Positioning System for 4-Wheel Mobile Robot: Encoder, Gyro and Accelerometer Data Fusion with Error Model Method

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ABSTRACT

In this sensor fusion approach, combination of filtering encoder, gyro and accelerometer's signals was used to improve and correct the measurement of 4-wheel mobile robot's own position. The error model method was proposed for fusing encoder information with relative position measurement by gyro sensor and accelerometer's information to obtain more reliable position estimation. From this, we computed high-accuracy position estimation and had reduced the systematic and non-systematic errors during traveling and had succeeded in estimating the bias drift of gyro and accelerometer. The basic tool here is a Kalman filter supported by change detection from sensor diagnosis. Results and experience of real-time implementations are presented.

Key words: Sensor fusion; Odometry; Gyro; Accelerometer; Bias drift; Mobile robot

INTRODUCTION

Typically, mobile robot's behavior such as navigation, map building and estimation of own position is very important. There are lots of researches regarding the mobile robot (Watanabe and Yuta, 1990; Komori et al., 1992; Barshan, 1994; Cooper and Durrant-Whyte, 1994; Komoriya and Oyama, 1994; Maeyama et al., 1994; Tonouchi et al., 1994; Borenstein et al., 1996; Maeyama et al., 1996; Borenstein and Feng, 1997; Maeyama et al., 1997; Abott and Powell, 1999; Becker and Simon, 2000; Hashimoto et al., 2000). Basically, the method of estimation for a wheel-type mobile robot's position employs the rotation encoder (also called odometry system) of a wheel, etc. However, in outdoor environment, the estimated position by encoder has an unpredictable error caused by traveling over an unexpected small object or a bump under the wheels. When this happens, the accuracy of the estimated robot's position becomes worse instantaneously. Despite these limitations, most researchers agree that encoder is an important part of a robot's navigation system and that navigation tasks will be simplified if encoder accuracy can be improved. Since a gyro sensor and accelerometer (acceleration sensor) can measure directions and acceleration of a robot, unrelated to the condition of a road surface, they are very effective in position estimation. When we have the informations from different sources, the problem rises here is how to use them with fusion method (Ishikawa and Yamasaki, 1994; Luo, 1994; Toshiharu and Ishikawa, 1994; Becker and Simon, 2000). In this paper, we propose a method for fusing encoder information with relative position measurements by gyro sensor and accelerometer's information to obtain more reliable position estimation.

The research background and overview are described in Section 2. The system outline is described in Section 3. The implementation and design for each error model are described in Section 4. The experimental results are detailed in Section 5 while in Section 6 is our research conclusion.

BACKGROUND AND OVERVIEW

The sensor fusion method is to combine data from different sources with mathematical techniques such as discrete Bayesian method (Tonouchi et al., 1994), neural network, Kalman filter and etc. Borenstein et al., 1996 and Borenstein and Feng, 1997 has proposed a dead-reckoning algorithm called *Gyrodometry* (Borenstein et al., 1996) and researched in mobile robot positioning technique (Boreinstein and Feng, 1997) for mobile robot navigation systems. Borenstein et al. has concentrated on calibration method of odometry error with fusion of the gyro sensor data in dead-reckoning system (Boreinstein et al., 1996, and Borenstein and Feng, 1997). Komoriya et al. improved the Barshan model (Barshan, 1994), using the fiber optic gyro in mobile robot position estimations (Komoriya and Oyama, 1994). Hashimoto et al. also fused the odometry and gyro information for their directional vehicle (Hashimoto et al., 2000). The other researches (Watanabe and Yuta, 1990; Komoriya and Oyama, 1994; Maeyama et al., 1994) are used as a method of correcting the information on a gyro sensor and encoder, using such an external sensor and a landmark information for their position estimation and most researchers also use a Global Positioning System (GPS) to correct the fusion information between odometry and gyro sensor (Cooper and Durrant-Whyte, 1994; Abbott and Powell, 1999; Becker and Simon, 2000 (a); Becker and Simon, 2000 (b)). For most vehicle applications, GPS is augmented with inertial sensing to provide a higher degree of accuracy. However, GPS might not be able to calculate positioning accurately when GPS's signal or wave are disrupted, for example, when the mobile robot (which installs the GPS receiver) is moving inside of a tunnel, skyscraper, trees, around tall buildings and others.

