DUDF: Differentiable Unsigned Distance Fields with Hyperbolic Scaling

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Abstract. In recent years, there has been a growing interest in training Neural Networks to approximate Unsigned Distance Fields (UDFs) for representing open surfaces in the context of 3D reconstruction. However, UDFs are non-differentiable at the zero level set which leads to significant errors in distances and gradients, generally resulting in fragmented and discontinuous surfaces. In this paper, we propose to learn a hyperbolic scaling of the unsigned distance field, which defines a new Eikonal problem with distinct boundary conditions. This allows our formulation to integrate seamlessly with state-of-the-art continuously differentiable implicit neural representation networks, largely applied in the literature to represent signed distance fields. Our approach not only addresses the challenge of open surface representation but also demonstrates significant improvement in reconstruction quality and training performance. Moreover, the unlocked field's differentiability allows the accurate computation of essential topological properties such as normal directions and curvatures, pervasive in downstream tasks such as rendering. Through extensive experiments, we validate our approach across various data sets and against competitive baselines. The results demonstrate enhanced accuracy and up to an order of magnitude increase in speed compared to previous methods.

Keywords: Neural implicit representations · Unsigned distance functions · Open surfaces · Deep neural networks.

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