Analecta Technica Szegedinensia

Vol. 18, No. 2 ISSN 2064-7964 2024

MEASUREMENT SYSTEM FOR THE CALIBRATION OF ACCELEROMETER ARRAYS

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Received: 14th June	Accepted: 24th July

ABSTRACT

This paper addresses accelerometer array calibration, focusing on determining the errors between multiple sensors. Micro-electromechanical system (MEMS) based triaxial accelerometers, key components of Inertial Measurement Units (IMUs), are used in localization, robotics, and navigation systems. The requirements of these applications necessitate low-cost sensors, which makes MEMS IMUs a reasonable choice. However, these low-cost IMUs are significantly affected by systematic (i.e., bias, misalignment, scale-factor) and random errors. Achieving reliable sensor output depends on the precision of the executed calibration method. While traditional laboratory-based sensor calibration using specialized equipment (i.e., three-axis turntable) is accurate, it is time-consuming and costly. In contrast, in-field calibration techniques, which can be performed using a mechatronic actuator or a robotic arm, have gained popularity. These techniques involve comparing sensor measurements to established reference values. The MEMS sensors are increasingly being used in multi-sensor applications, which demands not only individual sensor error calibration but also important to determine the axis misalignment between the used sensors. During calibration process, various optimization algorithms (e.g., GA, PSO) can also be used to find the error parameters. The proposed measurement system allows for individual calibration of misalignment, bias, and scale factor of the sensor array, and eliminates between-sensor misalignment errors.

Keywords: inertial measurement unit, accelerometer, in-field calibration

1. INTRODUCTION

Inertial Measurement Units (IMUs) combine three tri-axial sensors, the accelerometer, gyroscope and magnetometer. These sensors have a wide range of use in many applications, such as Unmanned Aerial Vehicle (UAV), Automatic Guided Vehicle (AGV), localization applications, human movement and terrain classification [1] [2] [3] [4] [5]. Due to their low cost and high-resolution output, they are becoming more and more popular nowadays. Unfortunately, these IMUs are still not able to match the accuracy on the output required by many applications (i.e., Inertial Navigation Systems – INS). Many commercially available, low-cost IMUs come without calibration. Imperfections in the manufacturing process of the circuit board and IMU boards can lead to discrepancies between the sensitivity axes of the IMU and the coordinate system of the sensor board. However, as with general measurement systems, IMUs suffer from several drawbacks such as misalignment of sensors because of packaging errors, large offsets, non-linearity, drift and random noise. Moreover, in the case of accelerometer arrays, the sensitivity axes of the sensors in the array are not perfectly aligned [2]. An overview of multi-IMU (MIMU) systems are presented in [2].
Micro-electromechanical systems (MEMS) triaxial accelerometer is the vital component of IMUs, providing high-accuracy acceleration information about each three axes. Acceleration information can be turned into useful data for position, velocity, and attitude determination of an object. Before deploying sensors like accelerometers, gyroscopes, and magnetometers, calibration is an essential step. While some high-quality MEMS-IMUs have been precisely calibrated and don’t require further calibration, most consumer-grade IMUs are not adequately or not calibrated at all. This is often due to the desire to cut costs associated with calibration efforts. A detailed overview of the possible methods of calibrating an accelerometer is shown in [6]. Literature mentions two main possible ways for calibrating an accelerometer. First part employs the

DOI: https://doi.org/10.14232/analecta.2024.2.30-37

traditional calibration methods that require costly rotation rigs (i.e., three-axis turntable), since the calibration of accelerometer can be done by using the fact that the vector magnitude should be the local gravity acceleration [7]. Where the magnitude of acceleration is $1g$. The second part of calibration methods is the in-field calibration, which is an alternative calibration procedure that does not require expensive turntables. In reference [8] [9] [10], the in-field calibration techniques were discussed. Furthermore, optimization algorithms, like Particle Swarm Optimization (PSO) [11] [12] and Genetic Algorithm (GA) [7] in addition Artificial Neural Networks (ANN) [13] [14] and Adaptive Neuro Fuzzy Inference System (ANFIS) [15] [16] can be used to calibrate the sensors by comparing the sensor outputs with an established ground truth data.
In this work, a measurement system was demonstrated using multiple IMUs and an industrial robotic arm, such as Universal Robots UR5. Using this measurement system the calibration of five IMU sensor errors can be performed at once, including the bias, scale factors and misalignment individually and the misalignment between the sensors as well. The robotic arm can provide the ground truth information for the compensation of the sensor readings.

