

Wind component estimation for UAS flying in turbulent air

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Abstract

One of the most important problem of autonomous flight for UAS is the wind identification, especially for small scale vehicles. This research focusses on an identification methodology based on the Extended Kalman Filter (EKF). In particular authors focus their attention on the filter tuning problem. The proposed procedure requires low computational power, so it is very useful for UAS. Besides it allows a robust wind component identification even when, as it is usually, the measurement data set is affected by noticeable noises.

Keywords: Wind estimation, UAS, EKF, auto-tuning

Acronyms

α = Angle of attack

ϑ = Elevation angle

u, w = velocity components in body reference frame (m/s)

\dot{u}, \dot{w} = acceleration of aircraft mass center along the body-fixed x-axis, z-axis (m/s²)

q = pitch rate (rad/s)

m = aircraft mass (kg)

I_y = aircraft moment of inertia (kg m²)

V = air speed (m/s)

C_L, C_D, C_m, C_T = lift, drag, pitch moment and thrust coefficients

$C_{L\alpha}, C_{m\alpha}, C_{Lq}, C_{mq}, C_{L\dot{\alpha}}, C_{m\dot{\alpha}}, C_{Y\beta}, C_{Yp}, C_{Yr}, C_{TV}$ = Stability derivatives

$C_{L\delta_e}, C_{m\delta_e}, C_{Y\delta_r}, C_{T\delta_{th}}$ = Control derivatives

T = thrust

$u(t)$ = control input

$v(t)$ = measurement noise

$w(t)$ = process noise

\hat{x}_k^- = a priori estimate vector at the time step k

\hat{x}_k = a posteriori estimate vector at the time step k

y_k = a priori output

Z = measurement vector

δ_e = elevator deflection

δ_{th} = throttle displacement

Item = $k = 0.033$ sec

t = time

1. INTRODUCTION

The flight of UAS is widely affected by atmospheric disturbances because of their small dimensions and their low airspeed.

Therefore it is important to determine wind components in order to improve safety of flight operations and to obtain good flight performances.

Different methodologies have been used to estimate wind vector. In the “wind triangle method” [1] the wind velocity and direction are determined from the difference between ground speed and airspeed. Unfortunately pitot probe for

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UAS are affected by relevant measurement noise [2]. Besides also GPS measurements are noisy signals [3]. So it is necessary to filter these data [4-9].

Another way to determine wind is the use of dynamic model of the UAS. In this approach wind components are inserted into the equations of motion. The state is compared with a measurements set gathered by sensors [10-14].

In [11] a linear observer is employed to construct a Disturbance Observer Based Control (DOBC).

In [12-13] wind components are determined by means of non-linear estimators. In particular [12] employs a constant matrix to insert wind into equations of motion. Then tunes gains and determines disturbances by integrating. Instead [13] employs a disturbance input matrix directly obtained by equations of motion. Like [12], it tunes the gains and determines disturbances by integrating them.

In [14] wind estimation is performed by scheduled EKF. To determine Kalman gains, a Jacobian scheduling law is used. Good results are restricted to slow dynamics.

Finally [15] employs three EKF working simultaneously to determine wind model starting from three known wind models (one for each filter). Then makes a weighted average of the obtained statistics.

All previous papers based on observers have to solve the problem of a proper tuning of the estimator.

The tuning is a very challenging problem. In several applications it is obtained using numerical optimization techniques [16]. Unfortunately the proposed tuning methods employ complex algorithms. So noticeable computational power is required and this is not at disposal of small UAS.

In the present paper, to reduce computational power, authors use an EKF as observer and propose a simple optimization procedure based on a metric related to prediction errors to perform the tuning. Constrains are imposed to airspeed, pitch rate and elevation.

The optimization procedure affords to determine automatically both the Process Noise Covariance matrix Q and the Measurement Noise Covariance matrix R .

The fundamental innovation of the tuned up procedure consists in the fact that the covariance matrices of both process and measurement noise are not treated as filter design parameters. In this way it is possible to determine the optimal values of the aforementioned matrices, without resorting to long and tedious tuning operations through trial and error procedures.

