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Brain Image Segmentation Based on FCM Clustering Algorithm and Rough Set

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ABSTRACT In this paper, a new image segmentation method is proposed by combining the FCM clustering algorithm with a rough set theory. First, the attribute value table is constructed based on the segmentation results of FCM under different clustering numbers, and the image is divided into several small regions based on the indistinguishable relationship of attributes. Then, the weight values of each attribute are obtained by value reduction and used as the basis to calculate the difference between regions and then the similarity evaluation of each region is realized through the equivalence relationship defined by the difference degree. Finally, the final equivalence relation defined by similarity is used to merge regions and complete image segmentation. This method is validated in the segmentation of artificially generated images, brain CT images, and MRI images. The experimental results show that compared with the FCM method, the proposed method can reduce the error rate and achieve better segmentation results for the fuzzy boundary region. And, the experimental results also prove that the algorithm has strong anti-noise ability.

INDEX TERMS Brain image segmentation, FCM clustering, rough set, system.

I. INTRODUCTION

Image segmentation refers to dividing an image into regions with different characteristics and proposing objects of interest. It is a key step in image processing to image analysis. Most of the segmentation algorithms proposed nowadays is aimed at specific problems, and there is no general segmentation algorithm suitable for all images [1]. In recent years, because more original image information is retained than traditional hard methods, fuzzy C-means (FCM) clustering algorithm is used. Method and image segmentation algorithm based on rough set theory have been successfully applied in medical diagnosis, target recognition and image segmentation [2].

The main purpose of FCM image segmentation algorithm is to divide the sample points of vector space into C subspaces according to some distance measure [3], [5]. Because the standard FCM algorithm not only converges too slowly, but also the similarity of gray scale membership degree of pixels in the boundary area of target and background results in inaccurate segmentation of boundary points, which makes the edges blurred. Many scholars combine the theory knowledge of rough set to solve this problem and overcome the defects of FCM clustering [5]. The rough set theory is used to improve the fuzzy mean clustering algorithm in some literatures [6], [7]. The roughness of the point in the image is used to describe the fuzzy classification matrix of the point in the current state, and then the membership function and clustering center are updated, which shortens the iteration times and improves the segmentation efficiency [8]. Document 1 combines FCM and rough set theory, proposes to construct attribute value table based on the segmentation results of FCM under different clustering numbers, and achieves region similarity through value reduction, but there are too many pixels and attribute value reduction is very cumbersome [9]. Document 2 proposes an image segmentation method based on the combination of rough set and FCM. First, the original image is rough set by moving window [10]. Smooth, and then apply the FCM algorithm to segment the image, even if the noise image, it can also be better than K-Means algorithm in segmentation accuracy and speed.

In this paper, a new image segmentation method is proposed by combining FCM clustering algorithm with rough set theory. Firstly, the attribute value table is constructed based on the segmentation results of FCM under different clustering numbers, and the image is divided into several small regions based on the indistinguishable relationship of attributes. Then, the weight values of each attribute are obtained by value reduction and used as the basis to calculate the difference between regions and then the similarity evaluation of each region is realized through the equivalence relationship defined by the difference degree. Finally, the final equivalence relation defined by similarity is used to merge regions and complete image segmentation. This method is validated in the segmentation of artificially generated images, brain CT images and MRI images. The experimental results show that compared with the FCM method, the proposed method can reduce the error rate and achieve better segmentation results for the fuzzy boundary region.

II. RELATED WORKS AND BASIC THEORIES

Brain image segmentation based on FCM clustering algorithm and rough set mainly involves the following areas and work.

A. RELATED WORKS

In previous image segmentation techniques, threshold-based segmentation is a basic method. The method is simple and has advantages in processing speed, but it is not suitable for the segmentation of blurred boundary areas in images [11], [12]. For the segmentation of blurred boundary areas, unsupervised clustering method is usually used, and K-means clustering method is commonly used. Such as Fuzzy C-means method, and ISO-DATA method. Among them, FCM method is a clustering algorithm with the ability of fuzzy decision-making [14], [15]. It is very effective for the segmentation of fuzzy boundary areas and has been widely used.

The most widely used method for image segmentation is histogram-based threshold segmentation [16]. It is assumed that uniform objects are aggregated in the image. The advantage of this method is that they do not need any prior information of the image. They are only based on the gray level and do not consider the spatial correlation of the same or similar elements. However, real-world images usually have strong correlation between adjacent pixels. In general, the adjacent pixels in an object are not independent of each other. In order to overcome this shortcoming, Cheng et al. adopted the rough homogeneity method. After extracting uniform regions from color images, regions are divided by the difference of intensity values between pixels and adjacent pixels. However, this method only considers the spatial correlation of adjacent pixels in the same plane. Literature [17] use a method called rough index as the basis of segmentation to improve the traditional histogram threshold algorithm. The concept of history introduced by Literature is used to determine the upper approximation, that is, the set of all points. The idea is perfected by choosing the histogram value as the lower approximation, and some results have been achieved. Although the effect is not good to some extent, the complexity and clustering degree have been improved.

B. FUZZY C-MEANS (FCM) CLUSTERING ALGORITHM

Fuzzy clustering algorithm is one of the most important branches of clustering algorithm [18]. Different from traditional clustering methods (such as K-means clustering algorithm), it divides each object to be classified into one category or another. Fuzzy clustering algorithm uses fuzzy method to cluster, and gives the degree of uncertainty of sample classification, which conforms to the nature of things in the real world. It can reflect the real world more objectively [19]. The mapping principle of FCM from input space to characteristic space as shown in figure 1.

