Segmentation of Tooth and Pulp from Dental Radiographs

Christy Elezabath Tom, Jerin Thomas

Abstract— Teeth and pulp segmentation for periapical radiographs is one of the most critical tasks for effective segmentation in periapical radiographs, and the process is difficult due to noise, low contrast, and uneven illumination of the dental radiographs. For accurate segmentation, images must be preprocessed either by image enhancement or image transformation or both so that the aforementioned problems will be reduced as much as possible. In this work, proposed an effective scheme to segment each tooth and pulp in periapical radiographs. The method consists of four stages: image enhancement using Contrast Limited Adequate Histogram Equalization(CLAHE), local singularity analysis using Hölder exponent, connected component analysis, and tooth segmentation using Chan-Vese segmentation.

Index Terms— Local singularity analysis,Contrast Limited Adequate Histogram Equalization(CLAHE),Chan-Vese segmentation,Periapical radiographs,gradient magnitude.

1 Introduction

TDental Radiographs (X-ray images) can support dentists in detecting dental anomalies around the gum tissues, or unrevealed under the surface of the cortical plate that cannot be detected during a visual examination, in dental clinical proceeding. Moreover, human inspection of such radiographs tends to be intuitive or inconsistent because a few number of dentists may not have adequate amount of specialized training or they have been loaded with too much work to concentrate enough when performing the task. Meanwhile, digital radiograph, due to its low radiation, has gradually gained its popularity in dental practices. Many segmentation techniques can be applied for medical images, such as (adaptive) thresholding, region growing, morphological watershed, clustering, and level set.

As the usage of digital dental X-ray images keeps growing, computer aided analysis becomes highly desirable for helping dentists identify and locate lesions more effectively and efficiently. There are three types of dental radiographs: bitewing, periapical, and panoramic, which have been used till date.

Segmentation of dental radiographs is a very challenging task because of the following problems: (i) dental radiographs are often subject to noise, low contrast, and uneven illumination; (ii) complicate topology of objects in the image; (iii) arbitrary teeth orientation; and (iv) absence of clear lines of demarcation between lesions and healthy teeth. There are several good methods of teeth segmentation for dental radiographs, which had been presented in the past few years.

Radiography being a non-destructive method plays a vital role in forensic dentistry to uncover the hidden facts, which cannot be seen by means of physical examination. Radiographic age estimation using teeth depends on developmental stages of teeth especially in children whereas in adults; the ceaseless deposition of secondary dentin throughout life illustrated by reduction in pulp area can be employed. Kvall et al. reported a method in 1995[11] that allows estimation based on morphological measurements of two dimensional radiographic features of individual teeth.

The measurements include comparisons of pulp and root length, pulp and tooth length, tooth and root length and pulp and root widths at three defined levels.

This paper, implemented an effective method to segment each tooth in dental periapical radiographs based on local singularity analysis and Chan-Vese segmentation method. The method consists of four stages: image enhancement using CLAHE, local

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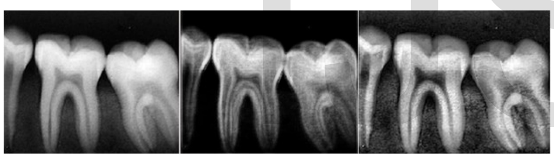
ISSN 2229-5518
singularity analysis using Hölder exponent, connected component analysis, and tooth delineation using Chan-Vese segmentation

TEETH SEGMENTATION

2.1 Contrast Limited Adaptive Histogram Equalization CLAHE

CLAHE was originally developed for medical imaging and has evince to be successful for enhancement of low-contrast images such as portal films. The CLAHE algorithm partitions the images into contextual regions and applies the histogram equalization to each one. This evens out the distribution of already available grey values and thus makes hidden features of the image more visible. The full grey spectrum is used to express the image.

