Ant Colony Clustering Algorithm and Improved Markov Random Fusion Algorithm in Image Segmentation of Brain Images

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Abstract: *New medical imaging technology, such as Computed Tomography and Magnetic Resonance Imaging (MRI), has been widely used in all aspects of medical diagnosis. The purpose of these imaging techniques is to obtain various qualitative and quantitative data of the patient comprehensively and accurately, and provide correct digital information for diagnosis, treatment planning and evaluation after surgery. MR has a good imaging diagnostic advantage for brain diseases. However, as the requirements of the brain image definition and quantitative analysis are always increasing, it is necessary to have better segmentation of MR brain images. The FCM (Fuzzy C-means) algorithm is widely applied in image segmentation, but it has some shortcomings, such as long computation time and poor anti-noise capability. In this paper, firstly, the Ant Colony algorithm is used to determine the cluster centers and the number of FCM algorithm so as to improve its running speed. Then an improved Markov random field model is used to improve the algorithm, so that its anti-noise ability can be improved. Experimental results show that the algorithm put forward in this paper has obvious advantages in image segmentation speed and segmentation effect.*

Keywords: *Brain image, FCM algorithm, Markov random field, Ant Colony algorithm.*

Introduction

With the advantages of soft tissue contrast and high signal-to-noise ratio [3], MRI (magnetic resonance imaging) can provide high resolution data. Medical image segmentation is an important foundation and key step in medical image processing technology, and it plays an important role in medical diagnosis. Han et al. have a more in-depth study of medical image [9]. In particular, Han and Li focus on the field of medical image watermarking [8]. Petkov et al. put forward using neural network for medical image modeling [16]. Hossain has studied the medical image of X-ray [10]. For brain diseases such as tumors, water, etc., MR has irreplaceable advantages. The method of using wavelet to enhance MR image is proposed by Luo [14]. In the segmentation of medical images, the research of brain MR image segmentation is more representative and has clinical practical value. Since the birth of medical imaging, an increasing number of image segmentation algorithms have entered into the field of medical imaging. The threshold algorithm was first proposed by Doyle in 1962 [4]. It generally uses the gray histogram of the image to determine the segmentation threshold and then uses the threshold to divide the image into several regions so as to complete the segmentation. In 1973, Dunn [6] proposed a fuzzy C-means (FCM) clustering algorithm, and it was improved by Bezdek [2] in 1981. The algorithm uses the iterative optimization objective function to obtain the fuzzy partition of a data set, which has a good convergence [1]. The image segmentation algorithm, which is based on Markov random field (MRF) [13], is also one of the prevailing research topics worldwide. It uses the spatial correlation of pixels to segment the image, which can accurately describe the dependence between the category of each pixel and the surrounding pixels. Zhang proposed a new segmentation algorithm for fingerprint image [18]. Proposed by Dorigo in 1991, the ant colony algorithm is widely used in medical image segmentation because of its excellent clustering characteristics [12].

On the basis of analyzing the research results of human brain MRI image segmentation at worldwide for many years, this paper has made in-depth research on the human brain image segmentation algorithm. The algorithm in this paper combines the fuzzy *C*-clustering algorithm with the ant colony algorithm, MRF and other algorithms to solve the problems in MR imaging of the human brain. Experiments show that this algorithm has a good segmentation effect, fast running rate and robustness. Fig. 1 expresses the function of image segmentation in image engineering.

