Available online at www.sciencedirect.com
SCIENCE DIRECT
Aerospace Science and Technology 6 (2002) 591–598
Aerospace Science and Technology
www.elsevier.com/locate/aescte

Flexible aircraft model identification for control law design

A. Bucharles *, P. Vacher

ONERA/DCSD, B.P. 4025, F31055 Toulouse, France

Received 20 February 2001; received in revised form 30 October 2001; accepted 6 November 2001

Abstract

The large commercial aircraft, developed today by manufacturers, are characterized by a high flexibility which results in a stronger interaction between the flight control system and the structural modes. The active control of the first elastic modes is needed to meet the performance requirements. This paper proposes an identification methodology of a flexible aircraft from flight test data, which is appropriate for control law design with modern control techniques (LQG, H2/H∞). In a first step a procedure based on Eigensystem Realization Algorithm (ERA) is used to determine an initial aeroelastic model which is subsequently combined with a linearized rigid-body model and optimized by an output-error minimization method. Two application examples show the good performances of the approach.

Résumé

Les avions commerciaux de grande taille, développés aujourd'hui par les constructeurs, se caractérisent par une plus grande souplesse et donc une interaction accrue entre le système de commandes de vol et les modes structuraux. Il devient nécessaire de contrôler activement les premiers modes souples pour atteindre les performances recherchées. Ce papier propose une méthodologie d'identification d'un modèle d'avion souple à partir de données d'essai en vol, adaptée à la conception de lois de pilotage par les techniques de commande modernes (LQG, H2/H∞). La procédure se déroule en deux étapes : un modèle aéroélastique est tout d'abord obtenu par une approche fondée sur l'algorithme ERA ; ce modèle est ensuite combiné avec un modèle linéarisé de la dynamique rigide, l'ensemble étant finalement optimisé par minimisation des erreurs de sortie. Deux applications à des données simulées et réelles illustrent les performances de la démarche.

Keywords: Flexible aircraft; ERA algorithm; Output error minimization; Identification for control

1. Introduction

The forecast passenger growth over the next twenty years is leading the major aircraft manufacturers to develop high-capacity long range aircraft. These new aircraft will exhibit a higher flexibility due to a global decrease of modal frequencies, which results in a stronger interaction between the flight control system and the aircraft's structural modes. A control law design based only on the rigid modes is no more sufficient to meet the performances requirements. Ensuring appropriate stability margins and providing satisfactory ride quality for passengers needs to actively control the first aeroelastic modes [7].

Accurate multivariable state-space models are therefore required to support control laws synthesis using modern control techniques (LQR/LQG, H2/H∞). These models must represent with high fidelity the relationships between the surface control deflections and the output signals used by the controller, at both low and high frequency. If the preliminary knowledge may provide theoretical models which are appropriate for a first design iteration of control laws, identification of the flexible aircraft model from in-flight data is required for the tuning of the control laws performances.

The identification techniques applied to the rigid aircraft aim mainly to the estimation of aerodynamic derivatives from static and dynamic flight tests. Among the available parameter estimation methods, the output error method is most widely used [4,8,9]. If time-domain algorithms prevail, the frequency-domain approach [6] is very appealing for linear systems due to a significant reduction of the number of parameters to be estimated and a strong data compression by working in a limited frequency range.

* Corresponding author.
E-mail addresses: bucharle@cert.fr (A. Bucharles), vacher@cert.fr (P. Vacher).

1270-9638/02/$ – see front matter
PII: S1270-9638(02)01197-5

In the field of structural dynamics, the goal is very often to estimate the modal parameters (frequencies, damping ratios, modes shapes) like in the flutter flight test analysis. Most techniques work in the frequency domain and aim to fit "measured" frequency response data with a rational transfer function model [12]. However, some identification techniques have been proposed for identifying state-space models, to be used for controller design. In his book, Juang [5] develops the Eigensystem Realization Algorithm (ERA), based on system impulse response (i.e. Markov parameters). Bayard in [1] proposes a two-step state-space frequency domain algorithm which combines curve fitting of frequency response data and state-space realization. In [10] a combined method, based on a realization algorithm followed by standard prediction error method, is studied for estimating the structural modes characteristics of a commercial aircraft. For these three cases a discrete-time multivariable state-space model is obtained. Najmabadi in [11] presents an identification process of a continuous-time model from in-flight control surface frequency sweep for a flexible aircraft. This single-input multi-output model is intended to be used to develop a compensator for active control of aircraft structural modes.

