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Title
A New Framework for Data-assisted Turbulence Modeling

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Abstract
Turbulence is often encountered in the aerodynamic design process and modeling it with high accuracy is crucial for the success of the design. The RANS method is usually used in the design process for turbulence modeling thanks to its low cost. Although the method is efficient, RANS turbulence models have difficulty in calculating separated flow accurately. To solve the problem, data-driven RANS modeling frameworks such as FIML [1] were proposed and have achieved substantial success in the prediction of separated flow. However, turbulence models obtained by such methods consist of black-box ML (Machine learning) models that are difficult to interpret physically and suffer from limited generalization ability. The portability of data-driven ML turbulence models also makes it hard to implement the same ML turbulence model to another set of CFD codes. In this study, an experimental data-assisted turbulence modeling framework is proposed to make the RANS model generated from data more portable and physically interpretable

The first part of the proposed framework focuses on field-inversion (FI) [1], and a correction factor (say, $\beta(x)$) is added to an existing turbulence model. Then, the "optimized" $\beta(x)$ distribution that can minimize the error between the RANS result and the high-fidelity data (from experiment, DNS, or LES) is found by the Discrete-adjoint method and optimization algorithms. Currently, FI is conducted on 2-D bump geometry and S809 airfoil by our program. 2-equation models ($k-\omega$ and $k-\omega$ SST) are used to do FI. The effect of the normalization term in the FI objective function and the implication of β distribution are also discussed in our work.

The second part of the framework aims to obtain an analytical relationship between the flow variables and the $\beta(x)$ field obtained in part I. The analytical relationship may not be as accurate as ML models on the training set, but it has a much higher portability and is more hopeful to have good generalization abilities. Currently, symbolic regression [2] is used successfully to reconstruct some of the functions in the original SA model. The result given by the reconstructed model (reSA) is almost identical to the original model, suggesting the effectiveness of symbolic regression and its potential in obtaining the relationship between $\beta(x)$ and flow variables.

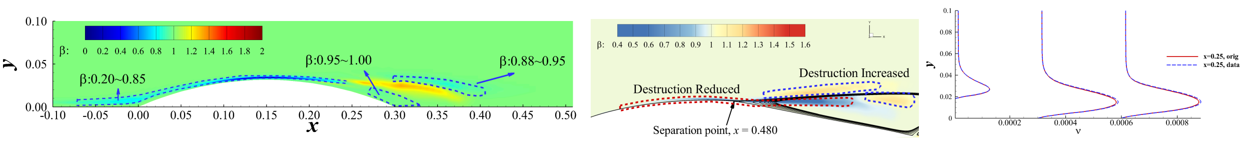

Figure left and middle: β distribution of the 2-D bump and S809 airfoil; right: velocity profiles obtained by reSA and SA

References
[1] Parish, Eric J., and Karthik Duraisamy. "A paradigm for data-driven predictive modeling using field inversion and machine learning." Journal of computational physics 305 (2016): 758-774.
[2] Cranmer, Miles. "PySR: Fast & parallelized symbolic regression in Python/Julia." (2020).