Performance Evaluation of The Fuzzy C-means Algorithm and Comparison with Gath_Geva algorithm for Color Images Segmentation

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Abstract

The aim of cluster analysis is the classification of objects according to similarities among them and organizing of data into groups or clusters. Fuzzy clustering can be used as a tool to obtain the image segmentation. The main objective of the research was how to take advantage of algorithms Fuzzy Clustering of the clustering color images into several clusters because of their great importance for a number of processors and applications, including (classification and compression). In this research we studied the FCM algorithm and the Gath_Geva algorithm for the different types of color images (medical, natural, and satellite) and compare the results of each of them and find the best in terms of changing the number of clusters and Cluster Validity Measures, Fuzzy Parameter and type of color image. So, we found that Gath_Geva algorithm is the best because of the distance scale which depends on several factors on the number of clusters, values of Cluster Validity Measures in addition it is faster implementation.

Keywords: Image processing , image segmentation, remote sensing image, medical image, Gath_Geva algorithm and FCM algorithm.

1- Introduction:

Color image segmentation is useful in many applications. From the segmentation results, it is possible to identify regions of interest and objects in the scene, which is very beneficial to the subsequent image analysis or annotation [Mohamed 2011]. Image Segmentation plays a crucial role in many medical imaging applications by automating or facilitating the delineation of anatomical structures. In the human brain imaging and diagnosis, Magnetic Resonance Imaging (MRI) can provide volumetric images of the brain with good soft tissue contrast segmentation is then a post-processing operation which abstracts quantitative description of anatomically relevant structures[H.P.Ng etal. 2006][R Venkateswaran etal. 2010]. Remote sensing image is an evolving technology with the potential for contributing to studies of the human dimensions of global environmental change by making globally comprehensive evaluations of many human actions possible. Image data enable direct observation of the land surface at repetitive intervals and therefore allow mapping of the extent, and monitoring of the changes in land cover. Evaluation of the static attributes of land cover and the dynamic attributes on satellite image data may allow the types of change to be regionalized and the proximate sources of change to be identified or inferred. This information, combined with results of case studies or surveys, can provide helpful input to informed evaluations of interactions among the various driving forces [Turcan 1998]. Fuzzy clustering method assigns one sample to multiple group according to their degree of membership[Han-Saem etal. 2005], [Zhou etal.
2007] used max cluster centers and miner cluster center where applied adaptive fuzzy clustering, this adaptive capability is achieved by using the mechanism of splitting and merging, also studied fuzzy C-mean in synthetic data with outliers and heavy tailed, overlapped groups of the data by Jacek [Jacek 2001] applied the cluster methods on many application, also Julien [Julien 2005] applied it on speech where showed that when clustering phonemes, certain acoustical and articulator features can be captured. Fuzzy clustering can improve cluster quality. In [Andrew 2001] the clustering algorithm utilized to biomole color data. [Hsiang-Chuan et al. 2009] improved fuzzy C-means algorithm based on different mahalanobis distances called FCM-M, FCM-CM and FCM-SM, of real data sets.

The well-known FCM is based on Euclidean distance function, which can only be used to detect spherical structural clusters. Gath_Geva algorithm was developed to detect non-spherical structural clusters, the former needs added constraint of fuzzy covariance matrix, the later can be used for the data with multivariate Gaussian distribution [Krishnapuram et al. 1999].

In the outline of the paper is as follows, in the next section the show fuzzy clustering, in section 3 show Parameters of the FCM Algorithm and Gath_Geva algorithm, and in section 4 Fuzzy C-means Clustering is showed, and Gath_Geva Clustering in section 5, clustering validity is showed in section 6, in section 7 the suggestion System Framework that contains operators and Algorithms of FCM and Gath_Geva algorithm, The Results and Discussion are discussed in a section 8, conclusion is showed in section 9.

2- **Fuzzy Clustering**

Clustering technique plays an important role in data analysis and interpretation. It groups data into clusters so that the data objects within a cluster have high similarity in comparison to one another, but are very dissimilar to those data objects in other clusters. Fuzzy clustering is a branch in clustering analysis and it is widely used in the pattern recognition field. The well-known ones, such as Bezdek’s Fuzzy C-Means (FCM) [Bezdek et al. 1981] [Hsiang-Chuan et al. 2009] [C.-H. et al. 2008] are based on Euclidean distance. These fuzzy clustering algorithms can only be used to detect the data classes with the same super spherical shapes.

