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GRADIENT METHODOLOGY FOR 3-AXIS MAGNETOMETER SCALAR CALIBRATION

Tomáš Kliment* — Dušan Praslička* — Katarína Draganová* — Josef Blažek**

The paper presents a novel easy-to-use iterative calibration algorithm for a magnetic field estimation accuracy improvement, which can be successfully applied to the estimation of a 3-axis magnetometer biases and scale factors of the each axis, extended to estimate non-linearity and non-orthogonality corrections. The theory is based on the neural network that creates an inverse function the uncalibrated sensor's transfer function. Learning process of the neural network uses a gradient methodology applying total differential on the scalar error function. The analysed theoretical principles are supplemented by simulations and experimental measurements. The performed simulations and experiments confirmed that the algorithm successfully converges to a good estimation of the calibration constants. Other advantage of this methodology is that the calibration procedure is based on the attitude independent sensor discrete random rotation in the 3D space without the need of any non-magnetic calibration platforms.

Keywords: calibration, linearity, magnetometer, orthogonality, sensitivity

1 INTRODUCTION

Calibration of magnetic field sensors leads to the significant improvement of the sensor's accuracy, therefore many authors have developed various calibration methods for calibration constants determination [1]–[6]. The goal of the presented calibration methodology is to introduce an easy-to-use calibration algorithm that can be used for a magnetic or other physical vector field estimation accuracy improvement. The paper presents a novel iterative calibration algorithm, which can be successfully applied to the estimation of a 3-axis magnetometer biases and scale factors of the each axis, extended to the estimation of non-linearity and non-orthogonality corrections.

2 THEORY

The calibration methodology is based on the one-layer feed-forward neural network consisting of 12 adaptive elements, learning mode for the network training and working mode is used for measured data correction. The neural network creates an inverse sensor's transfer function of the sensor.

Considering a 3-axial sensor of vector field with the bias, sensitivity, linearity and orthogonality errors, during a random rotation in a homogeneous normalized field we get for every step of repeated measurement x^k, y^k and z^k values representing uncalibrated almost orthogonal decomposition of the measured field vector in x, y and z axis, the scalar value T of which can be calculated as

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

The error function ε can be hence defined as a difference between the true scalar value of the vector field normalized in the scalar value to 1 and the square of the calculated value of the T of the given k step

$$\varepsilon^k = 1 - \left(T^k\right)^2 \tag{2}$$

For the each step of calibration the measured data are corrected using actual calibration constants for every step of the learning process. As the inversed model the odd Taylor series of the 3rd order supplemented by orthogonal correction for small deviations of angles was used

$$\begin{aligned}
\tilde{x}^k &= C_x^k \left(x^k\right)^3 + B_x^k x^k + A_x^k \\
\tilde{y}^k &= C_y^k \left(y^k\right)^3 + B_y^k y^k + A_y^k + O_{yx}^k x^k \\
\tilde{z}^k &= C_z^k \left(z^k\right)^3 + B_z^k z^k + A_z^k + O_{zy}^k y^k + O_{zx}^k x^k
\end{aligned} \tag{3}$$

where $\tilde{x}^k$, $\tilde{y}^k$ and $\tilde{z}^k$ are corrected measured data for the given step k and A, B, C and O are calibration constants used for bias, sensitivity, linearity and orthogonality error calibration, respectively.

The learning process of calibration constants in the learning mode is based on the gradient methodology, thus application of the absolute differential on the error function (2), resulting into iterative equations, based on which corrected values of the measured orthogonal decomposition of the field vector in the each step are calculated.

