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A Model-Free Hull Deformation Measurement Method Based on Attitude Quaternion Matching

YING HE, XIAOLI ZHANG, AND XIAFU PENG
Department of Automation, School of Aeronautics and Astronautics, Xiamen University, Xiamen 361005, China

Corresponding author: Xiaoli Zhang (zhxl@xmu.edu.cn)

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ABSTRACT Hull deformation is an important factor that affects the attitude accuracy of shipborne weaponry and equipment, and hull deformation should be estimated and compensated for a large ship to establish a high-precision attitude reference. The traditional inertial measurement matching methods for hull deformation estimation largely depend on prior deformation information. However, the real-time deformation data characteristics are commonly different from the characteristics of historical deformation data, and a measurement matching method based on an inaccurate deformation model will result in a larger deformation estimation error. To overcome this difficulty, a hull deformation measurement method based on attitude quaternion matching and an online neural network is proposed. First, a deformation measurement equation based on quaternion matching is established with the angular velocity information measured by inertial sensors. Then, an online neural network is used to fit the deformation angle in the measurement equation to avoid establishing the deformation model. Considering the real-time training of an online neural network, the connection weight coefficients are estimated using a nonlinear filter. The simulation results demonstrate that the proposed method can accurately estimate the deformation without prior information of the deformation.

INDEX TERMS Inertial sensors, hull deformation, attitude quaternion, online neural network.

I. INTRODUCTION

Inertial navigation is based on the basic property that the mass body has inertia. It uses inertial sensors, such as gyroscopes and accelerometers, to detect the motion state of objects and calculates the object position and velocity information to navigate. The inertial navigation system is based on the principle of inertia, which does not require external information or radiation information to the outside world, and can be globally positioned and oriented in three dimensions by the system in all weather conditions and media environments. Because of these prominent advantages, the inertial navigation system has become an indispensable core navigation device in the integrated navigation systems of the modern ship, aircraft, helicopters, vehicles and long-range precision-guided weapons [1]–[4]. Before entering the navigation state, the inertial navigation system must determine the initial value of the system, which is the initial position of the system and the direction of the initial attitude of the system.

Large ships are equipped with a high-precision inertial navigation system as the inertial guidance system of the main ship. Shipborne weapons, such as carrier-based aircraft, helicopters, missiles and other weapons, have their own inertial navigation systems; their accuracy is commonly not notably high relative to the main inertial navigation system (MINS), and they are called the slave inertial navigation system (SINS) [5], [6]. Generally, the slave inertial navigation system uses the information of a high-precision main inertial navigation system to set its initial system values; this process is referred to as a transfer alignment. However, the ship is not absolutely rigid; under the effect of the external environment and stress, such as the impact of waves, changes in the ship's own load and long- term thermal expansion and contraction effects, the shell of the ship will deform. The ship deformation will seriously affect the accuracy of the transfer alignment, which affects the rapid response and precision strike of the weaponry. Therefore, estimating the deformation of the hull and eliminating the effect of hull deformation have become a hot spot both at home and abroad.

At present, various hull deformation measurement methods have been consecutively proposed, such as optical measurement, strain gauge measurement, hydraulic measurement, photogrammetry and inertial measurement. Considering economic, equipment installation environment and other factors, these measurement methods have advantages and disadvantages. Among them, the inertial measurement matching method has become a hot research area because of its convenient installation, dynamic adaptability, etc. Its scheme is to lay inertial sensors near the MINS and SINS, establish the Kalman filtering state equation and measurement equation based on the inertial sensor detection data, hull deformation angle model and the relationship between the MINS coordinate system and the SINS coordinate system so that the hull deformation angle can be estimated in real time [7]–[9]. Deformation measurement equation and hull deformation modeling are the keys to this method. In the study of the deformation measurement equation, the matching methods based on angular velocity matching [10], [11] or the combination of angular velocity and velocity increment [12] have been proposed, but there is no deformation measurement equation based on attitude quaternion matching. In the aspect of hull deformation modeling, the hull deformation angle is divided into two parts (static deformation and dynamic deformation) and modeled. Because of the long period of static deformation, it is commonly modeled as a constant. According to the statistical properties of dynamic deformation, it is usually modeled as a two-order Markov process [13]. However, during the actual voyage, the deformation model of a ship is not always unchanged. Even if the model is correct, the parameters are also changing, and the inaccurate deformation angle model will reduce the estimation accuracy of the deformation.

