Metal Artifact Reduction Via Machine Learning

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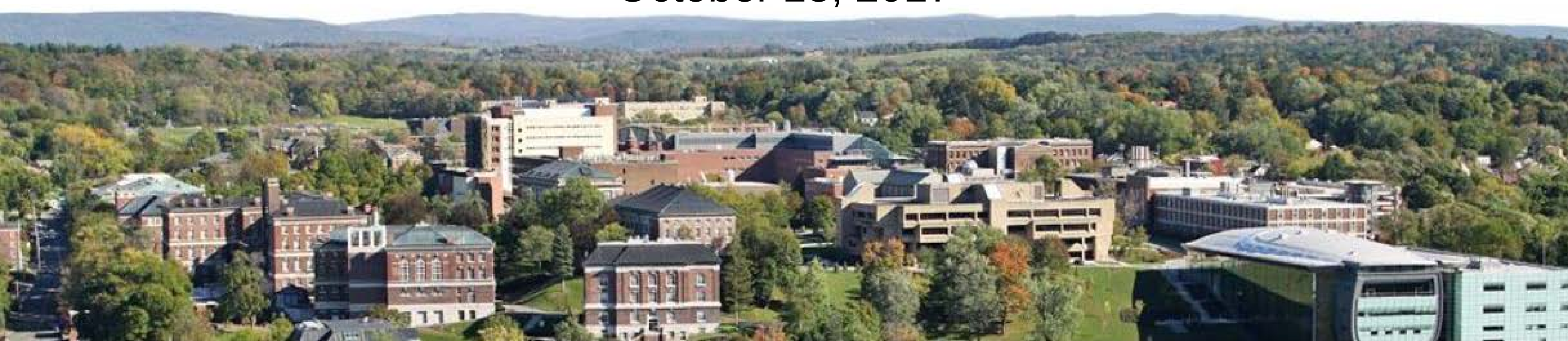
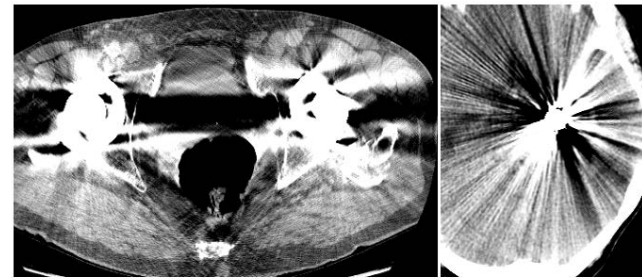


Benefits for TSA

- Metallic/dense objects cause severe metal artifacts
- Existing metal artifact reduction (MAR) algorithms are imperfect
- Relevant to airport scans of luggage & items for high sensitivity/specificity/throughput
- Smart techniques (machine learning/deep learning/CNN/etc.) can improve MAR

Metal Artifact Reduction

- Metal objects corrupt CT images
  - Beam-hardening, scatter, noise
- Projection completion[1-3]
- Iterative reconstruction[4]
- Image-based post-processing[5]