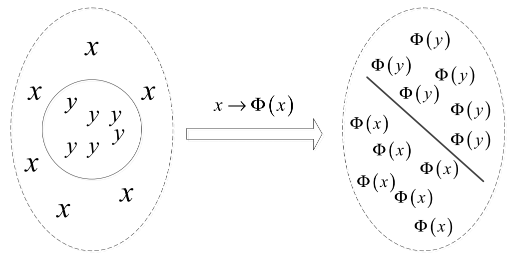

FIGURE 1. The mapping principle of FCM from input space to characteristic space.

Fuzzy C-means Clustering (FCM) algorithm is one of the most classical fuzzy clustering algorithms, which searches for the optimal extremes through repeated iterations [20]. Because the Euclidean distance is used as the distance measure in the objective function of FCM algorithm, the samples close to each other in the sample space will be clustered together. Clustering analysis largely depends on the distribution of data sets. If the sample space itself is linear ''agglomerative'', FCM can achieve good clustering effect; but if the sample space is non-linear ''agglomerative'', the clustering effect of this kind of method will be unsatisfactory. In document [21], the kernel function theory is introduced into cluster analysis, and a clustering method based on kernel function is proposed. In practical application, according to statistical theory, a function can be regarded as a kernel function as long as it satisfies Mercer condition. Kernel-fuzzy C-means clustering algorithm maps the samples in the original space to the high-dimensional feature space through the kernel function, and then carries out FCM clustering. This can make the linearly inseparable samples in the original space become linearly separable, and overcome the disadvantage that FCM is not suitable for the non-linear data distribution to a certain extent.

C. ROUGH SET THEORY

Rough set theory, first proposed by Z. Pawlak, a Polish mathematician, is a powerful tool for dealing with uncertain,

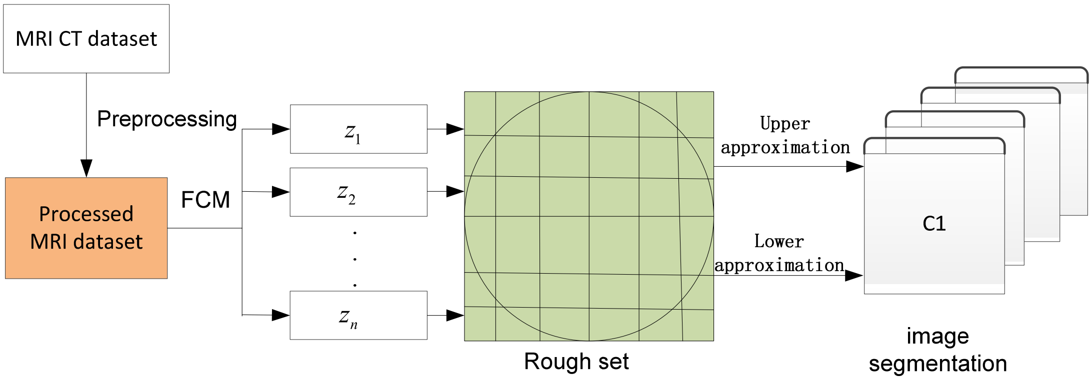

FIGURE 2. The architecture of brain image segmentation based on FCM clustering algorithm and rough set.

incomplete and inaccurate knowledge. This theory has become an important branch in the field of uncertain computing. Rough set granulates knowledge based on the concepts of indiscernibility, upper and lower approximation, and reduction and so on. It directly simulates the logical thinking ability of human beings, becomes the basis of artificial intelligence and cognitive science, and provides an effective processing technology for the processing of intelligent information [21].

Rough set data analysis usually carries out a series of processing, such as attribute reduction, rule extraction, value reduction, minimization of decision rules, etc. Because the concept of value reduction is used in the subsequent calculation of regional difference degree, it is necessary to briefly introduce it, similar to attribute reduction, for all domains of discourse, not all for one object. Attributes are necessary, so the problem of value reduction is called rule reduction in some literatures [22], [23].

Due to the complexity and correlation of image information, incompleteness and uncertainty are often encountered in the process of processing. Therefore, applying rough set theory to image processing sometimes has better performance than general hard computing methods. At present, rough set has been applied to image enhancement, image segmentation, and image filtering and so on. From the literature, we can know that image processing based on rough sets can achieve better results. Nevertheless, the application of rough sets in image field is still in the exploratory stage. New methods and techniques need to be further studied and discussed.

D. BRAIN IMAGE SEGMENTATION

Brain imaging plays an important role in today's medical diagnosis. Among them, image segmentation aiming at acquiring tissues and organs and related biological structures is one of the most important steps in medical imaging, and it is a powerful support for disease diagnosis, surgical planning, and treatment design and so on. Traditional image segmentation is mainly done by pathologists, which is monotonous and time-consuming. However, with the further popularization of medical images, the number and types of medical images have increased dramatically. Traditional manual segmentation cannot deal with a large number of medical images effectively. Automatic brain image segmentation arises at the historic moment, but it also faces two major challenges: the diversity of biological structure itself, and the low contrast and noise caused by the defects of brain image technology itself.

The goal of brain image segmentation is to describe the types of shape detectors and tissues of different anatomical structures on CT and MRI images according to the discontinuity in feature space [24]. However, the multivariate, inconsistent brightness, poor contrast and part of the vexed melt effect of biological tissue make segmentation a more difficult problem to deal with. However, in an image, the pixels belonging to the same object have similar spatial characteristics. They usually form a surface reflecting the shape of the object in space. Therefore, combining spatial information with pixel classification will be a meaningful segmentation method.

III. BRAIN IMAGE SEGMENTATION BASED ON FCM CLUSTERING ALGORITHM AND ROUGH SET

In this section, The Brain image segmentation based on FCM clustering algorithm and rough set will be designed and implemented.

