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Comparison of Fuzzy Algorithms on Images

Vikrant Dabas[1], Sachin Nandal[2], Prakhar Dogra[3]

[1]Department of Computer Engineering , Delhi Technological University, New Delhi, India

[2]Department of Information Technology, MaharajaSurajmal Institute of Technology, New Delhi, India

[3]Department of Computer Engineering, Delhi Technological University, New Delhi, India

Abstract: ***Image segmentation is a process by which an image is partitioned into regions with similar features. Many approaches have been proposed for image segmentation, but generally we use Fuzzy C-Means method, because it gives better results for large class of images. However, using this method is not suitable for images with noise and it is a lengthy process in terms of duration when compared with other method. For this reason, many other methods have been proposed to improve the shortcomings of image segmentation using fuzzy C-Means. Techniques like Credibilistic Fuzzy C-Means overcomes the problem of noise persisted using FCM. Intuitionistic Fuzzy C-Means introduces the concept of non-membership for a cluster. Krishnapuram and Keller [1] suggested usage of Possibilistic C-Means clustering which relaxes the column constraint of FCM so that membership matrix better reflects the typicality of particular data point in a cluster and noise could be avoided. We perform a comparison of these clustering algorithms on the basis of execution time and validity function for each algorithm applied on different kind of images taken in consideration.***

Keywords: clustering, segmentation, C-Means, fuzzy, images

1. Introduction

Clustering is a process for classifying objects or patterns in such a way that samples of the same group are closer than samples belonging to different groups. Differentstrategies for clustering have been used, broadly the hard clustering and the fuzzy clustering scheme, which are different to each other in a characteristic way. The conventional hard clustering method restricts each point of the data set to exclusively just one cluster. As a result, having such approach the segmentation results are often very crisp, i.e., each pixel of the image gets clustered to exactly one class. However, in the original situations, for images, problems like poor contrast,limited spatial resolution, noise, overlapping intensities, and intensity in homogeneities variation make this hard (crisp) segmentation a difficult task. Thanks to the fuzzy set theory [4], which produced the idea of partial membership of belonging described by a membership function. Among the fuzzy clustering methods, fuzzy c-means (FCM) algorithm [5] is the most popular method used in image segmentation because it has robust characteristics for ambiguity and can retain much more information than hard segmentation methods [6].

Various properties of clustering techniques are: clustering techniques must assign lower memberships to all the outliers for all the clusters[7], centroids generated by Clustering Techniques on noisy images should not deviate significantly from those generated for the corresponding noiseless images, obtained by removing the outliers, clustering techniques must be independent of any number of clusters i.e. able to identify outliers by changing the number of clusters for the same images, they should be independent of any amount of outliers i.e. Centroids generated by these techniques should not deviate by increasing the number of outliers[8].

Image segmentation is an important, challenging problem and a pre-requisite for image analysis as well as for interpretation of high-level image. Understanding highly detailed imaging produced by robotic vision, medical imaging etc. are few of the application of image segmentation. Main function of image segmentation is partition of an image into a set of disjoint regions with uniform and homogeneous attributes such as intensity, colour, tone or texture, etc. Many different segmentation techniques have been developed and detailed surveys can be found in references [2–3].

Synthetic-aperture radar (SAR) is a form of radar imaging which is used to create images of large objects, such as a landscape – these images can be 2Dimensional or 3Dimensional representations of the landscape or piece of land taken for consideration. “SAR creates high resolution images with comparatively small physical antennas”. [9]. In this document we compare the use of fuzzy based classification techniques over SAR and Hestain images and conclude which algorithm gives better results.

2. Theoretical Background for clustering

a. Fuzzy C-Means (FCM)

Fuzzy clustering in fuzzy logic deals with the degree ofbelonging of each point to a cluster, rather than belongingcompletely to just one cluster. It was first developed by Dunn[10] and improved by Bezdek [11] which proved to be base of all fuzzy clustering algorithm is specified in terms of membership matrix. There have been several clustering criteria proposed for identifying optimal fuzzy c-partitions. Out of all those, the most appropriate method is:

$$J_{FCM}(X:U,V)=\sum_{j=1}^{c}\sum_{i=1}^{N}(u_{ij})^{m}\left\|x_i-v_j\right\|^2, 1<m<\infty \quad (1)$$

