

A Robust Method for Image Segmentation of Noisy Digital Images

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Abstract— A robust image segmentation algorithm called Extended Fuzzy C means (EFCM) is presented in this paper which preprocesses the image to reduce the noise effect and then apply FCM algorithm for image segmentation. Preprocessing of image is influenced by the direct eight neighborhood pixels of study pixel of an image under consideration. The advantages of the propose algorithm is: (1) Least execution time compared to other techniques. (2) It yields regions more homogeneous than those of other techniques. (3) It removes noisy spots and is less sensitive to noise. The propose technique is a powerful method for noisy image segmentation with least computation time and convergence rate compared to other image segmentation techniques.

Keywords—Fuzzy Clustering, Fuzzy C-Means, Robust Image Segmentation

I. INTRODUCTION

A. Image segmentation

Image segmentation plays an important role in image analysis and computer vision. The goal of image segmentation is partitioning of an image into a set of disjoint regions with uniform and homogeneous attributes such as intensity, color, tone etc. The image segmentation approaches can be divided into four categories; thresholding, clustering, edge detection, and region extraction. In image processing, two terms are usually seen very close to each other: clustering and segmentation. When analyzing the color information of the image, e.g. trying to separate regions or ranges of color components having same characteristics, the process is called color clustering. Mapping the clusters onto the spatial domain and physically separated regions in the image is called segmentation. In color images, the boundaries between objects are blurred and distorted due to the imaging acquisition process. Furthermore, object definitions are not always crisp and knowledge about the objects in a scene may be vague. Fuzzy set theory and Fuzzy logic are ideally suited to deal with such uncertainties. Fuzzy clustering models have proved a particularly promising solution to the color clustering problem. Such unsupervised models can be analysis, clustering, and classifier designs in fields such as astronomy, geology, medical imaging, target recognition, used with any number of features and clusters. The Fuzzy C

means (FCM) [1] algorithm, proposed by Bezdek (1981), is the most widely used algorithm in image segmentation because it has robust characteristics for ambiguity and can retain much more information than hard segmentation methods. FCM has been successfully applied to feature and image segmentation. An image can be represented in various feature spaces and the FCM algorithm classifies the image by grouping similar data points in the feature space into clusters. In case the image is noisy or distorted then FCM technique wrongly classify noisy pixels because of its abnormal feature data. Various approaches are proposed by researchers to compensate this drawback of FCM.

B. FCM Related Extensions

Tolias and Panas post-processed the membership function to smooth the noise effect [2]. Acton and Mukherjee incorporated multiscale information to enforce spatial constraints [3]. The most popular approach for increasing the robustness of FCM is to modify the objective function directly. Dave proposed the idea of a noise cluster to deal with noisy data using the technique, known as Noise Clustering [4]. He separated the noise into one cluster but this technique is not suitable for image segmentation, since we cannot separate pixels from the image. Noisy pixels can be processed and assigned to most appropriate cluster. Another similar technique, PCM, proposed by Krishnapuran and Keller [5] interprets clustering as a possibilistic partition. However, it caused clustering being struck in one or two clusters. Ahmed et al. [6] modified the objective function of FCM by introducing a term that allowed the labeling of a pixel to be influenced by the labels in its immediate neighborhood. Zhang Yang, Fu-lai Chuang et al. [7] developed a robust clustering technique by deriving a novel objective function for FCM. Jiayin Kang et al. [8] proposed another technique which modified FCM objective function by incorporating the spatial neighborhood information into the standard FCM algorithm. Y. Yang et al. [9] proposed a novel penalized FCM (PFCM) for image segmentation where penalty term acts as a regularizer in the algorithm which is inspired by neighborhood maximization (NEM) algorithm [10] and is modified in order to satisfy the criterion of FCM algorithm. S. Shen, W. Sandham et al. [11] presented an algorithm called Improved FCM (IFCM) which changed the distance function used in FCM i.e. the distance between pixel intensity and cluster intensities and applied neural network

