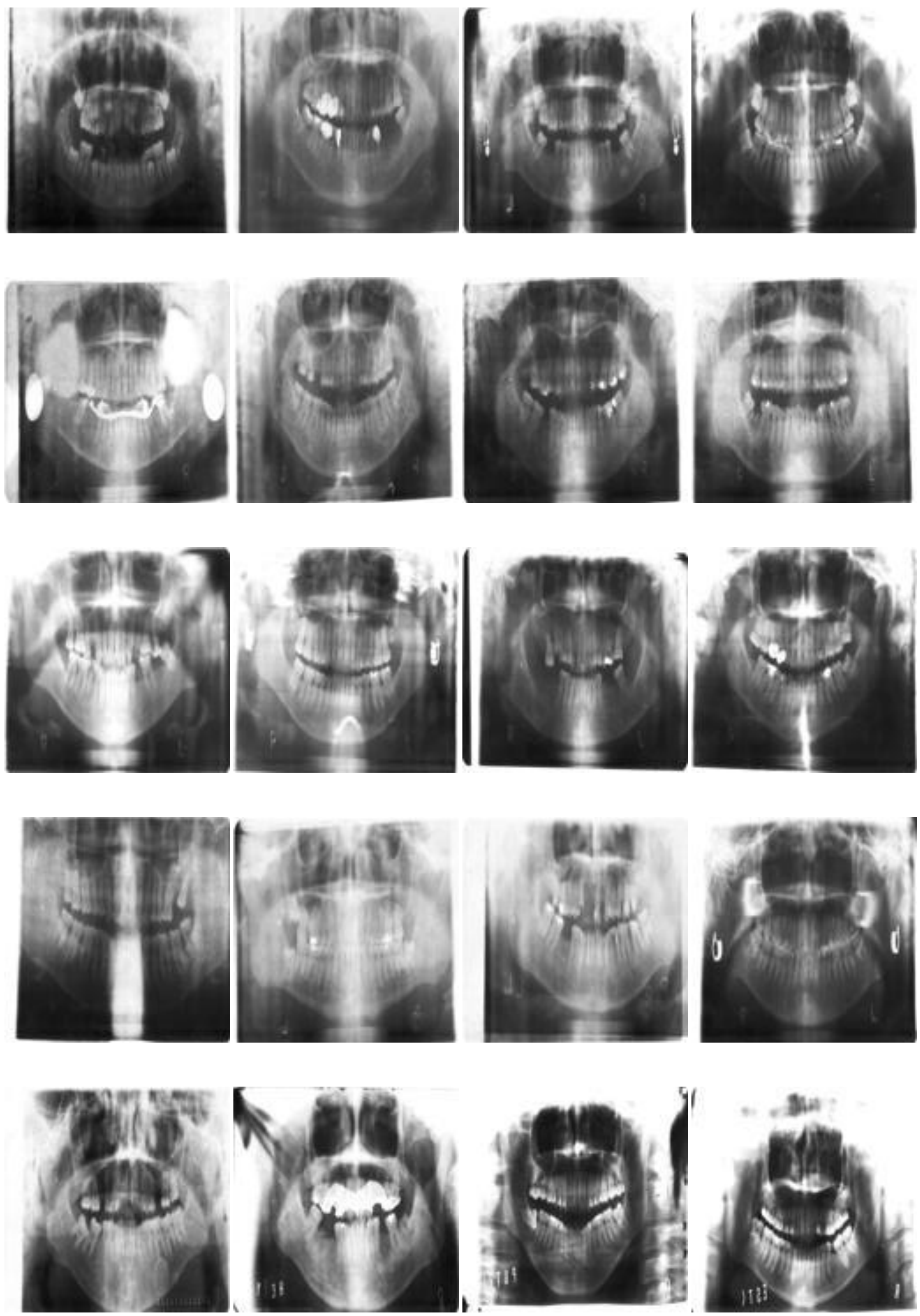
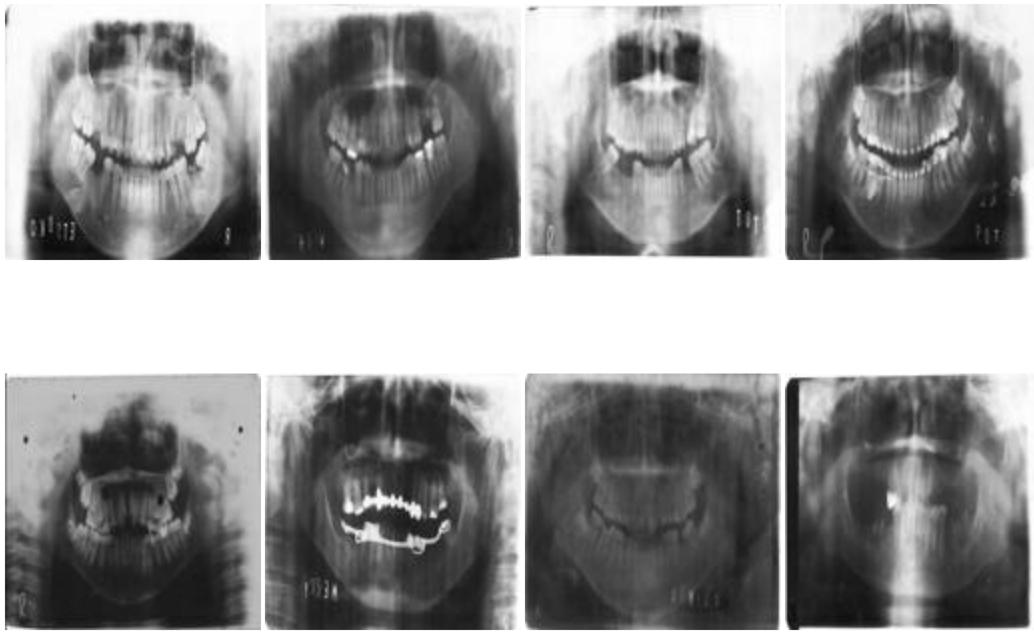
LAMPIRAN 1 DATA UJI

