A Review on Dental Image Processing for Human Recognizetion

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Abstract—The key tools in forensic recognizetion are biometric identifiers. With the development in information technology and the enormous volume of cases that need to be examined by forensic specialists, it has become important to automate forensic identification systems. The ante mortem (AM) identification, that is identification prior to death, is usually possible through comparison of many biometric identifiers. While, postmortem (PM) identification, that is identification after death, is impossible using behavioral biometrics (e.g. speech). Moreover, under severe situation, such as those encountered in mass disasters (e.g. airplane crashes, sever burn) or if identification is being attempted more than a number of weeks postmortem, under such situations, most physiological biometrics may not be employed for identification, because of the decompose of soft tissues of the body to unidentifiable states. So, a postmortem biometric identifier has to resist the early decay that affects body tissues. Because of their survivability and variety, the best candidates for postmortem biometric identification are the dental features. In this paper we present a review about an automated dental identification system for Missing and Unidentified Persons.

Keywords - ADIS, AM, PM, ROI, Dental Feature Extraction, Matching Technique

I. INTRODUCTION

A typical flowchart for human recognizetion system of AM & PM images is shown in fig.(1). The very first step in human recognizetion is dental image classification. That is based on the way dental features are captured. They are classified as periapical, panoramic, and bitewing dental images[5] as shown in figures (2) to (5). Bitewing images include the features of both upper and lower jaws signifying bite. While periapical images include only a particular jaw either upper jaw or lower jaw image. Panoramic images include features of both jaws including nasal area, sinuses etc. Though, for most dental processing bitewing images are used [6]. The dental radiograph can be divided into teeth areas (having highest intensity), Bone areas (having average intensity) and background area (having lowest intensity). The intensity of bone area and teeth area are much similar. So, they should be separated for fruitful feature extraction.

The second step is radiograph segmentation which includes dividing upper and lower jaw and then separating each individual tooth. Feature Extraction process follows tooth segmentation where in some particular features are defined which is further used for matching PM with AM images. There are two possible matching distance measures D1 (absolute distance) and D2 (Euclidean distance).The matching distance was found for each pair of PM-AM images based on D1 and/or D2 norm. The images from the database are ranked based on the matching distance. The least matching distance image is found as the best match of given PM image. The accuracy rate of the algorithm is found from the rank obtained by the most genuine AM image i.e. more the number of PM query images having lower rank of the genuine image, higher is the accuracy rate. For evaluating various techniques we have defined percentage of genuine images ranked as first as follows:

$$\% PI = A * 100 / P$$

Where % PI=performance index; A=no. of genuine AM images retrieved having Rank 1 & P=no. of PM query images on which technique was implemented.

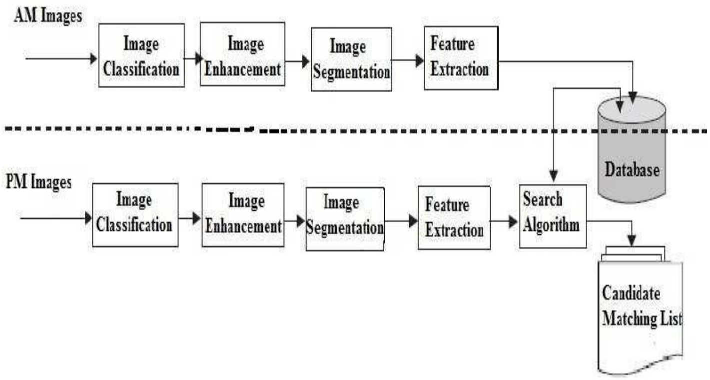

Fig. 1. Flowchart showing human identification process for AM & PM images [5]

II. REVIEW ON VARIOUS MATCHING TECHNIQUES

Thresholding based methods can easily be used for segmen- tation of teeth but they usually fail to distinguish between teeth and bone areas as their intensities are more or less alike in cases of uneven exposure. In order to eliminate this problem, in [2003], A. Jain et. al suggested extraction

Fig. 2. bitewing dental image [19]

