面向临床的深度医学图像降噪算法研究

Clinical-oriented Deep Medical Image Denoising Algorithms

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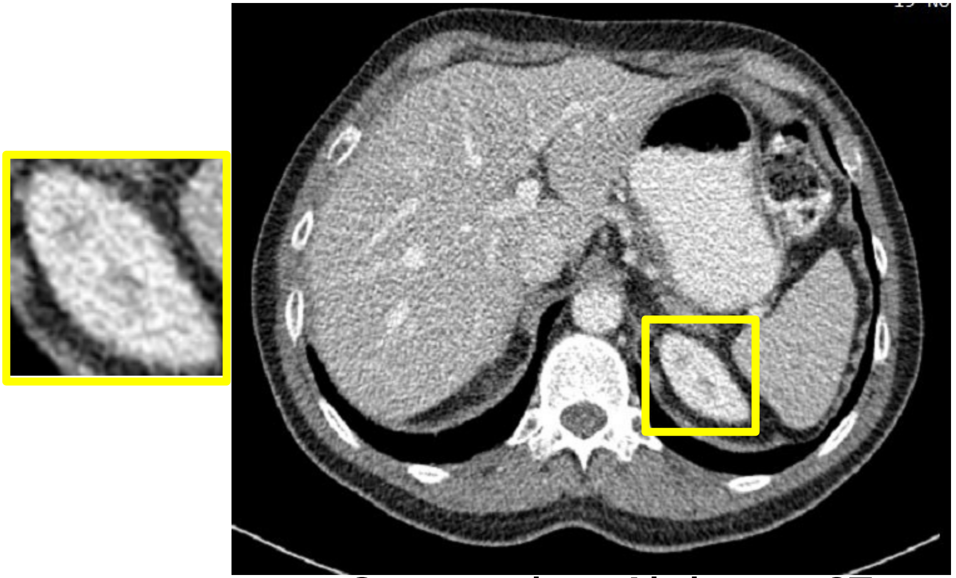
Background

CT

Quality Degradation

Dose Reduction

Normal-dose Abdomen CT

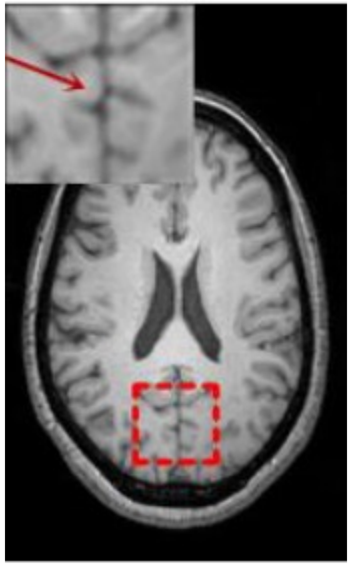


Quarter-dose Abdomen CT

Artifacts

Noise

MRI



T1w example of Noisy-free MRI

Quality Degradation

Imperfection of radio frequency coils/movement of the patient

T1w example of Noisy MRI

Background

Quality Optimization for Low-Dose CT (LDCT)--Main Stream

人民网>>人民健康网

低剂量CT：有效的肺癌筛查方法

张晓东

2018年12月13日08:42 来源：健康报网

肺癌已成为中国乃至全世界最常见的恶性肿瘤以及首位的癌症死亡原因。肺癌的早诊早治意义重大，然而肺癌早期一般没有明显或特征性的症状，因此早期诊断往往比较困难，导致患者预后不佳。在不久前的世界肺癌日上，北京大学人民医院呼吸科主任医师穆新林表示，低剂量CT是目前最有效的肺癌筛查方法，建议有肺癌高危因素的人群应在医师的指导下做低剂量CT检查。

- **A Full-Dose CT scan of the Chest has a Radiation Dose of up to 7mSv**
- **Low-dose CT Radiation Dose is only 1/5 of the full dose**

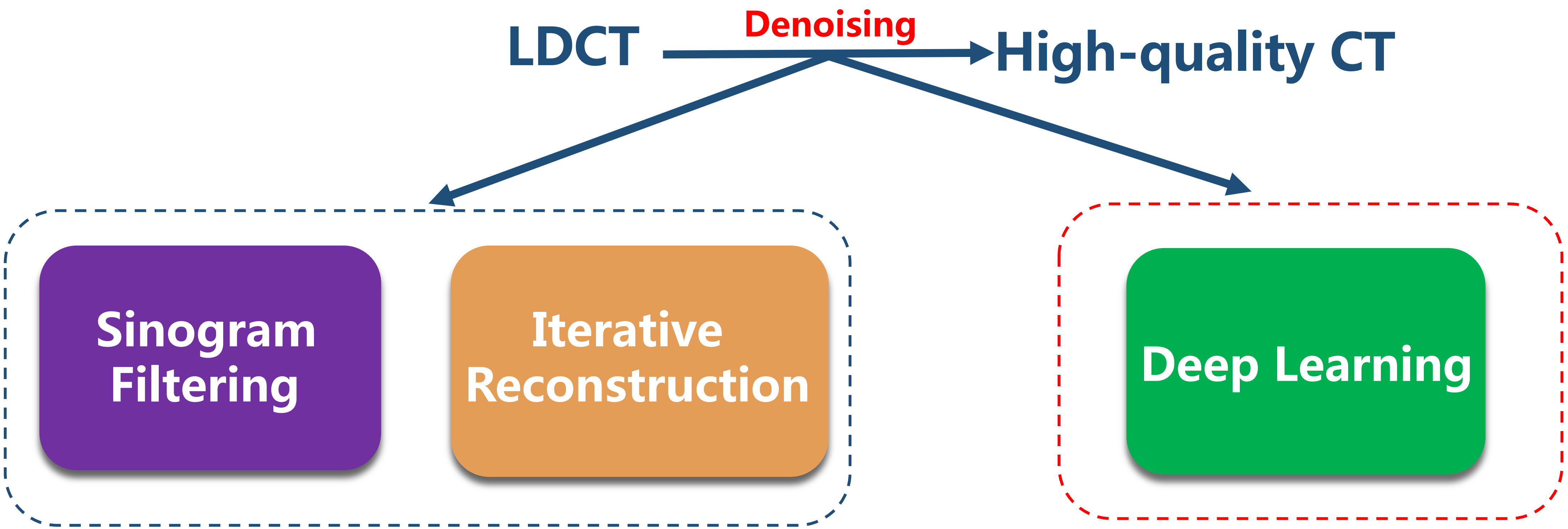
An Important Screening Method for *Lung Cancer* and *Covid-19 Pneumonia*

Background

Goals of LDCT denoising:

- √ Noise suppression（噪声抑制）
- √ Structure retention（结构保持）
- √ Artifacts suppression（伪影抑制）

Background



⊗ High Time-consumption

⊗ Sinogram (Projection) Data Unavailable

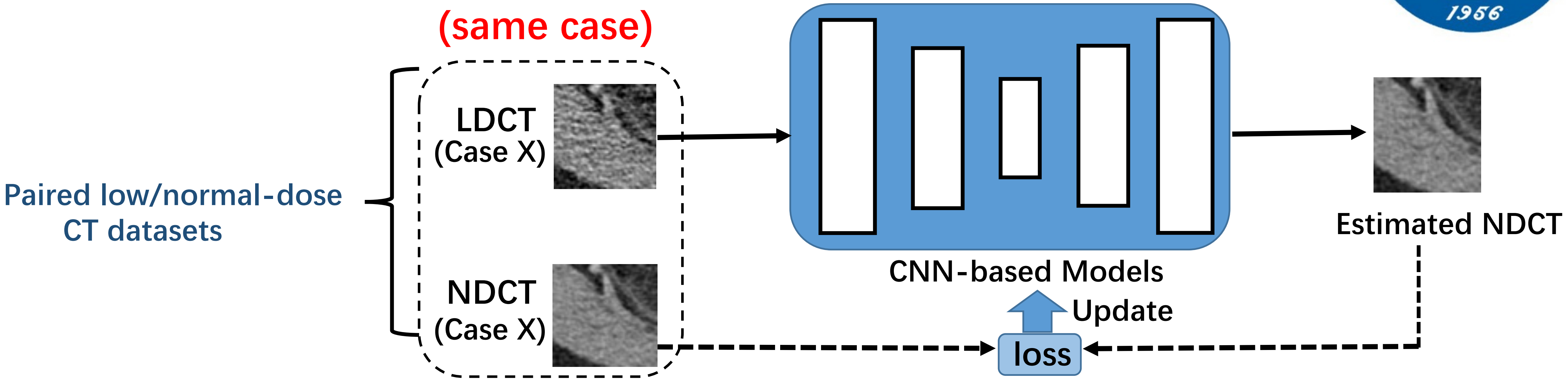
⊗ Limited Extension with AI-based Tasks

√ Fast Processing with GPU

√ Work on Image domain (Postprocessing)

√ Potential integration with AI-based Tasks

Background



Most deep learning-based LDCT denoising frameworks

Limitations of existing methods:

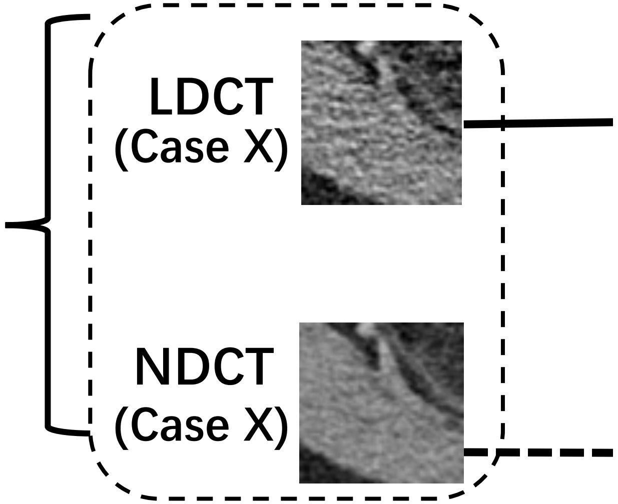
⊗ Over smooth or low noise suppression

⊗ Structure loss

⊗ Heavily rely on paired datasets

Background

Paired low/normal-dose CT datasets



Most deep l

Limitations of existing methods:

⊗ Over smooth or low noise suppression

⊗ Structure loss

⊗ Heavily rely on paired datasets

ISICDM 2020 挑战赛—低剂量 CT 图像质量优化竞赛说明

竞赛背景

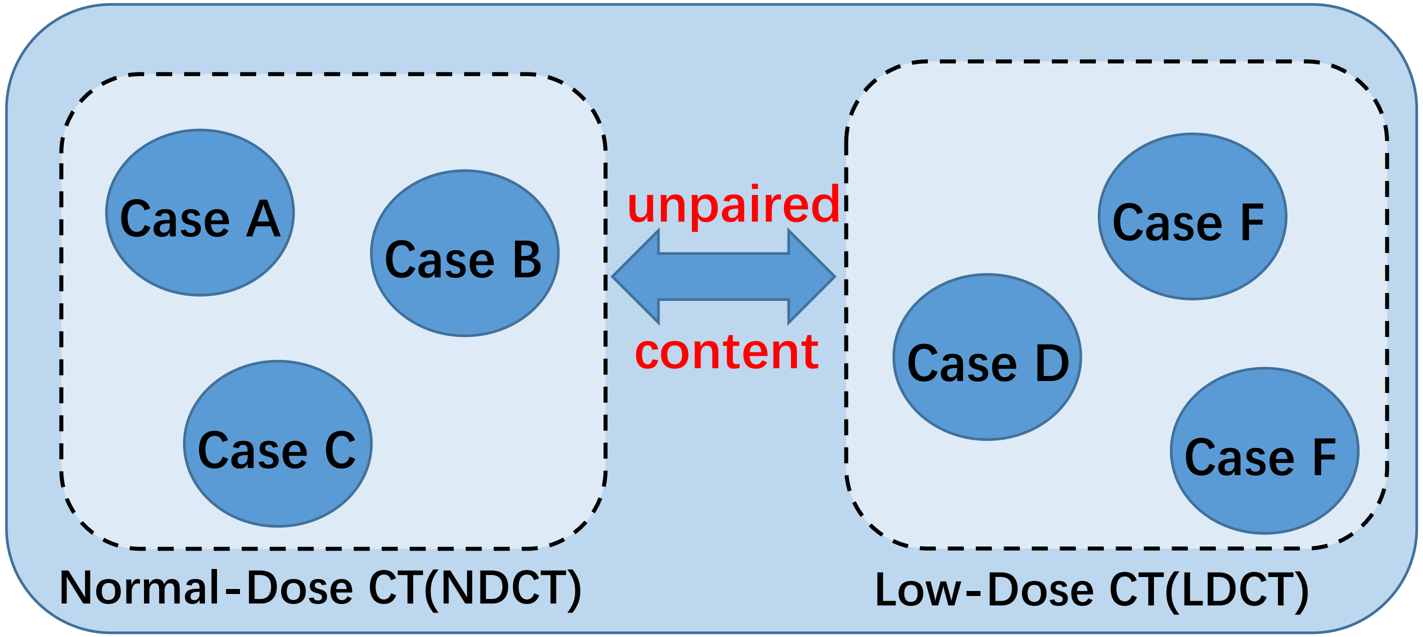
CT(Computed Tomography)，即计算机断层成像，其作为医学影像领域最重要的成像技术之一，能够实现快速的高空间分辨率、高密度分辨率三维成像，被广泛应用于神经系统、心血管系统、软组织器官以及骨骼等疾病的临床诊断。CT 利用 X 射线管环绕人体发射出 X 射线，X 射线被探测器接收后，经过数据校正及图像重建算法即可重建出人体组织对 X 射线的衰减系数分布图，即 CT 断层图像。在这一过程中，由于需要利用 X 射线照射人体，因此 CT 扫描过程会对人体造成一定剂量的电离辐射，对患者的健康造成潜在的危害。

为了尽可能的降低 CT 扫描对人体的伤害，可以通过降低 CT 扫描的扫描电流或电压来达到降低辐射剂量的目的，但降低扫描电流或电压，会直接导致图像噪声的增加，降低 CT 图像质量。因此，如何实现低放射剂量的同时保证 CT 成像质量一直是 CT 成像领域研究的重点。

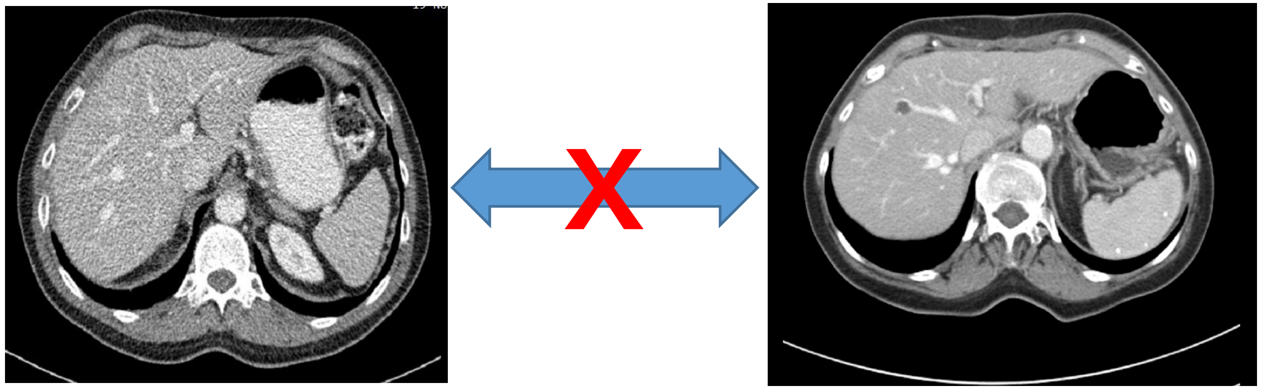
近些年，深度学习技术被广泛应用于图像的优化、检测以及分类等领域，并成为医学图像优化领域中的研究热点。在一些公开数据集中，相比于传统方法，基于深度学习的 CT 图像优化方法表现出了显著的优势，但深度学习技术在 CT 临床图像优化中的应用仍然面临一些困难：首先，仿真数据较难覆盖临床设备的各种扫描参数及模拟设备间差异，因此基于仿真数据训练的模型难以在临床中应用；同时，也难以采集到结构信息完全匹配的 CT 低剂量和高剂量图像用于有监督训练。因此，亟需创新性的方法的提出，以解决现有的低剂量 CT 增强方面所面临的困难。

LDCT Quality Optimization Towards Clinical Desire

①: Unpaired Data Set in Clinic



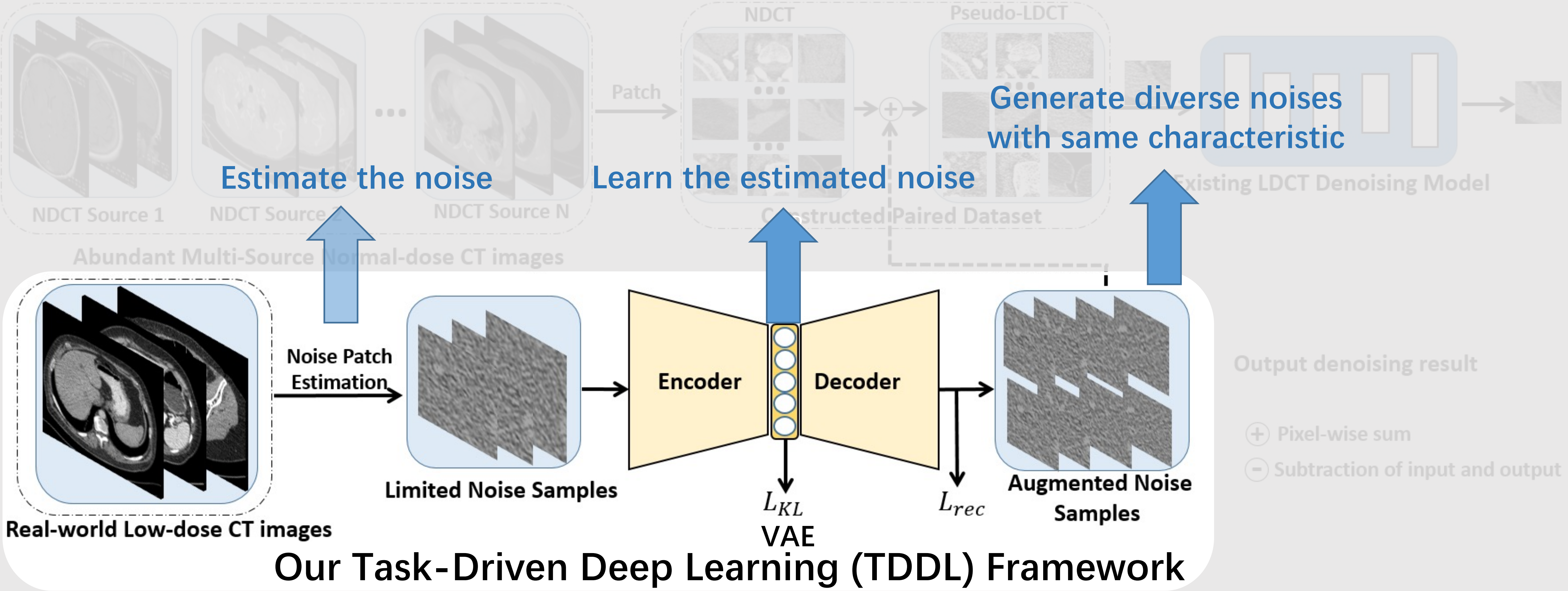
Data
(LDCT)



Label
(NDCT)

LDCT Quality Optimization Towards Clinical Desire: Unpaired Issue

Highlight 1: Learn real-world LDCT noise（学习噪声）



Chen K., Pu X., Ren Y., Qiu H., Li H., Sun J. (2020) Low-Dose CT Image Blind Denoising with Graph Convolutional Networks. ICONIP 2020.

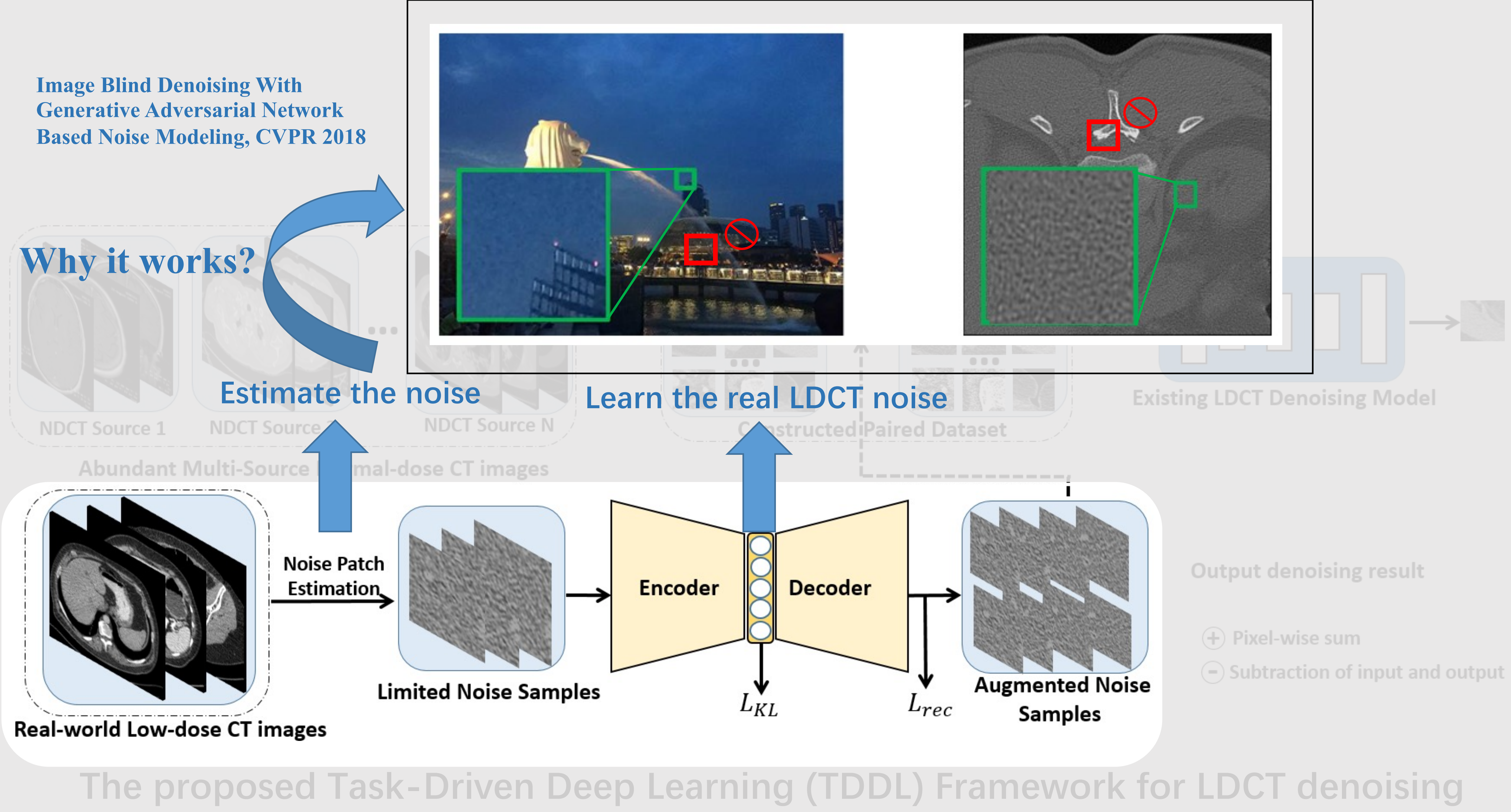
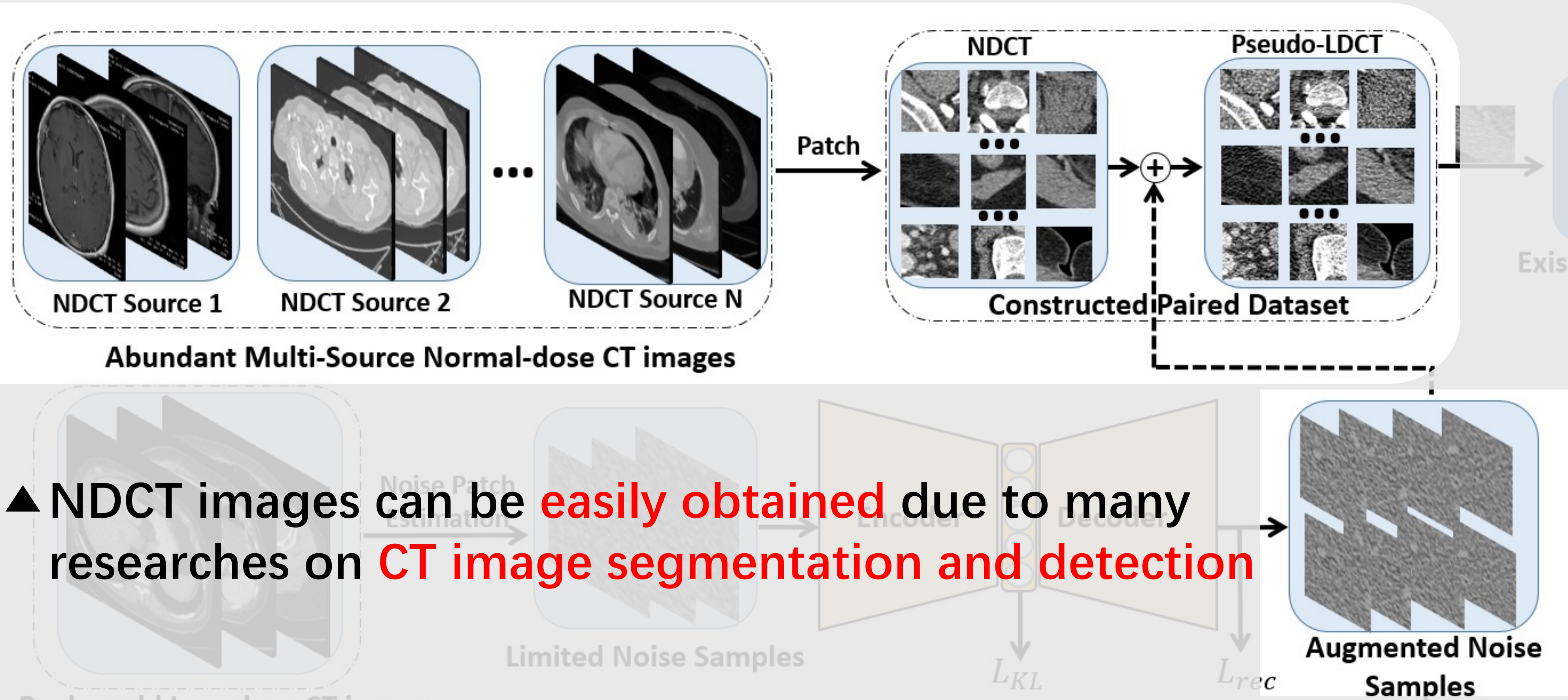


