Dental X-Ray Image Segmentation and Multiple Feature Extraction

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Dental x-ray image segmentation and multiple 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 study we present a method for segmentation and feature extraction of dental x-ray images. The method has been implemented by using clustering (k-mean) 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: dental x-ray image, segmentation, feature extraction, enhancement;

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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 (Eyad Haj Said D. E., 2006), (Omaima Nomir a. M.-M., 2007), (Anil K. Jain, 2004), (Eyad Haj Said G. F., 2004), (Omaima Nomir M. A.-M., 2005), (Jindan Zhou, 2005), (Diaa Eldin Nassar, 2008), (Phen-Lan Lin, 2011), dental diagnosis system and dental treatment system (Jiayin Kang, 2010), (Joao Oliveira, 2011), (Shuo Li, 2006), (Y.H. Lai, 2008), (P.L.Lin,

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2010), (Hui Gao, 2010). 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 appears from the fact that dental images must be depicted 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 mainly difficult tasks in image processing and it performs 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 obtain this aim we need to automate the process of the dental x-ray images segmentation 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, performed a semi-automatic contour extraction for tooth segmentation by using integral projection and Bayes method, since an initial valley gap point is compelled the integral projection applied semi-automatically for tooth separation (Anil K. Jain, 2004). Jindan Zhou and Mohamed Abdel-Mottaleb, performed a segmentation method that comprise of three steps: image enhancement, ROI determination, and tooth segmentation (Jindan Zhou, 2005). They used morphological operations and Snake method for dental images segmentation. (Omaima Nomir a. M.-M., 2007), improved a fully automated approach based on thresholding methods (iterative and adaptive) for segmentation on dental X-ray images. Keshtkar and Gueaieb present a swarm-intelligence based and a cellular-automata model method for dental images segmenting (Keshtkar F., 2006). (Eyad Haj Said D. E., 2006), performed a mathematical morphology and used a series of morphology filtering operations to improve the segmentation and analysis the connected components to achieve the desired regions of interests (ROIs) and conquests the problem of dental images segmentation. (Li S., 2007), performed a semi-automatic lesion detection framework by using the level set functions that initial contour are extracted from a trained support vector machine to detect areas of lesions from dental X-ray images.

For further study here is the some previous related work methods were specially deal with dental image segmentation: Mathematical Morphology (Eyad Haj Said D. E., 2006), (Eyad Haj Said G. F., 2004), (Joao Oliveira, 2011), (Xin Li, 2005), (Eyad Haj Said A. A., 2008),thresholding (Anil K. Jain, 2004), (Jindan Zhou, 2005), Active contours (Jindan Zhou, 2005), (Phen-Lan Lin, 2011), (Samir Shah, 2006), level-set segmentation (Shuo Li, 2006), (Hui Gao, 2010), clustering methods (fuzzy C-mean and K-mean) (Y.H. Lai, 2008), (KANG Jiayin, Dental Plaque Quantification using Mean-shift-based Image Segmentation, 2010), (KANG Jiayin, Dental Plaque Segmentation and Quantification using Histogram-aided Fuzzy C-Means Algorithm, 2010), mean shift based method (Jiayin Kang, 2010), wavelet transformation (Mohammad Hosntalab, 2010), (Thomas D. Faber, 2004).

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.

There are the main types of dental imaging acquisition techniques that are used for analyzing systems: conventional x-ray and computed tomography (CT) imaging. The most common x-ray used in dental imaging are either intraoral or extraoral, depending on whether the x-ray film is inside or outside the mouth and are classified by either bitewing X-rays, periapical X-rays or occlusal X-rays. In our system it is possible to use any type of intraoral dental x-ray images to do the segmentation and feature extraction.

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 (Dzung L. Pham, 2000). 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. Fig. (1) shows the conventional dental x-ray image analysis steps in our proposed method.

