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Improving the efficiency of Medical Image Segmentation based on Histogram Analysis

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Abstract

Image segmentation plays a vital role in medical field. There are various clustering techniques for segmentation of medical images. In clustering algorithms, centroids are initialized randomly and clusters are formed by partitioning the pixels to its nearest centroid. If the centroids are not initialized properly then the time taken for segmentation increases. In this paper a new algorithm is proposed for centroid initialization for improving the standard fuzzy c means clustering which reduces the number of iterations and CPU time in segmentation. Based on histogram, consider the pixels intensities in a continuous fashion ignoring the ends of the histogram if it has low averaged pixel intensities in the end. Then divide the considered histogram into number of partitions based on the required number of segments and from each partition consider the highest intensity pixel as centroids. Segmentation of simulated and real images works faster and better for real images and thus shows the superiority of the proposed algorithm.

Keywords- image segmentation, clustering algorithm, histogram, medical images, image filtering, fuzzy c means.

I. INTRODUCTION

Medical image segmentation is a challenging issue in the field of image processing as these images are easily affected by noise. The medical images are generally acquired by advanced imaging equipments such as CT, MRI and Ultrasound. The common cause for noise and distortion of medical images are random disturbance of these electron devices, the influence of ambient environment, and human factors during the imaging process. An ample statistical analysis gives conclusion that salt-and pepper noise (impulse noise) is one of the common noise sources. First step in image segmentation is removal of noise. The most widely used technique for removal of salt-and-pepper noise is Median filter.

There are so many clustering techniques are available to segment the image. It is an unsupervised classification of patterns into groups of similar objects. These are widely used in medical diagnostic studies, image analysis, image processing, decision making, machine learning situation etc [3]-[11]. While segmenting the image, clustering techniques iteratively computes the characteristics of each cluster and segment the image by classifying each pixel to the nearest cluster according to a distance metric. Segmentation results that can be obtained by this process are better but the major problem is over segmentation that must be faced. Image segmentation using clustering algorithms have been applied in numerous applications including medical applications, particularly in the biomedical image analysis. The objective of medical image segmentation is to group it into various anatomical structures. Several previous studies have proven that clustering algorithms is capable in segmenting and determining certain regions of interest on medical images [12], [13]. It is because in the biomedical image segmentation task, clustering algorithm is often suitable since the number of clusters for the structure of interest is usually known from its anatomical information [14]. The most frequent clustering-based segmentation methods used for image segmentation are Fuzzy C Means. Fuzzy C Means algorithms with spatial constraints have been proven effective in the field of image segmentation.

The rest of this paper is organized as follows: Section 2 presents the removal of salt and pepper noise, section 3 presents FCM clustering algorithm, Section 4 presents the proposed algorithm for centroid initialization for improved fuzzy c means, Section 5 presents experimental results and analysis and finally Section 6 report conclusion.

II. SALT AND PEPPER NOISE DETECTION AND CANCELLATION

Based on the assumption that an image corrupted with salt-and-pepper noise will produce two peaks at the noisy image histogram [15], the detection stage begins by searching for these two peak intensities from both ends. Let us consider an 8-bit gray scale digital image with 256 gray levels in the interval [0, 255]. Generally, a Salt-and-Pepper noise takes on the high-end and low-end intensities. It can either be positive or negative where the intensity value for the positive impulse is near 255 (i.e., appears white known as the salt), and the negative impulse with the intensity value of near 0 (i.e., appears black known as the pepper). These two Salt-and-Pepper noise intensities will be used to identify possible ‘noise-pixels’ in the image. As in [1], [2], a binary noise mask N(i, j) will be created to mark the location of ‘noise-pixels’ by using;

$$N(i, j) = \begin{cases} 0, & P(i,j) = L_{Upper} \text{ or } L_{Lower} \\ 1, & \text{Otherwise} \end{cases} \tag{1}$$

Where P(i, j) is the pixel intensity at the location (i, j) . N(i,j)=1 represents the 'noise-free' pixel to be retained at the location (i,j) in the next clustering stage while N(i,j)=0 represents the pixel located at (i,j) is 'noise' pixel.