In our work, a new model-free hull deformation measurement method based on the attitude quaternion matching is proposed. The proposed method chooses two ring laser gyro units (LGU), which are two sets of three mutually orthogonal gyros as the inertial sensors, and uses the attitude quaternions of two measuring points near the MINS and SINS to build a deformation measurement equation. To avoid the problem of using historical deformation data to establish deformation models, an online neural network with two layers of parameters is used to estimate the deformation angle in the deformation measurement equation. In addition, to train the neural network online, a nonlinear filtering optimization method is applied to estimate the weights of the neural network so that the hull deformation angle can be estimated in real time. Simulation results verify that the proposed method in this paper is superior to the traditional deformation modeling method without a prior deformation model.

II. ATTITUDE QUATERNION MATCHING ALGORITHM

A. COORDINATE SYSTEM DEFINITION

As illustrated in Fig. 1, two ring laser gyro units LGU1 and LGU2 are installed on the hull center and the bow, respectively. The LGU1 coordinates are $ox1y1z1$; the x-axis $ox1$ is along the starboard side of the hull, the y-axis $oy1$ is parallel

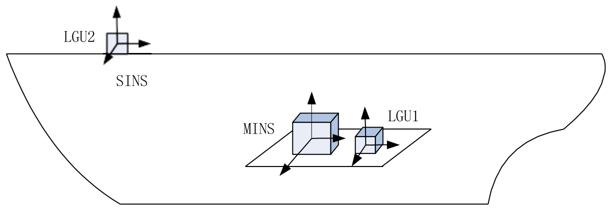

FIGURE 1. Schematic diagram of the deformation measurement with ring laser gyros.

to the longitudinal axis of the hull, and the z-axis $oz1$ is perpendicular to the deck. The LGU1 coordinates $ox1y1z1$ have been aligned with the carrier coordinates $b1$. The LGU2 coordinates $ox2y2z2$ are defined as the coordinates $ox1y1z1$ and consistent with the carrier coordinates $b2$. The total misalignment Euler angle between the coordinates $ox1y1z1$ and $ox2y2z2$ is φ. The carrier coordinates $b1$ at the initial time $t0$ are selected as the inertial frame $i1$ for the LGU1. The carrier coordinates $b2$ at the initial time $t0$ are selected as the inertial frame $i2$ for LGU2. However, because of the gyro drift, the inertial frames used by LGU1 and LGU2 in the process of attitude computation are $\tilde{i}_1$ and $\tilde{i}_2$, respectively; we call $\tilde{i}_1$ and $\tilde{i}_2$ the calculation inertial frames.

B. ATTITUDE QUATERNION MATCHING ALGORITHM PRINCIPLE

According to the definition of the coordinate system, the relationship between the attitude matrices is expressed as

$$C_{b_2}^{b_1} = C_{b_1}^{\tilde{i}_1 T} C_{\tilde{i}_1}^{i_1 T} C_{i_2}^{i_1} C_{\tilde{i}_2}^{i_2} C_{b_2}^{\tilde{i}_2} \tag{1}$$

where $C_{b_2}^{b_1}$ is the direction cosine matrix between $b1$-frame and $b2$-frame; $C_{b_1}^{\tilde{i}_1}$ is the attitude matrix of LGU1; $C_{b_2}^{\tilde{i}_2}$ is the attitude matrix of LGU2; $C_{\tilde{i}_1}^{i_1}$ and $C_{\tilde{i}_2}^{i_2}$ are the rotation matrices from the calculation inertial frames to the ideal inertial frames; $C_{i_2}^{i_1}$ is the direction cosine matrix between $i1$-frame and $i2$-frame at initial time $t0$.

