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Automated Dental Identification based on Orthogonal Locality Preserving Projection

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Abstract

Major disasters have highlighted the significance of automated dental identification systems. For example in the 9/11 attacks, many victims were identifiable only from pieces of their jaw bones. This is the main motivation for building the Automated Dental Identification System (ADIS). The archiving and retrieving processes of dental records from large databases is a challenging task and has received inadequate attention in the literature. This paper presents a new technique for retrieving dental records for ADIS. Our approach consists of two main stages. The first stage is the preprocessing stage of the dental records that includes segmentation and teeth labeling classification in order to obtain reliable appearance-based, low computational-cost features. In the second stage we propose a technique based on using the Orthogonal Locality Preserving projection algorithm to produce a candidate list. The experiment results show that the proposed approach provides fast and effective results to search and retrieve a list of candidates from the database compared to other approaches suggested in the literature.

Keywords: Dental Identification; Teeth Appearance Based; Laplacianteeth Spaces, Candidate List; Orthogonal Locality Preserving Projections (OLPP); Potentional Match Search Componet.
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1. Introduction

The identification of the deceased individuals in major disasters is difficult. In such cases, most physiological biometrics as iris, fingerprint, and face may not be viable options for identification, because of the decay of the body soft tissues. The Dental features are one of the best candidates for postmortem biometric identification as shown in Fahmy et al., 2004: They resist early decay of body tissues, withstand severe conditions in mass disasters.

The main objective of this paper is to present a new technique that reduces the time needed to retrieve the candidates list while maintaining accuracy. The process compares a subject dental image record (postmortem PM) with a set of reference dental image records (ant mortem AM that are stored into database. This candidate list must have a very high probability of containing the target record, and its size is very short compared to the original database size. Architecturally, ADIS is composed of three main components:

- Dental Record Preprocessing Component, where the digitized dental image is segmented into isolated teeth regions, and each tooth is classified into incisors, canines, premolars and molars.
- The Potential Matches Search component manages archiving and retrieval of dental records and produces a candidate list. The most important

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features for this search engine are fast performance, and optimum accuracy.

- The Image Comparison component conducts teeth alignment and comparison between the subject and the corresponding teeth of each candidate, thus producing a short match list for a forensic expert to use. This component is computationally intensive Abaza et al., 2009.

The retrieval of postmortem dental radiography was addressed by several researches. In Chen et al., 2005, Chen and Jain present an automated method for matching dental radiographs. The matching is performed in three steps. First, a shape registration method is proposed to align and compute the distance between two teeth on the basis of tooth contours. In Zhou and Abdel-Mottaleb, 2005 present a content-based archiving and retrieval system of dental images. It contains three major stages: dental image classification, bitewing image segmentation and retrieval based on teeth shapes using bidirectional Hausdorff distance. It extracts the contours of molars and premolars, which are then used to archive the images in an AM database. During retrieval, a PM bitewing image is segmented to extract teeth contours, which are used to find the most similar images in the AM database using Hausdorff distance measure. The methods above are based on contour alignment and matching to find the distance between two dental images. These methods are typically very slow although they can be very useful in the image registration stage. Both techniques use teeth contour features (shape based); the automatic extraction of teeth contour is computationally intensive and the output itself may not be precise as shown in Shah et al., 2006, and the performance is slow for a potential match search. Abaza et al., 2009 introduced a technique that is based on dimensionality reduction using principle component analysis (PCA) that initially each segmented tooth is compared to the corresponding reference tooth based on a EigenTeeth. By fusing multiple tooth matching scores, it calculated the similarity between the subject record and all the reference records in the database. Then retrieved records based on the minimum Euclidean distance.

The aim of this paper is to present a new technique to search and retrieve the candidate list of the reference dental images from the database using the appearance features of the teeth (Laplacian Teeth). The proposed approach consists of two main stages. In the first stage, the preprocessing of the dental records (segmentation and teeth labeling) is performed in order to get a reliable appearance-based, low computational-cost features. In the second stage, we used a technique based on Laplacian Teeth using Orthogonal Locality Preserving projection (OLPP) algorithm to produce candidate list.

