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Range Sensing, Localization, and Error Elimination of Two-Wheeled Mobile Robots

Kuan-Chieh Tseng, Ming-Tzuoo Yin, and Feng-Li Lian

Abstract—**In this paper, the platform of a two-wheeled mobile robot (TWMR) is studied and the bias errors about postures of TWMR, i.e., effects of skidding and slipping, are classified and modeling. The data of range sensors are processed as localization methods to eliminate the external error which encoder odometry cannot be detected. Two concepts about localization method fusion and error elimination architecture are proposed. The first one combines results of localization methods and determines the best results based on the performance of localization methods in different scenarios. The second one contains the former and makes the posture information more reliable. In addition, the methods could correct the encoder odometry with the knowledge of skidding and slipping.**

I. Introduction

Wheeled mobile robots (WMRs), especially two-wheeled mobile robots (TWMRs), are very popular platforms in environment exploration and robot navigation [12: Oriolo et al. 2002]. For both applications, the sensing information of TWMRs is important for strategic decision and control. Two kinds of sensors of TWMRs are classified: odometry sensor for detecting the position of a robot, and range sensor for detecting obstacles in the environment. By both kinds of sensors, the information about robot's position [1: Siegwart and Nourbakhsh 2004], [12: Oriolo et al. 2002] and environment are obtained and the proper control commands are decided according to them. Therefore, the correctness of sensing data plays an important role in control strategies. In other words, the control strategies cannot be proper if the sensing data do not reveal the truths.

In reality, many kinds of errors exist in the environment. Some control theories derive the error models and make the influence of errors decay. For example, if the noise in robot is the white Gaussian variable with time, the Kalman filter can be used to eliminate the errors and make the results be more reliable [3: Gelb 2000]. However, there still exist biased errors in sensing part that cannot be eliminated just by the Kalman filter. For example, the slipping of the robot results in a biased error of robot posture measurement. In order to solve this problem, the biased errors model should be defined and a new approach is introduced in this paper to calibrate the robot kinematic model.

The platform studied in this paper is a two-wheeled mobile robot with range sensors. Two main sensors are set up in the robot: odometry sensors and range sensors. The odometry sensors are encoders of wheels to record degrees of rotating and translate them to the moving distance. The range sensors are eight ultrasonic sensors [9: Borenstein & Koren 1991] and a laser rangefinder. When there is no error in the ideal case, the sensing information is correct and helpful to control strategies. In reality, however, errors from actuating part and sensing part will make the sensing information differ from real situation.

In the paper, the error classification is established and the kinematic model of robot with sensor errors is derived. According to the error model, an error elimination procedure, which combines the sensor data and control commands, is applied to correct the sensor data and obtain the right information about postures and environment. After this procedure, the odometry data and range sensor are more reliable.

The main idea of the error elimination procedure is that two localization methods based on range sensors are defined. They use the environment information and some assumptions to measure the robot postures. According to the postures, the transformation from encoder odometry to real posture is derived. Because two kinds of localization methods have different performances in different situation, a concept of localization method fusion [10: Freire et al. 2004] is described to choose proper results of localization methods.

The error elimination procedure can be used in two purposes: offline calibration and online error elimination. The former is based on known environment information and calibrates the characteristics of sensors and the robot model after the motion. The latter calibrates the characteristics of sensors and the robot model when the robot is moving. When this procedure is used for calibration of robot, the environment information is assumed to be known. When it is used for online error elimination, the laser rangefinder is assumed that it has little error.

This paper has three sections, including the Introduction section. Section II describes the situation when errors exist. The errors in Section II are focus on those about robot posture, such as the errors from skidding and slipping or the errors from encoder odometry. These errors will cause the incorrectness of localization and mapping of robot. The consequences of robot posture when evaluating these errors

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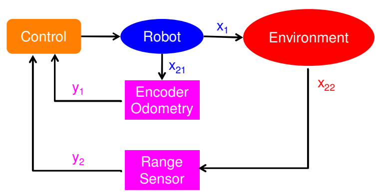
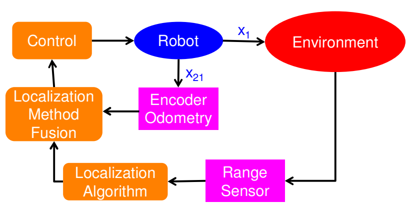
are revealed in Section II. In order to eliminate errors and obtain reliable odometry results, two methods, called "DVDL" and "GPDL" which use range sensor data to correct odometry result are derived in Section III. Section IV shows experimental results and the analyses of the error elimination architecture to support the approach in Section II. The conclusions and the future works are discussed in Section V.

