Convolutional Approximations to the General Non-Line-of-Sight Imaging Operator

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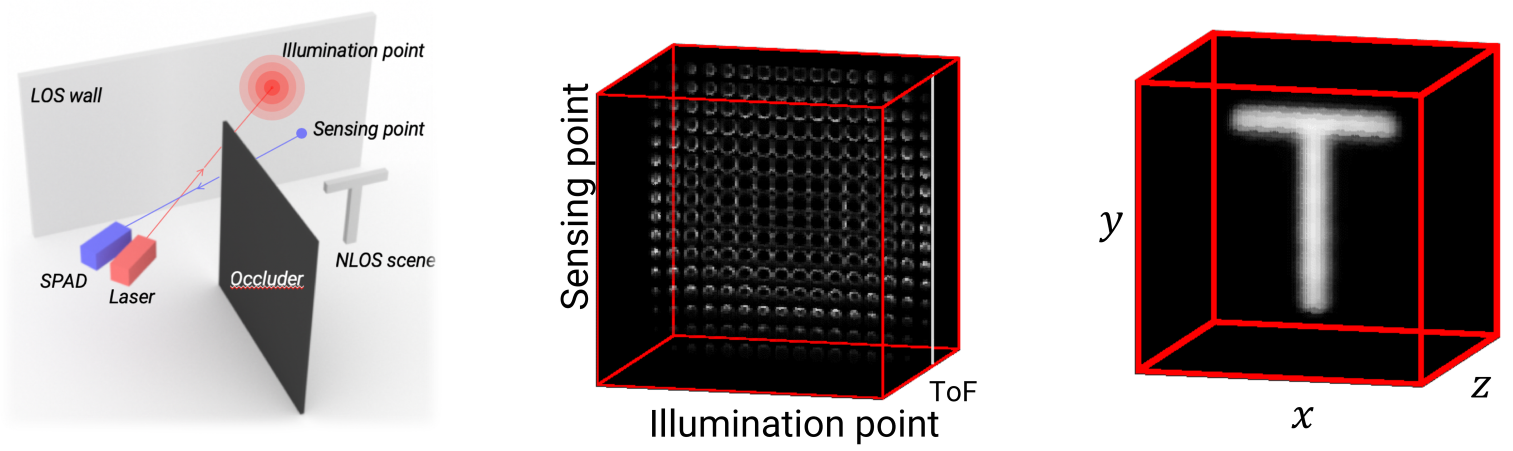
DARPA NSF KFAS Korea Foundation for Advanced Studies

http://imaging.cs.cmu.edu/conv_nlos/

Non-Line-of-Sight (NLOS) Imaging

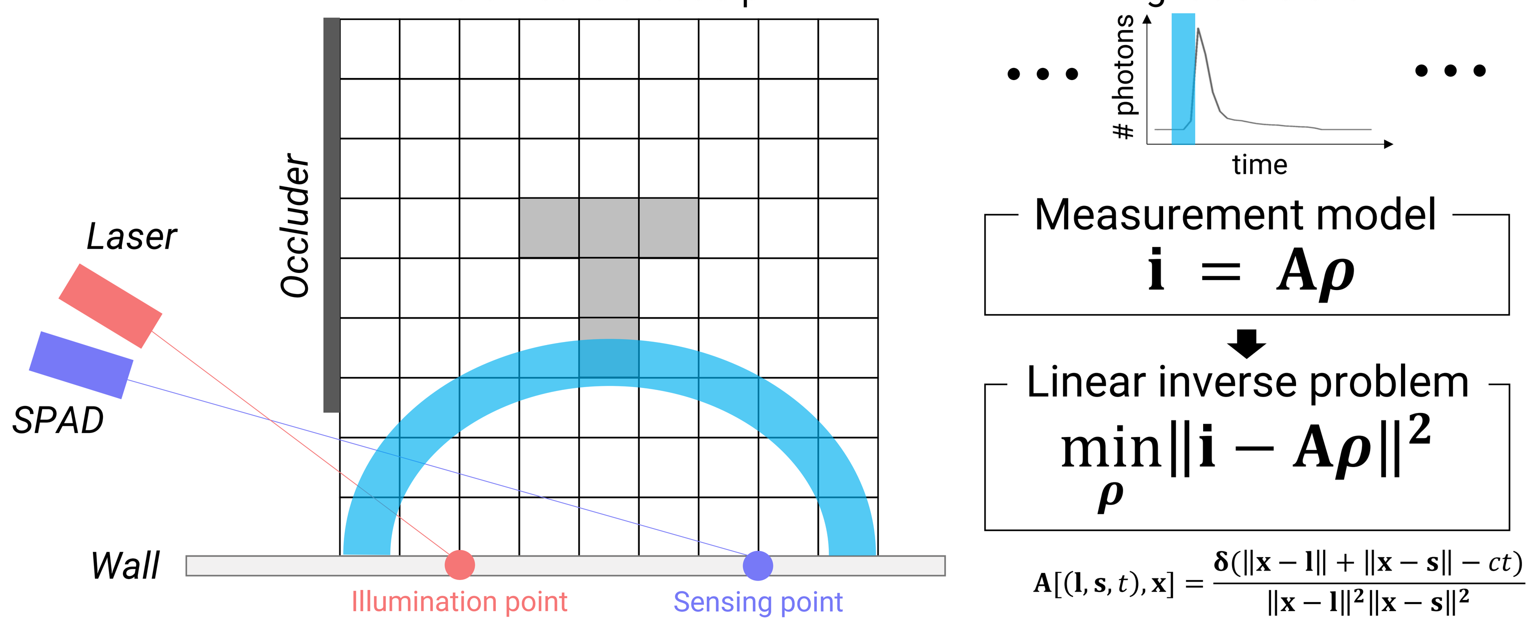
What is NLOS Imaging?

