STUDY OF SEMI-SUPERVISED ADAPTIVE FUZZY CLUSTERING FOR IMAGE SEGMENTATION

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Abstract : Dental X-ray image segmentation (DXIS) is a crucial process in dentistry for diagnosis the diseases from an X-ray image. DXIS used specialized data mining method to achieve higher accuracy of segmentation. Clustering algorithm is used to determine the common boundaries of teeth samples. In this paper, we propose a new cooperative scheme that applies semi-supervised adaptive fuzzy clustering algorithms. Specifically, the Otsu method is used to remove the Background area from an X-ray dental image. Then, the FCM algorithm is chosen to remove the Dental Structure area from the results of the previous steps. Semi-supervised Entropy regularized Fuzzy Clustering algorithm (eSFCM) is adapted for clarifying and improve the results based on the optimal result from the previous clustering method. It solves the model by Interactive model by using cluster centers and membership matrix. The feature is extracted using the method of Linear Binary Pattern (LBP). In the view of expert systems, this method made use of knowledge-based algorithms for a practical application. The achieved results are then rectified by mean of eSFCM with a pre-defined membership matrix being taken from the FCM reduction by the maximum operating. A new semi-supervised adaptive fuzzy clustering algorithm segments (SSAFCM) a dental X-Ray image. The adaptive FCM allows pixels that belong to numerous clusters with changeable degrees of membership. It may able to determine final segmentation results from the pattern in a reasonable processing manner. The various schemes are (i) SSAFC-LBP with Otsu have better performance than the relevant methods such as Fuzzy C-Means, Otsu, and other semi-supervised fuzzy clustering algorithms namely eSFCM and SSFCLBP for dental X-ray image segmentation problem. The usefulness and significance of this research are clearly demonstrated within the extent of real-life applications.

IndexTerms - Dental Image Segmentation, Fuzzy Clustering, Semi supervised Entropy regularized Fuzzy Clustering Algorithm, Semi Supervised Adaptive Fuzzy Clustering.

I. INTRODUCTION

An X-ray dental image has three main parts. (i) Teeth area: which have high value of gray scale (ii) dental area: have a medium value of gray scale (iii) Background area: have the lowest value of gray scale. The Dental X-ray image segmentation is more crucial than the traditional image segmentation

Image segmentation is the process of partitioning a digital image into multiple segment. The most popular available methods for image segmentation are model based segmentation and clustering method. Among the clustering methods, the prevalent method for image segmentation is Fuzzy C Means. Bezdek et al.[1984] proposed for image segmentation to incorporate the spatial information among neighbouring pixels.Ayala et al.[2015] proposed a beta differential evolution (BDE) algorithm for determining the n-1 optimal n-level threshold on a given image using ostu's criterion. chen et al.[2012] proposed a semi supervised image segmentation algorithm to segment the noisy image with a large amount of object with the same color features. Maraziotis et al.[2012] proposed a novel semi supervised fuzzy clustering algorithm to the intrinstic problem of gene expression profiles clustering. yasunori et al.[2009] proposed semi supervised classification algorithm based on fuzzy c means clustering in which some membership grades are given as supervised membership grades. In this paper the segmentation accuracy in dental X-ray Image segmentation by means of FCM, eSFCM, SSAFCM. Thus the contribution are highlighted as follows.

Otsu's Method to remove the background area form Dental X-ray image. The main advantage of otsu's Method is fast processing and effectively identify the threshold.
FCM Algortihm to remove the structure of the dental image from the previous step.
eSFCM Algorithm to improve the results being achieved by step 2.
SSAFCM Algorithm to calculate the neighbourhood value of the each pixels in the image.

II. THE PROPOSED WORK

In this section we propose a new cooperative scheme described in following section. The Details of the otsu's method, Fuzzy C Means, eSFCM and SSAFCM are described in the next sub section respectively.

III. OTSU'S METHOD

The Otsu's Method removes the background area from an X-ray image. This method is fast processing and easily determine the background area from the X-ray dental image so this method is used in the preprocessing method. Otsu method is proposed Otsu (1975) which converts the original image to a binary image. The image can be sectioned as 3 regions. The lowest density region corresponds to the background the medium density region corresponds to the bone and the highest density region corresponds to the teeth. In some of the cases density of teeth region is close to the bone density region. This 2 regions are perfectly identifying by using the Otsu's Method. Otsu's Method is one of the threshold method. The simplest way in the threshold method is to partition the image into two regions based on the global Threshold. In Otsu's Method determine the threshold to minimize the change of black and white pixels and label the each pixel in the image area (r0) or background area (r1).

