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Localization of a cerebral pathology on magnetic resonance images by the level set without re-initialization and local region based method

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Abstract: The rapid development of medical imaging technology is revolutionizing medicine every day. Medical imaging allows scientists and doctors to disclose potentially vital information by scanning the human body non-invasively. The objective of this study is to locate or detect a cerebral pathology by the method of the active contour. The present work is a study on the possibility to define the outline of brain pathology using two methods: Level Set without re-initialization and local based region method. The processed images are given by a magnetic resonance scanner (MRI) 1.5 tesla; of three patients included in the medical imaging center A BOUKHATEM Oran in Algeria. Knowing that the images are T2, T1 weighted. To give credibility to this study, a comparative study is implemented between the two methods studied. In the final analysis, we will reap the benefits of each method and the Downside. Results have been able shown that the evolution of the level set algorithm without re-initialization is faster than the algorithm of based local Region, but is still less accurate in the localization of the pathology. For cons, the evolution of the algorithm based local area is very slow but much more accurate than the level set method without re-initialization. The only inconvenience is the requirement to initialize the curve C adjacent of pathology instead of taking the whole image. It was found that the time required for calculating the contour of the image by using magnetic resonance in the two methods, is considerably reduced and the image quality obtained at the end of treatment is remarkable to be able make a good medical diagnosis.

Keywords: **Medical imaging, Image segmentation, edge extraction, level set, local based region.**

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1. INTRODUCTION

Medical imaging is used to analyze the tissues with extremely diverse media, their farms and their interpretations can finer establish the medical diagnosis. The imaging techniques are numerous, based on different types of radiation (magnetic field, ultrasound, x-ray, gamma ray, ...). An imaging modalities most frequently used, in which we were interested in this work, is Magnetic Resonance Imaging (MRI), which has become an indispensable tool for any clinical examination. It has the advantage of being non-invasive and allows the acquisition of two or three dimensional image on which the different contrasts are possible. This modality has become an increasingly important medical research in brain or cognitive neuroscience fields of exploration that can be offered by this technique are broad: MRI anatomy that can be observed with a fine resolution cerebral tissue, functional MRI, which offers the possibility to visualize cerebral activity and diffusion MRI which to explore the aspect of connectivity brain areas.

In fact the study of the human brain is a difficult problem and remains a highly topical research, because an understanding of its operation still incomplete. To diagnose certain diseases related to internal cerebral damage, the doctor must analyze medical images. To study the evolution of a tumor, it is necessary to know accurately the changes in these images. The visual interpretation of brain MRI is not always safe. This is why the need for an automatic interpretation allows assist the doctors in their decision making was felt. Thus, for a reliable identification and reliable diagnosis in the medical field, precision is paramount. In terms of image analysis, it is necessary that the segmentation is accurate. Possibilities of automatic processing of these images prove difficult however, because the capacity as insignificant the human eye as the recognition of an object presents real difficulties for computers.

The objective of this study is to isolate possible pathologies through segmentation; it is considered the heart of medical imaging. Several methods have been proposed; including the method of active contours that outline research chained evolving from an initial form. This form is predetermined as a result of an optimization method using the image data at the locations of control points of the curve deformable. Both methods are studied respectively level set method without re-initialization and the local region based method proposed by the authors respectively Chunming Li et al. [1] and

Shawn Lankton [2]. This article describe new methods that can be remedied this problem. The extraction by active contour was our choice. We chose for this, two methods; the Level Set without Re-initialization and the local based region implement. Both algorithms are applied to radiological images taken by magnetic resonance in two weights:

- Highly contrasting Images in T2 weighted of three patients who wear different pathologies.

- The low contrast images in T1 weighted for the fourth.

The results are then compared with two studies: the energy evolution of the general function according to the number of iterations and compilation time. And an analysis of the importance of contrast product on low contrast images T1-weighted. In order to delimit the boundaries of each pathology; a third algorithm is used to extract each pathology of the resulting image following application of both algorithms on a black background.

2. The Level Set Method

The principle of the Level Set method is to define a developments function in the computing field with the zero level curves described by the relationship below:

$$C(t) = \{(x, y) \mid \phi(t, x, y) = 0\} \quad (1)$$

Solving a convection equation called Level Set equation [3] can predict the movements of the changes in the velocity field:

$$\frac{\partial \phi}{\partial t} + F|\nabla \phi| = 0 \quad (2)$$

With F is the speed function.

For image segmentation, this depends on its data and functionϕ. The function ϕ is then initialized as a signed distance function before the evolution and "remodel" as a function of signed distance periodically during evolution [4, 5]. Reset is to solve the following equation:

$$\frac{\partial \phi}{\partial t} = sin\,n\,(\phi_0)(1 - |\nabla \phi|) \quad (3)$$

where ϕ_0 is the function to be re-initialization, and the signed function φ [4, 6, 7].

2.1 Removal process of re-initialization by the energy penalty

It is crucial to maintain the evolution function of the level set as a signed distance function approximate course of evolution. It is well known that a signed distance function must satisfy a desirable property $|v\phi|=1$ [8]. Naturally, this process begins by calculating internal energy:

$$P(\phi) = \int_\Omega \frac{1}{2}(|\nabla \phi| - 1)^2\, dxdy \quad (4)$$

The variational formulation is as follows:

$$\varepsilon(\phi) = \mu P(\phi) + \varepsilon_m(\phi) \quad (5)$$

Where n > 0 is a parameter controlling the effect of penalizing the deviation of ϕ from a signed distance function, and $\varepsilon_m(\phi)$ is the energy that will drive the movement of the zero level curve ϕ.

We denote by $\partial\varepsilon/\partial\phi$ first variant [9] of the functional ε and the evolution equation as follows:

$$\frac{\partial \phi}{\partial t} = -\frac{\partial \varepsilon}{\partial \phi} \quad (6)$$

During the evolution of ϕ in function of the gradient flow (6) that minimizes the functional (5), the curve of the zero level is moved by the external power ε_m. Meanwhile, due to the effect of penalizing the internal energy, the evolution function ϕ is automatically maintained as an approximate signed distance function during the evolution. Therefore, the re-initialization procedure is completely eliminated in the proposed formulation.

