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An Algorithm for Parameter Identification of UAS from Flight Data

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Abstract: The aim of the present work is to realize an identification algorithm especially devoted to UAS (unmanned aerial systems). Because UAS employ low cost sensor, very high measurement noise has to be taken into account. Therefore, due to both modelling errors and atmospheric turbulence, noticeable system noise has also to be considered. To cope with both the measurement and system noise, the identification problem addressed in this work is solved by using the FEM (filter error method) approach. A nonlinear mathematical model of the subject aircraft longitudinal dynamics has been tuned up through semi-empirical methods, numerical simulations and ground tests. To take into account model nonlinearities, an EKF (extended Kalman filter) has been implemented to propagate the state. A procedure has been tuned up to determine either aircraft parameters or the process noise. It is noticeable that, because the system noise is treated as unknown parameter, it is possible to identify system affected by noticeable modelling errors. Therefore, the obtained values of process noise covariance matrix can be used to highlight system failure. The obtained results show that the algorithm requires a short computation time to determine aircraft parameter with noticeable precision by using low computation power. The present procedure could be employed to determine the system noise for various mechanical systems, since it is particularly devoted to systems which present dynamics that are difficult to model. Finally, the tuned up off-line EKF should be employed to on-line estimation of either state or unmeasurable inputs like atmospheric turbulence.

Key words: System identification, EKF, UAS.

1. Introduction

Despite of the rapid development of UAV (unmanned aerial vehicle) platforms widespread application, specific system identification techniques have yet to occur for this kind of vehicles. Devoted identification algorithms are necessary because of cost restrictions limit availability and quality of onboard sensors. Therefore, usually, inaccurate mathematical models of the aircraft dynamics are determined during the design phase. Finally, due to physical airframe size, small wind components represent relevant non measured inputs.

Recently, to cope with the peculiar characteristics of unmanned aircraft, some works on identification techniques applied on UAS (unmanned aerial systems) have been published. Therefore, popular system identification algorithm has been implemented in commercial software [1]. Different methods have been proposed, either in frequency domain or in time domain. Usually, reduced models of UAS dynamics are employed. Jameson and Cooke [2] propose a post-maneuver parameter estimation. The parameters of Cranfield Jetstream 31 are determined and validated by using EEM (equation error method) in the frequency domain by means of two postulated models for the reduced order short period and Dutch roll modes. Kallapur and Anavatti [3] make parametrical estimation in the time domain through EKF (extended Kalman filter) only considering the three moment equations.

Nicolosi et al. [4] estimate aircraft stability derivatives from acquired flight data using the OEM (output error method) technique. In this work,

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longitudinal and lateral dynamics are decoupled and they only use two equations of lateral dynamics to determine derivatives.

Frequency domain techniques have the advantages to require a small number of data points for parameter estimation; nevertheless, flight data are recorded in time domain. A very accurate transformation from time to frequency domain has to be performed. In fact, any errors in such a transformation affect the accuracy of the data in the frequency domain, which in turn impacts accuracy of identified parameters. To cope with both quick development and low cost constrains typical of UAS, accurate transformation of flight data from time to frequency domain should be avoided.

Time domain techniques afford to take out such a transformation. Nevertheless, to cope with both system noise (due to inaccurate mathematical models and non measurable inputs like atmospheric turbulence) and strong measurement noise, an identification technique which affords to determine the system noise should be employed. To take into account stochastic characteristics of the measurement and process noise, a simple procedure based on FEM (filter error method) has been designed to look at dynamics and identify longitudinal stability and control derivatives.

To determine dependencies between system parameters, a parametric non linear three DoF (degrees of freedom) model of UAV has been designed through semi-empirical methods, numerical simulations and ground tests.

To take into account model nonlinearities in the present paper, an EKF has been implemented as the estimation algorithm to propagate the state [5, 6].

The paper is organized as follows: Section 2 describes FCRL (Flight Control Research Laboratory) with particular attention on on-board sensors and their accuracy; Section 3 illustrates the state space model of the UAS, expresses the functional relations between aerodynamic coefficients and state variables, and selects both the unknown parameters to estimate and the measured variables. Section 3 also describes the implemented identification algorithm and the tuning of EKF; Section 4 describes the designed input signals and obtained results according to the modal characteristics of the longitudinal dynamics of the UAS; Section 5 concludes the paper and describes advantages of the tuned up procedure highlighting that it is particularly devoted to UAS and/or to systems with unmodelable dynamics.

