Machine learning and sparse optimization for modeling, sensing, and controlling fluid dynamics

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Abstract

Many tasks in fluid mechanics, such as design optimization, sensor selection, modeling, and control, are challenging because fluids are nonlinear and exhibit a large range of scales in both space and time. This range of scales necessitates exceedingly high-dimensional measurements and computational discretization to resolve all relevant features, resulting in vast data sets and time-intensive computations. Indeed, fluid dynamics is one of the original big data fields, and many high-performance computing architectures, experimental measurement techniques, and advanced data processing and visualization algorithms were driven by decades of research in fluid mechanics. Despite the increasing volumes of fluid data, low-dimensional patterns often exist, and there are considerable efforts to model the evolution of these dominant coherent structures that are important for engineering objectives. In this talk, I will explore a number of emerging techniques in machine learning and sparse optimization that complement existing numerical and experimental efforts in fluid mechanics. Machine learning comprises a powerful set of techniques to uncover these low-dimensional flow patterns, which in turn enables sparse optimization for efficient sampling and computations. The resulting models are parsimonious, balancing model complexity with descriptive ability, while avoiding overfitting. Because fluid dynamics is central to transportation, health, energy, and defense systems, I will emphasize the importance of machine learning solutions that are interpretable, generalizable, and that respect known physics.