

Topological Indoor Localization and Navigation for Autonomous Mobile Robot

Hongtai Cheng, *Member, IEEE*, Heping Chen, *Senior Member, IEEE*, and Yong Liu, *Senior Member, IEEE*

Abstract—Mobile robot typically has limited on-board resources and may be applied in different indoor environment. Thus, it is necessary that they can learn a map and navigate themselves autonomously with lightweight algorithms. A novel topological map-building-based localization and navigation method is proposed in this paper. Based on the depth curve provided by a 3D sensor, a progressive Bayesian classifier is developed to realize direct corridor type identification. Instead of extracting features from single observation, information from multi-observations are fused to achieve a more robust performance. A topological map generation and loop closing method are proposed to build the environment map through autonomous exploration. Based on the derived map and the Markov localization method, the robot can then localize itself and navigate freely in the indoor environment. Experiments are performed on a recently built mobile robot system, and the results verify the effectiveness of the proposed methodology.

Note to Practitioners—Experiments were performed using a real mobile robot system in a typical indoor environment. The results show that noise can be eliminated using the proposed methods and the corridor type can be identified efficiently and robustly. Based on the generated topological map, the robot can localize and navigate itself autonomously. Therefore, such a mobile robot can be applied to the hazard industrial environments like offshore oil platform replacing human workers. Instead of utilizing huge image data, the method is based on simple depth curve and thus requires very low memory and computational resources. Furthermore, because the localization and navigation are based on pure topological representation, the developed techniques are compatible with human knowledge and can be directly implemented in the industrial application to realize man-machine collaboration.

Index Terms—Autonomous mobile robot, localization and navigation, progressive Bayesian classifier, Markov localization.

Manuscript received August 11, 2013; revised December 30, 2013; accepted June 14, 2014. This paper was recommended for publication by Associate Editor V. Isler and Editor A. Bicchi upon evaluation of the reviewers' comments. This work was supported in part by the Research Enhance Program (REP) under Grant 9000000936, Texas State University, San Marcos, in part by the Startup Research Fund under Grant 02090021233043, in part by Northeastern University, China, in part by the National Natural Science Foundation of China under Grant 61175082, and in part by Jiangsu Prospective Joint Research Project under Grant BY2013046.

H. Cheng is with the Department of Mechanical Engineering and Automation, Northeastern University, Shenyang, Liaoning Province, 110819 China (e-mail: chenght@me.neu.edu.cn).

H. Chen is with the Ingram School of Engineering, Texas State University-San Marcos, San Marcos, TX 78666 USA (e-mail: hc15@txstate.edu).

Y. Liu is with the Department of Computer Science and Technology, Nanjing University of Science and Technology, Nanjing, Jiangsu Province 210094, China e-mail: liuy1602@njust.edu.cn.

Digital Object Identifier 10.1109/TASE.2014.2351814

I. INTRODUCTION

DIFFERENT from the industrial robots, mobile robots can move around to different locations and interact with the large scale environment. Meanwhile, they can also be equipped with different sensors, tools or manipulators (even industrial robot, named industrial mobile manipulator) to afford various tasks like supervising, exploring, manipulating, etc. Therefore, the mobile robot can be applied to a variety of scenarios like industrial, military, and home care.

An autonomous mobile robot should be able to acquire the following information, the current position/where is the robot (Localization) and the destination/where to go (task assignment) and the guidance/how to go (Navigation) [1], [2]. In this paper, we will focus on the problem of localization and navigation in the typical indoor environment. Different from the outdoor environments where robots such as Google's Autonomous Car can localize itself by GPS and navigate itself using the huge available information like maps and vertices, in the indoor environments, the robot has to learn how to localize and navigate itself without prior information. Indoor environments like office or residential buildings generally consist of many rooms which are connected by corridors. To go across the corridors and find the target places, the robot has to obtain a map or guide information from the environment [3], [4]. The maps can be classified into three types: obstacle-based grid maps, feature-based metric maps, and topological maps [5]–[9], which can be generated by human beings or robot itself with vision or related sensors.

As a highly abstracted knowledge expression form, compared to the other maps, the topological map is simple, effective, and compatible with human knowledge. A topological map is a graph-based representation of the environment. Each node corresponds to a characteristic feature or zone of the environment, and can be associated with an action, such as turning, crossing a door, stopping, or going straight ahead. This kind of map is suitable for long distance qualitative navigation, and specially for path planning. In general, they do not explicitly represent free space so that obstacles must be detected and avoided online by other means. Topological maps are simple and compact, take up less computer memory, and consequently speed up computational navigation processes.

As mentioned in [5], arguably, the most efficient map among the three is the topological map. However, it is difficult for a robot to build a topological map autonomously without human assistance. Usually, a topological map is generated by transforming from other maps, like grid maps [7] and metric maps.

The recently developed Simultaneous Localization And Mapping (SLAM) technique is a technique for building a metric map of an unknown environment (without a prior knowledge), or updating a map of a known environment (with a prior knowledge from a given map) [3], [4], [10]–[12]. Although the generated color point cloud maps are effective in path planning and robot navigation, they are difficult to integrate with human knowledge and occupy huge resources.

The problem of direct topological map-building-based indoor navigation has been studied by many researchers. Their approaches differ from how to express and identify nodes/landmarks.

a) Expressing nodes as junctions and learning nodes from image features [13]–[19].

NEURO-NAV [13] is an example of topological map-building-based navigation algorithm. The environment is expressed as lines and nodes which represent the hallways and the corresponding landmarks around them. Artificial neural networks (ANNs) are utilized to follow the hallways and detect the landmarks (like doors, corners, walls, edges). With this information, the robot is able to identify the front junction type and make navigation decisions. This algorithm is also improved to FUZZY-NAV [14] using fuzzy functions to deal with blurred variables. However, this method is based on the complex image transformation and feature detection which could limit the system efficiency and the corresponding ANNs or Fuzzy rules have to be predefined or trained which requires a lot of human effort. The algorithm was not tested using different kinds of junction types.

b) Expressing nodes as images/histograms/views and learning nodes by matching the online image with the pre-obtained images [20]–[24].

Winters and Gaspar [25] used an omnidirectional camera to create a topological map from the environment during a training phase. They treated nodes as images of characteristic places and links as sequences of various consecutive images between two nodes. When the robot moves around, the position is determined by matching the online image with previously recorded images. However, this method is not able to provide accurate information of landmark positions for path transversal. Kosecka [21] proposed a different way to classify the landmarks such as hallway intersections, corners, and doorways. During the exploration process, environmental videos are recorded and converted into histograms frame by frame. They treated the nodes as the gradient orientation histogram and during the navigation phase, the gradient orientation histogram of each frame is compared with the view prototypes to determine the location it most likely comes from using the nearest neighbor classification. However, although the histogram feature classifier is effective and a 95.4% succeed rate is achieved, there is still room for improvement and there is no determined rule for choosing the feature parameters of the gradient orientation histogram.

Remazeilles *et al.* [22] propose a topological environment representation and a qualitative positioning strategy. Nodes are represented by views captured in a training phase and edges represent the possibility of moving from one scene towards another. The robot navigates itself by tracking landmarks over consecutive frames and keeping them inside the field of view. The lo-

calization strategy used in this approach is qualitative since it informs that the robot is in the vicinity of a node, instead of giving exact world coordinates. However, although it is not a model-based algorithm, human assistant information is not removed because a set of images describing the environment have to be acquired during an offline step.

Although the aforementioned methods can realize topological navigation or map-building-based navigation, human efforts have to be integrated to define the node model and generate the topological maps, which limits the flexibility of the mobile robots. Furthermore, the utilized monocular vision system cannot provide the required depth information efficiently which is important for the robot navigation task.

