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IMAGE SEGMENTATION: FCM CLUSTER CENTER INITIALIZATION FOR COLORED IMAGES

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Background

Nowadays, the image segmentation is a very challenging task. The Fuzzy c-means is considered as most popular method for data classification and hence image segmentation. The study find out that it is suffered from many problems such as cluster number, sensitivity to noise, trapping to local minima and center initialization.

Results:

This paper address the cluster center initialization problem. The proposed method initializes the cluster centers using SOM classification method. The computed cluster centers are close to the actual cluster centers. Then these initialized cluster centres are fed to the FCM having some spatial constraints. The addition of spatial constraints makes the proposed method noise robust. The effect of noise on image 1 is Vpc 2.3 % and Vpe 25 % for SOM-FCM method whereas for FCM it is Vpc 26% and Vpe 46% which confirms the noise robustness of the proposed SOM-FCM method. The results of proposed SOMFCM are compared with the conventional FCM and it shows that the proposed method outperforms the conventional FCM.

Conclusions

The research concluded that the proposed method finds the good initial cluster center for FCM which leads to better segmentation results whereas the inclusion of spatial constraints in FCM makes it more noise robust. The proposed method is applicable to real world color images and produce good results.

Keywords: Fuzzy c-means, cluster center, cluster initialization, Self-Organizing maps, k-means, image segmentation, spatial constraints.

1. INTRODUCTION:

Clustering is a crucial area of research having great importance in image segmentation. It partitions the image into different groups which have similar properties within the group and the dissimilar properties to other groups. These partitions of an image should have meaningful interpretation and the process is called image segmentation.

In the past decades, clustering is considered as most widely used image segmentation technique. Especially, Fuzzy c-means clustering because of its fuzziness for belonging of each pixel to the cluster as compared to the K-means crisp nature [5]. The Fuzzy-c means clustering can be applied to many real world images, colored images, medical images etc. because it has the ability to retain the information from original image to the image after segmentation [24]. Along with this ability fuzzy c-means also have some drawbacks such as sensitivity to noise, trapping in local optima, cluster center initialization and cluster number [9, 20, 22]. In this paper cluster center initialization problem is considered.

The standard Fuzzy c-means (FCM) algorithm selects cluster centers and initialize them randomly. As a result, different initial values are given to centers for different runs and thus quality of segmentation affects. The quality of segmentation can be attained by making the cluster center consistent, that is having optimum value which remains same for every run and that cluster center should represent group of similar objects [33]. In this paper, the new novel method is proposed that uses Self-Organizing Maps (SOM) for cluster center initialization. The self-organized maps is a type of Artificial Neural Network which is also inspired by biological models of neural systems from the 1970s. It is used as clustering technique which helps to reduce multidimensional complex problem to easy low dimensional problem [28]. This makes our method possible to directly apply on colored images. This clustering gives us initial centroids which are used as input to FCM. Along with this, to make the proposed method noise robust the spatial constraints are added to the objective function of FCM. The results of this proposed method shows that it outperforms the standard FCM as they have consistent initial cluster centers along with spatial constraint which makes it noise robust.

The rest of this paper is structured as follows: In section 2 basic concepts of Fuzzy C-means and brief overview of existing center initialization techniques are introduced. Section 3 briefly explains SOM as clustering technique. Section 4 describes the proposed Self Organized Maps based FCM (SOMFCM) method for initializing the cluster centers. Section 5 experimentally demonstrates the performance of the proposed method. Finally, section 6 discusses the conclusion of this paper along with the future scope.

1.1 Fuzzy C-means

The standard FCM is one of the most widely used clustering algorithm. In FCM pixels are grouped in different clusters in such a way that one pixel may belong to two or more clusters. The degree of membership defines the similarity of pixel to the cluster [31]. The membership of each pixel is calculated by the membership function, equation is as follows:

$$u_{ij} = 1 \Big/ \sum_{k=1}^{c} \left(d_{ij} \big/ d_{ik} \right)^{\left(\frac{2}{m}-1\right)} \qquad (1)$$

Where u_{ij} is membership of ith pixel to the jth cluster center, d_{ij} represents Euclidean distance between the ith pixel and jth cluster center, m is the fuzziness index, and c represents cluster number. Along with the membership function, the cluster center is also updated in each iteration.

$$v_j = \frac{\left(\sum_{i=1}^{n} (u_{ij})^m x_i\right)}{\left(\sum_{i=1}^{n} (u_{ij})^m\right)}, \forall j = 1,2, \dots c \qquad (2)$$

Where v_j represents the jth cluster center, n is the number of pixels and x_i is the ith pixel.

