Magnetic Anomaly-Matched Trajectory and Dead Reckoning Fusion Mobile Robot Navigation

Yong Hun Kim
Department of Intelligent Mechatronics Engineering and Department of Convergence Engineering for Intelligent Drone, Sejong University, 05006, Seoul, Republic of Korea

Bo Sung Ko
Department of Intelligent Mechatronics Engineering and Department of Convergence Engineering for Intelligent Drone, Sejong University, 05006, Seoul, Republic of Korea

Jin Woo Song
Department of intelligent Mechatronics Engineering and Department of Convergence Engineering for Intelligent Drone, Sejong University, 05006, Seoul, Republic of Korea

E-mail: jwsong@sejong.ac.kr
https://sites.google.com/view/incsl

Abstract

Environments with varying magnetic field distortion cannot be navigated stably with magnetic anomaly based navigation algorithms. In this study, we propose a stable navigation solution for various indoor environments by fusing magnetic anomaly matched trajectories and mobile robot inertial trajectories. The proposed method uses dead reckoning as the primary navigation system and compensates for the navigation sensor error with a feedback structure through the optimization of the anomaly matching trajectory and dead reckoning trajectory. In addition, by determining the trajectory key-frame, the extended Kalman filter measurement update is performed using only the localization results with high accuracy. An open dataset was used to verify the performance of the algorithm, which was compared with existing algorithms. The proposed method is cost-effective, because the proposed method uses only an odometer, gyroscope, and magnetometer for indoor navigation.

Keywords: Mobile robot, Navigation, Magnetic sensor, Trajectory matching, Hidden Markov model

1. Introduction

Positioning is essential However, in indoor conditions where global navigation satellite system signals cannot be received, fusing sensors are required to calculate the position [1-4] without divergence [5,6]. However, recent studies have mostly focused on suppressing the divergence of position to achieve acceptable navigation accuracy, and do not consider the cost. When the cost is considered, the magnetic anomaly matching localization method can be a superior solution, and several studies have established it as an acceptable indoor positioning system [7,8].

However, owing to the similar steel structure inside the building, there are multiple distorted magnetic fields with similarities, which results in position errors. When the magnetic anomaly localization results are merged using the extended Kalman filter (EKF), this position error propagates and causes navigation errors. Magnetic fields are distorted due to several reasons, and thus, the measurement covariance, which is the localization accuracy, cannot be defined with a constant value. This may result in large navigation errors or failures.

In this study, to solve this problem, the position result calculated through magnetic anomaly localization is configured as a trajectory and used for navigation. The calculated trajectory is compared with dead reckoning (DR), which calculates the position and altitude using mobile robot wheel spin and gyroscope. In the process of optimizing the trajectory, the navigation sensor error was calculated, and the navigation performance was improved by compensating it with a feedback structure. In addition, a stable and accurate indoor navigation algorithm was implemented by performing position measurement updates by detecting a straight section with a high localization accuracy of the magnetic anomaly-matched trajectory as a key-frame. The implemented algorithm was verified using an open dataset.

The remainder of this paper is organized as follows. In Section 2, magnetic anomaly matching and trajectory optimization techniques are described. Section 3 describes the evaluation of the algorithm quantitatively using an open dataset, and Chapter 4 presents the conclusions.

2. Mobile robot navigation using magnetic anomaly-matched trajectory

2.1. *Magnetic anomaly-matched trajectory*

Magnetic anomaly based localization is divided into methods that use a cost function and those that use a probability model.

In this study, each technique must be independently localized, because we consider that the magnetic anomaly and DR trajectory are fused. The cost function-based method has low accuracy when only the magnetic anomaly matches; therefore, in this study, a magnetic anomaly-matched trajectory was constructed using a probability-based hidden Markov model (HMM).

Fig. 1 shows the HMM in which each parameter is connected at the current time t and previous time t-1. Each hidden parameter of the HMM was selected as a magnetic map grid point within 3 m based on the previous location, and the transition probability a_{Nj} was modeled as the distance of the grid point based on the previously determined location.

$$a_{Nj} = \frac{1}{\sqrt{2\pi}\sigma_d} exp\,(-\frac{(\|\boldsymbol{Map}(N) - \boldsymbol{Map}(j)\|^2)}{2\sigma_d^2}) \tag{1}$$

