A novel region-based active contour approach relying on local and global information

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A NOVEL REGION-BASED ACTIVE CONTOUR APPROACH RELYING ON LOCAL AND GLOBAL INFORMATION

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ABSTRACT

This paper proposes a novel approach that allows region-based active contour energy to be re-expressed in a local and global manner. The basic idea of this technique consists in extracting locally image statistics from the heterogeneous region (foreground or background) and globally from the other region at each point along the curve. By exploiting benefits of both local-based and global-based statistics, this technique proves to be robust against heterogeneity and noise and shows low sensitivity to curve initialization. Experimental results for synthetic and real images reveal significant improvement compared to conventional methods.

Index Terms— Active contour, Image segmentation, local and global statistics

1. INTRODUCTION

Active contour (AC) is a technique that has become very popular and has been widely used in image segmentation [2-5]. The main objective of this technique is to segment an object by iteratively deforming a contour until it reaches the object boundaries by minimizing a given energy functional.

The region-based AC models aim to identify each region of interest by using a certain region descriptor to guide the motion of the AC. These models are often based on the assumption that image intensities are statistically homogeneous in the region of interest. In fact, intensity inhomogeneity often occurs in real images due to different modalities; therefore it will be difficult to maintain the global constraint on the image data. To address this problem, authors in [4] have considered local instead of global image statistics where the AC is moved based on local information. These local region-based ACs showed their capability of segmenting heterogeneous objects that would be difficult to segment accurately using a standard global method.

However, neither the standard global methods nor the local ACs resolve absolutely the problems encountered in the segmentation by the ACs. Standard global methods [2, 5] are robust to curve initialization and noise but they fail to segment heterogeneous objects. Local approach [4] is however robust against the heterogeneity by allowing foreground and background to be described in terms of local regions, but it is more sensitive to curve initialization and noise. Based upon these above observations and to effectively alleviate the problems encountered by the heterogeneity in noisy images or by an inadequate curve initialization, this paper proposes a novel region-based AC approach that combines the benefits of both local-based and global-based image statistics. A variational formulation in which we minimize an energy function is presented to satisfy, at each point along the curve, a criterion inside and outside the AC depending on where the heterogeneity appears. For instance, if the object of interest is heterogeneous compared to the background, the image statistics are extracted locally inside the AC and globally outside it. However, in the case of heterogeneity in the background, image statistics are extracted locally outside the AC and globally inside it.

The rest of the paper is organized as follows. In section 2, a description of our approach and its variational formulation are presented. In section 3, experimentations on synthetic and real images highlight the improved performance of the proposed technique over conventional methods. Section 4 concludes the paper.

2. ACTIVE CONTOUR DRIVEN BY LOCAL AND GLOBAL REGION-BASED INFORMATION

In this section, we describe the proposed approach for guiding AC to the object boundaries. Our model is presented drawing upon techniques of curve evolution, statistical function, and Level-Set method.

2.1. Background and terminology

Let I denote a given image defined on the domain Ω and $I(x)$ the intensity of the pixel x where $x \in \Omega$. One approach to implement the AC segmentation is to use the Level-Set method which considers the original curve as the zero level of a surface. The distortion of the entire surface induces a deformation of the curve shape. This process stimulates the evolution of the AC and achieves, at the end, the object of interest segmentation. Let C be a closed contour represented as the zero level set of a signed distance function Φ, i.e., $C=\{x|\Phi(x)=0\}$. The purpose of this process is to implicitly evolve the contour C such that, at the convergence, $\Phi < 0$ (inside of C) and $\Phi > 0$ (outside of C) represent the object of interest and the background, respectively. In Level-Set formulation, a smoothed Heaviside function $\mathcal{H}\Phi(x)$ is used to specify the inside and the outside of C, by one and zero value, respectively. The energy functional is computed only in a narrow band around

C as presented in [1] in order to decrease the computational complexity of the standard Level-Set method. This area around C is specified by the derivative of $\mathcal{H}\Phi(x)$ and it is defined by a smoothed Dirac delta function $\delta\Phi(x)$ which is equal to one along C and zero elsewhere.

