Time-delay Compensation Using Inertial Measurement Sensors for Quadrotor Control Systems*

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***Abstract*—A new observer-predictor algorithm (OP-A) to estimate the roll and pitch angles in an aerial vehicle is proposed in this paper. The OP-A is based on a Kalman Filter (KF) and a discrete-time predictor. First, the KF estimates the desired states. It is well-known that an inherent delay is introduced during its computation. The predictor improves these measurements counteracting the delay. The algorithm is validated in real-time using gyroscopes and accelerometers of a low-cost inertial measurement unit. These results are compared with the measurements coming from a commercial IMU with good precision and the results show that the proposed scheme improves substantially the angular measurements.**

Keywords—Attitude estimation, Inertial Measurement Unit, Kalman Filter, Discrete-Predictor, Real-time Validation

I. Introduction

In the past years there has been an increasing interest in Unmmaned Aerial Systems (UAS). Among the UAS, quadrotors are of special interest in control from both perspectives, theoretical and applied [1]. Disregarding the control strategy, a high-performance attitude tracking subsystem is a requisite for developing any other high-level controlling task. The key state variables to be estimated are the attitude and the angular velocity, as they are the primary variables used in attitude control of the vehicle [2]. Inertial Measurement Units (IMUs), which are the core of lightweight robotic applications have experienced a proliferation, resulting in cheaper, and more accurate devices [3]. Nevertheless, these cheaper devices usually provide only raw measurements from gyroscopes and accelerometers.

Different approaches to the attitude estimation problem have been reported in literature, e.g., Kalman filters [4], [5] or complementary filters [6]. Although its convergence is not guaranteed, the Extended Kalman Filter (EKF) has been the workhorse of real-time spacecraft attitude estimation for quite some time [7]. On the other hand, some processes are internally performed before the observer algorithms are computed. For example, during the data acquisition process in an IMU, the signals are low-pass filtered to remove noise and avoid aliasing effects. The filter introduces a time delay in the measurements, which results in an attitude estimation which is also delayed by the same amount of time. One of the unavoidable sources of delay is the low-pass filtering before sampling. The other one is the computational time required to run the estimation algorithm.

It is well-known that measurement delays decrease the phase margin and can even lead to the instability of the controlled process [8]. The incorporation of delayed measurements into the Kalman filter while preserving optimality is far from being trivial. When the delay consists only of a few sample periods, the problem can be handled optimally by augmenting the state vector [9]. However, for larger delays, the computational burden of this approach becomes too large. This topic has been investigated in [10]. More recent work on this topic has been done in [11], where a general delayed Kalman filter framework is derived for linear-time invariant systems.

Dead-time compensation techniques are frequently used in the control of time-delay systems [12]–[14]. In [15] a discrete predictor for continuous-time plants with time delay is proposed and the closed-loop stability is proved. Later, the proposed predictor has been explored to perform in different scenarios [16]–[21]. Nowadays, almost any control system application is implemented by using a computer, discrete-time predictor-based control schemes are increase their internes in practical applications [22], [23].

The goal of this paper is to improve the estimation of the pitch and roll angle with a low-cost IMU by proposing an observer-predictor algorithm (OP-A). The proposed scheme uses a KF and a discrete-time predictor to fuse the measurements coming from this sensor. The KF estimates the roll and pitch angles and corrects the bias of the gyroscopes, while the predictor counteracts the inherent delay in the estimated states.

The paper is structured as follows. The problem statement is described in section II. In this section, the mathematical equations of a quad-rotor aerial vehicle and the representation of the inertial sensors are given. Also the problem of delays in attitude estimation is presented. The proposed algorithm is described in Section III. This section deals with the presentation of the KF and the OP-A and the simulation validation. The proposed scheme is validated in flight tests and some graphs are selected and shown in section IV to show the real-time results. At the end of the paper in section V, some discussions about this work are presented.

II. Problem Formulation

In this section the kinematic and dynamic models of the quadrotor are introduced. Moreover, some preliminar-

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ies regarding to the sensor characterization considered for the Kalman filter derivation are also presented. Finally, the problematic of delays in attitude estimation is explained and illustrated with an example.

