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TEETH CLASSIFICATION IN DENTAL IMAGES USING SUPPORT VECTOR MACHINE

Vijayakumari Pushparaj

Department of ECE, MepcoSchlenk Engineering College, Virudhunagar, Tamil Nadu, India

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ABSTRACT

In the present day world, individual identification with some reliable means is emerging as a significant state of affairs. Since teeth pattern is unique for the individual human being, it can be treated as a suitable biometric means. It is playing the major role in mass disaster identification and individual identity. In order to ease the process of human identification using dental images, teeth classification is desired as an imperative process. This paper introduces teeth classification using linear and multi-class support vector machine. Teeth information can be acquired by either radiographic or photographic means. The algorithm is implemented by performing preprocessing initially, then teeth separation followed by feature extraction and classification. The accuracy of linear support vector machine yields 91% for radiographs and 95% for photographs in terms of number of teeth tested and correctly classified. Multi class support vector machine improves the performance of classification with the inclusion of canine teeth in radiographs, achieved an accuracy of 90.5%, which is comparable with the existing algorithms.

KEYWORDS: *Teeth Classification, Signature, Geometric Features, Confusion Matrix, Photographs, Radiographs*

INTRODUCTION

Biometrics is a branch in which human identification can be performed by means of some physiological and behavioral traits. The conventional means like iris, fingerprint, palm print and hand print etc… are not meaningful in some major fire accident or flood incident. In such circumstance, some other useful means of biometrics are also used. Forensic Odontology is a specialized field of dentistry which utilizes dental radiographs for human identification. Forensic odontologist uses dental evidences in order to identify the persons and support law enforcement agencies. Dental evidences have been proven as an excellent biometric means in the recent day disasters. Since teeth are hardest and more robust in the human body, it plays the major role in human forensic identification. It provides resistance to decay in natural disaster situations. Designing an Automated Dental Identification System (ADIS) is a primary goal in forensic odontology. In order to design an ADIS, several issues like handling of severe occlusion, usage of panoramic, photographic images, detection of the missing tooth, identifying dental implants, teeth numbering, and classification have to be considered.

Among the various issues, the challenges in teeth classification are handled in this paper. The goal of teeth classification is to categorize the teeth into molar, premolar and the like in order to ease the process of human identification with reduced computation time. If a teeth is categorized before matching Ante-Mortem (AM) and Post Mortem (PM) records, it reduces database search in a turn computation time is reduced.

Contour based individual identification [1] by matchingAM and PM dental radiographs is explained by Chen et al. The related work on even transform based matching [2] is detailed in the literature. It is a semi automated approach extracts the crown and the root shape individually. Banumathi et al, used morphological contour and Gaussian filtering methods for dental shape extraction as given in [3]. It fails to handle severe occluded images. Connected and fast connected component algorithms [4] are utilized in the dental shape extraction, which improves the hit-rate performance. Vijayakumari et al, followed a slightly variant approach of matching dental records using both similarity and distance metric [5]. The usage of photograph for human identification in addition to radiographs [6] is also detailed.Dental bitewing radiographs are analyzed using both shape and also appearance [7]. In [8], three different possible matching algorithms are dealt. It improves the matching accuracy. Teeth classification and numbering are the main goals of ADIS system. Teeth classification was introduced by Mahoor et al, uses Fourier descriptor based Bayesian classifier [9]. Support Vector Machine (SVM) based classification was demonstrated by Lin et al., four bitewing radiographs [10] only. It is followed by Faraein et al., with inclusion of Mesiodistal neck [11] as an additional feature for classification, in order to classify the tooth as molar and premolar. Another approach for classification using SVM and template matching based numbering [12] is also available in the literature.

This work concentrates mainly on dental radiographis and photographic images.Classification of photographic images is desired for individual identification is ongoing with photographic images also.The radiographs include both betweenand panoramic images. The classification of teeth in panoramic image is difficult, since the shape of each tooth is not as clear as in bitewing images. Hence this paper aims to achieve improved accuracy with multi-class SVM.

MATERIALS AND METHODS

The flow diagram of suggested method is shown in Figure 1. It explains the methodology in three steps. After acquiring the input dental images, it has to be preprocessed to remove any occlusion or noise effect. Then teeth separation is performed to separate each and every tooth individually. Finally, features are extracted and classification is performed using both linear and multi class SVM.

Preprocessing

The dental radiographic image is pre-processed to sharpen the edges. Edge sharpening in radiographic image is achieved through a Butterworth band pass filtering process followed by homomorphic filtering as explained in [12].

Teeth Separation

To perform teeth classification, the dental radiographs have to be partitioned as Maxilla (Upper jaw) and Mandible (Lower jaw) as well as single toot has followed in [12].

