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A modified skull-stripping method based on Morphological Processing

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***Abstract*— In the paper, we first discussed the method of skull-stripping based on edge detection in detail. The method can extract the brain tissue from a normal MRI (magnetic resonance image) quickly and accurately. But if there are tumors at the boundary of the brain tissues whose intensity is different with normal tissues', some unwanted edge will appear while detecting the boundary of the brain tissue. So,we proosed a modified method to solve this issue in this paper. Our procedure consists of three steps. First, the MRI is processed with an anisotropic diffusion filter to encourage intraregion smoothing in preference to smoothing across the boundaries. And then find the region between the skull and the brain tissue using thresholding methods. It is difficult to remove the unwanted edges directly, but we found that when we processed it using a skeletonization algorithm, the unwanted edges became the branches on the skeleton of the region. Finally, use a sequence of morphological and connected component operator to make sure the region is closed. The closed region is that we wish for. Results on 2-D MR images are provided.**

Keywords-Medical image; Skull-stripping; Anisotropic diffusion ;Morphology;LOG operator;

I. INTRODUCTION

In medical image segmentation, our work is focused on the predominant tissues of the brain: grey matter (GM), white matter (WM), and cerebrospinal fluid (CSF). The non-brain tissues such as skin, fat, skull and dura have a negative effort for extracting the predominant tissues. So it is necessary to remove the non-brain tissue.

At present, there are many algorithms for the extraction of brain tissue. These methods can be divided into two types. One is based on boundary detection[1] .In the method, first, the MRI is processed by boundary detector to obtain the binary image of boundary; second, and then process the boundary image using a sequence of mathematical morphology operators to locate the brain region of MR image which is largest connected region. The other is based on region segmentation. Among them, watershed segmentation method is a typical method. The watershed algorithm is a non-liner based on mathematic morphological segmentation method which was first proposed by Vincent.Luc and Soille.Pierre [2] for image processing. In this paper, we follow the former.

This paper is organized as follows: section 2 describes a traditional algorithm for the brain tissue extraction based on boundary detection. Section 3 discusses the disadvantage of the above method, and then proposes a modified algorithm to solve these issues. In this section, some experimental results are presented. In section 4, we compare our scheme with the conventional scheme and present some conclude remarks.

II. BOUNDARY-BASED SEGMENTATION METHODS

The part of brain tissue is the largest region except for the background in the brain image. And the boundary of brain tissue is very clear, so it is relatively easy to segment the brain tissue. In 2000, David [3].etc first proposed such a boundary-based segmentation method. The procedure consists of three steps. First, the MRI is processed with an anisotropic diffusion [4] [5] filter to encourage intraregion smoothing in preference to smoothing across the boundaries. Then detect the edge of the filtered image using LOG operators [6] and obtain a binary image of the boundary. Third, find the region of brain tissue using a sequence of mathematic morphological operator. In the step, our purpose is to find a binary image (template) which only conclude the largest connected region (the brain tissue region),in which the gray-value is 1 and others is 0. Multiply the filtered image by the template, our wanted image can be got.

1. Anisotropic Diffusion Filtering

In medical image we often face a relatively low SNR with good contrast, or a low contrast with good SNR. Fortunately the human visual system is highly effective in recognizing structures even in the presence of a considerable amount of noise. But if the SNR is too small or the contrast too low it becomes very difficult

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to detect anatomical structures because tissue characterization fails. Usually, the linear spatial filter[7] does reduce the amplitude of the noise fluctuation, but also degrades some sharp details such as lines or edges. The anisotropic diffusion filter can overcome the drawback of conventional spatial filter, and significantly improve image quality.

