Machine Learning-Based Physics Inference from High-Fidelity Solutions: Vortical Features & Flow Separation

Nathan Hariharan
HPCMP CREATE^{TM} Technical Operations, Alexandria, VA, 22315

Jennifer N. Abras
HPCMP CREATE^{TM} Quality Assurance Group, Alexandria, VA, 22315

Corresponding author – Nathan Hariharan (nathan.s.hariharan.ctr@mail.mil, nathanaarti@gmail.com)

Abstract: The field of machine learning is broad, covering many different areas and applications. The identification of aerodynamic flow features is one such possible application. Training a machine learning model to classify aerodynamic flow features opens a whole field of potential applications such as automated data extraction, onboard solution assessment, and volume solution physics comparisons. In this study, Convolutional Neural Network based ML systems are built to recognize vortical structures and simple flow separation patterns. The system then is deployed to automatically identify & extract such features from 3D flowfields such as rotorcraft wakes. The full paper will detail verification of this method and demonstrate application for physics extraction from flowfield of rotors and wings.

Keywords: Machine Learning, Hi-fidelity Simulations, Physics Inference, Vortices, Flow Separation, CFD, Convolutional Neural Networks

1. Introduction:

Machine learning refers to a vast class of mathematical, statistical, and optimization methods that can infer useful information from observed data [1]. A compelling class of methods is the neural-inspired Deep Learning networks [2][3]. These methods mimic the fundamental canonical elements of human neuron interaction at its core level and have non-linearity inbuilt into the modeling process. In the field of physics-based modeling, deep-learning networks are gaining traction through several avenues, i.e., infusion of physics into the learning mechanism [4], augmenting predictive modeling [5]. A quick literature search yields an exploding list of applications related to aerospace engineering, in general, and aerodynamics, in particular.

A specific form of deep-learning network known as the Convolutional Neural Network (CNN) [6][7] has been spectacularly successful in the field of vision and image processing. In this work, a CNN is architected for the specific purpose of classifying physics in large-scale 3D fluid-dynamic-simulation result visualization. In present-day workflows involving physics-based simulations, human-in-the-loop visualization of results forms a fundamental basis for inferring physics and assessing the accuracy of the computed results. The primary intent of the current work is to assess if CNN-based deep-learning networks can effectively classify physics such as vortical systems or flow separations in computational simulation results and aid further automation of the workflow for routine simulations.

One of the corollary benefits is to aid verification and validation. Widely used physics-based software tools such as HPCMP CREATE^{TM}-AV Kestrel/Helios are subject to rigorous forms of software engineering [8] practices and undergo continuous testing [9] before any new capability is released. With increasing modeling capabilities to simulate real-world model challenges, the permutations required to test the capabilities before a new version is released scale-up correspondingly. Traditionally, automated testing of full-up capabilities compares integrated quantities from "gold-standard" test results and random checks for output quantities to ensure existing capabilities have not been adversely affected. Visual human-engineer spot-checking of underlying field physics is only performed when tests fail. The current effort also explores if visually observable physics (i.e., separation, vortex structure) can be auto-verified by CNN-based systems to ensure high confidence in the automated V&V processes.

An immediate motivation for developing a CNN-based classifier is to extract vortex systems from simulations of rotorcrafts in hover [10]. The flow field underneath a hovering rotor-blade consists of complex 3D vortex dynamics in the wake of the rotor-blade and is non-trivial to capture accurately. A critical aerodynamic efficiency factor for rotorcraft hover performance is the figure-of-merit, a measure of total thrust generated for a given torque required. Understanding the detailed characteristics of the vortical system and how this relates to the predicted hover performance is an essential metric for evaluating a computational model. However, the extraction of such information is a time-consuming, manual process. Furthermore, when these extractions are performed manually, only a sparse sample of points are feasible. An automated machine learning-based model to identify vortices can be further developed into an automated system to identify and extract vortex information. By applying this enhanced automated extraction on a routine basis, more insight into the correlation of the wake structure to integrated hover performance results is possible.

2. Machine Learning Methodology and Sample Results:

The Convolutional Neural Net architecture was constructed using TensorFlow 1.15 [11] with the Keras library [12]. The vortex classification CNN architecture is illustrated in Fig. 2. The input is processed through a series of convolution and pooling layers before being flattened and then processed through a series of fully-connected layers. The final two-class output provides the prediction confidence of the vortex and no-vortex classes. While the prediction confidence isn't a mandatory output for classification, this parameter has proven to be helpful in assessing the quality of the trained CNN. After initial verification with simple canonical structures, the method was applied to high fidelity wake solution from a hover rotor. Hovering rotor wakes contain significant variability in vortex dynamics, and the real test of this method is the ability to identify vortices and core centers for the full 3D wake geometry (figure 3)

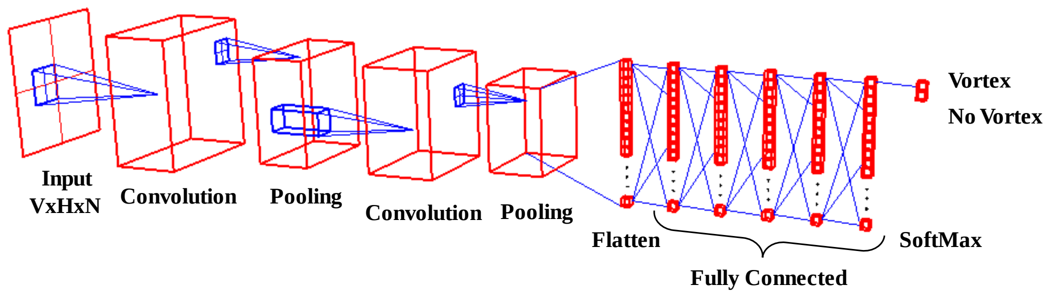

Fig. 2. CNN vortex classification architecture.