2.2. Variation formulation of level set without re-initialization of the active contour

In the image segmentation, active contours are dynamic curves which move towards the object limit. To achieve this goal, we must explicitly define an external energy that can move the zero level curves toward the object boundaries. Let **I** be an image and **g** the edge indicator function defined by:

$$g = \frac{1}{1+|\nabla G_\sigma * I|^2}, \qquad (7)$$

Where Gσ is the Gaussian kernel with standard deviation σ. The external energy $\varepsilon_{g,\lambda,\upsilon}$ that causes the zero level to the object boundaries, is defined for a function ϕ (x, y):

$$\mathcal{E}_{g,\lambda,\upsilon}(\phi) = \lambda \mathcal{L}_g(\phi) + \upsilon A_g(\phi) \qquad (8)$$

With λ>0, $\mathcal{L}_g(\phi)$ is operative energy to calculate the length of the curve of the zero level of ϕ in the conformal metric $ds = g(C(p))|C'(p)|dp$.

p ϵ [0,1] is differentiable curve that represents the set of zero ϕ.

$$\mathcal{L}_g(\phi) = \int_\Omega g\delta(\phi)|\nabla\phi|dxdy \qquad (9)$$

A_g is the operating energy that is introduced to accelerate the evolution curve:

$$A_g(\phi) = \int_\Omega g\mathcal{H}(-\phi)\,dxdy \qquad (10)$$

where δ is the Dirac dimensional function, and H is the Heaviside function.

The total energy functional is:

$$\mathcal{E}(\phi) = \mu P(\phi) + \mathcal{E}_{g,\lambda,\upsilon}(\phi) \qquad (11)$$

Internal energy μP(ϕ) penalizes the deviation of ϕ from a signed distance function during evolution. By calculating changes [9], the derivative of the functional ℇ can be written as:

$$\frac{\partial\varepsilon}{\partial\phi} = -\mu\left[\Delta\phi - div\left(\frac{\nabla\phi}{|\nabla\phi|}\right)\right] - \lambda\delta(\phi)div\left(g\frac{\nabla\phi}{|\nabla\phi|}\right) - \nu g\delta(\phi) \qquad (12)$$

Where Δ is the Laplacian operator. Function ϕ that minimizes this functional meets the Euler-Lagrange

$$\frac{\partial\mathcal{E}}{\partial\phi} = 0.$$

The process of minimization of the functional ℇ is gradient flow given by the following equation which represents the equation of motion of the Level Set function:

$$\frac{\partial\phi}{\partial t} = \mu\left[\Delta\phi - div\left(\frac{\nabla\phi}{|\nabla\phi|}\right)\right] + \lambda\delta(\phi)div\left(g\frac{\nabla\phi}{|\nabla\phi|}\right) + \nu g\delta(\phi) \qquad (13)$$

3. The Local Region Based method

The Local Region Based method directly manipulates regions. Or she leaves a first partition of the image, which is then modified by splitting or grouping of regions. Or she leaves some regions, which are grown by incorporation of pixels until the entire image is covered. This method is based on statistical modeling joint of the regularity of regions and grayscale of each region also exist. The analysis of local regions leads to the construction of a local energy family at each point along the curve. To optimize these local energies, each point is examined separately, and looks to minimize or maximize the energy calculated in its own local region. To calculate the local energy, local neighborhoods are divided into outside and inside local by the curve evolution. The energy optimization is then performed by fitting a model to each local region.

Is an I picture, defined to the domain Ω, and let C be a closed contour represented defined as the zero (zero Level Set) of a function ϕ signed distance, ie, C = {x | ϕ (x) = 0} [9, 10]. The specification of the inside contour C in the approximation of the smoothed Heaviside function:

$$\mathcal{H}\phi(x) = \begin{cases} 1, & \phi(x) < -\epsilon \\ 0, & \phi(x) > \epsilon \\ \frac{1}{2}\left\{1 + \frac{\phi}{\epsilon} + \frac{1}{\pi} sin\left(\frac{\pi\phi(x)}{\epsilon}\right)\right\}, & otherwise. \end{cases} \quad (14)$$

The exterior contour C is defined by $\left(1 - \mathcal{H}\phi(x)\right)$.

To specify the area just around the curve, use the derivative of $\mathcal{H}\phi(x)$, a smoothed version of the Dirac delta:

$$\delta\emptyset(x) = \begin{cases} 1, & \phi(x) = 0 \\ 0, & |\phi(x)| < \epsilon \\ \frac{1}{2\epsilon}\left\{1 + cos\left(\frac{\pi\phi(x)}{\epsilon}\right)\right\}, & otherwise. \end{cases} \quad (15)$$

We now introduce a second variable space y, using x and y as independent variables space, each representing a single point in the domain Ω. We then introduce a function B (x, y) is used to ignore local regions. The interaction of B (x, y) with the inner and outer regions is illustrated in Figure 1.

This circle is divided into regions by the contour interior and exterior local. In both images, each point is represented by a yellow dot. Neighborhood B (x, y) is represented by the large red circle. Figure 1(a) is within the local is the shaded circle. The shaded circle indicates the outside room is illustrated in Figure 1(b).

