Talk announcement

Alexandre Daby

(Solid Mechanics Lab of Polytechnique (UMR 7649, École Polytechnique, IPP, CNRS, MDISIM Team, INRIA), Palaiseau, France)

Tuesday, Oct 22, 2024
15:30, S2 416-1

Hybridising standard reduced-order modelling methods with interpretable sparse neural networks for real-time patient-specific lung simulations

Mechanics and, more specifically, stress fields possibly play a crucial role in the development of pulmonary fibrosis. This work aims to provide clinicians with diagnostic and prognostic tools based on mechanical simulation. Personalisation of these tools is critical for clinical pertinence, thus requiring numerical techniques for real-time estimation of patient-specific mechanical parameters.

This work proposes hybridising classical model-order reduction methods with machine learning capabilities to provide a fine-tuned surrogate model of the non-linear mechanics problem.

Similarly to techniques like the Proper Generalised Decomposition (PGD) or the High-Order Singular Value Decomposition (HOSVD), the parametric mechanical field is represented through a tensor decomposition, effectively mitigating the curse of dimensionality associated with high-dimensional parameters. Each mode of the tensor decomposition is given by the output of a sparse neural network within the HiDeNN framework, constraining the weights and biases to emulate classical shape functions used in the Finite Element Method.

This hybridisation preserves interpretability while affording greater flexibility than standard model-order reduction methods. For instance, it allows for employing diverse meshes for each mode in the tensor decomposition, with

the added capability of mesh adaptation during the training stage. Moreover, the model's architecture results directly from the number of nodes and the order of elements used for the interpolation, thus eliminating the arbitrariness in its choice.

In this framework, the training stage amounts to solving the minimisation problem classically encountered with classical model reduction methods. However, the automatic differentiation tools naturally available in the neural network framework allow greater flexibility in solving the non-linear problem when its linearisation is not straightforward. Finally, this framework allows for transfer learning between different models with different architectures, leading to high efficiency in the model's design and limiting the wasteful use of resources.