Dental Identification based on Teeth and Dental Works Matching for Bitewing Radiographs

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Abstract
This paper presents an enhanced human identification method based on matching both the contours of teeth and the shapes of dental works (DWs) using bitewing radiographs. To reduce teeth matching error due to unsatisfactory alignment of two incomplete tooth contours, we propose an enhanced contour alignment by pruning the outliers from both contours after they are aligned with the original contours using an adopted regular alignment method then realigning the pruned contours again, and a revised Hausdorff distance for measuring the distance between two contours. To compensate DW matching error based on the distance of DWs’ contours due to imperfect alignment of the teeth in which they reside, we propose using alignment-invariant Fourier descriptors of DWs’ contours as an additional feature. The distance between the contours of teeth and the distance between the shapes of DWs are weightily combined for improving identification matching. Experiments on a small database show that (1) matching with pruned tooth contours improved 8% accuracy for the top-1 retrieval when compared to the result of matching with original contours; (2) matching with the combined frequency and spatial features of DWs improved about 19% and 5% accuracy, respectively, when compared to matching with only the spatial and the frequency feature for the top-1 retrieval; and (3) matching with the pruned tooth contours and both the spatial and frequency features of DWs, the retrieval accuracy in identification matching achieved to 100% for the upper, the lower, and both jaws.

Keywords: bitewing radiographs, automatic dental identification system, postmortem identification, dental work matching, tooth matching.

Introduction
Biometrics is an identification technology for uniquely recognizing individuals based on measuring the subject’s physical or behavioral traits, such as fingerprint, iris, and voice. In the law enforcement sector, forensic identification is carried out after death and is called postmortem (PM) identification. Most of behavioral and physiological traits are not suitable for PM identification when the victims are under severe decaying of soft tissues or mass disasters such as fire or collision. Teeth, being the hardest and the most impregnable part of human body, are thus regarded as the best candidate for PM identification [1].

In traditional dental identification, forensic odontologists manually compare PM dental radiographs with all of antemortem (AM) dental radiographs stored in the database by using distinctive features such as dental restoration, dental work, morphology of root, and teeth. Such work is time consuming and often not good enough to correctly identify individuals. For more efficient and accurate identification, some Automatic Dental Identification Systems (ADIS), which involve teeth segmentation, teeth classification, teeth numbering, and human identification had been proposed [2][3][4] to search the AM database for the best matches to a given PM dental radiograph.

Many methods of dental identification that mainly used tooth contours as the matching feature had been reported in literature [2][3][5]. However, using tooth contours as the only feature in dental identification is not always reliable due to several challenges [6]: (1) Poor quality radiographs, which will influence the precision of teeth segmentation, and consequently affects the matching accuracy. (2) Changes of tooth shape over time, which will lead to difficulty in matching with AM radiographs. (3) View variation of radiographs, which will result in a non-linear deformation of images and influence the precision of alignment. (4) Small interclass variation, which will produce very similar features in the same category from different individuals due to that dental radiographs are 2D projection of 3D objects [4]. Figures 1(a) and (b) are two dental radiographs of the same person acquired in the year 2003 and 2008, respectively. We can notice that the tooth shapes become different after a long time (especially in bicuspids) and appear deformed in different views.

On the other hand, dental works (DWs) usually appear brighter than teeth, and their contours are not as noisy as tooth contours and not as sensitive to view variation. Thus, shapes of DWs can be used as another salient feature for dental matching. Chen and Jain [7] utilized an area-based metric for matching DWs, and then fused both the similarity measurements of tooth contours and DWs to improve the identification accuracy. Hofer and Marana [8] presented a dental identification method based on the information of all DWs in the image, including position, size, and distance between neighboring DWs. Figures 1(c) and (d) show two dental radiographs with DWs of the same person captured in the year 2005 and 2009, respectively. However, using spatial domain features of DWs, such as area-based metric used in [7], relies
heavily on teeth alignment. Incorrect DW matching can occur when two tooth contours are either unreliable or incompletely overlapped due to poor image quality or images taken in rather different angles.

