Research Article

Temperature Energy Influence Compensation for MEMS Vibration Gyroscope Based on RBF NN-GA-KF Method

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This paper proposed three methods to compensate the temperature energy influence drift of the MEMS vibration gyroscope, including radial basis function neural network (RBF NN), RBF NN based on genetic algorithm (GA), and RBF NN based on GA with Kalman filter (KF). Three-axis MEMS vibration gyroscope (Gyro X, Gyro Y, and Gyro Z) output data are compensated and analyzed in this paper. The experimental results proved the correctness of these three methods, and MEMS vibration gyroscope temperature energy influence drift is compensated effectively. The results indicate that, after RBF NN-GA-KF method compensation, the bias instability of Gyros X, Y, and Z improves from 139°/h, 154°/h, and 178°/h to 2.9°/h, 3.9°/h, and 1.6°/h, respectively. And the angle random walk of Gyros X, Y, and Z was improved from 3.03°/h^{1/2}, 4.55°/h^{1/2}, and 5.89°/h^{1/2} to 1.58°/h^{1/2}, 2.58°/h^{1/2}, and 0.71°/h^{1/2}, respectively, and the drift trend and noise characteristic are optimized obviously.

1. Introduction

MEMS vibration device has some advantages such as small volume, light weight, low energy consumption, low cost, high reliability, and performance-cost ratio and is widely used in the area of consumer electronics, energy harvest, attitude controlling, aviation and space flight, stabilization, guidance, and inertial navigation [1–10]. The MEMS vibration gyroscope is one of the most important applications of MEMS vibration devices, and temperature energy influence drift restrains its high-precision application [11]. Plenty of literatures focus on improving the temperature characteristics of the MEMS vibration gyroscope. However, there are mainly two methods to improve the temperature compensation of the MEMS vibration gyroscope.

One is employing hardware to improve the MEMS vibration gyroscope temperature performance, and a large number of methods of hardware compensation have been reported which include architecture improvement and circuit control. For example, Cao and Li investigated how the Gyro structure mechanical model is affected by temperature and proposed methods to improve the silicon

structure temperature robustness [12]. Liu et al. proposed robust structural design for the MEMS vibration gyroscope to compensate the temperature energy influence drift [13]. Cao et al. established a new silicon structure equivalent electric model in order to improve the accuracy of performance under higher temperature [14]. Fu et al. proposed a simpler and more applicable compensation method which is provided with a new circuit to reduce the influence of damping coefficient and resonating frequency [15]. Yang et al. proposed an architecture that utilizes the on-chip temperature sensor of the micro-Gyro to achieve the on-chip temperature compensation and used the integrated serpentine microheater to realize the on-chip temperature control of the micro-Gyro [16]. Cao et al. proposed a temperature compensation bandwidth expanding method [17]. Although hardware compensation is used in many MEMS vibration gyroscopes, more and more money and time is wasted.

The other is to establish the mathematical model to acquire temperature compensation which are called software compensations. Software compensations spend less money and time to improve the measurement precision, and its

