MEMS based IMU adaptive 3D calibration

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Abstract: *Intensive development of different sensors based on microelectromechanical system (MEMS) technology has led to them being used in various fields that require simple and frequent measurements. One such application is inertial navigation systems (INS). Due to their low cost, small size and weight MEMS sensors can be used as a basis for inertial measurement unit (IMU) because they move together with the object they are attached to, thus reflecting the objects motion. MEMS sensors used for tracking the objects motion usually comprise of a 3-axial accelerometer and a 3-axial gyroscope. Although constantly improving, MEMS technology can not be directly used in INS due to different sensor inaccuracies such as zero-level bias, various nonlinearities, inaccurate sensitivity and misalignment of the sensor sensitivity axes. These inaccuracies introduce system error into the INS which needs to be compensated by means of various calibration methods. In this paper, we present a time efficient and adaptive 3D calibration method based on simultaneous motion of all axes on a 3-axes precision turntable. The calibration procedure for accelerometers as well as gyroscopes will be explained in detail. Finally, the results of the calibration will be discussed and conclusions drawn.*

Keywords*: IMU calibration, triaxial MEMS, least squares method*

1. Introduction

Intensive development of different sensors based on microelectromechanical system (MEMS) technology has led to them being used in various fields that require simple and frequent measurements [1-3]. One such application is inertial navigation systems (INS). MEMS sensors used for tracking the objects motion usually comprise of a 3-axial accelerometer and a 3-axial gyroscope. Nowadays, 3-axial gyroscope and a 3-axial accelerometer are readily available in a single and compact package, which makes the design of the IMU significantly easier and significantly cheaper. The packaging of MEMS sensors is usually small in size and lightweight, so their impact on the observed motion is negligible. Also, these sensors consume a small amount of energy which makes them suitable for energy efficient devices as well as many other commercial applications due to their low cost.

Given all the properties of the MEMS sensors, they can be used as a basis for inertial measurement unit (IMU) because they move together with the object they are attached to, thus reflecting the objects motion. Although constantly improving, MEMS technology can not be directly used in INS due to different sensor inaccuracies such as zero-level bias, various nonlinearities, inaccurate sensitivity and misalignment of the sensor sensitivity axes [4]. Zero-level bias or bias error is defined as deviation from a zero measurement or measured acceleration when the sensor is not subject to any acceleration, i.e. when it is stationary [2,4]. Scale factor corresponds to the ratio of input-output changes or the sensibility of the sensor. Misalignment represents the mounting error in the fabrication process that results in non-orthogonal axes in the sensor body frame [5]. Besides these errors, sensor outputs usually differ with changing temperature, so for optimal sensor performance some form of temperature stabilization is required. Temperature stabilisation can be achieved either by waiting for the sensor to reach operating temperature or by stabilizing the sensors temperature by using external devices.

These inaccuracies introduce system error into the INS which needs to be compensated by means of various calibration methods [6-20]. Navigation systems that use inertial sensors are heavily affected by these errors because the errors accumulate over time, thus degrading the position accuracy causing severe drifts [21,22]. These errors can be modeled and compensated through a calibration process in which the sensor outputs are compared with known reference information. This knowledge is used to estimate the coefficients in order to make the sensors outputs and known reference information coincide with each other. Usually, a precision turntable is used to create the known reference information. The inertial measurement unit is mounted into the turntable and subjected to various predefined motions to create a range of data that will be used in the estimation process. Least mean square algorithm or heuristic methods can be used to estimate the unknown parameters [23-25].

In this paper, we present a time efficient and adaptive 3D calibration method based on simultaneous motion of all axes on a 3-axes precision turntable. Besides the introductory section, the paper is organized in 4 more sections. Section 2 introduces the sensor model as well as the measurement model. The next section explains the proposed calibration procedures. Section 4 presents the obtained results. Finally, section 5 contains the conclusion and ideas for future work.

2. Sensor and measurement models

In order to implement the navigation and alignment algorithms and make the inertial navigation system functional, calibration of the sensor errors has to be performed. Besides the mathematical model of the sensors, the calibration also requires a predefined motion profile so that a measurement model can be created.