In this paper, we use a combination of tooth contours and shapes of DWs as the matching features to improve the identification accuracy. To reduce the matching error caused from aligning two incompletely overlapped tooth contours, we propose pruning the outliers from each tooth contour after the first alignment so that the two contours can be aligned better before matching. To compensate the errors when matching with the spatial feature of DWs due to imperfect tooth alignment, we propose using an additional frequency feature of dental works that’s not affected by the tooth alignment so that both features can compensate the drawback of each other. Meanwhile, to have more distinctive teeth available in a better quality image in general, we use bitewing radiographs instead of panoramic or periapical radiographs.

Fig. 1. Two sets of dental radiographs from two persons acquired in different years. (a) From person-1 in 2003. (b) From person-1 in 2008. (c) From person-2 in 2005. (d) From person-2 in 2009.

Feature extraction

According to the view and coverage, the most commonly used dental radiographs are panoramic, periapical, and bitewing. Panoramic has complete upper and lower jaws, but has little fine detailed teeth information. Periapical, on the other hand, shows the entire view of specific teeth, including crowns and roots, but it always has few teeth. Bitewing presents crowns and parts of the roots of molar and premolar teeth, which are more distinctive than other teeth. Also, bitewing usually has better image quality and more teeth than periapical.

Tooth feature

1) Segmentation of teeth: Both shapes and sizes of teeth provide important information for dental identification. As the scale, the orientation, and the translation of PM and AM radiographs are generally different due to view and age variations, each tooth must be segmented and the matching tooth pair must be well aligned to each other so that the pair can be matched fairly in the spatial domain. Several good progresses for teeth segmentation had been made in the past few years [2][3][8]. In this paper, we use the segmentation method in [1] and slightly refine the contours manually. That is, we first apply iterative thresholding to the enhanced image to obtain a binary image with teeth in white and background in black. We then apply horizontal projection followed by vertical projection to separate the image into regions of interest (ROIs) so that each one contains a tooth. Finally an edge operator is applied to each ROI followed by equal point sampling and B-spline fitting to obtain the contour of each tooth.

2) Contour extraction and alignment: The contour of each tooth is the feature used for teeth matching. After teeth segmentation, a connected component analysis starting from the left or the right end point [9] is applied to each tooth to obtain a sequence of \( N \) connected contour points \( Q_{Teeth}(n) = (x(n), y(n)) \), \( n = 1,...,N \). As mentioned in 1), \( Q_{Teeth} \) must be well aligned to the database tooth contour \( D_{Teeth} \) so that a valid distance between the two can be computed. The alignment method adapted from [10] is as follows.

Let the rotation angle be \( \theta \), the translations along \( x \) and \( y \) axes be \( t_x \) and \( t_y \), respectively, and the scaling factors of horizontal and vertical be \( s_x \) and \( s_y \), respectively. A contour point \( Q_{Teeth}(n) \) is transformed to \( T(Q_{Teeth}(n)) \) by

\[
T(Q_{Teeth}(n)) = \begin{bmatrix}
\cos \theta & \sin \theta \\
-\sin \theta & \cos \theta
\end{bmatrix}
\begin{bmatrix}
s_x & 0 \\
0 & s_y
\end{bmatrix}
\begin{bmatrix}
x(n) \\
y(n)
\end{bmatrix} + \begin{bmatrix}
t_x \\
t_y
\end{bmatrix}
\] (1)

where the five parameters are optimized to obtain the best fit between the transformed query contour \( T(Q_{Teeth}) \) and the database contour \( D_{Teeth} \).

3) Pruning the contours: The contours of both the query and the genuine database teeth may not be fully overlapped due to the view variation, as shown in Figs. 2(a) and (b). When aligning directly with these two incompletely overlapped contours, some points of either tooth contour become outliers of its counterpart and have no corresponding points for matching. As a result, unsatisfactory alignment occurs, as shown in Fig. 2(c). Thus, we propose an enhanced contour alignment by pruning the outliers from both contours after they are aligned with the original contours using the method in [10] then realigning the pruned contours again. The enhanced contour alignment algorithm is described in the following and the alignment result of the pruned contours is as shown in Fig. 2(d), which is significantly better than the alignment result of the original contours.

