

Estimation and Non Linear Observer of the Attitude of a Robot via Quaternion

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Abstract

Generally, the attitude estimation and the measurement of the angular velocity are a requirement for the attitude control. As a result, the computational cost and the complexity of the control loop are relatively high. In the present paper, a technique for attitude stabilization is proposed; the technique proposed is designed with attitude estimation based in data fusion of an Attitude and Heading Reference System AHRS. With this approach, only the measurements of at least two non collinear directional sensors are needed. Since the control laws are highly simple and a model based in an observer for angular velocity reconstruction is not needed, the proposed new strategy is very suitable for embedded implementations. The global convergence of the estimation techniques is proved. Simulations with some robustness tests are performed.

Keywords: *Data fusion, MEMS sensors, quaternion, non linear observer, global optimization, Robotic*

1. Introduction

Autonomous robotic systems have been suggested for a number of applications such as unmanned aerial vehicles, unmanned underwater vehicles and robots manipulators in medical applications and Mobile Robot. The field of mobile robot navigation is active and vibrant, with more great systems and ideas being developed continuously. For this reason the examples presented in this paper serve only to represent their respective categories, but they do not represent a judgment by the authors. Many ingenious approaches can be found in the literature, although, for reasons of brevity, not all could be cited in this paper.

1.1 Related Work

Exact knowledge of the position of a vehicle is a fundamental problem in mobile robot applications. In search for a solution, researchers and engineers have developed a variety of systems, sensors, and techniques for mobile robot positioning [4][7]. The many partial solutions can roughly be categorized into two groups:

relative and absolute position measurements [6]. Because of the lack of a single good method, developers of mobile robots usually combine two methods, one from each group. The two groups can be further divided into the following seven categories:

1. Odometry
2. Inertial Navigation
3. Magnetic Compasses
4. Active Beacons
5. Global Positioning Systems
6. Landmark Navigation
7. Model Matching

In this paper a model and inertial navigation system is presented.

A fundamental requirement for an autonomous vehicle is its ability to localize itself with respect to its environment. Navigation on a flat and horizontal ground only requires estimations of position and heading. However, in many cases, the environment is not so well structured, and the angular orientation of the vehicle may change along its path. In this case, a real time estimation of the attitude may be necessary. Indoor mobile robots generally need an accurate navigation system. If they move on inclined planes, the orientation can be used to correct the position and heading estimations provided by odometry, or to interpret external sensor data, proximity, in order to build an accurate model of the environment, recent use of MEMs has been introduced.

The attitude estimation of an autonomous vehicle is a subject that has attracted a strong interest the last years. This is due to the fact that can be applied to multiple applications, such as spacecrafts, satellites, tactical missiles, where the attitude is essential for control or monitoring purposes. In the last decade the application of Micro-Electro-Mechanical-Systems (MEMS) has gained a strong of interest. Furthermore, this increasingly interest has motivated the development of low cost, lightweight and low-power consumption Attitude and Heading Reference System (AHRS).

An AHRS is composed of inertial and magnetic sensors, namely, three rate gyros, three accelerometer and three magnetometers, orthogonally mounted such that the sensor frame axes coincide with the body frame in question. The attitude (orientation) of a rigid body can be parameterized by several methods: for instance, Euler’s angles, Cardan angles and unit quaternion. The unit quaternion is a four parameter representation with one constraint. Therefore, it yields the lowest dimensionality possible for a globally non-singular representation of the attitude. For more details on attitude representations, the reader can refer to the survey written by Shuster [10]. Several approaches have been applied to the attitude estimation problem. These estimators fall into three main families.

The first one deals with a constraint least-square minimization problem proposed firstly by Wahba [12]. These techniques have been adapted to sequentially estimate time-varying attitude [5].

The second approach is within the framework of the Extended Kalman Filter [2] (EKF). Its major feature concerns the ability to fuse signals acquired from different sensor types. An excellent survey of these methods is given in [10].

The third approach issues from nonlinear theory, and non linear observers are applied to the attitude determination problem [8], [11], [12]. In this approach, the convergence of the error to zero is proved in a Lyapunov sense.