Berikut ini merupakan citra dental *x-ray* yang digunakan pada saat eksperimen:



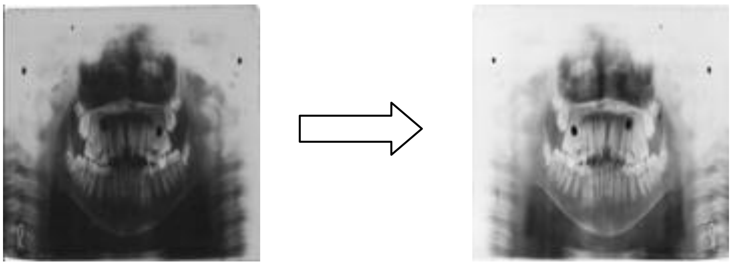
Lampiran 1. Data Uji (Lanjutan)

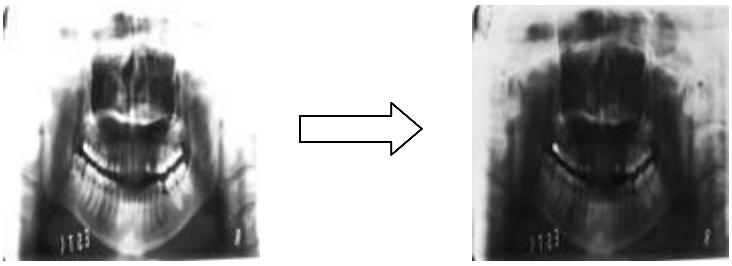


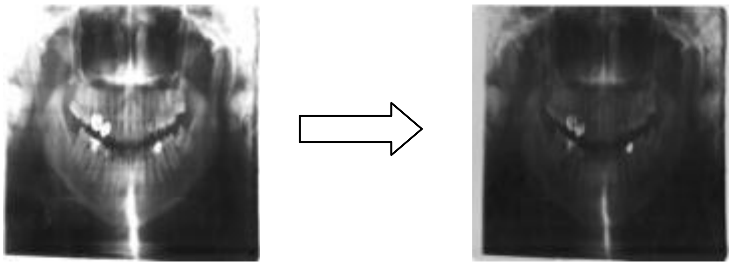
LAMPIRAN 2 DATA UJI YANG GAGAL DIKENALI

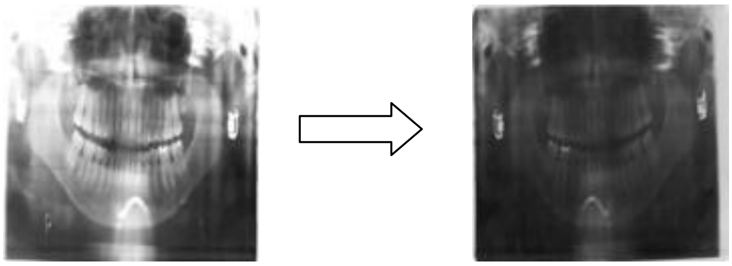
Berikut ini merupakan input pada skenario citra beda kontras yang gagal dikenali:

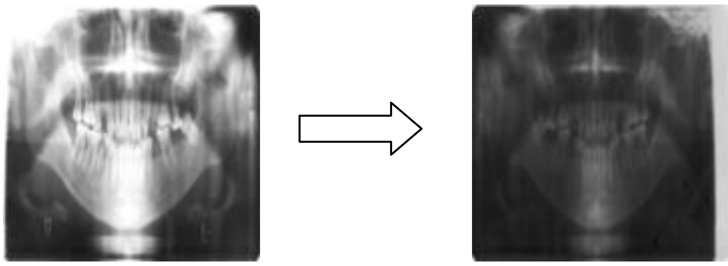
Citra biner

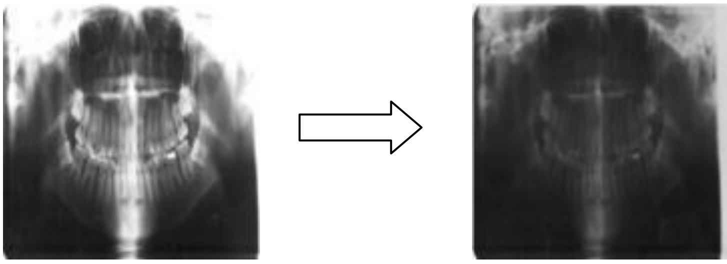




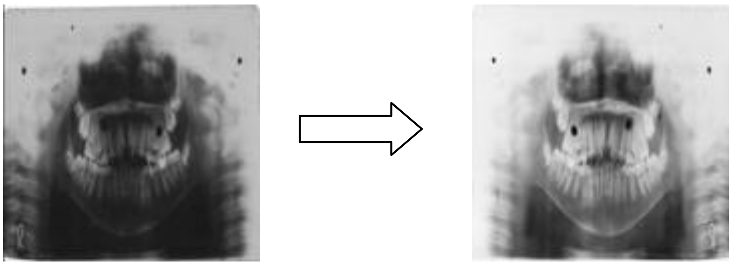


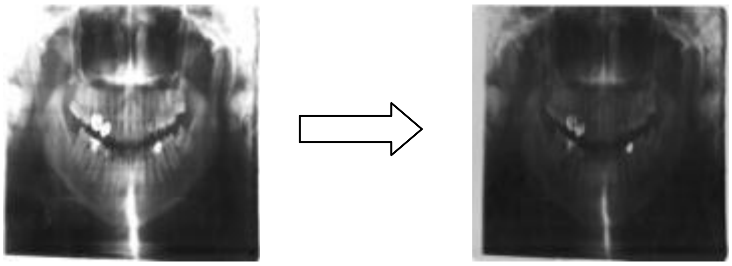


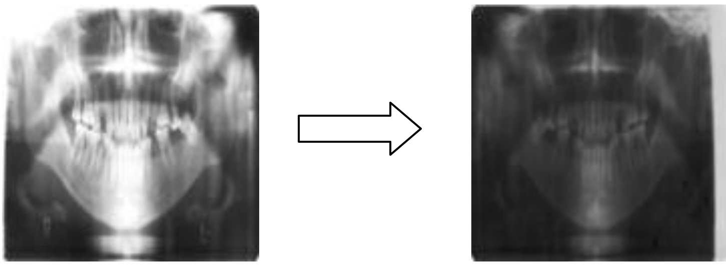


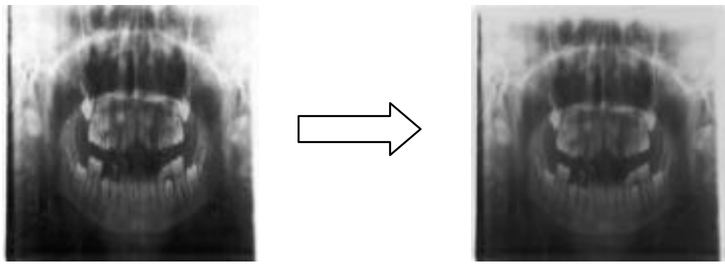


Citra Grayscale



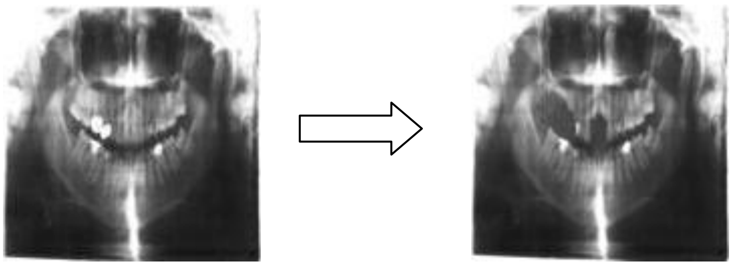






Lampiran 2. Citra Uji Yang Gagal Dikenali (Lanjutan)

Berikut ini merupakan input pada skenario citra distorsi yang gagal dikenali:



LAMPIRAN 3 PUBLIKASI PAPER

Dental Matching For Disaster Victim Identification Using Zernike Moments

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ABSTRACT

Disasters often happen in Indonesia, it is caused by human and nature. In order to identify the victim of the disaster, police have their own procedures. A common way to identify is by using finger print identification, but it is not often that the victims have badly body decay. The alternate way is using dental matching process. This process is very time consuming because the matching processes have to compare one by one the dental condition of the victim manually. Using dental X-Ray as an input, an application to do matching process is developed. The application can automatically identify the victim by doing dental matching process. In this application, Zernike moments are used as feature extraction. Zernike moments are chosen because it has ability to recognize image accurately, even the image has rotated or distorted. The experiment also compare binary and gray scale image as input for Zernike moments. The application can 100% recognize the victim for some case, so it is powerful tool according to its ability to identify victim fast and accurately.

Key words: Dental matching, victim identification, Zernike moments, Zernike normalization

1. Introduction

The scale of disaster in Indonesia is often categorized as a mass disaster. In 26 Dec. 2004, tsunami created unpredictable damage, it is reputed to have claimed the lives of around 160.000. When greater victims have to be processed, well equipped and fully functional tools might have to be set up to support identification process.

In identification process, finger print is used as the first identification method but it is often that the body of the victim is decayed, so it hard to do finger print identification. The alternative way for identifying the victim is by using dental X-Ray matching process [1]. The Interpol standardized this identification process that is known as dental charting system and it is also applied as the World Dental Federation tooth numbering system [2]. Dental matching is a comparative identification that is used to establish that the remains post mortem (dental condition) of a victim and a person represented by ante mortem (dental records before death) is the same individual [3, 4]. This method is used because most of the victim dental shape and structure is still intact and every human has a unique dental condition [5]. Unfortunately, this method is very time consuming, so it is very hard for the police to do it manually. Because of that, a tool is developed to do dental records matching automatically.

