RESEARCH ARTICLE

CBCT image based segmentation method for tooth pulp cavity region extraction

¹Lei Wang, ¹Ju-peng Li, ²Zhi-pu Ge and ²Gang Li

¹Signal and image processing laboratory, School of Electronic Information Engineering, Beijing Jiao tong University, Beijing, China; ²Department of Oral and Maxillofacial Radiology, Peking University, School and Hospital of Stomatology, Beijing, China

Objectives: A method was proposed to segment the tooth pulp cavity region in cone beam CT) images, which aimed to make the extraction process more efficient and generate more reliable results for further research.

Methods: Cone beam CT images of 50 teeth from 10 patients were randomly collected with the help of Peking University Hospital of Stomatology. All slice images have a ground truth tooth pulp cavity region delineated by two doctors manually. After necessary gamma transform in pre-processing stage, three kinds of information in an image such as greyscale, neighbour average greyscale and gradient were fused to search an optimal segmentation threshold by using plane intercept histogram of reciprocal cross entropy algorithm. With the optimal threshold, binarization was conducted and the tooth pulp cavity regions in slice images can be extracted. Qualitative and quantitative analyses compared to ground truth are involved with the evaluation criterion of average non-coincidence rate (R_{ANO}). Independent repeated experiments were carried out to test the stability of this segmentation method.

Results: Accurate and complete segmentation results are obtained. The proposed method reaches the lowest R_{ANO} values in most cases and owns more competitive robustness under various interferences compared with the other popular segmentation methods like reciprocal cross entropy method, active contour-based method, region growing method and level set method. Quantitative analysis verified the effectiveness of this method.

Conclusions: The proposed method can extract tooth pulp cavity regions from teeth efficiently. The segmentation results of this method are more accurate compared to other popular methods under different circumstances and can be used for subsequent applications.

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Introduction

After the formation of dentine, the volume of human tooth pulp cavity gradually shrinks as the age increases.¹ The significance of obtaining complete morphological volume parameters for applications such as age identification in clinical medicine and forensics is great. However, the pulp cavity is surrounded by dentine and in the root region, the pulp cavity is slender and narrow, which poses a major challenge for measuring

its volume using the traditional methods.² Likewise, the measurement of the pulp cavity volume in living bodies is limited. Therefore, obtaining the pulp cavity volume through tooth imaging combined with medical image processing approaches is a research hotspot.

Cone beam CT (CBCT) has shown much progress in three-dimensional (3D) imaging used for dental applications.^{3,4} It breaks through the limitation of volumetric CT that can only obtain two-dimensional (2D) images. By using 2D surface detectors to collect the complete morphology of teeth and other organizational tissues,

Correspondence to: Lei Wang, E-mail: arenchdlaam@163.com

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CBCT provides a new way for 3D imaging of tissue structures. It also lays the foundation of the 3D reconstruction and the volume measurement of tooth pulp cavity with its high spatial resolution and outstanding imaging quality. Thus, it is possible to measure the volume of pulp cavity by simply calculating the area of pulp cavity region in each slice and then integrate areas with image thickness to get the volume result by various methods.^{5,6} During this process, segmenting complete pulp regions is critical to the final results.

Medical image segmentation has shown great performance under the assistant of a variety of image segmentation methods. For instance, Wang *et al* proposed a fast and automatic algorithm based on Otsu's threshold segmentation theory to extract cerebral vessels from brain magnetic resonance angiography.⁷ Nakib *et al* combined exponential entropy with 2D histogram to do brain MRI segmentation in a fast mode, and the spatial information also remained.^{8,9} These threshold kind segmentation methods are easy to implement with good performance achieved, but still facing with the limitation of spatial information and complex structures. For this reason, some region-based and cluster-based methods are posed. Li *et al* applied active contour model to segment spine CT image by introducing energy function.¹⁰ Nagaraju *et al* introduced region growing method with an affinity-based model to reduce computational complexity, which reached promising performance on skull CT images.¹¹ Some other effective methods like fuzzy C-means and level set-based methods are also lead into the domain of medical image segmentation.^{12,13} Even though manual interaction is possibly required, these methods can also obtain well-performed segmentation results aiming at different kinds of medical images. Image segmentation for oral cavity has also shown much interest in recent studies.^{14–16} With the low resolution of a single tooth image slice, it requires quite a little bit of work to extract the pulp regions with a smaller proportion to the teeth. Due to the significant difference in grey levels between the tooth pulp cavity and the dentine tissues in the image, threshold-based segmentation methods seems more efficient. Among the popular threshold segmentation methods, the entropy-based threshold segmentation method is widely used in medical image processing due to its high segmentation accuracy.^{8,9,17} Kapur *et al* proposed an one-dimensional maximum entropy method based on the global histogram which attracts much attention.¹⁸ Subsequently, to fix the fault of computationally complex and zero-valued defects in the log entropy computation, Pal *et al* proposed an improved method that used exponential functions instead of logarithmic to represent entropy increasing.¹⁹ The interference problem of non-additive information in the image was not efficiently solved until Albuquerque replaced the Shannon entropy with non-generalized Tsallis entropy.²⁰ Later, Pal *et al* proposed a minimum cross entropy based on Gaussian distribution to achieve threshold segmentation of

