

Splitting-Based Statistical X-Ray CT Image Reconstruction with **Blind Gain Correction**

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Outline

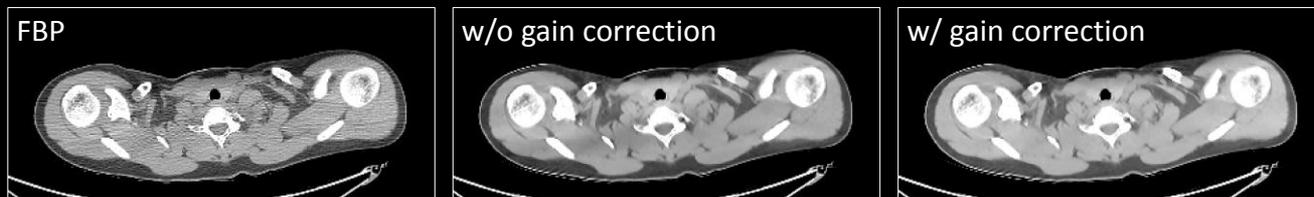
I. Description of purpose

$$(\hat{\mathbf{x}}, \hat{\mathbf{g}}) \in \underset{\mathbf{x}, \mathbf{g}}{\operatorname{argmin}} \left\{ \Psi(\mathbf{x}, \mathbf{g}) \triangleq \frac{1}{2} \|\mathbf{y} - \mathbf{A}\mathbf{x} - \mathbf{g} \otimes \mathbf{1}\|_{\mathbf{W}}^2 + R(\mathbf{x}) \right\}$$

II. Method

$$\hat{\mathbf{x}} \in \underset{\mathbf{x}}{\operatorname{argmin}} \left\{ \Psi(\mathbf{x}) \triangleq \frac{1}{2} \|\mathbf{y} - \mathbf{A}\mathbf{x}\|_{\mathbf{W}}^2 + R(\mathbf{x}) \right\}$$

III. Results



IV. Conclusion

Outline

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$$(\hat{\mathbf{x}}, \hat{\mathbf{g}}) \in \underset{\mathbf{x}, \mathbf{g}}{\operatorname{argmin}} \left\{ \Psi(\mathbf{x}, \mathbf{g}) \triangleq \frac{1}{2} \|\mathbf{y} - \mathbf{A}\mathbf{x} - \mathbf{g} \otimes \mathbf{1}\|_{\mathbf{W}}^2 + R(\mathbf{x}) \right\}$$

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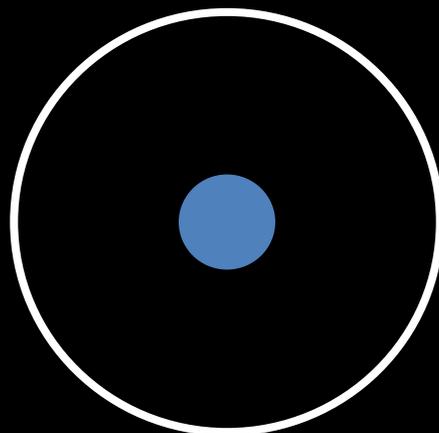
III. Results



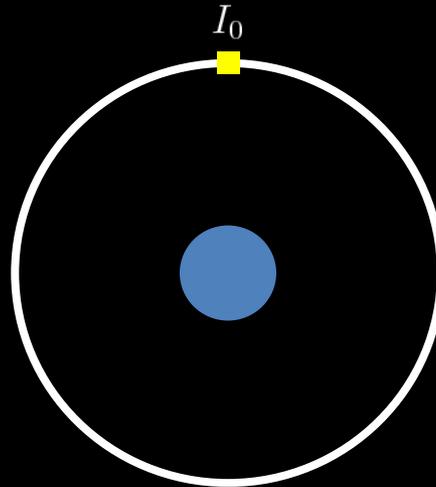
IV. Conclusion

Gain fluctuations in CT scans

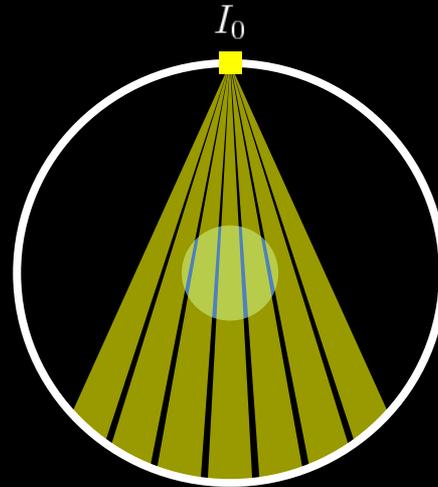
Gain fluctuations in CT scans



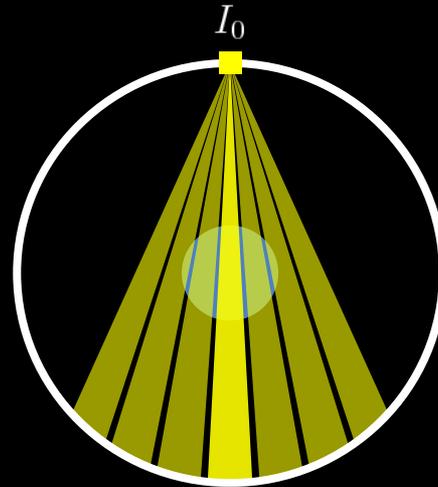
Gain fluctuations in CT scans



Gain fluctuations in CT scans

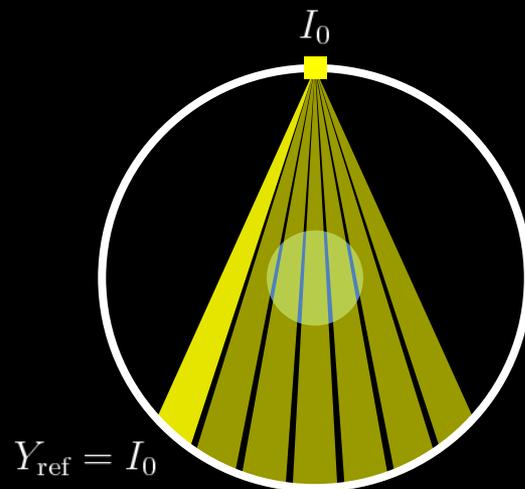


Gain fluctuations in CT scans

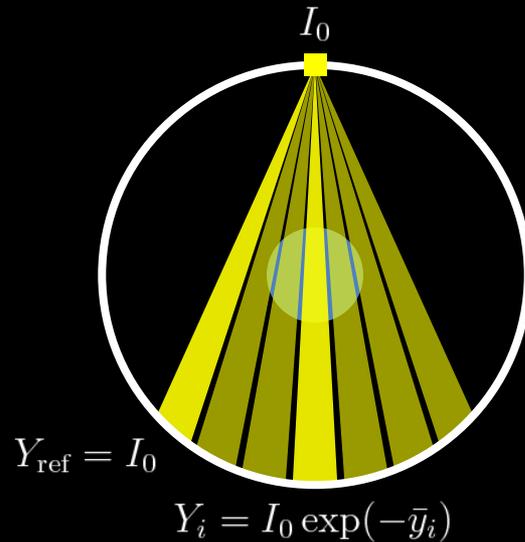


$$Y_i = I_0 \exp(-\bar{y}_i)$$

Gain fluctuations in CT scans

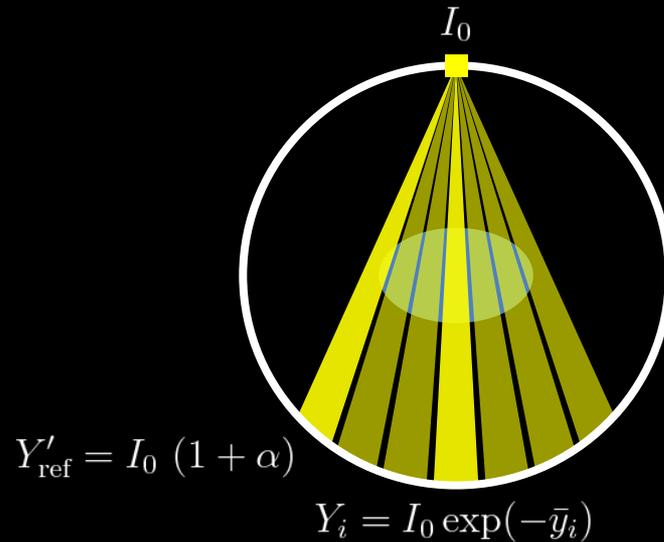


Gain fluctuations in CT scans

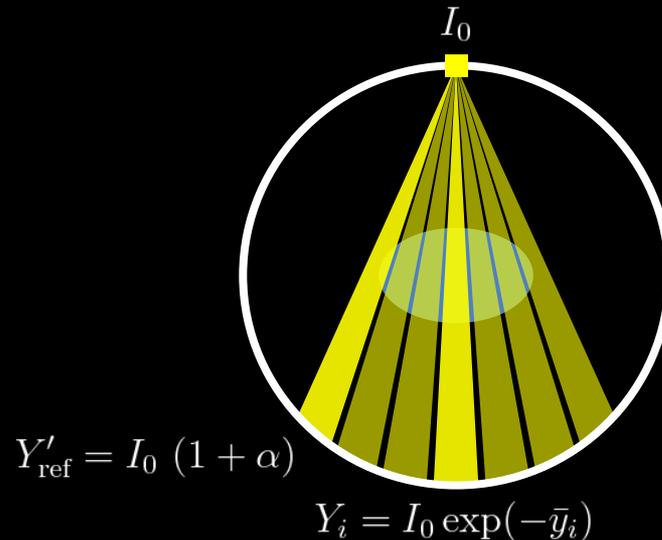


$$\bar{y}_i = \ln \left(\frac{Y_{\text{ref}}}{Y_i} \right) = \ln \left(\frac{I_0}{Y_i} \right)$$

Gain fluctuations in CT scans

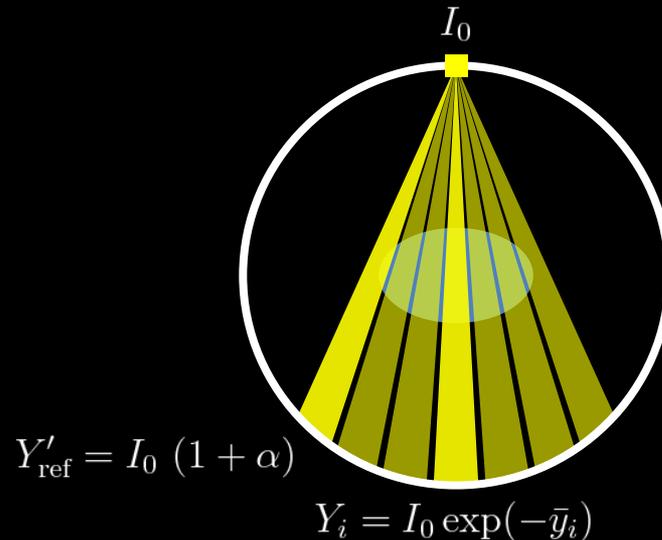


Gain fluctuations in CT scans



$$y_i = \ln \left(\frac{Y'_{\text{ref}}}{Y_i} \right) = \ln \left(\frac{I_0}{Y_i} \right) + \ln(1 + \alpha) = \bar{y}_i + \bar{\alpha}$$

