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Filtering Algorithm for Reliable Localization of Mobile Robot in Multi-Sensor Environment

Yong-Shik Kim[1], Jae Hoon Lee[1], Bong Keun Kim[1],
Hyun Min Do[1] and Akihisa Ohya[2]
[1]UFRG, AIST, Central 2, 1-1-1 Umezono, Tsukuba, 305-8568, Japan
Email: yongshik.kim2009@gmail.com, {jh.lee, bk.kim, hyunmin.do}@aist.go.jp
[2]Intelligent Robot Laboratory, University of Tsukuba, Tsukuba, Japan
Email: ohya@roboken.esys.tsukuba.ac.jp

Abstract:
Localization problem of mobile robot in an environment of interest is one of research fields that are not still completely solved. Many methods to settle this problem are unceasingly being examined. Although a lot of researchers have dedicated themselves to this problem, it demands new but more accurate method by which mobile robot itself recognizes its own position while moving. It tries to find solution by making mention of various localization problems with estimation method in this chapter. Robot researchers had to recognize the current position information for movement control of mobile robot to last destination. It is being adopted from the conventional Kalman filter, which was proposed to reduce stochastic noise error, to complicated algorithms in the field of target tracking. The localization of the mobile robot occurred in various environments such as indoor, outdoor, warehouse, harbors, airports, and offices is based on estimation theories of target tracking field. The estimation method to be proposed in this chapter is mentioned with localization problem in the text. As the most widely used method for providing the current position of mobile robot, odometry is inexpensive method to implement in real time, but has vital demerit of accumulation of position error for long distance navigation. Various external sensors were used to supplement this problem, but the adopted sensors have also intrinsic errors. GPS, used as a global sensor in the outdoors, has a fatal weak point suffering from multi-path effects in the surrounding of buildings or trees. In this chapter, method for decreasing the above error occurred in localization problem are provided and embodied. This error is assumed as bias error. New nonlinear estimation method included in data integration method to reduce that error is derived and evaluated through experiment. The proposed integration method is provided to take full advantage of characteristics of mobile and outdoor environment sensors.

1. Introduction

Localization of moving object is one of the main subjects in the area of robotics. In particular, the service robot has aimed at providing position information for the running of the robot to support man's vital function. In the viewpoint of the robot, it is necessary to recognize the position in the given environment to carry out the desired duty in daily life. The robot may receive information from not only the sensors that robot has but also devices distributed on the ambient environment. There exist various sensing technologies to recognize the current position of mobile robot in the given environment. For such case, sensors can be classified as the following two categories in the view of information provider: i) Odometry, inertial measurement unit (inertial navigation system), ultrasonic sensor, laser range finder, moving camera such as stereo camera; ii) Camera array system, radio frequency identification (RFID), global positioning system (GPS), starLITE sensor suite, ultrasonic satellite (U-SAT), stargazer, laser range finder with reflectors. Odometry is the most widely used method for determining the current position of the mobile robot. An odometric sensor is simple, inexpensive, and easy to implement in real time. The disadvantage of odometry, however, is the accumulation of position errors for long distance navigation. In order to solve this problem, absolute and global information to the running robot is needed. As one of the aiding methods for that information of a mobile robot, the widely used sensors include starLITE sensor suite, vision system, GPS, and RFID. Differential GPS (DGPS) method has been developed to reduce the odometry error in real time. Nevertheless, the DGPS accuracy cannot be guaranteed all the time in environments where partial satellite occlusion and multi-path effects between buildings can prevent normal GPS receiver operation. Therefore, for the localization of mobile robot, it is indispensable to consider each characteristic of the used sensors because each sensor receives data with different method. It can be considered as registration error of mobile sensors. Data registration problem can be settled down by pre-processing of sensor data [9], [21]. In this chapter, sensor data transformed from local coordinate reference system to global coordinate reference system is used as inputs of integration filter.

Information fusion of various sensors enables one to obtain better information than independent that of each sensor. Sensor data fusion is indispensable for localization of a mobile robot in the given environment. Data fusion techniques are used to employ a number of sensors and to fuse the information from all of these sensors and environment. But, sensor data or information may be of different types. In that case, integration can be used as a special form of data fusion after sensor registration. Various integration methods using dead-reckoning and external information have been in the literature [1], [2], [5], [11], [14], [15], [18]-[20]. Nebot and Durrant-Whyte [16] presented the design of a high-integrity navigation system for use in large autonomous mobile vehicles. Decentralized integration architecture was also presented for the fusion of information from different asynchronous sources. The integration includes a complementary fusion [2], [8], a centralized integration [2], [13], and a distributed integration method [4], [6], [7], [22]. For integrating information of DGPS and odometric data, a complementary integration approach is proposed [2], [3], [19]. The used integration filtering method uses odometry data as system state and DGPS data as measurements. It needs difference between two sensor data as input variables of filter. The extended Kalman filter (EKF) [2] is used as integration filter to estimate sensor data error. In addition, the filtering output is resent to odometry system to correct robot position. However, even after data integration, the undesirable result may be obtained. This is due to multi-path phenomenon of the DGPS sensor [8], [16], [19]. Novoselov et al. [17] presented the algorithm

