

# Method for In-Field User Calibration of MEMS Accelerometer using Hybrid Genetic Algorithm

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## Abstract

The Inertial Measurement Unit (IMU) using MEMS sensor contains 3-axis accelerometer, 3-axis gyroscope, 3-axis magnetometer, thermometer, etc. in a single microchip, but the installing axes are not ideally perpendicular to each other and calibration is needed.

This paper describes the approach to the static calibration of an accelerometer without using any mechanical equipment on the basis of the fact that the norm of MEMS accelerometer outputs measured in the static position is ideally equal to 1. By using genetic algorithm, we verified the initial values of scale factors and zero bias ones. Taking these as the initial values of the Sequence Quadratic Programming (SQP), we found the optimal solution. We proved the effectiveness of the calibration using the measurements of MEMS accelerometer in the static position. The experimental result shows that the static calibration approach using the estimated Hybrid Genetic Algorithm (HGA) is better than the others.

**Keywords:** MEMS accelerometer; Auto-calibration; Genetic algorithm; SQP; Bias

## Introduction

Navigation is the law to determine the position, velocity and attitude of a moving body in the space and in practice navigation parameters such as position, velocity and attitude are determined using accelerometer and gyroscope.

With the rapid development of MEMS technology, light and low-cost inertial sensors that have low power consumption are made and widely used in different sectors in our life [1-3].

Since the Inertial Measurement Unit (IMU) using MEMS sensor contains 3-axis accelerometer, 3-axis gyroscope, 3-axis magnetometer, thermometer, etc. in a single microchip, we can realize a good navigation.

However, these 3-axis sensors are not ideally perpendicular to each other, so we have to calibrate them before use [4, 5].

Calibration can be defined as a process of comparing sensor outputs with known reference information and determining coefficients that make the output agree with the reference information over a range of output values.

Calibration in use is classified into mechanical equipment based calibration, semi-mechanical calibration and calibration without external equipment.

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Mechanical equipment based calibration needs an expensive turntable so many approaches to calibrate at any place without using mechanical equipment are widely studied in the world [6-10].

In general, in order to calibrate an accelerometer IMU is located in different random positions and the parameters of misalignment, zero bias and factors are computed so that the measurements of acceleration may be equal to the known reference value.

The main idea of calibration of an accelerometer is that the norm of 3-axis accelerometer outputs is equal to the acceleration of gravity,  $g$  in the static positions [3].

Using this idea, we can only measure the output of MEMS accelerometer at random directions. On the basis of the measurements of the accelerometer measured at every moment in the static positions and gravitational acceleration the error model is made. And then the parameters of the model, that is, scale factors, zero biases and non-orthogonal errors are determined so that the values of errors may get less.

I. Frosio and I. Skog proposed a calibration method in which the first search was done with Newton's method on the basis of the assumption that there's no cross-coupling influence between the sensor axes. The result of this search was regarded as the initial values in the case of the cross-coupling to perform the second search [2, 3].

In order to guarantee the convergence of a solution, scale factors and zero biases of a sensor were found at 30 random directions. The experiment showed the mean error of the calibrated accelerometer was always less than  $2^\circ$  and the maximum standard deviation was less than  $3^\circ$ . Newton's method, however, needs the operation of the second derivative, has a narrow convergent zone and is sensitive to the initial values.

In order to overcome these disadvantages they proposed a calibration approach by Levenberg-Marquardt (LM) nonlinear optimization which is the combination of Gradient Descent Method and Gaussian-Newton's method.

When this calibration approach was used in the experiment, the mean square error was less than  $1.5 \times 10^{-4} g$ .

This approach also has its own disadvantages. The variance of the mean square error gets bigger according to the initial values. With the development of artificial intelligence technology, the genetic algorithm is used in optimization, control and the calibration of sensors [4].

The genetic algorithm uses the principle of the genetic evolution that a population with high adaptability, in the course of evolution, survives, but the population with low one becomes extinct.

We applied iteration method less than 25 times to get 9 parameters of non-orthogonal errors, scale factors and zero biases using

genetic optimization method, and proved through simulation that the mean value of errors is less than  $3.5 \times 10^{-5} g$  and the standard variance is less than  $1.6 \times 10^{-5} g$ .

This method improves the correctness of path computation 250 times higher than the case without any calibration, and guarantees the computation correctness 10 times compared with the algorithm with 6 parameters.

Theoretically the genetic algorithm is a probable search method and it has already been proved that the optimal solution can be found with the probability of 1, but in the real application early convergence occurs so that the same individual is searched iteratively.

Consequently the path error becomes bigger exponentially after over 20 seconds. The combination of optimization methods such as genetic algorithm, Newton's method and Quasi-Newton's method makes it possible to overcome this drawback.

In the paper we proposed an approach to optimal solution by using the hybrid genetic algorithm that is the combination of genetic algorithm and Sequence Quadratic Programming (SQP).