In this paper we propose a general methodology for identifying a multivariable continuous-time state-space model for a flexible aircraft, including rigid-body and structural dynamics, which is appropriate for control law synthesis using modern techniques. This methodology combines the ERA algorithm for getting an initial aeroelastic model and an output-error minimization. It does not assume specific flight tests. It has been developped in the research project COVAS (COVAS = COntrôle du Vol de l'Avion Souple), led in co-operation with AIRBUS France. The paper is organized as follows. Section 2 introduces the identification methodology which is described in more details in Sections 3 and 4. The performances are illustrated in Section 5 on simulated and in-flight test data. The paper closes with some concluding remarks in Section 6.

2. The identification methodology

Active control laws design for a flexible aircraft with modern techniques requires a linear state-space model including rigid-body and structural dynamics. In an initial step a simplified model can be extracted from a general preliminary modelization based on theoretical computations and wind-tunnel/structural tests data. The linearization of the flight mechanics equations at the flight condition provides the rigid-body model while the Roger's or Karpel's approximations of the generalized forces may be used to derive a linear state-space representation of the structural behaviour.

To retain a similar model structure in the identification process is very tempting for several reasons:

- to keep the physical meaning of the model coefficients;
- to be able to directly apply parametric optimization techniques;
- to make easier the updating of the control law using the identified model.

If such an approach does not raise any problem for the rigid-body model, it does not appear appropriate for the aeroelastic part:

- Roger's and Karpel's approximations lead to models with many coefficients;
- all modal characteristics cannot be estimated from a limited number of measurements and it is not possible to know a priori which modes are identifiable and which are not;
- a mode may be absent from the initial model.

Therefore we have developed a two-step identification procedure. In the first step, a multivariable representation of the structural dynamics including only modes which are visible from the measurements, is determined from specific flight tests, typically frequency sweeps, thanks to the ERA algorithm. Then this model is transformed into a real block-diagonal form, which provides a minimal parametric representation. In the second step, a state-space model of the flexible aircraft is obtained by bringing together the structural model and the rigid-body linearized model, both in state-space form. The coupling is performed just by adding the outputs of the two models. This new model is taken as initialization for the minimization of an output error criterion by the Gauss–Newton method in the frequency domain. The identification is based on both usual rigid-body excitations and excitations dedicated to flexible modes. If necessary a preliminary estimation of the rigid-body model coefficients may be performed by a classical output error approach. The whole identification process is shown in Fig. 1.

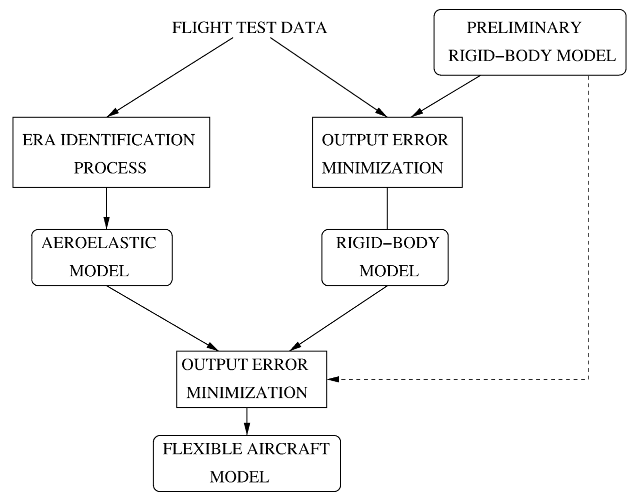

Fig. 1. General chart of the identification procedure.

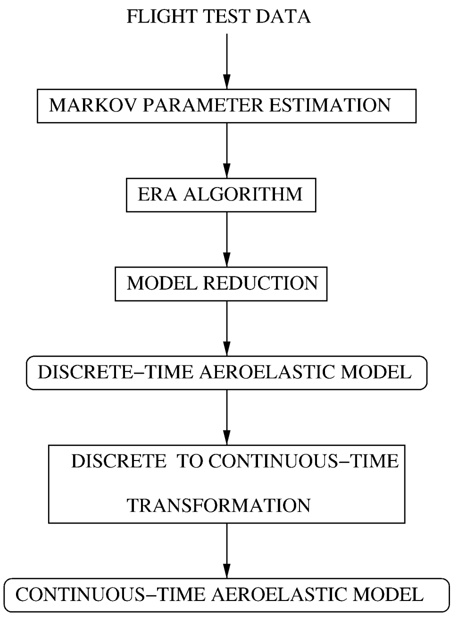

Fig. 2. ERA identification process.

3. Aeroelastic model identification by ERA approach

The ERA algorithm is the core of the aeroelastic model identification process, depicted in Fig. 2. We will subsequently give a description of the algorithm and review the different operations which are necessary before ERA to put the input-output measurements into an adequate form and afterwards to cancel the estimated modes which are not significant.

3.1. The ERA algorithm

This algorithm, introduced in the eighties by Juang [5] and which can be seen like an extension of the famous Ho–Kalman algorithm to noisy measurement data, is based on the availability of system Markov parameters and takes advantage of the excellent numerical properties of the singular value decomposition (SVD).