algorithm can be adjusted easily to improve the accuracy of the MEMS vibration gyroscope. Wang et al. proposed the relationship between temperature and frequency on the Hemispherical Resonator Gyro, and a method by changing the frequency is provided to compensate temperature energy influence drift [18]. Aggarwal et al. proposed an efficient thermal variation model for low-cost MEMS inertial sensors and units in order to compensate the temperature [19]. Song et al. proposed a new hybrid algorithm back propagation (BP) NN optimized by the artificial fish swarm algorithm (AFSA), and it is used to describe the temperature energy influence drift characteristic of FOG [20]. Chen and Shen proposed a novel method based on the forward linear prediction (FLP) algorithm to decrease noise and a novel temperature compensation by using the ambient temperature change rate which can reduce the influence of intense temperature variation effectively [21]. Feng et al. proposed an adaptive algorithm of strong tracking KF to compensate the bias drift of the MEMS vibration gyroscope in different temperatures and successfully improved the accuracy of the MEMS vibration gyroscope [22]. Chong et al. proposed a modeling method based on Elman NN and GA with multiple temperature variable inputs in [23], and the temperature model was established based on temperature, temperature variation rate, and the coupling term. In [24], Wei et al. proposed GA and successfully used in the modeling of ring laser Gyro for temperature energy influence drift, and GA was employed to select the optimal parameters of support vector regression. Ding et al. proposed a modified RBF NN method of temperature compensation for laser Gyro and improved the accuracy of laser Gyro under different temperatures [25], and this method can quickly and accurately identify the effect of temperature on laser gyro zero bias. Cheng et al. proposed a modification of an RBF ANN based on temperature compensation models for IFOGs and improved the accuracy of temperature compensation [26], and three temperature-relevant terms were extracted including temperature of fiber loops, temperature variation of fiber loops, and temperature product term of fiber loops. Xia et al. proposed a temperature prediction and control based on BP NN and fuzzy-PID control method and successfully used to reduce the zero rate output [27]. Software compensation based on MEMS vibration gyroscopes is more convenient than hardware compensation.

In this paper, in order to improve the accuracy of the MEMS vibration gyroscope, a temperature energy influence drift model is established, and three methods are proposed to compensate temperature energy influence drift. Instead of a single algorithm, RBF NN, RBF NN based on GA and fusion algorithms of RBF NN based on GA with KF which is first used in temperature compensation of MEMS vibration gyroscope are proposed to analyze and compensate the temperature energy influence drift.

2. Model and Algorithm

2.1. Temperature Energy Influence Drift Model. A new temperature energy influence drift model of MEMS is

established in this paper: temperature, temperature variation rate, and temperature product term are considered to combine with the temperature energy influence drift model. These three factors can easily reflect the performance of the MEMS vibration gyroscope; therefore, D is defined as the matrix of three factors:

$$D = [T \quad \dot{T} \quad T \times \Delta T]', \quad (1)$$

where T is the temperature, $\dot{T}$ is the temperature variation rate, $T \times \Delta T$ is the product term. After that, these three factors are all the inputs of the drift model as shown in Figure 1. In order to establish a complex model as inputs to NN, a function is constructed as a target function to be trained, as shown in the following equation:

$$F(X) = F\{[T \quad \dot{T} \quad T \times \Delta T]'\}. \quad (2)$$

2.2. The Algorithm of RBF NN. RBF is a kind of nonnegative and nonlinear functions which has features of local distribution and radial symmetry attenuation of the center point. Local distribution is described that the meaningful nonzero response will be achieved by the RBF of hidden unit when the input is placed in a small designated area. Radial symmetry attenuation of the center point is described as the center of RBF with the equal input of the radial distance, and then, the equal output is produced by the RBF of hidden layer points, and the closer the distance between input and the center of RBF is, the bigger response of the hidden node will be. By using the hidden layer of neural work into RBF, the RBF NN is established. RBF NN, a typical multilayer feedforward neural network, is shown as Figure 2 which has a multilayer structure of sensation-association-reaction that includes the input layer, the hidden layer, and the output layer. Compared with other neural networks, there are plenty of advantages which belong to the RBF NN. For example, in the RBF NN, the training time can be shorter, the functional approximation can be optimal, and the RBF NN can be approximated to arbitrary continuous function with arbitrary precision [26].

The basis function of RBF NN is shown in the following equation:

$$\alpha_j(x) = \psi_j\left(\frac{\|x - c_j\|}{\sigma_j}\right), \quad (3)$$

where c_j is the center point of the basis function in j , σ_j is the breadth of the center point around the basis function which is a freedom factor, $\|x - c_j\|$ is the distance between x and c_j which is the norm of $x - c_j$, and ψ_j is a function of radial symmetry which has a unique maximal value at c_j , with the increasing of $\|x - c_j\|$ and ψ_j is quickly decreased to zero. For the determined output of $x \in R^n$, only a little processing element is activated, where the center is closed to x .

