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RELIABLE MONITORING OF MODAL PARAMETERS DURING A FLIGHT VIBRATION TEST USING AUTONOMOUS MODAL ANALYSIS AND A KALMAN FILTER

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Abstract: Lightweight construction is required for efficient aircraft design, but it poses challenges due to loads and vibration during flight. Aircraft dynamic aeroelastic behavior, described by modal parameters like eigenfrequencies and damping ratios, varies with altitude and velocity, potentially leading to flutter—an unstable self-excited vibration. Predicting and preventing flutter involves identifying modal parameters through ground and flight vibration tests. However, uncertainties in flight tests, especially concerning damping ratio estimates, result from conditions regarding time-varying systems, low signal-to-noise ratios, and unobservable or unmeasured influences. This study proposes a real-time uncertainty estimation method using clustering-based automated modal analysis and uncertainty reduction using a Kalman filter. For the first time, the Kalman filter-based monitoring has been applied in-flight during a flight vibration test (FVT). The German Aerospace Center (DLR) operates the ISTAR research aircraft (In-flight Systems and Technology Airborne Research), a modified Dassault Falcon 2000 LX. In 2023, an FVT with ISTAR was conducted in Germany. ISTAR, which is permanently equipped with 62 accelerometers and a certified measurement system, records vibration data and operational parameters during every flight. The study shows some of the flight data collected by this extensively instrumented aircraft. The system continuously processes online streamed data every two seconds during the FVT, conducting spectral analysis, modal parameter identification, automated modal analysis (AMA), and Kalman filtering for robust flutter monitoring. The flight test campaign included varying flight levels, fast and slow accelerations and decelerations with and without artificial excitation, enabling a comprehensive comparison of output-only modal parameter identification methods. Monitoring based on the Kalman filter was able to track eigenfrequencies and damping ratios of the aircraft robustly and continuously. These results are promising for online assessment and reliable online prediction of flutter critical speeds; however, the fight tests were performed with the aircraft in a baseline configuration, which is flutter stable in the whole flight test envelope.

1 INTRODUCTION

Flight vibration testing is a crucial phase in the development and validation of aircraft systems and structures. It plays an important role in ensuring the safety and airworthiness of aircraft by proving an aeroelastically stable, i.e. flutter-free, flight behavior in the overall flight envelope. The aeroelastic stability can be identified in terms of damping during flight. In a conventional flight vibration test (FVT) discrete measurement points are sampled within the envelope as can be seen in Figure 1. Based on the identified damping at set measurement points, the subsequent measurement points can then be reached as long as the damping is sufficiently high and does not show trends of significant decrease. This process results in a damping flutter curve illustrated in Figure 2. An overview of conventional FVT strategies is given in [1, 2]. It is self-evident that more sample points result in more detailed flutter curves. However, in conventional FVT several minutes of test data is recorded at each measurement point. Time pressure in certification and high financial costs associated with flight test activities result in tight time constraints for FVT. Therefore, only a limited number of test points are investigated in conventional FVT. The German Aerospace Center (DLR) has developed another approach for more efficient FVTs. At several flight altitudes of the flight envelope, the aircraft is continuously accelerated from the lowest air speed towards the maximum flight speed (Vne). If this acceleration is "slow", continuous operational modal analysis (OMA) can be used to identify quasi-continuous modal parameters (among others the damping ratio) [3-5]. This approach is illustrated in Figure 3 and 4. Using efficient implementation of OMA methods, this quasi-continuous identification can be done within two seconds which can be seen as real-time considering slow air speed variations. Since several minutes are spent on each discrete measurement point in conventional FVT and an offline analysis between some measurement points is necessary on ground, even a slow acceleration like 0.5 kn/s would lead to the same required time to analyze one flight level. But with the similar flight time, the data resolution of the results will be higher.

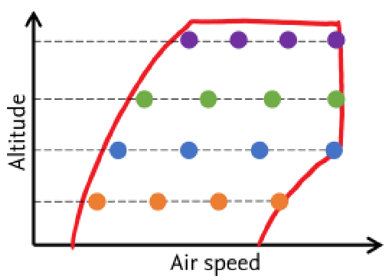


Figure 1: Conventional FVT with discrete measurement points

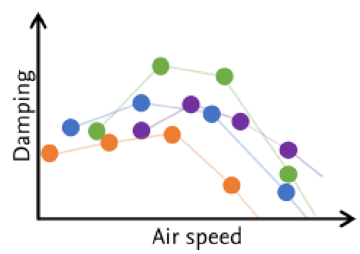


Figure 2: Discrete damping estimations based on conventional FVT

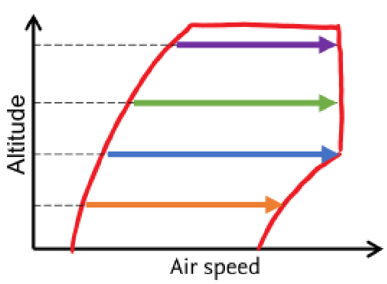


Figure 3: Quasi-continuous FVT

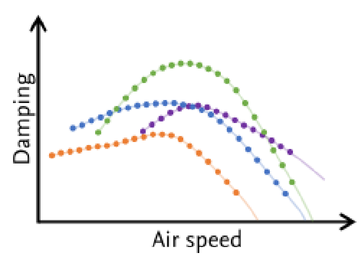


Figure 4: Quasi-continuous damping estimations based on continuous FVT

The theory and application examples of real-time OMA for FVT is presented in [3, 5, 6]. The core identification methods from OMA assume the identified system to be linear time-invariant (LTI). Even though the system is varying only slowly, the uncertainty of the identification is increased. In addition, low signal-to-noise ratios in FVTs, the variance of excitation and unobserved influences on the aeroelastic behavior increase the identification uncertainties further.

