A REAL-TIME ATTITUDE ESTIMATION SCHEME FOR HEXAROTOR MICRO AERIAL VEHICLE

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Abstract. *Position and attitude estimation is vital for vertical take-off and landing - unmanned aerial vehicle (**VTOL-UAV**) that can be executed by integrating the output of gyros, accelerometers and magnetometers with respectively gravity and local magnetic field vectors. For this purpose, a Kalman filter with different variant as extended, unscented and complementary has been largely used in the literature. Another technique, vision data to navigate an unknown, indoor, GPS-denied environment with optical flow or visual servo based on image or position was used. Without external sensing, an estimation system that relies only on integrating inertial data will have rapidly drifting position estimates. **VTOL-UAVs** are stringently weight constrained, leaving little margin for additional sensors beyond the mission payload.*
*The aim of this paper is to present a realtime sensor fusion scheme based on nonlinear filtering, for hexarotor **UAV** to localization problem. The absolute attitude estimation use the extended Kalman filter based on quaternion to avoid singularities. Results obtained in realtime system to the hexarotor **UAV** shows the better attitude performance.*

Keywords: *hexarotor, UAV, attitude estimation, EKF*

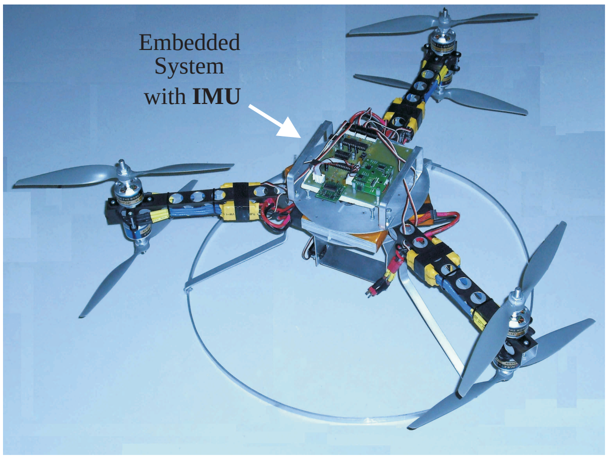
1. INTRODUCTION

Sensor system with combined measurements such as rate gyros, inclinometers and accelerometers are generally used for attitude determination that is an essential task for an Unmanned Aerial Vehicle (**UAV**) (Earl and D'Andrea, 2004; Suh *et al.*, 2010; Hall *et al.*, 2008; Xue *et al.*, 2009; Bae and Kim, 2010). It is possible to use a rate gyro to derive attitudes by integrating the rigid body kinematic equations while accelerometers can provide gravity direction. With high quality gyros and good initial values these estimates can be very accurate over long periods of time. However, if the aim is an autonomous unmanned aerial vehicle then the attitude estimate should be reliable over an infinite time scale. In contrast, accelerometers signals need not be integrated since they provide direct values of tilt angles. Unfortunately, outputs of accelerometers also are sensitive to translational accelerations and should only be used during phases of low accelerations. To provide an absolute reference of the attitude, inclinometers and accelerometers which relate the body to the gravity vector can be used. There is a large literature on attitude filtering techniques, most of the advanced filter techniques (particle filtering, etc.) are computationally demanding and unsuitable for the small scale embedded processors in **UAV** systems (Lim and Hong, 2010; Yafei and Jianguo, 2010).

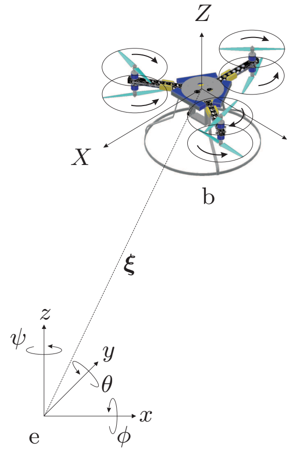
Two methods that are commonly employed are extended Kalman filtering (**EKF**) (Thrun *et al.*, 2006) or some form of constant gain state observer, often termed a complementary filter due to its frequency filtering properties for linear systems (Euston *et al.*, 2008; Neto *et al.*, 2009). The **EKF** has been studied for a range of aerospace applications and is known to have an unpredictable behavior even though they often can be used successfully. Attitude estimation via different ensembles of the above mentioned sensors has been studied in many works (Choukroun *et al.*, 2006). Such filters, however, have proved difficult to apply robustly (Edwan *et al.*, 2011). In practice, many applications use simple linear single-input single-output complementary filters. Earl and D'Andrea (2004) use a decomposition approach to develop a real-time filter that estimates the attitude of a small four rotor helicopter. The filter uses measurements from a three axes gyro system and an off-board computer vision system. In Alarcón *et al.* (2009) present an experimental evaluation of an attitude estimation algorithm based on an **EKF** and a minimum squared error criterion based sensor fusion procedure.

