Improved Fuzzy Connectedness Segmentation Method for Medical Images with Multiple Seeds in MRI

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Abstract: Image segmentation is a key step in medical image processing, since it affects the quality of the medical image in the follow-up steps. However, in the practice of processing MRI images, we find out that the segmentation process involves much difficulty due to the poorly defined boundaries of medical images, meanwhile, there are usually more than one target area. In this study, an improved algorithm based on the fuzzy connectedness framework for medical image is developed. The improved algorithm has involved an adaptive fuzzy connectedness segmentation combined with multiple seeds selection. Also, the algorithm can effectively overcome many problems when manual selection is used, such as the un-precise result of each target region segmented of the medical image and the difficulty of completion the segmentation when the areas are not connected. For testing the proposed method, some original real images, taken from a large hospital, were analyzed. The results have been evaluated with some rules, such as Dice's coefficient, over segmentation rate, and under segmentation rate. The results show that the proposed method has an ideal segmentation boundary on medical images, meanwhile, it has a low time cost. In conclusion, the proposed method is superior to the traditional fuzzy connectedness segmentation methods for medical images.

Key words: Fuzzy connectedness, image segmentation, region growing, multiple seeds.

1. Introduction

Image segmentation is the first step and one of the most critical procedures in image processing. Its effects directly determine the final quality of the follow-up work [1]–[2]. In the recent years, the image segmentation field has emerged many outstanding results [3]–[4], such as threshold segmentation method [5], regional growing method [6], clustering method [7], neural network method [8], etc. In the field of medical image processing, the image segmentation is indispensable, but because of the human structure and a variety of human and machine factors, the medical images have inevitably fuzzy and uneven characteristics.

In the recent years, many researchers have proposed different fuzzy connectedness algorithms to achieve and improve medical image segmentation. The fuzzy connectedness algorithm is a region-based segmentation method, which was originally proposed by Udupa, *et al*. They constructed the concept of fuzzy connectedness degree, relative fuzzy connectedness degree, and the framework of fuzzy connectedness theory [9]. Later, they improved and expanded their theory in [10] and [11]. Their work led the theoretical basis of fuzzy connectedness, and achieved significant results in medical image segmentation [12].

On the basis of the fuzzy connectedness framework, many scholars have put forward their own improved methods. On the whole, the improvements were mainly in the following two aspects:

The first aspect was in the calculation method of fuzzy connectedness. Ciesielski *et al.* proposed an optimization calculation method of fuzzy connectedness, and applied it to medical image segmentation [13] and [14]. After that, they came out with an improved algorithm for multiple seeds, since the previous algorithm could only be applied to the single seed areas [15]. Jianjiang Pan *et al.* proposed an improved method in [16]. They pointed out that the use of native fuzzy connectedness calculation method would lead to poor segmentation effects on the images that have gradation of gray values. However, since their algorithm was based on a single seed pixel, the representation of the target area was insufficient. Also, in their algorithm, when the target area was long and thin, this would cause the target area to be incomplete.

The second aspect was that the extensions of the fuzzy connectedness algorithm were mainly combined with other classic image processing methods. Bejar and Miranda combined the concept of fuzzy connectedness with the direction of region growing, excluding the results which were illogical [17]. Skoura *et al*. combined the fuzzy connectedness with feature detection of target area [18]. And Rueda *et al*. combined the fuzzy connectedness with the feature detection of the target region [19]. All these extensions enhanced the robustness of the classical fuzzy connectedness algorithm. Chunlan Yang *et al*. proposed a method of combining the confidence degree of connection and the fuzzy connectedness. Their method made the searching process of seed pixel s more concise and accurate. It effectively overcame the problem of selecting inaccuracies caused by artificial selection of the seed area. Moreover, the factorial equation in the fuzzy connection degree formula was improved to make it adaptive with different kinds of target areas [20]. Luo and Chen proposed an improved algorithm where the seed pixel must be input manually in the classical algorithm. Their improved algorithm located the salient pixels of the image through the construction of visual attention model, and achieved the automatic choice of the seed pixel [21]. Harati *et al*. also put forward an automatic segmentation method, which needed to know the distribution, location, and size of the target area in advance [22]. But the shortcomings of the above two methods were that the characteristics of the target area must be pre-known before the division process, and this led to a lack of universality.

