



# **A Scientific Approach for Segmentation and Clustering Technique of Improved K-Means and Neural Networks**

**K.Srinivas**

Research Scholar, Dept. of CSE  
K.L.University, Vaddeswaram  
A.P., India.

**Dr. V.Srikanth**

HOD, Dept. of CSE  
K.L.University, Vaddeswaram  
A.P., India.

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**Abstract:** *The image segmentation is an effort to classify similar colors of image in the same group. It clusters colors into several groups based on the closeness of color intensities inside an image. In preprocessing to use Enhancement there are two segmentation techniques to apply for Image clustering & Artificial Neural Network. Algorithms based on cluster methods are normally used to obtain data, which are based on the features space, where these groups are represented by clusters. In existing local threshold and fuzzy set measure is used in that we can only classify the images. Now we apply Neural Network segmentation relies on processing small areas of an image using an artificial neural network or a set of neural networks. After such processing the decision-making mechanism marks the areas of an image accordingly to the category recognized by the neural network.*

**Key Words:** *Image Segmentation, Enhancement, Improved K-means, ANN*

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## **I. Introduction**

In this paper we discussed and apply the image segmentation algorithm technique for both natural and bio-medical images. The objective of the image segmentation is to extract the dominant colors. The image segmentation is very important to simplify an information extraction from images, such as color, texture, shape, and structure. The applications of image segmentation are diversified in many fields such as image compression, image retrieval, objects detection, image enhancement, and medical image processing.

There are many applications that use image processing algorithms in outdoor scenes. Here improved K-means cluster and artificial neural network (ANN) were studied with the purpose of obtaining a set of algorithms that can be combined in order to achieve a better performance in image segmentation. A comparative study has been carried out to find out which algorithms perform best for the plant species images case.

Fuzzy c-means (FCM) clustering [1][5][6] is an unsupervised technique that has been successfully applied to feature analysis, clustering, and classifier designs in fields such as astronomy, geology, medical imaging, target recognition, and image segmentation. An image can be represented in various feature spaces, and the FCM algorithm classifies the image by grouping similar data points in the feature space into clusters. This clustering is achieved by iteratively minimizing a cost function that is dependent on the distance of the pixels to the cluster centers in the feature domain.

Several approaches have been already introduced for image segmentation. The most popular method for image segmentation is K-means algorithm [1][2][12]. It is widely a used algorithm for image segmentation because of its ability to cluster huge data points very quickly. Hierarchical clustering is also widely applied for

image segmentation Many researchers used Gaussian Mixture Model with its variant Expectation Maximization [9][15].

## II. Methods

### A. Thresholding Technique

Thresholding is a technique for segmentation of colored or gray scaled images based on the color or grayscale value, which transforms an image into a binary image by transforming each pixel according to whether it is inside or outside a specified range. The user chooses lower and upper threshold values to process the histogram. If a pixel is inside of this range, it is assigned an "inside" value. Otherwise it is assigned an "outside" value. So, thresholding may be viewed as an operation that involves tests against a function  $T$

$$T = T[x, y, p(x, y), f(x, y)] \quad \text{----- 1}$$

Where  $f(x, y)$  is the grey level of point  $(x, y)$  and  $p(x, y)$  denotes some local properties of this point, e.g., the average grey level of a neighborhood. The actual part of thresholding consists of setting background values for pixels below a threshold value and a different set of values for the foreground. A thresholded image,  $g(x, y)$  is then defined as:

$$g(x,y) = \begin{cases} 0 & \text{if } f(x) < T \\ 1 & \text{otherwise} \end{cases} \quad \text{----- 2}$$

Notes:

- (1). Global  $T$  depends on  $f(x, y)$  only.
- (2). Local  $T$  depends on  $f(x, y)$  and  $p(x, y)$ .
- (3). Dynamic  $T$  depends on  $(x, y)$  as well.

