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文献阅读

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CT Reconstruction

由X光重建CT

1. 单张X光重建CT
2. 两张正交的X光重建CT

由低剂量的CT重建正常剂量的CT

1. Low-Dose CT with a Residual Encoder-Decoder Convolutional Neural Network (RED-CNN)
2. A Sparse-View CT Reconstruction Method Based on Combination of DenseNet and Deconvolution

由X光重建CT

- Motivation:

1. 传统的CT成像需要上百张X光片经过滤波迭代得到，存在很高的辐射剂量，会对人体进行损伤。

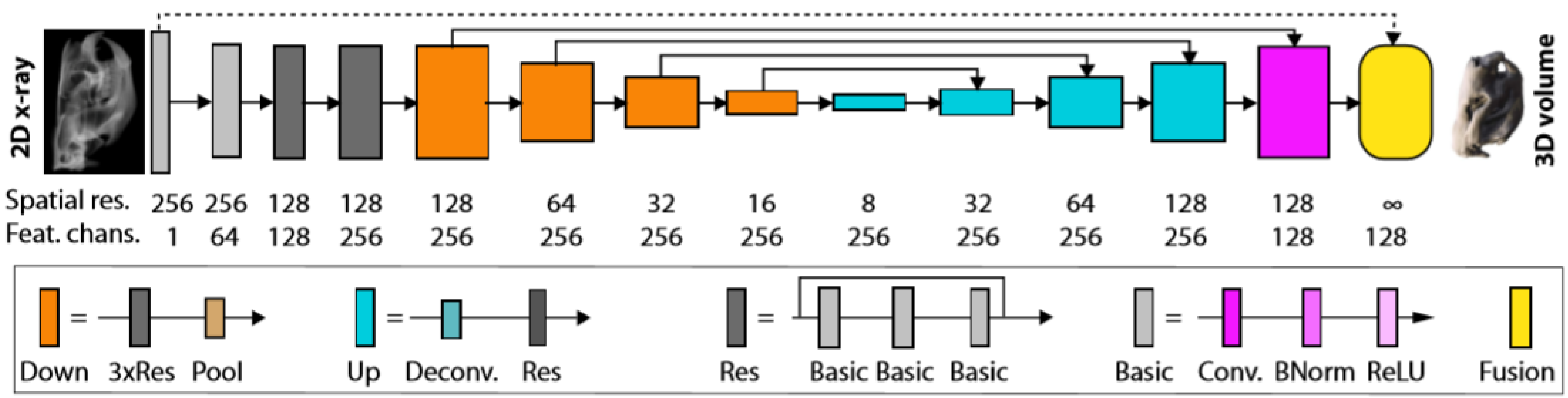
2. X光片存在软组织相互覆盖的问题，在临床中诊断价值低。

- Challenge:

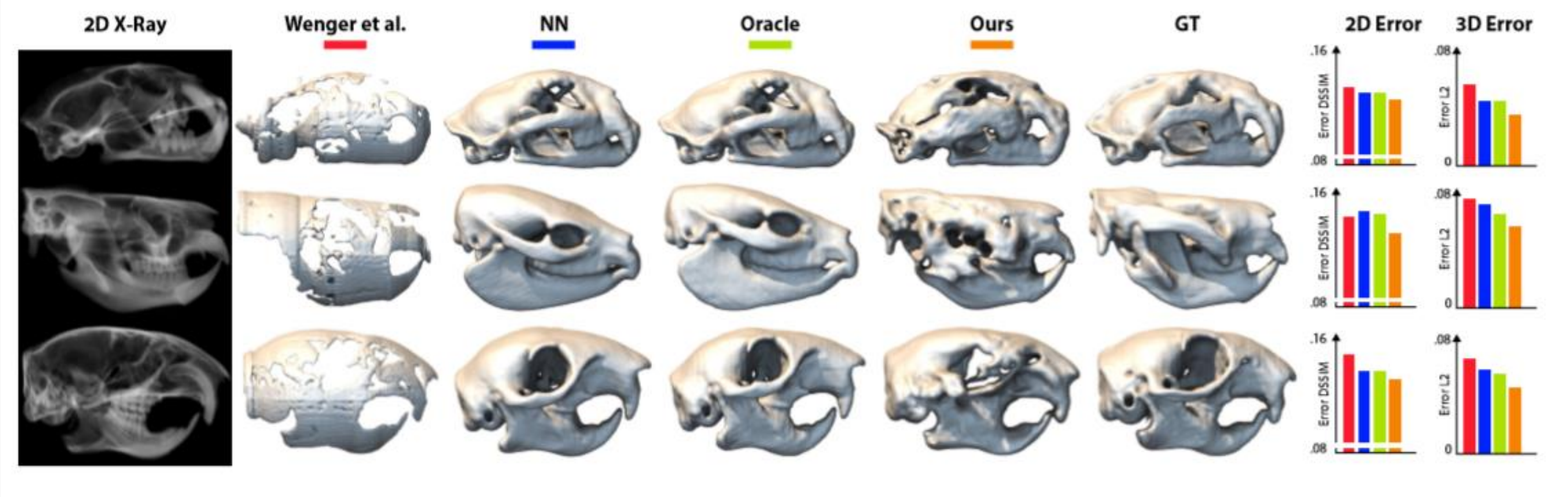
从X光片重建CT是增加维度的过程。由于X光片是2D的，对人体内部信息存在模糊性。

