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IMM-based INS/EM-Log Integrated Underwater Navigation with Sea Current Estimation Function

Seong Yun Cho[1†], Hojin Ju[2], Jaehyuck Cha[3], Chan Gook Park[3], Kijeong Yoo[4], Chanju Park[4]

[1]Department of Robotics Engineering, Kyungil University, Gyeongsan 38428, Korea
[2]Automation and Systems Research Institute, Seoul National University, Seoul 08826, Korea
[3]Department of Mechanical and Aerospace Engineering, Seoul National University, Seoul 08826, Korea
[4]Agency for Defense Development, Daejeon 34186, Korea

ABSTRACT

Underwater vehicles use Inertial Navigation System (INS) with high-performance Inertial Measurement Unit (IMU) for high precision navigation. However, when underwater navigation is performed for a long time, the INS error gradually diverges, therefore, an integrated navigation method using auxiliary sensors is used to solve this problem. In terms of underwater vehicles, the vertical axis error is primarily compensated through Vertical Channel Damping (VCD) using a depth gauge, and an integrated navigation filter can be designed to perform horizontal axis error and sensor error correction using a speedometer such as Electromagnetic-Log (EM-Log). However, since EM-Log outputs the forward direction relative speed of the vehicle with respect to the sea and sea current, INS correction filter using this may cause a rather large error. Although it is possible to design proper filters if the exact model of the sea current is known, it is impossible to know the accurate model in reality. Therefore, this study proposes an INS/EM-Log integrated navigation filter with the function to estimate sea current using an Interacting Multiple Model (IMM) filters, and the performance of this filter is analyzed through a simulation performed in various environments.

Keywords: INS/EM-log, underwater navigation, current estimation, IMM filter

1. INTRODUCTION

Since the visual range is limited in the underwater environment, manned and unmanned underwater vehicles are inevitably controlled based on high-precision navigation information. Since it is impossible to receive GPS signals underwater, navigation is performed based on an Inertial Navigation System (INS) using an Inertial Measurement Unit (IMU). The performance of INS depends on the performance of the gyro and accelerometer, the inertial sensors that make up the IMU. When using a high-performance inertial sensor, accurate navigation can be performed with a single INS alone. However, navigation errors gradually increase over time due to INS-based navigation calculation mechanism. In particular, when performing underwater navigation for a longer period of time than 24 hours, a single INS-based navigation causes serious problems in the control and guidance of underwater vehicles. In general, a complex navigation system using auxiliary sensors is used to address such problems (Farrell & Barth 1999, Kinsey et al. 2006).

The auxiliary sensors used in underwater environments include depth gauge and speedometer, and the speedometer includes the Doppler Velocity Log (DVL), Electromagnetic-Log (EM-Log), and Propeller Log (Tal et al. 2017). The vertical axis position error and velocity error are primarily corrected through the Vertical Channel Damping (VCD) using a depth gauge (Seo et al. 2004). Then, a speedometer is used to drive the filter in order to estimate the horizontal axis navigation error and sensor error. Among the speedometers used here, the DVL uses ultrasound to

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†**Corresponding Author**
E-mail: sycho@kiu.kr
Tel: +82-53-600-5584 Fax: +82-53-600-5599

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provide the ground speed of the vehicle's body coordinate system, thus providing the most accurate integrated navigation, but it has disadvantages because it cannot be used when the distance between the vehicle and the ground is far or when the vehicle is operating at high speeds. On the other hand, EM-Log provides log speed or speed through water by measuring the forward direction speed through the voltage difference generated by the sensor according to the flow velocity (Dmitriev et al. 2012). Therefore, when there is no sea current, it obtains the accurate forward direction speed of the vehicle and estimates the navigation error through filter operation using the measured value in order to suppress the divergence of INS navigation error. However, in the case of sea current, this will cause additional errors through filter operation. To solve this problem, a filter is used that adds a state variable that estimates the sea current through sea current modeling. If the model is similar to the actual sea current, the filter can estimate the sea current in the observable direction, but it is a virtually impossible assumption to model the sea current, which changes according to time, place, and weather, synchronized to the environment. Therefore, incorrect sea currents are estimated through filters using the wrong model, which causes the navigation error to increase even more than in the case of a single INS.

This study proposes a method that uses an INS/EM-Log integrated navigation filter which uses an Interacting Multiple Model (IMM) filter (Bar-Shalom et al. 2005, Cho & Kim 2008). The IMM subfilters are composed on the basis of multiple models of sea current, and using the residual and residual covariance of each subfilter, various types of sea currents can be properly estimated through the mixing of subfilters. This study verified the performance of the proposed filter by performing Monte-Carlo simulations based on Matlab and analyzing the results.

