LOW COST INTEGRATED NAVIGATION SYSTEM FOR UNMANNED VESSEL

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ABSTRACT

Large errors of low-cost MEMS inertial measurement unit (MIMU) lead to huge navigation errors, even wrong navigation information. An integrated navigation system for unmanned vessel is proposed. It consists of a low-cost MIMU and Doppler velocity sonar (DVS). This paper presents an integrated navigation method, to improve the performance of navigation system. The integrated navigation system is tested using simulation and semi-physical simulation experiments, whose results show that attitude, velocity and position accuracy has improved awfully, giving exactly accurate navigation results. By means of the combination of low-cost MIMU and DVS, the proposed system is able to overcome fast drift problems of the low cost IMU.

Keywords: Low cost; MEMS; Inertial navigation; Integrated navigation

INTRODUCTION

Unmanned vessel (UV) is an effective tool in ocean exploitation. The recent upsurge of interest in ocean exploitation necessitates the development of small and lightweight UVs[1]-[5]. Precision navigation is one of the key technologies and of great importance for UVs and UV-based ocean surveying and exploitation. This paper focuses on mini-sized unmanned vessels, which have a limited weight, size and cost, making low cost navigation system the best, and most of time, the only choice.

This paper presents a navigation system scheme for UVs. Low cost Micro-Electro-Mechanical Systems (MEMS) based inertial measurement unit (IMU) is used, to determine the position, velocity and attitude of the UV, in which the IMU is fixed - this is so called inertial navigation system (INS). The operation of inertial navigation systems depends upon the laws of classical mechanics as formulated by Isaac Newton.

It is the process whereby the measurements provided by gyroscopes and accelerometers are used to determine the position, velocity and attitude of the vehicle in which they are installed. Inertial navigation system is entirely self-contained within the vehicle, in the sense that they are not dependent on the transmission of signals from the vehicle or reception from an external source. So it is widely used. But inaccuracies arise because of initial alignment errors, imperfections in the performance of the inertial instruments and limitations in the computational process. For high-precision IMU, the position error will increase slowly; so INS still give high-precision navigation information in not a long time. Yet for low cost MIMU, large errors (as shown in Table I) lead to huge navigation errors, even wrong navigation information even in a minute. It cannot be used in isolation. So we combined INS and doppler velocity sonar (DVS) to an integrated navigation system, to improve the accuracy of the inertial navigation system[6]-[9].

Tab. I. Functional specifications of MIMU used in this work

Parameter	Gyroscope	Accelerometer
Range	±150 deg/s	±10 g
Bias	0.1 deg/s	0.5 mg×Range
Bias stability	0.02 deg/s	0.1 mg×Range
Scale Factor non-linearity	0.5%	0.5%

THE INTEGRATED NAVIGATION SYSTEM DESIGN

INERTIAL NAVIGATION SYSTEM ERRORS EQUATION

The navigational function is fulfilled by combining the measurements of vehicle rotation and specific force with knowledge of the gravitational field to compute estimates of attitude, velocity and position with respect to a pre-defined reference frame. A schematic representation of such an inertial navigation system is shown in Figure 1.
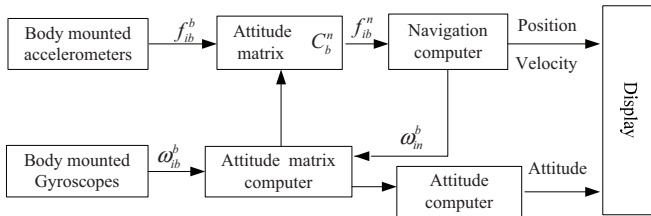

Fig. 1. Inertial navigation system schematic

(1) Inertial navigation system errors equation

Inertial navigation system attitude errors, velocity errors and position errors are as follows[10][11]:

$$\begin{cases} \dot{\varphi}^n = \delta\omega_{ie}^n + \delta\omega_{en}^n - (\omega_{ie}^n + \omega_{en}^n) \times \varphi^n + \varepsilon^p \\ \delta\dot{V}^n = f^n \times \varphi^n + \nabla^p - (2\delta\omega_{ie} + \delta\omega_{en}) \times \dot{V}^n - (2\omega_{ie} + \omega_{en}) \times \delta V^n \\ \delta\dot{L} = \dfrac{\delta V_y}{R_n} \\ \delta\dot{\lambda} = \dfrac{\delta V_x}{R_E}\sec L + \dfrac{V_x}{R_E}\sec L \, tgL \, \delta L \end{cases} \quad (1)$$