The advantages of the inertial systems are lower in cost and simpler to implement in most computer system and mobile robot navigation systems. Also, the inertial systems can even be used on unpaved road without initial knowledge of the traveling environments (unknown environments). It is because of the fact that inertial systems use only odometry and internal sensors for its own position estimation.

In this paper, we propose the fusion of inertial sensors for mobile robot dead-reckoning system. We propose to use a fusion of the rotation encoder data, gyro sensor and accelerometer for the 4-wheel mobile robot to recognize its own position. The method we use is called error model method where each sensor will measure the accumulated error and compare it to the robot's own position. In Maeyama et al., (1997), they combined the angular rate signal measured from odometry and gyro to get more accuracy to robot direction, but they did it in different method compared to ours. Maeyama et al., (1996, 1997) used the *rule based data fusion* method in fusion process. Basically, when more information source is given, more accuracy we can get about that information. So here, for our method we add an accelerometer to get more information to combine with odometry's information. In our proposed method, we combine the rotation encoder data with accelerometer and gyroscope data, using the *error model* method to estimate more reliable position. The main advantages of our proposed method are:

1) Fusion of the odometry, gyro and accelerometer sensor's information, and more accurate position estimation can be acquired. Figure 1 shows, the position (x_a, y_a) measured by accelerometer combined with position (x_e, y_e) measured by odometry. And also, the robot angle measured by gyro, θ_g combined with angle measured by odometry, θ_e in estimator part.

2) Our system also has a function that monitors all errors occurred which can give information about mechanical system breakdown or facing the road surface obstacle during traveling. This function can be useful when the monitored error became higher than normal or evaluation value. However, in this paper we did not evaluate above function at present time but will consider it in the future.

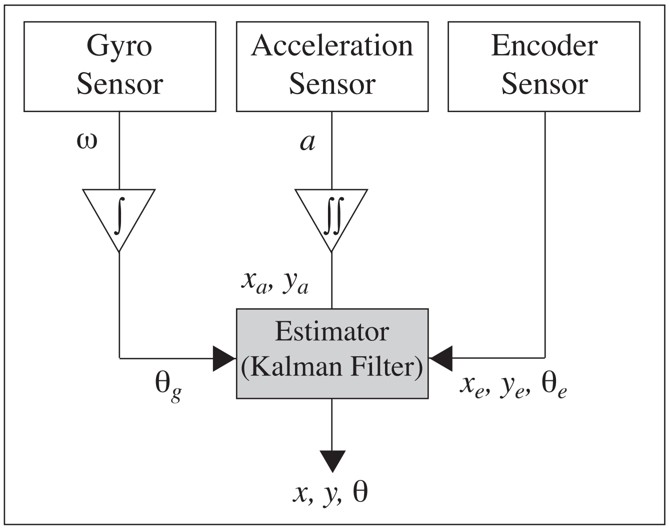

Figure 1. Overview of Sensor Fusion System. ω is angular velocity data from gyro sensor, a is acceleration data from accelerometer and θ_e is angle data and w_e, y_e are position data from encoder. After the one and twice integration process for gyro and accelerometer data, we get θ_g for the angle and x_e, y_e are for the positions. From the position estimator, we get the new estimated position for the mobile robot after fusion of the gyro, accelerometer and encoder's information through the Kalman filter, as x, y, θ.

The estimation method of the rotation speed error and a rear wheel distance error is used most widely, using a two-wheel drive mobile robot modeling. But in our research, we proposed the four-wheel drive mobile robot system.

SYSTEM OUTLINE

In our system (Figure 2), we used two rotary encoders, one accelerometer and one gyro sensor. From the rotation of the back wheels, rotary encoder will give a pulse signal to Universal Pulse Processor (UPP) card (RATOC *made*-REX 5059) as a pulse count. The specifications of rotary encoder are shown in Table 1. Gyro and accelerometer outputs are first led to 2nd and 4th order Butterworth low pass filter stages to prevent aliasing and to reduce noise.

These filters have a cutoff frequency of 30 Hz and are followed by an amplifier to perform optimum signal range adaptation at the A/D converter in the same UPP card. The A/D converter voltage input range is 0–5V and 10 bit of resolution ability. The software features all necessary structures to fetch acquired data and to calculate and display actual accelerations, angular and translatorial speeds and the current position of the mobile robot.