This paper is organized as follows. Chapter 2 describes the principle and problems of EM-Log and sea current models from previous studies, while Chapter 3 designs the IMM filter-based INS/EM-Log integrated navigation filter. Chapter 4 verifies the performance of the proposed filter through simulation analysis, and the conclusions are made in the final chapter.

2. EM–LOG AND CURRENT MODEL

This chapter examines the principle and problems of EM-Log used as an auxiliary sensor for the navigation of underwater vehicles, and analyzes the sea current model which needs to be considered based on data from previous studies.

2.1 EM-Log

The EM-Log is a sensor that measures the relative speed of the underwater vehicle with respect to the seawater using the law of electromagnetic induction. According to Faraday's law, the induced electromotive force generated by the movement of the vehicle is proportional to the movement speed of the vehicle with respect to the sea water.

$$\varepsilon = \frac{d\Phi_B}{dt} = Bl(V_x^b - V^C) \tag{1}$$

where, ε is the magnitude of the induced electromotive force, Φ_B is the magnitude of the magnetic flux, B is the intensity of the magnetic field, and l is the height of the magnetic field cross-section. In addition, V_x^b and V^c indicate the speed of the sea current flowing in the same direction as the forward direction movement speed of the vehicle, respectively.

If there is no sea current, V_x^b can be calculated by dividing the induced electromotive force generated from EM-Log by Bl. However, since sea current is always present in actual environment, the information output through EM-Log becomes the log speed or speed through water. Since the speed calculated by INS is the ground speed, a corresponding difference between the EM-Log output speed and sea current occurs, and a correct sea current model is required for the filter design considering this matter.

2.2 Sea Current Model

Sea current consists of sea current and ocean current. Sea current is the flow of seawater created by the gravitational pull of the moon and the sun, and the speed and direction are determined according to time and location. On the other hand, the ocean current is difficult to predict as it is the flow of seawater created by the surface water moved by the frictional force against wind and the deep-sea water moved by the difference of temperature and salinity.

Methods for predicting sea current based on measured information and advance information include ACDIRC, CH3D, and ROMS, but actual implementation is practically difficult. This paper uses the first-order Markov type sea current model proposed by Dmitriev et al. (2012).

$$V_{k+1}^C = \left(1 - \frac{1}{T^C}\Delta t\right)V_k^C + \Delta t \cdot \sigma^C \sqrt{\frac{2}{T^C}} w_k^C \tag{2}$$

where, T^c is a time constant of the correlation interval of the sea current speed, Δt is the data generation time interval, σ^c

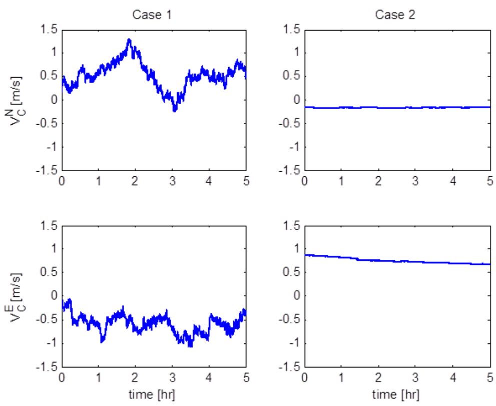


Fig. 1. An example of current generation.

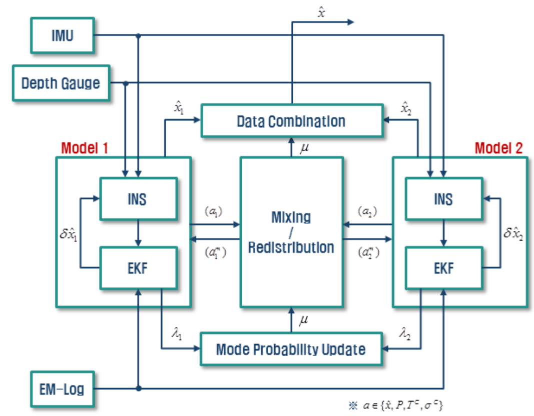


Fig. 2. Structure of INS/EM-Log integrated navigation based on the IMM filter.

is the Root Mean Square of the sea current speed, and w^c is the white noise with standard normal distribution.