3.1 Formulation of the functional energy

The operating energy E is defined according to the generic force F, which is defined by the following relationship:

$$E(\phi) = \int_{\Omega_x} \delta\phi(x) \int_{\Omega_y} \boldsymbol{\mathcal{B}}(x,y) \cdot F\left(I(y),\phi(y)\right)dydx + \lambda \int_{\Omega_x} \delta\phi(x)\|\nabla\phi(x)\| \ dx \quad (16)$$

With F is a generic measure of internal energy used to represent the local membership at each point along the contour, is expressed by [11, 12]:

$$F = \mathcal{H}\phi(y)(I(y) - u_x)^2 + \left(1 - \mathcal{H}\phi(y)\right)(I(y) - v_x)^2 \quad (17)$$

With u_x and v_x which respectively represent the intensity of the medium inside and outside the contour located in B (x, y) at a point x:

$$u_x = \frac{\int_{\Omega_y} \mathcal{B}(x,y) \cdot \mathcal{H}\phi(y) \cdot I(y)\, dy}{\int_{\Omega_y} \mathcal{B}(x,y) \cdot \mathcal{H}\phi(y)\, dy}$$

$$v_x = \frac{\int_{\Omega_y} \mathcal{B}(x,y) \cdot (1 - \mathcal{H}\phi(y)) \cdot I(y)\, dy}{\int_{\Omega_y} \mathcal{B}(x,y) \cdot (1 - \mathcal{H}\phi(y))\, dy}$$

And

$$\boldsymbol{\mathcal{B}}(x,y) = \begin{cases} 1, & \|x - y\| < r \\ 0, & otherwise \end{cases}$$

λ is parameter for maintain the smooth curve and regularization term penalizing the arc length of the curve. Taking the first variation of this energy with respect to ϕ, we obtain the following evolution equation:

$$\frac{\partial\phi}{\partial t}(x) = \delta\phi(x) \int_{\Omega_y} \boldsymbol{\mathcal{B}}(x,y) \cdot \nabla_{\phi(y)} F\left(I(y),\phi(y)\right)dy + \lambda\delta\phi(x) div\left(\frac{\nabla\phi(x)}{|\nabla\phi(x)|}\right) \quad (18)$$

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4. Results and discussion

To test the two methods studied in this article, the choice is based on medical images snuff with a magnetic resonance scanner 1.5 tesla. Figure 2.a present tumoral process of the temporal fossa of the left cavernous cranial, figure 2.b show a lesion process solido-cystic right fronto-parietal and figure 2.c illustrate a little expansive formation oedematogene moderately compressive in the left cerebellar hemisphere with cystic and tissular component. Both algorithms were compiled with a dual-core processor at 3.4 Ghz. The Level Set method without re-initialization method and Local Region Based will begin with an initialization of the curve C in the form of a rectangle, Figure 3. Figure 4 gives the results obtained by the method of level-set without re-initialization for an iterations number of 1500 and the computation time for the three cases respectively 138s, 145s and 150s. We can easily notice that the contour of the initial curve is perfectly fit the contour of the pathology. The computation time for the final detection of the pathology increases with the complexity of the disease.

Figure 5 and 6 gives the results obtained by the method of local based region. This time too, the outline of the initial curve takes shape of the contour of the pathology more accurately than the previous method. In the Figure 5, the number of iterations is 3000 which is higher compared to the first method and increases the calculation time which is 740 seconds. The initial curve C cannot surround the pathology despite the increased iterations number, is due to the complexity of the information contained in the image. That time can be reduced if the algorithm is applied directly near the pathology. However, in Figure 6, curve C is initialized adjacent of the disease, this solution gives very good results because it manages to perfectly surround the disease. With an iteration number of 500, this is 6 times less reduced.

4.1 Pathology extraction of the image

The pathology extraction of the all image is performed following the three transformations:

- Extract the outline produced by the two methods,
- Change the outline of a white spot,
- Rebuilding the disease from the white spot.

First, for extracting the contour, all pixels in the image will be set to zero, that is to say, black color except for the contour pixels will retain their original color, green for the outline produced by the Local Region Based method, and red for the level set method without re-initialization. This produces a black image with single information that represents the outline (Figure 7). Secondly, the contour obtained from the first stage will be transformed into a white spot on a black background. It will initialize four images m1, m2, m3 and m4; Figure 8. The algorithm changes the color of all contour pixels, within the contour well as respectively the pixels of the right, left, low, high contour in white. For the white spot, the algorithm does the product of four matrices (image). Figure 9 illustrate the results for three pathologies, with the method mentioned in this section. We note that, using this process, the local area based method allowed us to accurately detect the disease in contrast to the level set without re-initialization method.

4.2. Performance of the Level set and local region based method on contour extraction of pathology for low contrast images

So far the two algorithms we were tested on high-contrast images, where the pathology is visible. The applications presented in this section are applied to low-contrast images, images are taken by T1-weighted magnetic resonance before and meadows have injected contrast material. Figure 10 and Figure 11 show the cerebral images of a patient who is suffering from a tumor of the right ventricular junction process can evoke a meningioma. Figure 10 shows the results obtained by both algorithms before injection of contrast product. The algorithm of the Level Set method fails to detect the edges of the pathology. The evolution curve converges towards the inner portion of the image until it disappears completely. By against, the algorithm the Local Regions based method can hardly surrounded pathology, this is due to the initialization of the evolution curve at the edge of the pathology. Figure 11 indicates that the pathology is easily detected by the two methods used in this study after injection of contrast product, knowing that this product (gadolinium) is a radiological contrast agent with opacifying properties prescribed for an MRI exam

In this section we can say that the Level Set without re-initialization method and based Local Regions method are performing and provide a good localization of the pathology with injection of contrast material to the case of images with low contrast.The table below presents a quantitative measurement results obtained by the two methods for ten patients. According to this analysis, ten patients were able to deduce that 67.5% of tests done we were satisfied.

4.3. Comparative study of two methods

To give credibility to this study, a comparative study is implemented between the two methods studied in this article. First time we even variation of the energy as a function of number of iterations, after which the time variation versus the number of iteration.

4.3.1 Variation of energy according to the iterations number

The evolution of the energy as a function of the iterations number for level set methods without re-initialization for three different patients is shown in Figure 12a. This figure clearly shows that the variation of the energy with the number of iteration is different from one case to another. This difference is due to the type of information contained in each image. The energy varies continuously for the three cases studied, this means that if the choice of the number of iterations is not good for stopping the algorithm, the energy will continue to vary. This will probably push the evolution curve to ignore the edges of the pathology.

Figure 12b shows the variation of the energy according of the iteration number for the method Local Region based. There is a difference in the evolution of energy from one case to the other is due to information that contains each image. All times its allure remains the same for all three cases. The energy increased in a manner proportional with the iteration number, until it reaches a stabilization point. It was noted that it is this point that the curve of evolution will happen to detect the pathology. This leads us to say that for the local region based method once the object is detected, the energy ceases to vary in contrast to that obtained by the level set method without re-initialization, which continues to vary even after the detection of the object, which makes the level set method without re-initialization less accurate.

