Ph.D. Topic – 3IA Côte d’Azur

Learnable Representations for 3D Shapes and Scenes: Models and Guarantees

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Context. The rapid growth of 3D sensing technologies has produced massive, heterogeneous, and often incomplete geometric data, creating a dire need for learnable representations capable of capturing the structure and variability of 3D shapes. Common geometric models struggle with noise, sparsity, and topological complexity, while recent neural approaches (implicit fields, point-based networks, neural splatting, and hybrid representations [1-5]) offer new ways to encode geometry with continuity, robustness, and generative power. Yet, fundamental challenges remain: learning representations that are accurate, usable in downstream applications, and scalable to real-world scenes.

Scientific Objective.

This Ph.D. thesis aims to investigate next-generation learnable representations for 3D shapes, with the ambition to unify mesh-based reconstruction, geometric consolidation, and structural understanding within a single differentiable framework. Despite major progress in neural implicit fields, point-based networks, and hybrid representations, current approaches remain limited when the goal is to produce high-quality surface or volume meshes endowed with strong geometric guarantees.

A central challenge is to design representations that are fully differentiable (thus compatible with modern learning pipelines) while still capable of generating meshes that are intersection-free, composed of well-shaped elements, and exhibiting high-order regularity.

Beyond producing a single mesh, the thesis will explore representations that naturally generate multi-resolution families of meshes, enabling levels-of-detail with controllable complexity–distortion trade-offs.

Another key objective is to provide explicit control over the shape and anisotropy of mesh elements, allowing the same representation to produce isotropic meshes for visualization, anisotropic meshes for simulation, or hybrid structures for CAD-like modeling.

The thesis will also address consolidation capabilities: recovering sharp features, reconstructing missing regions, and enforcing structural coherence even from sparse or noisy point clouds.

Finally, we will investigate how to embed notions of discrete differential geometry directly into the learning process, so that the resulting meshes tend toward high regularity (e.g., approximating C^2 smoothness), while preserving geometric fidelity and feature sharpness.

The overarching goal is to develop a unified neural representation that bridges raw point clouds, high-quality meshing, and structural geometric reasoning, paving the way for robust, controllable, and theoretically grounded 3D shape learning.

References

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