스네이크를 이용한 뇌 자기 공명 영상에서 종양의 경계선 추출

Tumor boundary extraction from brain MRI images using active contour models (Snakes)

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요 약

본 연구는 스네이크를 이용하여 뇌의 자기 공명 영상에서 자동 혹은 반 자동으로 종양 또는 병변의 정확한 윤곽선을 찾기 위함이다. 본 연구에서 기존의 스네이크가 가지고 있는 에너지 최적화 문제를 동적 프로그래밍을 이용하여 개선하였고, Image Force로 Canny Edge Detector의 값을 이용하여 스네이크가 잡음에 덜 민감하도록 하였다. 병변의 윤곽선이 추출되면, 병변의 면적, 중심 좌표, 둘레 등을 계산하도록 하였다. 또한 병변에 대한 다수의 2차원 단면 영상을 합성하여 3차원으로 재구성하여 병변의 입체적인 모양을 볼 수 있도록 하였다. 본 연구에서 제안된 방법은 뇌 종양 환자의 치료 계획 수립 뿐 아니라 경과를 평가하는데 유용하게 활용될 것으로 기대된다.

ABSTRACT

The study is to automatically or semi-automatically detect the accurate contour of tumors or lesions using active contour models (Snakes) in the MRI images of the brain. In the study we have improved the energy-minimization problem of snakes using dynamic programming and have utilized the values of the canny edge detector by the image force to make the snake less sensitive in noises. For the extracted boundary, the inside area, the perimeter and its center coordinates could be calculated. In addition, the multiple 2D slices with the contour of the lesion were combined to visualized the shape of the lesion in 3D. We expect that the proposed method in this paper will be useful to make a treatment plan as well as to evaluate the treatments.

Key words : Boundary extraction, Snakes, Dynamic programming, Canny edge dectector

I. Introduction

MRI is a non-invasive method for producing three-dimensional tomographic images of the human body. MRI is most often used for the detection of tumor, lesions and other abnormalities in soft tissues, such as the brain. Several techniques for automatically segmenting brain tissues in MRI scans of the head have been developed [1][2].

A boundary extraction is an important process to analysis area, volume, major axis, perimeter, center coordinates and minor axis. It is also to preprocess three dimensional reconstruction in medical image processing. Many boundary extraction methods have been developing up to the now, but those methods have the limits and the higher level processing is demanded.

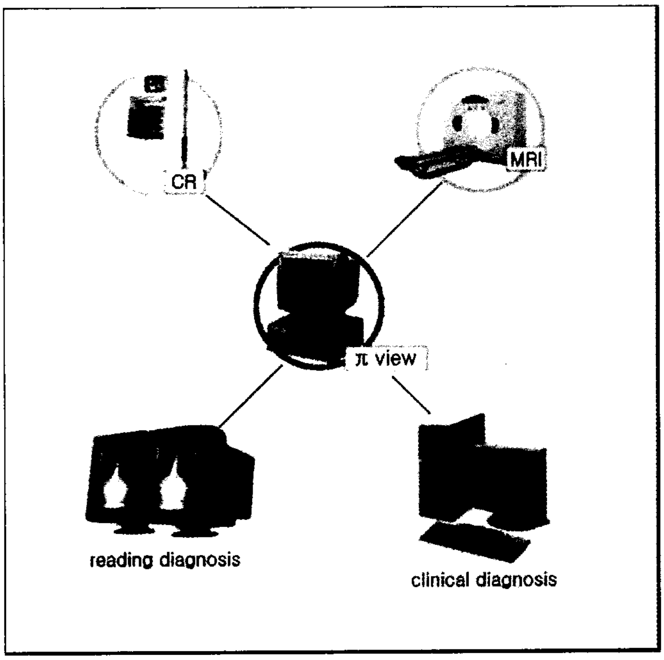
In this paper we extract a region of tumor using Active contour models (Snakes Algorithm) in an MRI brain image. The snakes is the first proposed by Kass et al. [3]. The objective of the snakes algorithms is to find the closest contour around the natural boundary of an object. A snakes deformation is controlled by an energy function that consists of the internal and external energy. Several algorithms proposed are trying to solve various problems such as noise trap, snakes initialization, energy function optimization, concavity issues, etc. [4][5][6][7]. We have improved energy -mini mization problem of snakes using a dynamic program ming and noise trap using Canny edge detector [6,8]. And we visualized a shape of tumor from 2D slices of which number is eight and number of snaxels (snake pixels) is twenty using a software OpenGL.

