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Calibration and performance evaluation of low-cost IMUs

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***Abstract* – IMUs (Inertial Measurement Units) are extensively used in many robotics applications such as navigation and mapping tasks. In almost all these systems, inertial measurements are fused with data coming from other sensors (e.g., GPS sensors, range finders, cameras, ...). For better results, the IMU should be carefully calibrated, in order to minimize the propagation of systematic errors. But what happens if for brief periods data coming from the other sensors are missing? Can we trust the IMU in these cases?**

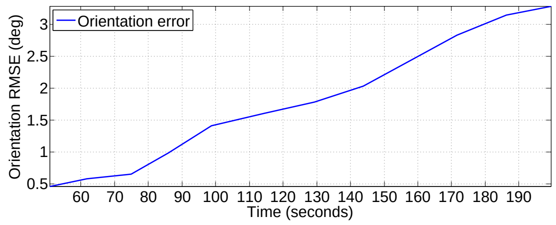
In this paper, we present a robust and simple method to calibrate an IMU without any external equipment. We then use the calibration results to analyze the behavior of two types of MEMS based IMUs employed as a single sensor in full 3D orientation and egomotion estimation tasks.

I. INTRODUCTION

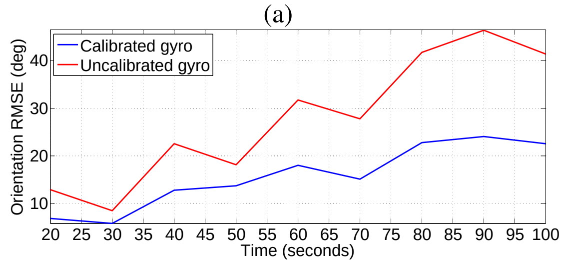
Inertial Measurement Units (IMUs) used in robotics are usually based on MEMS (micro electro mechanical systems) technology: besides being very cheap, these types of sensors are present in almost all the recent smartphones, enabling these devices to be used as navigation units in low-cost and lightweight robots as small mobile platforms or low-cost UAV (unmanned aerial vehicle).

Unfortunately, low-cost IMUs are affected by systematic errors, biases drifts and random errors that greatly reduce the accuracy in the position and attitude estimation. While systematic errors can be compensated through a prior calibration process, biases and random errors introduces unbounded drift errors that prevent MEMS based IMUs to be used as independent sensors in complex tasks such as localization and mapping.

In these paper we address the systematic errors presenting an effective and semi automatic IMU calibration method that enables to improve at no cost the performances of low-cost, poor calibrated, IMUs. The presented method has been tested using two types of sensor: a Xsens MTi IMU and a Samsung Galaxy S4 smartphone. In the first case, we compare the estimated calibration parameters with the calibration parameters reported in the IMU datasheet. In the second case, we compare the orientation errors obtained in several known trajectories using uncalibrated and calibrated measurements (Fig. 1(b)). Furthermore, we present an investigation on how random errors will propagate through the whole navigation system.



(a)



(b)

Fig. 1. Root-mean-square error (i.e., the mean of the yaw, pitch and roll errors, in degrees) in the orientation estimation in several known trajectories using only the calibrated gyroscopes: (a) A Xsens MTi IMU; (b) A Samsung Galaxy S4 smartphone. In the second case, we also report the orientation error obtained using the uncalibrated measurements.

A. Related Works

Inertial navigation is a relatively mature research field. Technologies, physical principles and applications of inertial navigation are presented, among others, in [1]. An gentle introduction to MEMS-based inertial navigation, along with an analysis on the propagation of the orientation errors caused by the noise perturbing gyroscope signals, is presented in [2]. In robotics, among others, IMUs have been exploited for inertial-only navigation [3], attitude estimation [4], and visual-inertial navigation [5], also using a smartphone device [6]

The calibration method presented in this paper has been introduced by the authors in [7]: this method is based on the multi-position method firstly introduced by Lotters *et al.* in [8]. They proposed to calibrate the biases and the scale factor of the accelerometers using the fact that the magnitude of the static acceleration must be equal to the gravity's magnitude. This technique has been extended in [9] to include the accelerometer axis misalignment: this method requires a single axis turntable to provide a strong rotation rate signal. In [10] authors presented a calibration scheme that does not require any external mechanical equipment. Similarly to our approach, the authors calibrate the accelerometers exploiting the high local stability of the gravity vector's magnitude, and then gyroscopes calibration is obtained comparing the gravity vector sensed by the calibrated accelerometer with the gravity vector obtained by integrating the angular velocities.