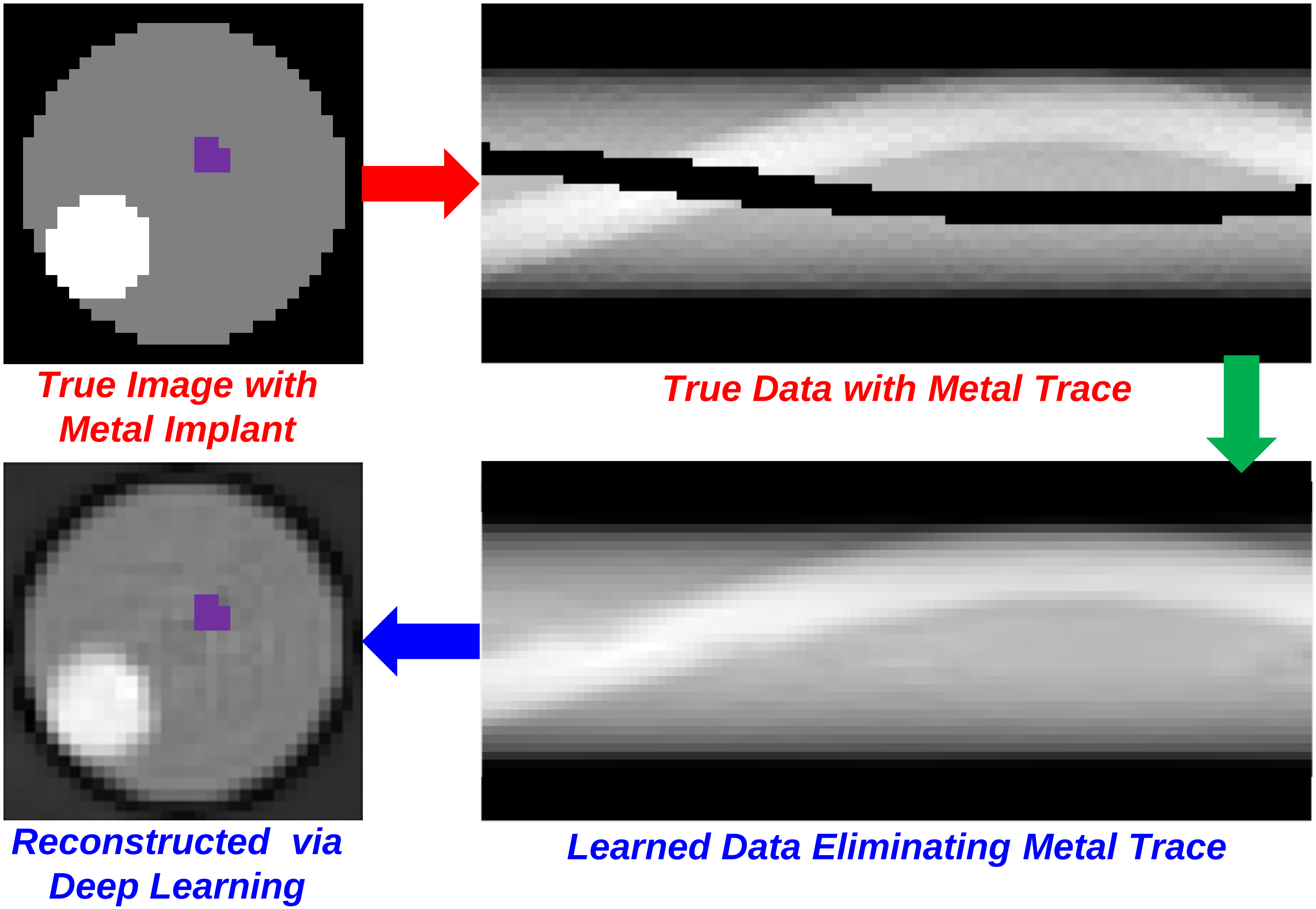


E. Boas and D. Fleischmann, *Imaging. Med., 4(2),* 2012

- Image quality remains insufficient (RT planning[6])

