

Identification of types of obstacles for mobile robots

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Abstract For service robots coexisting with humans, both safety and working efficiency are very important. In order for robots to avoid collisions with surrounding obstacles, the robots must recognize obstacles around them. In dynamic environments, not only currently moving obstacles but also movable obstacles should be recognized. In this paper, three types of obstacles, such as stationary, movable and moving, are defined, and a method to identify the type of obstacles is proposed. The experiments using a mobile robot were conducted to evaluate the usefulness of the method.

Keywords Mobile robot · Laser range finder · Obstacle map

1 Introduction

In recent years, there have been growing demands for service robots, such as delivery robots, security robots, and cleaning robots, and elemental technologies of robotics have been developing. Service robots are developed to be useful for humans. Therefore, they are required to move fast to improve working efficiencies. On the other hand, these types of robots generally coexist with humans in the same place, therefore safety is one of the most important issues.

If robots always move fast to improve working efficiency, collision risk between robots and humans will become very high. On the other hand, if robots consider unlikely collision risk and act in a too cowardly manner, the robots will be useless. In other words, there is a trade-off between safety and working efficiency.

In order to achieve a good balance between them, robots should move fast when there is low collision risk and move slowly where there is high collision risk. In order to consider collision risk, the robots have to recognize obstacles around them.

Many researchers have studied on detection and recognition of moving obstacles [1–5] or map building in dynamic environments [6–8]. Laugier et al. [9] presented an approach for SLAM, recognition of obstacles, and motion planning in dynamic environments. Most studies classified obstacles into two types: stationary obstacles and moving obstacles.

However, this classification can lead to the following problems: assuming that a robot is moving through a hallway where there is a trolley:

1. if the robot regards the trolley as a stationary obstacle and moves fast by the side of it, collision will possibly occur when the trolley will be moved by a person, and
2. if the robot regards the trolley as a moving obstacle, the robot will move slowly with unnecessary care even when there is no person to move the trolley.

In other words, robots are expected to have an ability to distinguish obstacles which cannot move by themselves but have a possibility to be moved by someone from stationary and moving obstacles. If robots can distinguish such obstacles from others, they will be able to move safer and faster by making an appropriate judgement depending on the situation.

In this study, three types of obstacles are defined as follows:

- Stationary obstacle: It cannot move neither by themselves nor by others. A wall, a column, etc.
- Movable obstacle: It cannot move by themselves but can be moved by others. A trolley, a chair, a door, etc.

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- Moving obstacle: Moving obstacles can move themselves. A person, a robot, etc.

The objective of this study is to propose a method to identify the above three types of obstacles from a moving robot and to build an obstacle map for safe motion of mobile robots.

This paper is organized as follows. In Sect. 2, we describe a way for sensing and localization of a mobile robot. After that, a method to identify the kinds of obstacles is discussed in Sect. 3. In Sect. 4, experiments for building obstacle maps are described and discussed. We conclude this paper in Sect. 5.

2 Sensing and localization

We assume that robots are equipped with laser range finders (LRFs) that allow them to measure distances to surrounding obstacles. As shown in Fig. 1, LRFs provide a two-dimensional range map of the environment.

A data point (x^i, y^i) in the world coordinate system is calculated by the following equations.

$$\begin{cases} x^i = x^R + d^i \cos(\theta^R + \phi^i) \\ y^i = y^R + d^i \sin(\theta^R + \phi^i), \end{cases} \quad (1)$$

where (x^R, y^R) and θ^R are a position and an orientation of the robot in the world coordinate system, and ϕ^i and d^i are angle and distance of i th data obtained by a LRF, respectively.