4.3.2 Time variation in the iteration number

In this section, we study the time variation versus the number of iteration. Figure 13 shows the evolution with time of the iteration number. Time variation is almost identical to the 3 cases tested; we also note that the computation time of the level set method without re-initialization is much reduced that the method Local Region Based. Proceeding now to a comparison between the results of two methods studied, we can deduce that the following points:

- The evolution of the level set algorithm without re-initializing is faster than the algorithm of based local Region, but is still less accurate in the localization of the pathology.

- For cons, the evolution of the algorithm based local area is very slow but much more accurate than the level set method without re-initialization. The only inconvenience is the requirement to initialize the curve C adjacent of pathology instead of taking the whole image.

5. CONCLUSION

The present work is an implementation of two new methods to ensure that the contour extraction to the medical image acquired by magnetic resonance. The models described are respectively Level Set without Re-Initialization and the Local Based Region method. The main advantage of these two approaches is in the computation time, which is considerably reduced. The results achieved are quite remarkable, except that, despite all best efforts to accelerate the algorithm, it remains relatively long.

We can deduce the following points:

- The level set method without re-initialization is faster than the method local region based.

- The change in time is not dependent on the information includes the image but the number of iterations.

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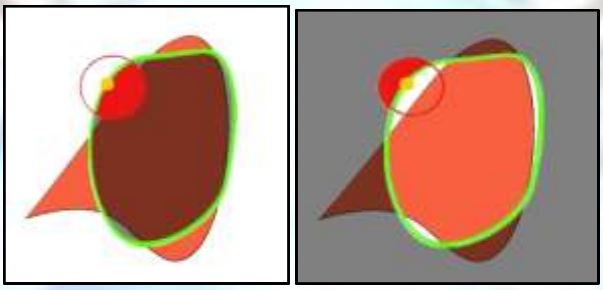
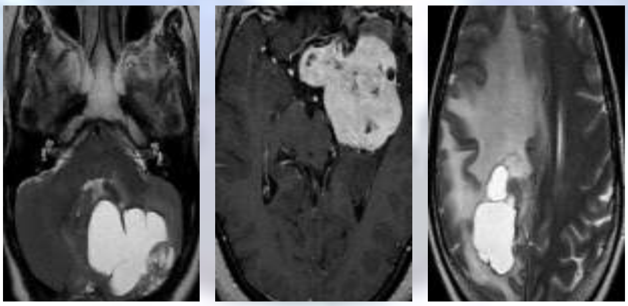
Figures



(a) (b)

Fig. 1: Each point along the contour is represented by a circle.



(a) (b) (c)

Fig.2: Definition of cerebral pathology

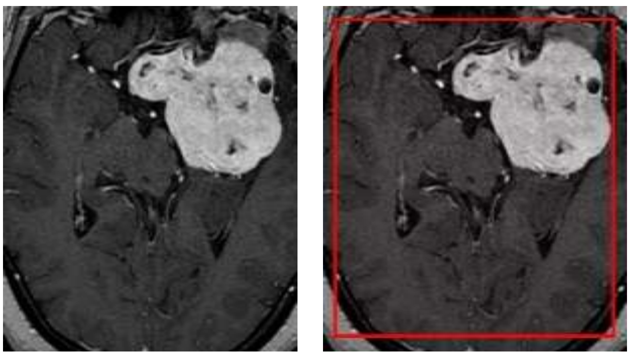


Fig. 3: Initialization of the curve

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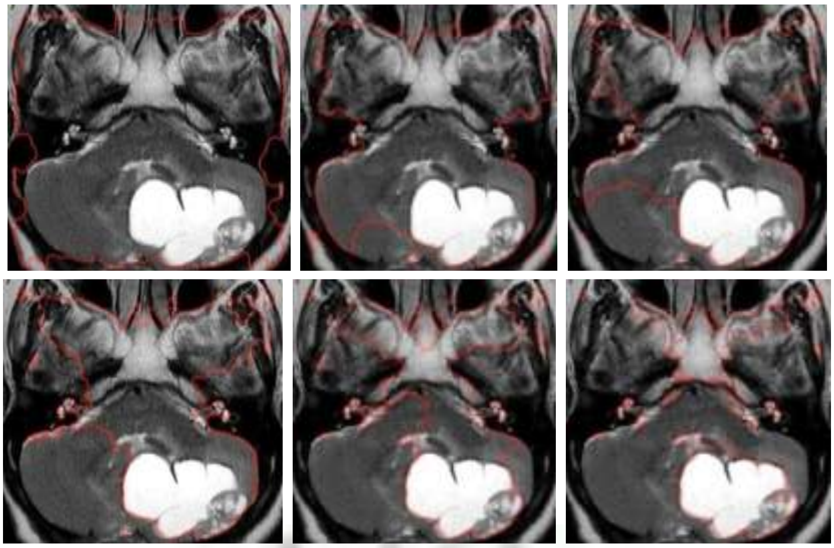
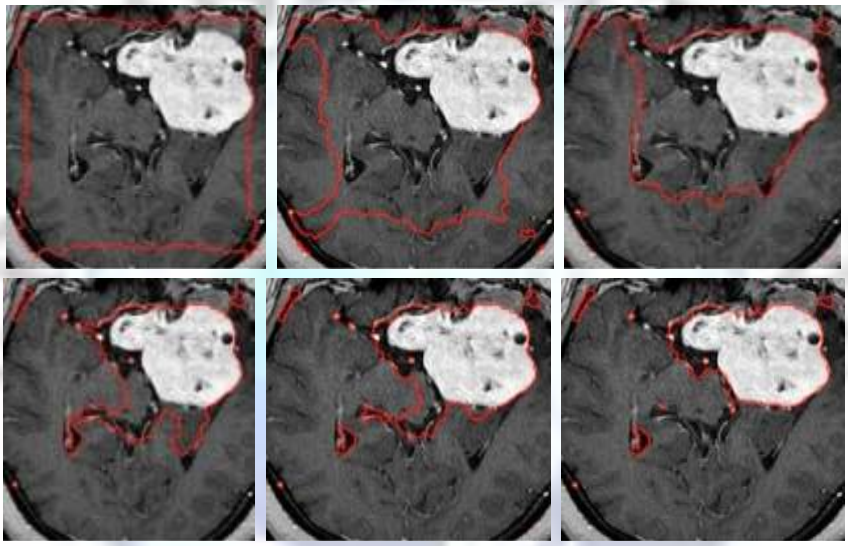
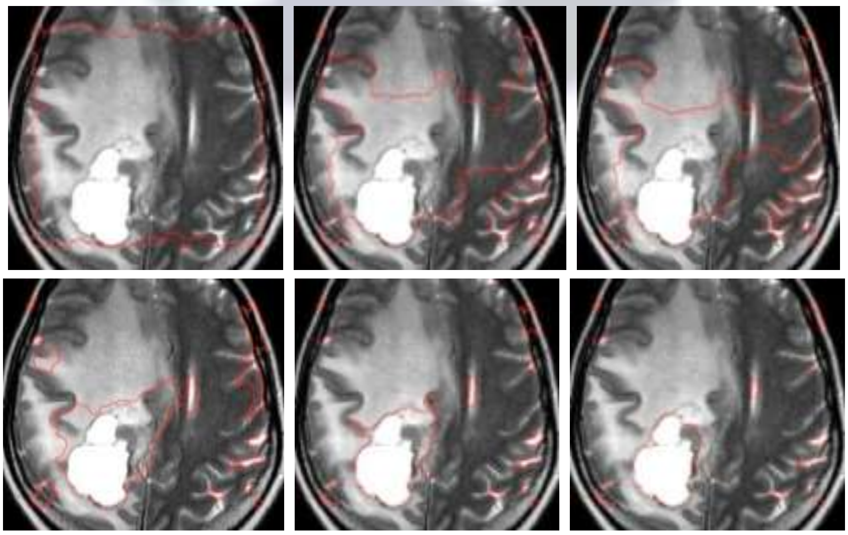