The transfer function of RBF neurons has many different forms; in this paper, Gaussian basis function is shown in the following equation:

FIGURE 1: The framework of the temperature energy influence drift model.

FIGURE 2: Model of radial basis function neural network.

$$a_j(x) = \psi_j \left(\frac{\|x - c_j\|}{\sigma_j} \right) = e^{-\left(\|x - c_j\|^2 / 2\sigma_j^2 \right)}. \quad (4)$$

As is shown in Figure 3, RBF NN is formed with two parts: one part achieve the nonlinear mapping method from x to $a_j(x) = \psi_j(\|x - c_j\|/\sigma_j)$ and the other part achieve the linear mapping from $\alpha_j(x)$ to y , which is shown as

$$y = W\alpha(x), \quad (5)$$

$$y_i = \sum_{j=1}^m w_{ij} \alpha_j(x), \quad i = 1, 2, \dots, r.$$

The learning algorithm of connection weight is shown in the following equation:

$$w_{ij}(l+1) = \frac{w_{ij}(l) + \beta[y_i^d - y_i(l)]\alpha_j(x)}{\alpha_j^T(x)\alpha_j(x)}, \quad (6)$$

where β is the learning rate, and β is decided from 0 to 2 in order to erform the convergence of iterative learning algorithms.

In the training process of NN, $\alpha_j(x)$ is nearly equal to 0 when x is far from c_j , and the output of $\alpha_j(x)$ is also nearly equal to 0 when pass by the linear neural of the second layer. The corresponding weight value will be influenced when $\alpha_j(x)$ is more than a value such as 0.05, the output of the layer is nearly equal to 1 when the distance between x and c_j is small, the output value will nearly be equal to the weight value on the second layer when pass by the second layer. After these trainings, the advantage of the quick study speed of the local network is provided with RBF NN.

FIGURE 3: The system of the fusion algorithm of RBF NN + GA + KF.

2.3. The Algorithm of RBF NN Based on GA. GA is an intelligent method based on group optimization, which is followed by the rule of survival of the fittest to look for optimal solution and has advantages of global searching ability, being independent of initial value, and fast convergence rate. The GA mainly includes five basic steps: parameter coding, initial population, fitness function choice, genetic operators, and trainable connection setting. The process of GA is shown in Figure 4, and the steps can be described as follows:

- (1) The initial set of RBF NN (initial population) is produced by a random number generator and consists of the GA parameters.
- (2) Fitness function is provided to express the adaptive ability of the environment to individual according to the objective function.
- (3) According to the fitness function, parameters are renewed by selection, crossover, and mutation.
- (4) Repeat the steps and decide whether the fitness function meets the end condition. If the answer is

FIGURE 4: The process of RBF NN based on GA (RBF NN + GA).

yes, then stop training and send the output parameters to RBF NN, and if the answer is no, repeat step (3) until the output parameters meet the end conclusion.

(5) Stop training and export the optimal results.

2.4. RBF NN Based on GA with KF. The process of KF is shown in Figure 5, it indicates that the process of KF needs two steps: time upgrading and measurement upgrading, and the process of calculating can be divided into two steps which are plus loop and filter loop. In other words, the process is recursive.

Therefore, the process of KF can be described as the following five equations:

$$\begin{aligned}
 \hat{X}_{k/k-1} &= \Phi_{k,k-1} \hat{X}_{k-1}, \\
 \hat{X}_k &= \hat{X}_{k/k-1} + K_k (Z_k - H_k \hat{X}_{k/k-1}), \\
 K_k &= P_{k/k-1} H_k^T (H_k P_{k/k-1} H_k^T + R)^{-1}, \\
 P_{k/k-1} &= \Phi_{k,k-1} P_{k-1} \Phi_{k,k-1}^T + \Gamma_{k-1} Q \Gamma_{k-1}^T, \\
 P_k &= (I - K_k H_k) P_{k/k-1},
 \end{aligned} \tag{7}$$

