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Influence of Noise Distribution on Active Contour Models: Medical Images Segmentation

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ABSTRACT
The segmentation methods by active contour models have been widely used in recent years and have given great satisfaction in different applications. However, for a given application, the choice of appropriate model is difficult to define. In this study we review the active contour models and we propose a robustness quantification of these models through different noise distributions. Robustness is evaluated on various images.

Key words: Active contour models, images segmentation, influence of noise, medical images

INTRODUCTION
Medical imaging is an important diagnostic tool, its aim is to help specialists. The exploitation of these images requires a low-level processing such as segmentation, which is a real challenge for researchers. Indeed, for each organ (brain, heart, etc.), the used approach is different: the segmentation tool must be adapted to a particular organ, according to a particular modality of acquisition (scanner, radiography, magnetic resonance imaging) and for a particular image sequence. The objective is the quantification of the information, for example, the volume: volume of a tumour in the brain, study of cardiac ventricular cavity, etc. The segmentation quality, i.e., the location accuracy and non-confused regions have a direct impact on application performance. The methods of image segmentation are numerous and all have advantages but are not entirely satisfactory. All must be adapted to applications that we intend to achieve. Among these methods, there are active contours that are becoming increasingly popular. These are regular mathematical curves, such piecewise polynomial curves (spline) or parametric curves (ellipses defined by their centre and their axes), manually initialized and changing to best represent the contours of an object. Many active contour models have been proposed since the introduction of this concept by Kass *et al.* (1987). They differ by the type of curves, the imposed constraints on them, the used numerical methods, etc. (Caselles *et al.*, 1997; Djemal *et al.*, 2004, 2006; Cohen, 1991; Mumford and Shah, 1989). In practice, the implementation of active contours by native user is delicate: the active contour model must be selected according to the type of image, the type of objects in the image.

The initialization of the active contour model is also problematic: it must be simple, possibly automatic, but close enough so that the model is trapped by insignificant objects. This study aims to present a quantification of the robustness of different active contour models through different levels of Gaussian noise. We divide the approaches by active contours in two categories: contours based approaches and regions based approaches. We try to compare the quality of the segmentation of different approaches on synthetic and real medical images under two performance criteria. The first considered criterion is based on the area measurement, where the reference area measurement is obtained from synthetic image without noise. The second is the convergence time for each algorithm.

Classical active contour: In the classical active contour (Kass *et al*., 1987), the deformation is related to the minimization of energy functional, constructed so that a local minimum lies on the border with the detected object. This functional of energy noted E composed by two terms: the curvature term called internal energy $E_{int}(C)$ and the external energy term $E_{ext}(C)$ related to the image data.

Let v(s) = (x(s), y(s)) the current point of the contour C, where the curvilinear abscissa s $\in[0, 1]$:

$$E(c) = \alpha\int_0^1 |c'(q)|^2 dq + \beta\int_0^1 |c''(q)|^2 dq - \lambda\int_0^1 |\nabla I(c(q))| dq \tag{1}$$

With α, **β** and λ positive reals, first two terms of Eq. 1 are related to the internal energy and the third to the external energy. The approach tends to minimize the energy functional. The implementation of this approach has led to many implementations, we can identify the classical variational approach, proposed by Kass *et al*. (1987) and the dynamic programming methods presented by Amini *et al*. (1988). We have used the greedy algorithm proposed by Williams and Shah (1992) which is the implementation that most used. The principle algorithm is to evolve the active contour by minimizing the energy functional as follows:

$$E(c) = \sum_{i=1}^{N} a.E_{intensity}(M_i) + c.E_{continuity}(M_i) + b.E_{curvature}(M_i) + g.E_{gradient}(M_i) + d.E_{ballon}(M_i) \tag{2}$$

With M_i, i = [1..N], set of ordered points and a,c,b,g and d positives real. $E_{intensity}$,$E_{continuty}$, $E_{curvatuve}$, $E_{gradient}$ and E_{ballon} are, respectively intensity, continuity, curvature, gradient and balloon energies. For each point of the active contour, we chose a number of neighbors for which we will calculate the energy, the point will move when the neighbor who has the lowest energy. It therefore seeks the set M of points for which the energy is minimal. So an iterative algorithm that moves a single point to form a new active contour at each iteration. All points are treated successively at each iteration.

