

# DuDoNet: Dual Domain Network for CT Metal Artifact Reduction

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# Contributions

- End-to-end trainable dual-domain refinement network for metal artifacts reduction.
- A mask pyramid U-Net for sinogram refinement
- A Radon inversion layer (RIL) to connect sinogram domain and image domain.
- A radon consistency (RC) loss to penalize secondary artifacts in the image domain.

**Intuition:** image domain performance can be improved by fusing information from the sinogram domain, and inconsistent sinograms can be corrected by the learning signal-back-propagated from the image domain to reduce secondary artifacts.

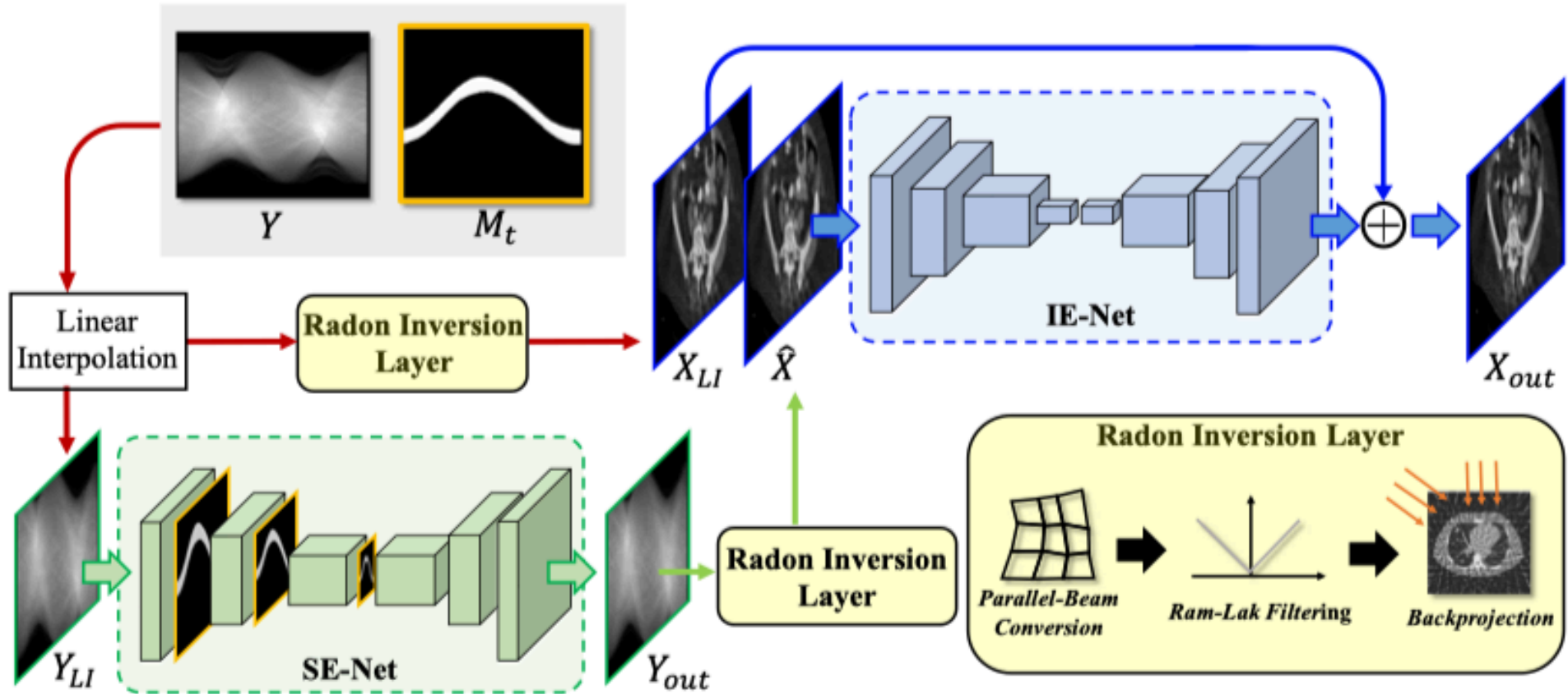


Figure 2: The proposed Dual Domain Network (DuDoNet) for MAR. Given a degraded sinogram  $Y$  and a metal trace mask  $M_t$ , DuDoNet reduces metal artifacts by simultaneously refining in the sinogram and image domains.

