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# Odometry Calibration using Home Positioning Function for Mobile Robot

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*Abstract*— **Odometry calibration is a first and essential step to do for a successful navigation because most of control algorithms are based on odomety information. Odometry error can be categorized as systematic and non-systematic error. In this paper, we suggest a novel method to calibrate systematic error using inherent home positioning capability of home cleaning robot. The method is designed for a differential drive type and take advantage of Augmented extended Kalman Filter(AKF) Algorithm to estimates systematic error parameters. Our approach has both characteristics of on-line and off-line. By simulation and experiment, we evaluate the method and the result shows that the proposed method gives odometry error reduction by several times.**

## I. INTRODUCTION

Let odometry be defined as the use of encoder measurements at the wheels to estimate the configuration of robot state(position and orientation). To achieve successful autonomous mobile robot navigation, accurate odometry is essential because localization, mapping and path-planning algorithms which are fundamental for robot navigation basically use odometry information.

Odometry error falls into two categories: systematic odometry error and non-systematic error. Usually internal systematic factors cause a rise of systematic error and that shows biased characteristic. In contrast, non-systematic error is independent on systematic features and has a unbiased(random) characteristic.

### A. Previous works

To get more improved odometry information, numerous attempts have been made by scholars and various methods have been developed. From a general point of view, the existing methods can be classified into two groups by a distinction which regards when the calibration process is executed.

*1) Off-line methods :* The main point of off-line methods is that calibration is executed after following a suitable test trajectory. Using the difference between actual end point and estimated end point, calibration is accomplished. Off-line methods have a merit that calibration is possible using only encoder profile at the wheels without any external sensors. However the aspect that the final pose is usually obtained by manual methods, in other words, by hand is critical weakness and this makes automation or self-calibration difficult. Borenstein et al. analyzed the possible source of odometry error [1], [2]. Based on these research, Borenstein introduced a popular geometric method, UMB method [3] for the calibration of certain systematic errors on rectangular closed trajectories. Kelly[4] proposed the general solution using linearized error equation for any trajectory and any error model. Antonelli[5] presented a calibration method based on the least-squares technique. Doh et al. [6] suggested an odometry calibration procedure called the PC-method. This method includes an idea that a robot should move forth and back along the same trajectory generated by the Generalized Voronoi Graph.

*2) On-line methods :* In the on-line methods, calibration is executed through continuous steps when a robot is able to estimate the pose of itself by external sensors: ultrasonic, vision and laser. On-line calibration methods have an advantage that automation is easy and it is more probabilistic approach which makes calibration more robust than off-line methods. In the frame of on-line methods, Roy and Thrun [7] suggested an algorithm that uses the robot's sensors to automatically calibrate the robot as it operates. Larsen [8] and Martinelli [9] apply an AKF (Augmented extended Kalman filter) algorithm that uses the robot's sensors(vision and laser) to automatically calibrate the robot as it operates. This method can estimate simultaneously the robot configuration and the parameters characterizing the systematic error. In despite of these merits, there is a significant problem. Calibration performance relies on the performance of sensors.

### B. Our contribution

In this paper, we suggest a novel method focused on a practical aspect using home positioning. We will use the term "home positioning" to refer a robot returning to its home position after following an arbitrary trajectory which was started from home position. Home positioning is carried out frequently because of various purposes: recharge or initialization of mapping and localization. By the reason, many companies which are related to mobile robot developed the module for autonomous homing. Nowadays, it is not difficult to see mobile cleaning robots have autonomous homing function. The proposed method is basically AKF algorithm to estimates the parameters for odometry calibration, and has merits as followings:

- Awareness of home positioning by physical contact can provide a direct information which is as truthful as that

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of off-line method. Note that, in off-line methods, the measurement is obtained by manual way.

- This method can be carried out without any external sensors.
- If we take advantage of an autonomous homing module, it is possible to develop an automatic process for self-calibration.

As we mentioned above, the proposed odometry calibration using home positioning is a complementary procedure to overcome the limitations of conventional on-line and off-line method and more practical than previous methods.

This paper is organized as follows. In section II, we define the odometry error model which we deal with. Based on the discussion of section II, in section III, we will introduce more detail algorithm to compensate systematic error. Section IV shows simulation and experiment for evaluation of the method. Finally, conclusion follows on Section V.

