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CORRECTION, DENOISING AND SEGMENTATION OF MRI IMAGES VIA LEVELS SET METHOD

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ABSTRACT

The revolution of digital imaging has led to an explosion in the information produced. In particular, the potential of MRI and its numerous acquisition sequences that explore various additional features of the brain. To cope with this mass of information generated, the automatic interpretation of MRI brain has become a major issue. Hence the importance of the view that segmentation is crucial link in image processing.In this paper we propose a method of correction, denoising and segmentation of MRI images, This problem can be solved by a coupled system of linear and nonlinear diffusion-reaction equations. These equations are proposed and tested for the denoising of magnetic resonance images, in order to be applied for the segmentation of medical images MRI.

Keywords: *Active Contours, Level-Sets, Segmentation, Variational Method, Medical Images MRI, Denoising; Medical Image*

1. INTRODUCTION

Imaging by nuclear magnetic resonance is one of several non-invasive imaging techniques that have emerged in recent decades; The medical field is not the only one who can benefit from the contributions of this technique. For example, it is possible to use MRI to study the materials [1].
In the literature of image processing, different denoising methods have been proposed and developed. Among these techniques we found filters based on nonlinear diffusion like the anisotropic diffusion introduced by Perona and Malik [18]. Anisotropic diffusion has been applied to the medical ultrasound images that are naturally affected by speckle noise which degrades the quality of the medical images and make it difficult for the visual interpretation for sonographers. Another technique for medical image restoration was discovered in 1992 by Rudin [27] known as total variation based on the minimization of an energy function made by partial differential equations, the advantage that brings this approach to the denoising field is that it is always possible to develop algorithms for minimizing this energy function more than the Euler Lagrange system for example. Techniques that replace a pixel by the sum of its neighbors is another procedure for denoising, like the Non-Local Means algorithm[19]. These techniques are strong methods for denoising, because they seek not only adjacent neighbors of the pixel to reduce noise, but all the pixels that are similar to this pixel (the criterion of similarity used is Euclidean distance). Pizurica and Phillips [20] have proposed a new approach based on a multi-scale denoising by estimating the noise contained in each image details while providing an opportunity for radiologists for monitoring the suppression of the noise.
The goal of denoising is to remove noise and/or spurious details from a given possibly corrupted digital picture while maintaining essential features such as edges. The goal of segmentation is to divide the given image into regions that belong to distinct objects in the depicted scene [17].
Segmentation is a process of image processing which aims to gather pixels / voxels them according to predefined criteria leading to a partition of the processed image. In medical imaging, segmentation is used to associate an anatomical structure at each position in space. In MRI it differentiates tissues (MG, MB and LCR), anatomical structures, and / or lesions and tumors.
There are many methods of segmentation that vary strongly in their approach to the problem of image segmentation. We will present a few. In general we can distinguish the outlines approaches and approaches regions.

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Medical imaging techniques are multiples based on different types of radiation (magnetic field, ultrasound, x-ray, gamma ray ...) [1, 2].

The level set method (sometimes abbreviated as LSM) is a numerical technique for tracking interfaces and shapes. The LSM allow to perform numerical computations involving curves and surfaces on a fixed Cartesian grid without having to parameterize these objects (this is called the Eulerian approach)[1]. This advantage represents our motivation to use this method. The LSM has obviously many applications in the field of imaging, and also in robotics and for the determination of minimum path for the movement of an autonomous vehicle. The existing LSM can be broadly classified as parametric active contour models or classical discrete models according to their representation and implementation .In the first class we have generally four methods, Geodesic active contour[3], Chan & Vese methods [4],Yezzi methods [5] and Lankton methods[6],the second class where the implicit function is modeled as a continuous parametric function expressed on a B-spline basis. Starting from the active-contour energy functional, we show that this formulation allows us to compute the solution as a restriction of the variational problem on the space spanned by the B-splines[7].In this work, we propose to study and improve global certain denoising and segmentation models that are known to have local minima on real medical images (Ge system, BrainWeb: Simulated Brain Database)[14,15].

The rest of this paper is organized as follows. In section (2) we will give a brief view about Formation of an MRI image. In section (3), we will discuss concerning with the noises in medical images. In section (4) we have denoising approaches in medical images MRI we will deal with the segmentation of MRI images by the level set method in section (5). The complete results and their comments will be presented in section (6) followed by conclusion in Section (7).

