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Restricted nonlinear model for reinforcement-learning-based control of turbulent channel flow

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Abstract

Restricted nonlinear (RNL) model, a physics-based reduced order flow representation, is used as to train the deep reinforcement learning (DRL) control strategies of turbulent channel flow at high Reynolds numbers under much less training expenses. Order reduction of RNL is realized by restricting the nonlinear interactions between the fluctuations about a streamwise-averaged flow. It well predicts the coherent structure and its dynamics such as the self-sustaining process near the wall with much fewer streamwise computational grids, since only the active streamwise wave numbers need to be simulated. DRL control strategies trained by RNL flow fields are applied to the direct numerical simulations (DNS) at $Re_\tau = 180, 550$ and 950. For practical considerations, only wall quantities are used as the input of DRL agent to modulate the wall blowing and suction for larger drag reduction without any requirement of internal flow field information. Substantial drag reduction rates up to 19% and 16% are obtained based on the spanwise and streamwise wall shear stresses, respectively. Two different drag reduction mechanisms are discovered by DRL with the input of streamwise and spanwise wall shear stress, respectively. DRL control strategy with the input of spanwise wall shear targets at suppressing the streamwise vortices near the wall similar to the traditional opposition control. Instead, when using streamwise wall shear stress as input, DRL obtains drag reduction by suppressing the strength of velocity streaks and the sweep and ejection events near the wall. The present study provides a perspective that combining the RNL with DRL control can be effective and computationally economical; for example, compared with the DRL models trained by DNS, the training cost decreases by over thirty times at $Re_\tau = 950$. Also, the proposed method can be easily extended to turbulent flows at higher Reynolds numbers.

Keywords: drag reduction, turbulence control, machine learning, restricted nonlinear model