where H_k is the measurement matrix, K_k is the filter gain matrix, $P_{k/k-1}$ is the matrix of prior estimate error covariance, P_k is the matrix of estimation error variance, R is the covariance of measurement noise covariance, and Q is the covariance of process noise. From what have been discussed above, as long as the initial value of $\hat{X}_0$ and P_0 can be determined, based on the measurement vector of Z_k at k moment, the state estimation of $\hat{X}_k$ ($k = 1, 2, \dots$) at k moment can be calculated.

As for two methods RBF NN and RBF NN + GA, a new method which is a fusion of RBF NN and GA with KF (RBF NN + GA + KF) is carried out in this section. The fusion algorithm of RBF NN + GA + KF not only provided the advantage of online real time but also provided the advantage of studying ability. The flow chart of the fusion algorithm of RBF NN + GA + KF is shown in Figure 3.

The steps of the fusion algorithm of RBF NN + GA with KF can be described as follows:

- (1) The initial parameters are produced by temperature experiment and set as input data to KF
- (2) KF model is established by the time series analysis method, and the output data of KF is ready for correcting the output data based on the method of RBF NN + GA.
- (3) Temperature energy influence drift model is established.
- (4) By the temperature energy influence drift model in step (3), RBF NN + GA steps are worked which is shown in Figure 3.
- (5) The original data after processing are output by RBF NN + GA and the correction of KF.

3. Experiment Proposal

The structure and shell of LPMS-USBAL2 MEMS vibration gyroscope that 10 Hz of sampling rate is a system-in-package featuring a 3D Gyro, which the bias stability is 0.05°/s for Gyros. The main test device is a temperature-controlled oven, which can provide the ranges of temperature from -50°C to $+150^\circ\text{C}$. The equipment of the experiment setup is shown in Figure 6, which was used to collect above data. In order to test the temperature characteristic of the MEMS vibration gyroscope, a temperature experiment is set up.

The MEMS is kept on the temperature-controlled oven in order to output the signal of MEMS vibration gyroscopes and not influenced by outside temperature variation; then, the ranges of temperature and the temperature rate are set from -40°C to 60°C and $1^\circ\text{C}/\text{min}$, respectively. Firstly, the initial temperature should be set as 60°C and keep the temperature for an hour in order to make sure that the inside temperature of the MEMS vibration gyroscope is stabled at 60°C . Secondly, the temperature is reduced at the speed of $-1^\circ\text{C}/\text{min}$ into -40°C and the temperature is kept for an hour to make sure that the inside temperature of the MEMS vibration gyroscope is -40°C . The temperature-

FIGURE 5: The process of KF.

FIGURE 6: The equipment of temperature test.

controlled oven should be stayed at each 10°C for an hour in order to collect the output of the MEMS vibration gyroscope and make sure that the inside temperature of the MEMS vibration gyroscope is stable and equal to oven temperature.

4. Verification and Analysis

Based on the temperature experiment of the MEMS vibration gyroscope, the output data of Gyro X, Gyro Y, and Gyro Z are shown in Figure 7.

From Figure 7, it can be observed that three MEMS vibration gyroscopes output signals varied about $3^\circ/\text{s}$ during -40°C to 60°C temperature range. In order to overcome the drift of temperature, three methods are used to compensate the temperature energy influence drift. From Figures 8–10, the temperature energy influence drift models based on RBF NN, RBF NN + GA and RBF NN + GA + KF are established.

Based on the established model, the compensation drift of three methods can be calculated. From Figures 8–10, it can be seen that the modal curves of three methods follow the original signal well, and the noise performance of RBF NN + GA + KF is the best. And based on this phenomenon, RBF NN + GA + KF method is used for compensation.

