An efficient Image Segmentation based on Generalized FCM

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Abstract

   Image segmentation plays a significant role in computer vision and pattern recognition. It divides an image into strong correlated regions. Fuzzy C-Means technique is one of the most suitable methods to obtain optimal threshold to segment low contrasted images and uneven illuminated images. However this technique does not gives satisfactory results for different kinds of noises. It required preprocessing step for removing noise. To avoid these limitations a new method with independent factor to organize the control of neighborhood pixels is proposed. It can be done with most influenced pixel in the image. The result of this method is compared with Fuzzy C-Means and its derivative techniques. It gives satisfactory results over the segmentation techniques.

Key words— **Fuzzy C-Means (FCM), Image segmentation, Clustering, Spatial constraints**.

1. Introduction

Image segmentation plays of the essence role in image processing applications and it refers to the method of partitioning a digital image into various segments. The division of an image into meaningful structures is often an essential step in image analysis, pattern recognition, revelation and many other tasks in image processing. Different segmentation techniques have been developed for image segmentation. Fuzzy C-mean (FCM) is one of the most used methods in image segmentation. FCM is not considering any spatial information in image context so that it is high sensitive to noise. Bezdek et al. [1] proposed that fuzzy objective functions are used in pattern recognition system. In [3], FCM is used for noise free images and noisy images. FCM technique provides the better results than the EM algorithms. FCM is modified in categorize to compensate intensity in homogeneity and allow the labeling of pixel to be influenced by the immediate neighborhood. Neighborhood labeling is computed in each iteration step that is time consuming. In [4], proposed the enhanced FCM (EnFCM) algorithm to accelerate the clustering technique. The structure of EnFCM is different from FCM-S and its variants. Computational time is reduced compared with FCM-S because number of gray levels in an image is lesser than the number of its pixels. In [5], proposed KFCM algorithms with spatial constraints have more robustness to noise and reduce the computational time. In [6], proposed Fast Generalized Fuzzy C-Means algorithm (FGFCM) which incorporates spatial and gray levels of the image. FGFCM computational time is very small, since the clustering is performed on the basis of gray level histogram. In [7],

automatic histogram threshold approach is presented and it presents higher performance to low contrasted and multi resolution images. For low contrasted images this method gives the better results. In [8], proposed a new modified FCM that integrate spatial and membership function that improves the segmentation results. The new spatial constraints are used on two factors: one is the distance between center pixel and its neighbor pixels and other one is based on the value difference of center pixel and its neighbor pixels. In [9], FCM produced close results to K-means but FCM was required extra estimation point in time. In [10], developed a fuzzy rule based schema and it is used for high quality image zooming. In [11], a new active contour was developed by fuzzy Gaussian distribution for medical images. In [12], fuzzy Local Binary Pattern (LBP) was used to extract the facial features for detection and classification. In [13], projected flame recognition algorithm that is based on saliency detection performance. In [14], developed MR-FCM algorithm was parallelized by map reduced technique and it is not suitable for large data..In [16], a new method of clustering algorithm based on interval valued fuzzy set (IVIFS) to analyze tumor for MRI images. In [17], structure sensitive saliency detection technique was developed. In [18-20], Type2 fuzzy logic is used to get high quality of the images. In [21], fuzzy entropy thresholding technique was developed for low contrasted images. The structure of this paper is prearranged as follows. Section 2 describes the FCM and its derivative methods. Generalized FCM algorithm is introduce in section 3. Experimental outcomes are obtained in section 4 and conclusions are described in section 5.

2. Existing Algorithms

2.1. Fuzzy C-means(FCM) algorithm

   FCM clustering algorithm was introduced by Dunn [2] and afterward enhanced by Bezdek [1]. FCM is an iterative grouping method that produces an optimal cluster screen by minimizing the weighted group sum of squared objective function Θ_{ω}.

$$\Theta_{\omega} = \sum_{i=1}^{\aleph} \sum_{j=1}^{\ell} \upsilon_{ji}^{\omega} \zeta^2 \left(\chi_i, \vartheta_j \right) \qquad (1)$$

Where $X = \{\chi_1, \chi_2, ..., \chi_\aleph\} \subseteq \Re^\omega$ is the facts set in the ω-dimensional vector space, $\aleph$ is the number of facts items, ℓ is the number of similar group of objects with $2 \le \ell < \aleph$, υ_{ij} is the degree of membership of χ_i in the jth cluster, ω is the weighting exponent on each fuzzy membership, ϑ_j is the prototype of the middle of cluster j, $\zeta^2(\chi_i, \vartheta_j)$ is a Euclidean space between object χ_i and cluster center ϑ_j. A result of the object function Θ_ω can be obtained through iterative practice by

setting $\ell, \omega, \in$ and $\upsilon^{(0)}$ and repeat the calculation of $\vartheta_j^{(b)}$ and υ_{ij} until $\max\left\{\upsilon^{(b)} - \upsilon^{(b+1)}\right\} < \in$. The formulas for $\vartheta_j^{(b)}$ and υ_{ij} are given below.