From the basic conceptual framework of fuzzy connectedness, the whole calculation process of MRI image segmentation is divided into the following sub-procedures: The first is finding the seed pixel; then, calculating the affinity between adjacent pixels; the third is calculating the fuzzy connectedness degree; and the final sub-procedure is the segmentation according to the value of the fuzzy connectedness. Since each of these sub-procedures could be optimized, the focus of the researchers in their studies was on these optimizations.

However, in the most common cases, when the gray value and the gradient value of the target area are non-uniform, and at the same time, the areas to be segmented are not continuous, the above-mentioned methods cannot solve the image segmentation problem and find the optimal segmentation algorithm. Therefore, we propose an improved image segmentation method based on the fuzzy connectedness theory. This method combines the region growing method and the segmentation algorithm based on multiple seed pixels. And thus, it effectively overcomes the inaccuracy of the manual selection method for finding the seed pixels and the incomplete segmentation in the face of a number of non-adjacent target areas.

The proposed method in this paper consists of the following steps: First, enhancing the contrast by pre-processing the image; second, specifying manually multiple seed pixels; third, getting the region growing related parameters through the calculation of the seed and its around pixels and then, applying the region growing in order to get the original seed pixel set; fourth, calculating the fuzzy connectedness related parameters from the seed pixel set after finding the growth of the multi-block regions. The fifth step is calculating the fuzzy connectedness degree for the whole image. Finally, the last step is extracting the target area by using a threshold. In the selection of the test data, we have selected real images obtained from a large hospital in order to get closer to the real situation. And we have used Dice Possibility (Dice), Over-division Rate (OR), and Under-division Rate (UR) to evaluate the segmentation results.

The selection of multiple seed pixels not only enhances the diversity of the initial position, but also enhances the representation of the target area. The calculation of multiple seed pixels in the same target area tends to make the initial parameters of the target area representative, and hence it enhances the effect of the final division process. The selection of multiple seed pixels can not only split out the target areas completely, but also it can enhance the integrity of each part of the target areas, and thus, the proposed method has the effect of killing two birds with one stone.

The test results show that the improved algorithm has no effect on the segmentation speed and it improves the precision of the segmentation. Through the input of multiple seed pixels, the method not only overcomes the problem of multi-object segmentation, but it also makes each target area better segmented than the traditional methods. Finally, according to the experimental results, the method has a very good robustness and satisfactory segmentation effect.

In the rest of this paper, we will discuss the improved fuzzy connectedness segmentation algorithm for medical images by applying multiple seeds and present the step of this algorithm in section 2. In section 3, we will discuss the experimental results and the analysis of the method. And finally, we conclude the paper in section 4.

2. Improved Fuzzy Connectedness Segmentation Method for Medical Images with Multiple Seeds

In this section, we will firstly discuss the preprocessing of medical images in subsection (2.1.). Then in subsection (2.2.), we will discuss applying region growing algorithm to find seed pixel set. Then in subsection (2.3.), we will briefly introduce the concept about fuzzy connectedness and then introduce an improved affinity calculation method in subsection (2.4.). In subsection (2.5.), we come up with the method of combining multi-seeds input with previous steps. Finally in subsection (2.6.), we summarize the steps of the proposed algorithm.

2.1. Preprocessing of Medical Image

In order to enhance the contrast of the medical image, we have used a morphological-based method called the White and the Black top-hat transformation.

