Laser-based Tracking of People and Vehicles by Multiple Mobile Robots

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Abstract: This paper presents laser-based tracking of moving objects conducted by a group of mobile robots located near one another. Each robot finds moving objects such as people, cars, and bicycles in its own laser-scanned images using a binarized occupancy-grid-based method. It then sends laser measurements related to the detected moving objects to a central server. The central server estimates the pose and size of the moving objects via the Kalman filter based on received measurements; it then feeds that information back to the robots. Rule-based and global-nearest-neighbor-based data associations are applied for matching of tracked objects and laser measurements in multitarget environments. In this cooperative tracking method, the central server collects the laser measurements from all robots; hence, the robots can always track invisible or partially invisible objects. The experimental results for two robots in an outdoor environment validate our tracking method.

1 INTRODUCTION

Tracking (*i.e.*, estimating the motion of) multiple moving objects is an important issue for the safe navigation of mobile robots and vehicles. The use of stereo cameras or laser scanners (LS) in mobile robotics and vehicle automation has attracted considerable interest (Arra and Mozos, 2010, Mertz et al., 2013, Ogawa et al., 2011, Sun et al., 2006). We have presented a people-tracking method that uses LS mounted on mobile robots and automobiles (Hashimoto et al., 2006, Sato et al., 2010). To introduce robots (such as service and rehabilitation robots) into human environments, higher accuracy and reliability of moving-object tracking systems are required.

Most conventional moving-object tracking focuses on people under the assumption that a moving object is a mass point. However, in the real world, many kinds of moving objects, such as people, cars, bicycles, and motorcycles, exist. Therefore, we should treat a moving object as a rigid body and estimate both pose (position and velocity) and the object size. Tracking of a rigid body is known as extended object tracking, and many studies related to extended object tracking have been conducted (Fayad and Cherfaoui, 2007, Miyata et al., 2009, Zhao et al., 2012).

Recently, many studies related to multirobot coordination and cooperation have also been conducted. When multiple robots are located near one another, they can share their sensing data through intercommunication. Thus, the multirobot team can be considered a multisensor system. Therefore, even if moving objects are located outside the sensing area of a robot, the robot can recognize them based on tracking data from the other robots in the team. Hence, multiple robots can improve the accuracy and reliability of tracking moving objects (Chou, 2011, Tsokas and Kyriakopoulos, 2012).

As shown in Fig. 1, in an intelligent transport system (ITS), if tracking data are shared with neighboring vehicles, each vehicle can efficiently recognize moving objects. Therefore, an advanced driver assist system can be built that detects people suddenly running on roads and vehicles making unsafe lane changes in crowded urban environments.

For this purpose, our previous work (Kakinuma et al., 2012, Ozaki et al., 2012) presented a people-tracking method using multiple mobile robots. In this paper, we extend our previous method (people tracking) to tracking both people and vehicles; their pose and size are estimated using multiple mobile

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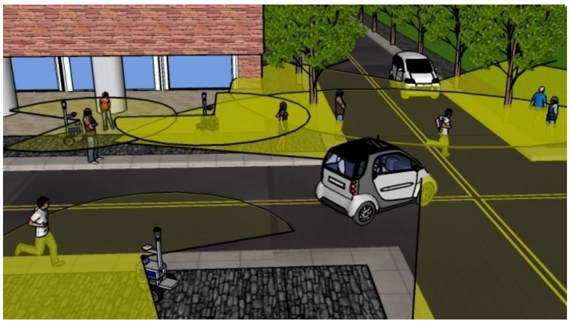


Figure 1: Example of cooperative tracking in ITS.

Figure 2: Overview of the mobile robot system.

robots.

For simplicity, in this paper, moving-object tracking by multiple mobile robots is referred to as *cooperative tracking*, whereas that by an individual robot in a team is referred to as *individual tracking*. The rest of the paper is organized as follows. Section 2 gives an overview of our experimental system. In Section 3, cooperative tracking is presented. In Section 4, to validate our method, we describe an experiment of moving-object tracking by using two mobile robots in an outdoor environment; we then present our conclusions.

