Abstract:
Dental radiographs have been widely used by dentists in finding periodontal lesions or monitoring the progress of the periodontal defect treatment that is either impossible or difficult for human naked eyes. In this paper we propose a fully automatic gums lesion detection method for periapical dental X-ray images. The method includes two stages: (i) teeth-parts removing and (ii) lesion-region localization and severance labeling. In stage (i), morphological operations and histogram equalizations are first applied to enlarge the contrast between teeth and gums parts, then thresholding is used to separate the two types of regions. In stage (ii), gums-parts are first segmented into regions of normal, possible lesion or lesion, and serious lesion using a level set method with three coupled level set functions, and then the possible lesion or lesion region are further segmented into lesion and possible lesion regions using the same level set method. The experimental results demonstrate that our proposed method can detect and label all lesion regions in six periapical dental X-ray images which conform very well to human visual perception, and is robust to illumination variation to ±30 intensity levels, as well.

Keywords:
Periapical dental X-ray images; Automatic lesion detection; Variational level set method; Illumination variation

1. Introduction

Dental radiographs have been widely used by dentists in finding periodontal lesions or monitoring the progress of the periodontal defect treatment that is either impossible or difficult for human naked eyes. With the advantage of digital dental X-ray images, such as the immediate availability, the lower radiation dose, the possibility of image enhancement, and image reconstruction, etc., the usage of digital dental X-ray images has a great increase in the past decade in both forensic identification [1-4] and clinical diagnosis [5].

Despite of rapid growing popularity of digital dental X-ray images, automatic lesion detection in these images by computers still is a big challenging task because of the following reasons: (1) poor image quality such as noise, low contrast, varying illumination; (2) complicated topology of lesion regions; (3) arbitrary teeth orientation; (4) lack of clear lines of demarcation between healthy and problem teeth or gums.

To meet the above challenges (1) and (2), (variational) level set methods, such as in [6], [7], [8], [9], have become increasingly popular in medical imagery because of their ability to capture the topology of shapes and robustness to noise. And to the challenges (3) and (4), Li et al. had presented an automatic segmentation framework for computer-aided analysis [5] and a semi-automatic computer aided lesion detection framework [9], respectively, for dental X-ray images. In their framework, representative images are firstly segmented using hierarchical level set region detection [8] to train a support vector machine (SVM) classifier. The SVM classifier then provides initial contours which are close to correct boundaries for three coupled level sets in clinical segmentation for acceleration.

Unlike Li et al.’s lesion detection framework that uses level set methods in both training and clinical segmentation stages, we propose a fully automatic gums lesion detection method for periapical dental X-ray images in this paper, which applies level set methods in clinical segmentation stage only. Our method first removes teeth-parts from the image then segment the gums image into regions of normal, lesion or possible lesion, and serious lesion simultaneously using Samson et al.’s level set method [7] with the three initial level set contours being obtained from Otsu’s thresholding method. The lesion or possible lesion regions are segmented again into lesion and possible lesion using only one level set function. The experimental results demonstrate that our proposed method can correctly detect and label all lesion regions in six periapical dental X-ray images, and is robust to illumination variation to ±30 intensity levels.

The rest of the paper is as follows. In Section 2, the applied level set method is introduced. In Section 3, our
The proposed method is described with an example. Experimental results are shown in Section 4, and conclusions are in Section 5.

2. Variational level set function

The variational level set method, which derives the level set function by energy minimization, has become increasingly popular in segmenting medical images because of its ability to capture the topology of shapes and robustness against noise. Chan et al.’s method [8], which uses a Mumford-Shah functional, is very good for segmenting an image into two regions and is robust to the position of the initial contour.

