REMOVING RING ARTIFACTS IN CBCT IMAGES VIA GENERATIVE ADVERSARIAL NETWORK

Shuyang Zhao, Jianwu Li, Qirun Huo

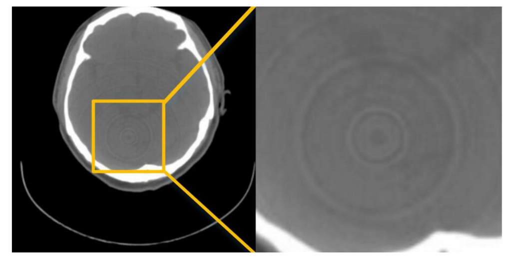
Add me !

Overview

We present an algorithm to remove ring artifacts in CBCT Images:

- Avoid the loss of image details resulting from the coordinate transformation.
- Using an image to-image network based on Generative Adversarial Network.
- Greatly improved the integration of image quality by using loss consolidation.

Motivation



CBCT images has been widely used in the medical fields. However, due to the limitations of system technology, CBCT images often have a series of ring artifacts, which have the same center with the reconstructed image and different gray levels with the surrounding pixels.

The existing methods mostly remove artifacts by different filters, so that it is inevitable to result in loss of details and blurred edges in the image. Therefore, how to remove ring artifacts without affecting image quality is critical for the application of CBCT.

***Key Idea*: We used a joint loss strategy, which joints the target loss and the generative adversarial loss as a new loss function to solve this issue.**

The proposed method

• Smooth Loss

The CBCT image that contains artifacts can be expressed mathematically as:

$$I(x,y) = S(x,y) + n(x,y)$$

The original CBCT image — The ideal image without artifacts — The artifacts information

Then we can get the gradients in the x and y directions:

$$\begin{cases} \partial_x I(x,y) = \partial_x S(x,y) + \partial_x n(x,y) \\ \partial_y I(x,y) = \partial_y S(x,y) + \partial_y n(x,y) \end{cases}$$

To make sure the image is smooth enough, the objective functions can be written as:

$$\min_S \left(\lambda_1 \sum_p (\partial_x S_p - \partial_x I_p)^2 + \lambda_2 \sum_p (\partial_y S_p - \partial_y I_p)^2 \right)$$

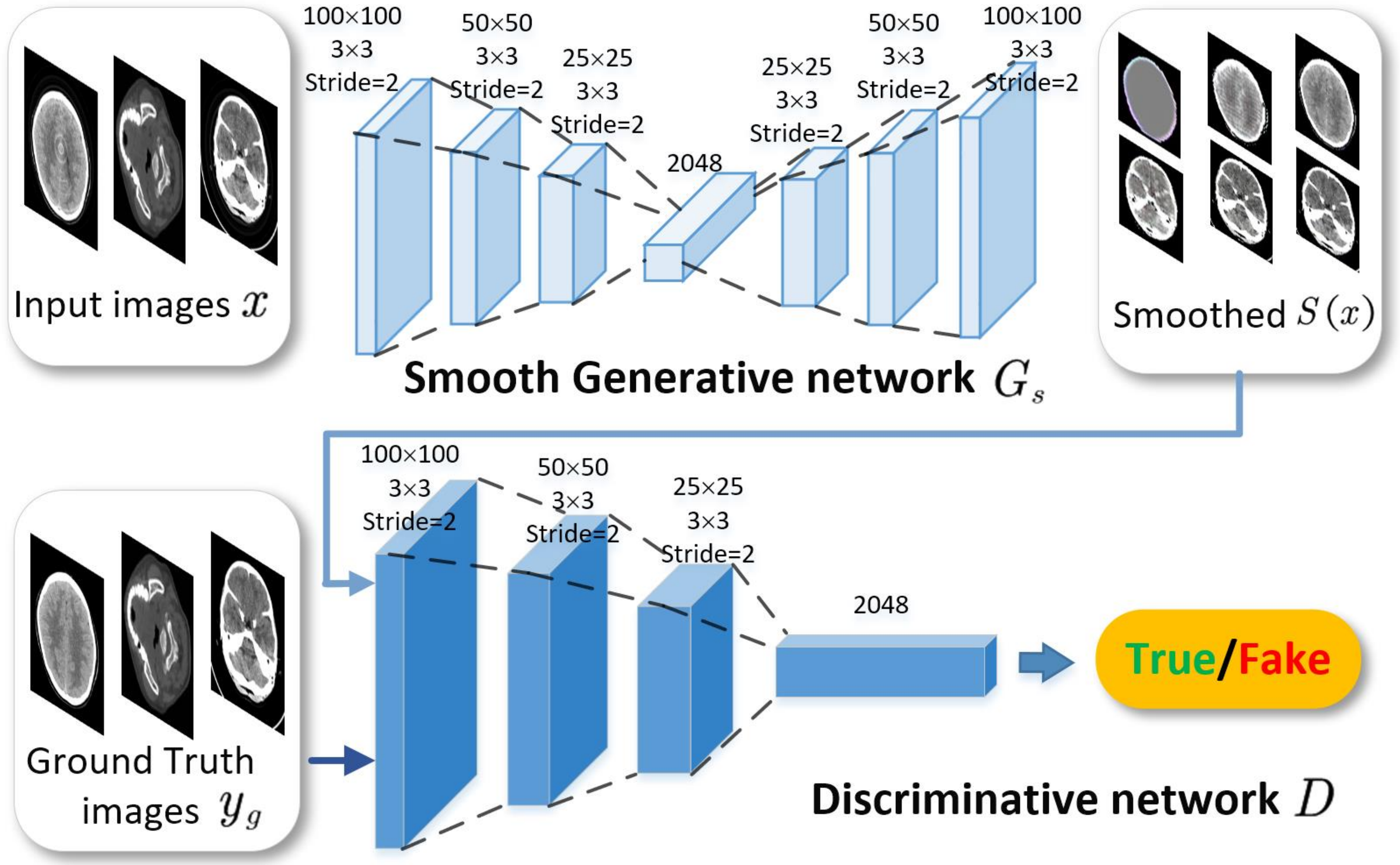
Two fidelity terms can ensure the smoothed image S is similar to the original image I.

