Interactive Segmentation of Conditional Spatial FCM with Gaussian Kernel-Based for Panoramic Radiography

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***Abstract*—Dental image segmentation is widely used for various real applications such as dental diagnosis, teeth numbering, dental age estimation, dental plaque analysis and etc. Dental image segmentation is a challenging task in panoramic radiography because the difficulty due to noise, low contrast, uneven illumination, complicate topology of objects and unclear lines of demarcation of the panoramic radiography. Unsupervised segmentation of Conditional Spatial FCM with Gaussian Kernel-Based incorporate spatial information and gaussian kernel function to overcome inhomogeneous regions. However, it encountered significant obstacles in obtaining effective segmentation to differentiate teeth with other dental features. To alleviate the problem, an interactive segmentation method involves the user to engage in the segmentation process by incorporating prior-knowledge, thus lead to accurate segmentation results. This paper proposes a novel strategy of conditional spatial FCM with Gaussian Kernel-Based in interactive segmentation for panoramic radiography image. The representative sample area chosen by the user causes the initialization value will affect the membership function in the segmentation process, thus it will overcome the lack of algorithm in distinguishing the tooth and background areas. This strategy gives a higher segmentation accuracy than automatic segmentation method with a few user samples.**

Keywords—interactive segmentation; dental segmentation; conditional spatial FCM with Gaussian kernel-based

I. Introduction

Dental segmentation is the process of dividing the dental image into isolated parts according to different purposes and objectives [1]. Dental image segmentation is widely used by dentistry researchers for various real applications such as dental diagnosis, teeth numbering, dental age estimation, dental plaque analysis and etc. Segmentation of panoramic radiography is a very challenging task because of noise, low contrast, uneven illumination, complicate topology of objects in the image, arbitrary teeth orientation and unclear lines of demarcation [2]. There is three main area of panoramic radiography, they are tooth area, dental structure area and background area [3]. The main part of the image, the tooth area, has a high grayscale value. Dental structure area has a medium grayscale value and consists of gum, bone and periodontitis structure. The background has the smallest grayscale value among them and shows the background of the teeth structure. The grayscale color pixels of those three parts have a small difference making it difficult to distinguish between them.

Fuzzy C-means (FCM) is an effective soft clustering method that is widely used in image segmentation because it does not assign pixels exclusively to one cluster, but it allows pixels to have relationships with multiple clusters with varying membership levels more sense in resolving inhomogeneities [4][5]. Spatial information FCM was developed because conventional FCM algorithms are very sensitive to noise and imaging artifacts. The spatial function considers summarizing the membership value of each neighboring pixels. Conditional spatial fuzzy C-means (csFCM) uses spatial information to illustrate the degree of pixels involvement to build clusters and incorporate spatial information of each pixel into membership functions [6][7]. Thus, this algorithm can resolve the regions homogeneously, reduce the spurious blobs and eliminate noisy spots by incorporating local and global spatial information into a weighted membership function. Conditional spatial fuzzy C-means with Gaussian kernel function (csFCM-GK) algorithm is developed on X-ray image segmentation using Gaussian kernel function as an objective function of conditional spatial fuzzy C-means algorithm [8]. The Gaussian kernel function is used to overcome the number of points that almost in the same cluster

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and the outlier data that always affect the poor clustering results of Euclidean distance.

Interactive image segmentation combining user interaction into dental segmentation by supervised or semi-supervised manner has attracted much attention in recent years [9]. Segmentation processes that are generally done manually by doctors are time-consuming and tedious. Therefore, an interactive segmentation method involving users to engage in the segmentation process by incorporating prior knowledge, thus leading to accurate segmentation results. A semi-supervised fuzzy clustering algorithm based on interactive Fuzzy satisficing developed the dental X-ray image modeling into the spatial objective function then integrated into the new semi-supervised fuzzy clustering model. The interactive Fuzzy satisfacing method applied to get the center cluster and matrix membership model [10]. Interactive segmentation based on region merging using discriminant analyzes developed on dental panoramic radiography [11]. The measurement of new similarities between regions combines regions that have a minimal inter-class variance either with cluster objects or backgrounds. The sample area that has been chosen by the user affects to keep the similarity between the regions combined with the removed samples.

