A method of compensating magnetic compass’s temperature error using BP network

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Abstract. Magnetic compass can be widely used, error compensation is important to magnetic compass. In this paper, we analyse the influence of temperature on heading error and put forward an algorithm based on BP network to compensate the heading error of magnetic compass. When the temperature is in 17°C--40°C, this algorithm can control the heading error after compensation in 1.13 degree.

1. Introduction

Magnetic compass can be used to detect azimuth based on earth’s magnetic field. It can be widely used in navigation systems for cars, ships, submarines, GPS locators, and mobile phones. Because of instrument errors and surroundings magnetic field errors, the precision of magnetic compass is poor. So error compensation is important to magnetic compass.

A basic compensation algorithm is base upon compass deviation equation that is formed by colligating interferential magnetic field of carrier. D. Gebre-Egziabher utilized “non-linear two-step estimation algorithm” to estimate scale factors and bias by calculating ellipse equation. And then the heading errors are compensated [2]. The compensation method presented by R. B. Smith [3] is based on the relationship equation of induced magnetic field, permanent magnetic field, Earth’s magnetic field and measured magnetic field. In this method twelve coefficients about induced magnetic field and permanent magnetic field are calculated to compensate heading errors. Another compensation method [4], which combines rate gyros with TCM2 and GPS, can enhance precision of heading. Jau-Hsiung Wang and Yang Gao put forward a magnetic compass calibration algorithm using neural networks [5]. But all of these methods mentioned above don’t consider influence of temperature.

In this paper, it is proved that temperature has influence on heading in theory and experiment, and an algorithm based on BP network is presented to compensate the heading error of magnetic compass. Finally, this algorithm is proved can compensate heading error better in experiment.

2. Experiment and result

The handbook of Honeywell shows that the sensitivity, bridge offset and resistance coefficient change with temperature. This change will affect the measure of magnetic fields. So a conclusion is got that temperature affects heading error. To prove this conclusion we design a series of experiment. Figure 1 shows heading error graph, which is measured every 10° from 0° to 350° under three different temperatures. In this experiment magnetic compass is set in horizontal plane. From this figure it can be found that the heading error curves change with temperature but the trend has rule. It is also found that
the heading error has nonlinear relationship with temperature and measured heading. In a word, temperature has influence on heading.

![Figure 1. Heading error graph of training data.](image)

3. Modelling neural network and compensation

3.1. BP neural network

BP network is a multi-layer feed-forward neural network, which utilizes back-propagation algorithm to train network. A forward pass and a backward pass are included in this algorithm. In the forward pass, the input of network is transmitted to output layer and the heading error between output and its expected value is calculated. If the heading error is larger than reference value the backward pass is called, in which the heading error is pass back to adjust the synaptic weight. This process continues until the network reaches a steady state [5]. BP network can be applied in approximation, pattern recognition, classification and data compression. The advantage of BP neural network is that can provide a model-free input-output nonlinear mapping without requiring the relationship of input and output in advance. BP neural network also has generalization. So in this paper, BP network is used to mapping the nonlinear relationship of measured heading, temperature and the heading after compensation.

3.2. Confirm the model parameter of BP network

The structure of network including input, output, the number of neurons and layers must be confirmed firstly. The data showed in figure 1 is used as training data to set up basic model of network with the toolbox about neural network of MATLAB. And Levenberg-Marquardt arithmetic is utilized in training.

The network has three layers and appropriate neurons can approximation any function. So the network that has three layers is used to mapping relationship of temperature, measured heading and expectation heading. The sigmoid activation function and a pure linear activation function are utilized in hidden layer and output layer respectively.

It is proved that temperature has influence on heading error of magnetic compass above. So temperature and measured heading are used as the network inputs, and the heading after compensation is defined as the network output. The input data must be standardization because of the characteristic of BP network’s transfer function. Standardization not only can improve the characteristic of BP network but also assemble the input data in response extent [-1,1] of tansig function. We utilize equation (1) to standardize the input data.

\[ x_t = -1 + 2 \times \frac{(x - x_{\text{min}})}{(x_{\text{max}} - x_{\text{min}})} \]  

(1)
where \( x, x_1 \) are the input data and its value after normalization. \( x_{\text{min}} \) and \( x_{\text{max}} \) are the minimal and maximal value of input data respectively. The output of network is in- normalized utilizing equation (2):

\[
y = (y_1 + 1) \times \left( \frac{y_{\text{max}} - y_{\text{min}}}{2} \right) + y_{\text{min}}
\]

where \( y_1, y \) are the output data and its value after in- normalization. \( y_{\text{min}} \) and \( y_{\text{max}} \) are the minimal and maximal value of expected output data respectively.