In this study, an autonomous real-time monitoring system is presented which uses autonomous modal analysis (AMA) and a Kalman filter (KF) to reduce the uncertainties of modal parameter monitoring in FVT. This system is tested on an FVT with the DLR research aircraft ISTAR with different flight maneuvers.

2 KALMAN FILTER-BASED MODAL PARAMETER MONITORING

The modal parameter monitoring system is based on real-time AMA. The process of time data buffering, AMA and modal tracking is introduced in Section 2.1. The KF for reliable aeroelastic monitoring is described in Section 2.2.

2.1 Quasi-continuous modal parameter monitoring

Structural dynamic system identification is mainly based on sensors such as accelerometers or strain gauges. In this study, acceleration signals are used as the input for modal parameter identification and monitoring. Those signals are buffered in a first-in-first-out (FIFO) buffer that enables an analysis of the acceleration data of the near past, see top left plot in Figure 5. On the one hand, this buffer should be as short as possible, to reduce the effect of the time-variation in FVT. On the other hand, a longer time buffer reduces the uncertainties of modal parameters identified in OMA, since more repetitions of each vibration are recorded. Therefore, the buffer length is chosen depending on the application as a trade-off usually between 30 and 120 seconds. The buffered time data is analyzed using an OMA method called Stochastic Subspace Identification (SSI) [7, 8], see top right plot in Figure 5. The results of SSI are further analyzed using clustering methods. The clustering provides unique physical modes and estimated uncertainties of those modal parameters (eigenfrequencies and damping ratios), see middle row plots in Figure 5. These clustering steps are summarized as AMA. The modes are finally tracked over time, i.e. analysis blocks or mode sets, using similarity metrics like the modal assurance criterion (MAC) and the eigenvalues themselves, see the results in lower row in Figure 5. The automated clustering method is presented in [9]. The clustering as well as the OMA method need hyperparameters to run optimally. This might be e.g. the Hankel matrix block size of SSI or a clustering threshold. Another hyperparameter of real-time monitoring is the time buffer length as described above. The optimization of all these hyperparameters for real-time monitoring in FVT is described in [10]. The optimization of the hyperparameters reduces the uncertainties of modal parameter identification, however the uncertainties of identified damping ratios remains high.

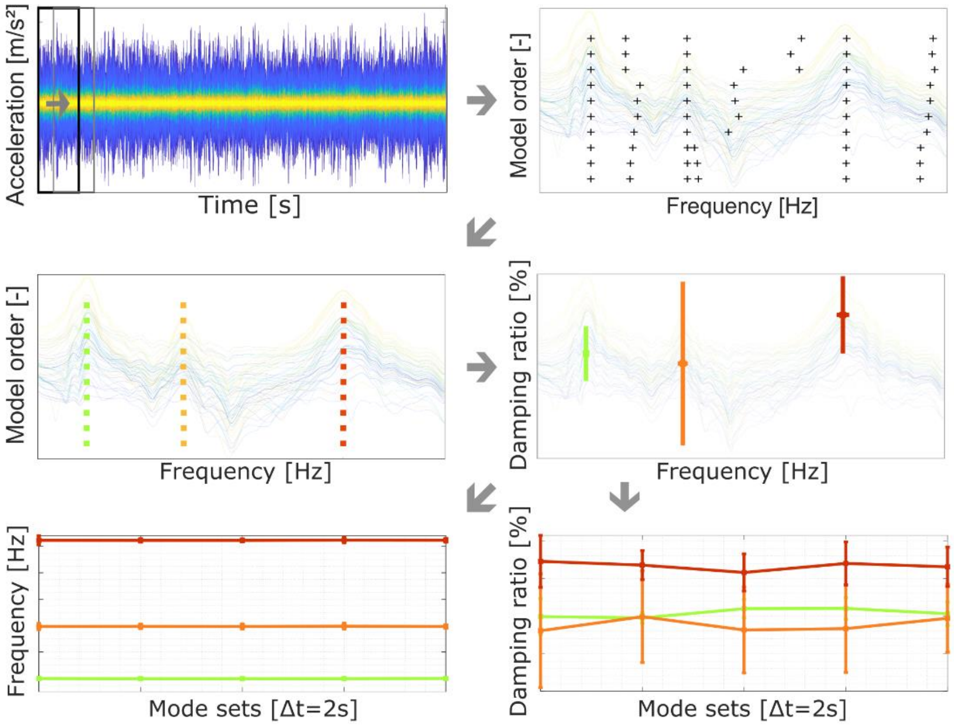


Figure 5: Automated modal parameter identification and tracking (adapted from [11])

2.2 Kalman filter for aeroelastic monitoring

The main idea of this study is to reduce the uncertainties of modal parameters identified in real-time using AMA and a KF. The DLR approach utilizes a continuous but slow acceleration of the aircraft on a constant flight level. Considering the monitoring system described in Section 2.1, the basic measurement information is stored in a time buffer of e.g. 60 seconds. An update of this FIFO buffer is done every two seconds. Therefore, the overlap of the buffer is 96.7%. If the excitation does not change significantly from one time step to the next one two seconds later, the vibration information included in the buffer does not change significantly. This assumption is an extension to the classical OMA assumption of stationary and random excitation signals. This should be considered with caution. The random excitation throughout the time buffer, e.g. in the beginning of a time buffer and 50 seconds later, is assumed to be stationary. This is unlikely to be fully realized in flight testing, therefore a resulting uncertainty can be expected. Considering those challenges as noise in the KF model, the change of the aeroelastic state identified from two subsequent time buffers with high overlap can be assumed linear. We define the state of a mode as

$$\boldsymbol{x} = \begin{bmatrix} f \\ \xi \\ \Delta f \\ \Delta\xi \end{bmatrix} \tag{1}$$

where f is the eigenfrequency, ξ is the damping ratio, Δf is the change of the eigenfrequency from a time step to the next one and $\Delta\xi$ is the change of the damping ratio. A time step is the elapsed time from one modal analysis to the next one two seconds later. The state is modeled as a Gaussian distribution with $\boldsymbol{x}_k \sim \mathcal{N}(\widehat{\boldsymbol{x}}_k, \boldsymbol{P}_k)$. The KF receives measurements to update its predictions from the real-time AMA as

$$\boldsymbol{z}_k = \begin{bmatrix} f_{AMA} \\ \xi_{AMA} \end{bmatrix}. \tag{2}$$