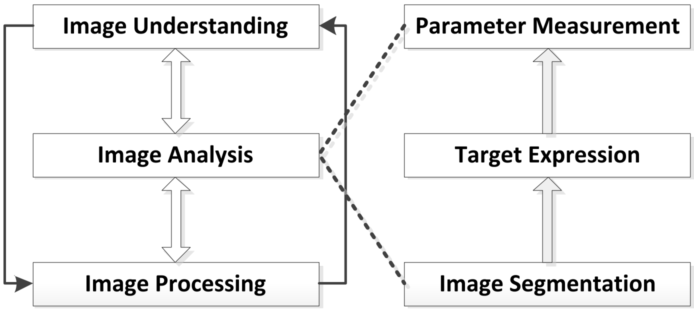

Fig. 1 The role of image segmentation in image science

Materials and methods

Characteristics of brain MR image segmentation and FCM clustering algorithm

Characteristics of brain MR image segmentation

In addition to the basic features of MRI imaging, brain MR images also have some special properties, such as no texture, less tissue types, gray value of pixels in each organization in a small range, and large contrast between different groups. These advantages have made MRI one of the best methods in the diagnosis of brain disease. Brain MR routine scans are plane axial, plane sagittal, and plane coronal.

Accurate MR image segmentation is a prerequisite to 3D visualization, surgical planning, early detection and pathological quantitative morphology. Brain MRI segmentation segments the white matter, gray matter and CSF in brain tissue structure, and also extracts some special tissues in the grey matter, such as the caudate nucleus and lenticular nucleus. Since many mental illnesses (such as mental retardation, senile dementia, etc.) are related to these assemblies accurately extracting different brain tissues from the brain MRI is particularly important.

FCM (Fuzzy C-means) clustering algorithm

Clustering refers to the distinction and clarification of a sample set without a class label. Clustering analysis is an important method of data partition and grouping processing. The operation aims to divide vectors without labels into several subsets according to some criteria of similarity, so that each subset can represent some characteristics and properties of the whole sample set. In reference [5], some clustering criteria are summarized, such as error square sum criterion, the minimum variance criterion and scatter criterion. The error square sum criterion is the simplest and most widely used criterion in cluster analysis. Clustering methods can be divided into many kinds. The existing clustering algorithm can be divided into two categories: the hierarchical clustering algorithm and the objective function clustering algorithm [11]. Among them, FCM the clustering algorithm is a typical representative of the objective function clustering algorithms. Fig. 2 expresses the process of clustering.

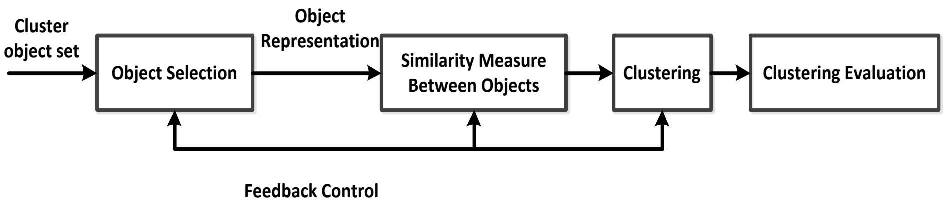

Fig. 2 The process of clustering

The FCM algorithm is carried out through the iterative optimization of the objective function and fuzzy clustering to the data samples. It previously sets the category number of samples, initial cluster center and initial membership matrix. In the process of iterative optimization, the cluster centers and membership matrix are constantly updated, until the objective function reaches the minimum value. The classification result is represented by a fuzzy membership matrix $U = \{u_{ij}\} \in R_{cN}$. In order to extend this algorithm to the practical value, Dunn squared weights the distance between each sample to the cluster [6]. Therefore, the FCM algorithm used for image segmentation iteratively optimizes the objective function according to the pixels in an image and the weighted membership of each center in the C cluster centers. FCM's clustering objective function is:

$$J_m(U, V) = \sum_{k=1}^{n} \sum_{i=1}^{C} U_{ik}^{m} \left(\left\| X_k - V_i \right\| \right)^2 , \tag{1}$$

where, $X = \{x_1, x_2, x_3, ..., x_n\}$ are the data sets; C is the class number of clustering and $2 \le C < n$; m is the fuzzy weighting exponent and $1 \le m < \infty$; $V = \{v_i\}$ is the set of cluster centers.

The criterion of fuzzy clustering is to obtain the minimum of $J(U, V)$.

