

Automatic Human Identification based on Dental X-Ray Images

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Oral Presentation Preferred

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Abstract ---- This paper presents an automated system for human identification using dental radiographs. Given a dental image of a postmortem (PM), the proposed system identifies the person from an antemortem (AM) database by matching automatically extracted teeth shapes of the PM image to the teeth shapes in the AM database. Experiments on a small database show that our method is effective for teeth segmentation, separation of teeth into crowns and roots, and matching.

Keywords *dental biometrics, image segmentation, Human Identification, Forensic odontology*

1. Introduction

Human identification from dental features is regarded as the best candidate for postmortem biometric identification. Dental features not only represent a suitable repository for such unique and identifying features, but they also survive most postmortem events that can disrupt or change other body tissues. Traditionally, dental identification methods are manual, where postmortem (PM) dental records are analyzed and compared against antemortem (AM) records to confirm identity based on features of dental restoration and dental work. In the future, these features may be difficult to use due to the advances in dentistry. Consequently, it is important to identify some inherent dental features, like shapes of roots and crowns, and space between teeth, for future automated dental identification systems.

. In this paper we present an automated system for human identification based on bitewing dental radiographs. The goals and objectives of automated dental identification are similar to automated fingerprint identification [2] but using dental characteristics [6], especially geometry based (shape) features. Our system contains three steps: image enhancement, teeth segmentation from the background and separation into crown and root, and matching.

2. The components of the system

2.1 Enhancement

Dental radiographs contain three distinctive regions: background, teeth, and bones. Usually the teeth regions have the highest intensity, the bone regions have high intensity that sometimes is close to that of the teeth, and the background has a distinctively low intensity. It is easy to separate the background by threshold-based methods, but these methods usually fail to discriminate teeth from bones, especially in cases of uneven exposure. To overcome this problem, the first step we use is to enhance the image's contrast.

Top-hat and bottom-hat filters can be used to extract light objects (or, conversely, dark ones) on a dark (or light) but slowly changing background [4]. We use both the top-hat and the bottom-hat filters on the original image, and combine the results by adding to the original image the result of the top-hat filter, and subtracting the result of the bottom-hat filter. Figure 1 shows an example, where the teeth regions are enhanced and the bone regions are suppressed.

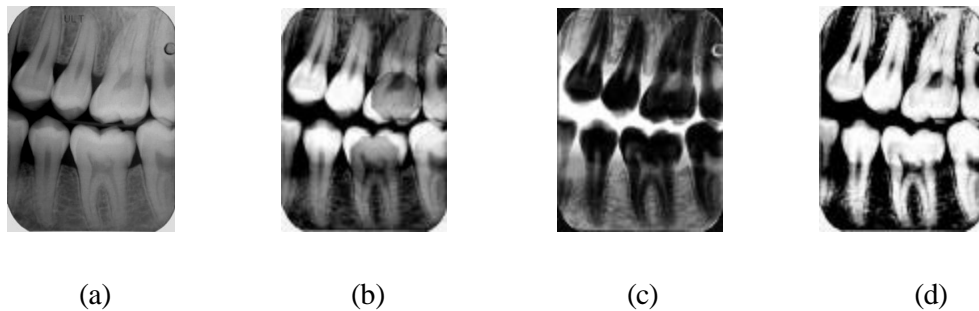


Fig. 1. (a) Original image; (b) Result of top-hat filtering; (c) Result of bottom-hat filtering; (d) The enhanced image.

2.2 Teeth segmentation

We use window-based adaptive threshold [3] to segment the teeth. The idea is to examine the

intensity values of the local neighbors of each pixel. If the intensity value of the pixel is larger than the average intensity values of its neighbors, then it is classified as a tooth pixel, otherwise it is classified as background. Figure 2a shows the result of the window-based adaptive threshold method on the image in Figure 1a. To separate each tooth, we apply a binary morphological transformation [1] to eliminate small noisy parts and smooth the teeth regions as shown in Figure 2b. Then, we subtract the teeth areas from the original image to obtain the bones and the background regions, and then apply simple thresholding to separate the bones from the background (figure 2c).

The positions of the bones provide information to approximate the gum line and separate the crown and root parts of the teeth, see Figure 3. To determine the gum lines we need to separate the bones of the upper and the lower jaws and identify the tips of the bones. The line that connects the tips of the bones approximates the gum line. From the detected bones images (figure 2c), the upper and lower jaws are separated using integral projection [5]. The bones between adjacent teeth are also separated using integral projection. The tips of the bones are then used to separate the crowns from the roots (see points in figure 3).

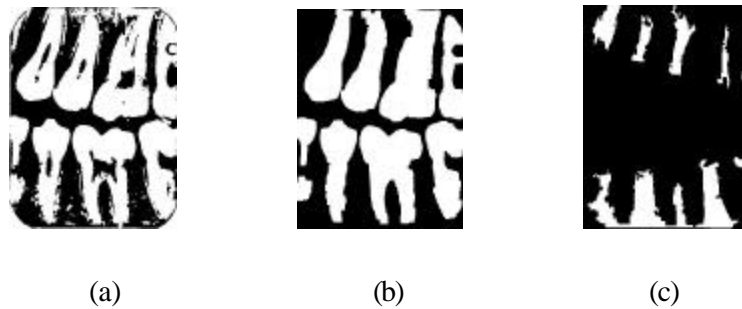


Fig.2. Example of segmentation. (a) Result of Adaptive thresholding (b) Final Result of segmented teeth; (c) Segmented bones.

