

Toward Physics-Based Transition Modeling for Subsonic to Hypersonic Boundary Layers

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Outline

- 1 Motivation
- 2 Results
 - Convolutional Neural Network Model
 - Recurrent Neural Network Model
- 3 Summary and Concluding Remarks

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Physics-Based Transition Modeling

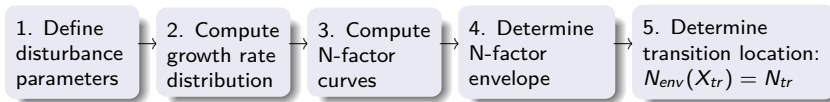
- Transition prediction is critical element of the CFD process for multiple aerospace vehicles across the speed regime
- According to CFD Vision 2030 study,¹ the basic set of capabilities must include, at a minimum:
 - ① Emphasis on **physics-based, predictive modeling**
 - ② Higher degree of automation in all steps of the analysis process
- Desirable attributes of transition models
 - ① Applicable to all **relevant transition mechanisms**
 - ② Accurate, efficient, parallelizable, automated prediction
 - ③ suitable for multiple turbulence models

Proposed approach

- Integrate physics-based BLT modeling based on N-factor method into CFD

¹J. Slotnick et al. *CFD vision 2030 study: A path to revolutionary computational aerosciences*. Tech. rep. CR-2014-218178. NASA, 2014.

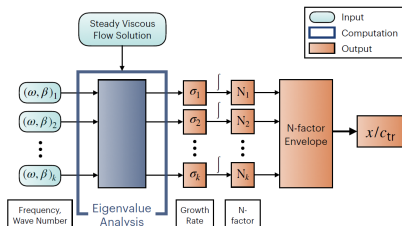
N-factor Based Transition Prediction



- Established approach in transition research, but difficult to integrate with CFD codes!

- Challenges:

- ▶ Nonrobustness of linear stability calculations
- ▶ High demands on basic state accuracy
- ▶ Need for significant user expertise



(Rajnarayan & Sturdza AIAA 2011-3813)

Proposed approach

Metamodels based on deep learning could alleviate the challenges, and help enable the CFD Vision 2030 goal of integrating physics-based correlations with CFD solvers

Outline

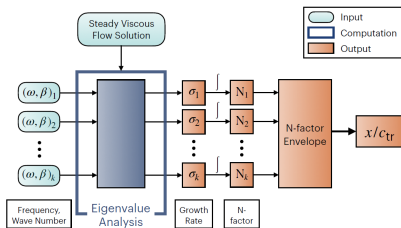
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Results

Convolutional Neural Network Model

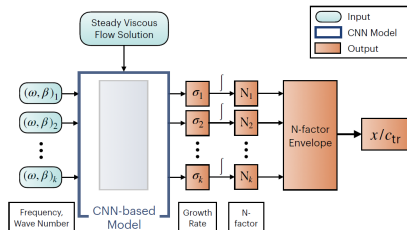
N-factor Prediction based on CNN Model^{2,3}

• Linear Stability Theory (LST)



(Rajnarayan & Sturdza AIAA 2011-3813)

• Convolutional Neural Network (CNN)



(Zafar et al. PRF 2020)

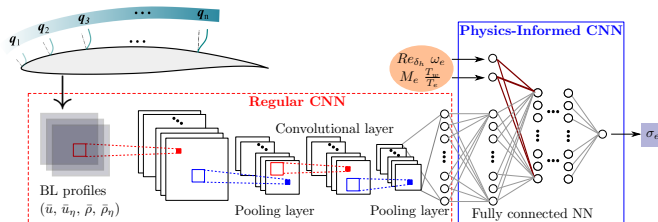
- CNN predicts local growth rate for a given instability mode (ω, β)
- Range of frequencies/wavelength needs to be defined to compute individual N-factor curves and then the envelope

²M.I. Zafar et al. "Convolutional neural network for transition modeling based on linear stability theory". In: *Physical Review Fluids* 5 (2020), p. 113903.

³P. Paredes et al. "Toward a practical method for hypersonic transition prediction based on stability correlations". In: *AIAA Journal* 58.10 (2020), pp. 4475–4484.