To overcome the drawback due to Euclidean distance, we could try to extend the distance measure to Mahalanobis distance (MD). However, [Krishnapuram et al. 1999] pointed out that the Mahalanobis distance cannot be used directly in clustering algorithm. Gath_Geva (GG) clustering algorithm [Gath et al. 1989] were developed to detect non-spherical structural clusters.

However, the added fuzzy covariance matrices in their distance measure were not directly derived from the objective function. In GG algorithm, the Gaussian distance can be used for the data with multivariate normal distribution [Hsiang et al. 2009].

3- **Parameters of the FCM Algorithm and Gath_Geva algorithm:**

Before using the FCM algorithm and Gath_Geva, the following parameters must be specified: the number of clusters, c, the ‘fuzziness’ exponent, m, the termination tolerance, ε, and the norm-inducing matrix, A. Moreover, the fuzzy partition matrix, U, must be initialized. The choices for these parameters are now described one by one.

- **Number of Clusters.**

  The number of clusters c is the most important parameter, in the sense that the remaining parameters have less influence on the resulting partition. When clustering real data without any a priori information about the structures in the data, one usually has to make assumptions about the number of underlying clusters. The chosen
clustering algorithm then searches for \( c \) clusters, regardless of whether they are really present in the data or not. Two main approaches to determining the appropriate number of clusters in data can be distinguished [Bezdek et al. 1981][ Balasko 2002][ ROBERT 2009]:

- **Validity measures.**
  Validity measures are scalar indices that assess the goodness of the obtained partition. Clustering algorithms generally aim at locating well-separated and compact clusters. When the number of clusters is chosen equal to the number of groups that actually exist in the data, it can be expected that the clustering algorithm will identify them correctly. When this is not the case, misclassifications appear, and the clusters are not likely to be well separated and compact.
  Hence, most cluster validity measures are designed to quantify the separation and the compactness of the clusters. However, as [Bezdek et al. 1981] points out, the concept of cluster validity is open to interpretation and can be formulated in different ways.

- **Iterative merging or insertion of clusters**
  The basic idea of cluster merging is to start with a sufficiently large number of clusters, and successively reduce this number by merging clusters that are similar (compatible) with respect to some well-defined criteria [Robert 2009].
  One can also adopt an opposite approach, i.e., start with a small number of clusters and iteratively insert clusters in the regions where the data points have low degree of membership in the existing clusters [Gath and Geva, 1989].

- **Fuzziness Parameter.**
  The weighting exponent \( m \) is a rather important parameter as well, because it significantly influences the fuzziness of the resulting partition. As \( m \) approaches one from above, the partition becomes hard (\( u_{ik} \in \{0,1\} \)) and \( v_i \) are ordinary means of the clusters. As \( m \to \infty \), the partition becomes completely fuzzy (\( u_{ik} = \frac{1}{c} \)) and the cluster means are all equal to the mean of \( Z \). These limit properties of (4.6) are independent of the optimization method used [Robert 2009]. Usually, \( m = 2 \) is initially chosen. Also a Gath_Geva algorithm used The weighting exponent (\( w \)) which determines the fuzziness of the clusters. It must be given as a scalar greater or equal to one.

- **Termination Criterion**
  The FCM algorithm stops iterating when the norm of the difference between \( U \) in two successive iterations is smaller than the termination parameter \( \varepsilon \). For the maximum norm \( \max_{ik}(\|u_{ik}^{(0)} - u_{ik}^{(0-1)}\|) \), the usual choice is \( \varepsilon = 0.001 \), even though \( \varepsilon = 0.01 \) works well in most cases, while drastically reducing the computing times [Robert 2009].