Table 1. Rotary Encoder Specifications.

Voltage DC	4.5~5.5 V
Resolution Ability	500 P/R
Max. Reply Frequency	50 kHz
Starting Torque	4.9x10^{-4} N.m
Angular Acceleration	1x10^{4} rad/s^{2}
Max R.P.M.	600 rpm

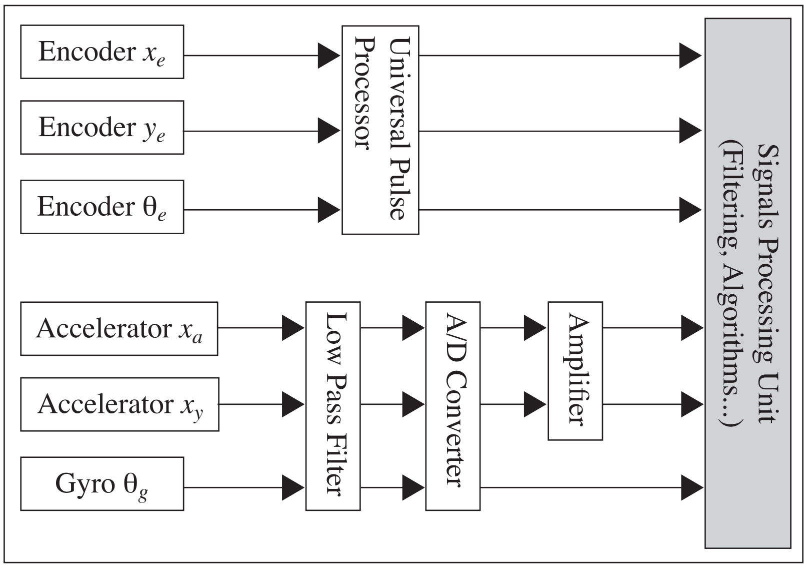

Figure 2. The System Outline.

IMPLEMENTATION OF DEAD-RECKONING SYSTEM

Dead-reckoning system should be designed to be able to minimize growth in position and orientation errors. This can be accomplished by meticulously modeling sensor errors and by the efficient design of a filter. In this paper, we implement an indirect Kalman filter that combined all sensors information as error model.

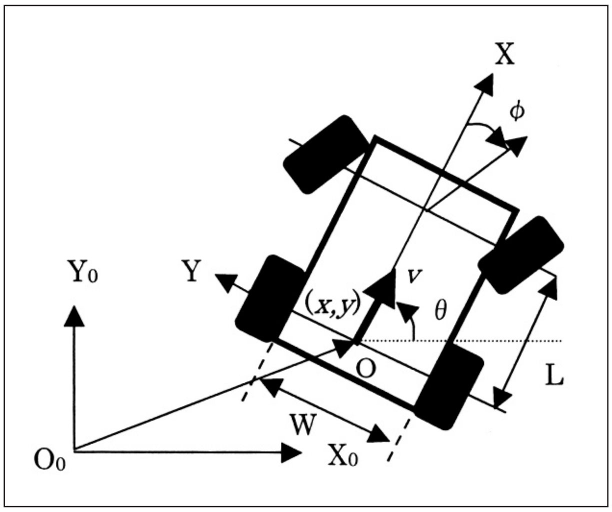

Figure 3. 4-Wheel Mobile Robot Model.

The Error Model for Odometry

Odometry is based on simple equations which holds true when wheel revolutions can be translated accurately into linear displacement relative to the floor.

However, in case of wheel spillage and some other more subtle causes, wheel rotations may not translate proportionally into linear motion. Systematic errors are those resulting from kinematics imperfections of the robot, e.g., unequal wheel diameters or uncertainty about the exact wheelbase. Non-systematic errors are those that result from the interaction of the floor with the wheels, e.g., wheel slippage or bumps and cracks (Boreinstein and Feng, 1996, 1997).