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Here J is an objective function and where $\|x_i - v_j\|^2$ is a chosen distance measure between a data point x_i and the cluster centre v_j, is an indicator of the distance of the *n* data points from their respective cluster centres and here distance measure is Euclidean distance. Fuzzy partitioning is carried out through an iterative optimization of the objective function shown in the equation above, with the updating of membership u_{ij} and the cluster centres v_j by:

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

$$v_j = \frac{\sum_{i=1}^{N} u_{ij}^m x_k}{\sum_{i=1}^{N} u_{ij}^m}, \forall j = 1,.....c \quad (3)$$

This iteration will stop when $\max_{ij}\left(u_{ij}^{k+1} - u_{ij}^{k}\right) < \in$, where $\in$ is a termination criterion between 0 and 1, whereas *k* is the number of iteration steps. This procedure converges to a local minimum or a saddle point of J_m using Lagrange's multiplier theorem these values have been calculated. In this clustering algorithm, centre of cluster defined is assumed, m is a degree of fuzziness and value of m > 1 in fuzzy clustering algorithms. The fuzzy clustering technique using alternatingly equation (2) and (3) is called Fuzzy C Means.

b. Possibilistic C-Means (PCM)

Krishnapuram and Keller [1] suggest relaxing the column constraint of FCM so that membership matrix better reflects the typicality of particular data point in a cluster and noise could be avoided. Here they have calculated typicality matrix as T.

$$T = [t_{ik}]_{cxn}$$

Here T represents possibility of an object belongs to particular matrix with the associated weight, the value of the weight function is estimated from the data and the membership values can be interpreted as degrees of possibility of the points belonging to the clusters implies the compatibilities of the points with the class prototypes. The Primary aim of possibilistic clustering was to overcome the problems and limitations of fuzzy clustering methods. Krishnapuram and keller proposed a possiblistic approach by minimizing the objective function as

$$J_{PCM}(U,V) = \sum_{i=1}^{c}\sum_{k=1}^{N} t_{ik}^m d_{ik}^2 + \sum_{i=1}^{c}\gamma_i \sum_{k=1}^{N}(1-t_{ik})^m$$

Where U is the membership function, V is the centre matrix of clusters, γ_i gives the weight associated with all clusters which is user defined and $\gamma_i > 0$. In the above equation the first term tries to reduce the distance from data points to centroids as low as possible and second term forces t_{ik} to be as large as possible.

c. Credibilistic Fuzzy C-Means(CFCM)

To reduce the effect of outliers Krishna K. Chintalapudi [7] proposed credibilistic fuzzy c means (CFCM) and introduced a new variable i.e. credibility. CFCM defines Credibility as:

$$\Psi_k = 1 - \frac{(1-\Theta)\alpha}{max_{j=1,n}(\alpha j)}, 0 \le \beta \le 1$$

Where $\alpha_k = i = 1, \dots . c^{min}(d_{ik})$

Setting ɵ=1 reduces the scheme to FCM while ɵ=0 assigns zero membership to the most noisy vector. If ɵ is set to 1 then there is no noisy vector that is present in the dataset, thus we choose ɵ=0 in all our implementations. CFCM partitions X by minimizing (the objective function of FCM):

$j_{cfcm} = \sum_{i=1}^{i=c}\sum_{k=1}^{k=n} u_{ik}^m \|x_k - v_i\|^2$,

Subject to constraints,

$$\sum_{i=1}^{i=c} u_{ik} = \Psi_k ; k = 1, \dots ., n.$$

The conditions for local minima are,

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

Memberships generated by CFCM for outliers are lower than those generated by FCM because for outliers credibility is very small. Main advantageous function of CFCM is reducing the effect of outliers on regular clusters.

d. Intuitionistic fuzzy c-means (IFCM)

Intuitionistic fuzzy c-means work on generalized fuzzy sets in which elements are characterized by both characteristics of membership, and non-membership value. Degree of belongingness is indicated by membership value, whereas the degree of non-belongingness of an element tothat set is indicated by non-membership values. Atanassov introduced a parameter called hesitation degree, $\pi_A(x)$, which explains lack of knowledge in defining the membership degree of all elements x in the set A. It is calculated as:

$\pi_A(x) = 1 - \mu_A(x) - v_A(x)$

The objective function for intuitionistic fuzzy c-means [12] include modified objective function of FCM and intuitionistic fuzzy entropy.

$$J_{IFCM} = \sum_{i=1}^{c}\sum_{k=1}^{n} u_{ik}^{*m} d_{ik}^2 + \sum_{i=1}^{c} \pi_i^* e^{1-\pi_i^*}$$

$u_{ik}^* = u_{ik} + \pi_{ik}$, in which u_{ik}^* denotes the intuitionisticfuzzy membership

u_{ik} gives the normal fuzzy membership of the k^{th} data in i^{th} class.

