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Indoor mobile robot and pedestrian localization techniques

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Abstract: This paper presents indoor localization techniques for mobile robot and pedestrian navigation. Two different methods are examined and the performance and superiority of each method are discussed. A dead reckoning method is established for the mobile robot navigation and a wireless localization network is used for the pedestrian navigation. The purpose of the dead reckoning system is to integrate three internally-mounted sensors such as accelerometer, odometer, and heading angle sensor for positioning the mobile robot without depending on any external reference information. However, in the case of pedestrian, it is difficult to install inertia sensors to the human body. So, for the pedestrian navigation, we use a wireless sensor network. The key issue in wireless localization network is that the measurement of wireless sensor network contains lots of noises whose noise characteristics are time-varying. In this paper, we propose a simple algorithm that can reduce the noise effect without using any noise characteristics.

Keywords: Indoor localization, Mobile robot, Pedestrian navigation, Wireless sensor network, Dead reckoning.

1. INTRODUCTION

In indoor mobile robot applications, one of the toughest problems is to estimate the robot and object positions as accurately as possible [1], [2], [3], [9]. The pedestrian localization is fundamentally required in navigating the mobile robot for the purpose of obstacle avoidance, human well-fare service, and so on [4], [5], [11]. Typically, the robot navigation can be carried out using the measurement from the inertia sensor mounted within the robot or based on ambient information. The key problem in indoor mobile robot navigation is to fuse various sensors such that drawback of each sensor can be compensated. In the case of pedestrian navigation, however the classical sensor fusion method cannot be used because it is difficult to install inertia sensors to the human body. So, for the pedestrian navigation, it is necessary to make use of external sensing information or natural landmark in order to reduce the number of sensors attached to the human body. It can be thus said that internally-mounted sensors play an important role for the robot navigation; however external sensing and/or external signal information are important for the pedestrian localization. In this paper, we consider two extreme cases for the robot navigation and pedestrian navigation respectively. It is assumed that the robot can use odometer measurement, accelerometer output and a heading rate sensor information. Note that all these sensors (odometer, accelerometer, and heading rate sensor) are internally-mounted sensor; that is, their measurements are all due to the robot movement (rotation and linear movement). In the pedestrian navigation, it is assumed that a small-size tag, which is a part of wireless sensor network, can be attached to the human body. The small-size tag can interchange wireless radio signal with wireless reference sensor nodes, which are fixed to particular points. So, in the pedestrian localization, only an external wireless communication signal is used (none of internal sensing information is required).

2. DEAD RECKONING SYSTEM FOR MOBILE ROBOT NAVIGATION

The goal of the dead reckoning system considered in this section is to estimate bias noise in accelerometer measurements without using any external reference information. Only three internal measurements; odometer output, accelerometer measurement, and angular rate information, are used. The extended Kalman filter is used to integrate these three sensing signals. The odometer provides rotation speeds of the left and right wheels; the accelerometer measures the linearly-moving acceleration; and the angular rate sensor measures the heading rate and rotated-heading angle of the robot with respect to an initial direction. The state space of mobile robot consists of $[x(k), y(k), v_x(k), v_y(k)]^T$, where x, y are positions in x, y directions and $v_x(k), v_y(k)$ are speeds. The motion of robot is governed by the propagation equation given in (1). In (1), Δt is the sampling interval; $I_{2\times 2}$ is 2×2 identity matrix; a_x, a_y are true accelerations in x, y directions respectively. In the propagation equation (1), accelerometer output and heading sensor information are combined to calculate a_x and a_y. Since the moving speed of the mobile robot can be measured from the odometer; the measurement equation is now designed as

$$\widetilde{z} = (v_x)^2 + (v_y)^2 + w \qquad (2)$$

where w is the measurement noise from the odometer. In (1), the true accelerations can be rewritten as $a_x = \widetilde{a}_x - n_{a_x}$ and $a_y = \widetilde{a}_y - n_{a_y}$ where $\widetilde{a}_x$ and $\widetilde{a}_y$ are measured accelerations, and n_{a_x} and n_{a_y} are measurement noises contained in actual measurements. So, using actual measurements we can establish the process equation