2.1 Sensor model

In order to do so, the sensor model has to be introduced first:

$$
\begin{aligned}
\delta a_{bx} &= a_x + a_{xx} a_{bx} + a_{xy} a_{by} + a_{xz} a_{bz} \\
\delta a_{by} &= a_y + a_{yx} a_{bx} + a_{yy} a_{by} + a_{yz} a_{bz} \\
\delta a_{bz} &= a_z + a_{zx} a_{bx} + a_{zy} a_{by} + a_{zz} a_{bz} \\
\delta \omega_{bx} &= \beta_x + \beta_{xx} \omega_{bx} + \beta_{xy} \omega_{by} + \beta_{xz} \omega_{bz} + \\
&\quad + \left(\beta_{xyz} a_{bx} + \beta_{xyy} a_{by} + \beta_{xyz} a_{bz}\right) \omega_{by} + \\
&\quad + \left(\beta_{xzz} a_{bx} + \beta_{xzy} a_{by} + \beta_{xzz} a_{bz}\right) \omega_{bz} \\
\delta \omega_{by} &= \beta_y + \beta_{yx} \omega_{bx} + \beta_{yy} \omega_{by} + \beta_{yz} \omega_{bz} + \\
&\quad + \left(\beta_{yxx} a_{bx} + \beta_{yxy} a_{by} + \beta_{yxz} a_{bz}\right) \omega_{bx} + \\
&\quad + \left(\beta_{yzx} a_{bx} + \beta_{yzy} a_{by} + \beta_{yzz} a_{bz}\right) \omega_{bz} \\
\delta \omega_{bz} &= \beta_z + \beta_{zx} \omega_{bx} + \beta_{zy} \omega_{by} + \beta_{zz} \omega_{bz} + \\
&\quad + \left(\beta_{zxx} a_{bx} + \beta_{zxy} a_{by} + \beta_{zxz} a_{bz}\right) \omega_{bx} + \\
&\quad + \left(\beta_{xyz} a_{bx} + \beta_{zyy} a_{by} + \beta_{xyz} a_{bz}\right) \omega_{by}
\end{aligned}
$$

Parameters in the model are denoted as follows:

- $\delta a_{bi} (i = x, y, z)$ − Accelerometer errors in projections on the body frame.
- $\delta \omega_{bi} (i = x, y, z)$ – Gyro errors in projections on the body frame.
- a_i – Accelerometer biases.
- a_{ii} – Accelerometer scale factors.
- a_{ij}– Accelerometer installation errors $(i \neq j)$.
- a_{bi}– Specific force projections.

- β_i – Gyro biases.
- β_{ii} – Gyro scale factors.
- β_{ij} – Gyro installation errors $(i \neq j)$.
- β_{ijk} – Flexure errors.
- ω_{bi} – Absolute angular velocities in projections on the body frame.

Flexure errors will not be considered in the remainder of the paper, which leads to a much simpler sensor model that can be expressed in matrix form:

$$\delta\begin{bmatrix} a_{bx} \\ a_{by} \\ a_{bz} \end{bmatrix} = \begin{bmatrix} a_{xx} & a_{xy} & a_{xz} \\ a_{yx} & a_{yy} & a_{yz} \\ a_{zx} & a_{zy} & a_{zz} \end{bmatrix}\begin{bmatrix} a_{bx} \\ a_{by} \\ a_{bz} \end{bmatrix} + \begin{bmatrix} a_x \\ a_y \\ a_z \end{bmatrix}$$

$$\delta\begin{bmatrix} \omega_{bx} \\ \omega_{by} \\ \omega_{bz} \end{bmatrix} = \begin{bmatrix} \omega_{xx} & \omega_{xy} & \omega_{xz} \\ \omega_{yx} & \omega_{yy} & \omega_{yz} \\ \omega_{zx} & \omega_{zy} & \omega_{zz} \end{bmatrix}\begin{bmatrix} \omega_{bx} \\ \omega_{by} \\ \omega_{bz} \end{bmatrix} + \begin{bmatrix} \omega_x \\ \omega_y \\ \omega_z \end{bmatrix}$$

Besides these errors sensor outputs usually differ with changing temperature. Thermal dependence of the MEMS sensor outputs should be included into the sensor model if the sensor is to be used in an IMU that is not thermally stabilized. This dependence can be evaluated by performing the calibration procedure at different temperatures of the sensor. In this paper, thermal dependence of the sensor is not included in the model, because the IMU used is thermally stabilized at the temperature value recommended by the MEMS supplier.