II. Error Analysis of a Wheeled Mobile Robot



(a)



(b)

Figure 1. (a) The system architecture of a wheeled mobile robot. (b) The modified system architecture to correct the posture error.

Figure 1(a) shows the system architecture of a TWMR with odometry and range sensors. When the desired control commands are executed, the wheels of the robot turn and make the robot moves for a distance in an environment. The odometry measures the posture of robot according the encoders of wheels, and some range sensors measure distances between the robot and obstacles around it. That information is adopted by the controller for deciding the next control commands.

In the figure, the interaction paths between blocks are characterized and defined. The interaction paths are classified as two categories: x for interactions of hardware and y for interactions of software.

The latter, like y_1 for data transportation from the odometry to the controller, and y_2 for data transportation from range sensors to the controller, may have some kinds of errors. For example, when sensors measure some values and record them as the digital data, the quantization error happens. Take another striking example, sometimes the controller obtain the data labeled time t, but this data are actually recorded on time t', which is less than t. The unmatched time may causes error of speed detection or motion estimation. However, the errors are usually tiny so they can be ignored.

The analyses about paths labeled x are explained as follows. The path x_1 is data transportation about the interaction between the robot and the environment. Effect of both skidding and slipping shown in [5: Wang & Chang 2008] belongs to the errors of path x_1. In general, the skidding effect has little influence when the robot does not turn violently. That means that, when robot moves straight, the path x_1 can be evaluated and it only has errors of slipping.

The paths x_{21} and x_{22} are data transportations from the robot to odometry and from environment information to range sensors, respectively. The former and the uncertainty are shown in [6: Martinelli 2002]. Note that the posture information from the feedback of odometry is incorrect because the uncertainty from itself and, the most important, the errors from path x_1. Even if the path x_{21}, form robot to environment, has no error, the posture information is still incorrect [8: Borenstein 1998]. In order to obtain more precise data, a mechanism of odometry calibration by range sensors is applied. By the data from range sensors and environment information, the range sensors can be regarded as an odometry to measure the robot postures.

The encoder odometry can measure the posture directly and fast, but it cannot detect the error from path x_1. Although the encoder odometry is not aware of the external errors from path x_1, the relationship between detected value from encoders and real posture can be modeled by the theory, which is derived in the next section.

In order to correct those posture errors, which the encoder odometry cannot detect, a modified system architecture is introduced in Figure 1(b). Localization algorithms, which apply range sensor data to estimate the robot posture, are combined with the encoder odometry and the result of the localization method fusion reveals more precise robot posture than the encoder odometry.

III. Error Elimination Approach

A. Dynamic Velocity Detecting Localization (DVDL)

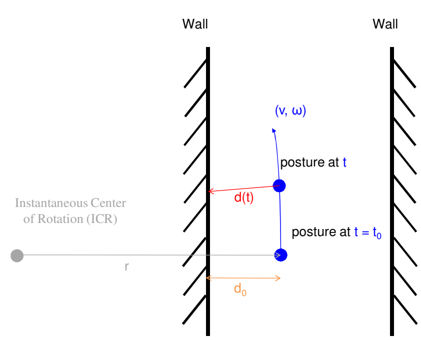


Figure 2. Robot with the ultrasonic sensor moving at a corridor.

A new approach of a "Dynamic Velocity Detecting Localization" or DVDL for short, which estimates postures by ultrasonic data, is proposed in this section. In this paper, the approach is applied when the robot moves along walls or a corridor. The environment for this approach is shown in Figure 2. In the beginning, the heading angle of robot is parallel with corridor. The length d_0, detected by the left side ultrasonic sensor at time t_0, is the distance between robot and wall. When robot moves as a constant velocity pair (v, ω), the detected value d is a function of time **t** shown in (1):

$$d(t) = d_0 \sec(\omega t - \omega t_0) + \frac{v}{\omega}[1 - \sec(\omega t - \omega t_0)] \ . \quad (1)$$

