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ASPECTS OF SYSTEM IDENTIFICATION OF HELICOPTERS

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Abstract

Aspects of system identification with respect to unique characteristics of helicopters are presented. Emphasis is placed on problems associated with helicopter instabilities and high vibration levels.

Computer simulated data for a Sikorsky S 61 helicopter were evaluated to show how identification results are influenced by run duration, input signal design, and single versus multiple run evaluation.

Using flight test data for the MBB BO 105 helicopter, the effects of digital smoothing of noisy data are presented and examples of identification results are given.

Notation

$L_{(\ )}$	Rolling moment due to variable indicated in subscript	u	Longitudinal velocity
$M_{(\ )}$	Pitching moment due to variable indicated in subscript	v	Lateral velocity
$N_{(\ )}$	Yawing moment due to variable indicated in subscript	w	Vertical velocity
$X_{(\ )}$	Longitudinal force due to variable indicated in subscript	θ	Pitch angle
$Y_{(\ )}$	Lateral force due to variable indicated in subscript	θ_C	Lateral cyclic pitch
$Z_{(\ )}$	Vertical force due to variable indicated in subscript	θ_R	Pitch angle of rotor tip path plane
a_x	Longitudinal acceleration	θ_S	Longitudinal cyclic pitch
a_y	Lateral acceleration	θ_{TR}	Pitch angle of tail rotor
a_z	Vertical acceleration	ϕ	Roll angle
p	Roll rate	ϕ_R	Roll angle of rotor tip path plane
q	Pitch rate		
r	Yaw rate	ω	frequency

1. Introduction

Reliable mathematical models of aircraft are needed for detailed stability and control analysis, for accurate ground-based and in-flight si- simulations, and for meaningful handling qualities research.

These models and their coefficients may be theoretically derived or extracted from wind tunnel experiments. They also can be calculated through an appropriate analysis of flight test data. This approach, based on the evaluation of measured input and output data is referred to as system identification (Figure 1).

For fixed wing aircraft, identification techniques have been used frequently; however, their application to rotary wing aircraft is still not common. Molusis extensively investigated the influence of various model structures and different identification methods on identification results (Reference 1). Gould and Hindson evaluated flight test data from a Bell 205 helicopter using independent models for longitudinal and lateral-directional motions (Reference 2) and Tomaine identified a large crane helicopter (Reference 3).

System identification techniques are based on the evaluation of the input-output relationship of the system under test. Therefore, the overall identification procedure must include the following four phases:

- preparation, including input design and identifiability studies
- flight tests
- data processing
- identification and interpretation.

This report concentrates mainly on aspects of the preparation and the data processing phases and presents identification results from both simulated and flight test data.

After an introduction to identification methods, problems of helicopter identification and criteria for input design are discussed. Identification results from computer simulated data are presented with emphasis on the effects of both run duration and different input signals. BO 105 helicopter flight test data are used to illustrate the effect of smoothing procedures on noisy data. Finally, identification results for the BO 105 helicopter are given.

2. Methods of System Identification

There are various different methods for parameter identification. They range from simple pencil and paper methods (Reference 4), through analog and hybrid matching techniques (References 5 and 6), to highly sophisticated methods requiring modern digital computers (Reference 7).

According to the criteria used, three main classes of identification methods can be defined: equation error methods, output error methods, and statistical methods that allow gust estimation. At the DFVLR Institut für Flugmechanik, work has been concentrated mainly on three methods for the identification of linear models. These are the least squares and instrumental variable techniques (Reference 8), both equation error methods, and the maximum likelihood output error method (Reference 9).

2.1 Equation Error Methods

- Least squares

This method minimizes the equation errors of the model in a least squares sense. Its main drawback is that each equation is identified independently without consideration of the characteristics of the complete model. On the other hand, this method is computationally efficient since the solution is obtained in one step with no iterations or integrations. The computation time is very short and only a small amount of storage capacity is required. Furthermore, à priori values for the unknown parameters are not needed. This method allows use of information from multiple data runs.

- Instrumental variable

This iterative method is similar to the least squares method, but also uses the state variables from an à priori model or the last model obtained in the estimation procedure. Thus the characteristics of the complete model influence the final results although each equation is still identified separately. In general, computation time is relatively short, since the instrumental variable technique converges quickly even with quite inaccurate à priori values. Like the least squares method, this technique also can handle multiple data runs.

2.2 Output Error Methods

Output error methods minimize the differences between calculated outputs of the identified model and measured system outputs. For this "curve fitting" task, various criteria and search algorithms have been developed.

- Maximum likelihood

The name of this iterative technique is derived from the cost function used. For its minimization, a modified Newton-Raphson algorithm is applied. In general, this is one of the most powerful methods available. It is able not only to estimate the coefficients but also to determine state variable initial conditions and zero shifts.

The computation time, which is highly dependent on the number of unknown parameters and the order of the model, is relatively long for helicopter identifications. The maximum likelihood technique is sensitive to increases in the number of unknown parameters. This can cause convergence problems. Therefore, both good à priori values and an adequate model structure are required for the application of this method.

3. Problems of Rotorcraft Identification

In comparison to fixed wing aircraft, parameter identification of rotorcraft is a more complicated task. This is mainly due to three characteristics of helicopters: their coupled behaviour, their high vibration levels, and their inherent instabilities.

The helicopter has a large number of highly coupled degrees of freedom. When only low frequency behaviour is of interest, it is possible to consider only the rigid body degrees of freedom. However, in general, a further reduction of the model, e.g. separation into longitudinal and lateral-directional motions, is not appropriate because of the strong coupling effects.

Rotorcraft flight test data, particularly acceleration data, is usually very noisy because of the high vibration levels. This causes severe identification problems, especially with equation error methods. Therefore, procedures to smooth the data must be applied.

Instabilities, inherent to most helicopters, complicate the identification for two reasons. First, there is high sensitivity to gust disturbances and inaccurate trim - state variables diverge even with no control input. Second, the time for a data run is limited because increasing amplitudes quickly invalidate the small perturbation assumptions of the linear model. Because of the short time span of a run it is very important that the data contains sufficient information to allow a successful identification.

In addition to these problems there are measuring difficulties. This is expecially the case in measuring air speed components for hover and low speed flight conditions.

Another characteristic of some helicopters that may cause severe identifiability problems is discussed in Reference 10. Evaluating the transfer functions of analytical models, it can be shown that systems with neighbouring poles and zeros are very sensitive in the identification.

4. Input Signal Design

The requirement to obtain maximum information from short data runs necessitates the design of optimal input signals (References 11 and 12).