The key to modeling network is to define the number of neuron in hidden layer. The less neuron used the less information will be obtained; In contrast, the local minimum may increase, and the network may converges to local minimum mostly. Thus the network’s precision will fall.

But there is not a rule in defining the number of neurons in hidden layer. In general, the optimal number is empirically chosen based on the physical complexity of the problem at hand [5]. In addition, the network’s precision must high, the less neuron used the better and the network doesn’t over “fitting”. In this paper we finally select six neurons in hidden layer.

In conclusion, three layers, two inputs-one output network with six neurons in hidden layer is established and showed in figure2.

**Figure 2.** The model of BP network.

### 4. Experimentation

Another set of data is used to test the network established above. In measuring experimental data we set magnetic compass in horizontal plane and the biases and scale factors on \( x \) and \( y \) the same as measuring training data.

The experimental data is measured every 10° from 0° to 350° under variation temperature. Table 1 shows the heading error fore-and-aft compensation of experimental data. We can see that the RMS of heading error is drops from 1.4998 to 0.4563 although the heading errors of some point are increase. A conclusion is gained that BP neural network seek for global optimization but not local optimization during approximation.

### 5. Conclusions

Temperature has influence on heading error is proved firstly. Then an algorithm to compensate the heading error of magnetic compass is put forward. This algorithm can mapping the nonlinear relationship between temperature, measured heading and the heading after compensation. The experiment result shows that the heading error can be controlled in 1.13. But the magnetic is in horizontal plane; so further research work includes extending the neuron network to compensate the heading error of temperature and magnetic deviation in all-stance situation.
Table 1. The heading error fore-aft compensation. Unit: degree

| Reference heading | Temp °C | Error before compensation | Error after compensation | Reference Heading | Temp °C | Error before compensation | Error after compensation |
|-------------------|--------|----------------------------|--------------------------|-------------------|--------|----------------------------|--------------------------|
| 0                 | 33     | 0.34                       | 0.78                     | 180               | 39     | 0.13                       | -0.49                    |
| 10                | 33     | 0.16                       | 0.40                     | 190               | 39     | -0.68                      | -0.76                    |
| 20                | 33.88  | -0.13                      | 0.33                     | 200               | 39     | -0.80                      | -0.61                    |
| 30                | 34     | -0.76                      | -0.03                    | 210               | 38.7   | -0.81                      | -0.53                    |
| 40                | 34     | -0.90                      | 0.10                     | 220               | 38     | -0.04                      | -0.11                    |
| 50                | 35     | -1.11                      | 0.14                     | 230               | 37     | 0.45                       | 0.00                     |
| 60                | 35     | -1.38                      | -0.24                    | 240               | 36     | 0.65                       | -0.24                    |
| 70                | 36     | -0.92                      | -0.12                    | 250               | 36     | 1.48                       | -0.08                    |
| 80                | 36     | -0.18                      | -0.05                    | 260               | 35     | 1.72                       | -0.06                    |
| 90                | 36     | 0.27                       | -0.62                    | 270               | 35     | 1.35                       | -0.60                    |
| 100               | 36     | 1.67                       | -0.23                    | 280               | 34     | 1.23                       | -0.46                    |
| 110               | 37     | 2.83                       | 0.25                     | 290               | 34     | 0.98                       | -0.37                    |
| 120               | 37     | 3.33                       | 0.32                     | 300               | 34     | 0.88                       | 0.04                     |
| 130               | 38     | 3.51                       | -0.01                    | 310               | 34     | 0.71                       | 0.42                     |
| 140               | 38     | 3.18                       | -0.35                    | 320               | 34.10  | 0.64                       | 0.79                     |
| 150               | 38.05  | 2.83                       | -0.12                    | 330               | 34.29  | 0.93                       | 1.13                     |
| 160               | 39     | 2.05                       | -0.13                    | 340               | 34.27  | 1.15                       | 1.07                     |
| 170               | 39     | 1.19                       | -0.15                    | 350               | 35     | 1.36                       | 0.52                     |

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