## II. The Odometry Error Model

In this paper, we deal with differential drive type which is widely used in mobile robotics and apply the kinematic model proposed by Chong and Kleeman [10] for the motion model of differential drive type. The model satisfies the following relation and basic notation follows those of the paper of Martinelli[8].

$$\delta\rho_k^{eR/L} = 2\pi R^{R/L}\frac{n_k^{R/L}}{N} \tag{1}$$

$$\delta\rho_k = \frac{\delta\rho_k^{eR} + \delta\rho_k^{eL}}{2}, \quad \delta\theta_k = \frac{\delta\rho_k^{eR} - \delta\rho_k^{eL}}{d\delta_d} \tag{2}$$

$$\begin{pmatrix} x_{k+1} \\ y_{k+1} \\ \theta_{k+1} \end{pmatrix} = \begin{pmatrix} x_k \\ y_k \\ \theta_k \end{pmatrix} + \begin{pmatrix} \delta\rho_k \cos(\theta_k + \frac{\delta\theta_k}{2}) \\ \delta\rho_k \sin(\theta_k + \frac{\delta\theta_k}{2}) \\ \delta\theta_k \end{pmatrix} \tag{3}$$

where $R^{R/L}$ is measured radius of right/left wheel, $d$ is the distance between two wheels, namely, base length as shown in Fig. 1, $n_k^{R/L}$ is the number of right/left encoder signals at $k^{th}$ step, $N$ is encoder resolution, $\delta\rho_k^{eR/L}$ in (1) is traveled distance induced from a measured radius and encoder signals, $\delta\rho_k$ is translation of the robot related to the $k^{th}$ step, $\delta\theta_k$ is change of heading angle.

In the ideal case, the state of mobile robot(position and orientation) is updated by (3), to put it another simple way, the state is predicted by the relation: $X_{k+1} = f(X_k, U_k)$, $U_k = \begin{pmatrix} n_k^R & n_k^L \end{pmatrix}^T$. But in the real world, it is very difficult to have ideal case because there are many sources invoking systematic and non-systematic errors. For the odometry calibration, we have to establish an error model which expresses the sources of error. A simple way to represent the odometry error for a mobile robot with a differential drive type is to model separately the error in the translation of each wheel.

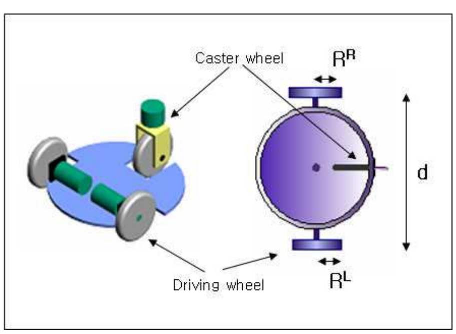


Fig. 1. The kinematic model of differential drive type

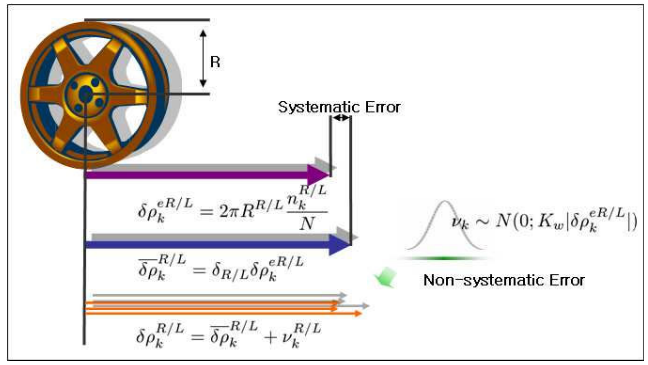


Fig. 2. The translation model of the right/left wheel at the $k$th step considering systematic and non-systematic error

