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Application of unscented Kalman filter to novel terrain passive integrated navigation system

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Abstract: To improve the navigation accuracy of an autonomous underwater vehicle (AUV), a novel terrain passive integrated navigation system (TPINS) is presented. According to the characteristics of the underwater environment and AUV navigation requirements of low cost and high accuracy, a novel TPINS is designed with a configuration of the strapdown inertial navigation system (SINS), the terrain reference navigation system (TRNS), the Doppler velocity sonar (DVS), the magnetic compass and the navigation computer utilizing the unscented Kalman filter (UKF) to fuse the navigation information from various navigation sensors. Linear filter equations for the extended Kalman filter (EKF), nonlinear filter equations for the UKF and measurement equations of navigation sensors are addressed. It is indicated from the comparable simulation experiments of the EKF and the UKF that AUV navigation precision is improved substantially with the proposed sensors and the UKF when compared to the EKF. The TPINS designed with the proposed sensors and the UKF is effective in reducing AUV navigation position errors and improving the stability and precision of the AUV underwater integrated navigation.

Key words: autonomous underwater vehicle; strapdown inertial navigation system; unscented Kalman filter; extended Kalman filter; terrain passive integrated navigation system

Autonomous underwater vehicle (AUV) navigation has been in the vanguard of underwater technology development for a long time. Navigation of most AUVs and submarines is based on SINS due to its specific advantages of small volume and high precision[1]. Doppler velocity sonar (DVS) and the magnetic compass are usually exploited to bound the drift in inertial systems. Even with these aids the position error of inertial systems drifts off with time because of the scale effects of velocity sensors[2–3]. Position fixes are needed to allow the vehicle to stay submerged for longer operations. The global positioning system (GPS) position fixes are unavailable when an AUV submerges because electromagnetic signals are blocked by water. It is, therefore, necessary to develop novel methods for obtaining position fixes while the vehicle is submerged. Acoustic positioning is often utilized to provide precision position fixes which also greatly restricts the AUV voyage area within the sonar transponders[4]. A hybrid navigation system based on inertial sensors aided with acoustic velocity sensors was successfully proposed in Refs. [5 – 8]. Bar-Shalom and Bucy et al.[9–10] proposed integrating DVS signals to the long baseline (LBL) system to enhance the position accuracy at deep sea levels. The error sources of the DVS-based navigation systems are misalignment, environmental noises and scale effects, which directly affect navigation performance. Gade[11] proposed an inertial navigation algorithm assisted by DVS, depth and heading sensors. The inertial navigation aided by the DVS indicates slow drift in estimated position because of the integration of inherent errors from the sensors.

Position fixes derived from terrain profile measurements are obtained to overcome the deficiency of area restriction existing in the underwater acoustic positioning. Few applications of underwater terrain navigation have been published though terrain navigation has been exploited for decades in air and land navigation systems. A novel terrain passive integrated navigation system (TPINS) is presented in this paper to make an efficient navigation system which consists of the strapdown inertial navigation system (SINS), the terrain reference navigation system (TRNS), the DVS and the magnetic compass and satisfies the requirements of low cost and high accuracy.

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1 Principle of TPINS

The TPINS consists of the SINS, the DVS, the TRNS and the magnetic compass. The DVS and the magnetic compass provide accurate velocity information relative to the sea bottom and precision heading of the AUV, respectively. The TRNS installed in the AUV is able to provide position fixes intermittently whenever the navigation information of underwater terrain is abundant enough, and it can be valuable information to TPINS especially when DVS cannot detect the bottom reflection. SINS composed of three accelerometers measuring specific force and three gyros measuring turning angular rate are fascinating sensors for the localization and navigation of AUVs because of the advantages of low cost and small volume that can be self-contained in a pressure vessel. The SINS calculates position, velocity and attitude using output data from the inertial measurement unit (IMU) at a frequency of 100 Hz. Therefore, TPINS is an adequate solution to provide a navigation system that has superior performance in comparison with the traditional systems. Information fusion technology is applied with the assistance of digital charts and sensors for ocean geographical features. The block diagram of TPINS for the AUV is shown in Fig. 1.

