Vision-Aided Complementary Filter for Attitude and Position Estimation: Design, Analysis and Experimental Validation

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Abstract: This paper presents a navigation system based on Kalman complementary filtering for position and attitude estimation, with an application for Unmanned Air Vehicles (UAVs), in denied Global Positioning System (GPS) areas. Using inertial measurements, vector observations and landmarks positioning, the proposed complementary filters provide attitude estimates resorting to Euler angles representation and position estimates relative to a fixed inertial frame, while compensating for rate gyro and velocity biases using a gyroscope noise and velocity bias models. Stability and performance properties for the operating conditions are derived and the procedure on how to tune the parameters of the filters in the frequency domain is emphasized. Requirements on low computational burden were a priority in both the vision algorithm and navigation system, making it suitable for off-the-shelf hardware. Experimental results obtained in real time with an implementation of the proposed algorithm running on a laptop communicating with an AR.Drone 2.0 via Wi-Fi are presented and discussed.

Keywords: Kalman Filter, UAV, Navigation Systems, Vision Sensors, Stability, Lyapunov

1. INTRODUCTION

Nowadays, the technological development and interest in low-cost UAVs have been on the rise in both civilian and military aviation sectors to accomplish different missions such as coastal surveillance operations, rescue, monitoring, security and inspection (see Mohamed et al. (2018)).

In regular UAVs, Micro Electro Mechanical Systems (MEMS) are employed, which are low-cost and low-power consumption sensors, for the Inertial Navigation Systems (INS). Compared with high-end sensors like active ring-laser and interferometric fiber-optic sensor (P. Crain et al. (2010)), MEMS suffer from strong non-linearities such as bias and noise that degrade the accuracy of the estimates. To improve the performance and robustness of MEMS based INS, sensor fusion with an appropriate model are required to achieve a better attitude and position estimation and tracking. To achieve optimal results with proved stability, Kalman filters (KFs) are the workhorse to fuse inertial measurement unit (IMU) and GPS measurements. One of the main limitations of the GPS-aided INS configuration is GPS denied environments (e.g. indoors, underground, underwater, in space, etc). In some cases, Visual-Aided INS can provide precise state estimates replacing the GPS.

This paper focuses on the development of a Visual-Aided landmark positioning system aided IMU using complementary filters on-board of an AR.Drone 2.0. An innovative method is proposed by using color feature recognition for landmark tracking to compute position and attitude relative to a target via the algebraic Robust O(a) solution to the Perspective-n-Point (RPnP) from Li et al. (2012). The obtained measurements are fused with the MEMS sensor outputs and with the Optical Flow (OF) velocity from the UAV. The problem of accurate position and attitude is addressed by exploiting the different range of relevant frequency regions presented in each measurement.

The choice of filter’s type in INS ranges from classical methodologies to recently proposed approaches. In the classical approach, KF is applied in real-time applications to fuse data from different sensors in an optimal way. The idea is to get independent and redundant information about navigation states, with the requisite of having a prior information about the covariance values of both INS and position sensor as well statistical properties of each sensor system, see Gelb (1974). Extended Kalman Filter (EKF) is a nonlinear filtering technique where a linearization occurs each time to get Kalman gains. However, the linearization implicit leads to performance degradation or even filter divergence if the assumption of local linearity is violated (Maybeck (1994)). In Crassidis et al. (2007) and Mahony et al. (2008) a number of other alternative techniques are introduced, namely Unscented Kalman Filters (UKF), Particle Filters (PF), Adaptive Methods and Nonlinear Observers.

The INS in this paper is designed to be easily implemented in a low-cost, low-power consumption hardware architecture. Therefore, high computation cost filters like EKF, UKF and PF were out of the equation. The complementary Kalman filters proposed in this work are time-varying, although the gains are computed offline using an auxiliary linear time-invariant (LTI) design system that by means of a Lyapunov transformation becomes the proposed filter (see Vasconcelos et al. (2011)). The main contribution of this paper is the real time INS performance validation onboard of an AR.Drone 2.0.

This paper is organized as follows. Section 2 presents the deduction of the complementary filters and their stability and performance properties are discussed. Section 3 shows the implementation of the INS using both attitude and position filters combined. Filter observations based on IMU and vision sensors are discussed. In Section 4 the INS experimental results on-board of an AR.Drone 2.0 are shown and its performance analyzed. Concluding remarks and future work are pointed out in Section 5.
2. ATTITUDE AND POSITION COMPLEMENTARY FILTERS

In this section, complementary filters for attitude and position are proposed and their performance and stability is proven. The attitude filter is design making use of the angular velocity Allan Variance to model its noise and a vector of measurements computed from accelerometer data. The position filter is designed in the frequency domain using the OF’s velocity as input and position measurement from a landmark.