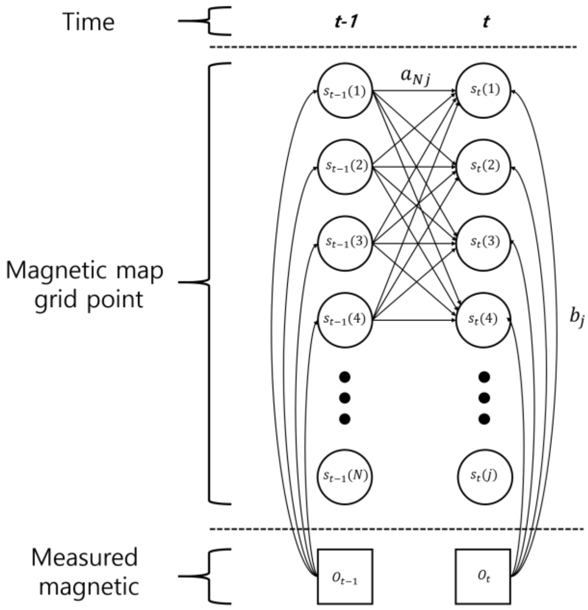

Fig. 1. HMM model for magnetic anomaly-matching.

Eq. (1) gives the transition probability, where $\mathbf{Map}(\cdot)$ means a matrix that stores the positional coordinates of the preconfigured magnetic field grid points, $\boldsymbol{N}, \boldsymbol{j}$ is an index representing a row, and σ_d is the variance value according to the distance, selected as $\sqrt{3}$, which is the area setting value.

The emission probability b_j is modeled by the difference between the measured magnetic field and the constructed magnetic field map.

$$b_j = \frac{1}{\sqrt{2\pi}\sigma_m} \exp\,(-\frac{(\mathbf{Mag}(j) - mag)^2}{2\sigma_m^2}) \tag{2}$$

In Eq. (2), $\mathbf{Mag}$ is the magnetic field stored at a pre-configured grid point, and $\boldsymbol{mag}$ is the magnetic field measured at the current time. Here, σ_m is $var(\mathbf{Mag})$, the variance of the total magnetic field recorded in the magnetic field map.

Using Eqs. (1) and (2), the forward probability at each time point can be calculated, as shown in Eq. (3).

$$\mathrm{s}_t(j) = \Sigma_{i=1}^{N} \mathrm{s}_{t-1}(i) a_{ij} b_j \tag{3}$$

After calculating the parameter probability, and decoding using the Viterbi algorithm to form the trajectory. Therefore, a trajectory is constructed by collecting the positions of the grid points with the maximum probability among the forward probabilities. The trajectory was smoothed using spline fitting, and the trajectory arrangement interval was 1 second.

2.2. *Key-frame detection and error compensation techniques*

In this study, to minimize the error of the magnetic anomaly matched trajectory and DR trajectory, stable navigation is performed by compensating for the odometry scale factor error, which is the wheel rotation error and gyroscope bias.

In the case of the turning section, wheel slip occurs significantly, and magnetic anomaly matching results become inaccurate. Thus, the odometry scale factor error and gyro bias are compensated through trajectory information, not position error compensation.

$$e(o_s, bg) = \underset{o_s, b_g}{argmin} \|\mathbf{M}_{tr} - \mathbf{D}_{tr}\|^2 \qquad (4)$$

In Eq. (4), $\mathbf{M}_{tr}$ is the position of the magnetic anomaly-matched trajectory, and $\mathbf{D}_{tr}$ is the position of the trajectory calculated by DR. Stable navigation is performed by calculating the odometry scale factor $\boldsymbol{o_s}$ and gyro bias $\boldsymbol{b_g}$ that minimize the position errors of mutual trajectories and then compensating for them.

Even if the odometry scale factor error and gyro bias are compensated, the position eventually diverges over time if the position is not compensated. Therefore, in a straight section with a relatively high magnetic anomaly matching accuracy, the position error is compensated by using the matched position as the position measurement of the EKF.

The turning and straight sections were detected according to the gradient change in the magnetic anomaly-matched trajectory. When the detection result was straight, EKF measurement was performed to compensate for the position error.

Fig. 2 shows the trajectories of the detected turning and straight sections. After calculating the trajectory, the odometry scale factor and gyro bias that minimize the error between dead reckoning and magnetic anomaly matching trajectory were calculated and compensated.

The EKF navigation model and process are described in [9], and the algorithm structure of the mobile robot navigation system proposed in this study is illustrated in Fig. 3.

