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Welcome Message from
General Chairs

On behalf of the Organizing Committee of this International Conference on Advanced Computer Science and Information System 2009 (ICACISIS 2009), we would like to extend our warm welcome to all of the participants and speakers, in particular, we would like to express our sincere gratitude to those who give plenary speeches.

This conference is organized by Faculty of Computer Science - Universitas Indonesia. This conference is intended to be a first step toward an Asian-Europe conference on Computer Science and Information System. We believe that this International Conference will give opportunities for sharing or exchanging original research ideas and opinions amongst members of Indonesian research communities, together with researchers from Japan, Germany, Singapore, and Malaysia.

This conference focuses on the development of computer science and information systems. Along with 5 plenary talks, the proceeding contains 75 papers that are presented during the conference. This ICACISIS 2009 conference receives a total of 100 submissions from nine different countries. Among those paper submissions, 75 papers are accepted in the conference program.

We hope that all participants enjoy the program and gain inspiration for future research. We would like to take this opportunity to express our sincere appreciation to the members of the Program Committees for the careful review of the submitted papers, as well as the Organizing Committees for devoting their time and energy in making the program fruitful and for editing the proceeding. We would also like to appreciate the authors who have submitted excellent papers for this conference. Last but not least, we would like to extend our gratitude to Minister of Education and Minister of Communication and Information Technology - Republic of Indonesia for their continuous supports, to Rector and Dean of Computer Science Faculty of Universitas Indonesia for their supports for the ICACISIS 2009 conference.

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Abstract— Panoramic radiographs are usually taken to examine dental diseases. Other works used them for early detecting individuals with general skeletal bone diseases, such as osteoporosis. However most works in computer-aided diagnosis on panoramic radiographs heavily depend on the performance of the segmentation method, due to unevenly illumination and low contrast of the images. We conduct an exhaustive survey for four excellent image thresholding methods and provide their performance comparison on experimental images consisting special area of interest on panoramic radiographs. The methods include Multistage Adaptive Thresholding, Otsu, Hierarchical Cluster Analysis, and Fuzzy Sets Type II methods. The comparison is carried out based on the combined performance measures. We identify the MAT method perform better over teeth image applications.

Index Terms— image segmentation, local thresholding, local image statistic, dental panoramic radiographs.

I. INTRODUCTION

Dental panoramic radiographs are frequently taken by any people especially who have dental diseases. Every year, the availability of these images is approximately 10 million in Japan, 17 million in the United States, and 1.5 million in England and Wales [1]. That is important for examining dental diseases such as dental caries and periodontal disease. It would be both economical and beneficial if these radiographs could be used for identifying postmenopausal women with undetected osteoporosis so that dentists could refer them to medical professionals for DXA testing. Recently we have developed some computer-aided systems for measuring cortical bone and trabecular bone on dental panoramic radiographs for detecting osteoporosis postmenopausal women. Teeth images are also important to segment because it can result some information regarding someone conditions.

Most works in computer-aided diagnosis on panoramic radiographs heavily depend on the capability of the segmentation tools so as to have segments which are ready to be measured. However, performance of the method usually can not achieve excellent results. Due to unevenly illumination and low contrast of the original images.

Thresholding algorithm produces a binary image whose one state will indicate the foreground objects, that is, teeth, while the complementary state will correspond to the background. The foreground can be represented by gray- level 0, and the background by the highest luminance, that is 255 in 8-bit images, or conversely the foreground by white and the background by black. Various factors, such as nonstationary and correlated noise, ambient illumination, busyness of gray levels within the object and its background, inadequate contrast, and object size not commensurate with the scene, complicate the thresholding operation.

In this paper we provide an exhaustive survey for some excellent image thresholding methods for thresholding area of interest consisted of teeth on dental panoramic radiographs. This paper also assess their performance comparatively using a set of objective segmentation quality metrics.