2. SENSOR MODELING

The readings from the accelerometer are affected by several errors, which can be categorized into systematic errors and random errors (also referred to as noise). Systematic errors that typically affect the performance of the system include bias, scale factor, frame misalignment and non-orthogonality errors, as depicted in Fig. 1. Sensor misalignment generally originates from two primary sources:

- The discrepancy between the sensor board and the sensor chip itself, as the two frames may not be perfectly aligned. This misalignment can be a result of the manufacturing process.

- Errors that occur when the sensor board is installed onto an external device (carrying body).

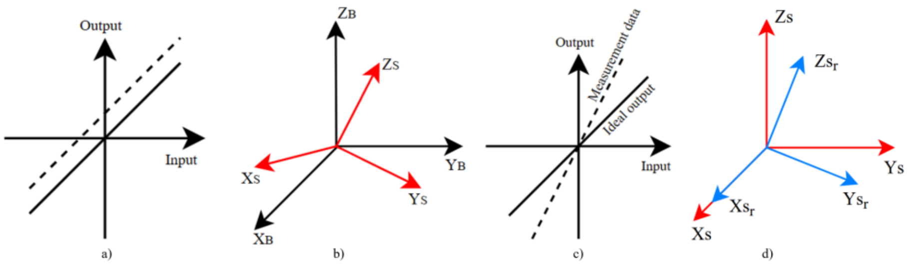

Figure 1. Most common systematic errors: a) bias, b) misalignment, c) scale factor and d) non-orthogonality

When an IMU sensor is installed on a different external object, particularly when the body frame changes, it's crucial to calibrate the misalignment error. Given that both the body frame and sensor frame are assumed to be perfect and orthogonal, we need to compute a minor angle rotation matrix, as shown in equation (2), that can translate the readings from the sensor frame to the body frame. The data gathered with the MEMS accelerometer can be represented as follows:

$$\begin{bmatrix} A_x \\ A_y \\ A_z \end{bmatrix} = \begin{bmatrix} S_x & S_{yx} & S_{zx} \\ S_{xy} & S_y & S_{zy} \\ S_{xz} & S_{yz} & S_z \end{bmatrix} \cdot \begin{bmatrix} a_x \\ a_y \\ a_z \end{bmatrix} + \begin{bmatrix} b_x \\ b_y \\ b_z \end{bmatrix} \tag{1}$$

The misalignment errors can be represented using the three rotation matrices. This facilitates a more accurate alignment of the sensor with the external body. Rotation matrices $R_x(\phi)$, $R_y(\theta)$ and $R_z(\psi)$ indicate the

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rotation deviation among the frames (i.e., sensor board, sensor chip, external surface). Combining all matrices (i.e., $R = R_x \cdot R_y \cdot R_z$), the main R rotation can be expressed as (2), where the trigonometric functions are introduced in abbreviated forms ($s\alpha = \sin\alpha$, and $c\alpha = \cos\alpha$).

$$R = \begin{bmatrix} c\theta c\psi & c\theta s\psi & -s\theta \\ -c\theta s\psi + s\phi s\theta s\psi & c\phi c\psi + s\phi s\theta s\psi & s\phi c\theta \\ s\phi s\psi + c\phi s\theta c\psi & -s\phi c\psi + c\phi s\theta s\psi & c\phi c\theta \end{bmatrix} \quad (2)$$

3. PROPOSED MEASUREMENT SYSTEM AND DATA ACQUISITION

The measurement system consists of an ESP32 NodeMCU microcontroller unit (MCU) and five MPU9250 IMUs. Each offering 9 degrees of freedom (9DoF). These components are connected to the MCU and together, they form a Robot Operating System (ROS) node. The MPU9250 (GY-9250) is a popular consumer-grade IMU shown in Fig. 2. It was selected due to its cost-effectiveness, and since it combines three tri-axial sensors: a 3DoF accelerometer, a 3DoF gyroscope, and a 3DoF magnetometer.

