Analysis and comparison of attitude estimation algorithms applied on Inertial Measurement Units

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***Abstract*—This paper presents the results obtained comparing the performance of two attitude estimation filters applied on data measurements from an Inertial Measurement Unit (IMU). The device used for this work is called iNEMO, which includes a tri-axis gyroscope, a tri-axis accelerometer and a tri-axis magnetometer, as well as a pressure sensor. The first attitude estimation algorithm is called Tilted Compass, which has been developed by STMicroelectronics. The second filter is the Madgwick filter, which is supposed to provide a better performance (mainly in terms of accuracy) for the attitude estimation. The values of roll, pitch and yaw angles have been computed by using these two algorithms and the results compared.**

***Keywords*—Attitude estimation, Inertial Measurement Unit, Kalman filter, Madgwick filter, MEMS sensors, sensor calibration**

I. INTRODUCTION

Inertial Measurement Units have become very popular in the last few years, thanks to their versatility and simplicity. The purpose of using an Inertial Measurement Unit is to obtain the attitude angles of roll, pitch and yaw starting from the measurements of gyroscope, accelerometer and magnetometer. Several approaches have been used so far in order to achieve this goal: one of the most used filters is the Extended Kalman Filter, as well as the algorithm introduced by *Julier et al.* [9]. Other new approaches have been explored and led to more accurate results, such as the Mahony [8] and Madgwick [7] filters. In particular, the latter will be used in this work in order to test its accuracy when using a general IMU. Its results will then be compared to the ones obtained when using a simpler attitude estimation algorithm called Tilted Compass, developed by STMicroelectronics. This work is mainly focused on identifying and discussing the main reasons behind the accuracy of the results obtained when using a specific attitude estimation algorithm. In particular, the importance of good measurements from the magnetometer is also emphasized and investigated. This paper is organized as follows: section II describes the device used to obtain our results, which is an IMU called iNEMO and provided by STMicroelectronics; section III presents some differences between the commercial version of the IMU and the version used for our research purposes. Section IV describes the two algorithms used by also providing some theoretical explanation. Section V shows and compares the performance and results obtained for the attitude estimation when using these two algorithms.

II. INERTIAL MEASUREMENT UNIT: iNEMO

The Inertial Measurement Unit used in this research project is called iNEMO and provided by STMicroelectronics. Such device is based on MEMS (Micro Electro-Mechanical Systems) and it is made of the following components, as shown in Fig. 2:

Fig. 1: The Inertial Measurement Unit iNEMO

- LPS331AP, a pressure sensor which has not been used for the purpose of this work
- L3GD20, a three-axis gyroscope in which data is saved in 16-bit registers and sent to the microprocessor through SPI communication. The values registered for speed are in *dps* (degrees per second). Possible values are within these ranges: ±250dps, up to ±2000 dps.
- LSM303DHLC, module that has both an accelerometer and magnetometer. For this sensor, I2C is the communication protocol used. The user can select the preferred range amongst the following ones: ±2g, ±4g, ±8g for the accelerometer while ±1.3, ±2.6 and ±8.1 Gauss for the magnetometer.

Programming the iNEMO is not an easy task, since a direct USB connection is missing. This means that it can be connected only by using single wires to the proper pins in order to communicate with it. This is the reason why an external device has been used, called STM32F4 and also provided by STMicroelectronics [1], since it provides some pins that allow to use the device as an external programmer.

A. *Configuration of sensors*

Meaningful data from sensors can be obtained by using some specific structures defined in C programming language. An issue that needed to be solved is related to the proper configuration of the magnetometer. In fact, such device can be configured to work in three different modes: Continuous, Single or Sleep mode. Continuous mode is the one that has to be selected in order to obtain measurements from the