Geodesic active contour: The variational approach of Kass *et al*. (1987) has shown the benefits of active contours, but has also allowed several issues knowing that the model depends on many parameters. Recent work has improved the active contour model, where the complex shapes can be segmented without prior on object topology. Indeed, motivated by the evolution interfaces theory of curves and to eliminate the negative effects of conventional active contour (Caselles *et al*., 1997; Malladi *et al*., 1995) have introduced geometric models that take into account the geometric measures internal and external. They have chosen first **β** = 0 in the energy functional (1). This choice is justified by the fact that the regularizing effect active contours from the waves based on the curvature are obtained only with the other terms. This

$$E(c) = \alpha \int_0^1 \left|c'(q)\right|^2 dq - \lambda \int_0^1 \left|\nabla I(c(q))\right| dq \tag{3}$$

gives smooth curves without having to introduce a regularization of second order. We try and locate the points where the gradient of the image is strong while keeping certain curve regularity.

To overcome the parameterization problem, we use an implicit formulation for the active contour. We are redefining the length concept of curve by the following formula Eq. 4.

$$L_R = \int_0^{L(c)} g(\left|\nabla I(c((q)))\right|)\left|c'(q)\right| dq \tag{4}$$

To deform the initial curve to a local minimum of L_R, the curve should follow the following evolution equation:

$$\frac{\partial c(t)}{\partial t} = g(I)k\vec{N} - (\nabla g.\vec{N})\vec{N} \tag{5}$$

The Level set formulation (Osher and Sethian, 1988) is used in our study for the implementation of the geodesic active contour model (Caselles *et al.*, 1997; Malladi *et al.*, 1995):

$$\frac{\partial \phi}{\partial t} = g(I)\left|\nabla\phi\right| \operatorname{div}\left(\frac{\nabla\phi}{\left|\nabla\phi\right|}\right) + v\nabla g(I).\nabla\phi = g(I)(v+k)\left|\nabla\phi\right| \tag{6}$$

where, v positive constant responsible for forcing the contour evolution to the object borders where acts as a balloon force introduced by Cohen (1991) in the classical active contour. The curve evolution is stopped when g tends to zero, which corresponds to contour of the object.

These methods based contours, often require pre-treatment methods can reduce the intensity noise or remove it if it has a priori knowledge on the model.

Region-based active contours: The segmented regions may have different properties of texture, homogeneity or movement that can be included in a single contour integral. The main objective of the region-based active contours is to introduce global information in the evolution equation of the active contour and more local information provided by the terms based contours.

In this study, we implement the proposed approach by Chan and Vese (2001) as region-based active contours model, this approach is based on segmentation techniques proposed by Mumford and Shah (1989) and we can obtain many advantages. This model can detect objects with or without strong gradient, automatically detect interior contours and the initial curve can be placed anywhere in the image.

Let I an image that contains an object and a background, we want to evolve a curve C to detect the objects. Let c_1 and c_2 the mean inside and outside of the curve. Let u_0 the pixel intensity of the image, the curve cuts the image into two regions which have the intensity of a pixel values u^1_0 and u^2_0, then we have $u_0 = u^1_0$ inside the curve and $u_0 = u^2_0$ outside. This gives us an energy of the image composed of the sum of the energy outside and inside the curve C. We obtain an energy F considering C, c_1 and c_2 such that:

$$
\begin{aligned}
&F(C, c_1, c_2) = \mu.\text{length}(C) + v.\text{area}(\text{inside}C) \\
&+\lambda_1 \int_{\text{inside}(C)} |u_0 - c_1|^2 dxdy + \lambda_2 \int_{\text{outside}(C)} |u_0 - c_2|^2 dxdy
\end{aligned} \tag{7}
$$

With μ, λ_1, λ_2 and v the positive parameters.

The level set formulation of this active contour model is given as follow:

$$
\frac{\partial \phi}{\partial t} = \delta_\varepsilon(\phi(x,t))\left[\mu k - v - \lambda_1(u_0 - c_1)^2 + \lambda_2(u_0 - c_2)^2\right] \tag{8}
$$

INFLUENCE OF NOISE DISTRIBUTION

In order to compare the performances of the different algorithms, we designed an experiment with various noise levels where the original image is degraded by a Gaussian noise of various intensities. Two performance criteria are considered, the first is based on the area measurement, where the reference area measurement is obtained from synthetic image without noise. The second is the convergence time for each algorithm. On one synthetic image we present the obtained results of the three segmentation approaches, classical active contour, geodesic active contour and region-based active contour.

Classical active contour evaluation: We applied the classical active contour algorithm *greedy* on synthetic images and after several tests we have chosen the following optimal parameters of different energies: b = 0.7, c = 0.45, a = 0.1, g = 0.98 and d = -0.65.

