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Wind Shear On-Line Identification for Unmanned Aerial Systems *

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Abstract

An algorithm to perform the on line identification of the wind shear components suitable for the UAS characteristics has been implemented. The mathematical model of aircraft and wind shear in the augmented state space has been built without any restrictive assumption on the dynamic of wind shear. Due to the severe accelerations on the aircraft induced by the strong velocity variation typical of wind shear, the wind shear effects have been modeled as external forces and moments applied on the aircraft. The identification problem addressed in this work has been solved by using the Filter error method approach. An Extended Kalman Filter has been developed to propagate state. It has been tuned by using a database of measurements through off-line identification of the process noise covariance matrix. Afterwards the implemented EKF has been employed to estimate onboard either aircraft state or turbulence, with significant savings in terms of time and computing resources. Robustness of implemented algorithm has been verified by means of several tests. The obtained results show the feasibility of the tuned up algorithm. In fact it is possible, by using a few numbers of low cost sensors, to estimate with a noticeable accuracy the augmented state vector. Besides a very short computation time is required to perform the augmented state estimation even by using low computation power.

1. Introduction

This work addresses the on line identification of wind shear components which interact with the aircraft, changing both the attitude and the flight path (especially during the critical phases of take-off and landing). Wind shear consists essentially in a spatial and temporal abrupt change of both wind speed and direction. This general definition, groups a set of atmospheric phenomena that give rise to the phenomenon as Microburst, Gust front, Sea breeze and Flow past terrain. The state of the art, in research and identification of wind shear, is related to the instrumental measurements carried out by land based locations near airports or on board the aircraft, such as doppler radar. However, the use of these detection techniques, is severely limited, as they are related to the morphology of the terrain and to the precision of the instrumentation. Therefore only the average speeds of the components of the wind are measured. To determine the wind speed with increasing height, there are two main techniques the Log law and the Power law. Both of these laws have derived by using semi-empirical relations since they come from solution of Navier-Stokes equations and from field experiments. Both laws, however, are dependent by the coefficient of roughness of the ground. Usually [1], the wind shear is assumed to be the same as the atmospheric planetary boundary layer. This method is based on a prior knowledge of the velocity profile and intensity of the wind. The wind shear, instead, is a phenomenon in which the velocity components of the wind, have got strong gradients both in time and space and then the behavior is characterized by the accelerations. In [2], the effects of wind shear on aircraft motion and aerodynamics are modeled using the techniques described in Frost and Bowles [3], Stengel [4] and Oseguera and Bowles [5]. In [6], to design the longitudinal guidance and control system for an aircraft, able to compensate the wind-shear effects, an Adaptive Back Stepping control law is implemented. The wind shear model is based on an available set of experimental data collected during a real situation in presence of wind shear [7]. In the present paper, the longitudinal 3DoF mathematical model of aircraft and wind shear in the augmented state space is built taking into account the acceleration components of the wind, without any restrictive assumption on the dynamic of the wind shear. Because of the strong velocity gradients that characterize the wind shear it has been decided to study only the components of acceleration of the wind. Since either longitudinal, normal or angular accelerations due to wind shear have been included into the equations of motion. So the space state dimensions is increased by the number of wind shear components. The identification problem addressed in the present work has been

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solved by using the Filter error method approach. Actually, such a stochastic processes, based on the use of the Extended Kalman Filter for both state estimation and Actually, such a stochastic processes, based on the use of the Extended Kalman Filter for both state estimation and output variables reconstruction, seeks to minimize the error between instrumental measurements and estimated outputs [2, 8]. An algorithm has been implemented to reconstruct the evolution of turbulence starting from instrumental measurements. The proposed procedure is articulated into two steps. In the first one the off-line identification of the process noise covariance matrix of the aircraft flying in turbulent air is performed. In this way the tuning of the EKF is obtained. In the second step, by using the tuned up filter, the on-board estimation of either state or turbulence is made with significant savings in terms of time and computing resources.

2. Aircraft Dynamic Model

In the classical equations for longitudinal dynamics of aircraft, the state space vector is

$$\mathbf{x} = \begin{bmatrix} V & \alpha & q & \vartheta \end{bmatrix} \tag{1}$$

where the elements are the airspeed, the angle of attack, the pitch rate and the flight attitude respectively. The classical equations consider the aircraft in still air [9]. To describe the problem of an aircraft in the turbulent air, we need an additional set of equations. Due to the accelerations on the aircraft induced by the strong velocity gradients in space and time typical of wind shear, such equations are obtained by modeling wind shear effects as external forces and moments applied on the aircraft

$$F_e = \begin{bmatrix} m\dot{u}_g \\ m\dot{w}_g \\ I_y\dot{q}_g \end{bmatrix} \tag{2}$$

where $\dot{V}_g = \begin{bmatrix} \dot{u}_g & \dot{w}_g & \dot{q}_g \end{bmatrix}^T$ are the linear acceleration (along x and z) and the rotational acceleration respectively. In this way no assumptions about the dynamics of the wind shear has been made, but only on the effects that this induces on the aircraft. With the above assumption, the aircraft equations of motion are defined in the state space domain as:

$$\dot{\xi}(t) = \begin{bmatrix} \dot{x} & \dot{V}_g \end{bmatrix}^T = f\begin{bmatrix} x(t) & u(t) & \beta \end{bmatrix} + \dot{V}_g \tag{3}$$

$$y(t) = g\begin{bmatrix} x(t) & u(t) & \beta \end{bmatrix} + \dot{V}_g \tag{4}$$