The matrix column vectors are independent of each other, and then the following result can be obtained:

$$\min J\ (U, V) = \min \left\{ \sum_{k=1}^{n} \sum_{i=1}^{C} U_{ik}^{m} d_{ik}^{2})^2 \right\} = \sum_{k=1}^{n} \min \left\{ \sum_{i=1}^{C} U_{ik}^{m} d_{ik}^{2} \right\} \tag{2}$$

The condition for the above formula is $\sum_{j=1}^{c} \mu_{ij} = 1$, and by using the Lagrange multiplier method, the results can be obtained as follows:

$$F = \sum_{i=1}^{c} (\mu_{ik})^m d_{ik}{}^2 + \lambda (\sum_{i=1}^{c} \mu_{ik} - 1) \tag{3}$$

Through the first order derivative of the original function, the necessary condition for obtaining the minimum of $J(U, V)$ is as follows:

$$\mu_{ik} = 1 / \sum_{j=1}^{c} [d_{ik} / d_{jk}]^{\frac{2}{m-1}}, \tag{4}$$

$$v_j = \sum_{k=1}^{m} (\mu_{ik})^m x_k / \sum_{k=1}^{n} (\mu_{ik})^m, \ j = 1, 2, ..., c. \tag{5}$$

The algorithm steps of FCM are as follows:

1. Collect and count data sample set x, and then set the initial category number C, the iteration stop threshold ε, the weighting exponent m, the iteration counter $t = 0$.
2. Initial cluster center $V' = \{v_1', v_2', ..., v_c'\}$ and initial membership matrix takes random values.
3. Calculate the distance between each sample point and C initial centers $V' = \{v_1', v_2', ..., v_c'\}$, and then obtain the initial objective function value and the new membership matrix.
4. Calculate the new cluster center and the objective function value, and finally arrive at a new membership matrix through Eq. (5), and make $t = t + 1$.
5. Check whether the result meets the threshold. If yes, output the membership matrix U and exit the operation; otherwise repeat the previous step.

The FCM algorithm is a simple and efficient unsupervised clustering algorithm. When the initial condition is given, it always converges effectively. Actually, the human brain MR image is fuzzy and its boundaries are not clear. Using the FCM clustering algorithm can describe this fuzziness well, but the traditional FCM algorithm also has two obvious disadvantages in noise image segmentation. One is that the FCM algorithm does not use the spatial information of the image, which makes it sensitive to image noise and image degradation. The other disadvantage is the problem of its low speed, which hinders its application in image processing.

Markov random field and Ant Colony algorithm

The definition of MRF

As a branch of probability theory, Markov Random Field (MRF) describes the characteristics of a group of physical entities which interact and are dependent on each other. In 1984, the Gibs distribution was introduced into the Markov random field theory in [17], thus propelling the research on MRF into a period of rapid development. MRF constructs priori models through analyzing the priori information of the image, using uncertainty to describe the local correlation of the image, and ultimately achieves the image analysis. Therefore, MRF has an unparalleled advantage in image analysis, especially in image segmentation.

In MRF, there are several important concepts, such as the neighborhood system and clusters, the Markov random field and the Gibbs random field (GRF). The Markov random field can well describes the local qualities of the neighboring pixels, while the Gibbs random field can describe their global qualities. The Hammersley-Clifford theorem [7] establishes the equivalence between these two random fields. The content of the Hammersley-Clifford theorem states that given the space location set S has a neighborhood system N, if the random field X in S is a GRF, then it is also a MRF.

The combination of MRF and GRF makes it possible to express random fields' joint probability, and it provides a priori probability based on the cluster function $V_c(x)$ for image segmentation. This combination considers the local and global properties of images, and therefore, has a great research value.

Basic theory of Ant Colony algorithm

Studies show that ants rely on the information that they secrete on their crawling path to identify the path. When choosing a path, ants will give priority to the path of high concentration according to the pheromone concentration of each path. That is because pheromone will gradually evaporate over time, and their intensity will weaken.