Unsupervised segmentation of csFCM-GK encountered significant obstacles in obtaining effective segmentation to differentiate teeth with other dental features. In this paper, we propose a novel strategy of conditional spatial FCM with Gaussian Kernel Based Function in interactive segmentation to segment the low contrast panoramic radiography image. Firstly, the region of interest of panoramic radiography is enhanced using Contrast Limited Adequate Histogram Equalization (CLAHE), then is segmented into tooth and background region. User interactive input is involved in the segmentation process by incorporating prior-knowledge of the segmentation process. The representative sample area chosen by the user causes the initialization value will affect the membership function in csFCM-GK, thus it will overcome the lack of algorithm in distinguishing the dental and background areas effectively.

II. Conditional Spatial FCM with Gaussian Kernel-Based (csFCM-GK)

This Gaussian membership function and spatial information function identify the similarity of the whole and neighboring pixels, then affect to handle the noise and outlier pixel. The objective function JS_m of csFCM-GK represent n data $X = \{x_1, x_2, \ldots, x_n\}$ to be partitioned to c cluster by calculating the center of clusters a and the membership matrix U=[μ_{ij}] with the degree of fuzziness m using Gaussian radial basis function (RBF) kernel function 1-$K(x_j, a_i)$ [8].

$$JS_m^k(\mu, a) = \sum_{i=1}^{c}\sum_{j=1}^{n}\mu_{ij}^m\left(1 - K(x_j, a_i)\right) \tag{1}$$

The equation of $K(x_j, a_i)$ is defined as (2).

$$K(x_j, a_i) = exp\left(\frac{-\left(\sum_{i=1}^{d}|x_i - a_i|^r\right)^s}{\sigma^2}\right) \tag{2}$$

Notation d is the dimension of vector x and $r \geq 0$ and $1 \leq s \leq 2$. Notation σ^2 is a variance of the image intensity.

$$\sigma^2 = \frac{\sum_{i=1}^{d}\|x_i - \bar{x}\|^2}{n} \tag{3}$$

Mean $\bar{x}$ of n data x defined as

$$\bar{x} = \frac{\sum_{i=1}^{d}x_i}{n} \tag{4}$$

The kernel function is incorporated to a radial basis function (r=2, s=1) [8], then the equation (2) can be simplified as

$$1 - K(x_j, a_i) = 1 - exp\left(-\frac{\|x_j - a_i\|}{\sigma^2}\right) \tag{5}$$

The membership function μ_{ij} and the cluster center a_i is represented as [7].

$$\mu_{ij} = \frac{\left(1-K(x_j, a_i)\right)^{-\frac{2}{m-1}}}{\sum_{k-1}^{c}\left(1-K(x_j, a_i)\right)^{-\frac{2}{m-1}}} \tag{6}$$

and

$$a_i = \frac{\sum_{j=1}^{m}\mu_{ij}^m K(x_j, a_i)x_j}{\sum_{j=1}^{m}\mu_{ij}^m K(x_j, a_i)} \tag{7}$$

If the neighboring pixels have similar characteristics, the center pixel must have a higher cluster probability to the same cluster as the neighboring pixels. Spatial function h_{ij} represent the level of spatial information involvement as a weighted membership function. h_{ij} represent the probability that pixels x_j belongs to the ith cluster. $NB(x_j)$ represent a square window of pixel x_j in the spatial domain (for example 3 × 3, 5 × 5 or 7 × 7) and M is the number of neighboring pixels [7].

$$h_{ij} = \frac{\sum_{k \in NB(x_j)}\mu_{ik}}{M} \tag{8}$$

Gaussian RBF also affects to the membership of spatial information function u_{ij} that represents the probability of the neighboring pixel with spatial function h_{ij} [8].

