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Compensation of Magnetometers Error Based on Nonlinear Models for Multimotor Aerial Robots Applications

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***Abstract*—In this paper we describe the compensation of magnetometers error which are result of high current flows in their vicinity. This kind of errors can be found in multirotor applications where measurement unit is located in the platform center, while motors with propellers are mounted on a relatively short arms around the platform body. Varying current flows have an impact on magnetic field around the magnetometers what results in an apparent angular changes of the unmanned platform. In order to compensate this unwanted effect, we have builded nonlinear model relating motors control inputs with the magnetic field changes and employed it in a compensation scheme.**

I. Introduction

In several recent years, there has been a great boom on many kinds of the unmanned aerial vehicles (UAVs), especially vertical take-off and landing platforms with multirotor actuators. One of the main reasons for the gain of their popularity, is the ability to perform vertical takeoff and landing tasks. It allows to operate indoors and/or with low linear speeds making it an useful tool for surveillance missions. One of the problem which arises during the development of this kind of platform, is how to ensure its ability to maintain desired values of the attitude/altitude because of the structural instability. Although the development of Micro Electro- Mechanical Systems gave the opportunity to design very small in size and powerful electronic circuits that consist of miniature sensors and high performance microprocessors which can be used in a character of control units [1], there still exists problem of the measurements and the methodology of control system prototyping.

Multirotor control schemes require reliable information about platform angular position. Most basic instrumentation used for Euler angles estimation consists of gyroscopes, accelerometers and magnetometers. Each of these instruments has its own characteristic errors related to the measurement principles. In case of accelerometers we have to deal with a high frequency noise, impact of linear and centrifugal accelerations and non zero bias. Also gyroscopes have non zero bias. Magnetometers are strongly affected by the changing magnetic field which can be result of high current flows or vicinity of ferromagnetic masses. Even if we don't have to deal with magnetic field changes due to appearing ferromagnetics, in case of multirotor platforms we can't avoid the influence of current flow on magnetometers measurements.

Attitude determination problem can be formulated as calculation of transformation matrix, which transforms vector quantities from inertial to UAV body frame. This problem can be formulated as minimization of the following performance index and is known as Wahba's problem [8]:

$$J(\mathbf{R}) = \frac{1}{2}\sum_{k=1}^{N} a_k ||\mathbf{w}_k - \mathbf{R}\mathbf{v}_k||^2 \tag{1}$$

where: $\mathbf{R}$ is transformation matrix to be estimated, $\mathbf{w}_k$ is vector quantity in body frame and $\mathbf{v}_k$ is vector quantity in inertial frame. It is important to notice, that with a use of only one vector measurement, it is not possible to fully determine the platform attitude. Survey on algorithms addressing this problems in a deterministic manner can be found in: [5], there exist also a large number of publications addressing the problem of attitude determination by use of stochastic estimation methods [2],[7]. Deterministic methods can be also combined with stochastic approaches [3]. Instead of fully determining attitude, often only pitch and theta angles are computed based on IMU (Inertial Measurement Unit), this method makes use of accelerometer measurements ignoring magnetometers as a source of information [4]:

$$\hat{\phi}_{acc} = \arctan\frac{\tilde{a}_y}{\tilde{a}_z} \tag{2}$$

$$\hat{\theta}_{acc} = \arcsin\frac{\tilde{a}_y}{g} \tag{3}$$

where ϕ_{acc} and θ_{acc} are calculated roll and pitch angles, $\tilde{a}_y$ and $\tilde{a}_z$ are accelerometer measurements along its y and z axes, g is value of gravitational acceleration. One of the reasons for omitting magnetometers in the process of attitude determination are aforementioned issues related to magnetic

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field changes. One could expect, that magnetometers information could improve attitude estimates.

