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An IMU dynamic zero compensation algorithm based on LSTM neural network model

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Abstract

The inertial measurement unit (IMU) will constantly drift in the zero position due to the influence of temperature and running time during measurement. This type of drift will affect the long-term accuracy of the IMU measurement. In response to this problem, according to the long and short-term memory network (LSTM) model, using its memory unit characteristics, combining the previous and current moments of the IMU runtime, continuously updating the data of the attitude instrument, thus establishing a model based on the LSTM neural network IMU dynamic zero compensation equation. According to experimental verification, in the case of temperature changes, the zero position of the IMU can increase the accuracy of the test heading angle by 9.4%. Under constant temperature conditions, the measurement error of long-running IMU can be reduced by 5-6 times.

Keywords

Inertial measurement unit; Dynamic bias; Long and short-term memory network.

1. Introduction

An inertial measurement unit (IMU)[1] is a device that measures the three-axis attitude angle (or angular rate) and acceleration of an object. Generally, an IMU contains three single-axis accelerometers and three single-axis gyroscopes[2, 3]. The gyroscope is a key component in the inertial navigation technology and is widely used in aerospace, military, navigation and other fields. The performance of the gyroscope is one of the key factors affecting the performance of the inertial navigation system. Therefore, the performance of the gyroscope is improved. Performance plays a very important role in the accuracy of inertial navigation. Among them, the stability of the bias is an important performance index of the gyroscope[4]. There are many algorithms for suppressing the bias of the gyro, and these algorithms can also effectively suppress the bias of the IMU. After the zero offset of the inertial sensor device is suppressed [5], the zero drift of the inertial sensor device is suppressed to a certain extent. However, affected by factors such as temperature and operating time, the zero position of the inertial sensor will continue to drift to a certain extent. Such drift cannot be ignored in higher-precision engineering applications. IMU to achieve dynamic measurement, the gyroscope must effectively compensate for zero drift within the entire measurement time and operating temperature range [6].

Based on the above, this article first analyzes the difference between the LSTM neural network model and the general network model, and analyzes the characteristics of the LSTM neural network model, and then establishes the IMU dynamic zero compensation equation based on the LSTM neural network model[7], and then derives the gradient descent method For the solution process of the objective function, the experimental platform of the laboratory was used to verify the zero compensation algorithm proposed in this subject [8, 9].

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2. IMU dynamic zero compensation algorithm based on LSTM neural network model

The most important external factors that affect the zero position of the vibrating gyroscope are time T and running time t, so the input variables at time t are Tt and tt, and the input variables at time t are also ct-1 and ht-1, so the nerves in this topic The input variable X of the network model is：

$$X = [T_t, t_t, c_{t-1}, h_{t-1}] \tag{1}$$

Enter the weight value of the variable W：

$$W = [\omega_T, \omega_t, \omega_c, \omega_h] \tag{2}$$

Then：

$$z = W \bullet X \tag{3}$$

In this subject, since the opening of the input gate is only related to the domain of temperature T and operating time t, that is, if T is not between -40℃ and 100℃, and t is not between 0 and 1800s, then it is not Within the research scope of this subject, the input gate will block the input, so there is：

$$z_i = (T, t) \bullet (w_{iT}, w_{it}) \tag{4}$$

$$f_i = sigmoid(z_i) \tag{5}$$

If the calculated zero value is significantly higher than the possible value of the zero offset, the output of the value is blocked by the output gate, so the only factor that affects the output gate is the model output value, so there is：

$$z_o = h * w_{oh} \tag{6}$$

$$f_o = sigmoid(z_o) \tag{7}$$

The update of the memory unit can be obtained in two ways: multiplicative update method and additive update method. However, if the algorithm requires a large amount of data iteration, the multiplicative update will infinitely enlarge or infinitely reduce the small error value, so addition is applied in this topic. The way of updating to update the amount in the memory unit.

$$c_t = f_f c_{t-1} + f_i \triangle c_t \tag{8}$$

$$\triangle c_t = z_i + \omega_h h_{t-1} \tag{9}$$

In the algorithm model, the value in the memory unit will accumulate an error value as the data is continuously updated iteratively, just like the cumulative error of a gyro, which needs to be updated, so the forget gate is introduced. It should be noted that the forgetting door does not update the data when it is opened, and updates the data when it is closed. In most cases, the forgetting door is open. In this topic, whether the forgetting door is closed or not is updated by the attitude angle. Data information decision.