# Mask pyramid

$$Y_{out} = \mathcal{M}_t \odot \mathcal{G}_s(Y_{LI}, \mathcal{M}_t) + (1 - \mathcal{M}_t) \odot Y_{LI}. \quad (6)$$

# Loss functions

$$\mathcal{L}_{\mathcal{G}_s} = \|Y_{out} - Y_{gt}\|_1, \quad (7)$$

$$\mathcal{L}_{RC} = \|f_R(Y_{out}) - X_{gt}\|_1, \quad (11)$$

$$\mathcal{L}_{\mathcal{G}_i} = \|X_{out} - X_{gt}\|_1. \quad (13)$$

# Dataset

- 4000 images from 320 patients for training
- 200 images from 12 patients for testing
- Images dimension: 416\*416
- A total of 100 metal shapes, 90 metal shapes are paired with 4000 images, generating 360000 combinations in the training set.
- In training set, the size of metal implants range from 16 to 4967 pixels.
- In the testing set, the size of metal implants range from 32 to 2054 pixels.

# Results

PSNR(dB)/SSIM	Large Metal $\longrightarrow$ Small Metal					Average
A) SE-Net <sub>0</sub>	22.88/0.7850	24.52/0.8159	27.38/0.8438	28.61/0.8549	28.93/0.8581	26.46/0.8315
B) SE-Net	23.06/0.7868	24.71/0.8178	27.66/0.8463	28.91/0.8575	29.19/0.8604	26.71/0.8337
C) IE-Net	27.54/0.8840	29.49/0.9153	31.96/0.9368	34.38/0.9498	33.90/0.9489	31.45/0.9269
D) SE-Net <sub>0</sub> +IE-Net	28.46/0.8938	30.67/0.9232	33.71/0.9458	36.17/0.9576	35.74/0.9571	32.95/0.9355
E) SE-Net+IE-Net	28.28/0.8921	30.49/0.9221	33.76/0.9456	36.26/0.9576	36.01/0.9574	32.96/0.9350
F) SE-Net <sub>0</sub> +IE-Net+RCL	28.97/0.8970	31.14/0.9254	34.21/0.9476	36.58/0.9590	36.15/0.9586	33.41/0.9375
G) SE-Net+IE-Net+RCL	29.02/0.8972	31.12/0.9256	34.32/0.9481	36.72/0.9595	36.36/0.9592	33.51/0.9379

Table 1: Quantitative evaluations for different components in DuDoNet.

A) SE-Net<sub>0</sub>: The sinogram enhancement network without mask pyramid network.

B) SE-Net: The full sinogram enhancement module.

C) IE-Net: Image enhancement module. IE-Net is applied to enhance  $X_{LI}$  without  $\hat{X}$ .

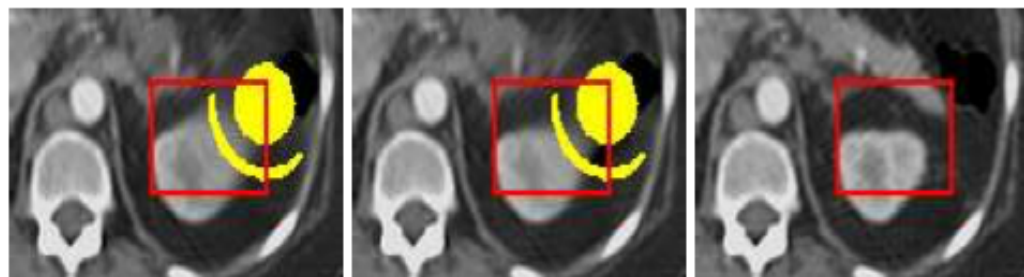
D) SE-Net<sub>0</sub>+IE-Net: Dual domain learning with SE-Net<sub>0</sub> and IE-Net.

E) SE-Net+IE-Net: Dual domain learning with SE-Net and IE-Net.

F) SE-Net<sub>0</sub>+IE-Net+RCL: Dual domain learning with Radon consistency loss.

G) SE-Net+IE-Net+RCL: Our full network.

# Ablation results

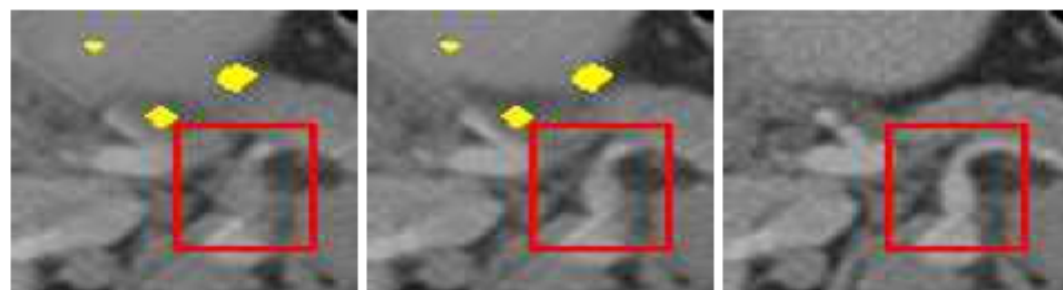


Without RC loss

With RC loss

Ground Truth

Figure 4: Visual comparisons between models without RC loss (E in Table 1) and our full model (G in Table 1).

