REFINMENT OF ACTIVE CONTOUR BASED THALAMUS SEGMENTATION USING GENETIC ALGORITHM

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***Abstract*—Active contour models have frequently used in medical imaging. Although the active contour models have considerable success in segmentation of different structures of the brain in MR images but one of the most common problems will occur when dealing with an improper initialization. The common problem brain structures segmentation is that the active contours may trap in to the local minimum because of bad initialization. We showed that Genetic Algorithm (GA) can be a powerful solution of this problem. We proposed a new method which is more stable due to the extra step which uses GA to find the accurate boundaries of the structure in MR images. Our method consists of two steps: the first is a new energy based evolution of contour, and the second step is the fining process using genetic algorithm. We demonstrate that using GA, we can successfully overcome the improper initialization problem. Our Results show the high accuracy of the method in boundary detection.**

I. INTRODUCTION

SEGMENTATION of sub-cortical structures of the brain in medical images has considerable importance in medicine. There are several applications including, surgical planning, disease classification, investigating the relation between various diseases and changes in the shapes and sizes of different structures in the brain [1]. According to these various applications the importance of the exact detection of boundaries is obvious. But exact boundaries of most structures are not easily detectable due to their soft tissue and the existence of noise and the field inhomogeneity in MR imaging. Thalamus is one of the most important structures in the field of brain segmentation. It is the biggest structure of the diencephalons. Sensory-motor analysis, identification of painful stimuli, excitatory reflexes, is some of its principle functions. due to the contrast of thalamus with respect to the white matter in T1 weighted images we preferred to use T1 weighted images. Thalamus is adjacent to ventricle which appears almost black in T1 weighted images, on one side and it is neighbored with white matter on the other side while it's gray scale is increasing. Therefore difficulties arise due to this complex structure. Various methods are proposed in order to segment such structures with unclear boundaries, like thalamus and hippocampus. some of these recent methods are Ghanei et. al., [3], Bathmanghelich et. al. [4] and Amini et. al. [2]. Ghanei's method is incapable of segmenting objects like thalamus since it is just based on the gradient of the image. In addition Batmanghelich's method as is mentioned in his paper was not successful in detecting the exact boundaries of thalamus, also in order to improve the accuracy of the detection of unclear boundaries of thalamus, in Amini's method, fuzzy clustering procedure is added to Active contour method. This reduces the overall speed of the algorithm, and increases it's dependencies to various parameters. In addition the proper initialization is very important in almost every active contour based method, and the result is fully affected by improper initialization. Our proposed method is consist of two steps. In the first step, two separate contours for each thalamus will evolve based on the new method, which is a combination of gradient based and region based methods. Using proposed method the unclear boundaries of thalamus were exactly detected. Then it is shown that an improper initialization will lead to an undesired local minimum. In order to have a complete stable algorithm even in improper initialization, we proposed the second step. In this step two fuzzy characteristics where introduced which are based on priori-knowledge. Using genetic algorithm boundaries with optimized characteristics are found. Novel cross-over operation is proposed in genetic algorithm and the search space is constrained around the result of the previous step.

In this method the level set theory Osher and Sethian, 1988 [6], is used in order to solve the evolution equation in first step. The contour is represented as a zero level set of a higher dimensional function. This implicit representation was first introduced by Caselles (1993) and Malladi (1995) [6]. Using Level Set has various advantages that increase it's application in medical imaging. In second step an interaction is made between two contours and the most accurate contours are found by means of parallel genetic algorithm.

The outline of this paper is as follows: in the second section the level set method is reviewed and also gradient based and region based methods are discussed. The next section belongs to the proposed method and the results and conclusion are mentioned in the last two parts.

II. LEVEL SET METHOD

A. Review

In order to solve the equation of the evolution, the Level Set theory is used in the proposed method. The active contour is equal to the zero crossing of a higher dimensional signed distance function $\phi(x,t)$. Suppose that the evolving contour is represented with $\Gamma(t):[0:\infty]\rightarrow R^{N}$, and the initial contour is identified by $\Gamma(0)$. $\phi(x,t=0)$: $x\in R^{N}$, is then introduced so that $\phi(x,t=0)=\pm d$ is the distance between the point x and the initial contour $\Gamma(t)$. Negative (positive) points are related to the points inside (outside) the contour [5]. $\phi(x,t)$ can be any function but because of it's properties distance function is used in papers [5],[6]. It is obvious that the active contour can implied with the zero level set of distance function $\Gamma(\boldsymbol{t})=\{\boldsymbol{\phi}(\boldsymbol{x},\boldsymbol{t})=0\}$. Solving the Euler equation of ϕ and finding out pixels in which ϕ equals to zero, results final boundary [5], [7].

$$\frac{\partial\phi}{\partial t}=F\left|\nabla\phi\right| \tag{1}$$

ϕ is the Level set function, F is called the evolving force which force the contour into the desired boundaries. Using this method enables us to follow the topological changes of the contour. Also using narrow-band or fast marching approaches makes it possible to increase the evolving speed. In addition the geometric parameters of boundary such as curvature, $K=div(\frac{\nabla\phi}{\left|\nabla\phi\right|})$, or the normal vector $N=\frac{\nabla\phi}{\left|\nabla\phi\right|}$, is accessible according to the distance function ϕ. None of the above features can be observed in classical active contours like Snake method [8].