optimization technique to adjust parameters in the modified distance function. Keh-Shih Chuang, Hong-Long Tzeng et al. [12] presented a FCM algorithm that incorporated spatial information into the membership function of clustering. The membership weighting of each cluster is altered after the cluster distribution in the neighbourhood is considered. Rhee and Hwang [13] proposed Type 2 fuzzy clustering. Type 2 fuzzy set is the fuzziness in a fuzzy set. In this algorithm, the membership value of each pattern in the image is extended as Type 2 fuzzy membership by assigning membership grades (triangular membership function) to Type 1 fuzzy membership. The membership values for the Type 2 membership are obtained as:

$$a_{ik} = u_{ik} - \frac{1 - u_{ik}}{2}$$

where a_{ik} and u_{ik} are the Type 2 and Type 1 fuzzy membership respectively. The cluster centers are updated accordingly using conventional FCM taking into account the new Type 2 fuzzy membership.

Problem with all these methods is that they increase the complexity of the algorithms by introducing new equations into the standard equations of FCM algorithm which inevitably introduced computation issues. By changing the objective function and membership function of standard FCM algorithms, we are losing the continuity from FCM, which is well-realized function in many types of software, such as MATLAB. In this paper, a new extension to FCM is proposed, which consists of image enhancement and segmentation. We are pre-processing the image before segmentation to reduce the noisy pixels which is influenced by the direct eight neighborhood pixels of noisy pixels. Strength of the propose algorithm is its least execution time and convergence rate compare to other robust image segmentation techniques.

The organization of the paper is as follows: Section II, briefly review Fuzzy C-Means (FCM) [1], Spatial FCM (sFCM) [12], and cluster validity functions for the evaluation of segmentation performance. Section III describes the proposed algorithm, Extended Fuzzy C Means (EFCM). Section IV evaluates the performance of the proposed EFCM algorithm and compares it with sFCM, FCM type-II, and conventional FCM algorithm followed by concluding remarks in Section V.

II. BACKGROUND INFORMATION

This section briefly discusses the Fuzzy C-Means (FCM) and Intuitionistic Fuzzy C means (IFCM) algorithms. In this paper, the data-set is denoted by 'X', where $X = \{x_1, x_2, x_3, \dots, x_n\}$ specifying an image with 'n' pixels in M-dimensional space to be partitioned into 'c' clusters. Centroids of clusters are denoted by v_i and d_{ik} is the distance between x_k and v_i .

A. The Fuzzy C-Means Algorithm

FCM [1] is the most popular fuzzy clustering algorithm. It assumes that number of clusters 'c' is known in priori and minimizes the objective function (J_{FCM}) as:

$$J_{FCM} = \sum_{i=1}^c \sum_{k=1}^n u_{ik}^m d_{ik}^2 \quad (1)$$

Where $d_{ik} = \|x_k - v_i\|$, and u_{ik} is the membership of pixel ' x_k ' in cluster 'i', which satisfies the following relationship:

$$\sum_{i=1}^c u_{ik} = 1; \quad i = 1, 2, \dots, n \quad (2)$$

Here 'm' is a constant, known as the fuzzifier (or fuzziness index), which controls the fuzziness of the resulting partition. m=2 is used in this paper. Any norm $\|\bullet\|$ can be used for calculating d_{ik} . Minimization of J_{FCM} is performed by a fixed point iteration scheme known as the alternating optimization technique. The conditions for local extreme for (1) and (2) are derived using Lagrangian multipliers:

$$u_{ik} = \frac{1}{\sum_{j=1}^c \left(\frac{d_{ik}}{d_{jk}} \right)^{\frac{2}{m-1}}} \quad \forall k, i \quad (3)$$

where $1 \leq i \leq c; 1 \leq k \leq n$ and

$$v_i = \frac{\sum_{k=1}^n (u_{ik}^m x_k)}{\sum_{k=1}^n (u_{ik}^m)} \quad \forall i \quad (4)$$

The FCM algorithm iteratively optimizes $J_{FCM}(U, V)$ with the continuous update of U and V, until $|U^{(l+1)} - U^{(l)}| \leq \epsilon$, where 'l' is the number of iterations. FCM works fine for the images which are not corrupted with noise but if the image is noisy or distorted then it wrongly classifies noisy pixels because of its abnormal feature data which is pixel intensity in the case of images, and results in an incorrect membership and improper segmentation.

