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Segmentation Algorithm Based on Neutrosophic Fuzzy C-Means Clustering and Its Application

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Abstract: Image segmentation technology has become a key technology from image processing to image analysis. As the current image segmentation algorithms still have many defects, it is becoming more and more important to develop a suitable image segmentation algorithm. Although there are many achievements in this area, they all have shortcomings. In order to solve the shortcomings of traditional image segmentation algorithms, this article combines the neutrosophy image segmentation algorithm of LPG&PCA and improves the original FCM algorithm through in-depth research on the neutrosophy image segmentation method. After the experiment, it is found that when the improved algorithm is the lowest index function, the value of the original FCM algorithm is 0.8531, the value of the improved algorithm is 0.4751, and the categories of the original FCM algorithm and the improved algorithm are both 7, indicating the improved algorithm At the lowest exponential function, the correct clustering category can be obtained like the original FCM algorithm.

1 Introduction

As one of the research hotspots in related fields such as digital image engineering and machine vision, good image segmentation technology is conducive to people's subsequent analysis and processing of images. Due to the complexity and ambiguity of real images, image segmentation based on fuzzy clustering methods is getting widespread attention and applications [1]. Image processing technology, analysis technology and image understanding are the three in-depth processes of image engineering. Image processing is the foundation of image engineering, while image segmentation is the technology of image processing technology. A behavior of segmentation, the image after segmentation is more simplified than the expression of the image before segmentation, and it is easier to understand and analyze the image. The essence of image segmentation is to summarize and summarize the pixels of the image separately, and add corresponding labels, and through the act of labeling the pixels, the pixels with the same label in the image form the same visual characteristics [2]. After the image segmentation and feature extraction, the previous pixel representation of the image is converted into a non-graphic symbolic representation, that is, image analysis, which is a middle-level operation in image engineering. Image understanding further studies the relationship between objects in images, which is a high-level operation. Therefore, image segmentation is a key step in image engineering, and accurate image segmentation makes it possible to analyze and understand the middle and high level.

There are a lot of researches in this area at home and abroad. Yan W et al. proposed a regional competition law. This method combines the advantages of the Snake/balloon model and the Bayes/MDL method, so that the algorithm can converge to a local minimum and can be implemented in a unified public statistical framework [3]. Namburu A and Samamayamantula SK proposed a new possibility clustering algorithm. This new algorithm has obtained a new possibility model based on existing related theories, which can effectively supervise the clustering of images [4] . Wang C et al. improved the constraint conditions on the basis of the FCM algorithm, and proposed that when the PCM algorithm is used to segment the image, the ability to recognize image noise is enhanced [5].

Although previous studies on this area are rich, most of the proposed algorithms have their limitations. From the current research status of fuzzy clustering algorithms, people are constantly advancing on the tortuous road of studying fuzzy clustering algorithms. In view of the shortcomings of this algorithm, people have proposed many improved algorithms from multiple angles and achieved many results, which just shows that the algorithm still needs to be improved. Therefore, the fuzzy clustering algorithm is used in image segmentation. The research on image segmentation has always been a valuable work, and the research on image segmentation is still in deepening. In this regard, the main innovations of this paper are 1) based on neutrosophic fuzzy theory, propose a new fuzzy C-means clustering segmentation algorithm 2) improve the traditional FCM algorithm, improve its noise reduction level 3) proposed A new fuzzy clustering algorithm, on the basis of the traditional fuzzy C-means clustering algorithm, to improve the defects of the algorithm itself.

2. Experimental Method of Fuzzy c-Means Clustering Segmentation Algorithm

2.1. Basic Theory and Application of Neutrosophic Fuzzy

In 1965, Zadeh proposed the fuzzy theory, and then people introduced the concept of fuzzy in the algorithm. Since then, a lot of fuzzy theory algorithm research has appeared [6]. Fuzzy theory mainly uses fuzzy set theory to describe the blur phenomenon. However, the widespread uncertainty in image processing affects people's true expression of images, such as the loss of information during image imaging, and the accuracy of imaging. Not enough, the gray level of the image is uncertain, etc. The uncertainty of the image is not generated randomly, so it is not suitable for general probabilistic knowledge to solve such problems [7]. Image processing technology, analysis technology and image understanding are the three in-depth processes of image engineering. Image processing is the foundation of image engineering, as shown in the following figure 1:

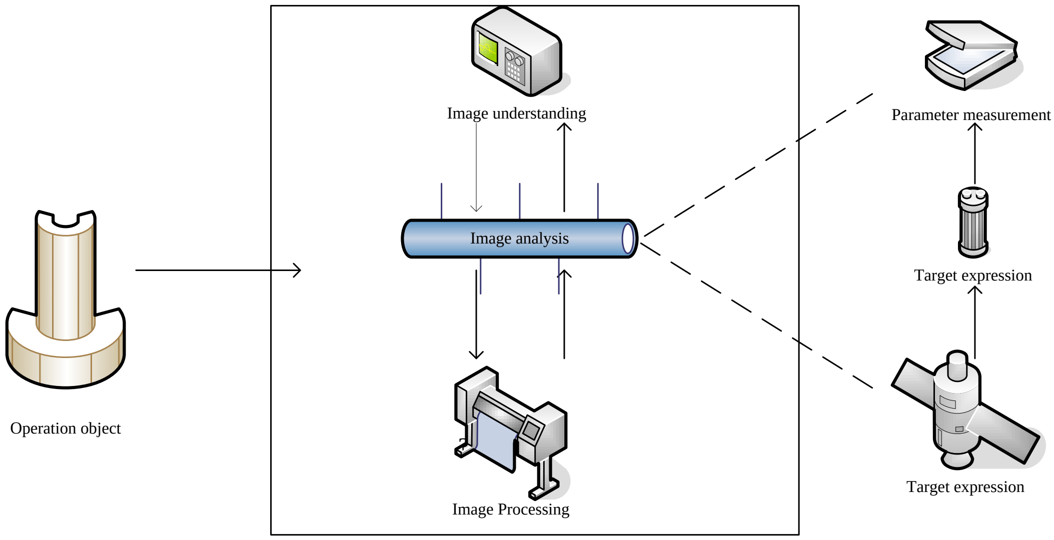

Figure 1. The position of image segmentation in image engineering

Some research scholars use neutrosophy theory in image processing, it may be able to deal with the image well: the degree of brightness, the boundary of the target, the texture of the image, etc. Neutrosophic theory has been applied to image processing. It has become one of the most important tools for studying uncertain information in images. It will also be combined with existing image processing algorithms to form new image processing algorithms[8]. Therefore, the neutrosophy theory has received widespread attention from scholars in image processing. Neutrosophy mainly studies a part of logic science, so it is also called Sima Rendaqi logic. Neutrosophy theory is the generalization and generalization of Frorentine Smarendazi's theory including fuzzy logic. Compared with other logics, neutrosophy theory will be more in line with people's way of thinking, mainly because it can not only express the uncertainty problem well, but also solve the problems that cannot be solved in fuzzy theory [9]. Neutrosophy theory is an emerging discipline extended by fuzzy logic. It mainly integrates Eastern and Western cultures. It also considers the unity of opposites, explores from logic to natural sciences and social sciences, and at the same time addresses the frontiers of science and technology. Difficulties-uncertainty issues.

2.2. Introduction to Fuzzy Set Algorithms

The theory of using mathematical methods to process and explain the phenomenon of image blur is called fuzzy mathematics. The emergence and progress of fuzzy mathematics comes from the development of computers. The two promote the development of each other. The development of computers greatly promotes the progress of fuzzy science, and fuzzy Learning theory has also greatly released the computing power of computers [10]. The object of fuzzy research is uncertain and imprecise, so this theory provides a theoretical basis for people to deal with various uncertain problems in reality. Fuzzy mathematics is more widely used than traditional mathematics. It contains both the vagueness of things and the clarity of things. Now, because there are fuzzy concepts in all walks of life, fuzzy science is applicable to all fields, whether in medicine, agronomy, ecology, artificial intelligence and information technology, it has played an important role [11]. The initial cluster analysis division is called hard division. Because many substances do not have attributes in a strict sense, the results of the division using traditional division methods are sometimes unrealistic, while soft division can better deal with these problems. [12]. The classification of many things in the real world is not obvious, and there is no definite attribution. Due to the particular characteristics of things, it is difficult to be sure whether they belong to a certain set. In real life, real things have non-single attributes. And attribution makes it difficult for people to classify them accurately, and the emergence of fuzziness undoubtedly solves this problem very well. People can explain and describe things with multiple directions through fuzziness, explain their trends and tendencies, summarize different categories according to the different characteristics of the element points of the image, and use a set to describe the degree of element points in the set. [13]. Undoubtedly, the description of this ambiguity problem can better reflect the real structure of the real world and data objects, and effectively solve various uncertain problems in real life.

2.3. Improvement of Fuzzy c-Means Clustering Algorithm

Fuzzy has developed rapidly, and now there are many related fuzzy clustering algorithms. Among them, the fuzzy C clustering algorithm is currently the most comprehensive and the most developed fuzzy theory [14]. The so-called cluster analysis is a means of inductively dividing related data. Through clustering analysis, we can summarize the data without labels in the spatial characteristics, and then divide them separately, so that each set represents a part of the overall characteristics. [15]. Although the fuzzy C-means clustering algorithm effectively solves many ambiguous uncertainties in real life, it can also reflect the real structure of the real world and data objects, but there are still many problems in this algorithm, such as determining clustering The number of centers, the performance of the algorithm depends on the choice of the initial center, it is sensitive to noise images, the amount of calculation is large and the convergence speed is slow, etc. In response to these shortcomings, this article proposes a new FCM type algorithm. Discriminant functions related to class validity:

Let n be any set, the ordered binary relation set P is defined as a fuzzy subset belonging to n

$$P = \{(n, \delta_p(n) \mid n \in N\} \tag{1}$$

Among them, δp:N—[0,1] is called the membership function describing P to N. For the set N, the binary fuzzy relationship β is an N×N fuzzy subset, which is defined as:

$$\beta = \{(x, y), \delta_\beta(x, y) \mid (x, y) \in N \times N\} \tag{2}$$

Among them δβ: N×N—[0,1], there is a set of x-dimensional hyperspace bodies, which are divided by the x-dimensional Euclidean space R by the orthogonal hyperplane. These hyperspace bodies are called the Euclidean space When X=2, R is a plane, and the two-dimensional space corresponds to the image. Therefore, the space element corresponding to the space is called a pixel; when n=3, R is a cube space, so it is called One element of space is cubic element [16]. If an x-element array is used to measure the coordinates of space elements, it can correspond to points in the hyperspace coordinate system Z. If the hyperspace coordinate system Z has a fuzzy relationship β with reflexivity and symmetry, it is called β is a kind of proximity relationship [17]. Suppose the two spatial elements are point a and point b. Generally speaking, the membership function should be inversely related to the distance between a and b, that is, the closer the distance, the higher the degree of membership. In the following, β corresponding to a set of Z sums is called fuzzy number space (Z, β). The fuzzy proximity relationship defined in the hyperspace is:

$$\delta_\beta(a,b)=\left\{\frac{1}{1+k(\sqrt{\sum(a-b)^2})}\right\} if \sum_{i=1}^{n}|a-b|\leq x \tag{3}$$