At the DFVLR Institut für Flugmechanik pseudo-stochastic input signals have been developed . They consist of a sequence of step functions which are optimized in the frequency domain to fulfill three essential criteria:

1. Wide frequency range

   Figure 2 compares the power spectrum and bandwidth of an optimized input signal with a doublet. The spectrum can be shifted in the frequency domain by adjusting the time duration of the signal. Based on an à priori model, a procedure to determine the frequency range required for proper excitation of the system under test has been developed (Reference 13). Experience has shown that the bandwidth of the pseudo-stochastic signal generally is sufficient to properly excite the rigid body modes of aircraft. In addition, because of the wide frequency range of the input signal, low sensitivity to errors in the à priori model is achieved.

2. Short time duration

   Because of the inherent instabilities of helicopters this restriction is very important. Depending on the frequency range required, the total duration of the signals usually is about seven seconds.

3. Easily flyable by the pilot

   The amplitudes of the input signals have been restricted to three discrete levels to make the signals easily flyable. If possible, the pilot should be given some help, using visual or audiovisual means to obtain proper timing of the signal pulses. For a fixed wing aircraft flight test program this was achieved using a relatively simple two needle instrument (Figure 3). One needle is controlled by a signal generator and the other shows the control input, e.g. the elevator deflection. Once the signal is started, the pilot attempts to keep the needles lined up.

   Figure 4 shows the first attempts at flying doublet and pseudo-stochastic input signals and then the results after some practice.

5. Identification from Computer Simulated Data

Theoretical investigations were conducted using computer simulated data which was based on a linear model of the Sikorsky S 61 helicopter in hover. Emphasis was placed on the quality of identification results as influenced by

- different time duration of data runs
- different input signals
- single versus multiple data run evaluation.

This section first gives a description of the mathematical models used for the simulation and identification. Then the simulation phase is described and, finally, identification results are discussed.

5.1 Mathematical Models

Four different mathematical models must be distinguished: the 6 degrees of freedom (DOF) simulation model, the mathematically reduced 4 DOF model, the 6 DOF identified model, and the 4 DOF identified model (Figure 5).

The simulation model contains two rotor tip path plane DOF and four rigid body DOF (Reference 14). The state variables are θ_R, ϕ_R, u, v, p, q, θ, and ϕ. For flight conditions near hover, vertical and yaw motions are virtually uncoupled and can be treated separately. For the flight condition simulated, the S 61 helicopter has two pairs of unstable poles (ω_1=0.36 rad/sec, ω_2=0.5 rad/sec).

For the identification, two different model structures were used:

1. a 6 DOF identified model - identical to the simulation model.
2. a rigid body model with four DOF.

Assuming instantenous rotor tilting, a 4 DOF mathematically reduced model was derived from the 6 DOF simulation model. For this 4 DOF mathematically reduced model, the influence of the rotor is included in the rigid body derivatives.

The identification results of the 4 DOF identified model were evaluated by comparing them to the 4 DOF mathematically reduced model.

5.2 Simulation Phase

For the simulation phase, seven different input signals were used (Figure 6):

- four doublets of two, four, six, and eight seconds duration (Signals A, B, C, and D)
- an arbitrary sequence of step functions (Signal E)
- two optimized pseudo-stochastic signals (Signals F and G).

Seven runs were simulated using the signals as longitudinal cyclic inputs and another seven runs were simulated using the signals as lateral cyclic inputs.

Two more runs were simulated with combined input signals. That is, both longitudinal and lateral cyclic inputs were simultaneously applied.

Thus, a total of sixteen runs were simulated. The time duration of each run was twenty seconds.

5.3 Identification Results

For the identification, the instrumental variable method was applied. The à priori values were obtained using the least squares technique. The following section first discusses results obtained by identifying each run independently from the others. Then, results obtained by evaluating a combination of two runs are presented.

- Evaluation of single runs

Each run was identified four times under different conditions. These conditions were defined by the identification model used and by the time span selected from the run:

	Identification Model	Time Span
1.	6 DOF	all 20 seconds
2.	6 DOF	first 10 seconds
3.	4 DOF	all 20 seconds
4.	4 DOF	first 10 seconds.

For the 6 DOF model, all parameters were identified to an accuracy of six digits or more. Different input signals and/or time spans had no significant effect on the identification results.

When the 4 DOF model is identified the structures of the identification model and the simulation model are no longer identical. Therefore the estimation procedure has to compensate for the differences between the two models to approximate the original data.

First, the identification was conducted using the total run duration of twenty seconds and then the time span was limited to the first ten seconds. Figure 7 presents the results for three significant derivatives of the pitch moment equation and one control derivative. Also shown is the average error for all identified parameters. This error was defined as:

$$\text{Av. Error} = \frac{1}{N} \sum_{n=1}^{N} \left| (I_n - R_n)/R_n \right|$$

where N is the number of identified derivatives, I_n is the value of the identified derivative, and R_n is the value of the mathematically reduced model derivative.

The evaluation of data runs of twenty seconds duration gave satisfactory results. Most of the derivatives could be identified with minor errors. Except for the run with the two second duration doublet input, the average errors are below 10 %.

However, the identification of data runs of ten seconds duration caused severe difficulties. A comparison with the values of the mathematically reduced model shows that the results are of low quality. The average errors range from about 50 % to about 130 % depending on the input signal applied.

The large differences can be interpreted using the power spectra of the input signals (Figure 6). For the first four runs, different time duration doublets and, consequently, different frequency ranges were used. The average errors for these runs indicate that an excitation in the frequency range generated by the four second doublet yields the best results. Shifting the spectra to higher (two second doublet) or lower (eight second doublet) frequencies gives poorer results.

This consideration clearly shows the dependency of identification results on the excitation frequencies.

A detailed investigation of the simulation model proved that in this case only a relatively narrow frequency band excitation is required for the identification. Therefore no significant improvement can be expected from a wide frequency band signal compared to an accurately adjusted narrow frequency band signal like the doublet. In practice, however, the appropriate frequency range for the excitation has to be evaluated from an à priori model. The quality of the excitation calculated using the à priori model depends on the accuracy of the à priori model. The calculated input signal may be significantly different from the excitation required by the real system. Errors of this type result in a low quality identification when narrow frequency band signals are used. On the other hand the identification is rather insensitive to this kind of error when wide band excitations are used.

The identification results obtained using the arbitrary input signal show that arbitrary input signals in general are not suited for system identification. The combined input - simultaneous use of two controls - did not improve the results.

Although the parameters were identified with large errors, there is good agreement between the time histories from the identified, the mathematically reduced, and the simulation models (Figure 9). This means that the dynamics of the system were accurately determined. This is sufficient when only knowledge of the characteristics of the system (e.g. damping, natural frequencies, transfer functions, etc.) is of interest. However, with respect to the extraction of stability and control derivatives, the identification results are not satisfactory.