Suh *et al.* (2010) have proposed a smoother for an attitude estimation problem using inertial and magnetic sensors. The smoother consists of an indirect Kalman filter used as a forward and a backward filter, which is one of standard smoother structures. A quaternion is used to represent attitude. In this kind of attitude estimation problem deal with the external acceleration as a number of segments based on accelerometer norm values. In the recent works, a variety of analysis approaches were used to determine the benefits of maneuvering, experiments were used to evaluate the effects of thrust acceleration and changes in pitch attitude on in-flight **IMU** alignment, axial and lateral maneuvers to evaluate the effects of these maneuvers on in-flight **IMU** alignment.

In this paper we will provide a solution to fusing data from a three axes rate gyro, a three axes accelerometer and a three axes magnetometer that will provide stable estimates the tracking position of hexarotor micro aerial vehicle. The inertial measurement unit **IMU** is used as the sensor in this work is a low-cost and small size sensor suitable to attach to the body of hexarotor. The **IMU** comprises orthogonal accelerometers, gyroscopes and magnetometers aligned on the three axes to estimate the position, velocity and attitude with respect to the environment. The paper is organized as follows: Section 2 describes a background of tracking methodology. The experimental set to determine the hexarotor's



(a) Hexarotor **UAV**.



(b) System references.

Figure 1. Micro-aerial vehicle in **UFRN**.

attitude is exposed in section 3, including its analysis and discussion. Section 4 provides the conclusion and future works.

2. METHODOLOGY

The flying vehicle we have built is a three-coaxial-rotor helicopter, also called hexarotor depicted in figure 1(a), consist of three rigid axes that are equidistant from its center of gravity. The six rotors are arranged as three counter-rotating co-axial pairs without gears installed on each rotor axis. The co-axial layout doubles the thrust without increasing the size of the footprint, and naturally eliminates loss of efficiency due to torque compensation. An embedded system with power supply and additional electronics system are mounted at its center of gravity to localization and navigation tasks (Sanca *et al.*, 2010a,b). In the next subsections are developed the attitude estimation using the sensors independently and finally, the technique used to fuse all data producing the better estimation.

2.1 Atitude estimation based on acelerometers measurements

The measurement of the Earth's gravity vector, by means of the three accelerometers that compose the inertial measurement unit, is used to generate the first estimate of the hexarotor's attitude, considering only pitch (θ) and roll (ϕ) angles. These sensors are mounted along three orthogonal axes. We also assume the existence of a frame fixed to the Earth's plane, usually know as north, east and down (**NED**).

We know from the kinematic principles of rigid bodies that if we consider the **IMU** frame fixed to the hexarotor's body, the acceleration experienced by a point described by a vector $\vec{\mathbf{r}}_{\mathrm{a}}$ in relation to the hexarotor's center of mass (**CM**), and fixed to the hexarotor's body is given by $\vec{\mathbf{a}}_{\mathrm{ideal}} = \vec{\mathbf{a}}_{\mathrm{CM}} + \vec{\boldsymbol{\alpha}} \times \vec{\mathbf{r}}_{\mathrm{a}} + \vec{\boldsymbol{\omega}} \times (\vec{\boldsymbol{\omega}} \times \vec{\mathbf{r}}_{\mathrm{a}})$, where, $\vec{\mathbf{a}}_{\mathrm{ideal}}$ represent the ideal measured accelerations which include the acceleration of the hexarotor's axes at the center of mass $\vec{\mathbf{a}}_{\mathrm{CM}}$, $\vec{\boldsymbol{\omega}}$ are body-fixed angular rates and $\vec{\boldsymbol{\alpha}}$ are body-fixed angular accelerations. The characteristic of the accelerometer measurement suffer uncertain parameters, such as gaussian white noise $\vec{\mathbf{a}}_{\mathrm{noise}}$ and a slowly varying bias $\vec{\mathbf{a}}_{\mathrm{bias}}$ involved in the process due to the lack of orthogonality among the sensors. The measured accelerations contain error sources are defined as $\vec{\mathbf{a}}_{\mathrm{meas}} = \vec{\mathbf{a}}_{\mathrm{ideal}} \times \mathbf{A}_{\mathrm{SFCC}} + \vec{\mathbf{a}}_{\mathrm{bias}} + \vec{\mathbf{a}}_{\mathrm{noise}}$, where $\mathbf{A}_{\mathrm{SFCC}}$ is a $3-$by-3 matrix of scaling factors on the diagonal and misalignment terms in the nondiagonal.

If we consider the use of a three axial sensor to measure this vector, we will also observe the effect of the gravity acceleration of the Earth. In general, this effect is subtracted from the final result, in order to simplify the use of the **IMU** data. The accelerometers do not measure accelerations directly, but rather the external specific force $\mathbf{f}^{\mathrm{b}}$. Both linear accelerations $\vec{\mathbf{a}}^{\mathrm{e}}_{\mathrm{ideal}}$ and the Earth's gravitational field contribute to the specific force. The equation 1 represents the values measured by the sensor. In this arrangement, it is possible to represent the gravity acceleration vector as $\vec{\mathbf{g}}^{\mathrm{e}} = [0, 0, \mathrm{g}_0]^{\mathrm{T}}$, which is constant in relation to the Earth's frame, and whose value is approximately $\mathrm{g}_0 = 9.78\mathrm{m/s}^2$.