Gain fluctuations in CT scans



$$y_i = \ln \left(\frac{Y'_{\text{ref}}}{Y_i} \right) = \ln \left(\frac{I_0}{Y_i} \right) + \ln(1 + \alpha) = \bar{y}_i + \bar{\alpha}$$

$$[\mathbf{Ax}]_i \triangleq \bar{y}_i = y_i - \bar{\alpha}$$

Correction of gain fluctuation

Correction of gain fluctuation

Without gain correction:

$$\hat{\mathbf{x}} \in \operatorname{argmin}_{\mathbf{x}} \left\{ \Psi(\mathbf{x}) \triangleq -\ln L(\mathbf{y}; \mathbf{x}) + R(\mathbf{x}) \right\}$$

Correction of gain fluctuation

Without gain correction (statistical PWLS formulation):

$$\hat{\mathbf{x}} \in \operatorname{argmin}_{\mathbf{x}} \left\{ \Psi(\mathbf{x}) \triangleq \frac{1}{2} \|\mathbf{y} - \mathbf{A}\mathbf{x}\|_{\mathbf{W}}^2 + R(\mathbf{x}) \right\}$$

Correction of gain fluctuation

Without gain correction (statistical PWLS formulation):

$$\hat{\mathbf{x}} \in \operatorname{argmin}_{\mathbf{x}} \left\{ \Psi(\mathbf{x}) \triangleq \frac{1}{2} \|\mathbf{y} - \mathbf{A}\mathbf{x}\|_{\underline{\mathbf{W}}}^2 + R(\mathbf{x}) \right\}$$

Statistical weighting accounts
for **measurement variance**

Correction of gain fluctuation

Without gain correction (statistical PWLS formulation):

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With gain correction (statistical PWLS formulation):

Correction of gain fluctuation

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The **unknown** correction term

Correction of gain fluctuation

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GOAL:

Correction of gain fluctuation

Without gain correction (statistical PWLS formulation):

$$\hat{\mathbf{x}} \in \operatorname{argmin}_{\mathbf{x}} \left\{ \Psi(\mathbf{x}) \triangleq \frac{1}{2} \|\mathbf{y} - \mathbf{A}\mathbf{x}\|_{\mathbf{W}}^2 + R(\mathbf{x}) \right\}$$

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GOAL:

Find an **equivalent PWLS formulation** so that we can **jointly (but implicitly) reconstruct** $\underline{\mathbf{x}}$ and $\underline{\mathbf{g}}$ using **existing methods** such as **CG**, **ADMM**, and **OS** that guarantee convergence*!

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Single-view analysis

Single-view analysis

$$(\hat{\mathbf{x}}, \hat{\mathbf{g}}) \in \operatorname{argmin}_{\mathbf{x}, \mathbf{g}} \left\{ \sum_{k=1}^K \frac{1}{2} \|\mathbf{y}_k - \mathbf{A}_k \mathbf{x} - g_k \mathbf{1}\|_{\mathbf{W}_k}^2 + \mathbf{R}(\mathbf{x}) \right\}$$

Single-view analysis

$$\begin{aligned}(\hat{\mathbf{x}}, \hat{\mathbf{g}}) &\in \operatorname{argmin}_{\mathbf{x}, \mathbf{g}} \left\{ \sum_{k=1}^K \frac{1}{2} \|\mathbf{y}_k - \mathbf{A}_k \mathbf{x} - g_k \mathbf{1}\|_{\mathbf{W}_k}^2 + \mathbf{R}(\mathbf{x}) \right\} \\ &= \operatorname{argmin}_{\mathbf{x}} \left\{ \min_{\mathbf{g}} \left\{ \sum_{k=1}^K \frac{1}{2} \|\mathbf{y}_k - \mathbf{A}_k \mathbf{x} - g_k \mathbf{1}\|_{\mathbf{W}_k}^2 \right\} + \mathbf{R}(\mathbf{x}) \right\}\end{aligned}$$

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$$\hat{g}_k(\mathbf{x}) = \frac{\mathbf{1}^\top \mathbf{W}_k (\mathbf{y}_k - \mathbf{A}_k \mathbf{x})}{\mathbf{1}^\top \mathbf{W}_k \mathbf{1}}$$

$$\Rightarrow \|\mathbf{y}_k - \mathbf{A}_k \mathbf{x} - \hat{g}_k(\mathbf{x}) \mathbf{1}\|_{\mathbf{W}_k}^2 = \|\mathbf{y}_k - \mathbf{A}_k \mathbf{x}\|_{\tilde{\mathbf{W}}_k}^2,$$

$$\text{where } \tilde{\mathbf{W}}_k = \mathbf{W}_k - \frac{\mathbf{W}_k \mathbf{1} \mathbf{1}^\top \mathbf{W}_k}{\mathbf{1}^\top \mathbf{W}_k \mathbf{1}}$$

Single-view analysis

$$\begin{aligned}(\hat{\mathbf{x}}, \hat{\mathbf{g}}) &\in \operatorname{argmin}_{\mathbf{x}, \mathbf{g}} \left\{ \sum_{k=1}^K \frac{1}{2} \|\mathbf{y}_k - \mathbf{A}_k \mathbf{x} - g_k \mathbf{1}\|_{\mathbf{W}_k}^2 + R(\mathbf{x}) \right\} \\&= \operatorname{argmin}_{\mathbf{x}} \left\{ \min_{\mathbf{g}} \left\{ \sum_{k=1}^K \frac{1}{2} \|\mathbf{y}_k - \mathbf{A}_k \mathbf{x} - g_k \mathbf{1}\|_{\mathbf{W}_k}^2 \right\} + R(\mathbf{x}) \right\} \\&= \operatorname{argmin}_{\mathbf{x}} \left\{ \sum_{k=1}^K \frac{1}{2} \min_{g_k} \left\{ \|\mathbf{y}_k - \mathbf{A}_k \mathbf{x} - g_k \mathbf{1}\|_{\mathbf{W}_k}^2 \right\} + R(\mathbf{x}) \right\} \\&= \operatorname{argmin}_{\mathbf{x}} \left\{ \sum_{k=1}^K \frac{1}{2} \|\mathbf{y}_k - \mathbf{A}_k \mathbf{x}\|_{\tilde{\mathbf{W}}_k}^2 + R(\mathbf{x}) \right\}\end{aligned}$$

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Proposed equivalent formulation

$$\hat{\mathbf{x}} \in \operatorname{argmin}_{\mathbf{x}} \left\{ \Psi(\mathbf{x}) \triangleq \frac{1}{2} \|\mathbf{y} - \mathbf{A}\mathbf{x}\|_{\tilde{\mathbf{W}}}^2 + R(\mathbf{x}) \right\}$$

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$$\tilde{\mathbf{W}} \triangleq \operatorname{diag} \left\{ \tilde{\mathbf{W}}_1, \tilde{\mathbf{W}}_2, \dots, \tilde{\mathbf{W}}_K \right\}$$

Proposed equivalent formulation

$$\hat{\mathbf{x}} \in \operatorname{argmin}_{\mathbf{x}} \left\{ \Psi(\mathbf{x}) \triangleq \frac{1}{2} \|\mathbf{y} - \mathbf{A}\mathbf{x}\|_{\tilde{\mathbf{W}}}^2 + R(\mathbf{x}) \right\}$$



$$(\hat{\mathbf{x}}, \hat{\mathbf{u}}, \hat{\mathbf{v}}) \in \operatorname{argmin}_{\mathbf{x}, \mathbf{u}, \mathbf{v}} \left\{ \frac{1}{2} \|\mathbf{y} - \mathbf{u}\|_{\tilde{\mathbf{W}}}^2 + \Phi(\mathbf{v}) \right\} \text{ s.t. } \mathbf{u} = \mathbf{A}\mathbf{x}, \mathbf{v} = \mathbf{C}\mathbf{x}$$

Proposed equivalent formulation

$$(\hat{\mathbf{x}}, \hat{\mathbf{u}}, \hat{\mathbf{v}}) \in \operatorname{argmin}_{\mathbf{x}, \mathbf{u}, \mathbf{v}} \left\{ \frac{1}{2} \|\mathbf{y} - \mathbf{u}\|_{\tilde{\mathbf{W}}}^2 + \Phi(\mathbf{v}) \right\} \text{ s.t. } \mathbf{u} = \mathbf{A}\mathbf{x}, \mathbf{v} = \mathbf{C}\mathbf{x}$$

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$$\left\{ \begin{array}{l} \mathbf{x}^{(j+1)} = \left(\rho \mathbf{A}^\top \mathbf{A} + \eta \mathbf{C}^\top \mathbf{C} \right)^{-1} \left(\rho \mathbf{A}^\top \left(\mathbf{u}^{(j)} + \mathbf{d}^{(j)} \right) + \eta \mathbf{C}^\top \left(\mathbf{v}^{(j)} + \mathbf{e}^{(j)} \right) \right) \\ \mathbf{u}^{(j+1)} = \left(\tilde{\mathbf{W}} + \rho \mathbf{I} \right)^{-1} \left(\tilde{\mathbf{W}} \mathbf{y} + \rho \left(\mathbf{A} \mathbf{x}^{(j+1)} - \mathbf{d}^{(j)} \right) \right) \\ \mathbf{v}^{(j+1)} \in \underset{\mathbf{v}}{\operatorname{argmin}} \left\{ \Phi(\mathbf{v}) + \frac{\eta}{2} \left\| \mathbf{v} - \left(\mathbf{C} \mathbf{x}^{(j+1)} - \mathbf{e}^{(j)} \right) \right\|^2 \right\} \\ \mathbf{d}^{(j+1)} = \mathbf{d}^{(j)} - \mathbf{A} \mathbf{x}^{(j+1)} + \mathbf{u}^{(j+1)} \\ \mathbf{e}^{(j+1)} = \mathbf{e}^{(j)} - \mathbf{C} \mathbf{x}^{(j+1)} + \mathbf{v}^{(j+1)} \end{array} \right.$$

Proposed equivalent formulation

$$(\hat{\mathbf{x}}, \hat{\mathbf{u}}, \hat{\mathbf{v}}) \in \underset{\mathbf{x}, \mathbf{u}, \mathbf{v}}{\operatorname{argmin}} \left\{ \frac{1}{2} \|\mathbf{y} - \mathbf{u}\|_{\tilde{\mathbf{W}}}^2 + \Phi(\mathbf{v}) \right\} \text{ s.t. } \mathbf{u} = \mathbf{A}\mathbf{x}, \mathbf{v} = \mathbf{C}\mathbf{x}$$

