Optimization of temperature compensation model on angle sensor based on nonlinear fitting

Siqi Liu\textsuperscript{1,2}, Yueli Hu\textsuperscript{1,2,3}, Jieming Chen\textsuperscript{1,2}, Jiale Wang\textsuperscript{1,2} and Kun Jia\textsuperscript{1,2}

\textsuperscript{1} Shanghai Key Laboratory of Power Station Automation Technology, Shanghai 200072, China
\textsuperscript{2} Shool of Mechatronic Engineering and Automation, Shanghai University, Shanghai 200072, China
\textsuperscript{3} E-mail: huyueli@shu.edu.cn

Abstract. In industrial measurement, the accuracy of accelerometer is much sensitive to the change of environmental temperature. Although previous work can achieve good performance about reducing the temperature impact, all of them cannot achieve a high accuracy. A new nonlinear fitting method is proposed to eliminate temperature influence on the accuracy of accelerometer. When using an accelerometer to calculate an object's tilt angle, the change of temperature will lead to drift on the value of accelerometer. This drift will lead to the increase of angle calculation bias. In order to solve this problem, this paper proposes a new experimental nonlinear fitting temperature compensation method. With the measurement data and the quadratic model evolution, this method can effectively eliminate the influence of temperature on the accuracy of accelerometer and improve the precision and the accuracy of angle calculating. The experimental results show that this method has an advantage of high compensation accuracy.

1. Introduction
When calculating the tilt angle of an object using an accelerometer, the method of gravity difference is generally used \cite{1}. This method can get the angle of the sensor by calculating the gravity pressure of the measuring axis. It can effectively reduce the hardware system error and improve the measurement accuracy \cite{2}.

The angle conversion formula is based on the physical characteristics of the accelerometer. According to the inclination angle of the sensor, the weight of the ball is distributed on the x-axis and y-axis \cite{3}. The angle \(\theta\) in the figure 1 satisfies the equation (1):

\[
\tan(\theta) = \frac{x_{\text{MID}} - x}{y_{\text{MID}} - y}
\]

(1)

\(X\) and \(Y\) are the values read from the \(X\)-axis and \(Y\)-axis of the gravity accelerometer respectively. \(x_{\text{MID}}\) and \(y_{\text{MID}}\) are the median value of the \(X\)-axis and \(Y\)-axis. The angle \(\theta\) can be calculated by the equation (2):

\[
\theta = \arctan\left(\frac{x_{\text{MID}} - x}{y_{\text{MID}} - y}\right)
\]

(2)

As long as the relative values of the two axes are operated by the arctangent function, the angle between the two axes can be obtained \cite{4}. Since the pressure of the accelerometer is affected by the temperature of change, the values got from the same location at diverse temperatures are different \cite{2}. The effect of temperature on acceleration eventually reflects on the angle calculation. In the actual the
process of the measurement, the error rate can reach up to 50%. If the effect of temperature was
ignored, the physical angle calculated by the accelerometer cannot represent the true value.

![Figure 1. The accelerometer physics schematic.](image)

In order to reduce the influence of temperature on the angle sensor, the method commonly used in
industrial control is to use the linear temperature compensation algorithm to directly compensate the
data collected by the accelerometer sensor [5]. This method establishes the first-order linearity model
between the temperature and the acceleration sensor [6]. Uses error compensation model based on the
least square method and achieves a good performance in practical application. This method
compensates the output of the angle sensor rather than accelerometer sensor. In this paper, a high-
order non-linear fitting method is proposed. The temperature compensation works on the output of
the accelerometer, which can effectively reduce the influence of temperature [7].

The rest of the paper is organized as follows. Section 2 analyses the linear relationship between
temperature and accelerometer. Section 3 analyses high-order nonlinear model which can compensate
the output data more precisely. Section 4 concludes this work.

2. Using a linear relationship to solve temperature compensation problems
As the angle is obtained through dealing with the values of different axes of the accelerometer, there
will be a certain mathematical relation between the temperature and each axis data. As [8], it uses
neuro-fuzzy network to approximate the model between accelerometer and temperature. We can get
the relationship by the multiple data fitting.

We collect the angle data of the sensor at different temperatures and filter the data to obtain the
following valid data:

| number | temperature/°C | angle/°  | standard deviation |
|--------|----------------|---------|--------------------|
| 1      | 0              | -62.20  |                    |
| 2      | -30            | -62.48  |                    |
| 3      | -45            | -62.91  | 0.374              |
| 4      | 22             | -62.39  |                    |
| 5      | 60             | -61.90  |                    |
| 6      | 85             | -61.79  |                    |

According to equation (2) we model the temperature and angle error as:

\[
\frac{\Delta x + T \cdot K + \Delta K}{\Delta y + T \cdot K + \Delta K} = \frac{\Delta x}{\Delta y} = \tan \theta
\]

(3)

The model shows the relationship between the temperature \( T \) and the angle \( \theta \), and \( \Delta K \) is the
deviation value of the temperature at 0 °C. \( \Delta x \) represents the initial deviation of the \( X \)-axis data and \( \Delta y \)
represents that of the \( Y \)-axis data respectively.