Equation (3) is defined as:

$$\dot{V} = -\frac{\bar{q}S}{m}C_D + g\sin(\alpha-\vartheta) + \frac{T}{m} + \dot{u}_g\cos\alpha + \dot{w}_g\sin\alpha \tag{5}$$

$$\begin{aligned} \dot{\alpha} = -\frac{\bar{q}S}{mV}C_L + q + \frac{g}{V}\cos(\alpha-\vartheta) + \\ -\frac{T}{mV}\sin(\alpha+\alpha_t) - \frac{\dot{u}_g\sin\alpha}{V} + \frac{\dot{w}_g\cos\alpha}{V} \end{aligned} \tag{6}$$

$$\dot{q} = \frac{\bar{q}Sc}{I_y}C_m + \dot{q}_g \tag{7}$$

$$\dot{\vartheta} = q \tag{8}$$

where:

$$\bar{q} = \frac{1}{2}\rho V^2 \tag{9}$$

$$C_D = C_{D_0} + C_{D_V}V + C_{D_\alpha}\alpha + C_{D_{\delta_e}}\delta_e \tag{10}$$

$$C_L = C_{L_V}V + C_{L_\alpha}\alpha + C_{L_{\dot{\alpha}}}\dot{\alpha} + C_{L_q}q + C_{L_{\delta_e}}\delta_e \tag{11}$$

$$\begin{aligned} C_m = C_{m_0} + C_{m_V}V + C_{m_\alpha}\alpha + C_{m_{\dot{\alpha}}}\dot{\alpha} + \\ + C_{m_q}q + C_{m_{\delta_e}}\delta_e \end{aligned} \tag{12}$$

Moreover T is the thrust.
(Notice that derivatives like C_{DV} are defined by $\frac{\partial x}{\partial V}\left[\frac{second}{meter}\right]$)

To identify the process noise covariance matrix of the aircraft flying in turbulent air, $\dot{V}_g$ has to be modeled. Because of it is not possible to have a priori information on the wind-shear components, the following equations have been added to the system (5-8):

$$\ddot{q}_g = 0 \tag{13}$$

$$\ddot{V}_{g_x} = 0 \tag{14}$$

$$\ddot{V}_{g_z} = 0 \tag{15}$$

Obviously equations (13-15) don't approximate the unknown wind-shear components. These equations have been used to identify the process noise covariance matrix in presence of noticeable model errors. In this way, the state space mathematical model (3) is formed by equations (5-8) and (13-15) The on board instruments measure the outputs vector $y = \begin{bmatrix} V & \alpha & q & \vartheta & q & a_x & a_z \end{bmatrix}_m$. In the output equation (4), which describes analytically the outputs of the system, $\begin{bmatrix} V & \alpha & q & \vartheta \end{bmatrix}$ is equal to the state vector and $\dot{q}$, a_x, a_z are defined as:

$$\dot{q}_m = \frac{\bar{q}Sc}{I_y} C_m + \dot{q}_g \quad (16)$$

$$\dot{a}_{x_m} = \frac{\bar{q}S}{m} C_x + \frac{F_e}{m} + \dot{u}_g \quad (17)$$

$$\dot{a}_{z_m} = \frac{\bar{q}S}{m} C_z + \dot{w}_g \quad (18)$$

where C_x and C_z are referred to the body reference frame.

Taking into account the above equations, the state vector is inclusive of both the state variables of the aircraft and the wind shear components. So, the expanded state is defined as:

$$x = \begin{bmatrix} V & \alpha & q & \vartheta & \dot{u}_g & \dot{w}_g & \dot{q}_g \end{bmatrix}^T \quad (19)$$

3. Identification procedure

As it is known, real processes and experimental data are affected by measurement noise in the sensors and modeling errors, therefore unmodeled dynamics have to be taken into account. So to solve the identification problem, addressed in the present work, a procedure of estimation based on statistical criteria has to be used. The Filter Error Method [10] approach have been used to estimate unknown parameters, because of such a method takes into account both the measurement noise and the system noise.

In the theory of parameter estimation it is required to deduce the values of the unknown parameter vector, using a database of measurements, that are taken from the same data sample.

A likelihood function, in this theory, is defined as:

$$p(z \mid \vartheta) = \prod_{k=1}^{N} p(z_k \mid \vartheta) \quad (20)$$

where:

- z is the measurement sampled
- $\vartheta = \begin{bmatrix} \beta & Q \end{bmatrix}$ is the unknown parameter vector, it includes the parameters of the aircraft β and the components of the process noise covariance matrix (Q)
- N is the number of samples analyzed
- $p(z \mid \vartheta)$ is the probability of z given ϑ

The Criterion of Maximum Likelihood (ML), introduced by Fisher as a general procedure for estimating, try to select that value of ϑ which maximizes $p(z \mid \vartheta)$, in a permissible range. The likelihood function is the probability density of the observed variables, in the continuous case, and the probability in the discrete case. Since in the present case the available data are extracted from a sample of discrete data, the function represents the probability. To maximize the probability, the function $\ln p(z \mid \vartheta)$ is usually minimized with numerical procedure. The first derivative is set equal to zero:

$$\frac{\partial \ln p(z \mid \vartheta)}{\partial \vartheta} = 0 \quad (21)$$

By linear expansion of the (21) around the first value ϑ_0 it is obtained

$$\frac{\partial \ln p(z \mid \vartheta_1)}{\partial \vartheta} \approx \frac{\partial^2 \ln p(z \mid \vartheta_0)}{\partial \vartheta} + \frac{\partial \ln p(z \mid \vartheta_0)}{\partial \vartheta^2} \Delta\vartheta \quad (22)$$

where

$$\vartheta_1 = \vartheta_0 + \Delta\vartheta \quad (23)$$

By recalling (21), it is obtained:

$$\frac{\partial^2 \ln p(z \mid \vartheta_0)}{\partial \vartheta^2} \Delta\vartheta = -\frac{\partial \ln p(z \mid \vartheta_0)}{\partial \vartheta} \quad (24)$$