Single-image Tomography: 3D Volumes from 2D Cranial X-Rays

1. encoder-decoder residual跳接结构
2. 把特征通道直接当作第三个维度



Single-image Tomography: 3D Volumes from 2D Cranial X-Rays

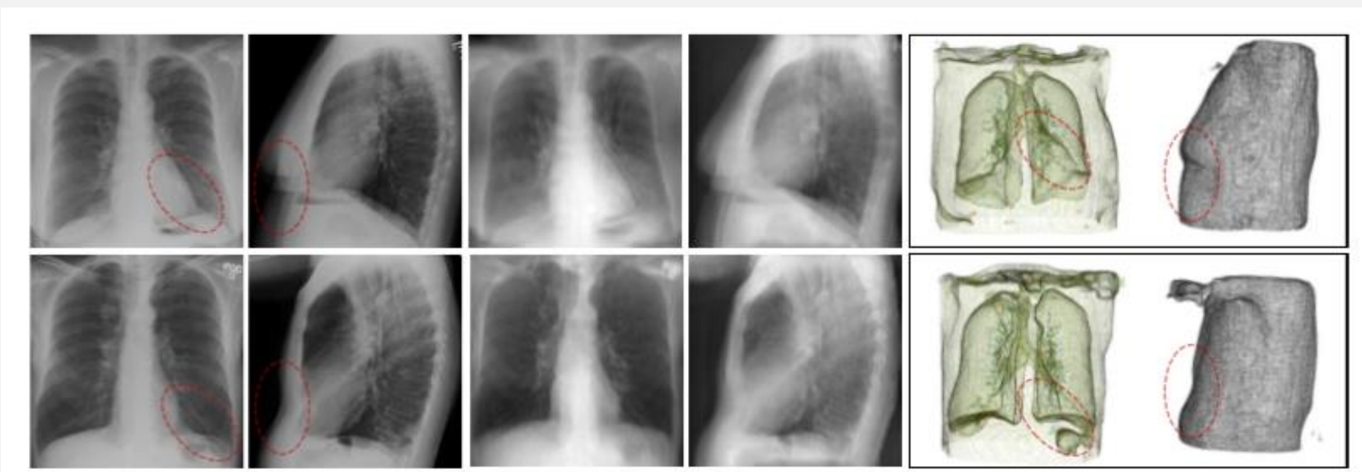


X2CT-GAN: Reconstructing CT from Biplanar X-Rays with Generative Adversarial Networks

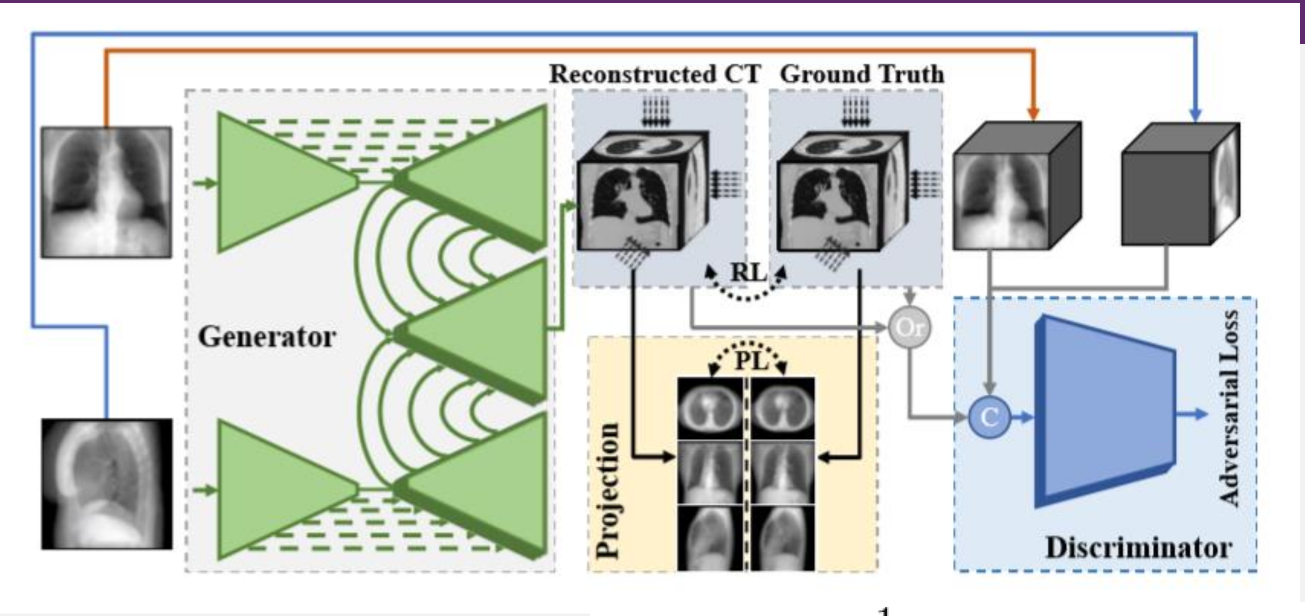
Xingde Ying[*,†,♭], Heng Guo[*,§,♭], Kai Ma[♭], Jian Wu[†], Zhengxin Weng[§], and Yefeng Zheng[♭]