$$\vec{\mathbf{a}}_{\mathrm{IMU}} = \mathbf{f}^{\mathrm{b}} = \mathbf{R}^{\mathrm{be}}(\phi, \theta, \psi)(\vec{\mathbf{a}}^{\mathrm{e}}_{\mathrm{ideal}} - \vec{\mathbf{g}}^{\mathrm{e}}) + \vec{\mathbf{a}}^{\mathrm{b}}_{\mathrm{bias}} + \vec{\mathbf{a}}^{\mathrm{b}}_{\mathrm{noise}} \tag{1}$$

The gravity vector can also be described with respect to the **IMU** frame by multiplying $\vec{\mathbf{g}}^{\mathrm{e}}$ by a rotation matrix $\mathbf{R}^{\mathrm{be}}$ that relates the two frames. However, in order to apply this rotation, it is necessary to compute this matrix or, in other words, to know what are the sensor's orientation angles in space. To simplify the mathematics, it will be assumed that the **IMU** is mounted exactly on the hexarotor's center of gravity, which in the real case this may not necessarily be true. However, the chosen approach works well even if the difference between the actual location of the center of gravity and the sensor location is not very large. Therefore, we assume that the hexarotor frame, b, as shown in figure 1(b)) and **IMU** frame, are coincident. We will also ignore all types of noise that corrupt the signals measured in this case. These considerations allow us to simplify the previous equation 1 by

$$\vec{\mathbf{a}} = \vec{\mathbf{a}}_{\mathrm{IMU}} = -\mathbf{R}^{\mathrm{be}}(\phi,\theta,\psi)(\vec{\mathbf{g}}^{\mathrm{e}}). \tag{2}$$

Stripping the above matrix equation and rewriting the angles as functions of the projection of the vector $\vec{\mathbf{a}}_{\mathrm{IMU}}$ on each one of the **IMU** axes, it is possible to obtain estimates for ϕ and θ using the measurements from each of the accelerometers, as seen in the next equations.

$$\theta_{\mathrm{a}} = \arcsin\left(\frac{\mathrm{a}_x}{\|\vec{\mathbf{a}}\|}\right), \tag{3}$$

$$\phi_{\mathrm{a}} = \arcsin\left(\frac{a_y}{-\|\vec{\mathbf{a}}\|\cos\theta_{\mathrm{a}}}\right), \tag{4}$$

where a_x and a_y are the acceleration measured vector's components along the **IMU** x and y axes.

A few assumptions are made at this stage:

Assumption 1 *The sensors were mounted along perfectly orthogonal axes. Therefore, the measurements do not present misalignment bias, or if it exists, it is negligible. In addition, there are no other biases on the sensors, and the measurement noise is additive, approximately gaussian with zero mean.*

Another important point is that the equation 4 may present singularity problems for $\theta_{\mathrm{a}} = \pm\pi/2$ angles. However, under normal operating conditions, the pitch angle is restricted to values smaller $\pi/2$. Likewise, it is assumed that the roll angle is restricted to even lower values than those of the pitch angle.

Assumption 2 *The accelerometer is measuring only the gravity vector. This assumption is only valid when the hexarotor is at an inertial state. Although restrictive, this assumption is valid for the range of movements performed. Therefore, the low frequency signals from the accelerometers provide reliability to the estimate of ϕ and θ. It will be shown later that this information will be combined with the information from the gyros and magnetometers mounted on the hexarotor. In the case where the hexarotor is hover, $\|\vec{\mathbf{a}}\|$ is equal to g_0.*

2.2 Atitude estimation based on magnetometers measurements

The earth has a magnetic field. The field lines make their way along a path roughly parallel to the Earth's surface, the magnetic south pole toward the north magnetic pole. The sensor that is capable of providing the orientation with respect to the Earth's plane is a magnetometer, usually embedded in a digital compass. In the experiments presented in later on, we show the use of a digital compass composed of two orthogonally mounted magnetometers, which is calibrated to measure the orientation of the Earth's magnetic field. In general, only two element sensors are used, mounted in a plane parallel to the Earth's plane. As done before, we can represent the signal measured by the compass as a three-dimensional vector $\vec{\mathbf{m}}$ composed of the sum of the Earth's North orientation $\vec{\mathbf{N}}$ transformed by a rotation matrix $\mathbf{R}^{be}$ in relation to the yaw angle (ψ), and a noise vector $\vec{\mathbf{m}}_{\mathrm{noise}}$, written as.

$$\vec{\mathbf{m}} = \vec{\mathbf{m}}_{\mathrm{IMU}} = \mathbf{R}^{\mathrm{be}}(\psi)\vec{\mathbf{N}} + \vec{\mathbf{m}}_{\mathrm{noise}} \tag{5}$$

Again we make some assumptions in order to simplify the problem of estimating the orientation of the hexarotor:

Assumption 3 *The first one, as before, is to the neglect the uncertainties involved in the process.*

