Automatic Image Processing Based Dental Image Analysis Using Automatic Gaussian Fitting Energy and Level Sets

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Abstract-- Identification of the Root canal length is a major concern in the dentistry worldwide, which currently seeks the manual calculation in order to detect the measurement of the teeth. Intensity inhomogeneity often is a major problem in dental x-rays which causes considerable difficulties in segmentation. For better computer-aided diagnosis in dentistry, having a precise tooth segmentation is a critical task, as the cysts and inflammatory lesions generally occur around tooth root areas and these areas in radiographs are generally subject to noise, poor contrast, and very uneven illumination. This paper presents an effective segmentation method using a combinational approach of Local Gaussian Distribution fitting energy along with level sets. Here the local intensities of images are defined by Gaussian distributions which are combined with the level set function for accurate segmentations of teeth contour. The experimental results indicate that segmentation achieves the less number of iterations making it computationally fast and work in real time situation.

Keywords-- Segmentation; CLAHE, Bilateral filter, Gaussian Distribution; Independent level sets

I. Introduction

A dental x-ray provides valuable diagnosis information to dentists such as root canal treatment, detection of caries and many other anomalies. Research shows that ninety percent of people irrespective of the age and gender are suffering from dental problems.[1] Various types of images are used in dentistry for correct diagnosis and treatment planning which includes bitewing X-ray, periapical X-ray or panoramic X-rays out of which this paper focuses on periapical images.[2]

For root canal procedures and diagnosis, dentists usually rely on periapical dental images. Image segmentation plays a significant role in medical applications which has also caught the attention of dentists worldwide. The objective of radiograph segmentation is to identify the region of each tooth. Most of the clinical scoring systems for tooth segmentation depends on individuals because measurements are dependent on the clinician's expertise in demarcation of the root canal length by visual examination primarily. This might be leading to inter-operator errors.

There are different clinical challenges faced by dentists such as quality of dental images which are mainly affected by low contrast, uneven exposure. These conditions influence the segmentation which leads to false teeth contour delineation. This inhomogeneity causes the trouble in manual demarcation of the tooth for the root canal procedure. Dentists face problems when they need to determine the length of the teeth prior to the root canal procedure.

A few decent techniques for teeth division pertaining to dental radiographs was introduced in the previous couple of years. A self-loader shape extraction strategy by utilizing vital projection and Bayes lead, wherein the indispensable projection is somewhat naturally connected for the tooth separation. Many papers have reported techniques that comprise of picture improvement, district of intrigue limitation, and shape extraction [3] utilizing morphological operations and snake strategy[4]. Some have built up a completely mechanized approach in view of iterative thresholding and versatile thresholding while some examination has presented a swarm-insight based and a cell automata demonstrate approach. [5][6]Numerous strategies have joined homomorphic sifting, homogeneity-based differentiation extending, and versatile morphological change then got the coarse forms of teeth by utilizing edge administrator.[7][8]

In this paper, the proposed method uses the CLAHE for contrast enhancement as the dental x- rays usually suffer from low contrast and poor illumination. The enhancement filters sometimes washes out the edges therefore this paper uses bilateral and box filtering approach to preserve the edges and at the same time image quality is also improved. The segmentation approach uses the combination of Gaussian distribution fitting energy in combination along with level sets. The local intensities of images are described by Gaussian distributions with different values of mean and variance to handle intensity inhomogeneity. The level sets with the help of this distribution energy works better in case of boundary concavities. The proposed combination has achieved output in terms of some geometric parameters and time consumption. The geometric features of the segmented gives a clinical significance of the proposed work as it aids the dentists to figure out the approximate length for drilling.

The rest of the paper is settled as follows: Section II which describes the adopted methodology. Section III gives the description of Experimental Results obtained using periapical images and section IV concludes the paper.

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II. METHODOLOGY

The dental X-ray images are obtained on request from the database of ISBI. There are 40 images out of which we have considered 10 images with different teeth orientations, illumination and various artifacts so that the robustness of the proposed work can be checked. Figure 1 shows the flow diagram of proposed methodology.

