## 1.1 Sensors Calibration Overview

Figure 1.1 shows some error and noises may related to sensors which can affect the accuracy of the measurement.

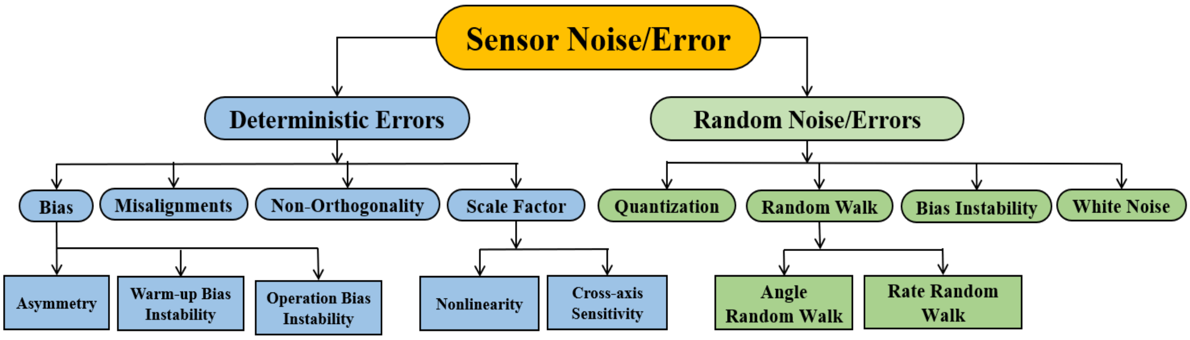


**Figure 1.1:** Sensors some noises and errors classifications

### 1.1.1 Sensor Deterministic Errors

Sensor deterministic errors encompass a range of inaccuracies and biases in sensor measurements that exhibit consistent and predictable patterns [70]. Some specific examples of sensor deterministic errors include:

#### 1.1.1.1 Sensor Zero-Bias Errors:

Optimal sensor output measurement should be Null when the measured physical quantity is zero. In reality, the output is typically not zero; this is termed zero-bias error [11]. A zero-bias error, sometimes called zero-position error, may be split into asymmetry error, warm-up zero-bias instability and operational zero-bias instability. This kind of error often resulting from a manufacturing defect. Figure 1.1 depicts the sensor zero-bias errors.

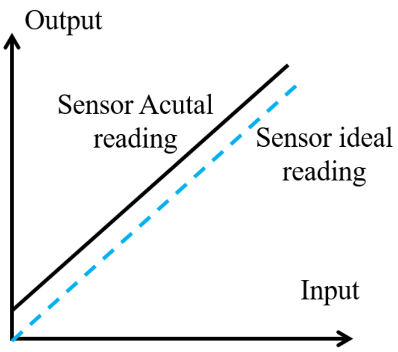


**Figure 1.1:** Sensor Zero-bias Error

#### 1.1.1.1 Sensor Scale Factor Error

The Scale factor, or proportionality factor, or sensitivity fault. Mathematically, the scale factor is the difference come from the variation in the sensor output amount and the change in its input amount. Every axis' scale factor must ideally be identical. Where the input changes and output changes should be identical. In reality, there are several scale factors, Figure 1.3 depicts the scale factor errors.