A. Quadrotor model

Let us denote by $\{\hat{\boldsymbol{e}}_1, \hat{\boldsymbol{e}}_2, \hat{\boldsymbol{e}}_3\}$ the unit basis vectors of the Earth-Centered Earth-fixed (ECEF) reference frame, $\{E\}$, which is assumed to be inertial.

Let $\boldsymbol{\omega} = \boldsymbol{\omega}^B_{B/E} = [p, q, r]^T$ be the angular velocity of the aircraft with respect to $\{E\}$ expressed in the body frame $\{B\}$. The rotational kinematic relating these angular velocities to the Euler angles, $\boldsymbol{\eta} = [\phi\,\theta\,\psi]^T$, is expressed by

$$\dot{\boldsymbol{\eta}} = \begin{bmatrix} 1 & \sin\phi\tan\theta & \cos\phi\tan\theta \\ 0 & \cos\phi & -\sin\phi \\ 0 & \frac{\sin\phi}{\cos\theta} & \frac{\cos\phi}{\cos\theta} \end{bmatrix} \boldsymbol{\omega} \tag{1}$$

where ϕ, θ, and ψ denote the roll, pitch and yaw angle, respectively.

The rotational dynamics of the quadrotor is governed by Euler's law of motion according to

$$\boldsymbol{\tau} = \boldsymbol{I}\ddot{\boldsymbol{\eta}} + \boldsymbol{\omega} \times \boldsymbol{I}\boldsymbol{\omega} \tag{2}$$

where $\boldsymbol{\tau} = [\tau_\phi,\, \tau_\theta,\, \tau_\psi]^T$ is the vector of external torques. It has been showed in several works (and corroborated in flight tests) that the rotational dynamics of the quadrotor can be reduced to a double integrator on each axis as

$$\ddot{\boldsymbol{\eta}} = \tilde{\boldsymbol{\tau}} \tag{3}$$

where $\tilde{\boldsymbol{\tau}}$ denotes the new control inputs.

The orientation of $\{B\}$ with respect to $\{E\}$ is represented by means of the rotation matrix, ${}^{\mathrm{B}}\boldsymbol{R}_E$, which can be expressed in terms of the Euler angles by

$${}^{\mathrm{B}}\boldsymbol{R}_E = \begin{bmatrix} c\theta c\psi & c\theta s\psi & -s\theta \\ s\phi s\theta c\psi - c\phi s\psi & s\phi s\theta s\psi + c\phi c\psi & s\phi c\theta \\ c\phi s\theta c\psi + s\phi s\psi & c\phi s\theta s\psi - c\phi c\psi & c\phi s\theta \end{bmatrix} \tag{4}$$

using the conventional sequence of roll-pitch-yaw.

B. Sensors characterization

It is important to express in a mathematical form the relationship between the external forces acting on the vehicle and the accelerations and angular rate measurements coming from the inertial sensors. Notice that, the accelerometers in strap-down configuration measure the specific force acting on the vehicle expressed in $\{B\}$ as they are aligned with the body-fixed reference frame. Thus, without loss of generality, the measurement can be expressed by

$$\boldsymbol{a}^B = \frac{1}{m}\left(\boldsymbol{f}^B - {}^{\mathrm{B}}\boldsymbol{R}_E(mg)\hat{\boldsymbol{e}}_3\right) = \dot{\boldsymbol{v}}^B - {}^{\mathrm{B}}\boldsymbol{R}_E g\hat{\boldsymbol{e}}_3 \tag{5}$$

where $\dot{\boldsymbol{v}}^B$ is the acceleration vector due to the external forces expressed in $\{B\}$, m denotes the mass of the aerial vehicle and $\boldsymbol{f}^B$ represents the vector of external forces that act on the quadrotor. Since the accelerations in stable flight regimes are usually small compared to the gravity acceleration, neglecting the linear acceleration ($\dot{\boldsymbol{v}}^B = 0$) is a classical assumption [24]. Normalizing the vector of acceleration measurements facilitates to express the roll and pitch angles as

$$\boldsymbol{a} = \frac{\boldsymbol{a}^B}{|\boldsymbol{a}^B|} \approx -{}^{\mathrm{B}}\boldsymbol{R}_E\hat{\boldsymbol{e}}_3 = \begin{bmatrix} \sin\theta \\ -\sin\phi\cos\theta \\ -\cos\phi\cos\theta \end{bmatrix} \tag{6}$$

