Geometric Active Contour Model Using Level Set Methods for Objects Tracking in Images Sequences

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Abstract

In this paper we present an automatic follow-up method of changing objects of topology in a sequence of images. The method we propose is based on an algorithm of image segmentation with deformable active contour and an algorithm of objects localization. The segmentation algorithm is based on a new modeling of the image using the geometrical active contour model. This modeling allows a bidirectional evolution of contour and limit the constraints of initialization. The formulation by level set method of the active contour model allows an automatic management of the changes of topology. We have then used this segmentation algorithm to develop an objects localization algorithm using a local dynamic prediction of displacements.

1 Introduction

Since the introduction of the active contour model [7], many works have been improved in order to realize an automatic segmentation of an object in an image and to obtain closed contours representing its borders. These methods based on the original model [7] have problems of instabilities and constraints of initialization. To limit these problems the geometrical active contours model has been introduced [2] in the following form :

$$\frac{\partial \Gamma(t)}{\partial t} = F.\vec{N} = \vec{\nu}. \tag{1}$$

The principle is to make evolve a contour Γ under the action of a force F in the direction of its normal $\vec{N}$ at a speed $\vec{\nu}$. The methods recently suggested [8, 3] using this geometrical model, use an evolution speed expression which depends on the gradient of the original image. This speed is either always positive or always negative what allows an evolution of contour in only towards the interior or towards outside but not in the two directions simultaneously. This last point is a major disadvantage if we want to carry out an automatic follow-up of an object in images sequence. Several recently work was published based on the work of Amadieu $et\ al.$ [1]. Into Vese [11], they introduce the distribution of Dirac and the function of haviside for better determining contour. Besson $et\ al.$ [6], for the segmentation of the video images is based on a constant background in each treated image or uses an image of reference. From proposed work [1, 4, 9] we propose a method of segmentation with deformable active contour based on a modeling of the image allowing a bidirectional evolution and using the geometrical model of active contour. In our approach, we consider that the objects and background domains evolves in the same segmentation process. To manage automatically the changes of topology, we use the suggested method [10], whose active contour is implicitly formulated by a level set function. We have used this automatic segmentation method to develop a localization algorithm of objects changing of topology in images sequence. This paper is organized as follows : in section 2, we present a deformable active contour segmentation algorithm. We present section 3, objects localization algorithm in images sequence. Section 4, we illustrate the performence of our method on synthetic and real images.

2 Active contour segmentation algorithm

2.1 Image modeling and criterion to minimize

To carry out an automatic follow-up of a changing object of topology during a sequence, several points are necessary. It is first of all necessary to preserve a bidirectional evolution of contour, then to manage the changes of topology. Finally, it is possible to use only one initial contour placed by the user at the beginning of the process. We consider that the image contains two regions, illustrated figure 1, the object region D_1 and background D_2 [1, 4]. The image to be segmented $f(x,\ y)$ is a function defined for $(x,\ y) \in \Omega \subset \Re^2$, where Ω is the image domain. We suppose that the image $f(x,\ y)$ represents image $I(x,\ y)$ disturbed by an additive noise considered Gaussian $\eta(x,\ y)$ as follows :

$$f(x,\ y) = I(x,\ y) + \eta(x,\ y). \tag{2}$$

The image $I(x,\ y)$ is represented by two constant values, I_1 the grey level of the objects region, and I_2 the background. We use a geometrical active contour model by (PDE) Partial Differential Equation (1). At the beginning, the initial active contour $\Gamma(t = 0)$ divides the image into two regions ω_1 and ω_2 such as $\{\omega_1 \cap \omega_2 = \Gamma\}$ and $\{\omega_1 \cup \omega_2 \cup \Gamma = \Omega\}$, illustrated figure 1. We wish at the time of convergence $\omega_1 = D_1$ the objects region and $\omega_2 = D_2$ that of the background. In [1] the constant ones representing the objects and the background are known $a\ priori$. In this work we approach the homogeneous regions considered by their averages calculated on domains which evolve with time. From an initial image