We proved the effectiveness of the calibration by applying the measurements of MPU 9250 MEMS accelerometer that we found in the static positions. The result of the experiment shows that the mean square errors of the sensor model parameters are smaller than the other calibration approaches. When the test is done on the ground vehicles with the calibrated accelerometer, the navigation errors were much less than the case with uncalibrated accelerometer. The experimental result shows that when the accelerometer is calibrated using the hybrid genetic algorithm, the computation accuracy of orientation is higher than the other calibration approaches. When the calibrated accelerometer is used, the estimation accuracy of orientation can be increased in Attitude and Heading Reference System (AHRS) [11].

### Calibration Principle of MEMS Accelerometer

The simple structure of an IMU is shown in **FIG. 1**.

As shown in **FIG. 1**, if all the sensors are installed perpendicularly to each other, then each sensor measures only the acceleration in the direction of the axis on which the sensor is installed.

But for the real inertial measurement unit it is difficult for each sensor to form an ideally orthogonal frame, which is shown in **FIG. 2**.

In **FIG. 2**,  $\alpha_{ij}$  is the rotation of the  $i^{\text{th}}$  sensor axis of the accelerometer about the  $j^{\text{th}}$  axis of a platform.

Therefore, the transformation matrix from the Accelerometer Orthogonal Frame (AOF) to the Accelerometer Body Frame (ABF) is as follows.

$$\mathbf{T} = \begin{bmatrix} 1 & -\alpha_{yz} & \alpha_{zy} \\ \alpha_{xz} & 1 & -\alpha_{zx} \\ -\alpha_{xy} & \alpha_{yx} & 1 \end{bmatrix} \quad (1)$$

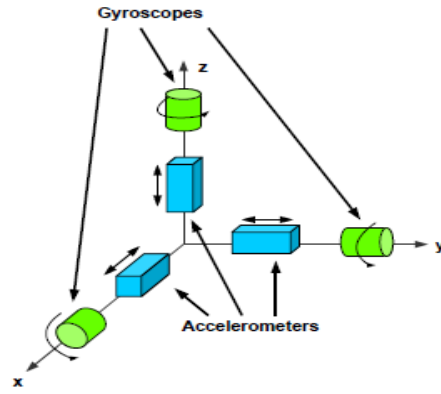


FIG. 1. Simplified Scheme of an IMU.

Considering Eq. (1), the measurement model of an accelerometer can be written as follows [4].

$$\mathbf{a}^o = \mathbf{T} \times \mathbf{K} \times (\mathbf{a}^M - \mathbf{b} - \mathbf{n}) \tag{2}$$

Where  $\mathbf{a}^o$  the acceleration is vector in (AOF) and  $\mathbf{a}^M$  is the acceleration vector in (ABF).

$$\mathbf{K} = \begin{bmatrix} s_x & 0 & 0 \\ 0 & s_y & 0 \\ 0 & 0 & s_z \end{bmatrix} \text{ is the matrix of scale factors.}$$

$$\mathbf{b} = \begin{bmatrix} b_x \\ b_y \\ b_z \end{bmatrix} \text{ is the vector of biases.}$$

$\mathbf{n}$  is assumed as the measurement noise vector which is zero mean white Gaussian noises.

Measurements are averaged in time to remove random errors:

$$\bar{\mathbf{a}}^o = \mathbf{T} \times \mathbf{K} \times (\bar{\mathbf{a}}^M - \mathbf{b}) \tag{3}$$

Ideally, scale factor matrix is a unit matrix and all the elements of bias vector should be zero.

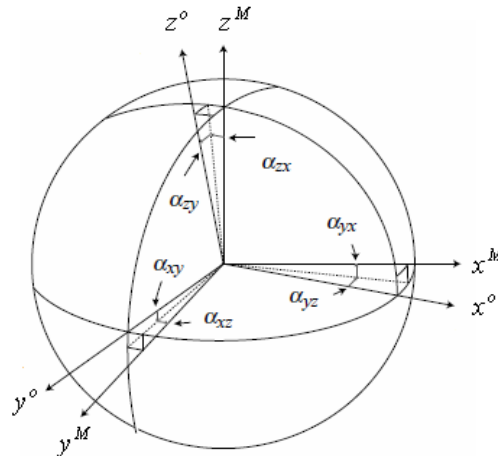


FIG. 2. Relation between the accelerometer orthogonal frame ( $x^o, y^o, z^o$ ) of and the accelerometer body frame. ( $x^M, y^M, z^M$ ).

In Eq. (3)  $\bar{\mathbf{a}}^o$  is the average acceleration vector in AOF and  $\bar{\mathbf{a}}^M$  is the average measured acceleration vector in ABF

The main idea of calibration of an accelerometer is that the norm of 3-axis accelerometer outputs is equal to the acceleration of gravity,  $g$  in the static positions [3].

When the accelerometer is in a stationary position, the vector  $\bar{\mathbf{a}}^o$  is equal to the gravitational acceleration vector  $g$ , and we can rewrite Eq. (3) as follows.

$$g = \mathbf{T} \times \mathbf{K} \times (\bar{\mathbf{a}}^M - \mathbf{b}) \quad (4)$$

Modern digital MEMS accelerometers data are not read in  $\text{ms}^{-2}$ , but in the units of  $g$ .

