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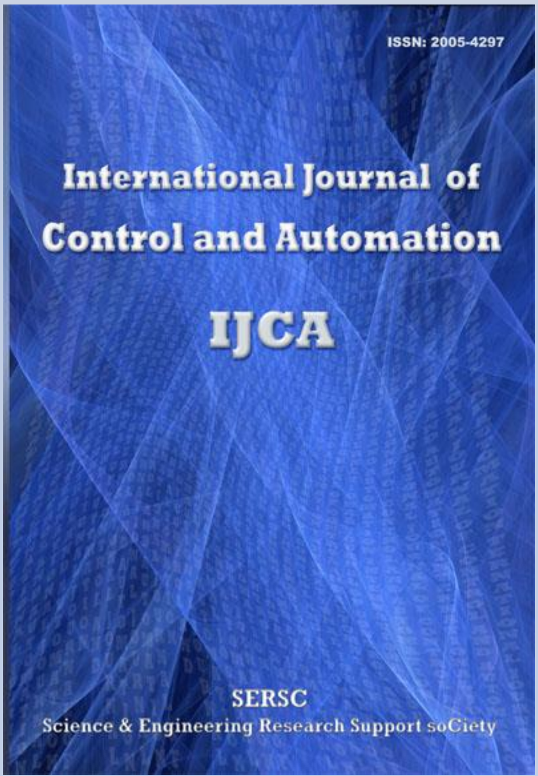

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Mobile Robot Localization Using Optical Mouse Sensor and Encoder Based on Kalman Filter Algorithm

Sang-Hyung Park[1] and Soo-Yeong Yi[2]
[1,2]*Seoul National University of Science and Technology*
[1,2]*Dept. of Electrical and Information Engineering*
[1]*scrtrees@gmail.com*, [2]*suylee@seoultech.ac.kr*

Abstract

An optical mouse sensor is widely used to estimate the dead reckoning motion of a mobile robot because of its potential to overcome the estimation error caused by the robot wheel slippage. However, motion estimation using an optical sensor is vulnerable to signal noise and kinematic error. To reduce the error associated with the coordinate estimation for a mobile robot, this study presents a new localization algorithm based on the Kalman filter, which uses an optical mouse sensor together with an encoder sensor of driving wheels. Experiments were conducted to verify the performance of the proposed algorithm in the case when an insufficient number of optical mouse sensors is used.

Keywords*: Mobile robot, Localization, Optical mouse sensor, Kalman filter algorithm*

1. Introduction

Localization is essential for autonomous navigation of a mobile robot. Herein, the localization refers to estimation of mobile robot's coordinates, $[x \ \ y \ \ \theta]^t$, including the heading angle in the global coordinate system. Inaccurate estimation of the coordinates causes a tracking error of the mobile robot for given desired trajectories. Dead reckoning is a well-known localization method, which uses odometric sensor such as encoder or optical mouse sensors. The optical mouse sensor can solve the wheel slip problem, and thus, it is widely used for the dead reckoning estimation of a mobile robot's motion [1]. The optical mouse sensor is a type of image sensor capable of measuring displacement in a small time interval, and outputting velocity data based on the displacement measurement. Kim *et al.* investigated the optimal configuration of the multiple optical mouse sensors for estimating the velocity of a mobile robot [2-3]. They showed that a regular polygonal array of multiple optical sensors is an optimal configuration for velocity estimation of a mobile robot, in the sense of the least squared errors. Similar results were reported for the optimal location of the optical mouse sensors in [4]. In general, additional complementary sensors are used together with the odometric sensors because the dead reckoning estimation is subject to cumulative error. To compensate the cumulative error of the optical mouse sensor, Sekimori *et al.* proposed the use of a global camera at the surrounding environment of a mobile robot [5]. In [6], a ranging sensor was combined with the optical mouse sensors to compensate for the error in the motion estimation of a mobile robot.

In general, the driving wheels of a mobile robot have indispensable encoder sensors for tracking control; this assists the coordinate estimation of a mobile robot by combining the encoder sensors and the optical mouse sensors. In [7] and [8], the encoder sensor was used together with the optical mouse sensor for velocity estimation of a mobile robot. The use of an additional integration process is necessary to obtain the coordinate estimation from the velocity estimation.