2.2 Measurement model

The goal of the calibration procedure is to determine the unknown parameters from the sensor model. For the calibration procedure to be successful IMU axes have to be determined first. The axes of the IMU can be labeled X, Y, Z and should coincide with North, East and Up directions of movement. When mounting the IMU onto the 3-axes precision turntable, its axes should be oriented precisely with respect to the local-level frame. By rotating the IMU axes with respect to the local level frame by the different angles, the measurement model for the calibration can be created. The extraction of the unknown parameters from the sensor model is possible due to the different projections of the Earth rotation rate U and apparent gravity vector g on the body frame in the different IMU positions.

The initial position of the IMU should be the following:

$$X_b = E, Y_b = N, Z_b = Up$$

Projections of the Earth's rotation rate U on the body axes of the IMU at given latitude φ are the following:

$$\omega_x^b = 0,\ \ \omega_y^b = Ucos(\varphi),\ \ \omega_z^b = \ Usin(\varphi)$$

Projections of specific force on the body frame are the following:

$$a_x^b = 0, a_y^b = 0, a_z^b = g$$

The accelerometer and gyro measurements in this case according to the sensor model can be written as:

$$\begin{aligned}
\delta a_{bx} &= a_x + a_{xz}g \\
\delta a_{by} &= a_y + a_{yz}g \\
\delta a_{bz} &= a_z + a_{zz}g + g \\
\delta\omega_{bx} &= \beta_x + \beta_{xy}Ucos(\varphi) + \beta_{xz}Usin(\varphi) \\
\delta\omega_{by} &= \beta_y + \beta_{yy}Ucos(\varphi) + \beta_{yz}Usin(\varphi) + Ucos(\varphi) \\
\delta\omega_{bz} &= \beta_z + \ \beta_{zy}Ucos(\varphi) + \beta_{zz}Usin(\varphi) + Usin(\varphi)
\end{aligned}$$

Similarly, by rotating the local level frame by 90 degrees about the Y axis, we obtain the following projections:

$$X_b = -Up, Y_b = N, Z_b = E$$

$$\omega_x^b = -Usin(\varphi),\ \ \omega_y^b = Ucos(\varphi),\ \ \omega_z^b = \ 0$$

$$a_x^b = -g, a_y^b = 0, a_z^b = 0$$

Taking these projections into consideration as well as the sensor model, the measurement model is the following:

$$\begin{aligned}
\delta a_{bx} &= a_x - a_{xz}g - g \\
\delta a_{by} &= a_y - a_{yz}g \\
\delta a_{bz} &= a_z - a_{zz}g \\
\delta\omega_{bx} &= \beta_x - \beta_{xx}Usin(\varphi) + \beta_{xy}Ucos(\varphi) - \ Usin(\varphi) \\
\delta\omega_{by} &= \beta_y - \beta_{yx}Usin(\varphi) + \beta_{yy}Ucos(\varphi) + Ucos(\varphi) \\
\delta\omega_{bz} &= \beta_z - \ \beta_{zx}Usin(\varphi) + \beta_{zy}Ucos(\varphi)
\end{aligned}$$

Using the above method to create a measurement model, it is possible to define the accelerometer and gyro indications for the different rotation angles of the IMU. With the measurement model defined in this way and with the help of the least squares method it is possible to determine the unknown parameters described in the sensor model.

3. The proposed calibration method

The proposed calibration method separately calibrates accelerometers and gyros in the IMU. The proposed method is based on simultaneous rotations of the turntables axes. Rotating all three axes simultaneously leads to a much faster calibration process.

3.1 Accelerometer calibration

According to the sensor model introduced above, output signals of the accelerometer can be expressed as a sum of g independent biases along the body axis and matrix product of a 3x3 matrix of g dependent biases induced by accelerations along the body axis and a vector of measured signals in the body frame. Diagonal elements of the matrix represent the scaling factors of the accelerometers axes while other coefficient in the matrix represents the axes misalignment or cross-coupling coefficients.