Fig. 1 shows an example of sea current generation. Case 1 is set to T^c=2[hr], σ^c=0.5[m/s], while Case 2 is set to T^c=20[hr], σ^c=0.05[m/s]. In other words, Case 1 is the case in which the size and direction of the sea current speed changes frequently due to the influence of the ocean current rather than the sea current in a short period of time, while Case 2 is the case where the change of sea current speed is not large. However, it is practically impossible to set parameter values that accurately predict sea current in a real-world environment that varies depending on the location, time, and weather.

3. IMM-BASED INS/EM-LOG INTEGRATED NAVIGATION FILTER

The purpose of this paper is to design an integrated navigation filter that corrects INS error using EM-Log measurements. However, as described above, the error may increase if the sea current included in the EM-Log measurements is not properly compensated. Therefore, a filter should be designed to compensate by adding the sea current to the state variable of the filter. In this case, the first-order Markov model shown in (2) can be used for the sea current model, but if the parameters included in this model are not correctly set, the sea current cannot be properly estimated, which makes the results of the integrated navigation worse that the results of the single INS. Considering these problems, this study sets a sea current model with two different parameters, and based on this, uses the IMM filter to configure INS/EM-Log integrated navigation filter as shown in Fig. 2.

3.1 INS time propagation

As shown in Fig. 2, the time propagation of the navigation information is performed in two independent INS blocks using the output of IMU and depth gauge. First, VCD is performed to correct the vertical axis velocity and position using the depth gauge (Seo et al. 2004). Then, the time propagation of the state variable $\bar{x}=[L \quad l \mid v_N \quad v_E \mid \phi \quad \theta \quad \psi]^T$ is performed, which is composed of the horizontal axis position, velocity, and attitude (Farrell & Barth 1999). In this state variable, L and l are the latitude and longitude, $V^n=[v_N \quad v_E]^T$ is the north/east direction velocity, and $[\phi \quad \theta \quad \psi]^T$ is the Euler angle. Then, time prop-agation is performed by using the estimate of sea current $V^C=[v_N^C \quad v_E^C]^T$ in the north/east direction in the time propagation Eq. (3) derived from Eq. (2).

$$\hat{v}_{j,k+1}^C=(1-\frac{1}{T_i^C}\Delta t)\hat{v}_{j,k}^C, \quad j\in\{N,E\} \tag{3}$$

where, $i\in\{1,2\}$ refers to the number of the model configured with different parameters, and the two time-constants are set through simulation.

3.2 INS/EM-Log Measurement Update

If the EM-Log measurements are acquired periodically, update the measurements according to this cycle. First, set the error state variable for updating the measurements based on the Extended Kalman Filter (EKF) as shown in Eq. (4).

$$\delta x=[\delta L \quad \delta l \mid \delta v_N \quad \delta v_E \mid \varphi_N \quad \varphi_E \quad \varphi_D \mid \nabla_x \quad \nabla_y \quad \nabla_z \mid \varepsilon_x \quad \varepsilon_y \quad \varepsilon_z \mid \delta v_N^C \quad \delta v_E^C]^T \tag{4}$$

where, $\varphi^n=[\phi_N \quad \phi_E \quad \phi_D]^T$ is the attitude error expressed in the navigation coordinate system, and $[\nabla_x \quad \nabla_y \quad \nabla_z]^T$ and $[\varepsilon_x \quad \varepsilon_y \quad \varepsilon_z]^T$ are the accelerometer bias and gyro bias, respectively.

The Jacobian matrix is configured as shown in Eq. (5).

$$\Phi_k = e^{F(t)\Delta k} \tag{5}$$

where, Δk is the measurement update cycle, and $F(t)$ is shown in Eq. (6).

$$F(t) = \begin{bmatrix} F_{INS}^{13}(t) & 0_{13\times 2} \\ 0_{2\times 13} & F_{EM-Log} \end{bmatrix} \tag{6}$$

where, $F_{INS}^{13}(t)$ is a term based on the 13th order INS error model excluding the vertical axis position error and velocity error, in reference to (Seo et al. 2006). And $F_{EM\text{-}Log}$ is shown in Eq. (7).

$$F_{EM-Log} = \begin{bmatrix} -1/\mathrm{T}^C & 0 \\ 0 & -1/\mathrm{T}^C \end{bmatrix} \tag{7}$$

The output of the EM-Log is the forward direction speed of the underwater vehicle, which can be configured as shown in Eq. (8) when this is used as the measurement value for the filter.

$$\begin{aligned} z &= \hat{C}_n^b(\hat{V}^n - \hat{V}^C) - \tilde{V}_{EM-Log} \\ &= C_n^b(\mathrm{I} + \varphi^n \times)\left((V^n + \delta V^n) - (V^C + \delta V^C)\right) - (V^b - C_n^b V^C - w_{EM-Log}) \\ &\cong C_{n(1:2)}^{b(1)} \delta V^n - C_{n(1:2)}^{b(1)} \delta V^C - C_{n(1:3)}^{b(1)}\left((V^n - V^C)\times\right)\varphi^n + w_{EM-Log} \end{aligned} \tag{8}$$

where, $C_{n(a:b)}^{b(c)}$ is a matrix configured with row c and column a : b of matrix C_n^b.

