2013 IEEE/RSJ International Conference on
Intelligent Robots and Systems (IROS)
November 3-7, 2013. Tokyo, Japan

Semantic Mapping and Navigation: A Bayesian Approach

Dong Wook Ko, Chuho Yi, and Il Hong Suh, *Senior Member, IEEE*

***Abstract*— We propose Bayesian approaches for semantic mapping, active localization and local navigation with affordable vision sensors. We develop Bayesian model of egocentric semantic map which consists of spatial object relationships and spatial node relationships. Our topological-semantic-metric (TSM) map has characteristic that a node is one of the components of a general topological map that contains information about spatial relationships. In localization part, view dependent place recognition, reorientation and active search are used for robot localization. A robot estimates its location by Bayesian filtering which leverages spatial relationships among observed objects. Then a robot can infer the head direction to reach a goal in the semantic map. In navigation part, a robot perceives navigable space with Kinect sensor and then moves to goal location while preserving reference head direction. If obstacles are founded in front, then a robot changes the head direction to avoid them. After avoiding obstacles, a robot performs active localization and finds new head direction to goal location. Our Bayesian navigation program provides how a robot should select either an action for following line of moving direction or action for avoiding obstacles. We show that a mobile robot successfully navigates from starting position to goal node while avoiding obstacles by our proposed semantic navigation system with TSM map.**

I. INTRODUCTION

It is important for a robot to navigate effectively and accurately from current location to destination by using a memorized map and observed data [1]. When a robot tries to fulfill its mission, a robot must have adaptive capacities to cope with unexpected obstacles and to plan optimal path in map [2]. So, map building is essential for navigation. Various mapping approaches have been proposed to represent environments in the robotics. A robot requires precise map to use information for navigation as shown in Fig.1. Probabilistic Roadmaps (PRM) [3] are a commonly used class of algorithms for robot navigation tasks. However, most PRM approaches rely on the assumption that the planner knows the locations of all obstacles in the environment. In other words, it needs precise map that includes all obstacles. To build a precise map, expensive sensors are required such as laser scanner. In case of human, there will be no trouble in navigating without accurate information and exact map. Human navigation relies on local landmarks and personal directions to navigate and visualize a pathway. They remember a few landmarks that constitute the space such as a specific structure and distinct objects, and they

Dong Wook Ko is with the Department of Intelligent Robot Engineering, Hanyang University, Seoul, Korea. pumpblack@hanyang.ac.kr
Chuho Yi is with the Department of Electrical and Computer Engineering, Hanyang University, Seoul, Korea. d1uck@hanyang.ac.kr
Il Hong Suh is with the Department of Computer Science and Engineering, Hanyang University, Seoul, Korea. All correspondences should be addressed to I. H. Suh. ihsuh@hanyang.ac.kr

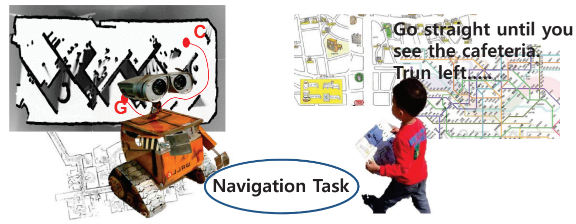


Fig. 1. Discrepancy of representations for space between robot and human.

reconstruct the spatial knowledge using spatial relationships among objects as shown in Fig.1. Then they utilize the spatial knowledge again for navigation [4]. There are discrepancies in representations of space between human and robot. Indeed, human navigation processes are still open questions in cognitive science [5]. Therefore, it will be helpful if we understand human navigation better to model a robot navigation better.

We focus on human-like semantic navigation to be applied to mobile robot navigation. The problem of navigation task can be decomposed into the following three questions: “Where am I?”, “Where am I going?” and “How should I get there?” [6] [7]. First question is localization problem. Humans look around to know where they are. Similar to the way of humans, active localization has been applied to robot localization [8] [9]. The second and third questions are specifying a goal and planning a path, respectively. The spatial relations among objects are used for semantic mapping. These spatial relationships can deduce the direction to go to the goal place. Such human-like semantic navigation tasks can be very compact and distinctive. To support these navigation tasks, we develop Bayesian models of semantic mapping, active localization and local navigation with affordable vision sensor. In semantic mapping, our semantic map inspired by the human navigation paradigm is represented by a symbolic description. A semantic map represented by Bayesian model has been developed for spatial relationships among trained objects [10]. Similar to the works by both Blanco in [11] and LAGADIC team in [12], our method uses local-metric maps and combines topological information to build a global map. In contrast, observed distances, bearings for object are represented egocentrically by semantic metrics [10].

