Thermally Induced Bias Drift Integrated Compensation for the IFOG Strapdown Inertial Navigation System

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The large thermally induced bias drift is the main factor affecting the performance of the interferometer fiber optic gyroscope (IFOG) in practical engineering applications. The thermally induced bias drift is investigated in order to improve the accuracy of IFOG in the strapdown inertial navigation system (SINS). A triaxial integrated linear multi-variable model (TILMM) is presented based on experiments. The model is composed of the temperature gradient, polynomial temperature and temperature square. Due to the linear character of the model, model parameters are identified from the temperature and system outputs by least-square (LS) estimation methods. The drift data sets are collected to validate the effectiveness of this model. The rough experiment data is preprocessed by the proposed sliding window median absolute deviation (SWMAD) technology to identify outliers firstly, then the gradient inverse weighted (GIW) filter is used to initially lower the noise, and the singular value decomposition (SVD) is used to reduce the noise of the experiment data. The verification experiment of compensation is conducted and shows that the TILMM is effective, and SINS bias stability is improved in comparison with single-axis compensation.

Key Words: Compensation, Model, Triaxial Integrated, Interferometer Fiber Optic Gyroscope (IFOG), Thermally Induced Bias Drift

Nomenclature

- \(a, a_{dc}, a_{ac}\): constant coefficients
- \(\Phi_i\): equivalent phase error caused by interferences circuit
- \(\Phi_m\): equivalent phase error of demodulation
- \(\beta_0 = 2\pi/\lambda\): propagation constant of light in vacuum
- \(\partial n/\partial \theta\): temperature coefficient
- \(z\): coordinates of fiber layers
- \(L\): total length of fiber
- \(n\): refractive index of optical fiber
- \(c_0\): speed of light in wave guide
- \(\varepsilon\): bias drift of IFOG SINS
- \(\theta\): temperature
- \(\dot{\theta}\): temperature gradient
- \(a_1, b_2, c_2\): constant coefficients
- \(\varepsilon_c\): error after compensation
- \(\delta(\dot{\theta}, \dot{\theta})\): compensation value

1. Introduction

The interferometer fiber optic gyroscope (IFOG) is a new type of angular rate sensor with high precision, small size, light weight, large dynamic range, and shock and vibration resistance, etc.\(^1\) The basic concept of the IFOG is based on the Sagnac interferometer. The fiber coil keeps rotating in the clockwise (CW) direction. Consequently, to meet at the same exit point to interfere with each other, the CW and counter-clockwise (CCW) rotating lights need to enter the coil at different times at different points. In other words, the different entering times mean different entering points because of the rotated fiber coil. With the expanded research, the demand of the moderated highly-precision has been enhanced.\(^2\) The source of many random noises and bias drift have been discovered and resolved, and many technical problems have been settled. Huge efforts on techniques, which are devoted to the development of low-noise and low-drift IFOG mainly based on materials, machining and fabrication, etc. have been exerted to increase performance of the IFOG. However, the kernel components are still sensitive to temperature so that the temperature becomes one of the most difficult problems for IFOG in specific engineering applications.\(^3,4\) The CW and the CCW light-wave experience different phase delay results from the temperature distribution changes with respect to the center of the coil; therefore it results in an output error or drift. In view of this situation, researchers studied the complex mechanism of the temperature effect but found the influence to temperature drift from each component is a complex equation without any prior assumption.\(^5\)

Recently, researchers have studied and eliminated the drift from two aspects. One was to employ machining techniques and experimental approaches.\(^6\) However, using currently available experimental approaches to reduce errors complicates the structure (with the additional elements) and increases the cost. Therefore, it is necessary to develop further practical and effective processing techniques for eliminating effects of drift in IFOG. The other approach is to use some modeling compensation techniques. Shupe\(^7,8\) pointed out that the varying thermal field results in nonreciprocity phase error, which yields the apparent rotation rate
error. This became the theoretical basis for further studies and design of IFOG. In 1996, Mohr\(^9\) modeled the heat propagation with an electrical line circuit, and the Mohr thermal model matches well with the heating experiment result. Furthermore the quadruple (QAD) coiling schemes were confirmed to be the most efficient winding approach in terms of thermal error suppression by far. However, at the same time, the residual thermal drift induced by the imperfect QAD coil cannot be ignored. Therefore, based on the conclusion of Shupe and Mohr, modeling and compensation the techniques have been investigated recently; for example: the polynomial model,\(^{11,12}\) neural network model,\(^{13-17}\) fuzzy model\(^{18}\) and controlled Markov chain model,\(^{19}\) etc.