Consequently, the norm of the vector of gravitational acceleration vector becomes 1 and the Eq. (4) can be written as follows.

$$1 = \left\| \mathbf{T} \times \mathbf{K} \times (\bar{\mathbf{a}}^M - \mathbf{b}) \right\| \quad (5)$$

The measurements averaged in quite different positions of the accelerometer are taken.

Using Eq. (5) and the data from these measurements, the fitness function can be defined as follows:

$$e(\hat{\boldsymbol{\theta}}) = \sum_{i=1}^N \left( 1 - \left\| \mathbf{T} \times \mathbf{K} \times (\bar{\mathbf{a}}_i^M - \mathbf{b}) \right\| \right)^2 \quad (6)$$

Where  $\hat{\boldsymbol{\theta}} = [\hat{\alpha}_{yx}, \hat{\alpha}_{zy}, \hat{\alpha}_{zx}, \hat{\alpha}_{xz}, \dots, \hat{b}_x, \hat{b}_y, \hat{b}_z]^T$  are the parameters to be evaluated,  $\bar{\mathbf{a}}_i^M$  is the vector of average measurements in different positions and  $N$  is the number of positions.

## In-field Calibration of MEMS Accelerometer using Hybrid Genetic Algorithm

### Design of hybrid genetic algorithm

Genetic algorithm, as one of the optimal search methods, which is the imitation of biological evolution, has got a discontinuous objective function or singular point, and it can be used to solve various optimization problems.

In practical application, however, genetic algorithm has got some drawbacks.

One of the drawbacks is that due to the early convergence, the same individual is iteratively searched. Therefore, even though the optimal solution range is found, the capability of local search within the range is very weak. On the contrary, some optimization methods such as gradient method and Newton's method have got very strong capability of local search.

Therefore, if you configure hybrid genetic algorithm using this optimization method in search of genetic algorithm, you can improve the execution efficiency and the quality of the genetic algorithm. In the paper we are going to determine the calibration parameters to calibrate MEMS sensors using the hybrid genetic algorithm that is the combination of genetic algorithm and sequence quadratic programming. **FIG. 3** shows the block diagram of the designed hybrid genetic algorithm.

When you add the local search to the genetic algorithm, you can improve the overall performance of the population by making a

local search on the basis of the phenotype corresponding to each individual of the population and by finding the local optimal solution in the existing situation of each individual. Also, you can perform the operation of the next-generation genetic evolution on the basis of a new population by coding the local optimal solution obtained in the course of local search and transforming them into new individuals.

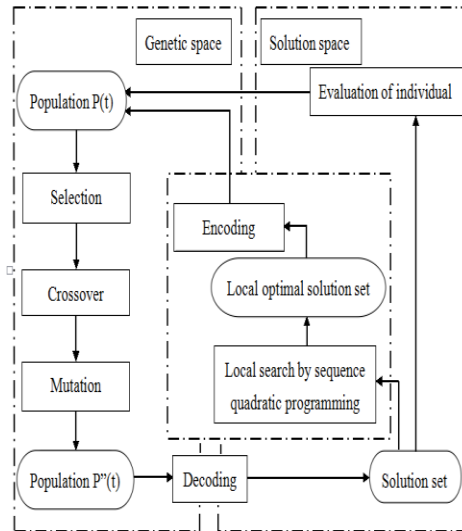


FIG. 3 Block diagram of hybrid genetic algorithm.

Execution process of the hybrid genetic algorithm;

Step 1: Initialization of the number  $t$  of evolution generation, that is,  $t = 0$

Step 2: Production of initial population  $P(t)$  randomly

Step 3: Fitness evaluation of the population  $P(t)$

Step 4: Selection of individual and crossing-over by crossover probability  $P_c$ :  $P'(t) \leftarrow \text{Crossover} [P(t)]$

Step 5: Mutation by probability  $P_m$ :  $P''(t) \leftarrow \text{Mutation} [P'(t)]$

Step 6: Execution of SQP:  $P'''(t) \leftarrow \text{SQP} [P''(t)]$

Step 7: Fitness evaluation of the population  $P'''(t)$

Step 8: Selection of individual and reproduction:  $P(t+1) \leftarrow \text{Reproduction} [P(t) \cup P'''(t)]$

Evaluation of stopping condition: if the stopping condition is not satisfied, take  $t \leftarrow t+1$  and go back to step 4.

If the stopping condition is satisfied, output all the optimal individuals finalize computation.

Each stage of the genetic algorithm is set as follows.

Size of population: 300, Encoding: floating number encoding

$$\text{Fitness function: } y = 1 / \left\{ \sum_{i=1}^n \left( 1 - \left\| \mathbf{T} \times \mathbf{K} \times \begin{pmatrix} -M \\ \mathbf{a}_i \\ -b \end{pmatrix} \right\| \right)^2 \right\}$$

Scale transformation: Sequence transformation

Selective operation: Tournament selection, Crossover operation: Algebraic crossover, Mutation: Real number mutation operator

Stopping criterion: in case that the change in the best fitness functions is less than  $10^{-15}$  when the maximum generation number reaches 200 or within 70 generations.