From the above equation,π_{ik} denotes the hesitation degree, which is:

$\pi_{ik} = 1 - u_{ik} - (1 - u_{ik}^{\alpha})^{1/\alpha}$, $\alpha > 0$

Yager gave an intuitionistic fuzzy complement which is used to calculate above defined constant:

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$N(x) = (1-x^{\alpha})^{1/\alpha}$, $\alpha > 0$

Intuitionistic fuzzy entropy (IFE), is the second term of objective function for IFCM.Zadeh introduced fuzzy entropy, which is the measure of fuzziness in a fuzzy set. Mathematically IFE is derived as:

$$IFE\ (A) = \sum_{i=1}^{n} \pi_A\ (x_i) e^{[1-\pi_A(x_i)]}$$

Where $\mu_A\ (x_i)$ is the membership degree

$v_A(x_i)$ is the non-membership degree

$\pi_A(x_i)$ is the hesitation degree

As Euclidian distance measure is used in IFCM, hence only hyper-spherical clusters can be detected in the data[13]. Non-linearly separable data can't be worked upon by IFCM.

3. Results

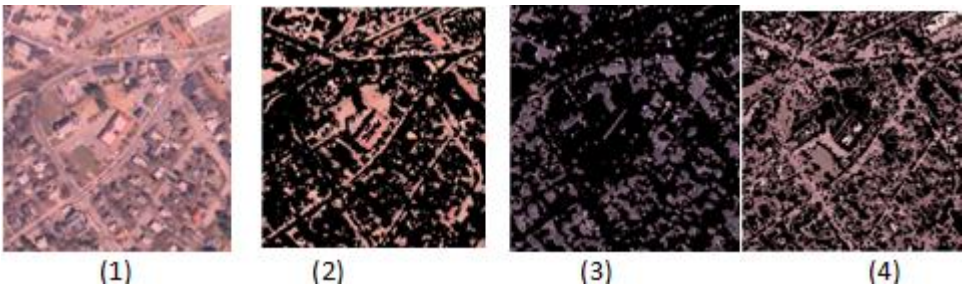
Performance evaluation of the algorithms have been done over certain parameters which distinguishes there potential to be used for image segmentation. To find the most suitable method of image segmentation using fuzzy clustering techniques we used two images which are generally used for image analysis.We can see the results on images after using different clustering techniques.

A. Westconcordaerial.png [14]

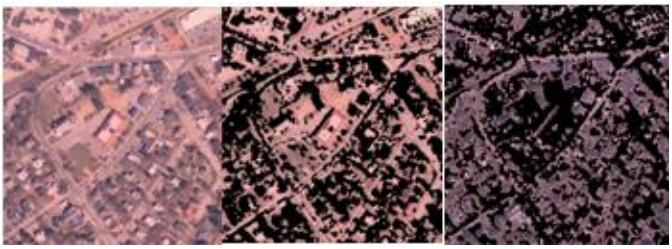
Westconcordorthophoto.png, the Mass GIS georegisteredorthophoto. It is a panchromatic (grayscale) image, supplied by the Massachusetts Geographic Information System (MassGIS) that has been orthorectified to remove camera, perspective, and relief distortions (via a specialized image transformation process). The orthophoto is also georegistered (and geocoded) — the columns and rows of the digital orthophoto image are aligned to the axes of the Massachusetts State Plane coordinate system. In the orthophoto, each pixel center corresponds to a definite geographic location, and every pixel is 1 meter square in map units.