The input to a thresholding operation is typically a grayscale or color image. In the simplest implementation, the output is a binary image representing the segmentation. Black pixels correspond to background and white pixels correspond to foreground (or *vice versa*). In simple implementations, the segmentation is determined by a single parameter known as the *intensity threshold*. In a single pass, each pixel in the image is compared with this threshold. In

our study, if the pixel's intensity is higher than the threshold, the pixel is set to white in the output. If it is less than the threshold, it is set to black.

Figure 1 shows two probability density functions. Optimal thresholds can usually be extracted from bimodal histograms. If the histogram is not bimodal, then threshold determination will become difficult (see Figures 1 and 2)

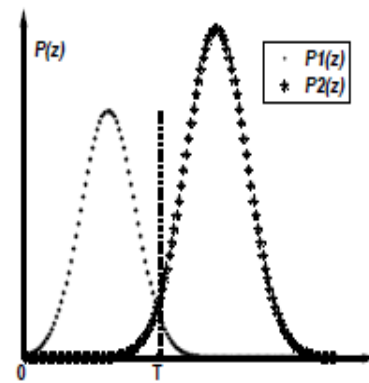


Fig.1. Gray-level probability density functions of two regions in an image

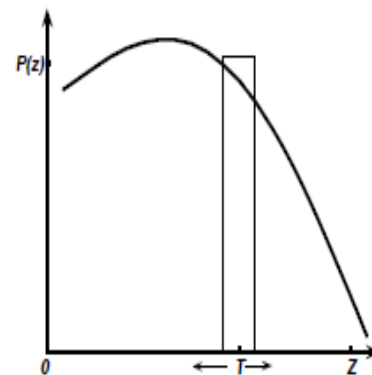


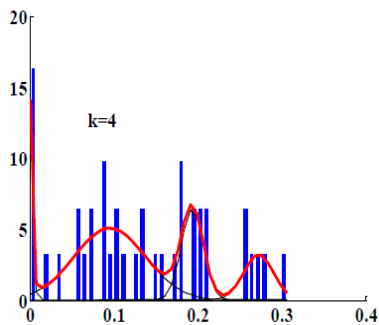
Fig. 2. Non-optimal histogram for threshold selection.

To verify the performance of our method, a set of various images was tested by our methods. For all the tested images, the images labeled 3(a) are original images. Figure 3(b) is a comparison between the probability density function (PDF) of image vs. its Gaussian mixture model. Figure 3(c) is thresholding images of our method. We examine the

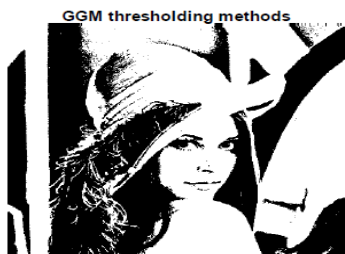
performance of the EM algorithms with respect to the mixing weights, the mean value of each class, the variances in each class, and the number of classes in the image.



3(a)



3(b)



3(c)

Fig.3. (a) Original image; (b) A comparison between the PDF of image vs. its Gaussian mixture model. The solid line is image histogram and the ‘-’ line is mixture model. (c) Result of an image conversion to a binary image [15].

### B.Improved K-means Algorithm

K-means clustering algorithm works on the assumption that the initial centres are provided. The search for the final clusters or centres starts from these initial centres. Without a proper

initialisation the algorithm may generate a set of poor final centres and this problem can become serious if the data are clustered using an on-line k-means clustering algorithm. In general, there are three basic problems that normally arise during clustering namely dead centres, local minima and centre redundancy.

Dead centres are centres that have no members or associated data. These centres are normally located between two active centres or outside the data range. The problem may arise due to bad initial centres, possibly because the centres have been initialised too far away from the data. Therefore, it is a good idea to select the initial centres randomly from the training data or to set them to some random values within the data range. However, this does not guarantee that all the centres are equally active. Some centres may have too many members and be frequently updated during the clustering process whereas some other centres may have only a few members and are hardly ever updated.