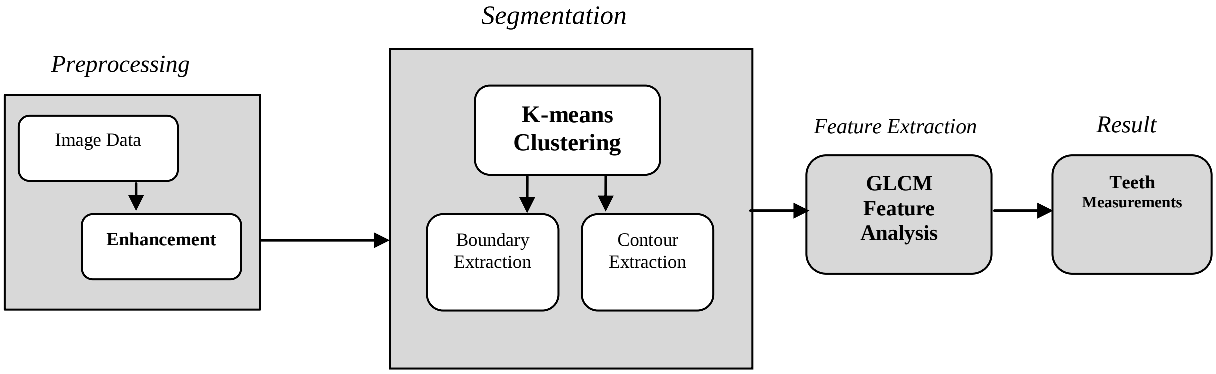


Fig 1. Conventional Dental X-ray image Analysis system

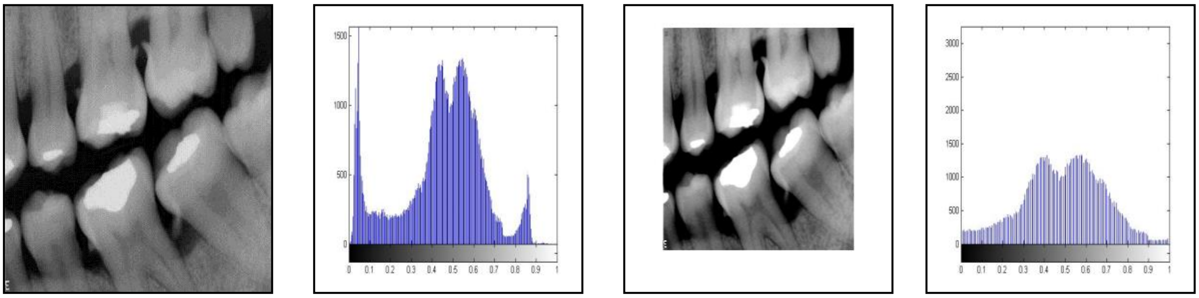
3. Image Enhancement

Image enhancement algorithms are used to reduce image noise and increase contrast of structure of image. In image where the distinction between normal and abnormal tissue is subtle, accurate interpretation may become difficult if noise levels are relatively high (Isaac N. Bankman, 2000). Enhancement of a dental x-ray image is the process of producing an improved quality image out of a degraded quality input image of a dental x-ray image. Most segmentation techniques require high definition of object boundaries. From an image processing point of view, a digitized dental x-ray image is an 8-bit gray scale.

The simplest form of the transformation T is when the neighborhood is of size 1×1 (a single pixel). In this case, the value of g at (x,y) depends only on the intensity of f at that point, and T becomes an intensity or gray-level transformation function. These two terms are used interchangeably, when dealing with monochrome (i.e., gray-scale) images. When dealing with color images, the term intensity is used to denote a color image component in certain color spaces. Because they depend only on intensity values, and not explicitly on (x,y) intensity transformation functions frequently are written in simplified form as

$$S = T(r) \tag{1}$$

Where r denotes the intensity of f and s the intensity of g, both at any corresponding point (x,y) in the images. Fig (2) shows dental x-ray images before and after enhancement.



(a) (b) (c) (d)

Fig. 2. (a) Original dental x-ray image (b) image histogram before enhancement (c) x-ray image after enhancement (d) image histogram after enhancement.

4. 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 used in this purpose.

