A Hybrid Segmentation Framework for Computer-Assisted Dental Procedures

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SUMMARY Teeth segmentation in computed tomography (CT) images is a major and challenging task for various computer assisted procedures. In this paper, we introduced a hybrid method for quantification of teeth in CT volumetric dataset inspired by our previous experiences and anatomical knowledge of teeth and jaws. In this regard, we propose a novel segmentation technique using an adaptive thresholding, morphological operations, panoramic re-sampling and variational level set algorithm. The proposed method consists of several steps as follows: first, we determine the operation region in CT slices. Second, the bony tissues are separated from other tissues by utilizing an adaptive thresholding technique based on the 3D pulses coupled neural networks (PCNN). Third, teeth tissue is classified from other bony tissues by employing panorex lines and anatomical knowledge of teeth in the jaws. In this case, the panorex lines are estimated using Otsu thresholding and mathematical morphology operators. Then, the proposed method is followed by calculating the orthogonal lines corresponding to panorex lines and panoramic re-sampling of the dataset. Separation of upper and lower jaws and initial segmentation of teeth are performed by employing the integral projections of the panoramic dataset. Based on the above mentioned procedures an initial mask for each tooth is obtained. Finally, we utilize the initial mask of teeth and apply a variational level set to refine initial teeth boundaries to final contour. In the last step a surface rendering algorithm known as marching cubes (MC) is applied to volumetric visualization. The proposed algorithm was evaluated in the presence of 30 cases. Segmented images were compared with manually outlined contours. We compared the performance of segmentation method using ROC analysis of the thresholding, watershed and our previous works. The proposed method performed best. Also, our algorithm has the advantage of high speed compared to our previous works.

key words: teeth segmentation, PCNN, panorex line, panoramic projection, variational level set

1. Introduction

Teeth are the hardest tissues in the human body and one of the most important anatomical structures in the face. Teeth arrangement is essential in face ergonomics and health. Healthy teeth have critical roles in mastication, phonetics and esthetics [1].

In modern dentistry, computer-assisted procedures such as surgical preoperative planning, intra-operative navigation and post-operative assessments in common clinical procedures such as tooth restoration, mechanized dental implants, orthodontic planning and orthognathic surgery are getting more attention day by day. The need for automation these procedures is currently rising due to the growing public awareness of the role of teeth and the financial crisis in public health care in many countries.

Accurate knowledge of the 3D shape and structure of each tooth, arrangement of teeth with respect to each other and the location of the roots in the mandible and maxilla is very important in many maxillofacial surgical applications, endodontic procedures and treatment simulations [2]–[7]. The 3D tooth model in which each tooth can be manipulated individually is an essential component for the simulation of maxillofacial surgery and treatment.

Various computer-assisted procedures for medical application in quantitative dentistry require automatic segmentation and volumetric visualization of teeth. An important image processing technique used in providing a realistic 3D tooth model is segmentation of teeth from computed tomography (CT) images.

Several authors have reported different techniques for teeth segmentation in conventional dental radiography such as panoramic, perapical and bitewing images. In [8], a semi-automatic tooth contour extraction method based on integral projection and Gaussian mixture model was proposed. The approach in [9] was based on applying morphological operators and adaptive thresholding to separate each tooth from its surroundings. In [10], iterative thresholding followed by adaptive thresholding is used to segment teeth from background. The watershed algorithm was utilized in [11] to find orthodontic feature of teeth from 3D profile of dental images of imprints. In [12], a method based on the pulse coupled neural network (PCNN) was introduced to perform segmentation of teeth and other bony tissues by an adaptive thresholding technique. In [13], segmentation based on active contours for low-contrast radiographs was described. In [14], the teeth contour was extracted by employing active contour with gradient directional models. The active contour without edge was utilized in [15] to trace the teeth contour.
In [16], [17], a variational level set segmentation technique for computer aided dental X-rays analysis was proposed. In [18], a hybrid technique based on pathological modeling, principal component analysis (PCA) and support vector machine (SVM) was presented for teeth segmentation.

To our knowledge, segmentation of dental images, particularly in CT volumetric dataset have not adequately been studied in the previous works. An image segmentation algorithm based on B-spline curve fitting to produce smooth tooth regions from such CT slices was proposed in [19]. The proposed algorithm prevented the mal-fitting problem of the B-spline algorithm by providing accurate initial tooth boundary for the fitting process. This technique proposed an optimal threshold scheme using the intensity and shape information obtained by previous slice for the initial boundary generation and an efficient B-spline fitting method based on genetic algorithm. In [20], the teeth were segmented interactively based on curvature values of the triangle mesh. These feature points are connected to feature regions for extracting feature lines from these regions. Therefore, feature contour can be obtained with the help of user supplied information. Using feature contour, the tooth are segmented individually. In [21], a semi-automatic method for drawing the contours of teeth in dental CT images was proposed. First of all, a reference slice from CT slices was selected and carried out tooth segmentation interactively based on shape characteristic of each tooth. The dental CT images have the following distinct characteristic: in two neighboring CT slices, the size, location and intensity of corresponding tooth are very similar, so the bounding box of the tooth whose contour has been drawn onto the next slice as the operation region of corresponding tooth is projected. Then, the segmentation operation is performed tooth by tooth in the operation region based on the region growing algorithm using the information passed from the previous slice. With the reference slice as the starting slice, the tooth segmentation was carried out slice by slice automatically.

In the area of segmentation, manual segmentation is not only a tedious and time consuming process, it is also often unfeasible and inaccurate. Segmentation by experts is variable up to 20% [22]. Also, conventional approaches, such as global thresholding that employed in most existing 3D reconstruction systems, are not adequate for segmentation of teeth in CT images. Therefore, computer-based automatic segmentation methods that are accurate and require as little user interaction as possible are desirable for fully exploiting medical data.

