CALIBRATION PROCESS OF TWO – AXES MATGNETOMETER BY NEURAL NETWORK

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The article presents an option how to design neural networks to solve the errors of 2D vector fields sensors: magnetometers and accelerometers. The introduction deals with the errors of the sensor. The theory describes that gradient method was used for learning corrective constants. The next, modelling, presents the development of corrective constants under the ideal conditions. We assembled, the real experiment confirms the theory and the modelling. The utilization of neural networks was directly shown on the improved course measuring.

K e y w o r d s: two – axes magnetometers, sensors setup, calibration, neural network

1 INTRODUCTION

Neural networks for removal of multiplicative additive and orthogonal errors were used for calibration of 2D sensors. Sensor performs a random plain rotation in homogenous magnetic field during calibration. The vector has to have its projection on the plain field rotation. Sensor errors manifest on the transfer characteristic, this is shown on the Fig. 1.

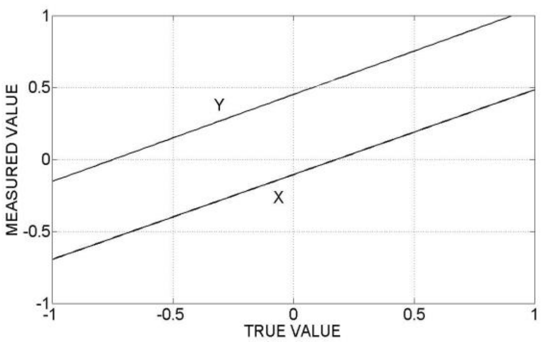

Fig. 1, Transfer function of 2D sensor with additive, multiplicative and orthogonal error

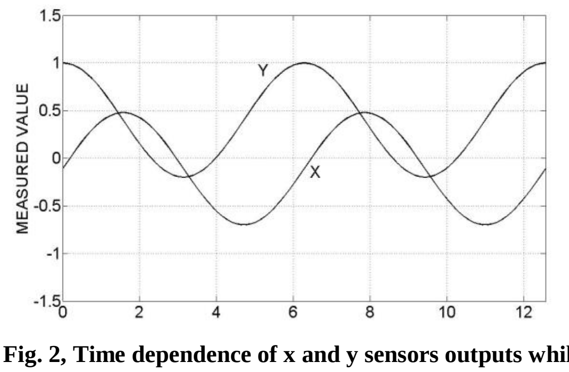

Fig. 2, Time dependence of x and y sensors outputs while harmonic rotation

Additive errors cause a shift in the harmonic functions in line of axis y and the multiplicative error causes functions to have different values. Orthogonal error is manifested as a bilateral shift of functions against each other in the line with the axis x (Fig.2).

2 THEORY

Designed neural networks solve the errors of 2D vector fields sensors. Performance of every network consists of two processes: learning process that serves to set up individual corrective coefficients and corrective process when the sensor measures with the learnt corrective coefficients. During the measuring we get values x^k and y^k , which create orthogonal decomposition of normalized vector field **B** of magnetic field induction in plain field. Hitherto, it is evident that the value of projection of the vector in k step is:

$$B^k = \sqrt{\left(x^k\right)^2 + \left(y^k\right)^2}; \tag{1}$$

Largeness of the projection is standard value and is equal to 1. Then we can define the error equation as:

$$\begin{aligned} \varepsilon^k &= 1 - B^k; \\ \left(\varepsilon^k\right)^2 &= (1)^2 - \left(B^k\right)^2; \end{aligned} \tag{2}$$

To get to the newly corrected values, we need to define the relations that correct the measured values:

$$\begin{aligned} x_1^k &= M_x^k x^k + A_x^k; \\ y_1^k &= M_y^k y^k + A_y^k + 0^k; \end{aligned} \tag{3}$$

After that, we need to find such multiplicative constants M, additive constants A, and orthogonal constant O which would converge error ε to zero. After the application of absolute differential to error equation we will get to the method for iterating the constants, to the gradient method:

$$\begin{aligned} M_x^{k+1} &= M_x^k + 2x^k x_1^k \alpha\varepsilon; \\ M_y^{k+1} &= M_y^k + 2y^k y_1^k \alpha\varepsilon; \\ A_x^{k+1} &= A_x^k + 2x_1^k \alpha\varepsilon; \\ A_y^{k+1} &= A_y^k + 2y_1^k \alpha\varepsilon; \\ O^{k+1} &= O^k + 2x^k y_1^k \alpha\varepsilon; \end{aligned} \tag{4}$$