- **Norm-Inducing Matrix.**
  The shape of the clusters is determined by the choice of the matrix \( A \) in the distance measure. in FCM algorithm , a common choice is \( A = I \), which gives the standard Euclidean norm:
  \[
  D_{ik}^2 = (x_k - v_i)^T(x_k - v_i)
  \]  
  … (1)
  In Gath_Geva , clustering algorithm employs a distance norm based on the fuzzy maximum likelihood estimates is Gauss distance , proposed by [Balasko 2002]

- **Initial Partition Matrix.**
  The partition matrix is usually initialized at random, such that \( U \in M_{fc} \). A simple approach to obtain such \( U \) is to initialize the cluster centers \( v_i \) at random and compute the corresponding \( U \)[Robert 2009].
4- Fuzzy C-means Clustering

The fuzzy c-means (FCM) is one of the most widely used methods in fuzzy clustering. It is based on the concept of fuzzy c-partition, introduced by [S. Nascimento et al. 1999], summarized as follows.

Let \( X = \{x_1, \ldots, x_n\} \) be a set of given data, where each data point \( X_k \) (\( k = 1, \ldots, n \)) is a vector in \( \mathbb{R}^p \), \( U_{cn} \) be a set of real \( c \times n \) matrices, and \( c \) be an integer, \( 2 < c < n \).

Then, the fuzzy c-partition space for \( X \) is the set

\[
M_{fcn} = \{ U \in U_{cn} : u_{ik} \in [0,1] \sum_{i=1}^{c} u_{ik} = 1, 0 < \sum_{k=1}^{n} u_{ik} < n \} \quad \ldots (2)
\]

where \( u_{ik} \) is the membership value of \( x_k \) in cluster \( i \) (\( i = 1, \ldots, c \)). The aim of the FCM algorithm is to find an optimal fuzzy c-partition and corresponding prototypes minimizing the objective function

\[
J_m(Z, U, V) = \sum_{i=1}^{c} \sum_{k=1}^{n} u_{ik}^m \| x_k - v_i \|^2 \quad \ldots (3)
\]

In (3), \( V = (v_1; v_2, \ldots, v_c) \) is a matrix of unknown cluster centers (prototypes) \( v_i \in \mathbb{R}^p \), \( \| . \| \) is the Euclidean norm, and the weighting exponent \( m \in [1, \infty) \) is a constant that influences the membership values. To minimize criterion \( J_m \), under the fuzzy constraints defined in (2).

5- Gath-Geva Clustering

The fuzzy maximum likelihood estimates (FMLE) clustering algorithm employs a distance norm based on the fuzzy maximum likelihood estimates, proposed by [J. Abonyi et al. 2003]:

\[
D_{ik}(z_k, v_i) = \frac{(2\pi)^{m/2} \det(F)}{a_i} \exp\left(\frac{1}{2} (x_k - v_i)^T F_i^{-1} (x_k - v_i)\right) \quad \ldots (4)
\]

Note that, this distance norm involves an exponential term and thus decreases faster than the inner-product norm. \( F_{wi} \) denotes the fuzzy covariance matrix of the \( i \)-the cluster, given by:

\[
F_i = \frac{\sum_{k=1}^{n} u_{ik}^w (x_k - v_i)(x_k - v_i)^T}{\sum_{k=1}^{n} u_{ik}^w} \quad \ldots (5)
\]

where \( w = 1 \) in the original FMLE algorithm, but we use the \( w = 2 \) weighting exponent, so that the partition becomes more fuzzy to compensate the exponential term of the distance norm. (The reason for using this \( w \) exponent is to enable to generalize this expression.) This is because the two weighted covariance matrices arise as generalizations of the classical covariance from two different concepts [Balasko 2002].

6- Cluster validity

Cluster validity refers to the problem whether a given fuzzy partition fits the Data all. The clustering algorithm always tries to find the best fit for a fixed Number of cluster sand the parameterized cluster shapes. Different scalar validity measures have been proposed in this search, none Of them is perfect by one self, there for we used several indexes in this work which are described below [Balasko 2002][ Metin 2005]:

a- Partition Coefficient (PC): measures the amount of "overlapping" between cluster. It is defined by [Balasko 2002] as follows:

\[
PC(c) = \frac{1}{N} \sum_{i=1}^{c} \sum_{j=1}^{N} (u_{ij})^2 \quad \ldots (6)
\]

where \( u_{ij} \) is the membership of data point \( j \) in cluster \( i \). The disadvantage of PC is lack of direct connection to some property of the data themselves. The optimal number of cluster is at the maximum value.

