DINAME 2019 - Proceedings of the XVIII International Symposium on Dynamic Problems of Mechanics,
M.A. Savi, T.G. Ritto and W.M. Bessa (Editors), ABCM, Buzios, RJ, Brazil, March 10th to 15th, 2019

Parameter Identification for a Flexible Unmanned Aerial Vehicle Using Extended Kalman Filtering

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Abstract: This paper describes a system identification of a Flexible Unmanned Aircraft Vehicle (FUAV) using a extended Kalman filter. Currently, Technological Institute of Aeronautics (ITA), in partnership with Flight Technologies (FT), are developing an FUAV with a large wingspan, built with composite materials, with the purpose of making the wing structure flexible. Flight data may contain considerable amount of noise; in addition, there may be trends and states not observed in the system model to be estimated, so filtering techniques are generally employed. This difficulties mentioned above make the problem of state and parameter estimation a nonlinear filtering problem. Extended Kalman Filter (EKF) is an excellent tool for this matter with the property of recursive parameter identification and excellent filtering. Then the goals of this paper is identify the longitudinal aerodynamic and elastic derivatives using a extended Kalman filter.

Keywords: aircraft parameter estimation, flexible aircraft dynamics, Extended Kalman Filter, Flexible Unmanned Aircraft Vehicle

1 INTRODUCTION

Technological Institute of Aeronautics, in partnership with Flight Technologies Ltda, is developing a large Flexible Unmanned Aerial Vehicle (FT100Flex - Eolo), Fig.1, built with composite materials. The objective of this partnership is research the knowledge and mastery of the effects of low-frequency structural vibration on the aircraft control system.

Figure 1 – FT100Flex - Eolos.

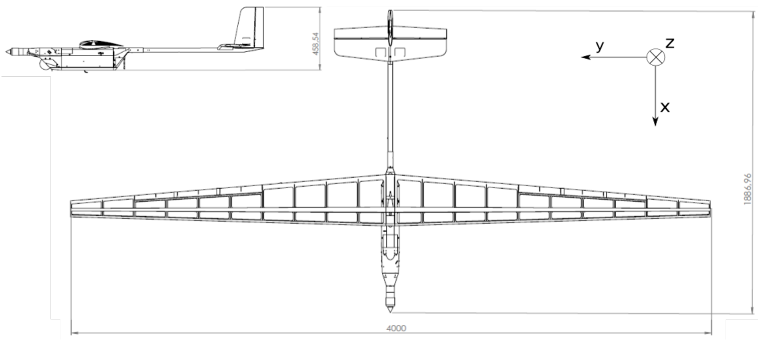

Figure 2 – FT100Flex - Three view.

The FT100Flex-Eolo have a wingspan of 4 m, built with composite materials, height of 0.45 m and lenght of 1.89 m. The tail boom are built in carbon fiber. The power system components are the RimFire 50mm brushless outrunner motor. The geometry and mass parameters are summarized in the Tab 1.

Table 1 – Geometry and mass parameters

Parameters	Symbol	Values
Wing area	S	0.85 m^2
Wing chord	$\bar{c}$	0.23 m
Wing span	b	4.00 m
Aspect ratio		19
Fuselage length		1.89 m
Wing mass	m_w	2 kg
total mass	m_t	9 kg

In a way to build a more realistic mathematical and computational model is necessary obtain the parameters that defines the problem. Thus it requires method to identification of this parameters that guarantees an accurate model of the flight dynamics, which shows the stronger interaction between flight control system and the structural modes [13].

Aerodynamic parameter estimation provides an effective way for aircraft system modeling using measured data from flight test [7], especially for the purpose of developing elaborate simulation environments and control systems design of Flexible Unmanned Aerial Vehicle (FUAV) with short design cycles and reduced cost.

Recursive systems identification techniques are based mainly on recursive parameter estimation, where flight data is measured through sensors in the aircraft and estimates the required aerodynamic derivatives in real time [2]. Stochastic filtering methods is a two-step procedure, consisting of prediction or updating of time and correction or update of measurement. The procedure developed by Kalman provides an optimal sequential state estimator that is ideal for recursive implementations [11]. The most popular nonlinear filtering technique in the aerospace industry is the extended Kalman filter (FKE) that uses instant linearizations at each step of time to approximate nonlinearities. FKE can be difficult to tune and implement when it comes to significant nonlinearities and exhibits disagreements in extreme cases.

The aim of this paper is to identify the longitudinal aerodynamic and elastic derivatives of the FUAV using the extended Kalman filter.

