Direct Reconstruction from Sinogram Data using Stacked Back Projection

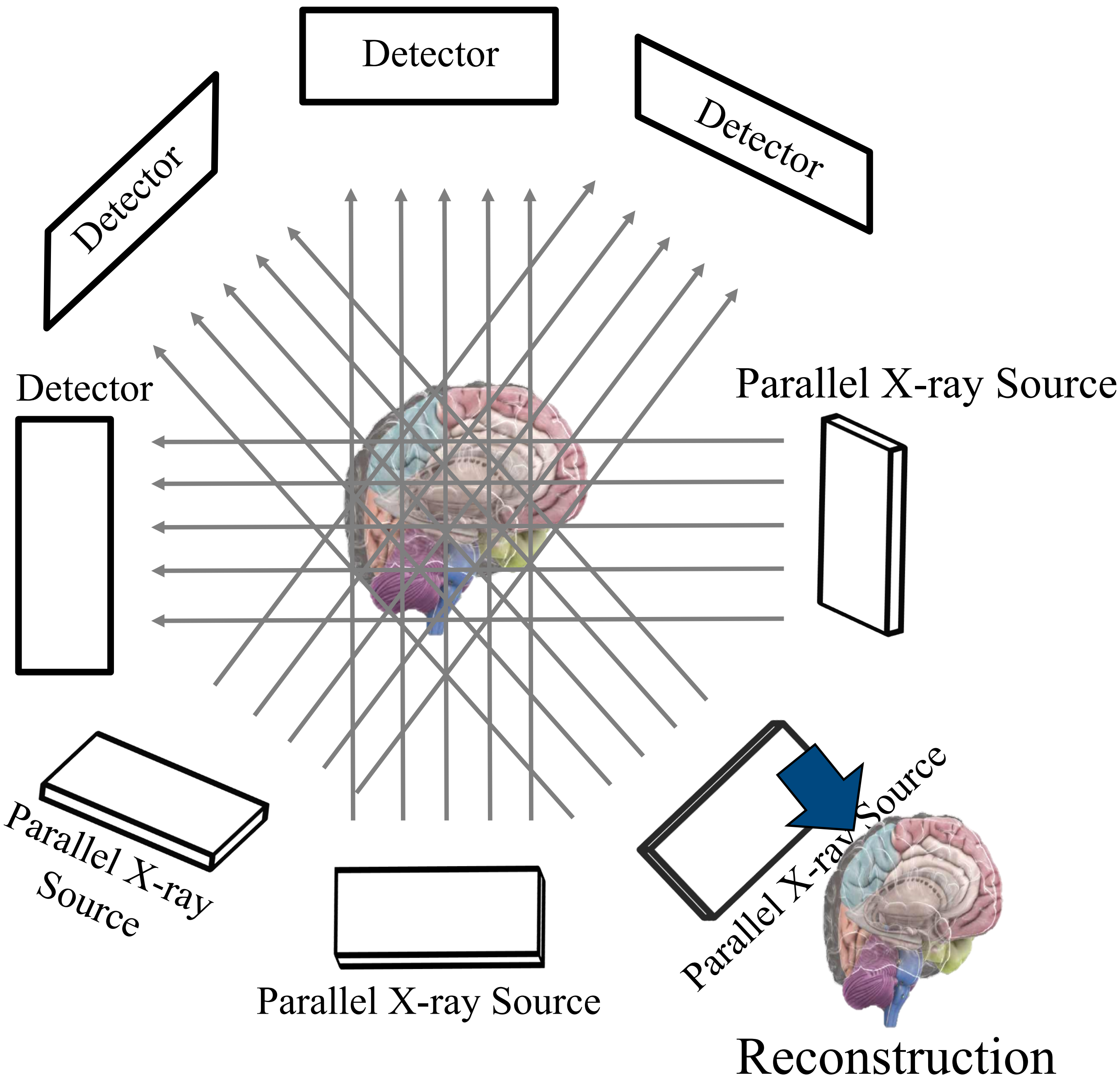
Wenrui Li, Gregery T. Buzzard, and Charles A. Bouman
Purdue University

ICCV Workshop on
Learning for Computational Imaging: Sensing, Reconstruction, and Analysis
Seoul Korea, 2019-11-02

INTEGRATED IMAGING

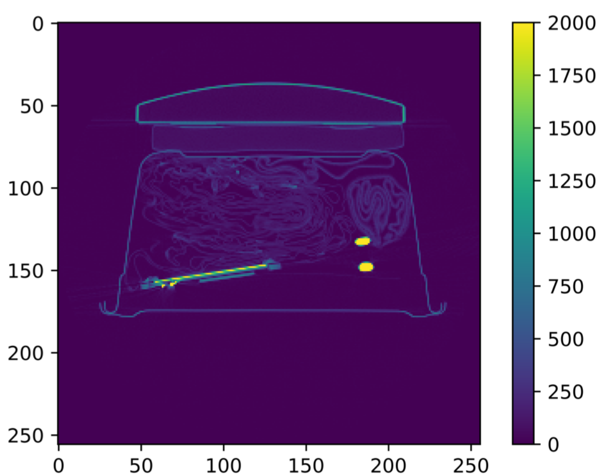
Thank you ALERT:
This material is based upon work supported by the U.S. Department of Homeland Security, Science and Technology Directorate, Office of University Programs, under Grant Award 2013-ST-061-ED0001. The views and conclusions contained in this document are those of the authors and should not be interpreted as necessarily representing the official policies, either expressed or implied, of the U.S. Department of Homeland Security.

Computed Tomography (CT)

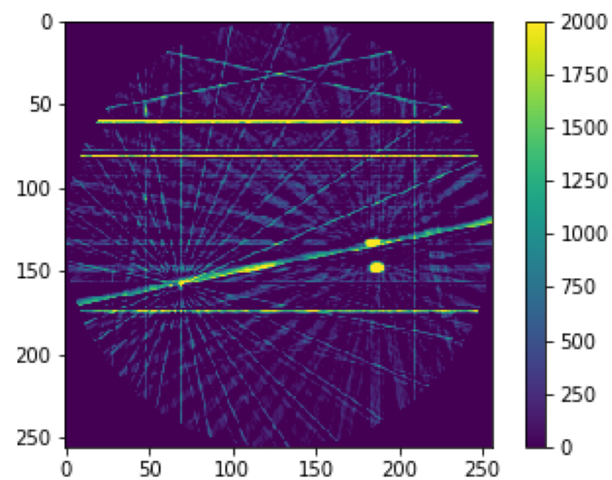


Sparse View Reconstruction

- Conventional Reconstruction
  - Filtered Back Projection (FBP) commonly used
  - Requires 256 views for a 256×256 reconstruction
- Sparse view reconstruction:
  - You can’t always get a full set of views
- Example of 16 view FBP recon

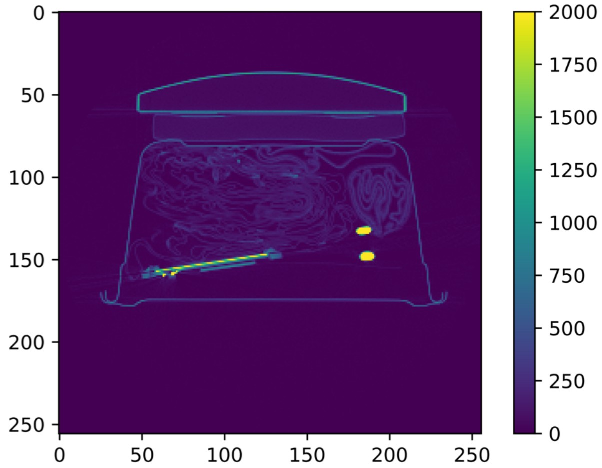


Ground Truth

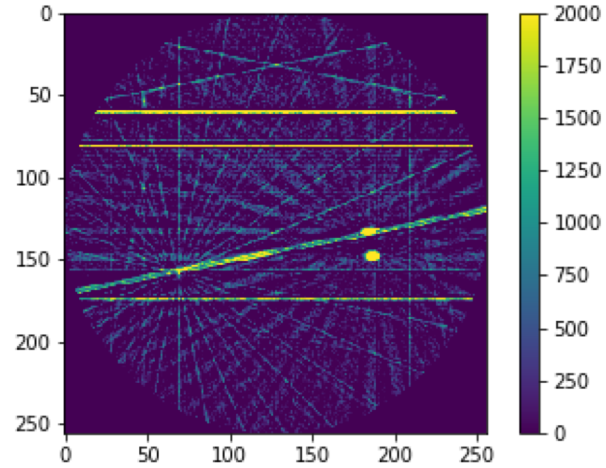


Sparse View Recon

Why does 16 view FBP look so bad?



Ground Truth



16 View Recon

- Why so bad?
  - Sparse views violate Nyquist.
  - Under-sampled by 16x (should have 256 views)
  - Noisy projections through dense objects (metal)
- Solution?
  - MBIR with PnP - Iterative recon works, but is slow

Goal of Research

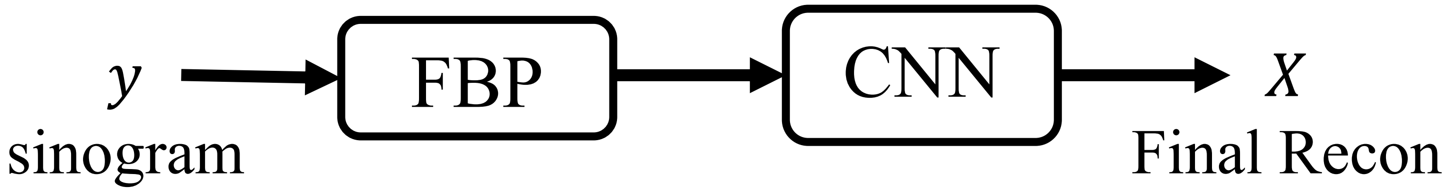
- Use DNNs for direct sparse view reconstruction
  - Avoid use of MBIR-PnP, but not as flexible
  - Get MBIR or better quality from sparse and noisy data
  - Fast reconstruction
  - Use all the sonogram data

Not PnP, Heresy!

