

# FUZZY CLUSTERING BASED ANT COLONY OPTIMIZATION ALGORITHM FOR MR BRAIN IMAGE SEGMENTATION

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## ABSTRACT

The conventional methods for segmenting MR brain images with various noises were less effective. In this paper, we aimed for a novel method which intellectually determines the cluster centers before applying the (FCM) fuzzy c-means, thus increasing the iteration efficiency and reducing the computation time. The main feature of this proposed method is to utilize Ant Colony Optimization Algorithm (ACO) to initialize the cluster centers and classification is made from thereafter using the initial values. Thus it helps to avoid the noisy pixel to be wrongly placed under any of the classes during the iterative process of FCM clustering algorithm, hence a better segmentation of MRI brain images which were scanned for detection of tumors was achieved. The methodology has been successfully carried out on Magnetic Resonance Imaging (MRI) images and efficient segmentation is carried out on brain tumor images.

**Keywords:** *Ant Colony Optimization Algorithm (ACO), Fuzzy C-Means (FCM), Magnetic Resonance Imaging (MRI), Clustering and Brain Tumor.*

## 1. INTRODUCTION

Image segmentation plays an important role in image analyses and was considered as one of the difficult and challenging problems in image processing technology [4]. 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 [7]. Related researches have been reported a considerable progress over the past decade. However, since in many cases images contain a significant amount of noise, causing the segmentation process a difficult one.

Image segmentation could be carried out through various modes of operations performed on a pixel or on different regions of an image. Off all the methods, Fuzzy based clustering method such as 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. In

this research, convergence rate is compared between the conventional FCM and the improved FCM. In the case of PCM [3], it 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 of the  $k^{\text{th}}$  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 Algorithm (ACO) [5] 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 ACO and then clusters the image data set with FCM [10]. 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 ACOFCM clustering algorithm in detail and Section 4 shows results and comparison of our proposed algorithm. Finally, Section 5 contains discussion and conclusion.

## 2. RELATED WORKS

A series of researches were undertaken based on various clustering algorithms. The most reliable and better performing algorithms were discussed as follows.

### 2.1 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. 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 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)

$$J_m = \sum_{i=1}^N \sum_{j=1}^C \mu_{ij}^m \|X_i - C_j\|^2 \quad (1)$$

$1 \leq m < \infty$

Where  $m$  is the fuzzification parameter and it is greater than 1.  $\mu_{ij}$  is a fuzzy membership qualification indicating the membership of sample  $i$  to the  $j$  cluster.  $x_i$  is the  $i^{\text{th}}$  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 was considered as a good clustering algorithm, the above algorithm also has some disadvantages. The computational time was 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 based FCM.

### 2.2 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,

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

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

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

The value of  $\eta_i$  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  $\eta_i$  can be set or modified based upon each iteration. This can be achieved by modifying the values of  $d_{ij}$  and  $\mu_{ij}$ . 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.

However, as pointed out by Nikil et al. [3], the price PCM pays for its freedom to ignore noise points is that PCM is very sensitive to initializations, and it sometimes generates coincident clusters. Moreover, typicality can be very sensitive to the choice of the additional parameters needed by the PCM model. Timm et al. [13]–[15] proposed two possibilistic fuzzy clustering algorithms that can avoid the coincident cluster problem of PCM. 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, and  $x_i$  and  $y_i$  represents the mean values of two different sets of parameters,  $X$  and  $Y$ .  $\sigma_i^2$  and  $\sigma_j^2$  represents the corresponding variances, and  $\rho_{ij}$  indicates the coefficient of correlation between  $i^{\text{th}}$  and  $j^{\text{th}}$  variants.