The obtained coordinate values of data points are quantized and a grid map is formed. In what follows, the quantized data point is represented as p^i . A LRF obtains the environ-

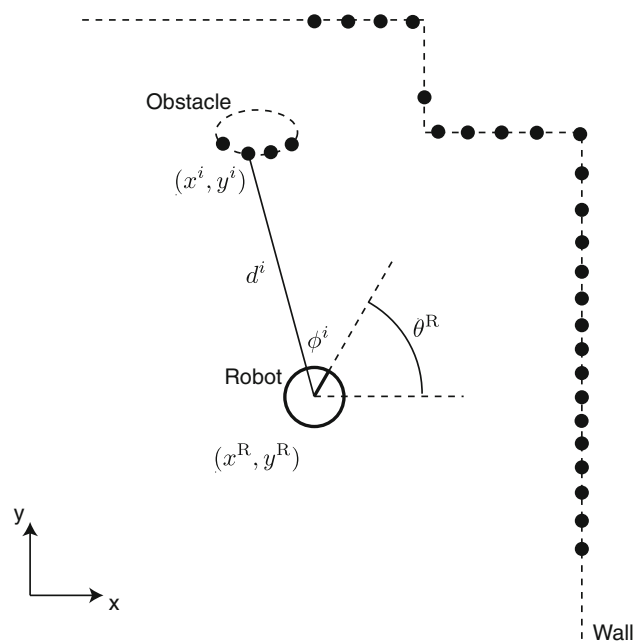


Fig. 1 Schematic view of obtained range data from a LRF mounted on a robot

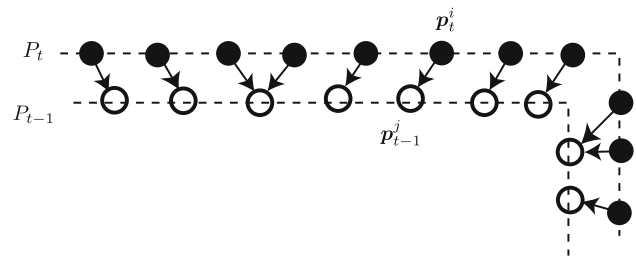


Fig. 2 Schematic view of matching scan data at time $t - 1$ and t

mental data at a constant frequency. Because of the sensing noise and movement error, it is generally impossible to perfectly match the data at time $t - 1$ and t . To solve this problem, we apply iterative closest point (ICP) algorithm [10] to the obtained data.

Let $P_t = \{p_t^1, \dots, p_t^N\}$ be a set of obtained data points at t , q_{t-1}^i , the nearest data point at $t - 1$ from p_t^i , is calculated as follows.

$$q_{t-1}^i = \underset{p_{t-1}^j}{\operatorname{argmin}} \|p_{t-1}^j - R p_t^i - t\| \quad (2)$$

where R and t are a rotation matrix and a translation vector of the robot from time $t - 1$ to t , respectively.

Figure 2 shows an schematic view of matching the obtained data at time $t - 1$ and t .

Based on this, the rotation matrix and the translation vector are calculated to minimize the following equation.

$$E(R, t) := \sum_{i=1}^N \|q_{t-1}^i - R p_t^i - t\|^2, \quad (3)$$

To minimize the above equation, the initial values of R and t are set to the data obtained from odometry and the procedure represented as Eqs. (2) and (3) is iterated until convergence.

3 Identification of types of obstacles

In order for mobile robots to safely move in a human–robot coexisting environment, it is important to know where a risk of collisions exists. In this study, therefore, we do not treat obstacles as an individual object, but we handle information which types of obstacles exist at one location. Here, each grid of a map is allocated a type of obstacles out of four types, such as *stationary*, *movable*, *moving*, and *free*. In this study, such map is called an “obstacle map”. Based on the localization with the ICP algorithm, the robot identifies the type of obstacles on the map in the world coordinate system. In what follows, a method to identify the type of obstacles is presented.

Fig. 3 Identification of a moving obstacle. **a** The robot calculates the visible area at time $t - 1$. **b** The robot and an obstacle move from time $t - 1$ to t . **c** At time t , the robot identifies the obstacle as *moving* by referring the visible area of time $t - 1$

