An Effective Teeth Segmentation Method for Dental Periapical Radiographs Based on Local Singularity

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Abstract—Dental radiographs play an important role for dental diagnosis, as most anomalies are hidden under the surface and cannot be seen during a visual examination. For effective computer-aided dental diagnosis, accurate teeth segmentation is one of the most critical tasks, because cysts and inflammatory lesions usually occur around tooth periapical (tooth-roots) areas and these areas in radiographs are often subject to noise, low contrast, and uneven illumination. In this paper, we propose an effective scheme to segment each tooth in dental periapical radiographs based on local singularity analysis. At first, a proposed adaptive power law transformation is applied to reduce variations of contrasts between teeth and alveolar bones (gums). Then local singularities measured by Hölder exponent are computed to obtain a structure image in which the structures of teeth are much smoother than the structures of gums. Otsu’s thresholding is applied to segment teeth from gums and finally, connected component analysis and morphological operations are applied to isolate each tooth. Experimental results demonstrate that out of 18 teeth in six tested periapical images, all teeth are successfully segmented with 17 extracted tooth-contours almost completely conforming to human visual perception.

I. INTRODUCTION

In dental clinic practices, radiographs (X-ray images) can assist dentists to diagnose dental anomalies, which are hidden under the surface and cannot be seen during a visual examination [1]. As the usage of digital dental X-ray images keeps growing, computer aided analyses become highly desirable for improving the accuracy of lesion detection and efficiency of treatment planning. For effective computer-aided dental diagnosis, accurate teeth segmentation is one of the most critical tasks, because cysts and inflammatory lesions usually occur around tooth periapical (tooth-roots) areas and these areas in radiographs are often subject to noise, low contrast, and uneven illumination.

Several good methods of teeth segmentation for dental radiographs had been presented in the past few years. Li et al. [1] presented a segmentation method for dental X-ray analysis using variational level set. Jain and Chen [2] proposed a semi-automatic contour extraction method by using integral projection and Bayes rule, in which the integral projection is semi-automatically applied for tooth isolation. Zhou and Abdel-Mottaleb [3] presented a method that consists of image enhancement, region of interest localization, and contour extraction using morphological operations and snake method. Nomir and Abdel-Mottaleb [4] developed a fully automated approach based on iterative thresholding and adaptive thresholding. Keshtkar and Gueaieb [5] introduced a swarm-intelligence based and a cellular-automata model approach. Lin and Lai [6] presented a method that firstly enhanced the image based on homogeneity then applied k-means clustering using entropy and edge value as the features, and finally applied fuzzy inference to speculate degrees of pixel belonging to either part according to a set of membership functions associated with textures and clustering result. Lin et al. [7] presented a method that firstly enhanced both contrast and illumination evenness of the radiographs by combining homomorphic filtering, homogeneity-based contrast stretching, and adaptive morphological transformation then obtained the coarse contours of teeth by using edge operator, and finally fine adjusted each contour by equal point sampling and B-spline fitting. Lin et al. [8] presented a method that firstly applied morphological operation to stretch the contrast then edge operator to obtain the coarse contour, and finally fine adjusted each contour point by performing local histogram equalization then Otsu’s thresholding.

Most of the aforementioned methods are for bitewing images except [1] and [8]. However, instead of segmenting teeth from the image, the main purpose of the method in [1] is to segment abnormal regions from the image. Paper [8] demonstrated six segmentation results of periapical images; nevertheless, not all shapes of the segmented teeth conformed to human perception.

In this paper, we propose an effective scheme to segment each tooth in dental periapical radiographs based on local singularity analysis. In follows, we start with a brief explanation of local singularity. We then present our proposed image enhancement method followed by local singularity analysis, coarse segmentation and fine segmentation. Finally, experimental results are presented to demonstrate the effectiveness of our proposed method.
II. LOCAL SINGULARITY

Complex signals or structures can be seen as superpositions of singularities [9]. One way of detecting the pointwise singularity of an observed structure \( S \) is to measure the Hölder exponent \( \alpha \) at any given point, which is defined as the limiting value of \( \alpha_i \) as follows [10].

\[
\alpha = \lim_{\varepsilon \to 0} \alpha_i = \frac{\ln(\mu(S_i))}{\ln(\varepsilon)}
\]

where \( S = \cup S_i \), \( S_i \) is a non-overlapping box of size \( \varepsilon \), and \( \mu(S_i) \) is some amount of measure within box \( S_i \). For digital images, however, possible box size is an integer multiple of pixels because of their discrete nature. Thus, the singularity of each pixel may be characterized as

\[
\alpha_i(x, y) = \frac{\ln(\mu_i(x, y))}{\ln(\varepsilon)}, \quad i = 1, 2, 3...
\]

where \( \mu_i(x, y) \) is the amount of measure within the observed box with size \( \varepsilon = i \) centered at the pixel \((x, y)\). It follows that \( \varepsilon \) cannot approach to 0 since \( \varepsilon_{\min} = 1 \), hence the limiting value of \( \alpha_i(x, y) \) is estimated indirectly as the slope of a linear regression line of those points on the log-log diagram.