To navigate by using our semantic map, novel navigation strategies are needed. Human can go to goal location by identifying both local navigable space and direction toward the goal and by recalling previously learned landmarks. We propose human-like semantic navigation strategies for mobile robots: view-dependent place recognition, active localization,

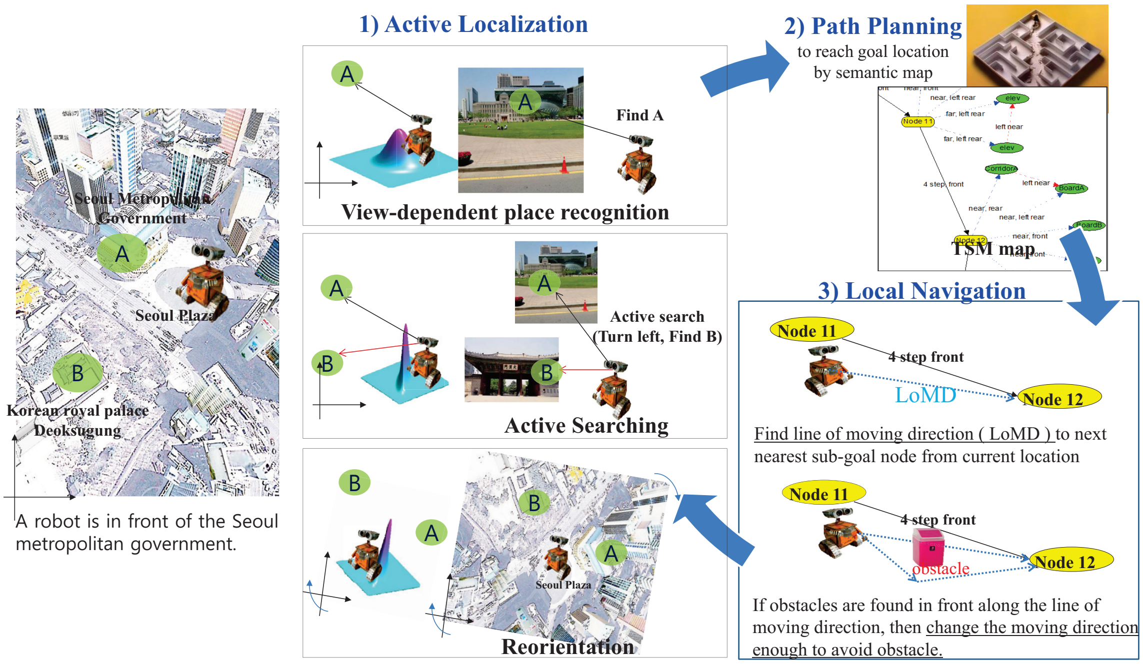


Fig. 2. Principles of Human-like semantic navigation

reorientation, path planning and local navigation. The process of human-like semantic navigation as shown in Fig.2 is summarized as follows: 1) a robot estimates the probability distribution of current location using view-dependent place recognition strategies, active searching and reorientation rule. 2) a robot finds next nearest node to reach goal location in semantic map. 3) After getting to know where to go next, a robot infers its head direction to reach a goal. We define this reference head direction between next nearest sub-goal node and current location as line of moving direction (LoMD). Then, a robot moves to next nearest sub-goal node while keeping LoMD. If obstacles are found in front along the line of moving direction, then a robot changes its moving direction enough to avoid obstacle. After avoiding obstacles, a robot performs active localization and finds new head direction to goal location. A Bayesian Program (BP) [13] is designed for building probabilistic models of local navigation. This BP decides whether the robot follows LoMD or avoids obstacles. Using these strategies as shown in Fig.2, a robot can go anywhere by using semantic map and local navigation.

II. What is a topological-semantic-metric map?

Our topological-semantic-metric(TSM) map consists of spatial object relationships and spatial node relationships. In a topological-semantic metric map, a node is one of the components of a general topological map that contains information about spatial object relationships. TSM map can be considered as a hybrid map combining topological map with semantic metric map. A topological map is represented by connections between nodes, and a semantic-metric map is represented by spatial context among objects rather than a numerical representation. Node relationship is represented as spatial relationship between the nodes, where physical path between the nodes is not taken into consideration. The spatial node relationships are represented by the approximate distance and bearing from one node to another. On the other hand, It is noted that spatial relationships among available objects at a node have to be invariant with respect to robot location. For this, there will be created a local coordinate system at a node with reference to objects observed at the node. This is identified as a local coordinate system at the time when a robot measures the distance and bearing from the center of the camera's axis position when viewing a recognized object in front of it.

