Metal Artifact Reduction in CT-based Luggage Screening

Project Review for Reconstruction Initiative

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Executive Summary

- We use numerical optimization to reconstruct an intermediate image, forward-project this intermediate image, and these forward projections guide the replacement of metal projections in a sinogram
  - Sinogram replacement: Naidu et al [3]
  - Intermediate image : critical component
- Metal artifacts are reduced visually and quantitatively
  - 17 images
  - Visually: dark and bright streaks are reduced
  - Quantitative measurement was only in 37 uniform objects: $\bar{\sigma}$:197 => 121 HU
- Limitation is the amount of metal (as expected)
- Much to explore to improve the close neighborhood of metal

Our approach: Generate “Prior-image”

- Ideal (noise-free, mono-energetic, etc.)

$$Ax = b,$$

  where
  A is the forward model : image -> sinogram
  x is the image
  b is the scanner sinogram
- We use constrained optimization
  - Weighted least-squares: reduced weights on metal samples
  - Constraint for beam hardening and scatter
    - Measured projections are lower than ideal
  - Regularization by total variation norm

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Constrained optimization

$$\min_{x}\ (Ax-b)^T W(Ax-b) + \ \beta\|x\|_{TV}$$
$$\text{s.t. } I_P(Ax-b) + 3\sigma_s \succcurlyeq\ 0$$

W : more metal => smaller weight

$$W\ = diag\ w(i) = \exp\left(-\gamma\sum_{j=1}^{V} a_{ij}\, I_1(j)\right)$$

M_1= 4000 MHU

$$I_1(j) = f\left(x_j\right) = \begin{cases} 1, & x_j\ > M_1 \\ 0, & otherwise \end{cases}$$

$$\mathrm{I}(\mathrm{s},\theta) = \mathrm{I_0}\exp\left(-\sum_{j\,\in L(s,\theta)} \mu_j\right),$$

The constraint: Beam hardening and scatter

$$I_P = \mathrm{diag}(p(i))$$

$$p(i) = \begin{cases} 1 & \sum_{j=1}^{V} a_{ij} I_2(j) > 0 \\ 0 & otherwise \end{cases}$$

$$I_2(j) = \begin{cases} 1 & x_j \geq M_2 \\ 0 & otherwise \end{cases}$$

M_1= 4000 MHU
M_2=10,000 MHU

σ_s is the expected noise per sample.

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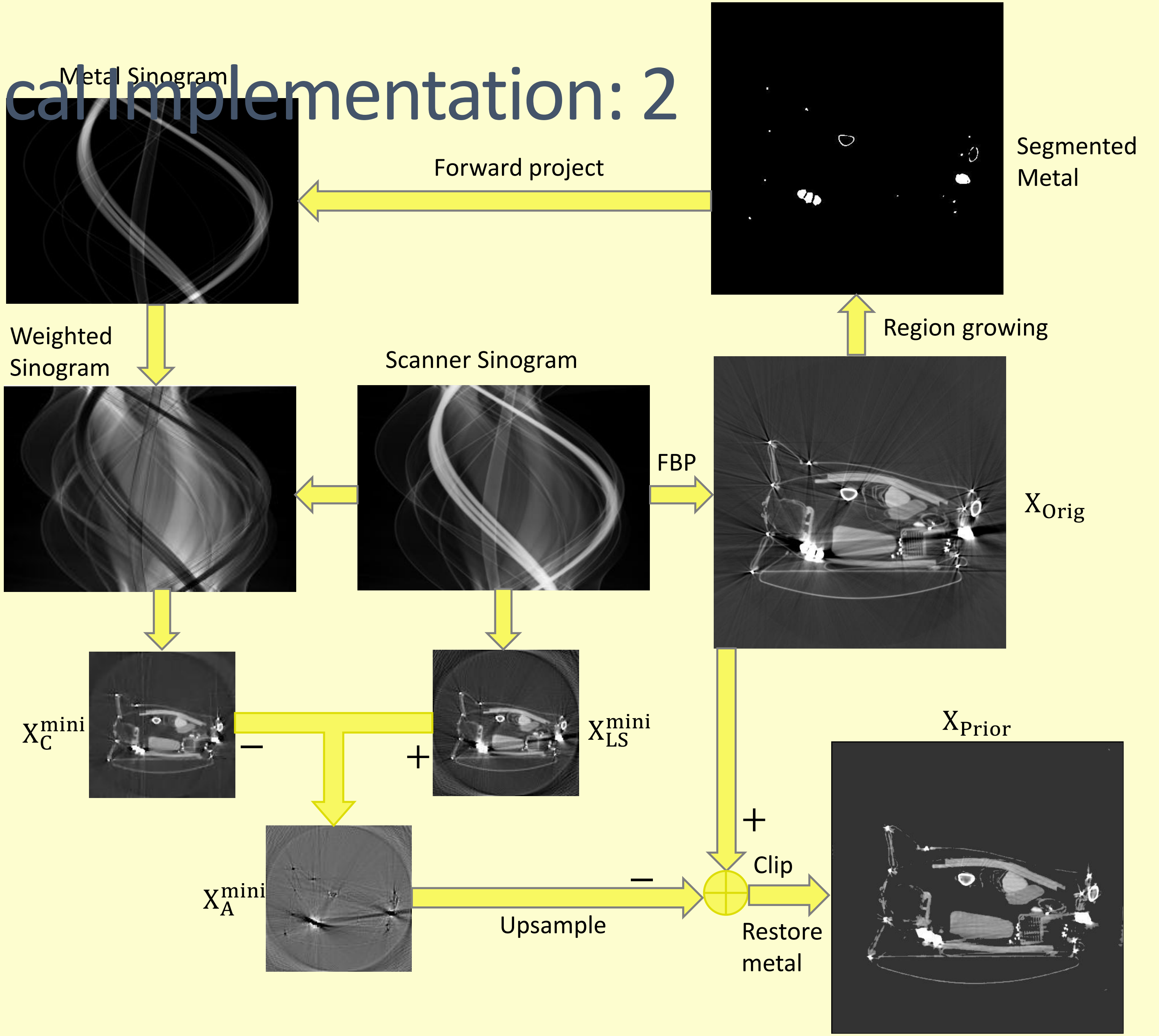
Practical Issues

- Convex problem is too big to solve with solvers like Mosek: size of A $\approx 10^6 \times 10^5$
- Practical implementation:
  - Miniaturization: but resolution mismatch in FBP and optimal solution
  - Isolate artifacts by solving two convex problems

    Artifacts = Least Squares - Constrained WLS
  - Least squares matches the FBP solution re: artifacts

