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Spatial Condition in Intuitionistic Fuzzy C-Means Clustering for Segmentation of Teeth in Dental Panoramic Radiographs

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Abstrak

Hasil Segemntasi pada Citra Panoramik Gigi akan sangat bergantung pada performa metode segmentasi dikarenakan pencahayaan yang tidak merata dan kontras yang Rendah. Conditional Spatial Fuzzy C-mean (csFCM) Clustering telah diusulkan dimana fungsi spasial ditambahkan dalam proses clustering di FCM. Namun pada csFCM tidak memperhitungkan final membership dan final non-membership (Intuitionistic Fuzzy Set) yang menyebabkan hasil segmentasi kurang begitu optimal dikarenakan Pencahayaan yang tidak merata dan kontras yang Rendah. Pada penelitian ini, kami mengusulkan Conditional Spatial in Intuitionistic Fuzzy C-Means Clustering for Segmentation of Teeth in Dental Panoramic Radiographs. Metode yang diusulkan menambahkan hesitation function pada final membership dengan tujuan menambahkan pengetahuan pada Final membership guna mendapatkan hasil segmentasi yang lebih baik. Hasil percobaan menunjukkan metode yang diusulkan berhasil melakakukan segmentasi yang lebih baik dengan misclassification error (ME) sebesar 4.77 dan relative foreground area error (RAE) 4.27.

Kata kunci*— Segmentasi, radiografi panoramik Gigi, Fuzzy C-mean, Conditional Spatial, Intuitionistic Fuzzy Set*

Abstract

Dental panoramic radiographs heavily depend on the performance of the segmentation method due to the presence of unevenly illumination and low contrast of the images. Conditional Spatial Fuzzy C-mean (csFCM) Clustering have been proposed to achieve through the incorporation of the component and added in the FCM to cluster grouping. This algorithm directs with consideration conditioning variables that consider membership value. However, csFCM does not consider Intuitionistic Fuzzy Set to take final membership and final non-membership value into account, the effect does not wipe off the deviation by illumination and low contrast of the images completely for improvement to skip some scope. In this current paper, we introduced a new image segmentation method namely Conditional Spatial in Intuitionistic Fuzzy C-Means Clustering for Segmentation of Teeth in Dental Panoramic Radiographs. Our proposed method adds hesitation function aiming to settle the indication of the knowledge lack that belongs to the final membership function to get a better segmentation result. The experiment result shows this method achieves better segmentation performance with misclassification error (ME) and relative foreground area error (RAE) values are 4.77 and 4.27 respectively.

Keywords— *Image Segmentation, Dental panoramic radiographs, Fuzzy C-mean, Conditional Spatial, Intuitionistic Fuzzy Set*

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1. INTRODUCTION

Dental panoramic radiographs can assist dentists in diagnosing dental anomalies located in the mineralized tissues, or hidden under the surface of the cortical plate that is unable to be noticed during a visual examination [1]. However, human inspection of such radiographs tends to be subjective or inconsistent because some dentists may not have enough specialized training or they have been loaded with too much work to concentrate enough when performing the task. Medical image processing is assessed and turned out to be an essential tool for researchers in clinical medicine, as well as for dentists. Teeth segmentation importantly takes part to enhance starting detection and during the process of detection. The detection process itself contributes to making a precise diagnosis for specialists and dentists [2].

Fuzzy c-means (FCM) clustering algorithm, a clustering technique which is unsupervised, has completely been applied for image segmentation [4]. Conventional FCM algorithm employs the theory of fuzzy set running the image segmentation. Yet, the spatial information is not respected by the FCM algorithm. Without spatial information leads FCM to be susceptive to noise [5] and thus less suitable for image segmentation medic.

A number of researchers these days have integrated information from the spatial domain to basic FCM algorithm in enhancing the image segmentation result by converting the final membership function [3,6]. [3] Conditional Spatial Fuzzy C-mean Clustering (csFCM) have been proposed to engage by incorporating of conditioning effects. An auxiliary (conditional) variable establishes the conditioning effects in regard to every pixel that visualizes a level of involvement of the developed clusters and domain spatial pixel to the membership functions. However, csFCM does not consider Intuitionistic Fuzzy Set to take final membership and final non-membership value into account, the effect does not wipe off the deviation by illumination and low contrast of the images completely for improvement to skip some scope.

In this current paper, we introduced a new image segmentation method Conditional Spatial in Intuitionistic Fuzzy C-Means Clustering for Segmentation of Teeth in Dental Panoramic Radiographs (IcsFCM). Our proposed method adds hesitation function aiming to settle the indication of the knowledge lack, that belongs to the final membership function to get a better segmentation result.