IV. FUZZY C MEANS

Fuzzy clustering is a process of generating the membership levels, and then using them to assign data elements to one or more clusters. Fuzzy clustering is an approach operating towards fuzzy logic. It provides the flexible method of assigning the data points to the cluster. The disadvantage of Fuzzy C Means is Computational Complexity, Performance degraded by Noise. The proposed Fuzzy C Means based segmentation method is clustering based segmentation methodology. This process makes the image to have the same range of intensity in the whole image. Each pixel in the image is checked whether it satisfies the rule generated. If the rules were satisfied means the values were taken as the similar groups. The numbers of rules generated were default and they vary for different images. At each time the rule generation strategy changes in the Fuzzy C Means segmentation. Based on the generated rules the needed portions are identified. Finally the performance of the segmentation method is measured. The Objective function of FCM is defined as follows:

$$J_m = \sum_{k=1}^{c} \sum_{i=1}^{n} u_{ki} \, \|X_i - V_k\|^2 \tag{1}$$

$$s.t. \sum_{k=1}^{c} u_{ki} = 1, u_{ki} \varepsilon \, [0,1], \tag{2}$$

$$\sum_{i=1}^{n} u_{ki} \leq n$$

Where M is the membership function weighting exponent. To update the membership value and cluster center

$$u_{ki} = \frac{1}{\sum_{l=1}^{c} \left(\frac{\|X_i - V_k\|^2}{\|X_i - V_l\|^2} \right)^{\frac{1}{m-1}}} \tag{3}$$

$$V_k = \frac{\sum_{i=1}^{n} u_{ki}^{m} X_i}{\sum_{i=1}^{n} u_{ki}^{m}} \tag{4}$$

Steps for FCM

Step 1: t=0;

Step 2: $u_{ki}^{(t)}$ random; (k=$\overline{1,N}$; j $= \overline{1,C}$ Satisfy condition

Step 3: Repeat

Step 4: t=t+1

Step 5: compute V_k; by formula(4)

Step 6: Until $\|x_i - V_k\| \; \varepsilon \; or \; t > maxstep$

V. SEMI SUPERVISED ENTROPY REGULARIZED FUZZY CLUSTERING

Semi-Supervised Entropy Regularized Fuzzy Clustering algorithm (eSFCM) proposed by Yasunori et al. (2009) using the given membership degree to increase the clustering performance. The objective function of eSFCM is as below

$$J(u,v) = \sum_{k=1}^{N} \sum_{j=1}^{c} u_{kj} \, \|X_k - V_j\|_A^2 + \lambda^{-1} \sum_{k=1}^{N} \left(|u_{kj} - \overline{u_{kj}}| \; ln |u_{kj} - \overline{u_{kj}}| -> Min \right) \tag{5}$$

Solve the equation (3) & (5), we obtain the solution

$$u_{kj} = \overline{u_{kj}} + \frac{e^{-\lambda \|X_k - V_j\|_A^2}}{\sum_{i=1}^{C} e^{-\lambda \|X_k - V_j\|_A^2}} \left(1 - \sum_{i=1}^{C} \overline{u_{ki}}\right) \tag{6}$$

κ=$\overline{1,N}$, φ= $\overline{1,C}$

$$V_j = \frac{\sum_{k=1}^{N} u_{kj} X_k}{\sum_{k=1}^{N} u_{kj}} \tag{7}$$

Steps for eSFCM

Step 1: Calculate matrix P uses a formula (9) with given matrix $\overline{U}$ and the initial cluster centers $\overline{V_j}$

Step 2: t=1

Step 3: Repeat

Step 4: t=t+1

Step 5:Compute $U_{kj} (K = \overline{1,N}; j = \overline{1 - C})$ by formula (6)

Step 6: Compute $V_j^{(t+1)} (j = \overline{1,C}\ )$ by formula (7)

Step 7: Until $\left\|U^t - U^{(t-1)}\right\| \le \varepsilon \ or \ t > maxstep$

VI. SEMI SUPERVISED ADAPATIVE FUZZY CLUSTERING

The Semi supervised Adaptive Fuzzy Clustering algorithm segments the dental X-ray image of cluster center and membership degree function. The Adaptive Fuzzy clustering method to calculate the neighborhood value of each pixel in the image. This method proposes to prevent the blurring from the edges.
The Proposed method introduces the global intensity to address the intensity homogeneity which combines the local and the global intensity information to ensure the smoothness of the derived optimal bias field. Thus the segmentation accuracy also improved.