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In this study, a coordinate estimation algorithm based on a Kalman filter, using both of the encoders and the optical mouse sensors is presented. The proposed localization algorithm for estimating a mobile robot's coordinates has an augmented state to avoid the additional integration process. This paper is organized as follows: In Section II, the dead reckoning estimation of robot motion is briefly explained using multiple optical mouse sensors [2]. Furthermore, the motion estimation with the encoder sensors of driving wheels is addressed in this section. In Section III, the coordinate estimation algorithm employed in this study is presented and the results of the experiments are presented in Section IV to validate the performance of the proposed algorithm. Through the experiments, the result of the coordinate estimation is demonstrated in the case of an insufficient number of optical mouse sensors. Finally, concluding remarks are presented in Section V.

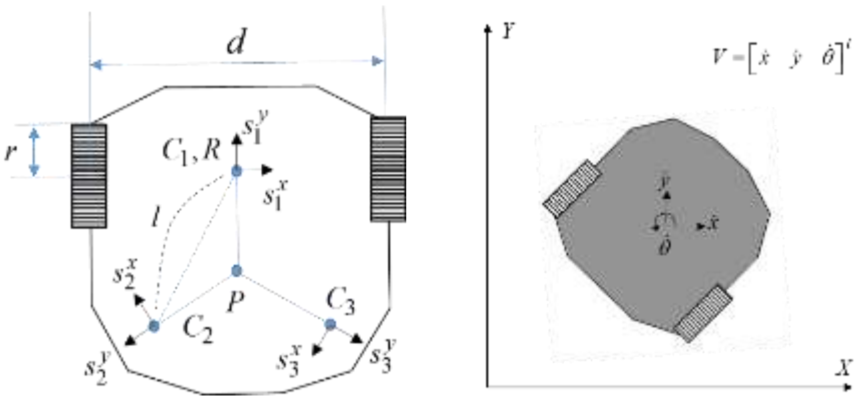
2. Motion Estimation of Mobile Robot

2.1. Estimation by Optical Mouse Sensors

It is assumed that a mobile robot has three optical mouse sensors at C_1, C_2, and C_3 around the center position, P, as shown in Figure 1, without loss of generality. The angle between the optical mouse sensors is 120°. The reference position, R, of the robot is at C_1. The distance between each sensor location C_i is denoted as l. The coordinate system for optical mouse sensor is drawn in Figure 1.

The velocity vector measured by the three optical mouse sensors is represented as follows.

$$S_k = \begin{bmatrix} s_{1,k}^x & s_{1,k}^y & s_{2,k}^x & s_{2,k}^y & s_{3,k}^x & s_{3,k}^y \end{bmatrix}^t \tag{1}$$



(a) Placements of Optical Mouse Sensors (Left) (b) Velocity of Mobile Robot in Global Coordinate System (Right)

Figure 1. Mobile Robot with Optical Mouse Sensors

The superscript in each element represents the direction of the velocity data from an optical mouse sensor in its own coordinate system, and the subscript indicates each sensor index. For example, $s_{2,k}^y$ represents the velocity data in the y axis of the second optical mouse sensor at a time instant k.

According to the coordinate frames assigned in Figure 1 (a), it is easy to obtain the velocity relationship between the measurement vector and the velocity vector at R:

$$S = G \cdot V \tag{2}$$

where S denotes the measurement velocity as in (1) and $V = \begin{bmatrix} \dot{x} & \dot{y} & \dot{\theta} \end{bmatrix}^t$ represents the velocity vector of the robot in the global coordinate system, as shown in Figure 1 (b). The velocity relationship G in (2) is written as

$$G = \begin{bmatrix} 0 & -1 & 0 \\ 1 & 0 & 0 \\ \frac{\sqrt{3}}{2} & \frac{1}{2} & -l\frac{\sqrt{3}}{2} \\ -\frac{1}{2} & \frac{\sqrt{3}}{2} & -\frac{l}{2} \\ -\frac{\sqrt{3}}{2} & \frac{1}{2} & -l\frac{\sqrt{3}}{2} \\ -\frac{1}{2} & -\frac{\sqrt{3}}{2} & \frac{l}{2} \end{bmatrix} \begin{bmatrix} \mathrm{c}(\theta) & \mathrm{s}(\theta) & 0 \\ -\mathrm{s}(\theta) & \mathrm{c}(\theta) & 0 \\ 0 & 0 & 1 \end{bmatrix} = \begin{bmatrix} \mathrm{s}(\theta) & -\mathrm{c}(\theta) & 0 \\ \mathrm{c}(\theta) & \mathrm{s}(\theta) & 0 \\ \mathrm{c}\left(\theta+\frac{\pi}{6}\right) & \mathrm{s}\left(\theta+\frac{\pi}{6}\right) & -l\sqrt{3}/2 \\ -\mathrm{s}\left(\theta+\frac{\pi}{6}\right) & \mathrm{c}\left(\theta+\frac{\pi}{6}\right) & -l/2 \\ -\mathrm{c}\left(\theta-\frac{\pi}{6}\right) & -\mathrm{s}\left(\theta-\frac{\pi}{6}\right) & -l\sqrt{3}/2 \\ \mathrm{s}\left(\theta-\frac{\pi}{6}\right) & -\mathrm{c}\left(\theta-\frac{\pi}{6}\right) & -l/2 \end{bmatrix} \tag{3}$$