Furthermore, by using the proposed procedure, it is eliminated one of the typical EKF problems. As it is well known, in fact, if the filter is tuned in a specific condition, it determines optimal estimates in the afore mentioned condition, but the quality of the estimates worsen if it is used in different conditions.

Because of the proposed algorithm determines, during the estimation process, the optimal values of Q and R depending on the dynamic evolution of the system and it always give raise to optimal estimates.

Present paper is organized as follow:

- Section 2 explains the proposed procedure describing both the aircraft model in turbulent air (2.1) and the tuning procedure (2.3);
- Section 3 shows obtained simulation results and compares these ones with those obtained with classical tuning procedure;
- Section 4 concludes the paper.

2. PROPOSED PROCEDURE

As it is well known, the structure of the EKF includes a predictor and a corrector. These ones work as shown in Figure 1.

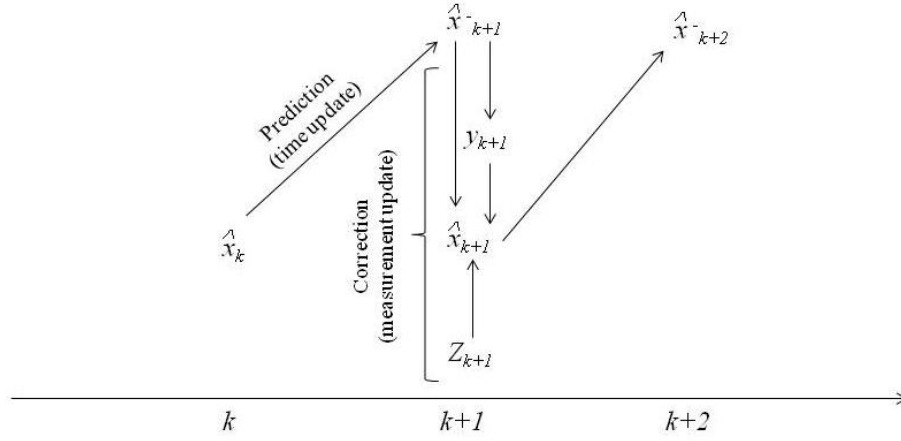


Figure 1: Operations of the Extended Kalman Filter

In the present paper, the corrector of such a filter employs a set of measurements gathered in turbulent air. The selected measured variables are:

$$Z = [V, q, \vartheta, x_E, h]^T$$

where V is the airspeed, q is the pitch rate, ϑ is the angle of elevation, x_E is the spatial coordinate of the center of mass and h is the altitude of the aircraft.

Obviously:

$$\begin{aligned} V &= \sqrt{(u + u_g)^2 + (w + w_g)^2} \\ \alpha &= \text{atan} \frac{w + w_g}{u + u_g} \\ q &= q + q_q \end{aligned} \quad (1)$$

with - (u_g, w_g, q_g) unknown wind components in body axes.

2.1 Aircraft model in turbulent air (Predictor)

An accurate non-linear mathematical model of the aircraft flying in turbulent air constitutes the predictor. The classical rigid body equations of motion in body axes have been used [18].

$$\begin{aligned} m \dot{u} &= -m q w - m g \sin \vartheta + F_x \\ m \dot{w} &= +m q u - m g \cos \vartheta + F_z \\ I_y \dot{q} &= M \\ \dot{\vartheta} &= q + q_g \\ \dot{x} &= u \cos \vartheta + w \sin \vartheta \\ \dot{h} &= u \sin \vartheta - w \cos \vartheta \end{aligned} \quad (2)$$

where:

$$\begin{aligned} F_x &= \frac{1}{2} \rho V^2 S C_x \\ F_z &= \frac{1}{2} \rho V^2 S C_z \\ M &= \frac{1}{2} \rho V^2 S C_m c \\ T &= \frac{1}{2} \rho V^2 S C_T \end{aligned} \quad (2.1)$$

Into (2.1)

$$\begin{aligned} C_x &= C_L \sin\alpha - C_D \cos\alpha + C_T \\ C_z &= -C_L \cos\alpha - C_D \sin\alpha \end{aligned} \quad (2.2)$$

