

NEURAL IMPLICIT GEOMETRY REPRESENTATION FOR GRADIENT-BASED SHAPE OPTIMIZATION

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Abstract

A fundamental aspect of shape optimization is the choice of geometry representation. Established approaches such as CAD-based parameterizations, free-form deformation techniques, and node-based methods are widely used in practice. However, these strategies either require significant manual effort and restrict the admissible design space, potentially excluding relevant optima, or introduce a large number of design variables that require filtering and smoothing to maintain regular geometries. As a result, geometry parameterization often becomes the limiting factor in optimization workflows. Recent advances in neural networks for implicit geometry representation offer a promising alternative.

In this work, we present a neural implicit geometry representation framework for gradient-based shape optimization. The geometry is represented implicitly as the zero-level set of a neural signed distance function. Building on the concepts of Deep Local Shapes and continuous latent fields, the design domain is parameterized by a spatially smooth latent parameter field defined via B-spline control points. A shared neural decoder maps spatial coordinates and the latent field to signed distance values, resulting in a continuous and differentiable geometry model. This method offers improved scalability, can handle complex topologies, and allows training data to be generated from simple primitive geometries while generalizing to a broad class of shapes.

Within the shape optimization framework, the latent variables serve as design variables and are updated iteratively during the optimization process. A differentiable surface extraction method is employed to transform the implicit representation into a computational mesh. Together with the differentiable nature of the neural decoder, this ensures that sensitivities can be propagated through the geometry model, enabling efficient gradient-based optimization.