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INTERACTIVE IMAGE SEGMENTATION USING NEIGHBOURHOOD SPATIAL INFORMATION AND STATISTICAL GREY LEVEL

Shabrina Choirunnisa, Ari Firmanto, Agus Zaenal

Department of Informatics, Faculty of Information and Communication Technology, Sepuluh Nopember Institute of Technology, Surabaya, 60111, Indonesia

shabrinacnisa@gmail.com, arifirmanto@gmail.com, agusza@cs.its.ac.id

Abstract

In dental panoramic radiographs, grey-level intensity information has been widely used for object segmentation in digital image. However, low contrast in the radiograph image causes high ambiguity that can cause the inconsistency of classification result. Since the grey-level intensity of background and object is almost similar, so in order to improve the segmentation result, the spatial distance on neighbourhood region is applied. In this paper, we proposed a novel strategy to measure the distance using neighbourhood spatial information and statistical grey level technique for image segmentation. The proposed method starts by calculating adjacency matrix and measured spatial distance on neighbourhood region. Since the value of both distances are not in the same range, then the normalization is needed. The distances merging is approached by tuning the weight using several constant values. The experiment results show that our proposed merging strategy has better segmentation result based on Relative Foreground Area Error value.

Keywords: *Dental Panoramic Radiograph, Interactive Image Segmentation, Low Contrast, Spatial Information*

Abstrak

Pada citra radiografi panoramik gigi, informasi intensitas tingkat keabuan telah banyak digunakan untuk melakukan proses segmentasi objek pada citra digital. Namun, kontras rendah pada gambar radiografi menyebabkan ambiguitas tinggi yang dapat menyebabkan inkonsistensi hasil klasifikasi. Karena intensitas tingkat abu-abu pada latar belakang dan objek hampir serupa, sehingga untuk meningkatkan hasil segmentasi, jarak spasial pada wilayah lingkungan diterapkan. Dalam tulisan ini, kami mengusulkan strategi baru untuk mengukur jarak menggunakan informasi spasial lingkungan dan teknik statistik tingkat abu-abu pada segmentasi gambar. Metode yang diusulkan dimulai dengan menghitung matriks ketetanggaan dan mengukur jarak spasial di wilayah lingkungan. Karena nilai dari kedua jarak tidak dalam kisaran yang sama, maka diperlukan normalisasi. Penggabungan jarak diperoleh dengan menyetel bobot menggunakan beberapa nilai konstanta. Hasil percobaan menunjukkan bahwa strategi penggabungan yang diusulkan memiliki hasil segmentasi yang lebih baik berdasarkan nilai Relative Foreground Area Error.

Kata Kunci: *Radiografi Panoramik Gigi, Segmentasi Gambar Interaktif, Kontras Rendah, Informasi Spasial, Penggabungan Area*

1. Introduction

In the field of image analysis, the background and foreground separation is one of the most important stage to obtain the useful information from image. Inaccurate segmentation results can lead to misclassification or fatal diagnostic errors primarily in medical implementation. Therefore, developing the efficient methods and algorithms for segmentation in the medical field always continues to grow.

One of the most popular technique to obtain the separated background and foreground region is thresholding. In general, thresholding is assigned by validating whether the grey-level reaches a certain threshold value then it will be classified into a class, otherwise, it is assigned to other class. The well-known method is Otsu thresholding [1], fuzzy entropy measure-based thresholding method by Huang and Wang et al [2], and valley-seeking methods by Chi et al [3]. While Soon. H. Kwon proposes a thresholding measurement by considering not only grey level but also the spatial information of images [4].

Many segmentation methods are also approached and classified based on how to obtain the region information: automatic segmentation, semi-automatic segmentation, and manual segmentation. The features of shape, texture, and colour are usually used for automatic segmentation. Meanwhile, semi-automatic segmentation is the combination of manual and automatic segmentation by processing the marking input from user to help the system for object extraction.

Since dental panoramic radiographs has low contrast, therefore the object separation is a challenging task while using automatic segmentation technique. Other than that, it also can has some noises such as speckle noise that make the segmentation process be more challenging. There are some preceding noise reduction techniques: Kuan filter, Weiner Filter, NLM filter, and Lee filter that efficient in reducing the speckle noise.

In this research, we improve the previous approach by A. Arifin, et al [5] that developing the hybrid of spatial information and statistical grey level technique to address the ambiguity issue. The fundamental reason is because sometimes the same histogram representative is obtained from the different image types and details. So that, the hybrid method hopefully can reduce the ambiguity issue and get the more accurate of region of interest segmentation.