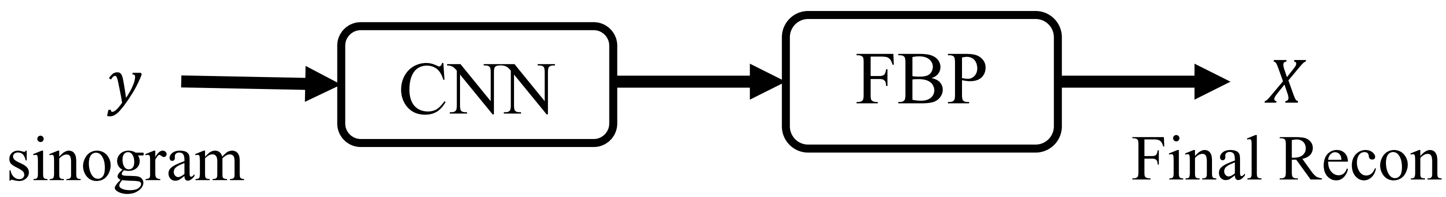
(but might be fun)

DNN Processing Approaches

- Image Domain DNN



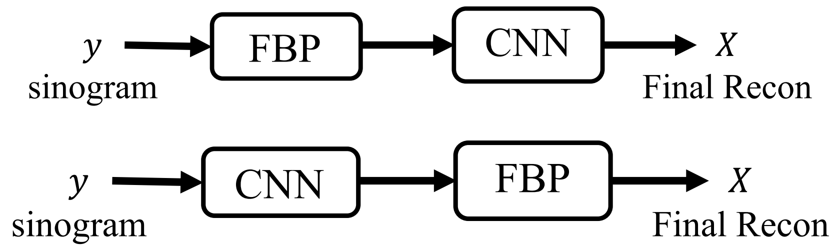
- Sinogram Domain DNN



- Direct DNN (AUTOMAP)

DNN Processing Approaches

- Image and Sinogram Domain DNN



  - Can use CNNs
  - Simple and fast
  - Don't use all the information

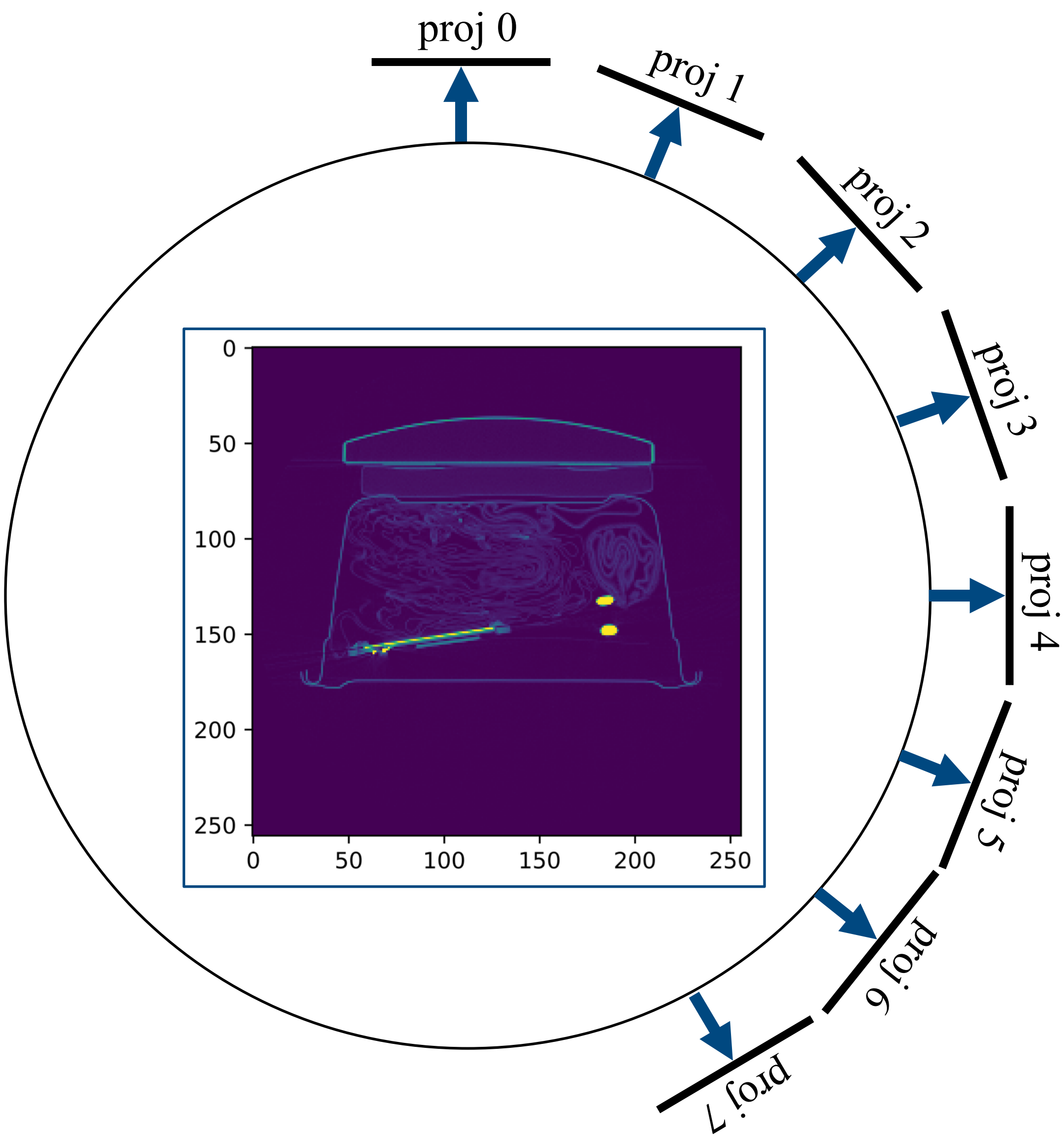
- Direct DNN (AUTOMAP)

  - Uses all the information
  - <u>Can't use CNNs</u>
  - Difficult to design and use

Approach: Stacked Back Projection

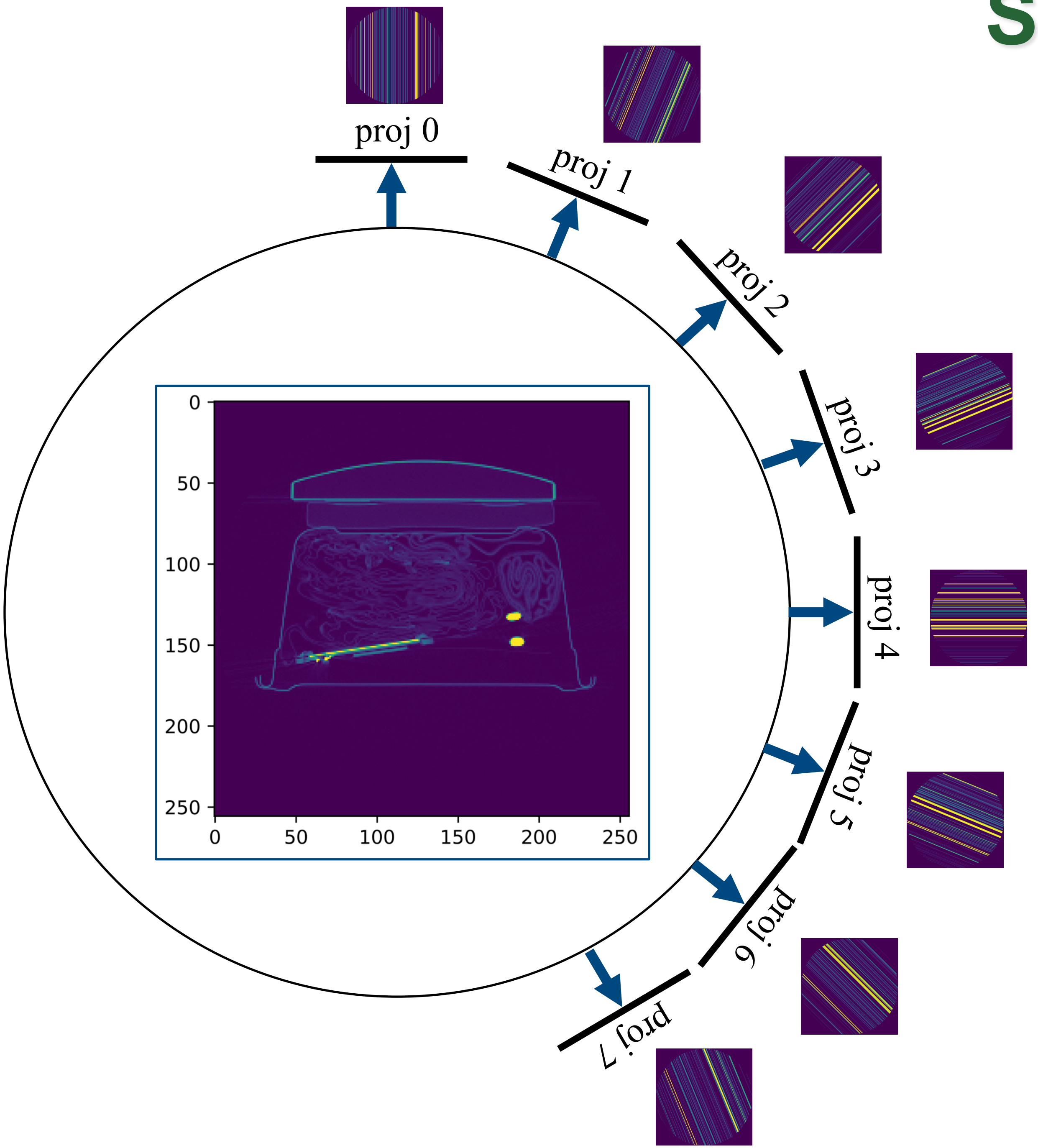
- Stacked Back Projection (SBP)
  - SBP contains <u>all</u> the sonogram data, but in image domain
  - Direct reconstruction using CNNs
  - Fast, simple and easy to train
  - LSTM processing across views

Stacked Back Projection

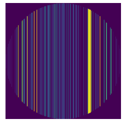
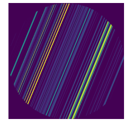
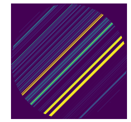
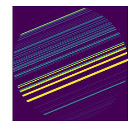