Figure 3 is a model of four-wheel mobile robot where x and y represent the mobile robot position in the navigation frame, θ is the heading angle, ϕ is the steering angle, v is a velocity of the mobile robot, L is the length between the front and back wheels and W is the right and left wheel width. The mobile robot's position and heading angle are calculated from the output of incremental encoders by Eq. (1).

$$\begin{aligned}
&x(k+1)=x(k)+V(k)\cdot\cos\theta(k)\cdot\Delta k\\
&y(k+1)=y(k)+V(k)\cdot\sin\theta(k)\cdot\Delta k\\
&\theta(k+1)=\theta(k)+\left(\frac{Vl(k)-Vr(k)}{W}\right)\cdot\Delta k\\
&V(k)=\frac{Vl(k)+Vr(k)}{2}
\end{aligned} \tag{1}$$

where $V(k)$ is the average of the left and right rear wheel incremental speed respectively, k is the present sampling time and k+1 is the sampling time after 1 sampling-interval progress. Δk is a 1 sampling time.

It is well known that odometry is subject to systematic errors caused by factors such as unequal wheel diameters, imprecisely-measured wheel diameters or an imprecisely-measured wheel separation distance. Subject to these errors, the robot's position and its heading angle are computed by Eq. (2).

$$\begin{aligned}
\hat{x}(k+1)&=\hat{x}(k)+\frac{1}{2}\{(Vr(k))+\delta Vr(k))+(Vl(k)+\delta Vl(k))\}\cos\hat{\theta}(k)\cdot\Delta k\\
\hat{y}(k+1)&=\hat{y}(k)+\frac{1}{2}\{(Vr(k))+\delta Vr(k))+(Vl(k)+\delta Vl(k))\}\sin\hat{\theta}(k)\cdot\Delta k\\
\hat{\theta}(k+1)&=\hat{\theta}(k)+\frac{1}{\mathrm{W}+\delta\mathrm{W}}\{(Vl(k))+\delta Vl(k))-(Vr(k)+\delta Vr(k))\}\cdot\Delta k
\end{aligned} \tag{2}$$

$$\begin{aligned}
\hat{x}(k)&=x(k)+\delta x(k)\\
\hat{y}(k)&=y(k)+\delta y(k)\\
\hat{\theta}(k)&=\theta(k)+\delta\theta(k)
\end{aligned} \tag{3}$$

From Eq. (3), the estimated position and heading angle are shown with hat symbols. δ symbols are added respectively for each error. From Eqs.(1), (2) and (3), will yield the error propagation equations as shown in Eq. (4).

$$\begin{aligned}
\delta x(k+1)&=\delta x(k)+\frac{1}{2}(Vr(k)+Vl(k))\sin\theta(k)\cdot\Delta t\cdot\delta\theta(k)+\frac{1}{2}\cos\theta(k)\cdot\Delta t\cdot\delta Vr(k)+\frac{1}{2}\cos\theta(k)\cdot\Delta t\cdot\delta Vl(k)\\
\delta y(k+1)&=\delta y(k)-\frac{1}{2}(Vr(k)+Vl(k))\cos\theta(k)\cdot\Delta t\cdot\delta\theta(k)+\frac{1}{2}\sin\theta(k)\cdot\Delta t\cdot\delta Vr(k)+\frac{1}{2}\sin\theta(k)\cdot\Delta t\cdot\delta Vl(k)\\
\delta\theta(k+1)&=\delta\theta(k)-\frac{1}{W^2}(Vl(k)-Vr(k))\cdot\Delta t\cdot\delta W-\frac{1}{W}\cdot\Delta t\cdot\delta Vr(k)+\frac{1}{W}\cdot\Delta t\cdot\delta Vl(k)
\end{aligned} \tag{4}$$

where we assumed that $\delta\theta(k)$ was small and we also assumed that there was no error in wheel alignment. We considered left and right unit of the wheels to cause radius estimation errors, where the rotation of the wheel itself causing incremental distance errors. Also the wheel width contributes to width estimation error. Finally, the wheel length also contributes to wheel length error where this error is regarded as random noise due to their slow time-varying characteristics. In this error model system, the random constant noise represents the average values of the irregular errors.