Although the drift of the zero position of the gyroscope is non-linear, the function body can be set to：

$$h(c) = k \bullet c + b \tag{10}$$

2.1. Gradient descent method to solve the objective function in the model

Establish the loss equation $L(h) = L(b, k)$

$$L(b, k) = \sum_n (\hat{h}_n - h(c))^2 \tag{11}$$

There are many ways to find the optimal solution of this function. In this topic, the gradient descent method is used to solve the problem. The specific solution process is as follows:

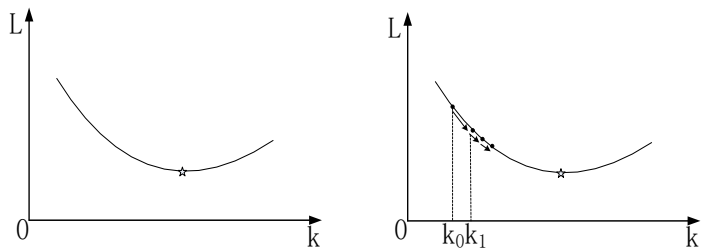
$$L(b, k) = \sum_n (\hat{h}_n - b - k \bullet c)^2 \tag{12}$$

Let the loss function partially differentiate the two parameters *b* and *k*:

$$\frac{\partial L(b, k)}{\partial k} = \sum_n 2(\hat{h}_n - b - k \bullet c)(-c) \tag{13}$$

$$\frac{\partial L(b, k)}{\partial b} = \sum_n 2(\hat{h}_n - b - k \bullet c)(-1) \tag{14}$$

Take equation (12) as an example：



(a) (b)

Fig.1 Schematic diagram of loss function and its optimal solution

2.2. Experimental verification of IMU dynamic zero compensation algorithm

Based on the existing equipment in the laboratory, the following two sets of comparative experiments are designed to verify the reliability of the IMU dynamic zero compensation algorithm, including whether there is a zero compensation algorithm under variable temperature that results in the calculation of the heading angle error comparison experiment and the normal temperature three-axis turntable Whether there is a zero compensation algorithm under motion leads to a comparative experiment of solving the attitude angle error. The equipment required for the experiment includes IMU, temperature-controlled single-axis turntable, three-axis turntable and host computer, as shown in Figure 3. Since the purpose of this article is to obtain a more accurate attitude angle by compensating for the zero drift, in order to better demonstrate the influence of the zero compensation algorithm on the final attitude angle calculation, the inertial measurement unit in the experiment includes installation error compensation procedures and passed The program for calculating the attitude angle by the quaternion method is to measure the pros and cons of the compensation algorithm by comparing the accuracy of the attitude angle calculation with or without the compensation algorithm.

(a)Temperature controlled single-axis turntable (b)Three-axis turntable

Fig.2 Experimental platform

3. Contrast experiment on whether there is a zero compensation algorithm under variable temperature that leads to the calculation of the heading angle error

In the experiment, first put the inertial measurement unit without zero compensation algorithm into the single-axis thermostat, and fix the Z-axis of the inertial measurement unit vertically on the single-axis table; turn on the thermostat, and first adjust the temperature of the thermostat to -40 °C, half an hour later, set the single-axis turntable to a swing motion with an amplitude of 5°, and turn on the attitude indicator at the same time. After the swing amplitude of the turntable is in place, start to operate the thermostat to increase the temperature by 1°C every 5s for 600 seconds After the temperature rises to 80°C, the heading angle information is the sensitive state of the movement during this process, and the heading angle data is continuously sent to the host computer interface through the serial port and saved. Then, download the program containing the zero compensation algorithm to the inertial measurement unit, repeat the above process, and use MATLAB to plot the data.

