Reinforcement learning for control of dynamical systems

Machine learning strategies are nowadays ubiquitous in most scientific disciplines as an alternative or as a complement of more traditional applications relying on modelling, numerical simulations or experiments. **Deep reinforcement learning** (DRL) algorithms have been recently considered for the control of instabilities in fluid dynamics and complex systems. DRL encompasses a large variety of algorithms and strategies, all of which characterized by being **fully data-driven**: these tools do not require any a-priori knowledge of the equations governing the system to be controlled and solely rely on the local measurements of the flow. The **agent/controller** is capable of learning a **policy** by directly **interacting/exploring with the environment** (see Fig. 1a). These features make DRL particularly relevant for real-life applications.

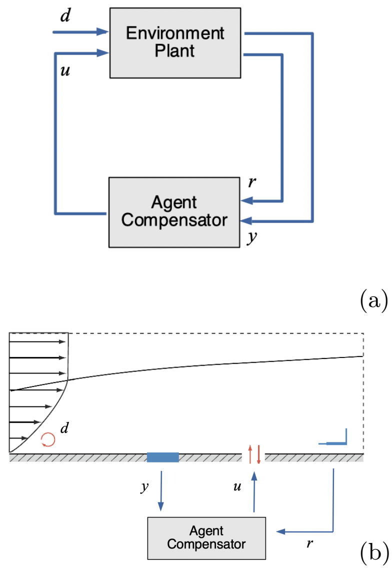

Figure 1: Control scheme in (a) is valid for feedback closed loop control and reinforcement learning controllers: $d(t)$ is the disturbance acting on the system, $u(t)$ the control signal, $r(t)$ the reward, $y(t)$ the estimation signal. The sketch in (b) depicts control setup of wall shear layers

Reinforcement learning is firmly grounded into nonlinear optimal control theory, although it relies on numerous approximations introduced for making it feasible, in particular for regularizing the learning process based on **neural networks** and dealing with the **exploration–exploitation trade-off**. As such, the possibility of controlling dynamical systems such as the ones found in fluid dynamics is rather intriguing; despite a growing literature being available, there are several aspects to be considered for a successful application of DRL, ranging from observability problems (within the linear limit or not), multi-agent interaction, efficient learning strategies. Within the internship, one of these subjects will be tackled, according to the background of the candidate. We will consider mainly **boundary layer flows** (see Fig. 1b) or 1D models such as the **Ginzburg-Landau equation**. The project can be adapted also towards different applications such as navigation problems in turbulent flows.

The internship will be carried out between LISN (`https://www.lisn.upsaclay.fr/`) and ∂'Alembert-Sorbonne Université (`http://www.dalembert.upmc.fr/ijlrda/`). PhD positions at LISN are envisageable starting in September/October 2024.

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