In this method, the White top-hat transformation refers to the subtraction of the original image from the result image of the opening operation. By contrast, the Black top-hat transformation refers to the subtraction of the original image from the result image of the closing operation. The above two mentioned transformations are shown in Fig. 1 respectively. These transformations can be expressed in the following two equations:

$$I_w = I - I \circ SE \tag{1}$$

$$I_\mathrm{b} = I \bullet SE - I \tag{2}$$

Herein, in the above equations, I represents the original image, SE represents the structuring element, "$\circ$" represents opening operation, and "$\bullet$" represents closing operation. The structuring element used in this paper is a 3 × 3 square, and the result is shown in Fig. 1.

It can be seen that after applying the preprocessing described above, the boundaries between the different regions of the image become clearer. As a prerequisite for segmentation, the preprocessing can improve the effect of the subsequent processes.

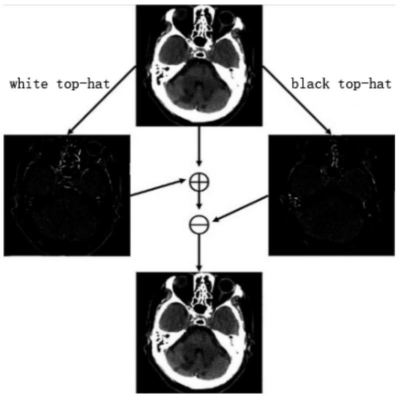


Fig. 1. Flowchart of preprocessing.

In Fig. 1, the left and the right figures are the White and the Black top-hat transformations respectively. The top and the bottom figures are the original image and the result image respectively.

2.2. Region Growing Algorithm

The basic idea of region growing algorithm is to combine the pixels in the seed pixel set with the pixels that have similar properties (i.e., similar in the average gray scale and the standard deviation) to form a region. Specifically, we need to find a seed pixel as the starting pixel of each region, and then calculate the average gray scale and the standard deviation according to the pixels within a certain range around the seed pixel. Then, we need to merge the pixels which are adjacent of the seed pixel set, that have the same or similar average gray scale and standard deviation, to the seed pixel set. This new pixel set is then taken as the new seed pixel set. We repeat the above process until there is no pixel can be added. In this study, we have selected a 3 × 3 square medical image that it centered on the original seed pixel which is considered as the initial seed pixel set.

The steps for implementing the proposed algorithm are as follows:

(1) Add the original seed pixel and its adjacent 8 pixels to the seed pixel set, and then calculate the average gray scale and the standard deviation of the seed pixel set.

(2) Select a pixel which is adjacent to the seed pixel set, and calculate the gray scale of this pixel. If it is in the range of $[m-l\sigma, m+l\sigma]$ (where l is variable factor), then add the pixel to the seed pixel set.

(3) Calculate the average gray scale and the standard deviation of the new seed pixel set.

(4) Repeat step 2 and step 3 until there is no pixel can be added.

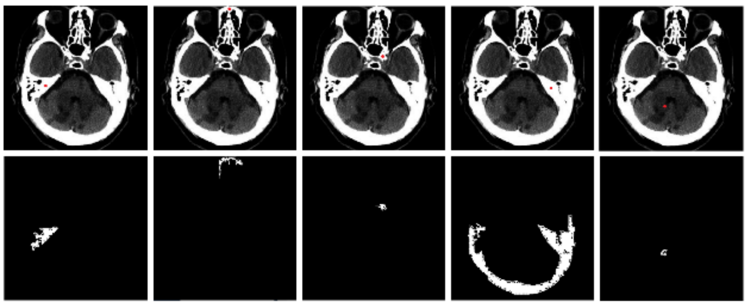


Fig. 2. Seed pixel set obtained by different initial seed pixel.

The results of the region growing algorithm mentioned above with different initial seed pixels on a skull image are shown in Fig. 2. The figure shows that the results obtained by different initial seed pixels are different.