The KF also receives estimated uncertainties of f_{AMA} and ξ_{AMA} given by the AMA procedure [10]. These uncertainties are transformed into a diagonal measurement noise covariance matrix $\boldsymbol{R}_k$. $\boldsymbol{R}_k$ is time dependent because e.g. the excitation from turbulence and the noise level change during flight. The measurement model is defined as

$$\boldsymbol{z}_k = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \boldsymbol{x}_k + \boldsymbol{m}_k\,, \tag{3}$$

where zero-mean noise $\boldsymbol{m}_k \sim \mathcal{N}(0, \boldsymbol{R}_k)$. The change of the modal parameters (Δf and $\Delta \xi$) is not given by the identification but estimated implicitly by the KF using the transition matrix

$$\boldsymbol{A}_k = \begin{bmatrix} 1 & 0 & \Delta t_k & 0 \\ 0 & 1 & 0 & \Delta t_k \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, \tag{4}$$

where Δt_k is the time difference between k and $\mathrm{k}-1$. Using the linear transition matrix, the process model is given by

$$\boldsymbol{x}_k = \boldsymbol{A}_k \boldsymbol{x}_{k-1} + \boldsymbol{v}_k\,, \tag{5}$$

with $\boldsymbol{v}_k \sim \mathcal{N}(0, \boldsymbol{Q})$ is the process noise. The assumption of a linear change of eigenfrequency and damping ratio from one time step to the next one is not exact, but a reasonable approximation given the time buffer-based signal processing. If the change of the aircraft flight condition (i.e. flight speed and altitude) follows another rule than the one described, the transition model should be adapted. The KF is able to fuse subsequent modal parameter estimations smoothly which results in significantly reduced uncertainties, as illustrated in Figure 6. The KF uses the previous change of modal parameters to predict the next ones. A new identification by AMA is used to update the prediction towards the final fusion of subsequent estimations.

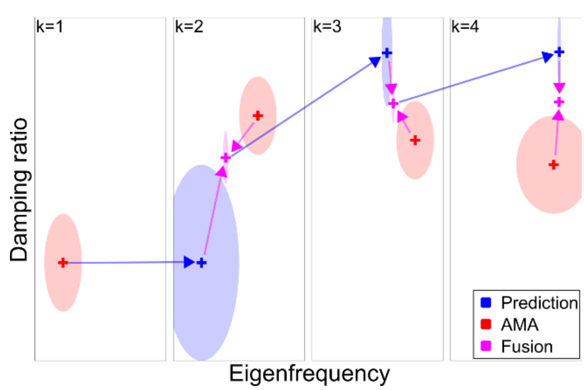


Figure 6: Uncertainty propagation of modal parameters using AMA and a KF

The transition model assumes linear change of the modal parameters because the DLR FVT approach assumes a continuous slow change of the flight speed. A resulting non-linear change of modal parameters from small changes of the flight speed is neglected in this approach. If the flight maneuvers are different, the KF can be chosen in a more sophisticated way as an adaptive KF [11] or with alternative transition models.

3 FLIGHT VIBRATION TEST

The presented KF-based modal parameter monitoring system was tested during the FVT with the DLR research aircraft ISTAR. It is a modified Dassault Falcon 2000 LX business jet with two engines, a wing span of 19.5 m, maximum take-off weight of 19.4 t and a maximum cruise speed of 893 km/h. The aircraft is shown in Figure 7. The aircraft is unique for its high-density instrumentation, which consists of 62 permanent accelerometers and other sensors such as strain gauges connected to a CRONOSflex measurement system from imc Test & Measurement. The distribution of the acceleration sensors is shown in Figure 8. The measurement system is capable to record data during every flight as well as stream the data online to analysis computers inside the cabin.

Figure 7: ISTAR research aircraft at FVT in front of the hangar at Brunswick Airport

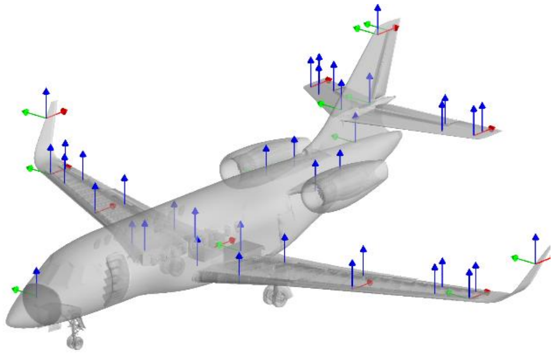


Figure 8: Acceleration sensor plan of ISTAR flight test instrumentation

During the flight test campaign several maneuvers were performed. In this paper, a small subset of these maneuvers is shown in which the aircraft is accelerated and decelerated on a constant altitude, hereinafter referred to as level acceleration and deceleration (LAD). Those maneuvers were performed on multiple altitudes, however in this paper the results of the KF-based monitoring is shown with respect to mainly one flight level for the sake of simplicity. Figure 9 shows the acceleraton flight data of the flight number 5. In total eight LAD maneuvers are performed on flight level 11000 ft (FL110). The maneuvers are described in Table 1. Since in each identification step an LTI system is assumed, the variation of the system should be slow. However, it is difficult to determine in advance how slow is slow enough. The modal parameter monitoring system is evaluated on those fast and slow maneuvers in order to assess the suitability.

