A Region Growing Segmentation Approach for MRI Brain Image Processing

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***Abstract*—Magnetic resonance imaging (MRI) is a crucial medical imaging methodology for diagnosing the disease. Image segmentation refers to the division of various sectors which is regarded as a significant job in medical image processing. This paper introduces an approach based on the region growing method for MRI brain image processing. In the pre-processing, the images will be filtered through anisotropic diffusion filtering algorithm so as to remove the noises and avoid the indistinctness. In the region growing stage, the threshold will be slightly increased and the objective function will be used for segmentation processes. The experimental results show the better performance of the proposed approach comparing with mean value filter and medium value filter methods.**

Keywords—image segmentation; region growing; MRI image; image processing

I. INTRODUCTION

Magnetic resonance imaging (MRI) refers to a kind of medical imaging technology which is used in radiology[1]. The aim of MRI is to get images of the anatomy and the physiological processes. MRI scanners are able to utilize magnetic fields and gradients as well as radio waves to generate pictures of the organs in a body without involving X-rays[2, 3]. Since its invention in the 1980s, MRI has been approved to be an efficient and effective technique in biomedical research field[4].

Image segmentation plays an important role in medical image processing. It is usually conducted at the first that is important in many diagnosis applications for different disease. Take brain MRI analysis as an example, image segmentation is adopted to measure and examine the brain's anatomical structures, brain changes detection, etc[5-7]. During the past decades, various segmentation techniques have been developed and designed in the literature for MRI segmentations considering the accuracy and effectiveness[8]. There are some challenges when conducting the segmentation. Firstly, analysis of the huge and complex MRI images is a tedious and time-consuming task for doctors and technicians. They have to manually pick up critical information from several images. This operation results in large number of errors and mistakes so that it largely influences the diagnosis[9]. Secondly, there are some challenges when conducting data analysis of MRI images which requires advanced computational methodologies to improve disease detection, examination, and testing. However, these methods for MRI image segmentation are limitedly reported to segment different sections to help doctors in doing their daily operations and check.

Region growing refers to an efficient image segmentation method which is classified as a pixel-based image processing approach[10]. The approach is based on iterations, which has the same principle of data clustering algorithms[11]. Region growing has some difficulties in MRI segmentation such as high sensitivity to noise, threshold determination, unreliability in segmentation, and low speed. In order to deal with the difficulties, this paper introduces an approach based on the region growing method for MRI brain image processing. In the pre-processing, the images will be filtered through anisotropic diffusion filtering algorithm so as to remove the noises and avoid the indistinctness. In the region growing stage, the threshold will be slightly increased and the objective function will be used for segmentation.

This paper has several sections. Section 2 presents the anisotropic diffusion filtering algorithm. Section 3 talks about the region growing algorithm and Section 4 reports on the experiments with some discussions. Section 5 concludes this paper by giving our contribution and future research directions.

II. ANISOTROPIC DIFFUSION FILTERING ALGORITHM

Anisotropic diffusion filtering algorithm (ADFA) is able to remove the noise and keep the clear of the boundary of image when filtering MRI images where huge noisy data is existing[12]. It is based on the initial value of equation from the processed image. Partial differential model is used for solving the initial image. The solutions from the model are the final results from smoothening the edges. ADFA could be expressed as:

For an image $I : \Omega \subset R^2 \rightarrow R$, we can get

$$\begin{cases} \dfrac{\partial I(x,y,t)}{\partial t} = g(|G_\sigma \times \nabla I|)\,|\nabla I|\,div(\dfrac{\nabla I}{|\nabla I|}) \\ I(x,y,0) = I_0(x,y) \end{cases} \quad (1)$$

Gaussian filter approach is used in the partial differential model. After that, the smoothness of the edges is determined by the gradients. In this paper, the most frequent value has been utilized to replace the Gaussian filter. The most frequent value is worked out by the trimmed mean value filter[13]. The following procedures are used in this paper for the purposes:

1) Use the most frequent value to filter the image;

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2) Repeat the processing for N times;
3) Repeat m×n time based on the rows and columns;
4) Work out the mean value of 3×3 window in the image;
5) Calculate the distance of each pixel to the mean value;
6) Delete the two pixels with furthest distance in the image;
7) Calculate the medium value of the rest pixels;
8) Replace the pixel values in corresponding locations using the trimmed mean value;
9) Repeat the operation until all the pixels are scanned;

III. THE PROPOSED ALGORITHM

The region growing approach is based on the selection of the growing rules and seed points. For the selection of seed points, this paper uses the central of RIO to pick the points. Based on the point, the mean value *m* and deviation δ of 5×5 neighbors district as the benchmark. This paper uses threshold value T and δ as the growing rules.

