Energy-Based Physics-Informed Neural Networks for Nonlinear Contact Mechanics

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The reliable and efficient simulation of contact problems remains a subject of interest in computational mechanics due to their inherent non-smoothness and strong nonlinearities. While established approaches solve such problems with classical numerical methods such as the Finite Element Method (FEM), we approach this challenge by applying physics-informed machine learning techniques, specifically energy-based physics-informed neural networks (EPINNs). The overarching goal is to develop machine learning surrogates that are not only physically consistent but also fast to evaluate, thereby enabling their use in multi-query settings such as optimization, uncertainty quantification, or inverse analysis; applications which are often computationally intractable when relying solely on conventional high-fidelity models.

Although classical data-driven approaches have demonstrated promising results in several engineering contexts, their reliance on extensive and high-quality datasets poses a fundamental limitation. In many practical scenarios, generating such data via FEM simulations is prohibitively expensive and experimental data acquisition may be infeasible. Physics-based machine learning attempts to overcome this issue by reducing the dependence on training data through the incorporation of physics-based regularization into the training process. Therefore, the recently proposed EPINN framework [1] formulates the learning task in an energy-minimization setting and trains a neural network to directly minimize the total potential energy functional.

In this contribution, we extend the EPINN framework for frictionless contact mechanics by introducing an incremental solution strategy that enables the network to recover the entire nonlinear load path rather than only the final equilibrium configuration. This is achieved by decomposing the full nonlinear optimization problem into a series of optimization problems with weaker nonlinearities. While current approaches employ a simple yet effective penalty potential to impose contact constraints [2], we also investigate an Augmented Lagrangian approach and compare both methods. Our numerical results will be quantitatively validated against high-fidelity FEM reference solutions to ensure accuracy and stress that this ML-based approach is also comparable to established methods in terms of performance.

References

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