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Ebrahim. Aghajari
Research Student, Department of Electronic Science University of Pune Pune-India, eba@electronics.unipune.ac.in

Dr.Mrs. Gharpure Damayanti
Associate Professor, Department of Electronics Science University of Pune Pune-India, dcg@electronics.unipune.ac.in

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Incorporating FCM and Back Propagation Neural Network for Image Segmentation

Ebrahim.Aghajari
Research Student, Department of Electronic Science
University of Pune
Pune-India
eba@electronics.unipune.ac.in

Dr.Mrs. Gharpure Damayanti
Associate Professor, Department of Electronics Science
University of Pune
Pune-India
dcg@electronics.unipune.ac.in

***Abstract*— Hybrid image segmentation is proposed in this paper. The input image is firstly preprocessed in order to extract the features using Discrete Wavelet Transform (DWT) .The features are then fed to Fuzzy C-means algorithm which is unsupervised. The membership function created by Fuzzy C-means (FCM) is used as a target to be fed in neural network. Then the Back Propagation Neural network (BPN) has been trained based on targets which is obtained by (FCM) and features as input data. Combining the FCM information and neural network in unsupervised manner lead us to achieve better segmentation .The proposed algorithm is tested on various Berkeley database gray level images.**

Keywords: Image Segmentation, Fuzzy C-Means (FCM), Neural network (NN), Discrete Wavelet transforms (DWT)

I. INTRODUCTION

Image segmentation was, is and will be one of the most challenging and critical problem topics for many researchers. Segmentation algorithm is a process, which aims to extract and partition the image into homogeneous and meaningful regions (where meaningful typically refers to separation of image regions into different semantic objects). As image segmentation is the core of many image analysis problems, any improvement in segmentation methods can lead to important impacts on many image processing and computer vision applications. [24]

Many algorithms have been proposed for segmentation and there are a variety of approaches available for image segmentation. However all the research work performed on image segmentation can be classified into two broad categories. [1]

I) Traditional methods based on thresholding, morphological method, edge based segmentation [11], Normalized cut method (NC) [19] implemented by Shi and Malik [14], Efficient graph-based method (EG) [18] implemented by Felzenszwalb and Huttenlocher [16], Mean shift method (MS) [12] implemented by Comaniciu and Meer [13],Level-set method (LS) [17] implemented by Fan [15],Ratio-contour method (RC) [20] implemented by Wang et al, [21] and many more which is called non Artificial Intelligent based(NON- AI). **II)** Artificial intelligent (AI) techniques. Among AI techniques, Fuzzy Theory and Artificial Neural Network are predominantly used for segmentation and are preferred by researchers because of its adaptive nature and accuracy. [1] This paper is organized as follows: section **II** introduces a brief description about importance of hybrid method for image segmentation. In Section **III**, the proposed method and its concepts will be elaborated. The experimental result and evaluation of method will be described in section **IV** and **V** respectively. Finally the conclusions are given in section **VI**.

II. IMPORTANCE OF HYBRID METHOD FOR IMAGE SEGMENTATION

It has been shown in the literature through many research works that Neuro-fuzzy systems are more efficient and flexible for clustering and classification than other approaches. [6-7-8-9].There are several image segmentation methods based on fuzzy theory [5] and fuzzy concept reported in [2-4] among which fuzzy clustering [4] is a well known technique for this purpose. To deal with the ambiguity, it is helpful to introduce some "fuzziness" into the formulation of the problem. For example, the boundary between clusters could be fuzzy rather than crisp; that is, a data point could belong to two or more clusters with different degrees of membership. In this way, the formulation is closer to the real- world problem and therefore better performance may be expected. This is one of the reasons for using fuzzy models for segmentation. Neural network based segmentation has three basic characteristics *1)* highly parallel ability and fast computing capability, which make it suitable for real-time application. *2)* unrestricted nonlinear degree and high interaction among processing units, which make this algorithm able to establish modeling for any process;*3)* satisfactory robustness making it insensitive to noise [25] .Therefore the significant advantages to use ANN is the fact that it can take decision based on complex and noisy data which is true in the core of many images. In this paper we have proposed a new algorithm to combine and use the prior information created by Fuzzy clustering method for training neural network, particularly, to formulate image segmentation as extracting the single most salient structure in the image.

