Bias Estimation of DGPS Multi-Path Data for Localization of Mobile Robot

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Abstract: In this paper, a localization method is provided estimating bias error due to multi-path phenomenon of DGPS sensor. In order to recognize the position of mobile robot, it is necessary data structure to integrate information from sensor data. To take full advantage of two sensor data, an integration mechanism is provided and implemented. It is provided bias detection and bias estimation for multi-path phenomenon of DGPS sensor in the surrounding of buildings. A performance evaluation is shown through an outdoor experiment data with Yamabico mobile robot.
Keywords: State estimation, Kalman filter, multi-sensor, localization, data integration, bias estimation

1. Introduction

There exist various sensors used to recognize the current position of mobile robot in an outdoor environment. 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. 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 autonomous navigation of a mobile robot, it is indispensable to consider each characteristic of sensors used 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 [6], [14]. In this paper, sensor data transformed from local coordinate reference system to global coordinate reference system is used as inputs of integration filter. The aim of this study is to understand each characteristic of sensor data and develop an integration structure dealing with those data for the localization of mobile robot in spite of sensor data fault.

Sensor data fusion is indispensable for localization of a mobile robot. Data fusion techniques are used to employ a number of sensors (which may be of different types) and to fuse the information from all of these sensors. Integration is a special form of data fusion. Various integration methods using dead-reckoning and external sensor have been in the literature [1], [12], [13]. Nebot and Durrant-Whyte [10] 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 [1], [5], a centralized integration [1], and a distributed integration method [3], [4]. In this work, for integrating information of DGPS and odometric data, a complementary integration approach is proposed [1], [2], [10]. 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) [1] is used as integration filter to estimate sensor data error. In addition, the filtering output is resent to odometry system to correct robot position.

Even after data integration, the undesirable result may be obtained. This is due to multi-path phenomenon of the DGPS sensor [5], [9], [11]. Novoselov et al. [9] 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 [8] 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 [7]. In [7], 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.

This paper is organized as follows. In Section 2, for localization of mobile robot under data fault in outdoor environment, two different integration sensors and their characteristics are described. Also, a complementary integration structure is proposed. In Section 3, under sensor data fault, it is proposed an integration method with bias estimation to compensate bias error. Outdoor Yamabico robot is used to verify the proposed mechanism in Section 4. Section 5 concludes the paper.

2. Outdoor Localization

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. Data 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 $x(t)=[\eta(t)\ \ \xi(t)\ \ \theta(t)]^T$ and its error covariance is denoted as $\sum_{P(t)}$. Then, the robot position and its estimated error are represented as follows:

$$x(t+\tau)=x(t)+\tau\begin{pmatrix} v(t)\cos(\theta(t)) \\ v(t)\sin(\theta(t)) \\ \omega(t) \end{pmatrix}, \tag{1}$$

$$\textstyle\sum_{P(t+\tau)}=J\sum_{P(t)}J^T+K(t)\sum_{v(t)}K(t)^T+\sum_N \ , \tag{2}$$

$$\textstyle\sum_{P(t)}=\begin{pmatrix} \sigma_{\eta o}(t)^2 & \sigma_{\eta\xi o}(t) & \sigma_{\eta\theta o}(t) \\ \sigma_{\eta\xi o}(t) & \sigma_{\xi o}(t)^2 & \sigma_{\xi\theta o}(t) \\ \sigma_{\eta\theta o}(t) & \sigma_{\xi\theta o}(t) & \sigma_{\theta o}(t)^2 \end{pmatrix} \tag{3}$$

where τ is a sampling period. v(t), $\theta(t)$, and $\omega(t)$ is velocity, orientation, and angular velocity, respectively. J(t) is Jacobian of P(t) with respect to η, ξ, and θ. K(t) is Jacobian of P(t) 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.

2.2. Stochastic Modeling

Assuming no bias error, consider the following nonlinear dynamic system and measurement equations:

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

$$z_i(k)=h_i[x(k)]+\upsilon_i(k), \quad i=1,\cdots,N \tag{2}$$

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 $\hat{x}(k\,|\,k-1)$, the nonlinear function in (1) is expanded in Taylor series around the latest estimate $\hat{x}(k-1\,|\,k-1)$ with terms up to first order, to yield the first-order EKF. The vector Taylor series expansion of (1) up to first order is

$$\begin{aligned} x(k)=f[\hat{x}(k-1\,|\,k-1)]+f_x(k-1)[x(k-1)-\hat{x}(k-1\,|\,k-1)] \\ +\mathrm{HOT}+\omega(k-1) \end{aligned} \tag{3}$$

where HOT represents the higher-order terms and

$$f_x(k-1)=[\nabla_x f(x)']'\,|_{x=\hat{x}(k-1|k-1)} \tag{4}$$

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 [1], [2], [10]. The complementary configuration is shown in Fig. 2 [1]. 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 extended Kalman filter (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.