2.1 Attitude Filter

**Gyroscope Noise Model.** According to Unver (2013), the most predominant noises in a MEMS gyroscope are the angle random walk (ARW), bias instability (BI) and rate random walk (RRW). For more information about gyro’s noises and how they can be modelled, please refer to Petkov and Slavov (2010).

ARW is a high-frequency noise modelled as a zero-mean white noise (WN) with an approximated variance:

\[
\sigma_{\text{arw}}^2 = \frac{N^2}{\Delta t}
\]

where \( \Delta t \) is the sampling time interval and \( N \) is the ARW parameter from the Allan Deviation (AD) plot.

BI has an impact on long term stability and can be approximated by a Markov process (Petkov and Slavov (2010)), with a process standard deviation proportional to the AD parameter \( B \). The discrete time of \( \eta_k \) at time \( k \) subject to the sample-and-hold method is given by:

\[
b_{\omega, k+1} = \left( 1 - \frac{1}{T} \Delta t \right) b_{\omega, k} + \eta_k
\]

where \( k \) is the index of time \( t = k \Delta t, \) \( \eta_k \) is a random process, \( T \) corresponds to the correlation time of BI and \( \eta_k \) a driven zero-mean WN with variance \( \sigma_\eta^2 = \sigma_\eta^2 (1 - e^{-2\Delta t/T}) \), where \( \sigma_\eta^2 = \frac{\lambda B}{2\pi} \ln(2) \) is the variance of BI. \( T \) can be obtained from AD plot around the BI region.

RRW occurs whenever a zero-mean WN is integrated over time. The discrete time of \( b_{\omega} \) at time \( k \) subject to sample-and-hold method, is given by:

\[
b_{\omega, k+1} = b_{\omega, k} + \eta_k
\]

where \( \eta_k \) is a zero-mean WN with variance \( \sigma_\eta^2 = \Delta t K^2 \) and \( K \) is the RRW parameter from AD plot.

In line with the previously described noises formulations, the gyro noise model is given in discrete state-space form as:

\[
b_{\omega, k+1} = \begin{bmatrix} 1 - \frac{1}{T} \Delta t & 0 \\ 0 & 1 \end{bmatrix} b_{\omega, k} + \begin{bmatrix} \frac{\lambda B}{2\pi} \ln(2) \sqrt{K^2 \Delta t} \\ 0 \end{bmatrix} \eta_k
\]

\[
y_k = \begin{bmatrix} 1 & 0 \end{bmatrix} \begin{bmatrix} b_{\omega, k} \\ \eta_k \end{bmatrix} + \begin{bmatrix} \sqrt{\frac{\lambda B}{2\pi} \ln(2)} \sqrt{K^2 \Delta t} \end{bmatrix} \xi_k
\]

where \( y_k \) and \( \xi_k \) are normally distributed zero-mean WNs.

**Filter.** Let \( \lambda = [\psi \ \theta \ \phi]^T \) be the vector containing the true Euler angles yaw, pitch and roll, respectively. Euler angles kinematics is given by:

\[
\lambda = Q(\lambda) \omega, \quad Q(\lambda) = \begin{bmatrix} 0 & \sin(\phi) \sec(\theta) & \cos(\phi) \sec(\theta) \\ 0 & \cos(\phi) & -\sin(\phi) \\ 1 & \sin(\phi) \tan(\theta) & \cos(\phi) \tan(\theta) \end{bmatrix}
\]

where \( \omega = [\dot{\psi} \ \dot{\theta} \ \dot{\phi}]^T \) is the true angular velocity in the body frame. The discrete-time equivalent system of (5), resorting to the step invariant method, is:

\[
\lambda_{k+1} = \lambda_k + \Delta t Q(\lambda_k) \omega_k
\]