III. PROPOSED METHOD

In this subsection, a basic set of definition are presented to provide the preliminaries of the proposed method. First we defined the Fuzzy C- means (FCM) clustering method. The second part discusses about back propagation neural network and finally discrete wavelet transform (DWT) and gradient method will be defined.

A. FCM

Fuzzy C-means (FCM) proposed by Bezdek in 1973[5], is a clustering technique which is separated from hard k-means that employs hard partitioning. The FCM employs fuzzy partitioning such that a data point can belong to all groups with different membership grades between 0 and 1.FCM is an iterative algorithm. The aim of FCM is to find cluster centers (centroids) that minimize a dissimilarity function. To accommodate the introduction of fuzzy partitioning, the membership matrix (U) is randomly initialized according to Equation A.1.

$$\sum_{i=1}^{c} u_{ij} = 1, \forall j = 1,...,n \qquad \text{(A.1)}$$

The dissimilarity function which is used in FCM is given Equation

$$J(U, c_1, c_2, ..., c_c) = \sum_{i=1}^{c} J_i = \sum_{i=1}^{c}\sum_{j=1}^{n} u_{ij}{}^m d_{ij}{}^2 \qquad \text{(A.2)}$$

U_{ij} is between 0 and 1;

C_{ij} is the centroid of cluster i;

d_{ij} is the Euclidian distance between i_{th} centroid(c_i) and j_{th} data point;

m є [1,∞] is a weighting exponent or fuzziness parameter.

To reach a minimum of dissimilarity function there are two conditions. These are given in Equation A.3 and Equation A.4.

$$c_i = \frac{\sum_{j=1}^{n} u_{ij}{}^m x_j}{\sum_{j=1}^{n} u_{ij}{}^m} \qquad \text{(A.3)}$$

$$u_{ij} = \frac{1}{\sum_{k=1}^{c}\left(\frac{d_{ij}}{d_{kj}}\right)^{2/(m-1)}} \qquad \text{(A.4)}$$

Precisely speaking, initially the Uij and the centers of the clusters are assigned randomly, moreover the Uij is updated in each iteration. The iterative process stops when

$$\left\|U^{(S)} - U^{(S-1)}\right\| = \max\left|u_{ij}^{(S)} - u_{ij}^{(S-1)}\right| \prec \varepsilon \qquad \text{(A.5)}$$

This algorithm determines the following steps [4].

Step1. Randomly initialize the membership matrix (U) that has constraints in Equation (A.1)

Step2. Calculate centroids (c_i) by using Equation (A.3).

Step3. Compute dissimilarity between centroids and data points using equation (A.2). Stop if its improvement over previous iteration is below a threshold.

Step4. Compute a new U using Equation (A.4). If condition (A.5) is False Go to Step 2.

By iteratively updating the cluster centers and the membership grades for each data point, FCM iteratively moves the cluster centers to the "right" location within a data set.

FCM does not ensure that it converges to an optimal solution, because of cluster centers (centroids) are initialize using U that randomly initialized. (Equation A.3).

B. Back Propagation neural network (BPN)

The back propagation algorithm is a generalization of the least mean square algorithm that modifies network weights to minimize the mean squared error between the desired and Actual outputs of the network. Back propagation uses supervised learning in which the network is trained using data for which inputs as well as desired outputs are known. Once trained, the network weights are frozen and can be used to compute output values for new input samples.

Back propagation Algorithm:

Step1. Design the structure of neural network and input parameters of the network.

Step2. Get initial weights W and initial θ values from randomizing

Step3. Input training data matrix X and output matrix T.

Step4. Compute the output vector of each neural unit.

a) Compute the output vector H of the hidden layer

$$net_k = \sum WikXi - \theta_k$$
$$H_k = f(net_k) \qquad \text{(B.1)}$$

b) Compute the output vecter Y of the output layer

$$net_j = \sum Wkj\ H_i - \theta_j$$
$$Y_j = f(net_j) \qquad \text{(B.2)}$$

Step5. Compute the distances d

(a) Compute the distances d of the output layer

$$\delta_j = (T_j - Y_j) \bullet f'(net_j)$$

(b) Compute the distances d of the hidden layer

$$\delta_k = (\sum \delta_j W, y) \bullet f'(net_k) \qquad \text{(B.3)}$$

Step6. Compute the modification of W and θ (η is the learning rate)