Bring the data of table 1 into equation (3), the relationship between temperature \( T \) and \( \theta \) can't be
achieved. The reason is that the effect of temperature on the angle sensor is reflected on the three-
axis’s AD converter of the accelerometer. The temperature compensation needs to be applied to the output of the AD conversion of the accelerometer.

3. Modeling using high-order nonlinear relationships

Through the above model calculations, it can be concluded that there is no linear relationship between the accelerometer axis and the temperature [9]. Modeling the non-linear relationship between the temperature and the accelerometer by multiple measurements of the accelerometer at various temperatures.

The measurement data must be satisfied with the requirements are as follows:
1. three accelerometer measurements are in the same chip.
2. During the measurement process, the position of the sensor is kept unchanged.
3. measuring temperature is divided into 23 °C, 10 °C, 0 °C, -10 °C, -30 °C, -45 °C, 60 °C, 85 °C.
4. When the test platform reaches the set temperature, it needs to stabilize after 20 minutes to start measuring.

Test data is as in table 2:

| temperature/°C | X average | Y average | Z average |
|----------------|-----------|-----------|-----------|
| 23             | 734.2     | 505.4     | 421.3     |
| 10             | 734.9     | 505.9     | 420.5     |
| 0              | 736.2     | 506       | 419.9     |
| -10            | 736.2     | 506       | 419       |
| -30            | 739.2     | 506.3     | 418       |
| -45            | 740.7     | 506.3     | 417       |
| 60             | 732.5     | 504.9     | 425       |
| 85             | 720.6     | 503.1     | 425.6     |

As the calibration always takes room temperature, we set the value of $X_{22}$ (or $Y_{22}$, $Z_{22}$) as the median value at 22 degrees. Each measure data should subtract the $X_{22}$ (or $Y_{22}$, $Z_{22}$), then is carried out to do square processing, as the following equation:

$$X_{Tm} = (X_T - X_{22})^2$$

Where $X_T$ is the data read from the $X$-axis of the accelerometer at time $T$. $X_{Tm}$ refers to the quadratic error of the x-axis accelerometer at time $T$. The deviation at each temperature is shown in figure 2 (red is $X$-axis data, green is $Y$-axis data, yellow is $Z$-axis data, all images are the same in the following).

**Figure 2.** The error in the data of three axes at temperature variation.

**Figure 3.** The accelerometer error fitting data compared with the original data.
3.1. Quadratic and cubic nonlinear fitting model
It can be seen from figure 2 that the temperature model approximately conforms to the quadratic model, and the least squares method is used to analyze the model parameters. The calculation result is:

\[
\begin{align*}
X_{Tm} &= 0.00183 \times T^2 - 0.04804 \times T + 0.37022 \\
Y_{Tm} &= 0.00025 \times T^2 - 0.00478 \times T + 0.29276 \\
Z_{Tm} &= 0.00068 \times T^2 - 0.02571 \times T + 1.25917
\end{align*}
\]

Comparing with the original data shown in figure 3 and assuming that the model is a cubic function model, the least square method is used to analyze the model. The equation (6) can be obtained as following:

\[
\begin{align*}
X_{Tm} &= 0.00002 \times T^3 + 0.00085 \times T^2 - 0.10191 \times T + 1.09092 \\
Y_{Tm} &= 0.00001 \times T^3 + 0.00004 \times T^2 - 0.01621 \times T + 1.09092 \\
Z_{Tm} &= 0.00001 \times T^3 + 0.00091 \times T^2 - 0.01339 \times T + 1.09092
\end{align*}
\]

Comparing the fitting data with the original image, as shown in figure 4:

![Figure 4](image)

**Figure 4.** The three-order fitting data of the accelerometer compared with the original data.

Taking the temperature range (from -60 °C to 100°C) into consideration, the cubic function is more suitable for this model. As the data at 22°C is taken as the base point and the two sides have unequal changes, the effect of temperature on ADC is not same at different positions. This issue can be ignored, as its influence on the nonlinear fitting model is not great. It can be seen from the figure 4 that the effects on the value of the sensor are different in various positions by the same temperature. The data which are close to 512 (median, changed with different circumstances) have the smaller changed.

3.2. Optimization of the nonlinear fitting model
From the above data, we can see that the cubic coefficient is smaller, indicating that the cubic coefficient is not the main item. So we choose the quadratic model as the main model. To ensure the convenience of the data, we convert the equation (5) to a vertex type:

\[
\begin{align*}
X_{Tm} &= 0.00183 \times (T - 22)^2 - 0.03248 \times (T - 22) + 0.19906 \\
Y_{Tm} &= 0.00025 \times (T - 22)^2 - 0.00622 \times (T - 22) + 0.30860 \\
Z_{Tm} &= 0.00068 \times (T - 22)^2 - 0.00421 \times (T - 22) + 1.02267
\end{align*}
\]

