Limited View Angle Iterative CT Reconstruction

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Introduction: Security vs. Medical applications of X-ray CT

- Object scene is vastly different
  - Passenger bags may contain almost anything
  - In security applications, objects of interest often fall within a highly cluttered scene which distorts morphology and quantitative measures in the reconstruction
- Throughput is a primary driver
  - System must process a constant flow of scan objects (e.g. bags or cargo containers)
  - Requires fast acquisition (perhaps sparsely sample limited angles) and fast reconstruction
  - Dosage is typically not a major concern, but high duty cycles requirements limit tube output and dense object reduce SNR.
- An important context for security applications is *limited view angle* projection reconstruction in *highly cluttered scenes*

Prior Literature in CT for Transportation Security

- General reviews of CT in transportation security
  - E.G. Riveros, “The digital radiographic and computed tomography imaging of two types of explosive devices,” *Applied Radiation and Isotopes*, vol. 57, pp. 861-865, 2002.
  - S. Singh and M. Singh, “Explosives detection systems (EDS) for aviation security,” *Signal Processing*, vol. 83, pp. 31-55, 2003.
  - Y. O. Yildiz, D. Q. Abraham, S. Agaian, and K. Panetta, “Bag Separation Algorithm,” Mobile Multimedia/Image Processing, Security, and Applications, SPIE vol. 6982, 2008.
  - S. M. Song, C. R. Crawford and D. P. Boyd, “Three-dimensional electronic unpacking of bags using 3-D images,” Computational Imaging VII, SPIE vol. 7246, 2009.
  - R. C. Smith and J. M. Connelly, “CT Technologies,” in *Aspects of Explosives Detection*, Elsevier 2009.
- Dual energy CT
  - Z. Ying, R. Nam and C. R. Crawford, “Dual energy computed tomography for explosive detection,” *Journal of X-Ray Science and Technology*, vol. 14, pp. 235-256, 2006.
  - M. Ellenbogen and R. Bijjani, “Liquids and Homemade Explosive Detection,” Optics and Photonics in Global Homeland Security V, SPIE vol. 7306, 2009.
- ART algorithm
  - H. Zhang, Y. Sun, and L. Wei, “Explosives Detection Method Based on Improved Algebraic Reconstruction Technique,” *Proceedings of the World Congress on Intelligent Control and Automation*, 2008.

Some Prior Literature in Limited View Tomography

- CT with limited-angle data and few views
  - IRR algorithm
    - Iterative Reconstruction-Reprojection (IRR) : An Algorithm for Limited Data Cardiac-Computed Tomography by M. Nassi et. Al. (1982)
  - ART algorithm
    - Accurate image reconstruction from few-views and limited-angle data in divergent-beam CT by E. Y. Sidky, CM Kao, and X. Pan (2006)
    - Few-View Projection Reconstruction With an IRR Algorithm and TV Constraint by X. Duan et. al. (2009)
  - Bayesian algorithm
    - Globally Convergent Edge-Preserving Regularized Reconstruction: An Application to Limited-Angle Tomography by A.H. Delaney and Y. Bresler (1998)
    - Bayesian approach to limited-angle reconstruction in computed tomography by K. M. Hanson and G. W. Wecksung (1983)

Objectives

- We compare three reconstruction algorithms:
  1. Filtered backprojection (FBP)
  2. Model based iterative reconstruction (GMRF prior)
  3. Model based iterative reconstruction (qGGMRF prior)
- Evaluate degradation as number of projection angles decreases
- Evaluate the effect of background clutter on CT accuracy

Model-Based Image Reconstruction

- Compute the “best” reconstruction given the data and the assumed statistics of the image
- Uses iterative process to fit reconstruction to measurements
- Typically more robust compared to filtered back-projection (FBP)

MAP Reconstruction

- A classical approach to model-based inversion (i.e. CT reconstruction) is the maximum a posteriori (MAP) estimate

Data term **Prior term**

$$\hat{x}_{MAP} = \arg\max_{x \geq 0} \{ \log p(y \mid x) + \log p(x) \}$$

  - *y* is the projection measurement vector and x is an image vector
  - p(y|x) is the forward projection model
  - p(x) is the prior distribution which regularizes the reconstructed image

- Reconstruction typically proceeds by optimizing an objective function that incorporates an accurate forward projection model, a noise model, and a prior model.