Samson et al. presented a method [7] that can simultaneously segment an image into multiple regions without having to apply 2-region level set segmentation hierarchically. Their method contains three phases: partition condition, data term, and length shortening of interface set.

\[
\Omega \rightarrow \mathbb{R} \text{ be a Lipschitz function associated to region } \Omega \text{ with the open domain } \Omega.
\]

The partition condition phase is defined as

\[
F^p(\Phi_1, \ldots, \Phi_k) = \frac{\lambda}{2} \int \left( \sum_{i=1}^{k} H_s(\Phi_i - 1)^2 dx \right)
\]

where \(\alpha\) and \(\lambda\) are real constants, \(H_s\) is the Heaviside function.

\[
H_s(x) = \begin{cases} 
1 & \text{if } |s| \leq \alpha \\
1 + \frac{s}{\alpha} \left(1 + \frac{1}{\pi} \sin \frac{\pi}{\alpha} \right) & \text{if } |s| > \alpha \\
0 & \text{otherwise}
\end{cases}
\]

The data term phase, which takes into account the observed data and the Gaussian distribution property of the classes, is defined as

\[
F^d(\Phi_1, \ldots, \Phi_k) = \sum_{i=1}^{k} c^i \int H_s(\Phi_i) \left( \frac{u_i - \mu_i}{\sigma_i} \right)^2 dx
\]

where \(c^i \in \mathbb{R}, \mu_i\) is the mean, and \(\sigma_i\) is the standard deviation of domain \(\Omega_i, \forall i\).

The length shortening of interface set phase is defined as

\[
F^l(\Phi_1, \ldots, \Phi_k) = \frac{1}{2} \int \delta_\sigma(x) |\nabla \Phi| dx
\]

where \(\delta_\sigma\) is the Dirac delta function.

Finally, the sum of three phases leads to the global function

\[
F(\Phi_1, \ldots, \Phi_k) = \frac{\lambda}{2} \int \left( \sum_{i=1}^{k} H_s(\Phi_i - 1)^2 dx \right) + \frac{\alpha}{2} \int \left( \sum_{i=1}^{k} c^i \int H_s(\Phi_i) \left( \frac{u_i - \mu_i}{\sigma_i} \right)^2 + \lambda \int \delta_\sigma(x) |\nabla \Phi| dx \right)
\]

The level set function (LSF) obtained is given by

\[
\frac{\partial \Phi}{\partial t} = \delta_\sigma(\Phi) \left( \frac{\nabla \Phi}{|\nabla \Phi|} - \epsilon \left( \frac{u_i - \mu_i}{\sigma_i} - \lambda \sum_{i=1}^{k} H_s(\Phi_i - 1) \right) \right)
\]

where \(H_s\) is the Heaviside function and \(\delta_\sigma\) is the Dirac delta function.

3. Gums lesion detection

Our proposed gums lesion detection method for periapical X-ray images includes two stages: (i) teeth-parts removing and (ii) lesion-region localization and severance labeling. Generally, periapical X-ray images contain both teeth- and gums parts, where the gray levels of the teeth-parts appear similar to those of the normal gum tissues, and the gray levels of the (possibly) infected tissues are darker. As our goal is to locate lesion-regions only in gums-parts, we remove the teeth-parts first then conduct segmentation to the remaining gums-part image for lesion detection and severance labeling.

3.1. Teeth-parts removing

Both upper and lower periapical images could be taken for examination depending on the lesion locations. In this paper, we assume that the image is pre-classified to be either an upper or a lower periapical image then rotated to become a lower periapical image if it is an upper one. The proposed teeth-part removing algorithm is as follows:

**Algorithm: teeth-parts removing**

Input: a lower periapical image

Output: the image without teeth parts

1. Denoise and contrast stretching
   a. Apply average filter to the image with mask size of 25x25.
   b. Do morphological grayscale dilation then histogram
equalization, where the morphological grayscale dilation is defined as
\[(A \oplus B)(x, y) = \max\{A(x + s, y + t) - B(s, t)\}\]  
(A is a grayscale image, and B is a structuring element.