B. Spatial Fuzzy C Means (sFCM)

Spatial Fuzzy C means [12] algorithm modifies FCM membership function by introducing spatial information into it. sFCM defines spatial function as:

$$h_{ij} = \sum_{k \in NB(x_j)} u_{ik} \quad (5)$$

where $NB(x_i)$ represents a square window centered on pixel x_j in the spatial domain. sFCM considered 5x5 window. Just like the membership function, the spatial function 'h_{ij}' represents the probability that pixel x_j belongs to ith cluster. Spatial function is incorporated into membership function as:

$$u'_{ij} = \frac{u_{ij}^p h_{ij}^q}{\sum_{k=1}^c u_{ij}^p h_{ij}^q} \quad (6)$$

where 'p' & 'q' are parameters which control the relative importance of both functions. For a noisy pixel, this formula reduces the weighting of a noisy cluster by the labels of its neighboring pixels. Disadvantage of this algorithm is that it is a two-pass process for every pass of FCM algorithm. In the first pass, conventional FCM algorithm is used to calculate membership function and in the second pass, the membership information of each pixel is mapped to the spatial domain, and the spatial function is calculated from that. The FCM iteration proceeds with the new membership that is incorporated with the spatial function. Hence, the complexity of this algorithm is very high compared to FCM technique, which introduces computational issues.

C. Cluster Validity Functions

To evaluate the performance of segmentation quantitatively, two types of cluster validity functions are generally used: the fuzzy partition and the feature structure. The representative functions for the fuzzy partition are partition coefficient [14] and partition entropy [15]. They are defined as:

$$V_{pc}(U) = \sum_{i=1}^n \sum_{k=1}^c u_{ki}^2 \quad (7)$$

$$V_{pe}(U) = -\frac{1}{n} \left\{ \sum_{i=1}^n \sum_{k=1}^c [u_{ki} \log u_{ki}] \right\} \quad (8)$$

Best clustering results can be achieved when the value V_{pc} is maximal or V_{pe} is minimal. Disadvantage of V_{pc} and V_{pe} are that they measure only the fuzzy partition and do not specify featuring property. To solve this problem, other validity functions based on the feature structures are used [16], [17]. They are defined as:

$$V_{fs}(U, V; X) = \sum_{k=1}^c \sum_{i=1}^n u_{ik}^m (\|x_i - v_k\|^2 - \|v_k - \bar{v}\|^2) \quad (9)$$

Where $\bar{v} = \frac{1}{c} \sum_{k=1}^c v_k$

$$V_{xb}(U) = -\frac{\sum_{k=1}^c \sum_{i=1}^n u_{ki}^2 \|x_i - v_k\|^2}{n * \left(\min_{k \neq j} \{ \|v_k - v_j\|^2 \} \right)} \quad (10)$$

Where V_{fs} is a Fukuyama-Sugeno function and V_{xb} is Xie-Beni function. When either V_{fs} or V_{xb} is minimal, a better clustering result is achieved [16], [17].

III. THE PROPOSED TECHNIQUE, EXTENDED FUZZY C MEANS (EFCM)

Earlier, we proposed a robust clustering algorithm, called Density Oriented Fuzzy C-Means (DOFCM) [18] for numerical data. The concept of DOFCM was to identify noise points, based upon the number of other points in its neighborhood, before clustering and separate it into one cluster. In case of image segmentation that algorithm is not appropriate as we cannot separate noisy pixels from the image. But noisy pixels can be processed and assign to the appropriate cluster. Here, in the propose technique, we are using the same concept i.e. processing image before segmentation and modifies DOFCM algorithm for image segmentation.

FCM is a good segmentation technique if there is no noise in the image. Keeping this in view, we are proposing a very simple and effective method, which preprocess noisy pixels in the image and then apply conventional FCM algorithm for segmentation.