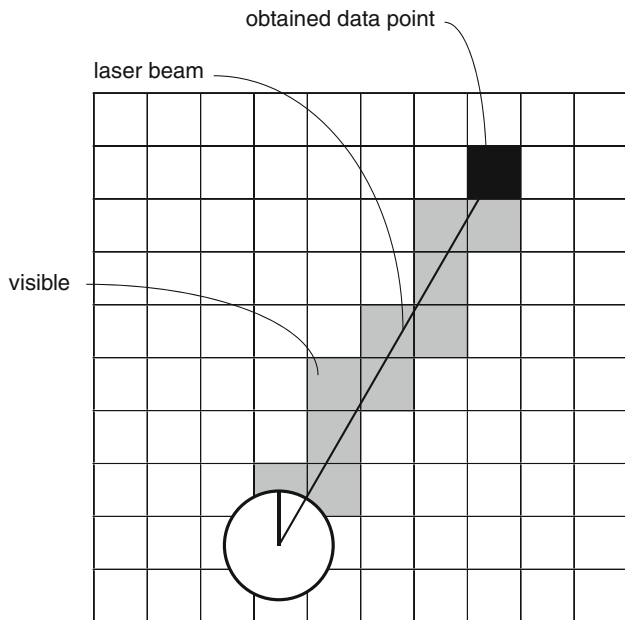
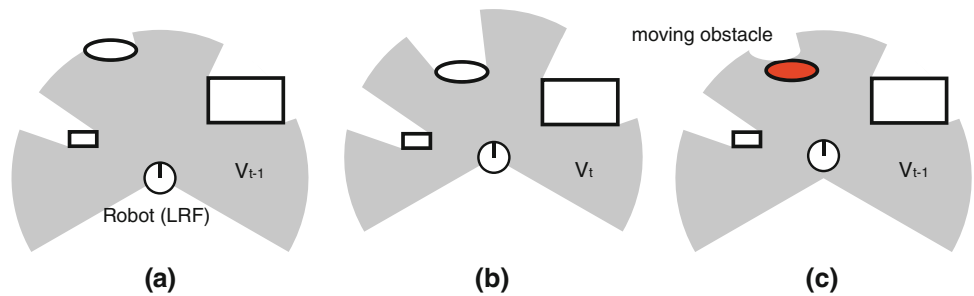


Fig. 4 Calculation of a visible area from obtained data

3.1 Identification of moving obstacles

First of all, moving obstacles at time t are identified as follows.

In order to detect moving obstacles, we introduce a concept of a visible area (Fig. 3).

A visible area at time t is calculated as follows. For each direction i ($i = 1, \dots, N$),

- if data are not obtained because of an upper limit of a LRF, grids that are passed through by a line segment between (x_t^R, y_t^R) and $(x_t^R + d^{ul} \cos(\theta_t^R + \phi^i), y_t^R + d^{ul} \sin(\theta_t^R + \phi^i))$ are judged as visible, where d^{ul} represents the upper limit of the LRF.
- If data are obtained, grids that are passed through by a line segment between (x_t^R, y_t^R) and p_t^i are judged as visible (Fig. 4).

Here, a set of data points judged as visible at t is designated as V_t

If data points are observed at time t in the visible area of time $t - 1$, the data points will be regarded as part of moving obstacles and corresponding grids will be identified as *moving*.

3.2 Identification of movable obstacles

In this study, a movable obstacle is defined as an obstacle that cannot move by themselves but can be moved by others. However, it is generally impossible to distinguish a movable obstacle from a stationary one by a single observation. Here, we identify an obstacle that was observed as a moving obstacle but is currently resting as a movable obstacle.

In order to identify movable obstacles, there are three types of judgments, such as addition, retention, and deletion. A newly identified movable obstacle is written in a map by an addition step. When the obstacle remains stationary, the location of the obstacle is stored in the map by a retention step. When the obstacle moves and is not observed at the location, the obstacle is deleted from the map.

3.2.1 Addition

When a moving obstacle was observed at a location at time $t - 1$ and an obstacle is observed at the location at t , the obstacle is regarded as transiently stationary and identified as a movable obstacle.