Fuzzy clustering is carried out through an iterative updation of membership function and cluster center and optimization of the objective function.

$$J(U,V) = \sum_{i=1}^{n} \sum_{j=1}^{c} (u_{ij})^{m} \left\|x_i - v_j\right\|^2 \qquad (3)$$

'$\left\|x_i - v_j\right\|^2$' is the Euclidean distance between ith data and jth cluster center.

The Fuzzy C-Means has wide areas of applicability such as image analysis, neural networks, data mining etc. Though it is very simple and robust in clustering large data sets, the method suffers from a few drawbacks. The user needs to provide the number of clusters which is difficult to know in advance for many real world data sets. But the major problem it suffers is very sensitive for the selection of initial cluster centers. As a result, it cannot always produce global optimum results and trap in local optima. Lu et. Al. (2008) introduced a hierarchical approach to initialize the centers which requires less computation time [18]. Cao et. Al (2009) gave a neighborhood based method to initialize K-means cluster centers [3]. Reddy et. Al (2012) proposed the Voronoi diagram based method to initialize cluster centers in K-means [25]. Yang et.al (2017) proposed a hybrid distance method which defines density of pixels according to the number of its neighbors as well as the distance between pixels and their neighbors[32].

In the literature study, found that there are few solutions proposed to this problem of FCM and many for K-means only. The K-means solutions may or may not be applied to FCM. So, this paper focuses on the initialization of FCM cluster centers. In FCM clustering algorithm the convergence totally depends on the initial cluster centers. The all methods present in literature are application specific [11, 12, 17, 23]. There is as of now, no general or universal method to initialize the cluster centers of FCM. Thus the cluster center initialization is gaining so much interest in research area.

1.2 Self- Organizing Maps

The Self organizing map(SOM) is an unsupervised learning algorithm introduced by Kohonen and also called as Kohonen's Map [14, 21]. It is used as data clustering or classification method. It has the property to map the high dimensional data onto a low dimensional data consists of 2-d grid of nodes called neurons [4]. The SOM network consists of two layers consisting input layer and another is an output layer also called Kohonen layer. The Kohonen layer is usually designed as a two dimensional arrangement of neurons that maps N-dimensional input to two dimensions, preserving topological order. For the purpose of the identifying cluster membership, a one dimensional Kohonen layer. The Kohonen layer computes the Euclidean distance between the weight vector for each of the Kohonen neurons and the input pattern. The Kohonen neuron that is closest, is the winner with an activation value of one while all other neurons have activation of zero [19] [8].

The network undergoes a self-organization process through a number of training cycles, starting with randomly chosen weights for the nodes in the Kohonen layer. During each cycle, every input vector is considered in turn and the winner node is such that:

$$\|x_v - w_i\| = min\ \|x_v - w_i\| \qquad i=1,\ldots\ldots N \qquad (4)$$

Where $\|.\|$ indicates Euclidean distance which is the most common way of measuring distance between vectors. The weight vectors of the winning node and the nodes in the neighbourhood are updated using a weight adaption function based on following Kohonen Rule:

$\Delta w_i = \alpha\left(x_v - w_i^{old}\right), for\ i\epsilon\ N_r$ (5)

Where α is the learning coefficients, xv is the input vector and Nr is the collection of nodes in the neighborhood of radial distance r. for a two dimensional Kohonen layer, there could be up to a total of eight neighboring nodes when r=1. The process will adjust the weights of the winning node, along with its neighbor nodes closer to the value of input pattern. The neighborhood size (r) can change, and it is usually reduced as training progress.

