Laser-Based Pedestrian Tracking in Outdoor Environments by Multiple Mobile Robots

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Abstract—This paper presents an outdoor laser-based pedestrian tracking system by multiple mobile robots. Each robot detects pedestrians from its own laser scan image using an occupancy-grid-based method, and the robot tracks the detected pedestrians via Kalman filtering and global-nearest-neighbor (GNN)-based data association. The tracking data is broadcast to multiple robots, and the results are combined using covariance intersection (CI). For pedestrian tracking, each robot identifies its own posture using real-time-kinematic (RTK)-GPS and laser scan matching. Using our tracking method, all the robots share the tracking data with each other, so that individual robots always recognize pedestrians that are invisible to other robots. The experimental results of tracking three pedestrians by three mobile robots validate the proposed method.

I. INTRODUCTION

Tracking (i.e., estimating the motion) of a pedestrian is an important issue for safe navigation of mobile robots and vehicles. There has been much interest in the use of stereo vision or a laser range sensor (LRS) in mobile robotics and vehicle automation [1–5]. We previously presented a pedestrian tracking method using LRSs mounted on mobile robots and automobile [6, 7, 8].

Recently, many studies related to multi-robots coordination and cooperation have been conducted [9, 10]. When these robots and vehicles are located near each other, they can share their sensing data with each other. This implies that the robots and vehicles are considered to be a multi-sensor system. Therefore, even if pedestrians are located outside the sensing area of any individual robot or vehicle, it can detect pedestrians using the tracking data received from other robots and vehicles in the vicinity, and thus, multiple robots can improve the accuracy and reliability of pedestrian tracking.

In intelligent transport system (ITS), if the tracking data is shared with neighboring vehicles through vehicle-to-vehicle communication, each vehicle can detect pedestrians efficiently. This facilitates the construction of an advanced driver-assistance-system. Even if pedestrians suddenly run into roads, the vehicles can detect them, and hence drivers can stop their vehicles to prevent an accident.

This paper presents an outdoor pedestrian tracking method by multiple mobile robots. Most studies of cooperative tracking by multiple mobile robots focus on motion planning and controlling issues. These studies attempt to keep many moving objects visible to the mobile robots at all times while consuming as little motion energy as possible [11, 12, 13]. In this paper, we address sensor-data fusion, through which pedestrian tracking is achieved by combining the tracking data from multiple mobile robots located in the vicinity.

There has been considerable research in cooperative pedestrian tracking using multiple static sensors located in the environment [14–18] and multisensors on robots [19, 20]. Our previous study [7] presented a pedestrian tracking method using multiple mobile robots in an indoor environment; pedestrians were tracked by each robot using Kalman filter. To enhance tracking performance, the tracking data was combined using covariance intersection (CI) method [23].
In this paper, we extend our previous indoor method to pedestrian tracking with multiple mobile robots in an outdoor environment. Our method contributes toward building a cooperative pedestrian tracking system using vehicles such as mobile robots, cars, and electric personal assistive mobility devices (EPAMD), as illustrated in Fig. 1. This paper is organized as follows: In Section II, we present an overview of our experimental system. In Sections III and IV, we present methods of pedestrian tracking and robot localization. In Section V, we describe a pedestrian tracking experiment conducted using three mobile robots in an outdoor environment to validate our method, and then, followed by our conclusions.

II. EXPERIMENTAL MOBILE ROBOT SYSTEM

Figure 2 shows our mobile robot system used in the experiments. Three robots each have two independent-drive-wheels. A wheel encoder is attached to each of the drive wheels to measure the wheel velocity. A yaw-rate gyro is attached to the chassis of the robot to measure the turn velocity.

Each robot is equipped with a forward-looking laser range sensor, which captures laser scan images. The images are represented by a sequence of distance samples in the horizontal plain of $270[\text{deg}]$. The angular resolution of the LRS is $0.5[\text{deg}]$, and the number of distance samples is 541 in one scan image.

Each robot is equipped with an RTK-GPS to identify its own outdoor position. The sampling period of the sensors is $10[\text{Hz}]$. We use wireless LAN broadcast communications to share the data among the robots. It takes approximately $40[\text{ms}]$ to exchange information between the robots. We use a ring type of network structure such that the robots transmit information in the order of robots #1, #2, and #3.

III. PEDESTRIAN TRACKING

A. Overview

As shown in Fig. 3, we define two coordinate frames: the world coordinate frame, $\Sigma_w(O_w : X_wY_wZ_w)$, and the $i$-th robot coordinate frame, $\Sigma_i(O : X_iY_iZ_i)$, where $i = 1, 2, 3$.

