Intelligent Update of a Visual Map Based on Pose Reliability of Visual Features

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Abstract *–*A mobile robot works in dynamic environments with uncertainties. These uncertainties are caused by either humans or various static obstacles and they have a great impact on localization. Environmental uncertainties often increase along with localization failure. Therefore, a robot should robustly localize itself in dynamic environments. For successful localization, the robot should be capable of recognizing the environmental changes and updating a map to reflect these changes. This paper proposes a method for the intelligent update of a visual map using a probabilistic approach. The intelligent update of a visual map can make service robots to operate semi-permanently in dynamic environments and improve localization performance.

Keywords - Intelligent map update, visual map, localization, mobile robot, pose reliability.

1. Introduction

Autonomous navigation of a mobile robot consists of many basic techniques such as mapping, localization, path planning, collision avoidance, system architecture and so on. Among these, localization is the most important task since a robot must know its pose to reach the desired destination reliably. Localization is a method for estimating the robot pose using the environmental map and the sensor information. Therefore, localization performance increases as the differences between the map and the real environment decrease. Representative examples of map matching based localization are as follows.

MCL (Monte Carlo Localization) method [1][2], which robustly estimates the robot pose, compares the information from the sensors mounted on the robot with the environment map. The vision-based SLAM using the SIFT (Scale Invariant Feature Transform) algorithm [3] based on a stereo camera was also proposed [4] [5].

The above localization methods have been applied to many mobile robots and their performances were verified. The localization schemes, however, tend to show poor performance when the map is different from the real environment due to artificial or natural changes in the environment. If the robot can detect such changes occurring in the environment and reflect them on the map, navigation performance can be maintained even for the environmental changes. In this research, a new method for recognizing the environmental changes and updating the current map is proposed. With this approach, the robot can navigate autonomously with high reliability and thus offer better services to humans.

Despite the importance of map update, little attention has been paid to the update algorithm of the constructed map. This paper proposes a method for updating the constructed map reliably and simply. The particle filter algorithm [6], which ~~is~~ has been used for localization, is adopted for the map update. If the robot recognizes a visual feature, new samples representing the candidates for the robot pose are drawn around the visual feature. After newly drawn samples converge, the similarity between the poses of new samples and those of the current robot samples is evaluated. The pose reliability of the recognized object is calculated by applying the similarity to the Bayesian update formula [7]. Then the object whose pose reliability is below the predetermined value is discarded. On the other hand, the new position of the moved visual feature is registered to the visual feature map if its pose reliability is greater than the predetermined value.

The remainder of this paper is organized as follows. Section 2 illustrates an overview of the navigation system which is the main framework of this research. Section 3 introduces the concept of the intelligent update of a visual map. Experimental results are shown in section 4 and finally in section 5 conclusions are drawn.

2. Overview of Navigation System

This section overviews the navigation system so as to help to understand the proposed intelligent update of a visual map. The autonomous navigation system used in this research works based on a range sensor and a vision sensor. Figure 1 shows the structure of the integrated navigation system. This system is classified into two parts; a vision framework and a navigation framework. Each framework consists of general components which are segmented in a task unit and a control component which supervises general components. When a robot receives the order to move to the goal, the navigation system activates the 'Mobile Supervisor' component and the 'Vision

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Supervisor' component. Detection of the environmental changes and the map update are executed in the 'Localizer' component and the 'MapBuilder' component, as shown in Fig. 1. With this method, the robot is able to perceive the changes occurring in the environment by itself during autonomous navigation.