2. Related work

There are some proposed segmentation of radiograph image. Cortical bone from dental panoramic radiographs can be used as osteoporosis detection. S. Geary, et al [6] and M. S. Kavitha, et al [7] approach the system to detect the osteoporosis earlier in women.

Due to the ambiguity of grey-level on images, there are some proposed research to segment the ROI more clearly such as [1] [2] [4] [8]. Chang C. C, et al [8] using a very well-known filter: high pass and low pass to get the area of object. While Huang et al [2], propose thresholding technique by using fuzziness function. Otsu, et al [1] propose thresholding by using histogram of grey intensity. Kwon, et al [4] propose not only using intensity information, spatial information is also added to determine the threshold.

In this research, we propose a new distance measurement by using neighbourhood spatial information and statistical grey level on dental panoramic radiograph.

3. Proposed method

Our work is based on [5] for interactive image segmentation that consists of four main processes: region splitting, user marking, distance measurement, and region merging (as seen in Fig. 1). Our contribution is focused in combining both statistical grey level and neighbourhood spatial information while measuring the distance. Other than that, region adjacency graph is also added to select only the neighbourhood-split-region that will be processed for the next stage.

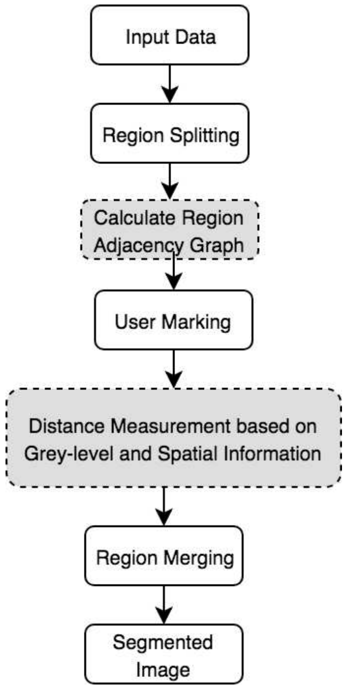

Fig. 1. Flowchart of the proposed method

3.1 Region Splitting

Firstly, the region splitting is developed using Edison software that use mean shift algorithm. The pixels are split based on the density probability function. The centre of cluster are shifted until it will be convergence. The process will stop until the zero vectors are achieved.

In region splitting, the split regions will be obtained from an image I into K regions [1,2,3,…K]. There regions will be gathered into a cluster called non-marked cluster C as represented in Equation 1.

$$I = C = \{Ci\}_{i=1,2,3\ldots K} \quad (1)$$

3.2 Region Adjacency Graph

After the labels of split regions are obtained, then the adjacency matrix is applied. The purpose of region adjacency graph is to select the neighboring adjacent regions so that the next stage can be processed more efficiently [9]. Figure 2 is illustrated the simple process of RAG. In an image *I,* there are some cluster regions *K*, then each region has a respective label. As seen in graph representation, each region also has the nearest neighbor region. This connection of neighborhood is represented as an edge (Figure 1 on the right).

(a) (b)

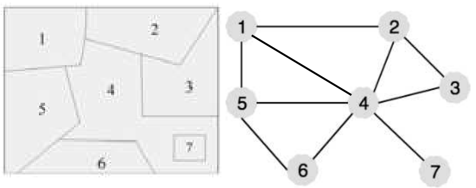

Fig. 2. Adjacency Graph Illustration

An adjacency matrix is established to represent the connection among each region as seen in Table 1. If there is a neighbourhood connection among two regions, then the value is1, otherwise it will be 0.

TABLE 1
THE ADJACENCY MATRIX OF REGION GRAPH

Region	1	2	3	4	5	6	7
1	0	1	0	1	1	0	0
2	1	0	1	1	0	0	0
3	0	1	0	1	0	0	0
4	1	1	1	0	1	1	0
5	1	0	0	1	0	1	0
6	0	0	0	1	1	0	0
7	0	0	0	1	0	0	0

While Equation 2 is denoted matrix *A* after adjacent matrix process where its value consists of binary 0 or 1 and *K* is the number of cluster regions.