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$$\begin{pmatrix} x(k+1) \\ y(k+1) \\ v_x(k+1) \\ v_y(k+1) \end{pmatrix} = \begin{pmatrix} I_{2\times2} & \Delta t \cdot I_{2\times2} \\ 0_{2\times2} & I_{2\times2} \end{pmatrix} \begin{pmatrix} x(k) \\ y(k) \\ v_x(k) \\ v_y(k) \end{pmatrix} + \begin{pmatrix} 0_{2\times2} \\ \Delta t \cdot I_{2\times2} \end{pmatrix} \begin{pmatrix} a_x \\ a_y \end{pmatrix} \tag{1}$$

$$\begin{pmatrix} x(k+1) \\ y(k+1) \\ v_x(k+1) \\ v_y(k+1) \end{pmatrix} = \begin{pmatrix} I_{2\times2} & \Delta t \cdot I_{2\times2} \\ 0_{2\times2} & I_{2\times2} \end{pmatrix} \begin{pmatrix} x(k) \\ y(k) \\ v_x(k) \\ v_y(k) \end{pmatrix} + \begin{pmatrix} 0_{2\times2} \\ \Delta t \cdot I_{2\times2} \end{pmatrix} \begin{pmatrix} \widetilde{a}_x \\ \widetilde{a}_y \end{pmatrix} - \begin{pmatrix} 0_{2\times2} \\ \Delta t \cdot I_{2\times2} \end{pmatrix} \begin{pmatrix} n_{a_x} \\ n_{a_y} \end{pmatrix} \tag{3}$$

given in (3). The process noises n_{a_x} and n_{a_x} are noises contained in the measured-accelerations. However, the measured-accelerations include bias noises, which are not just random white Gaussian; so it is usually critical to find the bias for an accurate position tracking. Let us write the measured-accelerations as:

$$\widetilde{a}_x = a_x - \delta a_x \tag{4}$$

$$\widetilde{a}_y = a_y - \delta a_y \tag{5}$$

where δa_x and δa_y are biases of the measurements. Let us assume that the bias is governed by random white Gaussian noise such as

$$\frac{\delta a_x(t+1) - \delta a_x(t)}{\Delta t} := f_t \tag{6}$$

where f_t is a white Gaussian noise. Then, considering δa_x and δa_y as states, we can obtain the process equation (7) that takes account of the bias noises. An extended Kalman filter can be easily designed using (2) and (7) to estimate the robot position. In (7), $\widetilde{a}_x$ and $\widetilde{a}_y$ are measured by combining acceleration output and heading angle measurement.

3. A SIMPLE PEDESTRIAN LOCALIZATION ALGORITHM

The pedestrian localization has obtained much attention recently due to its fundamental importance in intelligent robot navigation [11]. However, the pedestrian navigation is considered much tougher than the robot localization because it is highly difficult to install navigation sensors to the human body. In this section, it is assumed that a small-size wireless localization tag can be attached to a person. The wireless localization tag can be a UWB tag, ZigBee sensor node, or small-size WLAN card [6], [7], [8], [10]. A critical problem in wireless localization network is that there could be lots of measurement noises in the computed-localization information and/or measured signal strength [10], which significantly degrades the performance of wireless localization network. In this paper, we provide a localization filtering which is very simple, but effective in reducing the measurement noise effect. For convenience, let us denote the measured position by $\widetilde{P}_i$; the true position by P_i; and the estimated position by $\widehat{P}_i$. Also, let us assume that $i^* = \arg_i \min\{\|\widetilde{P}_i - P_i\|,\ i = 1, \ldots, N\}$ is known. The localization filter proposed in this paper is summarized in the following algorithm.