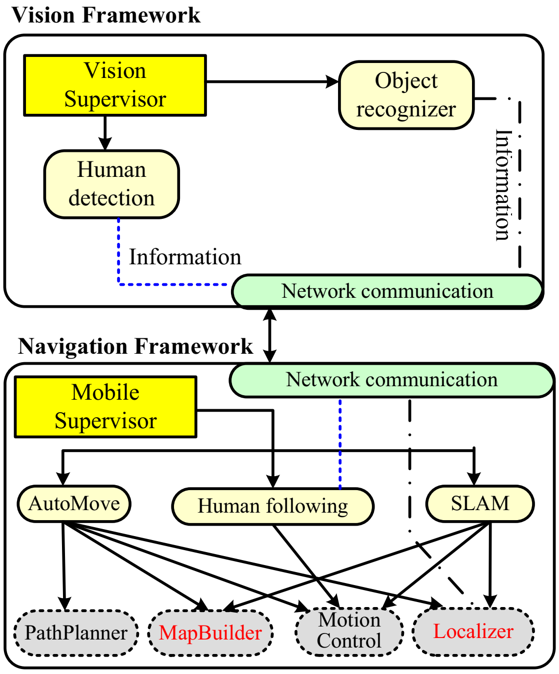

Fig. 1. Architecture of navigation system.

The operation scheme of the navigation system is as follows:

Step 1: Control component loads 'AutoMove' component.

Step 2: AutoMove component loads specific modules (Localizer, PathPlanner, etc.).

Repeat from Step 3 to 6 until the robot reaches the goal.

Step 3: Estimate the current robot pose from 'Localizer.'
(a) Obtain visual information from 'Object recognizer.'
(b) Detect environmental changes.

Step 4: 'MapBuilder' constructs the map.
(a) Update a grid map.
(b) Update a visual map.

Step 5: 'PathPlanner' generates a path to the goal.

Step 6: Command translational and rotational velocities to 'MotionControl.'

3. Intelligent Update of a Visual Map

3.1 Problem Statement

Range-based localization tends to fail when many objects in the environment cannot be detected by range sensors. In order to overcome this problem, sensor fusion based localization, which combines range information and visual information, is adopted in this research [8]. A brief explanation on this sensor fusion is described in the following paragraph.

With a vision sensor, a robot recognizes the objects stored in the database, as shown Fig. 2 and estimates its pose by fusing the visual and range information. However, the objects which can be used as visual features are limited in the real environment. Thus, if there is no visually recognized object, the robot has to estimate its pose with the range sensor alone, as shown in Fig. 3(a). If the robot recognizes objects stored in the database, however, the robot estimates its pose by fusing the visual and range information, as shown in Fig. 3(b). The method of object recognition used in this research is based on the SIFT algorithm, which extracts the feature points that are scale and rotation invariant.

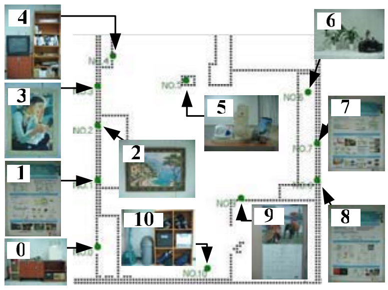

Fig. 2. Hybrid grid/visual map of environment.

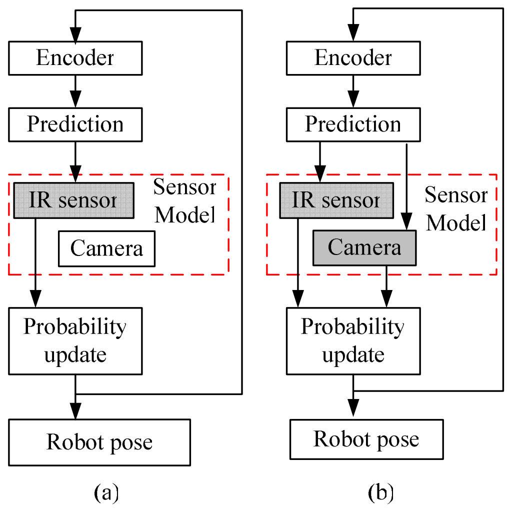

Fig. 3. Sensor models; (a) without and (b) with visually recognized objects.

