Evaluation of Current Dental Radiographs Segmentation Approaches in Computer-aided Applications

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Abstract

With a wide variety researches on Image segmentation techniques in biomedical and bioinformatics area, it is important to analyze the performance of these approaches in specific problems. Image segmentation is one of the most significant processes of dental X-ray image analysis. Therefore, to obtain the proper result, it is required to perform the accurate and efficient segmentation approach which proved itself in the aspect of X-ray image segmentation. The aim of this review paper is to understand the different image segmentation approaches which have been used for dental X-ray image analysis over the past studies. In this paper, different available approaches of dental X-ray image segmentation, reviewed and their advantages, disadvantages, and limitations are discussed.

Keywords

Dental radiographs, Medical image segmentation, Segmentation methods.

1. Introduction

Dental X-ray imaging is one of the most common and low cost ways to get the image (information) of teeth. The X-ray images can be used in computer applications such as human identification systems or assisting in clinical aspects like dental diagnosis systems and dental treatment systems. However, to analysis such an X-ray image, we need to use some process on the images to obtain the information. Most important image-processing procedure used for analyzing medical images and computer-aided medical diagnosis systems is image segmentation [1].

Segmentation of such medical images has more difficulty in process due to a vast variety in topologies, the intricacy of medical structures, and poor image qualities caused by some conditions such as noise, low contrast, and similarity of body tissues, some sort of artifacts, and limitation of scanning methods, which results in un-successful segmentation. "Segmentation subdivides an image into its constituent regions or object" [2]. In other definition, image segmentation procedure is defined as the process of extracting region of interest (ROI) from the image background. There are two basic properties which generally image segmentation approaches are based on, one of these two intensity values are: similarity and discontinuity. The major approaches in the first methods are based on segmenting an image into regions that are similar according to a set of predefined criteria. The approach of second methods is to segment an image based on sudden changes in intensity, such as edges in an image [3]. We can classify the segmentation methods based on the pixel values and their relationships into three areas; pixel-based, edge-based, and region-based. In pixel-based approaches, the classification is based on pixel gray-level values in images. Edge-based segmentation approaches are based on abrupt changes of intensity values in image areas. And, region-based segmentation methods are based on differences in predefined values of neighboring pixels in the image. Figure 1 demonstrates the classification of segmentation approaches. Moreover, we can classify another group as "Hybrid" which is based on combination of other methods.

Analysis of dental X-ray images has some difficulty in comparison with other medical images which makes segmentation a more challenging process. The difficulties are like: sample of artifacts, impacted teeth, variations of tooth, space between missing tooth, and also problems in imaging process. Figure 2 illustrates the difficulties which can appear on teeth images. Due to these problems, still finding the accurate and proper method in the segmentation of dental X-ray images is a challenging process. Nonetheless, many surveys on medical image processing have been published in different journals, but none of them focused on dental X-ray images. To overcome this lack, in this review paper, the various approaches of image segmentation techniques that are widely used in the area of computer vision with application to dental X-ray images are reviewed and

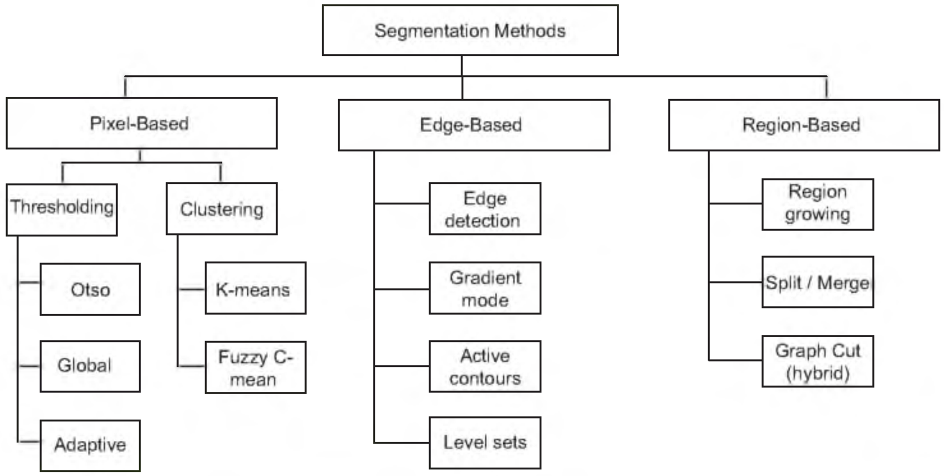

Figure 1: Classification of image segmentation methods.