MAP objective function

- In this study, we use a 2nd order Taylor series expansion to approximate the data term, resulting in

$$\hat{x}_{MAP} = \underset{x \geq 0}{\operatorname{argmin}} \left\{ \frac{1}{2}(y - Ax)^t D(y - Ax) + \log p(x) \right\}$$

  - *A* is the forward system matrix, and *D* is a diagonal weighting matrix.
  - The matrix *D* is given by $D = diag(\lambda_1, \lambda_2, ..., \lambda_N)$, where
  - λ_T is the initial photon counts at the source

$$\lambda_i = \lambda_T e^{-y_i}$$

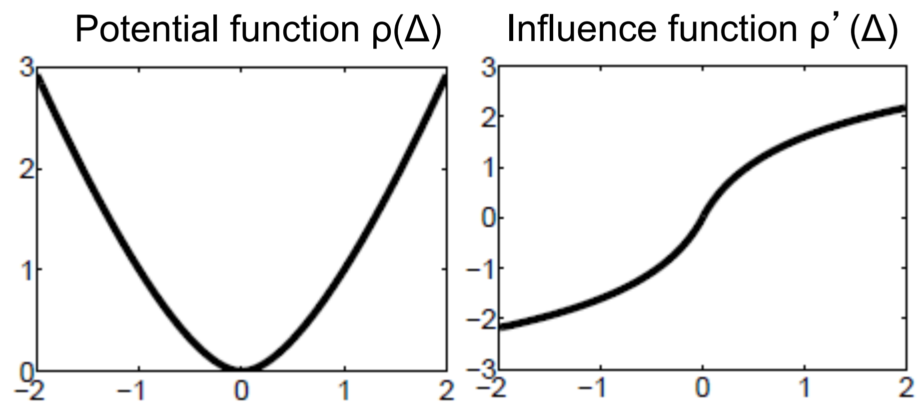
- MAP optimization
  - Optimization performed using Iterative Coordinate Descent (ICD)
  - The ICD method is a greedy strategy which updates locally with respect to each pixel

Q-Generalized Gaussian MRF prior

- Define x_s-x_r as Δ. The q-generalized Gaussian Markov random field prior (qGGMRF) prior is defined as

$$p(x) = \frac{1}{z}\exp\left\{ -\frac{1}{q\sigma_x^q} \sum_{\{s,r\}\in C} g_{s,r}\rho(\Delta) \right\}$$

where $$\rho(\Delta) = \frac{|\Delta|^p}{1+\left|\frac{\Delta}{c}\right|^{p-q}}$$



p=2.0, q=1.2, and c=1.0 case

- This model controls both low-contrast and high-contrast behavior
- The parameter *c* determines the transition point
- $If\ |\Delta|<c\quad then\quad \rho(\Delta)\approx|\Delta|^p$ and $If\ |\Delta|>c\quad then\quad \rho(\Delta)\approx|\Delta|^q$
- The Gaussian MRF (GMRF) prior is the special case where p=q=2, i.e. $\rho(\Delta)=\Delta^2$

Ground truth for simulations

Image attributes :

- CT bag scan
- Masked to remove original CT artifacts
- Assumed FOV of 80 cm
- Values linearly scaled to attenuation bounded by air and iron at 300KeV.

