Image Segmentation Integrated with Tower-like Hierarchical Algorithm and FCM

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Abstract
Because image segmentation operation has deficiencies such as too intensive operand and sensitivity to noise, this paper has proposed an image segmentation method based on tower-like hierarchical algorithm and FCM. Firstly, tower-like hierarchical framework is used to reduce the time complexity of FCM, and the pixel membership of the target image is constrained, and then constraint items are introduced to the objective function in FCM to restrain neighborhood information effectively, and finally simulation experiments are conducted to test its properties. The experimental results show that the proposed method of image segmentation takes shorter time, and can effectively preserve the regional details of image segmentation, which has improved the accuracy of image segmentation.
Keywords: İMAGE SEGMENTATION; FUZZY C-MEAN CLUSTERING ALGORITHM; TOWER-LIKE HIERARCHICAL ALGORITHM; SEGMENTATION ACCURACY

1. Introduction

Image segmentation means dividing the image into different region son the basis of the pixel-feature, and there are significant differences between different regions to separate target from background, providing the basis for subsequent processing in computer vision, and it has been widely applied in the fields of license plate recognition, road tracking, handling of bank notes and so on [1]. Quality of image segmentation is directly related to subsequent image analysis, identification and interpretation of results, and therefore looking for a fast and accurate image segmentation algorithm has become the focus in the study of image processing [2].

Since the image segmentation has very important practical value, it has caused widespread concern of scholars who conduct extensive and in-depth research and has made a number of findings, proposing many image segmentation algorithms [3]. Image segmentation is actually a problem of pattern recognition, and the current image segmentation algorithm can be divided into: edge detection segmentation algorithm, threshold segmentation algorithm, region segmentation algorithm, neural network-partition algorithm and fuzzy theory segmentation algorithm [4]. Neural network segmentation algorithm requires artificial setting of related parameters with relatively large but limited sample images, likely to cause errors of excessive segmentation, and segmentation accuracy is difficult to meet the actual requirements of the applications [5]. Threshold segmentation algorithm has advantages of simplicity and easy to implement, etc., but the influence of the threshold setting on the segmentation accuracy is quite large. However, there is no unified theory to guide the threshold setting currently. The setting is conducted all depending on experience, and there are also great division errors in non-adjacent regions with identical gray values, resulting in empty areas and unreliable segmentation results [6]. For edge detection segmentation algo-

rithm and regional segmentation algorithm, the effect of image with complex edges and uneven lighting is not ideal, and the scope of application is subject to certain restrictions [7]. Since the image is fuzzy and uncertain, clustering segmentation algorithm of fuzzy theory becomes the main research directions, in which FCM is the most widely used image segmentation algorithm. It performs image segmentation by conducting fuzzy clustering of uniform pixels in images through membership matrix and via iterative optimization of object function [8]. In practice, FCM has some shortcomings, such as artificial appointment of initial cluster centers, for once the choice of initial cluster centers is inappropriate, it is easy to fall into local optimum. Also, only the color information of image is considered without utilizing spatial neighhood information provided by image [9]. For deficiencies of FCM algorithm, many researchers make corresponding improvements of it, proposing to optimize the initial cluster centers using genetic algorithm and simulated annealing algorithm, which has improved the accuracy of image segmentation to some extent. There are still some defects difficult to overcome in these algorithms, such as intensive computation, prone to over-segmentation and so on [10, 11].

In order to improve the accuracy of image segmentation, for deficiencies existed in traditional fuzzy clustering algorithm, this paper proposes an image segmentation method based on tower-like hierarchical algorithm and fuzzy clustering algorithm. The method adopts tower-like hierarchical algorithm to reduce the time complexity of the operation, while constrains the pixel membership of target image, introducing constraint items to the objective function of the traditional method, which has effectively constrained neighborhood information. Simulation results can prove that optimization algorithm in this article can keep the details of image ideally, so that results of image segmentation can be more accurate.