$$\vartheta_j^{(b)} = \frac{\sum_{i=1}^{\aleph}\left(\upsilon_{ji}^{(b)}\right)^{\omega}\chi_i}{\sum_{i=1}^{\aleph}\left(\upsilon_{ji}^{(b)}\right)^{\omega}} \quad and \quad \upsilon_{ji}^{(b+1)} = \frac{1}{\sum_{i=1}^{\ell}\left(\frac{\varsigma_{ji}}{\varsigma}\right)^{\frac{2}{\omega-1}}} \quad (2)$$

2.2. Fuzzy Clustering with constraints (FCM-S) and its variants

Ahmed et al. [3] projected a alteration of standard FCM by introducing a new term that allows the labeling of a pixel to be influenced by labels in its neighborhood. The objective function of FCM-S is define as follows:

$$\Theta_{\omega} = \sum_{i=1}^{\aleph}\sum_{j=1}^{\ell}\upsilon_{ji}^{\omega}\zeta^2\left(\chi_i, \vartheta_j\right) + \frac{\alpha}{N_R}\sum_{i=1}^{\aleph}\sum_{j=1}^{\ell}\upsilon_{ji}^{\omega}\sum_{r\in N_i}\zeta^2\left(\chi_r, \vartheta_j\right) \quad \textbf{(3)}$$

Where χ_i is the ith pixel gray level value, $\aleph$ is the total number of pixels, ϑ_j is the jth center prototype value, υ_{ji} represents the fuzzy membership of the ith pixel w.r.to cluster j, N_R is its cardinality, χ_r represents the neighbor of χ_i and α is the parameter which is used to control the effect of neighbors term. By the definition, χ_i satisfies the

$$\sum_{j=1}^{l}\upsilon_{ji} = 1.$$ The formulas for $\vartheta_j^{(b)}$ and υ_{ij} are given below.

$$\upsilon_{ji} = \frac{\left(\zeta^2\left(\chi_i, \vartheta_j\right) + \frac{\alpha}{N_R}\sum_{r\in N_i}\zeta^2\left(\chi_r, v_j\right)\right)^{\frac{1}{\omega-1}}}{\sum_{k=1}^{l}\left(\zeta^2\left(\chi_i, \vartheta_k\right) + \frac{\alpha}{N_R}\sum_{r\in N_i}\zeta^2\left(\chi_r, \vartheta_k\right)\right)^{\frac{1}{\omega-1}}} \quad and$$

$$\vartheta_j = \frac{\sum_{i=1}^{\aleph}\upsilon_{ji}^{\omega}\left(\chi_i + \frac{\alpha}{N_R}\sum_{r\in N_i}\chi_r\right)}{(1+\alpha)\sum_{i=1}^{\aleph}\upsilon_{ji}^{\omega}} \quad (4)$$

The second term $\frac{1}{N_R}\sum_{r\in N_i}\chi_r$ in the numerator of (4) is in a neighbour average gray level value around χ_i within a window. In an image which is composed by all the neighbour average values around the pixel called mean filter image.

2.3. Enhanced Fuzzy C-Means Clustering (EnFCM)

EnFCM algorithm was prjected by Szilagyii et al. [4],EnFCM algorithm is used to rate up the clustering progression for gray level images. In order to improve FCM_S, linearly weighted sum image ψ is in advance formed from the original image and its neighbor average image in terms of:

$$\psi_i = \frac{1}{1+\alpha}\left(\chi_i + \frac{\alpha}{N_R}\sum_{j\in N_i}\chi_i\right) \quad (5)$$

Where ψ_i the gray level is value of ith pixel of the image ψ and N_i denotes the set of neighbors χ_j falling into window around χ_j. The parameter α is used to control the effect of neighbor's term. The clustering way is performed on the gray level histogram of the generated image ψ. The objective function Θ_{ω} is defined as:

$$\Theta_{\omega} = \sum_{i=1}^{M}\sum_{j=1}^{l}\gamma_i u_{ji}^{\omega}\zeta^2\left(\psi_i, \vartheta_j\right), \upsilon_{ji} = \frac{\left(\psi_i - \vartheta_j\right)^{\frac{2}{\omega-1}}}{\sum_{k=1}^{\ell}\left(\psi_i - \vartheta_k\right)^{\frac{2}{\omega-1}}} \quad and \quad \vartheta_j = \frac{\sum_{i=1}^{M}\gamma_i\upsilon_{ji}^{\omega}\psi_i}{\sum_{i=1}^{M}\gamma_i\upsilon_{ji}^{\omega}} \quad (6)$$

Where ϑ_j represent the model of the jth cluster, υ_{ji} represents the fuzzy membership of gray level value i w.r.to cluster j, M represents the number of gray levels of image ψ, which is generally little lesser than $\aleph$, and γ_i is the number of pixels having gray level values are equal to i. Thus $\sum_{k=1}^{M}\gamma_k = N$ and

$\sum_{j=1}^{\ell}\upsilon_{ji} = 1$ for any i, the Θ_{ω} is minimized. EnFCM algorithm is similar to FCM in the iterative process, but it is applied to the new image ψ by using equations υ_{ji} and ϑ_j. EnFCM provides like segmenting results to FCM-S, but the segmenting excellence depends on window size, the parameter α and the filtering method.