Consider the linear time-invariant system described by

$$\begin{cases} x_{k+1} = Ax_k + Bu_k, \\ y_k = Cx_k + Du_k \end{cases}$$

and assume n the system order. The Markov parameters are given by

$$h_k = \begin{cases} 0 & k < 0, \\ D & k = 0, \\ CA^{k-1}B & k > 0. \end{cases}$$

If we define the (α, β) Hankel matrix of the system by

$$H_{k;\alpha,\beta} = \begin{bmatrix} h_{k+1} & h_{k+2} & \cdots & h_{k+\beta} \\ h_{k+2} & h_{k+3} & \cdots & h_{k+\beta+1} \\ \vdots & \vdots & \ddots & \vdots \\ h_{k+\alpha} & h_{k+\alpha+1} & \cdots & h_{k+\alpha+\beta-1} \end{bmatrix}$$

it is straightforward to verify that $H_{k;\alpha,\beta}$ can be factored as

$$H_{k;\alpha,\beta} = \mathcal{O}_\alpha A^k \mathcal{C}_\beta$$

where

$$\mathcal{O}_\alpha = \begin{bmatrix} C \\ CA \\ \vdots \\ CA^{\alpha-1} \end{bmatrix}$$

and

$$\mathcal{C}_\beta = \begin{bmatrix} B & AB & \ldots & A^{\beta-1}B \end{bmatrix}$$

are respectively the extended observability and controllability matrices of the system. Note in particular that

$$H_{0;\alpha,\beta} = \mathcal{O}_\alpha \mathcal{C}_\beta.$$

If the system is controllable and observable, $\mathcal{O}_\alpha$ and $\mathcal{C}_\beta$ and hence $H_{0;\alpha,\beta}$ have rank n, equal to the system order.

Conversely, assume now that $\widehat{H}_{0;\alpha,\beta}$ is an estimated Hankel matrix where α and β are chosen to exceed the largest expected system order. From this starting point the ERA algorithm proceeds in two steps:

- selection of the system order;
- estimation of the system matrices $\widehat{A}$, $\widehat{B}$, $\widehat{C}$, $\widehat{D}$.

The key feature is the SVD factorization of $\widehat{H}_{0;\alpha,\beta}$

$$\widehat{H}_{0;\alpha,\beta} = USV^{\mathrm{T}}$$

where U and V are orthogonal matrices and the diagonal matrix S contains the singular values in non-increasing order on the diagonal. In the case of noisy impulse response measurements, the $\widehat{H}_{0;\alpha,\beta}$ matrix is full rank and the user must decide how many singular values can be neglected, which determines the system order n. Estimates of extended controllability and observability matrices are given by

$$\widehat{\mathcal{O}}_\alpha = U_n S_n^{1/2} \quad \text{and} \quad \widehat{\mathcal{C}}_\beta = S_n^{1/2} V_n^{\mathrm{T}},$$

where U_n and V_n are submatrices formed from the first n columns of U and V and the diagonal matrix S_n contains the n principal singular values.

Then the system matrices are derived from $\widehat{\mathcal{O}}_\alpha$ and $\widehat{\mathcal{C}}_\beta$

- $\widehat{B}$ and $\widehat{C}$ are given by the first m columns of $\widehat{\mathcal{C}}_\beta$ and the first p rows of $\widehat{\mathcal{O}}_\alpha$ respectively, where m and p denote the number of inputs and outputs;
- $\widehat{A}$ is obtained using the shifted-block Hankel matrix $\widehat{H}_{1;\alpha,\beta}$ by solving
  $$\widehat{H}_{1;\alpha,\beta} = \widehat{\mathcal{O}}_\alpha A \widehat{\mathcal{C}}_\beta;$$
- $\widehat{D}$ is taken equal to $\hat{h}_0$.

Besides singular values, others indicators (modal amplitude coherence, mode singular value) have been developped by Juang to evaluate the validity of the models provided by the ERA algorithm and especially give information about the accuracy of the estimated modes. They help the operator to compare several models of different orders and decide the best order. The modal amplitude coherence, based on the comparison of the pulse responses of "measured" and identified modes, has been extended in order to take into account the behaviour with respect to inputs as well through the controllability matrices. For this new indicator, which ranges from 0 to 1, a value close to 1 indicates that the estimated mode is reliable; on the other hand, the mode is considered to be a noise mode if the indicator value is low. The modal amplitude coherence indicators may be stuck at each mode for each tested order and plotted on a so-called stabilization diagram. This diagram visualizes the frequency location of the modes versus model order as well as their accuracy through vertical bars whose length is equal to the corresponding indicator value. When the model order increases, the estimated frequencies stabilize with higher indicators. This allows the operator to quickly assess the effect of changing the model order and to decide the optimal order.