2. FCM and Tower-like Hierarchical Algorithm

2.1. FCM Algorithm

Assumed that I of the image size M × N of = {f (i, j), i = 1,2, ... M, j = 1,2, ..., N} has a total of c regions, and namely, class c, cluster center is indicated as $V = \{v_1, v_2, \mathrm{n}, v_c\}$; f (i, j) is the gray value of image pixel, and U = [u_k (i, j)] indicates fuzzy membership matrix. FCM algorithm obtains the optimal partition of data sample by seeking appropriate membership and cluster centers, and the objective function can be described as follows [12]:

$$J(U,V) = \sum_{j,j}\sum_{k=1}^{c}(u_k(i,j))^m(d_k(i,j))^2 \quad (1)$$

In the formula, m is the fuzzy weighted index of membership and d_k (i, j) represents Euclidean distance from f (i, j) cluster center v_k, which is calculated as:

$$d_k(i,j)^2 = \|f(i,j) - v_k\|^2 = (f(i,j) - v_k)^T(f(i,j) - v_k) \quad (2)$$

Formula(1) satisfies the following constraints

$$\begin{cases} \sum_{k=1}^{c} u_k(i,j) = 1 \\ u_k \in [0,1] \end{cases} \quad (3)$$

Lagrange multiplier method is used to optimize objective function, seeking the partial derivatives of membership u_k (i, j) and the cluster center v_k, and iterative update expression of membership and cluster center is

$$\begin{cases} u_k(i,j) = 1 / \sum_{p=1, p\neq k}^{c} (d_k(i,j) / d_p(i,j))^{2/m-1} \\ v_k = \sum_{i,j}(u_k(i,j))^m f(i,j) / \sum_{i,j}(u_k(i,j)^m \end{cases} \quad (4)$$

2.2. Tower-like Hierarchical Algorithm

Compared to the FCM algorithm, tower-like hierarchical algorithm can better maintain the details of target image, significantly reducing the time complexity of operations on the other hand with better noise endurance [13]. Specific value of the pixel f1 (x, y) in the coordinate (X, y) at first layer is obtained by the approach that, firstly, pixel values of fl-1 (2x-1,2y), fl-1 (2x-1,2y-1), and fl-1 (2x, 2y-1) located in 1-1 layer are arranged in ascending order, and these four pixel values form an array indicated by array [4]. The pixel f1 (x, y) is obtained by the formula (5).

$$f_{l-1}(x,y) = (Array[1] + Array[2])/2 \quad (5)$$

Obviously, the number of image pixels located in 1 layer is 1/4 of the number located in layer 1-1, and therefore the image size of 1 layer is 1/2 of that in layer 1-1.For pixel located in 1 layer, its cluster center c_q and membership u_{pq} are acquired by the clustering algorithm, and initialization process is implemented for cluster center located in layer 1-1 through cluster center c_q. If u_{pq} satisfies the formula (6), the membership remains constant in clustering process.

$$u_{pq} = \max\{u_{p1}, u_{p1}, \mathrm{n}, u_{pg}\} \geq \mathrm{T} \quad (6)$$

In the formula, T represents the threshold of membership.

Grayscale of target image is indicated by 1, and the threshold T of membership is obtained by the formula (7):

$$T = \frac{1}{L}\sum_{q=1}^{L-1} \max\{u_{p1}, u_{p1}, \mathrm{n}, u_{pg}\} \tag{7}$$

Because of the introduction of tower-like hierarchy, the initialization of cluster centers in upper layer for cluster centers in lower layer can be performed directly, and the determination of cluster centers in lower layer can be more efficient, but also reduces the iterative calculation of the membership in upper layer, or the algorithm significantly shortens time.