**Enhanced contour alignment algorithm:**

Input: Two contours \( Q_{Teeth} \) and \( D_{Teeth} \)

Output: Two pruned and well aligned contours \( T(\tilde{Q}_{Teeth}) \) and \( \tilde{D}_{Teeth} \) ready for matching

(a) Perform contour alignment [10] for each point as \( Q_{Teeth} \) and \( D_{Teeth} \) and obtain an aligned contour \( T(\tilde{Q}_{Teeth}) \).
(b) Resample each of contours $T(Q_{Teeth})$ and $D_{Teeth}$ evenly from the left-end to the right-end clockwise to obtain two sequences of $N$ points $T(Q_{Teeth}(i))$ and $D_{Teeth}(i)$, $i=1,...,N$.

(c) Trace the contour points $T(Q_{Teeth}(i))$ and $D_{Teeth}(i)$ from $i=1$ to $N$. The points with their $y$-coordinates falling in the range $\{\min\{T(Q_{Teeth}(1)), D_{Teeth}(1)\}, \max\{T(Q_{Teeth}(1)), D_{Teeth}(1)\}\}$ and $\{\min\{T(Q_{Teeth}(N)), D_{Teeth}(N)\}, \max\{T(Q_{Teeth}(N)), D_{Teeth}(N)\}\}$ are regarded as outliers.

(d) Remove all the outlier points from $T(Q_{Teeth})$ and $D_{Teeth}$ to obtain two pruned contours $\tilde{Q}_{Teeth}$ and $\tilde{D}_{Teeth}$.

(e) Align $\tilde{Q}_{Teeth}$ to $\tilde{D}_{Teeth}$ to obtain the final result $T(\tilde{Q}_{Teeth})$ using the contour alignment method [10].

(f) Return $T(\tilde{Q}_{Teeth})$ and $\tilde{D}_{Teeth}$.

Fig. 2. A comparison of teeth alignment using the method in [10] and our enhanced alignment method. (a) The query tooth. (b) The genuine database tooth. (c) Alignment using the method in [10]. (d) Alignment using our enhanced method.

Dental work feature

1) Segmentation of dental works: Since dental radiographs often have uneven illumination problem that causes non-dental works (DWs) such as enamels appeared as bright as or even brighter than DWs. Thus, using a single threshold for the entire image without preprocessing would often mistake some non-DWs as DWs. To extract DWs more accurately, instead of directly thresholding the entire image to get the coarse shapes of DWs in the first stage as in [8], we preprocess the image to reduce most irrelevant information before thresholding and result in coarse contours of all DWs. We then obtain the complete shape of each DW by region growing in the second stage, unlike using a separate snake as in [8]. Our method is as follows.

Stage 1: Locate the coarse contours of all DWs.

(a) Apply Canny edge filter [11] to obtain the edge pixels around DWs.

(b) Refine the edges by replacing each edge pixel with the brightest one within its neighborhood.

(c) Take the intensity histogram of (b) and smooth it with average filter.

(d) Select the right most valley of the histogram as the intensity threshold and filter the image with this threshold.

(e) Compute the length of each connected contour and filter out the ones with length less than a preset length threshold.

Stage 2: Obtain the complete shapes of DWs.

(a) Use the center point of each located contour as the seed.

(b) Grow outward from each seed to obtain the complete shapes of DWs.

Fig. 3. Segmentation of dental works. (a),(d) Original radiographs. (b),(e) The results after Stage 1. (e),(f) The results after Stage 2.

Figure 3 gives the extracted DWs from two radiographs, where (b) and (e) are the extracted coarse contours of all DWs in (a) and (d), respectively, after Stage 1, and (c) and (f) are the segmentation results after Stage 2.

2) Feature extraction of dental works: Spatial information such as shape, size, location, and orientation should all be considered when matching DWs. In order to include spatial information besides shape among the matching criteria while tolerating the differences caused from imperfect alignment and boundary disturbances, we propose using both spatial and affine-transformation invariant frequency domain features.