Let us consider the following model for the inertial sensors,

$$\begin{aligned} \bar{\boldsymbol{\omega}} &= \boldsymbol{\omega} + \boldsymbol{\beta}_\omega + \boldsymbol{\eta}_\omega \\ \bar{\boldsymbol{a}} &= \mathbf{a} + \boldsymbol{\eta}_a \end{aligned} \tag{7}$$

where the velocity measurement $\bar{\boldsymbol{\omega}}$ is composed of its actual value $\boldsymbol{\omega}$, plus the bias $\boldsymbol{\beta}_\omega$ and noise in the measurement $\boldsymbol{\eta}_\omega$. The same applies for the acceleration measurement but the biases are not included. The measurement noises are subject to a Gaussian representation as follows,

$$\begin{aligned} \mathbb{E}[\boldsymbol{\eta}_\omega] &= 0 \qquad & \mathbb{E}[\boldsymbol{\eta}_\omega\boldsymbol{\eta}_\omega^T] &= \boldsymbol{\Sigma}_\omega = \sigma_\omega^2\boldsymbol{I}_3 \\ \mathbb{E}[\boldsymbol{\eta}_a] &= 0 \qquad & \mathbb{E}[\boldsymbol{\eta}_a\boldsymbol{\eta}_a^T] &= \boldsymbol{\Sigma}_a = \sigma_a^2\boldsymbol{I}_3 \end{aligned} \tag{8}$$

where $\boldsymbol{\Sigma}_\omega$ and $\boldsymbol{\Sigma}_a$ define the diagonal covariance matrices.

The following random walk process,

$$\dot{\boldsymbol{\beta}}_\omega = \boldsymbol{\eta}_\beta, \tag{9}$$

$$\mathbb{E}[\boldsymbol{\eta}_\beta] = 0, \qquad \mathbb{E}[\boldsymbol{\eta}_\beta\boldsymbol{\eta}_\beta^T] = \boldsymbol{\Sigma}_\beta = \sigma_\beta^2\boldsymbol{I}_3, \tag{10}$$

is used to model the "slowly-varying" biases of the gyros, where $\boldsymbol{\eta}_\beta$ is white noise and $\boldsymbol{\Sigma}_\beta$ is its diagonal covariance matrix. The variance σ_β^2 determines how much the bias drifts.

C. Time delays in inertial sensors

In practice, it is observed that attitude estimation obtained by applying fusing algorithms to the inertial sensors measurements exhibit a delay with respect to their real value. For illustration purposes, the angular measurements coming from a commercial IMU (the Mircrostrain 3DM-GX2) are compared with those of set of encoders. It is well know that the encoders are faster and more accurate than any IMU. Thus, the delayed measurement of the commercial IMU is represented in Fig. 1 along with the ideal value measured by encoders. The experimental platform that allows taking these measurements is described in detail in Section IV.

One of the unavoidable sources of delay is the low-pass filtering before sampling. During the data acquisition process in an IMU, the signals are low-pass filtered to remove noise and avoid aliasing effects. The other one is the computational time required to run the estimation algorithm, which is often carried out in an on-board microcontroller. In addition, it is well-known that measurement delays decrease the phase margin and can even lead to the instability of the controlled process.

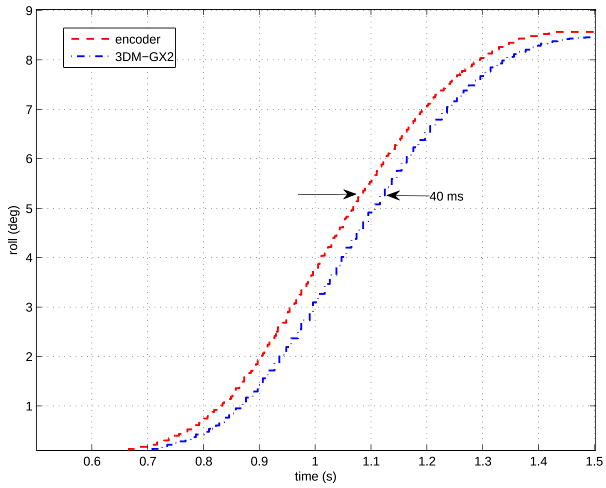

Figure 1. Time-delay comparison when estimating the angular position using an encoder and the 3DM-GX2 commercial IMU.

