Geometric Artifacts Correction for Computed Tomography Exploiting A Generative Adversarial Network

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Abstract. Geometrical accuracy of an X-ray Computed Tomography (CT) system is crucial to achieve high quality tomographic reconstructions. Methods to correct the resulting geometric artifacts have been comprehensively described in the past few years. Deep convolution neural network is increasingly used in CT imaging, which has a great potential in image feature learning and processing tasks. In this work, a geometric artifact correction method exploiting generative adversarial networks (GAN) is developed. The U-Net structure is employed as the generator of the network to extract the CT image features with geometric artifacts. The convolutional neural network (CNN) based on image block perception acts as a discriminator for the network, further constraining the optimization of the generator. The proposed method has been shown experimentally feasible for geometric artifacts correction in circular cone beam CT by performing more accurate feature extraction. The peak signal to noise ratio (PSNR) of the corrected phantom images increased by 11.812 on average, and the root mean square error (RMSE) decreased by 9.982 on average.

1. Introduction
Computed tomography (CT) is a kind of imaging technology that uses the ray projection of different angles of objects to reverse the density information of objects[1]. It has the advantages of fast scanning speed, high spatial resolution, no contact and non-destructive realization of three-dimensional imaging of the interior of objects. However, in practical applications, CT images are inevitably affected by various factors to produce different artifacts[2]. Among them, geometric artifacts severely reduce the spatial resolution and sharpness of CT images, which may lead to complete loss of image detail information in severe cases. Therefore, how to optimize the industrial CT system, eliminate geometric artifacts and improve the imaging quality of reconstructed images is the primary solution for the advancement and development of CT technology.

With the development of CT technology, a large number of studies have been conducted at home and abroad on how to reduce and eliminate geometric artifacts in reconstructed images. According to the different principles of geometric image correction algorithm, the current geometric image correction methods are broadly divided into three categories: phantom-based methods, self-calibration methods and geometric correction method based on depth learning.

For phantom-based methods, the principle is to obtain the geometric parameters of the CT system using the calibration phantom with known geometric relationships. Common correction phantoms are composed of standard metal pellets and regular holes[3]. In 2000, Noo et al[4] designed a correction method to solve the geometric parameters of CT systems analytically using double spherical phantoms.
In 2019, Benjamin et al.[5] tested the effect of the phantom projection tensor on the correction result when using a multi-sphere phantom for parameter calibration.

Phantom-based methods have high calculation accuracy and high generality. However, the correction accuracy of the method depends on precise and particular phantoms, which are difficult to manufactured. Therefore, the correction method without phantom has been developed. The self-correction method uses the characteristic information of the scanned object to establish the cost function, and uses an iterative method to approximate the true value to correct geometric artifacts. In 2008, Panetta et al.[6] first implemented the correction of the geometric parameters of the CT system using the projection redundancy of the central fan-beam plane of the X-ray at different angles of the measured object. In 2016, Chen et al.[7] used the method of local linear interpolation of the geometric pseudoimage part of the CT reconstructed image in combination with the method of iterative reconstruction to achieve the solution of the geometric parameters of the CT system. These methods have to iteratively reconstruct images for better optimization, so the trade-off between efficiency and accuracy of results must be considered.

In recent years, deep learning has been gradually applied to the field of CT image correction and is developing towards in-depth study. In 2018, Satoshi Kida et al.[8] designed a deep convolutional neural network (CNN) for correction of scattering artifacts and truncation artifacts. In 2019, Harms et al.[9] proposed a cycle generative adversarial networks (GAN) method for correction of scattering pseudopacities. In 2019, Xiao et al.[10] proposed a geometric artifacts correction method based on a fully convolutional neural network. These demonstrate the effectiveness of deep learning applied to CT artifacts correction.

In this paper, a GAN-based geometric artifacts correction method is proposed. The U-Net structure was used as the generator of the network to extract the CT image data features with geometric artifacts. The deep CNN acts as a discriminator for the network, further constraining the optimization of the generator. We constructed a simulation dataset and an actual scan dataset. The network performs geometric artifacts correction for these two types of phantoms separately. The artifacts correction effect, peak signal to noise ratio (PSNR), root mean squared error (RMSE) are used to evaluate the correction images.

