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A Multiplicative Filter for GLMAV Attitude Estimation

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***Abstract*— In this paper the authors investigate the problem of attitude estimation applied to the Gun Launched Micro Aerial Vehicle (GLMAV), using low cost sensors. The main contribution of the paper consists in the design of a sliding window filter for quaternion estimation. The proposed approach is considered in an EKF framework in order to ensure a better robustness to external perturbations. Finally, high performances of the filter are shown through numerical simulations.**

NOMENCLATURE

Notations

A^T	=	Transpose of matrix A
A^{-1}	=	Inverse of matrix A
I_r	=	Identity matrix of dimension r
x	=	State vector
$E(x)$	=	Expectation of x
$\hat{x}$	=	Estimate of x
$\tilde{x}$	=	Estimation error of x, $\tilde{x} = x - \hat{x}$
y	=	Measurements vector
$f(x_k)$	=	Discrete nonlinear states dynamic map
$h(x_k)$	=	Discrete nonlinear measurement model
$\mathbf{a}$	=	A three elements vector
$\times$	=	is the cross product
$\otimes$	=	is the quaternion product

$$\text{diag}[a_1\ a_2\ \dots\ a_k] = \begin{bmatrix} a_1 & 0 & 0 & 0 \\ 0 & a_2 & 0 & 0 \\ 0 & 0 & \ddots & 0 \\ 0 & 0 & 0 & a_k \end{bmatrix}$$

$$tr(A) = \text{Trace of the matrix A, } tr(A) = \sum_{i=1}^{n} a_{ii}$$

I. INTRODUCTION

In this paper the authors propose a filtering method for attitude estimation applied to the Gun Launched Micro Aerial Vehicle (GLMAV) concept, using low-cost sensors. The GLMAV is a new concept of Micro Aerial Vehicle (MAV) which uses the energy delivered by a gun, in order to go quickly onto the scene to be observed [1] (see Fig 1).

The behavior of the system is composed by distinct phases (see Fig 2). First, the MAV is packed in a projectile shell and launched by a 80 mm gun (ballistic flight). After, the deployment of the two rotors is quickly performed and then the observation mission can begin. The final phase is the landing of the vehicle. Since the beginning of the project some results were obtained especially concerning the modeling and identification of the deployed model [2], [3], in order to design control laws for the hover flight phase.

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Fig. 1. GLMAV concept

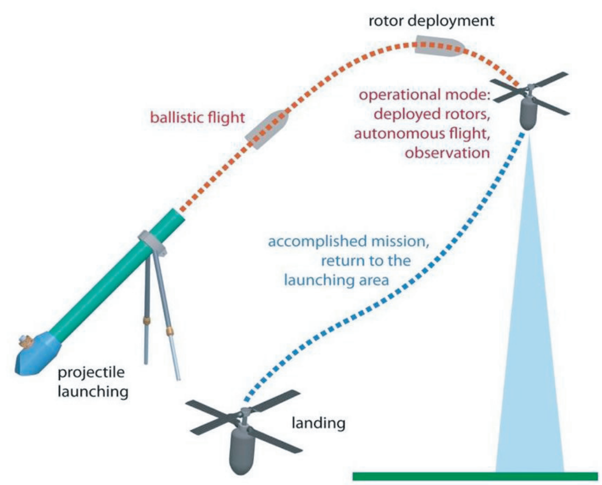

Fig. 2. GLMAV sequences

The control of the GLMAV (deployment signal / attitude correction) requires the knowledge of the attitude information (angular position of the body frame from the inertial frame). Since the years 1960 the problem of attitude estimation from embedded sensors is central for the control of satellites, aircrafts, etc. An overview of the current methods is available in [4]. If vector measurements only are considered, the problem of attitude estimation is known as the Wabha problem [5]. Numerous direct methods have been almost immediately proposed to solve it [6]. Unfortunately, those methods cannot be applicable for the considered problem for two main reasons:

- usually, it involves a loss function minimized by an

iterative algorithm (Gauss Newton, least squares, etc.), and so is incompatible with real-time constraints;
- if less than two vectors are available and without other informations, the problem becomes unsolvable.

