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Ocean Vehicle Inertial Navigation Method based on Dynamic Constraints

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This paper proposes a dynamic aided inertial navigation method to improve the attitude accuracy for ocean vehicles. The proposed method includes a dynamic identification algorithm and the utilisation of dynamic constraints to derive additional observations. The derived additional observations are used to update the filters and limit the attitude error based on the dynamic knowledge. In this paper, two dynamic conditions, constant speed cruise and quasi-static, are identified and corresponding additional velocity and position observations are derived. Simulation and experimental results show that the proposed method can improve and guarantee the accuracy of the attitude. The method can be used as a backup method to bridge external information outages or unavailability. Both the features of independence of external support and integrity of the Inertial Navigation System (INS) are enhanced.

KEYWORDS

1. Ocean vehicle. 2. Dynamic constraint. 3. Inertial navigation system. 4. Attitude. 5. Kalman filter.

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1. INTRODUCTION. Inertial Navigation Systems (INS) are widely adopted for their autonomous navigation ability. However, the navigation error will accumulate with time due to the integration working principle (Wang and Gao, 2010). Two important features of ocean vehicle navigation are requirements for long operational durations and high accuracy. Therefore, the disadvantage of an INS will become obvious in a short period. To counter this, INS are frequently aided with external information to eliminate error drift.

The common existing methods for marine INS include gyrocompass and filters, integrating Doppler Velocity Log (DVL) (Xu et al., 2014) or Global Navigation Satellite Systems (GNSS) (most commonly the Global Positioning System (GPS)) with INS (Hwang et al., 2005). The major drawback of these methods is the dependence on external information. The availability of accurate and secure external information cannot be guaranteed. GNSS signals can suffer from outages (Atia et al., 2011), signal blockage and are susceptible to be disruption by jamming and spoofing (Wang et al., 2015). DVL is an independent velocity measuring equipment commonly used on ships (Xu et al., 2014; Gao et al., 2014). However, environment factors have a direct impact on DVL measurement accuracy. These

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defects pose challenges to ocean vehicle navigation with the existing external information aided solutions.

To overcome the drawback of external information aided solutions, navigation methods based on Artificial Intelligence (AI) have been suggested to overcome the inadequacies of the common existing methods (Chen and Fang, 2014; Noureldin et al., 2011; Chen et al., 2013). The essential pre-trained model of the AI-based method operates in prediction mode to correct INS errors in the case of external information outages. The model is obtained through a large amount of computation and sample data ranges, and it should be retrained if there are changes in the operating conditions. The real-time application is hard to achieve, and it cannot cope with the situation of long external information outages.

These limitations motivated research to investigate alternative methods, predominantly on the methods with aiding of the vehicle dynamic knowledge. The dynamic constraint methods have been applied in land vehicle navigation (Wang and Gao, 2010; Dissanayake et al., 2001; Wang et al., 2005). The idea behind the approach is to derive additional observations from dynamic knowledge, which are utilised to curb the stand-alone INS navigation divergence. For instance, the changes of velocity and angular rate are assumed to be zero in the stationary condition, and no significant motion acceleration along the transverse direction exists when moving along a straight track (Wang and Gao, 2010). In Wang and Gao (2010), typical dynamic conditions are firstly defined by combining analysis of inertial data and a fuzzy expert system, and then the dynamic aiding data is applied to update a Kalman Filter (KF) when GPS is unavailable.

To further improve the performance of an ocean vehicle navigation system, the utilisation of two ocean vehicle dynamic constraints are proposed to aid the inertial navigation. Differing from a land vehicle, constant speed cruise and quasi-static modes are the typical dynamics. In this paper, the quasi-static condition refers to when an ocean vehicle is in the anchored condition or moored condition. There is wave motion along the waves and almost no displacement. We derive additional velocity and position observations separately in these two conditions and apply them to update the KF. More importantly, before applying the observations properly, the dynamic conditions should be identified accurately. In this paper, we firstly select the accelerometer and gyroscope measurement-related features and then accomplish identification through a multiple-layer strategy by using the selected features. To some extent, the INS character of independence from external support can be enhanced by the proposed method. Simulation and experiment results show that the proposed method can maintain high attitude accuracy even when external information is missing for a long period.

2. ADDITIONAL DYNAMICALLY-DERIVED OBSERVATIONS.

2.1. *Dynamic constraints.* Ocean vehicles are in the condition of constant speed cruise or moored for a great part of time. In a constant speed cruise condition, the ocean vehicle sails on a fixed heading at a constant speed. In this condition, unchanged velocity and heading are distinguishing features. The traditional navigation equations can be simplified as follows:

$$\dot{V} = 0 \tag{1}$$

$$\dot{\phi}_u = 0 \tag{2}$$

where V is the vehicle velocity, ϕ_u is the heading. Equations (1) and (2) indicate unchanged velocity and heading. When the ocean vehicle remains moored, the most obvious feature is

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the unchanged position. The velocity is disturbed by the wave motion and does not remain at zero. Thus, it is nearly static, and in this paper, we define the condition as a quasi-static condition. The dynamic constraint can be expressed as Equation (3):

$$\dot{P} = 0 \tag{3}$$

where P is the position. Thus, at these two specific conditions, it is possible to directly obtain velocity and position information without any external support equipment.

