Detail-Revealing Deep Low-Dose CT Reconstruction

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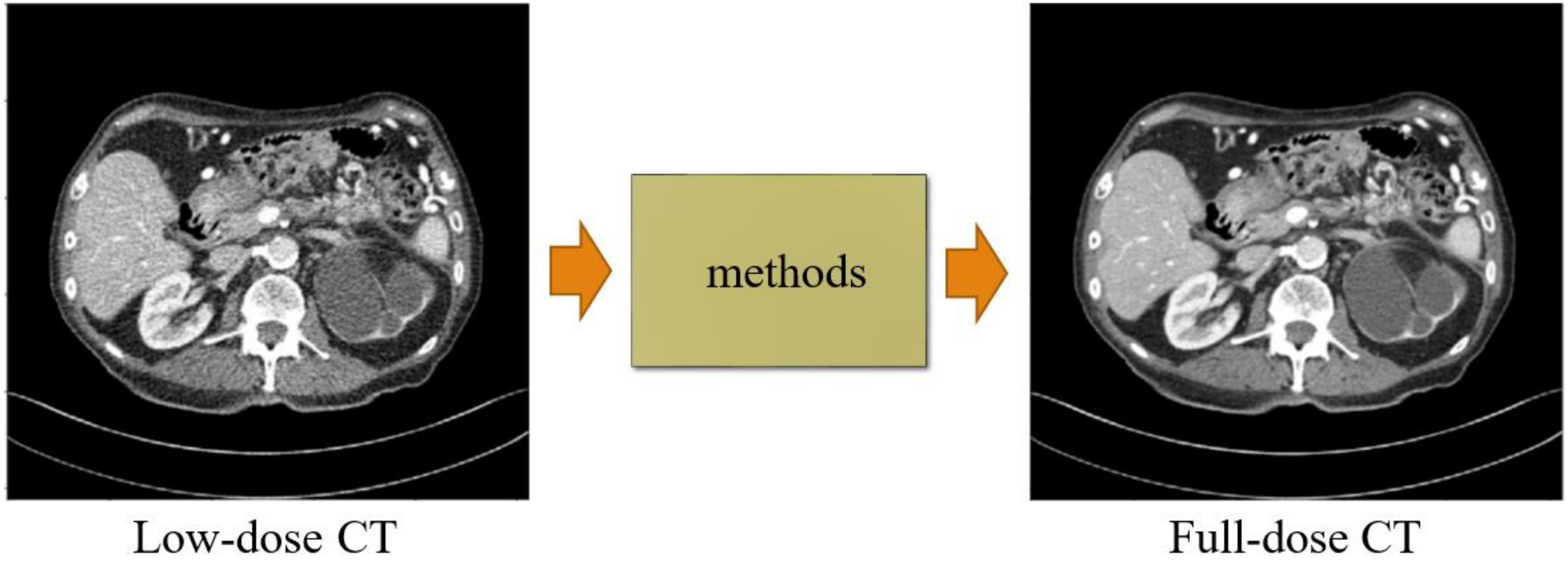
Low dose CT Reconstruction