The Error Model for Gyro Sensor

Inertial navigation uses gyros and accelerometers to measure rate of rotation and acce-leration respectively. Measurements are integrated once (or twice, for accelerometers) to yield position. Inertial navigation systems have the advantage that they are self-contained, that is, they don't need external references. However, inertial sensor data drift with time because of the need to integrate rate data to yield position. The heading angle from a gyro sensor with bias drift is represented in Eq. (5).

$$\begin{aligned}
\theta_g(k+1)&=\theta_g(k)+\omega(k)\cdot\Delta k+Bb_g(k)\\
\hat{\theta}_g(k+1)&=\theta_g(k)+(\omega(k)+\delta\omega(k))\cdot\Delta k+\hat{B}_g(k)\\
\hat{B}_g(k)&=Bb_g(k)+\delta B_g(k)\\
\hat{\theta}_g(k)&=\theta_g(k)+\delta\theta(k)
\end{aligned} \tag{5}$$

where the hat symbol stands for estimation values and δ symbols are added respectively for each error. $\theta_g(k)$ is the true heading angle using the gyro sensor. $B_g(k)$ is a gyro bias drift and $Bb_g(k)$ is the theoretical gyro bias drift.

$$\begin{aligned} &\delta\theta_g(k+1)=\delta\theta_g(k)+\delta\omega(k)\bullet\Delta k+\delta B_g(k)\\ &\delta B_g(k+1)=\delta B_g(k)+w(k)\\ &\delta\omega(k+1)=\delta\omega(k)+w(k) \end{aligned} \tag{6}$$

A heading angle error equation for the gyro sensor is obtained from Eq. (5), as shown in Eq. (6). Where $w(k)$ is a system noise, bias drift can be modeled as random noise.

The Error Model for Accelerometer

Same as gyro sensor, accelerometer also suffers from extensive drift with time due to the twice-integrate rate data to yield position. The mobile robot position from an accelerometer with bias drift is represented in Eq. (7).

$$\begin{aligned} &v(k+1)=v(k)+a(k)\bullet\Delta k+Bb_a(k)\\ &x_a(k+1)=x_a(k)+v(k)\cos\theta(k)\bullet\Delta k\\ &y_a(k+1)=y_a(k)+v(k)\sin\theta(k)\bullet\Delta k \end{aligned} \tag{7}$$

where $Bb_a(k)$ is a theoretical bias drift and $v(k)$ is a true velocity of the mobile robot.

$$\begin{aligned} &\hat{v}(k)=v(k)+\delta v(k)\\ &\hat{x}_a(k)=x_a(k)+\delta x_a(k)\\ &\hat{y}_a(k)=y_a(k)+\delta y_a(k)\\ &\hat{B}_a(k)=Bb_a(k)+\delta B_a(k) \end{aligned} \tag{8}$$

$$\begin{aligned} &\delta v(k+1)=\delta v(k)+\delta a(k)\bullet\Delta k+\delta B_a(k)\\ &\delta x_a(k+1)=\delta x_a(k)-v(k)\sin\theta(k)\Delta k\bullet\delta\theta(k)\\ &+\cos\theta(k)\Delta k\bullet\delta v(k)\\ &\delta y_a(k+1)=\delta y_a(k)+v(k)\cos\theta(k)\Delta(k)\bullet\delta\theta(k)\\ &+\sin\theta(k)\Delta(k)\bullet\delta v(k) \end{aligned} \tag{9}$$

where $B_a(k)$ is an accelerometer bias drift. A position error equation for the accelerometer is obtained from Eq. (7) and Eq. (8), as shown in Eq. (9). Bias drift can be modeled as random noise.

Implementation of the Kalman Filtering

Using the above error models, we design the indirect feedback Kalman filter, (Chui and Chen, 1990), as the state equations of the system.

$$\mathbf{x}(k+1)=\mathbf{A}(k)\mathbf{x}(k)+\mathbf{w}(k) \tag{10}$$

The error model for odometry in Eq. (4), the error model for gyro sensor in Eq. (6) and the error model for accelerometer in Eq. (9) are used for Kalman filter state equation as Eq. (10).

where **w(*k*)** refers to system noise. Taking the error of positions and heading angle difference between the angular rates measured by odometry and measured by gyro, and position measured by odometry and measured by accelerometer, the measurement equations are givens by Eq. (11) and Eq. (12).

- Odometry and Gyro sensor

$$y_1=\delta\theta_e(k)-\delta\theta_g(k)+v_1 \tag{11}$$

- Odometry and Accelerometer

$$y_2=\delta x_e(k)-\delta x_g(k)+v_2$$
$$y_3=\delta y_e(k)-\delta y_a(k)+v_3 \tag{12}$$

where $\mathbf{v}(k)$is measurement noise. It is assumed that $\mathbf{w}(k)$ and $\mathbf{v}(k)$ are zero-mean Gaussian white noise sequences. $\mathbf{A}(k)$ are system matrices.