The angular velocity is measured by the gyroscope subjected to noise is given by:

\[
\omega = \tilde{\omega}_k + y_k
\]

where \( \tilde{\omega}_k \) represents the value of angular velocities and \( y_k \) the output of the noise model (4) for each velocity. Rewriting the kinematic of Euler angles (6-7) in state space form yields:

\[
\begin{bmatrix} \lambda \\ b_{\omega, 1} \\ b_{\omega, 2} \end{bmatrix}_{k+1} = \begin{bmatrix} I & -\Delta t Q(\lambda_k) & -\Delta t Q(\lambda_k) \\ 0 & I & -\Delta T^{-1} \\ 0 & 0 & I \end{bmatrix} \begin{bmatrix} \lambda \\ b_{\omega, 1} \\ b_{\omega, 2} \end{bmatrix}_k + \begin{bmatrix} \Delta t Q(\lambda_k) \\ 0 \\ 0 \end{bmatrix} y_k
\]

\[
y_k = \begin{bmatrix} I & 0 \\ 0 & I \end{bmatrix}^T \begin{bmatrix} b_{\omega, 1} \\ b_{\omega, 2} \end{bmatrix}_k + \Theta_k
\]

where \( b_{\omega, 1} \) and \( b_{\omega, 2} \) are sensor bias vectors correspondent to the angular velocities \( \omega \). Considering the following nonlinear feedback system of (8), as the proposed attitude filter, depicted in Fig. 1:

\[
\begin{bmatrix} \lambda \\ b_{\omega, 1} \\ b_{\omega, 2} \end{bmatrix}_{k+1} = \begin{bmatrix} I & -\Delta t Q(\lambda_k) -\Delta t Q(\lambda_k) \\ 0 & I & -\Delta T^{-1} \\ 0 & 0 & I \end{bmatrix} \begin{bmatrix} \lambda \\ b_{\omega, 1} \\ b_{\omega, 2} \end{bmatrix}_k + \begin{bmatrix} \Delta t Q(\lambda_k) \\ 0 \\ 0 \end{bmatrix} y_k
\]

\[
y_k = \begin{bmatrix} I & 0 \end{bmatrix} \begin{bmatrix} \lambda \\ b_{\omega, 1} \\ b_{\omega, 2} \end{bmatrix}_k + \Theta_k
\]

where \( \hat{\lambda}_k \) is the estimated Euler angles corrupted by a Gaussian zero-mean WN \( \Theta_k \) and \( K_{\lambda 1}, K_{\lambda 2}, \) and \( K_{\lambda 3} \in M(3,3) \) are feedback gain matrices. The attitude observation \( \lambda_h \) can be obtained by measuring the Earth’s gravitational and magnetic fields or by other observations such as cameras. Rewriting the attitude kinematics (8) considering \( I \) instead of \( Q(\lambda) \) and \( \omega = 0 \) results in a LTI system:

\[
\begin{bmatrix} X_k \\ X_{\omega, 1} \\ X_{\omega, 2} \end{bmatrix}_{k+1} = \begin{bmatrix} I & -\Delta t I & -\Delta t T \\ 0 & I & -\Delta T^{-1} \\ 0 & 0 & I \end{bmatrix} \begin{bmatrix} X_k \\ X_{\omega, 1} \\ X_{\omega, 2} \end{bmatrix}_k + \begin{bmatrix} -\Delta t 0 \\ 0 \end{bmatrix} \begin{bmatrix} n_{\text{arw}} \\ n_{\text{rrw}} \end{bmatrix}_k
\]

\[
y_X = \begin{bmatrix} I & 0 \\ 0 & I \end{bmatrix} \begin{bmatrix} X_k \\ X_{\omega, 1} \\ X_{\omega, 2} \end{bmatrix}_k + \Theta_k
\]

The hat superscript is used to denote an estimate, \( \hat{\lambda}_k \) is the observed Euler angles about a Gaussian zero-mean WN \( \Theta_k \) and \( K_{\lambda 1}, K_{\lambda 2}, \) and \( K_{\lambda 3} \in M(3,3) \) are feedback gain matrices. By definition, the filter (11) is UAS if its origin is UAS in the absence of state and measurement noises, see Jawzinski (1970). Nonetheless, the state and measurement noises are explicit in the proof for convenience. The system (10) can be rewritten in a compact state space formulation:

\[
\dot{X}_k = F X_k + G n_k, \quad y_X = H X_k + \Theta_k
\]