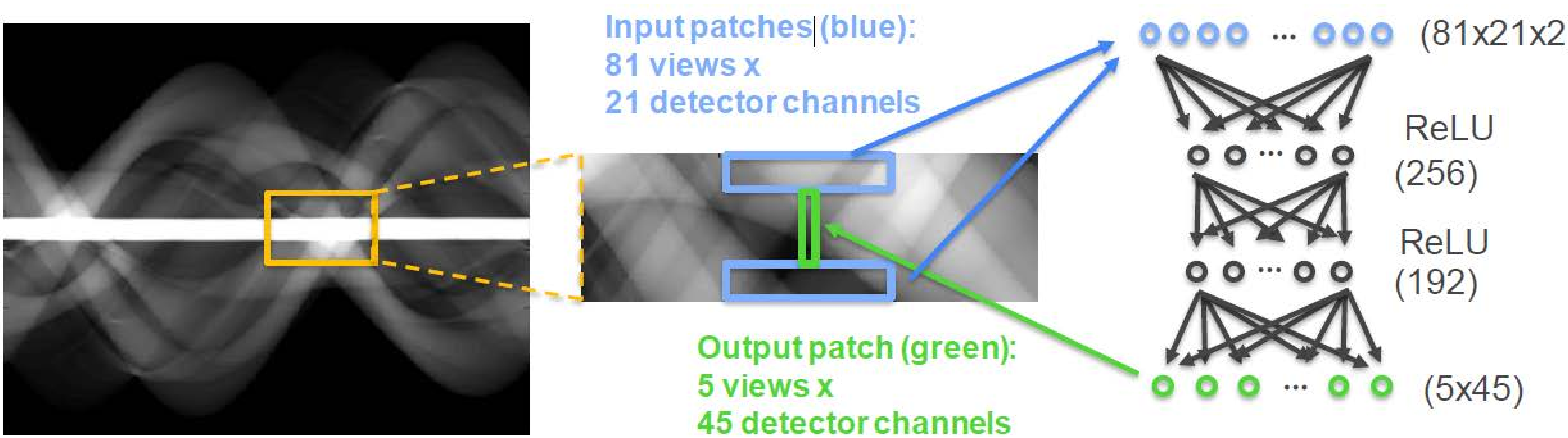
1. W. Kalender et al., Radiology, 164(2), 1987.
2. M. Bal and L. Spies, Medical Physics, 33(8), 2006.
3. **E. Meyer et al., Medical Physics, 37(10), 2010** **(Referred to as NMAR)**
4. J. Stayman et al., IEEE Trans. Med. Imag., 31(10), 2012.
5. O. Watzke et al., European Radiology, 14(5), 2004.
6. C. Reft, et al., Med. Phys. 30(6), 2003.
7. **http://ieeexplore.ieee.org/document/7565564/, 2016** **(Latest review)**

Toy Example of Deep MAR



Wang G: Perspective on Deep Imaging, 2016
http://ieeexplore.ieee.org/document/7733110/

Learning in the Data Domain

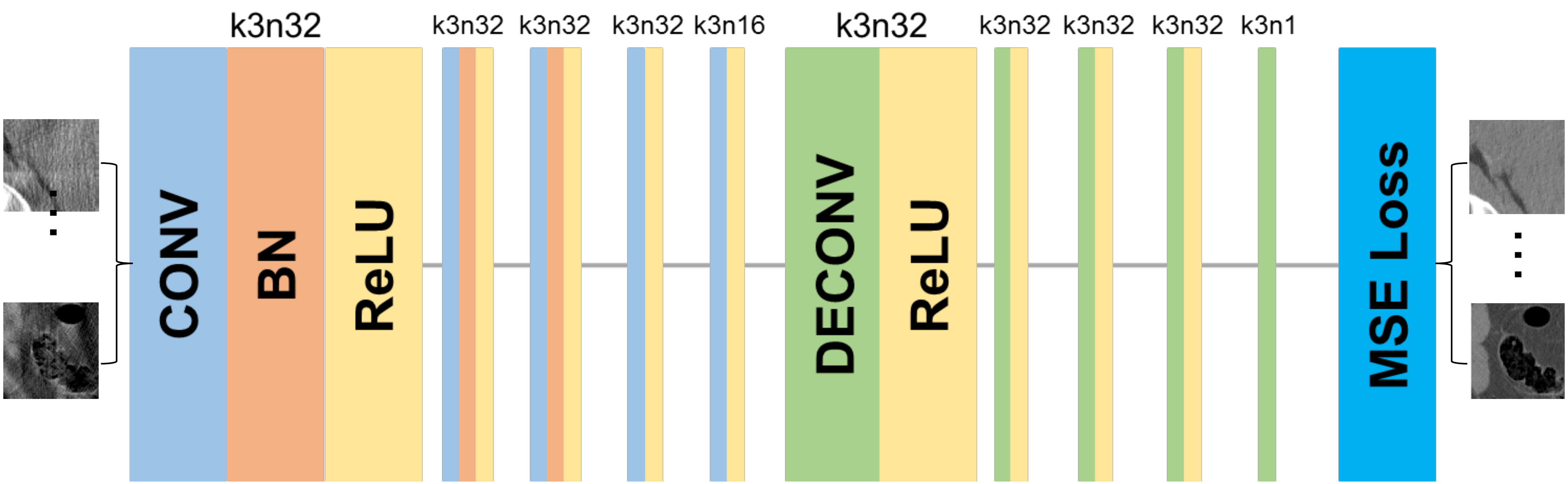


Metal-Artifact Reduction Using Deep-Learning Based Sinogram Completion: Initial Results