Based on this, the measurement matrix can be configured as shown in Eq. (9).

$$H = [0_{1\times 2} \quad C_{n(1:2)}^{b(1)} \quad -C_{n(1:3)}^{b(1)}\left((V^n - V^C)\times\right) \quad 0_{1\times 3} \quad 0_{1\times 3} \quad -C_{n(1:2)}^{b(1)}] \tag{9}$$

In terms of updating the measurements every second, the process noise covariance matrix corresponding to the sea current speed is configured as shown in Eq. (10) based on Eq. (2).

$$Q^C = \begin{bmatrix} 2(\sigma^C)^2/T^C & 0 \\ 0 & 2(\sigma^C)^2/T^C \end{bmatrix} \tag{10}$$

After updating the measurements of the error state variable and the error covariance matrix using the Jacobian matrix and measurement matrix shown in Eqs. (5) and (9), the results are used to correct the errors. As shown in Fig. 2, INS/EM-Log measurement updates based on the sea current model set with two different parameters are independently performed.

3.3 IMM Mixing

After updating the measurements, the error-compensated state variable ($\hat{x}_i$) and the error covariance matrix (P_i) are outputted from two models, respectively. In the process of updating the measurements for each model, the measurement residual (r_i) and residual covariance matrix (C_i) are formed as shown in Eqs. (11) and (12).

$$r_i = \hat{C}_{n(1:2)}^{b(1)}(\hat{V}_i^n - \hat{V}_i^C) - \tilde{V}_{EM-Log} \tag{11}$$

$$C_i = H_i P_i^- H_i^T + R \tag{12}$$

where, $i \in \{1, 2\}$.

In order to mix the results of both models, first assume that the continuous residuals of the two models have a standard normal distribution, and calculate the likelihood ratio as shown in Eq. (13) (Cho & Kim 2008).

$$\lambda_i = \frac{1}{\sqrt{2\pi\|C_i\|}} \exp\left\{-\frac{1}{2} r_i^T C_i^{-1} r_i\right\} \tag{13}$$

Based on this, update the Mode probability as follows. Mode probability is a probability that indicates which of the two models is more reliable in the process of updating the current measurement value.

$$\mu_i = \frac{1}{\sum_{j=1}^{2} \lambda_j n_j} \lambda_i n_i \tag{14}$$

where, n is calculated as shown in Eq. (15).

$$\begin{bmatrix} n_1 \\ n_2 \end{bmatrix} = M^T \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} \tag{15}$$

where, M is the Markov chain transition matrix and its component m_{ab} is the probability of being converted from model a to model b. This matrix is configured in advance at the early stage of operating the filter. And the Mode probability initial value is set to $[0.5 \quad 0.5]^T$.

Using the updated Mode probability, calculate the Mixing probability to mix the outputs of the two models as shown in Eq. (16).

$$\begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix} = \begin{bmatrix} m_{11}\mu_1 / \sum_{i=1}^{2} m_{i1}\mu_i & m_{12}\mu_1 / \sum_{i=1}^{2} m_{i2}\mu_i \\ m_{21}\mu_2 / \sum_{i=1}^{2} m_{i1}\mu_i & m_{22}\mu_2 / \sum_{i=1}^{2} m_{i2}\mu_i \end{bmatrix} \tag{16}$$

Using the Mixing probability, to converge the outputs of the two models and the sea current information are mixed as shown in Eqs. (17-20).