We distinguish four thresholding algorithms including Multistage Adaptive Thresholding (MAT), Otsu, Hierarchical Cluster Analysis (HCA), and Fuzzy Sets Type II methods. We choose MAT because this method due to its robustness in the presence of noise. While Otsu method is widely used method in the world, even in the commercial image processing software. HCA and Fuzzy are two recently proposed that seems superior in segmenting image and robust to noise.

This paper focuses on bi-level thresholding that often called as binarization. An image as a result of thresholding process can be presented in histogram image, to know distribution of pixel intensity values to image or specific part of it. For images with bi-modal distribution, its histogram can be partitioned by determining its threshold value.

The methods were evaluated using Misclassification Error (ME) and Relative foreground Area Error (RAE) to know the performance of each method and to conclude which method is the best performance.

II. MULTISTAGE ADAPTIVE THRESHOLDING (MAT)

General algorithm that is used to thresholding image is using Multistage Adaptive Thresholding (MAT) method described as follows:
1) Preprocessing.
2) Determine two global threshold $T_0$ and $T_1$ that
have been used in stage of calculation of threshold value based on criteria.

3) Calculate k (pixel ratio that is classified as object and background) automatically. Value k also will use in calculation threshold value based on criteria.

4) Determine adaptive neighborhood size "h".

5) Calculate threshold value based on criteria.

A. Locally Adaptive Thresholding

Given an input image \( f(x) \), thresholding may be viewed as an operation that involves tests against the function of \( t(x) \). A thresholded image \( g(x) \) is defined as

\[
g(x) = \begin{cases} 
1 & \text{if } \{ t(x) = 0 \\
0 & \text{if } \{ t(x) = 1 \\
\end{cases}
\]

Label of 1 and 0 correspond to object and background, respectively. In global threshold algorithm, we first compute a fixed threshold \( T \) and then define the threshold function as

\[
t(x) = f(x) - T
\]

This method uses the local image statistics, in a linear combination, of the mean and the standard deviation. The thresholding function is defined as

\[
t(x) = f(x) - \mu_x - k \sigma_x
\]

where

\[
\mu_x = \frac{1}{N} \sum_{i=1}^{N} f(x) \quad \text{and} \quad \sigma_x = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N} (f(x) - \mu_x)^2}
\]

are the mean and the standard deviation, respectively, in a \( b \times b \) neighborhood region \( S \) centered at \( x \), \( N = b \times b \), and \( k \) is a constant coefficient. The threshold function becomes:

\[
t(x) = p(x) - \mu_x - k \sigma_x
\]

B. Multistage Thresholding

Global threshold method does not solve the problem in which some part of an object has higher intensity than background but lower than other part in same object. So, we need two global thresholds, i.e. low threshold \( T_0 \) and high threshold \( T_1 \). Pixels with gray value less than \( T_0 \) are classified as background, whereas pixels with gray value more than \( T_1 \) are classified as object. Strategy for resulting two global threshold \( T_0 \) and \( T_1 \) is using a modified multilevel thresholding Otsu method [8]. A threshold function is combined as MAT becomes [4]:

\[
t(x) = \begin{cases} 
\mu_x - T_1 & \text{if } p(x) \leq T_1 \\
\mu_x - T_0 & \text{if } p(x) \leq T_0 \\
\mu_x - k \sigma_x & \text{if } p(x) \leq \mu_x
\end{cases}
\]

C. Automatic Calculation of \( k \)

Coefficient \( k \) in Equation (7) is used for determining pixel ratio that is classified as object and background [4]. In general, the smaller the chosen \( k \), the more likely it is for pixels to be classified as objects. Therefore, the selection of \( k \) directly affects the thresholding result.