Anisotropic diffusion filtering was proposed as an image processing method by Perona and Malik [5]. Their anisotropic diffusion filtering method is mathematically formulated as a diffusion process, and encourages intraregion smoothing in preference to smoothing across the boundaries. This process can be formulated mathematically as follows, assume the image defined in the two-dimensional space. The original image is I(x,y,0)=I(x,y).

$$\begin{cases} \dfrac{\partial}{\partial t} I(x,y,t) = div(c(x,y,t)\nabla I(x,y,t)) \\ I_0 = I(x,y,0) \end{cases} \quad . \tag{1}$$

where we indicate with div the divergence operator, and ∇ with Δ and respectively the gradient and Laplacian operators with respect to spatial variables. The variable t is the process ordering parameter, in the discrete implementation it used to enumerate iteration steps. The diffusion strength is controlled by diffusion coefficient c(x,y,t). The image is hoped to be smoothed within a moderately continuous region while not smoothed across sharp discontinuities. So, the diffusion coefficient c(x,y,t) should be away from 0 in the homogeneous regions, while c(x,y,t) in the unhomogeneous regions. Fortunately, the gradient of image intensity can used to distinguish the homogeneous and unhomogeneous regions. According to the above description, such a function needs to be constructed. $g(w) = g(\|\nabla I(x,y,t)\|)$. The g(w) is monotonically decreasing function and satisfies the equation $\lim_{w \to \infty} g(w) = 0$. Perona and Malik provided such two diffusion coefficient in their model:

$$g_1(w) = \exp[-(\frac{w}{K})^2] \tag{2}$$

$$g_2(w) = \frac{1}{1+\left(\dfrac{w}{K}\right)^{1+\alpha}} \qquad \alpha > 0 \tag{3}$$

Let $c(x,y,t) = g(\|\nabla I(x,y,t)\|)$, and substitute it in the equation (1). Here the gradient threshold K should draw our more attention. The choice of constant K is very important for the specific application of image processing. If the K value is closed to the gradient of the noise formation, it will be helpful for the image denoising processing. While if the K value is slightly less than the gradient magnitude of edge, it will be helpful for edge enhancement. For estimates of gradient threshold K, Perona and Malik recommend using canny operator of the noise estimation. But considering the calculated amount, we make a choice by empirically. The equation (3) is selected as our diffusion coefficient in this paper. The next task is to discrete the equation (1).

$$\begin{aligned} I(x,y,t_{n+1}) = I(x,y,t_n) + \delta t\{ \ldots \\ \frac{1}{\delta d_N^2}[c_N(x,y,t_n) * \nabla_N I(x,y,t_n)] + \ldots \\ \frac{1}{\delta d_S^2}[c_S(x,y,t_n) * \nabla_S I(x,y,t_n)] + \ldots \\ \frac{1}{\delta d_W^2}[c_W(x,y,t_n) * \nabla_E I(x,y,t_n)] + \ldots \\ \frac{1}{\delta d_E^2}[c_E(x,y,t_n) * \nabla_W I(x,y,t_n)]\} \end{aligned} \tag{4}$$

Where

$$\nabla_N I(x,y,t) = I(x-1,y,t) - I(x,y,t);$$
$$\nabla_S I(x,y,t) = I(x+1,y,t) - I(x,y,t);$$
$$\nabla_E I(x,y,t) = I(x+1,y,t) - I(x,y,t);$$
$$\nabla_W I(x,y,t) = I(x,y-1,t) - I(x,y,t);$$

The diffusion coefficient is:

$$c_N(x,y,t) = g(|\nabla_N I(x,y,t)|);$$
$$c_S(x,y,t) = g(|\nabla_S I(x,y,t)|);$$
$$c_W(x,y,t) = g(|\nabla_E I(x,y,t)|);$$
$$c_E(x,y,t) = g(|\nabla_W I(x,y,t)|);$$

I(x,y,t)is the intensity of the pixel indexed by (x,y) at the n-th timestep, δ d is the distance between two adjacent pixels. δ t is the size of timestep used to discretize the system. To ensure stability, δ t is selected to be $0 \leqslant \delta t \leqslant 1/7$ [11]. All intensity values in the image are updated at every iteration. To obtain better isotropy, it is also calculated between diagonally neighboring pixels, resulting in an eight-way-connected network. The longer distance between diagonal neighbors is taken into account by setting δ d to $\sqrt{2}$.