To identify the victim, the method is to match one by one the dental condition (post mortem) of the victim with the dental records (ante mortem). This method is very unstable, because it wastes time and makes the process become inaccurate if there are so many dental records that must be matched. So, an application is developed to do this process automatically and is designed with high recognition rate. Matching process used Zernike moments, a tool for image recognition that is able to recognize image, even when the image is already distorted or rotated. Dental condition of the victim will become distorted if the dental condition deformed. Besides that, there is also a possibility of inaccurate angle when taking a dental X-Ray of the victim. The output of this application is to identify whether the dental condition of the victim has a high similarity rate with the dental records, so that the identity of the victim will be known.

This application tried to overcome the problem of identifying victim of disaster that have deformed very badly. The identification process can be done fast and accurately because the dental matching process is done by computer. This application can match the dental even it is already distorted and rotated.

2. Zernike Moments

Zernike moments were introduced by Teague [6], and it involved complex computation than other moment function like Geometric and Legendre. Researchers develop these moments to accelerate the computational cost and time. On the other hand, Zernike moments have been proven as a good feature extraction because it has ability to recognize an image even the image is already distorted and rotated [7].

Complex Zernike functions constitute of a set of orthogonal basis functions that mapped over the unit circle. There are three main properties of Zernike moments [8, 9]:

- The orthogonality: this property ensures that the contribution of each moment is unique and independent.
- The rotation invariance: the magnitude of Zernike moments is independent of any planar rotation of a pattern around its center of mass.
- The information compaction: low frequencies of a pattern are coded into the low order moments. As a result, relatively small descriptors are robust to noise or deformations

The kernel of Zernike moments are orthogonal Zernike polynomials defined over the polar coordinates inside the unit circle. The Zernike moment of order p and repetition q are defined as [6]

$$Z_{pq} = \frac{p+1}{\pi}\int_0^{2\pi}\int_0^1 V_{pq}{}^*(r,\theta) f(r,\theta) r dr\, d\theta,$$

$$r \le 1 \quad \textbf{(2.1)}$$

In above expression, p is a non-negative integer, and q is an integer such that p-|q| is even, and |q| ≤ p. If N is the number of pixels along each axis of the image, then eq. (2.1) can be written with discrete form [6]

$$Z_{pq} = \frac{p+1}{\pi(N-1)^2}\sum_{x=1}^{N}\sum_{y=1}^{N} V_{pq}{}^*(r,\theta) f(x,y) \quad \textbf{(2.2)}$$

where $r = \frac{(x^2+y^2)^{\frac{1}{2}}}{N}$, and $\theta = tan^{-1}\left(\frac{y}{x}\right)$.

Zernike polynomials $V_{n,m}(r,\theta)$ of order n and repetition m are defined as functions of the polar coordinates r, θ as [6]

$$V_{n,m}(r,\theta) = R_{nm}(r) e^{jm\theta} \quad \textbf{(2.3)}$$

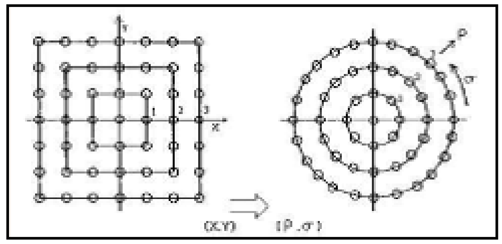


Fig 1. Square to Circle Transformation [6]

where j = $\sqrt{-1}$, $r = \sqrt{x^2+y^2}$, θ = arctan(y/x), dimana (x,y) ∈ $[-1,1]^2$.

Equation (2.3) above is related to Euler's formula. Euler's formula is a mathematical formula in complex analysis that shows a deep relationship between the trigonometric functions and complex exponential functions [10]. Euler's formula states that, for any real number x,

$$e^{ix} = \cos(x) + i\, sin\,(x) \quad \textbf{(2.4)}$$

So, according to Euler's formula, $e^{-jm\theta}$ can be computed as

$$e^{-jm\theta} = \cos(m\theta) + (-j)\sin(m\theta) \quad \textbf{(2.5)}$$

To calculate the Zernike moments of an image f (x, y), the image (or region of interest) must be mapped to the unit disk using polar coordinates, where the centre of the image is the origin of the unit disk like in fig. 1 above. Those pixels falling outside the unit disk are not used in the calculation. The coordinates are then described by r which is the length of the vector from the origin to the coordinate point and θ which is the angle from the x axis to the vector r, by convention measure from the positive x axis in a counter clockwise direction.

In polar coordinates, R_{nm} (r) is real-valued radial polynomial given by [6]

$$R_{nm}(r) = \sum_{s=0}^{(n-|m|)/2} (-1)^s \frac{(n-s)!}{s!\left(\frac{n-2s+|m|}{2}\right)!\left(\frac{n-2s-|m|}{2}\right)!} r^{n-2s}$$

$$n = 0,1,2,\dots\infty;$$

$$0 \le |m| \le n; and\ n-|m| is\ even \quad \textbf{(2.6)}$$

The magnitudes of the Zernike moments invariants vary large with the order of the moment functions, and to reduce the large dynamic range of invariants, the Zernike moment Z_{pq} are usually normalized to the functions $\hat{Z}_{pq}$, as follow [7]:

$$\hat{Z}_{pq} = \frac{Z_{pq}}{m00}; m00 = \sum_x \sum_y f(x,y) \quad \textbf{(2.7)}$$

3. Proposed Dental Matching Process

In this section, we discussed about dental matching process that we proposed on this application. Dental matching process in this paper is based on Zernike moment to get the feature extraction of dental image. There are two kinds of process that are evaluated on experimental section. First, the process used black and white image and then use gray scale image like on fig. 2 below.