3. Image Segmentation Method Integrated with Tower-like Hierarchical Algorithm and FCM Algorithm

At the same time, there are some deficiencies in tower-like hierarchical algorithm. For instance, in the construction of tower-like hierarchy, the acquisition of upper cluster centers and the membership, specific thresholds must be set manually in order to select the appropriate membership, and the algorithm has weak adaptivity. Therefore, this paper proposes an image segmentation method integrated with tower-like hierarchical algorithm and FCM algorithm, so that threshold can make adaptive censoring, thereby combining the distribution of membership to select threshold value automatically, and to enhance adaptivity of algorithm, as specified in the formula (8).

$$J = \sum_{p=1}^{n}\sum_{q=1}^{g}[u^m{}_{pq}\left\|d_p - c_q\right\|^2 + u^m{}_{pq}\sum_{\substack{k\in N_p\\ k\neq p}}\frac{\left\|d_k - c_q\right\|^2}{\left\|d_k - d_p\right\|^2 + 1} f_l(u_{pq})] \tag{8}$$

In the formula, Np represents neighboring pixel collections of pixel p in the target image, and fl (u_{pq}) indicates the membership degree of pixel p located in 1-1 layer to the cluster center q located in 1 layer in tower-like hierarchical framework.

The key information of target image in l-1 layer is retained in the first layer, and the classified information of target image located in l-1 layer can be transmitted by fl (u_{pq}) is to 1 layer, thereby better controlling the affiliation of pixel located l-1 layer. Algorithm this paper has added the constraint term, realizing effective restraint of neighborhood information and membership. Among them, the constraint point is indicated by D_k, if the distance between D_k and c_q is small enough, it shows that all the neighborhoods of pixel p are all very close to the cluster center that fl (upq) belongs to, which also indicates that the pixel and the neighborhood pixels are in the same cluster center. It is thus clear that the supplementary constraint items in the proposed algorithm can improve membership of pixels to get more reasonable cluster centers [16].

D_k and c_q are adjusted so that formula (8) can reach the minimum value, and by the introduction of the Lagrange multiplier algorithm, it can be obtained:

$$J = \sum_{p=1}^{n}\sum_{q=1}^{g}[u^m{}_{pq}\left\|d_p - c_q\right\|^2 + \lambda(1 - \sum_{q=1}^{g} u_{pq}) \\ u^m{}_{pq}\sum_{\substack{k\in N_p\\ k\neq p}}\frac{\left\|d_k - c_q\right\|^2}{\left\|d_k - d_p\right\|^2 + 1} f_l(u_{pq})] \tag{9}$$

In the formula, λ represents Lagrange multiplier.

Supposed:

$$D_{p,q} = \sum_{\substack{k\in N_p\\ k\neq p}}\frac{\left\|d_k - c_q\right\|^2}{\left\|d_k - d_p\right\|^2 + 1} \tag{10}$$

Because $\partial F/\partial u_{pq} = 0$, then:

$$\frac{\partial F}{\partial u_{pq}} = mu^{m-1}{}_{pq}\left\|d_p - c_q\right\|^2 \\ -\lambda + mu^{m-1}{}_{pq}D_{p,q}f_l(u_{pq}) = 0 \tag{11}$$

$$u_{pq} = \frac{\lambda}{m}(\left\|d_p - c_q\right\|^2 + D_{p,q}f_l(u_{pq})^{-1/m-1} \tag{12}$$

Value Upq meets the following conditions:

$$\sum_{q=1}^{g} u_{pq} = 1 \quad 0 \le u_{pq} \le 1, \forall p \in [1, n] \tag{13}$$

Hence, it shows:

$$\sum_{i=1}^{g}\frac{\lambda}{m}(\left\|d_p - c_i\right\|^2 + D_{p,i}f_l(u_{pi})^{-1/m-1} = 1 \tag{14}$$

$$\lambda = m\sum_{i=1}^{g}(\left\|d_p - c_i\right\|^2 + D_{p,i}f_l(u_{pi})^{-1/m-1} \tag{15}$$

They are brought to formula (13):

$$u_{pq} = \left(\frac{\left\|d_p - c_q\right\|^2 + D_{p,q}f_l(u_{pq})}{\sum_{i=1}^{g}(\left\|d_p - c_i\right\|^2 + D_{p,i}f_l(u_{pi})}\right)^{-1/m-1} \tag{16}$$