- Identification of multiple data runs

The identification results of single runs show that the information content in a run of ten seconds duration obviously is not sufficient to accurately determine parameters.

Since the equation error methods allow use of information from multiple data runs, two different runs of ten seconds duration each were evaluated. For this investigation, the four input signals that gave the best results in the single run evaluation were selected:

- four second duration doublet (B)
- two pseudo-stochastic signals (F, G)
- combined excitation using signal E and signal F.

The identification results presented in Figure 8 show good agreement between the theoretical and identified values. For the doublet and pseudo-stochastic input signals the average errors of all identified derivatives are less than 10 % which is acceptable. For the run with simultaneous control inputs the errors are still relatively large. The improved results from the evaluation of two data runs are a consequence of the increased information content. This increased information content is because:

- total time span evaluated was twenty seconds
- both longitudinal and lateral motions were excited.

6. Evaluation of Flight Test Data

In cooperation with the Messerschmitt-Bölkow-Blohm Company (MBB) a derivative identification program was conducted. The BO 105 helicopter used is a slightly modified version (S 3) equipped with a fly-by-wire system (Reference 15). A description of the research program is given by Reference 16.

The following section concentrates on one aspect of the program - reduction of the noise on the data - and presents identification results.

6.1 Digital Filtering and Differentiation

In the data processing phase, flight test data was filtered by an analog low pass filter with a cutoff frequency of 16 Hz. Then the data was digitized with each channel being sampled every .011 seconds. On some data channels additional data processing had to be used:

- Acceleration and rate data had to be smoothed because of the high vibration levels.
- Measured rates had to be differentiated because rotational accelerations are required for the application of equation error methods and for C.G. position corrections.

Digital filters and differentiators developed at the DFVLR Institut für Flugmechanik were used. Figure 10 shows the smoothing effect on acceleration and rate data after the application of a digital low pass filter with zero phase shift and a cutoff frequency of 6.25 Hz.

Differentiation always causes problems because of noise on the data. Therefore a numerical differentiator which included a low pass filter was used. Its phase shift is 90 degrees for all frequencies. Figure 11 shows that the angular accelerations obtained are relatively smooth although the rates are noisy.

6.2 Identification Results

BO 105 flight tests were conducted at a trim speed of 70 knots TAS. At this air speed the aircraft is slightly unstable. Depending on the input signal amplitudes, runs of 20 to 35 seconds duration could be flown during calm weather conditions.

A 6 DOF rigid body model was used for the identification. Much modelling work was done to investigate the significance of the various parameters. Only the significant parameters have to be identified and the others can be considered to be equal to zero.

Identification examples are now presented. They differ in the input control used, the identification method applied, and the number of runs evaluated.

Using both the least squares and the instrumental variable techniques, a 20 second duration run with a lateral cyclic control input was identified in two ways: first as a single run and then together with a 20 second duration run where a longitudinal cyclic input was used. The time histories of the measured data and the identified models are shown in Figures 12 and 13.

A comparison of these time histories clearly shows the improvement of the identification results when two data runs are evaluated.

Using the maximum likelihood method, a 20 second duration run with a longitudinal cyclic input was evaluated. The time histories of the measured data and the identified model are shown in Figure 14.

The identification models used for the evaluation with the equation error methods had identical structures whereas a slightly different model was used for the application of the maximum likelihood method.

Some of the identified parameters and also the values from an à priori model are given in Table 1. Comparing the results, it should be noted that they were obtained from different data runs and different identification model structures. Therefore identical results cannot be expected. However it can be stated that there is relatively good agreement between the results. This is especially the case for the derivatives obtained from the instrumental variable method when two runs are evaluated and from the maximum likelihood technique.

7. Concluding Remarks

In this paper emphasis was placed on some of the problems associated with the system identification of helicopters. Using both computer simulated and flight test data, it was shown that identification from short data runs (a consequence of inherent helicopter instabilities) is successful when optimal input signals are used and multiple data runs are evaluated. The use of digital smoothing techniques on noisy data reduced the noise to tolerable levels particularly when measured data was differentiated.

Emphasis was also placed on the application of two relatively simple identification methods, the least squares and the instrumental variable. Their computational efficiency makes them attractive for the identification of complex systems like helicopters. It was shown that they yield satisfactory results particularly when multiple data runs are evaluated.

To conclude, we feel that further extensions - e.g. drift estimation, weighting of â priori values, etc. - can make these techniques even more powerful tools for the identification of helicopters.

8. List of References

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Derivative	quasi-static	IDENTIFICATION RESULTS: SINGLE RUN LS	SINGLE RUN IV	MULTIPLE RUNS LS	MULTIPLE RUNS IV	ML
X_u (1/sec)	-0.035	-.037	-.038	-.0388	-.037	-.0437
Y_v (1/sec)	-0.125	-.1076	-.137	-.0487	-.142	-.184
Z_w (1/sec)	-0.982	-.408	-.487	-.621	-.667	-.693
L_u (1/m sec)	-0.051	-.05	-.055	-.0333	-.0394	-.0415
L_v (1/m sec)	-0.291	-.16	-.151	-1.42	-.196	-.0336
L_p (1/sec)	-10.49	-2.68	-2.54	-2.95	-3.8	-2.58
L_q (1/sec)	1.67	5.233	6.252	3.0	3.17	3.9
M_u (1/m sec)	0.047	.0162	.0295	.0159	.0197	.0186
M_w (1/m sec)	0.055	.00578	.0429	.014	.033	.0534
M_p (1/sec)	-1.37	-.31	-1.63	-.196	-.523	-.924
M_q (1/sec)	-4.43	-1.95	-5.11	-1.88	-2.7	-3.58
N_r (1/sec)	-1.39	-.864	-1.11	-.695	-1.23	-2.14
$M_{\theta s}$ (1/sec^2)	0.97	-	-	.324	.419	.456

Table 1 Identification results from the least squares (LS), the instrumental variable (IV), and the maximum likelihood (ML) methods compared with quasi-static derivatives (BO 105, 70 kts)