Various technologies can be used to build the 3D scanning devices, like time-of-flight, triangulation, and structured lighting, etc. These devices have been utilized in the robot localization and navigation research, from mapping [3], [4], [26], landmark detection [27], [28] to navigation [29]–[31]. However, to our knowledge, the 3D information-based topological localization and navigation are not discussed. In this paper, we propose a corridor type identification method which can help to realize human-like map-less navigation, direct topological map generation and map-based topological localization and navigation. The human effort is eliminated from the methodology and the robot can accomplish the localization and navigation task autonomously.

System structure is shown in Fig. 1. The key for realizing topological indoor localization and navigation is to identify the heading corridor. With this ability, the mobile robot can navigate itself freely inside the indoor environment and learn the map by itself like what a human does when he goes into an unknown building. In this framework, we treat nodes as the vertices like intersections and treat links as the corridors connecting the vertices. The map building functionality is divided into two sub-tasks, topological map generation and landmark detection. The first task aims to build the skeleton of the topological map and the later task aims to add interesting places into the skeleton. With these abilities, a topological map containing rich information can be obtained. Considering the fact that landmark detection is a standalone process and has been investigated by many researchers [32], in this paper, only the topological map generation task is presented.

II. PROBLEM FORMULATION

A. Corridor Types Encoding

Without considering irregular buildings, common corridors can be classified into eight types, as shown in Fig. 2.

The difference between various corridor types lies in whether there exists an outlet in the left, front, and right side of the corridor. If we denote the case without outlet as “0” and case with outlet as “1,” the corridor types can be encoded from “000” to “111” which can also be denoted as Y_0 to Y_7 .

B. Progressive Bayesian Classifier

The corridor classification problem is solved while the mobile robot is moving along the corridors. Because it takes some time for the robot to pass through each corridor and during that

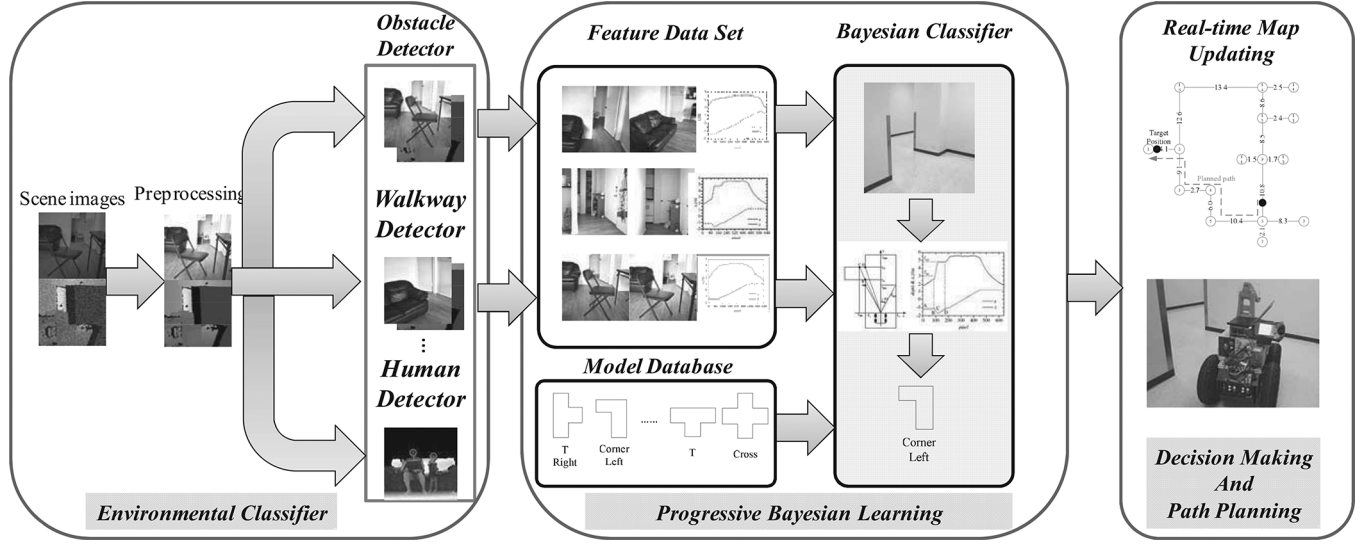


Fig. 1. Diagram of topological indoor localization and navigation for autonomous intelligent industrial manipulator.

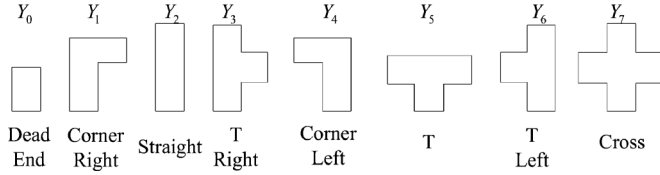


Fig. 2. Types of corridors.

TABLE I
RELATION BETWEEN N CLASSES OF OBJECTS AND M FEATURES

	Y_1	Y_2	\dots	Y_N
F_1	1	0	\dots	0
F_2	0	1	\dots	1
\dots	\dots	\dots	\dots	\dots
F_M	1	0	\dots	1

time the robot can make many observations from different views and distances, the classification process can be performed relatively slowly and gradually to avoid getting wrong results. The following algorithm is proposed to fuse the multi-observations.

1) *Classification Problem Formulation*: The following classification problem is formulated. Objects to be classified belong to N classes $Y_0 \dots Y_{(N-1)}$ and there are totally M features $F_1 \dots F_M$ which can be used to characterize these N classes. Each feature has the value 0 or 1 which refers to the existence of the corresponding feature (as shown in Table I). Thus, the feature vector $X = [F_1 \dots F_M]^T$ can be used to classify the objects. Ideally, $N = 2^M$ and each feature vector relates to a specific class. If $N < 2^M$, we can define the virtual classes to ensure each feature vector belong to a specified class or reselect features to make $N = 2^M$. It is easy to conclude that the aforementioned corridor classification problem has $M = 3$ and $N = 8$.

If a feature vector can be extracted in a single observation, we can easily determine its class. However, due to observation limitation and environment uncertainty, it is possible that not all features can be extracted in a single observation with high confidence, thus it is not reliable to use the incomplete or complete

TABLE II
INCOMPLETE OBSERVATIONS WITH FEATURE VALUE -1

Observations	F_1	F_2	\dots	F_M
X_1	-1	0	\dots	0
X_2	0	1	\dots	-1
\dots	\dots	\dots	\dots	\dots
X_k	1	-1	\dots	1

but low-confidence feature vectors to make decisions because the feature extraction errors can directly propagate to the classifier. This imposes high requirements for the design of the feature extractor.

An alternative solution is to learn the corridor type from a series of different observations instead of a single observation and extract high confidence features instead of all features. The observed low confidence features are filled with -1 which means this feature cannot be detected with full confidence. Consequently, the number of the possible feature vectors is 3^M since there are three possible values $\{-1, 0, 1\}$ for each feature, as shown in Table II.

2) *Progressive Bayesian Classifier*: Suppose there are k observations X_1, X_2, \dots, X_k , posterior probability of class Y_i can be obtained by

$$P(Y_i | X_1, \dots, X_k) = \frac{P(X_1, X_2, \dots, X_k | Y_i) P(Y_i)}{\sum_{j=1}^N P(X_1, X_2, \dots, X_k | Y_j) P(Y_j)} \quad (1)$$

With the assumption that each observation is independent, one gets

$$P(Y_i | X_1, \dots, X_k) = \frac{P(Y_i) \prod_{l=1}^k P(X_l | Y_i)}{\sum_{j=1}^N \left[P(Y_j) \prod_{l=1}^k P(X_l | Y_j) \right]} \quad (2)$$

Equation (2) can be used to classify the corridor types based on the observations if the prior probability $P(Y_j)$ and the conditional probability $P(X_l | Y_j)$ are known. The usual way of deriving these parameters is to train the classifier (such as naive

Bayesian Classifier) using labeled observation data sets. Although such training process can generate more reliable parameters, obtaining the data sets requires additional human effort and reduces the mobile robots' autonomy.