The aim of this paper is to introduce an efficient approach that can be potentially used in segmentation and 3D visualization of teeth. In the previous work [23], we introduced a multi-step method based on the level set for teeth segmentation of CT images. In addition, we proposed a new technique based on panoramic re-sampling and variational level set for teeth segmentation in CT volumetric data in [24], [25]. In this research, inspired by our previous experiences, considering the imaging constraint of dental CT and anatomical knowledge of teeth and jaws, we propose a hybrid technique for teeth segmentation in multi-slice computed tomography (MSCT) dataset. Also, we develop a novel metal artifact reduction (MAR) algorithm.

The rest of this paper is organized as follows. In Sect. 2, the proposed techniques are given in details. Experimental results are mentioned in Sect. 3. In Sect. 4, we clarify the practical aspects of the proposed algorithms, i.e. the benefits and the limitations. The paper ends with concluding remark and future steps made in Sect. 5.

2. Materials and Methods

In this section, we describe the dataset and proposed technique in details. Dentistry requires several accurate assessments such as 3D measurements and representation of the teeth and jaws for diagnostic and treatment purposes. In the last decade, CT has become the most frequently used imaging modality to provide clinical datasets for dental practitioners and maxillofacial surgery. Teeth data might be acquired by conventional CT scanners and/or cone beam computed tomography (CBCT) imaging system [26]. Recently, the flat panel volumetric computed tomography (fpVCT) is a new CBCT device applicable to improve resolution in the imaging of human maxillofacial region [27].

In this study, teeth volumetric data were acquired by a SIMENS CT-SOMS SPI System (CT SIMENS Sensation 64). CT images are acquired with a DICOM 3.0 Protocol, generally with 512 × 512 pixel resolution, 16 bit depth (grayscale), 1 mm slice thickness and 0.8 mm inter-slice distance. Images were taken under the exposure condition of 120 kV (X-ray tube voltage) and 81 mA (X-ray tube electric current). As shown in Fig. 1, these datasets were taken from 30 different individuals, ranging in age from 21 to 73 years of age. The available datasets have been of different dental structures, shapes and sizes.

We propose a hybrid approach for teeth segmentation and visualization in CT volumetric dataset. Major steps of the proposed techniques are as follows: (1) Localization of operation region in CT images; (2) Bonny tissue classification in CT dataset; (3) Teeth tissue classification in CT dataset; (4) Localization of each tooth in the panoramic projection of CT images; (5) final segmentation of teeth in volumetric CT dataset; (6) 3D visualization of teeth in CT im-

![Fig. 1](image-url) The age distribution of the datasets: 30 different individuals, ranging in age from 21 to 73 years of age, were selected in this research.
The proposed method is summarized in Fig. 2. After obtaining the cropped images, bony tissues are classified from non-bony tissues by a novel adaptive thresholding technique based on the 3D pulses coupled neural networks (PCNN). The panorex lines of the upper and lower jaws then estimated by employing Otsu thresholding and by many mathematical morphology operators. Subsequently, the teeth are segmented from other bony tissues by utilizing panorex lines and anatomical knowledge of teeth in the jaws. The proposed method is followed by calculating the orthogonal lines corresponding to panorex lines and panoramic re-sampling of the dataset. Separation of upper and lower jaws and initial segmentation of teeth are performed by employing the horizontal and vertical projections of the panoramic dataset, respectively. In this case, an initial mask for each tooth is obtained. Then, we relocate the initial mask on the original dataset and apply the variational level set algorithm to refine each initial boundary to the final tooth contour. Finally, a surface rendering algorithm is applied to the classified slices for the purpose of volumetric visualization. Details are given in the rest of this section.

2.1 Localization of Operation Region in CT Images

In dental CT images, in addition to teeth, other bony structures such as maxilla, mandible, and cervical vertebral are also visible. As long as, the CT images were performed in standard clinical conditions, we first determine the operation region which is included teeth tissues for reducing calculation and increasing process speed. In this case, a slice that contains most teeth tissues and higher intensity value is selected.

We have cropped the size of the original input images to $256 \times 256$ pixels. An enclosing rectangle that tightly fits the $256 \times 256$ area is constructed for selected slice. A point inside this rectangle is called the Center “C”. The distance of C to the top of the original image is one third the length of image, and the distance of C to the other two sides of original images are equal. Therefore, the position of C in selected slice is $(256, 170)$. Then we crop this slice and others. By this, we will have images which include teeth and jaws regions. Typical teeth CT images and the result of cropped images are shown in Fig. 3.

2.2 Bony Tissue Classification in CT Dataset

In cropped images, there is a distinctive difference between the intensity level of the bony tissues and other structures (background and soft tissue). We separate bony tissues from non-bony tissues in CT images by applying a novel adaptive thresholding technique based on the 3D pulses coupled neural networks (PCNN) [12].

A pulsed coupled neural networks is a single layered, two dimensional, laterally network of pulse coupled neurons. The network groups the images pixels based on the spatial proximity and brightness similarity. In the previous works, the PCNN was employed for image processing applications including image smoothing, segmentation and
feature extraction [28], [29]. As we will explain in Sect. 4, finding an appropriate threshold value for classification of bone from other CT tissues fails in most cases. Therefore, we have used a novel PCNN for adaptive thresholding of CT data. Block diagram of one neuron of the PCNN is given in Fig. 4 (a). A typical CT images and result of separation of bony tissues is given in Fig. 4 (b) and (c), respectively.