2.4. Fast Generalized Fuzzy C-Means Clustering (FGFCM)

Cai et al. [6] projected the fast Generalized Fuzzy C-Means (FGFCM) algorithm to get better the clustering results. To progress the clustering consequences FGFCM uses a local similarity measure that combines both spatial and gray level image information. FGFCM objective function generating a new image ψ like follows:

$$\psi_i = \frac{\sum_{j\in N_i}\delta_{ij}\chi_j}{\sum_{j\in N_i}\delta_{ij}},$$

$$\delta_{ij} = \begin{cases} e^{-\frac{\max\left(|p_i-p_j|, |q_i-q_j|\right)}{\lambda_S} - \frac{\zeta^2(\chi_i, \chi_j)}{\lambda_g\sigma_i^2}}, & i\neq j \\ 0, & i = j \end{cases} \quad and \quad \sigma_i = \sqrt{\frac{\sum_{j\in N_i}\zeta^2\left(\chi_i, \chi_j\right)}{N_R}} \quad (7)$$

Where ψ_i denotes the gray level value of the i-th pixel of the image ψ, χ_j represents the gray level value of the neighbors of

χ_j denotes the gray level value of the neighbors of χ_i, N_i is the set of neighbors and δ_{ij} is the local similarity measure between the i-th and j-th pixel. λ_s and λ_q are two scale factors which are similar to factor a in EnFCM. The FGFCM algorithm can be calculated by setting $\ell, \omega, \in$ and $U^{(0)}$. The new image ψ can be calculated by (7) and repeat the calculation of $\vartheta_j^{(b)}$ and υ_{ij} by (6) until $\max\{\upsilon^{(b)} - \upsilon^{(b+1)}\} < \in$. FGFCM provides good segmenting outcome, but its quality depends on the parameters λ_s, λ_g and window size.

3. Proposed Method

All the methods described in the preceding section gives the better clustering consequences for usual images but still have drawbacks as segmenting noisy images. Preceding awareness of noise is essential. The parameter λ in their objective function is used to balance between robustness to noise. Effectiveness of the image and its selection is generally by experience or trial and error experiments. Most of the algorithms are applied on static images for which the original image could be lost depending on the method used to produce the new image. In order to overcome the draw backs, FCM objective function is needed a new factor. The extraordinary characteristics of the new factor G_{ki} is dynamically changes depending upon the noise and contrast of the image with specified formulae (8) & (9) whereas λ is selected with trial and error method in existing fuzzy c means techniques. Depending on the distance from the center pixel it controls the influence of the neighborhood pixels to avoid the preprocessing steps that could cause the missing details of image. The specific parameter G_{Ki} is selected based on the formula (9) so need not to use trial and error technique it is independent of specific value. By using Fuzzy factor G_{ki}, we suggest a strong FCM skeleton for image clustering, named as Generalized FCM (GFCM). GFCM is a clustering algorithm and it incorporates local spatial and gray level information into its objective function. The objective function defined as:

$$\Theta_\omega = \sum_{i=1}^{N}\sum_{k=1}^{\ell}\left[\upsilon_{ki}^{\omega}\zeta^2(\chi_i, \vartheta_k) + G_{ki}\right] \quad and \quad G_{ki} = \sum_{\substack{j \in N_i \\ i \neq j}}\frac{1}{\zeta_{ij}+1}\left(1 - \upsilon_{kj}\right)^{\omega}\zeta^2(x_j, \vartheta_k) \quad (8)$$

$$\upsilon_{ki} = \frac{1}{\sum_{j=1}^{\ell}\left(\frac{\zeta^2(\chi_i, \vartheta_k) + G_{ki}}{\zeta^2(\chi_i, \vartheta_j) + G_{ji}}\right)^{\frac{1}{\omega-1}}} \quad and \quad \vartheta_k = \frac{\sum_{i=1}^{N}\upsilon_{ki}^{\omega}\chi_i}{\sum_{i=1}^{N}\chi_{ki}^{\omega}} \quad (9)$$

The essential circumstances for Θ_ω to be its local extreme, with respect to (9). The GFCM be able to be summarize as follows:

1) locate ℓ clusters, fuzzification parameter ω and termination criteria $\in$
2) Initialize the fuzzy matrix

3) Set b=0 as the loop counter
4) Membership values and cluster prototype are evaluated by using (9)
5) If $\max\{\upsilon^{(b)} - \upsilon^{(b+1)}\} < \in$ then stop, otherwise set b=b+1 and go to step 4.

When the algorithm has converged, a defuzzification progression takes place in order to converge the fuzzy matrix υ to a crisp partition. The utmost membership procedure is the most important method that has developed defuzzify the matrix υ. This process assigns the pixel i to the class C with the membership:

$$C_i = \arg\{\max\{u_{ki}\}\}, \quad k = 1, 2, 3, ..., l$$

(10).