Given background ratio with object \( \rho \) that can be estimated by global threshold result on input image, coefficient \( k \) can be calculated by

\[
\int_{-\infty}^{+\infty} N_{\rho,L}(x) dx = \rho
\]

using \( z \) table after the transformation of \( z = (X - \mu)/\sigma \).

a. Find global threshold \( T_g \) for image input \( f(x) \) by using Otsu algorithm [8].

b. Estimation \( \rho \) ratio by using formula:

\[
\rho = \left( \frac{\sum_{i=1}^{N} c_i}{(M \times N)} \right)
\]

\[
c_i = \begin{cases} 
1 & \text{if } f(i) < T_g \\
0 & \text{otherwise.}
\end{cases}
\]

where \( M \) and \( N \) are width and height \( f(x) \)

c. Calculate \( k \) by using Equation (8).

III. OTSU THRESHOLDING

This method is from viewpoint of discriminant analysis. It directly approaches the feasibility of evaluating the optimal threshold and automatically selecting in optimal threshold. An optimal threshold is selected by the discriminant criterion to maximize the separability of the resultant classes in gray levels. The procedure is simple, utilizing only the zeroth and the first order cumulative moments of the gray level histogram.

This method is done by minimizing the weighted sum of within-class variances of the foreground and background pixels to establish an optimum threshold. Recall that minimization of within class variances is tantamount to the maximization of between-class scatter. This method gives satisfactory results when the numbers of pixels in each class are close to each other.

In order to find and evaluate the goodness of the threshold (at level \( k \)) using discriminant criterion measures (measures of class separability) used in discriminant analysis:

\[
\lambda = \frac{\sigma^2_\eta}{\sigma^2_\xi}, \quad x = \frac{\sigma^2_\eta}{\sigma^2_\xi}, \quad \eta = \frac{\sigma^2_\xi}{\sigma^2_\eta}
\]

where

\[
\sigma^2_\xi = w_x \sigma^2_\xi + w_\xi \sigma^2_\xi
\]

\[
\sigma^2_\eta = w_x (\mu_x - \mu_\xi)^2 + w_\eta (\mu_\eta - \mu_\xi)^2
\]

\[
\xi = \sum_{i} (i - \mu)^2 \rho
\]

are within class variance, the between class variance and the total variance of levels, respectively.

\( \sigma^2_\eta \) that is based on the second order statistics (class variances) and \( \sigma^2_\xi \) that is based on the first order statistics (class means) are functions of threshold level \( k \) but \( \sigma^2_\xi \) is independent of \( k \). Therefore, \( \eta \) is the simplest measure with respect to \( k \) and as criterion measure to evaluate the separability of the threshold at level \( k \). So, the optimal threshold \( k \) is maximizes \( \eta \) or
IV. HIERARCHICAL CLUSTER ANALYSIS (HCA)

This method attempts to develop a dendrogram of gray levels in the histogram of an image, based on the similarity measure which involves the inter-class variance of the clusters to be merged and the intra-class variance of the new merged cluster.

The bottom-up generation of clusters employing a dendrogram by this method yields a good separation of the clusters and obtains a robust estimate of the threshold. Such cluster organization will yield a clear separation between object and background even for the cases of nearly unimodal or multimodal histogram. Since this method performs an iterative merging operation, the extension into multi-level thresholding problem is a straightforward task by just terminating the grouping when the expected number of clusters of pixel values are obtained. This method improves its merging criteria by involving inter-class variance and intra-class variance in the similarity measurement, so as to maximize the distance of cluster means, as well as the variance of the new merged cluster.

1. We assume that the target histogram contains \( K \) different non-empty gray levels. At the beginning of the merging process, each cluster is assigned to each gray level, i.e. the number of clusters is \( K \) and each cluster contains only one gray level.

2. The following two steps are repeated \((K - 1)\) times for \( t \)-level thresholding:
   a. The distance between every pair of adjacent clusters is computed. The distance indicates the dissimilarity of the adjacent clusters, and will be defined in the next subsection.
   b. The pair of the smallest distance is found, and these clusters are unified into one cluster. The index of clusters \( C_i \) and \( C_j \) are reassigned since the number of clusters is decreased one by the merging.