Among them, k is a non-negative coefficient. For the two-dimensional space, it is a subset of the hyperspace, so the corresponding binary fuzzy relationship β must have all the characteristics of the fuzzy relationship, such as reflexivity and symmetry, etc., which can give this kind of binary fuzzy The relationship takes an image name, which is a kind of proximity relationship [18]. In practice, this proximity relationship can be freely defined. A basic function describing the proximity relationship is:

$$\delta_\beta(a,b)=\begin{cases}1 & if \|a-b\|\leq 1\\ 0 & otherwise\end{cases} \tag{4}$$

For the above formula, it means that only neighboring points whose distance metric value is not greater than 1 are considered. This is a simple and commonly used method for calculating proximity. In a membership field belonging to the digital space (Z, β), the concept of fuzzy connectivity expresses the value of the similarity between all points in an image and the seed point. If you need to calculate this value, you must first calculate the relative value. The similarity of neighboring points, if for any binary fuzzy relationship k on Q, it can measure the similarity between two points, and it can be defined as the affinity of fuzzy elements [19]. In practice, the affinity of fuzzy elements is often positively correlated with the similarity between elements. For all (a,b)∈Y×Y, we can define the fuzzy affinity function δk(a One of the calculation formulas of b) is:

$$\delta_k(a,b)=\frac{\delta_\beta(a,b)}{1+k|f(a)-f(b)|} \tag{5}$$

In the above formula, δβ represents the measurement value of the distance between a and b. For this formula, it reflects the similarity of the results mapped by the transformation function f between the two points a and b. One of the simple calculation methods It is based on the similarity of colors [20]. For example, if only the gray value is considered, the value of the function should be the gray value of the point. For two non-adjacent points in the image, there can be many paths that can connect them, each of which is a path. Since there is already a calculation method for the similarity of adjacent points in the image, then The concept of path connectivity can be derived [21]. Let T=(A, f) be a membership field belonging to the digital space (Z, β). In actual situations, there are many paths from point a to point b in T, and let Q denote that point a is the starting point , The path with point b as the end point. For a certain path Q, the value of the path connection degree is defined as the weakest connection among all the sub-paths of the path. In other words, it is the link of all the sub-paths on the path. The minimum value of element affinity, assuming that the path connectivity is represented by δβ, its definition is represented by the function as:

$$\delta_\beta(Q)=\delta_\beta(a,b)=\min(\delta_k(c^1,c^2) \tag{6}$$

For many paths that can connect two non-adjacent points, each has its own path connectivity value [22]. Let Q denote the set of paths with point a as the starting point and point b as the end point, and the fuzzy connectivity is represented by δy, and its definition is represented by a function as:

$$\delta_y(Q)=\max(\delta_\beta(Q) \tag{7}$$

After calculating the fuzzy element affinity, to the path connection, and then to the fuzzy connection, the fuzzy connection value in the whole image can be calculated [23]. The process of finding the following fuzzy subset O is the extraction of fuzzy objects containing o:

$$\delta_o(a)=\begin{cases} f(c) \ if \ \{a\in A, \delta_o(a)\geq n\} \\ 0 \quad otherwise \end{cases} \tag{8}$$

In the calculation process of the whole fuzzy connection theory framework, the preprocessing method, the selection method of seed points, the definition method of fuzzy affinity, and the method of threshold segmentation are the key points, except for the definition of fuzzy affinity. Three points outside the method, here is the definition of fuzzy affinity [24]. K is the input seed point, and the gray value of each pixel on the path is f(K). The gray value of the pixel increases one by one. If we take the proximity function as:

$$\delta\beta(k,c)=\begin{cases} 1 \ if \ \|k-c\|\leq 1 \\ 0 \ otherwise \end{cases} \tag{9}$$

$$\delta_k(k,c)=\frac{\delta_\beta(k,c)}{1+k\left|f(k)-f(c)\right|} \tag{10}$$

The second method is that the cuckoo algorithm is an emerging algorithm in recent years. It borrows the life habits of cuckoo to form a new heuristic algorithm idea. The cuckoo algorithm introduces the lévy flight mode in the search process to search the solution space [25]. This model has been proved that when searching in a limited space, the global optimal solution can be searched for the fastest and most efficiently. In addition, during the experiment, it was found that the initialization process of the search algorithm has a certain impact on the later algorithm execution process. Therefore, the improved cuckoo algorithm based on the initialization strategy introduces a unique initialization strategy to the cuckoo algorithm to maximize the distribution range of bird eggs as uniformly as possible. At the same time, the local search ability of the cuckoo algorithm is improved to make the algorithm converge quickly. Set special termination conditions. The improved cuckoo algorithm is applied to Otsu's multi-level threshold segmentation, and the experimental results show that the improved cuckoo algorithm proposed in this paper can achieve fast and accurate convergence. In the cuckoo algorithm, a random solution is generated by executing equation (11):

$$Y_{O+1,i}=Y_{k,i}+\beta\oplus levy(\lambda) \tag{11}$$

In the formula, Yk,j represent the i-th solution of the kth generation, and β is a step-length control parameter used to control the size of the cuckoo search range, usually taken as 1. Lévy(λ) represents the search path of Lévy's flight. Cuckoo's algorithm generates a new solution through (12):

$$Y_{O+1,i}=Y_{k,i}+\beta\frac{\varsigma\times n}{|v|^{\frac{1}{\lambda}}}(Y_{k,i}-Y_{k,best}) \tag{12}$$

