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Classification and Numbering of Dental Radiographs for an Automated Human Identification System

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Abstrak

Identifikasi manusia berbasis data gigi umum digunakan dalam forensik. Dalam kasus investigasi yang besar, proses pengidentifikasian manusia yang dilakukan secara manual memerlukan waktu yang lama. Pada makalah ini dikembangkan sebuah sistem identifikasi manusia otomatis menggunakan radiografi gigi. Sistem yang dibangun bekerja dengan 2 tahapan utama. Tahapan pertama adalah menyusun sebuah database berisi data radiografi gigi berlabel. Tahapan kedua adalah melakukan pencarian pada database untuk mendapatkan hasil identifikasi. Kedua tahapan tersebut menggunakan serangkaian proses pengolahan citra dan klasifikasi serta penomoran untuk mendapatkan pola dan fitur radiografi gigi. Pertama, dilakukan prapemrosesan yang meliputi perbaikan dan binarisasi citra, ekstraksi gigi tunggal, dan ekstraksi fitur. Selanjutnya, dilakukan proses klasifikasi gigi untuk mengklasifikasikan gigi menjadi molar dan premolar dengan menggunakan metode binary support vector machine (SVM). Setelah itu, proses penomoran pada gigi dilakukan sesuai pola molar dan premolar yang diperoleh pada tahap sebelumnya. Percobaan menggunakan 16 radiografi gigi yang terdiri dari 6 radiografi bitewing dan 10 radiografi panoramik dengan total 119 objek gigi menunjukkan nilai akurasi yang baik, yaitu 91,6% untuk proses klasifikasi gigi menjadi molar dan premolar dan 81,51% untuk proses penomoran gigi.

Kata kunci: *forensik, identifikasi manusia, radiografi gigi, segmentasi, sistem penomoran gigi*

Abstract

Dental based human identification is commonly used in forensic. In a case of large scale investigation, manual identification needs a large amount of time. In this paper, we developed an automated human identification system based on dental radiographs. The system developed has two main stages. The first stage is to arrange a database consisting of labeled dental radiographs. The second stage is the searching process in the database in order to retrieve the identification result. Both stages use a number of image processing techniques, classification methods, and a numbering system in order to generate dental radiograph's features and patterns. The first technique is preprocessing which includes image enhancement and binarization, single tooth extraction, and feature extraction. Next, we performed dental classification process which aims to classify the extracted tooth into molar or premolar using the binary support vector machine method. After that, a numbering process is executed in accordance with molar and premolar pattern obtained in the previous process. Our experiments using 16 dental radiographs that consist of 6 bitewing radiographs and 10 panoramic radiographs, 119 teeth objects in total, has shown good performance of classification. The accuracy value of dental pattern classification and dental numbering system are 91.6 % and 81.5% respectively.

Keywords: *forensic, human identification, dental radiographs, segmentation, dental numbering system*

1. Introduction

Biometric is a tool of identification that has been broadly used in many applications. A biometric identification system is based on physical characteristics such as face [1], fingerprint, palmprint [2], eyes (iris, retina) and DNA. However, many of those characteristics are only suitable for ante mortem (AM) identification when a person to be identified is still alive. They cannot be used for postmortem (PM) identification especially in the case of decay or severe body damage caused by fire or collision [3].

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Teeth are parts of human organ that are not easily decayed, located inside mouth and thus they are more protected from decaying after human's death. Therefore, teeth based identification is one of reliable tools for PM identification.

On average, human has 32 teeth; each tooth has five surfaces, meaning that inside a mouth there are 160 tooth surfaces with various conditions. If we use dental features as a tool of identification, manual matching of AM with PM data needs a large amount of time and some expertise. Therefore, a computer-aided for an identification system is needed.

In order to create an automated identification system, dental features on a dental radiograph need to be extracted and saved in a database. During identification, features of each tooth on the input are extracted and compared to those in the database. This matching process will take a long time to complete if we do not reduce the search space. In this paper, we reduce the search space by comparing the pattern and numbering of teeth only. This results in a list of matched dental and numbering pattern. Therefore, we can enhance the effectiveness of the identification system.