2.2. *Dynamic-derived observations and error analysis.*

2.2.1. *Constant speed cruise condition.* When the vehicle moves at a constant speed on a fixed heading, the velocity is an effective observation to correct the attitude error. If it is detected that the vehicle is in the constant speed cruise condition, the current velocity can be used as a useful observation.

$$V_{obs} = V(t_N) \tag{4}$$

where $V(t_N)$ is the velocity measurement at the current time t_N, V_{obs} is the velocity observation. The accuracy of the current velocity is a key factor affecting the estimation accuracy of filters. For an ocean vehicle, the heading error has a common relationship with the velocity error which according to the Octans user guide (iXblue, 2008), can be expressed in Equation (5):

$$\delta\phi_u = \frac{\delta V_N}{5\pi}\sec L \tag{5}$$

where $\delta\phi_u$ is the heading error, δV_N is the equivalent north velocity error and L is the latitude. Take an INS with accelerometer bias 50 μg (1σ) and gyroscope bias 0·01°/h (1σ) for example. Without external information for one hour, the accumulated velocity error is only approximately 1 m/s and will lead to a heading error $\delta\phi_u$ of about 0·1° sec L. This demonstrates that the current velocity obtained in this condition is acceptable to be used as the observation.

2.2.2. *Quasi-static condition.* The direct observation during the moored condition is the unchanged position:

$$P_{obs} = P(t_N) \tag{6}$$

where $P(t_N)$ is position at the current time t_N and P_{obs} is the position observation. For an ocean vehicle, the moored condition is an approximately static condition due to the wave effect. So, in this paper, it is defined as a quasi-static condition. In this condition, the velocity is variable and cannot be predicted. However, the position is limited in a range. For an INS with accelerometer bias 50 μg (1σ) and gyroscope bias 0·01°/h (1σ), the position error of the pure inertial navigation algorithm is about 1 nautical mile for one hour, namely 1 minute of arc angular position error. The position error is acceptable to the INS requiring 1° sec L heading accuracy. Therefore, the position is adopted as the observation.

3. DYNAMIC IDENTIFICATION. The dynamic conditions should be identified accurately before applying the obtained observations. In practical applications, the inertial sensor output will be contaminated by noise and affected by the operating environment factors, as described in the last section. Therefore, the identification process of dynamic conditions is carried out with the capability of dealing with the effect of the above factors.

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The quasi-static condition can be considered as a special case of the constant speed cruise. Therefore, the identification consists of two steps. Firstly, it is judged whether it satisfies the requirements of constant speed cruise. If it satisfies, a further judgement is taken to conduct the quasi-static identification. The specific identification criteria follow.

3.1. *Constant speed cruise condition identification.* We denote the body frame by b, the navigation frame by n, the inertial frame by i and the Earth frame by e. When the vehicle moves on a constant heading, the vertical angular rate is very small. Further, if the speed is kept constant, the horizontal acceleration is approximately zero. Thus, the judgment includes two parts: vertical angular rate and horizontal acceleration.

(1) $|\omega^b_{nbz}(t_N)| < \varepsilon_1$
(2) $|\bar{f}^b_x(t_N)| < \varepsilon_2$ and $|\bar{f}^b_y(t_N)| < \varepsilon_2$

where ω^b_{nbz} is the vertical angular rate measured in the body frame at the current time t_N, $|\bar{f}^b_x(t_N)|$ and $|\bar{f}^b_y(t_N)|$ are the averages of the horizontal acceleration during a time interval until t_N; here we set the time interval as one minute. ε_1 and ε_2 are corresponding thresholds.

Compared with the vertical angular rate caused by vehicle motion, the effect of noise on the raw gyroscope measurement is small and the raw gyroscope measurement is used directly in the judgment. In contrast, the quantised noise of the raw accelerometer measurement is relatively large. So, the averages of the horizontal acceleration are used in the judgment. The thresholds are set according to the precision level of the INS and the operating environment. For example, ε_1 and ε_2 will be set as 0·005 rad/s and 0·1 m/s^2 for the INS with accelerometer bias 50 μg (1σ) and gyroscope bias is 0·01°/h (1σ) in the common operating environment.

3.2. *Quasi-static condition identification.* When the accelerometer and gyroscope measurements satisfy the constant speed cruise condition, a further quasi-static judgment will be taken. When an ocean vehicle remains moored, the acceleration of the vehicle changes, and is different from the moving condition. Thus, the difference of the averages of the horizontal acceleration in one minute is used in this step. The further criterion is:

(3) $|d_f^b_x(t_N)| < \varepsilon_3$ and $|d_f^b_y(t_N)| < \varepsilon_3$

where

$$\begin{aligned} d_f^b_x(t_N) &= \bar{f}^b_x(t_N) - \bar{f}^b_x(t_N - n) \\ d_f^b_y(t_N) &= \bar{f}^b_y(t_N) - \bar{f}^b_y(t_N - n) \end{aligned} \tag{7}$$

where $\bar{f}^b_x(t_N)$ and $\bar{f}^b_y(t_N)$ are the averages of the horizontal acceleration in one minute until t_N. $\bar{f}^b_x(t_N - n)$ and $\bar{f}^b_y(t_N - n)$ are the averages in the last minute. ε_3 will be set as 0·002 m/s^2 for the INS with accelerometer bias 50 μg (1σ) and gyroscope bias is 0·01°/h (1σ) for the common operating environment.