Bernhard E. H. Claus, Yannan Jin, Lars A. Gjesteby, Ge Wang, Bruno De Man

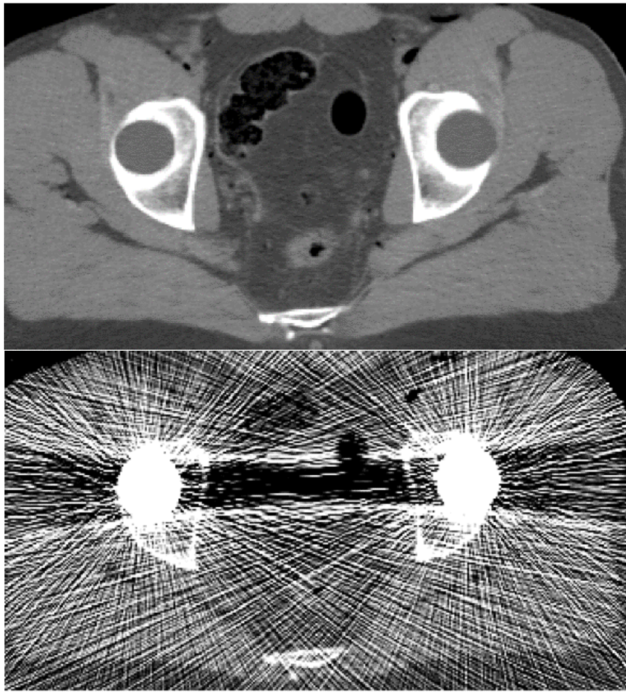
Learning in the Image Domain

- Input image: Already with good MAR
- Output image: Further MAR through CNN
- CNN: Five convolution and five deconvolution layers
- Supervised learning: Ground truth from simulation and/or experiments
- 3x3 convolution kernel denoted by *k*, number of filters denoted by *n*
- Batch normalization (BN) in the first three layers, ReLU for activation
- ~50,000 32x32 patches for training; 12,000 for testing
- Caffe (*UC Berkeley*): One million iterations, with learning rate initialized to 10^{-4} and decreased by 0.5 every 100k iterations