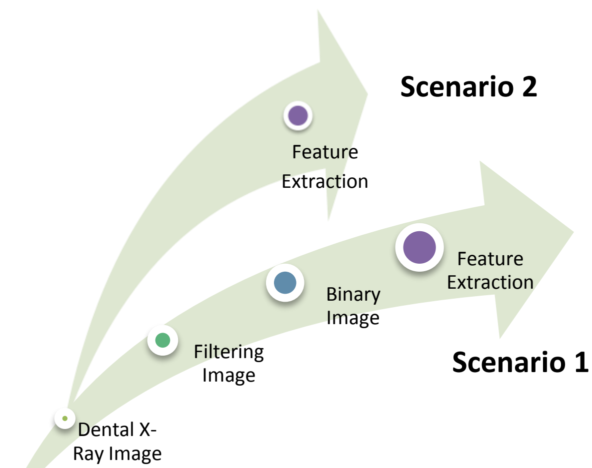
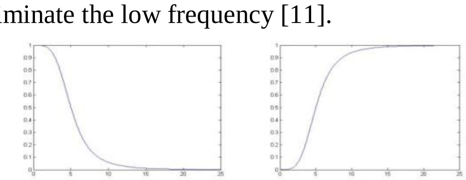


Fig 2. Experiment Scenario

Scenario two is using binary image as input in Zernike moment function. Gray scale image is filtered using high-pass Butterworth filtering. This filter is used to make the edge of the image become sharper. This process is expected to reduce the noise on dental X-Ray. High-pass Butterworth filtering pass high frequency and eliminate the low frequency [11].



$$f(x) = \frac{1}{1 + (x/D)^{2n}} \qquad f(x) = \frac{1}{1 + (D/x)^{2n}}$$

Fig 3. Butterworth Filtering

To make a high-pass filtering, there are 4 steps [11]:

1. Design an Butterworth high-pass matrix (circular filter)
2. Read the image, and make its DFT (Discrete Fourier Transform)
3. Multiply the filter and the DFT
4. Inverse-DFT the result

Besides using binary image, the experiment also used gray scale image as in scenario 2 and then there are comparison between gray scale image and binary image as an input. In dental matching process using gray scale image, raw image of X-Ray is scanned and it become an input in Zernike moment process.

There are 2 features in this application. First feature is uploading data to database and second feature is matching the dental. Uploading process is finding the feature extraction of dental image and then save it in xml file. The moment computed on order 40 that is maximal order that available in this application. Matching feature is identifying whose dental image it is. The matching process computed Zernike moment of the dental image and then compared it with Zernike moment in database.

The absolute value of a Zernike moment is rotation invariant as reflected in the mapping of the image to the unit disk. This absolute value can be used to recognize rotated image. The rotation of the shape around the unit disk is expressed as a phase change, if θ is the angle of rotation, $Z^r{}_{pq}$ is the Zernike moment of the rotated image and Z_{pq} is the Zernike moment of the original image then [7]:

$$Z^r{}_{pq} = Z_{pq} \exp(-jm\theta) \quad \textbf{(3.1)}$$

$$|Z^r{}_{pq}| = |Z_{pq}| \quad \textbf{(3.2)}$$

According to equation (3.2), rotate image has the same magnitude value with the original image. So, the similarity distance of two shapes with our proposed descriptor is calculated by summing up the weighted absolute differences of each moment, similarity distance is

$$D = \sum_{(p,q)\in D} \sum (|Z_{pq}| - |Z'_{pq}|)^2 \quad \textbf{(3.3)}$$

4. Experimental Result

To evaluate the performance of the dental matching application using Zernike moment, experiments have been conducted. The experiments mainly address to see the recognition power of Zernike moment in dental matching process. Images of dental X-Ray are carried out from Dental Faculty in University of Indonesia. There are 28 dental X-Ray images from 28 persons that used to evaluate the dental matching application.

Fig 4. Dental Matching Application

On fig. 4 above, it is a screenshot of an application that have been developed. On right side of application is picture of dental and left side is the identity of dental.

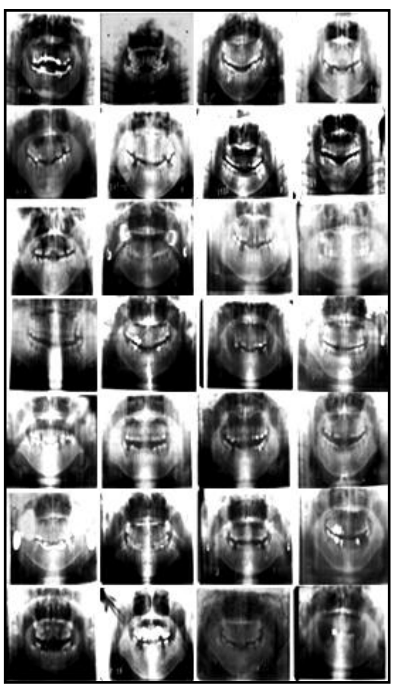


Fig 5. Dental Image

There are 3 testing images as described below:

1. Rotation: The image is rotated to the following angles: 5^o, 30^o, 50^o, 90^o, 120^o, and 150^o.
2. Distortion: The image is given random noises to distorting the image.
3. Different Contrast: The image is scanned with different contrast.