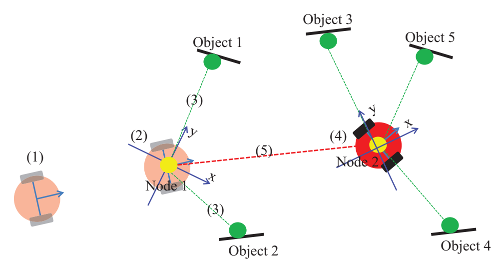


Fig. 3. The process of creating the semantic map

The process of creating the map is summarized as follows: As shown in Fig.3, (1) when a robot starts, topological-semantic metric map is empty, and no new local coordinate system is generated. (2) When a robot finds the object that a robot knows from landmark DB, a robot creates a local coordinate. If the observed object did not exist

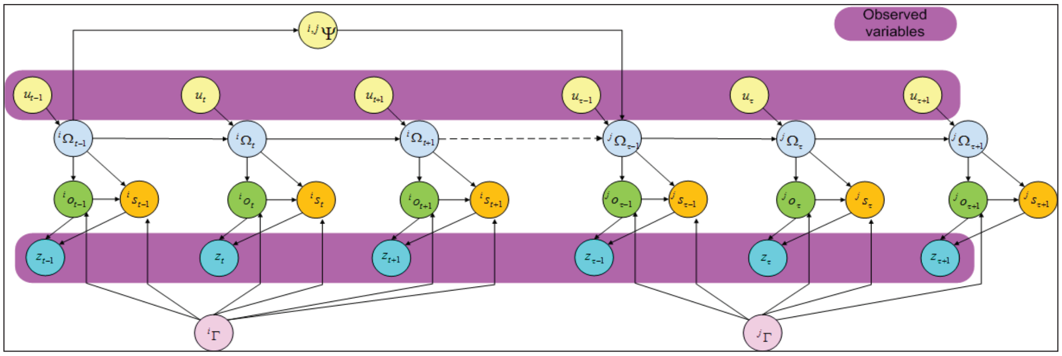


Fig. 4. Graphical model of Bayesian semantic mapping and localization.

in a previous map, a new node is defined and a local coordinate system is created. (3) A robot creates spatial object relationships about the observed objects around it. If no other objects are observed, then the semantic-metric map building is complete with the current node. (4) A robot moves around the new object to measure distance and bearing. If the object did not appear on a previous map, a new node is generated, as depicted by the new local coordinate system. (5) Spatial node relationships are created from the previous node to the current node. A set of semantic relations employed in the local semantic metric map are summarized as follows: A set of semantics for spatial node relationships containing distance and bearing is denoted by s_v^ρ and s_v^ω. Each distance relationship is represented by one of a set of distance symbols, that is, $s_v^\rho = \{$ 1 step, 2 step, ..., k step$\}$. k step(N1,N2) means that the location of node 1 is k steps from the location of node 2. The n-n bearing relationship denoted by $s_v^\omega = \{$front, left front, left, left rear, rear, right rear, right, right front$\}$ is the bearing of the node relative to the node. front(1, 2) means that the location of node 1 is in front of node 2. On the other hand, the node-to-object (n-o) distance relationship denoted by s_o^ρ is the distance of the object from a robot. Each distance relationship is represented by one of a set of distance symbols, that is, $s_o^\rho = \{$ nearby, near, far$\}$. Here, nearby(O1, N1) means that the location of object 1 is nearby the location of the node or robot 1. The n-o bearing relationship denoted by $s_o^\omega = \{$front, left front, left, left rear, rear, right rear, right, right front$\}$ is the bearing of the object relative to a robot. front(O1, N1) means that the location of object 1 is in front of the node or robot 2. The o-o bearing relationship denoted by $s_o^\zeta = \{$left far, left near, left nearby, right nearby, right near, right far$\}$ is the relationship among objects. left far(O1, O2) means the location of object 1 is left and far from the location of object 2.

Fig. 4 shows a graphical model of semantic mapping and localization model. Control u_t and observation z_t are the observed variables. o is object, s_t is spatial object relationships that are distance and bearing to objects and bearing between objects transformed by the symbolizing function for the spatial relationship. Here, robot locations ${}^i\Omega$ and ${}^j\Omega$ are connected between topological edges as ${}^{i,j}\Psi$. The final robot location Ω_t and map M can be expressed as follows:

$$\begin{aligned} &p(\Omega_t, M|o_t, s_t, z_t, u_t) \\ &\quad = p(\Omega_t|o_t, s_t, z_t, u_t)p(M|\Omega_t, o_t, s_t, z_t, u_t) \end{aligned} \tag{1}$$

where $p(\Omega_t|o_t, s_t, z_t, u_t)$ is the estimated path and $p(M|\Omega_t, o_t, s_t, z_t, u_t)$ is the estimated semantic map.

III. SEMANTIC NAVIGATION

Three step procedures are repeated for semantic navigation. At first step, a robot estimates its location using by Bayesian filtering with spatial relationship among observed objects above mentioned section 2. Reorientation rules, view-dependent place recognition and active localization are used for robot localization. Second step, a robot finds an optimal path (node to node) in TSM map with spatial node relationships. After getting to know where to go next, a robot performs the local navigation in third step. In local navigation step, a robot infers the head direction to reach a goal from semantic map. When a robot moves to sub-goal node according to reference head direction, a robot should be able to perceive whether the space toward the head direction is navigable space or not. If obstacles are founded in front of reference head direction, then the robot changes its head direction to avoid them. We define this head direction to avoid them as navigable direction.

