Oral presentation | Data science and AI

Data science and AI-III

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[11-C-04] PDE-free Models for Transitional Flows: a Universal Substituted Machine Learning Framework

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PDE-free Models for Transitional Flows: a Universal Substituted Machine Learning Framework

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1 Introduction

Accurate simulation of the laminar-turbulent transition is of great importance in engineering applications. At present, the mainstay of industrial transition prediction has been carried out by the Reynolds-averaged NavierStokes (RANS) methods incorporated with well-calibrated transition models, and is likely to persist for a long time. Thereinto, the intermittency factor (γ)-based models are most popular [1]. However, more human-art interventions and free parameters are invoked compared with their full-turbulence RANS counterparts, let alone the higher computational cost. Such deficiencies are difficult to overcome based on traditional approaches. Owing to the flourishing achievement of machine learning (ML) techniques in fluid mechanics community, the present study aims to construct a PDE-free artificial neural network (ANN) model for γ, which is expected to share the equivalent accuracy and engineering usability to the PDE-based models while eliminating the defect of its traditional counterparts.

2 The Proposed USML Framework

Depicted in Figure 1 is the a universal substituted machine learning (USML) framework for PDE-free transition modeling. As is well recognized, RANS modeling is more along the lines of surrogate model for specific types of flows. Therefore, verifying the performance of baseline model in transitional flows is the logically first step. Once a tradition model is derived with the approved accuracy (recalibrated/modified or not), the process of USML rolls into the "training" phase, which definitively shapes the overall performance of ML-substituted transition model. In the "testing" phase, *a priori* test is employed to quantify how well the regression predictions approximate the baseline. The established ML-alternative model is tested *a posteriori* to evaluate the comprehensive substitutability for traditional transition model along with their efficiency. In this study, ANN is chosen as the ML approach, users can change other RANS models and ML algorithms based on the actual flow regimes.

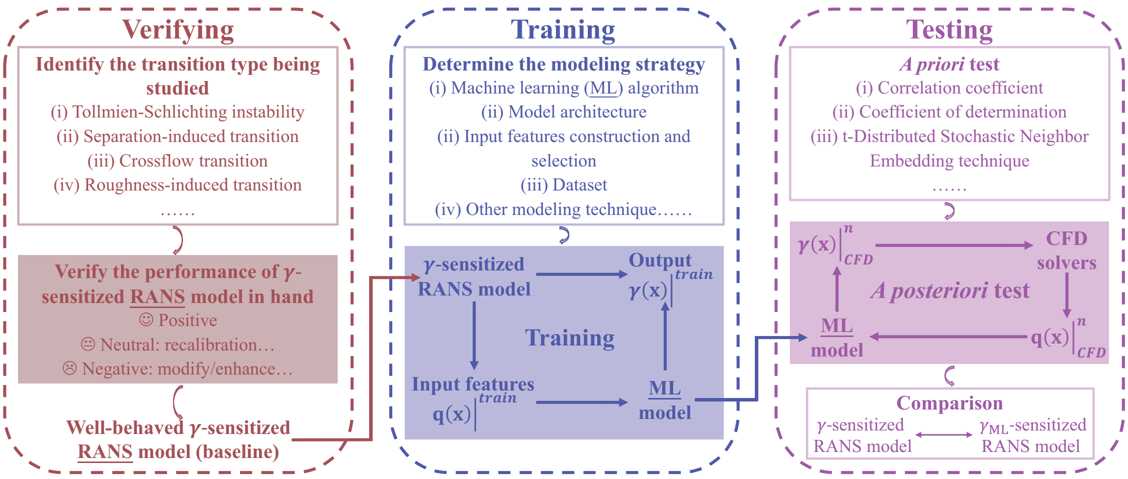

Figure 1: The USML framework for PDE-free transition modeling.

3 Models Formulation and Results

As listed in Table 1, three ANN-alternative transition models are derived through the USML framework. Taking shear stress transport (SST)-γ model as the benchmark, two airfoils with various angles of attack (AoAs) and Mach (Ma) numbers are selected as the training set, and three other airfoils over broader ranges of AoAs and Ma numbers are employed as the testing set. The *a posteriori* test results manifest that the skin friction coefficient C_f, laminar separation bubble, Reynolds stress, etc., predicted by SST-γ_{ANN} are in excellent accordance with the baseline SST-γ model [2].

To validate the applicability of USML to other RANS models and further explore the generalization ability in Reynolds number, ANN-alternative Spalart-Allmaras (SA)-γ model is selected as the second example. It is demonstrated that the USML also holds as in the former case and can be well generalized to different Reynolds numbers [3].

However, the above models are rather insufficient for practical engineering applications. When shifting toward the practical aerodynamic adoptions, improving the predictive capability of baseline model in three-dimensional (3D) transitional flows becomes the overarching business. To this end, flows past the infinite swept NLF(2)-0415 wing are adopted as the training set, while flows around NLF(2)-0415, finite ONERA M6 swept wing, and more complicated configurations of non-wing-like geometry 6:1 inclined prolate spheroid are employed as the test-bed. The results show that SST-γ_{ANN} aligns well with the CF-enhanced SST-γ model, completely breaking through the barrier encountered by original SST-γ model (see Figure 2). Two effective *a priori* analysis strategies are proposed for beforehand evaluation. In addition, verification concerning the calculation efficiency, grid-dependence, etc., are also implemented to inspect its industrial feasibility. Furthermore, the underlying rationale behind the preliminary success and transferability of USML are elucidated [4].

Transition type	Baseline performance	Model comparison	Generalization
2D, TS, separation-induced	Positive	SST-γ vs. SST-γ_{ANN}	Geometry, AoA, Ma
2D, TS, separation-induced	Positive	SA-γ vs. SA-γ_{ANN}	Geometry, AoA, Ma, Re
3D, TS, separation-induced, and crossflow (CF)	Negative	SST-γ vs. SST-γ_{ANN}	Geometry, AoA, Ma, Re

Table 1: Three examples of the present USML framework.

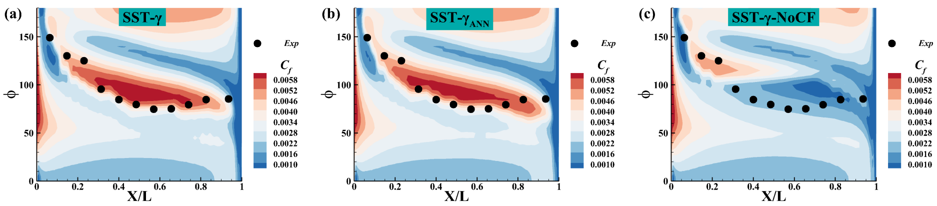

Figure 2: Contours of skin friction coefficient predicted by three models for 6:1 inclined prolate spheroid.

To summarize, through the proposed USML framework, one can derive a PDE-free transition model with more computationally efficient property and nearly identical precision, robustness, and generalizability in comparison with its traditional counterpart. Indeed, the philosophy and formalisms employed in the present USML are of a general nature, which is demonstrated to be an attractive alternative for various routine engineering design processes.

References

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