2. FORMATION OF AN MRI IMAGE

In this first section we describe the process of formation of MRI to understand the model that will be used later and to be able to identify limitations. We were inspired by various documents explaining the physics of MRI, it seemed necessary to develop the implementation of the model we will use later in our paper.

This chapter introduces the basic concepts necessary to understand this work. At first we present some elements of the central nervous system anatomy, to clarify the vocabulary and concepts that are then used in a second step, we briefly introduce the physical principles of magnetic resonance imaging in emphasis particularly on the difficulties arising from this acquisition technique.

2.1. Elements of Cerebral Anatomy

This first section presents some basics of brain anatomy. It defines key terms and concepts to better understand what is seen with brain imaging. The central nervous system consists of the spinal cord located in the spinal canal, and brain. In what follows we describe the anatomy of the latter, including the components of interest in this study [ref].

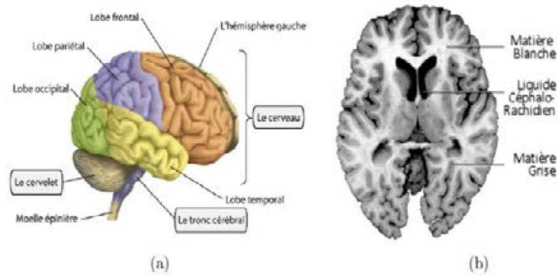

Fig. - The image (a) shows the brain consisting of the brain, cerebellum and brainstem. Image (b) shows a histological section of the brain showing the three main subjects of the brain.

2.2. The Main Substances in The Brain

Besides the presence of cerebral veins, tissues using walls, or many small structures such as glands, brain mainly contains three substances (Figure):
a. The cerebrospinal fluid (CSF) (or cerebrospinal fluid, CSF) is the fluid that bathes the brain and cerebellum. It is a transparent substance made up of 99% water with an average volume of 150ml, it is absorbed by the cerebral venous system and continually renewed.
b. Gray matter (GM) (or gray) corresponds to the cell bodies of neurons with their dense network of dendrites.
c. White matter (MB) (or white matter) corresponds to the myelin sheath covering the axons of neurons to accelerate conduction. The myelinated axons are assembled into bundles to establish connections between groups of neurons.

2.3. Observation Of The Brain

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The observation of two-dimensional slices of the brain can be performed in several angles. Thus, there are three anatomical axes to make cuts [ref] (Fig).

- Axial: These cuts are virtually identical to a horizontal plane. In magnetic resonance imaging, they correspond to a plane perpendicular to the axis of the main magnetic field.
- Sagittal: These cuts are taken in planes parallel to the inter-hemispheric. These lateral views of the brain.
- Coronal: These are cut perpendicular to the axial slices. They correspond to views from the front of the brain.

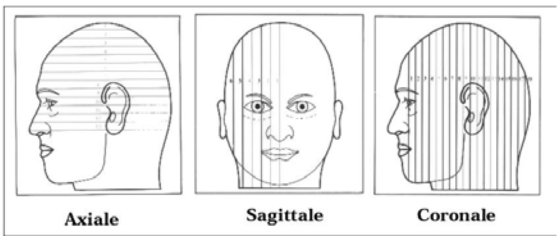

Fig. : three cutting axes for viewing of the brain.

3. NOISES IN MEDICAL IMAGES

During the acquisition of medical images we often found distributions of different sounds depending on the acquisition process, voluntary or involuntary patient motion such as blood circulation, breathing .... The presence of noise gives an image a mottled, grainy, textured, or snowy appearance. Now we briefly discuss the best known distributions of noise based in the medical imaging modalities.

3.1. Speckel Noise

The main source of noise in MRI images is the thermal noise in the patient [21]. The MRI image is commonly reconstructed by computing the inverse discrete Fourier transform of the raw data [14,15].
Speckle noise affects all coherent imaging systems including medical images MRI.
The only drawback with this modality is that it‘s usually affected by Speckle noise [21] that gives a snowy appearance to the noisy image. This multiplicative noise is defined as shown in equation (1) where Y presents the noisy observation, R describes the real observation and n presents the noise.

$$Y(i;j)=R(i;j)n(i;j) \quad (1)$$

3.2. Additive Whit Gaussien Noise (AWGN)

AWGN is a channel model in which the only impairment to communication is a linear addition of wideband or white noise with a constant spectral density (expressed as watts per hertz of bandwidth) and a Gaussian distribution of amplitude.
Gaussian noise is commonly founded in medical image especially in tomography images (CT) [22]. The Gaussian noise follows the distribution given in equation (2) where R present data free noise, Y describes the noisy observation and n is the white Gaussian noise.

$$Y(i;j)=R(i;j)+n(i;j) \quad (2)$$

3.3. Poisson Noise

There are some medical modalities that are corrupted by non-Gaussian noise like Poisson noise which affect the quality of scintigraphy images [23].