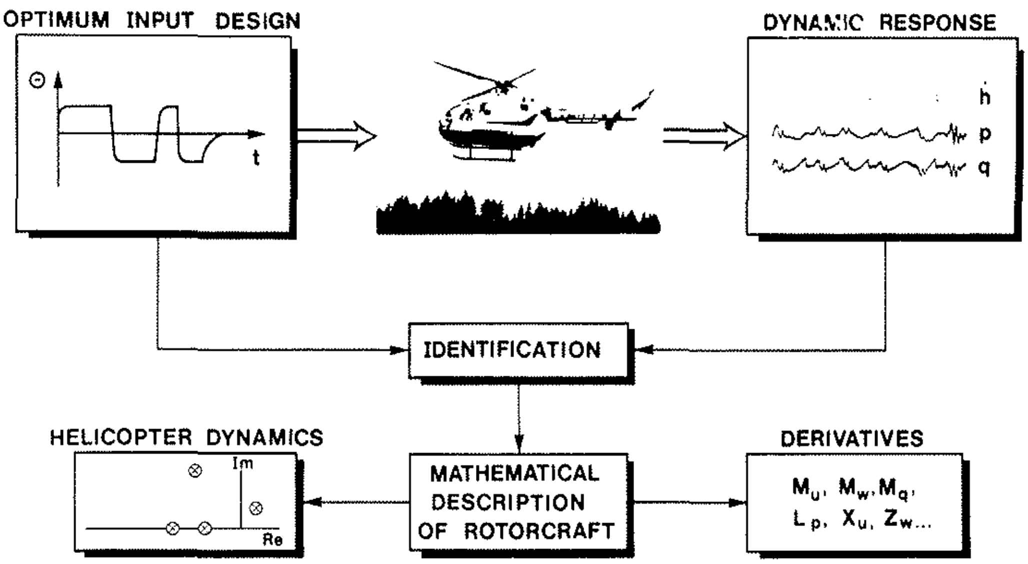

Fig. 1 Helicopter identification procedure

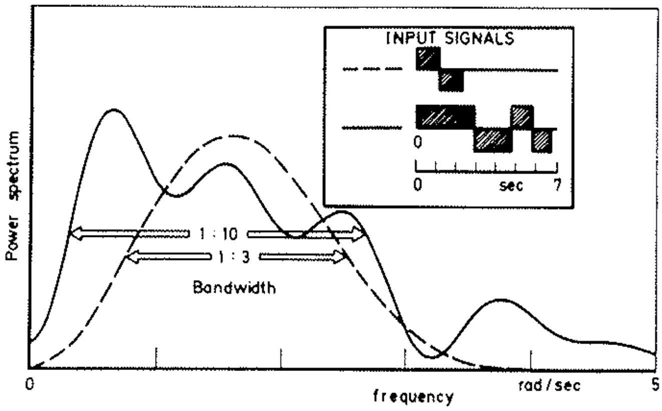

Fig. 2 Power spectrum and bandwidth (half power point) of doublet and pseudo-stochastic signals

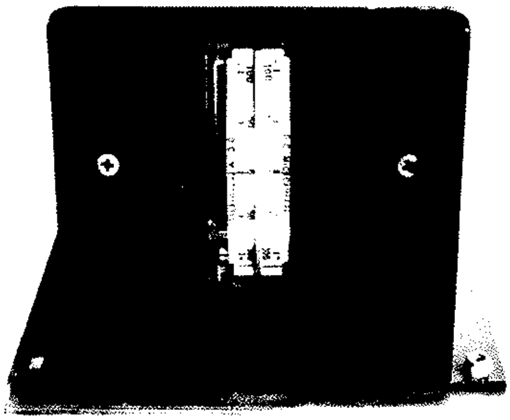

Fig. 3 Pilot's display to help fly input signals

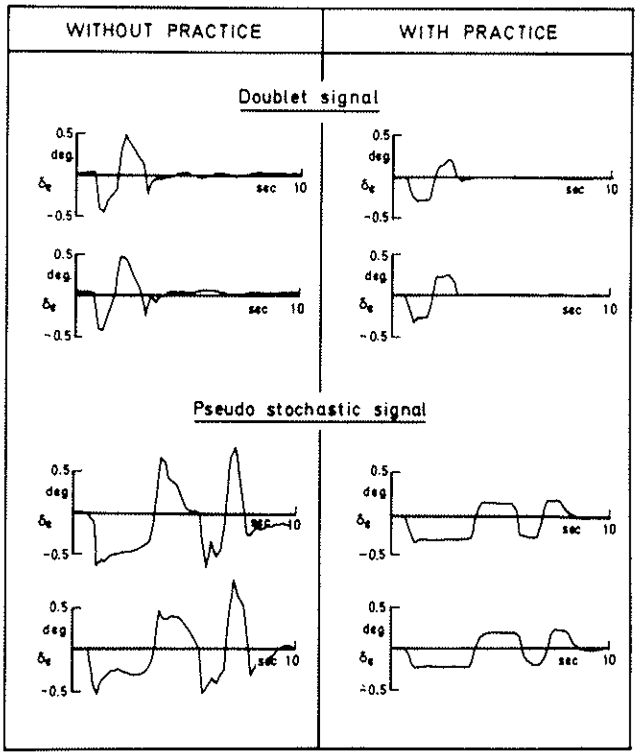

Fig. 4 Examples of pilot flown input signals (Casa C212 airplane)

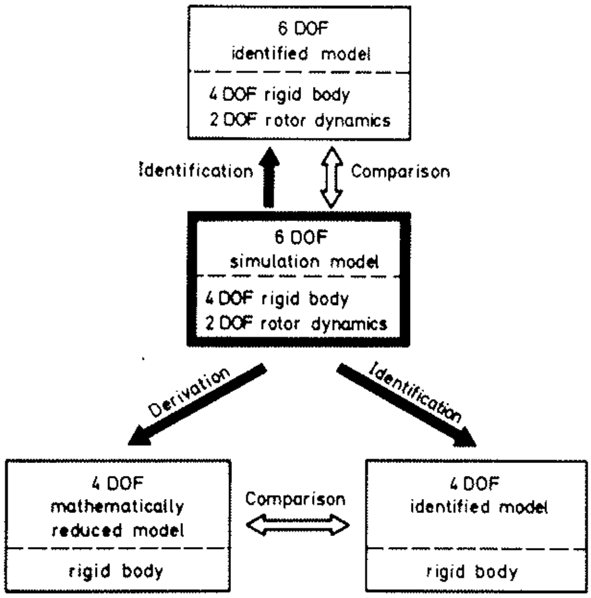

Fig. 5 Analytical and identified models for the Sikorsky S 61 helicopter in hover

