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FINE SEGMENTATION USING GEOMETRIC ATTRACTION-DRIVEN FLOW AND EDGE-REGIONS

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ABSTRACT. A fine segmentation algorithm is proposed for extracting objects in an image, which have both weak boundaries and highly non-convex shapes. The image has simple background colors or simple object colors. Two concepts, geometric attraction-driven flow (GADF) and edge-regions are combined to detect boundaries of objects in a sub-pixel resolution. The main strategy to segment the boundaries is to construct initial curves close to objects by using edge-regions and then to make a curve evolution in GADF. Since the initial curves are close to objects regardless of shapes, highly non-convex shapes are easily detected and dependence on initial curves in boundary-based segmentation algorithms is naturally removed. Weak boundaries are also detected because the orientation of GADF is obtained regardless of the strength of boundaries. For a fine segmentation, we additionally propose a local region competition algorithm to detect perceptible boundaries which are used for the extraction of objects without visual loss of detailed shapes. We have successfully accomplished the fine segmentation of objects from images taken in the studio and aphids from images of soybean leaves.

1. INTRODUCTION

In the segmentation problems to extract objects from an image to make, for examples, 3D VR (virtual reality) contents or to estimate sizes of objects, a key issue is fine segmentation which means that the objects can be extracted without visual loss of detailed shapes. Our research is motivated by making 3D VR contents of commercial products. It makes an e-catalog that customers can browse a product in three dimensional virtual space on internet markets. A common way of making a 3D VR content starts from taking hundreds of photographs of a product with different view angles in

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a photo studio. The most difficult step is to extract the product from a background without visual loss of detailed shapes. The images taken in the studio have well-known difficulties in segmentation problems even though they usually have simple background colors and small amount of noises such as JPEG artifacts. The difficulties mainly come from lighting conditions in the studio and complex shapes of products. Most of lighting conditions make shadows which cause weak boundaries between dark objects and the background. More serious weak boundaries are produced by a reflection on some parts of an object due to bright lighting conditions and properties of materials of the object. It changes colors of objects into almost white which is normally used as a background color. Note that other simple colors on a background except white are not usually used because of color bleeding effect. In addition, there is another difficulty; shapes of objects can be highly non-convex.

There have been many boundary-based segmentation algorithms. The snake model in [1] has been a foundation of curve evolution based on the minimization of an energy. After a curve evolution was formulated by the level set method in [2], geodesic active contour model was introduced in [3] as the minimization of a weighted length. Although the model has many advantages over the classical snake, it has drawbacks such as dependence on positions of initial curves, incapacity for capturing weak boundaries changed smoothly from strong boundaries, and slow convergence in non-convex boundaries. Numerous modifications of the snake model and the geodesic active contour model have been developed to address these drawbacks. In [4], the gradient vector flow was proposed for a fast convergence to non-convex boundaries. In [5], a curvature vector flow was introduced to overcome a limitation of [4] for capturing highly non-convex shapes. In [6], the region-aided geometric snake was proposed for more robust detection of weak edges. If an object in an image has both weak boundaries and highly non-convex boundaries, most of boundary-based segmentation algorithms suffer from capturing such boundaries all around the object. Even though they may capture the boundaries, it is not enough to be a fine segmentation for extracting the detailed object from an image.