We rewrite the above formula as

$$C_{b_1}^{\tilde{i}_1 T} = C_{b_2}^{b_1} C_{\tilde{i}_2}^{b_2} C_{i_2}^{\tilde{i}_2} C_{i_1}^{i_2} C_{\tilde{i}_1}^{i_1} \tag{2}$$

which corresponds to the quaternion equation as follows

$$Q_{b_1}^{\tilde{i}_1} = Q_{b_1}^{b_2} \otimes Q_{b_2}^{\tilde{i}_2} \otimes Q_{\tilde{i}_2}^{i_2} \otimes Q_{i_2}^{i_1} \otimes Q_{i_1}^{\tilde{i}_1} \tag{3}$$

Let θ_{1i} and θ_{2i} be the Euler angles that correspond to $Q_{i_1}^{\tilde{i}_1}$ and $Q_{i_2}^{\tilde{i}_2}$, respectively. Let φ_0 be the Euler angle that correspond to $Q_{i_2}^{i_1}$.Then, the above formula is approximated as

$$Q_{b_1}^{\tilde{i}_1} = Q_{b_1}^{b_2} \otimes Q_{b_2}^{\tilde{i}_2} \otimes \begin{bmatrix} 1 \\ -\frac{\theta_{2i}}{2} \end{bmatrix} \otimes \begin{bmatrix} 1 \\ \frac{\varphi_0}{2} \end{bmatrix} \otimes \begin{bmatrix} 1 \\ \frac{\theta_{1i}}{2} \end{bmatrix} \tag{4}$$

where

$$\begin{bmatrix} 1 \\ -\frac{\theta_{2i}}{2} \end{bmatrix} \otimes \begin{bmatrix} 1 \\ \frac{\varphi_0}{2} \end{bmatrix} \otimes \begin{bmatrix} 1 \\ \frac{\theta_{1i}}{2} \end{bmatrix} = (1 - \frac{\theta_{2i}}{2}) \otimes (1 + \frac{\varphi_0}{2}) \otimes (1 + \frac{\theta_{1i}}{2})$$

$$= 1 + \frac{\theta_{1i}}{2} - \frac{\theta_{2i}}{2} + \frac{\varphi_0}{2}$$

$$= \begin{bmatrix} 1 \\ \frac{\theta_{1i}}{2} - \frac{\theta_{2i}}{2} + \frac{\varphi_0}{2} \end{bmatrix}$$

Omitting the second-order small quantities, we have

$$Q_{b_1}^{\tilde{i}_1} = Q_{b_1}^{b_2} \otimes Q_{b_2}^{\tilde{i}_2} \otimes \begin{bmatrix} 1 \\ \frac{\theta_{1i}}{2} - \frac{\theta_{2i}}{2} + \frac{\varphi_0}{2} \end{bmatrix} \tag{5}$$

Multiplying both sides of (5) by $Q_{\tilde{i}_2}^{b_2}$, we obtain

$$Q_{\tilde{i}_2}^{b_2} \otimes Q_{b_1}^{\tilde{i}_1} = Q_{\tilde{i}_2}^{b_2} \otimes Q_{b_1}^{b_2} \otimes Q_{b_2}^{\tilde{i}_2} \otimes \begin{bmatrix} 1 \\ \frac{\theta_{1i}}{2} - \frac{\theta_{2i}}{2} + \frac{\varphi_0}{2} \end{bmatrix} \tag{6}$$