Ⅱ. MATERIAL AND IMAGE ACQUISITION

We acquired the three dimensional data of MRI. We transferred data to a personal PACS workstation which sets up π-view (Pi-View 2 , Mediface Corporation, *http://www.mediface.com*). An image data acquisition process is shown in figure 1.

Fig1. Image data acquisition process.

In this study we consider some brain MRI images. The imaging methods are Gradient dephase and T2



and the image axis is axial. We used eight slices which have a tumor of one set images. Besides we can use imaging methods of T1, T2, FSE, SE and axial, coronal, sagittal axis image.

We have implemented a program of Visual C++ 6.0 and OpenGL which run on a Pentium Ⅲ 866 with memory 384 MB.

Ⅲ. ACTIVE CONTOUR MODELS

1. Active contour models (Snakes)

The snakes algorithm is to find the closet contour around the natural boundary of an object. The contour is initially placed near an edge under consideration, then image forces draw a contour to the edge in the image. As the algorithm iterates, the energy terms can be adjusted by higher level processes to obtain a local minimum that seems most useful to that process. There are some differences of results according to the minimization algorithm or parameters etc. The energy function E is written in Eq. 1.[3]

$$E = \int_0^1 E_{snake}(v(s))ds$$
$$= \int_0^1 E_{int}(v(s)) + E_{image}(v(s)) + E_{con}(v(s))ds \quad (1)$$

where v(s) is the position of a Snakes, E_{ins}, E_{image} and E_{con} are the internal energy, image force and constraint energy, respectively.

The internal energy E_{int} represents the forces which constrain the curve to be smooth, E_{image} represents the forces derived from the image which constrains the curve to take the shape of features presented in the image, and the constraint energy E_{con} is the energy of a spring connected between a point on the contour and a point in the plane. The image energy is a linear combination of three terms all of which are derived from the image.

$$E_{image} = w_{line}E_{line} + w_{edge}E_{edge} + w_{term}E_{term} \quad (2)$$

where E_{line} is the image intensity it self, then depending on the sign of w_{line}, E_{edge} is finding edge function then w_{edge} is weight value, E_{term} is smooth function and w_{term} is weight value.

We adopted the first and second term of the energy function proposed by Williams et. al.[9].

$$E = \int (\alpha(s)E_{con} + \beta(s)E_{curv} + \gamma(s)E_{image})ds \quad (3)$$

where $\alpha(s)$, $\beta(s)$, $\gamma(s)$ is weight value

The first terms in Eq.3, namely, a continuity expressed by Eq. 4 will have the minimum value when the snaxels have distance near the average.

$$Continuity\ term = \bar{d} - |v_i - v_{i-1}| \quad (4)$$

where $\bar{d}$ is average distance of snaxels, v_i is current snaxel position and v_{i-1} is previous snaxel position

The second term in Eq. 3, namely, a curverture expressed by Eq. 5 is causes the snaxels to be relatively spaced.

$$Curvature\ term = |v_{i-1} - 2v_i + v_{i+1}|^2 \quad (5)$$

The third term in Eq. 3 is image gradient which is the image force and is written as Eq. 6.

$$Image\ force = -|\nabla I(x,y)|^2 \quad (6)$$

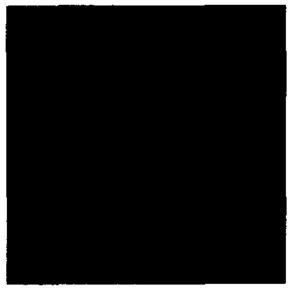
where $I(x,y)$ is intensity value of x, y position

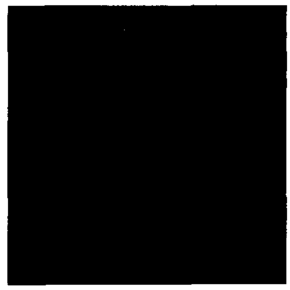
These values are normalized by dividing by the largest value in the neighborhood to which the point may move, giving a value in 0 to 1.

