Design of a Modified Madgwick Filter for Quaternion-Based Orientation Estimation Using AHRS

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Abstract: This paper presents a quaternion-based modified Madgwick filter for real-time estimation of rigid body orientations using attitude and heading reference system (AHRS). The filter consists of a cluster of a tri-axis accelerometer, a tri-axis magnetometer, and a tri-axis angular rate sensor. The proposed filter implementation incorporates gyroscope bias drift compensation. Additionally, an estimated magnetic reference along with low-pass filter are adopted to compensate for the magnetic perturbations. An optimized Levenberg-Marquardt (LM) algorithm is applied to the Whaba's problem to obtain the body orientations. The hessian matrix of the algorithm was analytically derived to reduce the numerical calculations cost. This algorithm ensures adaptive damped parameter for accurate and fast iterations. The filter performs the calculations of rotations using quaternions rather than Euler angles, which avoids the singularities issue associated with attitude estimation. The accelerometer and magnetometer are calibrated off-line prior to the data fusion process. The magnetometer calibration is made using the ellipsoid fitting technique. Experimental validation of the filter with the actual sensor data proved to be satisfactory. Testing cases included the presence of large dynamics and magnetic perturbation were carried out. In all situations the filter was found to converge and accurately track the rotational motions.

Key words: AHRS, madgwick filter, data fusion, inertial measurement units, magnetic distortion, motion capture, Whaba's problem, Levenberg-Marquardt algorithm.

1. Introduction

Computation of accurate heading and position data is an essential mission in most of the tracking motion systems including biomechanical systems [1], [2]. Numerous products are found in the market which can perform the computations accurately. However, they are expensive. It is, therefore, the need of developing a precise navigation system with a reasonable price is the main target of the many researches in the field. The Attitude Heading Reference System (AHRS) is based on micro-electromechanical systems (MEMS) technology are widely used in many substantial applications, such as under-water navigation, aircraft guidance control and human body motion tracking [1]-[8]. Systems such as automatic pilots also use the attitude information generated by an AHRS. Until recently, cost-sensitive unmanned aerial vehicles (UAV) and general aviation applications mostly relied on AHRS [9].

An accelerometer and magnetometer measure the earth's gravitational and magnetic field respectively, where an absolute reference of orientation can be obtained directly from those measurements. However, they are most likely subjected to high levels of external disturbances. For example, vibrations due to fluctuating motion will distort the pitch and roll angles calculated based on accelerometer gravity vector as

well as the magnetic disturbances will affect the calculations of the yaw angle [10], [11]. It is also well-known that the orientations can be obtained using a discrete-time integrator applied to the gyroscope observations, in case the initial condition are pre-defined [12]. Nevertheless, the zero-bias integration of gyroscope observations will lead to an accumulating error in the calculated orientation. Hence, neither a combined accelerometer/magnetometer nor the gyroscope can be used as standalone measurement unit. Therefore, it is a requirement to compute a single estimate of orientation through an optimal fusion filter of accelerometer, magnetometer, and gyroscope measurements [13].

The problem of finding the optimal attitude estimation, given multiple reference vector correspondences across the body and sensor frames, was formulated by Whaba in 1965 [14]. Many algorithmic solutions of Whaba's problem have been proposed in literature. Most of these solutions are providing an optimal algorithm using more than a minimal set of observations and finding the attitudes by minimizing an appropriate cost/objective function [3], [8]-[10], [13], the most commonly adopted methods are Extended Kalman filtering (EKF) and complementary filters [15]. The Kalman filtering techniques adopt a probabilistic determination of the state modeled as a Gaussian distribution. However, Kalman filtering techniques are computationally expensive. On the other hand, A Complementary filter is a common alternative to the EKF due to its simplicity and effectiveness. This simple filter uses the frequency domain methods to filter out the signal and obtains the estimations without any the need to any statistical assumptions [16].

Most of the recent sensor fusion algorithms for inertial/magnetic sensors are designed to perform the orientation estimation in quaternion form. Quaternions are part of a powerful mathematical tool which requires less computation time because of their minimal number of parameters [16], [17]. Additionally, they avoid the singularity configurations unlike the Euler representation.