In this paper, an attitude estimator using quaternion representation is studied. Two approaches are jointly used, namely a constraint least-square minimization technique and a prediction technique. The prediction is performed in order to produce a pseudo-estimate of the acceleration and of the attitude quaternion. This predictor is driven by a quaternion pseudo-measurement error which is obtained from the quaternion propagated through the kinematic equation and the one obtained via the constraint minimization problem. Actually, this latter problem is divided in three steps. First, the body accelerations are estimated from the previously computed quaternion. Using these updated accelerometer measurements together with the magnetometer measurements; a pseudo-measure quaternion is estimated via an optimization technique.

In this work an inertial navigation system (AHRS) is used and presented in section 3 that provided the data necessary to the model presented in section 4.

The present paper is organized as follows. In section 2 a quaternion-based formulation of the orientation of rigid body is given. The problem statement is formulated in section 3. The attitude’s estimation and prediction is presented in section 4. Simulation results are given in

section 5-A. The paper ends with some concluding remarks given in section 6.

2. Mathematical Background

Consider two orthogonal right-handed coordinate frames: the body coordinate frame, $E^b = [\vec{e}_1^b \vec{e}_2^b \vec{e}_3^b]$, located at the center of mass of the rigid body and the inertial coordinate frame, $E^f = [\vec{e}_1^f \vec{e}_2^f \vec{e}_3^f]$, located at some point in the space. The rotation of the body frame E^b with respect to the fixed frame E^f is represented by a quaternion, consisting of a unit vector \vec{e} , known as the Euler axis, and a rotation angle β about this axis. The quaternion q is then defined as follows:

$$q = \begin{pmatrix} \cos \frac{\beta}{2} \\ \vec{e} \sin \frac{\beta}{2} \end{pmatrix} = \begin{pmatrix} q_0 \\ \vec{q} \end{pmatrix} \in \mathbb{H} \tag{1}$$

Where

$$\mathbb{H} = \{q \mid q_0^2 + \vec{q}^T \vec{q} = 1\} \\ q = \begin{bmatrix} q_0 \\ \vec{q} \end{bmatrix}^T, q_0 \in \mathbb{R}, \vec{q} \in \mathbb{R}^3 \tag{2}$$

$\vec{q} = [q_1 \ q_2 \ q_3]^T$ and q_0 are known as the vector and scalar parts of the quaternion respectively. In attitude control applications, the unit quaternion represents the rotation from an inertial coordinate system $N(x_n, y_n, z_n)$ located at some point in the space (for instance, the earth NED frame), to the body coordinate system $B(x_b, y_b, z_b)$ located on the center of mass of a rigid body.

If \vec{r} is a vector expressed in N , then its coordinates in B are expressed by:

$$b = \bar{q} \otimes r \otimes q \tag{3}$$

where $b = [0 \ \vec{b}^T]^T$ and $r = [0 \ \vec{r}^T]^T$ are the quaternions associated to vectors \vec{b} and \vec{r} respectively. \otimes denotes the quaternion multiplication and \bar{q} is the conjugate quaternion multiplication of q , defined as:

$$\bar{q} = [q_0 \ -\vec{q}^T]^T \tag{4}$$

The rotation matrix $C(q)$ corresponding to the attitude quaternion q , is computed as:

$$C(q) = (q_0^2 - \vec{q}^T \vec{q})I_3 + 2(\vec{q} \vec{q}^T - q_0 [\vec{q}^x]) \tag{5}$$

where I_3 is the identity matrix and $[\vec{q}^x]$ is a skew

symmetric tensor associated with the axis vector ξ :

$$[\xi^x] = \begin{pmatrix} \xi_1 \\ \xi_2 \\ \xi_3 \end{pmatrix}^x = \begin{pmatrix} 0 & -\xi_3 & \xi_2 \\ \xi_3 & 0 & -\xi_1 \\ -\xi_2 & \xi_1 & 0 \end{pmatrix} \quad (6)$$

Thus, the coordinate of vector \vec{r} expressed in the B frame is given by:

$$\vec{b} = C(q)\vec{r} \quad (7)$$

The quaternion attitude error used to quantify the mismatch between two attitudes q_1 and q_2 is computed by:

$$q_e = q_1 \otimes \bar{q}_2 \quad (8)$$

3. Problem Statement

In the case of the attitude estimation, one seeks to estimate the attitude and accelerations of a rigid body. From now on it is assumed that the system is equipped with a tri axis accelerometer, three magnetometer and three rate gyros mounted orthogonally.