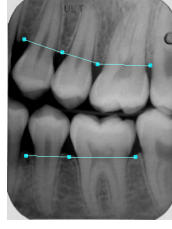


Fig. 3. Separation of crown and root

2.3 Shape matching

The shapes of the crowns of the segmented teeth are used to find a match between the PM case and the cases in the AM database. The matching is performed by finding a transformation, (i.e., rotation, scale and translation), that results in a minimum matching distance. The transformation is expressed as:

$$T(P) = A * P + t = \begin{pmatrix} \cos \mathbf{q} & \sin \mathbf{q} \\ -\sin \mathbf{q} & \cos \mathbf{q} \end{pmatrix} * \begin{pmatrix} s & 0 \\ 0 & s \end{pmatrix} * \begin{pmatrix} x \\ y \end{pmatrix} + \begin{pmatrix} t_x \\ t_y \end{pmatrix} \quad (1)$$

Where the $T(P)$ is the transformed result of the query shape P , A is the rotation matrix and t is the translation vector. For each query shape and database shape pair, the matching distance (MD) that needs to be minimized is defined as:

$$MD = \frac{1}{L(\tilde{P})} \sum_i^{P(i) \in \text{query shape}} \min_{\tilde{P}(j) \in \text{database shape}} |T[P(i)] - \tilde{P}(j)| \quad (2)$$

Where $P(i)$ is a point on a PM tooth boundary. $\tilde{P}(j)$ is a point on an AM tooth boundary. The distance is normalized for the scale using $L(\tilde{P})$, which is the length of the minor axis of the AM tooth region. The four parameters, \mathbf{q} , s , t_x and t_y , are optimized to obtain the minimum distance between the query tooth and the database tooth.

3. Experimental Results

The segmentation algorithm was evaluated on 20 bitewing X-ray dental images. Figure 4 shows one example of the results.

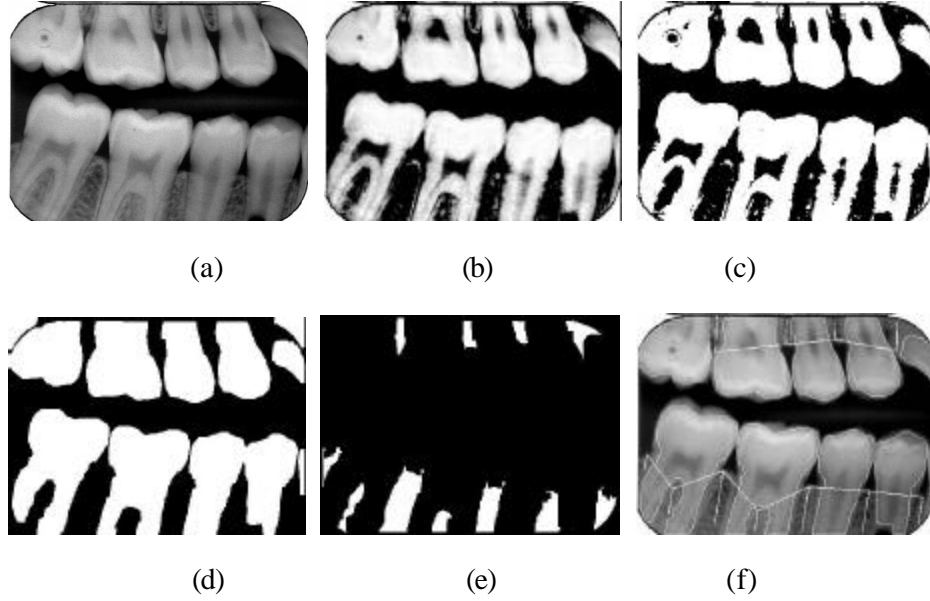


Fig.4. (a) Original image; (b) Result of enhancement; (c) Result of a daptive thresholding; (d) Result of segmented teeth using morphological operation; (e) Bones image; (f) Final result of separated roots and crowns.

In the 20 bitewing dental images , there are 105 teeth, 92 teeth have been correctly segmented. This means a detection ratio of 88%. For the 92 teeth, 69 teeth were correctly separated into crowns and toots, i.e., 75% success rate.

To test the matching we took one PM image , and used every tooth as a query for retrieval from a database that had 33 AM radiographs of five pe ople with 160 teeth. Figure 5 shows one of the matching results. For five out of the six queries, the correct results were retrieved as the first best match. In case of the sixth query, the correct match was the second best match, while the first match

was an image for the same person, but the match was with a different tooth.

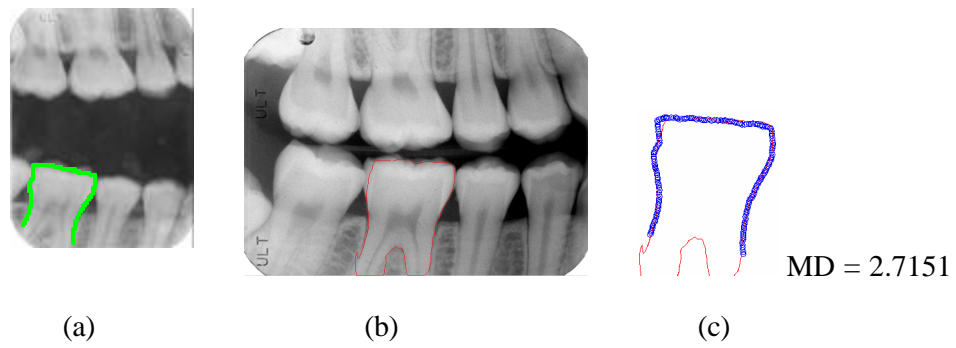


Fig.5. (a) PM images with an extracted query tooth shape; (b) Best matching tooth shape in AM database; (c) Query shape and its match overlaid.

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