(a) Spatial domain feature: Same as the method used in feature extraction of teeth, the contour pixels of DW are represented as $Q_{DW}(n) = (x(n), y(n))$. However, two DWs with the same shape but different orientation/position should be considered from two different subjects, as shown in Figs. 4(a) and (c). If we directly align the query DW in (a) to the DW in (c) using the method in [10], the differences between them in translation, rotation, and scale will all be neglected, and lead to a matching error. Thus, to preserve the spatial relationship, we apply the affine transform using Eq. (1) with the optimum parameters obtained from teeth alignment, so that two DWs under matching will be well aligned with their spatial relationship preserved. Figures 4(d) and (e) show two sets of DW contours after affine transforming the DW in (a) with the optimum parameters obtained from teeth alignment of (a) to (b) and to (c), respectively. Notice that the query DW (a) is well overlapped with the genuine DW (b), as shown in (d) and completely separated from the imposter DW (c), as shown in (e).
$U(n) = DFT(u(n)) = \frac{1}{N} \sum_{k=0}^{N-1} u(k) e^{-2\pi ink/N}$  

where $n = 0, 1, \ldots, N-1$, is the $n$th Fourier transform coefficient. The resulted series of coefficient is then normalized using

$$Q_{DW}^0 = \left[ \frac{U(2)}{U(1)}, \frac{U(3)}{U(1)}, \ldots, \frac{U(N-1)}{U(1)} \right]$$

Notice that discarding the first coefficient is to achieve translation invariance, dividing all other coefficients by the second is to achieve scale invariance, and taking the magnitude of the coefficients is for rotation invariance [12].

**Dental identification**

Teeth matching, dental work matching, and identification matching are performed for dental identification. The matching is performed by measuring the distances between the query object (tooth, dental work, or image) and each of the database objects to generate a matching list. The list is then ranked in an ascending order. The accurate top-$K$ retrieval of a given query object means that the rank of the corresponding genuine object in the database is the $Kth$ smallest in the matching list and accurate top-$K$ retrievals means that the rank of the corresponding genuine object in the database is less than or equal to the $Kth$ smallest in the matching list. Thus, the retrieval accuracy using top-$K$ ($\%$) retrievals is calculated by the total number of accurate genuine objects ranked less than or equal to $Kth$ in the matching list divided by the total number of objects in the database. Three metrics for teeth matching, dental work matching, and identification matching are proposed as follows.

**Teeth matching**

The distance metric ($d_{Teeth}^{RD}$), which is used to measure how different the query tooth contour $Q_{Teeth}$ is from the database tooth contour $D_{Teeth}$, is calculated by a revision of partial bi-directional Hausdorff distance [2] as follows.

$$d_{Teeth}^{RD}(Q_{Teeth}, D_{Teeth}) = \max \{ h_k(D_{Teeth} Q_{Teeth}), h_k(Q_{Teeth} D_{Teeth}) \}$$

where $h_k(D_{Teeth} Q_{Teeth}) = \frac{1}{N} \sum_{k=0}^{N-1} h_k(d(a,b))$ and $h_k(Q_{Teeth} D_{Teeth}) = \frac{1}{N} \sum_{k=0}^{N-1} h_k(d(a,b))$.

$$h_k(d(a,b)) = \frac{1}{N} \sum_{k=0}^{N-1} h_k(d(a,b))$$

where $Q_{Teeth}$ and $D_{Teeth}$ are well aligned and pruned. Note that in [2], $h_k(Q_{Teeth} D_{Teeth})$ and $h_k(D_{Teeth} Q_{Teeth})$ are the $Kth$ and $Lth$ largest values in the set of distances instead of the maximum value used in traditional Hausdorff distance, where the parameters $K$ and $L$ determine how many points
each tooth contour can be discarded. According to our observation, we found that discarding the largest 20% point distances from each contour will allow us to reduce the effect of noises resulted from poor image quality. Therefore, we simply use the largest value of the remaining 80% points in \( Q_{\text{teeth}} \) and \( D_{\text{teeth}} \), respectively, to decrease the effect of noises resulted from poor image quality.