The sensors were mounted on a 3D printed tool at the robot's end-effector, as shown in Fig. 3. All the IMU sensors were placed in one plane, with uniform spacing between the sensor chips, as demonstrated in the Fig. 2. The coordinate system of the five IMUs corresponded to the robot's Tool Center Point (TCP) frame.

The MCU was used to read sensor data via the SPI interface and transmit them to a PC through a USB serial port. The ESP32 established a ROS publishing node using the rosserial library. Sensors were sampled at a frequency of 100Hz, and the data were published to ROS on dedicated IMU topics with a timestamp.

The device that performed the motions for the calibration of the accelerometer array was a Universal Robots UR5 robotic arm, which was also operated within ROS. A node was developed that can control the robotic arm to desired positions in three-dimensional space and the motion planning was achieved using predefined joint states. These angle values can be used to move the robot to the specific desired joint coordinates using joint motion. Concurrently with the execution of the motion, the IMU measurements can also be recorded in ROS. In addition to the sensor readings, the robot's TCP position and orientation can be logged. The ROS framework enables the logging of these data during the robot's movements, facilitating the creation of a comprehensive database. The calibration of the accelerometers can be done by the comparison of the achieved acceleration by the robot's end-effector and the sensors.

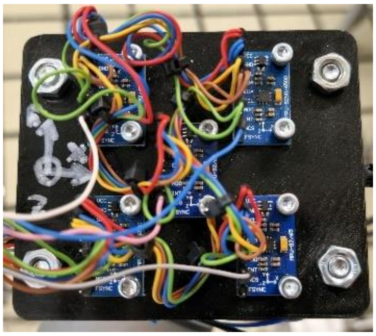

Figure 2. Arrangement of IMUs on the 3D printed end-effector

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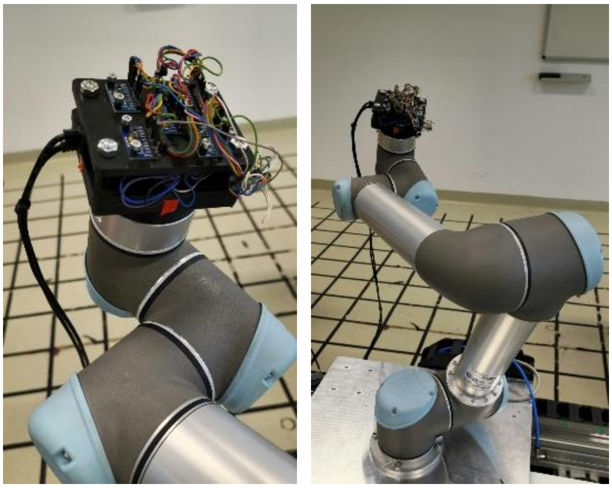

Figure 3. IMU array fixed to the UR5 robotic arm

3.1. Executed trajectories and accelerometer measurements

With the UR5 robotic arm, a spherical workspace with a maximum diameter of 1700mm can be accessed. The proposed method allows for the creation of trajectories that consist solely of joint movements. The TCP paths were constructed randomly using joint coordinates. The aim was to generate such trajectories (Fig. 4.) which, when executed, can provide the right amount of acceleration with the sensors mounted on the robot for the calibration. During the execution the five IMU sensors were sampled, in addition the position, and the orientation of the end-effector has been recorded. Fig. 4. shows some of the executed trajectories based on the collected TCP position.
By using the position of the TCP, the true acceleration can be calculated, which can be the ground truth for the calibration. The first derivative of position results in velocity (3), and its second derivative will result the acceleration (4).

