Orientation Estimation Using Filter-Based Inertial Data Fusion for Posture Recognition

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Abstract. In this article, the Kalman filter, Mahony filter and Madgwick filter are implemented to estimate the orientation from inertial data, using an IMU called 9×3 of the MoMoPa3 project which contain various sensors including a gyroscope, an accelerometer and a magnetometer, each one of them, equipped with three perpendicular axes, in the magnetometer the measurement was modified to correct the distortions by hard metals, demonstrating improvements in the accuracy of the orientation estimates. In addition, the Kinovea video analyzer software is used as reference and gold standard to calculate the Root-Mean-Square Error (RMSE) with each filter. When comparing the angles estimated by the filters with those obtained from Kinovea, it was observed that one of the filters was better in performance. The information obtained in this article can be involved in several fields of science, one of the most important in the field of medicine, helping to control Parkinson's disease since it allows to evaluate and recognize when a patient suffers a fall or presents Freezing of the gait (FOG).

Keywords: Orientation estimation · IMU · Kalman filter · Madgwick filter · Mahony filter · Magnetometer distortion

1 Introduction

The life expectancy throughout the world has increased continuously for more than half a century [1], diseases caused by age or longevity in people has increased, being Parkinson's disease considered of special importance. Parkinson's disease (PD) is a complex degenerative neurological condition that appears in adulthood and is the second most common neurodegenerative disease, mainly affecting the motor system [2–4]. According to the Global Declaration for Parkinson's Disease, PD affects up to 6.3 million people worldwide [5], Parkinson's disease is increasingly a public health challenge in our progressively aging societies.

The main clinical features of Parkinson's disease are related to body movement including tremor, spontaneous shaking (mainly in the upper limbs), muscle stiffness and bradykinesia (slow-moving physical movements) [6], in the advanced phase of the disease freezing of gait (FOG) is present, which is a disabling symptom and a movement disorder, and becomes a problem that could cause falls, this can be prevented by identifying when the FOG happens, with that, being able to control and help the patient by means of auditory signals to not lose coordination and freezing of the motor system, for this, it is necessary being able to recognize the orientation of the patient.

When observing the high index affectation of Parkinson's Disease, the developed project tries to improve the quality of life of the people who suffer it, raising the objective of recognizing the freezing of gait (FOG) of the patients, to avoid falls during this stage, in order to achieve this, first it needs to be able to estimate the orientation of the individual, for this, inertial sensors, such as, accelerometer, gyroscope and magnetometer are used, which together form an Inertial Measurement Unit (IMU). The device with these characteristics used in this article, was originally created for the MoMoPa3 project [7], which provides raw data, later this information from the sensors will be processed and filtered through the use of Kalman filter, Madgwick filter and Mahony filter to evaluate which filter best estimates the position compared to the angles obtained by a video analyzer software called Kinovea, each of the filters was implemented in Matlab.

The remaining of this article is organized as follows Sect. 2 describes briefly related works on orientation estimation with inertial sensors in different fields of science, Sect. 3 shows each of the filters used, and mathematically what corrections had to be made before inputting the measured data to the filters as well as how the angles were calculated from the coordinates given by Kinovea, on Sect. 4 we show the results obtained with each filter compared to our gold standard and finally in Sect. 5 conclusions and future works that could be done are shown.

2 Related Works

The orientation estimation is useful in several areas of research, one of which is to control unmanned aerial vehicles (UAV) or aerial robots, which allow the autonomous or semi-autonomous development of missions that cover the defense and security sectors [8]. In order to guarantee the permanent availability of the control system, it is essential to have certain instruments and sensors to control the stability of an UAV, such as the inertial measurement unit or IMU that provides data from the course followed by the UAV [9].