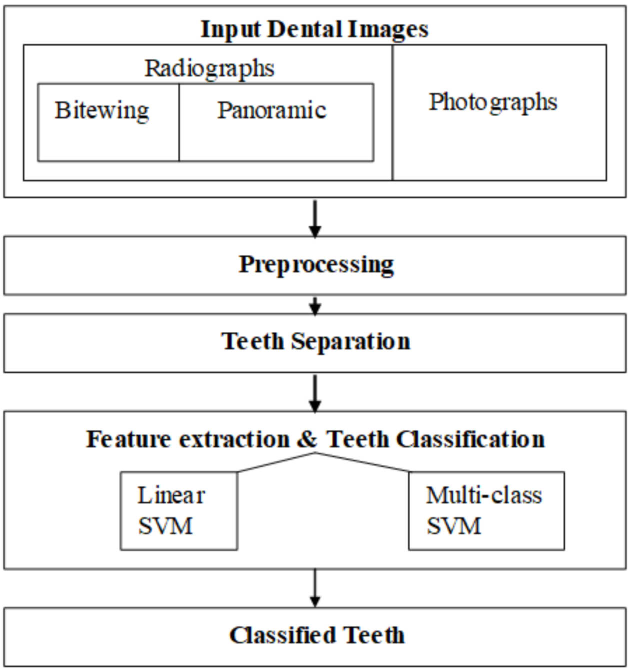


Figure 1: Proposed Flow diagram

Teeth Classification

Teeth classification is performed here in two steps. Binary SVM is used to classify two teeth like Molar (M) and premolar (P) in case of radiographs and Central Incisor (CI), Lateral Incisor (LI) in the case of photographs. In most of the existing papers, only molar and premolar classes were considered, since it uses between images only. While going for panoramic teeth classification, other teeth also have to be considered. Hence Multi-class SVM (MSVM) is employed. The features are extracted in three different means like Projected Principal Edge Distribution (PPED) vectors, signature and geometrical features.

PPED Vectors

PPED feature extraction tries to capture the information content of an image by modeling its edge distribution along different principal directions or orientations. The four principal directions are horizontal (H), Vertical (V), clockwise (+45) and anti-clockwise (-45). Since two-dimensional edge information is reduced to a feature vector by projecting edge flags to the principal directions, it is named as projected principal edge distribution. The isolated tooth image is subjected to edge detection, filtering in the principal directions namely, horizontal, vertical, clockwise and anticlockwise. The maximum edge intensity is compared with the threshold value to detect the presence of edge. This eliminates the effect of noise. In order to determine the threshold value for edge detection, all the absolute value differences between two neighboring pixels are calculated in both horizontal and vertical directions and the median is taken as the threshold. The filtering kernels used for edge detection are given in our earlier work [12].

Signatures

A shape signature is a 1D representation of 2D boundary. The centroid distance function of the boundary points from the centroid (x_c,y_c) of the shape is:

$$r(t) = ([x(t) - x_c]^2 + [y(t) - y_c]^2)^{1/2} \tag{1}$$

where, $x_c = \frac{1}{N}\sum_{t=0}^{N-1} x(t)$ & $y_c = \frac{1}{N}\sum_{t=0}^{N-1} y(t)$

where N is the maximum size of the image.

Geometrical Features

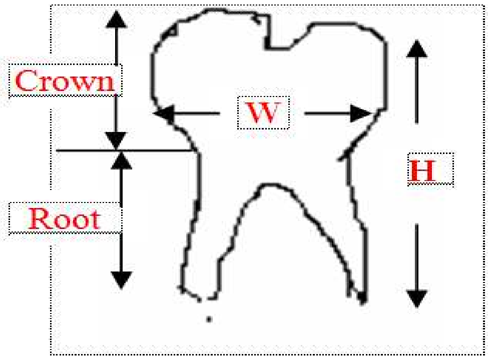


Figure 2: Geometrical Features

The geometrical information of each tooth like its width (W) of the whole crown region and height (H) as noted in Figure 2 will serve as additional features.

Binary SVM Classifier

Binary Support Vector Machine (SVM) is used as a classifier tool to categorize the tooth as molar or premolar in case of radiographic images. The basic idea behind SVM is that transferring the data into higher dimensional space and finding the optimal hyperplane with maximal separation between classes. By assuming the data as linearly separable, the hyperplane of SVM has the form of $w.p + b = 0$, where w is the normal to the hyperplane and $b/\|w\|$ is the perpendicular distance between the origin and the hyperplane. Consider some randomly selected data from the whole data set as the training set for finding the optimal hyperplane $w^*.p + b^* = 0$, which is as far as possible from the closest members of both classes. Few of the training vectors called support vectors will fall on either side of the two planes $B_1 : w.p + b = 1$ and $B_2 : w.p + b = -1$.Thus, the hyperplane $w^*.p + b^* = 0$ is called the decision boundary of the binary classifier. Each training data are denoted by a tuple (p_i, q_j), where 'p' corresponds to the feature vectors and 'q' refers to the class label (i.e.) $q \in \{1, -1\}$. The optimal w^* and b^* of binary SVM model can be calculated as:

$$w^* = \sum_{i=1}^{M} \alpha_i q_i p_i \tag{2}$$

$$b^* = \frac{1}{N}\sum_{s \in S}(q_s - \sum_{m \in S} \alpha_m q_m p_m . p_s) \tag{3}$$

where α is the Lagrange multiplier such that $\sum_{i=1}^{M} \alpha_i - (1/2)\alpha^T B \alpha$ is maximized, subject to the constraints $\alpha_i \geq 0 \forall i$ and $\sum_{i=1}^{M} \alpha_i q_i = 0$, B is a matrix with $B_{ij} = q_i q_j p_i . p_j$ and S is the set of support vectors whose $\alpha_i > 0$. The signum function is used to group the test data into either of the class after constructing the decision hyperplane:

$q' = \text{sgn}(w^{*}.p' + b^{*})$. It is observed that, if *q'*>0 it belongs to molar otherwise premolar tooth.

Multi-Class SVM

Several techniques have been developed to deal multi class problems. Among the various methods, one-against-rest is considered here. Multi-class SVM formulation [13] with K-class is defined as:

$$\underset{w_1,\ldots\ldots,w_k}{\text{minimize}} \ \frac{\lambda}{2}\sum_{c=1}^{K} w_c^T w_c + \sum_{i=1}^{N} \xi_i \tag{4}$$

$$\text{subject to } (w_{yi} - w_c)^T x_i \geq 1 - \xi_i - \delta_{yi,c}$$

$$\forall i = 1,\ldots\ldots.,N, \quad c = 1,\ldots\ldots,K$$

Here c refers to each class and w_c is its weight vector, and each of the N training vectors x_i has a label y_i. The indicator function $\delta_{yi,c}$ =1 if $y_i = c$ and 0 otherwise. The variable ξ_i refers to slack variables for each data item, in such a way that the margin between correct class and most confusing class is penalized.

RESULTS AND DISCUSSIONS

The proposed method is evaluated in the presence of real database, including panoramic, between dental radiograph\s captured among the age group of 17 years to 70 years supplied by Digital Dental X-Rays, Madurai, Tamilnadu and photographic images captured among the age group of 21 to 24. This algorithm is implemented using MATLAB-R2010b using a Pentium IV CPU on a Microsoft windows XP environment. Few of the sample images are shown in Figure 3, Figure 4 shows the corresponding preprocessed outputs. The preprocessed image shows the clear vision of dentine and pulp layers. After applying teeth separation logic, individual tooth is segregated and a database of #73 premolars, #82 molars, #60 canine, #45 central incisors and #50 lateral incisors is created. For every tooth, the features like PPED vectors and signatures are generated. It seems to be unique for all the teeth.

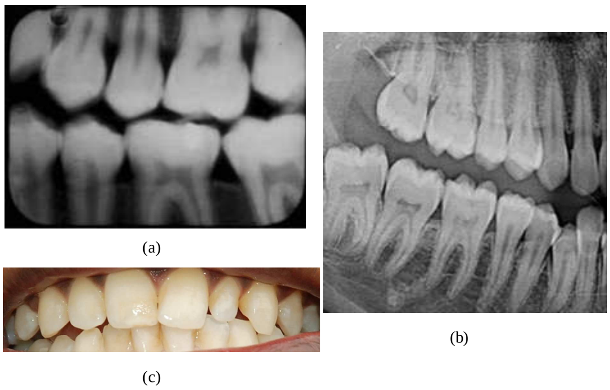


Figure 3: Sample Input Images (a) Bitewing Radiograph (b) Panoramic Radiograph (c) Photograph

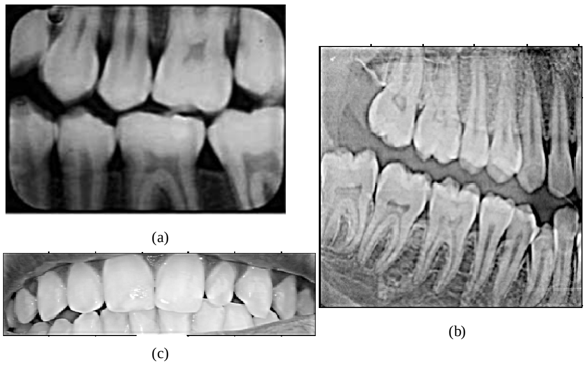


Figure 4: Sample Input Images (a) Bitewing Radiograph (b) Panoramic Radiograph (c) Photograph