Naturally, many Extended Kalman Filter (EKF) based methods were proposed, because the EKF is usually the first approach used to deal with a non-linear estimation problem. Psiaki published an EKF based approach [7] in which only magnetometers are used, but a good modeling of the moments is required to obtain a good estimate. Some others classical methods based on the same famous filter can be found in [8], [9], [10] and they usually work well without perturbations and with a good initialization. Thus, if the initialization error is large or in presence of high disturbances, the filters (like the EKF) can diverge.

In the GLMAV case, the problem is complex. Usually, vector sensors (accelerometers, magnetometers,...etc) can be used coupled to rate-integrating gyros and/or GPS sensor. During the launch phase, and due to the high accelerations applied to the body, accelerometers cannot be used for attitude estimation, nor the GPS, because of the initializing time of such a device. Another problem is the fact that when the electrical motors are used (during the hover flight), the generated magnetic field may disturb the magnetometers measurements. So the problem is the following:

- Considering the multiple dynamic models (including an uncertain one for the deployment phase) and using only magnetometers, gyros and accelerometers, how to estimate the attitude from the ballistic flight (the shot) until the end of the mission?

An attractive approach is the Multiplicative Extended Kalman Filter (MEKF) [9], where no torque model is required and the attitude is parametrized by a quaternion. This choice is motivated by the fact that an attitude quaternion does not present any singularity, and so can represent all angular positions of a rigid body. Nevertheless, quaternion estimation is not easy since the quaternion needs to be unity, so the norm of its components must be equal to one. This constraint is equivalent to estimate an orthogonal attitude matrix. By a mathematical point of view, it is a non-linear estimation problem subject to a non linear constraint, which cannot be properly treated by an EKF. If this kind of filter is directly applied to the system, the "unity" constraint is relaxed, and the filter can easily diverge (even if a "brute force" normalization is performed at each time step). The MEKF is particularly designed to overcome those constraints and moreover presents some advantages:

- the unity quaternion is intrinsically preserved, a normalization may be used but only in order to eliminate the accumulated numerical errors;
- the order of the system is reduced because only three elements are estimated against four if the EKF is directly applied;

Nevertheless, this approach suffers of the same drawbacks than the EKF. It may diverge if the initialization errors are large and / or when high disturbances appears during the using of it. This paper is especially dedicated to improve the MEKF from this point of view, by using a Sliding Window Multiplicative Extended Kalman Filter (SWEKF). The main idea is to take account of a sliding window of the N previous measurement in order to obtain a better estimate of the next state (in opposition to the classical case where only one measurement). A formulation of this filter for parameters identification has ever shown its good performances when it is applied to magnetometers calibration [11] or aerodynamical coefficients and disturbances [3] estimation. A more general formulation of the filter is provided here, where non linearities are considered both in state dynamics and measurements equations. The proposed approach combine the advantages of the MEKF and the SWEKF because it does not requires the GLMAV torque modeling and is more robust to the disturbances, especially during the transitional step (rotors deployment).

The paper is organized as follow, the first section presents the proposed filter, then the second section describes the system modeling including the quaternions kinematics and the considered sensors. The third part presents the application of the filter to the attitude estimation problem. Finally, the last section presents the numerical results, where the advantages of the proposed approach are shown through the simulations.

II. Filter Synthesis

A. Structure of the Filter in General Case

The main contribution of the paper is a sliding window based estimator. The main drawback of the EKF in its traditional form is the high sensitivity to initial conditions and noisy signals, especially if the noise is not white and gaussian. As an answer to this problem, the authors propose a new formulation of the EKF which uses a sliding window of previous measurements in order to improve the stability and robustness to noise and disturbances of the filter. The proposed approach must not be seen as a smoother filter even if the formulation seems to be similar. The main difference is that this filter does not estimate an increased state vector, nor uses future measurements to estimate past states. The approach could be seen as a filter which takes advantage of past informations to obtain the best estimate as possible and eventually enlarge its basin of attraction.