To greatly increase the power of autonomous mobile robots, a set of predefined parameters are used according to our daily experience. Assuming probability of dead end is q , while other corridors are $2q$, one gets $q = 1/15$. Therefore, probability of the dead end corridor $P(Y_0)$ is set to be $1/15$, while others are set to be $2/15$. Based on the fact the probability of observing no feature or all features are lower than other situations, we assume such two cases have the probability of p and others have the probability of $2p$. There is

$$p = \frac{1}{2^{M+1} - 2}. \quad (3)$$

The conditional probabilities are calculated using

$$P(X_i|Y_j) = \begin{cases} \frac{1}{2^{M+1}-2}, & (\text{fully unconfident}) \quad 1 \\ \frac{1}{2^M-1}, & (\text{partly confident}) \quad 2^M - 2 \\ \frac{1}{2^{M+1}-2}, & (\text{fully confident}) \quad 1 \\ 0, & (X_i, Y_j \text{ conflicted}) \quad 3^M - 2^M \end{cases} \quad (4)$$

The observed feature vectors are buffered first and fused until a higher confidence level is reached. This framework can ensure the correctness of the classification but requires a lot of observations before obtaining a result. However, as aforementioned, for the corridor type classification problem, the drawback is overcome because the robot motion is relatively slower than the observing and processing units.

III. CORRIDOR TYPE IDENTIFICATION

A. Sensor Input and Preprocessing

Considering the similar textures and varying lightening conditions in the indoor environment, it is better to use depth information to recognize the corridor types. Different techniques can be utilized to obtain the depth image and further transform the depth image into a 3D point cloud. For example, the depth image provide by Kinect [33], [34] can be transformed into the camera coordinates (x, y, z) with the following equation:

$$\begin{cases} x = d(p_x - c_x)/f_x \\ y = d(p_y - c_y)/f_y \\ z = d \end{cases} \quad (5)$$

where d is the depth along the Z axis of the camera coordinate frame, f_x and f_y are the equivalent focal lengths and (c_x, c_y) are the optical center coordinates. After conversion, the depth image is converted to a 3D point cloud. Although for problems such as obstacle avoidance, it is important to use the whole point set, for the corridor classification problem, since the difference between each rows is small, it is enough to extracted features from one depth curve which can also decrease the system complexity.

B. Corridor Classification

1) *Corridor Outlet Modeling*: A simple depth curve contains rich information about width of the corridor, width of the outlet,

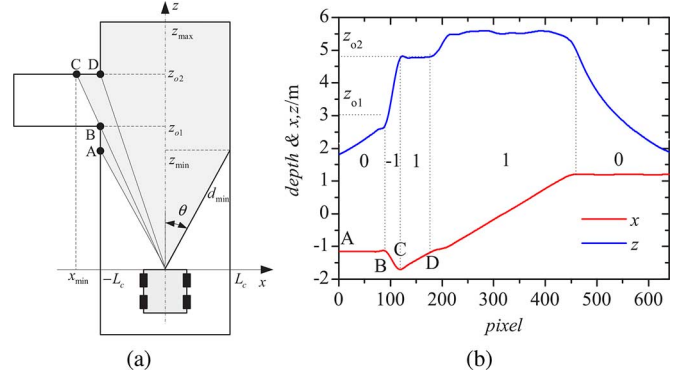


Fig. 3. (a) Geometrical model of corridor. The area with gray color refers to the area that is visible to the robot. (b) Projection of depth curve to the X and Z axis. The critical points A, B, C, and D in (a) can be matched with points in (b). Therefore, the width of the outlet and the distance of the turning position can be calculated.

and outlet positions. Fig. 3(a) is the figure showing a mobile robot placed in a corridor with an outlet on the left side.

If the smallest measured distance is obtained, which is usually d_{\min} on the left or right side, the width of current corridor is $2L_c$ can be calculated by

$$L_c = d_{\min} \sin(\theta) \quad (6)$$

where θ is half the view angle of the depth sensor (for Kinect $\theta = \pi/6$). If there is no outlet on the left side, the minimum X coordinate will be $-L_c$; otherwise there exists a span [corresponding to the spans B, C, and D in Figs. 3(a) and (b)] with lower values. The Z coordinates $z_{o1} < z_{o2}$ of such span can be calculated from depth curve, respectively, as shown in Fig. 3(b). Consequently, width W_o and depth D_o of the outlet can be obtained by

$$\begin{aligned} W_o &= z_{o2} - z_{o1} \\ D_o &= -L_c - x_{\min}. \end{aligned} \quad (7)$$

2) *Depth Curve Segmentation*: The variables z_{o2}, z_{o1}, L_c and x_{\min} are all related to points A, B, C, and D shown in both Fig. 3(a) and (b). From Fig. 3(b), we can find that the segments AB, BC, and CD have zero, negative, and positive slopes, respectively. After segmentation, the continuous depth curve is segmented into spans with discrete slope values $(-1, 0, 1)$.

3) *Feature Extractor*: From the above discussion, it is known that three adjacent spans with $(0, -1, 1)$ slopes indicate there is an outlet [as the case shown in Fig. 3(b)]. However, not all real depth curves are as ideal as Fig. 3(b). Due to sensor noises, irregular surface or obstacles, the segmentation contains fake information. For example, a small opened door or a hollow wall can lead to an outlet-like pattern. To overcome these disturbances, only the following four features are considered:

- If there is no side outlet, the front corridor can be seen as an outlet if the distance D_f between the camera and the front wall meets $D_f > \omega_f^{L1}$ or cannot be seen as an outlet if $D_f < \omega_f^{L1}$. Otherwise, it cannot be determined with high confidence. ($\omega_f^{L1}, \omega_f^{H1}$ are the corresponding thresholds).
- Wide enough pattern $(0, -1, 1)$ is a left outlet (ω_l^L, ω_l^H are the corresponding thresholds).

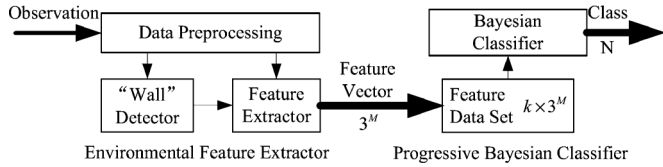


Fig. 4. Diagram of the environmental feature extractor and progressive Bayesian classifier.

- Wide enough pattern $(1, -1, 0)$ is a right outlet (ω_r^L, ω_r^H are the corresponding thresholds).
- If the front wall is farther than left or right outlet, the front corridor can be seen as an outlet ($\omega_f^{L2}, \omega_f^{H2}$ are the corresponding thresholds).

If the existence of the outlet can be determined confidently, the feature will be set to 1 if there is an outlet and 0 if there is no outlet; otherwise, the feature is set to -1 indicating the feature cannot be confidently observed. Such representation exactly meets the requirements of the progressive Bayesian classifier proposed in Section II which can be used to identify the true corridor type with incomplete observations. The structure of the progressive Bayesian classifier is shown in Fig. 4.

When the mobile robot moves along the corridor, it receives multi-observations and progressively obtains the final classification results.

Remark 1: The features used for corridor classification are derived based on the geometric model shown in Fig. 3(a). These features highly dependent on the corridor assumptions shown in Fig. 2 and the robot-corridor orientation. In this paper, instead of using the orientation to compensate the depth measurement, an alternative robot controller is utilized to ensure the robot moves along the central line between the side walls. During the reposition phase (such as the turning and obstacle avoiding phase), the corridor classification process is suspended to prevent the wrong observation.