2.2. Active contour energy

To perform AC segmentation, we first define an objective about what we want to extract from the image, and then we develop an energy that will be minimized when this objective is achieved. The region-based energy is expressed in general by an integral domain of a region descriptor and the choice of a relevant energy expression is a significant aspect that has been widely addressed by several authors. In this paper, we employ two region-based energies defined in [2] and [5] where the region of interest is represented by its mean intensities. The first used descriptor, presented in [2], assumes that foreground and background regions should have maximal separate mean intensities and it is given by:

$$k(x,\Omega) = -\frac{1}{2}\left(\mu_{in}(\Omega_{in}) - \mu_{out}(\Omega_{out})\right)^2 , \qquad (1)$$

where Ω_{in} and Ω_{out} denote respectively the inside and the outside the contour C, and μ_{in} and μ_{out} denote respectively the mean intensities inside and outside C.

The second descriptor considered in this paper is described in [5], and it is expressed as:

$$k(x,\Omega) = \left(I(x) - \mu_{in}(\Omega_{in})\right)^2 + \left(I(x) - \mu_{out}(\Omega_{out})\right)^2 . \qquad (2)$$

This descriptor models foreground and background as constant intensities represented by their means.

Therefore, according to the used descriptor, the energy functional in the Level-Set formulation takes the form:

$$E(\Phi) = \int_{\Omega} \delta\Phi(x).\, k(x,\Omega)\, dx \ . \qquad (3)$$

The evolution equation of C is expressed by:

$$\frac{\partial\Phi}{\partial t}(x) = \delta\Phi(x).\nabla k(x,\Omega) + \lambda\delta\Phi(x).\, div\left(\frac{\nabla\Phi(x)}{|\nabla\Phi(x)|}\right) , \qquad (4)$$

where ∇ and div represent the gradient and the divergence operators, respectively. The second term in (4) is used to keep the curve C smooth. It is weighted by a parameter λ.

The choice for the local image statistics inside and outside the AC is based on defining a ball function B to mask local regions by overlapping it with inside and outside the AC as similarly presented in [4]. This ball function (centered at x) is expressed as:

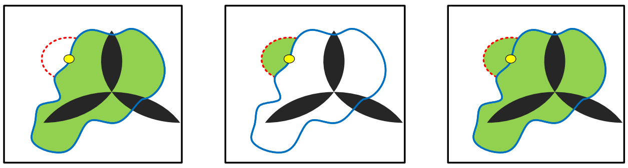
$$B(x,l) = \begin{cases} 1, & \|x-l\| < rad \\ 0, & otherwise \end{cases} , \qquad (5)$$

where rad is the ball radius and l is a point in Ω that evaluates B at 1 on the local region and 0 elsewhere. The main difference with the approach presented in [4] is that we extract the local image statistics only inside or outside the AC depending on where the heterogeneity appears; while global image statistics are extracted from the other region.

In the following two subsections, we describe the principle of the proposed approach in the case of heterogeneity in the background or heterogeneity in the object of interest. In fact two techniques are proposed here, and one of them is used depending on where the heterogeneity appears.

2.3. Global IN-Local OUT based information technique

If the background is heterogeneous compared to the object of interest, the technique, named, *Global IN-Local OUT* based information, is employed and it consists to extract locally the image statistics outside the AC and globally inside it. Figure 1 illustrates this principle.



(a) (b) (c)

Fig.1 Global IN–Local OUT based information technique.

From Fig.1(a, b and c), the object of interest is illustrated in black. The global interior region (Fig.1(a)) refers to the entire shaded interior part (green area) of the AC (blue curve) while the local exterior region (Fig.1(b)) refers to the local exterior neighborhood represented by the half shaded circle (dotted arc) and it belongs to the exterior region of the AC. The area used by this technique is therefore the entire shaded part as shown in Fig.1 (c) and that for each point along the AC.

Using this technique, the global exterior heterogeneity does not affect the energy value; instead only local exterior information is extracted with global interior information to guide the AC evolution.

The energy functional is expressed in *Global IN-Local OUT* based information as follows:

$$E(\Phi) = \int_{\Omega_{in}} \delta\Phi(x).k(x,\Omega_{in})\, dx + \int_{\Omega_{out}} \delta\Phi(x) \int_{\Omega_l} B(x,l).k(l,\Omega_{out})\, dl\, dx , \qquad (6)$$

where Ω_l represents the local region centered by x.