The pixels in an image are highly correlated i.e. the pixels in the immediate neighborhood possess nearly the same feature data. In the propose technique, we are trying to regenerate the value of noisy pixels by processing every pixel of an image based upon its immediate neighborhood pixels. Neighborhood structure considered in the propose technique is shown in Fig. 1. Value of every pixel is influenced by its eight direct neighborhood pixels. We are considering an image in RGB format. Let size of an image is $R * C * K$, where R is the number of rows, C is the number of columns, and K is 3 (for color image). So every pixel will be processed using equation:

$$pixel(l, m, k) = \sum_{k=1}^3 \frac{1}{N} \left(\left(\sum_{i=l-1}^{l+1} \sum_{j=m-1}^{m+1} pixel(i, j, k) \right) - pixel(l, m, k) \right) \quad (11)$$

Where N = 8, denoting 8 neighborhood points of a study pixel

pixel (i, j, k) = intensity value of pixel at i,j,k location

pixel (l, m, k) = intensity value of study pixel

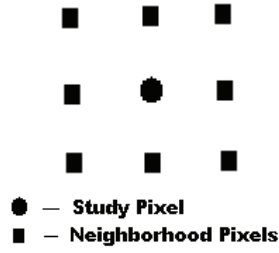


Figure 1. Neighborhood structure for study pixel

In the homogeneous region, this function simply fortifies the same characteristics and the clustering result remains unchanged. However, for a noisy pixel, this formula tries to regenerate the value of original pixel. As a result, misclassified pixels from noisy regions can easily be corrected. After processing the noisy pixels, FCM is used to do segmentation. Here, we are processing the image only once before segmentation, which does not increase the complexity of the program compare to Spatial FCM and other robust clustering algorithms for image segmentation. Other methods mostly changed the standard FCM equations and introduced new functions which are calculated for every pass of the FCM algorithm i.e. they are extremely computationally intensive so the strength of the proposed technique is its least execution time, which is approximately equal to the conventional FCM method. Also, it does not modify FCM algorithm so does not lose the continuity of FCM function which is given in many softwares like MATLAB. Various steps involved in the proposed technique used for image segmentation are shown in Fig. 2.

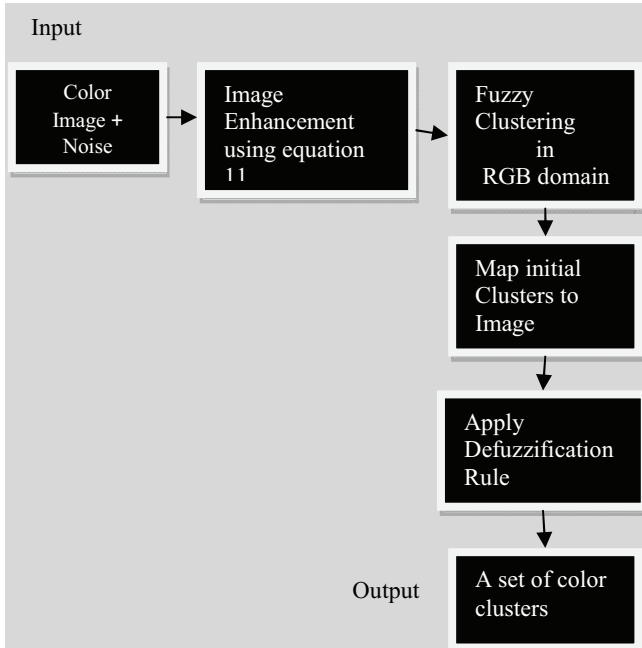


Figure 2. Block diagram of the steps used for image segmentation using proposed method along with input and output.

IV. RESULTS

In this section, experimental results are presented to compare the segmentation performance of EFCM with FCM, FCM Type II, and sFCM. Two types of images are used: (1) Synthetic images (2) Real world image. For all data-sets, we are assuming the following computational protocols: $\varepsilon = 0.00001$, Total number of iterations = 100. We chose $m=2$, which is a common choice for fuzzy clustering. Experiments are implemented and simulated using MATLAB Version 7.0.