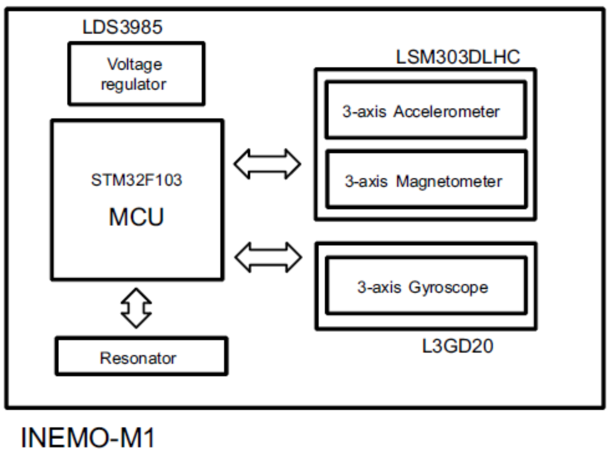

Fig. 2: Internal implementation of the iNEMO

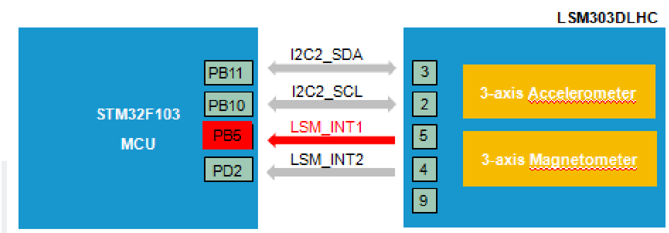

Fig. 3: Configuration of the beta version of iNEMO

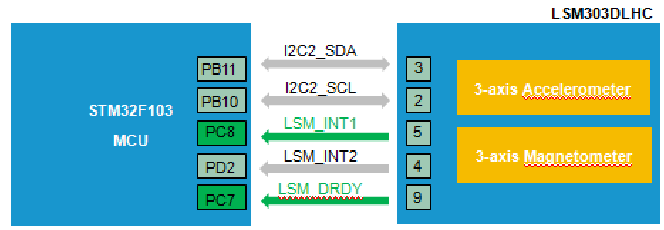

Fig. 4: Configuration of the commercial version of iNEMO

sensor continuously. However, the magnetometer was initially not working as expected and only a single measurement was detected by the sensor. In particular, such misbehaviour was related to a bit in the system register of the sensor which is wrongly set. This issue was solved by changing the configuration mode of the magnetometer, switching between Continuous and Sleep mode at every execution step.

B. *Differences with the commercial version*

The version of iNEMO used in this project is a beta version of the sensor, and therefore slightly different compared to the one available on the website of STMicroelectronics, as shown in Fig. 3. and Fig. 4. In particular, there are some differences about how to configure the communication with the accelerometer/magnetometer. In the commercial version, two pins (PC8 nd PD2) are used for the interrupts received from the accelerometer and magnetometer, respectively. There is also an additional connection (LSM_DRDY) which is specifically used for data, after the interrupt has been handled, which is pin PC7. In the beta version of iNEMO the connection LSM_DRDY is not available, and therefore both interrupt connections (for accelerometer and magnetometer) are also used for data transmission. In addition, in the beta version LSM_INT1 has a different pin number, PB5. Such a difference is very important for the proper configuration of the communication between microprocessor and sensor, since the pin number has to be specified when enabling the interrupts.

III. Attitude Estimation Algorithms

In order to compute the attitude estimation, the Kalman filter [5] has been widely used over the years. However, recent studies have shown that the Kalman filter is computationally expensive and therefore simpler filters have been preferred. On of these is the Madgwick filter, that allowed to explore new possibilities about the usage of MARG and IMU sensors. In particular, these kind of sensors are low power devices or where frequency update is very high. Firstly, we need to introduce the Tilt Compass algorithm, provided by STMicroelectronics, whose results have been compared to the ones obtained by using the Madgwick filter.

