

## An Adaptive Threshold Algorithm for MRI Brain Image segmentation on Level set method

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**Abstract**— When using thresholding method to segment an image, a fixed threshold is not suitable if the background is rough. Here, we propose a new adaptive thresholding method using level set theory. The method requires only one parameter to be selected and the adaptive threshold surface can be found automatically from the original image. An adaptive thresholding scheme using adaptive tracking and morphological filtering. Our method is good for detecting large and small images concurrently. It is also efficient to denoise and enhance the responses of images with low local contrast can be detected. The efficiency and accuracy of the algorithm is demonstrated by the experiments on the MR brain images. The above process of segmentation showed a considerable improvement in the evolution of the level set function.

**Keywords**- Adaptive thresholding, Image segmentation, Level set method.

### I. INTRODUCTION

Thresholding techniques are often used to segment images consisting of dark objects against bright backgrounds, or vice versa. It also offers data compression and fast data processing [1]. The simplest way is through a technique called global thresholding, where one threshold value is selected for the entire image, which is obtained from the global information. However, when the background has non-uniform illumination, a fixed (or global) threshold value will poorly segment the image. Thus, a local threshold value that changes dynamically over the image is needed. This technique is called adaptive thresholding.

Basically these techniques can be divided into region-based and edge-based thresholding. Region-based technique uses the whole image to extract the information for the threshold value computation, while edge-based technique is based on the attributes along the contour between the object and the background.

For region-based technique, most of the early introduced techniques are based on the image histogram. In 1979, Otsu [2] presented a technique that considered the image histogram as having a two gaussian distribution representing

the object and the background. A threshold is selected to maximize the inter-class separation on the basis of the class variances.

For the edge-based thresholding technique, the idea of applying the boundary based attributes is based on the fact that discriminant features exist at the boundary between the object and the background [3]. Thus, the edge-based thresholding technique has become more popular for exploration. Milgram [10] applied edge information to segment images by proposing “superslice” method. In this method, the edge information (gradient) is integrated with the recursive region splitting technique. The superslice method was also applied and improved in [3, 11].

The level set method is [4-7] based on geometric deformable model, which translate the problem of evolution 2-D (3-D) close curve(surface) into the evolution of level set function in the space with higher dimension to obtain the advantage in managing the topology changing of the shape. The level set method has had great success in computer graphics and vision. Also, it has been widely used in medical imaging for segmentation and shape recovery [8-9]. However, there are some insufficiencies in traditional level set method.

### II. ADAPTIVE THRESHOLDING

We adapt this technique with some optimization. The following outlines Hoover’s adaptive thresholding:

- 1) Binarize the image with a single threshold  $T$
- 2) Thin the thresholded image
- 3) Erase all branchpoints in the thinned image
- 4) All remaining endpoints are placed in the probe queue and are used as a starting point for tracking
- 5) Track the region with threshold  $T$
- 6) If the region passed testing,  $T=T-1$ , go to 5)

The testing in step 6) is some constraints to guarantee the region is image segment. Very small segments that remain after thresholding will be “size-filtered”. But this step is

preceded by the application of morphological filter to fill the small gaps between image.

III. THE MODIFICATION TO THE LEVEL SET METHOD

The level set method was invented by Osher and Sethian [4] to hold the topology changes of curves. A simple representation is that when a surface intersects with the zero plane to give the curve when this surface changes, and the curve changes according with the surface changes. The heart of the level set method is the implicit representation of the interface. To get an equation describing varying of the curve or the front with time, we started with the zero level set function at the front as follows:

$$\phi(x, y, t) = 0, \text{ if } (x, y) \in \Gamma \dots\dots\dots(4.1)$$

Then computed its derivative which is also equal to zero

$$\frac{\partial \phi}{\partial t} + \frac{\partial \phi}{\partial x} \cdot \frac{\partial x}{\partial t} + \frac{\partial \phi}{\partial y} \cdot \frac{\partial y}{\partial t} = 0 \dots\dots\dots(4.2)$$

Converting the terms to the dot product form of the gradient vector and the x and y derivatives vector, we go

$$\frac{\partial \phi}{\partial t} + \left( \frac{\partial \phi}{\partial x} \cdot \frac{\partial x}{\partial t} \right) \bullet \left( \frac{\partial \phi}{\partial y} \cdot \frac{\partial y}{\partial t} \right) = 0 \dots\dots\dots(4.3)$$

