SEGMENTATION OF IMAGES USING HISTOGRAM BASED FCM CLUSTERING ALGORITHM AND SPATIAL PROBABILITY

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ABSTRACT

During last decades, image segmentation has been a interestinging area for research and developing efficient algorithms. Medical image segmentation demands an efficient and robust segmentation algorithm against noise. The renowned conventional fuzzy c-means algorithm is efficiently used for clustering in medical image segmentation. But FCM is highly sensitive to noise because it uses only intensity values for clustering. So in this paper for the segmentation, histogram based efficient fuzzy c-means algorithm is proposed. The input image is clustered using proposed Improved Histogram based Spatial FCM algorithm. Robustness against noise is improved by using the spatial probability of the neighboring pixel. The medical images are denoised, before to segmentation with effective denoising algorithm. Comparative study has been done between conventional FCM and proposed method. The histogram based experimental results has obtained and shows that the proposed approach gives reliable segmentation accuracy with noise levels. And it is clear that the proposed approach is more efficient compared to conventional FCM.

KEYWORDS: *Medical images, clustering, fuzzy c-means (FCM), image segmentation, spatial probability, denoising, histogram, membership function, Improved Histogram based Spatial FCM (IHSFCM).*

I. INTRODUCTION

Image segmentation is an important and challenging problem and a necessary first step in image analysis as well as in high-level image interpretation and understanding such as robot vision, object recognition, geographical imaging and medical imaging [1]. In general, image segmentation is a process of partitioning an image into non-overlapped, consistent regions that are homogeneous with respect to some characteristics like intensity, color, tone or texture, and more [2][3]. According to reference [4], the different approaches are suggested in literature for image segmentation and are categorized into eight methods [10]: Thresholding, Clustering, Classifiers, Region growing, Artificial Neural Networks (ANNs), Deformable models, Markov Random Field (MRF) models, Atlas-Guided approaches edge detection and region extraction.

A clustering based approach is extensively used and utilized for image segmentation. Clustering is the classification of similar objects into different groups, or more precisely, the partitioning of a data set into subsets (clusters), so that the data in each subset (ideally) share some common trait – often proximity according to some defined distance measure. Many clustering schemes are categorized based on their special characteristic, such as the hard clustering scheme and the fuzzy clustering scheme. The conventional hard clustering method restricts each point of the data set to exclusively just one cluster. As a consequence, with this approach the segmentation results are often very crisp, i.e., each pixel of the image belongs to exactly just one class. However, in many real situations, for images, issues such as limited spatial resolution, poor contrast, overlapping intensities, noise and intensity in-homogeneities variation make this hard (crisp) segmentation a difficult task [1]. The fuzzy set theory [5] has proposed the idea of partial membership of belonging and described by a membership function; fuzzy clustering as a soft segmentation method has been widely studied and successfully applied in image segmentation [1] [7–9].

Among the fuzzy clustering methods, fuzzy c-means (FCM) algorithm [6] 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. The conventional FCM algorithm has a serious limitation that it does not incorporate any information about spatial context, and it is sensitive to noise and imaging artifacts. This drawback of FCM can be overcome by smoothing the image before segmentation. The conventional smoothing filters can loss important image details, especially image boundaries or edges. It is difficult to have the trade-off between smoothing and clustering. Other different approaches have been proposed. Tolias et al. [8] proposed a fuzzy rule-based scheme called the rule-based neighborhood enhancement system to impose spatial continuity by post-processing on the clustering results obtained using FCM algorithm.

In another approach [9], spatial constraint is imposed in fuzzy clustering by incorporating the multi-resolution information. Noordam et al. [11] proposed a Geometrically Guided FCM (GG-FCM) algorithm based on a semi-supervised FCM technique for multivariate image segmentation. In their work, the condition of each pixel is determined by the membership Image Segmentation by FCM Clustering Algorithm values of surrounding neighboring pixels and then is either added to or subtracted from the cluster. Recently, some approaches [12–14] were proposed for increasing the robustness of FCM to noise by directly modifying the objective function. In [12], a regularization term was introduced into the standard FCM to impose the neighborhood effect. Later, Zhang et al. [13] incorporated this regularization term into a kernel-based fuzzy clustering algorithm. More recently, Li et al. [14] incorporated this regularization term into the adaptive FCM (AFCM) algorithm [15] to overcome the noise sensitivity of AFCM algorithm. Although the latter two methods are claimed to be more robust to noise, they show considerable computational complexity.