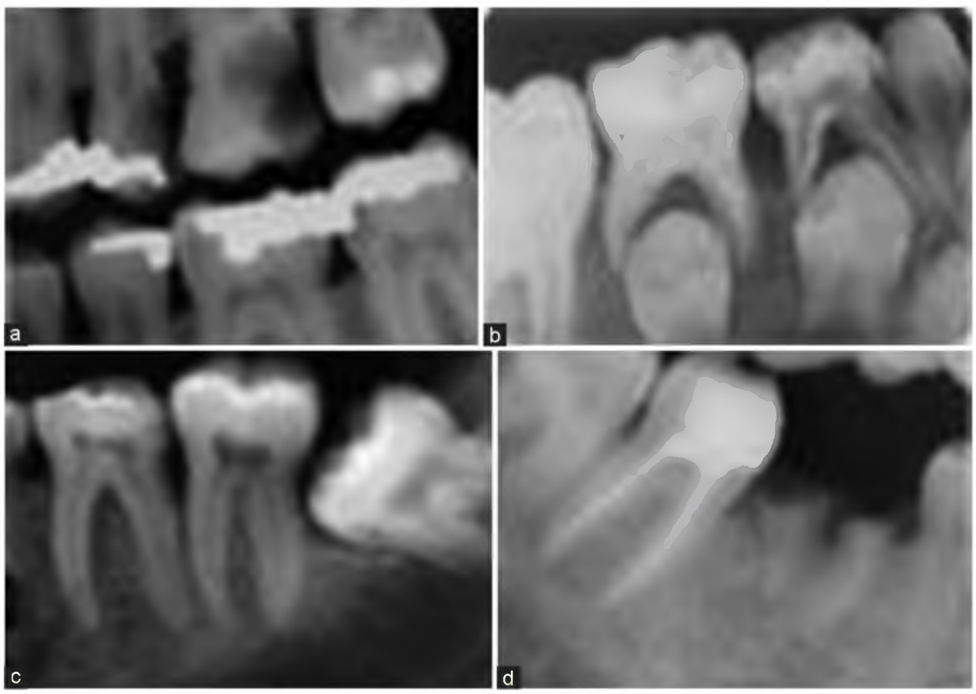

Figure 2: Teeth problems in teeth (a) Artifacts used to fill teeth; (b) Impacted teeth; (c) Different variation in tooth and (d) Space of missing tooth.

discussed. The segmentation methods that have been done on dental X-ray images are as follows:

1. Thresholding methods
2. Active counter or snake method
3. Level set methods
4. Clustering methods
5. Region growing

2. Dental X-ray Image Segmentation Approaches

Segmentation is one of the essential steps in dental X-ray image analysis applications. In dental image viewpoint, segmentation is to identify and classify individual tooth in the dental X-ray image or parts of the tooth such as a crown and a root. Each tooth or part of each tooth extracted from the image illustrates the ROI that includes important data which will be used in later steps in any applications. Image segmentation methods have been improved in the past several decades but it remains a complex and challenging process due to differences in the images. A proposed segmentation method on one problem area may perform well but on another problem area may perform weak and not considerable. Therefore, it is very difficult to obtain a certain segmentation method that is comprehensively suitable for an extension of problem areas [4].

A suitable and proper segmentation method is an important phase of medical image analysis and it is necessary to obtain the accurate and assured result in any application on medical area. In this study, we use three sample dental X-ray images for test of these approaches, which the images are intraoral and exteraoral. The images are original and enhancement is not applied [Figure 3]. The result shows the performance of each approach.

3. Segmentation Using Thresholding Method

Thresholding is the simplest and fastest pixel-based method. There are many techniques in thresholding. The simplest technique in thresholding is to partitioning the image histogram into two areas and assigning the single global threshold "T" [Figure 4]. Segmentation is then performed by sequentially scanning the image pixels and labeling each pixel as the foreground or background. Labeling is based on value of pixel in gray level, whether it is greater than "T" value or lesser than it [2]. If its value is higher than threshold value, then the pixel will be considered as "foreground" and if it is lesser than threshold value, then pixel will be considered as "background." The foreground pixels will set to the white pixels and background pixels will set to black pixels in the image [5].

Thresholding is simple and suitable for the images which contain solid objects with uniform brightness on background. Selection of appropriate threshold value is important to the success of thresholding process [6]. For simplicity and without loss of generality, we assume that a global single threshold T is used to segment the image into two regions: 0 = foreground and 1 = background. A predicate function P can be defined as follows:

$$P(R_0)= \text{true, if } \forall\ x \in R_0, f(x) \geq T,$$
$$P(R_1)= \text{true, if } \forall\ x \in R_1, f(x) < T, \quad (1)$$

Thus, the pixels labeled 1 belong to the foreground and the pixels labeled 0 belong to background of images. Figure 5 shows the result of applied global thresholding method.

$$g(x) = \begin{cases} r_0 \text{ if } f(x) \geq T \\ r_1 \text{otherwise} \end{cases} \quad (2)$$

3.1 Adaptive Thresholding Technique

Sometimes, it is not possible to segment an image with a single global threshold. This might happen in an image with a varied background and ununiformed brightness. Instead of applying a single global threshold to all pixels in the image, adaptive thresholding changes the threshold dynamically over the image. In local adaptive thresholding, each pixel is considered to have an n × n neighborhood around it, from which a threshold value is calculated (from the mean or median of these values) and the pixel set to black or white, according to whether it is below or above this local threshold, TL. The size of the neighborhood, n, has to be large enough to cover

