Deep Learning-based Prior toward Normalized Metal Artifact Reduction in Computed Tomography

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ABSTRACT

X-ray computed tomography (CT) often suffers from scatter and beam-hardening artifacts in the presence of metal. These metal artifacts are problematic as severe distortions in the CT images deteriorate the diagnostic quality in clinical applications such as orthopedic arthroplasty. The normalized metal artifact reduction (NMAR) method effectively reduces the artifacts by normalizing the sinogram with the metal traces through the forward projection of the prior image. Because the prior image is the thresholded CT image with the values of the air and soft tissues replaced, the image is noticeably different from the ideal CT thereby making normalized sinogram not completely flat. In this paper, we propose the novel NMAR method with the deep learning-enhanced prior image which is denoised by learning the relationship between NMAR and clean image without metal artifact. The denoised prior image is then forward projected to correct the sinogram with the metal trace. The experimental results on simulated rat phantom dataset demonstrate that our proposed deep prior NMAR achieves higher structural similarity index (SSIM) and peak signal-to-noise ratio (PSNR) than the original NMAR.

Keywords: Metal Artifact Reduction, Computed Tomography, Deep Learning Prior

1. INTRODUCTION

Computed tomography (CT) suffers from the artifact when imaging objects with metal objects are present. Due to the metal's high x-ray absorption rate, the detectors receive low signals when the x-ray goes through the metal objects. This results in scattering and beam-hardening effects in the CT image. Metal artifacts make it difficult to observe small details around the metal objects and affect throughout the image by severe streaks and shading. Therefore, it is necessary to reduce the metal artifacts in CT images for reliable diagnosis in clinical applications such as orthopedic arthroplasty.

Various metal artifact reduction (MAR) methods have been developed to deal with the metal artifacts. For example, filtering[1,2] or interpolation[3,4] methods directly corrects the sinogram in the metal trace. These sinogram-based methods show the limited performance as the image information is not taken account and back projection of the corrected sinogram often causes the secondary artifacts in non-metal areas. Iterative methods[5,6] reconstruct the MAR image through the Bayesian optimization with both forward (sinogram) and prior (image) model, but they are computationally expensive due to the iterative optimization. Recently, deep learning-based approaches[7,8] have been also applied to reduce metal artifacts and demonstrated its effectiveness. However, they are processing only in the image domain without taking account into the sinogram information, thereby showing blurring in the MAR image.

The normalized metal artifact reduction (NMAR) is one of the efficient and effective MAR methods which utilizes both sinogram and image information. The NMAR normalizes the sinogram with the metal traces before the interpolation to remove metal artifacts effectively while minimizing other artifacts caused by the interpolation. The sinogram is normalized using the prior image, which is the thresholded image of the CT image with metal artifacts. Since the normalization is the most important process, the NMAR method is highly dependent on the

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7th International Conference on Image Formation in X-Ray Computed Tomography,
edited by Joseph Webster Stayman, Proc. of SPIE Vol. 12304, 1230434