In this paper, we propose a fine segmentation algorithm for extracting objects in an image without visual loss of detailed shapes, which have both weak boundaries and highly non-convex shapes. There are two concepts, geometric attraction-driven flow (GADF) and edge-regions, which are combined to capture boundaries of objects in a sub-pixel resolution. Since an image is a two dimensional manifold, we obtain GADF by comparing two lengths of curves along the direction of the largest change in the manifold. Edge-regions contain most of edges. They are obtained by computing inward fluxes in the gradient field of a strength of edges. The main strategy to segment boundaries of objects is to construct initial curves close to objects by using edge-regions and then make a curve evolution in GADF. Both problems of dependence on positions of initial curves and slow convergence in non-convex boundaries are naturally solved because the initial curves are already close to objects regardless of shapes. Moreover, weak boundaries are captured because the orientation of GADF near boundaries of objects points to edges from each side of the boundaries regardless of strength of boundaries. According to the purpose of segmentation, for examples, fine extraction of objects or measurement of sizes of objects, we additionally propose a local region competition algorithm to obtain perceptible boundaries which are used for extraction of objects without visual loss of detailed shapes. We have successfully accomplished the fine segmentation of objects from images taken in the studio. Our algorithm can be applied to other kinds of segmentation problems by taking the appropriate strategy for selecting the edge-regions. An example is to extract aphids from images of soybean leaves. We may count the number of aphids that live on the sampled leaves and obtain an exact size of each aphid. Those information gives the appropriate time to dust powder in a huge farmland.

2. ALGORITHMS

The proposed algorithm consists of five steps to extract objects from an image without visual loss of detailed shapes even though there are weak edges and highly non-convex shapes. We derive GADF in Step 1. Regions which contain most of edges, which we call edge-regions, are detected in Step 2. Initial curves close to boundaries of objects are obtained in Step 3 from edge-regions. In Step 4, we segment objects by using a curve evolution in GADF with the initial curves from Step 3. For a fine segmentation, a post processing is needed in Step 5. The detailed explanation and derivation for each step is appeared in the paper

Step 1: Derivation of GADF. We derive a vector flow whose orientation near boundaries of objects points to edges from each side of the boundaries regardless of the strength of edges. We call the vector flow as geometric attraction-driven flow (GADF). GADF is obtained by a geometric analysis of eigenspace in a tensor field on a color image as a two-dimensional manifold. Note that the attraction term in the well-known segmentation algorithms [3, 4, 6] does not help to segment weak boundaries changed smoothly from strong boundaries because it is based on the gradient of the strength of boundaries. To the contrary, since the orientation of GADF is regardless of the strength of boundaries, GADF gives a possibility of capturing such weak boundaries in Step 4 when initial curves are close to objects. So, we will focus on finding such curves in Step 2 and Step 3.

Step 2: Detection of edge-regions. Edge-regions are roughly defined as a union of regions that include most of edges in objects. They are obtained by computing inward fluxes in the gradient field of a strength of edges. We use two steps to detect the edge-regions. The first step is to select candidates of edge-regions. It uses global constants applied to all images without considering an individual characteristic in each image. So, the candidates of edge-regions contain useful information in common all through similar images and also contain some points that are unnecessary or even harmful in finding initial curves close to objects. These points usually come from a lack of careful consideration for an individual characteristic in each image. Therefore, we focus on deleting bad candidates of edge-regions in the second step. The edge-regions will give important information in Step 3 to construct initial curves for the segmentation process.

Step 3: Construction of Initial Curves for Segmentation. The main goal in this step is to obtain initial curves for evolution of curves, which is the segmentation process in Step 4. Generally, initial curves close to objects in boundary-based segmentation algorithms [3, 4] solve both problems of dependence on initial curves and slow convergence in non-convex shapes. We will obtain such initial curves by connecting edge-regions along boundaries of objects. In [7], line connection algorithms for contour completion were proposed by using an anisotropic diffusion operator. With the algorithms, the edge-regions become thick due to the diffusion process and it is hard to decide how large areas to be regarded as connected edge-regions. Instead, we propose a Hamilton-Jacobi equation for a curve evolution.

Step 4: Segmentation using GADF and edge-regions. In Step 1, GADF was derived, whose orientation near boundaries of objects points to edges from each side of the boundaries, and initial curves close to the boundaries were obtained in Step 3 by connecting edge-regions in Step 2. In this step, we solve a simple advection equation in order to segment objects:

$$\begin{aligned} &\frac{\partial}{\partial t}\phi(x,t) + \vec{F}(x)\cdot\nabla\phi(x,t) = 0 \quad \text{in} \quad \Omega\times(0,T], \\ &\phi(x,0) = \psi(x) \quad \text{in} \quad \Omega, \end{aligned} \tag{1}$$

where $\vec{F}$ is the GADF and $\psi(x)$ is a signed distance function which has the zero level set as the curves obtained in the Step 3. It is the simplest equation which really works for segmenting both highly non-convex shapes and weak edges in images.