IV. AUTONOMOUS LOCALIZATION AND NAVIGATION

In the previous section, the corridor type identification problem is discussed. With the proposed weak feature extractor and progressive Bayesian classifier, the mobile robot can determine types of the upcoming corridors when moving in the indoor environment. With this ability, the robot can perform autonomous navigation if it is told the turning direction at each corridor, like what our human beings do in our daily life. However, if there is no map or such assistant information, the robot will get lost. To avoid this, human knowledge has to be integrated into the robot system which is time and effort consuming. In this paper, we propose to let the robot learn the human compatible topological map autonomously based on the aforementioned ability.

A. Autonomous Environmental Exploration

Since the indoor environment is consisted of different rooms and connected by different corridors, it can be abstracted into a topological map containing vertices/nodes (rooms, intersections) and edges/branches (corridors). Such abstraction is compatible with human knowledge and can be easily integrated with

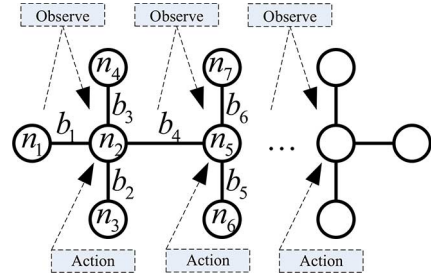


Fig. 5. Generating topological map directly from the identified corridors. The circles refer to the nodes and lines refer the branches. By iteratively receiving observations and moving in random directions, the map can be generated autonomously. As aforementioned, there are eight types of observations. For each node, there are as much as three moving directions: turning left, moving ahead, and turning right.

human guide information such as the turning direction or the target location. Compared to other map-based localization and navigation methods, it is not necessary to integrate precise guide information such as “Turn Left at 3.5 m” or “The target is located at $(x, y) = (4.8, 3.6)$.” Furthermore, the ability of directly identifying the corridor type can greatly decrease the difficulty of constructing such a topological map.

As shown in Fig. 5, the initial position can be seen as node n_1 . When the robot moves ahead and identifies a new corridor type, the current branch b_1 , a new node n_2 , the corresponding branches b_2, b_3, b_4 and the connecting nodes n_3, n_4, n_5 are added into the map. The connecting nodes are not observed directly, thus the underlying topological information is unknown. The robot has to choose a moving direction to explore the unknown region and repeat the previous steps.

According to the previous assumption, for each node, there are at most four connected branches and from different point-of-views, different corridor type can be observed. The straight corridor (type:Y2) is an exception. Because straight corridors are with no outlets, going forward is the only available action. They are actually pure branches with no junctions or nodes. Therefore, in the topological navigation and mapping process, straight corridor is not considered as a node and is not used in the map generation process. The robot needs to explore the environment to find all the nodes and branches. With such a procedure, an acyclic graph (tree) is constructed. However, not all the indoor environments can be described as an acyclic graph and there are possibly different paths connecting two rooms. Thus, a cyclic graph and the loop closing problem have to be considered.

B. Loop Closing Problem

To build a cyclic map, the loop closing problem, which is a task of determining whether the currently observed node is a previously visited node, or a new portion of the world being explored, has to be solved.

Assuming that in the existing topological map, there are n branches b_1, \dots, b_n and m nodes n_1, \dots, n_m . Since there are two directions in the n branches, there are $2n$ possible locations which are denoted by

$$s_{ij} = (b_i, n_j), i \in 1 \dots n, j \in 1 \dots m \quad (8)$$

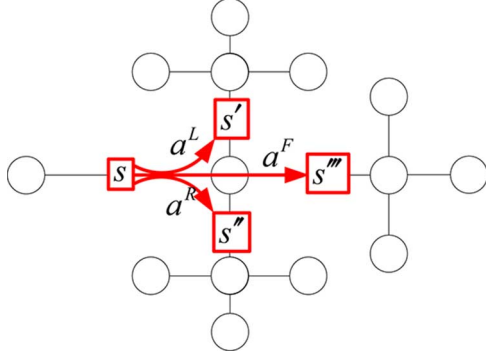


Fig. 6. State transition process in the explored topological map. For each state, there are at most three possible actions according to the type of the heading node. Different actions lead to different states.

where b_i specifies the location and n_j specifies the heading direction. When the robot moves towards the unknown environment, it randomly selects a moving direction and receives observations. Denoting the initial position as n_0 , there is

$$n_0 \xrightarrow{a_1} n_1^* \xrightarrow{a_2} n_2^* \cdots \xrightarrow{a_k} n_k^* \quad (9)$$

where a_k is the k_{th} moving direction, o_k is the k_{th} observed corridor types and n_k^* is the temporarily founded node after k steps. The loop closing problem is to determine whether n_1^* is a known node. To describe the probability of each states, a belief state is introduced

$$\begin{aligned} \text{Bel}(s_{ijk}) &= P[s_{ij} | (a_1 \dots a_k), (o_1 \dots o_k)] \\ &= \frac{P[(a_1 \dots a_k), (o_1 \dots o_k) | s_{ij}] P(s_{ij})}{\sum_{r,t=1,1}^{n,m} P[(a_1 \dots a_k), (o_1 \dots o_k) | s_{rt}] P(s_{rt})} \end{aligned} \quad (10)$$

The Belief state is the posterior probability of $s_{ij} = n_1^*$ when performing k actions and observations. For the explored maps, there is a transition function $T(S, A) : S \times A \rightarrow S$, where S is the state set and A is the action set. The transition function maps the current state s and the current action a to the upcoming state s' , as shown in Fig. 6. For the current state s , according to the type of the heading node, there are at most three possible actions: turning left a^L , going ahead a^F and turning right a^R . After executing these actions, the robot moves from the current state s to different states. Substituting the state transition function, we have

$$\begin{aligned} P[(a_1 \dots a_k), (o_1 \dots o_k) | s_{ij}] \\ = \prod_{l=0}^{k-1} [P(o_{l+1} | T^l(s_{ij}, a_{l+1}))] \end{aligned} \quad (11)$$

where $P(o_l | s_{ij})$ is the probability of observing o_l at state s_{ij} . According to the definition of the corridor types: Y0–Y7, there is a deterministic relation between the observation o and the topological connection of b_i and n_j . Hence, we are able to calculate the observation probability $P(o_l | s_{ij})$ in the existing topological map.

Substituting (11) into the (10) and assuming prior probability for each state is equal, one gets

$$\text{Bel}[s_{ijk}] = \frac{\prod_{l=0}^{k-1} [P(o_{l+1} | T^l(s_{ij}, a_{l+1}))] P(s_{ij})}{\sum_{r,t=1,1}^{n,m} \prod_{l=0}^{k-1} [P(o_{l+1} | T^l(s_{rt}, a_{l+1}))] P(s_{rt})} \quad (12)$$

In the map generation process, when the robot observes a new node, it will traverse all the nodes and branches in the existing map and calculate belief $\text{Bel}(s_{ij0})$ for each state. Once the belief $\text{Bel}(s_{ij0}) \neq 0$ for some states, further observation will be needed to update the belief $\text{Bel}(s_{ijk})$ until the belief $\text{Bel}(s_{ijk}) = 0$ for all states or there is $\text{Bel}(s_{ijk}) = 1$, where $k \geq 4$ for a state. Fig. 7 shows a loop closing process. The belief state is updated at each step. b_k refers to the maximum belief in each step. After repeating several times, the belief will converge to one state. $\text{Bel}(s_{ijk}) = 1$ means that n_j is same as node as n_1^* , and $\text{Bel}(s_{ijk}) = 0 | \forall i, j$ means n_1^* is a new node which should be added to the topological map.

Remark 2: As previously mentioned, in this paper, only the topological map generation process is discussed. The landmark detection is a standalone process which can be easily integrated into this framework. Without these landmarks and other geometric information like corridor lengths, it will be difficult for the loop closing algorithm to distinguish symmetrical environment and environment with nested loops.

These assistance information can be fused into the observation function $P(o|s)$ where o not only refers to the observation of the corridor types, but also refers to landmarks, etc. With this transformation, the loop closing algorithm can deal with a complex environment.