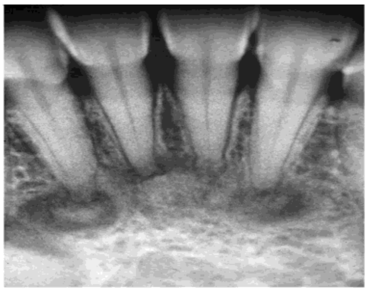

Fig. 4. lower periapical dental image [21]

Fig. 3. upper periapical dental image [20]

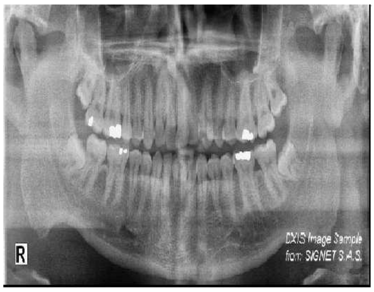

Fig. 5. panoramic dental image [22]

of tooth contour as a feature since they remain more invariant over time compared to other features of teeth. Due to considerable noise in the radiographs, edge detection methods would be inappropriate for all the images in the database & manual selection of Region of Interest (ROI) would be time consuming. Therefore, the matching algorithm was divided into 3 main tasks (1) Radiograph Segmentation, (2) Contour Extraction and (3) Shape Matching. Radiograph Segmentation is done to separate upper and lower jaw and individual tooth (Tooth Isolation). Crown Extraction is done to separate Crown part and root part. At last, a matching distance between PM and AM images is found and ranking of database images is generated with respect to their least matching distance. A smaller matching distance signifies better match. However, this algorithm fails in the some cases like poor quality of images, tooth partially visible, query image partially occluded, inherent similarity between teeth shapes of different individuals, different imaging angles of AM and PM images. In addition, the upper and lower jaw may not be always allied along a horizontal line for which the radiograph is divided into vertical strips which is found to be inappropriate in some cases. The %*P*I achieved by this method is 65.7895%.

In [2004], H.Said et.al have suggested a tooth segmentation algorithm which uses automated morphological wavelet based approach for tooth segmentation which first enhances the quality of the image by gray scale contrast stretching trans- formation & after that morphological operators, 2-D wavelet transform kernels are used for separating upper and lower jaws in bitewing radiograph. After that individual tooth (ROI) is segmented using horizontal and vertical integral projection. Though, for some images, the morphological filters could not capture fine edges between different teeth through its multi-resolution property.

Developing an Automated Dental Identification System (ADIS) requires not only recognizetion of the subject but also maintaining the system such as updating reference records, techniques and substandard performance [3]. In order to solve the difficulty arising due to poor quality of image, in [2004], M. Mottaleb et.al presented iterative and adaptive thresholding. After that horizontal and vertical integral projection is used for separating the upper and lower jaws as well as individual tooth. The case in which jaws are not allied along a horizontal line the image was rotated in a small range of [-20,20]degrees and the angle which produces minimum horizontal projection is found. A set of salient points from object contour is selected & a signature vector that captures information of each salient point is generated. Each constituent in Signature vector is the distance between the point on the contour and salient point. Then matching distance is found from the ranking & signature vector based on minimum matching distance is performed. Best matching AM tooth correspond to minimum matching distance. This technique was not successful in matching images due to poor quality of images. As the shape of teeth could have changed with time as PM images were taken after a long time AM images were captured. Ahe%*PI* Achieved Ay Ahis method is %2.4138%.

In [2005] H.Chen et.al, the problem defined in [2004] A.Jain et.al of aligning the partial contour in case of occluded image is addressed and contours of tooth and shapes of dental work are used for recognizetion. Upper and lower jaws and individual tooth are separated using horizontal and vertical integral projection as in [1]. A point association between two curves is established and after that the distance between the curves is computed based on these points. Here, contours and their relative positions are explored to contribute to matching. Difference between contour of teeth and contours of dental work are combined via likelihood estimates for better similarity results. Matching is done by computing the matching distance between one PM and all AM images. Then image to subject distances are averaged over all images to obtain matching distance. The ranking generates a list of candidates from the distance between PM image & all subjects in AM database. However, this technique was also unable to produce desired results in cases of poor image quality like subjects with missing teeth and it moreover it required a larger database for evaluating the algorithm.