**Search for local optimal solution using sequence quadratic programming**

Step 1: Setting of the problem of quadratic programming with linear limit to determine the search direction and its solution

From the data of sensor we can see the upper and lower limits to establish the following restrictive conditions.

$$\left\{ \begin{array}{l} a_1 \leq \alpha_{xy} \leq b_1 \\ a_2 \leq \alpha_{xz} \leq b_2 \\ a_3 \leq \alpha_{yx} \leq b_3 \\ a_4 \leq \alpha_{yz} \leq b_4 \\ a_5 \leq \alpha_{zx} \leq b_5 \\ a_6 \leq \alpha_{zy} \leq b_6 \\ a_7 \leq s_x \leq b_7 \\ a_8 \leq s_y \leq b_8 \\ a_9 \leq s_z \leq b_9 \\ a_{10} \leq b_x \leq b_{10} \\ a_{11} \leq b_y \leq b_{11} \\ a_{12} \leq b_z \leq b_{12} \end{array} \right\} \Rightarrow \left\{ \begin{array}{l} g_1(\theta) = a_1 - \alpha_{xy} \leq 0, \quad g_2(\theta) = \alpha_{xy} - b_1 \leq 0 \\ g_3(\theta) = a_2 - \alpha_{xz} \leq 0, \quad g_4(\theta) = \alpha_{xz} - b_2 \leq 0 \\ g_5(\theta) = a_3 - \alpha_{yx} \leq 0, \quad g_6(\theta) = \alpha_{yx} - b_3 \leq 0 \\ g_7(\theta) = a_4 - \alpha_{yz} \leq 0, \quad g_8(\theta) = \alpha_{yz} - b_4 \leq 0 \\ g_9(\theta) = a_5 - \alpha_{zx} \leq 0, \quad g_{10}(\theta) = \alpha_{zx} - b_5 \leq 0 \\ g_{11}(\theta) = a_6 - \alpha_{zy} \leq 0, \quad g_{12}(\theta) = \alpha_{zy} - b_6 \leq 0 \\ g_{13}(\theta) = a_7 - s_x \leq 0, \quad g_{14}(\theta) = s_x - b_7 \leq 0 \\ g_{15}(\theta) = a_8 - s_y \leq 0, \quad g_{16}(\theta) = s_y - b_8 \leq 0 \\ g_{17}(\theta) = a_9 - s_z \leq 0, \quad g_{18}(\theta) = s_z - b_9 \leq 0 \\ g_{19}(\theta) = a_{10} - b_x \leq 0, \quad g_{20}(\theta) = b_x - b_{10} \leq 0 \\ g_{21}(\theta) = a_{11} - b_y \leq 0, \quad g_{22}(\theta) = b_y - b_{11} \leq 0 \\ g_{23}(\theta) = a_{12} - b_z \leq 0, \quad g_{24}(\theta) = b_z - b_{12} \leq 0 \end{array} \right. \tag{7}$$

The error function  $E(\theta)$  of accelerometer is used as it is as an objective function.

And  $\theta$  are the calibration parameters to be found and expressed as follows.

$$\theta = [\alpha_{yz}, \alpha_{zy}, \alpha_{zx}, \alpha_{xz}, \alpha_{xy}, \alpha_{yx}, s_x, s_y, s_z, b_x, b_y, b_z]^T \tag{8}$$

From this, when the initial point  $\theta_1$  is obtained using genetic algorithm, the problem of quadratic programming is established as follows to select the optimal direction  $S$  from the set of allowable search direction vectors.

$$\left\{ \begin{array}{l} q_1(S) = \beta_1 g_1(\theta_1) + \nabla g_1(\theta_1)^T S \leq 0 \\ q_2(S) = \beta_2 g_2(\theta_1) + \nabla g_2(\theta_1)^T S \leq 0 \\ q_3(S) = \beta_3 g_3(\theta_1) + \nabla g_3(\theta_1)^T S \leq 0 \\ \vdots \\ q_{23}(S) = \beta_{23} g_{23}(\theta_1) + \nabla g_{23}(\theta_1)^T S \leq 0 \\ q_{24}(S) = \beta_{24} g_{24}(\theta_1) + \nabla g_{24}(\theta_1)^T S \leq 0 \end{array} \right. \tag{9}$$

$$\min : Q(S) = \nabla E(\theta_1)^T S + \frac{1}{2} S^T [H] S$$

where  $[H]$  is a positive matrix that is given as a unit matrix at the beginning. And it is updated in the course of iteration so that it may converge into Hessian matrix of Lagrange function.

The constant  $\beta_j, \bar{\beta}$  is a number that is taken to prevent the limited region from being separated completely from the admissible

region.

$$\bar{\beta} = 0.9$$

$$\beta_j = \begin{cases} 0: g_j(\theta) = 0 \\ 1: g_j(\theta) < 0 \\ \bar{\beta}: g_j(\theta) > 0 \end{cases} \quad (10)$$

Search direction is  $S = [s_1, s_2, \dots, s_{12}]^T$ .