B. Using Gradient

The evolving force F, must be specified in such a way that moves the contour into the desired boundaries. It's general form is as follows [5], [6], [8].

$$\frac{\nabla\phi}{\nabla t}=C(x)(k+V_{0})\left|\nabla\phi\right|+\nabla C.\nabla\phi + \frac{V_{0}}{2}x.\nabla c.\left|\nabla\phi\right| \tag{2}$$

$C(x)$ is the gradient of the blurred image, in the following equation the main image is represented with $I(x)$ and $G_{\sigma}(x)$ is Gaussian filter with standard deviation of σ.

$$\boldsymbol{C}(\boldsymbol{x})=\frac{\alpha}{1+\nabla[\boldsymbol{G}_{\sigma}(\boldsymbol{x})*\boldsymbol{I}(\boldsymbol{x})]} \tag{3}$$

K represents the curvature which causes the contour to evolve smoothly with the least curvature. V_{0} is a constant force.

The second term is acting as an stopping force near the boundaries of interest and the last term is used in order to minimize the area of the contour while it is evolving, but this type of methods which use the image gradient are incapable in finding unclear boundaries of thalamus. In order to overcome such problems, new groups of region based methods are investigated.

C. Region based method

Another group of methods are used due to the unclear boundaries of some structures such as thalamus. They are just based on region characteristics such as gray scales. Active contour without edge can be mentioned as one of the most important of these groups of methods [9].

$$\begin{aligned}E(c_{1},c_{2},\phi)&=\mu.Length(c)+v.Area(Inside(c))\\&+\lambda_{1}.\int_{inside(c)}\left|u_{0}(x,y)-c_{1}\right|^{2}dxdy\\&+\lambda_{2}.\int_{outside(c)}\left|u_{0}(x,y)-c_{2}\right|^{2}dxdy\end{aligned} \tag{4}$$

$$\mu\geq 0, v\geq 0, \lambda_{1},\lambda_{2}\geq 0$$

u_{0} represents the main image and $c_{1}(c_{2})$ is the average of the grayscales inside (outside) the contour. λ_{1} and λ_{2} are used in order to control the force applied to the contour. Using Level Set method, we can solve the equation (4), with an initial contour as follows:

$$\frac{\partial\phi}{\partial t}=\delta\ (\phi)\left[\mu.div(\frac{\nabla\phi}{\left|\nabla\phi\right|})-v-\lambda_{1}(u_{0}-c_{1})^{2} + \lambda_{2}(u_{0}-c_{2})^{2}\right] \tag{5}$$

In equation (5), $\delta\ (\phi)$ represents the Dirac delta function, In order to numerically solve such equation it is necessary to approximate $\delta\ (\phi)$. The used approximation is as follows:

$$H\ (z)=\begin{cases}1 & if \quad z>\varepsilon\\ 0 & if \quad z<-\varepsilon\\ \frac{1}{2}\left[1+\frac{z}{\varepsilon}+\frac{1}{\pi}\sin(\frac{\pi z}{\varepsilon})\right] & if \quad \left|z\right|\leq\varepsilon\end{cases} \tag{6}$$

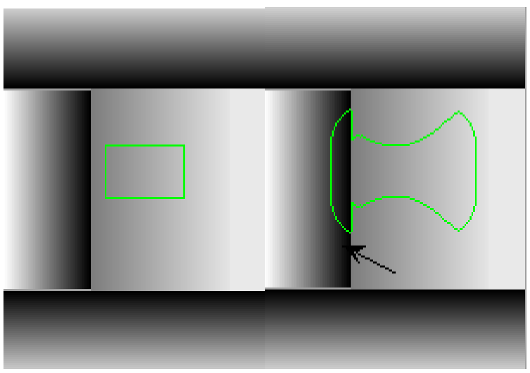
In which $H\ (z)$ is an approximation for an ideal step function and $\delta\ (\phi)$ is it's derivative. ε refers to a very small positive number.

D. *Problems in segmentation of thalamus*

Thalamus is surrounded by ventricle which appears very darker than thalamus on one side and on the other side thalamus is getting brighter without showing any specific boundary. It is impossible to detect this unclear boundary, just using the force in (5).