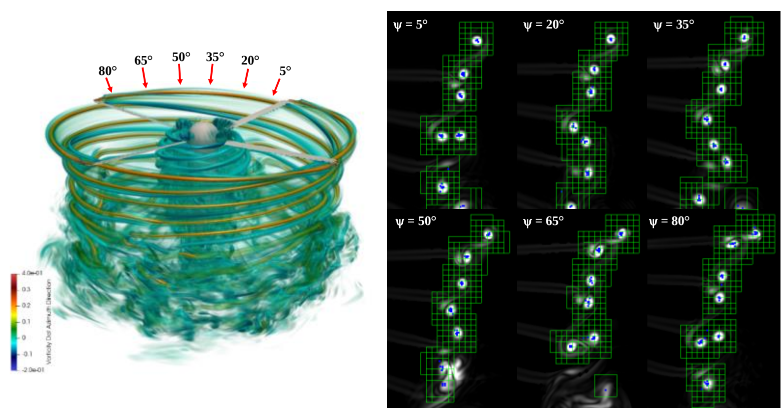

Fig. 1. Raw classification (green boxes) and localization (blue points) predictions on a typical rotor wake.

3. Conclusions and Future work:

A machine learning framework has been developed to automatically extract flow features such as vortices and flow separations from large 3D computational data sets. The method has been refined specifically for extracting tip vortex structures for rotors in hover. The full paper will include results from auto extraction for the S-76 and PSP rotor blades, and correlation against manually extracted solutions. Some preliminary results from investigation of identification of separated flows over 3D wings will also be presented. The method promises to automate & enormously speed-up the human-in-the-loop aspect of visualization and extraction of physics inference from 3D high fidelity CFD simulations. Such a capability will also enable ML-enabled verification & validation that includes physics comparisons, extraction of high-fidelity physics constructs such as vortical elements and separation patterns to feed to surrogate models, and automated sanity-checks to ensure correct end-use of CFD software.

References

[1]Hastie, T., Tibshirani, R., and Friedman, J., "The Elements of Statistical Learning: Data Mining, Inference and Prediction," Springer-Verlag, New York, 2009

[2]Goodfellow, I., Bengio, Y., and Courville, A., "Deep Learning," MIT Press, 2016

[3]Ng, A., "Deep-Learning," deeplearning.ai, 2018

[4]Raissi, M., Perdikaris, P., and Karniadakis, G., "Physics-informed Neural Networks: A deep-learning framework for solving forward and inverse problems involving nonlinear partial differential equations," *Journal of Computational Physics*, Volume 378, pp 686-707, February 2019

[5]Singh, A., Medida, S., Duraisamy, K., "Machine Learning-augmented Predictive Modeling of Turbulent Separated Flows over Airfoils," *AIAA Journal*, Volume 55, Number 7, July 2017

[6]LeCun, Y., Bottou, L., Bengio, Y., and Haffner, P., "Gradient based learning applied to document recognition," Proceedings of the IEEE, Volume 86, Issue 11, November 1998

[7]LeCun, Y., Kavukcuoglu, K., and Farabet, C., "Convolutional networks and applications in vision," *IEEE International Symposium on Circuits and Systems*, Paris, France, May/June 2010

[8]Hallissy B., Hariharan N., Laiosa J., Shafer T., Hine D., Forsythe J., Abras J., Lillian C., and Dahl C., " CREATE-AV quality assurance: best practices for validating and supporting computation-based engineering software," *52nd AIAA Aerospace Sciences Meeting*, National Harbor, MD, January 13-17, 2014

[9]Kendall, R., Hariharan, N., and Park, L., "HPCMP CREATE™ Operational Practices Guide," HPCMP CREATE™ White Paper, January 2020.

[10]Hariharan, N., Abras, J., and Narducci, R., "An Overview of Wake Breakdown in High-Fidelity Simulations of Rotor-in-Hover," *Vertical Flight Society 76th Annual Forum*, Virginia Beach, VA, October 6-8, 2020

[11]Abadi, M., Agarwal, A., Barham, P., Brevdo, E., Chen, Z., Citro, C., Corrado, G., Davis, A., Dean, J., Devin, M., Ghemawat, S., Goodfellow, I., Harp, A., Irving, G., Isard, M., Jozefowicz, R., Jia, Y., Kaiser, L., Kudlur, M., Levenberg, J., Mané, D., Schuster, M., Monga, R., Moore, S., Murray, D., Olah, C., Shlens, J., Steiner, B., Sutskever, I., Talwar, K., Tucker, P., Vanhoucke, V., Vasudevan, V., Viégas, F., Vinyals, O., Warden, P., Wattenberg, M., Wicke, M., Yu, Y., and Zheng, X., "TensorFlow: Large-scale machine learning on heterogeneous systems," https://www.tensorflow.org/, 2015

[12]Chollet, F., et al., "Keras," https://keras.io, 2015