A. Circle Image

A grayscale circle image (256x256 pixels) representing two intensity levels is used. It is corrupted with gaussian noise. The intensity levels of two classes are 0 and 255. Fig. 3(a) & 3(b) show original and noisy version of circle image. Fig. 3(c)-(f) shows the segmentation result of FCM, sFCM, EFCM, and Fuzzy Type-II respectively. Although FCM, Fuzzy Type-II, and sFCM successfully segmented the image into the desired regions but did not totally recover it from the noise whereas, EFCM totally recovered the image from noise.

In addition to the analyses of the qualitative evaluation presented above, a quantitative evaluation using several cluster validity functions is necessary. As described in part II.C, the better performance of clustering is achieved if the partition coefficient V_{pc} is maximal and/or the partition entropy value V_{pe} , the Fukuyama-Sugeno function V_{fs} , and the Xie-Beni function V_{xb} are minimal. Table I shows performance comparison of FCM, Fuzzy type-II, sFCM, and our proposed EFCM in terms of cluster validity functions.

B. Square Image

A synthetic square image (160 x 170 x 3 pixels) consisting of 9 squares is generated. It contains gaussian noise to create noisy version of original image (Fig. 4a) as shown in Fig. 4(b). The image represents three intensity levels with the values 255, 128 and 0. Fig. 4(c)-(f) shows segmentation results of FCM, sFCM, EFCM, and Fuzzy Type-II. FCM, Fuzzy type-II, and sFCM did not completely remove the noise where as EFCM totally removed noise in the same intensity region but noise effect can be seen at the boundaries where the intensity level is changing. TABLE-I shows performance comparison of these algorithms in terms of cluster validity functions.

C. Bacteria Image

A real bacteria image (126 x 140 x 3 pixels) consisting of two classes is considered and it is corrupted with gaussian noise to show the performance of purpose technique. The bacteria are separated from its background using all the three methods. Fig. 5(a)-(b) show original image and its noisy version respectively. Fig. 5(c)-(f) shows segmentation result and 5(g)-(j) shows clustering result of FCM, sFCM, EFCM, and Fuzzy type-II respectively. It is observed that EFCM is able to retain the boundary of bacteria more effectively as compared to other methods. TABLE-I shows

performance of these algorithms quantitatively using cluster

validity functions.

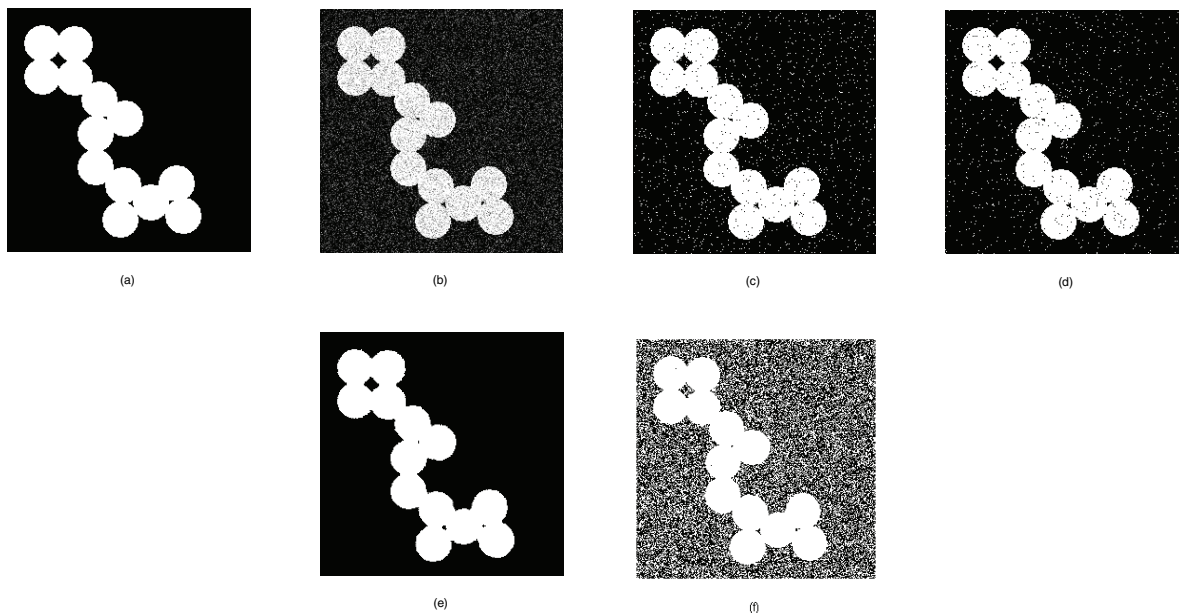


Figure 3. (a) Original Image (b) Image with noise (c) Segmented image using FCM (d) Segmented image using sFCM (e) Segmented image using EFCM (f) Segmented image using FCM Type-II

