# WEIGHTED FEATURE GRAPH VIA HIERARCHICAL CLUSTERING

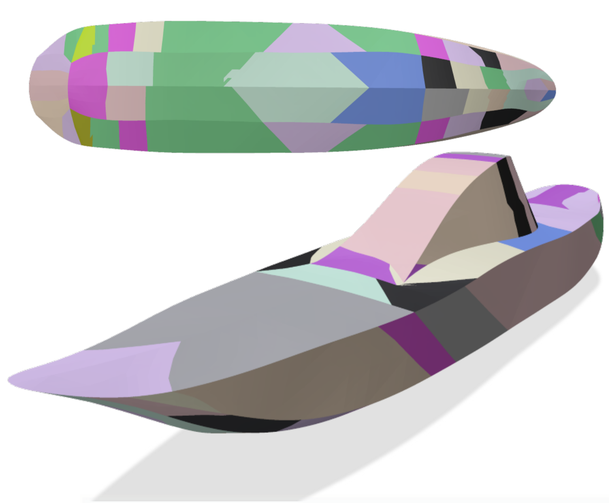
M. Ladeuil, M. Trabucato, A. Vaisse and N. Faraj
University of Montpellier, CNRS, LIRMM, France
Virtuos

## PROBLEM

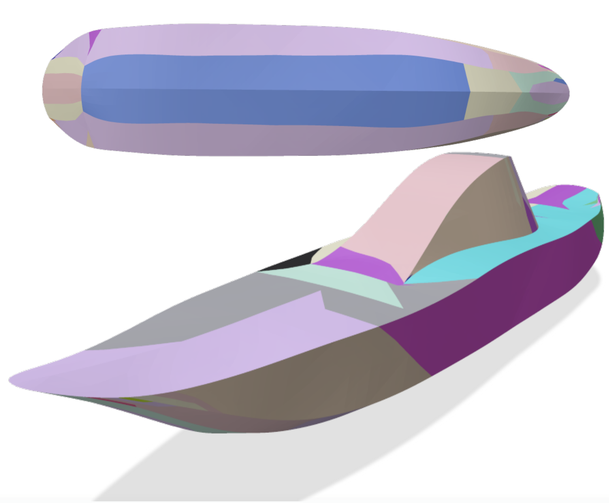
Identifying and preserving sharp features in 3D shapes is a fundamental challenge in geometry processing, with direct implications for geometric mesh clustering. Previous work by Garland [1] fails to capture sharp features, we propose to use an adjacency metric as a single linkage term, to delay merging of clusters separated by a sharp feature. By leveraging persistent homology, we quantify the stability of geometric features and emphasizing the most persistent.

We construct a weighted feature graph : edges are boundaries of hierarchical face clustering and edge weights encode the persistence of geometric features across scales. Our target application is a feature aware k-way partitioning.

Garland's Hierarchical Clustering



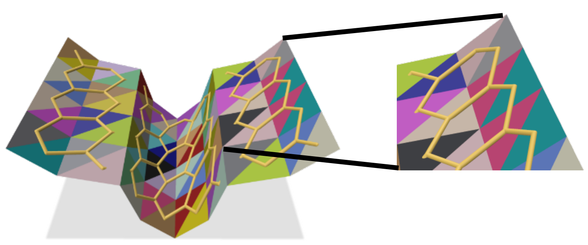
Our Hierarchical Clustering



## METHODOLOGY

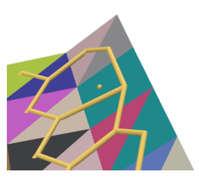
### HIERARCHICAL FACE CLUSTERING

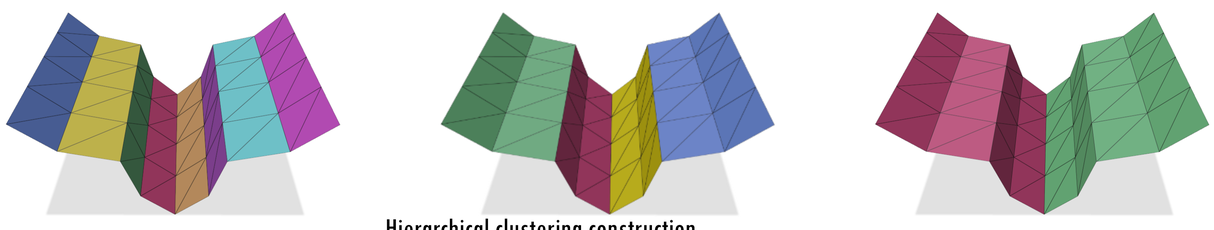
Starting from the mesh dual graph, we perform edge contraction between the nodes resulting in a hierarchical clustering.