**Dental works matching**

1) **Matching with spatial domain feature**: Similar to teeth matching, the partial bi-directional Hausdorff distance \( d_{\text{DW}} \) defined in (8) is used as the matching metric for DWs in spatial domain. Note that we use \( T \left( Q_{\text{DW}}^S \right) \) instead of \( Q_{\text{DW}}^S \) because the set of points in the contour of the query dental work must firstly be affine transformed with the optimum parameters obtained from the teeth alignment. Thus, \( d_{\text{DW}} \) not only measures the difference of the shapes but also the position/orientation distance between the two DWs under matching.

\[
d_{\text{DW}} \left( T \left( Q_{\text{DW}}^S \right), D_{\text{DW}}^S \right) = \max \left( h_{\text{c}} \left( D_{\text{DW}}^S, T \left( Q_{\text{DW}}^S \right) \right), h_{\text{c}} \left( T \left( Q_{\text{DW}}^S \right), D_{\text{DW}}^S \right) \right) \tag{8}
\]

2) **Matching with frequency domain feature**: The frequency domain metric \( d_{\text{FD}} \) measures the matching distance between two sets of Fourier descriptors which represent the respective contour of query and database DWs. It is affine-transform invariant, and hence no alignment between the objects are required. The metric \( d_{\text{FD}} \) is defined as

\[
d_{\text{FD}} = \frac{1}{nc} \sqrt{\sum_{i=1}^{nc} \left| Q_{i}^{F_{\text{dw}}} - D_{i}^{F_{\text{dw}}} \right|^2} \tag{9}
\]

where \( Q_{i}^{F_{\text{dw}}} \) and \( D_{i}^{F_{\text{dw}}} \) are the \( i \)-th normalized FD of the query set and the database set obtained from (2) and (3), respectively, and \( nc \) is the total number of FDs used for each set. In general, the first few coefficients (i.e. the top 10~20%) of the descriptors are enough for differentiating two different shapes [9]. Thus, we propose using the first 10% of FDs so that they are not only enough to differentiate the shape difference but also insensitive to boundary noises.

3) **Matching with combined features**: As mentioned earlier, using spatial feature \( Q_{\text{DW}}^S \) can not handle imperfect alignment situation, but frequency feature \( Q_{\text{DW}}^F \) can because it’s affine-transform invariant. On the other hand, using affine-transform invariant frequency feature \( Q_{\text{DW}}^F \) will confuse retrievals from objects which are similar in shape but different in positions and orientations, whereas the spatial feature \( Q_{\text{DW}}^S \) will not because it considers the relative spatial relationship. To compensate each other’s drawback while taking the advantage of each individual, a combined matching metric of dental works \( d_{\text{DF}} \) defined in the following is used.

\[
d_{\text{DF}} = \min \left( \text{Nor} \left( d_{\text{HD}} \right), \text{Nor} \left( d_{\text{FD}} \right) \right) \tag{10}
\]

where

\[
\text{Nor} \left( a \right) = \frac{a}{\max \left\{ b : \forall b \in A \right\}} \tag{11}
\]

is for normalizing distance values to be within \([0, 1]\).

**Identities matching stage**

The similarity between the query PM image and each AM image in the database is measured by the average matching distances of 1) all teeth only, and 2) all teeth and dental works in the query image, respectively.

1) **Identification by teeth**: The metric \( d_{\text{image}}^T \), which only uses tooth contour as its matching feature, is calculated by

\[
d_{\text{image}}^T = \frac{1}{Nq} \sum_{i=1}^{Nq} \min \left( d_{\text{Teeth}}^T \right) \tag{12}
\]

where \( d_{\text{Teeth}}^T \) represents the distance obtained by matching the \( i \)-th tooth of the query image with the \( j \)-th tooth of the database image; \( Nq \) and \( Nd \) are the number of teeth of the upper or the lower jaw in the query image and database image, respectively. In other words, for each tooth in the query image, the minimum matching distance among all teeth in the database image is firstly identified. All the minimum matching distances in the query image are then averaged as the matching distance of the query image.