Consider the general form of a stochastic nonlinear discrete time system:

$$\begin{cases} x_{k+1} = f(x_k) + w_k \\ \\ y_k = h(x_k) + v_k \end{cases} \quad (1)$$

$x_k \in \mathbb{R}^n$ and $y_k \in \mathbb{R}^p$ denote the state and output vectors at time instant k, respectively. The nonlinear maps $f(x_k)$ and $h(x_k)$ are assumed to be continuously differentiable with respect to x_k. The proposed state estimator is given by:

$$\hat{x}_{k+1} = f(\hat{x}_k) + K_k \begin{pmatrix} y_k - h(\hat{x}_k) \\ y_{k-1} - h(\hat{x}_{k-1}) \\ \vdots \\ y_{k-N+1} - h(\hat{x}_{k-N+1}) \end{pmatrix} \quad (2)$$

First, the state error is defined as:

$$\tilde{x}_{k+1} = x_{k+1} - \hat{x}_{k+1} \tag{3}$$

and the output error as

$$\tilde{y}_k = \begin{pmatrix} y_k - h(\hat{x}_k) \\ y_{k-1} - h(\hat{x}_{k-1}) \\ \vdots \\ y_{k-N+1} - h(\hat{x}_{k-N+1}) \end{pmatrix} \tag{4}$$

B. Synthesis of the Gain K_k

Now, the considered state error covariance matrix is:

$$P_k^k = E(\tilde{x}_k \tilde{x}_k^T) \tag{5}$$

Classically, the following approximations are considered:

$$f(x_k) - f(\hat{x}_k) \simeq A_k \tilde{x}_k \tag{6}$$
$$h(x_k) - h(\hat{x}_k) \simeq C_k \tilde{x}_k \tag{7}$$

where

$$A_k = \frac{\partial f}{\partial x_k}(\hat{x}_k)\ ,\ C_k = \frac{\partial h}{\partial x_k}(\hat{x}_k)$$

and

$$E(w_k) \ = \ E(v_k) = 0 \tag{8}$$

P_{k+1}^{k+1} is developed to obtain

$$\begin{aligned} P_{k+1}^{k+1} = {} & A_k P_k^k A_k^T + K_k H_k \bar{P}_k H_k^T K_k^T \\ & - A_k [P_k^k \ P_k^{k-1} \ \cdots \ P_k^{k-N+1}] H_k^T K_k^T \\ & - K_k H_k \begin{pmatrix} P_k^k \\ P_{k-1}^k \\ \vdots \\ P_{k-N+1}^k \end{pmatrix} A_k^T + K_k R K_k^T + Q \end{aligned} \tag{9}$$

where Q and R are the process and measurements noise covariance matrices respectively:

$$Q = E(w_k w_k^T) \quad \text{and} \quad R = E(v_k v_k^T) \tag{10}$$

where H_k is defined as the observation matrix:

$$H_k = \begin{pmatrix} C_k(\hat{x}_k) & & 0 \\ & \ddots & \\ 0 & & C_k(\hat{x}_{k-N+1}) \end{pmatrix} \tag{11}$$

In (9), the global error covariance matrix $\bar{P}_k$ is introduced:

$$\bar{P}_k = \begin{pmatrix} P_k^k & P_k^{k-1} & \cdots & P_k^{k-N+1} \\ P_{k-1}^k & P_{k-1}^{k-1} & & \\ \vdots & & \ddots & \vdots \\ P_{k-N+1}^k & & \cdots & P_{k-N+1}^{k-N+1} \end{pmatrix} \tag{12}$$

where each element is computed by:

$$P_{k+1}^{k-i} = E(\tilde{x}_{k+1} \tilde{x}_{k-i}^T) \tag{13}$$

$$P_{k+1}^{k-i} = A_k P_k^{k-i} - K_k H_k \begin{pmatrix} P_k^{k-i} \\ P_{k-1}^{k-i} \\ \vdots \\ P_{k-N+1}^{k-i} \end{pmatrix} \tag{14}$$

Now, the gain K_k must be defined such that it minimizes the trace of the matrix P_{k+1}^{k+1}:

$$\frac{\partial \text{tr}(P_{k+1}^{k+1})}{\partial K_k} = 0 \tag{15}$$

After simplification, the following gain matrix K_k (satisfying (15)) is obtained:

$$K_k = A_k \Big[P_k^k \ P_k^{k-1} \ \cdots \ P_k^{k-N+1} \Big] H_k^T \Big(H_k \bar{P}_k H_k^T + R \Big)^{-1} \tag{16}$$