dual-model and multimodel images.²¹ Wu *et al* proposed a line intercept histogram of reciprocal cross entropy method,²² which turned out to be a good approach to do threshold segmentation in multiple types of medical images. Additionally, the computational complexity is remarkably reduced when compared with other 2D cross entropy methods.

CBCT is widely used for investigation of diseases. But due to low radiation, images affected by noise and low contrast are not always fine for directly image processing business. Almost every research that deals with CBCT images has the same procedure that is to use image processing technology to eliminate such effects mentioned above, like image enhancement, image denoising, image filtering etc. Although these steps indeed improve image qualities, while interferences and some losses of details that human cannot directly observe are also emerged to affect the final results. This situation frequently shows when the image resolution becomes smaller. Thus, reduce such effects as much as possible is very important.

This study focuses on pulp cavity region segmentation in a single tooth. The tooth images are selected from a whole CBCT image so that the resolutions are rarely low. What's more, the exposure time of CBCT can directly affect the brightness and contrast of images. According to these attributes, threshold segmentation seems more plausible to handle this situation. In order to fully exploit the edge information of pulp cavity regions, this paper proposes a pulp cavity region segmentation method for CBCT images based on plane intercept histogram of reciprocal cross entropy.

Methods and materials

Data acquisition

CBCT images were obtained using NewTom VG (Quantitative Radiology, Verona, Italy), and the exposure parameters were 110kVp, 5.14–89.37 mAs. Based on clinical need, the field of view of images contains 6×6 cm, 8×8 cm, 12×8 cm, 15×12 cm, 15×15 cm. Acquired images were subsequently reconstructed with a voxel-size of 0.15 mm and formatted in the digital imaging and communications in medicine standard as a series of 16-bit grey scale. In this experiment, 50 teeth composed of incisors, canines, premolars and molars were randomly picked out from 10 patients. The data sets mentioned in this paper were agreed by patients. All test images are transformed into Bitmap (BMP) format and have the corresponding ground truth that the tooth pulp cavity regions were delineated manually by two doctors, which will be utilized as evaluation criteria at the end of segmentation by the proposed method. To test the reproducibility of the delineation procedure, 146 slices of images from five teeth were first delineated by doctor A and doctor B simultaneously. The same data was re-delineated by Doctor A 3 months later. The area of the delineated tooth pulp cavity in each

Figure 1 The flowchart of the whole segmentation scheme. The method executes in order from up to bottom. Firstly, select a single tooth from the whole CBCT image, and then, gamma transform is applied to enhance image contrast, followed by calculating neighbour average image and gradient image separately. After that, three kinds of images are added together to a mixed map, based on which an optimal threshold can be inferred. With the threshold, a binary map is generated by threshold segmentation. Finally, wiping out redundant borders and a clear pulp cavity region image appears. CBCT, cone beam CT.

slice was computed and compared to test the inter- and intraobserver reproducibility. The intraclass correlation coefficient is 0.985 for interobserver test and 0.980 for intraobserver test, which shows a good reproducibility.

The flowchart in [Figure 1](#) gives an overview of this segmentation method. When single tooth region is selected from the whole image, the first task is to enhance image contrast by using gamma transform,²³ followed by computing neighbour average image and gradient image separately. These two images combined with the grey image are pixelwise added to form a mixed map. Based on this map, a histogram can be inferred to find an optimal threshold. After the optimal threshold is discovered, the mixed map is converted to a binary image by comparing each pixel value in the map with the threshold. Eventually, all the undesired tissues with connectivity along the boundary of image are cleaned up and only the pulp cavity region is left. The doctor's manual segmentation results are used as evaluation

criteria for the proposed method. To show the effectiveness of the proposed method, some popular methods like reciprocal cross entropy method (RCE), active contour based method (AC), region growing method (RG) and level set method (LS) are introduced to conduct comparative experiments.