Contrast Limited Adaptive Histogram Equalization, CLAHE, is an improved version of AHE, or Adaptive Histogram Equalization. Both overcome the constraints of standard histogram equalization.



a b c

Fig.1- Image after Enhancement (a) shows the original image, (b) result after APLT, (c) after applying CLAHE

A variety of adaptive contrast-limited histogram equalization techniques (CLAHE) are provided. Sharp field edges can be supported by selective enhancement within the field boundaries. Selective enhancement is accomplished by first finding the field edge in a portal image and then only processing those regions of the image that lie inside the field edge. Noise can be reduced while maintaining the high spatial frequency content of the image by implementing a combination of CLAHE, median filtration and edge sharpening. This technique known as Sequential processing can be recorded into a user macro for repeat application at any time. A variation of the contrast limited technique called adaptive histogram clip (AHC) can also be applied. AHC automatically adjusts clipping level and moderates over enhancement of background regions of portal images.

2.2 LOCAL SINGULARITY ANALYSIS [1]

Complex signals or structures can be seen as superpositions of singularities. One way of detecting the point-wise singularity of an observed structure S is to measure the Holder exponent, at any given point, which is explained as the limiting value of α_i as follows:

$$\alpha = \lim_{\varepsilon \to 0} \alpha i \frac{\ln \mu_i(S_i)}{\ln \varepsilon}$$

where $S = \cup S_i$, S_i is a non-overlapping box of size ε, and $\mu_i(Si)$ is some amount of measure within box Si. For digital images, however, possible box size an integer multiple of pixels because of their discrete nature. It follows that ε cannot approach to 0 since $\varepsilon_{min} = 1$, hence the limiting value of $\alpha_i(x,y)$ can be estimated indirectly as the slope of a linear regression line of those points on the log–log diagram.

$$\alpha_i = \frac{\ln \mu_i(x,y)}{\ln i}, \; i = 1,2,3....$$

where $\mu_i(x,y)$ is the amount of measure within the observed box with size $\varepsilon = i$ centered at the pixel (x,y). For estimating the Holder exponent in (3.5), different measures μ_i (x,y) may be used to give different information on the singularities encountered.

Fig.2- Image after local singularity analysis

ISSN 2229-5518

2.3 GRADIENT MAGNITUDE

Gradient domain image processing is a relatively new type of digital image processing that operates on the differences between neighbouring pixels, rather than on the pixel values directly. Mathematically, an image gradient represents the derivative of an image, so the goal of gradient domain processing is to construct a new image by integrating the gradient, which results by solving Poisson's equation.

Image gradients can be used to extract information from images. Gradient images are created from the original image (generally by convolving with a filter, one of the simplest being the Sobel filter) for this purpose. Each pixel of a gradient image calculates the change in intensity of that same point in the original image, in a given direction. Gradient images in the x and y directions are computed, to get the whole range of direction.

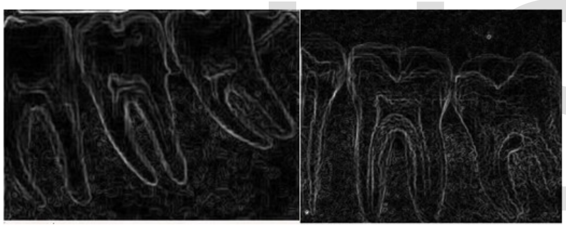


Fig. 3- Resultant image after gradient magnitude

One of the most common uses is in edge detection. Pixels with large gradient values become possible edge pixels, after gradient images have been computed, Edges may be traced in the direction perpendicular to the gradient direction, the pixels with the largest gradient values in the direction of the gradient become edge pixels.

The gradient of a two-variable function (here the image intensity function) at each image point is a 2D vector with the components set by the derivatives in the horizontal and vertical directions. At each image point, the gradient vector points in the direction of largest possible intensity increase, and the length of the gradient vector corresponds to the rate of change in that direction.

Since the intensity function of a digital image is only known at discrete points, derivatives of this function cannot be defined unless here assume that there is an essential continuous intensity function which has been examined at the image points. With some additional assumptions, the derivative of the continuous intensity function can be computed as a function on the sampled intensity function, i.e., the digital image. Approximations of these derivative functions can be defined at varying degrees of accuracy. The most common way to approximate the image gradient is to convolve an image with a kernel, such as the Sobel operator or Prewitt operator.