$$u_{ij} = \frac{h_{ij}\left(1-K(x_j, a_i)\right)^{-\frac{2}{m-1}}}{\sum_{k-1}^{c}\left(1-K(x_j, a_i)\right)^{-\frac{2}{m-1}}} \tag{9}$$

The weighted membership function z_{ij} combie the global membership value μ_{ij} and spatial membership value u_{ij} which independently of each other. Parameter r and s control the importance level of both the global membership functions and spatial membership functions [7].

$$z_{ij} = \frac{(\mu_{ij})^r (u_{ij})^s}{\sum_{k=1}^{c}(\mu_{kj})^r (u_{kj})^s} \tag{10}$$

The updated cluster center w_i is affected by the weighted membership function [7].

$$w_i = \frac{\sum_{j=1}^{m} z_{ij}^m x_j}{\sum_{j=1}^{m} z_{ij}^m} \tag{11}$$

This Gaussian membership function and spatial information function get better identifying the similarity of the whole and neighboring pixels, then affect to handle the noise and outlier pixel. The proposed Gaussian RBF for conditional spatial information fuzzy C-means algorithms can be summarized in the following step [8]

Input: Specify the values for the number of clusters c, the degree of fuzziness m, r, s and the error ε.

Step 1: Initialize randomly the centers of clusters $a_i^{(0)}$ and the center of joint cluster $w_i^{(0)}$
Step 2: For $t = 1, 2, \ldots, t_{max}$ do
a) Calculate the membership value $U^{(t)}$ using the centers $a_i^{(t-1)}$ using Eq. (6) and Eq. (7).
b) Calculate the conditional spatial membership value $u_{ij}^{(t)}$ using the centers $w_i^{(t-1)}$ using Eq. (9)
c) Calculate weighted membership value $z_{ij}^{(t)}$ using Eq. (10)
d) Update the center of joint cluster $w_i^{(t)}$ using Eq. (11)
e) Update the centers $a_i^{(t)}$ using $U^{(t)}$ using Eq. (7)
f) if $\|a_i^t - a_i^{t-1}\| < \varepsilon$ then stop
Step 3: Return the center of joint cluster w_i and the weighted membership value z_{ij}; $i = 1, 2, \ldots, c$; $k = 1, 2, \ldots, n$.

The parameters number of cluster c, the fuzzifier m, stopping threshold ε, square window NB, a conditional parameter of spatial information r and s are defined by the user. The suggested value of those parameters in the relevant articles are often $c = 2$ (background and tooth part), m=2 and ε=0.001 [10], and $NB = 3$, $r = 2$ and $s = 2$ [11]. Nonetheless, we can adjust the parameters for specific analysis. The variance σ^2 is calculated from the global variance pixels and neighborhood variance pixels.

III. METHODOLOGY

Data were obtained from the Pramita clinic laboratory, Sidoarjo, Indonesia, which served panoramic radiographic images. The original image is divided into some part of the teeth as shown in Fig. 1. Fig 1(a) is the panoramic image and Fig 1(b) is observed images of mandibular areas which contains a complete tooth from the crown to the root.

The steps of interactive segmentation with csFCM-GK processes are illustrated in Fig 2. The goal of the framework is segmentation of tooth and background that separate the region of interest that show the part of a tooth from the crown until the root of the tooth by removing other parts of the tooth such as the gums, tissues, bones, and teeth adjacent to it. Segmentation process consists of image enhancement, user marking, csFCM-GK segmentation, black and white conversion and finding the largest area.