based on the Schmidt-Kalman filter for mitigating the effects of residual biases on sensor attitude error and measurement offset and scale errors. Huang and Tan [12] investigated the characteristics of DGPS measurements under urban environments. In addition they proposed novel DGPS noise processing techniques to reduce the chances of exposing the EKF to undesirable DGPS measurements due to common DGPS problems such as blockage and multipath. When one of several sensors provides bad information in multi-sensor structure, the proposed mechanism detects a sensor fault from integrating result and compensates information by bias estimation. The used bias estimation was originated by Friedland [10]. In [10], the estimation mechanism is composed of two parts: bias-free filter and bias filter. The estimation of the bias is decoupled from the computation of the bias-free estimate of the state. Therefore, the aim of this study is to use each characteristic of sensor data and to develop an integration structure dealing with those data for the localization of mobile robot in spite of sensor data fault or bias error.

This paper is organized as follows. In Section 2, for localization of mobile robot two different integration sensors and their characteristics are described. The problem is formulated to integrate information from odometry sensor and ambient environment, and integration structure is proposed in Section 3. It is also proposed an integration method with bias estimation to compensate bias error. The problem with data fault phenomena is mentioned and recovered. Outdoor robot Yamabico is used to verify the proposed mechanism in Section 4. Section 5 concludes the paper.

2. Localization without Bias Compensation

For the localization of mobile robot using odometry and DGPS sensors, an integration mechanism taking use of characteristics of sensor data is needed. This section will, therefore, focus on the integration method of two sensors. It is worthwhile to note that integrated localization depends on characteristics of sensor data. So, the integration problem can be stated as how to best extract useful information from multiple sets of data with different characteristics being available.

2.1. Characteristics of Sensors

First, odometry system equation as dead-reckoning and DGPS for the localization aid are briefly discussed, respectively. Odometric sensor is a positioning sensor which estimates both position and orientation of the mobile robot by integrating the measurement of driving wheel rotations. The robot's position is defined as $x(k) = [\eta(k) \ \xi(k) \ \theta(k)]^T$ and its error covariance is denoted as $\sum_{x(k)}$. Then, the robot position and its estimated error are represented as follows:

$$x(k + \Delta T) = \begin{bmatrix} \eta(k) \\ \xi(k) \\ \theta(k) \end{bmatrix} + \begin{pmatrix} \Delta T V(k) \cos(\theta(k)) \\ \Delta T V(k) \sin(\theta(k)) \\ \Delta T \phi(k) \end{pmatrix} + w, \tag{1}$$

$$\sum_{x(k+\Delta T)} = J \sum_{x(k)} J^T + K(k) \sum_{V(k)} K(k)^T + \sum_N, \tag{2}$$

$$\sum\nolimits_{x(k)} = \begin{pmatrix} \sigma_{\eta_0}(k)^2 & \sigma_{\eta_0\xi_0}(k) & \sigma_{\eta_0\theta_0}(k) \\ \sigma_{\xi_0\eta_0}(k) & \sigma_{\xi_0}(k)^2 & \sigma_{\xi_0\theta_0}(k) \\ \sigma_{\theta_0\eta_0}(k) & \sigma_{\theta_0\xi_0}(k) & \sigma_{\theta_0}(k)^2 \end{pmatrix} \tag{3}$$

where ΔT is a sampling period. $V(k)$, $\theta(k)$, and $\phi(k)$ is velocity, orientation, and angular velocity, respectively. $J(k)$ is Jacobian of $x(k)$ with respect to η, ξ, and θ. $K(k)$ is Jacobian of $x(k)$ with respect to V and θ.