Either the range-based or vision-based scheme alone cannot overcome these sensor limitations; sensor fusion based localization should be implemented to compensate for the shortcomings of each sensor. However, if the visual information is not correct, performance of sensor fusion based localization can be worse than that of the range-based localization. For example, Fig 3(a) shows localization with information of a range sensor alone. The ellipse enclosing the robot represents its pose uncertainty. Figure 3(b) represents the case when the robot uses information of both sensors, but the object recognizer provides wrong information because of either false matching or the change in position of object 1. Note that false matching means the robot mistook object 2 for object 1. If both pieces of information were correct, the pose uncertainty would be decreased. When compared to Fig. 4(a), however, the pose uncertainty in Fig. 4(b) increased due to the wrong information from the camera.

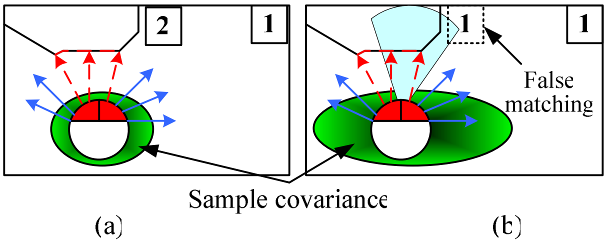

Fig. 4. Problem of localization due to wrong information; (a) localization with range information alone, and (b) localization with wrong visual information.

3.2 Detection and map update

The localizer not only estimates the robot pose, but also detects the environmental changes. The method for detecting the environmental changes is explained below in detail.

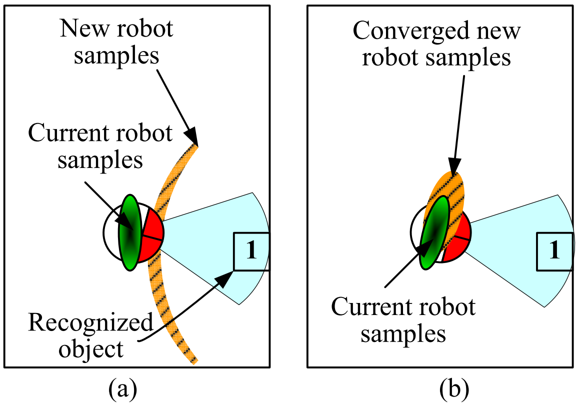

Fig. 5. Example of detecting environmental changes.

The robot recognizes the object which is registered on the visual feature map. Then new random robot samples (NR_{sample}), which are the candiates for the robot pose, are drawn near the recognized object, as shown in Fig. 5(a). The area of the newly distributed samples are restricted to the circle with a radius of the measured range and centered at the recognized object. The number of samples is 300. After the new samples converge as shown in Fig. 5(b), the similarity between the poses of the new robot samples (NR_{sample}) and those of the current robot samples (R_{sample}) are evaluated. The similarity can be obtained by

$$p(R, NR, i) = \frac{r}{d} \tag{1}$$

where r is the radius of convergence bound for R_{sample}, and d is the distance between the means of R_{sample} and NR_{sample}.. The probability $p(R, NR, i)$ represents the similarity between R_{sample} and NR_{sample} when NR_{sample} converges with the information of the i-th object. If NR_{sample} exists in the convergence bound as shown in Fig. 6(a), which means $d < r$, the similarity is set to 1. As shown in Fig. 6(b), the similarity approaches 0 as the two samples become apart from each other.

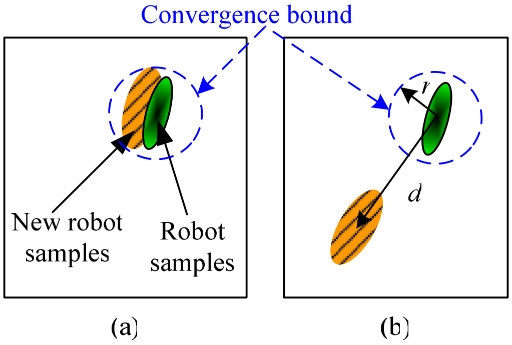

Fig. 6. Example of similarity between new and current robot samples.