2. METHODS

Cluster classification involve two distinct problems: determination of cluster number and assignment of cluster centers. To determine these values one must have prior knowledge of the data and which is not always the case. The SOM attempted to solve the second problem in this paper. It gives the initial cluster centers to FCM. The spatial constraints [27] are added to objective function of FCM to make it more noise robust.

There are various comparisons of SOM with Hierarchical, K-means and other clustering algorithms that shows that the SOM provides better clustering results [4, 6, 10, 13, 15, 21, 29].

2.1 Proposed Algorithm

This paper proposes a cluster center initialization method for FCM. The literature survey concluded that there is a need of universal center initialization method that works equally effective for all applications [7, 16, 26]. So, a method based on Self Organizing Maps is proposed. The proposed algorithm consists of following steps:

1. Read a colored image: a real or synthetic colored image can be used as input to this algorithm. As it directly applied on the image, so no conversion to another color space is required.
2. Input cluster number: to check the efficiency of the proposed method different cluster numbers starting from 2 to Kmax is applied.
3. SOM: Self-Organizing Maps has two layer architecture one is input layer and another is output layer. The cluster number is given to the input layer and output layer provides the cluster centers.
4. Membership Matrix with spatial constraints: this FCM incorporates spatial constraints to the membership function. It is the summation of membership function in the neighborhood of each pixel under consideration. It has the following benefits: it is noise robust, yields more homogeneous regions and reduces the spurious blobs.
5. The FCM is applied and the segmented output is obtained.

2.2 Algorithm:

1. Read an input image.
2. Repeat the steps for K=2 to Kmax(k is cluster number)
3. Apply SOM
4. First it initializes the weights of size(n,K) where K is number of clusters. Then training over the input data, for each training example, it updates the winning vector (shortest Euclidean distance). Repeat for all training sets. Then cluster the training set. The cluster centers are obtained.

To include a spatial information, a spatial function is defined as:

$h_{ij} = \sum_{k\epsilon NB(x_j)} u_{ik}$ (6)

Where NB(xj) represents a square window (3*3)centered on pixel xj in the spatial domain. This spatial function is incorporated to the FCM membership function and now the new membership function becomes:

$$u'_{ij} = \frac{u_{ij}^{p} h_{ij}^{q}}{\sum_{k=1}^{c} u_{ij}^{p} h_{kj}^{q}} \quad (7)$$

where p and q are parameters to control the relative importance of both functions. For a noisy image this formula reduces the weighting of a noisy pixel whereas in non-noisy image clustering results remains unchanged.

5. The FCM objective function is applied and the segmented output is obtained.

In the proposed method no pre-processing technique such as noise removal filters, image enhancement functions etc. are applied. Hence, the results present a better way to evaluate the proposed algorithm.

3. RESULTS

The proposed method is applied on five colored real world images taken from Berkeley's database. The figure 1 shows the test images. The cluster numbers from 2 to 6 are applied to these images and cluster validity index Vpc and Vpe are used to find the appropriate cluster number for all the image.

The PC determines the belongingness of data or can say that it measures amount of overlap between clusters [1, 30, 34]. PE determines the entropy measurement or fuzziness of clusters [2]. The best and optimal partition is achieved by minimizing PE or maximizing PC. For better partitioning the value of PC should be one and PE should be zero.

$$PC(c) = \frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{c} u_{ij}^{2} \quad (8)$$

$$PE(c) = -\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{c} u_{ij}\, log_2\, u_{ij} \quad (9)$$

Where c is the number of clusters, N is the number of pixels, uij is the membership degree of ith pixel for jth cluster.

Image1			
Image 2			
Image 3			

Image 4			
Image 5			

(a) (b) (c)

Figure 1: Shows the 5 test images (a) original images taken from Berkeley's image dataset (b) FCM segmented image (c) SOMFCM segmented image

The Figure 1 shows the test images taken from Berkeley's image dataset. The test images are segmented using FCM and proposed method SOMFCM for different cluster numbers to find out the suitable cluster number. The figure 1 shows the segmented images using suitable cluster number found from the table 1.