2. Flight Control Research Laboratory

The studied aircraft is used in the context of the Italian National Research Project PRIN2008 as a FCRL. It is equipped with a research avionic system composed by sensors and computers and their relative power supply subsystem.

In particular, the sensors subsystem consists of:

- inertial measurement unit (three axis accelerometers and gyros);
- magnetometer (three axis);
- air data boom (static and total pressure port, vane sense for angle of attack and sideslip);
- GPS (global positioning system) receiver and antenna;
- linear potentiometers (aileron, elevator, rudder and throttle command);
- RPM (revolutions per minute) (hall effect gear tooth sensor);
- outside air temperature sensor.

The standard deviations of onboard sensors are showed in Table 1.

The subject vehicle shown in Fig. 1 has two unpressurized seats, taking 4,190 N maximum take-off weight aircraft. It features a non-retractable, tail wheel, landing gear and a power plant made up of

Table 1 Standard deviations of measurement errors.

σ_α	σ_γ	σ_q	$\sigma_{\dot{q}}$	$\sigma_{x_e} = \sigma_{z_e}$	σ_V	$\sigma_{a_x} = \sigma_{a_z}$
3.2×10^{-4} rad	0.0001 rad	0.001 rad/s	0.001 rad/s^2	1 m	0.094 m/s	0.01 m/s

reciprocating engine capable of developing 60 HP, with a 1.50 m diameter, two bladed, fixed pitch and tractor propeller. The aircraft stall speed is 22 m/s; therefore, it is capable of speeds up to about 59 m/s (sea level) and it will be cleared for altitudes up to 10.000 ft.

Geometrical characteristics of the vehicle are:

- wing area S: 11.15 m^2;
- wing chord c: 1.20 m;
- wing span b: 9.30 m.

3. Problem Formulation

In this work, we focus on longitudinal flight and rigid body dynamics is of interest. As a consequence, aircraft motion can be described by means of the following equations [7].

$$\dot{V} = \frac{T}{m}\cos(\alpha_T + \alpha) - \frac{\bar{q}Sc_D}{m} - g\sin(\theta - \alpha) \tag{1}$$

$$\dot{\alpha} = -\frac{T}{mV}\sin(\alpha_T + \alpha) - \frac{\bar{q}Sc_L}{mV} + \\ + \frac{g}{V}\cos(\theta - \alpha) + q \tag{2}$$

$$\dot{q} = \frac{\bar{q}Sc_m c}{I_y} \tag{3}$$

$$\dot{\theta} = q \tag{4}$$

where,

$$\bar{q} = \frac{1}{2}\rho \cdot V^2 \tag{5}$$

$$c_D = c_{D_0} + c_{D_V} \cdot V + c_{D_\alpha} \cdot \alpha + c_{D_{\delta_e}} \cdot \delta_e \tag{6}$$

$$c_L = c_{L_V} \cdot V + c_{L_\alpha} \cdot \alpha + c_{L_{\dot{\alpha}}} \cdot \dot{\alpha} + c_{L_q} \cdot q \\ + c_{L_{\delta_e}} \cdot \delta_e \tag{7}$$

$$c_m = c_{m_0} + c_{m_V} \cdot V + c_{m_\alpha} \cdot \alpha + \\ c_{m_{\dot{\alpha}}} \cdot \dot{\alpha} + c_{m_q} \cdot q + c_{m_{\delta_e}} \cdot \delta_e \tag{8}$$

Moreover, T is the thrust and α_T is the thrust angle of attack.

Derivatives respect to angular and linear velocity are evaluated in dimensional form.

Normal flight regimes are considered; so, to take into account unsteady aerodynamic effects, it is sufficient to assume a dependence of the lift L, the drag D and the pitching moment M only on the first time derivatives of speed V, angle of attack α and pitch rate q.

Dynamics of the bare airframe in clean configuration and out of ground effect is of concern. Moreover, since for the subject aircraft variations of mass m and center of gravity location are relatively slow and the effect of altitude is relatively weak, identification is performed for a fixed combination of weight, center of gravity location and altitude. This clearly implies that, to obtain identification of aircraft dynamics over the whole flight envelope, the space of admissible values of weight, center of gravity location and altitude must be divided into sub regions of appropriate size and the identification has to be performed in each sub region.

