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Titre : Data driven turbulence modeling for turbulent boundary layer control

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Descriptif :

Subject

This thesis aims to apply the concepts and methods of machine learning to the modeling of turbulent boundary layer flows. The implementation of efficient data driven methods in the framework of turbulent flows faces a number of challenges, particularly when we addressed the issues associated to the boundary layer modeling and control. Among those we can notably identify on three main tasks

1. Incorporate into the machine learning process the symmetry and invariance properties characteristic of the turbulent flows.
2. Extend the applicability and efficiency of data-driven turbulence models to complex flows using huge data banks generated by experiments or numerical simulations in the laboratory and beyond.
3. Explore the potential for machine learning as enhancement to or replacement for traditional turbulence models and furthermore as efficient method to control turbulent boundary layer flows with adverse gradient or more complex configurations as airfoils involving separation.

Key Words : data-driven techniques; neural networks; turbulent modeling; machine learning; data analysis; aerodynamics; separated flows; control.

Context and objectives

The flow control remains a major topic in the field of fluid mechanics. Despite the numerous studies that have been dedicated to it, the understanding of the physics and the development of boundary layer control devices remain a very high potential issue, especially at large Reynolds number and in particular with the possible presence of adverse gradients. These studies have indeed as one of major aim, for exemple, to minimize drag, the energy consomption, or to increase the maneuverability of aircrafts, rockets, shuttles, etc …

The rise of high performance computing has led to a growing availability of high fidelity simulation data performed using direct numerical simulations (DNS) or large eddy simulations (LES). These data open up the possibility of using machine learning algorithms, such as neural networks or random forests, to develop more accurate and general empirical models. A key question, when using data-driven algorithms to develop these empirical models, is how domain knowledge should be incorporated into the machine learning process. This thesis will specifically address this problem of incorporating physical properties of the turbulent flows, as symmetry, invariance properties or invariant quantities, to provide new turbulent models which could be more efficient to predict the flow dynamics and which could notably be included in the control loop for turbulent boundary layer flows.

Different methods for teaching a machine learning model an invariance property will be assessed and compared. This could be done by constructing a basis of invariant inputs and using the machine learning model to trained upon this basis; or by embedding the invariance into the model. In this second approach, the algorithm could be trained on multiple transformations of the raw input data until the model learns invariance to that transformation. The behavior of these data-driven processes will be discussed in the case of turbulence modeling in the scope of evaluating their performance in terms of computational training costs and modeling capacity.

The second part of the thesis will be devoted to the application of the machine learning techniques developed during the thesis to more applied problems as the control of turbulent boundary layers with adverse gradient or with separated flows, which are characteristic configurations of flows handled by the different groups («Ecoulements turbulents & Contrôle », «Métrologie et Analyse de Données », « Dynamique du vol », « Machines tournantes ») of the new laboratory (LMFL) built by the merging of the ER2 team of « Laboratoire de Mécanique de Lille » and the ONERA. This thesis can be considerate as being as subject of interest for all the different teams of the new laboratory and will strongly contribute to launch the new common activities emerging from this fusion.