3.4. Rician noise

(MRI) provides high spatial resolution but suffers from Rician noise that can be approximated to Gaussian noise under some conditions.

4. DENOISING APPROACHES IN MEDICAL IMAGES MRI

In digital image processing, image denoising is a procedure aiming at the removal of noise, which may corrupt an image during its acquisition or transmission, while retaining its quality[24].
In this section we will describe the techniques for denoising MRI medical images and the existing algorithms for the restoration of medical images.

4.1. Wavelet Coefficients Thresholding

Decomposing the image using discreet wavelet transform (DWT) [24] is an efficient approach that demonstrates it capacity of providing a compromising between noises suppression and conserving the most important features of signal. The first denoising using wavelet was done by Weaver [25]. The denoising algorithm in this case follows three steps. In the first step we choose the appropriate wavelet and the number of decomposition levels, in the second we apply a soft or hard thresholding as need for each level, and finally we reconstruct the image using the new coefficients. Generally, if we take a small value of Threshold it could leave many noisy coefficients,

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therefore the denoised image still contains noise then when we apply a higher value for Thershold, the image may contain a lot of artifacts and blur.

4.2. Nl-Means

This algorithm is based on the redundancy of information in the image. It looks for the pixel that their neighborhood looks like a pixel to be denoised then replace the value of the noisy pixel by the non-local average of other pixels that are similar in order to remove noise.

4.3. Total Variation

We consider R the free noise image, Y the image that we want to restore. Remove noise using Total Variation is based on the minimization of the function describes in equation (4).

$$ArgMin\varphi(x) = \int \|\nabla R(x)dx\| + \gamma \int \|Y(x) - R(x)dx\| * \|Y(x) - R(x)dx\|dx \quad (4)$$

4.4. Anisotropic Diffusion

Unlike linear filters as Gaussian filtering that destroy the finer details in the image like edges, anisotropic diffusion remove noise progressively without suppressing images edges. This approach is based on Partial Differential Equations (PDE) (Equation (3)) and it has proved an efficient denoising method for ~~(~~MRI~~)~~ data.

$$U = div(g(|\nabla Y|)\nabla Y) \quad (3)$$

Where U represents a denoising image, $\nabla$the Gradient operator, g the function of the diffusion that control the smoothing, Y represents noisy image and div the divergence operator which is a linear differential operator.

The only problem with this approach is that it's based on Gradient operator to determine edges that's not enough for localizing edges when noise like Speckle is present in the image.

4.5. Pizurica and Philips's Approach

The authors in [9] have introduced a new denoising technique called Generalized Likelihood (GinLik), which can be applied to unknown noises distributions and also it gives to medical expert the ability of balanced a parameter to control the quality of denoised image. It based on wavelets and it was applied with success for Ultrasound and MRI data denoising.

5. SEGMENTATION OF MRI IMAGES BY THE LEVEL SET METHOD

The Osher-Sethian level set method tracks the motion of an interface by embedding the interface as the zero level set of the signed distance function. The motion of the interface is matched with the zero level set of the level set function, and the resulting initial value partial differential equation for the evolution of the level set function resembles a Hamilton-Jacobi equation. In this setting, curvatures and normals may be easily evaluated, topological changes occur in a natural manner, and the technique extends trivially to three dimensions. This equation is solved using entropy-satisfying schemes borrowed from the numerical solution of hyperbolic conservation laws which produce the correct viscosity solution [5].