2.3 Teeth Tissue Classification in CT Dataset

It is known that the shape, size and location of each tooth in different axial slices of CT images might be different. In addition, shapes of teeth are different from each other. In order to find an initial contour for teeth, we have estimated the dental arc or panorex lines [4] of the upper and lower jaws. Dental arc formation and alignment of the individual teeth, and their contacts with those in the opposing arc are the most important elements.

The CT images have been extracted in open-bite condition. In this case, finding a slice that does not include teeth is a simple matter and we can separate the upper and the lower jaws from each other. We have estimated an initial panorex line of each jaw by employing the slice that contains most teeth tissues. In the lower jaw, several middle slices only contain teeth. We have used these slices to establish an initial panorex line for the lower jaw to follow the operations.

As shown in Fig. 5, the axial image is initially binarized with an adaptive thresholding such as Otsu’s thresholding [30] with hysteresis in order to extract the foreground object, i.e. the anatomic structure. Then, morphological operations [31] are cascaded to extract the interest panorex line. A closure operator, provided by a number of dilation operators followed by the same number of erosion operator with a window $3 \times 3$ structural element is provided. For filling the teeth gaps and obtaining a smoothing line, morphology processing followed by dilation is employed. Eventually, if necessary a further filling operation is done. Finally, a process of thinning is provided, that iteratively searches for the locus of the points that are equi-distant to the teeth border. The final set of points is shown in the fifth image of Fig. 5. Finally, the line is quantized, coded with chain code [32] and represented by a B-spline [33] if it is necessary.

By the result obtained in Sect. 2.2, panorex lines and knowledge of teeth in the jaws, teeth structures are separated from other bony structures in the operating region as well. A typical result is shown in Fig. 6.

2.4 Localization of Each Tooth in the Panoramic Projection of CT Images

Although the techniques proposed in Sects. 2.2 and 2.3 are effective to segment the bony tissues from other tissues, seg-

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Footnotes:

1) We use same slice that was employed to define the operation region.
2) Procedures for obtaining the arc of the upper jaw can be conducted in a similar manner.
3) For obtaining a smooth panorex line, we employ 2 to 4 number dilation operator.
dentation of teeth from each other is a serious challenge. When automatic panoramic lines is computed, the orthogonal lines corresponding to the panoramic lines then calculated.

The volumetric CT data are re-sampled with respect to these orthogonal lines. We perform the panoramic image of the dataset by coronal projection of the re-sampled data [25]. In the available datasets, due to symmetry of upper and lower jaws, the whole upper and lower teeth are visible in the panoramic images. Results are shown in Fig. 7 (a), (b) and (c), respectively.

If we can separate the panoramic image into blocks, where each block contains only one tooth. It helps us to define an initial ROI associated with each tooth [9], [10]. The initial separation between the upper and the lower jaws in panoramic image is made by calculating the lowest intensity in the horizontal projection. Due to open bite constraint during data acquisition, it is possible to separate the upper jaw from the lower jaw by a straight line. The integral projection along that line will be minimized as follows:

\[ H(x) = \sum_y I(x, y) \]  

where the \( I \) is the original image.

The method to separation each tooth from its neighbors is similar to the method to separate the lower and the upper jaws. The goal is to find the lines that separate adjacent teeth. This can be achieved by using the integral projection method in the vertical direction. Due to different teeth alignment, the lines are not always vertical or parallel. Therefore, we rotate the image in a small range of angles, e.g. \([-30:30]\), and calculate the vertical projection for each angle in this range. Where the \( I' \) is the original image rotated by \( \theta \), \( y \) and \( \theta \) together determine the minimum vertical lines.

\[
\begin{align*}
V(\theta, y) &= \sum_x I'(x, y) \\
\theta, y &= \text{argmin}_{\theta, y} V(\theta, y)
\end{align*}
\]

Figure 7 (d) shows the detected separating lines overlaid over the panoramic image.

2.5 Final Segmentation of Teeth in CT Dataset

Since active contour model was first proposed in [34], has been widely studied and used in the field of image processing and computer vision. Active contours are curves that deform within digital images to recover object shapes. They are classified as either parametric active contour models [35] or geometric active contour models [36] according to their representation and implementation. In particular, parametric active contours are represented explicitly as parameterized curves in a Lagrangian formulation. Geometric active contours are represented implicitly as level sets of two dimensional distance functions which evolve according to an Eulerian formulation [37]. They are based on the theory of curve evolution implemented via level set techniques [38]. Level set method provides an alternative solution to energy minimization-based image segmentation problem. The level set methods have been extensively used in medical image segmentation due to its ability to capture the topology of shapes in medical imagery. Level set method based on edges is driven by the derivatives of image intensities. Mathematical formulation of level set is explained as follow:

Let \( \Omega \) be a bounded open subset of \( \mathbb{R}^2 \) with \( \partial \Omega \) as its boundary. Let \( U_0 : \Omega \to \mathbb{R} \) be a given image, and \( C : [0, 1] \to \mathbb{R}^2 \) be a parameterized curve. The curve \( C \) is represented implicitly via a Lipschitz function \( \phi \) by \( C = \{(x, y) \mid \phi(x, y) = 0\} \), and the evolution of the curve is given by the zero-level curve at time \( t \) as the function \( \phi(x, y, t) \). Evolving the curve \( C \) in normal direction with speed \( F \) leads to differential equation

\[
\begin{align*}
\frac{\partial \phi}{\partial t} &= |\nabla \phi| F, \\
\phi(x, y, 0) &= \phi_0(x, y)
\end{align*}
\]

where the set \( C = \{(x, y) \mid \phi_0(x, y) = 0\} \) defines the initial contour. A particular case is the motion by mean curvature, when \( F = \text{div} \left( \frac{\nabla \phi}{|\nabla \phi|} \right) \) is the curvature.