A. Localization in TSM map

First question (Where am I?) have usually led to model which allows a robot to localize itself. To answer the first question, we use three strategies of human navigation. Reorientation rules, view-dependent place recognition and active search are used for robot localization by using symbolic inference. Reorientation means that the relative bearings of landmarks are determined automatically when a robot observes at least one remembered landmark between relationships. When a robot observes memorized landmark

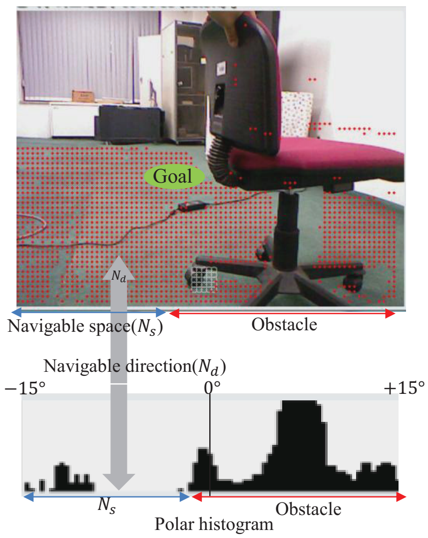


Fig. 5. Result of extraction of all horizontal plane segments and polar histogram

Program / Description / Separation

Five pertinent variables:
$Lomd, N_s, N_d, Act, Vel$

Decomposition:
$P(Lomd, N_s, N_d, Act, Vel|\pi_{localnavi}) =$
$P(Lomd|\pi_{localnavi}) \times P(N_s|\pi_{localnavi})$
$\times P(N_d|\pi_{localnavi}) \times P(Act|N_s, \pi_{localnavi})$
$\times P(Vel|Lomd, N_s, N_d, Act, \pi_{localnavi})$

Parametric Forms:
$P(Lomd\ |\pi_{localnavi})$ =Uniform
$P(N_s|\pi_{localnavi})$ =Uniform
$P(N_d|\pi_{localnavi})$ =Uniform
$P([Act = avoidance]\ |N_s, \pi_{localnavi}) = \text{Sigmoid}_{\alpha,\beta}(N_s)$

$P(Vel|Lomd, N_s, N_d, [Act = avoidance], \pi_{localnavi})$
$\equiv P(Vel|N_s, N_d, \pi_{avoidance})$

$P(Vel|Lomd, N_s, N_d, [Act = follow\ LoMD], \pi_{localnavi})$
$\equiv P(Vel|Lomd, \pi_{follow\ LoMD})$

Identification:
No learning

Question:
$P(Vel|Lomd, N_s, N_d, \pi_{localnavi})$

Fig. 6. Bayesian program for local navigation

with spatial relationships, reorientation applies the associated relationships of the relative change as defined by the reorientation rules based on a robot movement. To determine the robot's current location, a robot estimates egocentric distances and bearings using reorientation rules of spatial relationship. Next, a robot will choose the action for more precise localization. A robot determines actions to find other landmarks, which are spatially related to the perceived landmark. If a robot fails to observe landmarks, it can still infer its next action plan using spatial relationships. Then, a robot updates its location by using view-dependent place recognition. As mentioned section 2, we used likelihood of object similarity, spatial relationship, and motion model. A robot estimates the posterior distribution of its location sequentially by Bayesian filtering.

B. Path Planning

A robot can select easily optimal path (node to node) represented by semantic metric distance. In path planning, a robot finds sequential node path to reach goal location in TSM map. For example, TSM map has spatial node relationship with set of distance symbols ${}^{i,j}s_v^{\rho} = \{$`1 step, 2 step,..., k step`$\}$ among nodes. A robot can find optimal node path using this node relation. After finding a next nearest goal node, a robot extracts semantic-metric distance and bearing in TSM map. Then, a robot converts symbolic representation to numerical form by desymbolizing function. As previously stated, we defined LoMD between current location and sub-goal node. We converts this LoMD from "left front" to normal distribution of bearing as distribution of LoMD in Fig.9 (d). So, the mean of distribution of LoMD will be reference head direction to go to next nearest goal node.

C. Local Navigation

Vector Field Histogram (VFH) is a real time motion planning algorithm proposed by [14]. VFH is currently one of the most popular local planners used in mobile robotics. The VFH utilizes a statistical representation of robot's environment through the so called histogram grid, and therefore place great emphasis on dealing with uncertainty from sensor and modeling errors. However the change of the environment can not be reflected well and the movement of mobile obstacle is not considered. We propose local navigation model. After planning to optimal path to reach a goal location, a robot finds line of moving direction (LoMD) between next nearest sub-goal node and current location node. Because our semantic map has spatial node relationship with set of bearing relationship denoted by $s_v^{\omega} = \{$`front, left front, left, left rear, rear, right rear, right, right front`$\}$, a robot can easily select LoMD by desymbolizing function. If obstacles are found in front along the line of moving direction, then change the moving direction enough to avoid obstacle. We need two composed simple reactive behaviors (Follow LoMD, Avoidance) for local navigation. We require an action command to switch from "Follow LoMD" to "Avoidance". Bayesian program [13] is used for building probabilistic models and for solving decision and inference problem on local navigation model.