2 EXTENDED KALMAN FILTER

The Extended Kalman Filter (EKF) gives a solution to the combined state and parameter estimation problem. The EKF involves linearization of the postulated nonlinear model about some suitable point and the use of the Kalman filter.

Estimation of parameters applying the filter approach is an indirect procedure, which needs transformation of the parameters estimation problem into a state estimation problem. Considering the system parameters vector Θ, and the augmented parameter state vector $x_a = [x \ \ \Theta]^T$. The extended system as:

$$\begin{aligned} \dot{x}_a =& \ f[x_a(t),\ u(t)] + F\omega(t) \\ y(t) =& \ g[x_a(t),\ u(t)] \\ z(k) =& \ y(k) + G\nu(k) \end{aligned} \tag{1}$$

where F and G are the noise distribution matrices and $\nu(t)$ and $\omega(t)$ are the process noise and measurement noise respectively (assumed to be zero mean, uncorrelated and mutually independent).

The EKF computational procedure are separate in to steps: Prediction step (Time update) and correction step (measurement update).

Prediction step

$$\tilde{x}_a(k+1) = \ \tilde{x}_a + \int_{t_k}^{t_{k+1}} f[x_a(t),\ u(t)]dt \tag{2}$$

$$\tilde{P}_a(K+1) = \ \Phi_a(k+1)\hat{P}_a\Phi_a(k+1)^T + \Delta t F F^T \tag{3}$$

$$\Phi_a(k+1) = \ e^{A_a(k)\Delta t} \approx \ I + \Delta t + A_a(k) + A_a^2(k)\frac{\Delta^2}{2!} + \dots \tag{4}$$

$$A_a(k) = \ \left.\frac{\partial f[x_a(t),\ u(t)]}{\partial x_a}\right|_{x_a=\hat{x}_a(k)} = \ \left[\begin{array}{c|c} \partial f/\partial x & \partial f/\partial \Theta \\ \hline 0 & 0 \end{array}\right]_{x_a=\hat{x}_a(k)} \tag{5}$$

with initial conditions $\hat{x}_a(1) = \ x_{a0}$ and $\hat{P}_a(1) = \ P_{a0}$.

Correction step

$$\tilde{y}(k) = g[\tilde{x}_a(k),\ u(k)] \tag{6}$$

$$K(k) = \tilde{P}_a(k)C_a^T[C_a\tilde{P}_a(k)C_a^T + R]^{-1} \tag{7}$$

$$\hat{x}_a(k) = \tilde{x}_a(k) + K_a(k)[z(k) - \tilde{y}(k)] \tag{8}$$

$$\hat{P}_a(k) = [I - K(k)C_a]\tilde{P}_a(k)[I - K(k)C_a]^T + K(k)RK(k)^T \tag{9}$$

where

$$C_a(k) = \left.\frac{\partial g[x_a(t),\ u(t)]}{\partial x_a}\right|_{x_a=\tilde{x}_a(k)} = \left[\begin{array}{c|c} \partial g/\partial x & \partial g/\partial \Theta \\ \hline 0 & 0 \end{array}\right]_{x_a=\tilde{x}_a(k)} \tag{10}$$

the tilde ($\sim$) is the predicted variables and the hat ($\wedge$) are the estimate / updated variable, K is the Kalman gain matrix and $R = GG^T$ is the covariance matrix. For the propagation of the states across the two discrete times points according to eq. 2 is necessary apply a Runge-Kutta method.

3 LONGITUDINAL MODEL OF A FLEXIBLE AIRCRAFT

Following the Non Linear Linear Dynamics Methodology (NFLS) adopted by references [3], [4] and [7]. This methodology is an extension of the classic flight dynamics in which the linear structural dynamics and non-linear flight dynamics are considered. Starting from the hypothesis that the UAV is considered a continuous elastic body it is possible to obtain its equations from the use of the Langrange equation and the principle of the virtual work.