Noise cancellation and clustering:

In order to permit more adaptable and effective techniques of clustering-based segmentation in noisy images, after the binary noise mask N(i, j) is created, a linearly-fuzzy weighted correction value of 'noise' pixel is obtained using:

$$P'(i,j) = (1 - F(i,j)\, P(i,j) + F(i,j)\, M(i,j) \qquad (2)$$

where P'(i, j) denotes the corrected 'noise' pixel value, and M (i, j) is the median value of the pixel at location (i, j). Generally the window size we select is 3X3. In the equation (2) F(i,j) is the fuzzy membership used to weigh the linear relationship between the processing pixel, P(i,j), and the median pixel, M(i,j).

Prior to that, the median of the 'noise' pixels is extracted in a 3X3 window as follows:

$$M(i, j) = \text{Median}\ \{P(i+x, j+y) \text{ with } x, y \in (-1, 0, 1) \qquad (3)$$

After the median pixel is found, the absolute luminance difference, d(i, j), is computed by using;

$$d(i+x,j+y) = |P(i+x,j+y) - P(i,j)| \text{ with } (i+x,j+y) \neq (i, j) \qquad (4)$$

Then the local information of the 'noise' pixels in 3X3 window is calculated by taking the maximum value of the absolute luminance difference given by;

$$D(i, j) = \text{Max}\{\ d(i+x, j+y)\ \} \qquad (5)$$

The choice of the maximum operator rather than minimum operator is justified in [2]. Then for the extracted local information D(i, j) the fuzzy concept is applied.

The fuzzy membership function F(i, j) is defined as;

$$F(i, j) = \begin{cases} 0 & ;\ D(i, j) < T1 \\ D(i, j) - T1/T2\text{-}T1 & ;\ T1 \leq D(i, j) < T2 \\ 1 & ;\ D(i, j) \geq T2 \end{cases} \qquad (6)$$

For optimal performance, the threshold values T1 and T2 are set to 10 and 30 respectively as described in [2]. Next, the noise pixel is corrected using (2).

III. FUZZY C-MEANS (FCM) CLUSTERING

The Fuzzy C-Means algorithm applies fuzzy partitioning such that a pixel can belong to all clusters with varying membership grades between 0 and 1. The objective is to find cluster centers that minimize dissimilarity function. By iteratively updating the cluster centers and the membership grade for each pixel, the algorithm iteratively moves the cluster centers to the "correct" location within the data set. The FCM algorithm is used to group the data to nearest center.

Let N be the number of pixels to be clustered into n_c clusters. Let v_t be the t^{th} pixel where t=1, 2,…, N and c_k is the k^{th} center. For the conventional FCM, the objective function of segmenting an image into c_k clusters is given by [16].

$$J = \sum_{k=1}^{n_c} \sum_{t=1}^{N} \left(M_{kt}^{m} \right) \left\| v_t - c_k \right\|^2 \tag{7}$$

Where m>1, m is the fuzziness integer exponent. The new position for each center is calculated using:

$$c_k = \frac{\sum_{t=1}^{N} M_{kt}^{m} v_t}{\sum_{t=1}^{N} M_{kt}^{m}} \tag{8}$$

with each fuzzy membership function, M_{kt}^{m}, satisfying

$$M_{kt}^{m} = \frac{1}{\sum_{l=1}^{n_c} \left(\frac{d_{kt}}{d_{lt}} \right)^{2/(m-1)}} ;\ \text{if } d_{lt} > 0, \forall\ l, t \tag{9}$$

$$\left. \begin{array}{l} M_{lt}^{m} = 1 \\ M_{kt}^{m} = 0; \text{for } t \neq l \end{array} \right\} \quad \text{if } d_{lt} = 0;$$

Where $d_{kt} = \|v_t - c_k\|^2$

All processes are repeated until the cluster centers or memberships for successive iteration differ by more than some prescribed value 'e' (where 'e' is a termination criterion value between 0 and 1).