In the MRI images, the correlation of the pixels from background and targeted areas is high. That means the grey values for them are very similar. Due to that similarity, we use the space information to work out the gradient to present the grey changes of the background and targeted areas. The deviation from a certain district can indicate the consistency of that area. Thus, a model based on the edge mean gradient and class mean deviation is presented. The objective function is the sum of them.

For an image $f(x,y)$, we can define the gradient which is presented:

$$\nabla f(x,y) = [\mathrm{G}_x, \mathrm{G}_y]^T = [\frac{\partial f}{\partial x}\frac{\partial f}{\partial y}] \tag{2}$$

$$\nabla f = \sqrt{G_x^2 + G_y^2} \tag{3}$$

$$\theta(x,y) = \arctan(\frac{G_y}{G_x}) \tag{4}$$

Using (2)-(4), we can get the gradient image. In the MRI image, the edges of tissues will have highlighted grey values which will have the few noise after ADFA. The gradient can help for getting the growing regions. Assume that, after *t* iterations, a set of areas would be formed $p = \{p_j\}$, *0<j<t*. let *i* is the grey degree, n_i is the pixels number whose grey is *i*. l_j is the boundary of different areas. m_j is the pixel quantity in l_j. Then, the average gradient g_{p_j} could be expressed as:

$$g_{p_j} = \frac{\sum_{k=1}^{n_j} g_k}{n_j} \tag{5}$$

$$G_{p_j} = \frac{1}{g_{p_j}} \tag{6}$$

We can get the mean grey value u_{p_j} and deviation $\sigma_{p_j}^2$ in p where $i \in p_j$:

$$u_{p_j} = \frac{\sum_{i=0}^{L-1}(in_i)}{\sum_{i=0}^{L-1} n_i} \tag{7}$$

$$\sigma_{p_j}^2 = \frac{\sum_{i=0}^{L-1}(i-u_{p_j})^2 n_i}{\sum_{i=0}^{L-1} n_i} \tag{8}$$

The objective function is:

$$s_{p_j} = \alpha G_{p_j} + \beta \sigma_{p_j} \tag{9}$$

$$s = \min\{s_{p_j}, p_j \in p\} \tag{10}$$

For selecting the weights α and β. The following equation is used.

$$\begin{cases} \alpha / \beta = \dfrac{\sigma}{\pi} / 2\pi \\ \alpha + \beta = 1 \end{cases} \tag{11}$$

Based on that, the proposed approach could follow:

1) Trimmed mean value filter is used for processing the image;
2) Initial the growing seed points T_0, growing step length;
3) Calculate the targeted value h_0 of the segmentation area using the equation (2)-(4);
4) Update the $T=T_0+1$ and calculate the targeted value h_1;

If $h_1 \le h_0$, stop. Otherwise update $h_0 = h_1$ and T_0=T until the end of iteration.