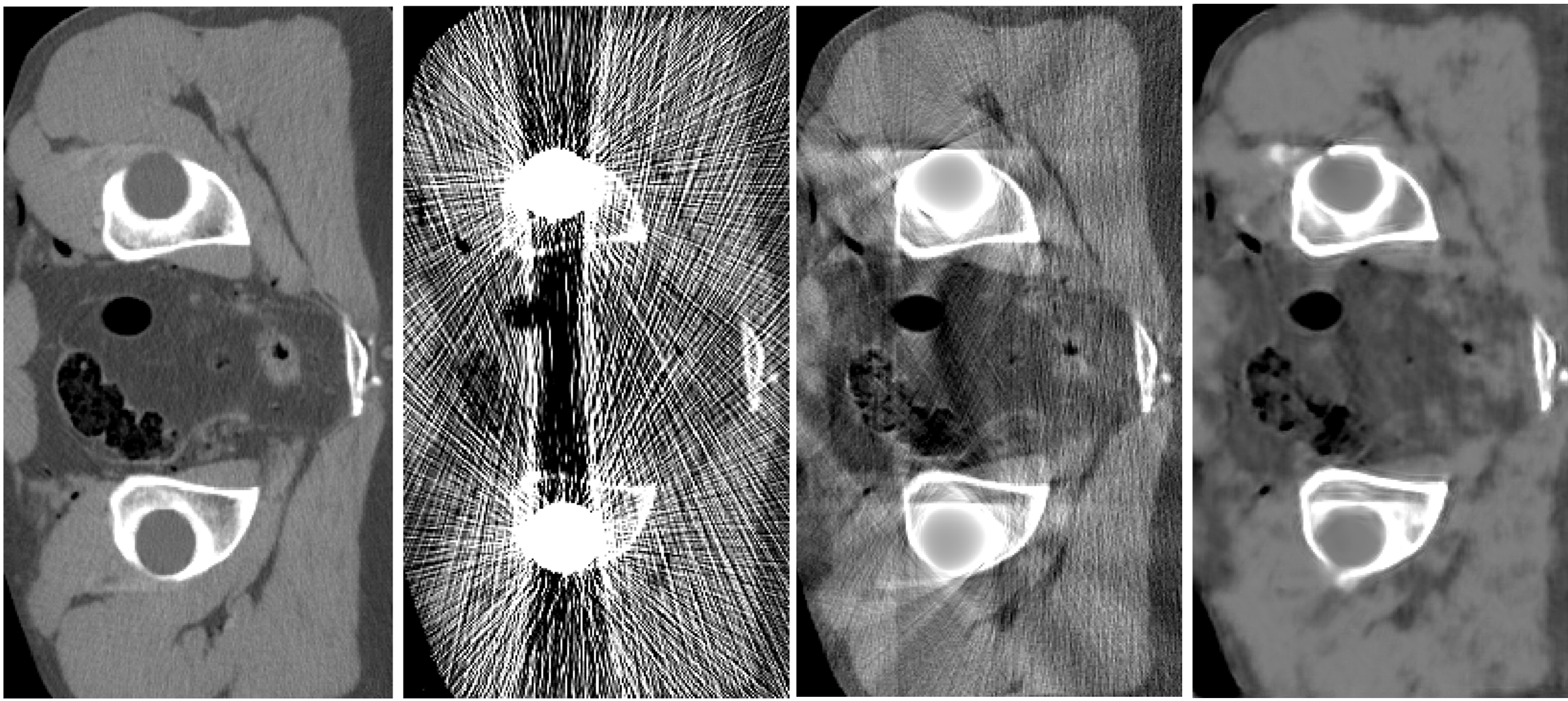
Data Generation

- Voxelized hip phantoms from the Visible Human Project
- Industrial-grade CT simulator (*CatSim, GE Global Research Center*)
- 40 slices (512^2) through abdomen (a pilot study)
- Fan-beam geometry
- Metal-free (ground truth)
  - 100 keV monoenergetic photons, 300 mA, 720 views
- Titanium-added
  - 120 kVp, 300 mA, 720 views
  - NMAR algorithm applied



