

# Adaptive unsupervised Fuzzy C mean based image segmentation

Arunkumar Rajendran<sup>1,\*</sup>, Thamarai Muthusamy<sup>2</sup>

<sup>1</sup>M E Communication Systems, Karpagam College of Engineering, Coimbatore, India

<sup>2</sup>ECE Department, Karpagam College of Engineering, Coimbatore, India

## Email address:

arunece.r@gmail.com (Arunkumar R.), sreethamarai2000@yahoo.co.in (Thamarai M.)

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**Abstract:** In this paper an optimized method for unsupervised image clustering is proposed. Generally a Novel Fuzzy C Means (FCM) or FCM based clustering algorithm are used for clustering based image segmentation but these algorithms have a disadvantage of depending upon supervised user inputs such as number of clusters. Our proposed algorithm enhances an unsupervised preliminary process known as Double Cluster Tree Structure (DCTS) whose boundary structure process handled before each iteration of FCM clustering. The combined structure of these two algorithms form Adaptive Unsupervised Fuzzy C Means (AUFCM), AUFCM analyzes and segments whole dataset (image) in an unsupervised manner. The results of this algorithm show a significant improvement in segmentation Performance.

**Keywords:** Fuzzy C Means, Image Segmentation, Unsupervised Learning, AUFCM and DCTS

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## 1. Introduction

Image segmentation is a process of partitioning an image data in to some meaningful portion of details. The Partitioning of these image portions is based on the requirement of application for which it is used. The applications are such as content based retrieval, video surveillance, object recognition, traffic control etc. There are many ways and methods to segment an image such as thresholding [1], by extracting directional information, Region growing, histogram based methods and by clustering. In our paper we are concentrating only on clustering based image segmentation [3]. Clustering is a process of grouping elements in a dataset which shares similar characteristics. This clustering process is used for many applications like image segmentation mentioned above. Clustering process constrains with two categories they are hard clustering and soft clustering [2]: In hard clustering process each element in a dataset is tested for category, that it belongs to the particular cluster or not, and in the case of soft clustering process each element in a dataset is tested for category, that each object belongs to each cluster to a certain degree. Also there is countable number of clustering method [3] families (Hierarchical [4], Centroid based [5], Distribution and

Density based [6]) available for processing different kind of dataset which suits different applications.

Previously many clustering approaches been developed for the purpose of image segmentation such as K-means, FCM based approaches etc., the details of these algorithm and the problem definitions are given below.

The traditional method such as K-Means has a problem of local optimum, and need a supervised input for clustering where as in FCM solves some of the problems of K-Means [12], but this algorithm also faces some problems of its own such as provoking of bad clustering of noisy pixels of white region. Now most of the recent works uses the methodology of K-Means and FCM [7]. There are many algorithms proposed in terms of version of K-Means and FCM [2] like FCM\_S1 and FCM\_S2, which has Mean and Median filter as extension to FCM focuses on removing noise. There is another [13] version, referred as EnFCM (Enhanced FCM) also focuses on removing noise in a different approach which a parameter  $\epsilon$  to calculate the gray level values, this parameter  $\epsilon$  is used in membership function additionally to make the process more optimized. The Modified K-Means solves several K Means problems mentioned above. But all

these algorithms still need a supervised input for number of clustering [8], [9], [10].

Since traditional Clustering algorithms have same limitations of getting no of cluster centers by means of its user. This makes clustering difficult to use, where there are unpredictable datasets are available. So to solve this problem AUFCM is used. The AUFCM implementation is described in the following section.

## 2. Novel Fuzzy C Means Algorithm

Fuzzy C Means (FCM) is a well-known clustering algorithm which clusters the dataset in fuzzy way. The FCM is an iterative process which involves three stages of operation (a). Calculation of Cluster Center  $Cls$  (b). Formation of Membership degree function  $Mem$  (C). Calculation of Objective Function  $Obj$ .

$$Obj(Iter) = \sum_{i=1}^N \sum_{j=1}^c [Mem^{ff} \|Dv_i - Cls_j\|^2] \quad (1)$$

$$Cls_j = \frac{\sum_{i=1}^N Mem^{ff} DV_i}{\sum_{i=1}^N Mem^{ff}} \quad (2)$$

$$Mem(Iter) = \frac{1}{\sum_{k=1}^c \left(\frac{d_{ji}}{d_{ki}}\right)^{2/ff-1}} \quad (3)$$

Where,  $Dv_i$  is a data in vectored form, the Calculation of Cluster center is done by finding centroids/mean of each cluster. The  $Cls$  always changes iteratively depends on the current  $m$ . Cluster Center  $Cls$  is given by equation (2). The Manipulation of Membership Function  $Mem$  is done by forming clusters through taking nearest distance elements of a  $Cls$ . Membership always depends on the Cluster centers formed in previous iteration. This function contains our final output i.e. the segmented data represented by equation (3). Since the Process is iterative it needs to be stopped somewhere, there we get our clusters in a good quality without any miss and false hit and this stage is known as convergence stage. For the purpose of stopping the iteration Objective Function  $Obj$  is used. FCM iteration is minimized based on  $Obj$  which is represented by equation (1). The process algorithm is as follows