where $c(\cdot)$ and $s(\cdot)$ imply $\cos(\cdot)$ and $\sin(\cdot)$, respectively. Thus, it is possible to estimate the velocity of the robot from the sensor measurement (1) as follows:

$$V = \left(G^t G\right)^{-1} G \cdot S \tag{4}$$

where the pseudo-inverse matrix of G is used in the sense of the least-squared error for the overdetermined or the underdetermined case of G. It is necessary to integrate (4) with time to obtain a position-level coordinate estimation of the robot motion.

2.2. Estimation by Encoder Sensor

Eq. (5) represents the motion of a mobile robot in two-dimensional $x-y$ space:

$$\begin{aligned} \dot{x} &= v\cos\theta \\ \dot{y} &= v\sin\theta \\ \dot{\theta} &= w \end{aligned} \tag{5}$$

where v and w are the linear and the angular velocities, respectively. Assuming that there is no slippage on the wheels of the robot, the linear and the angular velocities are given as follows:

$$\begin{aligned} v &= \frac{r}{2}\left(\omega_r + \omega_l\right) \\ w &= \frac{r}{D}\left(\omega_r - \omega_l\right) \end{aligned} \tag{6}$$

where ω_r and ω_l are the angular velocities of the right and left wheels of the robot, respectively. The driving motor of each wheel has a ready-to-use encoder sensor and the angular velocity of the wheel, ω_r or ω_l, is measurable by the encoder sensor. Thus, it is possible to estimate the velocity of the robot, $V = \begin{bmatrix} \dot{x} & \dot{y} & \dot{\theta} \end{bmatrix}^t$, by using (5) together with (6) from the encoder sensor measurement, which is the well-known dead reckoning estimation. In order to have a position-level coordinate estimation of the robot motion, (5) should be integrated with time as before.

3. Kalman Filter Algorithm for Coordinate Estimation

The estimation of the robot's motion can be improved using the optical mouse and the encoder sensors. Data from two different types of sensors were combined to obtain the coordinates of a mobile robot, using an estimation algorithm based on the Kalman filter with augmented states presented below.

By using the first-order discretization, (7) is obtained for data from the optical mouse sensor:

$$S_{k+1} \cong G \begin{bmatrix} \dfrac{x_{k+1}-x_k}{\Delta T} \\ \dfrac{y_{k+1}-y_k}{\Delta T} \\ \dfrac{\theta_{k+1}-\theta_k}{\Delta T} \end{bmatrix} = \frac{1}{\Delta T} G \begin{bmatrix} -1 & 0 & 0 & 1 & 0 & 0 \\ 0 & -1 & 0 & 0 & 1 & 0 \\ 0 & 0 & -1 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_k \\ y_k \\ \theta_k \\ x_{k+1} \\ y_{k+1} \\ \theta_{k+1} \end{bmatrix} \tag{7}$$

where ΔT denotes the sampling interval. The discretization in (7) is valid because the optical mouse sensor measures displacement during a sampling interval. Eq. (7) is rewritten as follows:

$$S_{k+1} = H \cdot X_{k+1}, \quad H = \frac{1}{\Delta T} G \begin{bmatrix} -1 & 0 & 0 & 1 & 0 & 0 \\ 0 & -1 & 0 & 0 & 1 & 0 \\ 0 & 0 & -1 & 0 & 0 & 1 \end{bmatrix} \tag{8}$$

where $X_{k+1} = \begin{bmatrix} x_k & y_k & \theta_k & x_{k+1} & y_{k+1} & \theta_{k+1} \end{bmatrix}^t$ represents an augmented state.