II. SEMI-AUTOMATIC IMU CALIBRATION

Low-cost MEMS based IMUs (20-100 $) and the IMU sensors that equip current smartphones are usually poorly calibrated, resulting in measurements coupled with not negligible systematic and random errors. Common source of errors are: axis misalignments of the accelerometer and gyroscopes triads, non accurate scaling, cross-axis sensitivities, variable biases and noises. Medium-cost IMUs (1000 - 2000 $) usually use conventional, low-cost sensor sets, but they are factory calibrated, with the calibration parameters stored into the firmware or inside a non-volatile memory. Calibration in these cases is performed using standard but effective methods, where the device outputs are compared with known references. Unfortunately, the overhead cost for the factory calibration is predominant.

We present a semi-automatic calibration method, that provides misalignments and scale factors for both the accelerometers and gyroscopes triads, while estimating the sensors' biases. Our method is based on the multi-position method[1] [8], it does not require any parameter tuning and simply requires the sensor to be moved by hand and placed in a set of different static positions. Unlike previous multi-position based methods, we exploit a larger number of static states with reduced periods, in order to increase the cardinality of the dataset while preserving the assumption of local stability of the sensors biases. We introduce an effective and parameterless static detector operator to detect the static intervals used in the calibration. Moreover, we improve the calibration accuracy employing Runge-Kutta 4th order normalized method in the gyroscopes integration.

A. *Dataset acquisition and data classification*

Our method requires to collect IMU measurements in a set of different, static, attitudes (between 36 to 50 distinct orientations), after an initial period with no motions (Fig. 2). The accuracy of the calibration strongly depends on the reliability in the classification between static and motion intervals. We define "static interval" as a period of time in which the sensor remains in a static (fixed) position. Unfortunately, during these periods the IMU readings are not zero, since they are affected by biases drifts and random noises, while the accelerometer also perceives the gravity acceleration. In our experience, band-pass filter based operators, like the *quasi-static detector* used in [10], perform poorly with real datasets: detected static intervals frequently includes some small portion of motion. Moreover, they require a fine tuning, since they depend on three parameters. We propose to use an operator based on the variance magnitude of the accelerometer signals:

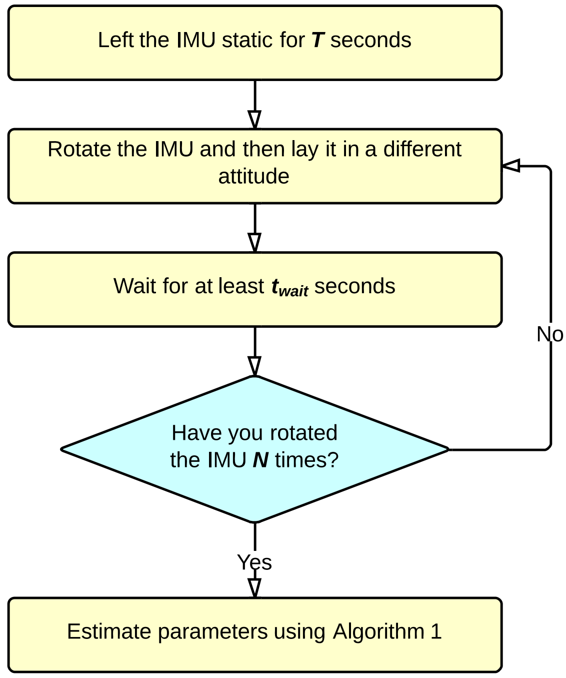


Fig. 2. Diagram of the dataset acquisition protocol

$$\varsigma(t) = \sqrt{[var_{t_w}(a_x^t)]^2 + [var_{t_w}(a_y^t)]^2 + [var_{t_w}(a_z^t)]^2} \quad (1)$$