Equ. (1) is inertial navigation system errors equation. It may be expressed as a matrix error equation as follows:

$$\dot{X}_I = F_I X_I + W_I \quad (2)$$

where

$$X_I = \begin{bmatrix} \delta V_E & \delta V_N & \varphi_E & \varphi_N & \varphi_U & \delta L & \delta\lambda \end{bmatrix}$$

(2) Inertial sensor errors

The inertial sensor errors are considered to be the forms of random bias and white noise as follows:

$$\begin{cases} \varepsilon = \varepsilon_b + w_g \\ \nabla = \nabla_b + w_a \end{cases} \quad (3)$$

where

ε_b and w_g, ∇_b and w_a are gyroscopes random bias and white noise, accelerometers random bias and white noise respectively, and:

$$\begin{cases} \dot{\varepsilon}_b = 0 \\ \dot{\nabla}_b = 0 \end{cases} \quad (4)$$

Three gyroscopes random biases and three accelerometers random biases included, the system equation is as follows:

$$\dot{X} = FX + W \quad (5)$$

where

$X = \begin{bmatrix} \delta V_E & \delta V_N & \varphi_E & \varphi_N & \varphi_U & \delta L & \delta\lambda & \nabla_{bx} & \nabla_{by} & \varepsilon_{bx} & \varepsilon_{by} & \varepsilon_{bz} \end{bmatrix}$;

$$F = \left[\begin{array}{cccccc|ccc} \dot{L}tgL & \tilde{\omega}_z & 0 & -f_U & f_N & \omega_1 & & & \\ -2\tilde{\omega} & 0 & f_U & 0 & -f_E & -\omega_2 & 0 & c_{11} & c_{21} & \mathbf{O}_{2\times3} \\ 0 & -\dfrac{1}{R_N} & 0 & \tilde{\omega}_z & -\tilde{\omega}_y & 0 & 0 & c_{12} & c_{22} & \\ \cline{7-10} \dfrac{1}{R_E} & 0 & -\tilde{\omega}_z & 0 & \tilde{\omega}_x & -\omega_5 & \mathbf{O}_{3\times3} & & & \mathbf{C}_b^n \\ \dfrac{tgL}{R_E} & 0 & \tilde{\omega}_y & -\tilde{\omega}_x & 0 & \omega_3 & & & \\ \hline & 0 & \dfrac{1}{R_N} & & \mathbf{O}_{1\times10} & & & & \\ \hline \dfrac{\sec L}{R_E} & \mathbf{O}_{1\times4} & & \omega_4 & \mathbf{O}_{1\times6} & & & & \\ \hline & & & \mathbf{O}_{5\times12} & & & & & \end{array} \right];$$

$$W = \begin{bmatrix} w_{v_E} & w_{v_N} & w_{\varphi_E} & w_{\varphi_N} & w_{\varphi_U} & w_{\delta L} & w_{\delta\lambda} & 0 & 0 & 0 & 0 & 0 \end{bmatrix}^T;$$

c_{ij} – the element of direction cosine matrix C_n^b;