where \( X, n_k, y_X k, F \) and \( G \) are the vectors and matrices found in (10). It is straightforward to show that the
observability and controllability matrices of system (10) are full rank, hence the close-loop system 
\[ \tilde{X}_{k+1} = (F - KH) \tilde{X}_k + G n_k - K \Theta_k \] (13)
where \( K = [K_{1a} K_{2a} K_{3a}]^T \) is UAS, see Anderson and Moore (1979). Define the Lyapunov transformation of variables:
\[ \begin{bmatrix} \tilde{X}_X \\ \tilde{b}_{w1 X} \\ \tilde{b}_{w2 X} \\ \tilde{X}_{\lambda} \\ \tilde{b}_{w1 \lambda} \\ \tilde{b}_{w2 \lambda} \end{bmatrix}_k = T_k \begin{bmatrix} \tilde{X}_X \\ \tilde{b}_{w1 X} \\ \tilde{b}_{w2 X} \\ \tilde{X}_{\lambda} \\ \tilde{b}_{w1 \lambda} \\ \tilde{b}_{w2 \lambda} \end{bmatrix}_k , \quad T_k = \begin{bmatrix} Q(\lambda_{k-1}) & 0 & 0 \\ 0 & I & 0 \\ 0 & 0 & I \end{bmatrix} \] (14)
which according to Rugh (1996) is well defined with the assumption that \( \lambda \) is bounded. Applying the Lyapunov transformation \( T_k \) to (13) yields:
\[ \begin{bmatrix} \tilde{X}_X \\ \tilde{b}_{w1 X} \\ \tilde{b}_{w2 X} \end{bmatrix}_{k+1} = \begin{bmatrix} Q(\lambda_{k-1}) & -\Delta t Q(\lambda_{k-1}) & -\Delta t Q(\lambda_{k-1}) \\ -\Delta t Q(\lambda_{k-1}) & I - \Delta t T^{-1} I & 0 \\ -\Delta t Q(\lambda_{k-1}) & 0 & I \end{bmatrix} \begin{bmatrix} \tilde{X}_X \\ \tilde{b}_{w1 X} \\ \tilde{b}_{w2 X} \end{bmatrix}_k + \begin{bmatrix} \omega_1 \\ 0 \\ 0 \end{bmatrix} \sigma_{\lambda} \] (15)

The origin of (13) is UAS and, by the Lyapunov transformation properties, the origin of (15) as well. Therefore, the origin of (11) is uniformly asymptotically stable.

Considering slow maneuvers, the performance of the proposed attitude filter with the steady state Kalman gains of the system (10) is identical to that of a Kalman filter designed for the time-varying system (8).

**Proposition 2.** Let the state and observation disturbances in the attitude kinematics (8) be characterized by the zero-mean Gaussian WNs \( n_{arw} \), \( n_{aw} \), \( n_{ary} \), and \( v_{aw} \), respectively, and assume that pitch and roll angles are constant. Then the complementary filter (9) is the 'steady state' Kalman filter for the system (8) in the sense that the Kalman feedback \( K_{opt k} \) converges asymptotically as follows:
\[ \lim_{k \to \infty} \| K_{opt k} - \frac{Q(\lambda_{k-1})}{K_{1a} - I + Q(\lambda_{k-1})} \| = 0 \] (16)

**Proof.** An analogous proof can be found in theorem 2 of Vasconcelos et al. (2011).

This holds for small variations in pitch and roll. For aggressive maneuvers with a time-varying pitch and roll the filter's performance can be compared offline by computing the estimation error covariances of the filters as in Appendix A of Vasconcelos et al. (2011).

2.2 Position Filter

The proposed position filter is based on the complementary attitude filter proposed by Vasconcelos et al. (2011), where the Euler angles become the UAV inertial position \( p \) and the input instead of being the angular velocity will be UAV body frame's velocity \( B_v \). The continuous-time position kinematics are given by:
\[ \dot{p} = v \] (17)
where \( p \) and \( v \) are the position and velocity in the chosen inertial frame coordinates. Let \( R^T \) be the rotational matrix from body frame \( \{b\} \) to inertial frame \( \{I\} \). The discrete-time equivalent subject to a sample-and-hold becomes:
\[ p_{k+1} = p_k + \Delta t R^T B_v \] (18)

The OF from bottom camera measures the velocity relative to the ground on UAV body frame giving:
\[ B_v = B_k + b_{v k} + n_{vk} \] (19)

where \( B_k \) denote the true body velocity, \( b_{v k} \) the velocity bias and \( n_{vk} \) a zero-mean WN.

