MODE-Lab
Models of dynamics for engineering

DIMEC
INGENIERÍA MECÁNICA
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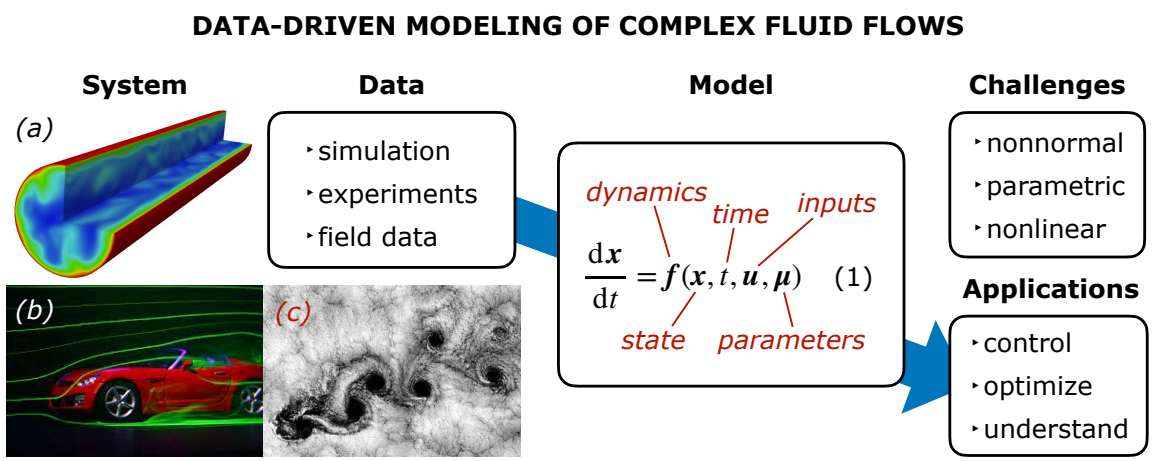
Open Positions

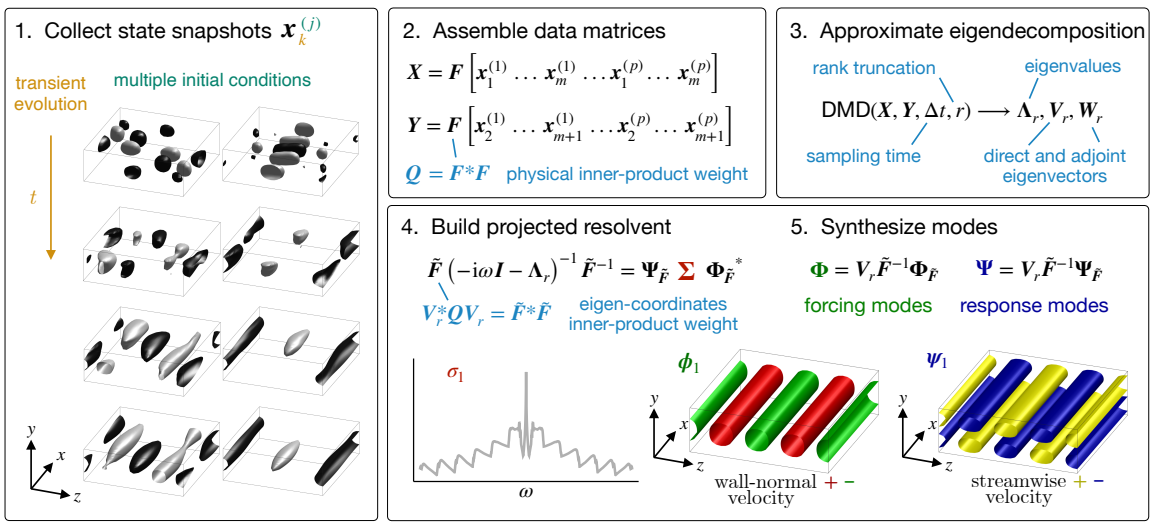
We are looking for highly motivated PhD students to work at the intersection between machine learning algorithms, dynamical systems theory, and fluid mechanics applications. At present, **3 positions are available** with partial funding from ANID through Fondecyt project 11220465. Candidates are expected to have a strong mathematical background, as well as demonstrated experience in scientific computing. If interested, please send your CV and grade transcripts to B. Herrmann at benjaminh@uchile.cl. For more information about our research group visit `mode-lab.ai`.



