



# Image segmentation algorithm based on improved fuzzy clustering

Xiangxiao Lei<sup>1,2</sup>  · Honglin Ouyang<sup>2</sup>

Received: 9 August 2017 / Revised: 11 November 2017 / Accepted: 8 February 2018 / Published online: 12 March 2018  
© Springer Science+Business Media, LLC, part of Springer Nature 2018

## Abstract

Fuzzy clustering algorithm is the main method of image segmentation, but it can't be widely used in various fields. Therefore, an image segmentation algorithm based on improved fuzzy clustering was proposed in this paper. The fuzzy clustering theory and analysis method were described in detail, and the research of image segmentation algorithm was discussed in this paper. And then the method of sub graph decomposition and region merging was used to improve the clustering method of fuzzy C mean clustering image segmentation algorithm and the algorithm was verified by an example. The results showed that the algorithm was feasible. Compared with other existing algorithms, the algorithm had more advantages in running time and image segmentation accuracy.

**Keywords** Fuzzy clustering · Image segmentation algorithm · Improvement

## 1 Introduction

The ways and channels of information transmission have changed fundamentally in the information society [1]. A great deal of information spreads rapidly to all corners of society in various ways. The explosive growth of information received in our daily lives occurs. The image has become one of the important carriers of information dissemination by virtue of its simple, easy to understand and intuitive features in the dissemination of information [2]. According to the relevant statistics, the results show that more than 70% of the information is transmitted in an image in the information society [3]. However, the information contained in the image is not all the information needed by the receiver, so it is necessary to extract the information from the image. It is found that the information in the image is often concentrated in certain areas, and they only need to separate the information contained in the specific region from the image to obtain relevant information in the process of image information extraction [4].

There are many ways to extract the information from the image, but the most widely used method is image segmentation [5].

Generally, it includes image segmentation, image analysis and information extraction from three to low level in the process of extracting information from images using image segmentation [6]. Image segmentation is the basis of image information extraction, and the result will directly affect the subsequent steps of image information extraction [7]. The user generally divides the image according to the image features such as gray level, texture or color in the process of image segmentation. And then valuable images are extracted from these regions [8]. Image segmentation has become the main means of image information extraction after decades of development, which involves more and more fields, [9] such as military, industrial and medical fields. Image segmentation has been a very active topic in the academic field in addition to the field of engineering. The related research theories and achievements are also very fruitful. It is because of the image segmentation in the field of application and academic fields are of great value that all over the world have carried out in-depth research and the relevant papers and research results emerge [10]. However, there is still no general image segmentation algorithm for image segmentation. Its application is limited to specific areas [11]. The purpose of this paper is to improve the algorithm of image segmentation based on

---

✉ Xiangxiao Lei  
hndxdqgclxx@163.com

<sup>1</sup> College of Electrical and Information Engineering, Hunan University, Changsha 410082, Hunan, China

<sup>2</sup> Changsha Social Work College, Changsha 410004, Hunan, China

Improved Fuzzy clustering, which provides a theoretical basis for the general image segmentation algorithm.

## 2 Fuzzy clustering and image segmentation

### 2.1 Theoretical basis and analysis method of fuzzy clustering

Fuzzy clustering theory is a branch of fuzzy mathematics, which was proposed by an American Professor Zadeh in 1965 for theoretical characterizations of fuzzy phenomenon. This theory is a generalization of the traditional set theory [12]. The relationship between elements and sets is very clear, and there is no ambiguity in the traditional set theory [13]. Fuzzy set theory is different and the relation between the elements and the set is used to measure the degree of relationship between them. An element can belong to more than one set at the same time. It is precisely because of this that the fuzzy set theory has a wider range of applications and adaptability. After a long period of development, the theory of fuzzy sets has formed a complete theoretical system [14].

The definition domain of fuzzy set theory is similar to the classical set theory.  $U$  is set the theoretical field of fuzzy set theory, which represents the range of the research object. The membership function  $g(u)$  is used to characterize whether the element  $u$  in the fuzzy set is membership domain  $U$ .  $g(u)$  maps  $u$  to a real number on a closed field  $[0,1]$ . Formula is expressed as follows:

$$g : U \rightarrow [0, 1] \tag{1}$$

$$g \rightarrow g(u)$$

In the formula, the  $A$  of the function  $g(u)$  on  $U$  is the fuzzy set of  $U$ . The higher the value of membership, the higher the degree of correlation between elements and sets are. When the value is 1, the element is dependent on the set completely. When the value is 0, the element is not related to the set.

In order to make the relationship between the elements in the domain and the membership more image, Professor Chad gives different representations according to different fields. When there are finite discrete elements in the universe, the fuzzy set of the Analects is expressed in the following formula:

$$A = \sum_{i=1}^n g(u_i)/u_i \tag{2}$$

In the formula,  $g(u_i)/u_i$  represents the membership of the element  $u$  in the domain, and  $\sum$  represents the content of a fuzzy set.

When the field is continuous, the fuzzy set is represented by the following formula:

$$A = \int_{u \in U} g(u)/u \tag{3}$$

When a fuzzy set is used to describe a fuzzy thing, the definition of membership function is the key. At present, there are three definitions, and they are normal, small and large. The formula is as follows:

Normal type:

$$g(u) = \exp \left[ - \left( \frac{u - a}{b} \right)^2 \right] \tag{4}$$

Small size:

$$g(u) = \begin{cases} [1 + a(u - c)^b]^{-1} & u \geq c \\ 1 & u < c \end{cases} \tag{5}$$

Partial large:

$$g(u) = \begin{cases} [1 + a(u - c)^b]^{-1} & u < c \\ 1 & u \geq c \end{cases} \tag{6}$$

The operation of fuzzy sets should conform to the following rules. Idempotent rate:  $A \cup A = A, A \cap A = A$ . Distribution rate:  $(A \cup B) \cap C = (A \cap C) \cup (B \cap C), (A \cap B) \cup C = (A \cup C) \cap (B \cup C)$ . Exchange rate:  $A \cup B = B \cup A, A \cap B = B \cap A$ . Absorptivity:  $(A \cup B) \cap A = A, (A \cap B) \cup A = A$ . Recovery rate:  $(A^c)^c = A$ . Dual rate:  $(A \cup B)^c = A^c \cap B^c, (A \cap B)^c = A^c \cup B^c$ . Rate of combination:  $(A \cup B) \cup C = A \cup (B \cup C), (A \cap B) \cap C = A \cap (B \cap C)$ . Two grade rate:  $A \cup \phi = A, A \cap \phi = \phi, A \cup U = U, A \cap U = U$ .