(a) Compute the modification of W and θ of the output layer

$$\Delta W_{kj} = \eta \delta j Hk$$
$$\Delta \theta_j = -\eta \delta_j \qquad \text{(B.4)}$$

(b) Compute the modification of W and θ of the hidden layer

$$\Delta W_{ik} = \eta \delta k Xi$$
$$\Delta \theta_k = -\eta \delta_k \qquad \text{(B.5)}$$

Step7. Renew W and θ

a) Renew W and θ of the output layer

$$\text{Wkj} = \text{Wkj} + \Delta\ \text{Wkj}$$
$$\theta_j = \theta_j + \Delta \theta_j \qquad \text{(B.6)}$$

b) Renew W and θ of the hidden layer

$$\text{Wik} = \text{Wik} + \Delta\ \text{Wik}$$
$$\theta_k = \theta_k + \Delta \theta_k \qquad \text{(B.7)}$$

Step8. Repeat step 3 to step7 until convergence.

C. Discrete Wavelet Transform (DWT)

The wavelet transform is important to provide a compact description of signals (or images) that are limited in time (or spatial extent) and it is very helpful in description of edge and line that are highly localized. Wavelet transform decomposes a signal into a set of basis functions. These basis functions are called wavelets. Wavelets are obtained from a single prototype wavelet $\psi_{a,b}(t)$ called mother wavelet by dilations and shifting:

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi(\frac{t-b}{a}) \qquad (C.1)$$

Where (a) is the scaling parameter and (b) is the shifting parameter. The scaling and wavelet function are two variable functions denoted $\phi(x,y)$ and $\psi(x,y)$ here.

The scaled and translated basis functions are defined as

$$\phi^{i}_{j,m,n}(x,y) = 2^{j/2}\phi(2^{j}x-m, 2^{j}y-n) \qquad (C.2)$$

$$\psi^{i}_{j,m,n}(x,y) = 2^{j/2}\psi(2^{j}x-m, 2^{j}y-n), \quad i=\{H,V,D\}.$$

There are three different wavelet functions, $\psi^{H}(x,y)$ $\psi^{V}(x,y)$ and $\psi^{D}(x,y)$ .Conceptually, the scaling function is the low frequency component of the previous scaling function in 2 dimensions. Therefore, there is one 2D scaling function. However, the wavelet function is related to the order to apply the filters. If the wavelet function is separable, i.e. f(x, y) = f_1(x) f2(y). These functions can be easily rewritten as:

$$\phi(x,y) = \phi(x)\phi(y), \qquad (C.3)$$

$$\psi^{H}(x,y) = \psi(x)\phi(y), \qquad (C.4)$$

$$\psi^{V}(x,y) = \phi(x)\psi(y), \qquad (C.5)$$

$$\psi^{D}(x,y) = \psi(x)\psi(y). \qquad (C.6)$$

After each filtering the resulting coefficient image is decimated by half in each coordinate. As a result four different images containing the four wavelet coefficient (LL, LH, HL, HH) are generated .Indeed, by using wavelet on an image for one level, four images will be obtained which correspond to the approximation and detail images.

The approximation coefficients matrix CA and details coefficients matrices CH, CV, and CD (horizontal, vertical, and diagonal, respectively), obtained by wavelet decomposition of the input matrix X is the same as (LL,LH,HL,HH) which have been used as a features for proposed algorithm.[11]

D. Image Gradient

An **image gradient** is a directional change in the intensity or color in an image. Image gradients may be used to extract information from images. Mathematically, the *gradient* of a two-variable function (here the image intensity function) is at each image point a 2D vector with the components given by the derivatives in the horizontal and vertical directions. At each image point, the gradient vector points in the direction of largest possible intensity increase, and the length of the gradient vector corresponds to the rate of change in that direction. Image gradients can be used to extract information from images. The gradient of an image is given by the formula [11]:

$$\nabla f = \frac{\partial f}{\partial x}\hat{x} + \frac{\partial f}{\partial y}\hat{y} \qquad (D.1)$$

Where:

$\frac{\partial f}{\partial x}$: is the gradient in the x direction (GX)

$\frac{\partial f}{\partial y}$: is the gradient in the y direction (GY)

E. Implementation and the Proposed Algorithm

In this section, the main proposed segmentation algorithm is introduced and explained. The block diagram of algorithm is presented in figure.1.