In this paper we address the influence of the BLDC (Brushless DC) motors on magnetometers measurements and propose a compensation scheme of this effect. At the beginning we have to define what will be understood under term overall throttle. We assume that UAV platform of our interest is quadrotor, what means it is equipped with four motors with propellers. Angular movement of platform is controlled by changes of motors angular rates what corresponds to producing appropriate moments. On the other side, actuator system has to provide enough force to maintain fixed altitude. Therefore we can assume that input of each motor δ^i consists of two terms: δ^i_{thr} and δ^i_{ang} for $i = 1, 2, 3, 4$ (i is motor index) where first term is responsible for altitude stabilization while second for attitude stabilization:

$$\delta^i = \delta^i_{thr} + \delta^i_{ang} \tag{4}$$

furthermore it can be assumed that amount of energy needed for attitude stabilization is much lower than amount of energy required for altitude stabilization, it means that following conditions should be met:

$$\delta^i_{thr} \gg \delta^i_{ang} \tag{5}$$
$$\delta^i \approx \delta^i_{thr} \tag{6}$$

Because the most common way to stabilize altitude in this kind of platforms, relies on changing the values of δ^i_{thr} simultaneously in the same manner for each motor, we can assume that $\delta^1_{thr} = \delta^2_{thr} = \delta^3_{thr} = \delta^4_{thr}$ and define overall throttle as the following sum:

$$\delta_{thr} = \sum_{i=1}^{4} \delta^i_{thr} \tag{7}$$

We will treat value of δ_{thr} as the main source of magnetic field changes caused by the actuator system.

Now we can give better illustration of a stated problem, we assume following magnetometer measurement model in the multirotor platform:

$$m_{meas} = m + \mu + \Delta mag_i(\delta_{thr}) + \eta(\delta_{thr}) \tag{8}$$

where m is "true" value of magnetic field in a given magnetometer axis, m_{meas} is its measurement, by μ we denote zero mean measurement errors that are not related with operation of actuators. Quantities $\Delta mag_i(\delta_{thr})$ and $\eta(\delta_{thr})$ are respectively non-zero mean and zero mean errors which are functions of overall throttle. Our task is to model function $\Delta mag_i(\delta_{thr})$ for each magnetometer axis and use it in a compensation scheme.

II. Experiment setup

Experiment setup consisted of quadrotor platform with additional weight preventing it from taking off, motor control unit, data logging unit, power unit and personal computer. It was possible to directly control angular rates of each motor bypassing autopilot board. At the same time, measurements coming from IMU were logged on a computer. Block scheme of experiment setup is shown on Fig. 1.

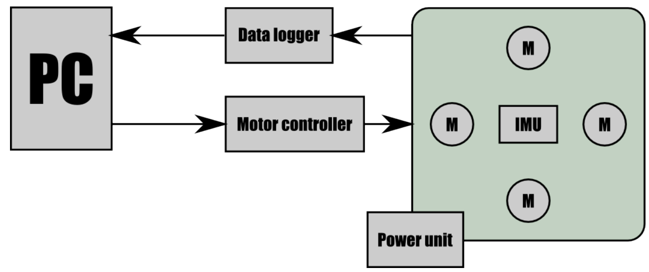

Fig. 1. Block diagram of experiment setup

During the experiment a number of measurement series were taken. During each of them the overall throttle have been raised from zero to the maximum value in a stair wise character. After each round the batteries were charged to their full capacity.

We are interested in modeling changes of magnetic field Δmag_i as a function of overall throttle. In order to obtain value of Δmag_i at a given point, we have subtracted magnetometer reading when motors weren't moving (commanded overall throttle had zero value):

$$\Delta mag_i(\delta_{thr}) = mag_i(\delta_{thr}) - mag_i(0) \tag{9}$$

where mag_i is magnetometer measurement along i-th axis. Results of experiment are shown on Fig. 3 and Fig. 2. We can see that until the control input does not exceed certain point (approximately 37 units), the motors aren't moving. Control value for which motors are starting to move, can be clearly seen on the plots. From obtained results it becomes clear, that the relation between the control input and deviations from nominal magnetometer measurements is of nonlinear nature. At the same time variance of these deviations grows along with control input.

III. Local linear models of magnetometers errors due to current flow

A. Local linear models

Among many black-box nonlinear identification methods, we have chose one which is build on the basis of local linear models. This decision is based on several factors such as: simplicity of the results interpretation, parameter estimation method which doesn't require multiple iterations or assuming any initial values and possibility to model even highly nonlinear phenomenas. Comprehensive description of local linear models can be found in [6].