Image Blind Denoising With
Generative Adversarial Network
Based Noise Modeling, CVPR 2018
Why it works?
Estimate the noise
Learn the real LDCT noise
NDCT Source 1
NDCT Source N
Abundant Multi-Source
mal-dose CT images
Constructed Paired Dataset
Existing LDCT Denoising Model
Output denoising result
Pixel-wise sum
Subtraction of input and output
Noise Patch
Estimation
Limited Noise Samples
Encoder
Decoder
L_{KL}
L_{rec}
Augmented Noise
Samples
Real-world Low-dose CT images
The proposed Task-Driven Deep Learning (TDDL) Framework for LDCT denoising

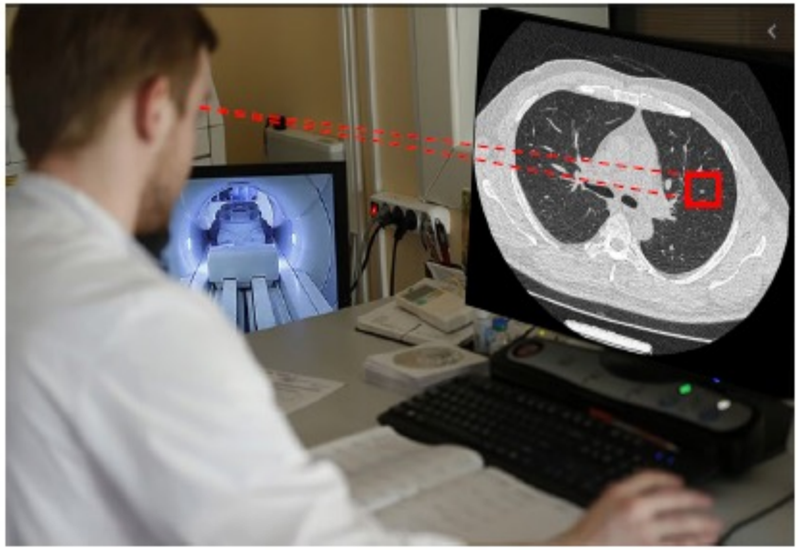
Highlight 2: Obtain the paired datasets with LDCT images only（带噪声图像对）



▲NDCT images can be easily obtained due to many researches on CT image segmentation and detection

Highlight 3: Imitate radiologists (模拟影像医生)

Both local and non-local Information sensitive



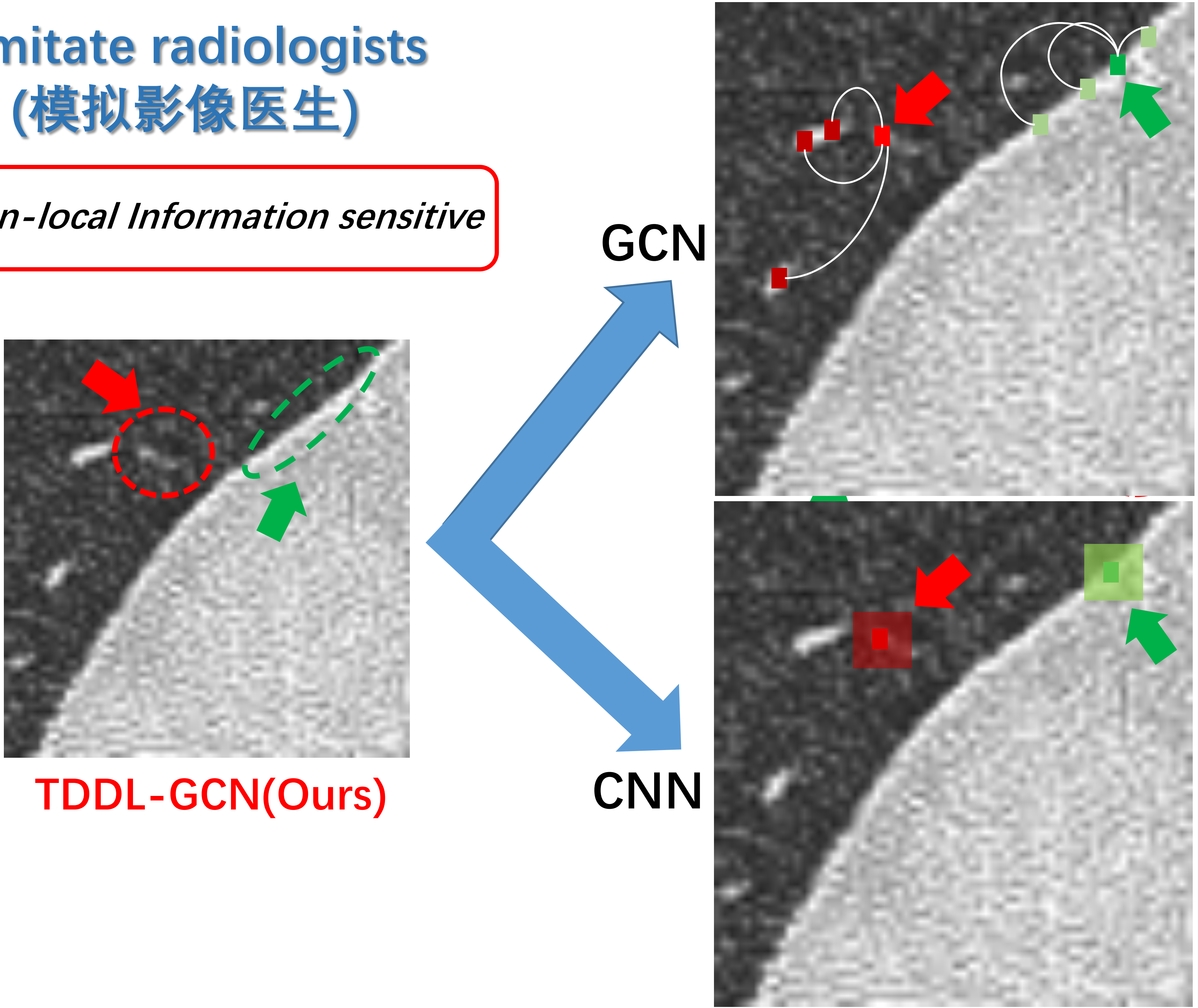
Step 1: Local Information

Step 2: Non-local Information

Step 3: Context Information

Highlight 3: Imitate radiologists (模拟影像医生)

Both local and non-local Information sensitive

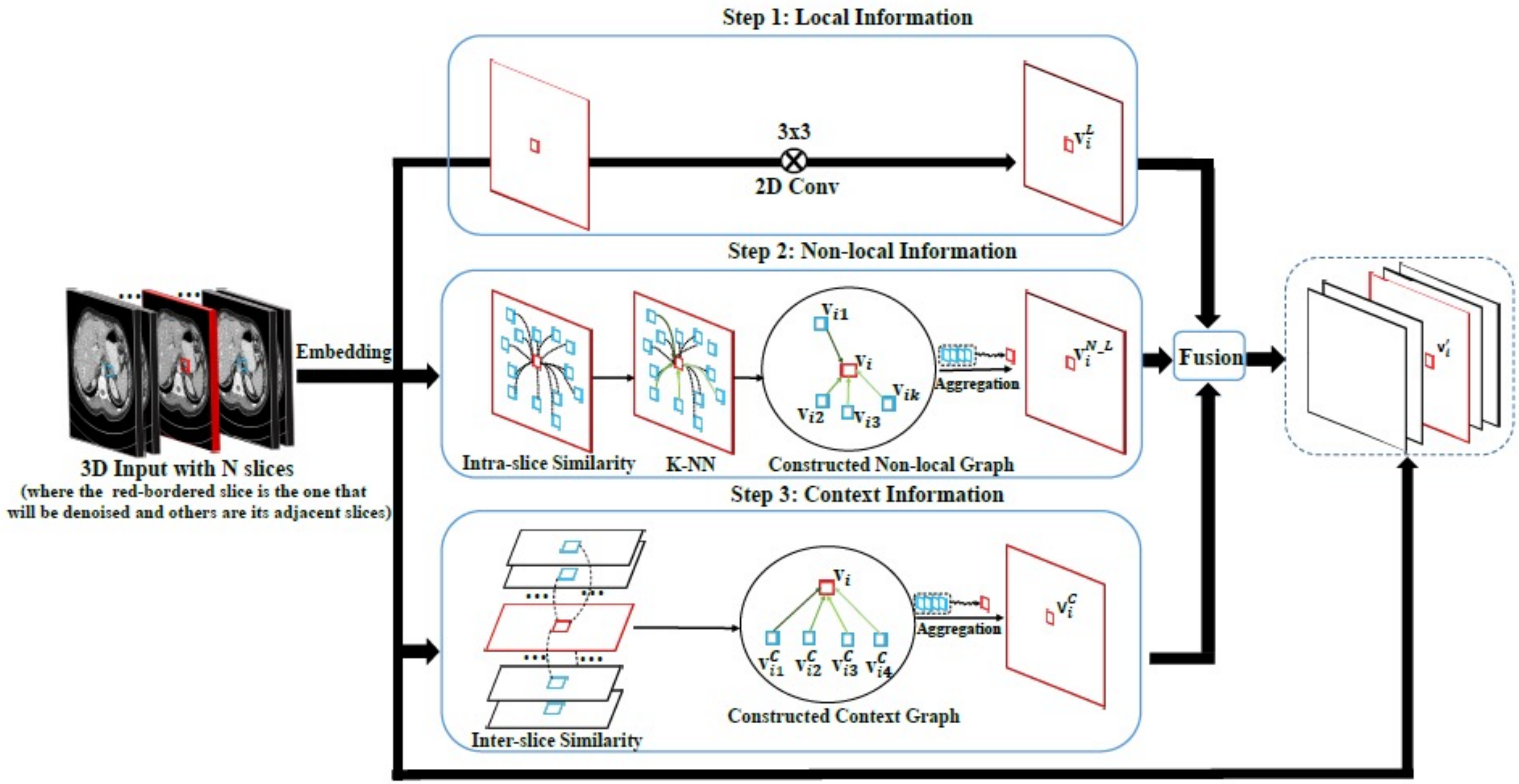


TDDL-GCN(Ours)