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$$(\hat{\mathbf{x}}, \hat{\mathbf{u}}, \hat{\mathbf{v}}) \in \underset{\mathbf{x}, \mathbf{u}, \mathbf{v}}{\operatorname{argmin}} \left\{ \frac{1}{2} \|\mathbf{y} - \mathbf{u}\|_{\tilde{\mathbf{W}}}^2 + \Phi(\mathbf{v}) \right\} \text{ s.t. } \mathbf{u} = \mathbf{A}\mathbf{x}, \mathbf{v} = \mathbf{C}\mathbf{x}$$

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Solved exactly and efficiently using the **Sherman-Morrison formula**

Non-blind gain correction

$$(\hat{\mathbf{x}}, \hat{\mathbf{g}}) \in \operatorname{argmin}_{\mathbf{x}, \mathbf{g}} \left\{ \Psi(\mathbf{x}, \mathbf{g}) \triangleq \frac{1}{2} \|\mathbf{y} - \mathbf{A}\mathbf{x} - \mathbf{g} \otimes \mathbf{1}\|_{\mathbf{W}}^2 + R(\mathbf{x}) \right\}$$

Non-blind gain correction

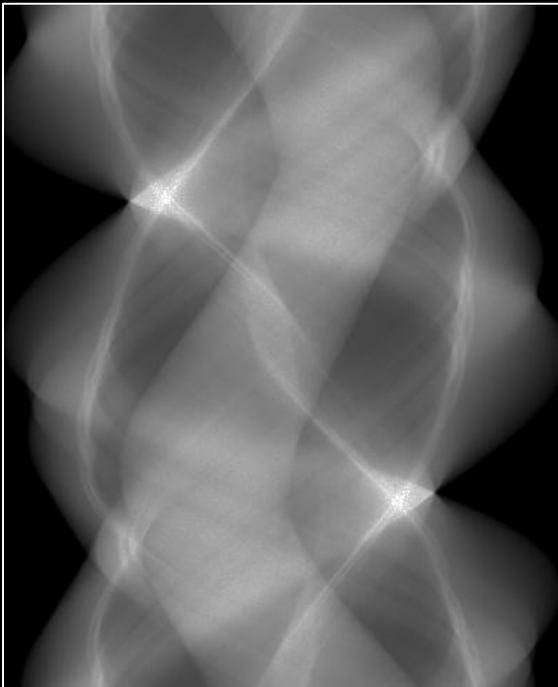
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Correct **all** views
(i.e., **blind** gain correction)

Non-blind gain correction

$$(\hat{\mathbf{x}}, \hat{\mathbf{g}}) \in \operatorname{argmin}_{\mathbf{x}, \mathbf{g}} \left\{ \Psi(\mathbf{x}, \mathbf{g}) \triangleq \frac{1}{2} \|\mathbf{y} - \mathbf{A}\mathbf{x} - \mathbf{g} \otimes \mathbf{1}\|_{\mathbf{W}}^2 + R(\mathbf{x}) \right\}$$

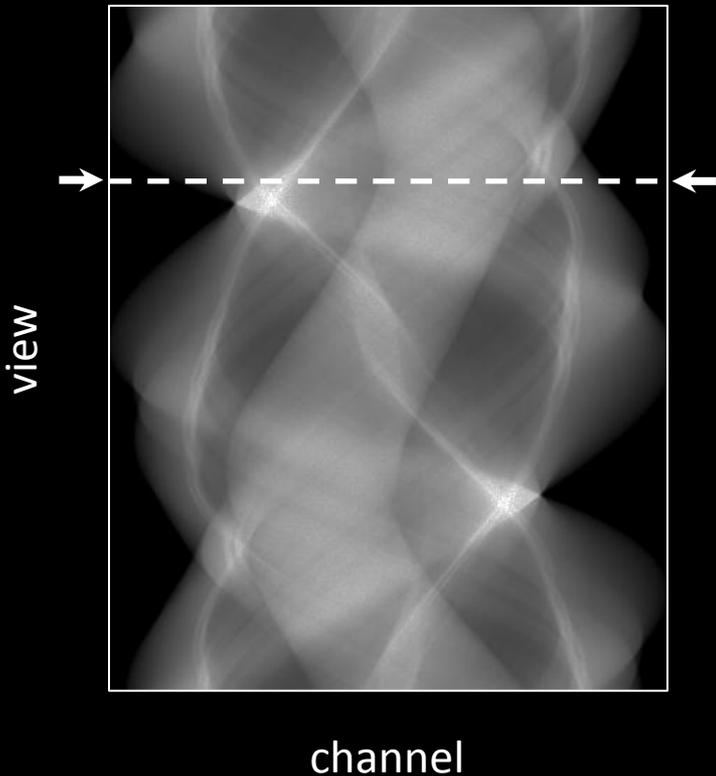
view



channel

Non-blind gain correction

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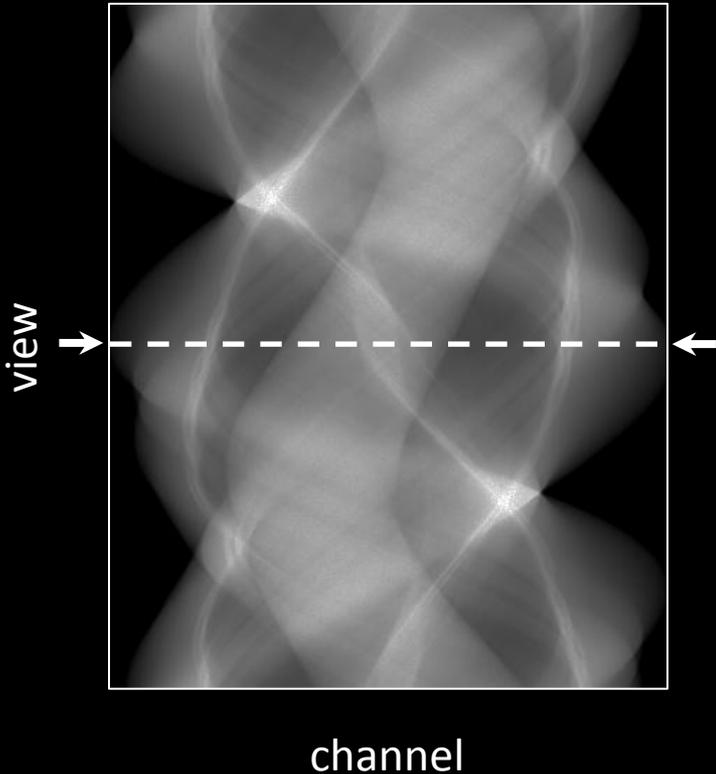
Object is *inside* FOV.

⇒ Reference channel is possibly *not blocked*.

⇒ Gain fluctuation (g_k) is possibly *zero!!!*

Non-blind gain correction

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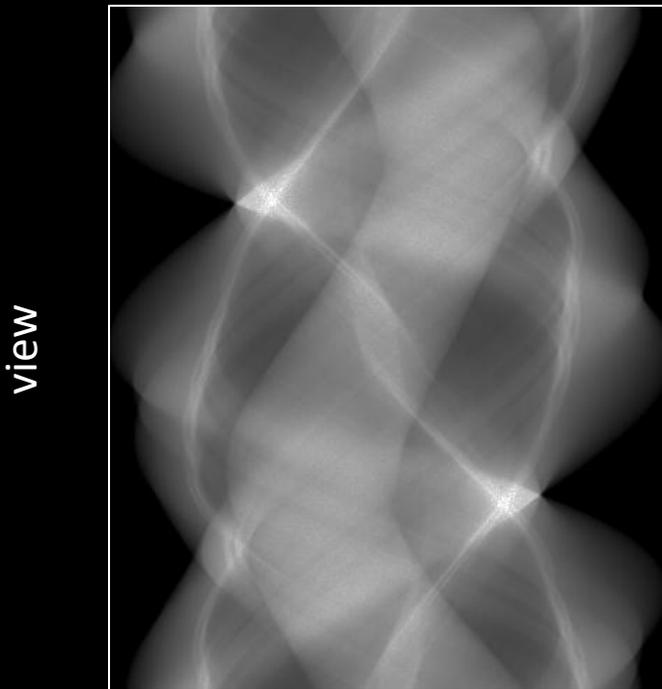


- Object is **outside** FOV.
- \Rightarrow Reference channel is possibly **blocked**.
- \Rightarrow Gain fluctuation (g_k) is possibly **non-zero!!!**

Non-blind gain correction

$$(\hat{\mathbf{x}}, \hat{\mathbf{g}}) \in \underset{\mathbf{x}, \mathbf{g}}{\operatorname{argmin}} \left\{ \Psi(\mathbf{x}, \mathbf{g}) \triangleq \frac{1}{2} \|\mathbf{y} - \mathbf{A}\mathbf{x} - \mathbf{g} \otimes \mathbf{1}\|_{\mathbf{W}}^2 + R(\mathbf{x}) \right\}$$

s.t. $[\mathbf{g}]_k = 0$ if $k \notin \mathcal{K}$



Object is **inside** FOV.

⇒ Reference channel is possibly **not blocked**.

⇒ Gain fluctuation (g_k) is possibly **zero!!!**

Object is **outside** FOV.

⇒ Reference channel is possibly **blocked**.

