Global Localization of a Mobile Robot by Data Fusion Attitude and Heading Reference Systems

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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:

I: Relative Position Measurements (also called Dead-reckoning)
1. Odometry
2. Inertial Navigation

II: Absolute Position Measurements (Reference-based systems)
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.

Inertial Navigation

Inertial navigation uses gyroscopes and accelerometers to measure rate of rotation and acceleration, respectively. Measurements are integrated once (or twice, for accelerometers) to yield position. Inertial navigation systems have the advantage that they are self-contained, that is, they don't need external references. However, inertial sensor data drift with time because of the need to integrate rate data to yield position; any small constant error increases without bound after integration. Inertial sensors are thus mostly unsuitable for accurate positioning over an extended period of time [3].

Position of the work

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. In addition to traditional attitude estimation in aerospace and automobile communities, the reduced cost of MEMS inertial sensors has spurred new applications in robotics, virtual reality and biomechanics [1]. 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. This attitude estimation problem is described as following: Rate gyros provide continuous attitude information with good short-term stability when their measurements are integrated. 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

As mentioned in the introduction, the attitude of a rigid body can be represented by a unit 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:

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

Where

$$\mathbb{H} = \begin{cases} q \mid q_0{}^2 + \vec{q}^T\vec{q} = 1 \\ q = [q_0\vec{q}^T]^T, q_0 \in \mathbb{R}, \vec{q} \in \mathbb{R}^3 \end{cases} \qquad (2)$$

$\vec{q} = [q_1\ q_2\ q_3]^T$ and q_0 are known as the vector and scalar partis of the quaternion recpectively. In attitude control aplications, 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:

$$b = \bar{q} \otimes r \otimes q \qquad (3)$$

Where $b = \begin{bmatrix} 0 & \vec{b}^T \end{bmatrix}^T$ 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:

$$\bar{q} = [q_0 \quad -\vec{q}^T]^T \qquad (4)$$

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

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

Where I_3 is the identity matrix and $[\xi^x]$ is a skew symmetric tensor associated with the axis vector ξ:

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

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

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

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

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

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.
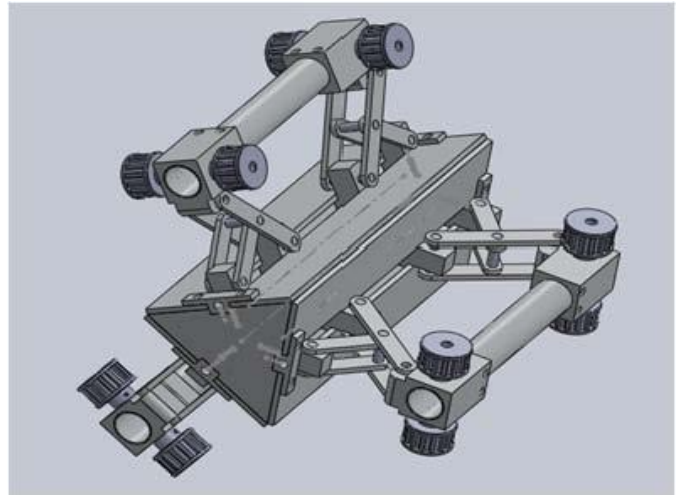

Figure 1. Prototype of the mobile robot.

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

$\vec{w} = \begin{bmatrix} w_x & w_y & w_z \end{bmatrix}^T$ From this, it follows.