Into (2.2), aerodynamic coefficients are expressed by:

$$\begin{aligned} C_L &= C_{L_\alpha} \alpha + C_{L_{\dot{\alpha}}} \dot{\alpha} \frac{c}{2V_0} + C_{L_q} q \frac{c}{2V_0} + C_{L_\delta} \delta_e \\ C_D &= C_{D_0} + 0.001625 C_L^3 + 0.30061 C_L^2 + 0.007446 C_L \\ C_m &= C_{m_0} + C_{m_\alpha} \alpha + C_{m_{\dot{\alpha}}} \dot{\alpha} \frac{c}{2V_0} + C_{m_q} q \frac{c}{2V_0} + C_{m_\delta} \delta_e \\ C_T &= C_{T_V} \frac{V - V_0}{V_0} + C_{T_\delta} \delta_{th} \\ C_{T_V} &= -3 C_{T_e} + C_{T_e} \frac{V_e}{\eta_e} \left(\frac{\partial \eta}{\partial V} \right)_e \end{aligned} \quad (2.3)$$

Equations (2) have been modified by inserting the wind components into the aerodynamic forces and moments using Equations (1).

The state of the system is constituted by both the six aircraft state variables in body axes and the wind components to be determined:

$$x = [u, w, q, \vartheta, x_E, h, u_g, w_g, q_g]^T \quad (3)$$

To estimate the disturbance, the following equations are inserted into the predictor:

$$\begin{aligned} \dot{u}_g &= 0 \\ \dot{w}_g &= 0 \\ \dot{q}_g &= 0 \end{aligned} \quad (4)$$

In this way, no hypothesis has been made about wind dynamics and the filter is forced to estimate disturbances by using measurements.

The mathematical model has been applied on an UAS that is a 1:5 scale model of the ultra-light aircraft N3-PUP. Such a model is the same used in previous researches.

In Table 1 and Table 2 are reported UAS model geometrical characteristics and fundamental performances

Table 1: UAS model geometrical characteristics

	Value
Mean chord c	0.24 m
Wing span b	1.86m
Wing area S	0.4464 m ²
Mass W/g	2.5 kg
Inertia moment I_y	0.1080 kg m ²
Maximum Power	27.56 kg m/sec

Table 2: UAS fundamental performances

	Value
V _{ms}	7.08 m/sec
V _{max,OF}	27 m/ses
V _{cruise}	23.6305 m/sec

2.2 Extended Kalman Filter

As it is well known, the Extended Kalman Filter is an optimal estimator for stochastic systems in presence of process noise ($w(t)$) and measurement noise ($v(t)$). In the derivation of EKF, both noises are white noise processes.

The general state equation of a time varying dynamical system is:

$$\dot{x}(t) = f(t, x(t), u(t)) + w(t) \quad (5)$$

$$Z(t) = h(t, x(t), u(t)) + v(t) \quad (6)$$

The initial value x_0 in Equation (5) has known mean value and known covariance matrix \bar{P}_0 .
If the process is governed by the non-linear difference equations:

$$x_k = f(x_{k-1}, u_{k-1}, w_{k-1}) \quad (7)$$

$$Z_k = h(x_k, v_k) \quad (8)$$

In this case the non-linear function f in the difference equation (Eq. (7)) relates the state at the previous time step to the state at the current time step. It includes as parameters any driving function and the zero-mean process noise w_k . The non-linear function h in the measurement equation (Eq. (8)) relates the state to the measurement. By using numerical partial differentiation to linearize the problems, it is possible to write:

$$x_k \approx \hat{x}_k^- + \bar{A}(x_{k-1} - \hat{x}_{k-1}^-) + \bar{W}w_{k-1} \quad (9)$$

$$Z_k \approx y_k + \bar{H}(x_k - \hat{x}_k^-) + \bar{V}v_k \quad (10)$$

In Equations (9) and (10) x_k and Z_k are the actual state and measurement vectors, \hat{x}_k^- and y_k are a priori state and measurement vectors, \hat{x}_k is an a posteriori estimate of the state at step k . Besides [17]:

$$\bar{A} = \frac{\partial f}{\partial x}(\hat{x}_{k-1}^-, u_{k-1}, 0)$$

$$\bar{W} = \frac{\partial f}{\partial w}(\hat{x}_{k-1}^-, u_{k-1}, 0)$$

$$\bar{H} = \frac{\partial h}{\partial x}(\hat{x}_k^-, 0)$$

$$\bar{V} = \frac{\partial h}{\partial v}(\hat{x}_k^-, 0)$$

The state estimation error is

$$\varepsilon = x - \hat{x}$$

By using Equations (9) and (10), it is obtained:

$$\dot{\varepsilon}(t) = (\bar{A} - \bar{K}\bar{H})\varepsilon(t) \quad (11)$$

where K is the Kalman gain matrix.