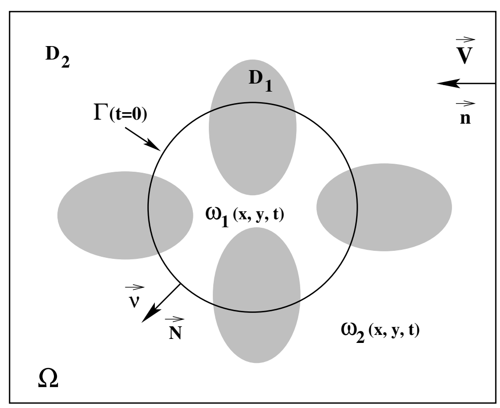


Figure 1. *Regions considered in the image.*

$g(x,\ y,\ t = 0)$ we seek the image $g(x,\ y,\ t = t_c)$ taking the values $g_1(t = t_c)$ and $g_2(t = t_c)$ which will be closest to the required image $I(x,\ y)$. The image $g(x,\ y,\ t)$ is defined as follow :

$$g(x,\ y,\ t) = \begin{cases} g_1(t) & \text{if} \quad (x,\ y) \ \in \ \omega_1(t) \\ g_2(t) & \text{if} \quad (x,\ y) \ \in \ \omega_2(t), \end{cases} \tag{3}$$

with :

$$\begin{aligned} g_i(t) &= \frac{1}{P_{\omega_i(t)}} \int_{\omega_i(t)} f(x,\ y)\ dxdy, \\ P_{\omega_i(t)} &= \int_{\omega_i(t)} dxdy, \end{aligned} \tag{4}$$

with $i = [1,\ 2]$. The value t_c corresponds to time with convergence towards an optimal solution. Under these conditions the image must check the minimum of the following criterion :

$$J(t) = \int_{\Omega(t)} \big(f(x,\ y) - g(x,\ y,\ t)\big)^2\ dxdy, \tag{5}$$

where $J(t_c) = \min_t J(t)$.

2.2 Evolution speed expression

The active contour $\Gamma(t)$ is moving according to PDE of equation (1). Our problem consists in finding the evolution speed expression $\vec{\nu}$ according to the following form :

$$\vec{\nu}(x,\ y,\ t) = \gamma(x,\ y,\ t)\ \vec{N}(x,\ y,\ t), \tag{6}$$

where γ indicates a force of evolution and $\vec{N}$ unit normal vector to $\Gamma(t)$. With an aim of finding this evolution speed, the expression of criterion (5) must be differentiated respect time t. To differentiate this criterion, we use the theorem of the particulate derivative of an integral of volume, [5]. As we are interested by the evolution of the curve $\Gamma(t)$ in the direction of its normal, the problem can easily change to an integral of surface. The differentiate of $J(t)$ is given by the following expression :

$$\begin{aligned} \frac{dJ}{dt}(t) &= \int_{\Omega(t)} \frac{\partial}{\partial t}\big(f(x,\ y) - g(x,\ y,\ t)\big)^2\ dxdy \\ &+ \int_{\partial\Omega(t)} \big(f(x,\ y) - g(x,\ y,\ t)\big)^2 . \vec{V}\vec{n} ds \\ &+ \int_{\Gamma(t)} (k_{\omega_2} - k_{\omega_1}) \vec{\nu}.\vec{N} ds, \end{aligned} \tag{7}$$

where $(k_{\omega_2} - k_{\omega_1})$ represents the jump of $\big(f(x,\ y) - g(x,\ y,\ t)\big)^2$ through $\Gamma(t)$. The second term of the equation (7) is null because the external edges $\partial\Omega$ of the image are fixed, figure 1. We apply the theorem of the particulate derivative [5] to domains $\omega_1(t)$ and $\omega_2(t)$. and with the model definition of the image $g_1(t)$ and $g_2(t)$ we obtain finally the following result :

$$\begin{aligned} \frac{dJ}{dt}(t) = -\int_{\Gamma(t)} &\big[\big(f(x,\ y) - g_2(x,\ y,\ t)\big)^2 \\ &- \big(f(x,\ y) - g_1(x,\ y,\ t)\big)^2\big] \vec{\nu}.\vec{N} ds. \end{aligned} \tag{8}$$

