AUTOMATIC CLASSIFICATION OF TEETH IN BITEWING DENTAL IMAGES[1]

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ABSTRACT

We present an automated algorithm to classify teeth in bitewing dental images, using Bayesian classification, and assign an absolute number to each tooth based on common numbering system used in dentistry. Fourier descriptors of the contours of the molar and the premolar teeth in bitewing images are used in the Bayesian classification of these two types of the teeth. Then, the spatial relation between the two types of the teeth is considered to number each tooth and correct the misclassification of some teeth in order to obtain high precision results. Experiments with 50 bitewing images containing more than 400 teeth show that our method is capable of classifying and assigning absolute index number to the teeth with high accuracy.

1. INTRODUCTION

Forensic radiography is part of forensic medicine, which is concerned with identifying people using the postmortem radiological images of different parts of the body including skeleton, skull and teeth. Radiological images of the decedent's body are compared with antemortem records of a missing person to evaluate similarities between them. Traditionally, dental-based identification relies on information such as missing teeth and dental works [1]. Nowadays with the advancements in dentistry and care of teeth by people, these methods might not be reliable; hence, developing new methods that use inherent dental features for identification is important [2].

In order to build an automated dental identification system (ADIS), we need to extract features from the teeth in the dental images of missing people and archive them in a database. During retrieval, the features for each tooth in the query image need to be extracted and compared to those stored in the database. If we limit the comparison of the teeth to the ones that have the same index number, this will help limit the search space and increase the robustness of the system. In this paper, we present an algorithm for the classification and numbering of teeth to be used during archiving and retrieval in/from the database. The algorithm starts by classifying each tooth in a bitewing image based on its inherent shape and then it considers the relationship between the neighboring teeth in the bitewing image to correct any initial misclassification. Finally, using the results of the classification, it assigns a number to each individual tooth based on the common numbering system of dentistry [1].

The Adult dentition contains 32 teeth, 16 teeth in each jaw. We divide the jaws into four equal quadrants which each quadrant contains eight teeth, two incisors, one cuspid (canine), two premolars (bicuspid), and three molars. As shown in figure 1, The numbering system numbers permanent teeth from 1 to 32, beginning at the maxillary right third molar (#1), extending across the maxilla to the left third molar (#16), then continuing to the left mandibular third molar (#17), and going around the mandibular arch to the right third molar (#32).

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

Figure 1. The universal numbering system of adult teeth.

In this paper we deal with bitewing images. These images usually contain two types of teeth, i.e., molar and premolar teeth. Section 2 presents our method for classification. Section 3 gives properties of Fourier

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descriptors as a method for shape analysis and description. Section 4 discusses final classification using context information of teeth in bitewing images. Results of our method are presented in section 5 and conclusions are in section 6.

2. METHOD

Figure 2 shows our method for the classification of molar and premolar teeth in bitewing images. The method has three main steps: Teeth segmentation, Bayesian pre-classification using Fourier descriptors of each tooth contour, and final classification and numbering.

The goal of the segmentation step is to obtain the contour of each individual tooth. We use the segmentation results obtained from our two methods reported in [3, 4]. The first method [3] performs enhancement of the original image by applying the top-hat and bottom-hat morphological operators to the x-ray image. After obtaining an enhanced image, segmentation of teeth and background is achieved by adaptive thresholding to reduce the effect of noise and uneven intensity.

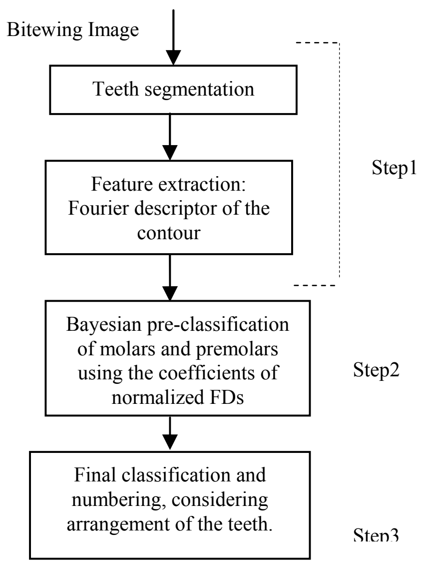
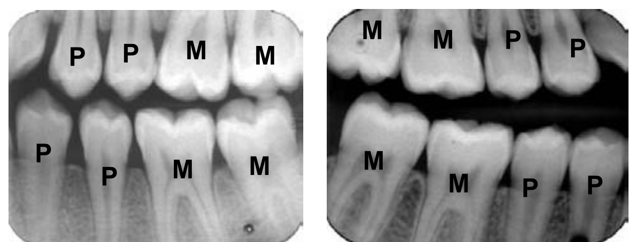


Figure 2. Dental classification method diagram

In the second method [4], iterative thresholding followed by adaptive thresholding is used to segment teeth from background. The iterative thresholding starts by applying Canny edge detection to the original image and then applying the morphological dilation to the binary edge image to obtain pixels around the location of the edges. After obtaining the dilated image, the average gray value of the corresponding pixels from original image is used as an initial threshold. Then the threshold is iteratively updated based on the results. After the iterations end, integral projection is used to separate each tooth from its surrounding. We used the results of these two segmentation methods by applying connected component analysis using 8-connectivity to extract the external contour of each individual tooth in the image.