Based on an occupancy-grid-based method [6], each robot independently detects pedestrians using its own laser image. Detected pedestrians are tracked using the following two tracking modes (Fig. 4):

(a) Individual tracking with a single robot: Each robot individually tracks pedestrians without any tracking data from other robots. The robot can only track pedestrians inside the sensing area of its own LRS.

(b) Cooperative tracking with multiple robots: The robots track pedestrians by sharing their own tracking data, so that each robot can track pedestrians both inside and outside the sensing area of its LRS.

B. Individual Tracking

A pedestrian position in $\Sigma_w$ is denoted by $(x_p, y_p, z_p)$. If the pedestrian is assumed to move at nearly constant velocity, his/her rate kinematics is given by

$$x_p(t) = Fx_p(t-1) + G\Delta x_p(t-1)$$  (1)
where \( x_0 = (x_o, \dot{x}_o, y_o, \dot{y}_o)^T \). \( \Delta x_o = (\Delta \dot{x}_o, \Delta \dot{y}_o)^T \) is an unknown acceleration (plant noise). \( F \) and \( G \) are constant system matrices.

The measurement model related to the pedestrian is then
\[
\mathbf{z}_i(t) = H_i(t) \mathbf{x}_i(t) + H'_i(t) \mathbf{q}_i(t) + \mathbf{w}_i(t) \quad (2)
\]
where \( \mathbf{z}_i = (z_i, y_i)^T \) is the measurement represented in \( \Sigma_i \). \( \Delta \mathbf{z}_i \) is the measurement noise. \( \mathbf{q}_i = (x_i, y_i)^T \) is the position of the \( i \)-th robot in \( \Sigma_m \). \( H_i \) and \( H'_i \) are given by
\[
H_i = \begin{bmatrix}
\cos \psi_i & 0 & -\sin \psi_i & 0
\end{bmatrix} \quad \text{and} \quad H'_i = \begin{bmatrix}
\cos \psi_i & -\sin \psi_i & \sin \psi_i & \cos \psi_i
\end{bmatrix}.
\]
\( \psi_i \) is the orientation of the \( i \)-th robot in \( \Sigma_m \). The posture (position and orientation), \( \mathbf{x}_i = (x_i, y_i, \psi_i)^T \) is determined using the localization system described in Section IV.

From Eqs. (1) and (2), the pedestrian is tracked using Kalman filter [21].

To track multiple pedestrians, as shown in Fig. 5 (a), a validation region with a constant radius is set around the predicted position of each tracked pedestrian. The measurements inside the validation region are considered to be obtained from the tracked pedestrian, and it is applied to the track updated with Kalman filter. On the other hand, the measurements outside the validation region are considered to be false alarms, and are therefore, discarded. In our experiments described in Section V, the radius of the validation region is set at 1.0 [m]. In crowded environments, as shown in Figs. 5 (b)-(d), multiple measurements exist inside a validation region; multiple tracked pedestrians also compete for measurements. To achieve a reliable data association (matching of tracked pedestrians and measurements), we apply global-nearest-neighbor (GNN) algorithm [23, 24], in which a cost matrix based on the laser measurements, \( H \), can always track pedestrians both inside and outside the sensing area of its own LRS.

Pedestrians always appear in and disappear from the sensing area of the LRS. They also meet interaction and occlusion. In order to handle such conditions, we implement a tracking management system based on the following rules [6].

C. Cooperative Tracking

When the robots are located near each other, they communicate with each other and exchange their own tracking data. They estimate the position and velocity of tracked pedestrians and their associated covariance. By sharing their own tracking data among themselves, each robot can always track pedestrians both inside and outside the sensing area of its own LRS.

To explain our cooperative tracking, we consider two robots: robots \#1 and \#2. The tracking data of the \( j \)-th pedestrian tracked by robot \#1 is denoted by \( \mathbf{I}^{(j)}_1 = \{ \hat{x}^{(j)}_1, \hat{P}^{(j)}_1 \} \), where \( j = 1, 2, \cdots \). \( \hat{x}^{(j)}_1 \) is an estimate consisting of the position estimate \( \hat{q}^{(j)}_1 \) and the velocity estimate \( P^{(j)}_1 \) is the associated covariance.

The tracking data of the \( k \)-th pedestrian tracked by robot \#2 is also denoted by \( \mathbf{I}^{(k)}_2 = \{ \hat{x}^{(k)}_2, \hat{P}^{(k)}_2 \} \), where \( k = 1, 2, \cdots \). We consider that robot \#1 combines the tracking data sent from robot \#2 with its own tracking data. Combining the tracking data of robot \#1 with that of robot \#2 can be achieved similarly.

First, we set a validation region around the position estimate, \( \hat{q}^{(j)}_1 \), of the \( j \)-th pedestrian tracked by robot \#1. We consider the positional estimate, \( \hat{q}^{(k)}_2 \), of the \( k \)-th pedestrian tracked by robot \#2 as the measurement, and then, we can determine data association (one-to-one matching of pedestrians tracked by robots \#1 and \#2) using the GNN algorithm.

