A COMBINED ACTIVE CONTOURS METHOD FOR SEGMENTATION USING LOCALIZATION AND MULTIRESOLUTION

Eva M. Yáñez, Carlos Cuevas, and Narciso García

Grupo de Tratamiento de Imágenes - E.T.S. Ing. Telecomunicación
Universidad Politécnica de Madrid - Madrid - Spain
{eyg, ccr, narciso}@gti.ssr.upm.es

ABSTRACT

Image segmentation is a fundamental step in many image processing applications. To achieve high-quality segmentations active contours are commonly used. However, state of art strategies are not able to provide successful results in all the conditions. Additionally, the strategies that get the best overall results are computationally expensive and need to manually set some parameters, which decreases their usability.

Here, we propose a novel active contours-based segmentation method that, through the combination of boundary-based and region-based energies and a multiresolution analysis, provides very high-quality results while significantly increasing both the computational efficiency and the usability of previous approaches.

Index Terms— Active contours, segmentation, localization, multiresolution

1. INTRODUCTION

Image segmentation is one of the first and most fundamental tasks in a wide variety of image processing applications and computer vision tools such as, for example, segmentation of medical images [1], object detection [2], tracking [3], or remote sensing [4]. Therefore, several works have been proposed in the literature to perform this task. Among the proposed strategies, those based on active contour models are the most popular [5].

First active contours models take as starting point the *snakes* model in [6], which is a seminal work that is based on the application of partial differential equations to guide the evolution of a segmented line or spline by minimizing an energy functional. This functional depends on the image features and on the shape of the spline. A local minimum is reached when the curve is attracted to the contour of the object. These algorithms are computationally simple and provide satisfactory segmentations in many kind of images. However, they have some important drawbacks. Their main problem is that the final contour depends on the parametrization of the curve, not only on its geometry. Therefore, since the topology of parametrized curves cannot be easily changed [7], they do not provide successful results in images with multiple objects. Moreover, they usually need user input parameters, which reduces their usability.

More recently, to eliminate the parametrization dependency and improve the quality of the segmentations in complex images, level sets [8] were introduced, first in *geometric* active contours [7] and later in *geodesic* active contours [9], which are a generalization of the geometric contours. Level sets-based approaches allow contours to change their topology in a natural way: they can split and merge, so multiple objects and holes do not need any special processing. Additionally, geodesic contours approach the problem as the minimization of the length of the curve, defined in a Riemannian space [9]. That is, they try to find the geodesic (or minimal length) curve in that space, where distances are weighted by some property of the pixels in the image. If this feature is properly related to the existence of the boundary of the object, the geodesic contour will fit adequately the object to segment.

Attending to the chosen feature, many different approaches can be found, which can be classified into boundary-based methods, region-based methods, and combined methods [10].

Boundary-based methods, by associating boundaries with the detection of edges through gradients, for example by finding high gradient values in the image [9], provide successful results in certain kinds of imagery. However, since gradients provide very localized information, they are very sensitive to noise and to the initialization of the curve [11], failing in some cases. Additionally, these algorithms also fail in images where boundaries have low gradient values (for example, in blurred contours).

Region-based methods try to establish statistical models of the object and the background using different appearance characteristics such as, for example, intensity [12] or shape [13]. However, these models are too simple to deal with complex images if no a priori information is available, since in these situations both background and the object to segment may be formed by very dissimilar regions [11].

Combined methods integrate the information given by region-based and boundary-based methods, trying to overcome the disadvantages of both [14] [15]. However, these algorithms are usually complex (not user friendly) and computationally inefficient.

Here, using level set-based active contours, we propose a novel and efficient image segmentation method that improves the quality of the results provided by previous approaches in several types of imagery, while preserving the computational requirements of simpler algorithms, and removing the need of parameters for a more convenient use in engineering. This method, as is explained in Section 2, takes as starting point the algorithms proposed in different keystone active contours strategies [9] [11] [12]. On the one hand, to improve the global region statistic modeling segmentations, we minimize a combination of boundary-based and region-based energies in a local neighborhood along the curve. On the other hand, to increase the speed of the segmentation process and improve its usability, we apply an efficient multiresolution analysis.