where $var_{t_w}(\mathbf{a}^t)$ is an operator that compute the variance of a general signal $\mathbf{a}^t$ in a time interval of length t_w seconds centered in t. A sample at time t is considered "static" if its variance magnitude is lower then a threshold. A uninterrupted sequence of static samples define a single static interval. As a threshold, we consider an integer multiple of the variance magnitude computed over a static initialization period of length T_{init} (see Fig. 2), where the multiplier is automatically estimated (see Sec. C.). In all the experiments, we use $t_w = 1\ sec$ and $T_{init} = 30\ sec$. An example of the static detector applied to a data stream is reported in Fig 3.

[1]The multi-position method assumes that in a static position, the norms of the measured accelerations is equal to the magnitudes of the gravity plus a multi-source error factor.

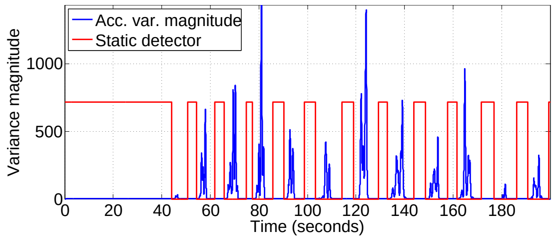


Fig. 3. An example of the presented static detector operator applied to the accelerometers data (the square of the variance magnitude is reported).

B. Accelerometer and gyroscope calibration

In an ideal IMU, the 3 axes of the accelerometers and the 3 axes of the gyroscopes define a single, shared, orthogonal 3D frame. In the real case, due to assembly inaccuracy, the two triads form two distinct (i.e., misaligned), non-orthogonal, frames. For small angles, these misalignments can be linearly compensated by means of two misalignment matrices, T^a and T^g, one for the accelerometers and one for the gyroscopes. Assuming that the IMU frame coincides with the accelerometers orthogonal frame:

$$T^a = \begin{bmatrix} 1 & -\alpha_{yz} & \alpha_{zy} \\ 0 & 1 & -\alpha_{zx} \\ 0 & 0 & 1 \end{bmatrix} \quad (2)$$

$$T^g = \begin{bmatrix} 1 & -\gamma_{yz} & \gamma_{zy} \\ \gamma_{xz} & 1 & -\gamma_{zx} \\ -\gamma_{xy} & \gamma_{yx} & 1 \end{bmatrix} \quad (3)$$

Both the accelerometers and the gyroscopes are also affected by scale errors:

$$K^a = \begin{bmatrix} s^a_x & 0 & 0 \\ 0 & s^a_y & 0 \\ 0 & 0 & s^a_z \end{bmatrix}, K^g = \begin{bmatrix} s^g_x & 0 & 0 \\ 0 & s^g_y & 0 \\ 0 & 0 & s^g_z \end{bmatrix} \quad (4)$$

and biases:

$$b^a = \begin{bmatrix} b^a_x \\ b^a_y \\ b^a_z \end{bmatrix}, b^g = \begin{bmatrix} b^g_x \\ b^g_y \\ b^g_z \end{bmatrix} \quad (5)$$

so the complete sensor error model is:

$$a^O = T^a K^a (a^S - b^a - \nu^a) \quad (6)$$

for the accelerometers, and:

$$\omega^O = T^g K^g (\omega^S - b^g - \nu^g) \quad (7)$$

for the gyroscope, where ν^g and ν^g are the measurement noises.
In the multi-position method, the norms of the measured accelerations is assumed to be equal to the (known) magnitudes of the gravity plus a multi-source error factor. In order to calibrate the accelerometers triad, we need to estimate the unknown parameter vector θ^{acc} that includes 3 misalignment component, 3 scale components and 3 biases components:

$$\theta^{acc} = \left[\; \alpha_{yz}, \alpha_{zy}, \alpha_{zx}, s^a_x, s^a_y, s^a_z, b^a_x, b^a_y, b^a_z \; \right] \quad (8)$$