$$\hat{x}_i^m = \sum_{j=1}^{2} \hat{x}_j g_{ji} \tag{17}$$

$$P_i^m = \sum_{j=1}^{2} P_j g_{ji} \tag{18}$$

$$T_i^{C,m} = \sum_{j=1}^{2} T_j^C g_{ji} \tag{19}$$

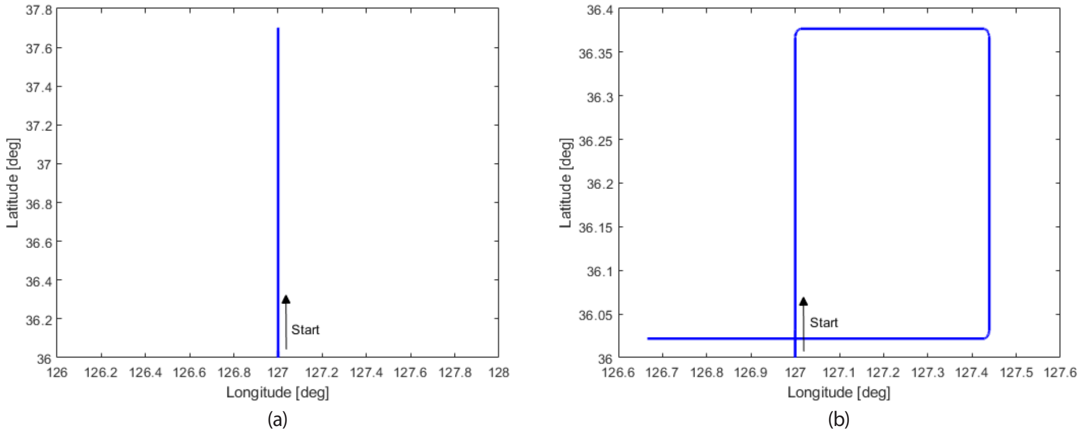


Fig. 3. Simulation trajectory. (a) trajectory 1 (b) trajectory 2

$$\sigma_i^{C,m} = \sum_{j=1}^{2} \sigma_j^C g_{ji} \tag{20}$$

The mixed state variables and the error covariance matrix are redistributed to each model, where these values replace the state variable and the error covariance matrix of each model. The final value of IMM filter is as shown in Eq. (21).

$$\hat{x} = \sum_{i=1}^{2} \hat{x}_i \mu_i \tag{21}$$

4. SIMULATION ANALYSIS

This study performed a simulation to verify the performance of the proposed IMM-based INS/EM-Log integrated underwater navigation filter. The specifications of the sensors used for the simulation are summarized in Table 1. The sensor data output frequency of the IMU was set to 100 Hz, and the data output frequency of EM-Log and depth gauge was set to 1 Hz. Therefore, the time propagation is driven at 100 Hz and the measurement update is at 1 Hz.

The simulation first drives an initial precision alignment filter through zero velocity correction for 15 minutes. Then performs INS/GPS integrated navigation on the surface for the next 6 minutes. At this time, the trajectory is linear, accelerating for 20 seconds and then operates at a constant velocity. Then, INS/EM-Log integrated navigation is performed for the next 5 hours. The trajectory is set in two ways as shown in Fig. 3. The performance of the single EKF-based INS/EM-Log integrated navigation and the IMM-based INS/EM-Log integrated navigation was analyzed after implementing each method. The Monte-Carlo analysis was performed after implementing 10 simulations. The Root Mean Square Error (RMSE) of the location and sea current estimate was printed out as pictures for analysis.

Table 1. Spec. of sensors.

Sensor	Error	Spec.
Accelerometer	Bias repeatability	0.03 mg
Gyro	Bias repeatability	0.001 deg/hr
EM-Log	Noise	0.1% (3σ)
Depth gauge	Noise	0.5 m

The two cases for simulation are shown in Fig. 1, where Case 1 is set to T^c=2[hr], σ^c=0.5[m/s], and Case 2 is set to T^c=20[hr], σ^c=0.05[m/s]. The initial values for the IMM filter are set as follows.

- Markov chain transition matrix: $M = \begin{bmatrix} 0.9 & 0.1 \\ 0.1 & 0.9 \end{bmatrix}$
- Model 1: $T_1^c = 0.2$[hr], $\sigma_1^c = 5$[m/s]
- Model 2: $T_2^c = 200$[hr], $\sigma_2^c = 0.005$[m/s]

Model 1 is modeled as a case where the sea current changes more rapidly than Case 1, and Model 2 is a case where the sea current changes more slowly than Case 2. Through this, the IMM filter is expected to estimate various sea currents.