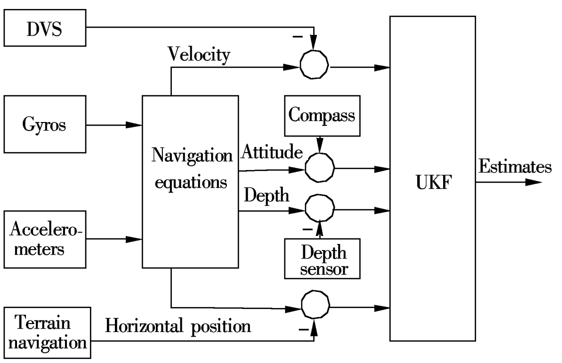

Fig. 1 Block diagram of TPINS

The sensors in TPINS are used to measure the underwater geographical features and the related data processing algorithm estimates the corresponding position. Based on this estimated position, the digital chart is used to fit optimal matching points of the AUV. Finally, the matching position is applied to modify the SINS output.

The UKF exploits various navigation sensors for aiding SINS in a mathematically nonlinear manner. The TPINS indicates that navigation variables, the output of DVS, terrain elevation map and all above estimated variables are fed into the TPINS unscented Kalman filter to obtain accurate estimates.

2 Unscented Kalman Filter

The navigation algorithm performs three major filtering tasks: It estimates the pitch and roll angles, computes the vehicle heading using the magnetic compass measurements and corrects for static magnetic disturbances, and finally estimates the vehicle position using the unscented Kalman filter.

The Kalman filter can be applied to nonlinear systems if a consistent set of predicted quantities can be calculated. These quantities are derived by projecting a prior estimate through a nonlinear transformation. Linearization as applied in the EKF is widely utilized in information fusion[12], while the alternatives induce substantial costs in terms of derivation and computational complexity. Therefore, there is a strong need for a method that is provably more accurate than linearization but does not incur the implementation or computation costs of other higher order filtering schemes. The UKF is developed to meet these needs.

The UKF is founded on unscented transform (UT) which is founded on the intuition that it is easier to approximate a probability distribution than it is to approximate an arbitrary nonlinear function. A set of points (sigma points) from the state-space is deterministically chosen so that their means and covariances match the given means and covariances of the state. The nonlinear function is applied to each point to yield a cloud of transformed points. The statistics of the transformed points can then be calculated to form an estimate of the nonlinearly transformed mean $\bar{\boldsymbol{X}}$ and covariance $\boldsymbol{P}_X$. The sigma points $\boldsymbol{\chi}$ and their corresponding weights W are chosen as follows:

$$\left.\begin{aligned}
\boldsymbol{\chi}^{(0)} &= \bar{\boldsymbol{X}} \\
\boldsymbol{\chi}^{(i)} &= \bar{\boldsymbol{X}} + \left(\sqrt{(n+c)\boldsymbol{P}_X}\right)_i \\
i &= 1, 2, \dots, n \\
\boldsymbol{\chi}^{(i)} &= \bar{\boldsymbol{X}} - \left(\sqrt{(n+c)\boldsymbol{P}_X}\right)_{i-n} \\
i &= n+1, n+2, \dots, 2n \\
W^{(0)} &= \frac{c}{n+c}, \; W^{(i)} = \frac{1}{2(n+c)} \\
i &= 1, 2, \dots, 2n
\end{aligned}\right\} \tag{1}$$

The filter algorithm is implemented using the principle of unscented transformation. The algorithm of the TPINS unscented Kalman filter is as follows[13]:

Step 1 At time t_k the state estimate is $\boldsymbol{X}_k$ and the covariance is $\boldsymbol{P}_k$.

Step 2 Set the off-diagonal element of $\boldsymbol{P}_k$ to zero and compute the sigma points and their corresponding weights.

Step 3 Transform the sigma points through the nonlinear process model.