Euston *et al.* [18] carried out a non-linear quaternion-based complementary filter to estimate the attitude from a low-cost Inertial Measurement Unit (IMU) observations.

Recently, Madgwick *et al.* [19] presented a simplistic filtering approach, where a fixed gain filter is adopted to estimate the attitude in quaternion form of a rigid body by using data from AHRS observations. Madgwick's filter splits the problem into stages as follows: (1) First quaternion estimation is obtained by the integration of gyroscope output, (2) and later it is corrected by a quaternion estimates from the accelerometer and magnetometer measurements computed through a gradient descent algorithm. Madgwick's method maintains good attitude estimation at low computational cost. Furthermore, it handles the local magnetic disturbances that, when present, affect all the orientation components (roll, pitch, and yaw). By reducing the constraint of the magnetic field vector rotation, it can limit the effect of the magnetic disturbances to only affect the yaw component of the orientation. The two fixed gain filters developed by Euston et. al. and by Madgwick et. al., are commonly used because they offer good performances at low computational cost [20].

In this work, Madgwick's filter was chosen to be the core base of the proposed filter due to its accuracy at relatively low computational cost. However, the filter was modified by replacing the gradient-descent algorithm with an optimized Levenberg-Marquardt (LM) algorithm to solve the Whaba's problem. The LM advantages among the original gradient-descent algorithm is seen from its capability to adapt the convergence rate of the iterations. Consequently, an adaptive damping strategy is implemented with the optimization step. Moreover, the magnetic distortion was treated more deeply by applying a low-pass filter for the magnetometer raw data prior to the filter algorithm itself. The use of low-pass filter will reduce the effect of the magnetic distortion on the yaw angle, this is another modification to the original magnetic compensator used by Madgwick's filter.

A complete derivation of the proposed filter is presented in this work. Experimental tests were conducted

to evaluate the performance of the filter under aggressive condition of rapid magnetic distortion. Procedure for Paper Submission

2. Mathematical Modeling

2.1. Orientation Derived from Angular Rate

Orientation can be defined as a set of parameters that relates the angular position of sensor frame to earth reference frame. In most often, Euler angles and quaternions are used. A tri-axis gyroscope will provide the angular rate about the x, y and z axes of the sensor frame, termed ω_x, ω_y and ω_z respectively. If these parameters (in $rads^{-1}$) are arranged into the vector ω_t at time t, defined by Eq. 1, the quaternion derivative describing rate of change of the earth frame relative to the sensor frame $\dot{q}_{\omega,t}$ can be calculated [13] as Eq. 2. The $\otimes$ operator denotes a quaternion product, the ˆ accent denotes a normalized vector of unit length and $\hat{q}_{est,t-1}$ is latest estimated quaternion.

$$\omega_t = [0 \quad \omega_x \quad \omega_y \quad \omega_z] \tag{1}$$

$$\dot{q}_{\omega,t} = \frac{1}{2}.\hat{q}_{est,t-1} \otimes \omega_t \tag{2}$$

It is, therefore the orientation of earth frame relative to the sensor frame at time t, $q_{\omega,t}$ is computed using a discrete-time integrator. The quaternion derivatives $\dot{q}_{\omega,t}$ are then numerically integrated, provided that the initial conditions are pre-defined.

$$q_{\omega,t} = \hat{q}_{est,t-1} + \dot{q}_{\omega,t}\Delta t \tag{3}$$

Note, that ω_t in these equations is a 4×1 vector with zero first element and the gyroscope angular rates measured at time t, Δt is the sampling rate of the filter. Sub-script ω indicates that the quaternion is calculated from angular rates.