2 EXPERIMENTAL SYSTEM

Figure 2 shows the mobile robot system used in our experiments. Each of the two robots has two independently driven wheels. A wheel encoder is attached to each drive wheel to measure the wheel's velocity. A yaw rate gyro is attached to each robot's chassis to sense the turn velocity. These internal sensors calculate the robot's pose based on dead reckoning.

Each robot is equipped with a forward-looking LS (SICK LMS100). It captures laser-scanned images that are represented by a sequence of distance samples in a horizontal plane of 270 deg. Each robot is also equipped with RTK–GPS (NovAtel GPS-702-CG). The sampling period of the sensors is 10 Hz. The angular resolution of the LS is 0.5 deg, and each scan image consists of 541 distance samples. We use broadcast communication by wireless LAN to exchange information between the central server and the robots.

3 MOVING-OBJECT TRACKING

3.1 Overview

As shown in Fig. 3, each robot independently finds moving objects in its own laser image based on a binarized occupancy-grid method (Hashimoto et al., 2006). The robot uploads laser measurements related to moving objects to a central server.

Laser measurements (positions) from the same moving object have similar values, whereas those from different objects are significantly different. Thus, the central server clusters laser measurements by checking the gap between two adjacent measurements. Subsequently, the server tracks moving objects (estimates their size, position, and velocity) and transmits the tracking data to the robots.

The grid map is represented on a world coordinate frame. To map the laser-scanned images onto the coordinate frame, each robot needs to identify its own pose with a high degree of accuracy on the world coordinate frame. To define the world coordinate frame, we consider the GPS base station as the origin. Each robot determines its own pose based on dead reckoning and GPS information via the extended Kalman filter.

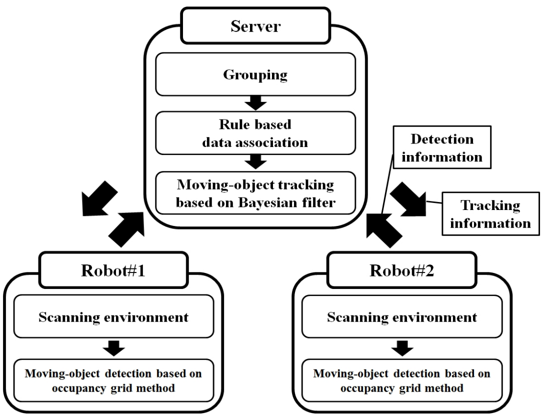


Figure 3: System overview of cooperative tracking.

3.2 Size and Pose Estimation

We assume that the shape of the moving object is represented by a rectangle with width W and length L. As shown in Fig. 4, we define an $x_v y_v$-coordinate frame on which the y_v-axis aligns with the heading direction of a tracked object. From clustered laser measurements related to a moving object (hereafter, *moving-object measurements*), we extract the width W_{meas} and length L_{meas}. The size of the tracked object is then estimated by the following equation (Fayad and Cherfaoui, 2007):

$$\begin{cases} W_k = W_{k-1} + G(W_{meas} - W_{k-1}) \\ L_k = L_{k-1} + G(L_{meas} - L_{k-1}) \end{cases} \quad (1)$$

where W and L are estimates of width and length, respectively, k and $k-1$ are time steps. G is the filter gain, given by $G = 1 - \sqrt[k]{(1-p)}$, and p is a parameter; the larger the value of p, the more reliable the current measurements, W_{meas} and L_{meas}. To extract W_{meas} and L_{meas} from the moving-object measurements, we need to obtain the heading direction of the tracked object; as shown in Fig. 4, we extract two lines based on the split and merge method (Nguyen et al., 2009) from the moving-object measurements and determine the heading direction of the tracked object from the orientation of the lines. When we cannot extract the two lines, we determine the heading direction of the tracked object from the velocity estimate of the object, which is estimated by the following method.