The cost function to be minimized is:

$$L(\theta^{acc}) = \sum_{k=1}^{M} (||g||^2 - ||h(a^S_k, \theta^{acc})||^2)^2 \quad (9)$$

where M is the number of static intervals, a^S_k represents the raw sensor readings, h is a function that corrects the readings applying the current parameter vector and $||g||$ is the actual magnitude of the gravity vector. In order to minimize Eq. 9, we employ the *Levenberg-Marquardt* (LM) algorithm.
We use the same static intervals also to calibrate the gyroscopes: in this case, we can assume a bias-free system averaging the initial static signals to obtain the biases, but we need also to estimate the rigid body rotation between the gyroscopes and the accelerometers frames. The unknown parameter vector θ^{gyro} includes in this case 6 misalignment component and 3 scale components :

$$\theta^{gyro} = \left[\; \gamma_{yz}, \gamma_{zy}, \gamma_{xz}, \gamma_{zx}, \gamma_{xy}, \gamma_{yx}, s^g_x, s^g_y, s^g_z \; \right] \quad (10)$$

We use the calibrated accelerometers as a reference: given an initial gravity vector, integrating a set of gyros readings, we can estimate a final estimated gravity vector and compute the difference from the references. In this case, the cost function is:

$$L(\theta^{gyro}) = \sum_{k=2}^{M} ||u_{a,k} - u_{g,k}||^2 \quad (11)$$

where $u_{a,k}$ is the acceleration versor measured averaging in a temporal window the calibrated accelerometer readings in the k-th static interval, and $u_{g,k}$ is the acceleration versor computed integrating the angular velocities between the $k-1$-th and the k-th static intervals. The integration is obtained using a robust Runge-Kutta 4th order normalized method[11], that outperforms the standard linear integration procedure providing higher accuracy results.

C. The proposed algorithm

In the following, the proposed calibration algorithm is reported:

Algorithm 1

1. Acquire the dataset as described in Sec. A. (the dataset must include an initial static period of length T_{init})

2. Estimate in the initial static period the gyro biases and accelerometer variance magnitude acc_{vm}
3. Remove the biases from the gyro readings
4. For $mult = 1$ to k do

   -Compute the static intervals using as threshold $mult * acc_{vm}$
   -Calibrate the accelerometers using these static intervals and compute the residuals

5. Take the accelerometer calibration with the lowest residual
6. Use the calibrated accelerometers readings to calibrate the gyroscopes.

D. *Calibration results*

We tested our method using a factory calibrated Xsens MTi IMU, enabling the so called "uncalibrated data mode". Using this setting, the sensor streams directly the raw, uncalibrated data of both the accelerometer and gyroscopes triads (i.e., the outputs of the analog-to-digital converters, ADCs, connected to each sensor). The calibration obtained with our method is comparable to the factory calibration parameters given by the data-sheet, see tables starting from Table 1. For each table, we report the factory calibration parameters (on the left), and our calibration parameters (on the right). Note that the offsets estimations (Table 5 and 6) include also the time-variant sensor biases. Nevertheless, the estimate is very close to that provided by the data-sheet.