IV. THE PROPOSED IMPROVED HISTOGRAM ANALYSIS FCM (IHAFCM) CLUSTERING TECHNIQUE

Conventional FCM does not ensure that it converges to an optimal solution in an optimal time, as the cluster centers (centroids) are initialized randomly. The performance of Fuzzy C Means depends on initial centroids. Hence the selection of a centroid is important in FCM.

In the proposed algorithm remove the histogram bins in the histogram from both ends if the pixels average intensity is less then threshold 'T'. Then the remaining histogram bins are divided into 'n' equal partitions, where 'n' is the number of segments. Then from each partition we select the intensity of the histogram bin for which maximum peak occurs and make it as centroid. If there are 'n' clusters then we get 'n' centroids. In the next step, using these centroids apply the conventional FCM algorithm.

The proposed algorithm is as follows.

Algorithm: IHAFCM (a, n)

// Image pixels to be segmented into 'n' clusters.

//Histogram of the image is stored into vector a[1:256].

Input: 256 gray scale image.

Output: Given image is segmented into 'n' partitions.

Method:

1. Remove the noise in the image (as mentioned in section 2).
2. Construct histogram of the image and store it in the vector a[1:256].
3. i=3; j=254;
4. i=i+1;
5. avg= average of (a[1:i]);
6. If (avg<T) then //T is a nonnegative threshold
   Goto step 4;
7. j=j-1 ;
8. avg= average of (a[j:256]);
9. If(avg<T) then
   Goto step 7;
10. startbin=i-1; endbin=j+1;
11. plen=(startbin-endbin+1)/n;

//plen represents each partition size.

12. c1=Max(a[startbin:startbin+plen-1]);

c2=Max(a[startbin+plen:startbin+2*len-1]);

c3=Max(a[startbin+2*len:startbin+3*plen-1]);

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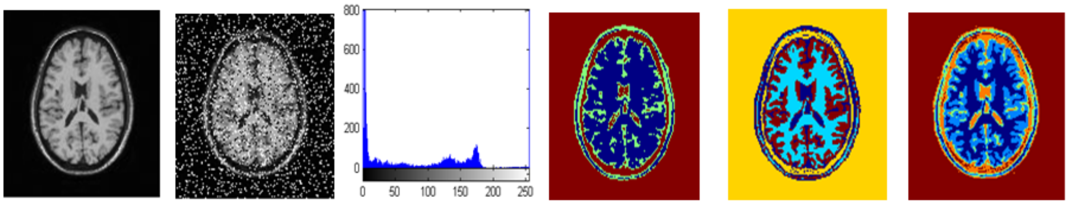
cn=Max(a[startbin+(n-1)*plen:endbin]);

13. Using centroids c1, c2, c3… cn apply the conventional FCM algorithm.

V. EXPERIMENTAL RESULTS AND ANALYSIS

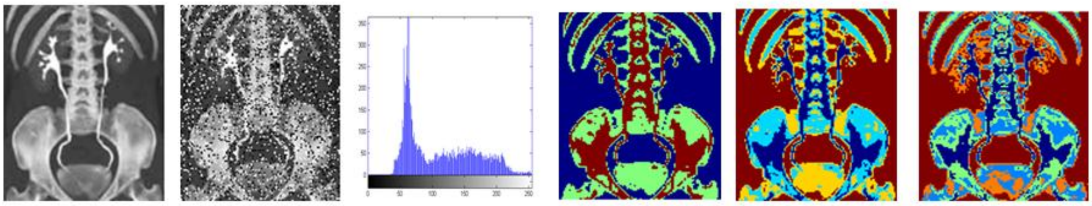
In this section, the performance of the IHAFCM is compared with conventional FCM. The experimental results are showcased on several standard images. In this experiment, images corrupted with salt-and-pepper noise are taken to test the effectiveness and the efficiency of the proposed IHAFCM algorithm. The experiments were performed in a 2.99 GHz Intel Core 2 Duo processor, Windows 7 with 4 GB RAM, using Matlab R2010a. The images are collected from the databases, http://www.radiologyinfo.org, http://www.med.harvard.edu.