Applying the ERA algorithm requires to select α and β which determine the size of the Hankel matrix. Using a simplified model of a flexible aircraft we have found that, for a given number of pulse response measurements data, a square Hankel matrix was preferable for reducing the noise influence. This observation agrees with the result in [2]. Therefore α is chosen so that $p\alpha \approx m\beta$ under the constraint $\alpha + \beta = K$, with K the impulse response length.

3.2. Markov parameter estimation

The response y of a linear causal discrete-time system to an arbitrary input u can be expressed as the discrete convolution

$$y_k = \sum_{i=0}^{k} h_k\, u_{k-i}$$

where h denote the system Markov parameters. Conversely, the first K Markov parameters can be determined from input and output measurements by solving

$$[\, y_0 \quad \dots \quad y_{K-1} \,] = [\, h_0 \quad \dots \quad h_{K-1} \,] \begin{bmatrix} u_0 & u_1 & \dots & u_{K-1} \\ 0 & u_0 & \dots & u_{K-2} \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & u_0 \end{bmatrix}$$

or

$$Y = HU.$$

By assuming that the number of measurements is higher than the impulse response length, Markov parameter estimates are obtained as the least squares solution of an overdetermined system. However the result is not very satisfactory in noisy situation. It can be strongly improved by use of the singular value decomposition: all singular values of the input matrix U, smaller than a selected threshold, are set to zero before computing the pseudo-inverse of U.

3.3. Model reduction

A characteristic of the ERA algorithm is to yield extraneous modes, not present in the system to be identified. These modes, which seem sensitive to how the Hankel matrix is built, may have significant coherence indicators and well stabilized frequencies. So they are very difficult to recognize from physical modes and cannot be suppressed just by looking at the stabilization diagram. However they must be canceled not to disturb the further identification procedure. We have defined an elimination procedure based on the analysis of the contributions of each mode in the responses of the identified model to the flight test inputs.

4. Flexible aircraft identification by output error minimization

Once an initial aeroelastic model has been obtained, it must be converted into a suitable continuous-time representation and combined with the linearized rigid-body model to feed a parametric output-error minimization procedure. In this section we will briefly describe the optimization method by showing the advantage to work in the frequency-domain and explicit the parametrization of the aeroelastic model.

4.1. Output error minimization in frequency domain

The system is assumed to be described by the equations

$$\begin{cases} \dot{x}(t) = Ax(t) + Bu(t), \\ y(t) = Cx(t) + Du(t) \end{cases}$$

where the matrices A, B, C, D contain the unknown parameters Θ. In the time-domain the estimates of parameter vector Θ are obtained by minimizing the cost function

$$J(\theta) = \frac{1}{2} \sum_{n=1}^{N} \varepsilon(n,\theta)^{\mathrm{T}} R^{-1} \varepsilon(n,\theta)$$

with R the measurement noise covariance matrix and ε the error vector between the measurement and the model output. Starting from suitable initial values of the parameter vector, new estimates are obtained iteratively using a non-linear optimization algorithm like the Gauss–Newton method.

For linear systems the same problem may be solved in the frequency-domain. Applying the Fourier transformation, the system equations get transformed into

$$\begin{cases} (\jmath\omega)x(\omega) = Ax(\omega) + Bu(\omega), \\ y(\omega) = Cx(\omega) + Du(\omega). \end{cases}$$

Using the Parseval's formula, the cost function to be minimized becomes

$$J_{\text{freq}}(\theta) = \frac{1}{2} \sum_{l=1}^{L} \varepsilon(\omega_l,\theta)^{\mathrm{T}} S^{-1} \varepsilon(\omega_l,\theta)$$

with $S^{-1} = \frac{\Delta f}{\Delta t} R^{-1}$; Δf and Δt denote respectively the frequency resolution and the sampling period.

A significant advantage of identifying parametric models in the frequency rather in the time-domain is the capability to work in a restricted frequency-range, which results in filtering the high-frequency measurement noise and provides consistent reduction of the data amount to be processed. Furthermore, by dropping the zero-frequency in the cost function, bias parameters or linearization conditions need not to be accounted for in the optimization process, significantly reducing the number of parameters to be estimated. Finally the method is suitable for unstable or near-unstable systems because no numerical integration is involved in the frequency domain: there is no risk of divergence.