The quadratic term of the model is to conform to the quadratic function, and the quadratic coefficient changes with the position of the sensor. The coefficient of the first term does not change in the quadratic model, and the change will be used to make the linear coefficient related to the original data. After the change, the linear coefficient is constant and set to 0. Then correct the quadratic coefficient so that the new model approaches the original model within the range of -45°C to +80°C, and the following equations are obtained:

\[
\begin{align*}
X_{Tm} &= 0.00183 \times (T - 22)^2 + 0.00012 \times (734.2 - 512) \times (T - 22) \\
Y_{Tm} &= 0.0003 \times (T - 22)^2 + 0.00012 \times (505.4 - 512) \times (T - 22) \\
Z_{Tm} &= 0.0009 \times (T - 22)^2 + 0.00012 \times (421.3 - 512) \times (T - 22)
\end{align*}
\]
The quadratic coefficient term will be transformed into 0.00183, 0.0003, and 0.0009, and all linear coefficient items will be changed to 0.00012. The new model is compared with the original model, as shown in figure 5. From figure 5, it can be seen that the two models are not much different, and the new model is compared with the original data, as shown in figure 6.

![Figure 5](image1.png)  ![Figure 6](image2.png)

**Figure 5.** The quadratic model data compared with the original fitting data.  **Figure 6.** The quadratic model data compared with the original data.

Taking the error into account, it is assumed that the model is still available. As the coefficient presents a quadratic type relationship, the quadratic model can be established again for the quadratic coefficient and the solution is:

$$A_{51} = 0.000000044 \times (M)^2 + 0.000048069 \times M + 0.013311037$$  (9)

Convert it to vertex equation:

$$A_{51} = 0.000000044 \times (M - 512)^2 + 0.00000301 \times (M - 512) + 0.00023405$$  (10)

Where M is the data read from the acceleration at 22°C. The curve is shown in figure 7. And at the T temperature the X value becomes:

$$X_T = \left(0.000000044 \times (X - 512)^2 - 0.00000301 \times (X - 512) - 0.00023405 \right) \times (T - 22)^2 - 0.00012 \times (X - 512) \times (T - 22)$$  (11)

The final compensation effect is shown in figure 8. The x-axis represents the temperature, the y-axis represents the sensor position, and the z-axis represents the compensated value.

![Figure 7](image3.png)  ![Figure 8](image4.png)

**Figure 7.** The quadratic coefficient fitting curve.  **Figure 8.** The accelerometer temperature compensation diagram.

### 4. Conclusions

Through high-order nonlinear fitting, the nonlinear relationship between temperature and data of the acceleration sensor can be approximated. The fixed-parameter methods can greatly reduce the
complexity of the model and allow the model to run on embedded devices. The temperature compensation model algorithm is tested under the same device and conditions. The result is shown in table 3. The standard deviation has been reduced from 0.374 to 0.193. It can be seen that this method can effectively reduce the influence of the temperature on the angle sensor. In the industrial temperature range (from -45 °C to 85 °C), the angle sensor has a measure error less than 0.12 degree, as it can be 1.12 degree before using the nonlinear model compensation. This model takes the location of the sensor into account, so it has universal applicability. The same method can also be used to optimize other accelerometer temperature compensation models.

### Table 3. angle data at diverse temperatures by using nonlinear model Compensation.

| number | temperature/°C | angle/° | standard deviation |
|--------|---------------|--------|--------------------|
| 1      | 0             | -62.49 |                    |
| 2      | -30           | -62.53 |                    |
| 3      | -45           | -62.64 | 0.193              |
| 4      | 22            | -62.41 |                    |
| 5      | 60            | -62.15 |                    |
| 6      | 85            | -62.12 |                    |

References

[1] Tan C W and Park S 2005 Design of accelerometer-based inertial navigation systems *IEEE Transactions on Instrumentation & Measurement* **54**(6): 2520-2530

[2] Norling B L and Cornelius C J 1988 Accelerometer with isolator for common mode inputs *US, US4766768*

[3] Zheng wei W U, Chen D Y, Yang M M & Lei X U 2006 A pendulous micromachined silicon accelerometer *Transducer & Microsystem Technologies*

[4] Ojeda L, Chung H & Borenstein J 2000 Precision calibration of fiber-optics gyroscopes for mobile robot navigation *IEEE International Conference on Robotics and Automation*

[5] Du Y P & He X Y 2009 Discussion on Sensor Temperature Compensation Technology *Electronic Design Engineering* **17**(6):63-64

[6] Jia P G, Liu X W & Wu X C 2013 Attitude sensor temperature compensation method *Modern Electronic Technology* **2013**(20): 118-120

[7] Norling B L 1988 Temperature compensation of an accelerometer *EP, US4750363[P]*

[8] Grigorie L T 2007 The bias temperature dependence estimation and compensation for an accelerometer by use of the neuro-fuzzy techniques *Transactions-Canadian Society for Mechanical Engineering* **32**:383-400

[9] Quinchia A G, Ferrer C & Falco G 2013 Constrained non-linear fitting for stochastic modeling of inertial sensors *Design and Architectures for Signal and Image Processing*