Based on the above assumptions, the state of the system is given by $\mathbf{x} = [V, \alpha, q, \theta]^T$, while the set of inputs $\mathbf{u} = [\delta, T]^T$ is made up of the longitudinal control surfaces deflections and the thrust.

According to Eqs. (6)-(8), the set of the unknown aircraft parameters is given by:

$$\beta = [c_{D_0} c_{D_\alpha}\, c_{D_{\delta_e}}\, c_{L_\alpha}\, c_{L_{\dot{\alpha}}}\, c_{L_q}\, c_{L_{\delta_e}}\, c_{m_0}\, c_{m_\alpha}\, c_{m_{\dot{\alpha}}}\, c_{m_q} \\ c_{m_{\delta_e}}\, c_{D_V}\, c_{L_V}\, c_{m_V}]^T$$

Eqs. (1)-(4) represent the aircraft state equations, and the corresponding set of longitudinal observation equations is:

$$V_m = V \tag{9}$$

$$\alpha_m = \alpha \tag{10}$$

$$q_m = q \tag{11}$$

$$\theta_m = \theta \tag{12}$$

$$\dot{q}_m = \frac{\bar{q} \cdot S \cdot c}{I_y} \cdot C_m \tag{13}$$

$$a_{xm} = \frac{\bar{q} \cdot S}{m} \cdot C_x + \frac{T}{m} \tag{14}$$

$$a_{zm} = \frac{\bar{q} \cdot S}{m} \cdot C_z \tag{15}$$

where, the subscript m denotes the measured variables, C_x and C_z are referred to the body reference frame and $\alpha_T = 0$.

Fig. 1 FCRL based on N3 Ultrapup.

Obviously, observation equations have to take into account that experimental data are affected by measurement noise in the sensors, besides state equations are affected by modeling errors (e.g., unmodeled dynamics), finally used flight data could be gathered in presence of atmospheric turbulence. Because both measurement noise and process noise (atmospheric turbulence) are random process, a procedure of estimation based on statistical criteria has to be used for the determination of the parameters. The FEM (filter error method) [8-10] accounts for both measurement noise and process noise such as atmospheric turbulence, and it allows to determine the process noise covariance matrix **Q**. Even in the case of flight manoeuvres in smooth air, it could lead to better estimation because modeling errors are treated as process noise.

In this case, the mathematical model is given by the stochastic equations:

$$\dot{x}(t) = f(x(t), u(t), w(t), \theta) \tag{16}$$

$$y(t) = h(x(t), u(t), \theta) \tag{17}$$

$$z(k) = y(k) + v(k) \tag{18}$$

$$x(t_0) = x_0 \tag{19}$$

where, f and h are dimensional general nonlinear real valued vector functions, θ contains the unknown system parameters β and the elements of process noise covariance matrix **Q**, z is the measurement vector, $w(t)$ is the process noise and $v(k)$ is the measurement noise.

According to theory, the measurement noise is assumed to be characterized by a sequence of independent Gaussian random variables with zero mean and covariance matrix **R**. The goal of the identification process is to estimate θ from the discrete measurements of the system response z to the given inputs u based on the mixed continuous-discrete system model postulated in Eqs. (16)-(19).

The maximum likelihood estimates of the unknown parameters are obtained by minimization of the negative logarithmic likelihood function (cost function):

$$J = \frac{1}{2}\sum_{i=1}^{N}[z(k) - \hat{y}(k)]^T \hat{R}^{-1}[z(k) - \hat{y}(k)] + \\ + \frac{N}{2} ln(\|\hat{R}\|) \tag{20}$$

Starting from the specified initial values of θ, new updated estimates are obtained by applying the Gauss-Newton method which leads to a system of linear equations:

$$\theta_{i+1} = \theta_i + \Delta\theta_1 \tag{21}$$

$$\Delta\theta = \left(\sum_{k=1}^{N}\left[\frac{\partial y(t_k)}{\partial\theta}\right]^T \mathbf{R}^{-1}\left[\frac{\partial y(t_k)}{\partial\theta}\right]\right)^{-1} \left(\sum_{k=1}^{N}\left[\frac{\partial y(t_k)}{\partial\theta}\right]^T \mathbf{R}^{-1}\left[z(t_k) - y(t_k)\right]\right) \quad (22)$$

The first term in braces on the right-hand side is an approximation of the second gradient $\frac{\partial^2 J}{\partial\theta^2}$. This approximation helps to reduce the computational costs without significantly affecting the convergence.