⇒ Gain fluctuation (g_k) is possibly **non-zero!!!**

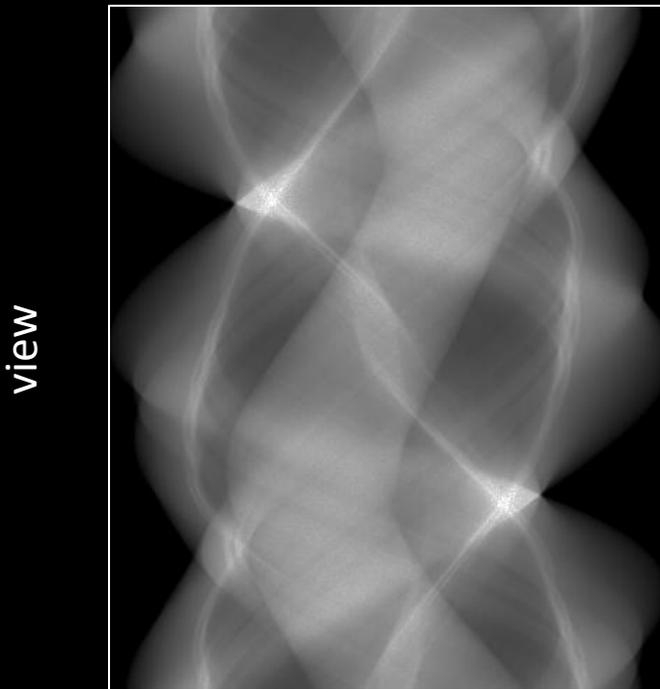
channel

Non-blind gain correction

$$(\hat{\mathbf{x}}, \hat{\mathbf{g}}) \in \underset{\mathbf{x}, \mathbf{g}}{\operatorname{argmin}} \left\{ \Psi(\mathbf{x}, \mathbf{g}) \triangleq \frac{1}{2} \|\mathbf{y} - \mathbf{A}\mathbf{x} - \underline{\mathbf{g}} \otimes \mathbf{1}\|_{\mathbf{W}}^2 + R(\mathbf{x}) \right\}$$

s.t. $[\mathbf{g}]_k = 0$ if $k \notin \mathcal{K}$

Correct **some** views
(i.e., **non-blind** gain correction)



- Object is **inside** FOV.
- ⇒ Reference channel is possibly **not blocked**.
 - ⇒ Gain fluctuation (g_k) is possibly **zero!!!**

- Object is **outside** FOV.
- ⇒ Reference channel is possibly **blocked**.
 - ⇒ Gain fluctuation (g_k) is possibly **non-zero!!!**

channel

Non-blind gain correction

$$(\hat{\mathbf{x}}, \hat{\mathbf{g}}) \in \underset{\mathbf{x}, \mathbf{g}}{\operatorname{argmin}} \left\{ \Psi(\mathbf{x}, \mathbf{g}) \triangleq \frac{1}{2} \|\mathbf{y} - \mathbf{A}\mathbf{x} - \mathbf{g} \otimes \mathbf{1}\|_{\mathbf{W}}^2 + \mathcal{R}(\mathbf{x}) \right\}$$

s.t. $[\mathbf{g}]_k = 0$ if $k \notin \mathcal{K}$

$$\hat{\mathbf{x}} \in \underset{\mathbf{x}}{\operatorname{argmin}} \left\{ \Psi(\mathbf{x}) \triangleq \frac{1}{2} \|\mathbf{y} - \mathbf{A}\mathbf{x}\|_{\tilde{\mathbf{W}}}^2 + \mathcal{R}(\mathbf{x}) \right\},$$

\Leftrightarrow where $\tilde{\mathbf{W}} \triangleq \operatorname{diag}\{\tilde{\mathbf{W}}_1, \tilde{\mathbf{W}}_2, \dots, \tilde{\mathbf{W}}_K\}$ and

$$\tilde{\mathbf{W}}_k = \begin{cases} \mathbf{W}_k & , \text{ if } k \notin \mathcal{K} \\ \mathbf{W}_k - \frac{\mathbf{W}_k \mathbf{1} \mathbf{1}^\top \mathbf{W}_k}{\mathbf{1}^\top \mathbf{W}_k \mathbf{1}} & , \text{ otherwise.} \end{cases}$$

Gain correction using OS-SQS

$$\hat{\mathbf{x}} \in \underset{\mathbf{x}}{\operatorname{argmin}} \left\{ \Psi(\mathbf{x}) \triangleq \frac{1}{2} \|\mathbf{y} - \mathbf{A}\mathbf{x}\|_{\tilde{\mathbf{W}}}^2 + \mathbf{R}(\mathbf{x}) \right\},$$

where $\tilde{\mathbf{W}} \triangleq \operatorname{diag}\left\{ \tilde{\mathbf{W}}_1, \tilde{\mathbf{W}}_2, \dots, \tilde{\mathbf{W}}_K \right\}$ and

$$\tilde{\mathbf{W}}_k \triangleq \mathbf{W}_k - \frac{\mathbf{w}_k \mathbf{1} \mathbf{1}^\top \mathbf{w}_k}{\mathbf{1}^\top \mathbf{w}_k \mathbf{1}} \cdot \mathbb{I}_{k \in \mathcal{K}} \text{ for } k = 1, 2, \dots, K$$

1. $\nabla \Psi(\mathbf{x}) = \mathbf{A}^\top \tilde{\mathbf{W}} (\mathbf{A}\mathbf{x} - \mathbf{y}) + \nabla \mathbf{R}(\mathbf{x})$
2. $\nabla_\ell \Psi(\mathbf{x}) = L \cdot \mathbf{A}_{(\ell)}^\top \tilde{\mathbf{W}}_{(\ell)} (\mathbf{A}_{(\ell)} \mathbf{x} - \mathbf{y}_{(\ell)}) + \nabla \mathbf{R}(\mathbf{x})$,
where $\tilde{\mathbf{W}}_{(\ell)} \triangleq \operatorname{diag}\left\{ \tilde{\mathbf{W}}_k \mid k \in \text{the } \ell\text{th ordered subsets} \right\}$
3. Diagonal majorizer = $\mathbf{D}_{\text{WLS}} \triangleq \operatorname{diag}\left\{ \mathbf{A}^\top \mathbf{W} \mathbf{A} \mathbf{1} \right\}$

Outline

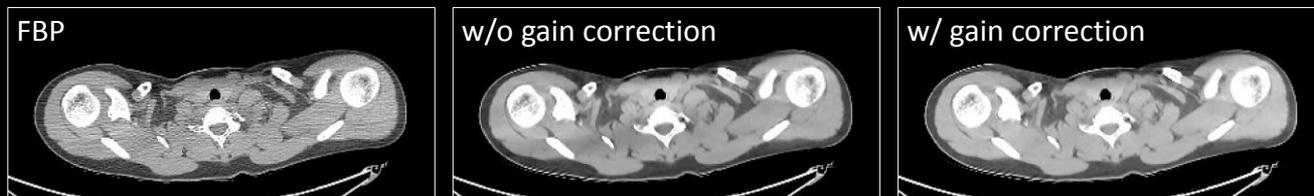
I. Description of purpose

$$(\hat{\mathbf{x}}, \hat{\mathbf{g}}) \in \underset{\mathbf{x}, \mathbf{g}}{\operatorname{argmin}} \left\{ \Psi(\mathbf{x}, \mathbf{g}) \triangleq \frac{1}{2} \|\mathbf{y} - \mathbf{Ax} - \mathbf{g} \otimes \mathbf{1}\|_{\mathbf{W}}^2 + R(\mathbf{x}) \right\}$$

II. Method

$$\hat{\mathbf{x}} \in \underset{\mathbf{x}}{\operatorname{argmin}} \left\{ \Psi(\mathbf{x}) \triangleq \frac{1}{2} \|\mathbf{y} - \mathbf{Ax}\|_{\mathbf{W}}^2 + R(\mathbf{x}) \right\}$$

III. Results



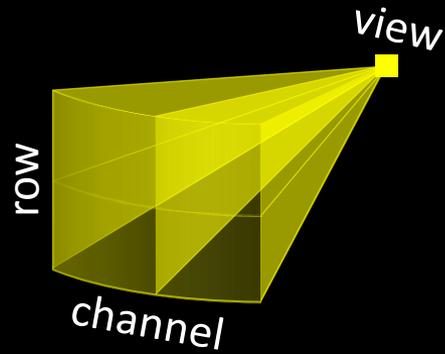
IV. Conclusion

Gain correction in 3D X-ray CT

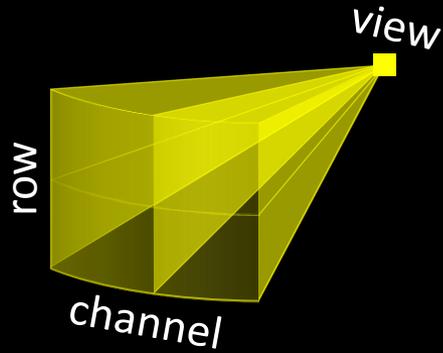
Gain correction in 3D X-ray CT

view
■

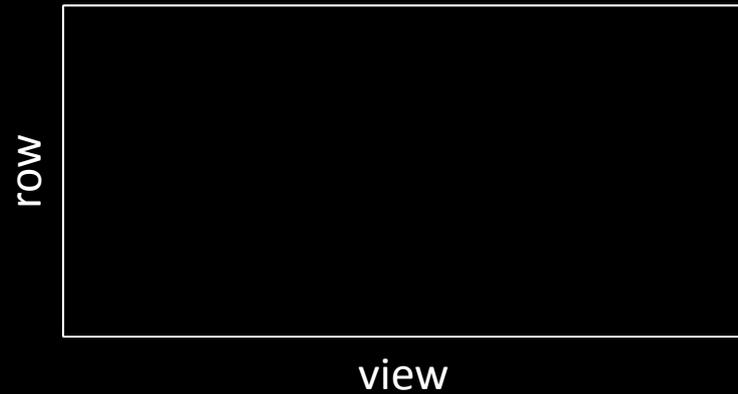
Gain correction in 3D X-ray CT



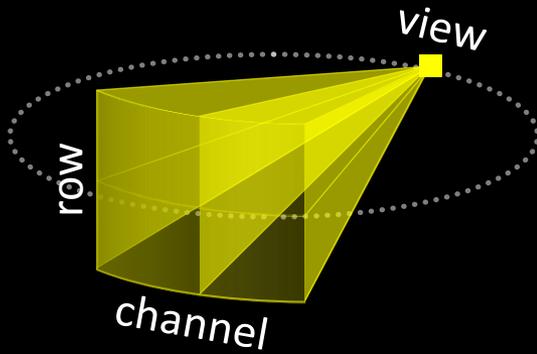
Gain correction in 3D X-ray CT



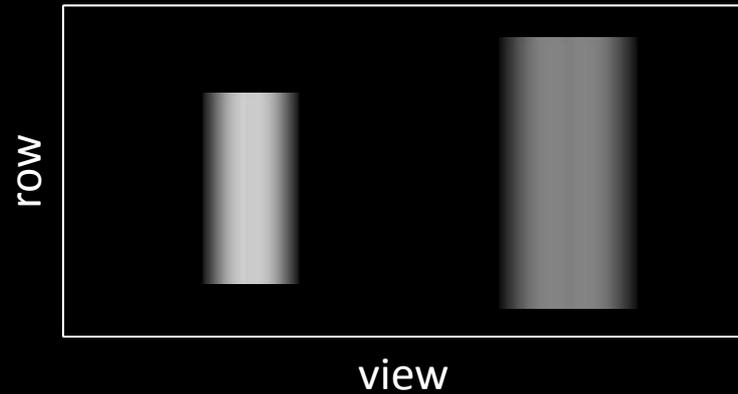
Gain fluctuations:



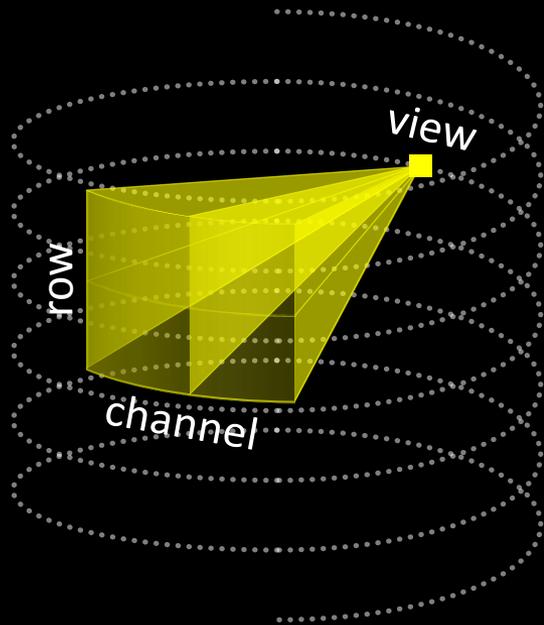
Gain correction in 3D X-ray CT



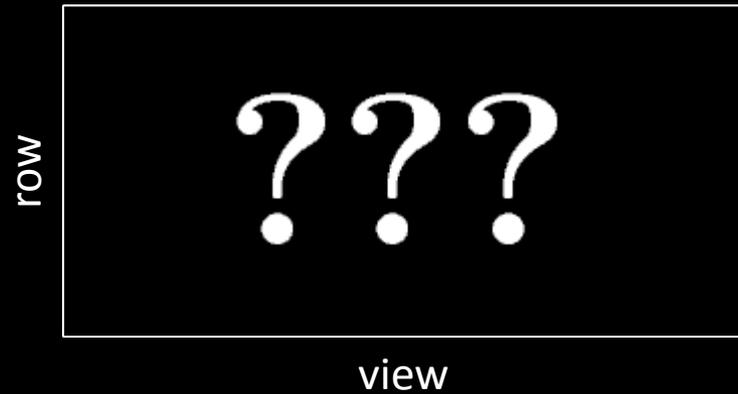
Gain fluctuations: **axial**



Gain correction in 3D X-ray CT



Gain fluctuations: **helical**



3D axial CT – using ADMM

3D axial CT – using ADMM

Image:

128 x 120 x 100 30cm-diameter cylinder
with three bone-like inserts
Voxel size: **3.9062 x 3.9062 x 3.9062 mm³**

Geometry:

128 x 120 x 144 3D axial CT
Orbit: **360°**
Pitch = **0**
Detector channel spacing = **8 mm**
Detector row spacing = **8 mm**

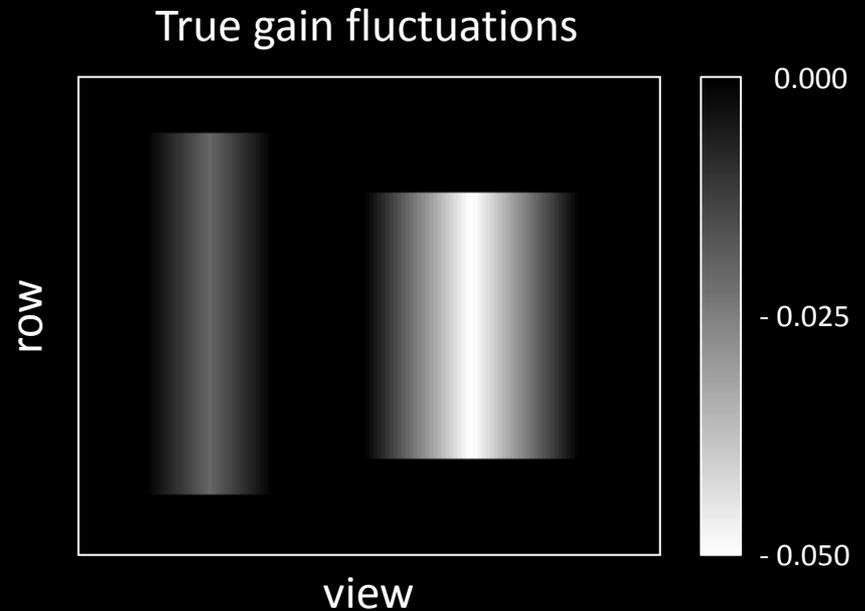
3D axial CT – using ADMM

Image:

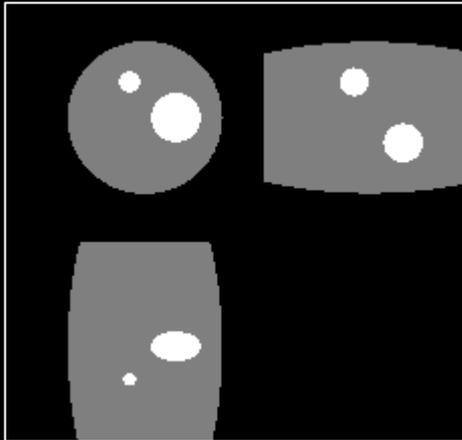
128 x 120 x 100 30cm-diameter cylinder
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Geometry:

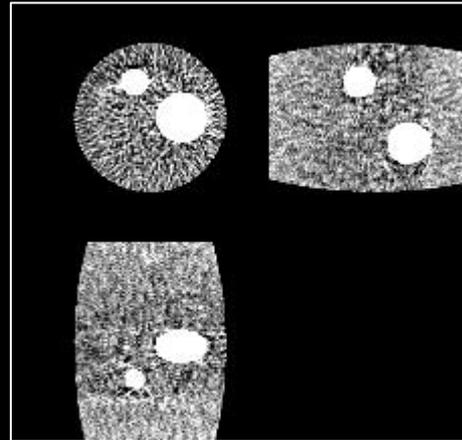
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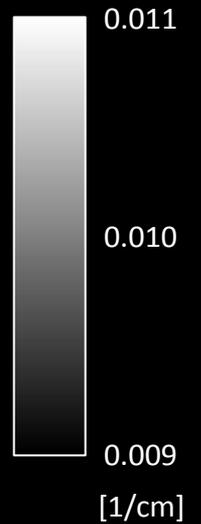
3D axial CT – using ADMM



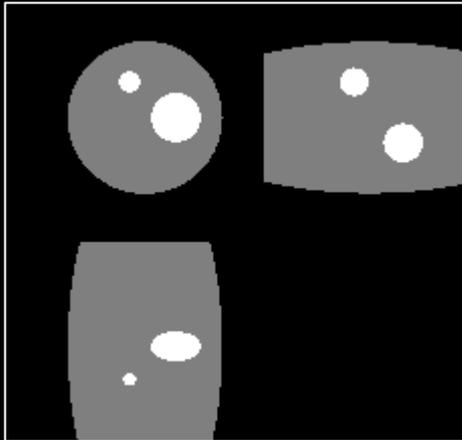
True image



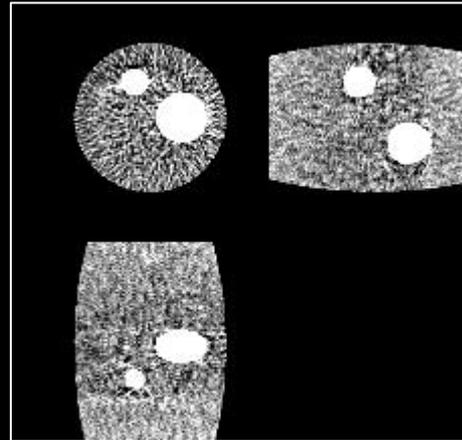
FDK (initial image)



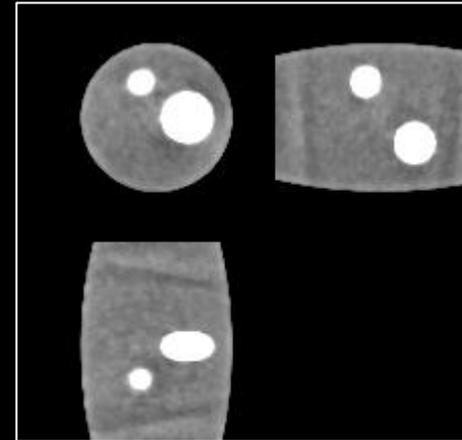
3D axial CT – using ADMM



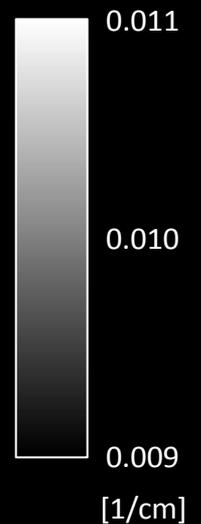
True image



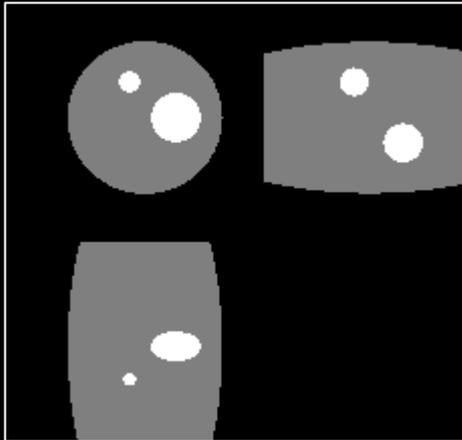
FDK (initial image)



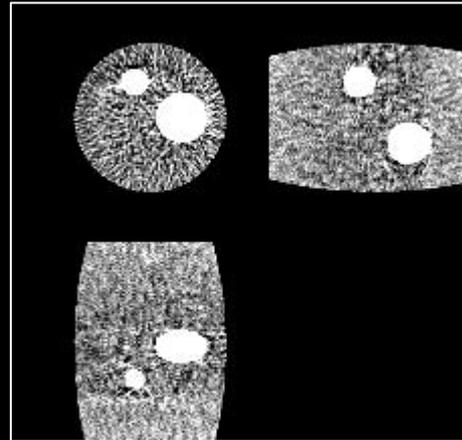
No gain correction



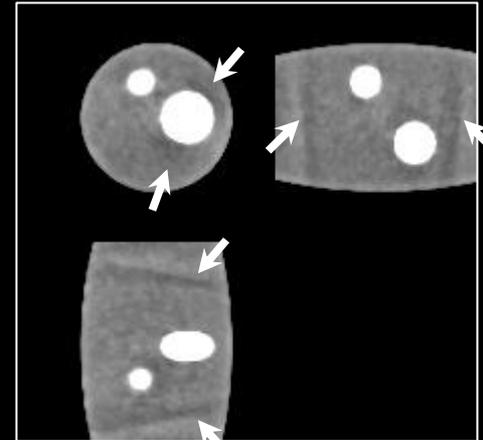
3D axial CT – using ADMM



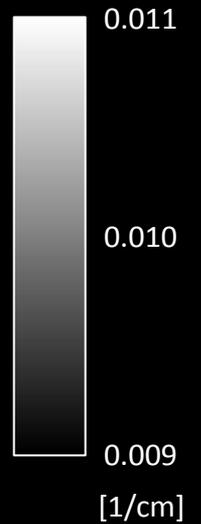
True image



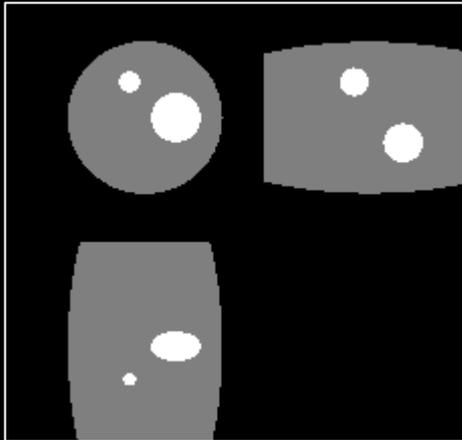
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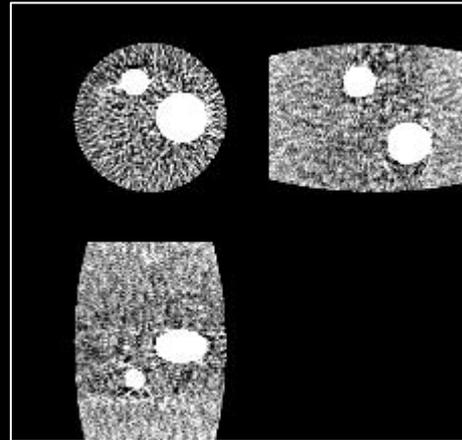
No gain correction