The whole identification process is shown in Figure 1. At the end of the process, if $d_f^b_x(t_N)$ and $d_f^b_y(t_N)$ satisfy the criteria, the vehicle is in a quasi-static condition and the position information is used as the observation; if not, the vehicle is in constant speed cruise, and the velocity information is used as the observation.

4. DESIGN OF THE NAVIGATION FILTER. With the dynamically-aided observations, a Kalman Filter (KF) is designed to estimate the inertial sensor error and navigation

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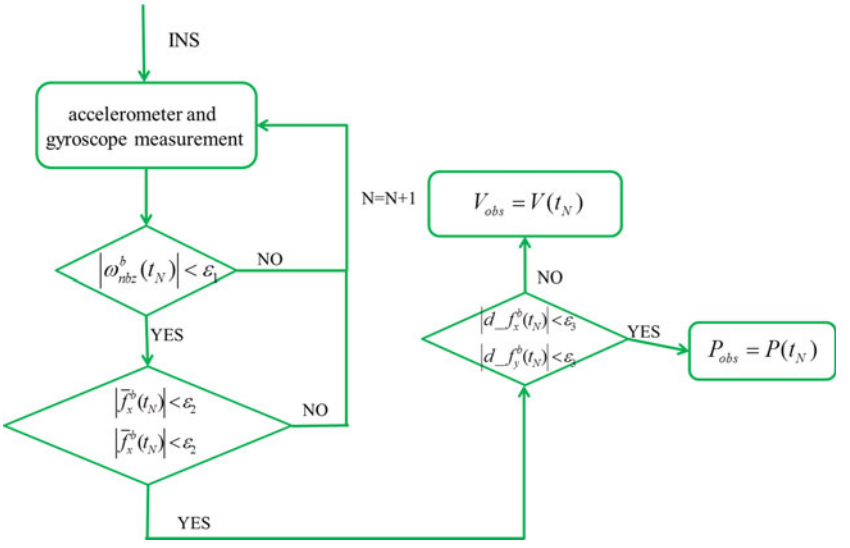


Figure 1. Flowchart of the identification process.

error. In this paper, the derived observations are only available in velocity and position and the design of the filter aims to obtain high attitude accuracy. The system and measurement models are designed as follows.

4.1. *System model.* For an ocean vehicle, the systemic error equations are developed in the navigation n-frame. We chose angular position error $\delta\theta_x$, $\delta\theta_y$ horizontal velocity error δV_x, δV_y, attitude (pitch, roll, heading) error ψ_x, ψ_y, ψ_z, gyroscope bias ε_x, ε_y, ε_z, and accelerometer bias ∇_x, ∇_y as the state vector X. They are all expressed in the n-frame. The system error equations can be expressed in this frame as follows:

$$X = \begin{bmatrix} \delta\theta_x & \delta\theta_y & \delta V_x & \delta V_y & \psi_x & \psi_y & \psi_z & \varepsilon_x & \varepsilon_y & \varepsilon_z & \nabla_x & \nabla_y \end{bmatrix}$$

$$\begin{cases} \delta\dot{\theta}_x = -\dfrac{v_z}{R}\delta\theta_x - \dfrac{1}{R}\delta V_y \\ \delta\dot{\theta}_y = -\dfrac{v_z}{R}\delta\theta_y - \dfrac{1}{R}\delta V_x \\ \delta\dot{V}_x = -g\delta\theta_y + 2\omega_{iez}^n \delta V_y - f_z\psi_y + f_y\psi_z + \nabla_x \\ \delta\dot{V}_y = g\delta\theta_x - 2\omega_{iez}^n \delta V_x + f_z\psi_x - f_x\psi_z + \nabla_y \\ \dot{\psi}_x = \omega_{iez}^n \psi_y - \omega_{iny}^n \psi_z - \varepsilon_x \\ \dot{\psi}_y = -\omega_{iez}^n \psi_y + \omega_{inx}^n \psi_z - \varepsilon_y \\ \dot{\psi}_z = \omega_{iny}^n \psi_x - \omega_{inx}^n \psi_y - \varepsilon_z \\ \varepsilon_x = C_{11}\varepsilon_x^b + C_{12}\varepsilon_y^b + C_{13}\varepsilon_z^b \\ \varepsilon_y = C_{21}\varepsilon_x^b + C_{22}\varepsilon_y^b + C_{23}\varepsilon_z^b \\ \varepsilon_z = C_{31}\varepsilon_x^b + C_{32}\varepsilon_y^b + C_{33}\varepsilon_z^b \\ \nabla_x = C_{11}\nabla_x^b + C_{12}\nabla_y^b \\ \nabla_y = C_{21}\nabla_x^b + C_{22}\nabla_y^b \end{cases} \tag{8}$$

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where f is the accelerometer output in the n-frame, R is the earth radius, ω_{ie}^n is the Earth rotation rate and ω_{in}^n is the rotation rate of the i-frame with respect to the b-frame expressed in the n-frame. C_{ij} is the element of C_b^n in the j-th column of the i-th row. C_b^n is the direction cosine matrix representing the rotation from the b-frame to the n-frame.

4.2. *Measurement model.* Dynamically-derived measurements were discussed in the last section. The corresponding measurement models for the constant speed cruise condition and the quasi-static condition are now given.