The bird's nest will be discarded according to the probability of discovery. When the discarding is executed, a new bird's nest will be generated, and a new bird's nest position will be generated by formula (13):

$$Y_{O+1,i}=Y_{k,i}+r(Y_{k,j}-Y_{k,e}) \tag{13}$$

Where r is the scaling factor, which is a random number in the interval [0,1], which obeys a uniform distribution, Yk, j and Yk, e represents two random bird nest positions of the kth generation, where:

$$\delta_k(a,b) = \delta_\beta(a,b)\left[\omega_1 p_1(f(a), f(b)) + \omega_2 p_2(f(a), f(b))\right] \tag{14}$$

$$\omega_2 = 1 - \omega_1 \tag{15}$$

Comprehensive formula 11-15 can be obtained:

$$\delta k(a,b) = \delta_\beta(a,b)\left[\frac{p_1{}^2(f(a), f(b)) + p_2{}^2(f(a), f(b))}{p_1(f(a), f(b)) + p_2(f(a), f(b))}\right] \tag{16}$$

It can be obtained from the above formula that the coefficient $\delta k(a,b)$ for measuring the gray value part and the $\delta_\beta(a,b)$ for measuring the gradient value part are dynamically changed according to the magnitude of the value modified by the two, so that the characteristics of the two can be integrated, thereby avoiding the feature of large value A situation occurs where features with small values are masked.

3. Experimental Design of Neutrosophic Fuzzy c-Means Clustering Segmentation Algorithm

3.1. Subjects

In fuzzy theory, neutrosophy theory can not only better express uncertainty problems, but it can also better solve practical engineering application problems. Therefore, we introduce neutrosophy theory into image processing, which is a region-based segmentation algorithm, that is, the application of neutrosophy set theory. It can solve the uncertain information in the image, thereby improving the precision of image segmentation.

3.2. Experimental Method of Neutrosophic Fuzzy c-Means Clustering Segmentation Algorithm

This paper mainly focuses on the research on the neutrosophic fuzzy C-means clustering segmentation algorithm and its application, and the neutrosophy image segmentation algorithm based on LPG&PCA, the improved fuzzy C-means clustering algorithm and the image segmentation technology based on fuzzy clustering algorithm In-depth study of the presence of noise and blur.

3.3. Statistical Processing

All data analysis in this article adopts SPSS22.0, statistical test adopts two-sided test, significance is defined as 0.05, and $p<0.05$ is considered as significant difference. The statistical results are displayed as mean±standard deviation (x±SD). When the test data obeys the normal distribution, the double T test is used for comparison within the group, and the independent sample T test is used for comparison between the groups. If the regular distribution is not sufficient, two independent samples and two related samples will be used for inspection.

4. Experimental Analysis of Neutrosophic Fuzzy c-Means Clustering Segmentation Algorithm

4.1. Neutrosophy Image Segmentation Algorithm Based on LPG&PCA

The neutrosophy image segmentation algorithm of LPG&PCA can not only suppress noise interference, but also effectively restrain the uncertainty information in the image, and can also greatly improve the quality of image segmentation. According to the neutrosophic set theory, the spatial uncertainty information of an image can be quantified, and at the same time, based on this quantified information, the accuracy of image segmentation can be effectively improved. The new algorithm can also remove the noise in the image, which is suitable for segmenting the image with noise. The new algorithm performs new permutations and combinations of uncertain and unreal neutrosophy images. Through algorithm operations, the uncertainty of the information in the picture can be effectively processed, and the quality of picture segmentation can be improved. When the image is affected by noise and the image has uncertain information, use the neutrosophy image segmentation algorithm of LPG&PCA to process the image, and the specific steps to obtain the required part are shown in the following figure 2:

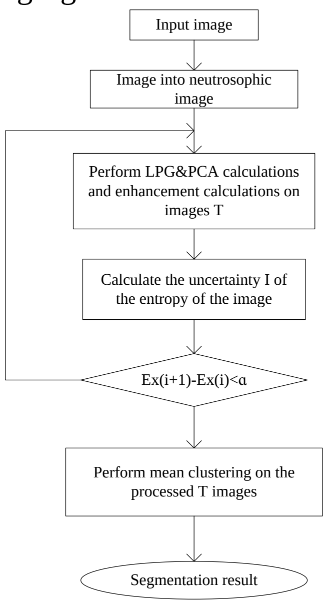

Figure 2. Algorithm flow chart

It can be seen from Figure 2 that the first step of this algorithm is to transform our original pictures into related pictures according to the neutrosophy theory, and then the neutrosophic pictures are calculated and enhanced according to the algorithm. After completing these two steps, we pass the image Perform calculations to obtain the entropy value of the image, and then construct a new pixel set based on various uncertain information in the image, and perform mean cluster analysis on the image. Converting an image into a neutrosophy image is called P, that is, P={A(i,j),B(i,j),C(i,j)}, where.

$$A(\mathrm{i},\, j) = \frac{f(i,\, j) - f_{\min}}{f_{\max} - f_{\min}} \tag{17}$$

$$B(i,j)=\frac{\delta(i,j)-\delta_{\min}}{\delta_{\max}-\delta_{\min}} \tag{18}$$

In the formula, f(i,j) is the gray value of the pixel (i,j), fmax and fmin respectively represent the maximum and minimum values of f(i,j), and δ(i,j) is f(The absolute difference of i, j). Figure 3 shows the edge information of the intellectually transformed image in the noise-free Lena graph.

x Image i Image

Figure 3. Neutrosophy image

It can be seen from Figure 3 that the real image x after neutrosophy image processing has blurred edges and unclear contours, while the processed uncertain image i mainly displays the information of the edge of the image. Then we filter the image, which can effectively eliminate the interference of image noise, which will provide us with high convenience for subsequent image segmentation. The main process of the filtering algorithm is to establish a model diagram, as shown in Figure 4, in the j×j window, a vector is established as m={m1...mx}t, noise mv=m+v, Then the noise vector is expressed as mv={m1v...mxv}t, and finally the PCA algorithm is used to filter and denoise.