By using Eqs. (21) and (22), the iterative update of system parameter may be performed. The update requires:

(1) computation of the observation variables *y*;

(2) computation of the response gradients $\frac{\partial y}{\partial\theta}$ at each time point.

Because the process under examination contains unmeasurable stochastic inputs (i.e., turbulence) and a non-linear dynamic model of the aircraft is used, an EKF through knowledge of the outputs has been designed to estimate and propagate the state of the system.

To determine the Kalman gains *K*, the known measurement noise covariance matrix **R** of the on board sensors has been employed. In this way, the tuning of the filter has been made through the identification of the process noise covariance matrix **Q**.

The EKF equations are,

$$\tilde{y}(k) = g[\tilde{x}(k), u(k), \beta] \quad (23)$$

$$\mathrm{K}(k) = \tilde{P}(k)C^{\mathrm{T}}[C\tilde{P}(k)C^T + \mathrm{R}(k)]^{-1} \quad (24)$$

$$\hat{x}(k) = \tilde{x}(k) + \mathrm{K}(k)[z_k - \tilde{y}(k)] \quad (25)$$

$$\hat{P}(k) = [I - \mathrm{K}(k)C]\tilde{P}(k)[I - \mathrm{K}(k)C]^T + \mathrm{K}(k)R(k)\mathrm{K}^{\mathrm{T}}(k) \quad (26)$$

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 is the average of the control input, β is the parameter vector, $[z_k - \tilde{y}(k)]$ are 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.

So the unknown vector **θ** is:

$$\boldsymbol{\theta} = [\beta, diag(Q)]^{\mathrm{T}} \quad (27)$$

The block schematic of the implemented algorithm is shown in Fig. 2.

To accelerate identification process, a first set of stability and control derivatives has been calculated by linearization of the preliminary nonlinear mathematical model of the subject aircraft longitudinal dynamics. A cruise altitude $h = 500$ m and a rectilinear horizontal flight condition with $V = 27$ m/s, which represents the cruise speed of the studied aircraft, have been chosen. The obtained non-dimensional stability and control derivatives are shown in Table 2.

The set of parameters shown in Table 2 has been used to initialize the identification process $\boldsymbol{\theta}_0 = [\beta_0, \mathrm{diag}(\mathbf{Q})]^{\mathrm{T}}$. In this way, by using reasonable initial guess, a faster convergence of the algorithm may be performed.

Besides the proper guess of initial parameter values determines small errors in the approximation of the gradient $\frac{\partial J}{\partial\theta}$, consequently, the iterative update of **θ** with the application of the Gauss-Newton method (Eqs. (21) and (22)) is performed efficiently.

Because aircraft parameters are related to physical phenomena, we have postulated typical uncertainties on the various model parameters and imposed constraints on their standard deviation σ_0. In this way, the identification problem, solved implementing a constrained optimization algorithm, requires a few numbers of iterations.