Experimentally these parameters allow converge to better solutions.

Considering the assumption that the ideal result of segmentation is obtained without noise and to evaluate the performance of this segmentation method we calculate the surface (area) of the segmented object after convergence of the algorithm for each noise distribution.

The results of Fig. 1c show the classical active contour ability to detect traditional boundaries of the object in a non noisy synthetic image. The images in Fig. 1d-i show the influence of noise on the final result of segmentation. In Fig. 1d, we note that an image degraded by Gaussian white noise with variance $\sigma^2 = 5$ the classic active contour was able to detect the borders of the object, but gradually as we increase the noise, we note that the convergence of the active contour toward the desired contour is not fully reached, because the contour has been attracted by the noise.

Figure 2 shows the variation of the surface according to different distributions of Gaussian noise. Indeed, we can see that the greater the intensity of noise increases the more active contour is difficult to converge towards the borders of the object.

Geodesic active contour evaluation: The geodesic model was applied to the same images used for the classic active contour which resulted from the segmentation are shown in Fig. 3. Experimentally we have chosen the velocity v = 0.7 which gave a best processing time of segmentation.

The images in Fig. 3 show the influence of noise on final segmentation result. In Fig. 3d and e, we note that on degraded synthetic image by Gaussian noise with $\sigma^2 = 5$ and $\sigma^2 = 10$, respectively, the geodesic active contour was able to detect boundaries of objects, but gradually as

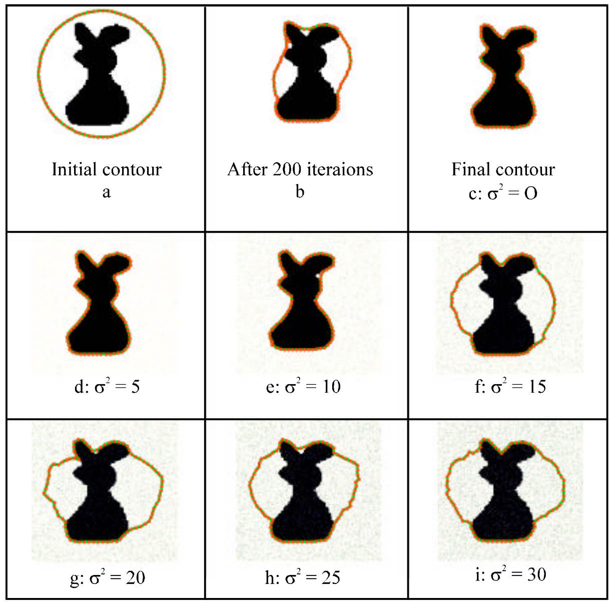

Fig. 1: Synthetic image segmentation using classical active contour model through different noise levels

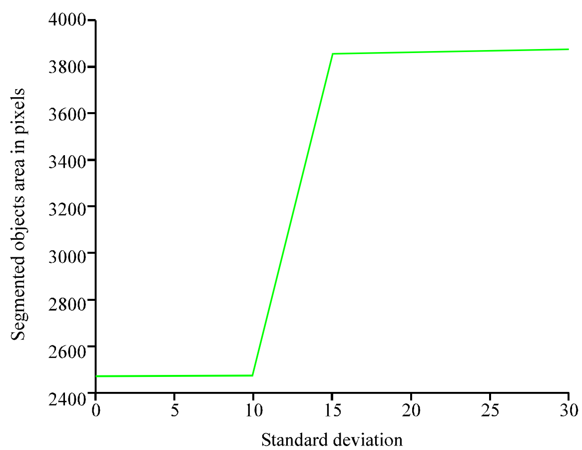

Fig. 2: Area variation of the segmented region according to the noise level, using classical active contour model

one increases the noise, we note that convergence contour towards the desired contour is not fully realized because the contour was drawn by the noise.

Figure 4 illustrates the surface variation according to the intensity of noise.

Region-based active contour evaluation: We have implemented a region-based active contour using Eq. 8. To validate the model, tests are performed on the same synthetic image used for classical and geodesic models. In our implementation, we choose the optimal values $\lambda_1 = \lambda_2 = 1$, $v = 10$ and $\varepsilon = 0.001$. The numerical model is made with a step-size $\Delta t = 0009$. The parameter μ will be determined by the properties of the image to be segmented.