In equation (22), the matrix

$$\frac{\partial^2 \ln p(z \mid \vartheta_0)}{\partial \vartheta^2}$$

is assumed invertible, so from equation (24) it is possible to obtain the update parameter vector $\Delta\vartheta$. The second derivative of the logarithm of the Likelihood function is called Fisher Information matrix.

By defining the following function as cost function:

$$J(Z \mid \vartheta, R) = -\ln p(Z \mid \vartheta) \quad (25)$$

The Likelihood Function is linked to measurement noise covariance matrix R, therefore the cost function is related to the covariance measurement noise matrix, as:

$$J(Z \mid \vartheta, R) = \frac{1}{2} \sum_{k=1}^{N} [z(t_k) - y(t_k)]^T R^{-1} [z(t_k) + -y(t_k)] + \frac{N}{2} \ln[det(R)] + \frac{N n_y}{2} \ln(2\pi) \quad (26)$$

If the measurement noise covariance matrix is known a priori, the second and third term of (26) are considered constant. The minimization procedure can be simplified as follows:

$$J(Z \mid \vartheta, R) = \frac{1}{2}\sum_{k=1}^{N}[z(t_k) - y(t_k)]^T R^{-1}[z(t_k) - y(t_k)] \quad (27)$$

After defining the cost function and its relation with the measurement noise covariance matrix, equations (21-22), through the use of equations (25-27), lead to:

$$\frac{\partial J(\vartheta)}{\partial \vartheta} = 0 \quad (28)$$

$$\left(\frac{\partial J(\vartheta)}{\partial \vartheta}\right)_{i+1} \approx \left(\frac{\partial J(\vartheta)}{\partial \vartheta}\right)_i + \left(\frac{\partial^2 J(\vartheta)}{\partial \vartheta^2}\right)_i \Delta\vartheta \quad \left(\frac{\partial J(\vartheta)}{\partial \vartheta}\right)_{i+1} = 0 \quad (29)$$

where i is the index of the iteration whereby

$$\Delta\vartheta = -\left[\left(\frac{\partial^2 J}{\partial \vartheta^2}\right)_i\right]^{-1}\left(\frac{\partial J}{\partial \vartheta}\right)_i \quad (30)$$

with

$$\frac{\partial J}{\partial \vartheta} = -\sum_{k=1}^{N}\left[\frac{\partial y(t_k)}{\partial \vartheta}\right]^T R^{-1}[z(t_k) - y(t_k)] \quad (31)$$

$$\frac{\partial^2 J}{\partial \vartheta^2} = \sum_{k=1}^{N}\left[\frac{\partial y(t_k)}{\partial \vartheta}\right]^T R^{-1}\frac{\partial y(t_k)}{\partial \vartheta} + + \sum_{k=1}^{N}\left[\frac{\partial^2 y(t_k)}{\partial \vartheta^2}\right]^T R^{-1}[z(t_k) - y(t_k)] \quad (32)$$

By considering noise with zero mean and diagonal matrix R, (i.e. the components of noise vector are uncorrelated), it is possible to simplify equation (32) of the cost function, as follows:

$$\frac{\partial^2 J}{\partial \vartheta^2} \approx \sum_{k=1}^{N}\left[\frac{\partial y(t_k)}{\partial \vartheta}\right]^T R^{-1}\left[\frac{\partial y(t_k)}{\partial \vartheta}\right] \quad (33)$$

since $z(t_k) \cong y(t_k)$ in the vicinity of the convergence of the algorithm.

In this way, the Maximum Likelihood try to select, in a permissible range, the value of ϑ which minimizes $J(z \mid \vartheta, R)$. Because of equation (25) features a non-linear optimization problem usually to determine ϑ the Gauss-Newton method is used. Such approach leads to a system of linear equations, which can be represented in general form as follows:

$$\vartheta_{i+1} = \vartheta_i - F^{-1}G \quad (34)$$

Where F is the Fisher information matrix and G is the gradient vector, defined as:

$$F = \sum_{k=1}^{N}\left[\frac{\partial y(t_k)}{\partial \vartheta}\right]^T R^{-1}\left[\frac{\partial y(t_k)}{\partial \vartheta}\right] \quad (35)$$

$$G = -\sum_{k=1}^{N}\left[\frac{\partial y(t_k)}{\partial \vartheta}\right]^T R^{-1}[z(t_k) - y(t_k)] \quad (36)$$