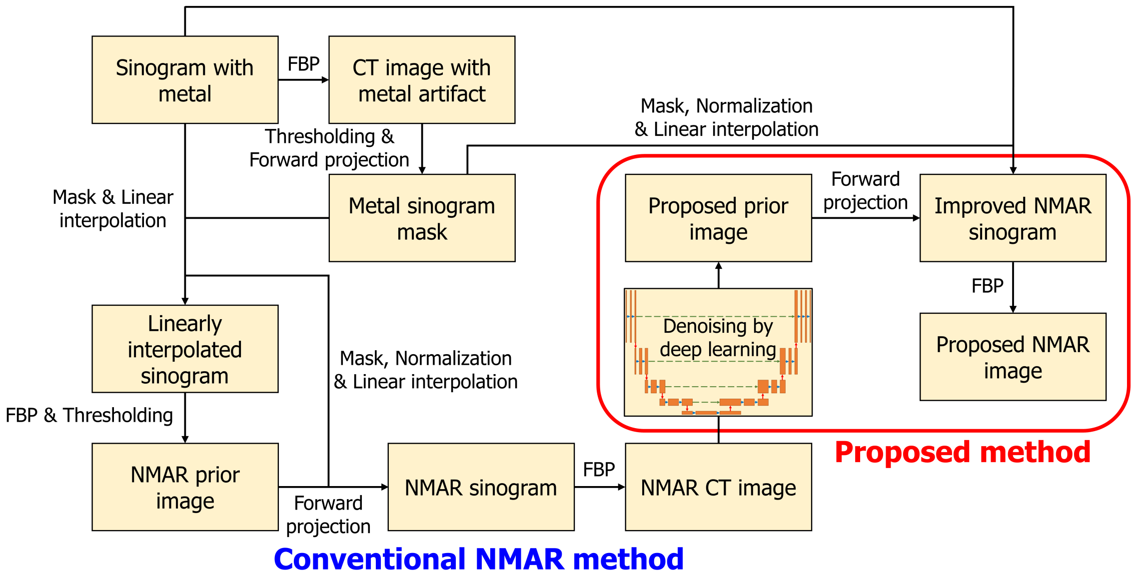

Figure 1. The overview of the proposed method. The sinogram with metal trace is processed with the original NMAR method to obtain the artifacts reduced image. Then, the NMAR result is processed with the deep learning network to obtain the prior image for the proposed method. With the denoised prior image, the NMAR method is performed again.

quality of the prior image. The NMAR method may have residual artifacts in the results due to the inaccurate prior image, depending on the metal size and locations.

In this paper, we combine the NMAR with a deep learning to further reduce the metal artifacts while preserving the details in the tissue. We use the NMAR results as the input to the deep denoising network and use the output as the prior image for the second trial of the NMAR. The deep learning-based denoising effectively reduces the residual streak and shading artifacts after the NMAR. However, as other deep learning-based MAR methods, it may cause a blurring in the outcome and lose the details in the tissue and not be sufficient for the clinical purposes. Instead, we propose to use it as the improved prior image and perform the NMAR again to further reduce the residual artifacts. We validate the proposed method with the simulation dataset of rat phantom. We demonstrate that the proposed method shows less artifacts in terms of improved peak signal-to-noise ratio (PSNR) and structural similarity index (SSIM) compared to the original NMAR.

2. METHODS

Fig. 1 illustrates the overall procedures of our proposed deep prior NMAR. We first apply the conventional NMAR by generating the thresholded prior image. We then denoise the NMAR image with the trained deep neural network and feed the denoised image as the prior image for further metal artifact reduction. In following, we describe the existing NMAR and proposed deep prior NMAR.

2.1 Normalized Metal Artifact Reduction (NMAR)[4]

As described in Fig. 1 (blue arrow), the NMAR creates the metal trace mask for sinogram by thresholding the CT image to find the location of the metal objects, then forward-projecting the metal location. For the forward projection, we use the counting model. The expected number of x-ray photons is given by,

$$\bar{\lambda} = \int_0^\infty S\left(E\right) \exp\left(-\int \mu_a(\vec{r}, E) d\vec{r}\right) dE, \tag{1}$$

where $S(E)$ is the system model, including the x-ray incident spectrum and the detector response.[9] We omit the specific x-ray path in the model for the sake of simplicity. X-ray with a 90 kVp incident spectrum is used with 2mm Aluminum pre-filtration. Total of 130,000 incident photons are used, and photons with less than 20 keV were ignored. We use 511 detectors (0.25mm /channels) with 768 views per rotation. We apply the fanbeam geometry (equi-distance) and used the ASTRA toolbox.[10,11]

The obtained metal trace is then linearly interpolated to get the prior sinogram. Filtered back projection (FBP) of the prior sinogram gives the CT image with less metal artifacts. The CT image is thresholded to segment it into three materials, air, soft tissue, and bone, and then replace the pixel values of air to -1000 [HU] and soft tissue to 0 [HU] to make the prior image. The original sinogram with the metal traces are divided pixel-by-pixel by the forward projection of the prior image. The normalized sinogram has similar values except the metal traces which gives an advantage to the linear interpolation. The normalized sinogram is masked and interpolated in the same way as the prior sinogram and then, de-normalized to get the final outcome followed by FBP.

2.2 Proposed Deep Prior NMAR

The proposed method is an extension to the original NMAR method. The NMAR method effectively removes the metal artifacts, but there are severe streak and shade artifacts remained depending on the size and location of the metals. The remaining artifacts are caused by the fluctuation in the normalized sinogram due to the difference between the original sinogram and the sinogram of the prior image. To utilize the benefit of the normalization fully, better prior image is required. Thus, we propose the deep prior NMAR method which we replace the prior images with the denoised NMAR results by the deep neural network. As shown in Fig. 1, we train the deep learning network to obtain the denoised image, focusing on removing shading and streak artifacts after the NMAR. By using the denoised image as the prior image, we can acquire the image with the metal artifacts reduced better than the original NMAR method with details remained. Note that we have not applied any thresholding to the prior image (denoised one) before the projection.