4.1 K-Mean Clustering

K-mean is unsupervised clustering technique. Clustering involves dividing the set of objects in to groups (clusters) so that objects from the same group are more similar to each other than objects from different groups [26]. Often similarity is determined by a distance measure, such as the Euclidean distance or Mahalanobis distance. Given a known number of clusters K and numbers of data points N , the matrix

$$U_{k\times n} = [u_{ki}], k = 1, \dots, k \ and \ i = 1, \dots, N \tag{2}$$

represent the partitions of the data set, where describe the membership of data point in cluster . The clustering is considered hard if is either 1 (is a member of) or 0 (is not a member of) and is determined by Boolean membership functions. Let be the centroid of cluster . Then can be calculated from

$$v_k = \sum_{i=1}^{N} u_{ki}\, x_i \,/ \sum_{i=1}^{N} u_{ki} \ , k = 1, \dots, k. \tag{3}$$

k-means also called hard c-means. The membership value u_{ki} must satisfy

$$\forall k, \forall i, u_{ki} = \{0,1\}, \forall i, \sum_{k=1}^{K} u_{ki} = 1, and \ \forall k, 0 < \sum_{i=1}^{N} u_{ki} < N. \tag{4}$$

By defining the distance function d_{ki}, for example, the Euclidean distance is

$$d_{ki} = \|x_i - v_k\|, \tag{5}$$

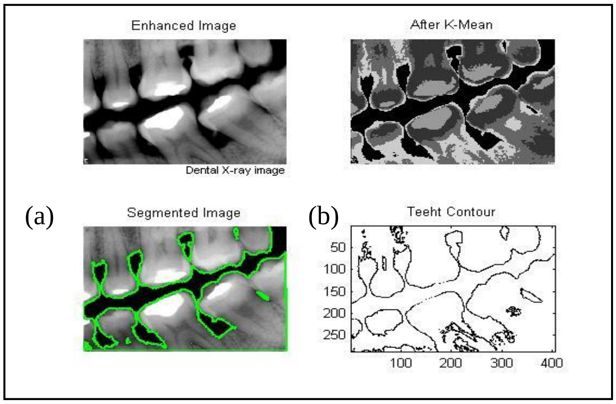
Then the task is to find U satisfies the membership constrains in (3) and minimizes

$$J(U,v) = \sum_{k=1}^{K} \sum_{x_i \in c_k} {d_{ki}}^2 \quad (6)$$

A common way to find U is by using the iterative method was proposed by Lloyd (1982). The algorithm is described below:

1. Given number of clusters k, initiate centroid v_k for each cluster k randomly or heuristically.
2. Calculate each u_{ki} in membership matrix U. u_{ki}= 1 if x_i is closest to cluster k based on the selected distance measure d (e.g. Eq. 5), otherwise $u_{ki} = 0$.
3. Recalculate cluster centroid from U using Eq. 3.
4. Repeat 2-3 until all cluster centroid (or matrix *U*) are unchanged since the last iteration.

After enhancement of the input dental x-ray image we choose k=5 as data image clusters for representing the background, some layer of teeth and gums in dental x-ray image (reason to choose the five cluster is that to recognize some irregular teeth surface such as filled tooth or dental cavity or dental caries also); this iterative partitioning minimizes the sum, over all clusters, of the within-cluster sums of point-to-cluster-centroid distances. K-mean returns an n-by-1 vector containing the cluster indices of each point. By default, k-means uses squared Euclidean distances. When all of points are completed, the centroid of each cluster is recalculated. Repeating the pixel appointment and centroid updating until all cluster centroid (or matrix U) are unchanged since the last iteration. Fig.3(c) and Fig.4(c) shows the result of K-means clustering, in which teeth can be approximately distinguished from background and gums. However, to obtain complete shape, the teeth part needs to be further expanded for better close to the real contour of teeth.



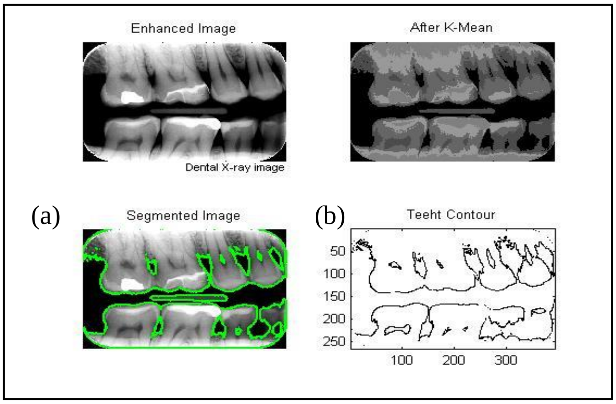


Fig. 3. and Fig 4; (a) Enhanced x-ray image. (b) Result of k-mean algorithm. (c) Segmented teeth with correspondence boundary around teeth. (d) Contour of teeth image.