First, the simulation results performed in trajectory 1 are shown in Figs. 4 and 5, respectively. Fig. 4 is the case where the sea current is set to Case 1, and Fig. 5 is the case where the sea current is set to Case 2. The RMSE of the location and sea current estimate after conducting ten simulations are shown, where the blue dotted line in each figure is the simulation results based on the single EKF (EKF-C1) set as the parameter in Case 1, and the green dotted line is the simulation results based on the single EKF (EKF-C2) set as the parameter in Case 2. The red solid line is the IMM filter-based simulation result. In addition, the thick gray solid lines in each figure (a) are the results of performing only VCD using INS as the depth gauge, indicating the position error when EM-log is not used (No-Aiding). In this case, the position error has a Schuler cycle of 84.4 minutes, and the

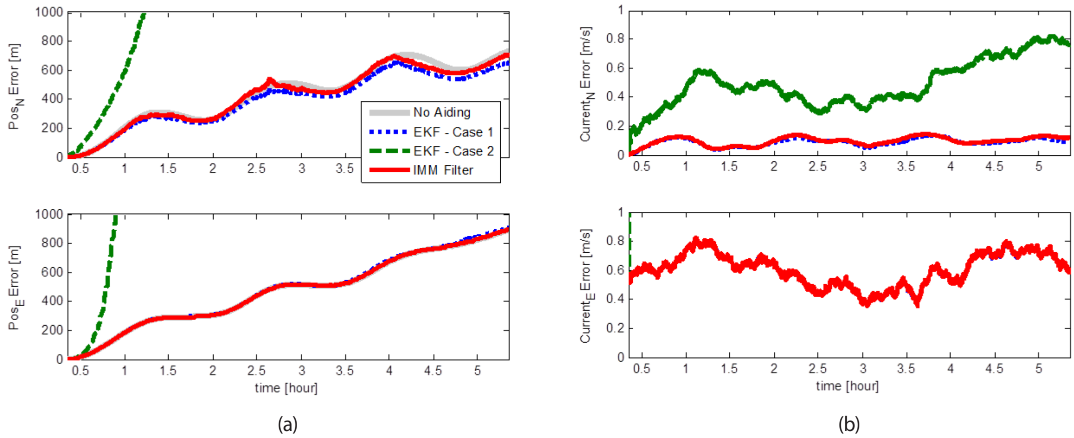


Fig. 4. Simulation results (trajectoroy 1, Case 1). (a) RMSE of position estimates (b) RMSE of current estimates

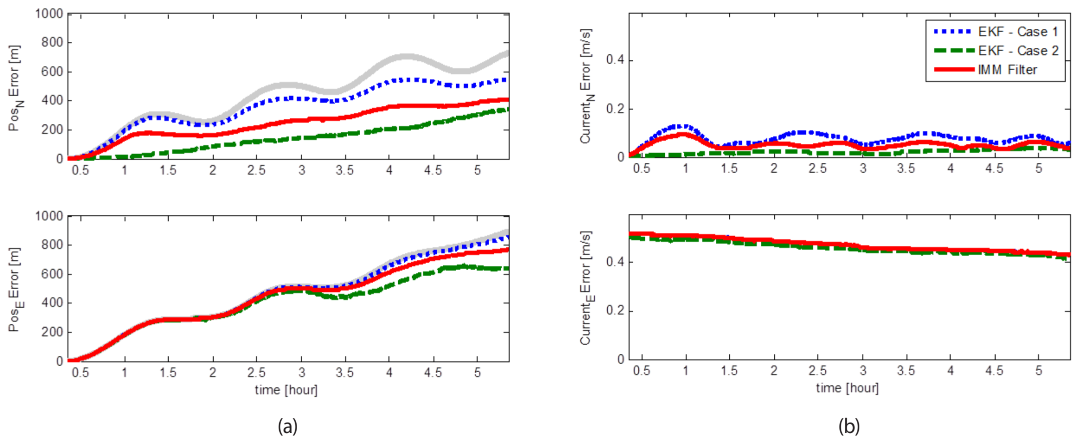


Fig. 5. Simulation results (trajectory 1, Case 2). (a) RMSE of position estimates (b) RMSE of current estimates