In order to calculate the matrices F and G, it is necessary to determine the state of the system and then the sampled outputs $y(t_k)$ by means of the measured outputs $z(t_k)$. An Extended Kalman Filter (EKF), through knowledge of the outputs, has been implemented to estimate state. Moreover, because of, equations (5-18) describe a non-linear dynamic model of the aircraft, and the process contains stochastic inputs not directly measurable (i.e. wind shear), the EKF afford to propagate the state of the system. Because of the characteristics of the on board instrumentation are known, the measurement noise covariance matrix (R) has been considered to be known and constant. The tuning of the filter has been made through the identification of the process noise covariance matrix (Q). The used Extended Kalman filter equations are:

$$\tilde{y} = g[\quad \tilde{x}_k, u_k, \beta] \quad (37)$$

$$K(k) = \quad \tilde{P}(k)C^T[C \quad \tilde{P}_k C^T + R(k)]^{-1} \quad (38)$$

$$\hat{x}(k) = \quad \tilde{x}(k) + K(k)[z(t_k) - \quad \tilde{y}(t_k)] \quad (39)$$

$$\hat{P}(k) = [I - K(k)C] \quad \tilde{P}(k)[I - K(k)C]^T + +K(k)R(k)K^T(k) \quad (40)$$

where:

- $\tilde{y}$ is the predicted output variables
- g is a nonlinear function

- $\tilde{x}$ and $\hat{x}$ denote the predicted and corrected state vector
- u the average of the control input
- $[z_k - \tilde{y}(k)]$ is the residuals
- K is the Kalman filter gain matrix
- $\hat{P}$ is the covariance matrix of the state-predictions error

Since in Kalman Filtering theory, the process noise covariance matrix (Q) is usually chosen as diagonal matrix, the hypothesis that the components of the noise vector are statistically mutually independent, has been adopted.
With the above introduced hypothesis, the parameters vector ϑ is constituted through the aircraft parameters

$$\beta = \begin{bmatrix} C_{D_0} & C_{D_\alpha} & C_{D_{\delta_e}} & C_{L_\alpha} & C_{L_{\dot\alpha}} \\ C_{L_q} & C_{L_{\delta_e}} & C_{M_0} & C_{M_\alpha} & C_{M_{\dot\alpha}} \\ C_{M_q} & C_{M_{\delta_e}} & C_{D_V} & C_{L_V} & C_{M_V} \end{bmatrix}^T \quad (41)$$

and the diagonal terms of Q

$$diag(Q) = [Q_{11} \quad Q_{22} \quad Q_{33} \quad Q_{44} \quad Q_{55} \quad Q_{66} \quad Q_{77}]^T \quad (42)$$

So it is defined as:

$$\vartheta = [\beta, diag(Q)] \quad (43)$$

Because of the parameter vector β of the aircraft is known, the identification algorithm allows to estimate the process noise covariance matrix components.
So, the update parameters vector is:

$$\begin{bmatrix} C_{D_0} \\ C_{D_\alpha} \\ C_{D_{\delta_e}} \\ C_{L_\alpha} \\ C_{L_{\dot\alpha}} \\ C_{L_q} \\ C_{L_{\delta_e}} \\ C_{M_0} \\ C_{M_\alpha} \\ C_{M_{\dot\alpha}} \\ C_{M_q} \\ C_{M_{\delta_e}} \\ C_{D_V} \\ C_{L_V} \\ C_{M_V} \\ Q_{11} \\ Q_{22} \\ Q_{33} \\ Q_{44} \\ Q_{55} \\ Q_{66} \\ Q_{77} \end{bmatrix}_{i+1} = \begin{bmatrix} C_{D_0} \\ C_{D_\alpha} \\ C_{D_{\delta_e}} \\ C_{L_\alpha} \\ C_{L_{\dot\alpha}} \\ C_{L_q} \\ C_{L_{\delta_e}} \\ C_{M_0} \\ C_{M_\alpha} \\ C_{M_{\dot\alpha}} \\ C_{M_q} \\ C_{M_{\delta_e}} \\ C_{D_V} \\ C_{L_V} \\ C_{M_V} \\ Q_{11} \\ Q_{22} \\ Q_{33} \\ Q_{44} \\ Q_{55} \\ Q_{66} \\ Q_{77} \end{bmatrix}_{i} + \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ \Delta_{11} \\ \Delta_{22} \\ \Delta_{33} \\ \Delta_{44} \\ \Delta_{55} \\ \Delta_{66} \\ \Delta_{77} \end{bmatrix}_{i} \quad (44)$$

As explained above, the algorithm reduces errors between the estimated and measured outputs by manipulating only the values of Q.
The identification process is performed by the following items:

- Choose suitable initial values for the unknown parameters (ϑ_0)
- Computation of Kalman gain matrix, Eq. (38)
- Estimation and propagation of the state through the EKF
- Updating ϑ by the Gauss-Newton method, Eq. (34)
- Computation of a new Kalman gain matrix with the updated parameters ϑ

The schematic block of identification procedure is shown in Figure 1.

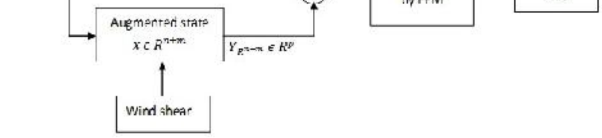

Figure 1. Block schematic of identification algorithm

where n is the state vector dimension, n+m is the augmented state vector dimension and p is the output vector dimension.
Once the off-line identification of the process noise covariance matrix (Q) is performed, known the measurement noise covariance matrix (R), the Extended Kalman Filter is tuned.
By using the tuned up EKF it is possible to perform the online identification of wind-shear through the estimation of the augmented state vector (19).
Notice that, as previous stated, in the tuned up EKF the predictor (5-8 and 13-15) is affected by noticeable process noise due to errors in equations (13-15). Therefore the identified values of the process noise covariance matrix (Q) allow to estimate the augmented state without adequate information about the wind-shear dynamics.