In this paper, Improved Histogram based Spatial FCM (IHSFCM) clustering algorithm for image segmentation is presented. The algorithm is developed by incorporating the spatial neighborhood information into the standard FCM clustering algorithm by a priori probability. The probability is given to indicate the spatial influence of the neighboring pixels on the centre pixel, which can be automatically decided in the implementation of the algorithm by the fuzzy membership. The new fuzzy membership of the current centre pixel is then recalculated with this probability obtained from above. The algorithm is initialized by a given histogram based FCM algorithm, which helps to speed up the convergence of the algorithm. The advantage of this algorithm is that it can handle small and large amounts of noise. In this algorithm the membership is changed while the centroid computations are the same as in the standard FCM algorithm. Hence, it is easy to implement.

The renowned unsupervised fuzzy clustering algorithm FCM is employed in the proposed approach to achieve effectual segmentation. To make the proposed approach robust against noise, the spatial probability of neighboring pixels is integrated into the conventional FCM. By using an efficient denoising algorithm, the input noisy medical image is first denoised so as to improve its robustness further. The integration of spatial information into the conventional FCM takes longer time to converge as well as there are lots of possibilities to converge in the local minima. As a result, in the presented approach, to evade local minima, the parameters of the FCM algorithm are initialized using histogram. Comparing to the conventional FCM, the histogram based FCM converges very swiftly. The employed denoising algorithm and the integrated spatial information have increased the robustness of the proposed approach against noise. The experimental results demonstrate the robustness and efficiency of the proposed segmentation approach. In addition, a comparative analysis is made between the conventional FCM and the proposed segmentation approach.

The rest of the paper is organized as follows. The conventional FCM method for image segmentation is introduced in section 2. The proposed improved histogram based FCM algorithm for the segmentation of noisy images is explained detailed in section 3. The experimental results and comparisons are presented in Section 4. Finally, Section 5 gives our conclusions and several issues for future work.

II. CONVENTIONAL FCM

Clustering is the process of finding groups in unlabeled dataset based on a similarity measure between the data patterns (elements). A cluster contains similar patterns placed together. The fuzzy clustering technique generates fuzzy partitions of the data instead of hard partitions. Therefore, data patterns

may belong to several clusters, having different membership values with different clusters. The membership value of a data pattern to a cluster denotes similarity between the given data pattern to the cluster. Given a set of n data patterns [1], X $=x_1,\ldots, x_k\ldots,x_n$, the fuzzy clustering technique minimizes the objective function, O_{fcm}(U,C):

$$O_{fcm}(U,C) = \sum_{k=1}^{n}\sum_{i=1}^{v}(u_{ik})^m\ d^2(x_k, c_i) \tag{1}$$

Where, x_k - k^{th} D-dimensional data vector,
c_i - center of cluster i,
u_{ik} - Degree of membership of x_k in the ith cluster,
m - Weighting exponent,
$d\,(x_k\,,\,c_i\,)$ - distance between data x_k and cluster center c_i,
n - Number of data patterns,
v - Number of clusters.

The minimization of objective function O_{fcm}(U, C) can be brought by an iterative process in which updating of degree of membership u_{ik} and the cluster centers are done for the each iteration.

$$u_{ik} = \frac{1}{\sum_{J=1}^{V}(\frac{d_{ik}}{d_{jk}})^{\frac{2}{m-1}}} \tag{2}$$

$$c_i = \frac{\sum_{k=1}^{n}(u_{ik})^m x_k}{\sum_{k=1}^{n}(u_{ik})^m} \tag{3}$$

Where, $\forall\, i$ u_{ik} satisfies: $u_{ik} \in [0,1]$, $\forall\, k \sum_{i=1}^{v} u_{ik} = 1$ and $0 < \sum_{k=1}^{n} u_{ik} < n$.

Thus the conventional clustering technique clusters an image data only with the intensity values but it does not use the spatial information of the given image. From the theory of Markov random field says that pixels in the image mostly belong to the same cluster as their neighbors but conventional FCM algorithm computes the centroid and membership function pixel-by-pixel, when employed for image segmentation. This made the convergence of the algorithm a time-consuming one, which in turn makes it more impractical for image segmentation.