In this work, DGPS (Trimble DSM212L) receiver is used as external sensor. DGPS can reduce the measurement error within one or several meters from original GPS data. The output data format is NMEA-0183 which offers a series of characters through a RS232C communication channel. Accuracy and resolution of the DGPS receiver was tested in the wide parking lot with the RTK-GPS. The DGPS sensor used in this study has data error of 30cm-50cm. Fig. 1 shows the DGPS sensor using in this experiment.
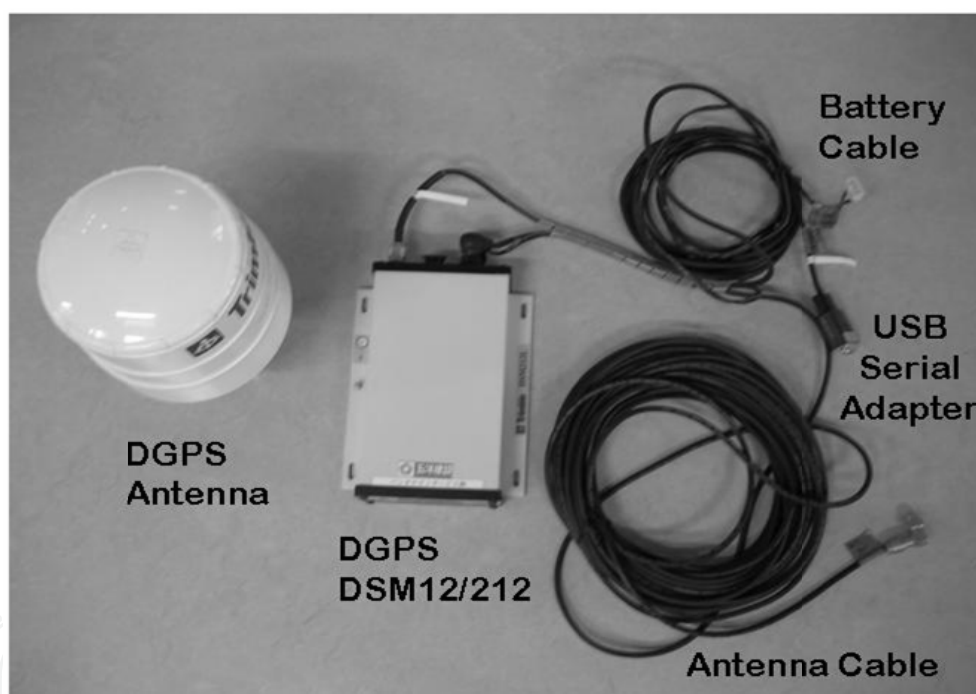

Fig. 1. DGPS experiment equipment.

2.2. Stochastic Problem Formulation

Considering such a kinematics of odometry, the following nonlinear dynamic system and measurement equations can be written:

$$x(k) = f[x(k-1)] + \omega(k-1), \ k = 1, 2, \cdots, \tag{4}$$

$$z_i(k) = h_i[x(k)] + \upsilon_i(k), \qquad i = 1, \cdots, N \tag{5}$$

where $x(k) \in \Re^n$ is the state vector at time k, f is a nonlinear function, $\omega(k) \in \Re^n$ is

the process noise, $z_i(k) \in \Re^{m_i}$ is the observation vector at ith local sensor, $h_i \in \Re^{m_i \times n}$ is the nonlinear measurement function, $\upsilon_i(k) \in \Re^{m_i}$ is the observation noise, $m_1 + \cdots + m_N = m$, and N is the number of sensors. In order to obtain the predicted state $\hat{x}(k \mid k-1)$, the nonlinear function in (4) is expanded in Taylor series around the latest estimate $\hat{x}(k-1 \mid k-1)$ with terms up to first order, to yield the first-order EKF. The vector Taylor series expansion of (4) up to first order is

$$x(k) = f[\hat{x}(k-1 \mid k-1)] + f_x(k-1)[x(k-1) - \hat{x}(k-1 \mid k-1)] + \text{HOT} + \omega(k-1) \quad (6)$$

where HOT represents the higher-order terms and

$$f_x(k-1) = [\nabla_x f(x)']' |_{x = \hat{x}(k-1 \mid k-1)} \quad (7)$$

is the Jacobian of the vector f evaluated with the latest estimate of the state.

2.3. Complementary Integration without Bias Compensation

For integrating information of DGPS and odometric data, a complementary integration approach is proposed [2], [3], [19]. The complementary configuration is shown in Fig. 2 [2]. According to the complementary integration scheme, the odometry sensor data is used as system information and DGPS data is used as measurements. It needs difference between two sensor data as input variables of filter. An EKF is used as integration filter to estimate sensor data error. In addition, the key in the suggested filter design is that filter output is resent to odometry system to correct robot position.
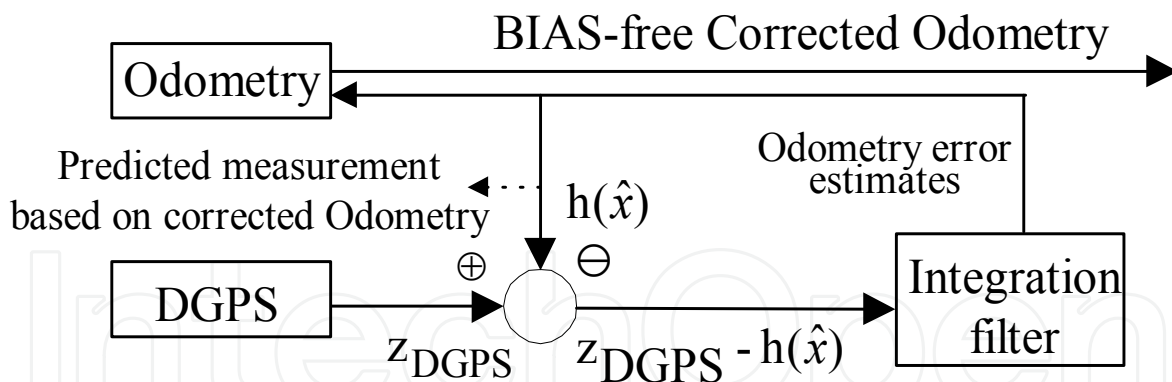

Fig. 2. Configuration of complementary integration.