(a) 1500 iteration, Time: 138s

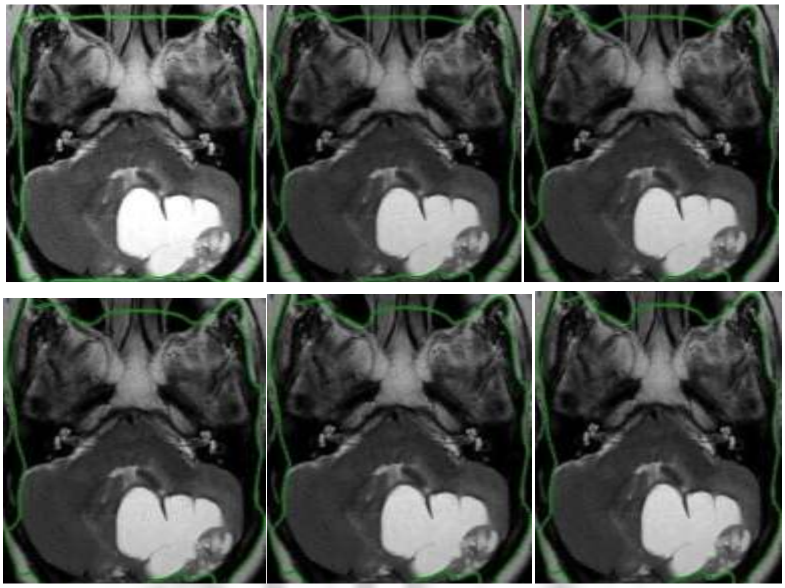


(b): 1500 iteration, Time: 145s



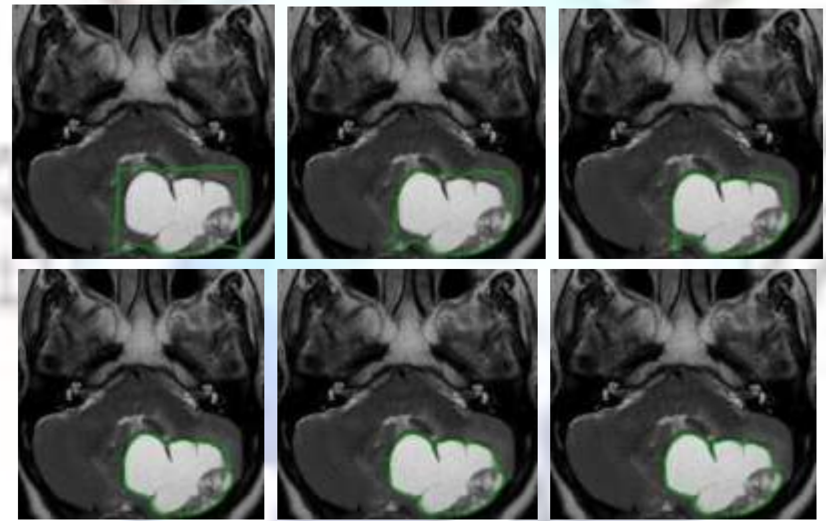
(c): 1500 iteration, Time: 150 s

Fig. 4: Evolution of the Level Set without re-initializat

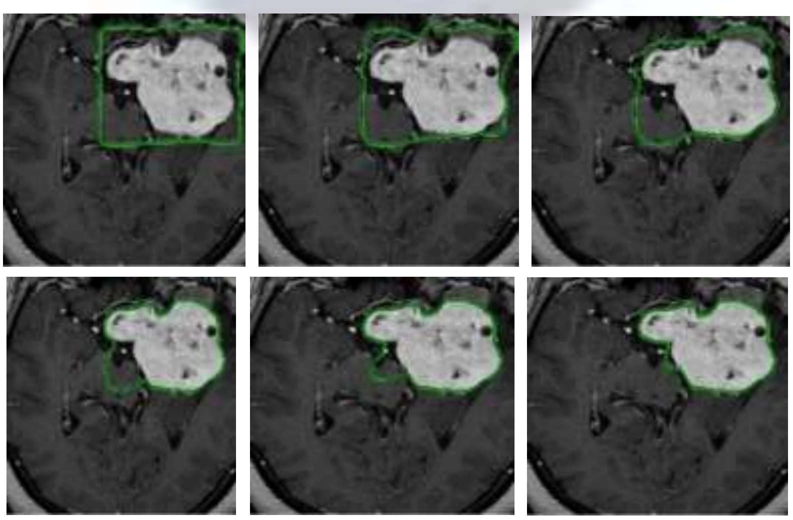


Iteration: 3000, Time: 740 s

Fig. 5: Evolution of the Local Region Based for the entire image



(d) Iteration: 500, Time: 105