Similarly, by using the first-order discretization, the expression of (5) in discrete-time domain is as follows:

$$\begin{aligned} x_k &= x_{k-1} + \Delta T \cos\theta_{k-1} v_{k-1} \\ y_k &= y_{k-1} + \Delta T \sin\theta_{k-1} v_{k-1} \\ \theta_k &= \theta_{k-1} + \Delta T\, w_{k-1} \end{aligned} \tag{9}$$

where v_{k-1} and w_{k-1} are the linear and the angular velocities of the robot measured by the encoder sensors, respectively, as shown in (5). From (9), it is possible to obtain the following equation at $k+1$:

$$\begin{aligned} x_{k+1} &= x_{k-1} + \Delta T \cos\theta_{k-1} v_{k-1} + \Delta T \cos\theta_k v_k \\ y_{k+1} &= y_{k-1} + \Delta T \sin\theta_{k-1} v_{k-1} + \Delta T \sin\theta_k v_k \\ \theta_{k+1} &= \theta_{k-1} + \Delta T\, w_{k-1} + \Delta T\, w_k \end{aligned} \tag{10}$$

By combining (9) and (10), we obtain the following augmented state equation:

$$X_{k+1} = AX_k + BU_k \tag{11}$$

where the input vector, U_k, is defined as

$$U_k = \begin{bmatrix} v_{k-1} & w_{k-1} & v_k & w_k \end{bmatrix}^t \tag{12}$$

The system matrix, A, and the input matrix, B, represent the following:

$$A = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \end{bmatrix}, \; B = \Delta T \cdot \begin{bmatrix} \cos\theta_{k-1} & 0 & 0 & 0 \\ \sin\theta_{k-1} & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ \cos\theta_{k-1} & 0 & \cos\theta_k & 0 \\ \sin\theta_{k-1} & 0 & \sin\theta_k & 0 \\ 0 & 1 & 0 & 1 \end{bmatrix} \tag{13}$$

The measurement (8) and the augmented state (11) including the sensor signal noise become

$$\begin{aligned} S_{k+1} &= H\, X_{k+1} + r_{k+1} \\ X_{k+1} &= AX_k + z_k + B(U_k + q_k) \end{aligned} \tag{14}$$

The matrices, r_k, z_k, and q_k, in (14) indicate Gaussian noise with a zero mean, and a covariance of $Z \in R^{6\times 6}$, $Q \in R^{4\times 4}$, and $R \in R^{6\times 6}$, respectively. Based on the Kalman filter algorithm, the position-level coordinate estimation for robot motion is given as follows:

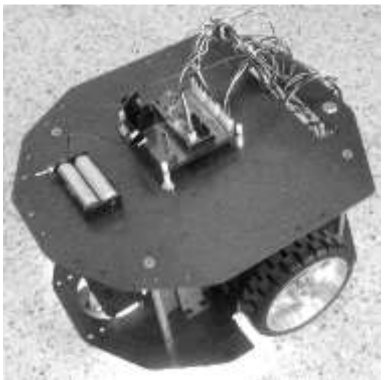
$$\begin{aligned} \hat{X}_{k+1}^{-} &= A\hat{X}_k + BU_k \\ P_{k+1}^{-} &= AP_k A^t + Z + BQB^t \end{aligned} \tag{15}$$

$$\begin{aligned} K_{k+1} &= P_{k+1}^{-} H^t \left(HP_{k+1}^{-} H^t + R \right)^{-1} \\ \hat{X}_{k+1} &= \hat{X}_{k+1}^{-} + K_{k+1} \left(H\hat{X}_{k+1}^{-} - S_{k+1} \right) \\ P_{k+1} &= \left(I - K_{k+1} H \right) P_{k+1}^{-} \end{aligned} \tag{16}$$

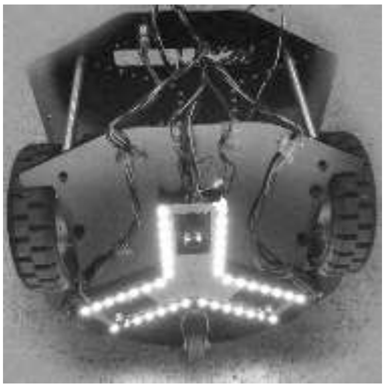
In (13), $\hat{X}_{k+1}^{-}$ and $\hat{X}_{k+1}$ indicate a priori and a posteriori estimation of the augmented state variables, respectively. The matrices, $P_{k+1}^{-} \in R^{6\times 6}$ and $P_{k+1} \in R^{6\times 6}$, represent a priori and a posteriori estimation of the error covariance, and $K_{k+1} \in R^{6\times 6}$ is the Kalman filter gain.