Looking around corner using ToF of multiply scattered photons



Problem Setup: Ellipsoidal Tomography

Ellipsoidal tomography is a linear inverse problem



Measurement model
$$\mathbf{i} = \mathbf{A}\boldsymbol{\rho}$$

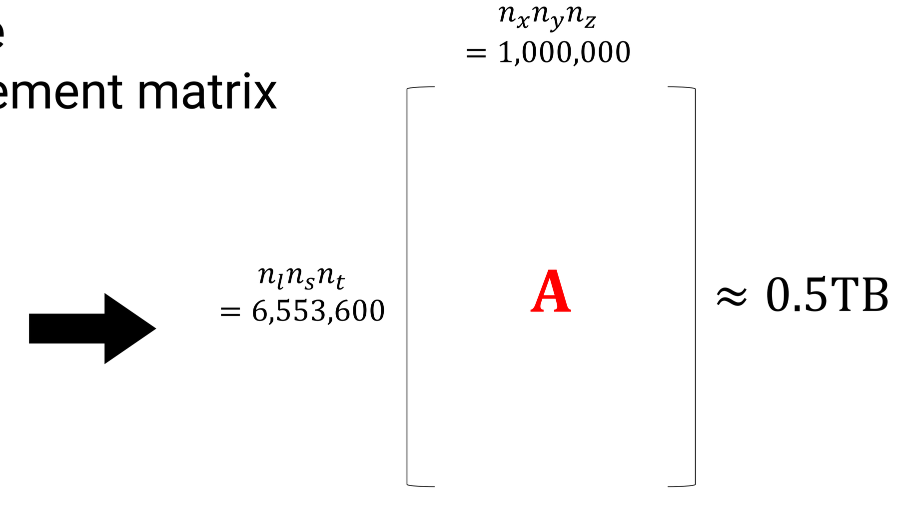
Linear inverse problem
$$\min_{\boldsymbol{\rho}} \|\mathbf{i} - \mathbf{A}\boldsymbol{\rho}\|^2$$

$$\mathbf{A}[(\mathbf{l},\mathbf{s},t),\mathbf{x}] = \frac{\delta(\|\mathbf{x}-\mathbf{l}\| + \|\mathbf{x}-\mathbf{s}\| - ct)}{\|\mathbf{x}-\mathbf{l}\|^2\|\mathbf{x}-\mathbf{s}\|^2}$$

Why is it Difficult to Solve?