4. Results

As previous stated the implemented on line Wind Shear identification algorithm has been performed by means of the research aircraft FCRL (Flight Control Research Laboratory) used for the Italian National Research Project PRIN2008. The studied vehicle, a Preceptor N3-Ultra-PUP, is an unpressurized 2 seats, 427 [Kg] maximum take of weight aircraft. It is equipped with a research avionic system composed by low cost sensors and computers and their relative power supply subsystem The geometric and aerodynamic characteristics of the aircraft, evaluated by using analytical or semi-empirical relations are summarized in Table 1 and Table 2.

Table 1
Geometric characteristics of the aircraft

$m = 27[kg]$	$I_y = 694.41[kgm^2]$	$S = 11.14[m^2]$
$c = 1.20[m]$	$b = 9.28[m]$	$n_{max} = 3.8$

Table 2
Aerodynamic characteristics of the aircraft (dynamic derivatives are dimensional quantities)

C_{D_0}=0.0665	C_{D_α}=0.4807	$C_{D_{\delta_e}}$=0.0082
C_{L_α}=3.997	$C_{L_{\dot\alpha}}$=0.0317	C_{L_q}=0.1360
$C_{L_{\delta_e}}$=0.1561	C_{M_0}=-0.0757	C_{M_α}=-1.2833
$C_{M_{\dot\alpha}}$=-0.0816	C_{M_q}=-0.2131	$C_{M_{\delta_e}}$=-0.398
C_{D_V}=0	C_{L_V}=0	C_{M_V}=0

In a previous paper identification has been performed for aircraft stability and control derivatives. The obtained results are shown in Table 3.

Table 3
Aircraft parameters (β) determinated with Identification algorithm (dynamic derivatives are dimensional quantities))

C_{D_0}=0.0762	C_{D_α}=0.4845	$C_{D_{\delta_e}}$=0.0042
C_{L_α}=3.9942	$C_{L_{\dot\alpha}}$=0.0359	C_{L_q}=0.1377
$C_{L_{\delta_e}}$=0.1566	C_{M_0}=-0.0757	C_{M_α}=-1.3069
$C_{M_{\dot\alpha}}$=-0.0861	C_{M_q}=-0.2131	$C_{M_{\delta_e}}$=-0.4057
C_{D_V}=-5.2*10^{-4}	C_{L_V}=-0.0015	C_{M_V}=-2.1*10^{-4}

The identification procedure represented in Fig. 1 has been employed to perform the off-line estimation of the process noise covariance matrix components (44) by using results shown in Table 3. The designed algorithm employees the known measurement noise covariance matrix (R):

$$diag(R) = [0.09, 10^{-7}, 10^{-6}, 10^{-4}, 10^{-4}, 10^{-4}, 10^{-4}]^T$$

to identify the process noise covariance matrix (Q). Obtained results are showed below.

$$diag(Q) = \begin{bmatrix} -12.60 \\ -18.62 \\ -26.28 \\ -24.46 \\ 28.67 \\ 13.38 \\ -48.70 \end{bmatrix}$$

Because of Q and R are strictly connected, by varying the measurement noise covariance matrix R, different values of Q are computed.
Once the Q matrix has been determined, the filter tuning is performed. The online determination of wind shear components has been carried out by using the Extended Kalman Filter procedure.
A flight database was obtained through simulation because no experimental data are available in the presence of wind shear.
A simulator has been designed, in which the wind shear has been introduced.
A Gaussian white noise has been added to simulation results in order to obtain noisy measurement data.
So obtained measurement have been employed in the wind-shear estimation procedure.
A first set of simulations has been performed by choosing a flight altitude h=500 $[m]$ and a rectilinear horizontal flight condition with V=27 $[m/s]$ which represents the cruise speed of the studied aircraft.
To cope with the strong gradient in space and time of the wind-shear components, various simulation have been performed varying the shape of the wind-shear components (Gaussian white noise, high frequency random noise and square wave noise).