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

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

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

$$\Xi(q) = \begin{bmatrix} q_0 I_{3x3} + [\vec{q} \times] \\ \dots \\ -\vec{q}^T \end{bmatrix} \qquad (11)$$

The quaternion must be:

$$q^T q = \vec{q}^T \vec{q} + q_0^2 = 1 \qquad (12)$$

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

$$\begin{aligned} \Xi^T(q)\Xi(q) &= q^T q I_{3x3} \\ \Xi(q)\Xi^T(q) &= q^T q I_{4x4} - q^T q \\ \Xi^T(q)(q) &= 0_{3x1} \end{aligned} \qquad (13)$$

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

$$C(q) = (q_0^2 - \vec{q}^T\vec{q})I_{3x3} + 2\vec{q}\vec{q}^T - 2q_0[\vec{q} \times] \qquad (14)$$

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

3. 1. Modeling sensors

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 $\vec{\upsilon}$, belonging to space $\mathbb{R}^3$. The rate gyro measurements are modeled by [7]:

$$\vec{\omega}_G = \vec{\omega} + \vec{\upsilon} + \vec{\eta}_G \qquad (15)$$

$$\dot{\vec{\upsilon}} = -T^{-1}\vec{\upsilon} + \vec{\eta}_\upsilon \qquad (16)$$

Where $\vec{\eta}_G$ and are $\vec{\eta}_\upsilon$ 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 $\vec{\upsilon}$ 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:

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

Where $\vec{g}=[0 \quad 0 \quad g]^T$ 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 m/sec2 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 $\vec{h}_M=[h_{Mx} \quad 0 \quad h_{Mz}]^T$. Since the measurements take place in the body frame B, they are given by:

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

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

4. Attitude' Estimation and Prediction

The attitude estimator uses quaternion representation. Two approaches are jointly used, namely an estimation with a constraint least-square minimization technique and a prediction 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 an estate 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. Then, the influence of the body accelerations is predicted from the accelerometer measurements. 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.

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

$$f(x) = \frac{1}{2}\left[\mu\left(\sum_{j=1}^{n}\left(MesEstimated - v_{mes}(j)\right)^2\right) + (1-\mu)\|\hat{x} - x\|_2^2\right] \tag{19}$$

with $q^T q - 1 = 0$

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

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

$$H_q = \left[\frac{\partial^2 f}{\partial q^2}\frac{\partial q}{\partial x}\right]^T \tag{20}$$

Similarly, is the obtention for the gradient of the state for the case of acceleration.

Finally, the total Gradient is obtained by the fusion between the calcule show for the quaternion case a the gradient omitted for the acceleration case.

$$F(x) = \begin{bmatrix} H_q & \frac{\partial_{gq}}{\partial a} \\ \frac{\partial_{ga}}{\partial x} & H_a \end{bmatrix} \tag{21}$$

For the prediction's process of $\hat{x}$, several technique have been validated, for purpose of simplicity, the prediction via spline is chosen. Cubic spline is a spline constructed of piecewise third-order polynomials which pass through a set of n control points.

Suppose we are n+1 data points $(\hat{x}_k, MS_k)$ such that.

$a = x_0 < .. < x_n$, Then the coefficients of the vector μ exists cubic polynomials with coefficients $\mu_{i,j}$ $0 \le i \le 3$ such that the following hold.

1. $\mu(\hat{x}) = \mu_j(\hat{x}) = \sum_{j=0}^{3}[\hat{x} - x_j]^i$ $\forall \hat{x} \in [\hat{x} - x_{j+1}]$ $0 \le k \le n-1$
2. $\mu(x_j) = y_k$ $0 \le k \le n-1$
3. $\mu_j(x_{j+1}) = \mu_{j+1}(\mu_{j+1})$ $0 \le k \le n-2$
4. $\mu_j'(x_{j+1}) = \mu_{j+1}'(x_{j+1})$ $0 \le k \le n-2$
5. $\mu_j''(x_{j+1}) = \mu_{j+1}''(x_{j+1})$ $0 \le k \le n-2$

So we see that the cubic spline not only interpolates the data $(\hat{x}_k, MS_k)$ but matches the first and second derivatives at the knots. Notice, from the above definition, one is free to specify constrains on the endpoints. The end point constrain $\mu''(a) = 0$ $\mu''(b) = 0$ is chose.