In [2005] J. Zhou et.al proposed and algorithm which consists of 3 step segmentation: ROI localization, Image Enhancement and tooth segmentation. By using snake model ROI localization is done. Initial line to separate both jaws is obtained by horizontal integral projection & after that several iterations on initial line by snakes, both the jaws are separated. Missing tooth is detected by integral projection & a feature value is assigned to it. After that, morphological filters are applied for enhancing the imageand then window based adaptive threshold is used to segment the enhanced image to minimize influence of uneven intensity & noise in bone region & then snake model is used to refine the contour. Here, as a feature, the tooth contour is extracted. Shape matching is performed using partial bidirectional Haus-dorff distance and Minimum Hausdorff distance is found using Quadratic Programming Optimization method. Poor image quality, variance in viewing angles for AM & PM images, tooth shape variance with age and overlap between teeth were some of the reasons due to which desired results were not obtained with this algorithm. In addition, the snake was not able to detect the contours of many tooth entities and extracted tooth does not fit tightly around actual boundary of tooth [13]. The %*PI* achieved by this method is 82.5000%.

In [2005], O. Nomir et.al suggested masking is done on original image with binary image to enhance the feature of the image. To separate teeth areas & bone areas iterative thresholding is used. However, applying iterative thresholding technique to segment the teeth from the background sometimes does not lead to helpful results. Hence applying adaptive thresholding to the result of binary masked image gives accurate results. Both jaws as well as individual teeth are separated using horizontal & vertical integral projection respectively. A set of salient points form the object contour and a signature vector for each salient point is generated. These signature vectors are then used for object matching intention. A matching distance is found from the signature vector which are ranked in ascending order. The best matching AM tooth will correspond to minimum distance. This technique showed accurate results except in cases where teeth borders were not correctly segmented due to poor quality of images and in some cases bones were considered as a part of tooth. The %*PI* achieved by this method is 74.4186%.

In [2006], E. Said et.al suggested teeth segmentation technique using mathematical morphology. The dental x-rays were segmented using top hat transformation and closing. After that gray line profiles for bones between teeth, gap valley between upper and lower jaw & gap between teeth was found. A rectangular structuring element with dimensions [w/,*h/]
for periapical images and [w/4,h/2] for bitewing images was created here w=width of image & h=height of image.
Thresholding was done to separated wanted teeth from back- ground. At this point, a single is thresholding is not sufficient so three thresholds are taken.

$$T1=mean(filtered\ image);\ T2=0.66T1;\ \&\ T3=0.33T1.$$

Connected component labeling of thresholded image is performed based on their connectivity. After that, assign them labels that identify different connected components. Thereafter, refinement of the connected components is done based on geometric properties to determine qualifying ROI. Then unqualified objects are eliminated. Refinement is based on rules summarized in Table I:

Table 1. ***RULES FOR REFINEMENT OF CONNECTED COMPONENTS [7]***

Type of Image	**Range of ROI Height**	**Range of ROI Width**	**ROI Area**
For Bitewing Images	0.15h to 0.7h	0.15w To 0.4w	>(0.0225h*w)
For Periapical Images	0.3h to 0.9h	0.15w To 0.5w	>(0.045h*w)

In [8], panoramic dental X-rays were used for segmentation and feature extraction which involved four main tasks: (1) shape model generation; (2)Image pre-processing; (3)Teeth segmentation (4)morphometric data extraction. The object to be explained is referred by landmark points which are determined in a set of straining images. They are stacked in shape vectors. After that PCA or KL-Transform is applied to the shape vectors (Shape model generation). Image preprocessing step involves two main tasks (1) applying a low pass filter (2) quad tree decomposition. The mask obtained from quad tree is Xored with Otsu's image & then finally binary erosion and flood fill are applied to eliminate teeth overlap problem. Border analysis step is performed to select the teeth among aligned curves.The mean shape is translated along the main axes direction in order to seek for a curve that enlarge image energy. A snake model is used for morphometrics data extraction which is used to compute matching between snake & mean shape. The algorithm could recognize tooth boundary and then eliminate strange bodies without the need to separate both the jaws. Furthermore, the quad tree mask was unable to separate segments and hence zonal mask in Fourier domain along with a band pass filtering was proposed which although eliminated the overlap problem but seriously affected the quality of image.