Plane intercept structure

To overcome the deficiency of simply using greyscale information for segmentation, the concept of 2D graph incorporating neighbour average greyscale information is proposed. In the 2D framework, different axis represents different threshold selection basis. When a point in the plane coordinate both satisfies the threshold of transverse and longitudinal axes, it is regarded as the target (or the background) point. This threshold selection method is also known as the regional division method.²⁴ As shown in [Figure 2\(a\)](#), the traditional region division method

Figure 2 Two kinds of regional division methods. (a) Is the traditional division method using two thresholds S and T to divide the coordinate into an object and background parts, denoted by O and B , shadows in (a) are the negligible noise and edges. (b) Is the oblique division method, a straight line k with slope one perpendicular to the diagonal line divides the coordinate into two part as in (a), only one threshold T is required.

considers that an image is divided into four regions representing the target, the background, the edges and the noise. In general, the noise and edge information are ignored. Therefore, an image requires two threshold $g(x,y)=S$, $f(x,y)=T$ to determine the target region and the background region denoted as O and B respectively. After that, the 2D graph oblique division theory is put forward.²² As shown in Figure 2(b), this theory deems that a straight line k with slope one perpendicular to the diagonal line can divide the image into target and background regions, where the noise and edge information in an image are also contained within. Noting that only one threshold is used in the greyscale axis $g(x,y)$ and neighbour average greyscale axis $f(x,y)$, which can be determined by the intercept histogram.

The edge information of the pulp cavity region is a critical factor for image segmentation. In order to fully exploit the role of edge information plays in the determination of image segmentation threshold, this paper involves gradient information of the image and fuses edge and greyscale information as the basis for threshold selection. To show the changes of edge pixel values after adding gradient information, pixel values covered by red line are selected in Figure 3(a) to plot a curve. The result of adding neighbour average greyscale and gradient compensation is shown in Figure 3(b). It can be found that the addition of gradient compensation can reduce the smoothness caused by adding neighbour average greyscale information and better restore the original greyscale trend of the image. Figure 3(c) shows the contrast of grey levels when gradient compensation is positive and negative. It is obvious that the grey level is closer to the original greyscale change of the image when the gradient compensation is negative. Thus, putting greyscale information, neighbour average greyscale information and gradient compensation together to form a 3D space, as shown in Figure 4. This space is a combination of the 2D plane of Figure 2(b) and a third axis $G(x,y)$ representing gradient compensation.

The entire space is divided into an object zone O and a background zone B by a plane α , in which grey value and the neighbour average grey value of point (x,y) is known as $g(x,y)$ and $f(x,y)$ respectively, also the gradient compensation is denoted as $G(x,y)$. T is the segmentation threshold in the 2D plane determined by greyscale $g(x,y)$ and neighbour average greyscale $f(x,y)$, and GT is the gradient compensation when the threshold is T ($GT < T$). For each threshold T , GT is a fixed value corresponding to it. Thus, the optimal segmentation plane α is only determined by T . finding an optimal plane α is equal to find the best threshold T , and the value T is determined by the straight line k in the 2D plane, namely $g(x,y) - f(x,y) = T - G(x,y)$. Every line k crosses through the dotted line v , so the number of such lines is $2L-1$, which means the threshold range is $T \in 1, 2, \dots, 2L-1$.

Gradient calculation

In order to further improve the contrast of images, this paper uses Gamma transform for pre-processing purpose. The gamma transform of an image is defined as

$$g_g(x,y) = 255 \times \left(\frac{g(x,y)}{255} \right)^{\gamma} \quad (1)$$

Where $g(x,y)$ is the pixel value at the point (x,y) , γ is the parameter that should be designed. In this study, the value of γ is settled to 2. $g_g(x,y)$ is the pixel value after gamma transform.

Calculate the gradient values of every point in both horizontal and vertical directions. Given a point (x,y) in an image of high N and width M , where $x \in \{1, 2, \dots, M-1, M\}$ and $y \in \{1, 2, \dots, N-1, N\}$, the gradient values of horizontal and vertical directions can be calculated by equation (2), denoted as $G_H(x,y)$ and $G_V(x,y)$ respectively. The final gradient of point $G(x,y)$ is a combination of gradient values in both directions, which can be derived by equation (3)

Figure 3 (a) Is the original image, take data covered by the red line in (a) to plot curves. (b, c) Are comparisons of different combinations of greyscale, neighbour average greyscale and gradient, represented by g , f and G respectively.