The inertial measurement unit that includes the zero-bias suppression algorithm has the heading angle information closer to the set amplitude of the turntable, and is relatively stable under the entire temperature state; while the inertial measurement unit that has not undergone the zero-bias suppression only corresponds to 300s to 400s In the interval, that is, the data in the interval close to normal temperature is relatively stable.

Table 1 Comparison table of attitude angle accuracy and stability under different conditions

State	Heading angle accuracy	Heading angle stability
IMU after zero compensation	0.976	0.612
IMU without zero-crossing compensation	0.882	0.035

It can be seen that the zero compensation algorithm proposed in this subject can increase the accuracy of the heading angle by 9.4%, and can increase the stability of the heading angle by an order of magnitude.

The initial roll angle, pitch angle and heading angle of the IMU are 0°, 180°and 220° respectively. After a running time of 1800s, the attitude angle error of the IMU without the zero compensation algorithm and the IMU after the zero compensation algorithm Statistics are shown in

Table 2 Statistical table of heading angle calculation error under different states

State	Roll angle error	Pitch angle error	Heading angle error
IMU after zero compensation	3.75°	2.86°	4.87°
IMU without zero-crossing compensation	0.59°	0.53°	0.96°

It can be seen from the above table that the dynamic zero compensation algorithm proposed in this paper can reduce the calculation error of the attitude angle by 5 to 6 times.

4. Summary

This chapter first analyzes the difference between the LSTM neural network model and the general neural network model, and analyzes the characteristics of the LSTM neural network model, and then establishes the IMU dynamic zero compensation equation based on the LSTM neural network model, and then derives the gradient descent method for the target In the process of solving the function, the experimental platform of the laboratory was used to verify the zero compensation algorithm proposed in this subject.

References

[1] Marotta Luca,Reenalda Jasper. (Machine) Learning From IMU-derived Biomechanics To Detect Physical Fatigue In An Outdoor Run: 440[J]. Medicine & Science in Sports & Exercise,2021,53(8S Suppl 1):

[2] Fan Bingfei,Xia Haisheng,Xu Junkai,Li Qingguo,Shull Peter B.. IMU-based knee flexion, abduction and internal rotation estimation during drop landing and cutting tasks[J]. Journal of Biomechanics, 2021,124:

[3] Gongyu Hou,Le Li,Zhedong Xu,Qinhuang Chen,Yijun Liu,Bing Qiu. A BIM-Based Visual Warning Management System for Structural Health Monitoring Integrated with LSTM Network[J]. KSCE Journal of Civil Engineering,2021(prepublish):

[4] Sun Jie,Kim Jiwon. Joint prediction of next location and travel time from urban vehicle trajectories using long short-term memory neural networks[J]. Transportation Research Part C,2021,128:

[5] Li Xue,Ahmed Syed Hassan. Design and Implementation of Human Motion Recognition Information Processing System Based on LSTM Recurrent Neural Network Algorithm[J]. Computational Intelligence and Neuroscience,2021,2021:

[6] Mohamed Soha Abd ElMoamen,Mohamed Marghany Hassan,Farghally Mohammed F.. A New Cascade-Correlation Growing Deep Learning Neural Network Algorithm[J]. Algorithms,2021,14(5):

[7] Meng Xuhui,Babaee Hessam,Karniadakis George Em. Multi-fidelity Bayesian Neural Networks: Algorithms and Applications[J]. Journal of Computational Physics,2021(prepublish):

[8] [1]Sun Yuguo,Sun Ruixi. On Structure Dynamic Pitch Angle Remote Monitoring System Based on NB-IoT[C]//Abstracts of the 8th International Conference on Vibration Engineering (ICVE 2021), 2021:424.DOI:10.26914/c.cnkihy.2021.017294.

[9] GarcíaVillamil Guillermo,NeiraÁlvarez Marta,HuertasHoyas Elisabet,RamónJiménez Antonio, RodríguezSánchez Cristina. A Pilot Study to Validate a Wearable Inertial Sensor for Gait Assessment in Older Adults with Falls.[J]. Sensors (Basel, Switzerland),2021,21(13):