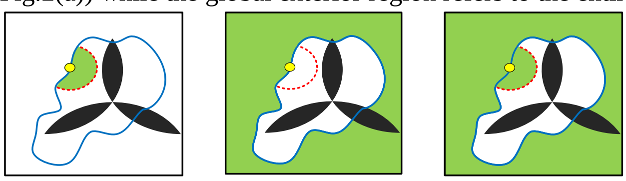
And the evolution equation of C will be expressed as:

$$\frac{\partial\Phi}{\partial t}(x) = \delta\Phi(x)\left[\nabla k(x,\Omega_{in}) + \int_{\Omega_l} B(x,l).\nabla k(l,\Omega_{out}) dl\right] + \lambda\delta\Phi(x).div\left(\frac{\nabla\Phi(x)}{|\nabla\Phi(x)|}\right) . \qquad (7)$$

2.4. Local IN-Global OUT based information technique

If the object of interest is heterogeneous compared to the background, we use the technique, named, *Local IN-Global OUT* based information that extracts image statistics locally inside the AC and globally outside it. Figure 2 illustrates the principle of this technique.

The local interior region refers to the local interior neighborhood represented by the half shaded circle (Fig.2(a)) while the global exterior region refers to the entire



(a) (b) (c)

Fig.2 Local IN–Global OUT based information technique.

shaded exterior part of the AC (Fig.2(b)). The area used by this technique is therefore the entire shaded part as shown in Fig.2(c) and that for each point along the AC. Using this technique, the global interior heterogeneity does not affect the energy value; therefore the AC is evolved based only on local interior information and global exterior information.

Using *Local IN-Global OUT* based information, the energy functional is expressed as follows:

$$E(\Phi)=\int_{\Omega_{in}}\delta\Phi(x)\int_{\Omega_l}B(x,l).k(l,\Omega_{in})\,dl\,dx+\int_{\Omega_{out}}\delta\Phi(x).k(x,\Omega_{out})\,dx\quad. \tag{8}$$

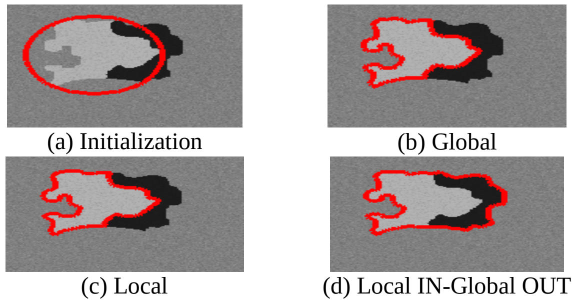
The evolution of the curve *C* will be expressed as:

$$\frac{\partial\Phi}{\partial t}(x)=\delta\Phi(x)\left[\int_{\Omega_l}B(x,l).\nabla k(l,\Omega_{in})dl+\nabla k(x,\Omega_{out})\right]+\lambda\delta\Phi(x).\mathrm{div}\left(\frac{\nabla\Phi(x)}{|\nabla\Phi(x)|}\right)\quad. \tag{9}$$

In contrast with standard global region-based approach that suffers from heterogeneity problems and with the local region-based approach that is sensitive to image noise and curve initialization, our proposed approach is robust against these above-mentioned problems; thanks to the global benefit (against noise and curve initialization) and to the local benefit (against heterogeneity).

3. EXPERIMENTAL RESULTS

To evaluate the performance of the proposed approach using *Global IN-Local OUT* or *Local IN-Global OUT* technique, we employ synthetic and real images and use two region-based AC energies presented in [2] and [5] as specified above. Our purpose is not to compare the obtained experimental results according to the used energy; but to present the performance of the proposed approach over conventional methods. Fig.3(a) shows a synthetic image with Poisson distribution noise where the object of interest is the light gray and black areas (presence of heterogeneity). By using an inadequate curve initialization as shown in Fig3(a), Fig.3(b-d) present the segmentation results obtained by different approaches. By using the descriptor presented in [2], Fig.3(b) shows the segmentation result using the global version that fails to successfully segment the object due to the heterogeneity presented in this object of interest. In fact, the AC segments a region that *globally* verifies a maximum error between the mean intensities inside and outside the AC. Fig.3(c) shows the result for the local version which seems to have the same segmentation result compared to the global version; but the reason is completely different. In fact, due to the inadequate curve initialization; close to wrong contours (separating the light gray and black areas), the local region statistics trapped the AC. This later was attached to these non-desired contours and captured only a part of the object of interest instead of the entire object. Fig.3(d) illustrates the segmentation result using our *Local IN-Global OUT* technique. As shown in this figure, the AC was protected from the interior heterogeneity by extracting only locally the interior information. Also, the close initialization to a wrong contours does not trapped the AC evolution due to the global exterior view that guides the AC