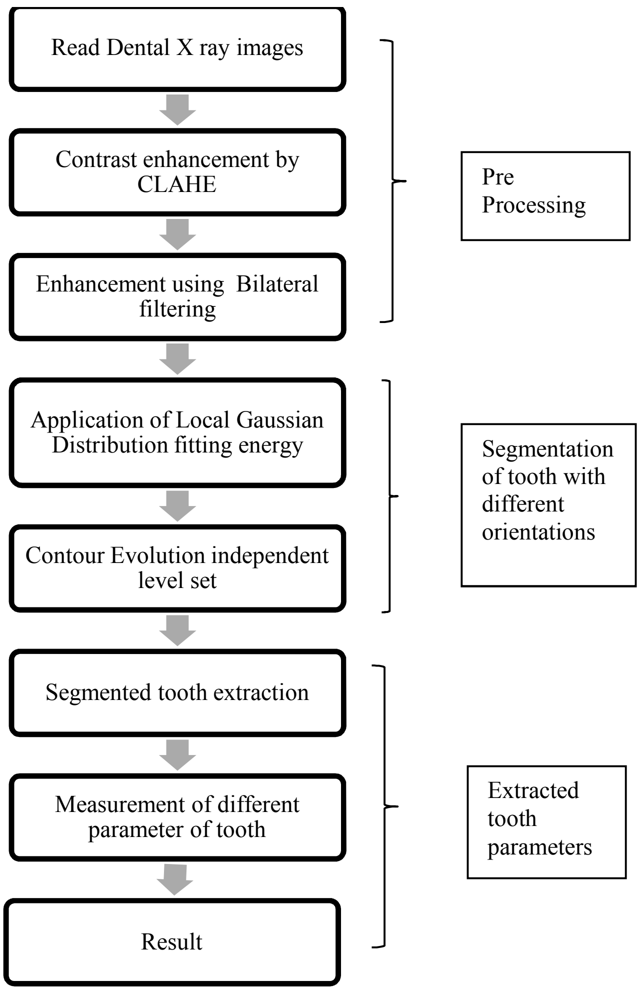


Fig. 1. *Flow-chart diagram of automatic segmentation of tooth in Dental X-Rays*

A. Contrast Enhancement

For the change of the visual representation of the picture, the procedure of histogram leveling is utilized. Since versatile technique registers a few histograms where each relates to an unmistakable segment of the picture. It is accordingly more profitable to enhance the nearby difference of a picture. The trap of histogram evening out is that it doesn't give any way to change upgrade level so the proposed technique defeats this downside by controlling the level of differentiation improvement. This method used is Contrast constrained Adaptive Histogram Equalization. Since the difference improvement is made versatile and adaptive by using the parameter α. Consequently, adaptive histogram equalization suffers from heavy contrast variations in an image so there was a need to limit the contrast. It is achieved by using contrast limited AHE which varies from conventional histogram in its complexity constraining. On account of contrast limited AHE, the complexity constraining method must be connected for every area from which a change capacity is determined. Contrast limited AHE was produced to keep the over enhancement of clamor that versatile histogram balance can offer ascent to.

This is accomplished by constraining the differentiation upgrade of AHE.

Let H is considered the histogram of original input image and let H_u be the uniform histogram of input image. Now we intend to obtain the modified histogram H_m such that its probability distribution has to be very closer to original distribution H. The goal is to obtain proper optimization which is achieved by varying value of α between 0 to 1. By varying value of α from 0 to 1, we get the image either over enhanced or under enhance. Therefore value of alpha is chosen experimentally.

$$H_m = \alpha \mathrm{H} + (1-\alpha)\, \mathrm{H_u} \qquad (1)$$

Eq (1) demonstrates the numerical detailing for altered histogram utilizing CLAHE of the info picture. The ideal estimation of α may change from one image modality to another.