Supposing *m* is the number of ants in the ant colony, d_{ij} is the distance between the city *i* and the city *j*; $b_i(t)$ is the number of ants in the city *i* at the time *t*; τ_{ij} is the number of pheromone left on the path, and the amount of residue on the path to leave the ants in the path of the pheromone quantity; $\Delta\tau_{ij}^k$ is the number of pheromone left on the path by the ant *k*, ρ $(\rho \in (0, 1))$ is the degree of volatilization of residual pheromone in unit time; η_{ij} is the heuristic information of the path (i, j), and generally $\eta_{ij} = 1/d_{ij}$; α represents pheromone weights; β represents the heuristic information weights; tabu list $tabu_k$ is used to record the city of ants, $allowed_k$ is the city position that ant *k* can select at the next step; L_k is the walking distance of ant *k*, p_{ij}^k is the selection probability of ant *k* from position *i* to position *j*.

$$p_{ij}^k(t) = \begin{cases} \dfrac{[\tau_{ij}(t)]^\alpha[\eta_{ij}(t)]^\beta}{\sum\limits_{s \in allowed_k}[\tau_{is}(t)]^\alpha[\eta_{is}(t)]^\beta}, \ j \in allowed_k \\ 0, \ j \notin allowed_k \end{cases}. \tag{6}$$

If the ants complete a traversal, that is, the ants find a loop to traverse all the cities, the pheromone on each path will be updated according to the next formula:

$$\tau_{ij}(t+n) = (1-\rho)\tau_{ij}(t) + \Delta\tau_{ij}, \Delta\tau_{ij} = \sum_{k=1}^{m}\Delta\tau_{ij}^k. \tag{7}$$

The global and discrete characteristics of the ant colony algorithm are very suitable for the discrete digital images. The path selection method which is based on probability has a broad application prospect in fuzzy clustering problems.

The image segmentation algorithm based on ant colony algorithm and improved MRF

Although the FCM algorithm is quite simple, efficient and has many applications in medical imaging, it still has a variety of problems; e.g., the long computation time and being sensitive to noise. This paper presents the integration algorithm by combining the FCM algorithm, ant colony algorithm, and MRF, which not only has a good segmentation effect and high robustness, but also solves the problems encountered in the operation of each algorithm separately.

Use of Ant Colony algorithm to improve FCM algorithm

This paper makes use of the global features and robustness of ant colony algorithm. First, the initial clustering center is determined as well as the clustering number of the magnetic resonance images, and then the obtained results are used as the initial cluster center and the cluster number of the FCM clustering algorithm. Through combining with ant colony algorithm, the problem of the FCM algorithm's running time being too long can be overcome. The specific algorithm process is as follows:

(1) Firstly, randomly select M representative points, and set the initial parameters.

(2) Calculate the distance d_{ij} between each pixel, $d_{ij} = \|P(X_i - X_j)\|_2$.

(3) Calculate the concentration of pheromone $\tau_{ij}(t)$ on each path:

$$\tau_{ij}(t) = \begin{cases} 1, & d_{ij} \le r \\ 0, & d_{ij} > r \end{cases}. \tag{8}$$

(4) Count the probability $p_{ij}(t)$ that pixel X_i is merged into the neighborhood of X_j:

$$p_{ij}(t) = \frac{[\tau_{ij}(t)]^{\alpha}[\eta_{ij}(t)]^{\beta}}{\sum_{s=1}^{j}[\tau_{sj}(t)]^{\alpha}[\eta_{sj}(t)]^{\beta}}. \tag{9}$$

If $p_{ij}(t)$ is larger than the threshold value P_0, then the pixel X_i will be merged into the neighborhood of X_j.

(5) Count the cluster centers according to the formula $O_j = \frac{1}{J}\sum_{k=1}^{J} X_k$.

(6) Calculate the total error $\varepsilon = \sum_{j=1}^{k} D_j$, where D_j is the deviation error of the cluster *j*. If $\varepsilon \le \varepsilon_0$, then output the cluster center v_j and *C*, the number of clusters.

Through the combination of the ant colony algorithm and FCM, this paper solves the problem that FCM clustering algorithm tended to select the local optimum when randomly searching the cluster centers. Meanwhile, it improves the quality of image segmentation and the convergence rate of the algorithm through inserting the initial cluster centers and the number of clusters searched by the ant colony algorithm into the FCM clustering algorithm.