Practical Implementation: 2



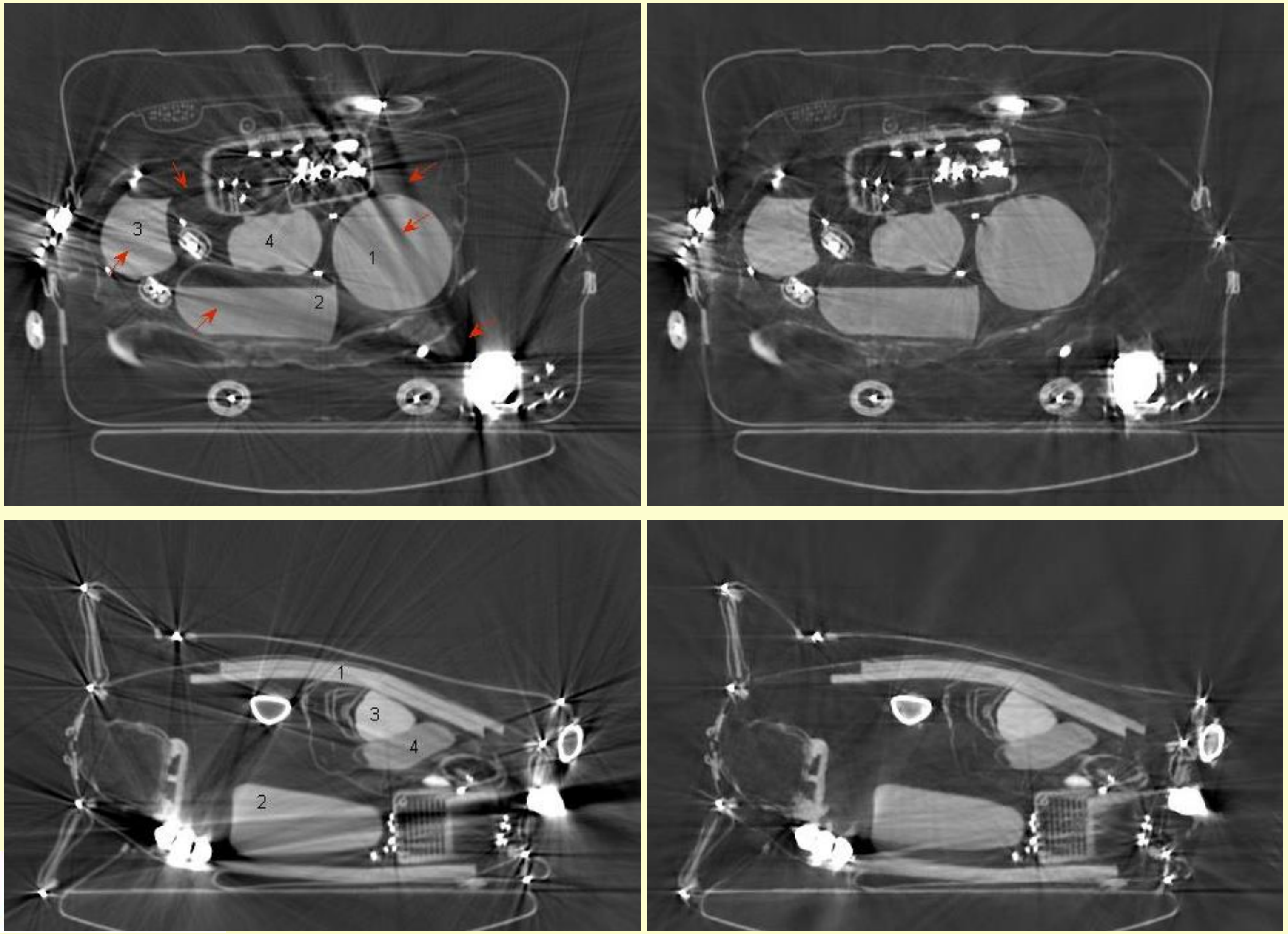
Evaluation: Visual and Quantitative

- Traditional evaluation of MAR is visual
  - Metal-free ground truth is unavailable
- Quantitative evaluation:
  - Ours
    - CT distribution within regions known to be uniform ("uniform objects")
    - We generated 2D masks for liquids, stacked sheets, blocks etc.
    - Variance decreases in MAR images, extrema closer to mean
    - KS2 test: distributions are different at 0.05 significance level
    - Autocorrelation is closer to ideal in MAR images
    - Segmentation (Region growing) followed by segmentation evaluation [13]
  - Stratovan clouds

Results 1

Test-statistic is shown
p-values not shown

Original | MAR



	Mean	Std	KS2
1	843	159	0.34
	893	53	
2	769	133	037
	833	70	
3	988	162	0.14
	1019	123	
4	1025	79	0.28
	979	74	

	Mean	Std	KS2
1	1150	106	0.06
	1138	99	
2	910	226	0.21
	907	177	
3	1337	72	0.25
	1355	58	
4	841	90	0.35
	900	69	

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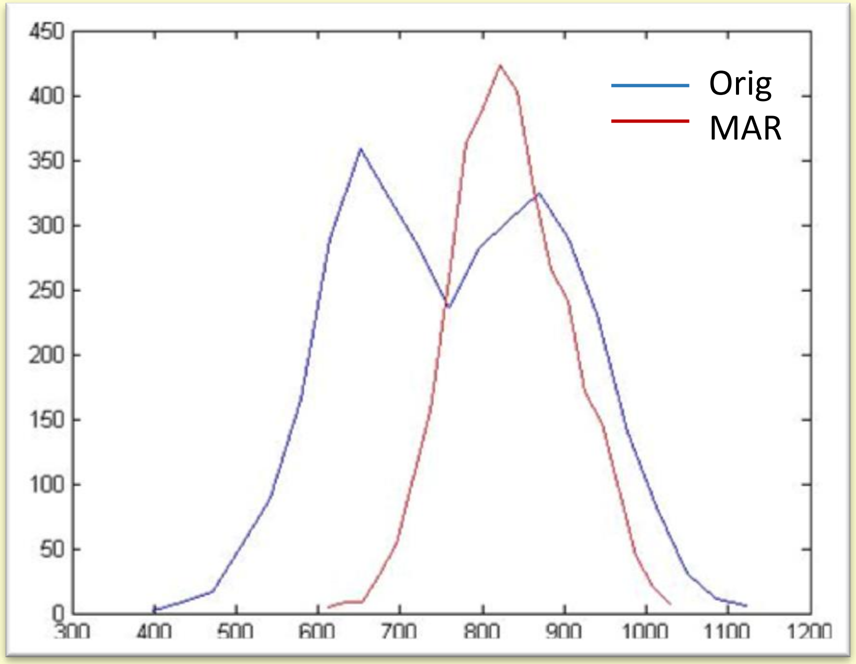
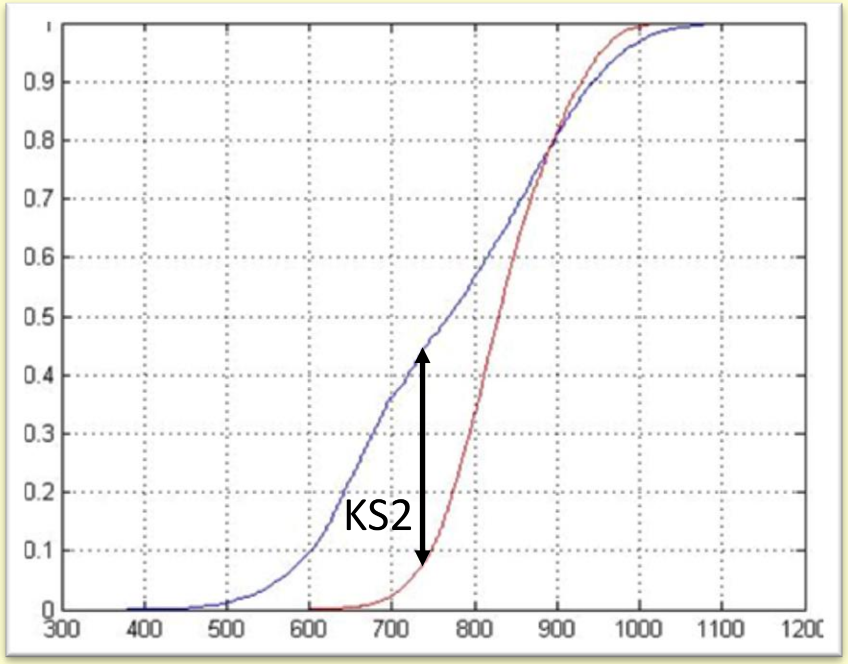
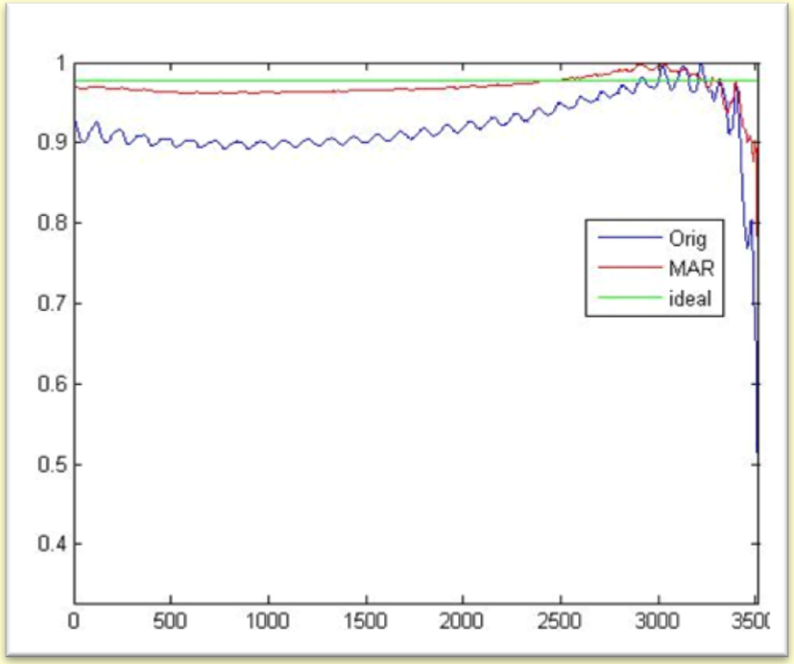
KS2 : Largest difference between CDFs