A. THE DESIGN AND IMPLEMENT OF BRAIN IMAGE SEGMENTATION FRAMEWORK

The architecture of brain image segmentation based on FCM clustering algorithm and rough set is designed as follows.

As is shown in the figure 2, brain image segmentation can be divided into five parts: image preprocessing, FCM classification, rough set reduction, image tissue classification, classification markers. In the next sections, we will introduce the detailed steps of the image segmentation, and the segmentation algorithm is implemented.

B. IMAGE PREPROCESSING

The main purpose of image preprocessing is to eliminate the noise caused by the difference of radio frequency amplitude and phase and to improve the classification effect. In this study, a binary masking image is established to detect large targets, which is given by formula (1). The background image can be obtained by the product of the masked image and the source image, which can be calculated by formula (2):

$$B_m = I > B_{th} \tag{1}$$

$$I_B = B_m \times I \tag{2}$$

where B_m is a binary masked image, I is MR image, B_{th} is the threshold of image binarization. It is obtained by Otsu threshold method; I_B is a black background image. The implement of the FCM algorithm is shown in the figure 3.

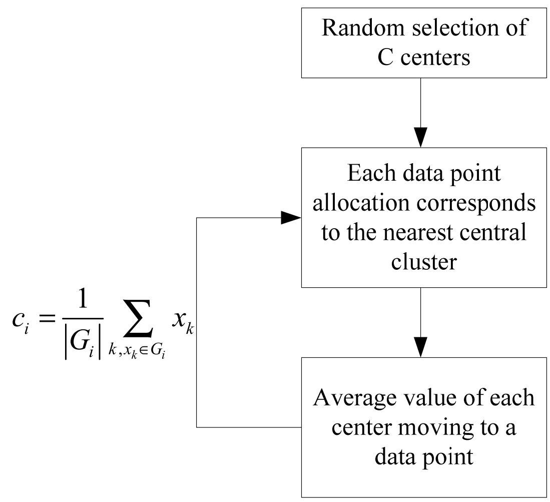

FIGURE 3. **The implementation of FCM.**

In order to avoid the omission of image edge vexes caused by window program, this paper adds $w/2$ background vexes to each edge. Next, the source image is divided into Ne sub-images by an overlapping window of size $w \times w$ from the upper right to the lower left of the image I_B, which is given by formula (3). Each extracted sub-image can be recognized by its central vexed [round $(w/2)$, round $(w/2)$]. The size of the sub-image corresponds to the extraction window, which facilitates subsequent processing.

$$N_e = \left[(n \times m) - 2 \times riybd(\frac{w}{2} + 2) \right]^2 \tag{3}$$

After graying the color image above, the gray image obtained is binarized. For binarization, the aim is to classify the background of the target user and prepare for the recognition of the following lanes. The most commonly used method of gray image binarization is threshold method. By using the difference between the object and the background in the image, he sets the image to two different levels and chooses an appropriate threshold to determine whether a pixel is the object or the background, so as to obtain the binarized image. In digital image processing, binary image plays a very important role. Especially in practical image processing, there are many systems based on binary image processing. In order to process and analyze binary image, first of all, gray image should be binarized to get binary image, which is conducive to further image processing, and the nature of the image set only. Relating to the position of the point whose pixel value is 0 or 255, the multi-level value of the pixel is no longer involved, which makes the processing simple and the amount of data processing and compression small. In order to obtain ideal binary images, closed and connected edges are usually used to define regions with non-overlapping meanings. All pixels whose gray value is greater than or equal to the threshold value are determined to belong to a specific object, and their gray value is 255. Otherwise, these pixels are excluded from the object area, and the gray value is 0, representing the background or the exceptional object area.

If a specific object has uniform gray value in the interior and it is in a uniform background with other gray values, the threshold method can be used to obtain a comparative segmentation effect. If the difference between the object and the background is not in the gray value (for example, the texture is different), the difference feature can be transformed into the gray difference, and then the image can be segmented by threshold selection technology. Dynamic adjustment of thresholds to achieve binarization of images can dynamically observe the specific results of the segmented images.

The gray value of the brain region and the background region is 1 and 0 respectively. In the follow-up experimental operation, the brain region needs to be studied, so the gray value of the brain region is restored by mask operation. Masking operation refers to the use of selected images or objects to occlude all or part of the processed image to control the area or process of image processing.

The functions of mask operation include: extracting region of interest, shielding, extracting structural features, and making special shape images. The mask operation is mainly used to extract the region of interest (ROI), and the hole-filled image is used as the template. The pixel-1 of the template is the region of interest (ROI) which is multiplied with the original image to obtain the image of the region of interest. The image value in the region of interest remains unchanged, while the pixel value of the image outside the region is set to 0.

C. INFORMATION TABLE CONSTRUCTION AND REGION DIVISION BASED ON FCM

In order to realize image segmentation, first of all, we need to construct an information table that can be used for image segmentation. By changing the number of FCM clustering, we can do multiple clustering calculations. Different clustering numbers are used as attributes of the pixels to be segmented, and clustering segmentation results are used as attributes. We can construct an information table that reflects the relationship between image segmentation, and use all clustering attributes as indistinguishable equivalence relations to segment the data. Basic class $\{z_1, z_2, \cdots, z_n\}$. z_i represents a small basic region of an image.