non-local
self-similarity

local
self-similarity
only

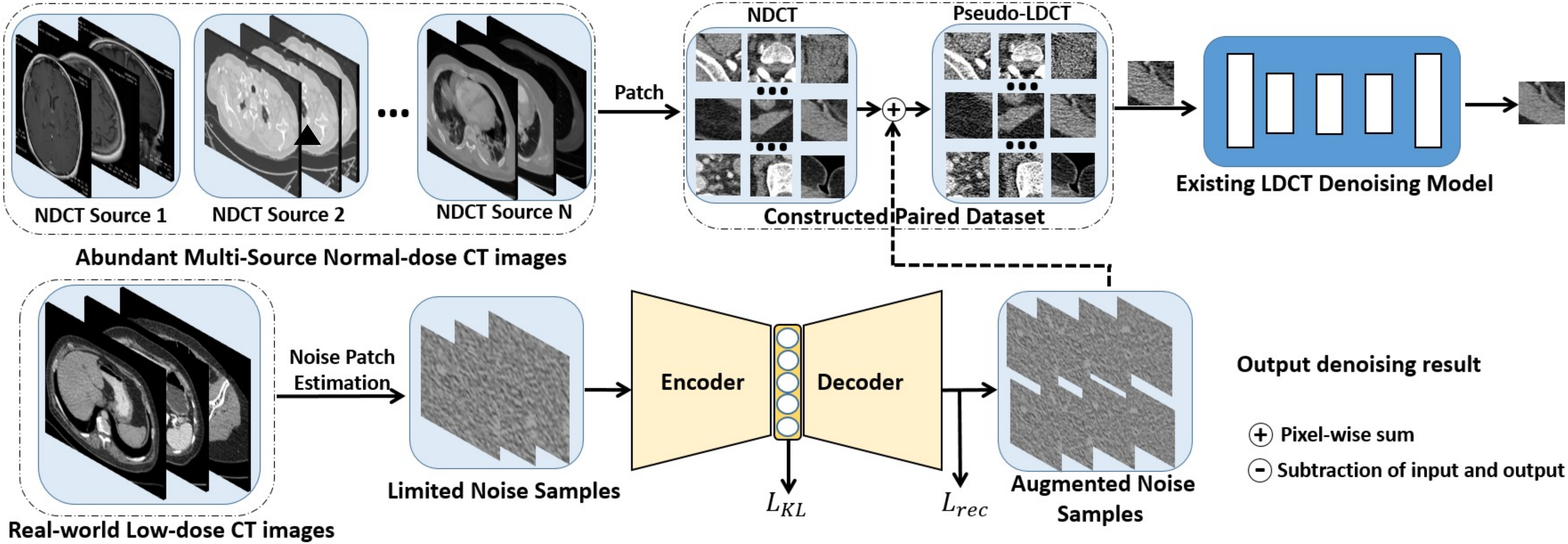
LDCT Quality Optimization Towards Clinical Desire: Unpaired Issue



Kecheng Chen, Yazhou Ren, et al., RIDnet: Radiologist-Inspired Deep Neural Network for Low-dose CT Denoising, arXiv, 2021 （under review）

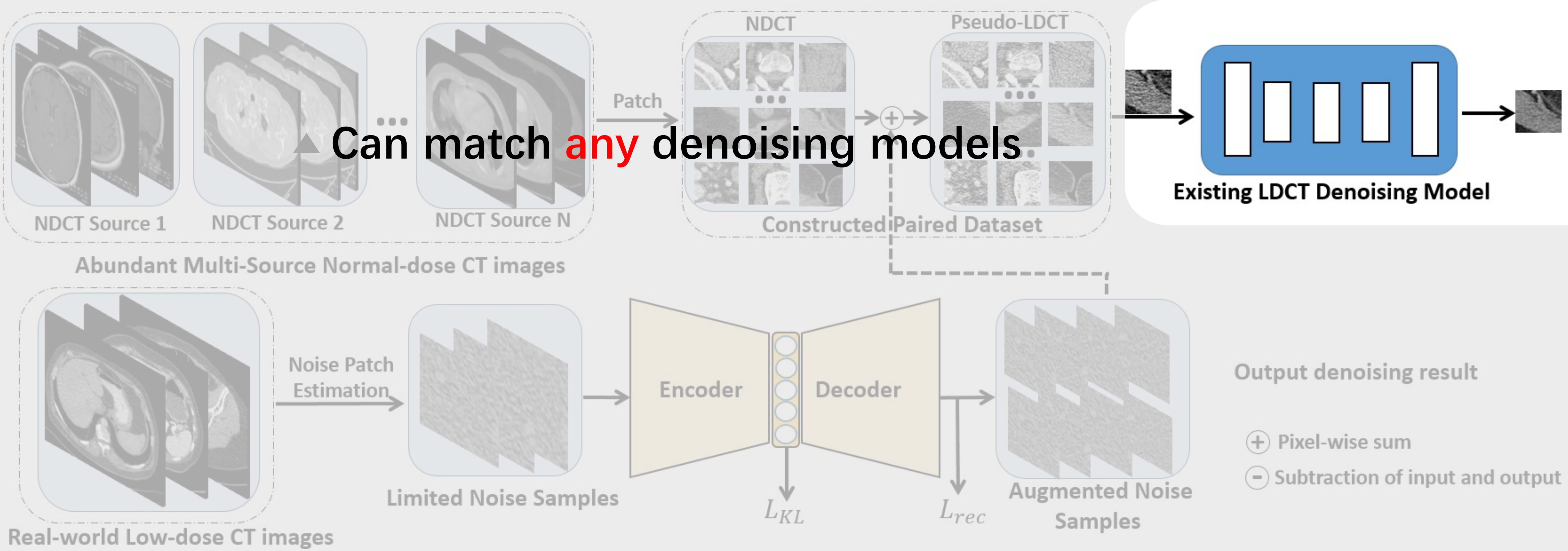
LDCT Quality Optimization Towards Clinical Desire: Unpaired Issue

Overall



Our Task-Driven Deep Learning (TDDL) Framework for LDCT denoising

Play-and-Plug

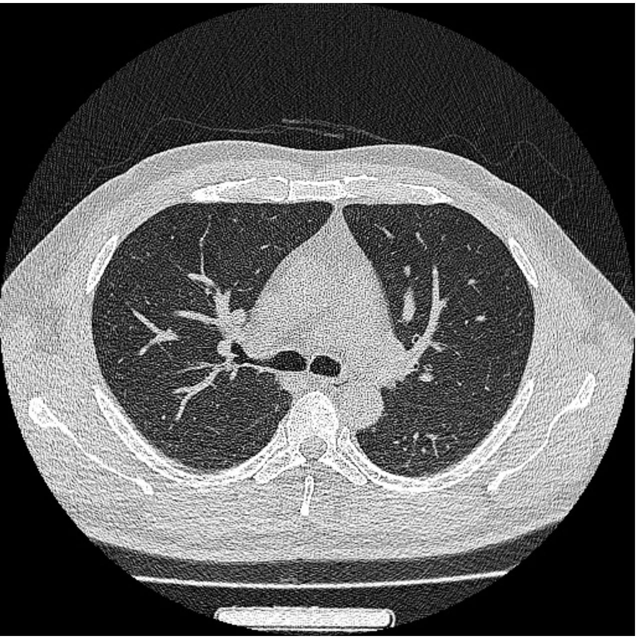


▲ Can match any denoising models

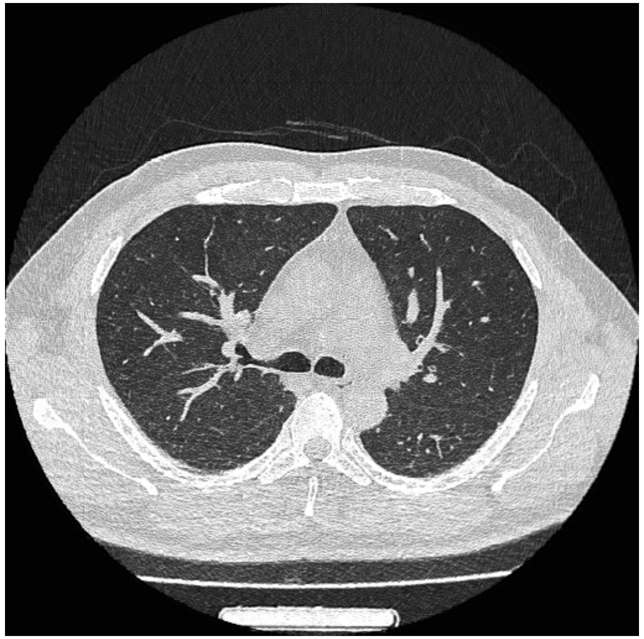
The proposed Task-Driven Deep Learning (TDDL) Framework for LDCT denoising

LDCT Quality Optimization Towards Clinical Desire: Unpaired Issue

Example: Denoising Results for Chest LDCT

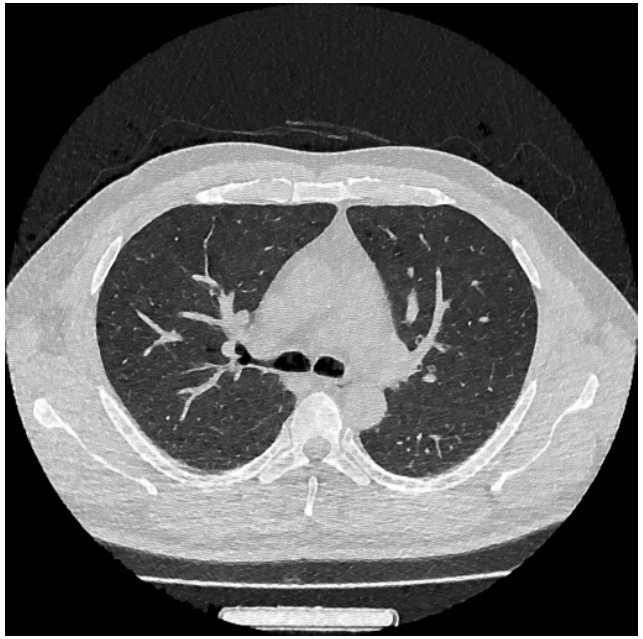


LDCT



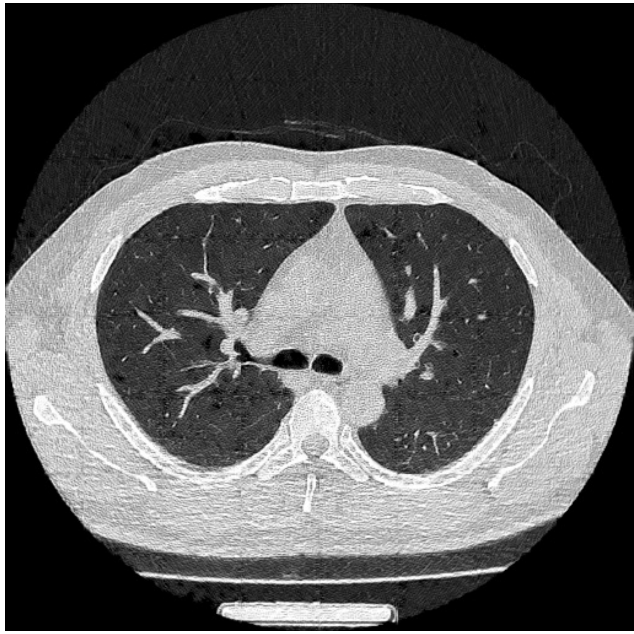
TDDL-GCN(Ours)