Data

1. 公开的肺部CT数据库LIDC-IDRI
   CT对应的X光片由DRR技术生成，并使用CycleGAN使其更逼真。
2. 使用两张正交的X光图像：正视图和侧视图，应用双视角信息。



Loss Functions



Adversarial Loss (LSGAN) :

$$\mathcal{L}_{LSGAN}(D) = \frac{1}{2}[\mathbb{E}_{y\sim p(CT)}(D(y|x)-1)^2 + \mathbb{E}_{x\sim p(Xray)}(D(G(x)|x)-0)^2],$$

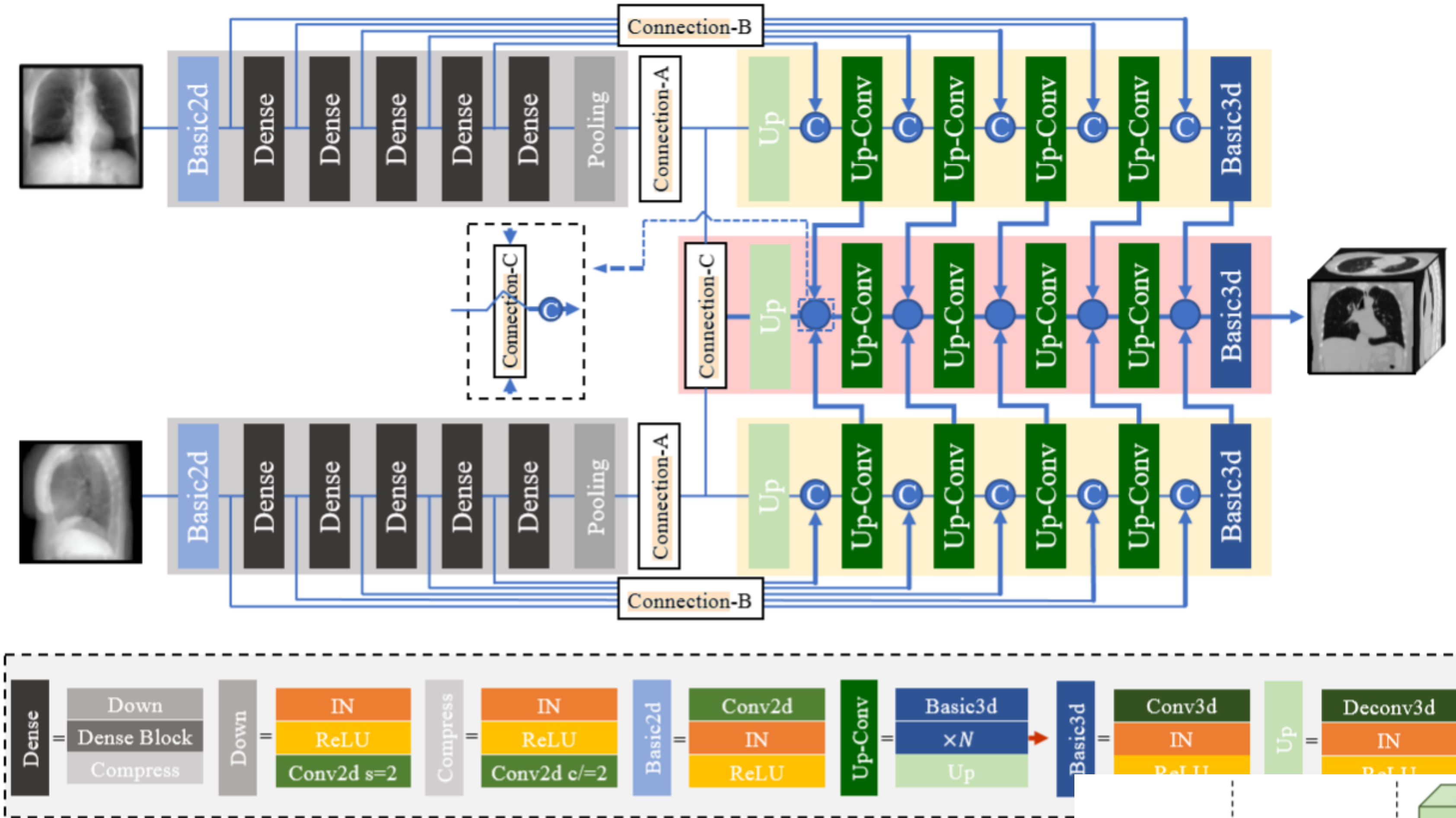
$$\mathcal{L}_{LSGAN}(G) = \frac{1}{2}[\mathbb{E}_{x\sim p(Xray)}(D(G(x)|x)-1)^2],$$