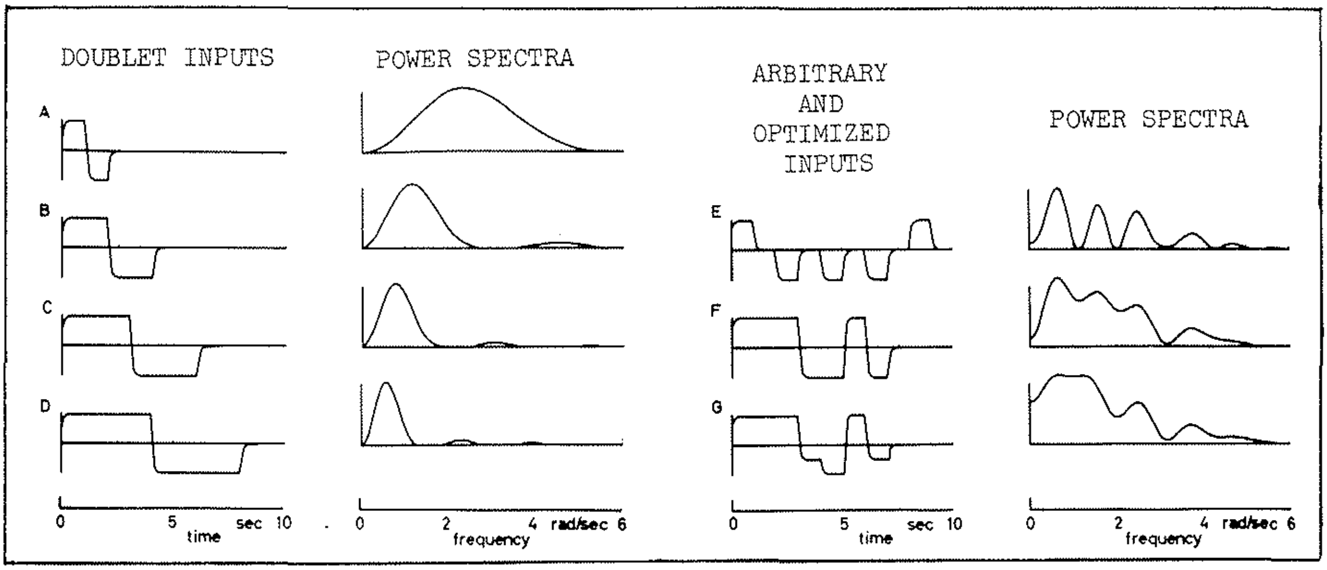

Fig. 6 Input signals with their power spectra

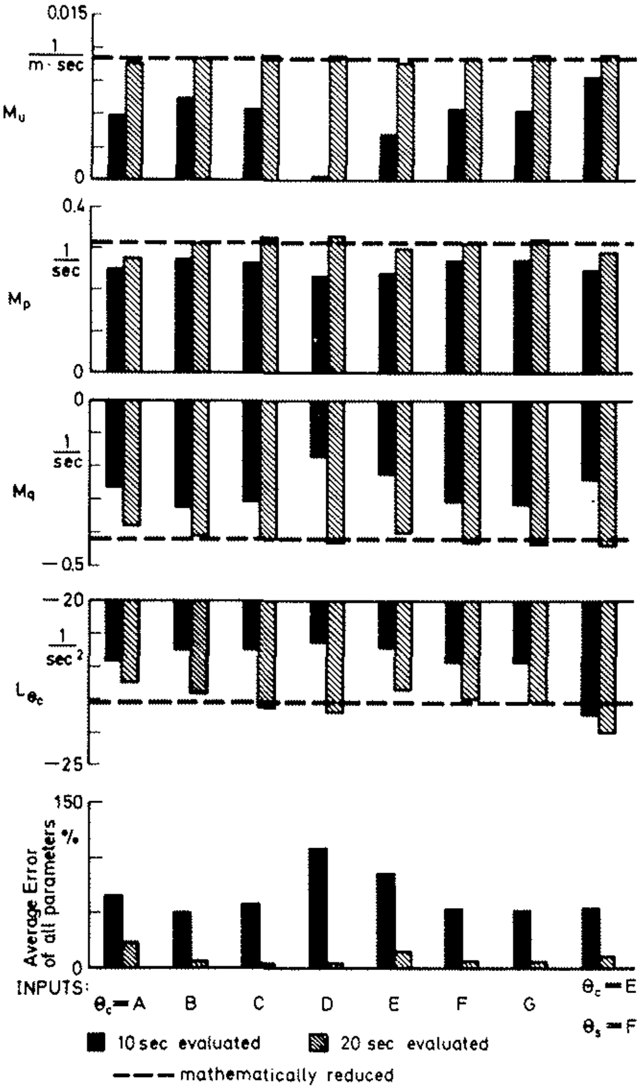

Fig. 7 Identification results from simulated S 61 hover data (Instrumental variable, one run evaluated)

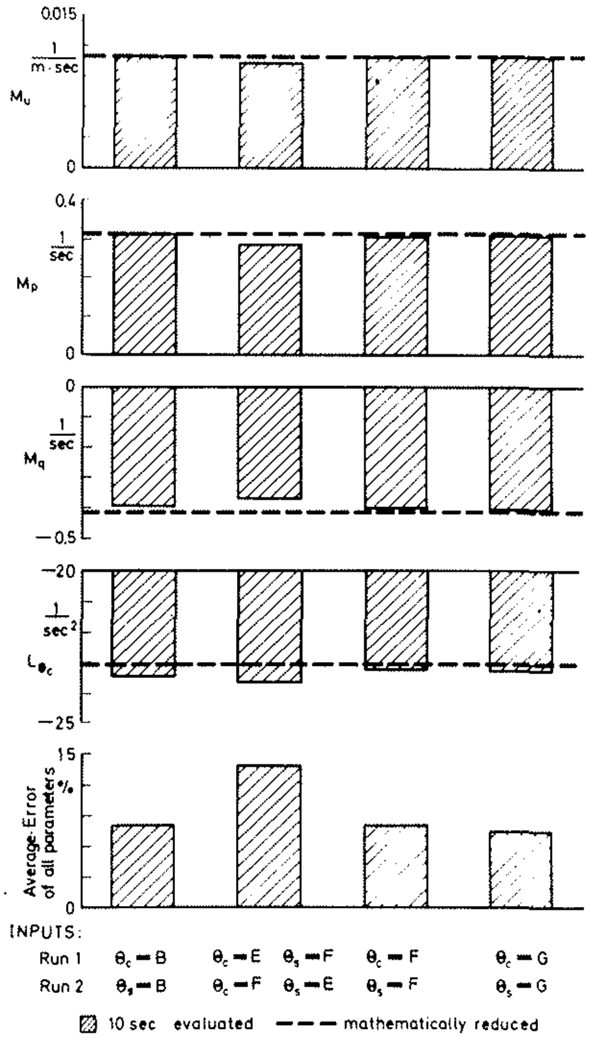

Fig. 8 Identification results from simulated S 61 hover data (Instrumental variable, two runs evaluated)