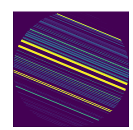
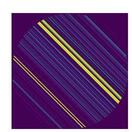
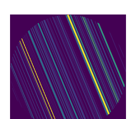
- Measure projections

Stacked Back Projection



- Measure projections
- Back project each projection

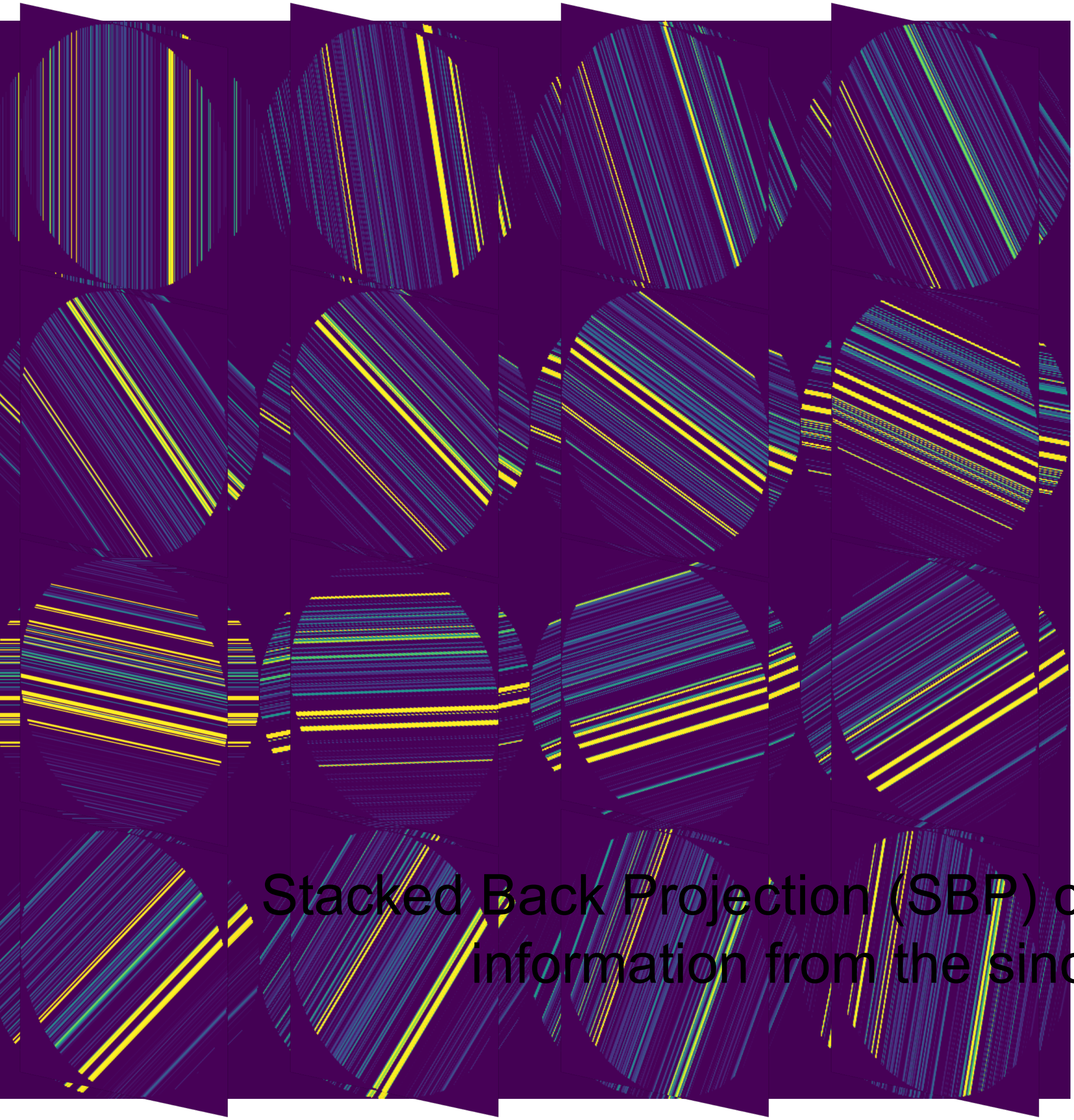





Stacked Back Projection

- Measure projections
- Back project each projection
- Stack them up as a tensor

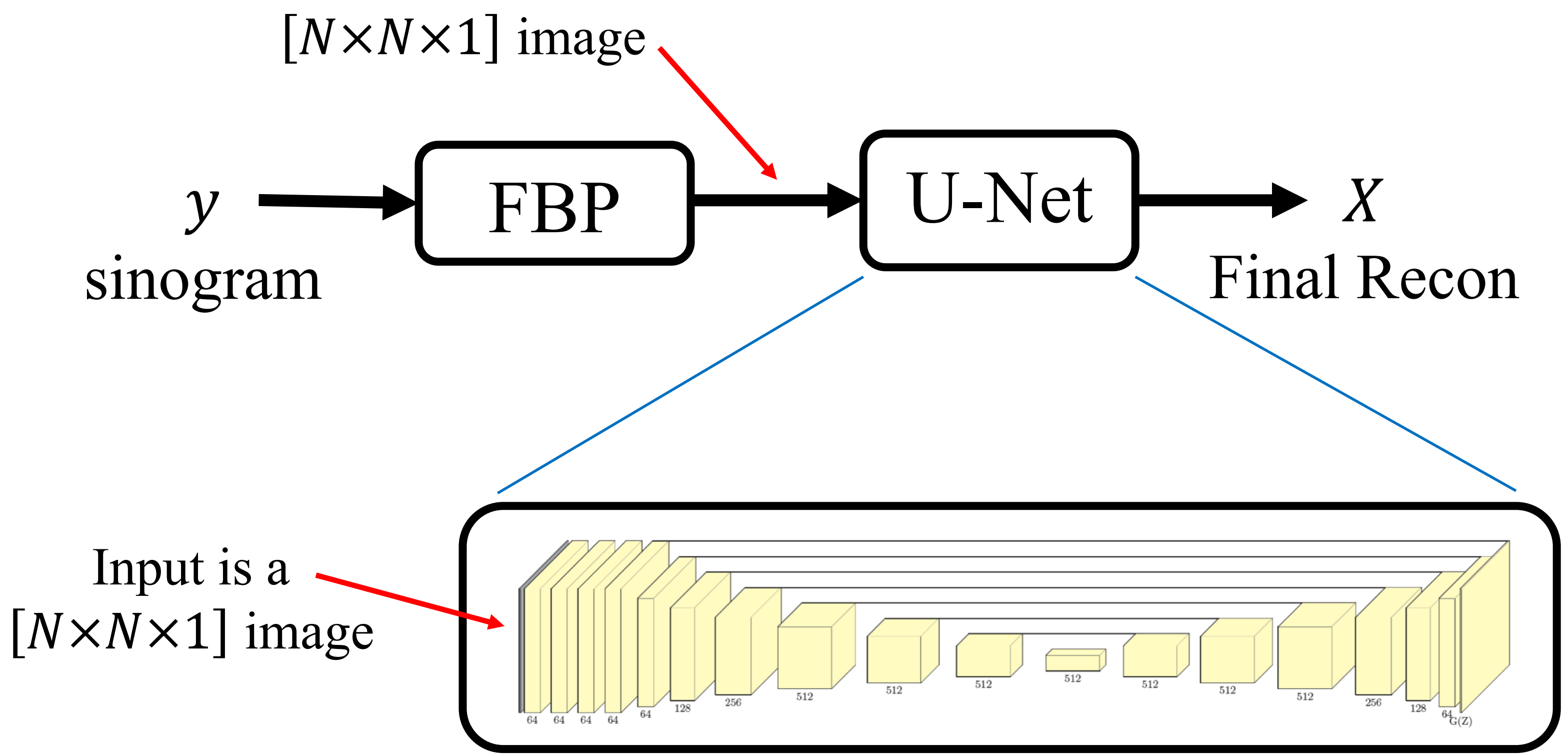
Stacked Back Projection for 16 Views



- SBP is a $256 \times 256 \times 16$ tensor
- SBP contains all the information in the sonogram
- Can be used to perform direct reconstruction

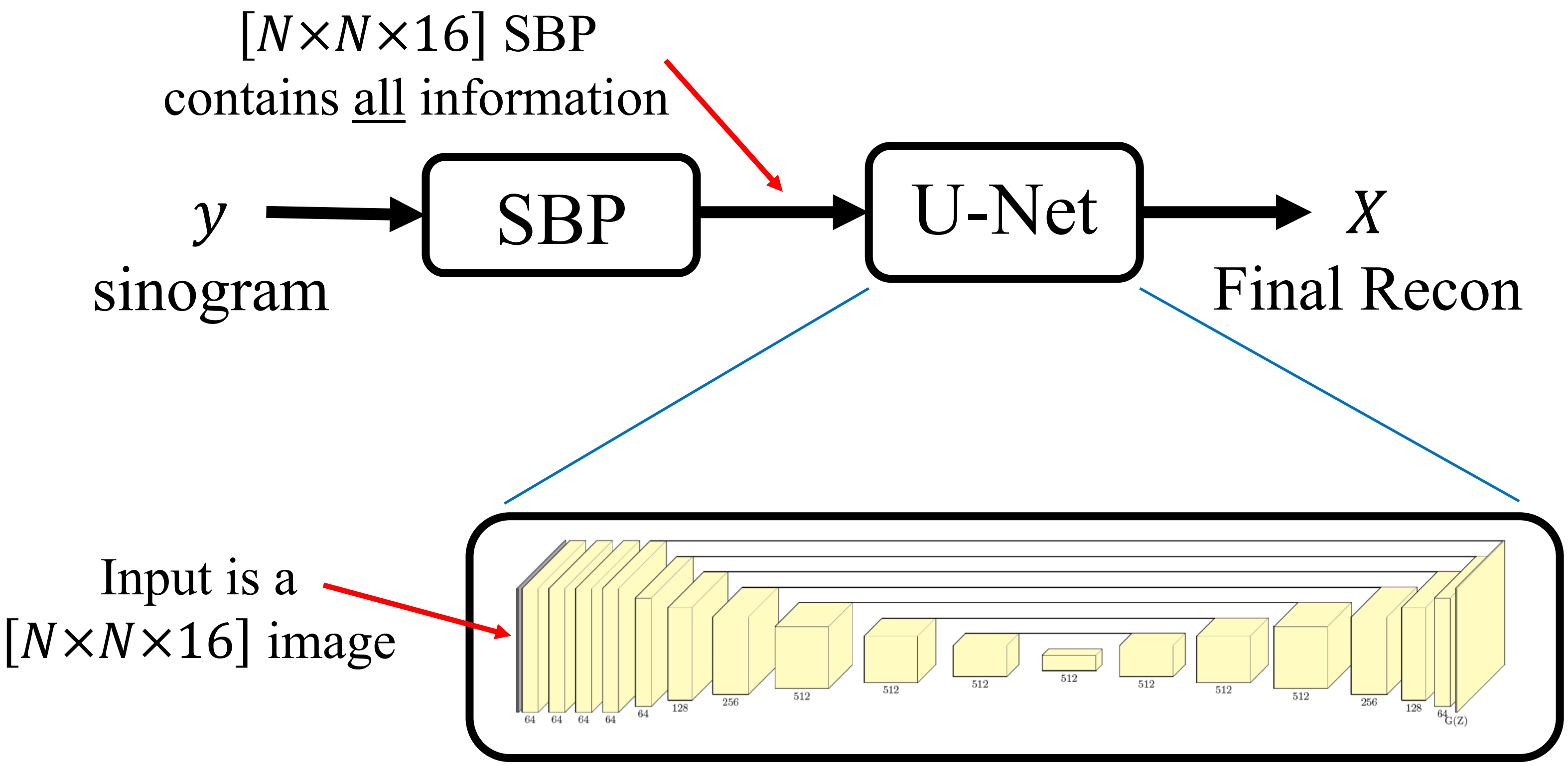
Stacked Back Projection (SBP) contains <u>all</u> the information from the sinogram

