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Digital Dental X-Ray Image Segmentation and Feature Extraction

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Abstract

The process of analysis of such images is important in order to improve quantify medical imaging systems. It is significant to analysis the dental x-ray images we need features of image. In this paper we present a method for segmentation and feature extraction of dental x-ray images. The proposed method has been implemented by using level-set method for segmentation after image enhancement and illustrate contour for teeth to complete the segmentation step. Furthermore, we extracted multiple features of dental x-ray images using texture statistics techniques by gray-level co-occurrence matrix. Extracted data can perform to obtain the teeth measurements for automatic dental systems such human identification or dental diagnosis systems. Preparatory experiments show the significance of the proposed method to extract teeth from an x-ray image.

Keywords: *segmentatio, feature extraction, level set method, GLCM.*

1. Introduction

In recent years, many attempt has been expanded in developing automatize systems in the area of biomedical and bioinformatics applications. Dental X-ray image analysis can be used for many applications such as human identification system [1, 2, 3, 4, 5, 6, 7, 8], dental diagnosis system and dental treatment system [9, 10, 11, 12, 13, 14]. Currently many researches are going on about the applications of dental image analysis but the point is which method will be the appropriate in most of the cases for this matter. Computational models of dental image analysis must address several problems such as improve the quality of image, segmentation of the image and extraction of features of image that could be used in systems, these problems arises from the fact that dental images must be represented in a way that best exploit the available teeth information to distinguish teeth from other tissues in dental x-ray images. The image segmentation problem is one of the most difficult tasks in image processing and it plays an important role in most subsequent image analysis, especially in pattern recognition and image matching.

The goal of this research is to automate the process of representation and extracting textural features of dental x-ray images to use in further applications. In order to achieve this goal we need to automate the process of segmenting the dental x-ray images and distinguish the teeth from background and other tissues. The segmentation of dental x-ray images could be difficult due to the shape variation and intensity variation within the same dental x-ray images and from one image to another. There are many researches about dental image analysis systems but it has to be evaluated to find the appropriate method.

Anil K [3], proposed a semi-automatic contour extraction method for tooth segmentation by using integral projection and Bayes rule, in which the integral projection is semi-automatically applied for tooth isolation since an initial valley gap point is required. Jindan Zhou and Mohamed Abdel-Mottaleb [6], presented a segmentation method that consists of three steps: image enhancement, region of interest localization, and tooth segmentation by using morphological operations and Snake method. Omaima Nomir, and Mohamed Abdel-Mottaleb [2], developed a fully automated approach based on iterative thresholding and adaptive thresholding for dental X-ray image segmentation. Keshtkar and Gueaieb [15] introduced a swarm-intelligence based and a cellular-automata model approach for segmenting dental

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radiographs. Eyad Haj Said, et al. [1], offered a mathematical morphology approach to the problem of teeth segmentation, which used a series of morphology filtering operations to improve the segmentation, and then analyzed the connected components to obtain the desired region of interests (ROIs). Li, et al. [16], proposed a semi-automatic lesion detection framework by using two coupled level set functions in which initial contour are derived from a trained support vector machine to detect areas of lesions from dental X-ray images.

In this paper we present a system to enhance the quality of input x-ray image for segmentation and finally archive the vector of extracted textural features of dental images for each x-ray image.

2. Methodology

Essential steps for dental image analysis systems in almost all of the applications are segmentation and feature extraction and in addition some image enhancement techniques also. Classically, image segmentation is defined as the partitioning of an image into nonoverlapping, constituent regions that are homogenous with respect to some characteristic such as intensity or texture [17]. In this way we can describe the segmentation of dental image analysis means, extracting teeth or particular tooth form the image background it my inclusive the gum and jaw. Each tooth or object extracted from image represents region of interest (ROI) that encompass important data used for later steps. Figure (1) shows the conventional dental x-ray image analysis steps in our proposed method.