In the decades to follow, advances in our ability to understand and manipulate complex fluid flows has the potential to transform industries where aerodynamic forces and mixing play a significant role, such as transportation, aeronautic, energy, and biomedical. However, flows relevant to modern engineering and scientific applications are typically high-dimensional dynamical systems that are particularly challenging to model because of nonnormality, parametric dependence, and nonlinearity. Fortunately, these systems often exhibit dynamics dominated by a few spatio-temporal patterns, known as coherent structures, that can be characterized using techniques from statistics, machine learning, and convex optimization. The main goal of the research project is to advance data-driven modeling as a critical enabler of control, optimization, and understanding of the underlying physics in complex fluid flows that arise in aerodynamics and thermal-fluids engineering applications. Models that capture the evolution of dominant coherent structures promise to have profound implications as eventual enablers of drag reduction of cars, trucks, trains and ships, lift increase of airplanes and wind turbines, mixing enhancement in chemical reactors and industrial processes, and improved thermal management of buildings, batteries and solar power technologies.

Position 1

For nonnormal systems, such as shear flows, resolvent analysis offers a low-rank representation of the input–output dynamics under external forcing. This allows the design of efficient open-loop control strategies in terms of expended input energy, by exciting the flow patterns that are most amplified by the linear dynamics of the system. However, application of this method to complex flows is mathematically and computationally laborious, as it requires intervening an existing numerical solver to obtain the linearized Navier–Stokes operator. Data-driven resolvent analysis is a recently developed method, summarized in the figure below, that avoids this challenge by being purely data-driven, thus it can be applied as a postprocessing algorithm to produce the same low-rank representation. The research seeks to leverage this technique to design controllers for systems in aerodynamics and thermal fluids engineering.

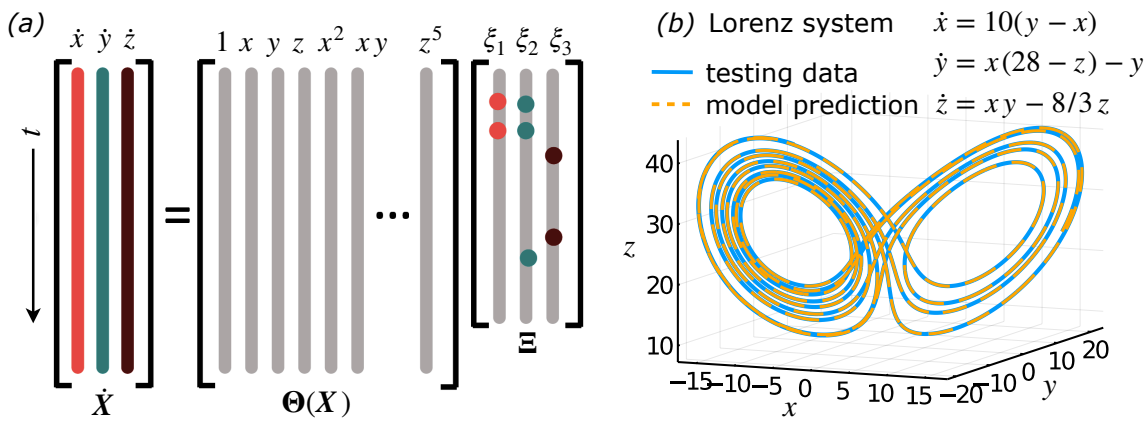


Relevant references

- B. J. McKeon and A. S. Sharma, "A critical-layer framework for turbulent pipe flow," *Journal of Fluid Mechanics*, vol. 658, p. 336–382, 2010
- M. R. Jovanović, "From bypass transition to flow control and data-driven turbulence modeling: An input–output viewpoint," *Annual Review of Fluid Mechanics*, vol. 53, pp. 311–345, 2021
- B. Herrmann, W. R. Calderón-Muñoz, G. Diaz, and R. Soto, "Heat transfer enhancement strategies in a swirl flow minichannel heat sink based on hydrodynamic receptivity," *Int. J. Heat Mass Transf.*, vol. 127, pp. 245–256, dec 2018
- C.-A. Yeh and K. Taira, "Resolvent-analysis-based design of airfoil separation control," *Journal of Fluid Mechanics*, vol. 867, pp. 572–610, 2019
- B. Herrmann, P. J. Baddoo, R. Semaan, S. L. Brunton, and B. J. McKeon, "Data-driven resolvent analysis," *Journal of Fluid Mechanics*, vol. 918, p. A10, 2021

Position 2

Even though the interest in data-driven modeling for engineering and applied science has exploded, many approaches in machine learning, such as neural networks, do not yield mechanistic models that can be interpreted, understood and communicated, which is essential for engineering decisions regarding physical systems. The *Sparse Identification of Nonlinear Dynamics* (SINDy) is a method that produces interpretable models of dynamical systems from data using sparse regression, as shown in the figure below. Moreover, the method is able incorporate parametric dependence. However, the method is known to suffer from poor scalability to high-dimensional state spaces. The research seeks to combine dimensionality reduction with SINDy on a low-dimensional embedding to obtain interpretable models of high-dimensional, parametric dynamical systems. These models will allow exploration of the parametric-dependence of complex engineering systems for tasks such as design optimization, which would be otherwise computationally intractable.