We assume the systematic error occurs by three factors. Two come from difference between actual radius and measured radius of two wheels. Last one is difference between actual base length and the measured one. To compensate these systematic disparity term, we bring in three systematic parameters $\delta_R$,$\delta_L$ and $\delta_d$. The term, $\delta_{R/L}$ is a parameter to correct radius and $\delta_d$ is for base length. That is to say, $\delta_{R/L}R^{R/L}$ is the actual value of a radius of right/left wheel and $\delta_d d$ is the actual base length. In case of non-systematic error, with respect to the Chong-Kleeman model, only one non-systematic error parameter($K_w$) is adopted to characterize both the variances for the right and left wheel. In this paper, the value of $K_w$ was given by apriority. we are not concerned here with non-systematic error parameter, $K_w$. Using four error parameters, we can represent the relation of motion model newly as:

$$\delta\rho_k^{R/L} = \overline{\delta\rho}_k^{R/L} + \nu_k^{R/L} \tag{4}$$

$$\overline{\delta\rho}_k^{R/L} = \delta_{R/L}\delta\rho_k^{eR/L} \tag{5}$$

$$\nu_k^{R/L} \sim N(0; K_w|\delta\rho_k^{eR/L}|) \tag{6}$$

$$\delta\rho_k = \frac{\delta\rho_k^R + \delta\rho_k^L}{2}, \quad \delta\theta_k = \frac{\delta\rho_k^R - \delta\rho_k^L}{d\delta_d} \tag{7}$$

The actual translation of the right/left wheel at $k^{th}$ step, $\delta\rho^{R/L}$ is assumed to be a gaussian random variable whose mean value, $\overline{\delta\rho}_k^{R/L}$ is given from the traveled distance $\delta\rho_k^{eR/L}$ which is the value before compensating disparity. Covariance of $\delta\rho^{R/L}$ is expressed by adding $\nu_k^{R/L}$ which has a characteristic as (6). Fig. 2 shows the relation of (4)-(6).

Based on (4)-(7), we get a new relation of motion model considering the systematic and non-systematic error. Now our purpose is to obtain more correct motion model to

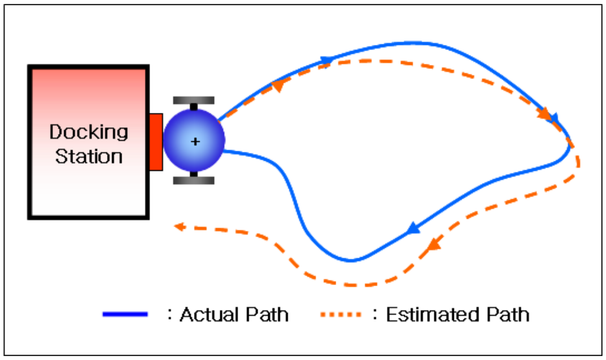


Fig. 3. Estimation of systematic parameters using home positioning

generate a right odometry path. In other words, by correct estimation of systematic parameters, we can calibrate biased error because the biased error is expressed by systematic parameters.

In section 3, based on the above analysis, we introduce the strategy to estimate systematic parameters using home positioning.

## III. Estimation of Systematic Parameters Using Home Positioning

To estimate systematic parameters, basically we use AKF algorithm proposed by Larsen[8]. Larsen[8] and Martinelli[9] utilized AKF for simultaneous localization and calibration method using vision/laser sensors. In our approach, we do not use sensors such as vision/laser/sonar/IR and just we take advantage of the failure of loop closing due to systematic and non-systematic errors. When robot arrives at home position, we can update the systematic parameters by comparing two points(estimated end point and home position). Repeat of this update pattern can make systematic parameters converge to the correct values. The scenario is as followings

1) The robot starts moving from its home position
2) Follow an arbitrary trajectory
3) Come back to its home
4) Compare the estimated end position with home position and update systematic parameters as shown in Fig. 3.
5) From 1 to 4 step, repeat until systematic parameters converge to certain values.

To make systematic parpameters($\delta_R$, $\delta_L$, $\delta_d$) converge to correct values, we use AKF algorithm and the detail explanation is given below.

### A. Augmented robot state

AKF in our algorithm is similar to EKF localization algorithm. The difference is that state vector of EKF localization algorithm includes only position and orientation vector $X = \begin{bmatrix} x & y & \theta \end{bmatrix}^T$, but augmented state of AKF has not only the original state vector but also systematic parameters as a state vector $X_a = \begin{bmatrix} x & y & \theta & \delta_R & \delta_L & \delta_d \end{bmatrix}^T$. AKF algorithm estimates a state(the augmented state) containing the robot configuration and the systematic parameters, through an EKF. Next steps are the prediction and update steps like conventional EKF.