b- Classification Entropy(CE): it measures the fuzziness of the cluster partition only, which is similar to the Partition Coefficient [Metin 2005].
\[ CE(c) = \frac{1}{N} \sum_{i=1}^{N} \sum_{j=1}^{N} (u_{ij})^2 \log(u_{ij}) \] \quad \text{...(7)}

c- Partition Index (SC): is the ratio of the sum of compactness and separation of the clusters. It is a sum of individual cluster validity measures, Normalized through division by the fuzzy cardinality of each cluster [Metin 2005].

\[ SC(c) = \sum_{i=1}^{c} \frac{\sum_{j=1}^{N} (u_{ij})^m \|x_j - v_i\|^2}{N \sum_{k=1}^{c} \|v_k - v_i\|^2} \] \quad \text{...(8)}

SC is useful when comparing different partitions having equal number of clusters. A lower value of SC indicates a better partition.

d- Separation Index (S): on the contrary of partition index (SC), the separation index uses a minimum-distance separation for partition validity [Balasko 2002].

\[ S(c) = \frac{\sum_{i=1}^{c} \sum_{j=1}^{N} (u_{ij})^m \|x_j - v_i\|^2}{N \min_{i \neq k} \|v_k - v_i\|^2} \] \quad \text{...(9)}

e- Xie and Beni's Index (XB): it aims to quantify the ratio of the total variation within clusters and the separation of clusters [Metin 2005].

\[ XB(c) = \frac{\sum_{i=1}^{c} \sum_{j=1}^{N} (u_{ij})^m \|x_j - v_i\|^2}{N \min_{i \neq j} \|x_j - v_i\|^2} \] \quad \text{...(10)}

The optimal number of clusters should minimize the value of the index.

f- Dunn index [Balasko 2002]

The Dunn index defines the ratio between the minimal intra cluster distance to maximal inter cluster distance. The index is given by:

\[ DI = \frac{d_{min}}{d_{max}} \] \quad \text{...(11)}

where \(d_{min}\) denote the smallest distance between two objects from different clusters, and \(d_{max}\) the largest distance of two objects from the same cluster. The Dunn index is limited to the interval [0, 1] and should be maximized.

g- Davies-Bouldin index [Julien 2005]

This index, DB, is defined as:

\[ DBI = \frac{1}{N} \sum_{i=1}^{N} \max_{j \neq i} \left( \frac{\sigma_i^2 + \sigma_j^2}{d(c_i, c_j)} \right) \] \quad \text{...(12)}

where \(n\) is the number of clusters, \(\sigma_i\) is the average distance of all patterns in cluster \(i\) to their cluster center \(c_i\), \(\sigma_j\) is the average distance of all patterns in cluster \(j\) to their cluster center \(c_j\), and \(d(c_i, c_j)\) is the distance of cluster centers \(c_i\) and \(c_j\). Small values of DBI correspond to clusters that are compact, and whose centers are far away from each other. Consequently, the number of clusters that minimizes DBI is taken as the optimal number of clusters.

7- The suggestion System Framework

In this section study two algorithm for deferent types from color images, where applied FCM and Gath_Geva and computed cluster validity of determinate number of the cluster centers and compared of the results of both these algorithms as following figure(1).
Figure (1) shows the Suggestion System Framework

7-1 Read of the Image:
In this stage, we read three different types color images natural, Medical and Remote Sensing images, where each image applied on FCM algorithm then compute the Validity Clusters then applied on Gath_Geva algorithm and compute the Validity Clusters then comparison the results.