The above mentioned techniques\(^{11-19}\) can really eliminate the temperature influence on zero-point and improve the measurement precision to some degree. Obviously, most techniques, including the neural network model, fuzzy model and controlled Markov chain model are time consuming in model training. However, conventional techniques compensate thermal drift for the single IFOG only. At the same time, IFOG strapdown inertial navigation system (SINS) is a temperature field in engineering applications. Furthermore, the IFOG and the integrated system interact with each other in practical circumstances. Therefore, it is necessary to process integrated compensation for the thermally induced bias drift in order to increase SINS theoretical precision. Nevertheless, many investigators are merely interested in the soft compensation techniques for thermal drift of individual IFOG, and parallel research reports have not been published on the integrated compensation for IFOG SINS. Thus, this paper presents a new triaxial integrated linear multi-variable model (TILMM) to compensate the thermally bias drift. The drift data sets are collected to validate the effectiveness of the presented model. The experimental data is preprocessed with proposed sliding window median absolute deviation (SWMAD) to identify outliers in data enhancement procedures.

The organization of this paper is as follows: the TILMM is described in section 2 in detail. In section 3, the new outliers identified technique is presented in experiment data to enhance processing and performance of compensation and is evaluated. Section 4 provides the discussion and conclusion.

2. Proposed Model

2.1. Shupe effect and drift

Shupe has pointed out that the environmental temperature change caused by nonreciprocal phase shift (Shupe error) will bring a large drift and affect the measurement accuracy of IFOG. The Shupe nonreciprocity phase error \(\Delta \phi_i\) generated by \(dz\) which is \(z\) far from endpoint is

\[
\Delta \phi_i = \frac{\rho_0}{c_0} \frac{dn}{\partial \theta} \int_0^L \theta(z, t)(L - 2z) dz
\]  

This paper assumes that the environment temperature fluctuates slowly when SINS is working. Thus, it could be supposed that the IFOG is affected by temperature fluctuation of SINS only. The thermal components of the IFOG can be regarded as a constant heat source. Therefore, temperature distribution of IFOG and SINS would influence each other. In this way, single-axis IFOG is not only affected by itself but also affected by an additional two-orthogonal axis. Hence this paper proposes the TILMM to compensate the thermally induced bias drift.

2.2. TILMM

In theory, the environment temperature change and the generated heat internally will affect the temperature distribution,\(^{20}\) which is the direct cause of gyroscope drift. Distribution model expressions of the drift for IFOG could be described as\(^{40}\)

\[
\varepsilon(\dot{\theta}, \theta) = a\dot{\theta} + \sum_{i=0}^{\infty} (a_i \Phi_c + a_m \Phi_m) \theta^i
\]  

Therefore, thermally induced bias drift has relationship between \(\dot{\theta}, \theta\) and high order of temperature. SINS is a finite size temperature field in engineering applications. Single-axis IFOG output drift is not only affected by itself but also affected by an additional two-orthogonal axis. Two main aspects could be considered: the temperature gradient and temperature change. Nevertheless, the bias drift and temperature are nonlinear.

The experimental device is fixed on a rotating table with temperature controlled. The thermal test equipment architecture and setup are shown in Fig. 1. Main technical parameters are as follows: bias repeatability is 0.03°/h, bias stability is 0.02°/h, random walk coefficient is 0.0017°/√h, scale factor error is 135 ppm, temperature resolution is 0.0625°C and data collection period is 0.005 s.

The observation of the thermally induced bias drift of SINS is considered as system output shown in Fig. 2 (vertical axes show outputs of \(x, y,\) or \(z\) axes). There are some
could extract a triaxial integrated model to compensate thermally induced bias drift estimation respectively. The procedure of analysis as:

(1) Temperature gradient induced bias drift
   \[ \varepsilon_1(\dot{\rho}) = a_1(\dot{\rho}) \]  
(2) Temperature induced bias drift
   \[ \varepsilon_2(\rho) = \varepsilon_0 + b_2 \rho + c_2 \rho^2 \]  
(3) Thermally induced bias drift
   \[ \varepsilon(\dot{\rho}, \rho) = \varepsilon_1(\dot{\rho}) + \varepsilon_2(\rho) \]