4.2. *Aeroelastic model parametrization*

The ERA identification process provides a multivariable discrete-time state-space model in balanced form. First this model is transformed into a continuous one using a zero-order hold. Then it is converted to a real modal block-diagonal form with the system matrix A

$$A = \begin{bmatrix} A_1 & & & 0 \\ & A_2 & & \\ & & \ddots & \\ 0 & & & A_{n/2} \end{bmatrix}$$

with

$$A_i = \begin{bmatrix} \Re(\lambda_i) & \Im(\lambda_i) \\ -\Im(\lambda_i) & \Re(\lambda_i) \end{bmatrix}.$$

$\Re(\lambda_i)$ and $\Im(\lambda_i)$ are the real and imaginary parts of the eigenvalue λ_i. The other system matrices are full.

This representation is not suitable for output error minimization owing to a too high number of parameters: all state variables can be scaled without affecting the input-output relations [3]. Consequently n conditions must be imposed on the B or C matrices. We have chosen to freeze the first column of B. So the parameters to be estimated include the real and imaginary parts of the eigenvalues and all coefficients of the system matrices B, C and D except the first column of B.

5. Applications

Two applications of the identification methodology to simulated and in-flight test data from a large transport aircraft are presented now. The results have been obtained using the package HARISSA, developped at ONERA.

5.1. *Simulated test data*

In this first example we use data from a general aircraft motion simulator, including a 6 dof flight mechanics modelization and a structural dynamics representation in a wide frequency range. We are interested only in the lateral-directional motion. Five pseudo flight tests are simulated through excitation of ailerons and rudder: two of them are dedicated to the aeroelastic model identification (frequency sweeps on aileron and rudder) and the three others (aileron and rudder pulse, rudder doublet) excite rather the rigid-body dynamics. The output signals consist of the lateral acceleration measured at front, mid and rear fuselage and roll and yaw rates at front and rear fuselage.

First the input and output signals for all tests are decimated to a sample rate of 20 Hz, which is justified by the control of the only first flexible modes.

The second step consists of the aeroelastic model identification by the ERA methodology and we consider only the two frequency sweep tests in this phase. The least-squares estimation of the impulse responses from unnoisy data does not raise any specific problem. The length of the estimated responses to aileron and rudder impulses is restricted to 10 seconds or 201 time samples.

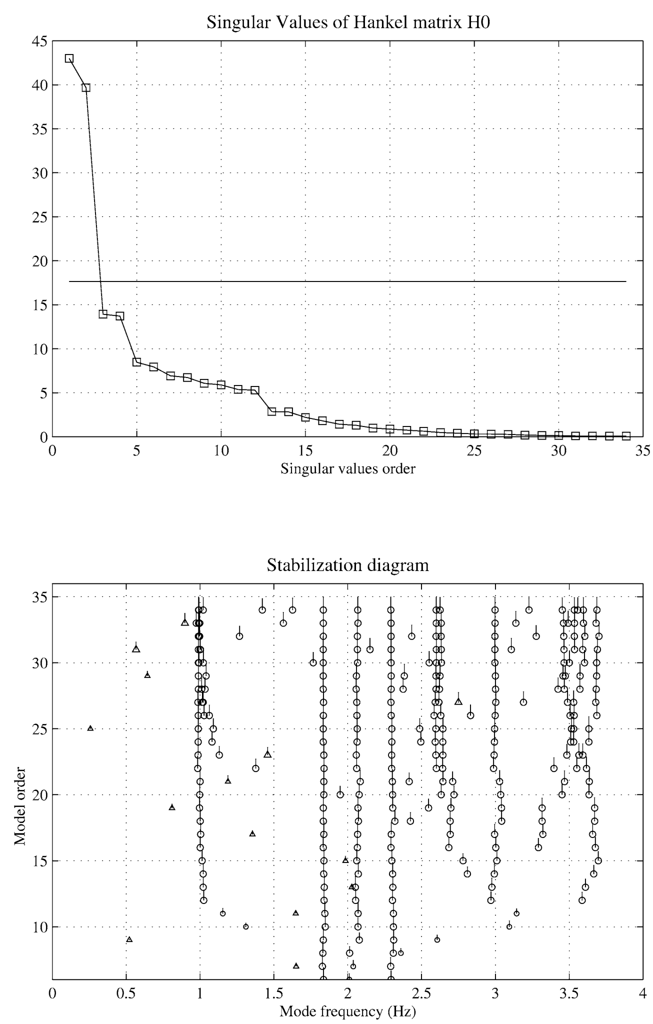

Fig. 3. Largest singular values of the Hankel matrix and stabilization diagram computed from simulated test data for models of order 6 to 34. *Circles* correspond to potential structural modes and *triangles* to real eigenvalues; the length of the *vertical bar* attached to each mode is equal to the value of the modal amplitude coherence indicator for this mode and ranges between 0 (noise mode) and 1 (high quality mode).

