Automatic Tooth Identification in Dental Panoramic Images with Atlas-based Models

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Abstract: After catastrophes and mass disasters, accurate and efficient identification of decedents requires an automatic system which depends upon strong biometrics. In this paper, we present an automatic tooth detection and labeling system based on panoramic dental radiographs. Although our ultimate objective is to identify decedents by comparing the postmortem and antemortem dental radiographs, this paper only involves the tooth detection and the tooth labeling stages. In the system, the tooth regions are first determined and the detection module runs for each region individually. By employing the sliding window technique, the Haar features are extracted from each window and the SVM classifies the windows as tooth or not. The labeling module labels the candidate tooth positions determined by the SVM with an atlas-based model and the final tooth positions are inferred. The novelty of our system is combining the atlas-based model with the SVM under the same framework. We tested our system on 35 panoramic images and the results are promising.

1 INTRODUCTION

Decedent identification after catastrophes is very crucial for many reasons including relieving the family's distress, issuing a death certificate for legacy, and insurance. Using dental panoramic radiographs (See Figure 1(a)) for decedent identification satisfies the limitations of the other biometrics, such as DNA and fingerprint, due to the durable structure of teeth (Sen, 2010). However, if identification is performed manually, it takes a long time. Moreover, if some changeable characteristics are utilized, the accuracy rate may decrease (Zhou and Abdel-Mottaleb, 2005). Therefore, an automatic dental identification system is very important for fast and reliable decedent identification.

There exist many studies in the literature (Lin and Lai, 2009; Mahoor and Abdel-Mottaleb, 2005; Pushparaj et al., 2013) for identification based on dental radiographs. The Automated Dental Identification System in (Abdel-Mottaleb et al., 2003) isolates the teeth using the integral intensity projection method and it is accepted as the pioneer in terms of the tooth isolation approach. In (Zhou and Abdel-Mottaleb, 2005), the snake method is employed to isolate the teeth in advance of using the integral intensity projection to determine the initial contours. These two studies are tested on bitewing images. In (Jain et al., 2003), the same method in (Zhou and Abdel-Mottaleb, 2005) is used for tooth isolation before applying the Bayesian rule to determine the tooth contours. It is tested on both bitewing and panoramic images; but, the system is semi-automatic. The system in (Jain et al., 2003) eliminates the inaccurate segmentation lines using the dental pulp which is also utilized in (Frejlichowski and Wanat, 2011) instead of the gaps between the teeth for separating the adjacent teeth. In (Lin et al., 2010), the SVM classifier runs with several geometrical tooth features to classify a tooth. The tooth identification is completed after labeling the teeth according to a particular pattern. The system is tested only on bitewing images. In (Jain and Chen, 2005), the fusion of three SVM classifiers are used for tooth classification and the Markov chain model is used for labeling. The system is tested on a few panoramic dental radiographs.

In this paper, we propose a novel tooth identification system based on machine learning and atlas-based models (Guzel, 2014). We combine the appearance information of teeth in panoramic images with the geometrical information under the atlas-based model. The appearance of teeth are extracted with Haar descriptors (Viola and Jones, 2001) and

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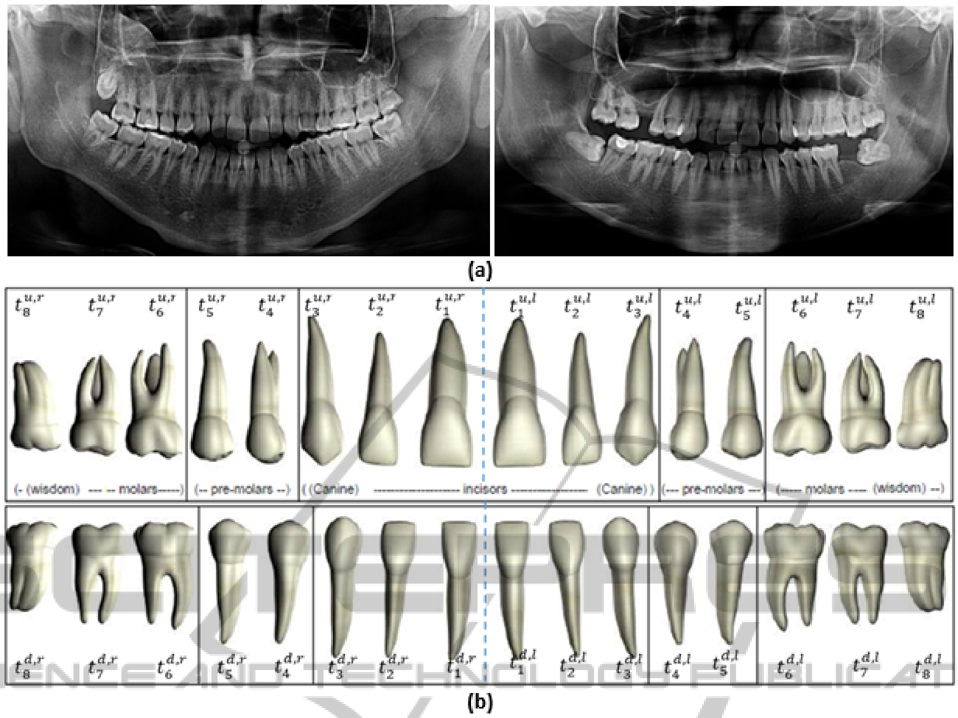