The difference between d_0 and $d(t)$ is

$$\begin{aligned} d_0 - d(t) &= d_0[1 - \sec(\omega t - \omega t_0)] - \frac{v}{\omega}[1 - \sec(\omega t - \omega t_0)] \\ &= (\frac{v}{\omega} - d_0)[\sec(\omega t - \omega t_0) - 1] \equiv D(v, \omega, t) \end{aligned} \ . \quad (2)$$

Equation (2) shows that, when the velocity pair (v, ω) are constant, $d_0 - d(t)$ is a secant function of t or a zero function when the robot moves straight. When $\omega(t - t_0)$ is small, the secant function can be approximated as a time squared function using the Taylor expansion like (3):

$$\begin{aligned} \sec(\omega t) - 1 &\approx \left\{ \sec 0 + \frac{\omega t}{1!} \sec 0 \tan 0 + \frac{(\omega t)^2}{2!}\left[\sec^3 0 + \sec 0 \tan^2 0\right] + \ldots \right\} - 1 \\ &\approx \left[1 + \frac{1}{2}(\omega t)^2\right] - 1 = \frac{1}{2}(\omega t)^2 \end{aligned} \ . \quad (3)$$

$$\Rightarrow d_0 - d(t) = (\frac{v}{\omega} - d_0) \cdot \frac{1}{2}[\omega(t - t_0)]^2 \approx \frac{1}{2} v\omega (t - t_0)^2$$

That means that, if the difference of ultrasonic data seems like a parabola curve, the coefficient of the squared term is close to half product of linear velocity and angular velocity of robot.

The above-mentioned approach is based on two important assumptions: $\omega(t - t_0)$ is so small that the Taylor expansion can be applied, and known linear velocity v. In general case, there is a *gradient descent* method [4: Aarts & Lenstra 1997] to estimate more proper velocity pairs. First, (v_u, ω_u) are defined as the linear velocity and angular velocity, respectively, which are estimated by ultrasonic data. Second, a function $\hat{D}(v_u, \omega_u, t)$ is defined as the estimated values of $d_0 - d(t)$ based on estimated velocity pair like (4):

$$\hat{D}(v_u, \omega_u, t) = (\frac{v_u}{\omega_u} - d_0)[\sec(\omega_u t - \omega_u t_0) - 1] \ . \quad (4)$$

A performance index H is defined to evaluate the correctness of (v_u, ω_u). The definition of H is shown in (5):

$$H = \frac{1}{2}\sum(\hat{D} - D)^2 |_{sampletime} \ . \quad (5)$$

The smaller H is, the greater the estimated performance will be. Now calculate the gradients of H are shown in (6) and (7):

$$\frac{\partial H}{\partial v_u} = \sum(\hat{D} - D) \cdot \frac{1}{\omega_u}[\sec(\omega_u t - \omega_u t_0) - 1] |_{sampletime} \ , \quad (6)$$

$$\begin{aligned} \frac{\partial H}{\partial \omega_u} = \sum(\hat{D} - D) \cdot \left\{ \frac{-v_u}{\omega_u^2}[\sec(\omega_u t - \omega_u t_0) - 1] + \right. \\ \left. (\frac{v_u}{\omega_u} - 1)[t_i \sec(\omega_u t - \omega_u t_0)\tan(\omega_u t - \omega_u t_0)] \right\} |_{sampletime} \end{aligned} \ . \quad (7)$$

Finally, (v_u, ω_u) are adjusted along the inverse direction of gradients of H, like (8). So that the new H will be smaller [2: Ioannou & Sun 1996].

$$\begin{aligned} v_u &\leftarrow v_u - K_v \frac{\partial H}{\partial v_u} \\ \omega_u &\leftarrow \omega_u - K_\omega \frac{\partial H}{\partial \omega_u} \end{aligned} \ . \quad (8)$$

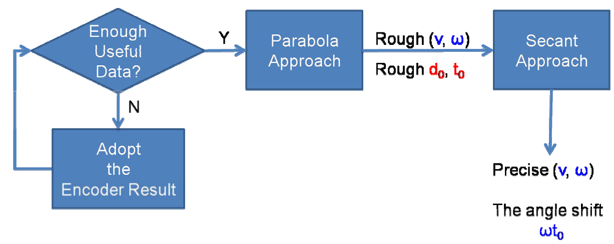


Figure 3. The procedure of the DVDL.