Step1: In the first phase, for the input image f(x, y) histogram values are calculated. This helps us to decide number of clusters.

Step2: The second phase of the project is feature extraction by using DWT coefficient in addition to gradient feature extraction.As mention in section III-C after each decomposition process, the resulting coefficient image is decimated by half in each coordinate. As a result, four different images containing the mentioned coefficient (CA, CH, CV, and CD) are generated, each being ¼ the size of the original images. Since every wavelet coefficient carries unique information, each has been preserved separately by selective reconstruction method. This has been implemented by reconstruction every wavelet coefficient by applying inverse DWT with others set to be zero. This results in four reconstructed images for wavelet decomposition of level one. [10]

Two more features have been added which extracted by gradient method in X and Y direction.(GX,GY) as discussed in section III-D.

Step3: In the third phase of the proposed algorithm we used FCM for clustering purpose. The process of FCM algorithm described in section III-A (Initial value m=2 $\varepsilon = 0.01$).FCM is unsupervised fuzzy clustering algorithm and it is motivated by the need to find interesting patterns or groupings in a given set of data. Clustering refers to identifying the number of subclasses input data sample.

The index label generated by FCM is used as a target for neural network. The trick of the algorithm is use of FCM for generating target value. So unlike much hybrid method, here the selection of targets is in unsupervised manner.

Step4: Fourth phase of proposed algorithm deals with selection of some random data samples from the entire image instead of taking all the pixels. As mentioned before, few pixels have been selected from each cluster equally for generating training data. Here we randomly select the pixels of image and consider features of those pixels as input neurons for input layer and FCM index label corresponding to those pixels as a target value.

Step 5: In the next phase the image is segmented by using neural network. The proposed network architecture is a feed forward network with supervised learning so the input and the target have to be specified to the neural network. Figure.2, illustrates the construction of BPN network. In this the random samples (N*6) passed as input. The target value is the FCM index value. The network input has 6 neurons and 1 hidden layer including 11 nodes. Number of neurons in output layer depends on number of clusters defined for Image segmentation. Network will be constructed and the weights W are randomly initialized. Then the input patterns consisting of six features along with target output from FCM are passed into the network in order to train the network. We use the original feature extraction data as simulation of the network.

Step 6: The segmented output image from the neural network will be processed to get the salient object and finally we evaluate the output of FCM and incorporative method.

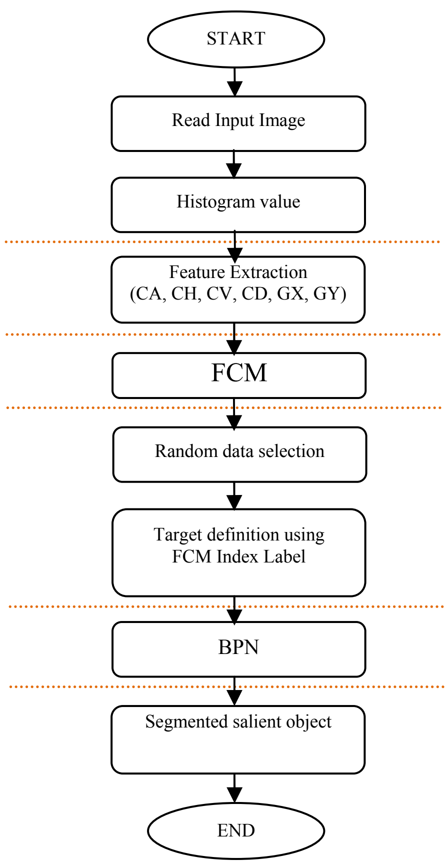

Figure 1: Implemented Algorithm for Image Segmentation

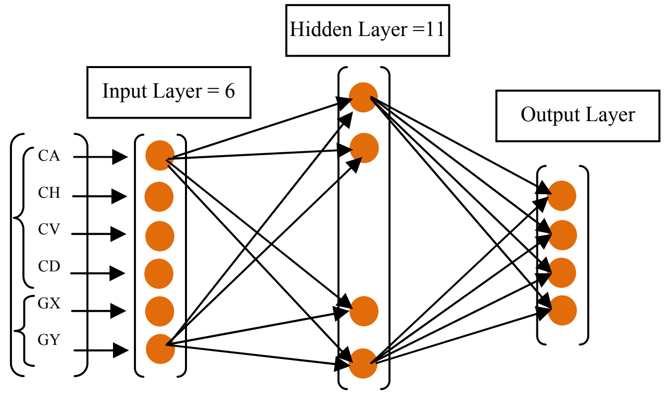

Figure 2: Construction of Back Propagation Neural Network (BPN)