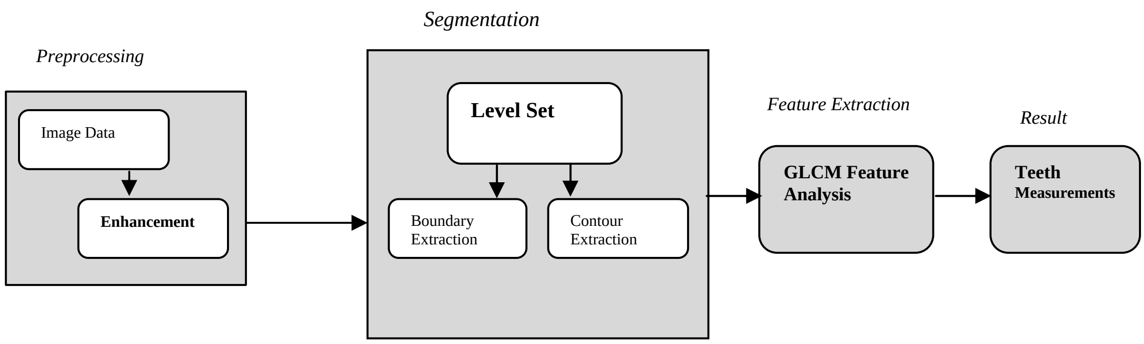


Figure 1. Conventional Dental X-ray image Analysis system

3. Segmentation

Segmentation of dental image analysis means, extracting teeth or particular tooth form the image background it my inclusive the gum and jaw. Each tooth or object extracted from image represents region of interest (ROI) that encompass important data used for later steps. In our case we need unsupervised method to do the segmentation on input images to represent automate process, so clustering methods such k-mean clustering method can be use in this purpose.

3.1. Segmentation using Level Set method

The level set method was first Proposed by Osher and J. Sethian for front propagation, being applied to models of ocean waves and burning flames [21]. Malladi applied it for medical imaging purposes [26]. level set methods have attracted more and more attention of researchers from different areas [22, 23, 25].

Here is the description of level set method formulated in [21]. We define the segmentation boundary as part of a surface where the contour level is 0, i.e., the zero level set. Let φ represent the implicit surface such that:

$$\varphi(X,t) = \pm d \quad (1)$$

Where x is a position in our domain (the image), t is time, and d is the distance between position x and the zero level set. The sign in front of d is positive if x is outside zero level set. Otherwise, the sign is negative. Note that the curve of interest is then marked by positions where $\varphi = 0$.

To evolve φ over time, use the chain rule:

$$\varphi_t + \varphi_x x_t + \varphi_y y_t = 0$$
$$\varphi_t + (x_t, y_t).\nabla_{\varphi} = 0. \quad (2)$$

Now, let $(x_t, y_t) = n + s$ where n is the vector normal to the front at point x and s is some arbitrary vector.

Note that since n and s are defined over the entire domain of x, they are actually vector fields. The above equation can then be written as:

$$\varphi_t + (n + s).\nabla_{\varphi} = 0$$
$$\varphi_t + n\,.\nabla_{\varphi} + s\,.\nabla_{\varphi} = 0$$
$$\varphi_t + \mathrm{V}_n|\nabla_{\varphi}| + s\,.\nabla_{\varphi} = 0 \quad (3)$$

Where V_n is some scalar [27]. The two values, V_n and s, can be viewed as two independent forces that evolve the surface. The scalar V_n will control how fast the surface will move in the normal direction. The vector s will be another force that dictates both direction and speed of evolution. The partial differential equation can then be solved when provided an initial condition, $\varphi(X, t = 0)$. Thus, the segmentation problem reduces to an initial value problem.

This formulation is to allow for a default expansion or contraction of the level set when no features are present in the image using V_n. When image details are present, V_n can fall off towards 0, and the vector s take over to lock the level set on to the actual edges. A valid question is to why not use only one of the forces? By using only V_n, the normal force may be too great for weaker edges. To solve this, the effect of V_n may be cut off early. However, this leaves a margin at the edges. When s is included, the font well converge to the edges.

Although efficient, level set methods cannot be directly used in dental clinic environments due to several reasons:

(1) high computational cost; (2) complicated parameter settings; and (3) sensitivity to the placement of initial contours where (a) the running time of the level set method relies greatly on the position and size of initial curves as well as the complexity of objects, and (b) in some cases, coupled level set functions do not converge for some placements of the initial contours. Level set methods naturally divide an image into two regions. Therefore, they are efficient for extracting an object in an image even if the object consists of several disconnected regions.

4. Textural Feature Extraction using Gray-level Co-Occurrence Matrix

Process of computing the texture feature is known as feature extraction. Different features are chosen to describe different properties of the image. To extract the textural features we used GLCM method which giving us many textural features of x-ray image. These features can be utilized for later applications such as identification systems or diagnosis systems. Figure (2) shows the diagram of extracting the features of image.

Gray-level co-occurrence matrix method was first proposed by Haralick in 1973 [18], and still is one of the most popular means of texture analysis [19]. The key concept of this method is generating features based on gray level co-occurrence matrices (GLCM). The matrices are designed to measure the spatial relationships between pixels. The method is based on the belief that texture information is contained in such relationships.

Co-occurrence features are obtained from a gray-level co-occurrence matrix. In our case texture information of teeth is very important for analysis of characteristics of teeth, so we used some features that extracted from GLCM matrix for feature extraction on dental x-ray images. Here are equations for many texture features [18, 19, 20].