2.3. Fuzzy Connectedness

Fuzzy connectedness is a fuzzy subset theory-based methodology. In this methodology, the algorithm starts from a seed and evaluates the affinity between the seed and the pixels in the image. Some basic concepts about fuzzy connectedness are as follows.

1) Fuzzy Relation:

Let X be any reference set. A fuzzy relation α in X is a fuzzy suVbset of $X \times X$

$$\alpha = \{(x, y), \mu_\alpha(x, y) \mid (x, y) \in X \times X\} \tag{3}$$

where $$\mu_\alpha : X \times X \to [0,1]$$

An example of fuzzy adjacency is the fuzzy relation g defined by:

$$\mu_\alpha(c,d) = \begin{cases} 1, & \| c-d \| \le 1 \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

where c and d are two different pixels.

2) Fuzzy Affinity:

Let $S = (C, f)$ be a membership scene and f is a transformation function of $C \to S$. Any fuzzy relation κ in C is said to be a fuzzy affinity in C if it is reflexive and symmetric. In practice, we could define one of the formulas as follows:

$$\mu_\kappa(c,d) = \frac{\mu_\alpha(c,d)}{1 + k\,|\,f(c) - f(d)\,|} \tag{5}$$

3) Path Connectedness:

Let κ be a fuzzy affinity. A nonempty path p_{cd} is a sequence $\langle c_1, c_2, \ldots, c_m \rangle (m \ge 2)$, where $c_i\,(i = 1 \ldots m) \in C,\ c_1 = c,\ c_m = d$.

The path connectedness is defined as follows:

$$\mu_\kappa(p_{cd}) = \min[\mu_\kappa(c_1, c_2), \mu_\kappa(c_2, c_3), \ldots, \mu_\kappa(c_{m-1}, c_m)] \tag{6}$$

4) Fuzzy Connectedness:

In practice, there are many paths between c and d, let P_{cd} represent the path set of c to d. The fuzzy connectedness μ_γ is defined as follows:

$$\mu_\gamma(c,d) = \max_{p_{cd} \in P_{cd}} \left[\mu_\kappa(p_{cd}) \right] \tag{7}$$

The steps for implementing the fuzzy connectedness algorithm are as follows:

(1) Set up a flag matrix F and initialize its values to all zeros, the value of each position represents the FC value of the pixel.

(2) Set up a temporary set Q and add the seed pixel set to it, and then set the corresponding position in set F to 1.

(3) Find the pixel in the set Q that has the largest FC value, take it out of Q, and calculate the affinity value for the adjacent pixels which have a smaller FC value.

(4) Compare the affinity values for the adjacent pixels with the value of the pixels which was taken out. If the affinity value of an adjacent pixel is bigger, then set the FC value of the pixel which was taken out to this

adjacent pixel, and, contrariwise, set the affinity value to it.

(5) The FC values of the adjacent pixels that have been processed are compared with the values of the corresponding pixels in the set F, if the new FC value is greater, then set the corresponding pixels in the set F to it, if not, then don't do anything.

(6) Add the adjacent pixel to set Q and repeat the steps from step (3) to step (6) until Q is empty.

(7) At this pixel, the value of each pixel in F is the final fuzzy connectedness value of the corresponding pixel.

2.4. Improved Affinity Calculation

In the original calculation of the fuzzy affinity, we only take into account the affinity between two adjacent pixels. This may result in some mistake. For example, the fuzzy affinity values for two pixels may be very close though their gray values are not similar at all, even though the gray values of every two adjacent pixels in the path are similar. In order to eliminate this situation, we use an improved affinity calculation method [20]. From the formula:

$$\mu_\kappa(c,d)=\mu_\alpha(c,d)\left[\omega_1 h_1(f(c),f(d))+\omega_2 h_2(f(c),f(d))\right] \tag{8}$$

where:

$$h_1(f(c),f(d)) = e^{-\frac{1}{2}\left[\frac{(f(c)+f(d))/2-m_1}{s_1}\right]^2} \tag{9}$$

$$h_2(f(c),f(d)) = e^{-\frac{1}{2}\left[\frac{(f(c)+f(d))/2-m_2}{s_2}\right]^2} \tag{10}$$