The pose reliability of the recognized object is calculated by substituting the similarity into Bayesian update formula as follows:

$$p_{t+1,i} = \frac{p(R, NR, i) \times p_{t,i}}{p(R, NR, i) \times p_{t,i} + \{1 - p(R, NR, i)\} \times (1 - p_{t,i})} \tag{2}$$

where $p_{t,i}$ is the accumulated pose reliability of object i at time t. The pose reliabilities of all objects are initialized to 0.5 and are continuously evaluated during navigation. The pose reliability serves as a criterion which determines whether the specific visual feature is updated or not. This procedure is illustrated in Fig. 7. New samples are drawn near the recognized objects, as shown in Fig. 7(a). After the drawn samples converge, the similarity between the newly drawn samples and the current robot samples are calculated using Eq. (1). Using Eq. (1) and Eq. (2), the pose reliability of object 1 is updated in Fig. 7(b). The pose reliability of object 1 increases up to 0.9. The method which detects the environmental changes and updates the map is explained below in detail.

The pose of object 2 was changed, as shown in Fig. 7(c), and the new robot samples, NR_{sample}, are drawn near the original pose of object 2. As shown in Fig. 7(d), the similarity between NR_{sample} and R_{sample} becomes low, and thus the pose reliability of object 2 decreases due to this low similarity. Since the pose reliability of object 2 is lower than 0.1, NR_{sample} is drawn near the actual pose of object 2, as shown in Fig. 7(e). The actual pose of object 2 can be obtained with the global pose of the robot and the object information from the stereo camera (e.g., the relative range and angle to the object). Then the pose reliability of object 2 is evaluated using the similarity between NR_{sample} and R_{sample}, as shown in Fig. 7(f). If the pose reliability of the newly registered pose of object 2 is greater than 0.5, the new pose of object 2 is registered in the database and the original pose is discarded from the visual feature map.

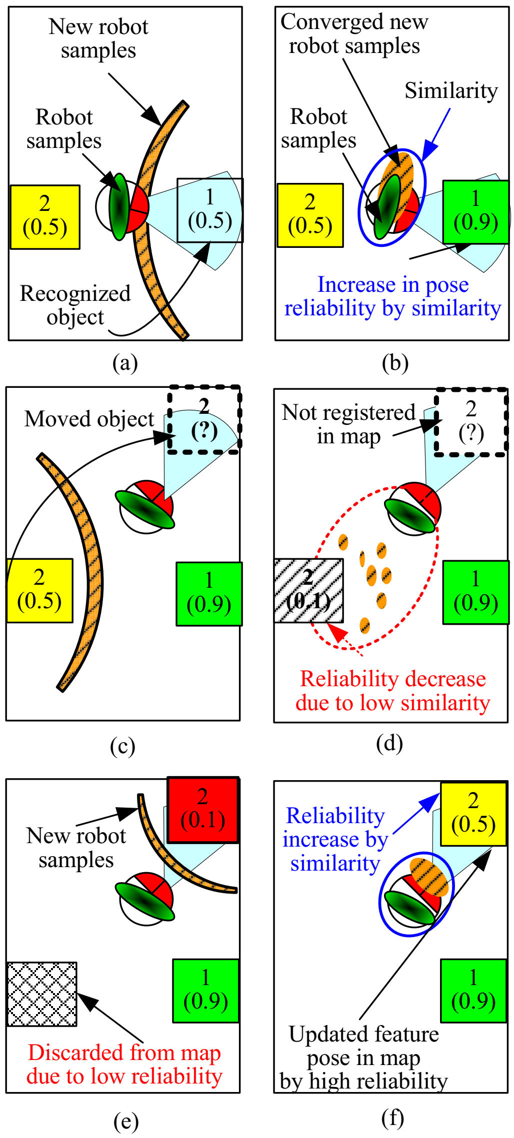

Fig. 7 Procedure of intelligent update of visual map.