EXPERIMENT

Experiment Setup

Figure 4. The Actual 4-Wheel Mobile Robot.

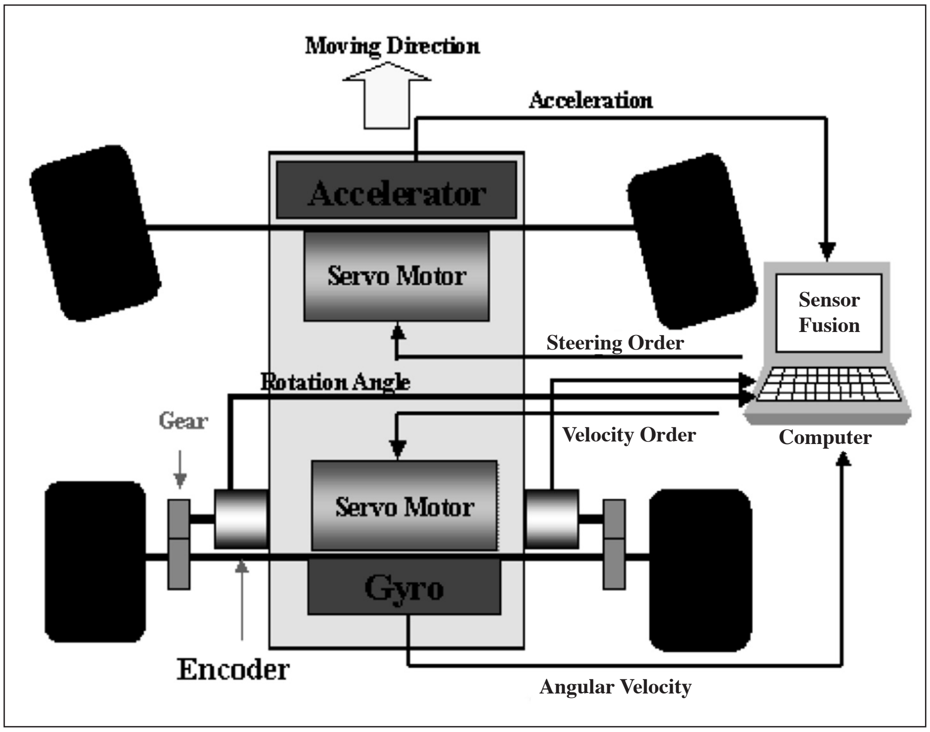

Figure 5. Structure of the Practical Mobile Robot.

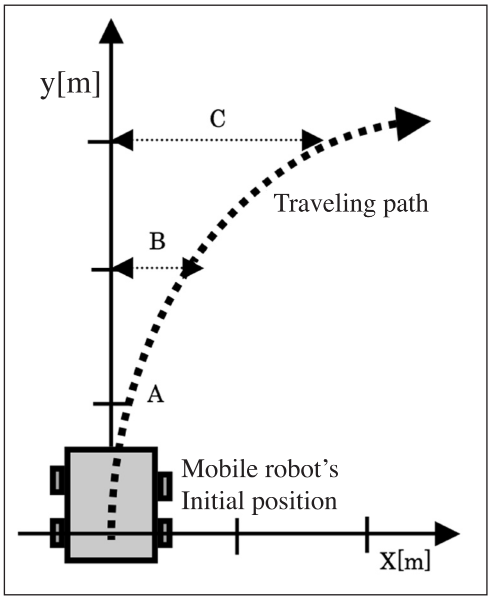

Figure 6. The Experimental Setup.

In our experiment (refer to Figure 4 and Figure 5), basically we used a 4-wheel remote control car (TAMIYA made) as a mobile robot, a personal computer and sensors. The personal computer was put on the mobile robot and used for signal processing. Then we fixed a rotation encoder sensor at the rear wheels. The gyro was installed at the center of rear-wheel axle. The accelerometer was installed at center of front-wheel axle. We used a vibration gyro ENV-05A type (MURATA *made*) and 2 axes of the accelerometer ADXL202 type (ANALOG DEVICE *made*).