We define the centroid position of the rectangle estimated by Eq. (1). From the centroid position, the pose of the tracked object (position and velocity, estimated by the Kalman filter under the assumption that the object moves at a nearly constant velocity.

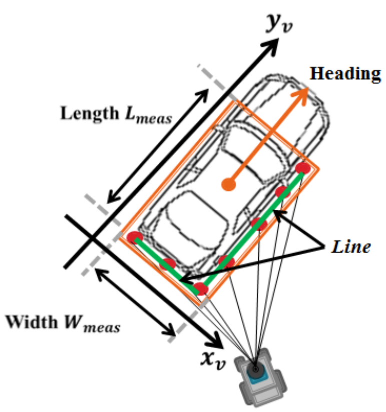


Figure 4: Size estimate. Red circles indicate moving-object measurements. Green lines indicate extracted lines based on these measurements. Orange rectangle indicates the estimate rectangle, and orange circle indicates the centroid of the rectangle.

Objects appear in and disappear from the sensing area of the LS. They also interact with and are occluded by each other and other objects in the environment. To maintain the reliable tracking under such conditions, we implement a rule-based tracking-management system (Hashimoto et al., 2006).

3.3 Data Association

To track objects in multi-object and multi-measurement environments, we need data association (one-to-one matching of tracked objects and laser measurements); a validation region is set around the predicted position of each tracked object. The shape of the validation region is rectangular, and its length and width are 0.8 m longer than those for the object estimated at the previous time step.

We refer to the representative of grouped moving-object measurements as the *representative measurement*. Representative measurements inside the validation region are considered to originate from the tracked object and are used to update the position of the tracked object using the Kalman filter, whereas those outside the validation region are identified as false alarms and discarded.

As shown in Figs. 5 and 6, in the real world, multiple representative measurements often exist inside a validation region; multiple tracked objects also compete for representative measurements. To achieve a reliable data association (matching of tracked objects and representative measurements), we introduce the following rules:

a) Person: Because person sizes are small, a person usually results in one representative measurement. Thus, if a tracked object is considered a person, matching of a tracked person and a representative measurement (one-to-one matching) is performed.

b) Vehicle: Because vehicle sizes are large, as shown in Fig. 5, a vehicle often results in multiple representative measurements. Thus, if a tracked object is considered a vehicle, matching of a tracked vehicle and representative measurements (one-to-many matching) is performed.

Based on the estimated size of the tracked object, we decide whether the object is a person or a vehicle; if the estimated size in length or width is larger than 0.8 m, the object is determined to be a vehicle; otherwise, a person.

On urban streets, people often move near vehicles, whereas vehicles move far away from each

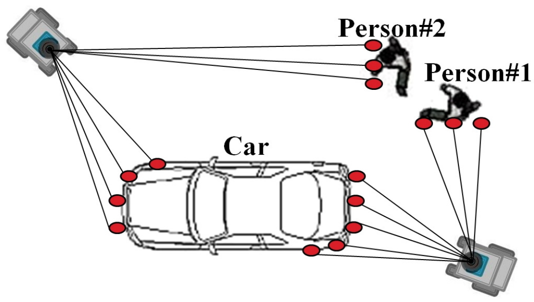
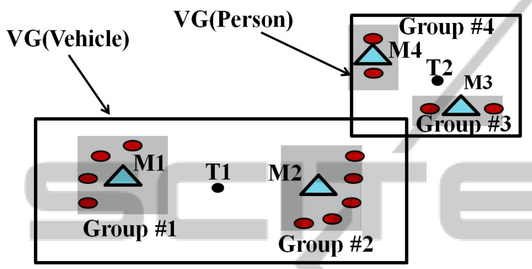


Figure 5: Laser measurements obtained using two robots.