Step 4 Compute the predicted mean, covariance, the filter gain and update the state estimates and the covariance estimates as follows:

$$\left.\begin{aligned} \boldsymbol{P}_k &= \sum_{i=0}^{2n_x} W^{(i)}(\boldsymbol{\chi}^{(i)} - \overline{\boldsymbol{X}}_k)(\boldsymbol{\chi}^{(i)} - \overline{\boldsymbol{X}}_k)^{\mathrm{T}} + \boldsymbol{Q}_k \\ \boldsymbol{K}_k &= \boldsymbol{P}_k^- \boldsymbol{H}^{\mathrm{T}}(\boldsymbol{H}\boldsymbol{P}_k^-\boldsymbol{H}^{\mathrm{T}} + \boldsymbol{R}_k)^{-1} \\ \overline{\boldsymbol{X}}_k^+ &= \overline{\boldsymbol{X}}_k^- + \boldsymbol{K}_k(\boldsymbol{Z}_k - \hat{\boldsymbol{Z}}_k) \\ \boldsymbol{P}_k^+ &= (\boldsymbol{I} - \boldsymbol{K}_k\boldsymbol{H})\boldsymbol{P}_k^- \end{aligned}\right\} \tag{2}$$

where $\boldsymbol{Z}_k$ is the position measurement from TRNS and $\hat{\boldsymbol{Z}}_k$ is the SINS position measurement estimate. Use $\overline{\boldsymbol{X}}_k^+$ to correct the SINS states and reset the error state to zero.

3 Filter Equations

To compare the performance of the UKF and the EKF, a comparable simulation experiment under the same condition is conducted to determine which algorithm is preferable for improving the AUV navigation accuracy. The linear filter equations for the EKF and nonlinear filter equations for the UKF are elaborated below.

The linear filter states considered in the EKF are the SINS position, velocity, attitude angles and the gyro and accelerometer constant drift. The state vector of the filter is $\boldsymbol{X}_{\mathrm{L}} = \{\delta\lambda,\ \delta L,\ \delta h,\ \delta V_{\mathrm{E}}, \delta V_{\mathrm{N}},\ \delta V_{\mathrm{U}},\ \phi_{\mathrm{E}},\ \phi_{\mathrm{N}},\ \phi_{\mathrm{U}},\ \nabla_X,\ \nabla_Y,\ \nabla_Z, \varepsilon_X, \varepsilon_Y, \varepsilon_Z\}^{\mathrm{T}}$.

The linear error equations can be expressed in a state-space form as[14]

$$\dot{\boldsymbol{\phi}} = -[\boldsymbol{\omega}_{\mathrm{it}}^{\mathrm{t}}]\boldsymbol{\phi} - \boldsymbol{C}_{\mathrm{b}}^{\mathrm{t}}\,\delta\boldsymbol{\omega}_{\mathrm{ib}}^{\mathrm{b}} + \delta\boldsymbol{\omega}_{\mathrm{it}}^{\mathrm{t}} \tag{3}$$

$$\begin{aligned} \delta\dot{\boldsymbol{V}}^{\mathrm{t}} = {}& \boldsymbol{f}^{\mathrm{t}}\boldsymbol{\phi} - (2\boldsymbol{\omega}_{\mathrm{ie}}^{\mathrm{t}} + \boldsymbol{\omega}_{\mathrm{et}}^{\mathrm{t}})\delta\boldsymbol{V}^{\mathrm{t}} + \\ & \boldsymbol{C}_{\mathrm{b}}^{\mathrm{t}}\,\delta\boldsymbol{f}^{\mathrm{b}} + \boldsymbol{V}^{\mathrm{t}}(2\delta\boldsymbol{\omega}_{\mathrm{ie}}^{\mathrm{t}} + \delta\boldsymbol{\omega}_{\mathrm{et}}^{\mathrm{t}}) \end{aligned} \tag{4}$$

$$\delta\dot{\lambda} = \frac{\delta V_{\mathrm{E}}}{(R_{\mathrm{n}}+h)\cos L} - \frac{V_{\mathrm{E}}\delta h}{(R_{\mathrm{n}}+h)^2\cos L} + \frac{V_{\mathrm{E}}\sec L\tan L\delta L}{R_{\mathrm{n}}+h} \tag{5}$$

$$\delta\dot{L} = \frac{\delta V_{\mathrm{N}}}{R_{\mathrm{m}}+h} - \frac{V_{\mathrm{N}}\delta h}{(R_{\mathrm{m}}+h)^2} \tag{6}$$