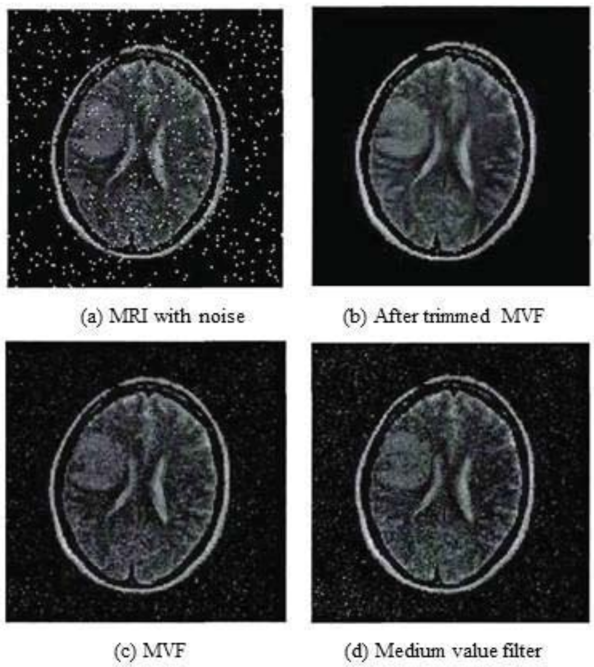
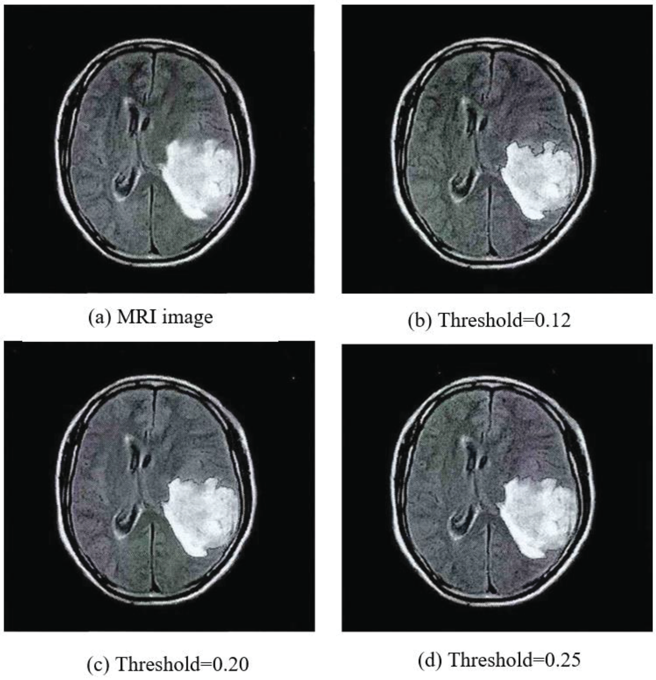


Figure 1. Filter results.



(a) MRI image (b) Threshold=0.12

(c) Threshold=0.20 (d) Threshold=0.25

Figure 2. Region growing results using different threshold.

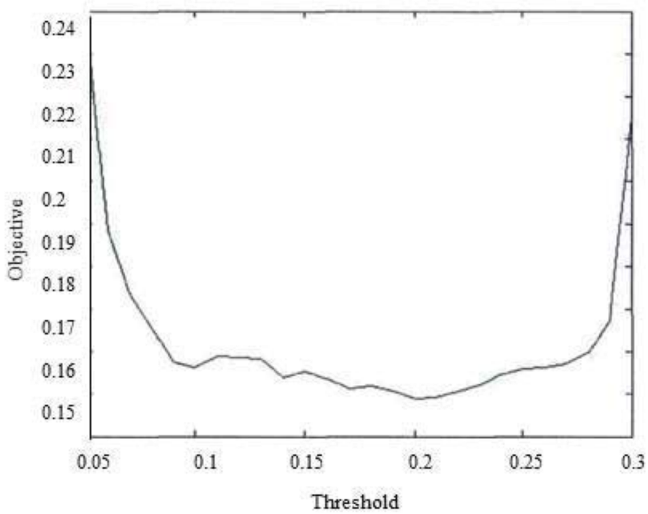


Figure 3. Relationship of threshold and objective function.

IV. Experiments and Discussions

The experiments are designed for evaluating the ADFA and proposed approach through some comparison analysis. Firstly, we put the pepper and salt noise into the MRI image. In the image processing, sharp and sudden disturbances will be caused by the noise. The pepper and salt noise is a type of impulse disturbance which will influence the analysis and examination of the images. The reduction of such noises is necessary sometimes when conducting precise processing such as in the MRI image which will be used for the diagnosis of any diseases and ill tissues that should be measured through professional doctors. These high frequencies from the noises also should be filtered that meaningful information or data from the pixels could be observed.