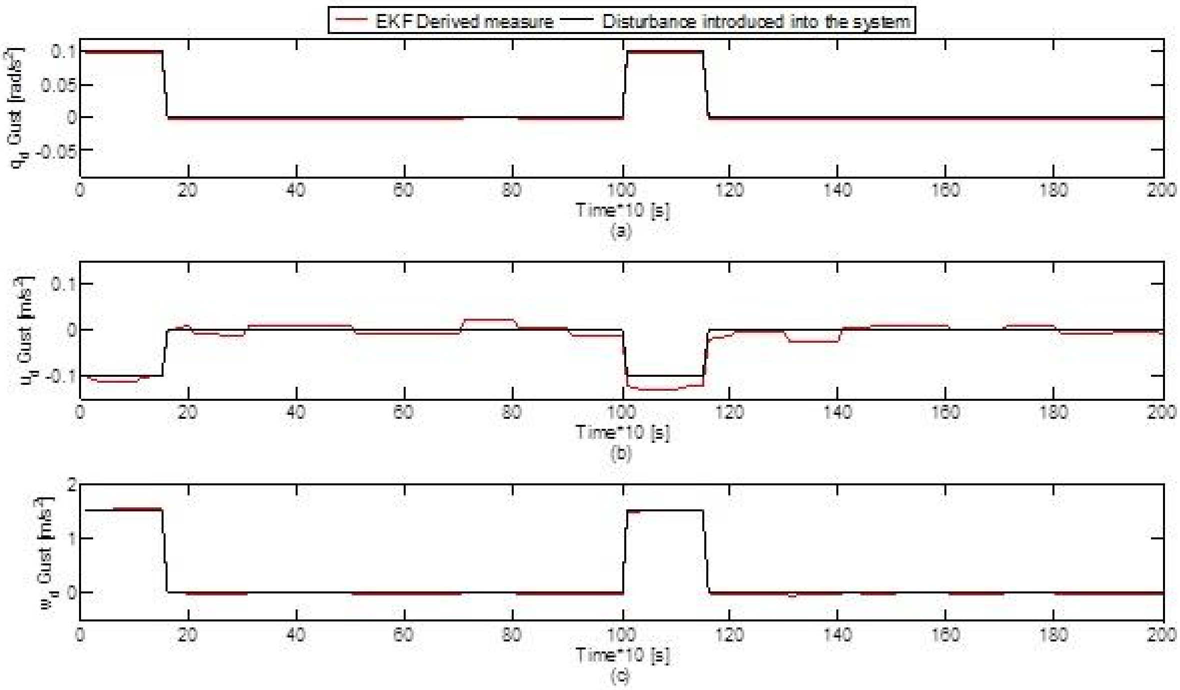

Figure 2. Reconstruction of wind shear components. Square wave pulses with 10 seconds period and 1.5 seconds pulse width. (a) Angular Gust Acceleration, (b) Linear Gust Acceleration along x and (c) Linear Gust Acceleration along z

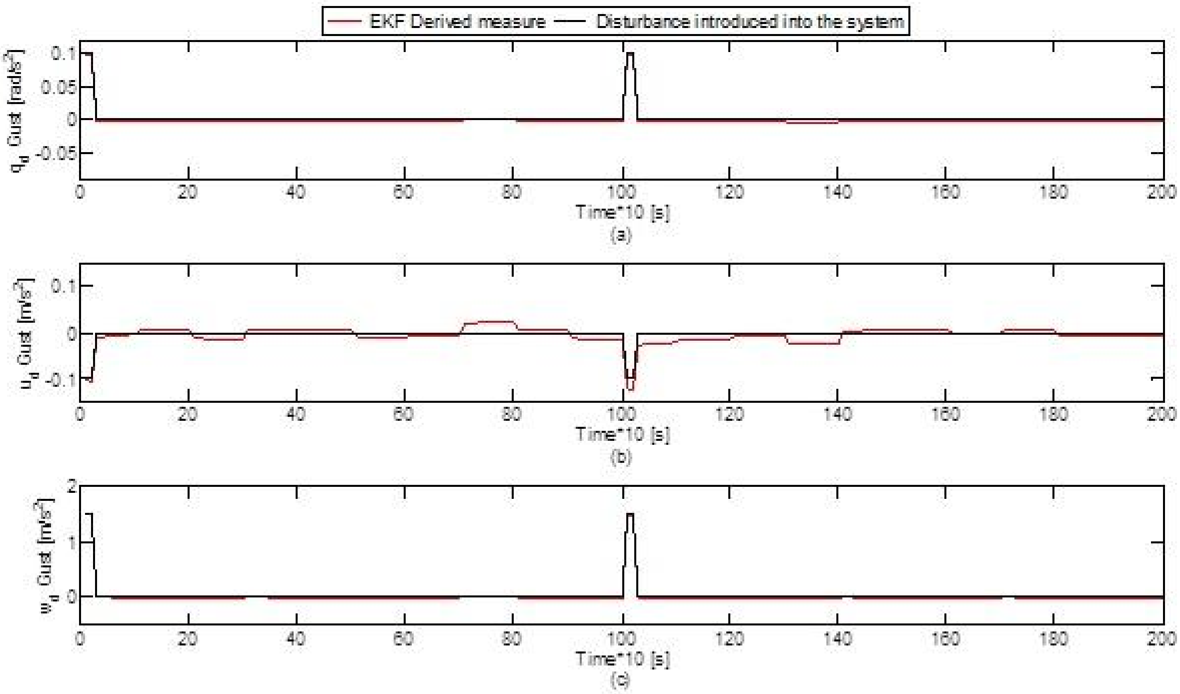

Figure 3. Reconstruction of wind shear components. Square wave pulses with 10 seconds period and 0.2 seconds pulse width. (a) Angular Gust Acceleration, (b) Linear Gust Acceleration along x and (c) Linear Gust Acceleration along z