With φ as the Euler angle corresponding to $Q_{b_1}^{b_2}$, we obtain

$$\begin{aligned} Q_{\tilde{i}_2}^{b_2} \otimes Q_{b_1}^{\tilde{i}_1} &= Q_{\tilde{i}_2}^{b_2} \otimes \begin{bmatrix} 1 \\ \frac{\varphi}{2} \end{bmatrix} \otimes Q_{b_2}^{\tilde{i}_2} \otimes \begin{bmatrix} 1 \\ \frac{\theta_{1i}}{2} - \frac{\theta_{2i}}{2} + \frac{\varphi_0}{2} \end{bmatrix} \\ &= \begin{bmatrix} 1 \\ Q_{\tilde{i}_2}^{b_2} \otimes \frac{\varphi}{2} \otimes Q_{b_2}^{\tilde{i}_2} \end{bmatrix} \otimes \begin{bmatrix} 1 \\ \frac{\theta_{1i}}{2} - \frac{\theta_{2i}}{2} + \frac{\varphi_0}{2} \end{bmatrix} \\ &= \begin{bmatrix} 1 \\ C_{b_2}^{\tilde{i}_2} \cdot \frac{\varphi}{2} \end{bmatrix} \otimes \begin{bmatrix} 1 \\ \frac{\theta_{1i}}{2} - \frac{\theta_{2i}}{2} + \frac{\varphi_0}{2} \end{bmatrix} \\ &= \begin{bmatrix} 1 \\ C_{b_2}^{\tilde{i}_2} \cdot \frac{\varphi}{2} + \frac{\theta_{1i}}{2} - \frac{\theta_{2i}}{2} + \frac{\varphi_0}{2} \end{bmatrix} \end{aligned} \tag{7}$$

Let

$$Q = Q_{\tilde{i}_2}^{b_2} \otimes Q_{b_1}^{\tilde{i}_1} = \begin{bmatrix} 1 \\ Q_1 \\ Q_2 \\ Q_3 \end{bmatrix};$$

multiplying both sides of (7) by 2 and taking the last three rows of both sides, we obtain

$$\begin{bmatrix} 2Q_1 \\ 2Q_2 \\ 2Q_3 \end{bmatrix} = \begin{bmatrix} C_{b_2}^{\tilde{i}_2} \cdot \varphi + \theta_{1i} - \theta_{2i} + \varphi_0 \end{bmatrix} \tag{8}$$

Let $Z = \begin{bmatrix} 2Q_1 \\ 2Q_2 \\ 2Q_3 \end{bmatrix}$; then, we rewrite the above formula as

$$Z = C_{b_2}^{\tilde{i}_2} \cdot \varphi + \theta_{1i} - \theta_{2i} + \varphi_0 \tag{9}$$

III. FITTING HULL DEFORMATION ANGLE BY ONLINE NEURAL NETWORK

To solve the problem that historical deformation data are required to model the hull deformation, an online neural network is used to estimate the deformation angle of the hull. The online neural network uses a two-layer parametric neural network, which is trained online using a non-linear filtering algorithm to achieve the real-time deformation estimation [14]–[18].

In the two-layer parameter neural network, the connection weight coefficient W contains the input coefficient W^r, input threshold b^r, output coefficient W^c and output threshold b^c:

$$W = [W^r, b^r, W^c, b^c]^T \tag{10}$$

where $W^r = [(W_1^r)^T, (W_2^r)^T, (W_3^r)^T]^{\mathrm{T}}$; $b^r = [b_1^r, b_2^r, \ldots, b_l^r]^T$ (l is the number of neurons in the middle layer)

$$\begin{aligned} W_i^r &= [W_{i,1}^r, W_{i,2}^r, \ldots, W_{i,l}^r]^{\mathrm{T}} \quad (i = 1, 2, 3) \\ W^c &= [(W_1^c)^T, (W_2^c)^T, \ldots, (W_l^c)^T]^{\mathrm{T}} \quad b^c = [b_1^c, b_2^c, b_3^c]^T \\ W_j^c &= [W_{j,1}^c, W_{j,2}^c, W_{j,3}^c]^{\mathrm{T}} \quad (j = 1, 2, \ldots, l) \end{aligned}$$

Let $g(Z, W)$ be the online neural network; its input is the measurement vector Z in formula (9), and its target output is $C_{\tilde{i}_2}^{b_2} \cdot [Z - (\theta_{1i} - \theta_{2i} + \varphi_0)]$, i.e., the hull deformation angle φ. We consider the connection weight coefficient W time-invariant, i.e., $\dot{W} = 0$. W is estimated using a nonlinear filter online.