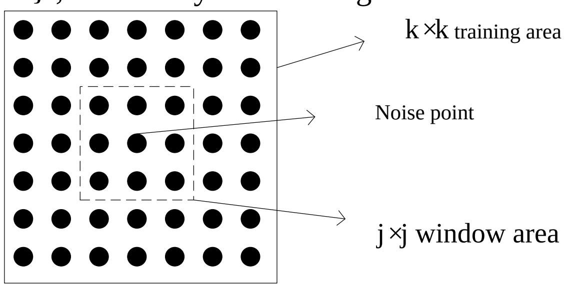

Figure 4. LPG&PCA filter model

It can be seen from Figure 4 that the principle of the LPG&PCA filtering model is: the noise image is expressed as mv=m+v, mv represents the noise image of m×n, m represents the original image, and v represents the noise. Only perform related operations on the x image, and the operation formula is:

$$T(a)=\begin{cases} T & B(i,j)\pi a \\ Ta & B(i,j)\geq a \end{cases} \tag{19}$$

The experimental results obtained by the calculation are shown in the figure 5 below:

Figure 5. Noisy image and LPG&PCA filtered image

It can be seen from Figure 5 that the processed image noise points are effectively eliminated, and uncertain fuzzy pixels become more uniform. In this calculation, the value of our parameter a is 0.83. After the algorithm is processed, the entropy of the uncertainty B(i,j) is reduced, and a uniform and noise-free picture can be obtained.

4.2. Improvement of Fuzzy c-Means Clustering Algorithm

Aiming at the problem of traditional FCM algorithm in clustering, this paper has derived a clustering category method based on particle swarm principle. This method mainly adopts density function for initial set classification. The specific operation step is to add the idea of particle swarms to the algorithm, analyze the clustering from the aspect of information granularity in the clustering process, and use the coupling degree and the separation degree to determine the validity of the clustering results. Analysis, and finally get the ideal clustering result. At present, in the process of image segmentation of large data sets, a large number of pixels will inevitably be generated. If certain operations need to be performed on these pixels, how to store these points is a problem that needs to be solved. At the same time, the traditional Euclidean When calculating multiple data, multiple intermediate values will be generated. The general storage method is inconvenient and error-prone. Based on the above factors, this article proposes an improved matrix based on the distance matrix. We can call this matrix a new distance matrix, because distance is an important parameter associated with each element in the cluster set, and it is also a measure of the importance of elements. standard. Let e(x,y) be the distance between pixels x and y, the following conditions need to be met:

$$\mathrm{e}(x,y)=0 \tag{20}$$

If and only if x=y :

$$\mathrm{e}(x,y)=e(y,x) \tag{21}$$

$$\mathrm{e}(x,y)+e(y,x)\geq e(x,z)=e(y,x) \tag{22}$$

The traditional distance matrix is a matrix composed of a set of distances between two points. The concept of distance matrix and adjacency matrix is similar, the difference is that the adjacency matrix only contains whether the elements are connected to each other, and does not contain the distance information between the elements. As shown in Figure 6:

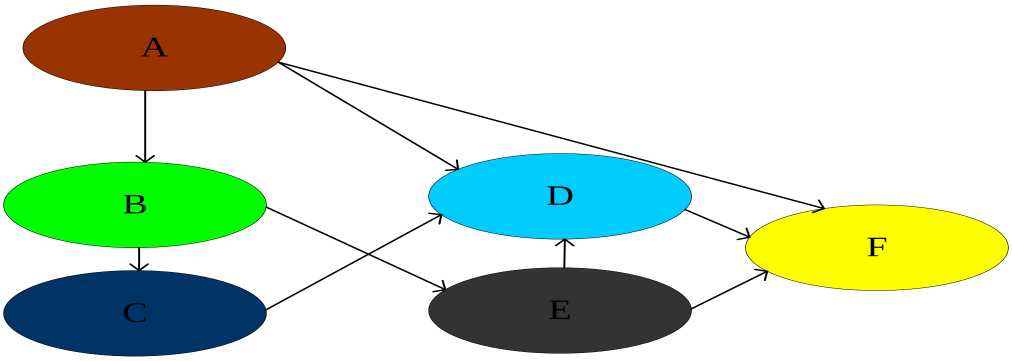

Figure 6. Schematic diagram of the location of objects in the collection

It can be seen from Figure 6 that the set m={A,B,C,D,E,F} contains six points. If the Euclidean metric between the pixels where the points are located is taken as the distance metric, point B and C The distance between the points is 48, and the distance between point D and point F, and point E and point F are equal, which is 95. The distance matrix formed by the points in the object set is as follows:

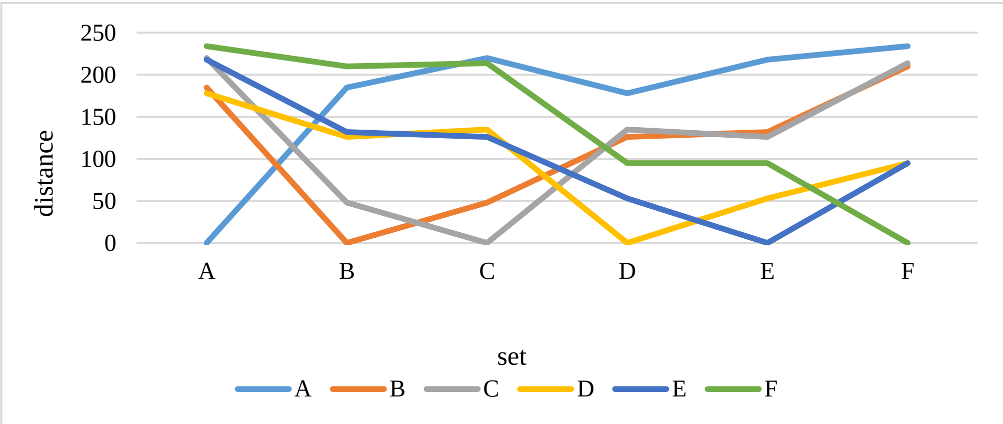

Figure 7. The distance matrix corresponding to set A

It can be seen from Figure 7 that in the new distance matrix, the distance between the elements is represented by a specific value, which can make the distance between the elements (including the distance between the element and itself) clear at a glance, and it is convenient to store and not easy to make mistakes. Due to the need for a large number of calculations, the generated distance matrix is prone to considered calculation errors. However, compared with the traditional Euclidean calculation method, the error generated by using the distance matrix to store the result is already very small compared with the former, so this part of the error is acceptable for the new matrix clustering. The FCM clustering algorithm based on the midpoint density function is divided into two steps in clustering. The first step is to determine the original initial center and the number of clusters, which are mainly determined by the combination of cluster function density method and midpoint method. The second step is to perform clustering processing based on the results obtained in the first step. The algorithm steps are as follows:

(1) Set the sample set as m={m1, m2,...mn}, set the fuzzy coefficient m=3, the iterative stop threshold §, θ=0.7, and the counter N=0.

(2) Determine all cluster center sets and cluster category number sets by using cluster density function method and midpoint method.

(3) Update the fuzzy clustering center v, and the membership matrix t,

(4) Perform cluster validity judgment on all clusters that meet the iterative condition, and calculate the validity criterion function E

(5) Choose the membership matrix corresponding to E as the best clustering result U, and the corresponding number of clusters c is the final number of clusters.

The original FCM algorithm clustering results and the improved FCM algorithm are used to cluster the data set. The results of multiple iteration calculations are shown in Table 1 and Table 2:

Table 1. Original FCM algorithm clustering results

Algorithm name	Number of cluster categories	Original indicator function value	Average number of iterations	Average accuracy
Original FCM algorithm	3	0.8782	31	74%
	4	0.7615	36	
	5	0.9425	31	
	6	0.8645	30	
	7	0.8531	34	
	8	1.0015	37	
	9	0.9542	40	

Table 2. Improved FCM algorithm clustering results

Algorithm name	Number of cluster categories	Original indicator function value	Average number of iterations	Average accuracy
Original FCM algorithm	3	0.5003	19	87%
	4	0.5346	20	
	5	0.5142	23	
	6	0.6432	26	
	7	0.4751	18	
	8	0.4156	22	
	9	0.7124	21	

It can be seen from Table 1 and Table 2 that when the algorithm is at the lowest index function, the value of the original FCM algorithm is 0.8531, the value of the improved algorithm is 0.4751, and the categories of the original FCM algorithm and the improved algorithm are both 7, indicating that the improved algorithm The algorithm in the lowest exponential function can be the same as the original FCM algorithm to get the correct clustering category. From the table, we can also know that the performance of the new algorithm is greatly improved compared to the traditional FCM algorithm. This is because the number of iterations of the new algorithm is less than that of the traditional algorithm. One of the main reasons for the improved performance of the improved algorithm is that it is at the beginning. The midpoint method is used to select the original initial clustering center, and the decrease in the number of iterations of the algorithm indicates the improvement of the performance of the algorithm. Moreover, because the improved algorithm has greatly improved the accuracy of clustering, because the new algorithm judges the clustering category of the data through the effective criterion function, so as to obtain more reasonable and accurate clustering results. Table 3 shows the experimental results of the new improved FCM algorithm in the 8 category subsets of the data set, and the corresponding improvement index function values when the number of cluster categories are different are shown in the following table.

Table 3. Index function value of improved FCM algorithm clustering

Number of cluster categories	Improve indicator function value	Number of cluster categories	Improve indicator function value
3	0.8765	8	0.6348
4	0.8641	9	0.5613
5	0.8253	10	0.6172
6	0.7521	11	0.7214
7	0.8462	12	0.7183

It can be seen from Table 3 that when the number of categories is 9, the improvement index function value is the smallest, which is 0.5613. From the comparison experiment of the above two algorithms and the verification experiment of the new algorithm, it can be obtained that the improved algorithm in this paper has a better clustering effect than the comparative algorithm in terms of clustering.

4.3. Application of Image Segmentation Based on Fuzzy Clustering Algorithm

We have introduced the advantages of the improved FCM algorithm before, and the improved algorithm can segment the image by calibrating and clustering image pixels, and then realize the image segmentation in turn. The objective function of the fast FCM algorithm based on gray-scale histogram is defined as follows:

$$W_m(n,v) = \sum_{t=0}^{v}\sum_{i=1}^{n} e_{\mathrm{mi}}(d_i)^2 h(j) \tag{23}$$

The large difference in the gray distribution of pixels is a problem in many images, especially those used in the medical field. Due to the complexity and volume effect of the pictures, the pictures usually have high noise, messy gray distribution, and discontinuous target boundaries, etc. And other issues. We can define any part of the image as the domain value N, and the domain value gray difference measure as A, and then compare the average gray levels of the pixels of the picture, that is