The error covariance of Equation (11) is:

$$\bar{P}(t) = E[(x - \hat{x})(x - \hat{x})^T] \quad (12)$$

By differentiating Equation (12) and using Equation (11) it is obtained:

$$E[\dot{\varepsilon}] = E[x] - E[\hat{x}] = E[x] - \hat{x}$$

Because of the process and measurement noises are zero-mean processes, the steady state value of $E[\dot{\varepsilon}]$ is zero. It follows that the estimates \hat{x} approach the $E[x]$.

In the same way it is possible to determine stochastic characteristics of the prediction error ε^- .

To minimize the state estimation error, it needs to minimize the error covariance $\bar{P}(t)$ by solving the Algebraic Riccati Equation (ARE) at every k .

2.3 Filter tuning

As previous stated, to tune the EKF, an optimization procedure has been implemented. The optimization process is based on the control of prediction errors. Since wind components modifies both flight path and attitude, constraints have been imposed on errors of angle of elevation, horizontal displacement and height.

As previous stated, the a priori estimate covariance matrix is:

$$\bar{P}_k^- = E[\varepsilon_k^- \varepsilon_k^{-T}]$$

To minimize the prediction error, it is necessary to determine, for each time step k , the a priori estimate covariance matrix.

A metric for the goodness of the obtained value of \bar{P}_k^- is the following quantity:

$$\hat{E}_k^- = \bar{P}_k^- \cdot \hat{x}_k^-$$

where \hat{x}_k^- is the a priori estimate vector at the time step k .

The imposed constrains are:

$$\hat{E}_{k\vartheta}^- \leq a \quad (13)$$

$$\hat{E}_{kx}^- \leq b \quad (14)$$

$$\hat{E}_{kh}^- \leq c \quad (15)$$

Values of a , b , and c are selected depending on UAS performances and desired flight path precision. In particular, in the present paper, values of imposed constrains are:

$$a = 0.05 \text{ rad} \quad (16)$$

$$b = 5 \text{ m} \quad (17)$$

$$c = 1 \text{ m} \quad (18)$$

Selected constrains have been chosen with the aim of using wind data in the design of a flight control system. Therefore, to perform a precise path tracking, it is necessary high precision in attitude determination. During cruise flight, because of the horizontal component of airspeed is much more than vertical one, errors on height are more important than distance ones. Selected values of b and c are strictly related to the considered cruise speed.

When one or more of previous constrains are not verified, the algorithm modifies any \bar{Q} and \bar{R} matrix elements.

In particular:

- if Eq. (13) is not verified, the algorithm decreases the \bar{Q} elements corresponding to w and w_g , q and q_g , ϑ , besides it increases \bar{R} elements corresponding to q and ϑ ;
- if Eq. (14) is not verified, the algorithm decreases the \bar{Q} elements corresponding to u and u_g , and x , besides it increases \bar{R} elements corresponding to V ;
- if Eq. (15) is not verified, the algorithm decreases the \bar{Q} elements corresponding to w and w_g , and z ;

In this way, when imposed constrains are verified, we obtain a precise wind component estimation.

In all cases, \bar{Q} values are reduced of 10% every time the constrain is not verified. Regarding to \bar{R} values:

- if Eq. (5) is not verified, R_q increases of 20% and R_g is multiplied by 10. R_g increases much more than R_q because the attitude values estimation, as it is well known, is a very difficult problem. Besides, R variations are heavier than Q ones because of R -matrix affects the estimates more than Q -matrix;
- if Eq. (6) is not verified, R_V is multiplied by 10.

It is important to note that to apply the proposed procedure to estimate both state and wind components simply the initial value of the covariance matrices of initial condition (\bar{P}_0), process noise (\bar{Q}_0) and measurement noise (\bar{R}_0) have to be selected.