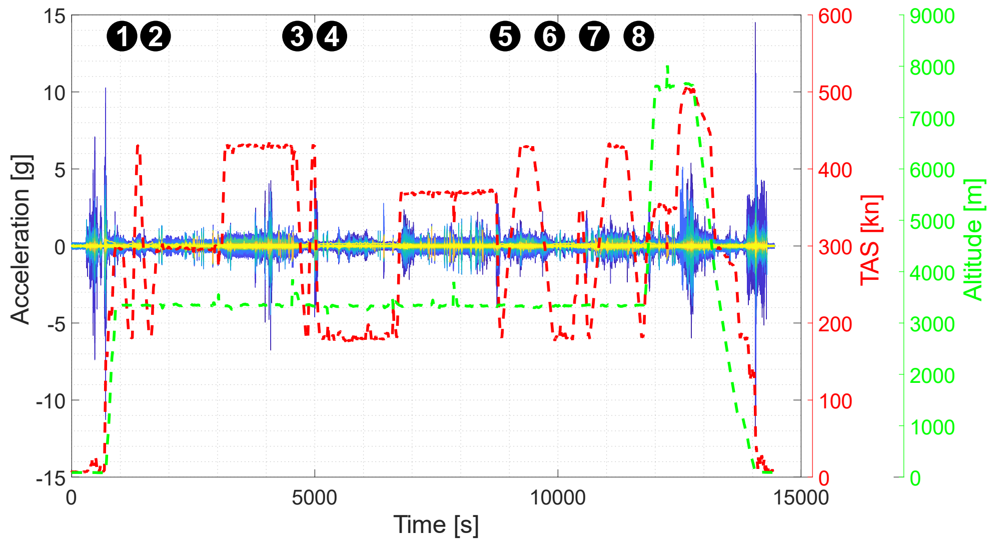


Figure 9: Time acceleration data of flight number 5 with eight LAD maneuvers on FL110

Table 1: Level acceleration and deceleration maneuvers at FL110

Number	Duration	TAS Range (kn)	Rate of acceleration	Feature
1	108 s	180 → 430	2.32 kn/s	Fast
2	201 s	427 → 183	1.22 kn/s	Fast
3	107 s	179 → 431	2.36 kn/s	Fast
4	116 s	431 → 179	2.17 kn/s	Fast with air brakes for deceleration
5	395 s	181 → 432	0.64 kn/s	Slow
6	426 s	429 → 179	0.58 kn/s	Slow
7	399 s	433 → 179	0.63 kn/s	Slow and randomized control surface pulses for excitation
8	335 s	429 → 181	0.74 kn/s	Slow and randomized control surface pulses for excitation

Figure 10 shows the data snippet of the fifth maneuver, i.e. the slow continuous acceleration from 181 kn to 432 kn. The altitude is almost constant and therefore neglected in the following discussion. The time data is analyzed in parallel with two methods, once using the real-time AMA (based on SSI) and once using AMA and the KF tracking. The modal analysis results are compared with the KF results in terms of eigenfrequencies in Figure 11. The squares indicate the eigenfrequencies identified by AMA, whereas the line shows the KF results. Different colors indicate the different modes. Up to 20 Hz 15 modes can be tracked with reasonable scatter. The modal parameters were tracked continuously without artificial excitation but only using natural turbulence excitation. It is a notable result, since with comparison to the GVT [12] all modes in the presented frequency range are identified and tracked continuously. One can also see significantly less scatter using the KF, however the main trends of eigenfrequencies are not manipulated by the KF.