Baseline: DNN Post Processing of FBP



- Input is the FBP image
  - [$N \times N \times 1$] image
  - Does not contain all the information in sonogram
  - Noisy projections are combined with low-noise projections

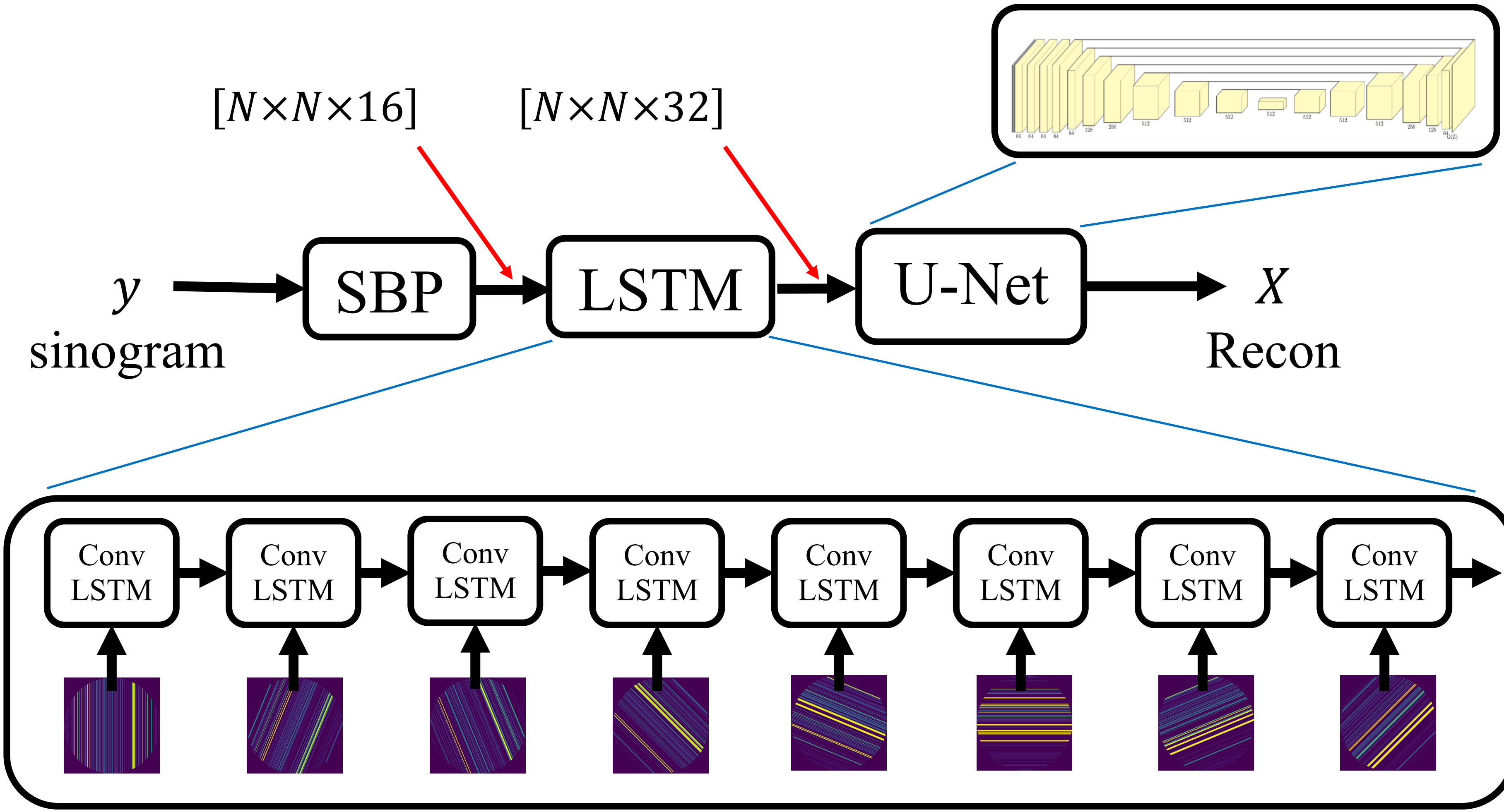
Direct Recon from SBP



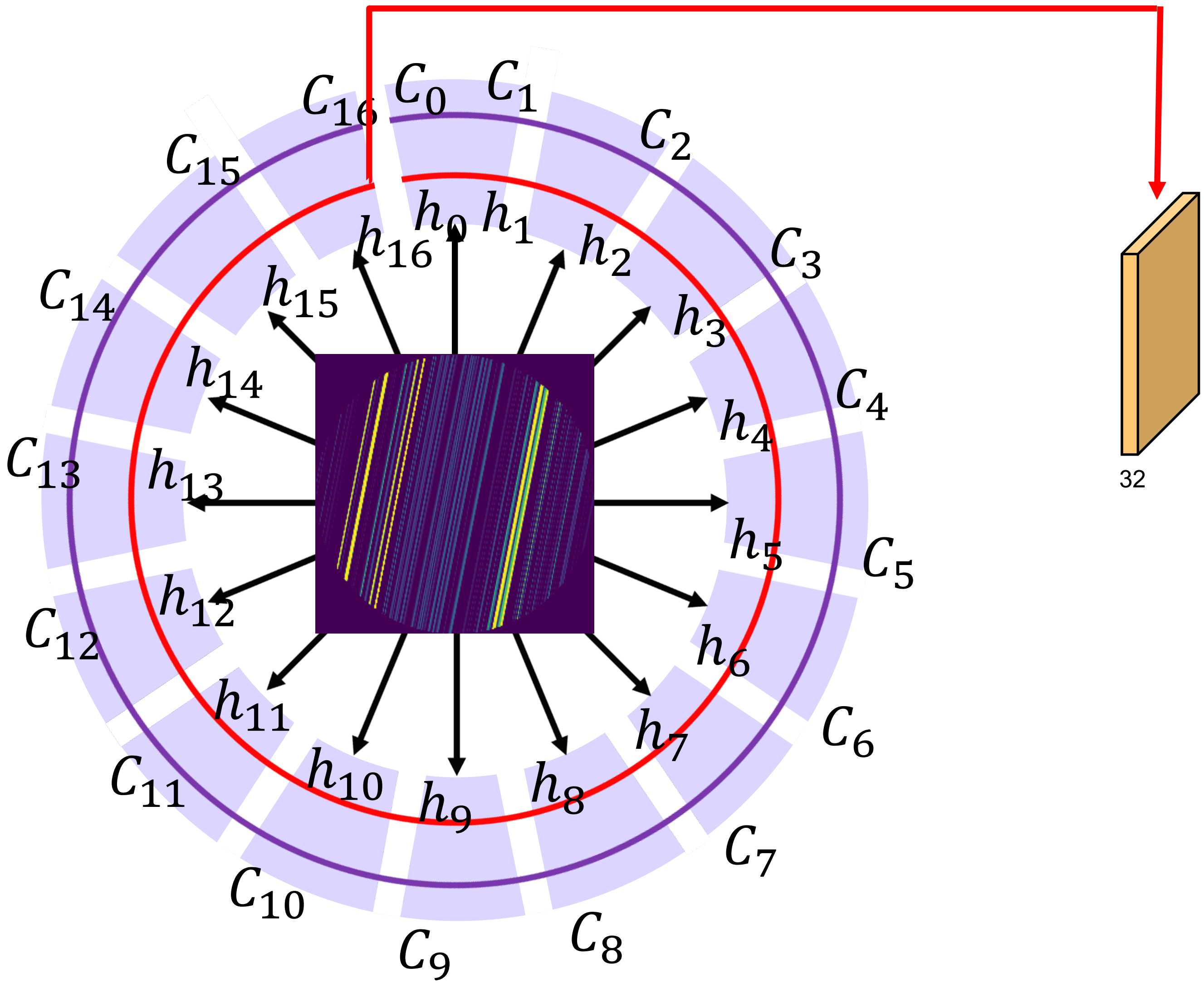
- Input is the Stacked Back Projection (SBP)
  - $[N \times N \times 16]$ image
  - Contain all the information in sonogram
  - Does not require fully connected network (FCN)