$$\delta\dot{h} = \delta V_{\mathrm{U}} \tag{7}$$

The nonlinear filter states considered in the UKF are the SINS position, velocity, quaternion errors and the gyro and accelerometer constant drift. The state vector of the filter is $\boldsymbol{X}_{\mathrm{N}} = \{\delta\lambda,\ \delta L,\ \delta h,\ \delta V_{\mathrm{E}},\ \delta V_{\mathrm{N}},\ \delta V_{\mathrm{U}},\ \delta q_0,\ \delta q_1, \delta q_2,\ \delta q_3,\ \nabla_X,\ \nabla_Y,\ \nabla_Z,\ \varepsilon_X,\ \varepsilon_Y,\ \varepsilon_Z\}^{\mathrm{T}}$.

The nonlinear error equations can be expressed in a state-space form as

$$\begin{aligned} \delta\dot{\boldsymbol{Q}}_{\mathrm{b}}^{\mathrm{t}} = {}& \frac{1}{2}\boldsymbol{\Omega}_{\mathrm{u}}(\boldsymbol{\omega}_{\mathrm{ib}}^{\mathrm{b}})\delta\boldsymbol{Q}_{\mathrm{b}}^{\mathrm{t}} - \frac{1}{2}\boldsymbol{\Omega}_{\mathrm{d}}(\boldsymbol{\omega}_{\mathrm{it}}^{\mathrm{t}})\delta\boldsymbol{Q}_{\mathrm{b}}^{\mathrm{t}} + \\ & \frac{1}{2}\boldsymbol{U}(\boldsymbol{Q}_{\mathrm{b}}^{\mathrm{t}})\delta\boldsymbol{\omega}_{\mathrm{ib}}^{\mathrm{b}} - \frac{1}{2}\boldsymbol{Y}(\boldsymbol{Q}_{\mathrm{b}}^{\mathrm{t}})\delta\boldsymbol{\omega}_{\mathrm{it}}^{\mathrm{t}} \end{aligned} \tag{8}$$

$$\begin{aligned} \delta\dot{\boldsymbol{V}}^{\mathrm{t}} = {}& \delta\boldsymbol{C}_{\mathrm{b}}^{\mathrm{t}}\boldsymbol{f}^{\mathrm{b}} - (2\boldsymbol{\omega}_{\mathrm{ie}}^{\mathrm{t}} + \boldsymbol{\omega}_{\mathrm{et}}^{\mathrm{t}})\delta\boldsymbol{V}^{\mathrm{t}} + \\ & \boldsymbol{C}_{\mathrm{b}}^{\mathrm{t}}\,\delta\boldsymbol{f}^{\mathrm{b}} + \boldsymbol{V}^{\mathrm{t}}(2\delta\boldsymbol{\omega}_{\mathrm{ie}}^{\mathrm{t}} + \delta\boldsymbol{\omega}_{\mathrm{et}}^{\mathrm{t}}) \end{aligned} \tag{9}$$

The definitions of $\boldsymbol{\Omega}_{\mathrm{u}}(\cdot), \boldsymbol{\Omega}_{\mathrm{d}}(\cdot), \boldsymbol{U}(\cdot), \boldsymbol{Y}(\cdot)$ and $\delta\boldsymbol{C}$ are described in Ref. [14].

The errors of the gyro and the accelerometer are composed of constant drift and random drift. The constant drift of the gyro and the accelerometer do not change with time.

$$\delta\boldsymbol{f}^{\mathrm{b}} = \begin{Bmatrix} \delta f_X \\ \delta f_Y \\ \delta f_Z \end{Bmatrix} = \begin{Bmatrix} \nabla_X \\ \nabla_Y \\ \nabla_Z \end{Bmatrix} + \begin{Bmatrix} W_{\mathrm{A}X} \\ W_{\mathrm{A}Y} \\ W_{\mathrm{A}Z} \end{Bmatrix} = \nabla + \boldsymbol{W}_{\mathrm{A}} \tag{10}$$

$$\delta\boldsymbol{\omega}_{\mathrm{ib}}^{\mathrm{b}} = \begin{Bmatrix} \delta\omega_X \\ \delta\omega_Y \\ \delta\omega_Z \end{Bmatrix} = \begin{Bmatrix} \varepsilon_X \\ \varepsilon_Y \\ \varepsilon_Z \end{Bmatrix} + \begin{Bmatrix} W_{\mathrm{G}X} \\ W_{\mathrm{G}Y} \\ W_{\mathrm{G}Z} \end{Bmatrix} = \boldsymbol{\varepsilon} + \boldsymbol{W}_{\mathrm{G}} \tag{11}$$