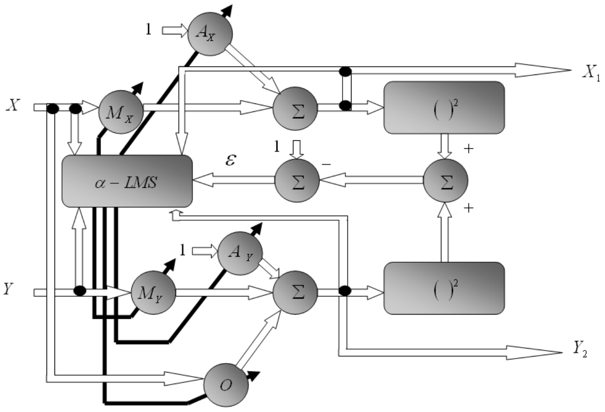

Fig. 3, Neural network for multiplicative, additive and orthogonal error rejection

These algorithms are iterative and represent a method how to remove errors from sensor so that absolute error is minimal. At commencing learning process, the scales are implicitly set to the ideal values: M = 1, A = 0 a O = 0.

3 MODELING

For testing the neural network, signals of axes x and y that simulated random movement of sensor in the plain field were created. It is a random discreet rotation which has even representation of the probable in the range of measured values. The learning process of convergent constants is depicted on the figures 4,5, and 6.

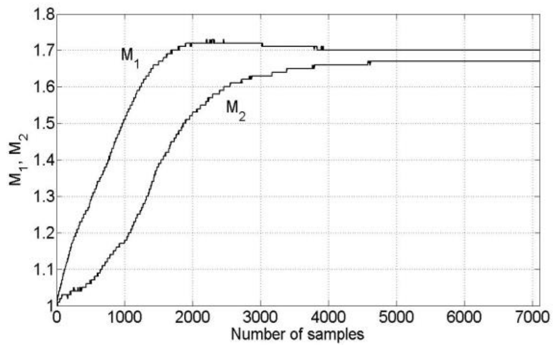

Fig. 4, Learning process of multiplicative constants of x and y channel

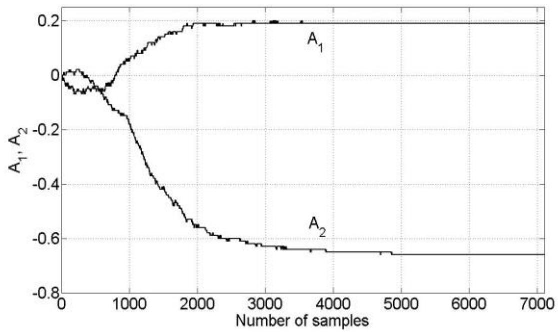

Fig. 5, Learning process of additive constants of x and y channel

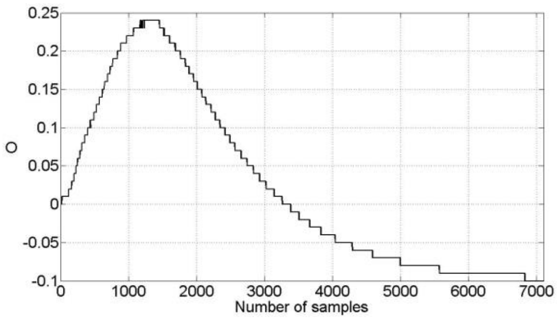

Fig. 6, Learning process of orthogonality constant

As is seen, the tuning of individual constants required circa 7000 samples. Fig. 7 depicts course of error E_2, which converges to zero. Error E_1 is without calibration and holds in the same range.

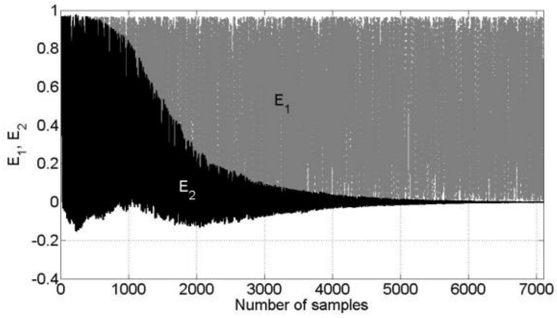

Fig. 7, Total error rejection, while learning process (discrete rotation)

The stability and velocity of convergence is managed by α and the value for this case was selected to be 0.1.

4 EXPERIMENT

The experiment followed after the simulation. MicroMag3 was chosen as magnetometer. In spite of the fact that this is three-axes magnetometer, it was functionally used as two-axes one. Constant α was set to 0.005. Sampling frequency of the magnetometer was set to 170 Hz. No filters were used to remove the noise. Calibration took place in the laboratory with 50Hz noise from power lines. Figures 8, 9, and 10 depict the learning process of corrective constants.

