Data-driven state-space identification of nonlinear feedback systems: application to an F-16 aircraft structure

Merijn Floren[1,2,*], Jan Swevers[1,2], and Jean-Philippe Noël[1]

[1]MECO Research Team, Department of Mechanical Engineering, KU Leuven, Leuven, Belgium
[2]Flanders Make@KU Leuven, Leuven, Belgium
[*]Corresponding author. Email: merijn.floren@kuleuven.be

1 Background

This work aims to learn the complex and nonlinear dynamics of vibrating structures from input-output measurements, by proposing a computationally efficient identification method that is robust to the many poor local minima seen during nonlinear optimization. The effectiveness of the proposed method is evaluated on a multi-output benchmark dataset of an F-16 fighter jet [1], where a shaker was placed underneath the right wing to excite the structure (see Fig. 1).

2 Problem statement

The complex F-16 dynamics can be adequately captured by means of so-called nonlinear feedback models, represented in state-space form as:

$$\begin{aligned} x_{k+1} &= Ax_k + B_u u_k + B_w w_k, \\ y_k &= Cx_k + D_u u_k + D_w w_k, \end{aligned} \tag{1a}$$

where A, B_u, C and D_u are the linear state, input, output, and direct feedthrough matrices, respectively. Moreover, x_k is the latent state vector and u_k and y_k are the measured inputs and outputs, respectively, at discrete time instant k. Coefficient matrices B_w and D_w determine how the feedback input enters the system. The nonlinear feedback itself is modeled as a neural network wit L hidden layers:

$$\begin{aligned} w_k &= W_L \sigma(W_{L-1} \cdots \sigma(W_0 z_k + b_0) + b_{L-1}) + b_L, \\ z_k &= C_z x_k + D_z u_k, \end{aligned} \tag{1b}$$

where $\{W_i, b_i\}_{i=0}^{L}$ are the weights and biases, and $\sigma(.)$ the nonlinear activation function. Assuming localized nonlinearities, the neural net input is z_k is typically a low-dimension subspace of the states and input, determined by the linear coefficient matrices C_z and D_z. To obtain the model parameters θ, we minimize:

$$J(\theta) = \sum_{k=0}^{N} ||y_k - \hat{y}_k(\theta)||_2^2, \tag{2}$$

where $\hat{y}_k(\theta)$ is the modeled output. Minimizing (2) is a high-dimensional and non-convex optimization problem that is prone to poor local minima. The aim of this work is to present a sequential identification approach that is computationally attractive and mitigates the risk of falling into poor local minima.

Figure 1: F-16 ground vibration test.

3 Method

The sequential identification procedure is initialized by the best linear approximation, which yields estimates for A, B_u, C and D_u. As a next step, we set up a convex optimization problem that infers the latent trajectories of the x and w in the time domain (similar to [2]), while simultaneously optimizing B_w and D_w. By doing so, we allow for the supervised learning of (1b), which in turn provides a good initial guess for the final optimization step that directly minimizes (2).

For higher-dimensional systems like the F-16, however, the supervised approach introduces a common adverse phenomenon in machine learning: the covariate shift, which occurs when the distribution of the training data does not match with the distribution during deployment. The reason for this is that during deployment, a neural net output at time k influences its own input at time $k+1$, which was not accounted for during training and can hence result in diverging simulations. We address this issue by actively preventing poor deployment performance during the training of (1b), without introducing a significant computational burden.

References

[1] J.-P. Noël and M. Schoukens, "F-16 aircraft benchmark based on ground vibration test data," in *2017 Workshop on Nonlinear System Identification Benchmarks*, pp. 19–23, 2017.

[2] M. Floren and J.-P. Noël, "Nonlinear restoring force modelling using Gaussian processes and model predictive control," 2022-04-07.