KKT theorem is used to solve this problem.

$$\begin{cases} \frac{\partial Q}{\partial s_1} + \sum_{j=1}^{24} \lambda_j \frac{\partial q_1}{\partial s_1} = 0 \\ \frac{\partial Q}{\partial s_2} + \sum_{j=1}^{24} \lambda_j \frac{\partial q_1}{\partial s_2} = 0 \\ \vdots \\ \frac{\partial Q}{\partial s_{11}} + \sum_{j=1}^{24} \lambda_j \frac{\partial q_j}{\partial s_{11}} = 0 \\ \frac{\partial Q}{\partial s_{12}} + \sum_{j=1}^{24} \lambda_j \frac{\partial q_j}{\partial s_{12}} = 0 \\ \lambda_j q_j = 0 \\ q_j = 0 \\ \lambda_j \geq 0 \end{cases} \quad (11)$$

$$j = 1, 2, \dots, 24$$

The solution of this problem is the search direction  $S$  and Lagrange multiplier  $\lambda_1, \lambda_2, \dots, \lambda_{24}$ .

Step 2: Search for step size using penalty function method of one variable

In case that the optimal direction is determined in the set of admissible direction vectors, the optimization problem to select the most reasonable step size within the admissible region is referred to the following problem of unconditional extreme value.

$$\varphi = f(\theta) + \sum_{j=1}^{24} \lambda_j (\max[0, g_j(\theta)]) \quad (12)$$

where

$$\lambda_j = \begin{cases} |\lambda_j|, & j = 1, 2, \dots, 30: \\ & \text{in the first iteration} \\ \max\left\{|\lambda_j|, \frac{1}{2}(\tilde{\lambda}_j + |\lambda_j|)\right\}, & \\ & \text{more than 2 iterations} \end{cases} \quad (13)$$

$\tilde{\lambda}_j$  is the value of  $\lambda_j$  that was set in the previous iteration stage

In order to find  $\theta_2$ , let



$$\theta_2 = \theta_1 + \alpha S \tag{14}$$

If Eq. (14) is put into Eq. (12),

$$\varphi(\alpha) = f(\theta_2) + \sum_{j=1}^{24} \lambda_j (\max[0, g_j(\theta_2)]) \tag{15}$$

Since the problem of extreme value is that of one variable with respect to step size  $\alpha$ , the step size  $\alpha$  can be determined easily.

Step 3: Update of Hessian matrix by BFGS method Hessian matrix uses BFGS method in the sequence quadratic programming and according to this method Hessian matrix is updated in each step size as follows.

First, Lagrange function is found from 30 limit conditions and objective function.

$$\tilde{L} = E(\theta) + \sum_{j=1}^{24} \lambda_j g_j(\theta) \tag{16}$$

where  $E(\theta)$  an objective is function for calibration and  $g_j(\theta)$  is calibration parameter definitions.

Meanwhile,

$$\gamma = \delta Q_1 + (1 - \delta)[H_1]P_1 \tag{17}$$

where  $Q_1 = \nabla_{\theta} \tilde{L}(\theta_2) - \nabla_{\theta} \tilde{L}(\theta_1)$  and  $\nabla_{\theta} \tilde{L}$  is as follows.

$$\nabla_{\theta} \tilde{L} = \left[ \frac{\partial \tilde{L}}{\partial S_{xx}}, \frac{\partial \tilde{L}}{\partial S_{xy}}, \frac{\partial \tilde{L}}{\partial S_{xz}}, \dots, \frac{\partial \tilde{L}}{\partial b_x}, \frac{\partial \tilde{L}}{\partial b_y}, \frac{\partial \tilde{L}}{\partial b_z} \right]^T \tag{18}$$

$$\delta = \begin{cases} 1.0 & : (P_1^T Q_1 \geq 0.2 P_1^T [H_1] P_1) \\ \frac{0.8 P_1^T [H_1] P_1}{P_1^T [H_1] P_1 - P_1^T Q_1} & : (P_1^T Q_1 < 0.2 P_1^T [H_1] P_1) \end{cases} \tag{19}$$

where  $P_1 = \theta_2 - \theta_1$ .

Therefore, Hessian matrix is updated as follows.

$$[H_2] = [H_1] - \frac{[H_1] P_1 P_1^T [H_1]}{P_1^T [H_1] P_1} + \frac{\gamma \gamma^T}{P_1 P_1^T} \tag{20}$$

Using the same method,  $\theta_3$  is computed from  $\theta_2$ .

Iteration method is stopped when the convergence criteria are satisfied.

$$\max \left\{ \left| \frac{\theta_n^k - \theta_{n-1}^k}{0.5(\theta_n^k + \theta_{n-1}^k)} \right| \right\}_{k=1,2,\dots,30} < \varepsilon \tag{21}$$

where  $\theta_n^k$  is the  $k^{\text{th}}$  element of  $\theta_n$  and  $\varepsilon$  is the threshold, which is used to evaluate the correctness of calibration.

The optimization criteria  $\varepsilon$  are set to  $10^{-5}$ .

### Orientation measurement

Once the auto-calibration procedure has been completed, we can compute the orientation using the accelerometer outputs.

The MEMS IMU is fixed on North-East-Down (NED) frame.

From the accelerations measured through (3) the roll and pitch angles,  $\phi$  and  $\theta$  can be estimated by means of the following equations [2]:

$$\begin{cases} \phi = \arcsin(a_y) \\ \theta = \arcsin(a_x) \end{cases} \quad (22)$$

Eq. (22) are frequently used with bi-axial accelerometers, but they suffer from a critical drawback:

The accuracy of the estimated  $\phi$  and  $\theta$  depends only on the values of  $\phi$  and  $\theta$ .