Low SNR

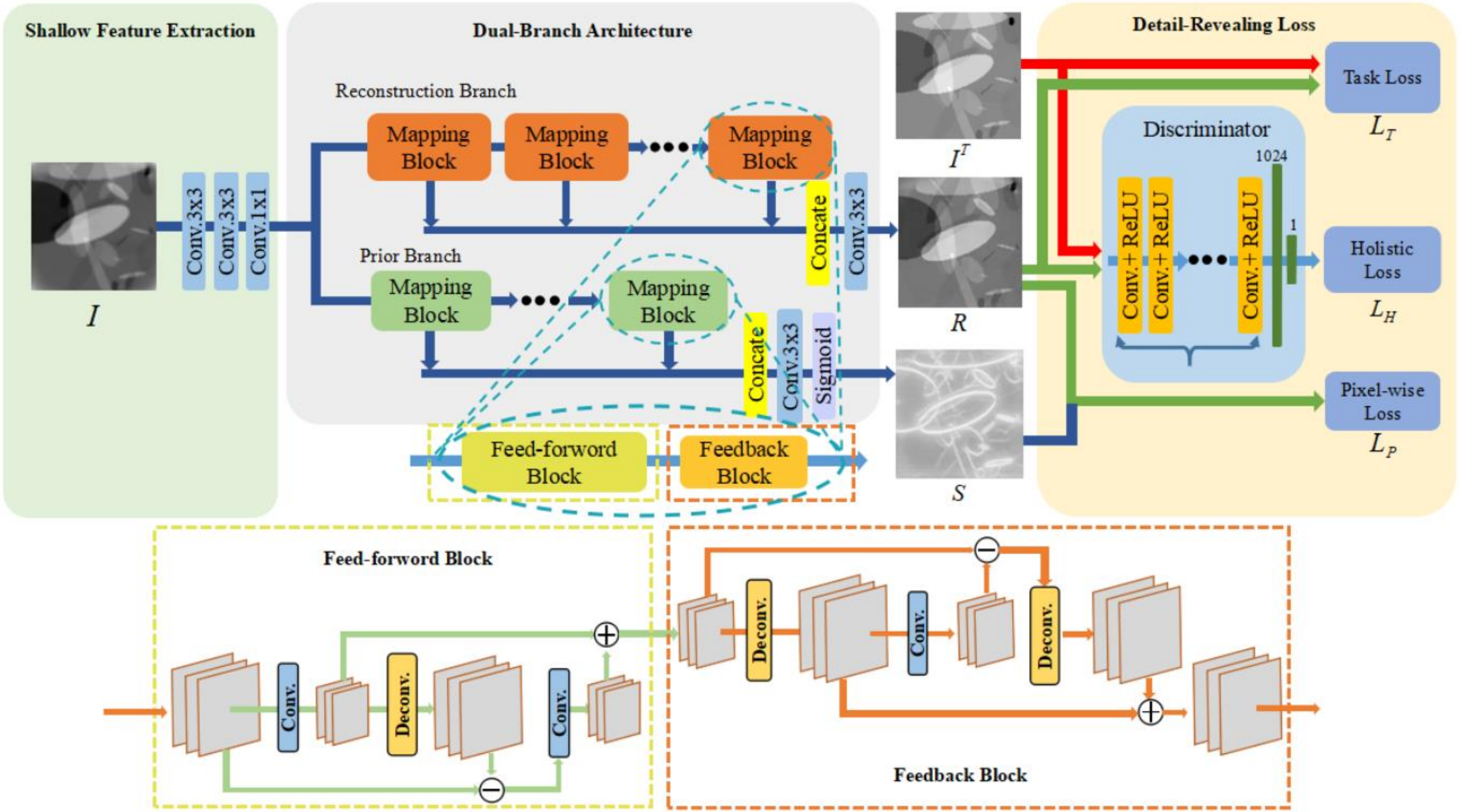
High SNR

Background & Motivation

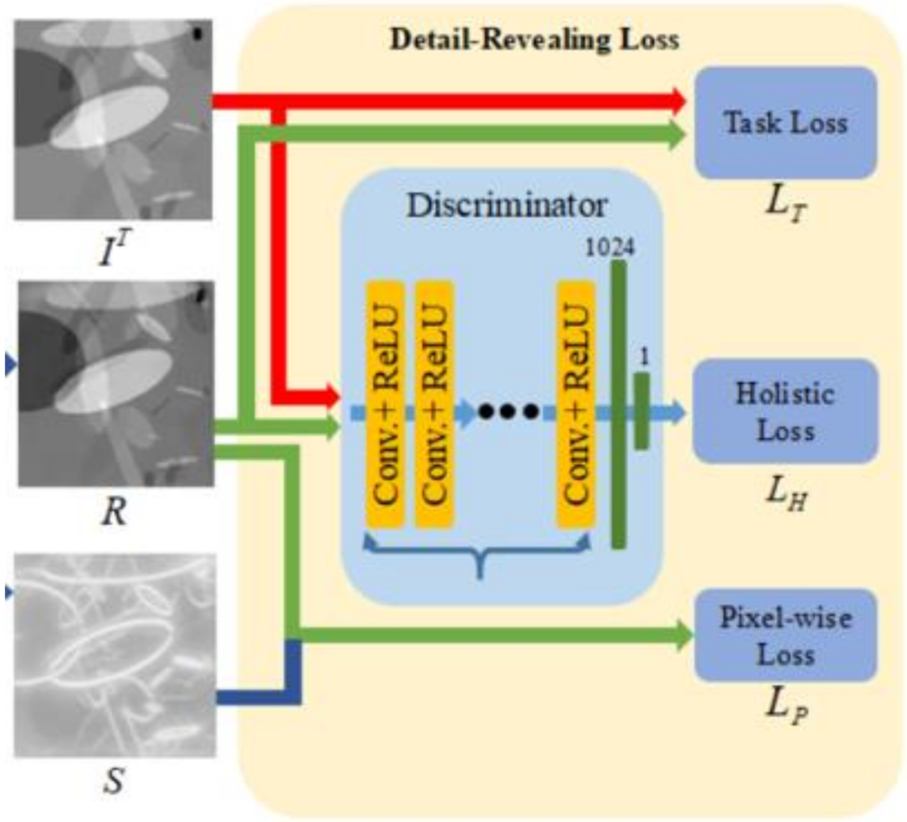
Existing methods & weaknesses：

- Raw data filtered reconstruction, e.g., Filtered Back Projection (FBP).
  - Hand-designed filters.
  - **No hand-designed filters and not rely on raw data.**
- Iterative reconstruction: Recast reconstruction as a iterative optimization process.
  - Objective functions based on naive assumptions.
  - **Define reconstruction better.**
- CNN-based methods: Learn the mapping between low-dose CT image and normal dose CT image with deep networks.
  - Details damage.
  - **Suppress the noise effectively and retain the structures well at the same time.**

Method


Shallow Feature Extraction
Conv.3x3
Conv.3x3
Conv.1x1
I
Dual-Branch Architecture
Reconstruction Branch