2.2. Orientation Derived from Accelerometer and Magnetometer Cluster

Since, the accelerometer and magnetometer data are not in direct relation to the orientation angles, a different approach is used based on Whaba's problem, which formulates the problem in cost function. This problem using the minimum-squared-error (MSE) approach. It is found that error can be minimized in either the sensor frame or in the earth frame. Error minimized in the sensor frame is adopted in this work. Now, if ε is assumed to be the error, then the cost function is defined as:

$$\varepsilon^T\varepsilon = z_t - M_t \times z_e \tag{4}$$

where, z_t is a 6×1 vector with the measurements of gravity and magnetic field in the sensor frame at time t, and z_e is a 6×1 vector with reference values of gravity and magnetic field in the earth frame. where M_t is a diagonal matrix, it represents the current time Direction Cosine Matrix (DCM) which rotates both the measurements vectors:

$$M_t = \begin{bmatrix} R_t & 0 \\ 0 & R_t \end{bmatrix} \tag{5}$$

The matrix R_t in Eq. 5 is defined by Eq. 6 as follows:

$$R_t = \begin{bmatrix} q_1^2 + q_4^2 - q_2^2 - q_3^2 & 2.(q_1.q_2 + q_3.q_4) & 2.(q_1.q_3 - q_2.q_4) \\ 2.(q_1.q_2 - q_3.q_4) & q_2^2 + q_4^2 - q_1^2 - q_3^2 & 2.(q_2.q_3 + q_1.q_4) \\ 2.(q_1.q_3 + q_2.q_4) & 2.(q_2.q_3 - q_1.q_4) & q_3^2 + q_4^2 - q_1^2 - q_2^2 \end{bmatrix} \tag{6}$$

The quaternion convention that is used in this work is the same of [21], q_t with q_4 as the real component.

And hence, z_t is measured by the accelerometer and magnetometer sensors and z_e is known, the error between them is a function of the matrix M_t, this error depends on quaternion components. Thus, the main target is to find iteratively the values of quaternion components that yield the minimum error (i.e. $\varepsilon \approx 0$).

In the Madgwick's filter approach the gradient-descent algorithm was used to find the solution for this optimization problem. However, this algorithm follows fixed damping strategy [22], this in turn reduces the accuracy whenever solutions require large or small step-size. LM algorithm provides better accuracy in terms of its ability to perform variable damping strategy by updating the step-size of the solation at each iteration [23]. By applying the Levenberg-Marquardt update rule on the cost function in Eq. 4,

$$q_{est,t}^k = q_{est,t}^{k-1} - (B + \lambda.diag[B])^{-1}J^T \varepsilon \qquad (7)$$

where B approximates Hessian matrix $(B = J^T J)$ and J is Jacobian matrix defined in Eq. 8.

$$J = -\left[\left(\frac{\partial M}{\partial q_1}\right).z_e \quad \left(\frac{\partial M}{\partial q_2}\right).z_e \quad \left(\frac{\partial M}{\partial q_3}\right).z_e \quad \left(\frac{\partial M}{\partial q_4}\right).z_e\right] \qquad (8)$$

where $q_{est,t}^k$ is updated estimate after total number of iterations k, at time t. The total number of iterations based on the LM algorithm depends on convergence rate (i.e. $k(\Delta\varepsilon)$),

$$\Delta\varepsilon_k = \varepsilon_k - \varepsilon_{k-1} \qquad (9)$$

The convergence criterion can then be best achieved based on the following damped stagey [23]:

$$\lambda = \begin{cases} \frac{\lambda}{\beta} & if\ \Delta\varepsilon_k\ < \Delta\varepsilon_{k-1} \\ \lambda.\beta & if\ \Delta\varepsilon_k\ \geq \Delta\varepsilon_{k-1} \end{cases} \qquad (10)$$

where, λ is called the damping parameter. The damping parameter is then adjusted at each iteration at time , corresponding to the value of $\Delta\varepsilon_k$. The adjusting rate is fixed and denoted by β which is called the decay rate. For a relaxed optimization solution with small oscillations, initial value of λ will be chosen to be close to zero, and typical decay rate ranges, $0 < \beta < 10$. Now, based on Eq. 10, if $\Delta\varepsilon_k \geq \Delta\varepsilon_{k-1}$ the estimate is rejected and λ is increased by a factor of β and if $\Delta\varepsilon_k < \Delta\varepsilon_{k-1}$ the estimate is accepted and λ is reduced by a factor of β. Finally, the estimated rate can be defined as follows:

$$\dot{q}_{est,t}\Delta t = q_{est,t} - \hat{q}_{est,t-1} \qquad (11)$$

3. Propsed Modified Filter Algorithm

3.1. Data Fusion Algorithm

The fusion of the quaternion estimates, $q_{filter,t}$ are obtained from both gyroscope angular rates, $q_{\omega,t}$ and the accelerometer and magnetometer data, $q_{est,t}^k$ is performed by Eq. 12 where μ and $(1-\mu)$ are fixed weights applied to each estimation.

$$q_{filter,t} = \mu.q_{est,t} + (1-\mu).q_{\omega,t}\ ,0 \leq \mu \leq 1 \qquad (12)$$

An optimal fusion can be exhibited by assuming weighted convergence rate of $q_{est,t}^k$ is equal or greater than physical rate of change of $q_{\omega,t}$. Therefore, a large value of μ is preferable as long as it will not affect the computational cost significantly and reduce the overall speed of the filter.

3.2. Magnetic Distortion Compensator

Magnetic distortions affect the performance of orientations estimation and it has radical errors that may be introduced by various sources including electrical appliances, metal furniture and metal structures within a buildings construction [24]. However, these sources of perturbations can be reduced, if an additional reference of orientation is available [13].

The magmatic reference of the earth's magnetic field in the earth frame at time t, h_t, can be computed as,

$$h_t = \hat{q}_{est,t-1} \otimes \hat{m}_t \otimes \hat{q}^*_{est,t-1} \tag{13}$$

where, $\hat{m}_t$ is normalized magnetometer observations vector at time t, and $\hat{q}^*_{est,t-1}$ is conjugate of $\hat{q}_{est,t-1}$. Since, the magnetic reference does not have a component aligned with y axis, the effect of an erroneous inclination of the measured direction earth's magnetic field, h_t, can be corrected. Thus, if b_t, is of the same inclination, it can be found by estimating h_t as h_t normalised to have only components in the earth frame x and z axes; as described in Eq. 14.

$$b_t = \begin{bmatrix} 0 & \sqrt{h_x^2 + h_y^2} & 0 & h_z \end{bmatrix} \tag{14}$$

This approach ensures that the magnetic distortion affects only the yaw angle (i.e., the heading orientation). It also avoids the need to set a pre-defined reference direction of the earth's magnetic field. However, in the proposed filter $\hat{m}_t$ observations are introduced to a low-pass filter to eliminate the distortion effects on heading orientation as well. This is simply illustrated in Fig. 1
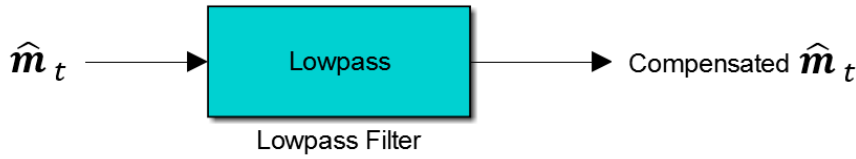

Fig. 1. Low-Pass filter to compensate for magnetic distortion effect on the heading estimate.

3.3. Gyroscope Bias Drift Compensator

It is well-known that the gyroscope constant bias will grow linearly over time. It is simply can be compensated by estimating constant bias offsets. However, due to motion and ambient factors a high frequency noise (usually in form of white Nosie) will drift over time to create an accumulated effect on the integration of orientations. In practical applications this drift must be minimized to a lower level. Mahony *et al*. [25] suggested that the gyroscope bias drift may be compensated for by a simple integral feedback of the error in the rate of change of orientation. This algorithm can be best described by the following equations,

$$\omega_{error,t} = 2 \cdot \hat{q}^*_{est,t-1} \otimes \dot{q}_{est,t} \tag{15}$$

$$\omega_{b,t} = \sigma \sum \omega_{error,t} \Delta t \tag{16}$$

$$\omega_{c,t} = \omega_{b,t} - \omega_{error,t} \tag{17}$$

The gyroscope bias, $\omega_{b,t}$ is found from the DC component of $\omega_{error,t}$ and so it can be removed as the integral of $\omega_{error,t}$ weighted by the gain, σ as in Eq. 16. This will result in compensated gyroscope measurement, $\omega_{c,t}$. This later result will be used instead of the original gyroscope observations vector, ω_t.