Modeling the Amplification of BL Instabilities

- Existing data-driven models based on analytical curve fits (Drela & Giles, 1987) or rapid interpolation techniques
 - not well-suited for large number of “stability modifiers”
 - do not allow easy modifications for custom/new data
- CNN-encoder architecture provides a computationally efficient alternative to conventional fully connected networks
 - can also enable physical interpretation of learned features of BL



CNN extracts information from BL profiles

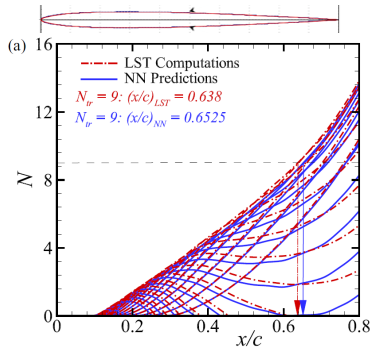
Physical quantities introduced into the fully connected NN

Approximated local growth rate obtained

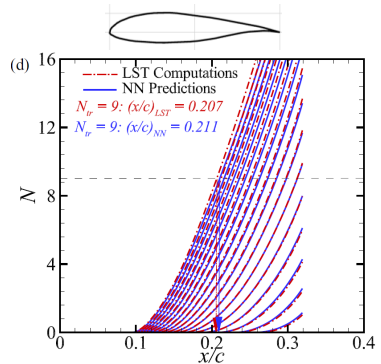
Transition due to TS on 2D Airfoils

- Validation of CNN trained with Falkner-Skan self-similar boundary layer data

- HSK: $\alpha = 0^\circ$, $Re_c = 1.23 \times 10^6$



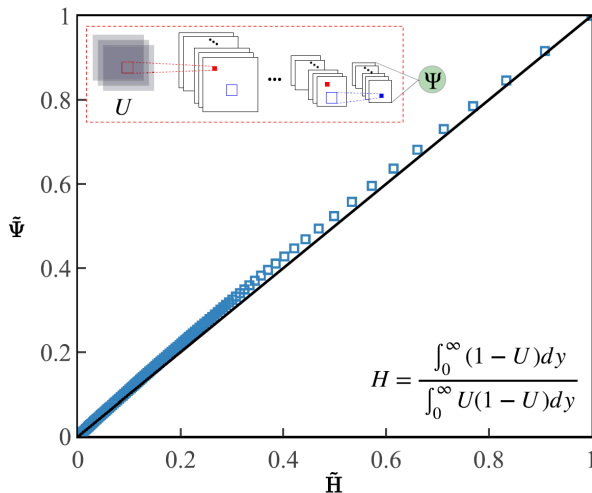
- NLF-0416: $\alpha = 5^\circ$, $Re_c = 9 \times 10^6$



- Transition location predicted within an error of 2 – 5% by the NN model

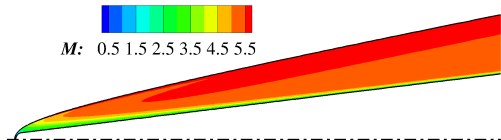
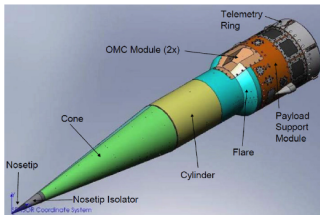
Physical Interpretation of CNN-Based Latent Features

- Correlation between feature (Φ) extracted by CNN from airfoil velocity profiles and profile shape factor (H) shows that
 - CNN is learning the velocity shape factor!**



Transition due to Mack Modes on Blunt Cone

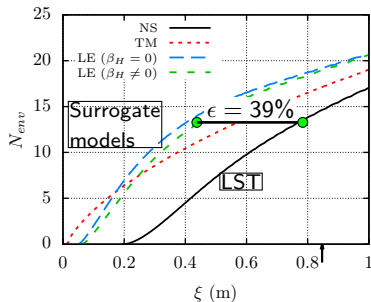
- HIFiRE-1 ascent-phase boundary-layer transition
 - ▶ Nonablating, 7° half-angle cone with $r_n = 2.5$ mm
 - ▶ Ascent phase: $M_\infty = 3.8 - 5.5$ & $AoA < 2^\circ$: Second-mode instability
- Nonzero (albeit small) nose radius alter mean flow characteristics
 - ▶ BL profiles differ from self-similar profiles with matching local BL properties
 - ▶ Entropy layer leads to challenges in reliable evaluations of integral characteristics
- CNN model uses entire input profiles, instead of scalar, integral parameter
- Database: automated generation of large database (693 conditions) of NS and LST computations



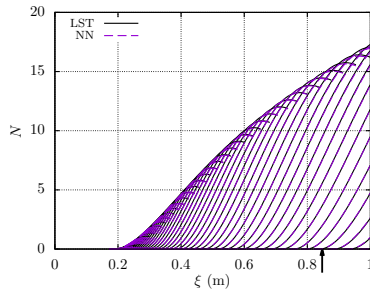
Transition due to Mack Modes on Blunt Cone