As previous stated, the algorithm modifies the values of \bar{Q} and \bar{R} and determines the optimal values of such a matrices. So these matrices vary, at any item, depending on prediction error.

Obtained values of \bar{Q} and \bar{R} are optimal values because they are obtained by the minimization of the covariance matrix of the state estimation error (\bar{P}_k).

It is noticeable that, according to the imposed constrains, optimal values of the covariance matrices are linked to: aircraft parameters, wind characteristics and aircraft flight path.

Finally the tuning is fully autonomous and the procedure requires low computational power.

3. Results and discussion

In simulation environment authors have studied many cases of different flight conditions and wind components. In particular infinite and finite step, harmonic and random wind components have been investigated. To simulate a real set of measurement data, various kind of noises have been added to measurement set.

Noticeable errors have been postulated for the initial condition x_0 :

$$\bar{P}_0 = \text{diag}[1 \ 1 \ 1 \ 1 \ 1 \ 1 \ 1 \ 1] * 10^2$$

Besides the initial values of the measurement noise covariance matrix, \overline{R}_0 has been selected according to the characteristics of the sensors today employed for UAS:

$$\overline{R}_0 = \text{diag}[1 \ 1 \ 1 \ 1 \ 1] * 10^{-2}$$

In order to speed up the process of determining optimal values of the elements of process noise covariance matrix \overline{Q} reasonable values have been selected for the initial covariance (\overline{Q}_0) of the state variables. Such a values have been determined by imposing the maximum admissible errors of $\alpha, \vartheta, q, x, z$.

In particular:

$$\varepsilon_{\alpha_{max}} = \varepsilon_{\vartheta_{max}} = 0.6 \text{ deg}$$

$$\varepsilon_{q_{max}} = 0.6 \text{ deg/sec}$$

$$\varepsilon_{x_{max}} = \varepsilon_{z_{max}} = 0.3 \text{ m}$$

In this way the filter is forced to reduce the prediction errors until the imposed constrains are verified, therefore the unknown wind components are estimated with the outmost precision.

Because of no hypothesis have been made about the disturbance dynamics, the covariance of the augmented state has been chosen higher than these of the state variables.

Moreover, the covariance of the wind component have been imposed higher than the measurement noise covariance.

According to the above mentioned hypothesis, the \overline{Q}_0 value is:

$$\overline{Q}_0 = \text{diag}[10 \ 0.001 \ 0.01 \ 0.01 \ 0.01 \ 0.01 \ 0.1 \ 0.1 \ 0.1]$$

In this way the filter is forced to estimate wind components from the measurement set that is affected by wind disturbances.

Simulation results have verified the feasibility of the proposed tuning procedure.

In particular results show the wind identification of an infinite wind step with following characteristics:

$$u_g = 5 \text{ m/s}$$

$$w_g = 2.5 \text{ m/s}$$

$$q_g = 0.05 \text{ rad/s}$$

Noisy measurements have been processed. In particular low and high frequency noises have been created to test the procedure. The low one (Figure 2) has been created by the following equation:

$$\text{Noise} = 0.1 \cos(t) - 0.2 \cos\left(\frac{t}{2}\right)$$

The high one (Figure 3) has been created by using a random signal with maximum amplitude equal to 1.

In all figures in x-axes are reported items (k) instead of time. Each item is 0.033 sec.

In order to have noise and measurement of the same order, noise added to measurements have been opportunely scaled.