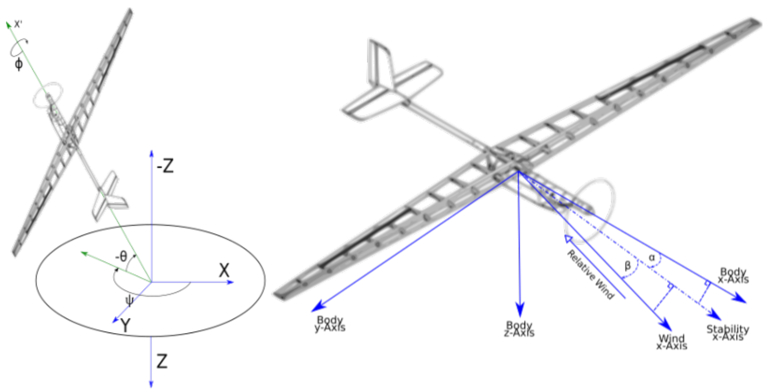

Figure 3 – Inertial reference frame and body axis reference

The equations of motion of the aircraft in six degrees of freedom [8], fallow the axis references show in Fig 3:

$$\begin{array}{l} \dot{u} - rv + qw + gsen(\theta) = \frac{X}{M} \\ \dot{v} - pw + ru + gsen(\phi)cos(\theta) = \frac{Y}{M} \\ \dot{w} - qu + pv + gcos(\phi)cos(\theta) = \frac{Z}{M} \\ I_{xx}\dot{p} - (I_{xy}\dot{q} + I_{xz}\dot{r}) + (I_{zz} - I_{yy})qr + (I_{xy}r - I_{xz}q)p + (r^2 - q^2)I_{yz} = L \\ I_{yy}\dot{q} - (I_{xy}\dot{p} + I_{yz}\dot{r}) + (I_{xx} - I_{zz})pr + (I_{yz}p - I_{xy}r)q + (p^2 - r^2)I_{xz} = M \\ I_{zz}\dot{r} - (I_{xy}\dot{p} + I_{yz}\dot{q}) + (I_{yy} - I_{xx})pq + (I_{xz}q - I_{zy}r)q + (q^2 - p^2)I_{xy} = N \\ \ddot{\eta}_i + 2\zeta_i\omega_i\dot{\eta}_i + \omega_i^2\eta_i = \frac{Q_i}{M_i} \end{array} \tag{11}$$

The six first equations above are described in relation to the reference system of the middle axis and are formally equivalent to the classical equations of the rigid body dynamics. The last expression is the structural response model in terms of the modal deflections η_i. The total modeling has $6 + n_F$ degrees of freedom, where n_F is the number of flexible modes retained in the model. Q_i represents the generalized forces acting in the $i-th$ structural mode and has aerodynamic origin.

Instead of working with the dimensional coefficients, the dimensionless ones are used. The coefficients are made dimensionless in the following way with $q = 0.5\rho U_0^2$ being the dynamic pressure and ρ the air density.

$$C_{M\alpha} = M_\alpha \frac{I_{yy}}{qS\bar{c}};\ C_{Mq} = M_q \frac{2U_0 I_{yy}}{qS\bar{c}^2};\ C_{M\delta e} = M_{\delta e} \frac{I_{yy}}{qS\bar{c}};\ C_{M\eta 1} = M_{\eta_1} \frac{I_{yy}}{qS\bar{c}};\ C_{M\dot{\eta} 1} = M_{\dot{\eta}_1} \frac{2U_0 I_{yy}}{qS\bar{c}^2}; \tag{12}$$

$$C_{L\alpha} = -Z_\alpha \frac{m}{qS};\ C_{Lq} = -Z_q \frac{2U_0 m}{qS};\ C_{\delta e} = -Z_{\delta_e} \frac{m}{qS};\ C_{L\eta 1} = -Z_{\eta_1} \frac{m}{qS};\ C_{L\dot{\eta} 1} = -Z_{\dot{\eta}_1} \frac{U_0 m}{qS}; \tag{13}$$

$$C_{Q1\alpha} = \Xi_{1\alpha} \frac{1}{qS\bar{c}};\ C_{Q1q} = \Xi_{1q} \frac{U_0}{qS\bar{c}};\ C_{Q1\delta e} = \Xi_{1\delta_e} \frac{1}{qS\bar{c}};\ C_{Q1\eta 1} = \Xi_{1\eta_1} \frac{1}{qS\bar{c}};\ C_{Q1\dot{\eta} 1} = \Xi_{1\dot{\eta}_1} \frac{U_0}{qS\bar{c}} \tag{14}$$

3.1 Longitudinal Dynamics

The longitudinal dynamics is a special case of eq 11, where $p = r = v = 0$. Then the motion is restrict to the plane os symmetry, oxz, like shoes the Fig 3.1.