### 2.3 Ant Colony Optimization Algorithm (ACO)

Ant Colony Optimization (ACO) is a meta-heuristic scheme was first proposed by Marco Dorigo in 1992 [15] and Dorigo et al. [14]. Originally, it was used just for solving discrete swarm optimization problems [11]. ACO is based on the inspiration observed from the natural behavior of ant species [6]. ACO is a heuristic algorithm which has been proven a successful technique and applied to a number of combinatorial optimization problems. The ants deposit pheromone [5,6] on the ground for foraging at each pixel position of the image, according to the movements of a number of ants which are dispatched to move on the image. Furthermore, the movements of these ants are driven by the local variation of the image's intensity values. Experimental results are provided to demonstrate the superior performance of the proposed approach 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. Theoretically, if the quantity of pheromone remained the same over time on all edges, no route would be chosen. However, because of feedback, a slight variation on an edge will be amplified and thus allow the choice of an edge. The algorithm will move from an unstable state in which no edge is stronger than another, to a stable state where the route is composed of the strongest edges. Thus, data clustering process is just like the process of food source searched by ants [4].

The Ant Colony Optimization techniques has emerged recently as a relatively novel meta-heuristic for hard combinatorial optimization problems. It is designed to simulate the ability of ant colonies to determine shortest paths to food. Although individual ants possess few capabilities, their operation as a colony is capable of complex behavior. Real ants can indirectly communicate by pheromone [6] information without using visual cues and are capable of finding the shortest path between food sources and their nests. The ant deposits pheromone on the trail while walking, and the other ants follow the pheromone trails with some probability which are proportioned to the density of the pheromone. The more ants walk on a trail, the more pheromone is deposited on it and more and more ants follow the trail. Through this mechanism, ants will eventually find the shortest path. Artificial ants imitate the behavior of real ants how they forage the food, but can solve much more complicated problems than real ants can. A search algorithm with such concept is

called Ant Colony Optimization. Figure1 shows how the ants find the shortest path [18].

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  $X_j$ .

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

$P_k$  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.

$$\tau_{ij} = \begin{cases} 1 & d_{ij} \leq r \\ 0 & d_{ij} > r \end{cases} \quad (6)$$

**Step 4:** Compute the probability of merging class  $X_i$  and  $X_j$ .

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

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

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

$$\bar{c}_j = \frac{1}{J} \sum_{k=1}^J X_k (X_k \in C_j) \quad (8)$$

**Step 6:** Compute the biased error of the  $j^{\text{th}}$  clustering.

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

Where  $c_{ji}$  is the  $i^{\text{th}}$  component of the  $j^{\text{th}}$  cluster center.

**Step 7:** Compute overall error  $\varepsilon = \sum_{j=1}^k D_j$ , if  $\varepsilon \leq \varepsilon_0$ , the whole process will pause. Please output the number of clustering  $m$  and cluster center  $\bar{c}_j$ . Otherwise, jumping step 3 and continuing iteration.

### 3. PROPOSED ACOFCM ALGORITHM

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. Consequently, clustering results are sensitive to clustering numbers. However, it is very difficult to assert the clustering numbers. Finally, it can drop into local optimization and find global optimum difficultly.

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 increases clustering efficiency. FCM clustering is one of the 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

$$\begin{cases} \sum_{i=1}^n U_{ij} = 1, j = 1, 2, \dots, c \\ 0 < \sum_{j=1}^c U_{ij} < n, i = 1, 2, \dots, n \end{cases} \quad (10)$$

Objective function of FCM is

$$J = \sum_{j=1}^N \sum_{i=1}^c (U_{ij})^m \|x_j - w_i\|^2 \quad (11)$$

where  $w_i$  is the  $i^{\text{th}}$  clustering center,  $i=1, 2, \dots, c$ ;  $j=1, 2, \dots, N$ ;  $m \in (1, \infty)$  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  $w_i(t)$ ,  $t=1, 2, \dots, c$ .

Step 3: Compute degree of membership  $u_{ij}$ , where  $i=1, 2, \dots, c$  and  $j=1, 2, \dots, n$ .

$$U_{ij}(k) = \frac{1}{\sum_{r=1}^c [(d_{ij}(k) / d_{ir}(k))^{2/(m-1)}]} \quad (12)$$

Where,  $m$  is weight coefficient.

Step 4: Amend all clustering center  $w_i(t+1)$ ,  $t=1, 2, \dots, c$ .

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

Step 5: Reduce the noise in a image Segment.

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

If  $e < e_{\max}$ , 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 ACO. The FCM is integrated with ACO and is known as ACOFCM.

