

Segmentation Technology of Medical Images Based on Regional Growth



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Abstract. This paper mainly studies the enhancement and segmentation of blood vessels in medical image processing. Firstly, the blood vessel images are preprocessed. In this paper, the gray-scale transformation method is used to enhance the image; then the principle of region growth and its advantages and disadvantages are analyzed. It is found that there are two key points in segmenting the blood vessel image by the method of region growth: one is the selection of seed points. Since manual selection of seed points is time-consuming and labor-intensive, this paper chooses to fix the seed points in the middle of the image. The second is the determination of the threshold T . In this paper, through the experiments of multiple groups, the appropriate threshold is finally determined. Experiments show that the proposed vascular segmentation algorithm can segment regional blood vessels with high efficiency and high quality and reduce human intervention, and has good robustness.

Keywords: blood vessel segmentation, gradation transformation, medical image, region growth, seed point selection

1 Introduction

As living conditions get better and better, people are paying more and more attention to their own health problems. As the number of vascular diseases continues to increase, it is the number one killer in human disease that is seriously threatening human health. According to the World Health Organization's 2015 report, the number of people dying from cardiovascular disease each year is as high as 36 million, accounting for 25% of the world's total mortality. The number of people who die from coronary heart disease each year in the country reaches 1.89 million. The sooner cardiovascular disease is discovered and treated, it can effectively curb the disease.

Vascular image segmentation plays an important role in computer-aided therapy, parametric analysis, and surgical navigation [1-2]. Hundreds of types of vascular image segmentation algorithms have been proposed, and a number of papers on vascular segmentation have been published each year, but to date no one has been able to extract vascular structures using a separate segmentation algorithm. The vascular image segmentation methods can be divided into four types: pattern recognition based methods, subdivided into multi-scale methods and regional growth methods, neural network-based methods, artificial intelligence-based methods, and tracking-based methods [3-6].

A variety of medical image segmentation methods have been developed, and the combination of various methods to give their respective advantages for medical image segmentation has become a development trend in this field. The computer can automatically segment the image, and with the development of technology and continuous improvement, automatic segmentation has strong adaptability and accuracy [7-8]. Although this method can be accurately measured, the complexity of the algorithm is high. Medical image segmentation is moving toward the following goals: (a) Automation, minimizing human-computer interaction. (b) High accuracy and close to the anatomy with optimized results. (c) High efficiency and can be processed in real time. (d). Adaptive, different applications can also adapt to

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self-learning. (e) Robustness, with good immunity to noise and ambiguity [9-11].

But these methods are either more complex or sensitive to threshold selection or time consuming [12-16]. To this end, this paper studies a comprehensive and effective method, which is based on regional growth of medical image segmentation technology. In this paper, the vascular image is enhanced by gradation transformation, and the seed point is fixed in the middle of the image, which realizes automatic segmentation of the image. Finally, this paper compares the algorithm of region growing with threshold segmentation and K-means segmentation method, and uses the error rate as the index to evaluate the experimental results, which proves that the segmentation accuracy of this algorithm is high and more feasible.

2 Thinking of the Algorithmic

Because the blood vessel image has many problems such as noise and blurring [17]. Therefore, before image segmentation, the image must be pre-processed to enhance the blood vessel image. Secondly, the seed point is used to automatically segment the image, which saves time compared to manually taking points. Then choose the appropriate growth criteria. Finally, the image is segmented [18]. Design ideas:

- (a) Estimating the seed point range [S1, S2] by a specific observation of the image histogram, and determining the threshold T;
- (b) Find a seed point in an area by image;
- (c) Use 8 connected directions to make the seed point as the center generating area;
- (d) Continue to use 8 connected directions, centering on the area, and merging nearby points that meet the growth conditions to generate new areas;
- (e) Repeat step d until the point where the growth condition is not met, the region growth process ends; the segmentation process is shown in Fig. 1.