C. Topological Map Generation

Flow chart of the proposed topological map generation algorithm is given in Fig. 8.

The robot starts with a map containing nodes n_1, n_2 and branch b_1 . The initial state is (b_1, n_2) . When the robot receives a new observation, if it is a dead end, it will return to the previous state otherwise the belief state and map are updated. When the loop closing criteria holds, the newly added nodes are removed and the loop is closed. The loop closing criteria used here includes the following two conditions:

- $\text{Bel}(s_{ijk}) = 1$;
- $k \geq 4$.

The second condition comes from the assumption of the corridor types. Although higher k can increase the confidence, it is not necessary because according to the assumption, a loop is consisted with at least four nodes.

After obtaining the topological map, the vertices in the map can be used to localize the robot itself with Markov Localization method [1]. The localization process is the same as the loop closing problem. The robot will update its belief on each possible state when it is moving. The robot will find its location when the belief state equals 1. Once determining its location, the robot can use the map to navigate itself in the environment autonomously.

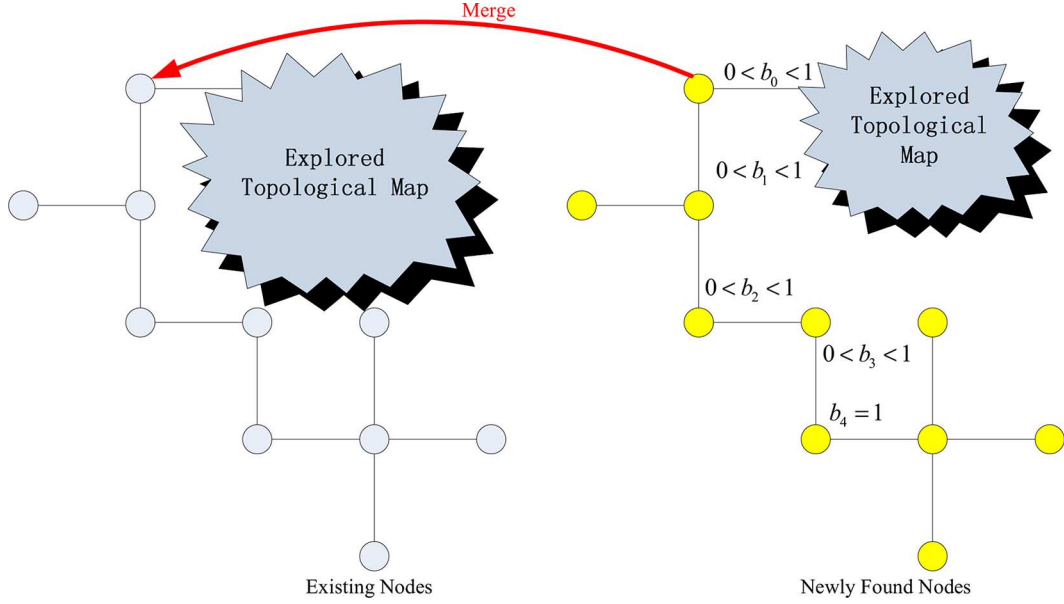
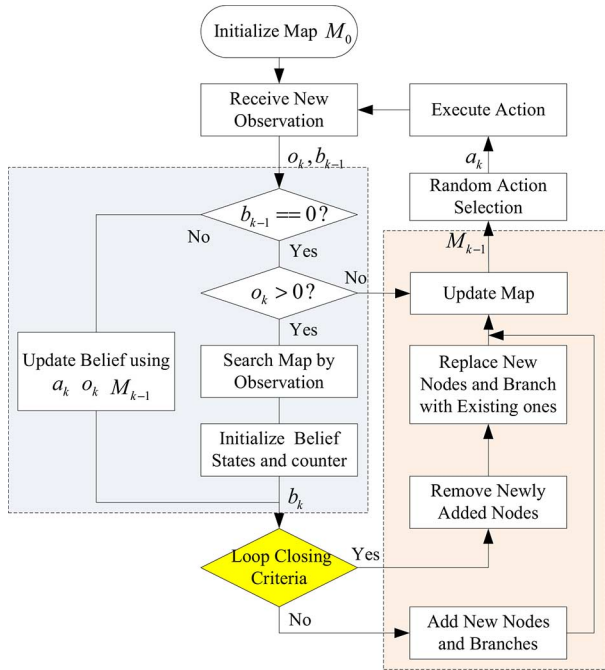


Fig. 7. The belief update process when closing the loops of a topological map.

Fig. 8. Flow chart of the looping closing algorithm. M_k is the generated topological map in each iteration. a_k and o_k are the turning direction and observation in each step and b_k is the maximum belief of each state $s_{i,j}$ in each iteration. The mobile robot updates continuously with more and more observation and closes the loops when loop closing criteria satisfies.

V. EXPERIMENTS AND RESULTS

To verify the effectiveness of the proposed methods for corridor type identification and topological map generation, the progressive Bayesian classifier and topological map generator are implemented using a real mobile robot system which is shown in Fig. 9.

A Segway RMP400 mobile platform is used as the test bed for the topological navigation algorithm and a Microsoft Kinect

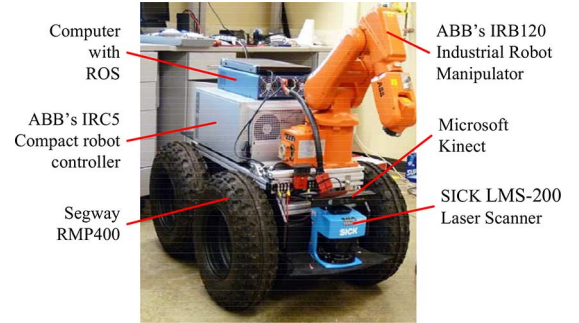


Fig. 9. The autonomous industrial mobile manipulator.

RGB-D sensor is chosen to provide the depth observation. Compared to the expensive omnidirectional cameras or high precision laser scanners, the Kinect is cheap but powerful which can provide both the RGB image and depth image at the resolution of 640×480 . Although the depth measurement is not highly precise, it is enough for the robot navigation application. However, the depth image is noisy and filled with gaps (where depth information cannot be obtained), thus, has to be preprocessed by filling the gaps and smoothing the values. The former task aims to fill the gaps while the later one aims to decrease the effect of noises. In this paper, a linear interpolation and locally weighted scatterplot smoothing (LOWESS) filter are utilized to achieve these two goals.

The robot starts from the robotic laboratory and navigates freely along the corridors. Before releasing the mobile robot, the feature extractor parameters have to be determined first. There are eight parameters: $\omega_f^{L1}, \omega_f^{H1}, \omega_f^{L2}, \omega_f^{H2}$ and $\omega_l^H, \omega_l^L, \omega_r^H, \omega_r^L$. The first four parameters are related with the front wall or front outlet. They are used to determine whether the front outlet is deep enough to hold the mobile robot. If the front wall is too close to the side outlet, it cannot be seen as a front outlet because it is not deep enough. If there is no side outlet and the front wall is too close to the robot, it cannot be

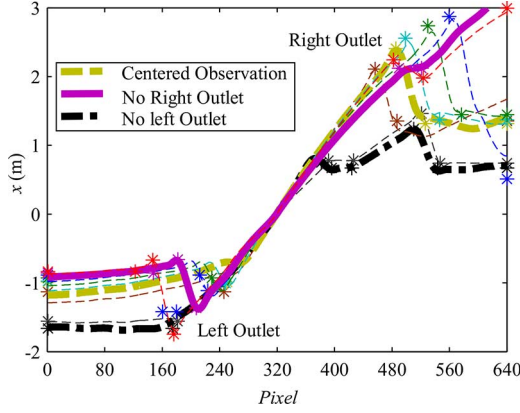


Fig. 10. The x coordinate and segmentation of the observed depth curves where the intersection ahead is a crossroad with both left outlet and right outlet. The curves with thick lines are typical cases of incomplete observations. The green dash curve and black dash dot curve contain no information about the left outlet, while the purple curve contains no information about the right outlet. The * marks are the critical points for each segmentation.

seen as a front outlet because it is a dead end and the robot has no way to go. That is why we choose $\omega_f^{L1} = 2$ m and $\omega_f^{L2} = 1$ m. The other three parameters are chosen accordingly; The second four parameters are related with the side outlet. In the current work, the main issue is to eliminate the effect of the opened doors. Hence, ω_l^H , ω_r^H are chosen to be 1.5 m to avoid recognizing opened doors as outlets because the corridors are mostly 2 m wide. The other three parameters are chosen accordingly.

