Improving Tooth Outline Detection by Active Appearance Model with Intensity-Diversification in Intraoral Radiographs

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Abstract

Automatic tooth detection of intraoral radiographs shows progressively importance in massive forensic verification. Since intraoral radiographs acquired from small oral cavity reveal great variation of intensity and distortion of structure morphology, automatic tooth detection poses a huge challenge. Enhancement methods may not effectively augment informative grayscale gradient. We proposed an intensity-diversification method to increase the detection rate of the tooth through different intensity spaces. The diversification process attempted to explore the image information that was expressible by intensity transform function. In this study, gamma transform was employed to generate different intensity-diversified images from the test radiograph. Deformable statistical Active Appearance Models (AAM) was used to detect a possible mandibular molar tooth region on the images. The AAM regions detected from intensity-diversified images were compared and ranked using three methods: histogram-based, edge-based and crown-root approximation-based methods. Since edge-based and crown-root approximation-based methods revealed higher accuracies, the top five matches in the ranking lists from these two methods were consequently voted by the Borda count to get the most suspected tooth region. Totally, 419 images from 367 patients were used in this study, 100 images for training and 319 images for testing. In our results, the correct detection rate was 71%, comparing to only 45% detection rate of the images without intensity-diversification. AAM outlines were detected in all 319 images, but not all of them belonged to valid tooth regions. In original images, 144 images had valid tooth outlines detected by AAM; 175 images were detected with invalid tooth regions. The true positive rate is 45% and the false positive rate 55%. With intensity-diversification and proposed matching methods, 227 AAM outlines detected were valid tooth regions, and 92 outlines were invalid tooth regions. The true positive rate is 71% and false positive 29%. This results supported that intensity-diversification process could improve automatic detection rate of mandibular molar in intraoral radiographs.
Keywords: dental imaging, intensity diversification, AAM, tooth detection

1. Introduction

In forensic dentistry, dental identification is employed to verify or identify a person by matching postmortem (PM) against labeled antemortem (AM) radiographs in a database. The main goal is to retrieve the same teeth appearance shown on the PM radiograph from a huge amount of radiographs inside the database. It can be achieved through imaging technology. Previous research of dental identification has reported the methods that compare the features of edges, teeth size, shape and restorative fillings [1]. An automated Dental Identification System (ADIS) was proposed for PM identification in 2004 [2]. It utilizes automatic image classification, feature extraction and image comparison between PM and AM dental radiographs. Prior studies have investigated in global and local image segmentation problems through “semi-automatic” approaches [2][3]. The global segmentation problem is to crop a composite digitized dental record into its constituent x-ray films. The second problem is the difficulty in segmenting the tooth to facilitate the extraction of features (e.g., crown and root contour) for identification use. The other studies [4, 5, 6] have proposed the “fully automatic” approach of tooth segmentation in dental radiographs by using iterative intensity thresholding to set the thresholded binary image. However, imperfect intensity thresholding may lead to improper segmentation especially for images with uneven illumination or excessive dental work. Poor image quality (due to low contrast and uneven exposure) and lack of clear edges (due to substantial noise and complicated structures) are the main challenges of tooth segmentation in dental radiographs [6, 7]. Moreover, low contrast intensities between root and bone structures pose difficulties in automatic segmentation. Although image enhancement such as histogram normalization or equalization [8] has shown improvement of the image quality for visual interpretation of dental x-ray images, no optimal enhancement method for automatic tooth segmentation has been concluded yet. This study fostered mainly on improving the performance of local tooth detection through alternating in image intensity level. The alternation would lead to a change of image features and might increase the possibility of augmenting the feature gradient along
the outline of the teeth.

With the use of the popular deformable Active Appearance Model (AAM) [9] and its searching algorithm, we focused on detection of lower first molar teeth in digital apical images collected from a dental clinic. The concept of AAM has been proposed in 1998 [9] to detect previous trained objects in the images. It is reported to have toleration of the variation in scale, rotation and translation of the deformable object in the image. Certain kind of applications has revealed its assistances in faces recognition [10], bone detection [11], cardiac ventricles segmentation [12, 13]. For its application in dentistry, AAM assisted cephalometric analysis, which required the detection of bony landmarks on lateral x-ray view of skull, was reported in 2005 [14]. Though leaving much room to be improved for cephalometric analysis, AAM is still catching attention in clinical application development.