A finite set $X = \{x_1, x_2, \cdots x_n\}$ is a set of n samples and c is a predetermined number of classes; $m_i (i = 1, 2 \cdots c)$ is the center of each cluster $\mu_j(x_i)$ is the membership degree of the first sample with respect to class j. The clustering criterion function is defined as a membership function:

$$J(M, V) = \sum_{j=1}^{c}\sum_{i=1}^{m}\left[\mu_j(x_i)\right]^b \left\|x_i - m_j\right\|^2 \tag{4}$$

where $\left\|x_i - m_j\right\|^2$ is the Euclidean distance. b is a fuzzy weighted power index, which can control the degree of ambiguity of clustering results. M is the fuzzy c partition matrix of X. V is the cluster center set of X. The result of clustering algorithm is to obtain M and V which minimize the criterion function. In the method of fuzzy mean clustering, the sum of membership degrees of samples to each cluster is required to be 1:

$$\sum_{j=1}^{x}\mu_j(x_i) = 1 \quad i = 1, 2\cdots n \tag{5}$$

Let the partial derivative of $J(M, V)$ to m_j and $\mu_j(x_i)$ be zero. The necessary condition for obtaining the minimum is:

$$m_j = \frac{\sum_{i=1}^{n}\left[\mu_j(x_i)\right]^b x_i}{\sum_{i=1}^{n}\left[\mu_j(x_i)\right]^b} \quad j = 1, 2\cdots c \tag{6}$$

$$\mu_j(x_i) = \frac{\left(1/\left\|x_i - m_j\right\|^2\right)^{1/b-1}}{\sum_{k=1}^{c}\left(1/\|x_i - m_k\|^2\right)^{1/b-1}} \tag{7}$$

When the algorithm converges, all kinds of clustering centers and samples are obtained. For each kind of membership degree, the fuzzy clustering division is completed. Finally, the results of the fuzzy clustering are de-fuzzified, and the fuzzy clustering is transformed into deterministic classification [27].

D. CALCULATION OF ATTRIBUTE WEIGHT AND BASIC REGIONAL DIFFERENCE BASED ON VALUE REDUCTION

Rough set describes knowledge from the point of view of pattern classification. Through indistinguishable equivalence relation, knowledge space is divided into different pattern equivalence classes, thus knowledge space is represented as granular structure. It is precisely because of this granular structure of knowledge that causes the roughness of knowledge representation.

Each attribute in the information table plays a different role in classification, so we must consider the importance of different attributes and give different weights in order to make reasonable decisions In the process of value reduction of objects, it is unnecessary for each object to have one or more attributes, while the value reduction of the whole universe is counted and all values are given. In reduction, the more frequent the attributes appear, the more important the classification is. Therefore, the weight of attributes can be defined on this basis [2].

If $z_i(i = 1, 2\cdots n)$ is the basic region of the segmented image, a_k is the kth attribute and v_i is the value attribute of z_i. $v_i(a_k)$ is the value of attribute a_k about value reduction v_i, l is the value reduction number of all basic regions, then the weight of attribute w_k is defined as follows:

$$w_k = 1 = \frac{\sum_{z_i} v_i(a_k)}{l} \tag{8}$$

$$v_i(a_k) = \begin{cases} 1 & a_k \in v_i \\ 0 & a_k \notin v_i \end{cases} \tag{9}$$

After obtaining the weights of the attributes, "the difference between the basic regions is defined as follows:

$$d(z_i, z_j) = \sum_{k=1}^{m}(w_k \times \lambda_{ij}^k) \tag{10}$$

$$\lambda_{ij}^k = \begin{cases} 0 & a_k(z_i) = a_k(z_j) \\ 1 & a_k(z_i) \neq a_k(z_j) \end{cases} \tag{11}$$

A finite set $X = \{x_1, x_2, \cdots x_n\}$ is a set of n samples and c is a predetermined number of classes; $m_i(i = 1, 2\cdots c)$ is the center of each cluster $\mu_j(x_i)$ is the membership degree of the first sample with respect to class j. The clustering criterion function is defined as a membership function:

E. SIMILARITY DOMAIN PARTITION BASED ON DIFFERENCE DEGREE AND SIMILARITY DEGREE

Setting a difference index α_d can define the initial equivalence relation $\{R_i\}\, i = 1, 2, \cdots n$ based on the difference degree; it divides the universe into similar domain $[z_i]_{R_i}$ and non-similar domain $[z_i]_{R_i}$.

$$\begin{cases} U/R = \left\{[z_i]_{R_i}, [z_i]_{R_i}\right\}, \quad i = 1, 2\cdots n \\ [z_i]_{R_i} = \left\{z_j | d(z_i, z_j) \leq \alpha_d\right\} \\ [z_i]_{R_i} = \left\{z_j | d(z_i, z_j) > \alpha_d\right\} \end{cases} \tag{12}$$

Finally, in order to achieve image segmentation, we must measure the similarity of the basic region, and set the similarity index α_s, define the initial equivalence relation $\{r_i\}\, i = 1, 2, \cdots n$ based on the difference degree, the dividing results are as follows:

$$U/r_i = \left\{\left\{z_j | s(z_i, z_j) \leq \alpha_d\right\}, \left\{z_j | s(z_i, z_j) > \alpha_d\right\}\right\} \tag{13}$$

where $s(z_i, z_j)$ is the similarity between the basic region z_i and z_j, it is defined as follows:

$$s(z_i, z_j) = \begin{cases} \dfrac{\sum_{k=1}^{n} in_k(z_i, z_j)}{n}, & i \neq j \\ 1, & i = j \end{cases} \tag{14}$$

$$in_k(z_i, z_j) = \begin{cases} 1, & z_i, z_j \in [z_i]_{r_i}, \\ 0, & else \end{cases} \tag{15}$$

And the Similarity Satisfies $s(z_i, z_j) = s(z_j, z_i)$.

