

Complex-Valued Data Partition for the Modal Analysis of a Fighter Jet via the Loewner Framework [†]

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Abstract

This work examines a complex-valued data partition within the improved Loewner Framework to enhance the efficiency of modal parameter identification for aerospace structures. The method is applied to the General Dynamics F-16 Ground Vibration Test dataset, assessing accuracy and computational performance against the standard real-valued formulation. The complex-valued approach reduces execution time by an order of magnitude while preserving the quality of the identified poles. The extracted modal parameters align well with established benchmark results, confirming the suitability of the proposed formulation for reliable and scalable modal analysis of aircraft structures.

Keywords: Loewner Framework; modal analysis; structural dynamics; ground vibration testing; modal parameters; fighter jet; tangential interpolation

1. Introduction

Modal analysis is a key method for determining and improving the dynamic behaviour of engineering structures. Originating in mechanical and aeronautical applications, it is now widely used in civil and space engineering. Increasing demands for lightweight, flexible, and robust structures—especially in aerospace—heighten susceptibility to vibrations, while stricter safety and reliability requirements highlight the need for accurate dynamic characterisation. Integrating dynamic parameters into the design process is therefore essential, and various tools derive them from experimental Ground Vibration Tests (GVTs). In particular, modal analysis remains essential for understanding the dynamic behaviour of lightweight, flexible engineering structures commonly used in aerospace applications, where it supports safe and reliable design by characterising vibration responses.

Several works state the importance of correctly understanding the vibrational response of structures. This approach is highlighted by National Aeronautics and Space Administration (NASA) design guides, published in the 60s [1]. A clear path to the characterisation of a system's dynamic behaviour is modal analysis, which, in [2], is defined as the process of determining the dynamic characteristics of a system by computing its natural frequencies (ω_n), damping ratios (ζ_n), and mode shapes (ϕ_n). Different ways to perform this task are proposed in the literature, such as experimental modal analysis (EMA), which can be seen as a generalisation of the aircraft GVT process. For instance, a novel approach is proposed



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in [3] for the fast identification and characterisation of nonlinearities in the experimental modal analysis of an Airbus A380.

Through the years, a plethora of modal parameter identification methods have been proposed. Recently, the Loewner Framework (LF) [4] has been extended to modal parameter extraction from mechanical systems, followed by a computationally improved version (iLF), allowing for the extraction of modal parameters from multi-input test setups [5], resulting in an extension to Multiple Input, Multiple Output (MIMO) systems. This technique is very promising for performing modal analysis efficiently and accurately due to its scalability to large systems and computational efficiency. However, the forced use of real values can potentially result in a computational bottleneck. Moreover, in [6], the Fast and Relaxed Vector Fitting (FRVF) technique is defined as an input–output system identification algorithm that can be used in single-input single-output (SISO) and single-input multiple-output (SIMO) systems. It is traditionally used in the frequency domain but has also been adapted for the time domain, though less commonly used. In [7], FRVF is applied to the same F-16 jet that will be studied in this work. Furthermore, the Eigensystem Realization Algorithm (ERA) is a modal analysis technique that can be used for MIMO data and that operates in the time domain. It is commonly used along with the Natural Excitation Technique (NExT) to identify modal parameters from ambient vibration, as proposed in [8]. In [9], ERA is combined with NExT to determine the modal characteristics of the T-34A Mentor acrobatic aircraft. Additionally, the Frequency Domain Direct Parameter Identification (FDPI) is a technique that operates in the frequency domain [10]: it first identifies system matrices and then computes the modal parameters. This technique has been applied to numerical systems and large aircraft structures in [11]. And the Least Squares Complex Exponential (LSCE) method can use frequency-domain data as input, despite operating in the time domain [11], as the impulse response function (IRF) is computed from a Frequency Response Function (FRF) by applying the inverse Fourier transform. Also, the Least Squares Complex Frequency Domain (also known commercially as PolyMAX) is an industry-standard non-iterative frequency-domain parameter estimation method that supports MIMO FRFs as input data and relies on a weighted least-squares approach [12], demonstrating highly stable pole identification capabilities. In [12], PolyMAX is compared with other methods, such as LSCE, in terms of efficiency and accuracy.

The great interest in modal identification algorithms and their frequent use across several engineering fields aims at developing and refining existing methods for increased precision and performance. For this, the contribution aims to apply an iLF variant using complex-valued sampling, rather than the standard real-valued method, to enhance the efficiency of the modal parameter extraction process.

Considering the main aim of this study, two related objectives have been identified:

1. Analyse the newly proposed complex-valued iLF implementation and determine its accuracy and computational efficiency against the real-valued counterpart;
2. Perform modal parameters extraction from the General Dynamics F-16 Fighting Falcon fighter aircraft Ground Vibration Testing (GVT) dataset from the Eindhoven University of Technology [13].

