Binerization of Panoramic Dental Image for Dental Anatomy Identification

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Abstract. Dental image is used for identification of a person because it can provide a lot of information about dental such as tooth contour, tooth position, and tooth shape. This research aims to process dental panoramic images in the form of greyscale images into binary images. Converting the greyscale image to binary is known as the thresholding process. The thresholding process is also called binerization. The input data used in this study is in the form of dental anatomical images produced by dental panoramic devices. The data used were 20 images, namely 10 abnormal dental images and 10 normal dental images. Results for the identification of dental anatomy with binerization the system and the manual calculation are the same. Identification normal dental are 50% and abnormal dental are 80%.

1. Introduction

Image processing is a system in which the process is carried out with input in the form of an image and the result is also in the form of an image. Initially this image processing was carried out to improve the image quality, but with the development of the computing world which was marked by the increasing capacity and speed of computer processes, as well as the emergence of computational sciences that enabled humans to retrieve information from an image, then image processing could not be released with the field of computer vision[1].

One of the fields of application for image processing is in the field of health, including identification of dental anatomy. Dental image is used for identification of a person because it can provide a lot of information about dental such as tooth contour, tooth position, tooth shape such as fillings or not and so on [2].

The tool used for dental anatomy identification is Dental Panoramic. This tool will produce images in the form of dental anatomy X-ray images. The results of dental anatomical images on panoramic dental have low contrast and detail and are unable to provide information from a cross sectional (one-part) perspective, so special methods or expertise are needed to avoid misinformation when interpreting images generated from these devices [3]. The tool used for dental anatomy is Dental Panoramic examination. This tool will produce images in the form of dental anatomy X-ray images. The results of dental anatomical images on panoramic dental have low contrast and detail and are unable to provide information from a cross sectional (one-part) perspective, so special methods or expertise are needed to avoid misinformation when interpreting images generated from these devices [3]. Dental image has been used for human recognition [4], forensic odontology [5], detection of granuloma disease [6], detection of dental caries [7].
Dental recognition has been carried out using principal components analysis[8], while this study aims to process dental panoramic images in the form of greyscale images into binary images. Converting the greyscale image to binary is known as the thresholding process. The thresholding process is also called binerization. Nafi’iyah (2017) uses a fuzzy self organizing map for the thresholding process in dental panoramic images [9]. In this study, the results of binaryisation were used to detect tooth anatomy. Research is expected to help identify the state of normal and abnormal dental.

2. Review on Various Matching Techniques

Nurtanio (2011) presents the application of active contour models (Snakes) for the segmentation of lesions in dental panoramic image. The aim is to assist the clinical expert in locating potentially cyst or tumor cases for further analysis (e.g. classification of cyst or tumor lesion). In order to apply the snake formulation, color images were converted into gray images. Then, with correct parameters, we can create a snake that is attracted to edges or termination. Initializing contour, choosing parameter value and number of iteration affect the behaviour of the snake in a particular way. Using Receiver Pperating Characteristic (ROC), an average accuracy rate of 99.67 % is obtained. Examples of Snake segmentation results of lesions are presented[10].

Patel et all (2012) analysis of dental image processing for human identification. The main challenge in developing an automated dental identification system is to deal with poor quality of images, dental overlap, imaging angle, dental shape change consideration due to aging, etc. One works to find a fast and better novel approach to enhance and segmentation method for dental radiograph and thereafter matching of PM image with AM images for better similarity results[11].

Nafi’iyah (2018) made a comparison of backpropagation and naïve bayes algorithms in the identification of human sex using panoramic dental. In the identification process so far the forensic team uses DNA, because its accuracy is very high. However, the time required is long. So the researchers created a system for identification of human sex in order to help the forensic team in the process of identifying victims of natural disasters en masse, because human dental are resistant to temperatures of 1000°C. The results of the comparison of two algorithms, namely: backpropagation can identify human sex with an accuracy of ± 85%. While the naïve bayes algorithm in identifying human sex has an accuracy of ± 81% [12].