2. Materials and methods

2.1. Datasets construction

During the dataset generation, we choose an simulated phantom and an actual phantom. The simulated phantom uses a head model proposed by Lemmens et al.[11]. The actual phantom is a medical oral model containing dental and skeletal features. Through simulation and actual scanning reconstruction, the reconstructed images without geometric artifacts and the reconstructed images with different degrees of geometric artifacts of the two phantoms were obtained.

Two types of datasets, 1000 images with or without geometric artifacts at a resolution of 256 × 256. We used 990 images for training and 10 pictures for testing.

Before training, the two images of each phantom are labeled as 0 and 1, respectively. The label 0 represents the image with geometric artifacts and label 1 represents the image without geometric artifacts, as shown in Figure 1.
2.2. Network and Training

2.2.1. Generator Network. We adopt U-net as the generator of GAN network \( G_{\theta_G} \) parametrized by \( \theta_G \), and the network structure is shown in Figure 2. U-net has the ability of multi-layer feature extraction and comprehensive analysis, and can better extract the edge information of each part in the image. Geometric artifacts show edge blurring and ghosting in the image, and the removal of geometric artifacts are completed using the edge feature extraction ability of U-net to generate geometric ghosting free images. Geometric ghosting exhibits edge blurring and ghosting in the image. The edge feature extraction ability of U-net was used to complete the removal of geometric artifacts and generate geometric artifact-free images.

2.2.2. Discriminator Network. Depth convolutional neural networks were selected for discriminator networks \( D_{\theta_D} \) parametrized by \( \theta_D \), and the network structure is shown in Figure 3, Where BN denotes batch normalization. It contains eight convolutional blocks and two fully connected layers. Each convolution block is followed by a batch normalization layer. The network ends with two fully connected layers, equivalent to a classification block. The last layer estimates that a given image belongs to the image without geometric artifacts or with geometric artifacts.
2.2.3. Loss function. The generator loss function consists of two parts, content loss and adversarial loss. Content loss is achieved using VGG loss. VGG19[12] is a popular deep neural network mainly used for image classification. The ninth layer of the pre-trained VGG19 network was used as a feature extractor to extract feature mappings from the generated and label images. VGG loss calculates the Euclidean distance between the feature map of the generated image $G_{\theta_G}(I_G)$ and the reference image $I_{WA}$ based on these extracted feature maps. The calculation formula is as follows:

$$l_{VGG} = \frac{1}{W_iH_i} \sum_{x=1}^{W_i} \sum_{y=1}^{H_i} (\Phi_{i,j}(I_{WA})x, y - \Phi_{i,j}(G_{\theta_G}(I^G_{WA})))x, y$$

Here $W_i$ and $H_i$ represent the dimensions of the feature maps within the VGG network respectively, $\Phi_{i,j}$ represents the feature mapping generated by the VGG19 network, $\Phi_{i,j}(I_{WA})$ represents the feature mapping extracted from the label images, $\Phi_{i,j}(G_{\theta_G}(I^G_{WA}))$ represent feature mappings extracted from the generated artifact-free images.

The adversarial loss is calculated based on the probability of the return of the discriminator network. In the discriminator model, the discriminator network receives images generated by the generated network. The formula for calculating the adversarial loss is as follows:

$$l_{Adv} = \sum_{n=1}^{N} -log D_{\theta_G}(G_{\theta_G}(I^G_{WA}))$$

Here $D_{\theta_G}(G_{\theta_G}(I^G_{WA}))$ represents the probability that the resulting image is an image free of geometric artifacts.

2.2.4. Network training. The objective function optimizer selected by the network was Adam, the initial learning rate of the optimizer was set to 0.002, the learning rate per 20,000 rounds decreased to 0.5 times of the original, and the optimization parameters were set to 0.5 and 0.999. The simulated head model performed 120,000 rounds of training, with the entire training process of about 10.5 hours, and the medical oral model performed 40,000 rounds of training, with the entire training process of about 3.5 hours. After network training was completed, during the test, it took less than one second to generate an image without geometric artifacts.