In the constant speed cruise condition, the velocity observation is available. The measurement is given as

$$\begin{aligned} Z_1 &= V_{INS} - V_{obs} \\ &= \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \delta V_x \\ \delta V_y \end{bmatrix} \end{aligned} \tag{9}$$

where V_{INS} is the velocity calculated by the INS.

In the quasi-static condition, the available observation is the position information. The corresponding measurement is given as

$$Z_2 = \begin{bmatrix} C_{23} \\ C_{31} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \delta\theta_x \\ \delta\theta_y \end{bmatrix} \tag{10}$$

where

$$C = \bar{C}_e^n C_n^e \tag{11}$$

$$\bar{C}_e^n = [I - (\delta\theta\times)]C_e^n = \begin{bmatrix} 1 & \delta\theta_z & -\delta\theta_y \\ -\delta\theta_z & 1 & \delta\theta_x \\ \delta\theta_y & -\delta\theta_x & 1 \end{bmatrix} C_e^n \tag{12}$$

where C_e^n is the position matrix and the direction cosine matrix representing the rotation from the e-frame to the n-frame. $\bar{C}_e^n$ is the corresponding corrected matrix. For an ocean vehicle, the angular position error $\delta\theta_x$, $\delta\theta_y$, $\delta\theta_z$ will be at the level of minute of arc even over one hour. So, the angular position error is considered as a small quantity.

5. SIMULATION AND EXPERIMENT. In order to evaluate the availability of the dynamic identification and the accuracy of the dynamically-aided Kalman filter method, both simulation and experiment are carried out in this section. To further validate its performance, the dynamically-aided Kalman filter method is compared with the pure inertial navigation method and GPS/INS integration method. In this section, we call the proposed method the dynamically-aided method.

For the result presentations, if the condition satisfies the identification criteria, the identification parameters will multiply a constant K. This aims to amplify the inertial senor output to the same magnitude as the GPS information, to show the results more directly. The value will be set to zero when the identification criteria are not satisfied.

5.1. *Simulation.* A trajectory of an ocean vehicle is simulated for 15,000 s. It includes a wharf start for 300 s, accelerating to 12 m/s over 30 s, constant speed cruise 14,340 s, decelerating to 0 m/s over 30 s and then remaining moored for 300 s. The inertial sensor error parameters of the INS are:

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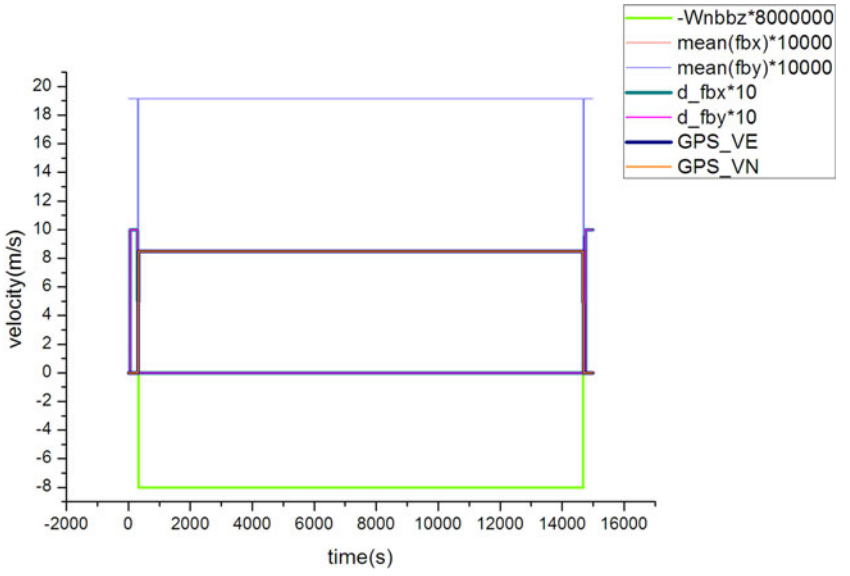


Figure 2. Identification results during the whole trajectory.

1) Gyroscope bias 0·01°/h, scale factor 50 parts per million (ppm), misalignment error 30 arc seconds (Asec) noise 0·005°/h/$\sqrt{Hz}$;
2) accelerometer bias 50 μg, scale factor 50 ppm, misalignment error 30 Asec, noise 20 μg/$\sqrt{Hz}$.

The main objective of the simulation is to evaluate how much the attitude accuracy can be improved by the proposed method under both constant speed cruise and quasi-static conditions. Equivalent noise is set to simulate the impact of sea factors on the Inertial Measurement Unit (IMU).

Firstly, the dynamic identification method is evaluated. Figures 2–4 show the dynamic identification results. Both the GPS reference velocity and related identification parameters are listed in the figures. *GPS_VE* and *GPS_VN* are the east and north velocity provided by GPS; *Wnbbz* represents ω_{nbz}^{b}, the vertical angular rate; *mean(fbx) and mean(fby) are* $\bar{f}_x^b(t_N)$ and $\bar{f}_y^b(t_N)$, the averages of the horizontal acceleration. *d_ fbx* and *d_ fby* represent the difference of acceleration averages, $d_f_x^b(t_N)$ and $d_f_y^b(t_N)$.