5. Textural Feature extraction using Gray-Level Co-occurrence Matrix

Figures must be embedded into the text and not supplied separately. Lettering and symbols should be clearly defined either in the caption or in a legend provided as part of the figure. Figures should be placed at the top or bottom of a column wherever possible, and as close as possible to the first reference to them in the paper.

Leave one line space between the heading and the figure. Process of calculating the texture feature is known as feature extraction. Distinctive features are chosen to depict different characteristic 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. Fig. 5 shows the diagram of extracting the features of image.

Gray-level co-occurrence matrix method was first presented by (R. M. Haralick, 1973), and it is one of the most successful methods of texture analysis (D. A. Clausi, 2002). The main idea of this method is producing the features based on gray level co-occurrence matrices (GLCM). The matrices are intended to estimate the measure of spatial relationships between pixels. The method is established upon the belief that texture information is comprised in such relationships.

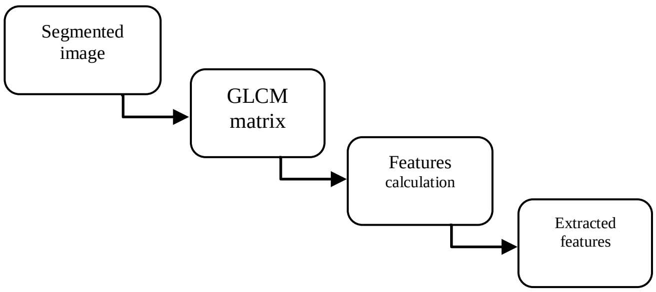


Fig. 5. Sequences of feature extraction step

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 (L. K. Soh, 1999).

Our initial supposition in describing image texture is that all the texture features is included in the gray-level Co-occurrence matrices. Hence all the texture features here are obtained from these gray-level Co-occurrence matrices.

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

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

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

Entropy: $-\sum_i \sum_j p(i,j) \log(p(i,j))$

Entropy is an infamous difficult term to deduce; the idea comes from thermodynamics. It relate to the quantity of energy that is constantly lost to heat ("chaos") every time a reaction or a physical transformation happen.

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

Difference and contrast outcome in wide numbers for more contrast windows. If the weight reduces away from the diagonal, the outcomes will be wider for windows with less contrast. The homogeneity weights values by the reverse of the contrast weight, with weights reducing exponentially away from the diagonal. The homogeneity feature also called as inverse different moment.

Energy: $\sum_i \sum_j p(i,j)^2$

Energy is, in this overall situation, the reverse of entropy. Energy can be accustomed to do useful work. In that sense it shows orderliness. This is why "Energy" is used for the texture that measures order in the image.

6. 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, in (fig. 6), it is easy to judge the entire tonal value distribution at a glance in image histogram of input image data which need to enhanced the image for get the better result in next steps.

Moreover, The experiment is intended to demonstrate the segmentation of dental x-ray images by using k-means algorithm by clustering the image into 5 cluster for distinguish background, teeth and gum, the reason to choose the five cluster is that to recognize some irregular teeth surface such as filled tooth or dental cavity or dental caries also. The segmented teeth represented with contour around the each tooth (fig. 7-c), after segmentation of teeth image we extracted some textural features such contrast, correlation, entropy, energy and homogeneity from Gray Level Co-occurrence Matrices, you can see the differences of each features of specific image in (table 1). For using this features we made 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.