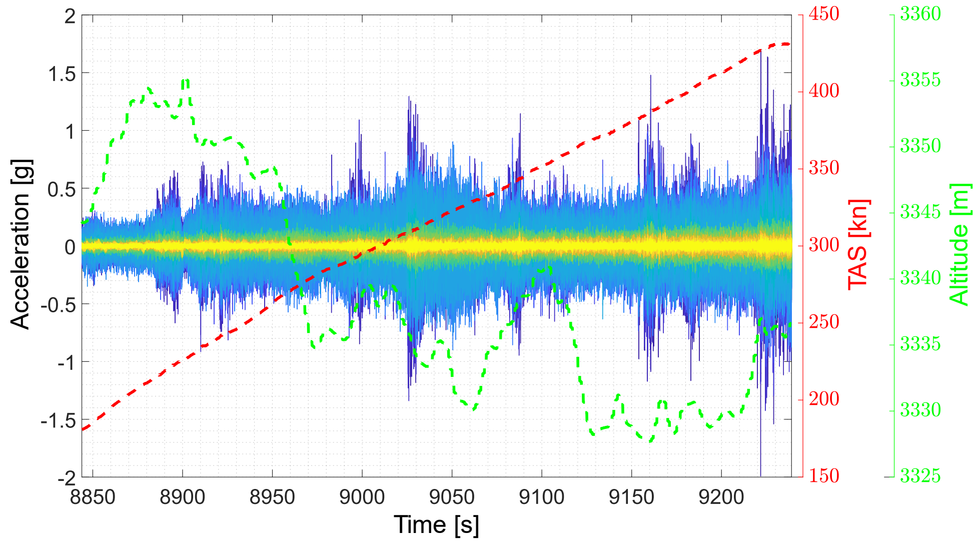


Figure 10: Time data of maneuver five, slow acceleration

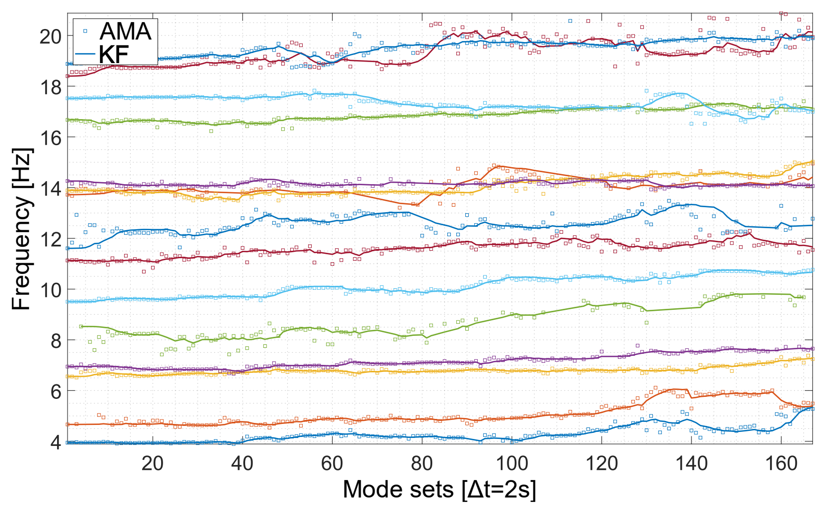
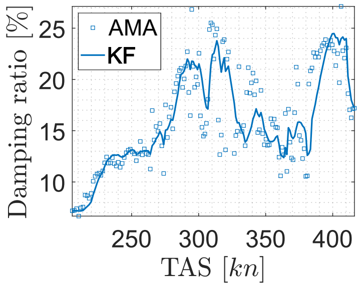
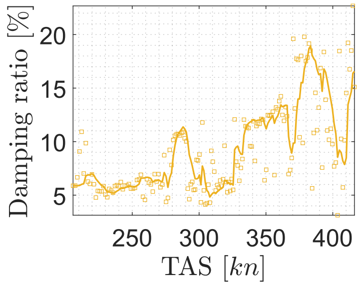


Figure 11: Eigenfrequency tracking comparison of autonomous modal analysis and Kalman filter for the fifth maneuver

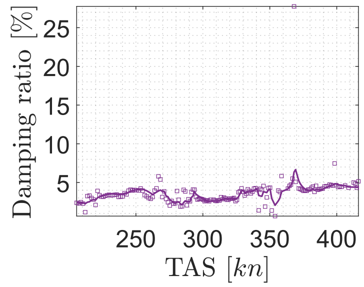
Since the identification of damping ratios is associated with higher uncertainties, the effect of the KF is of major interest. The damping ratio tracking of six example modes is shown in Figure 12. One can see that the scatter of the damping estimation can be reduced using the KF. For example, in Figure 12 d) one outlier of damping estimation can be seen at above 25% at 368 kn. The KF is capable to clean such an outlier reliably. However, other modes like e.g. the mode number 8 in Figure 12 h) shows unlikely trends. These might result from insufficient excitation or from unsteady event (i.e. control input of the pilot to recover after a gust, etc.). It should be noted that the results plotted in Figure 11 and Figure 12 are solely plotted as a function of flight speed. There are other test parameters which might cause changes in damping not plotted here. Therefore, the plots of Figure 11 and Figure 12 can be considered as results being available directly after completing a test flight. In the post processing, the changes in modal parameters must be verified also with other test parameters. This typically leads to a cleaning and smoothing of the plots indicating the changes of modal parameters with test conditions.