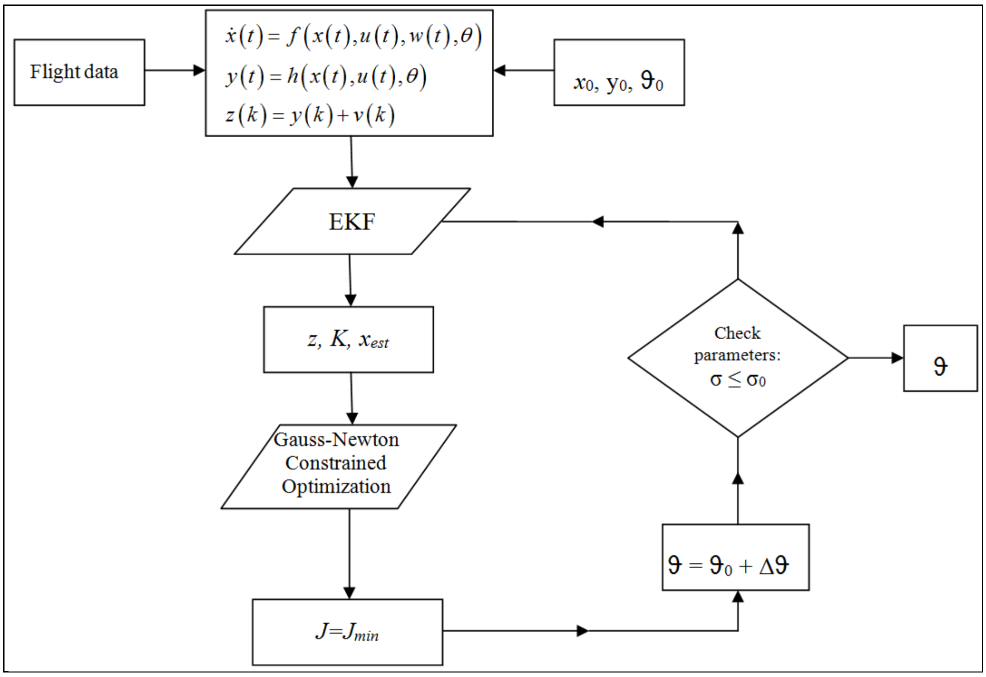

Fig. 2 Block schematic algorithm representation.

Table 2 Analytical aircraft parameter (initialization values).

c_{D_0}	c_{D_α}	$c_{D_{\delta_e}}$	c_{L_α}	$c_{L_{\dot\alpha}}$	c_{L_q}
0.0665	0.4807	0.0082	3.9977	1.4178	6.1571
$c_{L_{\delta_e}}$	c_{m_0}	c_{m_α}	$c_{m_{\dot\alpha}}$	c_{m_q}	$c_{m_{\delta_e}}$
0.1561	-0.0757	-1.2833	-3.6753	-11.304	-0.3983
c_{D_V}	c_{L_V}	c_{m_V}			
0	0	0			

4. Results and Discussion

To gain insight into the feasibility of the approach, the procedure has been tested using numerically generated data. A nonlinear mathematical model of the subject aircraft longitudinal dynamics has been tuned up through semi-empirical methods, numerical simulations and ground tests.

The preliminary nonlinear mathematical model of the subject aircraft longitudinal dynamics has been employed to generate state vector time histories to be used to test the identification process. The actual instrumentation used for performance and flight characteristics testing has been simulated by adding measurement errors to the true system responses generated by the model. Zero mean white Gaussian noise has been added to each state variable with root mean square values in accordance with the kind of measurement devices in use (Table 1).

Two input forms have been selected to perform the aerodynamic model parameter identification, the doublet input and the so-called 3-2-1-1 input (alternating pulses with width in the ratio 3-2-1-1). The selected inputs afford to maintain the flight condition essentially unchanged and consider the model parameter constant throughout the manoeuvre. Only elevator deflections have been employed ($\Delta\delta_e = \pm 0.1$ rad). To select the timing of the elevator pulse, the natural frequencies of the aircraft longitudinal dynamic modes have been determined by using the stability derivatives shown in Table 2. In this way, it has been possible to choose the timing of the doublets so that the associated frequencies bracket the expected natural frequencies of phugoid and short period modes (Fig. 3).

In the same way, the width of two pulses has been selected to correspond to half the period of the phugoid and short period modes (Fig. 4).

Because the selected maneuvers generate a relatively small set of data, such a small set leads to a reduction