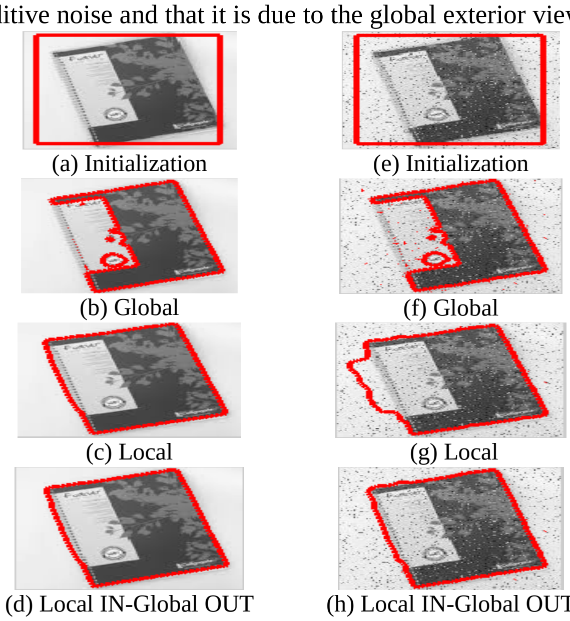


(a) Initialization (b) Global (c) Local (d) Local IN-Global OUT

Fig.3 Segmentation of heterogeneous object in a synthetic image with inadequate initialization and a "Poisson" noise.

to the desired object boundaries and consequently the maximum separate mean intensities is achieved. The proposed technique was able to segment the object of interest in the presence of heterogeneity using an inadequate curve initialization in a noisy image.

To study the additive noise in real image, Fig.4(a-d) show segmentation of a book in the original image and with a "salt & pepper" noise added in Fig.4(e-h). A same curve initialization is shown in Fig.4(a) and Fig.4(e). The second used descriptor presented in [5] looks for homogeneous regions represented by their mean intensities. From the result presented in Fig.4(b) and Fig.4(f), the global approach fails to segment the book due to the similarity in mean intensities between a part of the book and the background. With the same curve initialization, Fig.4(c) and Fig.4(g) give different results using the local-based approach due to the additive noise which prevents the AC to find the whole object boundary in Fig.4(g). The segmentation result using *Local IN-Global OUT* technique shown in Fig.4(d) provides an accurate segmentation as the case of using the local approach (Fig.4(c)). Also as shown in Fig.4(h), the *Local IN-Global OUT* technique remains robust against the additive noise and that it is due to the global exterior view