Table 1. Scaling - Accelerometer

415	0.00	0.00
0.00	413	0.00
0.00	0.00	415

414.41	0	0
0	412.05	0
0	0	414.61

Table 2. Scaling - Gyroscope

4778	0.00	0.00
0.00	4758	0.00
0.00	0.00	4766

4778.0	0	0
0	4764.8	0
0	0	4772.6

Table 3. Misalignment - Accelerometer

1.00	0.00	-0.01
0.01	1.00	0.01
0.02	0.01	1.00

1.0000	-0.0066	-0.0110
0.0102	1.0001	0.0114
0.0201	0.0098	0.9998

Table 4. Misalignment - Gyroscope

1.00	-0.01	-0.02
0.00	1.00	0.04
-0.01	0.01	1.00

0.9998	-0.0149	-0.0218
0.0003	1.0007	0.0433
-0.0048	0.0121	1.0004

Table 5. Offset - Accelerometer

33123	33276	32360

33124.2	33275.2	32364.4

Table 6. Offset - Gyroscope

32768	32466	32485

32777.1	32459.8	32511.8

III. FREE INERTIAL NAVIGATION

It is well known that systems based on free inertial navigation (the so called "strapdown systems", [1, 3]) are affected by unbounded drift due to the sensor errors propagation in the position estimate. Actually, inertial aided navigation systems allow to reduce or remove this drift. Unfortunately, not always data coming from the other sensors are available: for instance, in a GPS-aided system the GPS signal may be missing for short periods, or in a visual inertial navigation systems, the surrounding environment might be lacking of salient visual features. For these reasons, we want to investigate the performances and limitations of a MEMS based IMU calibrated with the method presented in Sec. ii. in the case of 3D free inertial navigation.
In the following experiments, we used a Xsens MTi IMU and a Samsung Galaxy S4 smartphone, both calibrated with the method presented in the previous section. We tested our system with trajectories taken moving the sensor by hand, that include quick motions along each directions and quick rotation around each axes. Moreover, each path represents a closed loop in which the starting point and the end point are the same point in the environment, with the same orientation. The accuracy is measured by checking the error between the start and the endpoints of the recovered trajectory. In these experiments we don't employ any filtering techniques, since we are interested on evaluating the final "raw" error.

A. *Orientation*

We start investigating the effect of the propagation of noises and inaccuracies perturbing the gyroscope signals. We can assume that the IMU is bias-free: for each trajectory, we estimated the biases averaging the gyroscopes signals taken from an initial static period. Assuming constant biases during each run and subtracting them to the gyroscopes signals, the system can be considered biases-free. As in Sec. ii., we employ quaternion arithmetic and the Runge-Kutta numerical integration method [11] to improve the estimation accuracy. Some results are shown in Fig. 1, where the root-mean-square errors of the final orientations are reported for several loop closures trajectories with different time lengths. In Fig. 1(a), results obtained with a Xsens MTi IMU are reported. We set in the Xsens MTi the "uncalibrated data mode" setting, enabling the sensor to stream directly the raw, uncalibrated data. The measurements have been then calibrated using the parameters presented in Sec. ii.: even after 2 minutes, the total

error (i.e., the mean of the yaw, pitch and roll errors) is less that 2 degrees.
We performed the same experiment using a Samsung Galaxy S4 smartphone (Fig. 1(b)): in this case, we report both the orientation errors obtained using the sensor readings provided by the phone (called ”uncalibrated gyro“ in the plot) and the orientation errors obtained with same data calibrated using the parameters estimated with our method (called ”calibrated gyro“ in the plot). The results obtained with the calibrated data show a significant accuracy improvement compared to the results obtained with the uncalibrated data.

