Dental X-ray Image Segmentation
Eyad Haj Said, Gamal Fahmy, Diaa Nassar, and Hany Ammar
Lane Department of Computer Science and Electrical Engineering
West Virginia University, Morgantown, WV 26506
Contact e-mail: hammar@wvu.edu

Abstract
Law enforcement agencies have been exploiting biometric identifiers for decades as key tools in forensic identification. With the evolution in information technology and the huge volume of cases that need to be investigated by forensic specialists, it has become important to automate forensic identification systems. While ante mortem (AM) identification, that is identification prior to death, is usually possible through comparison of many biometric identifiers, postmortem (PM) identification, that is identification after death, is impossible using behavioral biometrics (e.g. speech, gait). Moreover, under severe circumstances, such as those encountered in mass disasters (e.g. airplane crashers) or if identification is being attempted more than a couple of weeks postmortem, under such circumstances, most physiological biometrics may not be employed for identification, because of the decay of soft tissues of the body to unidentifiable states. Therefore, a postmortem biometric identifier has to resist the early decay that affects body tissues. Because of their survivability and diversity, the best candidates for postmortem biometric identification are the dental features.
In this paper we present an overview about an automated dental identification system for Missing and Unidentified Persons. This dental identification system can be used by both law enforcement and security agencies in both forensic and biometric identification. We will also present techniques for dental segmentation of X-ray images. These techniques address the problem of identifying each individual tooth and how the contours of each tooth are extracted.

1. Introduction
Forensic identification is typically defined as the use of science or technology in identifying human beings in the court of law. It has a wide area of applications in criminal investigations, court evidences and security applications.
Law enforcement agencies have been exploiting biometric identifiers for decades as key tools in forensic identification. With the evolution in information technology and the huge volume of cases that need to be investigated by forensic specialists, automation of forensic identification became inevitable. Forensic identification may take place prior to death and is referred to as Antemortem (AM) identification. Identification may as well be carried out after death and is referred to as Postmortem (PM) identification. While behavioral characteristics (e.g. speech) are not suitable for PM identification, most of the physiological characteristics are not appropriate for PM identification as well, especially under severe circumstances encountered in mass disasters (e.g. airplane crashers) or when identification is being attempted more than a couple of weeks postmortem. Therefore, a postmortem biometric identifier has to survive such severe conditions and resist early decay that affects body tissues. Dental features are considered the best candidates for PM identification. This is due to their survivability and diversity. Forensic odontology is the branch of forensics concerned with identifying human individuals based on their dental features. Traditionally, forensic odontologists relied on the morphology of dental restorations (fillings, crowns, .. etc.) to identify victims. However, contemporary generations have less dental decay than their predecessors did. Hence, it is becoming important to make identification decisions based on...
inherent dental features like root and crown morphology, tooth size, rotations, spacing between teeth and sinus patterns.

Based on the information provided by experts from the Criminal Justice Information Services Division (CJIS) of the FBI, there are over 100,000 unsolved Missing Persons cases in the National Crime Information Center at any given point in time, 60 percent of which have remained in the computer system for 90 days or longer. In 1997, The Criminal Justice Information Services Division (CJIS) of the FBI created a dental task force (DTF) whose goal is to improve the utilization and effectiveness of the National Crime Information Center’s (NCIC) Missing and Unidentified Persons (MUP) files [1]. The DTF recommended the creation of a Digital Image Repository (DIR) and an Automated Dental Identification System (ADIS) with goals and objectives similar to the Automated Fingerprint Identification System (AFIS) but using dental characteristics instead of fingerprints [2]. The proclaimed dental identification system is an automated system that when fed with raw PM dental records, will find a short list of candidate Antemortem (AM) records, ideally one, for each of the input Postmortem (PM) records. A victim identity is discovered once his/her PM record matches an AM record.