The main idea behind the level set formulation is to represent an interface $\tau(t)$ bounding a possibly multiply connected region in $\mathbb{R}^n$ by a Lipschitz continuous function ϕ [16], having the following properties:

$$\begin{cases} \phi(x,t) > 0 & if\ x\ exist\ inside\ \tau(t) \\ \phi(x,t) = 0 & \text{if x exicst into } \tau(t) \\ \phi(x,t) < 0 & if\ x\ exist\ outside\ \tau(t) \end{cases} \quad (4)$$

Some regularity must be imposed on ϕ to prevent the level set function of being too steep or flat near the interface. This is normally done by requiring ϕ to be a signed distance function to the interface:

$$\begin{cases} \phi(x,t) = d & \text{if x exist inside } \tau(t) \\ \phi(x,t) = 0 & \text{if x exicst into } \tau(t) \\ \phi(x,t) = -d & \text{if x exist outside } \tau(t) \end{cases} \quad (5)$$

where d(τ(t) ,x) denotes Euclidian distance between x and τ(t). Having defined the level set function ϕ as in (2), there is a one to one correspondence between the curve τ(t) and the function ϕ. The distance function ϕ obeys the Eikonal equation:

$|\nabla\phi| = 1$ (6)

The solution of (3) is not unique in the distributional sense. Finding the unique vanishing viscosity solution of (3) is usually done by solving the following initial value problem to steady state:

$$\left|\phi t + \text{sign}(\tilde{\phi})(\nabla\phi - 1)\right| = 1$$

$$\phi(x,0) = \tilde{\phi}(0)$$

In the above, $\tilde{\phi}$ may not be a distance function. When the steady state of equation (4) is reached, it will be a distance function having the same zero curve as $\tilde{\phi}$.

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The interface $\tau(t)$ is implicitly moved according to the nonlinear PDE:

$$\frac{\partial \phi}{\partial t} + v.\nabla\phi = 0$$

Where v is a given velocity field. This vector field can depend on geometry, position, time and internal or external physics. Usually only the velocity normal to the interface v N is needed, and ϕ is then moved according to the modified equation:

$$\frac{\partial \phi}{\partial t} + vN.\nabla\phi = 0$$

5.1. Classical Discrete Implementation

5.1.1. Caselles-Kimmel-Sapiro method

In this section we discuss about geodesic active contours proposed by [3] , in which the contour deforms to minimize the contour energy that includes the internal energy from the contour and the external energy from the image, built so that a local minimum is in the border with the object to be detected. The Energy criterion:

$$E(\Gamma)=\int_0^1 g\left(I(\Gamma(q))\right)\|\acute{\Gamma}(q)\|dq$$

Where

$$g\,(I)=\frac{1}{1+\|\nabla(G*I)\|^2}$$

I(.) corresponds to the image intensity, Γ is the parametric curve and G is a gaussian filter of variance 1.

The evolution equation is:

$$\frac{\partial\emptyset}{\partial t}(x) = g(I(x))\|\nabla\emptyset(x)\|(c+\kappa) + \nabla g(I(x))\nabla\emptyset(x)$$

Where $\kappa=\mathrm{div}(\frac{\nabla(\emptyset(x))}{\|\nabla\emptyset(x)\|})$ corresponds to the curvature of the evolving contour and c is a constant that acts as a balloon force.

5.1.2. Method of Chan & Vese

The Chan-Vese algorithm uses variational calculus methods to evolve the level set function. Variational methods work by seeking a level set function that minimizes some functional. In this context, by functional we mean a mapping that takes a level set function $\emptyset$ as input, and returns a real number [4].The aim is to converge to the contour of homogeneous regions according to the grayscale. The energy criterion is:

$$E(\emptyset)=\int_\Omega \{\left(I(\vec{x})-\mu_{in}\right)^2 H\left(\emptyset(\vec{x})\right) + \left(I(\vec{x})-\mu_{out}\right)^2 H\left(-\emptyset(\vec{x})\right)\}^{dx+}\lambda\oint_{\delta\Omega} ds$$

Where H is the Heaviside function.