Let $P_{t-1}^{moving} = \{p_{t-1}^{moving,1}, \dots, p_{t-1}^{moving,M}\}$ be a set of data points identified as moving obstacles at $t - 1$, $q_{t-1}^{moving,i}$, the nearest moving data point at $t - 1$ from p_t^i , is calculated as follows.

$$q_{t-1}^{moving,i} = \underset{p_{t-1}^{moving,j}}{\operatorname{argmin}} \|p_t^i - p_{t-1}^{moving,j}\| \tag{4}$$

If p_t^i and $q_{t-1}^{moving,i}$ satisfy the following equation, p_t^i will be identified as *movable* and added to an obstacle map.

$$\|p_t^i - q_{t-1}^{moving,i}\| < \epsilon, \tag{5}$$

where ϵ is a constant threshold value.

3.2.2 Retention

When a movable obstacle was observed at a location at time $t - 1$ and an obstacle is observed at the location at t , the obstacle is regarded as staying at the location and re-identified as a movable obstacle. This can prevent movable obstacles from being regarded as stationary obstacles.

Let P_{t-1}^{movable} be a set of data points identified as movable obstacles at $t - 1$, $q_{t-1}^{\text{movable},i}$, the nearest movable data point at $t - 1$ from p_t^i , is calculated as follows like the addition step.

$$q_{t-1}^{\text{movable},i} = \underset{p_{t-1}^{\text{movable},j}}{\operatorname{argmin}} \|p_t^i - p_{t-1}^{\text{movable},j}\| \quad (6)$$

If p_t^i and $q_{t-1}^{\text{movable},i}$ satisfy the following equation, p_t^i will be identified as *movable*.

$$\|p_t^i - q_{t-1}^{\text{movable},i}\| < \epsilon. \quad (7)$$

3.2.3 Deletion

If a robot observes that a movable obstacle moves from a location, the movable obstacle is deleted from the obstacle map.

If $p_{t-1}^{\text{movable},i}$ is a member of V_t , visible area at t , and is not identified as a movable obstacle at t , the location is identified as *free* and the movable obstacle is deleted from the obstacle map. If $p_{t-1}^{\text{movable},i}$ is out of the visible area at t , the movable data point is kept in the map.

3.3 Identification of stationary obstacles

It is the simplest way to identify stationary obstacles that the stationary obstacles are derived from observed obstacles by loss of moving and movable obstacles. However, this way can lead to miss assignment because part of moving obstacles is often not regarded as *moving*. If that happens, nonexistent stationary obstacles will be written to the obstacle map and this will disturb the motion of the robot.

Here, an idea of temporarily stationary obstacles is introduced and stationary obstacles are identified as follows.

Observed data points except those identified as moving or movable obstacles are defined as temporarily stationary obstacles, and a set of the temporarily stationary obstacles at t is designated as P_t^{ts} . If the following two equations are satisfied for each element of P_t^{ts} , the element $p_t^{\text{ts},i}$ is identified as *stationary*.

$$\|p_t^{\text{ts},i} - q_{t-1}^{\text{ts},i}\| < \epsilon, \text{ and} \quad (8)$$