IV. EXPERIMENTAL RESULT

As discussed in previous section, the performance of the FCM and proposed method can be observed in Figure.3 and Figure.4. [**Annexure I]** .Image segmentation based on above mentioned methods has been successfully applied in Berkeley Database [22].Each of the sample images has (481*321) pixels. Please remind that the proposed algorithm developed for extracting salient object (foreground) from background. In this experiment, we have used Matlab software on a 2.67GHZ dual core Intel CPU system with 4GB RAM for implementation of algorithm. The average execution time of the proposed algorithm was 19.9 seconds.

V. EVALUATION AND DISCUSSION

To assess and compare the result of image segmentation techniques proposed in this work the evaluation parameters such as sensitivity, specificity, segmentation accuracy and corresponding ration have been calculated. These parameters are determined for different criterion parameters such as True-Positive (TP), True Negative (TN), False-Positive (FP) and False-Negative (FN) as follows,

Sensitivity = ((TP/ (TP+TN))*100%

Specificity = ((TN/ (TP+TN))*100%

Accuracy = ((TP+TN)/ (TP+FN+TN+FP))*100%

Corresponding Ratio (CR) = ((TP-0.5*FP/ (TP+FN))

An ideal segmentation is the one which achieves 100% sensitivity, specificity an segmentation accuracy. In case of (CR), the value "0" indicates that the object is completely missing and the value "1" means the object is fully defined. The image and ground truth for evaluation references are available at Berkeley database. [22][23]. The table 1 and 2 [**Annexure I**]are providing the comparison parameter such as sensitivity, specificity, Accuracy and corresponding ratio for evaluation of the performance of FCM & proposed method (FCM&BPN).As it is clearly evident from both of the tables, the performance of FCM techniques are less effective compare to proposed method. For figure3, sensitivity of FCM and proposed method has been observed as % 94.19 and %98.49 respectively. It means the performance of proposed method was 4.3% more accurate to extract the salient object compare to other one. The same scenario is repeated for figure 4. It clearly indicates the advantage of incorporating fuzzy system information (here using membership function as a target definition) and neural network. In this case incorporating method was 5% more effective. The correspond ratio of the images for their salient objects has been determined in order to study the contribution of false positive factor on the true positive factor and are calculated values are tabulated in table 1 and 2. The correspondence ratio of proposed algorithm observed to produce the salient object segmentation defined for 0.89 and 0.80 for images of figure 3 and 4 on the other hand FCM has the correspondence ratio value of 0.83 and 0.75 for the same images. That shows 5% and 6% effectiveness of proposed algorithm in order to define the salient object for images shows in figure 3 and 4 respectively.

VI. CONCLUTION

To improve the accuracy of salient object segmentation of Image, a hybrid FCM &BPN approach is proposed in this method. In this approach we extracted the DWT and gradient features of an image and then clustered the image based on features using FCM. After that we selected some few random samples of an image equally to feed in neural network, the main part of the algorithm is the usage of corresponding FCM membership index label for each input pattern as a target value to be applied for BPN. We also find out that definition of target in the proposed manner gives good result along with the advantage of fast processing and time execution because of the less sample data as an input pattern. To validate the effectiveness of our proposed method we evaluate the output of FCM & its incorporation with BPN by determining sensitivity and corresponding ratio parameters and the output of combine method has been more accurate and effective.