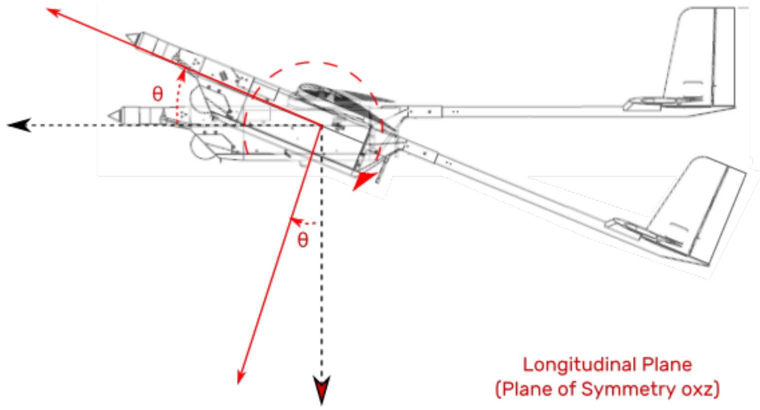

Figure 4 – Longitudinal plane of symmetry

A linearized formulation for longitudinal dynamics of a flexible aircraft in stable level flight can be found in [6]. Longitudinal motion is normally represented by small displacements from an equilibrium (unaccelerated) flight condition in the longitudinal plane. An approximation of short period dynamics is presented below according to the work of Pfifer, H. and Danowsky, B.P.(2016) [2].

$$\begin{bmatrix} \dot{\alpha} \\ \dot{\theta} \\ \dot{q} \\ \dot{\eta}_1 \\ \ddot{\eta}_1 \end{bmatrix} = \begin{bmatrix} Z_\alpha/U_0 & 0 & 1+Z_q/U_0 & Z_{\eta_1}/U_0 & Z_{\dot{\eta}_1}/U_0 \\ 0 & 0 & 1 & 0 & 0 \\ M_\alpha & 0 & M_q & M_{\eta_1} & M_{\dot{\eta}_1} \\ 0 & 0 & 0 & 0 & 1 \\ \Xi_{1\alpha} & 0 & \Xi_{1q} & \Xi_{1\eta 1} - \omega_1^2 & \Xi_{1\dot{\eta} 1} - 2\omega_1\zeta_1 \end{bmatrix} \begin{bmatrix} \alpha \\ \theta \\ q \\ \eta_1 \\ \dot{\eta}_1 \end{bmatrix} + \begin{bmatrix} Z_{\delta e}/U_0 \\ 0 \\ M_{\delta e} \\ 0 \\ \Xi_{1\delta 1} \end{bmatrix} \delta_e \tag{15}$$

where the state vector is given by $x = [\alpha \;\; \theta \;\; q \;\; \eta \;\; \dot{\eta}]$, δ_e is the elevator input, U_0 the velocity component of the trim speed in the x-direction. $Z_{(.)}$, $M_{(.)}$ and $\Xi_{(.)}$ denotes the dimensional aerodynamic derivatives. The entries ω_1 and ζ_1 are the frequency and damping of the first structural mode and g is the gravitational acceleration.

Measurement equation:

$$\begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \alpha \\ \theta \\ q \\ \eta_1 \\ \dot{\eta}_1 \end{bmatrix} \tag{16}$$

Then in Eq 16 one have the measurement equations. For this case is admitted that only the α and θ are measured.

The model, represented by the eq.15 [1], can be simplified by:

$$\begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \begin{bmatrix} \alpha \\ q \\ \eta_1 \end{bmatrix} = \begin{bmatrix} b_1 \\ b_2 \\ b_3 \end{bmatrix} \delta \tag{17}$$

where the coefficients (a_{ij} and b_{ij}) are the parameters to be estimated/identified in this model, being related to the aerodynamic and elastic derivatives of the model.

4 RESULTS

All the identification process is gonna following the QUAD M methodology. This methodology starts whit the excitation maneuvers, the aerodynamic measurements, the mathematical model, and the parameter estimation methods.

For the measurement of states it was used a simulator of the longitudinal dynamics of the FT-100Flex - Eolo. This simulator was create in a MatLab software code. For this scenario only the states α and q are considered measurable.