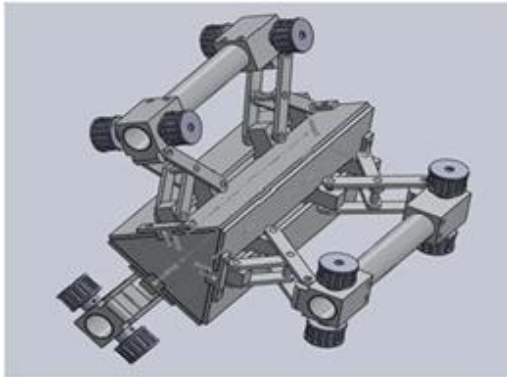


Fig. 1. Prototype of the mobile robot

In this section we describe the body's kinematic of the model. In the present work, our typical capture configuration relies primarily on on the Robot of figure 1 equipped with twelve 1 inch diameter wheels driven by 3 DC gear head motors. The mechanical model is based on single pinion architecture suitable for light vehicles. The combination of this information jointly to knowledge a priori of the robot makes possible to obtain information on the mobile robots respect to the base.

The controller was able to set the power level to each motor independently, but there was no feedback loop based on tachometers, or current sensing. In order to estimate the attitude robot position with respect to an inertial frame, a module containing three rate gyros, three accelerometer and three magnetometer assembled in tri axis, are positioned near the centre of robot. Thus, the attitude for the articulation is estimated. The combination

of this information jointly to knowledge a priori of the dynamic of the movement of the robot makes possible to obtain information of the attitude of the robot respect to the base.

The equation describing the relation between the quaternion and the body's kinematic is given in introducing the angular variation $\vec{w} = [w_x \ w_y \ w_z]^T$ from this, it follows.

$$\dot{q} = \frac{1}{2}\Omega(\vec{w})q(t) = \frac{1}{2}\Xi(q)\vec{w}(t) \quad (9)$$

where $\Omega(\vec{w})$ y $\Xi(q)$ are defined as:

$$\Omega(\vec{w}) = \begin{bmatrix} -[\vec{w} \ x] & \dots & \vec{w} \\ \dots & \dots & \dots \\ -\vec{w}^T & \dots & 0 \end{bmatrix} \quad (10)$$

$$\Xi(q) = \begin{bmatrix} q_0 I_3 x_3 + [\vec{q} \ x] \\ \dots \\ -\vec{q}^T \end{bmatrix} \quad (11)$$

The matrix $[\vec{w} \ x]$ and $[\vec{q} \ x]$ are obtained by the cross product issue of $\vec{d} \times \vec{b} = [\vec{d} \ x]b$ with $[\vec{d} \ x] \in \mathbb{R}^{3 \times 3}$:

$$[\vec{d} \ x] = \begin{bmatrix} 0 & -a_3 & a_2 \\ a_3 & 0 & -a_1 \\ -a_2 & a_1 & 0 \end{bmatrix} \quad (12)$$

The quaternion must be:

$$q^T q = \vec{q}^T \vec{q} + q_0^2 = 1 \quad (13)$$

In the other hand, the matrix $\Xi(q)$ has the relation:

$$\Xi^T(q)\Xi(q) = q^T q I_{3 \times 3} \quad (14)$$

$$\Xi(q)\Xi^T(q) = q^T q I_{4 \times 4} - q^T q$$

$$\Xi^T(q)(q) = 0_{3 \times 1}$$

Generally $\Xi^T(q)\lambda = -\Xi^T(\lambda)q$, for any $\lambda \in \mathbb{H}$.

$$A(q) = (q_0^2 - \vec{q}^T \vec{q})I_{3 \times 3} + 2\vec{q}\vec{q}^T - 2q_0[\vec{q} \ x] \quad (15)$$

That is denoted like the orientation matrix 3-D of dimension 3x3.