• Generative Adversarial Loss

$$\min_G \max_D E_{x\sim\mathcal{X}}[\log D(x)] + E_{z\sim\mathcal{Z}}[\log(1-D(G(z)))]$$

The generative network G is trained to map samples from noise distribution p_z to real-world data distribution p_{data} through playing a minimax game with the discriminative network D. And D aims to distinguish the real samples $x \sim p_{data}$ and the generated samples $G(z) \sim p_g$ in the training procedure.

SGAN (Smooth Generative Adversarial Networks)



We adapt the GANs learning strategy to remove ring artifacts in CBCT images:

$$\min_{G_s} \max_D E_{y_g\sim\mathcal{Y}}[\log D(y_g)] + E_{x\sim\mathcal{X}}[\log(1-D(S(x)))]$$

SGAN composing of two modules:

- The image generative network with smooth loss G_s ;
- The discriminative network D .

Given a pair of data: $(x, y_g) \in (\mathcal{X}_{input}, \mathcal{Y}_{without-artifacts})$, the loss function can be defined as:

$$D = -\log[D(y_g)] - \log[D(S(x)) - 1]$$

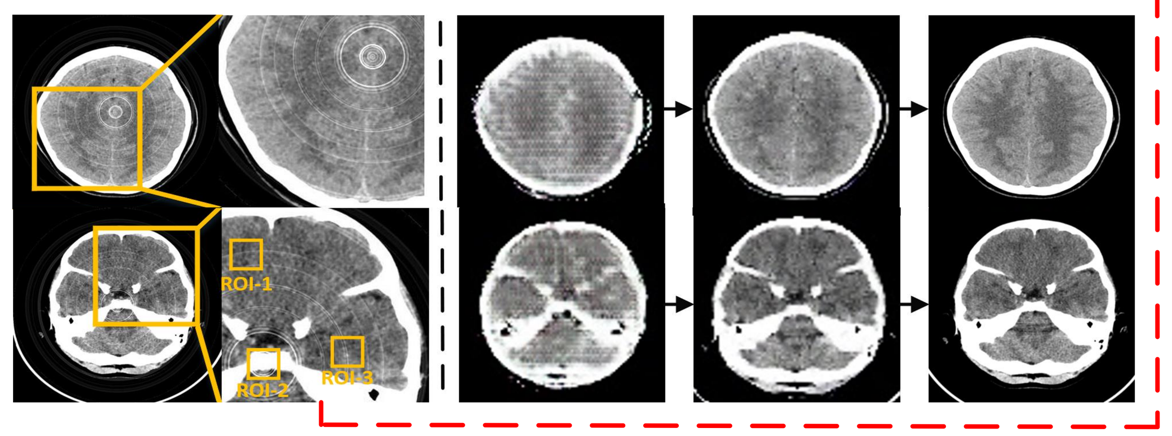
$$G_s = \log[D(S(x)) - 1] + \left(\lambda_1 \sum_p (\partial_x S(x) - \partial_x y_g)^2 + \lambda_2 \sum_p (\partial_y S(x) - \partial_y y_g)^2 \right)$$