Figure 1 shows the international dental numbering system which also shows the molar and premolar teeth. There are 32 teeth in adult people, sixteen teeth on each jaw. There are two jaws, maxilla and mandible. Each jaw is divided into two groups, left and right. Thus, each group consists of eight teeth comprised of two bicuspid, one cuspid, two premolar teeth, and three molar teeth. In this research we only use molar and premolar teeth as part of dental pattern, since molar and premolar teeth are usually stronger than others.

The international dental numbering system has teeth number from 1 to 32, starting from the third molar in the right maxilla (#1), going through the maxilla to the third molar in the left maxilla (#16). Next, the numbering is continued to the third molar in the left mandible (#17) and around the mandible until we find the third molar in the right mandible (#32) [4].

There are three kinds of dental radiographs: bitewing, panoramic, and periapical. In literatures [3 - 5], bitewing images are usually used for identification. However, in this paper, we tested our method not only to bitewing radiographs, but also to panoramic radiographs. Bitewing radiographs have wider space between upper and lower jaw, whereas, in panoramic radiographs, the upper and lower jaw are closer.

Automated dental based identification consists of extracting dental features and feature matching itself [5 - 7]. In this paper, the dental feature used for identifying human is the arrangement of Molar and Premolar teeth and the numbering of each radiograph. In order to have this arrangement, we have to classify each tooth in a radiograph into Molar or Premolar. But first, we have to extract the tooth using several image processing techniques. The tooth separation is crucial to the system. Our tooth separation method has been able to correctly extract single tooth. There are only two of sixteen images that have not been correctly segmented due to very high intensity in the lower jaw bone.

The rest of the paper is organized as follows. Section 2 gives an explanation of the method used in this research. Section 3 explains the results and analysis. In Section 4, we present the conclusion and future works.

Right *Maxilla*								Left *Maxilla*							
1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
32	31	30	29	28	27	26	25	24	23	22	21	20	19	18	17
Right *Mandible*								Left *Mandible*							

= molar *= premolar*

Figure 1. A system of dental numbering in adults

2. Research Method

In this section, the proposed system design and three main functions, namely pre-processing, teeth separation, classification and numbering system, are explained. All functions in the proposed system are implemented using Matlab 7.0.

There are two main phases in the proposed human identification system as shown in Figure 2. They are dental data recording phase and identification phase. In the dental data recording phase, dental radiographs are processed. There are three main functions in this phase, namely preprocessing, teeth separation, classification and numbering. The results of this phase are dental patterns, which next to be recorded in a database along with the original radiographs. The identification phase aims to identify a dental radiograph, called a query, belongs to which data in the database. The functions applied to the dental radiograph in the identification phase are similar to those applied to radiographs in the recording phase. The result of classification and numbering system in this phase is used as a search query which leads to an identification result.