B. Image Enhancement by Bilateral Filtering

This filter is a smoothing filter non-linear in nature. It reduces the noise as well as preserves the edges. Two pixels can be close to each other that indicated they may occupy nearby spatial location or they can be similar to each other which may yield similar values. It is therefore appropriate to take their average. The intensity at each pixel in the dental image is replaced by weighted average intensities of neighborhood pixels. The Gaussian distribution is considered for distribution in this paper. The calculated distance is Euclidean distance of pixels. It considers spatial filtering and range filtering which is a Gaussian function By joining both, one can acquire a reciprocal channel that can smooth pictures while safeguarding edges. The numerical equations for two-sided channel (BF) are as per the following. as shown in equation 2.

$$\mathrm{BF}_{\sigma d,\sigma r}(\mathrm{I}) = \frac{1}{K(P)} \sum_{p' \in \Omega} \mathrm{G_d}(\mathrm{P'}-\mathrm{P})\mathrm{Gr}(\mathrm{Ip}-\mathrm{Ip'})\, \mathrm{Ip} \qquad (2)$$

Where G_d and G_r are Gaussian functions with variance σ_d and σ_r, respectively, P is the location of the pixel, P' is the location of neighborhood pixel, I_P is the value of intensity of the pixel at P location, $I_{P'}$ is the value of intensity of the pixel at P' location, Ω is the neighborhood. The domain filering and range filtering are shift-invariant and the Gaussian function added to it makes it insensitive to any changes in the image intensity. Bilateral filtering parameters σ_d and σ_r are set as 3 and 0.1 respectively by hit and trial which gives best possible noise removal and edge preservation.

Then, the LGDF energy is applied into an independent level set formu1ation along with a regularization term of level set to achieve desired segmentation.

C. Image Segmentation by Gaussian distribution fitting energy and Level sets

As already discussed, the intensities of local images are portrayed by Gaussian distributions which has different values of mean and variance. The estimation of local intensity mean and variance helps to achieve the energy minimization using level set evolution which is a type of active contour fitting model. The energy of Gaussian fitting energy is calculated as shown in equation (3)

$$E_G^{LGDF} = \sum_{i=1}^{N} - \log_{pi,G}(l(y))dy \quad (3)$$

Local gaussian distribution with level sets is applied to the smoothened image so as to fit the curve with the boundaries of the teeth.

$$P_{i,G}(l(y)) = \frac{1}{\sqrt{2\pi}\sigma i(x)}\exp\left(- \frac{u_i(x)-L(y)^2}{2\sigma_i(x)^2} \right) \quad (4)$$

The probability density function $P_{i,x}(l(y))$ is the Gaussian density which is modelled using equation (4). In equation (4) $u_i(x)$ and $\sigma_i(x)$ are local intensity means and standard deviations. After this energy fitting approach, contour evolution is achieved by level set method. It advances the level set capacity as per a partial differential equation (PDE)as shown in equation 5.

$$\emptyset + F\,|\Delta\emptyset| = 0; given\ \emptyset(x,0) \quad (5)$$

F is the particle speed in normal direction. The contours represented by the level set function either break or merge naturally depending upon the demography of the image during the evolution. This nature of active contour using level sets helps to automatically handle topological changes as desired. To achieve this, an external energy is ordered that can move the zero level curve towards the boundaries of the object. If I is an image, and g is the edge indicator function defined as shown in equation (6).

$$g = \frac{1}{1+|\nabla G_\sigma * I|^2} \quad (6)$$

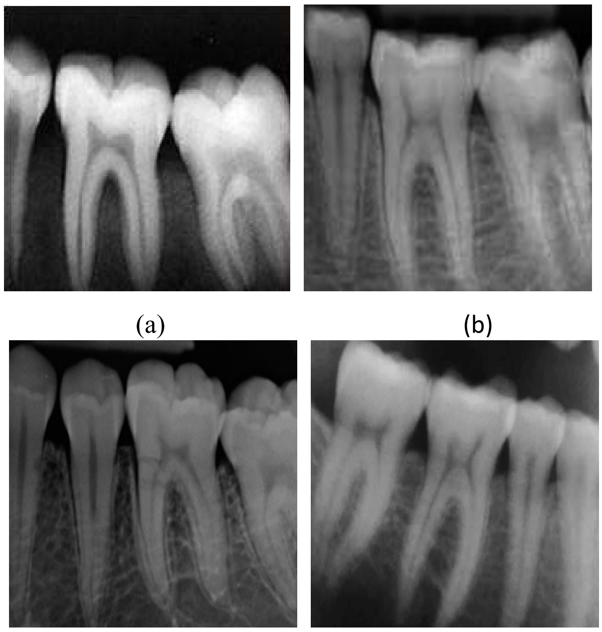
G_σ is the Gaussian kernel with variance σ^2. We can define an external energy for a function $\varphi(x, y)$ as shown in equation (7)

$$O_{g,\lambda,v}(\emptyset) = \lambda L_g(\emptyset) + vA_g(\emptyset) \quad (7)$$