There are several methods for the estimation of the orientation as in [10] a real-time system was developed to monitor tremors and detection of falls, because of freezing of gait (FOG) which is a symptom present in the late stages of Parkinson's disease. The system consists of a 3D camera sensor based on the Microsoft Kinect architecture, which is able to recognize episodes of freezing (a state of inactivity), tremors and fall incidents. In case of an event, an alert is sent automatically to relatives and health care providers. This project was developed on an ideal environment, so its operation is

influenced, depending on the vision range of the Kinect so in a real environment the algorithm can fail to find obstacles in the range of the visual sensor, where the test subject is placed, that's why it is more convenient to use sensors mounted directly on the patient, as proposed in this article.

Another development of great importance are exoskeletons for rehabilitation, which are used to assist movements and/or increase the capabilities of the human body [11]. In the article called "Lower-limb wearable exoskeleton" [12], it shows a system to compensate and evaluate the pathological gait, for applications, in real conditions, as a methodology of assistance of the problems that affect the mobility of individuals with neuromotor disorders. The implementation of sensors consists of an inertial measurement unit (IMU) on the foot (below the ankle joint in the orthosis), and a second unit in the lower bar of the exoskeleton, to achieve the control system of the exoskeleton, through the information acquired from the estimation of the orientation of each articulation. In this case, the work developed to obtain the estimation of the orientation of each articulation, is not robust enough, since it does not present an alternative system to be able to verify and compare that the estimated orientation is correct, in our project it is used both invasive and non-invasive sensors to be able to obtain the sensor orientation.

The determination of the orientation of objects in motion is involved in several fields of science [13]. In order to obtain relevant data for the estimation of the orientation it is necessary to process the signals received from the inertial measurement unit (IMU), the advanced methods of signal processing are strongly researched to optimize the performance of the existing detection hardware [13, 14]. When faced with a dynamic system, the magnitudes of the vector of parameters to be estimated will vary with time, which makes the problem more complex, in these cases, recursive estimation methods are used [15]. Currently there are several methods to manipulate the data, among the most important are the extended Kalman filter, Madgwick filter and Mahony filter, in this article each of the filters is implemented and then compared to obtain which one gives a lower error in the estimation of the orientation. In addition, it is intended to perform an exact system by using two different processes for the estimation of the orientation, using Kinovea as a visual sensor and using the IMU as inertial physical sensors, once the process of acquisition and processing of the data is completed, it is sought to get an autonomous system to incorporate the algorithm of orientation estimation, to be used in several applications within the field of health to detect FOG in Parkinson's disease.

3   Our Approach

3.1   Sensor

For the development of this research, an inertial measurement unit (IMU) was used. It is a device used in several fields, since they are effective, small and light. The IMU used is the same as the work done in [7] called 9×3 that has the objective of evaluating the symptoms of Parkinson's disease (PD). The 9×3 Unit can be used 2 or 3 days working continuously and it independently registers the signals of each of its

sensors. This device has several elements such as: three accelerometers, a gyroscope, a magnetometer and a barometer to detect small changes in altitude [7].

The signals used for the estimation of the orientation in this work are obtained only from the inertial sensors integrated in LSM9DS0 [16], which is a 9-axis system composed of a magnetometer module, a triaxial accelerometer and a triaxial gyroscope module, these signals are stored on a microSD card, with a sampling rate of 400 Hz.

3.2 Mahony Filter

The notation used to mathematize the filters that we are going to follow is the one described by Madgwick in [17]. For example: the symbol ^ denotes a normalized vector, the symbol * means the conjugate of the vector, the operator ⊗ denotes a quaternion product, $^A_B\hat{q}$ means the orientation of frame B with respect to frame A, $^A\hat{v}$ is a vector in frame A.