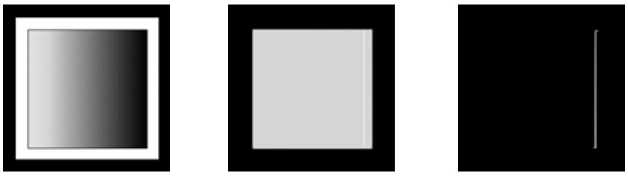
$$\omega_1=\frac{h_1}{h_1+h_2} \tag{11}$$

$$\omega_2=1 - \omega_1 \tag{12}$$

By combining equations (8), (9), (10), (11), and (12), we can get:

$$\mu_\kappa(c,d)=\mu_\alpha(c,d)\left[\frac{h_1^2(f(c),f(d))+h_2^2(f(c),f(d))}{h_1(f(c),f(d))+h_2(f(c),f(d))}\right] \tag{13}$$

By applying formula (13) as an improved affinity calculation in the segmentation process, as shown in Fig. 3, we can see that when we use the original affinity calculation, the entire middle region is considered as the target area, and by using the improved affinity calculation, we can effectively eliminate this error.



a b c

Fig. 3. The comparison of different calculation methods of affinity: (a) original image (b) segmentation result with old calculation method of affinity (c) segmentation result with new calculation method of affinity.

2.5. Multi-seeds Input

In the previous segmentation process, we can notice that the segmentation results are not complete when there is a small separation between the regions that should to be combined. Moreover, since the pixel's features contained in the target area are not completely uniform, the seed pixel which we have chosen may lack of representation. Therefore, in order to overcome the previous mentioned problems, there is a need to improve the previous segmentation process.

In the method proposed in this paper, we make the computer program receives any number of inputs, each one of these inputs represents a seed pixel, which is manually input by the program user. When the input is ended, the program takes all of the seed pixels as an initial seed pixel set, and applies region growing algorithm for the entire synchronized image to obtain a seed pixel set as an input of the subsequent step.

Since the algorithm of region growing depends on the local information of the image, and it is not related to the changes outside the growing area of the image, therefore, it possible to apply it for simultaneous growing of multiple regions of the image.

The selection of multiple seed pixels not only enhances the diversity of the position of the initial pixels, but also improves the representation of the target area. The calculation of multiple seed pixels in the same target area tends to make the initial parameters of the target region more representatives, and hence this enhances the final segmentation effect on the image, as it can be seen in Fig. 4.

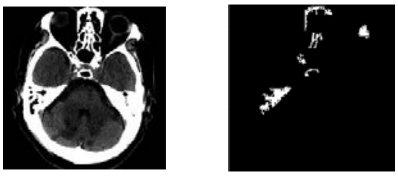


Fig. 4. Region growing result with multi-seeds input.

2.6. Steps of the Algorithm

The overall calculation method of this paper can be presented in the following steps:

1) Preprocessing the image to enhance its contrast;

2) Assigning manually by the user multiple seed pixels in the image;

3) Getting the parameters related to the region growing of the image through the calculation of the seeds' surrounding pixels, and applying the region growing algorithm in order to get the initial seed pixel set.

4) Calculating the fuzzy connectedness-related parameters from the seed pixel set.

5) Calculating the fuzzy connectedness value, and finally getting the fuzzy connectedness value of the whole image;

6) Extract the target area by a threshold segmentation, and getting the final resulted image.

The previous steps can be presented in the following flowchart shown in Fig. 5.