IV. ESTABLISHMENT OF THE FILTER MODEL FOR SHIP DEFORMATION

A. ESTABLISHMENT OF THE STATE EQUATION

The model of the laser gyro constant drift and random drift is

IMU1 constant drift: $\dot{\varepsilon}_{1o} = 0$

IMU1 random drift: $\dot{\varepsilon}_{1r} + \mu_i \varepsilon_{1r} = \sigma_i \sqrt{2\mu_i} w(t)$

IMU2 constant drift: $\dot{\varepsilon}_{2o} = 0$

IMU2 random drift: $\dot{\varepsilon}_{2r} + \mu_i \varepsilon_{2r} = \sigma_i \sqrt{2\mu_i} w(t)$

where ε_{1o} and ε_{2o} are the gyro constant drift of IMU1and IMU2, respectively; ε_{1r} and ε_{2r} are the gyro random drift of IMU1 and IMU2, respectively; μ_i is the first-order Markov coefficient of the gyro random drift; σ_i is the mean square deviation of the gyro drift; $w(t)$ is the white noise.

Because of the gyro drift, the calculated coordinate systems $\tilde{i}_1$ and $\tilde{i}_2$ gradually deviate from the actual coordinate systems i_1 and i_2. The transform relationship between the misalignment angle of the inertial space and the gyro drift is as follows

$$\begin{cases} \dot{\theta}_{1i} = -C_{b_1}^{i_1}(\varepsilon_{1o} + \varepsilon_{1r}) \\ \dot{\theta}_{2i} = -C_{b_2}^{i_2}(\varepsilon_{2o} + \varepsilon_{2r}) \end{cases} \tag{11}$$

$C_{b_1}^{i_1}$ and $C_{b_2}^{i_2}$ are the real attitude arrays of LGU1 and LGU2 whose values are approximated by $C_{b_1}^{\tilde{i}_1}$ and $C_{b_2}^{\tilde{i}_2}$, respectively, in the calculation.

The deformation angle φ_0 is a constant at initial time t_0, so we have

$$\dot{\varphi}_0 = 0 \tag{12}$$

Hence

$$\begin{cases} \dot{\varphi}_0 = 0 \\ \dot{\theta}_{1i} = -C_{b_1}^{i_1}(\varepsilon_{1o} + \varepsilon_{1r}) \\ \dot{\theta}_{2i} = -C_{b_2}^{i_2}(\varepsilon_{2o} + \varepsilon_{2r}) \\ \dot{\varepsilon}_{1o} = 0 \\ \dot{\varepsilon}_{1r} + \mu_i \varepsilon_{1r} = \sigma_i \sqrt{2\mu_i} w(t) \\ \dot{\varepsilon}_{2o} = 0 \\ \dot{\varepsilon}_{2r} + \mu_i \varepsilon_{2r} = \sigma_i \sqrt{2\mu_i} w(t) \end{cases} \tag{13}$$

We denote state vector X as

$$X = [\theta_{i_1} \quad \theta_{i_2} \quad \varepsilon_{1o} \quad \varepsilon_{2o} \quad \varepsilon_{1r} \quad \varepsilon_{2r} \quad \varphi_0]^T$$

Therefore, (13) can be simplified as follows

$$\dot{X} = FX + G \cdot w(t) = f(X) + G \cdot w(t) \tag{14}$$

$\hat{X} = [X^T, W^T]^T$ is a new state variable obtained by integrating state variable X and the weight coefficient of the neural network, and W is considered time-invariant.