After determining the final equivalence relation and dividing the region, the indistinguishable relation is formed by all

TABLE 1. The parameters of the algorithm.

target area	attributes		
	a1	a2	a_3
z1	1	1	*
z2	*	*	1
z3	*	3	2
z4	2	*	2
z5	*	1	3
z6	*	2	3
z7	*	*	4
Weight	0.714	0.429	0.143
'*'means the reducible unnecessary attributes			

equivalence relation $\{r_i\}\ i = 1, 2, \cdots n$. $ind(r)$ is defined as follows:

$$[z]_{ind(r)} = \bigcap_{r_i \in r} [z]_{r_i} \tag{16}$$

The final image segmentation is achieved by the ultimate indistinguishable relationship

IV. THE IMAGE SEGMENT RESULTS COMPARED WITH OTHER ALGORITHMS

To verify the effectiveness of the method, two groups of T1 weighted images with different resolutions were selected for simulation experiments:

1) The simulation Image dataset is from IBSR brain image database, the size of images was 256∗256∗63 individual elements;

2) In another simulation, the clinical case images were selected, and the size of images was 512∗512∗512 voxels. All simulation experiments were implemented on MATLAB platform.

The derailed comparison simulations are implemented as follows.

A. COMPARISON OF SEGMENTATION EFFECTS OF DIFFERENT OPTIMIZATION METHODS

In order to verify the reliability of this algorithm, sensitivity (Se), specificity (Sq), false positive likelihood (PL) and ginkgo likelihood (NL) are selected to evaluate the superiority of different optimization algorithms. The larger the first three indexes, the better the clustering effect and the more accurate the organizational segmentation is. The smaller the last index, the better the segmentation effect is. Specific indicators are given by the formula (17).

Among them, TN, TP, FN and FP represent the number of town-positive, true-negative, false-positive and false-negative organizations [25].

$$\begin{cases} PL = \dfrac{TP}{TP + FN}; \quad NL = \dfrac{TN}{TN + FP} \\ PL = \dfrac{Se}{1 - Sp}; \quad NL = \dfrac{1 - Se}{Sp} \end{cases} \tag{17}$$

The segmentation images obtained by different optimization algorithms are shown in Figure 4 (Where(a), (d) is the segment image under our algorithm; (b), (e) is the segment image under PCA algorithm; (c), (f) are the segment image under GA-SOM algorithm). It is obvious that PCA algorithm can't segment CSF tissue in cross-section and coronal plane. GA-SOM algorithm is unified by similar problems. The original segmentation algorithm based on FCM algorithm and rough set theory has successfully segmented white matter, gray matter and CSF regions. Se, Sq, PL and NL obtained by different optimization algorithms are shown in table 2. At white matter, gray matter and cerebrospinal fluid levels, Se, Sq, PL based on FCM algorithm and rough set theory are larger than those of the other two optimization algorithms, and NL is at the minimum.

TABLE 2. The index comparison under different algorithm.

algorithm	organization	Se	Sq	PL	NL
Our algorithm	White matter	0.81	0.95	19.0	0.19
	gray matter	0.76	0.96	21.2	0.24
	cerebrospinal fluid	0.80	0.99	24.0	0.19
PCA	White matter	0.75	0.90	8.03	0.27
	gray matter	0.71	0.91	8.08	0.30
	cerebrospinal fluid	0.70	0.92	8.89	0.32
GA-Son	White matter	0.76	0.80	3.86	0.29
	gray matter	0.72	0.83	4.27	0.33
	cerebrospinal fluid	0.63	0.85	4.27	0.43

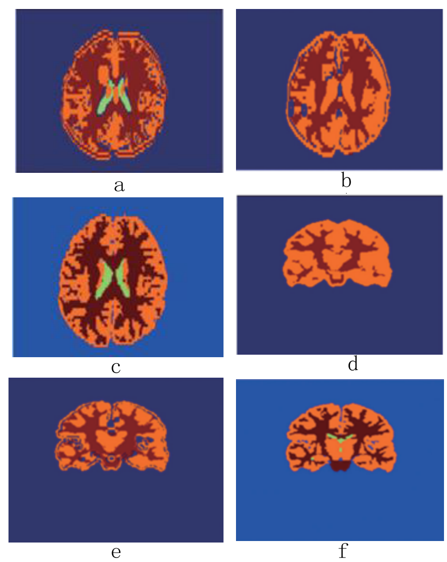

FIGURE 4. The comparison simulation under different image segment algorithm.

B. COMPARISON OF SEGMENTATION EFFECT WITH DIFFERENT CLUSTERING ALGORITHMS

The clustering process uses DBI and DUNN index to evaluate K-means and EG algorithm. The smaller the DBI index is,

TABLE 3. The index comparison of different cluster algorithm.

Cluster algorithm	DBI index	DBI variance	DUNN index	DUNN variance
K-means	0.73	0.0010	0.55	0.0025
FCM	0.52	0.0027	1.10	0.0064

TABLE 4. The t test of DBI and DUNN index.

	t index	p index	confidence interval
DBI	51.63	$<10^{-7}$	[1.16,0.29]
DUNN	82.15	$<10^{-7}$	[0.63,0.40]

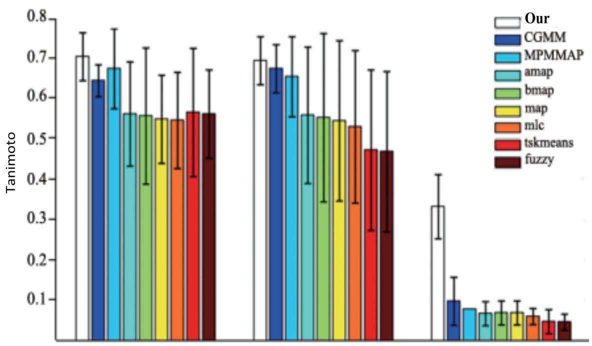

FIGURE 5. Tanimoto coefficients obtained by different segmentation algorithms.

the bigger the DUNN index is, the better the clustering effect is. The evaluation indexes are shown in formulas (18).

$$\begin{cases} DB_i = \dfrac{1}{n}\sum\limits_{i=1}^{n} \max\limits_{i\neq j}\left(\dfrac{\sigma_i+\sigma_j}{d(c_i,c_j)}\right) \\ DUNN_i = \min_{1\leq j\leq n}\left(\dfrac{d(i,j)}{\max d'(k)_{1\leq k\leq n}}\right) \end{cases}$$

The DBI index based on K-means and FCM clustering algorithm is 0.73 and 0.52, respectively. Obviously, the latter is smaller and corresponds to better clustering effect. The DUNN index based on FCM algorithm is larger, which proves the superiority of this algorithm (Table 3).