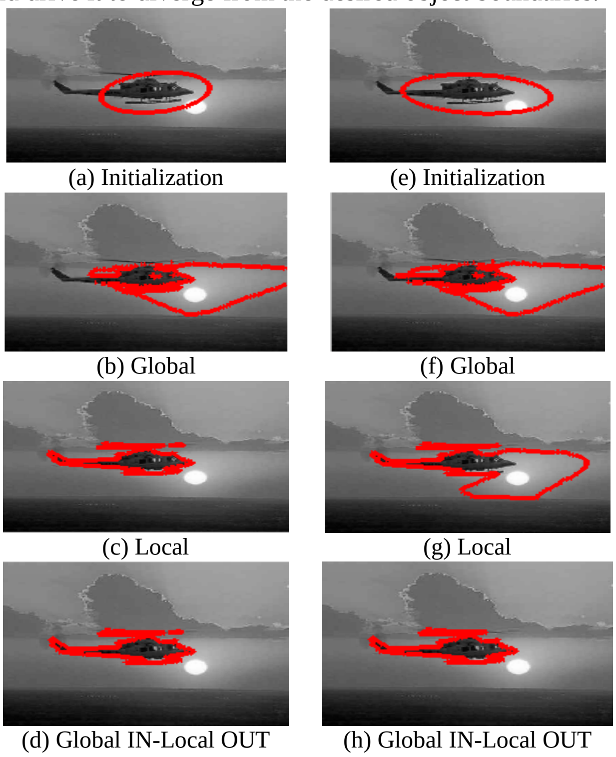


(a) Initialization (e) Initialization (b) Global (f) Global (c) Local (g) Local (d) Local IN-Global OUT (h) Local IN-Global OUT

Fig.4 Book segmentation with an added "salt & pepper" noise in the second column.

that gives the AC the possibility to continue its evolution until it reaches the whole object boundaries. Fig.3 and Fig.4 provide an example of using two different region-based energies in the same segmentation technique (*Local IN-Global OUT*).

To study the initialization curve effect in real image with the presence of heterogeneity in the background using our *Global IN-Local OUT* technique, Fig.5(b-d) show a helicopter segmentation using different approaches by using an adequate curve initialization as shown in Fig.5(a). While Fig.5(f-h) show the helicopter segmentation using an inadequate curve initialization as shown in Fig.5(e). With heterogeneous features, the global approach always fails to capture the object of interest as shown in both Fig.5(b) and Fig.5(f). While the local approach was able to segment the object in case of using an adequate initialization (Fig.5(c)); but it loses its accuracy when using an inadequate curve initialization (Fig.5(g)). This last obtained result can be explained by the fact that the statistic information extracted from the local regions trapped the AC during its evolution and drive it to diverge from the desired object boundaries.



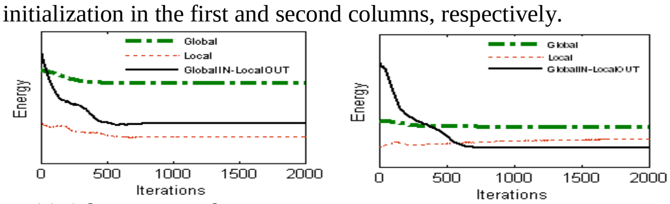
(a) Initialization (e) Initialization

(b) Global (f) Global

(c) Local (g) Local

(d) Global IN-Local OUT (h) Global IN-Local OUT

Fig.5 Helicopter segmentation using adequate and inadequate initialization in the first and second columns, respectively.



(a) Adequate initialization (b) Inadequate initialization

Fig.6 Energy convergence for the helicopter segmentation in Fig.5.

Using both adequate and inadequate curve initializations, our *Global IN-Local OUT* technique shows robustness against curve initialization (Fig.5(d) and Fig.5(h)). This second proposed approach uses only local exterior information that protects the AC from the background heterogeneity, while the global interior information allows the AC to evolve to the helicopter until it reaches properly the entire object boundaries. In this approach, we use the descriptor presented in [5] that was used in the previous example (Fig.4) to show also that a same descriptor can be used for the two proposed approaches. Fig.6(a) and Fig.6(b) illustrate the AC energy in terms of iterations of the above results obtained in Fig.5 where all curves were scaled to be shown at the same figure. For both kind of initialization, the global approach (dotted green line) converges first but it provides an incorrect segmentation (Fig.5(b) and Fig.5(f)). While using an adequate curve initialization, Fig.6(a) shows that the local approach (dotted red line) and our proposed technique (solid black line) take time to converge (around 500 iterations) but provide the correct segmentation (Fig.5(c) and Fig.5(d)). However, in the case of using inadequate initialization, Fig.6(b) shows that our technique converges slowly but outperforms the local approach by providing the correct segmentation (Fig.5(h)).

4. CONCLUSION

In this paper, we presented a novel region-based AC approach that performs object segmentation drawing upon the benefits of local-based and global-based image statistics to drive the AC toward the desired object boundaries. By using synthetic and real images, the proposed approach shows robustness against heterogeneous features with inadequate curve initialization and in noisy image. This approach provides satisfactory results using different types of images for both techniques *Global IN-Local OUT* and *Local IN-Global OUT* based information while the conventional methods fail to correctly segment the object of interest in some particular cases.

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