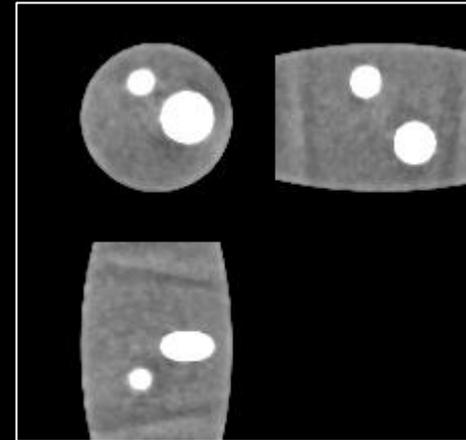
3D axial CT – using ADMM



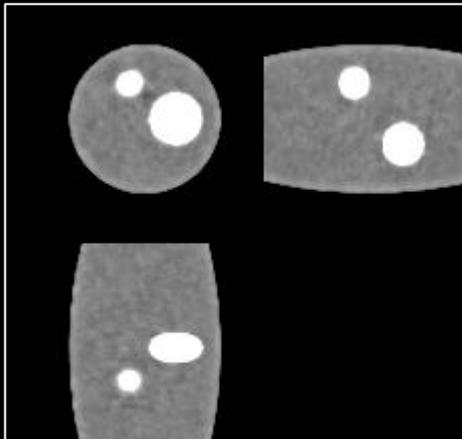
True image



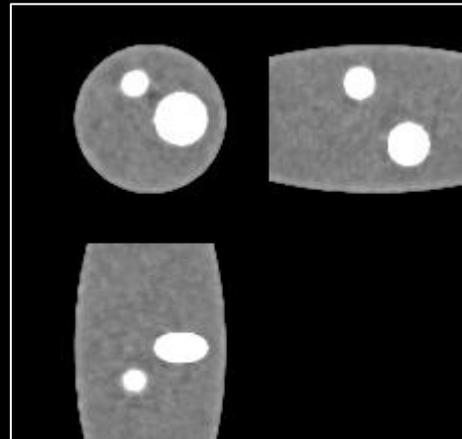
FDK (initial image)



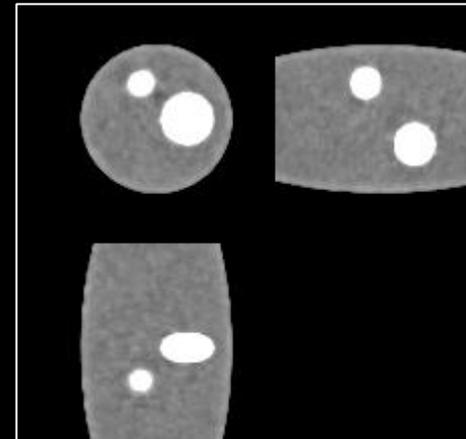
No gain correction



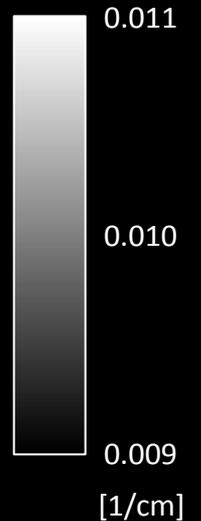
Blind gain correction



Non-blind gain correction



Reference recon.



0.011

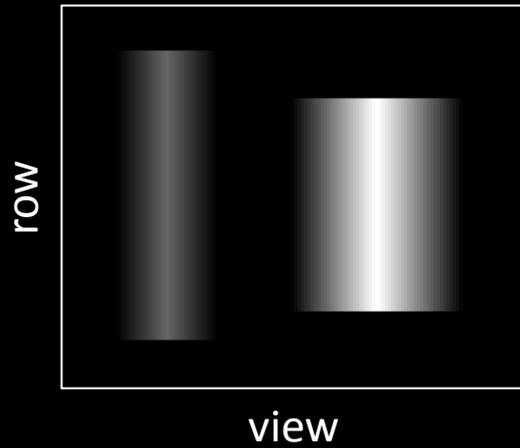
0.010

0.009

[1/cm]

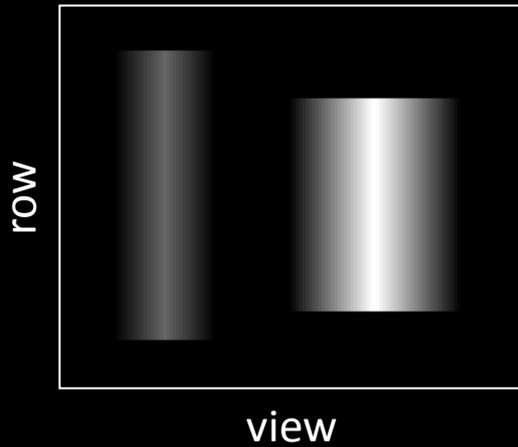
3D axial CT – using ADMM

True gain

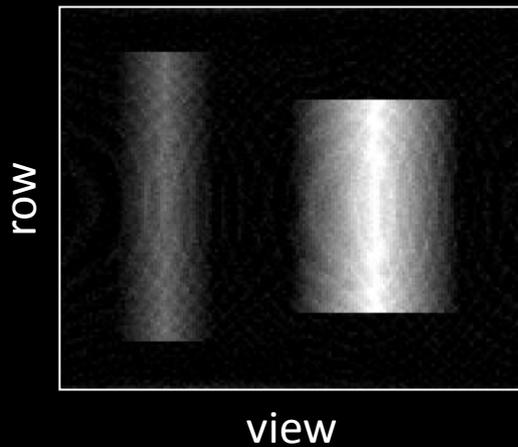


3D axial CT – using ADMM

True gain

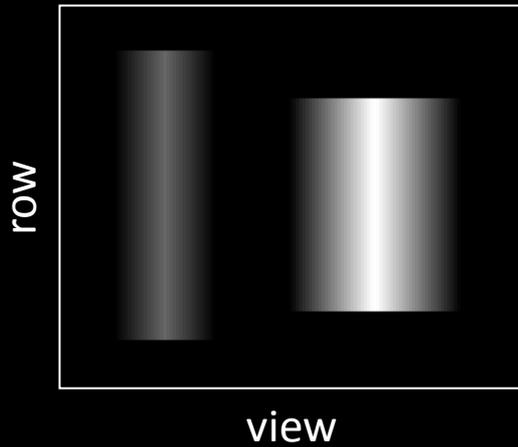


Est. gain (blind)

