# Teeth Segmentation in Digitized Dental X-Ray Films Using Mathematical Morphology

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Abstract—Automating the process of postmortem identification of individuals using dental records is receiving increased attention. Teeth segmentation from dental radiographic films is an essential step for achieving highly automated postmortem identification. In this paper, we offer a mathematical morphology approach to the problem of teeth segmentation. We also propose a grayscale contrast stretching transformation to improve the performance of teeth segmentation. We compare and contrast our approach with other approaches proposed in the literature based on a theoretical and empirical basis. The results show that in addition to its capability of handling bitewing and periapical dental radiographic views, our approach exhibits the lowest failure rate among all approaches studied.

*Index Terms*—Automated dental identification system (ADIS), dental X-ray enhancement, dental X-ray segmentation, mathematical morphology, postmortem identification, segmentation performance.

#### I. INTRODUCTION

**B** IOMETRIC systems play an important role in identifying individuals based on some physiological and behavioral characteristics [1], such as fingerprints, face, hand geometry, iris, voice, and signature. While most of these characteristics are not suitable for postmortem (PM) identification, especially under the severe circumstances usually encountered in mass disasters (e.g., airplane crashes), dental features are one of few biometric identifiers that qualify for PM identification. Dental features are manifested in root and crown morphology, teeth sizes, rotations, spacing between teeth and sinus patterns, as well as characteristics of dental work and restorations [2].

In 1997, the Criminal Justice Information Services (CJIS) division of the Federal Bureau of Investigation (FBI) formed a Dental Task Force (DTF), which recommended the creation of a digital image repository (DIR) and an automated dental identification system (ADIS) [3] with goals and objectives similar

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Fig. 1. (a) Bite-wing X-ray. (b) Periapical X-ray.

to the automated fingerprint identification system (AFIS) [4] but using dental characteristics instead of fingerprints [5]. PM dental identification is mainly achieved by comparing a subject dental record to a database of dental records. Dental radiographs are the most common forms of dental records used in PM identification. Fig. 1 shows two types of dental radiographs we use in our research, namely bitewing and periapical radiographs [6].

At a high level of abstraction, we view ADIS as a collection of the following megacomponents (as depicted in Fig. 2): 1) the record preprocessing component handles cropping of dental records (which contain different views) into dental films, enhancement of films, classification of films into bitewing, periapical, or panoramic views, segmentation of teeth from films, and annotating teeth with labels corresponding their location in a dental atlas, 2) the potential match search component manages archiving and retrieval of dental records based on high-level dental features (e.g., number of teeth and their shape properties) and produces a candidate list, and 3) the image comparison component mounts for low-level tooth-to-tooth comparison between subject teeth-after alignment-and the corresponding teeth of each candidate, thus producing a short match list. This framework broadly defines the collaborative research tasks between research teams from West Virginia University, Michigan State University, and the University of Miami—jointly developing a research prototype of ADIS [3].

In this paper, we address the problem of teeth segmentation from dental radiographic films. Image segmentation is one of the most difficult tasks in image processing [7] and it plays a critical role in most subsequent image analyses, especially in pattern recognition and image matching. Segmentation means partitioning an image into its constituent regions and extracting the objects of interest. However, there is hardly any image segmentation technique that performs well in all problems. In addition, the performance of a segmentation technique is greatly affected by noise embedded in images.

In the context of ADIS, segmentation is a step required to identify the extent of teeth comprised in a digital image of a



Fig. 2. Block diagram illustrating the architecture of ADIS.

dental radiographic film. At a finer level of detail, segmentation also serves in decomposing a tooth into a crown area and a root area. Each segmented tooth represents a region of interest (ROI) that contains distinctive features used in the subsequent steps of identification. We define a qualified ROI as a rectangular area in the image of dental film that bounds one tooth.

We tackle the problem of teeth segmentation using a mathematical-morphology (MM) approach. Our approach offers fully automated teeth segmentation, and is meant to reduce segmentation errors due to inherent and extrinsic background noise. Our interest in MM stems from its powerful capabilities for extracting a variety of shapes and image structures [7]. Morphological filtering [8] serves in a wide range of applications in image processing and analysis, such as feature extraction, shape representation and description, shape recognition, shape smoothing, enhancement, and noise suppression [8] to mention a few. We set the following objectives for teeth segmentation: 1) to automatically extract as many qualified ROIs as possible; 2) to operate on bitewing and periapical views; and 3) in the worst case scenario, to extract at least one qualified ROI from each film. The qualified ROI shows one tooth as a whole.