It should be mentioned that in the simulation, the operating environmental factors are not easy to simulate well. $d_f_x^b(t_N)$ and $d_f_y^b(t_N)$ are zero in the moored condition due to the simulation limitation. In order to show the identification result, when the condition is identified as quasi-static, $d_f_x^b(t_N)$ and $d_f_y^b(t_N)$ are set to one.

By comparing the identified conditions with the reference information provided by GPS, it is verified that the constant speed cruise condition and quasi-static condition are correctly identified. When the GPS reference velocity is relatively steady, it indicates that the ocean vehicle is at a constant velocity in a straight line. In this case, it can be seen from Figure 2 that the constant speed cruise is correctly identified. In Figure 3, the period of the first 55∼300 s is identified as the quasi-static condition; and in Figure 4, the period of the last 14,760∼15,000 s is also correctly identified.

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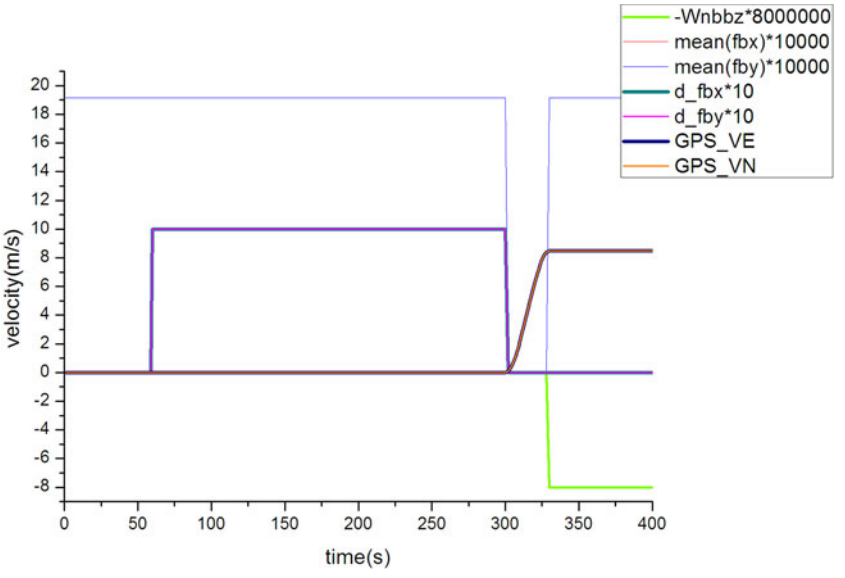


Figure 3. Identification results in the first 400 s.

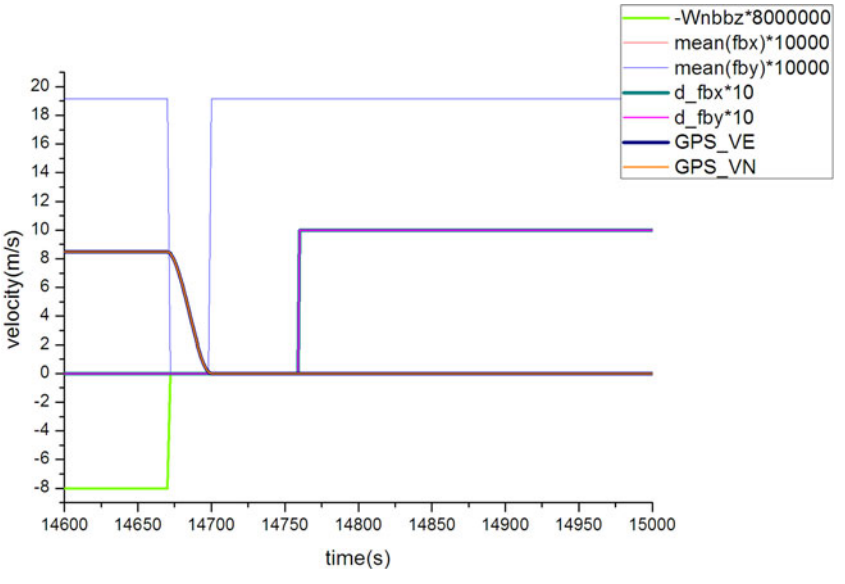


Figure 4. Identification results in the last 400 s.

The attitude errors of the proposed method, the pure inertial navigation method and GPS/INS integration method are shown in Figures 5–7. It can be seen that the pitch and roll estimation of the proposed method are more accurate than the pure inertial navigation method, and the accuracy is close to that of the GPS integration method. For the heading

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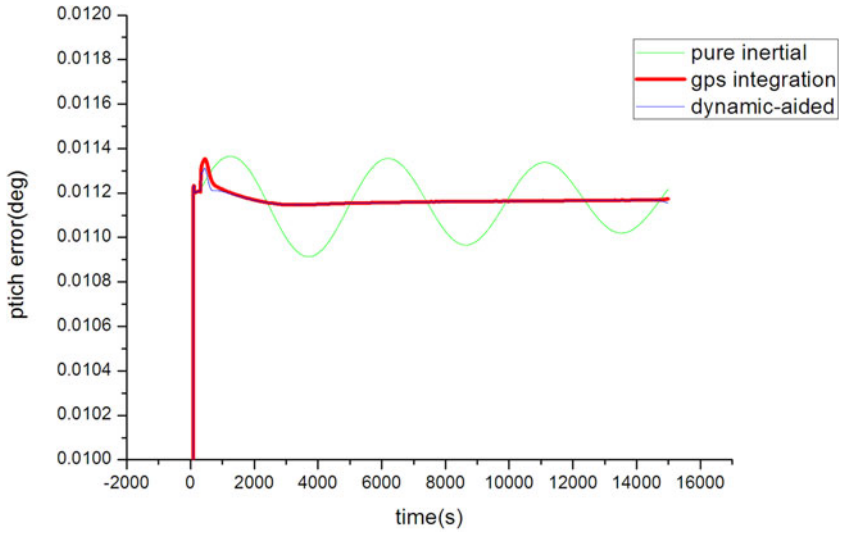


Figure 5. Pitch error.