In this study, we employed AAM for mandibular molar teeth detection because AAM considers both teeth contour (shape) and feature (texture) for appearance searching. We conducted the performance of the molar teeth detection with the alternation of image intensity from an intra-oral radiograph database.

The rest of the paper is organized as follows. In section 2 we introduce the materials and methods used in this study. In section 3 we show the results of the detections after intensity-diversification. In section 4 we discuss the results in this study.

2. Materials and Methods

2.1 Sample collection

Totally 419 digital dental radiographs from 367 patients during dental practice were used in this study, in which 104 images were from bilateral sides of 52 patients. The images were taken by an intraoral X-ray machine (Trophy Radiologie Type: 6510, Trophy, France) and an intraoral X-ray size2 CCD sensor (CygnusRay MPS, Cygnus Technologies LLC, USA). The X-ray machine was featured with voltage: 65kVp and current: 10mA, the X-ray sensor featured with 27.5 x 36 mm in size, 23 lp/mm, 16 bit depth, 4096 shades of gray and 2.05 Megapixels. The images were collected from the patients between 18 to 65 years old during the years 2005 to 2012. The images with original size of 1638 x 1248 pixels were resized to 20% to accelerate the computational efficiency. Each radiograph showed at least one complete lower first molar tooth, which should be consistent in structure. The structural consistence of a molar tooth on the image referred to a tooth having complete tooth structure that can be easily distinguished by its crown and root form. However, the tooth could have restoration with
opaque materials. If destruction of tooth structure existed, it could only be less than one quarter of either crown or root portions. Samples of radiographs were shown in Fig. 1. Teeth requiring endodontic treatments are usually being extensively destructed due to caries, injuries or other reasons. The destruction of tooth structures will cause defected or abnormal tooth outline shown on the radiographies. Moreover, after the teeth being endodontically treated and restored, the artificial non-translucent filling materials replaced the normal tooth structures. The extensive filling materials might ruin the tooth texture and affected the tooth appearance appeared on the X-ray images. The AAM training set selected only 100 radiographs in which lower first molar tooth had not been endodontically treated before. The other samples were used as the test images.

Fig. 1 Samples of dental radiographs used for training and test.

2.2 System flow

The system was divided into three major parts. In the first part, only the test image was undergone intensity transform, which was a gamma intensity adjustment in the experiments, to generate thirty images with varying intensities, as called diversified images in the study. For the second part, we adopted the Active Appearance Model (AAM) algorithm to search the tooth regions in these images. The AAM model was trained from the training set of 100 images without intensity
adjustment. The last part was to rank the detected regions according to three proposed similarity measurement methods, to be explained in Section 2.6. The candidate, after voted by Borda count [15], would be the most possible mandibular molar teeth region on the test image. The resulted region was verified by expert’s inspection. The system diagram of this study was depicted in Fig.2.

![System flow diagram in this study](image)

**Fig.2 System flow diagram in this study.**

### 2.3 Intensity diversification

Since the taking of x-ray images were operated at different angles, locations inside the mouth and at varying distances from x-ray sources, image intensities are greatly altering from image to image. There was no optimized algorithm to reduce the impact from intensity variations. In this study, we altered the image intensity through gamma correction to cover a wide range of the intensity values for AAM searching. The alteration was defined as an “intensity-diversifying” process which would lead to a change of image features and might increase the possibility of augmenting the feature gradient along the outline of the teeth. By this way, if
brightness and contrast adjustment was laid within the range of AAM detection, the object would be easily interpreted by its characteristics. In our study, the radiographs were intensity-diversified by a gamma equation to provide multiple detectable results. It is defined by the equation:

\[ I_{out} = (I_{in})^\gamma, \]

where \( I_{out} \) represents the intensity of output image, \( I_{in} \) the intensity of input image and \( \gamma \) is the gamma value. The gamma value \( \gamma < 1 \) produces a brighter image, while \( \gamma > 1 \) results in a darker image. In this study, the range of brighter to darker images was set for \( 0.1 \leq \gamma \leq 3.0 \), with an increment of one-tenth. Thus, thirty gamma diversifying images from each parent image were created for detection.