B. Position

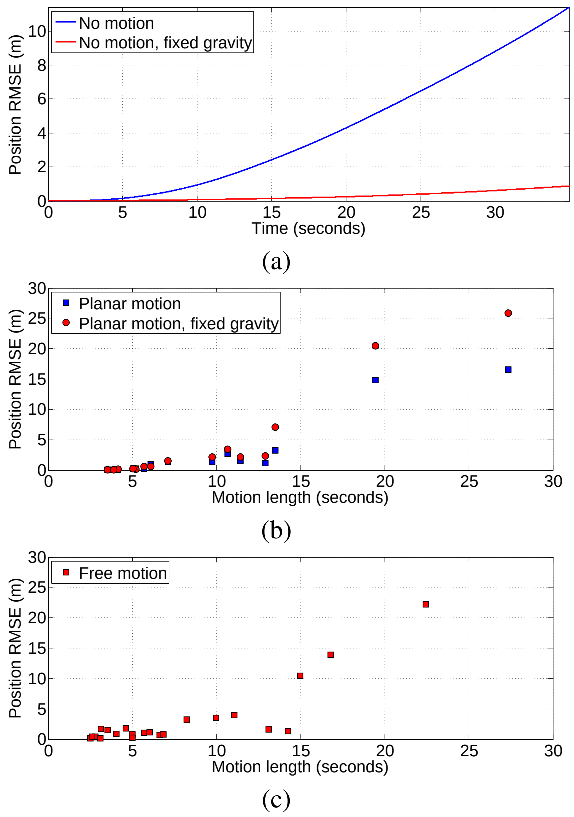


Fig. 4. Position drift for different types of motion: (a) No motion (b) Planar motions (c) 3D motions.

To test the performance of the system in the case of open loop position estimation, signals from the accelerometers should be doubly integrated. Here we can estimate and subtract the accelerometers biases following a simplified multi-position method: before each test trajectory, we moved the IMU in a set of static positions with different attitudes. Then we solved a least squares problem with the cost function defined in Eq. 9, with a parameter vector that includes only the accelerometer biases. During a static initialization period, we also computed the (bias free) acceleration components due to gravity. This vector is projected in each IMU frame using the orientations computed with the gyroscopes and subtracted to the current acceleration measurements. The remaining acceleration is then doubly integrated to obtain the displacement. In this experiment, we used only the Xsens MTi IMU, since the accuracy provided by the low cost sensors of a smartphone is not adequate to provide acceptable results, also for motions with very short duration.
A first test involved datasets taken from a stationary position, i.e. with no motions (Fig. 4(a), blue line): after 5 seconds the drift starts to quickly diverge. We repeated this estimation subtracting a constant gravity vector, i.e. without using the orientations computed with the gyroscopes for the projection (Fig. 4(a), red line). In this second case the estimation accuracy increase significantly. As pointed out in [2], this behavior suggests that *most of the error in the estimation is generated by small errors in the orientation estimate*, mainly introduced by the gyroscope noise. We repeated a similar test for a sequence of planar motions, taken moving the device on a plane (Fig. 4(b)). In this case, using a fixed gravity, the estimation accuracy *decreases*. Usually the z-axis of the device is not perfectly aligned with the gravity: in the case of planar motion with variable yaw rotation, the gravity direction should not be considered constant, and compensated using the current orientation. We finally tested the system with a sequence of different 3D motions (Fig. 4(c)): as in the previous cases, after a few seconds the drift starts to diverge. It is noteworthy that this quick drift can be mainly attributed to MEMS technology limitations (e.g., sensors noises and inaccuracies).

IV. CONCLUSIONS AND FUTURE WORKS

In this paper, we have presented a simple but effective IMU calibration method. We also presented an investigation on how random, non systematic errors of low-cost IMUs will propagate through an inertial navigation system. We experimentally show that: (1) it is possible to obtain reliable calibration results without using any external equipment (2) using the obtained calibration parameters, inertial-only navigation allows a few seconds of relatively stable full 3D egomotion estimation (at least for medium-cost IMUs as the Xsens MTi), and most of the localization errors are due to noise and inaccuracies of the gyroscope signals; (3) with a good initial estimation of the gyroscopes biases, the 3D orientation estimation obtained robustly integrating the gyroscope signals maintains a good accuracy even after a few minutes for medium-cost IMUs, and for 30 seconds for low-cost IMU sensors as the ones that equip the current smartphones.

As a future work, we plan to investigate the possibility to enable a visual inertial navigation system to reliably navigate for short periods even in the absence of visual features in the surrounding environment, using only the information coming from the IMU sensor.

An open-source C++ implementation of the presented calibration system is freely available for download at: `https://bitbucket.org/alberto_pretto/imu_tk`.

V. ACKNOWLEDGEMENTS

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