Achieving universal approximations with a novel neural network framework for isotropic polyconvex hyperelasticity

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Abstract

Incorporating physical principles and constraints into artificial neural networks can significantly enhance their ability to accurately capture the behavior of materials. This promising combination, however, comes with substantial challenges (1,2). Principles such as objectivity, polyconvexity and isotropy may interfere with each other and naive implementations can become too restrictive for the solution space.
This work hence introduces a novel neural network framework for hyperelasticity that inherently satisfies these fundamental constraints while maintaining flexibility. Unlike previous approaches, the proposed framework is based on the universal approximation theorem, ensuring the ability to approximate any objective, polyconvex and isotropic energy with arbitrary accuracy within this function space. Moreover, the approach enables the approximation of polyconvex hulls.

Numerical examples validate the effectiveness of the proposed framework and demonstrate its ability to approximate energy functions that were previously unattainable using other neural networks. Additionally, the computation of polyconvex hulls for non-polyconvex energies is demonstrated.

References

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