

# Brief Result of Relaxed Projected Gradient Descent CT Reconstruction

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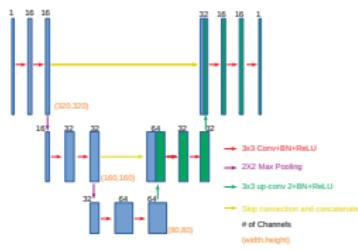
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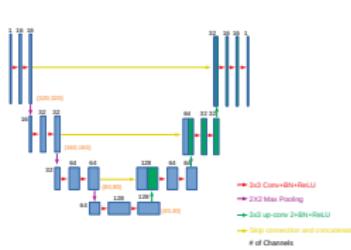
## U-NET training

- Basic structure of UNET is stated in [1]
- Due to lack of VRAM of the graphics card, the following proposed variants can cope up with a rather small batch size for training

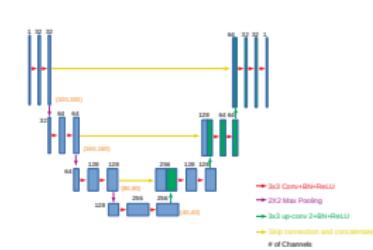
## Proposed U-NET structure



(a) 2 up/down layers



(b) 3 up/down layers



(c) (b) w/ 2X depth

Figure: 1

## U-NET training

### Sequential training stages:

- stage 1: Initialize a model and define a loss function

$$\begin{aligned}\hat{y} &= \text{model}(x) \\ \text{loss} &= \|\hat{y} - y_{true}\|_2\end{aligned}\tag{1}$$

- stage 2 : load model(stage 1) and change the loss function

$$\begin{aligned}\hat{y} &= \text{model}(x), y' = \text{model}(\hat{y}) \\ \text{loss} &= \text{mean}(\|\hat{y} - y_{true}\|_2 + \|y' - y_{true}\|_2)\end{aligned}\tag{2}$$

- stage 3: load model(stage 2) and change the loss function

$$\begin{aligned}\hat{y} &= \text{model}(x), y' = \text{model}(\hat{y}), \tilde{y} = \text{model}(y_{true}) \\ \text{loss} &= \text{mean}(\|\hat{y} - y_{true}\|_2 + \|y' - y_{true}\|_2 + \|\tilde{y} - y_{true}\|_2)\end{aligned}\tag{3}$$

# Relaxed Projected Gradient Descent

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## Algorithm 1: Relaxed Projected Gradient Descent

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**Input:** backprojection operator  $\mathbf{H}$ , backprojection operator  $\mathbf{H}^T$ , filtering operator  $\mathbf{A}$ , noisy measurement(sinogram)  $\mathbf{y}$ , a pre-trained CNN model, stepsize  $\gamma > 0$ , positive sequence  $\{c_n\}_{n \geq 1}$ ,  $\alpha \in [0, 1)$ .

$k \leftarrow 0$

$\mathbf{x}_0 = \mathbf{Ay} \in \mathbb{R}^N$

**while** not converge **do**

$$\mathbf{z}_k = \text{CNN}(\mathbf{x}_k - \gamma \mathbf{H}^T \mathbf{H} \mathbf{x}_k + \gamma \mathbf{H}^T \mathbf{y})$$

**if**  $k \geq 1$  **then**

**if**  $\|\mathbf{z}_k - \mathbf{x}_k\|_2 > c_k \|\mathbf{z}_{k-1} - \mathbf{x}_{k-1}\|_2$  **then**

$$|\quad \alpha_k = c_k (\|\mathbf{z}_{k-1} - \mathbf{x}_{k-1}\|_2 / \|\alpha_{k-1}\| \|\mathbf{z}_k - \mathbf{x}_k\|_2) \alpha_{k-1}$$

**else**

$$|\quad \alpha_k = \alpha_{k-1}$$

**end**

**end**

$$\mathbf{x}_{k+1} = (1 - \alpha_k) \mathbf{x}_k + \alpha_k \mathbf{z}_k$$

$$k \leftarrow k + 1$$

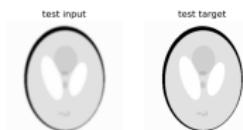
**end**

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## Artificial dataset[2]

### Data formation

- Schepp-Logan Phantom from MATLAB
- Adjusting the intensity value, center, angle and lengths in x- and y -axis
- blurr with 2D spatial filter in size of 5 ( $\frac{1}{25} \text{np.ones}(5,5)$ )
- Reconstruction w/o sinogram
- Not a meaningful experiment setup



### Artificial Dataset Simulation

Avg. SNR Original CT: 9.55 dB

	2layer	3layer	3layer & 2X
MSE	21.4	21.5	...
MLSE	21.2	24.0	<b>24.3</b>

Table: Avg. SNR Reconstructed CT(dB)

	2layer	3layer	3layer & 2X
MSE	11.9	12.0	...
MLSE	11.7	14.4	<b>14.8</b>

Table: Avg. SNR increase(dB)

## AAPM Low Dose CT Image and Projection Data [4]

### Case Study

- Patient: C002
- BodyPartExamined: Chest
- 278 slices Full dose CT images in size (512,512)
- Online DICOM viewer link
- First 200 slices for training and 20 slices for testing
- Carry out the experiment like [Experiment 1.](#) in [3]

