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Ant Colony Algorithm Linked Fuzzy C-Means Clustering Algorithm for MR Brain Image Segmentation

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Abstract : The most accurate and fuzzy C-Mean (FCM) clustering algorithm for segmenting MR brain image is very efficient and it's used to various fields, especially in medical image. In this paper we introduced a novel method on ant colony algorithm (ACA) is presented to avoid the noise in iterative process of fuzzy C-Mean (FCM) clustering algorithm and it's provide the better diagnosis. The MR image segmentation is difficult to achieve without noise less images. Many noises occur during the image capture because different configuration in the capturing devices. The various kind of noise such as (eddy currents, susceptibility artifacts, rigid body motion, and intensity inhomogeneity) occur in the original image. The most widely used clustering algorithm for brain image segmentation technique is Fuzzy C-Means (FCM) and Possibilistic C-Means Algorithm (PCM) clustering. But the both technique will give the poor segmentation result. To overcome this problem, Ant Colony algorithm (ACA) proposed segmentation result much better than the other two systems. The experimental result compared and analyzed for the proposed technique is better when compared to the existing methods.

Keywords : Ant Colony Algorithm, Fuzzy C-Means, Possibilistic C-Means, Magnetic Resonance Imaging (MRI), Segmentation.

1. INTRODUCTION

Image segmentation plays an important role in image analyses, and is considered as one of the difficult and challenging problems in image processing technology [4, 5]. It is a process of partitioning an image into non-overlapped and consistent regions which are homogeneous with respect to some image property such as intensity, color, texture, and so on [8, 9]. Image segmentation has a wide range of applications such as image content analysis, object recognition, and computer-assisted medical diagnosis [6, 7]. In particular, it has become an increasingly important pre-processing step in medical image analysis. Related research has reported considerable progress over the past decade [6, 7]. However, since in many cases images contain a signicant amount of noise causing the segmentation difficult, we need a robust method to noise.

Fuzzy clustering with the use of Fuzzy C- Means (FCM) algorithm [2] proved to be superior over the other clustering approaches in terms of segmentation efficiency. But the most important drawback of the FCM algorithm is the huge computational time required for convergence. The efficiency of the FCM algorithm [3] in terms of computational rate is improved by modifying the cluster center and membership value updation criterion. In this research, convergence rate is compared between the conventional FCM and the Improved FCM. Possibilistic C-Means (PCM), which relaxes the column sum constraint so that the sum of each column satisfies the looser constraint $0 < \sum_{i=1}^{c} U_{ik} \leq c.$ In other words, each element

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of the k^{th} column can be any number between 0 and 1, as long as at least one of them is positive. They suggested that in this case the value should be interpreted as the typicality of relative to cluster *i* (rather than its membership in the cluster). They interpreted each row of U as a possibility distribution over X. The PCM algorithm they suggested for optimization of the PCM objective function sometimes helps to identify outliers (noise points).Proposed a new clustering model named ant colony optimization (ACA) and clustering the image pixels with K-means algorithm. Also, Yu et al. [1] proposed a color image segmentation method which obtains the optimal initial cluster centers using ACA and then clusters the image data set with FCM. However, the proposed method is still sensitive to noise.

This paper is organized as follows. In Section 2, we review related works to our research. Section 3 describes our proposed ACAFCM clustering algorithm, and Section 4 shows results and comparison of our proposed algorithm. Finally, Section 5 contains discussion and conclusion.

2. RELATED WORKS

1. Fuzzy C Means (FCM)

Fuzzy clustering is also known as soft clustering, where the data elements can belong to more than one cluster, and associated with each element is a set of membership levels. These indicate the strength of the association between that data element and a particular cluster. Fuzzy clustering is an approach operating towards fuzzy logic and it provides the flexible method of assigning the data points to the clusters. The data points are given partial degree of membership in multiple nearby clusters. The central point in fuzzy clustering is always number of unique partitioning of the data in a collection of clusters. In this membership value is assigned to each cluster. Sometimes this membership has been used to decide whether the data points belong to cluster or not. The most widely used fuzzy clustering algorithm is Fuzzy C Means (FCM). The fuzzification parameter (*m*) in the range [1, *n*] was introduced, which determines the degree of fuzziness in the clusters. FCM is a method of clustering which allows one piece of data to belong to two or more clusters. The aim of FCM is to obtain the minimized objective function. The objective function is given equation (1)

$$J_m = \sum_{i=1}^{N} \sum_{j=1}^{C} \mu_{ij}^m \,||X_i - C_j||^2 \quad {}_{1 \le m < \infty} \tag{1}$$

Where *m* is the fuzzification parameter which is a real number greater than 1. μ_{ij} is a fuzzy membership qualification indicating the membership of sample *i* to the *j* cluster. x_i is the i^{th} data point. c_j is the cluster center. $||x_i - c_j||$ is the distance matrix from a point x_i to each cluster center to with taking the Euclidean distance between the point and the cluster center. Although FCM is considered good clustering algorithm, the algorithm have some disadvantage. The computational time is more, Sensitivity to the initial guess, Sensitivity to noise. In order to enhance the outcome of the FCM, the algorithm is optimized using Ant Colony Algorithm (ACA).

