Robust Segmentation of Voxel Shapes using Medial Surfaces

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Robust Segmentation of Voxel Shapes using Medial Surfaces

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ABSTRACT

We present a new patch-type segmentation method for 3D voxel shapes based on 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 demonstrate it on several examples.

Index Terms: I.3.5 [Computer Graphics]: Computational Geometry and Object Modeling—Geometric algorithms, languages, and systems;

1 INTRODUCTION

Shape segmentation is an important pre-processing step in many applications ranging from shape analysis, computer vision, compression, and collision detection. 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 also be problematic and 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 produces segmentations of 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. In contrast with mesh representations, the notion of an edge is implicit in the voxel representation. Furthermore, the resolution of the data is typically low, the data contains discretization artifacts and other noise, and boundary normals are not readily available.

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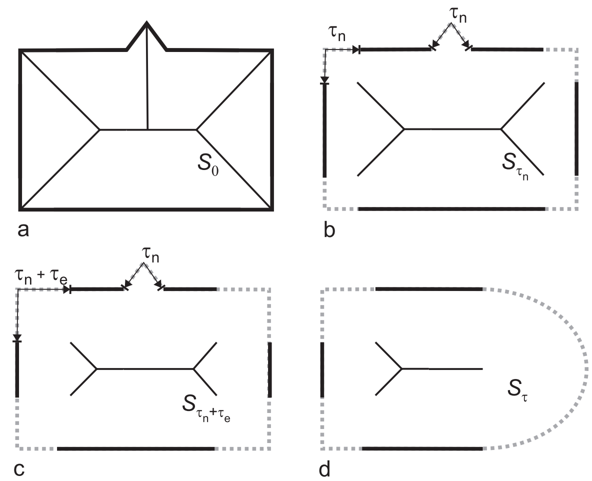

Figure 1: Non-simplified skeleton (a). Simplified skeleton at scale τ_n (b). Simplified skeleton at scale $\tau_n + \tau_e$ (c). Large gap due to round part (d). Thick lines represent feature collections V^{Ω}.

2 METHOD

Each point p on the surface skeleton $\mathscr{S}$ of a shape Ω has at least two points on the shape's boundary at minimum distance, called its *feature points*. Following [2], we simplify the skeleton using the medial geodesic function [1], which is defined as the shortest geodesic length between feature-point pairs. This importance measure ρ is lowest near the periphery of the skeleton, and increases toward its center. A simplified skeleton $\mathscr{S}_\tau$ is obtained by imposing a threshold τ on ρ. Let V^{Ω} be the set of feature points due to the simplified skeleton, called the *feature collection* of $\mathscr{S}_\tau(\Omega)$. Likewise, the feature collection $V^{\bar{\Omega}}$ of the background skeleton $\mathscr{S}_\tau(\bar{\Omega})$ can also be computed.

The key idea of our approach is that, by increasing the threshold τ on the importance measure ρ, gaps will appear in the feature collection V on and near shape edges (Fig. 2e,f), which we can detect. However, the parameter τ is also used to prune spurious skeleton parts that are due to boundary noise. Setting τ to the noise level τ_n opens V on the edges, but also on noisy parts. Therefore, we further increase τ to $\tau_n + \tau_e$: the feature collection V is opened further on edges, but not on boundary noise. This is illustrated in Fig. 1 in the 2D case (for the sake of clarity). In Fig. 1a, the non-simplified skeleton $\mathscr{S}_0$ of a box with a noise bump is shown. The feature collection (thick lines) covers the whole boundary. When τ is set to the noise level τ_n (Fig. 1b), the openings in V^{Ω} on the bump and near the non-noisy convex corners have the same size, so that we cannot differentiate between the two situations. By further increasing τ to $\tau_n + \tau_e$ (Fig. 1c), V^{Ω} is further opened on the corners, but not on the bump.

Hence, we can detect convex and concave edges by computing for each boundary point the geodesic distance to the feature collection of the fore- and background skeleton respectively: points at a distance of at least $\frac{1}{2}\tau_n$ are detected as edge points. The setting of

