



GE Healthcare



Model Based Iterative Reconstruction With Spatially Adaptive Sinogram Weights for Wide-Cone Cardiac CT

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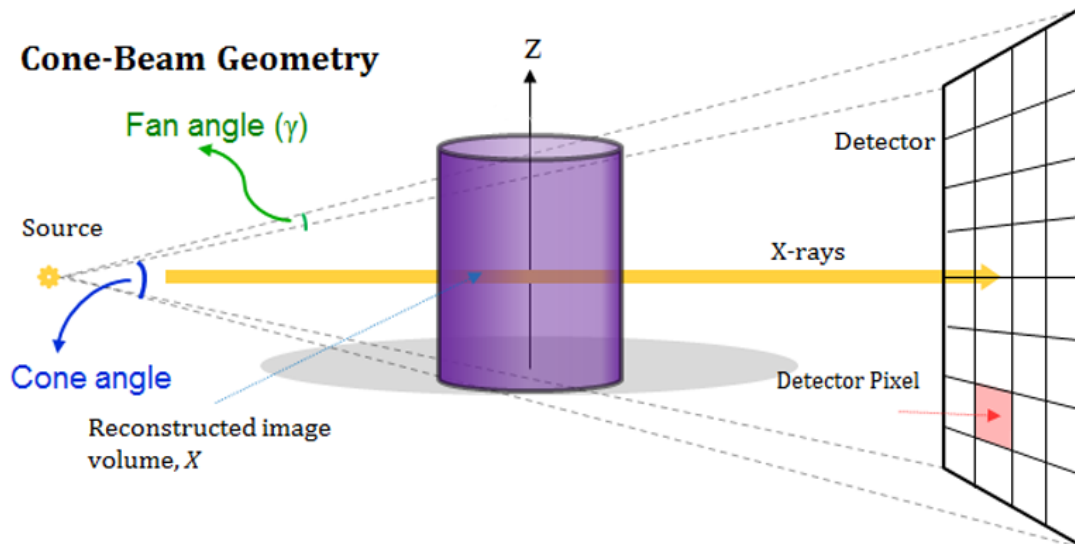
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- High Temporal Resolution For Cardiac CT
- Full-scan vs Half-scan Cardiac CT
- Spatially Adaptive sinogram Weighting MBIR (SAW-MBIR)
- Results
- Conclusions