2. Possibilistic C-Means Algorithm (PCM)

The Possibilistic C-Means method uses a Possibilistic type of membership function to demonstrate the degree of similarity. It is beneficial that the memberships for representative feature points are very high and unrepresentative points have low membership. The intention function, which suits the necessities, is as follows,

$$\min\left\{ J_m(x,\mu,c) = \sum_{i=1}^{c} \sum_{j=1}^{N} \mu_{ij}^m d_{ij}^2 + \sum_{i=1}^{c} \eta_i \sum_{j=1}^{N} (1-\mu_{ij})^m \right\} \tag{2}$$

Where, d_{ij} indicates the distance between the j^{th} data and the i^{th} cluster center, μ_{ij} represents the degree of belonging, *m* indicates the degree of fuzziness, η_i represents the appropriate positive number, *c* represents the number of clusters, and N represents the number of pixels. μ_{ij} can be found with the help of the following equation,

$$\mu_{ij} = \frac{1}{1+\left(\frac{d_{ij}^2}{\eta_i}\right)^{\frac{1}{m-1}}} \tag{3}$$

The value of η_i finds the distance at which the membership values of a point in a cluster happen to be 0.5. The major merit of this Possibilistic C-Means method is that the value of η_i can be set or modified based on every iteration. This can be achieved by modifying the values of d_{ij} and μ_{ij}. The Possibilistic C-Means technique is highly robust in the occurrence of noise, in determining suitable clusters, and in providing a robust approximation of the centers. Updating the membership values are based on the distance measurements. The Euclidean and Mahalanobis distance are two general distance measurements. The Euclidean distance performs better when a data set is dense or isolated and Mahalanobis distance considers the correlation in the data with the help of inverse of the variance-covariance matrix of data set which is described as below,

$$D = \sum_{i,j=1}^{i,j=p} A_{ij}(x_i - y_j)(x_j - y_j) \tag{4}$$

Where, x_i and y_i represents the mean values of two different sets of parameters, X and Y. σ_i^2 represents the corresponding variances, and ρ_{ij} indicates the coefficient of correlation between i^{th} and j^{th} variants.

3. Ant Colony Algorithm (ACA)

Traditional clustering algorithm has three problems when treat lots of objects. Firstly it is that efficiency will be discounted. Thus, they cannot do clustering learning work in data mining. Secondly, most of clustering algorithm needs clustering numbers which are given by users. And clustering results are sensitive to clustering numbers. However, it is very difficult to definite the clustering numbers. Third, it can drop into local optimization and find global optimum difficultly.

On the cluster analysis based on the ant colony algorithm, data can be seen as different attributive ants and the cluster center can be seen as ants' feeding source. Thus, data clustering process is just like the process of food source searched by ants [4]. The algorithm usually consists of following steps:

Step 1: Initialize all parameters, *n* fault symptom samples can be regarded as n classes.

Step 2: Compute weighted Euclidean distance between samples X_i and X_j.

$$d_{ij} = |D(X_i - X_j)|^2 = \sqrt{\sum_{k=1}^{m} P_k (x_{ik} - x_{jk})^2} \tag{5}$$

P_k is weighted factor which can be defined according to every component's contribution in clustering.

Step 3 : Compute the pheromone quantity of trail, *r* is described as cluster center and $\tau_{ij}(t)$ is intensity of the pheromone trail between X_i and X_j at time *t*. set the intensity of pheromone trail to 0 at time 0.

$$\tau_{ij} = \begin{cases} 1 & d_{ij} \le r \\ 0 & d_{ij} > r \end{cases} \tag{6}$$

Step 4: Compute the probability of mergering class X_i and X_j.

$$P_{ij} = \frac{[\tau_{ij}(t)]^{\alpha} . [\eta_{ij}(t)]^{\beta}}{\sum_{s=S} [\tau_{is}(t)]^{\alpha} . [\eta_{is}(t)]^{\beta}} \tag{7}$$

Where $S = \{s \mid d_{is} \le r,\ s = 1, 2, ... n\}$ and $\eta_{ij}(t)$ is weight coefficient. It can reflect expectation of mergering class X_i and X_j.