Figure 4 The space composed of greyscale (g), neighbour average greyscale (f) and gradient (G). A plane α in shadow divides the space into zone O (object) and B (background). Line k and threshold T are described in Figure 2(b). $-G_T$ is the corresponding gradient compensation of threshold T , so the plane α is only determined by T and $-G_T$.

$$G_H(x, y) = \begin{cases} \frac{g_g(x, 2) - g_g(x, 1)}{2} & Y = 1 \\ \frac{g_g(x, y+1) - g_g(x, y-1)}{2} & 1 < y < N \\ \frac{g_g(x, N) - g_g(1, N-1)}{2} & Y = N \\ \frac{g_g(2, y) - g_g(1, y)}{2} & X = 1 \\ \frac{g_g(x+1, y) - g_g(x-1, y)}{2} & 1 < x < M \\ \frac{g_g(M, y) - g_g(M-1, y)}{2} & x = M \end{cases} \quad (2)$$

$$G(x, y) = \sqrt{G_H(x, y)^2 + G_V(x, y)^2} \quad (3)$$

Where $G(x, y)$ is the gradient compensation in 3D space.

Threshold calculation and image segmentation

Due to the same threshold, T was used in both grey-scale and neighbour average greyscale axes and gradient compensation G_T is only determined by threshold T . A mixed map can be generated by adding a grey image, neighbour average image and gradient image together, denoted by

$$F(x, y) = f(x, y) + g(x, y) - G(x, y) \quad (4)$$

Note that the gradient image is $-G(x, y)$ as discussed in Figure 3c. With the mixed map, the best threshold can be found by calculating the corresponding histogram.

In the histogram, partition the mixed map with threshold T into part Ω_O and Ω_B , which means pixel value lower than T belongs to Ω_O , and the larger one belongs to Ω_B . These two parts represent the object region and background region respectively, as described in Equations (5) and (6)

$$\Omega_O = \{(x, y) | F(x, y) = 0, 1, \dots, T\} \quad (5)$$

$$\Omega_B = \{(x, y) | F(x, y) = T+1, T+2, \dots, 2L-2\} \quad (6)$$

Then, calculate the reciprocal cross entropy of object and background by equation (7), the derivation details can be inferred in the reference paper.²²

$$\eta(T) = \sum_{k=0}^T P(k) k \frac{1}{1 + \frac{k}{\mu_B(T)}} + \sum_{k=T+1}^{2L-2} P(k) k \frac{1}{1 + \frac{k}{\mu_O(T)}} \quad (7)$$

Where

$$\mu_B(T) = \frac{\sum_{m=0}^T P(m)m}{\omega_B(T)}, \omega_B(T) = \sum_{i=0}^T p(i) \quad (8)$$

$$\mu_O(T) = \frac{\sum_{n=T+1}^{2L-2} P(n)n}{\omega_O(T)}, \omega_O(T) = \sum_{i=T+1}^{2L-2} P(i) \quad (9)$$

$p(k)$ is the frequency of value k . $\eta(T)$ is the entropy between Ω_O and Ω_B , the aim is to find the best threshold T to make the entropy large enough. And the difference between object and background becomes the largest when the value of entropy reaches the highest. Thus, the best threshold can be obtained by maximizing the entropy function

$$\hat{T} = \underset{0 \leq T \leq 2L-2}{\operatorname{argmax}} \{ \eta(T) \} \quad (10)$$

Since the optimal threshold is discovered, the mixed map can be converted to a binary image based on the comparison of each pixel value with the threshold, as described in equation (11),

$$F(x, y) = \begin{cases} 1 & F(x, y) < \hat{T} \\ 0 & F(x, y) \geq \hat{T} \end{cases} \quad (11)$$

A binary image has the same size as the mixed map when the threshold segmentation is applied, the object region (pulp cavity region and other tissues) is bright and the background (dentine) is dark. Due to the tissues outside dentine are all bright and own an attribute of connectivity, they can be wiped out by the ergodic method. As shown in Figure 5(a), if a point is a foreground (number 1), and there exists at least one point around it (numbers 2–9) that also belongs to the foreground, these points make up a single connected domain. In Figure 5(b), the first point starts from the boundary of the image (number 1), through ergodic method all the points in the connected domain can be found and be wiped out by setting its value to the background, the clear result is shown in Figure 5(c). An example of clearing border is shown in Figure 5(d–e). As that is not the focus of this study, the function of *imclearborder* in Matlab Toolbox is used for convenience.