Histogram



CDF



Autocorrelation

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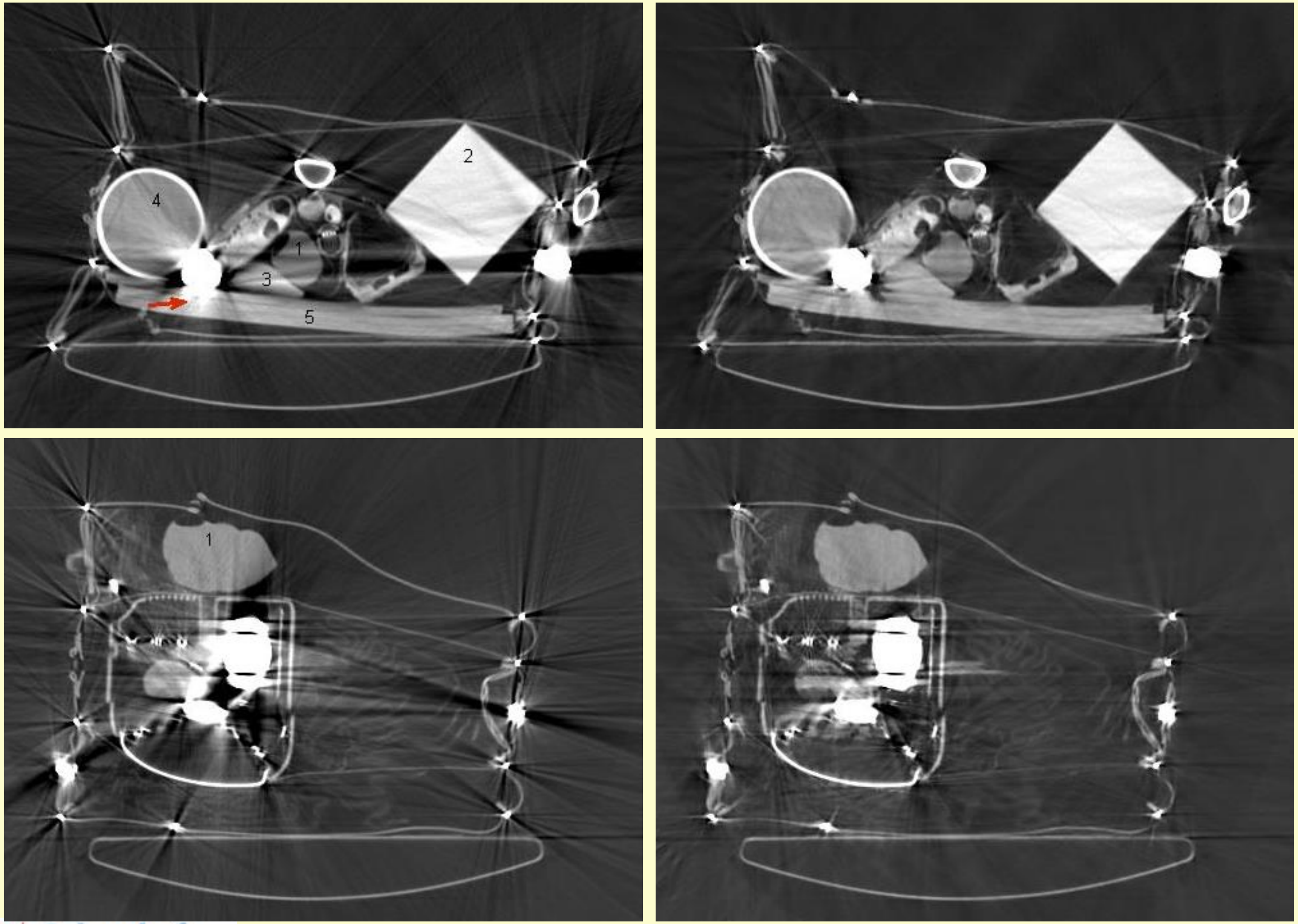
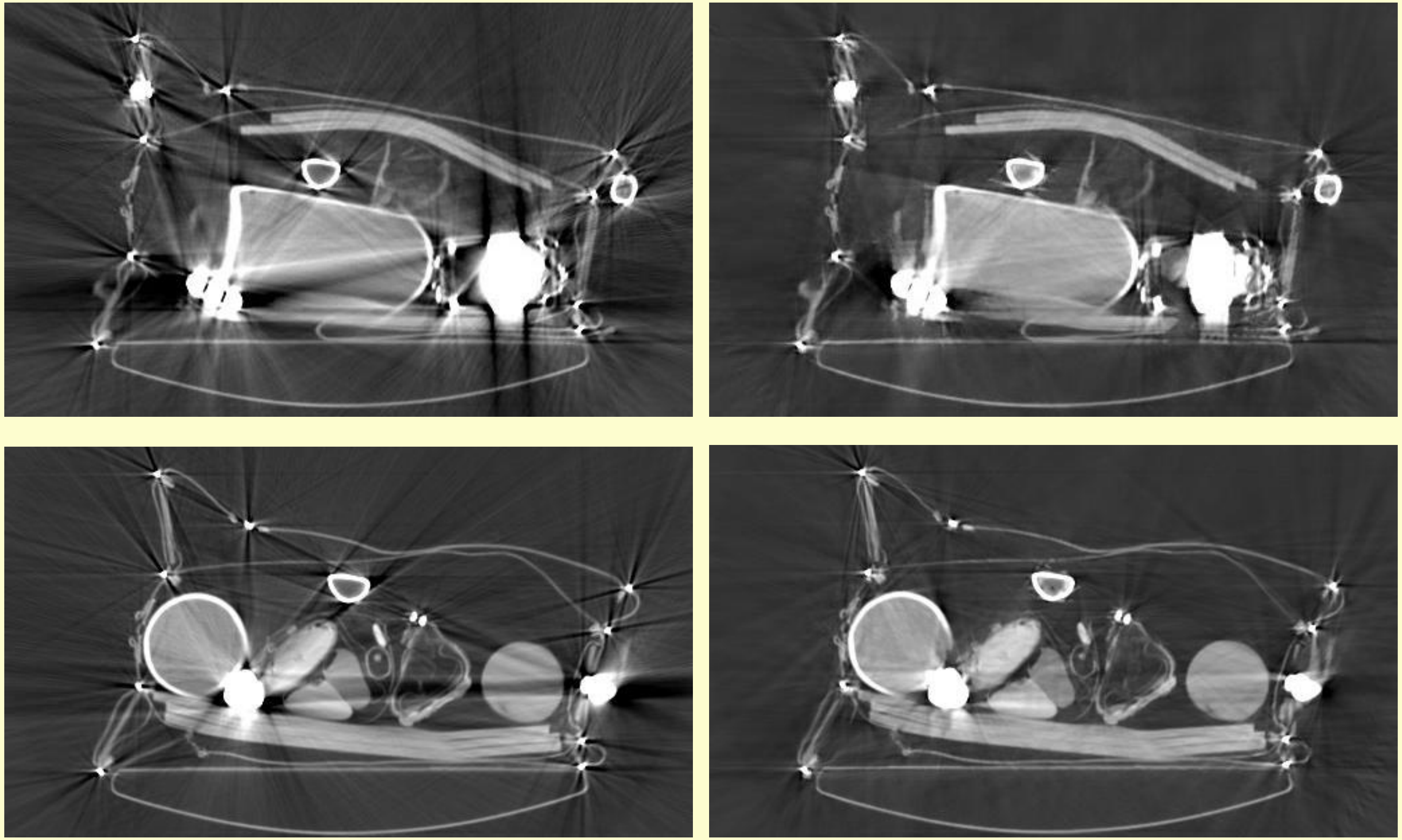
Results 2



	Mean	Std	KS2
1	695	201	0.42
	875	129	
2	1795	164	0.23
	1853	88	
3	1276	220	0.23
	1245	118	
4	1092	228	0.17
	1063	166	
5	1114	316	0.17
	1132	157	

	Mean	Std	KS2
1	917	111	0.09
	946	74	

Results 3



	Mean	Std	KS2
1	1022	356	0.31
	1167	158	
2	1071	189	0.15
	1068	133	

	Mean	Std	KS2
1	1034	144	0.29
	1110	145	
2	929	274	0.25
	1017	117	
3	878	237	0.4
	809	90	
4	1165	244	0.48
	1416	233	
5	1167	245	0.09
	1132	145	