Mapping Block
Mapping Block
Mapping Block
Concate
Conv.3x3
Prior Branch
Mapping Block
Mapping Block
Concate
Conv.3x3
Sigmoid
Feed-forword Block
Feedback Block
I^T
R
S
Detail-Revealing Loss
Task Loss
L_T
Discriminator
1024
Conv.+ReLU
Conv.+ReLU
Conv.+ReLU
1
Holistic Loss
L_H
Pixel-wise Loss
L_P
Feed-forword Block
Conv.
Deconv.
Conv.
Feedback Block
Deconv.
Conv.
Deconv.

Detail-Revealing Loss



$$L_T = \frac{1}{N}\sum_{t=1}^{N}\sum_{p_t}|R(p_t) - I^T(p_t)|$$

$$L_H = \frac{1}{N}\sum_{t=1}^{N}\{\mathbb{E}_{I^T\sim\mathcal{P}(I^T)}[D(I^T)] - \mathbb{E}_{R\sim\mathcal{P}(R)}[D(R|I)]\}$$

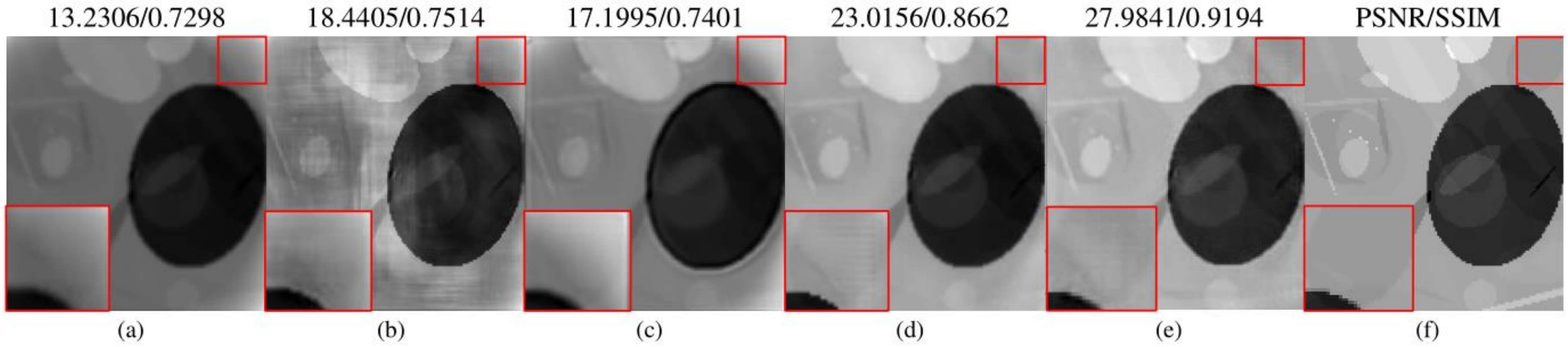
$$L_P = \alpha_1 L_p + \alpha_2 L_r.$$

$$L_p = \frac{1}{N}\sum_{t=1}^{N}\sum_{p_t}(||\nabla_x^2 R(p_t)||e^{-\gamma|S(p_t)|} + ||\nabla_y^2 R(p_t)||e^{-\gamma|S(p_t)|}),$$