We implement our models using Tensorflow deep learning framework on a CPU (Intel(R) Core(TM) i7-6850K, 3.60GHz) and a GPU (NVIDIA GTX-1080Ti, 2GB) system.

3. Results and discussion

3.1. Evaluation indicators
In order to quantitatively analyze the corrected image quality of the proposed method, peak signal to noise ratio (PSNR) and root mean squared error (RMSE) are selected as image quality evaluation indicators in this paper. The definitions of PSNR and RMSE are as follows:
$PSNR = 10 \cdot \log_{10} \left( \frac{M_{AX}^2}{\frac{1}{N} \sum_{i=1}^{N} |y(i) - y_0(i)|^2} \right)$

$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (y(i) - y_0(i))^2}$

Here $MAX$ is the maximum pixel value of the image, and uint8 data was used experimentally with a maximum pixel value of 255. $y$ and $y_0$ represent the image and the reference image respectively. $i$ indexes the pixel in the image. $N$ is the total number of pixels in the image. The larger the PSNR and the smaller the RMSE, the smaller the differences the image and the label image.

3.2. Experimental results

The network correction results of the simulation head phantom and the medical oral model phantom are shown in Figure 4. Among them, the first column is the input images with geometric artifacts, the middle is the GAN network output images, and the third column is the geometric artifact-free label images.

![Figure 4. Correction results of two phantoms.](image)

From the input in Figure 4 it can be seen that there are obvious geometric artifacts in the two phantoms, with blurred images and poor visibility of the details. After the trained GAN network, the output images are clear and the detailed information is recovered, which can reach the level equivalent to the label image. To further demonstrate the network performance, we use PSNR and RMSE metrics to evaluate the results of 10 test images, the simulated head phantom results are shown in Table 1, and the medical oral phantom results are shown in Table 2.

| Simulated head phantom | Test images | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|------------------------|-------------|---|---|---|---|---|---|---|---|---|----|
| PSNR                  | Input       | 23.620 | 25.884 | 26.903 | 27.294 | 27.454 | 28.674 | 29.481 | 30.962 | 31.312 | 32.152 |
| RMSE                  | Input       | 16.843 | 12.951 | 11.518 | 11.012 | 10.810 | 9.394 | 8.560 | 7.218 | 6.933 | 6.294 |

Table 1. PSNR and RMSE for different test images in simulated head phantom.

| Medical oral phantom | Test images | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|----------------------|-------------|---|---|---|---|---|---|---|---|---|----|
| PSNR                 | Input       | 18.416 | 18.982 | 19.414 | 19.988 | 20.234 | 21.277 | 22.084 | 23.068 | 20.354 | 21.328 |
| RMSE                 | Input       | 20.881 | 19.564 | 18.935 | 17.724 | 17.230 | 15.021 | 14.239 | 12.573 | 16.609 | 14.847 |

Table 2. PSNR and RMSE for different test images in medical oral phantom.
In the table, the input result is calculated from the image with geometrical artifacts and the label image, and the output result is calculated from the image generated by GAN Network and the label image. It can be seen from Table 1 and Table 2 that the PSNR values of the output images of both datasets are larger than the input images with geometric artifacts, with an average increase of 11.812. The RMSE values are smaller than those of the input images with geometric artifacts, with an average reduction of 0.982. These indicate that the GAN-generated images are closer to the label images, which is also consistent with the results shown in Figure 4. In a word, the GAN network implements geometric artifacts correction to generate high-resolution images.

4. Conclusions

In this paper, we design and implement a GAN-based geometric ghost correction method. We conclude that GAN can achieve the correction of geometric artifacts by training and testing simulated and real phantoms. To further validate the GAN network performance, we used the PSNR and RMSE metrics for evaluation and concluded that the corrected phantom image had a higher resolution and was closer to the label image. This also further illustrates the superiority of network performance.

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