Case 1: Medium Diameter

Ground Truth | **Uncorrected** | **NMAR** | **CNN**

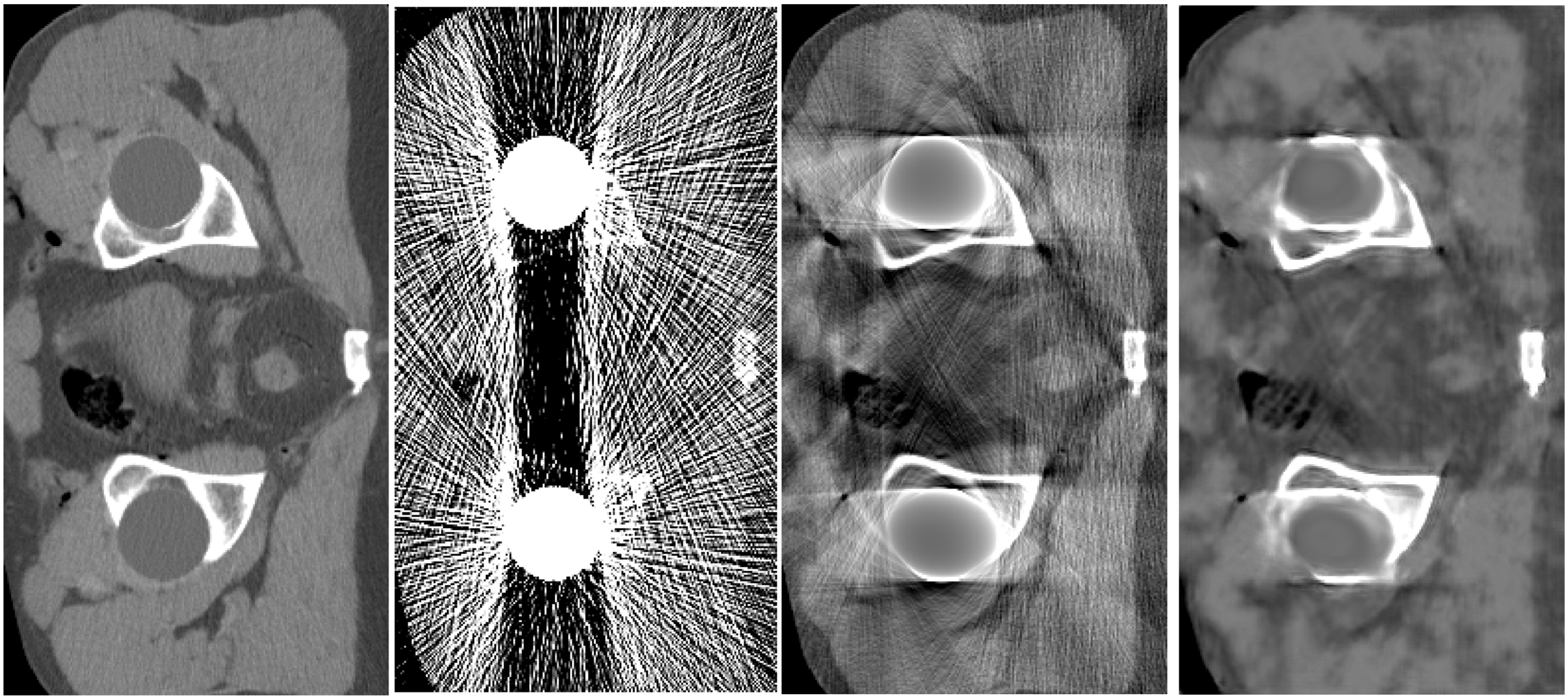


Window: [-250 350] HU

	NMAR	CNN
SSIM	*0.533*	*0.744*
PSNR	*22.878*	*25.361*

Case 2: Large Diameter

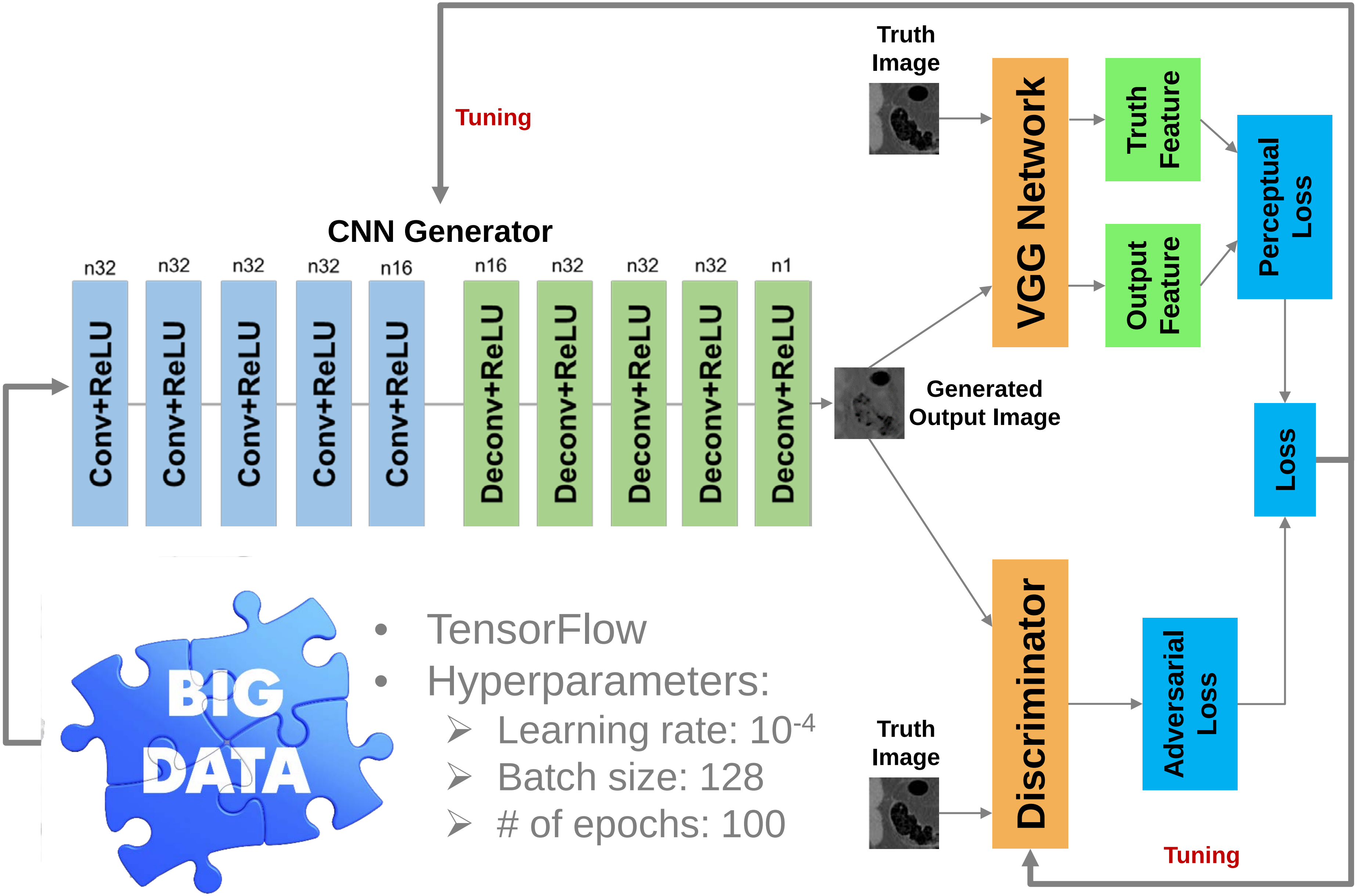
Ground Truth | **Uncorrected** | **NMAR** | **CNN**