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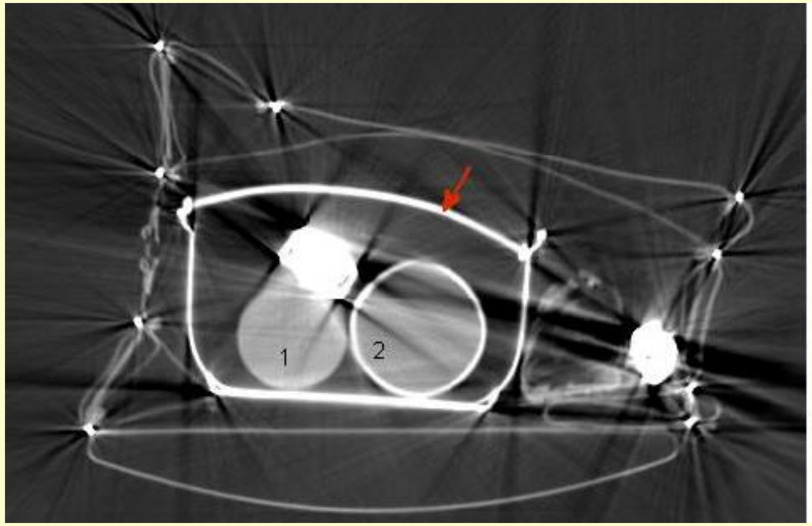
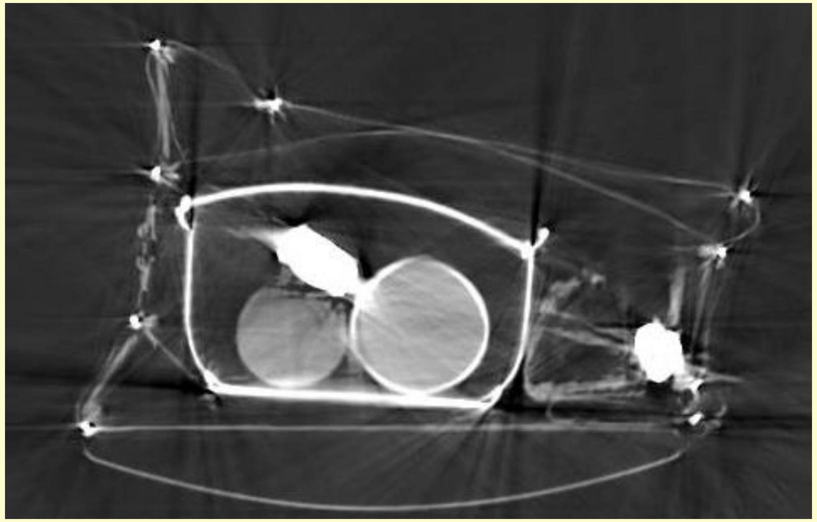
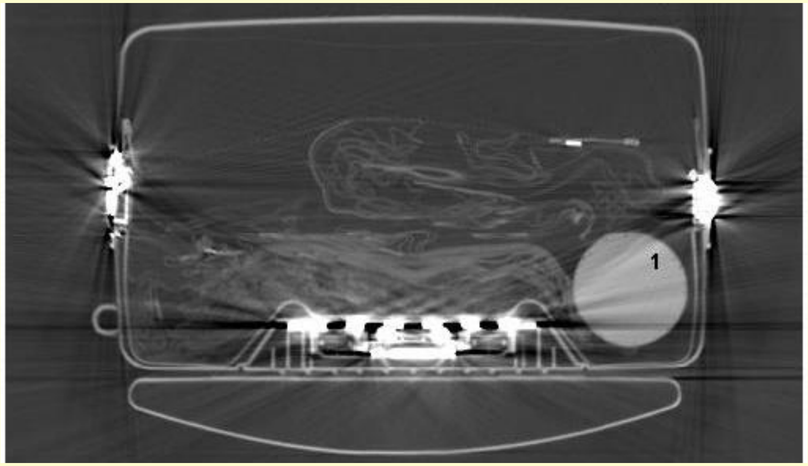
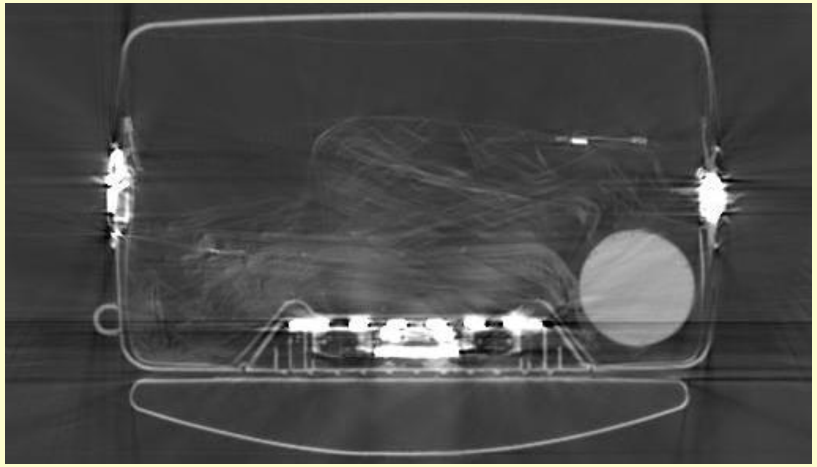
Results 4: Problems





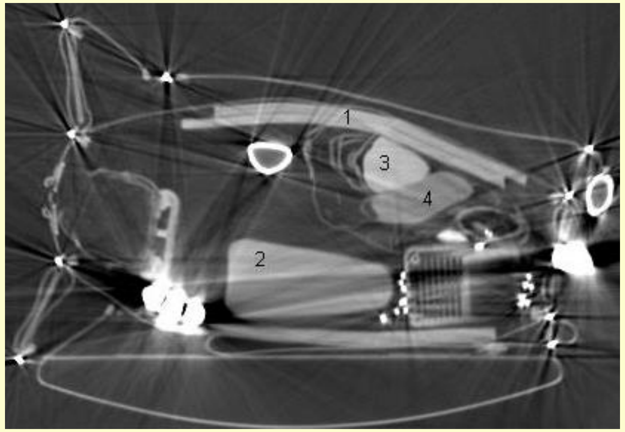
	Mean	Std	KS2
1	1244	143	0.73
	977	197	
2	935	306	0.56
	1245	114	



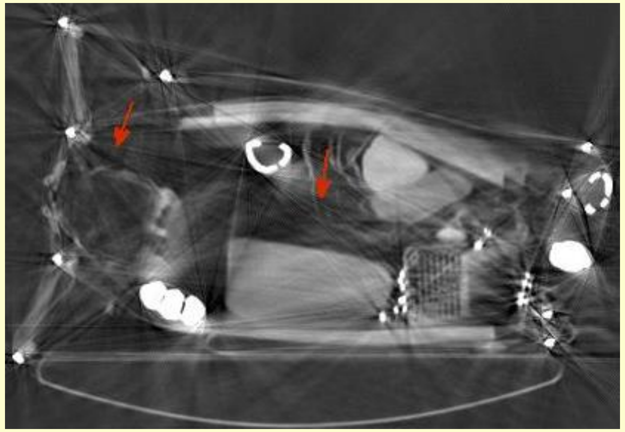


	Mean	Std	KS2
1	939	145	0.16
	958	91	

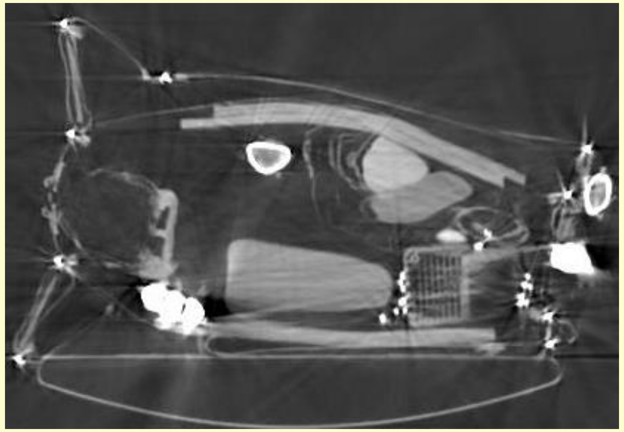
Results 5: Comparison with Iterative Projection Replacement



Original



IPR



Ours

Mean of standard deviation, weighted by object size

Number of Objects	Original	IPR	Ours
19 (8 images)	162	128	100
37 (17 images)	197	*	121

* Not yet done

Iterative Projection Replacement: Verburg 2012 [9]