Figure 1: (a) Examples of dental panoramic radiographs, (b) layout of the teeth where $t_i^{j,s}$ represents the i^{th} tooth on the jaw $j \in \{up, down\}$ and the side $s \in \{right, left\}$.

the Candidate Tooth Positions (CTP) are found by the SVM. The final tooth labels are determined according to the CTP and their spatial relationship using an atlas-based framework.

Our method has several advantages. First, the candidate teeth are detected with the textural descriptors without requiring a template for each tooth. The candidate teeth determined according to the local appearance are incorporated efficiently with the atlas-based models which are constructed considering the geometric information about the teeth. In addition, our system may work on intra-oral X-ray images with small modifications.

The organization of this paper is as follows: The framework of the proposed system is introduced in Section 2. Section 3 presents the detection module and Section 4 presents the labelling module. In Section 5, the experimental results are evaluated and Section 6 concludes the paper.

2 THE FRAMEWORK OF THE PROPOSED SYSTEM

Our system consists of two modules which are candidate tooth detection module and the labeling module (Figure 2). In the candidate tooth detection module, the SVM detects the CTP based on the Haar features. Then, in the labeling module, the optimal tooth positions are identified using the atlas-based modeling approach.

3 TOOTH DETECTION MODULE

Each tooth has unique shape and appearance characteristics. Most of the studies in the literature (Jain et al., 2003; Abdel-Mottaleb et al., 2003; Zhou and Abdel-Mottaleb, 2005) directly use the intensity values via histogram projection in order to detect the teeth. However, in panoramic images the gap between the teeth disappears and occlusions may occur because of stitching partial X-ray images taken from the circular shaped jaw onto a 2-D image (Frejlichowski and Wanat, 2011). Therefore, instead of detecting the teeth with intensity change information, we propose using the textural and intensity descriptors together without requiring a model for each tooth. Note that, the intensity based techniques (Abdel-Mottaleb et al., 2003; Zhou and Abdel-Mottaleb, 2005) use local image intensity information between the neighboring teeth, while our technique uses non-local information including the intensity and texture of the teeth.