$^E\hat{h}$ represents the direction of the magnetic field in the frame of the earth, calculated by means of the quaternary product of the previous estimation of orientation with the normalized magnetometer measurement and with the conjugate quaternion of the previous estimation of orientation, as can be seen in Eq. (1), m is the measure delivered by the magnetometer.

$$^E\hat{h}_t = {}^S_E\hat{q} \otimes \left(\hat{m} \otimes {}^S_E\hat{q}^* \right) \tag{1}$$

A quaternion is defined by Eq. (2).

$$^S_E\hat{q} = [q_1 \quad q_2 \quad q_3 \quad q_4] \tag{2}$$

Using the vector $^E\hat{b}$, which is the normalization of h, the effect of an erroneous inclination of the measured direction of the earth's magnetic field can be corrected, obtaining only components on the x and z axes of the earth, as shown in Eq. (3).

$$^E\hat{b}_t = \begin{bmatrix} 0 & \sqrt{h_x^2 + h_y^2} & 0 & h_z \end{bmatrix} \tag{3}$$

From Eqs. (4) and (5) the estimated direction of gravity and magnetic field, can be calculated respectively.

$$^E\hat{v} = \begin{bmatrix} 2 \times (q_2 \times q_4 - q_1 \times q_3); & 2 \times (q_1 \times q_2 - q_3 \times q_4); & q_1^2 - q_2^2 - q_3^2 + q_4^2 \end{bmatrix} \tag{4}$$

$$^E\hat{w} = \begin{bmatrix} 2 \times b_2 \times \left(0.5 - q_3^2 - q_4^2\right) + 2 \times b_4 \times (q_2 \times q_4 - q_1 \times q_3) \\ 2 \times b_2 \times (q_2 \times q_3 - q_1 \times q_4) + 2 \times b_4 \times (q_1 \times q_2 - q_3 \times q_4) \\ 2 \times b_2 \times (q_1 \times q_3 - q_2 \times q_4) + 2 \times b_4 \times \left(0.5 - q_2^2 - q_3^2\right) \end{bmatrix} \tag{5}$$

After that the Error is calculated with Eq. (6), which is the result of the sum of the cross product between the estimated direction and the measured direction of the field vectors, a is the measure by the accelerometer.

$$ {}^{E}\hat{e} = a \times {}^{E}\hat{v} + m \times {}^{E}\hat{w} \tag{6} $$

The Mahony filter is used particularly because it allows to correct the bias of the gyroscope, applying an integral and proportional controller with Eqs. (7) and (8), where sp is the sample frequency (400 Hz for this work) and $\hat{g}_{k-1}$ is the measurement given by the gyroscope.

$$ i_k = i_{k-1} + {}^{E}\hat{e} \times sp \tag{7} $$

$$ \hat{g}_k = \hat{g}_{k-1} + k_p \times {}^{E}\hat{e} + k_i \times i_k \tag{8} $$

At last, the quaternion change rate is calculated with Eq. (9) and integrated to produce the quaternion with Eq. (10), later converted to Euler angles to compare these measurements with the measurements of angles found in the analysis of Kinovea.

$$ \dot{q} = 0.5 \times {}^{S}_{E}\hat{q} \otimes {}^{E}\hat{g}_t \tag{9} $$

$$ {}^{S}_{E}\hat{q}_k = {}^{S}_{E}\hat{q}_{k-1} + \dot{q} \times sp \tag{10} $$

3.3   Madgwick Filter

The algorithm of this filter starts by normalizing the values obtained from the accelerometer and magnetometer, calculating the direction of the magnetic field in the frame of the earth and the effect of a wrong inclination measurement of the direction of the magnetic field, to find these values the same equations described in Sect. 3.2 are used.