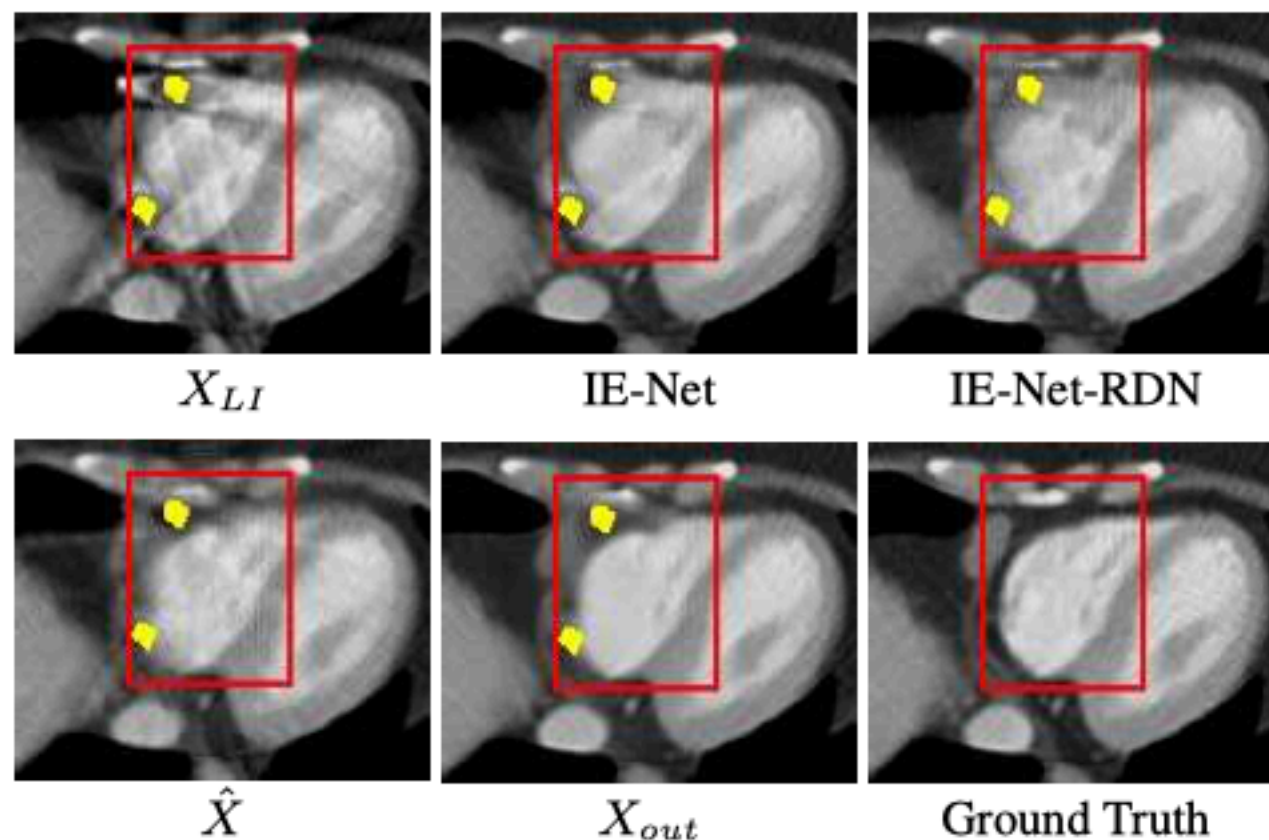


Without MP

With MP

Ground Truth

Figure 5: Visual comparisons between models without MP (F in Table 1) and our full model (G in Table 1).



$X_{LI}$

IE-Net

IE-Net-RDN

$\hat{X}$

$X_{out}$

Ground Truth

Figure 6: Visual comparisons between models without SE-Net (top row IE-Net and IE-Net-RDN) and our full model (bottom row  $\hat{X}$  and  $X_{out}$ ).



# Results

PSNR(dB)/SSIM	Large Metal $\longrightarrow$ Small Metal					Average
LI [12]	20.20/0.8236	22.35/0.8686	26.76/0.9098	28.50/0.9252	29.53/0.9312	25.47/0.8917
NMAR [18]	21.95/0.8333	24.43/0.8813	28.63/0.9174	30.84/0.9281	31.69/0.9402	27.51/0.9001
cGAN-CT [24]	26.71/0.8265	24.71/0.8507	29.80/0.8911	31.47/0.9104	27.65/0.8876	28.07/0.8733
RDN-CT [32]	<u>28.61/0.8668</u>	<u>28.78/0.9027</u>	<u>32.40/0.9264</u>	<u>34.95/0.9446</u>	<u>34.00/0.9376</u>	<u>31.74/0.9156</u>
CNNMAR [33]	<u>23.82/0.8690</u>	<u>26.78/0.9097</u>	<u>30.92/0.9394</u>	<u>32.97/0.9513</u>	<u>33.11/0.9520</u>	<u>29.52/0.9243</u>
DuDoNet (Ours)	<b>29.02/0.8972</b>	<b>31.12/0.9256</b>	<b>34.32/0.9481</b>	<b>36.72/0.9595</b>	<b>36.36/0.9592</b>	<b>33.51/0.9379</b>

Table 2: Quantitative evaluation of MAR approaches in terms of PSNR and SSIM.