The paper is organized as follows. Section II provides a brief introduction of the preprocessing operation of dental images. The proposed technique based on Orthogonal Locality Preserving projection (OLPP) is described in Section III. In Section IV, the experimental results are presented. Finally, Section V concludes the paper and describes the future work.

2. Teeth Preprocessing

To design a fast search engine that retrieves dental record images by comparing a subject dental image record with a set of reference dental image recodes, it takes more than one factor in determining the selected teeth features. These factors include the computational complexity and reliability of these features in the matching process. Methods based on teeth contour take a relatively long time to extract the tooth contour as well as they are less accurate (Shah et al., 2006). These reasons have led us to find an alternative method that depends on reliable appearance-based, low computational-cost features. To achieve this goal, we used the following preprocessing steps:

2.1. Teeth Segmentation

In this approach we used the teeth segmentation technique introduced in AlSherif et al., 2012, which starts with an iterative thresholding followed by an adaptive thresholding to binarize the teeth images. Then, we adapt the seam carving technique on the binary images, using both horizontal and vertical seams, to separate each individual tooth.

2.2. View Normalization

The view normalization and resizing step comes after the teeth segmentation stage, whose outcomes do not have standard view in terms of scale and rotation. The view normalization is an essential step to improve and overcome variations in orientation and scale. An input tooth is geometrically normalized. To perform geometric normalization of the segmented tooth, the most important step is to ensure that its lateral surface appears predominantly vertical Nassar et al., 2008.

2.3. Teeth classification

We tackled the classification problem using a two stage approach. The first stage utilizes low computational cost, appearance-based features for assigning an initial class. The second stage applies a string matching technique Nassar et al., 2008, based on teeth neighborhood rules, to validate the initial class and hence assign a number corresponding to the tooth location in the dental chart.

3. Proposed Approach

Our proposed approach for retrieving dental radiographs for post-mortem identification is appearance based using Orthogonal Locality Preserving Projection algorithm (OLPP). It differs from Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA), which preserves the euclidean structure of tooth space Vasuhi and Vaidehi, 2009. PCA and LDA are the two most popular methods used for face recognition. Recently, a number of research efforts have shown that face images possibly lie on a non-linear sub-manifold Kumar and Aravind, 2008. However PCA and LDA see only the global euclidean structure. They fail to discover the underlying structure if the face images lie on a non-linear sub-manifold. So the manifold structure needs to be modeled by preserving the local structure. Locality Preserving Projection (LPP) is a manifold learning technique which preserves the local structure. However, LPP is non-orthogonal. The Orthogonal Locality Preserving Projections (OLPP) on the other hand produces orthogonal basis functions and can have more locality preserving power than LPP.

The proposed technique consists of the two stages; section 3.1 presents an overview of the OLPP algorithm. In the second stage we used a technique based on Laplacian Teeth using OLPP algorithm in order to retrieve dental radiographs for post-mortem identification and produce a candidate list as described in section 3.2.

3.1. OLPP Algorithm, Deng et al., 2006.

To overcome the problem of singularity that is present if the number of the teeth images training set is much smaller than the dimension of the tooth image vector, we apply PCA to project the teeth into the sub-space without losing any information, so that the number of images in the training set will exceed the PCA coefficients of the image and it becomes nonsingular. In addition the PCA projected image is more robust to noise than the preprocessed one. In brief, the algorithm of OLPP to get LaplacianTeeth is started as follows: (i) PCA Projection: the training set of teeth images t_i is projected into the PCA subspace by throwing away the components corresponding to zero eigenvalue. The transformation matrix of PCA is denoted by W_{PCA}. The features are extracted with PCA projection are statistically uncorrelated. (ii) Constructing the adjacency graph: Let $X=[t_1,t_2,...,t_N]$ be a set of training set of teeth images. Let G denote a graph with N nodes where the i^{th} node corresponds to the tooth image t_i. If nodes t_i and t_j are connected then the (i, j) and (j, i) elements of the nearest-neighbor matrix get the values $S_{ji} = S_{ij} = e^{-(\|t_i - t_j\|)2} / t$ where t is a suitable constant. Otherwise they are zero. This is called the Heat kernel approach. The weight matrix S of graph G models the local structure of the teeth manifold.