To evaluate the performance of our strategy, it has been compared to four different active contours approaches in multiple standard test images. The obtained results have shown that our method

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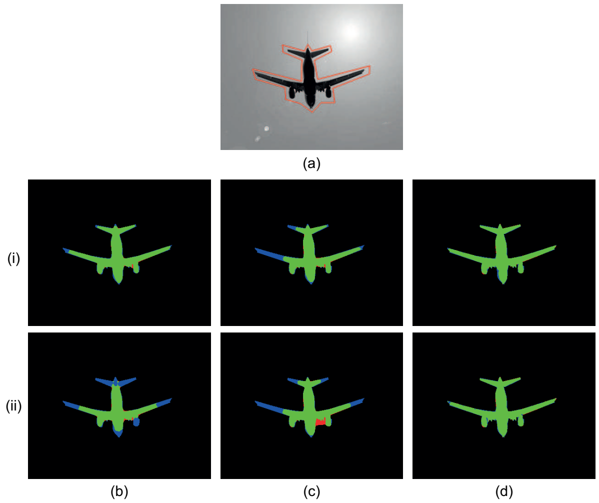

Fig. 1. Segmentations without using multiresolution (i) and using multiresolution (ii). (a) Original image and initial contour. (b) Results with the method in [9]. (c) Results with the method in [11]. (d) Results with the proposed strategy. Green: correctly segmented object pixels. Blue: object pixels erroneously segmented as background. Red: background pixels erroneously segmented as object.

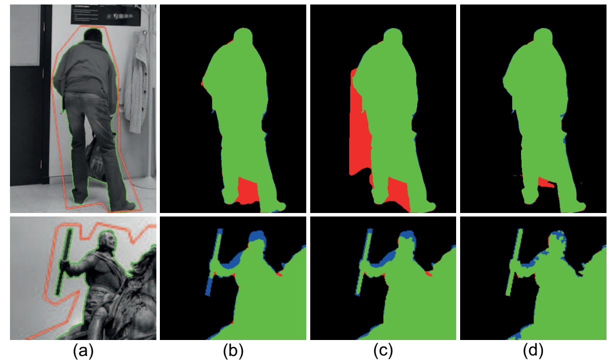

Fig. 2. (a) Original images with the initial contour (in red) and the target contour (in green). (b) Results with [9]. (c) Results with [11]. (d) Results with the proposed method.

equals the best overall quality while achieving the best computational efficiency.

2. DESCRIPTION OF THE PROPOSED STRATEGY

In this Section, we describe the proposed segmentation strategy, which is based on the application of a multiresolution analysis of an energy function resulting from the combination of gradients and a localized statistic modeling. First, in Section 2.1 the effect of the multiresolution applied to standard approaches is analyzed. In Section 2.2 we discuss the advantages and the disadvantages of boundary-based and region-based approaches, and compare their results with those provided by the proposed strategy. Finally, the description of the proposed model is detailed in Section 2.3.

2.1. Multiresolution

By incorporating the analysis to multi-scale versions of an image in segmentation we have observed that, although several versions of the same image must be analyzed, the total computational cost is much lower. It requires fewer iterations to converge and many of these iterations are computationally less expensive. However, we have observed that the quality of the final segmentations in previously proposed approaches also tends to decrease. This is due to the fact that the first iterations are running on low resolution versions that have lost many details, so the contour is attracted to erroneous boundaries. Figure 1 illustrates the lost of quality in the segmentation methods in [9] and [11] when a multiresolution analysis is used.

2.2. Region-based and boundary-based combined framework

As it has been explained before, boundary-based and region-based strategies provide different results depending on the characteristics of the analyzed image. In boundary-based methods the contours are attracted to large values of gradients even if they do not define a border (e.g. noise regions), whereas region-based methods tend to simplify the image and do not work well on complex objects with many different regions. To solve these problems, some authors have proposed methods that try to exploit this complementarity. However, they are noticeably complex and, consequently, its associated computational effort is extremely high.

We propose an efficient method based on the analysis of an energy resulting from a combination of gradients and intensity values which, as proposed in [11], improves the quality of the segmentations by performing this analysis on a local region around the curve.

It must be noted that the strategy in [11] has some important drawbacks. On the one hand, its associated computational cost is very high. Additionally, the quality of its results highly depends on the radius to determine the local region to analyze, which must be manually set by the user.

However, as it is proven in the results section, through the inclusion of the proposed multiresolution analysis these two important problems are solved.