In many dental CT slices, the gradient between the teeth and other bony tissues is not prominent and, hence, such techniques will not be able to accurately extract the
tooth contour. To address this limitation, we utilized a variational level set method. The variational level set method, which derives the level set function by energy minimization, was first proposed by Zhao et al. [39] and is now a very popular approach for image segmentation. Due to the energy minimization, the variational level set method naturally segments the image according to the energy functional. Due to this characteristic, a variational level set method is able to detect a boundary. Moreover, the variational level set method is very robust to noise, which presents serious challenge to many traditional image processing techniques, such as segmentation and feature detection.

Zhao et al. [39] proposed a coupled level set method for the motion of multiple junctions, e.g., of solid, liquid, and grain boundaries. They utilized an energy functional consisting of surface tension (proportional to length) and bulk energies (proportional to area) as shown in Eq. (6). This approach combines the level set method with a theoretical variational formulation. Assume there are disjoint regions \( \Omega_i \) (1 \( \leq i \leq n \)) in the image. The common boundary between \( \Omega_i \) and \( \Omega_j \) is denoted as \( \Gamma_{ij} \). Zhao et al.’s function can be expressed as

\[
\inf\ E = \sum_{1 \leq j \leq n} f_{ij}\text{Length}(\Gamma_{ij}) + \sum_{1 \leq j \leq n} v_i \times \text{Area}(\text{inside}(C_i))
\]

(4)

The level set function is expressed as

\[
\begin{align*}
\frac{\partial \phi}{\partial t} &= |\nabla \phi| \left( y \cdot \text{div} \left( \frac{\nabla \phi}{|\nabla \phi|} \right) - \varepsilon \right) \\
- \lambda \left( \sum_{i=1}^{n} H(\phi_i) - 1 \right),
\end{align*}
\]

(5)

\[
\frac{\partial \phi}{\partial n} = 0 \text{ on } \partial \Omega
\]

where \( n \) denotes the exterior to the boundary \( \partial \Omega \), and \( \partial \phi/\partial n \) denotes normal derivative of \( \phi \) at the boundary.

We employ a novel variational level set technique based on Chan et al. [40], [41] proposed for image segmentation. They proposed a Mumford-Shah function for variational level set segmentation [42]. They add a minimal variance term \( E_{MV} \). This model is able to detect contours with or without a gradient. Objects with smooth boundaries or even with discontinuous boundaries can be successfully detected. Moreover, the model is robust to the position of the initial contour. The 2D version of the model can be expressed as

\[
\inf_{(c_1,c_2)} E = \mu\text{Length}(C) + \nu \text{Area(Inside}(C)) + E_{MV}
\]

(6)

with

\[
E_{MV} = \lambda_1 \int_{\text{inside}(C)} (u_0(x,y) - c_1)^2 \, dx \, dy + \lambda_2 \int_{\text{outside}(C)} (u_0(x,y) - c_2)^2 \, dx \, dy,
\]

(7)

where \( C_i \) are the averages of \( u_0 \) inside and outside \( C \), and

\[
\mu \geq 0, \nu \geq 0 \text{ and } \lambda_i \geq 0 \text{ are fixed parameters. The level set function they obtain is given by}
\]

\[
\begin{cases}
\frac{\partial \phi}{\partial t} = \delta_{c}(\phi) \left[ \mu \cdot \text{div} \left( \frac{\nabla \phi}{|\nabla \phi|} \right) - \nu \\
- \lambda_1 (u_0(x,y) - c_1)^2 + \lambda_2 (u_0(x,y) - c_2)^2 \right] \\
\phi(x,y,0) = \phi_0(x,y) \text{ in } \Omega,
\end{cases}
\]

(8)

where \( n \) denotes the exterior to the boundary \( \partial \Omega \), and \( \partial \phi/\partial n \) denotes normal derivative of \( \phi \) at the boundary and \( \delta_c \) is the Dirac delta function. In order to solve this partial differential equation, we first need to regularize \( H_c(\phi) \) and \( \delta_c(\phi) \). Chan and Vese propose:

\[
\begin{cases}
H_c(\phi) = \frac{1}{2} + \frac{1}{\pi} \arctan \left( \frac{\phi}{\varepsilon} \right),
\delta_c(\phi) = \frac{1}{\pi} \frac{\varepsilon}{\varepsilon + \phi^2}.
\end{cases}
\]

(9)

It is easy to see that as \( \varepsilon \to 0, H_c(\phi) \) converges to \( H(\phi) \) and \( \delta_c(\phi) \) converges to \( \delta(\phi) \)

\[
H(\phi) = \begin{cases}
1 \text{ if } \phi \geq 0 \\
0 \text{ if } \phi < 0
\end{cases},
\]

(10)

The Chan and Vese function is very good for segmenting an image into two regions. We employ the initial boundaries performed in Sect. 2.4 to estimate the final contour of each tooth. In this regard, the estimated vertical lines in the panoramic images that separate teeth from each other are equivalent to the volume of interest (VOI) in the original CT data. Hence, the VOI associated with each tooth can be relocated in the original CT volume. We apply the variational level set to relocate initial contours to the final teeth masks. Results are demonstrated in Fig. 8.