The calibration is performed as a series of measurements at predefined turntable positions. In the i-th predefined position the accelerometer measurements can be expressed as:

$$\begin{aligned}
\delta a_{bxi} &= a_x + a_{xx}a_{bxi} + a_{xy}a_{byi} + a_{xz}a_{bzi} \\
\delta a_{byi} &= a_y + a_{yx}a_{bxi} + a_{yy}a_{byi} + a_{yz}a_{bzi} \\
\delta a_{bzi} &= a_z + a_{zx}a_{bxi} \ + a_{zy}a_{byi} + a_{zz}a_{bzi}
\end{aligned}$$

In order to reduce the output measurement noise, the IMU is stationary in each of the predefined positions and output signals are averaged over this time period, thus reducing zero-mean random biases. The 3-axes turntable is used for precision positioning of the IMU. Rearranging the accelerometer measurements we obtain the following matrix representation for each axis over n measurements:

$$\begin{bmatrix} \delta a_{bx1} \\ \delta a_{bx2} \\ \vdots \\ \delta a_{bxn} \end{bmatrix} = \begin{bmatrix} 1 & a_{bx1} & a_{by1} & a_{bz1} \\ 1 & a_{bx2} & a_{by2} & a_{bz2} \\ \cdot & \cdot & \cdot & \cdot \\ 1 & a_{bxn} & a_{byn} & a_{bzn} \end{bmatrix}\begin{bmatrix} a_x \\ a_{xx} \\ a_{xy} \\ a_{xz} \end{bmatrix}$$

$$\begin{bmatrix} \delta a_{by1} \\ \delta a_{by2} \\ \vdots \\ \delta a_{byn} \end{bmatrix} = \begin{bmatrix} 1 & a_{bx1} & a_{by1} & a_{bz1} \\ 1 & a_{bx2} & a_{by2} & a_{bz2} \\ \cdot & \cdot & \cdot & \cdot \\ 1 & a_{bxn} & a_{byn} & a_{bzn} \end{bmatrix}\begin{bmatrix} a_y \\ a_{yx} \\ a_{yy} \\ a_{yz} \end{bmatrix}$$

$$\begin{bmatrix} \delta a_{bz1} \\ \delta a_{bz2} \\ \vdots \\ \delta a_{bzn} \end{bmatrix} = \begin{bmatrix} 1 & a_{bx1} & a_{by1} & a_{bz1} \\ 1 & a_{bx2} & a_{by2} & a_{bz2} \\ \cdot & \cdot & \cdot & \cdot \\ 1 & a_{bxn} & a_{byn} & a_{bzn} \end{bmatrix}\begin{bmatrix} a_z \\ a_{zx} \\ a_{zy} \\ a_{zz} \end{bmatrix}$$

Rearranging the equations above it is possible to form a single matrix expression that represents the calibration procedure, i.e. the calibration equation. This is achieved by combining all the vectors on the right side into a single matrix and performing the same operation on the vectors on the left side which represent bias and cross-coupling coefficients for every axis. The calibration equation is the following:

$$\begin{bmatrix} \delta a_{bx1} & \delta a_{by1} & \delta a_{bz1} \\ \delta a_{bx2} & \delta a_{by2} & \delta a_{bz2} \\ \vdots & \vdots & \vdots \\ \delta a_{bxn} & \delta a_{byn} & \delta a_{bzn} \end{bmatrix} = \begin{bmatrix} 1 & a_{bx1} & a_{by1} & a_{bz1} \\ 1 & a_{bx2} & a_{by2} & a_{bz2} \\ \cdot & \cdot & \cdot & \cdot \\ 1 & a_{bxn} & a_{byn} & a_{bzn} \end{bmatrix} \begin{bmatrix} a_x & a_y & a_z \\ a_{xx} & a_{yx} & a_{zx} \\ a_{xy} & a_{yy} & a_{zy} \\ a_{xz} & a_{yz} & a_{zz} \end{bmatrix}$$

In short, the calibration equation can be represented in matrix form:

$$\delta A = A \cdot X$$

In the equation above, values δA and A represent the accelerometer indications for different rotation angles of the IMU which are calculated from the measurement model and IMU accelerometer sensor outputs respectively. Value X is the unknown parameter that has to be determined. X is the matrix of cross-coupling coefficients and biases that have to be determined for the calibration to be successful. The calibration equation can be solved by least-squares method. When applied, the least squares method yields the following result:

$$\dot{X} = (A^T A)^{-1} A^T \delta A$$

In the equation above, the symbol T represents matrix transpose and the symbol (-1) represents matrix inverse.

