Thesis subject 2021

Laboratory : Institut Jean le Rond d’Alembert
University: Sorbonne Université

Title of the thesis: Optimal control in shear flows using Reinforcement Learning

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Thesis’s summary (abstract):

In the last years, flow control attracted research interest for the potential impact that this technology can have on the reduction of pollutant emissions or the mitigation of acoustic noise in the transport sector. The focus of this phd proposal is on Reinforcement Learning (RL) and its viability as a strategy for the control of fluids in realistic conditions. RL algorithms do not require any knowledge of the system: by solely observing the system and the way it reacts to prescribed actions, these algorithms are capable to discover an optimal control policy. The main goal of the project is to provide major breakthroughs in flow control by revisiting RL, by integrating in this framework efficient techniques of learning/estimation, physics constraints and tools from control theory. Numerical simulations of increasing complexity, starting from the model governed by the Kuramoto-Sivashinsky (KS) equations for the verification and test of the algorithms, towards fluid mechanics cases such as the transitional boundary layer flow at moderate Reynolds numbers.
Context – Environmental needs are invigorating research interest in many engineering fields. A compelling example is provided by carbon dioxide emissions, widely considered one of the main causes of the global warming. This urgency extends to numerous applications including aeronautics, where it is recognized that the optimization of aerodynamic flows may have a deep impact on the reduction of pollutant emissions, mitigation of acoustic noise or control of highly complex conditions such as separation. We believe that Reinforcement Learning (RL) tools might provide solutions to some of these optimization problems in fluids. In particular, “Reinforcement Learning studies how to use past data to enhance the future manipulation of a dynamical system” [Rec19]. This definition applies equivalently in standard control theory, where the aim is to optimize the performance of a system based on the measurements and prior models; indeed, the two disciplines evolved in parallel, leading to the co-development of different approaches to similar problems. The common roots can be found in dynamic programming (DP), a nonlinear optimization protocol based on the Bellman equation [Bel58]. The solution of the Bellman equation is the nonlinear, optimal policy, and – in most cases – it results to be computationally impractical when direct, model-based methods are applied. On the other hand, iterative methods can be use with and without a physical model at hand: the model-free algorithms are encompassed within RL, are fully data-driven and solely rely on limited measurements. The absence of a model allows to circumvent some drawbacks of model-based control; for instance, approximations based on reduced-order models of the physical system for meeting real-time constraints can critically lose accuracy when control is applied, resulting in poor performance and lack of robustness. In RL, exploration replaces modeling, and makes use of past data for identifying the interaction of the system with the environment and the control policy. In the limit of full knowledge of the action-state space, the resulting policy is optimal. Note that the combination of RL and deep learning led to the development of the Deep Reinforcement Learning (DRL) framework [Goo16].

State of the art – The DP framework provides the theoretical ground of the RL algorithms and can be used for framing optimal control, model predictive control and adaptive filters [Lew12]. Many of these techniques have been widely used in fluid mechanics, due for their connection with adjoint methods and optimality properties within the linear/linearized limit [Kim07, Sch16]. From the physical viewpoint, the control mechanisms range from quenching the instabilities responsible for the transition to turbulence at relatively low Reynolds numbers [Sch16], to the modification of the mean-flow or of the large scale structures for turbulent cases [Kuh18]. Many of these applications are proof-of-concept: for instance, delaying the transition to turbulence by suppressing the growth of initial disturbances has been generally tested within the limit of infinitesimal amplitudes or in highly controlled wind-tunnel tests [Sem13, Fab14]. Higher amplitudes are characterized by nonlinearities limiting the application of simpler reduced-order models, although improvements can be achieved by using adaptive filters [Fab14] or robust control [Bew00]. On the other hand, RL has been considered in applications like optimal swimming [Ver18], point-to-point navigation [Bif19], and flow control [Gue16, Rab19, Fan20]. In [Buc19], our team demonstrated that an RL algorithm can control the highly nonlinear dynamics of the Kuramoto-Sivashinsky equation, without prior knowledge of the system and using partial observability. The work was among the first demonstrations of control of a chaotic dynamical systems by RL.
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Objectives and expected results – The main goal of the project is deepening the application of RL as a tool for flow control, while taking into consideration the challenges which have limited the success of standard control tools. In short, the phd thesis aims at

1) Comparing standard techniques of control with Reinforcement Learning, within simplified cases
2) Improving the exploration step, for reducing the amount of required data / local measurements
3) Testing the developed tools on a transitional shear flows at moderate Reynolds.

To achieve these goals, we will start from reconsidering the RL algorithms from a theoretical viewpoint. The seminal works on RL in flow control clearly showed the versatility of these algorithms in identifying optimal or suboptimal control laws in nonlinear regimes: this represents the biggest advantage with respect of standard, model-based control. However, in most cases, these performance were obtained by introducing large sets of sensors: a realistic application of RL would require a thorough analysis of the observability/sparsity of the measurements, possibly in presence of noise. Also, a detailed analysis of the robustness of these methods has been so far elusive; a successful protocol based on RL would require the assessment of the performance with respect of the uncertainties of the system, such as the evolution of the environment parameters, or the impact that the presence of input-output time-delays has on the performance of the controllers. In this project we aim at tackling some of these issues by revisiting RL, integrating in this framework efficient techniques of learning/estimation, physics constraints and tools from control theory. Low-dimensional nonlinear models will be used for testing the algorithms, namely the Ginzburg-Landau (GL) and/or the Kuramoto-Sivashinsky (KS) equations, that preserve challenging features that characterize input-output systems arising from the Navier-Stokes equations, such as chaotic behavior for given critical parameters and time-delays. As final testbed, we will consider transitional flows at low-moderate Reynolds numbers. In this regime, in presence of finite amplitude, the limitations of linear modeling have been classically addressed with adaptive or linear robust controller: we will test the classical approach against RL, in combination with localized actuation and limited sensor measurements for reproducing realistic conditions.

References


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