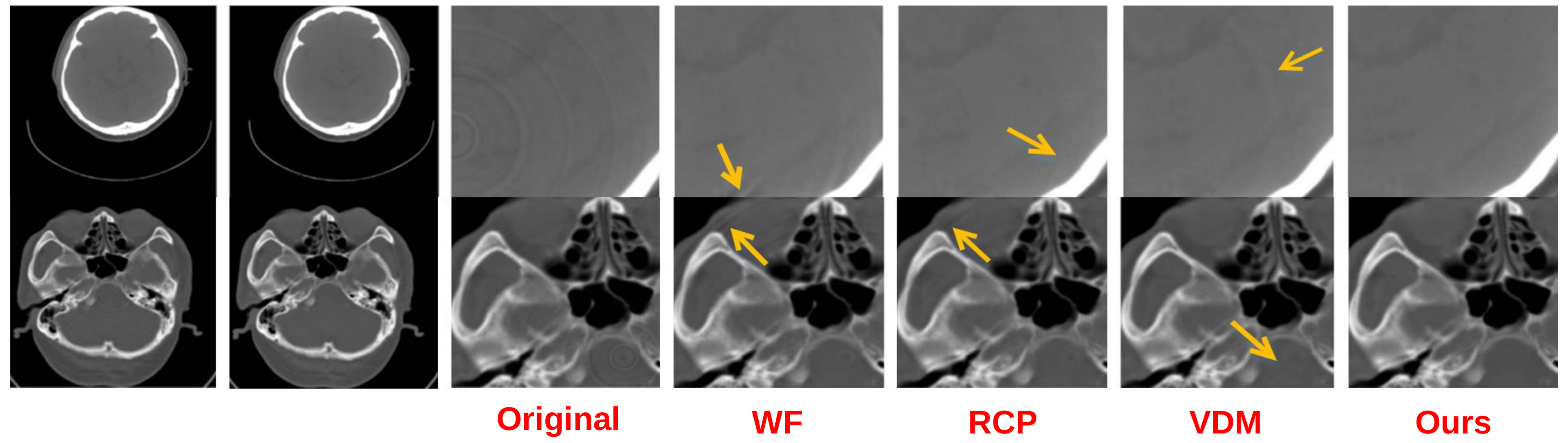
Experimental Results and Comparisons

We conducted experiments on both simulated and real data. These CBCT images are all gray scale and the values of all pixels were normalized to [0, 1].

• Qualitative Evaluation

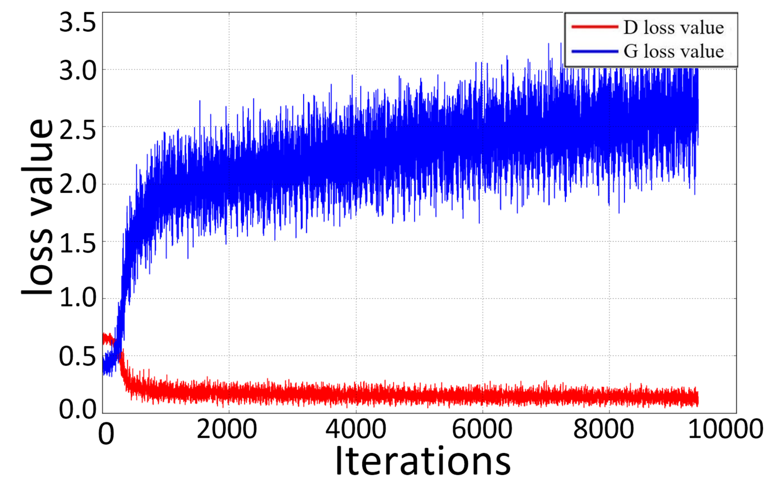
Here shows some generative processes on the two kinds of simulated CBCT images. Our method generated the high-quality CBCT images without ring artifacts gradually from the simulated CBCT images after many iterations of training.





