Different reduction techniques based on physical reduced order modeling and deep learning for geometrical exploration of turbulent and incompressible fluid flows

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ABSTRACT

In the following work we provide recent researches and developments in model reduction technologies applied to fluid dynamics problems, in particular for design exploration purposes of gaz turbines and fuel injectors of aircraft engines.

We present first a new physics based POD (Proper Orthogonal Decomposition)-Galerkin projection of the turbulent and incompressible Navier-Stokes equations. This reduced order model stabilization is based on an a priori enrichment by scales separation of the POD basis with dissipative modes of the velocity fields [2]. This a priori enrichment with space scales seperation, enables a stable dynamic reduced order model that could be used for very long time integration even for temporal extrapolation. We show that the temporal weights of the reduced modes which are solutions of the enriched reduced model are very stable.

Then, we present a physics based geometrical model order reduction of the unsteady and incompressible Navier-Stokes equations, that we solve efficiently with respect to a collection of a priori designs for an injector. This framework is based on a prediction step of the global aerodynamic field using the Gappy-POD approach [4] on a local high-fidelity solution associated with a new design and a correction step by extrapolation using the Galerkin projection of the governing Navier-Stokes equations upon global and local POD modes obtained in a particular fashion. This combination between data reconstruction techniques and physics-based ROM enables a good prediction of the geometrical aerodynamic field [3]. The accuracy of this prediction is quantified by computing the error on different quantities of interest with respect to the high-fidelity LES (Large Eddy Simulations). These quantities of interest are the recirculation zones which drive the flame stabilization.

Finally, we present a very recent work concerning the use of deep learning approaches for improving fluid mechanics simulations. Due to the statistical nature of the unsteady and turbulent fluid flows, data driven algorithms could potentially reduce the computational cost through reduced trained models. Among the novel paradigms emerging from the deep learning community, Generative Adversarial Networks (GAN)[1] are particularly relevant for our task. GANs aim to capture the data distribution such that they can then easily generate new realistic samples similar to the real ones. We present a study concerning the requirements for a deep neural network to learn a LES. To conclude, we illustrate the ability of the GAN to predict fluid flows in a variable domain.

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