# **Detail-Revealing Deep Low-Dose CT Reconstruction**

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### Low dose CT Reconstruction



an extra regularization term  $L_r$  is imposed on the structure map to encourage invalid predictions.

$$L_r = \frac{1}{N} \sum_{t=1}^{N} \sum_{p_t} |S_t(p_t)|^2 . \quad L_P = \alpha_1 L_p + \alpha_2 L_r.$$

• Holistic Loss  $L_H$ : LDCT image I, and produces refined CT image R ('fake sample'), NDCT image  $I^T$ .  $L_H = \frac{1}{2} \sum_{k=1}^{N} \{\mathbb{E}_{IT} \in \mathcal{D}(I^T)\} - \mathbb{E}_{P} \in \mathcal{D}(P[I])\}$ 



Low-dose CT

Full-dose CT

### Figure 1: CT reconstruction

- Existing methods & weaknesses :
- (1) Raw data filtered reconstruction, e.g., Filtered Back Projection (FBP). Hand-designed filters.
- (2) Iterative reconstruction: Recasts the reconstruction as a iterative optimization process. Objective functions based on naive assumptions.
- (3) CNN-based methods: Learn the mapping between low-dose CT image and normal dose CT image with deep networks. Details damage.

## Motivation

- (1) No hand-designed filters and not rely on raw data.
- (2) Learn better mapping between low-dose CT and full-dose CT.
- (3) Suppressing the noise effectively and retaining the structures well simultaneously.

$$\sum_{t=1}^{L_H} \sum_{t=1}^{L_H} \sum_{t=1}^{L_H}$$

• Total Loss *L*:

$$L = L_P + \alpha_3 L_T + \alpha_4 L_H. \quad L_T = \frac{1}{N} \sum_{t=1}^N \sum_{p_t} |R(p_t) - I^T(p_t)|$$





# Figure 3: Reconstruction results on ellipse phantom dataset. (a) to (f) indicate FBP, RED-CNN, WGAN-VGG, MAP-NN, ours and GT.



# Method

#### **Dual-Branch Network Architecture**



Figure 2: An overview of the proposed method.

FBP Figure 4: Clinic Mayo dataset: reconstruction results WGAN-VGG MAP-NN RED-CNN Ours Target



Figure 5: NOD test data sample of Osaka dataset.

Method	MGGO	HCM	NOD	EMP	RGGO	CON
FBP	17.5520/0.3218	17.4272/0.3312	17.8473/0.3294	17.5908/0.3258	17.8630/0.3174	17.6867/0.3292
RED-CNN	25.4023/0.5334	26.1479/0.5634	27.2621/0.6036	27.3236/0.6110	28.0048/0.6458	26.9475/0.5966
WGAN-VGG	21.4565/0.4304	21.0871/0.4275	22.1383/0.4797	22.0226/0.4803	22.7123/0.5201	21.9261/0.4783
MAP-NN	22.8305/0.4715	22.9790/0.4814	23.9418/0.5271	23.5418/0.5250	24.3455/0.5564	23.7720/0.5252
Ours	25.6587/0.5464	26.3172/0.5764	27.6888/0.6182	27.9948/0.6349	28.4401/0.6584	27.3671/0.6092

#### Table 1: Objective results of Osaka dataset.

Ablation



### **Detail-Revealing Loss**

• Pixel-wise Loss  $L_P$ :

$$L_{p} = \frac{1}{N} \sum_{t=1}^{N} \sum_{p_{t}} (||\nabla_{x}^{2} R(p_{t})||e^{-\gamma|S(p_{t})|} + ||\nabla_{y}^{2} R(p_{t})||e^{-\gamma|S(p_{t})|}),$$

where N is the total number of training samples.  $P_t$  means a given pixel at *t*-th sample. R and S are the refined CT image and the structure image obtained from reconstruction branch and prior branch, respectively.  $\gamma$  is a empirical parameter.



Ablation	PSNR	SSIM
only RB (feed-forward)	32.5246	0.8873
only RB (ours)	32.8656	0.8924
RB + Holistic	32.8775	0.8913
RB + PB	33.4323	0.9436
Ensemble	33.4088	0.9431

Ablations on branches and numbers of mapping blocks.