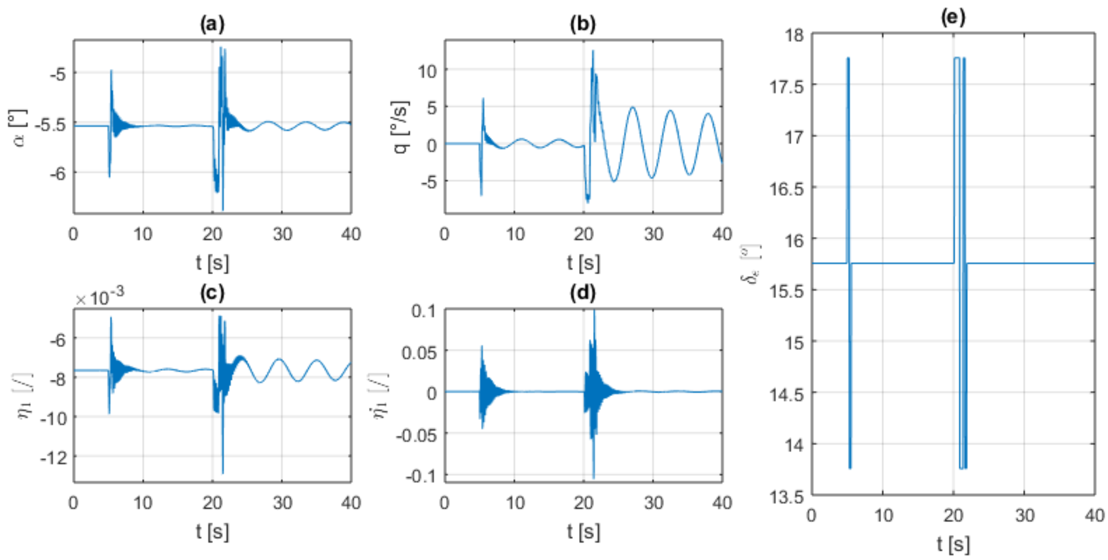

Figure 5 – States simulated (α, q) for a given elevator input δ_e

In the Fig 5 one has (a) time evolution of α in degrees, (b) time evolution of q in degrees per second, (c) time evolution of η_1, (d) time evolution of $\dot{\eta}_1$ e (e) time evolution of δ_e in degrees.

Applying the Kalman filter, express in the section 2, in the longitudinal model (section 3) one has:

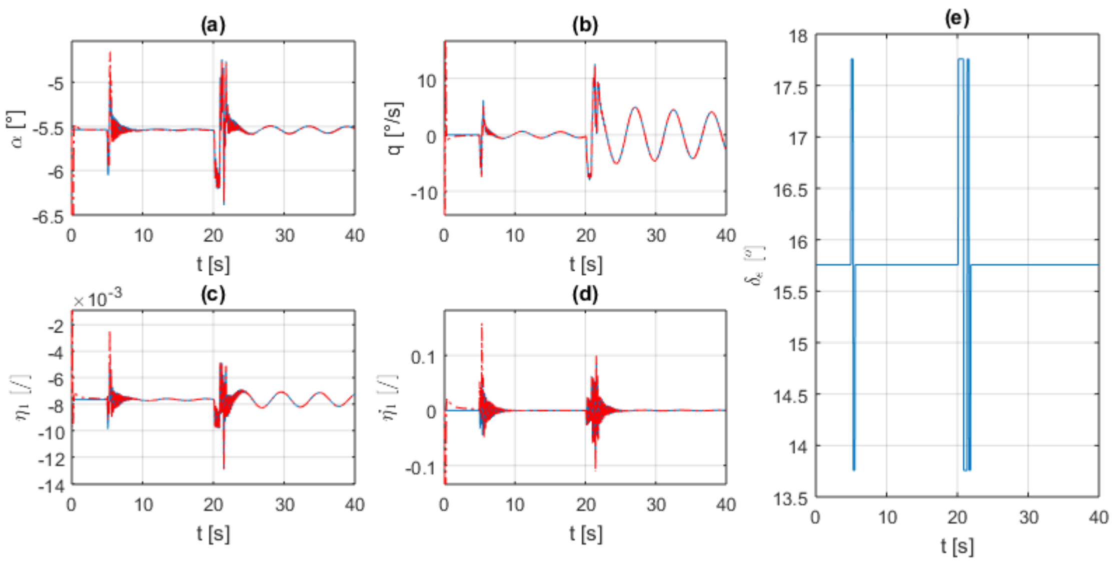

Figure 6 – States estimated, in blue the measured and in dotted red estimated

In Fig 6 shows (a) time evolution of α in degrees, (b) time evolution of q in degrees per second, (c) time evolution of η_1, (d) time evolution of $\dot{\eta}_1$ e (e) time evolution of δ_e in degrees. The blue line is the measured (same as Fig 5) and in dotted red estimated.