$$A = |x - y|, 1 \in N \tag{24}$$

$$y = \frac{1}{n}\sum_{i \in N} \mathrm{x} \tag{25}$$

On this basis, define the influence factor m of the neighborhood pixels, and compare the A of each neighborhood point with the current neighborhood, namely:

$$M = \left|A_1 - A\right| 1 \in N \tag{26}$$

If the M value is large, the gray calculation influence of the corresponding point is reduced. If the M value is small, the related influence is increased, and the influence weight of the threshold pixel can be controlled by an exponential function. The specific formula is as follows:

$$W = \exp(-M) = \exp\left|A_1 - A\right| \tag{27}$$

Where W is the weight of the neighboring pixel l relative to the center pixel i. To obtain the final linear weighted sum image, in order to compare the algorithm in this paper with the fuzzy C-means clustering algorithm, the experiment uses different algorithms to perform segmentation experiments on the image respectively given the same initial membership matrix. The experimental parameters are set as follows: the number of categories c is 10, the group size N is 20, the inertia weight is linearly reduced from w=0.9 to w=0.5, the learning factors c1 and c 2 are both 2, the maximum number of iterations is 1000, and the fuzzy index [42]m=2, the maximum length L=20. The experimental results are shown in the figure. Figure 8 is the comparison of the segmentation results of the standard cameraman image and the fuzzy C-means clustering algorithm based on gray histogram. Figure 9 is the standard lena image and the comparison of the fuzzy C-means clustering algorithm based on the gray histogram. Comparison of segmentation results.

Standard cameraman image — Segmentation of the resulting image based on gray histogram

Figure 8. Comparison of segmentation results of standard lena image and histogram

Standard lena image — Segmentation of the resulting image based on gray histogram

Figure 9. Is a comparison of the standard lena image and the segmentation result of the fuzzy C-means clustering algorithm based on gray histogram

It can be seen from Figure 8 and Figure 9 that the algorithm maintains the structural details in the image when segmenting the real image. The visual quality of each segmentation result image is relatively good, and it is relatively close to the original image. Both have achieved a relatively ideal segmentation effect. Therefore, the algorithm in this chapter can effectively achieve the segmentation of real images, and under the same initialization conditions, for images with similar gray levels of the target and background, the segmentation results of the fuzzy C-means clustering algorithm based on gray histograms Generally, the algorithm in this article is better than the traditional FCM image segmentation algorithm.

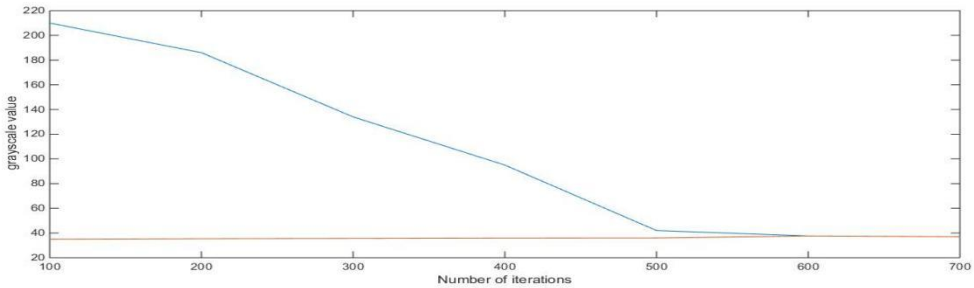

Figure 10. Convergence speed of image segmentation algorithm based on FCM

It can be seen from Figure 10 that by integrating the gray information and spatial information of the image into the fuzzy C-means clustering algorithm, we can find that the new image segmentation algorithm has a fast convergence speed, and at the same time for the segmentation of the new fuzzy C-means clustering algorithm The effect has also been greatly improved compared with the previous ones. In general, the algorithm performance of the improved algorithm proposed in this paper has been greatly improved.

5. Conclusion

Neutrosophic image segmentation algorithm can not only suppress noise interference, but also effectively restrain the uncertainty information in the image, and can also greatly improve the quality of image segmentation. According to the neutrosophic set theory, the spatial uncertainty information of an image can be quantified, and based on this quantified information, the accuracy of image segmentation can be effectively improved. By improving the FMC algorithm, in the process of image segmentation of large data sets, a large number of pixels can be avoided. If certain operations need to be performed on these pixels, the problem of storing these points is solved and it is not easy to make mistakes. By integrating the gray information and spatial information of the image into the fuzzy C-means clustering algorithm, we can find that the new image segmentation algorithm has a fast convergence speed, and the algorithm maintains the structural details in the image when segmenting the real image. The visual quality of each segmentation result image is relatively good, and is relatively close to the original image, and the algorithm has achieved a relatively ideal segmentation effect for each real image.

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Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

References

[1]Nongmeikapam K , Kumar W K , Singh A D . Fast and Automatically Adjustable GRBF Kernel Based Fuzzy C-Means for Cluster-wise Coloured Feature Extraction and Segmentation of MR Images. Iet Image Processing, 2018, 12(4):513-524. https://doi.org/10.1049/iet-ipr.2017.1102

[2] Chetih N , Messali Z , Serir A , et al. Robust fuzzy c-means clustering algorithm using non-parametric Bayesian estimation in wavelet transform domain for noisy MR brain image segmentation. IET Image Processing, 2017, 12(5):652-660. https://doi.org/10.1049/iet-ipr.2017.0399

[3] Yan W , Yang G . A New Brain Magnetic Resonance Imaging Segmentation Algorithm Based on Subtractive Clustering and Fuzzy C-Means Clustering. Journal of Medical Imaging and Health Informatics, 2018, 8(3):602-608. https://doi.org/10.1166/jmihi.2018.2309

[4] Namburu A , Samayamantula S K , Edara S R . Generalised rough intuitionistic fuzzy c-means for magnetic resonance brain image segmentation. Iet Image Processing, 2017, 11(9):777-785. https://doi.org/10.1049/iet-ipr.2016.0891

[5] Wang C , Pedrycz W , J Yang, et al. Wavelet Frame-Based Fuzzy C-Means Clustering for Segmenting Images on Graphs. IEEE Transactions on Cybernetics, 2019, 50(9):3938–3949.