7-2 Fuzzy C-Means Algorithm:
The FCM algorithm is defined as an alternating minimization algorithm as follows [Zhou et al. 2007][Julien 2005][Hsiang-Chuan et al. 2009][C.-H et al. 2008][Robert 2009]:
Choose a value for c; m and ε, a small positive constant; then, generate randomly a fuzzy c-partition U₀ and set iteration number l = 0. A four steps iterative process works as follows, Given the membership values u₀₁, …, u₀c,

Step 1: The cluster centers vᵢ (i=1…c) are calculated by

\[ v_i^l = \frac{\sum_{k=1}^{N} (u_{ik}^l)^m x_k}{\sum_{k=1}^{N} (u_{ik}^l)^m} \]  \hspace{1cm} (13)

Step 2: Compute the Euclidian distance by

\[ D_{ik}^l = (x_k - v_i^l)^T A (x_k - v_i^l) , \quad 1 \leq i \leq c, \quad 1 \leq k \leq N \]  \hspace{1cm} (14)

Step 3: Given the new cluster centers vᵢ', update membership values uᵢ',

\[ u_{ik}^{l+1} = \left( \frac{1}{\sum_{j=1}^{c} \left( \frac{\|x_k - v_j^l\|^2}{\|x_k - v_j^l\|^2} \right)^{m-1}} \right)^{-1} \]  \hspace{1cm} (15)

Step 4: The process stops when \[ \max_{ik} \left( \|u_{ik}^{(l)} - u_{ik}^{(l-1)}\| \right) < \varepsilon \], or a predefined number of iterations is reached.

7-3 Gath_Geva Clustering Algorithm:
In this section, the Gath_Geva (GG) clustering algorithm is presented [Balasko 2002][Julien 2005][J. Abonyi et al. 2003]. It is based on the minimization of the sum of weighted squared distances between the data points x_k and the cluster centers, vᵢ; i = 1, ..., c.

\[ J(X, U, V) = \sum_{i=1}^{c} \sum_{j=1}^{N} u_{ik}^m D_{ik}^2 \]  \hspace{1cm} (16)

where \[ V = [v_1, ..., v_c] \] contains the cluster centers and \[ m = [1;1] \] is a weighting exponent that determines the fuzziness of the resulting clusters. The fuzzy partition matrix has to satisfy the following conditions:
Initialization Given a set of data $X$ specify $c$, choose the weighting exponent $m > 1$ and the termination tolerance $\varepsilon > 0$. Initialize the partition matrix

Repeat for $l = 1, 2, \ldots$

Step 1 Calculate the cluster centers.

$$v_i^l = \frac{\sum_{k=1}^{N} u_{ik}^{l-1} x_k}{\sum_{k=1}^{N} u_{ik}^{l-1}}, 1 \leq i \leq c$$

Step 2 Compute the distance measure $D_{ik}^2$.

The distance to the prototype is calculated based the fuzzy covariance matrices of the cluster as eq(5), The distance function is chosen as eq(4), With the a priori probability $\alpha_i$

$$\alpha_i = \frac{1}{N} \sum_{k=1}^{N} u_{ik}$$

Step 3 Update the partition marix

$$u_{ik}^l = \frac{1}{\sum_{j=1}^{N} (\frac{D_{jk}(x_k-x_j)^2}{(m-1)})^{(m-1)/2}}, 1 \leq i \leq c, 1 \leq k \leq N$$

Until $\max \|U^l - U^{l-1}\| < \varepsilon$.

8- The Results and Discussion:

In this section several experiments are performed to demonstrate the described FCM compared to Gath_Geva algorithm. The images used, It is RGB color images of any number of pixels, a set of communally images as medical image (brain), remote sensing image (new York ) and natural image (flowers), It is used Visual basic as tool to implementation this work, several strategies are possible to obtain an initial set membership values for both algorithm, an obvious choice is a random initial set, and initial value of cluster centers either randomly or determinate maximum and minimum value, and determinate the parameters ($m$, $w$, $\varepsilon$, maxiteration ) in each case.

<table>
<thead>
<tr>
<th>Table(1) determine the all necessary parameters for FCM, Gath_Geva algorithms</th>
</tr>
</thead>
<tbody>
<tr>
<td>Name of parameter</td>
</tr>
<tr>
<td>$m$ (Fuzziness Parameter)</td>
</tr>
<tr>
<td>W only in Gath_Geva Algorithm</td>
</tr>
<tr>
<td>Maxim iteration</td>
</tr>
<tr>
<td>The other parameters (max_c, min_c, actually c)</td>
</tr>
</tbody>
</table>

8-1 First case

In this case applied FCM and Gath_Geva for natural image (flowers) , in figure (2) shows the original image and both results images form applied both algorithms .
Figure (2): show a: the original image, b: the result image after applied the Gath_Geva algorithm, c: the result image after applied the FCM algorithm. With 17 Iteration and 10 cluster centers in Table (2) show the values of the clusters center of each algorithms.