After the discretization of the above state equations, there is

$$X_{k+1} = f(X_k) + G \cdot w_k \tag{15}$$

The state equation after extending the state variables is

$$\hat{X}_{k+1} = \begin{bmatrix} X_{k+1} \\ W_{k+1} \end{bmatrix} = \begin{bmatrix} f(X_k) \\ W_k \end{bmatrix} + \begin{bmatrix} G & 0 \\ 0 & E \end{bmatrix} \cdot w_k$$
$$= f(\hat{X}_k) + \hat{G} \cdot w_k \tag{16}$$

where $E = \begin{bmatrix} 1 & & \\ & \ddots & \\ & & 1 \end{bmatrix}_{n_w \times n_w}$; n_w is the dimension of the coefficient of connection weight; the system state equation after extending the state variables is rewritten as

$$\hat{X}_{k+1} = f(\hat{X}_k) + \hat{G} \cdot w_k \tag{17}$$

B. ESTABLISHMENT OF THE MEASUREMENT EQUATION

According to (9), the measurement equation of the discrete system is expressed as

$$Z_{k+1} = h(\hat{X}_{k+1}) + C_{b_{2,k+1}}^{\tilde{i}_2,k+1} \cdot g(Z_{k+1}, W_{k+1}) + v_{k+1} \tag{18}$$

where $h(X_{k+1}) = \theta_{1i,k+1} - \theta_{2i,k+1} + \varphi_{0,k+1}$, and v_{k+1} is the measurement noise.

C. ESTIMATION OF THE OPTIMAL STATE USING A NONLINEAR FILTER FUNCTION

The system state equation and observation equation after extending the state variables are described as

$$\begin{cases} \hat{X}_{k+1} = f(\hat{X}_k) + \hat{G} \cdot w_k \\ Z_{k+1} = h(\hat{X}_{k+1}) + C_{b_{2,k+1}}^{\tilde{i}_2,k+1} \cdot g(Z_{k+1}, W_{k+1}) + v_{k+1} \end{cases} \tag{19}$$

Because the observation equation is nonlinear, the nonlinear filter is used to solve the system equation. In this paper, the Unscented Kalman filter (UKF) algorithm is adopted in the time update and measurement update stage; then, the ship deformation is estimated and compensated.

V. SIMULATION VERIFICATION AND RESULT ANALYSIS

A. SIMULATION CONDITIONS

The ship sways around three axes X, Y and Z with the sine law of amplitude of 4 degrees, 5 degrees and 3 degrees, respectively; the corresponding swing cycles on the three axes are 8 seconds, 7 seconds, and 6 seconds, respectively, and their initial phases are randomly selected. The hull deformation is composed of two parts: quasi-static deformation and dynamic deformation. The quasi-static deformation on the axes X, Y and Z is set to a sinusoidal regular motion with a period of 4 hours. The dynamic deformation is set to a second-order Markov process:

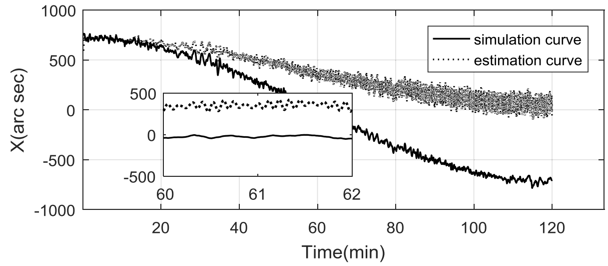

FIGURE 2. Estimation of the hull deformation angle on the x-axis with the traditional method.

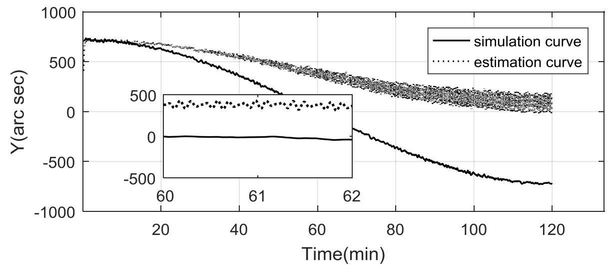

FIGURE 3. Estimation of the hull deformation angle on the y-axis with the traditional method.