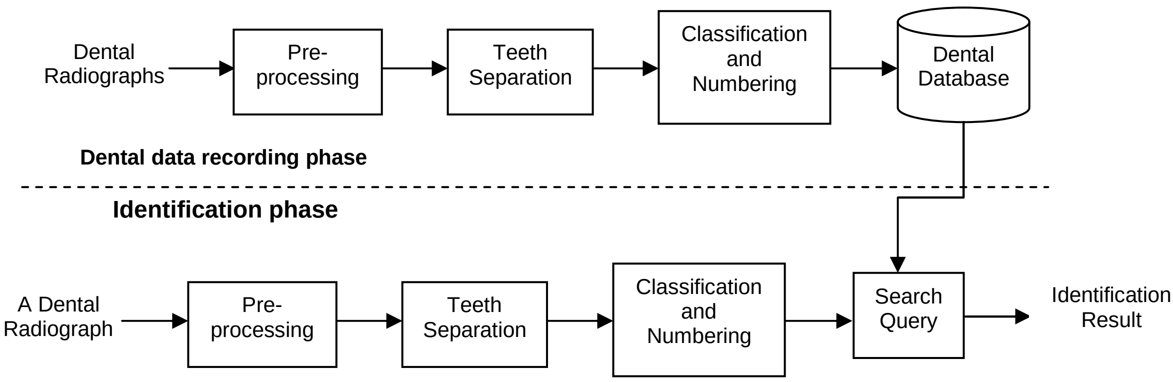


Figure 2. Design of the proposed human identification system

In the pre-processing step, a dental radiograph which has been digitalized are loaded from local hard disk. The dental radiograph can be bitewing or panoramic. For panoramic radiographs, we only take the molar and premolar part. Next, we perform image enhancement that aims to equalize the brightness level so that there is no pixel that has very high intensity level compare to its neighbors. This usually happens to dental fillings. Next, we perform the contrast enhancement. Generally, dental radiographs have low contrast. In order to facilitate process of teeth separation with the background, we increase the contrast using morphological operation and top-hat and bottom-hat operator [8]. After that, we perform local histogram equalization which is called Contrast-Limited Adaptive Histogram Equalization (CLAHE) [8].

After pre-processing, the grayscale digital radiographs are then converted into binary images using Otsu's thresholding method [8] followed by closing and opening operation to smooth the teeth contour and remove noises. Next, we perform horizontal integral projection [9] followed by spline method to separate the image into a maxilla image and a mandible image. Finally, we use the vertical integral projection method on each maxilla and mandible image independently to extract single tooth image.

The next process is dental feature extraction of each tooth. This step is used for classifying each tooth into molar or premolar class. The dental features are area of each tooth and ratio of each tooth's width and height. After feature extraction, we classify each tooth into molar or premolar class using binary support vector machine (SVM) method. SVM is a famous binary classification method. Given a set of training data, each marked as belonging to one of two classes, an SVM training method creates a model that predicts a new data is in one class or the other [10]. An SVM model is a representation of all data as points in space and a clear gap that separate data into two categories. This clear gap is often called as a hyperplane. This hyperplane is built as wide as possible. New testing data are then mapped into the same space and predicted as a member of a class based on which side of the hyperplane they fall on.

The molar-premolar pattern of each image is then refined using default patterns. There are two kinds of default patterns, as shown in Figure 3, namely patterns for right side of teeth (Pattern 1) and patterns for left side (Pattern 2). In this paper, the first step of numbering system is find which default pattern that has highest similarity value with the pattern sequence tested. The similarity matrix is computed using simplified Smith-Waterman algorithm [11] as in Equation (1). Let $T = t_1 t_2 \ldots t_m$ be a sequence of dental numbering, $P = p_1 p_2 \ldots p_m$ be a dental pattern and

$m \leq n$. The similarity matrix $\boldsymbol{O}$ = {O_{ij}} consists of similarity degrees between T_i and P_j segment pair.

$$O_{ij} = \begin{cases} O_{i-1,j-1} + 1 & \text{if } t_i = p_j \\ \max\{O_{i-1,j-1} - \frac{1}{3}, k, 0\} & \text{if } t_i \neq p_j \end{cases} \quad (1)$$

Using Equation (1), we compute four similarity matrices, namely Omax_1, Omax_2, Oman_1, and Oman_2. Then the maximum value of Omax_1 is added to that of Oman_1 and compared to sum of the maximum value of Omax_2 and Oman_2. If the sum of the maximum value of Omax_1 and Oman_1 is higher than that of Omax_2 and Oman_2, then we choose Pattern 1. Otherwise, we choose Pattern 2. The next step is defining position of dental numbering based on the chosen default pattern. First, find an element of similarity matrix O_{kl} that has maximum value, set a column index and a row index based on the element's position, i.e. the column index = k, and the row index = l. Then, label each tooth in maxilla and mandible with number as in default pattern numbering system, i.e. p_{l-k+i}, $1 \leq i \leq k$.