ε_{bx}, ε_{by}, ε_{bz}, ∇_{bx}, ∇_{by}, ∇_{bz}: gyroscopes random biases and accelerometers random biases respectively in xb, yb, zb axis of the body-fixed coordinate frame;

$$\omega_1 = (2\omega_{ie}\cos L + \dfrac{V_E}{R_E}\sec^2 L)V_N, \quad \omega_2 = (2\omega_{ie}\cos L + \dfrac{V_E}{R_E}\sec^2 L)V_E$$

$$\omega_3 = \omega_{ie}\cos L + \dfrac{V_E}{R_E}\sec^2 L, \quad \omega_4 = \dfrac{V_E}{R_E}\sec^2 L\sin L, \quad \omega_5 = \omega_{ie}\sin L$$

$$\begin{bmatrix} \tilde{\omega}_x \\ \tilde{\omega}_y \\ \tilde{\omega}_z \end{bmatrix} = \begin{bmatrix} -\dfrac{V_N}{R_E} & 2\omega_{ie}\cos L + \dfrac{V_E}{R_E} & 2\omega_{ie}\sin L + \dfrac{V_E tgL}{R_E} \end{bmatrix}^T,$$

$$\begin{bmatrix} \tilde{\tilde{\omega}}_x \\ \tilde{\tilde{\omega}}_y \\ \tilde{\tilde{\omega}}_z \end{bmatrix} = \begin{bmatrix} -\dfrac{V_N}{R_N} & \omega_{ie}\cos L + \dfrac{V_E}{R_E} & \omega_{ie}\sin L + \dfrac{V_E tgL}{R_E} \end{bmatrix}^T$$

THE INTEGRATED NAVIGATION SYSTEM DESIGN

The integrated navigation system scheme is shown in Figure 2. INS and DVS are combined to a Kalman filter, to estimate and correct IMU biases and inertial navigation system errors, in order to overcome fast drift problems of the low-cost INS, then improve navigation accuracy[11] [12].
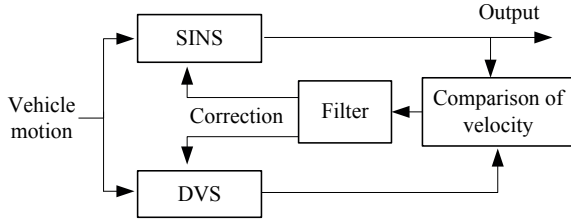
Fig. 2 Integrated navigation system schematic for unmanned vessel

INTEGRATED NAVIGATION SYSTEM FILTER DESIGN

System equation
Equation (5) is the Kalman filter system equation.

Measurement equation
The inertial navigation system output velocities are compared with DVS velocity measurements. The velocities difference of INS/DVS are used as Kalman filter measurements, to estimate and correct INS errors.

The inertial navigation system output velocities and DVS velocity measurements are as Equ. (6) and)7) respectively:

$$\begin{cases} v_{IE} = v_E + \delta v_E \\ v_{IN} = v_N + \delta v_N \end{cases} \tag{6}$$

$$\begin{cases} v_{DE} = v_E + \delta v_{DE} \\ v_{DN} = v_N + \delta v_{DN} \end{cases} \tag{7}$$

where δv_{DE}, δv_{DN} represent the errors in the DVS velocity measurements.

The differences between the DVS measurements and INS measurements are referred to as the filter measurements and are as follows:

$$\begin{aligned} \boldsymbol{Z}_v &= \begin{bmatrix} v_{IE} - v_{DE} \\ v_{IN} - v_{DN} \end{bmatrix} = \begin{bmatrix} \delta v_E - \delta v_{DE} + w_1 \\ \delta v_N - \delta v_{GN} + w_2 \end{bmatrix} \\ &= \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \boldsymbol{O}_{2\times10} \Big]_{2\times12} \begin{bmatrix} \boldsymbol{X}_I \\ \boldsymbol{X}_D \end{bmatrix} + \begin{bmatrix} w_1 \\ w_2 \end{bmatrix} \\ &\triangleq \boldsymbol{H}_v \begin{bmatrix} \boldsymbol{X}_I \\ \boldsymbol{X}_D \end{bmatrix} + V_v \end{aligned} \tag{8}$$

where $\mathbf{H}_v = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \mathbf{O}_{2\times10} \Big]_{2\times12}$, $\mathbf{V}_v = \begin{bmatrix} w_1 \\ w_2 \end{bmatrix}$ is assumed to be a zero mean, Gaussian white-noise process.