Figure 2 presents the results obtained through a typical region-based method [11], a typical boundary-based method [9], and the proposed method. In the upper example it can be observed that the method in [9] provides the better quality than [11], while in the bottom example [11] is better than [9]. However, it can be noted that the proposed method provides very high quality results in both cases.

2.3. Description of the model

Let us define an image as $I_0(x, y)$ in the domain Ω:$([1, w], [1, h])$. In the first place, since we use a multiresolution approach (similar to the isotropic space-scale technique in [16]), we calculate a family of L_M images $\{I_i(x, y)\}_{i=1}^{L_M}$. These images $I_i(x, y)$ correspond to the image I_0, convolved with a Gaussian kernel and scaled by a factor $k_i = 2^{1-i}$.

The number of levels is given by the minimum desired image size,

$$L_M = \left\lfloor \log_2 \left(1 + \min \left(\left\lfloor \frac{w}{w_{min}} \right\rfloor, \left\lfloor \frac{h}{h_{min}}) \right\rfloor \right) \right) \right\rfloor, \quad (1)$$

being (w_{min}, h_{min}) the minimum allowed size for image $I_{L_M}(x, y)$.

The proposed method is applied iteratively to all levels, starting from the image with coarsest resolution, I_{LM}. When the algorithm converges, a partial solution is got. This solution is used as the initial contour in the next level, which is obtained by duplicating the resolution of the previous level with bicubic interpolation. This process is repeated in each level until the application of the algorithm to the image with the finest resolution provides the final segmentation.

We formulate our model in terms of level sets. For details on this formulation, we refer the reader to [17]. The evolving contour is defined implicitly as $C = \{(x, y)|\phi(x, y) = 0\}$. C is the zero level set of the distance function $\phi(x, y) : \Omega \rightarrow R$, where $\phi(x, y) \leq 0$ defines the region inside the contour and $\phi(x, y) > 0$, the region outside. We use the Heaviside function to refer to the inside region of the curve:

$$\begin{aligned} &\text{Inside } C : H(\phi(x, y)) = \begin{cases} 1 & if \quad \phi(x, y) \leq 0 \\ 0 & if \quad \phi(x, y) > 0 \end{cases} \\ &\text{Outside } C : 1 - H(\phi(x, y)) \\ &\delta_0(\phi(x, y)) = \frac{\partial}{\partial \phi(x, y)} H(\phi(x, y)) \end{aligned} \tag{2}$$

We use the energies of the methods described in [9] and [12], modified with localization as proposed by [11], as the starting point of our own proposal because of their simplicity and performance.

According to the description of a geodesic active contour method, we transform the problem into the minimization of the length of the curve in a Riemanian space, given by [9]:

$$L_R(C) = \int_0^{L(C)} g(|\nabla I_i(C(s))|)\, ds, \tag{3}$$

where $\int_0^{L(C)} ds$ is the Euclidean length that is weighted by the edge-detector function:

$$g(|\nabla I_i(x, y)|) = \frac{1}{1 + |\nabla(G_\sigma(x, y) * I_i(x, y))|^2}, \tag{4}$$

being G_σ a Gaussian filter with standard deviation σ.

To take into account the homogenization of the inner and outer regions and the contrast between them, we add another energy term that depends on the mean of the intensities in the interior and exterior regions (u and v, respectively).

$$E = L_R(C) + \beta \cdot E(\phi, u, v), \text{ with } \beta > 0 \tag{5}$$

However, instead of using global statistics u or v, we take their localized versions as proposed in [11]. So, we calculate the energy of each point along the curve in its local neighborhood:

$$\begin{aligned} u =& u(x, y) = \\ =& \frac{\int_{\Omega'} B(x, y, x', y') H(\phi(x', y')) I_i(x', y')\, dx'dy'}{\int_{\Omega'} B(x, y, x', y') H(\phi(x', y'))\, dx'dy'}, \end{aligned} \tag{6}$$

$$\begin{aligned} v =& v(x, y) = \\ =& \frac{\int_{\Omega'} B(x, y, x', y')(1 - H(\phi(x', y'))) I_i(x', y')\, dx'dy'}{\int_{\Omega'} B(x, y, x', y')(1 - H(\phi(x', y')))\, dx'dy'}. \end{aligned} \tag{7}$$

The neighborhood of a point (x, y) is denoted $B(x, y)$. It depends on the parameter r (the localization radius), and is defined as:

$$B(x, y, x', y') = \begin{cases} 1 & \text{if } \sqrt{(x - x')^2 + (y - y')^2} < r \\ 0 & \text{otherwise} \end{cases} \tag{8}$$

