ACTIVE CONTOURS PROPAGATION IN A MEDICAL IMAGES SEQUENCE WITH A LOCAL ESTIMATION

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ABSTRACT

We present an automatic technique for contour detection of the abdominal aorta on a medical images sequence. We apply the method of region based active contours using local parameter estimation related to the object region. This method allows the automation of the detection process. The initialization of our algorithm is only done on the first image of the sequence. Our method, consists in defining for each cut of the sequence a local region to find the searched contour. The contour obtained for an image, after a dilatation, is then used for the initialization of the following image. All unneeded objects in the image will not be detected.

1 INTRODUCTION

This work takes place in the field of segmentation of medical images in order to do a 3D reconstruction of the abdominal aorta and its main collateral and terminal branches. Original images are a sequence of cuts obtained by X-ray computed tomography (CT). The technique of deformable active contours is well adapted to solve this problem. Moreover, it has the advantage of leading to an automatic segmentation and ensures obtaining closed contours. In the literature, the first approaches were based on contours information of the image [8]. In these approaches, the snake evolves to the zones with the strongest gradient of intensity. The regions based approaches avoid the problems of detection when the object to be segmented have not sharp contours, and cannot be distinguished from its context. Snakes and balloons methods [2] require good initialisation.

The section 2 introduces the actives contour methods. In the section 3, to develop a technique of contour propagation in the images sequences, we present how to propagate, to dilate and to fill an estimated local region. In section 4, we show some different results which can be obtained in a sequence.

2 ACTIVE CONTOURS

The utilisation of partial differential equations (PDE) for active contours, consists to develop a contour C according to the following equation:

$$\frac{\partial C}{\partial t} = F_c.\vec{N}, \quad (1)$$

where $\vec{N}$ is the normal to C and F_c a given speed depending of the curvature of C and of the image gradient to segment. The active contour, C evolves perpendicularly with himself with a speed F_c until to be to the edge of object to detect. The change of topology can be easily obtained using a level-set methods [6, 3].In this method C is the curve defined like the zero level set of a surface u. If C evolves according to (1) then the surface u evolve following this partial differential equations:

$$\frac{\partial u}{\partial t} = F_u.|\nabla u|. \quad (2)$$

A topology change of C does not imply a topology change of u. So, we can detect apart from one or more objects during the same detection processus. The method we used in [1, 4], in order to find the evolution law of the contour, consists to solve an inverse problem [11]. The model we choose to represent the image is :

$$f(x) = A(I(x)) + \eta(x), \quad (3)$$

with f original image and I the model. Where A is a Gaussian operator and η a noise. The image is defined on a domain Ω with :

$$I(x) = \begin{cases} I_1 & /x \in D_1 \\ I_2 & /x \in D_2 \end{cases} ; \begin{cases} D_1 & = \{x/u(x) < 0\} \\ D_2 & = \{x/u(x) > 0\} \end{cases} \quad (4)$$

with:

$$D_1 \cup D_2 = \Omega, \text{and } x \in \Omega. \quad (5)$$

D_1 is the domain of the object and D_2 is the background, illustrated figure 2.a.

We use a method generalizing [1] where the evolution law of u is defined by the minimization of this criterion :

$$F(t) = \sum_{i=1}^{p} \int_{R^2} ||AI_i(x,t) - f(x)||.dx, \quad (6)$$

where || || is a norm choosed to optimize the different objects separation [4] and p the domains number ($p = 2$ in our case). If we design the minimum of the criterion by α, the partial differential equation (2) becomes :

$$\frac{\partial u}{\partial t} + (\alpha(x,t) + \lambda.k)|\nabla u| = 0, \quad (7)$$

with λ a regulator coefficient and k the curvature.