3.4. Filter Algorithm Implementation

The proposed filter algorithm was developed in MatLab/Simulink environment. A rapid approach had been adopted using Simulink Real-time package for embedded coder for direct code generation for the target system. Additionally, the target enables designers to monitor and tune algorithms running on Arduino board from the same Simulink models.

An Arduino Mega 2560 was used as platform to test the filter. Arduino Mega 2560 is a microcontroller board based on the ATmega2560. The choice of this controller was only to test the ability of the proposed filter with low-cost open source board such Arduino Mega 2560.

The proposed filter algorithm is demonstrated in Fig. 2. It illustrates the LM-estimator and the other main components of the filter such as the magnetic distortion and reference, discrete-time integrator and drift compensator sub-system.
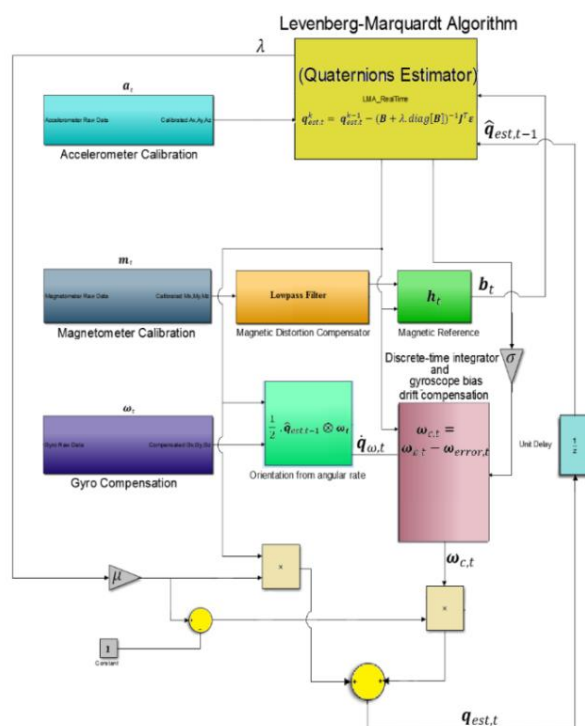
Fig. 2. Block diagram representation of the proposed filter for the AHRS data including the magnetic compensator and the low-pass filter.

4. Filter Validation and Tests

4.1. Sensors Calibration and Tests Conditions

The AHRS data were obtained using the GY-85, low cost 9-DoF cluster of tri-axis accelerometer, tri-axis magnetometer and tri-axis gyroscope. The test was conducted at relatively low frequency of $10 \, Hz$. Both accelerometer and magnetometer raw data were calibrated using ellipsoid fitting method [26]. The distribution of the magnetometer raw data before and after calibration are presented in Fig. 3 and Fig. 4, respectively.

