The Deep Learning on Supercomputers Workshop at SC 2019

# Deep Learning Accelerated Light Source Experiments

## Deep Learning Enhanced Tomography on Streaming X-Ray Projections

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Nov. 17th, 2019, Denver

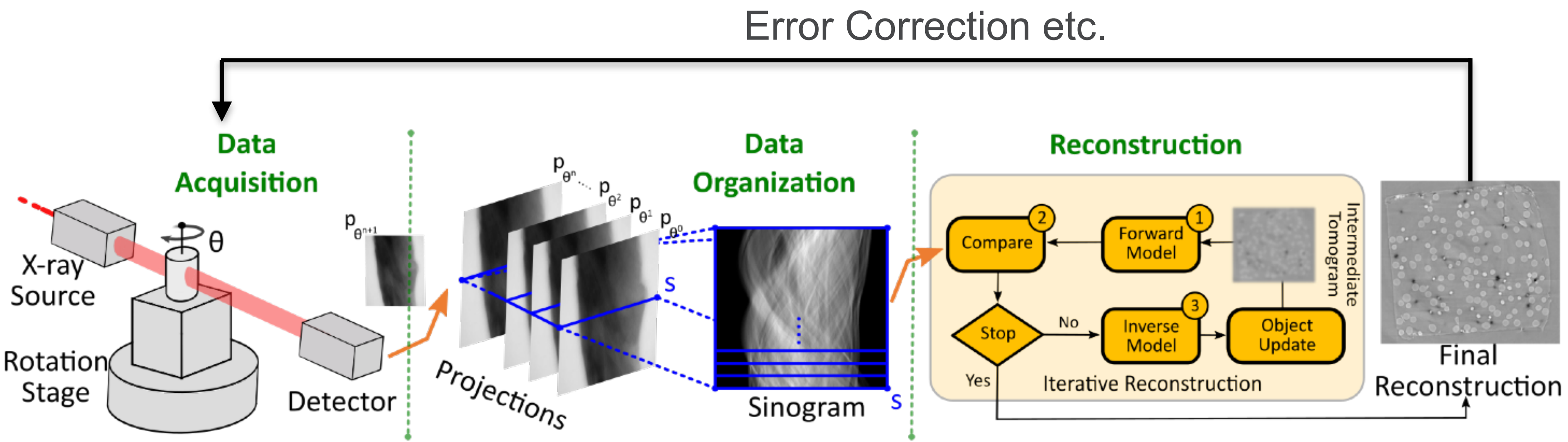
# Outline

- Introduction & Background
- Motivation
- System Design
- Experiment Results and Discussion