### B. Prediction

Until the robot arrives at its home, the augmented state vector should be continuously predicted by kinematic model and the augmented kinematic model can be represented as followings.

$$\overline{X}_{ak+1} = f_a(\overline{X}_{ak}, U_k), \quad U_k = \begin{pmatrix} n_k^R & n_k^L \end{pmatrix}^T \tag{8}$$

$$\begin{pmatrix} x_{k+1} \\ y_{k+1} \\ \theta_{k+1} \\ \delta_{R_{k+1}} \\ \delta_{L_{k+1}} \\ \delta_{d_{k+1}} \end{pmatrix} = \begin{pmatrix} x_k \\ y_k \\ \theta_k \\ \delta_{R_k} \\ \delta_{L_k} \\ \delta_{d_k} \end{pmatrix} + \begin{pmatrix} \delta\rho_k \cos(\theta_k + \frac{\delta\theta_k}{2}) \\ \delta\rho_k \sin(\theta_k + \frac{\delta\theta_k}{2}) \\ \delta\theta_k \\ 0 \\ 0 \\ 0 \end{pmatrix} \tag{9}$$

where $\overline{X}_{ak}$ is the mean of the augmented state related to the $k^{th}$ step, $U_k$ is control input at $k^{th}$ step which consists two variables, encoder signals : $n_k^R$ and $n_k^L$ and $f_a$ is the function of augmented motion model (9). (9) is the augmented form of (3).

As (9) shows, in prediction step, only upper parts of state vector are changed, augmented parts of the state vector are constant. That is to say, until a robot comes back to its home position, robot continuously predicts only its configuration.

The covariance is also predicted by the conventional EKF relation as following (10) to (13).

$$P_{k+1} = F_k P_k F_k^T + G_k Q_k G_k^T \tag{10}$$

$$F_k = \left.\frac{\partial f_a(X_a, U)}{\partial X_a}\right|_{X_a=\overline{X}_{ak-1}, U=U_k} \tag{11}$$

$$G_k = \left.\frac{\partial f_a(X_a, U)}{\partial U}\right|_{X_a=\overline{X}_{ak-1}, U=U_k} \tag{12}$$

$$Q = \begin{pmatrix} |\alpha_R \delta\rho_k^R|^2 & 0 \\ 0 & |\alpha_L \delta\rho_k^L|^2 \end{pmatrix} \tag{13}$$

where $P$ is the covariance of the augmented state, $F$ and $G$ are jacobians of augmented motion model. $Q$ is control noise model. The noise increases in proportional to control input until measurement happens.

### C. Update

We measure the robot pose when robot comes back to the home position as shown Fig. 4. If we think home positioning as a measurement, it has a powerful advantage. Many distance sensors (laser, IR and ultrasonic sensor) can provide only two dimensional information(range and anlge) and those can not determine three dimensional robot configuration. To get 3-D configuration, we need to calculate measurement from several readings. However home positioning as a measurement can give a three dimensional information($x$,$y$ and $\theta$) directly to determine the configuration state. Not only the dimensional problem, distance and vision sensors have a lot of uncertainty problem. Especially low-cost sensors (IR and sonar) which are used in commercial products have many critical uncertainty problems. In contrast, the accuracy of

Fig. 4. The moment when a robot approaches the home position

measurement obtained from home positioning is very high because the home positioning is done by physical contact. The measurement model is updated by followings.

$$z_k = h(X_k) = \begin{pmatrix} x_k & y_k & \theta_k \end{pmatrix}^T \tag{14}$$

$$\hat{z_k} = \begin{pmatrix} x_h & y_h & \theta_h \end{pmatrix}^T \tag{15}$$

where $X_k$ is the state at the $k^{th}$ step, $x_h$, $y_h$ and $\theta_h$ are the absolute position and the orientation of the robot at home.

Through the above measurement model, we can update mean and covariance of the state by the following relation:

$$\Psi_k = H_k P_k H_k^T + R_k \tag{16}$$

$$K_k = P_k H_k^T \Psi_k^{-1} \tag{17}$$

$$\hat{X}_k(+) = \hat{X}_k + K_k[z_k - \hat{z}_k] \tag{18}$$

$$P_k(+) = [I - K_k H_k]P_k \tag{19}$$

where $\Psi$ is innovation matrix, $H$ is jacobian matrix of h with respect to its state, $R$ is measurement noise matrix which is adopted by accuracy of home positioning and $K$ is Kalman gain. The mean and covariance of the state is updated by (18) and (19) respectively.