for $\quad i = 1:1:i^* - 1$
$\quad\quad \theta = \angle(\widetilde{P}_{i^*-i}, \widehat{P}_{i^*-i+1});$
$\quad\quad l = \|\widetilde{P}_{i^*-i} - \widehat{P}_{i^*-i+1}\|;$
$\quad$ if $l \le l_{max}$
$\quad\quad \Delta x = l\cos(\theta);\ \ \Delta y = l\sin(\theta);$
$\quad$ else if $l > l_{max}$
$\quad\quad \Delta x = l_{max}\cos(\theta);\ \ \Delta y = l_{max}\sin(\theta);$
$\quad$ end if
$\quad\quad \widehat{P}_{i^*-i} = \widehat{P}_{i^*-i+1} + [\Delta x, \Delta y]^T;$
end
for $\quad i = i^* + 1:1:N$
$\quad\quad \theta = \angle(\widetilde{P}_i, \widehat{P}_{i-1});$
$\quad\quad l = \|\widetilde{P}_i - \widehat{P}_{i-1}\|;$
$\quad$ if $l \le l_{max}$
$\quad\quad \Delta x = l\cos(\theta);\ \ \Delta y = l\sin(\theta);$
$\quad$ else if $l > l_{max}$
$\quad\quad \Delta x = l_{max}\cos(\theta);\ \ \Delta y = l_{max}\sin(\theta);$
$\quad$ end if
$\quad\quad \widehat{P}_i = \widehat{P}_{i-1} + [\Delta x, \Delta y]^T;$
end

The algorithm is used to filter the measurement noise in a post-processing. However, if the initial position is known accurately, then $i^* = 1$ because of $\|\widetilde{P}_i - P_i\| = 0$. So, in this case, the algorithm is used to filter the measurement noise in a real time. In the algorithm, it is required to select l_{max}. It is recommended to choose l_{max} as the maximum or average distance human can move in a sampling time (selecting the sampling interval is also system-dependent).

4. SIMULATION AND EXPERIMENTAL RESULTS

For the verification of the algorithm designed in the previous sections, computer-based simulation tests are carried out. For the mobile robot simulation, we assume that the variance of process noises is 0.001; the variance of measurement noises is 0.001; $\Delta t = 0.1$. The accelerations along the x-axis and y-axis are generated

$$\begin{pmatrix} x(k+1) \\ y(k+1) \\ v_x(k+1) \\ v_y(k+1) \\ \delta a_x(k+1) \\ \delta a_y(k+1) \end{pmatrix} = \begin{pmatrix} I_{2\times2} & \Delta t \cdot I_{2\times2} & (\Delta t)^2/2 \cdot I_{2\times2} \\ 0_{2\times2} & I_{2\times2} & \Delta t \cdot I_{2\times2} \\ 0_{2\times2} & 0_{2\times2} & I_{2\times2} \end{pmatrix} \begin{pmatrix} x(k) \\ y(k) \\ v_x(k) \\ v_y(k) \\ \delta a_x(k) \\ \delta a_y(k) \end{pmatrix} + \begin{pmatrix} (\Delta t)^2/2 \cdot I_{2\times2} \\ \Delta t \cdot I_{2\times2} \\ 0_{2\times2} \end{pmatrix} \begin{pmatrix} \widetilde{a}_x \\ \widetilde{a}_y \end{pmatrix}$$
$$+ \begin{pmatrix} (\Delta t)^3/6 \cdot I_{2\times2} \\ (\Delta t)^2/2 \cdot I_{2\times2} \\ \Delta t \cdot I_{2\times2} \end{pmatrix} \begin{pmatrix} f_{a_x}(t) \\ f_{a_y}(t) \end{pmatrix}. \quad (7)$$

