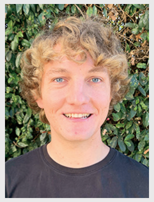
A Big-Data-Enhanced Adjoint Sensitivity Analysis for Minimal Channel Flow Turbulence



Estimating turbulent flow states in backward time from limited measurements is a challenging task with broad applications in data assimilation.

Attempts in reduced-order modelling, such as Proper Orthogonal Decomposition and Dynamic Mode Decomposition, have been utilized to project high-dimensional nonlinear flow fields onto a low-dimensional space. However, these models often are suboptimal for studying the nonlinear interaction of modes due to their linearity. The adjoint operator is the most effective tool for evaluating the sensitivity of a measurement to the precedent flow events, but it does not take into account the equilibrium distribution of statistically stationary turbulent fields.

To address these shortcomings, a neural-network-based autoencoder (AE) is trained to summarize the equilibrium distribution of turbulence in a low-dimensional embedding with a much lower degree of freedom. The AE compresses the direct numerical simulation (DNS) output of a minimal turbulent half-channel flow into a latent space 1/16 the size of the DNS resolution. The AE is combined with a physics-based adjoint method to evaluate the sensitivity of measurements in a minimal channel flow turbulence with a Reynolds number of 100.

The nonlinear nature of the framework enables us to reveal the dependence of finite deviations in sparse measurements to precedent flow events.

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