The learning process of the bias calibration constants A_x, A_y and A_z is based on following equations

$$\begin{aligned}
A_x^{k+1} &= A_x^k + 2\tilde{x}^k \alpha \varepsilon^k \\
A_y^{k+1} &= A_y^k + 2\tilde{y}^k \alpha \varepsilon^k \\
A_z^{k+1} &= A_z^k + 2\tilde{z}^k \alpha \varepsilon^k
\end{aligned} \tag{4}$$

where α constant influences stability and velocity of the learning process convergence. Sensitivity calibration constants marked as B_x, B_y and B_z can be calculated using equations

$$\begin{aligned}
B_x^{k+1} &= B_x^k + 2x^k \tilde{x}^k \alpha \varepsilon^k \\
B_y^{k+1} &= B_y^k + 2y^k \tilde{y}^k \alpha \varepsilon^k \\
B_z^{k+1} &= B_z^k + 2z^k \tilde{z}^k \alpha \varepsilon^k
\end{aligned} \tag{5}$$

For linearity calibration constants C_x, C_y and C_z we can write equations

* Department of Aviation Technical Studies, Faculty of Aeronautics, Technical University of Kosice, Rampova 7, 041 21 Kosice, Slovakia ** University of Security Management in Košice, Kukučínova 17, 040 01 Košice, Slovakia; katarina.draganova@tuke.sk

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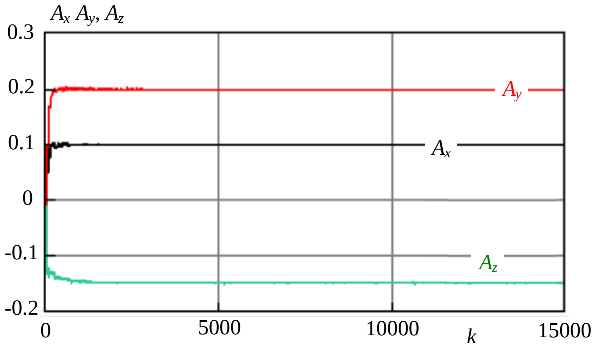

Fig. 1. Learning process of bias calibration constants

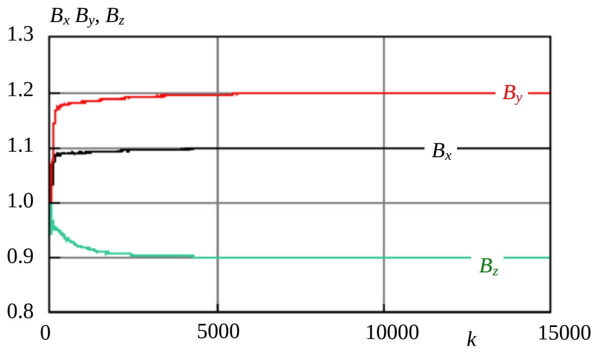

Fig. 2. Learning process of sensitivity calibration constants

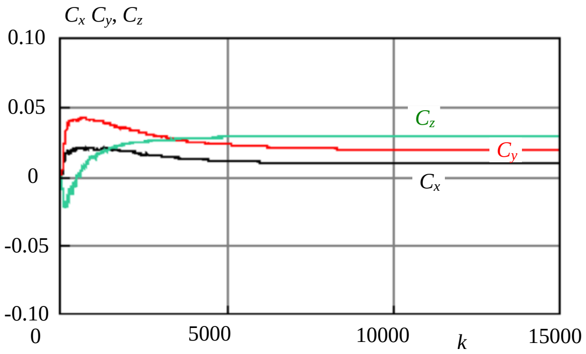

Fig. 3. Learning process of linearity calibration constants

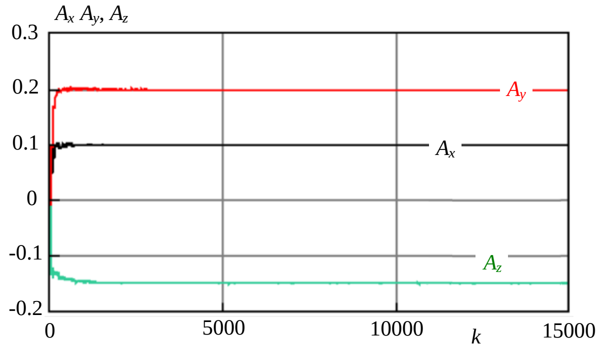

Fig. 4. Learning process of orthogonality calibration constants

$$
\begin{aligned}
C_x^{k+1} &= C_x^k + 2\left(x^k\right)^3 \tilde{x}^k \alpha \varepsilon^k \\
C_y^{k+1} &= C_y^k + 2\left(y^k\right)^3 \tilde{y}^k \alpha \varepsilon^k \\
C_z^{k+1} &= C_z^k + 2\left(z^k\right)^3 \tilde{z}^k \alpha \varepsilon^k
\end{aligned} \tag{6}
$$