Wide cone detector: image heart in a single rotation

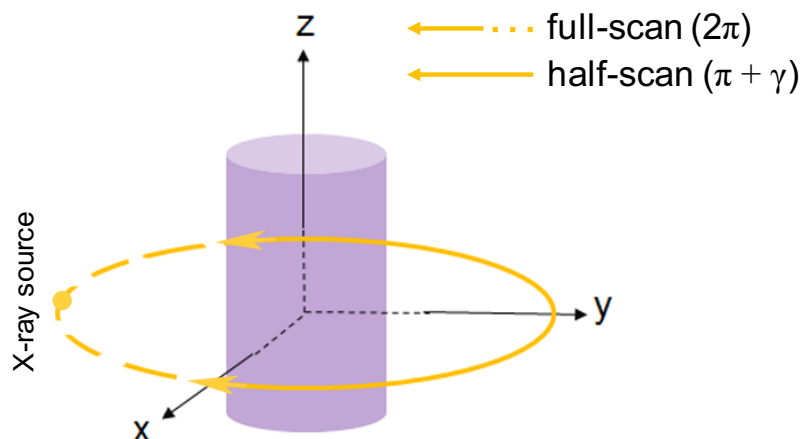


Full scan: Rotation of 2π

- Full ROI with suboptimal temporal resolution

Half-scan: Rotation of $\pi + \gamma$

- Smaller ROI with better temporal resolution

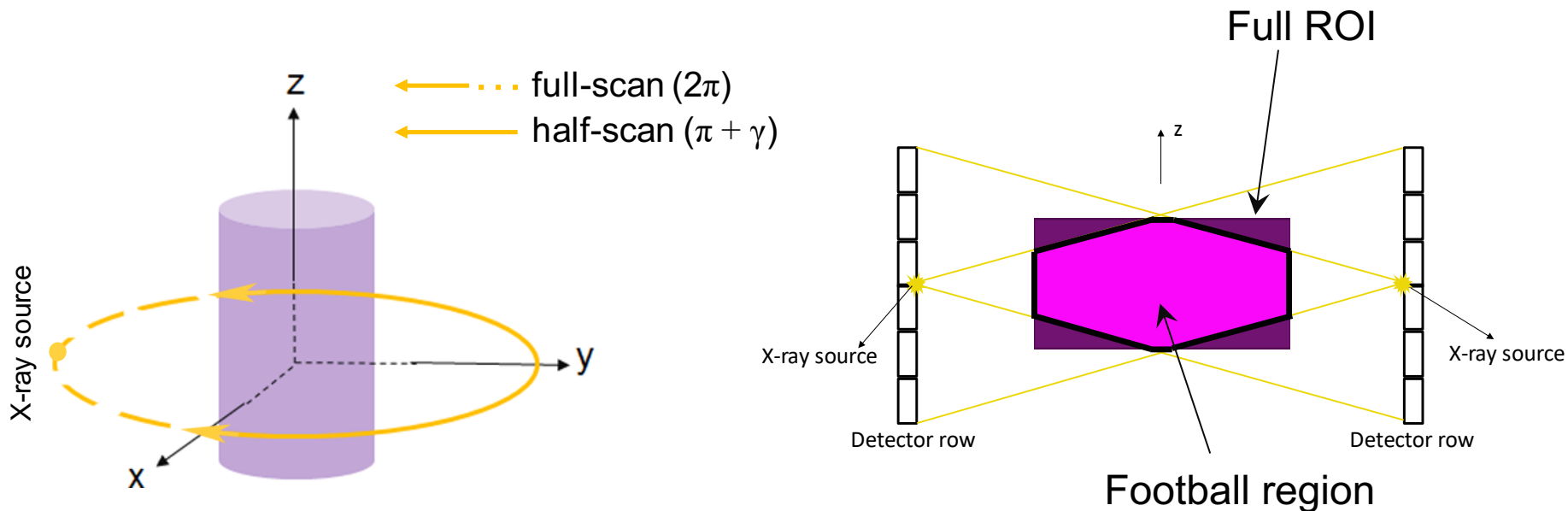


❑ Football region:

- Fully sampled by a half-scan

❑ Full ROI:

- **Not** fully sampled by half-scan





Our Goals



- Reconstruct full ROI with high temporal resolution:
 - Eliminate any motion artifacts
 - Properly reconstruct edges of ROI
 - Achieve this with a single reconstruction

- Several FBP based approaches exist in literature**
 - J. D. Pack, et al., Fully 3D , 2013.
 - J. Tang, et al., Medical Physics, 2010.
 - B. Chiang, et al., Nuclear Science

- Use full-scan as prior model for half-scan recon**
 - J. H. Cho, dissertation, 2014.

- Use additional full-scan measurements to extrapolate the half-scan measurements and statistical weights for reconstruction outside football region**
 - J. H. Cho, dissertation, 2014.

- Separate full-scan and half-scan reconstruction and merge the results**
 - Proposed in: J. H. Cho, dissertation, 2014.
 - Computationally expensive