The method of fuzzy cluster analysis based on fuzzy clustering theory is called fuzzy clustering analysis [15]. The fuzzy elements can't be classified into a certain category. The traditional clustering analysis method is not suitable for the situation of fuzzy boundary. The fuzzy clustering can get the membership degree of each component, and it can reflect the nature of the elements of the elements and establish the uncertain relationship between elements and sets [16]. Fuzzy clustering analysis is more in line with the real situation of the objective world, so it becomes the mainstream method of cluster analysis. Related research and results are also more. At present, there are four types of methods for fuzzy analysis. They are hierarchical clustering analysis method, clustering analysis method based on equivalence relation, clustering analysis method based on graph theory and clustering analysis method based on objective function. In the four basic cluster analysis methods, the calculation of the first three clustering methods is too large, and it is not suitable for

practical applications which require real-time or data. Finally, a clustering analysis method based on objective function is introduced to transform the problem into a constrained nonlinear programming problem. And then the optimal objective function is used to optimize the clustering elements. The iterative method is used to search the optimal solution of the objective function in the process of practical application. Therefore, with the rapid development of information technology, the fuzzy clustering analysis method based on objective function has been widely concerned in the practical application.

## 2.2 Image segmentation research

At present, there are many researches on image segmentation algorithms. The image segmentation algorithm has reached thousands of species after decades of development. There are hundreds of papers on image segmentation algorithm every year. However, there is no objective and unified image algorithm up to now [17]. There are many reasons for this. According to the definition of the relevant research on the image, the set of the whole picture is  $R$ , and the image is divided into non-empty set  $R_1, R_2, \dots, R_n$ . Then the nonempty set must satisfy the following conditions: (1)  $\bigcup_{i=1}^n R_i = R$ . (2) To all  $i$  and  $j$ ,  $i \neq j$ ,  $R_i \cap R_j = \phi$ . (3) To all  $i = 1, 2, \dots, n$ ,  $P(R_i) = TRUE$ . (4) When  $i \neq j$ ,  $P(R_i \cup R_j) = FLASH$ . (5) To  $i = 1, 2, \dots, n$ , it is China unicom. So far, none of these five conditions can be satisfied simultaneously, and any segmentation algorithm has its limitations. On the other hand, the characteristics of different areas of the image are also very different. No image segmentation algorithm can adapt to a variety of conditions. Therefore, the development of image segmentation algorithm is still a huge challenge [18].

Although there are many kinds of image segmentation algorithms, these algorithms will consider the following problems. The first is whether the image segmentation area is complete, and the second is how to avoid excessive image segmentation. Thirdly, it is the running time of image segmentation algorithm. That is the performance of image segmentation algorithm. Finally, it is how to realize the non-threshold of image segmentation algorithm. According to the problem of image segmentation algorithm, the current image segmentation algorithms are divided into several categories according to the different emphasis. These kinds of image segmentation algorithms are based on threshold segmentation algorithm, image segmentation algorithm based on region segmentation, image segmentation algorithm based on edge detection and image segmentation algorithm based on Clustering and some image segmentation algorithms based on specific theory. These several kinds of image segmentation

algorithm are common algorithms. And so many image segmentation algorithms also led to the image segmentation algorithm evaluation criteria are different. Up to now, there are still no objective and unified algorithm evaluation criteria to evaluate different image segmentation algorithms [19]. At present, the evaluation criteria of image segmentation algorithms have high evaluation value only in a specific environment. It can be roughly divided into two categories. One is the subjective evaluation. That is to say, through the eyes of the image segmentation algorithm to evaluate the results, the method is simple and easy to operate. The other is objective evaluation. This method is evaluated by setting the objective criteria, such as noise immunity. This method is easy to carry out quantitative analysis, but the operation is complex and easily influenced by objective conditions. It can be seen from research on the current image segmentation algorithm that image segmentation algorithm research still needs a long way.

## 3 Image segmentation algorithm based on Improved Fuzzy Clustering

### 3.1 Fuzzy C means clustering

Clustering analysis is an important and used widely method in the field of image segmentation. Whether the image is color or gray can use clustering analysis for image segmentation. Fuzzy C means clustering image segmentation algorithm is the most widely used image segmentation algorithm in clustering analysis (Fuzzy C-means, FCM). Fuzzy C mean clustering image segmentation algorithm was first proposed by Dunn in 1974, and Bezdek has supplemented and improved it. The improved fuzzy C mean clustering algorithm is an image segmentation algorithm based on the optimization objective function. As an unsupervised fuzzy clustering algorithm, it is widely used in medical diagnosis, target recognition and image segmentation.

The FCM algorithm was used to solve the extreme value of the objective function in the double layer iteration in this paper. The inner iteration was used to correct the clustering center and the membership matrix in the process of FCM operation. Outer iteration was used to determine whether the iteration to meet the convergence requirements mainly. After the completion of the iteration, the membership degree of the target elements can be obtained in the membership matrix, and then the membership of the elements can be determined. The algorithm is as follows, and the FCM algorithm defines the following form of the objective function.

$$J = \sum_{i=1}^n \sum_{j=1}^c \mu_{ij}^m \|X_i - V_j\|^2 \tag{7}$$

The objective function must satisfy the conditions:

$$\sum_{j=1}^c \mu_{ij} = 1, \forall i \in \{1, 2, \dots, n\} \tag{8}$$

In formula (7) and (8),  $\mu_{ij}$  represents the membership of the target element  $i$  on class  $j$ .  $X_i$  represents the feature vector of element  $i$ , and  $V_j$  represents the clustering center of the class  $j$ .  $m$  is the weight coefficient. In general,  $m = 2$ .