Figure 3 shows the procedure of the DVDL. The advantages of the DVDL are its short computing time and the ability of small bias angle detection. Besides, the DVDL has good performance in the simple environment. However, when the environment is complicated or the velocities of robot vary too rapidly. To resolve the problem, another localization method from range sensor data called “geometric posture detecting localization” is introduced to compensate the disadvantages of the DVDL.

B. Iterative Closest Point (ICP) Algorithm and Geometric Posture Detecting Localization (GPDL)

Iterative closest point, or ICP for short [7: Besl and Mckay 1992], is an algorithm to match two groups of points. The inputs of the ICP algorithm are a reference point set and an operated point set. After the ICP algorithm, a rotation matrix $\mathbf{M_R}$ and a translation matrix $\mathbf{M_T}$ are obtained. The data of the operated point set approximately match the reference point set after the operation of $\mathbf{M_R}$ and $\mathbf{M_T}$ shown in Figure 4.

In summary, the skidding effect causes a heading angle shift but does not influence the linear and angular velocities. The heading angle shift is close to a constant if the linear velocity and the angular velocity do not vary a lot. Therefore, the value of heading angle shift should be readjusted when the desired velocities pair varies violently.

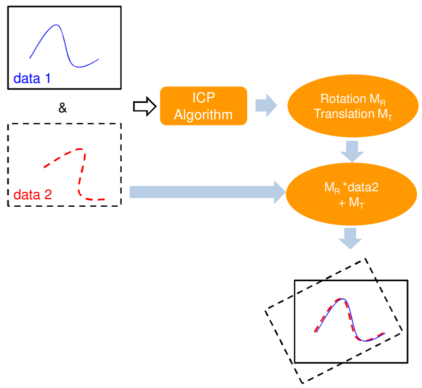


Figure 4. A schematic diagram of the ICP algorithm. The ICP algorithm can compute a rotation matrix M_R and a translation matrix M_T to make the point sets of data 2 match the point sets of data 1.

Four steps of the ICP algorithm are shown in the following. Firstly, every point in the operated point set searches the nearest point around it. Secondly, a squared cost function is used to estimate the performance of the matching. The parameters of $\mathbf{M_R}$ and $\mathbf{M_T}$ are tuning according to the cost function. Thirdly, the operated point set is transformed by $\mathbf{M_R}$ and $\mathbf{M_T}$ into a new operated point set, which is closer to reference set than the old one. Finally, iterate the first three steps until the stop criterion is satisfied. Applying the ICP algorithm which uses the laser range data and computing the parameters of transformation, the postures of the robot are estimated shown in Figure 5. This procedure is regarded as a localization method called "Geometric Posture Detecting Localization" or "GPDL" for short. When the present obstacle information can match with past obstacle information by the two matrices: $\mathbf{M_R}$ and $\mathbf{M_T}$, the present posture of the robot is decided by the same matrices.

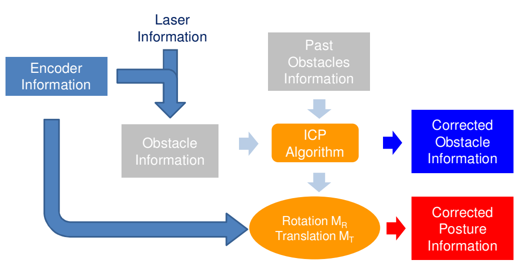


Figure 5. A concept of "Geometric Posture Detecting Localization" (GPDL) that using ICP method to correct environment information and posture information.

The GPDL method has high accuracy and good performance in the complicated environment. However, it needs huge data and long computing time. Besides, it has bad performance when the environment patterns are periodic. Fortunately, the DVDL can compensate these disadvantages.

C. Localization Method Fusion

Figure 6 shows the system architecture after the error elimination approach. Two main functions of the error elimination block are established: localization method fusion and parameter correction. The former is about posture information collected from three kinds of localization methods, and evaluating the environment information from range sensor to choose the dominated localization method. The latter is about the parameter tuning of transformation matrix, and sending this corrected information to encoder odometry to improve ability of encoder odometry. After the error elimination block, the real posture and real velocities pair are obtained and can be controlled by adaptive control laws.