The proposed IHAFCM clustering algorithm and conventional FCM clustering with varying number of clusters on images contaminated by different levels of salt-and-pepper noise are executed to investigate the robustness of the algorithms.



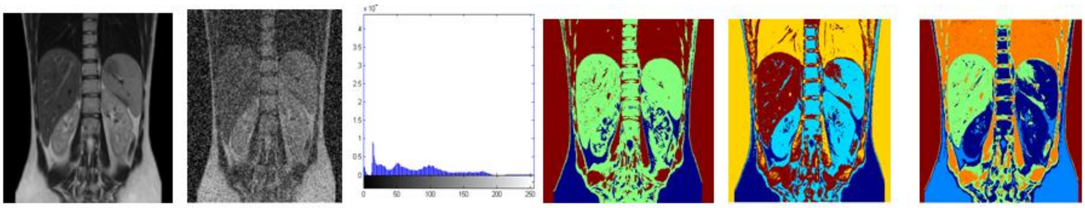
(a) (b) (c) (d) (e) (f)

Fig. 1. Segmentation results on MRI brain image with 20% salt and pepper noise. (a) original image (b) noisy image (c) histogram of the noisy image (d)IHAFCM with c=3 (e) IHAFCM with c=4 (f) IHAFCM with c=5.



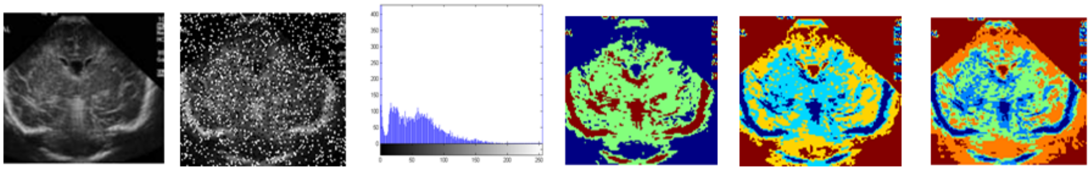
(a) (b) (c) (d) (e) (f)

Fig. 2. Segmentation results on CT view of kidneys with 20% salt and pepper noise. (a) original image (b) noisy image (c) histogram of the noisy image (d)IHAFCM with c=3 (e) IHAFCM with c=4 (f) IHAFCM with c=5.



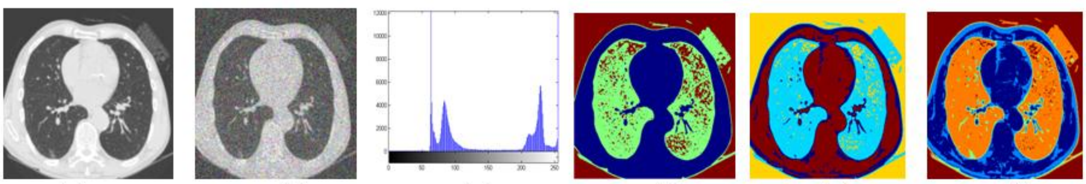
(a) (b) (c) (d) (e) (f)

Fig. 3. Segmentation results on MRI lungs image with 20% salt and pepper noise. (a) original image (b) noisy image (c) histogram of the noisy image (d)IHAFCM with c=3 (e) IHAFCM with c=4 (f) IHAFCM with c=5.