Then, the iterative formula is deduced by Lagrange’s conditional extreme value method.

$$F = \sum_{i=1}^n \sum_{j=1}^c \mu_{ij}^m \|X_i - V_j\|^2 + \lambda \left( 1 - \sum_{j=1}^c \mu_{ij} \right) = \lambda \left( 1 - \sum_{j=1}^c \mu_{ij} \right) + \sum_{i=1}^n \sum_{j=1}^c \mu_{ij}^m d_{ij}^2 \tag{9}$$

If we want to solve the extreme value of the function  $J$ , the first order necessary conditions must satisfy the following conditions:

$$\frac{\partial F}{\partial \lambda} = 1 - \sum_{j=1}^c \mu_{ij} = 0 \tag{10}$$

$$\frac{\partial F}{\partial \mu_{ij}} = m(\mu_{ij})^{m-1} (d_{ij})^2 - \lambda = 0 \tag{11}$$

According to the formula (11):

$$\mu_{ij} = \left[ \frac{\lambda}{m(d_{ij})^2} \right]^{\frac{1}{m-1}} \tag{12}$$

The formula (12) is added to the formula (10):

$$\sum_{j=1}^c \mu_{ij} = \left( \frac{\lambda}{m} \right)^{\frac{1}{m-1}} \left\{ \sum_{j=1}^c \left[ \frac{1}{d_{ij}^2} \right]^{\frac{1}{m-1}} \right\} = 1 \tag{13}$$

Thus get:

$$\left( \frac{\lambda}{m} \right)^{\frac{1}{m-1}} = \frac{1}{\sum_{j=1}^c \left[ \frac{1}{d_{ij}^2} \right]^{\frac{1}{m-1}}} \tag{14}$$

The formula (14) is added to the formula (12):

$$\mu_{ij} = \frac{1}{\sum_{i=1}^c \left[ \frac{d_{ij}^2}{d_{ij}^2} \right]^{\frac{1}{m-1}}} \tag{15}$$

Since  $d_{ij}$  may be equal to 0, it is necessary to discuss separately. Set  $\forall i \in \{1, 2, \dots, n\}$  to  $T_i$ , then  $T_i = \{j | 1 \leq j \leq c, d_{ij} = 0\}$ . The complement is  $T_i^c$ , then

$T_i^c = \{1, 2, \dots, c\} - T_i$ . In order to minimize the objective function  $J$ , the  $\mu_{ij}$  must satisfy the following conditions:

$$\begin{cases} \mu_{ij} = \frac{1}{\sum_{k=1}^c \left( \frac{d_{ij}}{d_{ik}} \right)^{\frac{2}{m-1}}} & T_i = \phi \\ \mu_{ij} = 0, \forall j \in T_i^c, \sum_{j \in T_i} \mu_{ij} = 1 & T_i \neq \phi \end{cases} \tag{16}$$

Then the same method can be used to obtain the iterative formula of the cluster center  $V_j$ :

$$V_j = \frac{\sum_{i=1}^n \mu_{ij}^m x_i}{\sum_{i=1}^n \mu_{ij}^m} \tag{17}$$

The FCM algorithm starts from the random initial value by formulas (16) and (17) approaching the extreme value.

After determining the algorithm flow of FCM, the rules are as follows. First, set the number of clusters  $c$  and parameters  $m$ . Secondly, cluster center  $V_j$  is initialized. And then iterate in accordance with the FCM algorithm process until the objective function satisfies  $|J_t - J_{t+1}| < \epsilon$ .  $\epsilon$  is a very positive number of admissible errors. When the result is satisfied, the result of clustering is proved to be good. Then, the new membership matrix is calculated according to the formula (16). Based on the current membership matrix, a new cluster center is calculated by formula (17). When the FCM algorithm converges, we can get all kinds of clustering centers and the membership values of the target elements for all kinds of objects.

### 3.2 Sub-graph decomposition and region merging

According to the FCM algorithm, we must first determine the number of clusters in the calculation, and then it can be calculated on this basis. However, the number of clusters is difficult to determine in the actual operation process, especially in the automation system is more difficult to achieve. Therefore, it is necessary to improve the FCM algorithm [20]. This paper mainly aimed at the improvement of the number of clusters, and the purpose was to make the FCM algorithm has the ability to automatically determine the number of clusters. Firstly, the image was decomposed by using the characteristics of the two dimensional space. The decomposition method was a four fork tree structure until the decomposition of the image histogram could meet the conditions after the decomposition. Then the clustering number of two FCM segmentations was carried out to achieve the initial image segmentation. Finally, according to the similarity of the adjacent region of the original image, the region was merged to complete the final segmentation of the image.

This procedure avoided the direct determination of the number of clusters.

- (1) Sub graph decomposition and the initial segmentation. The gray histogram of the image contains a wealth of information. Among them, the wave crest and trough position provides the most valuable information. Threshold based image segmentation method is based on the peak and trough position to determine the threshold. However, there are two problems in the analysis of image gray histogram. One is a false peak and trough. If the gray histogram is smoothed, it is possible to filter out the true peaks and troughs. The other is that if the histogram is uniform, it is difficult to provide valuable information. So we need a standard to measure the uniformity of gray histogram (Fig. 1).