For estimating the Hölder exponent in (2), different measures \( \mu_i(x, y) \) may be used to give different information on the singularities encountered. Some of the commonly used capacity measures are: max, min, iso, sum, defined as:

- **“max” measure:**
  \[
  \mu_i(x, y) = \max_{(k, l) \in \Omega} g(k, l)
  \]

- **“min” measure:**
  \[
  \mu_i(x, y) = \min_{(k, l) \in \Omega} g(k, l)
  \]

- **“sum” measure:**
  \[
  \mu_i(x, y) = \sum_{(k, l) \in \Omega} g(k, l)
  \]

- **“iso” measure:**
  \[
  \mu_i(x, y) = \text{card}((k, l)) |\{g(x, y) - g(k, l)| < \delta, (k, l) \in \Omega\}
  \]

where \( \Omega \) is a set of pixels \((k, l)\) within a specific measure domain, \( \Delta \) is a set of all nonzero pixels within a measure domain, \( g(k, l) \) is a gray-level intensity at point \((k, l)\), and \( \delta \) is a threshold value.

III. TEETH SEGMENTATION

For effective computer-aided dental diagnosis, accurate tooth segmentation is one of the most critical tasks, as cysts and inflammatory lesions usually occur around tooth periapical (tooth-roots) areas. The proposed tooth-segmentation method involves four stages: image enhancement, local singularity analysis, coarse segmentation, and fine segmentation. The details of each stage are given in the following subsections.


In dental periapical radiographs, tooth boundaries in root regions are often very vague, whereas boundaries in crown parts are usually very clear. Thus, global enhancement, such as histogram equalization or power-law transformation, is neither efficient nor effective for such problem, as the enhanced result of either method will appear over-enhanced in some regions or under-enhanced in other regions.

For reducing the contrast variations between poor-contrast tooth-root regions and well-contrast tooth-crown regions, we propose using an adaptive power-law transformation (APLT) to adjust the intensity of each pixel with the exponent in the power-law transformation being dynamically set based on the local intensity range of its neighborhood pixels. The mathematical expressions of the aforementioned enhancement scheme are as follows.

\[
g'(x, y) = g(x, y)\gamma
\]

\[
\gamma = \ln(1/d(x, y))
\]

\[
d(x, y) = \max\{g(x+p, y+q)| - \min\{g(x+p, y+q)\}
\]

where \( p = [\lfloor w/2 \rfloor - \lfloor w/2 \rfloor], q = [\lfloor w/2 \rfloor - \lfloor w/2 \rfloor] \). \( g(x, y) \) is the intensity of pixel at \((x, y)\), \( w \) is the size of a window centered at \((x, y)\). Note that we take the inverse of the intensity range in (8) so that pixels with poor contrast (i.e., small \( d \)) will have bigger \( \gamma \) while pixels with very good contrast (i.e., large \( d \)) will have smaller \( \gamma \).

Fig. 1 illustrates the effect of the proposed APLT on a well- and a poor-contrast blocks using different \( \gamma \), respectively, and Fig. 2 illustrates the effect on a dental periapical radiograph in which two of three tooth-root regions are poorly contrast. Notice that the low-contrast periapical regions (the rectangle-marked areas) in Fig. 2(a) become much well contrast in Fig. 2(b), while the originally better-contrast periapical region (the oval-marked area) in Fig. 2(a) becomes well-contrast in Fig. 2(b). Furthermore, the contrasts of the entire tooth boundaries of all three teeth in Fig. 2(b) appear much more uniform than those in Figs. 2(c) and 2(d), which are the results enhanced by the global power-law transformation using fixed \( \gamma \) of 2 and 0.5, respectively.