5.1.3. Yezzi method

The Yezzi method converges to the contour of homogeneous regions according to the grayscale. The energy criterion is:

$$E(\emptyset)=\int(\mu_{in}-\mu_{out})^{2+}\lambda\oint ds$$

5.1.4. Lankton method

This algorithm is a region-based method. Its feature term is computed locally. This property allows the algorithm to segment non homogeneous objects. However this make the method sensitive to initialization. The energy criterion is:

$$E(\emptyset)=\int_\Omega \delta(\emptyset(\vec{x}))\int_\Omega B(\vec{x},\vec{y})F(\phi)\,d\vec{x}d\vec{y} + \lambda\oint_{\delta\Omega} ds$$

Where

$$B(\vec{x},\vec{y}) = \begin{cases} 1 & \text{if}\|\vec{x}-\vec{y}\| < r \\ 0 & \text{if}\|\vec{x}-\vec{y}\| > r \end{cases}$$

and

$$F(\vec{x},\vec{y}) = \left(I(\vec{y})-\mu_{in}(\vec{x})\right)^2 H\left(\emptyset(\vec{y})\right) + \left(I(\vec{y})-\mu_{out}(\vec{x})\right)^2 H\left(-\emptyset(\vec{y})\right)$$

5.2. Parametric Implementation

We present in this section a different formulation where the implicit function is modeled as a continuous parametric function expressed on a B-spline basis. Starting from the active-contour energy functional, we show that this formulation allows us to compute the solution as a restriction of the variational problem on the space spanned by the B-splines[6].

A] Spline Level-Set Model

we define the function as a linear combination of B-spline functions

$$\emptyset(x)=\sum_{k\,e\,z} c[\vec{k}]\beta^n(\frac{x}{h}-k)$$

With $\beta^n(.)$B-spline function of degree n separable and dimension d, $c[\vec{k}]$ scalar coefficients.

In this approach we minimize the criterion of energy compared to coefficients $c[\vec{k}]$

$$c^{i+1} = c^i - \gamma\nabla_c E(c^i)$$

$\nabla_c E$ corresponds to the gradient of the energy compared the B-spline coefficients

$$\nabla_c E(c^i) = \frac{\partial E}{\partial c[\vec{k}]} = \int_\Omega \frac{\partial F(\vec{x})}{\partial\emptyset}\beta(\frac{\vec{x}}{h}-\vec{k})\,dx$$

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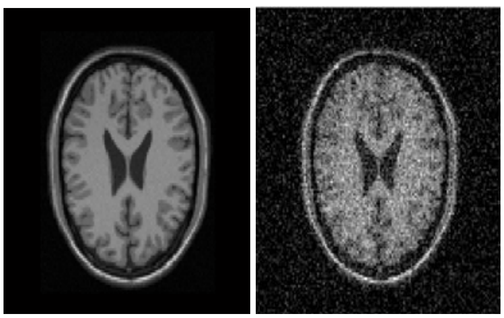
$\frac{\partial F(\vec{x})}{\partial \phi}$ is a function derived from F directly accessible representation discrete.

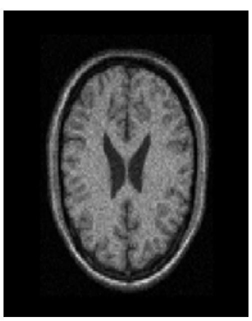
6. RESULTS AND DISCUSSION

6.1. Method

In this section, We turn to present results of numerical experiments which is performed on the MRI images i.e. Brain. White Gaussian,Rician,Poisson and Speckel noises are added to the MRI images and denoised with the methods described previously.



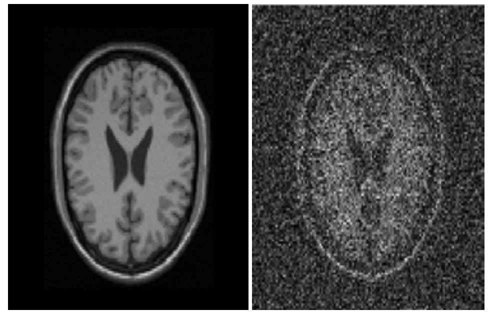
a) b)



c) d)

e)

Figure 1 :a.original MRI image b. noisy image Gaussian. c. Rician d. Poisson e. Speckel noise