3. Finally \( t \) clusters, \( C_1, C_2, \ldots, C_t \), are obtained. The gray levels \( T_0, T_1, \ldots, T_{t-1} \), which are the highest gray levels of the clusters, are the estimated thresholds. For the usual two-level thresholding, \( t = 2 \) and the estimated threshold is \( T_1 \), i.e., the highest gray level of the cluster lower brightness.

The distance between two adjacent clusters in the histogram is based on both the difference between the means of the two clusters and the variance of the resultant cluster by the merging.

\[
\text{Dist}(C_i, C_j) = \sigma_i^2(C_i \cup C_j) \sigma_j^2(C_i \cup C_j)
\]

The two parameters in the definition correspond to the inter-class variance and the intra-class variance, respectively. The inter-class variance, \( \sigma^2(C_i \cup C_j) \) is the sum of the square distances between the means of the two clusters and the total mean of both clusters. And The intra-class variance, \( \sigma^2(C_i \cup C_j) \) is the variance of all pixel values in the merged cluster.

V. FUZZY SETS TYPE II

Measure of fuzziness express difficulty level in determination whether an element or data will be a member or not in specified fuzzy sets. Difficulty level determines the highest level of data in fuzzy sets is achieved when degree of member has grade 0.5. The flat membership function shows high ambiguity level while the steep one shows low level of ambiguity. A flat membership function indicates high vagueness image and yields in difficulty of thresholding process.

Type II fuzzy sets is designed by making membership function in three dimension where each element in type II fuzzy sets has membership value in range \([0,1]\). The third dimension is an extension and adds degrees of freedom to get more information in represented fuzzy sets. Type II fuzzy sets are very useful when there is a difficulty in determining appropriate membership function for a fuzzy set and problem related with ambiguity.

![Type II fuzzy set reconstruction and type I fuzzy set.](image)

Type II fuzzy sets have a not sure membership value or named "fuzzy". Membership value in type II fuzzy sets can be any value in range \([0,1]\). This membership principal is called primary membership. Related with each primary membership, there is a secondary membership (also has a value in range \([0,1]\) that assign possibility to be primary membership. Type I fuzzy sets are special part for type II fuzzy sets where its secondary membership function is a subset consist of one element only.

Axis in Fig. 1 shows main variable as member of fuzzy set, ordinate shows primary membership value, and the third axis (up direction) shows secondary membership for each primary membership or called amplitude.

General algorithm to threshold the image based on type II fuzzy sets and measurement of ultrafuzziness is defined as follows:

1. Choose type of membership function to determine membership value \( \mu(x) \) and initialize value of \( a \). In this paper, two membership functions represent object fuzzy set and background fuzzy set, respectively.
2. Compute image histogram.
3. Determine initial position location of membership
function.

(4) Shift membership function along gray level range to calculate fuzziness total in each position as shown in Fig. 2. Maximum fuzziness total indicates optimal threshold value.

(5) Compute upper membership value and lower membership value, \( \mu_u(g) \) and \( \mu_l(g) \) in each position.

(6) Calculate ultrafuzziness value for object fuzzy set and background fuzzy set, respectively.

(7) Compute ultrafuzziness total value.

(8) Find position \( g_{opt} \) which has maximum ultrafuzziness total value.

(9) Threshold image using \( T = g_{opt} \).

\[ ME = 1 - \frac{|B_o \cap B_r| + |F_o \cap F_r|}{|B_o| + |F_o|} \]  \hspace{1cm} (19)

where \( B_o \) is background of ground truth image, \( F_o \) is foreground of ground truth image, \( B_T \) is background of tested image (thresholding result image) and \( F_T \) is foreground of tested image (thresholding result image).