The initialization of the proposed filter is given by the standard EKF i.e.:

$$\hat{x}_{k+1} = f(\hat{x}_k) + \bar{K}_k (y_k - h(\hat{x}_k)), \quad \text{for} \quad k = 0, ..., N$$

where $\bar{K}_k$ is given by:

$$\bar{K}_k = A_k S_k C_k^T (C_k S_k C_k^T + R)^{-1}$$

S_k is the state error covariance matrix of the EKF, it is used to compute each diagonal element of the initial error covariance matrix $\bar{P}_0$ as:

$$S_{k+1} = A_k S_k A_k^T - \bar{K}_k C_k S_k A_k^T + Q \tag{17}$$
$$= A_k \left(S_k^{-1} + C_k^T R^{-1} C_k \right)^{-1} A_k^T + Q \tag{18}$$

and

$$\bar{P}_0 = \begin{pmatrix} S_N & 0 & . & 0 \\ 0 & S_{N-1} & . & 0 \\ . & . & . & . \\ 0 & 0 & . & S_0 \end{pmatrix}$$

The use of a sliding window of measurements introduces the matrix $\bar{P}_{k+1}$ and its elements, and so the computation of K_{k+1} is different from that of the classical EKF. Thus the new estimator formulation takes account of the previous measurements. Therefore, the user do not have to compute all the matrix $\bar{P}_k$, but only the first raw - column of it. Thanks to this particularity of the algorithm, very few more computations are required.

III. System Modeling

A. Attitude Kinematics

A widely used tool to model the attitude of a rigid body is the quaternion representation [13], [14]. The main advantage is the fact that every orientations can be represented. The quaternion kinematics are given by:

$$\dot{q} = \frac{1}{2} \Omega(\boldsymbol{\omega}) \otimes q \tag{19}$$

where:

$$\Omega(\boldsymbol{\omega}) = \begin{bmatrix} -[\boldsymbol{\omega}\times] & \boldsymbol{\omega} \\ -\boldsymbol{\omega}^T & 0 \end{bmatrix} \quad (20)$$

Remark 1: A major interest of this formulation is the fact that if the angular velocity is perfectly known, the dynamic becomes LPV (Linear Parameters Variant).

B. Sensors modeling

The considered sensors are a triad of accelerometers, a triad of magnetometers and a triad of rate-integrating gyros, all mounted orthogonally.

• The *accelerometers* are known to measure a specific force, moreover, they are considered as "vector" sensor under the following assumption:

Assumption 1:

$$\|\boldsymbol{\gamma}\| \ll \|\mathbf{g}\| \quad (21)$$

Where $\boldsymbol{\gamma}$ is the acceleration applied to the center of mass of the body and $\mathbf{g}$ is the gravity vector.

• The *magnetometers* are used like the accelerometers under the previous assumption. The magnetic field is assumed to be known in the inertial frame and its projections are measured on board by a TAM (Three Axis Magnetometer). Those "vector" sensors can be summarized at the time instant k, as :

$$y_{vk} = \begin{bmatrix} \mathbf{A}_k(\underline{q})\mathbf{r}_1 \\ \mathbf{A}_k(\underline{q})\mathbf{r}_2 \\ \vdots \\ \mathbf{A}_k(\underline{q})\mathbf{r}_M \end{bmatrix} + v_{vk} \quad (22)$$

Where M is the number of considered sensors and $\mathbf{r}_i$ the reference vector (in the inertial frame). v_{vk} is the measurement noise and is assumed to be zero mean and gaussian.

• The *rate-integrating gyros* considered model is given by :

$$y_{gk} = \boldsymbol{\omega} + \boldsymbol{\beta} + v_{gk} \quad (23)$$

Where $\boldsymbol{\omega}$ is the angular rate, defined as $\boldsymbol{\omega} = [p\ q\ r]^T$. $\boldsymbol{\beta}$ is a constant bias and v_{bk} is the measurement noise and is assumed to be zero mean and gaussian.