Table 1 shows the cluster validity index values of five images for cluster number 2 to 6

IMAGES	**ALGORITHM**	**CLUSTER VALIDITY INDICES**	**CLUSTER NUMBERS**				
			2	**3**	**4**	**5**	**6**
IMAGE 1	**SOM-FCM**	**Vpc**	**0.9338**	0.9101	0.901	0.9012	0.8737
		Vpe	**0.1146**	0.1621	0.187	0.1859	0.2427
	FCM	**Vpc**	**0.8549**	0.7949	0.7643	0.7051	0.7248
		Vpe	**0.2462**	0.3781	0.4606	0.5917	0.5713
IMAGE 2	**SOM-FCM**	**Vpc**	0.8803	**0.9452**	0.8761	0.8803	0.8762
		Vpe	0.1347	**0.1009**	0.219	0.2137	0.2246
	FCM	**Vpc**	0.7537	**0.7913**	0.7715	0.7754	0.7601
		Vpe	0.3911	**0.3745**	0.4105	0.4265	0.4719
IMAGE 3	**SOM-FCM**	**Vpc**	0.8592	0.8186	**0.8921**	0.8631	0.85
		Vpe	0.1706	0.2424	**0.1525**	0.2452	0.2674
	FCM	**Vpc**	0.7972	0.7162	**0.7999**	0.7183	0.6954
		Vpe	0.482	0.5388	**0.3637**	0.5474	0.6116
IMAGE 4	**SOM-FCM**	**Vpc**	**0.9693**	0.9242	0.9045	0.8861	0.8311
		Vpe	**0.0527**	0.1322	0.1682	0.2021	0.2974
	FCM	**Vpc**	**0.9203**	0.8202	0.772	0.7339	0.681
		Vpe	**0.1466**	0.3322	0.4319	0.517	0.6224
IMAGE 5	**SOM-FCM**	**Vpc**	0.8405	0.8465	**0.8585**	0.8379	0.8571
		Vpe	0.2726	0.2866	**0.2705**	0.3058	0.2736
	FCM	**Vpc**	0.6671	0.6279	**0.6836**	0.6668	0.6751

		Vpe	0.5718	0.5605	**0.5227**	0.6789	0.6956

The Table 1 shows the values of cluster validity index Vpc and Vpe for five different images and for cluster number 2 to 6. The highest value of Vpc and lowest Value of Vpe for a particular cluster number specifies the cluster number of that image. So the Table 1 is used to find the appropriate cluster number of images which is 2,3,4,2 and 4 for images 1,2,3,4 and 5 respectively.

Table 2 Shows the noise robustness of proposed SOM-FCM method

IMAGES	**ALGORITHM**	**VALIDITY INDICES**	**GAUSSIAN NOISE**			**SALT AND PEPPER NOISE**		
			1%	**5%**	**10%**	**1%**	**5%**	**10%**
IMAGE 1	**SOM-FCM**	**Vpc**	**0.9123**	**0.906**	**0.8966**	**0.9297**	**0.928**	**0.907**
		Vpe	**0.1479**	**0.1589**	**0.1737**	**0.1176**	**0.1187**	**0.1583**
	FCM	Vpc	0.6536	0.625	0.60474	0.6902	0.6746	0.6558
		Vpe	0.3959	0.4009	0.4444	0.3458	0.3949	0.4883
IMAGE 2	SOM-FCM	**Vpc**	**0.8973**	**0.8719**	**0.869**	**0.9162**	**0.8991**	**0.8931**
		Vpe	**0.3366**	**0.2747**	**0.2969**	**0.1518**	**0.1941**	**0.1968**
	FCM	Vpc	0.6356	0.5947	0.5338	0.7899	0.7495	0.7026
		Vpe	0.6161	0.6679	0.6998	0.3714	0.4366	0.5126
IMAGE 3	**SOM-FCM**	**Vpc**	**0.7958**	**0.7697**	**0.7441**	**0.8837**	**0.8242**	**0.8147**
		Vpe	**0.538**	**0.533**	**0.5299**	**0.2085**	**0.3389**	**0.5468**
	FCM	Vpc	0.5123	0.5125	0.5124	0.7329	0.6804	0.6226
		Vpe	0.8955	0.9252	0.9454	0.5049	0.599	0.703
IMAGE 4	**SOM-FCM**	**Vpc**	**0.951**	**0.9579**	**0.9635**	**0.9531**	**0.9067**	**0.9339**
		Vpe	**0.0889**	**0.0755**	**0.0643**	**0.0809**	**0.1614**	**0.1147**
	FCM	Vpc	0.8567	0.8201	0.8073	0.8738	0.8422	0.8059
		Vpe	0.2538	0.2885	0.3871	0.2171	0.2997	0.3515
IMAGE 5	**SOM-FCM**	**Vpc**	**0.7828**	**0.7575**	**0.745**	**0.8317**	**0.818**	**0.7945**
		Vpe	**0.4414**	**0.4524**	**0.4301**	**0.3148**	**0.3465**	**0.5902**
	FCM	Vpc	0.5546	0.5149	0.5079	0.6829	0.6489	0.6103
		Vpe	0.8377	0.8571	0.8922	0.6189	0.6678	0.7454

