U-net based metal segmentation on projection domain for metal artifact reduction in dental CT

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Received: 25 January 2019 / Revised: 28 March 2019 / Accepted: 11 April 2019 / Published online: 29 April 2019
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Abstract

Unlike medical computed tomography (CT), dental CT often suffers from severe metal artifacts stemming from high-density materials employed for dental prostheses. Despite the many metal artifact reduction (MAR) methods available for medical CT, those methods do not sufficiently reduce metal artifacts in dental CT images because MAR performance is often compromised by the enamel layer of teeth, whose X-ray attenuation coefficient is not so different from that of prosthetic materials. We propose a deep learning-based metal segmentation method on the projection domain to improve MAR performance in dental CT. We adopted a simplified U-net for metal segmentation on the projection domain without using any information from the metal-artifacts-corrupted CT images. After training the network with the projection data of five patients, we segmented the metal objects on the projection data of other patients using the trained network parameters. With the segmentation results, we corrected the projection data by applying region filling inside the segmented region. We fused two CT images, one from the corrected projection data and the other from the original raw projection data, and then we forward-projected the fused CT image to get the fused projection data. To get the final corrected projection data, we replaced the metal regions in the original projection data with the ones in the fused projection data. To evaluate the efficacy of the proposed segmentation method on MAR, we compared the MAR performance of the proposed segmentation method with a conventional MAR method based on metal segmentation on the CT image domain. For the MAR performance evaluation, we considered the three primary MAR performance metrics: the relative error (REL), the sum of square difference (SSD), and the normalized absolute difference (NAD). The proposed segmentation method improved MAR performances by around 5.7% for REL, 6.8% for SSD, and 8.2% for NAD. The proposed metal segmentation method on the projection domain showed better MAR performance than the conventional segmentation on the CT image domain. We expect that the proposed segmentation method can improve the performance of the existing MAR methods that are based on metal segmentation on the CT image domain.

Keywords Metal artifact reduction · Metal segmentation · Deep learning · U-net · Dental CT

1 Introduction

The presence of high-density dental prosthetic materials, such as dental fillings and implants, often generates severe metal artifacts in dental computed tomography (CT) images, thereby compromising image readability. Metal artifacts are caused by many physical phenomena, such as beam hardening, Compton scattering, and photon starvation [1–3]. Despite many existing metal artifact reduction (MAR) methods for medical CT, dental CT images still suffer from

residual metal artifacts since current MAR methods do not work very well, particularly when there are many dental prosthetic materials in the human subject. Iteration-based MAR algorithms [4–7] and projection data correction-based MAR algorithms [8–19] have been developed to apply MAR in medical CT images. The iteration-based algorithms perform well in reducing the metal artifacts, but they need excessive computation; the projection data correction-based algorithms are widely used for clinical applications because they require less computation. In the projection data correction-based algorithms, the projection data on the metal regions are replaced with data estimated either by spatial interpolation [8, 9, 12, 13, 15] or re-projection of the intermediate CT images [10, 11, 14, 16–20]. Therefore, the metal regions should be accurately identified on the projection data

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to secure good MAR performance. However, the projection data correction-based algorithms often fail in reducing the metal artifacts in dental CT images, since the enamel layers of teeth are often mis-segmented as metal regions due to their similar X-ray attenuation behavior as compared to dental prosthetic materials. Severe metal artifacts around prosthetic materials also compromise the metal segmentation on dental CT images.

There are a few MAR algorithms developed and validated for dental CT [21–24]. Tohnaek et al. [21] developed a sequential substitution algorithm that replaces the corrupted projection data with the adjacent uncorrected projection data. They assumed that the slices of the teeth roots are free from metal artifacts, so they started the substitution process from the projection data of these slices. Therefore, this method highly depends on the metal segmentation accuracy. Yazdi et al. [22] also developed an algorithm that replaces the corrupted projection data with the values from the opposed projection data. They claimed that the opposite projection values are a better approximation than the linear interpolation. Karimi et al. [23] developed an algorithm that replaces the corrupted projection data with the data reprojected from a prior image. This prior image was derived from the classification of the original CT image into metal and tissue. This method showed good performance when tested on human head images having a dental filling and implants. The performance of this method also depends on the accuracy of the metal and tissue segmentation. Philips developed an MAR algorithm, so called OMAR, especially for orthopedic applications, but Kidoh et al. [24] have tested it for the dental CT image having a dental filling. It showed image quality improvement but the streak artifacts were still persistent.