4. Experimental Results

In this sector, we have shown the presentation of the proposed method by presenting numerical results and examples on various real and synthetic images, with different types of noises and characteristics. Further, we compare the efficiency and robustness of GFCM with four fuzzy algorithms FCM, FCM-S, EnFCM, and FGFCM. In order to verify the performance, we use the quality parameters Mean Square Error (MSE), Jaccard Indexing (JAC), Mean (μ) and Standard deviation (STD).

The mean square error (MSE) describes the cumulative squared error between ground truth image and resultant image. The following formula is define for MSE as

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left[x(i,j) - y(i,j)\right]^2 \quad (11)$$

Where $x(i,j)$ represents the ground truth image and $y(i,j)$ represents the output of noise image where i and j are the pixel positions of the MXN image. The ground truth image is always considered as a quality image. The original images are captured with different cameras of different resolutions so to make all images should be equal quality. We used the quality of the image which is improved by pre-existing tools like Photoshop manually and renamed it as a ground truth image. The methods which are apply on ground truth image definitely it produce quality output than original image output. In this paper we compared output of the proposed technique with ground truth image output and original image. Figure.1 shows that the ground truth image better contrast and quality than the original image. After applying the image segmentation if the output of noisy image is similar to the ground image then the image segmentation is robust segmentation. The MSE applied on the output of the noisy image and the output of the ground truth image. If the MSE value is low the quality of the segmentation is high. MSE is zero when $x(i,j) = y(i,j)$ i.e., both are the same.

Let A be the ground truth image and B be the output image then the Jaccard indexing measures similarity between ground truth and output image. It is defined as the size of the intersection divided by the size of the union.

$$Jac(A, B) = \frac{|A \cap B|}{A \cup B} X100\% \text{ and } 0 \leq Jac(A, B) \leq 1 \quad (12)$$

The Jaccardindex can be used to represent the similarity between the two images. A value "0" means the images are completely dissimilar, "1" that they are identical, and the values between 0 and 1 representing a degree of similarity.

Mean value of intensity levels is a measure of the mean intensity of the given image. A dark image has low mean value and brighter image has higher mean value. Mean is defined as follows:

$$mean(\mu) = \frac{1}{PQ} \sum_{x=1}^{P} \sum_{y=1}^{Q} f(x,y) \qquad (13)$$

Where P and Q are width and height of the image and $f(x,y)$ is gray value. The mean retains the lower and uniform pixel values and eliminate uneven pixel values. The high mean value shows the smoothness of the image. The thresholds are calculated for outputs of ground truth image and output of the noisy image and apply Euclidian distance for constructing Table 1.c, Table 2.c and Table 3.c by using mean threshold values shown in the results.

The standard deviation of gray intensity levels represents the contrast of an image. It characterizes the dispersion of the intensity levels with respect to the mean value. An image having high contrast will have a large standard deviation and an image having low contrast will have small standard deviation. The standard deviation of gray level image is calculated as follows.

$$std(\sigma) = \sqrt{\frac{1}{PQ} \sum_{x=1}^{P} \sum_{y=1}^{Q} (f(x,y) - \mu)^2} \qquad (14)$$

Where P, Q are the width and height of the image, is mean of the image, f(x, y) is gray level value of the image, is standard deviation.

These quality parameters are calculated on noise and denoised images and plays the values in the form of tables and drawn the graphs. The graphs and tables show the quality of the output images.
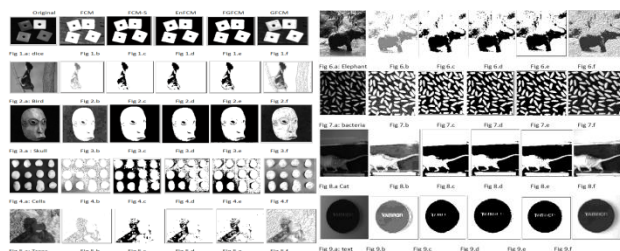

Fig .1 First Colum is original image, Second column is FCM, third column is FCM-S, Fourth column is EnFCM, Fifth column is FGFCM and Sixth column is GFCM for denoisy images

The above Fig. 1 shows the experimental results of the FCM and its derivative methods for dice, bird, skull, cells, elephant and rice, cat and text images. The dice, crow and cat images are having three regions of very dark, bright and overlapping of dark and bright regions. Second, we apply for noisy images either by histogram or a probability density function which is superimposed on the probability density function of the original images. FCM and derivative algorithms to a synthetic and real images corrupted by different level of Gaussian, Salt & Pepper and Speckle noises.