2.4 AAM model training

The tooth structures on the apical images subjected to the changes of scaling, rotation and distortion. Detection of these structures required consideration of morphological and textural variations. Active Appearance Model (AAM) first proposed in 1998 [9]. It utilizes statistical appearance models in both shape and texture for representing deformable objects. To build a suitable detection model representing teeth outline and texture (embedding intensity information of dentin, enamel and pulp structures), landmark features on the training set images should first be reduced into lower dimension by Principal Component Analysis (PCA). Therefore, the shape (\( s \)) of the tooth object is described by:

\[ s = \tilde{s} + \phi_s b_s, \]

where \( \tilde{s} \) is the mean shape, \( \phi_s \) is a matrix of eigenvectors of the covariance matrix arranged to their percentage of variation and \( b_s \) the shape model parameter. The tooth texture (\( t \)) is described by:

\[ t = \tilde{t} + \phi_t b_t, \]

where \( \tilde{t} \) is the normalized mean texture vector, \( \phi_t \) is a matrix of eigenvectors of the covariance matrix arranged to their percentage of variation and \( b_t \) the texture vectors parameter.

By combining shape and texture parameter \( b \), PCA is applied such that:

\[ b = \phi_c C, \]

### 2.2.1 Principle Component Analysis

The Principle Component Analysis (PCA) is a method used to reduce the dimensionality of a dataset consisting of a large number of interrelated variables. It does this by transforming the variable into uncorrelated variables called principal components. Each principal component is a linear combination of the original variables, and they are ordered such that the first principal component has the largest possible variance.

The PCA is applied to the training set images to reduce the dimensionality of the data. This reduces the computational cost of the detection process and also helps in reducing the noise in the data.

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where \( b = \begin{pmatrix} W_x b_x \\ b_y \end{pmatrix} \) and \( W_x \) a suitable weighting matrix between the pixel distance and pixel intensities (i.e. due to different measurement units). A complete model instance can thus be generated by combined parameters \( C \)

\[
    s = s + \phi_s W_s^{-1} \phi c, \quad (5)
\]

\[
    t = t + \phi_t \phi c, \quad (6)
\]

where \( \phi_c = \begin{pmatrix} \phi_{c,s} \\ \phi_{c,t} \end{pmatrix} \).

In this study, images in the training set were traced manually to outline the lower first molar teeth. Five points were labeled as major landmarks. Two were used to represent cemento-enamel (CE) junctions on each side, two were root apexes and one was the root furcation of the tooth, as shown in Fig. 3. A tooth exhibits different curvatures in the crown and root outline portions. We learnt from the sample images that 75 points, regardless the size of the tooth, would have good representation of the outline curvatures. According to the lower molar tooth appearance on the x-ray image, the points were evenly distributed on 3 parts of the outline, a crown and two roots. All point representations were calculated automatically using equal distance interpolation between the major landmarks. In this study, the outline of the molar tooth was marked by 75 points, in which 25 points representing the crown and 50 for the root structure. The interpolated points and landmarks are shown in Fig. 4.

Fig. 3 A lower first molar tooth traced in red outline manually. Five important
landmarks in blue color were drawn: 2 for cement-enamel junctions, 2 for root apexes and 1 for root furcation.

Fig. 4 Seventy-five landmarks points derived by automatic interpolation depicting the tooth outline.

Following the AAM training process, the mean appearance model consisting of shape and texture of a tooth variation was obtained (Fig. 5).

Fig. 5 Mean appearance model of the lower first molar teeth.

Besides the whole tooth model, we also trained the crown and root models separately. The crown and root models might help in validation of the AAM detected regions through the proposed matching method described section 2.6.3 later on.

2.5 AAM searching
To detect a molar tooth on a new image, the AAM searching algorithm was applied using the pre-trained model. The searching processing was performed at numerous iterations of suitable scaling, translation, rotation and deformation. We
employed the AAM-API software toolkits [16, 17] for AAM training and searching in this study. We used the AAM-API system defaulted parameters settings in which the deformable scale and rotation were limited within ±15% and ±15 degrees respectively. Convergence of the search take place until a stable position was obtained. Fig. 6 shows an example of the AAM searched result.

Fig. 6 One of the AAM searched result.