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Annexure I

Segmentation Image Results and Evaluation Tables for Proposed Algorithm

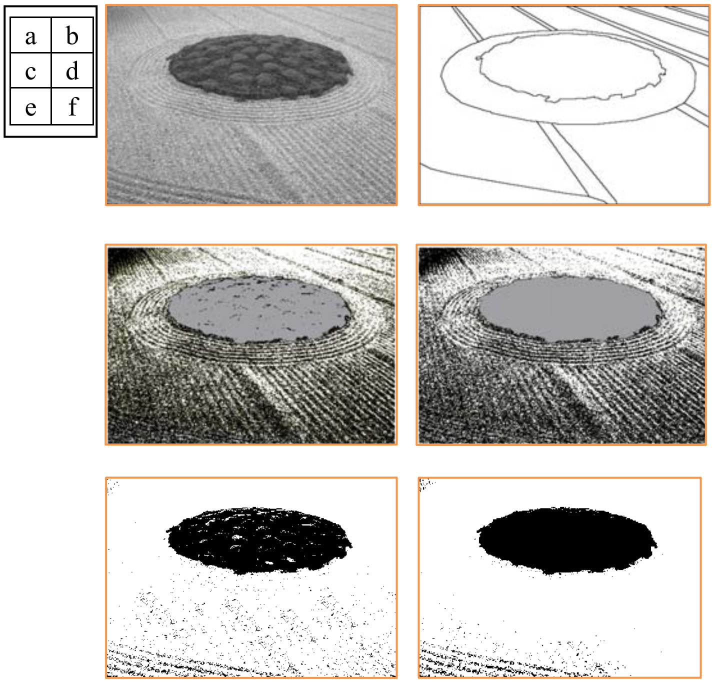

Figure 3: [a) Original Image, b) Ground Truth , c) FCM Segmentation Result , d) FCM&BPN Segmentation Result e) Extracting Salient object from FCM f)Extracting Salient object from Proposed Algorithm (FCM&BPN)]

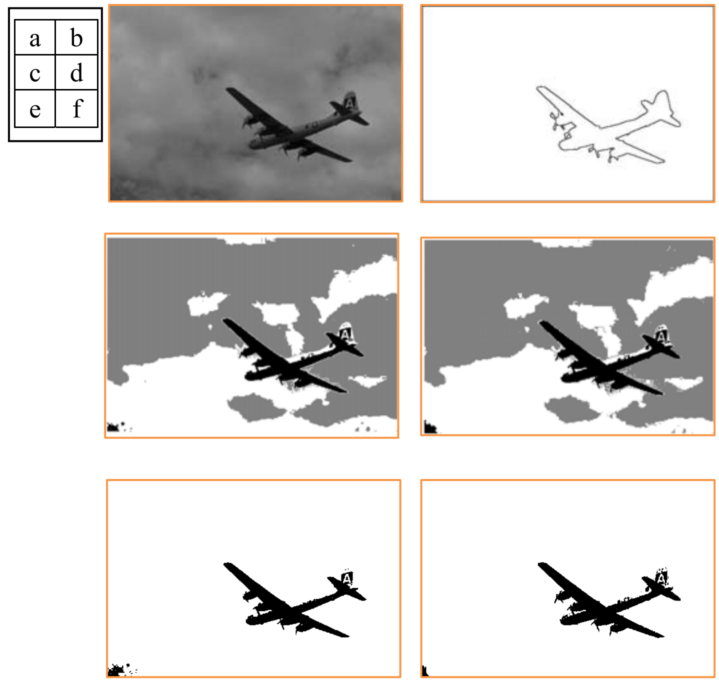

Figure 4: [a) Original Image, b) Ground Truth , c) FCM Segmentation Result , d) FCM&BPN Segmentation Result e) Extracting Salient object from FCM f)Extracting Salient object from Proposed Algorithm (FCM&BPN)]

Method	Sensitivity	Specificity	Accuracy	CR
FCM	% 94.197	% 96.47	% 95.74	0.83
FCM&BPN	% 98.49	% 96.73	% 97	0.89

Table 1: Evaluation Parameter of an Garden Segmented Image (Cluster=4, Fuzziness Parameter (m) = 2)

Method	Sensitivity	Specificity	Accuracy	CR
FCM	% 77.18	% 99.65	% 98.2	0.75
FCM&BPN	% 82.21	% 99.61	% 98.5	0.80

Table 2: Evaluation Parameter of an Aeroplane Segmented Image (Cluster=3, Fuzziness Parameter (m) = 2)