2. METHODS

A. Fuzzy C-means

The fuzzy C-means (FCM) algorithm is a fuzzy clustering method that is useful to minimize the degree of membership in which each cluster represents the cluster centroid. The FCM algorithm set pixels to every cluster by taking the degree memberships fuzzy. in 1973 by Dunn the FCM algorithm was proposed and in 1981 enhanced by Bezdek [6]. Let $X = \{x_1, x_2, \dots x_N\}$ represent an image with N number of pixels. That algorithm divides the pixels into groups of data that has a centroid $\boldsymbol{v}$ and the membership matrix $\mathbf{U}$, also simplifies the objective function J in regard to these centroids and degrees of membership defined with equation (1):

$$J = \sum_{i=1}^{C} \sum_{k=1}^{N} \mu_{ik}^{m} ||x_k - v_i||^2 \qquad (1)$$

Where μ_{ik} represent the membership function of pixel x_k of ith cluster, C is the number of clusters, m is parameter control to fuzziness of the resulting partition with any real number $(m > 1)$, $m = 2$ is used in this study and $||.||$ is any norm matrix the distance of similarity measure.

Usually, for FCM algorithm, it applies the Euclidean distance measurement. When high membership values define pixels approaching the most imminent centroid cluster, it diminishes the Objective function. Additionally, when pixels are distant from the centroid cluster, they derive the low membership values.

The membership functions μ_{ik} calculated by equation (2):

$$\mu_{ik} = \frac{1}{\sum_{c=1}^{C}\left(\frac{||x_k - v_i||}{||x_k - v_c||}\right)} \quad (2)$$

and centroid cluster v_i are calculated by the equation (3):

$$v_i = \frac{\sum_{k=1}^{N} \mu_{ik}^{m} x_k}{\sum_{k=1}^{N} \mu_{ik}^{m}} \quad (3)$$

The algorithm Start by initializing random for every cluster center, the FCM assembles to a solution for v_i which define the local minimum or an error value of the objective function. By opposing membership values; the two sequent repetitions which are not more than the error amount, similarity is commonly noticed. We noted the error value with value 0.01.

B. Conditional spatial Fuzzy C-means

In Dental Panoramic Radiographs, neighboring pixel is one of image essential features of. It has solid correlation and normally dependent on each other. The correlation between neighboring pixels is not respected in the basic FCM algorithm, fails to generate accurate clusters. In another word, when the neighboring pixels provide likely feature values, the centroid pixel is better to hold greater probability which stands on the same cluster as the great neighboring pixels.

Sudip et al. [3] proposed conditioning component and added in the FCM to cluster grouping. This algorithm directs with consideration conditioning variables that consider membership value $z_1, z_2, \ldots, z_n$ for all pixels $x_1, x_2, \ldots, x_n$ respectively. The z_k give a value of complicity pixel in the last membership values and then developed clusters. Let μ_{ik} and v_i are the parameters value of the basic FCM algorithm are define with equation (2) and (3), respectively. Conditional spatial parameter μ_{ik} is introduced to integrating the variable conditional for the membership function, which represent the appertain of pixel x_k to the ith centroid cluster v_i. Employing the conditional spatial information can be in the following:

$$h_{ik} = \frac{z_{ik}}{\sum_{c=1}^{C}\left(\frac{||x_k - v_i||}{||x_k - v_c||}\right)} \quad (4)$$

Where z_{ik} represents conditioning variable that describes the implication stage of pixel x_k ith cluster v_i by checking its neighborhood in a spatial domain. A spatial function is in the following:

$$z_{ik} = \frac{\sum j \epsilon Nb(x_k) \mu_{ik}}{M} \quad (5)$$

Where $Nb(x_k)$ represents a square window, which is fixed at pixel x_k in the spatial domain where M is the total around number of pixels in the neighborhood. This work applied a $3 X 3$ window. based on what has been experienced, to produce better output, there should be defined size.

To separate each parameter, there should take the global μ_{ik} and local h_{ik} membership values and also by integrating the two membership parameters. Another weighted membership is defined as follows:

$$f_{ik} = \frac{(\mu_{ik})^p (h_{ik})^q}{\sum_{c=1}^{C} (\mu_{ik})^p (h_{ik})^q} \qquad (6)$$

p and q variables represent the second weighting controller parameter membership function.