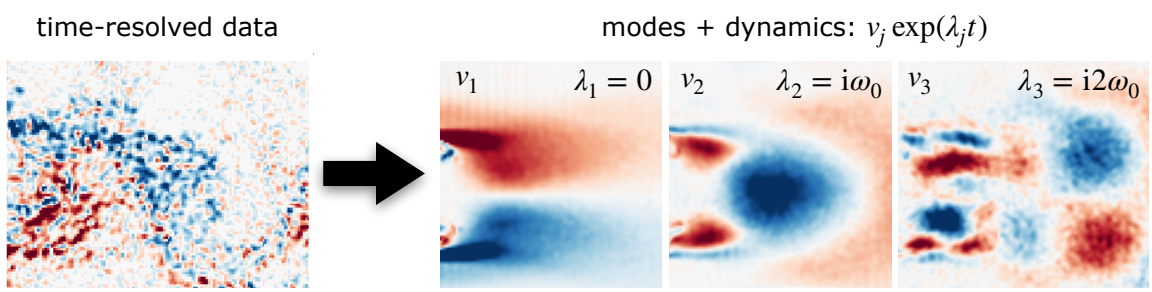


Relevant references

- J. Bongard and H. Lipson, "Automated reverse engineering of nonlinear dynamical systems," *Proceedings of the National Academy of Sciences*, vol. 104, no. 24, pp. 9943–9948, 2007
- M. Schmidt and H. Lipson, "Distilling free-form natural laws from experimental data," *science*, vol. 324, no. 5923, pp. 81–85, 2009
- S. L. Brunton, J. L. Proctor, and J. N. Kutz, "Discovering governing equations from data by sparse identification of nonlinear dynamical systems," *Proceedings of the National Academy of Sciences*, vol. 113, no. 15, pp. 3932–3937, 2016
- J.-C. Loiseau and S. L. Brunton, "Constrained sparse galerkin regression," *Journal of Fluid Mechanics*, vol. 838, pp. 42–67, 2018

Position 3

Nonlinearity is the fundamental mechanism for energy transfer in fluid mechanics, leading to frequency cross-talk and multi-scale behavior, and is thus at the heart of our limited understanding of complex fluid flows and turbulence. The Dynamic Mode Decomposition (DMD) has been consolidated as a basic tool for data-driven analysis of fluid flows, allowing simultaneous identification of coherent structures and their dynamics from time-resolved measurements, as shown in the figure below. However, with a linear regression at its core, DMD is unable to produce accurate models from recordings of dynamics that are inherently nonlinear, such as the response to large perturbations and the evolution on chaotic attractors. Other approaches, such as operator inference, attempt to simultaneously fit the linear and nonlinear contributions to the dynamics in a dataset by performing a regression onto a physically motivated model structure. However, although the resulting nonlinear models can produce respectable predictions, their linearization does not necessarily agree with the linearization of the original system. This research seeks to develop new data-driven modeling techniques that accurately capture the linear and nonlinear contributions to the dynamics.



Relevant references

- P. J. Schmid, "Dynamic mode decomposition of numerical and experimental data," *Journal of Fluid Mechanics*, vol. 656, pp. 5–28, 2010
- B. Peherstorfer and K. Willcox, "Data-driven operator inference for nonintrusive projection-based model reduction," *Computer Methods in Applied Mechanics and Engineering*, vol. 306, pp. 196–215, 2016
- B. J. McKeon, "The engine behind (wall) turbulence: perspectives on scale interactions," *Journal of Fluid Mechanics*, vol. 817, p. P1, 2017
- B. Herrmann, P. Oswald, R. Semaan, and S. L. Brunton, "Modeling synchronization in forced turbulent oscillator flows," *Communications Physics*, vol. 3, no. 1, pp. 1–9, 2020
- P. J. Baddoo, B. Herrmann, B. J. McKeon, and S. L. Brunton, "Kernel learning for robust dynamic mode decomposition: linear and nonlinear disambiguation optimization (lando)," *Proceedings of the Royal Society A*, vol. in press, 2021