As an illustration, suppose that patterns resulted from the SVM classification results are molar-molar-molar-premolar-premolar (MMMPP) for maxilla and MMPP for mandible. Using equation (1), the similarity matrices are as shown in Figure 4. Then find the maximum value of each matrix, i.e. $Smax_1$=5, $Smax_2$=3, $Sman_1$=4, $Sman_2$=2. Thus, the score of Pattern 1 is 9, while the score of Pattern 2 is 5. Therefore we choose Pattern 1 as the default pattern. Next, label each tooth using teeth alignment method described above. For the maxilla sequence (MMMPP), k = 5 and l = 5. Then the resulted number sequence is 1-2-3-4-5. For the mandible sequence (MMPP), k = 4 and l = 5. Therefore the number sequence is 31-30-29-28.

Pattern 1	M	M	M	P	P	P
Maxilla	1	2	3	4	5	6
Mandible	32	31	30	29	28	27
Pattern 2	P	P	P	M	M	M
Maxilla	11	12	13	14	15	16
Mandible	22	21	20	19	18	17

Figure 3. Two default patterns of dental numbering

Default Pattern 1							Default Pattern 2						
$Omax_1$	**M**	**M**	**M**	**P**	**P**	**P**	**$Omax_2$**	**P**	**P**	**P**	**M**	**M**	**M**
M	1	1	1	0	0	0	**M**	0	0	0	1	1	1
M	1	2	2	0.7	0	0	**M**	0	0	0	1	2	2
M	1	2	3	1.7	0.4	0	**M**	0	0	0	1	2	3
P	0	0.7	1.7	4	2.7	1.4	**P**	1	1	1	0	0.7	1.7
P	0	0	0.4	2.7	5	3.7	**P**	1	2	2	0.7	0	0.4
$Oman_1$	**M**	**M**	**M**	**P**	**P**	**P**	**$Oman_2$**	**P**	**P**	**P**	**M**	**M**	**M**
M	1	1	1	0	0	0	**M**	0	0	0	1	1	1
M	1	2	2	0.7	0	0	**M**	0	0	0	1	2	2
P	0	0.7	1.7	3	1.7	1	**P**	1	1	1	0	0.7	1.7
P	0	0	0.4	2.7	4	2.7	**P**	1	2	2	0.7	0	0.4

Figure 4. The similarity matrices between two default patterns and the pattern MMMPP-MMPP.

The last procedure in the proposed identification system is related to database access. Final images after the classification and numbering process are stored in the database along with dental data such as a unique serial number, name and age of the radiograph's owner, date or recording, molar-premolar pattern, numbering pattern, area and ratio features, and file path of the original image, picture of the owner, and the classified image.

We use the pattern of molar-premolar and numbering both in the maxilla and mandible as the query of identification process. The result of this kind of query may include more than one identified person. For further processing, user may add area and ratio features as part of the query. Using these features, the system will choose data in the database that has equal area and ratio.

3. Results and Discussion

We use 16 dental radiograph images, composed of 6 bitewing radiographs and 10 panoramic radiographs. Based on an expert identification, there are 37 teeth objects identified in the 6 bitewing radiographs. Whereas in the panoramic radiographs, there are 82 teeth objects identified by the expert. Therefore, there are 119 objects of tooth in total. Three samples of the system's input image are as shown in Figure 5(a-c).

3.1. Pre-processing and Teeth Separation

In the first process, input images are successfully enhanced as shown in Figure 6. However, in the case of tooth object having too low intensity approaches background's intensity, or in the case of lower jaw bone having too high intensity approaches teeth object's intensity, this process does not perform well, as in three out of sixteen images in our experiment.