In Section II, we briefly review the relevant literature. In Section III, we present our teeth segmentation algorithm, and then in Section IV, we present a grayscale contrast stretching transformation that improves the definition of teeth versus background and the segmentation performance. In Section V, we report our experimental results and compare the performance of the proposed approach to other recently published approaches. Finally, in Section VI, we conclude the paper and lay out plans for future work.

# TABLE I

SUMMARY OF COMPARISON BETWEEN THREE TEETH SEGMENTATION ALGORITHMS [13], [14], AND [15] AUTHOR: SHOULD "HONG" BE "CHONG" AND "NOMIR" INSTEAD OF "NOMAIR" AS THEY APPEAR IN REFS."

Algorithm	Algorithm Principles		Is it automated?
Jain and Hong	Internal projection	Bitewing and	No, semi-
[13]	integral projection	Panoramic	automated
Nomair and	Iterative and adaptive		
Abdel-Mottaleb	thresholding, integral	Bitewing only	Yes
[14]	projection		
Zhou and Abdel-	Mambala zu adautius		
Mottaleb	threshold internal universitien	Bitewing only	Yes
[15]	inresnoid, integral projection		

#### II. BACKGROUND

Several radiograph and magnetic-resonance (MR) image segmentation approaches have been presented in the last decade. In [9], a fully automated technique using Markov random fields was proposed for (MR) images. Noise, inhomogeneity, and structure thickness have a negative impact on the performance of the algorithm, and they tend to increase the segmentation error. In [10], the Hopfield neural network based on pattern classification using the fuzzy c-means algorithm was proposed. The computation time and finding the global minimum of the objective function affect performance. In [11], the segmentation approach is based on analyzing isolable-contour maps to identify coherent regions corresponding to main objects. In [12], the segmentation is based on an improved watershed transform that uses the prior information instead of usual gradient calculations. Although high accuracy was reported in the approaches presented in [11] and [12], user interaction is needed to select interesting regions.

There are few researches dedicated to the problem of dental radiograph image segmentation. In [13], Jain and Chen separate the upper jaw and the lower jaw in the bitewing and panoramic dental images by detecting the gap valley between them using the Y-axis projection histogram. Afterwards, the technique isolates each tooth from its neighbors in each jaw by detecting the gaps between them using intensity integral projection. This approach is semiautomated since an initial valley gap point is required to detect the gap valley between the upper and lower jaw. We found from our experiments that the segmentation outcome may vary if we change the position of the selected initial valley gap point. Fig. 3 shows two different segmentation results produced by choosing two different initialization points both of which are on the valley gap; the choice in Fig. 3(a) leads to perfect segmentation while the choice in Fig. 3(b) leads to total segmentation failure.

In [14], Nomir and Abdel-Mottaleb introduce a fully automated approach for dental X-ray images. The technique depends on applying the following stages: 1) iterative threshold to divide the image into two parts—teeth and background; 2) adaptive



Fig. 3. Two different results for the same image. (a) Completely segmented image. (b) Failed segmented image.

threshold in order to increase the accuracy and remove teeth interfering; 3) horizontal integral projection in order to separate the upper jaw from the lower jaw; 4) and, finally, vertical integral projection in order to separate each individual tooth.

Another fully automated approach for dental X-ray images is introduced by Zhou and Abdel-Mottaleb [15]. The technique depends on improving the image contrast by applying morphological transformation, and then using the window-based adaptive threshold and integral projection to segment the teeth and separate the upper and lower jaw.

Table I shows a brief comparison between the three algorithms based on underlying principles, type of dental film views they are reported to operate on, and the level of automation they achieve.

In [16], Nassar *et al.* present a metrics-based object counting approach for the empirical assessment of image segmentation. To evaluate the performance of the segmentation algorithm, reference images are used to record the outcome of the experiment in a tabular form as shown in Fig. 4.

Each cell  $P_{ji}$  of the results table contains the number of instances where the segmentation algorithm correctly detects jobjects out of i objects that are present in reference image, with  $\sum_{j=0}^{i} P_{ji} = F_i$ , where  $F_i$  is the number of reference images that contain exactly i objects. The results table is used in determining metrics of optimality, suboptimality, and failure based on the relative weights of the main diagonal, the subdiagonals,



Fig. 4. Tabular presentation of segmentation results (adopted from [16]).