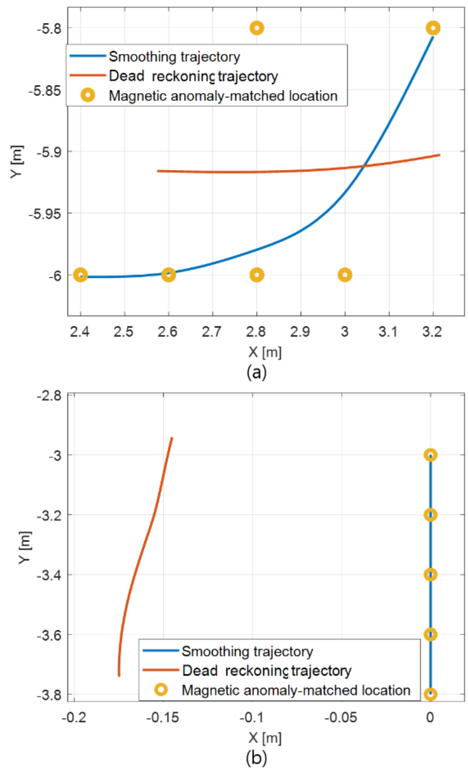

Fig. 2. Magnetic anomaly-matching result and smoothed trajectory (a) detected turning section (b) detected straight section.

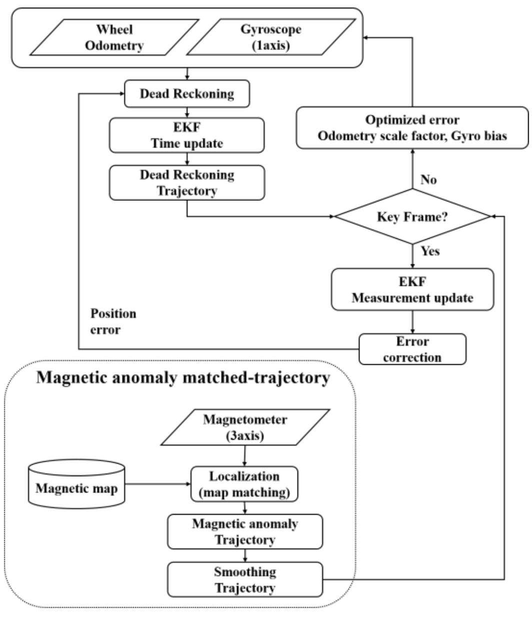

Fig. 3 Full block diagram of the proposed navigation algorithm

3. Verification using the open dataset

The proposed algorithm was verified using the MagPIE dataset [10]. The algorithm accuracy was analyzed for three trajectories out of the entire dataset, and the magnetic map grid size was selected as 0.2 m.

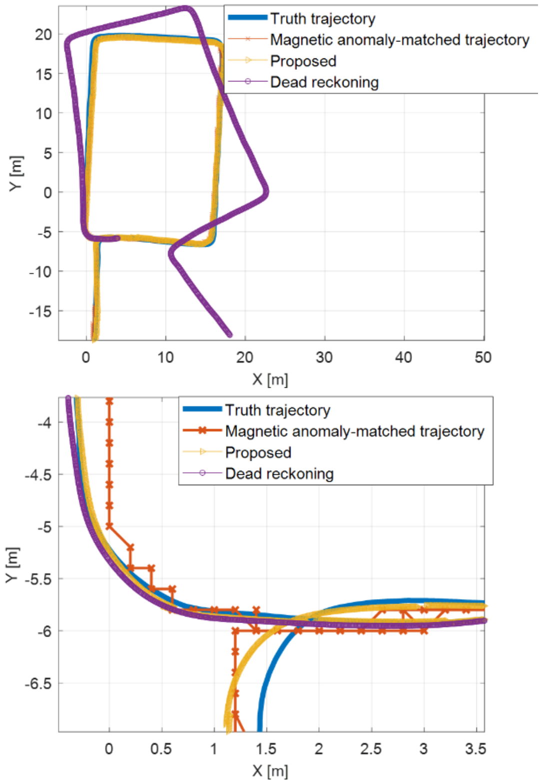

Fig. 4. Algorithm result for the entire section and turning section.

As shown in Fig. 4, it can be confirmed that stable navigation is realized. In addition, because the position is not used directly, a structure that compensates for the errors is used. Therefore, it is not dependent on magnetic anomaly matching results. The algorithm performances for the three experiments are presented in Table 1.

Table 1. Position RMSE (MM is magnetic anomaly matching)

	DR (m)	Proposed (m)
Dataset1	7.4037	0.2976
Dataset2	7.0465	0.3572
Dataset3	18.708	0.5583

The proposed technique enables navigation with very high accuracy compared to DR. In addition, the magnetic anomaly matching technique must determine the region corresponding to the candidate group based on the previous location. When using the proposed technique, the DR performance and localization accuracy of the magnetic anomaly matching technique are improved.