Table 1
Comparison of identified aeroelastic modes from simulated test data

Aeroelastic modes:	frequency (Hz)/damping ratio (‰)	
ERA	ERA after model reduction	Output error minimization
1.00/36.5		
1.83/46.2	1.83/46.2	1.83/47.4
2.07/48.6	2.07/48.6	2.07/59.2
2.29/12.7	2.29/12.7	2.29/12.8
2.68/33.3	2.68/33.3	2.62/41.0
3.00/32.5	3.00/32.5	3.00/27.0
3.29/170.0		
3.68/27.3		

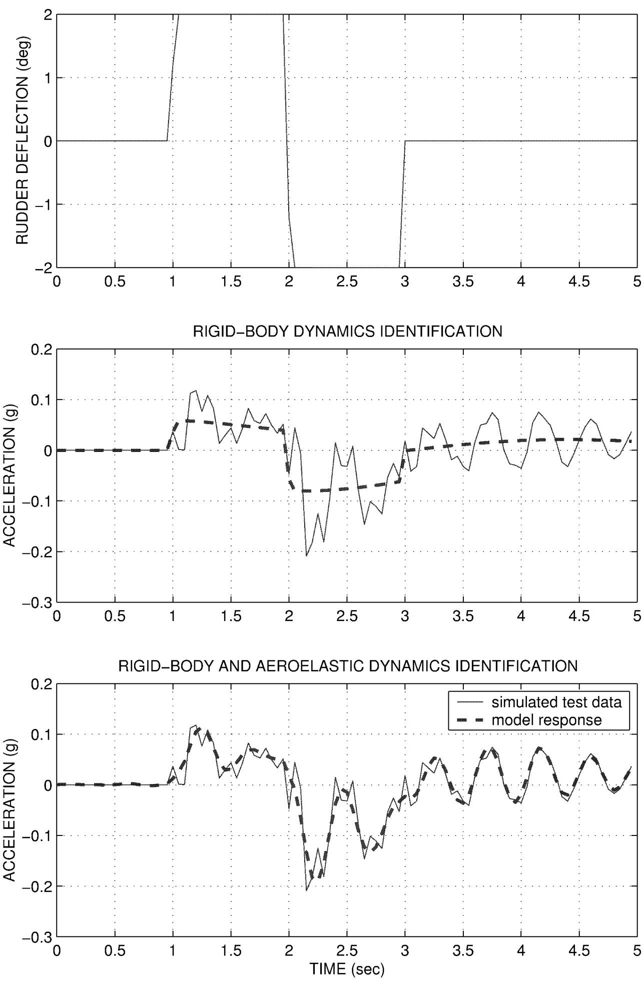

Fig. 4. Lateral acceleration of front fuselage for rudder doublet excitation: comparison of only rigid-body dynamics identification (middle) and rigid-body and aeroelastic dynamics identification (bottom).

Applying the ERA algorithm needs to form the Hankel matrix. The number of row and column blocks is selected to make the matrix almost square. The magnitudes of the largest singular values of the Hankel matrix as well as the stabilization diagram for model orders 6 to 34 are presented in Fig. 3. We observe that the singular values fall off sharply at order 12, suggesting to select 12 as model order. The

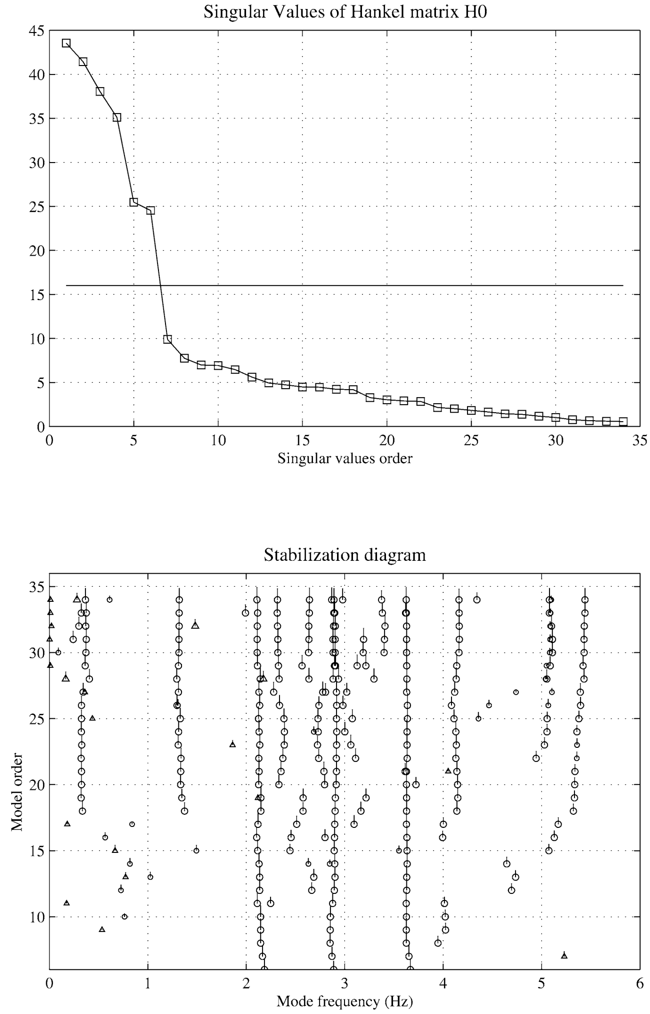

Fig. 5. Largest singular values of the Hankel matrix and stabilization diagram computed from flight test data for models of order 2 to 34.