A. Modeling sensors

In application of inertial and magnetics sensors, the inertial coordinate frame E^f is chosen to be the NED (North, East, Down) coordinate frame. In this work the origin of E^f is located at Mexico city, Mexico (GPS: 19°29'52''N; 99°7'37''W (19:497778;-99:126944°)). The "reference vectors" are the gravitational and magnetic vectors, whose are well known. The "vectors observations", i.e. the gravitational and magnetic vectors expressed in the body frame E^b , are obtained from an tri-axis accelerometer and a tri-axis magnetometer sensors. The angular velocity is obtained from three rate gyros orthogonally mounted.

1) **Rate Gyros:** The angular velocity $\vec{\omega}=[\omega_1 \ \omega_2 \ \omega_3]^T$ is measured by the rate gyros, which are supposed to be orthogonally mounted. The output signal of a rate gyro is influenced by various factors, such as bias drift and noise.

Since an integration step is required in order to obtain the current attitude quaternion (9), even the smallest variation of the rate gyro measurement will produce a wrong estimation of the attitude. The bias is denoted by \vec{v} , belonging to space \mathbb{R}^3 . The rate gyro measurements are modeled by [7]:

$$\vec{\omega}_G = \vec{\omega} + \vec{v} + \vec{\eta}_G \quad (15)$$

$$\dot{\vec{v}} = -T^{-1}\vec{v} + \vec{\eta}_v \quad (16)$$

Where $\vec{\eta}_G$ and $\vec{\eta}_v$ are supposed by Gaussian white noises and $T = \tau I_3$ is a diagonal matrix of time constants. In this case, the constant τ which has been set to 100 s. The bias vector \vec{v} will be estimated online, using the observer presented in the following section.

2) Accelerometers: Since the 3-axis accelerometer is fixed to the body, the measurements are expressed in the body frame B. Thus, the accelerometer output can be written as:

$$\vec{b}_A = C(q)(\vec{a} - \vec{g}) + \vec{\eta}_A \quad (17)$$

where $\vec{g} = [0 \ 0 \ g]^T$ and $\vec{a} \in \mathbb{R}^3$ are the gravity vector and the inertial accelerations of the body respectively. Both are expressed in frame N. $g = 9.81 \text{ m/sec}^2$ denotes the gravitational constant and $\vec{\eta}_A \in \mathbb{R}^3$ is the vector of noises that are supposed to be white Gaussian.

3) Magnetometers: The magnetic field vector \vec{h}_M is expressed in the N frame it is supposed to be $\vec{h}_M = [h_{Mx} \ 0 \ h_{Mz}]^T$. Since the measurements take place in the body frame B, they are given by:

$$\vec{b}_M = C(q)\vec{h}_M + \vec{\eta}_M \quad (18)$$

Where $\vec{\eta}_M \in \mathbb{R}^3$ denotes the perturbing magnetic field. This perturbation vector is supposed to be modeled by Gaussian white noises.

4.- Attitude Estimator

The attitude estimator uses quaternion representation. Two approaches are jointly used, namely an estimator with a constraint least-square minimization technique and a nonlinear observer via quaternion error of the estate at the instant k. The prediction is performed in order to produce a pseudo-estimate of the accelerations and the attitude quaternion. This prediction is driven by a estate which is obtained from the quaternion propagated through the

kinematic equation and the one obtained via the constraint minimization problem.

4.1 Non Linear Attitude Observer

The attitude nonlinear observer that includes the bias and the error update is given by :

$$\dot{\hat{q}} = \frac{1}{2} \Xi(\hat{q}) \left[\vec{\omega}_G - \hat{\vec{v}} + K_1 \vec{\varepsilon} \right] \quad (19)$$

$$\dot{\hat{\vec{v}}} = -T^{-1} \hat{\vec{v}} - K_2 \vec{\varepsilon} \quad (20)$$

where T has been defined in (11) and K_i ; $i = 1; 2$ are positive constant parameters \hat{q} is the prediction of the attitude at time t. It this obtained via the integration of the kinematics equation (19) using the measured angular velocity $\vec{\omega}_G$, the bias estimate $\hat{\vec{v}}$ and $\vec{\varepsilon} = \vec{q}_e$ which is the vector part of the quaternion error qe. Remember that qe measures the discrepancy between \hat{q} and the pseudomeasured attitude qps (19). In this paper, qps is obtained thanks to an appropriate treatment of the accelerometer and magnetometer measurements and it will be explained in the next section.