FCM is a local search optimization algorithm, and because of this it is very sensitive to the initial centroid. Therefore, the algorithm will obtain the local optimum solution easily [17], if the initial centroid is selected randomly. In order to shun the blindness of random evaluation and also to make the initial centroid approach the globally optimum solution, the gray level histogram of the image is utilized in the FCM algorithm that minimizes the number of iteration steps and improves the speed of segmentation. The incorporation of spatial information in the clustering process makes the algorithm robust to noise and blurred edges. But when using spatial information in the clustering optimization function may converge in local minima, so to avoid this problem the fuzzy spatial c means algorithm is initialized with the Histogram based fuzzy c-means algorithm. The optimization function for histogram based fuzzy clustering is given in the equation 4.

$$O_{fcm}(U,C) = \sum_{l=1}^{L}\sum_{i=1}^{v}(u_{il})^m\ H(l)\ d^2(l, c_i) \tag{4}$$

Where, H is histogram of the image of L-gray levels.

Gray level of all the pixels in the image lies in the new discrete set G= {0,1,…,L-1}. The computation of membership degrees of H(l) pixels is reduced to that of only one pixel with l as grey level value. The member ship functionu_{il} and center for histogram based fuzzy c-means clustering can be calculated as.

$$u_{il} = \frac{1}{\sum_{J=1}^{V}(\frac{d_{li}}{d_{lj}})^{\frac{2}{m-1}}} \tag{5}$$

$$c_i = \frac{\sum_{l=1}^{L}(u_{il})^m \, H(l) \, l}{\sum_{l=1}^{L}(u_{il})^m} \quad (6)$$

Where, d_{li} - distance between the cluster center *i* and the gray level *l* .

III. PROPOSED IMPROVED HISTOGRAM BASED FCM ALGORITHM

The block diagram of flow of proposed Histogram based methodology is shown in Figure 1.

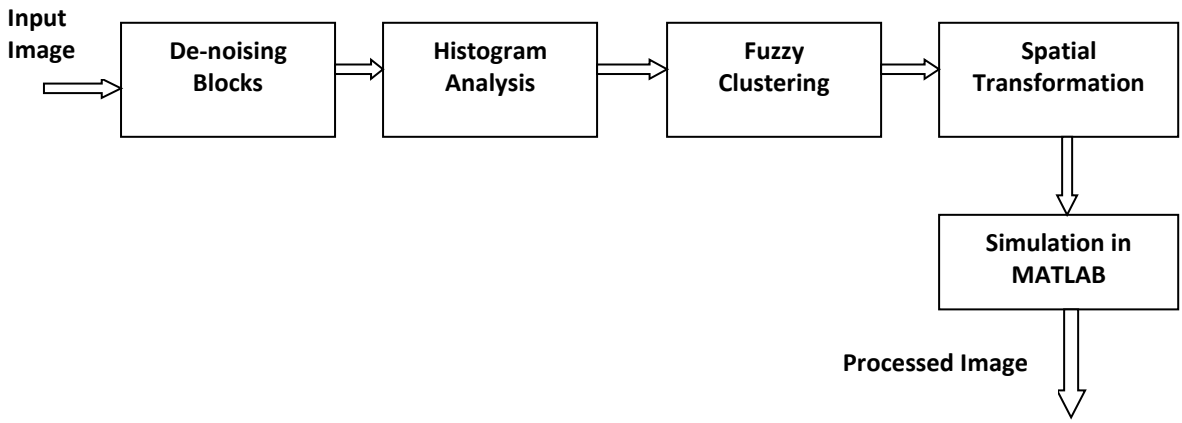


Figure 1: Block Diagram of flow of proposed methodology

Usually, the medical images obtained from sensors are bound to contain noise and blurred edges. The process of segmentation is made more intricate, owing to the presence of these artifacts in medical images. Consequently, denoising images prior to segmentation perhaps produce better segmentation accuracy. Recently, Lei Zhang *et al.* [18] presented an efficient denoising algorithm, i.e *LPG-PCA Based Denoising Algorithm* .This is used in the proposed approach.

We employed an efficient Principal Component Analysis (PCA) based denoising algorithm with Local Pixel Grouping (LPG). In order to preserve the image local structures in a better way, a pixel and its nearest neighbors are represented as a vector variable in which training samples are chosen from the local window with a help of block matching based LPG. The LPG methodology assures that merely the sample blocks with equal contents are utilized in the local statistics calculation for PCA transform estimation, so that the image local features can be well preserved after coefficient shrinkage in the PCA domain to reduce the noise. The LPG-PCA denoising process is repeated once, to increase the denoising performance further and the noise level is adjusted adaptively in the second stage.