$$A = \mathbb{Z}2^{kxk} \text{ , } \mathbb{Z}2 \in \{0,1\} \qquad (2)$$

3.3 Marking Input by User

After initial segmented image is obtained by using mean shift algorithm, user need to draw the object and background markers. This information will be used as the guide for interactive image segmentation. If user marks the region k as an object, then region k will be assigned to the cluster of object (*O*) that described in Equation 3. In contrast, the region k will be assigned to background cluster *(B)* if user marks it as background region (see Equation 4). The region *k* will be assigned as non-marked cluster *(C)* if it's neither background nor object. Then, the input image has three different clusters: object clusters, background clusters and non-marked clusters (as denoted in Equation 5).

$$O = \{O\text{i}\}, _{\text{i = 1,,2,3..,n}} \qquad (3)$$

$$B = \{B\text{i}\}, _{\text{i = 1,2,3,..,m}} \qquad (4)$$

$$I = \{C, O, B\} \qquad (5)$$

3.4 Distance Measurement based on Grey-Level and Spatial Information

For the distance measurement, the statistical grey-level distance is calculated using inter class variance between non marked region to either object region or background region. While for the spatial information, each pixel point of the region is calculated by measuring the distance to find the centre point. Since the range of each distance value (grey-level and spatial) is different, the normalization and weighting technique are obtained.

A. Grey-Level

After the object cluster *O*, background cluster B and non-marked cluster C are obtained, the distance based on grey-level is calculated. To earn the grey-level distance among the inter-class, we adjust the Inter-Class Variance formula [1] as written in Equation 6 and Equation 7.

$$DistGO_C = \sum_{i=1}^{n} \omega_{GC}\omega_{GOi} \| \mu_{GOi} - \mu_{GC} \| \qquad (6)$$

$$DistGB_C = \sum_{i=1}^{m} \omega_{BC}\omega_{Bi} \| \mu_{Bi} - \mu_{BC} \| \qquad (7)$$

Where $DistGO_{CK}$ is the grey-level distance of non-marked region to the object region. While $DistGB_{CK}$ is the distance of non-marked region to the background region. Moreover, ω is a weight or ratio parameter that obtained based on the variance value among two clusters. The weight area of region *C*, object and region clusters are denoted as ω_C, ω_{GOi}, ω_{Bi}, respectively.

μ_G parameter is denoted as the mean of intensity value and formulated in Equation 8.

$$\mu_{GC} = \frac{\sum_{i=1}^{Lk} x_i}{n_k} \qquad (8)$$

given the pixel values of region k be represented in levels [1, 2, …, *Lk*] and the number of pixels in region *k* at level *i* is denoted by x_i. Then the number of pixels in the region *k* is $nk = x_1 + x_2 + \ldots + x_{Lk}$.

B. Spatial Information

For the distance using spatial information, we inspired from Kwon, et al [4] that use the thresholding technique based on cluster analysis. Let Y=$\{y_1, y_2, \ldots y_{MxN}\}$ is the point coordinates of region and $y_k = (y_k^1, y_k^2)$ is denotes the kth point ($1 \le k \le n$), and y_k^j denotes the *j*th coordinate of the *k*th point. Then, the centre of cluster can be formulated as:

$$\mu_{KC} = \omega_{KC} \sum_{y_k \in Y} y_k \quad (8)$$

Finally, the distance calculation based on spatial information is denoted as Equation (and Equation 10.

$$DistKO_C = \omega_{KC} * (\mu_{KC} - \sum_{y_k \in y} \sqrt{\mu_{KO_i} - \mu_{KO_{n-1}}}) \quad (9)$$

$$DistKB_C = \omega_{KC} * (\mu_{KC} - \sum_{y_k \in y} \sqrt{\mu_{KB_i} - \mu_{KB_{n-1}}}) \quad (10)$$

where ω_{KC} is the weighting factor that formulated as Equation 11.

$$\omega_{KC} = \frac{1}{\|Y\|} \quad (11)$$

C. Normalization

After distance using grey-level and spatial information are obtained, the normalization is required since both distance have different range of value. The normalization form is generated by divided of object and background distance with summation distance respectively. Then using a constant parameter α={0,…,1} as the weighting ratio to adjust the ratio between spatial and grey level distance. Equation 12 and Equation 13 is denoted as the distance after.

$$DistO = \alpha\left(\frac{DistGO_C}{DistGTotal}\right) + (1-\alpha)\left(\frac{DistKO_C}{DistKTotal}\right) \quad (12)$$

$$DistB = \alpha\left(\frac{DistGB_C}{DistGTotal}\right) + (1-\alpha)\left(\frac{DistKB_C}{DistKTotal}\right) \quad (13)$$

where $DistGTotal$ and $DistKTotal$ are respectively the summation distance of grey-level and spatial information that represented as Equation 14 and Equation 15.

$$DistGTotal = DistGO_C + DistGB_C \quad (14)$$

$$DistKTotal = DistKO_C + DistKB_C \quad (15)$$

3.5 Region Merging

The region merging technique is adapted from [5], by examining if the region with the minimum distance is more near to either object cluster or background cluster. In other word, if the background distance is smaller than the object cluster, then the region is merged to background cluster, otherwise, it's clustered as object region.