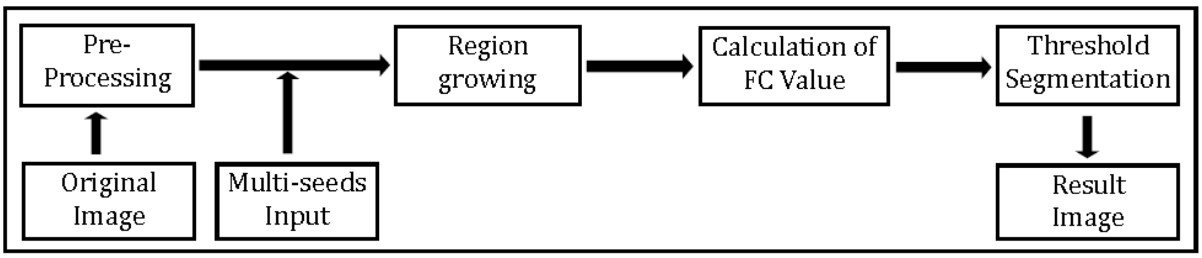


Fig. 5. Flowchart shows the steps of the improved calculation algorithm.

3. The Experimental and Analysis of Results

3.1. Test Methods

In this study, we have evaluated the segmentation effect of the improved algorithm by calculating the coincidence rate (Dice), the over segmentation rate (OR), and the under segmentation rate (UR) respectively, and compared the results with the result presented for other two previous algorithms (FC and AFCCC) which have been introduced in [9] and [20] respectively. The calculation method of the three evaluation indicators are given as follows:

$$\text{Dice}(R,S)=\frac{2\times|R\cap S|}{|R|+|S|} \tag{14}$$

$$OR(R,S)=\frac{|R-S|}{|R\cup S|} \tag{15}$$

$$UR(R,S)=\frac{|S-R|}{|R\cup S|} \tag{16}$$

where R is the result image from the proposed method and S is the standard segmentation result.

In this study, we have divided the test images to three groups of comparison tests. The first group was used to verify the advantages of the method for multiple target areas; the second group verified the effect of the method for multiple target areas and for non-uniform target areas simultaneously; and finally, the third group of tests shows the effect of the method on the single non-uniform target. These three groups of tests verify the segmentation effect of the proposed method from different angles as we will explain in the following subsection (3.2.).

3.2. Test Results

a b c d e

Fig. 6. Test results of skull MRI image: (a) original image (b) standard segmentation result (c) FC result (d) AFCCC result (e) the proposed method's result.

As it can be clearly seen from Fig. 6, and by comparing the standard segmentation results, shown in Fig. 6(b) for the original skull MRI image (Fig. 6(a)), with the segmentation results of the FC and AFCCC algorithms shown in Fig. 6(c) and (d) respectively, the FC and AFCCC algorithms do not have the adaptability when the region to be segmented is not continuous. However, the algorithm proposed in this paper has the advantages to overcome the situation of having a non-continuous region for segmentation which often occurs, and thus it has the integrity of the segmentation results as it can be seen in Fig. 6(e).

In Fig. 7, (d) and (f) present the results obtained by one and two seed pixels in the same target area respectively. When taking one initial seed, it means that we are actually applying the AFCCC method. Since the FC and the AFCCC can only segment the continuous target area, it can be seen from these two figures that the multiple seeds method can not only overcome this shortcoming, but it also has a better segmentation effect for a single target area. This is because the selection of multiple seed pixels can not only enhance the diversity of the positions of the initial pixels, but it can also improve the representation of the target area, since the target area is not completely homogeneous. Also, Fig. 7(g) and (h) present the results obtained by two initial seed pixels in different target areas, where one initial seed pixel is in the same half and the other is in the different half. Therefore, as we can see in these two figures, the selection of multiple seed pixels can not only segment out the target areas more completely, but it also can improve the integrity of each part of these areas, and hence the method can kill two birds with one stone.

