Internship proposal

Neural signed distance fields for the representation of 3D objects

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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 traditionnal 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 computationnal cost compared to traditionnal methods, as well as a difficulty to represent fine geometrical details.

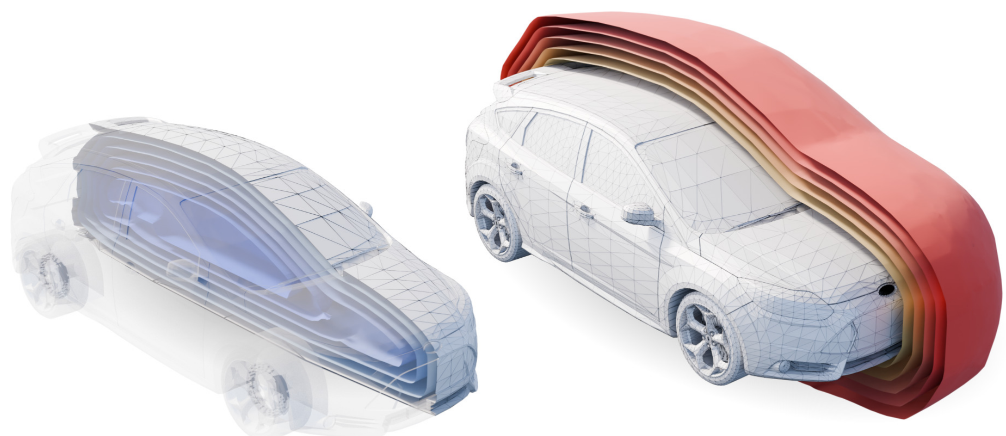

Figure 1: Iso-surfaces of a neural signed distance field computed from the mesh of a car. Current neural representations are able to produce regularly-spaced iso-surfaces which correspond to a good quality distance field but struggle to capture the fine geometrical features of the object.

Goals

The goal of this intership is to develop new neural network architectures and training procedures to improve neural representations of 3D geometrical objects. It will focus in particular on *neural distance fields*, where the implicit function gives the distance to the object at each point [1]. Two key points will be of interest:

Geometrical fidelity: Distance fields have discontinous 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.

How to extract a good quality mesh from the implicit representation? Current mesh extraction techniques from implicit functions either rely on discretization [3] or exactly extract the network's level set [7], which do not yield good quality meshes. 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).
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 4 to 6 months.

References

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[3] William E. Lorensen and Harvey E. Cline. 1987. Marching Cubes: A High Resolution 3D Surface Construction Algorithm. *ACM SIGGRAPH Computer Graphics* 21, 4 (Aug. 1987), 163–169. `https://doi.org/10.1145/37402.37422`

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[6] Vincent Sitzmann, Julien Martel, Alexander Bergman, David Lindell, and Gordon Wetzstein. 2020. Implicit Neural Representations with Periodic Activation Functions. In *Advances in Neural Information Processing Systems*, Vol. 33. Curran Associates, Inc., 7462–7473.

[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]

[8] Yiheng Xie, Towaki Takikawa, Shunsuke Saito, Or Litany, Shiqin Yan, Numair Khan, Federico Tombari, James Tompkin, Vincent Sitzmann, and Srinath Sridhar. 2022. Neural Fields in Visual Computing and Beyond. *Computer Graphics Forum* 41, 2 (2022), 641–676. `https://doi.org/10.1111/cgf.14505`