of this process. The cell p_1 in Fig. 3(a) is eliminated from the occupied cells because it satisfies all the conditions in step 1, while those in Fig. 3(b) and 3(c) are not because conditions ① and ④ of step 1 are violated, respectively.

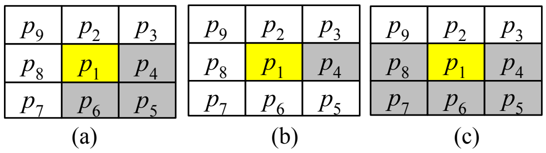

Figure 3. Examples showing thinning conditions. (The occupied cells are represented in gray.)

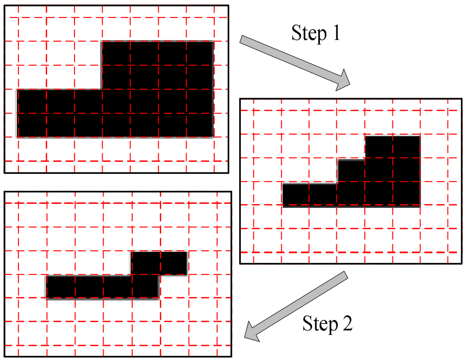

Figure 4. Thinning process.

Two steps of the thinning process are illustrated in Fig. 4. When step 1 and 2 are conducted sequentially, the outer cells corresponding to the object contour are eliminated (i.e., converted into empty cells). This process is repeated until only the occupied cells belonging to the medial skeleton of the object remain. In the topological map, however, the medial line for the empty space is required instead of the skeletons of the objects (i.e., obstacles). Therefore, the empty cells are denoted ‘1’ and the identical procedure is applied to generate the topological map. Figure 5 shows the thinning-based topological map simulated for two indoor environments. As can be seen in the figure, the thin lines correspond to the Voronoi edges consisting of a set of points equidistant to the objects.

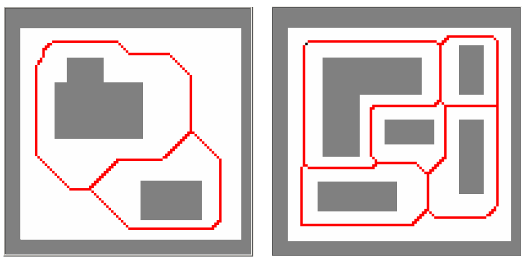

Figure 5. Construction of thinning-based topological maps for various environments. (Simulations)

The thinning-based topological map is constructed from the occupancy grid map which is updated probabilistically from the range data, and does not use the sensor data directly for mapping, thereby leading to robust nature. In the following, the features of the thinning-based topological map will be compared with the Generalized Voronoi Graph (GVG), which is also a robust and well-known technique in building of a topological map.

Figure 6 compares the topological map constructed by the Generalized Voronoi Graph (GVG) with that by the thinning process. The GVG generates the boundary edges which connect the meet points (or Voronoi vertices) to the nearest points on the concave boundary. The edges of a topological map can be used as a path for navigation in the exploration or SLAM [4]. In this respect, these boundary edges are unnecessary for the navigational map [5]. In contrast to the GVG, the thinning-based topological map do not generate such edges, thus it is more efficient for mobile robot navigation. On the contrary, the reduced number of nodes may bring difficulty in localization, but this will be overcome by employing the hybrid map that includes end points as nodes of the topological map and adds feature information from feature extraction explained in the next section.

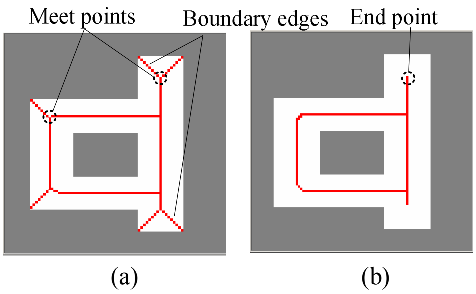

Figure 6. Topological maps: (a) GVG-based, and (b) thinning-based.