The accelerometer was found to have suitable distribution by only using the sensitivity gains provided by the manufacturing sheet without the need for any further calibration process. On the other hand, the gyroscope constant bias was accounted for by taking the average for $10 \, sec$; starting from the initialization of the filter and then subtract this average from the gyroscope raw data for each axis.
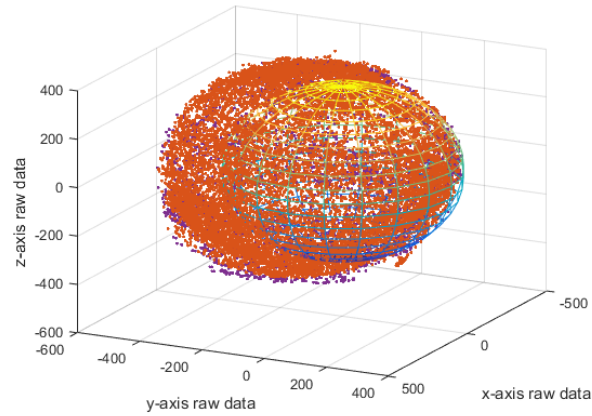
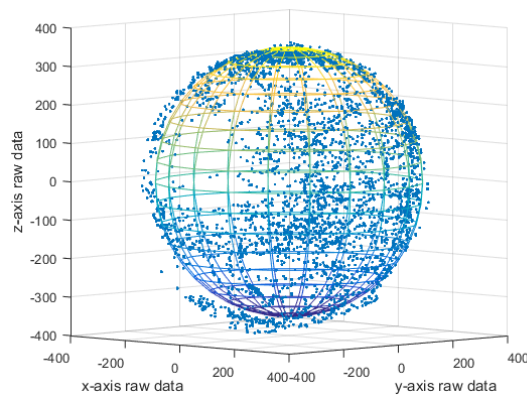Fig. 3. Before calibration: Magnetometer raw data is showing a shifted ellipsoid.

Fig. 4. After calibration: Magnetometer raw data is showing a centered semi-spherical distribution.

4.2. Performance Evaluation of the Proposed Filter

The filter convergence attitude to a pre-defined steady-state was first tested by performing a double-rotation as shown in Fig. 5.
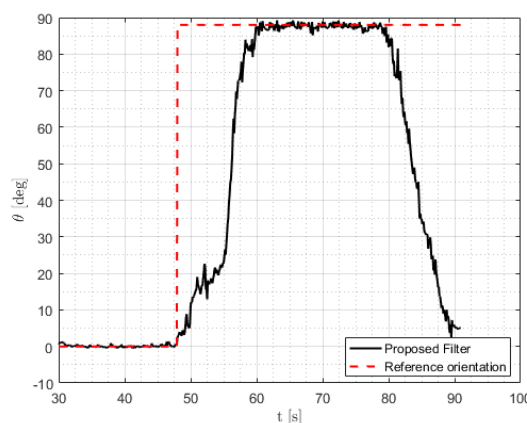

Fig. 5. Convergence of pitch angle from $0°$ to $90°$ steady-state conditions.

It is clear from the above test that the filter at the defined initial gains approached the steady-state orientation in a fast and moderate accuracy trend. The static RMS (Root-Mean-Square) error was estimated with respect to the reference pitch angle. A residual plot of static test for the pitch angle is shown in Fig. 6. The static RMS was then calculated and found to be **0.37°**.
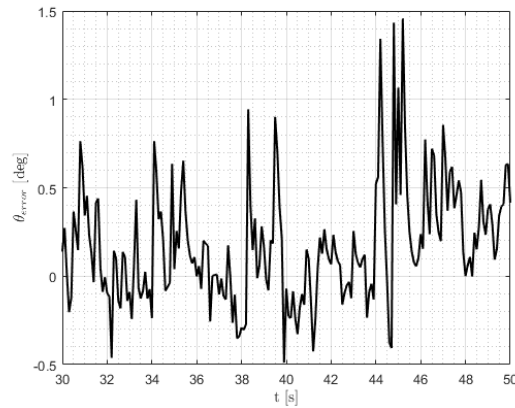
Fig. 6. Error vs. time plot of static pitch angle test.

Later, the sensor platform was subjected to aggressive base-excitation (High frequency vibrations), the result is shown in Fig. 7. The dynamics RMS at this aggressive condition was found to be **6.5⁰**.

The magnetic distortion algorithm that was adopted in the current was validated by applying a high amplitude-frequency magnetic perturbation around the sensor surrounding field.