III. Predictor-based Kalman filter

A. Kalman filter

The kinematics of an aerial vehicle and the measurement model can be expressed by (1) and (6), respectively. An advantage of the Euler formulation is that the yaw angle can be removed from the equations. Let us denote the state vector of estimated variables and the vector of measurements by $\hat{\boldsymbol{x}} = [\phi,\ \beta_x,\ \theta,\ \beta_y]^T$ and $\boldsymbol{y} = [\bar{a}_x,\ \bar{a}_y,\ \bar{a}_z]^T$, respectively. Thus, the a filter can be derived from (1), (6) and (9) as

$$\begin{aligned}\dot{\hat{\boldsymbol{x}}} &= \begin{bmatrix}(\bar{\omega}_x-\beta_x)+(\bar{\omega}_y-\beta_y)\sin\phi\tan\theta\\ 0\\ (\bar{\omega}_y-\beta_y)\cos\phi\\ 0\end{bmatrix}+\boldsymbol{w}\\ \boldsymbol{y} &= \begin{bmatrix}\sin\theta\\ -\sin\phi\cos\theta\\ -\cos\phi\cos\theta\end{bmatrix}+\boldsymbol{v}\end{aligned} \tag{11}$$

with $\boldsymbol{w}$ and $\boldsymbol{v}$ denote the process and measurement noises, respectively.

Assuming small angle approximations and neglecting the third axis of the accelerometer (the reader is referred to [25] for details), the following dicrete-time filter can be obtained

$$\begin{aligned}\hat{\boldsymbol{x}}_{k+1} &= \begin{bmatrix}1 & -T & 0 & 0\\ 0 & 1 & 0 & 0\\ 0 & 0 & 1 & -T\\ 0 & 0 & 0 & 1\end{bmatrix}\hat{\boldsymbol{x}}_k+\begin{bmatrix}T & 0\\ 0 & 0\\ 0 & T\\ 0 & 0\end{bmatrix}\boldsymbol{\omega}_k+\boldsymbol{w}_k\\ \boldsymbol{y}_k &= \begin{bmatrix}0 & 0 & 1 & 0\\ -1 & 0 & 0 & 0\end{bmatrix}\hat{\boldsymbol{x}}_k+\boldsymbol{v}_k\end{aligned} \tag{12}$$

where $\hat{\boldsymbol{x}}_k = [\phi_k,\ \beta_{x_k},\ \theta_k,\ \beta_{y_k}]^T$ and $\boldsymbol{y}_k = [\bar{a}_{x_k},\ \bar{a}_{y_k}]^T$ are the discrete state and measurement vectors, $\boldsymbol{\omega}_k = [\bar{\omega}_{x_k},\ \bar{\omega}_{y_k}]^T$ defines the system input which consists of angular velocities, and $\boldsymbol{w}_k$ and $\boldsymbol{v}_k$ represent the discrete process and measurement vectors, respectively.

B. h-step ahead Predictor

The discrete-time predictor algorithm used to improve the KF estimation is described in this part. The predictor algorithm compensates the delays in the estimated variables improving considerably the closed-loop stability.

The state of the plant is fully accessible but there is a known constant transmission delay τ, which is assumed to be a multiple of the sampling period T, i.e., $\tau = Td$. The measured state can be thus written as

$$\tilde{\boldsymbol{x}}_k = \boldsymbol{x}_{k-d} \tag{13}$$

An h-step ahead predicted state $\bar{\boldsymbol{x}}_{k+h}$, with $h \in \mathbb{Z}^+$ being a design parameter, is computed using the discrete-time model of the plan [15] in order to counteract the delay

$$\bar{\boldsymbol{x}}_{k+h} = \boldsymbol{A}^h\tilde{\boldsymbol{x}}_k + \sum_{i=0}^{h-1}\boldsymbol{A}^{h-i-1}\boldsymbol{B}\boldsymbol{u}_{k+i-h} \tag{14}$$

where $\boldsymbol{x} \in \mathbb{R}^n$, $\boldsymbol{u} \in \mathbb{R}^m$, $\boldsymbol{A} \in \mathbb{R}^{n\times n}$ and $\boldsymbol{B} \in \mathbb{R}^{n\times m}$.