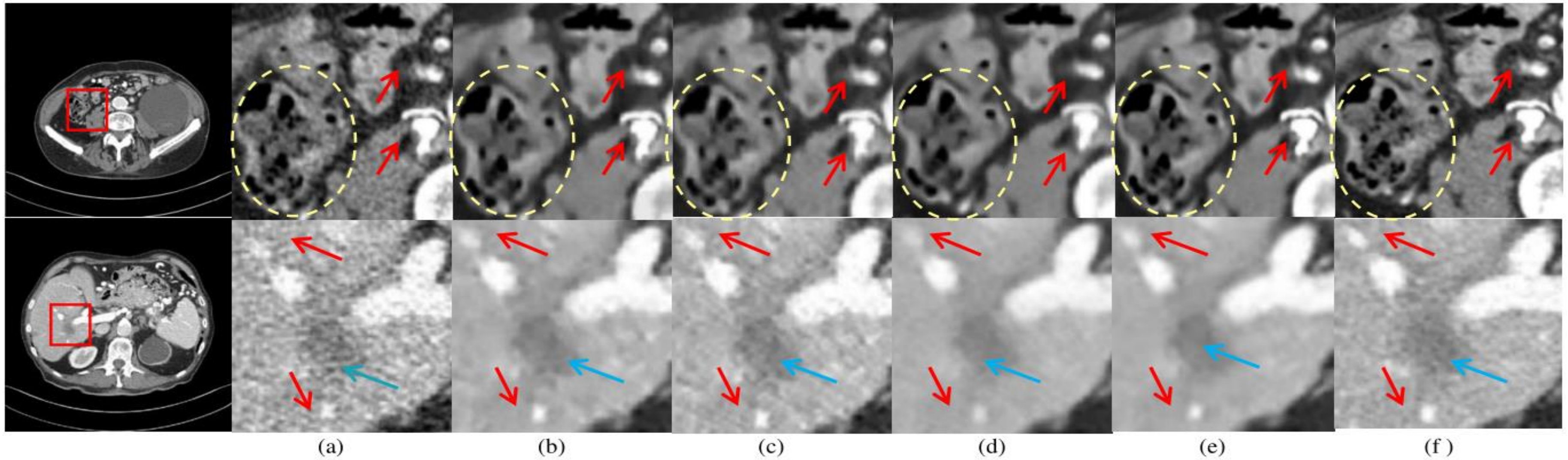
$$L_r = \frac{1}{N}\sum_{t=1}^{N}\sum_{p_t}|S_t(p_t)|^2.$$