The improved MRF

The traditional MRF considers the relationship between spaces. However, the traditional segmentation algorithm, based on MRF and bias theory, still has some shortcomings. It is sensitive to noise and its anti-noise capability is not very strong. Hence, the traditional MRF segmentation often cannot achieve the expected results. The traditional MRF model potential function, such as the *Ising* model potential function, only considers the relationship between the label field location and its neighborhood. Nevertheless, the observation field of medical images is a Markov random field, which contains rich information, including the gray values and distance of pixels. In the traditional potential function, this information is neglected. So, by using the information in the observation field, a new potential function is proposed. And by adding the gray information and the distance information of the observation field to the potential function, the expression of the two point potential is obtained as follows:

$$c(x_s, x_t) = \begin{cases} \beta \quad , & x_s = x_t \\ \dfrac{\sigma_s^2}{\left(\sigma_s^2 + (y_s - y_t)^2 d_{st}\right)} \beta, & x_s \neq x_t \end{cases}. \tag{10}$$

The fusion algorithm

In this paper, after combined with the ant colony algorithm, the FCM algorithm is joined with the improved MRF to obtain a new fusion algorithm. This new algorithm has a high efficiency and a good segmentation effect. By using the neighborhood relation property described by MRF, the constraint information of priori spaces is introduced to establish a new clustering objective function, which contains the gray level information and spatial information. Then the concept of the degree of rejection is proposed.

The neighborhood $N(i, j)$ of the point (i, j) is defined as follows: if the priori probability of a label on the point (i, j) is $p(i, j)$, $1-r(i, j)$ will be the rejection degree of the neighborhood $N(i, j)$ to the label. The concept of neighborhood and the prior probability is provided by MRF, so the rejection degree contains the spatial position information. Based on this, the new objective function of the improved FCM algorithm is as follows:

$$J = \sum_{ij} \sum_{k=1}^{c} \mu_k(i, j)(1 - P_k(i, j)) \left\| y(i, j) - v_k \right\|^2, \tag{11}$$

where $P_k(i, j)$ is the prior probability of labelling pixel (i, j) as the class k in the function of neighborhood $N(i, j)$; $(1 - P_k(i, j)$ is the corresponding rejection degree. With MRF introduced in this paper, the updating process of the membership matrix and the cluster center can be expressed by the following formula:

$$\mu_k(i, j) = \frac{\left(\left\| y(i, j) - v_k \right\|^2 \left(1 - P_k(i, j)\right)\right)}{\sum_{l=1}^{c} \left(\left\| y(i, j) - v_l \right\|^2 \left(1 - P_k(i, j)\right)\right)}, \tag{12}$$

$$V_{k=} \frac{\sum_{ij} \mu_k \left(i, j\right)^2 \left(1 - P_k\left(i, j\right)\right) y\left(i, j\right)}{\sum_{ij} \mu_k \left(i, j\right)^2 \left(1 - P_k\left(i, j\right)\right)}. \tag{13}$$

The steps of the improved algorithm can be expressed as follows:

(1) Determine the number of categories, set the iteration stop value $\varepsilon > 0$, and make the iteration $t = 0$.

(2) Obtain the initial classification result by running *k*-means [15].

(3) Combine with the ant colony algorithm, and calculate the initial cluster center and membership matrix.

(4) According to the above results, calculate the prior probability of each point belonging to different categories in the images.

(5) Calculate the updating cluster centers and membership matrix according to the improved MRF.

(6) According to the membership matrix and the principle of the maximum membership degree, the soft segmentation results are transformed into hard segmentation results.

(7) Judge whether the algorithm is convergent or achieves the maximum iteration, output the segmentation results, and the algorithm ends.

Results and discussion

In order to test the validity of the improved algorithm in this paper, we have conducted many experiments by using many actual medical images. Experiments show that this algorithm can effectively remove the noise, improve the segmentation rate, and therefore, achieve excellent segmentation results. The hardware of the experimental platform we use is Intel (R) Core (TM) @2.60GHz i5-4300M, 4GB memory, and the software is Windows 7 with MATLAB as the design language.