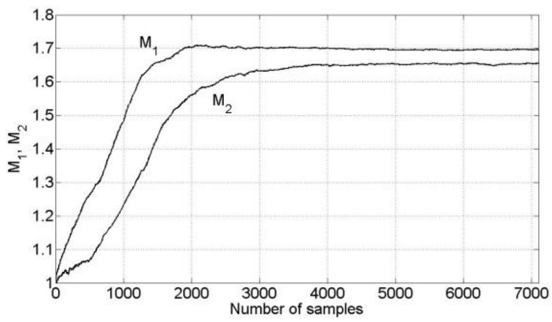

Fig. 8, Learning process of multiplicative constants of x and y channel in real experiment

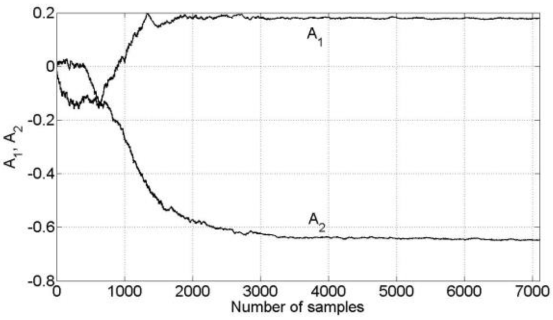

Fig. 9, Learning process of additive constant of channel x and y in real experiment

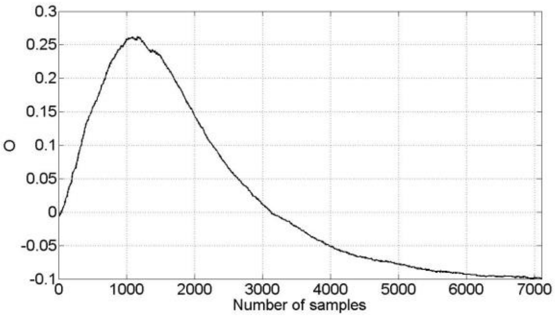

Fig. 10, Learning process of orthogonality constant in real experiment

The processes of learning corrective constants from the experiment are very alike to those from modeling. The course of error reduction is shown in the fig. 11.

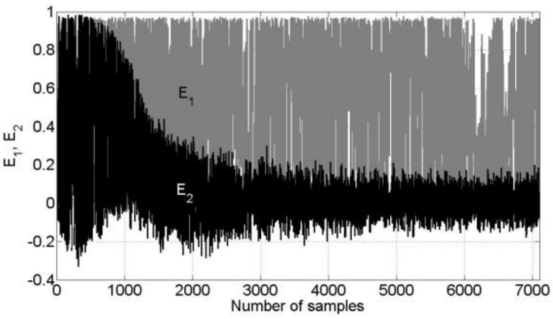

Fig. 11, Total error rejection, while learning process in real experiment

Error E_2 presents error during the calibration process. As is seen, it is decreasing over time, however it lacks the capacity to converge to zero as reached in the simulation. The cause is the 50Hz noise from industrial network and the noise of the sensor which is strong in this particular type of magnetometer. Error E_1 is error calculated from measured values of the sensor without any other corrections.

The next experiment focused on the course calculation. Course was calculated from the measured values and from the values which were corrected by corrective constants. Magnetometer was located on the rotation platform which was consequently slewed by 5°. The calculated course are depicted on the fig. 12.

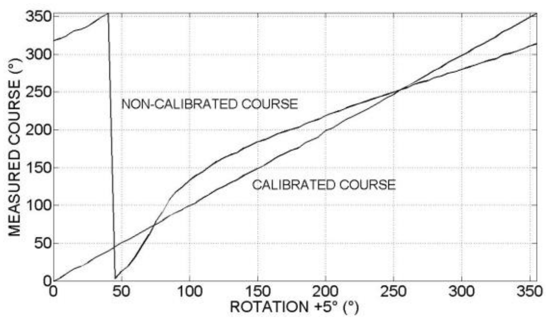

Fig. 11, Course calculated from measured and calibrated data

The course calculated from calibration data is linear while the course calculated from non-calibrated data is linear only weakly and in some spots it differs by as much as 40°.

5 CONCLUSION

In this article we present the possibility of using neural networks for setting 2D sensors. Experiment corresponds with the modelling to great extent. This way of calibration considerably improves the possibility to measuring accurate course. The environment that would be more homogenous than the laboratory field and reduction of sensor noise might ensure better results.

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