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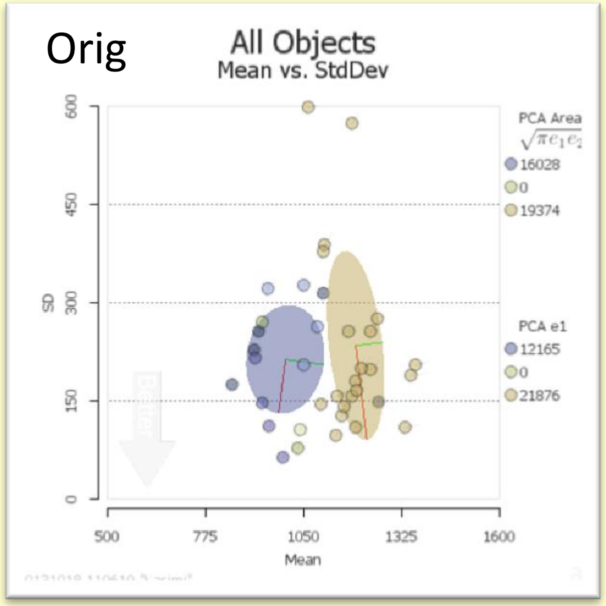
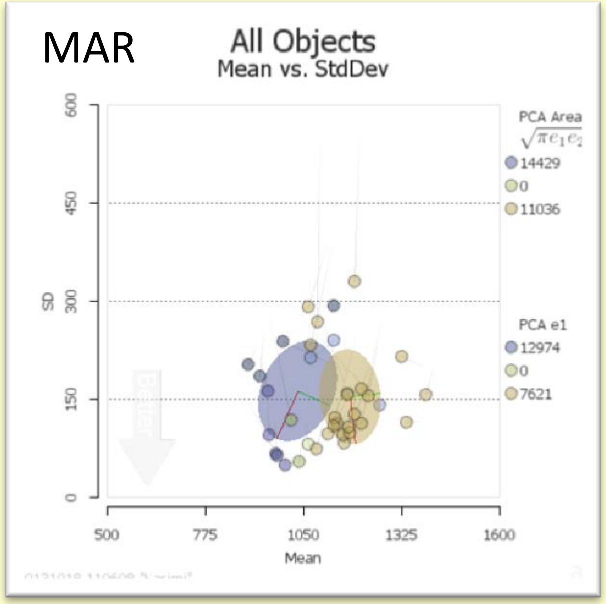
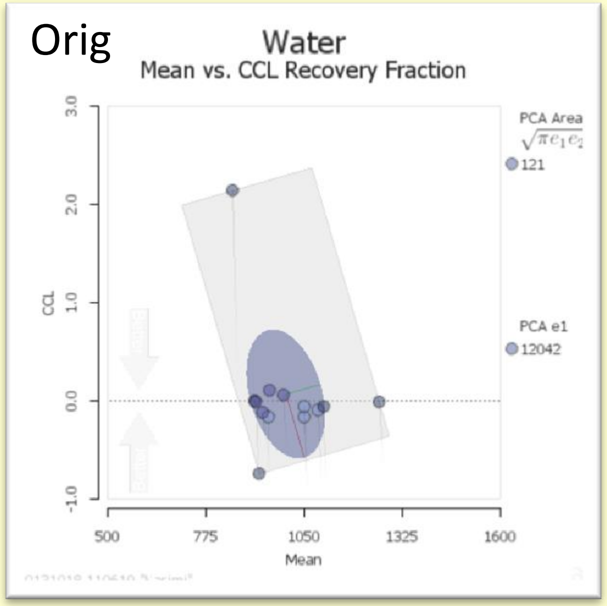
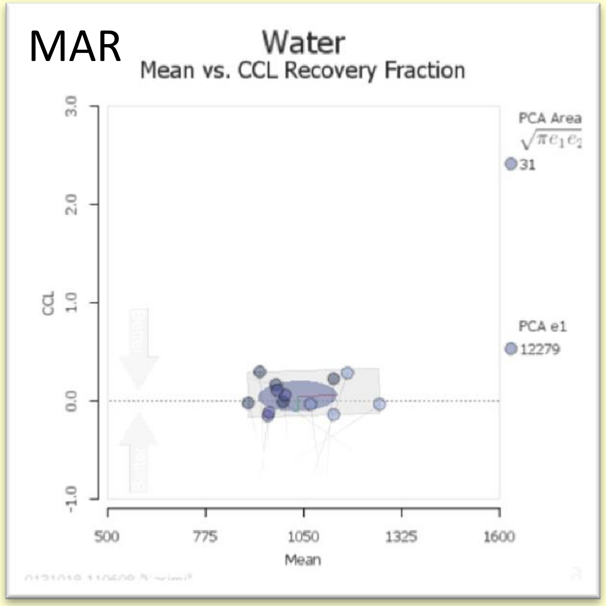
Cloud plots (Stratovan)

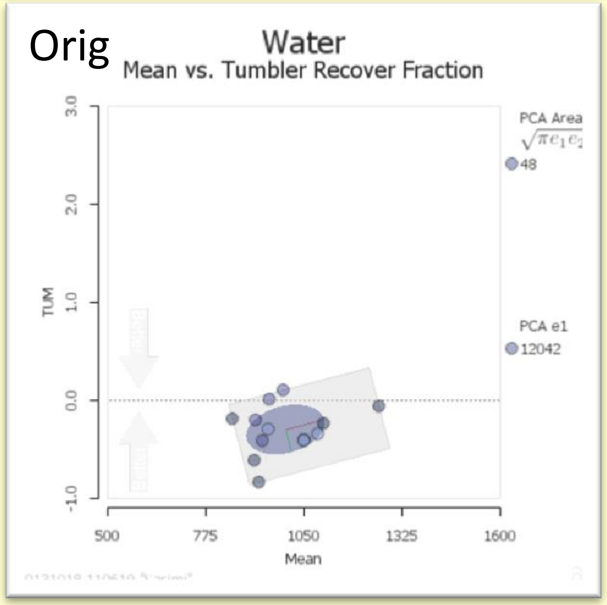


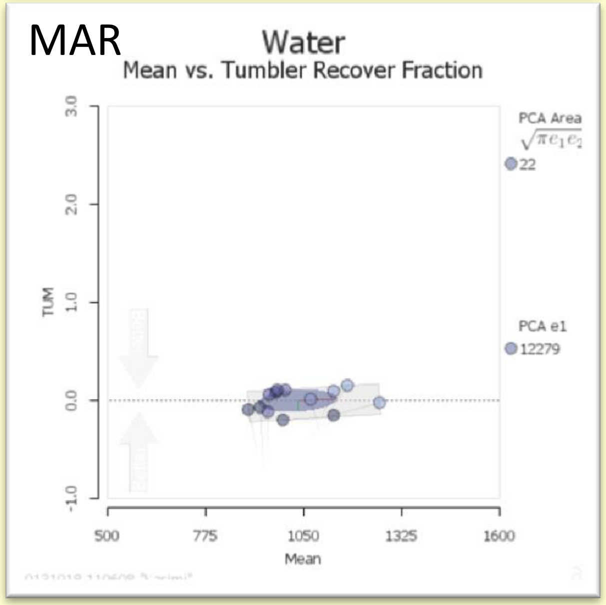


σ decrease with MAR









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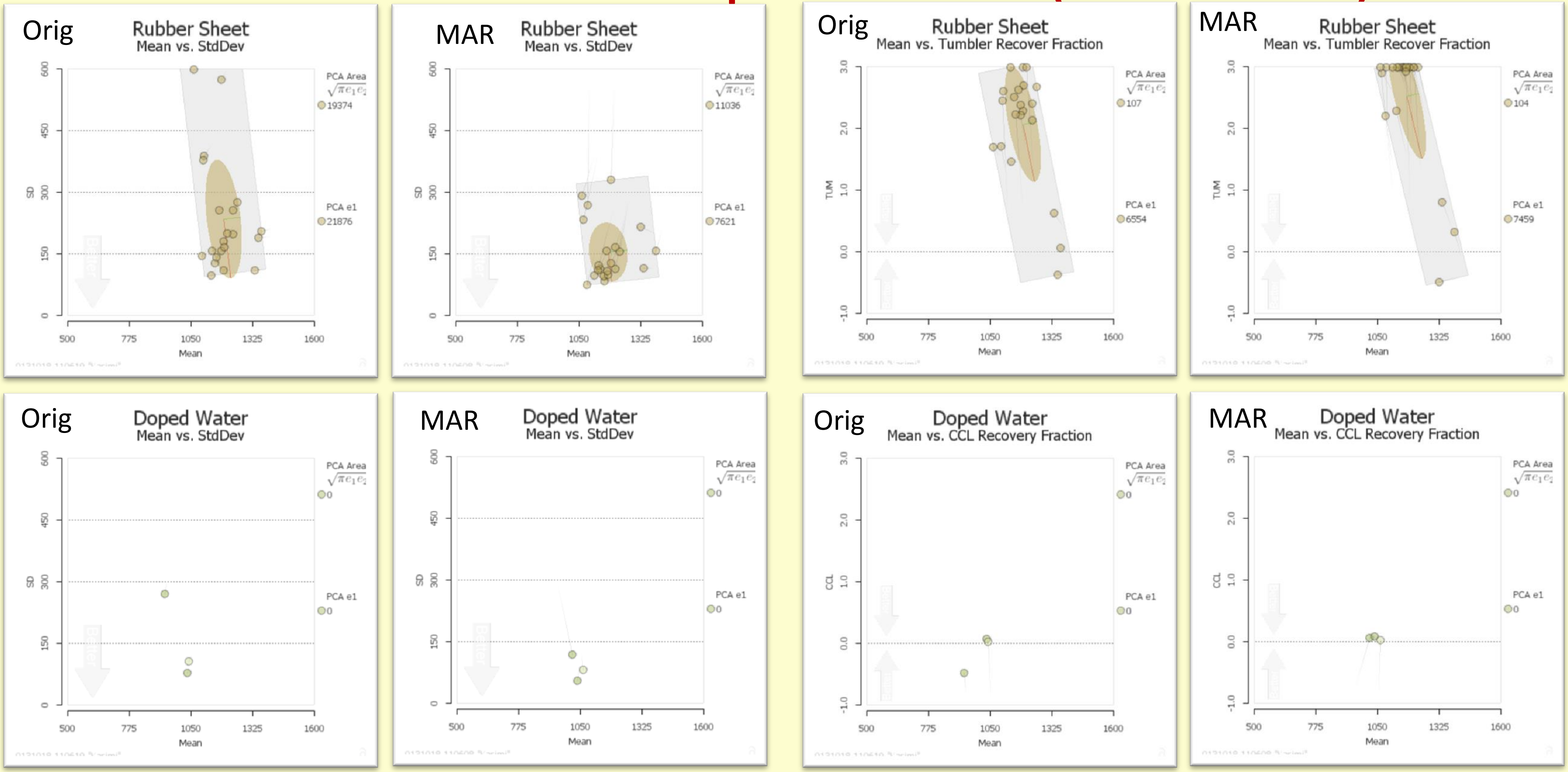
Rubber sheet and doped water (Stratovan)