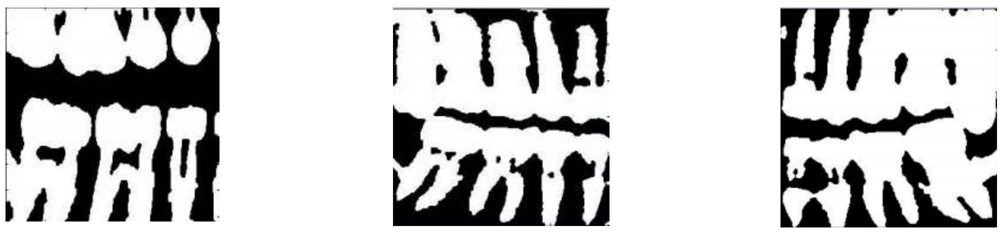
In the binarization process, the enhanced images are successfully converted into binary images. Except for the three images having the intensity problem as we explained before, all binary images have the properties as follows. The white pixels of the binary images represent teeth objects, whereas non-hole black pixels represent background. Sample outputs of the binarization process are as shown in Figure 7.

(a) (b) (c)

Figure 5. Sample input to the system: (a) a bitewing radiograph (b) a left-cropped panoramic radiograph (c) right-cropped panoramic radiograph

(a) (b) (c)

Figure 6. Results of enhancement process applied to three sample inputs as in Figure 5.



(a) (b) (c)

Figure 7. Results of binarization process applied to three enhanced images as in Figure 6(a-c).

The process after binarization is separating each radiograph into two parts, namely maxilla and mandible part. Our experiments show that using the horizontal integral projection followed by spline method, we can split the radiograph into two regions (maxilla and mandible) well (see Figure 8). Figure 8(a) and 8(d) are the two regions resulted from Figure 7(a). We can see that bitewing radiographs are easier to be horizontally separated. Figure 8(b, e) and 8(c, f) are resulted from Figure 7(b) and (c) respectively. Here, we can successfully separate the binary image into maxilla and mandible images although the upper and lower jaws are very close in panoramic radiographs.

Each region is processed further by applying the vertical integral projection followed by spline method to separate the teeth region into single tooth region. Overall our method performs well in our experiments except for two images that have very high lower jaw bone intensity. In the case of molar tooth that has double roots in mandible, our method performs well too because we only take 3/5 upper part of mandible. Hence pixel values of tooth root are not included in the computation of teeth separation.

3.2. Classification and Numbering

In the classification process, firstly we considered a tooth object is an isolated area having more than 6000 pixels. From each tooth object, we extracted its area, ratio of height and width, and its centroid. Based on these features, we classify each tooth into molar or premolar using binary SVM method. As a comparison, we also implemented the classification using k-nearest neighbor (kNN) method, a simpler method than SVM, with k = 9.

Based on our experiments, there is significant difference between accuracy of SVM classification result and that of kNN's result. Using the SVM method, the total accuracy value reaches 89.07% or 106 out of 119 objects were truly classified. Whereas, the average accuracy of the kNN method reaches 77.31% or 92 out of 119 objects were truly classified.

Next, we applied the numbering system by marking all teeth using a number and we also modified the class using standard numbering system in order to avoid abnormal molar and premolar pattern. As an example, if a classification process results in a pattern such as premolar-molar-premolar-premolar (P-M-P-P), then the pattern will be modified into M-M-P-P. This strategy has been able to improve the system's accuracy to 91.60%. Hence, 109 out of 119 objects are now classified correctly. The implemented numbering system also performs well. There are 97 out of 119 objects numbered correctly.

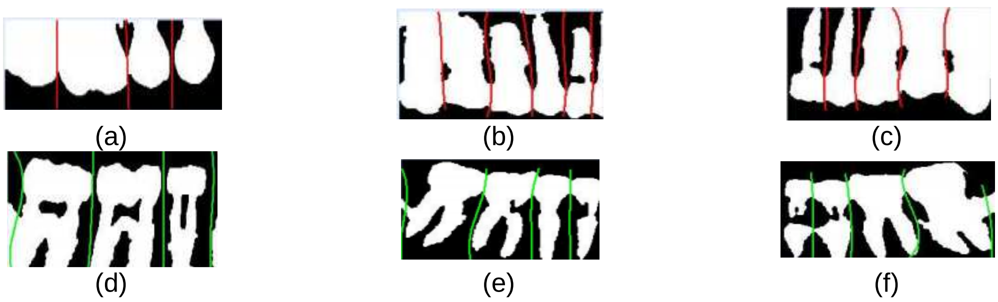


Figure 8. Results of teeth separation applied to three binary images as in Figure 7(a-c); Top row: maxilla regions. Bottom row: mandible regions.