In [2007], O. Nomir et.al suggested an algorithm to solve the problem of contour extraction defined in [8] by exploring the appearance and shape-based features. So, the image is first enhanced by binary image masking & after that adaptive thresholding is applied. Then horizontal integral projection followed by vertical integral projection is performed to separate individual tooth. The contour is extracted by Fourier descriptors. The appearance is described using force field energy function. Matching is done using both D1 norm (absolute distance) and D2 norm (Euclidean distance).In both the cases, majority voting is used to obtain the best matching image, because there is a large distance between one or two corresponding PM and AM teeth for the same person due to poor image quality, in some cases, that increases the total matching distance resulting in incorrectly extracted contours of same teeth. The %*PI* achieved by this method is 86.000%.

In [2008], O. Nomir et.al suggested a hierarchical chamfer matching method for contour matching. Teeth are seg-mented and numbered followed by matching in hierarchical fashion from lowest to highest resolution with AM and PM images having same tooth number. The first enhancement & segmentation steps are same as in [9]. At the feature extraction stage, the tooth contour pixels are extracted and then a Distance Transformation (DT) image is built for all the AM teeth in the database. Then after, a multi-resolution representation, which contains the DT images at different resolution levels, is formed for each tooth from the DT information at the higher resolution level. Least matching distance between the transformed query tooth & contour of AM tooth is found by hierarchical chamfer matching method. Because of the poor quality of images or some parts of the image are not clearly visible, the contours of tooth were not properly extracted. X-rays are 2D projection of 3D objects which led to incorrect matches since 2D shapes of contours were similar. Futhermore, if PM images are captured long after AM images were captured, the shapes of teeth may change because of artificial prosthesis, teeth growth & teeth extraction. The %*P*I achieved by this method is 85.000%.

In [2008], S. Kiattisin et.al proposed algorithm for two features of teeth for code matching. (1)labial view (having one root), (2)mesial view pattern (having two roots). Brightness Adjustment; Binary image Conversion were used for image enhancement and Chain code method was used for decoding a direction code from binary images based on special features of teeth. Matching is done by comparing the decoding code with the statistical code. So, the resulting chain of codes tends to be quite long. Therefore, any small disturbances along the boundary due to noise or imperfect segmentation causes change in code that may not be related to the shape of the boundary. The performance achieved by this method is: % of code match=90% for same code & 50% for different code.

The major constraint in developing a dental identification system is uneven exposure, lower contrast problems and poor quality of image. In order to remove this problem, in [2009], P. Lin proposed a novel image enhancement technique. In this paper, first using a homomorphic filtering technique uneven illumination was removed and then, gums and pulps were separated by applying texture enhancement method. Each tooth is classified based on relative length/width ratio each of tooth, pulp & crown size. For a skew and incomplete view of dental X-ray images, using only contour information as the classification feature often results in error. The proposed algorithm did not address the case of very poor images such as only 3 or 4 teeth left in images and also the case of teeth overlap. The performance achieved by this method is: Accuracy Rate=94.9% for molars & 95.6% for premolars.

In [2009], A. Abaza et.al suggested an algorithm which uses dimensionality reduction using Principal Component Analysis (PCA). Accuracy of class independent retrieval (cases where tooth class is unknown) and class dependent retrieval (cases where class of tooth is known: incisors, canines, premolars or molars) The process of teeth preprocessing is divided into 3 steps: (1) *Teeth Segmentation*: mathematical morphology is used. Here, first noise filtering is done on the dental image followed by thresholding to isolate teeth from background and then connected component labeling to determine ROI is performed. (2)*View Normalization*: The input tooth is normalized to ensure that its imaginative surface appears predominantly vertical. (3)*Teeth Labeling*: Low computational cost appearance based features for assigning initial class. The string matching technique based on teeth neighborhood rules are used and therefore assign a number corresponding to tooth location in dental chart. Finally subspace of each of the four classes of teeth is constructed and eigenvectors are arranged in descending order according to resultant Eigen values. In case of class independent retrieval, tooth image and reference image are first normalized and then input image is projected onto reduced subspace using matrix of eigenvectors. The resulting vector is compared with target vector using Euclidean distance in order to generate a match score.