$$L = L_P + \alpha_3 L_T + \alpha_4 L_H.$$

Experiments



synthetic dataset

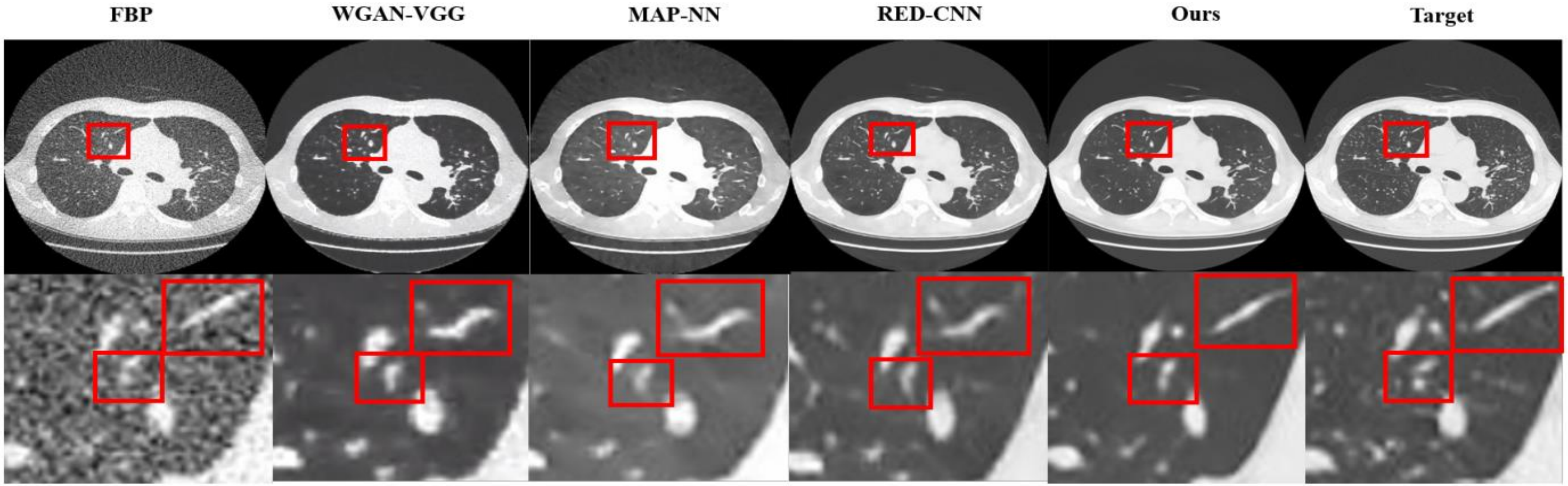


Methods	*PSNR*	*SSIM*
FBP [2]	29.2489	0.8759
RED-CNN [5]	32.9396	0.9085
WGAN-VGG [6]	32.8646	0.8953
MAP-NN [7]	33.1765	0.9422
Ours	33.4088	0.9491

Mayo clinic dataset

(a) to (f) indicate FBP, RED-CNN, WGAN-VGG, MAP-NN, ours and Target.