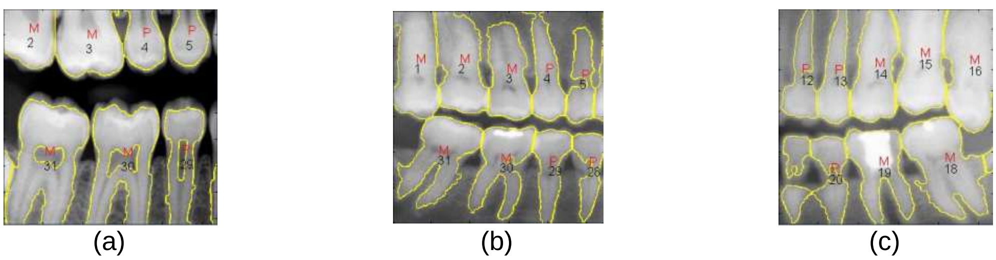


Figure 9. Results of classification and numbering process applied to extracted teeth as in Figure 8(a-f).

This leads to a total accuracy value of 81.51%. Details of classification and numbering accuracy value are shown in Table 1 and Table 2 respectively. Whereas, sample output images are shown in Figure 9. In Figure 9, extracted teeth are marked using a yellow line, labeled by M for molar class or P for premolar class followed by a number representing the numbering's result.

Table 1. The accuracy of molar-premolar classification

No	Filename	Classification Accuracy (%)		
		kNN	SVM	SVM followed by default pattern modification
1	bit1_Right.tif	100.00	100.00	100.00
2	bit2_Right.tif	71.42	100.00	100.00
3	bit3_Left.tif	80.00	80.00	80.00
4	bit4_Right.tif	71.42	100.00	100.00
5	bit5_Left.tif	57.14	71.42	85.71
6	bit6_Right.tif	33.33	66.67	66.67
7	pan1_Left.tif	100.00	100.00	100.00
8	pan1_Right.tif	87.50	100.00	100.00
9	pan25_Left.tif	88.89	88.89	88.89
10	pan25_Right.tif	100.00	100.00	100.00
11	pan34_Left.tif	75.00	100.00	100.00
12	pan34_Right.tif	71.42	100.00	100.00
13	pan50_Left.tif	50.00	75.00	75.00
14	pan50_Right.tif	55.56	55.56	66.67
15	pan70_Left.tif	87.50	100.00	100.00
16	pan70_Right.tif	100.00	87.50	100.00
Total accuracy out of 119 tooth objects		77.31	89.07	91.60

Table 2. The accuracy of numbering using teeth alignment

No	Filename	Numbering Accuracy (%)
1	bit1_Right.tif	60.00
2	bit2_Right.tif	100.00
3	bit3_Left.tif	60.00
4	bit4_Right.tif	100.00
5	bit5_Left.tif	85.71
6	bit6_Right.tif	00.00
7	pan1_Left.tif	100.00
8	pan1_Right.tif	100.00
9	pan25_Left.tif	88.89
10	pan25_Right.tif	100.00
11	pan34_Left.tif	100.00
12	pan34_Right.tif	100.00
13	pan50_Left.tif	50.00
14	pan50_Right.tif	33.67
15	pan70_Left.tif	100.00
16	pan70_Right.tif	100.00
Total accuracy out of 119 tooth objects		81.51

3.3. Identification System

The proposed automated human identification system was implemented using MySQL database server and Matlab 7.0. The system consists of four user interfaces. The first user interface is used for classification and numbering of dental radiographs. Sample input and output of the classification and numbering system is as shown in Figure 10. In the system's user interface, there are 6 buttons consisting of "Open Image" button to load an input image from local disk, "Proceed" button to perform the proposed methods, "Save" button to store the radiograph and its properties including dental pattern and numbering into the database, "Search" button to find a match of current radiograph in the database based on its properties, "Database" button to browse the database's contents, and "Exit" button to quit the application.