Edge collapse

Cluster merging





Hierarchical clustering construction

We use an adjacency metric combined with Garland's metric of normal deviation between clusters:

$$E = w_{adjacency} * E_{adjacency} + w_{dir} * E_{dir}$$

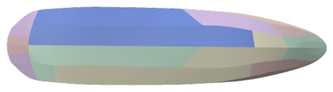
$$E_{adjacency,a,b} = 1. - 0.5 * (1 + \mathbf{n}_{i,a}\mathbf{n}_{j,b}{}^{\top})$$

$$E_{dir,a,b} = \frac{1}{w}\sum_i w_i \left(1 - \mathbf{n}_a^{\top}\mathbf{n}_{i,b}\right)^2$$

Max adjacency

Sum of adjacency

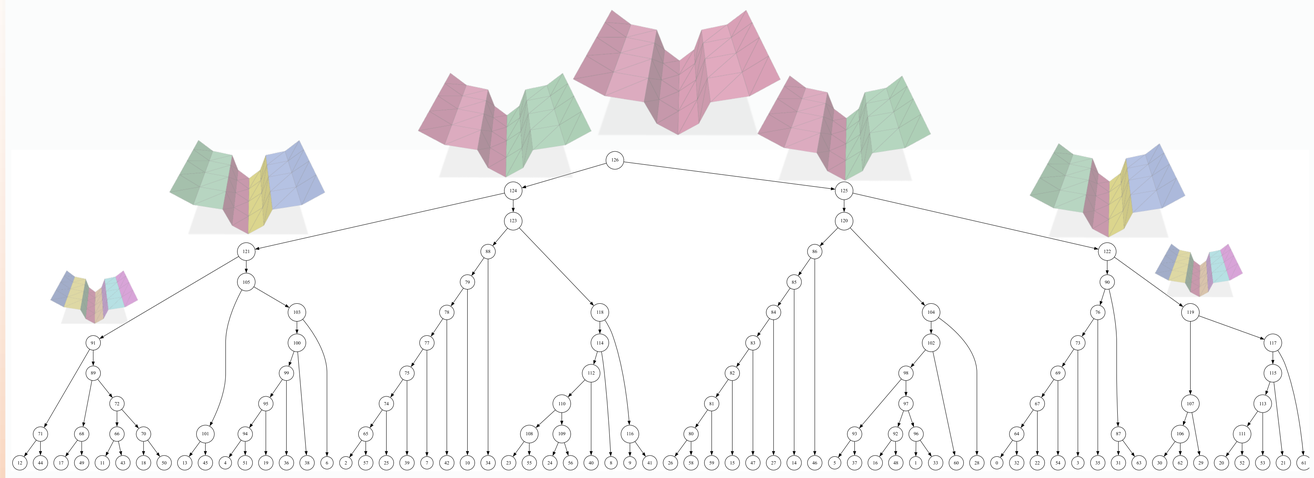
Average adjacency

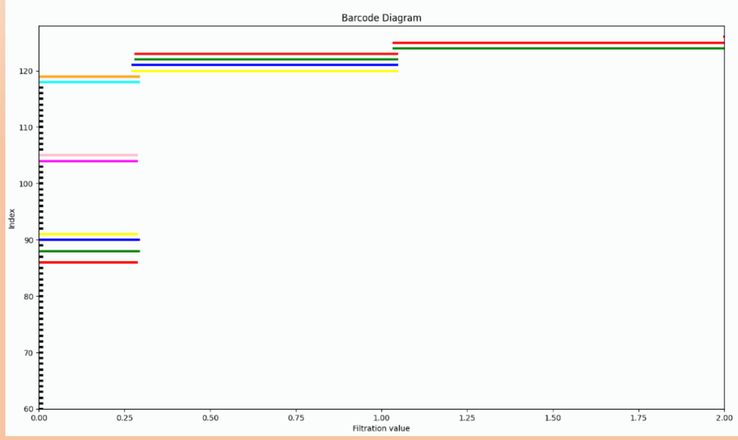


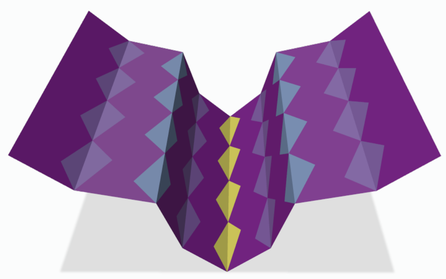
The **adjacency metric** prevents merging of clusters separated by a strong feature.

