

Robust Segmentation of Voxel Shapes using Medial Surfaces

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Abstract

We present a new method for robustly decomposing a 3D voxel shape into disjoint segments using the medial surface, also called surface skeleton. The boundaries of the simplified fore- and background skeletons map one-to-one to increasingly fuzzy, soft convex, respectively concave, edges of the shape. Using this property, we build a method for segmentation of 3D shapes which has several desirable properties. Our method robustly segments both noisy shapes and shapes with soft edges which vanish over low-curvature regions. As the segmentation is based on the skeleton, it reflects the symmetry of the input shape. Finally, multiscale segmentations can be obtained by varying the simplification level of the skeleton. We present a voxel-based implementation of our approach and illustrate it on several realistic examples.

1. Introduction

Shape segmentation is an important pre-processing step in many applications. The type of segments produced depend on the intended application, so a wealth of methods exist. Segmentation methods can be categorized by the type of segmentations they produce. *Patch-type* methods are geometry-oriented, typically use local shape information such as surface curvature, and produce segments that are quasi-flat and separated by high-curvature edges. *Part-type* methods, on the other hand, are more semantically-oriented, i.e. they try to find segments that a human would intuitively perceive a distinct logical parts of the shape. Such segments are not necessarily separated by high-curvature edges.

An issue with many patch-type methods is that they are ill-suited to handle shapes with smooth, low-curvature edges. Such methods distinguish the six faces of a box for example, but have problems finding these faces when the edges are smoothed. Noisy shapes might be problematic and might result in over-segmentation. We propose a patch-type segmentation method that addresses these problems by using the shape's simplified surface-skeleton. Our method

works on voxel shapes, in which the shape is sampled on a regular grid: a representation often used in the discrete-geometry and medical-imaging communities. Segmentation of voxel data brings its own difficulties. The notion of an edge is implicit, resolution of the data is typically low, the data contains discretization artifacts and other noise, and boundary normals are not readily available.

2. Overview

Each surface-skeleton point has at least two points on the shape's boundary at minimum distance, called feature points. Following [2], we simplify the skeleton using the medial geodesic function [1], which is defined as the shortest geodesic length between pairs of feature points. This importance measure ρ is lowest near the periphery of the skeleton, and increases toward its center. A simplified skeleton \mathcal{S}_τ is obtained by imposing a threshold τ on ρ . The feature points of the simplified skeleton disappear first on the small-scale features of the shape. Hence, spurious skeleton parts due to boundary noise can be eliminated by choosing τ higher than the noise level τ_n . The key idea is that by further increasing the level to $\tau = \tau_n + \tau_e$, the gaps in the feature points of \mathcal{S}_τ are further opened near convex shape edges, which we detect. Likewise, the skeleton of the shape's outside volume, or background, can also be computed and is used to detect concave edges. When combined, the detected convex and concave edges induce a number of connected components. The edges are eroded in a normal-sensitive manner to come to the final segmentation. Figure 1 illustrates our approach.

3. Results

We tested our implementation on various voxel shapes with resolutions ranging up to 300^3 voxels. Our approach has several desirable properties. First, we can detect soft and vanishing edges. For both weak and strong edges, setting a threshold of τ ensures gaps of at least width τ , regardless of the edge strength. Figures 2b,c show the segmentations of a smooth X- and H-shape. The vanishing