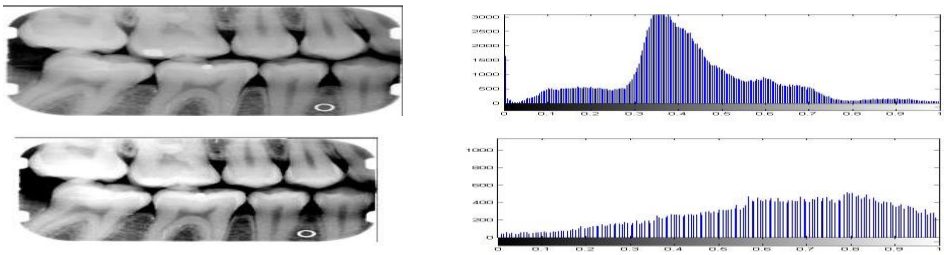
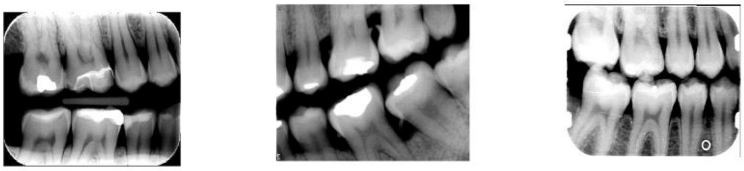


Fig. 6. Dental x-ray image before and after enhancement with respective histogram.

4. Conclusion

In this paper we present a method for automatic segmentation and feature extraction for dental x-ray images. The proposed method has been implemented using traditional image processing techniques, by using clustering k-mean method 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.



1 2 3

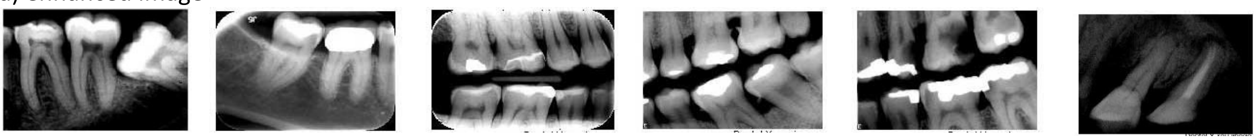
Table 1. Some extracted features from different dental x-ray images

Image No	Contrast	Correlation	Entropy	Homogeneity	Energy
1	0.4648	0.9665	1.7196	0.9512	0.2193
2	0.3160	0.9391	1.6385	0.9650	0.2258
3	0.4513	0.9302	1.5987	0.9637	0.2590

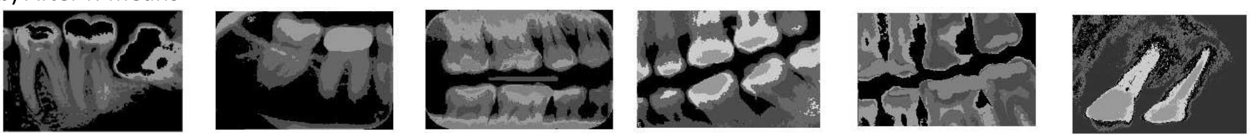
For the future work a better solution to distinguish each particular tooth in segmentation step and evaluation of segmentation methods are expected. However, this paper's method doesn't need to separate the jaws to find the teeth. In addition, it was developed a procedure to recognize the tooth boundary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

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

a) enhanced image



b) After K-means



c) Contour of teeth

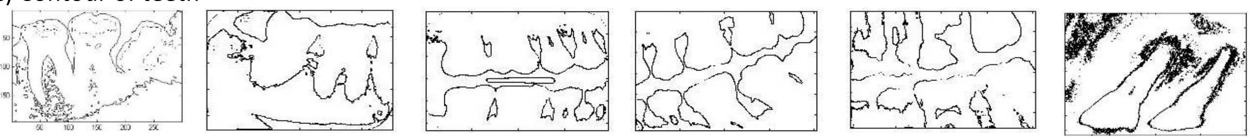


Fig. 7. a) enhanced input image. b) x-ray images after k-means clustering c) contour of teeth

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References

Anil K. Jain, H. C. (2004). Matching of dental X-ray images for human identification. Pattern Recognition, 1519 – 1532.

D. A. Clausi. (2002). An analysis of co-occurrence texture statistics as a function of grey level quantization. Can. J. Remote Sensing, 45–62.

Diaa Eldin Nassar, A. A. (2008). Automatic Construction of Dental Charts for Postmortem Identification. IEEE transactions on information forensics and security.

Dzung L. Pham, C. X. (2000). current methods in medical image segmentation. Annu. Rev. Biomed. Eng, 315–37.