Results

This section will give a rigorous analysis of segmentation results by the proposed method in quantitative and qualitative manners, which starts with an analysis of the integrity of segmentation results. And then, the performance of segmentation will be quantitatively discussed under the criteria of R_{ANOVA} with respect to doctor's ground truth. All experiments are conducted in the Intel(R) Core(TM) i7 CPU 3.40 GHz, Memory 16 GB, Matlab R2016a.

Qualitative evaluation

Since the pulp cavity region has a similar grey level to the background region, the pulp cavity region can be

Figure 5 (a) Is the example of a connected domain, (b) is the concept of how connected domains in image border are cleared, search points of the connected domain in ergodic mode and set them as background. (c) Is the result after border cleared. (d, e) are the results before and after function *imclearborder*.

indirectly obtained by segmenting the dentine and the background. According to the difference of the way of segmentation, the segmentation procedure and results vary from accuracy and efficiency. Two instances of comparison by methods of RCE method, AC-based method, RG method and LS method are given as follows.

Figure 6(a) is the original image. Figure 6(b) is the result of AC. The active contour method requires a designed area to indicate the region of convergence. As the greyscale around the pulp region shares the similarity, it is hard to classify each pixel to a certain class completely. Thus, the segmentation result seems excessive compared with the original. So, as the result of LS in Figure 6(c), but it looks worse, more points around the pulp region are mis-segmented. Figure 6(d) is the result of RG, this method needs a seed point inside the pulp region, and expand this region with iterations. Thus, an optimal seed point is critical to the final result. Besides, this method is sensitive to the connected domain, if the greyscale of a point that lies on the process of expansion does not fit the expansion growing rule, the procedure stops and causes segmentation incomplete. As emphasized in the red box, the connected area is lost. Figure 6(e-f) are results by RCE and the proposed method. As shown in the red boxes, it's clear to see that

the segmented areas by RCE are incomplete, especially on the connection part of both sides of pulp regions, where a leakage segmentation phenomenon appears. Compared with the other methods, since the gradient information of the image is fused, the proposed method has a strong sensitivity with edges of regions so that the segmentation of the pulp cavity region stays good integrity with more details left. What's more, both sides of pulp regions present a plump shape while no redundant dentine tissues are confessed to pulp regions.

The red box marked region in Figure 7 is the tiny pulp chamber buried in the tooth. Seen from the original image in Figure 7(a), the pulp cavity region is small and the colour is light, but it also can be seen that the pulp region is not well-distributed. Like the results in Figure 6, both AC and LS in Figure 7(b-c) are oversegmented due to they are not good at dealing with the slightly shift inside the pulp cavity region, and make the shallower part mis-segmented. Pulp cavity region segmented by RG in Figure 7(d) is a little small and misses another part. Even though the results in Figure 7(e-f) by RCE and the proposed method are both properly segmented, the pulp cavity region by the proposed method is much closer to the original. Focusing the boxes marked with blue in Figure 7(b-c, e-f), the boundary of the pulp cavity region segmented by the proposed method is

Figure 6 (a) Is the original image. (b~f) Are images segmented by AC, LS, RG, RCE and the proposed method. AC, active contour; LS, level set; RCE, reciprocal cross entropy; RG, region growing.

Figure 7 (a) Is the original image. (b~f) Are images segmented by AC, LS, RG, RCE and the proposed method. AC, active contour; LS, level set; RCE, reciprocal cross entropy; RG, region growing.

Figure 8 Comparison of R_{ANO} of fifty teeth from ten patients under the ground truth of Doctor A

more sleek and clear, which proves that fusing gradient information can efficiently correct the fuzzy boundaries caused by neighbour averaging. The proposed method can reduce the occurrence of burrs after segmentation and preserves the pulp cavity region boundary information of the original image as much as possible.

Quantitative evaluation

In order to further assess the segmentation accuracy of the proposed method, a quantitative evaluation was carried out with the criteria of R_{ANO} , which is known as the rate of the average non-coincidence area. This rate is proposed to evaluate how much the pulp area generated by the proposed method keep coincident with the doctors' ground truth; this criterion is defined as

$$R_{ANO} = \sum_{i=1}^N \frac{|A_a(i) - A_d(i)|}{A_d(i)} \quad (12)$$

Where N is the number of image slices, the areas of pulp region segmented by proposed method and doctors are denoted as $A_a(i)$ and $A_d(i)$ respectively, and i means the slice serial number. From the equation, we can know that the better accuracy algorithms can achieve when the R_{ANO} values are lower. All images of fifty teeth were involved in doing the evaluation experiment, and the results are shown in Figures 8 and 9, which are classified by different doctors.