Hashari (2018) constructed a MATLAB-based application using the Gabor Wavelet (GWT) method for feature extraction with the linear Discriminant Analysis (LDA) classification which reduced the dimensions of a group of images to identify an image, and obtained information about the type of molars and tooth age of the fossil tooth. The results obtained from this final research is the application based on MATLAB with 84.61% accuracy. To identify the age of fossil tooth death of gerham with total data 270 images consist of 140 image of train where 110 image for classification class 17-25 years and 30 image for classification class 25-35 years, test image total 130 image which consist of 100 image with class classification 17-25 years and 30 images with classification class 25-35 years. And 86.15% for identification of the type of molars with 270 images consisting of 140 training images where 70 images for upper tooth classification class class and 70 images for lower tooth classification class, test image total 130 images consisting of 100 images for the class upper tooth classification classification and 30 images for the lower tooth classification class [13].

2.1. Dental Panoramic Radiograph

Panoramic is one of the extra oral x-rays that has been used generally in dentistry to get a complete picture of the maxillofacial whole. One of the advantages of panoramic is the relatively small radiation dose wherein the radiation dose received by the patient for one panoramic photo is almost the same as a four-time intra-oral dose. Some of the advantages of Dental Panoramic Radiographs are as follows:

a. Increases the overall coverage of dental arches and related structures  
b. The relative production does not change the anatomy of the image  
c. Significantly reduces radiation dose for patients
d. Simplicity and speed of procedure
e. Reducing superimposition of anatomical structures
f. Minimal infection control procedure
g. Possible to detect caries, periodontal disease [14].

2.2. Thresholding Technique
It is simple image segmentation technique but powerful approach for segmenting images. From a gray scale image, thresholding can be used to create binary images. This technique is based on space regions i.e. on characteristics of image. In thresholding process, first convert gray scale image into binary image, by choosing proper threshold value T, divide image pixels into several space regions and separate objects from background. For example f(x,y) is intensity value of image pixel of object, if it is greater than or equal to T i.e., f(x,y)\geq T then it belongs to that object otherwise it belong to background. There are two types of thresholding methods with regarding selection of threshold value T: global and local thresholdings. In global thresholding threshold value T is constant where as in local thresholding value T is variable because of uneven illumination. Threshold selection is typically done interactively however, it is possible to derive automatic threshold selection algorithms [15]. Threshold technique can be expressed as:

\[ T = T(x,y), p(x,y), f(x,y) \]  

Where T is threshold value x,y are the coordinate of the threshold value point. p(x,y), f(x,y) are points of gray scale image. The threshold image g(x,y) is defined as:

\[ g(x,y) = 1 \text{ if } f(x,y) \geq T = 0 \text{ if } f(x,y) < T \] 

3. Method

3.1. The input data
The input data used in this study is in the form of dental anatomical images produced by dental panoramic devices. The data came from Rumah Sakit Jiwa (RSJ) Prof. Dr. Soerojo Magelang. The data used were 20 images, namely 10 abnormal dental images and 10 normal dental images. The image will be resized to 156 x 377 in size so that all images have the same size so that when the data enters the system can be analyzed with the same comparison. Changing the size of the image is done automatically on the system.

3.2. Software planning
Dental anatomy detection system in conducting research uses several methods, namely the study of literature obtained from journals, books, theses. Next is the design includes the design of software by making a dental anatomy detection program. This design uses a MATLAB GUI that is designed in such a way as to produce a matching system. System design drawings on the MATLAB GUI can be seen in Figure 1.
In the GUI design, dental anatomy is divided into 4 plots. The first plot is the plot to upload the image to be processed consisting of 2 axes that are used to upload images and used to refresh images according to the specified size. The second plot contains pre-processing for binerization. The third plot is for testing binary data and the fourth is for the button property. Figure 2 shows the flow diagram in the detection of dental anatomy by binerization.

