# PhD position in Computer Vision and Machine Learning

# Parametric shape approximation from 3D data measurements

**Context**

Shape detection from raw 3D data is a long-standing problem whose goal consists in turning a large amount of geometric data such as 3D point clouds into a higher level representation based on simple geometric shapes (see Figure 1). Instead of reasoning at the scale of 3D atomic elements such as points, triangular facets or voxels, it is often more appealing to directly handle larger geometric shapes in order to both reduce the algorithmic complexity and analyze objects with a higher representation level. Most common geometric shapes include lines, planes and quadrics. Shape detection is typically used as a prior step in a large variety of vision-related tasks ranging from surface reconstruction [8] to object recognition and data registration. Existing shape detection algorithms [1,2,3,4] are typically non-optimal iterative mechanisms that bring no guarantee on the quality of the returned configuration of shapes [5]. At best, they are able to recover some geometric interactions such as parallelism, orthogonality or symmetry between shapes. In addition, obtaining a representation that adequately describes the input data often requires time-intensive parameter tuning.

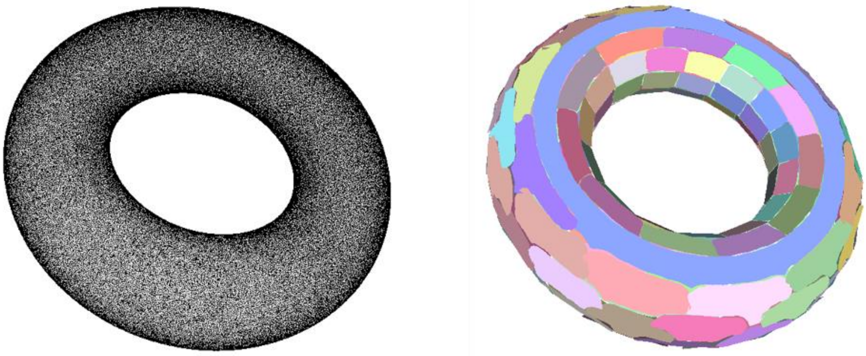

Fig.1 – Planar shape detection on a simple object. The input point cloud describing a torus (left) is approximated by a set of disconnected, independent planar regions (right).

**Objectives**

The goal of this PhD is to investigate new shape detection methods that are more controllable, more efficient and more optimal than existing algorithms. The results obtained by recent deep learning based algorithms, eg [7], suggest the design of an architecture that analyzes input points locally combined with an efficient training strategy on synthetic data can outclass traditional shape detection algorithms. However, many open questions need to be investigated in case of real-world data. For instance, how to exploit such learning strategies on imperfect 3D data measurements? How to control the level of abstraction of the output shape configurations? Or how to design efficient architectures that can operate under reasonable computational complexity on low-power devices? The candidate will investigate these questions and propose methods for detecting shapes and their geometric regularities in a more robust manner than the existing approaches.
In particular, recent work shows basic 2D geometric shapes could captured objects in images efficiently with deep learning architectures operating on continuous parameter space. With more complex 3D shapes, an important problem to tackle will be to design architectures with reasonable computational complexity. Another issue to address will be to create efficient and relevant training sets from synthetic models that can operate efficiently on real-world data. The proposed architectures will have to consolidate missing data and occlusions by using an efficient multi-scale shape representation.

The candidate will also investigate how to extend existing methods to non-planar shapes, more adapted to analyze the geometry of freeform objects. The candidate will investigate how to generalize the fitting algorithms to more complex parametric shapes, in particular NURBS functions. The experiments will be conducted from defect-laden 3D data highly corrupted by noise, outliers and occlusions.

**Keywords**

geometry processing, computer vision, deep learning, shape detection, model fitting

**Candidate profile**

The ideal candidate should have good knowledge in 3D geometry and applied mathematics, be able to program in C/C++, be fluent in English, and be creative and rigorous.

**Location**

The job will take place at Inria Sophia Antipolis, France. The research will be conducted in the Titane group (https://team.inria.fr/titane/). The group does research on geometric modeling of complex environments.

**Application deadline:** 9th of May 2021

**Contact**

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**References**

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