Step 5: If $P_{ij}(t) \ge P_0$ mergering X_i and X_j, computing cluster center after mergering.

$$\overline{c_j} = \frac{1}{J}\sum_{k=1}^{J} X_k (X_k \in C_j) \tag{8}$$

Step 6: Compute the biased error of j^{th} clustering.

$$D_j = \sum_{k=1}^{J}\sqrt{\sum_{i=1}^{m}(x_{ki} - c_{ji})^2} \tag{9}$$

Where c_{ij} is the i^{th} component of the j^{th} cluster center.

Step 7: Compute overall error $\varepsilon = \sum_{J=1}^{k} D_J$,if $\varepsilon \le \varepsilon_0$, the whole process will pause Please output the number of clustering m and cluster center $\overline{c_j}$. Otherwise, jumping step 3 and continuing iteration

3. PROPOSED ACAFCM ALGORITHM

Using ant colony algorithm linked with FCM does fuzzy cluster. One aspect is the robustness of ant colony algorithm can endure the sensibility of FCM initialization. On the other hand, the parallel and distributed computing of ant colony algorithm accelerates convergence and increase clustering efficiency. It is most important that intelligent search and self-adapting can help obtain global optimum. FCM clustering is one of fuzzy clustering algorithms and can give degree of membership of each sample. Matrix of degree of membership U can show the result of fuzzy clustering. U = [U_{ij}], where

$$\begin{cases} \sum_{i=1}^{n} U_{ij} = 1, j = 1,2,......,n \\ 0 < \sum_{j=1}^{m} U_{ij} < n, i = 1,2,....,c \end{cases} \tag{10}$$

Objective function of FCM is

$$J = \sum_{j=1}^{N}\sum_{i=1}^{c}(U_{ij})^m \,||X_j - W_i||^2 \tag{11}$$

where W_i is the i^{th} clustering center, i = 1,2,…, c; j = 1,2,…,N; $m \in (1, \infty)$ is weighted index. Objective function shows the sum of squares of weighted distance from each data member to relevant clustering center. Defining degree of membership as follows:

Step 1: Clustering numbers which are obtained from ant colony clustering algorithm can be regarded as classification c. Set allowable E_{Max} and t = 1.

Step 2: Clustering centers which are obtained from ant colony clustering algorithm can be regarded as FCM initialization clustering center $W_i(t)$, t = 1,2,…,c.

Step 3: Compute degree of membership U_{ij}, where i = 1, 2,…,c and j = 1, 2,…, n.

$$U_{ij} = 1 \Big/ \sum_{r=1}^{c}\left[(d_{ij}(k)/\mathrm{dir}(k))^{2/(m-1)}\right] \tag{12}$$

Where m is weight coefficient.

Step 4: Amend all clustering center $W_i(t+1)$, t = 1,2,…,c.

$$w(k+1) = \sum_{i=1}^{n} U_{ij}{}^{m}(k)x_i \Big/ \sum_{i=1}^{n} U_{ij}{}^{m}(k) \tag{13}$$

Step 5: Reduce the noise in an image Segment.

$$e = \sum_{i=1}^{c} \| W_i(t+1) - W_i(t) \|^2 \tag{14}$$

If $e < emax$, the algorithm is over. Otherwise, $t = t + 1$, jumping step 3 and continuing iteration.

The FCM algorithm results in local optimal solution and hence the method is optimized using ACA. The FCM is integrated with ACA and is known as FCMACA.

1. ALGORITHM FOR FCMACA

1. Initialize input parameters (i, j)
2. For each ant k (currently in state i)
   do
   Append the chosen move to the *k-th* ant's set. until ant k has completed its solution
3. Determine the cluster center using ACA_FCM.
4. For each ant move (ij)
   do compute D_{tij} update the trail matrix.
5. Terminate when global optimal solution is reached or at end of iteration.
6. Else go to step (2).