Table (2) shows the all values of the clusters center

<table>
<thead>
<tr>
<th></th>
<th>c1</th>
<th>c2</th>
<th>c3</th>
<th>c4</th>
<th>c5</th>
<th>c6</th>
<th>c7</th>
<th>c8</th>
<th>c9</th>
<th>c10</th>
</tr>
</thead>
<tbody>
<tr>
<td>FCM</td>
<td>125.9</td>
<td>76.17</td>
<td>57.8</td>
<td>10.6</td>
<td>38.08</td>
<td>160.29</td>
<td>98.9</td>
<td>236.74</td>
<td>197.74</td>
<td>98.86</td>
</tr>
<tr>
<td>Gath_Geva</td>
<td>87.29</td>
<td>154.9</td>
<td>140.13</td>
<td>149.26</td>
<td>78.71</td>
<td>52.46</td>
<td>52.95</td>
<td>156.53</td>
<td>51.65</td>
<td>95.82</td>
</tr>
</tbody>
</table>

After that computed the cluster validity values (PC, CE, SC, S, XB, DI, DBI) purpose of find best algorithm as table (3)

Table (3) shows the all values of the Validity Cluster

<table>
<thead>
<tr>
<th></th>
<th>PC</th>
<th>CE</th>
<th>SC</th>
<th>S</th>
<th>XB</th>
<th>DI</th>
<th>DBI</th>
</tr>
</thead>
<tbody>
<tr>
<td>FCM</td>
<td>0.98</td>
<td>2.95</td>
<td>3.41e+3</td>
<td>2.9e+3</td>
<td>1.497e+4</td>
<td>70.53e-2</td>
<td>41.24e-5</td>
</tr>
<tr>
<td>Gath_Geva</td>
<td>0.99</td>
<td>3.98</td>
<td>5.37e+3</td>
<td>1.43e+5</td>
<td>7.2e+4</td>
<td>78.64e-2</td>
<td>1.02e-8</td>
</tr>
</tbody>
</table>

8-2 Second case

In this case applied FCM and Gath_Geva for medical image (brain) that is casualty, in figure (3) shows the original image and both results images form applied both algorithms.
Figure (3): shows a: the original image, b: the result image after applied the Gath_Geva algorithm, c: the result image after applied the FCM algorithm. With 14 iterations in FCM and 8 iterations in Gath_Geva algorithm and 4 cluster centers in table (4) show the values of the cluster centers of each algorithm.

Table (4) shows the all values of the clusters center

<table>
<thead>
<tr>
<th></th>
<th>c1</th>
<th>C2</th>
<th>C3</th>
<th>C4</th>
</tr>
</thead>
<tbody>
<tr>
<td>FCM</td>
<td>120.02</td>
<td>27.82</td>
<td>250.18</td>
<td>195.81</td>
</tr>
<tr>
<td>Gath_Geva</td>
<td>89.8</td>
<td>98.37</td>
<td>227.63</td>
<td>60.79</td>
</tr>
</tbody>
</table>

After that computed the cluster validity values (PC, CE, SC, S, XB, DI, DBI) purpose of find best algorithm as table(5)

Table (5) shows the all values of the Validity Cluster

<table>
<thead>
<tr>
<th></th>
<th>PC</th>
<th>CE</th>
<th>SC</th>
<th>S</th>
<th>XB</th>
<th>DI</th>
<th>DBI</th>
</tr>
</thead>
<tbody>
<tr>
<td>FCM</td>
<td>0.7</td>
<td>5.45</td>
<td>3.86e+3</td>
<td>2.31e+3</td>
<td>4.01e+4</td>
<td>4.51e-3</td>
<td>4.51e-7</td>
</tr>
<tr>
<td>Gath_Geva</td>
<td>0.88</td>
<td>5.96</td>
<td>7.22e+3</td>
<td>2.24e+5</td>
<td>7.93e+4</td>
<td>3.9e-3</td>
<td>3.81e-7</td>
</tr>
</tbody>
</table>