Fig. 8 shows the heading angle after the magnetic distortion was compensated for using the low-pass filter. The distortion effect on the normalized magnetometer raw data is evident, a comparison between the compensated and the un-compensated raw data in Fig. 8 proves the ability of the FIR-lowpass filter to eliminate the high frequency magnetic perturbations.
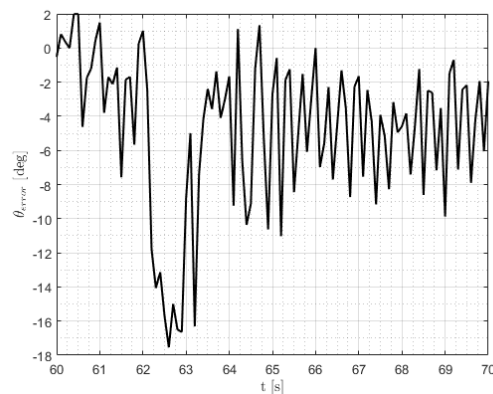

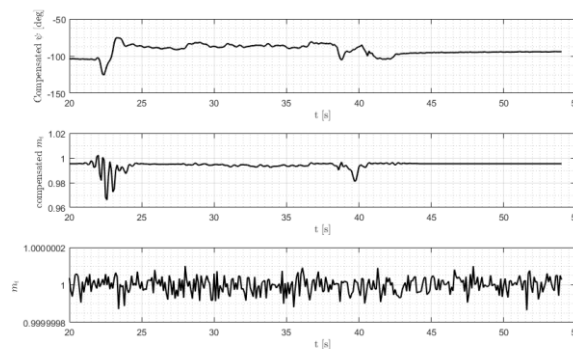Fig. 7. Error vs. time plot of aggressive base-excitation pitch angle test.

Fig. 8. Magnetic distortion in heading angle compensated using FIR-lowpass filter.

The filter damping paramter behavior during different static and dynamic rotations around the

three-axes of the AHRS was analyzed. Fig. 9, investigates the damped strategy of LM algorithm, the maximum number of iteration at each time t, was also examined along with associated Euler estimates (see Fig. 10). This test was conducted for $\lambda = 0.001$ and $\beta = 10$, where the σ was fixed at 0.041 and the fixed weight filter gain was fixed to 0.92. These values were chosen basically to ensure high accurate estimates regardless of their effect on the filter speed.

It was found from the previous test that filter damping parameter adjusts itself repeatedly at the initialization of the process. It also was noticed that the damping parameter reached the maxima when rapid oscillations in the orientations occurred as seen from Fig. 9 and Fig. 10. The trend of the maximum number of iterations per sample was observed to behave similarly as the damping parameter. However, at the steady-state conditions the maximum number of iterations approached an average of two iterations.
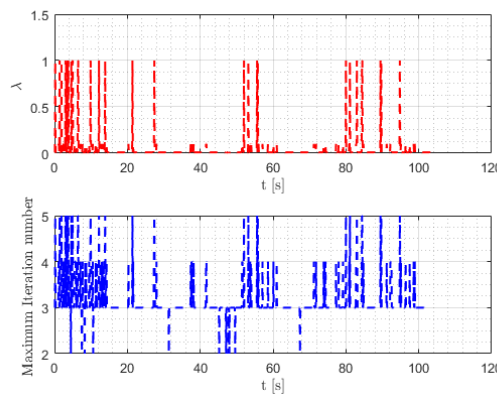

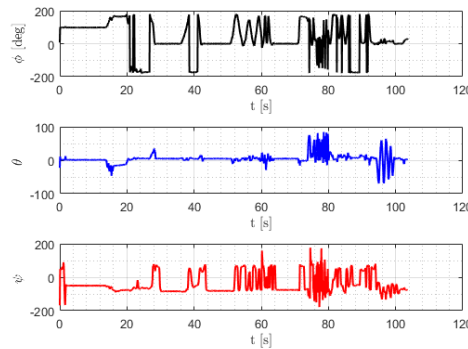Fig. 9. The LM damping parameter and the maximum iteration number during the fusion process.

Fig. 10. Euler estimates during the damped strategy investigation study.

The value of $\mu = 0.92$ corresponds to the LM-estimator term in Eq. 12. This in turns acts quite as high-pass filter with respect to the accelerometer and magnetometer measurements. On the contrary, it acts as low-pass filter with respect to the gyroscope measurements. The value of λ and β were relaxed by increasing them to .1 and 1, repectively. After filter relaxation, a modest accuracy (acceptable) and fast filter speed was observed. A tracking test was obtained during the filter relaxation for both the quaternions and Euler estimates as described in Fig. 11-Fig. 13.