Also the number of iterations should be set. It can be selected by empirically. In this paper, the value of K is set to30, while the number of iterations is 15. The filtered image is as shown in figure 1(b).

2. Edge Detection

In the step, the boundary of brain tissue in MRI is located by using LOG[6] [8]edge detector. Considering the purpose of this edge detection - to identify the connected region where the brain tissue is. Therefore, the LOG operator is selected which can works out more continuous edges.

LOG edge operator was first proposed by Marr and Hildreth in 1990. Simply，It can be described as follow. First, the image is processed by a Gaussian low-pass filter. And then detect the boundaries using Laplacian edge operator. This process can be formulated mathematically as follows:

$$LOG[I(x,y)] = \Delta(G_\sigma * I(x,y)) = \Delta G_\sigma * I(x,y) \quad (5)$$

Where, $$G_\sigma(x,y) = \frac{1}{2\pi\sigma^2}\exp(-\frac{x^2+y^2}{2\sigma^2}) \quad (6)$$

$$\Delta G_\sigma(x,y) = \frac{x^2+y^2-2\sigma^2}{2\pi\sigma^4}\exp(-\frac{x^2+y^2}{2\sigma^2}) \quad (7)$$

Then our work is to select the parameter σ and the size of the template. Experiences show that a better result will be got for the MR image when set σ to 0.7 and the size is 7x7.It is seen in figure 1(c).

3. Morphological Processing

Generally, the segmentation results often contain unwanted noisy parts. Furthermore, sometimes the segmentation results will contain parts in which the shape of the object we are interested in has been disturbed. Therefore, we must modify the shape of segmented regions to obtain the desired results. And this is the subject of the field of mathematical morphology [9].

The edge detection step produces a binary image I_edge(x,y). I_edge(x,y) represents edge pixels by value of 0 while non-edge pixels are represented by value of 1. Generally, the boundary of the brain tissue is not entirely connected. That is, the largest connected region often contains some extraneous surrounding structures, such as skin, dura. Fortunately, those structures are very thin, generally less than 2 mm. Therefore, they can be removed by structures using erosion with a circle of diameter 3. The algorithm (8) can describe this step.

The eroded image often consists of several connected regions. Mark the each connected region, and every connected region has one tag-value. If the number of each tag-value can be computed，it is very easy to find out the largest connected region. The number of tag-region in the largest connected region is larger than others'. In fact, this method is very easy to implement. An image X (template) with a same size of I_eroded can be got after above processing. In the template, the pixels in brain region have the value of 1, while others are 0. As long as multiply the filtered image by this template, our desired purpose can be achieved.

However, the template X is smaller than the actual brain region due to the previous operation of erosion. The solution is to dilate X with a circle of diameter 3. Suppose that X1 is the dilated template. Often, the template X1 contains pits in its surface or even holes within the connected region (seen in figure 1(d)). A closing routine, consisting of a dilation followed by erosion, will fill small pits in the surface and close off some holes that occur within the region. We use an octagonal morphological element that has a diameter of 9 pixels. The final template and skull-striping image is shown in figure 1(e) and (f).