In order to solve the above two problems, this paper put forward two indexes to measure the gray histogram of the image. An index is image gray histogram information entropy. According to the theory of Shannon's information theory, the entropy of image gray histogram is defined as follows:

$$\text{inf} = - \sum_{i=0}^{255} p_i \times \log_2 p_i \quad (18)$$

In formula (18),  $p_i = n_i/n$ , where  $n_i$  represents the number of pixels of the first level gray value, and  $n$  is

the total image of the image. The range of the pixel value of the digital image is generally  $0 \sim 255$ , so the range if  $i$  is  $0 \sim 255$ . This parameter can be used to measure the concentration of image pixels. The higher the value of information entropy is, the higher the degree of concentration of the image pixels is, and the more scattered it is. Experiments with two pixels of the same image can prove this conclusion, which can be seen in Fig. 2.

The entropy of the histogram of A is 6.9965 and the entropy of the histogram of B is 6.3989. As can be seen from Fig. 2, pixel gray value figure A is about 100. But the pixels are scattered with a peak of around 3000. Pixel gray values of figure B are mostly concentrated in about 200 with the peak value of about 10,000.

Another indicator is the number of image gray histogram clustering peaks. In view of the gray histogram of image, it can't deal with the false peaks and troughs. In this paper, a new method is used to calculate the number of wave crests. The specific steps of the method are as follows:

First step: the 256 level histogram of image is conducted to get the array *hist*. *hist* contains a total of 256 elements, and each element represents the number of pixels in the gray level of the image.