Structures which have boundaries brighter than the mean grayscale inside the structure and boundaries which are less bright than inside, can not be detected with the force in (5).

In figure 1, the mixture of grayscales is equal to thalamus and it's surrounding structures. As it is shown the boundaries couldn't be detected just using force in (5). also it is shown that using only the gradient based force is incapable of detecting such boundaries.



(a) (b)

Figure 1. a. contour couldn't detect the clear boundary. b.initial contour.

III. PRPOSED METHOD

A. *first step*

In our proposed method the both forces (Image gradient based force and region based force) are effecting each other simultaneously. Speed matrix based on image gradient is first introduced as follows:

$$C(x) = \frac{1}{1+\nabla[G_\sigma(x)*I(x)]} \tag{7}$$

The signed distance function is negative inside the contour, so if $\frac{d\phi}{dt} < 0$ ، the contour is getting bigger. In this method, λ_2 is made dependant to the speed Boundaries. The force which makes the contour bigger is being controlled with λ_2. Therefore the outward force will be as follows:

$$f(\nabla I, \lambda_2) \times (u_0 - c_2)^2$$

$$f(\nabla I, \lambda_2) = \begin{cases} \dfrac{\lambda_2}{1+\nabla[G_\sigma(x)*I(x)]} & \nabla I > T_G \\ \lambda_2 & \nabla I < T_G \end{cases} \tag{8}$$

The amount of T_G, is chosen, so that λ_2 will decrease in the vicinity of distinguished boundaries. Also the gradient is used, as a controller, for the movement of the contour in time. Therefore, controlling λ_2 will increase the evolution of contour inside the structure. The result is the fast deformation of contour until it gets near the boundaries. Using the speed function near the boundaries will decrease the movement of the contour, and on the other hand, the applied force to the contour. Therefore the evolving curve will stop exactly next to desired boundary. The overall force will convert into the (5) in the regions with no specified edges. This is due to the huge decrease in the effect of gradient in $f(\nabla I, \lambda_2)$ and convergence of speed matrix into zero, which together cause the correct detection of unclear boundaries.

Using this algorithm boundaries of thalamus were detected correctly. Initial and the final contours are shown in figure 2 and 3 respectively.

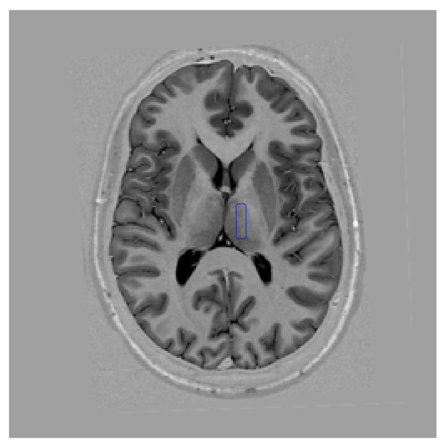


Figure 2. Initial contour is shown in blue.

The second step is proposed in order to handle improper initialization and leads such initialization to the best detection of boundaries.

B. Second step

Since the dynamic contours may trap into any local minimum near the desired boundary, especially dealing with an improper initialization, a proper fitness function is proposed in this step which its global minimum causes the accurate thalamus edge detection. This fitness function is optimized using Genetic algorithm. The Fourier representations of the contours are used as an individual chromosome. In the following section the fitness function and genetic algorithm structure will be discussed.

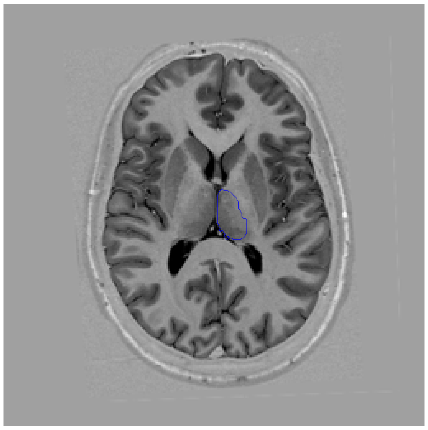


Figure 3. The final contour.

1) Fitness function –Fuzzy Features and Interactions

By investigation various samples and curvature evaluation of thalamus in both sides the equivalence is observed in both curvatures, so the more accurately the boundaries of each side are detected the less different should be seen between each contours. Using a normal reference curvature which is driven using the average of the training set. The first term of fitness function is as follows:

$$\tau_1 = abs(C_1 - C_{ref})$$
$$\tau_2 = abs(C_2 - C_1)$$
$$\tau = \tau_1 + \tau_2 \qquad (9)$$

Where C_1 represents the curvature of the thalamus which is more similar to the reference curvature. C_2 represents for the other side curvature and C_{ref} represents for the reference curvature which is driven from training set. The curvature of each contour is normalized by dividing it by length of each contour.