$$\dot{\nabla} = \{\dot{\nabla}_X,\ \dot{\nabla}_Y,\ \dot{\nabla}_Z\}^{\mathrm{T}} = \boldsymbol{0} \tag{12}$$

$$\dot{\boldsymbol{\varepsilon}} = \{\dot{\boldsymbol{\varepsilon}}_X,\ \dot{\boldsymbol{\varepsilon}}_Y,\ \dot{\boldsymbol{\varepsilon}}_Z\}^{\mathrm{T}} = \boldsymbol{0} \tag{13}$$

where $\boldsymbol{W}_{\mathrm{A}}$ and $\boldsymbol{W}_{\mathrm{G}}$ are zero mean Gauss white noises.

Let the real position of the vehicle be $(\lambda_{\mathrm{r}},\ L_{\mathrm{r}},\ h_{\mathrm{r}})$, the position obtained from the TRNS be $(\lambda_{\mathrm{T}},\ L_{\mathrm{T}},\ h_{\mathrm{T}})$, and the position information obtained from the SINS is

$$\lambda_{\mathrm{I}} = \lambda_{\mathrm{r}} + \delta\lambda,\ L_{\mathrm{I}} = L_{\mathrm{r}} + \delta L,\ h_{\mathrm{I}} = h_{\mathrm{r}} + \delta h \tag{14}$$

The position information obtained from the TRNS is

$$\lambda_{\mathrm{T}} = \lambda_{\mathrm{r}} - \frac{N_{\mathrm{E}}}{(R_{\mathrm{n}}+h)\cos L},\ L_{\mathrm{T}} = L_{\mathrm{r}} - \frac{N_{\mathrm{N}}}{R_{\mathrm{m}}+h},\ h_{\mathrm{T}} = h_{\mathrm{r}} - N_{\mathrm{h}} \tag{15}$$

where $N_{\mathrm{E}}, N_{\mathrm{N}}, N_{\mathrm{h}}$ are the position errors of the TRNS along the east, north and up directions, respectively.

The measurement equation of position is

$$\boldsymbol{Z}_{\mathrm{P}} = \begin{Bmatrix} (\lambda_{\mathrm{I}} - \lambda_{\mathrm{T}})(R_{\mathrm{n}}+h)\cos L \\ (L_{\mathrm{I}} - L_{\mathrm{T}})(R_{\mathrm{m}}+h) \\ h_{\mathrm{I}} - h_{\mathrm{T}} \end{Bmatrix} = \begin{Bmatrix} (R_{\mathrm{n}}+h)\cos L\delta\lambda + N_{\mathrm{E}} \\ (R_{\mathrm{m}}+h)\delta L + N_{\mathrm{N}} \\ \delta h + N_{\mathrm{h}} \end{Bmatrix} \tag{16}$$

Let the real velocity of the vehicle in a plane be $(V_{\mathrm{rE}},\ V_{\mathrm{rN}})$, the measured velocity from the DVS be $(V_{\mathrm{DE}},\ V_{\mathrm{DN}})$, and the velocity of the SINS is

$$\left.\begin{aligned} V_{\mathrm{E}} &= V_{\mathrm{rE}} + \delta V_{\mathrm{E}} \\ V_{\mathrm{N}} &= V_{\mathrm{rN}} + \delta V_{\mathrm{N}} \end{aligned}\right\} \tag{17}$$

The velocity from the DVS is

$$\left.\begin{aligned} V_{\mathrm{DE}} &= V_{\mathrm{rE}} - M_{\mathrm{E}} \\ V_{\mathrm{DN}} &= V_{\mathrm{rN}} - M_{\mathrm{N}} \end{aligned}\right\} \tag{18}$$

where $M_{\mathrm{E}}, M_{\mathrm{N}}$ are the measurement errors of the DVS along the east and north directions, respectively.