LSTM Processing of SBP

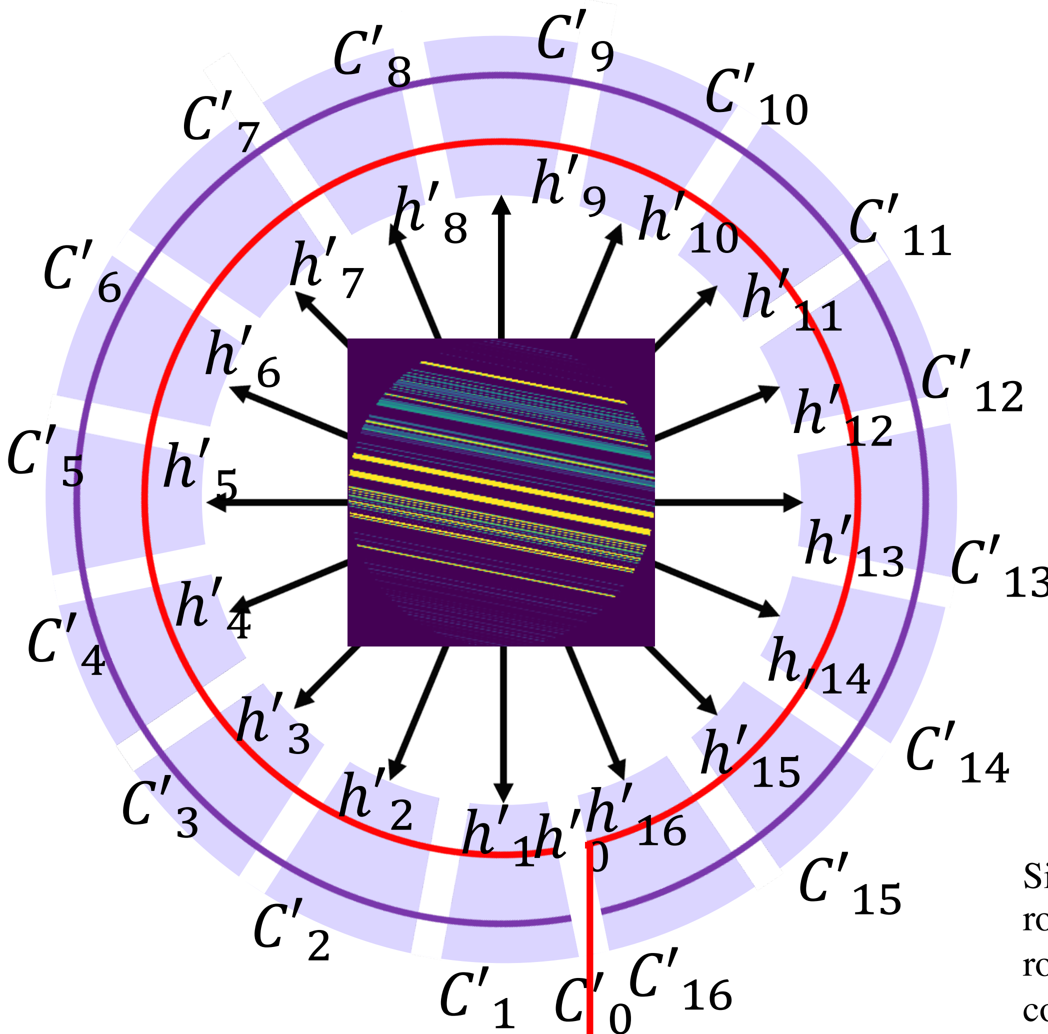
- Use LSTM processing of SBP with ConvLSTM2D

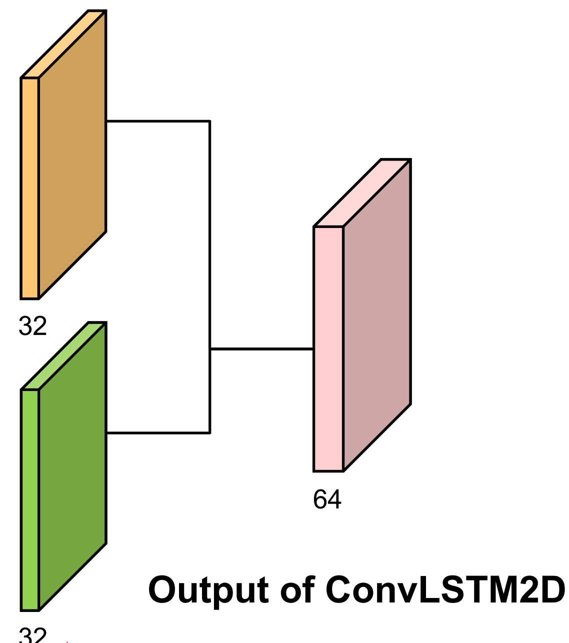


Rotational Stride of $\pi/4$



Rotational Stride of $\pi/4$





Since we use the uni-directional LSTM with a rotational stride of half-rotation, we train a non-rotational layer and a half-rotational layer and concatenate their output. Therefore, with F=32, the final output is (256,256,64).

Loss Functions

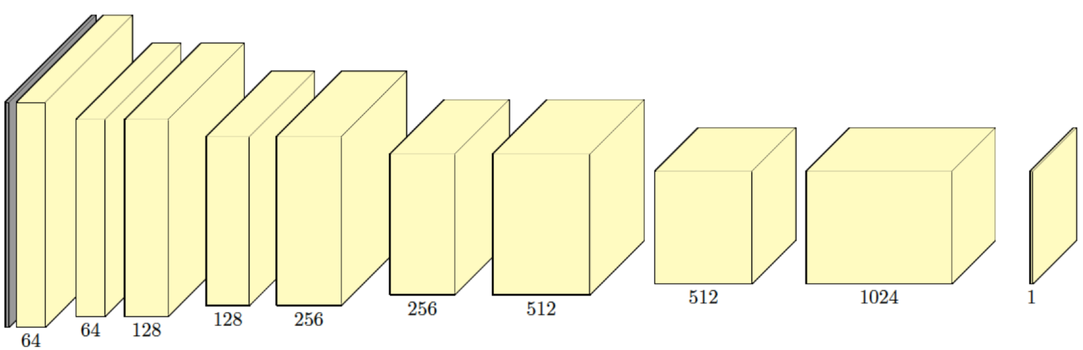
- Modified MSE Loss

$$L_{MSE} = \|f(x) - f(\hat{x})\|^2$$

where

$$f(x) = \frac{x}{|x| + 2000}$$

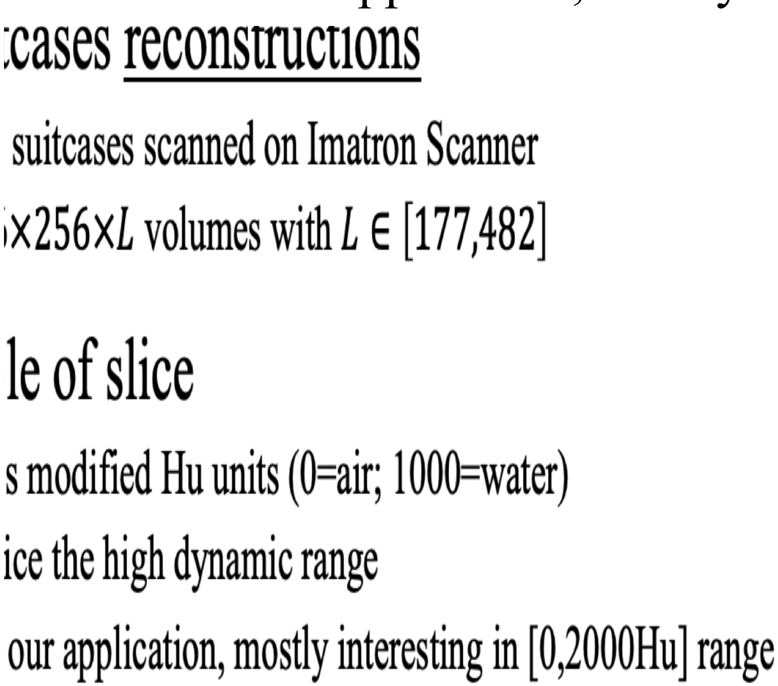
- CGAN adversarial loss function
  - $Loss = L_{MSE} + \lambda L_{CGAN}$
  - Based on $f(x)$ rather than x
  - Discriminator structure



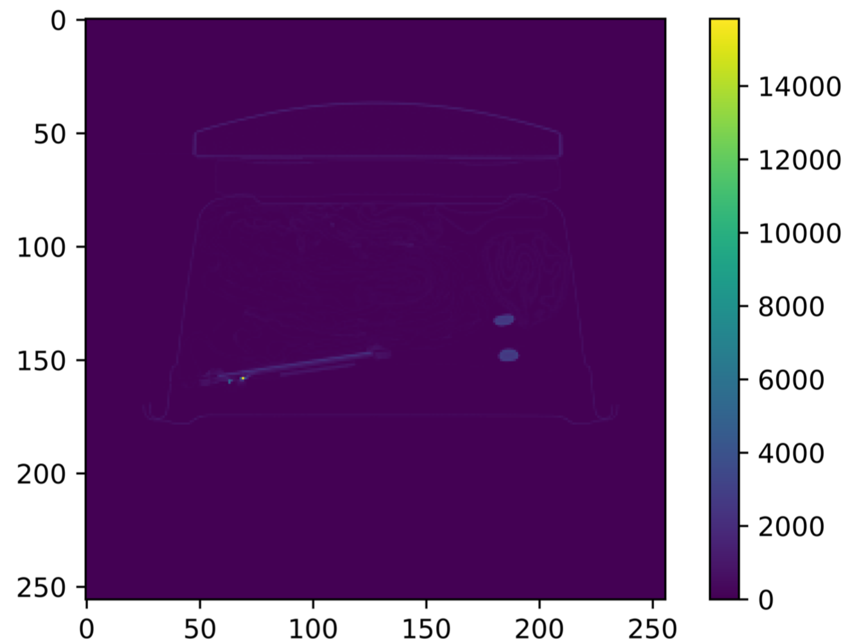
CT Data for this Research

- 3D suitcases <u>reconstructions</u>
  - 188 suitcases scanned on Imatron Scanner
  - $256 \times 256 \times L$ volumes with $L \in [177{,}482]$

- Example of slice
  - Uses modified Hu units (0=air; 1000=water)
  - Notice the high dynamic range
  - For our application, mostly interesting in [0,2000Hu] range



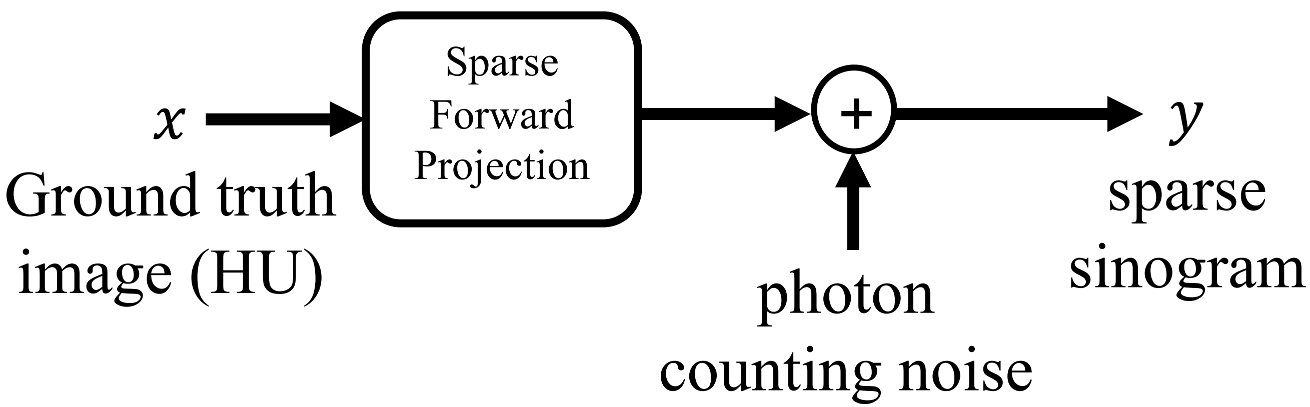
Display with [0,2000 Hu] window.



