Data-Assisted Turbulence Model Development

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Aeronautics and Astronautics Affiliates Meeting
Introduction

• Growing usage of CFD within industry

• Cannot routinely compute engineering flows with desired accuracy in many cases
Introduction

- Why? Lack of predictive capability in separation, transition, mixing, ...
- Impacts on high-lift, heat transfer, combustion, ...
Turbulence Modeling

• “Single most critical area in CFD ... is the ability to adequately predict viscous turbulent flows”
• And Yet: “Stagnation in the capabilities used in aerodynamic simulation”

Need a new path forward
What is new?

• Growing number of available high-fidelity

• Increased ability to process the available data
Objective

Explore the concept of creating a turbulence model using machine learning.

• Step toward the ultimate goal of a turbulence model learned from DNS

Many Questions:

• What are the correct inputs and outputs?
• Will the resulting functional form destabilize the PDE solver?

Need a principled way to approach this topic
Alternate Approach

1) Select representative datasets
   - Flat plates, pressure-driven channels, airfoils

2) Choose and extract input and output features
   - Spalart-Allmaras quantities

3) Select learning algorithm
   - Neural Network

4) Train learning algorithm
   - BFGS optimizer

5) Embed learned model within flow solver
   - SU2
Neural Networks

Inputs

Hidden Layers

Output
Results

Training data: Flat plates at Re = 3, 5, 7 * 10^6

Features: Learn full source term: \( \bar{s} = f(\bar{\Omega}, \chi, \bar{N}) \)

\[
\frac{\partial \hat{\nu}}{\partial t} + u_j \frac{\partial \hat{\nu}}{\partial x_j} = c_{b1}(1-f_{t2})\hat{S}\hat{\nu} - \left(c_{w1}f_w - \frac{c_{b1}}{\kappa^2}f_{t2}\right)\left(\frac{\hat{\nu}}{d}\right)^2 + \frac{1}{\sigma} \left( \frac{\partial}{\partial x_j} \left( (\nu + \hat{\nu}) \frac{\partial \hat{\nu}}{\partial x_j} \right) + c_{b2} \frac{\partial \hat{\nu}}{\partial x_i} \frac{\partial \hat{\nu}}{\partial x_i} \right)
\]

Convection \hspace{1cm} Production \hspace{1cm} Destruction \hspace{1cm} Diffusion \hspace{1cm} Cross Production
Results

Training data: Flat plates at $Re = 3, 5, 7 \times 10^6$

Features: Learn full source term: $\bar{s} = f(\bar{\Omega}, \chi, \bar{N})$

\[
\frac{\partial \hat{\nu}}{\partial t} + u_j \frac{\partial \hat{\nu}}{\partial x_j} = \text{Convection} + \text{Production} + \text{Destruction} + \frac{1}{\sigma} \left( \frac{\partial}{\partial x_j} (\nu + \hat{\nu}) \frac{\partial \hat{\nu}}{\partial x_j} \right) + \text{Diffusion} + \text{Cross Production}
\]

Test on NACA 0012 at 8°
Results – Learning Source

Capable of reproducing solution to high accuracy even with some errors in learning
• Onera M6 wing, $Re = 1.2 \times 10^7$, $M = 0.8$
• Training data: solution at $0^\circ$, $2^\circ$, $4^\circ$ angle of attack
• Testing data: $3.06^\circ$
• Fully replace SA source term
• Lift and drag coefficient match to within 2%
Conclusions

• Demonstrated procedure for creating a machine-learned turbulence model
• Successfully replicated Spalart-Allmaras turbulence model
• Good agreement seen on flows not in the training set

Future is building turbulence models from high-fidelity data
Questions?