In order to allow a discrete Kalman filter to be constructed, it is necessary to express the system error equation (5), the measurement equation (8) in discrete form as follows:

$$X_k = \varphi_{k,k-1} X_{k-1} + \Gamma_{k-1} W_{k-1} \tag{9}$$

$$Z_k = H_k X_k + V_k \tag{10}$$

Kalman filter process
Equations (9) and (10) are the system and measurement equations needed to construct a Kalman filter. The equations for the Kalman filter take the following form for the integrated navigation system for unmanned vessel considered here.

1) Filter prediction step
The covariance matrix is predicted forward in time using the expression:

$$P_{k/k-1} = \varphi_{k,k-1} P_{k-1} \varphi_{k,k-1}^T + \Gamma_{k-1} Q_{k-1} \Gamma_{k-1}^T \tag{11}$$

and the state prediction equation:

$$X_{k/k-1} = \varphi_{k,k-1} \hat{X}_{k-1} \tag{12}$$

2) Filter update
The estimates of the errors in the inertial navigation system states are derived using:

$$\hat{X}_k = X_{k/k-1} + K_k(Z_k - H_k X_{k/k-1}) \tag{13}$$

and the covariance matrix is updated according to:

$$P_k = (I - K_k H_k) P_{k/k-1} \tag{14}$$

where

$$K_k = P_{k/k-1} H_k^T (H_k P_{k/k-1} H_k^T + R_k)^{-1} \tag{15}$$

RESULTS

SIMULATION RESULTS

According to sample data from the MIMU we used, the following errors sources are included.

Gyroscope white noise = 40°/h, gyroscope bias =360°/h, accelerometer bias =2mg, accelerometer white noise =2mg.

Body motion: constant velocity=15m/s, initial latitude =32°, longitude=118°. Sine angular motion: initial yaw=45deg,

pitch=9deg, roll=12deg, and frequency: yaw=1/6, pitch=1/8, roll=1/10.

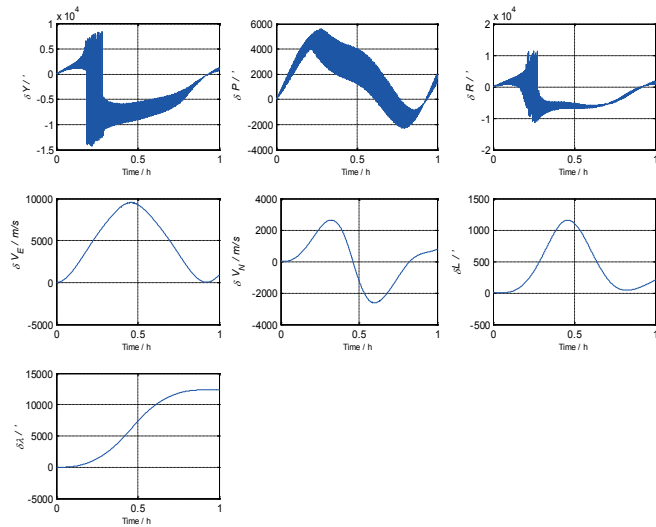The simulated INS errors are shown in Figure 3.

Fig. 3. Simulated INS errors

δY, δP, δR, δVE, δVN, δL and $\delta \lambda$ are yaw error, pitch error, roll error, east velocity error, north velocity error, latitude error, longitude error respectively.

Figure 3 shows huge navigation errors; this caused by the large errors from gyroscopes and accelerometers. The INS navigation results are worthless.

So we combined INS and DVS to the above integrated navigation system, then the simulated navigational accuracy is shown in Figure 4.
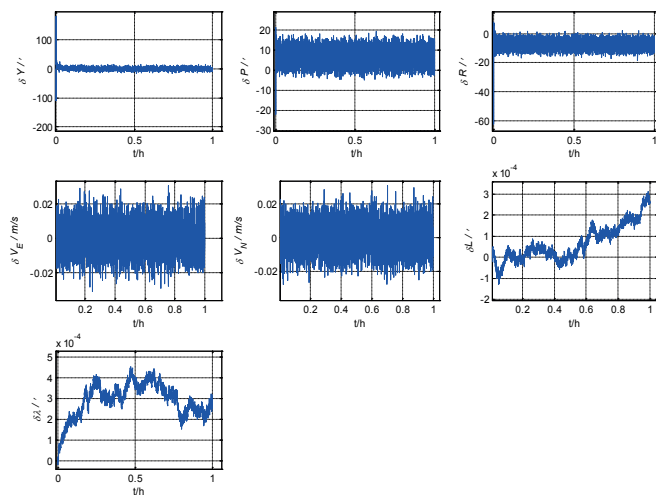
Fig. 4 Integrated navigation system errors