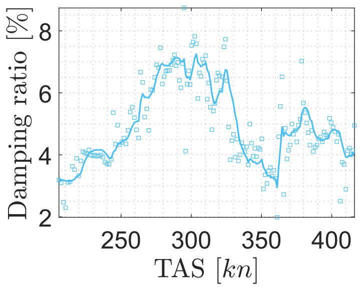
a) 1st mode



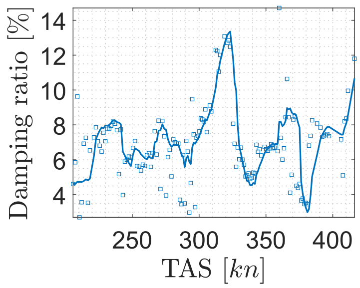
c) 3rd mode



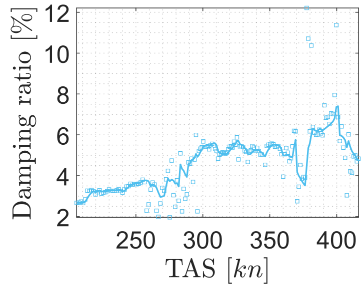
d) 4th mode



f) 6th mode



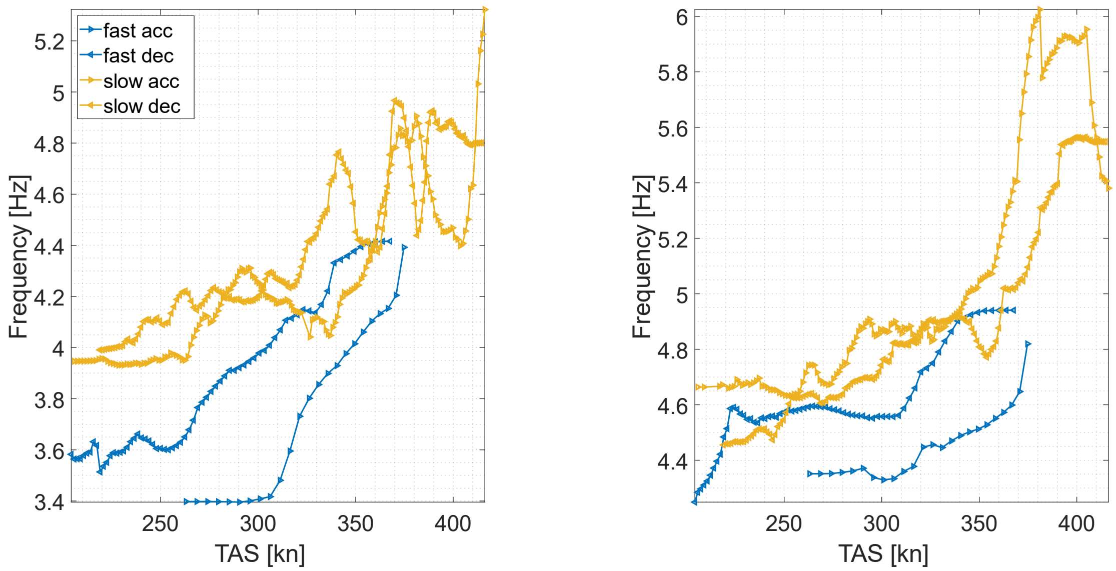
h) 8th mode



m) 13th mode

Figure 12: Damping ratio tracking examples of fifth maneuver using AMA and the KF

Because of the promising and robust tracking of most modes, the test results can be used to compare the different maneuvers for OMA based modal parameter monitoring of time-varying systems. A critical question is if the variation of the aeroelastic system is slow enough to be identified stepwise by the LTI approach. In Figure 13 the eigenfrequency tracking identified from fast maneuvers (1&2) are compared with the results from the slow maneuvers (5&6). The maneuvers with air brakes are not considered for this comparison, since the acceleration phase and deceleration phase would mix different configurations. The fast maneuvers are plotted in blue and the slow maneuvers in yellow. The accelerations are indicated with the right pointing triangle and the decelerations with the left pointing triangles. For both modes the yellow lines match for most of the TAS range whereas the blue curves differ significantly. This means that the fast system variation has significant influence on the identification, whereas the slow system variation leads to comparable results for acceleration and deceleration. This finding is important since the tracking lines of the blue curves are apparently with very little uncertainty, but obviously with a bias. The eigenfrequency shift between the yellow and blue curves is due to mass change caused by fuel burn. The maneuvers 1 and 2 were conducted significantly earlier in the flight than the maneuvers 5 and 6. A mass change however should not be significant between the subsequent maneuvers 1 and 2 on the one hand and 5 and 6 on the other hand. With such a process it is possible not only to continuously identify modal parameters but also check if the system variation was slow enough.



a) 1st mode

b) 2nd mode

Figure 13: Comparison of fast and slow air speed variation

In Figures 11 and 12 one can see that some modes are identified more clearly than others. For example, the eigenfrequencies of mode numbers 5 and 8 in Figure 11 at about 8 and 12 Hz respectively, are identified with high scatter. The KF reduces the variance, however the damping ratio of mode 8 trends remain with unreasonable variation, see Figure 12 h) at about 300-350 kn. The corresponding modes are related to engines and VTP, respectively. These aircraft components have just a few sensors installed, as can be seen in Figure 8. Therefore, observability of these modes can be improved. The strong variation might be a result of poor excitation. Poor excitation in this respect can mean too weak modal excitation level due to the spatial distribution of the natural turbulence excitation, but it can also mean non-stationary excitation over time. Non-stationary excitation is a violation of the assumptions on which OMA relies. It can therefore adversely affect the modal parameter estimation. To summarize, the KF can reduce the scatter on the identification of modal parameters, but cannot compensate if the scatter of the identification is larger than the physical trend of the modal parameters with changing airspeed. To improve this, one can try to artificially excite the structure in addition to the turbulent aerodynamic flow. In order to change the aeroelastic system as little as possible, the excitation is made by pulse-like deflections of the control surfaces (aileron, rudder and elevator). Example data from two of these maneuvers at FL350 are shown in Figure 14. The red line on the right-hand Y axis indicates that the speed is firstly increased and then reduced again. During acceleration and deceleration phases, the control surfaces are randomly used as pulse-like exciters. It should be noted that the aileron and rudder impulses (in purple) excite the anti-symmetrical modes, while the elevator impulses (in green) excite the symmetrical modes.

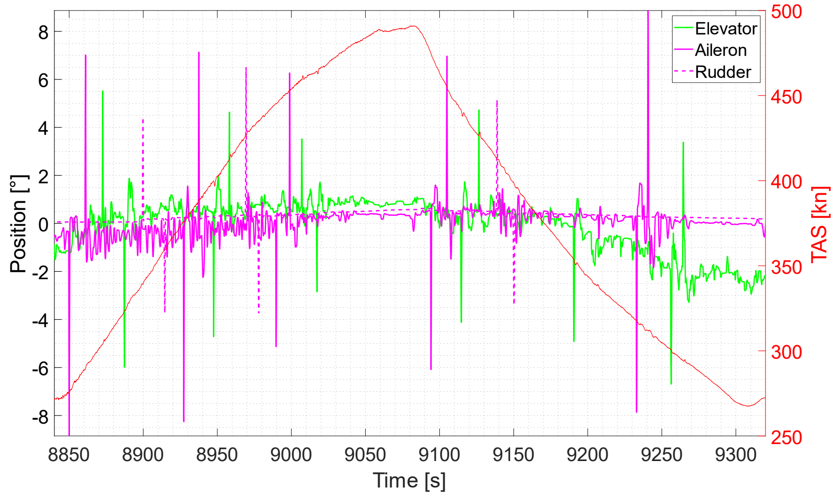
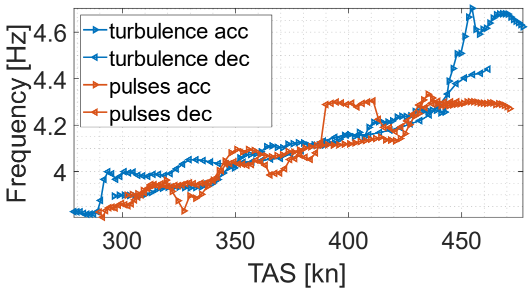
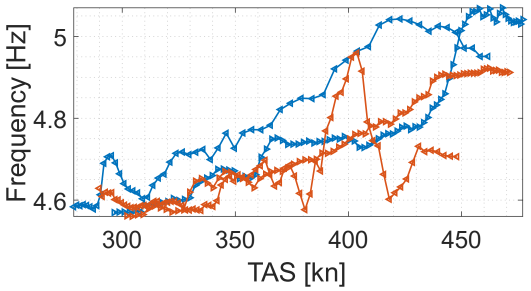