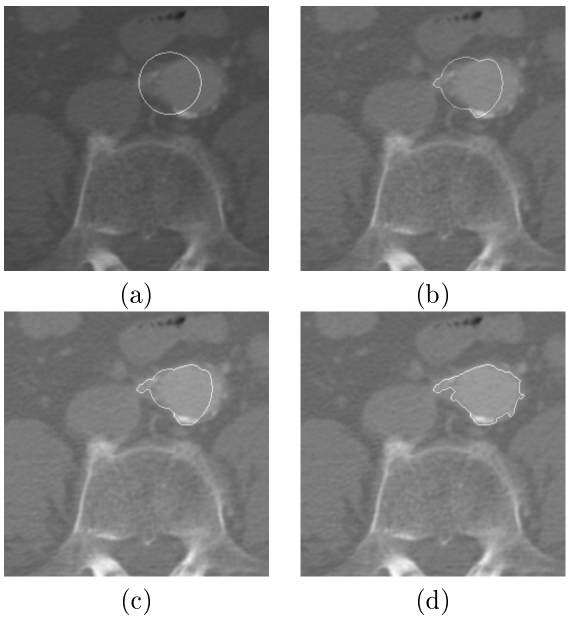


Figure 1: Operation related to the first image of the sequence a) Initialization, b and c) Propagation, d) Convergence.

The initialization on the first image is doing by circular contour, as illustrated figure 1.a. The iterative evolution of the active contour is function of the minimization of the criterion (6). After propagation, illustrated figures 1.b and 1.c, the algorithm converge when the minimum of the criterion is obtained, figure 1.d.

3 AUTOMATIC DETECTION IN AN IMAGES SEQUENCE

In this section, we present an automatic technique of contour propagation in the image sequence. Semi automatic methods quickly provide data [5, 7]. When a result is obtained with the used methods in imaging medical services, the quality of the result is not usualy valable [10]. From the contour resulting of the first cut, presented section 2, we propose to use it to detect automaticaly the other contours in all the sequence. In the subsection 3.1, we present how to propagate the first contour in the next image and to fill the interested region. In the subsection 3.2 we present the advantages of the local estimation in this case.

3.1 Propagation, Dilatation and Filling of the Interest Region

We know that the difference between two successive cuts is not important. From the contour obtained on the image n, we define a new region of interest ω^n for the next image $n+1$, with $n = [2, ..., N]$, if N is the number of cuts. From the equation (5), this region of interest is defined by :

$$\omega^n = d_1^n \cup d_2^n, \quad (8)$$

where d_1^n corresponds to the region of the object and d_2^n corresponds to the background only in the region of interest ω^n .

For the next image we have :

$$\omega^n = \beta.d_1^{n-1}, \quad (9)$$

where β is the dilatation factor with $\beta > 1$.

For the first image we define $d_1 = D_1$ as illustrated figure 2.a. From the second image, the region of interest ω^n is only a part of the image Ω, as illustrated figure 2.c .

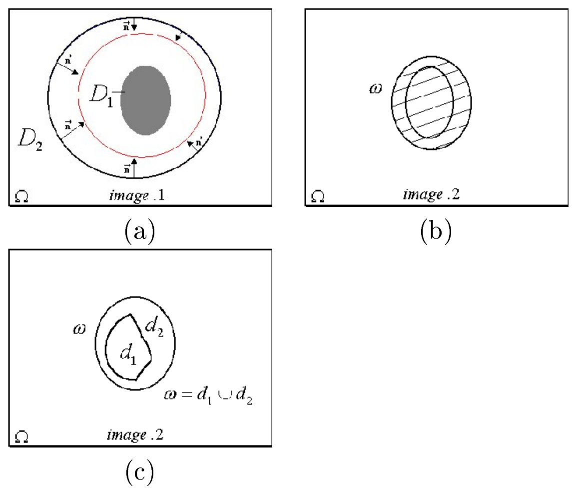


Figure 2: a) Domain of the object and the background in the first image, b) Dilatation of the region d_1^{n-1} in the image $n-1$ c) Propagation of the dilated region from d_1^{n-1} to get ω^n, the interested region in the image n.

