Soutenance de thèse – Romain PARIS

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« Potential and challenges of reinforcement learning for flow control»

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Devant le jury composé de :

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Résumé :

This thesis evaluates the potential of novel reinforcement learning methods applied to flow control. While, for fluid mechanics, state-of-the-art control generally relies on strong linear assumptions that often limit the reach of control laws, reinforcement learning associated with deep learning methods propose to break free from these constraints in order to derive effective, energy efficient and robust control policies.
Still, numerous challenges, coming from the specificity of flow control, are yet to be overcome in order to enable the development of such methods in experimental and industrial contexts. Contrary to the traditional test-bench environments on which state-of-the-art reinforcement learning methods are evaluated, flow control involves a large dimensionality, a generally non-linear behavior and a partial observability, whether it is in a numerical or experimental context.
This study thus aims at identifying these issues and the consequences they yield on training control policies for flow control and to propose novel algorithms built on-top of training methods that help circumvent these problems. Most of these come down to sample cost, i.e. the computational cost of acquiring training data, which is a major decision factor concerning the feasibility and the success of these control methods. Efforts concerning the reduction of both sensor and actuation layouts as well as the improvement of the state exploration efficiency give rise to proposed modifications of existing training algorithms or entirely novel methods aiming at accelerating training.

Mots clés : Flow Control, Reinforcement Learning, Computational Fluid Dynamics