2.6 Similarity measurement

For the 30 intensity-diversified images from each test image, the AAM detected outlines were selected as candidates in the following matching. With consideration of tooth morphology and feature pattern, the similarity measurement of the system was calculated from the results of histogram, edge and crown-root approximation-based matching.

2.6.1 Histogram-based matching

A reference intensity histogram of teeth was learnt from the training set. The candidate intensity histograms were acquired from the AAM detected regions on the thirty enhanced images. Through comparisons between reference and test histograms, the tooth region was ranked according to their similarities. The similarity of the histogram distributions was calculated using Bhattacharyya distance [18] between them. We used the Bhattacharyya coefficient ($\rho$) to measure degree of similarity between two histograms. Bhattacharyya coefficient, which is nearly optimal in terms of Bayes error as well as symmetric and numerically stable for comparison of two empirical distributions [19, 20], is widely adopted to measure similarity between image histograms [21, 22, 23, 24]. Supposing that $p$ and $q$ were the normalized reference and test histograms of the tooth regions respectively, and $t$ denoted the number of bins in the histogram. The equation of Bhattacharyya coefficient
was known as:

\[ \rho(p, q) = \sum_t \sqrt{p(t)q(t)}, \]  

(7)

where \( t \) is range from 1 to 8 in the experiments.

2.6.2 Edge-based matching

The outline of a tooth can be described by its edge from a test image. If AAM could correctly detect a tooth structure, the detected outline should closely match with the edge of the tooth in the image. We proposed an edge-based matching for measuring the close relationship between the AAM detected outline and the edge surrounding the tooth. The more edge pixels lay closely to the AAM outline border, the more possible that the detected outline included a tooth structure. An example of edge-based matching is shown in Fig. 7. Fig. 7 (a) shows the AAM searching result on an original image. The searched outline was thickened in order to include more possible adjacent edge pixels, as shown in Fig. 7 (b). We set the thickened width of ten pixels along the searched outline. The canny edge operator was applied to the original image to detect the edge of the teeth and other oral structures, as shown in Fig. 7 (c). The thickened border in Fig. 7 (b) was masked over the Canny edges [25], leaving the edge pixels within the border, as sin Fig. 7 (d). To include only the relevant edges, those edges with an angle more than sixty degree from the AAM outline on either size were considered as irrelevant and being removed, as shown in Fig. 7 (e). The final edge pixels were considered as relevant tooth edges nearby the AAM searched region. In other words, the number of edge pixels revealed the coincident rate in which the AAM searched border was similar to the tooth edge.
2.6.3 Crown-root approximation-based matching

Tooth is composed by two main parts: the crown, which is above the cement-enamel junctions, and the root, which locates underneath the cement-enamel junctions. Due to the superimposition of the root image and the bone image, the root is less visible as the crown in the radiographs due to the lower differential in tissue density [26, 27]. These characteristics might have impact on automatic detection performances of crown, root or the whole tooth when they were searched separately.

In the experiments, three models (crown, root and whole tooth) were pre-trained according to AAM algorithm. Fig. 10 demonstrates three sample images and their searching results using the three models. In the figure, the first to third rows represent three different images of varied intensity. The first, second and third columns show the tooth, crown and root detection by their appearance models respectively. Tooth detection, on the left column, succeeds in the first image and fails in the others. Crown detection succeeds only in second image, while root detection succeeds in both first and third images. In the first image, though tooth model can successfully detect the molar tooth, root model detects a best fitted root outline. In the second image, tooth and root models fail; crown model alone provides a good estimation of crown outline. In the last image, tooth model succeeds partially in detecting the
crown region while crown model alone fails. Root model searches perfectly in this image.

A crown could be presented by an outline drawn from the left CE junction along the crown profile in clockwise direction to the right CE junction in the image. A root was presented an outline drawn from the right CE junction along the crown profile in clockwise direction to the left CE junction. Typically, a whole tooth, with an outline drawing from left CE junction and back in clockwise direction, should have an optimum crown-root orientation that its crown and root portions joined together at the CE junctions on both sides to form a complete tooth region. Thus, the end points of these structural outlines should met with a closest approximated at CE junctions. To measure the crown-root approximation, we calculated the spatial distances in pixels between the end points of the AAM detected crown and root outline on both sides. The shorter the crown-root approximation distance, the higher the
possibility that the detected crown and root outline were come from the same tooth structure. The concept of crown-root approximation-based matching is shown Fig. 8. When the detected crown and root outlines were far from each other in the image (Fig. 8(a) and (b)), the detected region might not reveal a correct tooth structure. The outlines were said to be valid only if they approximated at the CE junctions and had the minimum spatial distance, such that a complete tooth form could be drawn (Fig. 8(c)). Fig. 8(d) shows a fail in crown-root approximation-based matching.