![Figure 1. Effect of the proposed APLT on a well-contrast and a poor-contrast blocks: (a) well-contrast, (b) result of APLT \( \gamma=0.348 \), (c) poor-contrast, (d) result of APLT \( \gamma=2.297 \).](image1)

![Figure 2. Effects of the proposed APLT and the global power-law transformation (GPLT) on a dental periapical radiograph: (a) original, (b) result of APLT, (c) result of GPLT \( \gamma=2 \), (d) result of GPLT \( \gamma=0.5 \).](image2)
B. Local Singularity Analysis

After enhancing the contrast of tooth boundaries, the next step is to analyze local singularity-Hölder exponent. In this paper, we choose small measure domains \( i = \{1, 3, 5\} \) and “avg” capacity measure defined in (10), which is a modified “sum” capacity measure, to calculate the value of \( a \) according to (2).

“avg” measure:

\[
\mu_i(x, y) = \frac{1}{|\Omega|} \sum_{(k,l) \in \Omega} g(k,l)
\]  

(10)

where \( |\Omega| \) is the size of the measure domain \( \Omega \). Choosing small measure domain is due to that the gap between each pair of teeth is normally less than the range of this domain, and choosing “avg” capacity measure is for reducing singularity variations within each tooth. Fig. 3(a) shows the \( \alpha \)-image derived from the image in Fig. 2(b), in which the intensity of each pixel is the normalized \( \alpha \)-value of the corresponding pixel in Fig. 2(b). Notice that most pixels on tooth boundaries have stronger intensities while pixels within each tooth have much weaker intensities.

Although most \( \alpha \)-values of the pixels within each tooth are smaller than those of pixels on tooth contours, some pixels within the tooth still have \( \alpha \)-values close to those of the contour pixels. Fig. 3(b), which is an enlarged view of the marked region in Fig. 3(a), depicts such result. Since bilateral filtering is often used for edge preservation and removal of fine textures, we adopt it to smooth the variations of \( \alpha \)-values within each tooth while preserving strong \( \alpha \)-values of the pixels on tooth contours.

![Figure 3. \( \alpha \)-images before and after applying bilateral filtering: (a) entire view before filtering, (b) enlarged view of the ROI before filtering, (c) enlarged view of the ROI after filtering](image)

C. Bilateral Filter

Traditional image smoothing filtering, such as Gaussian low-pass filtering, replaces the value of the target pixel by a weighted average of values in its neighborhood, where the weights decrease with the distance from the target pixel. The underlying assumption is that images usually vary slowly over space. Unfortunately, the assumption of slow spatial variation fails at edges so that edges are smoothed away after filtering. Bilateral filter, which consists of domain filter and range filter, is one of the most popular methods to overcome such problem. The idea is as follows [11].

Two pixels in an image can be close to each other, or they can be similar to each other. Closeness refers to vicinity in the spatial domain, while similarity referring to vicinity in the image value range. Domain filtering enforces closeness by weighing pixel values with coefficients that fall off with distance, whereas range filtering averages pixel values with weights that decay with dissimilarity. By combining both domain filter and range filter together, one can obtain a bilateral filter that can smooth images while preserving edges.

The mathematical formulas for bilateral filter (BF) are as follows.

\[
BF_{\sigma_d, \sigma_r}(I) = \frac{1}{K(P)} \sum_{P' \in \Omega} G_d(P-P') G_r(I_P-I_{P'})
\]  

(11)

\[
K(P) = \sum_{P' \in \Omega} G_d(P-P') G_r(I_P-I_{P'})
\]  

(12)

\[
G_d(x) = \exp(-x^2 / \sigma^2)
\]  

(13)

where \( G_d \) and \( G_r \) are Gaussian functions under the control of variance \( \sigma_d \) and \( \sigma_r \), respectively. \( P \) is the pixel location, \( P' \) is the neighborhood pixel location, \( I_P \) is the intensity value of the pixel at location \( P \), \( I_{P'} \) is the intensity value of the pixel at location \( P' \). \( \Omega \) is the bilateral filtering result of the marked ROI in Fig. 3(a) using \( 3 \) and \( 0.1 \) for \( \sigma_d \) and \( \sigma_r \), respectively, and block size of 25x25. It is easily seen that the variation of \( \alpha \)-values within the tooth is much reduced while the \( \alpha \)-values of tooth contour remain strong.

D. Coarse Tooth Segmentation

At this point, the image is ready for segmentation. Because the contrasts between teeth and gums and the contrasts between teeth and background are near-uniformly significant, simple thresholding should be able to segment teeth/background from gums. Thus, our coarse tooth segmentation is as follows.