The estimation of the torque is part of another work that is in process and only we present his basic model. Since the driver torque is not measured in line, we introduce an estimator for $\Gamma_{Mot} = \Gamma$, Essentially, the estimated value of the driver torque is

$$\Gamma_{iest} = G^{(-1)}(\Gamma_{LZ}(z) - H(z).\Gamma_{Mot(z)}) \tag{22}$$

Where Γ_{LZ} is the torque in the steering column part and Γ_{Mot} is the assist motor torque. In order that $G^{(-1)}$ can be physically realizable (numerator degree of the transfer function is always less or equal than denominator degree), it is necessary to introduce a correction transfer function $G_c(z)$ to maintain the properness. With this correction, the inverse transfer function becomes

$$\Gamma_{iest} = G^{(-1)} * G_c(z) * (\Gamma_{LZ}(z) - H(z).\Gamma_{Mot(z)}) \quad (23)$$

5. Results

5. 1. Simulation 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 accelerations 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. For the movements, the acceleration is $\vec{a}_{theo} = \begin{bmatrix} 1^*\sin(2\pi f_a t) & 0 & 0 \end{bmatrix}^T m/\sec^2$ (not weak case) and the quaternion is arbitrary with q0 far from the initial conditions.

5. 2. Experimental results

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 (Figure 3). Special attention was paid to the low power consumption requirements and weight, leading to the selection of the Digital Signal Controller dsPIC which was used with a clock speed of 4MHz. It contains extensive Digital Signal Processor (DSP) functionality with 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 (LY 530ALH) and a tri-axis magnetometer (Micromag3). 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. The total system supply voltage is 3.3 V. The dimension and weight are 60x40x15mm and 60g, respectively. 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 q0 = [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:

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

(2) The AHRS is still at q0 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 $\vec{a}_{int} = \begin{bmatrix} 2 & 1^*\sin(2\pi f_a t) & 0 \end{bmatrix}^T m/\sec^2$ 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).