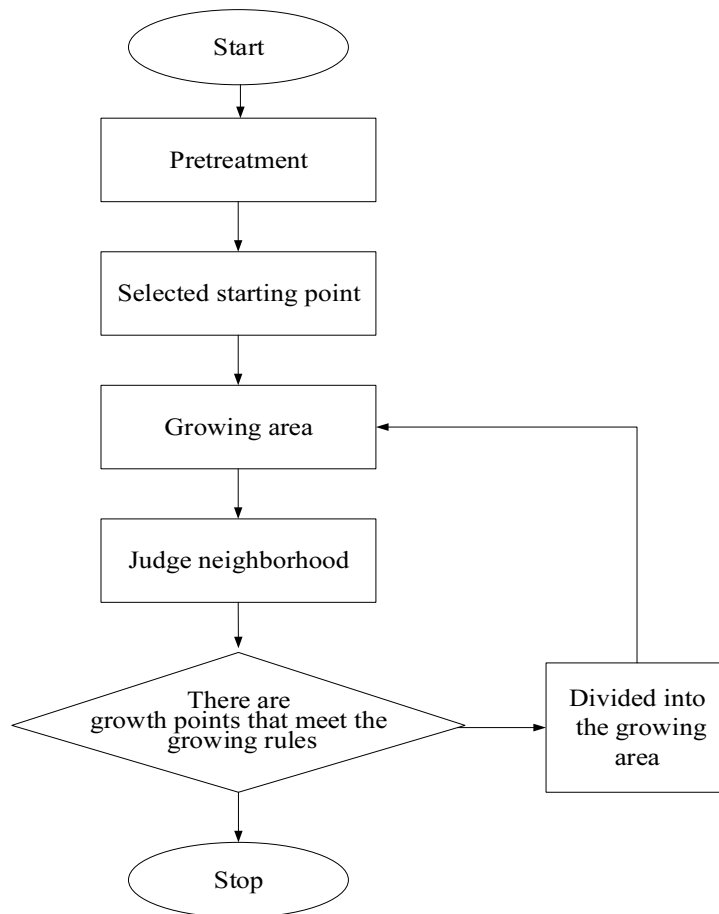


Fig. 1. Vascular segmentation process diagram

3 Introduction of the Algorithm

3.1 Image Preprocessing

Contrast is defined as the ratio of the maximum and minimum brightness. In the case of insufficient contrast, the recognition rate of the human eye viewing picture will be low. The gradation transformation is a method of changing the gradation value of each pixel in the original image point by point according to a certain transformation relationship. The apparently processed map becomes clearer. Fig. 2 is a preprocessing example 1, and Fig. 3 is a preprocessing example 2.