The feature identification thresholds are $\omega_f^{H1} = 5$ m, $\omega_f^{L1} = 2$ m, $\omega_l^H = 1.5$ m, $\omega_l^L = 0.5$ m, $\omega_r^H = 1.5$ m, $\omega_r^L = 0.5$ m, $\omega_f^{H2} = 3$ m, and $\omega_f^{L2} = 1$ m. During the navigation process, the robot faces different types of corridors. Some of the recorded depth curves which contain less noise is shown in Fig. 14 in Appendix I. As analyzed in Section III-B, the depth curve can be segmented using the x coordinates. It is easy to find that there are horizontal, positive slope and negative slope segments existing in the x curves. The peak reflects the outlet on the right side while the nadir reflects the outlet on the left side. For these ideal observations, the robot is able to classify different corridors directly from a single observation.

However, when the robot moves along the corridors and turns at the intersections, it is difficult to extract features robustly because the observed depth curves contain a lot of noise. Fig. 10 shows a difficult to detect all the features completely from these non-ideal observations. For example, the left outlet and right outlet cannot be detected from the thick black curve and thick purple curve in Fig. 10 due to noise. Therefore, the obtained feature vectors are incomplete.

The progressive Bayesian classifier is implemented to combine these incomplete observations and achieve a robust performance. New observations are progressively added to the existing observation set and the posterior probability of each corridor class is updated. Fig. 11 shows the variation of the maximum probability among the eight classes during one experiment.

The prior probability of the dead end is set to be 1/15, while that of other types is set to be 2/15. Thus, the default maximum

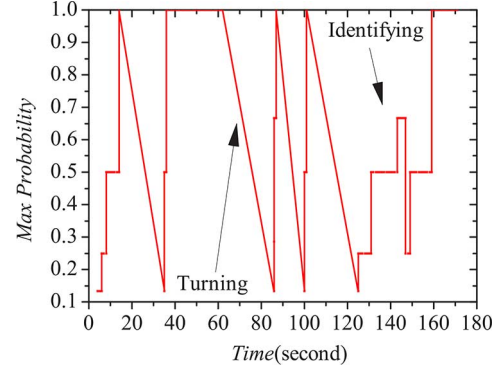


Fig. 11. The maximum posterior probability for the eight corridor classes. After obtaining a new observation, the posterior probability for each corridor class is updated. The classification problem is to find the class with maximum probability. The curve can be divided into continuous identifying stages and turning stages. During the identifying stage, with more and more observations, the posterior probability progressively changes. Once 1 is reached, a corridor is identified and a decision of turning left, right, or moving forward has to be made; During the turning stage, the posterior probability is reset to default value.

posterior probability is 2/15 if no observation is considered. By taking the new observations into account, the maximum posterior probability progressively increases. When the maximum posterior probability reaches 1, the corridor is classified into the corresponding class and the robot should choose to go forward or make a turn. As shown in Fig. 11, the robot starts with a default probability and updates the probability progressively when it moves along the corridor. When this probability reaches 1 and the corridor is identified, the robot turns and the probability is reset to default. For the case of straight road Y_2 , the robot has to move forward, thus the probability remains 1 until new corridors are found.

With the ability of directly identifying the corridor types, the robot is programmed to autonomously explore the environment and randomly traverse through each corridor and generate map of the environment. Fig. 12 gives the generated topological map and results of the looping closing process.

After several explorations, a topological map is generated, as shown in Fig. 12(b). The corresponding belief state is given in Fig. 12(a). It is noticed that before step 15 the loop closing criteria does not hold, thus all the nodes are added into the map. From step 16 and node 17, the belief state continues increase until 1, and finally, the loop closing criteria condition is satisfied. The loop is found and the newly added nodes shown in Fig. 12(c) are removed. The final map is shown in Fig. 12(d).

With the generated topological map, the robot is able to find the path connecting the initial position to the desired destination. The robot starts from node 1 and the target is located between nodes 7 and 10. The planned path is marked red in Fig. 12(d). The maximum motion speed is set to be 0.4 m/s. Fig. 13 shows the recorded images.

It takes about 90 s for the robot to navigate through these corridors and arrive at the target location. The robot successfully identified all the corridors as $Y_5 \rightarrow Y_2 \rightarrow Y_4 \rightarrow Y_1 \rightarrow Y_4 \rightarrow Y_7 \rightarrow Y_2$. The experimental results verify the effectiveness and robustness of the proposed corridor classification, topological map generation, localization and navigation algorithms.

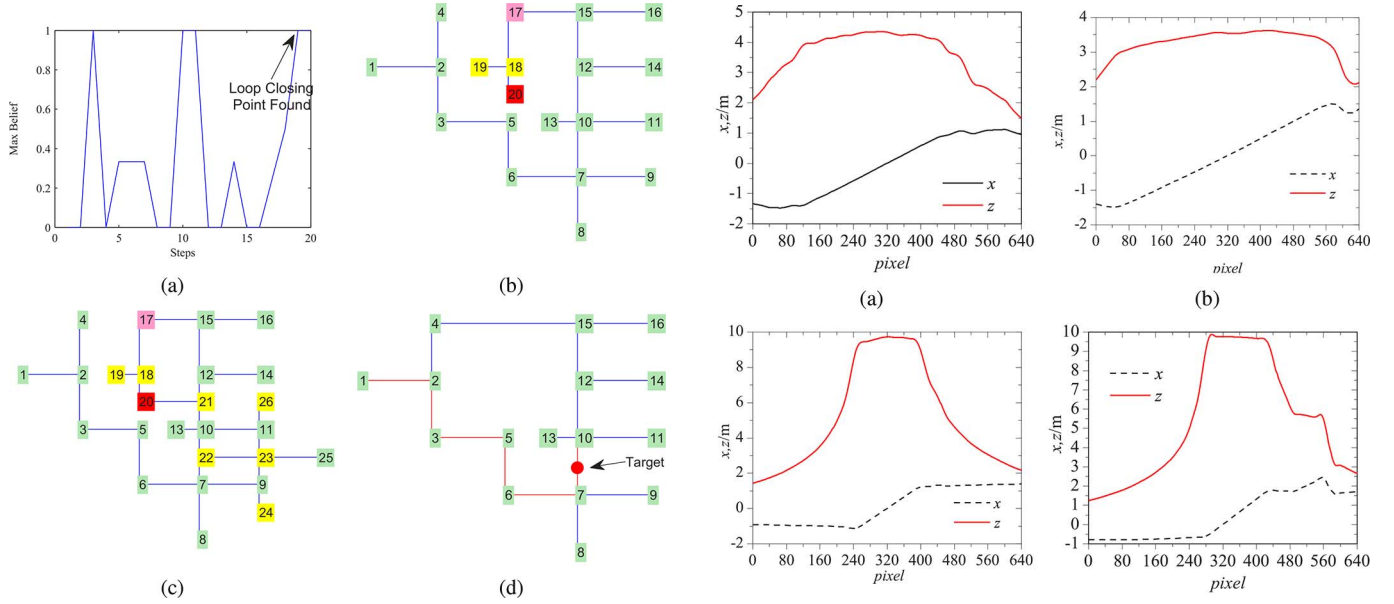


Fig. 12. The topological map generation process. (a) The belief update process, (b) The map before finding the loop closing point. (c) The temporary map when finding the loop closing point. (d) The final loop closed topological map.