Balanced Results



TDDL-REDCNN

Generate Extra Artifacts



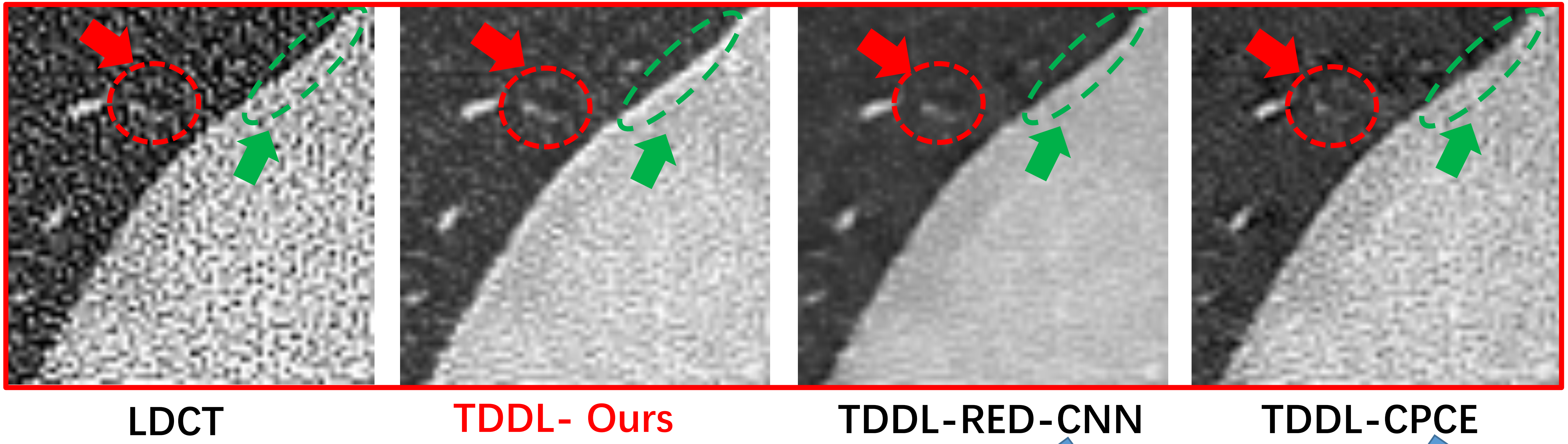
TDDL-CPCE

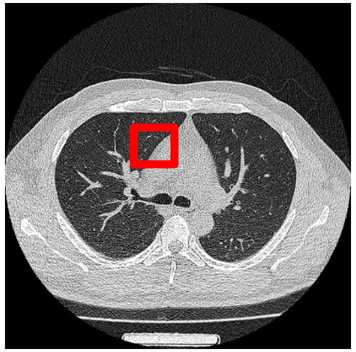
Generate Extra Artifacts

Chen K., Pu X., Ren Y., Qiu H., Li H., Sun J. (2020) Low-Dose CT Image Blind Denoising with Graph Convolutional Networks. ICONIP 2020. Lecture Notes in Computer Science.

LDCT Quality Optimization Towards Clinical Desire: Unpaired Issue

Example: Zoomed-in Denoising Results for Chest LDCT





Chen K., Pu X., Ren Y., Qiu H., Li H., Sun J. (2020) Low-Dose CT Image Blind Denoising with Graph Convolutional Networks. ICONIP 2020. Lecture Notes in Computer Science.

Publications

ICONIP 2020

Low-Dose CT Image Blind Denoising with Graph Convolutional Networks

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Abstract. Convolutional Neural Networks (CNNs) have been widely applied to the Low-Dose Computed Tomography (LDCT) image denoising problem. While most existing methods aim to explore the local self-similarity of the synthetic noisy CT image by injecting Poisson noise to the clean data, we argue that it may not be optimal as the noise of real-world LDCT image can be quite different compared with synthetic noise (e.g., Poisson noise). To address these issues, instead of manually distorting the clean CT to construct paired training set, we estimate

GCN: 局部+非局部特征

Chen K., Pu X., Ren Y., Qiu H., Li H., Sun J. (2020) Low-Dose CT Image Blind Denoising with Graph Convolutional Networks. ICONIP 2020. Lecture Notes in Computer Science.

ISICDM 2020

Task-Driven Deep Learning for LDCT Image Denoising

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ABSTRACT

Compared with normal-dose computed tomography (NDCT), low-dose CT (LDCT) images have lower potential radiation risk for patients while suffering from the degradation problem by noise. In the past decades, deep learning-based (DL-based) methods have achieved impressive denoising performances in comparison to traditional methods. However, most existing DL-based methods typically preform training on a specific pairs of LDCT/NDCT images and aim to generalize well on clinical scenarios with LDCT images only. It is a difficult task and challenge, denoising LDCT images with various noise characteristics due to different imaging protocols. We propose a task-driven deep learning framework for LDCT image denoising. Specifically, the variational autoencoder (VAE) is leveraged to learn noise distribution. By utilizing abundant open-source NDCT images as the latent references, we then construct pairs of induced-LDCT (namely pseudo-LDCT)/NDCT images rather than simply using pairs of non-induced-LDCT/NDCT images. Thus, the denoising model can perceive the noise within LDCT images directly.

1 INTRODUCTION

Computed tomography (CT) is the most widely adopted imaging technology in clinical diagnosis, as it was the first method to noninvasively acquire images of the inside of the human body that were not biased by superposition of distinct anatomical structures [2]. However, epidemiologic studies have indicated that the radiation dose from even two or three CT scans results in a detectable increase in the risk of cancer, especially in children [1]. In the past decades, compared with normal-dose CT (NDCT) imaging, low-dose CT (LDCT) imaging technology enables a lower radiation dose and has been used to preliminary screening of high risk disease [15], such as lung cancer. The main crucial limitation for LDCT is that the imaging quality will inevitably be degraded due to complex noise (caused by the negative impact of dose reduction).

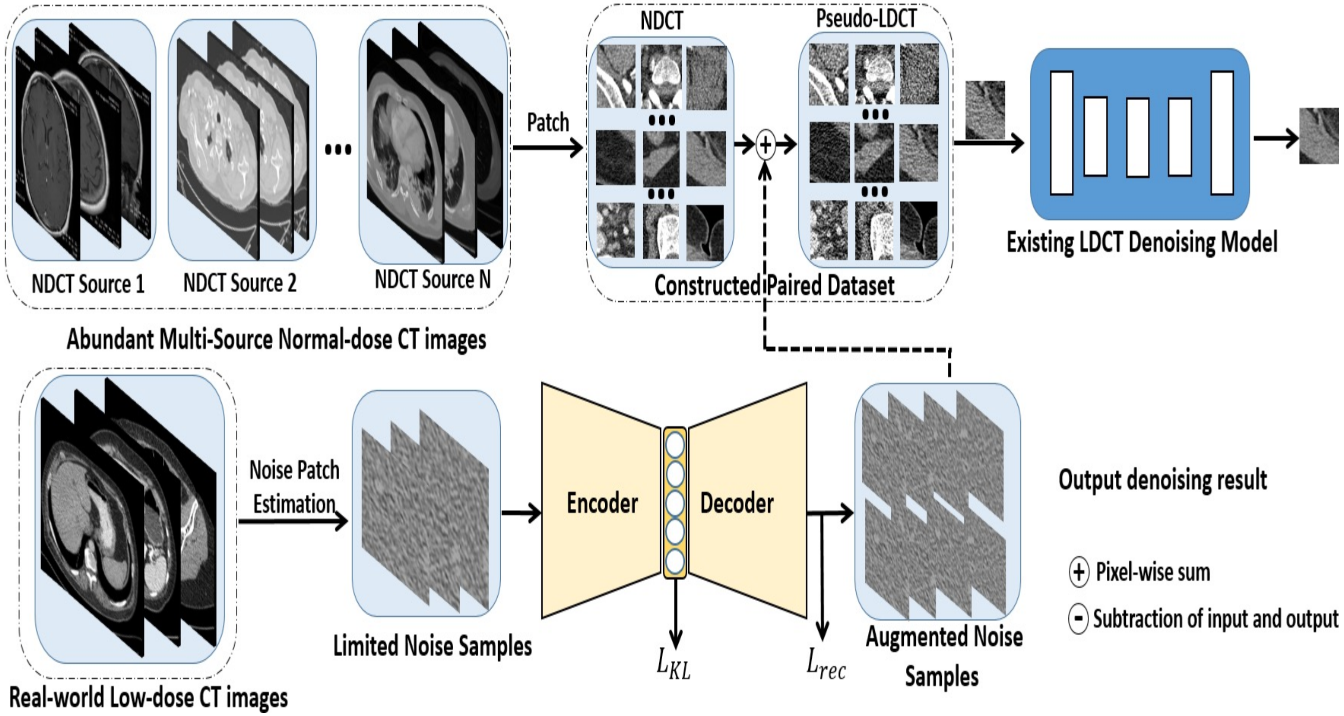
To improve the quality of LDCT image, many studies perform noise removal from LDCT images, which can be roughly categorized into three streams [6], i.e., sinogram filtration based methods, iterative reconstruction based methods and post-processing based

LDCT噪声学习、构建带噪声图像对

Chen K., Huang J., Sun J., Ren Y., Qiu H., (2020) Task-Driven Deep Learning for LDCT Denoising. ISICDM 2020

Award

Championship:
The Challenge LDCT Quality Optimization of ISICDM



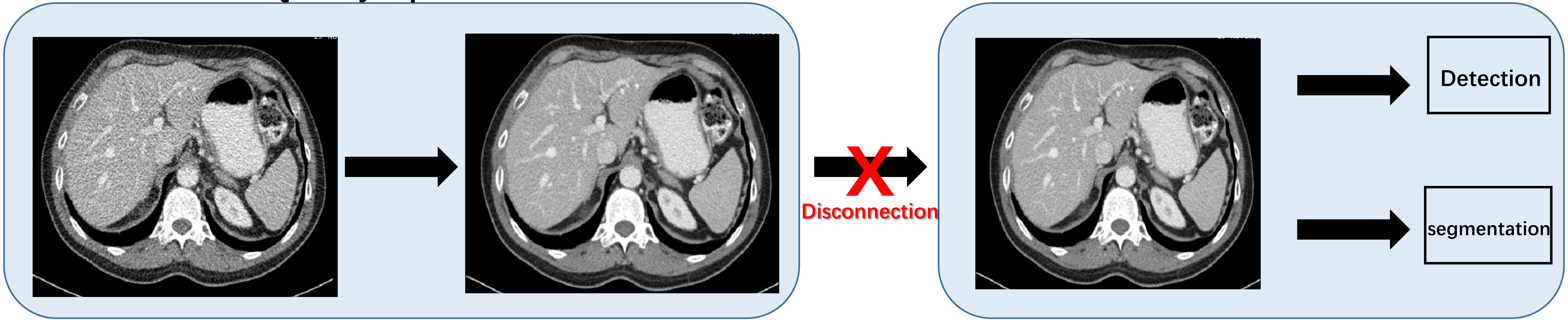
Our Task-Driven Deep Learning (TDDL) Framework for LDCT denoising