The second user interface aims to add a classified radiograph into the database. This interface only appears after users click the “Save” button in the first user interface. In this window, users may add additional information such as name, age, picture, and other information. Figure 11 shows an example of the action.

The third window appears when users click the “Search” button in the first user interface. This window aims to find whether there is matched data in the database based on the resulted pattern and numbering. The search process may results in zero, one, or more than one identity. This is because we only comparing the dental pattern including the dental numbering. Figure 12 shows an example when the system found exactly one matched result.

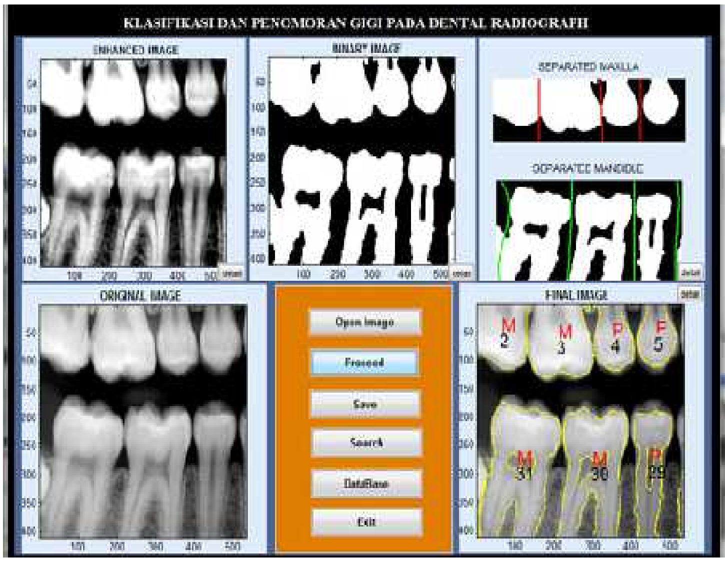


Figure 10. The classification and numbering system's user interface.

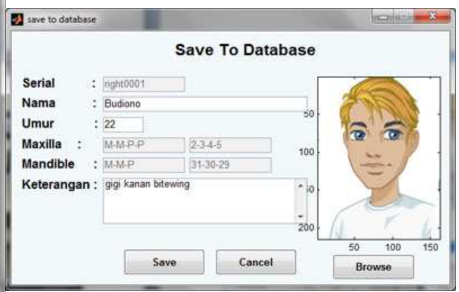


Figure 11. The user interface for saving new data into database.