Fig. 5. Main stages of proposed segmentation algorithm.

and the base row, respectively, the performance metrics are defined as follows [16]:

Optimality

$$\equiv 100 * \frac{\sum_{i=1}^{N} P_{ii} F_i}{\sum_{i=1}^{N} F_i^2} \%$$

Failure

$$\equiv 100 * \frac{\sum_{i=1}^{N} P_{0i} F_i}{\sum_{i=1}^{N} F_i^2} \%$$

 $m^{\rm th}$  Order Suboptimality

$$\equiv 100 * \frac{\sum_{i=1}^{N-m} P_{i(i+m)} F_{(i+m)}}{\sum_{i=1}^{N} F_i^2} \%$$

While optimality and failure percentages capture instances of extreme performance of a segmentation algorithm, suboptimality measures capture the performance of algorithms in between the two extremes. For example, in teeth segmentation, first-order suboptimality is a measure of the tendency of the algorithm to miss the detection of exactly one tooth and detect all of the others, but without failure.

In practical cases, it is difficult to achieve optimal performance with 100% images, and when comparing segmentation algorithms, one should favor those whose failure rates are the lowest and their optimality and low-order measures of suboptimality predominate the testing results [16].

The failure rate is especially important when assessing teeth segmentation algorithms, since those films where no teeth can be properly segmented cannot be used in the identification process.

# **III. TEETH SEGMENTATION**

We define three main classes of objects in the X-Ray dental images: teeth that map the areas with "mostly bright" grayscale, bones that map the areas with "midrange" grayscale, and a background that maps "dark" grayscale. The main goal of the proposed segmentation algorithm is to extract at least one ROI that represents exactly one tooth. We use a series of morphology filtering operations to improve the segmentation, and then analyze the connected components obtained from filtering in order to obtain the desired ROI's as shown in Fig. 5.

## A. Internal Noise Filtering

We start with the detection of the gap valley between the upper jaw and the lower jaw, bones between the teeth, teeth interference, and the gaps between the teeth. We define internal noise as the combination of these factors. Detection and suppression of the internal noise help to emphasize the teeth with respect to the background. Fig. 6 shows three samples of grayscale line profiles: the upper horizontal line profile illustrates the bones between the teeth, the lower horizontal line profile shows the gap between the teeth, while the vertical line profile illustrates the gap valley. Closing top-hat transformation, which is defined by subtracting the image from its morphological closing, provides an excellent tool for detecting pixels that are dark on the surrounding bright areas, and it



Fig. 6. Grayscale line profiles of the input image, the upper horizontal line profile illustrates the bones between the teeth, the lower horizontal line profile shows the gap between the teeth, while the vertical line profile illustrates the gap valley. AUTHOR: INCREASE FONT SIZE FOR TEXT IN THIS FIG. AND FIG. 7?



Fig. 7. Grayscale line profiles of the closing top hat transformed image that correspond to the same line profiles in Fig. 5.

locally performs suppression of teeth and emphasizes internal noise.

The grayscale line profiles of the closing top hat transformed image represented in Fig. 7 show the emphasized internal noise.

Fig. 8 shows an example of dental film before and after the removal (subtraction) of internal noise. We use a rectangular structuring element with dimensions [w/4, h/2] for bitewing images, and with dimensions  $[w/3, 2^*h/3]$  for periapical images, where w and h are the width and height of the image, respectively. Our choice of these structuring elements is based on an experimental study on a set of 60 bitewing views and 40 periapical views of different sizes and qualities.

## B. Thresholding

After reducing the noise effect, we use threshold operation to separate the desired teeth from the background and the remaining noise. Thresholding produces a binary image that simplifies the image analysis. In many of the dental radiographs, we notice the presence of a shading effect that manifests as a gradient of image brightness from side to side as shown in the horizontal grayscale line profiles of the image in Fig. 6. Therefore, choosing a single threshold value is not preferable because it may result in missing information pixels. The cumulative histogram of the filtered image, which contains the percentage of pixels below a certain grayscale level, gives the percentage of pixels that are set to zero after reducing the noise. In our example, around 50% of the image pixels are set to zero as shown in Fig. 9. According to an experimental study applied on a set of 100 dental images, we found that taking three threshold values would produce the most qualified ROIs in the following stages. The threshold values  $T_1, T_2$ , and  $T_3$  fall between the mean value of the filtered image and zero, where

$$T_1 = \text{mean}(\text{Filtered Image}), T_2 = 0.66T_1, T_3 = 0.33T_1.$$

Images in Fig. 10(a)–(c) show the three different results obtained from thresholding.