As shown in Fig. 6 (a), if a pedestrian is detected inside the sensing areas of both robots \#1 and \#2, the two estimates, \( \hat{P}^{(j)}_1 \) and \( \hat{P}^{(k)}_2 \), of the pedestrian can be matched. For the matched pedestrian, robot \#1 updates its own tracking data by the CI method [23].
\[ \begin{align*}
x_{i+1}^{(1)} &= \mathbf{P}^{(1)}_{i} - 1 \left[ \alpha \mathbf{x}_{i}^{(1)} + (1 - \alpha) \mathbf{P}_{i}^{(2)} - 1 \right] x_{i}^{(2)} \\
\mathbf{P}_{i}^{(1)} &= \alpha \mathbf{P}_{i}^{(1)} - 1 + (1 - \alpha) \mathbf{P}_{i}^{(2)} - 1 \end{align*} \]  

\text{(3)}

where \( \mathbf{I}^{(1)} = \{ \mathbf{x}^{(1)}, \mathbf{P}^{(1)} \} \) and \( \mathbf{I}^{(2)} = \{ \mathbf{x}^{(2)}, \mathbf{P}^{(2)} \} \) are the tracking data of the matched pedestrian. \( \mathbf{x}_{i}^{(1)} \) and \( \mathbf{P}_{i}^{(1)} \) are the updated tracking data and its associated covariance, respectively. The weight \( \alpha \) is determined such that the determinant of \( \mathbf{P}_{i+1}^{(1)} \) is minimized under the constraint \( 0 \leq \alpha \leq 1 \).

We combine their tracking data in a decentralized fashion. From a statistical viewpoint, their tracking data is highly correlated. Usually Kalman filter-based data fusion complicates the building of a decentralized system because it needs to calculate the degree of correlation. The CI method allows accurate fusion of the tracking data in a decentralized fashion without any knowledge of the degree of their correlation. For this reason, we apply the CI algorithm.

For non-matched pedestrian, as shown in Figs. 6 (b) and (c), robot #1 updates its own tracking data as follows:

1) When a pedestrian exists inside the sensing area of robot #1, but outside that of robot #2 as shown in Fig. 6 (b), robot #1 has the tracking data \( \mathbf{I}^{(1)} \), but robot #2 does not have \( \mathbf{I}^{(2)} \). Then, robot #1 sets \( \mathbf{I}^{(1)*} = \mathbf{I}^{(1)} \).

2) When a pedestrian exists inside the sensing area of robot #2, but outside that of robot #1 as shown in Fig. 6 (c), robot #2 has the tracking data \( \mathbf{I}^{(2)} \), but robot #1 does not have \( \mathbf{I}^{(1)} \). Then, robot #1 sets \( \mathbf{I}^{(1)*} = \mathbf{I}^{(2)} \).

Cooperative tracking with three or more robots can be achieved similarly.

IV. ESTIMATION OF ROBOT POSTURE

A. Overview

To map the tracking data onto \( \Sigma_w \), each robot needs to identify its own posture in \( \Sigma_w \). The robot determines its own posture by RTK-GPS, and to improve the accuracy of its posture, it determines its own posture by a scan matching based localization. If the robot cannot retrieve RTK-GPS information, only the scan matching based localization is applied to determine its own posture.

B. RTK-GPS based Localization

The robot estimates its own velocity (linear/turning) based on dead reckoning using the wheel encoders and gyro. Motion and measurement models of the \( i \)-th robot are given by Eqs. (4) and (5), respectively:

\[ V_{i}(t) = V_{i}(t-1) + \Delta V_{i}(t-1) \]  

\text{(4)}

\[ z_{i}(t) = \begin{pmatrix} 1 \quad -b/2 \\ 1 \quad b/2 \\ 0 \quad 1 \end{pmatrix} V_{i}(t) + \Delta z_{i}(t) \]  

\text{(5)}

where \( V_{i} = (v_{i}, \psi_{i})^{T} \); \( v_{i} \) is the linear velocity and \( \psi_{i} \) is the turning velocity. \( z_{i} = (z_{l}, z_{r}, \psi_{i})^{T} \); \( z_{l} \) and \( z_{r} \) are the velocities of the left and right wheels, respectively, measured by the wheel encoders, and \( \psi_{i} \) is the gyro output. \( \Delta V_{i} \) and \( \Delta z_{i} \) are unknown acceleration (disturbance) and the sensor noise, respectively. \( b \) is the tread length of the robot.