2. Contours extraction
   a. Apply canny edge operator \([10]\) and obtain the edge map LHMap.
   b. Do local histogram equalization to each pixel in LHMap, where the block size is 25x25.
   c. Obtain the contour threshold T by applying Otsu’s method \([11]\) to all pixels contained in these edge blocks.
   d. Perform thresholding using T.

3. Teeth-parts extraction and removing
   a. Calculate the center point of each connected component.
   b. Include each connected component into teeth-part (PT) if the Y-coordinate of its center point is in the lower 1/3 of the image and the size is >10% image size; otherwise, include it into gums-part (PG).
   c. Apply morphological closing to PT then remove it from the image, where the morphological closing is defined as
\[A \bullet B = (A \oplus B) \ominus B\]  
(\(\ominus\) and \(\bullet\) denote the morphological grayscale dilation and erosion, respectively.

Figure 1 shows the result of each major step in the teeth-parts removing algorithm. As shown, Figure 1(a) is an original lower periapical X-ray image, Figure 1(b) is the result after denoise and contrast stretching, Figure 1(c) is the edge map (LHMap) obtained from performing Canny edge operator, and Figure 1(d) is the result after performing local histogram equalization to each pixel in LHMap. The result after thresholding the image into teeth-parts and gums-parts is in Figure 1(e), and the result after removing teeth-parts is in Figure 1(f), respectively.

3.2. Lesion-region localization and labeling

According to the clinical pathological model, gums tissues can be classified into one of the four categories: normal, possible lesion, lesion, and serious lesion, depending on the degree of alveolar bone loss. As shown in Figure1, serious lesion tissues would appear quite dark and smooth in dental X-ray images, whereas normal tissues would appear much bright and smooth. For lesion and possible lesion tissues, both appear granulous with the former slightly darker and rougher than the latter. Thus, gums lesion regions in dental X-ray images can be detected and classified based on the intensity gray level and the texture of the regions. In this paper, we propose a classification method that segments the image into normal region (NR), possible lesion region (PL), lesion region (LR), and serious lesion region (SR) using Samson et al.’s level set method \([7]\). The algorithm of our proposed segmentation method is as follows:

**Algorithm: lesion detection and classification**

**Input:** a periapical image without the teeth parts (PG), the mean intensity of the teeth parts (PT), the mean intensity of the region X.

**Output:** the image segmented into NR, PL, LR, and SR

**Phase I segmentation**

1. Obtain the respective initial LSF of regions NR, SR, LR.
   a. Threshold the image PG by TNR and obtain the initial LSF of NR, denoted NRo, as the region containing pixels whose intensity >TNR. TNR is defined as
\[T_{NR} = \left\{ \begin{array}{ll} 
\mu(P_{G}) & \text{if } \mu(P_{G}) - \mu(P_{T}) \leq 5 \\
\mu(P_{T}) & \text{otherwise} \end{array} \right. \]  
(11)
   where \(\mu(X)\) is the mean intensity of the region X.
   b. Mask pixels whose intensity level >TNR or <TBG off the image P_G then locate edge pixels by applying Canny edge operator to the remaining image P'_G.
   c. Perform morphological grayscale dilation to the detected edge pixels using a 25x25 square structure element, then apply Otsu’s method to the dilated edge regions to obtain the threshold, denoted TSR, for separating SR from LR.
   d. Threshold the image P'_G by TSR and obtain the initial LSF of SR (SRo) as the region containing pixels whose intensity < TSR.
   e. Obtain the initial LSF of LR (LRo) as the region containing pixels whose intensity \(\leq T_{LR}\) and \(\geq T_{SR}\).

2. Apply Eq. (8) using the three initial LSFs: NRo, SRo, LRo, with parameters \(\epsilon_{SR}=0.25, \epsilon_{NR}=\epsilon_{LR}=0.3, \gamma=\lambda=1\), iteratively till convergence to obtain segmented regions of NR, SR, and LR.

3. Assign the overlapping regions between SR and LR to SR, and the overlapping regions between LR and NR to LR.
4. Mask the pixels in SR and NR off the image P_G then apply morphological grayscale opening to the remaining image, denoted as P"_G.

