

Internship proposal

Neural Signed Distance Fields for 3D Object Representation

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Context

Neural implicit representations are a promising tool for geometry processing that represent a solid object as the zero level set of a continuous function encoded in the parameters of a deep neural network [8, 4]. Unlike traditional geometrical data structures (point clouds, meshes, voxel grids), this approach does not rely on spatial discretization nor combinatorial structures and allows the use of modern autodifferentiation paradigms.

In the last few years, neural implicit representations have been made as memory efficient as meshes [2] and robust to geometrical queries like rendering or collision detection [5, 1]. However, they still suffer from a high computational cost compared to traditional methods, as well as a difficulty to represent fine geometrical details.

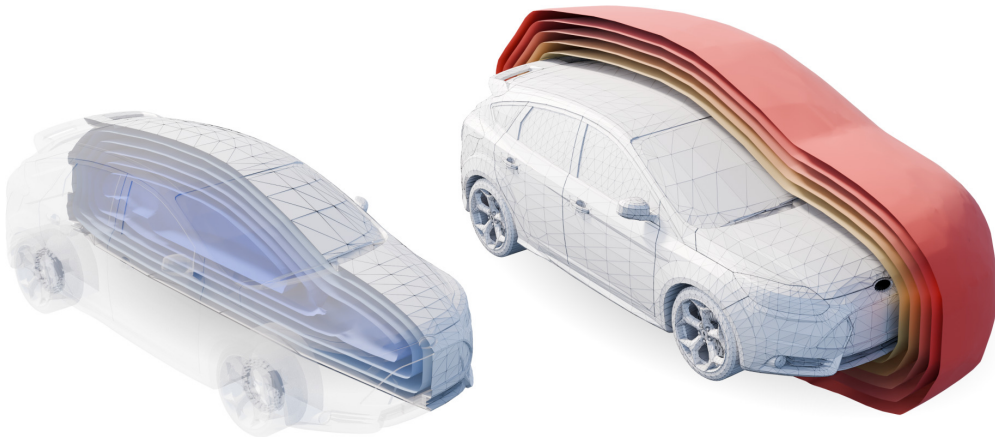


Figure 1: Iso-surfaces of a neural signed distance field computed from the mesh of a car. Current neural representations are able to produce regularly-spaced iso-surfaces which correspond to a good quality distance field but struggle to capture the fine geometrical features of the object.

Goals

The goal of this internship is to develop new neural network architectures and training procedures to improve neural representations of 3D geometrical objects. In particular, it will focus on *neural distance fields*, that is to say a neural representations where the implicit function gives the distance to the object at each point [1]. It will focus on one or several of the following aspects:

Geometrical fidelity. Distance fields have discontinuous gradients and their neural approximation are biased towards smooth functions which induces losses of geometrical details. We will explore regularization techniques and

new network architectures to improve geometrical fidelity to the initial object while preserving the properties of the distance field.

Training and inference efficiency. By using spatial partition techniques and carefully crafted neural architectures, we hope to speed-up convergence of a neural distance field to its target geometry, as well as improving inference time for a given point.

Extraction of a good quality surface mesh. Current conversion algorithms from implicit functions to meshes either rely on discretization [3] or exactly extract the network’s level set [7], which do not yield good quality meshes in general. We will explore alternative extractions methods that produce a suitable mesh for downstream applications.

Required skills

- Experience in python programming and with deep learning frameworks (pytorch, jax, tensorflow)
- Experience with geometry processing data structures and algorithms

Practical information

The internship will take place in the CRAFT research team in the Inria center of the Grenoble Alpes University (655 Avenue de l’Europe, 38330 Montbonnot-Saint-Martin, France). It can last from 4 to 6 months.

References

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- [7] Christian Stippel, Felix Mujkanovic, Thomas Leimkühler, and Pedro Hermosilla. 2025. Marching Neurons: Accurate Surface Extraction for Neural Implicit Shapes. <https://doi.org/10.48550/arXiv.2509.21007> arXiv:2509.21007 [cs]
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