Assumption 4 *Second, we will assume that the plane represented by the two orthogonal magnetometers is always parallel to the Earth's plane.*

The equation that computes the yaw angle as a function of the magnetometers measurements m_x and m_y in the compass frame. The ψ_{m} represents a previous estimate of the hexarotor heading relative to the **NED** frame, complementing the angular information.

$$\psi_{\mathrm{m}} = \arctan\left(\frac{\mathrm{m}_y}{\mathrm{m}_x}\right). \tag{6}$$

2.3 Atitude estimation based on gyrometers measurements

In addition to the accelerometers, the **IMU** contains three gyroscopes that measure the hexarotor's angular rates about the body axes. The gyrometers employed in this work actually measure the Coriolis acceleration caused on a proof mass by the rotation of the device. As the system operates on the Earth's surface, measurements from gyrometers and accelerometers, are affected by Earth's rotation, $\omega_{earth} \approx 15°/\text{hour}$. In this work, however, as the system operation time and the effects caused by Earth's rotation are modest when compared to sensor noise, those effects are neglected. Estimates can be obtained by integrating the differential kinematic equation, $\vec{\boldsymbol{\omega}}_{\text{meas}} = \vec{\boldsymbol{\omega}}_{\text{ideal}} \times \boldsymbol{\Omega}_{\text{SFCC}} + \vec{\boldsymbol{\omega}}_{\text{bias}} + \vec{\boldsymbol{\omega}}_{\text{noise}}$ that describe the system, where $\boldsymbol{\Omega}_{\text{SFCC}}$ is a $3-$by-3 matrix of scaling factors on the diagonal and misalignment terms in the nondiagonal, $\vec{\boldsymbol{\omega}}_{\text{bias}}$ are the biases and $\vec{\boldsymbol{\omega}}_{\text{noise}}$ are the uncertain parameters, such as gaussian white noise.

As previously seen, one of the problems is that the mathematics of the attitude parameters using Euler angles representation present singularities in some of its configurations. This can be harmful to the signal integration process, since it produces large discontinuities on the final results. Therefore, we chose to use the unit quaternion representation. The quaternion representation of the gyros is given by

$$\dot{\vec{\mathbf{q}}}^{\text{be}} = \frac{1}{2}\vec{\mathbf{q}}^{\text{be}} \odot \begin{bmatrix} 0 \\ \vec{\boldsymbol{\omega}}^{\text{b}}_{\text{eb,ideal}} \end{bmatrix} = \frac{1}{2}\mathbf{W}_{\text{ideal}}\vec{\mathbf{q}}^{\text{be}} = \frac{1}{2}\begin{bmatrix} 0 & -\omega_x & -\omega_y & -\omega_z \\ \omega_x & 0 & \omega_z & -\omega_y \\ \omega_y & -\omega_z & 0 & \omega_x \\ \omega_z & \omega_y & -\omega_x & 0 \end{bmatrix}\vec{\mathbf{q}}^{\text{be}} \tag{7}$$

where $\odot$ defines a quaternion product and the calibrated gyroscope signal $\vec{\boldsymbol{\omega}}_{\text{IMU}}$ contains measurements of the angular velocity $\vec{\boldsymbol{\omega}}^{\text{b}}_{\text{eb,ideal}}$ from body to earth ($_{\text{eb}}$) expressed in the body coordinate system ($^{\text{b}}$). The quaternion values, in turn, are obtained by integrating the equation (7), where ω_x, ω_y and ω_z are the ideal angular rates corresponding to the roll, pitch and yaw angles, respectively.

2.4 Attitude data fusion

Kalman filtering proposed by R. E. Kalman in 1960 represents one of the key filtering methods for integrated navigation systems. Extended Kalman filter modified from standard Kalman filter is a popular and efficient nonlinear filter (Thrun *et al.*, 2006), and is suitable for hexarotor's **UAV** attitude estimation; in witch system equation and measurement equation both are usually nonlinear. As mentioned above, this subsection is concerned with an experiment where an **EKF** algorithm is used to fuse the measurements from the sensor unit in order to compute estimates of orientation. The objective in sensor fusion is to recursively in time estimate the state in the dynamic model,

$$\mathbf{x}_{k+1} = f(\mathbf{x}_k, \mathbf{u}_k, \mathbf{w}_k), \tag{8}$$

$$\mathbf{y}_k = h(\mathbf{x}_k) + \mathbf{v}_k, \tag{9}$$

where $\mathbf{x}_k \in \mathbb{R}^{n_x}$ denotes the state, $\mathbf{y}_k \in \mathbb{R}^{n_y}$ denote the measurements from a set of sensors, $\mathbf{w}_k$ and $\mathbf{v}_k$ denote the stochastic process and measurement noise, respectively. The process model equations, describing the evolution of the states (attitude) over time are denoted by $f : \mathbb{R}^{n_x} \times \mathbb{R}^{n_u} \times \mathbb{R}^{n_w} \to \mathbb{R}^{n_x}$. Furthermore, the measurement model is given by $h : \mathbb{R}^{n_x} \times \mathbb{R}^{n_v} \to \mathbb{R}^{n_y}$, describing how the measurements from the **IMU** relate to the state. The goal is to infer all the information from the measurements onto the state.

