

A HYBRID APPROACH TO MESH OPTIMIZATION WITH NEURAL WARM-STARTS

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Abstract

Mesh optimization remains a computational bottleneck in numerical simulations, particularly in highly distorted or anisotropic meshes where local optimization becomes challenging. Classical optimization methods often require many iterations and are sensitive to poor initializations, leading to increased computational cost. While recent neural networks approaches can rapidly predict improved node positions, standalone neural approaches generally lack optimality guarantees and may fail to meet strict element quality criteria.

In this work, we propose a hybrid framework for local mesh optimization in which a neural network predicts a warm-start position for each interior mesh node based on the geometry and connectivity of its first-order topological neighborhood. This prediction is then used as the initial guess for a classical optimizer, effectively combining data-driven inference with guaranteed convergence. We assess different warm-start strategies, differing in how the neural predictor is coupled with the classical solver within the optimization loop, enabling different levels of interaction and correction.

Numerical experiments demonstrate that the proposed neural-guided initialization consistently reduces the number of internal iterations of the classical solver and the overall computational cost, while preserving the robustness and optimality properties of classical methods. The results highlight the effectiveness of neural-guided initialization as a practical strategy for accelerating mesh optimization without compromising solution quality.