3. EXPERIMENTS

The methods are validated on the simulated rat phantom. For each slice of the phantom, 25 images were generated with two stainless steel objects with the diameter of 3mm inserted in the random places; there were

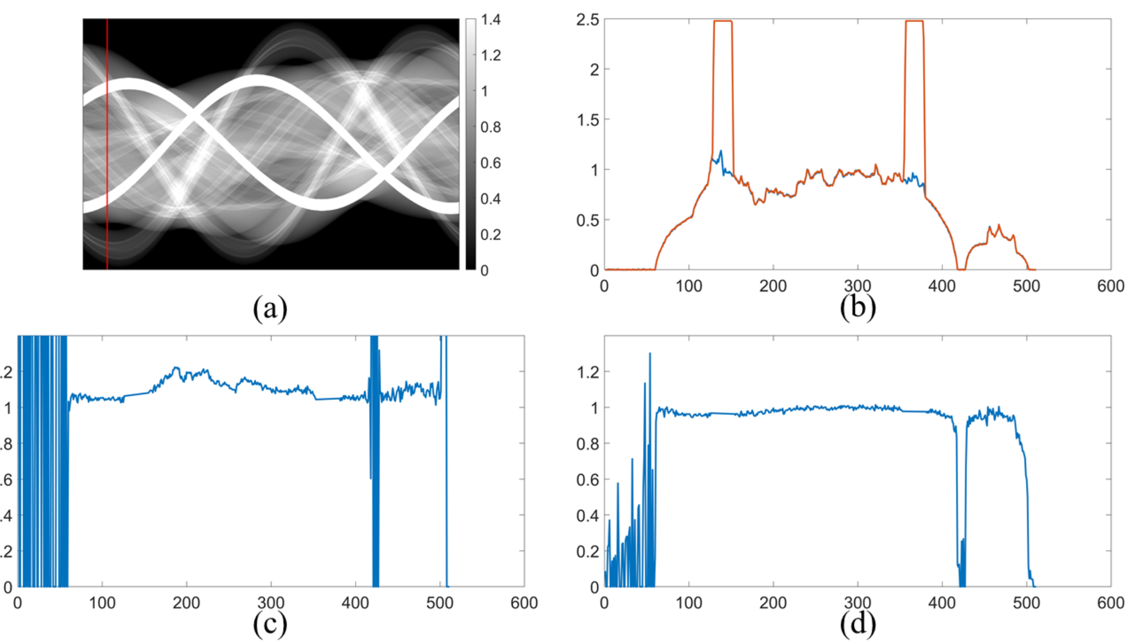

Figure 2. (a) The original sinogram with metal traces, (b) the profiles with and without metal traces, (c) the profile of the normalized and interpolated sinogram of the original NMAR method, (d) the profile of the normalized and interpolated sinogram of the proposed method. (All the profiles correspond to the specific angle view indicated by the red line in (a).)

100 slices, the width of each slice is 1 mm, in the chest and abdomen area, making 2,500 images for the dataset. The images were 512×512 pixels (0.125 mm/pixel).

We use U-Net structure to denoise the NMAR images.[12] The output activation function is removed for denoising purpose. The inputs are the NMAR images and the labels are the CT images without the metal artifacts. The network is trained for 300 epochs with L1 loss. From the 2,500 images dataset, 2,000 images were used for the training and the other 500 images were used as the test set. In order to make the test set include all parts of the body, images from every 5th slices from the 100 slices were set as the test set. The part of the training set, 400 images, are randomly chosen for validation dataset to find the best performing epoch. The network is trained with the GeForce RTX 3090 GPU.

3.1 Qualitative Evaluation

The normalized sinograms are displayed in Figure 2. The normalized sinogram of the proposed deep prior NMAR method is flatter than that of the original NMAR method. Since the quality of the metal artifact reduction is improved with the flatness of the normalized sinogram, the proposed method can reduce the metal artifacts better than the original method.

Figure 3 illustrates the experimental results of the original NMAR and the proposed deep prior NMAR method, respectively. The original CT images without and with metal objects are displayed as reference in Fig.3 (a, b). The difference images are obtained by subtracting the generated MAR image with the ground-truth CT image without metal objects. In Fig. 3(e, f), the original NMAR result still shows significant amount of artifacts, reflecting less flattened normalized sinogram. The prior image of the NMAR method (Fig. 3(c)) is computed by the thresholding method, therefore, it affects the normalization process in the NMAR method.

The deep learning denoised image (Fig. 3(g)) presents reduced metal artifacts, but the quality of the image is blurred from the deep learning process. The proposed deep prior NMAR method has noticeably reduced metal artifacts with image quality similar to the ground truth CT image without metal insertion.

Table 1. Mean and standard deviation of SSIM and PSNR of the NMAR and the proposed methods.