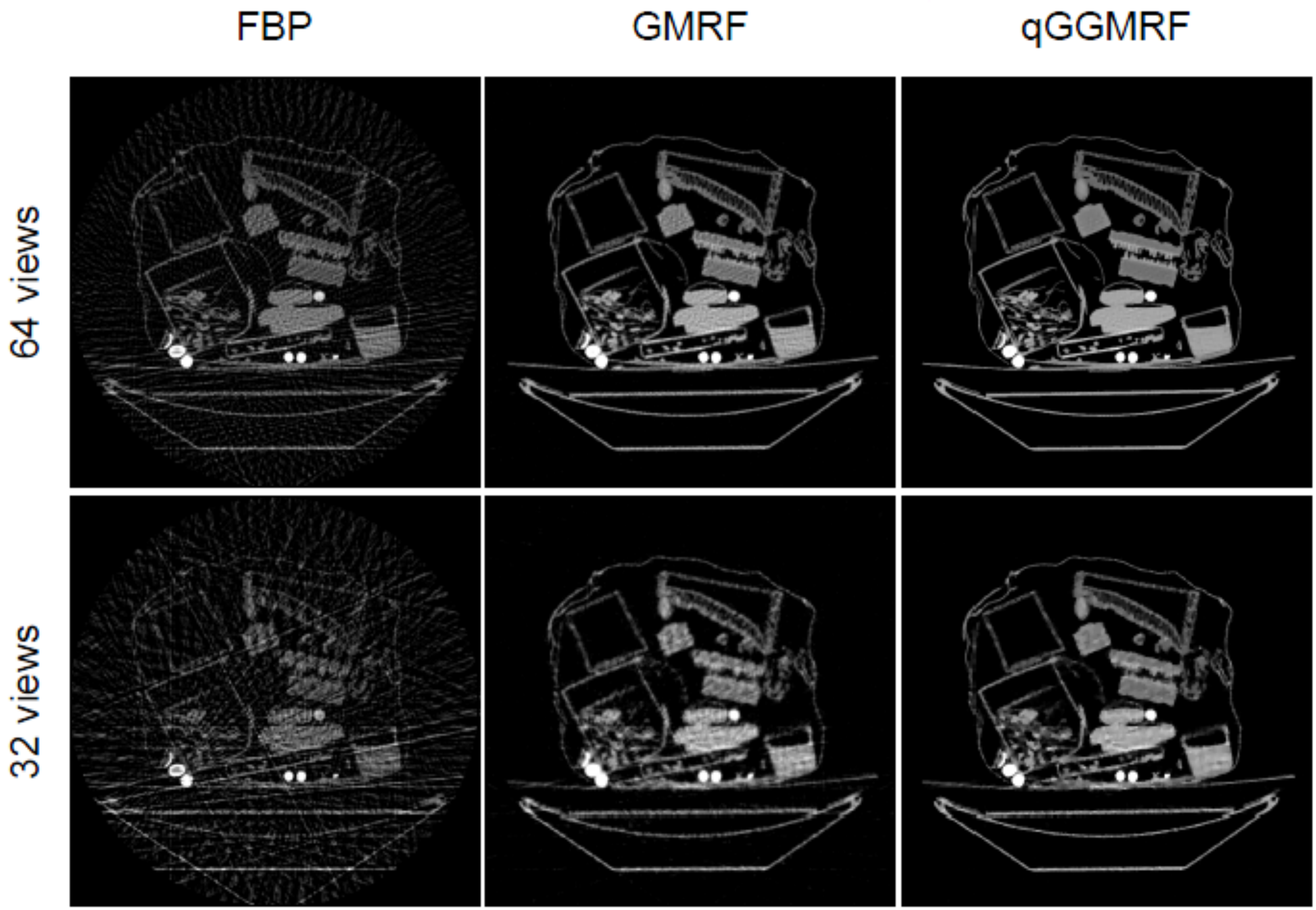
Original Image

Quality measures

- Visual image quality comparison
- Root mean-square error (RMSE) of reconstruction compared to ground truth
- Simulated target of known value inserted into ground truth at random location, evaluate accuracy of reconstructed CT numbers in target region