Multiplying and dividing by  $\nabla \phi$  and taking the other part to be  $F$  the equation was gotten as follows:

$$\frac{\partial \phi}{\partial t} + F|\nabla \phi| = 0 \dots\dots\dots(4.4)$$

According to literature [9][12], an energy function was defined:

$$E(\phi) = \mu E_{int}(\phi) + E_{ext}(\phi) \dots\dots\dots(4.5)$$

Where  $E_{ext}(\phi)$  was called the external energy, and  $E_{int}(\phi)$  was called the internal energy. These energy functions were represented as:

$$E_{int}(\phi) = \int_{\Omega} \frac{1}{2} (\nabla \phi - 1)^2 dx dy \dots\dots\dots(4.6)$$

$$E_{ext}(\phi) = \lambda L_g(\phi) + \nu A_g(\phi) \dots\dots\dots(4.7)$$

$$L_g = \int_{\Omega} g \delta(\phi) |\nabla \phi| dx dy \dots\dots\dots(4.8)$$

$$A_g = \int_{\Omega} g H(-\phi) dx dy \dots\dots\dots(4.9)$$

$$g = \frac{1}{1 + |\nabla G_{\sigma} * I|} \dots\dots\dots(4.10)$$

Where  $L_g(\phi)$  was the length of zero level curve of  $\phi$ ; and  $A_g$  could be viewed as the weighted area;  $I$  was the image and  $g$  was the edge indicator function. In conventional(traditional) level set methods, it is numerically necessary to keep the evolving level set function close to a

signed distance function[13][14]. Re-initialization, a technique for occasionally re-initializing the level set function to a signed distance function during the evolution, has been extensively used as a numerical remedy for maintaining stable curve evolution and ensuring desirable results.

From the practical viewpoints, the re-initialization process can be quite convoluted, expensive, and has subtle side effects [15]. In order to overcome the problem, Li et al [8] proposed a new variational level set formulation, which could be easily implemented by simple finite difference scheme, without the need of re-initialization. The details of the algorithm are in the literature [8]. However, because only the gradient information was imposed in the edge indicator function, Li's method has a little effect on the presence of fuzzy boundaries.

In the paper, a innovative method was proposed to modify the algorithm. The original image was threshold into some sub images by Adaptive threshold. The threshold boundary of each sub image was weighted by  $\alpha$ , the edge indicator function was redefined:

$$g' = g + \alpha \cdot g_2 \dots\dots\dots(4.11)$$

Where  $g_2 = \frac{1}{1 + |\nabla G_{\sigma} * I_1|}$

$I_1$  Was the image after threshold. The iterative equation of level set functional was:

$$\frac{(\phi^{n+1} - \phi^n)}{\tau} = \mu \left[ \Delta \phi - \text{div} \left( \frac{\nabla \phi}{|\nabla \phi|} \right) \right] + \lambda \delta(\phi) \text{div} \left( g' \frac{\nabla \phi}{|\nabla \phi|} \right) + \nu g' \delta(\phi) \dots\dots\dots(4.12)$$

Taking  $g' = g + \alpha \cdot g_2$  into 4.12

$$\phi^{n+1} = \phi^n + \tau \left\{ \begin{aligned} & \left[ \mu \left[ \nabla \phi - \text{div} \left( \frac{\nabla \phi}{|\nabla \phi|} \right) \right] \lambda \delta(\phi) \text{div} \left( g \frac{\nabla \phi}{|\nabla \phi|} \right) \right] \\ & + \nu g \delta(\phi) + \alpha \left[ \lambda \delta(\phi) \text{div} \left( g_2 \frac{\nabla \phi}{|\nabla \phi|} \right) + \nu g_2(\phi) \right] \end{aligned} \right\} \dots\dots\dots(4.13)$$

Where  $\alpha \in [0,1]$ . When processing images of weak boundary or low contrasts, a bigger  $\alpha$  was taken; otherwise, a smaller  $\alpha$  was taken.