- Relative foreground Area Error (RAE): to calculate expediency between thresholding result image and ground truth image.

\[ RAE = \begin{cases} \frac{A_o - A_r}{A_o} & \text{if } A_r < A_o \\ \frac{A_r - A_o}{A_r} & \text{if } A_r \geq A_o \end{cases} \]  \hspace{1cm} (20)

where \( A_o \) is foreground region of ground truth image and \( A_T \) is foreground region of thresholding result image.

Table 1 show the performance of thresholding based on ME and RAE value for each thresholding algorithm that is a comparison between threshold result image and ground truth image. According to ME evaluation, threshold result image that have applied MAT method give smallest value of ME. It has indicated that error ratio value of background pixel that is determined as foreground and conversely is smallest one. Whereas according to RAE evaluation, threshold result image that have applied MAT method also give smallest RAE value that has indicated that the compatibility of object region segmentation between threshold result image and ground truth image is highest one. Therefore, based on ME and RAE evaluation on Table 1, MAT method is the best method because it has smallest value of ME and RAE.

Table 1. Evaluation of thresholding performance between MAT method and other three methods based on ME and RAE

<table>
<thead>
<tr>
<th>Image Sample</th>
<th>Thresholding Method</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Otsu Method</td>
</tr>
<tr>
<td>ME</td>
<td></td>
</tr>
<tr>
<td>Image 1</td>
<td>15.52%</td>
</tr>
<tr>
<td>Image 2</td>
<td>6.03%</td>
</tr>
<tr>
<td>Image 3</td>
<td>10.72%</td>
</tr>
<tr>
<td>Image 4</td>
<td>26.44%</td>
</tr>
<tr>
<td>Image 5</td>
<td>41.65%</td>
</tr>
<tr>
<td>RAE</td>
<td></td>
</tr>
<tr>
<td>Image 1</td>
<td>21.29%</td>
</tr>
<tr>
<td>Image 2</td>
<td>7.61%</td>
</tr>
<tr>
<td>Image 3</td>
<td>24.81%</td>
</tr>
<tr>
<td>Image 4</td>
<td>43.85%</td>
</tr>
<tr>
<td>Image 5</td>
<td>54.96%</td>
</tr>
</tbody>
</table>

Note: Smallest value is written bold

The performance of image thresholding using ultrafuzziness optimization based on type II fuzzy sets has been proofed to be more optimal when compared with type I fuzzy sets thresholding.

VI. RESULT AND DISCUSSION

In experiment, we compare four methods, i.e.: (i) Otsu thresholding method [8], (ii) thresholding method by using Hierarchical Cluster Analysis (HCA) [1], and (iii) thresholding method by using Fuzzy Sets Type II [5]. To know the performance of each method, we have done the testing of 1-5 images (see Figure 3). Image result of MAT method can be seen on Figure 5, whereas Figure 6-8 have shown thresholding result image that using Otsu method, Hierarchical Cluster Analysis (HCA) method, and Fuzzy Sets Type II method.

Ground truth image is used to reference image to measure the performance of thresholding method. Ground truth images have been done manually based on original image as seen to Figure 4. We can see Figure 5 that thresholding result image is using MAT method that is dividing object and background successfully. Image of it result can correspond it well to ground truth image on Figure 4. Have a difference of image that result of three methods on Figure 6-8, they have been seen that it consist of several objects have classification error to background, so also it conversely.

Measurement is used to know the performance of each method, i.e. [1, 2]:

- Misclassification Error (ME): to correspond error ratio of background pixel that is determined as foreground and conversely.
I. CONCLUSION

Based on experimental images in segmenting teeth on dental panoramic radiographs, Multistage Adaptive Thresholding (MAT) method has better performance than Otsu method, Hierarchical Cluster Analysis (HCA) method and Fuzzy sets type II method. MAT method affords to correspond ground truth image for well. However MAT need to a proper neighborhood size. This variable can be determined well because we have specific object to segment, i.e. teeth.

REFERENCES