#### C. Connected Components Labeling

We group pixels of the threshold image based on their connectivity and assign them labels that identify the different connected components [7]. Images in Fig. 10(d)-(f) show the results of the connected components labeling for each thresholded image shown in Fig. 10(a)-(c), respectively. The connected components can be attributed to: 1) teeth that are considered as ROIs; 2) more than one tooth because of teeth interference, fillings, or high-intensity bone structures; 3) background or bones; and 4) part of the tooth such as the crown or root.

## D. Refinement

The purpose of refinement is to analyze the connected components based on geometric properties (area and dimension) and then to eliminate the unqualified objects. Table II shows the rules

Fig. 8. (a) Original image. (b) Filtered image.



Fig. 9. Cumulative histogram of the filtered image.



Fig. 10. (a)–(c) Thresholded images. (e)–(g) Result of connected component labeling for (a)–(c). (g)–(i) Qualified ROIs generated from (e)–(g).

used for refinement based on an experimental study applied on

 TABLE II

 Rules Used in Refinement Stage to Determine the Qualified ROIs

View Type	ROI height	ROI width	ROI area
Bitewing	0.15h <height<0.7h< td=""><td>0.15w<width<0.4w< td=""><td>Area&gt;0.0225hw</td></width<0.4w<></td></height<0.7h<>	0.15w <width<0.4w< td=""><td>Area&gt;0.0225hw</td></width<0.4w<>	Area>0.0225hw
Periapical	0.3h <height<0.9h< td=""><td>0.15w<width<0.5w< td=""><td>Area&gt;0.045hw</td></width<0.5w<></td></height<0.9h<>	0.15w <width<0.5w< td=""><td>Area&gt;0.045hw</td></width<0.5w<>	Area>0.045hw



Fig. 11. (a) Original image. (b)-(i) Results of segmentation.



Fig. 12. (a) Original image. (b) Filtered image. (c) Thresholded images. (d) Result of connected component labeling. (e)–(h) qualified ROIs.

100 images. We classify the image type (bitewing or periapical) according to dental image classification proposed in [15]. Images in Fig. 10(g)–(i) show the qualified ROIs. If two or more qualified ROIs are generated from the three different thresholds for the same tooth, we unify them to generate the single ROI. We apply the union operation on two ROIs if the centriod of each ROI belongs to the other and their intersection is at least 80% of the smaller ROI. The union of qualified ROIs represents the final results of segmentation as shown in Fig. 11.

The previous example shows the segmentation stages that applied to bitewing dental images. Fig. 12 shows the results of segmentation stages applied on periapical dental images.

Figs. 13–15 show some samples of image segmentation results. The images in Fig. 13 have fully succeeded; the images in Fig. 14 have partially succeeded, while the images in Fig. 15 have failed to give any ROI. In Figs. 13 and 14, there are two rows of images—the upper row shows the original images, while the lower row shows teeth obtained from segmentation. It is obvious that the better quality the dental image is, the more ROIs can be extracted from that image. We define the factors that introduce difficulties in segmentation as follows: 1) image blurring [Fig. 15(a) and (f)]; 2) fillings [Fig. 15(b)]; 3) teeth interfering [Figs. 15(b), (c), (f), and (h)]; 4) image scan quality



Fig. 13. Examples of completely successful images and their segmentation outcomes.



Fig. 15. Examples of completely failed images where no teeth can be extracted.

[Fig. 15(c)]; and 5) the intensity of the bones is very close to intensity of the teeth [Fig. 15(e)-(h)].