Computationally prohibitive because of size of measurement matrix

<Example setup>
- Scanning points: 16×16
- Time bin size: 100
- Voxel size: 100×100×100
- Element size: 8 byte
- Sparse matrix



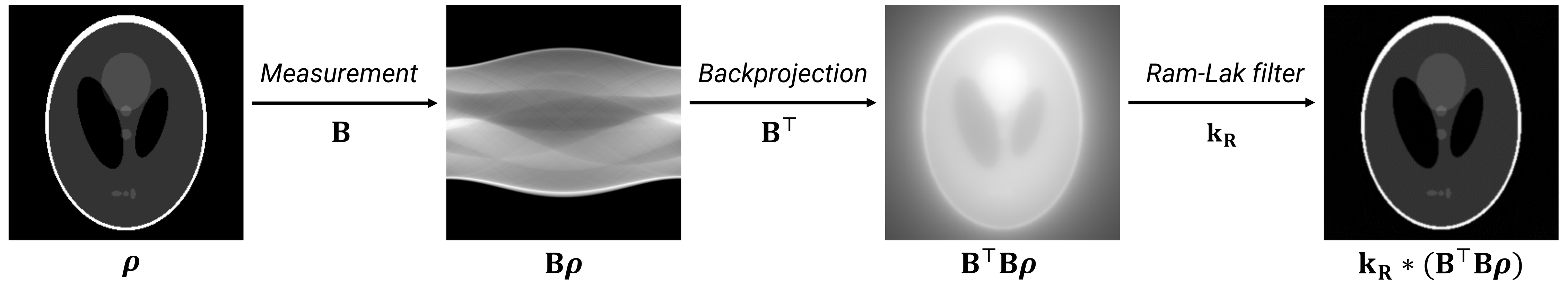
Measurement matrix

Approach

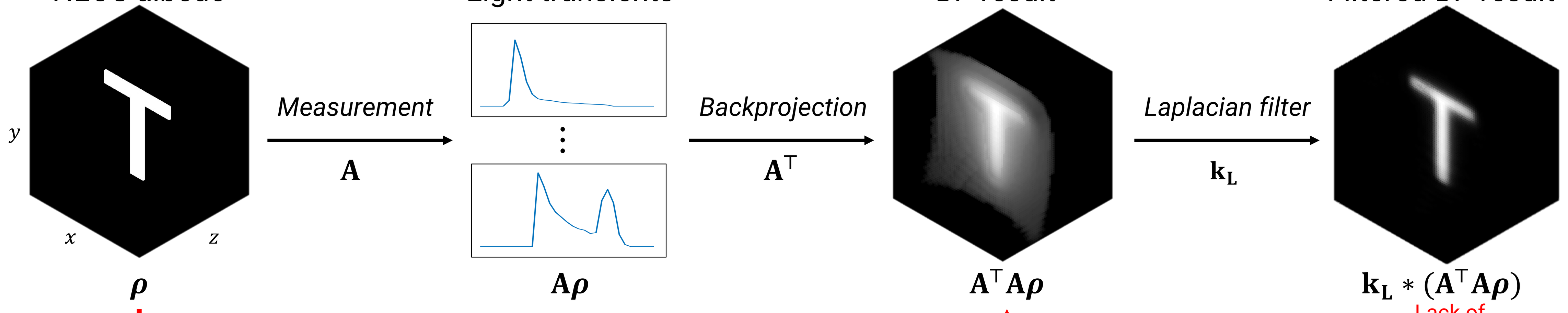
Conventional Method: Filtered Backprojection

Backprojection (BP) and sharpening filter (Analogous to CT)

Computed Tomography Pipeline



Filtered Backprojection Pipeline



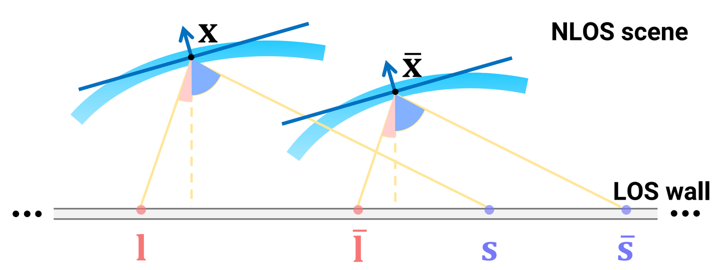
Proposed Method: $\mathbf{A}^\top\mathbf{A}$ is Convolutional

Solve computationally efficient equivalent problem

Proposed Convolutional Model

$$\mathbf{A}^\top\mathbf{A}\boldsymbol{\rho} \approx \mathbf{f} * \boldsymbol{\rho}$$

