Local Signatures for 3d Shapes using Topologigal Persistence
Internship proposal

Duration: 5/6 months.

Topic: computational geometry learning, topological data analysis.

Institution and Lab:
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General presentation:

The wide availability of measurement devices has led to an explosion in the amount of 3d data at our disposal, not only in academia and industry, but also among the general public. Large databases of 3d shapes are now available on the Internet, most often containing point clouds and meshes. In order to organize these databases, classify their content, and perform various learning tasks, it is necessary to define relevant similarity or proximity measures between shapes or parts of shapes, which should be invariant to sampling and isometric deformations of the shapes, and which should also be fast and easy to compute. Such measures can be defined directly between the shapes themselves, or between signatures that are computed from the shapes and that encode their local and global properties in a more compact and easy-to-use way.

Initially developped in the context of high-dimensional data mining [5], topological Persistence theory was recently proposed as a viable approach to defining signatures for 3d shapes [3]. The obtained signatures, called *persistence diagrams*, were proved formally to be stable under small perturbations of the shapes [4], and shown experimentally to be informative. Unfortunately, these signatures suffer from major shortcomings which make them unsuitable for supervised or semi-supervised classification tasks—for instance, they live in a space where the metric is costly to compute [6], where means and barycenters are not well-defined [8], and where kernels cannot be derived easily [1]. In addition, they are global by nature, describing a shape as a whole, and not parts or local neighborhoods on a shape.

Expected work: The goals of this internship are the following ones:

1. to adapt the global topological signatures from [3] so they can also characterize points and their neighborhoods on a shape, and to extend the existing stability results from topological persistence theory so they still apply in this context,

2. to assess the power of these signatures in 3d shape processing tasks such as segmentation, partial matching, or parts labeling [7],

3. to derive kernels from these signatures, possibly by first mapping them into some vector space (losing some information along the way), in the same spirit as what was done previously for *persistence landscapes* [2],
4. to test these kernels in supervised learning tasks involving shape parts, as a continuation of last year's work on entire shapes [1].

A first short period of the internship will be devoted to learning the basics of topological persistence theory. Then, the aforementioned tasks will be considered in this order, possibly with some overlap between theoretical and experimental aspects.

Required knowledge and background: A strong mathematical background and some knowledge in computational geometry/topology and/or statistical learning are recommended. Some notions of C/C++, Matlab, or Python, are also desireable.

References

[1] T. Bonis. Topological pooling, 2013. Rapport de stage, Master Mathématiques / Vision / Apprentissage.

[2] P. Bubenik. Statistical topology using persistence landscapes. Research report arXiv:1207.6437, July 2012.

[3] F. Chazal, D. Cohen-Steiner, L. J. Guibas, F. Mémoli, and S. Y. Oudot. Gromov-hausdorff stable signatures for shapes using persistence. *Computer Graphics Forum (proc. SGP 2009)*, pages 1393–1403, 2009.

[4] F. Chazal, V. de Silva, and S. Oudot. Persistence stability for geometric complexes. *Geometriae Dedicata*, 2013. To appear.

[5] Vin de Silva. A weak characterisation of the Delaunay triangulation. *Geometriae Dedicata*, 135(1):39–64, August 2008.

[6] H. Edelsbrunner and J. L. Harer. *Computational Topology. An Introduction*. American Mathematical Society, 2010.

[7] Evangelos Kalogerakis, Aaron Hertzmann, and Karan Singh. Learning 3d mesh segmentation and labeling. *ACM Transactions on Graphics (TOG)*, 29(4):102, 2010.

[8] Katharine Turner, Yuriy Mileyko, Sayan Mukherjee, and John Harer. Fr\'echet means for distributions of persistence diagrams. *arXiv preprint arXiv:1206.2790*, 2012.