The Haar descriptors are used for feature extrac-

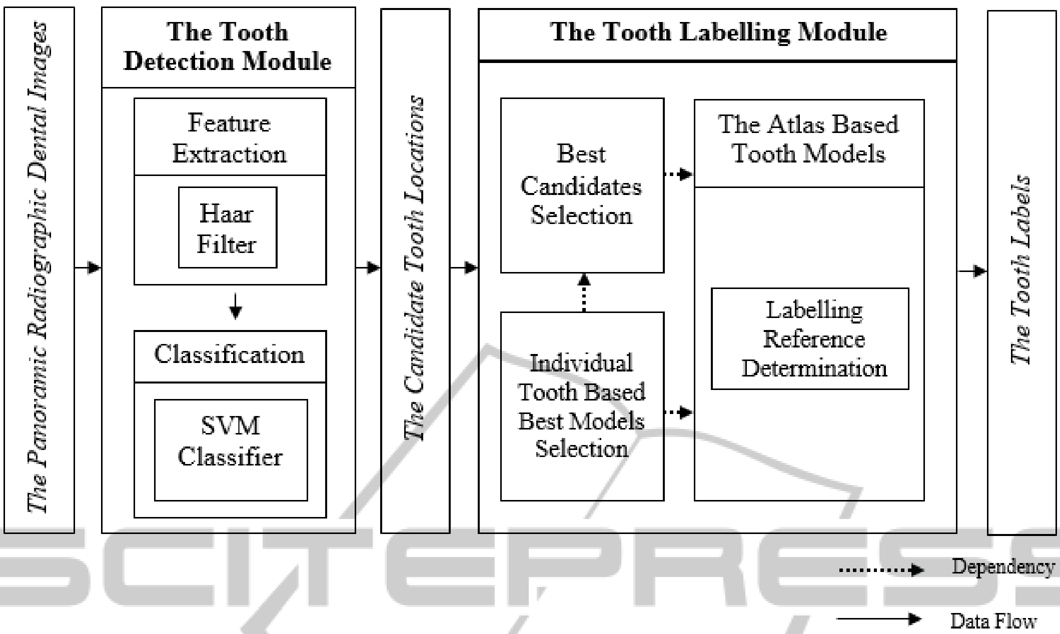

Figure 2: The proposed tooth identification system.

tion. The Haar features are similar to Haar basis functions (Papageorgiou et al., 1998) and they extract the intensity and texture features effectively.

There are 32 teeth in a normal adult mouth where 8 of them are incisors, 4 of them are canines, 8 of them are premolars, and 12 of them are molars. Let $t = \{t_1^{j,s}, t_2^{j,s}, ..., t_8^{j,s}\}$ be the tooth labels on a jaw where $j \in \{up, down\}$ is the upper or lower jaw and $s \in \{left, right\}$ is the side of the mouth. We divide the teeth on one side of the jaw into 3 different subsets where $t_m = \{t_1^{j,s}, t_2^{j,s}, t_3^{j,s}\}$ are the molar teeth on side s of jaw j, $t_{pm} = \{t_4^{j,s}, t_5^{j,s}\}$ are the premolar teeth on side s of jaw j, and $t_i = \{t_6^{j,s}, t_7^{j,s}, t_8^{j,s}\}$ are the incisors and canine teeth on side s of jaw j (Figure 1b).

Each tooth subset $\{t_m^{j,s}, t_{pm}^{j,s}, t_i^{j,s}\}$ on a jaw j is trained and tested separately with the SVM. For training, we use the manually delineated tooth images for positive samples and non-tooth regions around the tooth locations as negative samples. In testing, we use a sliding window approach. For a pair $\{v, y\}$, let v be the feature vector and $y = \{0, 1\}$ be the class where $y = 0$ is the non-tooth and $y = 1$ is the tooth class. The windows classified as tooth $(y = 1)$, are called as the CTP and they are used in the tooth labeling module.

4 LABELING MODULE

In order to infer the final positions and labels of teeth, we use an atlas based model. Let $A_k = \{a_1^{j,s}, a_2^{j,s}, ..., a_8^{j,s}\}$ be an atlas (Figure 3) where each node a_i in the atlas represents a tooth $t_i^{j,s}$. We consider the center of the mouth gap as the initial reference point for labeling to construct the model. Because, while taking the panoramic X-ray image, the movement of the patient is prevented by the the dental panoramic system positioning technology which involves bite fork, forehead support, and chin rest. As a result, corrupting the teeth order is prohibited. We use the integral intensity projection method (Zhou and Abdel-Mottaleb, 2005) to find the center of the mouth gap.

Consider $A = \{A_1, A_2, ..., A_n\}$ as the atlas set learned from the training set. According to the CTP, our objective is to infer the optimal atlas $A^* \in A$ that best matches with the geometrical information represented by the CTP. In order to find A^*, we first eliminate the inappropriate CTP according to the corresponding search space in the atlas based models. After that, the appropriate candidates are labeled for each tooth model. Let the cost $g_c(l_k, a_k)$ represent the distance of the candidate tooth position l_k to the corresponding tooth center a_k. The candidate l_k which is the closest one to the center a_k of the corresponding tooth in the model, namely whose $g_c(l_k, a_k)$ is the minimum, is selected as the best candidate l_k^* of the same labeled candidates l_k. In order to find the best tooth model A^*, our approach is to determine the best tooth model per tooth $t_k \in t_d^{j,s}$ in the search space. Let $||a_{k-1}, a_k||$ represent the distance between the centers of the adjacent teeth as the optimum distance and let