Display with [0,max Hu] window.

Synthetic Data Generation

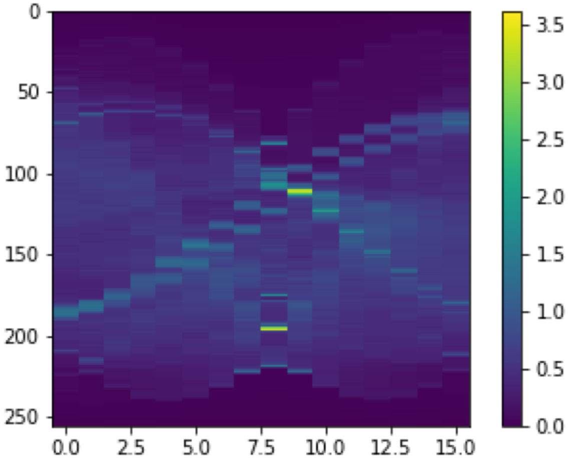
- 3D reconstructions of suitcases
  - 153 3D volumes used for training and validation
  - 35 3D volumes used for testing
- Sinogram data simulation
  - Parallel beam geometry
  - 16 equi-spaced view projections between 0 and π
  - pixel pitch=0.186 cm
  - FOV = 47.6 cm
  - water xray density=0.17 cm-1 (~100 keV)
  - photon dosage per projection λ_0 = 1,600



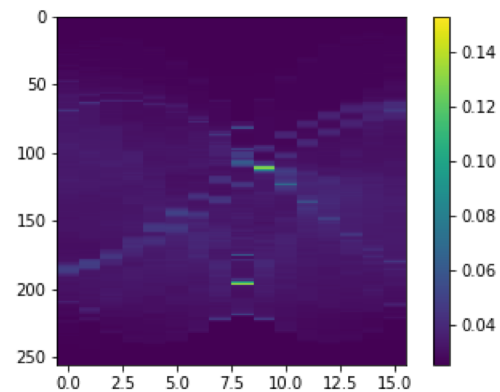
Full Sinogram

- Dense projections have much more noise

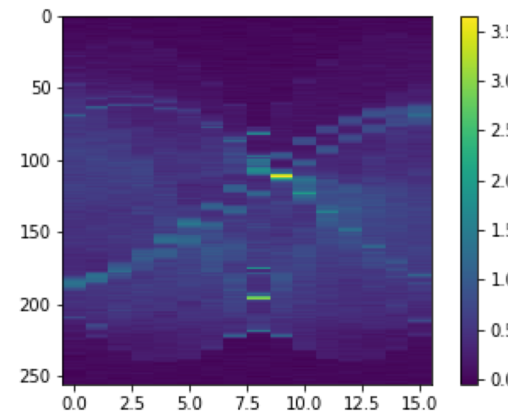
$$\sigma^2 = \frac{\exp\{y_i\}}{\lambda_0}$$



noiseless sinogram



noise

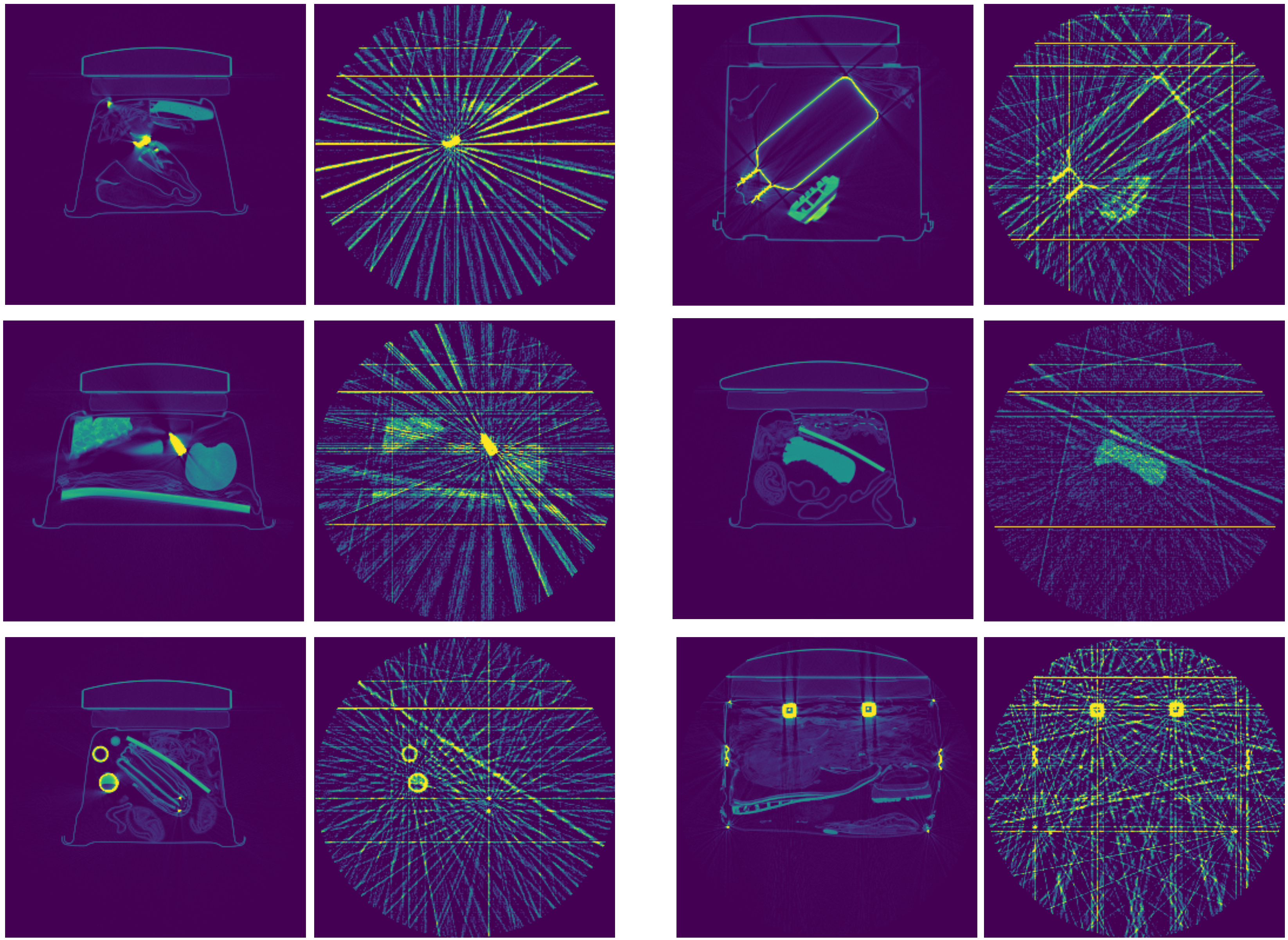


noisy sinogram

Experimental Results

- Synthetic data, but hopefully reasonably realistic
- Results:
  - FBP images
  - Metrics
  - Sparse view recons

FBP for 6 examples



Results: CGAN or Not?

- CGAN did not help with quantitative metrics

Type	Loss	NRMSE	SSIM
FBP with DNN	MSE	**0.033217993**	**0.902692077**
FBP with DNN	MSE/CGAN	0.033931074	0.895443116

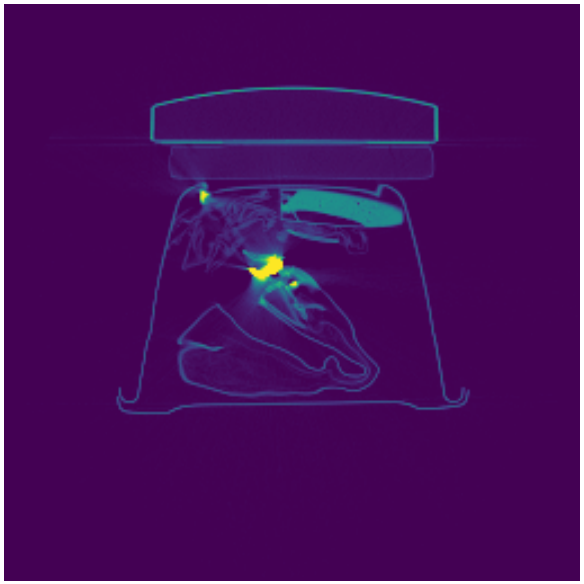
Type	Loss	NRMSE	SSIM
SBP with DNN	MSE	**0.032091032**	**0.907293357**
SBP with DNN	MSE/CGAN	0.032082014	0.906680897

Results: SBP or FBP?