We compared the proposed method with three existing methods: the wavelet Fourier filtering (WF) [1], the ring correction in polar coordinate (RCP) [2] and the variation-based destriping model (VDM) [3]. Our method effectively removed ring artifacts while preserving details and edges information of the CBCT images during smoothing.

Meanwhile, the loss of the generator and the discriminator converges gradually.



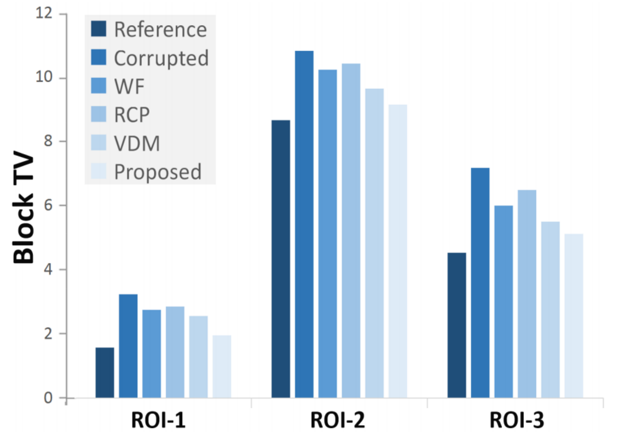
• Quantitative Evaluation

Methods	PSNR(dB)	MSSIM
WF	43.8253	0.9646
RCP	42.9617	0.9533
VDM	45.6575	0.9724
Proposed	**48.9887**	**0.9859**

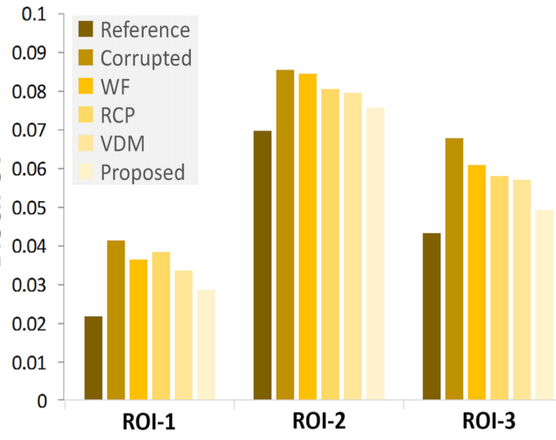
We used Peak Signal to Noise Ratio (PSNR) and Mean Structural Similarity (MSSIM) as quantitative assessments.

It can be observed that the proposed method retains the information of the original CBCT images to the largest extent.

We introduced the block total variation (TV) and the block coefficient of variance (CV) to measure local homogeneity and smoothness of images. We chose three different representative blocks as ROIs in simulated images. From the bar charts, the values of our method are the closest to base images.



$$TV(B^k) = \|\partial_x B^k\|_1 + \|\partial_y B^k\|_1, \ k = 1, 2, \cdots, N$$



$$CV(B^k) = \frac{\sigma(B^k)}{\mu(B^k)}, \ k = 1, 2, \cdots, N$$

Conclusions

We proposes the smooth generative adversarial networks (SGAN) to remove ring artifacts in CBCT images. It combines the generative adversarial loss and the smooth loss as a novel training loss function. Both of the generator and the discriminator can be trained to remove ring artifacts in CBCT images by means of image-to-image. Experimental results demonstrate that the proposed method is more effective on both simulated data and real-world CBCT images, compared with other algorithms.

That's the end of this paper. Thank you for watching!

[1] B. Munch, P. Trtik, F. Marone, and M. Stampanoni, "Stripe and ring artifact removal with combined wavelet Fourier filtering," Optics express, vol. 17, no. 10, pp. 8567–8591, 2009.
[2] D. Prell, Y. Kyriakou, and W. A. Kalender, "Comparison of ring artifact correction methods for flat-detector CT," Physics in medicine and biology, vol. 54, no. 12, p. 3881, 2009.
[3] L. Yan, T. Wu, S. Zhong, and Q. Zhang, "A variationbased ring artifact correction method with sparse constraint for flat-detector CT," Physics in medicine and biology, vol. 61, no. 3, p. 1278, 2016.