	T1	T2
M1	○	
M2	○	
M3		○
M4		○

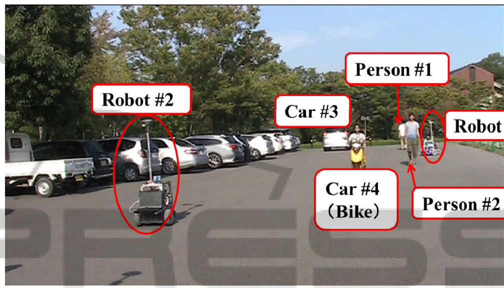
Figure 6: Data association. Black and red circles indicate tracked objects and moving-object measurements, respectively. Light blue triangles indicate representative measurements for moving-object measurements. VG stands for validation region.

other. Thus, when representative measurements of people exist in the validation region of a tracked vehicle, they might be matched to the tracked vehicle. To avoid that situation, we begin data association with people.

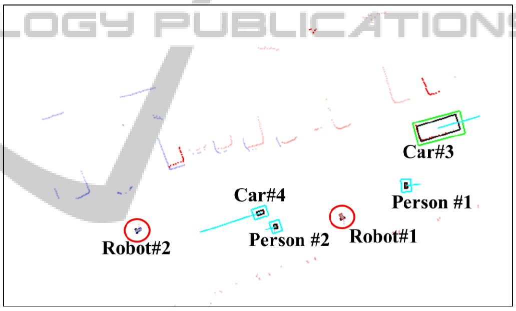
As shown in Fig. 6, if a tracked object T2 is determined to be a person, the representative measurement M3 is matched with T2 based on the global nearest neighbor (GNN) method (Konstantinova et al, 2003). Next, if a tracked object T1 is determined to be a vehicle, the two representative measurements M1 and M2 are matched with T1. The representative measurement M4 that is not matched with any tracked objects is considered either to originate from a new object or to be a false alarm. Therefore, we tentatively initiate tracking of the measurement with the Kalman filter. If the measurement is always visible, it is considered to originate from a new object and tracking is continued. If the measurement soon disappears, it is considered to be a false alarm and tentative tracking is terminated.

4 EXPERIMENTAL RESULTS

We evaluated our tracking method by conducting an experiment in an outdoor environment, shown in Fig. 7(a). Two robots that are moving around track two people, a car, and a motorcycle; Fig. 8 shows their movement paths. The moving speed of the robots, people, car, and motorcycle were about 3 km/h, 5 km/h, 15 km/h, and 20 km/h, respectively. Experimental time was 27 s (270 scans).



(a) Photo of the experimental environment.

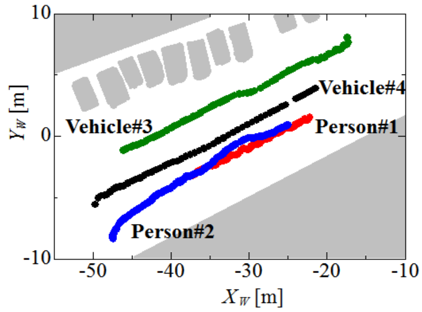


(b) Tracking result.

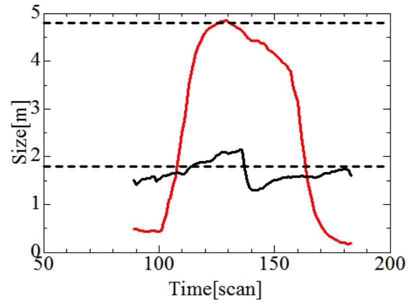
Figure 7: Moving-object tracking experiment. In (b), black rectangles indicate the estimated size of moving objects. Green and blue rectangles indicate the validation regions of cars and people, respectively. Blue bars indicate the estimated the moving direction. Red and blue points indicate laser images taken by robots #1 and #2, respectively.

Table 1: Tracking duration.

		Cooperative tracking	Individual tracking by	
			Robot #1	Robot #2
Moving object	#1	64–177[scan]	64–177	None
	#2	65–270	65–270	188–243
	#3	89–183	89–183	96–136
	#4	127–182	127–181	169–182

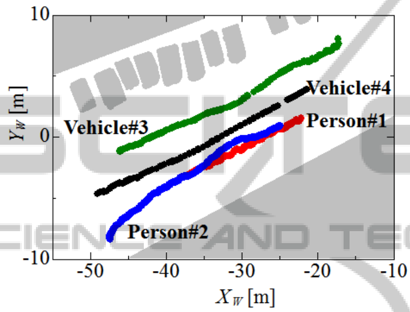


(a) Estimated track (pose) of moving objects.