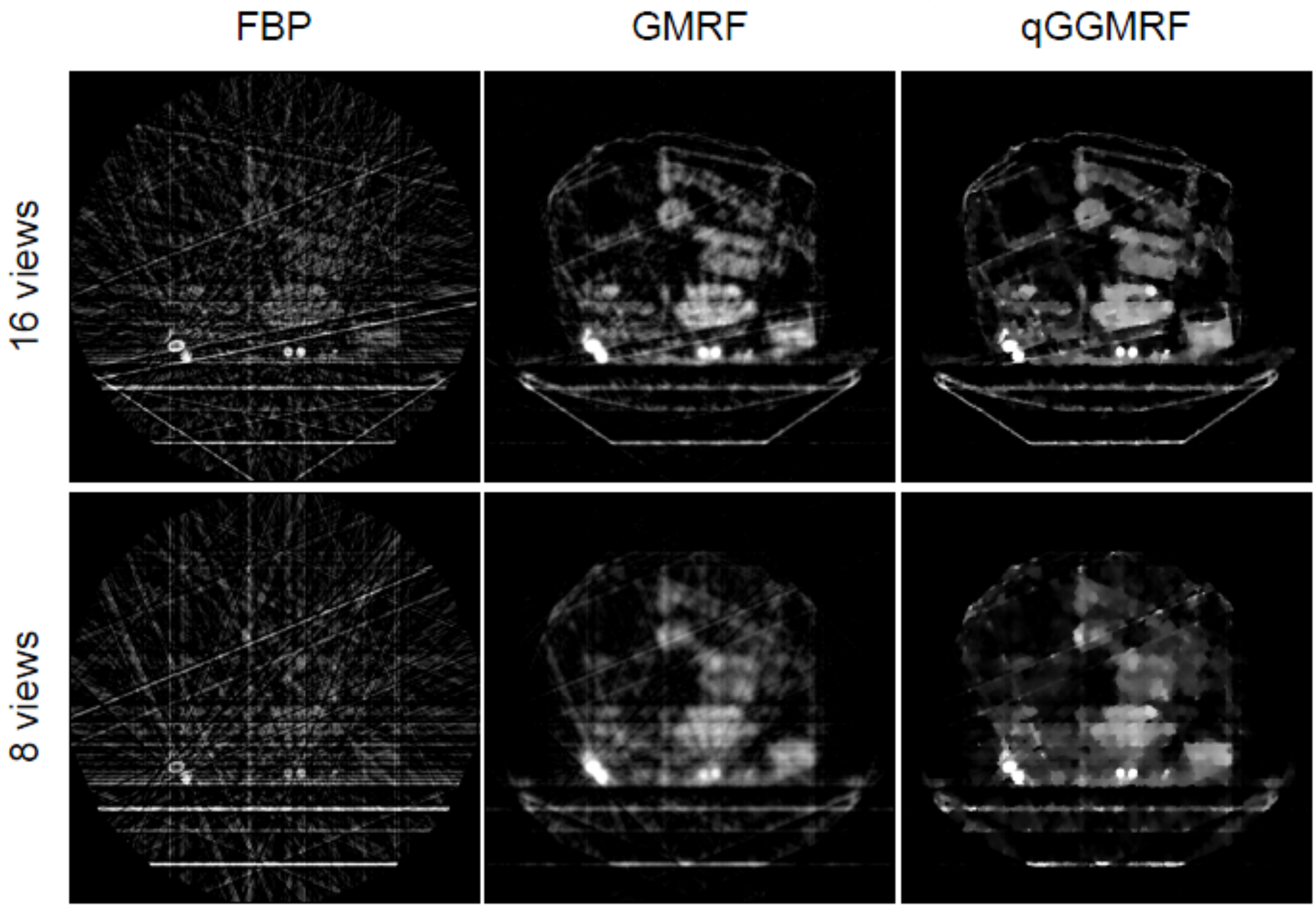
Reconstructions

- p=2, q=1, c=15 HU
- 1.0 mm voxel size
- gray map [0,2000] HU



Reconstructions

- p=2, q=1, c=15 HU
- 1.0 mm voxel size
- gray map [0,2000] HU



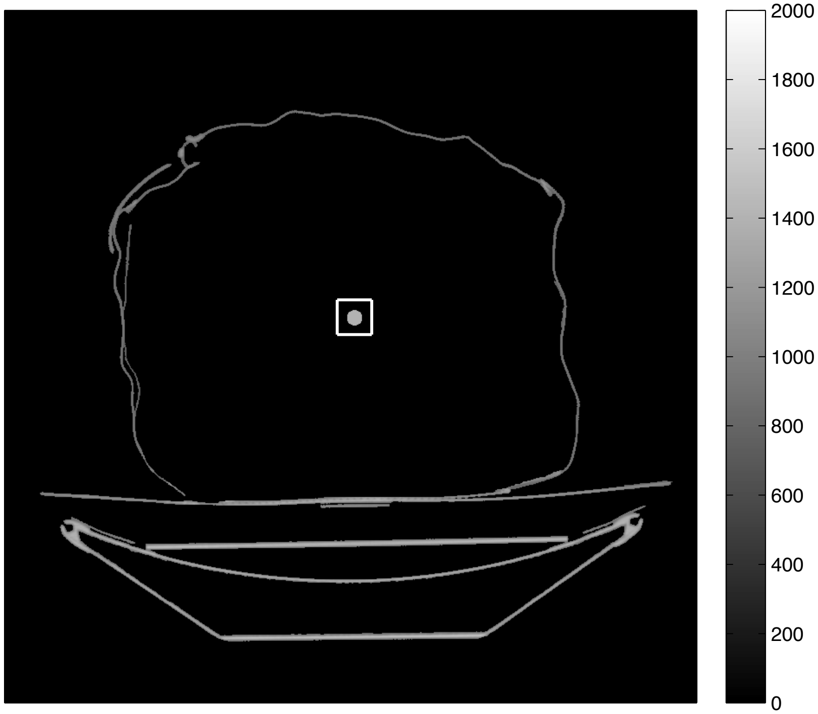
Reconstruction error

- Root mean-square error from ground truth for previous set of reconstructions

no. of views	FBP	GMRF	qGGMRF
64	481.0	237.8	112.8
32	628.4	361.1	277.1
16	746.2	498.9	453.8
8	854.4	607.1	598.5

Simulated target in low/high clutter background

- Round 1.7 cm diameter target of uniform value (1400 HU)