For the integration filtering, the covariance matrix and state estimate equations are as follows:

i) Time update (prediction)

$$\hat{x}(k \mid k-1) = f[\hat{x}(k-1 \mid k-1)],$$

$$P(k \mid k-1) = f_x(k-1)P(k-1 \mid k-1)f_x'(k-1) + Q(k-1). \quad (8)$$

ii) Measurement update

$$\hat{x}(k \mid k) = \hat{x}(k \mid k-1) + W(k)[z(k) - h_x(k)],$$

$$P(k \mid k) = P(k \mid k-1) - W(k)S(k)W'(k), \tag{9}$$

where $P(k \mid k)$ is the covariance matrix and $\hat{x}(k \mid k)$ is the state estimate vector. $h_x(k) = [\nabla_x h(x)']' \mid_{x=\hat{x}(k \mid k-1),j}$ is the Jacobian of the vector h evaluated at the predicted state $\hat{x}(k \mid k-1)$.

2.4. Data Fault by Multi-Path Phenomenon

DGPS sensor provides rather accurate information for long distance navigation as a sensing method providing an absolute position value. However, this accuracy cannot be guaranteed all the time in environments where partial satellite occlusion and multipath effects between buildings can prevent normal GPS receiver operation. Fig. 3 shows data fault by multi-path of RTK-GPS in the surrounding of buildings. Therefore, the correct position information for localization of mobile robot is not provided because of fault error by multipath of DGPS sensor,. In this paper, this fault error is considered as bias error of sensor.
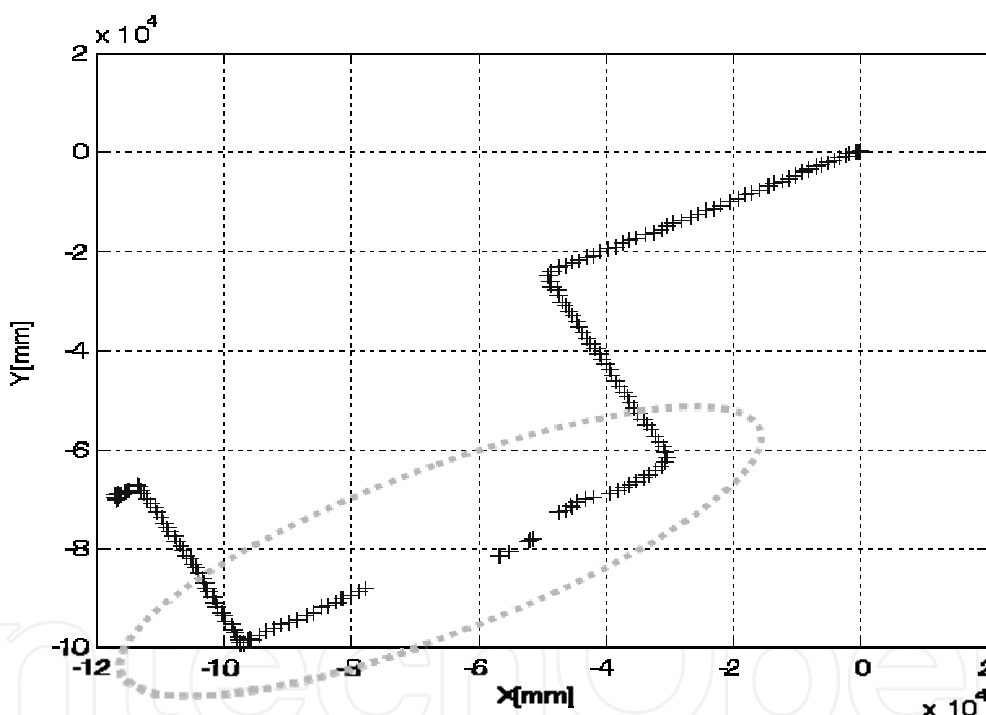

Fig. 3. Multi-path result of RTK-GPS data.

3. Integration Method with Bias Error Compensation

3.1. Problem Formulation

Assuming bias error in the system model and sensor model, the nonlinear dynamic system and measurement equations are as follows:

$$x(k) = f[x(k-1)] + B(k-1)b(k-1) + \omega(k-1), \ k = 1, \cdots, \tag{10}$$

$$z_i(k) = h_i[x(k)] + C_i(k)b(k) + \upsilon_i(k), \qquad i = 1, \cdots, N, \tag{11}$$

$$b(k+1)=b(k) \tag{12}$$

where $x(k) \in \Re^n$ is the state vector at time k, f and h_i is a nonlinear functions, $\omega(k) \in \Re^n$ is the process noise, $z_i(k) \in \Re^{m_i}$ is the observation vector at ith local sensor, $\upsilon_i(k) \in \Re^{m_i}$ is the observation noise, and N is the number of sensors. $b(\cdot) \in \Re^d$ denote constant bias vectors and enter linearly. $B \in \Re^{n \times d}$ and $C_i \in \Re^{m_i \times d}$ denote how to bias vector enters into the dynamics and sensor model. In order to obtain the predicted state $\hat{x}(k \mid k-1)$, the nonlinear function in (10) is expanded in Taylor series around the latest estimate $\hat{x}(k-1 \mid k-1)$ with terms up to first order, to yield the first-order EKF. The vector Taylor series expansion of (10) up to first order is