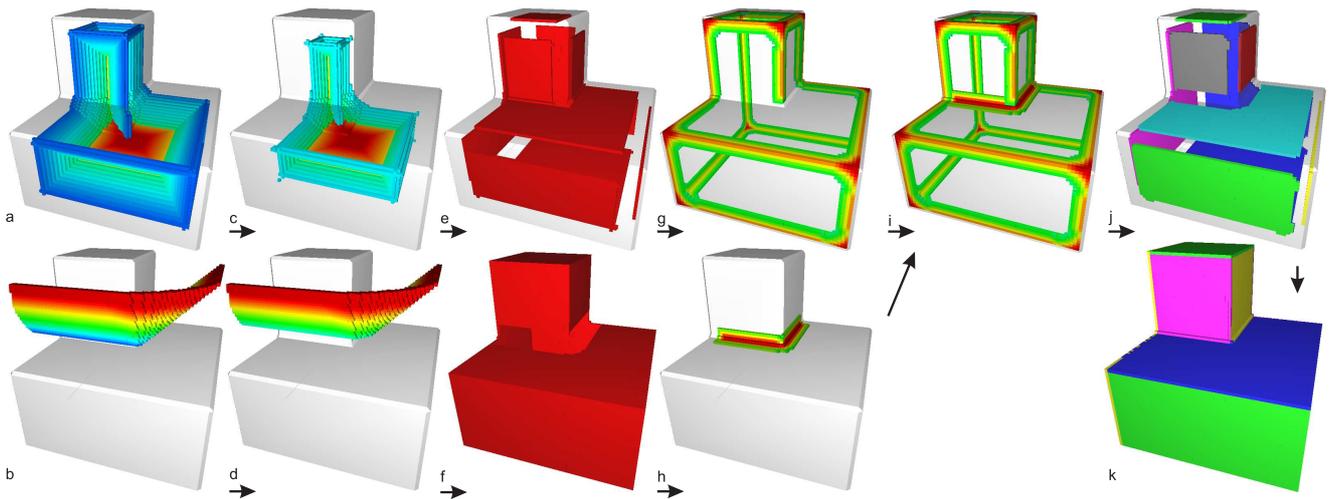


Figure 1. Overview. Fore- and background skeletons (a,b), color-map encodes importance measure. Simplified skeletons (c,d). Gaps in feature points (e,f). Convex edges (g). Concave edges (h). Combined edges (i). Connected components (j). Final segmentation (k).

edges of the shapes are detected well, and sharp, straight, segment borders are produced for them by the edge erosion step. Second, our method handles noisy shapes (e.g. Fig. 2d), as it uses the simplified surface-skeleton. For noisy shapes the scale parameter τ is set to at least τ_n , such that the skeleton does not contain any spurious parts due to noise. Noisy shapes are difficult to handle using traditional curvature-based segmentation approaches. Nevertheless, for very noisy shapes the feature points of \mathcal{S}_τ may become too sparse, potentially resulting in over-segmentation. Third, multiscale segmentations can be created by increasing the scale parameter τ beyond the noise level. Figs. 2e,f show two such coarse-scale segmentations. A feature of our method is that the coarse segment borders do not necessarily lie at curvature creases. Indeed, the simplified skeleton represents a smoothed version of the shape.

A few limitations exist. We have defined segments as the connected components in the non-edge voxels: a segment should be completely bordered by convex and/or concave creases. Second, for thin shape parts we might not detect weak corners.

References

- [1] T. K. Dey and J. Sun. Defining and computing curve-skeletons with medial geodesic function. In *Proc. of EG Symp. on Geometry Processing*, pages 143–152, 2006.
- [2] D. Reniers, J. J. Van Wijk, and A. Telea. Computing multiscale curve and surface skeletons of genus 0 shapes using a global importance measure. *IEEE TVCG*, 14(2):355–368, 2008.

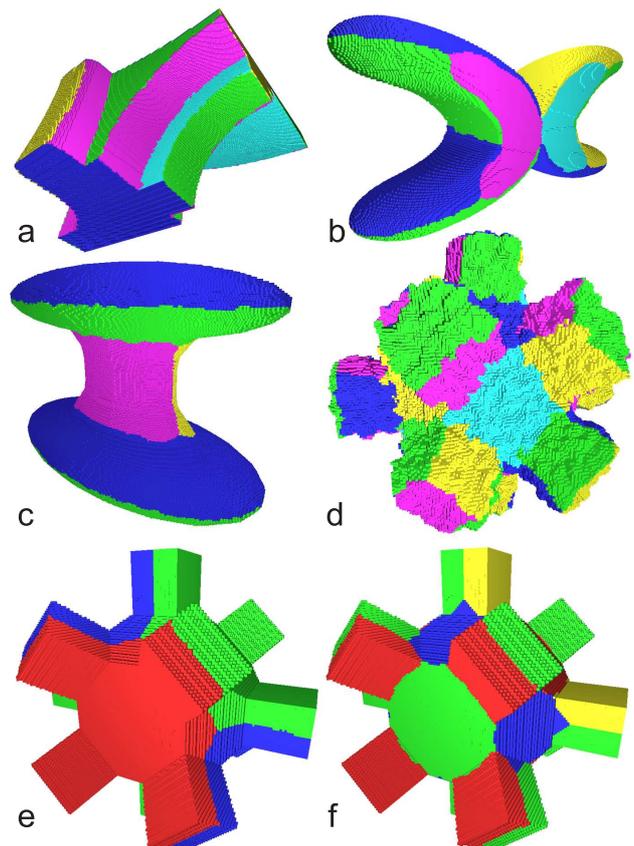


Figure 2. Results