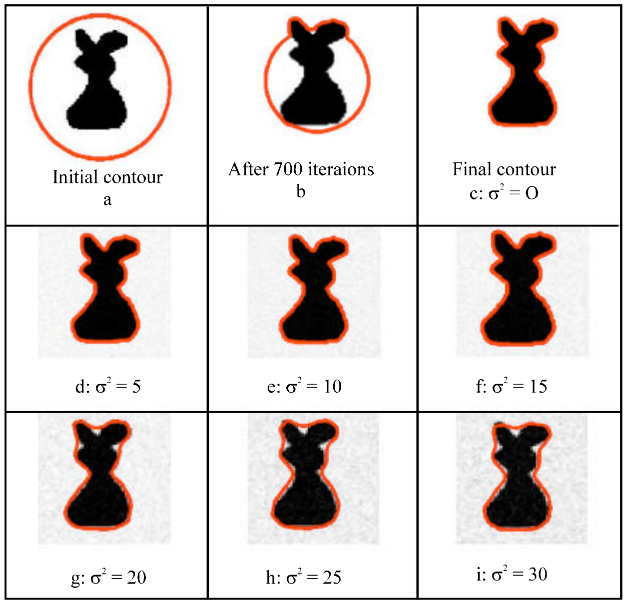

Fig. 3: Synthetic image segmentation using geodesic active contour model through different noise levels

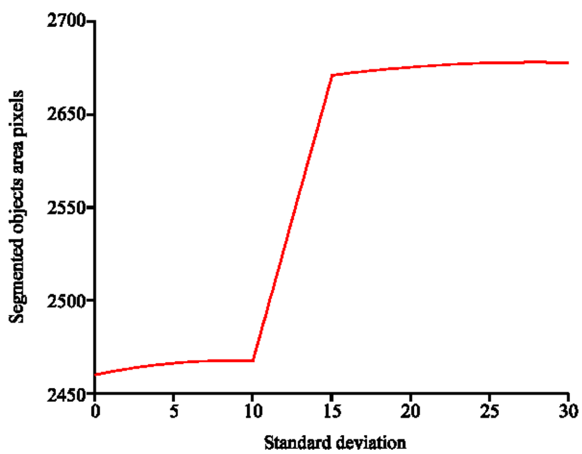

Fig. 4: Area variation of the segmented region according to the noise level, using geodesic active contour model

Figure 5 shows the image and the evolution of the contour. It starts in all cases by a simple closed curve. The circle curve is a better start because it has a regular curvature. For homogeneous regions, the segmentation by region-based active contour model is most suited. Indeed, we find that the results are faithful to the described model.

Figure 6 shows for each Gaussian noise level the area bounded by final contour. Generally we note that only when we have small area variations the model provides suitable segmentation.

Global performance evaluation: We can see that the obtained results on the synthetic image are faithful to implemented models. Figure 1i, 3i and 5i show the difference between these three

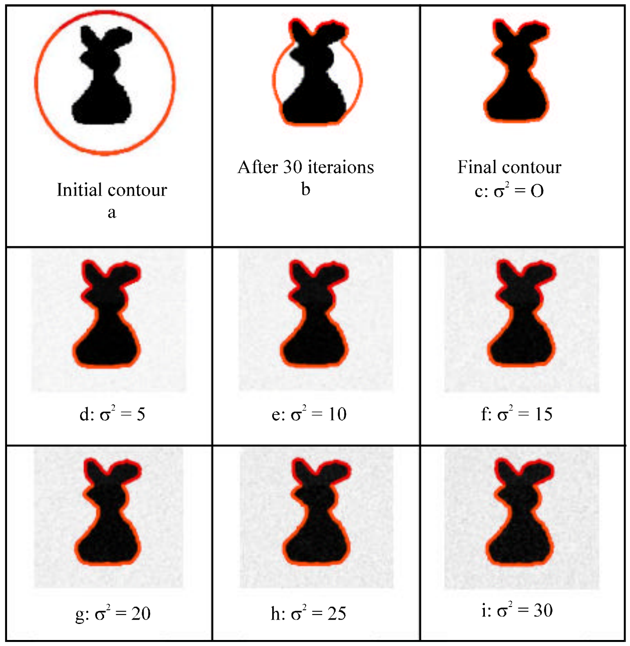

Fig. 5: Synthetic image segmentation using region-based active contour model through different noise levels