According to the iniquality Cauchy-Schwarz, the fastest decrease of $J(t)$ is obtained by choosing $\gamma(t) = \vec{\nu}(t).\vec{N}(t)$. We have then :

$$\begin{aligned} \gamma(x,\ y,\ t) &= \big(f(x,\ y) - g_2(x,\ y,\ t)\big)^2 \\ &- \big(f(x,\ y) - g_1(x,\ y,\ t)\big)^2 \end{aligned} \tag{9}$$

As we can note it γ can be positive or negative what allows a bidirectional evolution of contour.

2.3 Implicit representation using level set method

The implicit representation of contour $\Gamma(t)$ consists in the consideration of this same curve like zero level set of a deformable surface u represented by a chart of distance to contour [10] :

$$u\left[\Gamma(t),\ t\right] = 0. \tag{10}$$

This formulation makes it possible to directly consider the geometrical properties of the curve such as normal $\vec{N} = -\frac{\nabla u}{|\nabla u|}$ and the curvature $\kappa = div\left(\frac{\nabla u}{|\nabla u|}\right)$. The differentiate of (10) respect time t allows to obtain :

$$\nabla u.\nu + \frac{\partial u}{\partial t} = 0. \tag{11}$$

We replace the speed expression (6) in (11) and we add a term of minimization length of contour [3] and finally we obtain the PDE following :

$$\frac{\partial u}{\partial t} + \left(\gamma(x,\ y,\ t) + \lambda\kappa(x,\ y,\ t)\right)|\nabla u| = 0, \tag{12}$$

where κ the curvature and λ the regularization term.
This representation easily allows the management of the changes of topology. This last point is very significant in an object tracking procedure.

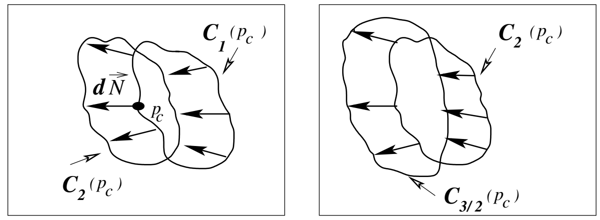
3 Object localization algorithm in images sequence

3.1 The principle

The segmentation algorithm, presented section 2.1, allows an extraction of contours, thus providing information on the shape of the required object. The algorithm characteristic allows the possibility to detect several objects in an image starting from only one initial contour and without true constraint of initialization. These advantages allow the realization of tracking algorithm of an object changing of topology in images sequence on the basis of only one initial contour placed by the user at the beginning of the process.

3.2 Object localization

In this section, we consider that the movements of the object between two images are small. The initialization of the second image of the sequence is realized directly by the contour obtained on the first image. From the third image of the sequence, we carry out a localization of the object by a local dynamic prediction of displacements between the two previous images. Let p_c a point of contour C_1 obtained on image 1, the deformation of the object in image 2 provided a point pertaining to contour C_2. If $d(p_c)$ is considered, the local displacement of the object of point p_c between images 1 and 2, we have then : $C_2(p_c) = p_c + d(p_c)$. Contours C_1 and C_2 represent respectively zeros levels of the level set functions $u_1(p)$ and $u_2(p)$, figure 2. These functions are obtained at the convergence of the segmentation algorithm on two images 1 and 2 such as $\{p \ / \ u_1(p) = 0\}$ and $\{p \ / \ u_2(p) = 0\}$. Under these conditions, we can



(a) (b)