4. Conclusion

This study aimed to improve the inaccuracy of the magnetic anomaly matching technique, which can be used to construct a low cost indoor navigation system. The proposed method used the localization result as trajectory information instead of the measurement of the EKF, and demonstrated that it is possible to perform navigation accurately and stably by compensating for the error with an optimization method in a turning section with less accuracy. In the future, we plan to conduct more rigorous verification by conducting our own experiments.

Acknowledgments

This research was supported by the MSIT(Ministry of Science and ICT), Korea, under the ITRC(Information Technology Research Center) support program(IITP-2022-2018-0-01423) supervised by the IITP(Institute for Information & Communications Technology Planning & Evaluation) and supported by the Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education (No.2020R1A6A1A03038540).

References

1. Gan, X., Yu, B., Wang, X., Yang, Y., Jia, R., Zhang, H., ... & Wang, B. (2019). A new array pseudolites technology for high precision indoor positioning. IEEE Access, 7, 153269-153277.
2. Kim, Y. H., Choi, M. J., Kim, E. J., & Song, J. W. (2019). Magnetic-map-matching-aided pedestrian navigation using outlier mitigation based on multiple sensors and roughness weighting. Sensors, 19(21), 4782.
3. Kwon, Y. S., Kim, Y. H., Do, H. V., Kim, H. J., & Song, J. W. (2021, October). Radar Velocity Measurements Aided Navigation System for UAVs. In 2021 21st International Conference on Control, Automation and Systems (ICCAS) (pp. 472-476). IEEE.
4. Kim, Y. H., Kwon, Y. S., & Song, J. W. (2020, October). Magnetic-map-matching Navigation For Odometry Using Low-cost Mobile Robot. In 2020

IEEE Eurasia Conference on IOT, Communication and Engineering (ECICE) (pp. 392-395). IEEE.
5. Yudanto, R. G., & Petre, F. (2015, October). Sensor fusion for indoor navigation and tracking of automated guided vehicles. In 2015 International Conference on Indoor Positioning and Indoor Navigation (IPIN) (pp. 1-8). IEEE.
6. Alatise, M. B., & Hancke, G. P. (2020). A review on challenges of autonomous mobile robot and sensor fusion methods. IEEE Access, 8, 39830-39846.
7. Gozick, B., Subbu, K. P., Dantu, R., & Maeshiro, T. (2011). Magnetic maps for indoor navigation. IEEE Transactions on Instrumentation and Measurement, 60(12), 3883-3891.
8. Wu, F., Liang, Y., Fu, Y., & Ji, X. (2016, April). A robust indoor positioning system based on encoded magnetic field and low-cost IMU. In 2016 IEEE/ION Position, Location and Navigation Symposium (PLANS) (pp. 204-212). IEEE.
9. Cho, B. S., Moon, W. S., Seo, W. J., & Baek, K. R. (2011). A dead reckoning localization system for mobile robotswmd using inertial sensors and wheel revolution encoding. Journal of mechanical science and technology, 25(11), 2907-2917.
10. Hanley, D., Faustino, A. B., Zelman, S. D., Degenhardt, D. A., & Bretl, T. MagPIE: A dataset for indoor positioning with magnetic anomalies. In 2017 International Conference on Indoor Positioning and Indoor Navigation (IPIN) (pp. 1-8). IEEE.

Authors Introduction

Mr. Yong Hun Kim

He received the B.S. degree in Robotics Engineering, from Hoseo University in 2018, and the M.S. degree in Software Convergence, in 2020, from Sejong University, Seoul, South Korea, where he is currently working toward the Ph.D. degree in Department of Intelligent Mechatronics Engineering and Convergence Engineering for Intelligent Drone. His research interests include indoor navigation, sensor fusion, INS/GNSS integration and nonlinear filtering.

Mr. Bo Sung Ko

He received the B.S. degree in Mechanical and Aerospace Engineering from Sejong University, Seoul, South Korea, in 2022, where he is currently pursuing the M.S. degree with the Department of Intelligent Mechatronics Engineering and Convergence Engineering for Intelligent Drone. His research interests include precision navigation, SLAM, sensor fusion

Dr. Jin Woo Song

He received the B.S. and M.S. degrees in control and instrumentation engineering and the Ph.D. degree in electrical, electronic and computer engineering from Seoul National University, Seoul, South Korea, in 1995, 1997, and 2002, respectively. From 2003 to 2014, he was a CTO with Microinfinity Company, Ltd. He is currently an Associate Professor with the school of Intelligent Mechatronics Engineering and Convergence Engineering for Intelligent Drone, Sejong University, Seoul, South Korea. His research interests include GPS/INS integration, robust and optimal control, MEMS inertial sensors and systems, indoor navigation, and robot localization.