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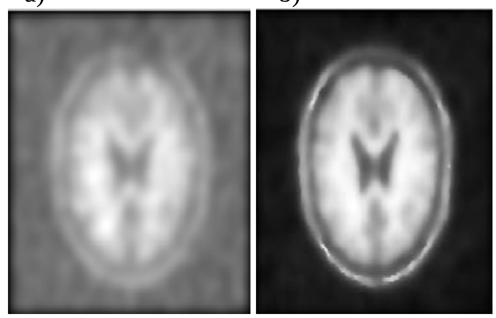
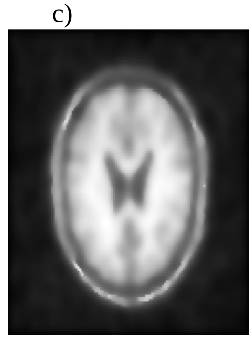
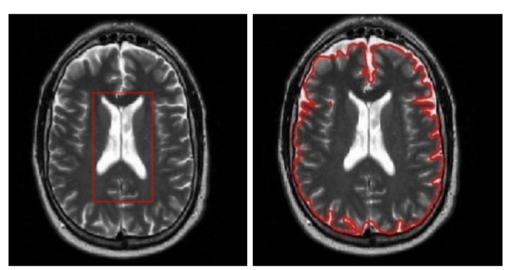


c) d)



e)

Figure 2. a: noisy image (=0.3of Gaussian). Denoised image by: b. Nlmeans,c. Pizurica, d: Total Variation and by e: Anisotropic diffusion



a) b)

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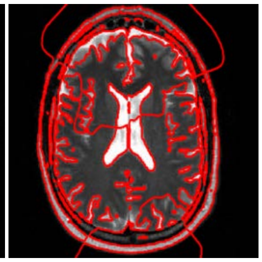
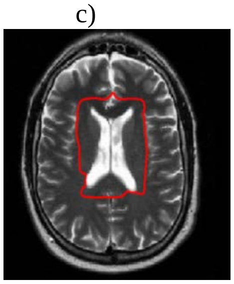


c) d)



e)

figure.3 . (a)Initial contour. (b) Geodesic active contour. (c) Chan and vese method. (d)Yezzi method. (e) Lankton method (f) Bernard method.

The implementation of the various methods starts with the identification of all the adjustable parameters for each method. We have implemented and tested real MRI images with and without noise. It starts in all cases by a simple and closed curve (circle or rectangle). Before the segmentation is activated, one needs to initialize the contour that will be shown in the first frame of the subsequent results. In general, five experiments will be conducted, and three methods are employed in this paper for performance comparison, i.e. the original level set by Caselles-Kimmel-Sapiro , the level set by Chan & Vese, the level set by Yezzi, the level set by Lankton and the level set by Bernard et al. The whole implementation (MatLab coding) is run on a PC with a 1.5GHz Intel(R) Pentium(R) CPU. Table 1 summarizes the performance comparison of these five methods in different circumstances, where in general the parametric scheme is superior to the others in terms of location accuracy and computational time. The details follow.

6.2. Evaluation Criteria

The criteria presented in this section are, for the most part indicators traditionally, used to evaluate segmentation in an unsupervised environment. The value each criterion increases with the quality of the result of segmentation. These values were normalized to facilitate their comparisons.

- Visual criterion: This criterion allows you to plot the results of the selected algorithms on the image to compare them with the reference you have selected.
- Computation time.

- Similarity criterion : Four similarity criteria can be computed between the result of the algorithms and the reference :
    - o Dice criterion:
    - o peak signal-to-noise ratio(PSNR)
    - o Hausdor_ distance

	Geodesic active contour	Chan and vese method	Yezzi method	Lanktn method	Bernad method
visual criterion	1	1	1	0	1
computation time	1.28	0.85	2.60	1.1	1.26
Dice	0.69	0.69	0.28	0.6	0.7
PSNR	10.63	8.86	8.31	7.19	9.01
Hausdor_ distance	21.35	31.98	21.54	16.97	20.10
MSSD	54.64	153.35	119.09	59.85	49.64

- o Mean Sum of Square Distance (MSSD)

TABLE: Criteria values for each of the methods for segmentation of MRI image

According to our tests, no segmentation method seems to be the best. It depends on the nature of the image, and other parameters. These criteria can also be operated segmentation or fusion of different segmentation results.

7. CONCLUSION

Original image form noisy image is not easy especially when complex noise like Speckle affects the image. In this paper we have studied the most commonly methods that are used in medicine for denoising images. These techniques had been evaluated with different noises levels. We have also presented a study of five deformable contour methods applied to segmentation of medical imagery. One important point to be noted here is that these methods are not mutually exclusive. Thus, in practice, a new deformable levels set method can be proposed to incorporate features from other methods in order to handle specific applications. In addition, the more information from image or object integrated in the evolution

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framework, the better segmentation results can be obtained.

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