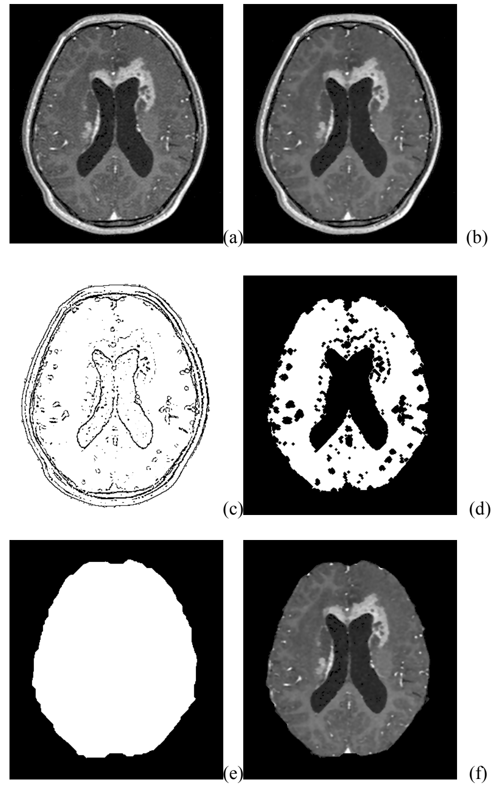


Figure1: the conventional method stages (a) initial image (b) the same image after anisotropic diffusion filtering (c) the edge map following application of LOG operator (d) the template X with largest connected region (e) the final template (f) the final image

III. Modified Segmentation Method

The above algorithm can obtain better results for the normal human brain MRI. But for the human brain MRI with tumors, the pits in the surface of X1 are not easy to be filled by a closing routine. Even if the pits can be filled by using a large morphological element, the edge of the template will be distorted. Because, if there are tumors in the boundaries of brain, some unwanted edge will produced while detecting the boundaries of the image. In the following morphological processing, these areas will be corroded away (seen in the figure 1(d)). It is these unwanted edges which lead to the pits in the surface of template. Finally, the brain tissue can't be extracted accurately from the MR image with tumors. It is noticed that the white part (tumor) has not been extracted completely in the bottom of the figure 1(f). Therefore, we modified the above algorithm to solve this tissue in this paper.

1. Anisotropic Diffusion Filtering

With respect to anisotropic diffusion filtering, we need not to repeat what has been described in section 2.

2. **Morphological Processing**

In order to solve the issues mentioned in the first paragraph of this section, we replace the step of boundaries detecting by threshold segmentation. Because the pixels in the part of background and CSF (cerebrospinal fluid) have lower gray values, while the others have higher gray values. The region between the skull and the brain tissue can be extracted by thresholding (see in figure 2(a)). But this region is not always closed; so we connect those discontinuous parts to make sure the brain region not connect with other tissues. The connected region is called ring in the following part which looks like a ring. We have mentioned that at the beginning of this section，some unwanted edges lead to the pits in the surface of template. And those unwanted edges always attach themselves with the closed ring. It is difficult to remove those unwanted edges directly. In order to remove those unwanted edges effectively, the process the ring using an algorithm of skeletonization. Because the skeletonization can preserve the region of the brain tissue. Meanwhile, the unwanted edges be simplified the burrs of the ring. And then we remove those burrs. The next step is to find the connected region which is same with above method. The Detailed steps are shown as follows:

1)Threshold processing

In this step, the region between the skull and the brain tissue will be found out. And this region to be segmented has significantly different gray values with other tissues. So the threshold operation can meet our requirement. The threshold processing can be described as follow:

$$g(x,y)=\begin{cases}0 & f(x,y)>T\\ 1 & f(x,y)\le T\end{cases} \qquad (8)$$

Where，T is the threshold. f(x,y) is the input image while g(x,y) is the processed image. The value of T can be determined according to the histogram.

2)link the gap

After the previous step of processing, our desired region has been found out. But sometimes this region is not closed. So it is necessary to link the gap in the region. Here, we only consider the pixels with the gray value of 0, and compute the distance from these pixels to the nearest pixels with gray value of 1. If the distance is larger than a certain threshold, change the gray value of 0 to 1. Or leave the gray value untouched. The gaps could be connected through above processing. Though the region has been widened, the location of the edge will not change after skeletonization.