We observed that the contrast made by dental prosthetic materials is dominant over the contrast made by teeth and maxilla bones on a projection image of dental CT. Enamel layers create little contrast on the projection image due to their thinness. Therefore, we tried to segment those metal regions on the projection domain on which no metal artifacts appear. In a projection image of a human subject, teeth and bone structures may appear with an intensity as high as prosthetic materials due to their high physical density and large size. However, the contrast of prosthetic materials is quite conspicuous over the background since most of the prosthetic materials have clear cutting edges. Therefore, we tried to segment the metal regions on the 2D projection domain of dental CT.

Currently, deep learning techniques are widely employed for medical image analysis. In the field of CT, deep learning techniques have been employed to reduce various kinds of artifacts caused by photon starvation, sparse view sampling, and metal objects [25–31], and are also employed to reduce noise in low-dose CT images [25, 26]. To achieve MAR with

deep learning, the deep learning network may be trained to estimate artifact-free CT images from the artifact-corrupted images if a huge number of artifact-corrupted images are available for network training, with the corresponding artifact-free images. Since acquiring so many images is, in practical terms, very difficult, some studies [28, 29] used simulated images to train the network. In another study [31], a deep learning technique was employed to create prior images for the correction of metal artifacts. In this study, we implemented a deep learning-based metal segmentation algorithm that can segment metal regions on the 2D projection domain of dental CT, with higher accuracy than the conventional segmentation on the CT image domain. We combined the segmentation algorithm with a projection data correction-based MAR method to finally evaluate the segmentation efficacy on MAR.

2 Methods

2.1 Preprocessing of projection data

Before inputting the projection data to the network, either for training the network or performing segmentation, we applied some preprocessing to the raw projection data of the dental CT. The matrix size was $600 \times 600 \times 450$ (number of horizontal pixels $\times$ number of vertical pixels $\times$ number of projection views). First, we took the logarithm of the raw projection data to get the true projection (line integral) image (P_o) of the X-ray attenuation. Then we applied the intensity normalization to P_o at every projection view to make sure that all the projection images had the same dynamic range over all the projection views:

$$P_n(u, v) = \frac{P_o(u, v) - \min(P_o)}{\max(P_o) - \min(P_o)}, \quad (1)$$

in which (u, v) are the horizontal and vertical coordinates on the projection domain. Since the max pooling operation in a convolutional neural network (CNN) is performed by a factor of 2, as will be discussed in the next section, we resized the normalized projection image to 512×512 by zooming it down with spatial interpolation. For better segmentation, we applied a 3×3 Sobel operator to the resized projection image (P_r) to get the gradient image (G). Then we combined P_r with G to get the edge-enhanced projection image (P_{en}). We input P_{en} to the network either to train the network or to perform the segmentation task.

2.2 Network architecture design and network training

The U-net is one of the most widely used deep CNNs, and it has shown high performance, particularly in image segmentation [26, 32–34]. The original U-net consists of multiple

stages connected by pooling layers in the encoding path and by upsampling layers in the decoding path. Each stage consists of two convolutional layers of 3×3 spatial filters with stride one, and each convolution is followed by a rectified linear unit (ReLU). In the encoding path, the number of channels of each convolution layer is doubled after the max pooling, while it is reduced to half in the decoding path after the upsampling. A scale-by-scale concatenation of the feature maps is applied at each upsampling to incorporate the higher-resolution structural information from the corresponding stage in the encoding path. At the last layer of the last stage, a 1×1 convolution layer is placed to map all features to the final image [34].