2. Image forces

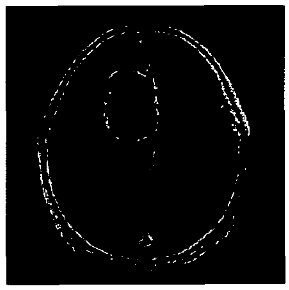
The image force of third terms in Eq. 3 pushes the curve to the significant lines which correspond to the desired attributes. The curve is then attracted by a local minima of the potential, which means the local maxima of the gradient edges. When it passes by edges, the curve is stopped if the edge is strong or passes through if the edge is too weak. This avoids the curve being trapped by spurious isolated edge point we used Canny edge detector[8]. To do this we define the attraction forces by simulating a potential defined by convolving the binary edge image with a Gaussian noise. And we apply values of various detectors in the image force and then extract the boundary of an interesting region.

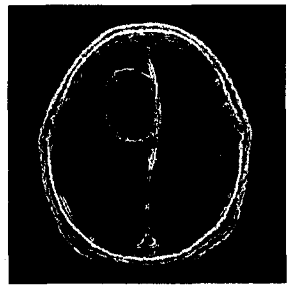
Fig. 2(a) is an original image and Fig. 2(b) is the image being added Gaussian noise to the original image. Fig. 2(c) is an edge image of the Fig. 2(b) using the Sobel edge detector. Fig. 2(d) is an edge image of the Fig. 2(b) using the Canny edge detector. Fig. 2(e) and Fig. 2(f) are the edge images of the Fig. 2(b) using the Laplasian and Prewitt edge detector, respectively. Fig. 2(c) image looks a better result than other images.



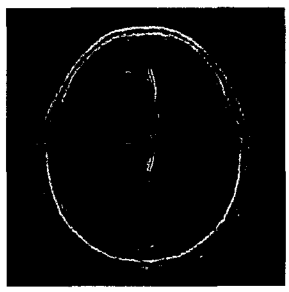


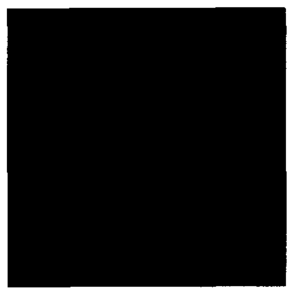
(a) Origianl Image (b) Added Gaussian noise





(c) Edge image using Canny edge detector in (b) (d) Edge image using Sobel edge detector in (b)





(e) Edge image using Laplasian edge detector in (b) (f) Edge image using prewitt edge detector in (b)

Fig. 2. Edge images by various image forces for an MRI brain image.

3. Dynamic programming

To reduce the computing costs, we adopted the dynamic programming approach proposed by Amini et al. [6]. Knowing that the energy function at each snaxel is based only on local image features, the total energy E_{total} of a snakes with n snaxels is

$$E_{total}(v_1, v_2, \cdots, v_n) = \quad (7)$$
$$E_1(v_1, v_2, v_3) + E_2(v_2, v_3, v_4) + \cdots + E_{n-2}(v_{n-2}, v_{n-1}, v_n)$$

where $E_{i-1}(v_{i-1}, v_i, v_{i+1})$ is the energy at each snaxel

v_i and $E_{i-1}(v_{i-1}, v_i, v_{i+1}) = E_{ext}(v_i) + E_{int}(v_{i-1}, v_i, v_{i+1})$

where E_{ext}, E_{int} are the external, internal energy function and v_i is current snaxel position, v_{i-1}, v_{i+1} are previous and next snaxel position.
optimal value function S_i in Eq. 8 is updated at each iteration, based on the information on its two adjacent snaxels.