2) **Identification by teeth and dental works**: The distance \( d_{\text{image}} \) is calculated by combining both the matching distances of teeth (\( d_{\text{Teeth}}^T \)) and dental works (\( d_{\text{DF}} \)) as:

\[
d_{\text{image}} = \frac{1}{Nq} \sum_{i=1}^{Nq} \min \left( w_1 \cdot d_{\text{Teeth}}^T + w_2 \cdot d_{\text{DF}} \right) \tag{13}
\]

where

\[
w_2 = \frac{\# \text{of teeth in the database}}{\# \text{of teeth and dental works in the database}} \tag{14}
\]

**Experiments and comparison**

We create a database of 53 AM images (containing a total of 329 teeth and 57 dental works) and 10 PM images (containing a total of 65 teeth and 22 dental works) to evaluate the performance of teeth matching, dental works matching, and identities matching. In order to increase the accuracy and reduce the search space when matching, each tooth or dental work is only matched against the teeth or the dental works in the same jaw. Table 1 lists the composition of the experimental database.

**Performance of teeth matching**

We compare the effectiveness of teeth matching based on the traditional Hausdorff distance (HD) of
the original contours (method-(1)) and revised Hausdorff distance (RHD) of the pruned contours (method-(2)). Table 2 shows the comparison of the teeth retrieval accuracy using both contours. Among all queries of teeth in both the upper and the lower jaws, the accuracy of method-(1) is 24/65 (36.9%) using the top-1 retrieval; whereas the accuracy of method-(2) improves to 26/65 (44.6%). Using top-10 retrievals, method-(1) and -(2) respectively recall 32 and 31 correct teeth and elevate the accuracy to 56/65 (86.2%) and 60/65 (92.3%), respectively. Comparing the matching results, we found that matching with RHD of the pruned contours can indeed improve the retrieval accuracy 8% and 6% for both jaws using top-1 and -10 retrievals, respectively.

Table 1. The composition of experimental database

<table>
<thead>
<tr>
<th>Teeth</th>
<th># of images</th>
<th># of teeth</th>
<th>upper jaw</th>
<th>lower jaw</th>
</tr>
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<tbody>
<tr>
<td>PM</td>
<td>10</td>
<td>15</td>
<td>35</td>
<td>30</td>
</tr>
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<td>AM</td>
<td>53</td>
<td>174</td>
<td>155</td>
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<table>
<thead>
<tr>
<th>Dental Works</th>
<th># of images</th>
<th># of dental works</th>
<th>upper jaw</th>
<th>lower jaw</th>
</tr>
</thead>
<tbody>
<tr>
<td>PM</td>
<td>10</td>
<td>11</td>
<td>10</td>
<td></td>
</tr>
<tr>
<td>AM</td>
<td>29</td>
<td>25</td>
<td>32</td>
<td></td>
</tr>
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</table>

Table 2. The comparison on teeth retrieval

<table>
<thead>
<tr>
<th>jaw</th>
<th>Top N (# of retrievals / # of teeth in PM)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>#</td>
</tr>
<tr>
<td>(1)</td>
<td>upper 11/35, 22/35, 27/35, 32/35, 35/35</td>
</tr>
<tr>
<td></td>
<td>lower 13/30, 18/30, 19/30, 24/30, 28/30</td>
</tr>
<tr>
<td>(2)</td>
<td>upper 13/35, 24/35, 29/35, 33/35, 34/35</td>
</tr>
<tr>
<td></td>
<td>lower 16/30, 22/30, 22/30, 27/30, 29/30</td>
</tr>
</tbody>
</table>