According to forensic experts [3], dental characteristics preserve their shape after death for a long period of time, however each individual teeth gets rotated and moved from its AM position due to the decay of gums and body tissues. Several individual tooth may get missed or filled after its AM record is taken, hence dental features needs to recorded based on the contour/shape on individual tooth rather than the contour of the whole jaw. This would require reliable automatic segmentation techniques that can extract the contour of each individual tooth for latter retrieval purposes. This would provide tooth based retrieval procedures in addition to eliminating gum and body tissues problems.

Different X-ray images have different resolutions, orientations and luminance content, depending of the X-ray machine and the dentist who took it. Several images suffer from low resolution and lighting which would affect the quality of the desired segmentation. Hence edge enhancement is crucial for many images in order to obtain successful segmentation results.

In this paper we address the problem of segmentation of X-ray dental films. We introduce the different challenges that are faced during this segmentation process and we proposed our approach for reliable automatic segmentation. We also present a dental image enhancement approach that eliminates poor resolution and lighting problems in different types of X-ray images.

We first present our image enhancement technique in section 4.1. Our segmentation procedure consists of two algorithms that are combined to produce the final result. The first algorithm is based on a morphological filtering based model and is presented in section 4.2, and the second approach is based on a novel modified 2-D wavelet transform and is presented in section 4.3. Experimental procedures and results are presented in section 5 and 6, respectively. Followed discussions in section 7 and conclusions in section 8.

2. Background

Image segmentation is typically defined as the process of extracting objects from the image background. It is usually performed by subtracting the object location from the rest of the image. This object location is usually calculated by an edge detection, an intensity measure or a target recognition algorithm. However most of these techniques suffer from different types of noise due low resolution or poor lighting, which results in un-successful segmentation.

Segmentation subdivides an image into it’s constitute regions or objects. In the Dental Image perspective, segmentation is to recognize and label individual tooth in the X-Ray image or parts of the tooth such as crown and root of the tooth. Each tooth or object extracted from the image represents Region of Interest (ROI) that contains important data used for later steps.

ROI is defined as a rectangular part of the image that focuses on one object of the extracted objects from the image. The following image represents an X-ray image and the specified object inside the rectangle represents the ROI. Figure 1 shows ROI extracted from the dental image.

In most of the segmentation algorithms, the segmentation is done either by extracting region based features, that can identify different objects and regions, or by applying a model and try to adjust its parameters to fit...
the processed objects or regions. Although the model based approaches are more complicated but they are more successful and reliable.

For a complete review of image segmentation the reader is referred to [4].

Enhancement of a dental radiograph is the process of producing an improved quality image out of a degraded quality input image of a dental radiograph. The term “higher quality” is a fuzzy term that should be further explained. Quality of an image is a measure of its suitability for an application-specific manipulation. In ADIS, good quality dental radiographs are those that would result in valid segments when used in conjunction with a suitable segmentation technique. Most segmentation techniques require high definition of object boundaries. From an image processing point of view, a digitized dental radiograph is an 8-bit gray scale (at least for the dental image database provided by the CJIS). The image size depends on the film type and the digitization resolution. Image resolution is characterized by the sampling rate (number of captured pixels per unit length) and the number of bits used in encoding the pixel colors (number of possible quantization levels). The CJIS database contains dental radiographs with various sampling rates. In [5], a comprehensive study about images enhancement and restoration is provided.

![Fig. 1 ROI extracted from the dental image.](image)

Mathematical morphology is a topological and geometrical based approach for image analysis. It is a powerful technique in extracting different shapes and structures in different applications such as texture classification, pattern analysis and content-based image coding and retrieval.

Morphological filtering is typically defined as grouping different pixels in the images based on their color, spatial frequency and intensity. Objects in the morphologically processed image are usually well identified by a group of pixels that represent the objects shape. The main morphological filters used in shape reconstruction (grouping different objects) are Erosion, Dilation, opening and closing. In [6], a complete review of morphological filtering is presented.