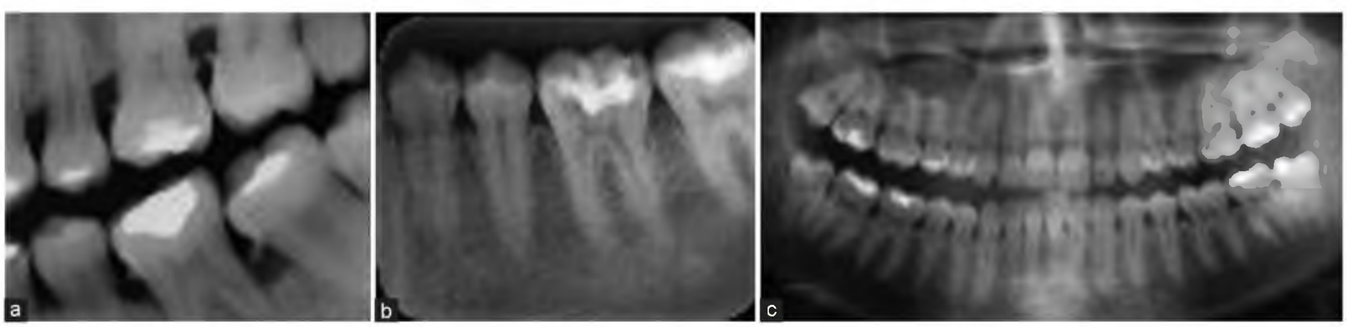

Figure 3: (a) Intraoral bitewing dental X-ray image; (b) Intraoral periapical dental X-ray image and (c) Extraoral panoramic dental X-ray image.

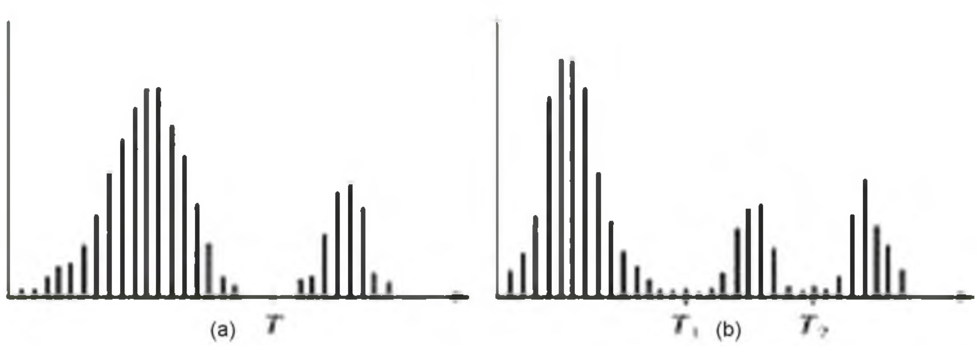

Figure 4: Gray-level histograms which threshold value can be selected by (a) Single threshold or (b) Multiple thresholds.

sufficient foreground and background pixels so that the effect of noise is minimal, but not too large that uneven illumination becomes noticeable within the neighborhood. Often the technique is even more successful when the local threshold, TL, is chosen as

TL = {mean or median} – C

where, C is a constant. The method is not unsupervised since values for the parameters n and C must be chosen [Figure 6].

3.2 Iterative Thresholding Technique

Since most of the applications typically have enough variability between images. Even global thresholding is an appropriate method, but an algorithm with ability of automatic estimation of a threshold value for each image is necessary. The algorithm of the iterative thresholding approach is as following:

1. Select an initial value, T
2. Segment the image based on T value. Produces two groups of pixels G1 with pixels intensity values >T, and G2 with pixels values <T
3. Compute the mean intensity values m1 and m2 for each group in G1 and G2
4. Compute new threshold value as
    1. T = ½ (m1 + m2)
5. Repeat steps 2 to 4 until the difference between the values of T in successive iterations is smaller than a predefined parameter ΔT. (Parameter ΔT used to control the number of iteration).

If the parameter ΔT is large, then the iteration of algorithm is less. The initial threshold value must be greater than minimum and less than the maximum of intensity level in the image. Therefore, to choose the initial threshold value better to select the average intensity of an image. Rider and Calvard [7] introduced an iterative method that finds the optimal threshold such that the threshold is equidistant to the two classes.

There are many research works, which have been used the thresholding methods in segmentation process [8-13]. For segmentation of dental X-ray images, O. Nomir and AbdelMottaleb [8-10] performed iterative thresholding followed by adaptive thresholding to segment the teeth from background and bone areas. They start the iterative threshold value by selecting the initial threshold based on the estimated threshold value from an area around the edges because of high contrast pixels. To obtain a new threshold for separating the image into the teeth area and background areas and also to achieve the mean grey values for the two areas, they used segmented original image by initial threshold. The average of the two mean values is a new threshold value. For enhancement of segmentation, the adaptive threshold is applied to the result of masked original image with binary image. Thresholding will be performed by comparing the adaptive thresholding value with the average of gray values

Figure 5: Dental X-ray sample images after global thresholding.