The state vector is chosen to be

$$\mathbf{x}_{k+1} = \begin{cases} \vec{\mathbf{q}}^{\text{be}}_{k+1} &= \vec{\mathbf{q}}^{\text{be}}_{k} + \frac{\Delta\text{T}}{2}\mathbf{W}_{\text{ideal},k}\vec{\mathbf{q}}^{\text{be}}_{k} \\ \vec{\boldsymbol{\omega}}^{\text{b}}_{\text{eb},k+1} &= \vec{\boldsymbol{\omega}}_{\text{IMU},k} - \vec{\boldsymbol{\omega}}^{\text{b}}_{\text{bias},k} - \vec{\boldsymbol{\omega}}^{\text{b}}_{\text{noise}} \\ \vec{\boldsymbol{\omega}}^{\text{b}}_{\text{bias},k+1} &= \vec{\boldsymbol{\omega}}^{\text{b}}_{\text{bias},k} + \vec{\boldsymbol{\eta}}^{\text{b}}_{\text{bias}} \end{cases} \tag{10}$$

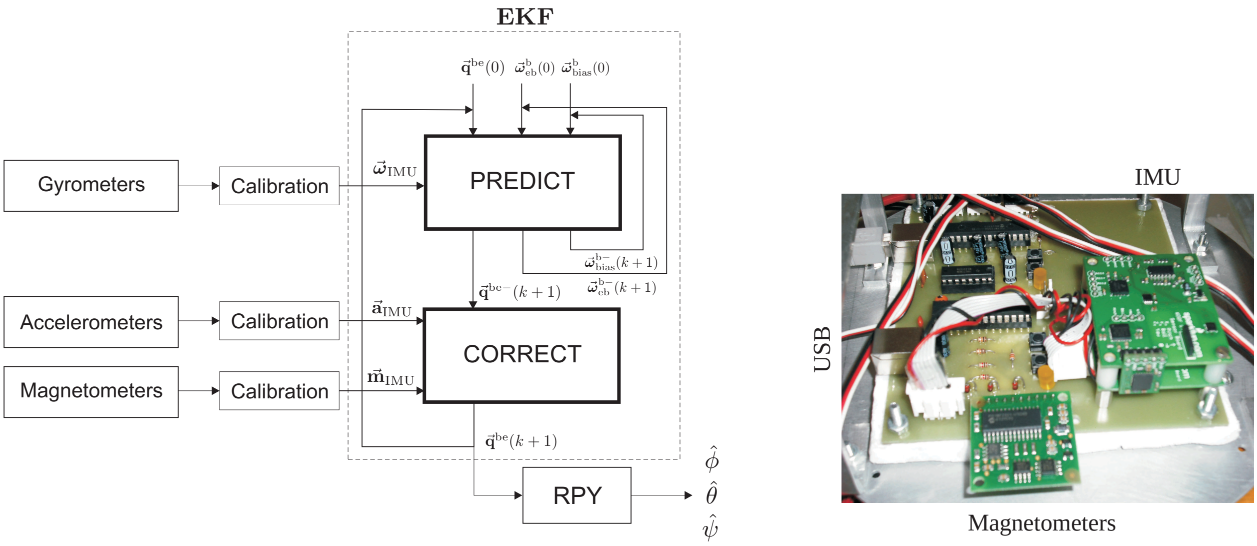
$$\mathbf{y}_{k+1} = \vec{\mathbf{q}}^{\text{be}}_{k+1} \tag{11}$$

Even though the gyroscope signal is corrected for temperature effects, some low-frequency offset fluctuations $\vec{\boldsymbol{\omega}}^{\text{b}}_{\text{bias},k}$ remain, partly due to the unmodeled acceleration dependency. The remaining error $\vec{\boldsymbol{\omega}}^{\text{b}}_{\text{noise}}$ is assumed to be zero mean white noise. The measurements are not accurate enough to pick up the rotation of the earth. This implies that the earth coordinate system can be considered to be an inertial frame. In equation (10), all quantities are three dimensional vectors, except for the orientation which is described using a four dimensional unit quaternion $\vec{\mathbf{q}}^{\text{be}}$, resulting in a state vector with ten elements and ΔT is the sampling interval.

The reason for using unit quaternions is that they offer a nonsingular parametrization with a rather simple, bilinear differential equation which can be integrated analytically and have only four parameters. In contrast, Euler angles have only three parameters, but suffer from singularities and have a nonlinear differential equation. Furthermore, rotation matrices have at least six parameters.