Another point is the so-called weak meet point which sometimes appears and sometimes disappears in the GVG structure as shown in Fig. 7(a). [5] That is, the occurrence of such the meet points depends on the depth of the indent on the wall and uncertainty of metric data. Such meet points do not contribute to navigation al all, and thus no appearance is desirable. It is observed that weak meet points do not occur in the thinning process as shown in Fig. 7(b).

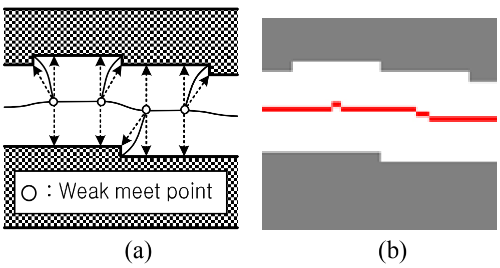

Figure 7. Edges and nodes for the environment prone to weak meet points; (a) GVG-based, and (b) thinning-based.

B. *Real-time building of a global topological map*

A global topological map is usually constructed from a global grid map using various methods. In this research, however, the global topological map is obtained by incrementally updating the local topological maps that are built from the local grid map. The robot collects the range data by scanning the environment using a laser rangefinder. Since the scanning rate is about 2 Hz 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 rule. This probabilistic approach to building a local grip map enhances the confidence of the underlying map for the 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. Since the thinning-based topological map building can be executed fast, the topological map can be constructed on the real-time basis.

In order to cover the large-scale environment, the hash table technique has been employed. The entire environment is divided into the small windows of 10m x 10m in size. Since each cell is 10cm x 10cm in size, each window contains 10,000 grid cells. When the current local grid map ranges over several windows (up to 4 windows at the same time), connectivity of the nodes in the neighborhood of the neighboring windows should be considered. After building the topological map, the grid maps are eliminated, thereby utilizing small memory only for the topological information.

III. Feature Map

A feature map used in this research is composed of the high-level features such as corners. These features are derived from the underlying primitive features such as line segments, which are usually obtained by segmentation and fitting. The segmentation determines which range data belong to which line cluster by the Hough transform, and the line fitting finds the best line for a given cluster of range data. In what follows, the procedure for feature extraction will be briefly discussed.

For segmentation of the scan data shown in Fig. 8, the slopes for each consecutive pair of range data are obtained by

$$s_i = \operatorname{atan2}\left(\frac{y_i - y_{i-1}}{x_i - x_{i-1}}\right) \tag{1}$$

From these slopes, the average slope $\bar{s}_i$ for the previous n-1 slopes are given by

$$\bar{s}_i = \sum_{i-n}^{i-1} \frac{s_i}{n-1} \tag{2}$$

From Eqs. (1) and (2), the condition for data i belonging to the segment is given by

$$s_i - \bar{s}_i < \varepsilon_s \tag{3}$$

where ε_s is the threshold.

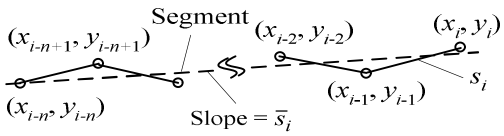

Figure 8. Segmentation of scan data

Another condition for correct separation of two consecutive segments with the same slope is given by

$$\sqrt{(x_i - x_{i-1})^2 + (y_i - y_{i-1})^2} < \varepsilon_d \tag{4}$$

where ε_d is the threshold. After the clusters for each different line, the line segments are obtained by the line fitting technique.

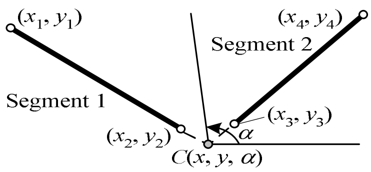

Figure 9. Two line segments used in corner extraction.