The complete output is finally given by $y_k = \begin{bmatrix} y_{vk} \\ y_{gk} \end{bmatrix}$

IV. Application of the Filter

A. Dynamic Model

The Kalman filter is widely used in the aeronautic field since a long time. For the specific problem of attitude estimation, a lot of Kalman based filter exist [9], [15], [16]. The approach presented here is generic and so it can be applied to all of them. In this paper, the choice is oriented to the multiplicative filter where the "real" attitude quaternion is represented by a quaternion product between a reference quaternion and an error. The main advantage of this representation is the fact that the error quaternion can be parametrized by a three vector since the error angle is "small". The choice of representation is discussed in [17]. The decomposition of the attitude quaternion is given by:

$$\underline{q} = \delta\underline{q}(\delta\mathbf{p}) \otimes \hat{\underline{q}}_{ref} \quad (24)$$

with

$$\delta\underline{q} \equiv [\delta\mathbf{q}^T\ \delta q_4]^T$$

A standard formulation which allows to obtain the three-vector error quaternion $\delta\mathbf{p}$ from the four-vector error quaternion $\delta\underline{q}$ (and vice versa) is given in [18], and the choice of the "error quaternion" is discussed in details in [17]. In this paper the Gibbs vector is preferred for a better numerical robustness, nevertheless some other useful representations are available in [17] and the choice is discussed. The Gibbs vector is given by:

$$\delta\mathbf{p} \equiv \frac{\delta\mathbf{q}}{\delta q_4} \quad (25)$$

According to [17], a first order approximation of the three-vector error kinematics is given, which leads to the discrete time jacobian matrix A_k:

$$A_k = \begin{bmatrix} I_{3\times3} - \triangle t\boldsymbol{\omega}\times & -\triangle t I_{3\times3} \\ 0 & I_{3\times3} \end{bmatrix} \quad (26)$$

Where $\triangle t$ is the sample time, using an Euler discretization method, for the following state vector: $\begin{bmatrix} \delta\mathbf{p} \\ \boldsymbol{\beta}_k \end{bmatrix}$.

Remark 2: Other discretization methods can be used like in [18], but a simple method is preferred here for a better simplicity. It should be notice that this is not a restrictive choice and it does not affect the filter design.

B. Sensors Output

The magnetometers and accelerometers output need to be reformulated in function of the state vector:

$$y_{vk} = \begin{bmatrix} \mathbf{A}(\delta\underline{q})\mathbf{A}(\hat{\underline{q}}_{ref})\mathbf{r}_1 \\ \mathbf{A}(\delta\underline{q})\mathbf{A}(\hat{\underline{q}}_{ref})\mathbf{r}_2 \\ \vdots \\ \mathbf{A}(\delta\underline{q})\mathbf{A}(\hat{\underline{q}}_{ref})\mathbf{r}_M \end{bmatrix} + v_{vk} \quad (27)$$

After some calculus, the complete output is expressed as:

$$y_k = \begin{bmatrix} \mathbf{v}_{1k} \\ \mathbf{v}_{2k} \\ \vdots \\ \mathbf{v}_{Mk} \\ \boldsymbol{\omega}+\boldsymbol{\beta} \end{bmatrix} = \begin{bmatrix} (I_{3\times3} - [\delta\mathbf{p}_k\times])\mathbf{b}_{1k} \\ (I_{3\times3} - [\delta\mathbf{p}_k\times])\mathbf{b}_{2k} \\ \vdots \\ (I_{3\times3} - [\delta\mathbf{p}_k\times])\mathbf{b}_{Mk} \\ \boldsymbol{\omega}+\boldsymbol{\beta} \end{bmatrix} + v_k \quad (28)$$

Where $\mathbf{b}_{ik} = \mathbf{A}(\hat{\underline{q}}_{ref})\mathbf{r}_{ik}$

The discrete time jacobian marix C_k is given by:

$$C_k = \begin{bmatrix} \mathbf{v}_{1k}\times & 0_{3\times3} \\ \mathbf{v}_{2k}\times & 0_{3\times3} \\ \vdots & \\ 0_{3\times3} & 0_{3\times3} \end{bmatrix} + v_k \quad (29)$$

Finally, the following algorithm resume the filtering method where $\underline{\hat{q}}_{ref}$ is referred in the algorithm as $\hat{\underline{q}}_{k+1}(-)$ and is the previously estimated quaternion:

Initialization;
$\hat{\underline{q}}_0(+) \leftarrow \hat{\psi}_0, \hat{\theta}_0, \hat{\phi}_0$;
$\hat{x}_0 \leftarrow$ *initial state*;
where $\delta\hat{\mathbf{p}}_1 \leftarrow [0\ 0\ 0]^T$;
for $k \leftarrow 0$ **to** *end* **do**