$$\ddot{\theta}_i + 2\mu_i\dot{\theta}_i + b_i^2\theta_i = 2b_i\sqrt{D_i\mu_i}w(t), \quad i = x, y, z \tag{20}$$

where the parameters are set as follows:

$$\mu = [\mu_x \quad \mu_y \quad \mu_z] = [0.1 \quad 0.08 \quad 0.06],$$
$$\lambda = [\lambda_x \quad \lambda_y \quad \lambda_z] = [0.1 \quad 0.1 \quad 0.1]$$
$$b^2 = \mu^2 + \lambda^2;$$
$$D = [D_x \ D_y \ D_z] = [3 \times 10^{-7} \ 2 \times 10^{-7} \ 8 \times 10^{-7}]。$$

The constant drift of the two sets of three-axis gyro is $0.05°/h$, and the random drift is a first-order Markov process. The sampling rate is set to 10 Hz, the simulation time is 120 minutes, and the Unscented Kalman Filter is used to solve the state equations and measurement equations of the system.

To verify the effectiveness of the proposed method, the traditional deformation measurement method is selected as the contrasting algorithm. This method has the identical matching model and unscented Kalman filter but requires deformation modeling. The traditional method models the deformation angle as static deformation and dynamic deformation. The static deformation is modeled as a constant value, and the dynamic deformation is modeled as a second-order Markov process, which is consistent with the dynamic model (20), but the model parameters are different from (20) to construct the simulation environment where the traditional method has an inaccurate deformation modeling.

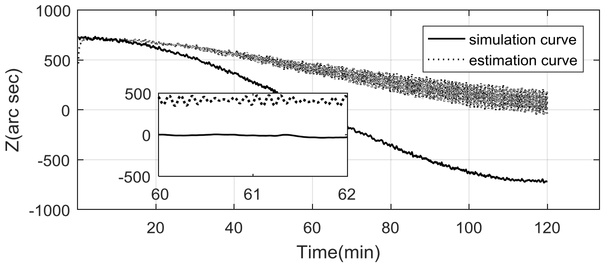

FIGURE 4. Estimation of the hull deformation angle on the z-axis with the traditional method.

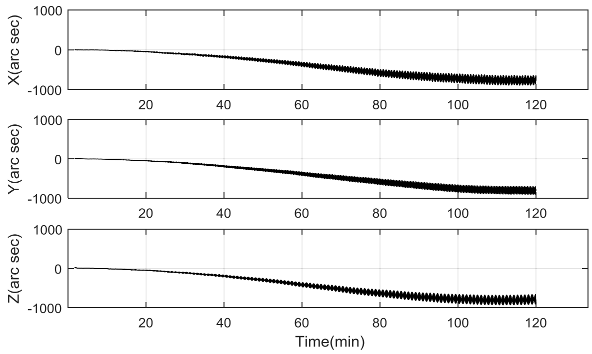

FIGURE 5. Estimation error of the hull deformation angle on the three axes with the traditional method (unit: arcsecond).

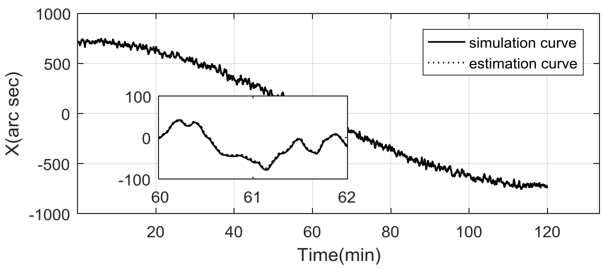

FIGURE 6. Estimation of the hull deformation angle on the x-axis with the proposed method.

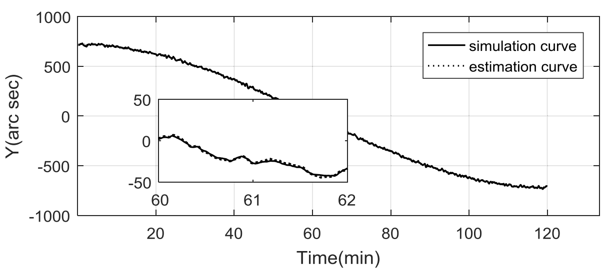

FIGURE 7. Estimation of the hull deformation angle on the y-axis with the proposed method.