Combining (9), (11), (14) and (20) the error model is expressed as:

$$\dot{q}_e = \frac{1}{2} \begin{pmatrix} 0 & \vec{\gamma}^T \\ -\vec{\gamma} & [2\vec{\omega}^\times] + [\vec{\gamma}^\times] \end{pmatrix} \begin{pmatrix} q_{e0} \\ \vec{q}_e \end{pmatrix} \quad (21)$$

$$\dot{\vec{v}} = -T^{-1} \vec{v} + K_2 \vec{\varepsilon} \quad (22)$$

Where $\vec{\gamma} = \vec{v} + K_1 \vec{\varepsilon}$ and $\vec{v} = \vec{v} - \hat{\vec{v}}$. The system (19)-(20) admits two equilibrium points $(q_{e0} = 1, \vec{q}_e = 0, \vec{v} = 0)$, and $(q_{e0} = -1, \vec{q}_e = 0, \vec{v} = 0)$. This is due to fact that quaternions q and -q represent the same attitude. From (1), one obtains:

$$q_{e0} = 1 \Rightarrow \beta = 0$$

$$q_{e0} = -1 \Rightarrow \beta = 2\pi \text{ (generally } 2n\pi)$$

that is, there is only one equilibrium point in the physical 3D space.

We can observe that the global asymptotically convergence of the error to zero $(q_{e0} = 1, \vec{q}_e = 0, \vec{v} = 0)$, and consequently the convergence of \hat{q} to the real q is given by:

$$\vec{\eta}_G = \vec{\eta}_v = 0 \quad \hat{q}_{ps} \approx q \quad (23)$$

where q is the "true" attitude quaternion of the rigid body. Thus, the convergence is guaranteed if and only if:

$$|q_{e0}| \rightarrow 1, \quad \vec{q}_e \rightarrow 0, \quad \vec{v} = \vec{v} - \hat{\vec{v}} \rightarrow 0 \quad (24)$$

Theorem 1: Consider the equilibrium states of the system (21)-(22) and let $\vec{\omega}_G$ be the measured angular velocity.

Then, the equilibrium point $(q_{e0} = 1, \vec{q}_e = 0, \vec{v} = 0)$ is globally asymptotically stable

Proof: Consider the candidate Lyapunov function V which is positive definite, radially unbounded and which belongs to the class C2:

$$V = K_2 \left((1 - q_{e0})^2 + \vec{q}_e^T \vec{q}_e \right) + \frac{1}{2} \vec{v}^T \vec{v} \quad (25)$$

The derivative of (25), together with (19) and (20), is given by (26):

$$\begin{aligned} \dot{V} &= -2K_2 \dot{q}_{e0} + \vec{v}^T \dot{\vec{v}} \\ &= -K_2 \vec{\gamma}^T \vec{q}_e + \vec{v}^T \left(-T^{-1} \vec{v} + K_2 \vec{\varepsilon} \right) \\ &= -K_2 \left(\vec{v}^T + K_1 \vec{\varepsilon}^T \right) \vec{q}_e - \vec{v}^T T^{-1} \vec{v} + K_2 \vec{v}^T \vec{\varepsilon} \end{aligned} \quad (26)$$

Since $\vec{\varepsilon} = \vec{q}_e$ and $\vec{v}^T \vec{q}_e = \vec{q}_e^T \vec{v}$, it comes that:

$$\dot{V} = -K_2 K_1 \vec{q}_e^T \vec{q}_e - \vec{v}^T T^{-1} \vec{v} \leq 0 \quad (27)$$

Using these updated accelerometer measurements together with the magnetometer measurements, a pseudo-measure estate is estimated via an optimization technique. In this way, the quaternion that is obtained by the estimation with a constraint least-square is insensitive to the body accelerations. Thus, no assumptions of the weakness (or not) of the accelerations are done, and no switching procedure from one model to another one is necessary. Therefore, the main advantage of the approach presented in this paper compared to others approaches, is that the estimated attitude remains valid even in the presence of high accelerations over long time periods.