3.2 Gyroscope calibration

According to the sensor model introduced above, output signals of the gyroscope can be expressed as a sum of biases along the body axis which may possibly depend on g and g^2 drifts and matrix product of a 3x3 matrix of biases induced by rotation along the body axis and a vector of measured signals in the body frame. Diagonal elements of the matrix represent the scaling factors of the gyroscopes axes while other coefficient in the matrix represents the axes misalignment or cross-coupling coefficients. In this paper g and g^2 bias dependencies will be ignored.

The calibration is performed as a series of measurements at predefined turntable rates. During the calibration the turntable simultaneously rotates all 3 axes at a constant rate. In order to reduce the output measurement noise, the IMU is stationary in each of the predefined positions and output signals are averaged over this time period, thus reducing zero-mean random biases. The i-th sensor measurement can be expressed as:

$$\delta\omega_{bxi} = \omega_x + \omega_{xx}\omega_{bxi} + \omega_{xy}\omega_{byi} + \omega_{xz}\omega_{bzi}$$
$$\delta\omega_{byi} = \omega_y + \omega_{yx}\omega_{bxi} + \omega_{yy}\omega_{byi} + \omega_{yz}\omega_{bzi}$$
$$\delta\omega_{bzi} = \omega_z + \omega_{zx}\omega_{bxi} + \omega_{zy}\omega_{byi} + \omega_{zz}\omega_{bzi}$$

The same rearranging process we applied on the accelerometer measurements is also applicable here. After the combining of equations we obtain the following gyro calibration equation:

$$\begin{bmatrix} \delta \omega_{bx1} & \delta \omega_{by1} & \delta \omega_{bz1} \\ \delta \omega_{bx2} & \delta \omega_{by2} & \delta \omega_{bz2} \\ \vdots & \vdots & \vdots \\ \delta \omega_{bxn} & \delta \omega_{byn} & \delta \omega_{bzn} \end{bmatrix} = \begin{bmatrix} 1 & \omega_{bx1} & \omega_{by1} & \omega_{bz1} \\ 1 & \omega_{bx2} & \omega_{by2} & \omega_{bz2} \\ \cdot & \cdot & \cdot & \cdot \\ 1 & \omega_{bxn} & \omega_{byn} & \omega_{bzn} \end{bmatrix} \begin{bmatrix} \omega_x & \omega_y & \omega_z \\ \omega_{xx} & \omega_{yx} & \omega_{zx} \\ \omega_{xy} & \omega_{yy} & \omega_{zy} \\ \omega_{xz} & \omega_{yz} & \omega_{zz} \end{bmatrix}$$

In short, the calibration equation can be represented in matrix form:

$$\delta\Omega = \Omega \cdot X$$

In the equation above, values $\delta\Omega$ and Ω represent the gyro indications for different rotation angles of the IMU which are calculated from the measurement model and IMU gyro sensor outputs respectively. Value X is the unknown parameter that has to be determined. X is the matrix of cross-coupling coefficients and biases that have to be determined for the calibration to be successful. The calibration equation can be solved by least-squares method. When applied, the least squares method yields the following result:

$$\dot{X} = (\Omega^T \Omega)^{-1} \Omega^T \delta\Omega$$

In the equation above, the symbol T represents matrix transpose and the symbol (-1) represents matrix inverse.

3.3 Adaptability

The proposed method is adaptive in the sense that it is applicable to any motion profile and any type of IMU. Also, the method is applicable not only to MEMS IMU units, but also to any IMU built with any type of accelerometer and gyroscope sensors organized so that triaxial measurements are supported. Since accelerometers and gyroscopes are calibrated separately, this method can be applied to any 3-axial accelerometer as well as any 3-axial gyroscope independently.

There are no physical limitations to motion profiles that are supported except the limits of the sensors used. The only existing limit is computational, because the method is represented by the calibration equation. The calibration equation is a system of linear equations. By Kronecker-Capelli theorem a system of linear equations $Ax = B$ has a solution if and only if the matrix of coefficients A has its rank equal to the number of columns. Thus, when designing the motion profile care needs to be taken so that the matrices A and Ω have its rank equal to 4.