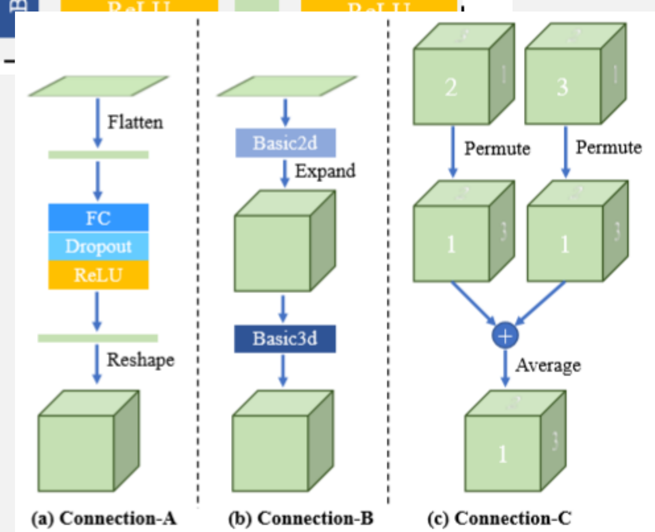
Reconstruction Loss:

$$\mathcal{L}_{re} = \mathbb{E}_{x,y}\|y - G(x)\|_2^2.$$

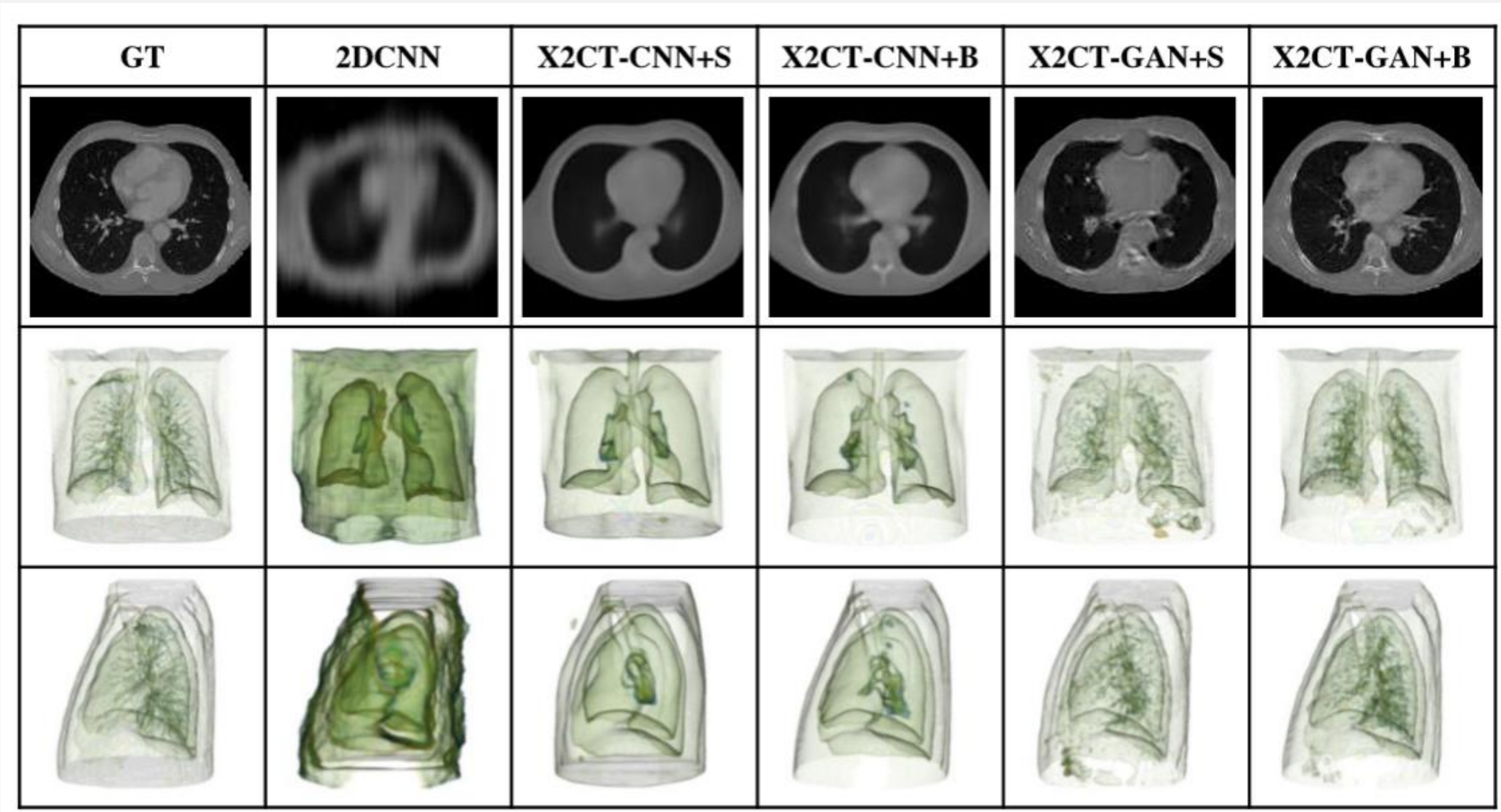
Projection Loss:

$$\mathcal{L}_{pl} = \frac{1}{3}[\mathbb{E}_{x,y}\|P_{ax}(y) - P_{ax}(G(x))\|_1 + \mathbb{E}_{x,y}\|P_{co}(y) - P_{co}(G(x))\|_1 + \mathbb{E}_{x,y}\|p_{sa}(y) - P_{sa}(G(x))\|_1],$$