8-3 Third case
In this case applied FCM and Gath Geva for remote sensing image (New York city), in figure(4) shows the original image and both results images form applied both algorithms.
Figure (4): show a: the original image , b: the result image after applied the FCM algorithm, c: the result image after applied the Gath_Geva algorithm

With 24 Iteration in FCM and 8 iterations in Gath_Geva algorithm and 17 cluster centers in table (6) show the values of the cluster centers of each algorithms

Table (6) shows the all values of the clusters center

|      | C1  | C2  | C3  | C4  | C5  | C6  | C7  | C8  | C9  | C10 | C11 | C12 | C13 | C14 | C15 | C16 | C17 |
|------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| FCM  | 39.3| 118.61| 91.34| 65.7| 10.114| 79.8| 127.5| 79.8| 246.78| 215.47| 45.82| 52.16| 188.11| 150.66| 109.9| 166.99|
| Gath_Geva | 46.17| 45.89| 46.15| 46.25| 45.8| 157.49| 127.5| 68.38| 215.47| 47.82| 137.9| 82.16| 188.11| 150.66| 109.9| 166.99|

After that computed the cluster validity values (PC ,CE, SC, S, XB, DI, DBI) purpose of find best algorithm as table(7)

Table (7) shows the all values of the Validity Cluster

<table>
<thead>
<tr>
<th></th>
<th>PC</th>
<th>CE</th>
<th>SC</th>
<th>S</th>
<th>XB</th>
<th>DI</th>
<th>DBI</th>
</tr>
</thead>
<tbody>
<tr>
<td>FCM</td>
<td>0.7</td>
<td>2.86</td>
<td>1.66e+3</td>
<td>5.76e+3</td>
<td>1.70e+4</td>
<td>20.44e-2</td>
<td>3.866e+3</td>
</tr>
<tr>
<td>Gath-Geva</td>
<td>0.98</td>
<td>6.69</td>
<td>8.33e+3</td>
<td>9.62e+7</td>
<td>4.347e+7</td>
<td>33.5e-2</td>
<td>3.94e-4</td>
</tr>
</tbody>
</table>

9- Conclusion
Through implementation this work for many color images find the following
1- When used simple images the difference is not clear between the two algorithms but when used complex images as medical image and remote sensing image, We find the Gath_Geva algorithm is best and it is more faster also, and as show in table (8).
2- Fuzzy C-Means (FCM) is based on Euclidean distance. This fuzzy clustering algorithm can only be used to detect the data classes with the same super spherical shapes. To overcome the drawback due to Euclidean distance, we could try to extend the distance measure to Mahalanobis distance (MD). However, [Krishnapuram 1999] pointed out that the Mahalanobis distance cannot be used directly in clustering algorithm. Gath-Geva (GG) clustering algorithm was developed to detect non-spherical structural clusters. In GG algorithm, the Gaussian distance can be used for the data with multivariate normal distribution.

3- According to validity cluster values show the Gath_Geva is better as show in table(8).

<table>
<thead>
<tr>
<th></th>
<th>Image 1</th>
<th>Image 2</th>
<th>Image 3</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>PC</td>
<td>CE</td>
<td>SC</td>
</tr>
<tr>
<td>FCM</td>
<td>0.98</td>
<td>2.95</td>
<td>3.41e+3</td>
</tr>
<tr>
<td>Gath_Geva</td>
<td>0.99</td>
<td>3.98</td>
<td>5.37e+3</td>
</tr>
</tbody>
</table>

A lower value of SC indicates a better partition, The Dunn index and XB are limited to the interval [0, 1] and should be maximized, the number of clusters that minimizes DB is taken as the optimal number of clusters, PC The optimal number of cluster is at the maximum value.

Regarding (Gath_Geva algorithm), When we used Randomly number of cluster centers, The results it’s were better than when were determine max and min of number of cluster centers, or determine constant number according to images.
References


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