For the pseudo-measure, a critter that takes in account the evolution of the attitude state via determination of $\mathbf{x} = [q_0, q_1, q_2, q_3, a_x, a_y, a_z]^T$ in the function $f(\mathbf{x})$ is proposed. The minimum error is chosen, but it takes in account the prediction of the state $\hat{\mathbf{x}}$ and the coefficients of weight for the state μ and the measures estimated (MesEstimated = MS) at the instant k.

$$f(\mathbf{x}) = \frac{1}{2} \left[\mu \left(\sum_{j=1}^n (\text{MesEstimated} - v_{\text{mes}}(j))^2 \right) + (1 - \mu) \|\mathbf{x} - \hat{\mathbf{x}}_2\|^2 \right]$$

with $\mathbf{q}^T \mathbf{q} - 1 = 0$ (28)

The process of Estimation and Prediction needs the determination of his gradient; this one is obtained by equation 19

$$H_q = \left[\frac{\partial}{\partial \mathbf{q}} \left(\frac{\partial f}{\partial \mathbf{q}} \frac{\partial \mathbf{q}}{\partial \mathbf{x}} \right) \right] \quad (29)$$

$$H_q = \left[\frac{\partial^2 f}{\partial \mathbf{q}^2} \frac{\partial \mathbf{q}}{\partial \mathbf{x}} \right]^T$$

5.- Experimental Results

In this section, some simulation results are presented in order to show the performance of the proposed control laws. A rigid body with low moment of inertia is taken as the experimental system. In fact, the low moment of inertia makes the system vulnerable to high angular acceleration which proves the importance to apply the control.

The proposed technique is compared to the existing methods (namely, the Multiplicative Extended Kalman Filter (MEKF) and the Additive Kalman Filter (AEKF)). Initial conditions are set to extreme error values in order to assess the effectiveness of attitude estimation. These results are depicted in figure 2. The proposed method performances are similar to those of the Extended Kalman Filter (Multiplicative and Additive). However, for extreme errors the convergence rate for our estimation-prediction is higher.

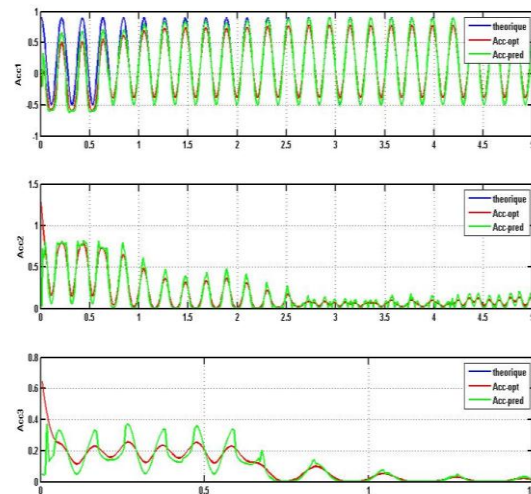


Fig. 2. Simulation Study

The estimation methodology proposed in this work is implemented and evaluated in real time, in order to assess

its effectiveness. For this purpose an embedded system was designed, and developed. Special attention was paid to the low power consumption requirements and weight, leading to the selection of the Digital Signal Controller dsPIC33FJ128MC802 which was used with a clock speed of 4 MHz. It contains extensive Digital Signal Processor (DSP) functionality with a high performance 16-bit microcontroller (MCU) architecture but without floating point unit. The sensor suite is based on a sensor board equipped with a tri-axis accelerometer (ADXL135), a dual axis gyro (LPR530AL) and single axis gyro (LY530ALH) and a tri-axis magnetometer (Micromag 3). All sensors outputs are analog except the Micromag 3 which is digital and uses the Serial Peripheral Interface (SPI) bus system as underlying physical communication layer. Furthermore, the system is equipped with a Bluetooth module (BlueSMiRF Silver), which provides wireless capabilities. The total system supply voltage is 3.3 V. The dimension and weight are 60x40x15 mm and 60 g, respectively. The system is depicted in Fig. 3



Fig.3. Implementation of AHRS prototype

For purpose of validation A Commercial AHRS [9] is used to acquire the data instead of the MEMS sensors presented in section (III-A)(Robot showed in virtual reality figure 1).