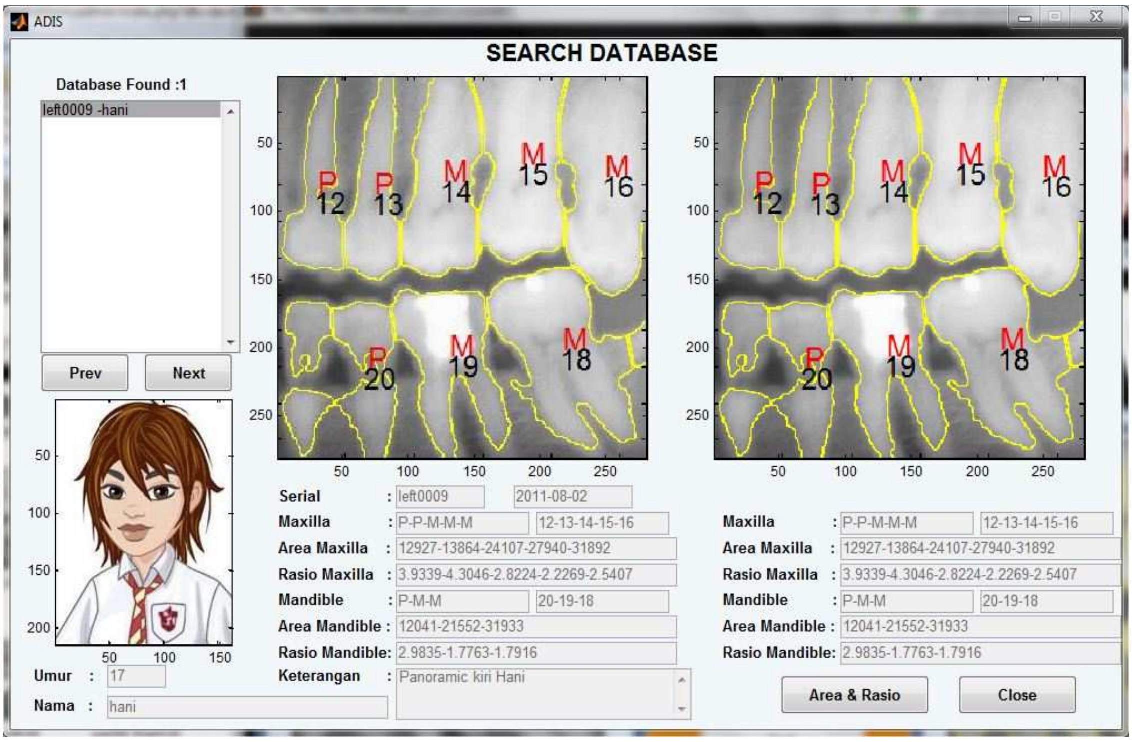


Figure 12. The user interface for searching process. Right image is the query, left image is the result.

The last user interface aims for viewing and querying the database. In this window, users are able to view all data in the database and to execute query based on pattern or numbering. Figure 13 illustrates query “14-15-16” that results in one found data.

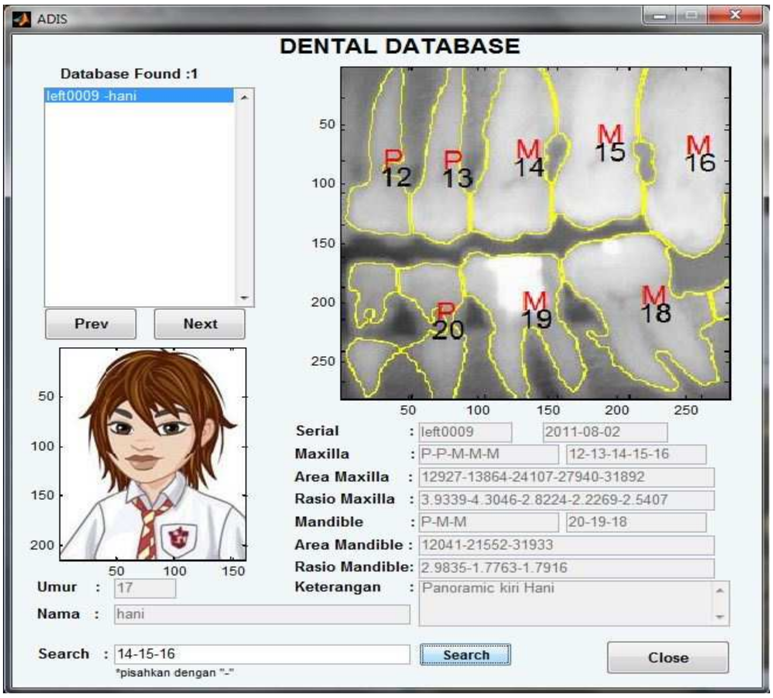


Figure 13. The user interface for querying database. Users are asked to enter the pattern or numbering in the Search textfield.

4. Conclusion

The proposed system has been successfully implemented and is able to generate dental pattern and numbering based on dental radiographs. In this paper, we have shown that our method can be applied not only to bitewing radiographs, but also to panoramic radiographs. The total accuracy value of dental pattern classification is 91.6% and the total accuracy of dental numbering system is 81.5%. However, there are some images that cannot be segmented correctly, due to low intensities of tooth objects. This error propagates into next processes and hence leads to incorrect classification and numbering. Therefore, the segmentation method still needs further research.

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