### IV. DENTAL FILM GRAYSCALE CONTRAST ENHANCEMENT

As we mentioned in Section III, the histogram analysis of dental radiographic films supports the intuition that most teeth areas (except for the pulp tissue) predominantly concentrate in upperband grayscales, while the areas of support bones and gums appear around midrange grayscales, and the air-gap areas are confined to the lower band of grayscales. Due to aging of their chemicals, radiographic films tend to lose their contrast over time. Therefore, in dental radiographs that are scanned after exhibiting contrast decay, it is difficult to identify clear boundaries between the grayscale bands of teeth, support bones/gums, and air gaps. In addition, the lack of a unified standard for scanning and digitization of dental radiographic films exacerbates the identification of the grayscale bands of concentration of these objects. To improve segmentation of teeth from low-contrast dental films, we propose to apply a preprocessing contrast stretching step using a parametric sigmoid transform. Thus, we map an input grayscale g to  $T_{Enh}(g, \alpha, \beta, g_{th})$ , according to the equation shown at the bottom of the page, where  $\alpha$  and  $\beta$  designate compression and expansion factors, respectively;  $g_{th}$  is a threshold grayscale between the compression and the expansion regions of  $T_{Enh}$ ;  $g_{TH}$  is the image of  $g_{th}$  under  $T_{Enh}$ ,  $g_{min}$ , and  $g_{max}$  are the minimum and maximum grayscales of the input image, respectively. We choose  $g_{TH}$  such that its proportionality to the new grayscale range [0, 255] resembles that of  $g_{th}$ to the grayscale range of the input image. Thus

$$g_{\mathrm{TH}} = \left\lceil 255 * (g_{\mathrm{th}} - g_{\mathrm{min}}) / (g_{\mathrm{max}} - g_{\mathrm{min}}) \right\rceil.$$

Let  $S_I$  denote the cumulative grayscale histogram of the input image (I). To determine the values of  $\alpha$ ,  $\beta$ , and  $g_{th}$ , we analyze

$$T_{\rm Enh}(g,\alpha,\beta,g_{\rm th}) = \begin{cases} \left\lfloor g_{\rm TH} * \frac{e^{\alpha(g-g_{\rm min})/(g_{\rm th}-g_{\rm min})}-1}{e^{\alpha}-1} \right\rfloor, & g_{\rm min} \le g \le g_{\rm th} \\ \left\lceil g_{\rm TH} + (255 - g_{\rm TH}) * \frac{e^{\beta(g_{\rm th}-g)/(g_{\rm max}-g_{th})}-1}{1 - e^{-\beta}} \right\rceil, & g_{\rm th} < g \le g_{\rm max} \end{cases}$$



Fig. 16. Membership functions of the transformation parameters.

	TOLLT OF		
	g <sub>hi</sub> is dark	g <sub>hi</sub> is gray	$g_{hi}$ is bright
g <sub>lo</sub> is dark	$\alpha$ is small $\beta$ is large	$\alpha$ is small $\beta$ is medium	$\begin{array}{c} \alpha \text{ is small} \\ \beta \text{ is small} \end{array}$
	$g_{th}$ is close to $g_{lo}$	$g_{th}$ is close to $g_{lo}$	$g_{th}$ is between $g_{lo}$ and $g_{hi}$
g <sub>lo</sub> is gray	Null	$\alpha$ is medium $\beta$ is medium	$\alpha$ is medium $\beta$ is small
		$g_{th}$ is between $g_{lo}$ and $g_{hi}$	$g_{th}$ is close to $g_{hi}$
g <sub>lo</sub> is bright	Null	Null	$\alpha$ is large $\beta$ is small
			$g_{th}$ is close to $g_{hi}$

TABLE III FUZZY CONTRAST STRETCHING DECISION TABLE

 $S_I$  to first determine two marker grayscales  $g_{\rm lo}$  and  $g_{\rm hi}$  as follows:

$$\begin{split} g_{lo} &= \min_{\langle g \rangle} \{ S_I(g) \geq \kappa_1 \} \\ g_{hi} &= \min_{\langle g \rangle} \{ S_I(g) \geq \kappa_2 \} \,, \qquad \text{where } 0 < \kappa_1 < \kappa_2 < 1. \end{split}$$

To choose suitable values for  $\kappa_1$  and  $\kappa_2$ , we studied several dental radiographic films with variability in their brightness and contrast. We varied these parameters and observed that most of the air-gap regions exist in  $S_I(g) \leq 0.25$ ; we also found that appreciable portions of gums and support bones appear in the range  $0.25 \leq S_I(g) \leq 0.75$ . Hence, we heuristically choose  $\kappa_1 = 0.25$  and  $\kappa_2 = 0.75$ .