C. Intuitionistic Fuzzy set

In 1986, Attanasov's [8] was proposed Intuitionistic Fuzzy Set (IFS). The method defines both the non-membership values v and the membership values f to be calculated. Membership value of IFS must be in interval between $[f_A(x) - v_A(x), f_A(x) + v_A(x)]$. Fuzzy complement have been proposed by Sugeno's [9] and calculated by equation (7)

$$N(\mu(x)) = \frac{(1-\mu(x))}{(1+\mu(x))} \ \lambda > 0 \qquad (7)$$

With equation (6), the Intuitionistic Fuzzy Set now can be represented as follows:

$$A = \{(x, \mu_A(x), \frac{(1-\mu_A(x))}{1+\mu_A(x)} \mid x \epsilon X\} \qquad (8)$$

hesitation degree is represented as follows:

$$\pi_A(x) = \frac{1-\mu_A(x)-(1-\mu_A(x))}{(1+\lambda\mu_A(x))} \qquad (9)$$

Converting the membership function can embrace the value of intuitionistic fuzzy set which is defined as follows

$$\mu'_{ik} = \mu_{ik} + \pi_{ik} \qquad (10)$$

D. Conditional Spatial in Intuitionistic Fuzzy C-Means Clustering

The Conditional Spatial in Intuitionistic Fuzzy C-Means Clustering (IcsFCM) can be described as follow:

Algorithm IcsFCM
Input: specify the number of clusters C, the variable degree of fuzziness $m = 2$, controlling variable $\lambda = 0.5$, $p = 1$, $q = 0$, and the error ε=0.01.
1. Initialize the centers of clusters $v_i^{(0)}$ with random.
2. $t = 1$
3. **Repeat**
   a. t = t+1
   b. The membership value $U^{(t)}$ can calculate using the cluster centers $v_i^{(t)}$ as follows:

$$\mu_{ik} = \frac{1}{\sum_{c=1}^{C} (\frac{||x_k - v_i||}{||x_k - v_c||})}$$

c. Calculate intuitionistic fuzzy set π_{ik}^{t} as follows:

$\mu'_{ik} = \mu_{ik} + \pi_{ik}$

Where $\pi_A(x) = \frac{1-\mu_A(x)-(1-\mu_A(x))}{(1+\lambda\mu_A(x))}$

d. Calculate the conditional spatial membership value $h_{ik}^{(t)}$ using the centers $v_i^{(t)}$ as follows:

$h_{ik} = \frac{z_{ik}}{\sum_{c=1}^{C}\left(\frac{\|x_k - v_i\|}{\|x_k - v_c\|}\right)}$

where $z_{ik} = \frac{\sum j \epsilon Nb(x_k)\mu_{ik}}{M}$

e. Calculate weighted membership value $f_{ik}^{(t)}$ as follows:

$f_{ik} = \frac{(\mu_{ik})^p (h_{ik})^q}{\sum_{c=1}^{C}(\mu_{ik})^p (h_{ik})^q}$

f. Update centers $v_i^{(t)}$ as: $v_i = \frac{\sum_{k=1}^{N}\mu_{ik}^{m}x_k}{\sum_{k=1}^{N}\mu_{ik}^{m}}$

4. Until $\left\|f_{ik}^{(t)} - f_{ik}^{(t-1)}\right\| < \epsilon$

5. **Return** the cluster center v_i and the membership value f_{ik}; $i = 1,2,\dots,C$; $k = 1,2,\dots\dots N$.

3. RESULTS AND DISCUSSION

A. Data

Dental panoramic radiographs are acquired from UNAIR Hospital. In the present study, there are 5 images with a size of 256 x 256 pixel are selected.

B. Parameter Setting

The parameters p and q as parameter control for membership function definitely impact on the final membership values w_{ij} and cluster centres μ_j. Table 1 show determine variation parameter of p and q with $NB(xj) = 3 \times 3$ It may be noted that IcsFCM algorithm provides superior results using $p = 1$ and $q = 0$. Neighborhood size parameter no effect on the results of segmentation in the current study.

C. Comparative Study

Presenting the robustness of the method, to measure performance related to the proposed method we did quantitatively with misclassification error (ME) [10] Foreground area relative error (RAE) [10] [11]. ME itself is adopted to quantitatively measure the performance of methods by calculating the percentages of the number of pixels which are misclassified. ME can be calculated as follows:

$$ME = 1 - \frac{|B_0 \cap B_t| + |F_0 - F_T|}{|B_t| + |F_0|} \qquad (11)$$

Table 1 Comparison Result Experiment on P And Q-Parameter

P	**Q**	**ME**	**RAE**
1	0	**4.77**	**4.27**
1	1	5.78	6.7
1	2	4.90	4.78
2	2	5.11	5.12

Table 2 Comparing the proposed algorithm with different algorithm based on ME

Image Sample	Segmentation Algorithm				
	Otsu Method	**HCA Method**	**Fuzzy Method**	**MAT Method**	**IcsFCM Method**
Image1	15.52%	34.03%	14.57%	10.17%	**8.40%**
Image2	6.03%	34.76%	1.87%	**0.19%**	0.75%
Image3	10.72%	11.94%	5.20%	4.89%	**4.17%**
Image4	26.44%	30.05%	1.43%	0.91%	**0.34%**
Image5	41.65%	46.18%	46.31%	11.16%	**10.20%**
Avg	20.07%	31.39%	13.88%	5.46%	**4.77%**