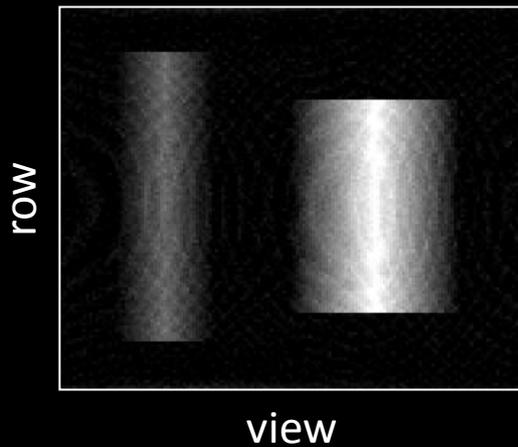


3D axial CT – using ADMM

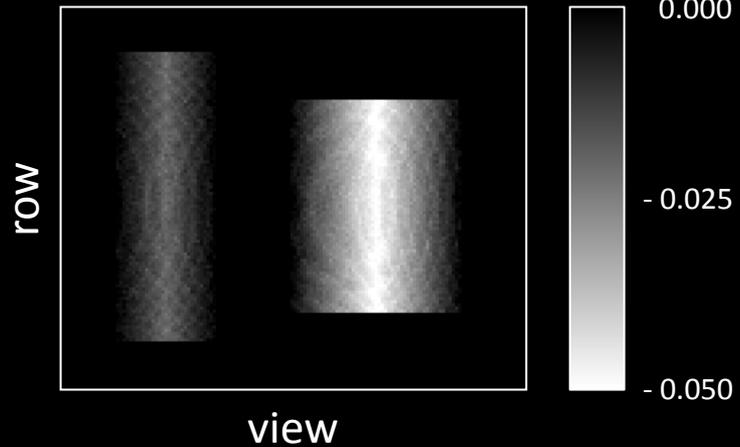
True gain



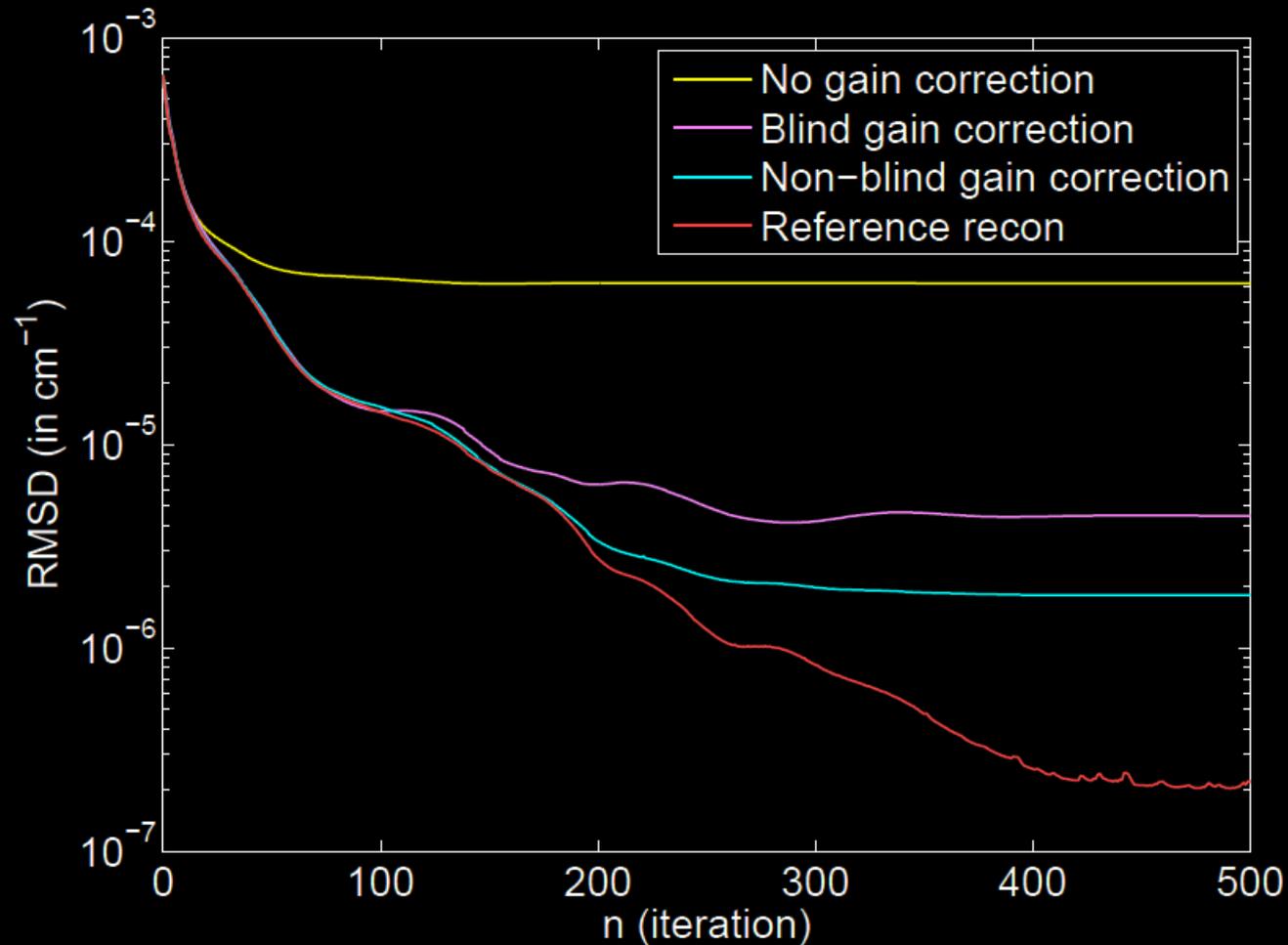
Est. gain (blind)



Est. gain (non-blind)



3D axial CT – using ADMM



3D helical CT – using OS-SQS

3D helical CT – using OS-SQS

Image:

512 x 512 x 109 patient (shoulder)

Voxel size: **1.3695 x 1.3695 x 0.6250 mm³**

Geometry:

888 x 32 x 7146 3D helical CT

Orbit: **2614°**

Pitch = **0.5312**

Detector channel spacing = **1.0239 mm**

Detector row spacing = **1.0964 mm**

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512 x 512 x 109 patient (shoulder)

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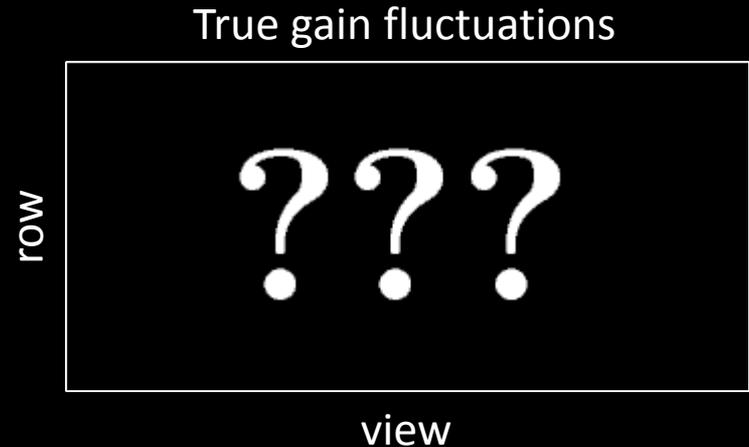
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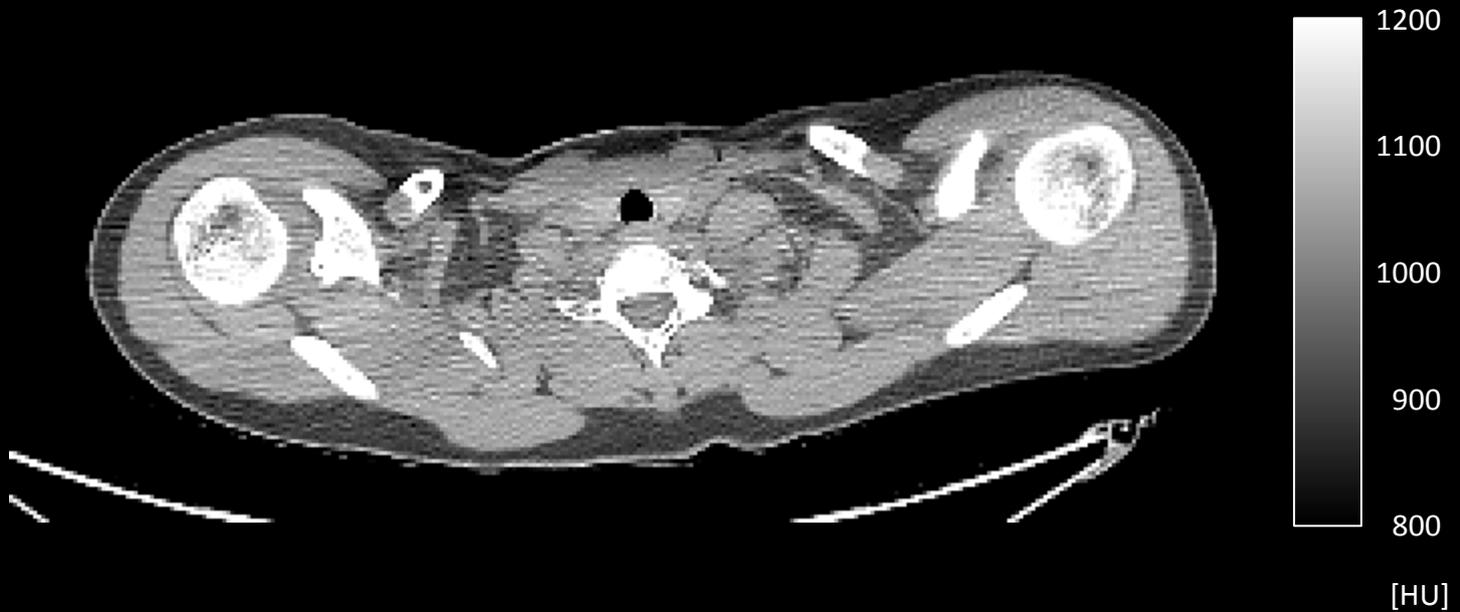
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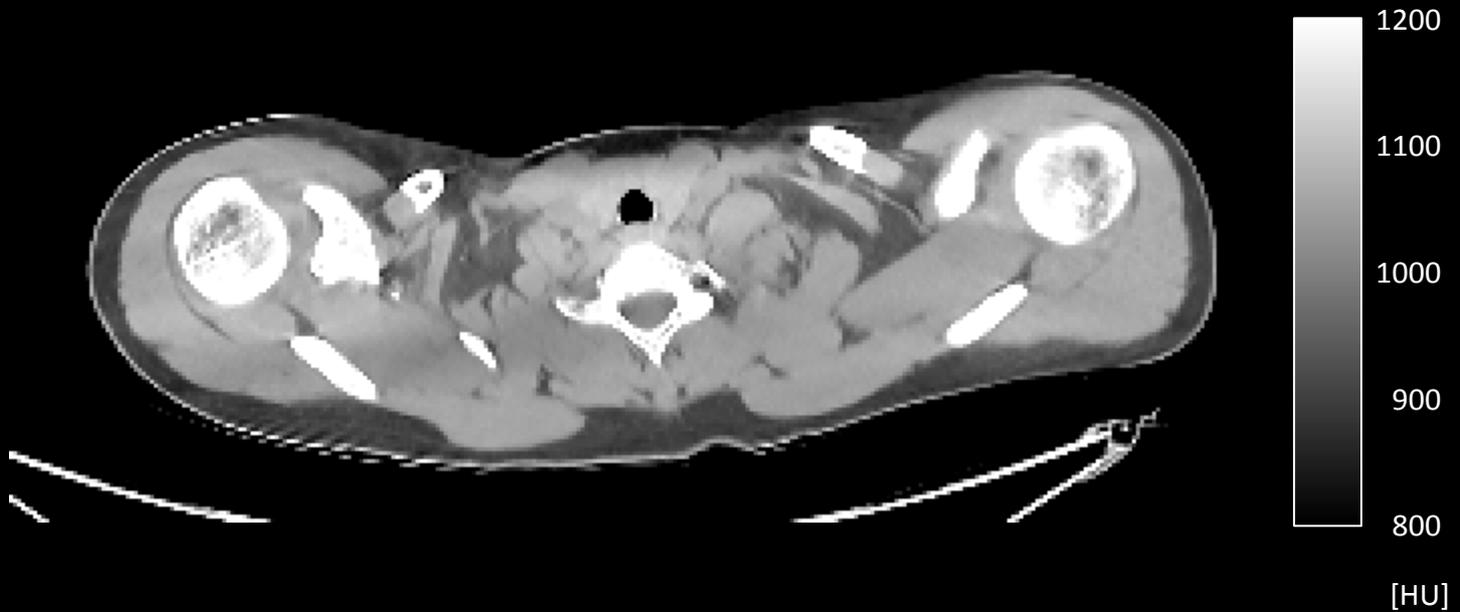
3D helical CT – using OS-SQS

