Center for Turbulence Research
Proceedings of the Summer Program 2022

Data-Driven Methods group: overview

Owing to the inherent scale separation encountered in high-Reynolds-number turbulent flows, resolving all scales of turbulent motion with direct numerical simulation remains computationally intractable for the predictive analysis of most engineering systems. The simulation of reacting turbulent flows, which is relevant for characterizing not only the performance of internal combustion engines but also the external aerodynamics of hypersonic flight vehicles, often requires even further resolution due to the additional length scales and timescales introduced by the chemistry. By combining physical intuition and domain expertise with techniques from optimization, resolvent analysis and deep learning, the six projects in the Data-Driven Methods group have pursued the development of reduced-order models in order to mitigate the computational cost associated with the simulation and control of complex turbulent flows. The projects fall into the following two categories: (i) accelerating the numerical solution of partial differential equations for multiscale systems with machine-learned closures, and (ii) model reduction of dynamic systems for physical insight, development of control techniques and prediction of extreme events in wall-bounded turbulence.

With application to reacting hypersonic boundary layers, Scherding *et al.* refined a data-driven algorithm for constructing a lightweight thermochemical modeling library. By accelerating the computation of molecular transport properties and chemical reaction rates, the surrogate model halved the overall computational cost associated with the simulation of a Mach-10 laminar boundary layer. Through the utilization of local similarity solutions as training data, significant improvements in the efficiency of the data-driven approach itself were also realized.

Developing a machine-learned closure model for the truncated harmonic-balanced Navier-Stokes equations, Rigas & Schmid applied deep learning to enable accurate numerical solution of time-periodic flows in the frequency domain with a limited number of harmonics. As such, a neural network was utilized to model the impact of unresolved high-frequency harmonics on the resolved dynamics of the flow. In applying the data-driven closure model to numerical simulation of flow past a cylinder, close agreement with direct numerical simulation was achieved with an appreciable reduction in the computational cost.

Investigating the relative importance of parametric and regenerative mechanisms for sustaining turbulence, Farrell *et al.* considered a set of modified Navier-Stokes equations for which a parameter is introduced to scale the magnitude of the fluctuation/fluctuation nonlinearity. In the context of Couette flow, modulation of this scaling parameter revealed the presence of two distinct regimes in which turbulence is maintained by parametric and regenerative mechanisms, respectively, together with a third regime characterized by laminarization. Further insight into the interaction between fluctuations and a time-varying base flow was achieved via application of time-dependent resolvent analysis.

In order to reduce the computational cost associated with resolvent analysis, Gomez *et al.* developed an adaptive method based on Bayesian optimization and Gaussian process regression to efficiently locate regions of maximum resolvent gain in spectral space. The algorithm demonstrated particular promise for reacting flows, for which the state vector is augmented by a large set of species' concentrations. The subsequent application of adaptive resolvent analysis to high-enthalpy hypersonic boundary layers revealed that chemical activity can significantly influence the resolvent mode shapes as well as the associated gains, with the largest differences observed in the relatively subsonic region of spectral space.

Finally, Doan *et al.* proposed a data-driven approach for the prediction of extreme events in turbulent flows. Comprised of a convolutional autoencoder for dimensionality reduction and an echo state network for time advancement in the latent space, the method was applied to turbulent channel flow. The composite neural network successfully predicted not only the statistical properties of the velocity field but also the temporal evolution of quasi-relaminarization events for the minimal flow unit. In order to provide additional insight into this machine-learning method, Magri & Doan presented a methodology based on differential geometry for interpreting the latent spaces of autoencoders, together with an associated proper latent decomposition for turbulent flows.

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