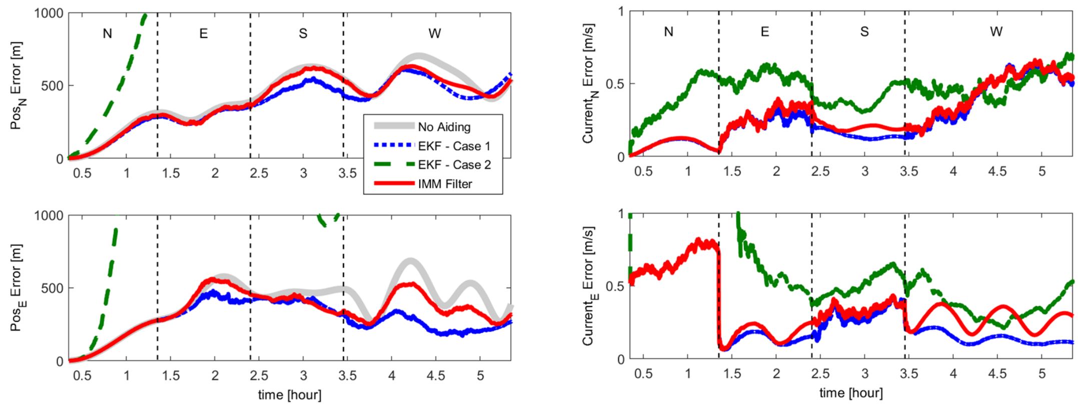
error gradually increases over time. Since it is a trajectory sailing in the north direction, only the sea current in the north direction is observed and estimated, and the sea current in the east direction is not observed and cannot be estimated. However, since the EM-Log output contains only the sea current in the north direction, the sea current in the east direction does not affect the navigation performance.

In terms of Fig. 4, the actual sea current is rapidly changing as shown in the left picture of Fig. 1, where the EKF-C1 and IMM filter have a relatively small RMSE and estimate the sea current in the north direction. The position estimation error due to this effect is reduced when compared to No-Aiding, but the effect is not significant. However, EKF-C2 does not estimate the sea current, and as a result, the position estimation error diverges greatly.

In terms of Fig. 5, the actual sea current is changing very slowly as shown in the right picture of Fig. 1, where EKF-C2 estimates and compensates the sea current in the north direction very accurately, so that the position estimation error falls to almost half of No-Aiding. On the other hand, EKF-C1 is not as accurate as EKF-C2 but shows an estimation performance similar to Case 1. In the case of the IMM filter, it estimates the sea current at levels between EKF-C1 and EKF-C2, and shows a similar performance for position estimation as well.

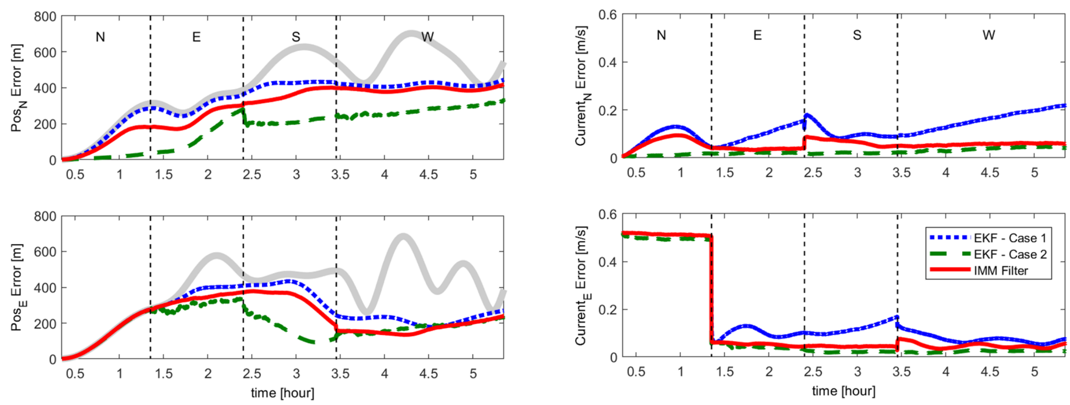
Next, the simulation results performed in trajectory 2 are shown in Figs. 6 and 7, respectively. Fig. 6 is the case where the sea current is set to Case 1, and Fig. 7 is the case where the sea current is set to Case 2. When the underwater vehicle sails to the north and south, the sea current in the north direction is observed, and when it sails to the east and west, the sea current in the east direction is observed and estimated. The simulation results in trajectory 2 are characterized by the change of sea current observability according to the sailing direction, and the performance is similar to that of trajectory 1.

The following conclusions are drawn from the simulation results.



(a) (b)

Fig. 6. Simulation results (trajectoroy 2, Case 1). (a) RMSE of position estimates (b) RMSE of current estimates



(a) (b)

Fig. 7. Simulation results (trajectoroy 2, Case 2). (a) RMSE of position estimates (b) RMSE of current estimates