$$\|p_t^{\text{ts},i} - q_{t-2}^{\text{ts},i}\| < \epsilon, \quad (9)$$

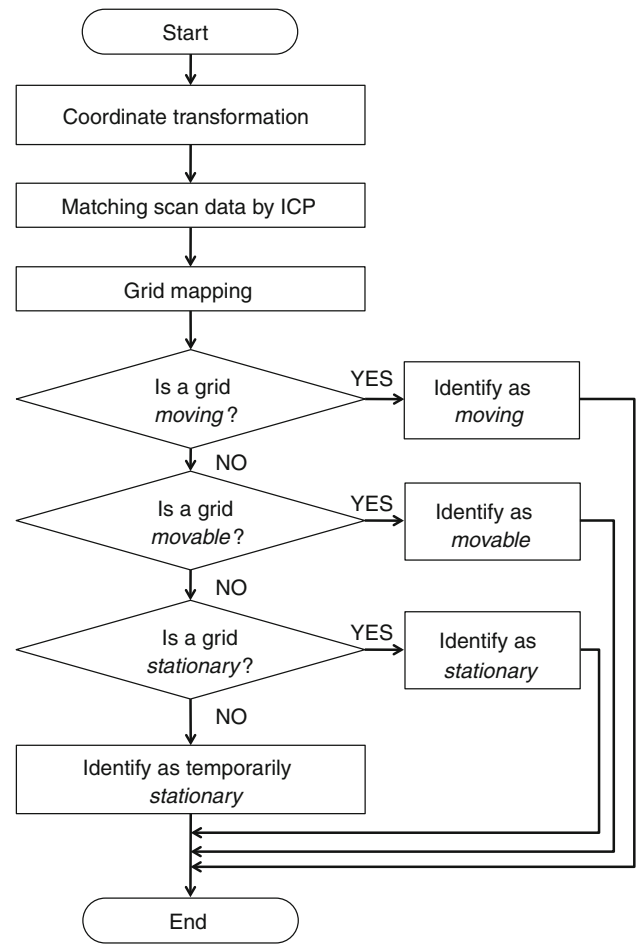


Fig. 5 Flowchart for identification of types of obstacles for each single data point

where

$$q_{t-1}^{\text{ts},i} = \underset{p_{t-1}^{\text{ts},j}}{\operatorname{argmin}} \|p_t^{\text{ts},i} - p_{t-1}^{\text{ts},j}\|, \text{ and} \quad (10)$$

$$q_{t-2}^{\text{ts},i} = \underset{p_{t-2}^{\text{ts},j}}{\operatorname{argmin}} \|p_t^{\text{ts},i} - p_{t-2}^{\text{ts},j}\|. \quad (11)$$

A set of data points identified as *stationary* is designated as $P_t^{\text{stationary}}$.

The flowchart for identification of types of obstacles is shown in Fig. 5.

4 Experiment

In order to validate the ideas presented in this paper, experimental tests have been performed.

In the experiments, an omni-directional mobile robot ZEN (Fig. 6) [11], which enables 3-DOF motion control by three correspondent actuators in a decoupled manner with no



Fig. 6 Omni-directional mobile robot used in the experiments

redundancy, was used. The robot was equipped with a LRF (URG-04LX, Hokuyo Automatic).

The experiments were carried out in the hallway of the University of Tokyo, Japan. The robot traveled straight with an average speed of 0.20 m/s. At first, a person walked pulling a suitcase and passed the robot, then he left the suitcase and went outside of the measurement field of the robot. After that, he turned back and walked toward the robot, finally he picked up the suitcase again and crossed the robot. Figure 7 shows the rough trajectories of the robot, the person, and the suitcase in the experiments, and Fig. 8 shows the rough time-line chart of the position of them.

The experiments were performed ten times.

Figure 9 shows an example of the identification of the moving obstacles [period (i) in Fig. 8]. In Fig. 9a, only the stationary obstacle was observed. In Fig. 9b, new obstacles (the person and the suitcase) were observed and identified as moving obstacles. In Fig. 9c, d, the moving obstacles were also successfully identified.

Figure 10 shows an example of the addition of the movable obstacle to the obstacle map [period (ii) in Fig. 8]. In Fig. 10a, b, moving obstacles were observed while the person was walking with the suitcase. In Fig. 10c, a movable obstacle was observed. At that time, although the person left the suitcase and the suitcase remained stationary, the suitcase was not identified as a stationary obstacle but a movable obstacle. In Fig. 10d, the movable obstacle was kept in the obstacle map.

Figure 11 shows an example of the deletion of the movable obstacle from the obstacle map [period (iii) in Fig. 8]. In Fig. 11a, b, the moving obstacle and the movable