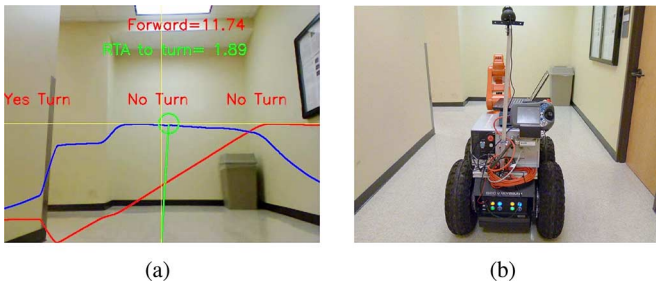


Fig. 13. (a) Snapshot of the on screen displayed image. The blue and red curve are the corresponding z and x depth curves. The upper red text shows the moving distance while the green text shows the distance before making a turn. The identified outlets are also marked on the image. (b) A photo shows the robot is performing a left turn.

VI. CONCLUSION AND FUTURE WORKS

This paper discusses the fundamental autonomous indoor localization and navigation problem for the mobile robots. Instead of generating a topological map indirectly from other maps, a method which treats corridors and their intersections as vertices and branches is proposed to directly generate the topological map and realize map-based localization and navigation. The map generation problem is transformed into a corridor classification problem and solved by the proposed progressive Bayesian classifier. Compared to other map-building-based methods, the proposed method has the following advantages: **Autonomous**—The algorithm requires no prior information and human assistant such as creating samples and training the classifier. The mobile robot can learn the map directly and autonomously. **Compatible with human knowledge**—Human-like guide information can be easily integrated to realize autonomous navigation. **Very low memory and computational requirements**—The corridor classification uses only depth curve and requires as low as 300 KB memory. Therefore, it can be easily integrated into the embedded systems. These properties are important for industrial applications.

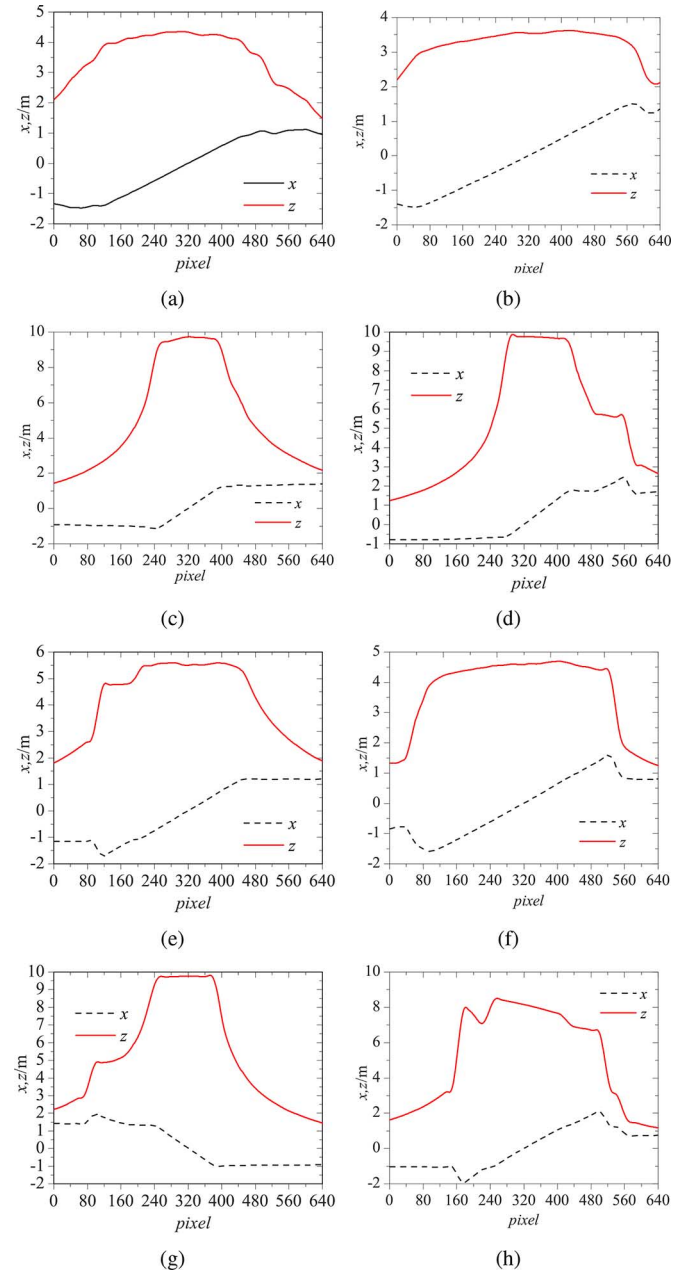


Fig. 14. Typical depth curves for different corridor types. (a) Y_0 : Dead end. (b) Y_1 : Right turn. (c) Y_2 : Straight road. (d) Y_3 : Right and front "T" type road. (e) Y_4 : Left turn. (f) Y_5 : Left and right "T" type road. (g) Y_6 : Left and front "T" type road. (h) Y_7 : Crossroad.

With the proposed techniques, the mobile robots are able to autonomously locate and navigate itself in the indoor environment. In the future, we will integrate the landmark detection into the topological map generation and navigation process to make the algorithm applicable with complex environments.

APPENDIX

Fig. 14 shows the recorded idealized depth curves. All features are clearly enough to determine the corridor types.

REFERENCES

- [1] D. Fox, W. Burgard, and S. Thrun, "Markov localization for mobile robots in dynamic environments," *J. Artif. Intell. Res.*, vol. 11, pp. 391–427, 1999.