$$v[n] = \frac{x[n] - x[n-1]}{\Delta t} \tag{3}$$

$$a[n] = \frac{v[n] - v[n-1]}{\Delta t} = \frac{(x[n] - x[n-1]) - (x[n-1] - x[n-2])}{(\Delta t^2)} \tag{4}$$

Where $v[n]$ indicates the velocity calculated from position $x[n]$. In addition, $a[n]$ denotes the acceleration that can be determined from the second derivative of position or first derivative of velocity. Δt is a small change in time.

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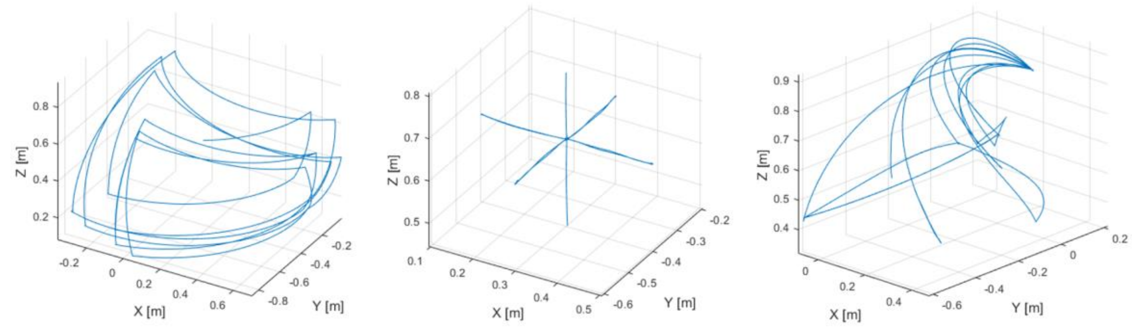
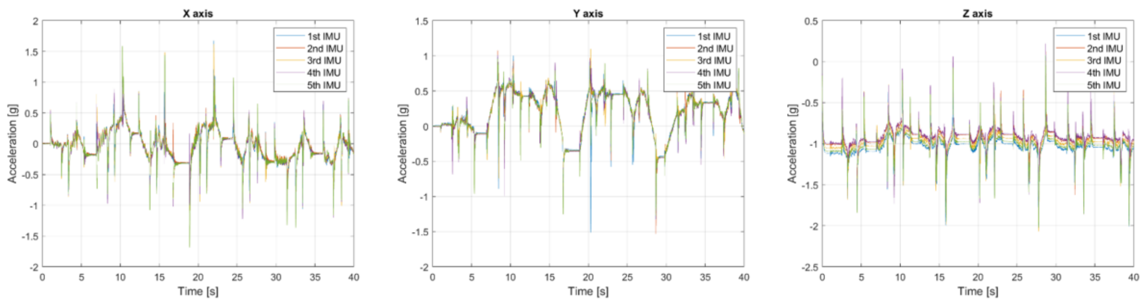


a) b) c)

Figure 4. Some of the executed trajectories by the UR5 robot



a) b) c)

Figure 5. Measurements with the five sensors for one trajectory

Fig. 5. demonstrates the raw measurements for one trajectory with the five accelerometers. The little difference presence between the sensor measurements is related to the sensor errors, that need to be calibrated.