4. Experimental results and discussion

The proposed method has been tested in several images. The experiments are tested using dental panoramic radiograph images, fruit images and color-blind test image. The result of segmentation is presented without using hole filling algorithm. In the previous method, hole filling algorithm is applied. To evaluate the performance of segmentation, Misclassification Error (ME) and Relative Foreground Area Error (RAE) are used [10].

The ratio of object pixels is calculated using Misclassification Error (ME) to measure the wrong classified region as background, and the opposite. ME is represented as Equation 16.

$$\mathrm{ME} = 1 - \frac{|O_g \cap O_r| + |B_g \cap B_r|}{|O_g| + |B_g|} \quad (16)$$

Let O_g and B_g is denoted as the object and background pixels of the ground truth image. While O_r and B_r is represented of the object and background pixels of the segmentation result. Other than that, the ratio of the difference among object's area in ground truth image and the segmentation result are evaluated by using Relative Foreground Area Error (RAE) measurement. RAE can be expressed as Equation 17.

$$\begin{cases} \frac{A_g - A_r}{A_g} & if\ A_r < A_g \\ \frac{A_r - A_g}{A_r} & if\ A_g < A_r \end{cases} \quad (17)$$

Given A_g as the object of the ground truth image and A_r is the object area of the segmentation result. The range of ME and RAE value are between 0 and 1. The ME and RAE comparison among proposed method and previous method [5] can be seen in Table 2.

TABLE 2. THE COMPARISON OF PROPOSED METHOD AND PREVIOUS METHOD [5]

No	Image Name	Proposed Method		Previous Method [5]	
		ME (%)	RAE (%)	ME (%)	RAE (%)
1	a	**6.14**	**4.83**	6.47	9.21
2	b	12.6	9.6	**10.14**	**1.27**
3	c	**0.0168**	**0.0122**	0.0277	0.030783
4	d	**0.1214**	**0.2620**	0.20471	0.44135
5	e	**0.0124**	**0.0222**	0.0403	0.07199

In Fig. 3c, our proposed method can obtain better results with the value of ME 0.0168 and RAE 0.0122. If we look at the picture then the hole in the middle of the apple closes perfectly. If using only gray level information will be very dependent on the marking of the user, for example in the apple picture there is a region with the value of gray that is not marked yet.