The Table 2 shows that as the density of noise increases the value of Vpc decreases and the Vpe increases that means that the belongingness of cluster decreases hence the clusters are misclassified. The image 1 of SOM-FCM in table 2 shows that the Vpc 0.9123 and Vpe 0.1479, Vpc 0.906 and Vpe 0.1589 and Vpc 0.8966 and Vpe 0.1737 for 1%, 5% and 10% of Gaussian noise respectively. As the values indicates the increased noise content decreases the Vpc and increases Vpe values. But when compared to the image 1 of FCM values of Vpc and Vpe, it is found that the effect of noise on SOM-FCM is less as on FCM. The effect of noise on image 1 is Vpc 2.3 % and Vpe 29.05 % for SOM-FCM method whereas for FCM it is Vpc 20% and Vpe 62% which confirms the noise robustness of the proposed SOM-FCM method.

4. DISCUSSION

The results of proposed method are compared with standard FCM methods and the results shows that the proposed method is more insensitive to noise than the standard method. The results also shows that the good initial values of cluster centers lead to the consistent and good clustering. It also shows that non-random initialization of cluster centers improves the quality of clustering.

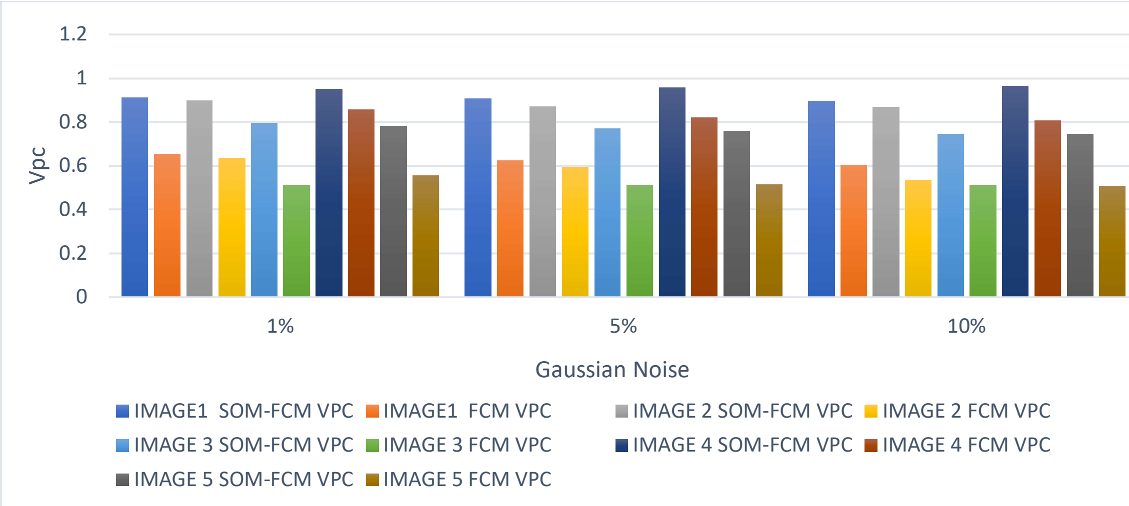

Figure 2: Comparison of FCM and proposed method based on effect of Gaussian noise (1%, 5% and 10%) with Vpc values

The figure 2 shows the graphical representation of effects of Gaussian noise at different intensities that are 1%, 5% and 10% on five test images. The graph shows the comparison of FCM and SOM-FCM for all five test images where each image has high SOM-FCM Vpc value than FCM.