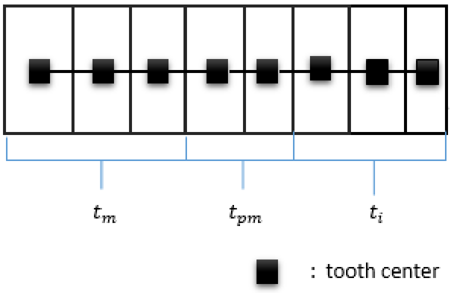

Figure 3: The atlas-based model used for labeling.

$||l_{k-1}, l_k||$ represent the distance between the CTP as the actual distance. The tooth cost $cost(t_k)$ computes the difference between the optimum and the actual distance as

$$cost(t_k) = abs(||a_{k-1}, a_k|| - ||l_{k-1}, l_k||), \quad (1)$$

where abs is the absolute value function. The procedure of computing the $cost(t_k)$ is repeated for all of the teeth $t_k \in t_d^{j,s}$ and for all of the atlas models $A_k \in A$. For each tooth, the tooth costs, which are computed according to the atlas models, are summed up to find the best model A^* per tooth and the teeth are labeled according to the selected atlas models for each tooth with the following equation:

$$A^* = argmin_{cost_i^{j,s}} \sum cost_i^{j,s}(t_k), \quad (2)$$

where $cost_i^{j,s}$ represents the cost of tooth t_i on jaw j and side s.

5 EXPERIMENTAL RESULTS

The proposed system is tested on a dataset containing panoramic dental images. The images are taken from 35 different subjects over 18 years old. The panoramic images involve implants, dental works, and missing teeth. In the detection stage, the SVM is trained using 50 positive and 100 negative delineated tooth images. The maximum size of the training tooth images is used as the window size.

Our software, which is written in C++, utilizes the Haar filters of the OpenCV library for feature extraction and uses the SVM function in the Waikato Environment for Knowledge Analysis (WEKA) (Hall, 2009) program for classification.

The prediction accuracy of the detection module is evaluated using the metric which calculates the rate of the accurate predictions to all the predictions. In order to measure the accuracy rate, we initially establish reference images for each test image in which the contours of the teeth are marked using our system according to the expert information. A prediction is evaluated as accurate if a tooth in the reference image is inside the corresponding window at least %70 rate. Table 2 shows the numerical results and Figure 4 shows the visual results of the detection module.

The accuracy rate of the detection module is low due to the similarity of teeth in the different tooth sets. Because the structure of the molars are very similar to the premolars, the neighboring molars are also detected as premolars. In addition, the extracted features may not be representative enough to detect a particular tooth of a tooth set in a dental panoramic image. Despite of the fact that the accuracy is increased by the labelling module, more robust features may be invented to get better results. It should be emphasized that this module only tries to find the CTP which limit the search space for the labeling module.

In the labeling module, we establish 7 atlas based models taking the minimum and the maximum tooth widths in the training set into account. We evaluate the labeling module using a similar metric with the detection module. However, in this module, a prediction is accepted as accurate if the center of the predicted window is inside the corresponding reference tooth contours. The numerical and visual results of the labeling module are presented by Table 1 and Figure 5, respectively.

Table 1: The average accuracy rates of the tooth labeling module.

Upper Jaw		Lower Jaw	
Right	Left	Right	Left
0.813%	0.808%	0.835%	0.800%

Table 2: The average accuracy rates of the proposed tooth detection module.

	Upper Jaw		Lower Jaw	
	Right	Left	Right	Left
molar	0.472%	0.478%	0.677%	0.685%
premolar	0.432%	0.423%	0.359%	0.419%
incisor	0.587%	0.595%	0.800%	0.842%

The labeling is based on (i) the candidate tooth locations, (ii) the mouth gap, (iii) the labeling model, and (iv) the labeling method. Therefore, the results may be enhanced if (i) the detection stage is improved, (ii) the image is enhanced before detection, (iii) more complex models such as the Markov chain graphical model is utilized to represent the mouth and the teeth better, and (iv) the methods are enhanced such that both the global and local relations between the teeth and the mouth are considered sufficiently. The results of the detection module is dis-