3.2. Gravitational force compensated measurements

The gathered values of roll (ϕ), pitch (θ), and yaw (ψ) angles illustrate the rotational relationship between the robot's base frame and the TCP frame, where the sensors were positioned. These values can be utilized to construct a rotation matrix, which can then be used to express the transformation between the two coordinate systems. This approach allows for the transformation of measurement vectors into the base, with the $1g$ (which can be represented as $[0\ 0\ 1]^T$) value being subtracted from them (5). The accelerometer measurements, which have been compensated with gravitational effects and the computed ground truth are depicted in Fig. 6.

$$\begin{bmatrix} A_{X_{base}} \\ A_{Y_{base}} \\ A_{Z_{base}} \end{bmatrix} = \left(R \cdot \begin{bmatrix} A_{X_{TCP}} \\ A_{Y_{TCP}} \\ A_{Z_{TCP}} \end{bmatrix} \right) - \begin{bmatrix} g_x \\ g_y \\ g_z \end{bmatrix} \quad (5)$$

Where the $3x1$ size A_{base} vector represents the transformed and compensated acceleration in the base frame, R $(3x3)$ indicates the rotation matrix constructed with the ϕ, θ and ψ angles and the $3x1$ A_{TCP} vector denotes the sensor readings in the TCP frame.

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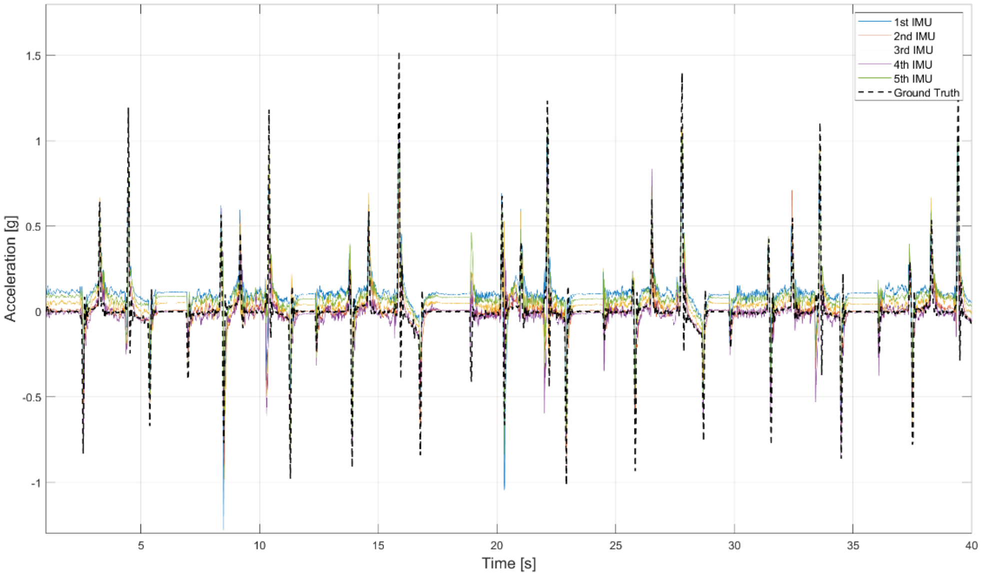

Figure 6. Compensated sensor measurements compared to the acceleration of the UR5 robot's TCP

The calculated ground truth accelerations can be applied as reference for the calibration of accelerometers, and it can be used to develop various specific algorithms for sensor calibration purposes.

4. CONCLUSIONS

In this work, a robotic arm-based measurement system was proposed, which can be used for the calibration of IMU arrays. The proposed measurement system consists of a Universal Robots UR5 robot that can perform dynamic motions and ensure its end-effector orientation for the ground truth data. In addition, ESP32 MCU was constructed as a ROS node along with five MPU9250 IMUs. The MCU was used to read and transmit the sensor measurements.

The used UR5 robotic arm is calibrated, so the obtained TCP position and orientation can be used to calculate the target for the calibration. Using this information any heuristic algorithm (e.g., PSO, GA, etc.) or an ANN can be used to correct the sensor readings. Misalignment, bias and the scale factor of the sensors can be calibrated individually and moreover the between sensor misalignment errors can be eliminated at the same time using the proposed method.

5. ACKNOWLEDGEMENT

The work was supported by the National Research, Development, and Innovation Fund of Hungary through project no. 142790 under the FK_22 funding scheme.

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