4. Result

4.1. Training data
The training data used in this study uses training data from dental anatomy images. To recognize the data must be determined in advance the minimum and maximum values. The minimum value is 0 and the maximum value is 1. For values 0-1 this is the initial range to determine the dental anatomy training data entered into the system. These 0 and 1 values will be used as a basic range for normal and abnormal dental diagnoses. The next process is the ANN data test using binary data test. The results of iteration and error in machine learning will be shown in Table 1.
| No | Iteration | Mean Squared Error |
|----|-----------|--------------------|
| 1  | 10        | 0.0084             |
| 2  | 12        | 0.0092             |
| 3  | 6         | 0.0052             |

4.2. Manual calculation
For proving the data using manual calculations, 5 trials have been carried out which will be used as testing data to find out normal and abnormal values in dental anatomy images. Error data used in manual testing is different from testing using the system. The following is a range of dental anatomy data for manual testing.

\[
0.0186 > \text{Abnormal} < 0.45124 \\
0.45124 > \text{Normal} < 0.9616
\]

4.3. Result of system testing
The results of testing the anatomy of an abnormal dental that has passed several stages can be seen in Figure 3 and 4. This is picture fig 3 and, for the original image has a less clear image quality, blur and does not have the accuracy of the image such as color clarity, texture clarity, so that it is clarified using the binary method, which looks to have a color density, making it easier for images to be analyzed. Tooth anatomy that has been entered into the system will enter several stages, namely resizing binaryization and a classification system, in this system there is a comparison of the results of natural teeth and teeth that have entered the binaryization stage. This stage has a 50% result because the system shows the comparison between the original image and the image that has been processed where the comparison has a less accurate presentation when loaded into the system.

![Original image](image1) ![Binary image](image2)

**Figure 3.** Results of image testing are abnormal

The results of testing the anatomy of a normal dental that has passed several stages can be seen in Figure 4.
4.4. Result of data on dental anatomy image normal and abnormal system test

Results of normal and abnormal dental anatomy testing can be seen in Tables 2 and 3.

**Table 2.** Normal dental image testing results on the system

| No. | Image | Binary value | Diagnosis Binary |
|-----|-------|--------------|------------------|
| 1   | N_1.jpg | 0.032749     | Abnormal         |
| 2   | N_2.jpg | 0.045205     | Abnormal         |
| 3   | N_3.jpg | 0.35048      | Normal           |
| 4   | N_4.jpg | 0.16924      | Normal           |
| 5   | N_5.jpg | 0.083734     | Abnormal         |
| 6   | N_6.jpg | 0.39687      | Normal           |
| 7   | N_7.jpg | 0.36502      | Normal           |
| 8   | N_8.jpg | 0.1101       | Abnormal         |
| 9   | N_9.jpg | 0.45679      | Normal           |
| 10  | N_10.jpg| 0.43623      | Abnormal         |

**Table 3.** Abnormal dental image testing results on the system

| No. | Image | Binary value | Diagnosis Binary |
|-----|-------|--------------|------------------|
| 1   | TN_1.jpg | 0.44267     | Normal           |
| 2   | TN_2.jpg | 0.088685    | Abnormal         |
| 3   | TN_3.jpg | 0.42647     | Abnormal         |
| 4   | TN_4.jpg | 0.28903     | Abnormal         |
| 5   | TN_5.jpg | 0.14826     | Abnormal         |
| 6   | TN_6.jpg | 0.32679     | Abnormal         |
| 7   | TN_7.jpg | 0.056068    | Abnormal         |
| 8   | TN_8.jpg | 0.19158     | Abnormal         |
| 9   | TN_9.jpg | 0.30136     | Abnormal         |
| 10  | TN_10.jpg| 0.16523     | Normal           |

Table 2 shows that the system test results can only identify images of normal dental 5 out of 10 (50%). Whereas in table 3, the system shows that it can identify abnormal dental 8 out of 10 images (80%). This is due to the structure of the image itself because each image has its own level of accuracy.
### 4.5. Manual Calculation of Normal and Abnormal Data

Manual calculations of normal and abnormal normal gear data are shown in Tables 4 and 5.