LDCT Quality Optimization Towards Clinical Desire

②: Disconnection between Quality Optimization and High-level Tasks

Step 1 AI-based Quality Optimization Process

Step 2 AI-based Lesion Detection/Segmentation

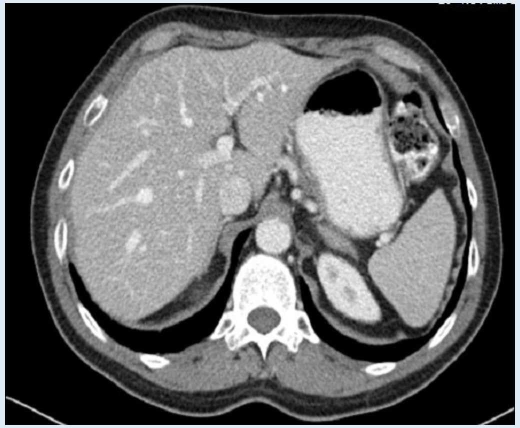


LDCT Quality Optimization Towards Clinical Desire

②: Disconnection between Quality Optimization and High-level Tasks

Step 1

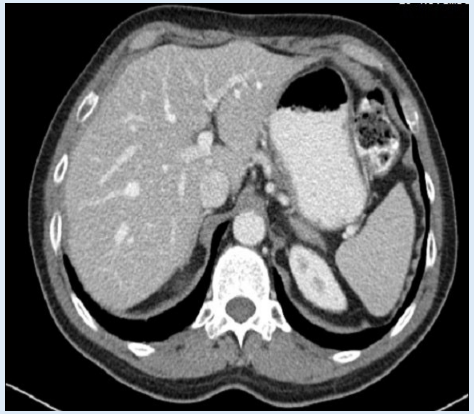
AI-based Quality Optimization Process



Disconnection

Step 2

AI-based Lesion Detection/Segmentation



Detection

segmentation

⊗ Unknown Usability for Step 2 in clinic

⊗ Don' t orient practical high-level tasks

⊗ Evaluated Difficulty for optimized image

LDCT Quality Optimization Towards Clinical Desire: Disconnection Issue

Connection between LDCT Quality Optimization and Lesion Detection

Lesion-Inspired Denoising Network: Connecting Medical Image Denoising and Lesion Detection

Kecheng Chen[1]*, Kun Long[1]*, Yazhou Ren[1]†, Jiayu Sun[2], Xiaorong Pu[1]†
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University of Electronic Science and Technology of China, Chengdu, 611731, China
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ABSTRACT

Deep learning has achieved notable performance in the denoising task of low-quality medical images and the detection task of lesions, respectively. However, existing low-quality medical image denoising approaches are disconnected from the detection task of lesions. Intuitively, the quality of denoised images will influence the lesion detection accuracy that in turn can be used to affect the denoising performance. To this end, we propose a play-and-plug medical image denoising framework, namely Lesion-Inspired Denoising Network (LIDnet), to collaboratively improve both denoising performance and detection accuracy of denoised medical images. Specifically, we propose to insert the feedback of downstream detection task into existing denoising framework by jointly learning a multi-loss objective. Instead of using perceptual loss calculated on the entire feature map, a novel region-of-interest (ROI) perceptual loss induced by the lesion detection task is proposed to further connect these two tasks. To achieve better optimization for overall framework, we propose a customized collaborative training strategy for LIDnet. On consideration of clinical usability and imaging characteristics, three low-dose CT images datasets are used to evaluate the effectiveness of the proposed LIDnet. Experiments show that, by equipping with LIDnet, both of the denoising and lesion detection performance of baseline methods can be significantly improved.

on Multimedia (MM '21), October 20–24, 2021, Virtual Event, China. ACM, New York, NY, USA, 10 pages. https://doi.org/10.1145/3474085.3475480

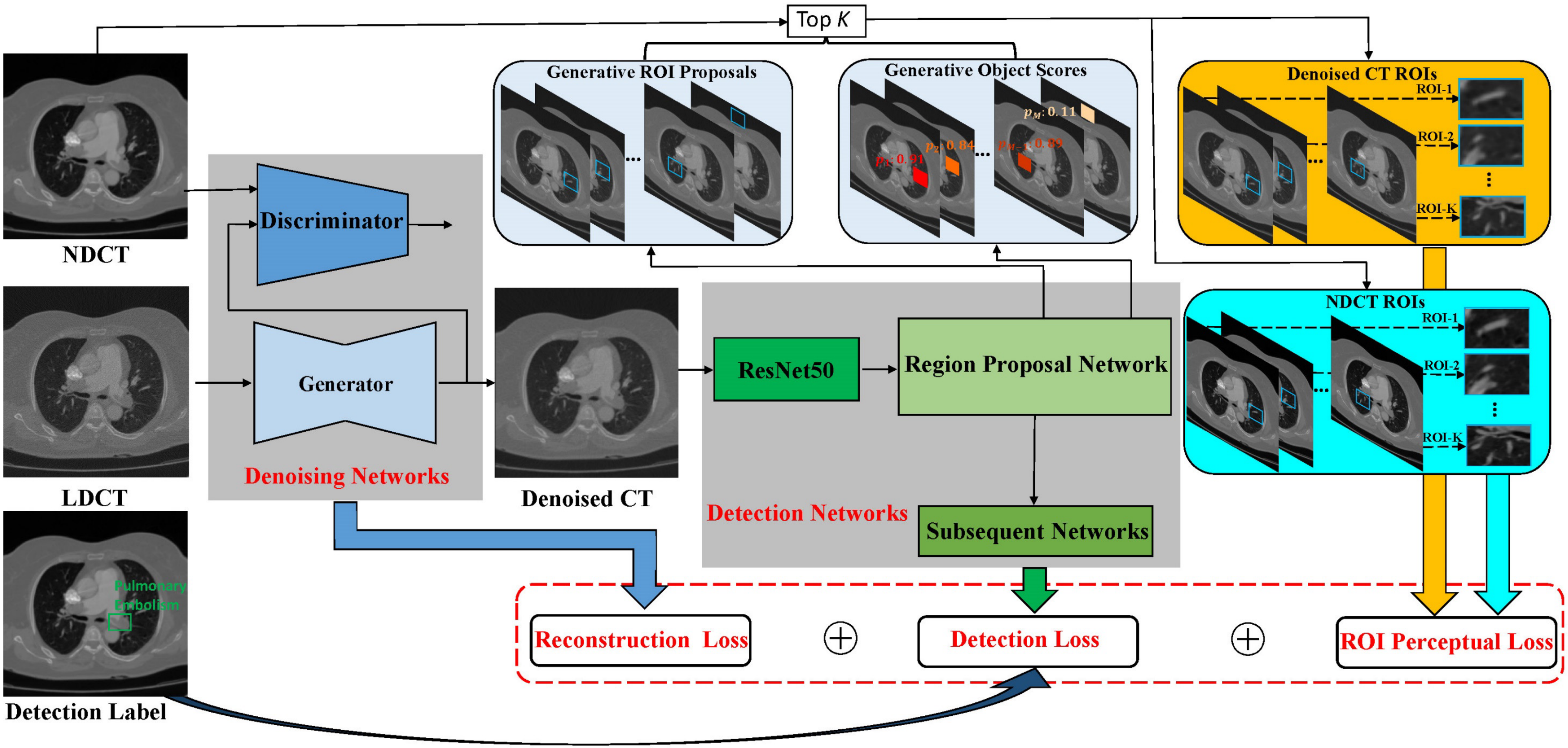
1 INTRODUCTION

The quality of medical images is crucial for the accurate diagnosis by the physicians [1, 7]. For medical artificial intelligence (AI) community, quite a few high-level medical image tasks (such as concerned lesion detection [32, 49], anatomical segmentation [21, 45], and multi-modal image registration[4, 20]) rely heavily on extremely high-quality input images, because 1) slight noise perturbation in low-quality images may take unexpected model degradation [18] and 2) some small lesions (e.g., the minute pulmonary nodules) in low-quality images will suffer from severe noise [10], leading to the difficulties of the post-processing and the diagnosis. The low-quality medical image will be disturbed by noise and artifacts [35]. The researchers therefore focus on low-quality medical image restoration such that the improved images can be used well in potential downstream tasks.

On consideration of clinical usability and imaging characteristics, the noise removal is the mainstream task for the medical image restoration [22, 40]. In various medical images, e.g., computed tomography (CT) image, magnetic resonance imaging (MRI) image, and ultrasonic image, CT image is most sensitive to the noise because the imaging quality will be greatly influenced by the

Kecheng Chen, Kun Long, **Yazhou Ren***, Jiayu Sun, Xiaorong Pu*. 2021. Lesion-Inspired Denoising Network: Connecting Medical Image Denoising and Lesion Detection. ACM MM,2021. (CCF-A)

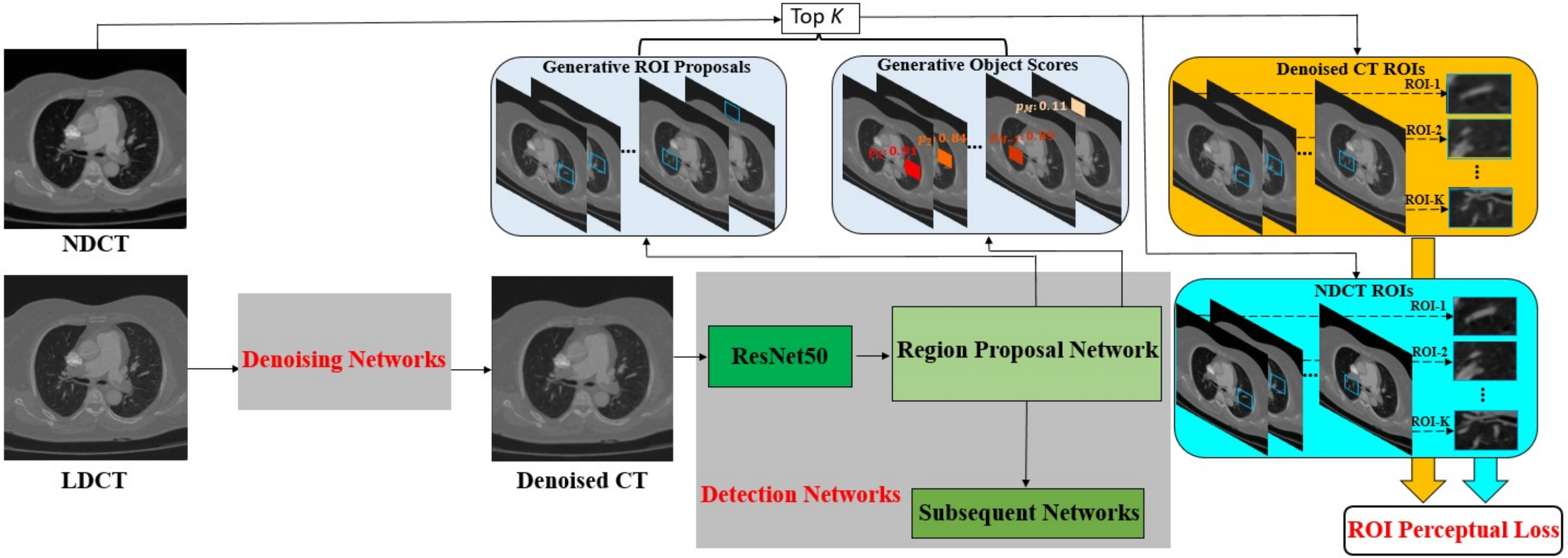
LDCT Quality Optimization Towards Clinical Desire: Disconnection Issue



Kecheng Chen, Kun Long, Yazhou Ren*, Jiayu Sun, Xiaorong Pu*. 2021. Lesion-Inspired Denoising Network: Connecting Medical Image Denoising and Lesion Detection. ACM MM,2021.