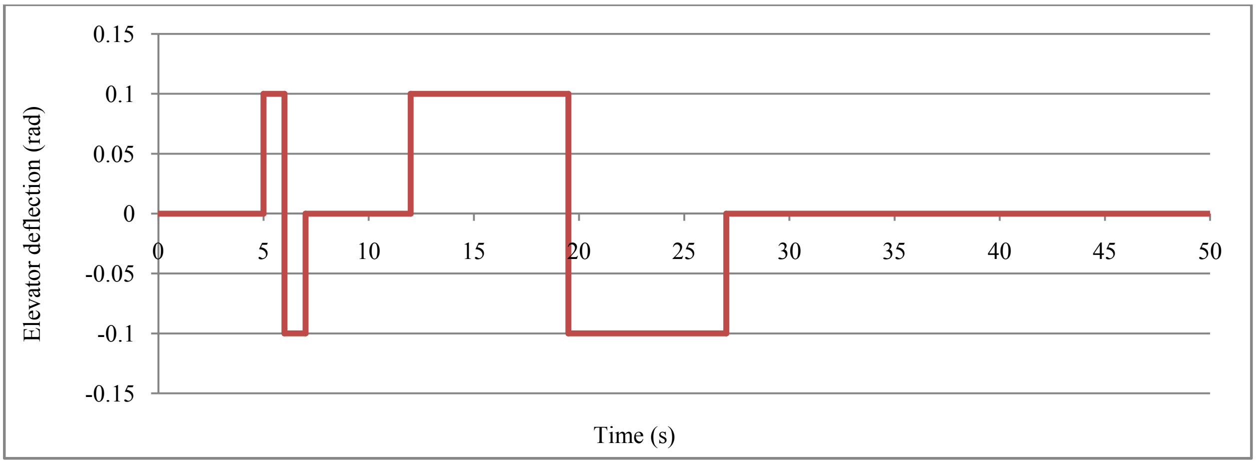

Fig. 3 Doublet input.

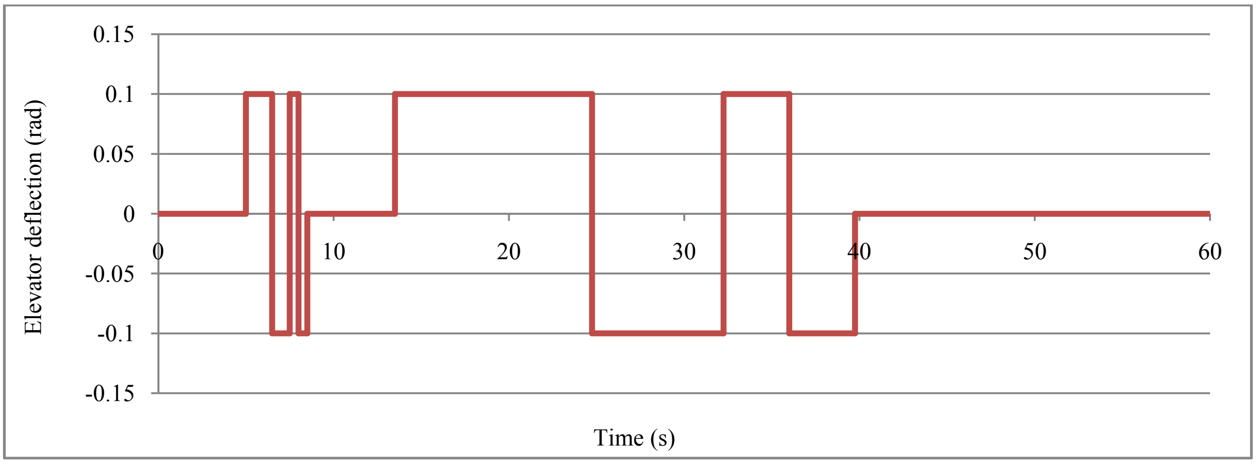

Fig. 4 3-2-1-1 input.

of the computational time. Nevertheless, the chosen inputs significantly excite both the aircraft longitudinal modes. In this way, it is possible to determine the whole set of aircraft derivatives.

By performing the previous described simulation, aircraft parameters showed in Table 3 have been obtained.

To take into account instrumental errors in the measurements of the elevator deflections, a zero mean white Gaussian noise has been added to input variables with a reasonable root mean square values. Table 4 shows the obtained aircraft parameters in the 3-2-1-1 input case.

A statistical analysis has been carried out on the effects of modeling errors. The identification process is repeated many times assuming random errors on the

Table 3 Identified parameters.

		Estimated doublet	Estimated 3-2-1-1
1	c_{D_0}	0.0748	0.0665
2	c_{D_α}	0.4839	0.4807
3	$c_{D_{\delta_e}}$	0.0013	0.0082
4	c_{L_α}	3.9941	3.9977
5	$c_{L_{\dot\alpha}}$	1.449	1.4265
6	c_{L_q}	5.3505	6.12
7	$c_{L_{\delta_e}}$	0.1529	0.561
8	c_{m_0}	-0.0837	-0.0757
9	c_{m_α}	-1.3150	-1.2833
10	$c_{m_{\dot\alpha}}$	-3.528	-3.6720
11	c_{m_q}	-11.102	-9.5895
12	$c_{m_{\delta_e}}$	-0.4123	-0.3983
13	c_{D_V}	-6.097×10^{-4}	-8.6885×10^{-6}
14	c_{L_V}	-0.0017	-0.0017
15	c_{m_V}	8.1146×10^{-4}	8.7862×10^{-4}