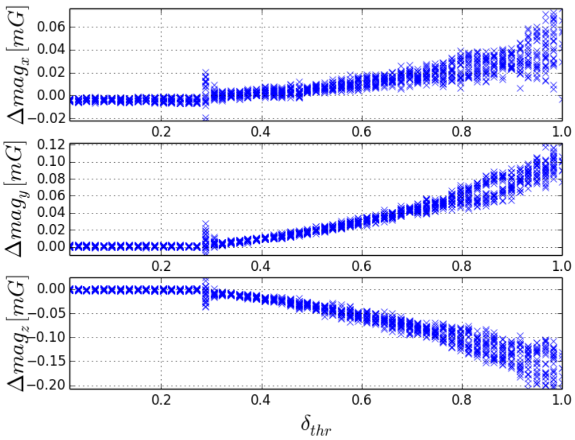

Fig. 2. Plots of $\Delta mag_i(\delta_{thr})$ for each axis, plotted values were used during validation.

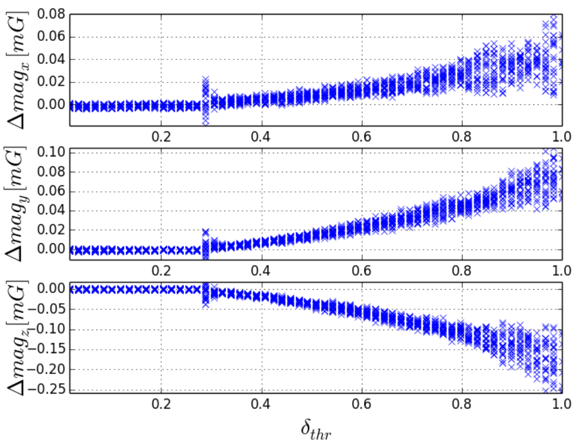

Fig. 3. Plots of $\Delta mag_i(\delta_{thr})$ for each axis, plotted values were used during identification.

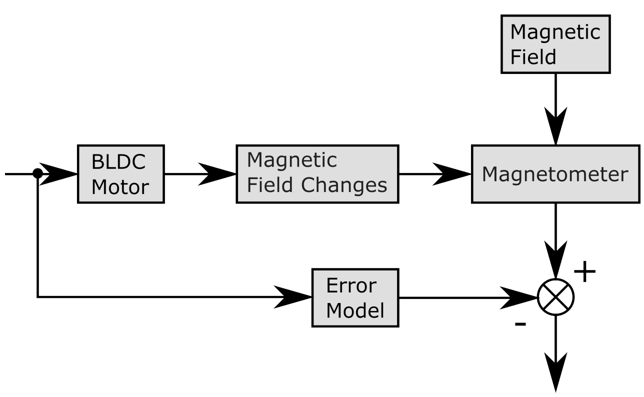

Fig. 4. Block scheme representing how motors affect magnetometer measurement together with error model used in a compensation scheme.

Local linear model (LLM) is based on a combination of a number of linear models with the same input. Output is calculated as a linear combination of linear models outputs, where weighting coefficients are in general nonlinear functions of inputs. Let us define i-th linear static model with j inputs in the following form (10):

$$y_i = a_{0i}u_0 + a_{1i}u_1 + ... + a_{Ni}u_N + b \tag{10}$$

where y_i is output of the model, u_j is the j-th input, a_j and b are model coefficients. Weighting coefficient as a function of inputs will be denoted as:

$$\phi_i = f(u_0, u_1, ..., u_N) \tag{11}$$

Then model output can be calculated using following formula:

$$y = \sum_{i=0}^{M} \phi_i y_i \tag{12}$$

One of the decisions to made, is the proper choice of weighting functions. The most popular choice is use of normalized radial basis functions (RBF), it means that weight ϕ_i is expressed as:

$$\phi_i^{UN} = e^{-(\varepsilon \| c_i - \mathbf{u} \|)^2} \tag{13}$$

$$\phi_i = \frac{\phi_i^{UN}}{\sum_{j=1}^{M} \phi_j^{UN}} \tag{14}$$

where c_k is the center of i-th unnormalized radial basis function ϕ_i^{UN}, $\mathbf{u}$ is the input vector and ε is a parameter by use of which, it is possible to set "width" of a given RBF. This choice of weighting function allows for easy setting the "area of importance" for each linear model with respect to actual input. Local linear model can be represented in a graphical way as can be seen on Fig. 5.