The wavelet transform decomposes the signal into a weighted sum of basis functions called wavelets. The wavelet transform represents image content in a multi-scale manner that resembles the processing done in the early human visual system. The wavelet transform produces a multi-scale representation of the spatial frequency content of an image at a lower computational cost. For this reason the wavelet transform is recognized as a powerful tool for texture analysis.

Due to the variety of applications with multi-Dimensional data, such as images, video, etc..., 2-Dimensional wavelet kernels became popular in different image processing applications. Because of its complexity in design and processing, 2-Dimensional kernels are usually simplified by superposing their processing and manipulation to two perpendiculars 1-Dimensional filter. This can only happen if the desired 2-Dimensional kernel is separable. Other Non-separable 2-Dimensional wavelet applications, such as seismic migration, can’t be split down to 1-Dimensional kernels.

In the 2-D wavelet transform, the image is typically decomposed into four spatial frequency bands, that also contains some orientation data as shown in fig xxx, using two 1-D filters (a lowpass filter and a highpass filter). Theses bands are typically labeled the LL band, the LH band, the HL band and the HH band. The LL band is the output of processing the lowpass filter in both the horizontal and vertical
directions of the image, the LH band is the output of processing the lowpass filter in the horizontal direction and the highpass filter in the vertical direction, and similarly is the case for the HL and HH bands, as in [7].

While the LL and HH band contains the lowest and highest spatial frequencies of the image, respectively, the LH and HL band contains directional data. In other words the LH band detects horizontal lines in the image while HL detects vertical lines in the image. This is due to the fact that horizontally adjacent wavelet coefficients in the LH band tend to have a lowpass power spectrum, while vertically adjacent wavelet coefficients tend to have a highpass power spectrum. Similarly in the HL band horizontally adjacent wavelet coefficients band tend to have a highpass power spectrum, while vertically adjacent wavelet coefficients tend to have a lowpass power spectrum.

3. Literature

Several X-ray image segmentation approaches has been presented in the last decade. In [8],[9], and [10] the Markov random field-based algorithm have been proposed for Magnetic Resonance (MR) segmentation. In [11], an unsupervised segmentation algorithm for two-dimensional adaptive fuzzy C-means algorithm is presented. In [12], another adaptive fuzzy segmentation algorithm is presented for two-dimensional and three-dimensional multi-spectral magnetic resonance images. In [13], novel radiograph image segmentation approach is presented using morphological filtering. In [14], a model-based computer vision system is presented for automatic segmentation of bones from digital hand radiographs.

We note here that most of the segmentation algorithms reported in the literature suffers from poor image quality, which will lead to poor segmentation performance, hence it is crucial to apply any type of image enhancement before applying the segmentation process. Most of the medical image segmentation techniques reported in the literature requires some type of manual human interaction, hence they are not fully automated. We also note that there is no prior working area of Dental X-ray image segmentation.

In this paper, we have introduced an automated morphological filtering wavelet based approach for tooth segmentation in X-ray images. We will show that the multi-resolution feature of the wavelet transform can capture fine details even with poor quality X-ray images.

4. Proposed Approach

Enhancement

In periapical and bite-wing views, fig 2 and fig 3, we identify three main classes of “objects”; teeth, gum, and air. A tooth maps to an area with mostly “bright” gray scales (except for the pulp tissue) while the gum maps to areas with “mid-range” gray scales, and air maps to “dark” gray scales. Thus, a “significant” contrast in gray scales within a “small” area of a dental radiograph indicates a transition from one object to another. In order to assist segmentation, it is desirable to transform poor quality dental radiographs using in a way that insures an appreciable degree of contrast between the dominant gray scales used in capturing the different classes of objects.