To overcome this problem, the following trigonometric equations are used here to compute the  $\phi$  and  $\theta$ .

$$\begin{cases} \phi = \arctan 2(a_y, a_z) \\ \theta = \arcsin \left( \frac{a_x}{\sqrt{a_x^2 + a_y^2 + a_z^2}} \right) \end{cases} \quad (23)$$

## Experiments Setup

To verify the effectiveness of the proposed approach, MEMS IMU has been installed on a precision 3-axis turntable.

The output of the MEMS accelerometer is calibrated using different methods. With these outputs orientations are determined and then they are compared with the angles that are set on the precision 3-axis turntable.

**FIG. 4** shows the device that was used in experimental equipment.

All comparisons are obtained on the MATLAB 2013b software on a TOSHIBA laptop with a CPU of i3-380M.

The turntable outputs the rotation angle with a repetitive positioning accuracy of  $0.5^\circ$  and it is used as reference angles for attitude in this experiments.

Setting range about the pitch and roll angles using turntable are  $-90^\circ \sim +90^\circ$ , respectively and setting range about the roll is  $0^\circ \sim 360^\circ$ .

For the static calibration of the accelerometer, we applied the proposed algorithm to the 3-axis accelerometer in MPU 9250 IMU (See **FIG. 5**).

The IMU that was used in the experiment is MPU9250IMU in which 3-axis accelerometer, 3-axis gyro and 3-axis magnetometer are embedded.

**TABLE 1. Main parameters of 3-axis accelerometer in MPU 9250 IMU.**

| Parameter                            | Conditions                                 | Typ       | Units                |
|--------------------------------------|--|-----------|----------------------|
| Measurement range                    | AFS_SEL=0                                  | $\pm 2$   | g                    |
| Nonlinearity                         | Best Fit Straight Line                     | $\pm 0.5$ | %                    |
| Sensitivity Scale Factor             | AFS_SEL=0                                  | 16384     | LSB/g                |
| Cross-Axis Sensitivity               |  | $\pm 2$   | %                    |
| Zero-G Initial Calibration Tolerance | Component-level, X,Y                       | $\pm 60$  | mg                   |
|                                      | Component-level, Z                         | $\pm 80$  | mg                   |
| Zero-G Level Change vs. Temperature  | $-40^\circ\text{C}$ to $+85^\circ\text{C}$ | $\pm 1.5$ | mg/ $^\circ\text{C}$ |

**TABLE 1** shows the technical specifications of MPU 9250 IMU.

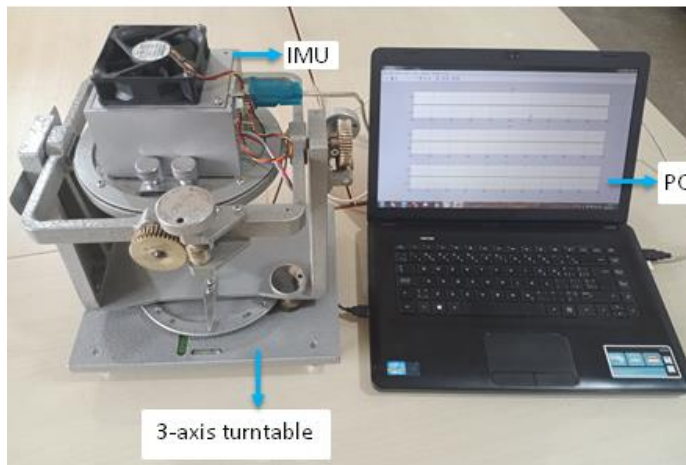
MPU 9250 IMU has been installed in a housing of duralumin and collected the sensor data in I2C mode.

The microprocessor is STM32F407.

To remove the drift according to the temperature change we first designed a thermostat.

Micro-controller processes the measurements from the IMU and sends the result to the host computer through USB-232 converter.

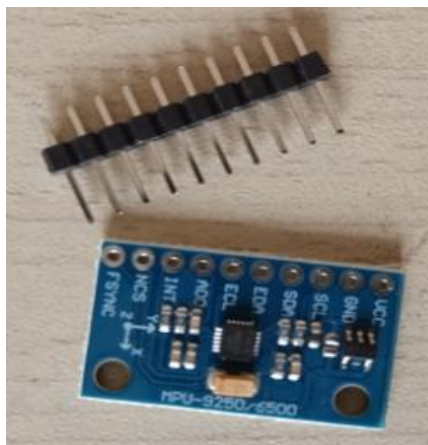
The host computer performs calibration using these measurements.



**FIG. 4 Experimental equipment.**

The sensor data is obtained in 23 different positions for 15 seconds.

Sampling period is 15 *ms* and measuring range is set to  $\pm 2g$  .



**FIG. 5 MPU 9250 IMU**

## Experiments and Results

### Static experiments

**FIG. 6** shows the calibration result of the accelerometer in 30 different positions. In the figure the green line is the size of reference

value ( $1g$ ), the blue line shows the size of static acceleration before calibration and the red one is the size of static acceleration after calibration.