4. Experimental Results

Experiments were performed using a robot equipped with an IR scanner (Hokuyo PBS-03JN) and a stereo camera (Videredesign STH-MDI-C). As shown in Fig. 8(a), the experimental environment was 9m x 7m. Figure 8(b) shows the visual feature which will be moved to other places during navigation.

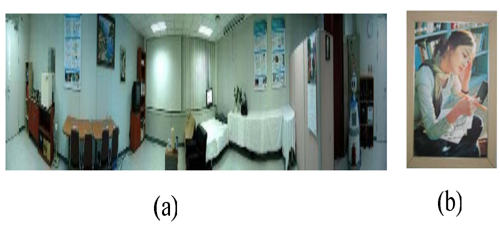

Fig. 8. (a) Experimental environment, and (b) typical visual feature.

4.1 Pose uncertainty due to environmental changes

These experiments were performed to find out the influence of the environmental change on the uncertainty of the estimated robot pose (i.e., position and orientation). No environmental change was made in Fig. 9(a), whereas the environment was changed in Fig. 9(b). In Fig. 9(c) and (d), the solid red line shows the uncertainty of the estimated pose when the map coincides with the environment. On the other hand, the dotted (blue) line indicates the pose uncertainty under the wrong visual information which means the changed position of object 3 is not updated in the map. As expected, the uncertainty of the estimated pose increases when the environmental changes are not reflected on the visual map,

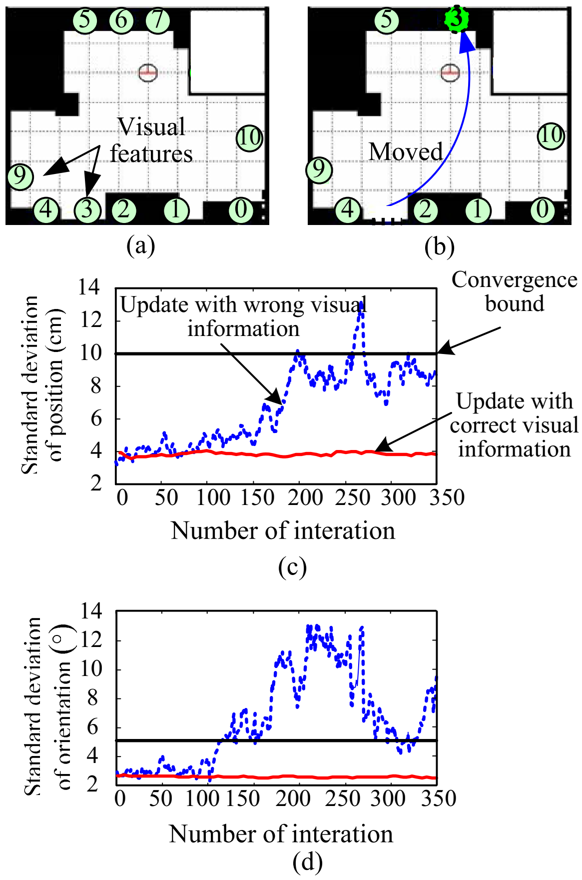

Fig. 9. Localization performance according to environmental changes; (a) experimental environment, (b) changed environment, (c) effect of changed environment on position uncertainty, and (d) effect of changed environment on orientation uncertainty.

4.2 Map update according to environmental changes

This experiment was performed to verify that the robot can update the visual map intelligently when the environment was changed by humans. In this experiment, the pose of object 3 registered in the visual map is changed. During navigation, the pose reliabilities of all visual features are initialized to 0.5, as shown in Fig. 10(a). In Fig.

10(b), the robot draws the new random robot samples NR_{sample} around object 7 which was just recognized.