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: q0 = [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 q0 = qf = [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.
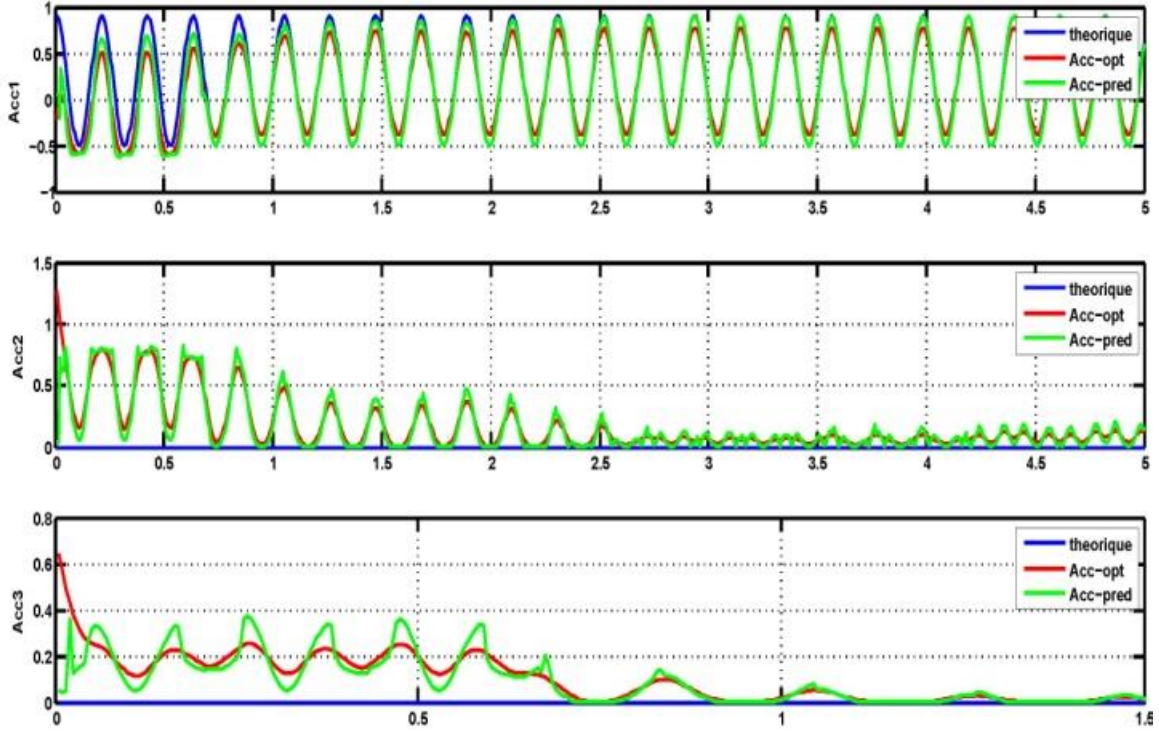
(a)
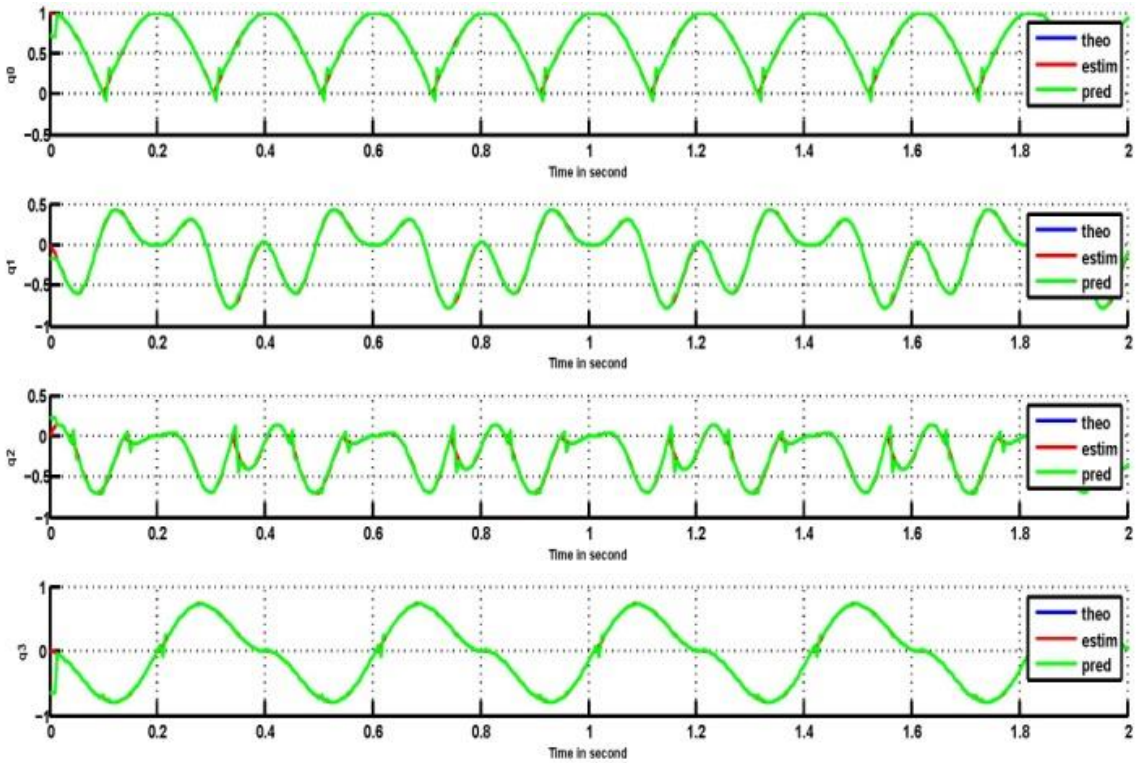
(b)

Figure 2. Simulation Study.

a)   Estimation and Prediction of the Acceleration ($\vec{a}$ Theorique in Blue, $\tilde{a}$ *Estimated in red and* $\hat{a}$ *Predicted in green*).

b)   Estimation and Prediction of the Quaternion $\vec{q}$ Theorique in Blue, $\tilde{q}$ Estimated in red   and $\hat{q}$ Predicted in green.