The state vector implies that the measurement model is given by accelerometers and magnetometers, expressed by equation (3), (4) and (6). The quaternion representation of the orientation is given by:

$$\vec{\mathbf{q}}^{\text{be}}_{\text{am},k+1} = \begin{bmatrix} \cos(\phi_{\text{a}}/2)\cos(\theta_{\text{a}}/2)\cos(\psi_{\text{m}}/2) + \sin(\phi_{\text{a}}/2)\sin(\theta_{\text{a}}/2)\sin(\psi_{\text{m}}/2) \\ \sin(\phi_{\text{a}}/2)\cos(\theta_{\text{a}}/2)\cos(\psi_{\text{m}}/2) - \cos(\phi_{\text{a}}/2)\sin(\theta_{\text{a}}/2)\sin(\psi_{\text{m}}/2) \\ \cos(\phi_{\text{a}}/2)\sin(\theta_{\text{a}}/2)\cos(\psi_{\text{m}}/2) + \sin(\phi_{\text{a}}/2)\cos(\theta_{\text{a}}/2)\sin(\psi_{\text{m}}/2) \\ \cos(\phi_{\text{a}}/2)\cos(\theta_{\text{a}}/2)\sin(\psi_{\text{m}}/2) - \sin(\phi_{\text{a}}/2)\sin(\theta_{\text{a}}/2)\cos(\psi_{\text{m}}/2) \end{bmatrix}. \tag{12}$$



(a) Block diagram of the **EKF** algorithm to attitude estimation. (b) Embedded System Board.

Figure 2. Block diagram for hardware in the experimental setup.

The process model of an **EKF** provides a prediction of the states of the hexarotor's attitude based on gyroscope measurement. The model predicts the attitude state, and the accelerometer and magnetometer measurements are used to update the prediction. This may provide greater performance than stand-alone gyroscope. The **IMU** process model is the mechanization equations used to derive the hexarotor attitude, velocity, and position. A block diagram of an experimental setup that was used validate this algorithm is shown in figure 2.

$$\hat{\phi} = \arctan\left(\frac{2(q_2q_3 + q_0q_1)}{q_0^2 - q_1^2 - q_2^2 + q_3^2}\right); \quad (13)$$

$$\hat{\theta} = -\arcsin\left(2(q_1q_3 - q_0q_2)\right); \quad (14)$$

$$\hat{\psi} = \arctan\left(\frac{2(q_1q_2 + q_0q_3)}{q_0^2 + q_1^2 - q_2^2 - q_3^2}\right). \quad (15)$$

3. RESULTS

The section describes a simple master-slave hardware/software architecture for a hexarotor **UAV** attitude estimation. The architecture uses the standard **USB** communication interface, where a C++ library, which makes possible communicate an embedded computer with a microcontroller using a standard Linux operational system. The **IMU** sensor from Sparkfun electronics, which is the $6-$**DOF** (degree of freedom) version 4.0, is used for the experiment, as shown in figure 2(b). It is composes of three axes accelerometers using the MMA7260Q chip from Freescale, three gyroscopes using the IDG300 chip with ± 300 degree/second from Invensense and magnetic sensors HMC1052L chip from Honeywell. Thus, it could provide acceleration measurements in three dimensions, angular rate about the three axes and magnetic measurement in three dimensions, respectively.

The sensor will be attached on the body center of mass of hexarotor to measure the acceleration, angular rate and magnetic data. The output signals from **IMU** sensor are converted by $10-$bit **A/D** (Analog to Digital converter) into a raw value and transferred by LPC2138 ARM7 processor to Embedded Computer for data logging. Then, it was post-processed by **EKF** to attitude estimation.

The figure 3, shows the **USB** acquisition times response and the **EKF** processing times about 2000 samples for the first experiment expected average of 7.3966ms and 2.5991ms respectively, being 9.9957ms the total time for a processing sample. This value depends on the time constant of sensor readings (update rate), which is generally slower than the embedded computer/microcontroller communication transfer interface. Notice that the graphic shows some peaks with different amplitude, these peaks probably are retransmissions, because in high level the exception handler did not notice any error. It happens because interrupt end points send or receive data at fixed intervals and if a communication loss occurs the system will try to retransmit previous data. This result can be considered reasonable for update rate (sampling rate) on the hexarotor's attitude controller and stabilization.

The figure 4(a), illustrates the attitude estimation result when no movement (steady state), we note that has no drift in the horizontal axis and the figure 4(b) shows independent movements for each axis ϕ, θ and ψ in (degrees) respectively.

The figure 4(b) shows a complete attitude estimation result in real time. The information data are viewed by the sensor readings and the behavior of the quaternion evolution, we can see that no exceed the unit value and finally their respective