In the above two figures, the transverse and longitudinal axes represent each tooth index and its corresponding R_{ANO} value. The red curves in two figures both

Figure 9 Comparison of R_{ANO} of 50 teeth from 10 patients under the ground truth of Doctor B.

Table 1 Variances of R_{ANOVA} values across 50 teeth under different methods and doctors

Doctors	Proposed	RCE	AC	RG	LS
A	0.0043	0.0378	0.0384	0.1271	0.0362
B	0.0038	0.0407	0.0388	0.1366	0.0287

AC, active contour; LS, level set; RCE, reciprocal cross entropy; RG, region growing;

show that the proposed method has a good adaptation to the range of contrast and brightness of images. Specifically, these fluctuations are usually caused by the different exposure time of CBCT. In order to better illustrate the generality of the algorithm, the variance of R_{ANOVA} values across 50 teeth is introduced to measure the adaptation of the method under various interference factors. The comparison details are listed in Table 1. Seen from the table, the proposed method reaches the lowest variance under the standards of two doctors. There remain distinct gaps between the proposed method and the other popular methods, indicating that the proposed method shows more strictly robustness to the different kinds of cases. On the contrary, the other methods are sensitive to these disturbance factors, because only greyscale is taken into consideration. What's more, the proposed method reaches the lowest R_{ANOVA} values in most tooth samples, and that is identical beyond different doctors. The proposed method combines image gradient to enhance the edge information reduced by the neighbour averaging, making the areas of pulp cavity similar to doctors' ground truth as much as possible. The lowest R_{ANOVA} values also prove that only a tiny portion of pulp region is lost, and these results can take the place of doctors' manually results to a certain extent.

Discussion

This study focuses on threshold selection in image segmentation, also illustrates how the aggregation of gradient information illuminates the segmentation results. The key point of restoring the details of the original image is that the addition of gradient is in the form of negative compensation, which has been discussed before. Mostly, gradients in an image are always neglected.^{25–27} Not than that, a number of methods deal with images with noise reduction and filtering, which contributes to the losses of edges and details, causing the objects to appear in unsaturated shapes.

A variety of methods are proposed to fit the certain problems. In another word, according to the attribute of images, it is necessary to find a suitable method for processing. Due to the low resolution of a single tooth, the methods like AC, RG and LS that have spatial consideration seems to have less advantage, because the pulp region is too small so that the generated connected domain cannot be robust, which means that one or two noise points could affect the searching process. Among the three methods, AC generates more reliable results than the other two methods because of the constraint of the energy equation, albeit accurate, it requires an

iterative operation to calculate the results. So, as the RG and LS methods, segmentation performance is dependent upon the number of iterations. Thus, the three methods are not efficient when dealing with images of high resolution.

Depending on the resolution and scale of tooth images, threshold segmentation is more reliable to realize accurate and efficient segmentation. The segmentation process is automatic when parameters are determined, all slices share the same parameter and no more reduplicated setting are needed. Compared to the methods of AC, RG and LS, all three methods require to manually specify a rectangle or a seed point related to the pulp region on every slice, which is time consumption. Besides, the manual action on an identical slice at each time may conduct different results. Thus, when processing with repeated segmentation, threshold segmentation is superior to others.

The pre-condition that ensures the proposed method works is that both pulp cavity region and background share the same grey level, explaining it with another point of view is that segmentation is done based on dividing the dentine region from pulp region and background. If there exists an obvious difference between the grey level of the pulp cavity and background or the area of the pulp cavity region is too small, the proposed method is not feasible. Although gamma transform has improved the contrast between them, there still remain some flaws, which are common in canines and incisors, but this phenomenon is not universal.

With the small resolution of the test images, the runtime of the proposed method is short to almost negligible. When handling segmentation of lots of slices, this method can be more efficient if the parameters are properly determined, and the results can be comparative. While, it seems plausible if human intervention was required to settle failure cases, and that would be discussed in the further studies.

Conclusion

This paper proposed an image segmentation method used for tooth pulp cavity region extraction. After qualitative and quantitative evaluations, this proposed method can segment pulp cavity regions precisely and completely. Under the criteria of doctors' ground truth, the results segmented by this method can be used for further research and meet the clinical needs; *e.g.* 3D reconstruction, volume measurement and age estimation.

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