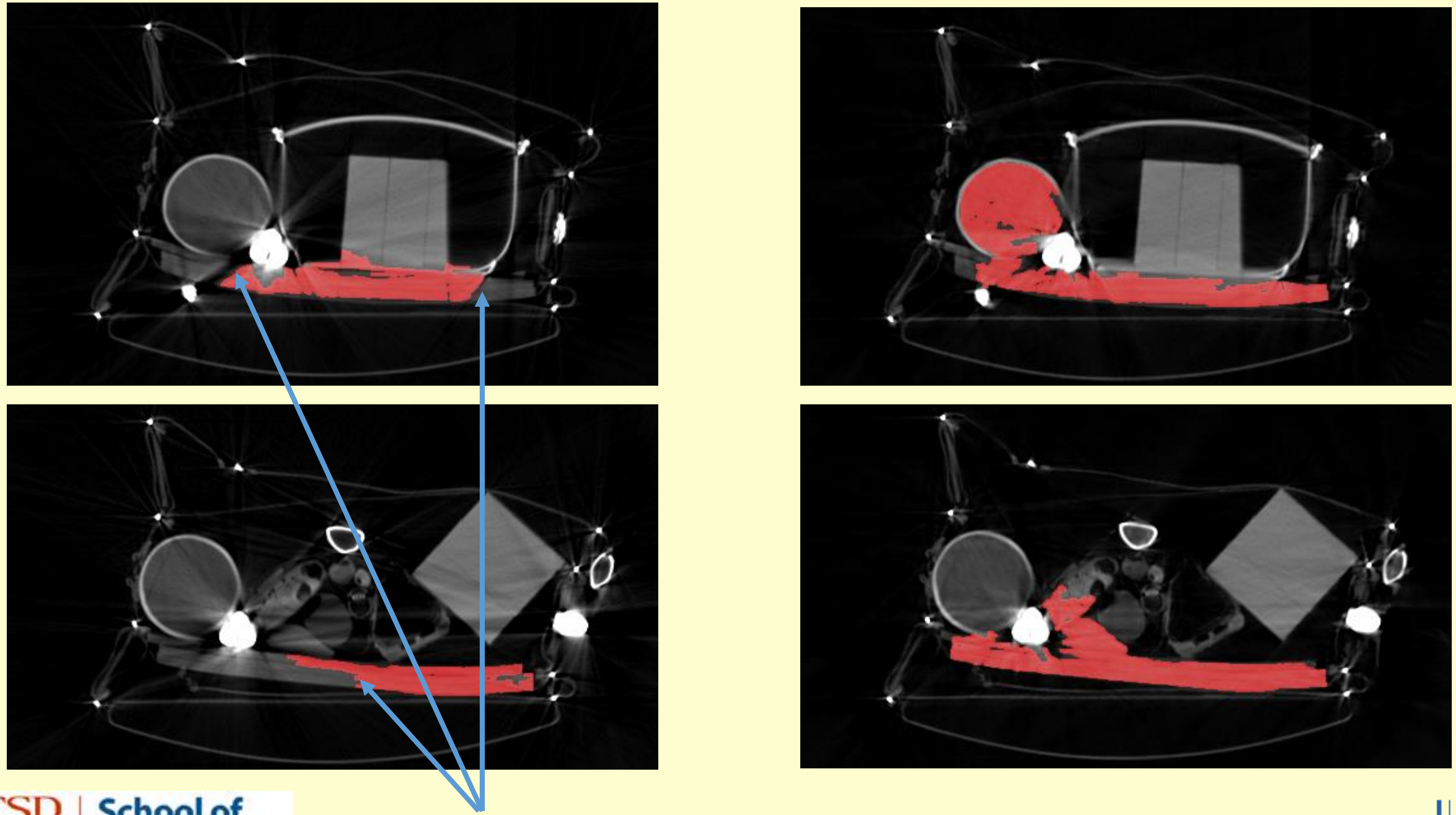


Some of the above results are misleading:

Original | MAR

Example 1

Example 2



Broken due to artifacts, not object properties

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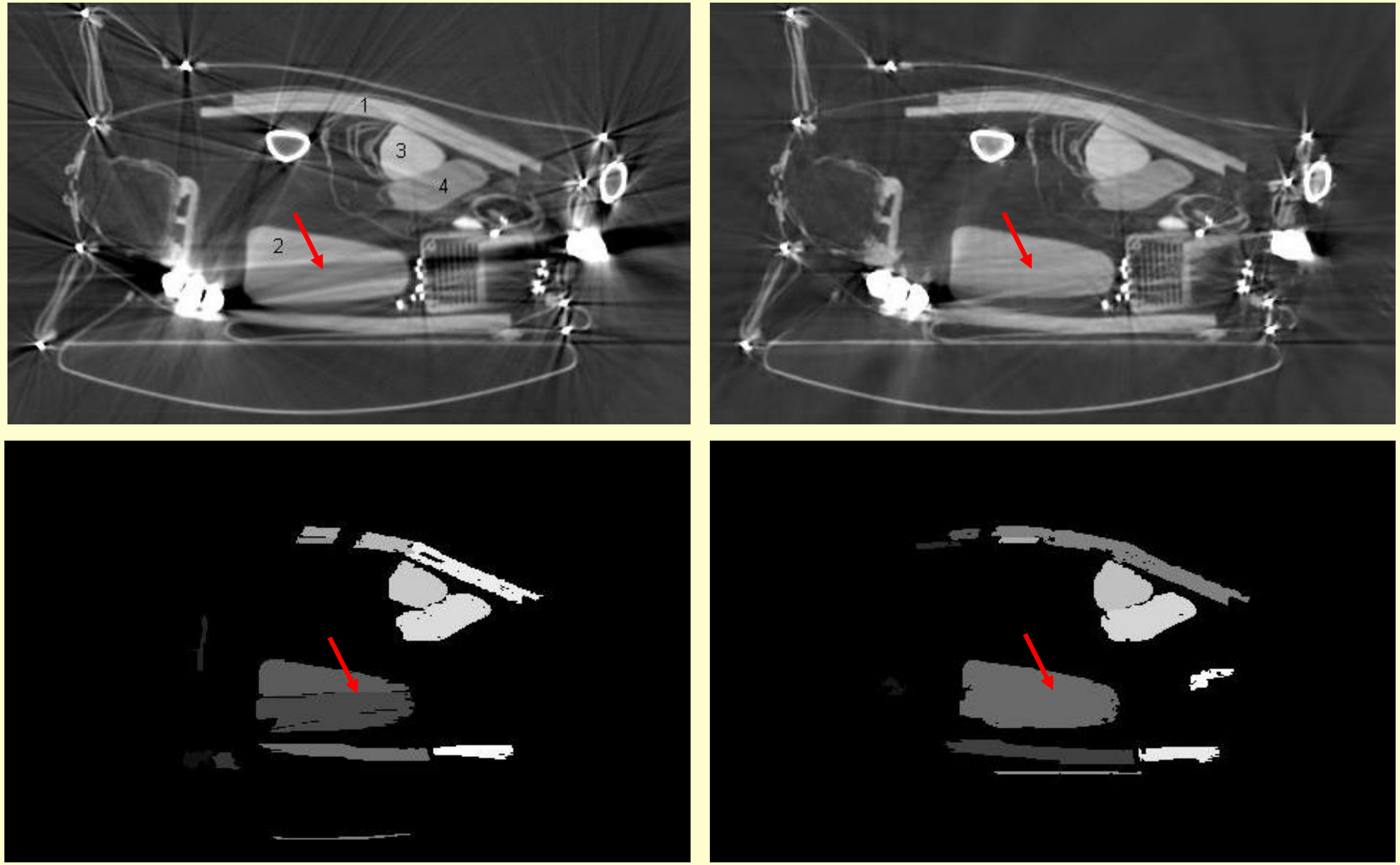
Our region growing results