# Results

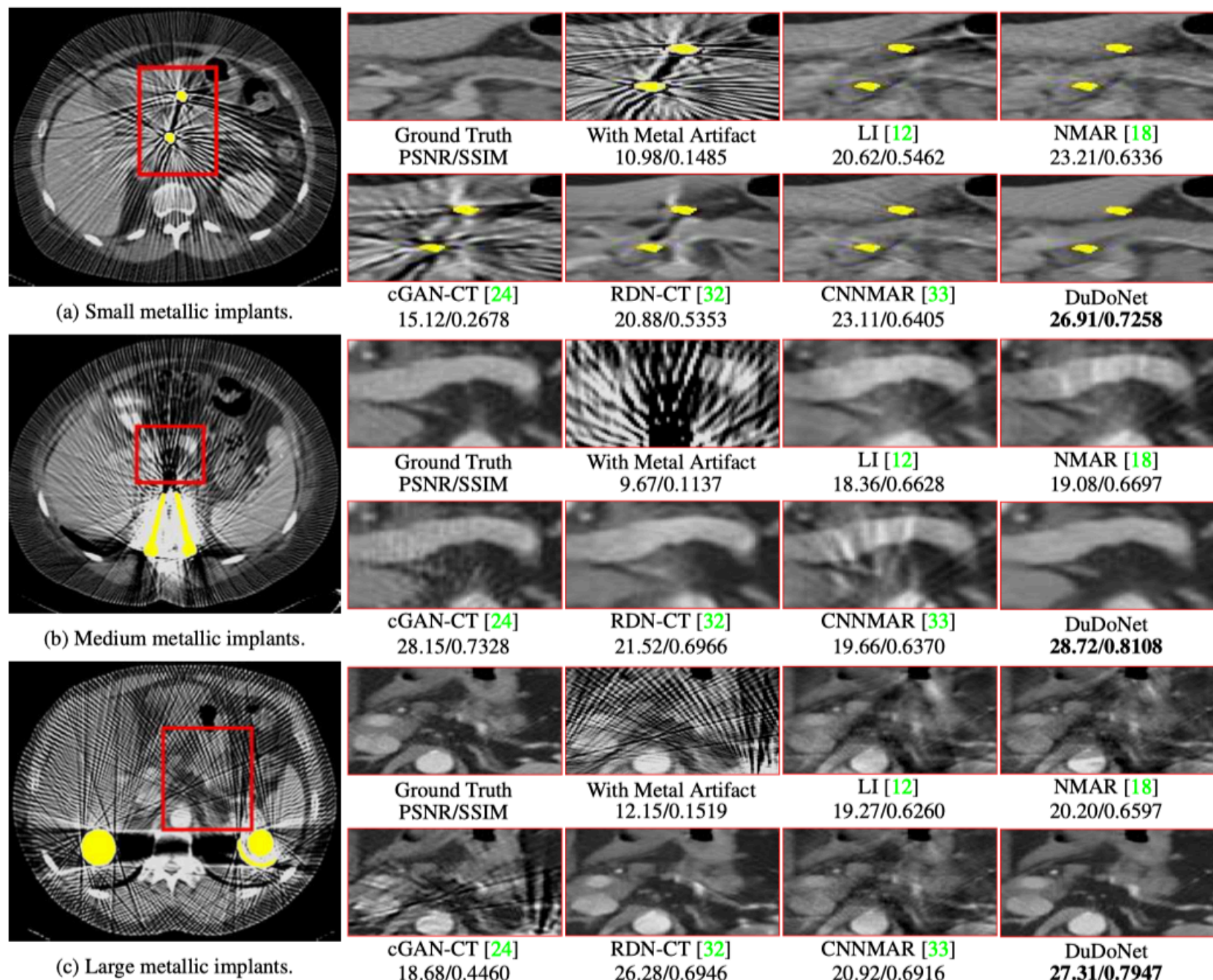


Figure 7: Visual comparisons on MAR for different types of metallic implants.

# Results

LI [12]	NMAR [18]	cGAN-CT [24]	RDN-CT [32]	CNNMAR [33]	DuDoNet (Ours)
0.0832	0.4180	0.0365	0.5150	0.6043	0.1335

Table 3: Comparison of running time measured in seconds.