This filter is characterized by adding a corrective stage using the gradient de-census algorithm, as described in [17]. Where the Jacobian is defined by Eqs. (11) and (12).

$$ f_b\left({}^{S}_{E}\hat{q}, {}^{E}\hat{b}, {}^{S}\hat{m}\right) = \begin{bmatrix} 2b_x\left(0.5 - q_3^2 - q_4^2\right) + 2b_z(q_2q_4 - q_1q_3) - m_x \\ 2b_x(q_2q_3 - q_1q_4) + 2b_z(q_1q_2 - q_3q_4) - m_y \\ 2b_x(q_1q_3 - q_2q_4) + 2b_z\left(0.5 - q_2^2 - q_3^2\right) - m_z \end{bmatrix} \tag{11} $$

$$ J_b\left({}^{S}_{E}\hat{q}, {}^{E}\hat{b}\right) = \begin{bmatrix} -2b_zq_3 & 2b_zq_4 & -4b_xq_3 - 2b_zq_1 & -4b_xq_4 + 2b_zq_2 \\ -2b_xq_4 + 2b_zq_2 & 2b_xq_3 + 2b_zq_1 & 2b_xq_2 + 2b_zq_4 & 2b_xq_1 + 2b_zq_3 \\ 2b_xq_3 & 2b_xq_4 - 4b_zq_2 & 2b_xq_1 - 4b_zq_3 & 2b_xq_2 \end{bmatrix} \tag{12} $$

Equations (13) and (14) combine the measurements of gravity and the magnetic field of the Earth, to provide a unique orientation.

$$ f_{g,b}\left({}^{S}_{E}\hat{q}, {}^{S}\hat{a}, {}^{E}\hat{b}, {}^{S}\hat{m}\right) = \begin{bmatrix} f_g\left({}^{S}_{E}\hat{q}, {}^{S}\hat{a}\right) \\ f_b\left({}^{S}_{E}\hat{q}, {}^{E}\hat{b}, {}^{S}\hat{m}\right) \end{bmatrix} \tag{13} $$

$$f_{g,b}\left({}_E^S\hat{q}, {}^E\hat{b}\right) = \begin{bmatrix} f_g^T\left({}_E^S\hat{q}\right) \\ f_g^T\left({}_E^S\hat{q}, {}^E\hat{b}\right) \end{bmatrix} \tag{14}$$

After that, compute rate of change with Eq. (15).

$$\dot{q} = 0.5 \times \left({}_E^S\hat{q}_{k-1} \otimes {}^E\hat{g}_k\right) - \beta \times S^T \tag{15}$$

Where S^T is the transpose matrix of the multiplication and normalization of Eqs. (14) and (15) and β is the proportional controller gain. Finally, the rate of change of quaternion is integrated as in Sect. 3.2 with Eq. (10), and this result later converted to Euler angles.

3.4   Kalman Filter

The Kalman filter is widely used to make data combinations with a lot of noise, in this case, the filter integrates the data given by the gyroscope (with Drift) and with the combination of the accelerometer and magnetometer, which tend to be quite noisy, an estimation is performed. and puts each one an appropriate weight from their models to be able to perform the estimation of the orientation.

The filter implemented in Matlab for this work is the same described in [18], where the algorithm consists of two important parts: the predictive part and the corrective part.

In the predictive part, the projection of the forward state must be carried out using the Eq. (16), and then project the error covariance forward with the Eq. (17).

$$\hat{x}_k^- = F\hat{x}_{k-1} \tag{16}$$

$$P_k^- = FP_{k-1}F^T + Q \tag{17}$$

Then, in the corrective part, the calculation of the Kalman gain with the Eq. (18) is performed, the state update is performed with the measurement z_k using the Eq. (19), and finally the covariance error was updated with Eq. (20), this corrective part we have to do twice, once to correct by measuring the magnetometer and another to correct by the accelerometer.

$$K_k = P_k^- H^T \left(HP_k^- H^T + R\right)^{-1} \tag{18}$$

$$\hat{x}_k = \hat{x}_k^- + K_k\left(z_k - H\hat{x}_k^-\right) \tag{19}$$

$$P_k = (I - K_k H)P_k^- \tag{20}$$

Where k is the step time; x, state vector, and has the quaternion values; z, input vector; F, state matrix; B input matrix, H output matrix; state and measurement noise; Q and R are covariance matrix from the state and the measurement noise, respectively. All this process is done repetitively.