by $a_x = a_x + \alpha(a_x + r_a)$ and $a_y = a_y + \alpha(a_y + r_b)$ where $alpha = 3/4$ and r_a and r_b are random variables bounded as $-1 \le r_a,\ r_b \le 1$. Fig. 1 shows the results of the simulation. In this figure, left-top plots represent true mobile robot trajectory and propagated trajectory based on accelerometer measurements. The right-top plots are true mobile robot trajectory and estimated trajectory from extended Kalman filter. The left-bottom plots are estimated velocities and actual velocities in x-axis and y-axis. The right-bottom plots are estimated speed and actual speed. Fig. 2 show simulated actual bias noises and estimated bias noises in x-axis and y-axis. As shown in these plots, the trajectory of mobile robot has been accurately estimated by way of calculating the actual bias noises of accelerometer measurements. For the simulation of moving pedestrian, variance of measurement noise is assumed 4.0 and the moving force is generated by $\Delta x = \beta(r_a - 0.55)$ and $\Delta y = \beta(r_b - 0.44)$ where $\beta = 2$ and $-1 \le r_a,\ r_b \le 1$. Fig. 3 shows actual pedestrian trajectory, measured trajectory from WSN, and estimated trajectory from the suggested algorithm. Plots in Fig. 4 are the error of the estimated and measured trajectories. From Fig. 4, we know that the proposed algorithm improved the accuracy by amount of $2 \sim 3$ meters.

5. CONCLUDING REMARKS

In this paper, we established a dead-reckoning system for mobile robot navigation. In the dead-reckoning method, we do not use any external reference information such as magnetic sensing; but only use internally-mounted sensors. For the pedestrian navigation, we developed a simple but effective localization filtering scheme. In the localization filtering proposed, we do not use any noise characteristics and any other complex estimation schemes. However, it is required to appropriately select l_{max} and the sampling interval. From simulations and experimental tests, the advantages and disadvantages, and effectiveness of the established-methods are illustrated. In our future efforts, we will provide a systematic and analytical method for choosing l_{max} and the sampling interval taking account of the desired performance.

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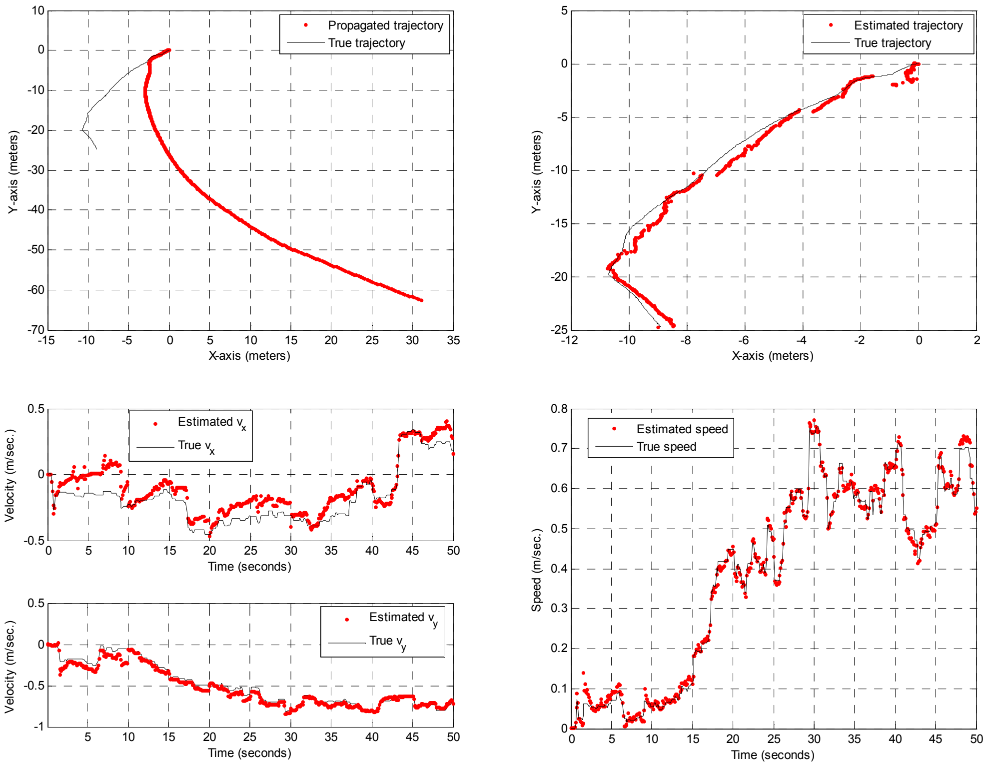

Fig. 1 Left-top: True mobile robot trajectory and propagated trajectory based on accelerometer measurements. Right-top: True mobile robot trajectory and estimated trajectory from extended Kalman filter. Left-bottom: Estimated velocities and actual velocities in x-axis and y-axis. Right-bottom: Estimated speed and actual speed.