Note: smallest value is written boldly

Table 3 Comparing the proposed algorithm with different algorithm based on RAE

Image Sample	Segmentation Algorithm				
	Otsu Method	**HCA Method**	**Fuzzy Method**	**MAT Method**	**IcsFCM Method**
Image1	21.29%	49.24%	19.60%	10.93%	**8.28%**
Image2	7.61%	44.49%	2.39%	1.18%	**0.88%**
Image3	24.81%	19.34%	9.8%	8.37%	**1.93%**
Image4	43.85%	49.90%	2.38%	**0.017%**	0.42%
Image5	54.96%	60.91%	61.08%	11.81%	**9.86%**
Avg	30.50%	44.78%	19.05%	6.46%	**4.27%**

Where B_0 and F_0 of the original image indicate the background and foreground, for the test image, continuously. Foreground area relative error (RAE) [10] [11], the reference image is compared to the segmentation result to measure the number of discrepancy of segmented image. It is defined as in the equation below.

$$RAE = \begin{cases} \frac{D_0 - D_r}{D_0} & if\ D_r < D_0 \\ \frac{D_r - D_0}{D_r} & if\ D_0 < D_r \end{cases} \quad (12)$$

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

Figure 1 Original images : (a) Image1, (b) Image2, (c) Image3, (d) Image4, (e) Image5

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

Figure 2. Groundtruth images : (a) Image1, (b) Image2, (c) Image3, (d) Image4, (e) Image5

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

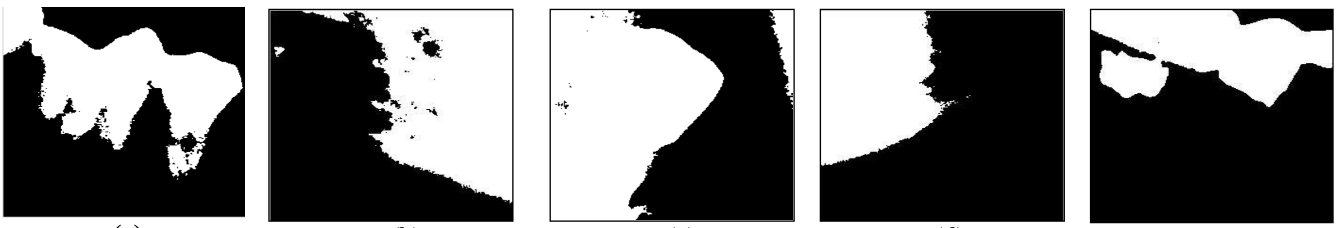
Figure 3.IcsFCM images : (a) Image1, (b) Image2, (c) Image3, (d) Image4, (e) Image5

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

Figure 4. MAT images : (a) Image1, (b) Image2, (c) Image3, (d) Image4, (e) Image5

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

Figure 5. Otsu images : (a) Image1, (b) Image2, (c) Image3, (d) Image4, (e) Image5



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

Figure 6. HCA images : (a) Image1, (b) Image2, (c) Image3, (d) Image4, (e) Image5

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

Figure 7. Fuzzy images : (a) Image1, (b) Image2, (c) Image3, (d) Image4, (e) Image5

where D_0 is the area of the ground truth image, and D_T is the area of the results of segmentation. as a comparison of our method, we are doing by comparing comparatively with the previous method, we have inferred Otsu thresholding -method [12], Hierarchical Cluster Analysis (HCA) [13], Fuzzy Sets Type II [14], and Multi adaptive thresholding (MAT) [15]. the smaller value of ME and RAE gives the better performance is shown in Table 2 and Table 3 for comparing methods. For the Qualitative Evaluation, Fig. 1 Show testing of 1-5 images dental Panoramic radiograph, Fig. 3 Show result of segmentation by IcsFCM algorithm, Fig. 4- 7 show the result of segmentation by Otsu, HCA, Fuzzy Set Type II, and MAT respectively.
From Table 2. and Table 3. show comparison the average value for five segmented part of Dental Panoramic Radiographs: the average ME and RAE value of the proposed IcsFCM algorithm for five images are close to 0 and smaller than of the Otsu, HCA, Fuzzy Set Type II, and MAT Algorithm. The findings infer that the IcsFCM algorithm performs well and is able to exceed from other methods in terms of accuracy using measurement scale ME and RAE with the presence of illumination and low contrast of the dental panoramic images.

