Contrats doctoraux en Intelligence Artificielle

Programme AHEAD
Artificial Intelligence for Health, Physics, Transportation and Defense

Office national d'études et de recherches aérospatiales

Simulation and control of bistable flows with AI

Research problem

Many applications in aerodynamics exhibit pitchfork bifurcations that may be detrimental to the object due to the appearance of asymmetric bistable flow states. For example, in the truck building industry, a dissymmetric wake induces increased drag [2]. On a fighter aircraft at high angles of attack, a dissymmetric vortex state at the nose may trigger a yawing moment that can destabilize the aircraft [3]. The flow on a helicopter carrier deck exhibits dissymmetric vortical states that may pose security issues at landing / take-off [4]. It is therefore of high interest to develop advanced tools that estimate the symmetry of the flow from sparse wall measurements and that trigger a symmetric state by controlling the large-scale turbulent asymmetric flow structures. A simple academic configuration which reproduces the main characteristics of the above mentioned applications is a diffuser flow subject to upstream noise (see figure below). This flow undergoes erratic low-frequency switches from top to bottom solutions. The objective is to maintain the flow in the symmetric state with a wall-sensor and an actuator.

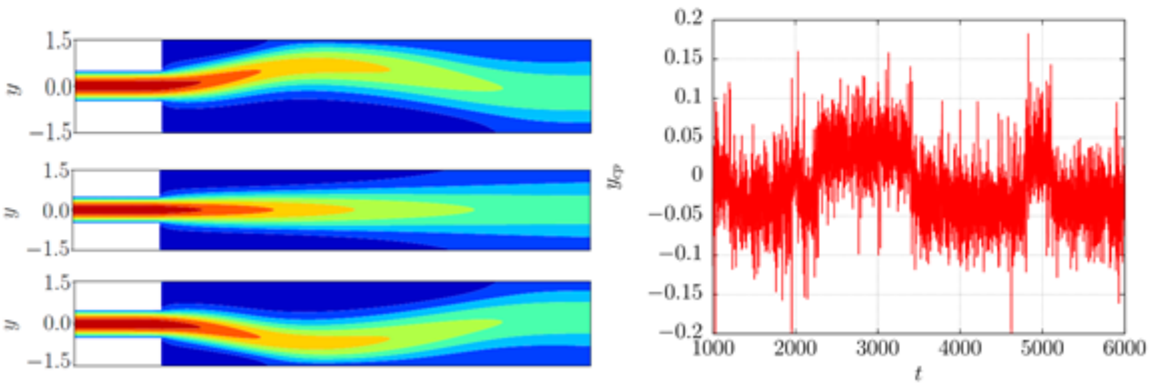

Figure 1. (Left): top, symmetric and bottom exact solutions existing for diffuser flow. The symmetric solution is unstable and in the absence of noise, the flow converges either to the top or bottom solutions. (Right): in the presence of upstream noise, the flow is erratically switching between the top and bottom solutions. The higher the noise, the more often the flow switches.

The objective of the thesis is to develop machine learning tools to model, reduce and control such flow configurations. The dynamics is strongly nonlinear due to the large amplitude fluctuations, which rules out linear modeling and control approaches. Data-driven machine-learning strategies are good candidates to tackle such problems, in particular Reinforcement Learning (RL) techniques [5]. The literature shows that RL may provide impressive performances to control low-dimensional dynamical systems (e.g. in the field of robotics, see for instance [6]). RL strategies have also been successfully applied to simple fluid's problems [7,8].

RL algorithms rely on the loop shown in figure 2: an agent has access to some observations of a given environment that it uses to choose an action. It is trained by collecting a user-defined reward based on the effect of its actions on the environment. To find efficient control laws, model-free RL algorithms have to try different action policies a large number of times, which makes such approaches data-hungry. Unfortunately, in fluid mechanics, the cost to converge an efficient control policy typically corresponds to running a few hundreds simulations or experiments [8], which is too high for practical configurations. It mainly comes from the need to learn from scratch the physical dynamics of the controlled flow.