2.4 CHAN-VESE SEGMENTATION

Segmentation is the process of partitioning a digital image into multiple segments (sets of pixels). Such common segmentation methods including segmenting written text and or segmenting tumors within the healthy brain tissue in an MRI image, etc.

Chan-Vese model for active contours is a flexible and powerful method which helps to segment many types of x-ray images, which includes a few that would be quite tough to segment in means of "classical" segmentation – i.e., using thresholding or gradient based methods. This model is based on the Mumford-Shah functional for segmentation, and used widely in the medical imaging field, especially for the segmentation of the brain, heart and trachea. The model is build on an energy minimization problem, which can be explicated in the level set formulation, mainly to an easier way to unfold the problem.

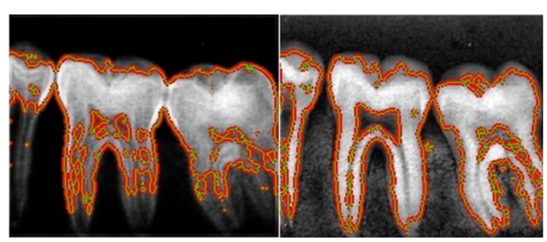


Fig.4- shows the final segmented image resulted by applying Chan-Vese Segmentation

International Journal of Scientific & Engineering Research, Volume 6, Issue 11, November-2015

ISSN 2229-5518

One of the main advantages of this approach is better robustness for noise. This algorithm acknowledges some "modern" approach for image segmentation, which depends on calculus and partial differential equations. Here introduced the Chan-Vese algorithm for image segmentation and shown that it is effective on a wide variety of images. Also it is useful in cases where an edge-based segmentation algorithm will not suffice, since it relies on global properties (gray level intensities, contour lengths, region areas) rather than local properties such as gradients. This means that it can handle gracefully with blurry images, noisy images, and images where the foreground region has a complicated topology (multiple holes, disconnected regions, etc).

EXPERIMENT ANALYSIS

A well contrast image is given as the input to the system with a low resolution and the given image is enhanced using adaptive power law transformation. The already implemented method suggests that the texture analysis, instead of intensity, should be used as the key feature for accurate teeth segmentation. Also proposes a local singularity analysis method using singularity measure as Holder exponent for the texture analysis in periapical images. From this method can be convinced that α-value of the APLT enhanced image is indeed a good feature for differentiating tooth pixels from alveolar bone pixels.

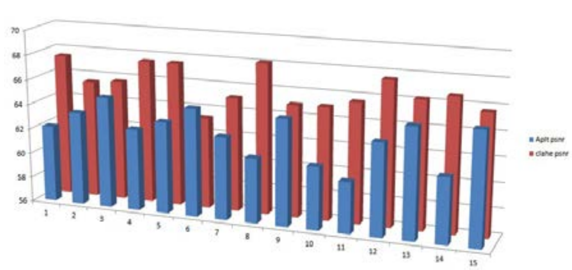


Fig.5- Graph showing the comparison between APLT and CLAHE psnr values

When doing the enhancement using APLT, APLT is used to reduce the contrast variations between poor contrast tooth-root regions and well contrast tooth-crown regions. And the proposed APLT adjusts 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. In the case of GPLT the γ-value is taken as fixed.

The CLAHE (Contrast Limited Adaptive Histogram Equalization) method, which is used basically to enhance the medical images like the mammogram images, which helps in enhancing the dental radiographs. This particular method divides the image into four different types of small blocks, in which it is applied with the suitable smoothing/sharpening techniques for various locations in the image. The CLAHE method does not reduce the contrast variations but it enhances each pixel by its own value. This method won't reduce the contrast variations in the image. It just enhances the value of each pixel in the image.

