Segmentation by Evolution for Visualization of the Lower Extremity of the Visible Man

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Medical image segmentation is the crucial process for three-dimensional (3D) modeling. Many studies have claimed to suggest more accurate ways of segmentation. However, such research seems to have the drawback that it works against the parsimony principle. These methods have to resegment the regions of interest (ROIs) for the already segmented data, without taking advantage of the vast amount of past segmentation results. The present report proposes a "segmentation by evolution" method. It is an advanced segmentation paradigm that incorporates the existing segmentation results. The "segmentation by evolution" paradigm was applied to the color images of the Visible Human data.

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SEGMENTATION of medical image is an essential process in three-dimensional (3D) modeling. There have been rich research results in segmentation. Most previous research used one of the following segmentation methods: thresholding, boundary-based, region-based, and hybrid methods.¹⁻³ Among these, the hybrid techniques attempted to integrate boundary-based methods and region-based methods as complements for each other. Chakraborty and Duncan utilized game theory to incorporate region and edge information.³ Using more than two segmentation methods could be complementary for each other, but it could be counteractive in some cases. Until now, the segmentation methods focused only on improvement of the segmentation algorithm itself. However, it is not guaranteed that newly suggested algorithms would produce better segmentation results.

This report proposes the "segmentation by evolution" paradigm, which is an approach to producing better segmentation results by utilizing previously segmented results. Segmentation results themselves are evolved from the previous segmentation results.

SEGMENTATION BY EVOLUTION

The segmentation by evolution paradigm improves segmentation results by taking advantage of the previously segmented data. A whole segmentation process consists of several segmentation stages.

In this report, the proposed paradigm is applied

to segmentation of the Visible Human data. The segmentation process of the Visible Human data consists of two stages. The initial stage is manual segmentation. The second stage is the user-steered balloon that incorporates manual segmentation results as an initial guess of a region boundary.

MANUAL SEGMENTATION

The Visible Human data set is made by the National Library of Medicine (NLM) in the United States. The color images are segmented by our segmentation paradigm. In order to reconstruct a 3D model of the Visible Human, several radiologists manually segmented the color images of the Visible Human data set over 5 years. An example of the manual segmentation is shown in Fig 1.

The segmentation results are robust in that there are no major segmentation errors, but they are not sufficient for high-quality 3D reconstruction due to minor errors. In order to acquire better segmentation results, tens of thousands of regions in the color images of the Visible Human need to be resegmented. It is economical to take advantage of the previously segmented regions. The manual segmentation results are used to get better results in the second stage of the segmentation by evolution paradigm, which is the user-steered balloon.

USER-STEERED BALLOON

Here, we propose the user-steered balloon, which is a semiautomatic hybrid segmentation

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Fig 1. Example of manual segmentation.

method. A user selects several boundary points, which are connected by the live wire.⁴ Next, the acquired boundaries are extended to outside when possible. In the extension, classification of boundary segments is performed. Finally, hybrid region growing (HRG) segments the region with help of the extended boundaries.

As the second stage of the segmentation process for the Visible Human data, the user-steered balloon uses manual segmentation results instead of user input control points. Next, minimum cost paths connecting control points are computed. Then, extension of the boundary is performed and the HRGs are done.

MINIMUM COST PATH

Minimum cost paths between control points are computed by the live wire.⁴ The cost of a path is calculated as the sum of all local costs of connecting pixels from a start point to a goal point. Results of minimum cost paths are shown in Fig 2.

The live wire can have limitations. A zig-zag path can result if two adjacent regions are close. Figure 2 shows a zig-zag pattern.

EXTENSION OF BOUNDARY

To overcome limitations of the live wire, the live wire boundary is extended when possible. A boundary is divided into segments of small size. Each segment extends outside if it is classified as

Fig 2. Results of the live wire: zig-zag.

Fig 3. Results of boundary extension.

extensible. The results of the extension are shown in Fig 3.

HYBRID REGION GROWING

Once boundaries are extended, a region is segmented by the proposed HRG. The HRG is a more general version of the seeded region growing (SRG). The SRG cannot segment a region composed of several heterogeneous regions.

To overcome such limitations, we propose the HRG. It can segment a region composed of heterogeneous regions such as zebra. For this, the HRG receives several seed points that represent heterogeneous regions in the target region. In growing, each seed point grows as long as a homogeneity predicate is satisfied. In growing, the HRG distributes neighboring pixels to appropriate groups. A pixel is compared with all heterogeneous regions, and sent to the most similar region if similarity is within the threshold. Similarity larger than the threshold means that the pixel belongs to the background. This algorithm can collect all of the connected heterogeneous regions into a region. The HRG can faithfully segment regions whose color variance is large. The HRG produced good results in segmenting cross-sectional arm color images. The arm image consists of muscles, bone, and fat. The fat in the arm image has a relatively large color variance, and contains small spots of blood, whose color is similar to that of muscle. A segmentation result by the SRG is shown in Fig 4a. Only a portion of the fat region is segmented because color of the fat has large variance. This limitation might be overcome if a large range of color is to be classified as fat, which may result in leakage. A segmentation result by the HRG contains all of the fat areas as shown in Fig 4b. It can contain the blood areas spotted in the fat due to multiple region growing.

Fig 4. Segmentation results of arm image.

RESULTS

The segmentation by evolution paradigm is implemented to apply the segmentation of the Visible Human data. The algorithm is tested on segmentation of torso, arms, vastus muscle in leg, etc. Results of gracilis muscle segmentation are illustrated in Fig 5. The first stage of the segmentation process, manual segmentation, is shown in Fig 5a. The second stage of the segmentation process, the user-steered balloon, is shown in Fig 5b. Erosion errors of the manual segmentation are overcome at the second stage.

Two hundred twenty images of vastus, torso, left arm, and right arm muscle were also segmented. Evaluation of the segmentation results is performed at the viewpoint of 3D reconstruction. Experts on 3D reconstruction evaluated all of the images in two dimensions and reconstructed 3D images, and then classified accuracy of the segmentation. Images received scores of 95% to 90%.

Fig 5. Gracilis muscle segmentation.

CONCLUSION

This report proposed the segmentation by evolution paradigm, which improved segmentation results by taking advantage of the previously segmented results. The segmentation by evolution paradigm was applied to segmentation of color images of the Visible Human data set.

In the experiments of the proposed segmentation by evolution paradigm, all of the tested color images of the Visible Human data set produced improved segmentation results in the second stage, that is, the user-steered balloon. The errors in segmentation of the user-steered balloon come from either two visually attached regions or large variations of color values. When two muscles are visually attached, only experts in the radiology field can accurately segment the muscles. This requires another stage for the segmentation process. Errors occurred from large variations of color may be overcome by improving the user-steered balloon to accommodate these large variances.

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