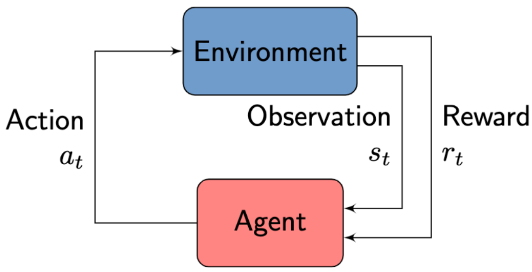

Figure 2. The Reinforcement Learning training loop.

The main challenge of the PhD will be to pour some physical knowledge within the algorithm to drastically reduce this cost. Even though a flow is a high-dimensional complex system, in many cases (in particular for the bistable systems mentioned earlier), its dynamics may be well estimated using low-order models. The PhD will therefore explore different strategies to derive such a model (based on a combination of Machine Learning and mathematical knowledge of the flow dynamics) and to include it within the RL framework. For instance, an approximated model may be used to guide the exploration of an RL algorithm to increase its sample-efficiency, while being corrected on-the-fly during the policy learning. Recent works in robotics such as that of [9] propose such strategies combining model-free and model based approaches, which may be a good starting point to develop new algorithms for flow control.

Work plan

The PhD will proceed in successive steps:

1/ *Reduced-order modeling (ROM) and model correction*.

We first consider approximate models that drastically reduce the solution cost, for example the Navier-Stokes equations projected on a very coarse grid or on a reduced POD (Proper Orthogonal Decomposition) basis. One possible strategy to accelerate computations is to reduce the number of degrees of freedom using ROM, such as dynamic mode decomposition (DMD) initially developed to analyze turbulent flows [13]. It permits the identification of a reduced dynamical system using the data from simulations or experiments. The candidate will explore different simplified models: explicit models (such as Stokes, Oseen equations [1], others), full model solved on a coarse grid, POD or DMD model. The model will be chosen so as to be compatible with the RL approach described below and with a sparse measurement constraint.

The aim of this part of the project is also to explore how one can use simplified models and complete them with a machine or deep learning process in order to correctly represent the physical phenomena for a reasonable computational cost.

We correct this model with measurements by training a neural net. The model is also required to well reproduce specific wall measurements that are able to detect the erratic switches. In this framework, we will focus on recent approaches that introduce physical properties into the learning procedure [14]. The idea is to couple these techniques to reduced order models within a computing platform in order to simulate flow control methods.

We will study the possibility to use machine learning and deep learning models to augment simplified physical models, as recently done in [10]. The main question to adapt this idea to the Navier-Stokes equation is to define how machine learning can help to speed up the simulation while maintaining the accuracy of a simulation run on a fine-grained grid.

2/ Correct the above model and control it simultaneously within a reinforcement learning scheme.

This step therefore goes further than pure data-driven reinforcement approaches by considering governing equations derived from first principles of physics.

- Having a cheaper simulation model from 1) to scale the RL setting to more complex situations. Here the idea is to have a (partial) physical model in the Model Based Reinforcement Learning (MBRL), and to use it to drive the forecast of future states. From 1), having the possibility to perform accurate forecasts with much lighted computation demand opens the way to perform many more forecasts and better explore the environment.
- Including the (corrected) physical model for guiding exploration (uncertainty, MI). The ML/MB forecast model can be used to extract relevant predictive uncertainty to better explore the environment in unknown situations. The reliable quantification of uncertainty in deep learning is not straightforward, and we will explore efficient approaches for epistemic [11] or aleatory uncertainties [12].
- Updating the (corrected) physical model from the learned policy?

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Required skills

Profile: The applicant should have a Master's or engineering degree in applied mathematics, mechanical engineering, scientific computing, computer science, artificial intelligence or equivalent. Knowledge of and experience in Python programming is a plus, and experience in deep learning frameworks (Tensorflow, Pytorch) is a must. The ideal candidate has a good knowledge of either artificial intelligence or numerical methods for PDEs (fluids).

Place and conditions: The PhD will take place both at CNAM (Paris) and Onera (Meudon). Start: between september and november 2022. Salary: ≈1900 €/month (net).

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