B. EXPERIMENTAL RESULTS AND DISCUSSION

Figs. 2-5 show that the traditional method with inaccurate deformation modeling causes larger deformation estimation errors such as 1000″. The root mean square error (RMSE) of the deformation measurement for the last hour on the X, Y and Z axes are 644.1181″, 666.3844″ and 693.5052″, respectively.

Figs. 6-9 show that the proposed method can accurately estimate the deformation angle without a priori

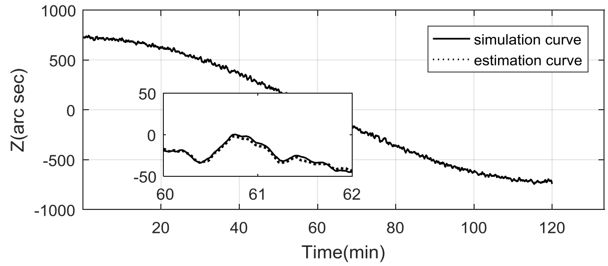

FIGURE 8. Estimation of the hull deformation angle on the z-axis with the proposed method.

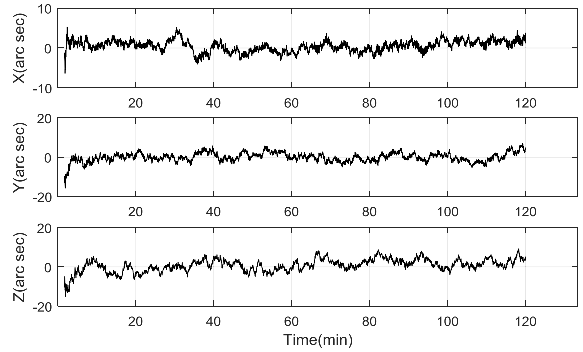

FIGURE 9. Estimation error of the hull deformation angle on the three axes with the proposed method (units: arcsecond).

deformation model. Figs. 6-8 show that the estimation curve almost coincides with the simulation curve. As shown in Fig. 9, the long-term measurement errors on the three axes are within 10″. The root mean square error (RMSE) of the deformation measurement for the last hour on the X, Y and Z axes are 1.3992″, 2.1133″ and 3.3144″, respectively. Figs. 2-9 show the effectiveness of the proposed method.

VI. CONCLUSION

A new hull deformation measurement method has been proposed in this paper to avoid establishing the priori deformation model based on the attitude quaternion matching and online neural network. A deformation measurement filter observation with the attitude quaternion has been established. The attitude quaternion is updated relative to the inertial space through the angular incremental data of two LGUs. Simultaneously, we apply an online neural network to estimate the hull deformation angles in the measurement equation without the priori deformation information. This method estimates the weights of online neural networks by the Unscented Kalman Filter (UKF) for the real-time performance of deformation estimation. The simulation results show that compared to the traditional method, we can accurately estimate the deformation without the accurate deformation model using the proposed matching method and online neural network.

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YING HE received the bachelor's degree in computational mathematics from Guizhou Normal University, Guiyang, China, in 2012, and the master's degree in computer applications technology from Southwest University, Chongqing, China, in 2015. He is currently pursuing the Ph.D. degree in control theory and control engineering with Xiamen University. His research interests include inertial measurement technology and integrated navigation.

XIAOLI ZHANG received the Ph.D. degree in control theory and application from Northeastern University, China, in 2001. From 2002 to 2003, he was a Post-Doctoral Research Fellow with the Department of Automation, Tsinghua University. Since 2004, he has been with the Department of Automation, Xiamen University, China, where he is currently an Associate Professor. His main research interests include switched systems, nonlinear systems, and robust control.

XIAFU PENG received the bachelor's and master's degrees in control theory and applications from the Harbin Institute of Naval Engineering, Harbin, China, in 1984 and 1994, respectively, and the Ph.D. degree in control science and engineering from Harbin Engineering University, Harbin, in 2001. Since 2002, he has been with the Department of Automation, Xiamen University, China, where he is currently a Professor.

His research interests include inertial technology and intelligent transportation system.