The original U-net was first applied to segment cells from in vitro images. In this application, the number of feature maps in the first layer was chosen to be 64, and this number was doubled at every encoding stage to enrich the number of training parameters. However, a large number of training parameters necessarily results in a high computational cost. To reduce the computational cost in applying a U-net to dental projection images in which dental prosthetic materials appear in high contrast and simple geometrical shape, we tried to reduce the number of parameters so as not to compromise the segmentation performance. We found a suitable U-net configuration empirically through evaluating a few different U-net configurations with the Dice similarity index [35] and the computational speed. In this study, we tried five different configurations and compared their performances to that of the original U-net configuration (Unet-64). The first four configurations, named Unet-32, Unet-16, Unet-8, and Unet-4, followed the original U-net structure, i.e., the two convolution layers in a stage had the same number of filters, and the number of filters was doubled at every encoding stage and reduced by half at every decoding stage. Therefore, the difference among the configurations can be identified from the number of filters in the first layer of the first stage. For example, Unet-32 starts with a convolution layer of 32 filters at the first stage, while Unet-16 starts with a convolution layer of 16 filters, and so on.

To train the network, we used clinical data of five patients which had different kinds of metal implants and dental fillings at different tooth positions. The patient data were acquired using a commercial dental CT scanner (RAYSCAN $\alpha+$, Ray, Korea) with a tube voltage of 80 kVp and a tube current of 10 mA. The number of projection views was 450 with the frame rate of 32 Hz. The pixel size was $0.3 \times 0.3 \times 0.3 \text{ mm}^3$ with the field of view (FOV) of $100 \times 80 \text{ mm}^2$. Since the projection data in the range of 0° – 180° is very similar to the one in the range of 180° – 360° , we chose first 200 projection images out of the original 450 projection images of five patients, thereby

making 1000 projection images. Despite the small number of patients, the number of projection images used for the training was enough. Since the projection image changes view by view because of the different projection view angles, the projection images from a patient may have quite diverse characteristics, as demonstrated in Fig. 1. Figure 1 shows the projection images of a patient at four different view angles (40° , 80° , 120° , and 160°). Clearly, the shape, position, and intensity of the projections of the metal objects, not to mention those of the teeth and nearby maxillary and mandible bones, change greatly view by view. In addition, the data were augmented to increase the number of training images: we flipped every image vertically and horizontally, so the number of training images was increased from 1000 to 3000.

To make the ground truth segmented images, we manually segmented metal regions on the training images using Adobe Photoshop CS6. We used the edge-enhanced images (P_{en}) as the input and the corresponding segmented images (M) as the targets to train the network, using the ADAM optimizer that uses a stochastic gradient descent method to minimize the loss function [36]. In this study, we used the cross-entropy loss function [37] for the optimization, so the optimization problem is described as follows:

$$\begin{aligned} \min L(M(u, v), \hat{M}(u, v)) \\ L(M(u, v), \hat{M}(u, v)) = \frac{1}{N_u N_v} \sum_{u=0}^{N_u-1} \sum_{v=0}^{N_v-1} ((M(u, v) \log(\hat{M}(u, v))) \\ + ((1 - M(u, v)) \log(1 - \hat{M}(u, v)))) \end{aligned} \quad (2)$$

in which $\hat{M}$ is the estimated segmentation image at each epoch, and N_u and N_v are the sizes of the projection images in the horizontal and vertical directions, respectively. To evaluate the segmentation accuracy at each epoch during the training, we first applied a threshold of 0.5 to $\hat{M}$ so that the pixels having an intensity above the threshold were set to 1 (metal region) and otherwise set to 0 (non-metal region). We calculated the percentage of pixels that matched correctly with the ground truth image (M). Figure 2 shows the loss function values, along with the accuracy of the model at each epoch. The latter was calculated from some of the training image data set that were not used for the training but were reserved for the validation.

Figure 3 shows the Dice coefficients and the computational speed of the U-net configurations when they were applied to segment metal regions on the training images of the five patients. The Dice coefficients of Unet-32 and Unet-16 are both 0.99, while their computation speeds are increased about 3.6 and 7.3 times as compared to Unet-64, respectively. This means that Unet-16 could segment the metal regions with an accuracy very close to the original U-net but with 7.3 times faster computation. The Dice coefficient of Unet-8 is 0.96, still close to 1, but the Dice

Fig. 1 Projection images of a patient at different view angles. **a** 40°, **b** 80°, **c** 120° and **d** 160°

Fig. 2 **a** The model accuracy and **b** the loss function value at each epoch during the training

coefficient of Unet-4 goes down to 0.85, which implies a significant degradation of the segmentation accuracy.