A. *The Tilted compass filter*

STMicroelectronics provides an algorithm to compute the attitude estimation of iNEMO by having values from gyroscope, accelerometer and magnetometer. The calibration of magnetometer is very important before computing the attitude estimation. The code provided by STMicroelectronics already provides a function that is specifically used to calibrate the magnetometer. The calibration of magnetometer is done through noise rejection. There are two different kind of disturbances: the ones called *Hard Iron* which is due to the presence of magnets nearby, and the ones called *Soft Iron*, that are caused by electrical fields [6], [2], [4], [3]. In case of no disturbance, the data plotted from the magnetometer should be a sphere centered in the origin. However, when these two kind of noises are affecting data obtained from magnetometer, the sphere is no longer centered in the origin and it is also deformed, which means that its more likely an ellipsoid rather than a sphere. In particular, hard noises are causing the sphere not to be centered in the origin, while soft noises are causing its deformation. This means that data from the magnetometer have to be multiplied by a factor, called Scale Factor, and subtracted by an offset in order to reject these two kind of noises. This is the easiest way to obtain calibration of the magnetometer. In order to get the offset value, the average value along each axis has to be computed, by also computing the minimum and maximum values obtained. At each step, the offset values need to be updated, by computing the overall average value again. The attitude estimation computed is actually reliable along pitch and roll axis, even without the calibration of the magnetometer, since measurements obtained from accelerometer affect the estimation obtained along these axes rather than data obtained from the magnetometer. On the other hand, accelerometer measurements do not play any role in the estimation of yaw angle, while magnetometer measurements are fundamental values to compute the estimation along this angle. This means that the magnetometer has to be calibrated properly for the estimation of the yaw angle. The Tilted Compass algorithm allows to obtain roll, pitch and yaw angles directly. Firstly, this algorithm normalizes measurements of accelerometer in order to obtain more precise attitude estimation, and then computes the values of roll, pitch and yaw angles through the function atan2.

B. The Madgwick filter

The Madgwick filter is an algorithm that can be used for the attitude estimation of an Inertial Measurement Unit (IMU), introduced by Madgwick [7]. The IMU is a device which is composed of several sensors that are all used to compute the attitude estimation: three-axis gyro, three-axis accelerometer and three-axis magnetometer. The Madgwick filter uses a technique called sensor fusion for data collected form the above mentioned sensors. In particular, the filter uses the measurements obtained from accelerometer and megnetometer as correction elements for the measurement errors for the direction which is obtained when integrating measurements from the gyroscope. In addition, the algorithm uses quaternions that allow to solve singularity issues when representing angles by using the Euler angles (Euler notation). These are the advantages in using this filter:

- Computationally less expensive than the Kalman filter
- The filter is efficient and accurate even when sampling at a low rate, while this is not always guaranteed when using the Kalman filter
- One or two degrees of freedom when calibrating the filter

This algorithm also checks that measurements from magnetometer are reliable (it checks that they are different from 0), and when such measurements are null, the attitude estimation is obtained only by using measurements from gyroscope and accelerometer. In this algorithm, there are two parameters that could be changed by the user: the value of beta (which is set to 0.1 by default) and *SampleFreq*, which sets the sampling frequency. The value of β represents all mean zero gyroscope measurement errors, expressed as the magnitude of a quaternion derivative. Another aspect to take into account is related to the sampling rates that have been used for the sensors, defined as follows:

- Gyroscope: 400 Hz and a cutoff frequency of 20Hz
- Accelerometer: 100 Hz
- Magnetometer: 200 Hz

Data obtained by using this algorithm are much less compared to the amount of data obtained when using the Tilted Compass, even though the performance of this algorithm heavily depends on the values set for parameters β and *SampleFreq*. In fact, the best value for beta in our case is 0.001, which allows the algorithm itself to be less sensitive to the measurement errors. When using greater values of beta (e.g., 0.1) the attitude estimation depends on the derivative of the error. About the value SampleFreq, when using a value around 200 Hz the attitude estimation is reasonable, even though such value affects the final estimation is less compared to beta. Since the values for the gyroscope are in *dps* (degrees per second) they have to be converted to radians per second in order to make them compatible with the Madgwick filter. In the Madgwick filter, quaternions are computed by using the Gradient Descent algorithm.

C. Analysis of data from the magnetometer

An important step when computing the attitude estimation is the calibration of the magnetometer. In fact, such device is slightly different compared to the other sensors like gyroscope and accelerometer, since the latter ones do not need any manual calibration. On the other hand, calibrating the magnetometer is crucial since there could be several disturbances that could affect the measurements obtained from this sensor. Such disturbances can be divided into two categories, called *Soft Iron* and *Hard Iron* disturbances, respectively. These two kind of noises are due to the presence of additional magnetic fields that affect the values detected by the magnetometer. If measurements are not affected by these disturbances, a sphere centered in the origin of axes will appear when plotting data collected from the sensor. However, noise shapes this sphere differently such that an ellipsoid is obtained instead. In particular, this is how *Soft Iron* and *Hard Iron* disturbances are affecting data obtained from the magnetometer, respectively:

- *Soft Iron* disturbance causes the shift of the sphere along the three axes
- *Hard Iron* disturbance causes the sphere to become an ellipsoid, since it changes the magnitude of data collected from the sensor

Calibration allows the correction of data which is subject to two disturbances mentioned above. In order to correct measurements, the following transformation has to be applied on data:

$$M_r = M_m \cdot M_{sf} + M_{off} \tag{1}$$

where M_m is the measurement obtained from the sensor, while M_{sf} and M_{off} are defined as the scale factor and the offset, respectively. There are several ways to compute the right values for M_{sf} and M_{off}. One of these is already implemented by STMicroelectronics within the Tilted Compass algorithm. It consists of performing a 360 degrees rotation of IMU along the horizontal plane followed by a 360-degree rotation along the vertical plane. However, such method is mainly useful to reduce the *Hard Iron* disturbance. Generally speaking, it is always good to perform calibration before using the IMU for attitude estimation purposes. Some tests are shown below, that have been performed without the calibration of the magnetometer, in order to analyze the default settings of the sensor. In particular, the IMU has been placed onto a goniometric platform and rotations have been done by 10 degree per time. This way, Coriolis acceleration can be neglected when processing data. The magnetometer has been aligned to the north on order to perform these measurements.

1) Rotation of 360°: This test has been performed by rotating the IMU of 360 degrees on the goniometric platform. As shown in Fig. 5, data collected from the sensor starts again from scratch when hitting $\pm 360°$.

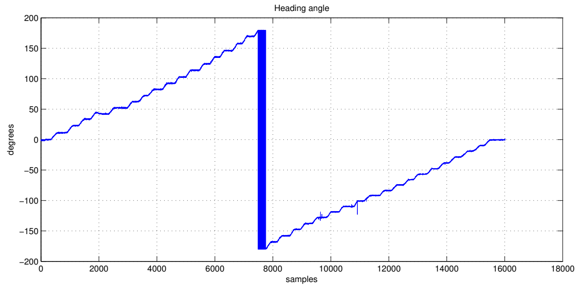

Fig. 5: Heading angle for a rotation of 360 degrees

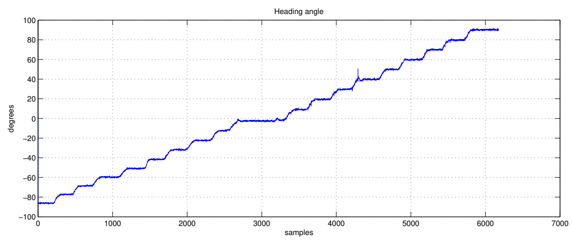

Fig. 6: Heading angle for a rotation of $\pm 90°$

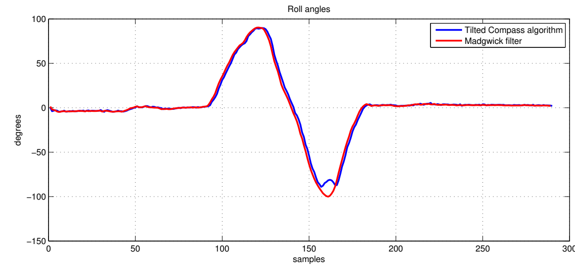

Fig. 8: Roll angle for a rotation of $\pm 90°$

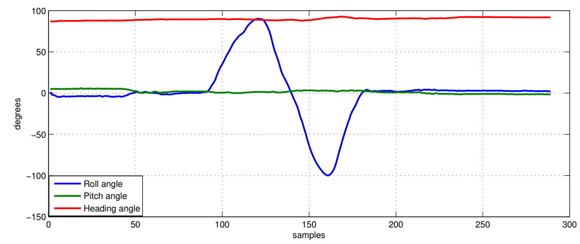

Fig. 9: Estimation of all the angles by using the Madgwick filter

2) Rotation of 90°: This test is composed of two parts. In the first one, a rotation of $\pm 90°$ was performed, while in the second part a rotation from 0 to 90° was done. The results obtained from the two tests are shown in Fig. 6 and Fig. 7, respectively.As shown from the figures mentioned above, the measurements obtained from the magnetometer are good enough such that its calibration is not needed. However, calibration of the magnetometer could also be helpful in order to reduce noise.

