Low-Dose CT: Reducing Tube Current, Number of Projections, or Both?

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Introduction

Due to the harmful nature of X-rays, dose reduction is one of the primary aims of CT research. Two widely discussed pathways are reducing the number of projections (sparse-view CT), and reducing the tube current (low-mAs CT). While these approaches introduce streaks or noise, respectively, deep learning-based post-processing promises to restore image quality [1-4]. In this work, we investigate the trade-off between reducing tube current and number of projections in conjunction with deep image correction.

Materials and Methods

Clinical CT scans were filtered in *z*-direction and forward-projected in parallel beam geometry with N projection angles covering 180° and 512 detector pixels of size 0.8 mm. To simulate low-mAs CT, we add Poisson noise to the sinograms with I photons. For sparse-view CT, we reduce the number of projections. We obtain high-dose CT images at N_{max} = 512 and I_{max} = 1.5 × 10^6. Low-dose images are simulated with a dose reduction of 80%, with $N \in \{512, 342, 229, 153, 102\}$ and $I_0 \in I_{max}\{0.2, 0.29, 0.45, 0.67, 1.0\}$. The training set for the neural network consists of 12 patients, the validation set of 2 patients, and the test set of 1 patient.

We employ a U-Net architecture with five downsampling stages for correction of the low-dose images as previously used in [1]. The network is trained seperately for each low-dose configuration for 50 epochs.

Results

Figure 1 shows uncorrected and corrected low-dose CT images. After correction, most noise and streak artifacts are removed. However, some structures are inconsistent with the ground truth, especially for sparser acquisitions. This is consistent with Table 1, where higher number of projections yield better RMSE and SSIM values.

Table 1: Quantitative results of low-dose CT denoising for different combinations of reducing tube current and number of projections.

RMSE [HU] /SSIM	Uncorrected	Corrected
0.20 *I*, *N* = 512	44.41/0.909670	**10.21**/*0.994951*
0.29 *I*, *N* = 342	44.48/0.909244	44.48/**0.994981**
0.45 *I*, *N* = 229	44.86/0.907238	*10.26*/0.994940
0.67 *I*, *N* = 153	49.68/0.885591	10.71/0.994528
1.00 *I*, *N* = 102	65.11/0.807300	12.18/0.992865

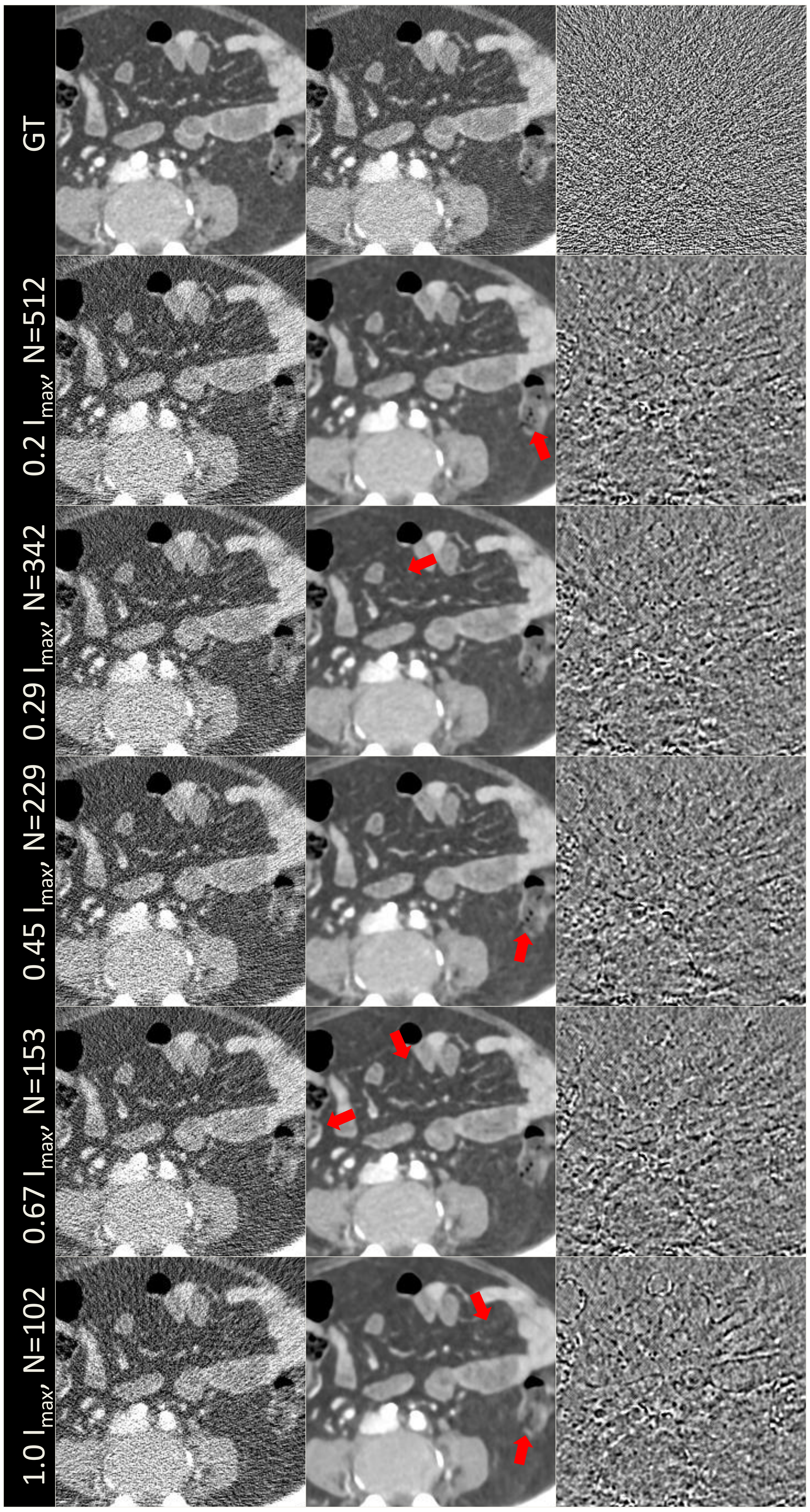

Figure 1: Denoising results for different combinations of mAs reduction and sinogram sparseness. Top row: no-noise ground truth, high-dose image, difference image. Rest: uncorrected image, corrected image, difference of corrected images to ground truth. C = 0 HU, W = 500 HU for CT images, C = 0 HU, W = 100 HU for right column.

Conclusions

The network is able to correct all tested low-dose reconstructions, reducing MSE by up to 80% and SSIM up to 23%. However, sparse-view CT lead to more inconsistencies with the ground truth and decreased visibility of some structures. Therefore, dose reduction should preferably be achieved by reducing tube current.

Acknowledgment

This study was supported by the German Federal Ministry for the Environment, Nature Conservation, Nuclear Safety, and Consumer Protection (BMUV) under grant 67KI2036B. Parts of the reconstruction software were provided by RayConStruct® GmbH, Nürnberg, Germany.

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