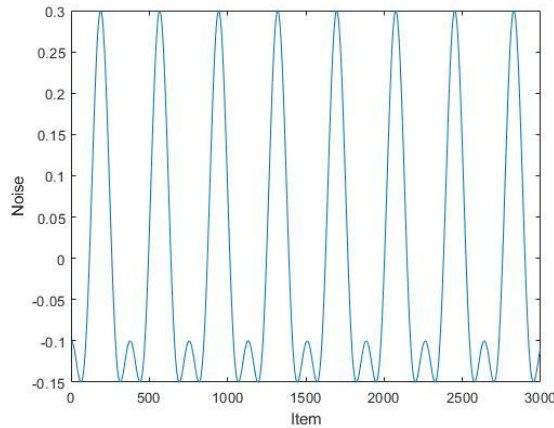


Figure 2: Low frequency noise

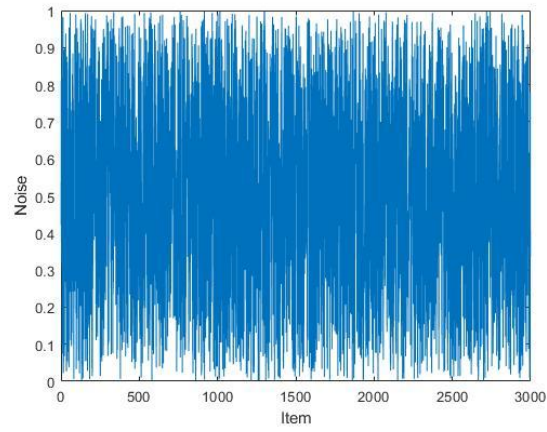


Figure 3: High frequency noise

In Figure 4-6 are reported the estimated wind components in case of horizontal flight and noisy measurements.

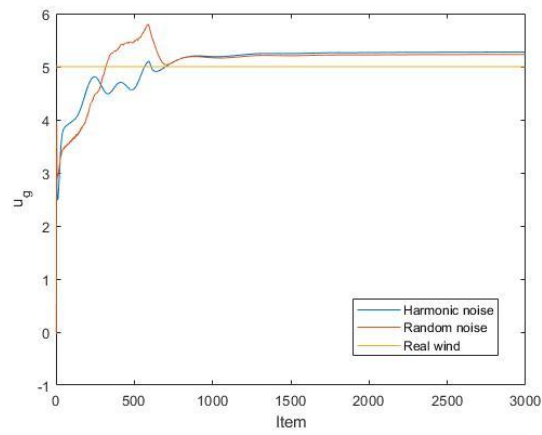


Figure 4: Estimated u_g

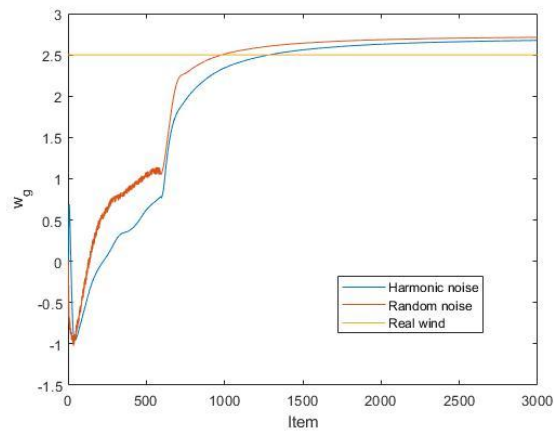


Figure 5: Estimated w_g

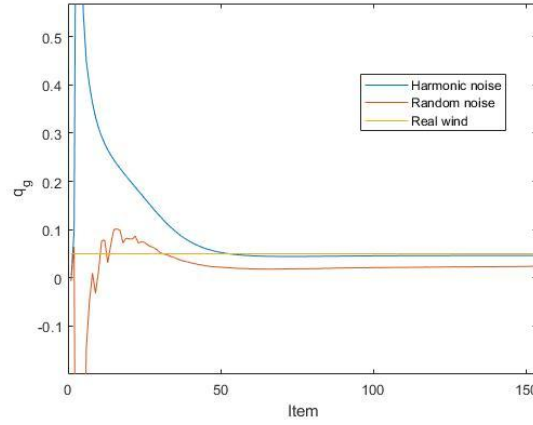


Figure 6: Estimated q_g

Results show how the automatic tuning procedure bring the wind estimation to the real value of the wind.

In case of low frequency noise measurements, the oscillation of the estimation is less than high frequency noise ones. The estimation time is almost equal for the two cases of noises.

The high frequency noise has more influence on the q_g component estimation; this is due to the high value of the noise respect to the wind to estimate.

As previous stated the proposed procedure affords to reduce the computational power needed to perform state estimation. Besides it give optimal estimates in every condition.