**Why streaming tomography?**

**How (much) can DL help to accelerate?**

# Background (Tomographic data acquisition and reconstruction pipeline)

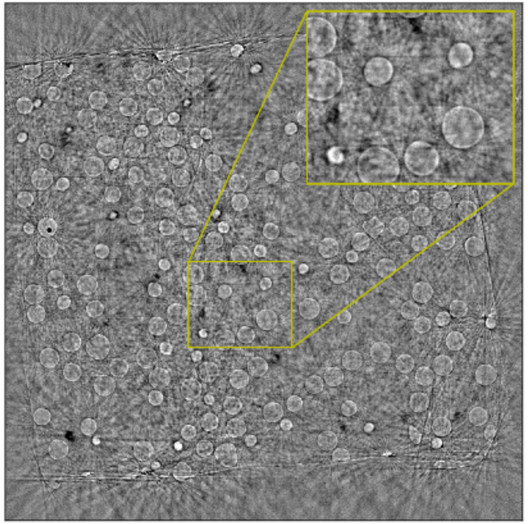


# Motivation of Streaming Tomography

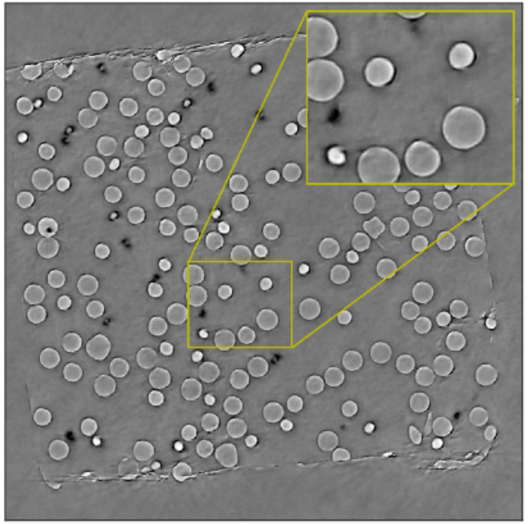
**Real-time feedback to enable:**

- Error Correction early in experiments;
- Experiment Steering, e.g., early stoping;
- Detection of features in hierarchical structures;
- Change data acquisition to capture dynamic features;
- Adjust experimental parameters on the fly;
- Enables smart and efficient experimentation;

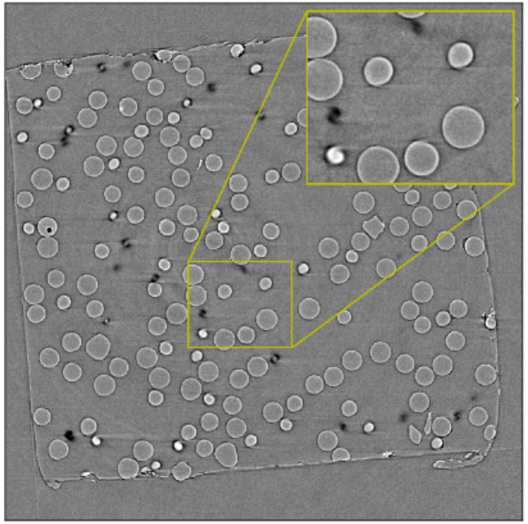
# **Motivation** (Streaming tomography image quality, with and without enhancement)



with data up to 462s (480 projections), before enhancement;



with the same data, after enhancement;

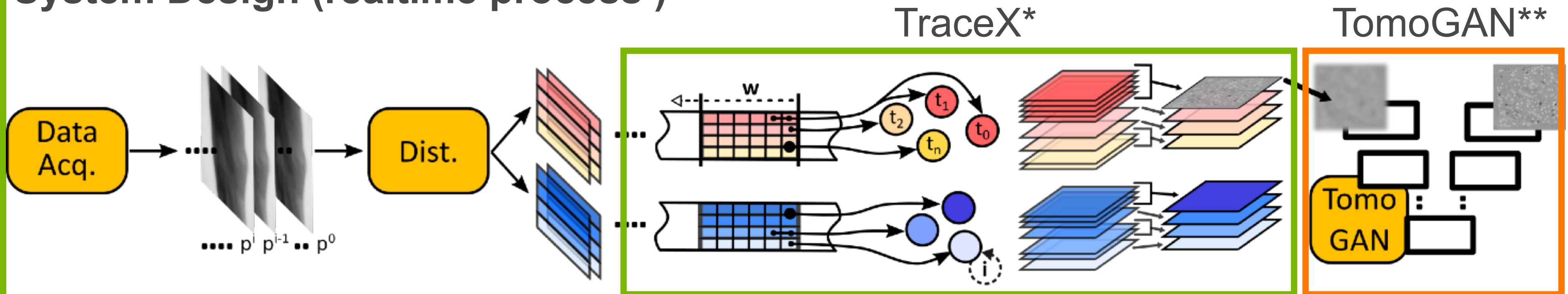


with data up to 1433s (1504 projections), before enhancement.

Three times faster turnaround time for domain scientists. A.K.A., three times increased throughput for the light source and computing facility.

Important as enablers of experiment steering, where quick turnaround is required.

# System Design (realtime process )




Tomographic reconstruction on a streaming experimental data with TomoGAN. $t_0, t_1, \ldots, t_n$ are separate threads. Simultaneous Iterative Reconstruction Technique (SIRT) is used here.