Referring to Figure 6, we set a mobile robot from initial point [0, 0]. The mobile robot moved forward using pre-input data of angle and speed calculated by the program. We attached a marker pen at the mobile robot rear section to record the moving path and distance. For every 1 m movement in Y-axis, we recorded the gap A, B and C for X-axis and plot in graph as a measured value. All sampling times, Δk is 0.01 s.

Experimental Results

We presented the results of experiments which were conducted in our Mechanical Faculty lobby. We compared our sensor fusion method with encoder-only method and accelerometer-only method to the actual data measured which are shown in Figure 7. In Figure 7, the experiments were conducted with input velocity rate and steering angle rate of the mobile robot, set to 1.0 m/s and 5.0 deg respectively. Based from Figure 7, the results show that our sensor fusion method accumulated the least deviation compared to other methods. Therefore, our sensor fusion method is very close to real measurement (measured) from the experimental data.

In Figure 8, we tried to make a traveling path become more curved with steering angle rate set to 10.0 deg. but the input velocity rate was the same as Figure 7. From that, we compared our sensor fusion method to the encoder-only method and the accelerometer-only method. Based on those figures, we also got good results for our sensor fusion method which showed the least deviation compared to real-measured data in experiments.

In Figure 9, we used the same path but increased the input velocity of mobile robot as v=1.5 m/s. From that figure, it showed that by using accelerometer-only method, it gave the worst result but when we changed to our sensor fusion method, it managed to reduce accumulated error substantially.

Then we performed the other two experiments. First experiment used only odometry sensor and the second experiment integrated the odometry and gyro sensor. We performed 20 individual, consecutive runs for each experiment. From this experiment results, we compared with our proposed method that integrated the odometry, gyro and acceleration sensors. From the measurement, the error of the actual position of mobile robot at the end-running with the setting goal of the mobile robot should reach in theory (theory position) at the end of these 3 experiments. The results of the average of the error from above experiments are summarized in Table 2. From that table, we saw that the improvement provided by previous method was relatively small compared to the improvement provided by our proposed method. This is because our positioning system, using the gyro and accelerometer information for calibration, was very accurate and could reduce the accumulative error which occurred during traveling with more effectiveness.

CONCLUSION

This paper presents a method for improving the dead-reckoning accuracy of a mobile robot based on odometry, gyro and accelerometer. From the experimental results, we understand that the accurate position estimation for the mobile robot can be realized by our sensor fusion method. The accumulated error which occurred due to wheel spillage or obstacles on the traveling path could be determined and estimated by our method to reduce the robot positioning error.

We also understand that, from the experiment results, the proposed sensor fusion method showed that the generated error was improvable from presuming the position and heading angle error which a mobile robot produces when traveling in the path by the error model systems. The effectiveness of the proposed sensor fusion method has been shown from the experiment results.

Table 2. The Average of the Postion Errors between the Actual Measured and Estimation Method at the Last Point of the Mobile Robot.

Method / Conditions (deg), (m/s)	Odometry only (cm)	Fusion of Odometry and Gyro (cm)	Proposed method (Error model method) (cm)
Φ=5, v=1.0	14.1	8.2	4.6
Φ=10,	v=1.0	5.6	5.0 4.4
Φ=10, v=1.5	67.4	49.4	47.8

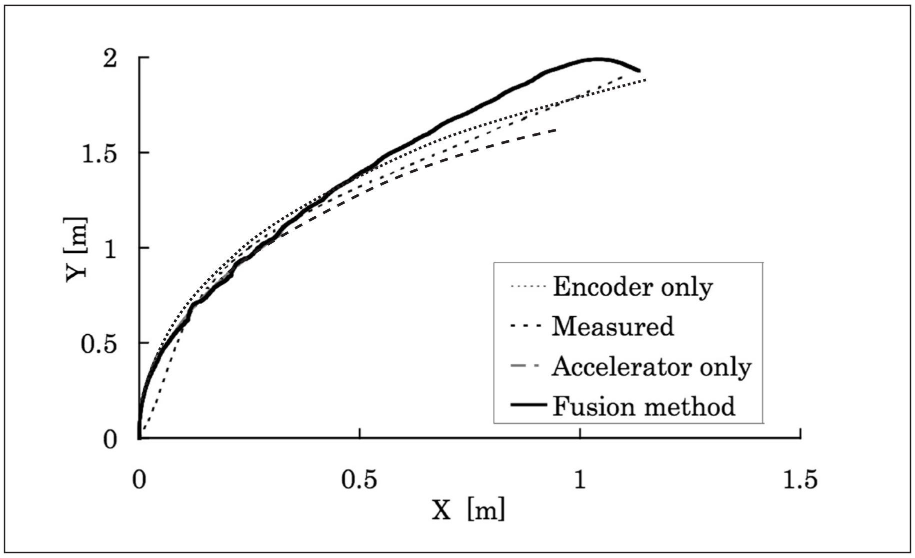

Figure 7. Position of the Mobile Robot (ϕ=5 deg, v=1.0 m/s).