4. CONCLUSIONS

In the present paper, Conditional Spatial in Intuitionistic Fuzzy C-Means Clustering for Segmentation of Teeth in Dental Panoramic Radiographs (IcsFCM) has been presented. The key point for the current method is defining hesitation function settling the knowledge deficiency. It is also integrated into the membership function on the conditional spatial FCM, which is able to improve the accuracy of ME and RAE in segmentation result. From the evaluation of the dental panoramic radiographs, IcsFCM achieves better segmentation performance by the value of misclassification error (ME) and relative foreground area error (RAE) are 4.77 and 4.27 respectively.

Further discussion for the upcoming work is needed to find the optimal centroid for the resolved problem because randomly initialized centroid process results in clustering of pixels are inefficient in terms of iterations and the computational time.

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REFERENCES

[1]. P.L. Lin, P.Y. Huang, P.W. Huang, H.C. Hsu, and C.C. Chen, “Teeth segmentation of dental periapical radiographs based on local singularity analysis”. Computer Methods and Programs in Biomedicine, vol. 113, pp. 433–445, October 2013.

[2]. Yusra Y. Amer and Musbah J. Aqel, “An Efficient Segmentation Algorithm for Panoramic Dental Images”, International Conference on Communication, Management and Information Technology, vol. 65, pp. 718-725, 2015

[3]. Sudip Kumar Adhikari, Jamuna Kanta Sing, Dipak Kumar Basu, and Mita Nasipuri, “Conditional spatial fuzzy C-means clustering algorithm for segmentation of MRI images”, Applied Soft Computing, vol. 34, pp. 758-769, June 2015

[4]. Xuemei Zhao, Yu Li, and Quanhua Zhao, “Mahalanobis distance based on fuzzy clustering algorithm for image segmentation”, Digital Signal Processing, vol. 43, pp. 8-16, April 2015.

[5]. F.B. Tek, A.G. Dempster, and I. Kale, “Noise sensitivity of watershed segmentation for different connectivity: experimental study”, Electronics Letter, Vol. 40, pp 1332–1333, October 2014.

[6]. Jiayin Kang, Lequan Min, Qingxian Luan, Xiao Li, and Jinzhu Liu “Novel modified fuzzy c-means algorithm with applications”, Digital Signal Processing, vol. 19, pp. 309–319, December 2009

[7]. J.C. Bezdek, “Pattern Recognition with Fuzzy Objective Function Algorithms”, Kluwer Academic Publishers, Norwell, MA, USA, 1981

[8]. Atanassov K. T., “Intuitionistic Fuzzy Set,” Fuzzy Sets Syst, Vol. 20, pp. 87-97, 1986.

[9]. Tamalika Chaira and Sneh Anand, “A novel intuitionistic fuzzy approach for tumour/hemorrhage detection in medical images,”Journal of Scientific and Industrial Research, vol. 70, pp.427-434, June 2011

[10]. Sezgin, M., and Sankur, B., “Survey over image thresholding techniques and quantitative performance evaluation”, Journal of Electronic Imaging, vol. 13 (1), 146–165. 2004

[11]. Zhang, Y.J., “A survey on evaluation methods for image segmentation”, Pattern Recognition, vol. 29, pp. 1335–1346, 1996.

[12]. Nobuyuki Otsu, “A Threshold Selection Method from Gray Level Histograms”. IEEE Trans. Systems Man Cybernet, vol. 9, pp. 62–66, 1979.

[13]. Agus Zainal Arifin and Akira Asano, “Image Segmentation by Histogram Thresholding using Hierarchical Cluster Analysis”, Pattern Recognition Letters, vol. 27, pp. 1515-1521, May 2006.

[14]. Agus Zainal Arifin, Aidila Fitri Heddyanna, and Hudan Studiawan, “Ultrafuzziness Optimization Based On Type II Fuzzy Sets for Image Thresholding”. ITB J. ICT, Vol. 4., No. 2, pp. 79-94, 2010.

[15]. Dini Adni Navastara and Agus Zainal Arifin, “Image Thresholding on Segmentation of Teeth In Dental Panoramic Radiographs”, International Conference on Advanced Computer Science and Information Systems December, vol. 7, 2009.