From Figure.1, it could be observed that, for the MRI images with pepper and salt noise, trimmed mean value filter (TMVF) outperforms MVF and medium value filter approaches. Figure.1 (a) show the MRI image with some noises from pepper and salt type where some white dots are existing. The identification of the image is thus greatly influenced by the noises. For example, the brain tissues are difficult to observe due to the noises. After trimmed MVF, Figure.1 (b) shows the results which indicate that the pepper and salt noises are significantly filtered. Thus, the processed MRI image is clear enough to identify the characteristics of various tissues such as gray and white matter, as well as cerebrospinal fluid. It is found that TMVF is able to remove the noise while keeping the clear boundary whose information could be used for further applications such as diagnosis of disease.

Figure.1 (c) shows the results from using MVF. It is found that, using this approach, the pepper and salt noises are removed in a certain level. The processed MRI image is much better than the Figure.1 (a) which is the original image with such kind of noises. However, there are still some noises which make the MRI image unclear. For instance, some tissues like white matter are difficult to be observed with their disturbances. Figure.1 (d) presents the results by using medium value filter to remove the pepper and salt noises. It could be found that this approach performs worse comparing with trimmed MVF and MVF since large number of noises are still existing. That confines the efficient and effectiveness of identifying the brain tissues. Additionally, the characteristics of different tissues are hard to be extracted due to the disrupt of such noises. Therefore, we can conclude that the trimmed MVP outperforms the other methods in the experiment for removing the pepper and salt noises.

The second experiment uses Matlab for testing the proposed approach using different thresholds to segment the MRI images. Figure.2 shows the results by suing different thresholds. Figure.2 (a) is the MRI image and (b) is the results from setting the threshold as 0.12. It could be found that the segmentation is efficient by comparing the processed image and original image. Some tissues such as white matter are highlighted after using the threshold with the value 0.12. Meanwhile, the boundaries for different tissues are more clear so that different tissues such as white and gray matters could be efficiently identified. Figure.2 (c) presents a result by increasing the threshold to 0.2 which shows the best results. First of all, the boundaries for different tissues are clear enough to be observed that the characteristics could be easily identified and seen for further diagnosis. Secondly, some tissues such as white and gray matters are highlighted after processing so that the segmentation operations could be efficiently conducted. From (c), it could be found that the white matter is significantly pointed out and the other tissues with very clear images are displayed. Figure.2 (d) shows the result from using the threshold with the value of 0.25. By increasing the threshold from 0.2 to 0.25, it could be observed that the efficiency and effectively of the segmentation for MRI images are not improved significantly from this experiment. It could be seen from (d) that the image is becoming unclear and the tissues in the MRI image are becoming mixed due to the fuzzy boundary.

It could be observed that, when the threshold is 0.2, the experimental results are the best from comparing with the results from using the threshold with 0.12 and 0.25. This experiment shows the best threshold for segmentation in this case. From 0 to 0.2, as the increasing of the threshold, the efficiency is increasing along the way. However, as the increasing of the threshold from 0.2 to 0.25, the efficiency is decreasing.

Figure 3 shows the relationship of threshold and objective function. From Figure. 3, it could be observed that from the threshold 0 to 0.1, the value for objective function is significantly decreased. That because the threshold affects the objective functions which are presented in Eq. (9) and (10) respectively. The weights will influence the value of the objective functions. While, from 0.1 to 0.25, it is stable without critical fluctuations. That means the threshold will influence the objective functions slightly due to the stable region growing efficiency. However, from 0.25 to 0.3, it increases slightly at first (from 0.25 to 0.28) and then profoundly since the threshold is over 0.28. It could be observed from this experiment, the minimum value of objective function attributes to the threshold of 0.2. That means, this value 0.2 for threshold should be used in the region growing so that the best performance could be obtained.

V. CONCLUSIONS

This paper presents a region growing segmentation approach based on the neighboring pixels for MRI image processing. This approach uses anisotropic diffusion filtering algorithm (ADFA) to remove the noise. Experiments show the outperformance of the proposed approach. Some contributions are significant. Firstly, (ADFA) is able to remove the noise and keep the clear of the boundary of MRI images. Secondly, experiments are conducted to show the outperformance of this approach. It is found that TMVF can remove the noise while keeping the clear boundary whose information could be used for further applications such as diagnosis of disease.

Future work will be conducted in the following aspects. First of all, this approach will be extended to other image processing such as X-ray images. Secondly, the proposed approach will be compared with other methods for segmentation such as dual clustering method and partial differential equation-based manner.

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