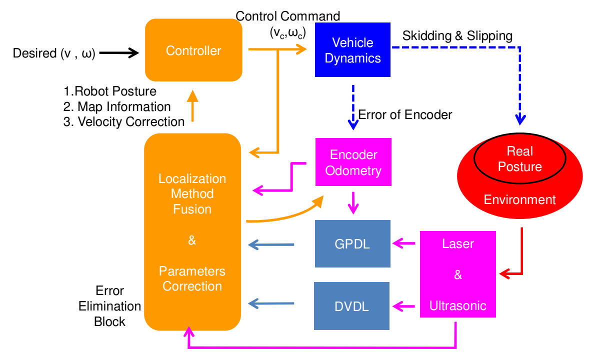


Figure 6. The whole architecture of localization method fusion and error elimination.

IV. EXPERIMENTAL TEST

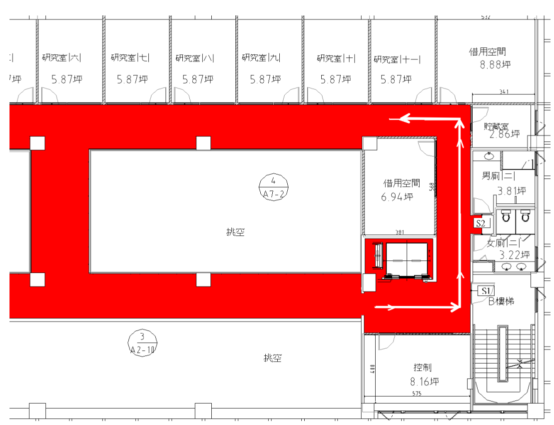


Figure 7. A design path labeled as dark line in this experiment.

The experimental platform is an indoor environment on the 6th floor at the MD building in NTU as shown in Figure 7, and a two-wheeled mobile robot PIONEER 3 with eight ultrasonic sensors and one laser rangefinder as shown in Figure 8. Besides, a laser rangefinder SICK LMS100 is set up on the PIONEER 3. The robot moves at the corridor and obtains data from encoders, ultrasonic sensors and laser rangefinder. When the robot posture and obstacle position from range sensors are drawn, a wrong environment pattern will reveal that the encoder is incorrect. That is the reason why the error elimination should be applied. After the algorithm of error elimination, the corrected robot path and environment pattern will fit the real environment pattern.

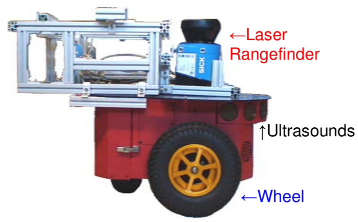


Figure 8. The picture of PIONEER 3 with the laser rangefinder SICK LMS100.

In this experiment, the robot moved as the control commands decided by the user, and the elimination architecture is operated after the robot moved. The designed paths shown in Figure 7 are classified as five phases.

In the first phase, the robot faces right and moves straight as the desired velocity (150 mm/s, 0 °/s) at a corridor. When the robot is located at the corner in the second phase, the robot turns left as the desired velocity (0 mm/s, 20 °/s) for 5 seconds. Although the ideal angle shift is 100°, the real tuning angle is only about 90° because of skidding and slipping. When the robot faces up on the map in the third phase, the desired velocity is the same as that in the first phase. The fourth phase has the same executive velocity as the second phase when the robot is located at the corner again. Finally, the robot faces left and moves as the same velocity as that in the first phase.

Figure 9(a) shows the actual path and the environment information and Figure 9(b) shows the uncorrected path before error elimination and the environment information detected by ultrasounds. Obviously, the path recorded by encoder odometry is so incorrect, which is accorded to wrong included angles between walls' pattern, that the localization method fusion should be applied.

The encoder odometry results are adopted when the results of DVDL and GPDL are not yet obtained. When the DVDL and GPDL are prepared, they are applied in different situation. When the robot is located at the corridor, the DVDL has higher priority to correct the encoder odometry. The corrected result is shown in Figure 9(c). When the robot moves at a new corridor, the DVDL should collect new ultrasonic data in the window to operate the algorithm. Therefore, the velocities cannot be corrected by the DVDL. In this situation, the posture measurements by the encoder odometry are the default results. In the other hand, the GPDL dominates the correction when robot is at the corner and turns.

After the localization method fusion, the corrected path and the environment information are shown in Figure 9(d). The experiment result shows the improvement of posture information from localization method fusion. Besides, the encoder odometry is calibrated by the error elimination architecture. That means the parameters of the velocities transformation matrix are adjusted. Figure 9(e) shows the results of corrected encoder odometry when the adjusted parameters are applied. Comparing Figure 9(e) with Figure 9(b), the correctness of the posture information is improved after the error elimination and the corrected results are more close to the actual measurement than that before the error elimination architecture.