![Successful crown detection](image1.png) ![Successful root detection](image2.png)

![Successful crown-root pair](image3.png) ![Failed crown-root pair](image4.png)

Fig. 8 Result images of crown-root approximation.

### 2.6.4 Precision of each method
The effectiveness of each method was evaluated by mean of their precisions. The precision rate is the fraction of retrieved regions that are relevant to the search and was calculated according to the equation (1):

$$\text{precision} = \frac{|\text{relevant regions}| \cap |\text{retrieved regions}|}{|\text{retrieved regions}|},$$

(8)
2.6.5 candidate selection based on Borda count

Borda count was used as combination rule for these matching measurements. It is a common voting method since it was devised by Jean-Charles de Borda in 1781 [15]. Borda count can be thought as a simple preferential voting system which makes a decision according to the order of preference. The voting is based on the assumption of additive independence among the contributing preference. In the experiments, all three methods were supposed to share the same weight. The labeled regions were ranked according to the similarity measured by each matching method. Thus, the first ranked region represented a highest relevant tooth region. While there were n regions (n = 31 in the experiments), the first ranked region in each method would be assigned n points, the second n-1 points, the third n-2 points, and so on. The candidate with highest total points among the methods was selected as the final candidate region.

3. Results

The lower first molar teeth in the x-ray images were pre-trained and searched in this study and the detection precision in different gamma variation were compared. Owing to the morphologic similarity of the first, second and third mandibular molar, the detection of these teeth on either side were considered successful in our result. The differences between left and right side molar were being neglected. The detected teeth regions in 319 test images were checked with the visual tooth regions which were identified by a domain expert/dentist. The criterion of a valid detected tooth region was set using the degree of overlapping area between two regions as calculated in the equation (2):

\[
\text{degree of overlapping area} = \frac{\text{regions intersection}}{\text{regions union}},
\]

where regions intersection denoted the intersection area between the detected and visual regions and regions union the union area of the regions. A valid tooth region in the experiments was defined as region having a degree of overlapping area \( \geq 0.8 \). Root canal treated molars, although not presented in the training set, were still considered as valid tooth if correct detection on such teeth were achieved. The samples of the correct and incorrect detection under the criteria are shown in Figs. 9 (a) and 9 (b).
3.1 The result of intensity-diversification

Fig. 13 shows the differences of AAM search for a tooth region before and after image intensity had been altered. The images on the left in each set were pre-adjusted images. The red outlines represent the search results of the AAM algorithm applied in these images. With applying an intensity transform, the adjusted images were shown on the right inside the sets. The $\gamma$ values for each image being transformed were shown on the top of the images. In these original images, AAM could not catch any relevant molar tooth. After the intensity adjustment, AAM could search very well for the teeth. Fig. 13(a) and (b) revealed good searches at different $\gamma$ values less than 1, which are lighter than the original images. Fig. 13(c) and (d) revealed good searches at $\gamma$ values larger than 1, which are darker than the original images. It could not, by any mean, be concluded that any degree of intensity transform could result in a better performance for automatic tooth detection. It is the reason why this study included a larger range of gamma value from 0.1 to 3.0 with an increment of every 0.1.
Fig. 13 Intensity-diversification influencing the result of AAM searching. (a) to (d) represent the AAM searching results, red outlines, on four pair of apical x-ray images in the experiment. Left images in each pair are the original images which show poor image quality for searching. The searching results are improved by either decreasing ((a) and (b)) or increasing ((c) and (d)) the $\gamma$ value.

3.2 Increase of valid regions in intensity-diversified images

The AAM search on the intensity-diversified images generated more detected tooth regions and, thus, more chances to have correct candidates. The percentage of valid regions observed in the intensity-diversified and original image groups are shown in Fig. 11. When the AAM tooth model employed for testing in the original group of 319 images, only 45% of detected outlines contained valid tooth regions verified by visual inspection. After the images were undergone intensity-diversification and AAM detection for tooth regions, at least one detected outlines contained valid tooth regions could be discovered in 91% of the intensity-diversified image sets through human inspection. The improvements were also observed for the crown and root model search.