From these observations, we concluded that if we set the number of filters in the first layer of the first stage between 8 and 16, the configuration would replace Unet-64 without significantly compromising the segmentation accuracy and MAR performance. We also observed that the second

convolution layer in each stage had a longer computation time than the first convolution layer due to the increased number of feature maps. So, we reduced the number of filters to half in the second layer. With arbitrarily setting the number of filters to be 10 for the first layer of the first stage, we chose a configuration, named Unet-red, as shown in Fig. 4. We evaluated the performance of Unet-red using the

Fig. 3 Comparison among different configurations of U-net architecture (Unet-64, Unet-32, Unet-16, Unet-8, Unet-4, Unet-red*). **a** The Dice similarity indices and **b** the segmentation speed of the configurations. *Unet-red is described in the next section

same metrics, as shown in Fig. 3. As also shown in Fig. 3, the Dice coefficient of Unet-red is 0.98, which is very close to those of Unet-16 and Unet-32, while the computation speed is improved to 18.2 images per second.

2.3 Evaluating segmentation accuracy by MAR performance

To validate the segmentation method, we used the metal segmentation results of four other patients, not used for the network training, for metal artifact reduction. For MAR, we used the projection data correction-based MAR method introduced in our previous work [38]. The four patients also

had different configurations of dental prostheses, including metal crowns, dental fillings, and dental implants. After identifying the metal pixels on the projection image using the network, we restored the original size of the projection image so that the segmented image ($\hat{M}$) had the same size as the input projection image. After resizing the segmented image, we had a metal mask image ($\hat{M}$) for the correction of the projection data. In the MAR process, we substituted the pixels on the metal trace of the projection data with the ones calculated from the region-filling process. Then we fused the CT image reconstructed from the region-filled projection data (I_{rf}) with the original CT (I_{orig}) image reconstructed from the raw projection data (P_0). Then we

Fig. 4 The feature-reduced version of the original U-net architecture, named Unet-red. Each stack of white boxes corresponds to multi-channel feature maps. The number of channels is denoted on top of the box. The red arrows represent a convolution operation with a ker-

nel size of 3×3 , while the black arrows represent a 1×1 convolution operation. The green arrows represent a merge operation of the two kinds of feature maps. The blue and yellow arrows represent a max pooling and upsampling, respectively. (Color figure online)

forward-projected the fused CT image after masking out the metal area (I_{mf}) to get the fused projection data (P_{fused}).

To get the final corrected projection data (P_c), we replaced the pixels on the metal trace of the original projection data with the corresponding pixels of the fused projection data. To get the final CT image (I_c), we reconstructed the final corrected projection data and then restored the CT pixel value of the metal from the original CT image. For the sake of comparison, we also reconstructed CT images from the projection data corrected by the conventional method, whereby we corrected the projection data on the metal traces that were found by forward-projecting the metal mask segmented in the CT image domain. In the comparative MAR correction, we used the same MAR algorithm except for the method of metal trace estimation. To get the metal mask in the CT image domain, we applied global thresholding to the edge-enhanced CT images. We set the global threshold so that any non-metal regions were not wrongly classified as metal regions. But in doing so, some parts of the metal objects were inevitably missing in the final metal mask found in the CT image domain. We summarized all the procedures of the MAR method combined with the proposed segmentation method in the flowchart shown in Fig. 5.