The histogram based FCM algorithm converges quickly since it clusters the histogram instead of the whole image. The center and member ship values of all the pixels are given as input to the fuzzy spatial c-means algorithm. The main goal of the IHSFCM is to use the spatial information to decide the class of a pixel in the image.

1. The objective function of the proposed IHSFCM is given by:

$$O(U, C) = \sum_{k=1}^{n}\sum_{i=1}^{v}(u_{ik}^{P})^m \, d^2(x_k, c_i) \quad (7)$$

Where, u_{ik}^{P} - spatial membership function of the proposed segmentation

The spatial membership function u_{ik}^{P} of the proposed segmentation approach is computed using the below equation:

$$u_{ik}^{P} = \frac{P_{ik}}{\left(\sum_{J=1}^{V}\left(\frac{d_{ik}}{d_{jk}}\right)^{\frac{2}{m-1}}\right)\left(N_k \sum_{z=1}^{N_k}\left(\sum_{J=1}^{V}\left(\frac{d_{iz}}{d_{jz}}\right)^{\frac{2}{m-1}}\right)\right)} \quad (8)$$

Where, P_{ik} - apriori probability of kth pixel which belongs to i^{th} cluster and is computed as:

$$P_{ik} = \frac{NN_i(k)}{N_k} \tag{9}$$

Where, $NN_i(K)$ is the number of pixels in the neighborhood of kth pixel which belongs to cluster i after defuzzification, N_k is the total number of pixels in the neighborhood, d_{iz} is the distance between i^{th} cluster and z^{th} neighborhood of ith cluster.

2. The center C_i^P of every cluster is manipulated as:

$$C_i^P = \frac{\sum_{k=1}^{n}(u_{ik}^{P})^m \quad x_k}{\sum_{k=1}^{n}(u_{ik}^{P})^m} \tag{10}$$

Two kinds of spatial information are incorporated in the member ship function of conventional FCM, Apriori probability and Fuzzy spatial information.

Apriori probability: This parameter assigns a noise pixel to one of the clusters to which its neighborhood pixels belong. The noise pixel is included in the cluster whose members are majority in the pixels neighborhood.

Fuzzy spatial information: In the equation (8) the second term in the denominator is the average of fuzzy membership of the neighborhood pixel to a cluster. Thus a pixel gets higher membership value when their neighborhood pixels have high membership value with the corresponding cluster.

IV. RESULTS AND DISCUSSION

The results obtained from the experiment on the proposed segmentation approach are presented in this paper. The proposed segmentation approach has been programmed in MATLAB (MATLAB 7.12.0). Since the objective function of the proposed segmentation approach is initialized with parameters obtained from histogram of the image, it converged very quickly. The experiment has been performed with images namely, synthetic brain MRI images and real world images. The quality of the segmentation results can be evaluated in terms of segmentation accuracy, A_s, which is calculated as follows:

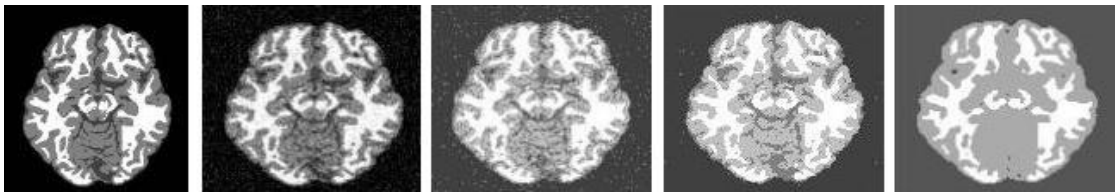
$$A_s = (N_c/T_p) \times 100$$

where N_c is the number of correctly segmented pixels and T_p is the total number of pixels in the given image. To evaluate the robustness of the proposed segmentation approach against noise, Additive White Gaussian Noise (AWGN) of different levels (10%, 20% and 30%) are added to the image.

Table1. Shows Segmentation accuracy with noise levels. The results have obtained for conventional FCM, proposed approach with de-noising and proposed approach without de-noising for different noise levels for base true image with 10%, 20%, and 30% noise levels. But only 30% noise level is portrays in Figure 2. For real life images, the camera man image is shown in Figure 3. From the Table 1, we can see that even at a higher noise level (30%), the segmentation accuracy remains stable for proposed approach with de-noising. The proposed approach without de-noising maintained its consistency up to 20% noise level. But the accuracy of conventional FCM decreases drastically for noise level greater than 10%.