Figure 14: Level acceleration and deceleration maneuver with pulse-like excitation using the control surfaces

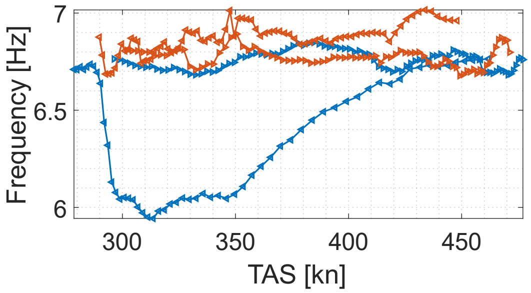
The comparison of eigenfrequencies is conducted for four example modes (two symmetric modes and two anti-symmetric modes) in Figure 15. The identifications based on pulse excitation (red) are significantly closer to each other in some areas than the curves without artificial excitation (blue), e.g. in Figure 15 a) for the 2n wing bending mode between 300 and 380 kn. In other areas, however, the identification using pulse excitation is worse, e.g. in Figure 15 b) between 370 and 420 kn.



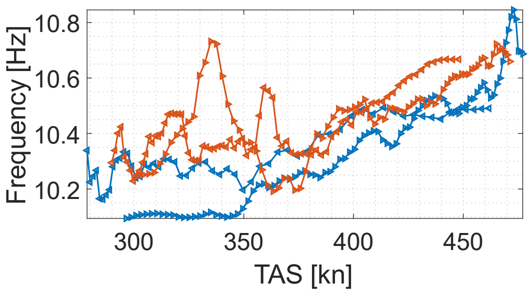
a) 2n wing bending (sym)



b) 3n wing bending (anti-sym)



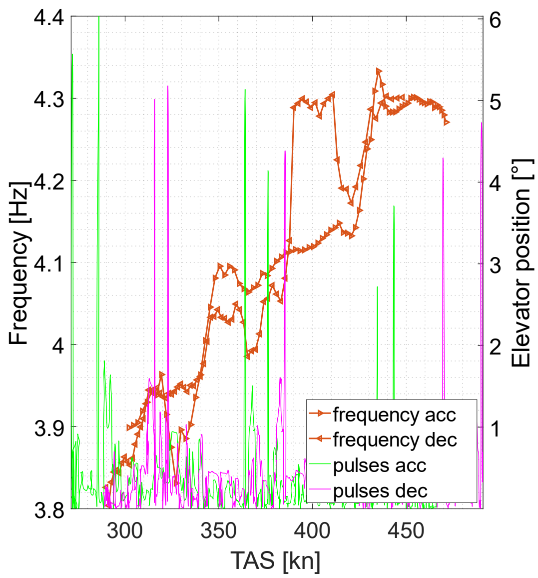
c) HTP roll (anti-sym)



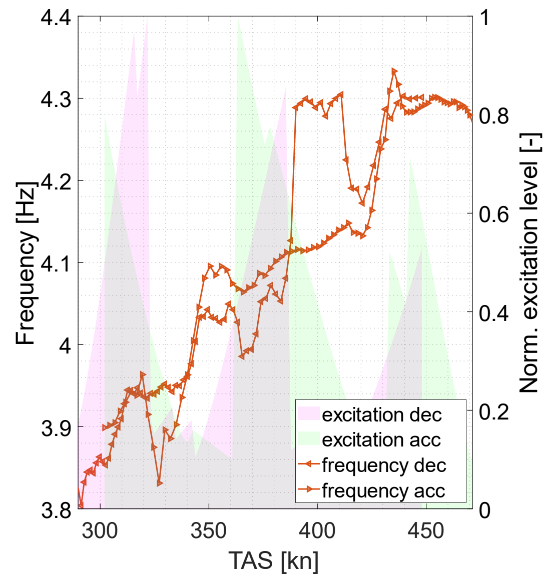
d) 4n wing bending (sym)

Figure 15: Comparison of eigenfrequency identification using turbulence excitation only and control surface excitation

Figure 16 a) shows the identification of the first mode (symmetrical) with the pulses from the acceleration and deceleration maneuvers. For the sake of simplicity only the pulses from the elevator are shown, since they excite the symmetric mode best. Considering the time buffering process, the excitation of a pulse is present in the time buffer for 60 seconds, whereby the influence of the pulse decreases with time. This means that the contribution from the excitation level is highest at the pulse and soon after the pulse and decreases until the next pulse is performed. This is shown in Figure 16 b) by means of a transparent area in which the excitation level is visualized. The higher the transparent area for a specific TAS, the better the excitation was for the TAS. For example, at about 360 kn a pulse occurred in the acceleration maneuver, therefore the green area is maximized and slowly decreased towards the right side. Consequently, the excitation level of the deceleration maneuver decreases towards the left side after a pulse. This illustration can be used to highlight TAS ranges in which the mode was well excited in the acceleration or deceleration maneuvers. It can be seen that between 400 and 430 kn there is no purple area, meaning no excitation in this airspeed range for the deceleration maneuver. This range is an example in which the identified eigenfrequencies from the acceleration and deceleration maneuvers differ strongly. In areas with good excitation in acceleration and deceleration maneuvers, e.g. at about 315 kn or 445 kn, the curves are close to each other.