To do so, the complex-valued iLF is used to obtain the poles of the FRFs from the aircraft's real experimental datasets. Both the real and complex-sampled iLF implementations are applied to determine which one is more efficient and accurate. Results are compared to results in the literature, coming from different methods and test scenarios.

2. The Loewner Framework

In this section, the mathematical background of the iLF implementation used in this work is briefly provided. The LF is introduced here following the approach proposed in [14], since this is the formulation on which the iLF modal identification is based upon [5].

The LF is used to solve the rational interpolation problem, stated as “Given the points s_j in the complex plane and the corresponding transfer function measurement $\mathbf{H}_j$ for a system with m inputs and p outputs”:

$$(s_j; \mathbf{H}_j), \quad j = 1, \dots, N$$

With m and p being much smaller than N , the problem is to find a transfer function $\mathbf{H}(s)$ that approximates the data:

$$\mathbf{H}_j \approx \mathbf{H}(s = s_j), \quad \forall j = 1, \dots, N$$

Thus, the transfer function, evaluated for any $s = s_j$, should be close to the corresponding $\mathbf{H}_j$. This can be achieved via tangential interpolation, such that the dataset is partitioned into two disjoint subsets. Next, the rational tangential interpolants are generated using the Loewner matrix, $\mathbb{L}$.

Consider a Linear Time-Invariant (LTI) system with m inputs, p outputs, and k internal variables, described as follows:

$$\begin{aligned} \Sigma : E \frac{d}{dt} \mathbf{x}(t) &= \mathbf{A} \mathbf{x}(t) + \mathbf{B} \mathbf{u}(t) \\ \mathbf{y}(t) &= \mathbf{C} \mathbf{x}(t) + \mathbf{D} \mathbf{u}(t) \end{aligned} \quad (1)$$

The transfer function of the previously defined system $\mathbf{H}(s)$ is given by the following:

$$\mathbf{H}(s) = \mathbf{C}(s\mathbf{E} - \mathbf{A})^{-1} \mathbf{B} + \mathbf{D} \quad (2)$$

The term $\mathbf{D}$ can be set to zero because its contribution does not affect tangential interpolation in the LF. Thus, the aim of the LF is to determine the system matrices from the dataset, enabling the construction of its transfer function (realisation problem). The Loewner and shifted Loewner matrices can be constructed after partitioning the data, and the singular value decomposition of those matrices can be performed, yielding the following:

$$\text{svd}(\zeta \mathbb{L} - \mathbb{L}_S) = \mathbf{Y} \mathbf{\Sigma}_l \mathbf{X} \quad (3)$$

The system realization is then defined as follows:

$$\mathbf{E} = -\mathbf{Y}^T \mathbb{L} \mathbf{X}, \quad \mathbf{A} = -\mathbf{Y}^T \mathbb{L}_S \mathbf{X}, \quad \mathbf{B} = \mathbf{Y}^T \mathbf{V} \quad \text{and} \quad \mathbf{C} = \mathbf{W} \mathbf{X}. \quad (4)$$

Finally, the modal parameters of the system are extracted through eigenvalue analysis of the matrices $\mathbf{A}$ and $\mathbf{C}$.

Complex-Valued Partitioning in the iLF

In previous works, the improved Loewner Framework (iLF) is employed in its real-valued formulation, for which the Loewner and shifted Loewner matrices contain only real entries. Besides extending the original Loewner Framework to MIMO systems, this implementation [5] reduces the computational cost with respect to the standard formulation. The construction of a real sampled iLF requires an additional transformation that maps the complex-valued data into real arrays and adopts a parametrisation in terms of squared frequencies; this choice typically improves the quality of the interpolation, since the off-diagonal entries decay more rapidly [15]. The extra transformation, however, leads to a

higher cost than a purely complex-sampled iLF, so operating directly with complex-valued data and avoiding real-valued partitions could shorten the overall runtime, although the associated effect on accuracy has not yet been assessed. This is the approach sought in this work.

3. General Dynamics F-16 Fighting Falcon Case Study

The case study selected is the General Dynamics F-16 Fighting Falcon fighter aircraft. The available experimental data is obtained from the Eindhoven University of Technology repository and was recorded in the Siemens LMS Ground Vibration Testing Master Class, held in September 2014 at the Saffraanberg military base in Belgium [13]. The instrumented system can be seen in Figure 1.



Figure 1. Ground Vibration Testing experimental setup. (a) F-16 aircraft prepared for the test; (b) the dummy payload on the tip of the right wing (retrieved from [13]).