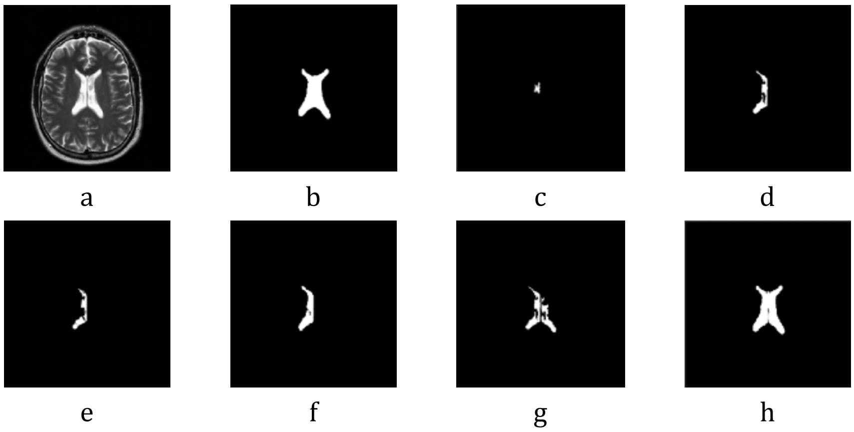


Fig. 7. Test results of brain MRI image 1: (a) original image (b) standard segmentation result (c) seed pixel set obtained by one initial seed (d) result obtained by one initial seed (e) seed pixel set obtained by two initial seeds which are located in the same target area (f) result obtained by two initial seeds which are located in the same target area (g) seed pixel set obtained by two initial seeds which are located in different target area (h) result obtained by two initial seeds which are located in different target areas.

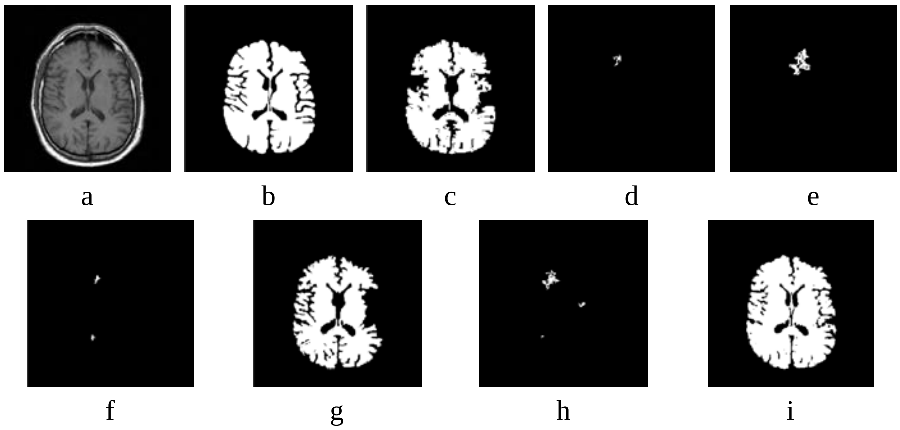


Fig. 8. Test results of brain MRI image 2: (a) original image (b) standard segmentation result (c) FC result (d) seed pixel set obtained by one initial seed (e) result obtained by one initial seed (AFCCC) (f) seed pixel set obtained by two initial seeds (g) result obtained by two initial seeds (h) seed pixel set obtained by three initial seeds (i) result obtained by three initial seeds.

In Fig. 8, it can be seen that the segmentation result is stable but not satisfactory for the FC algorithm. However, as for the AFCCC algorithm, there is a problem that the segmentation result is sensitive to the initial seed pixel. Different initial pixels will cause different segmentation effects. In fact, it is not ideal for a large area to be segmented since there is then a need to a threshold condition to be relaxed in order to effectively segment it. However, the proposed algorithm will get better segmentation results with more initial seed pixels. From the experiment and the result shown in Fig. 8(i), we can see that the segmentation result is stable and satisfactory when three initial seed pixels are selected.