The turntable has to be used for gyro calibration, because the rates of rotation need to be as stable as possible. For accelerometer calibration expensive equipment is not needed, because it consists of a series of measurements in predefined positions. A simple positioning model, i.e. a polyhedron, can be 3D printed and thus simulate the turntable's positioning in accelerometer calibration.

4. Results

Accelerometer calibration is performed as a series of measurements in predefined positions. At each position the turntable is stationary for a period of 30 seconds. During this period the data is averaged to produce a single measurement with zero-mean bias reduced as much as possible. At the beginning of the calibration the turntable's axes are positioned at zero. After each measurement the turntable's axes are simultaneously rotated by 5 degrees. When the turn table returns to the starting position the recording is stopped. This yields a total of 72 positions and 72 recordings that will be used in the calibration equation. After the recording is ended, the obtained accelerometer errors are displayed in figure 1.

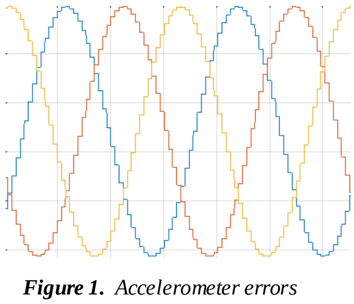

Figure 1. *Accelerometer errors*

After the calibration equation is solved with the least-squares method, the data is compared again and the calculated accelerometer errors are shown in figure 2.

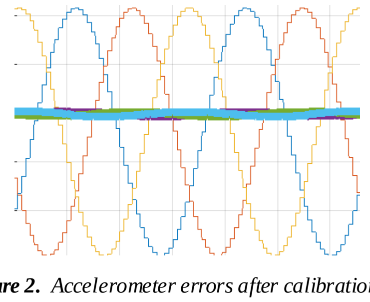

Figure 2. *Accelerometer errors after calibration*

Gyro calibration is performed as a series of measurements at predefined turntable rates. The rates are constant and range from 0 to 200 degrees/s in steps of 10. At each rate, the turntable maintains constant rate for a period of 60 seconds. The data recorded at each rate is averaged to produce a single measurement with zero-mean bias reduced as much as possible. This yields a total of 21 measurements and 21 recordings that will be used in the calibration equation. In order to ensure that the matrix Ω has rank 4, the desired turntable rate ω_i is projected to the turntable axes in the following manner:

$$\omega_{xi} = \omega_i, \quad \omega_{yi} = \sqrt{\omega_i}, \quad \omega_{zi} = \sqrt[3]{\omega_i}$$

Projecting the desired rate to the turntables axes in this manner creates a nonlinear dependence among columns, thus ensuring that the rank of matrix Ω is 4. At the beginning of each recording the turntable's axes are positioned at zero. Figure 3 shows the obtained gyro errors after the recording has ended.

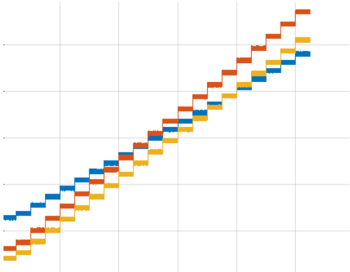

Figure 3. *Gyro errors*

After the calibration equation is solved with the least-squares method, the data is compared again and the calculated gyro errors are shown in figure 4.

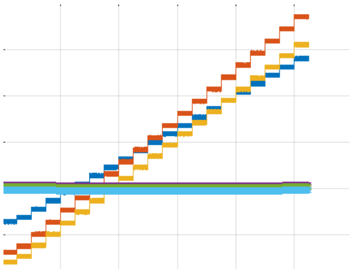

Figure 4. *Gyro errors after calibration*

5. Conclusion

In this paper we presented a method for calibration of MEMS based inertial measurement units. The method is based on angle rotations and proposes that the calibration be performed by simultaneous rotation of three axes of a precision turntable and least squares method. In the paper we discussed the adaptability of the method as well as its limitations. Finally, we presented the results we obtained when we applied the proposed method to a MEMS based inertial measurement unit.

6. References

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