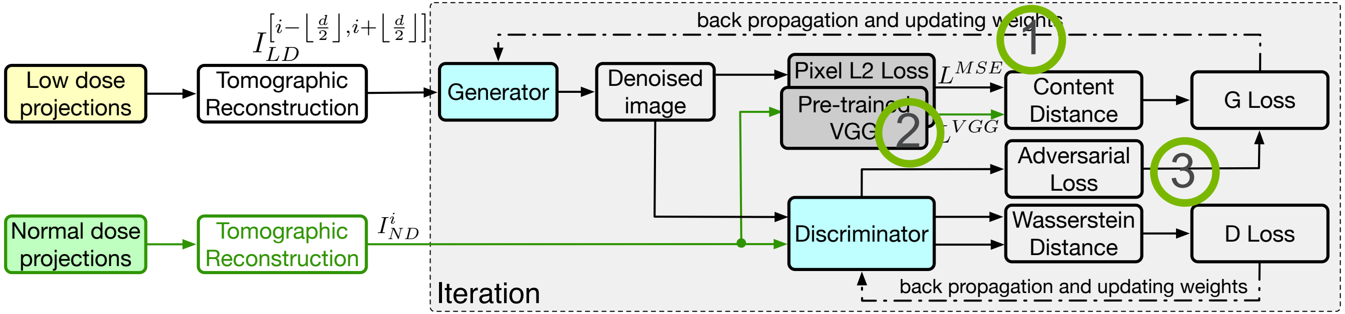
**Window size** $(W)$: number of projections you wait for an (additive) iterative reconstruction;
**Iteration** $(I)$: the number of SIRT iterations you perform for each window; the more, the longer turnaround time;
**Rotation** $(R)$: data acquisition rotations, i.e., the number of $W$. The more, the longer experiment time and more resource used. We minimize $W * R$ with minimum $I$



* T. Bicer. Advanced structural and chemical imaging. 2017
** Z. Liu. TomoGAN. arXiv:1902.07582

# TomoGAN

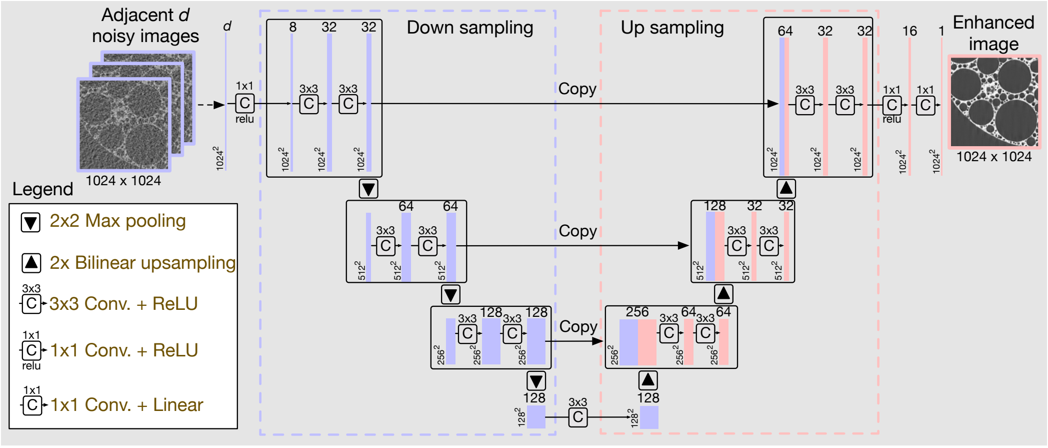
An image-denoising model based on generative adversarial networks originally developed for low-dose (less projections or shorted exposure time) x-ray imaging.




[arXiv:1902.07582](https://arxiv.org/abs/1902.07582)

In our model, the discriminator's job remains unchanged, but the generator is tasked not only with fooling (indistinguishable) the discriminator but also with being near the ground truth output in an L2 sense.

The discriminator works as a helper to train the generator that we need to denoise images.