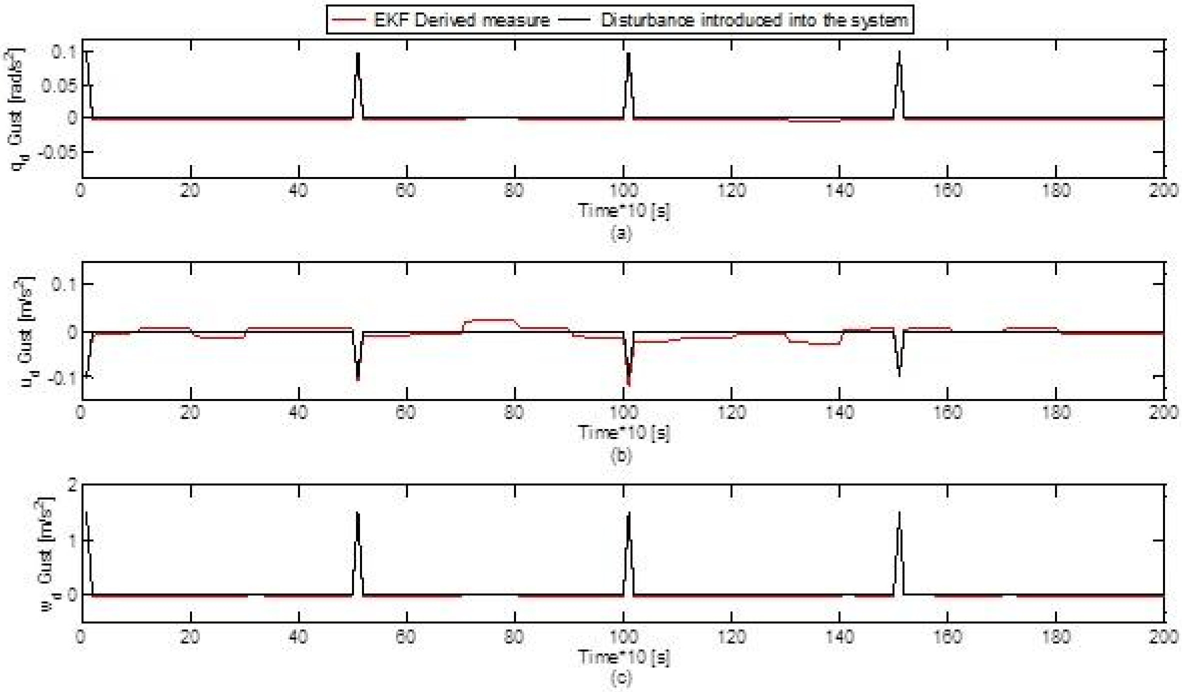

Figure 4. Reconstruction of wind shear components. Square wave pulses with 5 seconds period and 0.1 seconds pulse width. (a) Angular Gust Acceleration, (b) Linear Gust Acceleration along x and (c) Linear Gust Acceleration along z

Figures (2-4) show the comparison between estimated wind shear components and the noise introduced into the system in the case of the square wave having a very short pulse width.

Although the selected input don't represent a real turbulent wind-shear velocity variation, it has been chosen because the identification of a constant trend is the worst condition for the estimation, therefore the following results are the worst obtained.

In figure 2 the disturbance is a square waves pulses with 10 seconds period and 1.5 seconds pulse width, in figure 3 this one has 10 seconds period and 0.2 seconds pulse width and in figure 4 this one has 5 seconds period and 0.1 seconds pulse width.

Noise has not been added to the input to verify the suitability of the carried out procedure.

The obtained results show that the designed and tuned identification algorithm, estimates the wind shear components with excellent results. In fact the maximum error is 0.03 $[m/s^2]$ and it affects the gust acceleration along x. The minimum error is 0.004 $[rad/s^2]$ and it affects the gust rotational acceleration.

It is noticeable that the maximum error (negligible) is obtained when the signal to be estimated follow a constant trend. Besides, it is important to note that even if usually, the square wave reconstruction is affected by delays and errors due to the different dynamic between the phenomenon and the filter, the proposed algorithm reproduces the shape of the wave perfectly and the delays are negligible.

The presence of a bias in the estimates can be ascribed to the sub-optimality of the implemented EKF. The hypotheses of Kalman Filtering theory are not satisfied indeed, since i) the process noise in equation (3,4), which consists of both modeling errors and the unknown gust accelerations due to wind shear , are not a white noise processes; ii) modeling errors affect the whole set of aircraft dynamic equations so, the components of the noise vector are not statistically mutually independent . Matrix Q which describe process noise statistics should not be chosen as a diagonal matrix.

To cope with uncertainties of aerodynamic parameters, wind-shear identification has been performed by imposing reasonable variations of identified parameters. In particular we have randomly used the values within the ranges showed in Table 3:

Table 4
Aircraft parameters (β) determinated with identification algorithm (dynamic derivatives are dimensional quantities)

C_{D_0}=0.0762	C_{D_α}=0.4845	$C_{D_{\delta_e}}$=0.0042
C_{L_α}=3.9942	$C_{L_{\dot\alpha}}$=0.0359	C_{L_q}=0.1377
$C_{L_{\delta_e}}$=0.1566	C_{M_0}=-0.0757	C_{M_α}=-1.3069
$C_{M_{\dot\alpha}}$=-0.0861	C_{M_q}=-0.2131	$C_{M_{\delta_e}}$=-0.4057
C_{D_V}=-5.2*10^{-4}	C_{L_V}=-0.0015	C_{M_V}=-2.1*10^{-4}