The localization radius corresponds to the one calculated for the level L_M, and remains invariant regardless of the level of multiresolution that we are currently segmenting.

$$\begin{aligned} r =& \frac{1}{k_{L_M}} \frac{Area_{L_M}\{\phi(x, y) \leq 0\}}{Length_{L_M}\{\phi(x, y) = 0\}} = \\ =& \frac{1}{k_{L_M}} \frac{\int_\Omega H(\phi(x, y))dxdy}{\int_\Omega \delta_0(\phi(x, y))|\nabla\phi(x, y)|\, dxdy}, \end{aligned} \tag{9}$$

The performed experiments have shown that using an adaptive radius the computational efficiency of the strategy drastically decreases while the quality of the results barely increases. For this reason, we have decided to use a fixed localization radius.

To minimize the energy given in (7) with respect to $\phi(x, y)$, we deduce the Euler-Lagrange equation for $\phi(x, y)$. The implicit formulation for the descent of energy leads to the equation:

$$\begin{aligned} &\frac{\partial \phi}{\partial t}(x, y) = |\nabla\phi(x, y)|\, div\left(g(|\nabla I_i(x,y)|)\frac{|\nabla\phi(x, y)|}{|\nabla\phi(x, y)|}\right) + \\ &+ \delta_0(\phi(x,y))\int_{\Omega'} B(x,y,x',y')\delta_0(\phi(x',y'))M(x,y,x',y')\, dx'dy' \\ &\phi(x, y, t = 0) = \phi_0(x, y) \equiv \text{ initial contour} \\ &M(x,y,x',y') = (I_i(x',y') - u(x,y))^2 - (I_i(x',y') - v(x,y))^2 \end{aligned} \tag{10}$$

A combined method not only offers a good compromise between the two strategies, but it is also more robust to the negative effects of multiresolution (see Figure 1), allowing to use it, and therefore reducing the computational cost and execution time. Another advantage of using multiresolution is that we have decreased the dependency on the localization radius used in the original strategy described in [11], improving the usability of that method.

3. RESULTS

The proposed strategy has been tested on several standard images from commonly used benchmarks [18] [19] and on frames from our own database. In total, we have used a set of eleven images. Additionally, it has been compared to the methods proposed in [9] [11] [12] [20]. On the one hand, the algorithms in [9] and [12] are seminal works that have proven to be able to achieve very high quality results in many kinds of images. On the other hand, we have decided to compare our strategy with those in [20] and [11], since the first one is very fast and the second one, as we know, provides the best quality segmentations in complex images.

3.1. Quality analysis

To provide an objective measure of the quality of the obtained segmentations we have used the conventional *recall* and *precision* parameters [21],

$$recall = \frac{t_p}{t_p + f_n}, \; precision = \frac{t_p}{t_p + f_p}, \tag{11}$$

where t_p is the number of correctly segmented object pixels, f_p is the amount of background pixels erroneously segmented as object pixels, and f_n is the number of object pixels erroneously segmented as background. Moreover, we have also used the F measure,