(1) The AHRS (sensor module) was placed to a well-known orientation $q_0 = [1 \ 0 \ 0 \ 0]^T$ (the AHRS is still in the horizontal and it is headed toward the magnetic north) which correspond to shoulder angular position:

$$(\phi \ \theta \ \psi) = (0 \ 0 \ 0);$$

(2) The AHRS is still at q_0 for 10 s;

(3) The AHRS is placed at its initial angular position such that the final and initial orientations are identical;

(4) For the entire simulation time span, the signal $\vec{a}_{int} = [2 \ 1 \cdot \sin(2\pi f_d t) \ 0]^T \text{ m/sec}^2$ is added to accelerometers channels (That is done in order to show the ability of the proposed approach to estimate the

acceleration and in the same way to depict the insensibility to non-weak acceleration).

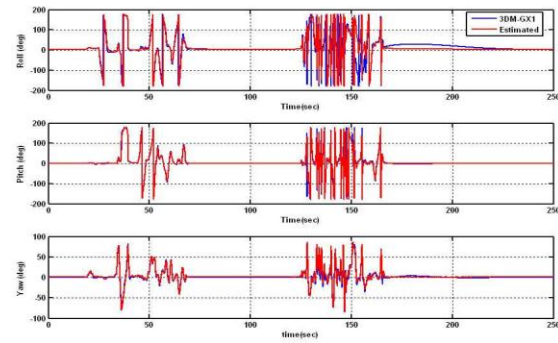


Fig.4. Experimental Result

In Fig. 4, the estimated quaternion \hat{q} and the measured quaternion are depicted. As expected, the attitude estimate reaches the true attitude (which in this case it is well known and represented by: $q_0 = [1 \ 0 \ 0 \ 0]^T$) in suitable time for practical implementation. It can be noticed that despite the noise, drift bias and non-weak acceleration introduced, the evolution of the quaternion estimated reaches the values of the initial attitude $q_0 = q_f = [1 \ 0 \ 0 \ 0]^T$.

This AHRS also provides the Euler angles. The methodology of estimation and prediction are implemented in real-time using the LabView environment. Remember that the attitude estimate is computed using a unit quaternion formulation. For comparison purpose, the estimate quaternion is converted into Euler angles.

As can be shown, after large angular velocity change over a long period, the AHRS has a low convergence rate (approx.1 min) compared to the one achieved with our proposed methodology. On the other hand, this system doesn't provide the acceleration of the body so for validation we have done slowly movement and abrupt movement to appreciate the effect of the acceleration in our method. In figure 4 the global convergence of the estimation techniques is proved.

6.- Conclusions

This paper presented a new strategy for attitude estimation of possibly non-symmetric rigid bodies. Two globally methods of calculation of the body's attitude are proposed, namely one methodology based in fusion data information provided by a tri-axis accelerometer, three magnetometer and three rate gyros mounted orthogonally jointly with prediction of the movement via cubic splines are studied and simulated. In order to achieve sub-degree accuracies in pitch and roll for ultra-short baseline attitude

systems it is necessary to utilize a known bias algorithm. This necessitates the development of multiple antenna common oscillator GPS receivers, in this paper a bias algorithm is presented using low cost MEMs sensors, the results are very encouraging.

Furthermore, the attitude estimation is independent of the body's inertia. The numerical simulations have showed the effectiveness of the proposed methodologies and their robustness with respect to sensors noise and far initial points.

Moreover, the simplicity of the methodology makes it suitable for embedded implementation. This control estimation will be tested in real time application

ACKNOWLEDGMENT

The authors would like to thank to the Instituto Politécnico Nacional (I.P.N.) - S.E.P.I. E.S.I.M.E. U.A and the S.I.P. for the projects 20140720, 20144093, 20144245, and 20140923, CONACyT, and the B.U.A.P. - F.C.E.

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