3.5   Magnetic Field Measurement with Magnetometer

The magnetic field that the magnetometer measures can be affected by metals that are around the sensor, this can be by components that are located on the same Printed Circuit Board (PCB) that the sensor is mounted, by metals found in the battery, or external metals, for example, the metal structure of the building where the measurements are made.

There's a way to prove that there are distortions in the measurement, this is done by moving around the sensor in space in a three-dimensional way, rotating it in angles from 0 to 360° in each of its axes and combinations, and the data in x, y, and z of the magnetic field are plotted as if they were point coordinates, a perfect sphere centered on the point (0, 0, 0) is obtained if there is no any type of interference, however, if there are distortions by metals that are affecting the sensor, this sphere is no longer centered.

In Fig. 1 we can observe data of how the measurements of the magnetometer used in this paper are affected by metals, where the sphere is not centered at the origin (distortion by hard metals).
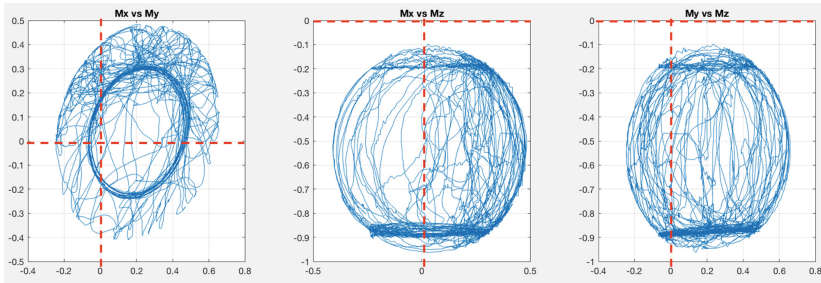

Fig. 1. Magnetic field with distortions due to metals

To correct this problem of hard metals, the following formulas can be used, which calculate offsets that can be added to the measurements on each axis of the Magnetometer measurement.

$$Offset_x = \frac{max(M_x) + min(M_x)}{2} \tag{21}$$

$$Offset_y = \frac{max(M_y) + min(M_y)}{2} \tag{22}$$

$$Offset_z = \frac{max(M_z) + min(M_z)}{2} \tag{23}$$

If we add to the data in Fig. 1 the offsets obtained by Eqs. (21), (22) and (23), we obtain Fig. 2 where we can see that the sphere is centered on the point (0, 0, 0).
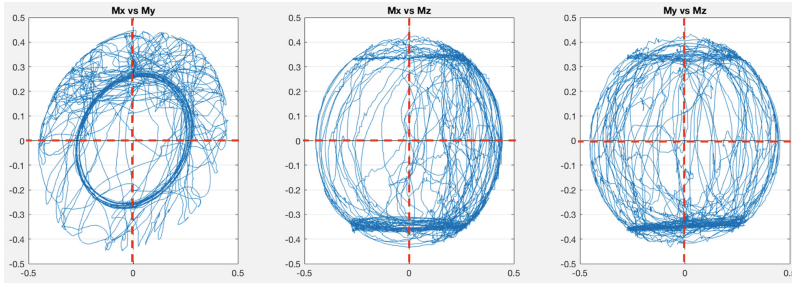
Fig. 2. Magnetic field with distortions due to metals with offsets applied

Another way to check if the measurements obtained are correct is with the module of each of the components of the magnetic field, this module should be a constant value and in the range between 0.25 and 0.65 Gauss, with an average of 0.5 Gauss [19]. With the on-line tool shown in [20] you can enter coordinates, altitude, a date and the software will give a value of the earth's magnetic field with those parameters entered, for example, in Vilanova i la Geltrú, where the tests were performed, when entering the coordinates of 41.223238 N, 1.733494 E, altitude of 10 m, and the date of October 10, 2017, a magnetic field value of 45.471.7 nT or 0.4547 Gauss is obtained, this is the value that will be used later to verify that the magnetometer reading is correct.