Same Set of Ellipsoids



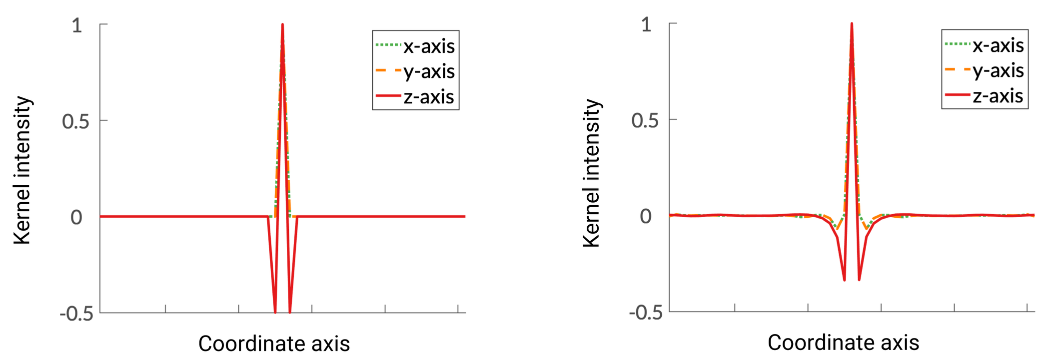
Original problem = Equivalent problem ≈ Proposed convolutional form = Deconvolution

$$\operatorname*{argmin}_{\boldsymbol{\rho}} \|\mathbf{i} - \mathbf{A}\boldsymbol{\rho}\|^2 = \operatorname*{argmin}_{\boldsymbol{\rho}} \|\mathbf{A}^\top\mathbf{i} - \mathbf{A}^\top\mathbf{A}\boldsymbol{\rho}\|^2 \approx \operatorname*{argmin}_{\boldsymbol{\rho}} \|\boldsymbol{\rho}_\mathrm{bp} - \mathbf{f} * \boldsymbol{\rho}\|^2 = \mathbf{f}^{-1} * \boldsymbol{\rho}_\mathrm{bp}$$

Use of Priors & Computational Complexity

Full linear reconstruction	Ours
$\operatorname*{argmin}_{\boldsymbol{\rho}} \|\mathbf{i} - \mathbf{A}\boldsymbol{\rho}\|^2 + \Gamma(\boldsymbol{\rho})$	$\operatorname*{argmin}_{\boldsymbol{\rho}} \|\boldsymbol{\rho}_\mathrm{bp} - \mathbf{f} * \boldsymbol{\rho}\|^2 + \Gamma(\boldsymbol{\rho})$
Time complexity per iteration: Matrix multiplication → $O(n^7)$	Time complexity per iteration: Convolution → $O(n^3 \log n)$

Theoretical Justification for Laplacian Filter

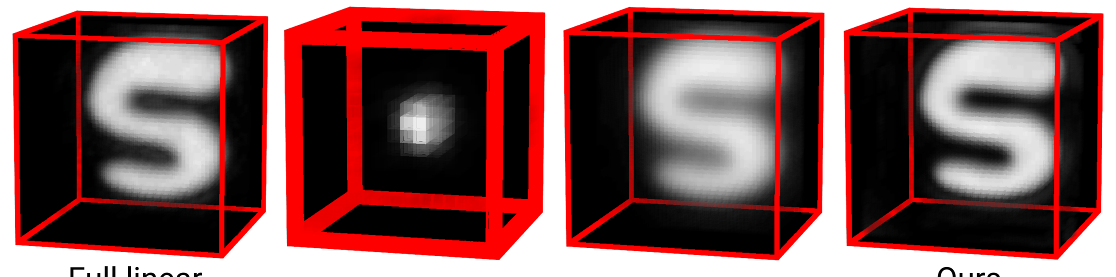


Laplacian kernel ($\mathbf{k}_\mathrm{L}$)   Our inverse kernel ($\mathbf{f}^{-1}$)