$$x(k) = f[\hat{x}(k-1 \mid k-1)] + f_x(k-1)[x(k-1) - \hat{x}(k-1 \mid k-1)]$$
$$+ \text{HOT} + B(k-1)b(k-1) + \omega(k-1) \tag{13}$$

where HOT represents the higher-order terms and

$$f_x(k-1) = [\nabla_x f(x)']' \mid_{x=\hat{x}(k-1 \mid k-1)} \tag{14}$$

is the Jacobian of the vector f evaluated with the latest estimate of the state.

3.2 Estimation with Bias Compensation

In this paper, two-stage estimator by Friedland [10] is used. The estimation mechanism is composed of two parts: bias-free filter and bias filter. The estimation of the bias is decoupled from the computation of the bias-free estimate of the state.

A. Bias-free estimator

The estimation progress of bias-free filter is as follows:

1) Predict bias-free covariance matrix

$$P(k \mid k-1) = f_x(k-1)P(k-1 \mid k-1)f_x(k-1)' + Q(k-1)$$

2) Predict bias-free state estimate vector

$$\hat{x}(k \mid k-1) = f_x(k-1)\hat{x}(k-1 \mid k-1)$$

3) Predict bias-free measurement

$$\hat{z}(k \mid k-1) = h_x(k)\hat{x}(k \mid k-1)$$

4) Compute bias-free Kalman gain

$$K_x(k) = P(k \mid k-1)h_x'(k)(h_x(k)P(k \mid k-1)h_x'(k) + R(k))^{-1}$$

5) Update bias-free covariance matrix

$$P(k \mid k) = P(k \mid k-1) - K_x(k)S(k)K_x'(k)$$

where $S(k) = H(k)P(k \mid k-1)H'(k) + R(k)$ is covariance matrix of the innovation vector $\tilde{z}(k \mid k-1)$.

6) Receive measurement data

$$z(k)$$

7) Calculate bias-free innovation vector

$$\tilde{z}(k \mid k-1) = z(k) - \hat{z}(k \mid k-1)$$

8) Update bias-free estimate of state vector

$$\hat{x}(k \mid k) = \hat{x}(k \mid k-1) + K_x(k)\tilde{z}(k \mid k-1)$$

B. Bias estimator

The procedure for calculating estimate of bias filter in the presence of bias error is as follows:

1) Update Ux matrix

$$U_x(k) = F(k)V_x(k) + B(k)$$

2) Compute T matrix

$$T(k) = h_x(k)U_x(k) + C(k)$$

3) Compute Vx matrix using the bias-free Kalman gain Kx

$$V_x(k) = U_x(k) - K_x(k)T(k)$$

4) Compute bias covariance matrix

$$M(k) = M(k-1) - M(k-1)T'(k)(h_x(k)P_x(k \mid k-1)$$

$$\times h_x'(k) + R(k) + T(k)M(k-1)T'(k))^{-1}T(k)M(k-1)$$

5) Compute bias Kalman gain

$$K_b(k) = M(k)(V_x'(k)h_x'(k) + C'(k))R^{-1}(k)$$

6) Compute bias estimate using the bias-free innovation vector

$$\hat{b}(k) = (I - K_b(k)T(k))\hat{b}(k-1) + K_b(k)\tilde{z}(k \mid k-1)$$

7) Compute bias correction

$$\sigma_k = V_x(k)\hat{b}(k)$$

8) Compute state estimate in the presence of bias error

$$\hat{x}_b(k \mid k) = \hat{x}(k \mid k) + \sigma(k)$$

C. Complementary Integration with Bias Compensation

First, the integration configuration proposed in this paper is shown in Fig. 4. According to the suggested integration scheme, the odometry sensor data is used as system information and DGPS data is used as measurements. It needs difference between two sensor data as input variables of filter. An EKF is used as integration filter to estimate sensor data error. In addition, the key in the suggested filter design is that filter output is resent to odometry system to correct robot position. In the suggested filter, contrary to the standard complementary integration, the integration filter is used for mitigating the effect of biases, since there is undesirable DGPS bias error in DGPS problems such as multipath phenomenon under urban environments. The proposed mechanism detects a data fault from the integrated result and compensates information by bias estimation.
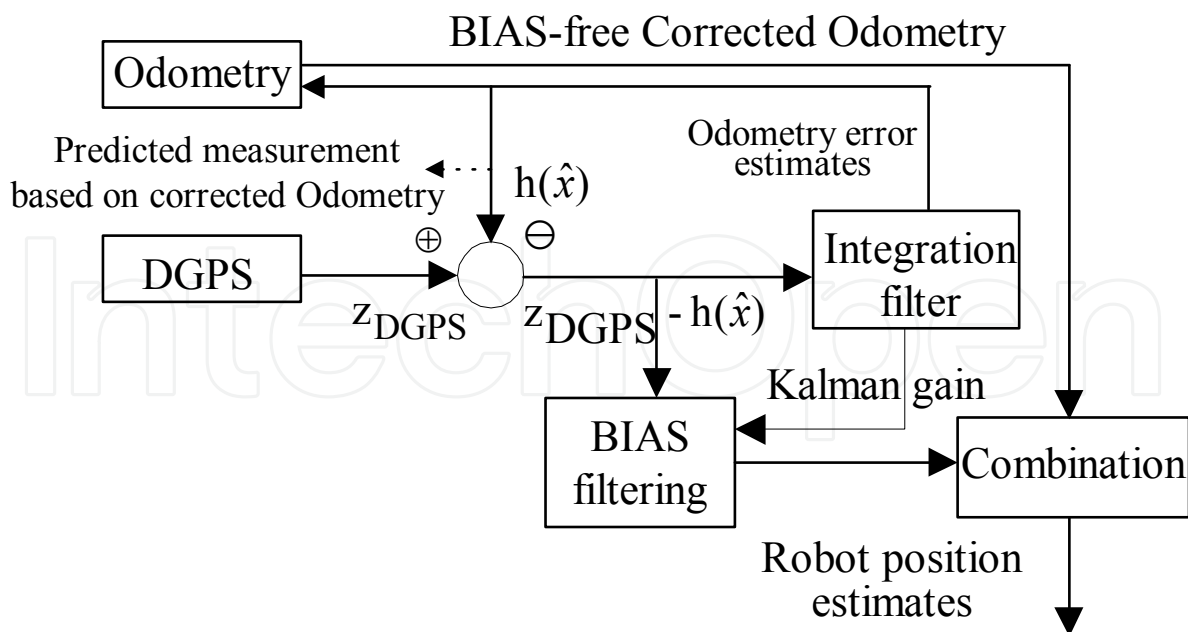
Fig. 4. Complementary integration with bias compensation.

4. Experiment and Results

4.1 System Configuration

In order to verify the integration method proposed in Section 3, position data of a Yamabico robot was received in outdoor environment. Fig. 5 depicts a configuration of the hardware system including three sensors and Yamabico robot for outdoor experiment. The used Yamabico robot was manufactured for outdoor experiment. The size of two wheels is bigger than those of indoor Yamabico robot. Air pressure of these wheels has to be checked before outdoor experiment.

For the experiment take into accounting characteristic of sensors, the parking lots and the surrounding of overcrowded buildings was selected as the experiment place. Data acquisition time of three different sensors equipped to the robot is different from each other. The sampling period of DGPS was 1sec. The sampling period of odometric sensor was about 5msec. Data from each sensor were received using a program considering these data receiving delay. Data communication between two sensors and laptop computer is transferred via RS232C.In this paper, an RTK-GPS as a measure for accuracy of DGPS was used. Data acquisition of the DGPS & Odometric receiver was carried out from the parking lots to the surrounding of building with the RTK-GPS.
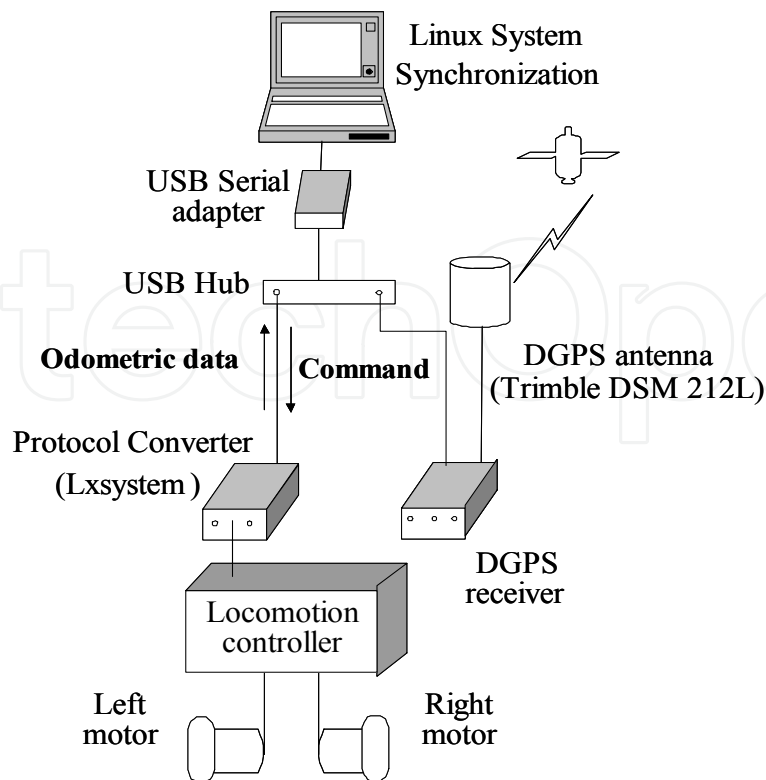
Fig. 5. H/W configuration.