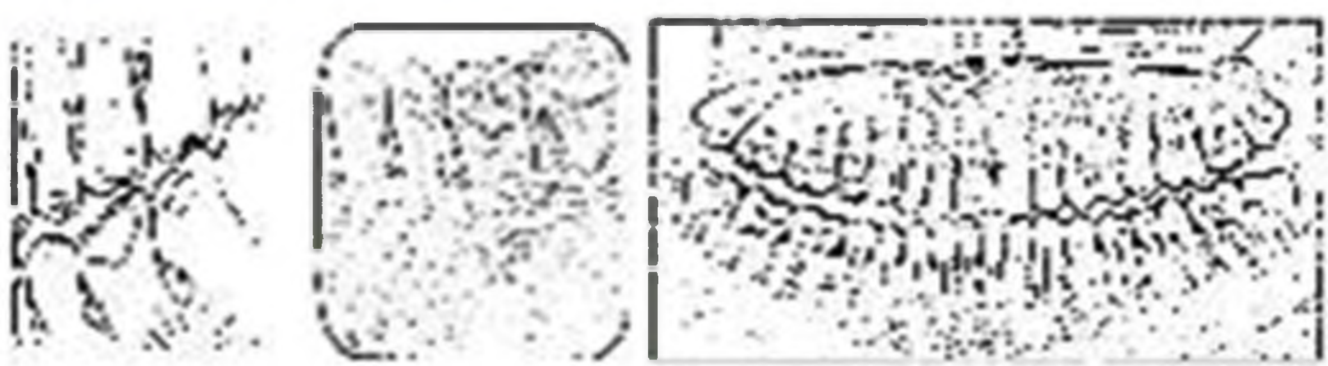

Figure 6: Dental X-ray sample images applied adaptive thresholding.

inside the given area of pixels. The proposed technique on dental bite-wing X-ray images shows the significant teeth segmentation result. However, the failure of images segmentation suffered due to the poor quality and noises in the images. In [14], they used three threshold values to produce the most qualified ROIs values as follows:

T_1 = mean (filtered image), $T_2 = 0.66T_1$, $T_3 = 0.33T_1$

However, using a single threshold value might lose some information and affect the result. In [12,13], after enhancement of original X-ray images, they used canny edge detection to detect all the edges, then they applied the iterative thresholding approach by utilizing the average intensity of the edge pixel as an initial threshold value to achieve the areas of teeth and background. Finally, they applied an edge operator to each ROI followed by equal sampling and B-spline fitting to get the contour of each tooth; the method they used to perform much better for handling uneven illuminated images. The drawback of this method is that it is computationally expensive and, therefore, is not appropriate for real-time applications [Figure 7].

3.3 Summary and Discussion of Thresholding Methods

The simplicity of thresholding methods leads to implementation that is highly fast and can even be implemented in hardware, which involves minimal implementation and computational requirement [15]. The threshold value can be chosen by analyzing the shape of the image histogram. It is not suitable for noisy images and also sensitive to image artifacts that alter the true intensity distribution [16]. Some preprocessing techniques such as image enhancement of images would be desirable to get better results in segmentation. For more and complete information about thresholding methods and threshold value selection, readers are referred to [17,18].

4. Segmentation Using Active Counter (Snake Method)

The concept of active contours (snake) method for image segmentation is entirely simple. The user must specify an initial point for the image contour, which can move from image-driven forces to the boundaries of the desired objects. This method contains two types of forces; the internal forces, which is defined inside the curve, and performs the smoothness of model during the deformation process. The external forces are defined to move the model outside of initial curve and toward the object boundary [19]. Kass [20] developed a new approach for image segmentation and it was able to solve a large class of segmentation problems. He proposed the idea of a snake, which was an active contour model using an energy minimizing spline guided by external constraint forces and influenced by image forces that pull it toward features such as lines and edges. This method was successful in performing tasks such as edge detection, corner detection, motion tracking, and stereo matching.

An active contour or snake is a controlled continuity contour which elastically snaps around and encloses a target object by locking onto its edges. It is possible to control the snake through energy function. The snake is active because it is continuously evolving so as to reduce its energy. To evolve the snake to have particular properties needs to specify the proper energy function. The method can easily be extended to dynamic image data and three-dimensional image data. The energy function in snake has two parts, the internal and external energies. Thus,

$$E_{snake} = E_{internal} + E_{external}$$

The internal energy relies on the natural characteristics of the snake, such as its length or curvature. The external energy depends on factors such as image structure and particular constraints the user has imposed. If we want the snake to shrink like an elastic band, we need to define an internal energy that increases with its length. User-defined control points, approximately equally spaced, specify the starting position of the snake, which should be a reasonable approximation to its desired position; the internal energy function can be taken as the sum of the squares of the distances between adjacent control points, to simulate springs which obey Hooke's Law connecting the control points. The sum is multiplied by

Figure 7: Dental X-ray sample images applied iterative thresholding.

an adjustable constant, K, corresponding to the strength of the springs. Thus,

$$E_{internal} = E_{elastic} = K\sum_{i=1}^{N}(d_i, 1-1) \quad (3)$$

where, i is the index of the control point with coordinates (x_i, y_i). Because the snake is a loop, control point 0 is the same as control point N. The corresponding forces on the ith control point, obtained by differentiating the energy function, are given by

$$F_i(x) = 2K((x_{i+1} - x_i) - (x_i - x_{i-1}))$$

$$F_i(y) = 2K((y_{i+1} - y_i) - (y_i - y_{i-1})) \quad (4)$$

Such forces pull a control point toward its two nearest neighbors. Geometrically, the force is toward the average position of the neighbors. Such forces applied to every control point will pull the snake inward and will pull the control points into line with one another, smoothing the snake. To adjust the position of the snake, the forces are used to act on each control point. The dynamics of the snake implemented by moving each control point by an amount proportional to the force acting on it at each time step. Thus, the updating equations are given by