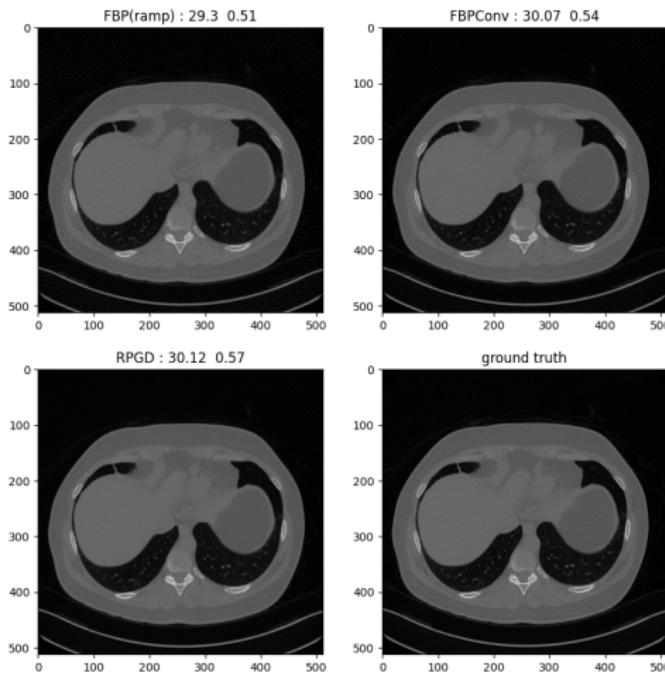
## Experiment Setup & Hyper-parameter configuration

parameter	quantity	parameter	quantity
<b>UNET training</b>			
train samples	200	test samples	20
batch size(train)	5	batch size(test)	20
optimizer	ADAM	LR(stage 1)	1.0e-3
LR(stage 2)	1.0e-3	LR(stage 3)	1.0e-3
train epoch(1)	40	train epoch(2)	20
train epoch(3)	100	momemetum(BN)	0.99
<b>RPGD for reconstruction</b>			
observation window			
$\alpha$	1.0	$\gamma$	1.0e-2
$c_k$	0.5	# of iterations	24

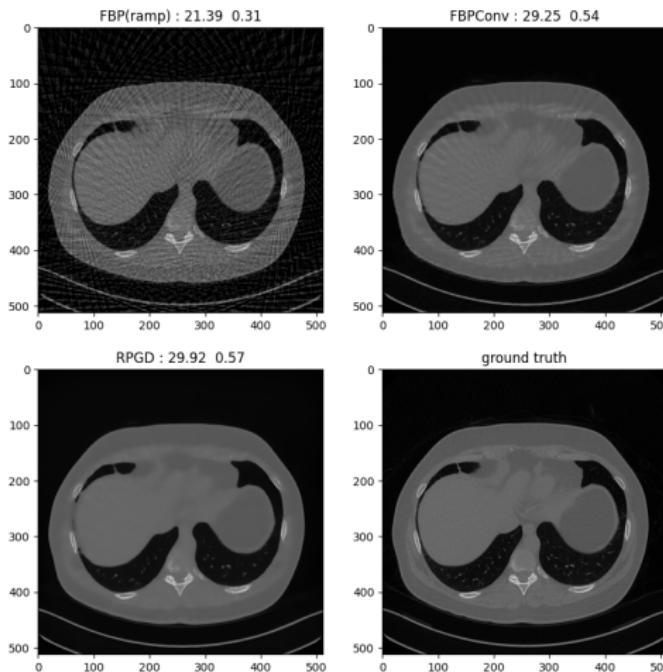
Table: list of parameters

- Only 1b is used to train the netwotk. 1c causes "OOM" problem due to lack of VRAM.
- Neither noise nor read-out error is added.(Input image SNR =  $\infty$ )
- Reconstruct CT images with differnet views of sinogram
- Confined observation window [0 HU, 2621 HU]
- Full result of reconstruction from 144 views sinogram link
- Full result of reconstruction from 45 views sinogram link

# Reconstruction from 144 views sinogram



# Reconstruction from 45 views sinogram



## Conclusion & Further works

- Artificial dataset will not be used any more.
- RPGD method outperforms **quite slightly** in all cases, which is similar to the result in [3].
- RPGD method has significant boost in image quality index when sinogram with fewer views is used.
- I will try the dataset from you later, which consists of 18 patients, later in this week

# References



<sup>1</sup>K. H. Jin, M. T. McCann, E. Froustey, and M. Unser, “Deep convolutional neural network for inverse problems in imaging”, *IEEE Transactions on Image Processing* **26**, 4509–4522 (2017) 10.1109/TIP.2017.2713099.

<sup>2</sup>*Deep-learning-based projected gradient descent for image reconstruction*,  
<https://github.com/PhanHuyThong/Image-Reconstruction-by-CNN-based-PGD>, Accessed: 2019-11-25.

<sup>3</sup>H. Gupta, K. H. Jin, H. Q. Nguyen, M. T. McCann, and M. Unser, “Cnn-based projected gradient descent for consistent ct image reconstruction”, *IEEE Transactions on Medical Imaging* **37**, 1440–1453 (2018)  
10.1109/TMI.2018.2832656.

<sup>4</sup>Moen, Chen, Holmes 3rd, Duan, Yu, Yu, Leng, Fletcher, and McCollough, *Data from low dose ct image and projection data [data set]. the cancer imaging archive.*  
<https://doi.org/10.7937/9npb-2637>, Accessed: 2019-11-25.