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Fast Automatic Saliency Map Driven Geometric Active Contour Model for Color Object Segmentation

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Abstract

Segmenting objects from color images to obtain useful information is a challenging research area recently. In this paper, a novel algorithm by combining a saliency map with an extension of a geometric active contour model is proposed to automatically segment the object of interest. The saliency map is first generated from the input image by a histogram based contrast method. The most salient regions are then detected as dominant parts of the object. After that, a contour is initialized using salient regions determined. Finally, by applying a geometric active contour model, the contour starts evolving iteratively to segment object boundaries. Experimental results attained on various natural scene images have shown that our proposed method is able to not only replace manual initialized contour and improve the accuracy, noise robustness of segmentation but converge to an optimal solution earlier than recent active contour models as well.

1. Introduction

Nowadays the usage of images is not only to save memories but also to extract their content as an input for higher processes such as image compression, object recognition, image retrieval, etc. Object segmentation becomes an attractive and important problem of image processing and computer vision. But there are still limitations applying to algorithms that try to identify arbitrarily shaped objects in color images.

Active contour models (ACMs) first introduced by Kass, Witkins, and Terzopoulos [1] and developed in turn by Osher and Sethian [2] as well as Chan and Vese [3] in the level set framework is one of basic segmentation methods for gray-scale images. Our work here modifies the energy functional of the ACM in [4] for color object segmentation. Although its results are promising, ACMs all need users' interactions as a requirement to control their progress. The segmenting performance mostly depends on the specified contour. Thus, an automatic initialization is necessary when semantic interactions are not determined.

To solve this issue, we suggest a novel model to automatically segment object boundaries based on a saliency map [5] and an extended ACM. Next, we describe our method with visual demonstration step by step. Section 3 has shown experimental results of applying this approach to a publicly available database. Finally, our conclusions are followed in section 4.

2. Proposed method

In our proposed method, there are three principal steps: saliency map generation, contour initialization and segmentation, depicted by a flowchart in figure 1. In each step, details of our main references can be referred to concerned papers.

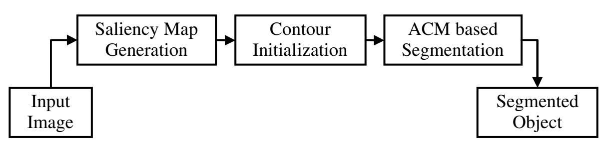

Figure 1. Flowchart of the proposed method

2.1. Saliency map generation and contour initialization

In natural color images, backgrounds are usually complicated by uninteresting objects, inhomogeneous regions, etc. So, it is not a trivial task to automatically locate a meaningful initial contour on the input image. In this paper, we apply the histogram-based contrast method [5] to compute a saliency map. Once we can find dominant parts of the object based on saliency values, segmentation will be done faster and more accurate. Its calculating progress is briefly described by following steps.

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Step 1: histogram based quantization to speed up histogram computation in the RGB color space due to efficiency requirements.

Step 2: L*a*b* color space conversion because of its perceptual accuracy.

Step 3: saliency map computation. In image I, for each pixel I_k, its saliency value is defined as

$$S(I_k) = \sum_{\forall I_i \in I} D(I_k, I_i) \quad (1)$$

where $D(I_k, I_i)$ is the color distance metric between pixels I_k and I_i in the L*a*b* space.

Step 4: saliency map refinement to reduce noisy salient results caused by quantization artifacts.

Since the saliency values of background pixels are normally lower than the saliency values of pixels of the main object, we then apply Otsu's method to compute a threshold for binarizing this map and obtain dominant regions from its background. Next, salient regions are chosen as initial contours for our proposed geometric active contour model.

Original image	Saliency map	Binarized map	Initial contour

Figure 2. Saliency map and an initial contour

2.2. Active contour based segmentation

From the previous steps, a contour is initialized near or around the object of interest based on its strong saliency value. To evolve this contour, ACMs usually use either edge information or region information to define their energy functional. In this paper, an extension of ACMs is proposed by adding these two information types to both internal and external energy terms.