- a The Initialize such as
  - (i) No of Clusters 'c'
  - (ii) Fuzzification factor 'ff'
  - (iii) Convergence Condition 'Cs'.
- b Initialize the Membership Function ' $Mem'_{ini}$  randomly (This is only used for first iteration).
- c Start a iteration loop let it be ' $Iter$ '
- d Finding  $Cls$  by using previous iteration  $Mem$  (for first iteration use ' $Mem'_{ini}$ )
- e Formation of new Membership function  $Mem(New)$  by means of current  $Cls$  is done. Finally at the end of iteration objective function  $Obj$  is calculated. check the value of  $Obj$  for current and previous iteration find it is converged
- f If yes: stop the iteration
- g If No: Repeat the steps from (d)

## 3. Double Cluster Tree Structure (DCTS)

DCTS is the hierarchal based tree structure which is assigned to manipulate FCM algorithm several times like a binary tree which divides the datasets into two clusters each time so that it called as Double Cluster algorithm. Normally the usage of any FCM algorithm will be once for a dataset. But in our process DCTS will acts as a boundary loop which makes FCM to process repeatedly. The details and algorithms are as follows.

To explain the process, Let the Dataset be DS

- (i) Initialize the No of Clusters as 2 (fixed and will not be changed for any dataset)
- (ii) Form a data vector DS, Let it be DS.
- (iii) By the reference to M separate DS into two groups. M is a mean of the cluster
- (iv) Let the first group be  $C\{1,1\}$  which contains all the values minimum to M, the second group be  $C\{1,2\}$  which contains all the values maximum to M.
- (v) Now we have two clusters i.e.  $C\{1, 1\}$  &  $C\{1, 2\}$ .
- (vi) Repeat the same process for  $C\{1, 1\}$  &  $C\{1, 2\}$  which give 4 clusters  $C\{2, 1\}$ ,  $C\{2, 2\}$ ,  $C\{2, 3\}$  &  $C\{2, 4\}$ . This is in level 2 processing
- (vii) The increase in level increases number of clusters such as

For level 0 there will be 1 cluster (probably Original Dataset)

For level 1 there will be 2 clusters

For level 2 there will be 4 clusters

and so on;

This process will be grown repeatedly until the termination condition is satisfied.

## 4. Adaptive Unsupervised Fuzzy C Means (AUFCM)

In this process a same procedure is handled as mention in DCTS the only difference is instead of taking mean to separate or cluster the data the FCM is used as follows

- i Initialize the FCM parameters as mention in section II, set, No of Clusters as 2 (fixed and will not be changed for any dataset), Let our database be DS
- ii Form a data vector from DS, Let it be DSv.
- iii To form a level 1 structure, cluster DSv by means FCM in which 2 clusters are formed  $C\{1,1\}$  &  $C\{1,2\}$ .
- iv For level 2 processing repeat the same process for  $C\{1, 1\}$  &  $C\{1, 2\}$  which gives 4 clusters  $C\{2, 1\}$ ,  $C\{2, 2\}$ ,  $C\{2, 3\}$  &  $C\{2, 4\}$ .
- v Until the termination condition is satisfied the double structured level grows depends on the data.

In each level the no of clusters will always be, in power of 2. But it is not sure that the final level of cluster will be in power of 2. The clustering process stop at particular stage in the branches of the Cluster structure if the terminating condition is satisfied.

### 5. Cluster Termination Methodology

During the clustering process certain things will happen as described below

- 1 Sometimes the cluster centers of the cluster will be nearer to each other which makes the increase in miss and false hit
- 2 Due to data insufficiency some cluster does not have even one element in the cluster.

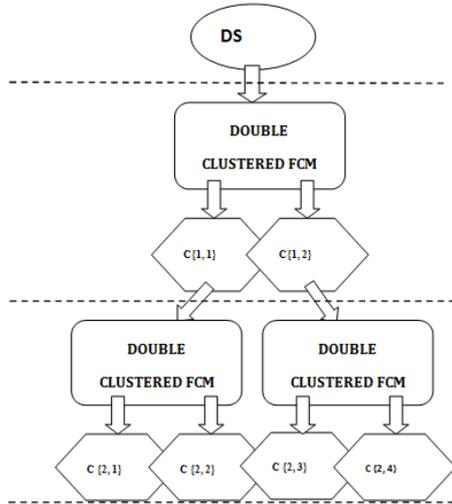


Figure 1. Diagrammatical representation of the AUFCM process

To avoid these kinds of problems the whole manipulations

Table 1. Comparison of different clustering methods based on Actual cluster and Occurred cluster

Methods		Occurred No. of Cluster using various Techniques				
Image Size	Actual no. of Cluster	K-Means	Fuzzy C- Means	Moving K- means	Fuzzy Moving K-Means	AUFCM
128 × 128	8					
256 × 256	14	7	9	9	11	13
512 × 512	16	12	14	14	13	15
1024 × 1024	16	14	13	14	14	16

are done in various accuracy levels. Before starting the process check how much accuracy user needs for the image segmentation. Based on that accuracy for each and every level, calculate the difference among the clusters. If it reaches 70% difference, then the algorithm stops clustering. This decides when to terminate cluster structure image segmentation.