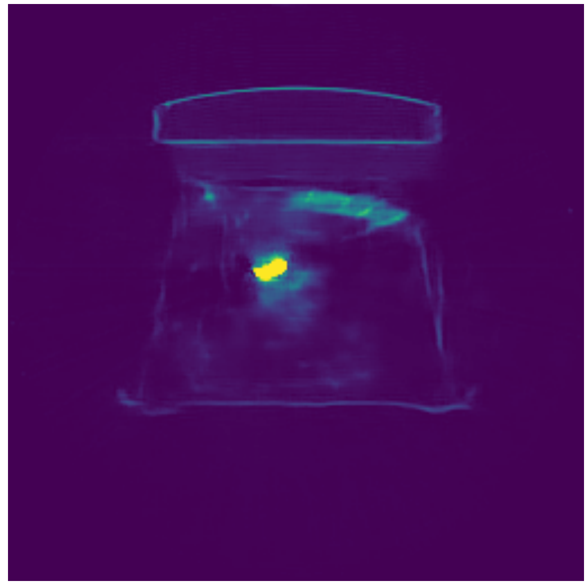
- FBP with DNN was good
- SBP with DNN was better
- SBP with LSTM/DNN was best

Type	Loss	NRMSE	SSIM
FBP with DNN	MSE	0.033217993	0.902692077
SBP with DNN	MSE	0.032091032	0.907293357
SBP with LSTM/DNN	MSE	**0.030437203**	**0.915121979**

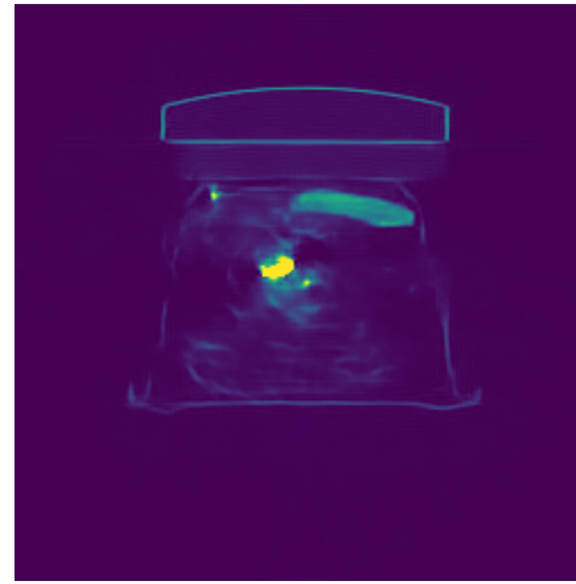
Result Compare (ALERT_G/Test/0034.hdf5)



Ground Truth



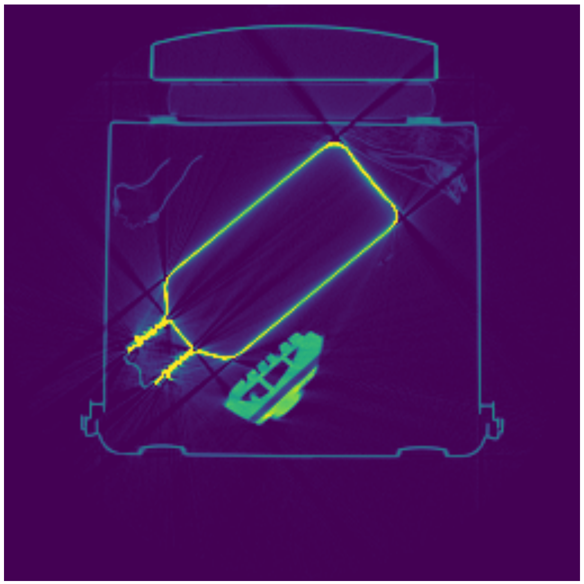
FBP DNN



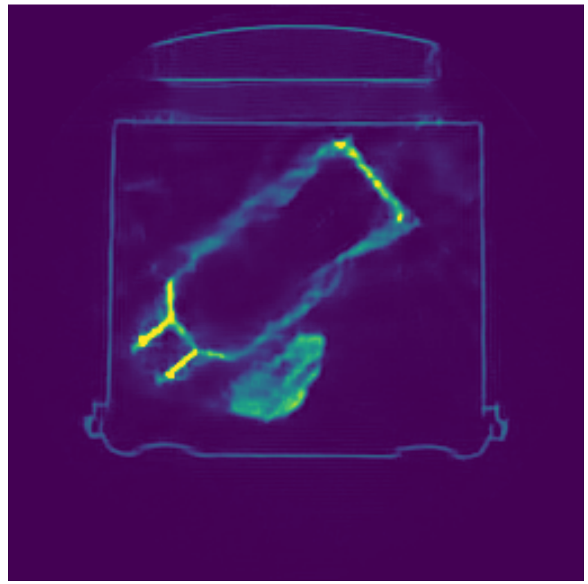
SBP with LSTM

Experiment	NRMSE	SSIM
FBP DNN	0.02668215	0.90408562
SBP LSTM	**0.02378725**	**0.92758713**

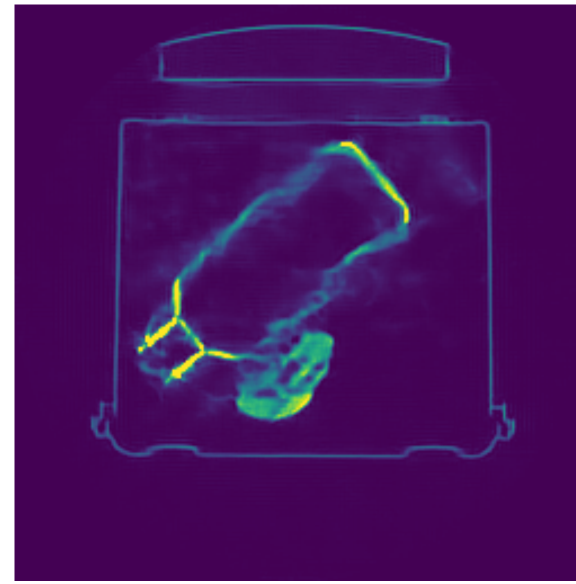
Result Compare (ALERT_G/Test/0106.hdf5)



Ground Truth



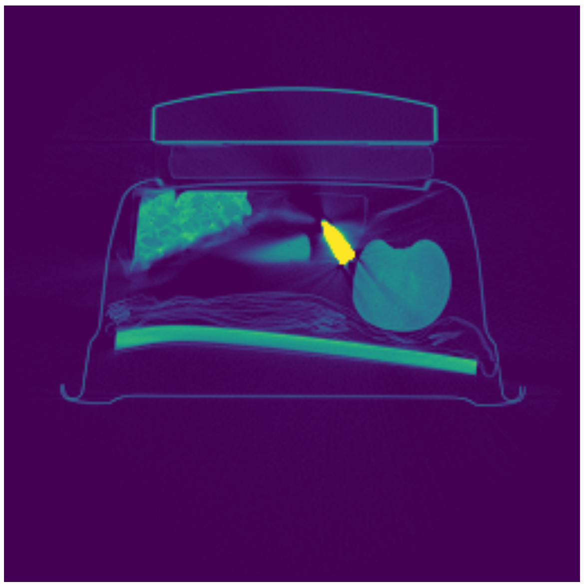
FBP DNN



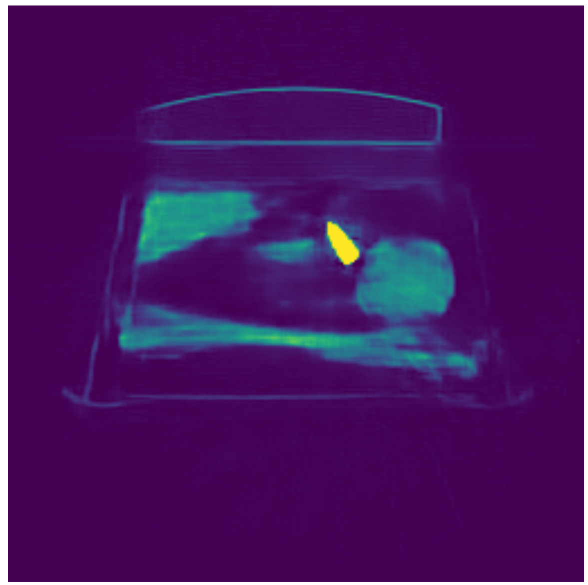
SBP with LSTM

Experiment	NRMSE	SSIM
FBP DL	0.037614	0.905294
SBP LSTM	**0.035336**	**0.915452**

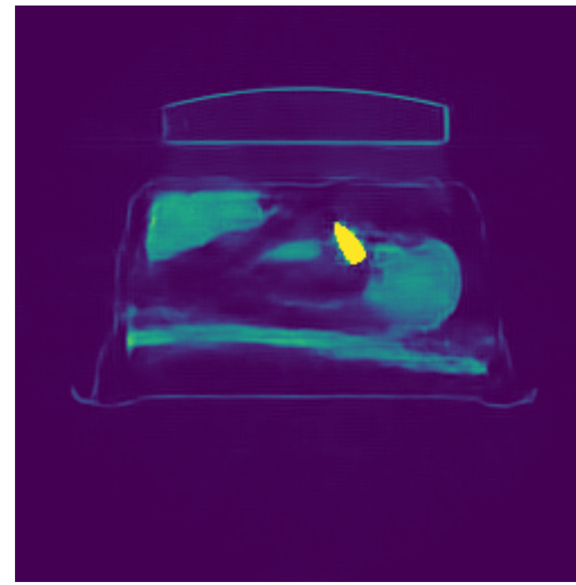
Result Compare (ALERT_G/Test/0129.hdf5)