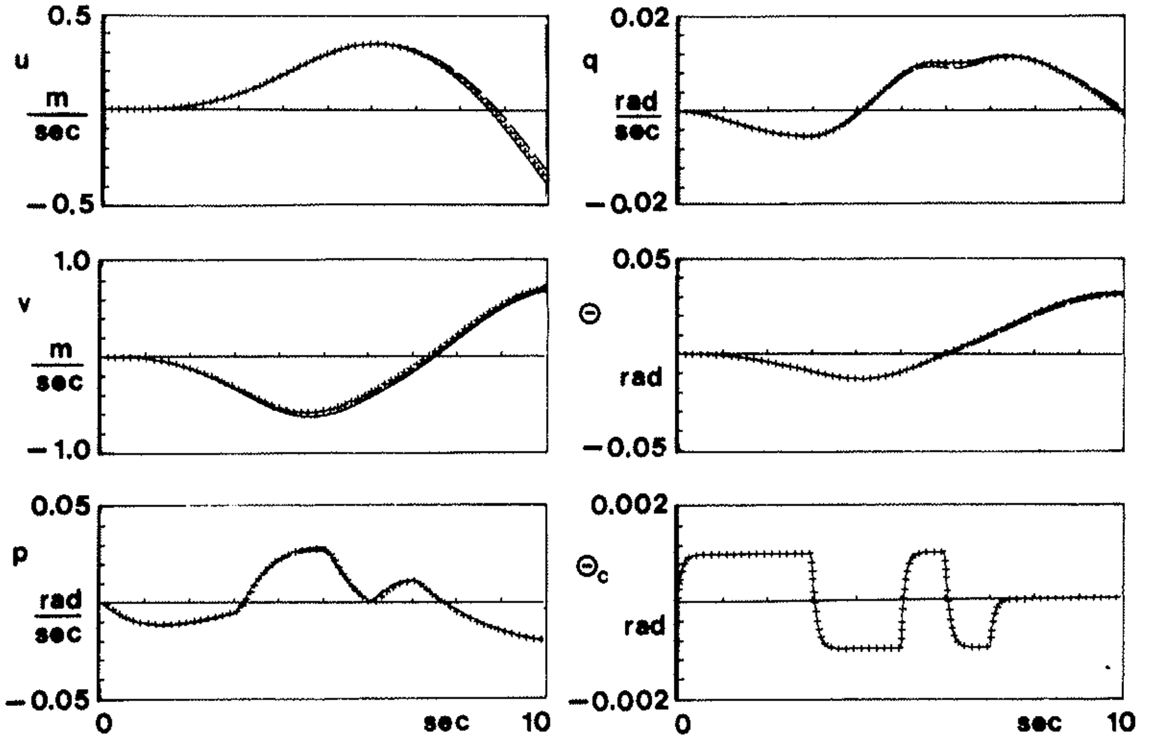

Fig. 9 Time histories from S 61 simulation model (+++), the mathematically reduced model (---), and the instrumental variable identified model (——), one run evaluated

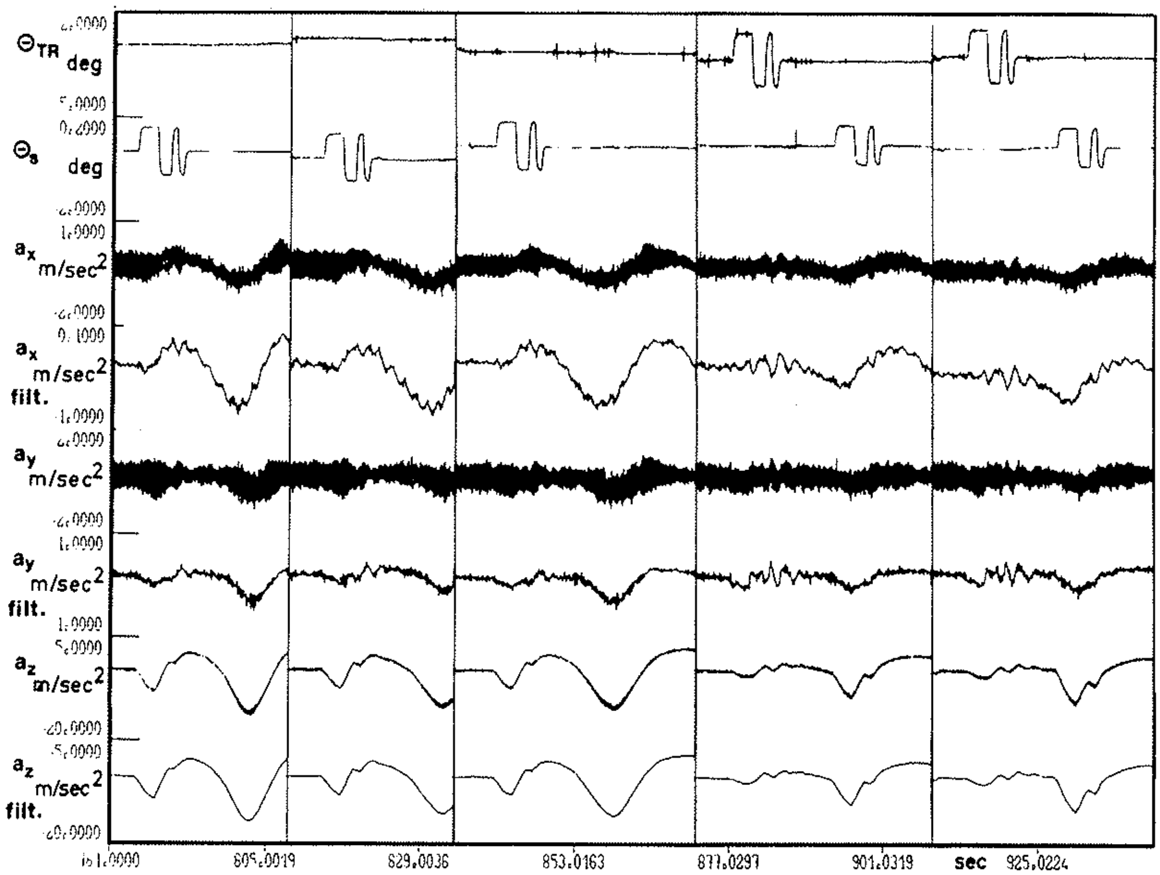

Fig. 10 Effect on digital filtering on acceleration data (BO 105 flight test)