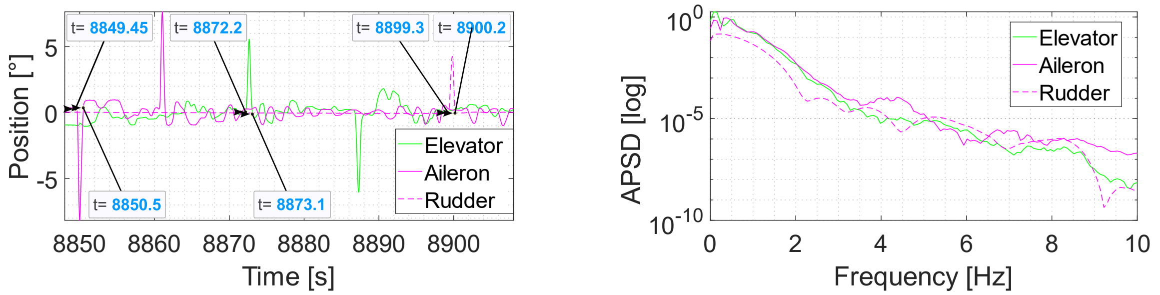
a) Eigenfrequency tracking of first mode from pulse excitation with elevator position



b) Excitation level in the analysis time buffer for modal analysis in acceleration and deceleration maneuvers

Figure 16: Control surface pulses and resulting excitation level for modal parameter monitoring purposes

This leads to the conclusion that artificial excitation can be used to improve the modal parameter monitoring in slowly varying conditions. However, it should take place more frequently and, if possible, alternately symmetrically and anti-symmetrically, so that all modes are continuously and sufficiently excited. Ideally, symmetrical and anti-symmetrical excitation should be present in every 60 seconds time buffer, preferably from several pulses, i.e. excitation pulses every two to five seconds or a continuous broadband excitation. Nevertheless, the presented approach can be used to identify TAS ranges with reliable identification results.



a) Impulses time data of a 60 s time buffer

a) Resulting spectra from impulses in shown time butter

Figure 17 Control surface impulse length and resulting excitation spectrum

A control surface impulse like the ones used in this study have an impulse duration of about one second, as can be seen in Figure 17 a). This leads to an excitation spectrum shown in Figure 17 b). Most of the excitation energy from the control surfaces is in the frequency range up to 4 Hz. In this flight test, this includes only one mode. In addition, e.g. the symmetric excitation is achieved only using the elevator. Therefore, an excitation of e.g. symmetric wing modes is more difficult. However, the impulse excitation could improve the identification. Eventually, the low frequency excitation of the aircraft might influence the resulting turbulence of the aerodynamic which excites the structure. In any case, the excitation of aircraft in FVT must be further investigated, especially for the continuous identification of modal parameters.

4 CONCLUSIONS

In conclusion, this paper has introduced a system for reliable monitoring of modal parameters in slowly time-varying systems. The identification of quasi-continuous flutter curves arises from slow and continuous acceleration at constant altitudes. Through the integration of automatic modal analysis (AMA) with a Kalman filter (KF) for uncertainty reduction, the real-time modal parameter identification uncertainty is significantly reduced. The aeroelastic stability can be reliably assessed within seconds already during flight tests.

However, fast acceleration maneuvers may introduce bias despite minimal scatter in identified modal parameters. This bias can be found if both acceleration and deceleration maneuvers are performed. This method is well suited to assess a possible bias of the modal parameters of the slowly changing system identified during the flight. A small variance of the identified modal parameters alone does not necessarily mean a correct identification

Some modes show high scatter in the damping trends. These might be caused by weak modal excitation from natural turbulence or even non-stationary effects like pilot maneuvers. In this case, artificial excitation, such as pulses, can enhance the quality of the identification of certain modes if the pulses occur frequently enough and with sufficient amplitudes, both symmetrically and anti-symmetrically. The duration of such an impulse should be as short as possible to increase the maximal excitation frequency. Given the high cognitive load on pilots during flight testing, it remains uncertain whether they can perform this excitation for several minutes while accelerating on level altitudes. Additionally, an excitation of the low frequency only, results in one-sided focus on these modes that might lead to neglecting the modes in the higher frequency range. Hence, an automated support system for broadband excitation could further improve modal parameter identification, especially in the higher frequency range. An alternative way could be one or multiple fins added to the aircraft in order to create wake vortices and thus a turbulent airflow, however this leads to manipulated aerodynamics. In future research, the presented results should be compared with simulation for a better assessment and more detailed interpretation of the damping ratio trends.

The overall results of the KF-based monitoring system are promising to improve the data utilization from flight vibration tests as well as reducing the overall flight test analysis time. In addition, the autonomous and fast identification and monitoring of modal parameters can be applied for further time-varying structures.

The KF predicts the state at the next time step using a linear transition model. In future research, the transition model could be based on a non-linear aeroelastic simulation model. This could reduce further the uncertainty in flutter flight testing.

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