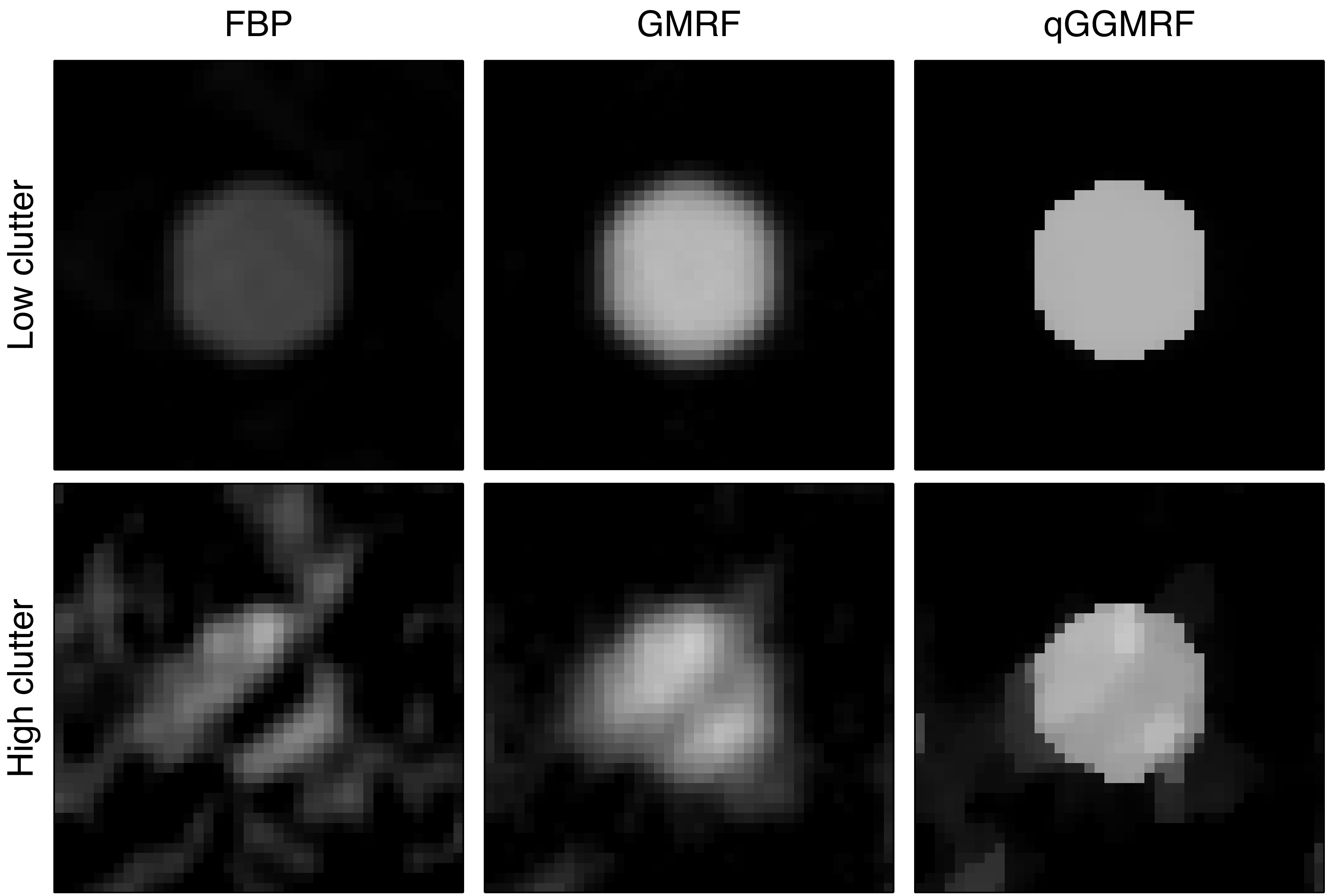


low clutter

high clutter

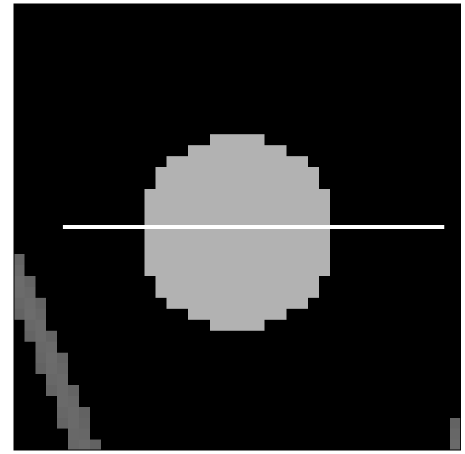