VII. EXPERIMENTAL ANALYSIS

In this section Experimental results are described as,
EXPERIMENTAL TOOLS: The Proposed algorithm – Otsu's-eSFCM FCM (Bezdek et al., 1984) and Otsu (Otsu 1975) are implemented.
EXPERIMENTAL DATASETS: Dental X-ray image from Hanoi Medical University Vietnam.

CLUSTERING VALIDITY MEASUREMENT:
1. DAVIES-BOULDIN (DB): equivalent to the variance ratio criterion, which depends on the ratio between the distance of the inner group and the other group. Partition of the quality can be determined by the formula

$$DB = \frac{1}{k}\sum_{l=1}^{k} D_l \quad (8)$$

$$D_i = max_{l \neq m}\{D_{l,m}\} \quad (9)$$

$$D_{l,m\square} = (\overline{d_l}+\overline{d_m}) / \delta_{\mu,\lambda} \quad (10)$$

Here $\overline{d_l} and\ \overline{d_m}$ are the average distance of clusters l and m, respectively. $d_{m,l}$ is the distance between these clusters.

$$\overline{d_l} = \frac{1}{N_l}\sum_{x_i \varepsilon C_l}\|x_l - \overline{x_l}\| \quad (11)$$

$$d_{l,m} = \|\overline{x_l} - \overline{x_m}\| \quad (12)$$

The lower value of DB criterion is the bestin

$$SSWC = \frac{1}{N}\sum_{j=1}^{N} S_{xj}$$

$$S_{xj} = \frac{b_{p,j} - a_{p,j}}{\max(a_{p,j}, b_{p,j})}$$

2. *PBM: depends on the distance of the cluster and can be determined by the formula*

$$PBM = \left(\frac{1}{K}\,\frac{E_1}{E_K}\,D_K\right)^2 \quad (14)$$

$$E_1 = \sum_{i=1}^{N}\|x_i - \bar{x}\|,\ \ E_K = \sum_{l=1}^{k}\sum_{x_i \epsilon C_l}\|x_i - \overline{x_l}\|$$

$$D_K = max_{l,m,\ldots k}\|\overline{x_l} - \overline{x_m}\| \quad (15)$$

In PBM criteria, higher range means higher algorithm performance.

$$IFV = \frac{1}{C}\sum_{j=1}^{c}\left\{\frac{1}{N}\sum_{k=1}^{N} u_{kj^2\left[log_2 C - \frac{1}{N}\sum_{K=1}^{N} log_2 u_{k,j}\right]^2}\right\}\left[log_2 C - \frac{1}{N}\sum_{K=1}^{N} log_2 u_{k,j}\right] \mathrm{X}\frac{SD_{max}}{\overline{\sigma_D}} \quad (16)$$

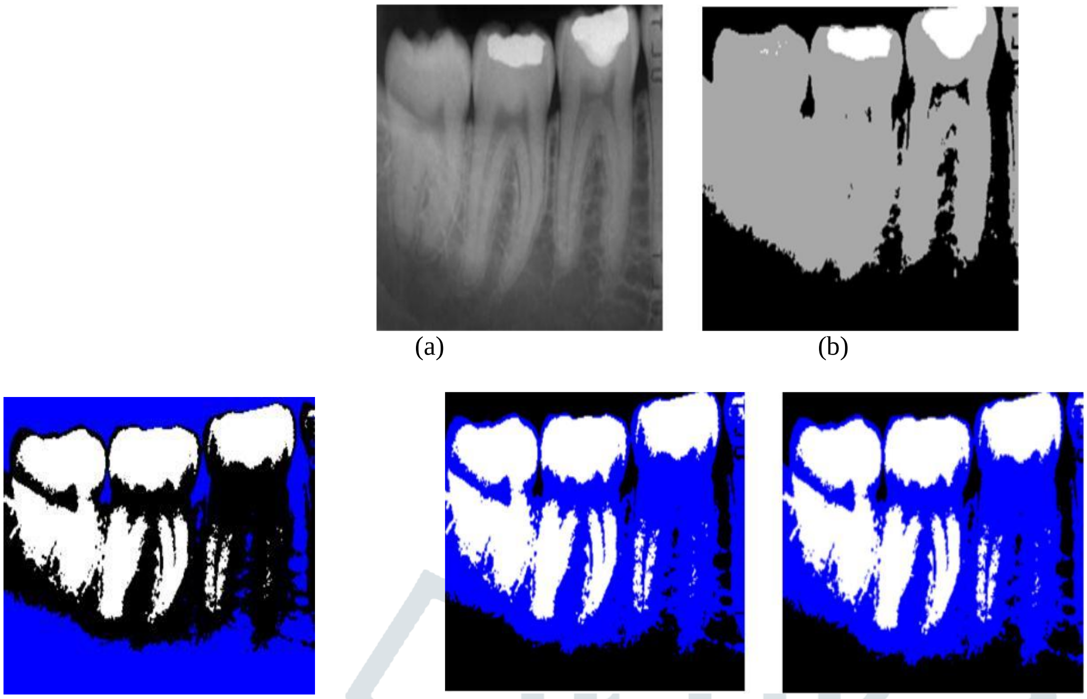
$$SD_{max} = max_{k \neq j\|V_k - V_j\|^2} \quad (17)$$