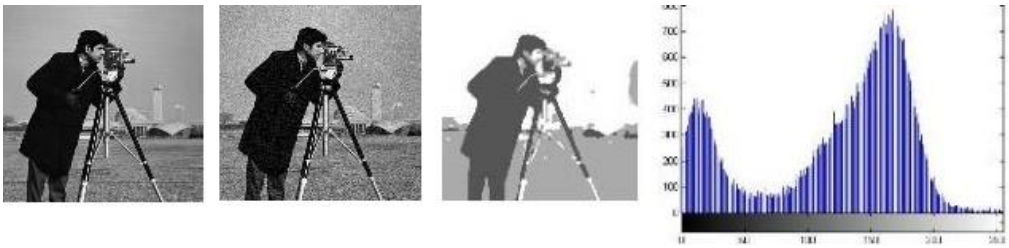
Table 1 Segmentation Accuracy v/s Noise level

Noise / Accuracy Methods	10%	20%	30%
FCM	98.19	92.09	87.92
IHSFCM without Denoising	97.33	96.73	94.80
IHSFCM with denoising	97.90	97.54	96.87



(a) (b) (c) (d) (e)

Figure 2. Segmentation results of synthetic brain MRI (a) Original Base true (b) With 30% noise (c) FCM (d) Proposed approach without de-noising (e) Proposed approach with de-noising.



(a) (b) (c) (d)

Figure 3. Segmentation results of cameraman (a) Original Cameraman (b) With 10% Noisy Image (c) Proposed approach (d) Histogram.

4.1 Screenshots of Histograms

The Screenshots of Histogram result is shown in Figure 4 and Figure 5.

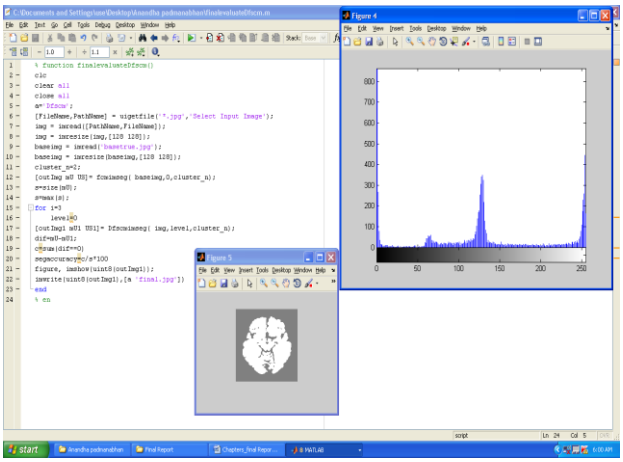


Figure 4. Histogram result of synthetic brain MRI

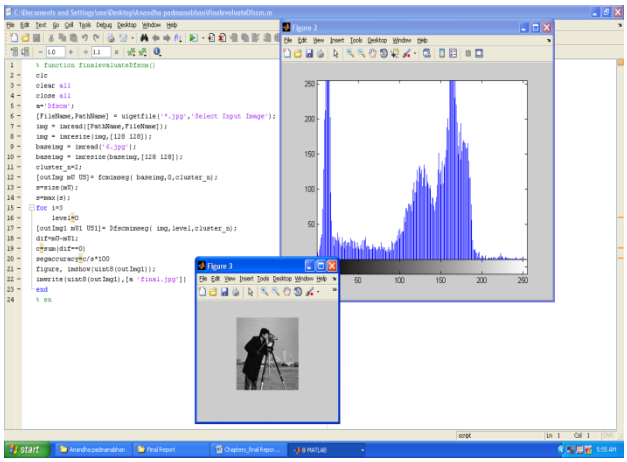


Figure 5. Histogram result of cameraman

V. CONCLUSION

Traditional FCM algorithm based pixel attributes lead to accuracy degradation. But in this paper, we have implemented an efficient approach for the segmentation of noisy images. The proposed approach made use of histogram based Fuzzy C-Means clustering with denoising & spatial probability for the segmentation of noisy images, which will give better segmentation accuracy. The incorporation of spatial probability into the objective function of FCM has improved segmentation accuracy. The denoising of noisy images before to segmentation has been found robust against various noise levels. The denoising of noisy images prior to segmentation with the aid of sparse 3D transform domain collaborative filtering strategy has further improved the robustness of the approach. The experimentation with synthetic and real images has demonstrated the efficiency and robustness of the proposed approach in segmenting noisy images. It was observed that as the numbers of clusters were increased there was a decline in segmentation accuracy values. Hence future scope of this paper may be to improve on the problems mentioned above.

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