**Table 4.** Binary calculations in normal dental anatomy images.

| No. | Image     | Error value | Binary value (abs= 1-e) | Binary result | Diagnosis |
|-----|-----------|-------------|-------------------------|---------------|-----------|
| 1   | N_1.jpg   | 0.9673      | 1-0.9673                | 0.0327        | Abnormal  |
| 2   | N_2.jpg   | 0.9548      | 1-0.9548                | 0.0452        | Abnormal  |
| 3   | N_3.jpg   | 0.3505      | 1-0.3505                | 0.6495        | Normal    |
| 4   | N_4.jpg   | 0.1692      | 1-0.1692                | 0.8308        | Normal    |
| 5   | N_5.jpg   | 0.9163      | 1-0.9163                | 0.0837        | Abnormal  |
| 6   | N_6.jpg   | 0.3969      | 1-0.3969                | 0.6031        | Normal    |
| 7   | N_7.jpg   | 0.3650      | 1-0.3650                | 0.635         | Normal    |
| 8   | N_8.jpg   | 0.8899      | 1-0.8899                | 0.1101        | Abnormal  |
| 9   | N_9.jpg   | 0.4568      | 1-0.4568                | 0.5432        | Normal    |
| 10  | N_10.jpg  | 0.5638      | 1-0.5638                | 0.4362        | Abnormal  |

In the Table above, it can be explained that the results of the first test accumulation on binaryization data have an unstable level of accumulation, because the data shows 50% normal data and 50% abnormal data. This is due to the structure of the image itself because each image has its own level of accuracy.

**Table 5.** Binary calculations in abnormal dental anatomy images

| No. | Image     | Error value | Binary value (abs= 1-e) | Binary result | Diagnosis |
|-----|-----------|-------------|-------------------------|---------------|-----------|
| 1   | TN_1.jpg  | 0.9113      | 1-0.9113                | 0.0887        | Abnormal  |
| 2   | TN_2.jpg  | 0.4427      | 1-0.4427                | 0.5573        | Normal    |
| 3   | TN_3.jpg  | 0.5735      | 1-0.5735                | 0.4265        | Abnormal  |
| 4   | TN_4.jpg  | 0.7110      | 1-0.7110                | 0.289         | Abnormal  |
| 5   | TN_5.jpg  | 0.8517      | 1-0.8517                | 0.1483        | Abnormal  |
| 6   | TN_6.jpg  | 0.6732      | 1-0.6732                | 0.3268        | Abnormal  |
| 7   | TN_7.jpg  | 0.9439      | 1-0.9439                | 0.0561        | Abnormal  |
| 8   | TN_8.jpg  | 0.8084      | 1-0.8084                | 0.1916        | Abnormal  |
| 9   | TN_9.jpg  | 0.6986      | 1-0.6986                | 0.3014        | Abnormal  |
| 10  | TN_10.jpg | 0.1652      | 1-0.1652                | 0.8348        | Normal    |

In the table above, it can be explained that the results of the first test accumulation on binaryization data have an unstable level of accumulation, because the data shows 20% normal data and 80% abnormal data. This is due to the structure of the image itself because each image has its own level of accuracy.

### 4.6. Comparison of system and manual calculations in binerization

The following is a comparison of system and manual calculations in binerization.

**Table 6.** Comparison of accuracy levels

| Dental anatomy | System | Manual |
|----------------|--------|--------|
| Abnormal       | 80%    | 80%    |
| Normal         | 50%    | 50%    |
So the conclusion from the above test is that the system and manual calculations have the same comparison for the calculation of dental anatomy, so it can be concluded that manual and system calculations have a comparable level of accuracy. Table 6 shows that results of both the system and the manual calculation for the identification of dental anatomy are the same. Identification normal dental are 50% and abnormal dental are 80%.

5. Conclusion
From the research that has been done, it can be concluded that the comparison of both the system and the manual calculation for the identification of dental anatomy are the same. Identification normal dental are 50% and abnormal dental are 80%. To improve identification results, further research needs to add methods, for example segmentation or edge detection.

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