4.2 Experiments and Simulation

A comparison of data received was carried out through computer simulation. Data registration was implemented using position data obtained from outdoor experiment. Basically, sensor data must transform to the global coordinate reference system. However, sensor data is not always transformed in all part. According to place or environment, a part of data can be lost. In such case, even if the coordinates is transformed, it can use no information in the interval where data was lost. Hence, in order to take full advantage of information, it is necessary to integrate considering data fault. In the parking lots without objects to its surrounding, the receiving condition of DGPS sensor is good. But, on the contrary, in the surrounding of the crowded buildings, DGPS data did not provide accurate position data due to the multi-path effect. Fig. 6 shows the result integrated by the conventional complementary method and the proposed complementary method. In spite of integrating two sensor data, in the surrounding of the building, the conventional complementary result did not provide accurate position information due to the multi-path effect. However, in the proposed method, robot position was corrected using data recovered by the bias estimation when the DGPS data can't be trusted. In order to detect bias error by the DGPS multi-path phenomena, the following normalized innovation square formula was used [2]

$$\tilde{r}'(k \mid k-1)S^{-1}(k)\tilde{r}(k \mid k-1)$$

where $\tilde{r}$ denotes the innovation vector and S denotes covariance matrix of the innovation vector. This value is compared with a threshold value determined by the chi-square distribution. In this study, for 95% probability, the theoretical threshold value is 7.81.
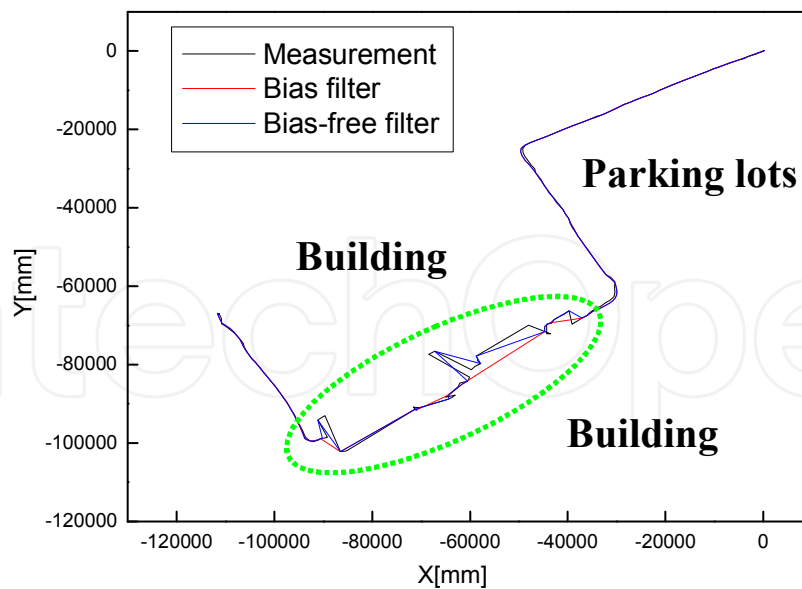
Fig. 6. Comparison of the standard and proposed complementary method.

5. Conclusions

In this paper, bias estimation based data integration method was provided. It is shown that the sensor data must be integrated with selection according to the sensing environment. Odometry and DGPS data can generally be used to localize mobile robot in outdoor environment. In the case there is slip phenomena by multi-path phenomena of DGPS sensor, however, the previous integration method can't solve data fault. The proposed data integration method is adequate to this condition. In this paper, the problem of data fault was solved by bias estimation. The proposed method, consisting of an estimator taking into account bias and a free-bias estimator, recovered the fault data and was used to localize mobile robot.

6. References

A. Adam, E. Rivlin, and H. Rotstein, "Fusion of fixation and odometry for vehicle navigation," IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans, Vol. 29, No. 6, pp. 593-603, 1999.

Y. Bar-Shalom, X. Li, and T. Kirubarajan, Estimation with Applications to Tracking and Navigation, John Wiley & Sons, INC, New York, 2001.

P. Bonnifait, P. Bouron, P. Crubille, and D. Meizel, "Data fusion of four ABS sensors and GPS for an enhanced localization of car-like vehicles," Proceedings of the IEEE International Conference on Robotics and Automation, Seoul, Korea, May 21-26, pp. 1597-1602, 2001.

S. B. H. Bruder, "An information centric approach to heterogeneous multi-sensor integration for robotic applications," Robotics and Autonomous Systems, Vol. 26, No. 4, pp. 255-280, March 1999.

R. Carelli and E. O. Freire, "Corridor navigation and wall-following stable control for sonar-based mobile robots," Robotics and Autonomous Systems, Vol. 45, No. 3-4, pp. 235-247, December 2003.