Connection-B
Basic2d
Dense
Pooling
Connection-A
Up
Up-Conv
Basic3d
C
Connection-C
Down
Dense Block
Compress
IN
ReLU
Conv2d s=2
Conv2d c/=2
Conv2d
Basic3d
×N
Conv3d
Deconv3d


Flatten
FC
Dropout
ReLU
Reshape
Basic2d
Expand
Basic3d
Permute
Average
2
3
1
(a) Connection-A
(b) Connection-B
(c) Connection-C

Result



low-dose CT->normal-dose CT

1. 降低辐射剂量最常用的方法是减小工作电流和缩短X射线管曝光时间。X通量越弱，CT图像中会出现噪声和伪影，影像诊断性能。

2. LDCT->NDCR重建问题可表述为

$$\mathbf{X} = \sigma(\mathbf{Y})$$

$$\sigma : \mathbf{R}^{m \times n} \rightarrow \mathbf{R}^{m \times n}$$

$$\arg\min_{f} \| f(\mathbf{X}) - \mathbf{Y} \|_2^2$$

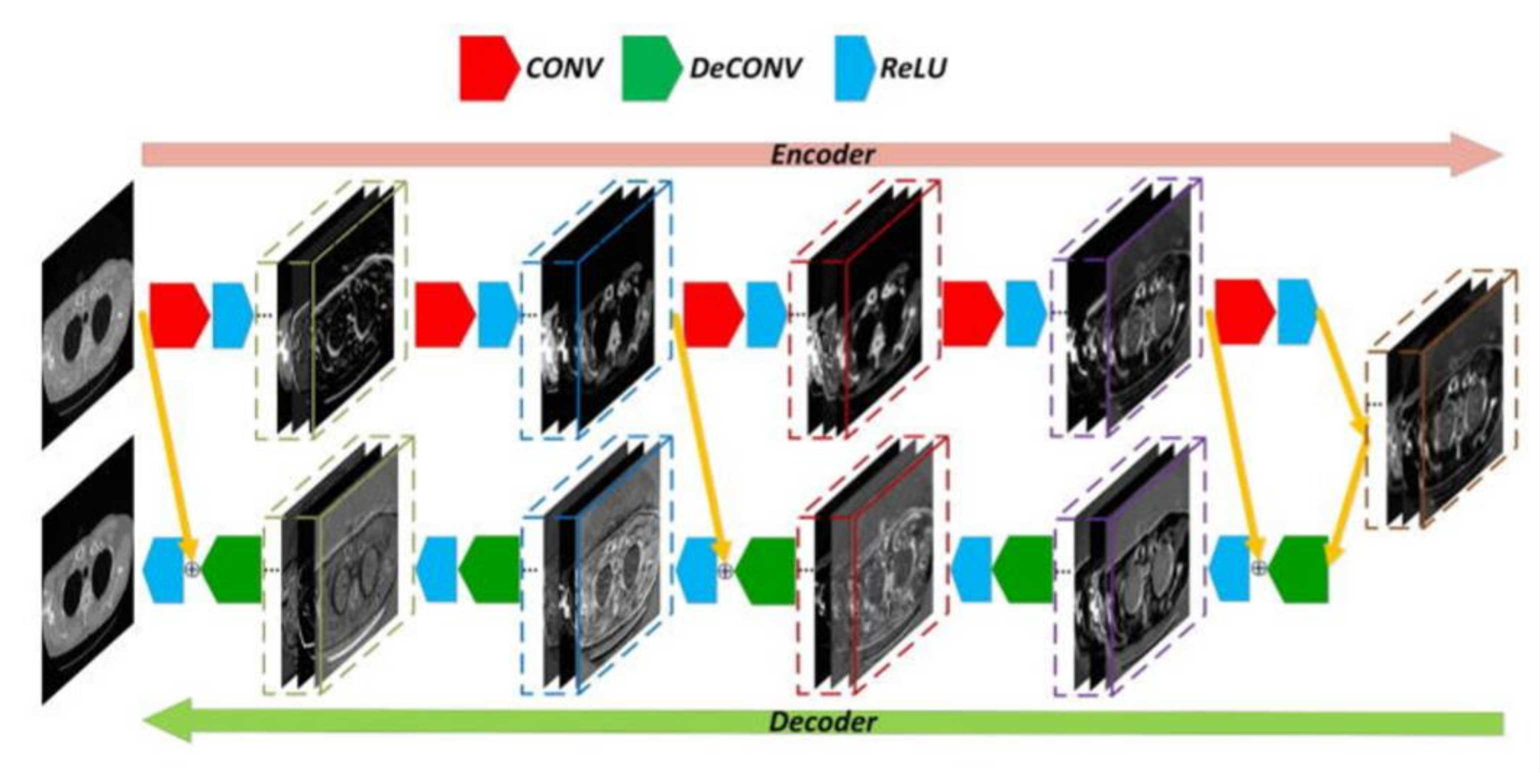
所求得的f实际上是δ^{-1}的最优解。

3. 理论依据：尽管CT影像是高维数据，但它实际上保持在一个非常低维的流形上，因此能够在这样的流形上用少量的数据点进行有意义的重建工作。

Low-Dose CT with a Residual Encoder-Decoder Convolutional Neural Network (RED-CNN)

Hu Chen, Yi Zhang, Member, IEEE, Mannudeep K. Kalra, Feng Lin, Yang Chen, Peixo Liao, Jiliu Zhou, Senior Member, IEEE, and Ge Wang, Fellow, IEEE

1. encoder(去掉噪声和伪影)-decoder（恢复结构细节）。Patch-based
2. 去掉了pooling层：避免漏掉图像细节。



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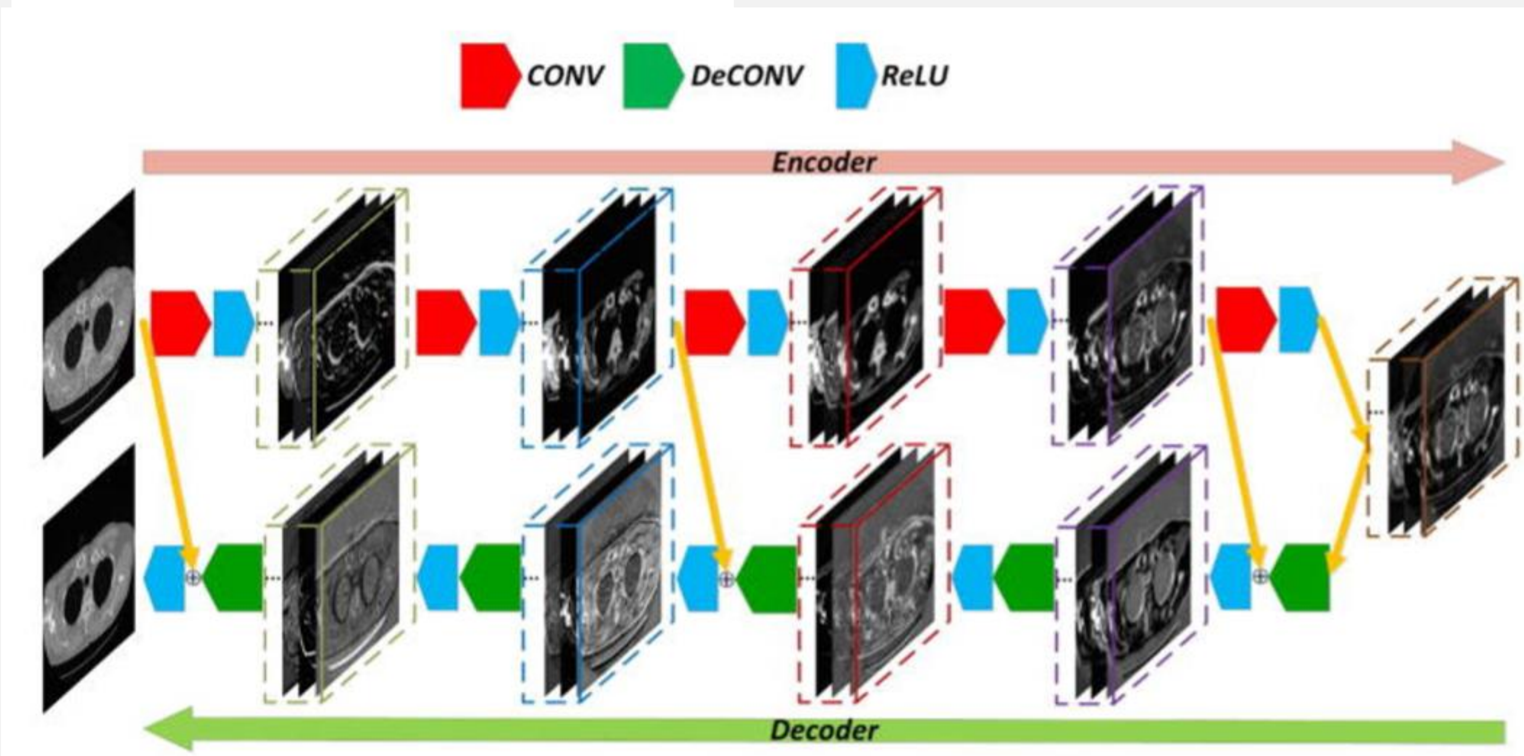
3. Residual结构。去除了残差求和前的RELU层，以去掉学习到残差为正的约束。跳接结构补偿了卷积层漏掉的图像细节。