CT

Region Growing

Label



original

MAR

Parameters:
High Thresh = 3000 HU
Low Thresh = -500 HU
Delta = 50 HU
Min Mass = 100 g

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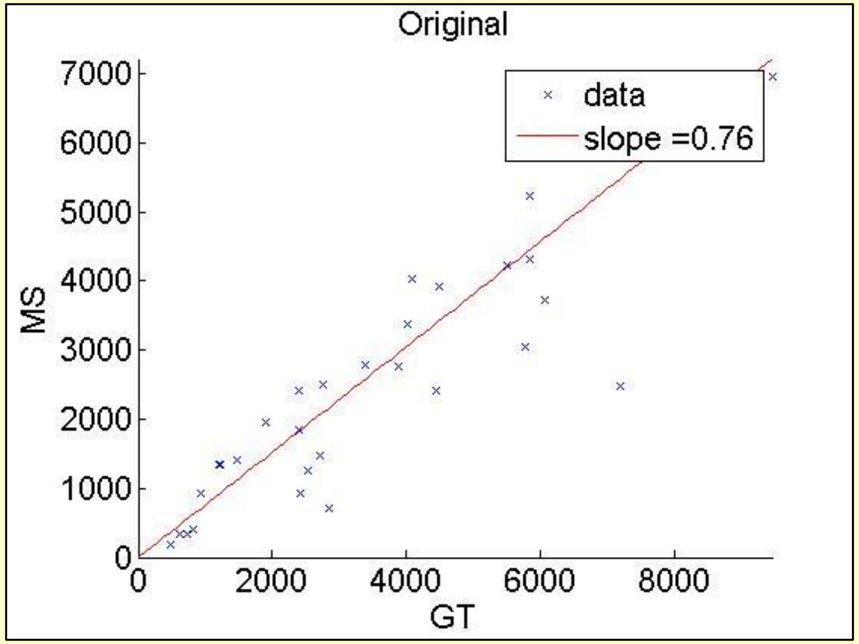
Our Segmentation Evaluation: R.G. +

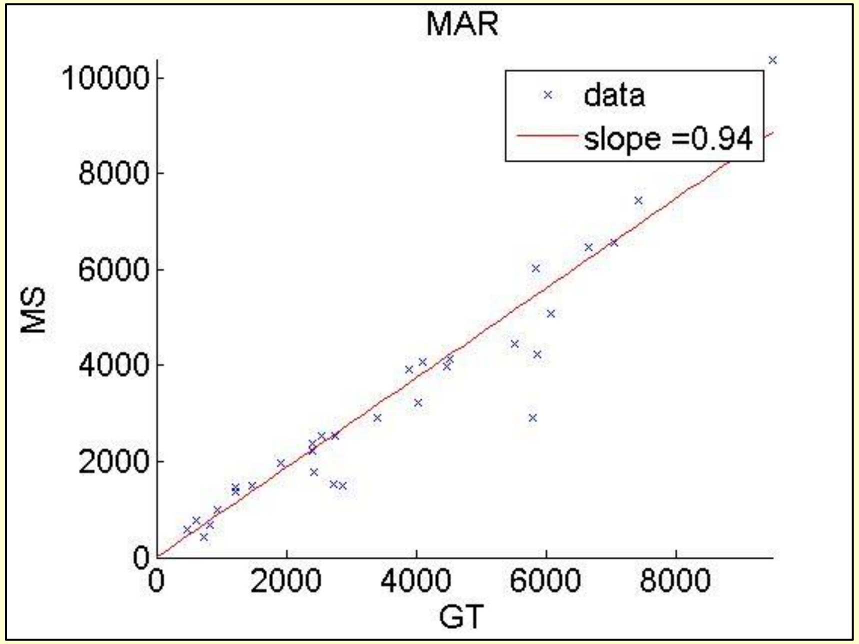
$$\frac{Mutual\ Info}{\sqrt{Entropy_{GT}\ EntropyMS}}$$

Original	MAR
0.87	0.95
0.70	0.77
0.69	0.83
0.71	0.92
0.68	0.75
0.65	0.65
0.73	0.76
0.54	0.77
0.59	0.82

Bipartite Match + Volume Recovery



L1 error=0.27



L1 error=0.2

Only done for images with > 1 object of interest

Strengths and Weaknesses

- Robustness from constrained optimization:
  - tested with 27 pieces of metal
- Weaknesses*
  - The neighborhood of metal is not reconstructed well: L2 error is not good enough
  - Slow: Using general purpose solver
  - Thin edges are degraded if they are parallel to streaks and within or close to them.

*We are working on improvements. The inherent limitation is the amount of metal in the scan, which is expected for any MAR algorithm

Recommendation for future projects

- New Objective Function
  - Elastic net
- Tighten Constraint
  - Reorder the metal projections in amplitude (still convex)
- Full-scale reconstruction
  - Alternate solvers (eg. projection onto convex sets)
- Probabilistic iterative reconstruction
  - Substitute weight matrix with a PDF
  - Compare the properties
- Suggestions on solving full-scale?
  - Cannot decompose & parallelize the problem

References

[1] Glover and Pelc, "An algorithm for reduction of metal clip artifacts in CT reconstructions," Med. Phys., vol. 8, 1981

[2] Kalender et al., "Reduction of CT artifacts caused by metallic implants," Radiology, vol. 164, 1987

[3] Naidu et al., US Patent 6,721,387, 2004.

[4] M. Bal and L. Spies, "Metal artifact reduction in CT using tissue-class modeling and adaptive prefiltering," Med. Phys., vol. 33, 2006.

[5] Li et al., "Metal artifact suppression from reformatted projections in multislice helical CT using dual front active contours," Med Phys., vol. 37, 2010.

[6] Meyer et al., "Normalized Metal artifact reduction in CT," Med. Phys., vol. 37, 2010.

[7] F. E. Boas and D. Fleischmann, "Evaluation of two iterative techniques for reducing metal artifacts in computed tomography." Radiology, vol. 259, 2011.

[8] C. Golden et al., "A comparison of four algorithms for metal artifact reduction in CT imaging," in SPIE Medical Imaging, Int. Society for Optics and Photonics, 2011,

[9] J. Verburg and J. Seco, "CT metal artifact reduction method correcting for beam hardening and missing projections." Phys. Med. Biol., vol. 57, 2012.

[10] X. Zhang et al., "Metal artifact reduction in x-ray computed tomography (CT) by constrained optimization," Med. Phys., vol. 38, 2011.

[11] Y. Zhang et al., "A hybrid metal artifact reduction algorithm for x-ray CT," Med. Phys., vol. 40, 2013.

[12] Y. Sidky and X. Pan, "Image reconstruction in circular cone-beam computed tomography by constrained, total variation minimization." Phys. Med. Biol, vol. 53, 2008.

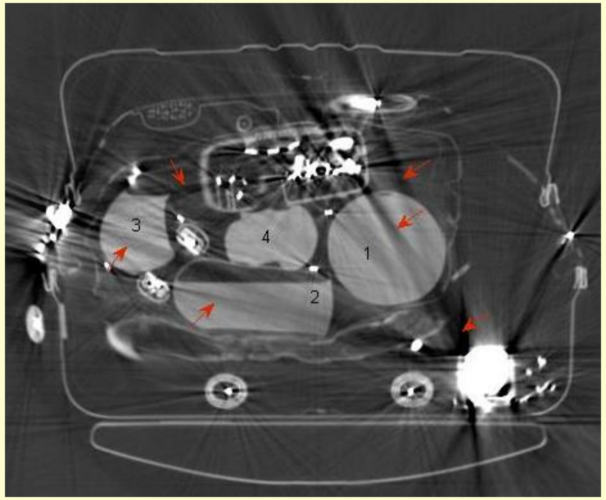
[13] S. Karimi, X. Jiang, P. Cosman, H. Martz, "Flexible Methods for Segmentation Evaluation: Results from Luggage Screening", submitted to J. X-ray Sci and Tech, Feb 2013.