The statistical significance test between DBI and DUNN obtained by the two algorithms is shown in Table 4. The results show that the P values of the two evaluation indicators are $p < 10^{-7}$, which indicates that there are statistical differences between the two indicators. Again, the clustering effect of EG algorithm is better than that of K-means algorithm.

C. COMPARISON OF THE RESULTS OF DIFFERENT SEGMENTATION ALGORITHMS

In this paper, Tanimoto coefficients are used to evaluate the results of different segmentation algorithms, and the similarities between the segmentation results of different segmentation algorithms and the real results are measured.

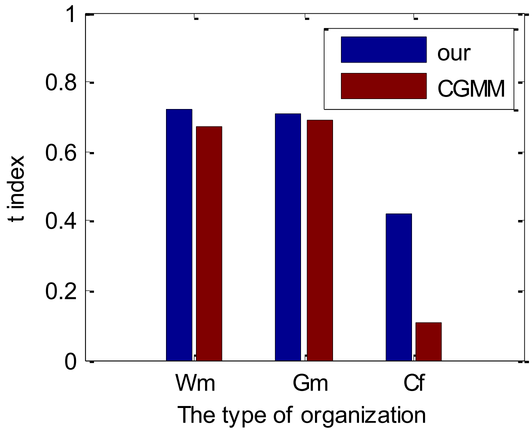

FIGURE 6. Comparing the results of this algorithm with those of CGMM algorithm.

The real results of this paper are obtained by expert manual segmentation. Tanimoto coefficient is given by formula (18). The bigger the Tanimoto coefficient is, the more accurate the image segmentation is [26].

$$T(S_1, S_2) = \frac{|S_1 \cap S_2|}{|S_1 \cup S_2|} \tag{18}$$

The average and standard deviation of Tanimoto coefficients obtained by this algorithm are superior in three organizational categories (Figure 5). Combining the results of document [15]– [17] and figure 4, CGMM algorithm is based on other existing segmentation algorithms. Therefore, the comparison between the segmentation algorithm and the different algorithms in this paper is transformed into the comparison between the CGMM algorithm, as shown in Fig. 6 and Table 5.

The average Tanimoto coefficients based on this algorithm are higher than CGMM algorithm in three tissue categories (Fig. 5), and have obvious advantages at CSF level, but they are not verified by statistics. The statistical analysis of Tanimoto coefficient T test is shown in Table 4. In white matter segmentation, the P value was 2.2 x 10-5, and in CSF segmentation, the P value was less than 10-7, showing statistical difference at the level of 0.05. However, in the segmentation of gray matter, P is 0.33, and the original assumption can not be rejected at the level of 0.05. That is to say, the average Tanimoto coefficients obtained by the two algorithms are different.

In conclusion, the proposed algorithm is superior to CGMM in white matter and cerebrospinal fluid segmentation. In gray matter segmentation, there is no significant difference between the proposed algorithm and CGMM algorithm.

V. THE SEGMENT COMPARISON RESULTS OF CLINICAL IMAGE

A. CLINICAL IMAGE SEGMENTATION RESULTS

The image has a high density resolution. The tissue density of the imaging area is expressed by different gray levels from

TABLE 5. The t test of DBI and DUNN index.

Organization type	T value of white matter	P value of white matter	T value of grey matter	P value of white matter	T value of cerebrospinal fluid	T value of cerebrospinal fluid
T test	5.76	2.2*10-5	0.97	0.33	12.58	<10-7
average	0.045	-	0.012	-	0.303	-
confidence interval	[0.028,0,061]	-	[-0.031,0.037]	-	[0.25,0.35]	-

black to white. The low-density area such as soft tissue-white area represents the high-density area, such as skeleton.

Clinical case images include not only white matter, gray matter and cerebrospinal fluid 3 tissues, but also scalp and skull, which increase the difficulty of brain image segmentation to a certain extent. Based on the segmentation effect of this algorithm, as we can see in Figure. 7. It can be seen that the original algorithm first segmented the scalp and skull, which is similar to that of the brain extraction tool with copper, and then accurate. Three kinds of tissues are separated. Among them, the attributes of establishing information tables are as follows: $a_1(k = 2)$, $a_2(k = 3)$, $a_3(k = 4)$, $a_4(k = 5)$. Threshold index $\alpha_d = 2$, $\alpha_s = 0.375$.

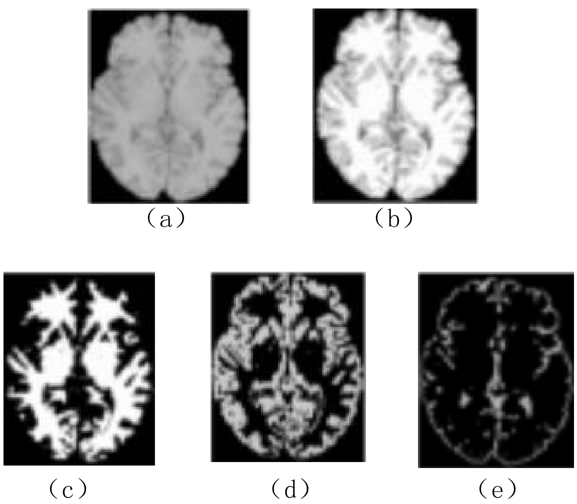

FIGURE 7. The segment results of MRI medical image.