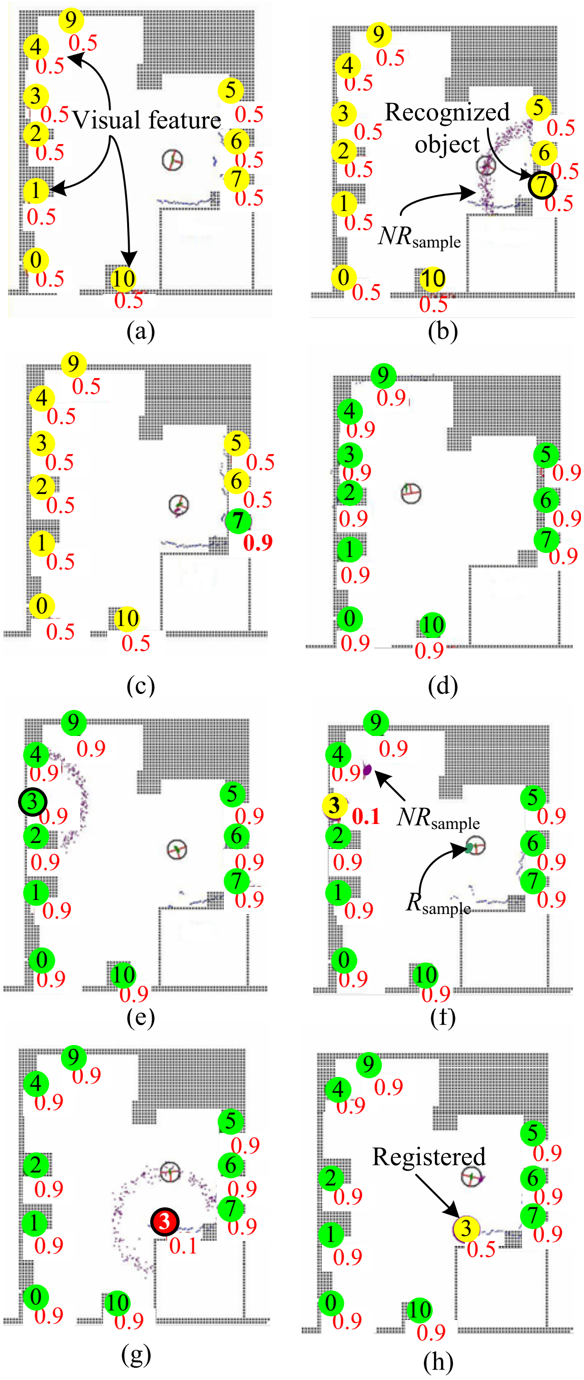

Fig. 10. Experimental results; (a), (b), (c) and (d) are procedure of increasing reliability of pose, (e),(f),(g) and (h) are procedure of intelligent update of visual map.

In Fig. 10(c), the pose reliability of object 7 increases to 0.9 due to the high similarity between NR_{sample} and R_{sample}, which means object 7 has a high pose reliability. All visual features have a high pose reliability through the above evaluation, as shown in Fig. 10(d). Object 3 is then moved to the place between object 7 and object 10. Fig. 10(e) shows that a robot draws NR_{sample} near the original pose of object 3, when it recognizes object 3 at the new pose. In Fig. 10(f), the pose reliability of object 3 of the visual map decreases due to the low similarity between NR_{sample} and R_{sample}. The robot deletes object 3 from the visual map if its pose reliability is below 0.1. Then NR_{sample} are drawn around the new position of object 3 and calculate the similarity between NR_{sample} and R_{sample}. The pose of the moved object is updated to the visual map if its pose reliability is greater than 0.5. Figure 10(h) shows the updated visual map. The capability of the robot which detect environmental changes and update the visual map intelligently can be verified through the above experiments.

5. Conclusions

In this paper, a probabilistic method which detects environmental changes and updates a map in dynamic environments was proposed. From this research, the following conclusions are drawn.

1. The differences between the environmental map and the real environment can be decreased through intelligent update of a visual map. It improves performance of localization and thus autonomous navigation.
2. The robot operator does not have to stop tasks of the robot because the robot autonomously reflects the environmental changes in the constructed map. In this sense, the proposed method can make a robot operate semi-permanently in dynamic environments.

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