The line segments extracted from the range data contain the good metric information. For the dynamic and uncertain environments, it is not easy to get the reliable segments. However, the corners formed from two intersecting lines are robust to the change in environment and can serve as natural landmarks in localization and navigation. A corner is defined as a point at which two adjacent line segments interest at right angles as shown in Fig. 9. The corner is represented by its coordinates and orientation in the space as $C(x, y, \alpha)$. Because of the uncertainties involved in the extracted line segments, two lines forming the corner may not meet each other or their angle may be slightly different from 90°. Thus if the distance between two adjacent points is less than a certain tolerance ε_{cd}, that is,

$$\sqrt{(x_2 - x_3)^2 + (y_2 - y_3)^2} < \varepsilon_{cd} \, , \tag{5}$$

and, if the angle error with 90° is also less than a tolerance ε_{cs},

$$\left| \tan 2\left(\frac{y_1 - y_2}{x_1 - x_2}\right) - \operatorname{atan2}\left(\frac{y_3 - y_4}{x_3 - x_4}\right) \right| - 90 < \varepsilon_{cs} \, , \tag{6}$$

then two segments are considered as forming a corner. The corner is characterized by the its corner point

$$x = \frac{x_2 + x_3}{2} \text{ and } y = \frac{y_2 + y_3}{2} \tag{7}$$

and the corner angle α

$$\alpha = \left[\operatorname{atan2}\left(\frac{y_1 - y_2}{x_1 - x_2}\right) + \operatorname{atan2}\left(\frac{y_3 - y_4}{x_3 - x_4}\right) \right] \Big/ 2 \, . \tag{8}$$

Extraction of the corners based on the above equations can be executed in real-time. Furthermore, this feature extraction is based on the same range data as used in building a topological map and thus no additional data are not necessary.

IV. Hybrid Map

As discussed before, two paradigms (i.e., metric and topological maps) for map building have their own advantages and disadvantages. The topological map represented in nodes and edges takes up small amount of memory for the large environment, but poses difficulty in localization because it does not include the local metric data. Particularly, the thinning-based topological map does not provide the boundary edges found in GVG, thus providing less topological information. In order to overcome this difficulty, the corners which can be found very often in the indoor environment are extracted to replace the boundary information.

It is desirable, therefore, that these two maps are integrated into one map by adopting the compactness of a topological map and the accuracy of a metric map. The hybrid map proposed in [7] first extracts features such as corners and openings, and then selects these features as nodes of the topological map. In this research, however, the hybrid map is constructed so that the underlying map paradigm is a thinning-based topological map, and the features such as corners are added to this topological map. In order to relate the extracted features to the topological map, new nodes are generated on the topological edge so that this feature-related node has the shortest distance to the corresponding feature. (See Fig. 13 for graphical representation) Then the feature information (i.e., coordinates and orientation for corners) is assigned to the database of this node. This information will be useful in the topological localization.

This hybrid map can be applied to navigation and localization efficiently. For example, the underlying topological map plays an important role in the hallway having few corner features, whereas the metric corner features are effectively used for localization in the room having many corners.

V. EXPERIMENTS

The proposed approach to a hybrid map has been tested on the various environments using the Pioneer 2 DX and the SICK LMS200 laser rangefinder. Only one rangefinder with 180° scan range is installed with the scanning area facing forward. Figure 10 illustrates the thinning-based topological map. Each grid cell in the figure is 10cm x 10cm in size and the dashed line shows 1m x 1m grids drawn just for reference. The large circle in the middle of the figure denotes the robot with the solid portion indicating the current heading direction. As shown in the figure, the topological edges built by means of thinning correspond to the Voronoi diagram whose edges are equidistant to the object boundaries. When the robot starts navigation, the 10m x10m window whose center is the robot's starting point is formed. When the robot goes into another window, the new dynamic memory is allocated for this new window by means of the hash table technique.