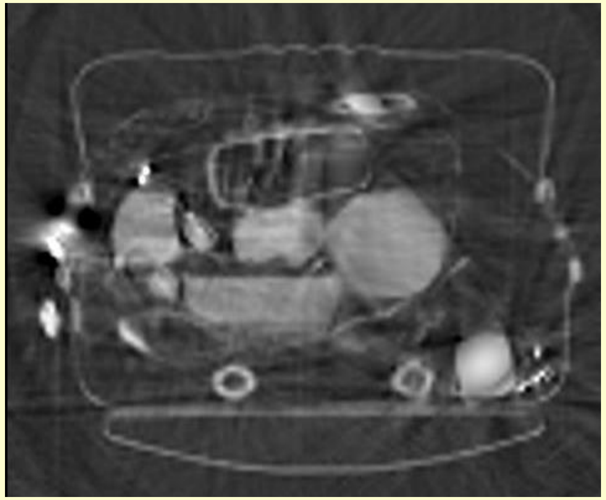
Impact of weighting and constraint

Objects fused: too many projections discarded

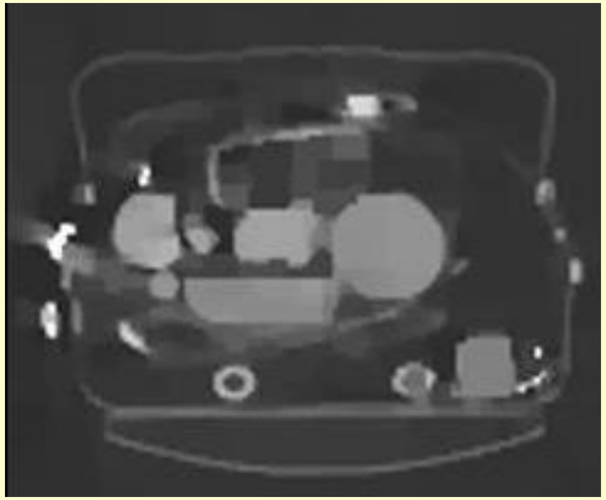
Intensity misrepresented

Original

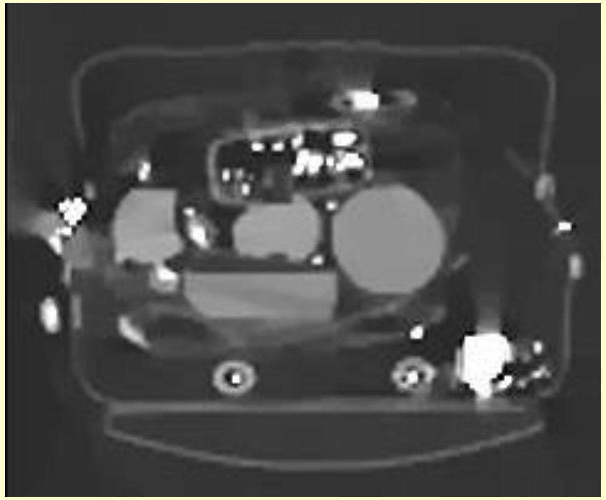




No metal, no constraints
Verburg 2012
Solver: NESTA



No metal, non-negativity
Zhang 2011
Solver: Mosek



Our weights, non-negativity
Solver: Mosek

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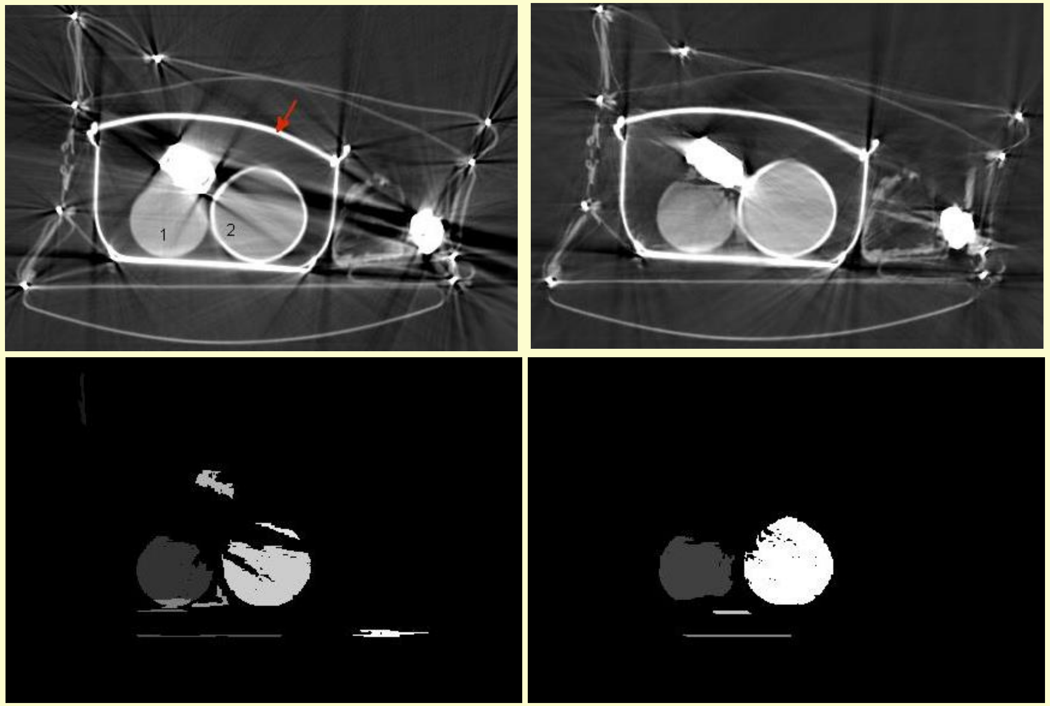
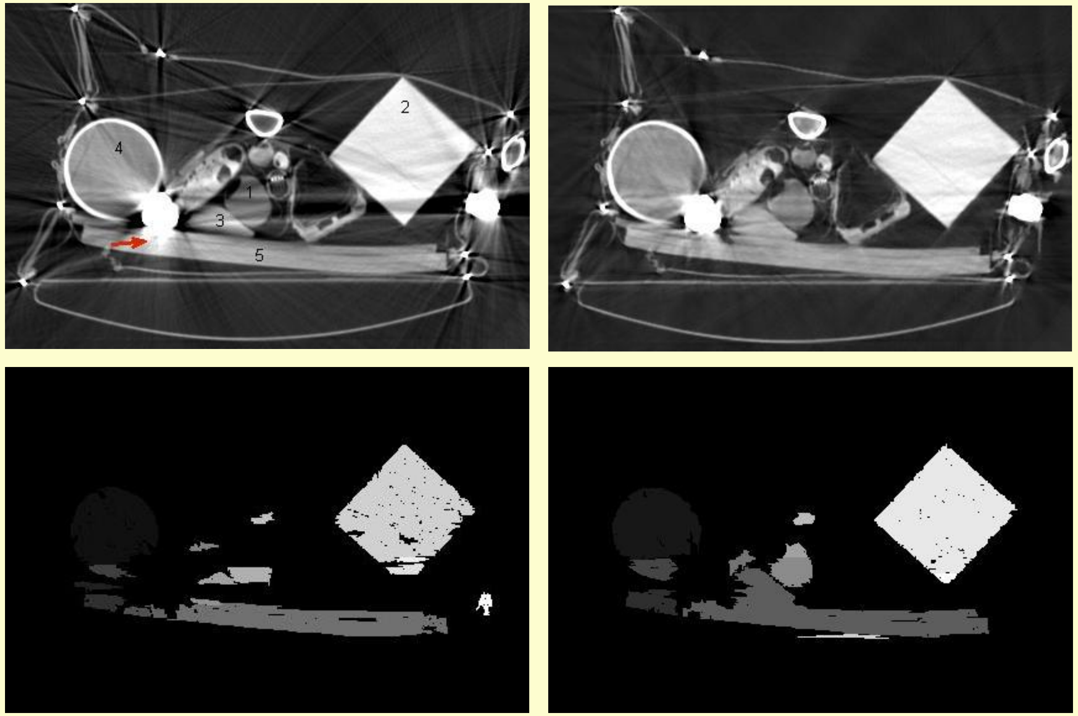


Region growing results



Parameters:
High Thresh = 3000 HU
Low Thresh = -500 HU
Delta = 50 HU
Min Mass = 100 g

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Improvement plots ?

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