3)Skeletonization and deburring

The goal of our modified method is remove that unwanted edges. In the figure 2(b), there are many white spots attaching to the ring. These spots cause the pits in the surface of brain tissue. But it is difficult to remove these spots directly. Skeletonization and the removal of burrs is the key step in this method. The skeleton of the ring is shown in figure 2(c). It is noticed that the

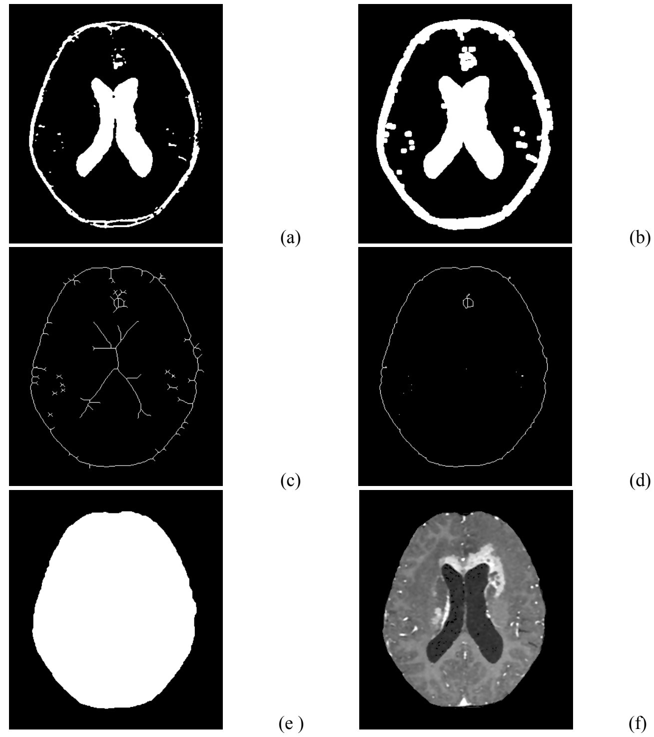


Figure2.modified method stages (a) the map after threshold processing (b)the map after linking the gap (c) the map after skeletonization (d) the map after deburring (e) the final template (f) the final image

spots are slimed as burrs. As long as these burrs removed, the desired results can be achieved.

We should not worry about that the skeletonization can distort the shape of brain tissue. Because the goal of skeletonization is to preserve the homotopy of the region, i.e., the number of connected components and holes. The deburred image is shown in figure 2(d).

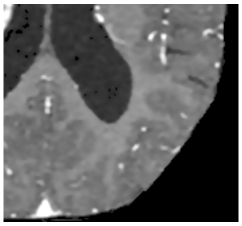
4)fill holes and modify

In the above step, we get only the skeleton of the ring but the final template. Fortunately, the region surrounded by the skeleton exactly is our wanted region. The template will be got after filling the region surrounded by the skeleton. But the template is slightly larger than actual brain tissue due to the skeletonization step. For this reason, we erode this template using the R structuring element to create a set the final template that will rightly cover nearly the entire brain region. the R is a round morphological element with a diameter of 6 pixels

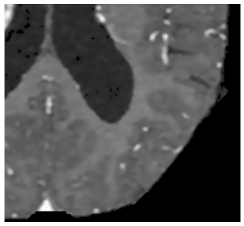
Finally, multiply the filtered image by the XD, our desired purpose can be achieved.

IV. CONCLUSIONS

In this paper, we proposed a modified skill-stripping method. This method can make up for the deficiencies of traditional methods. For the MR image with tumors, better results can be worked out using this modified method.



(a)



(b)

Figure3.the large version of the final images (a) the image processed by conventional method (b) the image processed by modified method

Figure1 (f) is the result using conventional skull-stripping method, and figure 2(f) is the result using our modified method. Both methods can accurately strip the skull in MR image. But when we observe the larger version of the same pictures (see in figure3) closely, we will find that the white spot is not completely preserved in the bottom of the figure 3(a), while it is completely preserved in figure 3(b). Meanwhile, a part of CSF is not completely removed in figure 3(a) but it is completely removed in figure 3(b).

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