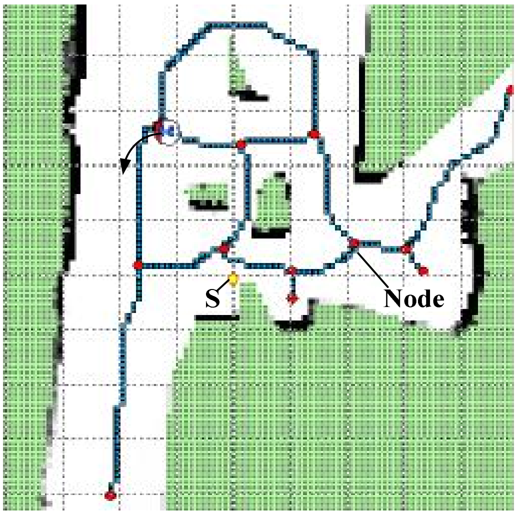

Figure 10. Real-time building of thinning-based topological map.

Figure 11 illustrates the update of the thinning-based topological map as a robot navigates in the environment. In Fig. 11(a) showing the stage just after the robot started to scan the free space without navigation, the free space the laser beam could reach was mostly modeled with the edges. Only lower portion of the rectangular object marked 'O' was observed at this stage. As the robot proceeded on its way, more free space was modeled. As shown in Fig. 11(c), even the edge behind the object was formed although the robot did not actually explore this region. This indicates that the thinning-based approach can cope with the occlusion problem.

Figure 12 shows the experimental results showing the corner detection. From the scan data, the line segments were extracted through the segmentation and line fitting. From these line segments, the corner features are extracted by checking the conditions (5) and (6). These corners provide the metric information (i.e., their coordinates and orientation) and thus serve as natural landmarks.

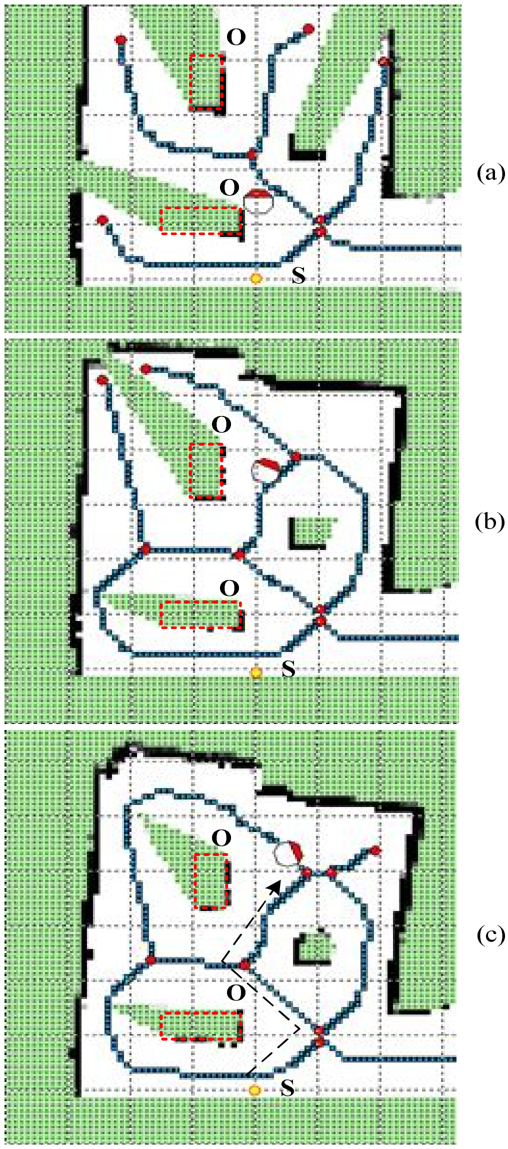

Figure 11. Incremental update of thinning-based topological map to global map.

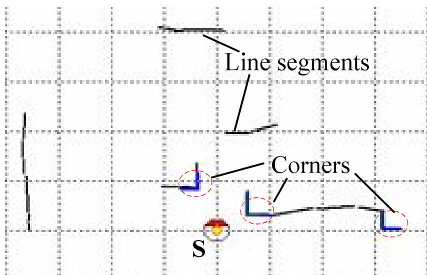

Figure 12. Corner detection from feature extraction.