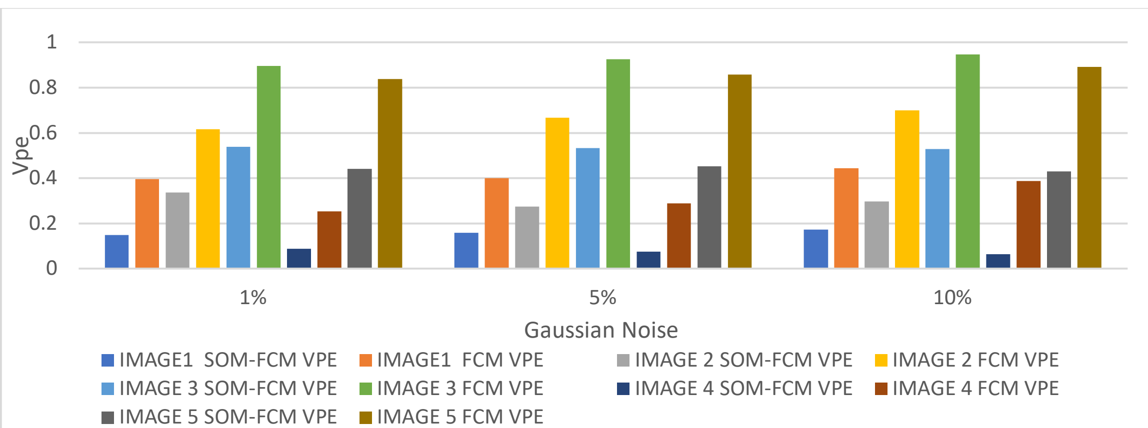

Figure 3: Comparison of FCM and proposed method based on effect of Gaussian noise (1%, 5% and 10%) with Vpe values.

The figure 3 shows Vpe values for all the test images having Gaussian noise at different intensities. The proposed method has lower values of Vpe than the FCM for all test images which is essential for good clustering result. It shows that the image 1 has 0.1479, 0.1589 and 0.1737 Vpe values for SOM-FCM having 1%, 5% and 10% Gaussian noise. It shows that the SOM-FCM has low effect of noise.