IV. EXPERIMENTAL RESULTS

The segmentation of image takes an important branch in the surgery navigation and tumor radiotherapy. In the experiment, The image data from the IBSR(Internet Brain Segmentation Repository) are included to test the accuracy



and efficiency of the proposed algorithm. The output of adaptive threshold algorithm figure 1 is as shown below. Firstly the original MRI brain image is as shown in figure (i) is transformed to a proposed adaptive threshold algorithm with the test images of the brain and original binary image, note the over segmentation. The approximate contour of white matter was got by adaptive threshold algorithm shown in Figure ii of Figure 1. The snoothing of regions else appear as a result of the in excess of segmentation. The initial evolution curve was obtained by the automated initialization.

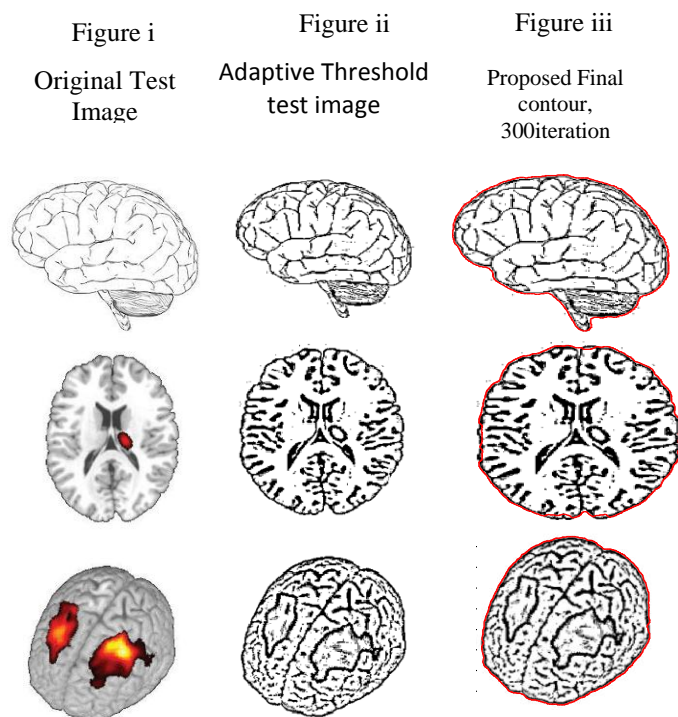


Figure:1

Figure i are the **original test images** ,  
 Figure ii are the **results of Adaptive threshold images** , to extracting the white matter.  
 Figure iii are the **results of final contour with proposed method**.

With the enhanced method, the curve was successfully evolved to the hollow white matter boundaries, but only to the approximately white matter boundaries with Li's method. At the same time, because the curve has been converged to the narrow region the object boundaries extraction could not be implemented with Li's method. But the enhanced method solved this problem better. On the similar computing proposal, under a 3.0GHz Pentium iv PC with 1 GB RAM on board, the average processing time of improved method was 9.6s, and that was 30.3s with Li's method. The evolution time was greatly reduced.

## V. DISCUSSIONS

The need of the re-initialization is completely eliminated by the proposal of Chunming Li, for pure partial differential equation driven level set methods, the variational level set methods. It can be easily implemented by using simple finite difference method and is computationally more efficient than the traditional level set methods. But, in this algorithm, the edge indicator has little effect on the low contrast image. So it is hard to obtain a perfect result when the region has a discrete boundary. Meanwhile, the initial contour of evolution needs to be determined by manual, and it has the shortcomings of time-consuming and user intervention.

In this paper, we projected a new method to transform the algorithm. The original image was partitioned with adaptive threshold algorithm, and the controlled action of the edge indicator function was increased. The result of adaptive threshold algorithm segmentation was used to obtain the initial contour of level set method. With the new edge indicator function, results of image segmentation showed that the improved algorithm can exactly extract the corresponding region of interest. Under the same computing proposal, the average time cost was lower. Alternatively the adaptive threshold algorithm is sensitive to noise; some redundant boundaries were appeared in the candidates. Consecutively to solve this problem, the algorithm of curve tracing was proposed

## VI. CONCLUSIONS

In this paper, we proposed an adaptive threshold algorithm with a level set method. The results of this paper confirmed that the mixture of adaptive threshold with the level set methods could be used for the segmentation of low contrast images and medical images. The method has the advantages of no reinitialization, automation, and reducing the number of iterations. The validity of new algorithm was verified in the process of exacting details of images. In the future research, noise was added in images prior information on the object boundary extraction with level set method, such as boundary, shape, and size, would be further analyzed. At the same time, the performance of image segmentation algorithms would be improved by modernization of classic velocity of level set method.

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