To get ω^n we should firstly fill the region limited by the founded contour in the previous image to obtain d_1^{n-1} and secondly dilate this region with a dilatation factor β, showed in figure 2.b and 2.c. Thus, we could realize a dilatation of the obtained contour to cover completely the surface of the object in the next cut.

3.2 Robust Local Estimation

In the section 2 the constants I_1 and I_2 related to the areas D_1 and D_2, respectivly the searched object and the background, are estimated on the entire image of the first cut with the robust estimator [9]. This estimator is formalized like a weighted least square problem [4]:

$$\hat{I} = Arg\ min \sum_i \frac{1}{2}\gamma_i (f_i - I)^2, \tag{10}$$

with:

$$\begin{cases} \gamma_i &= (1 - (\frac{|f_i - I|}{c})^2)^2 \quad /|f_i - I| < c \\ \gamma_i &= 0, \qquad\qquad\qquad\quad /|f_i - I| > c, \end{cases} \tag{11}$$

where c represents the maximum value of the residual to limite the contribution of some points. We have noticed that the variation of the image optical density between two neighbouring cuts changed ramdomly. Furthermore, this global estimation needs more computation time and also it is necessary to removed manually the other objects contained in the global domain Ω of the image, for example the spinal column.
Moreover, the value of the c parameter should be reconsidered for each image of the sequence.
In the case of a local estimation with ω^n, the value of c is computed only one time from the second image. We can use this value for all the images of the sequence.
The local estimation is based only on the interested region ω^n. In this region, the contribution of the other objects of the image is null and the computation time is acceptable. From the equation (10) the local estimation of the object is :

$$\hat{I}_1 = \frac{1}{\sum_i \gamma_i} \sum_i \gamma_i I_1. \tag{12}$$

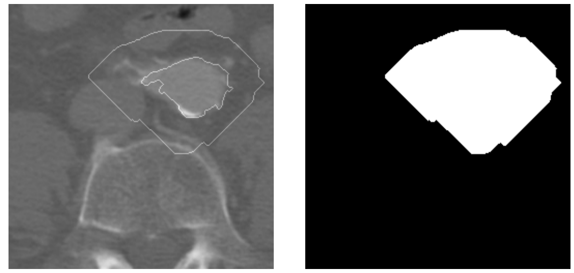
In the case of a local estimation, the stability of the c value provides that the background d_2^n is a minority part of the local region ω^n. In fact, from the previous cut, we estimate approximately the new region d_1^n of the object. So, the local estimation is based principaly on the region of the searched object because the number of points belonging to d_1^n is superior to the number of points to d_2^n.

4 RESULTS

In this section, we illustrate our methods on a part of a medical images sequence. For these results, we use 6 cuts in the central area of this sequence.

From the obtained contour of the first image, showed in figure 1, we could realize a dilatation of this contour, as illustrated in figure 3.a, to cover completely the surface of the object in the next cut, showed in figure 3.b. The local estimation can be done in this interested region ω^n.

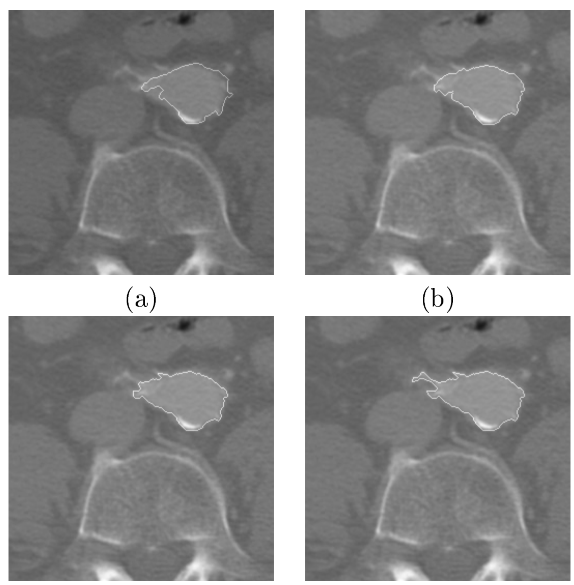
Experimentaly we have used $c = 5$ in the case of a local estimation for all images of the sequence. For the second image of our sequence we obtain the estimation of object represented in figure 4. In the case a global estimation, the value of c could changed for each image: $1 < c < 8$.