3 Results

3.1 Metal segmentation

Figure 6 shows some examples of the metal segmentation on the four patient data sets, not used for the network training, using the conventional and proposed segmentation methods. Figure 6a–d show the metal masks obtained with the conventional method. For better visualization, the boundaries of the metal masks are superimposed on the corresponding

projection images. Figure 6e–h show the metal masks obtained with the proposed method. Clearly, the conventional method has more false segmentations than the proposed method due to the metal artifacts in the CT image. False classifications of non-metal pixels into metal pixels can be seen in Fig. 6b–d, which would cause overcorrection of metal artifacts, leading to edge blurring and new streak artifacts. On the other hand, false classifications of metal pixels into non-metal pixels, as can be seen in Fig. 6a, would cause under correction of the metal artifacts, leading to residual streak artifacts. The proposed segmentation method mostly outperformed the conventional segmentation method in other projection images as well (not shown here).

To evaluate the segmentation performance quantitatively, we manually made ground truth labels for 15 projection data of each patient, and we measured the Jaccard index [39] and Dice similarity index [35] on the segmented images. We computed the indices for the proposed segmentation method and the conventional segmentation method based on global thresholding with reference to the ground truth labels. The Jaccard index and Dice similarity index measures the similarity between the segmented image and the ground truth image by computing the intersection and union between the two images. The metric values for the two methods are summarized in Table 1 for the four patients. In all cases, the proposed segmentation method outperforms the conventional segmentation method.

3.2 Metal artifact correction

We reconstructed CT images of the four patients, with the matrix size of $512 \times 512 \times 512$, by applying the Feldkamp algorithm [40] to the corrected projection data. Figure 7a–c show some CT images of patient 1 before applying the MAR algorithms. Metal artifacts appear in the form of blurring

Fig. 5 The flow-chart of the MAR method combined with the U-net based metal segmentation

Fig. 6 The metal masks superimposed on the projection images of the four patients. **a–d** The conventional segmentation method. **e–h** The proposed segmentation method

and streaks around the metal crown and dental filling. Figure 7d–f show the MAR images obtained with the conventional segmentation method and Fig. 7g–i show the MAR images obtained with the proposed segmentation method. Because of the greater segmentation errors in the conventional method, the corrected images have larger residual streak artifacts along with more smearing of tooth boundaries, as indicated by white arrows.

Figure 7 shows the MAR results for patients 2, 3, and 4 obtained with the conventional and proposed segmentation methods. Figure 8a–c are the original CT images before applying the MAR algorithm. The uncorrected images have severe streak artifacts near the metal crowns. Figure 8d–f, g–i show the MAR images obtained with the conventional and proposed methods, respectively. In this case, too, it can be seen that the proposed method shows better correction, i.e., clearer edge shape and fewer streak artifacts.

To quantitatively evaluate the MAR performance, we used the same MAR performance metrics as in our previous work [38]. We compared the original projection data with the forward-projected data from the corrected CT image using three metrics: the relative error (REL), the normalized absolute difference (NAD), and the sum of squared difference (SSD), as defined in the Ref. [41]. All those metrics reflect the similarity between the forward-projected data from the corrected CT images and the raw projection data acquired by the scanner. These metrics are known to be useful when artifact-free reference images are not available, as in the case of MAR [41]. The metric values for the two methods are summarized in Table 2 for the four patients. In all cases, the proposed method outperforms the conventional method. However, the performance is very close in the case of patient 4, whose teeth all had a dental prosthesis. On average over the four patients, the proposed segmentation method improved

Table 1 The quantitative analysis of the proposed segmentation method in contrast with the conventional segmentation method

Segmentation methods	Conventional method				Proposed method			
	Patient 1	Patient 2	Patient 3	Patient 4	Patient 1	Patient 2	Patient 3	Patient 4
Metrics								
Jaccard index	0.86	0.79	0.67	0.68	0.96	0.94	0.92	0.94
Dice similarity index	0.92	0.89	0.81	0.83	0.98	0.97	0.93	0.95

Fig. 7 The MAR results for patient 1. **a–c** The uncorrected images. **d–f** The images corrected by the conventional segmentation method. **g–i** The images corrected by the proposed segmentation method. (Contrast window [−1617 9327] in Hounsfield Unit)

MAR performances by about 5.7% for REL, 6.8% for SSD, and 8.2% for NAD.