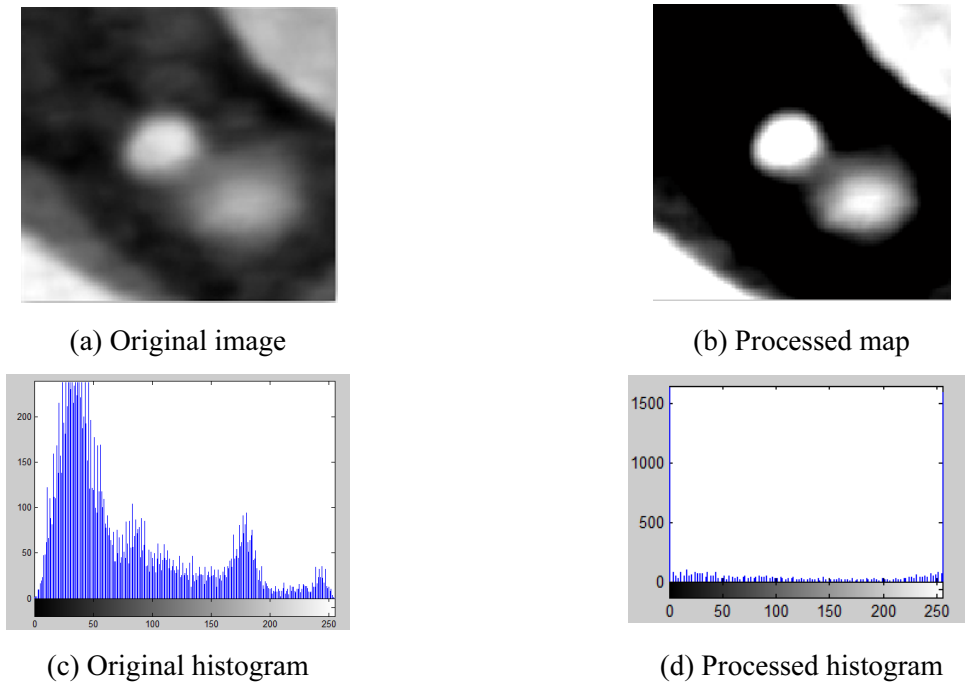


Fig. 2. Pretreatment example 1

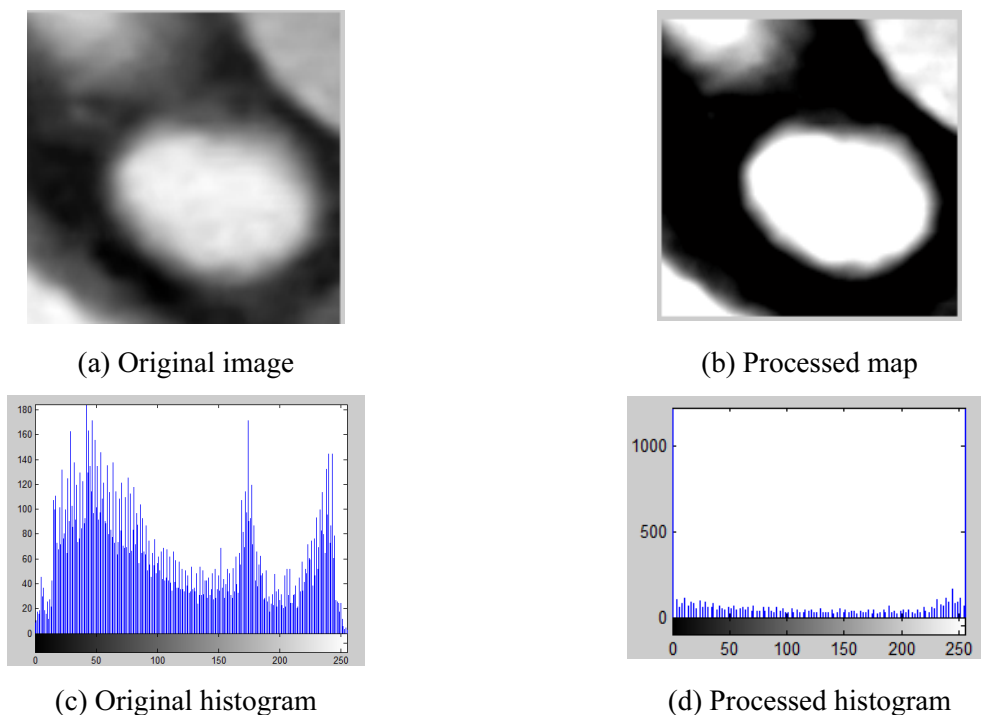


Fig. 3. Pretreatment example 2

3.2 Regional Growth Segmentation

The basic idea of regional growth is to grow objects in all directions starting from a given starting point. The basis for growth is the characteristics of the same type of area. Such as gray value, color and texture features. The result of image segmentation using region growing algorithm is mainly determined by two factors: one is the selection of seed points, and the other is the determination of growth criteria. There are two popular regional growth algorithms: one is based on the regional grayscale difference, and the algorithm uses the grayscale value of the pixel as the basic unit. One is based on the statistical properties of gray distribution in the region. This algorithm is based on regional similarity as the main factor for regional growth. The approximate steps of the region growing algorithm based on the regional gray scale difference are shown in Table 1. The region growing algorithm based on the statistical properties of the gray scale distribution in the region is shown in Table 2.

Table 1. Regional growth algorithm step based on regional gray difference

Regional growth algorithm step based on regional gray difference	
Step1	The area I is scanned to find the pixel I1 that is not yet owned.
Step2	Let I1 be the center, check the neighboring pixels around I1, compare I1 with each pixel of the field one by one, if the gray level difference between them is smaller than the previously set threshold T, then I1 and the domain pixel merge.
Step3	Taking the previously merged domain pixels as the new center, continue with Step2 until all the pixels that satisfy the condition are found, and no new pixels are merged.
Step4	Execute Step1 until all pixels are assigned. The area is growing.

Table 2. Regional growth algorithm steps for statistical properties of gray distribution in a region

Regional growth algorithm steps for statistical properties of gray distribution in a region	
Step1	The target image is segmented into a plurality of small regions that do not intersect each other.
Step2	The similarity of the gray levels of adjacent regions is compared by the similarity size. Merges them if they meet the similarity criteria.
Step3	To establish the conditions for the regional merger to stop, by repeating Step 2, the small areas are merged in turn until all the areas satisfying the conditions are merged. The termination condition of the merger is satisfied and the growth is over.

This method is easier to implement, but the efficiency is lower, and there is a greater dependence on the choice of the initial point of regional growth. It is impossible to ensure that the selected seed point is in the target area.

This method has a large dependence on the size of similar areas, and the size is too small or too large to get the desired result.

The following is an algorithm for segmenting blood vessel images using a region-based growth method. The advantage of the region growing algorithm is that the algorithm is easy and suitable for small structure segmentation. The basic idea of the regional growth method is to group pixels with similar characteristics to form an area. The regional growth method consists of three main steps:

- (a) Choose the right seed point.
- (b) Determine the similarity criterion (growth criterion): It can be formulated according to different rules, and ensure that adjacent area pixels with similar attributes can be merged into the area where the seed pixel is located.
- (c) The growth stop condition is determined: in general, when a pixel does not have any similar properties, the region growth stops.