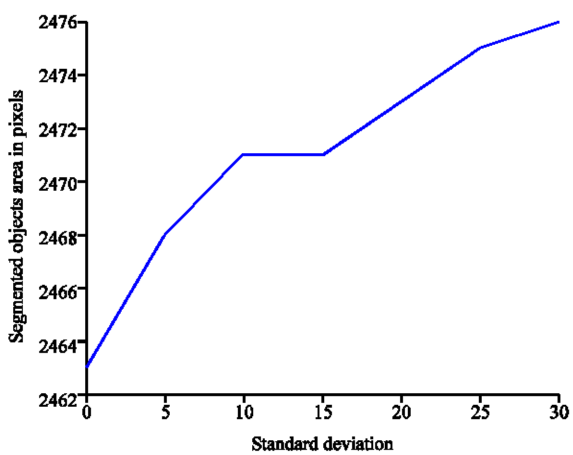

Fig. 6: Area variation of the segmented region according to the noise level, using region-based active contour model

models where the models based regions represents the best result. Indeed, taking into account the global characteristics of the regions to segment and decrease the influence of strong changes of gradient have achieved an acceptable segmentation result. The regions homogeneity contributes too to obtain a good segmentation performance.

To better illustrate the influence of noise on active contour models, we present in Fig. 7, affect on the delimitation of the object by calculating the area of the segmented region and we note that the region-based active contour is little sensitive to noise.

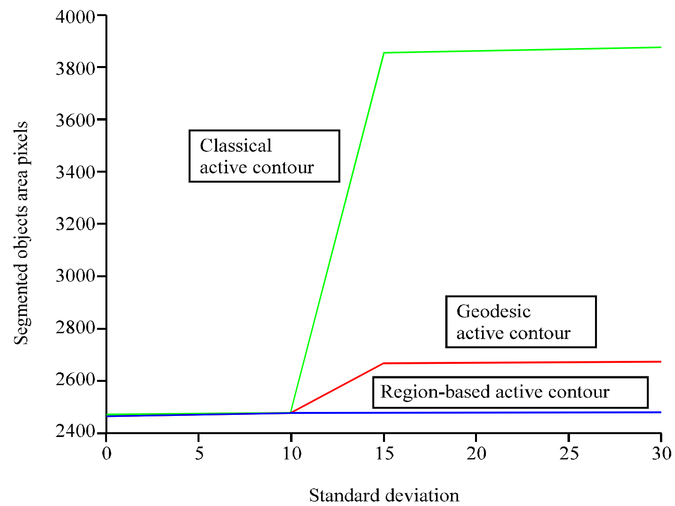

Fig. 7: Area variation of the segmented region according to the noise level, using three active contour models

Table 1: Classical active contour propagation time

Iterations	50	100	150	200	250	280
Time (sec)	12.74	19.73	27.44	34.26	41.67	45.08

Table 2: Geodesic active contour propagation time

Iterations	50	100	150	250	300	1240
Time (sec)	12.22	24.49	36.33	60.28	72.56	296.23

Table 3: Region-based active contour propagation time

Iterations	50	100	150	200	220
Time (sec)	7.47	14.56	20.59	27.63	30.48

The second considered performance criterion is the execution time to converge towards a final solution of each algorithm. For that we present in Table 1-3 the execution time obtained on the synthetic image with $\sigma^2 = 5$. We note in Table 1 for the classical active contours that the algorithm converges after 280 iterations in 45.08 sec. We get the best time of convergence with the region-based model (Table 3), in fact, the algorithm converges after 30.48 sec in 220 iterations.

MEDICAL IMAGES APPLICATION

The comparison of results between presented models is done on two medical images. The classical active contours are a powerful interactive tool that solves a great number of problems in image processing. However, this approach is sensitive to noise which causes the contour to converge to an unexpected, difficulty to adjusting various parameters, initialization problem: if the active contour is placed too far from the borders of the object, it will not be attracted by them and finally the classic active contour thus defined not change topology over time, it will remain a single closed curve and don't able to detect multiple objects in an image. Indeed, we observed the rigidity of