4. $$F(D;\Theta) = \frac{1}{N}\sum_{i=1}^{N} \| \mathbf{X}_i - M(\mathbf{Y}_i) \|^2.$$

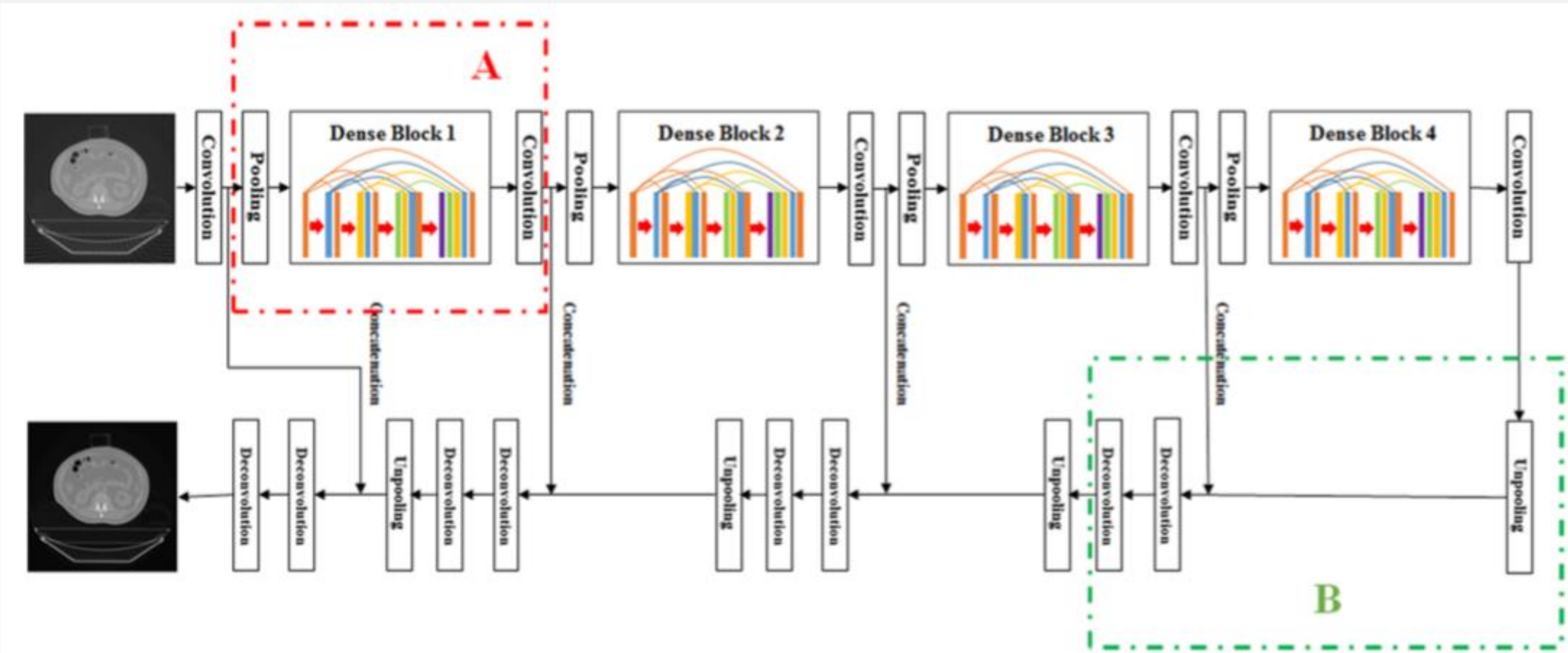


A Sparse-View CT Reconstruction Method Based on Combination of DenseNet and Deconvolution

Article in IEEE Transactions on Medical Imaging · April 2018
DOI: 10.1109/TMI.2018.2823338

Dense Net + Deconvolution

2种连接：1. dense block中的连接 2. 跳接结构



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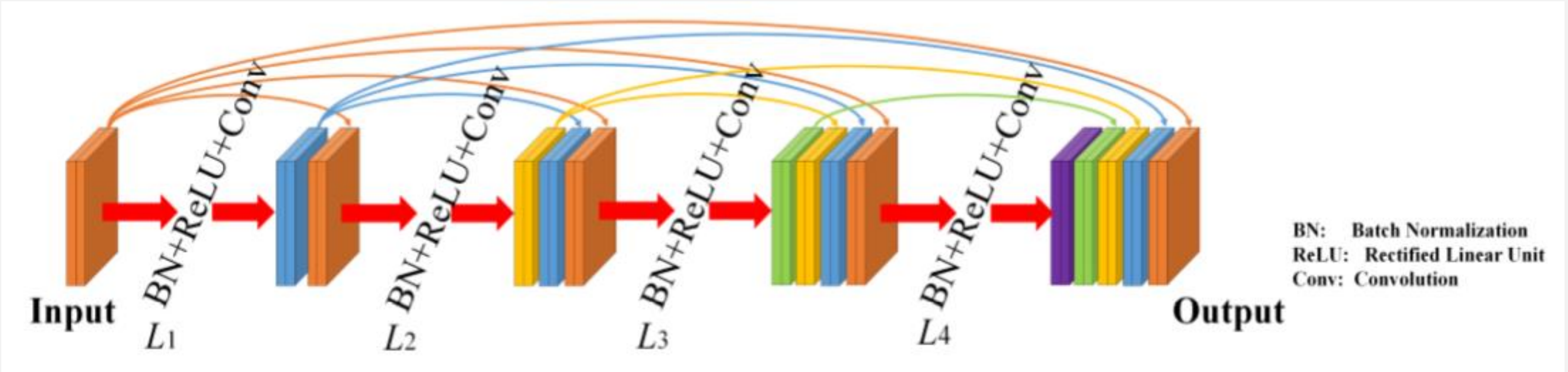
Denseblock