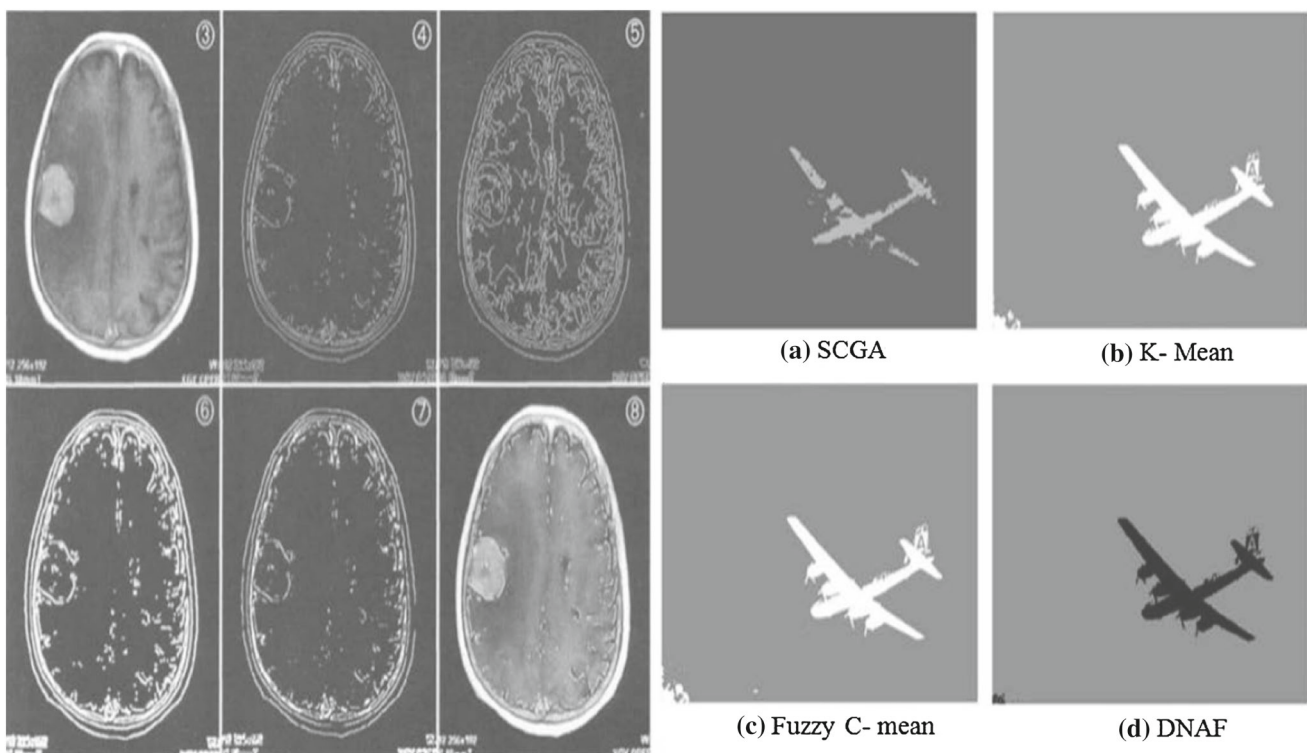


Fig. 1 Image segmentation algorithm

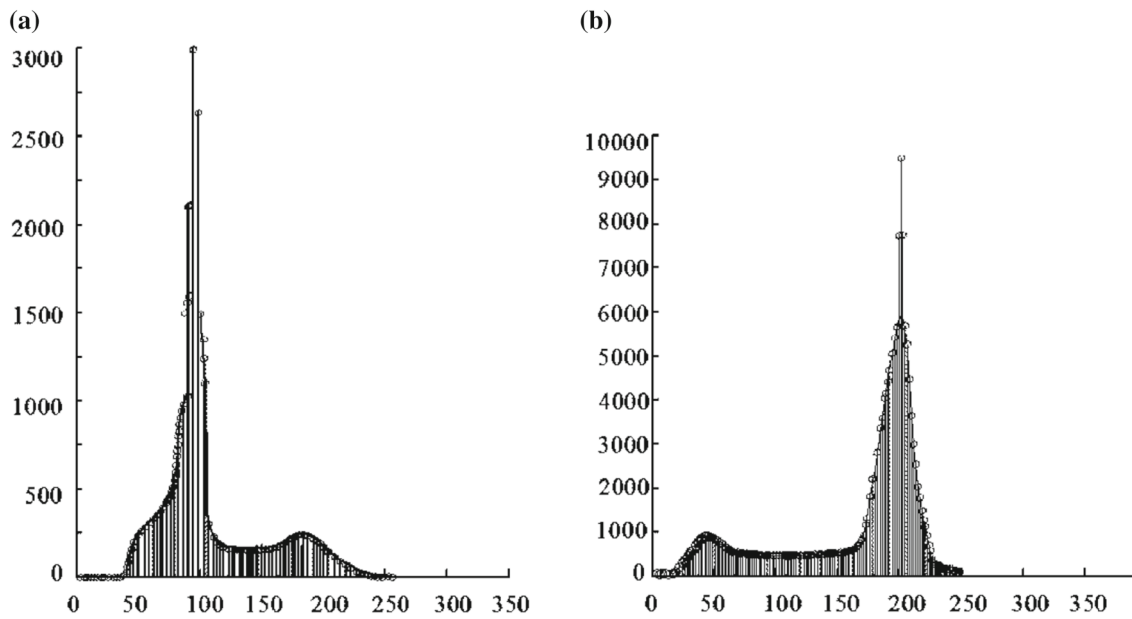


Fig. 2 Gray histogram of two pixels with the same pixel

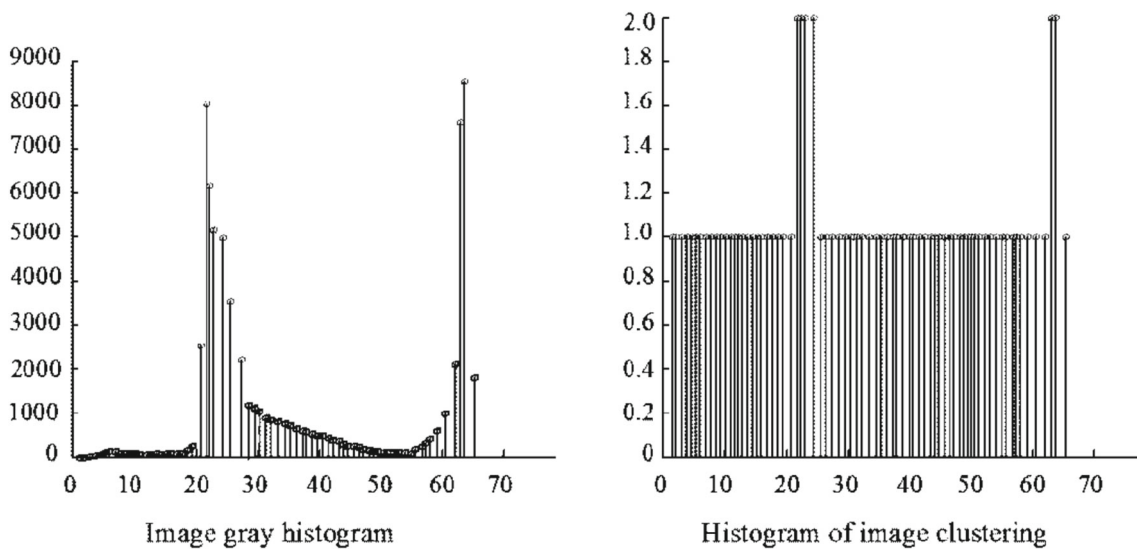


Fig. 3 Original histogram of image and histogram after clustering

The second step is to conclude normalized histogram:

$$normal\_hist = hist / \max(hist) \tag{19}$$

Third step: all elements of the normalized histogram take the clustering number of 2 for FCM clustering. The initial clustering center is {0} or {1}, and tolerance error is 0.001.

Fourth step: the elements are classified according to the principle of maximum membership degree to obtain *cluster\_hist*. The number of peaks of *cluster\_hist* is calculated as *peak\_n*, and is the

final value of the wave number.

In order to prove the validity of the method, the results were verified by an example. The results are shown in Fig. 3.

It can be seen from Fig. 3 that the original histogram has no small fluctuations after clustering, and has good regularity, and the number of peaks is also easy to statistics, which shows that the method is effective.

- (2) Regional consolidation. After image segmentation, region merging should be carried out according to

the similarity of adjacent regions. The criterion for judging the similarity of image gray histogram is the distance between the images, and the definition of PAP distance is as follows:

$$\rho(r, q) = \sum_{i=0}^{255} p_{ir} \times p_{iq} \quad , \quad p_{ir} = n_{ir}/n_r, p_{iq} = n_{iq}/n_q \quad (20)$$

In the formula,  $n_r$  represents the number of pixels in the region  $r$ .  $n_{ir}$  is the number of pixels in the region  $r$  of  $i$  gray level. The meanings of  $n_q$  and  $n_{iq}$  ibid are as above. The greater the distance, the higher the similarity of the two histograms is.