The proposed algorithm consists of applying the predictor to the Kalman measurement, i.e., $\tilde{\boldsymbol{x}}_k = \hat{\boldsymbol{x}}_k$. The resulting algorithm can be considered as a self-contained predictor-based observer, which is depicted in Fig. 2.

C. Simulations

Due to paper length restrictions and without loss of generality, only the roll axis of the quadrotor is considered in what follows. Therefore, the state of the plant is given by $\boldsymbol{x} = [\phi,\ \dot{\phi}]^T$ while the dynamic model is given by (3). Thus

$$\dot{\boldsymbol{x}} = \begin{bmatrix}0 & 1\\ 0 & 0\end{bmatrix}\boldsymbol{x} + \begin{bmatrix}0\\ 1\end{bmatrix}u \tag{15}$$

where $u = \tau_\phi$ represents the external torque in the roll axis. A zero-order hold discretization of (15) leads to

$$\boldsymbol{x}_{k+1} = \boldsymbol{A}\boldsymbol{x}_k + \boldsymbol{B}u_k \tag{16}$$

with

$$\boldsymbol{A} = \begin{bmatrix}1 & T\\ 0 & 1\end{bmatrix} \qquad \boldsymbol{B} = \begin{bmatrix}0\\ T\end{bmatrix} \tag{17}$$

The parameter h is chosen to be equal to the number of delayed sample periods d. In simulations, d is known, whereas in the experiments it has to be measured.

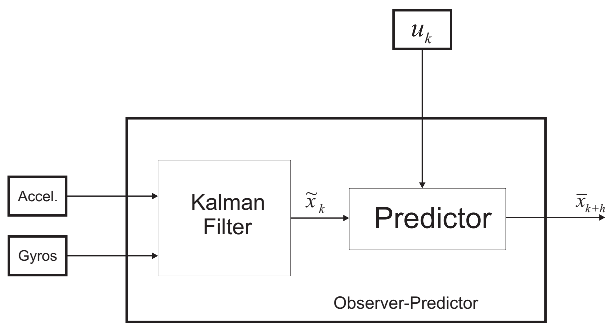

Figure 2. Observer-predictor scheme diagram

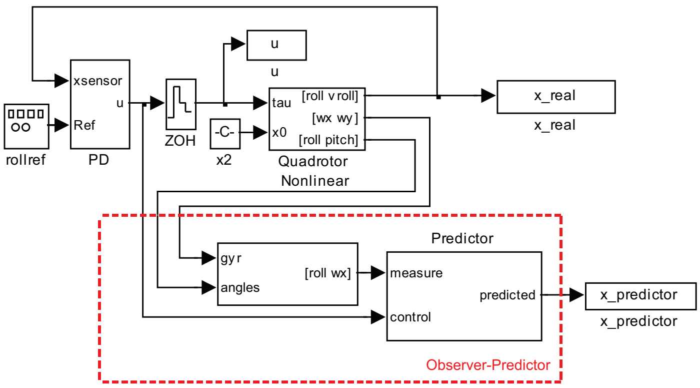

Figure 3. Simulink model

An h-step ahead prediction given by (14) is proposed to compensate the delay in the system. Simulations were carried out using the simulink model depicted in Fig. 3. The nonlinear quadrotor model in (2) is used to represent the plant. For the sake of simplicity, only references in the roll angle are applied while pitch and yaw are driven to zero using PD controllers. The predictor is applied to the estimation given by the Kalman filter. The results are shown in Fig. 4. Notice that in this figure the predictor algorithm improves the estimated value and compensates the delay.