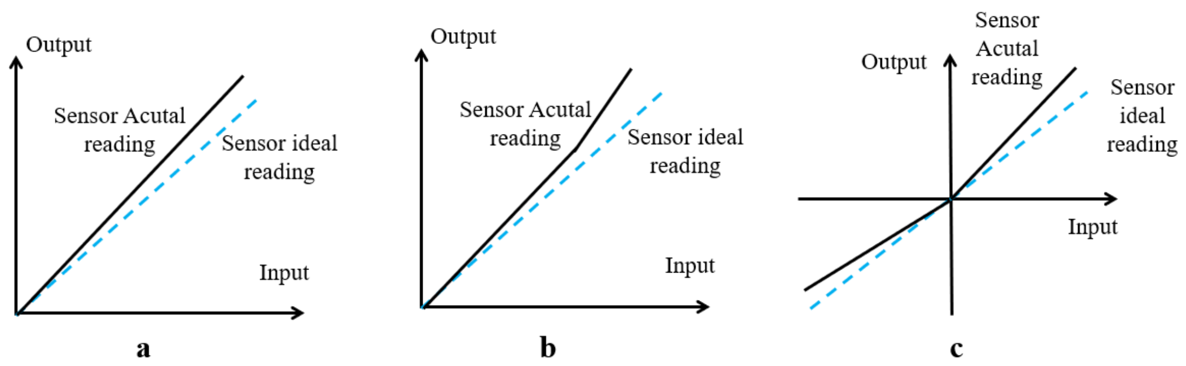


**Figure 1.3:** Sensor Scale factor: (a) linear errors. (b) nonlinear errors. (c) asymmetry errors

#### 1.1.1.3 <u>Cross-Axis Sensitivity</u>

The cross-axis influence is associated with non-orthogonality and the cross effect among distinct sensor channels. Non-orthogonality error refers to the error resulting from the faulty assembly of IMU chip or the intrinsic non-orthogonality resulting from the fact that the sensitivity axes in the sensors cannot be built correctly owing to real manufacturing limits.

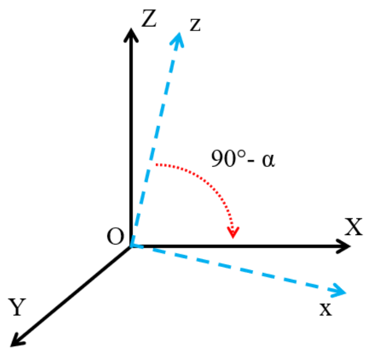


**Figure 1.4:** Sensor Cross-Axis Sensitivity

#### 1.1.1.4 <u>Misalignment Error</u>

Theoretically, all the orthogonal sensitive axis element of the sensor must be aligned with the host of sensor orthogonal axes, each both two axes must be matched and there is no angle between them. In reality, however, this is not guaranteed, and as a result, there is a mounting error in the angle between the two (sensitive element of the sensor and its host), leading to misalignment inaccuracies in the sensor's measurements. Figure 1.5 depicts the misalignment diagram.

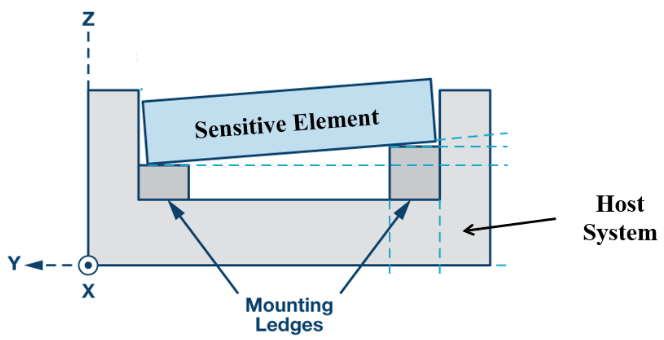


**Figure 1.5:** Sensor Misalignment Error

### 1.1.2 IME Sensor Calibration

The inertial measurement unit is a platform with multi-sensor that measures and reports the force of gravity and the angular speed of an associated object. composed of three accelerometers sensing vibration by help of piezoelectric material. And three gyroscopes use Coriolis effect in double-T structure element and drive arm rotates. And, in certain situations, three magnetometers, for each axis of roll, pitch, and yaw.

many scopes in the area of inertial sensor calibration have been treated by many kinds of literature [69-71]. Static multi-position method based on the direction of gravity and magnetic field of the earth was proposed by [72]. It is unsuitable for high-performance IMUs [72-74]. The least squares method (LSM) is used to estimate the error parameters, where LSM has been used experimentally by [75-76] demonstrate its feasibility when using a high accuracy equipment (turntable) which provides an accurate control to the orientation during the hole calibration processes, making it accurate and simple to implement. However, a high-precision turntable is not a cost-effective solution due to its high price [72][74]. Unfortunately, the high-precision turntable is not reachable by all searchers because of its high price. Kalman filter and extended Kalman filter have been also widely used for sensor calibration [76-77].