4 Discussion

Most conventional MAR algorithms rely on segmenting the metal regions on the CT image domain, which is vulnerable to metal artifacts. In this study, we performed the MAR processing with segmenting the metal regions on the projection domain, on which metal objects have less effects as compared to the CT image domain. In the CT image domain, a pixel belongs to either a metal region or a non-metal region if the pixel does not have the partial volume effect. This makes it easy to segment the metal regions if the CT image does not have any artifacts. However, in the projection domain, a pixel stands for the projection of both metal objects and tissues, thereby making it difficult to segment the metal regions by applying thresholding to the original or edge-enhanced projection image. To overcome this issue in the projection domain, we adopted a U-net-based deep learning network, and we tested the network using a few patient images. Even though the number of images used for the training and testing was small, the MAR performance of

the proposed method was better than that of the conventional method.

Although we tried to use patient images that had many different features in shape, size, and position of the metal objects, we still need to perform a far more large-scale study, employing many more images for the network training and testing, to secure the clinical applicability of the proposed method. Based on the observations we have made so far, we think our proposed method is worth a large-scale study in the future.

In applying deep learning techniques to medical image processing, their excessive computation time is a significant concern. Therefore, we focused on reducing the computation time of the deep learning network. With a customized network called Unet-red, the segmentation took about 24.78 s for the projection data of a size of $600 \times 600 \times 50$ (~55 ms/image) on a desktop computer (i7-4790@ 4 GHz, Intel, USA) that had a 2668-core GPU (GTX TITAN, NVIDIA, USA) and 6 GB memory. It took about 8 h to train the network with the five patient images of the same size. The network structure was implemented in a Python environment using Keras with a Tensorflow [42] backend.

Metal artifacts still cause great concern in dental CT imaging since the artifacts greatly compromise the image

Fig. 8 The MAR results for patients 2, 3 and 4. **a–c** The uncorrected images. **d–f** The images corrected by the conventional segmentation method. **g–i** The images corrected by the proposed segmentation method. (Contrast window [− 1617 9327] in Hounsfield Unit)

Table 2 The MAR performances of the conventional and proposed methods for the four patients

Methods	Conventional method				Proposed method			
	Patient 1	Patient 2	Patient 3	Patient 4	Patient 1	Patient 2	Patient 3	Patient 4
Metrics								
REL (%)	96.43	95.65	97.37	93.37	93.87	94.05	95.89	93.17
NAD (%)	95.89	94.73	96.87	92.75	93.01	92.03	95.73	92.21
SSD (%)	93.59	93.75	95.89	91.33	91.52	91.74	93.84	90.23

readability even after MAR. In our previous study, we showed that dual-energy imaging can greatly reduce the metal artifacts. However, the dual-energy imaging approach is costly in terms of scan time and X-ray exposure. To the best of our knowledge, there are few reported studies on MAR for dental CT using deep learning techniques. Recently, Xie et al. [27] used a deep learning technique in reducing streak artifacts caused by sparse view sampling in a low-dose CT scan. They used an improved version of the GoogleNet (inception network) to reduce the streak artifacts in the CT images. Zhang et al. [28] used the original U-net structure to correct several types of CT artifacts. They

trained the network for three different models which were specialized in reducing metal artifacts, low-dose artifacts, and sparse-view artifacts, respectively. They validated their method using simulated and experimental data; for the simulation data, the performance was very good, but for the experimental data, strong metal artifacts still persisted. Considering the variety of MAR algorithms and deep learning networks, we expect that many deep learning-based MAR algorithms will become available in the near future, and this study will hopefully make some contribution to future studies.

5 Conclusions

Our proposed U-net based metal segmentation worked well on the projection domain of dental CT, thereby leading to better MAR performance than the conventional method based on the metal segmentation on the CT image domain. We recognize that the present study has limited implications for clinical applications because, from the perspective of deep learning, the amount of data was very small (only five patients). Nevertheless, we believe our proposed method is worth further extensive studies.

Acknowledgements This work was supported by the National Research Foundation (NRF) of Korea funded by the Korean government (No: 2015M2A2A7A03043177).

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflicts of interest.

Ethical approval This article does not contain any studies with human participants performed by any of the authors. (The IRB has reviewed that this work is not applicable to the IRB' review).

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