4.1. Gaussian Noise

The Gaussian noise has useful for modeling natural process which introduces noise. Gaussian noise has a normal probability density function:

$$Gauss \ \text{noise} = \frac{1}{\sqrt{2\Pi}\sigma} e^{\frac{-(g-\mu)^2}{2\sigma^2}} \qquad (15)$$

Where g is the gray level, μ is the mean and σ is the standard deviation. Approximately 70% of the values are contained in $\mu \pm \sigma$ and 90% values are contained between $\mu \pm 2\sigma$. Gaussian noise must be performed using a filter with adequate shape size correlated to the Gaussian corrupts the image.
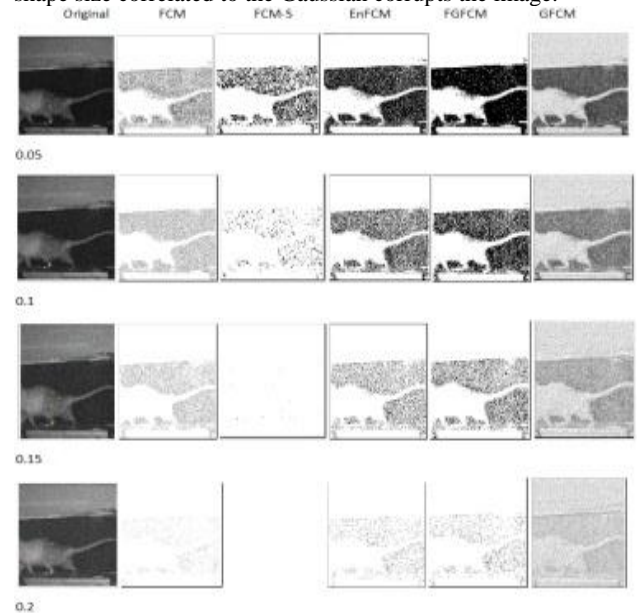

Fig.2 Gaussian Noise for cat image up to 20%

Fig. 2 illustrates the clustering results of a corrupted by Gaussian noise (20%) images like cat and Elephant. FCM, FCM-S, EnFCM and FGFCM are respectively affected by the noise to different extents, which indicates that these algorithms lack enough robustness to the Gaussian noise. Visually EnFCM and FGFCM remove most of the noise, but still their results are not satisfactory. GFCM removes all the added noise achieving satisfactory results for cat and elephant images. Table.1 and Table.2 gives the accuracy results of five algorithms on the specific synthetic image corrupted by different levels of noises. It is clearly shows that the proposed GFCM algorithm gives better performance than FCM, FCM-S, EnFCM and FGFCM.

Noise %	FCM	FCM-S	EnFCM	FGFCM	GFCM	Noise %	FCM	FCM-S	EnFCM	FGFCM	GFCM
0.05	0.8877	0.8873	0.8849	0.8836	0.8826	0.05	0.1091	0.1729	0.3476	0.4196	0.1846
0.1	0.8882	0.8888	0.8869	0.8858	0.8846	0.1	0.0946	0.0385	0.2082	0.296	0.1821
0.15	0.8885	0.889	0.8882	0.8878	0.8856	0.15	0.029	0.0165	0.0925	0.1315	0.1314
0.2	0.8889	0.889	0.8869	0.8888	0.8862	0.2	0.0162	0.0161	0.2082	0.0432	0.1163

Table 1.a: MSE   Table 1.b:JAC

Noise %	FCM	FCM-S	EnFCM	FGFCM	GFCM
0.05	0.8667	0.8269	0.654	0.5839	0.636
0.1	0.909	0.9614	0.7938	0.7124	0.7085
0.15	0.9348	0.9835	0.9089	0.8749	0.7745
0.2	0.9775	0.9839	0.7938	0.9595	0.8227

Noise %	FCM	FCM-S	EnFCM	FGFCM	GFCM
0.05	0.0429	0.0745	0.0723	0.0764	0.036
0.1	0.0363	0.0429	0.0715	0.0774	0.0264
0.15	0.0225	0.01	0.0541	0.063	0.016
0.2	0.0095	0.008	0.0715	0.033	0.016

Table 1.c: Mean   Table 1.d:Std
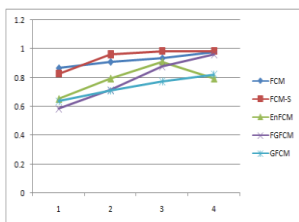
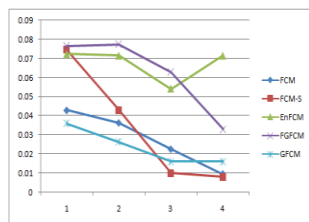Table 1: Gaussian noise up to 20% for cat image
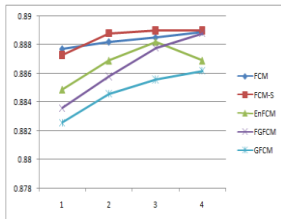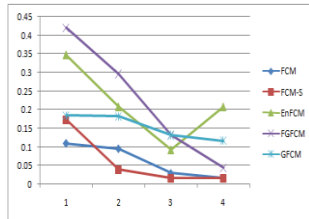
Graph 1.a: MSE   Graph 1.b: JAC