LDCT Quality Optimization Towards Clinical Desire: Disconnection Issue

Highlight 1: Towards Region-of-Interest Quality Optimization



A Novel ROI Perceptual Loss:

$$L_{perceptual\_loss} = L_{pl} = \mathbb{E}_{(x,y)}[\frac{\|\phi_{VGG}(F(x)) - \phi_{VGG}(y)\|_F^2}{whd}], \quad (1)$$

ROI

① $\{(t_1, p_1), (t_2, p_2), \ldots, (t_{M-1}, p_{M-1}), (t_M, p_M)\} = RPN(H(F(x))$

② $\{(t_1, p_1), (t_2, p_2), \ldots, (t_K, p_K)\} = select(\{RPN(H(F(x))_{i=1}^{M}\}),$
$s.t. \quad p_i > p_K.$

Inspire from Detection Task

③ $L_{ROI\_pl} = \mathbb{E}_{(x,y)} \frac{1}{K} \sum_{i=1}^{K} [\frac{\|T(F(x))_{t_i} - T(y)_{t_i}\|_F^2}{whd}],$

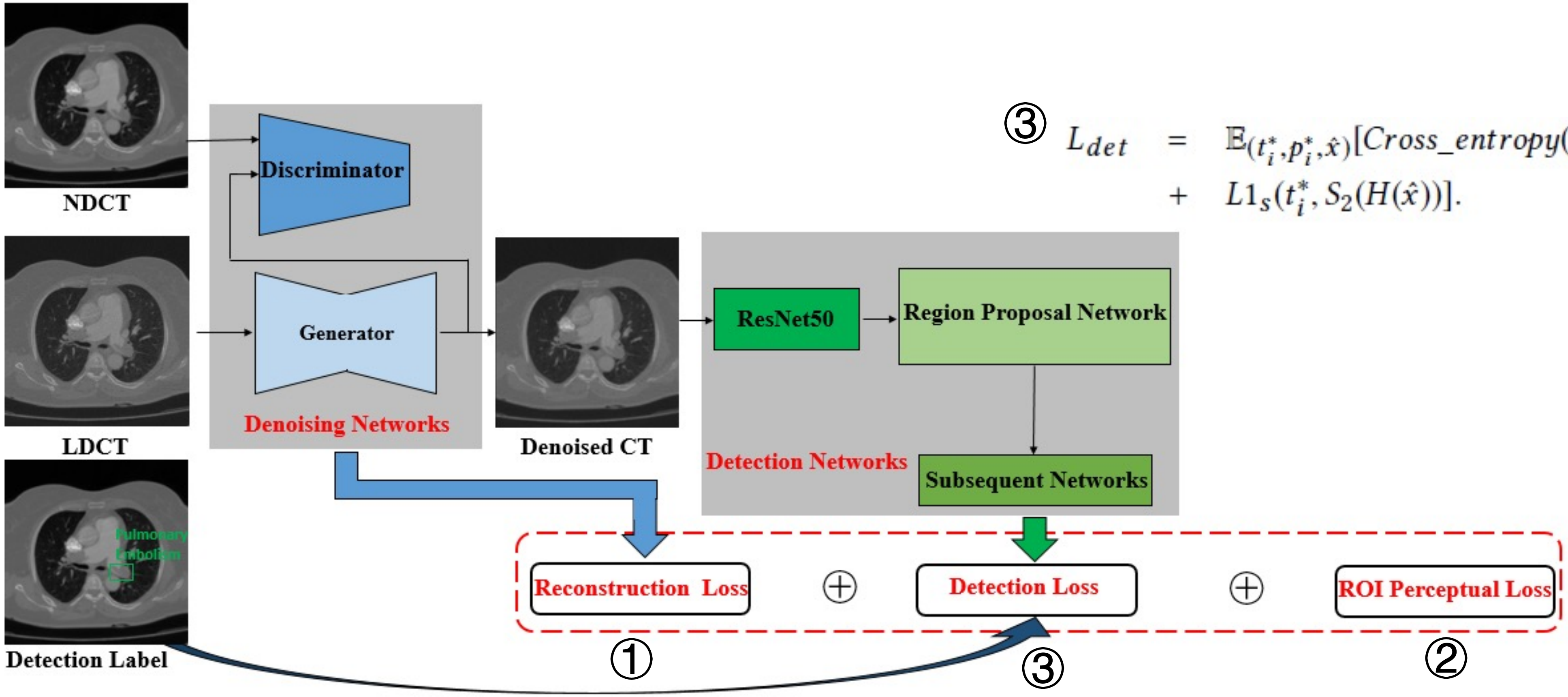
Existing methods: Work on overall feature map

Perceptual Loss: Evaluate the difference between images in feature space

LDCT Quality Optimization Towards Clinical Desire: Disconnection Issue

Highlight 2: Multi-loss Objective Integration with GAN

③
$$L_{det} = \mathbb{E}_{(t_i^*, p_i^*, \hat{x})}[Cross\_entropy(p_i^*, S_1(H(\hat{x})))) + L1_s(t_i^*, S_2(H(\hat{x}))].$$



① ② ③
$$L_{total} = \mathbb{E}_x[-D(G(x))] + \lambda_1 \mathbb{E}_{(\hat{x},y)} \frac{1}{K} \sum_{i=1}^{K} [\frac{\|T(\hat{x})_{t_i} - T(y)_{t_i}\|_F^2}{whd}] + \lambda_2 L_{det},$$

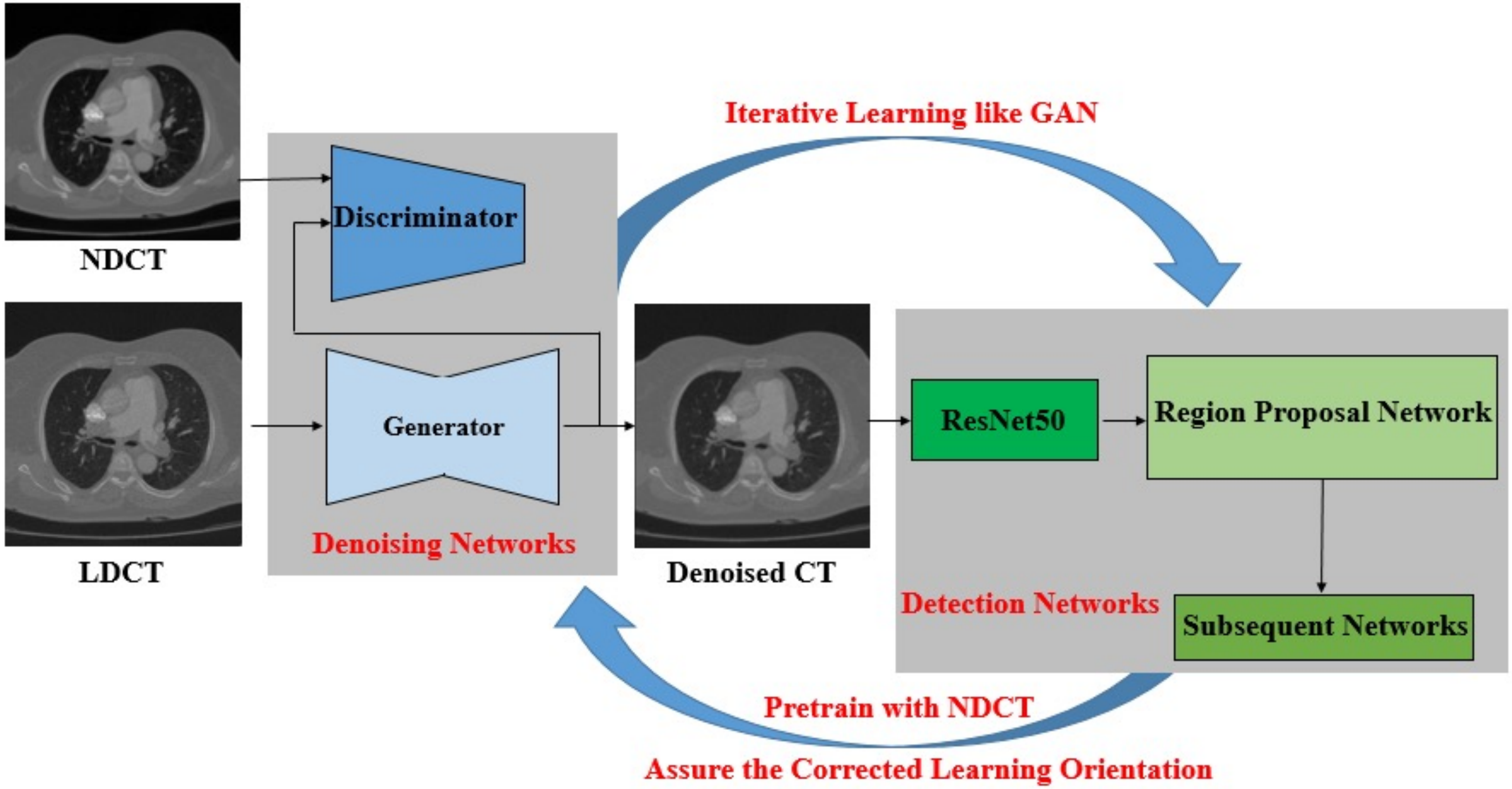
① Evaluate Content Difference

② Evaluate Difference in Latent Space

③ Evaluate the usability in Detection

LDCT Quality Optimization Towards Clinical Desire: Disconnection Issue

Highlight 2: Collaborative Training between Two Models



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Highlight 3: Collaborative Training between Two Models

Algorithm 1 The training procedure of proposed LIDnet.

Input:

LDCT images $X = \{x_1, \ldots, x_N\}$, corresponding NDCT images $Y = \{y_1, \ldots, y_N\}$, ground-truth object coordinates of NDCT images $T^* = \{t_1^*, \ldots, t_N^*\}$, and ground-truth object labels of NDCT images $P^* = \{p_1^*, \ldots, p_N^*\}$. Initial denoising network's parameters Θ and detection networks' parameters ψ.

Initial steps for pre-trained detection network T_1

Training steps of denoising network in a round T_2

Training steps of detection network based on denoise image in a round T_3

Output: Learned parameters: Θ^* and ψ^*.

Freeze Θ

for i=0 to T_1 **do**

  Sample a mini-batch X_d, Y_d, T_d^*, and P_d^* from X, Y, T^*, and P^*, respectively.

  Optimize ψ with (6) w.r.t. S_1, S_2 and RPN on Y_d, T_d^*, and P_d^*.

end for

while Stopping criterion is not met **do**

  Unfreeze Θ. Freeze ψ .

  for i=0 to T_2 **do**

    Sample a mini-batch X_d, Y_d, T_d^*, and P_d^* from X, Y, T^*, and P^*, respectively.

    Optimize Θ with (5) (7) w.r.t. D and G (or optimize Θ with (8) w.r.t. G) on X_d, Y_d, T_d^*, and P_d^*.

  end for

  Freeze Θ. Unfreeze ψ.

  for i=0 to T_3 **do**

    Sample a mini-batch X_d, Y_d, T_d^*, and P_d^* from X, Y, T^*, and P^*, respectively.

    Compute denoising output by denoising network: $X_{denoise} \leftarrow G(X_d)$

    Optimize ψ with (6) w.r.t. S_1, S_2 and RPN on $X_{denoise}$, T_d^*, and P_d^*.

  end for

end while

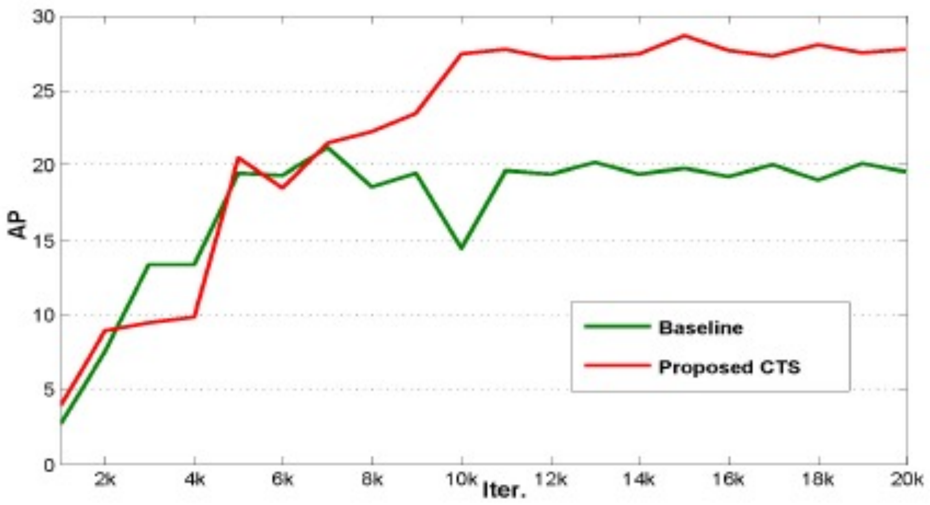

Figure 3: Ablation study on the effectiveness of proposed collaborative training strategy (CTS) for LIDnet. The AP is calculated through the training detection network.