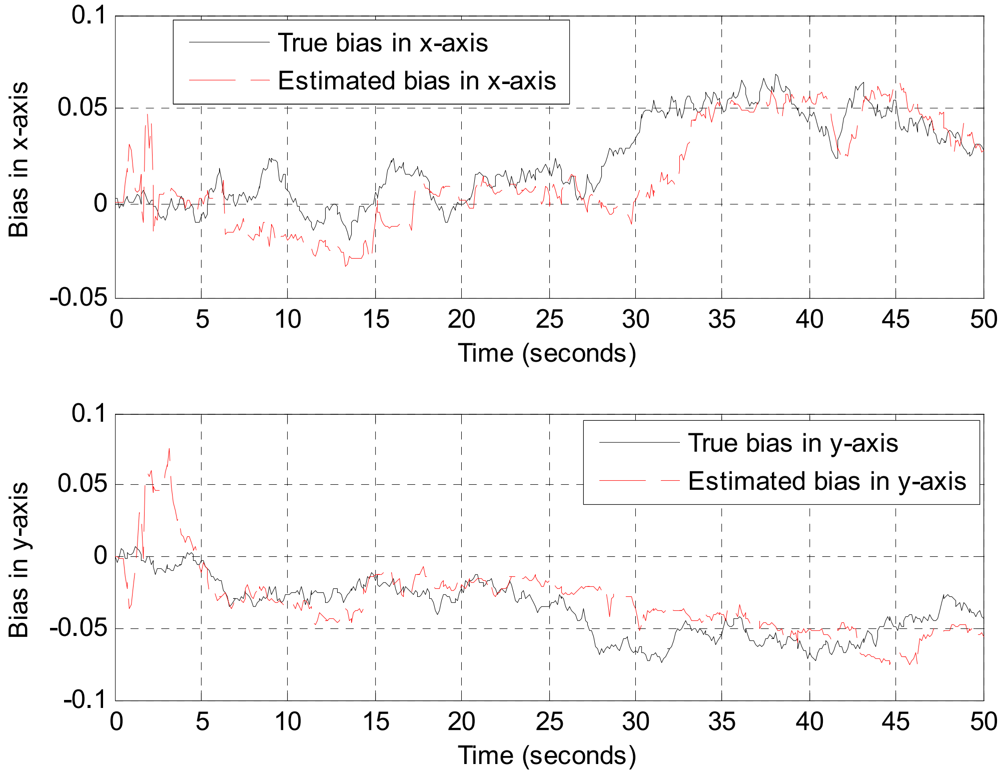

Fig. 2 Simulated actual bias noises and estimated bias noises in x-axis and y-axis.

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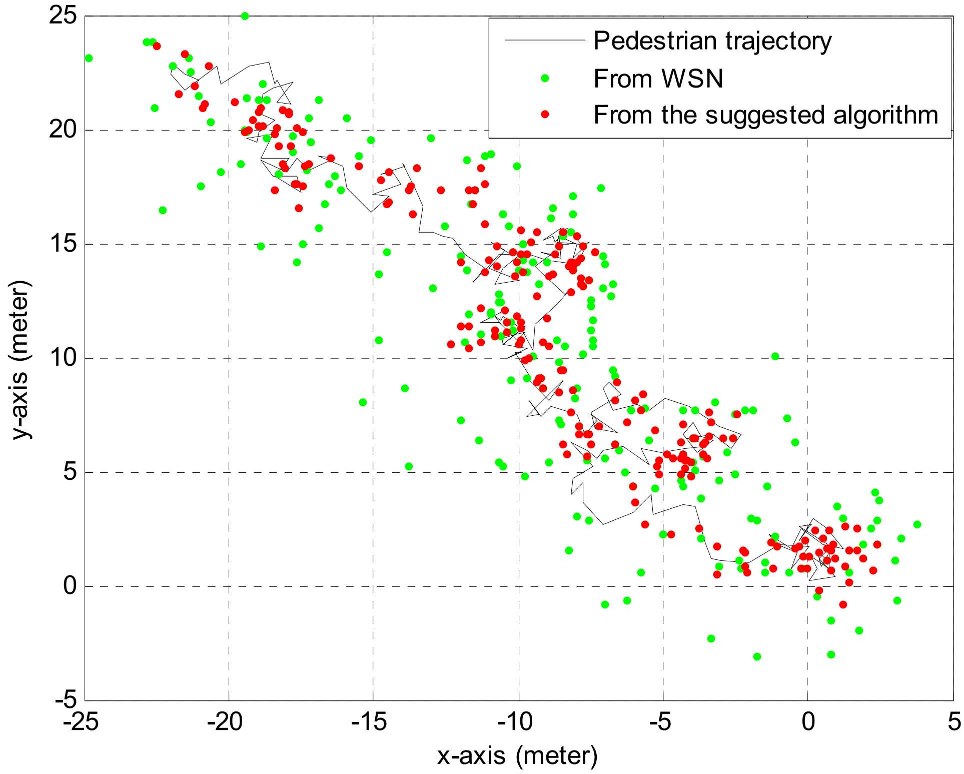