The centres in a RBF network should be selected to minimise the total distance between the data and the centres so that the centres can properly represent the data. A simple and widely used square error cost function can be employed to measure the distance, which is defined as:

$$E = \sum_{j=1}^N \sum_{i=1}^N \|v_i - c_j\|^2 \quad \text{----- 3}$$

The improved K-means algorithm is a solution to handle large scale data, which can select initial clustering center purposefully, reduce the sensitivity to isolated point, avoid dissevering big cluster. By using this technique locating the initial seed point is easy and which will give more accurate and high-resolution result. By using various techniques we can study or compare the results and find out which technique gives higher resolution. The initial centroid algorithm is useful to avoid the formation of empty clusters, as the centroid values are taken with respect to the intensity value of the image. Proposed algorithm is better for large datasets and to find initial centroid.

### C. Clustering Analysis

K-Means clustering algorithm – similar to nearest neighbor techniques (memory-based-reasoning and collaborative filtering) – depends on a geometric interpretation of the data  
Organizing data into clusters shows internal structure of the data

Ex. Clusty and clustering genes above  
Sometimes the partitioning is the goal

Ex. Market segmentation Prepare for other AI techniques

Ex. Summarize news (cluster and then find centroid) Techniques for clustering is useful in knowledge discovery in data

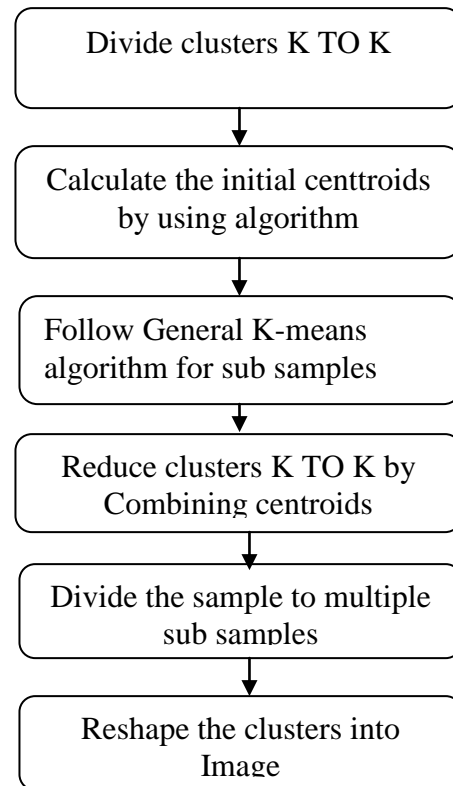
#### Algorithm Process Flow

Cluster the class A using the k-means algorithm into k cluster.

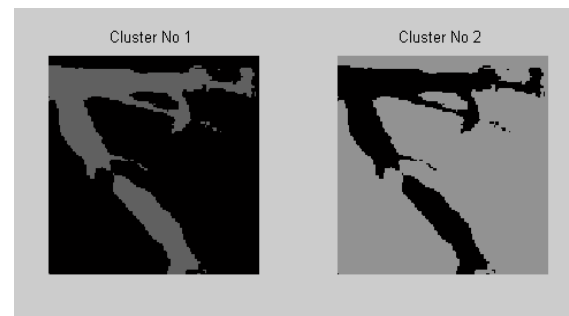
```

For each cluster cli (i:1..k) do
{ Sam(i) :={centroid(cli)};
j:=1;
For each x from cli do
{ Candidates [j].point :=x;
Candidates [j].location :=dist(x, centroid(cli)) ;
j:=j+1 ;};
Sort the array Candidates in descending order
with
respect to the values of location field;
j:=1;
While((card(Sam(i)))<Num_samples(cli))
and (j<card(cli)) do{min:=100000;
For each x from Sam(i) do
{ if dist(Candidates[j].point,x)<min
then min:= dist(Candidates[j].point,x) ;
}
if (min > ε) then
Sam(i):=Sam(i) ∪{Candidates[j].point};
j:=j+1; }
if card(Sam(i)) < Num_samples(cli) then
repeat {Sam(i):=Sam(i) ∪
Candidates[random].point
}
until (card(Sam(i)) = Num_samples(cli));
3-For i=1 to k do Out_sam:=Out_sam ∪ Sam(i);
    
```