Graph 1.c: Mean   Graph 1.d: Std

Graph 1: Gaussian noise up to 20% for cat image

4.2. Salt & Pepper Noise

Salt & Pepper noise is also called as shot noise or impulse noise. This noise can be caused by sharp and sudden changes in the image. Salt & Pepper noise presents itself as sparsely occurring white and black pixels. An effective noise reduction method for this type of noise is median filter. Salt & Pepper noise probability density function can be calculated as:

$$Salt\ \&\ Pepper\ noise = \begin{cases} P_a & for\ z = a \\ p_b & for\ z = b \\ 0 & other\ wise \end{cases} \quad (16)$$

We apply five Fuzzy clustering techniques to the real images with Salt & Pepper (40%). The clustering results are shown in Fig 3) with cat and elephant images. FCM and its derivative methods are influenced by the noise to different extents, which indicates that these algorithms lack enough robustness to the salt & Pepper noise. The proposed method GFCM can basically eliminate the effect of the noise up to 40%. The graphs and tables shows that accuracy results.
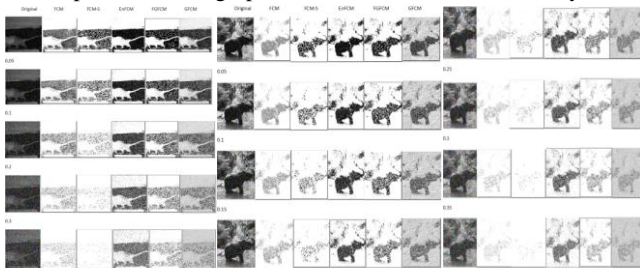

Fig 3: Salt & Pepper for Cat image up to 40% noise

Noise %	FCM	FCM-S	EnFCM	FGFCM	GFCM
0.05	0.886	0.885	0.883	0.884	0.884
0.1	0.886	0.887	0.884	0.885	0.884
0.2	0.887	0.888	0.884	0.886	0.885
0.3	0.888	0.888	0.885	0.887	0.885
0.4	0.888	0.889	0.886	0.888	0.886

Noise %	FCM	FCM-S	EnFCM	FGFCM	GFCM
0.05	0.2794	0.2859	0.4296	0.398	0.4151
0.1	0.2045	0.1756	0.403	0.3357	0.3719
0.2	0.1183	0.0712	0.3522	0.2379	0.2715
0.3	0.061	0.035	0.3061	0.1633	0.1889
0.4	0.0361	0.0216	0.2684	0.1117	0.1214

Table 3.a: MSE   Table 3.b: JAC

Noise %	FCM	FCM-S	EnFCM	FGFCM	GFCM
0.05	0.7506	0.7142	0.5709	0.6045	0.5932
0.1	0.7882	0.8244	0.5977	0.6676	0.6148
0.2	0.8545	0.9289	0.6484	0.7657	0.6644
0.3	0.9141	0.965	0.6946	0.8401	0.7041
0.4	0.9483	0.9784	0.7324	0.891	0.7384

Noise %	FCM	FCM-S	EnFCM	FGFCM	GFCM
0.05	0.0471	0.082	0.0705	0.0771	0.0544
0.1	0.045	0.0773	0.0706	0.0774	0.0483
0.2	0.0409	0.0552	0.0704	0.0739	0.041
0.3	0.0322	0.0395	0.0689	0.0645	0.034
0.4	0.0258	0.025	0.0645	0.0582	0.0274

Table 3.c: Mean   Table 3.d: Std

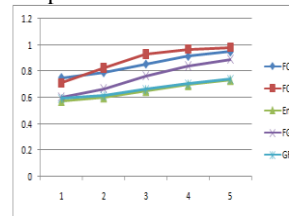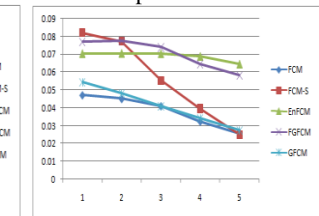Table 3: Salt & Pepper noise up to 40% for Cat image
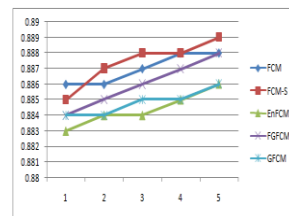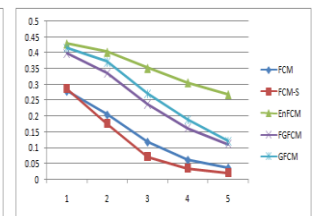
Graph 3.a: MSE   Graph 3.b: JAC

Graph 3.c: Mean   Graph 3.d: Std

Graph 3: Salt & Pepper noise up to 40% for Cat image

Noise %	FCM	FCM-S	EnFCM	FGFCM	GFCM
0.05	0.8881	0.8876	0.8863	0.8866	0.8855
0.1	0.8882	0.8882	0.8865	0.8871	0.8857
0.15	0.8884	0.8885	0.8867	0.8875	0.8859
0.2	0.8885	0.8887	0.8869	0.8878	0.8861
0.25	0.8886	0.8888	0.8871	0.888	0.8862
3	0.8887	0.8889	0.8872	0.8882	0.8864
0.35	0.8888	0.889	0.8873	0.8884	0.8865
0.4	0.8888	0.889	0.8874	0.8885	0.8866