- It is possible to estimate the sea current velocity in accordance with the direction of EM-Log sensing axis.
- EKF-C1: In terms of EKF-C1, modeled with a relatively large σ^c and small T^c, it provides a relatively good estimate of the sea current regardless of the degree of sea current change, but the resulting accuracy of position estimation is slightly improved in trajectory 1 compared to No-Aiding, and in trajectory 2 where the directions change, it improves slightly more compared to trajectory 1.
- EKF-C2: In terms of EKF-C2, modeled with small σ^c and large T^c, it estimates the sea current very accurately in environments where the sea current changes slowly as in Case 2, but in environments where the sea current changes rapidly as in Case 1, the sea current estimation error significantly increases, and the position estimation error also diverges accordingly.
- IMM filter: In terms of the IMM filter, which consists of Model 1 which is modeled with a small σ^c and large T^c, and Model 2 which is modeled with a large σ^c and small T^c, the performance is somewhat lower than that estimated by EKF-C2 in Case 2 environment, but provides a stable solution regardless of sea current change.
- Since it is impossible to know the degree of sea current change in actual environment, using a single filter based on an inaccurate model may lead to an integrated navigation result worse than that of No-Aiding. On the other hand, the IMM filter provides an INS/EM-Log integrated navigation solution which always shows better performance than No-Aiding.

5. CONCLUSIONS

This paper proposes an IMM-based filter for INS/EM-Log integrated navigation for underwater vehicles. Since EM-Log provides the log speed as a measured value, if the sea current is not correctly estimated and compensated, the integrated navigation will cause a rather large estimation error. This study modeled the sea current with the first-order Markov. The parameters used in this model are used in the Jacobian matrix and the process noise covariance matrix for the time propagation and measurement update of the state variables corresponding to the sea current. Therefore, a single filter using a wrong parameter estimates an incorrect sea current, which results in a large position estimation error. Considering these problems, this study designed a filter that integrates INS and EM-Log on the basis of the IMM filter. Two models using different parameters were mixed to improve the performance of estimating the sea current and location. A Monte-Carlo simulation was performed to verify the performance of the proposed filter. The simulation results showed that the proposed IMM-based INS/EM-Log integrated navigation system can properly estimate the sea current regardless of the sea current change, and also confirmed that it provides navigation information with improved position estimation accuracy. This is expected to improve the navigation performance of underwater vehicles, and enable the stable operations of underwater vehicles based on the improved navigation information.

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Seong Yun Cho received B.S., M.S., and Ph.D. degrees in Control and Instrumentation Engineering from Kwangwoon University in 1998, 2000, and 2004, respectively. From 2008 to 2013, he was with Electronics and Telecommunications Research Institute as a senior researcher. In 2013, he joined the faculty of the Department of Robotics Engineering at Kyungil University, where he is currently an associate professor. His current research topics include positioning and navigation systems, filtering theory for linear/nonlinear systems, sensors-based motion detection, and LBS application systems.

Hojin Ju received BS in Mechanical Engineering from Korea Aerospace University and Ph.D. degree in mechanical and aerospace engineering of Seoul National University in 2012, and 2018, respectively. He is currently a Research Fellow with Automation and Systems Research Institute in Seoul National University. His research interests include the MEMS-based pedestrian dead reckoning, inertial navigation systems, and nonlinear filtering techniques.

Jaehyuck Cha received B.S. degree in Mechanical Engineering from Yonsei University and the M.S. degree in Mechanical and Aerospace Engineering from Seoul National University in 2016, and 2018, respectively. He is currently pursuing the Ph.D. degree with the School of Mechan-ical and Aerospace Engineering, Seoul National University. His

research interests include inertial navigation systems, visual inertial odometry, and nonlinear filtering techniques.

Chan Gook Park received B.S., M.S., and Ph.D. degrees in Control and Instrumentation Engineering from Seoul National University in 1985, 1987, and 1993, re-spectively. From 1994 to 2003, he was with Kwangwoon University as an associate professor. In 2003, he joined the faculty of the School of Mechanical and Aerospace Engineering at Seoul National University, where he is currently a professor. His current research topics include advanced filtering techniques, inertial navigation system, GPS/INS integration, MEMS-based pedestrian dead reckoning, and FDIR techniques for satellite systems.

Kijeong Yoo received B.S., and M.S. in Control and Instrumentation Engineering from Ajou University in 1997, and 2002, respectively. From 2002 to present, he has been with Agency for Defense Development as a principle researcher. His current research topics include inertial navigation system for underwater vehicle, Kalman filtering techniques, and multi-sensor hybrid navigation.

Chanju Park received B.S., and M.S. degrees in Mechanical Engineering from Pusan National University and Ph.D. degree in Electronic Engineering from Chungnam National University in 1994, 1996, and 2009, respectively. From 1996 to present, he has been with Agency for Defense Development as a principle researcher. His current research topics include Kalman filtering techniques, multi-sensor hybrid navigation and inertial navigation system for underwater vehicle.