δ is the Dirac function, and H is the Heaviside function. This model eliminates the use of seed point selection as well as re-initialization. Significantly larger time step can be used to speed up the curve evolution but increasing this parameter may trigger the number of iterations which can make segmentation a little time consuming than desired. Here λ or σ are parameters controlling how penalizing the edges should be.

III. EXPERIMENTAL RESULTS

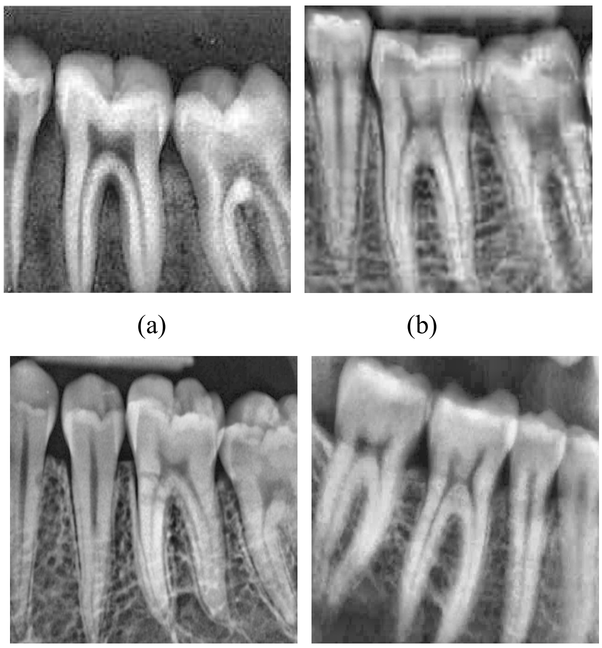
The proposed methodology was tested on 10 images out of 40 images with different teeth orientations and inhomogeneity.



(a) (b)

(c) (d)

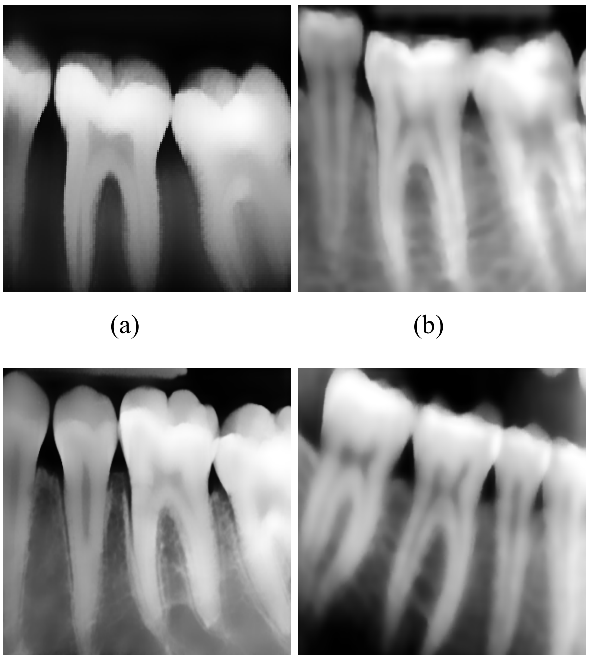
Figure 2. Original gray scale images of the teeth with different teeth orientations



(a) (b)

(c) (d)