*Open at: [https://github.com/ramsesproject/TomoGAN](https://github.com/ramsesproject/TomoGAN) (TF, C++ using DNNL, cudnn)*

## Experiments

### Model training

We used $W = 32; I = 1; R = 5$ to train the model 128 slices (e.g., 128 images, each with 2560x2560 pixels) with data argumentation.

We use SIRT with 100 iterations to generate the corresponding 128 slices (cleanest possible) and use them as ground truth.

Training take 6 hours using 1 NVIDIA V100 Card

### Model testing/evaluation

[Projection] Window size ($W$): 16, 32, 64, 128, 256

[Reconstruction] Iterations ($I$): 1, 5, 10

Rotations ($R$): $\left[1, \left\lceil \frac{1500}{w} \right\rceil\right]$

**So, totaling 548 cases, each with 128 images, for testing**

# Experiments

| SIRT iterations, $I$ | 1 | | | | | 5 | | | | | 10 | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Window size, $W$ | 16 | 32 | 64 | 128 | 256 | 16 | 32 | 64 | 128 | 256 | 16 | 32 | 64 | 128 | 256 |
| `Glass` Refresh time (s) | 1.5 | 1.6 | 1.8 | 2.4 | 4.0 | 7.5 | 7.9 | 9.7 | 12.9 | 20.4 | 15.4 | 16.4 | 20.1 | 26.4 | 40.8 |
| `Glass` Sustained Rate (p/s) | 10.7 | 20.8 | 36.9 | 56.0 | 75.1 | 2.1 | 4.1 | 6.7 | 10.6 | 14.7 | 1.0 | 2.0 | 3.2 | 5.2 | 7.3 |
| `Shale` Refresh time (s) | 1.1 | 1.1 | 1.2 | 1.6 | 2.7 | 5.3 | 5.4 | 6.7 | 8.8 | 13.5 | 10.6 | 10.5 | 13.6 | 17.8 | 27.3 |
| `Shale` Sustained Rate (p/s) | 15.2 | 30.2 | 52.9 | 83.0 | 112.8 | 3.1 | 6.0 | 9.8 | 15.5 | 22.2 | 1.5 | 3.1 | 4.8 | 7.7 | 11.0 |

Data processing time for different configurations, for Glass and Shale datasets.

Refresh time is the time it takes to generate an update (A.K.A. turnaround time).

The sustained data consumption rate is measured by the number of projection processed per second.

# Experiments (TomoGAN overhead)

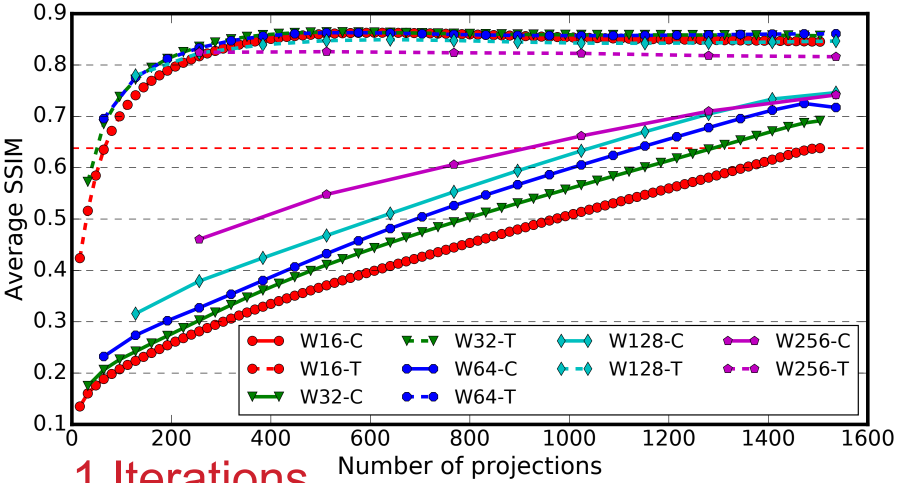
TomoGAN inference takes about 290ms to process one image with $2560 \times 2560$ pixels in our experiments using one NVIDIA Tesla V100 GPU card.