	NMAR	Proposed method
SSIM	0.8832 ± 0.0266	0.9038 ± 0.0137
PSNR	36.28 ± 2.901	39.12 ± 1.351

3.2 Quantitative Evaluation

The tables 1 report the SSIM and PSNR values of the conventional NMAR and the proposed deep prior NMAR. The proposed deep prior NMAR increases SSIM by 0.0206 and PSNR by 2.84dB compared with the conventional NMAR, while decreasing the standard deviation. This indicates that our proposed methods effectively reduces the metal artifact while preserving the fine details in the CT image by taking advantage of the denoised prior image through deep learning, showing potential for clinical applications such as orthopedic arthroplasty.

4. CONCLUSION

In this paper, we proposed the deep prior NMAR method to further reduce the metal artifacts from the conventional NMAR result. The proposed method denoises the NMAR image with the deep learning network and uses it as a prior image for flattened normalized sinogram. The experimental results on simulated rat phantom data showed that our deep prior NMAR method improved the MAR performance compared with the conventional NMAR method while maintaining the fine details of the original CT image. In addition, we validate the stability and robustness of our proposed method which will be useful for clinical applications like orthopedic arthroplasty.

ACKNOWLEDGMENTS

This work was supported by Institute for Information & Communications Technology Promotion(IITP) grant funded by the Korea government (MSIP) (No.2020-0-01524, Development of deep learning-based metal artifact reduction and organ segmentation techniques using spectral CT)

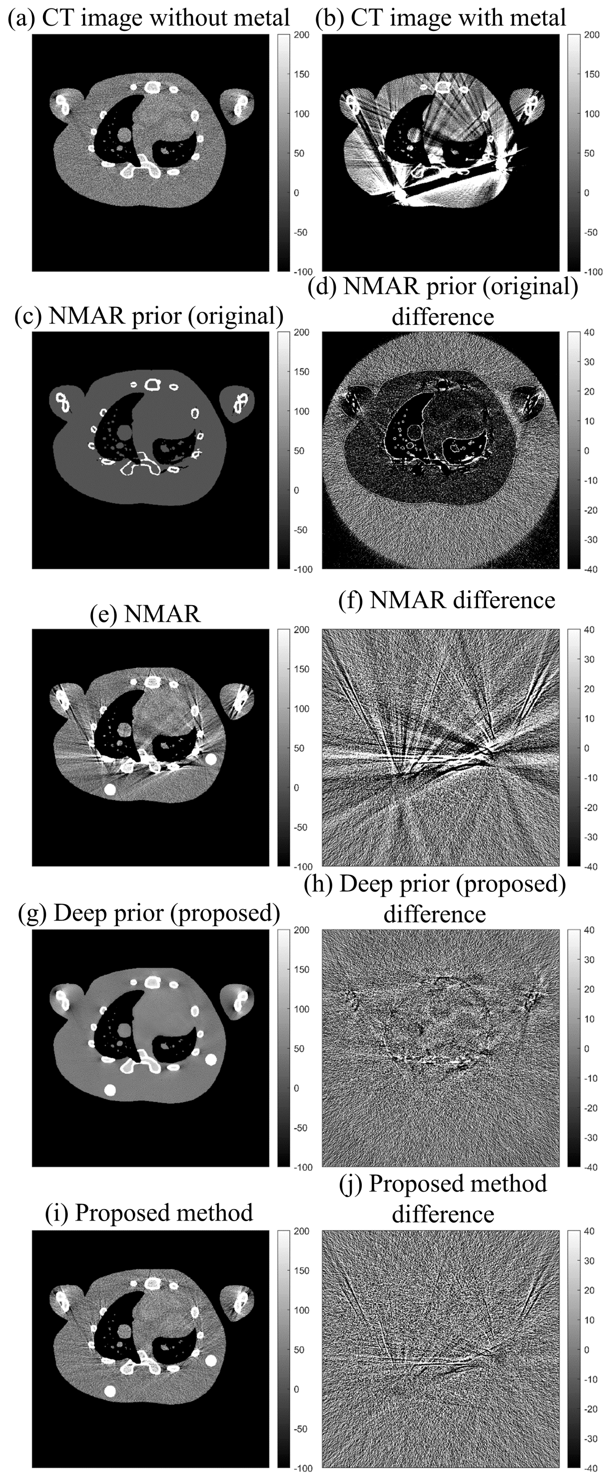

Figure 3. The results and the difference images using the original NMAR and the propose method with the associated prior images. The difference images are compared with the CT image without the metal objects. (a) The CT image without the metal objects, (b) the CT images with the metal objects, (c, d) the prior image for the NMAR method and the difference image, (e, f) the CT image from the NMAR method and the difference image, (g, h) the prior image for the proposed method and the difference image, (i, j) the CT image from the proposed method and the difference image.

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