### 3.3 Image segmentation algorithm based on improved fuzzy clustering

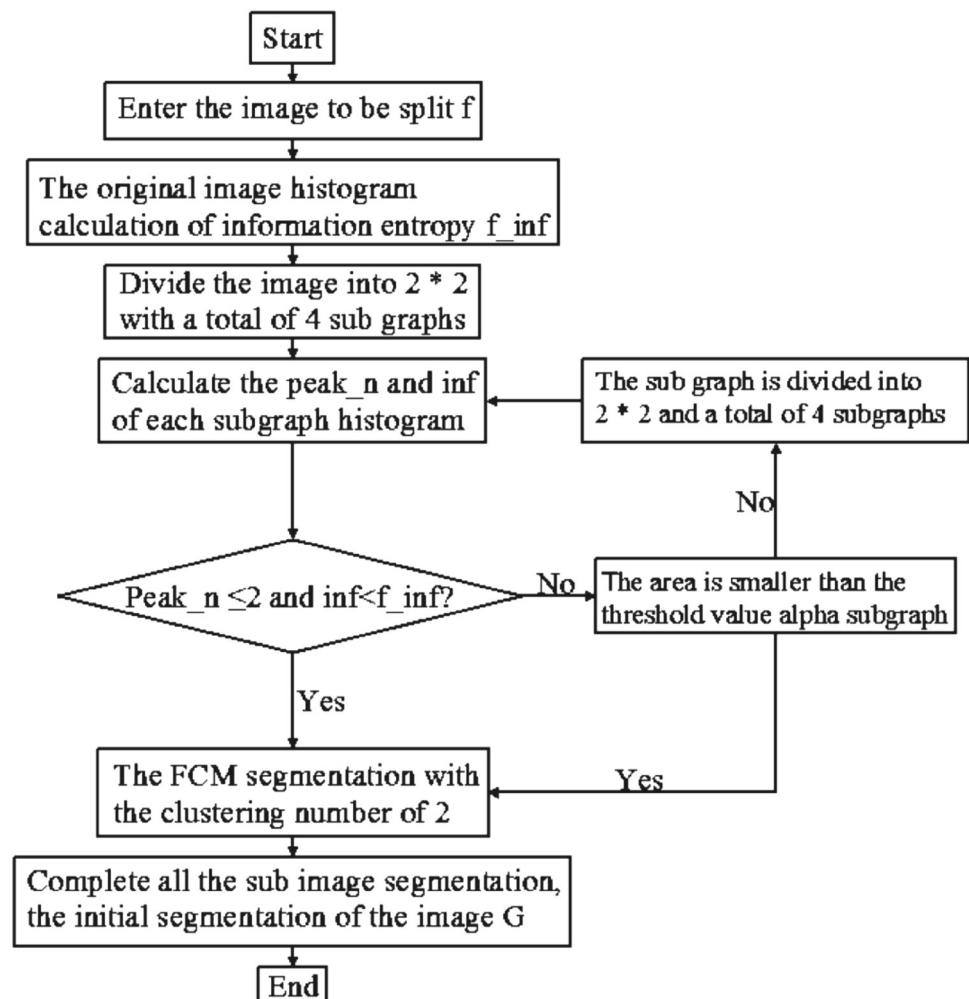
There are two main steps in image segmentation algorithm based on improved fuzzy clustering. The first step is mainly to the image in accordance with the four fork tree structure

graph decomposition. Secondly, the fuzzy C means clustering image segmentation based on the fixed number of clusters is performed. The image is divided into  $2 \times 2$  before image decomposition. Then, the gray histogram of each sub graph is analyzed. If the sub-graph satisfies one of the following two conditions:

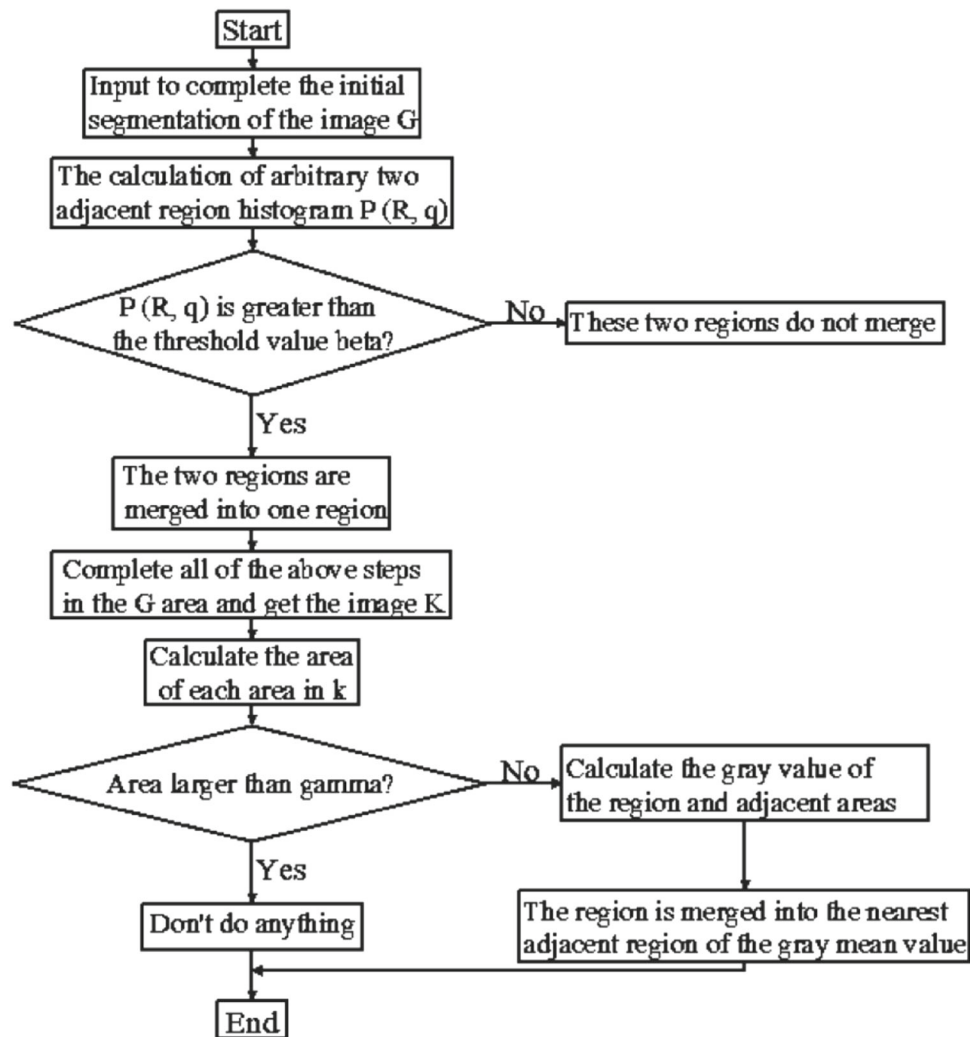
- (1) The information entropy  $\text{inf}$  of sub-graph histogram is smaller than the original histogram  $\text{inf}$ , and the wave number  $\text{peak}_n \leq 2$ .
- (2) The area of the sub-graph is less than the threshold value, and the value of alpha can be adjusted according to the histogram of the minimum area. Here the uniform value is 1024.