A comparison in terms of computational time between proposed procedure and classical one is not possible because of the length of trial and error tuning is not predictable. A comparison, always in terms of computational time, with tuning procedures employing numerical optimization techniques is not useful because of present procedure is designed for UAS with low computational power. So for this kind of aircraft it is not possible to employ procedures that use complex algorithms and require high computational power.

To evaluate the filter performances, in Figures 7-9 a comparison has been made between the obtained wind components estimates and those ones determined by using a classical trial and error procedure to tune the EKF. In particular, Figures 7a, 8a and 9a show the estimates of u_g , w_g , q_g obtained by using the present algorithm and Figures 7b, 8b and 9b show the wind component estimated by authors with a classical EKF (\bar{Q} and \bar{R} are constant matrices and their values have been determined by using trial and error procedure).

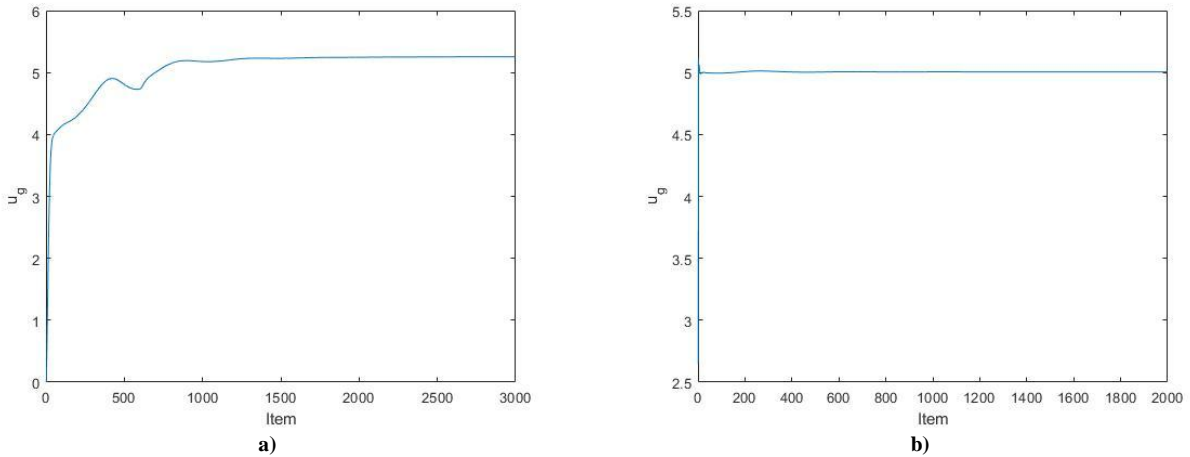


Figure 7: Comparison between estimated u_g with proposed procedure (a)) and trial and error tuning (b))

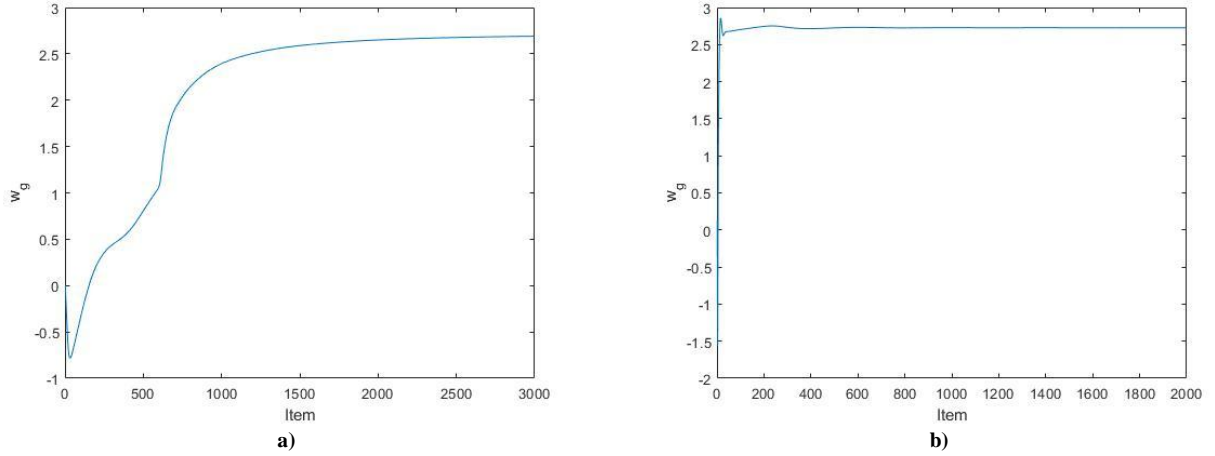


Figure 8: Comparison between estimated w_g with proposed procedure (a)) and trial and error tuning (b))