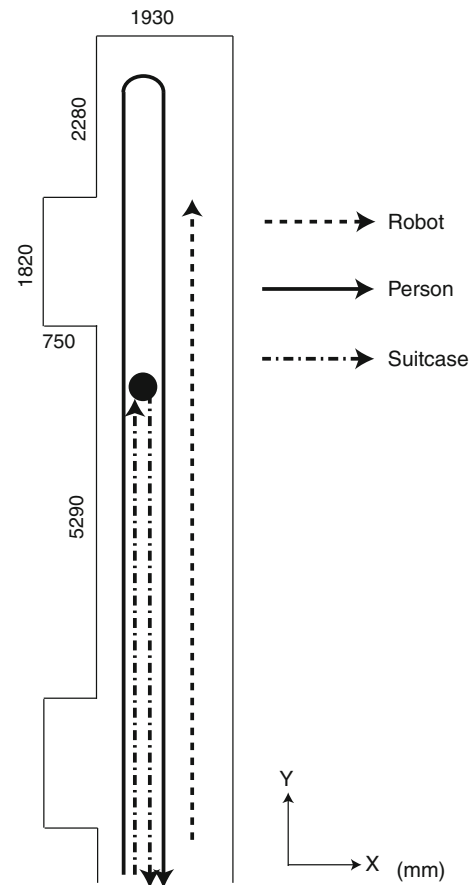


Fig. 7 Rough trajectories of the robot, the person, and the suitcase

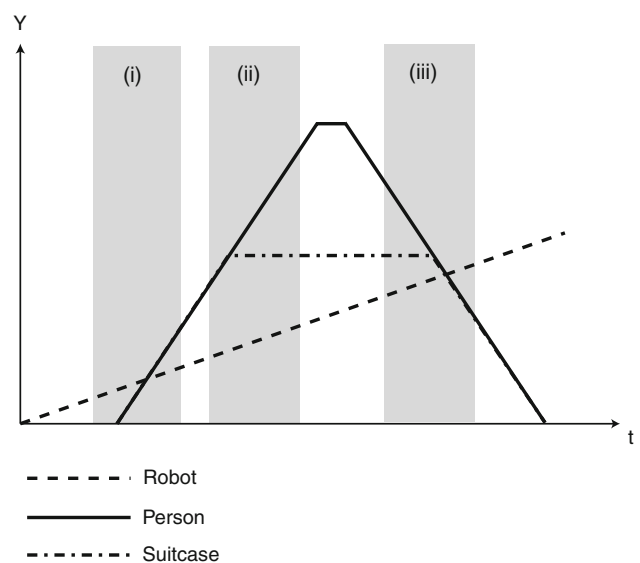


Fig. 8 Rough time-line chart of the position of the robot, person, and suitcase. First, the robot began to move straightforward. Then, the person began to walk pulling the suitcase, and he passed the robot (i). After that, he left the suitcase and went forward (ii). Finally, he came back to pick up the suitcase and passed the robot (iii)

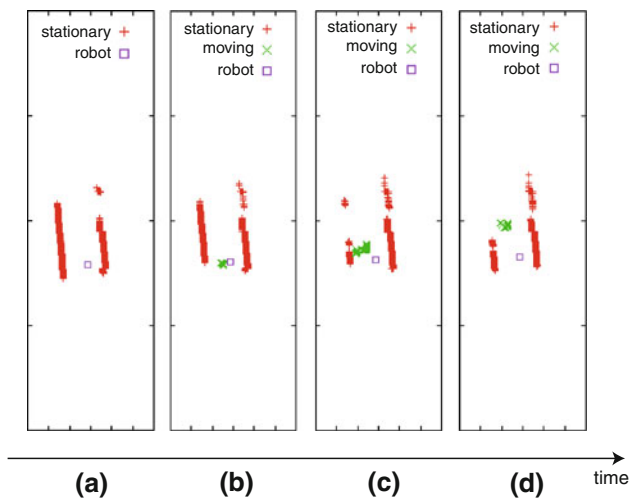


Fig. 9 Successful identification of the moving obstacle. **a** The robot detected only stationary obstacles. **b–d** It successfully detected moving obstacles (person and suitcase)

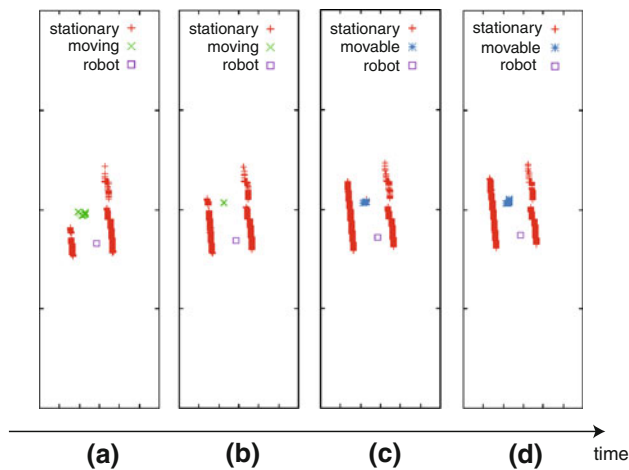


Fig. 10 Successful addition and retention of the movable obstacle. **a, b** The robot detected moving obstacles (person and suitcase). **c, d** It successfully detected and movable obstacles (suitcase) and held them as movable obstacles although the suitcase remained stationary