Figure 2. *Local dynamic prediction of displacements, (a) dynamic prediction, (b) Localization.*

use these level set functions to directly estimate displacements such as : $u_2(p_c) = u_1(p_c + d(p_c))$. Displacements are estimated in the direction of the normal to contour and are obtained by the following expression :

$$d(p_c)\vec{N} = [u_2(p_c) - u_1(p_c)] \cdot \frac{\nabla u_1(p_c)}{|\nabla u_1(p_c)|}. \quad (13)$$

After the estimate of displacements we define a new level set function $u_{3/2}(p_c)$ such as :

$$u_{3/2}(p_c) = u_2(p_c + d(p_c)). \quad (14)$$

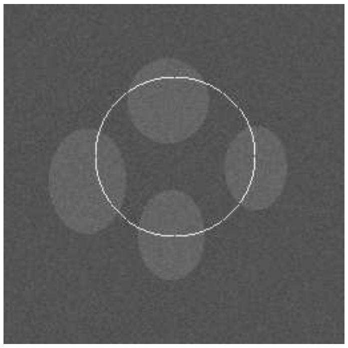
The initialization of the third image is realized by contour $C_{3/2}$ such as :

$$C_{3/2} = \left\{(x,\ y)/u_{2+1/2}(x,\ y) = 0\right\}. \quad (15)$$

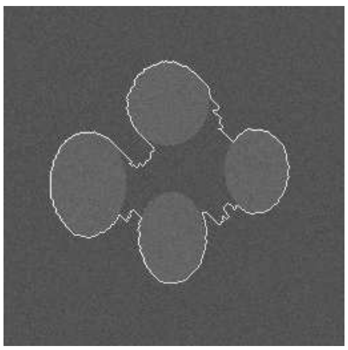
After convergence we obtain the contour C_3 on third image. This localization method is generalized for a sequence of n images. In final paper, we will give more demonstration and details.

4 Results

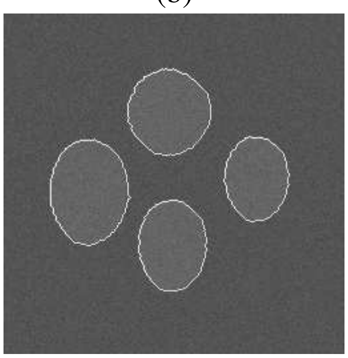
In this section, we apply our segmentation method on synthetic and real images. On the sequence of autumn leaves moving on the ground, we show the result of our tracking method.
In Figure 3, we show result on synthetic image, the grey level variation between the objects and the background is only 10. Morever this image is



(a)



(b)



(c)

Figure 3. *Result on synthetic image, (a) Initialization, (b) Propagation, (c) Convergence towards final contour.*

disturbed by an additive Gaussian noise with variance=9. From an initial contour Figure 3.a, the propagation, Figures 3.b is realized with a term of regularization $\lambda = 10$. When the minimum of the criterion is reached, it converges at the end of 256 iterations to obtain the result showed Figure 3.c. We can note that the obtained results are satisfactory and our method is relatively robust to noise. Figure 5, shows the results obtained on real image.

In Figure 4, we show result on synthetic image, our algorithm is able to detect only a dezired objects.

To show the effectiveness of our tracking method, we have filmed autumn leaves moving on the ground. At the beginning, those are gathered, then a displacement caused by the wind causes their dispersion. The segmentation of the first image of the sequence is showed Figures 6. This sequence contains 13 images, the sixth and the ninth images are showed Figures 7. The Figures 7.a, illustrate initialization with the contours obtained on the preceding images. Figures 7.b illustrate initialization by taking account of the localization algorithm. The Figures 7.c illustrate the final contours.

5 Conclusion

We have presented a method of automatic follow-up of objects changing of topology in images sequence. The automatic segmentation algorithm requires few parameters of initialization compared to other methods and authorizes the changes of topology. The objects localization algorithm based on a local dynamic prediction of displacements using the level set functions provides good results.