(e) Iteration: 500, Time: 165 s

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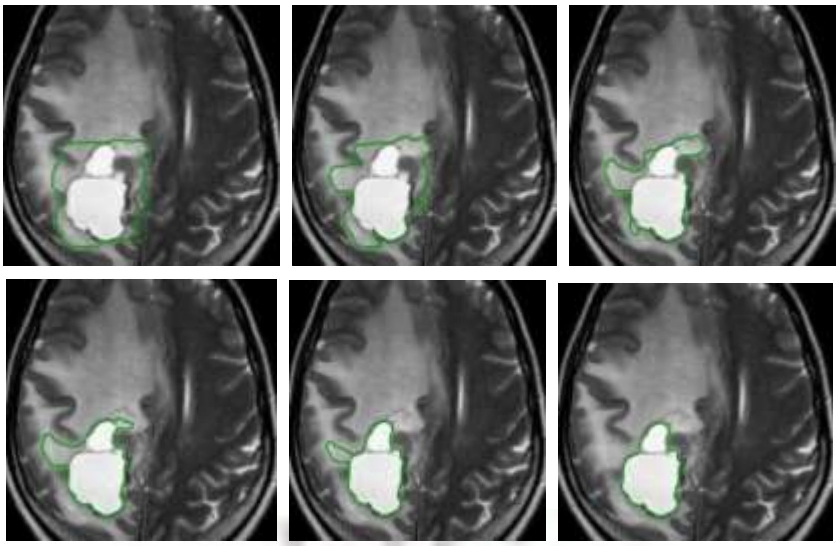


(f) Iteration: 500, Time: 141 s

Fig. 6: Evolution of the Local Region Based adjacent the pathology

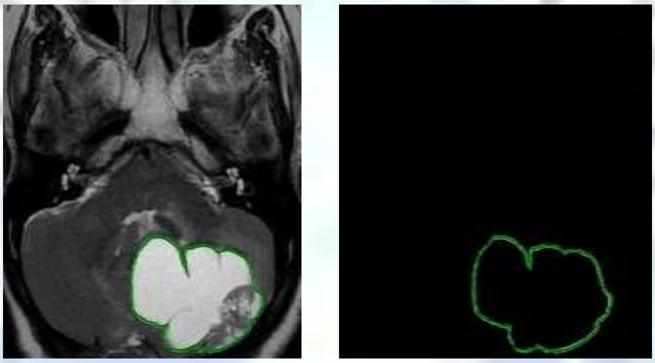


Fig.7: Extraction the contour

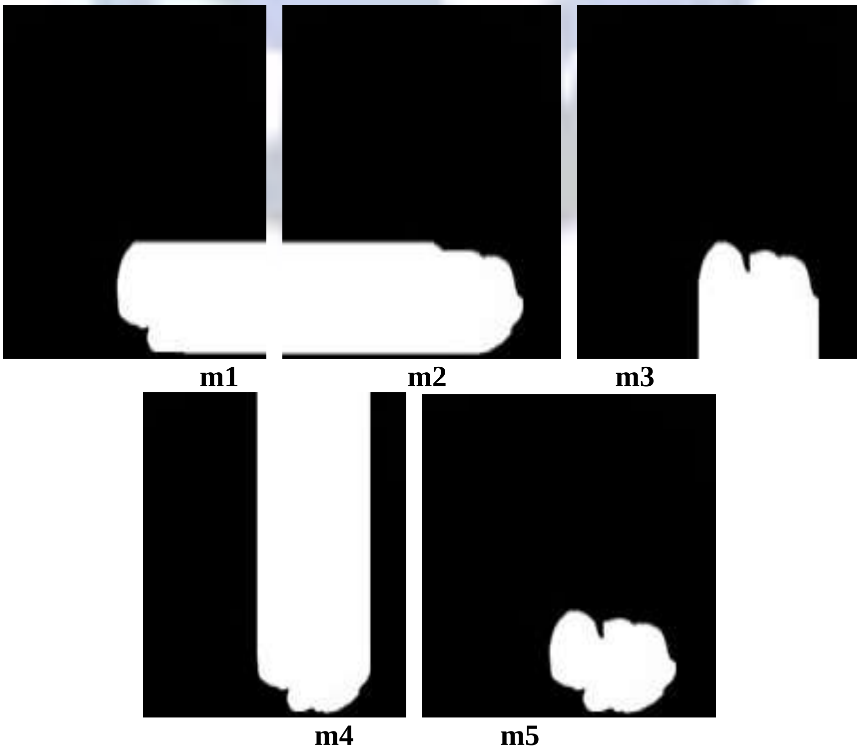
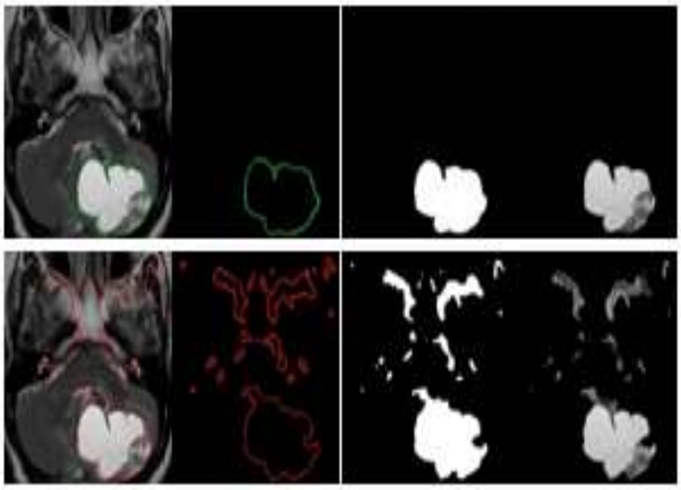
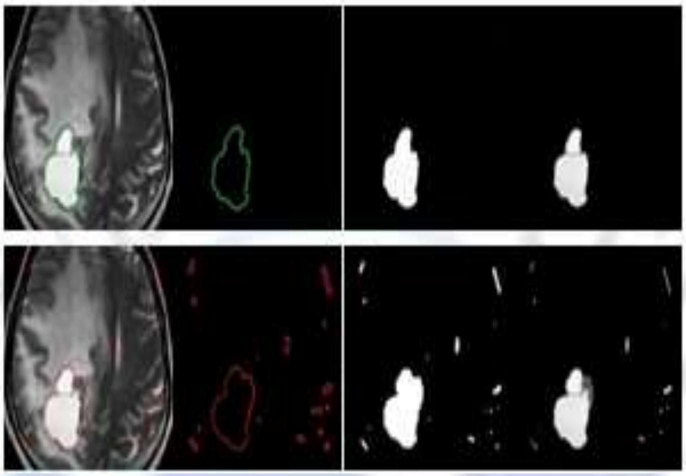