B. Model identification

Two well known solutions for parameter estimation of LLM exists. One is known as the global estimation second one as local approach, both of these are described in [6]. In order to develop solution described in this paper, we have used local approach.

In our case, we have only one input, overall throttle of motors. At the same time, we have assumed that use of three RBF will be enough to describe nonlinearity of function we would like to model. Weighting functions are depicted on Fig. 6.

Because of big differences between input (throttle) and output (magnetometers deviations) signals amplitudes, were normalized to values varying from 0 up to 1. Normalized values, were used in identification process. As was stated above, we have decided to use local approach in order to obtain estimates of LLM. This approach is based on the

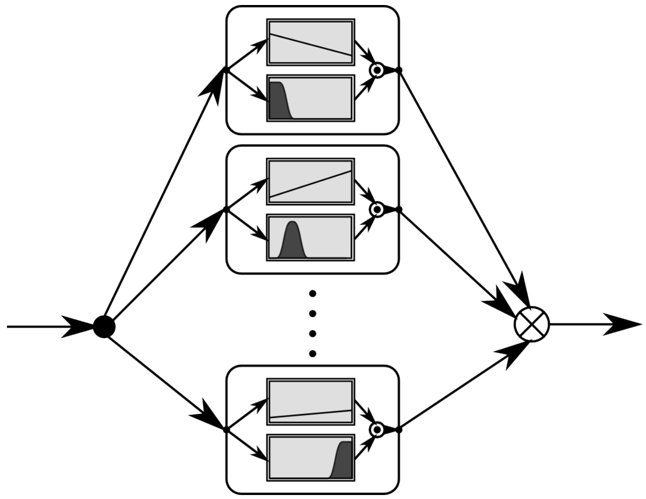

Fig. 5. Graphical representation of local linear model.

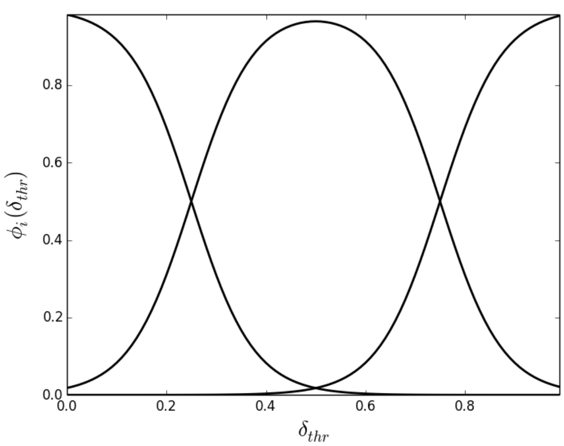

Fig. 6. Three normalized RBF used in a character of weighting functions in developed error model.

idea, that parameters of each local linear model can be estimated separately using following expression for ordinary least squares estimates:

$$\hat{w} = (X^T QX)^{-1} X^T Qy \tag{15}$$

where $\hat{w}$ is estimated vector of parameters, X is regression matrix, y is vector of outputs and Q is matrix of weights. In case of M local linear models, we have to solve M equations (15), one for each local linear model, thus we can write:

$$\hat{w_i} = (X_i^T Q_i X_i)^{-1} X_i^T Q_i y \tag{16}$$

Because in described case, we assumed local linear models of the form:

$$y_i = a_i \delta_{thr} + b_i \tag{17}$$

our regression matrices X_i have the following form:

$$X_i = \begin{bmatrix} \delta_{thr}(1) & 1 \\ \delta_{thr}(2) & 1 \\ \vdots & \vdots \\ \delta_{thr}(N) & 1 \end{bmatrix} \tag{18}$$

Weighting matrix has diagonal structure with values of weights ϕ_i on its diagonal:

$$Q_i = \begin{bmatrix} \phi_i(\delta_{thr}(1)) & 0 & \dots & 0 \\ 0 & \phi_i(\delta_{thr}(2)) & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \phi_i(\delta_{thr}(N)) \end{bmatrix} \tag{19}$$

using matrices X_i and Q_i of the above form, we have obtained estimates of each of local linear model by use of expression (16). In tables below we have gathered all parameters describing each of identified model:

a_i	b_i	c_i	ε
0.01393995	-0.00504612	0	4
0.04419968	-0.01422156	0.5	4
0.08254094	-0.0414244	1	4