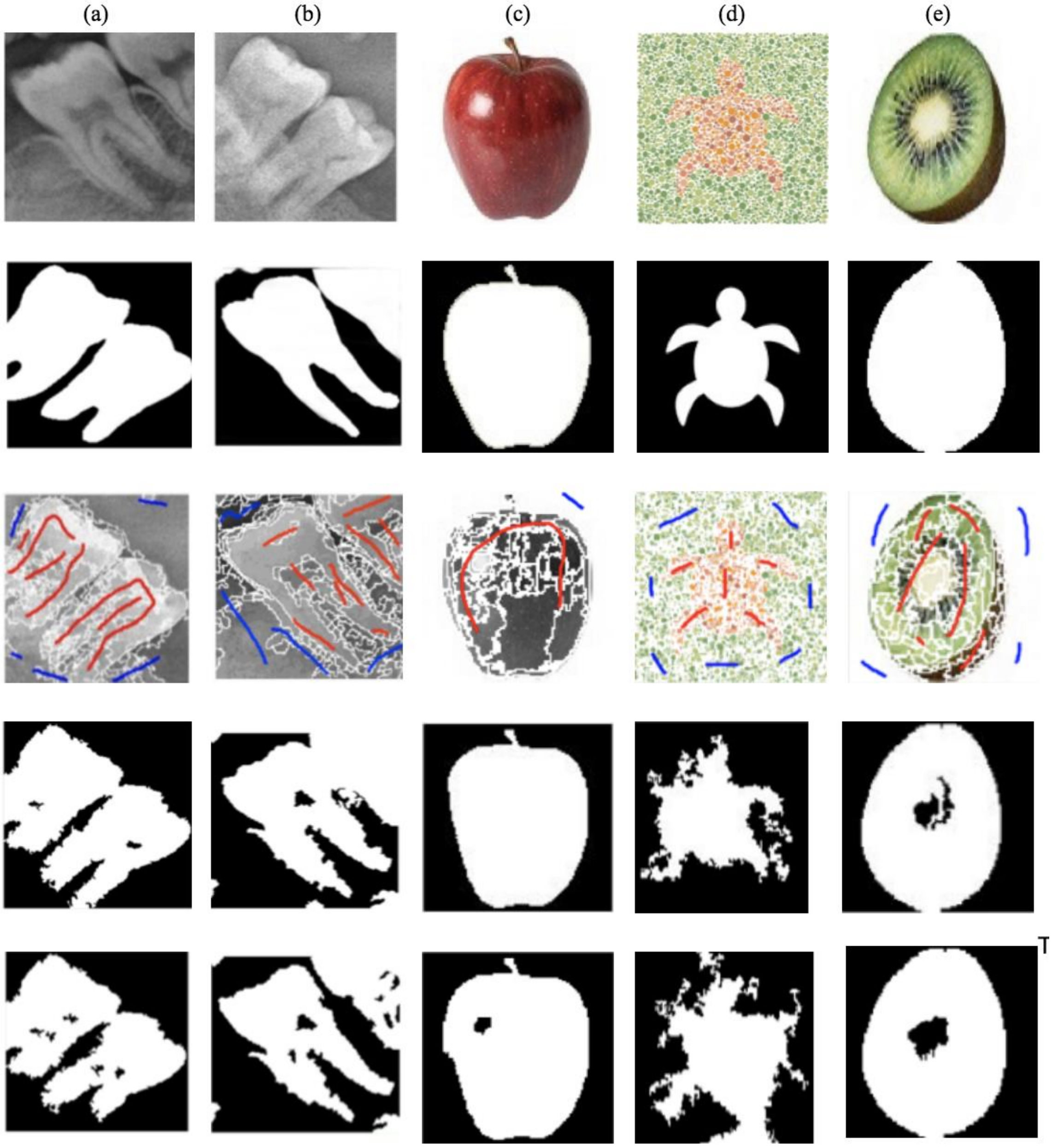

Fig. 3. 1st row: Original Images, 2nd row: Groundtruth Images, 3rd row: Splitted Regions by Edison and its markers. The red marker is the object and the blue marker is the background, 4th row: Proposed Method, 5th row: Previous Method [5] on 5 different testing images (a-e).

If we only use the gray level information then the region will automatically merged into the background as it is closer to white, while the marked object is closer to dark gray. By adding spatial information, it will be seen from the surrounding neighbors, if the surrounding neighbors are cluster objects then the distance value will tend to be closer to the cluster object.

Our method is inspired from Kwon [4] where in his research, the color blind test image is used as a testing image. In Fig. 3d, the color blind test is applied by our proposed method, and the result is better than the previous method [5] with RAE 0.2620 and ME 0.1214. However, there are still many areas that mis-classified, especially the region around the object.

As seen in Fig. 3 for image a, b, and e of the proposed method, we can reduce the holes in the segmentation result, but not all holes are covered because our method is highly dependent on the neighboring region of the object and in the background. Our method will be good as in Fig. 3c if the unmarked region has neighbor region either on cluster object or background, but if neither have neighbor region or neighbor region still unmarked not categorized to cluster object or background then our proposed method can not produce segmentation result in perfect, for example picture e in figure 3 there is a hole in the fruit, the middle region of the hole on the categorized background because neighboring surrounding is still unmarked region. This is because in our proposed method of distance calculation using the whole member of the cluster object and cluster background if unmarked region has no neighbor, therefore need better algorithm mechanism to find the neighbor first so that the result of segmentation will be better.

5. Conclussion

In this study, the gray level and spatial information is used for the interactive image segmentation process. We have some good images of color image, low constrast image, and color blindness test image The statistically obtained results proposed our existing methods with smaller values, and in view of the method we succeeded in reducing the hole which in the previous method [5] could not remove the hole without hole filling algorithm. So our method is more efficient, because without using hole filling algorithm good result can be achieved.

Our method relies on neighboring regions, if unmarked areas have adjacent territories then our method would be excellent in segmenting, otherwise our methods will missclassify between objects and backgrounds. For future work are required for various objects and background clusters better, the result of segmentation would be better.

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