Step 5: Post processing. In the previous step, we may consider the result as a final segmentation. However, the result is not fine enough for extracting objects from images without visual loss of detailed shapes. People usually recognize a little bit outside of the boundaries as borders of objects because human vision perceives objects without missing any part of the objects. We call such borders as perceptible boundaries of objects. The perceptible boundaries make a big difference for extracting objects from images where colors of objects are changed gradually near boundaries. We obtain perceptible boundaries of objects by using a local region competition algorithm based on comparison of local probability density functions; see [8]. As the region competition algorithm is applied locally, we deduce a Hamilton-Jacobi equation which has a force term based on the difference between local probability density functions.

3. Examples and numerical aspects

We illustrate a whole procedure of the proposed algorithm in Figure 1. It has strong edges mostly and weak edges on the bottom due to shadow. The image (a) is original.

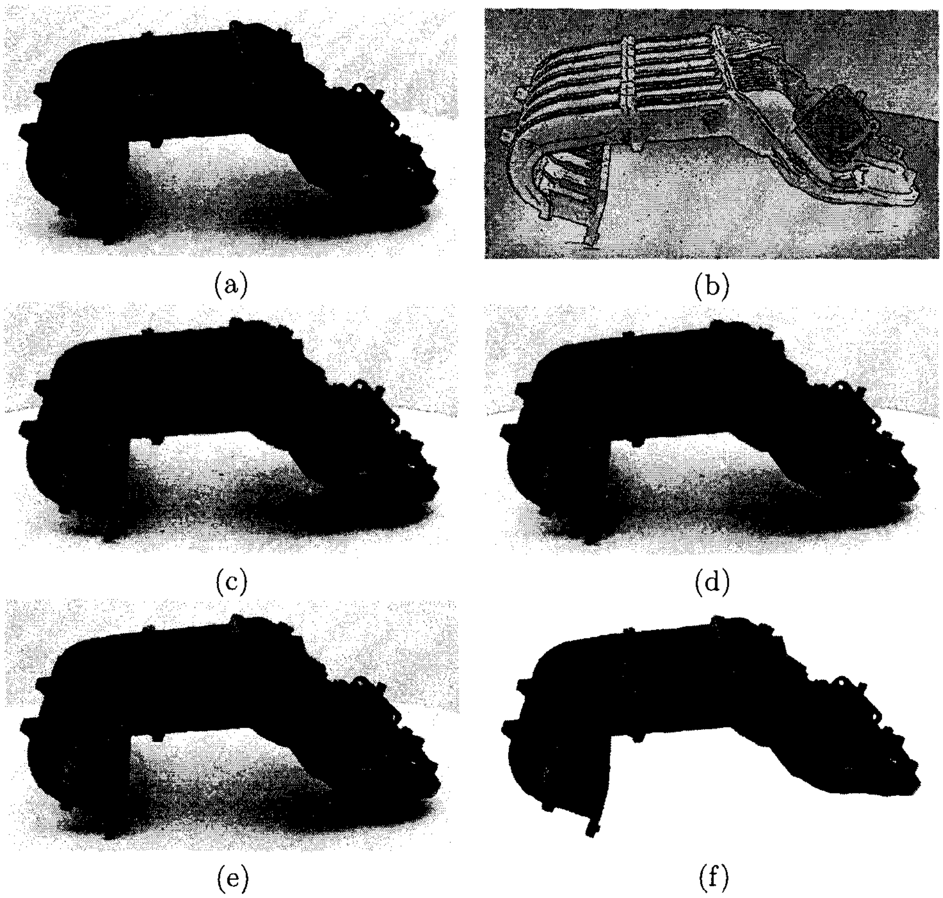

FIGURE 1. A procedure of a fine segmentation algorithm using GADF and edge-regions: (a) is an original image. The black regions in (b) are edge-regions. The curves in (c) are a result of step 3. In (d), initial curves for a segmentation process are shown. The curves in (e) are perceptible boundaries. The image in (f) is an extracted object on white background. The size of image is 940 by 544.