### PERSISTENT HOMOLOGY

We leverage **persistent homology** a method for computing the evolution of topology at varying scale. In our work, a topological change occurs when merging clusters. Thus, we use persistent homology and record the birth and the death of a given topological feature according to our metric of simplification. Persistent feature have a longer lifespan and are plotted with a Barcode Diagram.





We extract our weighted feature graph, for each boundary edge node as the maximum of the nodes' persistence.

## RESULTS

Wadj = 1. , Wdir = 0.

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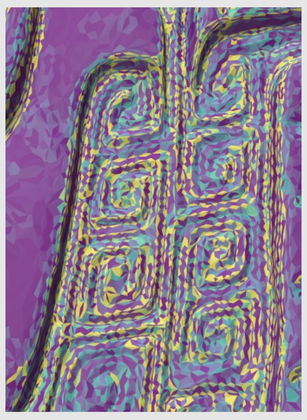
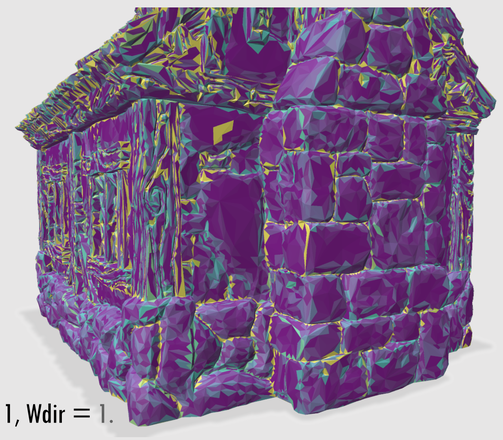
Wadj = 0., Wdir = 1.

Wadj = 0.1, Wdir = 1.

Our approach is heavily dependent on the metric, yet we have shown an interesting application of persistent homology to construct a weighted feature graph, future works will include in depth exploration of different metrics.

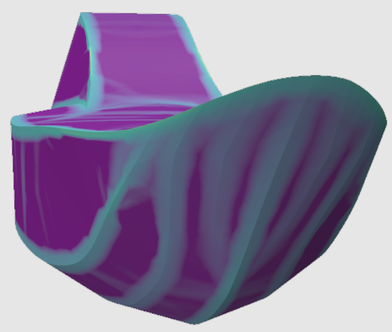


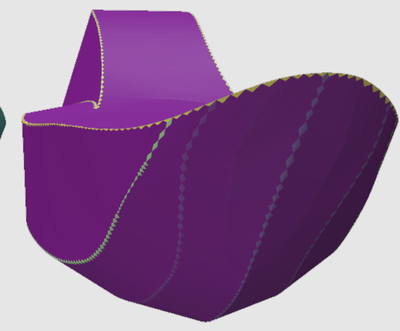


Wadj = 1, Wdir = 1.

## COMPARISONS

As opposed to our method, curvature does not provide continuous feature lines





Wadj = 1. , Wdir = 0.

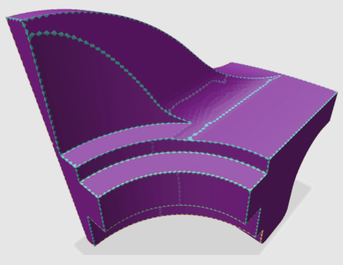
## K-WAY PARTITIONING

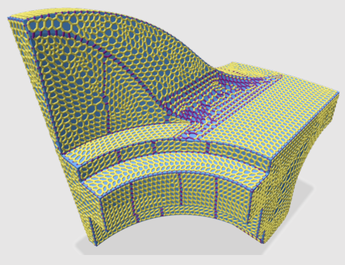
Our original goal for this work is to introduce a feature aware metric in the weights of the dual graph, before applying k-way partitioning algorithm so, cluster boundaries are attracted to features.

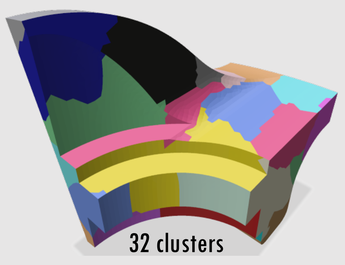
Uniform weights

Our weights

We can see on the fandisk that sometimes the k-way partitioning algorithm does not entirely follow the feature lines because there is also balanced partitions, we could do a regularization step to alleviate this.







32 clusters

256 clusters

## REFERENCES

[1] Garland , Willmott & Heckbert (2001). Hierarchical Face Clustering on Polygonal Meshes. Proceedings of the Symposium on Interactive 3D Graphics.
[2] Edelsbrunner, Letscher, & Zomorodian (2002). Topological persistence and simplification. Discrete & computational geometry 28

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