Our approach

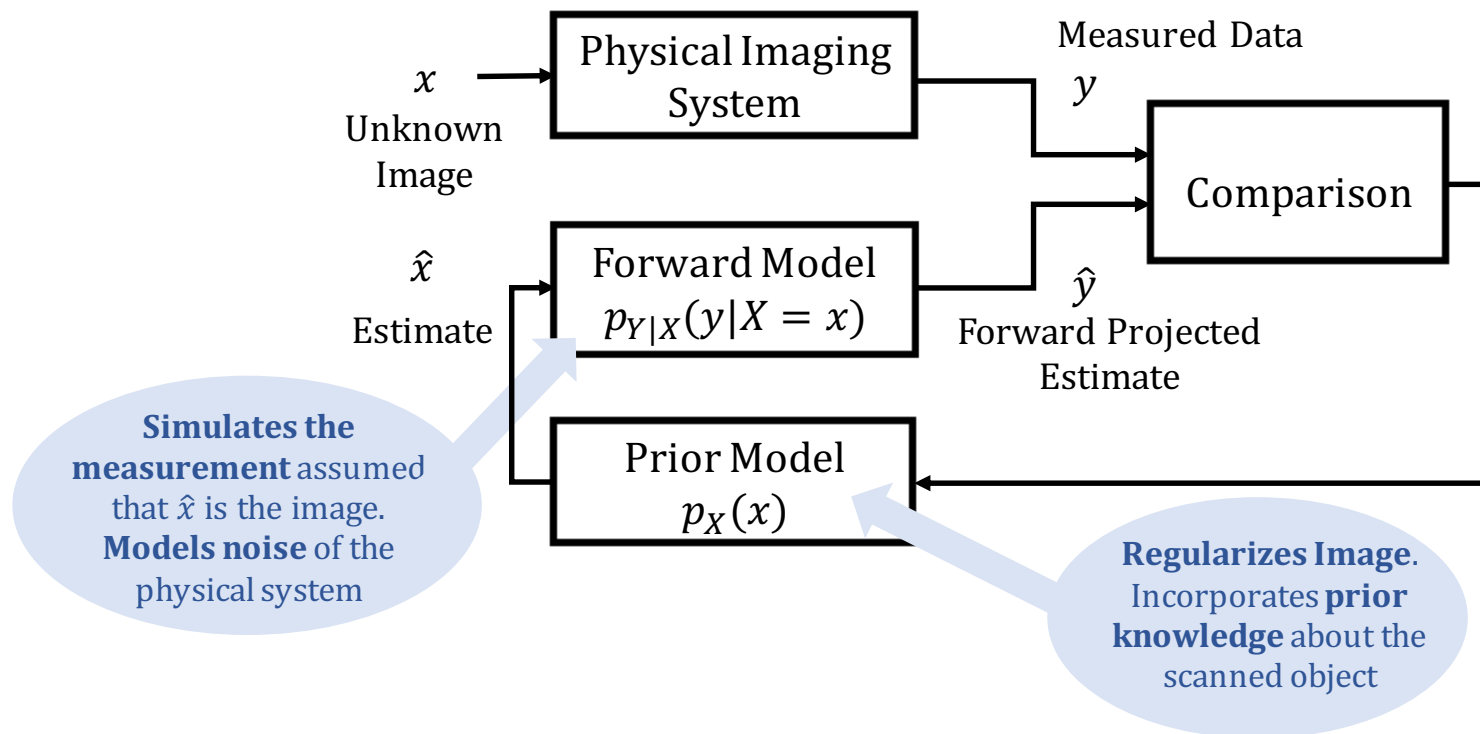


- **SAW-MBIR:**

Spatially Adaptive sinogram Weighting MBIR

- Idea:

Compute MBIR reconstruction with **unmatched** forward and back projectors, where the **proposed back-projection operator selectively back-projects full-scan data to improve temporal resolution in football region and maintain high quality outside football region**



Solution to inverse problem: **maximum a posteriori** estimate

$$\hat{x}_{\text{MAP}} = \arg \max_{x \geq 0} \{p_{X|Y}(x|Y)\} = \arg \min_{x \geq 0} \{-\log p_{Y|X}(Y|x) - \log p_X(x)\}$$

$$= \arg \min_{x \geq 0} \{\|Y - Ax\|_W^2 + \Phi(x)\}$$



Traditional Gradient Descent for MBIR



□ $y = Ax$ $A \in \mathbb{R}^{M \times N}, x \in \mathbb{R}^N, y \in \mathbb{R}^M$

□ MAP cost function:

$$\hat{x} \leftarrow \arg \min_x f(x) = \frac{1}{2} \|y - Ax\|_W^2 + \Phi(x)$$

Gradient Descent Algorithm For MBIR

$y \leftarrow$ measured sinogram

$x^0 \leftarrow$ FBP

$\alpha \leftarrow$ step size

For k iterations {

$$g^k = \nabla f(x) = -A^T W (y - Ax^k) + \nabla \Phi(x^k) \quad \text{Gradient of the Cost function}$$

$$x^{k+1} = x^k - \alpha g^k$$

}

$y = \begin{bmatrix} y_h \\ y_{h'} \end{bmatrix}$ – full data

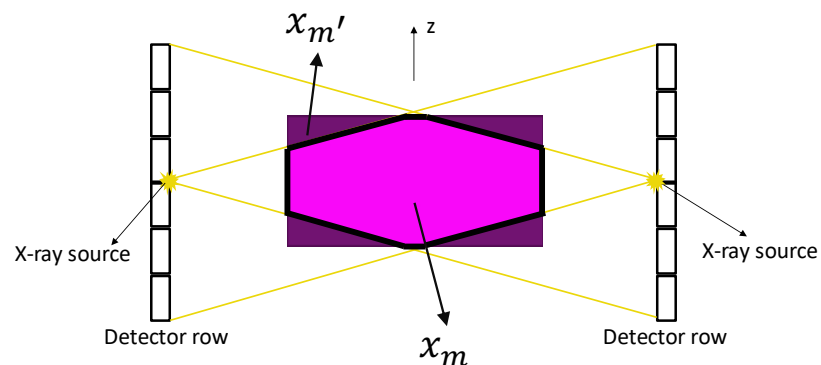
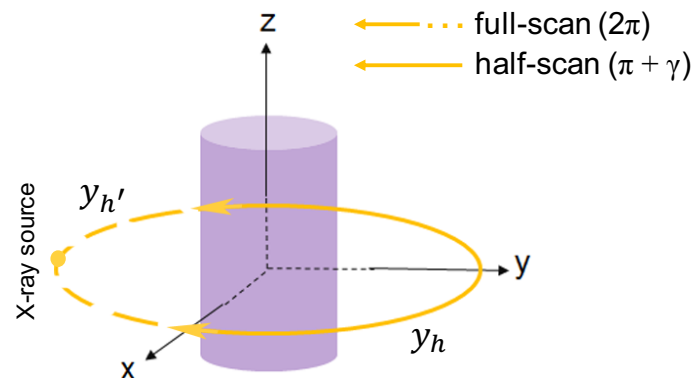
y_h – half scan data