(a) (b)

Fig. 1. (a) Panoramic radiography; (b) Observed images

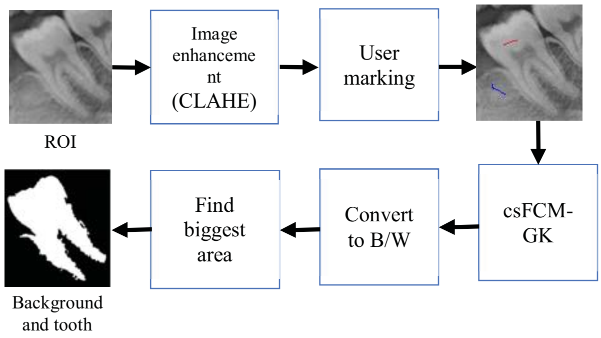
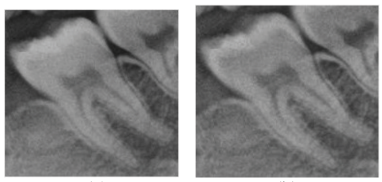


Fig. 2. Steps of the segmentation process

The CLAHE (Contrast Limited Adaptive Histogram Equalization) method helps in enhancing the dental radiographs. This particular method divides the image into four different types of small blocks, in which it is applied with the suitable smoothing/sharpening techniques for various locations in the image. The CLAHE method does not reduce the contrast variations but it enhances each pixel by its own value. This method won't reduce the contrast variations in the image. It just enhances the value of each pixel in the image. CLAHE method of the grayscale image I use 0.003 'ClipLimit' contrast factor to prevent oversaturation of the image specifically in homogeneous areas and rayleigh 'distribution' to specify the distribution that uses as the basis for creating the contrast transform function. The image enhancement result can be seen in Fig. 3.

```
I = adapthisteq
(I,'clipLimit',0.003,'Distribution','rayleigh');
```



(a) (b)

Fig. 3. Image after Enhancement (a) shows the original image, (b) after applying CLAHE

User marking cause the grayscale image has prior-knowledge on the tooth and background segmentation proses. The red color represents the tooth and the blue color indicates a background as shown in Fig. 4(a). the pixel location $I(i, j)$ that is marked as part of the tooth (obj) is given a value of 1.0 and the background part (bg) is given a value of 0.0 as (12). The value is given as initial initialization of the segmentation grayscale image with the double data type.

$$I(i,j) = \begin{cases} 1.0 \; if \; i = obj_i, j = obj_j \\ 0.0 \; if \; i = bg_i, j = bg_j \end{cases} \quad (12)$$

The interactive csFCM-GK segmentation processes the tooth and background segment based on the initialization given by the user using the algorithm in section 2. This algorithm notices the involvement of spatial information of the neighboring intensity values besides the global information to obtain better segmentation results in inhomogeneous data. The segmentation result is converted into two clusters of background and tooth into a binary image (black and white) according to the membership value of the two clusters using equation (13). Segmentation results with initial initialization produce better segmentation than without using user marking as shown in Fig. 4(b) dan Fig. 4(c).

(a) (b) (c)

Fig. 4. (a) User Marking; (b) Interactive csFCM-GK segmentation; (c) csFCM-GK segmentation without user marking

$$g(x) = \begin{cases} 0 & if\ (round(f(x),\ c_1) = 1 \\ 255 & else \end{cases} \quad (13)$$

The last process of the tooth and background segmentation is eliminating another part except for the ROI. This proses find the largest part of the image and remove the center hole in ROI by measuring the property set for the 8-connected component (object) in the binary image in contiguous regions and discontiguous regions as shown in Fig. 5. The algorithms of this proses can summarize in the following step:

1) Calculate the object measurements of the labeled image according to the area
2) Find all areas of the object measurements
3) Sort all areas in descending mode and give the sorted indexes
4) Find the biggest area
5) Fill the hole with a white color

(a) (b)

Fig. 5. (a) ROI with interactive segmentation; (b) ROI without interactive segmentation

IV. RESULT

Proposed method has been measured to evaluate its performance using five grayscale images of ROIs (region of interest) that consist of one tooth images of mandible molars as seen in Fig. 6. The dataset of dental panoramic radiographs is received from Pramita clinic laboratory, Sidoarjo, Indonesia. The corresponding ground truth segmentations of the test images are shown in Fig. 7 for tooth and background segmentation. We compare the segmentation results of tooth and background regions between csFCM-GK without user marking and csFCM-GK with user marking as shown in Fig. 8 and Fig. 9.

