Separation control in adverse-pressure-gradient turbulent boundary layers

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The need to save energy is becoming crucial with the global energy crisis of the past years. The use of flow-control techniques has been prevalent in addressing aeronautical problems. These techniques are employed to decrease energy consumption by means of reducing drag forces or optimizing the geometry. In parallel, over the past few decades, the rise in computational power has facilitated the utilization of numerical simulation as a way to investigate wall-bounded turbulence. Additionally, as a result of the increased availability of computational resources, there has been an increasing number of investigations in the field of fluid mechanics that involve the implementation of machine-learning techniques over the past decade. By combining these two approaches, we apply active flow control (AFC) to a turbulent boundary layer (TBL) subjected to an adverse pressure gradient (APG) strong enough to produce flow separation. Our approach uses the numerical code Sod[1], which was developed at the Barcelona Super Computing Center for scale-resolving simulations of compressible fluid flows in aeronautical applications. Sod is based on the spectral-element method (SEM) and offers high performance on general-purpose graphical-processing units (GPUs) and high accuracy by the SEM scheme.

To perform the AFC, we use several actuators or jets strategically placed in the domain, which will perform blowing or suction. We connect a neural network to the jets and use the deep-reinforcement-learning (DRL) method[2] to obtain an effective control strategy. With DRL techniques, the DRL algorithm learns non-linear control strategies through direct trial-and-error. After a sufficient number of episodes, the algorithm can optimize a desired reward function, such as delaying separation in our APG TBL.

As part of this study, a parametric analysis of the Clauser–Rotta pressure-gradient parameter (β) is performed, where β is defined as $\beta = \delta^*/\tau_w(\mathrm{d}p/\mathrm{d}x)$. Here δ^* is the displacement thickness, τ_w is the wall-shear stress and $\mathrm{d}p/\mathrm{d}x$ is the streamwise pressure gradient. Different simulations are performed for each β, which has an almost constant value throughout the entire boundary layer. Moderate to high Reynolds numbers are computed, reaching up to approximately $Re_\theta = 6000$, where Re_θ is the Reynolds number based on momentum thickness. A comparison of the different separation-control strategies for values of $\beta \gtrsim 7$ leading to separation is also presented. The physics of the obtained control strategies are thoroughly detailed.

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[1]Lehmkuhl, O. and Gasparino, L. and Muela, J., *HiFiLeD Symposium* December 14-16, Brussels, Belgium, (2022).

[2]Recent advances in applying deep reinforcement learning for flow control: perspectives and future directions, Vignon, C and Rabault, Jean and Vinuesa, R., *Physics of Fluids accepted*, (2023).