Table 4 Identified parameters with noisy inputs.

c_{D_0}	c_{D_α}	$c_{D_{\delta_e}}$	c_{L_α}	$c_{L_{\dot\alpha}}$	c_{L_q}	$c_{L_{\delta_e}}$	c_{m_0}	c_{m_α}	$c_{m_{\dot\alpha}}$	c_{m_q}	$c_{m_{\delta_e}}$	c_{D_V}	c_{L_V}	c_{m_V}
0.0661	0.4792	0.0032	3.9980	1.4175	5.3685	0.1627	-0.0837	-1.2590	-4.59	-11.102	-0.4419	-1.2×10^{-4}	-0.0012	-0.0016

model parameters, with probability density functions which describe typical uncertainties on the various model parameters. The resulting statistics of the estimated parameters show that the identification process is adequately robust with respect to uncertainties in the preliminary model. In fact, the biggest standard deviation obtained is equal to 4.4×10^{-4}.

5. Conclusions

The obtained results from simulation show that the implemented algorithm affords to determine aircraft parameter with noticeable precision.

Besides the tuned up procedure by proper choice of initial guess allows accelerating the identification process, in fact, the algorithm requires a short computation time to determine aircraft parameter with noticeable precision by using low computation power.

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 longitudinal derivatives. Finally, the tuned up algorithm has shown good robustness properties. In fact, by assuming random errors on the model parameters, it is possible, however, to estimate both stability and control derivatives with good precision.

Therefore, the implemented algorithm is very suitable for the UAS characteristics because the parametrical identification is performed by using low computational power and sensor characterized by high measurement noise.

Besides, by using the tuned up procedure to determine the process noise covariance matrix, it is possible to identify system failure.

In addition, the determination of process noise allows to employ low precision models. Such advantage reduces system design and development phases.

External disturbance may be determined by using an augmented state and consequently by the augmentation of the **Q** dimension.

Finally, systems with unmodelable dynamics may be identified.

At present time flight test campaign is in progress and experimental flight data will be utilized to validate simulation obtained results.

Further developments of the present research will be devoted to the online identification of the full set of stability and control derivatives by using a six DoF non-linear model of the studied aircraft.

References

[1] MatLab®, Neural Network Toolbox, available from: http://www.mathworks.com.

[2] Jameson, P. D., and Cooke, A. 2012. "Developing Real-Time System Identification for UAVs." Presented at the UKACC International Conference on Control, Cardiff, UK.

[3] Kallapur, A. G., and Anavatti, S. G. 2006. "UAV Linear and Nonlinear Estimation Using Extended Kalman Filter." Presented at the International Conference on Computational Intelligence for Modelling Control and Automation, and International Conference on Intelligent Agents, Web Technologies and Internet Commerce, Sydney, Australia.

[4] Nicolosi, F., Marco, A., and Della, V. P. 2010. "Stability, Flyiing Qualities and Parameter Estimation of a Twin-Engine CS-23/FAR 23 Certified Light Aircraft." Presented at the AIAA Guidance, Navigation, and Control Conference, Toronto, Ontario, Canada

[5] Welch, G., and Bishop, G. 2004. "An Introduction to the Kalman Filter." TR 95041, University of North Carolina at Chapel Hill.

[6] Grillo, C., and Vitrano, F. P. 2008. "State Estimation of a Nonlinear Unmanned Aerial Vehicle Model Using an Extended Kalman Filter." Presented at the XV AIAA International Space Planes and Hypersonic Systems and

Technologies Conference, Dayton, Ohio.

[7] Etkin, B. 1972. *Dynamics of Atmospheric Flight.* Chapter V, NY: John Wiley and Sons Inc.

[8] Jategaonkar, R. 2006. *Flight Vehicle System Identification: A Time Domain Methodology*. Chapter V. NY: AIAA Progress in Astronautics and Aeronautics Series.

[9] Jategaonkar, R., and Thielecke, F. 2000. "Aircraft Parameter Estimation—A Tool for Development of Aerodynamic Databases." *Sādhanā* 25 (2): 119-35.

[10] Jategaonkar, R. 1993. "A Comparison of Output Error and Filter Error Methods from Aircraft Parameter Estimation Results." *DLR-Mitt.* 3: 63-87.