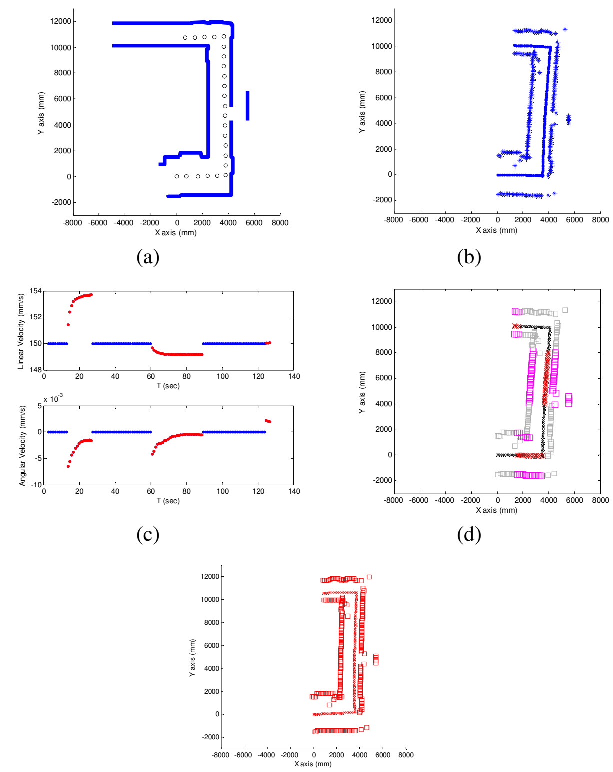
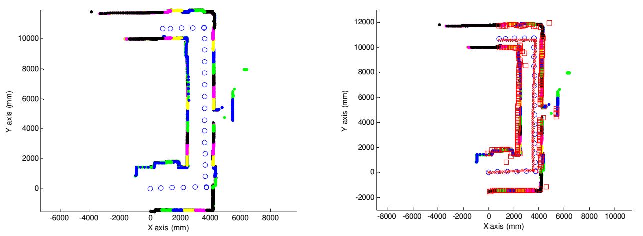


Figure 9. (a) The actual path records. (b) Uncorrected path record by encoder odometry. (c) Velocities estimation by the DVDL. (d) Corrected path by localization method fusion. (e) The result of corrected encoder odometry.

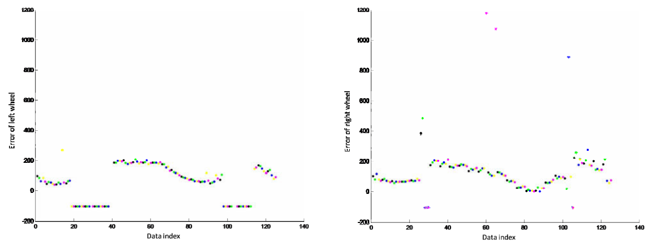
In order to quantify the performance after modification, the modified data from laser rangefinder by ICP algorithm are employed as a standard result and shown in Figure 10.

Figure 9(e) and Figure 10 are shown together. The minimum distances between obstacle positions in Figure 9(e) and standard positions detected by the laser rangefinder in Figure 10 are added up as an index of error analysis. Left wheel and right wheel error of each point are shown in Figure11. In both figures, some errors exceeding the limit of measurement are marked as value -100. They are regarded as outliers and not considered when the sum of errors is computed. The unit of transverse axle in the figures is order of all points, and the unit of vertical axle in the figures is millimeter. The average error per point is calculated to be 124.5 mm and 114.3 mm, respectively.



(a) (b)

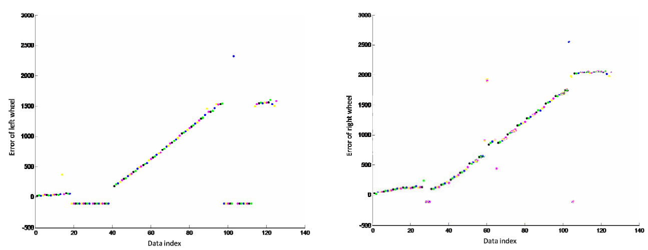
Figure 10. Plot of experimental field by modified data of laser range finder.



(a) (b)

Figure 11. Left (a) and right (b) wheel errors of all points from modified data of laser rangefinder.