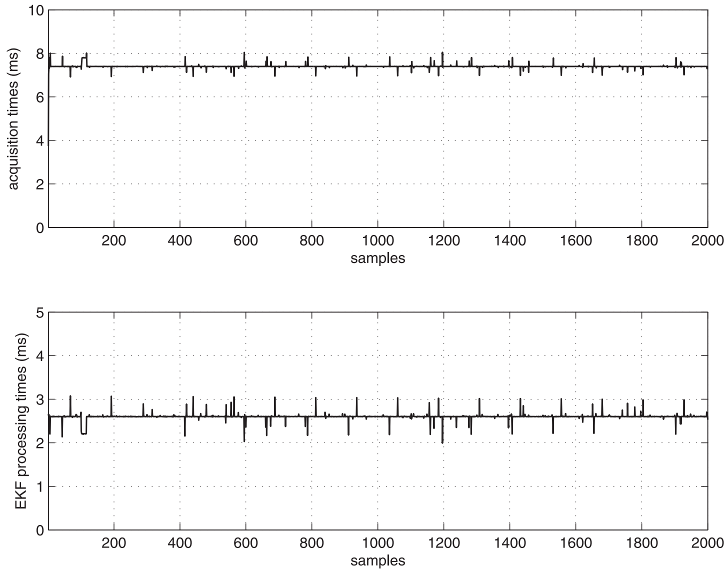
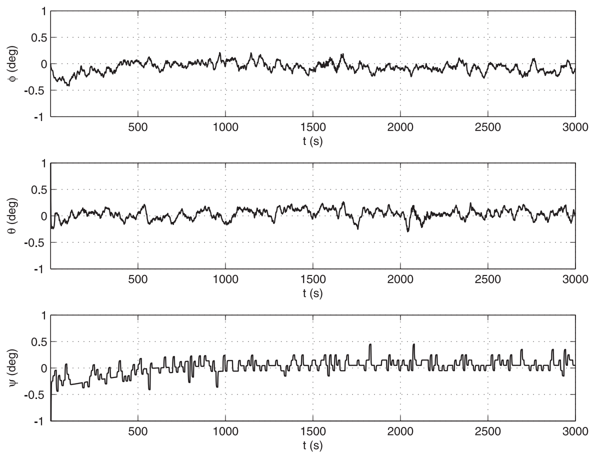
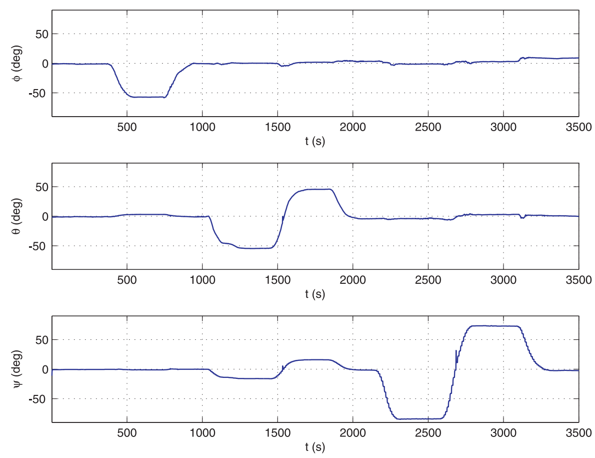


Figure 3. The **USB** acquisition and **EKF** processing times to attitude estimation.



(a) Roll (ϕ), Pitch (θ) and Yaw (ψ) estimation in steady state (hovering).



(b) Roll, Pitch and Yaw independent movements estimated for the **EKF**.

Figure 4. Roll, pitch and yaw estimation.

quaternion estimation error.

4. CONCLUSIONS

This paper was presented an attitude estimation method based on the **EKF** for quaternions. This estimator is built for attitude control and stabilization of the hexarotor. Future applications will be displayed the integration of a pose and attitude estimation based on **GPS**/**IMU**/ computer vision, resulting in an estimator of six degrees of freedom that will be used for tracking and navigation.

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6. REFERENCES

Alarcón, J.R.C., Cortés, H.R. and Vivas, E.V., 2009. "Extended kalman filter tuning in attitude estimation from inertial and magnetic field measurements". In *6th International Conference on Electrical Engineering, Computing Science and Automatic Control*. pp. 1–6.

Bae, J. and Kim, Y., 2010. "Nonlinear estimation for spacecraft attitude using decentralized unscented information filter".