Fig. 3 Actual pedestrian trajectory, measured trajectory from WSN, and estimated trajectory from the suggested algorithm.

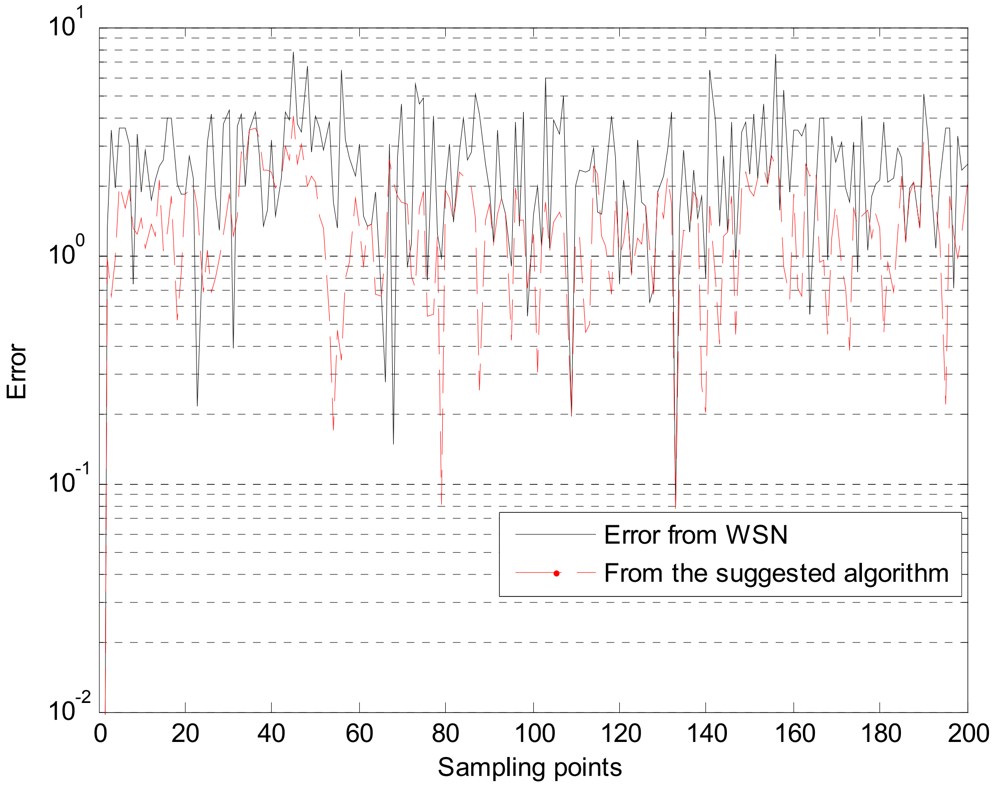

Fig. 4 Trajectory errors from WSN and the suggested algorithm.