	NMAR	CNN
SSIM	*0.523*	*0.700*
PSNR	*21.330*	*22.961*

Window: [-250 350] HU

Future: With WGAN



- TensorFlow
- Hyperparameters:
  - ➢ Learning rate: 10^{-4}
  - ➢ Batch size: 128
  - ➢ # of epochs: 100

Future: Without WGAN

arxiv.org/pdf/1710.05488.pdf

A Geometric View of Optimal Transportation and Generative Model

Na Lei * Kehua Su † Li Cui ‡ Shing-Tung Yau § David Xianfeng Gu ¶

Abstract

In this work, we show the intrinsic relations between optimal transportation and convex geometry, especially the variational approach to solve Alexandrov problem: constructing a convex polytope with prescribed face normals and volumes. This leads to a geometric interpretation to generative models, and leads to a novel framework for generative models.

By using the optimal transportation view of GAN model, we show that the discriminator computes the Kantorovich potential, the generator calculates the transportation map. For a large class of transportation costs, the Kantorovich potential can give the optimal transportation map by a close-form formula. Therefore, it is sufficient to solely optimize the discriminator. This shows the adversarial competition can be avoided, and the computational architecture can be simplified.

Preliminary experimental results show the geometric method outperforms WGAN for approximating probability measures with multiple clusters in low dimensional space.

First Workshop

RPI/CBIS/BIC
Deep Reconstruction Workshop

Coordinators: Ge Wang, PhD, Hongming Shan, PhD

Abstract: Computer vision and image analysis are both great examples showing successes of machine learning especially deep learning. Computer vision focuses on surfaces, image analysis deal with existing images, and in contrast to both tomographic reconstruction produces images of internal structures from indirect data. Recently, deep learning techniques are being actively explored for tomographic reconstruction by multiple groups worldwide, with encouraging results and potential biomedical impacts. We believe that deep reconstruction is a next major target of deep learning. Sponsored by Center for Biotechnology & Interdisciplinary Studies/Biomedical Imaging Center/RPI's NIGMS T32 Program, we organize the regional workshop for brainstorming and collaboration.

Date: This workshop will be held Nov. 18-19, 2017.
Place: CBIS Auditorium, Rensselaer Polytechnic Institute, 110 8th Street, Troy, New York 12180