L2 loss会导致边缘模糊、损失细节

$$\mathcal{L} = \| Y - f(X) \|_2^2 + \alpha \mathcal{L}_{MS-SSIM}(Y, f(X))$$

给定两个图像x和y，两张图像的结构相似性可按照以下方式求出 [1]：

$$\mathrm{SSIM}(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)}$$

其中μ_x是x的平均值，μ_y是y的平均值，σ_x^2是x的方差，σ_y^2是y的方差，σ_{xy}是x和y的协方差。$c_1 = (k_1 L)^2$，$c_2 = (k_2 L)^2$是用来维持稳定的常数。L是像素值的动态范围。$k_1 = 0.01, k_2 = 0.03$。

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数据预处理：FBP滤波

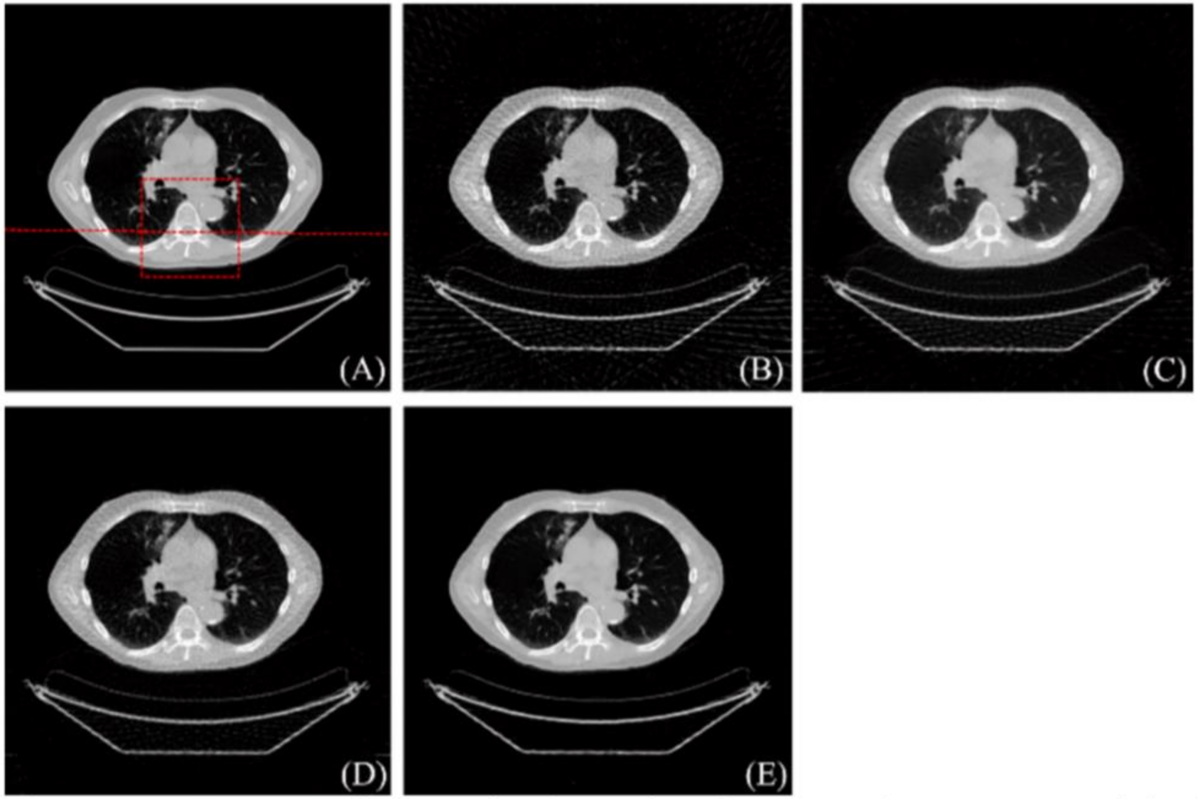

Figure 5. Reconstruction results from the chest CT dataset. (A) Original (B) FBP, (C) PWLS-TGV, (D) R-NLTV, (E) DD-Net. Display window was at [0, 0. 029] mm^{-1} .

谢谢大家!