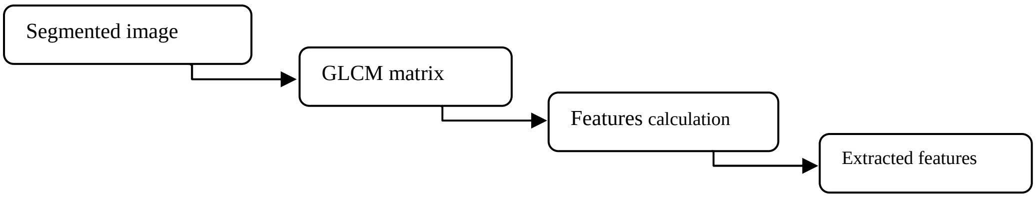


Figure 2. Sequences of Feature Extraction Step

Our initial supposition in characterizing image texture is that all the texture information is contained in the gray-level Co-occurrence matrices. Hence all the textural features here are extracted from these gray-level Co-occurrence matrices.

Contrast:

$$\sum_{n=0}^{N_g-1} n^2 \left\{\sum_{i=1}^{N_g}\sum_{j=1}^{N_g} p(i,j)\right\}, |i,j| = n \quad (4)$$

The contrast feature is a difference moment of the P matrix and is a measure of the contrast or the amount of local variations present in an image.

Correlation:

$$\frac{\sum_i \sum_j (i,j)p(i,j) - \mu_x \mu_y}{\sigma_x \sigma_y} \quad (5)$$

The correlation feature is a measure of gray-level linear dependencies in the image.

Entropy:

$$-\sum_i \sum_j p(i,j) \log (p(i,j)) \quad (6)$$

Entropy is a notoriously difficult term to understand; the concept comes from thermodynamics. It refers to the quantity of energy that is permanently lost to heat ("chaos") every time a reaction or a physical transformation occurs.

Homogeneity:

$$\sum_i \sum_j \frac{1}{1=(i,j)^2} p(i,j) \quad (7)$$

Dissimilarity and contrast result in larger numbers for more contrast windows. If the weight decreases away from the diagonal, the result will be larger for windows with little contrast. The homogeneity weights values by the inverse of the contrast weight, with weights decreasing exponentially away from the diagonal. The homogeneity feature also called as inverse different moment.

Energy:

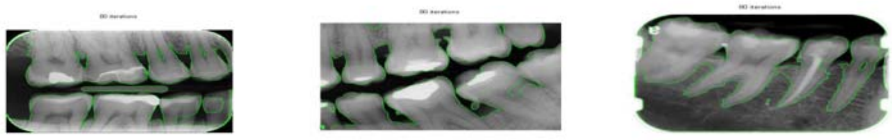
$$\sum_i \sum_j p(i,j)^2 \quad (8)$$

Energy is, in this context, the opposite of entropy. Energy can be used to do useful work. In that sense it represents orderliness. This is why "Energy" is used for the texture that measures order in the image.

5. Result and Discussions

In our case it is necessary to improve the image quality by enhancement techniques so the Image enhancement applied on images to reduce noise and increase contrast of structure of interest by increasing the intensity of image data, before the segmentation.

Moreover, The experiment is designed to illustrate the segmentation of dental x-ray images by using level set algorithm by distinguish background, teeth and gum. The segmented teeth represented with contour around the each tooth, after segmentation of teeth image we extracted some textural features such contrast, correlation, entropy, energy and homogeneity from Gray Level Co-occurrence Matrices, here is the differences of each features of specific image in (Table 1). To use this features we obtained a vector of features from each dental x-ray image for later purpose. It can use for dental diagnosis systems such as dental caries detection, or human identification systems from teeth.



1 2 3

Figure 3. Sample of Segmented Dental X-Ray Images

Image No	Contrast	Correlation	Entropy	Homogeneity	Energy
1	0.3611	0.1512	0.0587	0.9933	0.9833
2	0.0842	0.0859	0.0217	1.0	1.0
3	0.6750	0.8746	0.2878	0.9878	0.8760

6. Conclusion

In this paper we present a method for segmentation and feature extraction for dental x-ray images. The proposed method has been implemented using traditional image processing techniques, by using level set for segmentation, after image enhancement and illustrate contour for teeth to complete the segmentation step. Furthermore, we extracted some features of dental x-ray images using texture statistics techniques by gray-level co-occurrence matrix. The experimental results show that it is a promising technique for segmentation, but needs improvements. Extracted data can be perform to obtain the teeth measurements for automatic dental applications such human identification or dental diagnosis systems. Preparatory experiments show the significance of the proposed method to extract teeth from an x-ray image.

For the future work a better solution to distinguish each particular tooth in segmentation step and evaluation of segmentation methods are expected. However, this paper's method doesn't need to separate the jaws to find the teeth. In addition, it was developed a procedure to recognize the tooth boundary and eliminate other tissues.

The obtained results will be evaluate the segmentation method in order to quantify the precision of proposed method.

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