- [2] T. Rfer and M. Ingel, "Vision-based fast and reactive Monte-Carlo localization," in *Proc. IEEE Int. Conf. Robot. Autom.*, 2003, pp. 856–861, IEEE.
- [3] H. Du, P. Henry, X. Ren, M. Cheng, D. B. Goldman, S. M. Seitz, and D. Fox, "Interactive 3D modeling of indoor environments with a consumer depth camera," in *Proc. 13th Int. Conf. Ubiquitous Comput.*, New York, NY, USA, 2011, pp. 75–84.
- [4] P. Henry, M. Krainin, E. Herbst, X. Ren, and D. Fox, "RGB-D mapping: Using kinect-style depth cameras for dense 3D modeling of indoor environments," *Int. J. Robot. Res.*, vol. 31, pp. 647–663, 2012.
- [5] F. Werner, J. Sitte, and F. Maire, "Topological map induction using neighbourhood information of places," *Autonomous Robot.*, vol. 32, pp. 405–418, 2012.
- [6] D. Marinakis and G. Dudek, "Pure topological mapping in mobile robotics," *IEEE Trans. Robot.*, vol. 26, no. 6, pp. 1051–1064, Dec. 2012.
- [7] S. Thrun, "Learning metric-topological maps for indoor mobile robot navigation," *Artif. Intell.*, vol. 99, no. 1, pp. 21–71, 2012.
- [8] G. N. DeSouza and A. C. Kak, "Vision for mobile robot navigation: A survey," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 24, no. 2, pp. 237–267, Feb. 2002.
- [9] F. Bonin-Font, A. Ortiz, and G. Oliver, "Visual navigation for mobile robots: A survey," *J. Intell. Robot. Syst.*, vol. 53, pp. 263–296, 2012.
- [10] J. Tran, A. Ufkes, M. Fiala, and A. Ferworn, "Low-cost 3D scene reconstruction for response robots in real-time," *Robotics*, pp. 161–166, 2011.
- [11] H. Strasdat, J. M. M. Montiel, and A. J. Davison, "Real-time monocular SLAM: Why filter?," in *Proc. IEEE Int. Conf. Robot. Autom. (ICRA)*, May 2010, pp. 2657–2664.
- [12] C.-C. Wang and C. Thorpe, "Simultaneous localization and mapping with detection and tracking of moving objects," in *Proc. IEEE Int. Conf. Robot. Autom.*, 2002, vol. 3, pp. 2918–2924.
- [13] M. Meng and A. Kak, "Mobile robot navigation using neural networks and nonmetrical environmental models," *IEEE Control Syst.*, vol. 13, no. 5, pp. 30–39, Oct. 2012.
- [14] J. Pan, D. J. Pack, A. Kosaka, and A. C. Kak, "FUZZY-NAV: A vision-based robot navigation architecture using fuzzy inference for uncertainty reasoning," in *Proc. World Congr. Neural Netw.*, 1995, pp. 602–607.
- [15] F. Jafar, Y. Suzuki, Y. Tateno, T. Tabata, and K. Yokota, "An environmental visual features based navigation for mobile robot in a corridor environment," in *Proc. IEEE Int. Conf. Robot. Biomimetics (ROBIO)*, Dec. 2010, pp. 1612–1617.
- [16] J. Kim, J. Kim, S. You, Y. Oh, and S. Oh, "Actionable topological mapping for navigation using nearby objects," in *Proc. IEEE Int. Conf. Autom. Sci. Eng. (CASE)*, 2012, pp. 1162–1167.
- [17] L. Maohai, W. Han, S. Lining, and C. Zesu, "Robust omnidirectional mobile robot topological navigation system using omnidirectional vision," *Eng. Appl. Artif. Intell.*, vol. 26, no. 8, pp. 1942–1952, 2013.
- [18] W. Maddern, M. Milford, and G. Wyeth, "Towards persistent indoor appearance-based localization, mapping and navigation using cat-graph," in *Proc. IEEE/RSJ Int. Conf. Intell. Robot. Syst. (IROS)*, 2012, pp. 4224–4230.
- [19] M. Liu, C. Pradalier, and R. Siegwart, "Visual homing from scale with an uncalibrated omnidirectional camera," *IEEE Trans. Robotics*, vol. 29, no. 6, pp. 1353–1365, Dec. 2012.
- [20] J. Gaspar, N. Winters, and J. Santos-Victor, "Vision-based navigation and environmental representations with an omnidirectional camera," *IEEE Trans. Robot. Autom.*, vol. 16, no. 6, pp. 890–898, Dec. 2012.
- [21] J. Kosecka, L. Zhou, P. Barber, and Z. Duric, "Qualitative image based localization in indoors environments," in *Proc. IEEE Comput. Soc. Conf. Comput. Vision Pattern Recognit.*, Jun. 2003, vol. 2, pp. II-3–II-8.
- [22] A. Remazeilles, F. Chaumette, and P. Gros, "3D navigation based on a visual memory," in *IEEE Int. Conf. Robot. Autom.*, May 2006, pp. 2719–2725.
- [23] C. Valgren, A. Lilienthal, and T. Duckett, "Incremental topological mapping using omnidirectional vision," in *Proc. IEEE/RSJ Int. Conf. Intell. Robot. Syst.*, Oct. 2006, pp. 3441–3447.
- [24] J. Wang and Y. Yagi, "Efficient topological localization using global and local feature matching," *Int. J. Adv. Robot. Syst.*, vol. 10, no. 153, pp. 1–9, 2012.
- [25] N. Winters, J. Gaspar, G. Lacey, and J. Santos-Victor, "Omnidirectional vision for robot navigation," in *Proc. IEEE Workshop Omnidirectional Vision, South*, 2000, pp. 21–28.
- [26] M. Bosse, R. Zlot, and P. Flick, "Zebedee: Design of a spring-mounted 3-D range sensor with application to mobile mapping," *IEEE Trans. Robotics*, vol. 28, no. 5, pp. 1104–1119, 2012.
- [27] Y. Zhuang, N. Jiang, H. Hu, and F. Yan, "3-D-laser-based scene measurement and place recognition for mobile robots in dynamic indoor environments," *IEEE Trans. Instrum. Meas.*, vol. 62, no. 2, pp. 438–450, Feb. 2013.
- [28] B. Mobedi and G. Nejat, "3-D active sensing in time-critical urban search and rescue missions," *IEEE/ASME Trans. Mechatronics*, vol. 17, no. 6, pp. 1111–1119, Dec. 2012.
- [29] J. Biswas and M. Veloso, "Depth camera based indoor mobile robot localization and navigation," in *Proc. IEEE Int. Conf. Robot. Autom. (ICRA)*, 2012, pp. 1697–1702.
- [30] E. Marder-Eppstein, E. Berger, T. Foote, B. Gerkey, and K. Konolige, "The office marathon: Robust navigation in an indoor office environment," in *Proc. IEEE Int. Conf. Robot. Autom. (ICRA)*, 2010, pp. 300–307.
- [31] A. Vieira, P. Drews, and M. Campos, "Spatial density patterns for efficient change detection in 3D environment for autonomous surveillance robots," *IEEE Trans. Autom. Sci. Eng.*, vol. 11, no. 3, pp. 766–774, Jul. 2014.
- [32] K. Shubina and J. K. Tsotsos, "Visual search for an object in a 3D environment using a mobile robot," *Comput. Vision and Image Understanding*, vol. 114, no. 5, pp. 535–547, 2012.
- [33] K. Khoshelham and S. O. Elberink, "Accuracy and resolution of kinect depth data for indoor mapping applications," *Sensors*, vol. 12, no. 2, pp. 1437–1454, 2012.
- [34] J. Han, L. Shao, D. Xu, and J. Shotton, "Enhanced computer vision with microsoft kinect sensor: A review," *IEEE Trans. Cybern.*, vol. 43, no. 5, pp. 1318–1334, Oct. 2013.



Hongtai Cheng (M'12) received the B.S. and M.S. degrees in electrical engineering and Ph.D. degree in power electronics and electrical Drive from the Harbin Institute of Technology, Harbin, China, in 2006, 2008 and 2011, respectively.

He was with the Ingram School of Engineering, Texas State University-San Marcos, from 2011 to 2013, as a Research Associate. Currently, he is an Associate Professor with the Department of Mechanical Engineering and Automation, Northeastern University, China. His research interests include intelligent robot control, control system design and implementation, manufacturing automation and nonlinear control of underactuated mechanical systems.



Heping Chen (S'00–M'05) received the B.S. degree in control system engineering from the Harbin Institute of Technology, Harbin, China, in 1989, the M.Eng. degree in electrical and electronic engineering from Nanyang Technological University, Singapore, in 1999, and the Ph.D. degree in electrical and computer engineering from Michigan State University, East Lansing, MI, USA, in 2003.

He was with the Robotics and Automation Labs, ABB Corporate Research, ABB, Inc., Windsor, CT, USA, from 2005 to 2010. Currently, he is an Assistant

Professor with the Ingram School of Engineering, Texas State University-San Marcos. His research interests include micro/nanomanufacturing, micro/nano robotics, industrial automation, control system design and implementation.



Yong Liu received the B.S. degree and M.S. degree in material processing and control and the Ph.D. degree in pattern recognition and intelligent system from Nanjing University of Science and Technology, Nanjing, China, in 1997, 2000, and 2005, respectively.

Since 2000, he was with the Faculty of the Department of Computer Science and Engineering, Nanjing University of Science and Technology, Nanjing, China, where he conducted research in the area of theory and system for intelligent industrial

robot and application, uncalibrated camera-based positioning for uncalibrated robot, wall-climbing robot and its application, theory and systems for flying and adhesion robot. From 2007 to 2009, he was with the Department of Electrical and Computer Engineering, Michigan State University, East Lansing, MI, USA, as Visiting Scholar and Postdoctoral Fellow.