### 3.2.2.1 IMU Error Model Sensor and Calibration

#### *A) IMU* Sensor *Error Model*

Sensor Error Models (SEM) is a depiction of sensors, including uncalibrated primary-element measurement and its offset, misaligned axes and measurement scale factors, and in certain sensors, the magnetization effect, shown as hard iron and soft iron. The IMU calibration process needs pre-determination SEM for both Gyro and ACC. They come in a variety of representations with the same parameters, the calibration procedure is the only variable [78-80]. The SEM in equation 3.1 and 3.2, they are comprised of nine unknown values each, including three offsets, three correction scale factors, and three non-orthogonal angles.

$$\mathrm{ACC_f}=\mathrm{T_{no}}\mathrm{S_f}(\mathrm{ACC_n}-\mathrm{b})=\begin{bmatrix}\mathrm{ACC_{fx}}\\ \mathrm{ACC_{fy}}\\ \mathrm{ACC_{fz}}\end{bmatrix}=\begin{bmatrix}1 & 0 & 0\\ \mathrm{T_{xy}} & 1 & 0\\ \mathrm{T_{xy}} & \mathrm{T_{xy}} & 1\end{bmatrix}\begin{bmatrix}\mathrm{s_{fx}} & 0 & 0\\ 0 & \mathrm{s_{fy}} & 0\\ 0 & 0 & \mathrm{s_{fz}}\end{bmatrix}\left(\begin{bmatrix}\mathrm{acc_{nx}}\\ \mathrm{acc_{ny}}\\ \mathrm{acc_{nz}}\end{bmatrix}-\begin{bmatrix}\mathrm{b_x}\\ \mathrm{b_y}\\ \mathrm{b_z}\end{bmatrix}\right) \tag{3.1}$$

Where:

$\boldsymbol{ACC_n}$ is the measured acceleration vector.

$\boldsymbol{ACC_f}$ is the vector of compensated ACC final readings.

$\boldsymbol{S_f}$ is the matrix of scale factors

$\boldsymbol{T_{no}}$ is matrix of non-orthogonality, transformation from the non-orthogonal to orthogonal frame.

$\boldsymbol{b}$ is vector corresponding to sensor offset.

The gyro SEM is represented by the equation 3.2:

$$\boldsymbol{Y_g}-\boldsymbol{B_g}=\boldsymbol{T_g}\boldsymbol{M_g}\boldsymbol{S_g}\boldsymbol{U_g}\Rightarrow\begin{bmatrix}Y_{gx}-b_{gx}\\ Y_{gy}-b_{gy}\\ Y_{gz}-b_{gz}\end{bmatrix}=\begin{bmatrix}c_\theta c_\psi & -c_\varphi s_\psi+s_\varphi s_\theta c_\psi & s_\varphi s_\psi+c_\varphi s_\theta c_\psi\\ c_\theta s_\psi & c_\varphi c_\psi+s_\varphi s_\theta s_\psi & -s_\varphi c_\psi+c_\varphi s_\theta s_\psi\\ -s_\theta & s_\varphi c_\theta & c_\varphi c_\theta\end{bmatrix}^T *$$

$$\begin{bmatrix}1 & 0 & 0\\ \alpha_{xy} & 1 & 0\\ \alpha_{zx} & \alpha_{zy} & 1\end{bmatrix}\begin{bmatrix}S_{gx} & 0 & 0\\ 0 & S_{gy} & 0\\ 0 & 0 & S_{gz}\end{bmatrix}\begin{bmatrix}u_{gx}\\ u_{gy}\\ u_{gz}\end{bmatrix}. \tag{3.2}$$

Where:

$\boldsymbol{Y_g}$ is measured vector of the angular rates for the gyro undergoing calibration. $\boldsymbol{B_g}$ is offsets vector that prior-determined. $\boldsymbol{S_g}$ is matrix of scale factors. $\boldsymbol{T_g}$ is matrix represent the transformation from the non-orthogonal to orthogonal frame. $\boldsymbol{M}_g$ is the misalignment matrix between gyro and the referential frames Ug is vector of measured angular rates. $c_i$=cos $i$, $s_i$= $sin\, i$ and $\theta, \psi, \varphi$ represent Euler angles.