Besides 3 testing images, there are also 2 testing scenario that is used on this experiment as explanations before.

Scenario 1:

1. Image transforming: Transformation has been applied to the testing image.
2. Image filtering. Gray scale images are filtered to get binary (black and white) images.
3. Zernike moment computing. Zernike moment of testing binary image is computed.

Scenario 2:

1. Image transforming: Transformation has been applied to the testing image.
2. Zernike moment computing. Zernike moment of testing binary image is computed.

4.1 Scenario 1

On this scenario, the application filtered the image before it is processed using Zernike moment. The transformation from raw image into binary image can be seen on fig. 9 below.

The results of this scenario show that 100% the application can recognize rotated image and distorted image accurately. In fact, order of moment that is used to recognize both testing image only order-10.

For the third testing images (different contrast image), this scenario has 78.5% recognition rate. There are 6 dental images that cannot recognize well.

4.2 Scenario 2

Scenario 2 uses gray scale image as an input on Zernike moment process. This scenario is simple, after the feature extraction is done, it is matched with dental records in database.

The result of this scenario is 100% for rotated image and 96% for distorted image. For rotated image, this scenario can accurately recognize the dental image, but for distorted image, there is one dental image that can not be recognized accurately.

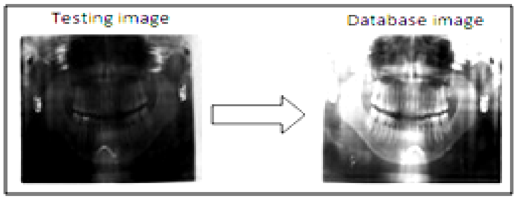


Fig 6. Different Contrast Image

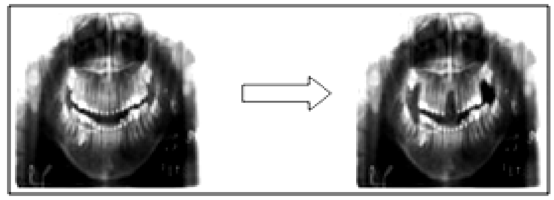


Fig 7. Distorted Image

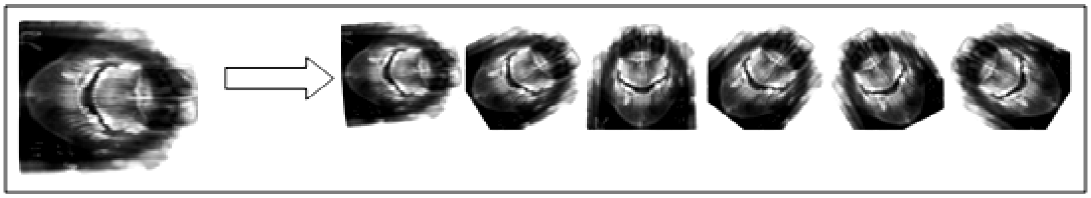


Fig 8. Rotated Image

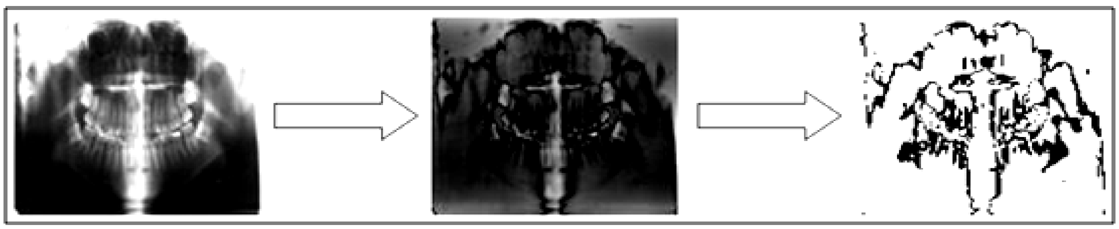


Fig 9. Image Transformation to Binary Image

For the third testing images, this scenario has 86% recognition rate. There are 4 images that cannot be recognized by this scenario.

4.3 Analysis

From the experiment, scenario 1 showed better performance than scenario 2 on recognizing rotated images and distorted images although the difference between those scenario is not too far. It is different for third testing image (different contrast image), scenario 1 has 78.5% recognition rate, and in the other hand, scenario 2 has 86% recognition rate.

Table 1. Experiment Result

	Rotated	Distorted	Different Contrast
Binary Image	100%	100%	78.5%
Gray Scale Image	100%	96%	86%

There are some analysis from the experiment. For overall performance, scenario 2 shows better performance. The weakness of scenario 1 is on the third testing image. This weakness can be caused by the transformation from gray scale image to binary image. The transformation really depends on the precission of the image. When the images have good precission, the shape of dental image that is produced by Butterworth filtering is clear.

In the other case, scenario 2 is not depend on any transformation. So, there is no process that can disturb recognition rates beside the matching process itself.