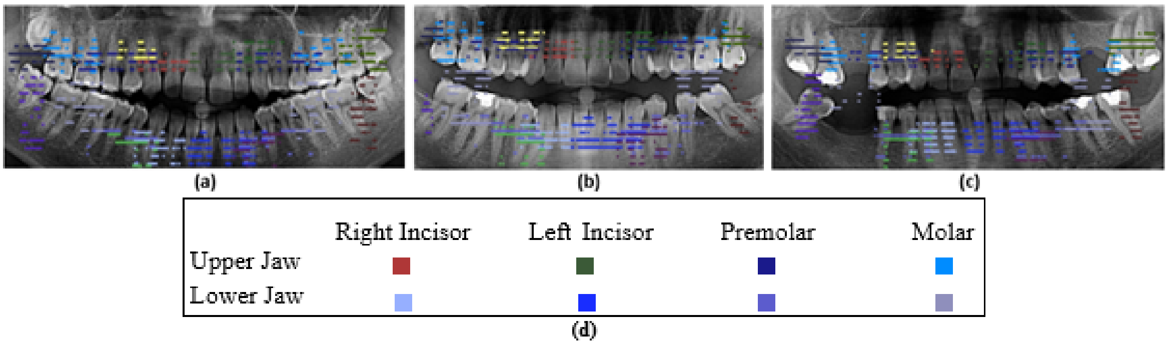

Figure 4: (a-c) The visual detection results. Each color represents one tooth class $t_c^{j,s}$ where $c \in \{molar, premolar, incisor\}$, jaw $j \in \{up, down\}$, and side $s \in \{right, left\}$, and (d) represents the colors and corresponding tooth classes.

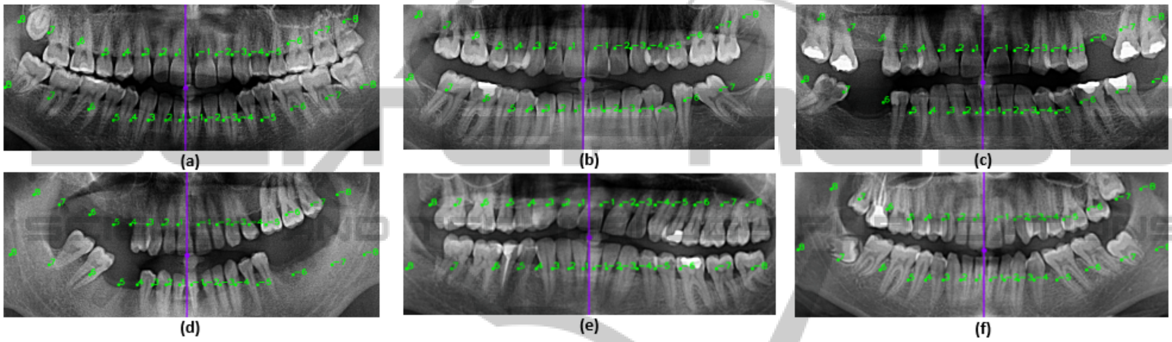

Figure 5: (a-f) The final labels determined by our system. In the images (a-c) the final labels are accurately determined; however in the images (d-f) some of the labels are inaccurately determined because of inaccurate mouth gap prediction in (d) and (f) and the obliquity in (e).

cussed above. In addition, instead of binary values, probability scores representing the accuracy degree may be produced for the candidate detections and these values may be utilized for labeling. Furthermore, different feature descriptors and classifiers may be fused to determine the most probable candidates.

6 CONCLUSIONS

In this paper, we introduce a tooth identification system consisting of the detection and labeling modules. The system first produces the CTP by the SVM classifier which uses the Haar features. After that, the labeling is employed according to the optimal atlas based model within the probable models which are constructed based on the geometrical information. The optimal model selection is performed with the cost function minimization technique. The cost function computes the distances of the candidate locations and the expected locations. The results show that our algorithm is promising to detect and label the teeth in the panoramic radiographic images.

As future work, we plan to enhance both the detection and the labeling approaches by taking the global appearance of the panoramic image into account and by using more salient tooth features for tooth detection. Moreover, the best candidates may be determined by fusing the results of several feature descriptors and the classifiers, such that each component increases the probability score if the candidate is detected. In summary, the system is capable to be enhanced to produce more accurate results.

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