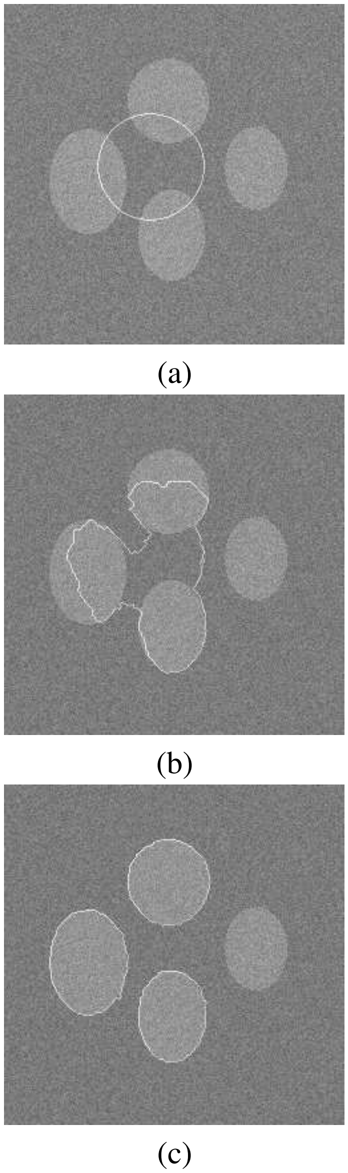


Figure 4. *Result on synthetic image with dezired object segmentation, (a) Initialization, (b) Propagation, (c) Convergence towards final contour.*

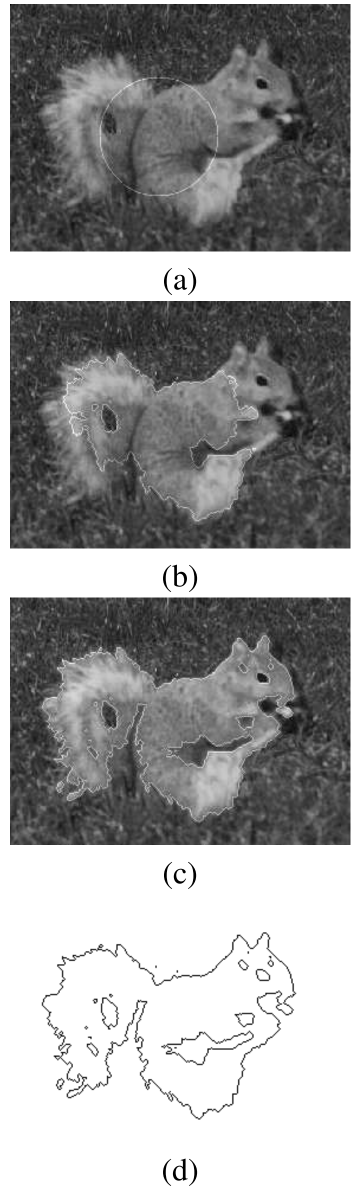


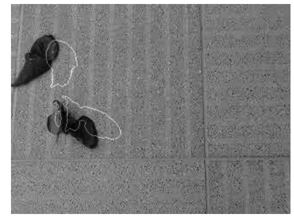
Figure 5. *Result on real image (a) Initialization, (b) Propagation, (c) Convergence, (d) Final contour.*

(a)

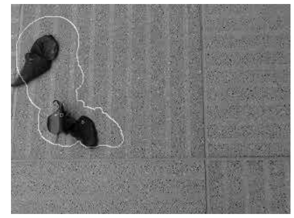
(b)

(c)

Figure 6. *Leaves moving on the ground, (a) Initialization on the first image, (b) Propagation of the contour, (c) Convergence towards final contour.*

(a1) (a2)

(b1) (b2)

(c1) (c2)

Figure 7. *Leaves moving on the ground, (a) Initialization on the sixth and ninth image of the sequence, (b) Localization, (c) Convergence towards final contours.*

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