ICF: A Shape based 3D Segmentation Method

Koji Kobayashi
koji.kobayashi@vocsis.com
Vocsis Corporation

Koichi Ito
ito@aoki.ecei.tohoku.ac.jp
Tohoku University

Takafumi Aoki
aoki@ecei.tohoku.ac.jp
Tohuku University

ABSTRACT

As a new method that can contribute to 3D shape analysis, we propose Incremental Contour Flow (ICF), which divides a 3D object into segments separated by boundary surfaces at narrow parts. ICF utilizes a property of distance transform that generates local maxima in a center of swollen part and bottleneck-like structures in a narrow part. Core of segment is defined as a local maximum layer that has a higher value than surrounding layers in a layer structure generated by converting the distance values to integers. Voxels in a surrounding layer of a core are added to the core incrementally, thereby 3D voxels are grouped to as many segments as the cores. As shown in an example to be discussed, ICF can generates combined soap bubble-like boundary surfaces from a 3D object made from merged three spheres. Since human organs tend to be distinguished by its shape in medical 3D images, ICF can be useful in the medical imaging applications.

CCS CONCEPTS

• **Computing methodologies** → **Volumetric models**; **Shape analysis**; Shape representations.

KEYWORDS

distance transform, 3D shape, segmentation, ICF

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1 INTRODUCTION

3D shape analysis is a difficult task due to its complexity, and much work has been done on the subject. They can be divided into two major categories. One depends on prior knowledge, the other does not. The former uses models, atlases, or training data set as prior knowledge. In the field of medical applications, U-Net [Jonathan et al. 2015] has recently received wide attention. The latter describes 3D objects by methods such as point clouds, spherical harmonics, statistical shape models or medial axis [Telea and Jalba 2012], and tries to recognize a new object by comparing model parameters.

ICF is a method that divides a 3D object into as many segments as the local maxima of distance transform. In other words, ICF can reduce the complexity of a 3D shape by dividing it into segments representing the local maximum.

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2 PROPOSED METHOD

Since the distance transform [Saito and Toriwaki 1994] calculates a Euclidean distance from each voxel constituting a 3D object to its nearest voxel on outside of boundary, the distance generates local maxima at a center of swollen part and has bottleneck like structures in narrow part.

ICF utilizes this property of the distance transform. The distance values are converted to integers, and iteratively enclosed contour layers are generated. Among the layers, one having a larger distance value than the adjacent layers is defined as a local maximum layer. Each of the local maximum layer becomes a core by being given a unique number by labeling. Extending the cores incrementally by adding adjacent voxels in the surrounding layer to the cores, the binary 3D data is divided into as many segments as the local maximum layers.

2.1 Isotropic Voxel Data

The input to the ICF is binary 3D data composed of unit cube voxels. For medical 3D data where the physical pitches between the two axes of tomographic images and the pitch of the images are different, the data is either resampled to an isotropic voxel space, or the pitches of the axes are set to 1 regardless of its physical sizes.

2.2 Distance Transform

Euclidean distance $d(a, b)$ between a voxel at $\mathbf{a} = (a0, a1, a2)$ and a voxel at $\mathbf{b} = (b0, b1, b2)$ is

$$d(\mathbf{a}, \mathbf{b}) = \sqrt{(a0 - b0)^2 + (a1 - b1)^2 + (a2 - b2)^2} \tag{1}$$

A 3D shape is defined in the 3D voxel space where a set of foreground voxels Sf have value 1, and the rests of the voxels as a set of background Sb have value 0.

$$\begin{aligned} Sf &= \{\mathbf{p} \mid f(\mathbf{p}) = 1\} \\ Sb &= \{\mathbf{q} \mid f(\mathbf{q}) = 0\} \end{aligned} \tag{2}$$

The distance transform $f^D(p)$ converts the value of the foreground voxels at p to a distance from a nearest background voxel q.

$$f^D(\mathbf{p}) = \min_{\mathbf{q}} d(\mathbf{p}, \mathbf{q}) \tag{3}$$

2.3 Contour Layer Generation

By converting the distance values to integers by rounding, a structure consisting of iteratively enclosed contour layers is generated.