Therefore, it has a strong ability to distinguish skeleton and soft tissue. Brain CT images are often used in clinical diagnosis of craniocerebral radiotherapy and craniocerebral surgery.

The segmentation of the key areas, namely gray matter and white matter, is not clear, and white matter is divided into several discontinuous regions. "With this algorithm, white matter can be divided into a connected whole region, so that white matter and gray matter have a clearer segmentation boundary. The segment results is shown in the figure 6, where (a) is the original image, (b) is the segmented image, (c) is segment result of the white matters, (d) is segment result of the gray matters, (e) is segment result of the cerebrospinal fluid. In FCM algorithm, the misadvised soft tissues are segmented accurately, and the skeleton and soft tissues are clearly segmented from the background. And the white matters, gray matters and cerebrospinal fluid are obvious in the segment results.

B. CLINICAL IMAGE SEGMENTATION RESULTS COMPARED WITH SYSTEM TOOLS

Brain tissue includes white matter, gray matter, cerebrospinal fluid, lesions and so on. Finally, the cluster number C = 5 was selected. Through the unified image processing, the image is converted into 512∗512, the value of the fuzzy factor is chosen as P=2, three different iteration stop thresholds e_m are selected, and the maximum iteration times are set to 300.

Clinical image contains not only white matter, gray matter and cerebrospinal fluid, but also scalp and skull, which increases the difficulty of brain image segmentation to a certain extent. The segmentation effect of brain image based on this algorithm is shown in Figure 8. It can be seen that

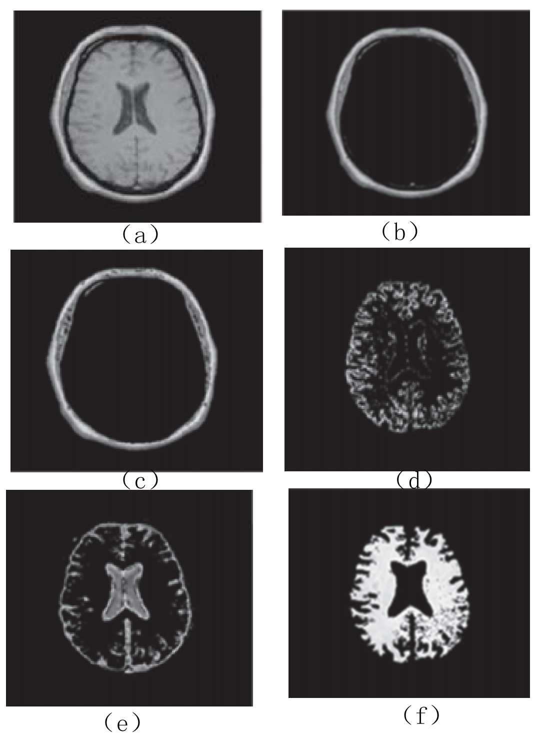

FIGURE 8. The segment results of MRI medical image.

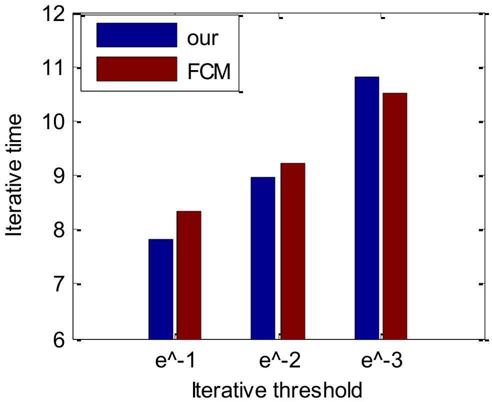

FIGURE 9. The relationship between iterative threshold and iterative time.

the algorithm first segments the scalp and skull, and the segmentation effect is the same as that of the brain extraction tool in the system, and then accurately segments three kinds of tissues.

Through the observation of Figure 7, where (a) original map; (b) system tool segmentation; (c) algorithm segmentation in this paper; (d) white matter; (e) cerebrospinal fluid; (f) gray matter. It is obvious that the brain segment results are significant. And the issues of brain are classified accurately.

C. THE SEGMENT RESULTS COMPARED WITH FCM

At present, although there are many mature theories and methods in medical image segmentation, there are many difficulties in the imaging process, such as equipment design defects, illumination differences and brain tissue is difficult to distinguish. Therefore, for different diseases, it is necessary to combine with actual needs to produce practical image processing methods. Starting from the segmentation of stroke MR images, this paper analyses the possible problems in the segmentation of stroke MR images, and carries out the segmentation of stroke MR images by combining the rough set theory with image processing technology.

From V_{pc}, we can see that in clustering algorithm, a pixel should belong to a certain class as far as possible, that is, the corresponding membership value of this class should be as large as possible, while the membership value of other classes should be as low as possible. Therefore, the larger the VPC of the experimental results, the better the clustering effect of the results is, and vice versa, the worse the clustering effect is. The relationship between iterative threshold and iterative time as shown in figure 9.

As can be seen from the definition of V_{xb}, this index mainly reflects the quotient between the degree of compactness within a class and the degree of separation between different classes. Among them, the compactness within the molecular representative class should be as large as possible, and the smaller the value, the better; denominator represents the degree of separation between different classes, and good clustering methods should have as large as possible. Therefore, this method is to find a balance point between the two.