The evaluation criteria measure the accuracy of the proposed segmentation algorithm. The evaluation compares the segmentation area between a depicted area with the doctor manually (that called ground truth) and resulted area by the proposed methodology. Evaluation of the proposed method results use Misclassification Error (*ME*) and Relative Foreground Area Error (*RAE*) [10].

The misclassification ratio of the object's pixel as background and vice versa is measured using ME that states as (14). The objects and background pixels in the ground truth image are represented as O_g and B_g. The object and background pixels obtained from the segmentation process (interactive or manual) of csFCM-GK are stated with O_r and B_r.

$$ME = 1 - \frac{|O_g \cap O_r| + |B_g \cap B_r|}{|O_g| + B_g} \quad (14)$$

The ratio of the difference between the area of the object in ground truth with the object in the csFCM-GK segmentation result (interactive or manual) is declared as RAE can be written as (15).

$$RAE = \begin{cases} \frac{A_g - A_r}{A_g}\ if\ A_r < A_g \\ \frac{A_r - A_g}{A_r}\ if\ A_r \geq A_g \end{cases} \quad (15)$$

The object area in ground truth is expressed as A_g and the area of the object in the csFCM-GK segmentation results (interactive or manual) is expressed as A_r. The *ME* and *RAE* values are in the range value of 0 and 1. The smaller the *ME* and *RAE* values show better segmentation results.

Table I shows the *ME* and *RAE* values of the tooth and background segmentation results (contains two clusters) of the proposed method compared with the segmentation ground truth images. The tooth and background segmentation results of five mandible molar X-ray image is compared between csFCM-GK without interactive user marking and with user marking. The average ME value of the interactive csFCM-GK and non-interactive csFCM-GK are 6.88% and 37.98% respectively. The average RAE value of the interactive csFCM-GK and non-interactive sFCM-GK are 5.8% and 19.96% respectively. The *ME* and *RAE* evaluation results show that the interactive sFCM-GK segmentation method obtains better segmentation than the non-interactive csFCM-GK method.

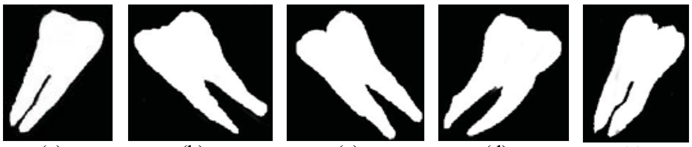
In general, some points can be obtained from the experimental results of the proposed interactive segmentation method. The tooth and background segmentation using interactive csFCM-GK generally produce better segmentation than without user marking as shown in Fig. 8 and Fig. 9. Fig 8 (a), (b) and (d) show segmentation results do not perfectly separate ROI with their adjacent teeth. User marking allows a well-separated ROI from adjacent teeth except for Fig. 9 (a). It is generally difficult to separate the ROI with adjacent tissue that has the same intensity as ROI. However, by using user marking, this error can be minimized.

TABLE I. PERFORMANCE EVALUATION OF INTERACTIVE CSFCM-GK AND NON-INTERACTIVE CSFCM-GK FOR TOOTH AND BACKGROUND SEGMENTATION

Data	Interactive csFCM-GK		Non-Interactive csFCM-GK	
	ME (%)	*RAE (%)*	*ME (%)*	*RAE (%)*
1	**13.9**	**14.6**	53.3	19.6
2	**5.1**	**0.1**	58.2	28.8
3	**3.4**	**4.6**	41.0	14.1
4	**6.1**	**8.4**	56.8	31.8
5	**5.9**	**1.3**	43.5	5.5

