BENCHMARKS FOR PHYSICS-INFORMED DATA-DRIVEN HYPERELASTICITY

Vahidullah Tac[1], Kevin Linka[2], Francisco Sahli-Costabal[3], Ellen Kuhl[2] and Adrian Buganza Tepole[1]

[1]Purdue University
[2]Stanford University
[3]Pontifica Universidad Catolica de Chile

ABSTRACT

Constitutive modeling of soft materials is undergoing significant changes and innovations with the adoption of data-driven methods. The past few years have been witness to the development of a number of physics-informed data-driven approaches in constitutive modeling of materials that satisfy physics-based constraints such as polyconvexity a priori. The models have outstanding flexibility owing to their data-driven nature, but also retain some extrapolation capabilities thanks to polyconvexity. In this study, we investigate and compare three promising data-driven frameworks: Constitutive Artificial Neural Networks (CANN), Input Convex Neural Networks (ICNN) and Neural Ordinary Differential Equations (NODE). We benchmark the three methods by training them with two datasets consisting of stress-strain data from rubber and skin. All three methods learn the training data flawlessly and exhibit some ability to extrapolate. The most significant difference between the models is observed in the second derivatives of the strain energy with respect to invariants of deformation. This could have important implications for derivative-based numerical solvers such as equilibrium finite element analysis. A study of efficiency of parameters reveals that the accuracy of the models increases with the number of parameters, as expected. Overall, all three methods constitute robust and flexible methods for modeling arbitrary hyperelastic behavior of materials while satisfying the relevant physics.