2) Gray scale based feature

Before introducing this feature we are about to explain a membership function which is trained according to the training set. The gray scale of the pixels near boundaries of the reference segmented image, are the inputs of this membership function, and the output is the average of their's belonging to the thalamus. Using bell shape membership function we proposed the gray based feature. First we divided region near the boundary of the curve into the interior and exterior region, which are represented with R_{in} and R_{out} respectively. The amount of belonging of x to the thalamus is represented with $\phi(x) > 0.5$. Using $\phi(x) > 0.5$ we can measure the part of the image which must be considered as thalamus and also $\phi(x) < 0.5$ can be used as a measurement of parts of image which doesn't belong to thalamus. Therefore optimizing G derives the thalamus points into the contour and also cause other structures to be outside the contour.

3) Fitness Function

We proposed our fitness function by summation of τ and G.

In fact our proposed fitness function can be interpreted as a regularizer for the evolving curve. Therefore in order to have a more stable curve which would have the least energy at the boundaries of the structure, we combined the fitness function and the without edge energy. This combination was used as our final fitness function.

C. Genetic algorithm

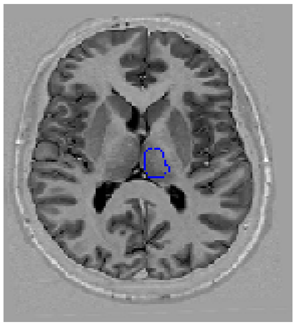
In order to cope with the local minimum Genetic algorithm was chosen to optimize this fitness function due to it's capability to find global minimum especially in the case of nonlinear object function [11]. In our genetic algorithm each chromosome is a contour which is represented by its Fourier series. In the proposed method the result of last step is used in order to produce the first generation. Genetic operations which were used in the algorithm are elitism and crossover. Crossover is done by intersection and union of selected pairs of contours. We used the following equation in order to produce the first generation [10].

$$f_{i,j}^{k} = (1 - \mathrm{sgn}(f_{i,j}^{k}).a)\, f_{i,0}^{k} + 2.a\left| f_{i,0}^{k} \right|.U(0,1) \qquad (10)$$

Where $0 < a < 1$, is the parameter which is used in order to control the search space. $U(0,1)$ is the random function in the range $[0,1]$. $f_{i,j}^{k}$ is the i'th coefficient of the j'th chromosome. $k = 1,2$ is used for the x and y coordinate of the contour respectively. $f_{i,0}^{k}$ is the i'th coefficient of the result of the pervious step. Each generation consist of 30 chromosomes [10]. The top 5 chromosomes were directly transferred to the next generation. Although the program was proposed in the way that the maximum

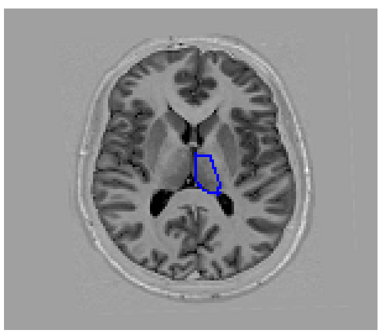
IV. EXPERIMENTAL RESULTS

The above approach was implemented and tested on a number of brain images. Algorithm was programmed and implemented in matlab. At first stage an improper initialization is used, the first step was done and the result is shown in the figure 4.



Figurer 4. Result of first step. (Improper initialization)

As it is shown the contour is trapped in a local minimum and thus the result curve is incorrect. This result is fed into the second step of the algorithm. The GA process is used in this step. The result is shown in figure 5.



Figurer 5. The result of figure 5. after applying the GA step. Boundaries of thalamus are detected correctly.

As it is obvious in figure 4 the boundaries were completely far from the correct answer. Figure 5, shows the correct segmentation of thalamus after applying GA.

We evaluated our method using images which were segmented by medical doctor. The evaluation and its results are shown in the following table.

Table 1. Results of the evaluation of the method.

$\frac{a}{a+c}$	**٪92**	**Sensitivity**
Intersection divided by the reference structure	**0.82**	**Accuracy**
$\frac{d}{d+b}$	**٪99**	**Detection percentage**

Where a,b,c,d represent for the pixels which are correctly considered not to be thalamus, wrongly detected as thalamus, correctly considered as thalamus and wrongly detected out of thalamus respectively.

V. CONCOLUSION

In this paper we have presented a genetic-algorithm based active contour method. It is applied to brain MR images to segment the thalamus which is a complex structure for segmentation. The encouraging experimental results show that our method does yield very good object description. By optimizing the result of first step, using genetic algorithm, the global optimum is obtained and improper initialization was solved using genetic algorithm.

VI. REFRENCES

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