SIRT runs on CPU, so TomoGAN and reconstruction algorithm can run in parallel and TomoGAN takes significantly less time than the reconstruction algorithm. Thus, no overhead but a delay for the first rotation output.

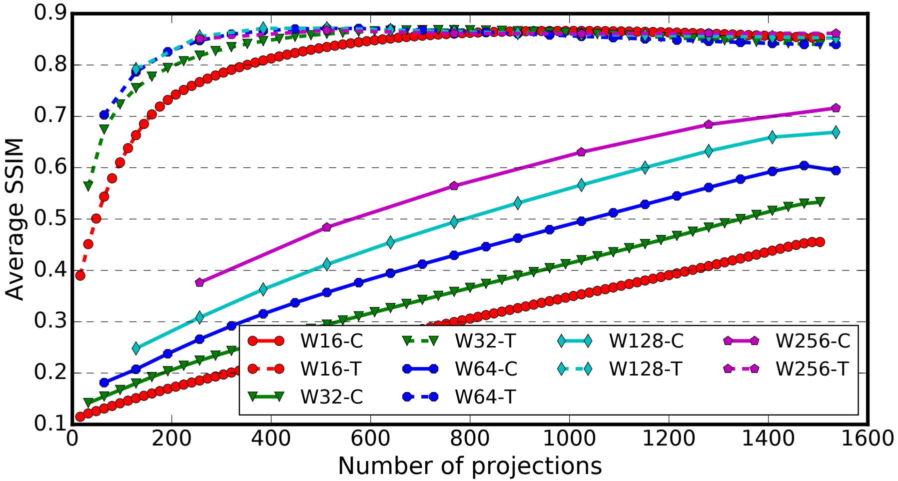
But, without a GPU…

It takes about 1050ms on KNL 7210 even with a C++ based implementation (1600ms using TF) and it cannot run in parallel with SIRT because of contention.

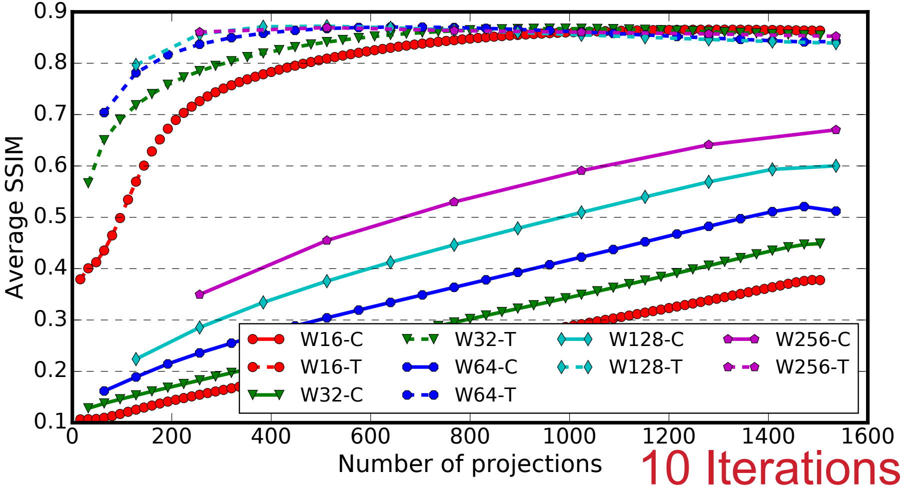
# Experiments (SSIM comparison)