and orthogonality calibration constants O_{yx}, O_{zy} and O_{zx} can be determined as

$$
\begin{aligned}
O_{yx}^{k+1} &= O_{yx}^k + 2x^k \tilde{y}^k \alpha \varepsilon^k \\
O_{zy}^{k+1} &= O_{zy}^k + 2y^k \tilde{z}^k \alpha \varepsilon^k \\
O_{zx}^{k+1} &= O_{zx}^k + 2x^k \tilde{z}^k \alpha \varepsilon^k
\end{aligned} \tag{7}
$$

3 MODELING AND SIMULATIONS

For the theoretical principles verification the mathematical model consisting of 24 000 samples representing random and discrete sensor rotation in the homogeneous normalized field with the bias, sensitivity, linearity and orthogonality errors the inverse model according to (3) of the simulated measured values was created.

For a better visualization of the initial part of the learning process of the bias, sensitivity, linearity and orthogonality calibration constants only the first 15 000 iteration steps are shown on Figs. 1 – 4, respectively. The convergence velocity α was set to 0.05 and the learning process of the sensitivity calibration constants starts with 1 and of the other constants with 0.

The linear error Δ of the iteration process can be defined as a deviation of the actual scalar value T from the normalized true value, which is equal to 1 in the given iteration step k:

$$\Delta^k = 1 - T^k \tag{8}$$

Figure 5 illustrates linear error Δ_m calculated from the uncalibrated data in comparison with the linear error Δ calculated during the learning process.

The linear error calculated from simulated uncalibrated data Δ_m varies from –0.2671 to 0.3655 with the peak to peak value of 0.6327 and during the calibration process the linear error Δ is reduced to the peak to peak value of 2.10^{-6}, which means a significant improvement of the modelled sensor's characteristics. In the simulation the determination of the calibration constants converged alm most exactly to the defined simulated values and the inverse model was then determined.

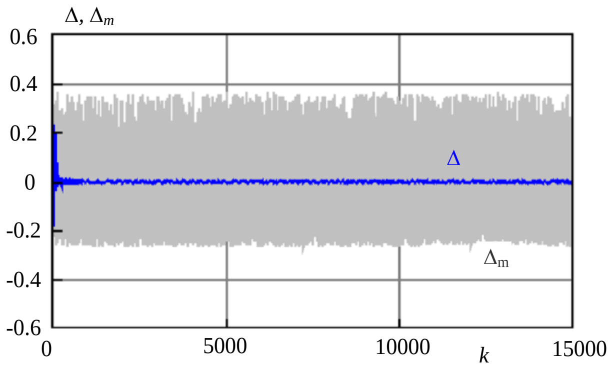

Fig. 5. Comparison of linear errors calculated from uncalibrated data and corrected data during the learning process

4 EXPERIMENTS AND RESULTS

As the simulation results confirmed correctness of this calibration methodology, experimental measurements were performed using the 3-axis simultaneous relax-type fluxgate Vema magnetometer with the resolution of 1.7 nT [7]. Experiment was performed in normal non-shielded laboratory conditions. The sampling frequency during the measurements was 1 kHz and each sample was obtained as an average consisting of 20 samples mainly because of the ambient 50 Hz noise and harmonics suppression. Measured data were during the measurement normalized to 1 according to the initial scalar values of the magnetic field measured by the Vema magnetometer. The data were measured by random rotation in the local magnetic field for 8 minutes.