2.6 Metal Artifact Reduction (MAR)

In X-ray computed tomography, artifacts are any discrepancy between the CT numbers represented in the image and the expected CT number based on the linear attenuation coefficient. Metal streak artifacts are the most common distortions or errors that affect the quality of CT images. Metal artifacts are caused by the presence of high density objects.
(usually made of metal), such as dental fillings. They appear as a streaking effect on an image. The primary reason that streaks occur from metal objects is because the objects exceed the maximum attenuation value that a CT system can image [43]. Attempts to reduce these streaks are commonly referred to as metal artifact reduction (MAR). Several researchers have tried to remove metal streak artifacts using various approaches, which are most based on the assumption that measured data affected by metal objects are useless for the reconstruction. These ‘corrupt’ data are either ignored or replaced by synthetic data [44].

In our opinion, to addressing this problem, the slices with metal artifacts are selected based on their high intensity values. A Butterworth low pass filter, i.e., \[ H(u, v) = \frac{1}{1 + \left(\frac{D(u,v)}{D_0}\right)^n} \] is then applied to corresponding slices in the dataset. The order of the filter \( n \) and cutoff frequency \( D_0 \) are selected as 5 and 2\%, respectively. In some other slices however, the above mentioned technique itself would not produce acceptable results. As seen in second column of Fig. 9, when artifact is severe, artifact line still remain unsolved. As artifact lines often appears as thin straight lines in dental CT images, we employed a morphological erosion followed by opening on gray CT images to reduce the artifact. In this case, we utilized a data element with a shape similar to that of a straight line to remove the artifact lines in the image. We then generate a binary mask and apply a size filter to remove remaining noise originated from artifacts in the background region. The proposed MAR algorithm and typical results of MAR are given in Fig. 9.

2.7 3D Visualization of Teeth in CT Images

Visualization plays an important role in the diagnostic and treatment process. In previous works[24], [25], the segmented teeth were visualized by MEDAL software [45]. In this research, a surface rendering algorithm is applied to the classified slices for the purpose of volumetric visualization. For surface rendering of segmented teeth and jaws, we used an algorithm, called Marching cubes (MC) that creates triangle models of constant density surfaces from 3D medical data [46], [47]. Using a divide-and-conquer approach to generate inter-slice connectivity, a case table that defines triangle topology is created. In this algorithm, we first specify a threshold value. For this value, some voxels will be entirely inside or outside the corresponding iso-surface and some voxels will be intersected by the iso-surface. In the first pass of the algorithm, the voxels that are intersected by the threshold value are identified. In the second pass these voxels are examined and a set of one or more polygons is produced, which are then output for rendering. Marching Cubes is an algorithm for rendering iso-surfaces in volumetric data. The basic notion is that we can define a voxel (cube) by the pixel values at the eight corners of the cube. If one or more pixels of a cube have values less than the user-specified iso-value, and one or more have values greater than this value, we know the voxel must contribute some component of the iso-surface. By determining which edges of the cube are intersected by the iso-surface, we can create triangular patches which divide the cube between regions within the iso-surface and regions outside. By connecting the patches from all cubes on the iso-surface boundary, we get a surface representation. The teeth that were segmented according to the proposed algorithm in Sect. 2.5 are visualized via the mentioned marching cube technique in Fig. 10.

3. Experimental Results

CT scans were performed on a SIEMENS CT_SOM5 SPI. The proposed technique was evaluated in the presence of 30 multi-slice CT dataset including 3600 images. The algorithm was implementation on Matlab R2006a environment [48]. We employed three measures of successful, acceptable and failed for assessment of the techniques presented in Sect. 2.4. In this regard, True positive (TP), false positive (FP), false negative (FN) and true negative (TN) were calculated as follows:

- TP pixels \( P_{TP} \): correctly segmented teeth tissues,
- FP pixels \( P_{FP} \): non-teeth tissues recognized as teeth tissues due to the failure of the technique,
- FN pixels \( P_{FN} \): missed teeth tissues,
- TN pixels \( P_{TN} \): correctly separated non-teeth tissues.

Success rate of separation technique was computed by: 
\[ SUCCESS = \frac{P_{TP}}{P_{TN}} \times 100; \] Error was determined by: 
\[ ERROR = \frac{P_{FP} + P_{FN}}{P_{TN}} \times 100; \] separation performance was classified into one of the three classes nominated as successful, acceptable and failed as follows:

![Fig. 9](image-url) Metal artifact reduction (MAR) algorithm.

![Fig. 10](image-url) 3D visualization of teeth in the upper and lower jaws. Several views are.
The proposed separation technique was applied to 30 reconstructed panoramic images from CT dataset which contains 804 teeth. It always correctly separates the upper jaw from the lower jaw for all the images. Summary of the results for separation individual teeth are shown in Table 1\textsuperscript{1}. In several cases, bones were considered as part of the tooth because of inaccurate segmentation. In this stage, the user may delete redundant segmentation lines and add missed segmentation lines before next operations.

As discussed in Sects. 2.4 and 2.5, the tooth contours performed by panoramic re-sampling were employed as initial boundary for the variational level set. We used the results of proposed method by applying connected component analysis using 8-connectivity to extract the external contour of each individual tooth in image. Final boundaries of teeth after applying the variational level set are illustrated in Fig. 11.

In order to validate the proposed method, manual segmentation of teeth datasets were performed by an expert. The manual segmentation was regarded as gold standard in the rest of operations. We utilized the several common performance measures of the proposed method were calculated. Table 2 shows the equations of sensitivity, specificity, precision, accuracy and mean error rate that can be calculated. For this purpose, the true positive ($P_{TP}$), false positive ($P_{FP}$), true negative ($P_{TN}$) and false negative ($P_{FN}$) values were computed, where $P_{TP}$ and $P_{TN}$, $P_{FP}$ and $P_{FN}$ are correct, false and missed pixels, respectively.