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

Fig. 6. Data input



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

Fig. 7. Ground truth of tooth and background segmentation

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

Fig. 8. Non-interactive csFCM-GK of tooth and background segmentation

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

Fig. 9. Interactive csFCM-GK of tooth and background segmentation

The segmentation result has been affected by the number and the significance of the samples that given by the user. However, a large number of samples does not always provide better segmentation results compared to small samples. In fact, the small number of user samples gives sufficient initialization value to the membership function in csFCM-GK and results a better segmentation than automatic segmentation. One sample for each different intensity values of area that is considered as an object and background have produced the desired segmentation. The balance of the samples given to objects and background also affects the results of segmentation. If the user gives a sample of objects with high intensity more significantly than objects with low intensity, the proposed method will associate objects with high intensity areas so that some areas with low intensity objects will be incorrectly classified as background. Therefore, it is recommended that users provide sufficient samples to represent each area of the object and background.

V. Conclusion

Interactive image segmentation is a semi-manual segmentation process that performs the segmentation process objectively by considering a manual sample from the user. The proposed csFCM-GK interactive segmentation method produces higher accuracy than the automatic segmentation method using a few representative samples from users. The proposed method can be considered as an appropriate segmentation method for dental panoramic radiography and other medical images that have low contrast.

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References

[1] E. Said, G. F. Fahmy, D. Nassar, H. Ammar, "Dental x-ray image segmentation, defense, and security". Int. Soc. Opt. Photonics, pp. 409–417, 2004.

[2] C. E. Tom and J. Thomas, "Segmentation of Tooth and Pulp from Dental Radiographs", International Journal of Scientific & Engineering Research, Vol 6, Issue 11, pp. 115-121, 2015.

[3] J. H. Scott. Introduction to dental anatomy. Edinburgh: Churchill Livingstone, 1977.

[4] J. C. Bezdek, R. Ehrlich and W. Full, "FCM: The fuzzy c-means clustering algorithm", Computers & Geosciences, Vol. 10 No. 2, pp. 191–203, 1984.

[5] R. Nilakant, H. P. Menon, and Vikram K,"A Survey on Advanced Segmentation Techniques for Brain MRI Image Segmentation," International Journal on Advanced Science, Engineering and Information Technology, Vol. 7 No. 4, 2017.

[6] K. S. Chuang, H. L. Tzeng, S. Chen, J. Wu, & T. J. Chen, "Fuzzy c-means clustering with spatial information for image segmentation", computerized medical imaging and graphics, Vol. 30 No. 1, pp 9-15, 2006.

[7] S. K. Adhikari, J. K. Sing, D. K. Basu, & M. Nasipuri, "Conditional spatial fuzzy C-means clustering algorithm for segmentation of MRI images", Applied Soft Computing, Vol. 34, pp. 758-769, 2015.

[8] A. Fariza, A. Z. Arifin, & E. R. Astuti, "Dental X-ray Image Segmentation using Gaussian Kernel-Based in Conditional Spatial Fuzzy C-means", International Journal on Advanced Science, Engineering and Information Technology, Vol. 7 No. 6, pp. 2159-2167, 2017.

[9] F. Zhao, & X. Xie, An overview of interactive medical image segmentation, Annals of the BMVA, Vol 7, pp. 1-22, 2013.

[10] T. M. Tuan, & T. T. Ngan, "A novel semi-supervised fuzzy clustering method based on interactive fuzzy satisficing for dental x-ray image segmentation". Applied Intelligence, Vol. 45 No. 2, pp. 402-428, 2016.

[11] A. Z. Arifin, R. Indraswari, N. Suciati, E. R. Astuti, & D. A. Navastara, "Region Merging Strategy Using Statistical Analysis for Interactive Image Segmentation on Dental Panoramic Radiographs", International Review on Computers and Software, Vol. 12 No. 6, pp. 63-74, 2017.