### *B) Calibration Process*

The static approach is utilized as an example of one of these common approaches in the calibration field. The calibration of the ACC is based on the ACC data set gathered at different orientations in static conditions with only gravitational impact. It is advised to collect the outputs of ACC at least in 21 orientations according to the Thin-Shell approach [81] and the reliability of this technique analysis reported in [82]. Moreover, to reduce the effect of temperature drift, it is recommended to warm up the ACC before starting the calibration process, in which it should hold the ACC in each orientation in static conditions and give some time for raw data averaging, which would minimize the impact of random noise. All averages have been conducted along all axes x, y, and z, with at least eight orientations along each axis Figure 3.6, where exact knowledge of these orientations is not necessary [82]. Using the minimization function approach to estimate the nine unknown coefficient of SEM, as a criteria function for minimization, the Root Mean Square Error (RMSE) presented in equation 3.4 has been utilized. This calibration technique assumes that in a static condition where there is no movement the ACC-measured output should equal gravity ‘$g$’.

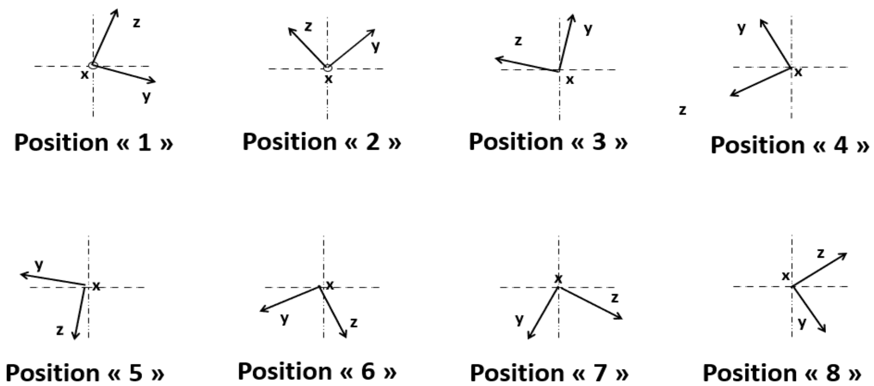


**Figure 3.6:** ACC calibration around eight orientations along “x” axis

In static conditions, the only force impacting the accelerometer is gravitational forces in the downward direction; this fact results in equation 3.3.

$$g_x^2 + g_y^2 + g_z^2 = |g|^2 \tag{3.3}$$

Where $g_i$ represents the projection of the gravity vector onto axes $i$. As a criterion function for minimization, RMSE is used.

$$RMSE(\Theta, g) = \sqrt{\frac{\sum_1^N(|a_i(\Theta)| - g)^2}{N}}, \text{ n=24}, \tag{3.4}$$

Where $|a_i(\Theta)| = \sqrt{acc_x{}^2 + acc_y{}^2 + acc_z{}^2}$ (3.5)

and $\Theta = (\Theta_1, \Theta_2, \dots, \Theta_9)$ is SEM nine coefficient being estimated, the total number of orientations about all axis is N (in our case n=9), m=24 in our case, g=1 is gravity vector, $a_i(\Theta)$ represent the SEM acceleration vector being estimated.

### 5.4.1 IMU Calibration Results

The experiment was carried out by collecting the average acceleration for each orientation along all axes Figure 5.37, minimizing the criteria function (RMSE) in equation (3.4), and using a gradient-based method to find the best of the nine SEM parameters that reduced the RMSE. The results are shown below:

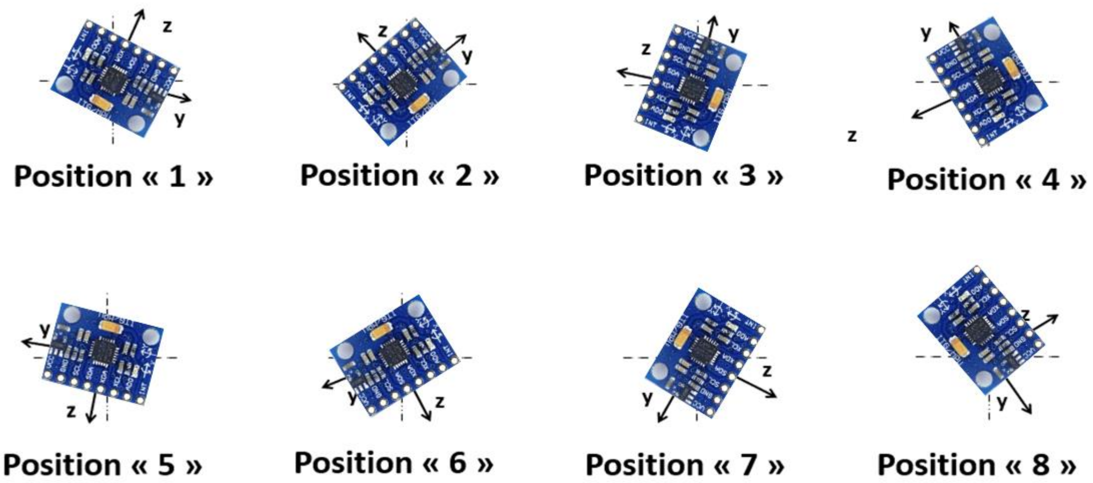


**Figure 5.37:** ACC calibration along "x" axis

$$T = \begin{pmatrix} 1.0000 & 0 & 0 \\ -0.0156 & 1.0000 & 0 \\ 0.0531 & 0.0034 & 1.0000 \end{pmatrix} \quad S = \begin{pmatrix} 1.0064 & 0 & 0 \\ 0 & 0.9969 & 0 \\ 0 & 0 & 0.9937 \end{pmatrix} \quad b = \begin{pmatrix} 0.0009 \\ -0.0052 \\ 0.0136 \end{pmatrix}$$

RMSE before calibration: 0.015470 g

RMSE after calibration: 0.000426 g

As an example:

the code of reading of IMU data has updated as following:

$$\begin{aligned} \mathrm{ACC}_{fx} &= 1.0064 * \mathrm{acc}_{nx} - 0.0100 \\ \mathrm{ACC}_{fy} &= -0.0157 * \mathrm{acc}_{nx} + 0.9969 * \mathrm{acc}_{ny} + 0.0053 \\ \mathrm{ACC}_{fz} &= 0.0534 * \mathrm{acc}_{nx} \quad 0.0034 * \mathrm{acc}_{ny} + 0.9937 * \mathrm{acc}_{nz} - 0.0140 \end{aligned}$$

Before calibration it was:

$$\begin{aligned} \mathrm{ACC}_{fx} &= 1.0 * \mathrm{acc}_{nx} \\ \mathrm{ACC}_{fy} &= 1.0 * \mathrm{acc}_{ny} \\ \mathrm{ACC}_{fz} &= 1.0 * \mathrm{acc}_{nz} \end{aligned}$$

Figure 5.38 demonstrates a significant reduction in the deviation (RMSE) before and after correction using SEM along 24 orientations.

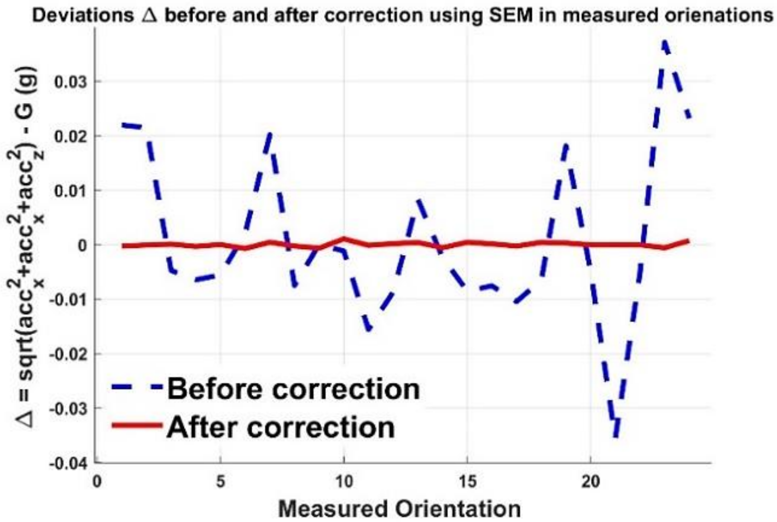


**Figure 5.38**: Deviation before and after correction

The IMU sensor calibration experiment showed a significant improvement in accuracy. Which indicated a reduction in deviation (RMSE) across 24 orientations before and after the correction with the application of SEM nine parameters. This highlights the effectiveness of the SEM correction method in calibrating the IMU sensor and enhancing its accuracy.