The results of assessment for 25 randomly selected datasets are depicted in Table 3. Table 4 shows these parameters for the proposed method and also for other algorithms proposed in the literature for 30 datasets.

Another parameter which is used for evaluation of the proposed algorithm is the receiver operating characteristic (ROC) curve\textsuperscript{49}, which is more accurate than the two conventional segmentation techniques including thresholding, watershed, and two previous works\textsuperscript{23},\textsuperscript{25}. This is illustrated in Fig. 12. The vertical axis is associated with Sensitivity and horizontal axis is associated with 1 – Specificity, where Sensitivity and Specificity are defined in Table 2. The sensitivity for a class is the percentage of members of that class that are correctly classified by the test. As such, it has to be as high as possible. The specificity for a class is the percentage of members of the other classes that are correctly classified by the test. The area under the ROC curve (AUC) is a reasonable performance statistic for classifier systems. The value of AUC for proposed method is equal to 0.979.

In Fig. 13 comparison of teeth area for every slice in a dataset, by both manually and proposed method are shown. Comparison of volume measurements of both manual and proposed method segmentations are shown in Table 5. To find volume of teeth, area of each slice is calculated by counting number of pixels included the segmented region and then multiplied by pixel spacing. These areas are summed up and multiplied by CT slice thickness yielding the total volume\textsuperscript{50}.

The results of volume measurement error for five randomly selected datasets are illustrated in Table 6\textsuperscript{11}. This parameter was evaluated for each class of teeth. Also, volume

\begin{equation}
\text{Volume Measurement error} = \left| \frac{\text{Volume}_{\text{automatic}}}{\text{Volume}_{\text{manual}}} - 1 \right| \times 100\%
\end{equation}

\textsuperscript{1}\text{The Adult dentition contains 32 teeth, 16 teeth in each jaw. We divide the two jaws into four equal quadrants that each quadrant contains eight teeth, two incisors, one canine (cuspid), two premolars (bicuspids), and three molars.}

\textsuperscript{11}\text{The universal numbering system numbers permanent teeth from 1 to 32, beginning at the maxillary right third molar (#1), extending across the maxilla to the left third molar (#16), then continuing to the left mandibular third molar (#17), and going around the mandibular arch to the right third molar (#32).}
Fig. 11  (a) Several teeth CT images. (b), (c) and (d) are associated with results after applying the variational level set.

Fig. 12  The ROC curves of the ‘proposed method’, thresholding, watershed and two previous works [23], [25].

Fig. 13  Comparison of teeth area in ‘manually’ and ‘proposed method’ segmentation.
Table 3  Performance measures of ‘proposed method’ on different datasets.

| Dataset | Sensitivity | Specificity | Precision | Accuracy | Mean Error Rate |
|---------|-------------|-------------|-----------|----------|-----------------|
| #1      | 0.8269      | 0.9974      | 0.9779    | 0.9832   | 1.6803          |
| #2      | 0.8425      | 0.9944      | 0.9371    | 0.986    | 1.4004          |
| #3      | 0.9570      | 0.9872      | 0.9322    | 0.9877   | 2.1173          |
| #4      | 0.8429      | 0.9959      | 0.9475    | 0.9874   | 1.2621          |
| #6      | 0.8596      | 0.9959      | 0.9322    | 0.9877   | 1.2897          |
| #7      | 0.8664      | 0.9860      | 0.9076    | 0.9800   | 1.9980          |
| #8      | 0.8357      | 0.9992      | 0.9449    | 0.9881   | 1.9343          |
| #9      | 0.8145      | 0.9957      | 0.9322    | 0.9874   | 1.2621          |
| #10     | 0.8778      | 0.9931      | 0.9322    | 0.9874   | 1.2621          |
| #11     | 0.8815      | 0.9942      | 0.9252    | 0.9816   | 1.9018          |
| #12     | 0.8763      | 0.9973      | 0.8684    | 0.9867   | 2.7325          |
| #13     | 0.9232      | 0.9939      | 0.9024    | 0.9894   | 1.0643          |
| #14     | 0.8758      | 0.9959      | 0.9701    | 0.9853   | 1.4659          |
| #15     | 0.8008      | 0.9967      | 0.9605    | 0.9872   | 1.2834          |
| #17     | 0.8627      | 0.9977      | 0.9446    | 0.9851   | 1.5850          |
| #19     | 0.8638      | 0.9867      | 0.9338    | 0.9818   | 1.7121          |
| #20     | 0.8755      | 0.9965      | 0.9654    | 0.9870   | 1.3012          |
| #21     | 0.8269      | 0.9919      | 0.9713    | 0.9733   | 1.1641          |
| #23     | 0.8351      | 0.9986      | 0.9708    | 0.9917   | 0.8308          |
| #24     | 0.9136      | 0.9923      | 0.9405    | 0.9882   | 2.0101          |
| #25     | 0.8884      | 0.9921      | 0.8595    | 0.9870   | 2.6180          |
| #27     | 0.8900      | 0.9958      | 0.8628    | 0.9908   | 1.6436          |
| #28     | 0.9645      | 0.9497      | 0.8193    | 0.9362   | 4.8762          |
| #29     | 0.9052      | 0.9924      | 0.8692    | 0.9851   | 2.1425          |
| #30     | 0.8666      | 0.9980      | 0.9775    | 0.9879   | 1.2115          |
| Average | 0.8720      | 0.9926      | 0.9283    | 0.9831   | 1.7491          |

Table 4  Performance measures of ‘proposed method’ and other algorithms.

| Method              | Sensitivity (%) | Specificity (%) | Precision (%) | Accuracy (%) | Mean Error Rate |
|---------------------|-----------------|-----------------|---------------|--------------|----------------|
| Proposed Method     | 87.99           | 99.30           | 93.09         | 98.42        | 1.7125         |
| A Previous Work [25]| 84.25           | 95.62           | 87.80         | 92.00        | 4.4612         |
| A Previous Work [23]| 83.00           | 92.73           | 81.09         | 89.75        | 5.8319         |
| Watershed           | 81.38           | 88.33           | 76.24         | 82.44        | 9.7826         |
| Thresholding        | 74.16           | 83.60           | 63.12         | 79.38        | 11.033         |

As seen, segmentation of molars is more difficult than other teeth.