$y_{h'}$ – residual data

$x = \begin{bmatrix} x_m \\ x_{m'} \end{bmatrix}$ – complete image

x_m – football image

$x_{m'}$ – residual image





Block Structured Forward Projector



- Forward projector

$$y = Ax$$

- Block structure forward projector

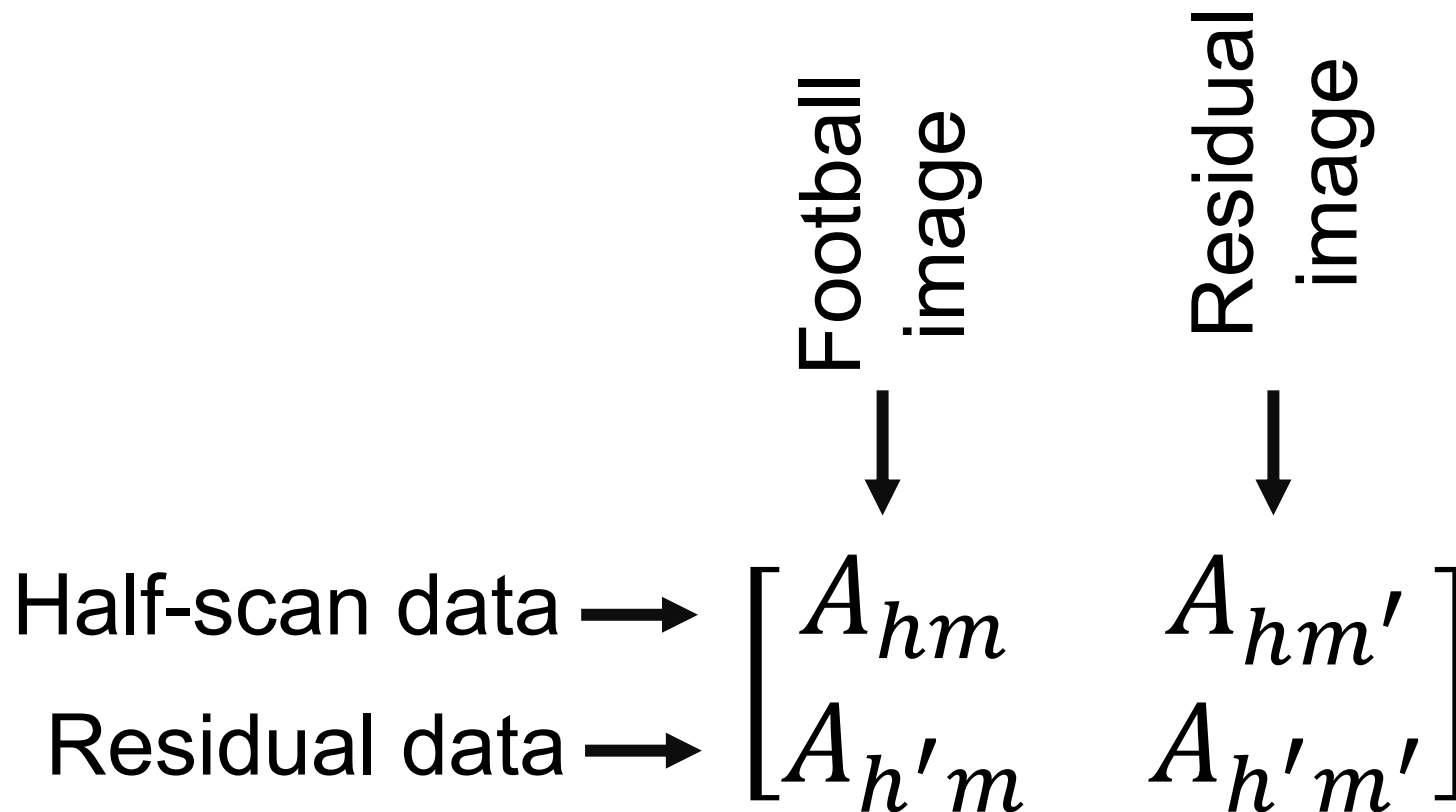
$$A = \begin{bmatrix} A_{hm} & A_{hm'} \\ A_{h'm} & A_{h'm'} \end{bmatrix}$$