$$x_i = CF_i(x) \rightarrow x_i$$

$$y_i = CF_i(y) \rightarrow y_i \quad (5)$$

Where, C is another user-defined constant, which determines the distance of point move for a given force. The elastic force rapidly pulls the snake into a smooth oval, which keeps contracting. Now consider the external energy of the snake, which determines its relationship to the image. Suppose, to latch the snake on the bright structures in the image, the external energy function is minus the sum of the gray levels of the pixels covered by the snake. Reducing this energy function will move the snake toward brighter parts of the image. Thus,

$$E_{external} = E_{image} = -K\sum_{i=1}^{N}P_i \quad (6)$$

where, Pi is the pixel value of the ith pixel and the constant k is user-defined. The force that this produces has a rather simple approximation:

$$F_i(x) = K/2(P_{xi+1, yi} + P_{xi-1, yi})$$

$$F_i(y) = K/2(P_{x, yi+1} + P_{x, yi-1}) \quad (7)$$

The control point is pulled to positive *x* direction when the pixel in direction of increasing *x* is brighter than the pixel in direction of decreasing *x* and as well for y. Useful snakes use more sophisticated estimate of the gray level gradient to prevent the effects of very local structure. When energies are added into their associated forces, snakes start with a closed curve and minimize the total energy function to deform until they reach their optimal state. In general, the initial contour should be fairly close to the final contour but does not have to follow its shape in detail: the active contour/snake method is semi-automatic since it requires the user to mark an initial contour.

The main advantage of the active contour method is that it results in closed coherent areas with smooth boundaries, whereas in other methods, the edge is not guaranteed to be continuous or closed. However, conventional snake model algorithms suffer from the inability to mold a contour to severe concavities in an object and they often generate unwanted contour loops; more recent loop-free snake algorithms have been developed to prevent these problems [6].

In [21], they used window-based adaptive thresholding to segment the enhanced images to minimize the influence of uneven intensity and noise in the bone regions. To overcome the problem of variation in quality of dental images, they perform snake method to refine the contours and obtain more reliable results by using the external energy function for leading the snake toward the boundaries of teeth. As following equation:

$$E_{ext} = -\left|\nabla\left[G_\sigma(x,y) * I(x,y)\right]\right|^2 \quad (8)$$

In [22] to detect the contour of teeth, they performed two algorithms, active contours without edges that proposed by [23] and also snakes method. The result of snake method in their experiments clearly shows that it is not able to detect the contour of many tooth entities in dental images and extracted contours does not fit tightly around the actual boundary of teeth and perhaps due to the implicit limitations of the snake-based evaluation technique. But the result of extracted contours obtained by using proposed active contour without edges method in their experiments demonstrate the contours tightly fit enough on the boundaries of teeth [Figure 8].

4.1 Summary and Discussion of Active Contour Method

The main advantage of snake's models is the ability of snakes to give a linear description of the object shape

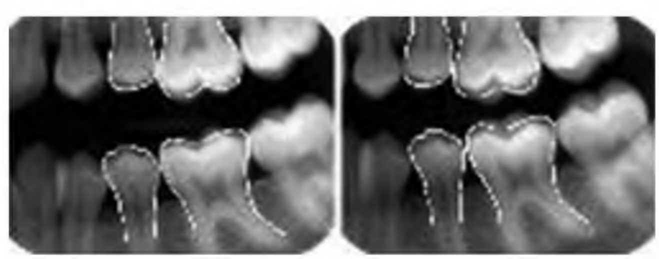

Figure 8: Dental X-ray image segmented by snake method from [13].

during the time of convergence without adding extra processing [24]. But what scientifically limits the use of snakes is the need of the method to have strong image gradients to be able to drive the contour [25]. It is able to generate directly the closed parametric curve by calculating the external force from the image [26]. And, also for robustness against noises, it includes a smoothness constraint. Nevertheless, the result of this method is very sensitive to the replacement of the initial contour, as it is manually performed [27]. Moreover, the difficulty in initialization and poor convergence to boundary concavities has limited its utility [28]. The snake is always attached to the strong edge in the above external image forces. However, this may not be a good behavior for medical image segmentation. For example, the active contour for the low contrast boundary may be attached to the nearby higher contrast structures [29].

5. Segmentation Using Level Set Method

The level set method was proposed by Osher and J. Sethian for "front propagation, being applied to models of ocean waves and burning flames" [30]. And, Malladi applied it for medical imaging purposes [31]. Level set methods have attracted more and more attention of researchers from different areas [32-34]. The concept of the level set method is to enclose a curve within a surface. Because of robust detection in image characteristics such as corners and topological changes, the level set method has been used extensively. The segmentation boundary can be defined as a part of the surface where the contour level is 0, i.e. the zero level set. Let φ represent the implicit surface such that

$$\varphi(X, t) = \pm d \tag{9}$$

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 the zero level set. Otherwise, the sign is negative.

$$\varphi(x,y,0) = \begin{cases} -d(x,y,\gamma) \text{ if } (x,y) \text{ inside the front} \\ 0 \\ d(x,y,\gamma) \text{ if } (x,y) \text{ outside the front} \end{cases} \tag{10}$$

To move the level set surface, lets define velocity field F, that specifies how contour points move in time. Based on application-specific physics such as time, position, normal, curvature, and image gradient, magnitude will be specified. Then, the initial value for the level set function, φ(x, y, t), based on initial contour will be computed. The value of φ will be adjusted over the times and current contour defined by φ(x(t), y(t))=0. Then, the iteration will be repeated until the convergence on the boundary of curve. The last obtained curve is the segmented area and final level in level set calculation.

