TFE projects in the frame of the INFLUENTIA-UC3M-CM project

Marco Raiola (Department of Aerospace Engineering)
Eduardo García Portugués (Department of Statistics)

Addressing noise reduction stands as a paramount challenge in the design of future aircraft: 1.3 million of European citizens were exposed to more than 50 daily aircraft noise events above 70 dB during 2019 [EASA, 2022], increasing the risk of health issues. Aircraft noise abatement, in particular for turbofan engine noise, is required to address this issue. This project aims at deepening the knowledge in subsonic jet noise, i.e. the noise produced by the flow expelled by the engine, which represents one of the predominant noise sources.

Subsonic jet noise is the result of the complex interplay between the more or less coherent flow structures covering the large wealth of turbulence scales which characterize the flow [Jordan and Colonius, 2013]. The nonlinear dynamics resulting from this interplay is ultimately responsible for the noise emission through a non-trivial relation. The lower number of scales involved in the noise which is propagated away from the jet suggests that only a handful flow structures are relevant for noise: suppressing/altering them could result in an abatement of noise levels without impacting effectively on the propulsive performances of the engine. However, the complex relation existing between flow structures and noise emission makes it difficult to identify which should be the objective of flow control for noise reduction. The objective of this research is to study this relation and use data-driven AI-based methods to identify the flow structures associated to noise (and conversely the patterns in sound pressure associated with flow states). Flow states/structures will be extracted from velocity fields either measured in jet experiments or resulting from CFD simulations. Sound patterns/states will be extracted from the acoustic pressure either measured in given location by microphone arrays or extracted from CFD data.

The following TFE (TFG/TFM) projects are available in the frame of this research project:

1. **Data-driven determination of representative patterns in point pressure measurements in a jet flow**

This TFE project aims at producing an algorithm that assigns a state label to a *tuple* of sound signals from pressure probes surrounding a turbulent jet. The data used to this scope are extracted flow Large Eddy Simulation of a turbulent jet flow. To achieve the goal, the student will exploit dimension-reduction and clustering techniques (i.e., unsupervised learning) to partition the space of observed signals into representative domains. Dimension-reduction tools available from the literature on Functional Data Analysis (FDA) will be explored. Possible candidates will include Functional Principal Components (FPCs) [Ramsay and Silverman, 2005], t-Stochastic Neighbor Embedding (t-SNE) [van der Maaten, 2008] or Multi-Dimensional Scaling (MDS) [Borg and Gronen, 2005] on different metrics of the signals. Additionally, dimension-reduction techniques designed for time series will be explored, such as dynamic principal components [see Peña and Tsai, 2021]. Some examples of the foreseen learned sound states are “no source in position x”, “pressure wavepacket with wavelength λ and peak at position x”, “quadrupole in position x”, “background noise”, etc. These states can be interpreted as alternatives to the beamforming maps for the microphone array, each associated to a specific kind of sound source in the turbulent jet.

2. Identification of velocity/pressure field patterns in jet flows

This TFE project will producing an algorithm that assigns a state label to temporal snapshots of 2D vector fields of the jet flow obtained in experiments or simulations. The choice of using 2D flow fields in this first stage is justified by the circular symmetry of the turbulent jet problem, where the azimuthal direction is homogeneous and thus effectively described via a Fourier decomposition. The use of 2D fields will reduce the amount of data recorded and fed to the algorithms. Extension to 3D flow field snapshots (using Tomographic PIV) will be considered for a limited dataset. Upon completion, the TFE will deliver an algorithm to cluster the space of the vector fields into different domains corresponding to separate flow patterns. To achieve this goal, we will consider the Spectral Proper Orthogonal Decomposition (SPOD) [Schmidt and Colonius, 2020], Hilbert POD [Raiola and Kriegseis, 2022], and nonlinear approaches exploiting the geometry of the vector field components, potentially creating adaptations of t-Stochastic Neighbor Embedding (t-SNE) [van der Maaten, 2008], or Multi-Dimensional Scaling (MDS) [Borg and Gronen, 2005]. Some examples of the foreseen learned fluid states are "streamwise vortices passing by x position", "ring vortices passing by x position", "mild fine-scale turbulence at position x", etc. The states of the flow can be interpreted as turbulent flow structures present in the flow.

References

- [Borg and Gronen, 2005] Borg, I. and Groenen, P. J. F. (2005). *Modern Multidimensional scaling: Theory and Applications*. Springer. doi:10.1007/0-387-28981-X.
- [EASA, 2022] European Aviation Environmental Report 2022, EASA. Available at URL.
- [Jordan and Colonius, 2013] Jordan, P. and Colonius, T. (2013). Wave packets and turbulent jet noise. *Annual Review of Fluid Mechanics*, 45:173–195. doi:10.1146/annurev-fluid-011212-140756.
- [Peña and Tsai, 2021] Peña, D. and Tsai, R. (2021). *Statistical Learning for Big Dependent Data*. Wiley. Available at URL.
- [Raiola and Kriegseis, 2022] Raiola, M. and Kriegseis, J. (2022). Extracting advecting flow structures through Hilbert Proper Orthogonal Decomposition. 1st Spanish Fluid Mechanics Conference, 19–22 June 2022, Cadiz.
- [Ramsay and Silverman, 2005] Ramsay, J. O. and Silverman, B.W. (2005). *Functional Data Analysis*. Springer, New York. doi:10.1007/b98888.
- [van der Maaten, 2008] Van der Maaten, L. and Hinton, G. (2008). Visualizing data using t-SNE. *Journal of Machine Learning Research*, *9*(11). Available at URL.