Tinoco

Motivation

Reynolds Averaged Navier-Stokes Equations:
\[
\frac{\partial U_i}{\partial t} + \frac{\partial (U_i U_j)}{\partial x_j} = -\frac{1}{\rho} \frac{\partial p}{\partial x_i} + \nu \frac{\partial^2 U_i}{\partial x_j^2} - \nabla \cdot \tau
\]
\[
\tau = -\mu \nabla^2 U_i + \frac{2}{3} \rho U_i \nabla U \cdot \nabla
\]
Hub of RANS models

Our Motivation:
- RANS modeled Reynolds stresses are known to be unreliable for many flows.
- LES/DNS simulations are still infeasible for many industrial flows.
- Is it possible to employ existing LES/DNS database to enhance the RANS simulations?

Objective and Approach

The objective of this work is to demonstrate that the RANS simulated Reynolds stress of a new flow can be improved via our PIML framework with existing LES/DNS database. Three essential parts of our PIML framework are: (1) representation of Reynolds stresses discrepancies as responses; (2) identification of mean flow features as inputs and (3) construction of regression functions from training data.

(1) Representation of Reynolds Stresses as Responses
\[
\frac{\partial U_i}{\partial t} + \frac{\partial (U_i U_j)}{\partial x_j} = -\frac{1}{\rho} \frac{\partial p}{\partial x_i} + \nu \frac{\partial^2 U_i}{\partial x_j^2} - \nabla \cdot \tau = 2\kappa \left( \frac{\tau}{2} + \frac{\tau}{A} \right) = 2 \left( \frac{1}{2} V A^2 \right)
\]
\[
\tau \rightarrow (\Delta \log \tau, \Delta A, \Delta V, \Delta \tau)
\]

(2) Identification of Mean Flow Features
Integrity Basis of \([S, \Omega, \nabla \rho, \nabla k] \rightarrow \mathbf{q}_i = (1, 2, \ldots, 47)

(3) Construction of Regression Functions
Random Forest or Neural Network

Physics-Informed Machine Learning Framework

(a) training: DNS data of elementary flows
(b) trained discrepancy functions
(c) prediction: complex, realistic flows

Procedures of PIML Framework:
- Perform baseline RANS simulations on both the training flows and the test flow.
- Compute the mean flow feature vector \( \mathbf{q} \) based on the RANS simulations.
- Compute the discrepancies field \( \Delta \tau = \frac{2}{3} \rho U_i \nabla U \cdot \nabla - \frac{2}{3} \rho \nabla^2 U_i \) between RANS modeled Reynolds stresses and the high-fidelity simulation data for the training flows.
- Construct regression functions \( f_i : \mathbf{q} \rightarrow \Delta \tau \).
- Compute the Reynolds stresses discrepancies for the test set by evaluating the regression functions.

Application I. Flow in a Square Duct

Application II. High Mach Number BL

Application III. Flow over Periodic Hills

Conclusions

In this work, we proposed a physics-informed machine learning (PIML) approach to predict RANS modeled Reynolds stresses discrepancies by utilizing DNS database. The potential impacts include:
- Utilizing current high-fidelity simulations database to improve the accuracy of RANS simulations
- Assisting turbulence modelers to derive better RANS models
- Inspiring other data-driven modeling approaches in computational mechanics

Bibliography

Further Information

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