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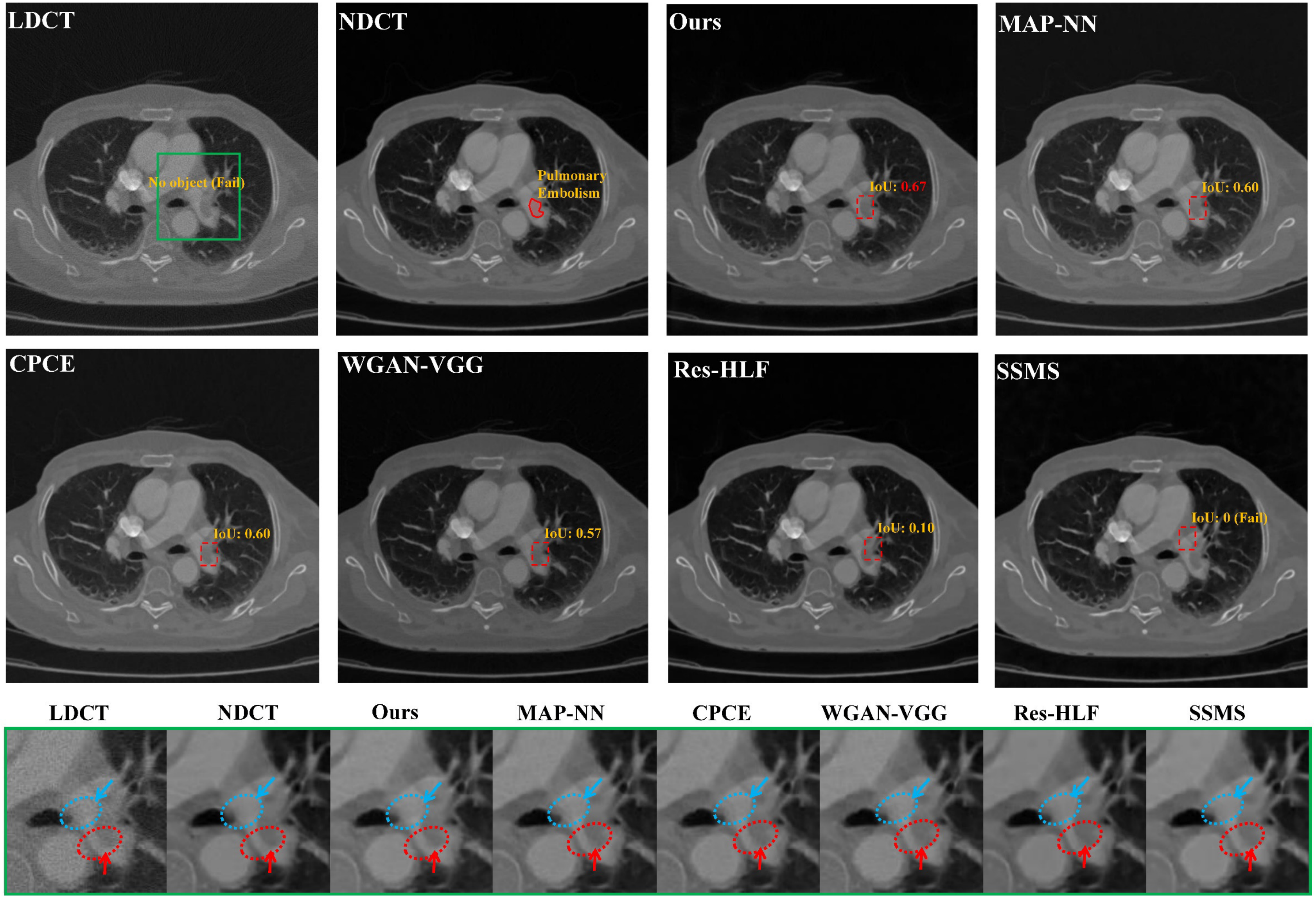
Example: Denoising Results for Chest LDCT



√ *Better Detection Results*

√ *Better Structure Retain*

√ *Detained Texture*

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Detection Evaluation

Table 2: The quantitative results of detection task on three datasets, in terms of AP-50, and AP-75, respectively. For adopted baselines, our proposed framework is used to implement their improved versions. The better score between the baseline and its improved version is bolded with blue. For the AP-50 and AP-75, the higher the better.

DATASET		WGAN-VGG[50]	Ours-WGAN-VGG	CPCE[44]	Ours-CPCE	MAPNN[43]	Ours-MAPNN	SSMS [52]	Ours-SSMS	Res-HLF[29]	Ours-Res-HLF
PE-CT	AP-50	74.56	**74.59**	74.60	**75.69**	75.03	**76.79**	73.16	**74.07**	74.34	**76.44**
	AP-75	25.46	**26.70**	25.74	**26.26**	25.75	**27.01**	23.02	**24.62**	**25.74**	24.77
L-CT-G	AP-50	93.90	**95.31**	91.62	**93.74**	92.84	**95.14**	91.15	**93.89**	94.24	**95.28**
	AP-75	46.15	**48.14**	35.89	**46.67**	45.04	**45.53**	38.76	**44.00**	47.74	**48.90**
L-CT-A	AP-50	**91.51**	91.31	88.01	**89.76**	86.98	**91.44**	84.02	**88.50**	89.32	**90.60**
	AP-75	41.34	**41.48**	41.30	41.30	40.00	**43.21**	37.49	**40.39**	39.85	**40.36**

Better Detection Results

LDCT Quality Optimization Towards Clinical Desire: Disconnection Issue

Denoising Evaluation

Table 3: The quantitative results of denoising task on three datasets for the ROIs and the overall image. For adopted baselines, our proposed framework is used to implement their improved versions. The better score between the baseline and its improved version is bolded with blue. For the correlation, homogeneity, RMSR, and energy, the lower the better. For the PSNR and the SSIM, the higher the better.

DATASET	PE-CT						L-CT-G						L-CT-A					
	ROI			Overall			ROI			Overall			ROI			Overall		
	Correlation	Homogeneity	Energy	PSNR	SSIM	RMSE	Correlation	Homogeneity	Energy	PSNR	SSIM	RMSE	Correlation	Homogeneity	Energy	PSNR	SSIM	RMSE
WGAN-VGG	0.023	**0.038**	**0.009**	27.49	99.97	0.046	**0.048**	**0.068**	0.019	26.74	99.97	0.049	**0.042**	**0.085**	**0.025**	27.18	99.94	0.049
Ours-WGAN-VGG	0.023	0.058	0.013	**35.51**	**1.00**	**0.017**	0.049	0.076	**0.018**	**30.94**	**99.99**	**0.032**	0.048	0.104	0.029	**29.13**	**99.96**	**0.042**
CPCE	0.021	0.045	0.012	26.34	99.97	0.049	0.055	0.090	0.022	28.45	99.98	0.042	0.049	0.109	0.030	26.30	99.93	0.057
Ours-CPCE	**0.019**	**0.034**	**0.009**	**31.76**	**99.99**	**0.028**	**0.054**	**0.078**	**0.018**	**29.90**	**99.99**	**0.035**	**0.043**	**0.105**	0.030	**28.01**	**99.95**	**0.047**
MAPNN	0.024	0.045	0.011	27.33	99.97	0.043	0.052	0.078	0.018	23.37	99.91	0.077	0.047	0.102	0.027	28.20	99.95	0.046
Ours-MAPNN	**0.018**	**0.038**	**0.009**	**31.85**	**99.99**	**0.027**	**0.046**	**0.077**	**0.017**	**30.70**	**99.99**	**0.032**	**0.045**	**0.101**	0.027	**28.45**	**99.96**	**0.045**
SSMS	0.040	0.138	0.043	**33.89**	99.99	**0.021**	0.071	0.109	0.022	24.55	99.95	0.061	0.047	0.125	0.032	**27.56**	99.94	**0.049**
Ours-SSMS	**0.028**	**0.087**	**0.021**	31.86	99.99	0.027	**0.070**	**0.010**	0.022	**29.84**	**99.99**	**0.035**	**0.046**	**0.105**	**0.030**	25.85	99.94	0.057
Res-HLF	**0.023**	0.107	0.031	31.35	99.99	0.030	**0.025**	0.080	0.022	**32.30**	99.99	0.027	**0.036**	0.105	0.029	29.70	99.96	0.049
Ours-Res-HLF	0.122	**0.106**	**0.021**	**32.11**	99.99	**0.027**	0.033	**0.063**	**0.016**	31.67	**99.99**	**0.026**	0.054	**0.097**	**0.026**	**30.78**	**99.98**	**0.034**

Conclusion

LDCT Quality Optimization Towards Clinical Desires:

①: **Unpaired Data Set in Clinic**

②: **Disconnection between Quality Optimization and High-level Tasks**

AI-based Quality Optimization in Medical Image

1. **K Chen, K Long, Y Ren*, J Sun, X Pu*. Lesion-Inspired Denoising Network: Connecting Medical Image Denoising and Lesion Detection. ACM MM (CCF A), 2021.**
2. **K Chen, X Pu*, Y Ren*, H Qiu, F Lin, S Zhang. TEMDnet: A Novel Deep Denoising Network for Transient Electromagnetic Signal With Signal-to-Image Transformation. TGRS (JCR Q1), 2020.**
3. **Chen K., Pu X., Ren Y., Qiu H., Li H., Sun J. (2020) Low-Dose CT Image Blind Denoising with Graph Convolutional Networks. ICONIP (CCF C)， 2020.**
4. **Chen K., Huang J., Sun J., Ren Y.*, Qiu H., (2020) Task-Driven Deep Learning for LDCT Denoising. ISICDM (EI), 2020.**
5. **The Championship: The Challenge for LDCT image quality optimization**

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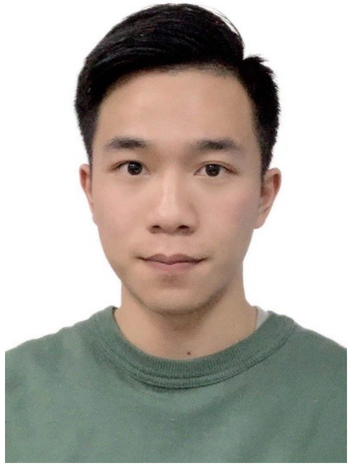

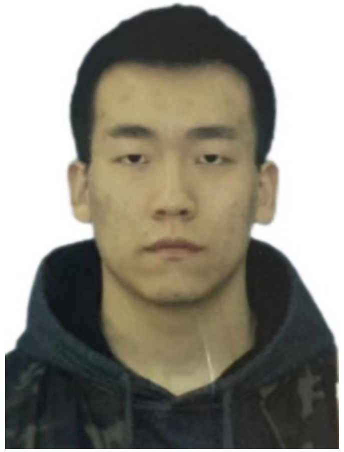

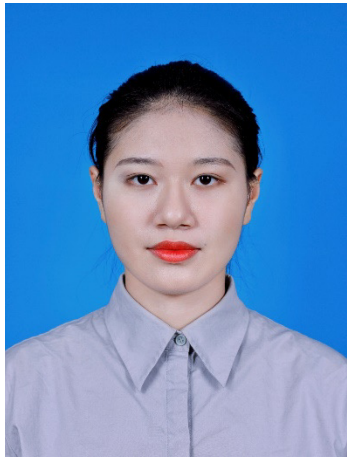

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Thanks！