Quaternion evolution
$\hat{\boldsymbol{\omega}}_k = y_{gk} - \hat{\boldsymbol{\beta}}_k$
$\hat{\underline{q}}_{k+1}(-) = f(\hat{\underline{q}}_k(+),\ \hat{\boldsymbol{\omega}}_k)$

Update of the previously estimated quaternion
$$\rho = \begin{bmatrix} \frac{\delta\hat{\mathbf{p}}_{k+1}}{2} \end{bmatrix} \otimes \hat{\underline{q}}_{k+1}(-)$$
$\hat{\underline{q}}_{k+1}(+) = \rho/|\rho|$

Reset of the error quaternion
$\delta\hat{\mathbf{p}}_{k+1} \leftarrow 0$

Estimation
$$K_k = F_k[P_k^k\ P_k^{k-1}\ \cdots\ P_k^{k-N+1}]\bar{H}_k^T(\bar{H}_k\bar{P}_k\bar{H}_k^T + R)^{-1}$$
$$\hat{x}_{k+1} = f(\hat{x}_k) + K_k \begin{pmatrix} y_k - h(\hat{x}_k,) \\ y_{k-1} - h(\hat{x}_{k-1}) \\ \vdots \\ y_{k-N+1} - h(\hat{x}_{k-N+1}) \end{pmatrix}$$

Incrementation
$\hat{x}_k = \hat{x}_{k+1}$
$\hat{\underline{q}}_k(+) = \hat{\underline{q}}_{k+1}(+)$
$\bar{P}_k = \bar{P}_{k+1}$

end

Algorithm 1: SW-MEKF

Remark 3: The reset step is required because of the update step, the complete explication is provided in [17].

V. Numerical Simulations

A. System description

The numerical simulations considers the complete "switched" model of the GLMAV, where a projectile model [19][20] is first used (the Fig. 3 shows the trajectory taken by the GLMAV) and then the coaxial bi-rotor model is used [21]. When the switching signal is send, a mechanical system deploy the rotors and place the MAV almost vertically in order to do the hover flight. Then an observer based control law [1] is applied in order to stabilize the MAV but this part will be treated in a future paper.

Usually, attitude estimation is more difficult when the body is spinning. In practice, a classical EKF may diverges, so the sliding window is particularly useful for those reasons. It should be noticed that during the launch phase, magnetometers are used instead of the accelerometers, because the acceleration due to the shot makes the assumption (21) false. After the deployment phase, the accelerometers are considered for the attitude estimation instead of the magnetometers, because the latter may be disturbed by the embedded electrical motors. The proposed filter is compared to the classical MEKF formulation from the shot until the hover flight phase.

[1]The GPS receiver cannot be used during the launch step, but is coupled with the observation algorithm during the hover flight

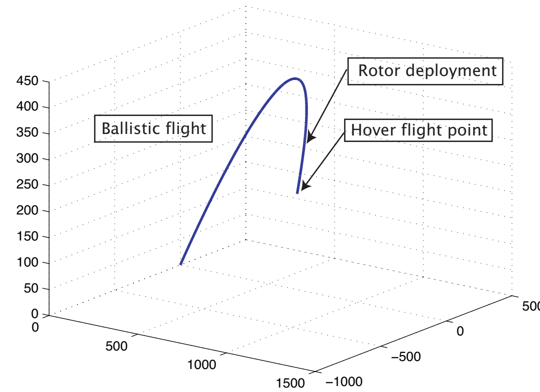

Fig. 3. Trajectory (m)

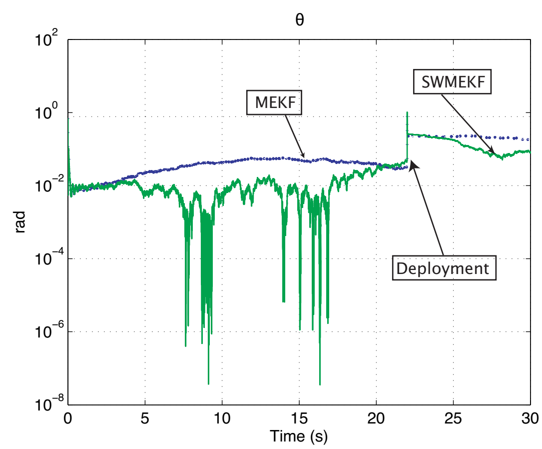

Fig. 4. Estimation error $\|\tilde{\theta}\|_2$ (semi-log)