SAR IMAGE

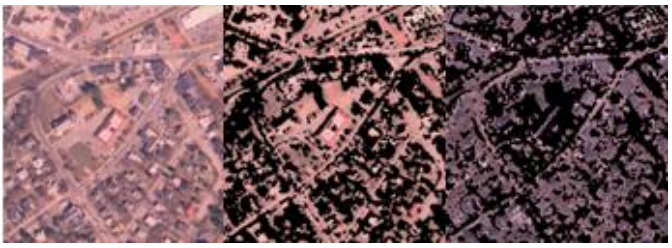
FCM for n=3



IFCM for n=2



PCM for n=2



CFCM for n=2

B. Hestain.png[15]

It is an image of tissue stained with hemotoxylin and eosin (H&E). This staining method helps pathologists distinguish different tissue types.

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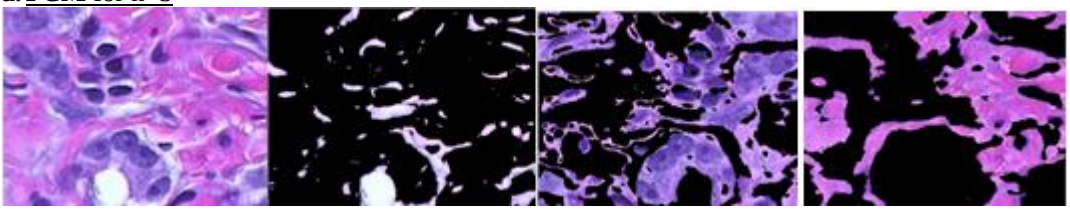
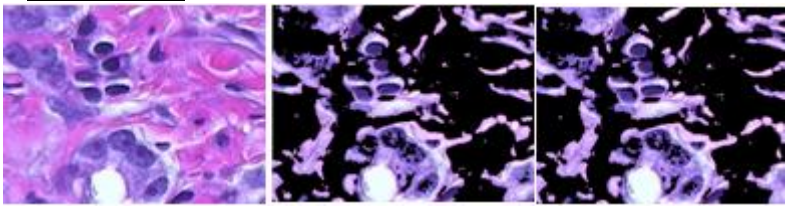
HESTAIN image