$$\overline{\sigma_D} = \frac{1}{C}\sum_{j=1}^{C}\left(\frac{1}{N}\sum_{K=1}^{N}\|X_k - V_j\|^2\right) \quad (18)$$

The minimum value of IFV indicates the best performance.

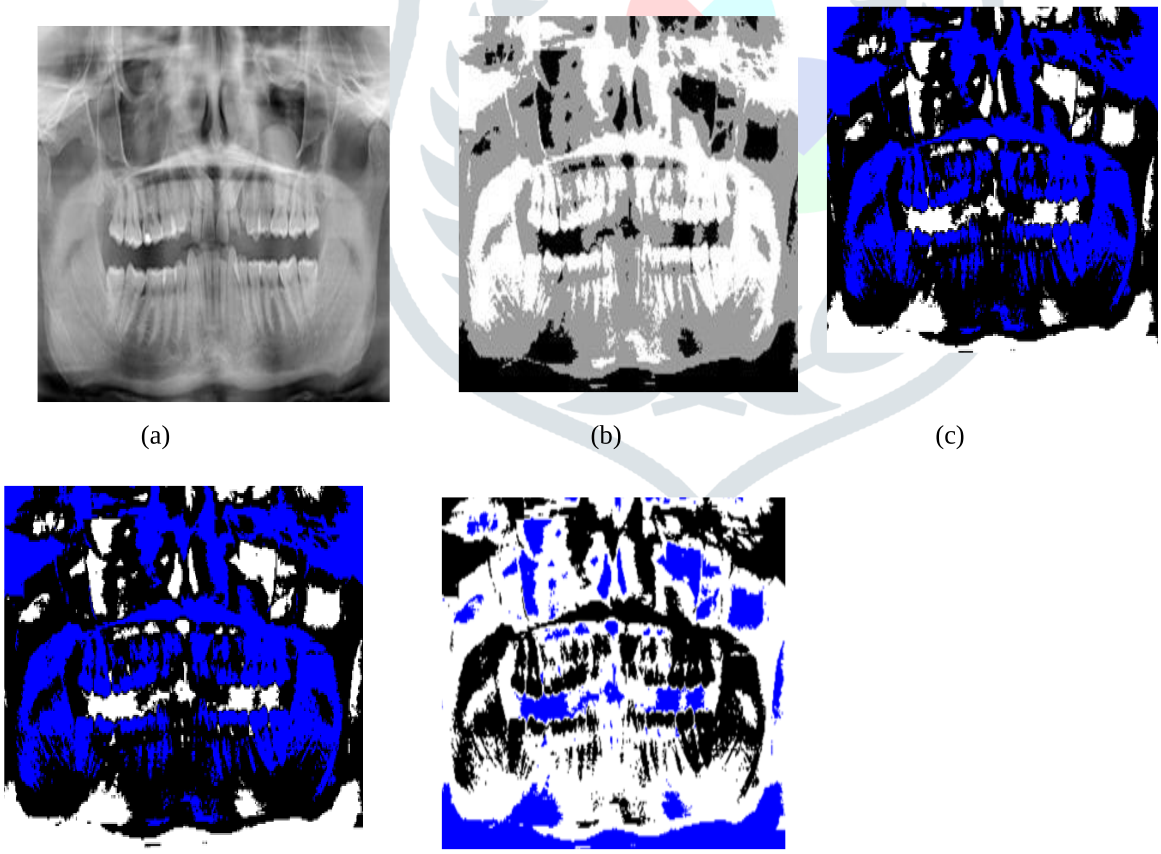
VIII. EXPERIMENTAL RESULTS

Fig 1. Experimental results on Data 1. (a) Original image; (b) After taking ostu method (c) FCM Clustering image (d) eSFCM Clustering image (e) SSAFCM Clustering image