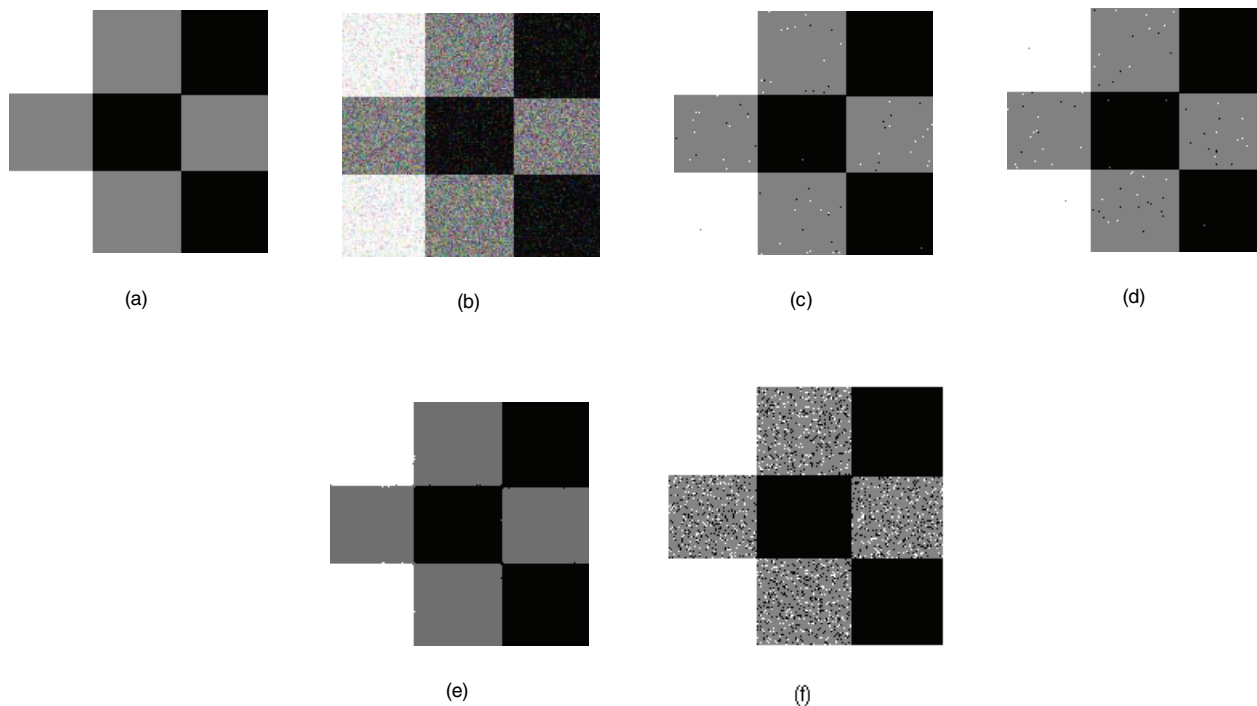


Figure 4. (a) Original Image (b) Image with noise (c) Segmented image using FCM (d) Segmented image using sFCM (e) Segmented image using EFCM (f) Segmented image using FCM Type-II