The measurement equation of velocity is

$$\boldsymbol{Z}_{\mathrm{V}} = \begin{Bmatrix} V_{\mathrm{E}} - V_{\mathrm{DE}} \\ V_{\mathrm{N}} - V_{\mathrm{DN}} \end{Bmatrix} = \begin{Bmatrix} \delta V_{\mathrm{E}} + M_{\mathrm{E}} \\ \delta V_{\mathrm{N}} + M_{\mathrm{N}} \end{Bmatrix} \tag{19}$$

Suppose that the real heading of the vehicle is ϕ_{r}, the heading from the magnetic compass is ϕ_{C}, the heading of the SINS and the compass are $\phi_{\mathrm{I}} = \phi_{\mathrm{r}} + \delta\phi_{\mathrm{I}}$

and $\phi_C = \phi_r - \delta\phi_C$.

The measurement equation of heading is

$$Z_{\phi} = \phi_I - \phi_C = \delta\phi_I + \delta\phi_C \tag{20}$$

4 Simulation Results

The simulation experiments of TPINS are carried out by Matlab/Simulink and VC++ tools. Suppose that the AUV is navigating on a flat plane at a certain depth. The AUV with TPINS has initial conditions and model parameters as follows: $V_E = 15$ m/s, $V_N = 15$ m/s, $\phi_E(0) = 45''$, $\phi_N(0) = 45''$, $\phi_U(0) = 2'$, $\Delta\lambda(0) = 5''$, $\Delta L(0) = 5''$, $\Delta h(0) = 2.0$ m, $\Delta V_E(0) = 0.1$ m/s, $\Delta V_N(0) = 0.1$ m/s, $\Delta V_U(0) = 0.2$ m/s. The gyro constant drift and random drift are 0.01°/h and 0.02°/h, respectively; the accelerometer constant drift and random drift are 50 and 100 μg, respectively. $\boldsymbol{P}(0) = \mathrm{diag}\{\boldsymbol{X}_i(0)^2\}$, $i = 1, 2, \dots, 15$; the measurement error covariance of DVS is 0.016 m^2/s^2; the measurement error covariance of the magnetic compass is 0.000 4 rad^2; and the position error of TRNS on a plane is 100 m. Simulation experiments are carried out with the EKF and the UKF in contrast under the same initial conditions.

Fig. 2 and Fig. 3 show the error variability of attitude angles and position with the EKF. The pitch and roll angles are less than 4′(RMS), and the heading error is less than 7′(RMS). The position errors are about 0.6′.

Fig. 4 and Fig. 5 show the error variability of attitude angles and position with the UKF. The pitch and roll angles are less than 2′(RMS), the heading error is less than 4′(RMS). The position errors are within 0.2′.

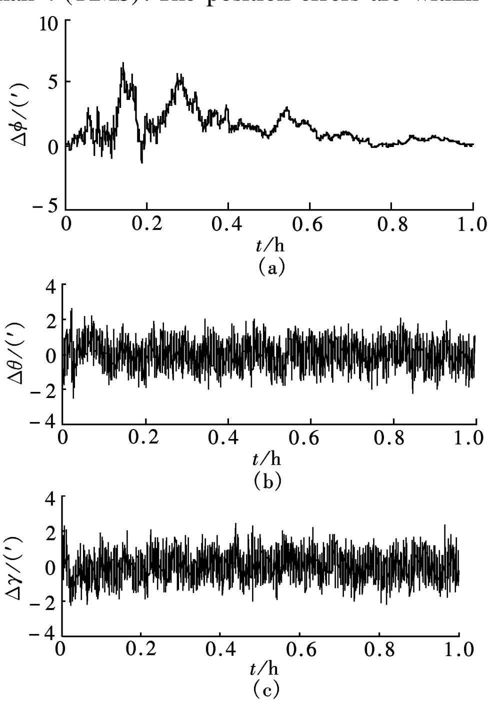

Fig. 2 Variability of attitude errors with EKF. (a) Heading error; (b) Pitch error; (c) Roll error