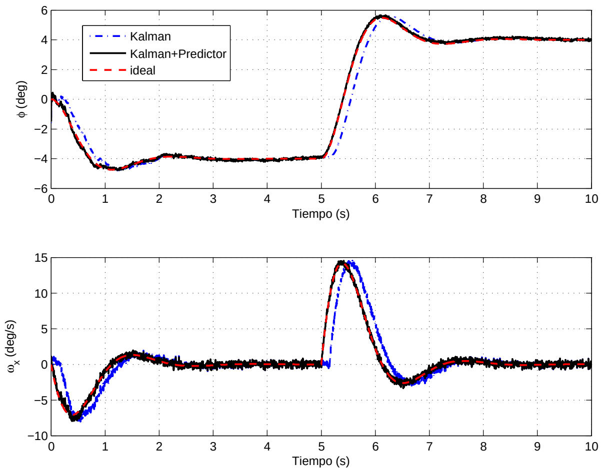

Figure 4. Simulated measurements

As aforementioned, a delayed measurement decreases the performance of a given controller. A simple state-feedback controller with reference tracking was used

$$u_k = [\phi_k^*,\, 0]^T - \boldsymbol{K}\boldsymbol{x}_k = k_p(\phi_k^* - \phi_k) - k_d\dot{\phi}_k \tag{18}$$

Fig. 5 shows the output of the closed-loop system and the control action when the different state measurements are fed to the controller. Notice how oscillations arise when the delayed measurement from the Kalman filter is used. However, the use of the predictor improves the performance substantially, and the response gets very close to that of the system when using a non-delayed measurement.