Noise %	FCM	FCM-S	EnFCM	FGFCM	FLJCM
0.05	0.0488	0.1483	0.2517	0.2311	0.2298
0.1	0.0516	0.0964	0.234	0.1898	0.1961
0.15	0.0444	0.0633	0.2182	0.157	0.1658
0.2	0.0399	0.0448	0.2027	0.1331	0.14
0.25	0.0321	0.0339	0.1918	0.1157	0.1147
3	0.031	0.0263	0.1807	0.0944	0.0938
0.35	0.0258	0.021	0.1698	0.0802	0.0746
0.4	0.0222	0.0189	0.1609	0.0681	0.0595

Table 4.a: MSE   Table 4.b:JAC

Noise %	FCM	FCM-S	EnFCM	FGFCM	GFCM
0.05	0.8979	0.8517	0.749	0.7716	0.6908
0.1	0.9107	0.9036	0.7667	0.813	0.7072
0.15	0.9255	0.9366	0.7824	0.8457	0.721
0.2	0.935	0.9552	0.7979	0.8697	0.733
0.25	0.947	0.9661	0.8087	0.8867	0.7448
0.3	0.9526	0.9737	0.8198	0.9077	0.7551
0.35	0.9626	0.9789	0.8303	0.9217	0.7642
0.4	0.968	0.9811	0.839	0.9336	0.7728

Noise %	FCM	FCM-S	EnFCM	FGFCM	FLJCM
0.05	0.0326	0.0685	0.0611	0.0594	0.034
0.1	0.0312	0.066	0.062	0.0607	0.031
0.15	0.0291	0.0559	0.0613	0.0596	0.0297
0.2	0.0287	0.0489	0.0625	0.0562	0.0289
0.25	0.0257	0.0406	0.0607	0.0573	0.0266
0.3	0.0237	0.0344	0.0595	0.0539	0.0245
0.35	0.021	0.0253	0.0585	0.0517	0.0222
0.4	0.0177	0.0195	0.0563	0.048	0.0213

Table 4.c:Mean   Table 4.d:Std

Table 4: Salt & Pepper noise up to 40% for Elephant image
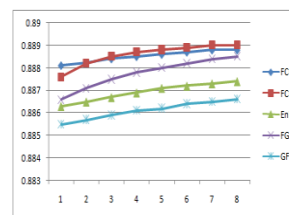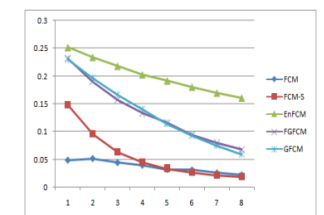
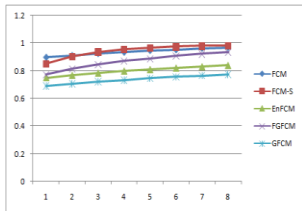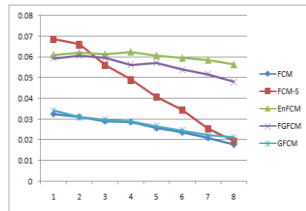Graph 4.a: MSE   Graph 4.b: JAC

Graph 4.c: Mean　　　　Graph 4.d: Std

Graph 4: Salt & Pepper noise up to 40% for Elephant image

4.3. Speckle Noise

Speckle noise can be modeled by random values multiplied by pixel of the image. The probability density function of the Speckle noise can be calculated as:

$$g(x, y) = f(x, y) * u(x, y) + \xi(x, y) \qquad (17)$$

Where f(x,y) is original image, g(x,y) is output image, u(x,y) multiplicative component and ξ is an adaptive component of speckle noise. We apply Fuzzy clustering techniques to the real images with Speckle noise up to 90%. The clustering results are shown in Fig 4) with cat image. FCM and its derivative methods are influenced by the noise to different extents, which indicates that these algorithms lack enough robustness to the Speckle noise. The proposed method GFCM can basically eliminate the effect of the noise up to 90%. The graphs and tables shows that accuracy results.
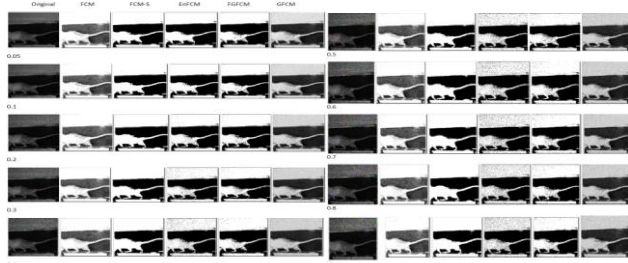

Fig 4: Speckle noise for Cat image

Graph 5.a: MSE　　　　Graph 5.b: JAC

Graph 5.c: Mean　　　　Graph 5.d: Std

Graph 5: Speckle noise for Cat image

All the tested images are corrupted by Gaussian noise up to 20%, Salt & Pepper 40% and Speckle noise up to 90%.