Comparing with error of original data, the relative results are shown in Figure 14, Figure 15. The average error per point is calculated to be 825 mm and 918.5 mm, respectively.



(a) (b)

Figure 12. Left (a) and right (b) wheel errors of all points from original data.

V. Conclusion and Future Work

A. Conclusion

In the beginning of this paper, the sensing part and the actuating part of a TWMR are characterized. For the sensing part of the TWMR, two kinds of sensors are used in common: odometry sensors and range sensors. Odometry sensors measure the postures of robot, and range sensors detect the distances between robot and obstacles. Besides, the obstacle positions are obtained based on the robot posture and the distance between robot and obstacles.

When evaluating the effect of skidding and slipping, which exists in reality and cannot be neglected sometimes, the kinematic model of robot with the slipping and skidding effect are studied and analyzed. Because of disability of external data sensing, the odometry from wheel encoders will obtain the wrong posture information. In order to detect skidding and slipping, the odometry by range sensors are necessary.

Two localization methods are developed: the GPDL and the DVDL. Furthermore, a concept of localization method fusion is demonstrated and the error elimination architecture is described. An error elimination block combined the results of localization methods, and determines the proper posture result which is closer to real posture than other results.

After the error elimination, the data from the sensing part are more reliable and the parameters of actuating part are adjusted to adapt the situation with skidding and slipping.

References

[1: Siegwart & Nourbakhsh 2004]
Roland Siegwart and Illah R. Nourbakhsh, "Introduction to Autonomous Mobile Robots," *The MIT Press*, London, England, 2004

[2: Ioannou & Sun 1996]
P. A. Ioannou & J. Sun, "Robust Adaptive Control," *Prentice-Hall*, Upper Saddle River, NJ, 1996

[3: Gelb 2000]
Arthur Gelb, "Applied Optimal Estimation," *The MIT Press*, London, England, 2001

[4: Aarts & Lenstra 1997]
E. Aarts and J. K. Lenstra, "Local Search in Combinatorial Optimization," *Wiley*, New York, 1997

[5: Wang & Chang 2008]
Danwei Wang, and Chang Boon Low, "Modeling and Analysis of Skidding and Slipping in Wheeled Mobile Robots: Control Design Perspective," *IEEE Transactions on Robotics*, Vol. 24, No. 3, pp. 676-687, Jun. 2008

[6: Martinelli 2002]
Agostino Martinelli, "The Odometry Error of a Mobile Robot with a Synchronous Drive System," *IEEE Transactions on Robotics and Automation*, Vol. 18, No. 3, pp. 399-405, Jun. 2002

[7: Besl and Mckay 1992]
Paul J. Besl and Neil D. Mckay, "A Method for Registration of 3-D Shapes," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 14, No. 2, pp. 239-256, Feb. 1992

[8: Borenstein 1998]
Johann Borenstein, "Experimental Results from Internal Odometry Error Correction with the OmniMate Mobile Robot," *IEEE Transactions on Robotics and Automation*, Vol. 14, No. 6, pp. 963-969, Dec. 1998

[9: Borenstein & Koren 1991]
Johann Borenstein and Yoram Koren, "Histogramic In-Motion Mapping for Mobile Robot Obstacle Avoidance," *IEEE Transactions on Robotics and Automation*, Vol. 7, No. 4, pp. 535-539, Aug. 1991

[10: Freire et al. 2004]
Eduardo Oliveira Freire, Teodiano Bastos-Filho, Mario Sarcinelli-Filho, and Ricardo Carelli, "A New Mobile Robot Control Approach via Fusion of Control Signals," *IEEE Transactions on System, Men and Cybernetics-Part B: Cybernetics*, Vol. 34, No. 1, pp. 419-429, Feb. 2004

[11: Gu & Hu 2006]
Dongbing Gu and Huosheng Hu, "Receding Horizon Tracking Control of Wheeled Mobile Robots," *IEEE Transactions on Control Systems Technology*, Vol. 14, No. 4, pp. 743-749, July 2006

[12: Oriolo et al. 2002]
Giuseppe Oriolo, Alessandro De Luca and Marilena Vendittelli, "WMR Control Via Dynamic Feedback Linearization Design, Implementation, and Experimental Validation," *IEEE Transactions on Control Systems Technology*, Vol. 10, No. 6, pp. 835-852, Nov. 2002