The position kinematics (18), using the OF's measurements, are described in state-space form by:
\[ \begin{bmatrix} p \\ b_{v k} \end{bmatrix}_{k+1} = \begin{bmatrix} I - \Delta t R^T_k \end{bmatrix} \begin{bmatrix} p \\ b_{v k} \end{bmatrix}_k + \begin{bmatrix} \Delta t R^T_k B_v \end{bmatrix}_k + \begin{bmatrix} \Delta t R^T_k 0 \\ 0 \end{bmatrix} n_{vk} \] (20)

where \( n_{vk} \) is a zero-mean Gaussian WN that accounts for disturbance in the position. The position observer, depicted in Fig. 1, is given by the following nonlinear feedback system:
\[ \begin{bmatrix} \dot{p} \\ \dot{b}_{v k} \end{bmatrix}_{k+1} = \begin{bmatrix} I - \Delta t R^T_k \end{bmatrix} \begin{bmatrix} \dot{p} \\ \dot{b}_{v k} \end{bmatrix}_k + \begin{bmatrix} \Delta t R^T_k B_v \end{bmatrix}_k + \begin{bmatrix} \Delta t R^T_k 0 \\ 0 \end{bmatrix} b_{v k} + \begin{bmatrix} R^T_k (K_{1p} - I) + R^T_k K_{2b} \end{bmatrix} R_{k-1}^T (p_k - \hat{p}_k) \] (21)

It is proved in Vasconcelos et al. (2011) that if \( K_{1p} \) and \( K_{2b} \) are the Kalman gains for the system (20) with \( R^T_k = I \), with the difference that for this case pitch does not have to be bounded, then the filter (21) is uniformly asymptotically stable (UAS). Another extended proof can be deduced from Vasconcelos et al. (2011) is that assuming zero-mean Gaussian noise for the state and observation disturbances, without the need of having roll and pitch constant, the complementary filter (21) is the 'steady state' Kalman filter for the system (20) in the sense that the Kalman feedback gain \( K_{opt k} \) converges asymptotically as follows:
\[ \lim_{k \to \infty} \| K_{opt k} - \frac{R^T_k (K_{1p} - I) + R^T_k K_{2b}}{R_{k-1}^T} \| = 0 \] (22)

3. NAVIGATION SYSTEM IMPLEMENTATION

This section presents the overall navigation system architecture composed of the two complementary filters derived in Section 2. Then it will be discussed all the measurement vectors and sampling rates exploited.

3.1 Observations

**Camera tracking system.** The measurement of the position filter (21) is given by a landmark localization system consisting of 6 markers. The landmarks were dispersed in the same plane. A YChCr color segmentation via Mahalanobis distance was used to segment the markers from the background. The choice of such distance is due to its scale-invariant property and since it takes into account not only the mean but also the covariance between color data, hence not ignoring uncertainties. According to Gonzalez and Woods (2002), the Mahalanobis distance is given by:
\[ D(z, a) = \sqrt{(z - a)^T C^{-1} (z - a)} \] (23)

where \( C \) is the estimated covariance matrix of the marker’s color, \( a \) is the estimate average and \( z \) represents the observed vector values of \( C_b \) and \( C_r \).

With this method it is possible to segment some specific color from an image in an efficient and effective way by performing the following statistical test:
\[ D(z, a)^2 \leq \gamma \] (24)

where gamma is the threshold that represents the correct associations allowed to be acceptable.

After segmenting the markers, their centroid is computed and the PnP problem arises. The RPnP, from Li et al. (2012), was chosen since it is faster and less prone to noise than the traditional Direct Linear Transform (DLT) solution for the number of used points, Zheng et al. (2013). This solution provides the position and orientation of the camera relative to the landmark’s plane. Only the position in X and Y-axis and the yaw angle is used as a measurement.
**Euler angles.** The attitude observation $\lambda_k$ in Euler angles is determined by the Earth's gravitational field and by a camera tracking system. The pitch and roll angles are obtained from the compensated accelerometer measurements by the centripetal acceleration:

$$\hat{a}_c = a_c - \omega \times (\hat{\omega} v - \hat{b}_v)$$  \hspace{1cm} (25)

and then a low pass filter with a cut off frequency of 5Hz is applied to cut high dynamics before computing roll and pitch as follows:

$$\phi = -\arctan2(\hat{a}_{cy}, -\hat{a}_{cx})$$

$$\theta = -\arctan2(-\hat{a}_{cx}, \sqrt{\hat{a}_{cy}^2 + \hat{a}_{cz}^2})$$  \hspace{1cm} (26)

The yaw observation $\psi$ is given by the camera tracking algorithm.

### 3.2 Filtering Design

The global architecture of the filter is depicted in Fig. (2). The proposed navigation system is composed of a coupled attitude and position complementary filters.