Target reconstructions

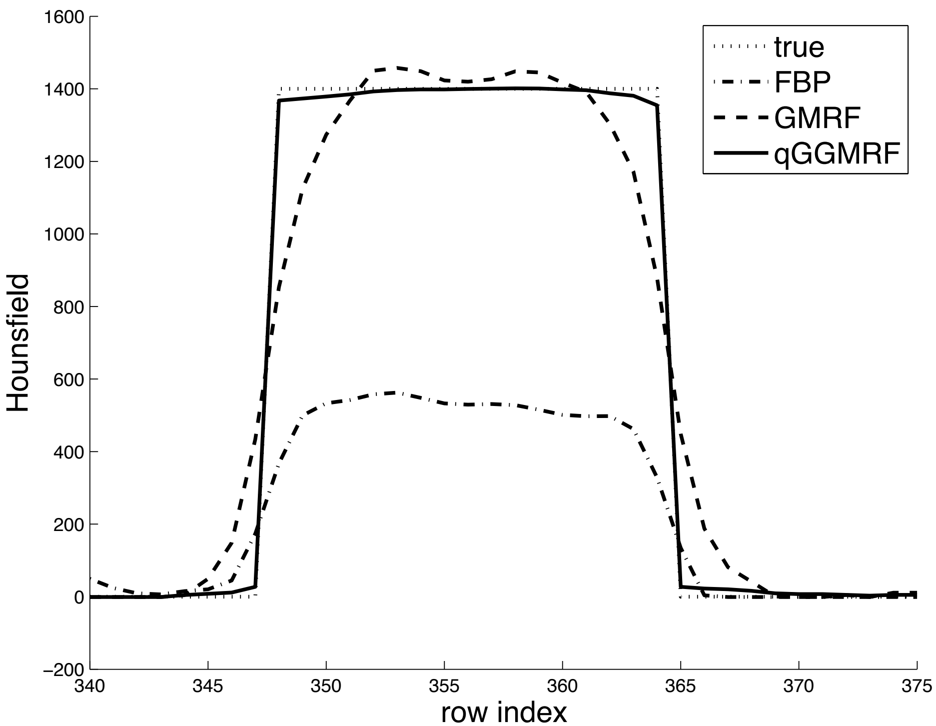
- 1.0 mm voxel size
- gray map [0,2000] HU