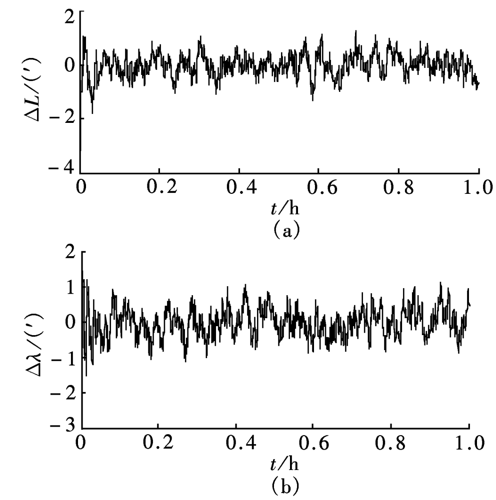

Fig. 3 Variability of position errors with EKF. (a) Latitude error; (b) Longitude error

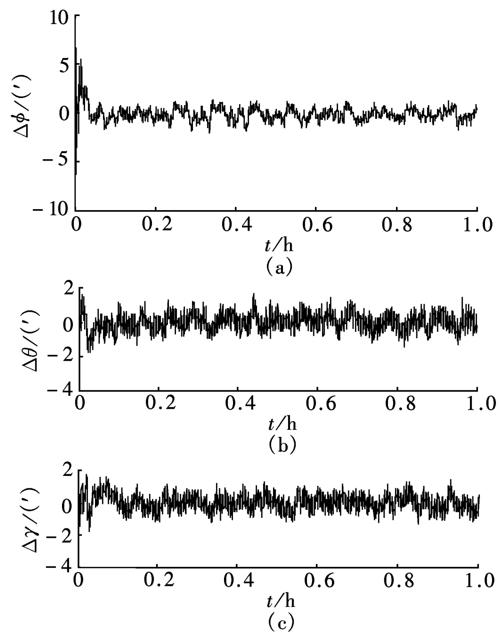

Fig. 4 Variability of attitude errors with UKF. (a) Heading error; (b) Pitch error; (c) Roll error

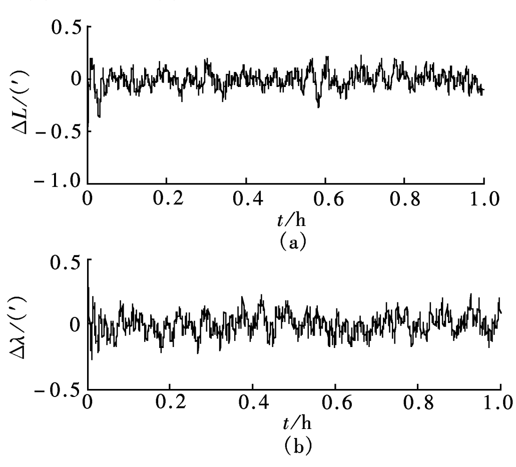

Fig. 5 Variability of position errors with UKF. (a) Latitude error; (b) Longitude error

5 Conclusion

A novel terrain passive integrated navigation system is presented that utilizes SINS, TRNS, DVS, and magnetic compass to passively bound SINS position error. The UKF provides better navigation performance than that using the EKF. The AUV position error is substantially reduced from the simulation experiment results and the precision of the underwater navigation is greatly improved. TPINS is of low cost, high performance and can satisfy the requirements for maintaining high stability and accuracy navigation for the AUV over a long time.

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无迹卡尔曼滤波在新型地形无源组合导航系统中的应用

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摘要:为了提高自主水下航行器的导航精度,提出了一种新型地形无源组合导航系统. 根据水下环境特点和航行器导航高精度和低成本的要求,采用捷联式惯性导航系统、地形辅助导航系统、多普勒速度声纳、电子磁罗经和利用 UKF 进行信息融合的导航计算机组成新型水下地形无源组合导航系统,并给出了 EKF 线性滤波方程、UKF 非线性滤波方程和导航传感器量测方程. 对比仿真实验表明,采用建议的传感器和 UKF 信息融合方式比采用 EKF 方式提高了水下航行器导航定位的精度. 采用不同的导航传感器和 UKF 信息融合方法的地形无源组合导航系统可以有效地减小水下航行器导航位置误差,提高组合导航的稳定性和精度.

关键词:自主水下航行器;捷联式惯性导航系统;无迹卡尔曼滤波;扩展卡尔曼滤波;地形无源组合导航系统

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