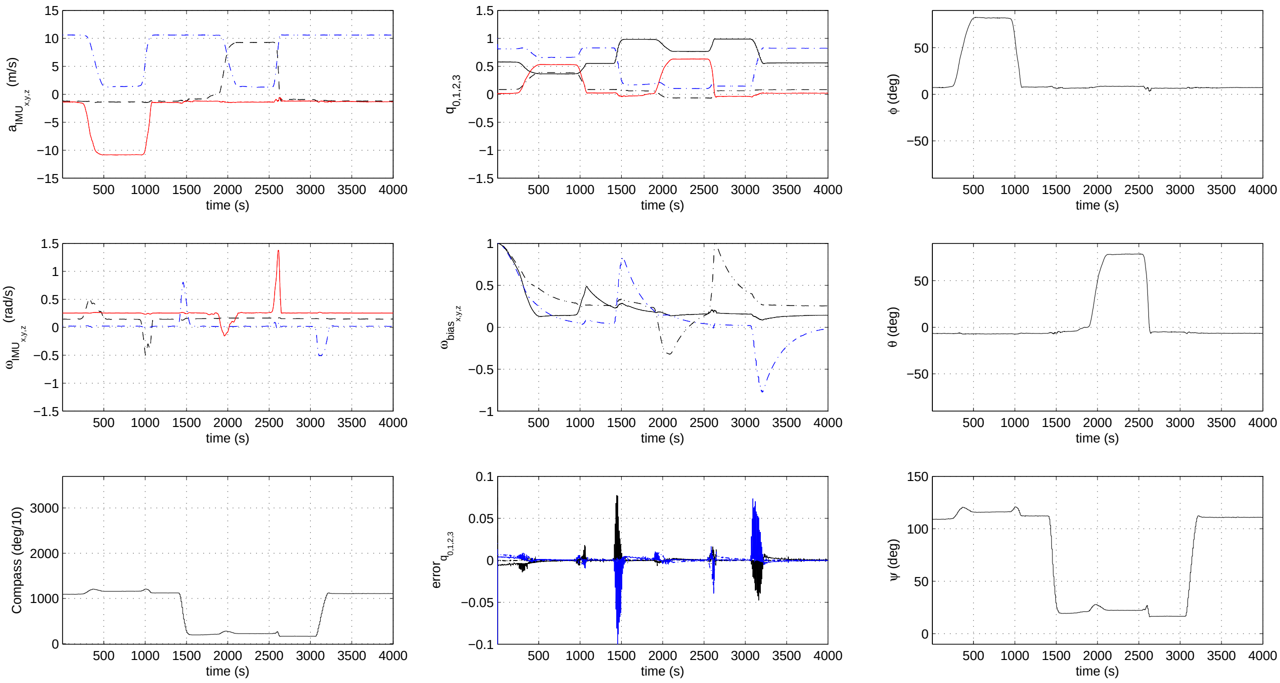

Figure 5. Attitude estimation result in real time with quaternion errors.

In *International Conference on Control, Automation and Systems in Kintex, Gyeonggi, Korea*. pp. 1562–1566.

Choukroun, D., Bar-Itzhack, I.Y. and Oshman, Y., 2006. "Novel quaternion kalman filter". *IEEE Transaction on Aerospace and Electronic Systems*, Vol. 42, No. 1, pp. 174–190.

Earl, M.G. and D'Andrea, R., 2004. "Real-time attitude estimation techniques applied to a four rotor helicopter". In *43rd IEEE Conference on Decision and Control, Atlantis, Paradise Island, Bahamas*. Vol. 4, pp. 3956–3961.

Edwan, E., Knedlik, S. and Loffeld, O., 2011. "Constrained angular motion estimation in a gyro-free imu". *IEEE Transaction on Aerospace and Electronic Systems*, Vol. 47, No. 1, pp. 596–610.

Euston, M., Coote, P., Mahony, R., Kim, J. and Hamel, T., 2008. "A complementary filter for attitude estimation of a fixed-wing uav". In *IEEE/RSJ International Conference on Intelligent Robots and Systems, Nice, France*. pp. 340–345.

Hall, J., Knoebel, N.B. and McLain, T.W., 2008. "Quaternion attitude estimation for miniature air vehicles using a multiplicative extended kalman filter". In *IEEE/ION Postion, Location and Navigation Symposium*. pp. 1230–1237.

Lim, J. and Hong, D., 2010. "Cost reference particle filtering approach to high-bandwidth tilt estimation". *IEEE Transactions on Industrial Electronics*, Vol. 57, No. 11, pp. 3830–3839.

Neto, A.A., Macharet, D.G., Campos, V.C.S. and Campos, M.F.M., 2009. "Adaptive complementary filtering algorithm for mobile robot localization". *Journal of the Brazilian Computer Society*, Vol. 15, No. 3, pp. 19–31.

Sanca, A.S., Alsina, P.J. and Cerqueira, J.J.F., 2010a. "Dynamic modeling with nonlinear inputs and backstepping control for a hexarotor micro-aerial vehicle". In *2010 Latin American Robotics Symposium and Intelligent Robotics Meeting*. pp. 36–42.

Sanca, A.S., Guimarães, J.P.F., Cerqueira, J.J.F. and Alsina, P.J., 2010b. "Hexarotor design project: Modeling and energy management for outdoor aerial robot". In *VI National Congress of Mechanical Engineering, Campina Grande, PB, Brazil*. pp. 1–9.

Suh, Y.S., Do, T.N., Ro, Y.S. and Kang, H.J., 2010. "A smoother for attitude estimation using inertial and magnetic sensors". In *2010 IEEE Sensors*. pp. 743–746.

Thrun, S., Burgard, W. and Fox, D., 2006. *Probabilistic Robotics*. The MIT Press.

Xue, L., Yuan, W., Chang, H. and Jiang, C., 2009. "Mems-based multi-sensor integrated attitude estimation technology for mav applications". In *Proceedings of the 2009 4th IEEE International Conference on Nano/Micro Engineered and Molecular Systems, Shenzhen, China*. pp. 1031–1035.

Yafei, Y. and Jianguo, L., 2010. "Particle filtering for gyroless attitude/angular rate estimation algorithm". In *First International Coference on Pervasive Computing, Signal Processing and Applications*. pp. 1188–1191.

7. Responsibility notice

The author(s) is (are) the only responsible for the printed material included in this paper