We fuzzify the crisp values of  $g_{\rm lo}$  and  $g_{\rm hi}$  using their membership functions shown in Fig. 16 and, hence, evaluate fuzzy rules that govern the values of  $\alpha$ ,  $\beta$ , and  $g_{\rm th}$ . The fuzzy rules we propose stem from our intuition that in a good-contrast image, the lowerband marker  $g_{\rm lo}$  is likely to fall in the dark region of the grayscales and, likewise, the upperband marker  $g_{\rm hi}$  falls in the bright region of the grayscales. Accordingly, the extent to which the darker regions should further be darkened (i.e., compressed) depends on the value of  $g_{\rm lo}$  and, similarly, the amount expansion of the brighter grayscales depends on the value of  $g_{\rm lo}$ . We also think that the threshold  $g_{\rm th}$  depends on the difference between  $g_{\rm lo}$  and  $g_{\rm hi}$ . The fuzzy rules that we use for determining the values of  $\alpha$ ,  $\beta$ , and  $g_{\rm th}$  are summarized in the decision table shown in Table III. The membership functions of the variables of our fuzzy system  $(g_{\rm lo}, g_{\rm hi}, \alpha, \beta, \text{and } g_{\rm th})$  are shown in Fig. 16. The crisp value of  $g_{\rm th}$  resulting from evaluating these fuzzy rules is normalized, and in order to substitute  $g_{\rm th}$  in (1), we have to denormalize it using  $g_{\rm th} = [g_{\rm lo} + g_{\rm th}(\text{norm})^*(g_{\rm hi} - g_{\rm lo})]$ .

Fig. 17 shows an example of a dental film before contrast stretching (a), the grayscale transformation  $T_{\rm Enh}$  (b), and the contrast-stretched film (c). We observe the fadeout of gums and support bones and the clearer definition of teeth regions with respect to their surroundings. In Fig. 18, we show some examples of images that could not be segmented before dental film grayscale contrast enhancement, but produced some qualified segments after contrast stretching.

#### V. PERFORMANCE ASSESSMENT

In this section, we compare the performance of the two variants of the segmentation algorithm proposed in Section III (i.e., with and without the enhancement step proposed in Section IV). We also compare the performance with those presented in [13]–[15]. We empirically compare between these algorithms on the basis of teeth count and their time complexities.

#### A. Teeth Count

We follow the performance evaluation methodology proposed in [16] in order to compare the performance of the algorithms. Our experiments use two test sets of 500 bitewing and 130 periapical dental radiographic films selected from large dental radiographic databases [17], [18]. All films in the



Fig. 17. (a) A dental film. (b) Computed  $T_{\rm Enh.}$  (c) The resulting contrast stretched film.



Fig. 18. Examples of films that could be partially segmented after enhancement.



Fig. 19. Testing results for of our teeth segmentation algorithm with bitewing views.

bitewing radiographic set contain up to ten teeth per film, and films in the periapical radiographic set contain up to five teeth per film.

In counting the number of correctly detected teeth in a film, we visually inspect the outcome of segmentation for each film using a simple rule of object containment within each segment of a given film.

Testing results of the algorithm we propose in Section III for bitewing radiographic set before and after enhancement are shown in Figs. 19 and 20, respectively, while testing results for periapical radiographic set before and after enhancement are shown in Fig. 21(a) and (b), respectively.

Testing results of the algorithms proposed in [13]–[15] are shown in Figs. 22–24, respectively. The bitewing set of dental images used for testing is the same as the one used for testing our segmentation approach. Fig. 25(a) shows a graphical comparison using the metrics in [16] between the dental film segmentation algorithm we proposed in Section III and the proposed algorithm after enhancement presented in Section IV with the analogous algorithms proposed in [13]–[15].

We conclude the following observations from Fig. 25(a) and Table IV.

- The optimality of the algorithm proposed in [13] is superior to other algorithms, but it is still a semiautomated algorithm.
- The optimality of the algorithm proposed in [15] is superior to other full-automated algorithms.
- Failure rate of the proposed algorithm is the lowest (Table IV).
- Slight improvement has been made in the failure rate of the proposed algorithm after applying the image enhancement scheme.
- Enhancement dropped the optimality of the proposed algorithm by approximately 3% for the cases lying between the axis of optimality and the second-order suboptimality.
- Enhancement increased the percentage of the cases lie between optimality and fourth-order suboptimality to 83%.