![Fig. 2 Bitewing dental images](image1)
![Fig. 3 Perapical dental images](image2)
The Enhancement transformation ($T_{Enh}$) in question maps a given gray scale ($g$) from the input image to a new gray scale $T_{Enh}(g)$ in the enhanced image. In fact $T_{Enh}$ is a discrete transformation, however, for ease of mathematical manipulation we will state some of its properties as if it was a continuous gray scale enhancement transformation. $T_{Enh}$ can be described as: $T_{Enh}(g)$: $[g_{min}, g_{max}]$ such that:

1. $T_{Enh}(g_{min}) = 0$,
2. $T_{Enh}(g_{max}) = 255$,
3. $T_{Enh}'(g) > 0 \forall g \in (g_{min}, g_{max})$,
4. $T_{Enh}'(g) > \gamma \forall g \in [g_{th} - \delta, g_{th} + \delta]$, and
5. $\Sigma H(T_{Enh}(I)) < \Sigma H(I)$; $\Sigma'$ is taken over $g \in [g_{th} - \delta, g_{th} + \delta]$.

Where: $g_{min}$ is the index of the “darkest” gray scale in the input image, $g_{max}$ is the index of the “brightest” gray scale in the input image, $g_{th}$ is the index of the “threshold” gray scale obtained from gray scale histogram analysis of the input image, $\gamma$ is the minimum tangent slope of the transformation curve over the range of input gray scales specified in (4), $\delta$ specifies the range of steep transition in the transformation curve, $H(-)$ is the gray scale histogram of $(-)$, and $I$ is the input image. Conditions 1 and 2 insure that the darkest and the brightest gray scales in $I$ are mapped to “black” and “white” respectively. Condition 3 insures that the transformation preserves the original relative order between gray scales. Condition 4 is meant to provide a steep transition in mapping gray scales in the neighborhood of $g_{th}$. Condition 5 guarantees that the contribution of the range of gray scales around $g_{th}$ decreases after enhancement.

The result of stretching the contrast of gray scales as described above would be an image with a gray scale histogram that has more density of lines towards its edges, and less density of lines around the range of steep transition. In other words the transformation tends to push the mid-range gray levels toward either end, leaving less concentration of gray levels in the neighborhood of the transformed $g_{th}$. Fig. 10 shows a plot of the gray scale contrast stretching transformation in question.

Fig. 4 Gray Scale Contrast Stretching Transformation.

The specifics of the gray-scale stretching transformation we use for enhancement is beyond the scope of this paper.

Segmentation

In this methodology, radiograph images are automatically post-enhanced and segmented. In the post-enhancement stage, dental radiographs contain three distinctive regions: background, teeth, and bones. Usually the teeth regions have the highest intensity, the bone regions have high intensity that sometimes is close to that of the teeth, and the background has a distinctively low intensity. It is easy to separate the background by threshold-based methods, but these methods usually fail to discriminate teeth from bones, especially in cases of uneven exposure. To overcome this problem, the first step we use is to enhance the image’s contrast. Top-hat and bottom-hat filters can be used to extract light objects (or, conversely, dark ones) on a dark (or light) but slowly changing background. We use both the top-hat and the bottom-hat filters on the original image, and combine the results by adding to the original image the result of the top-hat filter, and subtracting the result of the bottom-hat filter, so that the teeth areas can be enhanced and the bone and background areas can be suppressed as well. Fig. 5b and fig 5c shows a result of the enhancement algorithm.
2-D modified wavelet kernels can capture boundaries

The horizontal line that separates the upper jaw and the lower jaw in bitewing radiographs can be detected by processing the image through the LH kernel in the 2-D wavelet decomposition, as described in section 2. Similarly, vertical edges in x-ray images, which typically represent the boundaries between individual teeth in the same jaw, can be detected by processing the image through the HL kernel in the 2-D wavelet decomposition. Then, we perform integral projection of horizontal and vertical lines to detect boundaries of individual teeth, which we will call regions.

In our proposed approach, each region (tooth segment), is segmented from the radiograph image using our morphological approach as in section 4.1. Then boundaries of each region are matched with the horizontal and vertical boundaries in the radiograph image. Regions that its boundaries have a high threshold when matched with the wavelet detected horizontal and vertical edges are considered a valid region.