$$S_i(v_{i+1}, v_i) = \min_{v_{i-1}} S_{i-1}(v_i, v_{i-1}) + \alpha(|v_i - v_{i-1}|)^2 + \beta|v_{i+1} - 2v_i + v_{i-1}|^2 + E_{ext}(v_i) \quad (8)$$

in which the initial condition is set as $S_0(v_1, v_0) = 0$ and the search process starts from S_i. An energy matrix is used to store the minimization value of optimal functions in the neighborhood of v_i. After S_{n-1} is calculated, the snakes with the minimum energy in iteration is obtained by back-tracking of the energy matrix of snaxels. For finding the optimal contour, the iterative process continues until $E_{\min}(t)$ does not change with time.

If there are n point and m directions at each point, the complexity of calculating the elastic energy in one iteration is $O(nm^2)$. The active contour is guaranteed to converge to a final solution in a finite number of iterations since the energy measure is monotonically decreasing with time. The algorithm halts when there is no change in the total energy of the contour. Fig. 3 illustrates the correspondence between the decision set and image pixels. The two curved arrows depict the minimum energy configuration for the current iteration.

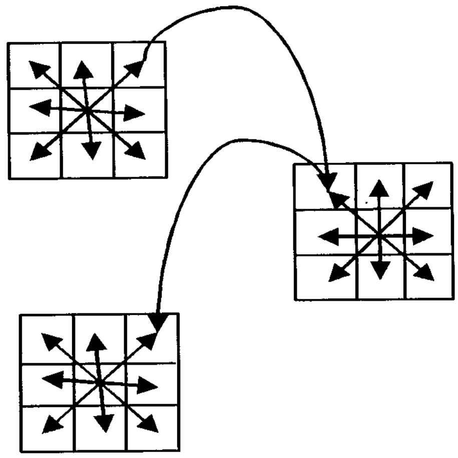
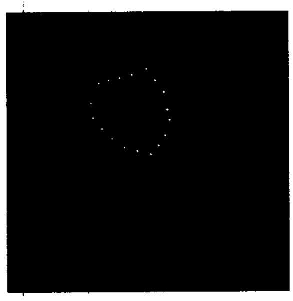


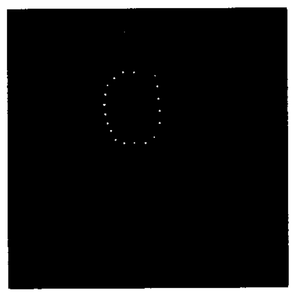
Fig. 3. The decision set of the dynamic programing.

Ⅳ. RESULTS AND VISUALIZATION

Fig 4 shows the images to Fig 2(b) obtained using the values of Sobel and Canny edge detector by the image force of the snakes, respectively. The image of Fig. 4(a). looks better in boundary detection than the Fig. 4(b) for the Gaussian noise.



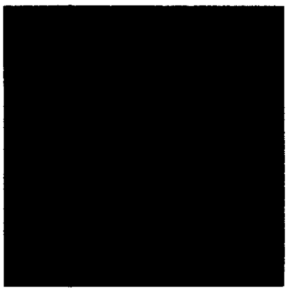
(a)



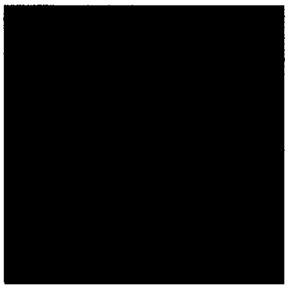
(b)

Fig. 4. Images using the snakes for the Gaussian noise.
(a) Sobel edge detector, (b) Canny edge detector

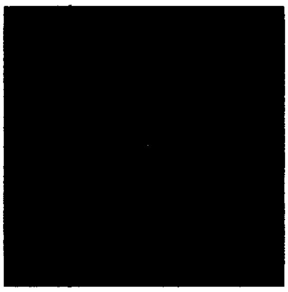
Fig. 5 shows the results of the snakes in other brain images with tumor. Fig. 5(a) and Fig. 5(c) are the initialized images for the snakes and Fig. 5(b) and Fig 5(d) are the images computed, respectively. We initialized the snakes by hand in this paper.