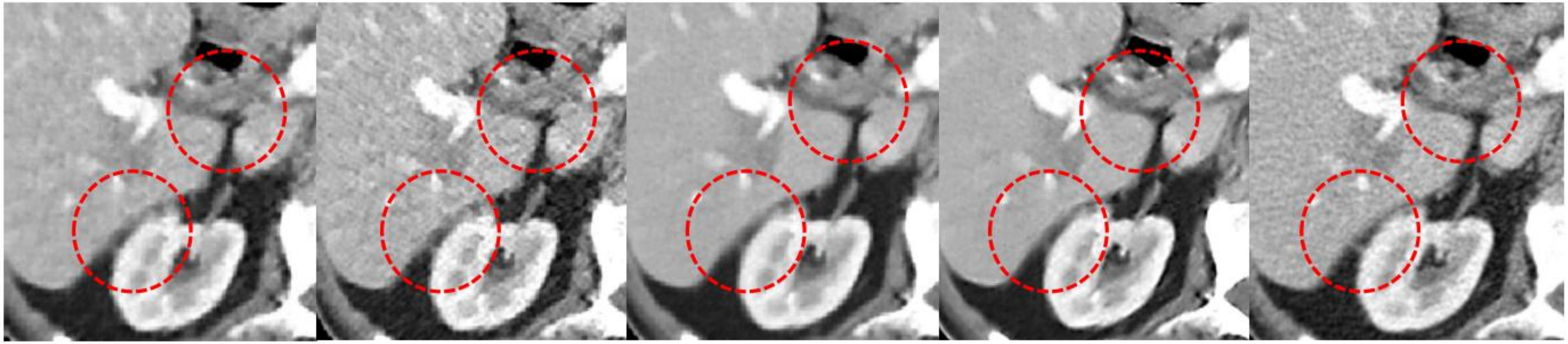
Experiments



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

Osaka clinic dataset

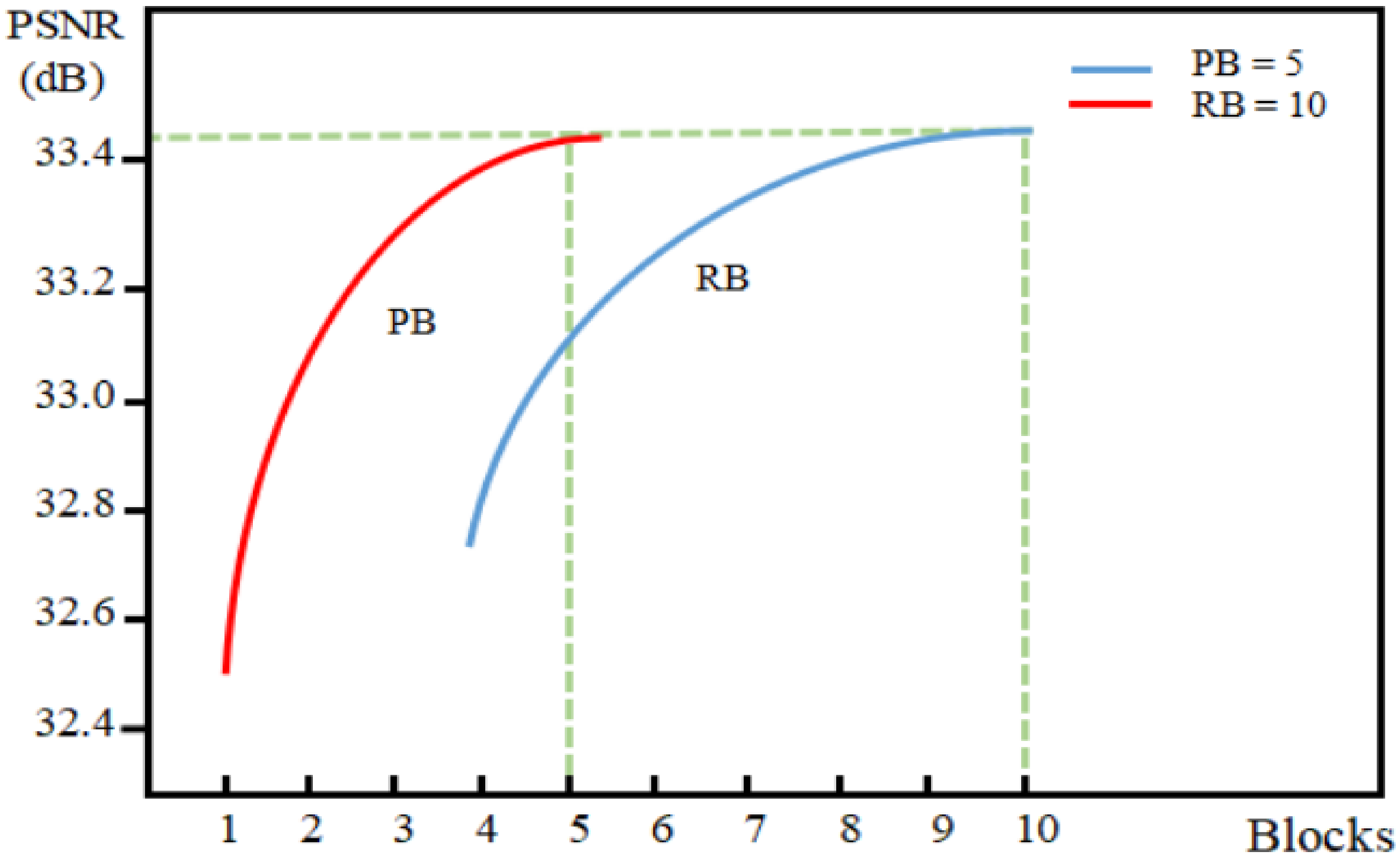
Ablation (on branches)



(a) (b) (c) (d) (e)

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

Ablation (on number of mapping blocks)



Finally, we use 5 blocks on PB and 10 on RB to achieve the best performance.

Conclusion

- We construct two separate branches to form a parallel learning architecture in the ensemble, in which each branch is accurate and specialized on capturing either reconstruction errors or structure details. And repeated feed-forward and feedback mechanism is used in both branches to fully exploit the features.
- A sophisticated detail-revealing loss is designed to guide the learning from both pixel-wise (local view) and holistic(global view).
- Extensive experimental results on one synthetic dataset and two real clinic datasets show that our method outperforms other state-of-the-art methods in both PSNR and SSIM metrics, and achieves superior visual performance.

Thank you ！