**Phase II segmentation**

5. Calculate \(\mu(P'_{G})\) as the threshold TLR to obtain the new initial LSF of LR (LR"_0) as the regions containing pixels whose intensity < TLR.
6. Apply Eq. (8) again using LR"_0 as the initial LSF with \(\epsilon_{LR}=0.3, \gamma=\lambda=1\), iteratively till convergence to further segment LR into regions of possible lesion (PL) and lesion (LR).

Note that we perform morphological grayscale opening to the image P"_G that contains regions which are neither NR nor SR. In other words, P"_G may contain regions which are
either of type LR or PL. As explaining earlier in this section, LR appears slightly darker and rougher than PL. Because morphological grayscale opening would suppress small bright details, the small bright details within the darker and rougher regions in $P_G$ would disappear, which makes the slightly darker regions even darker while the lighter regions remain nearly unchanged. As a result, discrepancies between these two types of regions would be increased, and $P_G$ can be further segmented into regions of possible lesion (PL) and lesion (LR).

Figure 2 gives an example of the proposed lesion detection and classification algorithm. As shown, Figure 2(a) is the original image, the green region in Figure 2(b) is the initial LSF of NR ($NR_0$), the red region in Figure 2(c) is the initial LSF of SR ($SNR_0$), and the yellow region in Figure 2(d) is the initial LSF of LR ($LR_0$), respectively. Figure 2(e) is the result of Step 3, and Figure 2(f) shows the final segmentation result, where the yellow (LR) region in Figure 2(e) has been further segmented into lesion (orange) and possible lesion regions (yellow).

4. Experimental results and analysis

We conduct two experiments to demonstrate (i) the capability of lesion detection and classification and (ii) robustness against variation of illumination of our proposed method.

In the first experiment, we perform lesion detection using four lower periapical X-ray images as shown in Figures 3(a)-(d), where each has different levels of lesion regions. The initial LSF’s for each image are shown in Figures 3(e)-(h), and the lesion detection results are shown in Figures 3(i)-(l), respectively, with the color scheme: green for NR, light green for possible lesion (PL), orange for LR, and red for SR. Notice that all four segmented results conform quite well to human visual perception.

In the second experiment, we perform lesion detection to the image shown in Figure 4(a) whose intensity is either lowered down or raised up 15, 30 levels, respectively, as shown in Figures 4(b)-(d), to simulate illumination variation. The lesion detection results are shown in Figures 4(e)-(h), respectively, using the same color scheme as in the first experiment. It’s clear to see that all four segmented results are very similar, which indicates that our proposed method is indeed robust against different illumination within a range of ± 30 intensity levels.

Table 1 lists the number of iterations for level set function convergence for all tested images, where the convergence rule is set to be the summation of the moving pixels of the LSFs less than 1% of total size. As shown, all numbers are about 13±2 for each phase of segmentation and about 20±5 for both phases of segmentation, with a couple of images converging either quite fast or slow.
Figure 4. Segmented results with different luminance. (a)(e): original image and the result, (b)(f): (a)+30 gray levels and the result, (c)(g): (a)-30 gray levels and the result, (d)(h): (a)+15 gray levels and the result.

Table 1. Number of iterations for LSF convergence

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5. Conclusions

We have presented a fully automatic gums lesion detection method for periapical dental X-ray images. Our method first removes teeth-parts from the image then segment the gums image into regions of normal, lesion or possible lesion, and serious lesion simultaneously using Samson et al.’s level set method with the three initial level set contours being obtained from Otsu’s thresholding method. The lesion or possible lesion regions are segmented again into lesion and possible lesion using only one level set function. We have tested six periapical dental X-ray images and the segmented results demonstrate that our proposed method can detect and label all lesion regions in all six images conforming very well to human visual perception, and is robust to illumination variation to ±30 intensity levels, as well.

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References