The algorithm of level set segmentation method is described as below:

1. Initialize the front γ(0)
2. Compute φ(x, y, 0)
3. Iterate:
   $\varphi(x, y, t+1) = \varphi(x, y, t) + \Delta\varphi(x, y, t)$ until convergence
4. Mark the front γ (tend)

Ma and Manjunath [35] described that in implementation, under such a scheme, a front might stop evolving at a position of two equidistant edges. In this condition, even edge seems like a realistic option to evolve or stop moving. Moreover, if the zero level set is affected only by vectors of just one edge, situation will be worse and the whole set will fail into that edge. It might happened if the zero level set is very near to only one side of object in the image. To overcome this problem, introducing the normal force is required. In other definition, generating the full vector field which covers the whole area and using only that is possible [36].

In [1,37], they had two phases in segmentation, a training and a segmentation phase. In the training phase, segmentation was performed on selected delegate images manually by using hierarchical level set region detection [38]. The hierarchical level set is able to achieve automatic segmentation. They used a pathological energy function for applying the hierarchical level set segmentation. "The dental images divided into four regions: the Normal Region (UNR), the Potentially Abnormal Region (UPAR), the Abnormal Region (UAR) and the Background Region (UBR)". During the training phase, to separate the UABR from the rest of image in hierarchical level set region detection at first, they used a level set function and then for separate AUR and UBR they used another level set function, and these results were used for train SVM classifier. Then, for each one of three regions (UNR, UPAR and UABR), the coupled level set functions are used. The final segmentation obtained by evolution of these three level set curves under the functional is described in the following Eqs:

$$E = E(\varphi NR, \varphi PAR, \varphi ABR) - \gamma_1 E_{LAP} + \gamma_2 E_{GAC} \tag{11}$$

where, γ_i are constants.

The geodesic active contour (E_{GAC}) and edge functional (E_{LAP}) are defined as:

$$E_{GAC}(C) = \iint g(c)\, dxdy \tag{12}$$

The edge functional (E_{LAP}) was proposed in [39] where Kimmel shows that the Laplacian edge detector DI provides optimal edge integration with regard to a very natural geometric functional. These terms are defined as:

$$E_{LAP}(C) = \int_C < \nabla, n > ds + \iint_{\Omega c} K_1 |\nabla 1| dxdy \quad (13)$$

where, g(x, y) is an inverse edge indicator function. As suggested in [40], K_1 is the mean curvature of the level set functions, n is the unit vector normal to the curve and *ds* is the arc length along the curve C.

$$\frac{\partial\varphi_i}{\partial_t} = \gamma_2\delta_\varepsilon(\varphi_i)div(g\frac{\nabla\varphi_i}{|\nabla\varphi_i|} - \lambda_i\delta_\varepsilon(\varphi_i)\frac{(u-c_i)^2}{\sigma_i^2}$$

$$-\beta\delta_\varepsilon(\varphi_i)(\sum_{i=1}^{K} H(\varphi_i)-1)^2 - \gamma_2\delta_\varepsilon(\varphi_i)u_{\varepsilon\varepsilon} \quad (14)$$

Where, $u=\Delta u - K_i|\nabla_u|$ and β is a constant.

However, effective, level set methods cannot be used directly in dental X-ray images due to several reasons: (1) vast of computation; (2) complexity of parameter settings; and (3) finding the initial contours are very sensitive where (a) the speed of the level set method highly depends on the size and position of initial curves as well as the complexity of objects, and also (b) in some conditions, coupled level set functions cannot converge the some placements of the initial contours. Figure 9 shows the result of this method.

5.1 Summary and Discussion of Level Set Method

This is the advantage of this method which all the level sets produce a nice representation of regions and their boundaries on the pixel grid, without necessity of using complex data structures. It considerably simplifies optimization [41,42]. For disadvantage of the level set method, it is considerably a level set function that is restricted to the separation of two regions. As soon as more than two regions are considered, the level set idea loses parts of its attractiveness [43]. The result varies due to initial contour placement [28].

6. Segmentation Using Clustering Methods

Similar to image segmentation, clustering involves dividing a set of objects into groups (clusters), so that objects from the same group are more similar to each other than objects from different groups, often similarity determined by a distance measure, such as the Euclidean distance or Mahalanobis distance [29]. Given a known number of clusters K and number of data points N, the matrix

$U_{K\times n} = [U_{Ki}]$, k = 1,…, k and i = 1,…, N

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

$$v_k = \sum_{i=1}^{N} U_{ki}x_i \Big/ \sum_{i=1}^{N} U_{ki}, k = 1,...,k \quad (15)$$

6.1 K-mean Clustering

K-mean is unsupervised clustering technique that is also called hard c-means. The membership value U_{Ki} must satisfy

$$\forall k, \forall i, u_{ki} = \{0,1\}, \forall i, \sum_{i=1}^{N} U_{ki} = 1, \text{and} \forall k, 0 < \sum_{i=1}^{N} U_{ki} < N \quad (16)$$