Figure 3. Implementation of AHRS prototype.

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.
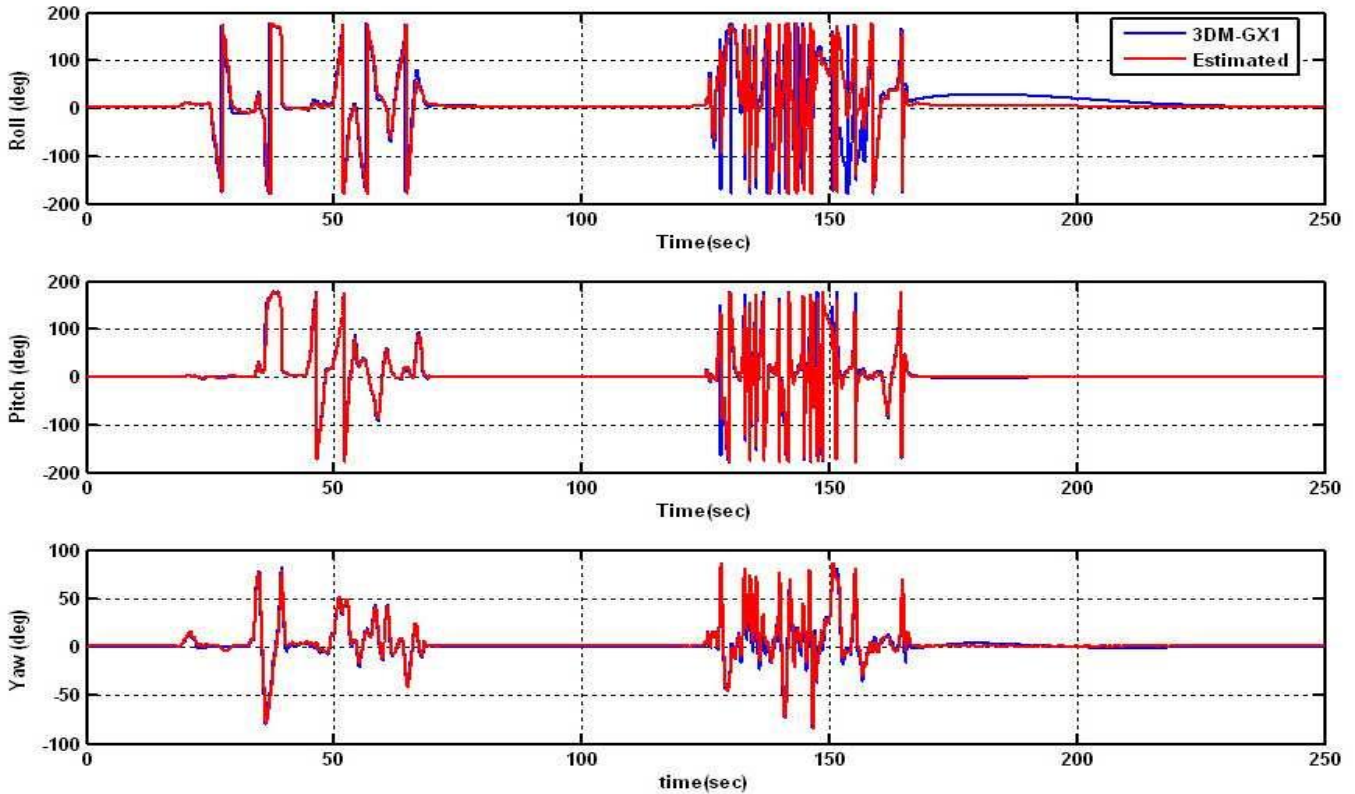

Figure 4. Experimental Data.

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 independents 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, choosing as application a mobile robots and the estimation of the signal in embedded technologies.

7. Acknowledgments

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