Once the contour of each individual tooth has been extracted by a contour following algorithm, we represent it as a complex signal $u(n)=x(n)+jy(n)$. We use the Bayesian classification method [5] to classify and distinguish between molar and premolar teeth.

Figure 3 shows the arrangement of molar and premolar teeth in the bitewing images of the left and the right quadrant. We assume that the images are not flipped vertically; therefore, molar teeth are in the most left side of the image for radiographs of the right quadrant and in the most right side of the image for radiographs of the left quadrant. There is one molar adjacent to a premolar in each quadrant. Above each mandibular molar (premolar), there is a maxillary molar (premolar). We consider the spatial arrangement of teeth in the bitewing images for final classification and automatic numbering of the teeth.



(a) (b)

Figure 3. Arrangement of teeth in dental bitewing images, (a) Left quadrant (b) Right quadrant, M: Molar, P: Premolar.

3. FEATURE EXTRACTION AND PRE-CLASSIFICATION

Shape description using Fourier descriptors, FDs, is considered a powerful method [6, 7, 8]. It has useful properties including: simplicity of implementation and concentration of the contour information in the first (low frequency) few coefficients [6]. We represent the contour of the teeth as a complex signal $u(n)$ defined based on the coordinates, $x(n)$ and $y(n)$, of the pixels that make the contour,

$$u(n) = x(n) + jy(n) \quad (1)$$

We then apply Fourier transform to this complex signal,

$$U(s) = \frac{1}{N}\sum_{n=0}^{N-1} u(n)\, e^{-j\frac{2\pi}{N}sn}, \qquad s = -\frac{N}{2}+1, \ldots, \frac{N}{2} \quad (2)$$

We use Fourier series representation of $u(n)$ to define a set of FDs that is invariant to translation, rotation and scaling as follows:

$$NFD(s) = \begin{cases} 0; & s = 0 \\ |U(s)| / |U(1)| & s \neq 0 \end{cases} \quad (3)$$

Translation invariance is achieved by discarding the first coefficient (s=0), scaling invariance is brought by dividing the other coefficients by the second coefficient (s=1), and rotation invariance is achieved by using only absolute values of the coefficients. The third, fourth and fifth coefficients of normalized *FD*s, i.e., *NFD*(s), where s = 2, 3, 4, were used for shape characterization in this work. The rest of the coefficients were ignored.

Let c_i denote tooth class *i*, i.e., molar or premolar, and *x* denote the feature vector, i.e., normalized Fourier descriptors. Suppose that we know the *a priori probabilities* $p(c_i)$ and the conditional densities $p(x|c_i)$. Bayes rule shows how observing the value of *x* changes the *a priori probability* $p(c_i)$ to the *a posteriori probability* $p(c_i|x)$ [5]:

$$p(c_i \mid x) = \frac{p(x \mid c_i)\, p(c_i)}{p(x)} \quad (4)$$

where $p(x) = \sum_{i=1}^{C} p(x|c_i)\, p(c_i)$

In order to obtain the a posteriori probability we need to estimate $p(x|c_i)$ and $p(c_i)$. We assume that the coefficients of $NFD(s)$ have a Gaussian distribution, therefore $p(x|c_i)$ can be defined as,

$$p(x \mid c_i) = \frac{1}{(2\pi)^{d/2} |\Sigma_i|^{1/2}} \exp[-1/2 (x - \mu_i)^t \Sigma_i^{-1} (x - \mu_i)] \quad (5)$$

where μ_i is the mean vector, Σ_i is the covariance matrix, and *d* is the dimension. We used equation 6 to estimate the mean vector μ_i and the covariance matrix Σ_i for class c_i,

$$\mu_i = \frac{1}{N_i} \sum_{j=1}^{N_i} x_{i,j} \quad (6\text{-a})$$

$$\Sigma_i = \frac{1}{N_i - 1} \sum_{j=1}^{N_i} (x_{i,j} - \mu_i)(x_{i,j} - \mu_i)^t \quad (6\text{-b})$$

where N_i is the number of observations in class *i*. For maximum a posteriori classification, we choose class c_i which maximizes Eq. 4. We define a decision function as the logarithm of $p(c_i|x)$. Since $p(x)$ is constant, we ignore it; therefore the decision function has the form,

$$g_i(x) = \ln(p(x \mid c_i)) + \ln(p(c_i)) \quad (7)$$

This means that a feature vector *x,* is classified as belonging to class c_i, if the condition in Eq. 8 is satisfied.

$$g_i(x) > g_j(x) \quad \text{for all } i \neq j \quad (8)$$

where i, j ε {1,2,…,C}.