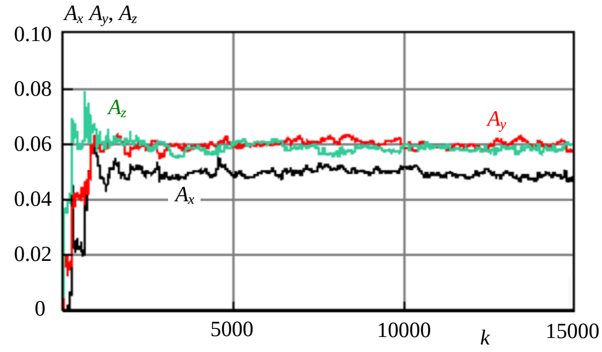

Fig. 6. Learning process of bias calibration constants

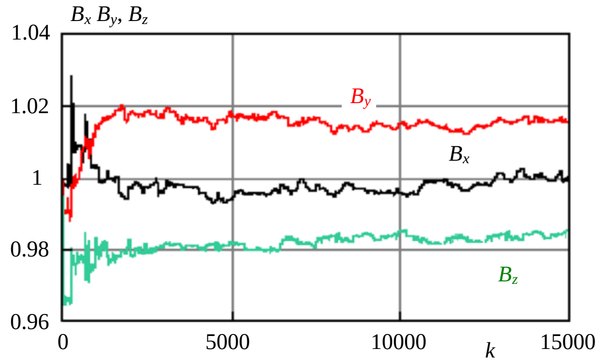

Fig. 7. Learning process of linearity calibration constants

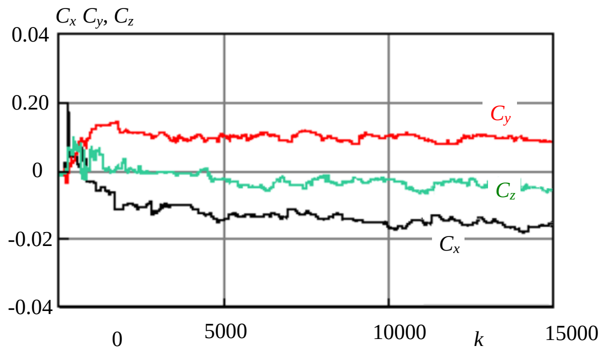

Fig. 8. Learning process of linearity calibration constants

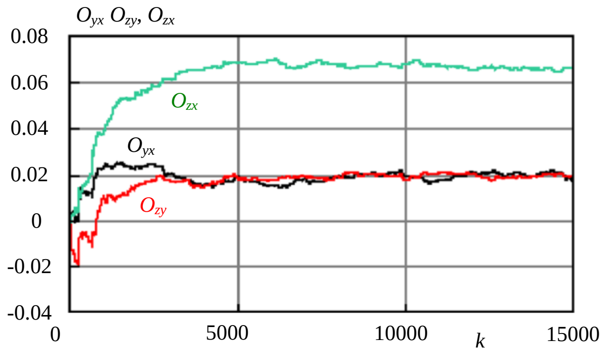

Fig. 9. Learning process of orthogonality calibration constants

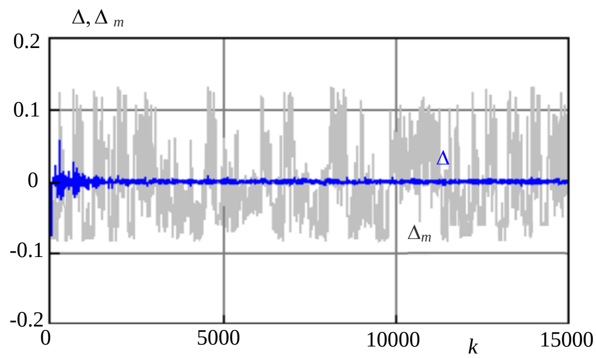

Fig. 10. Comparison of linear errors calculated from measured data and during the learning process