Through the above analysis, the selection of seed points and the formulation of regional growth criteria directly affect the segmentation effect. After the correct selection of the seed point, if the threshold is set too high, it will cause excessive segmentation, that is, the pixels outside the excessive target area are merged, and the resulting image will be much larger than the target area. If the threshold is set too small, it will cause under-segmentation, that is, the segmented area is not complete enough.

3.3 Typical Example

A typical example based on region growing is presented below. Fig. 4(a) is the original image, Fig. 4(b) is the image grayscale, Fig. 4(c) is the segmented blood vessel, and Fig. 4(d) is the segmented blood vessel spot.

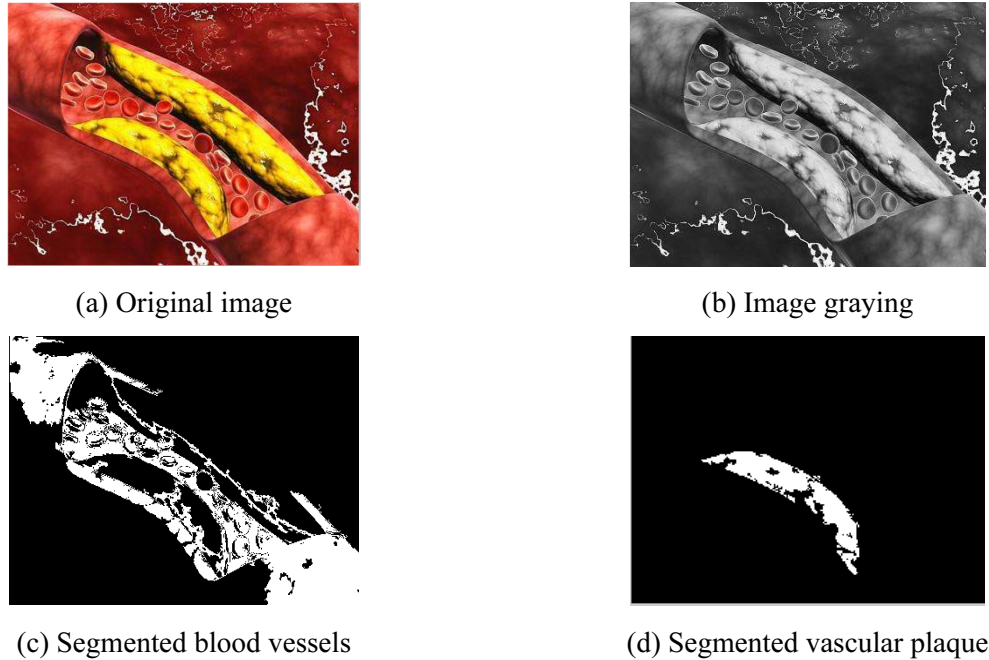


Fig. 4. Typical example

4 Regional Growth Algorithm Parameter Selection

This article uses accuracy as a standard definition of algorithm evaluation. The error rate is defined as the ratio of the area of the marked range to the area difference of the detected range. The formula is as follows:

$$\text{Error rate} = (\text{The area of the original mark} - \text{the area of the mark}) / (\text{The area of the original mark}) \quad (1)$$

There are two types of regional growth: manual segmentation and automatic segmentation. The selection of seed points is the basis for the success of the region growth segmentation method. The manual segmentation method relies on the experience of the doctor and is time consuming and labor intensive. Fig. 5 is a diagram showing two manual divisions under the premise that the threshold is completely unchanged. By observing Fig. 5(b) and Fig. 5(c), it can be found that under the same growth criterion, the effect of the segmented image is still very different.