4. Experiment

Experiments are performed to verify the performance of the coordinate estimation algorithm presented in this study. The aim of these experiments includes (a) comparing the performance of the coordinate estimation with the proposed algorithm and the simple dead reckoning with the integration of (4), and (b) verifying the proposed algorithm for the case when there is an insufficient number of optical mouse sensors. It is noteworthy that the integration of (4) fails to estimate the coordinates of the robot in the case when an insufficient number of the optical mouse sensors is used.



(a) Top Side



(b) Bottom Side

Figure 2. Mobile Robot with Optical Mouse Sensor

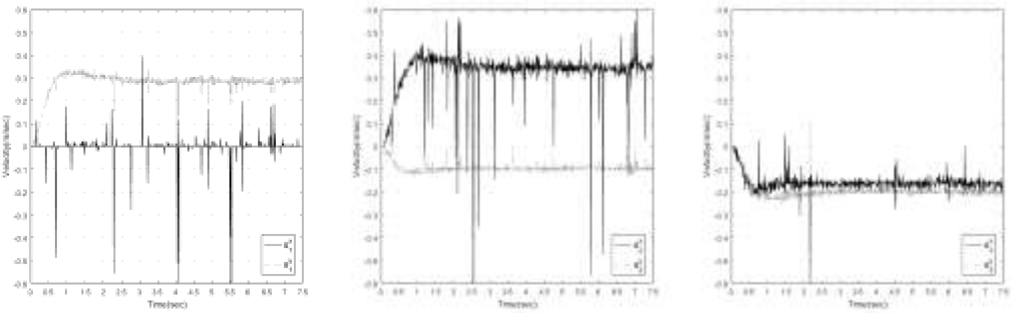
Figure 2 shows the mobile robot and the optical mouse sensors on the base of the robot. The radius of the wheels of the robot is $r = 0.075\,m$, the distance between the two wheels is $d = 0.29\,m$, and the distance between each optical mouse sensor is $l = 0.16\,m$ (Figure 1 (a)). The command trajectory is a circle of $0.87\,m$ diameter in 7.5s that requires $v = 0.3534\,m/\mathrm{s}$ and $w = -0.8125\,rad/\mathrm{s}$, as given in (5). The corresponding angular velocities of two wheels are $\omega_l = 2\pi\ rad/\mathrm{sec}.$ and $\omega_r = \pi\ rad/\mathrm{sec}.$ from (6). The starting position and heading angle of the robot are $[x_0 \quad y_0 \quad \theta_0]^t = [0 \quad 0 \quad 0]^t$.

The noise of the sensor signal in (14) is obtained from preliminary experiments. The covariance matrices of (14) are as follows:

$$\begin{aligned}
&Z = diag\left[\sigma_x^2 \quad \sigma_y^2 \quad \sigma_\theta^2 \quad \sigma_x^2 \quad \sigma_y^2 \quad \sigma_\theta^2\right]\\
&Q = diag\left[\sigma_v^2 \quad \sigma_w^2 \quad \sigma_v^2 \quad \sigma_w^2\right]\\
&R = diag\left[\sigma_{s1}^2 \quad \sigma_{s2}^2 \quad \sigma_{s3}^2 \quad \sigma_{s4}^2 \quad \sigma_{s5}^2 \quad \sigma_{s6}^2\right]\\
&\sigma_x = \sigma_y = \sigma_\theta = \sigma_v = \sigma_w = 0.002,\\
&\sigma_{s_1} = 0.0227, \sigma_{s2} = 0.0191, \sigma_{s3} = 0.0173\\
&\sigma_{s4} = 0.0139, \sigma_{s_5} = 0.0566, \sigma_{s_6} = 0.0173
\end{aligned} \tag{17}$$

where $diag[\ ]$ denotes a diagonal matrix.

Figure 3 shows the velocity vector, S_k, measured by the optical mouse sensors, whereas Figure 4 shows the velocity of the robot, $V = \left[\dot{x} \quad \dot{y} \quad \dot{\theta}\right]^t$ computed by (4).