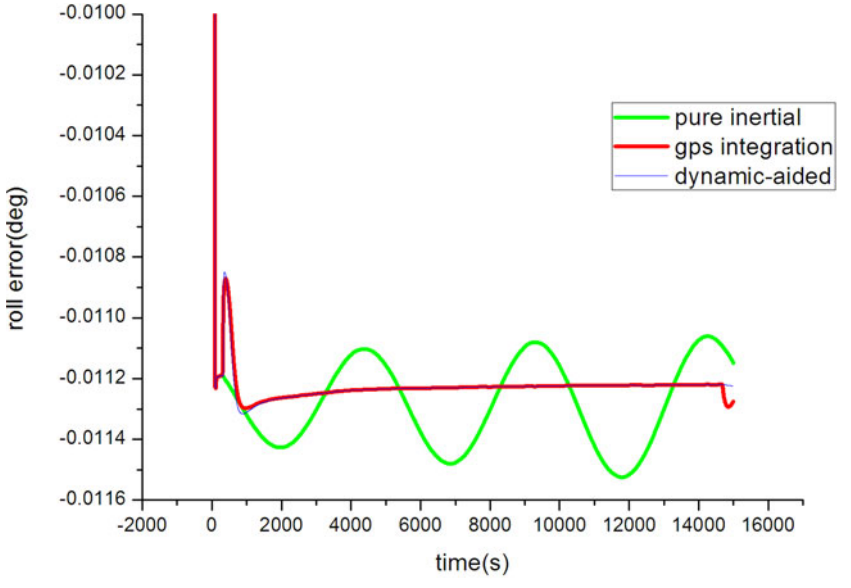


Figure 6. Roll error.

performance, the error of the pure inertial navigation method is 0·106°; however, the error of the proposed method is only 0·066°. Table 1 summarises the attitude error peak value, after the filter comes to the steady state, and the mean and standard variance. In summary, the dynamically-aided observations enable the stand-alone INS to limit the attitude error.

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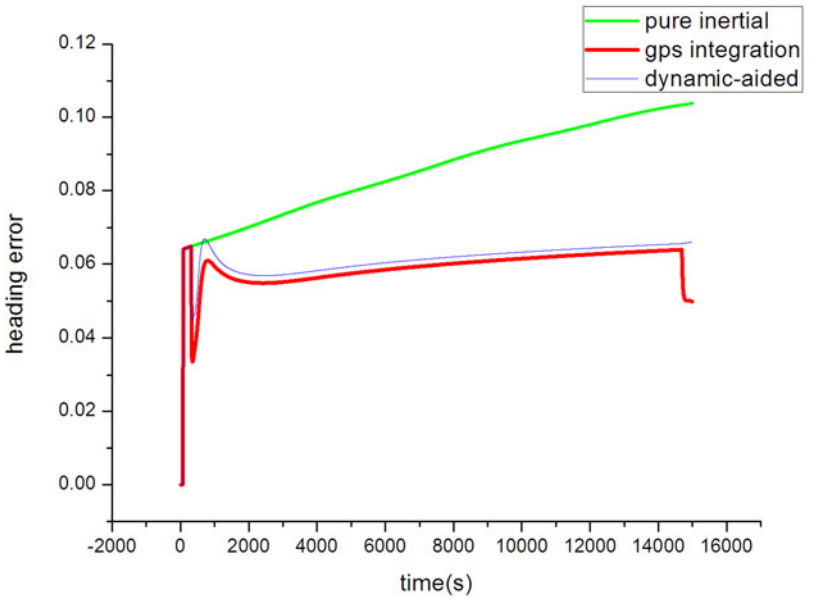


Figure 7. Heading error.

Table 1. Attitude estimation in the simulation.

Algorithm		Pure inertial navigation	Dynamic-aided method	INS/GPS method
Heading (deg)	peak value	0·10681	0·06602	0·06345
	mean	0·09289	0·06344	0·06092
	standard variance	0·00715	0·00151	0·00254
Pitch (deg)	peak value	0·01136	0·01117	0·01117
	mean	0·01117	0·01120	0·01116
	standard variance	0·00012	$3{\cdot}11 \times 10^{-6}$	$3{\cdot}86 \times 10^{-6}$
Roll (deg)	peak value	0·10581	0·01123	0·01129
	mean	0·09289	−0·01122	−0·01123
	standard variance	0·00715	$3{\cdot}32 \times 10^{-6}$	$1{\cdot}08 \times 10^{-5}$

5.2. *Experiment.* The sea experiment on a 10,000 tonne ocean-going ship includes various working conditions according to the motion path, including constant speed and turning manoeuvres. The test trajectory includes about 7,000 s sailing, followed by 2,000 s remaining moored. In the experiment, an INS with 50 μg accelerometer bias and a 0·02°/h fibre-optic gyroscope bias was chosen to evaluate the performance of the algorithm. The sample rate of GPS was 1 Hz, position accuracy 10 m and velocity accuracy 0·1 m/s. The INS was fixed at the mass centre of the ship. The sample rate of INS was 100 Hz and the GPS receiver was fixed into the INS. The GPS antenna was mounted above the ship's bridge. The lever arm between GPS and INS was measured and compensated. The INS and GPS data were calculated after time synchronisation. Using GPS-assisted inertial navigation as a reference, we made a comparison between the proposed method and pure inertial navigation.