- Conventional database lookup (surrogate models) versus CNN model

- N -factor envelopes



- N -factor curves



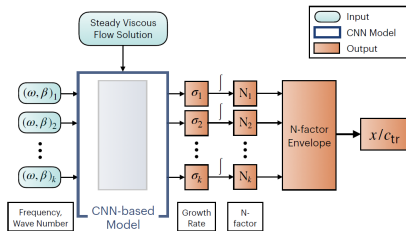
- Surrogate modes based on self-similar profiles lead to large discrepancies (up to 40%) in predicted transition location
- Nearly perfect prediction with CNN for both dominant and subdominant modes

Results

Recurrent Neural Network Model

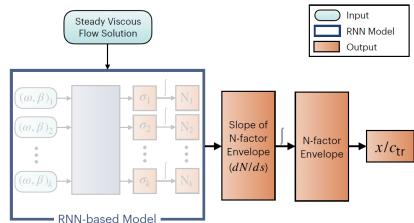
N-factor Prediction Based on RNN model⁴

- Convolutional Neural Network (CNN)



(Zafar et al. PRF 2020)

- Recurrent Neural Network (CNN)



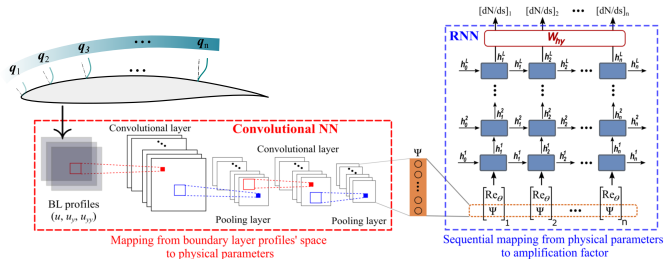
(Zafar et al. DCE 2021)

- In comparison with the CNN model, the RNN model does not require to
 - define the range of frequencies and/or wavelengths to compute local growth rates, integrate the individual N-factor curves, and then the envelope (serial process)
- RNN predicts local slope of N-factor envelope
 - direct calculation of N-factor envelope and transition location, yielding nearly end-to-end transition prediction**

⁴M.I. Zafar et al. "Recurrent neural network for end-to-end modeling of laminar-turbulent transition". In: *Data-Centric Engineering* (accepted) (2021), pp. 1–31.

Modeling the Amplification of BL Instabilities

- Boundary-layer profiles and the disturbance growth rates evolve in a continuous manner along the aerodynamic surface
- The RNN is a general-purpose architecture for modeling sequence transduction by using an internal state (memory) that selectively keeps track of the information at the preceding steps during the sequence



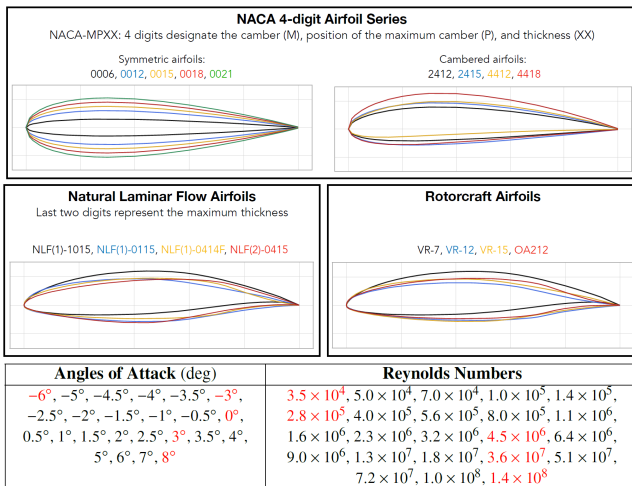
CNN extracts information from BL profiles

Physical quantities introduced into the RNN

Approximated local N-factor envelope slope obtained

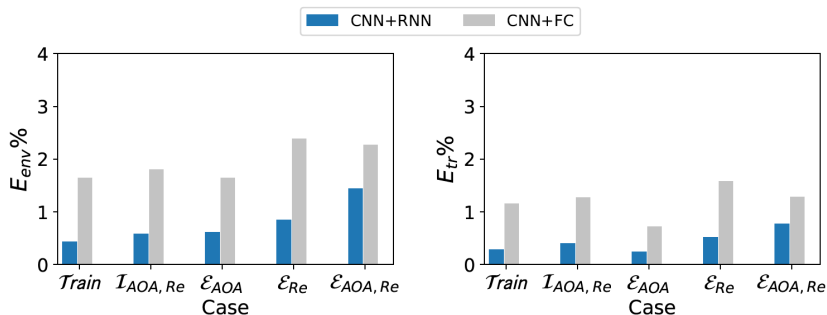
Database of TS Amplification over Airfoils

- **35K boundary-layer flows** at various flow conditions (airfoil contour, AoA, Re_c)
- Airfoil families: NACA 4, 5, & 6-digit series, natural laminar flow (NLF), rotorcraft, low Reynolds number, general aviation, high lift, transonic, wind turbine, etc.