(iii) Computing the Orthogonal Basis Functions: We define D as a diagonal matrix whose entries are column (or row, since S is symmetric) sums of S, $D_{ii} = \sum_j S_{ji}$ We also define L = D - S, which is called Laplacian matrix in spectral graph theory. Let $\{a_1, a_2, . . . , a_{k-1}\}$ be the orthogonal basis vectors, we define: $A_{k-1} = [a_1, a_2, . . . , a_{k-1}]$, $B_{k-1} = [A_{k-1}]^T (XDX^T)^{-1} A_{k-1}$. The orthogonal basis vectors $\{a_1, a_2, .. , a_{k-1}\}$ can be computed as follows: compute a_1 as the eigenvector of $(XDX^T)^{-1} XLX^T$ associated with the smallest eigenvalue. Compute a_k as the Eigenvector of:

$$M^{(K)} = \{I - (XDT^T)^{-1}A^{(K-1)}.[B^{(K-1)}]^{-1}[A^{(K-1)}]^T\}.(XDT^T)^{-1}\,XLX^T$$

associated with the smallest eigenvalue of $M^{(K)}$.

(iv) OLPP Embedding: Let $W_{OLPP} = [a_1, a_2, . . . a_L]$, the embedding is as follows: $x \rightarrow y = W^T x$ where $W = W_{PCA}W_{OLPP}$. Where y is a l-dimensional representation of the teeth image x, and W is the transformation matrix. (v) Matching Process: The Matching process computes similarity score between subject and the reference tooth images from a specific class ('M','P','C','I') based on their projection in the laplacian space.

3.2. LaplacianTeeth Construction

Fig. 1 depicts a sample of exemplars from the teeth. To setup the image subspaces from training set for each of the four teeth classes, a data set of exemplars was prepared using the dental image database provided by the Missing and Unidentified Persons Unit of the Washington State Patrol CJIS Division, 2000. 100 Molars, 100 Premolars, 20 Canines and 40 Incisors from records were segmented and preprocessed with total number of 260 teeth. In selecting these teeth, we tried our best to avoid unintentional bias towards the datasets. So we tried to select teeth evenly from upper and lower jaws, from the right and left sides of the mouth, and the teeth images of different intensity contrast.

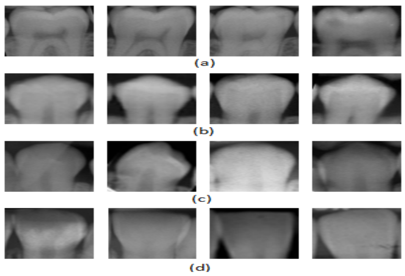

Fig 1. Sample of teeth used in constructing the image subspaces of the four teeth classes. (a) Molar. (b) Premolar. (c) Canine. (d) Incisor.

As described in Section 3.1, we used the Orthogonal Locality Preserving Projections (OLPP) algorithm for establishing a LaplacianTeeth space for each of the four teeth classes from the data training set of teeth images. Figure 2 shows the image representations of the first 11 eigenvectors of each class which are namely the LaplacianMolar space, LaplacianPremolar space, LaplacianCanine space and the LaplacianIncisor space. The image on the upper left corner of each set represents the sample average. In some cases, the class of the input tooth may not be known. To accommodate this condition, we create a general set of eigenvectors based on exemplars taken from multiple classes.