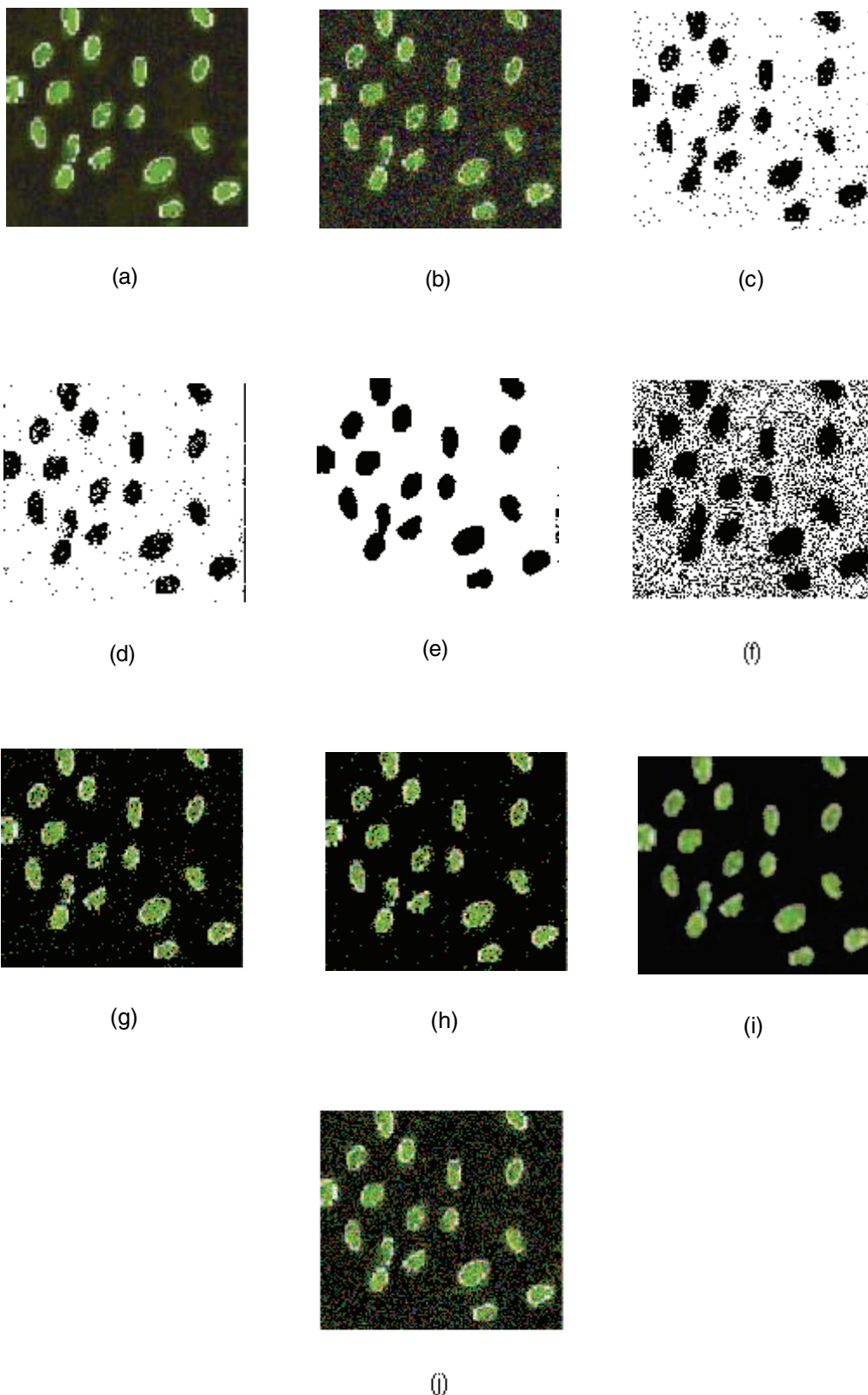


Figure 5. (a) Original Image (b) Image with noise (c)-(f) Segmented image using FCM, sFCM, EFCM, and FCM Type-II respectively (g)-(j) Objects shown in one cluster using FCM, sFCM, EFCM, and FCM Type-II respectively

Performance of algorithms based upon execution time

Fig. 6 shows bar chart of the execution time of FCM, Fuzzy type-II, sFCM, and EFCM for the above three images. TABLE-II lists execution time and number of iterations of the algorithms. Advantage of the propose technique is that it has least execution time compared to other color image segmentation techniques. From TABLE-II, it is observed

that almost in all cases, proposed technique converges even before FCM algorithm because it is preprocessing the image before applying FCM technique which increases the convergence rate. Its execution time is almost close to FCM technique.