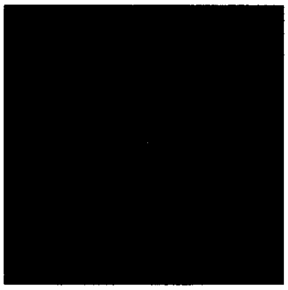
(a)



(b)



(c)



(d)

Fig. 5. Initializing and result of snakes (a),(c) is initialization snaxels in other brain tumor image. (b),(d) is result image of (a),(c)

The area, perimeter, x and y axis coordinate of the tumor acquired from the position of snakes for the 8 slices are shown in Table 1. The area of the tumor which is made up snaxels is computed by Eq. 9.

$$Area(P_{o}...P_{n-1}) = \frac{1}{2}\sum_{i=0}^{n-1}(x_i y_{i-1} - y_i x_{i+1}) \quad (9)$$

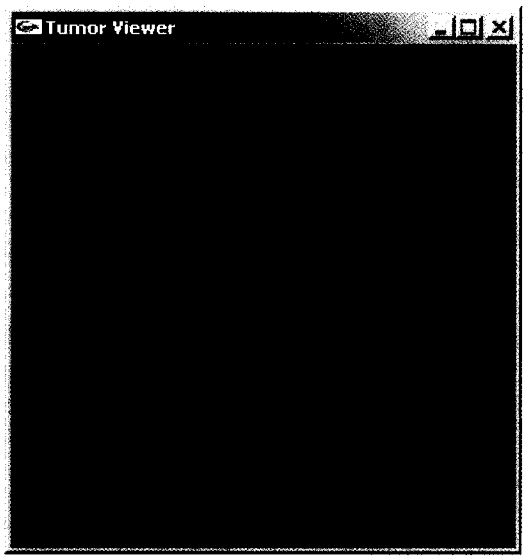
P_i is a snaxel and (x_i, y_i) is the coordinates of a snaxel.

Table 1. Computed features of the brain tumor (unit: pixel).

Feature / number	area	perimeter	x_center	y-center
slice 1	1488	145	114	91
slice 2	2553	185	116	92
slice 3	3075	203	113	93
slice 4	3501	220	111	98
slice 5	4023	237	114	102
slice 6	4873	259	120	116
slice 7	5623	286	122	140
slice 8	3603	218	125	132

We used the information of the snaxels to make the shape of a tumor. We constructed the shape of the tumor from the 8 slice images. Fig. 6(a) is a coronal section image of Fig. 5 and Fig. 6(b) is a 3D reconstruction for the tumor of the image.

(a) Coronal section of an MRI brain image with tumor



(b) 3-D reconstruction of the tumor

Fig. 6. reconstruction of result image

Ⅴ. CONCLUSIONS

Previous Snakes algorithms have problems such as noise trap, snakes initialization, energy function optimization, concavity issues, etc. In this study, we have improved the energy-minimization problem of snakes by means of a dynamic programming, so that a global minimum can be guaranteed. We applied various edge detectors of the image force. First, we added a gaussian noise to an original image and then applied Sobel and Canny detectors. The result for the applied snakes shows that the Canny detector is less sensitive to the noise and is better in edge detection accuracy than the Sobel edge detector.

The area, perimeter and center position are calculated with snaxels and visualized a shape of tumor in 3D from the eight slices of the 2D image with 20 snaxels using OpenGL in contour extraction.

We expect that the proposed method in this paper will be useful to make a treatment plan as well as to evaluate the treatments. In the future works, we will improve problems of concavity and consider the edge detection for the multiple lesions.

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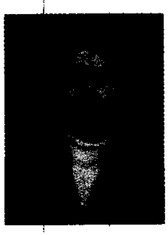

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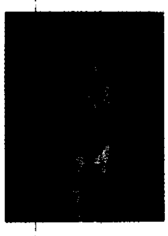

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