TABLE I. PARAMETERS OF MODEL RELATING δ_{thr} TO Δmag_x

a_i	b_i	c_i	ε
0.0181899	-0.00097538	0	4
0.09792892	-0.02581569	0.5	4
0.17656376	-0.0803944	1	4

TABLE II. PARAMETERS OF MODEL RELATING δ_{thr} TO Δmag_y

a_i	b_i	c_i	ε
-0.03699222	0.00264913	0	4
-0.17482412	0.04486959	0.5	4
-0.27373477	0.11159597	1	4

TABLE III. PARAMETERS OF MODEL RELATING δ_{thr} TO Δmag_z

Plot comparing validation dataset with obtained model is depicted on Fig. 7

As can be seen, model output reflects the mean magnetometers deviations in each of the axes. Use of LLM allowed for modeling linear and nonlinear part of function.

At this moment we can check, how our model can improve magnetometer measurements. We will compute differences between model output y and magnetometer measurements deviations Δmag_i. Difference between these two values according to our assumptions should have zero mean, if this will be true, then we could say, that by use of developed model it is possible to compensate nonzero mean error related to operation of BLDC motors. On Fig. 8 we have shown percentage of compensated magnetometer deviations

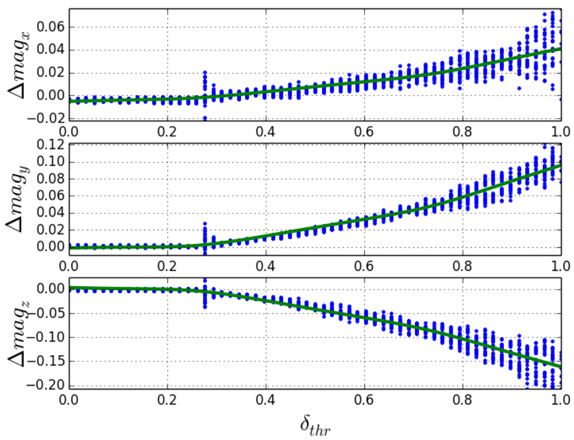

Fig. 7. Comparison of model output (solid line) against validation dataset (scattered points)

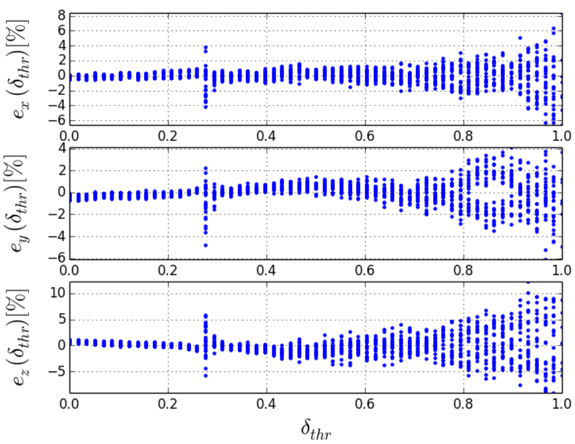

Fig. 8. Magnetometer deviation errors after compensation

related to the norm of magnetometer measurements, this value is computed by use of the following formula:

$$e_i(\delta_{thr}) = \frac{\Delta mag_i - y_i}{\|mag\|} 100\% \tag{20}$$

where $\|mag\|$ is norm of measured magnetic field.

Based on this picture, we can conclude that it was possible to compensate non-zero mean error in a broad range of operating conditions.

IV. Future work

In the next step we would like to implement compensation scheme in the AHRS (Attitude and Heading Reference System) processing unit in order to check its proper operation during the flight of unmanned platform. Interesting problem to consider is a possibility to adjust model parameters in on-line manner which can have positive effect on compensation results because of non-stationary nature of VTOL (Vertical Takeoff and Landing) actuator system. Another issue to consider, is to employ information about error variance of magnetometer measurements which could be also modeled as function of δ_{thr}. This information could be used in estimation algorithms which employ information about measurement error variance (like Kalman Filter).

V. Conclusion

As have been shown, it was possible to obtain model describing relation between total throttle of quadrotor to changes of magnetometer readings. Because of chosen identification method, we were able to obtain parameter estimates without need of assuming their initial values. Obtained model can be incorporated into attitude determination system in order to cope with changes of electromagnetic field.

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