(c) (d) (e)

Fig 2. Experimental results on Data 1. (a) Original image (b) After taking ostu method (c) FCM Clustering image (d) eSFCM Clustering image (e) SSAFCM Clustering image

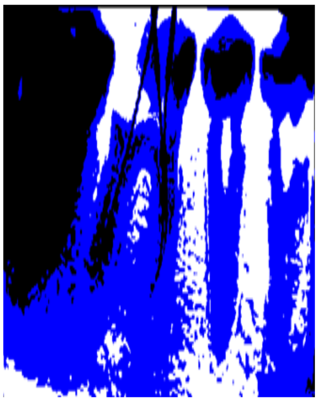


(d) (e)

Fig 3. Experimental results on Data 1. (a) Original image (b) after taking ostu method (c) FCM Clustering image (d) eSFCM Clustering image (e) SSAFCM Clustering image


(a)


(b)


(c)


(d)

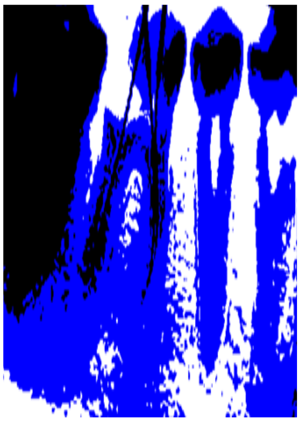

(e)

Fig 4. Experimental results on Data 1. (a) Original image;(b) After taking ostu method (c) FCM Clustering image (d) eSFCM Clustering image (e) SSAFCM Clustering image


(a)


(b)


(c)


(d)


(e)

The Comparison Result for the FCM clustering, eSFCM Clustering, SSAFCM Clustering Algorithm are shown in table 1.1

Table 1.1

S.No.	Method	FCM	eSFCM	SSAFCM
Data1	DB	4.7481	4.7481	0.0078
	IFV	3.88248	57.1526	382.8574
	PBM	4.0695e+03	4.0695e+03	6.09379e+08
Data 2	DB	4.9960	4.9960	0.0063
	IFV	4.9868	32.3850	385.5896
	PBM	2.4743e+03	2.4743e+03	1.6958e+09
Data 3	DB	5.2503	5.2503	2.1118e+07
	IFV	5.6211	64.8147	453.3718
	PBM	2.4198e+03	2.4198e+03	1.6243e+18
Data 4	DB	3.0587	3.0059	0.11
	IFV	15.9973	16.4938	320.6433
	PBM	1.89e+04	2.01e+04	2.99e+04

The Comparison of the performance for all the Algorithm is shown in the table 1.1. This shows the proposed method is having most significant than other method.

VIII. CONCLUSION

In this approach, we concentrated on the dental X-ray image segmentation with main approach being fuzzy clustering methodology. The contribution of this work is a new cooperative framework that combines Otsu threshold method, Fuzzy C-Means, semi-supervised fuzzy clustering (eSFCM) and Semi Supervised Adaptive Fuzzy clustering (SSAFCM). FCM classifies the Main part of a dental image into Teeth and Dental Structure areas. The achieved results are then rectified by mean of eSFCM with a pre-defined membership matrix being taken from the FCM reduction by the maximum operating. It turns out that the semi-supervised fuzzy clustering algorithm was able to determine final segmentation results.Performance of the new framework eSFCM-Otsu has been validated on real dental X-ray image datasets from the Hanoi Medical University. This method proposed a framework that is a combination of semi-supervised fuzzy clustering with thresholding with adaptive techniques for dental X-Ray image segmentation. Dental features are not used in the clustering process. It is obvious that a clustering algorithm employing spatial components in the objective function has more accurate achieved results than without using spatial components. This should be taken into account in the design of algorithms. The parameter values for each dental X-Ray image segmentation value should be derived. Even though we have stated the range of parameters, experiments should be done again to verify them and to have the best results. These drawbacks are under investigation in further studies. Need to integrate the segmentation results to a medical diagnosis system and perform a fast search method for verifying possible diseases.

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