4. EXPERIMENTAL RESULTS

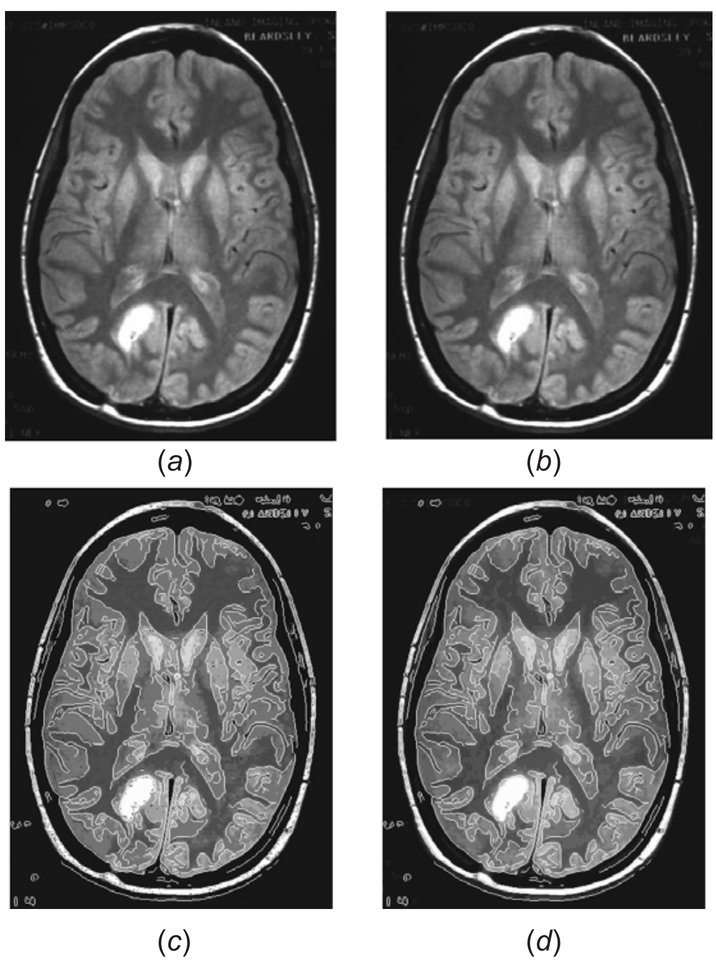

Figure 1: Segmentation results on MRI image (*a*) Original MRI image (*b*) segmented MRI brain image using FCM (*c*) segmented MRI brain image using PCM (*d*) segmented MRI brain image using ACAFCM

The proposed technique is analysis and evaluated on the MRI brain segmentation. Figure 1 shows the segmentation result for the existing and proposed segmentation methods. Figure 1(*a*) represent the original MRI brain image with noise, figure 1(*b*) represent the segmentation result using FCM technique, figure 1(*c*) represents the segmentation result using the ACA technique and figure 1(*d*) represents the segmentation result using the proposed PCM technique and 1(*e*) represents the segmentation result using the proposed ACAFCM technique. It can be clearly observed from the figure that the segmentation result obtained by the proposed technique is better when compared to the existing segmentation method. Figure 2 shows the similarity measure for the ACAFCM and proposed ACA with various noise levels.

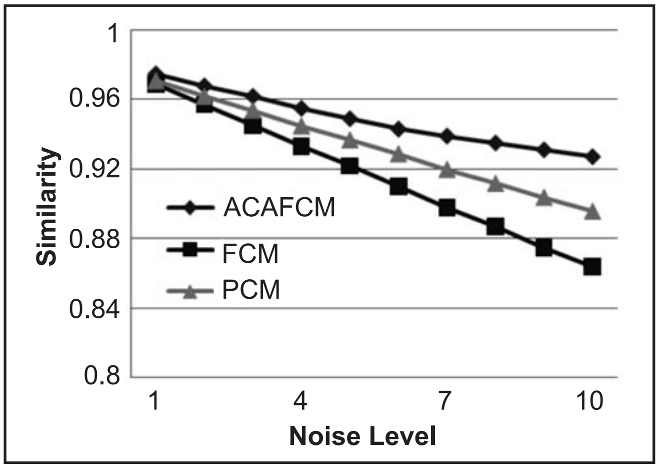

Figure 2: Similarity Measure for the Different Segmentation with Various Noise Level