The Bayesian program for local navigation is given in Fig.6. In the first specification step, we choose five pertinent variables $Lomd, Ns, Nd, Act$ and Vel for Bayesian model of local navigation. They are described below.

- $Lomd$ is a variable that represents bearing of moving direction between next nearest sub-goal node and current location. Using TSM map and active localization, a robot can extract bearing for moving direction.

- Ns and Nd represent the navigable space and direction to move respectively. In order to extract these sensory variables, we use an approach that directly computes the normal vector over the neighboring pixels in x and y image space with a Kinect sensor [15]. The red points are results of extraction of all horizontal plane segments by local surface normal in Fig.5. Using these plane segments, One dimensional polar histogram that is constructed around a robot's momentary location is acquired. Each sector in the polar histogram contains a value representing the polar obstacle density in that direction. Navigable space must be enough to large to avoid obstacle. Ns is a variable the represents width of navigable space, Nd is a variable of navigable direction.
- Act is a variable for action command to switch from "Follow LoMD" to "Avoidance".
- Vel is a variable that represents its rotation and translation speed.

In the second specification step, we give a decomposition of the joint distribution. We assume that the sensory variables Ns, Nd and extracted $Lomd$ are independent from one another. If the navigable space is enough to move, we want a robot to move toward line of moving direction to next nearest sub-goal node. If the navigable space is not enough to move, we want a robot to change the moving direction to avoid obstacle. Hence, we consider that Act should only depend on Ns. Finally, Vel must depend on the other four variables. Our choices lead to the following decomposition.

$$\begin{aligned} & p(Lomd, Ns, Nd, Act, Vel|\pi-_{LocalNavi}) \\ & \quad = p(Lomd|\pi-_{LocalNavi}) \times p(Ns|\pi-_{LocalNavi}) \\ & \quad\quad \times p(Nd|\pi-_{LocalNavi}) \times p(Act|Ns, \pi-_{LocalNavi}) \\ & \quad\quad \times p(Vel|Lomd, Ns, Nd, Act, \pi-_{LocalNavi}) \end{aligned} \tag{2}$$

We define the parametric forms. We have no *a priori* knowledge about either the Ns and Nd or the $Lomd$. Consequently, we state:

$$\begin{aligned} p(Lomd|\pi-_{LocalNavi}) &\equiv Uniform \\ p(Ns|\pi-_{LocalNavi}) &\equiv Uniform \\ p(Nd|\pi-_{LocalNavi}) &\equiv Uniform \end{aligned} \tag{3}$$

Act is a command variable to switch from "Follow LoMD" to "Avoidance". This means that when $Act = Avoidance$ a robot should behave according to the description $p(Vel|Ns, Nd, \pi-_{localNavi})$, and when $Act = followLoMD$, a robot should behave according to the description $p(Vel|Lomd, \pi-_{localNavi})$. We state:

$$\begin{aligned} & p(Vel|Lomd, Ns, Nd, [Act = Avoidance], \pi-_{LocalNavi}) \\ & \equiv p(Vel|Ns, Nd, \pi-_{Avoidance}) \\ & p(Vel|Lomd, Ns, Nd, [Act = FollowLoMD], \pi-_{LocalNavi}) \\ & \equiv p(Vel|Lomd, \pi-_{FollowLoMD}) \end{aligned} \tag{4}$$

We want a smooth transition from "Follow LoMD" to "Avoidance". Hence, we finally state:

$$\begin{aligned} & p([Act = Avoidance]|Ns, \pi-_{LocalNavi}) \\ & \equiv Sigmoid_{\alpha,\beta}(Ns) \\ & p([Act = FollowLoMD]|Ns, \pi-_{LocalNavi}) \\ & = 1 - p([Act = Avoidance]|Ns, \pi-_{LocalNavi}) \end{aligned} \tag{5}$$

While the mobile robot navigates from current location to next nearest sub-goal node, we don't know in advance when it should avoid obstacles or when it should go toward LoMD. We will use the following question where Act is unknown:

$$\begin{aligned} & p(Vel|Lomd, Ns, Nd, \pi-_{LocalNavi}) \\ & = \textstyle\sum_{act} p(Vel, Act|Lomd, Ns, Nd, \pi-_{LocalNavi}) \end{aligned} \tag{6}$$

Finally, developing for the two possible value of Act , we obtain:

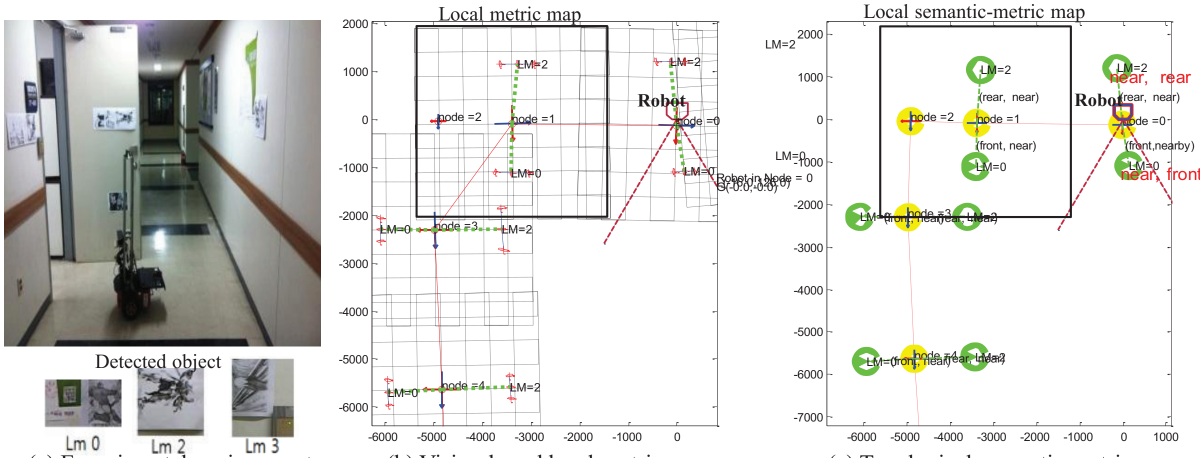
$$\begin{aligned} & p(Vel|Lomd, Ns, Nd, \pi-_{LocalNavi}) \\ & \quad = p([Act = Avoidance]|Ns, \pi-_{LocalNavi}) \\ & \quad\quad \times p(Vel|Ns, Nd, \pi-_{Avoidance}) \\ & \quad\quad + p([Act = FollowLoMD]|Ns, \pi-_{LocalNavi}) \\ & \quad\quad \times p(Vel|Lomd, \pi-_{FollowsLoMD}) \end{aligned} \tag{7}$$

If navigable space(Ns) is enough to large(Ns=100), $p([Act = FollowLoMD]|Ns, \pi-_{LocalNavi}) = 1$ and $p([Act = Avoidance]|Ns, \pi-_{LocalNavi}) = 0$, a robot uses pure "Follow LoMD". The probability distributions are obtained by proposed probabilistic model. If the obstacle is on the left, a robot needs to turn right to avoid it. This is what happens when a robot is close to the obstacle. When a robot is further from the obstacle, a robot moves following LoMD.

IV. Experiments

We demonstrate our human-like semantic navigation system in a corridor using the proposed semantic map. We attached some pictures on the wall. It will be objects(Landmarks) in TSM map. As long as the nodes are determined, a robot can automatically detect landmarks and extract spatial context among detected landmarks and nodes, such as node to landmarks and node to node. After building a TSM map, we verified the practicality of the human-like semantic navigation through experiments in indoor environments, a corridor, using a vision system. Experimental environment are described below.

- Robot platform: Pioneer 3DX
- Camera: Logitech Pro Webcam C910 for object recognition.
- Kinect for detecting navigable space
- Control module: Aria + Microsoft Visual Studio 2008 running in Windows.
- Semantic map building and Navigation system: Matlab 2010 running in Windows.
- Environment type: Corridor $(14 \times 26.5m)$
- Landmark: 30 pictures attached to a wall. A robot knows landmarks from database .



(a) Experimental environment (b) Vision-based local-metric map (c) Topological-semantic-metric map

Fig. 7. Experimental environment, vision-based local metric map and TSM map.

A. Semantic Mapping

As shown in Fig.7(a), some pictures were attached to the wall. Pictures in experiment to improve recognition efficiency are used for vision recognition module (SURF [16]). The vision system often produced false results. False positives are significantly more problematic than false negatives in semantic-knowledge instantiation and reasoning. Noisy sensor such as false positives and false negatives should be filtered for robust robot knowledge acquisition. We used the robust knowledge acquisition rules [17] by estimating confidence of the perception results. A robot detects objects $(Lm0, Lm2, Lm3)$ as shown in Fig.7(a). A robot detects a set of correspondence points (SURF) to recognize object. After recognizing visual landmarks (objects), a robot builds a vision-based metric map. To build a map with a single camera, we use the concept of bearing-only landmark initialization [18]. Two or more measurements are required to estimate the location of landmarks. The location of landmarks is represented in a Gaussian distribution using motion information from odometry and bearing data from the camera. Using this vision-based metric map and symbolizing functions in which metric data distance and bearing are converted semantic metric distance and bearing respectively, we extract spatial relationships among landmarks and nodes. A partial maps built by the proposed method are shown in Fig.7(c). After travelling around the fourth floor $(14\times 26.5m)$ of the IT.BT building at Hanyang university, a robot built the topological-semantic-metric map as shown in Fig.8.