3.6   Kinovea Angle Measurement

With the use of Kinovea, the tracking of points in a video is possible, from these points we can obtain data such as acceleration, speed, position and other parameters, this data is stored in a file that can then be read from Matlab, we are interested in examining the angle θ shown in Fig. 3 but the software does not record angles in the aforementioned file, because of this, from the coordinates of the points P1 and P2, and use basic trigonometry and the required angle θ can be calculated.
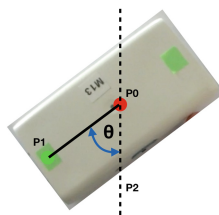

Fig. 3. Tracking points of 9×3 sensor for angle measurement

To calculate this angle, the function atan2 is used, this function is the four-quadrant inverse tangent between the intervals of [−pi, pi] as is shown in Eq. (24).

$$\theta = atan2\left(\left|det\begin{bmatrix} P2 - P0 \\ P1 - P0 \end{bmatrix}\right|, (P2 - P0) \cdot (P1 - P0)\right) \tag{24}$$

Where P0 and P1 are the tracking points placed on the device, P0 is the center point, P1 is an outer point and P2 is any point in the same vertical of the point P0.

4 Experimentation and Results

To evaluate the performance of each algorithm, the mean square error (RMSE) is used, where each Euler angle obtained by the filters is compared to a gold standard which is obtained from Kinovea.

The experiment consists of taking the sensor used in the MoMoPa3 project in which the signals of the magnetic field, acceleration and angular velocity are recorded, these signals are then passed through each one of the filters and the Orientation estimation is achieved.

At the same time that the signals of the IMU are being recorded, a video of the device is taken through a camera placed with a zenith perspective, this video is then analyzed image by image through Kinovea and coordinates of tracking points strategically placed in the sensor (green marks and center, see Fig. 4) are saved. Finally, through basic trigonometry (as show in Sect. 3.6) the angles that the device has traveled are obtained.

Fig. 4. Device tracking points (Color figure online)

In order to be able to synchronize the data obtained from the IMU, with the data obtained from Kinovea to calculate the RMSE, the sensor was placed in a vertical position and then was dropped horizontally, with this, the accelerometer records a peak of acceleration when the device touches the surface on which it is resting (see Fig. 5).
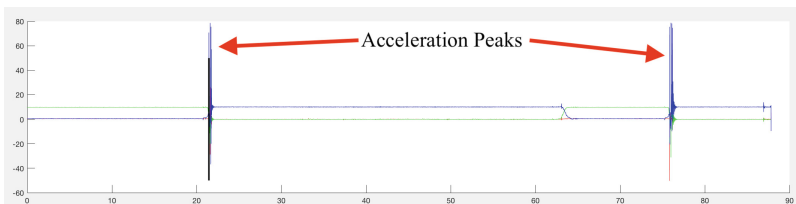

Fig. 5. Peaks of acceleration for synchronization

4.1   Measurement Correction of Magnetic Field

As seen in Sect. 3.5, a problem regarding the measurement of the magnetic field due to metal distortions that surround the sensor is present, but this can be corrected applying the previously explained formulas to obtain offsets and apply them to the original signal.

Some tests were made to find the average value of these offsets that are to be applied to each measurement on each axis of the Magnetometer and later to be able to use them with our orientation estimation algorithms. The values found in each test and an average of all of them can be observed in Table 1.

Table 1. Magnetometer offsets (Gauss)

Test	Mx offset	My offset	Mz offset
1	0.1861	0.0474	−0.5453
2	0.1864	0.0473	−0.5419
3	0.1802	0.0506	−0.5454
4	0.2056	0.0342	−0.5456
5	0.1765	0.0539	−0.5389
Average	0.18696	0.04668	−0.54342

These average value offsets are added to the raw data signals given by the magnetometer: 0.18696 to Mx, 0.04668 to My and −0.54342 to Mz. These values should not vary much if the sensor is used in the same place as the tests, but if it is moved to a different location, the new location may contain metals in the structure of the building that affect the measured magnetic field, or if it is placed next to nearby electronic devices, the offset values must be recalculated.