1. Threshold the filtered \( \alpha \)-image into classes \( C_0 \) (tooth/background region) and \( C_1 \) (gums region) using a threshold \( T \) obtained from Otsu’s method defined as [12], where regions classified to \( C_0 \) are regions of interests (ROI):

\[
T = \arg \max_{0 < t < 1} \left[ \alpha_{C_0}(\mu_0 - \mu_T)^2 + \alpha_{C_1}(\mu_1 - \mu_T)^2 \right]
\]  

(14)

where \( T \) is the threshold \( t \) for maximizing the variation between class \( C_0 \) containing all pixels with gray level in the range \([0, t]\) and \( C_1 \), containing all pixels with gray level in the range \([t+1, L-1]\), respectively. \( L \) is the total number of gray levels of the image, \( \alpha_{C_0} \) and \( \alpha_{C_1} \) are the probabilities of the two classes, \( \mu_0 \) and \( \mu_1 \) are the mean of the two classes, respectively, and \( \mu_T \) is the global mean of the image.

2. Obtain connected regions as follows [13].
   a. Scan the thresholded image from left to right and top to bottom.
   b. Find the first unlabeled object pixel and assign it to label \( N_i \), \( i = 1 \).
   c. Find the next unlabeled object pixel \( p \). If any of its 8-connected neighbors is labeled, label \( p \) as \( N_i \). Otherwise, label \( p \) as \( N_{i+1} \).
   d. Repeat step c until all object pixels are labeled.

3. Discard regions of size smaller than a percentage parameter \( s \). (e.g., \( s=2\% \) of the ROI size is used in this paper).
Note that background regions will be discarded in step 3 because the nature of our tested periapical images. Now, we have segmented all teeth from gums in the image. However, some teeth may not be well separated from one another. Fig. 4(a) shows the result after coarse segmentation of Fig. 3(a). As shown, all three teeth are segmented from gums/background; however, their crown parts between each pair of neighboring teeth are all connected together. Thus, breaking all connections between each pair of neighboring crown-parts is sufficient for isolating each tooth.

### E. Fine Segmentation

Noticing that almost all crown contours in the original image are well contrast, we conjecture that removing them should not be difficult. Thus, we devise a fine segmentation procedure as follows.

1. **Initial tooth isolation**
   a. Obtain crown-contour pixels of all teeth by applying Sobel operator to the original image.
   b. Remove the obtained crown-contour pixels from the result image of coarse segmentation.
2. Isolate each tooth by applying morphological erosion using a circular structure element of radius 3.
3. Refine the shape of each isolated tooth by applying morphological dilation using a circular structure element of radius 5.

Figs. 4(b) and (c) show the results of initial and final tooth isolation, respectively, and Fig. 4(d) shows each of the refined segmented teeth. Notice that some connections between each pair of neighboring tooth-crowns are broken after initial isolation, and all connections are broken after step 2. However, each isolated tooth is shrunk a little. After refinement, the shape of each segmented tooth is nearly the same as that in the original image.

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**Figure 4.** The results of coarse and fine segmentations: (a) result of coarse segmentation (b) result of initial tooth isolation (c) result of complete tooth isolation (d) result of shape refinement.

### IV. Experimental Results

We apply our proposed tooth segmentation method to six dental periapical radiographs of size approximately equal to 872x650 each, or vice versa. Among them, about half of the periapical regions are not well-contrast, as shown in images 1-6 in the first column of Fig. 5. For speeding up segmentation, all images are down-sampled to 1/4 first. Columns (a)-(b) illustrate the enhanced images by adaptive power-law transformation and the bilateral-filtered α-images, respectively, and column (c) shows the contours of final segmented teeth.

**Figure 5.** (a) Enhanced image by APLT (b) bilateral-filtered α-image (c) segmented result.

### V. Conclusions

We presented a very effective teeth segmentation method for dental periapical radiographs in this paper. Our method first conducted image enhancement using a proposed adaptive power law transformation to reduce the contrast variations between teeth and gums and between teeth and backgrounds. Then local singularities measured by Hölder exponent are computed to obtain a structure image in which the structures of teeth are much smoother than the structures of gums. Finally, Otsu’s thresholding is applied to segment teeth from gums and morphological operations are applied to isolate each tooth and refine its shape. We conducted experiments on six periapical radiographs and the results demonstrated that all 18 teeth were successfully segmented with 17 extracted tooth-contours almost completely conforming to human visual perception.

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### References