B. Semantic Navigation

These semantic map provides symbolic data that consist of linguistic representation of objects and their spatial relationships. To navigate using symbolic description in real environment, other information is needed. A robot extracts navigable space and direction with kinect sensor, and recognizes memorized landmarks with a camera to localize itself in semantic map, and infers line of moving direction(LoMD) to

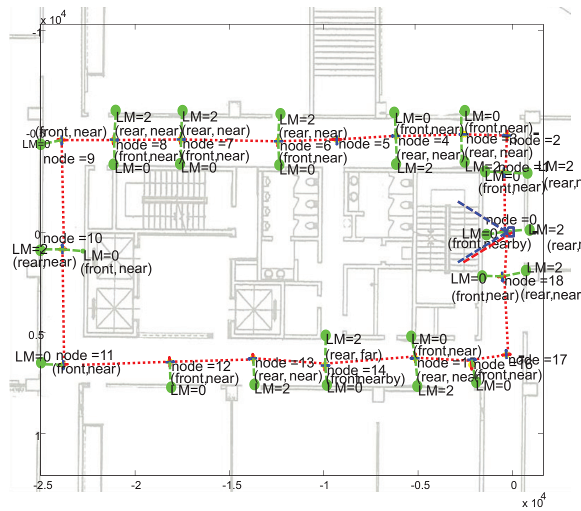


Fig. 8. Final TSM map for a corridor.

move next sub-goal in semantic map. Probabilistic methodologies offer possible solutions to the incompleteness and uncertainty problems encountered when programming a robot. We designed probabilistic model for semantic navigation as stated above in section III. A robot finds obstacle on its left front, and line of moving direction on its front in Fig. 9 (a). In this situation, the width of navigable space is less than $\alpha = 60$, and $p([Act = Avoidance]|Ns, \pi-_{LocalNavi})$ is more than $p([Act = FollowLoMD]|Ns, \pi-_{LocalNavi})$. So, we can choose $Act = Avoidance$. Distribution of $p(Vel|Lomd, \pi-_{FollowsLoMD})$ is shown Fig.9 (d). The result of combination $p(Vel|Lomd, Ns, Nd, \pi-_{LocalNavi})$ is shown in Fig.9 (f). According to our proposed method, a robot turn right to avoid obstacle. Because obstacle is on its front, Vel about rotation will be going up. Transition speed simply increases in proportion to Ns for experi-

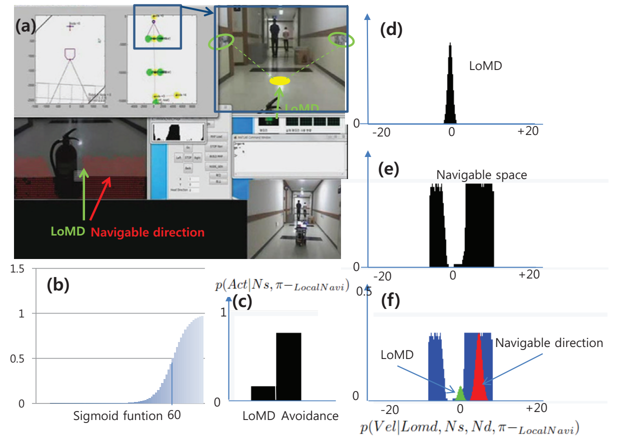


Fig. 9. Local navigation behaviour(Avoidance). A robot finds object on its left front, and line of moving direction in on its front. (b)sigmoid function for command variable. α =60, β=0.25. (c)the knowledge of the command variable Act. (d) Distribution shows the knowledge on Vel given by the LoMD using semantic map. (e) is N_s given by kinect. (f) The result of combination. In this situation, robot will turn right to avoid obstacle.

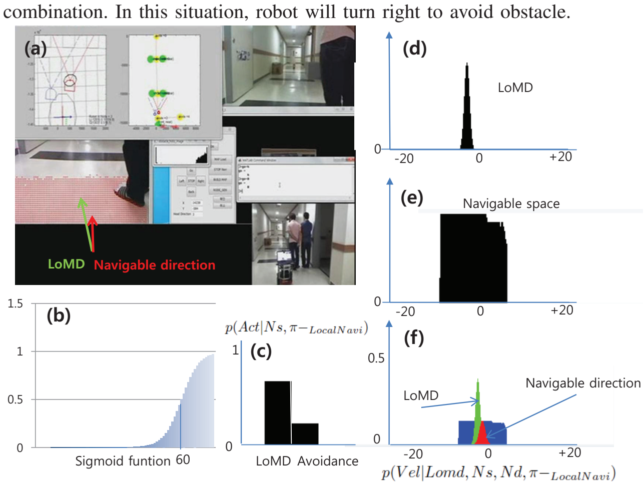


Fig. 10. Local navigation behaviour(Follow LoMD). A robot can go straight following LoMD. In this situation, robot will keep going following LoMD.

ment. Another result are shown in Fig.10. In this situation, the width of navigable space is more than $\alpha = 60$, and $p([Act = Avoidance]|Ns, \pi-_{LocalNavi})$ is less than $p([Act = FollowLoMD]|Ns, \pi-_{LocalNavi})$. So, we can choose $Act = FollowsLoMD$. In this situation, a robot will keep going following LoMD. We conduct a simple test to determine whether the mobile robot could navigate from a starting point to goal node. After a few tries, we verified that the mobile robot could navigate successfully with a semantic map and human-like semantic navigation strategies. The mobile robot could travel from its current position to anywhere using just simple visual perception like human.