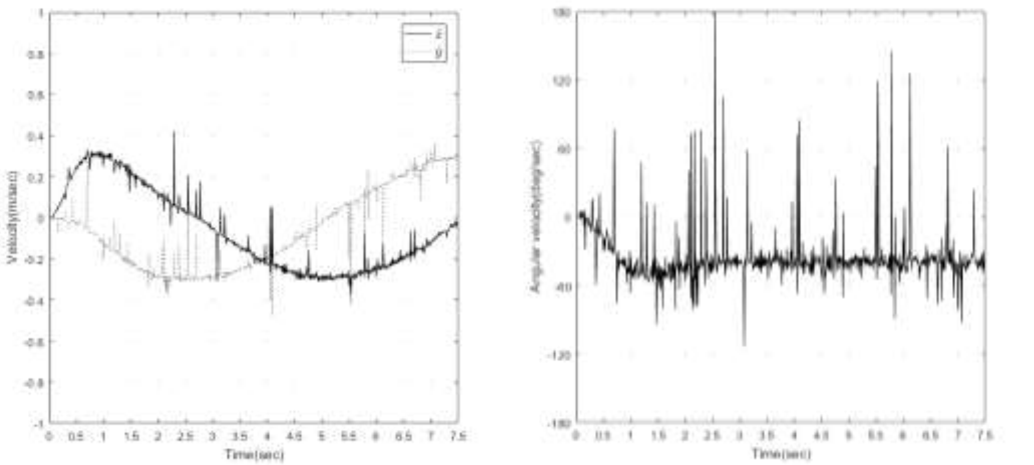


(a) At C_1 (b) At C_2 (c) At C_3

Figure 3. Measurement of Velocity Vectors from Optical Mouse Sensors

4.1. Comparison of the Coordinate Estimation

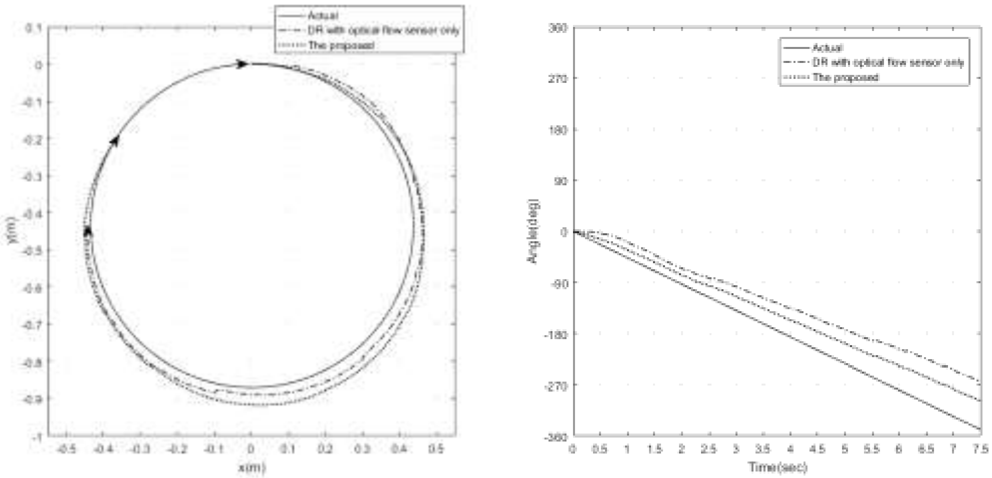
Figure 4 demonstrates the dead reckoning estimation of the robot motion, $V = \left[\dot{x} \quad \dot{y} \quad \dot{\theta}\right]^t$, computed by (4) from the optical mouse sensors. Furthermore, to obtain the position-level coordinate estimation, the velocity vector was integrated with time [7-8].



(a) $\dot{x}$ and $\dot{y}$ (b) $\dot{\theta}$

Figure 4. Velocity of Robot, $V = \left[\dot{x} \quad \dot{y} \quad \dot{\theta}\right]^t$

In comparison, the proposed algorithm in (15) and (16) estimate the augmented position-level coordinates of the robot without the additional integration. Figure 5 shows the comparison of the coordinate estimations between the dead reckoning by the optical mouse sensor (only) and the proposed algorithm by the optical mouse sensor and the encoder. In Figure 5, “DR with an optical mouse sensor (only)” represents the integration of $V = \begin{bmatrix} \dot{x} & \dot{y} & \dot{\theta} \end{bmatrix}^t$ in Figure 4, and “The proposed” denotes the coordinate estimation by the proposed algorithm in (15) and (16). The errors in the coordinate estimation are summarized in Table 1; the proposed algorithm produced the better performance.