## IV. Results

### A. Simulation

Before the experiment in the real world, we performed a simulation using MATLAB to evaluate the performance of the proposed method. The scenario of simulation is the same as the previous one. The configuration is summarized as:

- Simulation program : MATLAB 7.04
- Sampling time of encoder signal : 0.025 sec
- Measured radius of right and left wheels: 50mm
- Distance between two wheels: 400mm
- Resolution of encoder : 360 pulse/revolution
- Variance of motion noise: 10% of control inputs
- Variance of measurement noise : 30mm, 30mm, 0.1rad

Using the above condition, the simulation was performed and the results are shown in Fig. 5 and Fig. 6.

As Fig. 5 indicates, at the first step, the gap between actual path and odometry path is large but after repeating different trajectoris, the gap gets smaller. At the 10th step, odometry path is almost same as actual path and we can verify that the systematic parameters converge to the correct value. The parameters are shown in Fig. 6 and the result is summarized below. Note also that initially all parameters were set as 1.

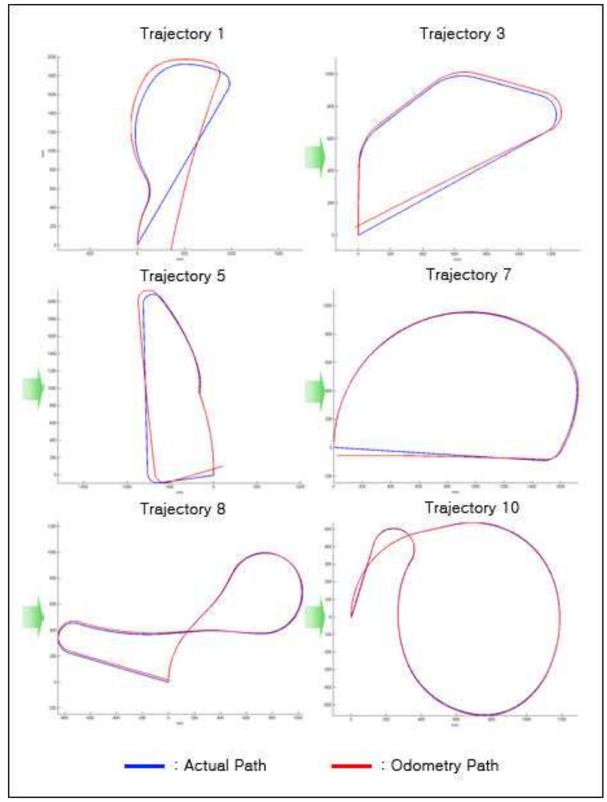


Fig. 5. Procedure of simulation

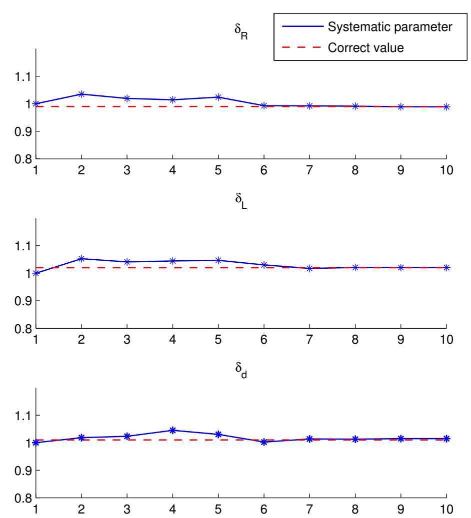


Fig. 6. Convergence of systematic parameters

- Finally estimated systematic parameters

- $\delta_R = 0.98862 \quad \delta_L = 1.0205 \quad \delta_d = 1.0149$

- Correct value

- $\delta_R = 0.99 \quad \delta_L = 1.02 \quad \delta_d = 1.01$

Fig. 7. iClebo-free, YUJINROBT Co.

## B. Experiment

After the simulation, we carried out experiments with real robot. The robot which we operated for experiment is a commercial vacuum cleaner robot, iClebo-free made by YUJINROBOT Co. The robot has a function of automatic homing and the detail account of the configuration is given below:

- Model : iClebo-free, YUJINROBT Co.
- Sampling time of encoder signal : 0.03 sec
- Measured radius of right and left wheels: 42mm
- Distance between two wheels: 298mm
- Resolution of encoder : 12 pulse/revolution ( enhanced to 900 by reduction gear )

It is noteworthy that the performance of encoder used is very poor, since we use encoder model which is currently adopted in commercial home cleaning robot.

