

Spectral-based Vertex Re-labeling for Mesh Segmentation

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Abstract Mesh segmentation can be achieved by considering (a) geometric, (b) topologic or (c) a combination of geometric and topologic features on the surface. Although considering geometric characteristics would be relatively easy, our main intention is to keep the discussion on the topological aspect given that topology-based methods are foggy in their basic understanding impairing consistent application. This article re-labels the vertices of the mesh based on the Fiedler vector (Laplacian 2nd eigenvector) for encoding the connectivity among part feature sub-meshes. Second differences of such vector with respect to the re-labeling are computed after a filter has been applied to determine the mesh partition. The segmentation achieved by the proposed algorithm locates properly several topological features, provided the homogeneity of the triangular mesh.

Keywords mesh segmentation · spectral analysis · Fiedler vector

1 Introduction

In CAD CAM CAE, mesh segmentation is an important task in areas such as mesh animation, surface parameterization, mesh compression and shape processing. The problem of mesh segmentation consists of breaking up the mesh of a connected surface into a set of smaller sub-meshes which together compose the original one. Such partition usually require that the computed sub-meshes have special properties such as being developable, having similarities to prim-

itive shapes (e.g spheres or cylinders) or being similar to previously known features (such as human body parts for classification [1]). Usually a geometric approach is followed where local properties of the surface are used for defining partition boundaries. However, in several cases topologic features may be relevant for the desired partition and cannot be determined by the geometric approach. The spectrum of the Laplace-Beltrami operator is known to capture such topologic properties of the surface and given its connection to graph Laplacian from spectral graph theory, it has been widely used for graph and mesh segmentation [2]. This article presents an algorithm where the Fiedler vector (Laplacian 2nd eigenvector) is used to re-label the vertices of the mesh. Afterwards, second differences are computed on the re-labeled Fiedler vector and a simple filtering algorithm (moving average) is then used to detect segmentation thresholds for the desired partition.

2 Literature review

Mesh segmentation algorithms can be classified in one of the following classes depending on which data is relevant for the segmentation: i) Geometry-based algorithms extract geometric data from the mesh such as geodesic distances [3] or local curvatures [4] and partition it using clustering algorithms (e.g. k -means) or by region-growing techniques [5]. ii) Topology-based algorithms on the other hand, rely on the features lying on the structure of the mesh. Algorithms such as Graph cuts [6] and Reeb graphs [7] locate partition boundaries by finding high topological changes in the Laplacian mesh graph. iii) Mixed-approach algorithms consider both geometric and topological aspects. Weighted Laplacians are usually used in this context where sharp features are assigned with low connectivity and then the spectrum of such Laplacian is used for segmentation [2]. All pre-

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vious algorithms either lack or are foggy about the relevant topologic information such as number of Laplacian eigenvectors and cutting thresholds.

3 Methodology

Fig. 1 presents the Fiedler vector of two full graphs connected by a single edge. The vertices labeled from 1 to 10 correspond to the first full graph while vertices from 11 to 20 correspond to the second graph. The gap between vertices 10 and 11 illustrates how low connectivity regions present high changes in the Fiedler vector with respect to this ordering. Based in this fact, our segmentation algorithm computes the graph Laplacian and Fiedler vector of the mesh. The Fiedler vector is then sorted in ascending order and the vertices of the mesh are re-labeled according to the sorting. Low connectivity areas will present higher rates of change with respect to the re-labeling while low connectivity areas will present low change rates. These abrupt changes can be identified by a second order derivative. Therefore, second differences of the Fiedler vector with respect to the re-labeling are computed. To compute segmentation thresholds, values of the Fiedler vector where the second differences attain a local maximum are selected as the segmentation values.

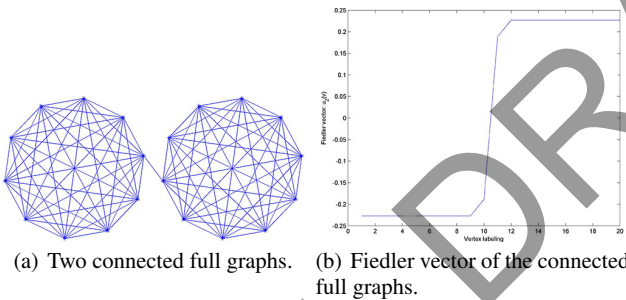


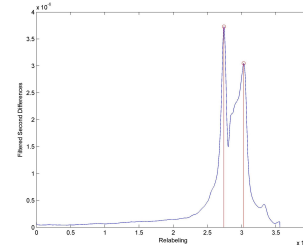
Fig. 1 Two full graphs of 10 vertices connected by a single edge and its corresponding Fiedler vector.

Due to the sampling, the second differences vector may present high noise complicating the computation of local maxima for the selection of segmentation thresholds. To overcome this problem, we propose to smooth the second differences vector with a (moving average) filter prior selection of thresholds.

4 Results

Fig. 2 presents the segmentation results for the Iron dataset. Fig. 2(a) plots the computed second differences (after the moving average filter has been applied) of the mesh Fiedler vector against the re-labeling. The red lines indicate the thresholds for segmentation chosen by finding the global maxima

of the second differences vector. Fig. 2(b) presents the segmented model where clearly 3 sub-meshes are identified by locating topological changes i.e., two zones of high connectivity (red and blue) are separated by a low connectivity region (green).



(a) Second differences of the Fiedler vector for the Iron dataset and segmentation thresholds (red). (b) Topology-based segmentation of the Iron dataset.

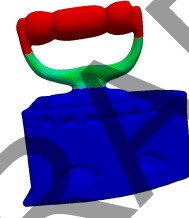


Fig. 2 Selection of the segmentation thresholds and resulting partition for the Iron dataset.

5 Conclusions and Future work

This manuscript presented an alternative to mesh segmentation based on the second differences of the Fiedler vector. Adequate segmentation could be achieved with only topologic features extracted from the mesh graph Fiedler vector. Future work addresses iterative application of the algorithm to progressively partition all features of the mesh.

References

1. Liu X., Zhang J., Liu R., Li B., Wang J. and Cao J., Low-rank 3d mesh segmentation and labeling with structure guiding, *Computer & Graphics*, 46(0), 99-109(2015)
2. Wang H., Lu T., Au O. K. C. and Tai C. L., Spectral 3d mesh segmentation with a novel single segmentation field, *Graphical Models*, 76(5), 440-456 (2014)
3. Cheng S. C., Kuo, C. T. and Wu D. C., A novel 3d mesh compression using mesh segmentation with multiple principal plane analysis, *Pattern Recognition*, 43(1), 267-279 (2010)
4. Tsuchie S., Hosino T. and Higashi M., High-quality vertex clustering for surface mesh segmentation using student-t mixture model, *Computer-Aided Design*, 46(0), 69-78(2014)
5. Yan D. M., Wang W., Liu Y. and Yang Z., Variational mesh segmentation via quadric surface fitting, *Computer-Aided Design*, 44(11), 1072-1082 (2012)
6. Brown S., Morse B. and Barrett W., Interactive part selection for mesh and point models using hierarchical graph-cut partitioning, *Proceedings of Graphics Interface*, 23-30 (2009)
7. Patane G., Spagnuolo M. and Falcidieno B., Reeb graph computation based on a minimal contouring, *IEEE International Conference on Shape Modeling and Applications*, 73-82 (2008)