The EKF state filtering performance is shown in Fig. 6, it can be seen that the EKF output matches well with the measured outputs;

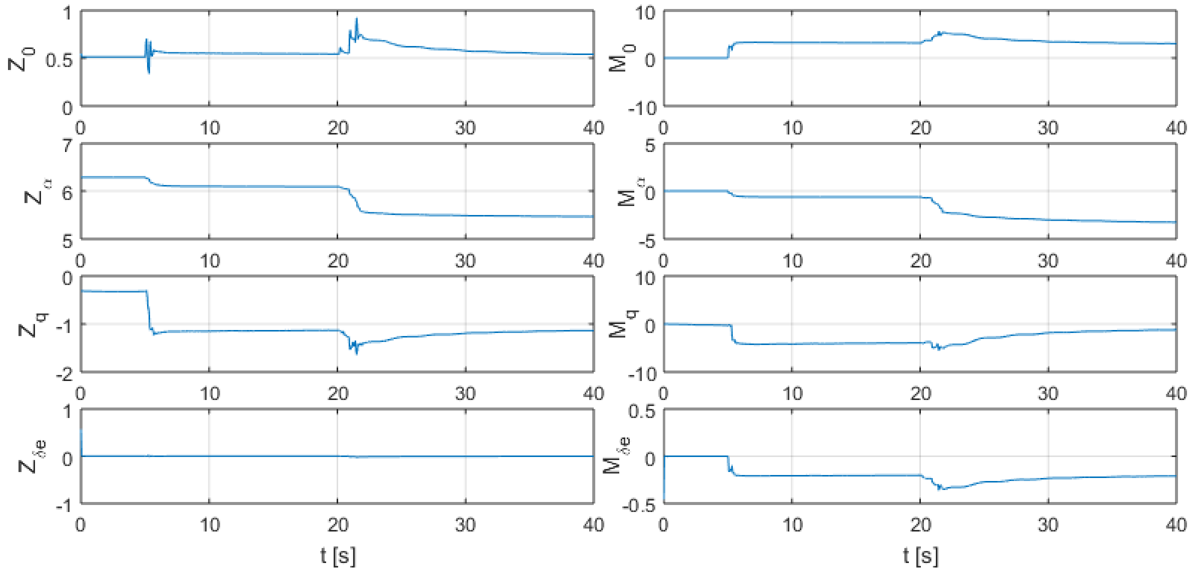

Figure 7 – Parameters estimated

In the Fig 7 is presented the time evolution of the parameters estimation. For this specific case the parameter are Z_0, Z_α, Z_q, $Z_{\delta e}$, M_0, M_α, M_q and $M_{\delta e}$.

For the statistics analyses of the Filter performance, the Table 4 shows the Std. derivation for the parameters estimated.

Table 2 – Parameter estimation applying Extended Kalman Filter (EKF)

No.	Parameter	Std. deviation	Relative Std. Dev (%)
1	6.68398e+00	1.0694e-02	0.16
2	-1.88616e+01	3.1988e-03	0.02
3	-1.15850e+00	1.4106e-04	0.01
4	-7.01587e+00	8.9064e-04	0.01
5	-4.62969e+01	2.6610e-02	0.06
6	-1.52836e+02	8.4089e-03	0.01
7	-7.30961e-01	4.3959e-04	0.06
8	-5.04775e+01	2.5538e-03	0.01

5 CONCLUSION

In this article it was explored and review the longitudinal model of a flexible aircraft, named FT-100 Flex - Eolo, and the identification of parameters using a EKF.

For this paper the logitudinal dynamics of the flexible UAV, FT100Flex-Eolo, was simulate in a MatLab code in a way to generate the synthetic data perturbed by a white noise. The Extended Kalman Filter was equated and implemented in a MatLab code. The synthetic data was considered like the measurement of a real flight for the the EKF.

The simulations shows that the EKF in this configurations analyzed was able to estimate the flexible generalized coordinate and gives the aerodynamics derivatives with a little desviation, like demonstrate in the Tab 4.

This article is an ongoing research that will consist of performing the identification of aerodynamic parameters from data collected from an in-flight campaign yet to be conducted. The contribution of this research will be focused on using the EKF in a flexible system. The next steps of this research will be the identification made from data obtained in campaign in flight.

ACKNOWLEDGMENTS

The authors are grateful for the funding of CAPES, the partnership between Flight Technologies Ldta, ITA and UNIFEI in the preparation of this article, as well as all those involved.

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