In simulation, we could acquire the correct values that systematic parameters should pursue. It was possible to compare the systematic parameters with reference values. Unfortunately, in the experiment, there is no way to know exact correct values. By the reason, for the evaluation of our approach, we utilized external sensor, indoor GPS system(NINETY SYSTEM Co.)[11], as shown in Fig. 8, which provides the 3-D position of robot in real time. Using indoor

Fig. 8. iGPS system, NINETY SYSTEM Co.

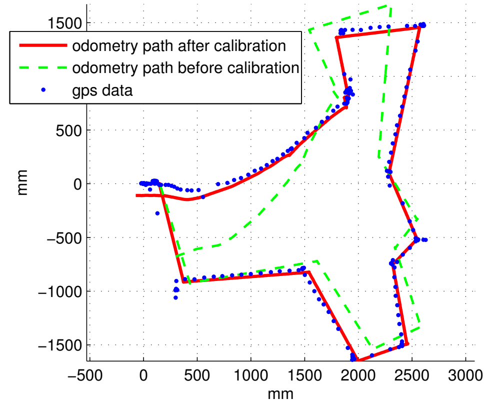


Fig. 9. Odometry path before/after calibration and GPS data

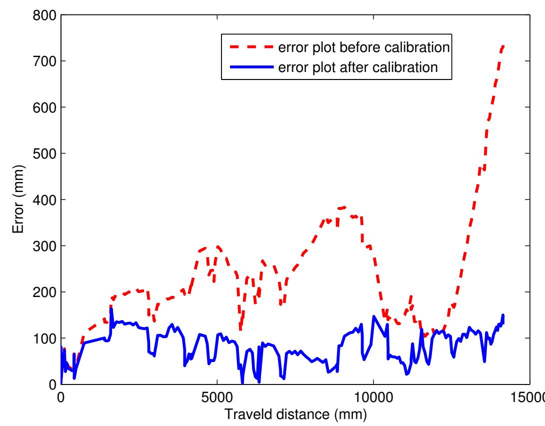


Fig. 10. Odometry error before/after calibration as the robot travles

GPS system, we were able to plot the actual robot path.

We controlled the robot to travel several different trajectories until systematic parameters converge to certain values. After all, we could notice the convergence of parameters after 17th home positioning step. After adopting the converged values as systematic parameters, we plot the the odometry path both before and after calibration, and to evaluate the paths, also we plot GPS data. Fig. 9 shows the result of the experiment. The path before calibration diverges from GPS data due to the systematic and non-systematic errors. In contrast, in the path after calibration, we could verify that the effect of biased error is small.

Fig. 10 is the plot to describe the increase of error as the robot travels. This plot shows that both of two path are affected by non-systematic errors, but remarkably indicates that the systematic error was reduced several times after calibration.

# V. CONCLUSIONS AND FUTURE WORKS

In this paper, we suggested a novel method for odometry calibration using home positioning function, and verified the performance through simulation and experiment. The point that systematic parameters are updated after a trajectory using difference between two points(estimated end point and the measured one) is the characteristic of off-line methods. Continuous tracking method(AKF) is the feature of on-line methods. Our approach has both properties of on-line and off-line calibration methods. These fused characteristics make it easy to develop an automatic process and to overcome the limitation of on-line calibration method that calibration performance depends on ther performance of external sensors. In addition to that, the quality of measurement is excellent as that of off-line method.

In practical sight, computational burden of EKF procedure is not heavy, therefore the implementation of the proposed method will be possible without additional high performance hardware. To get more reliable result, robot has to follow various trajectories and the paths should have different patterns as UMBMark does.

In simulation, we could see that the systematic parameters converged to the correct values. In experiment, using indoor GPS system, we could observe the improved odometry path. Especially a commercial robot, not a robot for research, was used for experiment and this shows the possibility for practical solution.

In this paper, we dealt with only calibrating systematic error parameters. Also, the results show that there are still some systematic errors. Performance enhancement and compensating possibly non-systematic errors will be the topic of future work.

## VI. Acknowledgment

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