5. Conclusions

In this paper, it is shown that the application is powerful tool for dental image matching. The accuracy of the application have up to 85% recognition rate for three testing image case. Efficiency and accuracy of the application have been tested and analyzed with several testing case.

Zernike moments also successfully implemented in the application. Another conclusion is that using gray scale images as input for this application is more reliable because for binary image transformation there is a weakness that this transformation is really rely on the contrast condition of the image. This statement has been proven by third testing case.

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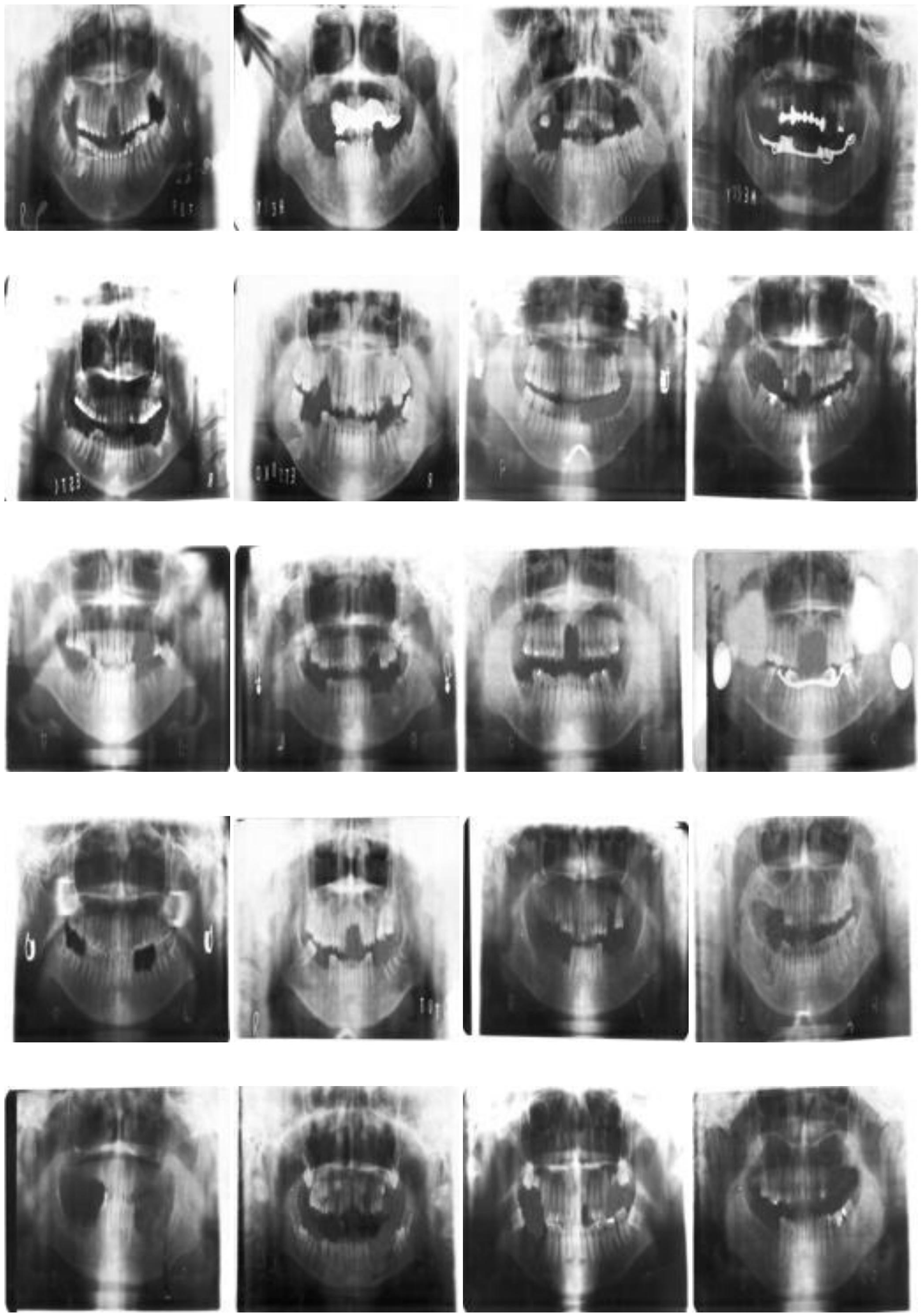
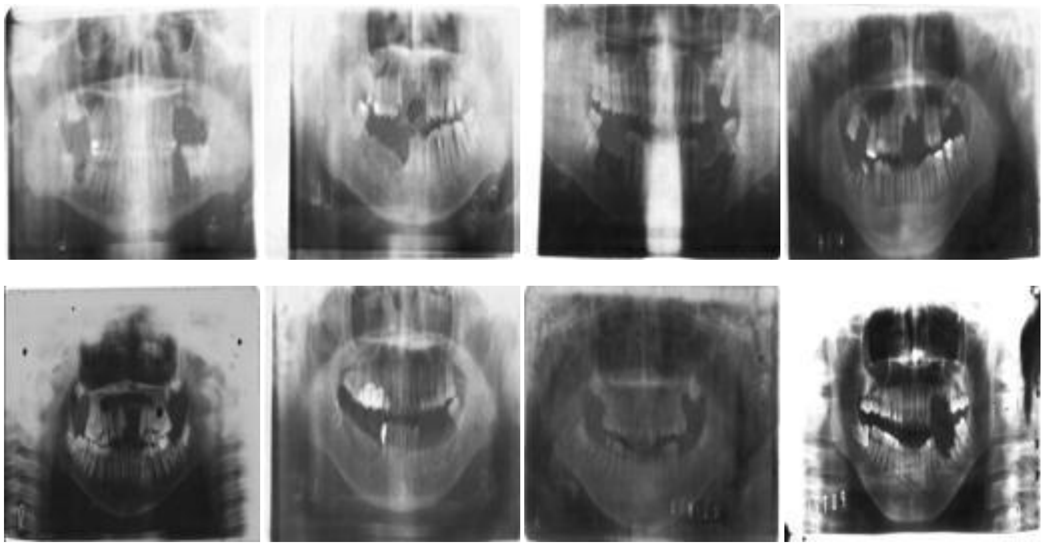
LAMPIRAN 4 DATA UJI DISTORSI