It is seen from Fig. 11 at $2 < t < 10 \, sec$ that the Euler angles are $\Phi = 0, \ \theta = 0, \psi = -100$, which are corresponding to the following quaternion vector $q_{2<t<10} = [0.581, 0.0, 0.0, -0.814]$. This later observation is confirmed from Fig. 12 and Fig. 13.

Fig. 13 shows clearly that the quaternion estimates obtained from gyroscope measurements are more

rapid, the reason of this comes from the fact the gyroscope sampling time is higher among the other sensors in the AHRS cluster.

In general, the results obtained from Fig. 11-Fig. 13 showed that the proposed filter has a fast convergence rate. It was also noticed that filter most often approaches the steady-state from the initial condition in suitable period. The LM algorithm was seen to adjust the optimization problem whenever massive oscillations were detected.
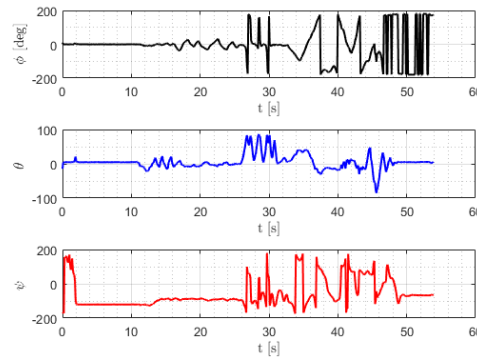

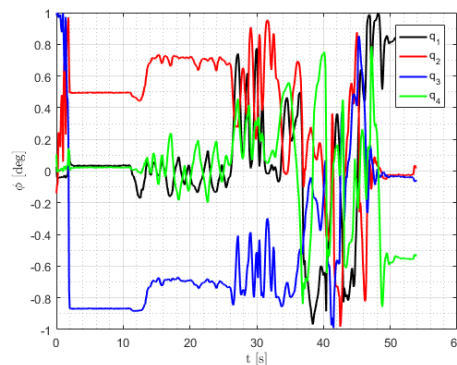Fig. 11. Tracking test results: Filter Euler angles estimates.

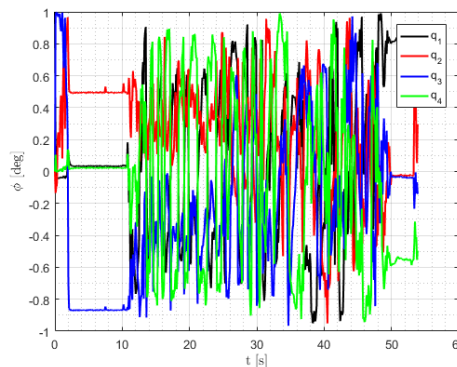Fig. 12. Tracking test results: LM algorithm quaternions estimates.

Fig. 13. Tracking test results: Gyroscope angular rate based-quaternions estimates.

5. Conclusion

In this paper, a modified algorithm to speed up the convergence and accuracy of Madgwick's filter was presented. In this modified algorithm the original gradient-descent algorithm was replaced by

Levenberg-Marquardt algorithm. This modification can be seen as an advantage, since the Levenberg-Marquardt algorithm provides the fusion process with a damped strategy through the definition of the damping parameter and decay rate. The damping parameter is found to influence both the accuracy and the speed of convergence of the filter.

The results of this work reveal a better accuracy in the situation where rapid oscillations do exist. Hence, the dynamics root-mean-square at aggressive vibration conditions was found to be relatively small ($\mathbf{6.5^o}$). Whereas the static root-mean-square shows preferable values with a low value of $\mathbf{0.37^o}$.

The filter was tested under high amplitude and frequency external magnetic perturbations, the results showed good compensation for these distortions and it was not limited to any of the estimates. The modified filter can be easily adopted for real life scenarios and on-line applications. Accordingly, several applications in navigation systems and biomechanical applications can be adopted as well.

Acknowledgment

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