Ground Truth



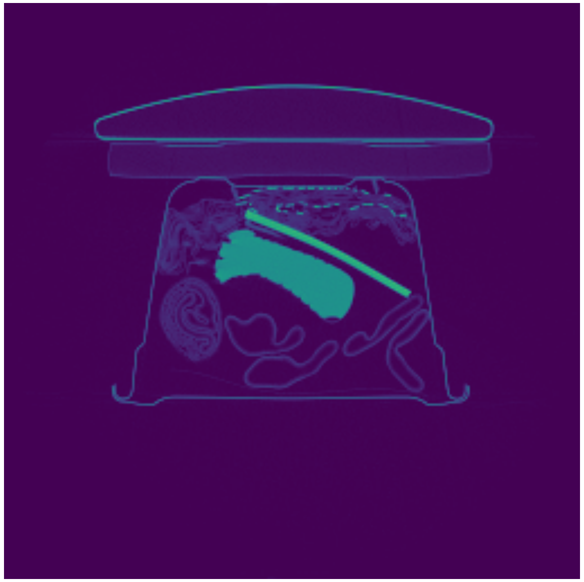
FBP DNN



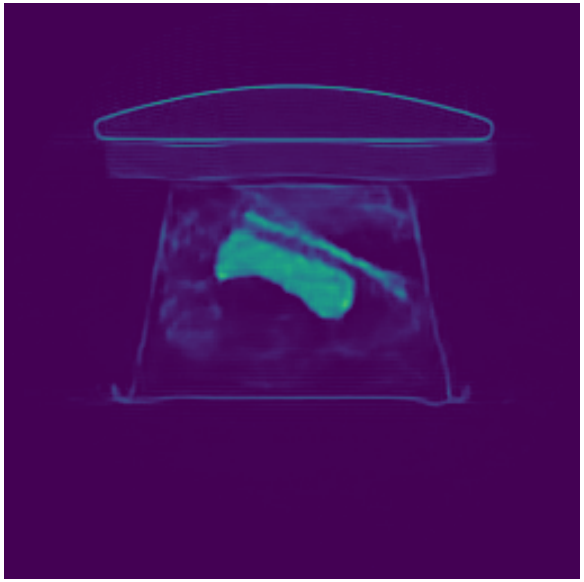
SBP with LSTM

Experiment	NRMSE	SSIM
FBP DL	0.035249551	0.895256487
SBP LSTM	**0.030629306**	**0.910768468**

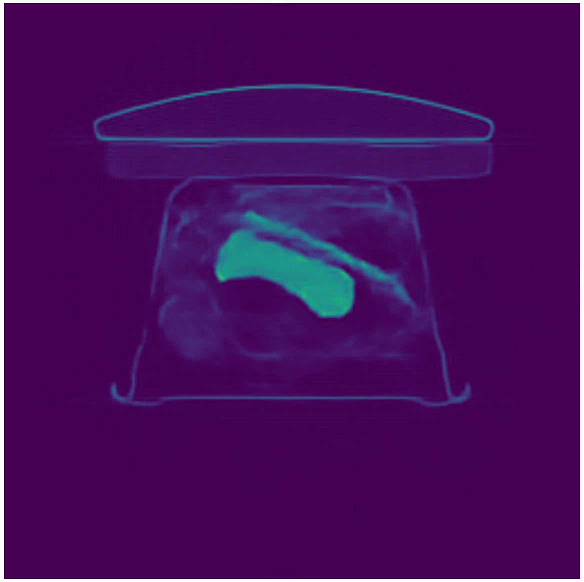
Result Compare (ALERT_G/Test/0218.hdf5)



Ground Truth



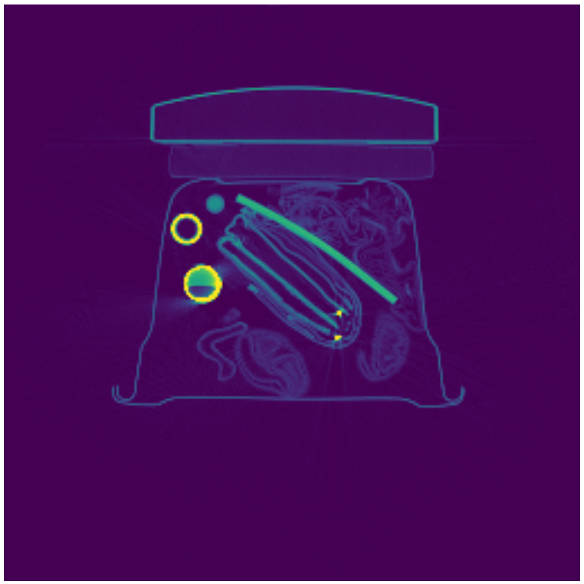
FBP DNN



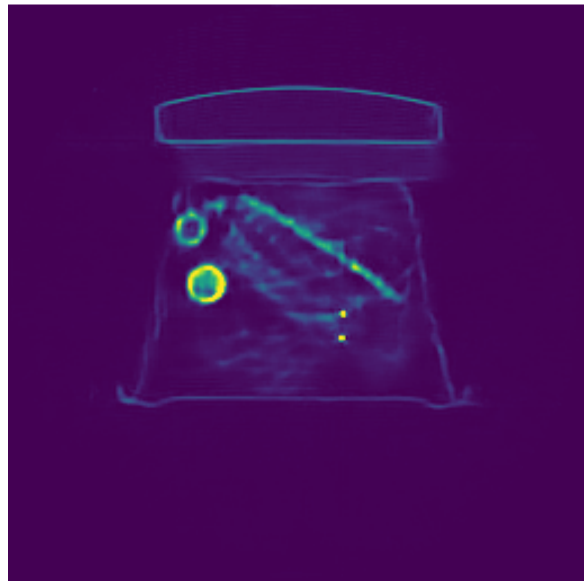
SBP with LSTM

Experiment	NRMSE	SSIM
FBP DNN	0.02332	0.93916
SBP LSTM DNN	**0.02213**	**0.94581**

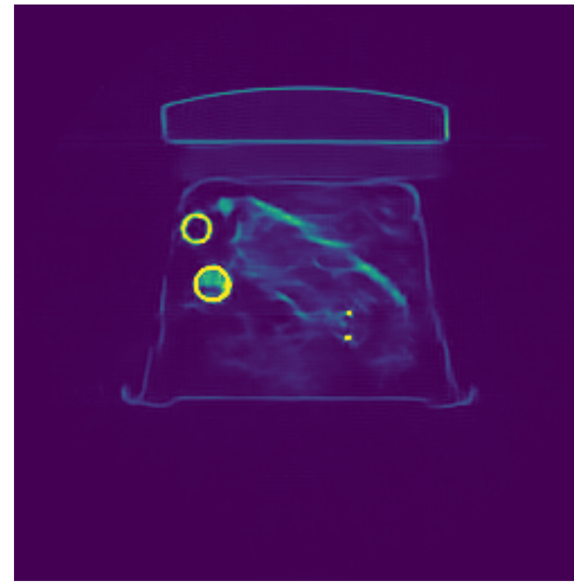
Result Compare (ALERT_G/Test/0221.hdf5)



Ground Truth



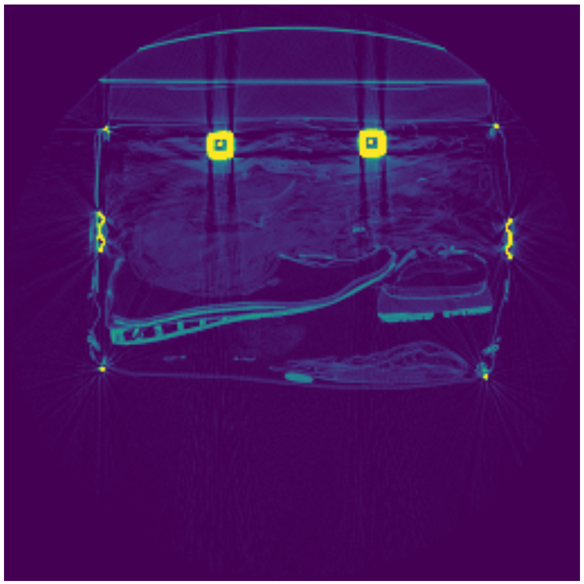
FBP DNN



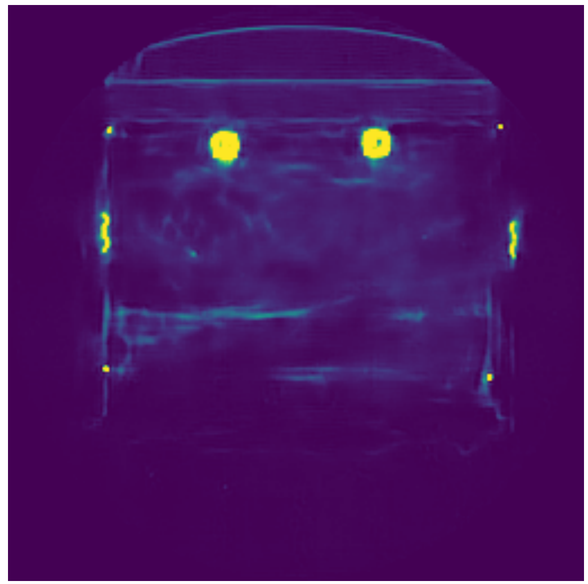
SBP with LSTM

Experiment	NRMSE	SSIM
FBP DNN	0.02978	0.9219
SBP LSTM DNN	**0.02784**	**0.92671**

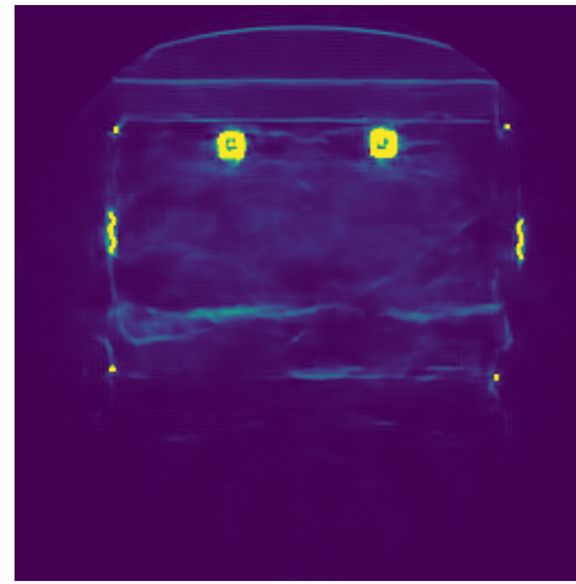
Result Compare (ALERT_G/Test/0340.hdf5)



Ground Truth



FBP DNN



SBP with LSTM

Experiment	**NRMSE**	**SSIM**
FBP DNN	0.04143	0.82955
SBP LSTM DNN	**0.03858**	**0.84829**

Takeaways

- DL reconstruction of sparse view data works
- Stacked Back Projection (SBP) allows for simple implementation of direct sinogram-to-image reconstruction.
- LSTM processing of SBPs generates best results and may be more practical to implement.
  - LSTM could allow for more memory efficient implementation
- Adversarial loss doesn't improve quantitative results (but might have other advantages).