DVS velocity noise is 0.01m/s. Figure 4 shows that the integrated navigation system improves navigational accuracy awfully, giving exactly accurate navigation results.

SEMI-PHYSICAL SIMULATION RESULTS

For further testing the integrated navigation system, semi-physical simulation was carried out. A low cost MIMU was used in this test. The MIMU was placed on a table under static coditions. About 5-10 minutes data are collected. The sample data are shown in Figure 5.
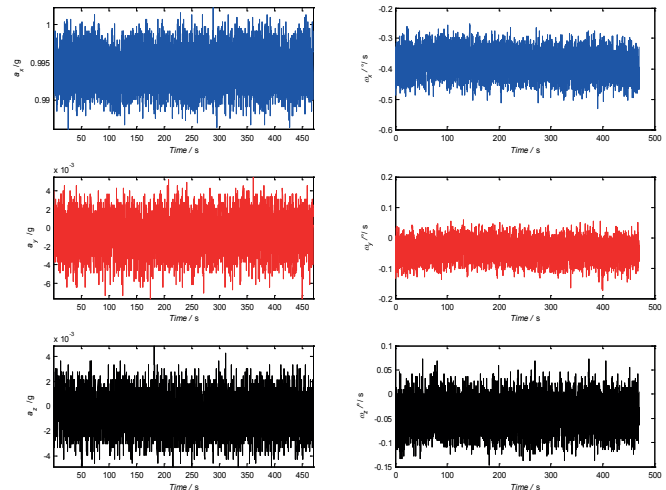

Fig. 5 MIMU Sample data under static conditions

ax, ay, az, ω_x, ω_y, ω_z are x-axis, y-axis and z-axis specific forces and angular rates respectively.

Figure 5 shows that the gyroscopes and accelerometers have notable null bias errors.

Using these data, we have gotten INS results shown in Figure 6. The navigational errors are quite notable. So it's not worth a straw if working by itself. Then we have gotten INS results after IMU errors compensation, shown in Figure 7.
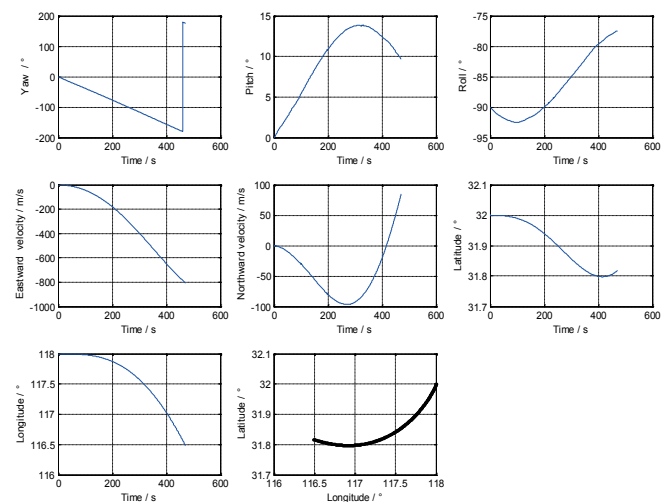