\( \dot{\rho}_x, \dot{\rho}_y \) and \( \rho_z \) are temperatures of triaxial points, and \( a_{ij}, a_{xy}, a_{xy}, b_{ij}, b_{xy}, b_{xy}, c_{ij}, c_{xy}, c_{xy} \) are influence coefficients of the system. \( \dot{\rho}, \rho \) are the input and output of the system, respectively.

\[
\begin{align*}
\dot{\varepsilon}_x(\dot{\rho}, \rho) &= \varepsilon_x(\dot{\rho}) + a_{xx} \dot{\rho}_x + a_{xy} \dot{\rho}_y + a_{xz} \dot{\rho}_z + b_{xx} \rho_x \\
&+ b_{xy} \dot{\rho}_y + b_{xz} \dot{\rho}_z + c_{xx} \rho_x^2 + c_{xy} \rho_y^2 + c_{xz} \rho_z^2 \\
\dot{\varepsilon}_y(\dot{\rho}, \rho) &= \varepsilon_y(\dot{\rho}) + a_{yx} \dot{\rho}_x + a_{yy} \dot{\rho}_y + a_{yz} \dot{\rho}_z + b_{yx} \rho_x \\
&+ b_{yy} \dot{\rho}_y + b_{yz} \dot{\rho}_z + c_{yx} \rho_x^2 + c_{yy} \rho_y^2 + c_{yz} \rho_z^2 \\
\dot{\varepsilon}_z(\dot{\rho}, \rho) &= \varepsilon_z(\dot{\rho}) + a_{zx} \dot{\rho}_x + a_{zy} \dot{\rho}_y + a_{zz} \dot{\rho}_z + b_{zx} \rho_x \\
&+ b_{zy} \dot{\rho}_y + b_{zz} \dot{\rho}_z + c_{zx} \rho_x^2 + c_{zy} \rho_y^2 + c_{zz} \rho_z^2
\end{align*}
\]

3. Modeling, Compensation and Discussion

3.1. Enhancing experimental data

Figure 2 shows that the signal-to-noise ratio of the experimental data is obviously so low that sophisticated techniques are required. The enhanced procedure of experimental data is shown in Fig. 4. The experimental data is preprocessed with the proposed sliding window median absolute deviation (SWMAD) to revise outliers firstly. The gradient inverse weighted (GIW) filter is then applied to reduce the noise level. Finally, the signal-to-noise ratio is increased by singular value decomposition (SVD) for experimental data. Each of the stages is explained in further detail in the following interpretations.
3.1.1. Improved outlier detection technique

A popular approach to identify outliers is the median absolute deviation (MAD; details shown in Refs. 21 and 22). Conversely, note that the MAD scale estimator can behave badly with coarsely quantized data. Specifically, if more than 50% of the points in the sequence \( \{ x_k \} \) have the same value, it follows that \( S = 0 \), causing all outlier data points to be rejected as outliers, regardless of how far they lie from \( x^* \).

In this section, SWMAD is proposed to avoid the aforementioned problem. The window length \( l \) (\( l \) is odd) based on experience. The numerical point \( x_k \) is identified outlier, the median \( \tilde{x}_k = \text{median} \{ x_{k-(l-1)/2}, \ldots, x_k, \ldots, x_{k+(l-1)/2} \} \) is obtained by first rank-ordering it from smallest to largest, and then the SWMAD threshold estimate is defined as:

\[
S_k = 1.4826 \cdot \text{median} \left| x_k - \tilde{x}_k \right|
\]  

Outlier identification results of experimental data by MAD and SWMAD are shown in Figs. 5 and 6 respectively. It is found that the SWMAD technique could reject outliers almost in Fig. 6(a), but MAD might ignore individual outliers in Fig. 5. The result shows that the SWMAD technique has better performance than MAD.

3.1.2. Gradient inverse weighted filter

A nonlinear filtering algorithm GIW filter presented by Wang\(^{23} \) is implemented to lower the noise level of the noise signal while minimizing the distortion of the true signal. Figure 7 shows that this technique can preserve edge and smooth noise effectively.

