Differentiable Computer Aided Design for Reverse Engineering 3D Shapes

Master-level internship

Adrien Bousseau, Inria Sophia Antipolis (France)
adrien.bousseau@inria.fr
http://www-sop.inria.fr/members/Adrien.Bousseau/

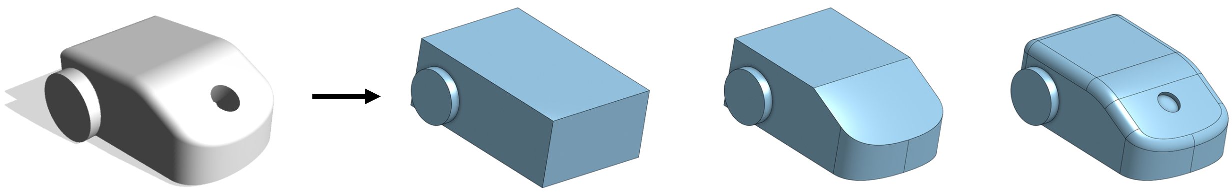

Figure 1: Illustration of our goal. *Given an existing 3D shape, represented as a triangle mesh of a point cloud (left), our goal is to recover a sequence of Computer-Aided-Design operations that reproduce well that shape (right).*

Context

Computer-Aided-Design (CAD) is the industry standard to create 3D shapes for product design and engineering [1]. A major strength of CAD modeling is to define a shape as a sequence of geometric operations, such that the shape can be modified by editing the parameters of these operations. But creating a CAD model by hand is a very tedious task, requiring significant expertise to select the sequence of operations that will produce the envisioned shape. Our long-term goal is to ease the creation of CAD models by automatically converting an existing geometry, such as a triangle mesh or a scanned point cloud, into an editable CAD sequence.

Goals and approach

Generating a CAD sequence requires jointly solving for discrete unknowns (which operations should form the sequence) and continuous unknowns (the parameters of each operation). The presence of discrete unknowns makes the problem NP-hard, as it is impractical to evaluate all possible sequences of operations. Recent work made this problem tractable by leveraging machine learning as a way to guide a search algorithm to only evaluate a subset of high-quality sequences [2,3]. However, training machine learning algorithms on this task is challenging because CAD operations are typically executed by black-box, non-differentiable geometric engines.

The goal of this internship is to implement a differentiable CAD engine suitable for gradient-based optimization of CAD parameters. As a first step, we will follow the recent work of Kania et al. [4], who rely on signed-distance-functions to represent shape primitives (cuboids and spheres) as differentiable functions. We will then extend their approach with a palette of primitives and operations on signed-distance-functions [5], focusing on the ones that are most frequently used in CAD datasets [6].

Work environment and requirement

The internship will take place at Inria Sophia Antipolis. Candidates should have strong programming and mathematical skills as well as knowledge in computer graphics, geometry processing and machine learning.

References

[1] OnShape CAD
https://www.onshape.com/en/

[2] CSGNet: Neural Shape Parser for Constructive Solid Geometry
Gopal Sharma, Rishabh Goyal, Difan Liu, Evangelos Kalogerakis, Subhransu Maji
CVPR 2018
https://github.com/Hippogriff/CSGNet

[3] Fusion 360 Gallery: A Dataset and Environment for Programmatic CAD Construction from Human Design Sequences
Karl D. D. Willis, Yewen Pu, Jieliang Luo, Hang Chu, Tao Du, Joseph G. Lambourne, Armando Solar-Lezama, Wojciech Matusik
ACM Transactions on Graphics 2021
https://github.com/AutodeskAILab/Fusion360GalleryDataset

[4] UCSG-Net - Unsupervised Discovering of Constructive Solid Geometry Tree
Kacper Kania, Maciej Zięba, Tomasz Kajdanowicz
NeurIPS 2020
https://kacperkan.github.io/ucsgnet/

[5] Signed distance functions
Inigo Quilez
https://www.iquilezles.org/www/articles/distfunctions/distfunctions.htm

[6] ABC: A Big CAD Model Dataset For Geometric Deep Learning
Sebastian Koch, Albert Matveev, Zhongshi Jiang, Francis Williams, Alexey Artemov, Evgeny Burnaev, Marc Alexa, Denis Zorin, Daniele Panozzo
CVPR 2019
https://deep-geometry.github.io/abc-dataset/