The dataset has been analysed by different authors in [16,17]. These serve as a benchmark for the iLF results reported later. All sources notice the presence of nonlinear effects originating from the payload-wing mounting interfaces. However, this work considers only one part of the dataset, which, due to the low amplitude of the excitation, can be considered as linear.

The output consisted of three accelerometer signals. The studied excitations are sine-sweep excitations with a linear negative rate of 0.05 Hzs^{-1} , applied by a shaker. The testing covered a range from 2 to 15 Hz, and seven different excitation levels were provided. Only the lowest level, at an input amplitude of 4.8 N, can be considered a linear dataset (and thus, used here). Both signals are band-pass filtered between 1.8 and 15 Hz and sampled at 400 Hz. A Fast Fourier Transform (FFT) is then applied to both signals to obtain their frequency-domain representations, such that the FRF is calculated with traditional elementwise division between the output and input signals' spectra.

Previous works report the presence of rigid body modes at low frequencies. Before, the first flexible mode (Mode #1) appears at 5.21 Hz. By using different excitation methods, up to 9 flexible modes are identified within the range of interest, with the one at around 7.39 Hz being the most sensitive to amplitude-related nonlinearities.

In Figure 2, the numerically obtained FRF magnitude and phase are plotted against frequency for the three channels. The peaks show the frequencies at which modes are expected to exist. These FRFs serve as the baseline for comparing numerical results obtained with the iLF, using both real- and complex-valued sampling, and are used to perform SIMO identifications on the given FRFs set.

For a given model order, the iLF generates a model (the LTI system matrices), identifies the poles, and computes a fitted FRF (from the identified LTI). The iLF (both real- and complex-valued sampling) is applied with incremental orders from 12 to 50, and the resulting poles are stored. Then, a stabilisation diagram is used to identify the stable modes. The stability criteria are set such that a stable pole must be within 1% for frequency and 3% for damping of a previous pole and that the Modal Assurance Criterion (MAC) value

is higher than 0.95. A pole is deemed stable when at least five consecutive orders' results satisfy these requirements.

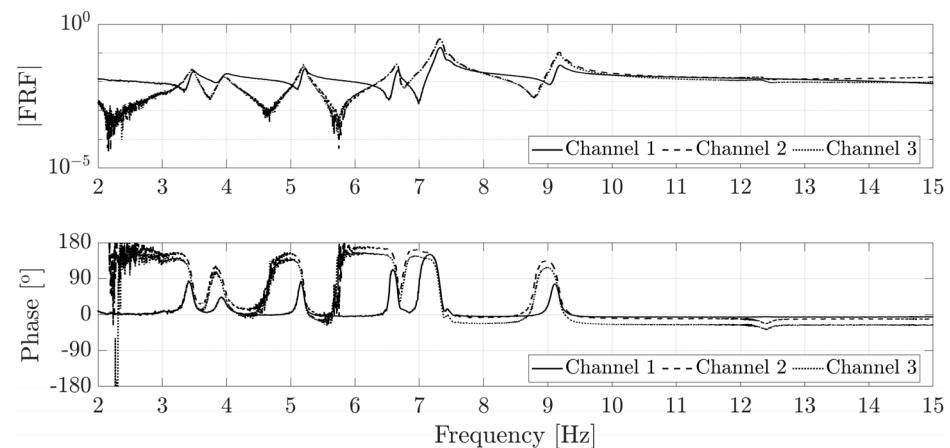


Figure 2. The numerical FRF for the three channels, between 2 and 15 Hz, is obtained as the division of the FFT between the input and output signals. The upper curve shows the absolute magnitude, and the lower one the wrapped phase.

Table 1 summarises the natural frequency results obtained with the complex-valued sampling iLF identification. The results show very good comparability in the identified modes. Only the complex-valued results are shown as they yield a perfect match with the real-valued sampling counterpart.

Table 1. Summary of the frequency of the identified modes with the iLF (Results), FRVF, PolyMAX and BLA methods.