All the methods discussed above are summarized in table 2.

III. CONCLUSION & FUTURE WORK

From the review of above papers, the main challenge in developing an automated dental recognizetion system is to deal with poor quality of images, imaging angle, teeth overlap, teeth shape change matter due to aging, occluded teeth, etc. From the performance index found in the preceding section, That is clear from the algorithm suggested by [2007], O. Nomir et.al is best among other techniques. So, one can work to find a fast & novel approach to enhance and segment the dental radiograph and after that matching of PM and AM images for better similarity results.

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Table 2. HUMAN IDENTIFICATION TECHNIQUES BASED ON DENTAL X-RAY MATCHING

Reference	Enhancement Technique	Segmentation Technique	Feature Extraction	Matching Technique	Accuracy
A. Jain et. al	Assumed that good quality images were used	Horizontal & Vertical integral pro- jection	teeth contour	Absolute dis- tance match- ing	Out of 38 PM query images,Rank I−25,Rank II−5, Rank V−8images
E. Said et. al	Gray scale contrast stretchin	Morphological & wavelet Segmen- Tation	feature extraction un- explored in this	matching is unexplored in this	—
M. Mottaleb et.al	binary image masking	Iterative & Adaptive Thresholding; Horizontal & vertical integral pro- jection	Signature vector from tooth contour	Absolute dis- tance match- ing	Out of 29 PM query im- ages, Rank I−21,4 out of 5PM images correctly re- trieved
H. Chen et.al	Assumed that good quality images were used	Horizontal & Vertical integral pro- Jection	Match contours of Dental Work	Absolute dis- tance match- ing	In 90% of cases, Genuine teeth were in top 15% of retrieved images
J. Zhou et.al	Morphological filters	Adaptive Threshold; Snake model	Teeth contour	Partial bidirectional Hausdorff distance	Out of 40PM query images, Rank I−33,Rank II−3, Rank III,IV,VII,XI−1 image each

O. Nomir et.al	Binary image masking	Canny Edge detection, Morpholog- ical dilation, Iterative & Adaptive thresholding;Horizontal & Vertical integral projection	Signature Vector of contour pixels	Absolute dis- tance match- ing	Out of 43 PM query images,Rank I−32,Rank II,IV,VII−3, Rank VI−2 images
P. Lira	Quadtree Decomposi- tion; Otsu's image	Teeth Separation is not required	Shape model and shape analysis (PCA)	Absolute matching distance between snake	—
O. Nomir et.al	Binary image masking	Radiograph Segmentation Adaptive thresholding; Teeth Separation Horizontal & Vertical integral projection	Forcefield function & Fourier descriptors	Euclidean distance & Absolute distance matching	Out of 50 PM query images Rank I−43, Rank II−4, Rank III−2,(both matching measures) and Rank V−1 images (Euclidean distance) & Rank IV−1 image(absolute matching)
O. Nomir et.al	Binary image masking	Radiograph Segmentation Adaptive thresholding; Teeth Separation Horizontal & Vertical integral projection	Tooth Contour	Hierarchical Chamfer Matching Method	Out of 40 PM query im- age, Rank I−34, Rank II−3, Rank III−1, Rank V−2 images.
S. Kiattisin et.al	Brightness Adjustment; Binary image Conver- sion	Chain code decoding	special features of teeth	absolute matching between decoding code &	% of same code match=90%(same pattern); 50%(different pattern).
P. Lin et.al	Homomorphic filtering; Adaptive Contrast Stretching &	Thresholding; Horizontal & Ver- tical integral projections; Iterative Thresholding	Relative length/width ratio of teeth,pulp & relative crown size	Only classifi- cation is per- formed	94.9% for molars; 95.6% for premolars.