V. Conclusion

In this paper, we proposed probabilistic model for TSM mapping and semantic navigation by using Bayesian approach. Although the accuracy of localization is relatively low in metric manner, a robot can build TSM map and easily localize itself by reasoning action. Additionally, the semantic map can be one of world model by which robots can infer knowledge. In order to navigate using symbolic description, we proposed the human-like semantic navigation. For the proposed method, we design the probabilistic model with information of navigable space, semantic knowledge, action commend. We verified the proposed method through experiment.

VI. Acknowledge

This work was supported by the Industrial Strategic Technology Development Program (10044009) funded by the Ministry of Knowledge Economy(MKE, Korea)"

References

[1] R. Siegwart and I. Nourbakhsh, *Introduction to autonomous mobile robots*. The MIT Press, 2004.

[2] J. Meyer and D. Filliat, "Map-based navigation in mobile robots:: Ii. a review of map-learning and path-planning strategies," *Cognitive Systems Research*, vol. 4, no. 4, pp. 283–317, 2003.

[3] L. E. Kavraki, P. Svestka, J.-C. Latombe, and M. H. Overmars, "Probabilistic roadmaps for path planning in high-dimensional configuration spaces," *IEEE Transactions on Robotics and Automation*, vol. 12, no. 4, pp. 566–580, 1996.

[4] C. Yi, I. Suh, G. Lim, S. Jeong, and B.-U. Choi, "Cognitive representation and bayeisan model of spatial object contexts for robot localization," *Advances in Neuro-Information Processing*, pp. 747–754, 2009.

[5] R. Wang and E. Spelke, "Human spatial representation: Insights from animals," *Trends in cognitive sciences*, vol. 6, no. 9, pp. 376–382, 2002.

[6] J. Leonard and H. Durrant-Whyte, "Mobile robot localization by tracking geometric beacons," *IEEE Transactions on Robotics and Automation*, vol. 7, no. 3, pp. 376–382, 1991.

[7] P. Bessière, C. Laugier, and R. Siegwart, *Probabilistic reasoning and decision making in sensory motor systems*. Springer Verlag, 2008, vol. 46.

[8] D. Fox, W. Burgard, and S. Thrun, "Active markov localization for mobile robots," *Robotics and Autonomous Systems*, vol. 25, no. 3, pp. 195–207, 1998.

[9] C. Yi, I. H. Suh, G. H. Lim, and B.-U. Choi, "Active-semantic localization with a single consumer-grade camera," in *IEEE International Conference on Systems, Man and Cybernetics*, 2009, pp. 2161–2166.

[10] C. Yi, I. H. Suh, G. H. Lim, and B. U. Choi, "Bayesian robot localization using spatial object contexts," in *IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2009, pp. 3467–3473.

[11] J.-L. Blanco, J.-A. Fernández-Madrigal, and J. Gonzalez, "Toward a unified bayesian approach to hybrid metric–topological slam," *IEEE Transactions on Robotics*, vol. 24, no. 2, pp. 259–270, 2008.

[12] S. Šegvić, A. Remazeilles, A. Diosi, and F. Chaumette, "A mapping and localization framework for scalable appearance-based navigation," *Computer Vision and Image Understanding*, vol. 113, no. 2, pp. 172–187, 2009.

[13] O. Lebeltel, P. Bessière, J. Diard, and E. Mazer, "Bayesian robot programming," *Autonomous Robots*, vol. 16, no. 1, pp. 49–79, 2004.

[14] O. Khatib, "Real-time obstacle avoidance for manipulators and mobile robots," *The international journal of robotics research*, vol. 5, no. 1, pp. 90–98, 1986.

[15] D. Holz, S. Holzer, R. Rusu, and S. Behnke, "Real-time plane segmentation using rgb-d cameras," in *Proc. of the 15th RoboCup International Symposium*, 2011.

[16] H. Bay, A. Ess, T. Tuytelaars, and L. Van Gool, "Speeded-up robust features (surf)," *Computer Vision and Image Understanding*, vol. 110, no. 3, pp. 346–359, 2008.

[17] G. H. Lim and I. H. Suh, "Robust robot knowledge instantiation for intelligent service robots," *Intelligent Service Robotics*, vol. 3, no. 2, pp. 115–123, 2010.

[18] A. Costa, G. Kantor, and H. Choset, "Bearing-only landmark initialization with unknown data association," in *IEEE International Conference Robotics and Automation, Proceedings*, vol. 2, 2004, pp. 1764–1770.