a. FCM for n=3

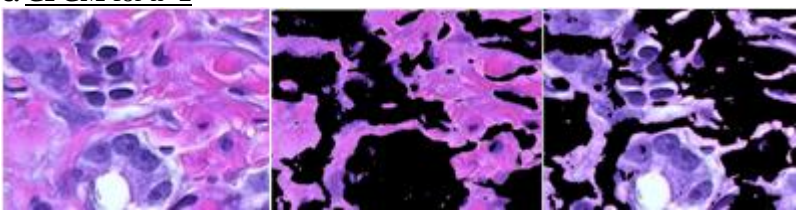


b. IFCM for n=2



PCM for n=4

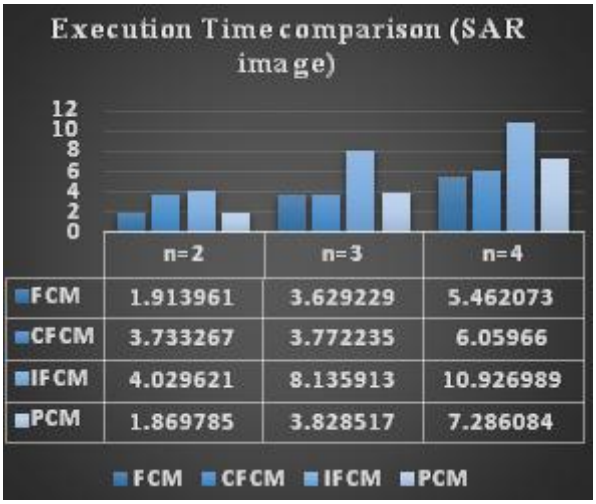
c. CFCM for n=2

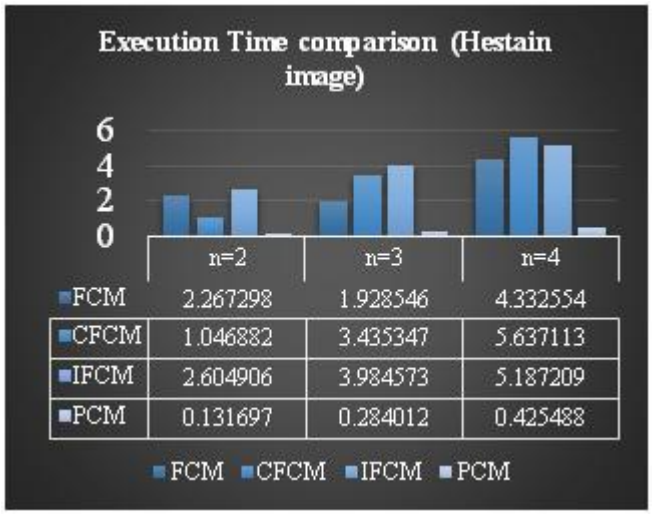


C. Performance Evaluation

a. Execution Time

We have used Tic Toc function of MATLAB to calculate the time taken for an algorithm in analysing the image. The function records the internal time at execution of the tic command. Display the elapsed time with the toc function. It is observed that in case of SAR Image, FCM technique has least execution time but the convergence rate of IFCM algorithm is best. Whereas in case of Synthetic image, PCM technique has least execution time but the convergence rate of IFCM algorithm is best.





b. **Validity Function**

The qualitative evaluation of the performance of segmentation is done using two types of cluster validity functions: the feature structure and the fuzzy partition. The functions that represents the fuzzy partition are partition entropy [16] and partition coefficient [17]. They are defined as:

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

$V_{pe}(u) = -\frac{1}{n} \{\sum_{i=1}^{n} \sum_{k=1}^{c} [u_{ki} log u_{ki}]\}$

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Best clustering results are achieved when $v_{pc}$is maximum or $v_{pe}$is minimum. Disadvantage of v_{pc} and v_{pe} are that they measure only the fuzzy partition and do not specify featuring property.

4. Conclusion

Digital images generally contain unknown noise and consider able 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. In this paper, we have compared Fuzzy C-Means (FCM), Intuitionistic Fuzzy C-Means(IFCM), Possibilistic C-Means(PCM), and Credibilistic Fuzzy C-Means(CFCM) methods under different environments. We observed the results of these four algorithms on two different types of images – Hestain.png which is a synthetic image, and Westconcordaerial.png which is a SAR image. We compared the experimental results of PCM, CFCM, FCM, IFCM on both the images. Quantitative and qualitative analysis of the results showed that the algorithm is more efficient compared to two others.

Table: Comparison of Fuzzy Algorithms on basis of Execution Time, and Validity Functions.

IMAGE	METHOD	Clusters	Execution Time	Vpc	Vpe
SAR	FCM	2	1.913961	1.0935e +05	-5.7167e +04
		3	3.629229	9.3171e + 04	-9.1313e + 04
		4	5.462073	8.1837 e + 04	-1.1828 e + 05
	PCM	2	1.86979	8.4912 e + 04	-8.0601 e + 04
		3	3.82852	1.0724 e + 05	-1.21182 e + 05
		4	7.28608	1.3083 e + 05	-1.6171e+05
	CFCM	2	3.733267	8.03e+04	-5.71e+04-
		3	3.772235	6.40e+04	-9.13e+04
		4	6.05966	5.54e+04	-1.18e+04
	IFCM	2	4.029621	1.0133e +05	-6.7873 e + 04
		3	8.135913	7.8841 e +04	-1.1373 e + 05
		4	10.926989	6.6688	-1.4593
HESTAIN	FCM	2	2.267298	5.3906 e+ 04	-2.4286 e+ 04
		3	1.928546	4.9789 e+ 04	-3.4080 e+ 04
		4	4.332554	4.5713 e+ 04	-4.3928 e+ 04
	PCM	2	0.1317	5.0280 e+ 04	-3.6214 e+ 04
		3	0.28401	5.3461 e+ 04	-5.6029 e+ 04
		4	0.42549	5.9751 e+ 04	-7.4691 e+ 04
	CFCM	2	1.046882	3.33e+04	-2.43e+04-
		3	3.435347	2.85e+04	-3.40e+04
		4	5.637113	2.37e+04	-4.40e+04
	IFCM	2	2.604906	4.5779 e+ 04	-3.4807 e+ 04
		3	3.984573	4.1051 e+ 04	-4.8399 e+ 04
		4	5.187209	3.2734 e+ 04	-6.6425 e+ 04

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