We collected two brain MR images as the experimental samples. Fig. 3 below shows the experimental object. People generally divide the neurocranium images into four types: white matter, gray matter, cerebrospinal fluid and the background. Compared with the traditional MRF algorithm and the FCM algorithm, the algorithm in this paper has obvious advantages in anti-noise capability, operation rate and segmentation effect, after being combined with the ant colony algorithm and the MRF algorithm.

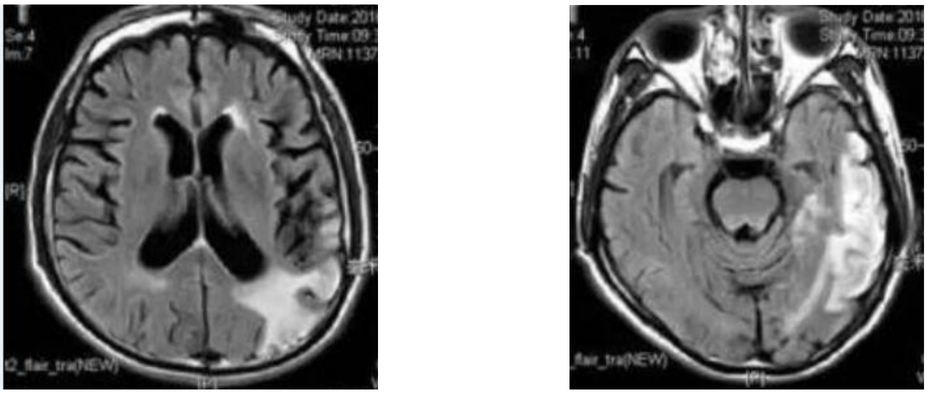

Fig. 3 The experimental sample image

Table 1 shows the accuracy of different algorithms in segmentation results of brain magnetic resonance images. Table 1 reveals that the segmentation accuracy of the proposed method is higher than other algorithms.

Table 1. Accuracy of segmentation of brain magnetic resonance images (%)

	Traditional FCM	MRF	Proposed method
Image 1	89.23	92.13	95.73
Image 2	87.66	91.22	94.89

Table 2 shows the time consumption of the segmentation of brain magnetic resonance images with different algorithms. Table 2 shows that this algorithm has obvious advantages, especially compared with the traditional FCM algorithm.

Table 2. Time consumption comparison
of brain magnetic resonance image segmentation algorithm (ms)

	Traditional FCM	**MRF**	**Proposed method**
Image 1	1563	1291	653
Image 2	2017	1468	889

Table 3 shows the accuracy of different algorithms for brain magnetic resonance image segmentation after adding noise. It can be seen in Table 3 that this algorithm has excellent anti-noise ability.

Table 3. The segmentation anti-noise results comparison of different algorithms (%)

	Traditional FCM	**MRF**	**Proposed method**
Image1	77.39	83.52	89.74
Image2	74.85	82.16	90.11

Conclusion

In this paper, the segmentation of human brain MR images has been studied, so that better service can be provided in the medical field by diagnosing diseases accurately and quickly. Firstly, it is difficult to determine the number of clusters using the traditional FCM clustering algorithm, and the search process is easy to fall into the local optimum. Based on such shortcomings of FCM, the ant colony algorithm is proposed to combine with it. By using the global convergence property of the ant colony algorithm, the clustering center and the number of the fuzzy C mean clustering can be determined quickly, so the running time of the FCM clustering algorithm in segmenting images can be greatly reduced. On this basis, this paper combines the improved MRF algorithm, to enhance the segmentation accuracy and strengthen the anti-noise capability of the algorithm. The experimental results show that compared with the traditional FCM algorithm and the MRF algorithm, the proposed algorithm in this paper has higher accuracy and its running time of image segmentation is also significantly reduced. Additionally, it has obvious advantages in segmenting noise MR images.

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