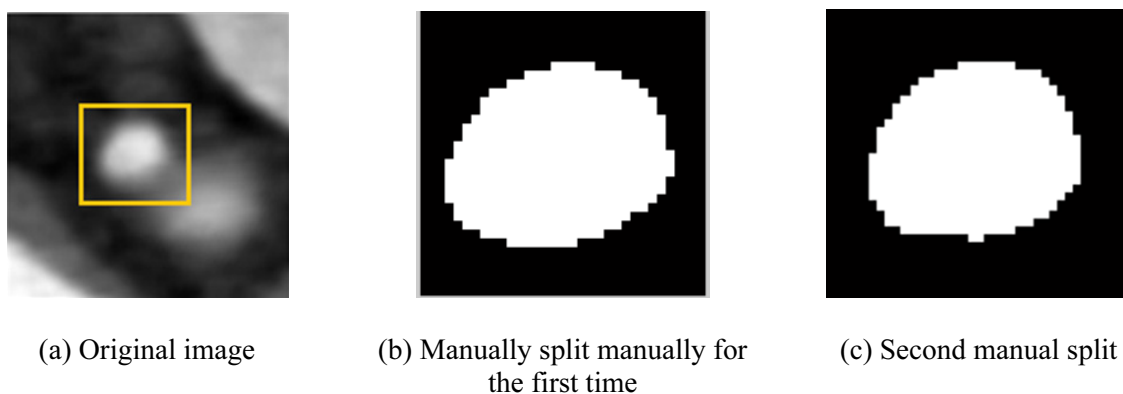


Fig. 5. Manually select seed point segmentation

In the process of image segmentation, the selection of the threshold also affects the segmentation effect. The setting of T has a direct impact on the segmentation results of the region growth method. Although the larger the T , the more adequate the target area is divided, it is easy to cause the segmented target area to be excessively larger than the actual target area. On the contrary, if the threshold T is set to a smaller value, although the segmented area is more precise, it will also result in under-segmentation. In this paper, the optimal threshold is found by iterative method, and the initial threshold is set to 0.05, which is increased by 0.05 each time. The two blood vessel images are segmented to find the optimal threshold T . Finally, it is concluded that the optimal result can be achieved when the threshold T is between 0.15 and 0.2. Fig. 6 is a segmentation of a blood vessel image using different thresholds.