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

$d_{ki} = ||x_i - v_k||$,

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

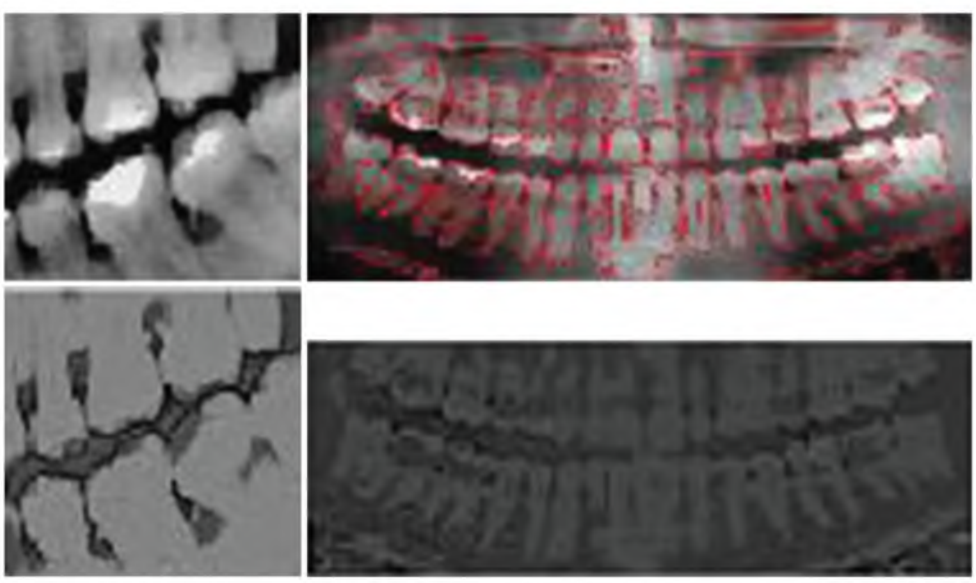

Figure 9: Dental X-ray sample image segmented by level set method.

$$J(u,v) = \sum_{k=1}^{k} \sum_{x_{i \in c_k}} d_{ki}^{\;2} \tag{17}$$

A common way to find U is by using the iterative method that was proposed by Lloyd [44]. 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, otherwise $u_{ki} = 0$
3. Recalculate cluster centroid from U
4. Repeat 2-3 until all cluster centroid (or matrix U) are unchanged since the last iteration [Figure 10].

6.2 Summary and Discussion of Clustering Method

Clustering methods are suitable for segmenting a site where the means of the intensity distribution of the tissue types are well separated [45]. It is able to detect small variations in intensity value and also combinations of any grouping criteria can be used, and the simplicity of clustering algorithm is easy for implementation [46]. "Similarly, the drawbacks are of how to determine the number of clusters and decrease the numbers of iteration" [47]. But here are some disadvantages of this method: Noise could be interpreted as new segments; incorporating spatial information makes it less general; the number of clusters, k, must be specified by the user; and it is time consuming and reduce the ability of full automatically operation [48-51].

7. Segmentation Using Region Growing

The idea of region growing technique is to extract an image area or region which is connected based on some pre-defined conditions. The conditions can be based on the information of edges or intensity in the image [52]. In its general way, the region growing requires a seed point which is manually selected by an operator and extracts all the pixels connected to the initial seed based on some pre-defined conditions. "Like thresholding, region growing is seldom used alone but usually within a set of image-processing operations, particularly for the delineation of small, simple structures such as tumours and lesions" [53-58]. There are some region growing methods which have differences in homogeneity criteria definition. The general algorithm of region growing is described below:

Region_Growing (Input: Seed)

1. Region r = {seed}
2. While r.neighbours $\neq$ {} For each voxel ξ in r.neighbours, if *P*(x, r) = true then add ξ to r End while
3. Return r

In this algorithm, r is the region that needs to be extracted. Based on homogeneities criteria, some region growing-based methods have been presented. In this algorithm, the fundamental region-growing method has been explained by evaluating the distance between voxel ξ and mean of the region and presented by function P [59]. P is

$$P(x, r) = |f(x) - \mu_r| < T \tag{18}$$

Where, μ_r is the region's mean of r and T is a threshold. Threshold can be selected manually or using an automated method [Figure 11].

The main disadvantage of region-growing method is that it needs manual interaction to achieve the seed point. Split and merge is an algorithm related to region growing, but it does not require a seed point [59]. Region growing is very sensitive to noises and it might influence the extracted regions by demonstrating the holes or disconnections. However, the partial-volume effects may be able to connect the separate regions [60]. To overcome these problems, a "homotopic region-growing algorithm has been proposed that preserves the topology between an initial region and an extracted region" [61]. And also, fuzzy analogies to region growing have been developed [57,62].