We defined two sets of classes for the lower and the upper jaws. We have two classes for the molar and the premolar teeth of the mandible and two other classes for the molar and the premolar teeth of the maxilla. Because we deal with the upper and lower jaws separately, we have two classes for each jaw, and the decision function for each jaw has the form,

$$g(x) = g_1(x) - g_2(x) \quad (9)$$

if $g(x)$ is positive, then we assign the feature vector *x* to class c_1 (Molar)*,* otherwise to class c_2 (Premolar).

4. FINAL CLASSIFICATION AND NUMBERING

During classification, we need to deal with the difficulties arising from missing part of the teeth at the border of the bitewing images. In addition, some images contain cuspid teeth, which are mostly like premolar teeth, and distinguishing them needs more consideration. Wisdom teeth, which are members of the molar teeth, are different in shape compared to other molar teeth. To resolve these problems and to classify the teeth correctly, the spatial relations between the teeth in bitewing images are considered.

If we assume that the bitewing image is not flipped vertically then we can assume that for the right quadrant, molar teeth are in the left side of the image and for the left quadrant; molars are in the right side of the image. Another important observation is that there is one molar that neighbors a premolar in each jaw. Also, as mentioned in section 2, if there is no missing tooth, above each molar in the lower jaw should be a molar tooth in the upper jaw and vice versa. Using this information, after the classification of the teeth as molars or premolars, we correct misclassifications and assign an index number to each individual tooth.

5. EXPERIMENTS AND RESULTS

Figure 4 shows an example of the results of the segmentation of the teeth in the bitewing images using the two different algorithms. The first method is more efficient than the second one which needed some manual correction in the segmented images for accurate results. After segmentation, we extract the contour of each tooth in the binary image by applying connected component analysis.

We used 25 bitewing images as a training set to estimate the *a priori distribution* and the *conditional distribution* (Eq. 5). Eq. 6 was used to estimate the mean and the covariance for each class.

(a) (b)

Figure 4. Results of segmentation (a) using the first method,(b) using the second method.

For classification, 50 images, different from the training set, containing 220 molar and 180 premolar teeth were randomly selected and segmented (half of them by the first algorithm and the other half by the second algorithm) and then tested by our classification method. Table 1 shows the results of pre-classification using the different segmentation algorithms.

Segmented Teeth	Performance Ratio % (Using first algorithm for segmentation)	Performance Ratio % (Using second algorithm for segmentation)
Molars in Mandible	95.5	89.7
Premolars in Mandible	86.4	87.2
Molars in Maxilla	93.7	91.2
Premolars in Maxilla	86.4	72.0

Table 1. Pre-classification of teeth using normalized Fourier descriptors in bitewing images.

Table 2 shows the results of the final classification with the consideration of the arrangement of the teeth. Our experiments show that the classification of premolars is more difficult than molars for both jaws. For maxillary teeth, the whole shape of the root part of the teeth is not visible in the radiographs and this makes the classification difficult. For mandibular teeth the crown of premolar teeth in some cases are similar to the crown of molar teeth. Molar teeth in mandible have at least two roots and both of the roots are visible in bitewing images, but molar teeth in maxilla have three or four roots which are projected on each other in bitewing images.

Teeth	Performance Ratio % (Using first algorithm for segmentation)	Performance Ratio % (Using second algorithm for segmentation)
Molars in Mandible	95.5	91.8
Premolars in Mandible	86.4	91.4
Molars in Maxilla	93.7	93.3
Premolars in Maxilla	92.0	82.0

Table 2. Final classification of the teeth using relationship between molar and premolar in bitewing images.

The classification of the teeth in the border of the images is difficult because parts of the teeth are not visible in the image and we have to ignore these teeth. In some cases there are some missing teeth and we loose information about the arrangement of the teeth in the jaw, therefore the final classification is affected. In figure 5, the results of numbering the teeth using common numbering system by our algorithm are shown.

6. CONCLUSION

In this paper we introduced a method for robust classification of molar and premolar teeth in bitewing images using Bayesian classification. After Bayesian classification, the algorithm considers the arrangement of the teeth in the jaw and assigns a number based on the common numbering system of dentistry to each individual tooth. Our experiments show that this method classifies molars and premolars with high accuracy.

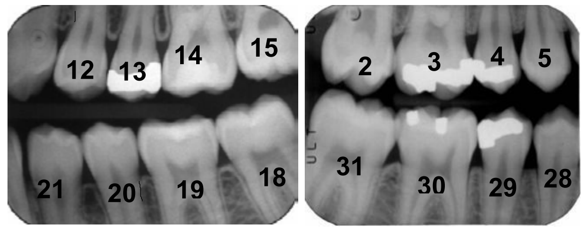


Figure 5. Results of numbering the teeth after classification.

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