Because $\partial F/\partial c_q = 0$, then:

$$\partial F/\partial c_q = \sum_{p=1}^{n}[2u_{pq}^m(d_p - c_q) + 2u_{pq}^m \frac{d_k - c_q}{\left\|d_k - d_p\right\|^2 + 1} f_l(u_{pq})] = 0 \quad (17)$$

$$c_q = \sum_{p=1}^{n} \frac{u_{pq}^m[d_p + \sum_{\substack{k \in N_p \\ k \neq p}} \frac{d_k}{\left\|d_k - d_p\right\|^2 + 1} f_l(u_{pq})]}{u_{pq}^m[1 + \sum_{\substack{k \in N_p \\ k \neq p}} \frac{1}{\left\|d_k - d_p\right\|^2 + 1} f_l(u_{pq})]} \quad (18)$$

In terms of image segmentation method algorithm based on tower-like hierarchical algorithm and FCM algorithm, firstly, stratified operation of target image is performed, and FCM is used to conduct clustering process for the top portion, while tower-like hierarchical algorithm and FCM algorithm are utilized to conduct clustering process for the bottom part. Specific steps are:

(1) Stratified operation is performed for the target image extracted in formula (5), the original image as l-1 layer, the new image as l layer;

(2) Traditional fuzzy C-means clustering method is used to implement clustering process of the new image, and the processing results are taken as the clustering center and membership of l layer;

(3) Obtained l layer clustering is used to initialize l-1 layer clustering centers, and the l layer membership is calculated by formula (6);

(4) l-1 layer clustering centers and membership are obtained by formula (16) and (18);

(5) If the formula (8) has reached the lowest value, and then go to step 6. Otherwise, go to the fourth step;

(6) l-1 Layer target image segmentation is performed combined with membership matrix, and it comes to an end.

4. Simulation Experiment

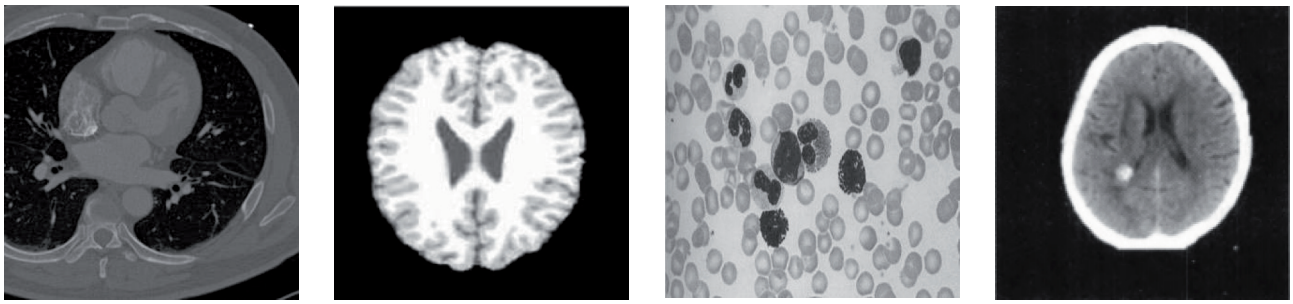
4.1. Simulation Environment and Objects

To test the performance of the proposed algorithm, simulation experiment is performed using VC in the computer featured by the Intel 4 core 2.65GHz CPU, 4G RAM, Windows XP operating system. The image selected by simulation experiment is shown in FIG. 1, and the traditional FCM algorithm is chosen to conduct comparative experiments.

4.2. Result and Analysis

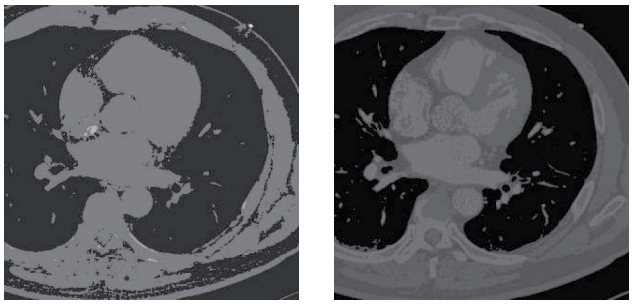
(1) Qualitative analysis

Segmentation results of the proposed algorithm and FCM algorithm are shown in Figure 2-5. As can be seen from segmentation results in Figure 2-5, the conventional FCM algorithm is difficult to obtain good segmentation results, and details of the image