Berikut ini merupakan citra dental *x-ray* yang digunakan pada saat eksperimen dengan skenario uji citra distorsi:

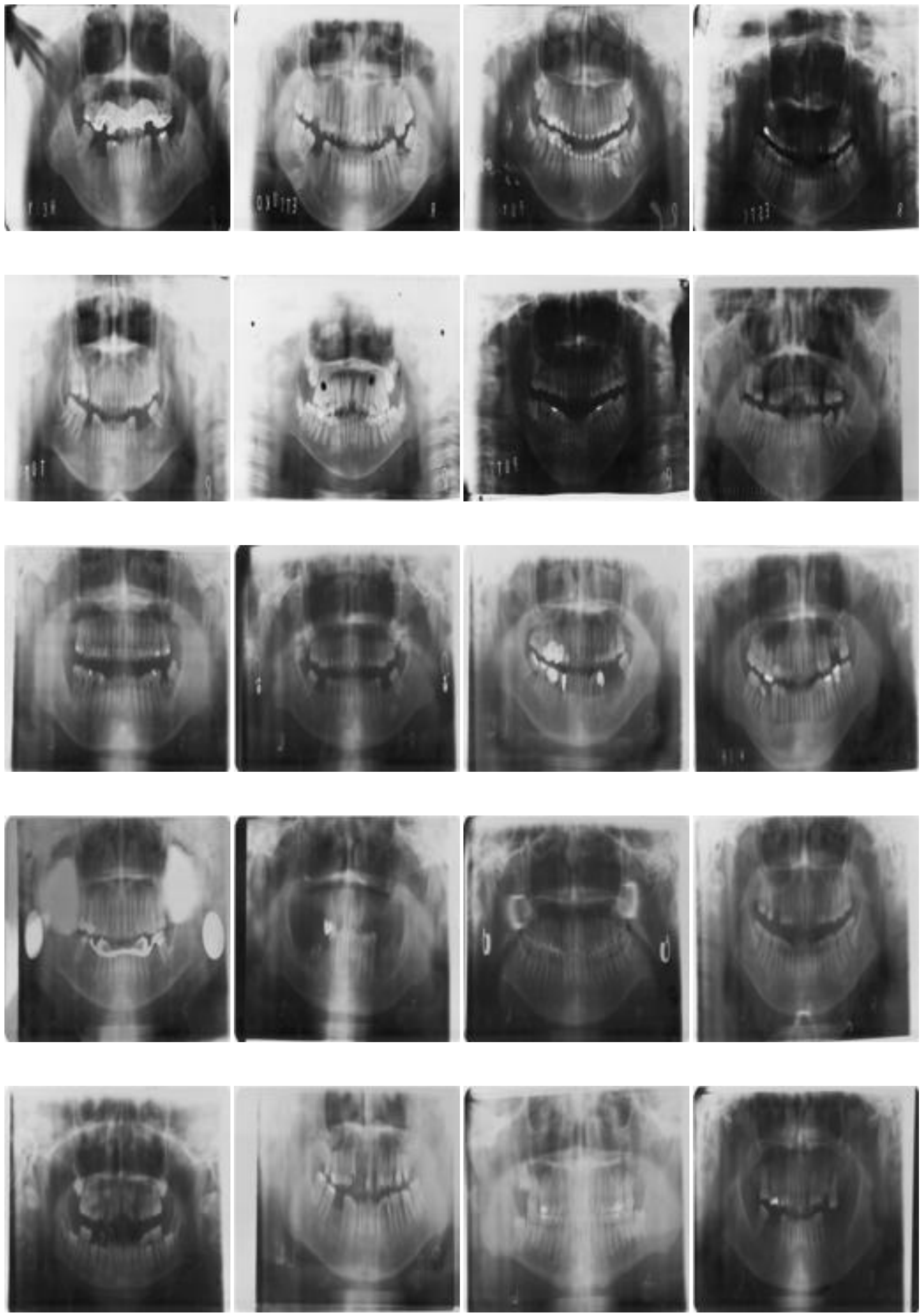


Lampiran 4. Citra Uji Distorsi (Lanjutan)



LAMPIRAN 5 DATA UJI BEDA KONTRAS

Berikut ini merupakan citra dental *x-ray* yang digunakan pada saat eksperimen dengan skenario uji citra beda kontras:



Lampiran 5. Data Uji Beda Kontras (Lanjutan)