Table 2
Comparison of identified aeroelastic modes from in-flight test data

Aeroelastic modes:	frequency (Hz)/damping ratio (‰)
ERA	Output error minimization
2.18/48.4	2.14/38.7
2.89/23.3	2.86/17.7
3.67/27.7	3.63/20.9

stabilization diagram confirms that it is a possible choice: the frequencies of the 6 modes obtained at order 12 are quite well preserved when the model order increases (they are well stabilized). Furthermore, the length of the vertical bar attached to all these modes indicates modes of good quality. Other stabilized modes appear for higher orders, for example two modes at 2.7 Hz and 3.3 Hz for order 16 or two modes close to 2.6 Hz from order 22. Finally a 16th order model is chosen. The characteristics of the 8 estimated modes are given in Table 1.

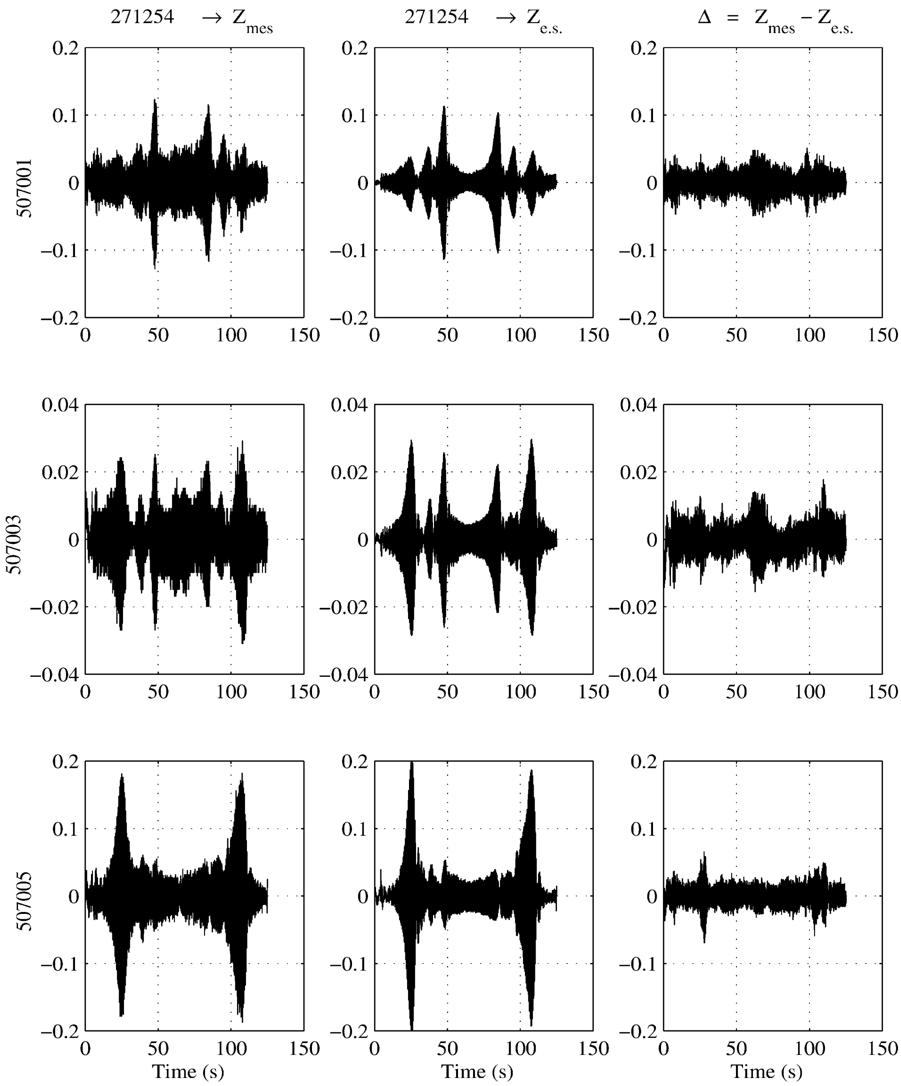

Fig. 6. Lateral accelerations for rudder frequency sweep: measurements Z_{mes} (left column), model responses $Z_{\mathrm{e.s.}}$ (middle column), reconstruction errors $\Delta = Z_{\mathrm{mes}} - Z_{\mathrm{e.s.}}$ (right column).