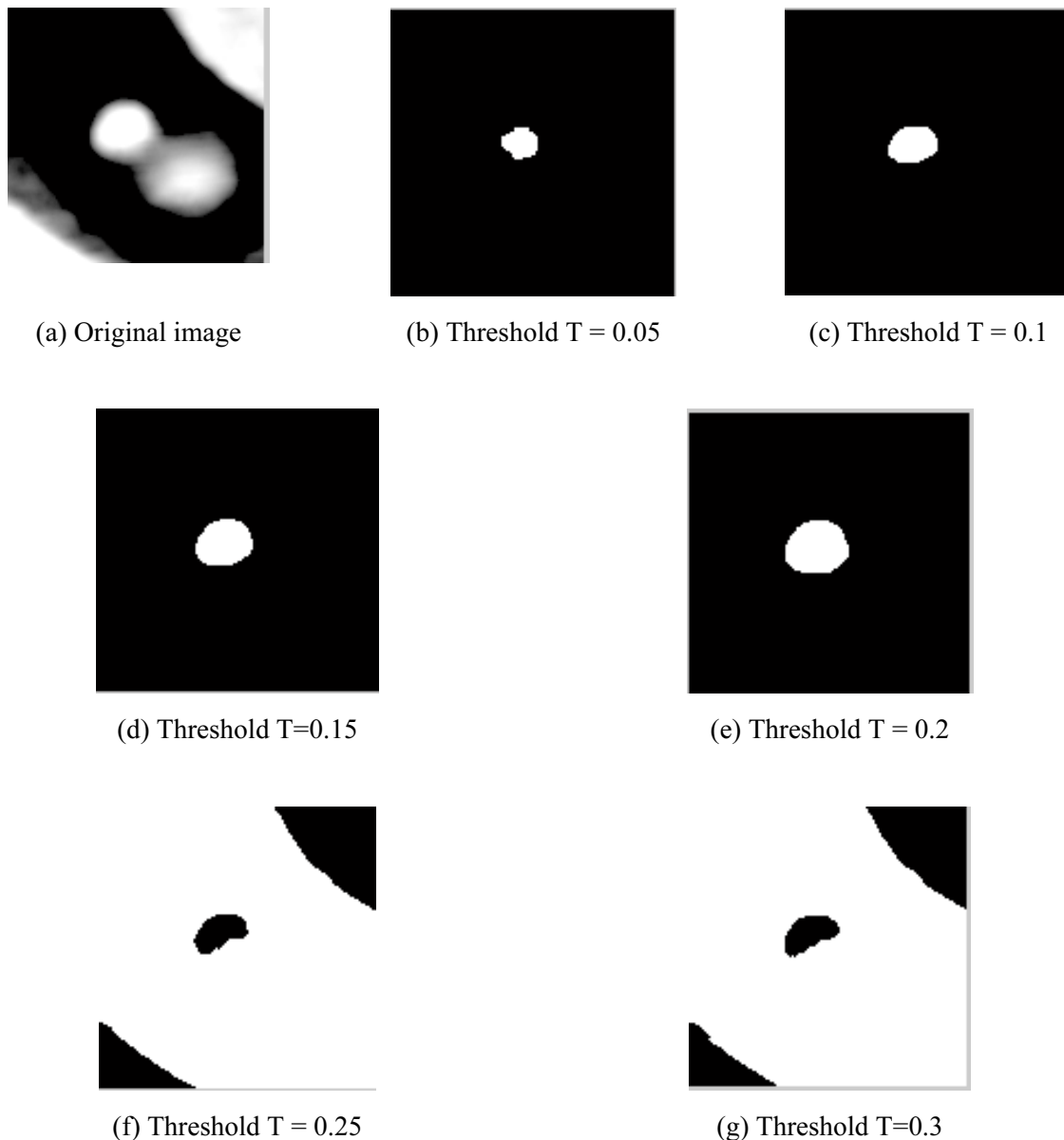


Fig. 6. Influence of different thresholds T

By observing Fig. 6, it can be found that when T is between 0.15 and 0.2, the optimal performance is achieved. When T is 0.05 to 0.1, it causes under-segmentation, and the segmented blood vessels are not complete enough. When $T = 0.25$ to 0.3, it caused excessive segmentation, and the segmentation was not a blood vessel. Fig. 6(g) may be uneven distribution of gray in the target area, causing the growth to terminate prematurely. As shown in Fig. 7, the four representative images are representative.

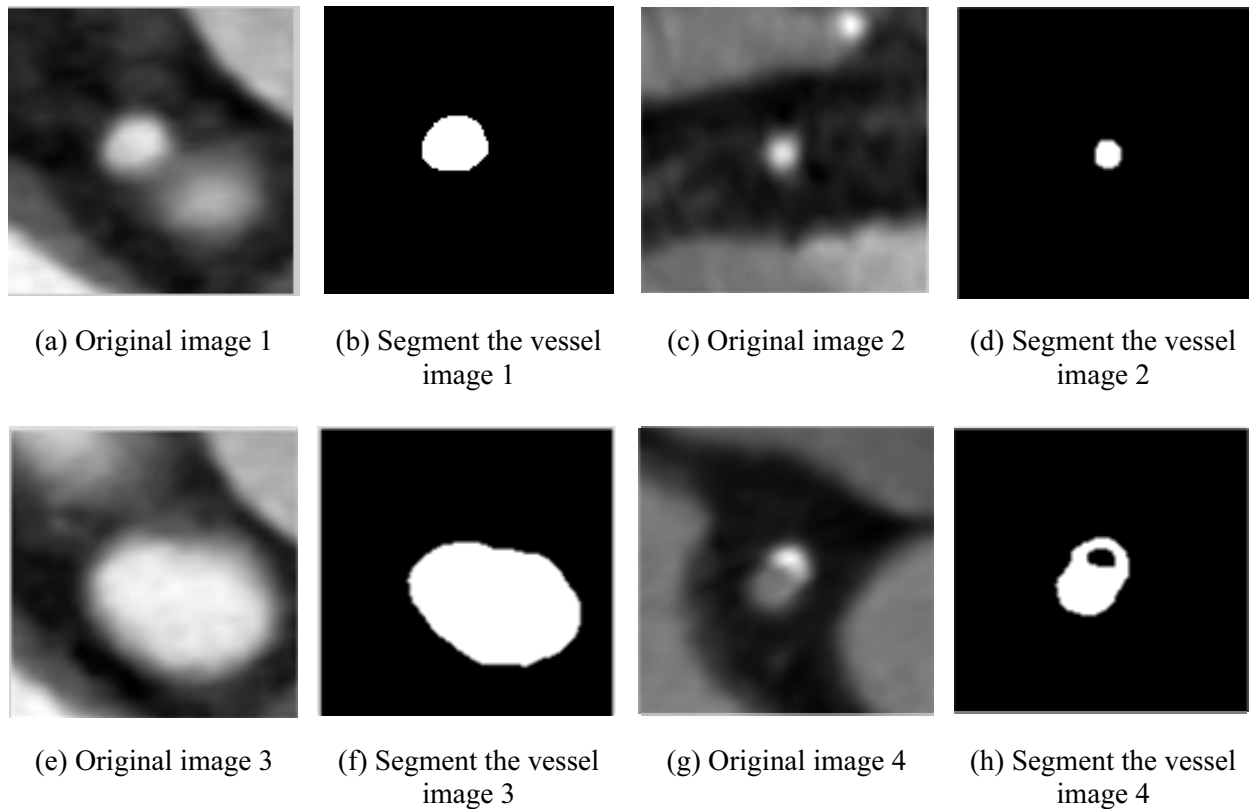


Fig. 7. Regional growth segmentation

In Fig. 7, a total of four maps are selected. Among them, Fig. 7(a), Fig. 7(c), and Fig. 7(e) have been successfully segmented. Since the blood vessels of most blood vessel images are in the middle of the image, the seed points set in this paper are also in the middle of the figure, and most of them are correctly segmented. Fig. 7(g) shows that there is under-segmentation when segmentation, which may be due to uneven distribution of gray in the target area, which leads to early termination of growth.