3.1.3. SVD filtering

In order to achieve better performance, some preprocessing is required to initially lower the noise level of the data. For this, we implement SVD filtering for noise reduction. It is known that the SVD is a very powerful tool in linear matrix theory, and it has been used extensively in many fields of engineering. In particular, as a noise reduction technique, it is also utilized elsewhere in speech and audio applications.\(^{24–26} \)

The reconstructed signal is shown in Fig. 8. It is found that signal-to-noise ratio obviously increases.

3.1.4. Tracking-differentiator

A feasible discrete second-order tracking-differentiator (TD)\(^{27,28} \) with the Euler method is implemented to achieve \( \dot{\theta} \). Figure 9 shows the estimations of the temperature and the temperature gradient. In Fig. 9(a) the solid line is the experimental temperature data and the dotted line is the temperature estimation. In Fig. 9(b) the solid line is the temperature gradient achieved by polynomial fitting and the dotted line is the temperature gradient estimation by the TD. It indicates that the temperature data is not tracked at the beginning processing, while the TD tracks the temperature data quickly after 500 s. Then, the TD displays a favorable tracking capability in this experiment.

3.2. Compensation

The principle of bias drift compensation is depicted in Fig. 10. The TILMM is acquired by limited temperature points; therefore it is necessary to verify the effect by non-experimental temperature points. Other groups of drift compensation tests are taken in an indoor environment. The experimental data (rotational angular velocity of the Earth is eliminated) and compensation results are shown in Figs. 11 and 12, respectively.

Figure 12 shows that the thermally induced bias drift is more significantly reduced after compensation.
The TD increases computation hugely. According to the principle of heat transmission, temperature gradient can be expressed by the difference in temperature similarly. Therefore, the temperature difference is replaced by the temperature gradient in the modeling process. Linear combination of $\Delta \dot{\vartheta}(n), \ldots, \Delta \dot{\vartheta}(n-m)$ exposes $\vartheta$, and

$$\Delta \dot{\vartheta}(n) = \dot{\vartheta}(n) - \dot{\vartheta}(n-1)$$

Then the compensation model is adapted as

$$\Delta \dot{\vartheta}(n) = \dot{\vartheta}_0 + \sum_{i=0}^{m} a_i^x \Delta \vartheta_x(n-i) + \sum_{i=0}^{m} a_i^y \Delta \vartheta_y(n-i) + c_{xx} \dot{\vartheta}_x^2 + c_{xy} \dot{\vartheta}_x \dot{\vartheta}_y + c_{xz} \dot{\vartheta}_x \dot{\vartheta}_z$$

(10)

$$\Delta \dot{\vartheta}(n) = \dot{\vartheta}_0 + \sum_{i=0}^{m} a_i^y \Delta \vartheta_y(n-i) + \sum_{i=0}^{m} a_i^z \Delta \vartheta_z(n-i) + c_{yy} \dot{\vartheta}_y^2 + c_{yz} \dot{\vartheta}_y \dot{\vartheta}_z + c_{xz} \dot{\vartheta}_x \dot{\vartheta}_z$$

(11)

$$\Delta \dot{\vartheta}(n) = \dot{\vartheta}_0 + \sum_{i=0}^{m} a_i^z \Delta \vartheta_z(n-i) + \sum_{i=0}^{m} a_i^x \Delta \vartheta_x(n-i) + c_{xz} \dot{\vartheta}_x \dot{\vartheta}_z + c_{yz} \dot{\vartheta}_y \dot{\vartheta}_z$$

(12)

In the same way, the compensation principle using the temperature difference is depicted in Fig. 13.

Figure 14 shows the compensation result. It is found that the thermally induced bias drift is also reduced after com-
compensation in the same way. Table 1 shows bias stabilities comparison of before compensation, single-axis compensation and triaxial integrated compensation. Obviously, bias stabilities improved after compensation, and accuracy of triaxial integrated compensation is higher than single-axis compensation (polynomial model12)). Moreover, by using simplified calculation of temperature difference, the large computation cost resulting from the TD is reduced with slight accuracy deterioration.

### 4. Conclusions

This paper presented the TILMM for thermally induced bias drift of FOG SINS. The model was composed of the polynomial of temperature gradient and temperature. Model coefficients were obtained using the least-square estimation method. Drift data sets were collected to validate the effectiveness of the proposed model. The testing data was preprocessed with the new SWMAD technique to reject outliers. The result showed that the TILMM was effective, and SINS bias stabilities improved after compensation.

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