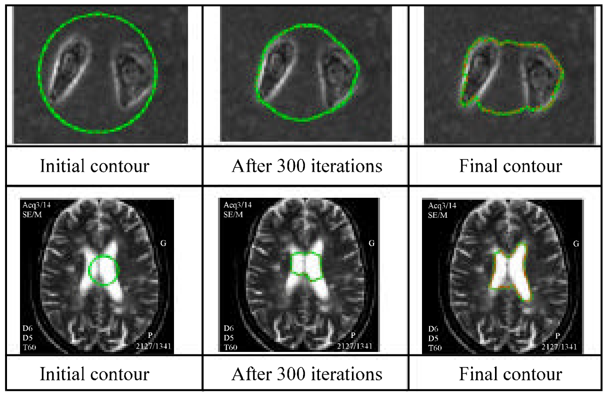

Fig. 8: Medical images segmentation by classical active contour model

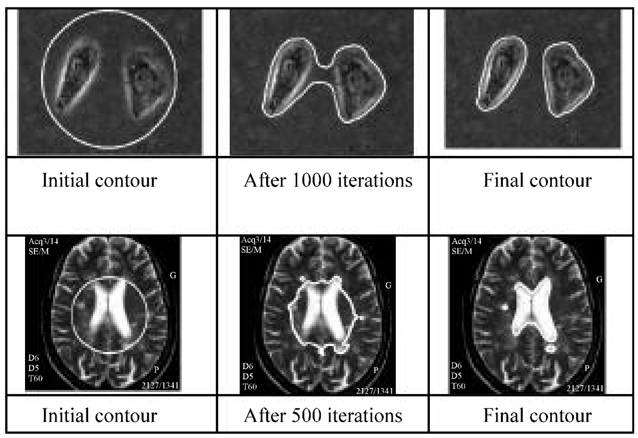

Fig. 9: Medical images segmentation by geodesic active contour model (v = 0.7)

classical active contour and its difficulties to converge on the border when the initial position and away from the correct solution (Fig. 8).

Geodesic active contours perceive the evolution of the curve as the propagation of a wavefront. The detection of a contour is then guided by solving a Partial Derivative Equation (PDE) and not by the minimization of an energy functional. This model suffers of the initialization problem of contour and noise sensitivity. This last point is the main drawback of the model, particularly in the case of real images. In practice, many efforts have been made to remedy this, including the introduction of region-oriented features at different levels of treatment (Paragios and Deriche, 1998, 2000). Acceptable segmentation results are obtained by the geodetic model (Fig. 9).

The obtained results by the region-based active contour are often the most effective segmentation of medical images. Unlike contour-based active contours (classical and geodetic), the model allows regions to introduce information on regions in the evolution equation of the active contour.

Figure 10 shows the images and the evolution of the contour during the segmentation process. The initial position of the contour may affect the final segmentation result and on the convergence

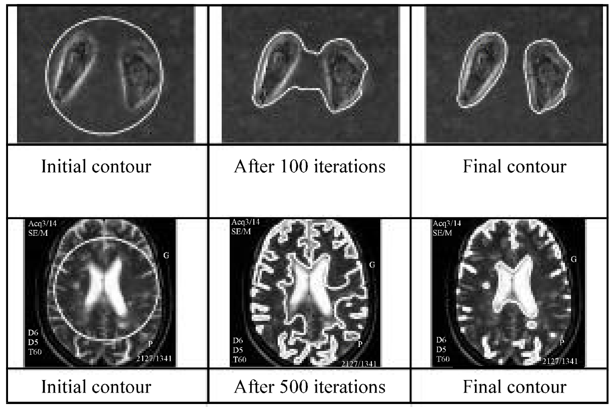

Fig. 10: Medical images segmentation by region-based active contour model

time. Indeed, the curve evolves towards the object but the speed of evolution will be different. We can easily notice that the contour of the curve perfectly detects regions of the image (Fig. 10).

CONCLUSIONS

Since, the introduction of active contour model by Kass *et al.* in the eighties, the active contour have been subject to a lot of research in various communities. This research have led to important improvements of the original model. Indeed, the geodesic active model is introduced to limit the initialization problems and decrease the used parameters number. Based on the geometric principle, the geodesic active contours allow the segmentation of objects with complex topology. However, these models only detect the edges of objects in images, this leads to poor segmentation if the images are very noisy. The region-based approaches, operates inside and outside the region defined by the initial active contour. These approaches can solve problems for which it is difficult to extract the contours of the object. This corresponds to images that are highly noisy and their regions are homogeneous.

In this study, we have presented the influence of the noise distribution on active contour models. Indeed, in order to compare and evaluate the performances of different algorithms, we have presented different experiments with various noise levels. The original image is degraded by a Gaussian noise of various intensities. Two performance criteria are considered, the area measurement and convergence time.

After evaluation on one synthetic image, the obtained results show the performances of the three segmentation algorithms, classical, geodesic and region-based active contour. For these three methods we obtain also satisfactory results on real medical images. The choice of active contour type is driven by the considered application, the type and the properties of the image to be segmented. We've noticed that for different models, it must play on the coefficients to get better results. The coefficients are different and depending on the images content, the object contrast in the image and also the initialization step.

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