(a) $x-y$ Coordinate (b) Heading Angle, θ

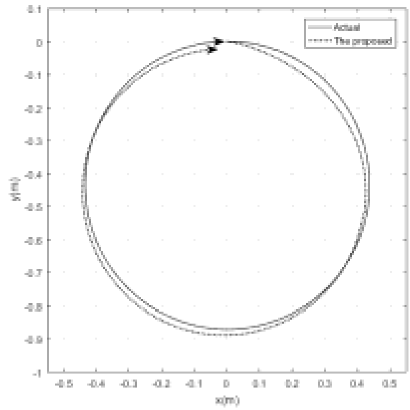
Figure 5. Position-Level Coordinates Estimation of Robot Motion

Table 1. Errors in Coordinate Estimation

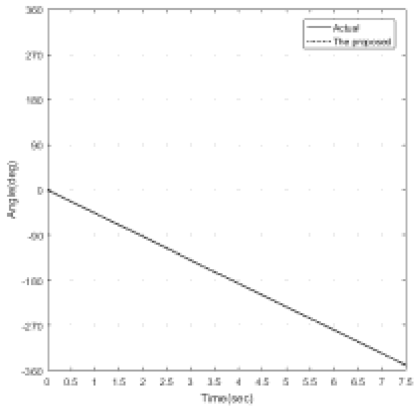
		Optical Mouse Sensor Only	The Proposed
Position(m)	Mean	0.3503	0.2196
	RMS	0.1596	0.1153
Angle(°)	Mean	-48.7765	-28.4800
	RMS	21.5149	13.2868

4.2. Coordinate Estimation in Case of Insufficient Optical Mouse Sensors

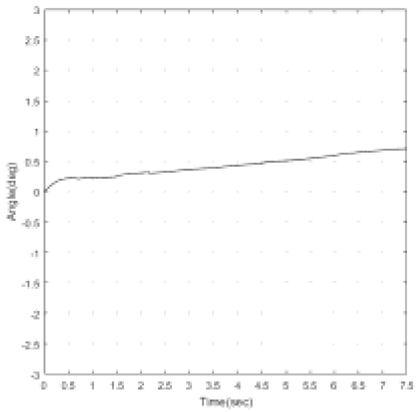
The integration of (4) fails to estimate the coordinates of the robot in the case of an insufficient number of optical mouse sensors. However, the proposed algorithm is able to estimate the coordinates of the robot with an insufficient number of the sensors because it utilizes the encoder sensors of the driving motor as well as the optical mouse sensors. Here, it is assumed that the robot has only one optical mouse sensor at C_2 and the measured data from the sensor is $S_k = \begin{bmatrix} s_{2,k}^x & s_{2,k}^y \end{bmatrix}^t$, without loss of generality. Figure 6 shows the estimated coordinates of the proposed algorithm in this case. To show the difference between the actual and the estimated heading angle, the estimation error of the heading angle is redrawn in Figure 6 (c).



(a) $x-y$ Coordinate



(b) Heading Angle, θ



(c) Heading Angle Error for the Proposed Algorithm

Figure 6. Coordinate Estimation of Robot Motion

5. Conclusion

The optical mouse sensor is cost-effective and capable of overcoming the motion estimation error caused by the wheel slippage of the mobile robot. However, the motion estimation using (only) the optical mouse sensor is subjected to signal noise and the kinematic errors in general. In this study, a localization algorithm based on a Kalman filter for a mobile robot that utilizes the optical mouse sensor together with the ready-to-use encoder sensor of driving wheels is investigated. The optical mouse sensor and the encoder sensor are complementary to each other, in terms of coordinate estimation. Instead of the velocity-level motion estimation that requires an additional integration process, the proposed algorithm has an augmented position-level state for the motion estimation. The performance of the algorithm is verified by two different experiments: (a) comparison of the performance of the coordinate estimation by the proposed algorithm and that by the dead reckoning using (only) the optical mouse sensor and (b) verification of the proposed algorithm for the case when an insufficient number of optical mouse sensors is used.

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