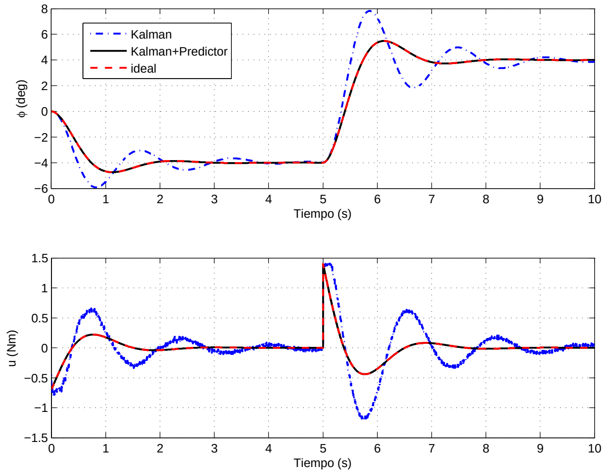

Figure 5. Simulated closed-loop response

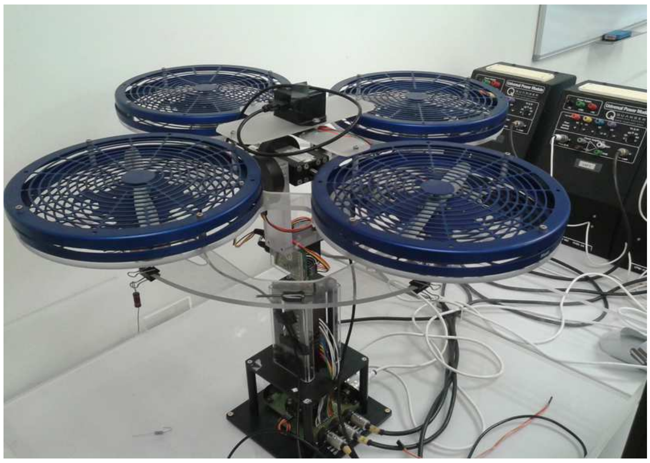

Figure 6. Experimental platform

IV. Experiments

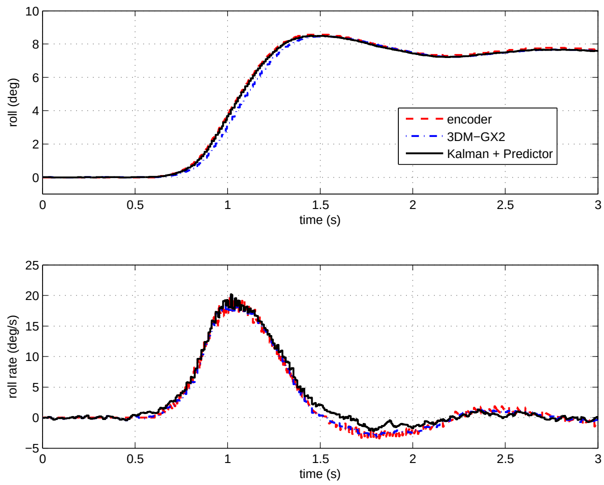

Figure 7. Experimental state measurements

Some experiments were carried out using the platform

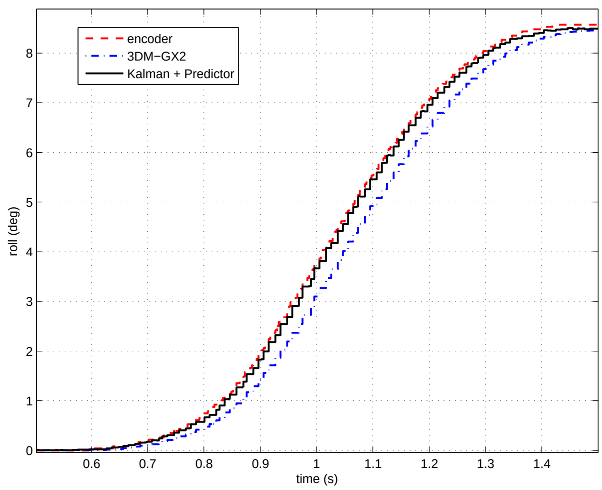

Figure 8. Delay of the 3DM-GX2, a commercial IMU

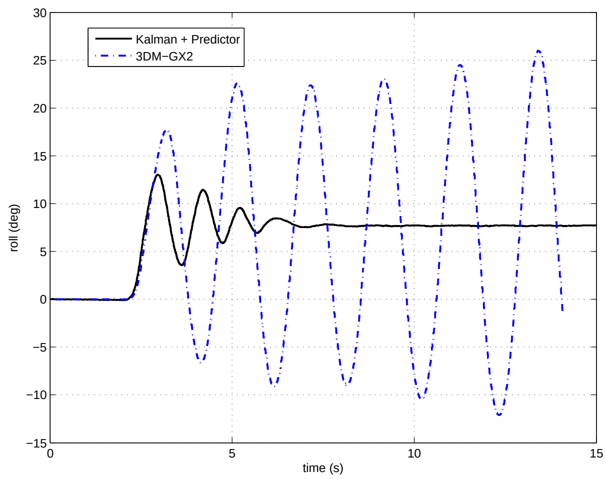

Figure 9. Experimental closed-loop response

shown in Fig. 6. It is thought of as a test bed platform of control algorithms for vertical lift off vehicles, so that the translational degrees of freedom are clamped for convenience. The orientation of the vehicle is measured by means of optical encoders with an accuracy of 0.04 deg. These encoders provide almost-true non-delayed angular measurements in three axis. The angular rate was computed offline from the encoder measurement by using central difference approximation and filtering. The same controller structure as in the simulations (18) was used for the experiments.

In order to illustrate the performance of the proposed algorithm, two experiments are carried out. First, the system is controlled via state feedback, according to (18), using the measurements coming from the 3DM-GX2. The different state estimations are shown in Fig. 7. A detail of the rising phase of the response can be seen in Fig. 8. The delay of the 3DM-GX2 is quantified as 40 ms, while the delay if the proposed OP-A is used is almost negligible.

In the second experiment, the benefits of using the measurement obtained with the OP-A are analyzed. For this purpose, the OP-A is implemented in real-time. The system is brought to marginal stability by increasing the gain of the controller, and a step reference of 8 deg is applied. The result is shown in Fig. 9. Notice that, for a given controller, the system becomes unstable when the measurement of the 3DM-GX2 is used. However, if the measurement obtained by the OP-A is used, the system remains stable.

V. Conclusion

A new attitude estimation approach for quadrotor vehicles based on an observer-predictor algorithm is presented in this paper. The scheme consists of a Kalman filter that estimates the desired states and an h-step ahead predictor that improves the estimated measurement. Several simulations were carried out to validate the proposed schema and some graphs were selected to illustrate its behavior. In addition, real-time validation was also carried out. Experimental results show that the proposed algorithm improves significantly the measurements of a commercial IMU. Finally, closed-loop experiments evidence the importance of having a non-delayed measurement in fast unstable system such as quadrotors. For a given state-feedback controller, the delayed measurements of the commercial IMU resulted in an unstable response while the measurements obtained with the proposed algorithm succeeded in stabilizing the system.

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