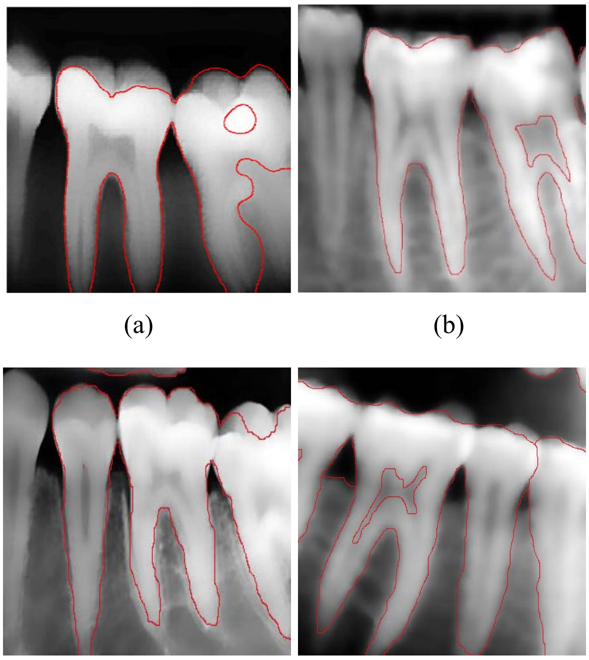
Figure 3. Contrast limited adaptive histogram equalized images with α= 0.6



(a) (b)

(c) (d)

Figure 4. Bilateral filtered output of four dental radiographs with $\sigma_d=3$ and $\sigma_r = 0.1$ respectively.



(a) (b)

(c) (d)

Figure 5. Segmented dental radiographs using Gaussian fitting followed by Independent Level Sets

After achieving combinational segmentation approach on the dental radiographs, the tooth is isolated to calculate the geometric values as shown in Table 1 and Table 2, which are significant for clinical inference.

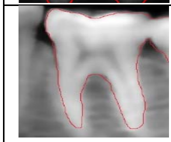
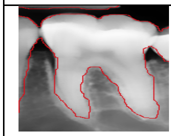
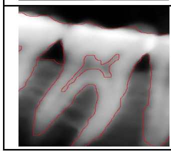
Samples	Total Time taken for segmentation	No. of iterations	Time per teeth
	19.25 s	600	7.700 s
	11.73 s	440	4.692 s
	32.01 s	880	9.863 s
	29.65 s	740	8.943 s

Table 1. Time consumption for segmentation

Table 1 shows the total time taken for segmentation and number of iterations for contour evolution. The geometric features are also calculated as shown in Table 2.

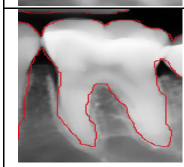
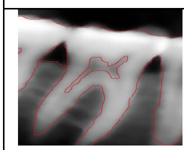
Samples	Min Radii	Max Radii	Mean Radius	Std Deviation	Co-eff of variation
	6.91	8.80	7.79	0.47	6.03
	7.22	9.99	8.31	0.75	9.08
	7.41	9.87	8.67	0.70	8.08
	7.53	9.54	8.15	0.63	8.57

Table 2. Geometric features of segmented tooth

Table 2 shows the different features of the extracted tooth which gives an approximation to dentist regarding the length and breadth of the dental procedure such as root canal treatment. However these values are not only criteria for the drilling, as there may be many other factors which are responsible for diagnosis and treatment during dental implants.

IV. CONCLUSION

In this paper, an improved and combinational segmentation approach for tooth extraction from dental radiographs is presented. The dental periapical radiographs are generally of low contrast and poor illumination. The traditional average filters may smooth the image but at the same time it washes out the edges. This makes segmentation more tedious, time consuming and requires user intervention. In the proposed method, the contrast enhancement is obtained using contrast limited adaptive histogram equalization. The enhancement part is achieved using bilateral filtering to reduce the contrast variations between teeth, gums and background artifacts. This combination of contrast enhancement and filtering approach removes the noise and other unwanted background information and at the same time preserves the edges. The segmentation using Gaussian fitting energy and independent level sets achieves the segmentation using very less number of iterations. The geometric features of the teeth are calculated which helps dentists in root canal procedures.

Future work may involve segmentation of overlapping teeth and detection of gums diseases through dental radiographs as well as detection of carious lesions using more features extraction and segmentation approaches.

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