It can be used to cluster the number of fuzzy C mean clustering of 2, and then the principle of maximum membership degree is classified. If the histogram of the sub-graph does not satisfy one of the above two conditions, the sub-graph is further decomposed until the condition is satisfied. The allowable error in this process is 0.001, and

**Fig. 4** Segmentation process based on sub-graph decomposition



**Fig. 5** Regional consolidation process



the initial cluster centers are  $\{0, 255\}$ . Detailed flow is shown in chart 4 (Fig. 4).

The second step is regional consolidation, and detailed flow is shown in Fig. 5. Because of the algorithm segmentation on the original image after decomposition, it is inevitable that there are many sub graphs in some areas. Therefore, it is necessary to merge the segmented regions. The merger process must meet one of the following two conditions:

First condition: the distance between adjacent regions of gray histogram is  $\rho(r, q) > \beta$ ,  $\beta = 0.22$ . Detailed flow is shown in chart 4.

Second condition: the segmented area is  $< \gamma$ ,  $\gamma = 50$ , and the region is similar to the gray value mean.

In order to verify the effectiveness of the fuzzy C mean clustering image segmentation algorithm based on sub-graph decomposition and region merging, the above algorithms were also analyzed.

## 4 Experimental analysis

### 4.1 Algorithm analysis

This paper used the classic rice image as the experimental image in the process of image segmentation algorithm. Some related data needed to be given in the course of the experiment. The fuzzy clustering number was 2 in the image segmentation algorithm. The initial cluster center was  $\{0, 255\}$  and the allowable error  $e = 0.001$ , and the weight function was  $m = 2$ . Figure 6 is the rice diagram in the experimental process of the decomposition of the 4 tree sub-graph.

Figure 6 shows the root node of the original 1. Nodes 2, 3, 4, 5 represented the original decomposition into a total of  $2 \times 4$  sub-graph. The node 6 ~ 14 was a sub-graph of 4, and the 5 was again decomposed into a total of four pairs of sub-graphs of  $\times 2$ . And so on, node 7 and 9 were the same true. Table 1 shows the information entropy, the peak value and the area statistics of each section.



We can see from Table 1 that the two images in the four picture only nodes, 3, represented by the two maps to meet the conditions in the decomposition of the original image. Their information entropy was less than the original number and the wave number was  $\leq 2$ . The node 4, 5 did not meet the conditions need further decomposition. Nodes 7 and 9 also did not meet the conditions for further decomposition in the second round of decomposition. The condition could satisfy the conditions of the node number of FCM segmentation. This result was consistent with the decomposition of the four fork tree sub-graph in Fig. 6.

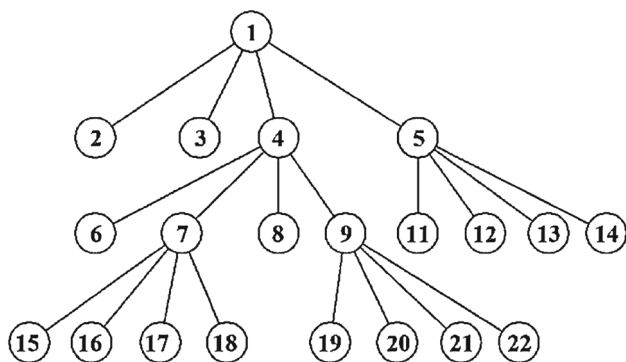


Fig. 6 Rice diagram of the fork tree sub-graph decomposition of the structure of Fig. 4

The number of the first round was 135 and the number of regions in the second round was about 86, and the third round was 74 in the decomposition process of the whole rice graph. The results show that the region merging can effectively avoid over segmentation and make the segmentation result more accurate.

### 4.2 Objective analysis

The objective index mainly included the running time and the segmentation accuracy of the image segmentation algorithm in the objective index analysis. These two indicators were mainly compared with the artificial clustering algorithm (FCM algorithm), F\_stl algorithm and SCG algorithm. Run time used Rice diagram, Bird diagram and Lena diagram for verification, and the correct rate of segmentation used Rice diagram verification. Set the algorithm to divide the actual number of pixels, the rice grain was  $n_1$ , the total image of the prime number was  $m_1$ , the actual number of pixels in the background was  $n_2$ , the total image of the background was  $m_2$ , then there were the following definitions, the accuracy of the element segmentation was  $n_1/m_1$ ; the background segmentation accuracy rate was  $n_2/m_2$ ; the overall segmentation accuracy rate was  $(n_1 + n_2)/(m_1 + m_2)$ .

It can be seen from Table 2 that the longest time was the SCG algorithm, followed by the F\_stl algorithm, once

Table 1 The data of each node of the four fork tree

Node	Peak number ( <i>peak_n</i> )	Information entropy ( <i>inf</i> )	The measure of area ( <i>area</i> )
1		6.99	16,384
2	1	6.07	16,384
3	1	6.49	16,384
4	6	6.99	16,384
5	2	7.08	16,384
6	1	6.27	4096
7	3	6.45	4096
8	2	6.23	4096
9	3	6.58	4096
10	2	6.25	4096
11	2	6.40	4096
12	2	6.28	4096
13	2	6.58	4096
14	1	5.76	1024
15	2	5.68	1024
16	4	6.14	1024
17	1	5.81	1024
18	3	5.80	1024
19	5	6.34	1024
20	2	6.03	1024
21	1	5.55	1024

**Table 2** Comparison of running time

Algorithm image	Paper algorithm (s)	<i>F_stl criterion algorithm</i> (s)	Manually determine the number of clusters (s)	<i>SCG criterion algorithm</i> (s)
Rice graph	10.45	484.87	47.78	459.83
Bird graph	7.20	502.52	43.06	489.92
Lena graph	6.73	456.97	41.44	396.23

**Table 3** Comparison of segmentation accuracy

Algorithm image	Paper algorithm (%)	<i>F_stl criterion algorithm</i> (%)	Manually determine the number of clusters (%)	<i>SCG criterion algorithm</i> (%)
Element	98.7	96.9	96.9	98.5
Background	95.9	92.3	91.3	80.8
Population	96.7	93.1	92.6	83.1

again to determine the number of artificial clustering algorithm, and the shortest algorithm was the three image segmentation algorithm in this article. The data statistics show that the algorithm in this paper had a great advantage in computing time.