In Fig. 15, segmented sample teeth are visualized by marching cubes algorithms that was designed via VTK toolkit [52], using visual C++ compiler. Also, comparison of canine and molar area teeth by both manually and proposed method are illustrated.

4. Discussion

In dental CT images, in addition to teeth, other bony structures are also available. As long as, the CT images were performed in standard clinical conditions, we have cropped the size of the original input images for determining the operation region which is included teeth tissues for reducing calculation and increasing process speed.

In this research, we employed a novel adaptive thresholding technique based on a 3D pulses coupled neural networks (PCNN) to classify dental bony tissues from other bony tissues. As bony tissues are not the same intensity ranges, applying conventional techniques such as thresholding was not effective to produce acceptable results. We experimentally found that a single thresholding approach would result in missed dental structures (high threshold values) or cause adjacent bony tissues to attach each other (low threshold values). Moreover, selecting several threshold values was a tedious work and would result in producing jagged surface for teeth in final visualization. In turn, the adaptive thresholding technique that is based on a PCNN compared to a conventional thresholding technique such as Otsu is more consistent to local intensity changes of dental images. Performing PCNN technique is extremely faster than our previous works [23]–[25].

In the previous works [23]–[25], we separated bony tissues from non-bony tissues by applying a level set technique [38]. In this regard, the head mask performed by the Otsu thresholding technique was employed as initial contour for the level set algorithm which is a large initial contour size. Therefore, the weakness of this method is that it is a relatively time-consuming.

In order to classify teeth tissue from other bony tissue and find an initial contour for teeth, we estimated the panorex lines of the upper and the lower jaws. The approach we propose makes a large use of mathematical morphol-
Table 6 Volume measurement error of each class of teeth.

| Dataset | Incisors (#7, #8, #9, #10) | Canines (#6, #11) | Premolars (#4, #5, #12, #13) | Molars (#1, #2, #3, #14, #15, #16) | Absolute of volume measurement error (%) | Incisors (#23, #24, #25, #26) | Canines (#22, #27) | Premolars (#20, #21, #28, #29) | Molars (#17, #18, #19, #30, #31, #32) | ΣU | ΣL | ΣU + ΣL |
|---------|-----------------|-------------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| #4      | 0.1985          | 0.0856            | 0.2839          | 0.3298          | 0.2044          | 0.0894          | 0.2809          | 0.3009          | 0.8756          | 1.7744          |                 |                 |
| #7      | 0.2176          | 0.1404            | 0.3527          | 0.5807          | 0.2148          | 0.1429          | 0.3456          | 0.3789          | 1.0822          | 2.3736          |                 |                 |
| #13     | 0.1081          | 0.0862            | 0.1289          | 0.1399          | 0.0994          | 0.0798          | 0.1294          | 0.1422          | 0.4508          | 0.9139          |                 |                 |
| #27     | 0.1447          | 0.0946            | 0.1803          | 0.1884          | 0.1393          | 0.0981          | 0.178           | 0.1808          | 0.5962          | 1.2042          |                 |                 |
| #30     | 0.1013          | 0.0608            | 0.1383          | 0.1449          | 0.1055          | 0.0537          | 0.1579          | 0.1422          | 0.4393          | 0.8846          |                 |                 |

Table 5 Volume measurement error of ‘manually’ and ‘proposed method’ segmentation.

| Dataset | Manually segmented volume (cm³) | Proposed method segmented volume (cm³) | Absolute of volume measurement error (%) |
|---------|---------------------------------|---------------------------------------|----------------------------------------|
| #1      | 30.781                          | 31.414                                | 2.056                                   |
| #2      | 29.100                          | 29.443                                | 1.179                                   |
| #3      | 31.750                          | 33.261                                | 4.759                                   |
| #4      | 28.745                          | 29.255                                | 1.774                                   |
| #6      | 28.010                          | 28.298                                | 1.028                                   |
| #7      | 29.391                          | 30.089                                | 2.375                                   |
| #8      | 31.962                          | 33.092                                | 3.535                                   |
| #9      | 30.070                          | 30.985                                | 3.012                                   |
| #10     | 23.779                          | 23.880                                | 0.425                                   |
| #11     | 31.111                          | 32.459                                | 4.333                                   |
| #12     | 27.161                          | 28.297                                | 4.182                                   |
| #13     | 25.283                          | 25.514                                | 0.914                                   |
| #14     | 26.022                          | 26.350                                | 1.260                                   |
| #15     | 26.660                          | 27.186                                | 1.973                                   |
| #17     | 30.423                          | 31.914                                | 4.900                                   |
| #19     | 28.949                          | 29.695                                | 2.577                                   |
| #20     | 28.202                          | 28.834                                | 2.241                                   |
| #21     | 26.315                          | 26.863                                | 2.082                                   |
| #23     | 27.690                          | 28.273                                | 2.101                                   |
| #24     | 30.126                          | 31.070                                | 3.134                                   |
| #25     | 24.721                          | 24.859                                | 0.558                                   |
| #27     | 25.370                          | 25.674                                | 1.198                                   |
| #28     | 31.745                          | 33.309                                | 4.927                                   |
| #29     | 22.043                          | 22.773                                | 1.043                                   |
| #30     | 26.363                          | 26.596                                | 0.884                                   |
| Average | -                               | -                                     | 2.338                                   |

If a multi segment line is computed (as in the fifth image of Fig. 5 for upper jaw or Fig. 16(f)), the longest one is selected.