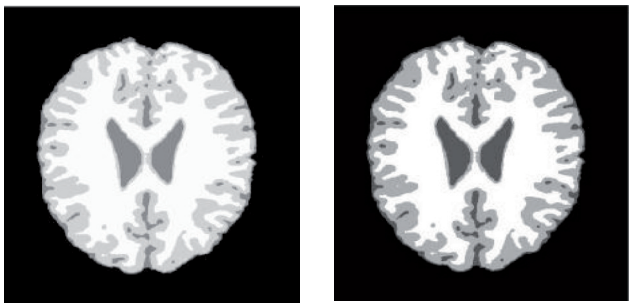
(a) CT image of chest (b) MRI image of brain (c) Image of congenital leukemia (d) CT image of brain

Figure 1. Simulation object



(a) Segmentation results of FCM algorithm (b) Segmentation results of the proposed algorithm

Figure 2. Comparison of segmentation results of chest CT images



(a) Segmentation results of FCM algorithm (b) Segmentation results of the proposed algorithm

Figure 3. Comparison of segmentation results of brain MRI images

cannot be well resolved, and there are many small pieces of region in segmentation results, while the proposed algorithm can better identify the main ingredients of the image, and after the segmentation, "trivial regions" in results are significantly reduced, and therefore, the proposed algorithm has better effect of the entire image segmentation than FCM algorithm.

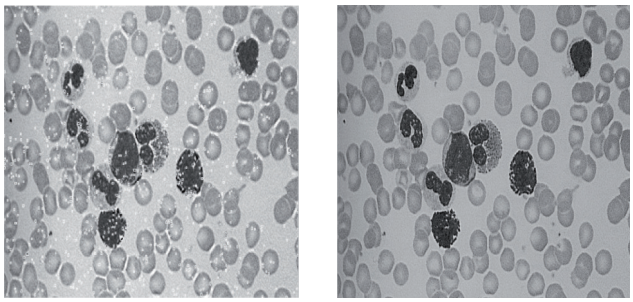
(2) Quantitative analysis

To evaluate the quality of image segmentation results more accurately, Liu coefficient is elected to describe difference between image after segmentation and the original image, which is defined as follows:

$$F(I) = \frac{\sqrt{C}}{n} \sum_{i=1}^{C} \frac{e_i^2}{\sqrt{A_i}} \tag{19}$$

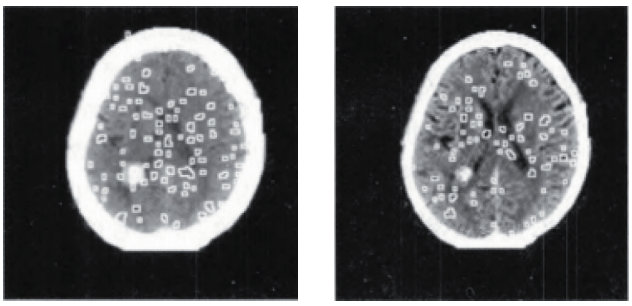
In the formula, A_i is the number of pixels in the i th class, and what e_i reflects is the color difference in a cluster between the image after segmentation and the original image.

From equation (20), that the segmentation algorithm with good performance will make the difference between images before and after segmentation as the smallest as possible, and the value F (I) is relatively small.



(a) Segmentation results of FCM algorithm (b) Segmentation results of the proposed algorithm

Figure 4. Comparison of segmentation results of congenital leukemia images



(a) Segmentation results of FCM algorithm (b) Segmentation results of the proposed algorithm

Figure 5. Comparison of segmentation results of brain CT images

Reconstruction error refers to the difference between the original image and the reconstructed original image of the segmented image, defined as follows:

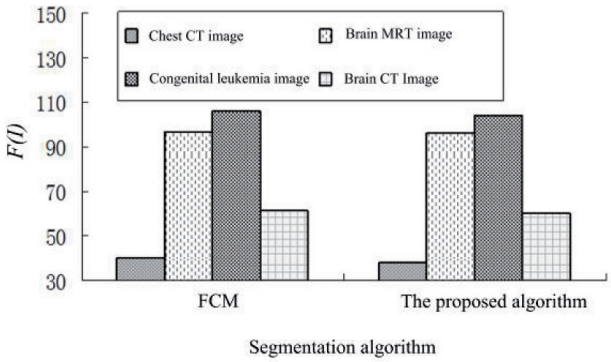
$$V_{RE} = \frac{1}{n} \sum_{i=1}^{n} \left\| I''(i) - I(i) \right\|^2 \tag{20}$$

In the formula, $I''(i)$ represents gray value of the i-th pixel in image after the reconstruction, defined as follows:

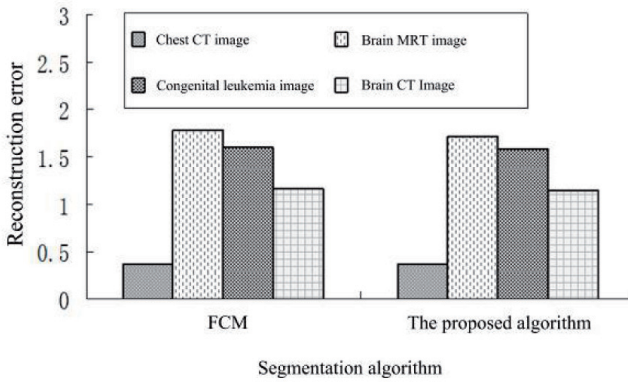
$$I''(i) = \frac{\sum_{k=1}^{C} u_{ki}^m I(i)}{\sum_{k=1}^{C} u_{ki}^m} \tag{21}$$

From equation (21), it shows that a good image segmentation algorithm should have a smaller reconstruction error.

Liu coefficient and reconstruction error of both image segmentation algorithms are shown in Figure 6 respectively. As can be seen from Figure 6, F (I) and VRE in the proposed algorithm are smaller relative to FCM algorithm, which shows that the proposed algorithm has improved the accuracy of image segmentation, and has reduced the error rate of the image, thereby obtaining a more desirable effect of image segmentation.



(a) Contrast of F (I) values



(b) Comparison of VRE values

Figure 6. Comparison of quantitative results of two algorithms

(3) Comparison of image segmentation efficiency

Under the same conditions, the average time of image segmentation of FMC algorithm and the proposed algorithm is shown in Figure 7. From Figure 7, the proposed algorithm has lesser image segmentation time relative to FCM algorithm, and comparative results demonstrate that under the premise of improved accuracy of image segmentation, the proposed algorithm reduces the calculated amount, speeding up the image segmentation, thus improving the efficiency of image segmentation.

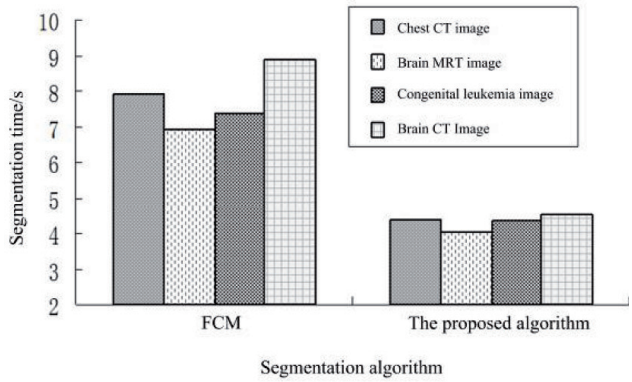


Figure 7. Segmentation time of two algorithms

5. Conclusion

Because FCM algorithm has deficiencies in image segmentation process, this paper has proposed an image segmentation method based on tower-like hierarchical algorithm and FCM. Tower-like hierarchical framework is adopted to reduce the time complexity of operations, and effective restraints of the pixel membership in target image are conducted, able to preserve image details ideally with more accurate effect of image segmentation. Simulation experiment results show that the proposed algorithm not only improves the accuracy of the image classification with strong robustness, but also overcomes the shortcoming that FCM algorithm is difficult to segment image details, improving the efficiency of image segmentation with higher practical value.

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