The diagrammatical representation of the AUFCM is as shown in figure 1.

Therefore by using AUFCM unsupervised image segmentation is achieved without any user inputs, by automatically analyzing the dataset.

### 6. Experimental Results

In this section, the performance of our proposed methods is compared with the conventional methods. The image shown in fig 2(a) & 3(a) are wpepper.png with dimension 256 × 256 and AT3\_1m4\_01.tif with dimension 512 × 512 taken from MATLAB standard image database for analysis. The Clustering process is achieved for the images without any user input in an unsupervised manner with 60% accuracy. The images 2(b) & 3(b) show the segmented output which is manipulated by AUFCM. Table-1 shows the comparison of different algorithms with our proposed which explains the capability of AUFCM. The target towards reaching actual cluster from ground truth segmentation is processed and the results are shown in table-1.

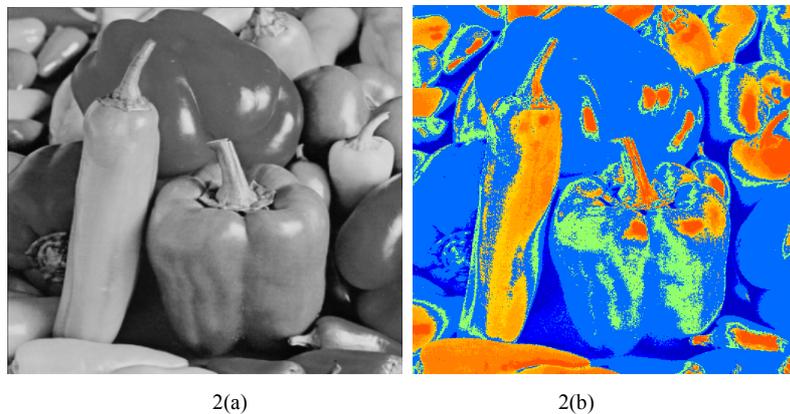


Figure 2. 2(a) –Input wpepper.png image 2(b)-segmented wpepper.png image

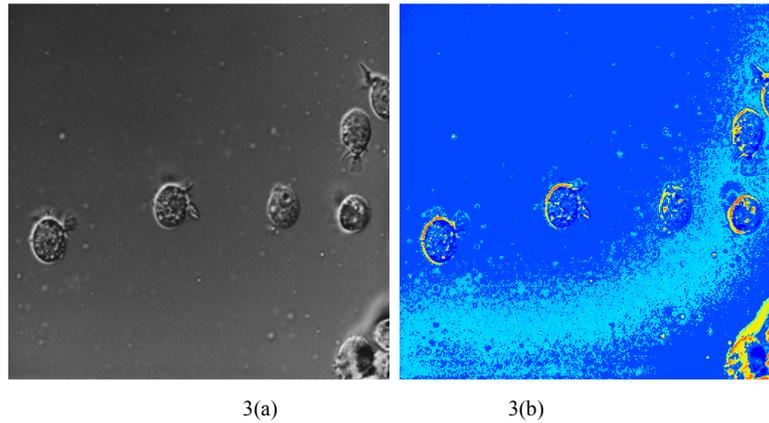


Figure 2. 3(a) –image 3(b)-segmented AT3\_1m4\_01.tiff image

Figure 2 shows the original 2(a) and segmented 2(b) output of wpepper image. Figure 3 shows the result of original 3(a) and segmented 3(b) output AT3\_1m4\_01 image. To indicate different segments from an image different gray scales are color mapped to the segmented image. For efficient segmentation, the no of cluster occurred should be equal to the actual clusters. The no of clusters produced by the AUFCM method is nearly equal to the actual clusters when compared to the other techniques. For example, an image of size  $256 \times 256$  the actual no. of clusters is 16. But the clusters obtained using k-means is 7 and fuzzy C Means and Moving K-Means are 9; Fuzzy Moving K Means is 11. Thus proposed method AUFCM improves the segmentation accuracy.

## 7. Conclusion

In this paper we have proposed AUFCM, a version of FCM based on DCTS to obtain an unsupervised logic that analyze the dataset automatically before clustering. The obtained result has shown a significant solution to the problem which most of the clustering algorithm forms. Also the results show the improved performance in finding even a slightest variation of image gray scale. The no of segmentation produced by algorithm depends on the accuracy the user needs or application depended.

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