where

$$\begin{array}{l} \text{Half-scan data} \rightarrow \\ \text{Residual data} \rightarrow \end{array} \begin{bmatrix} y_h \\ y_{h'} \end{bmatrix} = \begin{bmatrix} A_{hm} & A_{hm'} \\ A_{h'm} & A_{h'm'} \end{bmatrix} \begin{bmatrix} x_m \\ x_{m'} \end{bmatrix} \begin{array}{l} \leftarrow \text{Football image} \\ \leftarrow \text{Residual image} \end{array}$$

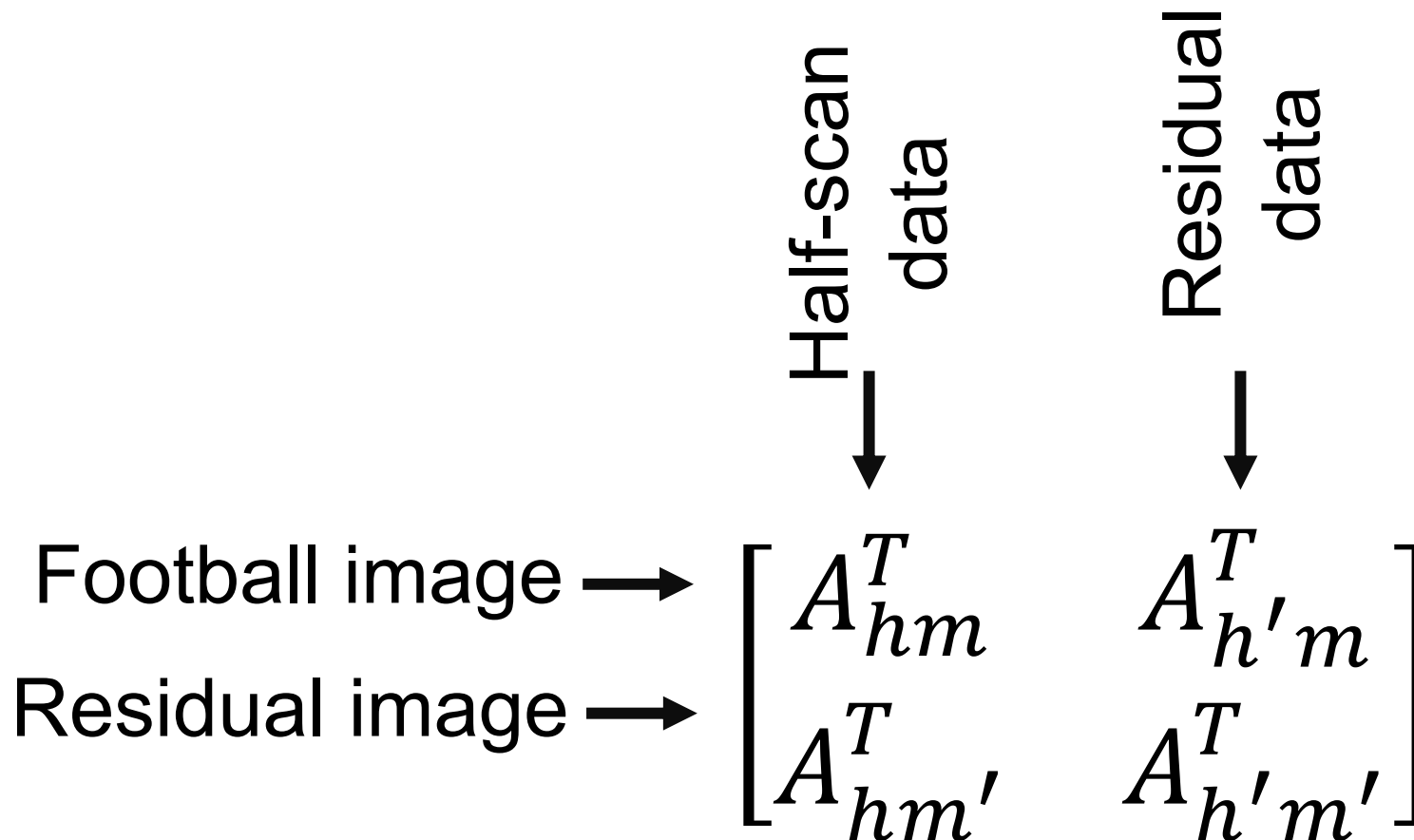


Complete Forward Projector



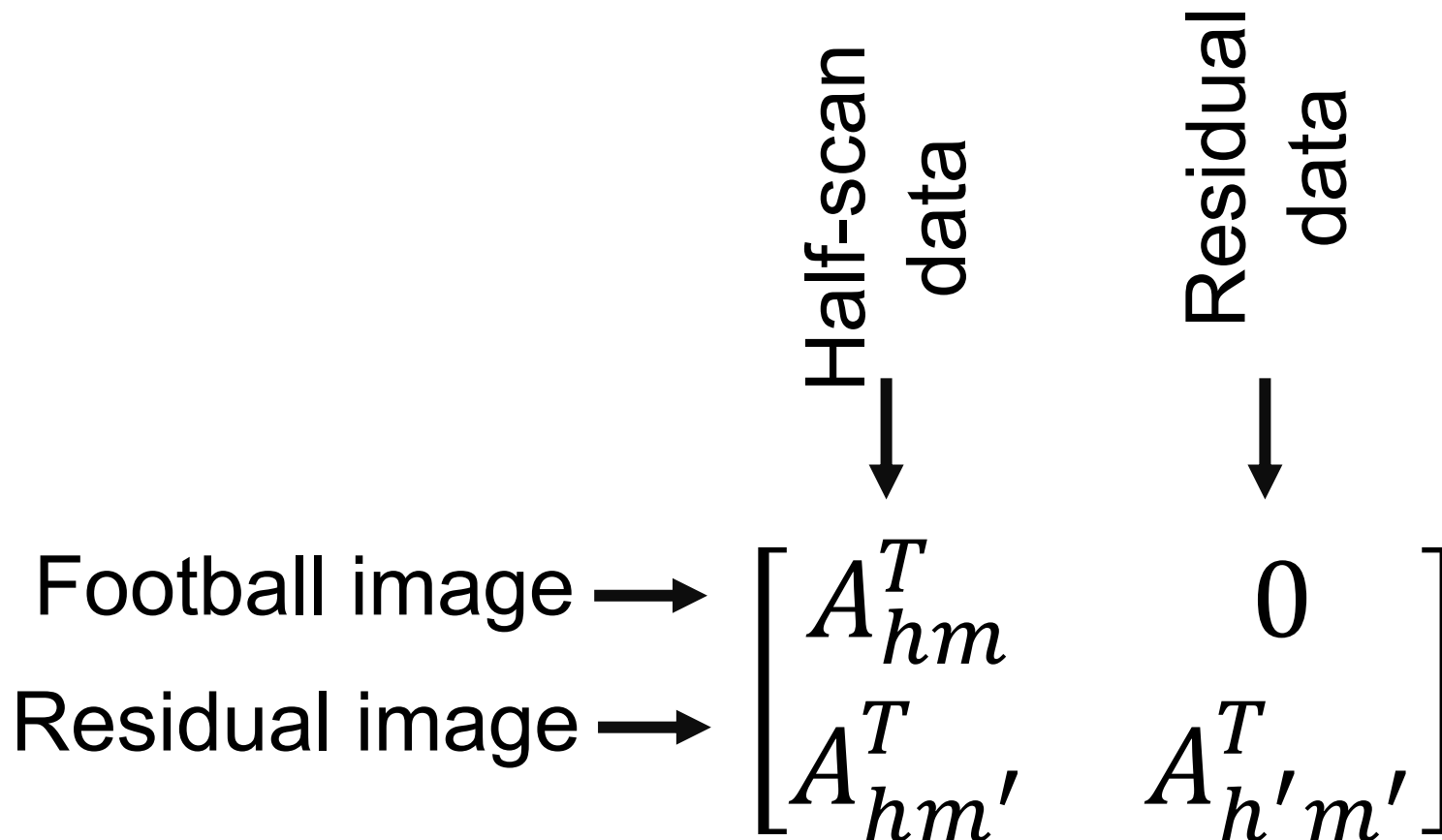


Complete Back Projector





Masked Back Projector



Residual data is not back projected to football image



Key idea: Residual full scan data is not back projected to football image

$$A_{mask}^T = \begin{bmatrix} A_{hm}^T & 0 \\ A_{hm'}^T & A_{h'm'}^T \end{bmatrix}$$