(a) (b)

Figure 3: a) Dilatation, b) filling of the interest region.

Figure 4: Local estimation of the aorta in the second cut.



(a) (b) (c) (d)

Figure 5: Operation related to the second and following images of the sequence a) Initialisation, b and c) Propagation, d) Convergence.

From the local estimation as illustrated figure 4, we initialize the contour on the second image with the obtained contour on the first image, figure 5.a. After propagation, illustrated in figures 5.b and 5.c, the algorithm converges in the second image to obtained the contour showed in figure 5.d.

The figures 6 shows the results of obtained contours after initialisation with previous contours on the third, fourth, fifth and sixth cuts of the sequence.

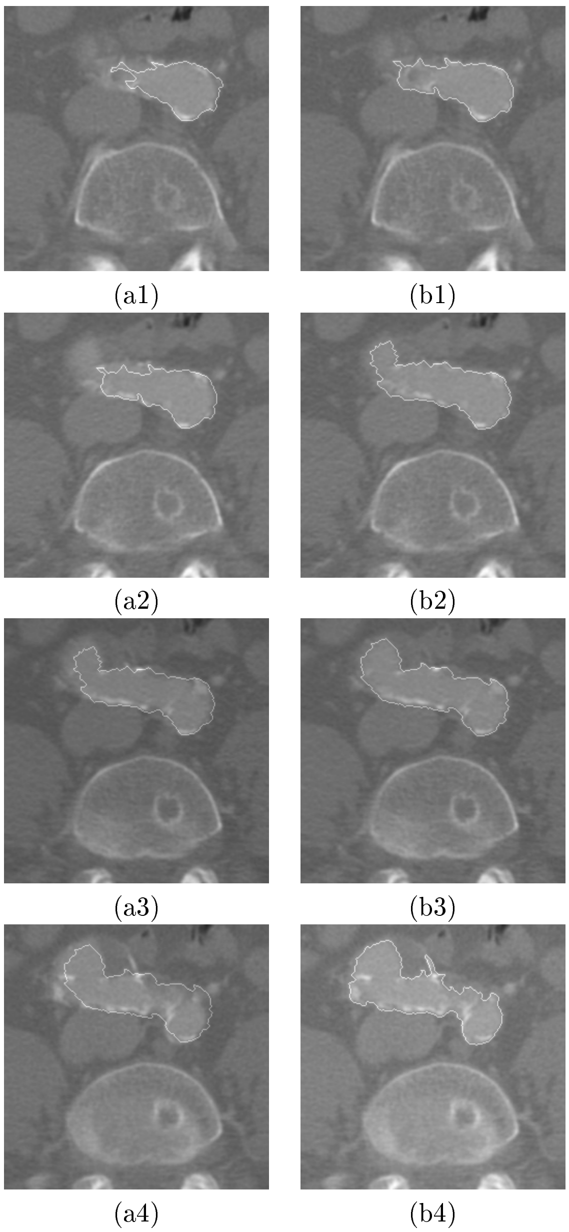


Figure 6: a) Initialisation on the third, fourth, fifth and sixth cuts of the sequence cuts, b) Convergence on these cuts.

5 CONCLUSION

This propagation method with deformable active contours in two directions on image sequence could be a solution accepted by doctors specialised in medical imaging. Indeed, the detected contours are precise in each cut, and in the case of a local estimation, the propagation of the contours on the sequence is faster than in a case of a global estimation. The 3D reconstruction of anatomic structure constitutes an important help for telediagnosis. The method we have presented is more automatic than the existing methods in medical imaging services.

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