Edge-regions are shown in (b) where original image is overlaid with edge-regions. The curves in (c) are a result of step 3 which connects edge-regions. The curves in (d) are the initial curves for the segmentation process in Step 4. Note that they are close to boundaries of objects. From Step 5, we solve a PDE to obtain final curves in (e). We use an explicit Euler scheme for time discretization. For space discretization a simple upwind scheme is used in Step 3 and a nonoscillatory upwind scheme is used in Step 4 and 5; see [9] for details of numerical schemes. Every computation related to level sets is done by using fast local level set method [10]. A stopping criterion is given by measuring an error in a small band [11].

4. Conclusions

We introduced a fine segmentation algorithm for extracting objects in an image, which have both weak boundaries and highly non-convex shapes. The image has simple background colors or simple object colors with small amount of noises. The main strategy to segment the boundaries is to construct initial curves close to objects by using edge-regions and then to make curve evolution in GADF. Since the initial curves are close to objects regardless of shapes, highly non-convex shapes are naturally detected and dependence on initial curves in boundary-based segmentation algorithms is removed. Moreover, weak boundaries are captured because the orientation of GADF is obtained regardless of strength of boundaries. For a fine segmentation, we additionally propose a local region competition algorithm to detect perceptible boundaries which are used for extraction of objects without visual loss of detailed shapes. The proposed whole algorithm consists of five steps. In Step 1, we compute GADF and edge-regions are obtained in Step 2. In Step 3, we connect edge-regions in order to find initial curves close to objects for segmentation. From the initial curves, we obtain the boundaries of objects in Step 4. Based on results in Step 3 and 4, we finally obtain the perceptible boundaries of objects in Step 5. The proposed whole algorithm is able to extract objects from an image without visual loss of detailed shapes even though there are weak edges and highly non-convex shapes.

References

[1] M. Kass, A. Witkin, and D. Terzopoulos, Snakes: Active contour models, Int. J. Comput. Vis., 1 (1988), 321-331.

[2] S. J. Osher and J. A. Sethian, Fronts propagating with curvature dependent speed: Algorithms based on Hamilton-Jacobi formulations, J. Comput. Phys, 79 (1988), 12-49.

[3] V. Caselles, R. Kimmel, and G. Sapiro, Geodesic active contours, Int. J. Comput. Vis., 22 (1997), 61-79.

[4] C. Xu and J. L. Prince, Snakes, shapes, and gradient vector flow, IEEE Trans. Image Processing, 70 (1998), 359-369.

[5] D. Gil and P. Radeva, Curvature vector flow to assure convergent deformable models for shape modelling, Lecture Notes in Computer Science, Springer Verlag, Proceedings of EMMCVPR, Lisbon, Portugal 2003.

[6] X. Xie and M. Mirmehdi, RAGS: Region-Aided Geometric Snake, IEEE Transactions on Image Processing, 13 (2004),640-652.

[7] D. Gil and P. Radeva, Extending anisotropic operators to recover smooth shapes, Computer Vis. and Image Understading, 99 (2005), 110-125.

[8] S. C. Zhu and A. Yuille, Region competition: unifying snakes, regions growing, and Bayes/MDL for mutiband image segmentation, IEEE Trans. Pattern Anal. Machine Intell., 18 (1996), 884-900.

[9] G. Aubert and P. Kornprobst, Mathematical problems in image processing, Applied mathematical sciences **147**, Springer-Verlag, New York, 2002.

[10] D. Peng and B. Merriman and S. Osher and H. Zhao and M. Kang, A PDE-based fast local level set method, J. Comput. Phys., 155 (1999), 410-438.
[11] H. Zhao and T. Chan and B. Merriman and S. Osher, A variational level set approach to multiphase motion, J. Comput. Phys., 127 (1996), 179-195.

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