![Bar chart showing the percentage of valid regions in intensity-diversified and original image groups.](image)

Fig. 14 The percentage of valid regions observed in the intensity-diversified and original image groups.

3.3 Precision of the measurement methods
These valid tooth regions searched primarily by AAM underwent different measurement methods to retrieve the candidate regions. Fig. 14 shows the precision rate of the matching methods: histogram-based, edge-based and crown-root approximation-based. The highest precision rate is achieved by crown-root approximation-based matching within first and second retrievals. Its maximum is reached after five retrievals and keeps unchanged thereafter. However, the overall precision rate in all the diversified images is much lower than the others. Edge-based matching presents an overall good performance after the second retrieval. Histogram-based matching does not match well in the first eight retrievals, but performs better in between the other methods afterward.

![Fig. 14 The precision rate of histogram, edge and crown-root approximation matchings on the thirty-one valid tooth regions.](image)

### 3.4 The voting result

In the Borda voting process, we considered only edge-based and crown-root approximation-based matching methods since histogram matching was not impressive in top few matches. We counted for the top five matches from the two methods and voted by their existences. The voting provides a highest mandibular molar teeth detection rate of 0.71 using our methods. Thus, 91% of
the valid tooth outlines could be retrieved from the 319 image samples through manual massive inspection of the intensity-diversified images. However, the proposed automatic matching methods were only able to retrieve 71% of valid tooth outlines from the image samples. There was a gap between manual and automatic retrieval precisions.

4. Discussion and Conclusion

Simply image enhancement such as histogram normalization or equalization [8] may increase the image quality of dental images for human perception. Other researchers disagree that the alteration of image brightness or contrast can have significant value in improving diagnostic accuracy [28, 29, 30, 31]. Traditional enhancement methods mostly improve the global contrast, which were more able to differentiate the high density crown from the dark oral background. The root, embedded inside the bone that has almost the same density, have similar gray values of the bone. Since global intensity normalization or equalization enhancement will cause root and bone enhanced at the similar level, it is the reason why traditional image enhancements are not helpful in automatic tooth segmentation of x-ray images. Our result revealed that the valid tooth regions automatically searched by AAM was increased (from 0.45 to 0.91) through intensity-diversification of the images. However, it leaded to heavy computation load. In the original image samples, the mean computational time of tooth, crown and root outline detection by AAM were 1.8, 3.7 and 2.9 seconds respectively. After the intensity-diversification, matching and voting methods, the mean computational time of the tooth, crown and root outline detection became 98.7, 154.3 and 121.6 seconds respectively. The computation was performed on a single processor Intel i7-2640M 2.80GHz machine. We concluded that adjusting intensity during automated detection could have promising results. AAM of root detection had higher performance than crown structure in the experiments.

The result revealed a different view point from Jain [3] who explained that crown is clearly visible in the radiographs and should be identified first. It might be caused by obvious curvilinear outline of molar root structure, composed of CE junctions, root apexes and furcation, that would favorite the AAM searching algorithm. In addition, since the roots embed deeply inside the bone, they were less likely to be attacked (by caries or tooth attrition) and could retain their outline form over time without great destruction. In most cases, the root appearances are preserved in good condition in the images.

With voting among edge-based and crown-root approximation matching, the
tooth detectable rate could be boosted to 0.71 following the intensity-diversification of the images. Compared to the valid regions existing in all diversified results (0.91), advanced technology might be introduced in the future to minimize the gap.

There were limitations in this study. We employed only mandibular molar teeth for detection in this study. The molar teeth are different from other teeth in human mouth that they have mostly multiple root structures with root furcations. Other teeth may develop to have only one (incisor, canine, premolar) or two (premolar) roots. Thus, it is possible that the precision rate might be different if tooth structures having different curvilinear appearance are selected. Moreover, the improvement in the intensity-diversified image detection might lead to an increase in computational load.

The technique used in this study could be applied when automated detections in dental x-ray images are required. The future work should be focused on simplifying the detection load in diversified images and applying the technique in other medical x-ray images.
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