#### Flow Chart



#### Segmentation using Initial centroids



### D. Artificial Neural Networks

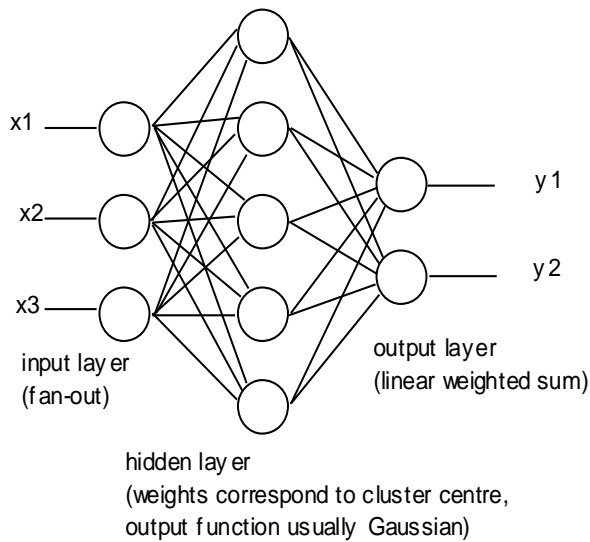
- A mathematical model to solve engineering problems, Group of highly connected neurons to realize compositions of non linear functions.
  - Tasks
    - Classification
    - Discrimination
    - Estimation
  - 2 types of networks
    - Feed forward Neural Networks
    - Recurrent Neural Networks

**RBF Network**

The basic architecture for a RBF is a 3-layer network, as shown in following Fig. A **Radial Basis Function (RBF) network** is an artificial neural network that uses radial basis functions as activation functions. It is a linear combination of radial basis functions. They are used in function approximation, time series prediction, and control. The input layer is simply a fan-out layer and does no processing. The second or hidden layer performs a non-linear mapping from the input space into a (usually) higher dimensional space in which the patterns become linearly separable.

**Output layer**

- The final layer performs a simple weighted sum with a linear output.
- If the RBF network is used for function approximation (matching a real number) then this output is fine.
- However, if pattern classification is required, then a hard-limiter or sigmoid function could be placed on the output neurons to give 0/1 output values.



**Distance measure**

- The distance measured from the cluster centre is usually the Euclidean distance.
- For each neuron in the hidden layer, the weights represent the co-ordinates of the centre of the cluster.

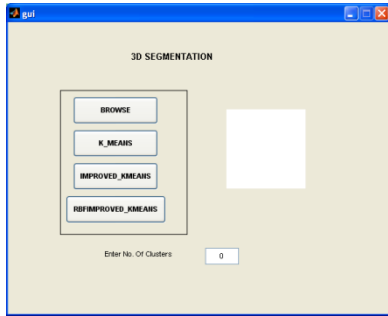
- Therefore, when that neuron receives an input pattern, X, the distance is found using the following equation:

$$r_j = \sqrt{\sum_{i=1}^n (x_i - w_{ij})^2} \quad \text{----- 4}$$

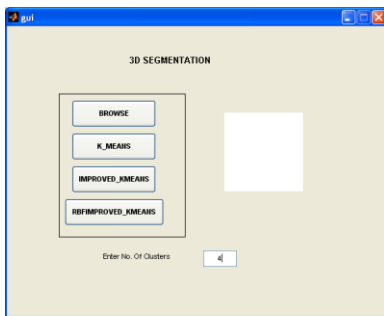
**Training hidden layer**

- The hidden layer in a RBF network has units which have weights that correspond to the vector representation of the centre of a cluster.
- These weights are found either using a traditional clustering algorithm such as the *k*-means algorithm, or adaptively using essentially the Kohonen algorithm.
- In either case, the training is unsupervised but the number of clusters that you expect, *k*, is set in advance. The algorithms then find the best fit to these clusters.
- The *k*-means algorithm will be briefly outlined.
- Initially *k* points in the pattern space are randomly set.
- Then for each item of data in the training set, the distances are found from all of the *k* centres.
- The closest centre is chosen for each item of data - this is the initial classification, so all items of data will be assigned a class from 1 to *k*.
- Then, for all data which has been found to be class 1, the average or mean values are found for each of co-ordinates.
- These become the new values for the centre corresponding to class 1.
- Repeated for all data found to be in class 2, then class 3 and so on until class *k* is dealt with - we now have *k* new centres.
- Process of measuring the distance between the centres and each item of data and re-classifying the data is repeated until there is no further change – i.e. the sum of the distances monitored and training halts when the total distance no longer falls.

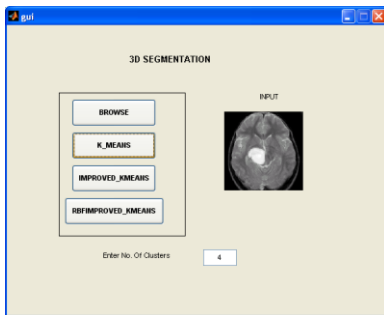
### III. EXPERIMENTAL RESULTS



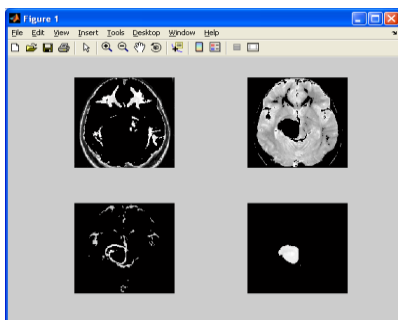
(a)



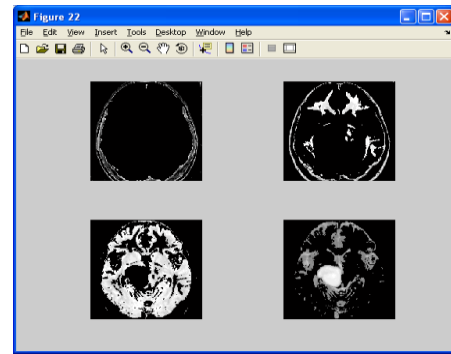
(b)



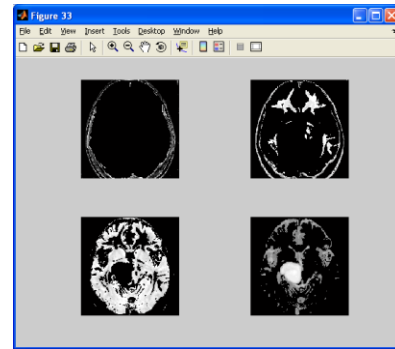
(c) K- Means Out put



(d) Improved K-Means



(e) RBF Improved K-Means



(f)

### IV CONCLUSION

In this paper we have done a both updating methods have been proposed and were tested using one simulated and two real image training. The simulation results showed that the proposed updating methods have significantly improved the performance of improved k-means clustering algorithm. K-means clustering algorithm that uses both the proposed updating methods. And also better segmentation result for both bio-medical and natural image processing to be applied. Due to the strong correlation between the good clustering and the overall RBF performance, both the proposed updating methods provide significantly better overall performance than the other three updating methods that are considered.

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Author 1: K. Srinivas, did his M.Tech from Nagarjuna University and pursuing Ph.D from K.L. University. Currently he is working as Assoc. Professor in the Department of MCA.



Author 2: Dr. V. Srikanth obtained his B.Tech and M.E degrees from Madras University and PhD from Nagarjuna university. Presently working as HOD of CSE, K.L. University, Vaddeswaram. AP.