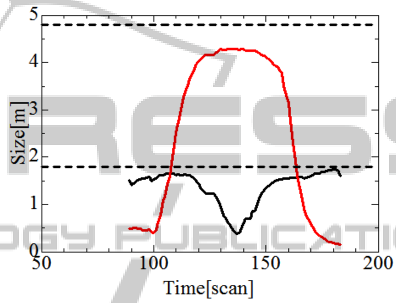


(b) Estimated size of vehicle #3.

Figure 9: Pose and size estimated by the cooperative tracking of two robots. In (b), red and black lines indicate the estimated length and width, respectively, of vehicle #3; two dashed lines indicate the true length and width of vehicle #3.

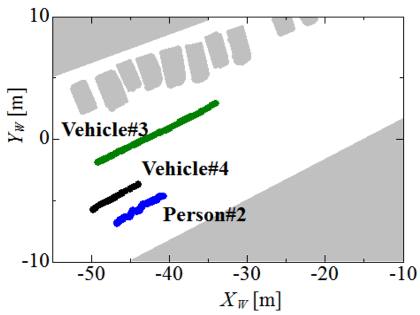


(a) Estimated track (pose) of moving objects.

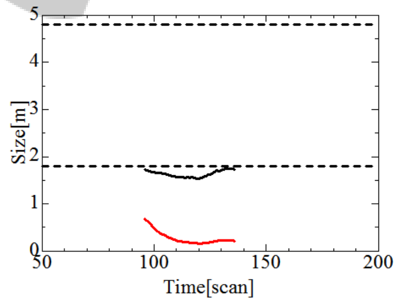


(b) Estimated size of vehicle #3.

Figure 10: Pose and size estimated by the individual tracking of robot #1.



(a) Estimated track (pose) of moving objects.



(b) Estimated size of vehicle #3.

Figure 11: Pose and size estimated by the individual tracking of robot #2.

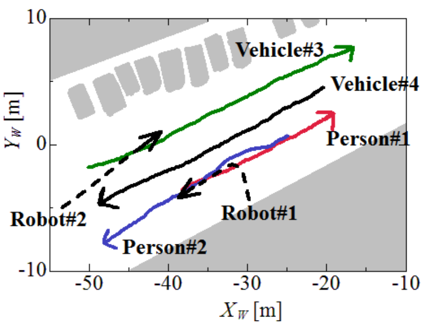


Figure 8: Movement path of moving objects.

In this experiment, the filter gain G from Eq. (1) is determined as follows:

$$G = \begin{cases} 1-\sqrt[k]{0.01} & \text{for } k \leq 10 \text{ scan} \\ 1-\sqrt[10]{0.01} = 0.369 & \text{for } k > 10 \text{ scan} \end{cases}$$

Figure 7(b) shows the tracking results at 16 s (160 scans). Figure 9 shows the tracking of people and vehicles as well as the size of vehicle #3, as estimated by two robots (cooperative tracking). For comparison, individual tracking by each robot was also conducted. The tracking results for robots #1 and #2 are shown in Figs. 10 and 11, respectively. Table 1 shows the tracking duration.

These results show that cooperative tracking using two robots can provide better tracking accuracy than individual tracking using either robot #1 or #2.

5 CONCLUSIONS

This paper presented a laser-based method for tracking of moving objects (people and vehicles) that uses multiple mobile robots located near one another. The size and pose (position and velocity) of the objects were estimated, and the method was validated by an experiment of people and vehicle tracking using two robots.

In our method, robots find moving objects in their sensing area and transmit object information to a central server, which then estimates the size and pose for each moving object. Such a server-client system is weak from the view-point of system dependability and computational burden. Future research will be directed to the design of a decentralized architecture in moving-object tracking.

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