Performance of CNN and RNN Models

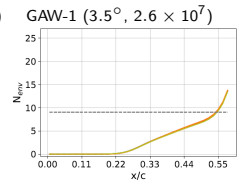
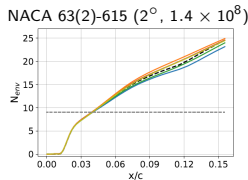
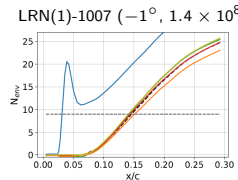
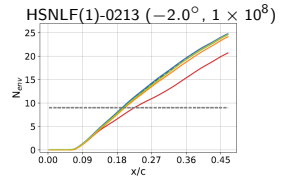
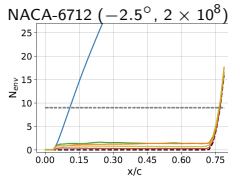
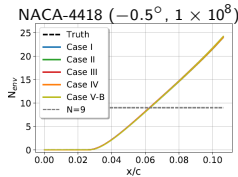
- Comparison of results for the
 - ▶ RNN based model (CNN+RNN)
 - ▶ CNN based model (CNN+FC)
- Dataset of 5 airfoils: NACA 0012, ONERA M6, NACA 2412, NACA 63-415, NLF(1)-0416



- Superior predictive performance for the RNN model vis-a-vis the CNN+FC model
- RNN model estimates x_{tr} 3 to 4 orders of magnitude faster than direct stability computations

Selection of Optimal Training Data

- Quality of deep learning model strongly influenced by selection of training data
- Casewise evaluation of different selections
 - ▶ Case I: Baseline (5 airfoils, $m = 2524$, $< 8\%$ of total data)
 - ▶ Case II: Random augmentation (Case I + 100 random flows from each, $m = 7026$)
 - ▶ Case III: Augmented set of airfoils (Case I + 5 largest error airfoils, $m = 4455$)
 - ▶ Case IV: Error based augmentation (Case I + highest error cases, $m = 5024$)
 - ▶ Case V-B: Randomly selected flows (100 random flows of each airfoil, $m = 5300$)



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What to Take Home

- Deep learning offers an attractive option to develop transition models based on instability amplification
- Possible to develop models that work for multiple instability mechanisms and a broad class of boundary layers
- CNN architecture allows the high-dimensional input space to be truncated to a small dimension
- RNN model (CNN+RNN) outperforms CNN model (CNN+FC)
 - ▶ does not require to define range of frequencies/wavelengths and compute individual N-factor curves and then the envelope
 - ▶ superior predictive performance

Future work

- Multimode prediction
- Integration into CFD codes
- Explore other neural network approaches

Thank you for your attention

- Acknowledgments

- ▶ NASA Transformational Tools and Technologies (TTT) Project of the Transformative Aeronautics Concepts Program (TACP)
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- ▶ ICTAM 2020 Congress Grant - waived registration fee



Outline

4 Backup slides

Transition to Turbulence in Boundary Layers: Mechanisms

Transition can occur due to multiple instabilities

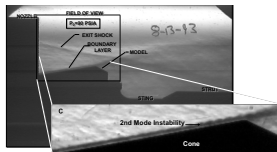
• 2D/Axisymmetric boundary layer

- ▶ planar Tollmien-Schlichting mode ($M_e < 1$), oblique first mode ($M_e \lesssim 4$) and planar second mode ($M_e \gtrsim 4$)
- ▶ Goertler instability (concave walls)
- ▶ separation-induced instability

• 3D boundary layers (those found in 2D BLs plus)

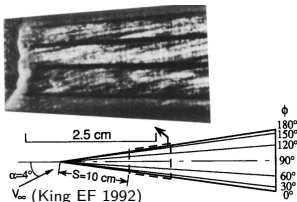
- ▶ crossflow instabilities
- ▶ streak/secondary instabilities
- ▶ attachment-line, corner flow, roughness-induced instabilities, ...

• Flared cone ($M_\infty = 6$)



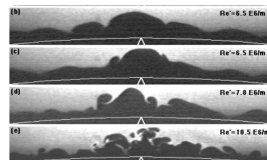
(Lachowicz PhD 1996)

• Circular cone ($M_\infty = 3.5$)



(King EF 1992)

• Elliptic cone ($M_\infty = 8$)



(Huntley & Smits EJFM 2000)