5. Conclusion

In this article we presented an efficient Generalized FCM (GFCM) algorithm. The proposed method can detect the clusters of an image to overcome the drawbacks of the FCM and its derivative methods. GFCM introduce the new factor G_{ki} as local for both spatial and gray level images and it provides more robust to different noises. Further all other FCM derivatives for image clustering exploit, in their objective function. Crucial parameters α or λ which is used to robust and effectiveness to the noise and these parameters are evaluated by random number generation. GFCM is free for any parameter evaluation and it shows that existing methods are performing the clustering on pre computed images, but GFCM applied to the original image. In this paper we conduct different noises for Gaussian noise up to 20%, Salt & Pepper up to 40% and Speckle up to 90% of noisy images and proved that proposed method provides satisfactory results. This paper is to get better the quality of segmentation without using any other smoothing filters to reduce computational complexity of algorithm. This improvement of results may be considered as a feature scope.

Noise %	FCM	FCM-S	EnFCM	FGFCM	GFCM
0.05	0.8858	0.8834	0.883	0.8828	0.8828
0.1	0.8857	0.8834	0.883	0.8828	0.8827
0.2	0.8856	0.8835	0.8829	0.8827	0.8825
0.3	0.8856	0.8836	0.8827	0.8827	0.8824
0.4	0.8855	0.8837	0.8827	0.8827	0.8824
0.5	0.8855	0.8837	0.8823	0.8827	0.8823
0.6	0.8855	0.8838	0.8822	0.8827	0.8824
0.7	0.8856	0.8838	0.8821	0.8827	0.8824
0.8	0.8856	0.8838	0.8821	0.8827	0.8824
0.9	0.8856	0.8839	0.8821	0.8828	0.8824
1	0.8856	0.8839	0.8821	0.8828	0.8824

Table 5.a: MSE

Noise %	FCM	FCM-S	EnFCM	FGFCM	GFCM
0.05	0.382	0.4404	0.4585	0.4741	0.4526
0.1	0.3817	0.4366	0.4605	0.4749	0.4533
0.2	0.3831	0.4305	0.4677	0.4773	0.4538
0.3	0.3831	0.4274	0.4796	0.4785	0.4553
0.4	0.3835	0.424	0.4917	0.4808	0.4562
0.5	0.3815	0.4212	0.4969	0.4797	0.4574
0.6	0.3771	0.4166	0.5027	0.4793	0.4565
0.7	0.3766	0.4148	0.5067	0.478	0.4551
0.8	0.3736	0.4132	0.5065	0.4769	0.4544
0.9	0.3695	0.4113	0.509	0.4744	0.4536
1	0.3662	0.4083	0.5097	0.4727	0.4535

Table 5.b: JAC

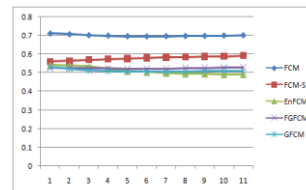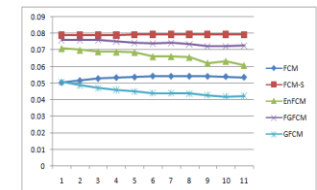| Noise %	FCM	FCM-S	EnFCM	FGFCM	GFCM
0.05	0.7109	0.5596	0.5419	0.5277	0.5309
0.1	0.7068	0.5634	0.54	0.5268	0.5216
0.2	0.7013	0.5693	0.5329	0.5246	0.5128
0.3	0.6988	0.5726	0.5213	0.5234	0.5086
0.4	0.6955	0.5759	0.5092	0.5212	0.5056
0.5	0.6948	0.5787	0.504	0.5222	0.5051
0.6	0.6959	0.5833	0.4984	0.5226	0.5054
0.7	0.6969	0.5852	0.4942	0.5241	0.5059
0.8	0.6973	0.5868	0.4944	0.525	0.5075
0.9	0.6996	0.5886	0.4919	0.5275	0.5084
1	0.7011	0.5915	0.4912	0.5292	0.5096

Table 5.c: Mean

Noise %	FCM	FCM-S	EnFCM	FGFCM	GFCM
0.05	0.0503	0.0789	0.071	0.0759	0.0508
0.1	0.0515	0.079	0.07	0.0759	0.04889
0.2	0.0527	0.0791	0.0691	0.0759	0.0472
0.3	0.0533	0.0791	0.0689	0.0751	0.046
0.4	0.0536	0.0792	0.0687	0.0744	0.0451
0.5	0.0542	0.0793	0.0661	0.0738	0.0439
0.6	0.0541	0.0793	0.0662	0.0741	0.0439
0.7	0.0541	0.0795	0.0656	0.0734	0.0438
0.8	0.054	0.0794	0.0621	0.0722	0.0427
0.9	0.0539	0.0795	0.063	0.0723	0.042
1	0.0535	0.0792	0.0607	0.0725	0.0425

Table 5.d: Std

Table 5: Speckle noise cat image

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