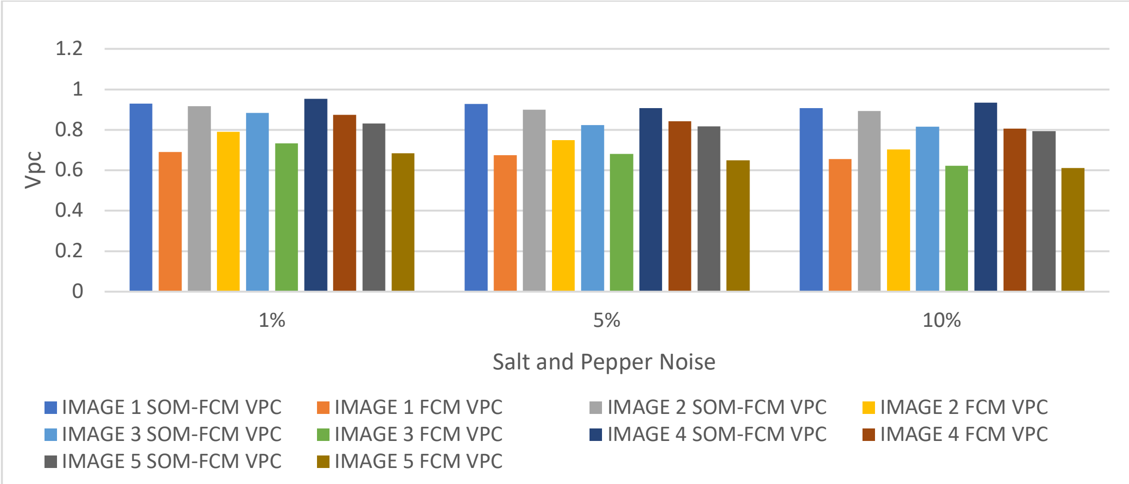

Figure 4: Comparison of FCM and proposed method based on effect of Salt and Pepper noise (1%, 5% and 10%) with Vpc values

The figure 4 shows the graphical representation of effects of Salt and Pepper noise at different intensities that are 1%, 5% and 10% on five test images. It shows that the Vpc of proposed method of each test image is higher than FCM which means it is having good clustering results.

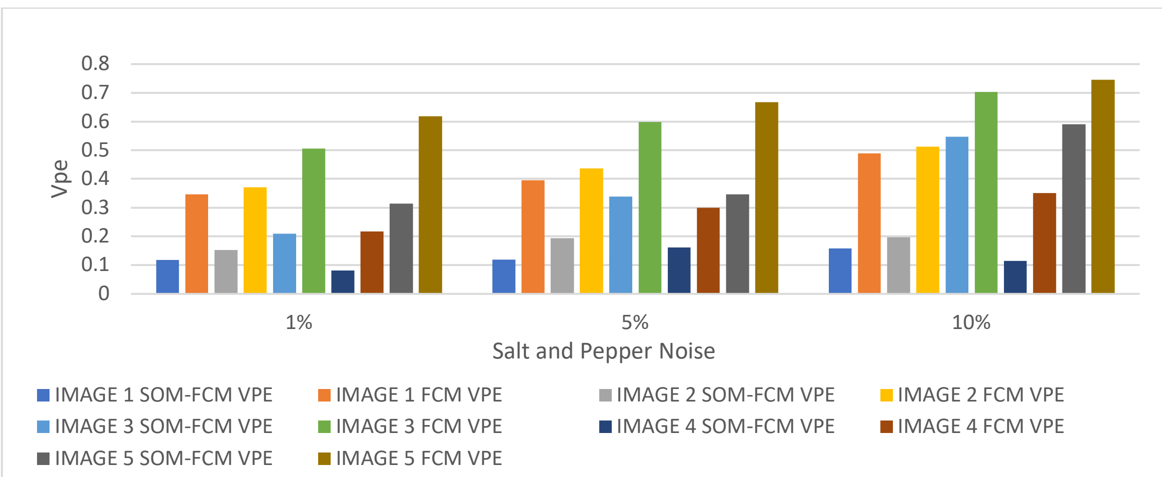

Figure 5: Comparison of FCM and proposed method based on effect of Salt and Pepper noise (1%, 5% and 10%) with Vpe values

The Figure 5 represents the impacts of Salt and Pepper noise (1%, 5% and 10%) on the test images. The Figure 4 shows the Vpc whereas the Figure 5 shows the Vpe values of proposed method which are better than FCM methods.

The results of proposed method are compared with standard FCM methods and the results shows that the proposed method is more insensitive to noise than the standard method. The results also shows that the good initial values of cluster centres lead to the consistent and good clustering. It also shows that non-random initialization of cluster centres improves the quality of clustering

5. CONCLUSIONS

FCM is simple and effective clustering algorithm, but it is sensitive to cluster centre initialization. This sensitivity leads to trapping in local optima and failed to get best partition.

To overcome this drawback Self-Organizing Maps along with spatial constraints are introduced. This will generate cluster centres which are close to final cluster centres. This makes the proposed method more robust to noise and produces more homogeneous regions. This lead to more effective and efficient segmentation algorithm. The results shows the superiority of proposed method over the standard FCM.

6. LIST OF ABBREVIATIONS

FCM: Fuzzy c-Means; SOM: Self Organizing Maps: SOMFCM: Self Organized Maps using Fuzzy c-means;PC: Partition Coefficient; PE: Partition Entropy

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