The attitude terms $R_k^f$ and $Q(\lambda_k)$ are obtained using the last available estimate of the attitude filter $\hat{\lambda}$, since it is the best estimation available. The body velocity is used to compute the centripetal acceleration compensated by the estimated bias $\hat{b}_v$, allowing the removal of the angular acceleration from the accelerometer.

The yaw angle measurement given by the camera algorithm has a frequency of 20Hz. Since the attitude filter works at 100Hz, whenever a measurement is not available the yaw estimate will depend on gyroscope only. To workaround the optimality of a multi-rate system see Bittanti et al. (1991).

The theoretical stability and performance properties of the filters derived and explained in Section 2 cannot be fulfilled for the entire architecture due to filter coupling and due to the use of pendular measurements in the attitude observation filter. This could be guaranteed if the roll and pitch measurements from the vision-based observation were used. This would require a higher rate and resolution in the segmentation algorithm to get less noisy attitude observations at the cost of high computational cost.

### 4. EXPERIMENTAL RESULTS

#### 4.1 AR.Drone 2.0 UAV

The data acquisition and telemetry processes were carried out off-board the Parrot AR.Drone 2.0 shown in Fig. 3. This UAV is a low-cost quadcopter available in the commercial market. A built-in Simulink application is used in this work, the AR.Drone Simulink Development-Kit V1.1 (DevKit) from Sanabria (2014). The inner control loop processes used are the factory ones and it runs on-board. The outer loop is then controlled via Wi-Fi and has limitations in terms of given references. This allows for the use of the factory OF’s velocity as an input in the position filter (21) and as a measurement in the outer control loop. To get access to the front camera in Simulink, a C++ open source project, CV Drone from Shinpuku (2017), was used to develop code to decode the stream with the help of OpenCV and then to send via UDP host to Simulink. The caused delay was practically the same as the DevKit platform, around 250ms.

All of the implementations run on the host computer that is connected to the drone via Wi-Fi. The UAV receives input controls of roll and pitch angles, yaw rate and vertical velocities and retrieves a packet with all data sensors and estimations of horizontal velocities, Euler angles and height. Nevertheless, all the code was tested and able to run in real time on-board of the UAV using the AR.Drone 2.0 Embedded Coder by Darenlee (2017). The experiment was not accomplished on-board due to the unavailability of an OF algorithm to get the velocities.

For this experiment, the only data used from the received packet was the gyroscopic raw, accelerometer raw, OF velocities and front camera video stream.

#### 4.2 Parameter Design

For both filters, (9) and (21), the optimal steady gains are achieved by using the LTI system (10) and the LTI version of (21) considering $R_k^f = I$. As discussed in Subsection 2.1 the proposed filter is identified with the steady-state Kalman filter for constant pitch and roll angles. In the case of time-varying angles, a degradation performance needs to be done using the covariance propagation set of equations discussed. This comparison is done offline using the real data from the flight and it shows that even for aggressive maneuvers, Fig. 7 at [150-175]sec, the estimation error covariance of the proposed filter is way less than 1% above the optimal estimation error covariance, see Fig. 4.

A constant sampling rate of 20Hz was used for both front camera and position filter systems with a resolution of $320 \times 180$ pixels. The attitude filter worked at 100Hz. The adopted weights, respective gains and gyroscopic correlation times $T$ are detailed in Table 1. The attitude process noise matrix was designed based on the AV noise covariance from the gyroscopic as explained in Section 2.1 and on the gyroscopic variance when the fans were
of small design weights but not that small to be able to account some higher dynamics of the UAV. Otherwise, the filter would not be able to compensate fast enough the big drift at 175sec.

The experimental results obtained on-board the AR.Drone 2.0 validate the proposed INS. The adopted design parameters yield the desired sensor fusion in the frequency domain accomplishing good attitude and position estimation. The attitude and position estimates were consistent with the given trajectory, and the INS endured landmark outage for small dynamics, which shows that the proposed complementary filter based architecture is suitable for GPS denied applications.

5. CONCLUSION

In this work, an INS based on complementary filters that rely on inertial and vision sensors was presented. The existence of a varying gyroscope bias based on AV was considered and its value estimated by the observer. A velocity bias model was considered too and compensated by observations from known landmarks in 3D space. Both filters, position and attitude, were proved to be UAS when uncoupled. Experimental results were carried out and its good performance validated. Future work will be devoted to the implementation of a complete system fully on-board of the UAV.

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Fig. 5. Trajectory estimation results in X and Y axis.

Fig. 6. Body angular (left) and linear (right) velocities biases estimation.

Fig. 7. Attitude estimation results.