Table 3 shows the statistical accuracy of the four algorithms for the correct segmentation of Rice graphs. From the elements, the background as well as the overall correct segmentation rate from high to low, they were the algorithm, the *F\_stl* algorithm, the algorithm to determine the number of clusters, *SCG* algorithm. The experimental results show that the proposed algorithm was more accurate and more advantageous than other algorithms.

## 5 Conclusions

Image segmentation is one of the main means to extract valuable information from images, and it also has double value in application and academic fields. Relevant research results are also very much. But so far, there is no objective and uniform image segmentation algorithm. In view of this, an improved fuzzy clustering algorithm for image segmentation was proposed in this paper. In this paper, the method of sub graph decomposition and region merging is used to improve the clustering method of fuzzy *C* value clustering algorithm. Then the improved image segmentation algorithm is verified by this method, and the verification is mainly from two aspects: algorithm and objective index. The analysis results showed that the algorithm was effective, and the image segmentation was more accurate when the image was over segmented. The results show that

the proposed algorithm had more advantages than the improved fuzzy clustering algorithm, *F\_stl* algorithm and *SCG* algorithm in the running time and the accuracy of image segmentation. The results showed that the algorithm was feasible. Of course, there were also some shortcomings, such as the determination of the threshold of the distance to improve the space, which can improve the accuracy of the operation.

**Acknowledgement** The National Natural Science Foundation of China, Research on power balance and power quality coordinated control theory of modular cascaded multilevel inverter system, No. 51677063.

## References

- Izakian, H., Pedrycz, W., Jamal, I.: Fuzzy clustering of time series data using dynamic time warping distance. *Eng. Appl. Artif. Intell.* **39**, 235–244 (2015)
- Bie, R., Mehmood, R., Ruan, S., et al.: Adaptive fuzzy clustering by fast search and find of density peaks. *Person. Ubiquit. Comput.* **20**(5), 785–793 (2016)
- Park, J.H., Yang, L.T., Chen, J.: Research trends in cloud, cluster and grid computing. *Cluster Comput.* **16**(3), 335–337 (2013)
- Wu, K.L., Yang, M.S.: A cluster validity index for fuzzy clustering. *Pattern Recogn. Lett.* **26**(9), 1275–1291 (2005)
- Valentini, G.L.: An overview of energy efficiency techniques in cluster computing systems. *Cluster Comput.* **16**(1), 3–15 (2013)
- Katz, S., Tal, A.: Hierarchical mesh decomposition using fuzzy clustering and cuts. In: *ACM SIGGRAPH*. ACM, pp. 954–961 (2003)
- Valentini, G.L.: An overview of energy efficiency techniques in cluster computing systems. *Cluster Comput.* **16**(1), 3–15 (2013)
- Ye, J., Xu, Z., Ding, Y.: Secure outsourcing of modular exponentiations in cloud and cluster computing. *Cluster Computing* **19**(2), 811–820 (2016)

9. Ma, M., Liang, J., Guo, M., et al.: SAR image segmentation based on Artificial Bee Colony algorithm. *Appl. Soft Comput.* **11**(8), 5205–5214 (2011)
10. Ye, J., Xu, Z., Ding, Y.: Secure outsourcing of modular exponentiations in cloud and cluster computing. *Cluster Comput.* **19**(2), 811–820 (2016)
11. Zheng, Y., Byeungwoo, J., Xu, D., et al.: Image segmentation by generalized hierarchical fuzzy C-means algorithm. *J. Intell. Fuzzy Syst.* **28**(2), 4024–4028 (2015)
12. Chen, Q., Zhao, L., Lu, J., et al.: Modified two-dimensional Otsu image segmentation algorithm and fast realisation. *IET Image Proc.* **6**(4), 426–433 (2012)
13. Zhao, F., Jiao, L., Liu, H., et al.: A novel fuzzy clustering algorithm with non local adaptive spatial constraint for image segmentation. *Sig. Process.* **91**(4), 988–999 (2011)
14. Yang, X., Zhao, W., Chen, Y., et al.: Image segmentation with a fuzzy clustering algorithm based on Ant-Tree. *Sig. Process.* **88**(10), 2453–2462 (2008)
15. Cao, J., Chan, A.T., Sun, Y., et al.: A taxonomy of application scheduling tools for high performance cluster computing. *Cluster Comput.* **9**(3), 355–371 (2006)
16. Smith, A.: Image segmentation scale parameter optimization and land cover classification using the Random Forest algorithm. *J. Spat. Sci.* **55**(1), 69–79 (2010)
17. Berman, A., Nagy, E.J.: Improvement of a large analytical model using test data. *AIAA J.* **21**(8), 1168–1173 (2012)
18. Zhou, Q.: Research on heterogeneous data integration model of group enterprise based on cluster computing. *Cluster Comput.* **19**(3), 1–8 (2016)
19. Park, J.H., Yang, L.T., Chen, J.: Research trends in cloud, cluster and grid computing. *Cluster Comput.* **16**(3), 335–337 (2013)
20. Chang, T.T., Liaw, Y.F., Wu, S.S., et al.: Long-term entecavir therapy results in the reversal of fibrosis/cirrhosis and continued histological improvement in patients with chronic hepatitis B. *Hepatology* **52**(3), 886 (2010)



**Xiangxiao Lei** Doctor of Engineering, Associate Professor. Graduated from the Central South University in 2005. Worked in Changsha social Work College. He research interests include intelligent control and digital image processing.



**Honglin Ouyang** Doctor of Engineering, Professor. Graduated from the Hunan University in 2005. Worked in Hunan university. He research interests include Power electronics and control engineering field.