2.4 Core Generation

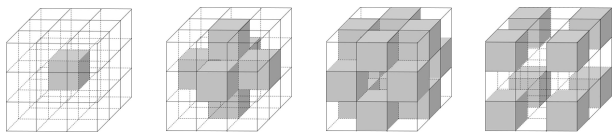
A contour layer having a distance value larger than adjacent layers is defined as a local maximum layer. The local maximum layer can be restated as a layer that contains no other layer inside. A core is

defined as a local maximum layer being given unique identification number by applying labeling to the local maximum layers.

2.5 Core Extension

Cores are extended by repeatedly adding adjacent voxels of the surrounding layer to the cores until all voxels of the surrounding layers have been added to either of the cores. The extension process is repeated on layers of a distance value, while the distance value starts from (largest distance - 1) down to 1. All voxels of the layers are added to either of the cores, and the segments are generated.

The adjacency between a voxel of a core to a voxel of a surrounding layer is defined in three modes: surface contact mode, line contact mode, and point contact mode, as shown in Figure 1. The extension process is executed for each mode in the order of surface, line, and point contacts per distance between voxels the shorter the earlier, where distance between voxels is 1, $\sqrt{2}$, $\sqrt{3}$, respectively. This measure equalizes the extension rates to directional difference.

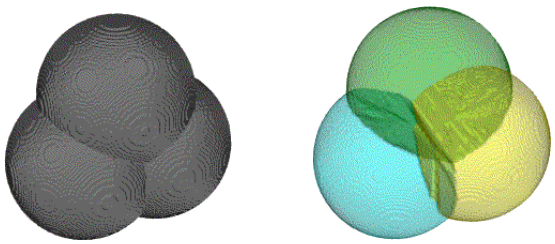


(a) (b) (c) (d)

Figure 1: A voxel (a) has 6 surface-contact voxels (b), 12 line-contact voxels (c), and 8 point-contact voxels (d).

3 EXPERIMENTS

Figure2 shows an example applying ICF to a shape in which three spheres are merged (a) to show the basic segmentation performance of ICF. It has been shown that ICF divides the shape into three segments (b) that correspond to the original spheres by boundary surfaces with small unevenness so that the segments look like three soap bubbles are stuck together.

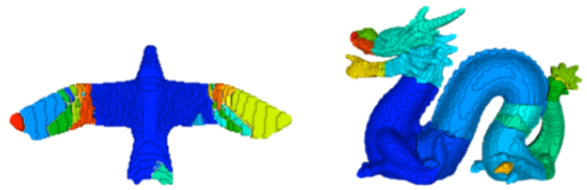


(a) Merged three spheres **(b) ICF segmented**

Figure 2: Three spheres with a radius of 50 are placed in a 200x200x200 space at vertices of an equilateral triangle. Positions of the spheres are slightly rotated so that boundary surfaces are not parallel to any of the axes to make the surfaces contain realistic noises.

Figure3 shows the results in which ICF is applied to 3D models available in the public domain [University of Groningen]. The models are placed on 200x200x200 space, so they are scaled to fit by making the largest size of the model to 200. The segments are colored from blue to red in descending order of the voxel size of the segments.

(a) Armadillo, 16 segments, max distance 25.8 **(b) Horse, 15 segments, max distance 34.9**



(c) Bird, 26 segments, max distance 11.0 **(d) Dragon, 25 segments, max distance 22.1**

Figure 3: On the armadillo model (a), both ears and head are in a same segment as body because there is no local maximum layer in the parts. The bird model (c) is divided into more segments than the more complicated dragon model (d). It is shown that the wings of the bird model have relatively many local maximum layers due to its thinness.

4 CONCLUSION AND FUTURE WORK

It has been shown that ICF uniquely divides an arbitrary 3D object into segments of no narrowing part by referencing the local maxima and the contour structure obtained by distance transform. ICF is expected to contribute to the analysis and understanding of 3D object by reducing the complexity of 3D shape.

A promising application of this technology is to recognize internal organs, which are often identified by its shape. Segmentation methods that refer to voxel value change cannot be applied to such organs of respiratory, digestive, and circulatory systems, because substances of air, food, or blood pass through adjacent organs, respectively.

It should be noted that ICF can be extended to any dimension other than three, such as two or four dimensions as examples.

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