TABLE 6. Comparison of segmentation results.

	threshold	e-1	e-2	e-3
Vpc	FCM	0.898	0.912	0.916
	our	0.925	0.927	0.933
Vxb	FCM	0.546	0.522	0.517
	our	0.491	0.481	0.474

The smaller the final value of V_{xb}, the better the clustering effect of this method. On the contrary, the worse the clustering effect of this method.

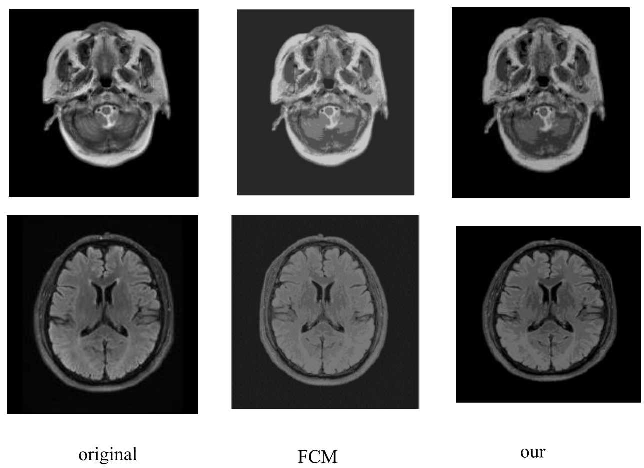

FIGURE 10. The segment results of MRI medical image compared with FCM.

Through the observation of Figure 10, we can find that under the same parameters, the clustering effect of our algorithm is obviously due to FCM, which is better for white matter and grey matter. Compared with FCM, our algorithm is slightly better in clustering, but has a great improvement in time.

D. THE ANTI-JAMMING PERFORMANCE OF IMAGE SEGMENT ALGORITHMS

The main objective of medical image processing is to achieve the doctor's visual effect and distinguish the focus. As far as the overall objective of medical image processing is concerned, almost all applications that affect the results of image processing are related to the segmentation of medical images. Because the segmentation of medical images is directly related to the diagnosis results of doctors, a robust segmentation algorithm is necessary.

Medical image segmentation requires that the algorithm has unpredictability to the target object of the image itself, connectivity of the segmentation region, and irregularity of boundary curve, such as contour and boundary of malignant and benign tumors, which are sometimes destroyed due to the problem of the algorithm model itself.

In order to verify the anti-jamming performance of the image segmentation algorithm, we set up the image to receive

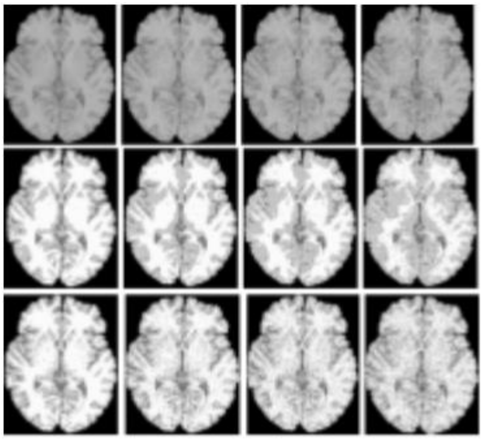

FIGURE 11. Comparison of robustness between two methods.

different degrees of noise interference. Using our segmentation algorithm, we observed the segmentation effect in the presence of noise interference.

During the simulations, we set original image and corresponding noising images which are produced by different Gaussian noise(mean is zeros and standard deviates are respectively 10, 15 and 20). The simulation is shown in the figure 11. As is shown in the figure 10, comparison of robustness between two methods, Original image and corresponding noising images which are produced by different Gaussian noise(mean is zeros and standard deviates are respectively 10, 15 and 20) are in the first line. The segmentation results by our method are indicated in the second line, and the segmentation results using FCM algorithm based on parameter invariance are indicated in the third line.

The segmentation results show that our algorithm can still segment perfectly in the presence of different degrees of Gauss white noise. Compared with FCM algorithm, our segmentation algorithm has stronger robustness, and the segmentation effect is more accurate than that of FCM.

VI. CONCLUSION

In this paper, a new image segmentation method is proposed by combining FCM clustering algorithm with rough set theory. Firstly, the attribute value table is constructed based on the segmentation results of FCM under different clustering numbers, and the image is divided into several small regions based on the indistinguishable relationship of attributes. Then, the weight values of each attribute are obtained by value reduction and used as the basis to calculate the difference between regions and then the similarity evaluation of each region is realized through the equivalence relationship defined by the difference degree. Finally, the final equivalence relation defined by similarity is used to merge regions and complete image segmentation. This method is validated in the segmentation of artificially generated images, brain CT images and MRI images. The experimental results show that compared with the FCM method, the proposed method can reduce the error rate and achieve better segmentation results for the fuzzy boundary region.

(1) This paper introduces a new image segmentation method based on FCM and rough set theory. This method has been applied and validated in the segmentation of artificially generated images, MRI images and CT images, and the algorithm has good segmentation effect, compared with FCM method, this method can reduce the error rate and has better segmentation effect on the blurred boundary areas.

(2) The segmentation algorithm based on FCM clustering and rough set theory has strong stability and high accuracy, and shows superiority in both simulated images and clinical examples. It is a feasible brain segmentation algorithm for MRI compared with CGMM method.

(3) As we all know, medical image has more or less noise interference in practical application. This paper verifies the segmentation performance of the segmentation algorithm by setting different white noise. The results show that the proposed algorithm has better robustness than the FCM algorithm, and has strong clinical application ability.

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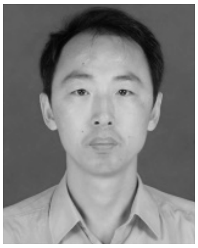

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