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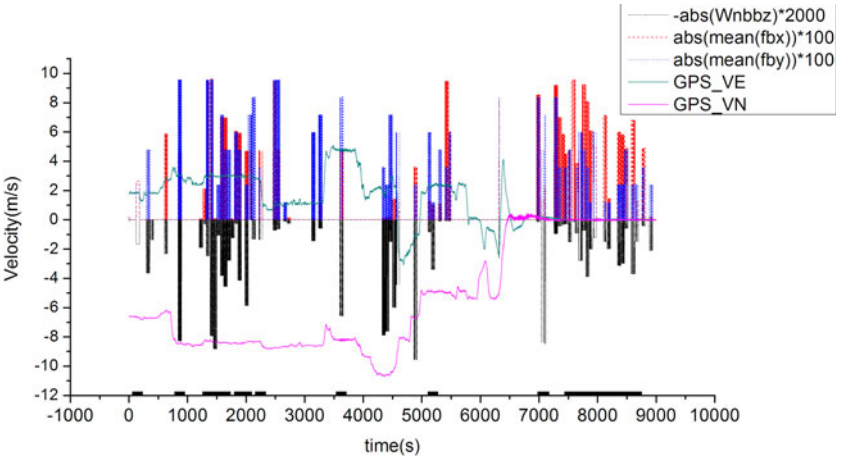


Figure 8. Constant speed cruise identification during whole trajectory.

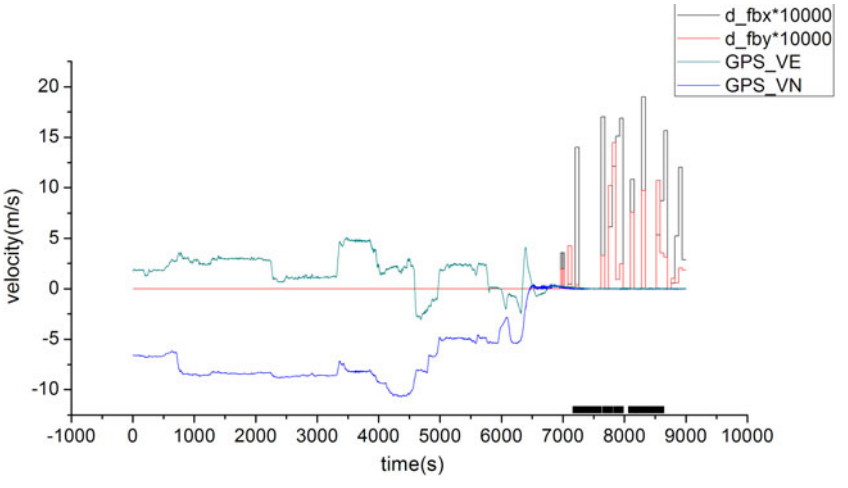


Figure 9. Quasi-static condition identification during whole trajectory.

The experimental results give the same results for the data processing method in the simulation when testing the dynamic identification algorithm. In Figures 8 and 9 the identified time windows are highlighted on the time axis. Figure 8 shows constant speed cruise identification results. It can be seen that when GPS_*VE* and GPS_*VN* were relatively steady, the related parameters were not zero and the constant speed cruise condition was identified. The velocity could thus be used as the filter observation. Figure 9 shows the quasi-static condition identification results. In the last 2,000 s, *d_ fbx* and *d_ fby* were not zero and the quasi-static condition was successfully identified. At this time, the position information is used as the observation.

In the experiment, an accurate attitude reference was not available, thus we took the attitude of the integrated INS/GPS as the reference to compare the attitude error of the proposed method and pure inertial navigation. When the filter came to the steady state

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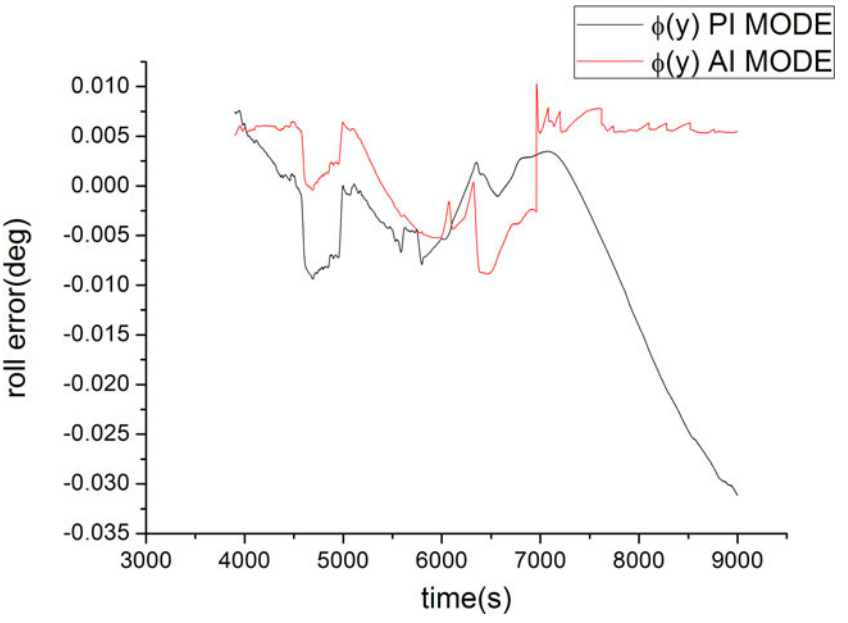