[6]Alsmadi, Mutasem K . A hybrid Fuzzy C-Means and Neutrosophic for jaw lesions segmentation. Ain Shams Engineering Journal, 2018, 9(4):697-706. https://doi.org/10.1016/j.asej.2016.03.016

[7]D Mújica-Vargas, Kinani J , Rubio J . Color-Based Image Segmentation by Means of a Robust Intuitionistic Fuzzy C-means Algorithm. International Journal of Fuzzy Systems, 2020, 22(3):901-916. https://doi.org/10.1007/s40815-020-00824-x

[8] Hua Z , Wang Q , Shi W , et al. A Novel Adaptive Fuzzy Local Information C-Means Clustering Algorithm for Remotely Sensed Imagery Classification. IEEE Transactions on Geoscience & Remote Sensing, 2017, 31(9):1-12.

[9] Yu W , Jing C , Gao W , et al. Particle Seed Images Segmentation Method Based on the Improved Fuzzy C-means Clustering Algorithm. Zhongbei Daxue Xuebao (Ziran Kexue Ban)/Journal of North University of China (Natural Science Edition), 2018, 39(2):177-182.

[10] Jiang Y , Zhao K , Xia K , et al. A Novel Distributed Multitask Fuzzy Clustering Algorithm for Automatic MR Brain Image Segmentation. Journal of Medical Systems, 2019, 43(5):65-69 https://doi.org/10.1007/s10916-019-1245-1

[11] Xu G , Zhou J , Dong J , et al. Multivariate morphological reconstruction based fuzzy clustering with a weighting multi-channel guided image filter for color image segmentation. International Journal of Machine Learning and Cybernetics, 2020, 11(3):23-28. https://doi.org/10.1007/s13042-020-01151-1

[12] Wu C , X Yang. Robust credibilistic intuitionistic fuzzy clustering for image segmentation. Soft Computing, 2020, 24(3):86-89.

[13] Singh M , Vishal V , Verma A , et al. Segmentation of MRI data using multi-objective antlion based improved fuzzy c-means. Biocybernetics and Biomedical Engineering, 2020, 40(3):123-126. https://doi.org/10.1016/j.bbe.2020.07.001
[14] Zhang X , Pan W , Wu Z , et al. Robust Image Segmentation Using Fuzzy C-Means Clustering With Spatial Information Based on Total Generalized Variation. IEEE Access, 2020, 16(99):1-10.
[15] Memon K H , Lee D H . Generalised fuzzy c-means clustering algorithm with local information. Fuzzy Sets & Systems, 2018, 11(1):1-12. https://doi.org/10.1049/iet-ipr.2016.0282
[16] Zeng P . Advanced MRI Image Segmentation using Fuzzy-C Means Clustering approach. Advances in computational sciences and technology, 2018, 11(12):1049-1058.
[17] Lei X , Ouyang H , Xu L . Kernel-Distance-Based Intuitionistic Fuzzy c-Means Clustering Algorithm and Its Application. Pattern Recognition and Image Analysis, 2019, 29(4):592-597.
[18] Le H S , Tuan T M . Dental segmentation from X-ray images using semi-supervised fuzzy clustering with spatial constraints. Engineering Applications of Artificial Intelligence, 2017, 59(34):186-195.
[19] Dhanachandra N , Chanu Y J . An image segmentation approach based on fuzzy c-means and dynamic particle swarm optimization algorithm. Multimedia Tools and Applications, 2020, 79(3):65-68. https://doi.org/10.1007/s11042-020-08699-8
[20] Zhang Y , Ye S , Ding W . Based on rough set and fuzzy clustering of MRI brain segmentation. International Journal of Biomathematics, 2017, 10(02):175-179.
[21]D Chen, Jin C , Cao Y , et al. Segmentation and Classification of Brain Anatomy in Magnetic Resonance Images Based on Fuzzy C-Means Clustering Algorithm. Journal of Medical Imaging and Health Informatics, 2017, 7(4):844-849. https://doi.org/10.1166/jmihi.2017.2090
[22] MekhmoukH A , Mokrani K . MR Brain Image Segmentation Using an Improved Kernel Fuzzy Local Information C-Means Based Wavelet, Particle Swarm Optimization (PSO) Initialization and Outlier Rejection with Level Set Methods. The international arab journal of information technology, 2018, 15(4):683-692.
[23] Chowdhary C L , Acharjya D P . Clustering Algorithm in Possibilistic Exponential Fuzzy C-Mean Segmenting Medical Images. Journal of Biomimetics, Biomaterials and Biomedical Engineering, 2017, 30(15):12-23.
[24] Gamino-Sanchez , Hernandez-Gutierrez I V , Rosales-Silva A J , et al. Block-Matching Fuzzy C-Means (BMFCM) clustering algorithm for segmentation of color images degraded with AWGN. Engineering Applications of Artificial Intelligence, 2018, 73(8):31-49. https://doi.org/10.1016/j.engappai.2018.04.026
[25] Shang R , Chen C , Wang G , et al. A thumbnail-based hierarchical fuzzy clustering algorithm for SAR image segmentation. Signal Processing, 2020, 17(1):107-112. https://doi.org/10.1016/j.sigpro.2020.107518