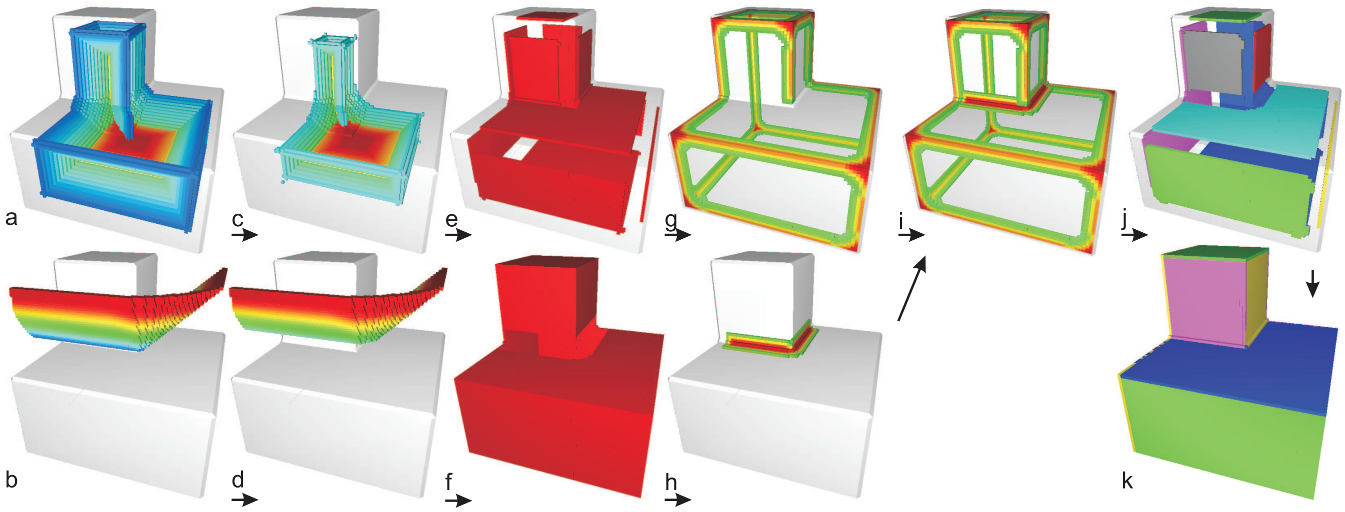

Figure 2: Overview. Fore- and background skeletons (a,b), color-map encodes importance measure. Simplified skeletons (c,d). Gaps in feature points (e,f). Convex edges (g). Concave edges (h). Combined edges (i). Connected components (j). Final segmentation (k).

τ_e controls the minimum detected edge width. In our voxel-based implementation, we verified that setting $\tau_e \geq 4$ gives good results. All in all, the combined convex and concave edges (Fig. 2i) divide the boundary into a set of connected components (Fig. 2j). The edges are then eroded in a normal-sensitive manner to come to the final segmentation (Fig. 2k).

The edge width parameter τ_e controls the minimum width of the detected edges, but not the maximum. In case of round parts of the shape (Fig. 1d), the openings in V and thus the edges might become thicker than τ_e. Both thick and thin edges are handled by the edge erosion step.

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 3b,c show the segmentations of a smooth X- and H-shape. The vanishing 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. 3d), 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 collections may become too sparse, potentially resulting in over-segmentation. Third, multiscale segmentations can be created by increasing τ_n beyond the noise level. Figs. 3e,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 edges.

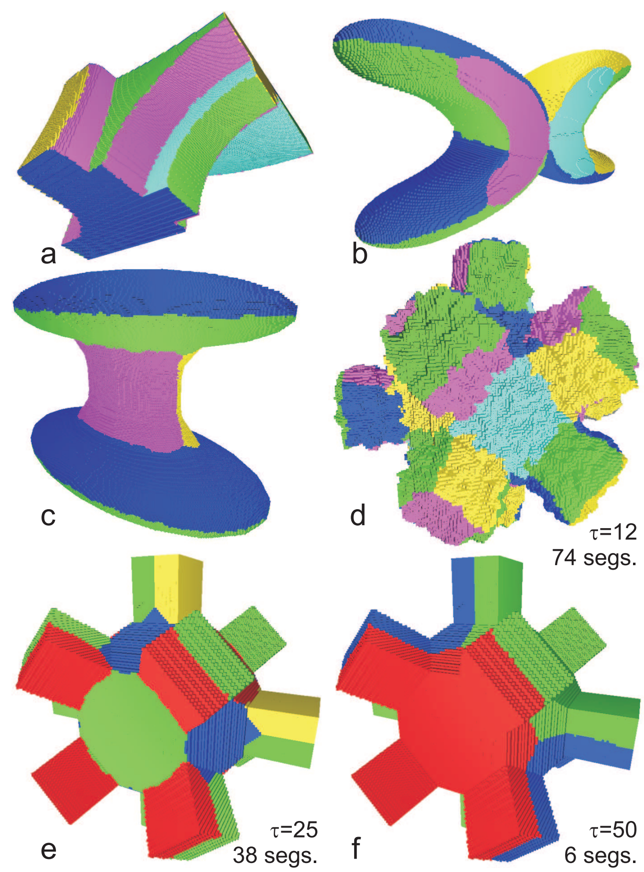

Figure 3: Segmentation results. Shape with high-curvature edges (a). Shapes with soft edges (b,c). Noisy shape (d). Multiscale segmentations (d,e,f).

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