IV. Results

This section analyzes the results obtained from applying the Tilted Compass and the Madgwick algorithm to data obtained from the sensors. A first remark is that the attitude estimation obtained when applying the Tilted compass filter is much more noisy compared to the one obtained from the Madgwick filter. In particular, the estimation seems to be more noisy for the yaw (heading) angle, since data from the magnetometer is crucial in order to obtain a good estimation for the value of this angle. The following subsections describe in more details how the attitude estimation has been obtained when performing rotations around a single angle only. In fact, this kind of test is very reliable in order to check the accuracy and performance of the attitude filter used.

A. Rotation around the x axis

In this test, a rotation of -90° around the x axis has been performed. As it can be noticed from Fig. 8, the Madgwick filter provides good estimation results for all the angles. In addition, the Madgwick filter provides more accurate results especially related to the estimation of the Yaw angle ϕ, as shown in Fig. 9. Such improvement happens exactly when the rotation around the x axis happens, which means that the Madgwick filter is more robust to reject drift errors.

B. Rotation around the y axis

This test has been performed by rotating the IMU of 90° first and -90° afterwards around the y axis. Good results have been achieved for both filters in this case, as shown in Fig. 10.

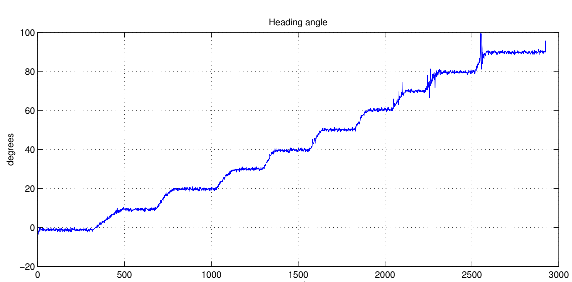

Fig. 7: Heading angle for a rotation from 0 to 90°

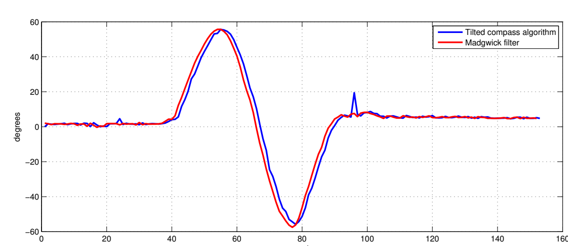

Fig. 10: Pitch angle for a rotation of $\pm 90°$

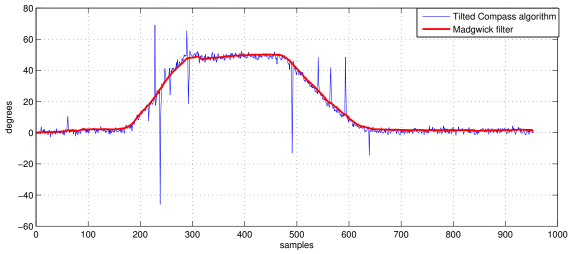

Fig. 11: Yaw angle for a rotation of -50°

C. *Rotation around the z axis*

This test has been performed by rotating the IMU around the z axis by -50°. In this case, the estimation performed by the Tilted Compass algorithm has an offset which is not present for the Madgwick filter, as shown in Fig. 11. In particular, the Madgwick filter can achieve good accuracy for attitude estimation even without calibration. This is because the algorithm automatically computes the lack of accuracy for data from magnetometer, as already explained before.

V. Conclusion

We have described and analyzed some algorithms in order to compute the attitude estimation of a low-cost Inertial Measurement Unit called iNEMO. In particular, this work proved that the performance and accuracy of these algorithms heaviy depend on the quality of measurement data collected from the sensors. The main issue related to the Tilted compass algorithm is how the attitude angles are computed numerically, since this introduces additional errors for the attitude estimation. On the other hand, the Madgwick algorithm has some enhancements since it performs additional computations in order to be robust against lack of accurate data from sensors. In addition, the Madgwick filter is computatioally less expensive than other filters commonly used for attitude estimation and therefore also suitable to be executed online.

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