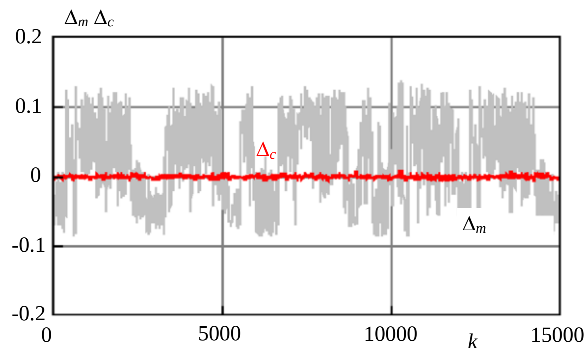

Fig. 11. Comparison of linear errors calculated using calibration constants before and after calibration in different data set

The true absolute scalar value of the magnetic field (48,700 μT) in the place of the experiment was for the purposes of the absolute final calibration also measured using a scalar proton magnetometer PM-1 (the value of scalar field changes slightly according to position of the probe at the level of 100nT per meter in vertical direction). To show the initial part of the iteration process the first 15 000 iteration steps from the overall 24 000 iterations of the learning process of bias, sensitivity, linearity and orthogonality calibration constants during the measurement is shown in Fig. 6 – Fig. 9, respectively. The convergence velocity α was set to 0.015 for all calibration constants.

Figure 10 illustrates linear error as calculated from the measured data in comparison with the linear error calculated during the calibration process. We can see a significant improvement of the sensor's precision – the linear error of the measured data Δ_m changes from –0.0856 to 0.1330, which corresponds to the peak to peak value of 10.646 μT (after the recalculation to the absolute value according to the proton magnetometer data) and after the stable state achievement the error Δ changes only from –0.0043 to 0.0066, which can be interpreted as the peak to peak value of 0.530 μT. The standard deviation of the absolute scalar value *T* was from the value of 2.806 μT eliminated to 0.104 μT. It means that with the 68 % probability the error in the determination of the absolute scalar value of the field will be for the given data set after the calibration is less than 104 nT in any sensor position – instead of uncalibrated 2 806 nT. So in 8 minutes without any hardware costs we get 27 times better results in determination of scalar value of the field for random 24 000 positions. For the final alignment we need just to align electrical axis x with the mechanical one.

Table 1. Overview of determined calibration constants

axis	calibration constant			
	A	*B*	*C*	*O*
x	0.0497	0.9984	–0.0171	–
y	0.0601	1.0130	0.0105	0.0193 (O_{yx})
z	0.0581	0.9859	–0.0061	0.0202 (O_{zy}) 0.0682 (O_{zx})

Table 1 summarizes calculated calibration constants calculated of the tested Vema magnetometer calculated as an average from last 4 000 iteration steps. The final deviations of the scalar value during rotation were probably caused mainly by the inhomogeneity and non-stationarity of local magnetic field, and then also by the axial asymmetry of used ferro-probes and subsequent cross-axis effects.

For the verification of the calibration results the calculated calibration constants were applied on another data set. In Fig. 11 is a comparison of linear errors calculated from measured (Δ_m) and calibrated (Δ_c) data. The standard deviation of the absolute scalar value *T* was from the value of 2.963 μT eliminated to 0.117 μT what corresponds very closely to previous results given by statistically different data set.

CONCLUSION

The theoretical principles of the adaptive attitude-independent calibration methodology for 3-axis sensors of vector physical fields calibration based on the one-layer feed-forward neural network consisting of twelve adaptive elements was confirmed by the simulation, during which a very good convergence and calibration constants' estimation was achieved. Simulation results were supplemented by the experimental measurements based on the adaptive real-time calibration process, which also proved the correctness of the proposed calibration algorithm.

Finally it can be concluded that the main advantages of the presented calibration methodology lie not only in the simplicity of the calibration algorithm, attitude independency of the sensor during the calibration measurements, no need of non-magnetic calibration platform utilization. Other advantages are in the calibration speed, precision and computational and memory undemandingness of the learning mode leading to the effective magnetometer calibration constants determination and calibration errors reduction.

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