A strong point when integrating region information into an energy functional is that this model has much larger convergence range and the initialization of the curve can be anywhere in the image. The Chan-Vese minimal variance criterion, or fitting term, for color images is given in [4] using region statistic information by

$$\begin{aligned} F_1(C) + F_2(C) = &\int_{inside(C)} \frac{1}{3} \sum_{i=1}^{3} \lambda_i^{+} \left(I_i - c_{1,i}\right)^2 dxdy \\ &+ \int_{outside(C)} \frac{1}{3} \sum_{i=1}^{3} \lambda_i^{-} \left(I_i - c_{2,i}\right)^2 dxdy \end{aligned} \quad (2)$$

where C is any curve and the optimal $c_{1,i}$, $c_{2,i}$ depending on C, are the average values of the image inside and outside C in each channel i, respectively. If C is on object boundary, then $F_1(C) \approx 0$, $F_2(C) \approx 0$, and the fitting term is minimized. In this term, $\lambda_i^{+}, \lambda_i^{-} > 0$ are weights which control evolving speed of the curve. Usually, these parameters are constants set by experiments that can be very difficult to correctly tune for specific images [6]. Based on its meaning, a measure of information content, the image entropy is described as

$$\begin{aligned} E_{in} &= -\sum_{k=1}^{n} p_k \log_2 p_k \qquad \left(k \in \text{inside}(C)\right) \\ E_{out} &= -\sum_{k=1}^{n} p_k \log_2 p_k \qquad \left(k \in \text{outside}(C)\right) \end{aligned} \quad (3)$$

where p_k is the probability of the k^{th} color level. This entropy reflects the diversity of intensity of the image. To apply this improvement, we assume that $\lambda_i^{+} = E_{in}^{i}$ and $\lambda_i^{-} = E_{out}^{i}$ in each channel i to let the evolvement be faster and more smoothly.

For color images, edge information is defined by classical Riemannian geometry results [7]. In this case, the value of each pixel at (u_i, u_j) is treated as an N-dimensional vector. Using the standard notation of Riemannian geometry, they describe $g_{ij} := \frac{\partial I}{\partial u_i} \cdot \frac{\partial I}{\partial u_j}$ and build a metric tensor $\left[g_{ij}\right]$. From this matrix, its eigenvectors $\theta_{\pm}$ and corresponding eigenvalues $\lambda_{\pm}$ are obtained. Values of λ_{+} and λ_{-} are called the maximal and minimal rate of change, respectively. As [7], the "strength" of edges in the vector-valued case is not simply the rate of maximal change but how λ_{+} compares to λ_{-}. Therefore, the first approximation (or gradient) of edges should be a function $f = f(\lambda_{+}, \lambda_{-})$.

In this paper, we select

$$f_{edge} = \lambda_{+} - \lambda_{-} \quad (4)$$

Finally, the vector-valued edges are used to define an edge stopping function as

$$g = \frac{1}{1 + \left(f_{edge} * S(I)\right)} \quad (5)$$

where $S(I)$ is the saliency map. This equation can increase the effect of pixels which are both in salient regions and at the object boundaries more than others to speed up the evolution of the contour to edges of the object.

To force the level set function to be close to initial contours as signed distance functions, a distance regularization term is introduced [8] as follows

$$R_p(\phi) = \int_{\Omega} p(\nabla \phi)\, dxdy \quad (6)$$

where p is a double-well potential function provided by the below construction

$$p(s)=\begin{cases}\dfrac{1}{(2\pi)^2}\left(1-\cos(2\pi s)\right) & \text{if } s\le 1\\[2mm] \dfrac{1}{2}(s-1)^2 & \text{if } s\ge 1\end{cases} \tag{7}$$

This term can eliminate the need of a costly re-initialization procedure completely. It can be seen as an internal energy term which penalizes the deviation of ϕ from a signed distance function during its evolution. The external energy term depending on the desired image feature is a summation of two components, the length of the zero level ϕ and the weighted area of the region inside ϕ as [8].

Finally, to improve performance of the ACM in different situations, we propose a new energy functional, which combines both the edge and region information, defined as

$$\begin{aligned}\varepsilon(\phi)&=\upsilon\int_\Omega p(\nabla\phi)\,dxdy+\mu\int_\Omega g\delta(\phi)|\nabla\phi|\,dxdy\\ &+\int_\Omega\frac{1}{3}\sum_{i=1}^{3}E_{in}^{i}\left(I_i-c_{1,i}\right)^2 H(\phi)\,dxdy\\ &+\int_\Omega\frac{1}{3}\sum_{i=1}^{3}E_{out}^{i}\left(I_i-c_{2,i}\right)^2\left(1-H(\phi)\right)dxdy\end{aligned} \tag{8}$$

where $\upsilon>0,\mu$ are constants, H is the Heaviside function, and δ is the univariate Dirac function by $\delta(\phi)=H'(\phi)$.