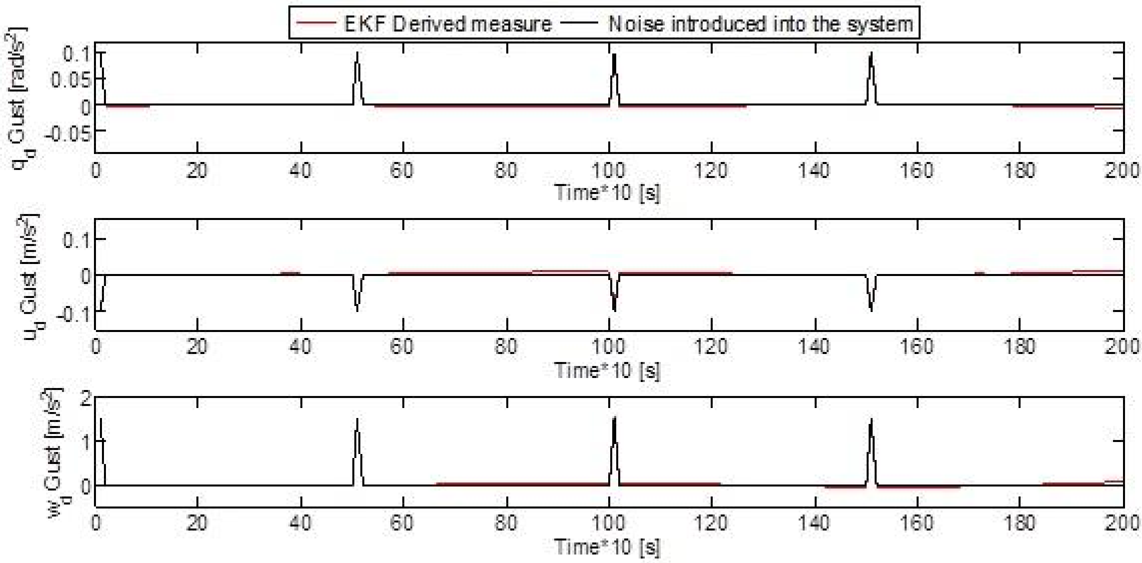

Figure 5. Reconstruction of wind shear components a rectilinear horizontal flight condition with V=24 [m/s]

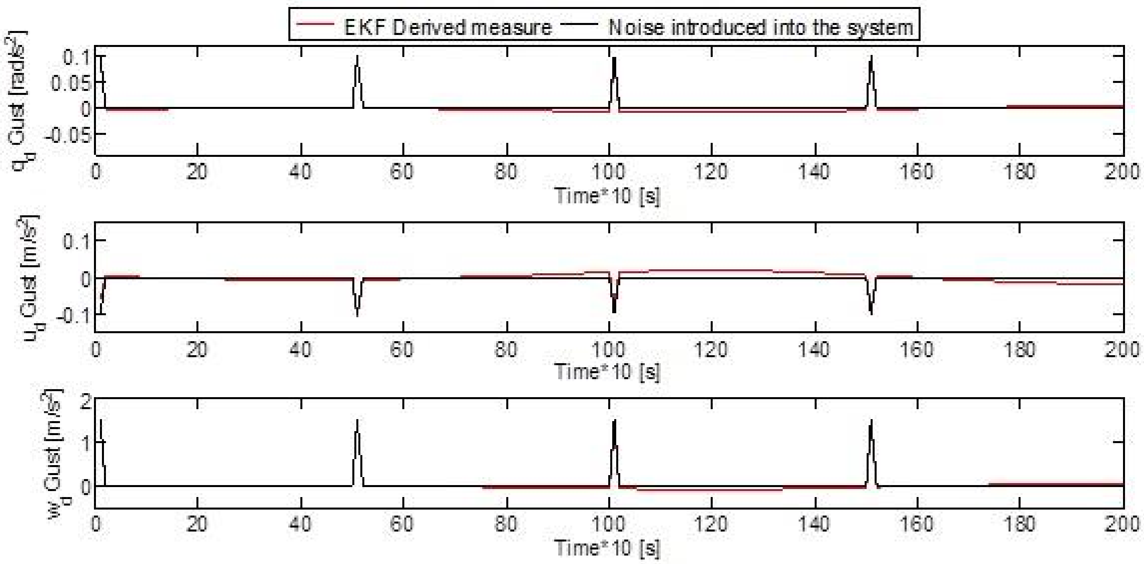

Figure 6. Reconstruction of wind shear components a rectilinear horizontal flight condition with V=30 [m/s]

The simulation results have shown that such variations have a small influence on the wind-shear components identification.
The range of applicability of the interval to estimate, represents a extremely important property to evaluate. This one represents the empirical basis for assuming that the estimate of turbulence, obtained as a function of the. available observations, may be useful to build a good control system. Because of the Kalman gains K have been determined referring to a specific flight conditions it becomes important to evaluate the robustness of the estimation process. By varying flight speed it is possible to test the robustness properties of the implemented algorithm. To cope with both high and low lift coefficients tests have been carried out in a range of speeds between the stall speed V_{ms} (22 [m/s]) and the never exceeding speed V_{NE} (40 [m/s]). Figures (5,6) show the obtained wind shear accelerations by injecting a pulse with 5 seconds period and 0.1 seconds pulse width to the model in following flight conditions: V=24 [m/s] (Figure 5) and V=30 [m/s] (Figure 6).
The figures (5,6) show the robustness of the estimation algorithm, which determines the turbulence introduced into the system, in a range rather ample compared to the reference speed for the optimization.

5. Conclusion

The obtained results show that both shape and intensity of the wind shear components are estimated with the utmost precision. Moreover the results attest the feasibility of the tuned up algorithm. In fact it is possible, by using a few numbers of low cost sensors, to estimate with a noticeable accuracy the augmented state vector. Finally the tuned up Extended Kalman Filter has shown good robustness properties; in fact by changing the flight conditions, it is possible however to estimate both the state and the wind shear components with noticeable precision.
Besides a very short computation time is required to perform the augmented state estimation even by using low computation power. Therefore the implemented algorithm is very suitable for the UAS characteristics. The estimated variables may be used to the implementation of the guidance and control algorithms taking into account the atmospheric turbulence. Wind shear detection on-line could contribute to an efficient safe insertion of UAS in the Civil Air Transport System. In fact it is possible an autonomous reactive motion planning where the vehicle's control system detects previously unknown disturbance, designs a new path in real time, and continues the mission.
Besides, by using the tuned up procedure to determine the process noise covariance matrix in case of failure on one or more control devices, it will possible the reconfiguration of the control system in order to ensure fault-tolerant operations.
Further developments of the present research, will be devoted to the online identification of the full set of wind shear components by using a six degree of freedom model of the studied aircraft and considering inputs affected by noise.

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