Figure 11 shows the compensation results of RBF NN + GA + KF method, and comparing with output data in Figure 7, RBF NN + GA + KF method successfully decreased the temperature influence drift. In order to have a quantitative evaluation of compensation result of the MEMS vibration gyroscope's temperature energy influence drift, the Allan variance method was applied to analyze the drift compensation result. The Allan variance curves are shown in Figure 12, and angle random walk (N) and bias instability (B) values are listed in Table 1.

From Table 1 and Figure 12, it can be seen that based on three methods, factors in Allan variance of B and N are declined, and the RBF NN + GA + KF method is better than the others. As for bias instability, Gyro X is from $139^\circ/\text{h}$ to $2.9^\circ/\text{h}$, Gyro Y is from $154^\circ/\text{h}$ to $3.9^\circ/\text{h}$, and Gyro Z is from $178^\circ/\text{h}$ to $1.6^\circ/\text{h}$. As for angle random walk, Gyro X is from $3.03^\circ/\text{h}^{1/2}$ to $1.58^\circ/\text{h}^{1/2}$, Gyro Y is from $4.55^\circ/\text{h}^{1/2}$ to $2.58^\circ/\text{h}^{1/2}$, Gyro Z is from $5.89^\circ/\text{h}^{1/2}$ to $0.71^\circ/\text{h}^{1/2}$.

5. Conclusion

In this paper, the MEMS vibration gyroscope temperature energy influence drift model is investigated, and three methods are proposed to compensate the temperature energy influence drift. RBF NN, RBF NN + GA, and RBF NN + GA + KF are proposed to compensate the temperature energy influence drift by using the temperature

FIGURE 7: (a–c) The output of MEMS in the temperature experiment.

FIGURE 8: The three temperature energy influence drift models of Gyro X.

FIGURE 9: The three temperature energy influence drift models of Gyro Y.

FIGURE 10: The three temperature energy influence drift models of Gyro Z.

FIGURE 11: The compensation results of Gyro X, Gyro Y, and Gyro Z based on three methods.

energy influence drift model which is established in this paper. Firstly, RBF NN is established to improve the accuracy of temperature energy influence drift, and RBF NN + GA is used to optimize parameters of RBF NN to improve the precision. Secondly, a novel algorithm RBF NN + GA + KF is proposed to improve the accuracy of these two

methods and the original output. Then, a novel temperature energy influence drift model is established by temperature, temperature variation rate, and temperature product term. Finally, the comparison results among three methods and the original data are shown by Allan variance coefficients obviously. Specifically, by using RBF NN + GA

FIGURE 12: Continued.

FIGURE 12: (a–c) Allan variance analysis of Gyros X, Y, and Z based on different algorithms.

TABLE 1: Three method results of Allan variance analysis.

	Denoising								Temperature compensation	
	Original data		RBF NN		RBF NN + GA		RBF NN + GA + KF		RBF NN + GA + KF	
	B (°/h)	N (°/h ^{1/2})	B (°/h)	N (°/h ^{1/2})	B (°/h)	N (°/h ^{1/2})	B (°/h)	N (°/h ^{1/2})	B (°/h)	N (°/h ^{1/2})
Gyro X	139	3.03	129	2.47	124	2.27	124	2.00	2.9	1.58
Gyro Y	154	4.55	148	3.58	137	3.27	126	2.98	3.9	2.58
Gyro Z	178	5.89	167	4.52	155	3.92	150	3.55	1.6	0.71

+ KF method, the bias instability of three axes is Gyro X from 139°/h to 2.9°/h, Gyro Y from 154°/h to 3.9°/h, and Gyro Z from 178°/h to 1.6°/h. As for angle random walk, Gyro X is from 3.03°/h^{1/2} to 1.58°/h^{1/2}, Gyro Y is from 4.55°/h^{1/2} to 2.58°/h^{1/2}, and Gyro Z is from 5.89°/h^{1/2} to 0.71°/h^{1/2}.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Authors' Contributions

Huiliang Cao and Chong Shen contributed equally to this work.

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