Figure 13 shows the actual hybrid map for the environment. The thinning-based topological map and corner features modeled the given environment reasonably well. Again the robot navigated just around the center portion of the environment, the complete topological map for the entire environment was drawn, thus indicating robustness to the occlusion problem. It is observed that the node denoted as 'N_t' (node associated by the topological map) is placed rather a long distance apart from the neighboring walls, which is caused by the characteristics of the thinning process. As mentioned before, this is not a disadvantage as far as navigation or exploration is concerned. Furthermore, the existence of the corner denoted 'C' compensates for this lack of the metric accuracy in the topological map. Information of corners (its coordinates and orientation) is assigned to the node denoted as 'N_f' (node associated with feature extraction) in the topological map. Thus the hybrid map is constructed by fusing topological information and feature information.

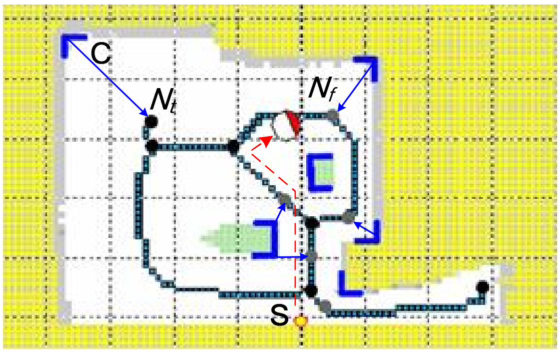

Figure 13. Hybrid map for real environment

VI. CONCLUSIONS

In this paper, a fast and simple approach to real-time building of a thinning-based topological map with metric features is proposed. From this research, the following conclusions are drawn.

1. The thinning algorithm can provide a simpler and more robust way of constructing a Voronoi diagram than the GVG. The thinning-based topological map can be built in real-time and does not create weak meet points or boundary edges which are unnecessary for navigation.

2. The metric features added to the topological map serve as natural landmarks in localization, thus leading to accurate navigation of a mobile robot.

The research on building of the more robust and accurate hybrid map is underway. In this research more features other than the corners will be added to the hybrid map.

ACKNOWLEDGEMENT

This research was supported by CIR (Center for Intelligent Robotics) under the 21C Frontier Program of the Korea Ministry of Science and Technology in 2004.

REFERENCES

[1] S. Thrun, "Learning Maps for Indoor Mobile Robot Navigation," Artificial Intelligence, Vol. 1, 1999, pp. 21-71.

[2] D. V. Zwynsvoorde, T. Simeon, and R. Alami, "Incremental Topological Modeling using Local Voronoi-like Graphs," Proc. of IROS, 2001, pp.897-902.

[3] H. CHoset and J. Burdick, "Sensor Based Planning. Part I: The Generalized Voronoi Graph," Proc. of ICRA, 1995, pp. 1649-1655.

[4] H. Choset and K. Nagatani, "Topological Simultaneous Localization and Mapping (SLAM) : Toward Exact Localization Without Explicit Localization," IEEE Transaction on Robotics and Automation, Vol. 17, 2001, pp. 125-137

[5] K. Nagatani and H. Choset, "Toward Robust Sensor Based Exploration by Constructing Reduced Generalized Voronoi Graph," Proc. of IROS, 1999, pp. 1687-1692.

[6] G. A. Baxes, "Digital Image Processing," John Wiley & Sons, 1994.

[7] N. Tomatis, I. Nourbakhsh, K. Arras, and R. Siegwart, "A Hybrid Approach for Robust and Precise Mobile Robot Navigation with Compact Environment Modeling," Proc. of ICRA, 2001, pp. 1111-1116.

[8] N. Tomatis, "Hybrid, Metric – Topological, Mobile Robot Navigation," Ph. D. Thesis, 2001.