“Pseudo-Gradient” is given by

$$g_s^k = -A_{mask}^T W(y - Ax) + \nabla \Phi(x)$$

- New **SAW-MBIR** algorithm: Spatially Adaptive sinogram Weighting MBIR

$$A_{mask}^T = \begin{bmatrix} A_{hm}^T & 0 \\ A_{hm'}^T & A_{h'm'}^T \end{bmatrix}$$

Pseudo-Gradient Descent Algorithm

$y \leftarrow$ measured sinogram

$x^0 \leftarrow$ FBP

$\alpha \leftarrow$ step size

For k iterations {

$$g_s^k = -A_{mask}^T W(y - Ax) + \nabla \Phi(x)$$

$$x^{k+1} = x^k - \alpha g_s^k$$

}

pseudo - Gradient

This algorithm does not minimize a cost function

Any fixed point, x , has the properties that

$A_{mask}^T(y - Ax) = \nabla\Phi(x)$

Interpretation: Prior gradient balances pseudo-gradient

Convergence

Empirically observed to converge

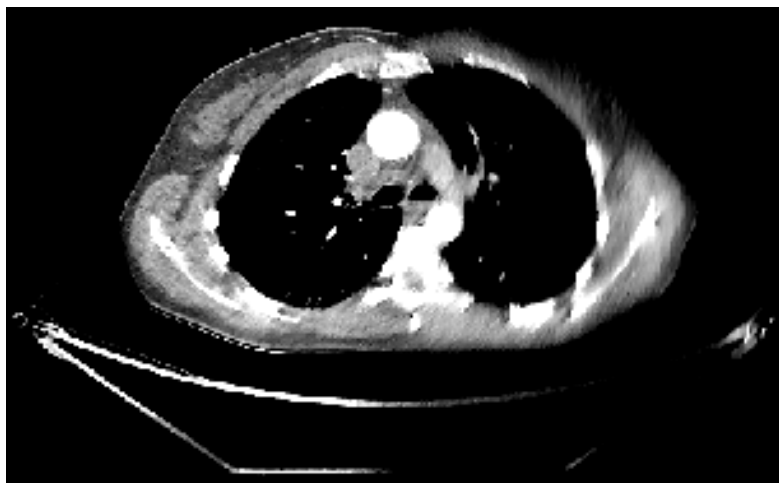
Sufficient condition: Converges if f is a contraction mapping where

$$f(x) = x + \alpha[A_{mask}^T W(y - Ax) - \nabla\Phi(x)]$$

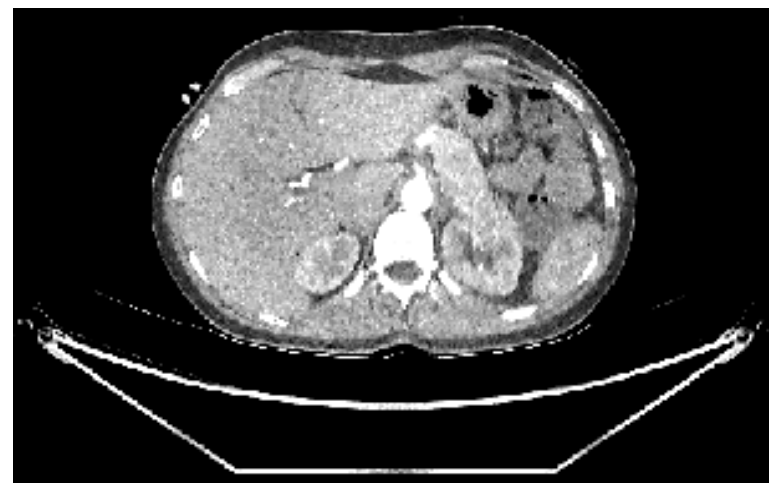
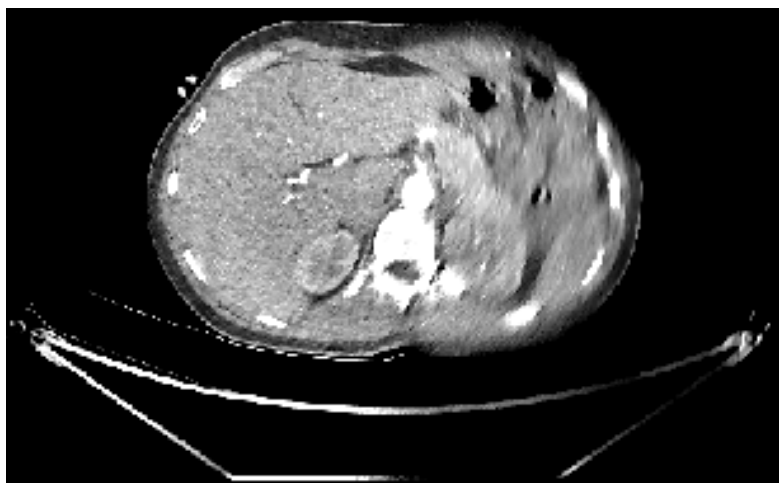
Half-scan