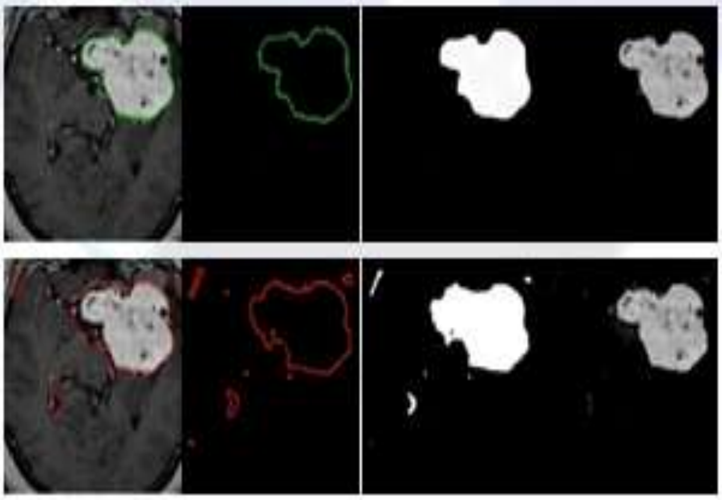
Fig.8: Transformation of the contour white spot



a) Patient 1



b) Patient 2



c) Patient 3

Fig 9: Extraction of the pathology for the tree patients

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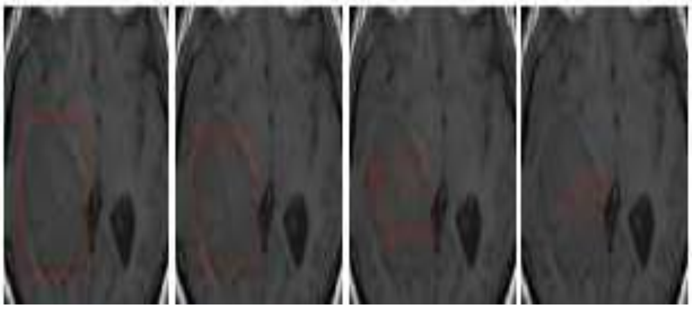
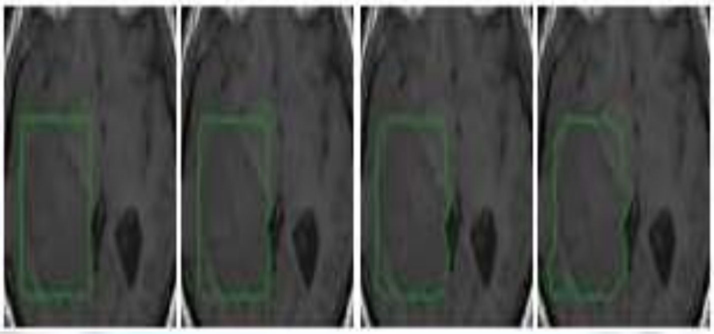
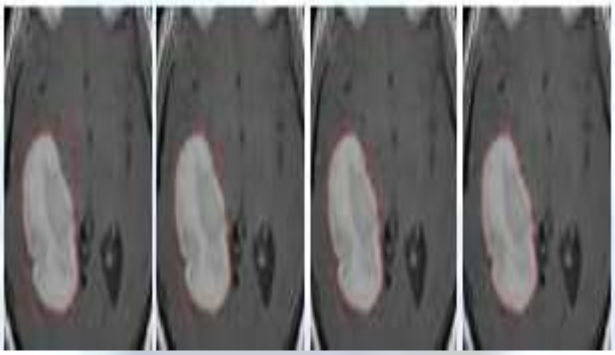