While the algorithms proposed in [13]–[15] do not work with the periapical dental radiographs, Fig. 25(b) shows a graphical comparison using the metrics in [16] between the proposed algorithm and the proposed algorithm with enhancement. It is clear that the enhancement decreases the failure rate from 9.4% to 6.7%, and it improves the optimality and first-order suboptimality.



Fig. 20. Testing results for our teeth segmentation algorithm with contrast stretched bitewing views.



Fig. 21. (a) Testing results for of our teeth segmentation algorithm with periapical views. (b) Testing results for of our teeth segmentation algorithm with contraststretched periapical views.



Fig. 23. Testing results of the Nomair AUTHOR: "NOMAIR" SPELLING OK? and Abdel-Mottaleb segmentation algorithm [14].

#### B. Time Complexity

To compare the time complexities of the proposed algorithm and those proposed in [13]–[15], we used 40 bitewing films with different dimensions. We invoked MATLAB implementations of each algorithm on an Intel Pentium 4 2.00-GHz, 512-MB DRAM platform. Table V summarizes the outcome of the time complexity comparison between the four teeth segmentation algorithms: h is the image height, w is the image width, and n is the size of the window used in adaptive thresholding. Fig. 26 records the execution times of the four teeth segmentation algorithms for each of the 40 bitewing films. Based on Fig. 26 and Table V, we observe that: 1) the proposed algorithm is the fastest among the other algorithms; 2) the difference in the average time execution between the proposed algorithm, algorithm [13], and algorithm [15] is small; and 3) the time complexity of the algorithm [14] is significant compared to the other algorithms.



Fig. 24. Testing results of the Zhou and Abdel-Mottaleb segmentation algorithm [15].



Fig. 25. (a) Performance comparison between bitewing segmentation algorithms. (b) Performance comparison between the proposed algorithm and proposed algorithm with enhancement for periapical views

TABLE IV COMPARISON BETWEEN THE FAILURE RATES OF THE VARIANT TEETH SEGMENTATION ALGORITHMS AUTHOR: SPELLING OK FOR "NOMAIR" AND "HONG"?

			<u>~</u>		
Algorithm	Haj Said, Nassar, Fahmy, and Ammar algorithm without enhancement	Haj Said, Nassar, Fahmy, and Ammar algorithm with enhancement	Jain and Hong [13]	Nomair and Abdel-Mottaleb [14]	Zhou and Abdel- Mottaleb [15]
Failure rate	2.12%	1.27%	2.61%	11.18%	3.47%



Algorithm	Haj Said, Nassar, Fahmy, and Ammar Algorithm	Jain and Hong [13]	Nomair and Abdel- Mottaleb [14]	Zhou and Abdel-Mottaleb [15]
Average time complexity (sec.)	4.614	5.658	57.251	7.323
Time complexity order	O(hw)	O(hw)	O(nhw)	O(nhw)

#### VI. CONCLUSION AND FUTURE WORK

We presented an automated dental image segmentation algorithm that handles bitewing and periapical dental images based on mathematical morphology. The proposed algorithm includes: 1) noise filtering, 2) thresholding to isolate the teeth from the background, and 3) analyzing connect components labeling to determine the qualified ROIs based on geometrical properties. We introduced the difficulties that face the proposed algorithm. These difficulties are image blurring, fillings, teeth interfering, image scan quality, and very low contrast between bones and teeth intensity.

We also presented a grayscale contrast stretching transformation to improve the performance of teeth segmentation. Applying it prior to segmentation increases the optimality and first-



Fig. 26. Time complexity distribution of 40 images for variants algorithms. AUTHOR: SPELLING OK FOR "NOMAIR" AND "HONG"

order suboptimality of the periapical image segmentation. It also drops the failure rate of bitewing and periapical image segmentation, which is one of the main objectives of our algorithm.

We also presented a performance comparison between variants of the bitewing dental image segmentation. The results show that 1) the proposed algorithm has the lowest failure rate in terms of the segmentation result, and it is the fastest in terms of time complexity, and it can handle both bitewing and periapical images; 2) the algorithm proposed in [13] has the highest optimality, but it is still a semiautomated algorithm and its performance is sensitive to the manually selected initial valley gappoint; and 3) the algorithm proposed in [15] has the highest optimality among the other full automated; **AUTHOR: WORD MISSING HERE?** ever, it only handles the bitewing images.

Our plan for the future is to develop the segmentation algorithm in order to improve handling poor quality images and to include the panoramic dental radiograph views in the segmentation process.

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