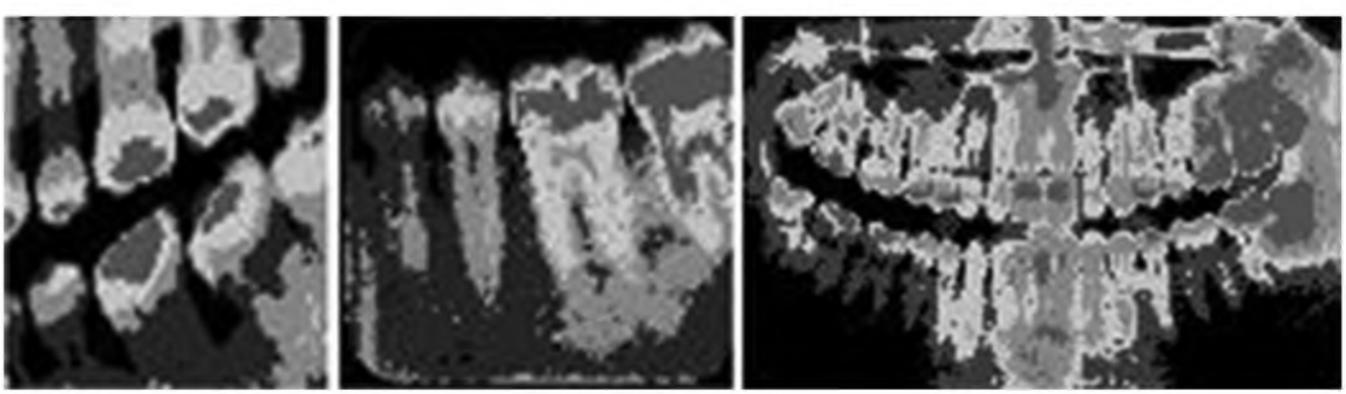

Figure 10: Dental X-ray sample image segmented by K-means clustering.

7.1 Summary and Discussion of Region Growing Method

The region growing is less sensitive to image noise than thresholding methods because of the use of regional properties and the resulting segmentation is piece-wise continuous [63]. Some region homogeneity criteria involve thresholds as well [64]. However, if the region mean is used as the homogeneity measure, since it can be calculated efficiently, the threshold can be interactively to obtain a suitable segmentation [65]. This method performs quite well when segmenting organs, such as teeth or bony structures, that have well-defined boundaries. Disadvantages of region growing are as follows:

Figure 11: Dental X-ray sample image segmented by region growing.

(1) Single segments that occur in more than one spatial location will not be accurately identified; (2) Incorrect pixels could be added to region while it is still small; and (3) The significance level, α (or tolerance t), must be specified by the user [66].

8. Conclusion

This paper reviews and summarizes some existing methods of segmentation that have been applied on dental X-ray images. Due to the variety of dental X-ray images, it is not proper to decide to use one certain method for segmentation and it depends on the specific situation of images. The methods discussed in this paper are: thresholding methods, active counter or snake method, level set methods, clustering methods, and region-growing method. The importance of accuracy and assure of method is significant in medical application area. Therefore, validation of segmentation is not only achieving the result, rather the accuracy, precision, assure, and computational speed of segmentation, as well as reducing the amount of manual interaction are considerable. Segmentation methods are specifically valuable in the area of computer-aided medical diagnosis applications where visualization of the parts which are difficult to identify by human vision is the critical component. Table 1 contains the summaries of advantage and

Table 1: Overview of current methods in dental image segmentation

Methods	Advantage	Disadvantage
Thresholding	Simplicity of implementation and less computational rate	Sensitive to image artifacts that alter the true intensity distribution Not suitable for noisy images
Active Contour	Ability of snakes to give a linear description of the object shape during the time of convergence without adding extra processing, It also includes a smoothness constraint for robustness against noise	The result of the method is sensitive to the replacement of the initial contour, as it is manually placed. Problems associated with initialization and poor convergence to boundary concavities has limited its utility
Level set	Produce a nice representation of regions and their boundaries of the pixel grid, without the need of complex data structures. Considerably simplifies optimization	It is considerable that level set function is restricted to the separation of two regions. As soon as more than two regions are considered, the level set idea loses parts of its attractiveness. The result varies due to initial contour placement
Clustering	Suitable for segmenting a site where the means of the intensity distribution of the tissue types are well separated. Detect small variations in intensity value. Simplicity of clustering algorithm is easy for implementation	Noise could be interpreted as new segments. Incorporating spatial information makes it less general. Number of clusters, k, must be specified by the user and its time consuming
Region growing	It is less sensitive to image noise. Perform quite well when segmenting organs, such as teeth or bony structures, that have well defined boundaries	Single segments that occur in more than one spatial location will not be accurately identified. Incorrect pixels could be added to region while it is still small. The significance level, α (or tolerance t) must be specified by the user

Table 2: Accuracy of methods on dental radiograph segmentation

Method	Reference	Work type	Purpose	Accuracy (%)
Thresholding	(Omaima Nomir M. A.-M., 2005)	Semi-auto	Teeth segmentation	82.5
Thresholding	(Eyad Haj Said, 2006)	Auto	Teeth segmentation	83
Thresholding	(Nomir & Abdel-Mottaleb, 2007)	Auto	Human identification	82.5
Active contour	(Samir Shah, 2006)	Auto	Teeth segmentation	58.1
Thresholding and integral projection	(Vo Phong-Dinh, 2008)	Auto	Dental segmentation	77.23
Active contour without edge	(Joao Oliveira, 2010)	Auto	Panoramic X-ray segmentation	71.91
Region growing	(Y.H. Lai, 2008)	Semi	Dental segmentation	83
Level-set	(Shuo Li T. F., 2007)	Semi	Lesion detection	95.1

disadvantages of segmentation approaches that have been used in X-ray images and Table 2 demonstrates the accuracy of previous works on dental radiographs which shows the high performance of level-set method.

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