Eyad Haj Said, A. A. (2008). Accurate Segmentation Of Digitized Dental X-Ray Records. IEEE.

Eyad Haj Said, D. E. (2006). Teeth Segmentation in Digitized Dental X-Ray Films Using Mathematical Morphology. IEEE transactions on information forensics and security.

Eyad Haj Said, G. F. (2004). Dental X-ray Image Segmentation, Biometric Technology for Human Identification. Proceedings of SPIE .

Hu, G. M. (2009). Survey of recent volumetric medical image segmentation techniques. Biomedical Engineering, InTech.

Hui Gao, O. C. (2010). Individual tooth segmentation from CT images using level set method with shape and intensity prior. Pattern Recognition , 2406–2417.

Isaac N. Bankman. (2000). hand book of medical imaging. A Harcourt science and technology company.

Jiayin Kang, Z. J. (2010). Dental Plaque Quantification using Mean-shift-based Image Segmentation. IEEE International Symposium on Computer, Communication, Control and Automation.

Jindan Zhou, M. A.-M. (2005). A content-based system for human identification based on bitewing dental X-ray images. Pattern Recognition , 2132 – 2142.

Joao Oliveira, H. P. (2011). Caries Detection in Panoramic Dental X-ray Images. Computational Vision and Medical Image Processing: Recent Trends, Computational Methods in Applied Sciences Springer Science Business .

KANG Jiayin, J. Z. (2010). Dental Plaque Quantification using Mean-shift-based Image Segmentation. IEEE, International Symposium on Computer, Communication, Control and Automation.

KANG Jiayin, J. Z. (2010). Dental Plaque Segmentation and Quantification using Histogram-aided Fuzzy C-Means Algorithm. Proceedings of the 29th Chinese Control Conference , 29-31.

Keshtkar F., G. W. (2006). Segmentation of Dental Radiographs Using a Swarm Intelligence Approach. IEEE Canadian Conference on Electrical and Computer Engineering, 328–331.

L. K. Soh, C. T. (1999). Texture Analysis of SAR Sea Ice Imagery Using Gray Level Co-Occurrence Matrices. IEEE Transaction on Geoscience and Remote Sensing .

Li S., F. T. (2007). Semi-automatic Computer Aided Lesion Detection in Dental X-rays Using Variational Level Set. Pattern Recognition , 2861– 2873.

Mohammad Hosntalab, R. A.-F. (2010). Classification and numbering of teeth in multi-slice CT images using wavelet-Fourier descriptor. Int. J CARS, 237–249.

Omaima Nomir, a. M.-M. (2007). Human Identification from Dental X-Ray Images Based on the Shape and Appearance of the Teeth. IEEE transactions on information forensics and security.

Omaima Nomir, M. A.-M. (2005). A system for human identification from X-ray dental radiographs. Pattern Recognition , 1295 – 1305.

P.L.Lin, Y. P. (2010). An effective classification and numbering system for dental bitewing radiographs using teeth region and contour information. Pattern Recognition , 1380–1392.

Phen-Lan Lin, Y.-H. P.-W. (2011). Dental biometrics: Human identification based on teeth and dental works in bitewing radiographs. Pattern Recognition , 934–946.

R. M. Haralick, K. S. (1973). Textural features for image classification. IEEE Transactions on Systems, Man, and Cybernetics, SMC, 610-621.

Samir Shah, A. A. (2006). Automatic Tooth Segmentation Using Active Contour without Edges. IEEE, Biometrics Symposium.

Shuo Li, T. F. (2006). An automatic variational level set segmentation framework for computer aided dental X-rays analysis in clinical environments. Computerized Medical Imaging and Graphics , 65–74.

Thomas D. Faber, D. C. (2004). Fourier and wavelet analyses of dental radiographs detect rabecular changes in osteoporosis. Bone , 403– 411.

Xin Li, A. A. (2005). Fast and Accurate Segmentation of Dental X-Ray Records. ICB , LNCS , 688–696.

Y.H. Lai, P. L. (2008). Effective Segmentation for Dental X-Ray Images Using Texture-Based Fuzzy Inference System. ACIVS LNCS Springer Verlag Berlin Heidelberg , 936–947.