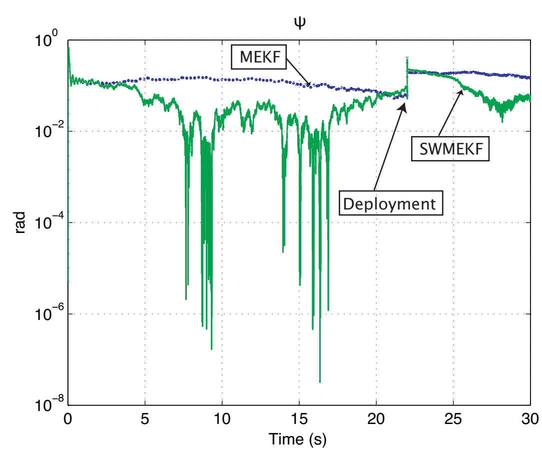

Fig. 5. Estimation error $\|\tilde{\psi}\|_2$ (semi-log)

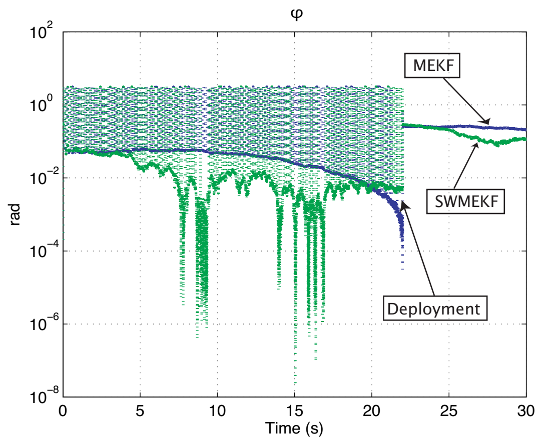

Fig. 6. Estimation error $\|\tilde{\phi}\|_2$ (semi-log)

B. Comments

The EKF is known to be difficult to tune, so to efficiently compare the two methods, the parameters of the filters are the same. The added bias is $\boldsymbol{\beta} = [2\ 0.5\ -0.5]^T$ expressed in rad/s, and the added noise is centered around 0 and represents 10% of the signal amplitude (on the gyros, magnetometers and accelerometers). The matrix R is adapted to the noise, the matrix Q is chosen as: $Q = 10^{-5} I_6$, and $S_0 = 10^3 I_6$. The yaw (ψ), pitch (θ) and roll (ϕ) angle presented here and not directly the quaternion in order to obtain a physical representation of the attitude. The GLMAV is launched at an initial linear velocity of 120 m/s, and with a spin rate of 60 rad/s to stabilize it in the atmosphere. It is obvious on the Figs. 4, 5 and 6 that the proposed approach (referred as the SWMEKF on the figures) presents better performances than the classical MEKF. The chosen size of the window is $N = 10$. The estimated error ($\tilde{\boldsymbol{\beta}} = |\boldsymbol{\beta} - \hat{\boldsymbol{\beta}}|$) biases are provided in the following table:

	MEKF	SWMEKF
$\tilde{\boldsymbol{\beta}}_1$	0.0268	0.0165
$\tilde{\boldsymbol{\beta}}_2$	0.007	0.006
$\tilde{\boldsymbol{\beta}}_3$	0.0022	0.0013

Where we can see the better accuracy of the proposed approach in the bias identification also.

VI. Conclusion & Future work

This paper presented a generic algorithm for the GLMAV attitude estimation using low cost sensors. The proposed method is designed in an MEKF framework and improve the robustness / accuracy of the latter by the using of a sliding window of measurements. Because of the lack of space, the local stability analysis (in the sense of Lyapunov) is omitted but will be added in an extended version. Finally the simulation results show the good performances of the proposed approach when they are compared to the classical approach.

Now our future work will focus on the design of the GLMAV control laws. The goal is to accomplish an observation mission, so the MAV must be able to follow a trajectory defined by the user, and ideally to land to a definite place in order to be reused later. Finally, a demonstrator will be realized to show the feasibility of the concept.

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