The following two tables (Table 1 and Table 2) show the results of the FC, the AFCCC, and the proposed algorithms for segmenting two different parts of a brain MRI image:

Table 1. Segmentation Results of Brain MRI Image 1 by FC, AFCCC, and the Proposed Methods

	Serial numbers	Dice	OR	UR
FC	1	0.7972	0.0000	0.2028
	2	0.7972	0.0000	0.2028
	3	0.5815	0.0001	0.4185
	4	0.7972	0.0000	0.2028
	5	0.5752	0.0001	0.4248
	$\mu \pm \sigma$	0.7097 ± 0.1199	0.0000 ± 0.0001	0.2903 ± 0.1199
AFCCC	1	0.8756	0.0000	0.1244
	2	0.8100	0.0000	0.1899
	3	0.9630	0.0005	0.0365
	4	0.6350	0.0003	0.3647
	5	0.7449	0.0001	0.2551
	$\mu \pm \sigma$	0.8057 ± 0.1250	0.0002 ± 0.0002	0.1941 ± 0.1250
the proposed method	1	0.9802	0.0048	0.0151
	2	0.9731	0.0023	0.0245
	3	0.9393	0.0001	0.0606
	4	0.9279	0.0000	0.0721
	5	0.9001	0.0010	0.0988
	$\mu \pm \sigma$	0.9441 ± 0.0330	0.0016 ± 0.0020	0.0542 ± 0.0345

Table 2. Segmentation Results of Brain MRI Image 2 by FC, AFCCC, and the Proposed Methods

	Serial numbers	Dice	OR	UR
FC	1	0.8788	0.0237	0.0975
	2	0.8788	0.0236	0.0976
	3	0.8788	0.0237	0.0975
	4	0.3529	0.0017	0.6453
	5	0.8788	0.0237	0.0975
	$\mu \pm \sigma$	0.7736 ± 0.2351	0.0193 ± 0.0098	0.2071 ± 0.2450
AFCCC	1	0.3648	0.0000	0.6352
	2	0.3589	0.0000	0.6410
	3	0.9330	0.0327	0.0342
	4	0.6456	0.0245	0.3014
	5	0.9237	0.0305	0.0569
	$\mu \pm \sigma$	0.6452 ± 0.2833	0.0175 ± 0.0162	0.3337 ± 0.2970
the proposed method	1	0.8715	0.0111	0.1174
	2	0.9323	0.0317	0.0360
	3	0.8800	0.0128	0.1072
	4	0.9301	0.0627	0.0072
	5	0.9192	0.0775	0.0033
	$\mu \pm \sigma$	0.9066 ± 0.0288	0.0392 ± 0.0298	0.0542 ± 0.0546

It can be seen from Table 1 and Table 2 and by comparing the results obtained by applying the previous three mentioned methods that the Dice coefficient of the proposed method is the best. Also, we can see that the OR and the UR of the proposed method are in a low level. And finally, we can notice that the deviation of the three indicators of the proposed method is also very small. Therefore, the proposed method improves the segmentation of the MRI images significantly.

4. Conclusion

In this paper, we have presented an improved fuzzy connectedness segmentation algorithm for medical images. The traditional segmentation algorithms (Such as FC and AFCCC) can only segment the continuous target area. However, as the experimental results showed in this paper, by using multiple seed pixels, the algorithm could not only overcome the previous shortcoming, but it also has a better segmentation effect for a single target area. The reason is that the selection of multiple seed pixels can not only enhance the diversity of the positions of the initial pixels, but it also improves the representation of the target area as it is not completely homogeneous. The calculation of multiple seed pixels in the same target area tends to make the initial parameters of the target area more representatives, and thus it enhances the effect of the final segmentation for the medical images. The choice of multiple seed pixels can not only separate the target areas completely, but it also can enhance the integrity of each part. On the whole, as the experimental results showed, the method has a very good robustness and a satisfactory segmentation effect.

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