Table 1: Features Extracted and Classified Outputs

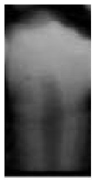
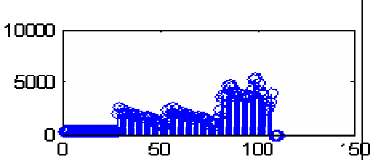
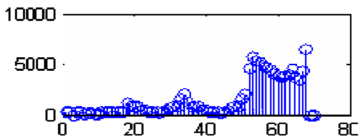
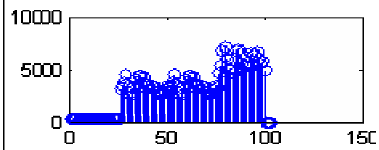
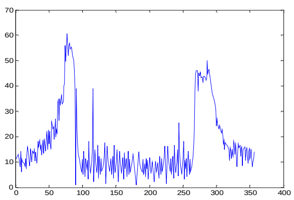
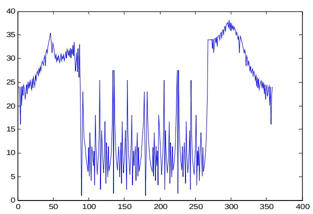
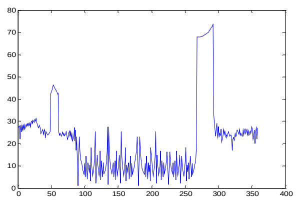
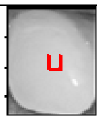
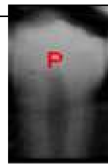
	Panoramic X-ray	**Photograph**	**Bitewing X-ray**
Images (Tooth from)			
PPED vectors			
Signature			
Geometric features W/H	36/101	49/70	55/95
Classified Teeth			

Table 2: Confusion Matrix of Radiographs

		Predicted Class		
		Molar(M)	**Premolar(P)**	**Canine(C)**
Known class	**M**	TP_M = 63	E_{MP} = 04	E_{MC} = 04
	P	E_{PM} = 03	TP_P = 67	E_{PC} = 03
	C	E_{CM} = 03	E_{CP} = 03	TP_C = 67

Additionally the geometrical information is also observed and which aids for useful classification results. The features extracted are shown in Table 1 for a few of the sample images. The table 1 shows a sample tooth for each category like periodiical, photographic and bitewing. The classification is initially tried using binary SVM. It yields better results for two teeth category like M and P for radiographs and CI, LI for photographs. The confusion matrix was created to observe the performance of classification. Then in radiographs an additional tooth category like canine is added. The similar features are used to train and test the multi class SVM. Table 2 and Table 3 are the confusion matrix obtained using multi class SVM for both radiographs and photographs respectively. While classifying, it is observed that the features of premolar and canine are closely related particularly the geometrical feature. Hence the miss classification rate is more in case of these teeth. Rarely, miss classification occurs in premolar and molar teeth of panoramic images. In case of bitewing radiographs, it is less pronounced because the teeth anatomy is very clear. The table 3 summarizes the precision and sensitivity values based on the confusion matrix. The precision and sensitivity values are categorized both for radiographs and photographs separately. Radiographs include both panoramic and betweeen teeth. It is observed from this table that, the molar class achieves an accuracy of 91.3%, 90.5% respectively for premolar and canine respectively. Similarly, in the case of photographs, the central incisor achieves 95.4% and lateral incisor with 94.3%. After a careful experimentation, it is realized that, approximately 0.5% accuracy improvement is achieved in multi class SVM than binary SVM. The performance measure observed is given in table 4.

Table 3: Confusion Matrix for Photographs

		Predicted Class	
		CI	**LI**
Known class	**CI**	TP_{CI} = 63	E_{CILI} = 04
	LI	E_{LICI} = 03	TP_{LI} = 67

Table 4 : Performance Measures

Measure	Radiographs			Photographs	
	M	**P**	**C**	**CI**	**LI**
Precision (TP/ TP+ FP)	91.3	90.5	90.5	95.4	94.3
Sensitivity (TP/ TP+FN)	92.6	91.7	91.7	94.1	95.7

CONCLUSIONS

Teeth classification is a desirable section in the Automated Dental Identification System. In this paper, classification is carried out using linear SVM and further improvement is achieved using multi class SVM. Individual identification using panoramic radiographs is in the budding stage now-a-days. Hence, this work will be useful in designing ADIS with panoramic radiographs. Similar way, if sufficient dental radiographs are not available, photographs will serve its role or otherwise additional information can also be gathered using photographs. In such situation, photographic teeth classification will be really fruitful. The novel geometric features added along with signatures and PPED vectors improve the classification accuracy. Thus, the experimental results reveal that the outcome of this work will certainly helpful to the Forensic odontologist in the automated dental identification system. In future, it can be extended to classify other teeth also.

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