N. A. Carlson and M. P. Berarducci, "Federated Kalman filter simulation results," Journal of the Institute of Navigation, Vol. 41, No. 3, pp. 297-321, 1994.

N. A. Carlson, "Federated square root filter for decentralized parallel processes," IEEE Transactions on Aerospace and Electronic Systems, Vol. 26, No. 3, pp. 517-525, 1990.

F. Caron, E. Duflos, D. Pomorski, and Ph. Vanheeghe,"GPS/IMU data fusion using multisensor Kalman filtering: introduction of contextual aspects," Information Fusion, 2005.

M. P. Dana, "Registration: a prerequisite for multiple sensor tracking," in Multitarget-Multisensor Tracking: Advanced Applications, Y. Bar-Shalom, Ed., Artech House, Norwood, Ma, 1990.

B. Friedland, "Treatment of bias in recursive filtering," IEEE Transactions on Automatic Control, vol. 14, pp. 359-367, 1969.

J. Guivant, E. Nebot, and S. Baiker, "Localization and map building using laser sensors in outdoor applications," Journal of Robotic Systems, Vol. 17, No. 10, pp. 565-583, 2000.

J. Huang and H. S. Tan, "A low-order DGPS-based vehicle positioning system under urban environment," IEEE Transactions on Mechatronics, vol. 11, no. 5, pp. 567-575, 2006.

T. G. Lee, "Centralized Kalman filter with adaptive measurement fusion: its application to a GPS/SDINS integration system with an additional sensor," International Journal of Control, Automation, and systems, vol. 1, no. 4, pp. 444-452, December 2003.

J. H. Lim and C. U. Kang, "Grid-based Localization of a mobile robot using sonar sensors," KSME International Journal, Vol. 16, No. 3, pp. 302-309, 2002.

R. Madhavan and H. F. Durrant-Whyte, "Natural landmark-based autonomous vehicle navigation," Robotics and Autonomous Systems, Vol. 46, pp. 79-95, 2004.

E. M. Nebot and H. Durrant-Whyte, "A high integrity navigation architecture for outdoor autonomous vehicles," Robotics and Autonomous Systems, Vol. 26, No. 2-3, pp. 81-97, February 1999.

R. Y. Novoselov, S. M. Herman, S. M. Gadaleta, and A. B. Poore, "Mitigating the effects of residual biases with Schmidt-Kalman filtering," International Conference on Information Fusion, Philadelphia, PA, USA, July 25-29, 2005.

K. Ohno, "A study on outdoor navigation of an autonomous mobile robot based on GPS," Ph.D. dissertation, Univ. of Tsukuba, Tsukuba, Japan, Mar. 2004.

K. Ohno, T. Tsubouchi, B. Shigematsu, S. Maeyama, and S. Yuta, "Outdoor navigation of a mobile between buildings based on DGPS and odometry data fusion," Proceedings of the 2003 IEEE International Conference on Robotics and Automation, Taipei, Taiwan, Sep. 14-19, pp. 1978-1984, 2003.

R. Thrapp, C. Westbrook, and D. Subramanian, "Robust localization algorithm for an autonomous campus tour guide," Proceedings of the 2001 IEEE International Conference on Robotics and Automation, Seoul, Korea, May. 21-26, pp. 2065-2071, 2001.

Y. Zhou, H. Leung, and E. Bosse, "Registration of mobile sensors using the parallelized extended Kalman filter," Opt. Eng. vol. 36, no. 3, pp. 780-788, March, 1997.

Y. Zhu, Z. You, J. Zhao, K. Zhang, and X. Li, "The optimality for the distributed Kalman filtering fusion," Automatica, Vol. 37, No. 9, pp. 1489-1493, 2001.
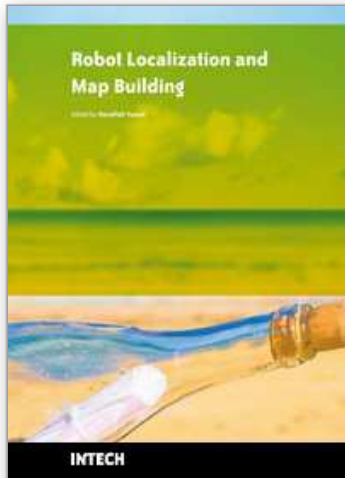
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Localization and mapping are the essence of successful navigation in mobile platform technology. Localization is a fundamental task in order to achieve high levels of autonomy in robot navigation and robustness in vehicle positioning. Robot localization and mapping is commonly related to cartography, combining science, technique and computation to build a trajectory map that reality can be modelled in ways that communicate spatial information effectively. This book describes comprehensive introduction, theories and applications related to localization, positioning and map building in mobile robot and autonomous vehicle platforms. It is organized in twenty seven chapters. Each chapter is rich with different degrees of details and approaches, supported by unique and actual resources that make it possible for readers to explore and learn the up to date knowledge in robot navigation technology. Understanding the theory and principles described in this book requires a multidisciplinary background of robotics, nonlinear system, sensor network, network engineering, computer science, physics, etc.

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