3.3. Using LaplacianTeeth for teeth matching

The proposed approach for potential match search is illustrated in Figure 3. The subject tooth (t_s) and the reference tooth (t_r) which have to be matched, first undergoes view normalization to: (i) adjust its dimension to comply with that of the LaplacianTeeth, and (ii) compensate for possible poor contrast. Second, the normalized subject and reference tooth input images are projected onto their corresponding LaplacianTeeth Space in order to get two vectors, one for the subject tooth and another for reference tooth. The two vectors (subject and reference) are used to measure the Least Square Error (LSE) which gives the score of matching between the subject and reference tooth.

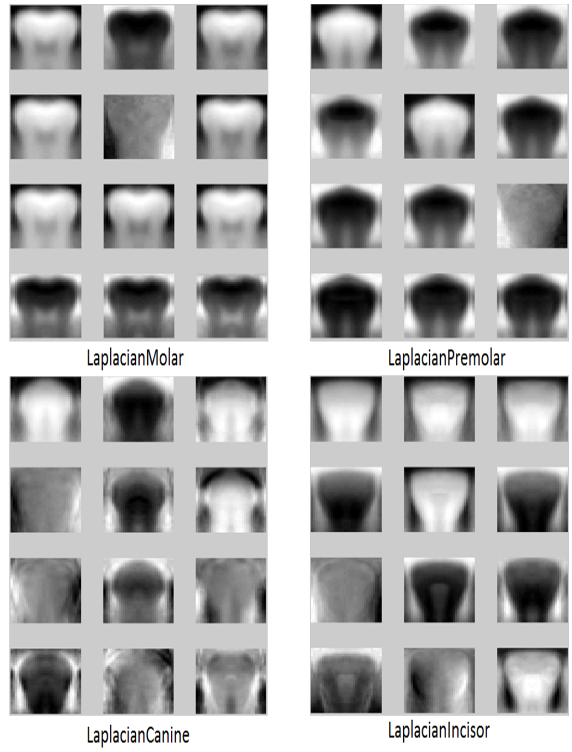

Fig 2. The LaplacianTeeth representation for the four classes of teeth.

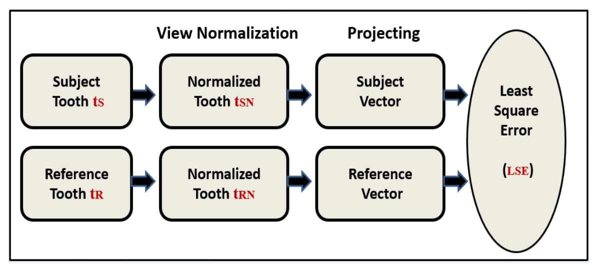

Fig 3. Block diagram of proposed method

To move from level tooth-to-tooth level to record-to-record matching level, two problems are encountered (as shown in Figure 4):

1. The same tooth may have multiple representations in either the reference record or the subject record or even both. At the tooth-level fusion, we want to calculate the matching score between the different views of the same tooth t_{si} of a subject record (t_{S1}, .., t_{S32}) and the available views of reference tooth t_{Ri} of a reference record (t_{R1}, .., t_{R32}), such that we produce a single distance representing the matching score between the subject tooth t_{Si} and reference tooth t_{Ri}, namely D_i (t_{Si}, t_{Ri}). We use min fusion rule for multiple teeth representation fusion.