SAW-MBIR

Top slice



bottom slice



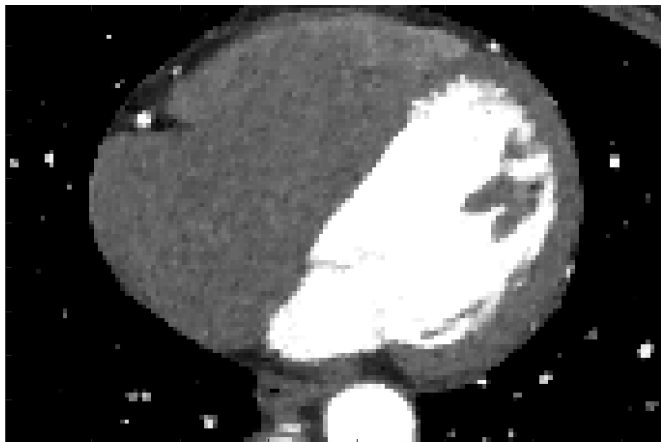
Half-scan

SAW-MBIR

Center slice

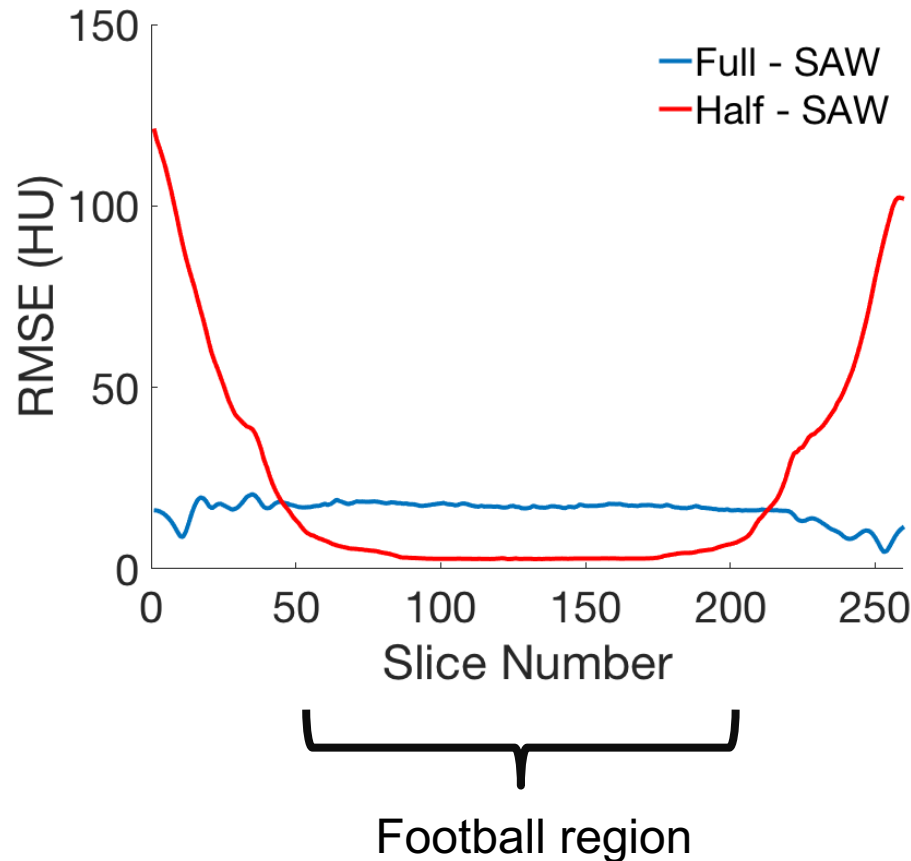


Center slice





Achieves best of Half and Full Scan Recons



○SAW-MBIR:

- Matches half-scan recon inside football
- Matches full-scan recon outside football

SAW-MBIR:

- Maintains same temporal resolution as half-scan MBIR
- Maintains same image quality as full-scan MBIR at the edge slices
- Empirically observed to converge to a fixed point

Future directions:

- Apply to spatially localized image artifacts/degradations
- Extend theory to better understand convergence properties



Thank You