Transaxial plane: FDK reconstruction



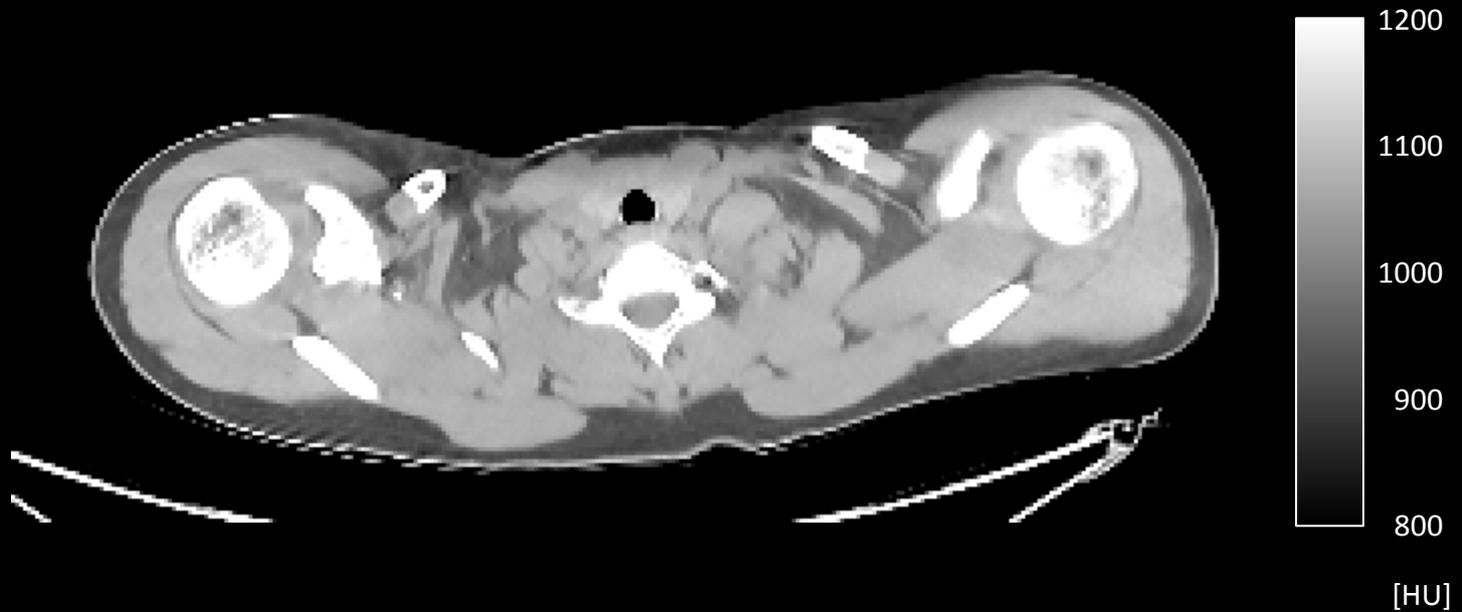
3D helical CT – using OS-SQS

Transaxial plane: OS-SQS-41 reconstruction (w/o gain correction)



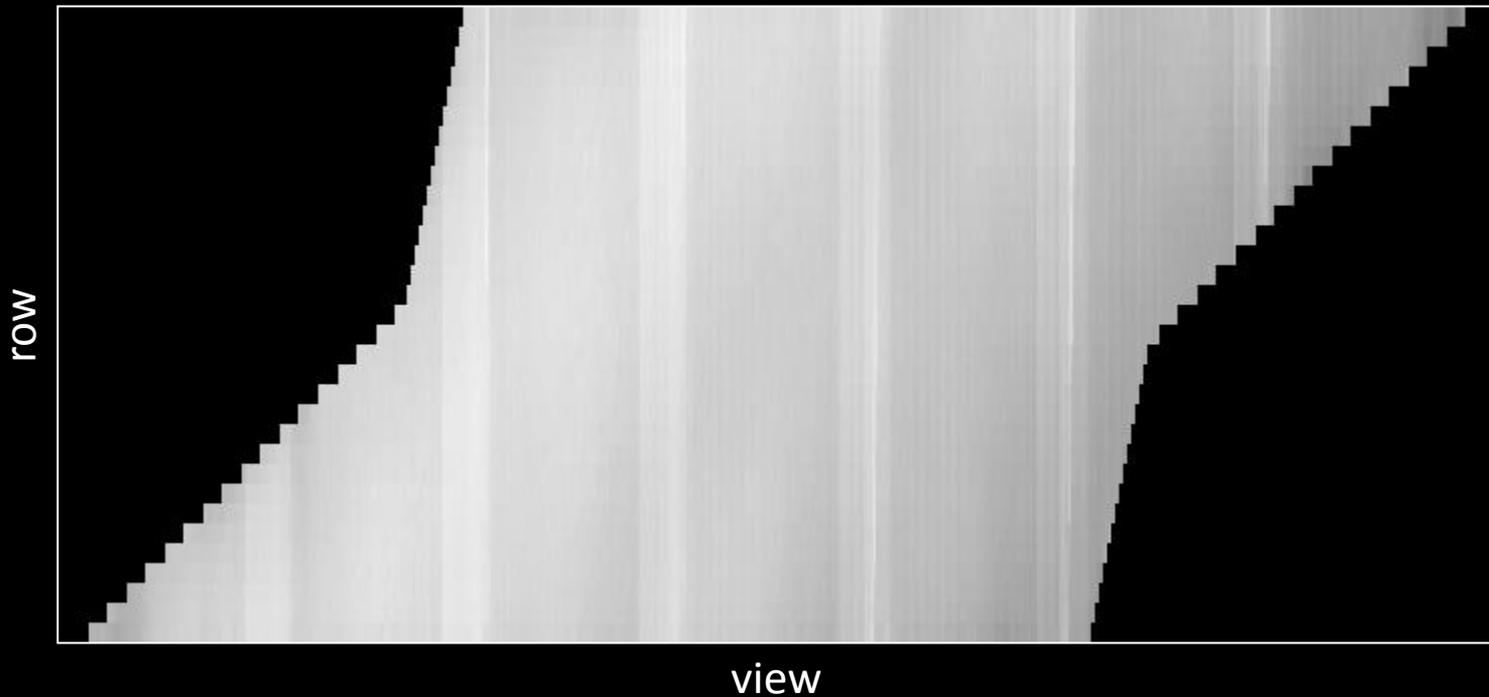
3D helical CT – using OS-SQS

Transaxial plane: OS-SQS-41 reconstruction (w/ blind gain correction)



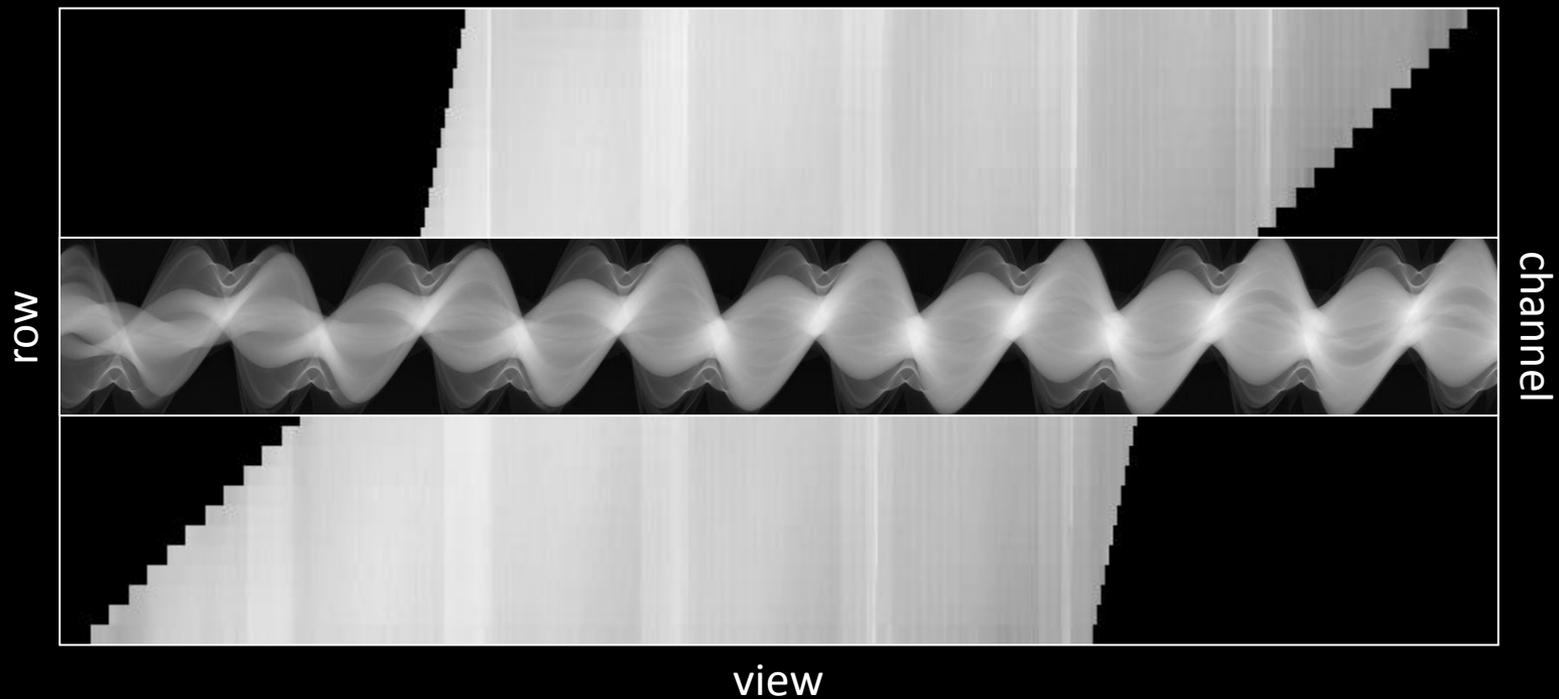
3D helical CT – using OS-SQS

Estimated gain fluctuations (blind gain correction)



3D helical CT – using OS-SQS

Estimated gain fluctuations (blind gain correction)



Outline

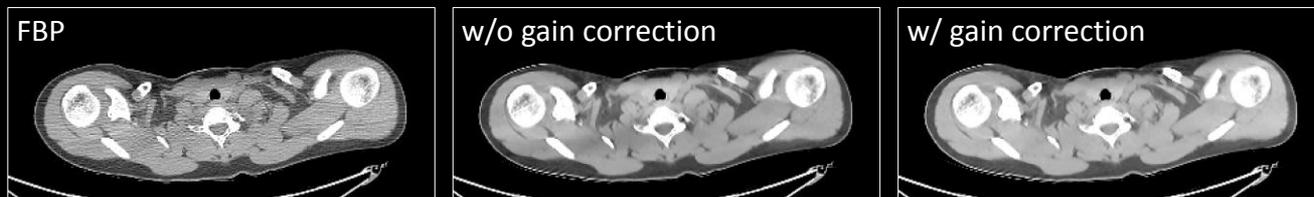
I. Description of purpose

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II. Method

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III. Results



IV. Conclusion

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Conclusion

- A **new variational formulation** for X-ray CT image reconstruction **with gain correction** is proposed
- Both **splitting-** and **OS-based** algorithms can be applied to the proposed formulation
- We've evaluated the proposed method with both **synthetic** and **real patient CT scans**
- Shading artifacts are **largely reduced** with **almost unchanged** complexity per iteration