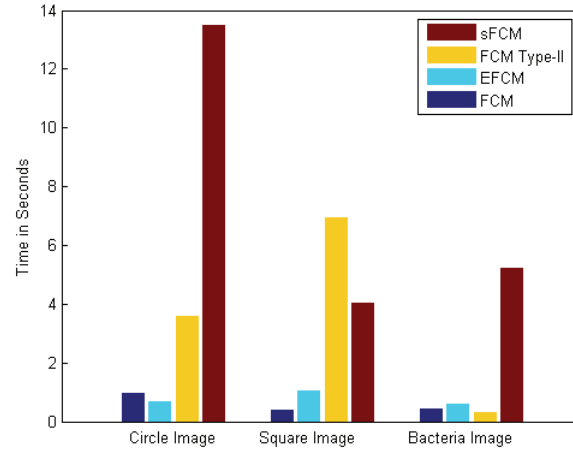


Figure 6. Performance of algorithms based upon execution time

TABLE-I
PERFORMANCE COMPARISON OF FCM, sFCM, FCM TYPE-II, AND EFCM IN TERMS OF CLUSTER VALIDITY FUNCTIONS

Image Name	Number of Clusters	Technique	The value of Validity Functions			
			V_{pc}	V_{pe}	V_{xb}	V_{fs}
Circle	2	FCM	0.93720	0.11520	0.020900	-613x10 ⁶
		sFCM	0.94270	0.10630	0.020941	-622x10 ⁶
		FCM TYPE-II	0.8361	-0.0794	3.8448	1.017x10 ⁸
		EFCM	0.98120	0.04000	0.006880	-628x10 ⁶
Square	3	FCM	0.84075	0.31734	0.052073	-24228
		sFCM	0.80990	0.36713	0.055247	-22762
		FCM TYPE-II	1.281	0.5018	1.6823	69705
		EFCM	0.95311	0.10662	0.012342	-29338
Bacteria	2	FCM	0.77803	0.36518	0.151760	4540
		sFCM	0.81035	0.32098	0.129740	4106.1
		EFCM	0.91911	0.15477	0.038946	3773.8
		FCM TYPE-II	0.4329	-0.3115	0.9543	1112.6

TABLE-II
PERFORMANCE COMPARISON OF FCM, sFCM, FCM TYPE-II AND EFCM IN TERMS OF EXECUTION TIME & CONVERGENCE RATE

Image Name	Technique	Execution Time in Seconds	Number of Iterations (Convergence Rate)
Circle	FCM	0.953	21
	sFCM	13.48	40
	FCM TYPE-II	3.594	52
	EFCM	0.65	13
Square	FCM	0.406	14
	sFCM	4.04	21
	FCM TYPE-II	6.93	200
	EFCM	1.03	12
Bacteria	FCM	0.43	32
	sFCM	5.235	62
	FCM TYPE-II	0.312	23
	EFCM	0.578	15

V.CONCLUSION

Digital images generally contain unknown noise and considerable uncertainty. Traditionally, FCM is a popular segmentation method for digital images. However, it is an intensity-based clustering algorithm which is not robust against noisy images. The pixels in an image are highly correlated and this spatial information is an important characteristic for color image segmentation which is not utilized in FCM. Although, many extended algorithms based upon FCM have been developed to overcome this shortcoming by incorporating spatial information either in the objective function or in the membership function of FCM algorithm. But they all have increased the complexity of the standard algorithm by introducing new equations for spatial membership that are calculated for every pass of FCM algorithm.

In this paper, we proposed an extended FCM (EFCM) algorithm which preprocesses the image before segmentation. Preprocessing of image is influenced by the direct eight neighborhood pixels of every pixel of an image under consideration. Its strength is its least execution time and fast convergence rate compared to other image segmentation techniques. It is tested on noisy synthetic images and real images and evaluated quantitatively with four different cluster validity functions. Results showed that the performance of proposed technique is best over FCM, Fuzzy Type-II, and sFCM.

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