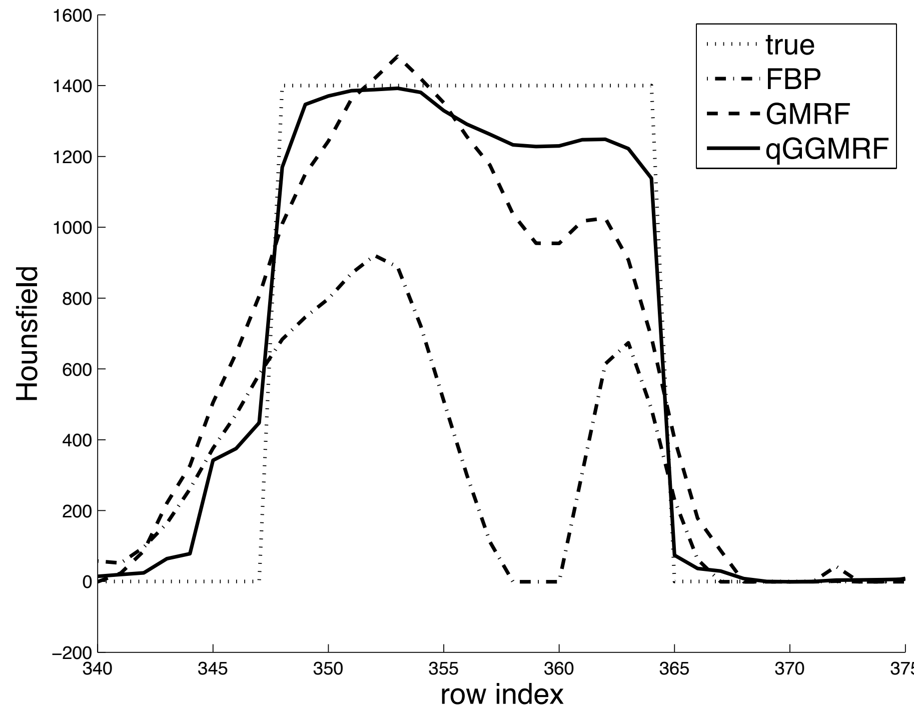
Reconstructed CT numbers

- Target CT Values along reference line





low clutter



high clutter

Evaluation metrics

- Averaged over 20 trials of random target position and orientation angle
- Includes average deviation of target pixels (from 1400 HU), and root mean-square error of target pixels

	Low clutter		High clutter	
	Dev.	RMSE	Dev.	RMSE
FBP	-895.1	899.1	-647.8	702.7
GMRF	-157.2	280.4	-179.8	332.7
qGGMRF	-14.2	25.8	-87.3	209.2

Conclusions

- Model based iterative reconstruction shows resiliency in reconstruction accuracy to both limited angle projection data and to background clutter
- Such properties make the methodology attractive to certain applications in the field of transportation security

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