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

i) Time update (prediction)

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

$$P(k\,|\,k-1)=f_x(k-1)P(k-1\,|\,k-1)f_x'(k-1)+Q(k-1)\,. \tag{5}$$

ii) Measurement update

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

$$P(k\,|\,k)=P(k\,|\,k-1)-W(k)S(k)W'(k)\,, \tag{6}$$

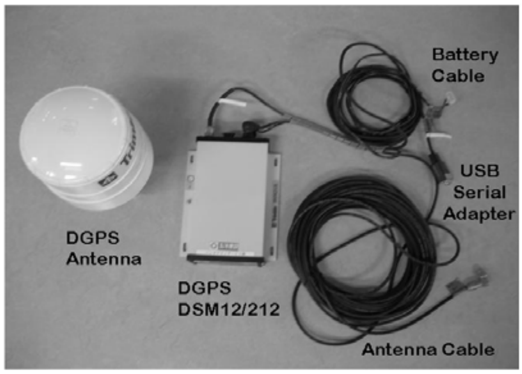

Fig. 1. DGPS experiment equipment.

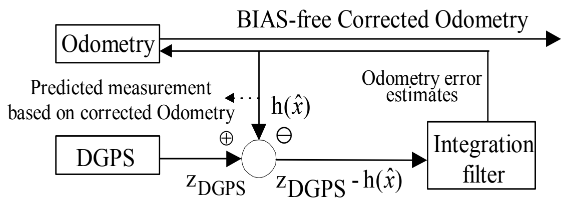

Fig. 2. Configuration of complementary integration.

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

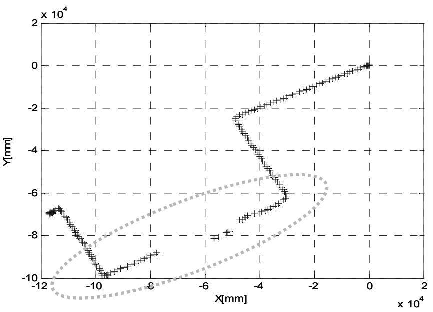

Fig. 3. Multi-path result of RTK-GPS data.

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:

$$x(k) = f[x(k-1)] + B(k-1)b(k-1) + \omega(k-1), \; k = 1, \cdots, \quad (7)$$

$$z_i(k) = h_i[x(k)] + C_i(k)b(k) + \upsilon_i(k), \quad i = 1, \cdots, N, \quad (8)$$

$$b(k+1) = b(k) \quad (9)$$

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 (7) 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 (7) up to first order is

$$\begin{aligned} x(k) = {} & f[\hat{x}(k-1 \mid k-1)] + f_x(k-1)[x(k-1) - \hat{x}(k-1 \mid k-1)] \\ & + \text{HOT} + B(k-1)b(k-1) + \omega(k-1) \end{aligned} \quad (10)$$

where HOT represents the higher-order terms and

$$f_x(k-1) = [\nabla_x f(x)']' |_{x=\hat{x}(k-1|k-1)} \quad (11)$$

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 [7] 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 [7]:

1) Update U_x 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 V_x matrix using the bias-free Kalma n gain K_x
$V_x(k) = U_x(k) - K_x(k)T(k)$

4) Compute bias covariance matrix

$$\begin{aligned} M(k) = {} & M(k-1) - M(k-1)T'(k)(h_x(k)P_x(k \mid k-1) \\ & \times h'_x(k) + R(k) + T(k)M(k-1)T'(k))^{-1}T(k)M(k-1) \end{aligned}$$

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

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

3.3. 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 extended Kalman filter (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.

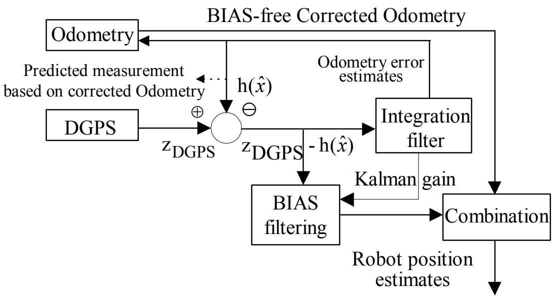

Fig. 4. Complementary integration with bias compensation.

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.

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 [1]

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

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.

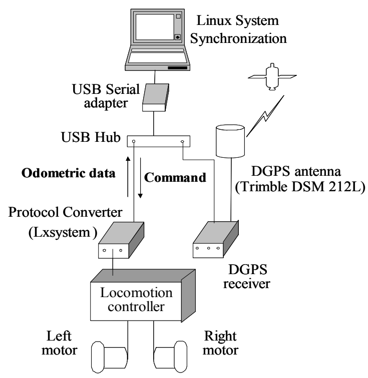

Fig. 5. H/W configuration.

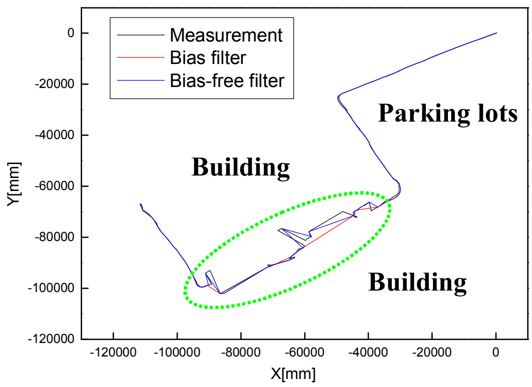

Fig. 6. Comparison of the standard and proposed complementary method.

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References

[1] Y. Bar-Shalom, X. Li, and T. Kirubarajan, *Estimation with Applications to Tracking and Navigation*, John Wiley & Sons, INC, New York, 2001, pp. 421-490.

[2] 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.

[3] 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.

[4] 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.

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

[6] 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.

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

[8] 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.

[9] 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.

[10] 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.

[11] 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.

[12] 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.

[13] 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.

[14] 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.