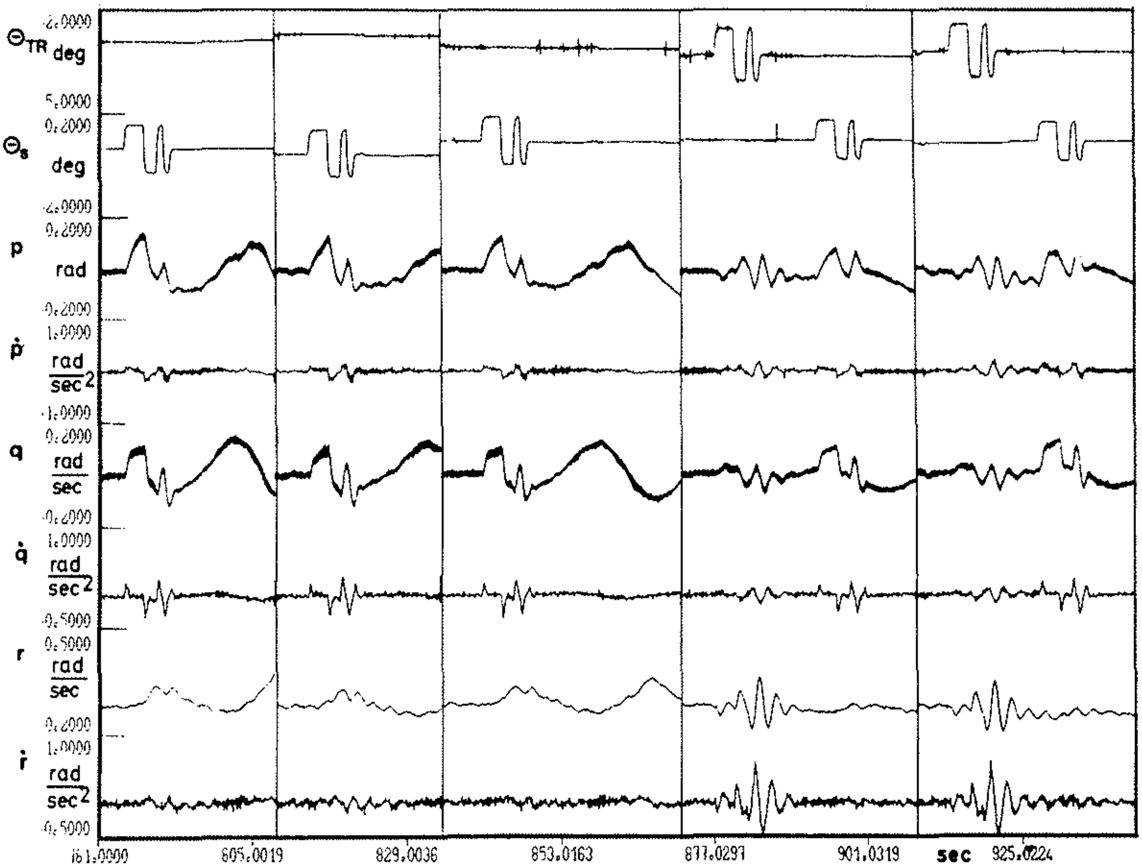

Fig. 11 Effect of digital differentiation on rate data
(BO 105 flight test)

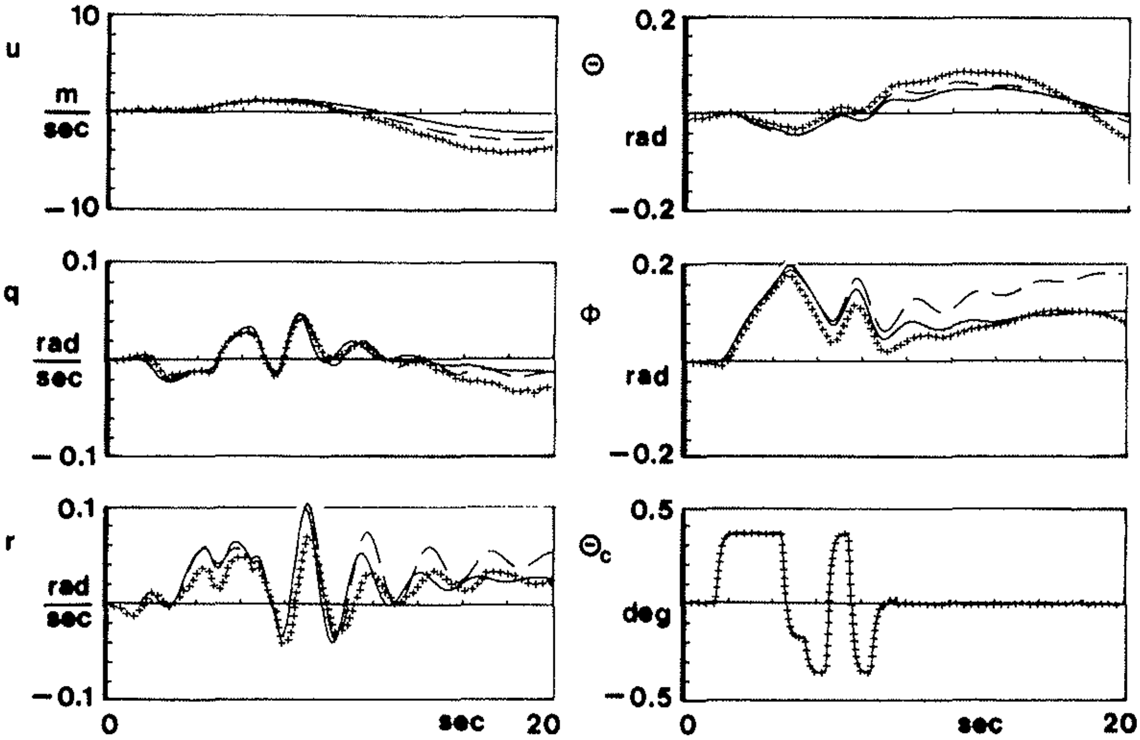

Fig. 12 Time histories of flight test data (+++), identified least squares (---), and instrumental variable models (——), one run evaluated (BO 105, 70 kts)