In order to verify that these offsets are appropriate, the module of the measurements of the magnetometer with and without these offset values is obtained, as shown in Fig. 6(a), the raw data of the magnetometer is outside the range of normal values of the
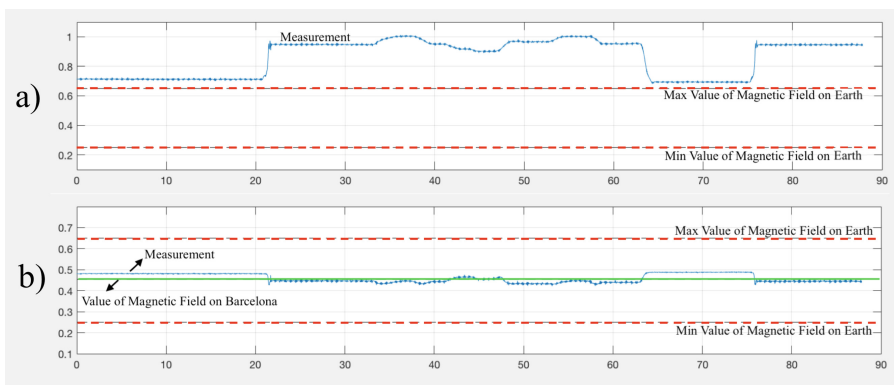

Fig. 6. (a) Raw magnetometer measurements (b) Magnetometer measurements with added offsets

earth's magnetic field (between 0.25 and 0.65 Gauss) and after applying the offset values (Fig. 6(b)) it is seen that, the measured values, besides being within the range, are close enough to the magnitude of the magnetic field in Barcelona, which is approximately 0.4547 Gauss.

4.2   Device Performance Compared to Gold Standard (Kinovea)

The signals obtained from Kinovea and the IMU have different sample frequencies (Fs), the data from Kinovea has a Fs of 30 Hz, that is 1 sample per image, each second contains 30 images (30 frames per second), the sampling frequency of IMU is 400 Hz, so in order to obtain the RMSE an upsampling of the Kinovea data from 30 Hz to 400 Hz had to be performed in order to match the sensor data.

In Table 2 the results obtained for RMSE are summarized for each filter for 5 different tests. The RMSE was calculated from the moment in which the sensor was dropped to be synchronized with the video, until it is back in a vertical position to the plane of movement. Then, between the tests, we calculate the average RMSE value for each filter and we can determine which one works best for our sensor (The MoMoPa3 project sensor). For each test, around 17000 angles were calculated, so, there's enough data to prove that the filters work properly.

Table 2 shows that the Kalman filter is the one that has a lower RMSE value (measured in degrees) with just 2.333° variation from the gold standard, followed up by the Madgwick filter with 3.47574° and then Mahony with 3.51594°, therefore Mahony and Madgwick get very similar results, these variations are acceptable for medical use, but they wouldn't be suitable in other purposes where an exact estimation is needed, like military application.

The maximum error that was obtained in the Kalman filter was 5.9523° in test number 2, while in Madgwick's filter was 7.6186°, and in Mahony's it was 7.9391°, i.e. the Kalman filter was the one with less error in all estimated angles.