Mode	Results (iLF)	FRVF [7]			PolyMAX Method		BLA Framework [18]
		Sweep Sine 4.8 N Excitation	Multisine 12.4 N Excitation	Multisine 12.2 N Excitation	RMS Force Amplitude of 8 N [16]	Low-Level Random Test, RMS 10 N [17]	Odd Multisine, Three Input Levels
0 (Rigid body motions)	2.89	n.a.	2.06; 2.10		2.50	n.a.	n.a.
	3.49	3.47	3.50	3.52	More than one rigid body motion before the first flexible mode is mentioned.		
	3.98	3.95	3.97				
1 (First wing bending mode)	5.21	5.20	5.20	5.17	4.82	5.16	5.20
2 (Anti-symmetric payload rotation mode)	6.67	6.65	6.62	6.94	6.18	6.61	n.a.
3 (Symmetric wing torsion mode)	7.39	7.32	7.27; 7.33	7.34	6.95	7.31	7.30
4 (Anti-symmetric wing torsion mode)	n.a.	n.a.	n.a.	n.a.	7.78	n.a.	n.a.
5 (Anti-symmetric wing torsion and vertical tail bending mode)	n.a.	n.a.	n.a.	8.56	8.85	n.a.	n.a.
6 (Anti-symmetric wing bending mode)	9.16	9.17	9.18	9.18	n.a.	9.14	n.a.
7 (Unknown)	n.a.	n.a.	n.a.	13.11	n.a.	n.a.	n.a.
8 (Unknown)	n.a.	n.a.	n.a.	14.22	n.a.	n.a.	n.a.
9 (Unknown)	n.a.	n.a.	n.a.	14.74	n.a.	n.a.	n.a.

Three rigid-body modes are detected, two aligning with those reported in [7] and a third showing no correlation with previous studies. Four flexible modes are successfully identified: 5.21 Hz (first wing bending), 6.67 Hz (anti-symmetric payload rotation), 7.39 Hz (symmetric wing torsion), and 9.16 Hz (anti-symmetric wing bending), which closely match the benchmark results in [7], although the 7.39 Hz mode appeared slightly higher, likely due to the aforementioned sensitivity to amplitude-induced nonlinearities. No modes between the 3rd and 6th modes, nor the high-frequency modes reported in other studies, were identified.

The damping ratios of the identified modes are also compared in Table 2. These values are more scattered than the identified natural frequencies. The discrepancies between damping ratios identified via iLF and the reference values vary across modes, with the largest relative deviation observed for Mode #2. In this case, the iLF estimate (0.48%) is substantially lower than the benchmark obtained under the 8 N sine-sweep condition (0.98%), leading to a relative error of 51%. Differences in this type are consistent with the well-known sensitivity of damping identification to excitation characteristics and to the local quality of the measured response, including signal-to-noise ratio and potential modal interaction. Importantly, despite the large *relative* error, the *absolute* discrepancy remains small in magnitude: for Mode #2, the difference is only $|0.48 - 0.98| \% = 0.5\%$. Since all reported damping ratios lie below approximately 1.5%, even sizeable relative deviations correspond to limited absolute changes and should therefore be interpreted with caution when assessing practical impact.

Table 2. Summary of the damping ratio of the identified modes with the iLF (Results) and the PolyMAX method (RMS Force Amplitude of 8 N and Low-Level Random Test RMS 10 N cases).

Mode		Damping Ratio [%]		
		RMS Force Amplitude of 8 N [16]		Low-Level Random Test RMS 10 N [17]
(Rigid body motions)	0	1.02	n.a.	n.a.
		1.43	n.a.	n.a.
		0.72	n.a.	n.a.
(Flexible modes)	1	0.95	0.74	0.84
	2	0.48	0.98	0.77
	3	0.48	0.72	0.43
	4	n.a.	1.25	n.a.
	5	n.a.	1.37	n.a.
	6	0.70	n.a.	0.74
	7	n.a.	n.a.	n.a.
	8	n.a.	n.a.	n.a.
	9	9	n.a.	n.a.

Moreover, the computational cost of the real- and complex-valued sampled iLF is analysed. The complex-valued sampled iLF offers a faster modal identification by decreasing the identification time to a sixth (an order of magnitude) of the real-valued sampling iLF. Nevertheless, the accuracy remains unchanged, since no significant changes have been seen between the results obtained by real-valued sampled iLF and by the complex-valued sampled counterpart.

4. Conclusions

The accurate characterisation of modal parameters is vital to designing more flexible and lighter structures that allow us to reduce fuel consumption and costs within the aerospace industry. In this study, the improved Loewner Framework is used due to its scalability to large systems, such as aircraft, and lower computational costs.

More specifically, this article serves to assess the behaviour of real- and complex-valued sampling of the iLF on the General Dynamics aircraft.

The main outcomes are as follows:

- Both implementations show similar accuracy; the complex-valued sampled iLF is more efficient, requiring about one-sixth the real-valued iLF time.
- The natural frequencies identified from the F-16 data are aligned with the literature values.

Thus, this study shows that the extra steps added to force real-valued sampling in the LF are an unnecessary computational burden that does not influence the quality of the identification.

Future studies will investigate datasets on other case studies with more channels for a better understanding of the efficiency of the complex-valued iLF. A comprehensive study on a numerical case, involving different cases of noise levels and inputs, will be also required.

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DURC. Authors advocate for responsible deployment, ethical considerations, regulatory compliance, and transparent reporting to mitigate misuse risks and foster beneficial outcomes.

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