$$F = \frac{2 \cdot recall \cdot precision}{recall + precision}, \tag{12}$$

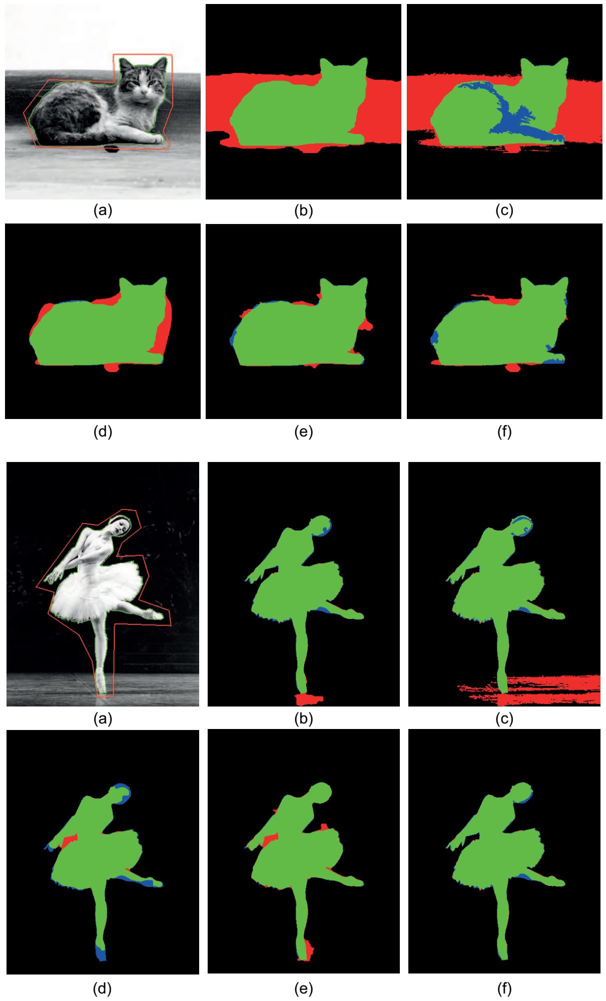

Fig. 3. Two examples of the comparison between methods: (a) Original image, with ground truth contour (green) and initial contour (red). Results of [12] (b), [20] (c), [11] (d), [9] (e), and the proposed method (f).

to jointly evaluate the *recall* and *precision* parameters.

The obtained results have shown that our method is able to provide as high quality segmentations as the best of the rest of the analyzed algorithms. Figure 3 illustrates some final segmentations resulting from the application of our method and those in [9] [11] [12] [20]. On the one hand, in the results corresponding to the first example it can be observed that, despite the similarity between the background and the target object, the proposed method is able to fit to the boundary as [9] or [11], while the strategies in [12] and [20] do not provide a good segmentation of the object. On the other hand, as it is shown in the second example, which corresponds to an image with a target object containing a large amount of small sharp details, the proposed segmentation method achieves the best result. It preserves sharp details without requiring to adjust any smooth factor.

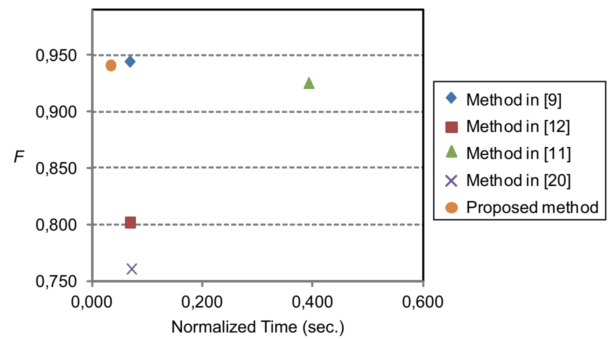

Fig. 4. Overall results (quality and computational efficiency) for the compared strategies. "Normalized time" refers to the total time (in seconds) to segment each image, divided by the number of pixels that form the object to segment, $t_p + f_n$. F is the parameter defined in eq. 12.

3.2. Computational analysis

The evaluation of the computational efficiency of the five compared image segmentation algorithms has been carried out using Matlab implementations on a 2.5 GHz CPU with 4 GB RAM.

The performed experiments have shown that the proposed algorithm not only is able to provide very high quality segmentations but also achieves the best computational efficiency. Figure 4 presents the summary of the obtained times against the average quality obtained with all the evaluated algorithms. The results in this figure show that the proposed method offers the best speed/quality trade-off. It is the fastest and its average quality is comparable to those obtained with high-quality segmentation methods such as [9] or [11]

Additionally, it must be noted that through the application of the multiresolution we eliminate the need for using external parameters. So, the proposed segmentation algorithm improves the usability of [11], which requires to manually select adequate values for the localization radius depending on the characteristics of the object.

4. CONCLUSIONS

We have proposed a novel and efficient image segmentation method based on active contours using level-sets. On the one hand, through the analysis of an innovative energy function, resulting from the combination of boundary-based and region-based energies in a local neighborhood along the curve, very high quality segmentations are obtained. On the other hand, by adding an efficient multiresolution analysis, the computational efficiency of the proposed strategy is drastically decreased and, additionally, the dependence of the results with the parameter required to establish the mentioned local neighborhood disappears.

The proposed strategy has been evaluated in multiple kinds of images and it has been compared to several previous keystone strategies. The obtained results have shown that the described method is able to equal the quality of the segmentations achieved by the methods with best quality results and, nevertheless, its computational effort is the lowest. Therefore, it has shown to be adequate for integration into last generation of computer vision tools requiring not only high quality results but also real-time processing.

5. REFERENCES

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