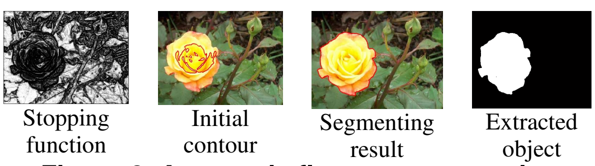

Figure 3. Automatic flower segmentation using our proposed method

3. Experimental results

To evaluate the performance of the proposed method, we have selected Achanta's dataset [9]. This database contains 1000 images and has ground truth in the form of accurate manually annotated labels. For computing the saliency map, authors' implementation in C++ language is used. For the segmentation step, we implemented in the environment of Matlab 2011a. All fix parameter values in equation (8) is in turn set as $\mu=0.9$ and $\upsilon=0.002$.

Figure 3 shows the result of our proposed method combining saliency map for automatic initialization and a new geometric active contour model for segmentation. In this case, our target is a primary flower (the yellow one) from a complex background in a 400×300 image. Its process totally takes 18 seconds after 100 iterations to return the final result.

Next, figure 4 presents the segmenting results of our proposed method attained in a noisy image. It is created by adding multiplicative noise to the first channel and salt and pepper noise to the second one of the input color image. Based on advantages of CV model, our algorithm can overcome the effect of noise without any pre-processing step for noise removal.

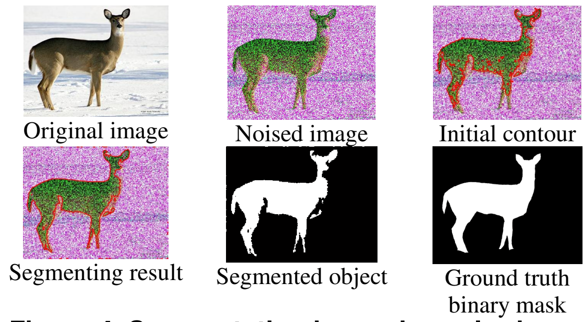

Figure 4. Segmentation in a noisy color image

In Table 1, we illustrate a visual comparison between the output of our proposed method and two state-of-art segmentation approaches, AC without edges for vector-value images [4] and RGAC model [10]. In all cases, the maximum iteration is 600 steps. The first row presents the original color images and their initial contours generated by saliency maps. As looking at the 2nd row, corresponding to the above initialization, results of our method are shown. These final contours look smoother with respect to the boundary of objects than others. And redundant salient regions are also removed. Conversely, final results of the AC without edges for vector-value images [4] are given at the 3rd row. Finally, the last row shows results of the RGAC method [10]. Its segmentation runs as well as our proposed method. But using this model to segment cannot obtain the contour so smooth as our method.

The precision, recall, and F-measure are compared over the entire ground truth database, with F-measure defined as,

$$F_\beta=\frac{\left(1+\beta^2\right)\text{Precision}*\text{Recall}}{\beta^2\text{Precision}+\text{Recall}} \tag{9}$$

We use $\beta^2=0.3$ as in both three methods to weight precision more than recall. The segmentation performance is summarized in Table 2. In terms of accuracy, our proposed method is most competent among three methods.

Table 2. Performance Comparison

Methods	Precision	Recall	F-measure
AC [4]	0.58	0.58	0.59
RGAC [10]	0.50	0.77	0.60
Our method	0.84	0.80	0.83

Regarding to processing time, our method has proved its advantage. The average processing time in seconds of three methods is shown in Table 3. The experiment is done in the testing environment of CPU Intel® Core™2 6700 2.66 GHz, 2.67 GHz, and 2GB of RAM. Due to our proposed method uses the saliency map based initialization, the contour almost matches the final result so that it is able to converge to an optimal solution earlier than the maximum iteration as well as other ACMs.

Table 3. Average processing time

Methods	AC [4]	RGAC [10]	Our method
Time (seconds)	50	55	30
Code	Matlab	Matlab	Matlab

4. Conclusions

In this paper, a novel color object segmentation method is presented. Our proposed geometric active contour model combining with the use of saliency map for automatic contour initialization can segment objects quickly in natural images. The obtained experiments show that this method can extract acceptable desired objects, generate promising smooth boundaries and reduce computational time significantly. In the future, our suggested method will be improved to provide better segmentation results as well as its fitness in more complex color images in both background and foreground.

5. Acknowledgement

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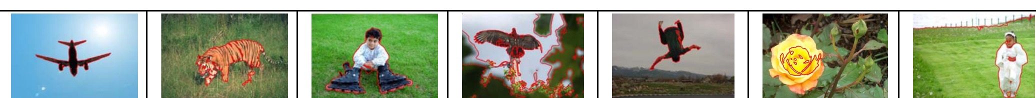
Table 1. Visual comparison of segmentation results between our proposed method and others

Original image and its initial contour	
Our method	
AC without edges [4]	
RGAC [10]