As shown in **FIG. 6**, the norm of the 3-axis acceleration measurements does not reach the ideal  $1g$  in the static positions before calibration.

In the experiment, we calibrated the accelerometer using the proposed approach and compared the result with the previous calibration approaches.

The comparison results of hybrid genetic algorithm, Newton’s method and LM method are given in **TABLE 2**.

From the datasheet of MPU 9250, the values for the initial tolerance of biases are given as:

$$b_x = b_y = \pm 60mg, b_z = \pm 80mg$$

As seen in **TABLE 2**, when the Hybrid Genetic Algorithm (HGA) is used, the error are much less than other approaches, and all the obtained estimated values are within this range of initial tolerance.

We simulated the proposed problem using the hybrid genetic algorithm and compared the result with that of the preceding calibration approaches.

**TABLE 2** shows the comparison results of calibration when Newton’s method, LM and HGA are used.

To evaluate the accuracy of calibration, the data is obtained in any static attitude for 1 minute and then the distance error of the obtained sensor data after calibrations are analyzed using Newton’s method, LM method and HGA.

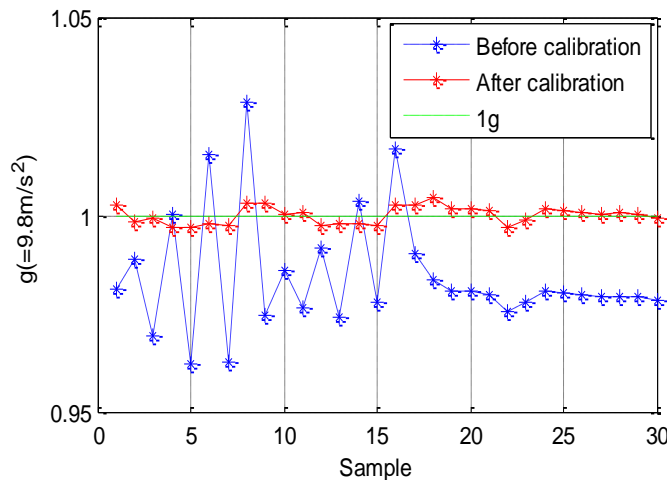
The distance error at every time is computed using the following equation.

$$\Delta s(t) = \sqrt{s_x(t)^2 + s_y(t)^2 + s_z(t)^2} - 0.5gt^2 \tag{24}$$

where  $s_x, s_y, s_z$  are the distance errors in the directions of  $x, y, z$  axes, respectively.

**FIG. 7** shows the distance errors when the different calibration approaches are used.

As shown in **FIG. 7**, the distance errors are 6 m, 5.05 m and 3.29 m respectively, and the distance error is the smallest when the hybrid genetic algorithm is used.



**FIG. 6 Typical results for accelerometer calibration.**

TABLE 2. Comparison results of calibration.

| Coefficients             | HGA        | Newton's  | LM        |
|--------------------------|------------|-----------|-----------|
| $\alpha_{xy}$            | 0.016417   | -0.00333  | 0.001921  |
| $\alpha_{xz}$            | -0.104562  | -0.007933 | -0.00124  |
| $\alpha_{yx}$            | -0.030346  | -0.007102 | -0.001734 |
| $\alpha_{yz}$            | 0.106299   | 0.007993  | 0.001228  |
| $\alpha_{zx}$            | 0.034101   | 0.007665  | 0.00172   |
| $\alpha_{zy}$            | -0.013885  | 0.003657  | -0.00196  |
| $S_x$                    | 0.961258   | 0.992782  | 0.990739  |
| $S_y$                    | 0.948658   | 0.988344  | 1.000908  |
| $S_z$                    | 0.964754   | 0.931339  | 0.984876  |
| $O_x$                    | 0.001229   | 0.030243  | 0.022078  |
| $O_y$                    | 0.028684   | 0.0113    | 0.020588  |
| $O_z$                    | -0.0122408 | -0.056756 | -0.00028  |
| Errors after calibration | 2.67E-06   | 3.16E-05  | 4.29E-05  |

### Orientation Measurement Experiments

Using the calibrated accelerometer, the roll and pitch angles can be measured in the static status.

We calibrated the navigation device on the 3-axis turntable using Newton's method, LM method and HGA and compared the measurement result of angles.

The navigation device is installed according to NED frame, the set values of roll and pitch angles are given by rotating the turntable and they are compared with the computation result of attitude that is obtained with the measurement values of accelerometer.

The curves are shown in **FIG. 8** and **FIG. 9** with the set values of roll and pitch angles taken as  $+10^\circ$  and  $-10^\circ$  after data filtering.

As can be seen from the figures, when HGA is used for calibration, the orientation error is less than  $0.15^\circ$  and the accuracy is much higher compared with the other two approaches.

Even when the experiment is done with the set values of orientation increased or decreased by  $10^\circ$ , the accuracy by HGA is higher than by other two approaches.