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

Fig. 4. Segmentation results on Ultra Sound brain image with 20% salt and pepper noise. (a) original image (b) noisy image (c) histogram of the noisy image (d)IHAFCM with c=3 (e) IHAFCM with c=4 (f) IHAFCM with c=5.



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

Fig. 5. Segmentation results on CT view of lungs with 30% salt and pepper noise. (a) original image (b) noisy image (c) histogram of the noisy image (d)IHAFCM with c=3 (e) IHAFCM with c=4 (f) IHAFCM with c=5.

TABLE I

Comparison of number of iterations of fig 1,fig 2,fig 3 with 20% noise, fig 4 and fig 5 with 30% noise using conventional FCM and proposed algorithm for threshold T=15

	Number of iterations FCM					**Number of iterations IHAFCM**				
No. of clusters	**Fig.1**	**Fig. 2**	**Fig. 3**	**Fig. 4**	**Fig. 5**	**Fig. 1**	**Fig. 2**	**Fig. 3**	**Fig. 4**	**Fig. 5**
3	39	25	44	39	59	21	19	31	31	36
4	26	37	86	31	38	16	25	71	19	16
5	106	157	74	141	80	80	131	69	127	26

TABLE II

Comparison of the CPU time taken by fig 1,fig 2,fig 3 with 20% noise, fig 4 and fig 5 with 30% noise using conventional FCM and proposed algorithm for threshold T=15.

	CPU time in seconds									
	FCM					**IHAFCM**				
No. of clusters	**Fig.1**	**Fig. 2**	**Fig. 3**	**Fig. 4**	**Fig. 5**	**Fig. 1**	**Fig. 2**	**Fig. 3**	**Fig. 4**	**Fig. 5**
3	4.1645	3.8594	7.4841	251.2197	154.3157	2.5412	2.25	3.7344	163.4531	92.2344
4	3.9844	8.4841	14.7497	271.5237	117.2969	2.152	3.75	10.3418	118.2188	49.1963
5	16.8945	26.7189	12.4127	1008.725	287.1563	11.6406	19.39	10.0186	841.573	90.5469

TABLE III

Comparison of number of iterations of 100 images with 20% noise using conventional FCM and proposed algorithm for threshold T=15.

No. of clusters	**Average number of iterations FCM**	**Average number of iterations IHAFCM**
3	40.6	26.23
4	46.3	30.45
5	117.2	85.3

TABLE IV

Comparison of the CPU time taken 100 images with 20% noise using conventional FCM and proposed algorithm for threshold T=15

No. of clusters	**Average CPU time in seconds** **FCM**	**Average CPU time in seconds** **IHAFCM**
3	420.2417	260.7491
4	481.4715	298.5712
5	1214.3761	847.5832

The data in table 1 and table 2 shows that the proposed algorithm reduces the iterations to a large extent resulting in the reduction of running time for generating segmented image. It can be observed that with the increased number of clusters the proposed method has produced good results. It can be observe from fig. 4 and fig. 5 in table 2 that if the image size is larger then there is vast CPU time difference between convention FCM and proposed algorithm. It takes more number of iteration for conventional FCM compared to proposed algorithm if the histogram bins towards front end or rear end empty or average number of pixels less than some threshold ‘T’. Most of the medical image histograms are like this so the proposed algorithm gives good results for medical images.

VI. CONCLUSION

This paper presents a new algorithm named Improved Histogram Analysis Fuzzy-C Means clustering algorithm for image segmentation, especially proposed for medical images corrupted with salt-and-pepper noise. The proposed algorithm produces results faster than the conventional FCM with the novel initialization method based on histogram analysis to start the FCM clustering for segmentation of an image. This algorithm is tested on several standard images, the results shows that the processing time is reduced to segment the image. It also produces better results through its inclusion of the noise detection and cancellation algorithm in its clustering process. Furthermore, this finding suggests the IHAFCM clustering works as a novel method for the segmentation of medical images and is efficient in terms of its computational time.

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