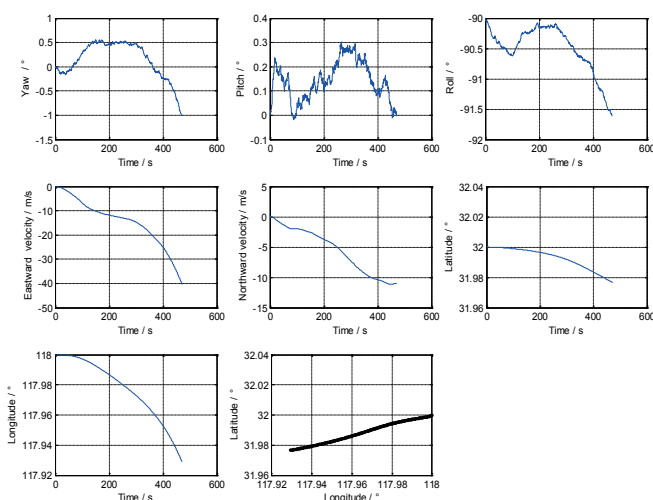*Fig. 6 INS navigational results – no IMU errors compensation*

Fig. 7. INS results – after IMU errors compensation

Fig. 9 Integrated navigation results - after IMU errors compensation

The navigational accuracy is improved greatly. Yet there are still large errors, esp. for velocity and position.

The MIMU sample data are used to the above integrated navigation system, then the navigational results are shown in Figure 8 and Figure 9.
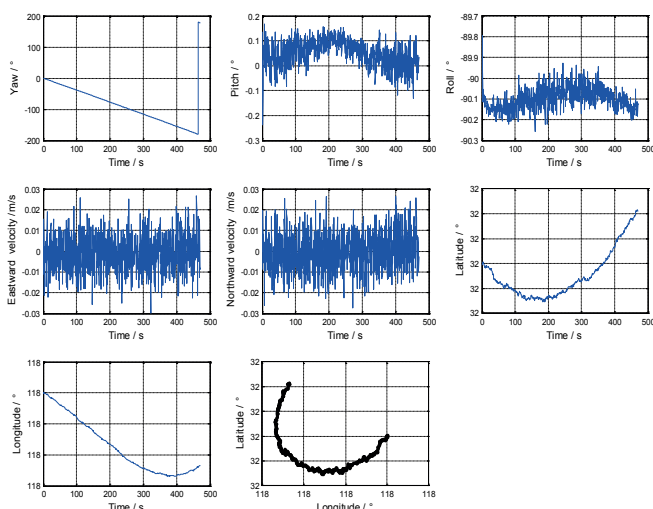

Fig. 8. Integrated navigation results – no IMU errors compensation.

Figure 9 shows that the results are much accurate. Yaw error is less than 0.3 deg; pitch and roll errors are less than 0.2deg; by Matlab data statistics tools, we can see the maximum position error is 0.65m. The integrated navigation system designed above improved navigational accuracy awfully, giving exactly accurate navigation results.
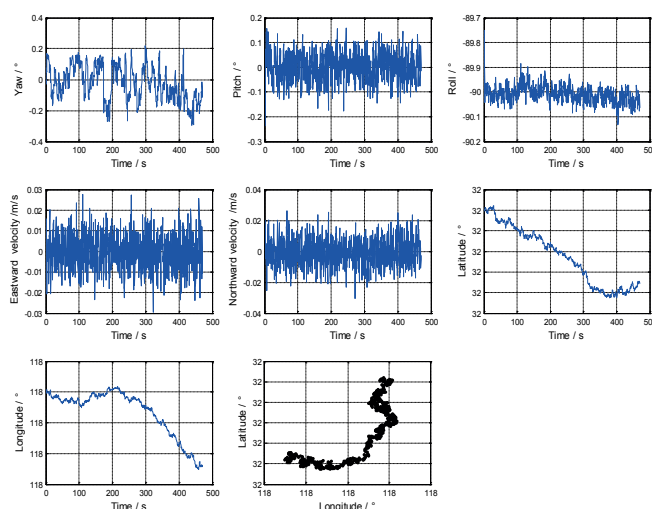
CONCLUSIONS

In this work, an unmanned vessel navigation system based on a low cost MEMS inertial measurement unit and a doppler velocity sonar has been presented. By fusing measurements from both sensor sources with a Kalman filter model, the problem that large errors of low cost MIMU will lead to huge navigation errors has been overcome. Simulation and semi-physical simulation results have demonstrated that the accuracy of the inertial navigation system has improved greatly.

ACKNOWLEDGEMENTS

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