Table 2. Root mean square in degrees

Test	N° of angles tested	Kalman filter (RMS | min-max)	Madgwick filter (RMS | min-max)	Mahony filter (RMS | min-max)
1	16360	1.6704 | 0.0001– 4.6665	3.1136 | 0.0001– 6.4581	3.5683 | 0.0002– 7.9391
2	20356	2.8683 | 0.0007– 5.9523	3.5744 | 0.00009– 7.6186	3.5573 | 0.0001– 6.3006
3	13784	2.7123 | 0.0002– 5.4585	3.6612 | 0.0001– 5.2534	3.6458 | 0.0019– 4.1583
4	18469	2.5317 | 0.00005– 4.3502	3.9126 | 0.0002– 7.3543	3.8167 | 0.0001– 6.6734
5	16696	1.8825 | 0.00006– 4.4998	3.1169 | 0.0002– 4.8514	2.9916 | 0.0001– 4.8533
Average		2.333 | 0.00022– 4.98546	3.47574 | 0.00013– 6.3071	3.51594 | 0.00014– 5.9849

Figure 7 provides an example of a recorded signal, in red the angle estimation obtained by the Kalman filter is shown and in blue our gold standard, i.e. the angles computed from the analysis given by Kinovea, one thing to point out is that the red line seems smoother than the blue one, that's because of errors of tracking made by Kinovea, so, the result obtained by the Kalman filter are, in some way, better than the ones on Kinovea.
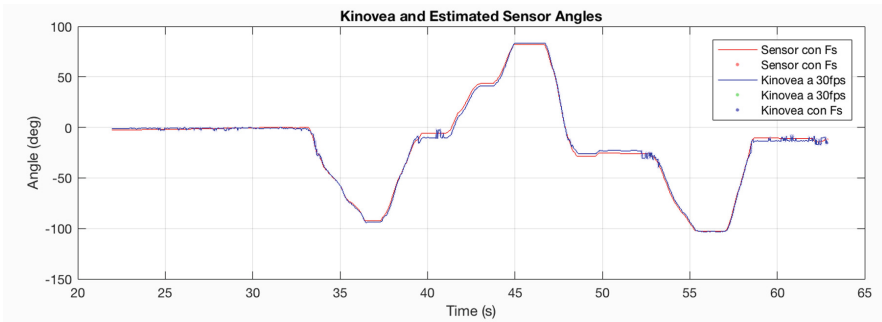

Fig. 7. Comparison between angles obtained with Kalman filter and Kinovea (Color figure online)

Video results are provided on https://www.youtube.com/watch?v=X0SCZ33uQX4.

5   Conclusions and Future Works

There are some ways to get the orientation of a device, robot, vehicle, etc., this could be done using encoders or inclinometers but these solutions are not feasible for certain applications such as wearables, as is the sensor used in the Project MoMoPa3, for these cases, inertial sensors, such as accelerometer, gyroscope and magnetometer are of better use, but with these, it is not possible to obtain directly an orientation measurement in degrees, for this it is necessary to use certain filters that allow the fusion of the data and as a result get an estimate of which direction the sensor is oriented.

In this work, a comparison was made between three filters, namely the Kalman filter, the Madgwick filter and the Mahony filter. The orientation estimation obtained by them, that is, the angles in which the sensor was positioned, was compared to a gold standard, the angles calculated from a video analysis performed by the Kinovea software, where it was obtained that the filter that gave the best results for the sensor used was the Kalman filter, followed by the Mahony filter and finally the Madgwick filter.

Before entering the raw data obtained from the inertial sensors of the IMU, a certain processing must be carried out to each one of them so that, in this way, better results can be achieved, the magnetometer must correct offsets which are produced due to soft and hard metals, in addition to certain interferences where the sensor is taking a measure, the gyroscope must add certain bias due to the problem of drift they have, and

the accelerometer must ensure that as long as no force is applied to it, values of 1G or 9.8 m/s corresponding to the measure of the acceleration of gravity that exists in the earth are to be obtained.

As a future work, genetic algorithms can be implemented in order to determine an adequate gain value for each filter, with this one could find an optimal measure that gives better results. In addition, with the angles obtained, future research should consider more the context of the medical field, that is, within the MoMoPa3 project or other applications that involve diseases that affect the human being, the ways of preventing them or forms of treatment.

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