Results

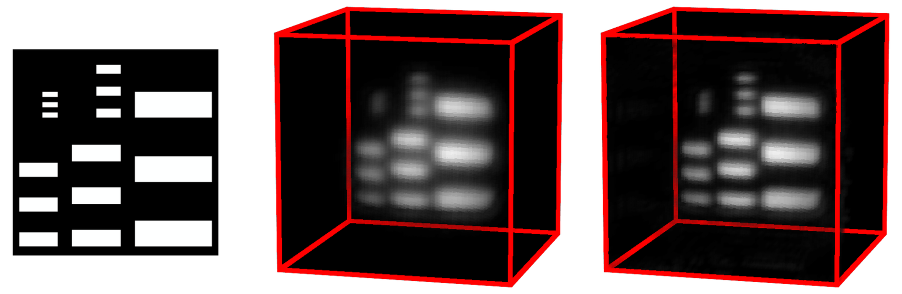
Comparisons

with Full Linear Reconstruction: Ours is computationally efficient



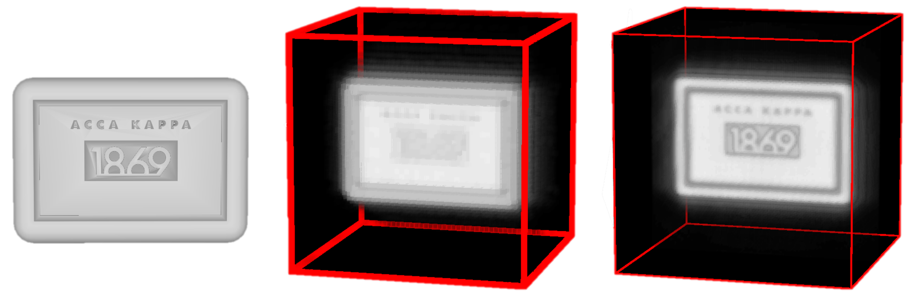
Full linear reconstruction | LCT | Filtered BP | Ours (w/o priors)

with Filtered Backprojection: Ours uses the exact inverse filter



Target object | Filtered BP | Ours (w/o priors)

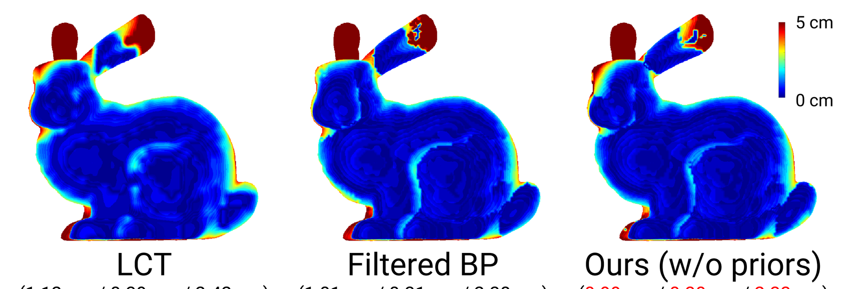
with Light Cone Transform: Ours fully exploits the ToF resolution



Target object | LCT | Ours (w/o priors)