Table 3. The comparison on dental works retrieval

<table>
<thead>
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<th>jaw</th>
<th>Top N (# of retrievals / # of dental works in PM)</th>
</tr>
</thead>
<tbody>
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<td></td>
<td>#</td>
</tr>
<tr>
<td>(1)</td>
<td>upper 7/11, 11/11, 11/11, 11/11, 11/11</td>
</tr>
<tr>
<td></td>
<td>lower 7/10, 9/10, 10/10, 10/10, 10/10</td>
</tr>
<tr>
<td>(2)</td>
<td>upper 10/11, 11/11, 11/11, 11/11, 11/11</td>
</tr>
<tr>
<td></td>
<td>lower 8/10, 10/10, 10/10, 10/10, 10/10</td>
</tr>
</tbody>
</table>

Table 4. The comparison on identities matching

<table>
<thead>
<tr>
<th>jaw</th>
<th>Top N (# of correct retrievals / # of PM)</th>
</tr>
</thead>
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<tr>
<td></td>
<td>#</td>
</tr>
<tr>
<td>(1)</td>
<td>upper 9/10, 8/10, 10/10, 10/10, 10/10</td>
</tr>
<tr>
<td></td>
<td>lower 8/10, 9/10, 10/10, 10/10, 10/10</td>
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Performance of dental works matching

We conducted dental works matching using the frequency-, the spatial-, and the combined-domain features (method-(1), -(2), -(3)), respectively. Table 3 shows the comparison of retrieval accuracy on dental works matching. Among all queries of dental works in both jaws, 14, 17, and 18 correct matches (67%, 81%, and 85.7%) were ranked the first and 20, 18, 21 correct matches (95%, 85.7%, and 100%) were ranked the first and the second, using methods-(1), -(2), and -(3), respectively. Comparing the data, we found that using spatial contour gives higher retrieval accuracy than using the FD for the top-1 retrieval, and using the FD gives higher retrieval accuracy than using the spatial contour for top-2 retrievals. We also found that using the combined features (method-(3)) can indeed compensate each other’s drawback and improves the accuracy of using FD and spatial contour 19% and 5%, respectively for the top-1 retrieval and 5% and 14.3%, respectively, for top-2 retrievals.

Performance of identities matching

To evaluate the performance of dental identification, 10 PM images were matched to 53 AM images by using (1) the original tooth contours, (2) the pruned tooth contours, and (3) a combination of dental works and the pruned tooth contours. The retrieval accuracy of these three matching methods is shown in Table 4. The results indicate that when matching all teeth in both jaws, all three methods achieve to 100% accuracy; whereas when matching teeth in either the upper or the lower jaw, using a combination of tooth contours and dental works (method-(3)) is more effective than only using tooth contour (method-(1), -(2)). The result also indicates that matching with the pruned tooth contours (method-(2)) can indeed improve the retrieval accuracy than matching with the original tooth contours (method-(1)).

Conclusion

We presented a dental identification method based on the contours of both teeth and dental works in bitewing radiographs. The contours of teeth are represented in a point series in spatial domain, and the dental work contours are represented in both the spatial and the frequency domains. As the scale, the orientation, and the translation of PM and AM radiographs are generally different due to view variation, each tooth was firstly segmented and the query PM tooth was then aligned against the AM tooth under matching using the best fit affine transformation. To reduce the error caused from aligning two incompletely overlapped tooth contours, we proposed pruning the outliers from each tooth contour after the alignment so that the two contours can be aligned better for matching. Meanwhile, matching the spatial contours of dental works relies heavily on the wellness of tooth alignment and is sensitive to boundary disturbances; whereas matching
with the affine-transform invariant Fourier descriptors will neglect the spatial information other than shape, we proposed using a hybrid of both features to compensate the drawbacks of each other while keeping their advantages. Experiments on a small database show that 1) matching with the pruned contours can improve 8% accuracy for the top-1 retrieval when compared to the result of using the original contours; 2), matching with the combined spatial and frequency features of dental works can improve about 19% and 5% accuracy, respectively, when compared to matching with single feature in the top-1 retrieval; and 3), matching with the pruned contours and both the spatial and frequency features of dental works, the accuracy rate in identity matching can achieve to 100% regardless of the upper, the lower, or both jaws. Our future works include enhancing the teeth segmentation and the matching metric of spatial contours so that higher teeth matching accuracy can be achieved.

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References