Algorithm for ACOFCM

- 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 ACOFCM.
- 4) For each ant move (ij)
  - do compute  $D_{ij}$  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

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 ACO technique and figure 1(d) represents the segmentation result using the proposed PCM technique and 1(e) represents the segmentation result using the proposed ACOFCM 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 ACOFCM and proposed ACO with various noise levels.



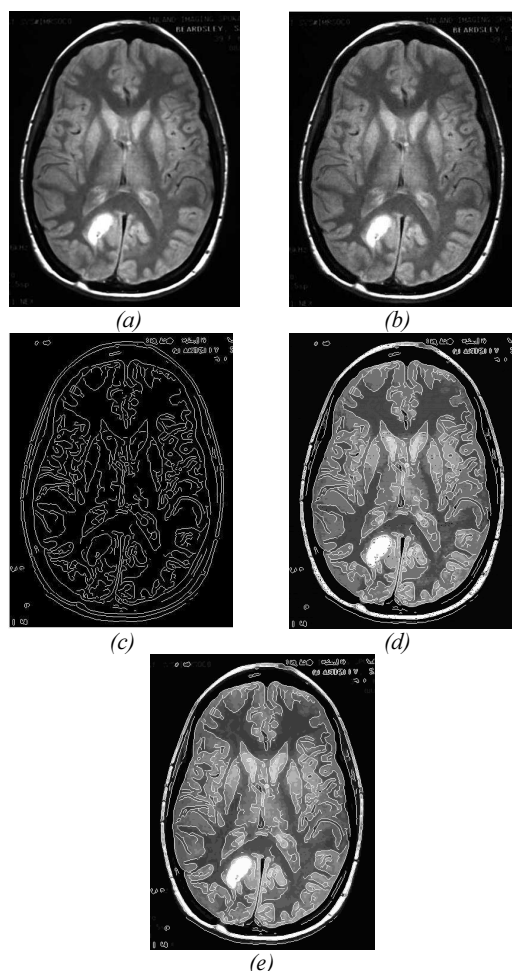


Figure 1: Segmentation Results On MRI Image (a) Original MRI Image (b) Segmented MRI Brain Image Using FCM (c) Segmented MRI Brain Image Using ACO (d) Segmented MRI Brain Image Using PCM (e) Segmented MRI Brain Image Using ACOFCM

When the noise level is 1, the similarity measure by using FCM is 0.969, PCM is 0.971 and 0.975 for using ACOFCM that us little higher than FCM and FCM techniques. 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 ACOFCM. For the noise level of 10, the similarity measure is 0.864 for FCM, 0.896 for the proposed ACOFCM and 0.927 which is higher than the existing FCM and PCM segmentation techniques. The image, fig.3 shows the extraction of different regions (three regions) from the corrupted input image.

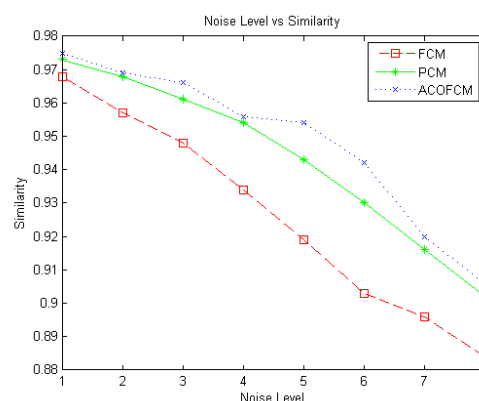


Figure 2: Similarity Measure for the Different Segmentation with Various Noise Level.



Figure 3: From Left To Right: Corrupted MR Image, White Matter, Gray Matter And CSF.

Overall, the segmentation result is better for the proposed ACOFCM 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 developed by us will help the doctors for better diagnostic inferences in the case of brain tumors scanned through MRI or CT techniques.

The earlier existing clustering techniques like FCM and PCM fails when more edges and noise are involved. We have successfully eliminated noise to a large extent without losing the originality of the input image. ACOFCM method (Ant Colony algorithm linked with fuzzy C-Means algorithm) segmented the MRI brain images with better similarity values when compared with previously existing clustering techniques like FCM and PCM. Further the experimental result shows that the proposed segmentation technique is very effective in reducing the bit error rate.

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