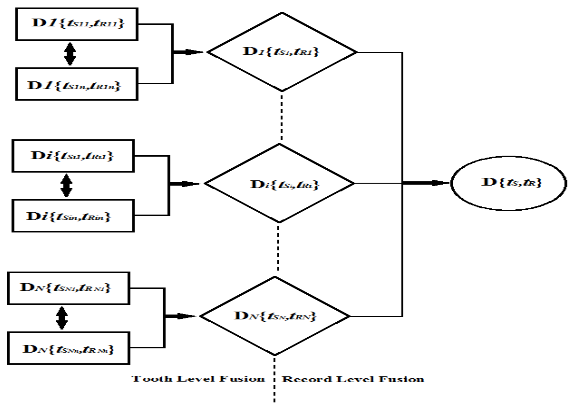

Fig 4. A hierarchical fusion scheme

2. Integrating the various teeth matching scores to have one matching score between the subject and reference records. With N teeth in common between the dental charts of a subject record and a reference record, we obtain N ($N \leq 32$) tooth-to-tooth matching scores. At the record-level, we are looking for an integration scheme for combining these N $\{D_i(t_{Si}, t_{Ri}), i = 1, .., N\}$ into a single record-to-record matching score $D(S, R)$. We studied two alternative rules for fusing the match scores, namely the mean and min rules. We found the mean rule yields better performance.

4. Experimental Results

To select the optimal normalized teeth image size, we found that moving from image size 16x16 to 32x32 enhances the matching performance. Moving to 64x64 and 128x128 didn't enhance the matching performance any more, while it takes more processing time. The tooth image size of 32x32 yields the best performance compared with 64x64 and 128x128 image sizes.

To test the proposed approach for dental image retrieval, a test set was prepared using the FBI's Criminal Justice Service (CJIC) ADIS database CJIS Division, 2002, which includes dental radiographs of ante-mortem (AM) and postmortem (PM). We used 104 records (about 500 bitewing and periapical films) involving more than 2000 teeth. There were 47 Antemortem (AM) records and 57 Postmortem (PM) records with 20 matched records.

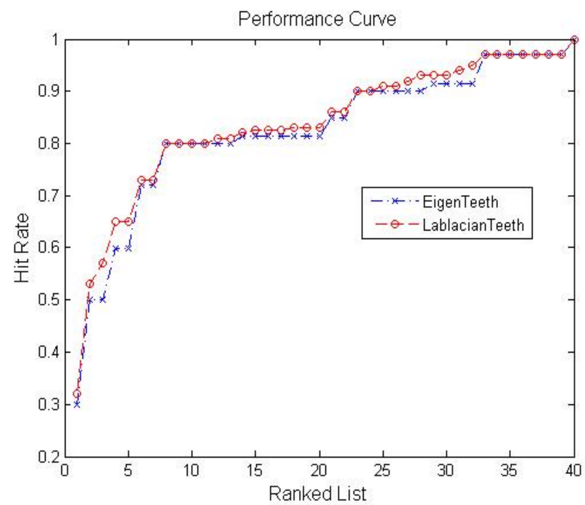

Fig 5. Matching performance comparison between the proposed method and the EigenTeeth based method.

Fig. 5 shows the results of the experiment, the proposed technique correctly retrieved the dental record 65% in the 5 top ranks while the other method based on the EigenTeeth remains at 60% [2]. It also shows the difference in accuracy even with the increase in size of the first position of the ranked list; our approach remains ahead in precision to the method based on EigenTeeth

Table 1 shows the computational time required for the comparison between the proposed algorithm, and the one based on EigenTeeth [2], where both algorithms were implemented in MATLAB platform under the same settings. The average time in proposed approach to match record to record comparison takes less than 0.17 seconds and the average time to retrieve the best matched AM reference dental record for given PM query dental record is about 0.17n seconds, where n is the number of records in the database. On the other hand, method based on EigenTeeth takes less than 0.09n. Both approaches have linear complexity where our approach is capable of achieving better performance than the method based on EigenTeeth in terms of hit rate.

Table 1. Computational time comparison between the proposed method (LaplacianTeeth) and the PCA based approach (EigenTeeth)

An example of a column heading	EigenTeeth	LaplacianTeeth
Average Record to Record	0.09 sec	0.17 sec
Average record retrieval of database of size 47 dental records (AM)	4.23 sec	7.99 sec

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