The analysis of the modal contributions shows that three modes do not affect very much the model outputs and can be dropped, leading to an initial aeroelastic model of order 10.

An initial rigid-body model is also required for the final optimization procedure. So we have been led to estimate the coefficients of the linearized model from the three rigid tests. As it can be seen in Fig. 4 (middle graph), the match between the model outputs and the test data is very poor. The estimated model is not able to explain the measurements.

Finally we identify the rigid-body and structural dynamics using all the tests. About 110 coefficients have to be estimated. The output error minimization is performed in the frequency-domain between 0.1 and 4 Hz. If the modal frequencies are hardly modified by the optimization procedure, the damping ratios are more affected as well as some coefficients of the rigid-body model. We see in Fig. 4 that the model matches almost perfectly the test data, the residual error resulting from a high-frequency mode which is not in the model.

5.2. In-flight test data

In order to validate the identification methodology in a more realistic context, we will apply it now to in-flight data obtained from a large transport aircraft. As flight tests consist of aileron and rudder frequency sweeps in the range 1.4–5.6 Hz, we will only be interested in the aeroelastic model. Three accelerometric measurements are available at the front, middle and rear fuselage with a sampling rate of 128 Hz.

After decimating the data with a factor of 5, we estimate the impulse response and apply the ERA algorithm. The singular value curve and the stabilization diagram (Fig. 5) suggest us to select a 6th-order model (the next suitable model order is 18). The aeroelastic modes are given in Table 2.

Then this model is refined with output error minimization. We note that, as previously, modal frequencies are less affected than damping ratios by the second step. A comparison between the measured data and the model responses is shown in Fig. 6. We observe that the reconstruction errors look like white noise, which means that the main aeroelastic information has been extracted from the accelerometric measurements.

6. Conclusion

A general two-step methodology for identifying a state-space model of a flexible aircraft, appropriate for control law design with modern control techniques, has been proposed. The first step based on the ERA algorithm provides an initial aeroelastic model of good quality which is next combined with a linearized rigid-body model. In the second step the flexible aircraft model, including rigid and elastic modes, is improved by an output error minimization method. The experimental results show a good correspondance between the measurements and the model responses at both low and high frequency. Future work is needed to get a better understanding of extraneous modes in the ERA algorithm, to take advantage of the specific structure of Toeplitz and Hankel matrices for the singular value decomposition, to make the procedure more if not fully automatic.

Acknowledgements

The authors would like to thank DPAC and SPAe who supported this work and AIRBUS France who provided flight test data.

References

[1] D.S. Bayard, An algorithm for state-space frequency domain identification without windowing distortions, IEEE Trans. Autom. Control 39 (9) (1994) 1880–1885.

[2] P. De Groen, B. De Moor, The fit of a sum of exponentials to noisy data, J. Comput. Appl. Math. 20 (1987) 175–187.

[3] P. Eykhoff, System Identification, Wiley, 1974.

[4] P.G. Hamel, R.V. Jategaonkar, Evolution of flight vehicle system identification, J. Aircraft 33 (1) (1996) 9–28.

[5] J.N. Juang, Applied System Identification, Prentice-Hall, 1994.

[6] V. Klein, Aircraft parameter estimation in the frequency domain, August 1978, AIAA Paper 78-1344.

[7] F. Kubica, New flight control laws for large capacity aircraft. Experimentation on airbus A 340, in: 21th ICAS Congress Proceedings, Melbourne, Australia, 1998.

[8] D. Liot, A. Bucharles, Outils d'identification de la mécanique du vol des Airbus, in: AGARD Symposium on "System Identification for Integrated Aircraft Development and Flight Testing", Madrid, Spain, 1998, pp. 4.1–4.9.

[9] R.E. Maine, K.W. Iliff, Identification of Dynamic Systems – Applications to Aircraft. Part 1: The Output Error Approach, in: AG300, Vol. 3, AGARD, 1986.

[10] T. McKelvey, T. Abrahamsson, L. Ljung, Vibration data analysis for a commercial aircraft, Automatica 32 (12) (1996) 1689–1700.

[11] K. Najmabadi, B. Fritchman, C. Tran, A process for model identification and validation of dynamical equations for a flexible transport aircraft, in: AGARD Symposium on "System Identification for Integrated Aircraft Development and Flight Testing", Madrid, Spain, 1998, pp. 13.1–13.13.

[12] R. Pintelon, P. Guillaume, Y. Rolain, J. Schoukens, H. Van Hamme, Parametric identification of transfer functions in the frequency domain – A survey, IEEE Trans. Autom. Control 39 (11) (1994) 2245–2260.