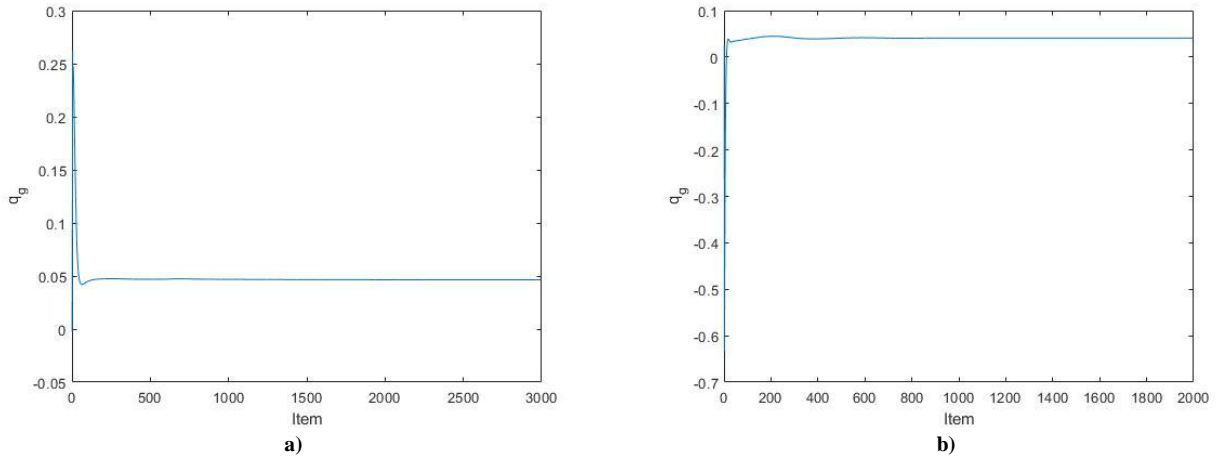


Figure 9: Comparison between estimated q_g with proposed procedure (a)) and trial and error tuning (b))

As it is possible to see by comparing obtained results, final values of the identified wind components are quite similar. The fundamental difference between the proposed procedure and the traditional one is that in the second case (Figures b) the identification is made in very few items, instead in the first case wind correct identification is performed after more time. This is due to the tuning procedure that, even if it is so quick, needs of any item to reach the steady state covariance values.

Because of the procedure has been designed for small UAS with low flight speed, the time to reach steady state covariance values is compatible with dynamic characteristics of the UAS.

4. Conclusions

Present procedure could improve the flight safety of UAS operations because of it allows to determine with the outmost precision the wind components.

Instead of using complex algorithms to tune the state observer, a simple optimization technique is developed. It determine automatically the filter parameters.

The obtained results show the effectiveness of the procedure in presence of either low frequency disturbances or high frequency ones. In addition, the performed comparison with results obtained by using an EKF tuned by a trial and error procedure demonstrates the effectiveness of the algorithm.

The proposed procedure requires low computational power, so it is very useful for UAS. Besides it allows a robust wind component identification even when, as it is usually, the measurement data set is affected by noticeable noises.

It is noticeable that the carried out procedure is adaptive. In fact the optimal values of the covariance matrices are linked to: aircraft parameters, wind characteristics and aircraft flight path.

In addition to reducing the computation time and/or the computational power needed to make the estimates, the proposed procedure removes one of the classical weaknesses of the state estimation by using EKF (optimal estimates in the tuning condition and sub-optimal ones in all the other ones: i.e. poor robustness).

In fact, since the tuning is not carried out before the estimates, but it is automatically done during the estimation process itself, the estimated state is always the optimal one.

At present time, authors are working to the on-board implementation of the carried out procedure.

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