5. Experimental Procedure

In our procedure we have followed the following steps

1- Apply enhancement with the gray scale stretching approach in section 4.1,

Fig. 6 shows an example of enhancing a periapical dental radiograph using our ADIS enhancement scheme, in section 4.1. The original radiograph is shown in (a), the result after applying the enhancement transform is shown in (b). Note that teeth edges are emphasized. The gray scale histograms before enhancement and after enhancement are shown in (c) and (d) respectively. The solid vertical lines in (c) represent the computed marker gray scales and the dotted line represents a threshold gray scale used for adaptive enhancement.
2- Perform morphological filtering
We have used the bottom hat morphological filtering algorithm, that emphasizes dark background areas and then subtract this dark background from the original image. We will call the resulting image the background eliminated image.

Fig 7 ADIS Dental Image Background Elimination

Then we use the top hat morphological filtering algorithm to emphasize the dental light regions on the background eliminated image and then add these areas to this image as in fig 7.
In teeth segmentation, we use window-based adaptive threshold to segment the teeth. The idea is to examine the intensity values of the local neighbors of each pixel. If the intensity value of the pixel is larger than the average intensity values of its neighbors, then it is classified as a tooth pixel, otherwise it is classified as background. To separate each tooth region, we apply a binary morphological operation to eliminate small noisy parts and smooth the teeth regions, as in fig 8. Then, we subtract the teeth areas from the original image to obtain the bones and the background regions, and apply simple thresholding to separate the bones from the background.

Fig 8 ADIS Dental Binary Morphological Operation

Perform for 2-D wavelet
For every image we detect the horizontal and vertical edges through the 2-dimensional wavelet transform. We used the 9X7 Antonini kernel [15], adopted in the JPEG2000 standard. Edges are enhanced through morphological operations as in step 3 in section 5.

6. Results
The proposed segmentation approach was tested on 2000 films of dental records provided from the CJIS division of the Federal Bureau Investigation research center, we defined our percentage of failure as number of images from where didn’t capture any true segmented region (tooth) to the whole number of images conducted in our experiments
Fig. 9 shows samples of our results with region based morphological filtering segmentation. Table 1 lists our segmentation results with and without enhancement.

![Fig. 9 Morphological Filtering Segmentation](image)

**Table 1 Segmentation Results**

<table>
<thead>
<tr>
<th>Segmentation Technique</th>
<th>Morphological Segmentation with out Enhancement</th>
<th>Morphological Segmentation with Enhancement</th>
<th>Morphological and wavelet Segmentation with out Enhancement</th>
<th>Morphological and wavelet Segmentation with Enhancement</th>
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<td>Percentage of Failure</td>
<td>87%</td>
<td>96%</td>
<td>63%</td>
<td>81%</td>
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![Fig. 10 Examples of Dental Image that require Wavelet based Segmentation](image)

**7. Discussion**

In our results we got successful segmentation results after enhancement using only the morphological filtering approach. It is also shown how much of segmentation improvement is obtained from the enhancement stage. In spite the fact that wavelet based segmentation and classification has achieved superior results, when dealing with dental images it was not very successful or meaningful. However for some types of images as shown in fig. 10, wavelet based segmentation was needed to capture the fine edges between different tooth through its multi-resolution property, that morphological filters couldn’t distinguish.

**8. Conclusion**

In this paper a novel dental image segmentation algorithm is presented. The proposed approach is part of an Automatic Dental Identification System for locating missing and un-identified personnel based on their dental characteristics. The proposed approach included an enhancement stage that eliminates poor image quality effects on the segmentation process. The proposed approach was also combined with a wavelet tool for enhancing the segmentation output for some cases that was not successful using the first technique. Our future work will address several important problems such as the migration from region-based image matching to case-based image matching, better for processing poor quality radiographs, and retrieval from the dental Image repository.
9. References