Figure 10. Roll error.

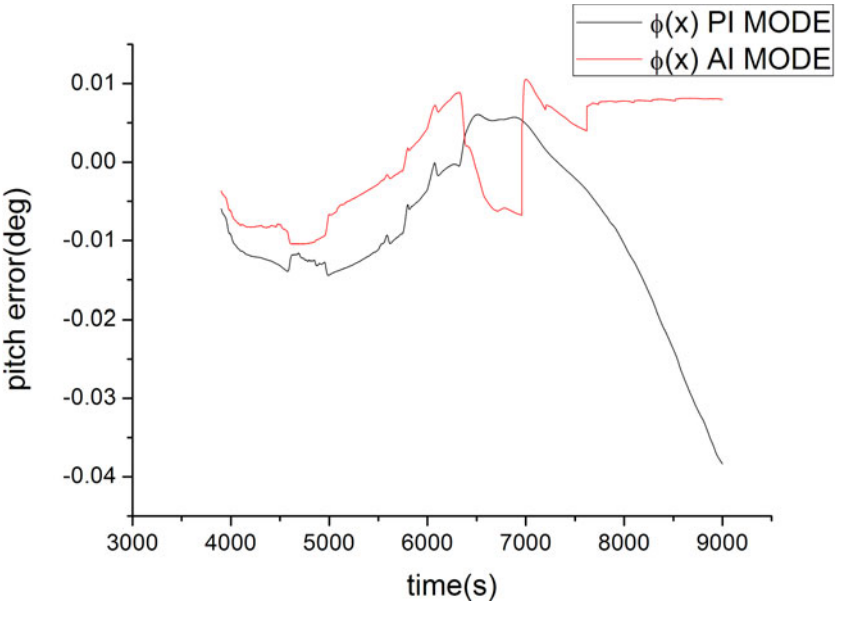


Figure 11. Pitch error.

after 3,900 s, we compared the attitude error for the following 5,100 s. Figures 10–12 show the comparison results. PI MODE refers to pure inertial navigation and AI MODE is the proposed method. The attitude error peak values after the filter came to a steady state and

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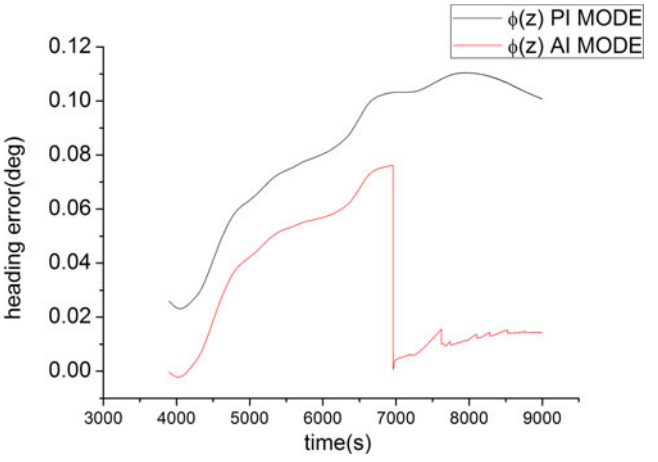


Figure 12. Heading error.

Table 2. Attitude error in the experiment.

	PI mode			AI mode		
Algorithm	Mean	Standard variance	Peak Value	Mean	Standard variance	Peak Value
Heading	0·08310	0·02674	0·11046	0·03099	0·02437	0·07617
Pitch	−0·00917	0·01029	−0·03839	0·00079	0·00695	0·01054
Roll	−0·00627	0·00987	−0·03115	0·00234	0·00474	0·01025

mean and standard variance are listed in Table 2. The results show that the proposed method has higher attitude accuracy and can limit the attitude error.

6. CONCLUSION. In this paper, a dynamically-aided inertial navigation method has been proposed to improve the ocean vehicle attitude accuracy. Additional observations were derived based on dynamic knowledge to update the filters. The proposed method includes two parts: the dynamic identification algorithm and the utilisation of dynamic constraints to derive additional observations. The simulation and experiment results show that the proposed dynamically-aided method has a relatively higher attitude accuracy than the pure inertial navigation method and can provide satisfactory navigation parameters over a long period. When external information, such as GPS and DVL, is in outage or unavailable, the proposed method can be a good backup. Without the need for external equipment, both the character of autonomy and integrity of Inertial Navigation System (INS) are enhanced. It is especially applicable to large warships with small mobility.

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