obstacle were observed while the person turned and was walking towards the suitcase. In Fig. 11c, the moving obstacle and the movable obstacle were close to each other. At that time, the person was picking up the suitcase. Finally, the person walked pulling the suitcase, and the movable obstacle was deleted from the obstacle map as shown in Fig. 11d.

Figure 12 shows the resulted map of stationary obstacles. As shown in this figure, the moving obstacle and the movable obstacle were successfully excluded. This means the identification of the types of obstacles was properly performed and miss identification was not occurred in the experiments conducted here.

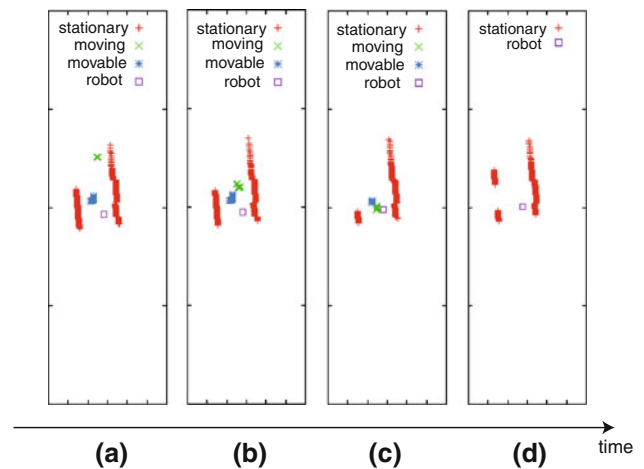
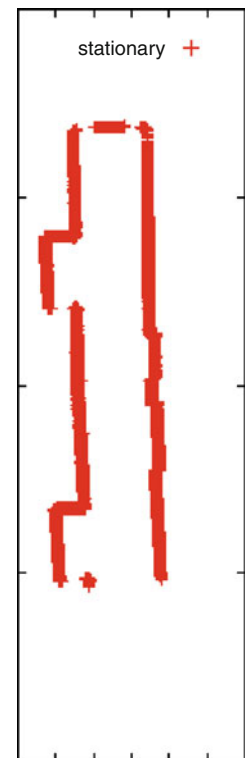


Fig. 11 Successful deletion of the movable obstacle. **a, b** The robot detected moving (person) and movable (suitcase) obstacles. **c** The person picked up the suitcase. **d** The movable obstacles were successfully removed from the map

Fig. 12 An example of the obtained map of stationary obstacles



5 Conclusion

In this paper, we classified obstacles into three types: stationary obstacles, movable obstacles, and moving obstacles. Introducing the idea of movable obstacles will enable robots to move safely. Based on the idea, we proposed the method to identify the types of obstacles from a mobile robot equipped with a LRF. In our method, we considered the visible area of the adjacent observation to detect moving and movable obstacles. If obstacles are detected in the area, they

will be identified as moving obstacles. If moving obstacles stop and remain stationary, the obstacles are identified as movable obstacles. The usefulness of the proposed method was demonstrated through the experiments.

For future works, motion planning of a mobile robot based on the obtained obstacle maps should be conducted. To achieve this, it would be necessary to distinguish one obstacle from another. Moreover, we plan to integrate the proposed method with a SLAM methodology to demonstrate the advantage in more complicated and realistic environments. Occlusion is another remaining problem. The proposed method can deal only with visible obstacles and the robot cannot avoid the invisible collision risk. To cover the limitation, we should integrate the proposed method with a method considering the potential risk of collision with some obstacles in blind area, such as [12].

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