a) Level set method without re-initialization

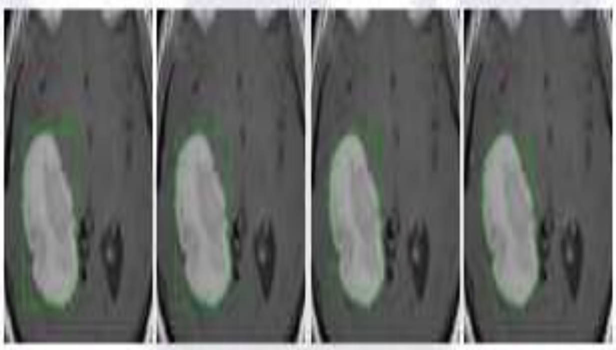


b) Local region based method

Fig. 10: The pathology detecting without the contrast injection

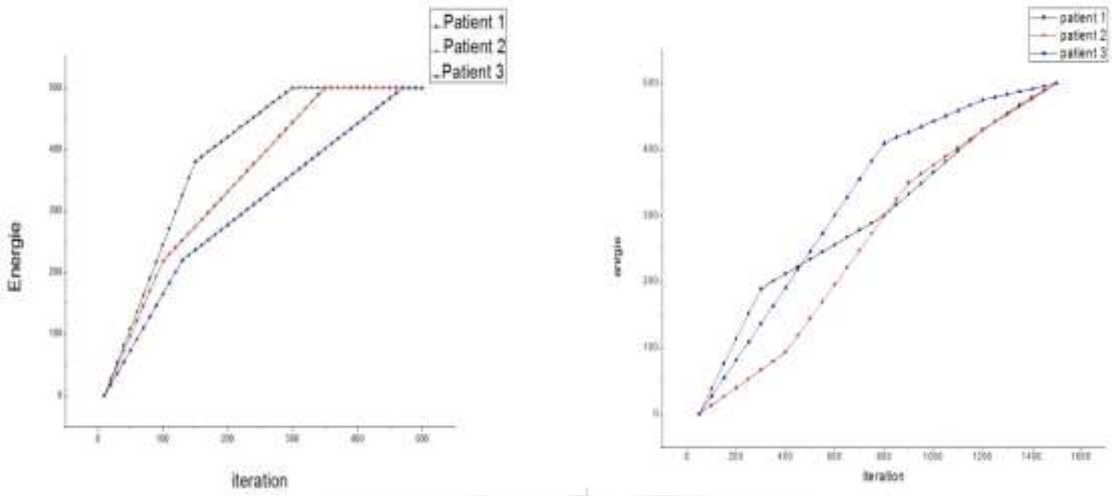


a) Levet set method without re-initialization



b) Local region based method

Fig.11: The pathology detecting with the contrast injection



a) b)

Fig.12: Variation of energy according to the iterations number for the method Local Region Based

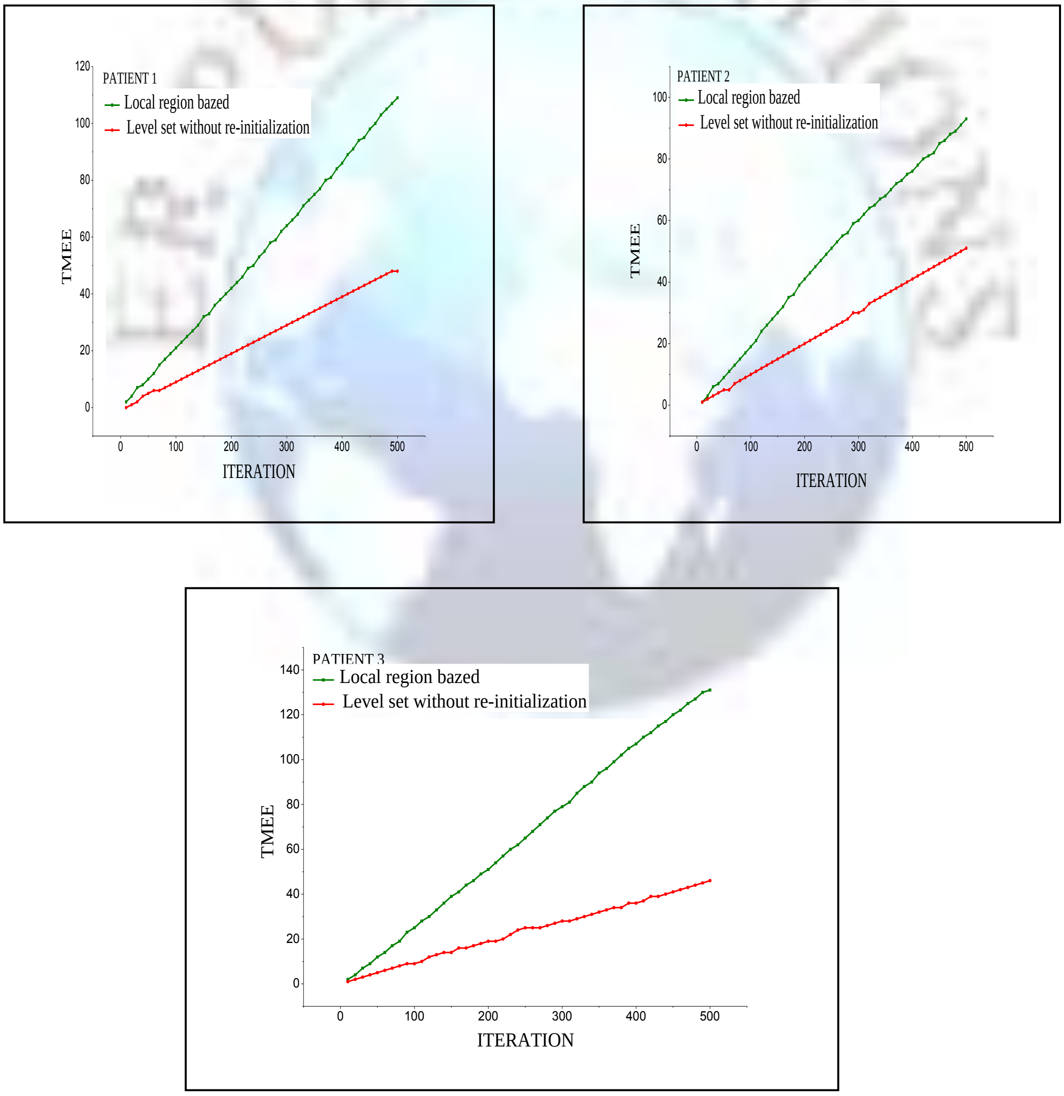


Fig.13: Time variation in the iterations number for the two methods

Table 1 Results of quantitative tested

method	Number of patients	T2-weighted		T1-weighted without contrast		T1-weighted with contrast		All successful tests	Average success
		Number of successful test	Estimated Percent	Number of successful test	Estimated Percent	Number of successful test	Estimated Percent		
Local region bazed	10 patients	8	80%	0	0%	7	70%	15	75%
Level set without re-initialization		7	70%	0	0%	5	50%	11	60%