From Eqs. (4) and (5), the robot velocity \( \mathbf{V}_{i} \) is estimated using Kalman filter. Based on velocity estimate, we can determine the posture of the \( i \)-th robot \( x_{i} = (x_{i}, y_{i}, \psi_{i})^{T} \):

\[ \tilde{x}_{i}(t) = f(\tilde{x}_{i}(t-1), \mathbf{V}_{i}(t-1)) \]

\[ = \begin{pmatrix} \tilde{x}_{i}(t-1) + V_{i}(t-1) \tau \cos(\psi_{i}(t-1) + \frac{\psi_{i}(t-1) \tau}{2}) \\ \tilde{y}_{i}(t-1) + V_{i}(t-1) \tau \sin(\psi_{i}(t-1) + \frac{\psi_{i}(t-1) \tau}{2}) \\ \psi_{i}(t-1) + \psi_{i}(t-1) \tau \end{pmatrix} \]  

\text{(6)}

If the robot obtains posture information from the RTK-GPS, the measurement model is given by

\[ z_{\text{GPS}}(t) = \mathbf{H}x_{i}(t) + \Delta z_{\text{GPS}}(t) \]  

\text{(7)}

From Eqs. (6) and (7), the robot can update its own posture using Kalman filter.

C. Scan Matching based Localization

When multiple robots are located near each other, they have an overlapping sensing area. They improve their own posture accuracy by exchanging their scanned images and matching them in their overlapping sensing area.

We define the posture of robot #2 relative to robot #1 by \( \mathbf{2z}_{i} = (x_{2}, y_{2}, \psi_{2})^{T} \) in \( \Sigma_w \). Because as shown in Fig. 7, the two robots are located near each other, their sensing areas partially overlap. Robot #1 (which can perform the RTK-GPS-based localization) broadcasts its own posture and a laser scan image obtained by its own LRS to robot #2. Robot #2 determines the relative posture, \( \mathbf{2z}_{i} \), by matching its own laser scan image with that sent from robot #1. Hereafter, we call the laser scan matching for estimating relative posture as...
Relative-scan matching.

Relative-scan matching gives the following measurement equation:

\[
\begin{bmatrix}
2z_i(t) = g(\hat{x}_1(t), x_2(t)) + \Delta^2 z_i(t) \\
\cos \psi_2(t) - \sin \psi_2(t) 0 \hat{x}_1(t) - x_2(t) \\
\sin \psi_2(t) \cos \psi_2(t) 0 \hat{y}_1(t) - y_2(t) \\
0 0 1 \Psi_1(t) - \Psi_2(t)
\end{bmatrix} + \Delta^2 z_i(t)
\]

(8)

where \( \hat{x}_1 \) is the posture of robot #1 estimated by the RTK-GPS-based localization. \( \Delta^2 z_i \) is the error of the relative posture.

From Eqs. (6) and (8), robot #2 can determine its own posture, \( x_2 \), using Kalman filter.

V. EXPERIMENTAL RESULTS

We conducted an experiment in an outdoor environment, as shown in Fig. 8 in order to evaluate the tracking method. Three robots and three pedestrians moved around in the environment, as in Fig. 9. The walking speed of pedestrians #1 and #2 was between 0.1 and 1.5[m/s], and that of pedestrian #3 was between 0.1 and 3.7[m/s], while the moving speed of the robot was less than 0.3 [m/s].

Figure 10 shows the results of individual tracking; subfigures (a), (b) and (c) show the tracks of three pedestrians, as estimated by the three robots. Each robot partially tracks pedestrians because the pedestrians exist inside and outside the sensing area of the LRS. Figure 11 shows the results of the cooperative tracking; because the three robots share the tracking data with each other, all three robots always track the three pedestrians.

Figure 12 shows the duration of the individual tracking; subfigures (a), (b) and (c) show the times during which robots #1, #2 and #3, respectively, track pedestrians using individual tracking. Figure 13 shows the duration of the cooperative tracking.

From these results, cooperative tracking provides a better tracking performance than individual tracking. Cooperative tracking detects pedestrian #3 who runs into the road 3.4[s] faster than individual tracking. The faster the pedestrians can be detected, the safer becomes robots’ navigation.

VI. CONCLUSIONS

This paper presents a pedestrian tracking method in outdoor environments using multiple mobile robots. Pedestrians were tracked by each robot using Kalman filter and GNN based data association. The tracking data obtained by each robot was broadcast to others robots, and was combined by CI method. Our method shares the pedestrian tracking data with all robots, and thus, collectively they can always recognize pedestrians that are invisible to individual robots. The experimental results of three pedestrians tracked by three robots validated our method.

To map the pedestrian tracking data on a world coordinate frame, we applied two localization methods: RTK-GPS-based and relative-scan-matching-based methods. We now apply a SLAM method to map the pedestrian tracking data; this allows multiple mobile robots to track pedestrians in urban city environments where they cannot receive GPS information.
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