

计算机辅助拓扑设计简介

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SERKING TRUIH Pursuing innovation

- 1. Introduction
- 2. Persistent Homology
- 3. Representation of Persistence Diagrams
- 4. Applications in Geometric Design
- 5. Conclusion

1. Introduction

Brief History



• Computational Topology is first presented in:

Dey T K, Edelsbrunner H, Guha S. Computational topology. Contemporary mathematics, 1999, 223: 109-144.

- Computational Geometry → Computational Topology
- **Topological Data Analysis:** Proposed in 2009, a classical application of TDA is published in 2011

Carlsson G. Topology and Data. Bulletin of the American Mathematical Society, 2009, 46(2): 255-308.

Monica Nicolau, Arnold J. Levine, and Gunnar Carlsson, "Topology-Based Data Analysis Identifies a subgroup of Breast Cancers with a Unique Mutational Profile and Excellent Survival," Proceedings of the National Academy of Sciences 108, no. 17 (2011): 7265–70.



Topological Structure of a Manifold







Connected components



A Void (Empty inside a solid)



Higher dimensional topological structures



Figure: A continuous deformation doesn't change the loop in the shape. (Wikipedia: Topology)

Motivation of Topological Data Analysis





• How to infer the essential topological features of a hidden shape?

- To extract components, loops, voids and higher dimensional features
- To measure their importance
- Stable with respect of small perturbations
- Mathematical Background
 - Algebraic Topology (Homology Theory)
 - Statistics
 - Geometry
- A promising bridge between topology and geometry in the view of computation

2. Persistent Homology

2.1 Homology





 $\partial_n \circ \partial_{n+1} = 0$ $H_n = Z_n / B_n$



Simplicial Complex

k-homology group contains different types of *k*-holes.

The rank of homology group is the **Betti numbers**.





As the radii of open balls grow, the **simplicial complex** can be constructed on point cloud data, which gives a nested complex sequence, a **filtration**.





- As time goes by, the radii of open balls grow
- New *k*-holes are **born**
- Some k-holes are destroyed by higher-dimensional simplex and die

2.4 Topological Summaries









The **Wasserstein distance** of two persistence diagrams is controlled by the small perturbations on the tame function *f*

3. Representation of Persistence Diagrams



3.1 Motivation



- Analysis and applications of PDs
 - To extract more statistical information from PDs
 - To learn from PDs via machine learning approaches
 - To design feature descriptors using PDs
- Space of PD with metric W_p
 - Irregular points on a PD
 - Inefficient to compute the W_p distance

PD should be transformed into a proper representation.

Vectorizing Representation of a PD: to map a PD into a Hilbert space.



$$W_p(PD^{(1)}, PD^{(2)}) = \inf_b (\sum_{u \in PD^{(1)}} ||u - b(u)||_{\infty}^p)^{1/p}$$

3.2 Vectorizing a PD or a barcode by binning in its second and the second and the



- To construct the filtration (a nested sequence of simplicial complexes) and to compute PD or barcode
- To convert a PD or a barcode into a function or a series of functions (generally, an element of a Hilbert space)
- To generate finite vector representations usually by binning, sampling, etc.







- Persistence landscapes (PL, Bubenik; 2015) provide a topological summary to analyze PDs with statistical approaches (means, confidential interval, distributions)
- PDs or barcodes are transformed into a series of 1-Lipschitz functions (shown in the left-bottom figure). And the stability of PL is guaranteed





- The persistence image (PI) provides a representation of the information in a persistence diagram that allows to transform it into a vector
- The Gaussian function is chosen at each point in the persistence diagram
- It makes the results of persistent homology available in ML algorithms such as linear SVM

[Adams et al., Persistence Images: A Stable Vector Representation of Persistence Homology, 2017]





- Transform a PD into the birth-persistence coordinates and assign a value to each point in a PD to illustrate the importance of the topological features
- Fit the data points in 3D by a cubic uniform B-spline surface using the technique of progressive and iterative approximation for least squares B-spline surface (LSPIA)
- Finally, the control grid is obtained to generate a vector by concatenating rows of z-coordinates of the control grid
- Persistence B-spline Grid is defined by the matrix formed by z-coordinates of the control points





- The idea is to define a kernel for persistence diagrams to enable a theoretically sound use of these summary representations in the framework of kernel-based learning techniques
- They include, persistence scale space kernel (PSSK, 2015; Reininghaus et al.), Persistent weighted Gaussian kernel (PWGK, 2016; Kusano et al.), Persistence Fisher Kernel (2018; Le and Yamada), etc.

4. Applications in Geometric Design and Related Areas





- The persistence diagram corresponding to this family is shown in the right
- The pink, blue, light blue, black and green points correspond to the middle, index, ring, pinky and thumb respectively

[Carrière et al, Stable Topological Signatures for Points on 3D Shapes, 2015]

4.2 Clustering of Point Clouds





Fig. 6. The twin spirals data set from Figure 2, processed using a smaller Rips parameter: (a) the persistence diagram; (b) the final clustering with late appearing connected components filtered out (in black).