In images with missing teeth as in Fig. 17(a), panorex line could be broken in some parts and we have a multi segmented line. This is illustrated in Fig. 17(b). In this case, the lines is quantized and coded with chain code and some points of the lines are select. After that, some control point manually selected by the specialist if it is necessary. In order to have a mathematics power instrument to manage the line and possibly modify it interactively, we exploit a B-spline representation [17]. Figure 17(c) shows the final panorex line overlaid over the CT slice.

As occlusion analysis has an important role in orthodontics and implantology, we can use the panorex line to the best simulation. Occlusion analysis also has a major role...
in maxillofacial surgery in treatment planning a congenital anomalies referred as dysgnathia.

The proposed teeth separation technique in panoramic images failed to produce accurate results, in the cases with overlaying teeth, adjacency of molar teeth in the upper and lower jaws and metal artifact in the images.

The variational level set is a region-based active contour model (active contour without edges model) that is an energy optimization technique is based on global image information, and hence, compared to a conventional technique such as thresholding is more consistent to local intensity changes of dental images. Also, a traditional method such as a Canny edge detector, however, due to its local edge detection behavior often fails to produce acceptable results for dental images. This is why the ROC curves of Fig. 12 is in the favor of the variational level set techniques. A Watershed is another conventional technique that is popular for image segmentation. In the experiments, the common draw back of Watershed technique, i.e., over-segmentation was a major obstacle in teeth segmentation. Our experiments show that the segmentation of molars is more difficult than other teeth for both jaws because they have at least two roots. The maxillary molars teeth have more volume measurement error than mandibular molars teeth. Because, molar teeth in maxilla have three roots, but molar teeth in mandible jaw have two roots which are laid in bony region.

The final result of the proposed technique outperformed the previous works [23]–[25] as well. The variational level set has been successful for images with two regions, each having a distinct mean of pixel intensity. It has the several advantages over edge-based models such as traditional level set. First, it does not utilize the image gradient and therefore have better performance for the image with weak teeth boundaries. Second, they are significantly less sensitive to the location of initial contours. In this regard, the variational level set was successful to produce consistent and continuous teeth contours which leads to better visualization.

The CPU times for proposed method, which were recorded from our experiments with Matlab code run on a PC, with Pentium 4 processor, 3.00 GHz (dual core), 2 GB RAM, with Matlab 2006b on Windows XP is significantly faster than our previous works [23]–[25]. Our algorithm is about 20–25 times faster than the previous works [23]–[25]. This demonstrates the significant advantage of our model in terms of computational efficiency.

The proposed algorithm were evaluated on the images acquired by convectional spiral-CT scanners. The CBCT scanner is an alternative imaging modality of teeth which reduces cost of operation and decrease exposure dose for the patient. In addition, image acquired by CBCT are of higher spatial resolution. However, the dynamic range of images intensity in CBCT is poor compared to that of convectional CT image. That is, different tissue such as bone, teeth, and soft tissue are less discriminated. In this case, segmentation
of teeth root and jaw bone in CBCT images are more difficult compared to convectional CT images. Further investigations are needed to modify and customize the proposed algorithm for dealing with CBCT images.

5. Conclusions

Teeth quantification in CT volumetric images is a challenging task in medical imaging analysis. Few algorithms have been developed in order to trace the teeth contour automatically. Our proposed method that inspired by our previous experiences, considering the imaging constraint and anatomical knowledge of teeth and jaws is based on a novel PCNN for adaptive thresholding of CT data, panoramic resampling and variational level set for teeth segmentation in CT volumetric data.

The variational level set technique was utilized to trace the contour of the teeth that is a level set model without an edge detector. One of the most popular variational level models is Chan-Vese model [40]. This technique was observed to be effective to discrepancies in the gradient of the images.

In our validation methodology, we compared the results from the implemented methods with the manual estimation of teeth contours by the experts. Experimental results on 30 volumetric CT data demonstrated the performance of the technique. Our algorithm has the advantage of high speed compared to our previous works. Therefore, considerable time could be saved by using this method.

In practice, in real images, we have different kind of errors and imprecision due to the fact that images are characterized by a large amount of sensorial noise (due to the acquisition system). Between sensorial noises, the noise due to metallic reflection creates artifacts that can confuse detection. Images contain a large quantity of semantic noise. In these cases with the algorithm failed to produce accurate results. We found that, dental metal artifact is a major obstacle in teeth segmentation and visualization.

However, teeth come in different shapes and their arrangements vary substantially from one individual to another. We believe that teeth segmentation and metal artifact reduction in a fully automatic manner is still an open research subject. We will also attempt to modify an automatically identifying panoramic line for dental implant and orthodontic planning. Building teeth generic shape models for computer assisted surgical planning is our future challenge. Such models could be added to an implant planner program and utilized in an optimization process for implant placement and procedures. This model can as well be compared to the plaster-cast based dentition planning in practical and ergonomical terms. Future directions of the use of this model can include an interaction with rapid prototyping of partial denture metal alloy framework that can be possible after exporting the surface data on virtual dentition.

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