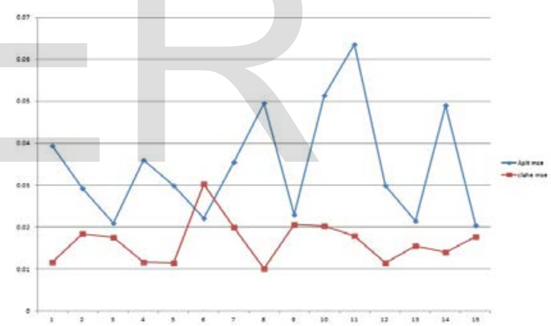


Fig.6- Graph showing the comparison of MSE values of APLT and CLAHE method

The gradient magnitude detects almost all the edges where ever there is a change in intensity, giving a clear idea about the intensity variations in the particular image. In active contour labelling, a mask is initialized with the size of the image to be labelled. The applied iterations vary from 1000 - 2000 so that the image get fine segmented. As the number of iterations increases the contour labelling will be getting smoother and finer.

ISSN 2229-5518

Aplt	
mse	psnr
0.0395	62.1662
0.0293	63.4667
0.0209	64.9271
0.036	62.5626
0.0299	63.3754
0.0222	64.6762
0.0355	62.626
0.0495	61.1829
0.023	64.5197
0.0515	61.0139
0.0637	60.0922
0.0299	63.3754
0.0215	64.8026
0.049	61.2288
0.0205	65.0156

Clahe	
mse	psnr
0.0117	67.4422
0.0184	65.4756
0.0176	65.6778
0.0116	67.5014
0.0115	67.5354
0.0303	63.3181
0.0199	65.1388
0.0101	68.102
0.0206	64.9929
0.0203	65.0523
0.0179	65.6074
0.0115	67.5354
0.0155	66.2294
0.014	66.671
0.0177	65.662

Table.1 and 2 – Comparison tables showing some MSE, PSNR values of few radiograph images after applying APLT and CLAHE methods

The number of iterations is high such that the process is consuming a lot of time for producing the output. To implement the segmentation in a much faster way going with another method of region based segmentation called Chan-Vese Segmentation method, which gives a much better segmentation result as well as taking less time to segment the image.

ssim
0.9997
0.9998
0.9999
0.9998
0.9998
0.9999
0.9998
0.9997
0.9999
0.9997
0.9996
0.9998
0.9999
0.9997
0.9999

Table 3 shows the ssim values of the radiographs after applying the enhancement technique

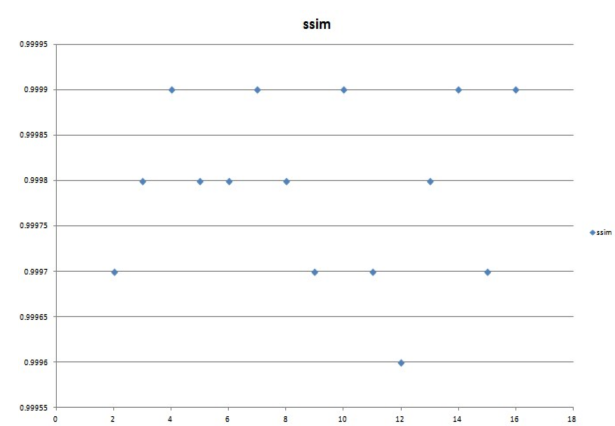


Figure shows the graph plotted for each radiograph with their corresponding radiographs

The number of iterations in active contour is between 1000 - 2000 and as the number of iterations increase the time also increases. The time is directly related to number of iterations, i.e., as number of iterations increase gradually the time taken for the segmentation process also increases. In Chan-Vese segmentation method only less than 100 iterations have been used such that the corresponding image got segmented in less time than the former method. And the segmentation is also much more perfect than the active contour method.

The poorly segmented image resulted when using the active contour labeling, and the successfully segmented image when applied the CLAHE and Chan-Vese Segmentation. This image shows how well the proposed method works than the already avail method.