[Chazal et al. Persistence-Based Clustering in Riemannian Manifolds, 2013]





- The rings are detected by the clustering method with persistence (left)
- Compared with the result obtained by spectral clustering (right) Chazal et al. Persistence-Based Clustering in Riemannian Manifolds, 2013

4.3 Topological Denoising





Figure 10. Temperature in the Hurricane Isabel data set (slice z = 20). Using persistence-based filtering, we create a hierarchy of scalar fields: with increasing persistence *P*, our method creates increasingly smoother versions of the data.

• Keep the salient features while using a denosing method

Günther et al., Fast and Memory-Efficient Topological Denoising of 2D and 3D Scalar Fields, 2014

4.4 Topology-aware Reconstruction





• Brüel-Gabrielsson, Rickard, et al. "Topology-Aware Surface Reconstruction for Point Clouds." Computer Graphics Forum. Vol. 39. No. 5. 2020.

4.4 Topology-aware Reconstruction

(c)



- Objective Function:
 - $-((d_1 b_1)^2 (d_2 b_2)^2)$ $-((d_2 b_2)^2 (d_3 b_3)^2)$

(b)



• Brüel-Gabrielsson, Rickard, et al. "Topology-Aware Surface Reconstruction for Point Clouds." Computer Graphics Forum. Vol. 39. No. 5. 2020.

(a)





Zhetong Dong, Chuanfeng Hu, Chi Zhou, Hongwei Lin, Vectorization of persistence barcode with applications in pattern classification of porous structures, Computers & Graphics, Volume 90, 2020, Pages 182-192





4.6 Multiscale Persistent Topological Descriptor



• Pipeline for generating multiscale persistent topological descriptor



Zhetong Dong, Junyu Pu, Hongwei Lin. Multiscale Persistent Topological Descriptor for Porous Structure Retrieval. SIAM-GD 2021, Computer Aided Geometric Design, 88: 102004 (2021)



• Retrieval results of the channel surfaces of DON



Retrieval performance on the synthetic porous data set

Methods/Accuracy (%)	NN	\mathbf{FT}	\mathbf{ST}	DCG
SI-HKS with histogram	90.1	73.3	91.6	92.7
SI-HKS with BoF	81.3	76.1	91.0	91.8
PL descriptor	68.1	59.3	75.0	83.4
PI descriptor	81.5	71.8	86.7	90.1
PRF descriptor	81.8	74.1	87.5	90.6
MSPTD (ours)	94.9	78.4	94.5	95.5

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4.7 Topology Editing for Point Cloud



Topology Editing Results:

- Cup with arc-shaped handle to cup with 3-shaped handle
- Cup without handle to cup with handle





Chi Zhou, Zhetong Dong, Hongwei Lin. Learning persistent homology of 3D point clouds. Computers & Graphics, 102: 269-279 (2022)

4.8 Point cloud interpolation



Interpolation Results:

- The left most and right most are the input point clouds
- The middle point clouds are generated by interpolation using topological implicit vector



4.9 Topology-controllable implicit surface reconstruction



Pipeline



Zhetong Dong, Jinhao Chen, Hongwei Lin. Topology-controllable Implicit Surface Reconstruction Based on Persistent Homology. Computer-Aided Design, 150: 103308 (2022)

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Surface reconstruction in different sampling cases

Sparse Sampling



(a) Results from sparse and uniform sampling point clouds.





Application: Topology repair

Motivation: To repair these topological errors through topology-controllable optimization.

Topology-controllable optimization: To minimize $L^{(1)} = \sum_{i=1}^{4} b_i$, where b_i 's denote the birth values of the four most persistent 1D features, representing four loop structures in the shape.

Result: The broken loop appeared on the extracted surface after topology-controllable optimization.

4.9 Topology-controllable implicit surface reconstruction





Application: Hole removal

Motivation: To remove the 1D holes (1D homology classes) on the shape.

Topology-controllable optimization: To minimize $L^{(1)} = d_2 - b_2$, where (b_2, d_2) represents the persistence pair of the second most persistent feature.

Result: The extracted surface was obtained with the removed small-scale handle loop.

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4.10 Connectivity-guaranteed porous synthesis



• Workflow:



Depeng Gao, Jinhao Chen, Zhetong Dong, Hongwei Lin. Connectivity-guaranteed porous synthesis in free form model by persistent homology. Computers & Graphics, 106: 33-44 (2022)

4.10 Connectivity-guaranteed porous synthesis



• Comparison with Boolean intersection:





Porous model obtained by the proposed method



(b)

Porous model obtained from Boolean operation

4.10 Connectivity-guaranteed porous synthesis



• Porous scaffold manufactured





5. Conclusion

5 Conclusion



- Computational Geometry \rightarrow Computational Topology
- Computer Aided Geometric Design \rightarrow Computer Aided Topologic Design

• 计算机辅助拓扑设计: 以持续同调为主要数学工具, 系统解决几何设计和几何处理中的拓扑问题