5 Comparison of Regional Growth Methods and Otsu Methods

By consulting the relevant literature [19-21], Otsu's method is simple to calculate, and the contrast and brightness of the image have no effect on it under certain preconditions. The shortcomings of this approach are obvious. To get the best threshold, he must traverse and calculate the variance of the grayscale pixels while also being disturbed by noise.

Fig. 8(b) results in over-segmentation of the image because the resulting threshold is not ideal. It is because the threshold of the target is close to the threshold of the background.

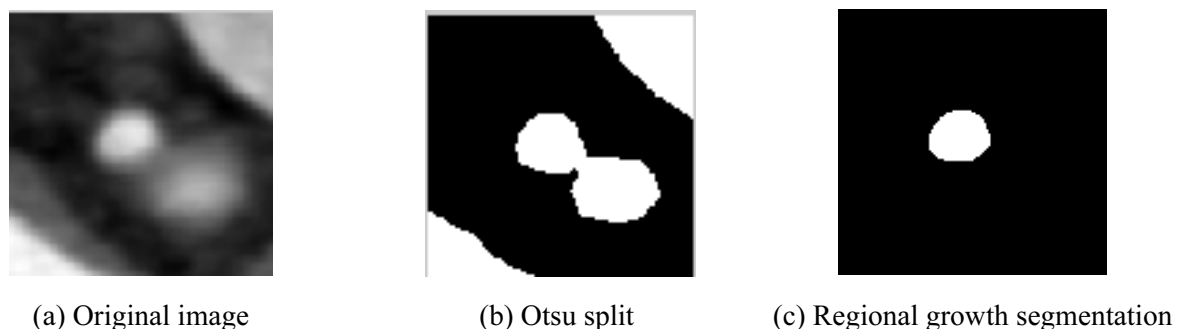


Fig. 8. Otsu and regional growth comparison chart

6 Comparison between Regional Growth Method and K-means Method

Thoughts are simple, easy to implement, and less time spent. These are the advantages of K-means; when large data sets need to be solved, the timeliness of clustering algorithms will be reflected [22]. The disadvantage is also obvious: the number of clusters k must be artificially given in advance. The selection of the initial center of clustering is also very important. If the initial cluster number K or the initial cluster center does not select an appropriate value, the amount of calculation will increase, and sometimes the wrong clustering result may be accompanied by different clustering. Class centers may produce very different results; using the K-means can only segment all the classifications of the vessel map. The specific K-mean is not directly available. You also need to do the next step to extract the blood vessels you want. This greatly increases the artificial time and the prior knowledge of the person.

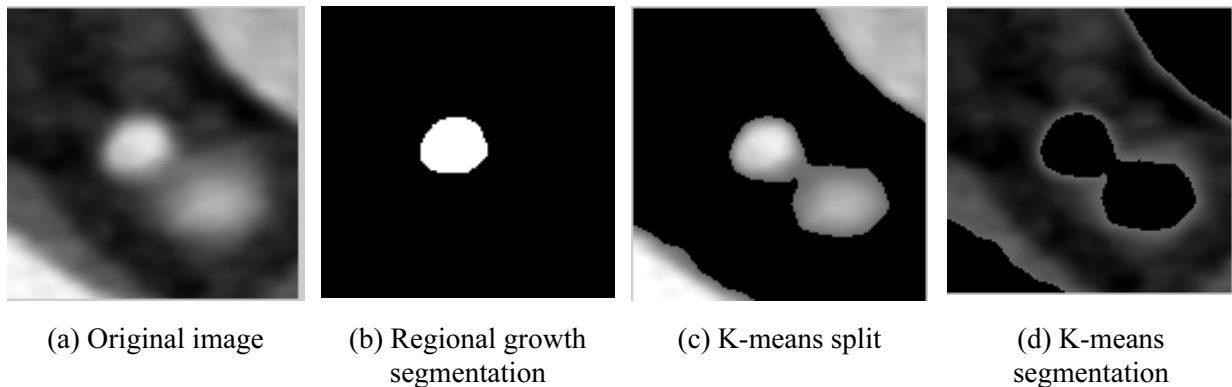


Fig. 9. K-mean and regional growth comparison chart

7 Experiment Analysis

In this paper, a total of 100 images of different sections on a blood vessel are segmented. The medical images of the blood vessels to be segmented mainly include grayscale values that are relatively close, and the grayscale values are relatively large. The blood vessels surrounding the blood vessels are relatively thick and some of the hundreds of images are relatively thick, and some blood vessels are compared. Fine, some of the images have two blood vessels, so the results of regional growth and segmentation of different images are also different. Through the result of the segmentation, the error rate of the segmentation of the blood vessel image is counted, and the results are shown in Table 3:

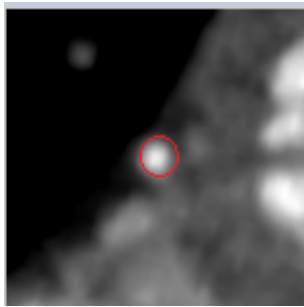
Table 3. Error rate

Error rate	Segmented graph
0-5%	14 pictures
6%-10%	15 pictures
11%-15%	21 pictures
15%-20%	20 pictures

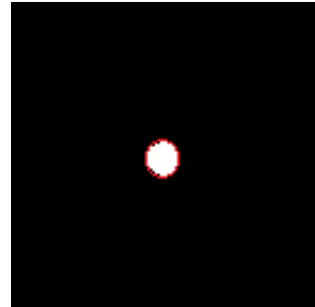
Replace the marked area with the marked pixels. According to the formula, the error rate = $(24 * 31 - 25 * 29) / (24 * 31)$, the error calculated in Example 1 is 5%, the error calculated in Example 2 is 10%, and the error calculated in Example 3 is 12 %, the error calculated in Example 4 is 19%.

8 Summary

This paper describes in detail the working principle of the region growing algorithm and the advantages and disadvantages of segmenting the blood vessel image. In this paper, the vascular image is enhanced by gradation transformation, and the seed point is fixed in the middle of the image, which

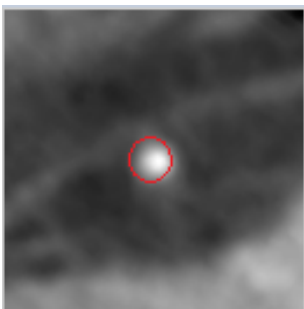


(a) 19*18 pixels

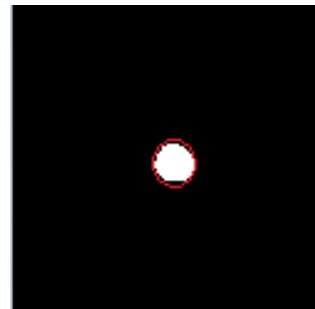


(b) 19*17 pixels

Fig. 10. Area chart example 1

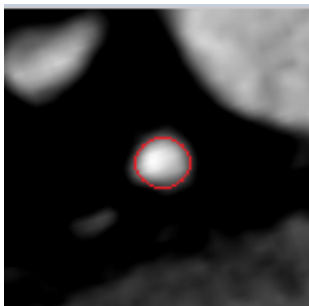


(a) 19*20 pixels

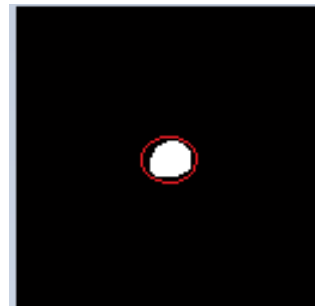


(b) 19*18 pixels

Fig. 11. Area chart example 2

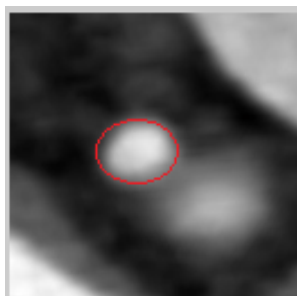


(a) 25*22 pixels

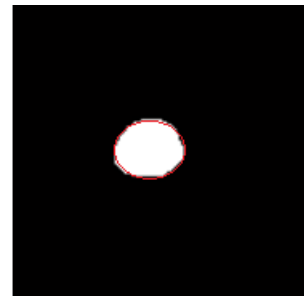


(b) 24*20 pixels

Fig. 12. Area chart example 3



(a) 37*29 pixels



(b) 32*27 pixels

Fig. 13. Area chart example 4

realizes automatic segmentation of the image. Finally, this paper compares the algorithm of region growing with threshold segmentation and K-means segmentation method, and uses the error rate as the index to evaluate the experimental results, which proves that the segmentation accuracy of this algorithm is high and more feasible. In addition, the algorithm used in this paper is mainly for the segmentation of blood vessel regions in CT images, and can be extended to other medical image segmentation. The research in this paper is only a two-dimensional image, and does not involve three-dimensional aspects. Subsequent work can be extended to three-dimensional segmentation and reconstruction of blood vessels.

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