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A deep learning approach for efficiently and accurately evaluating the flow field of supercritical airfoils

Ameya Jagtap

The efficient and accurate access to the aerodynamic performance is important for the design and optimization of supercritical airfoils. The aerodynamic performance is usually obtained by using computational fluid dynamics (CFD) methods or wind-tunnel experiments. But the computations of CFD are very time intensive and expensive, and the prior knowledge in wind-tunnel experiments plays a decisive role in engineering. Though many surrogate methods were proposed to alleviate the costs of these traditional approaches, most of them can only calculate the low-dimensional aerodynamic performance and is not able to provide the accurate prediction of transonic flow fields for supercritical airfoils. Since the flow fields are equipped with its own discipline as a physical system in fluid dynamics, it is therefore possible to learn this discipline via data-driven machine learning approaches. Deep learning is witness to expansive growth into diverse applications due to its immense ability to extract essential features from complicated physical systems. Generative adversarial networks (GANs) as a recent popular method in deep leaning are capable of efficiently capturing the distribution of training data. In this work, we proposed a surrogate model, ffsGAN, which leverage the property of GANs combined with convolution neural networks (CNNs) to directly establish a one-to-one mapping from a parameterized supercritical airfoil to its corresponding transonic flow field profile over the parametric space. Compared with the most existing surrogate models, the ffsGAN is superior in efficiently and accurately predicting the high- dimensional flow field rather than the low-dimensional aerodynamic characteristics. The ffsGAN method is first trained using 500 airfoils that sampled based on RAE2822. The flow fields are then predicted for unseen airfoils to evaluate the generalization of the model in terms of prediction accuracy. An in- vestigation of the effects of various hyper-parameters in the network architectures and loss functions is performed. The experimental results show that ffsGAN is a promising tool for rapid evaluation of detailed aerodynamic performance. The elaborate flow field predicted by ffsGAN is possible to be considered in airfoil design to further improve the design and optimization quality in the future.