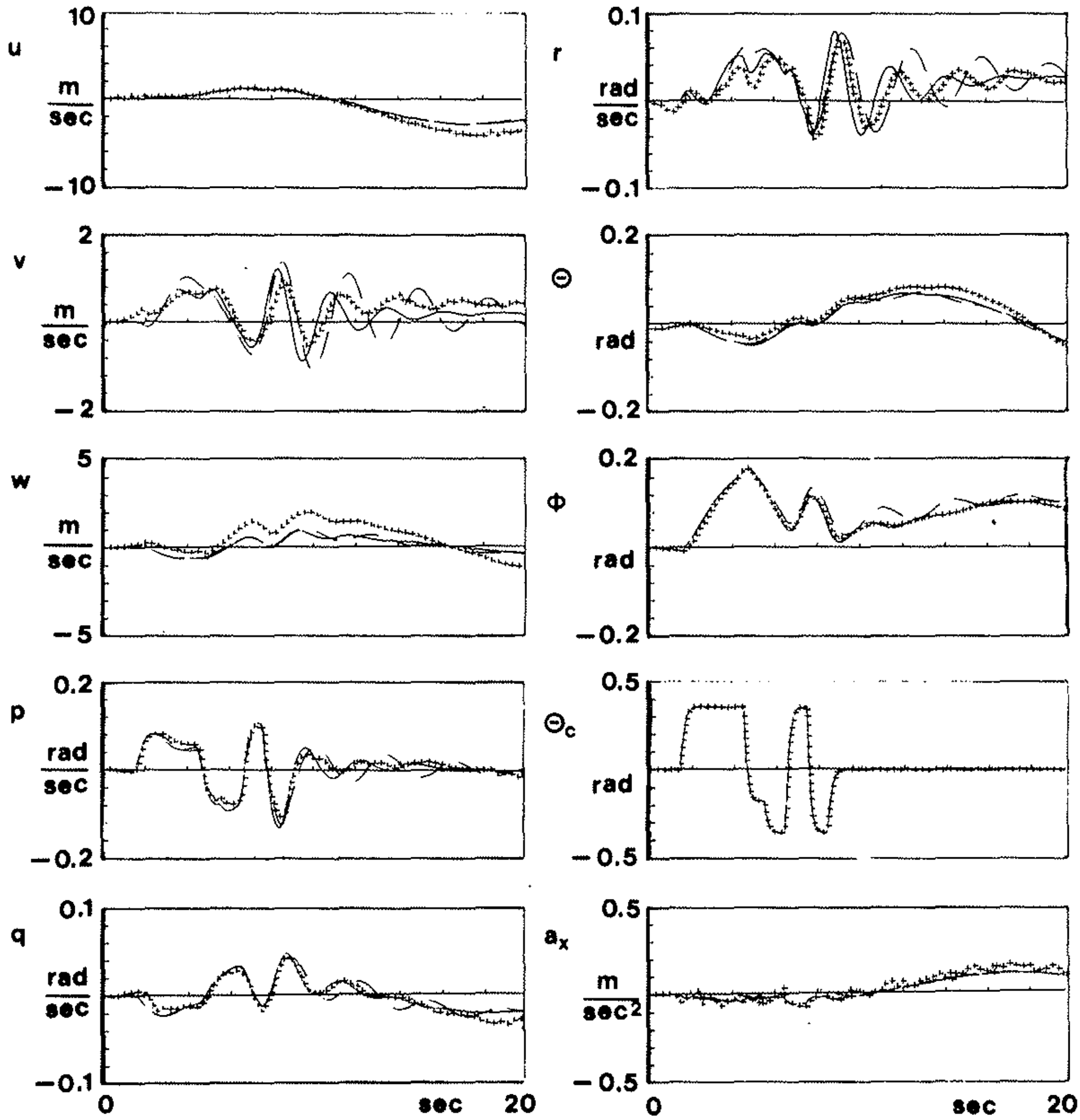

Fig. 13 Time histories of flight test data (+++), identified least squares (---), and instrumental variable models (——), two runs evaluated
(BO 105, 70 kts)

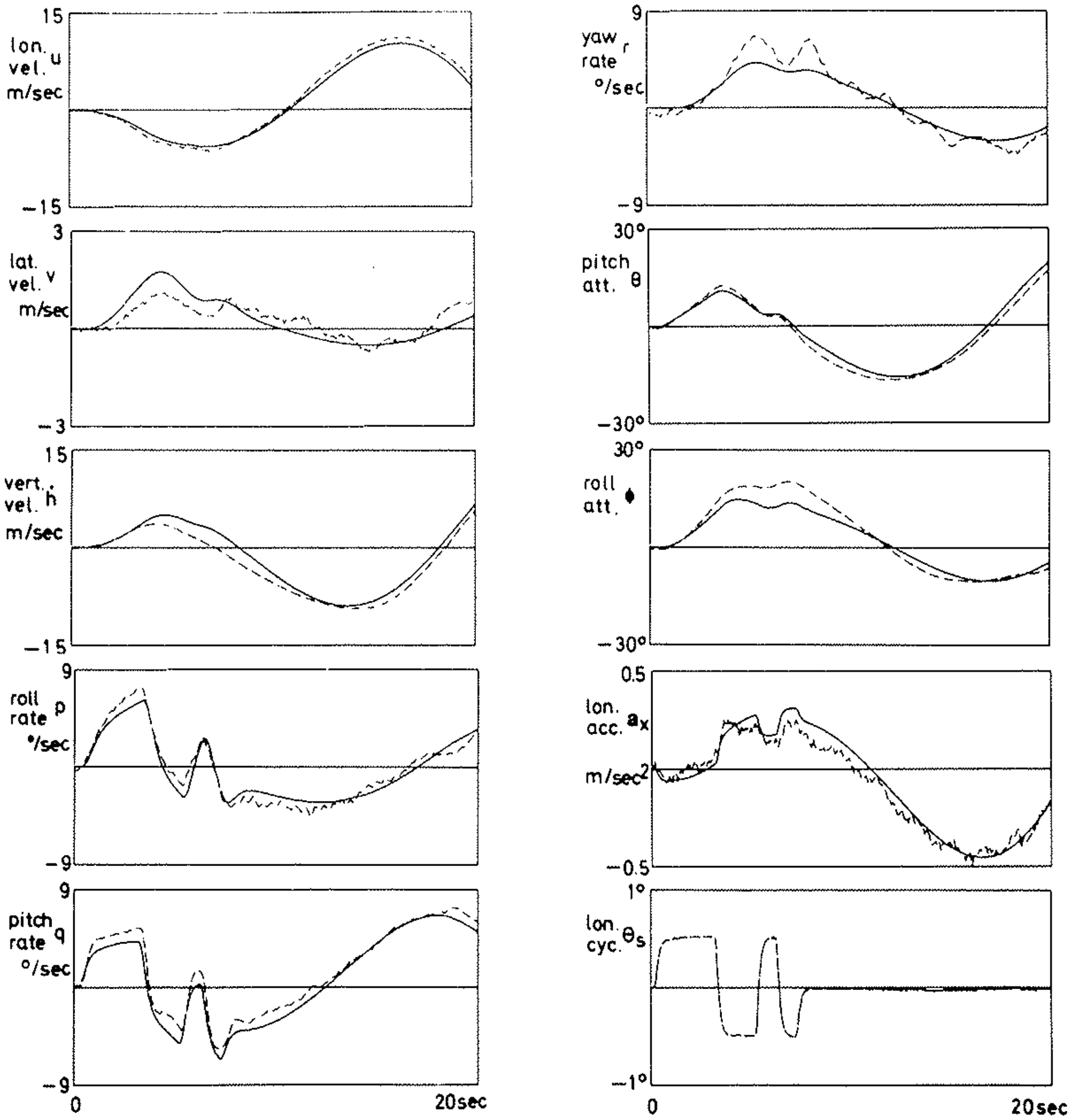

Fig. 14 Time histories of flight test data (---) and identified maximum likelihood model (——)
(BO 105, 70 kts)