The graph shows how better the proposed enhancement method has done than the system described method. This graph shows how well enhanced the image in CLAHE method than the APLT method

Also the SSIM value of an image is verified such that the structural similarity of the image is similar when the image is close to 1 and similarity varies when the value decreases.

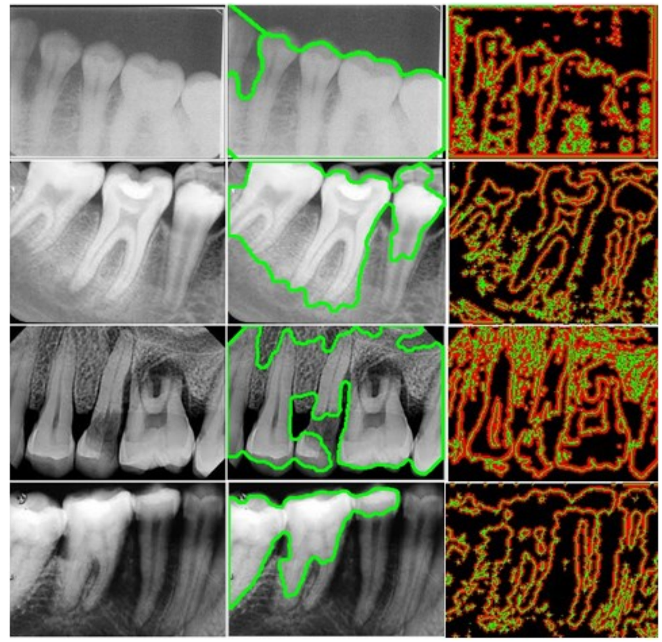
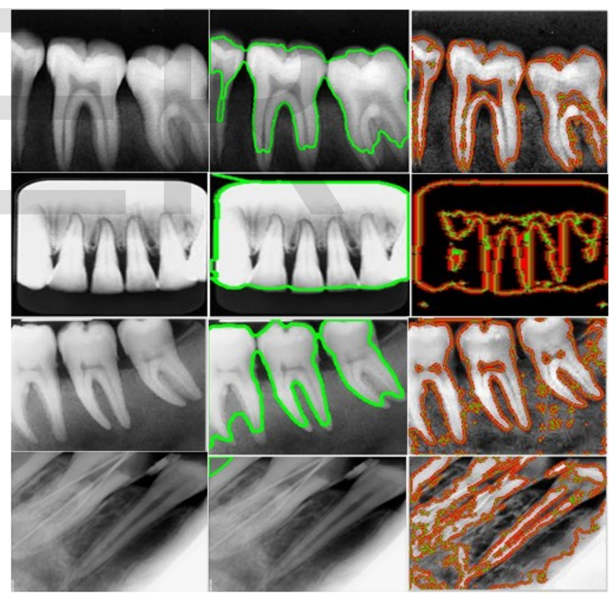


Fig.8 & 9 – Comparison showing segmnentation using active contour and Chan-Vese segmnentation, in Chan-Vese pulp area also getting extracted.



CONCLUSION

Finally implemented a teeth segmentation method for dental periapical radiographs. The method first applied CLAHE; it was originally evolved for medical imaging and has demonstrated to be successful for enhancement of low-contrast images such as portal films. Then local singularities of the enhanced image measured by Holder exponent are calculated to obtain a structure image in which the structures of teeth are much smoother than the structures of alveolar bones. Gradient Magnitude is applied to identify all the edges in the image including the pulp edge of the teeth. Finally, used Chan-Vese segmentation algorithm to segment both tooth and pulp from the given dental radiograph. Chan-Vese segmentation algorithm gives a clear segmentation of the image whether it is a low contrast or high contrast. When comparing the PSNR value between the both methods it shows the proposed method gives a high rate than the given method.

In the future, this method can be modified to segment the images more clearly and the same can be applied to segment teeth in the bitewing as well as in the panoramic radiographs for a much better result. Also after finding the ratio between the pulp and the tooth region can go for age estimation. In

ISSN 2229-5518
order to estimate the teeth first need to isolate each teeth and can proceed with age estimation.

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