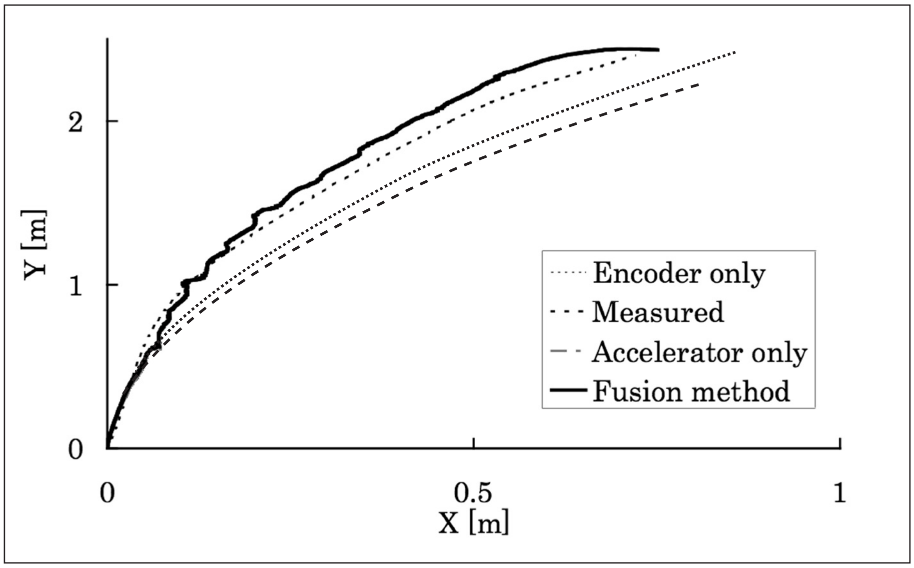

Figure 8. Position of the Mobile Robot (ϕ=10 deg, *v*=1.0 m/s).

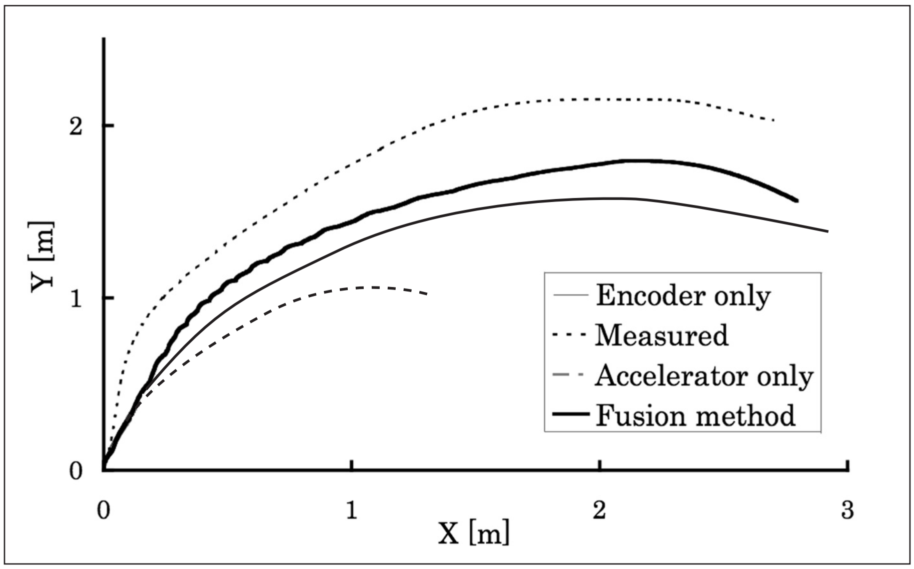

Figure 9. Position of the Mobile Robot (ϕ=5 deg, *v*=1.5 m/s).

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