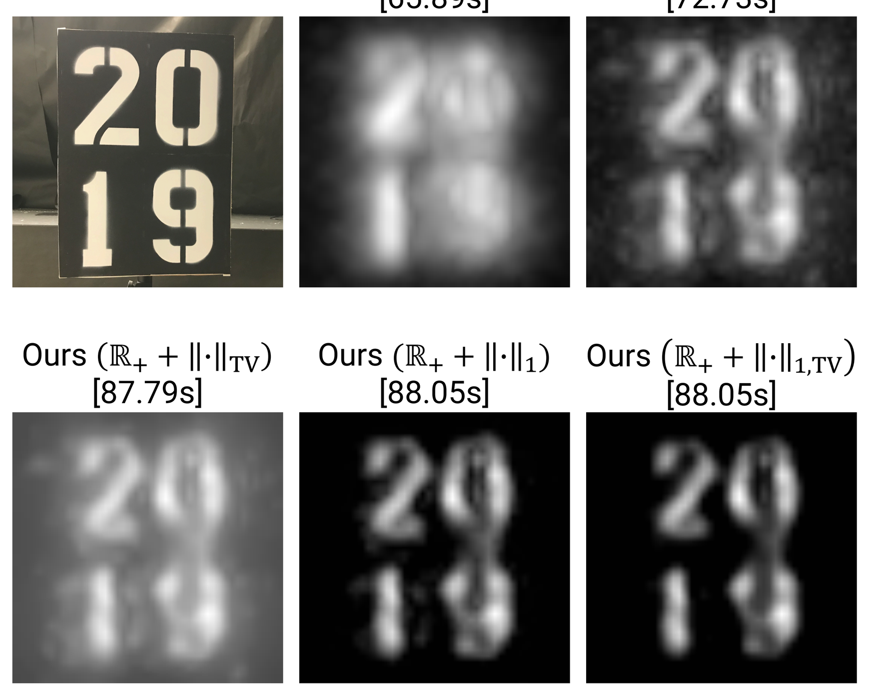
Evaluation

Quantitative Evaluation

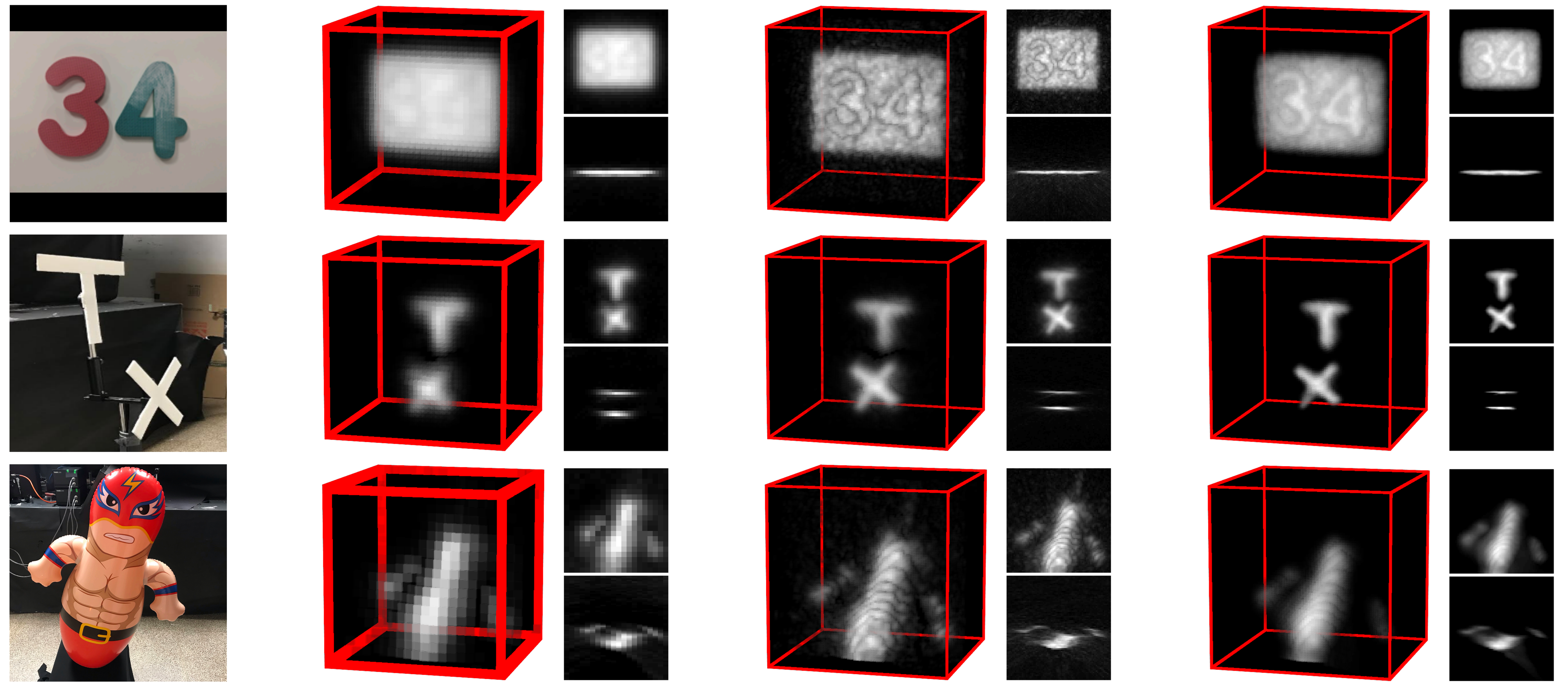


LCT (1.12 cm / 0.39 cm / 2.42 cm) | Filtered BP (1.01 cm / 0.31 cm / 2.38 cm) | Ours (w/o priors) (0.99 cm / 0.30 cm / 2.33 cm)

Reconstruction with Priors



Real Results



Target object | LCT | Filtered BP | Ours