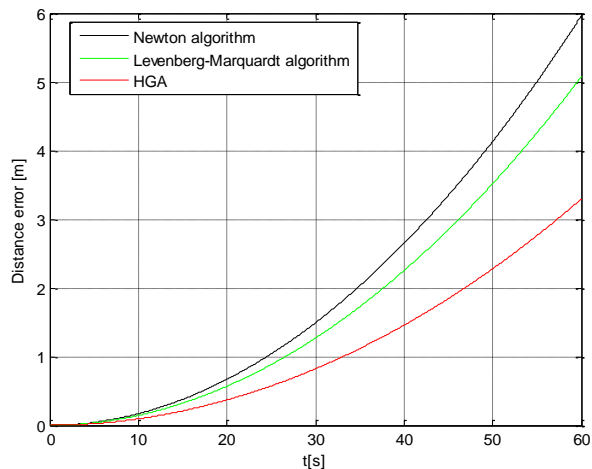


FIG. 7 Comparison of the distance errors after calibration.

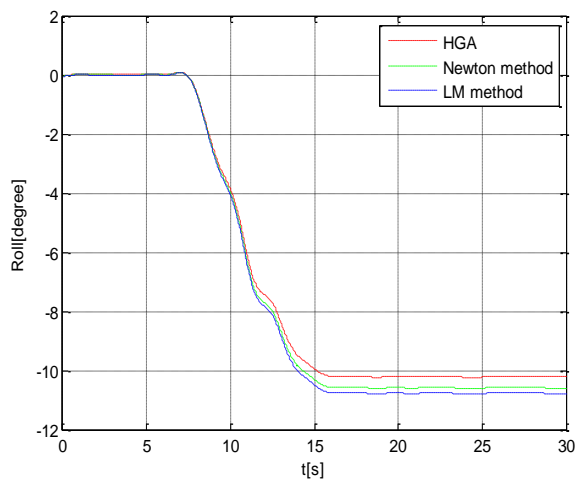
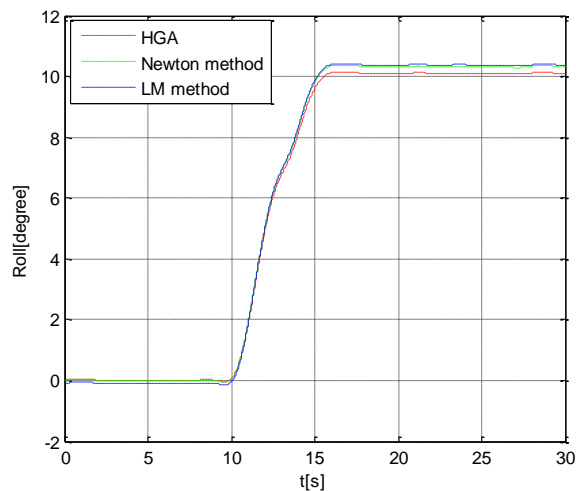


FIG. 8 Computation result of roll angle.

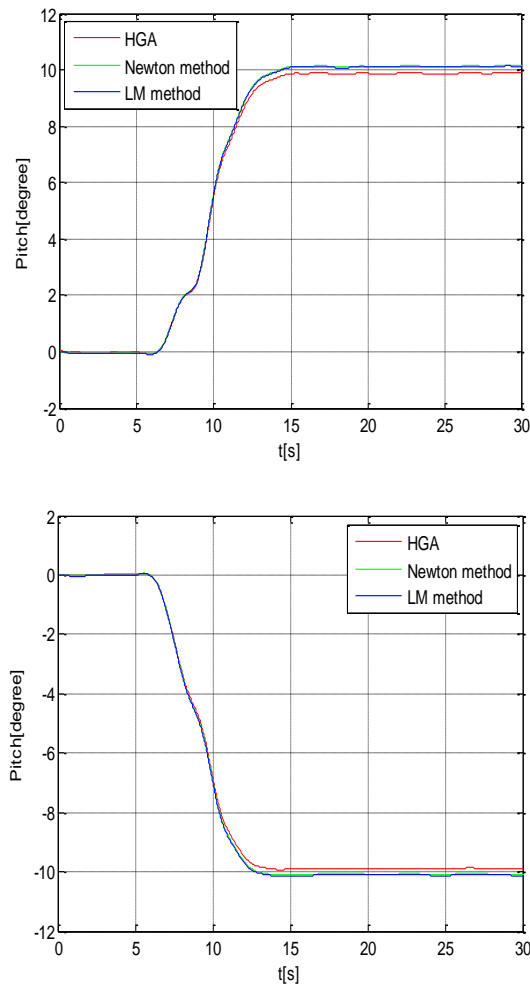


FIG. 9 Computation result of pitch angle

### Conclusion

In the paper we described the static calibration of MEMS accelerometer using hybrid genetic algorithm.

Using genetic algorithm, we verified the initial values of scale factor and zero bias ones.

Taking these as the initial values of the SQP, we found the optimal solution.

We proved the effectiveness of the calibration using the measurements of MPU 9250 IMU in the stationary position.

The experimental result showed that the navigation error was less when the calibration is done using hybrid genetic algorithm than when the other two approaches are used.

The calibration approach proposed in this paper can be used in the static calibration of gyros magnetometer.

When the accelerometers, gyros and magnetometers are calibrated using this approach, the computation accuracy of attitude can be increased in AHRS.

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