1 Iterations

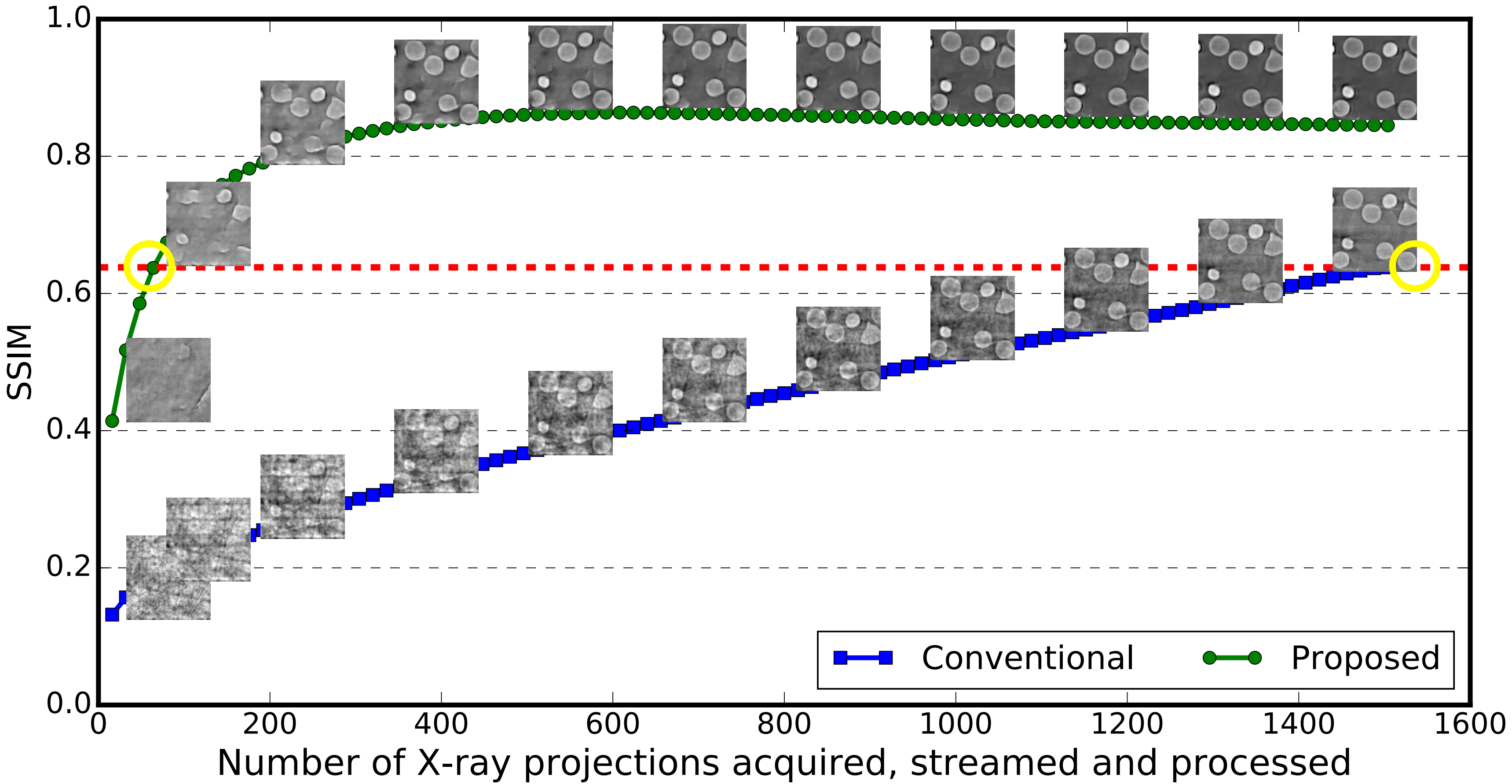



5 Iterations

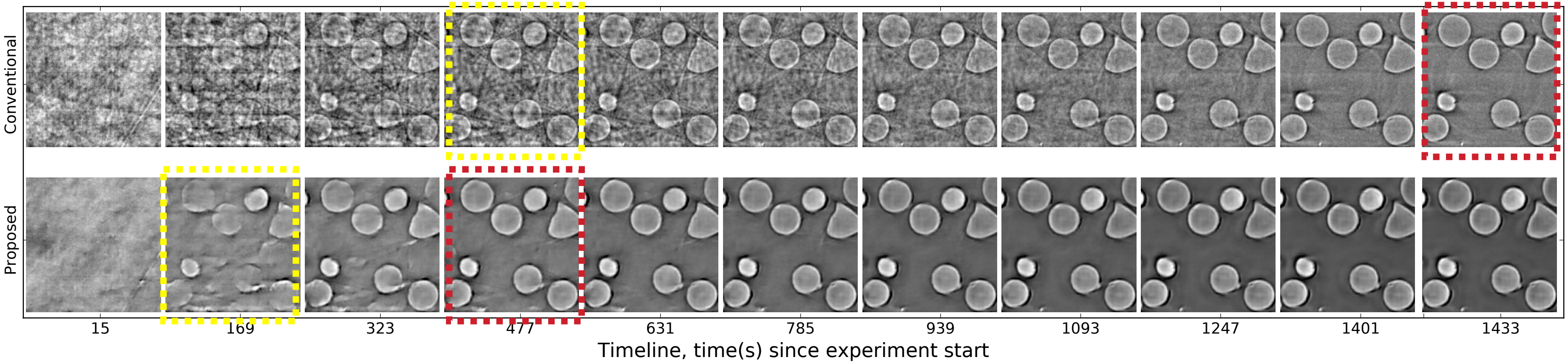


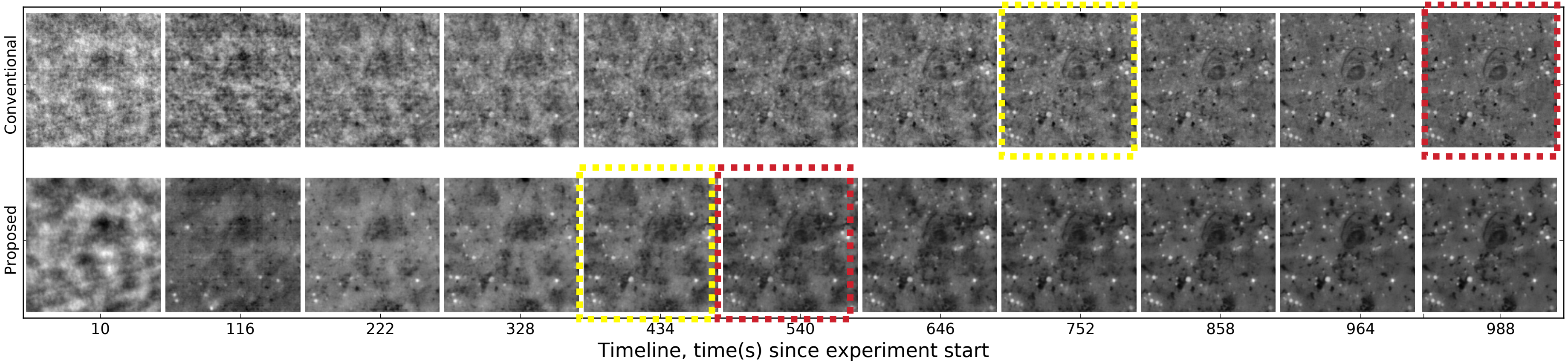

10 Iterations

# Experiments (SSIM is not enough)

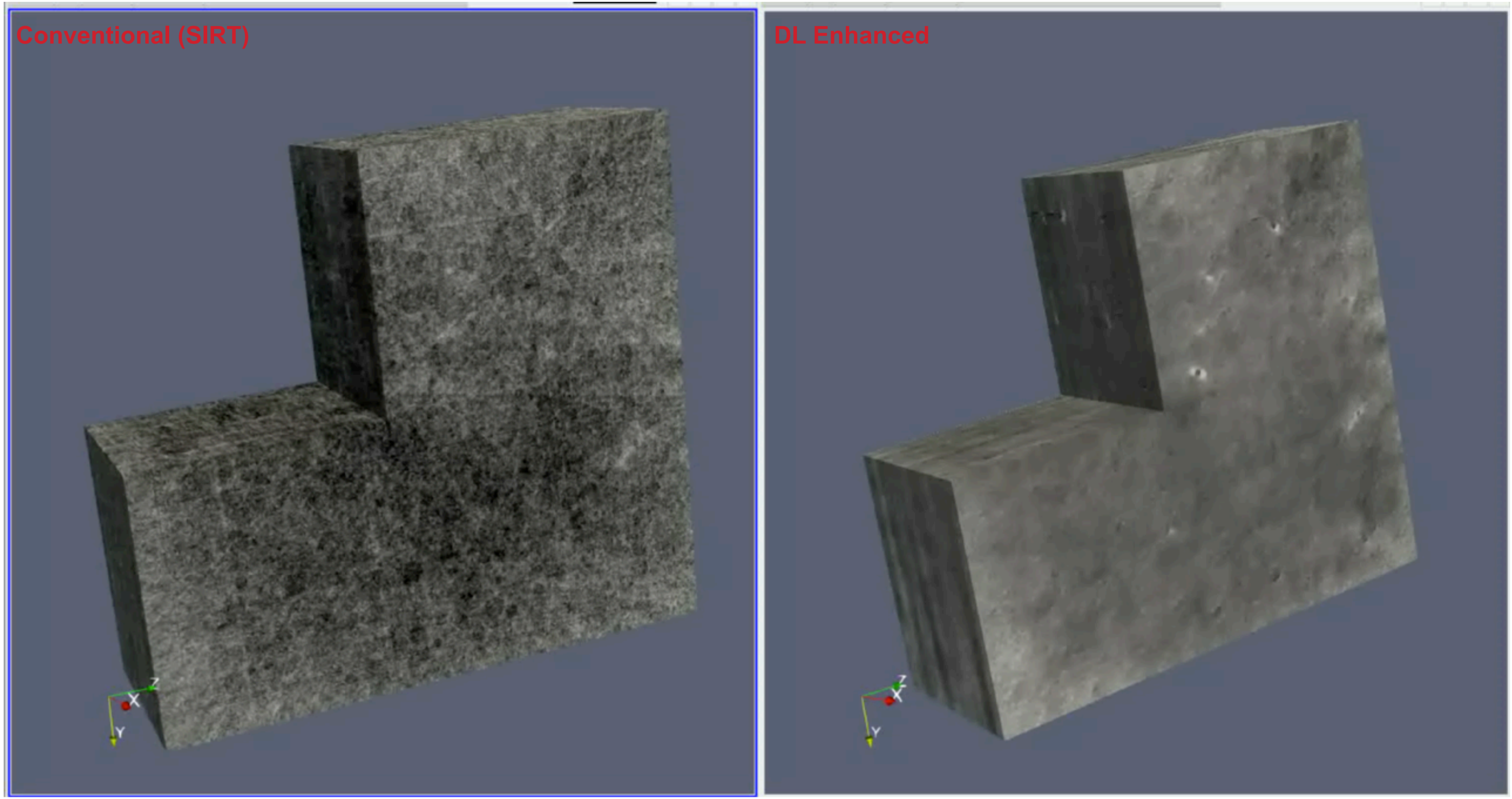


# Experiments (comparison by naked eyes)



# Experiments






**3D Vol => VTK => Catalyst/pvserver => pv CLient**

# Conclusion

- DL can significantly improve tomographic images with streaming data, model trained with one case works well for all others;
- In streaming case, it accelerates the experiment and improves light-source facility throughput (to domain scientist).
- It also saves network and computing resource compare without it in streaming tomography (to computer scientist :-).
- As we reported in our TomoGAN paper, it saves experiment time (less projections or shorter exposure time) and computing time (lightweight analytical CT + TomoGAN) even if you do not do streaming tomography reconstruction.

Thanks

Q & A

**Tuesday, November 19, 1:15 pm**
**SC Theatre adjacent to the SCinet booth in Exhibits**