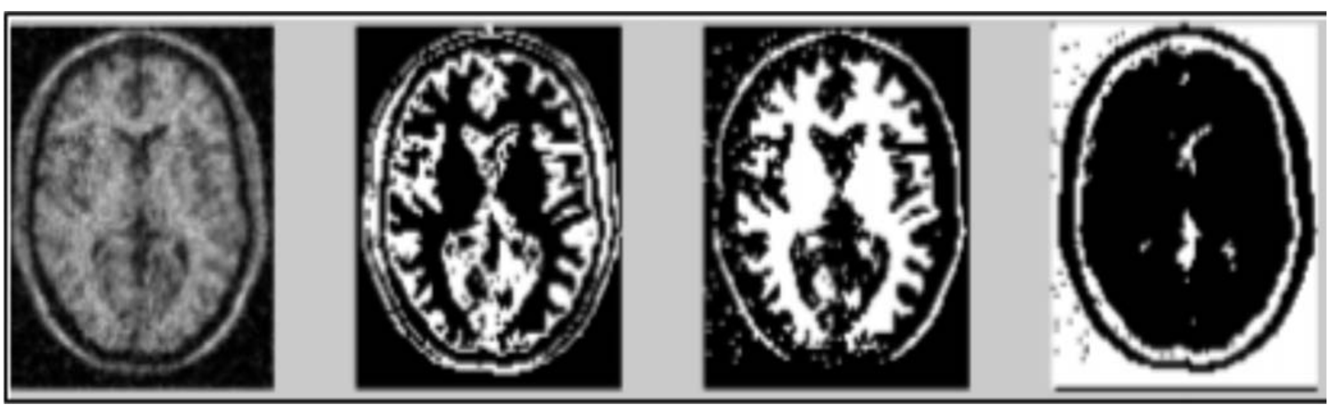

Figure 3: From left to right: corrupted MR image, white matter, Gray matter and CSF

When the noise level is 1, the similarity measure by using FCM is 0.969, PCM is 0.971 and 0.975 for using ACAFCM that us little higher than FCM and FCM techniques.

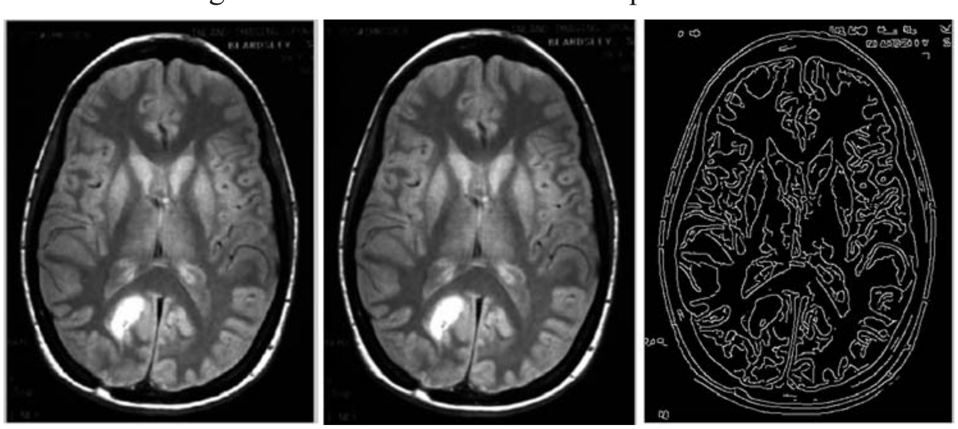

Figure 4: From Left to Right : Algorithm FCM, Algorithm PCM, Algorithm ANT with Linked Clustering

From the analysis of proposed Ant Colony Algorithim the Center Fast C-Mean values were calculated as per the listed below,

Table 1

Class Center FCM on Row 500; Coloumn 383; Channel 3 at Image Clustering on MRI (RBG)

Row	*Column*	*Channel*
1.7108	1.7108	1.7108
16.0650	16.0650	16.0650
39.9486	39.9486	39.9486
69.5543	69.5543	69.5543
92.7920	92.7920	92.7920
109.8484	109.8484	109.8484
127.8910	127.8910	127.8910
157.4675	157.4675	157.4675
189.9483	189.9483	189.9483
223.2507	223.2507	223.2507
253.1082	253.1082	253.1082

When the noise level starts increasing, the difference will also start increasing. When the noise level is 5, the similarity measure is 0.947 for FCM, for the proposed ACAFPCM. For the noise level of 10, the similarity measure is 0.864 for FCM, 0.896 for the proposed ACAFCM and 0.927 which is higher than the existing FCM and PCM segmentation techniques. Overall, the segmentation result is better for the proposed ACAFCM segmentation technique than the existing techniques.

5. CONCLUSION

MR image Segmentation in medical field is difficult to achieve the noise less image because of the noise occurrence in the captured image because of some faults in the capturing device. The new proposed algorithm will help the doctors to analyze the better image. This can be done with the help of image segmentation technique. This paper deeply analysis the MR brain image development with the help of image segmentation. Clustering is considered to be better segmentation technique because of its advantages. There are several techniques exist for this purpose, but those techniques fails when more edges and noise are involved. To overcome those problems using the proposed Ant Colony algorithm linked with Fuzzy C-Means algorithm for segmenting the MRI brain image, and also its bit error percentage were *31.39%*. Hence its PSNR Performance rate were good. The experimental result shows that the proposed segmentation technique is very effective in enhancing the MRI brain image better than the existing techniques.

6. REFERENCES

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