



HARVARD
MEDICAL SCHOOL

Sinogram-Sparsified Metal Artifact Reduction Technique (SSMART)

Massachusetts General Hospital

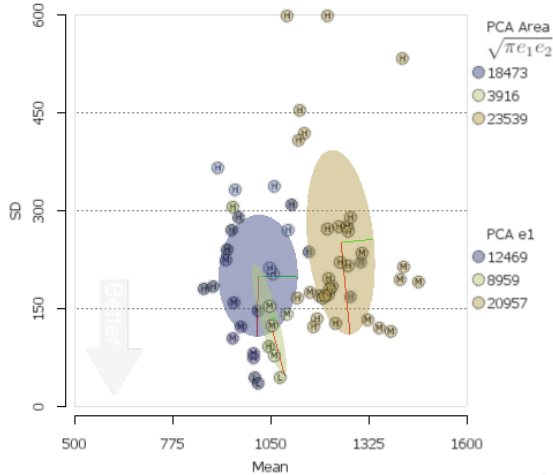
And Harvard Medical School

Synho Do, PhD

Clouds

Xrec

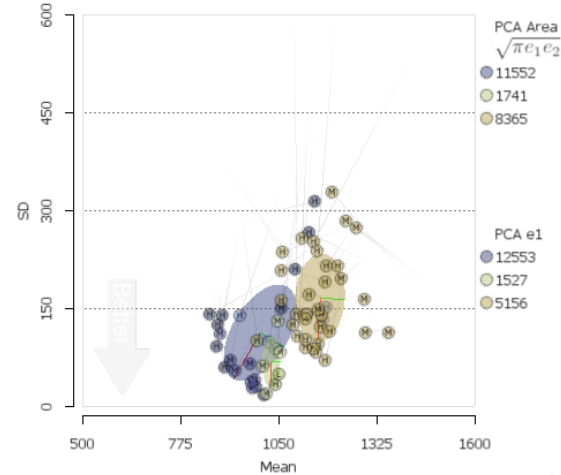
All Objects (Xrec)
Mean vs. StdDev



20131021 184052 "Do" scriptver 0x102 cloudver 0x104

SSMART

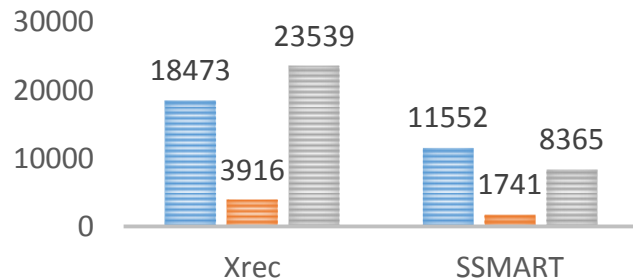
All Objects
Mean vs. StdDev



20131021 184052 "Do" scriptver 0x102 cloudver 0x104

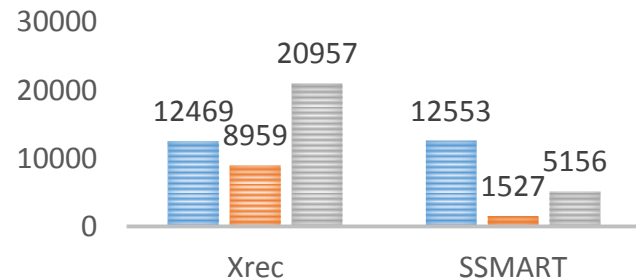
CLOUDS AREA

Water Doped Water Rubber Sheet



1ST PC

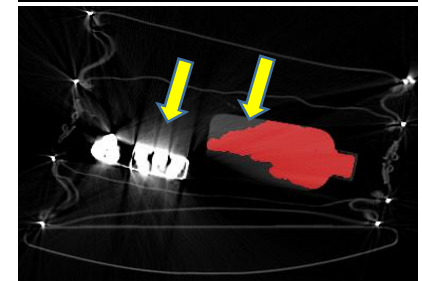
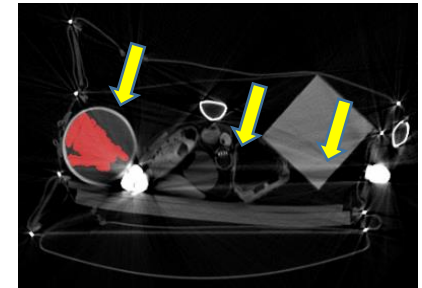
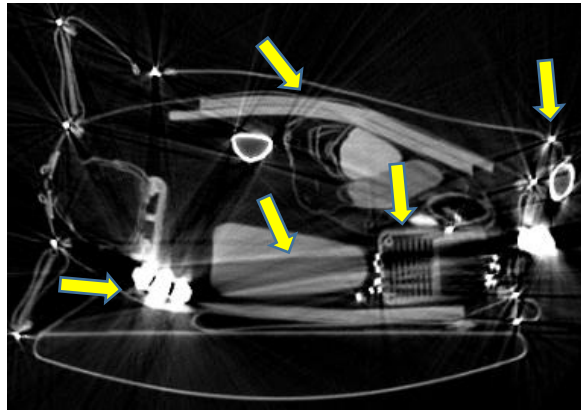
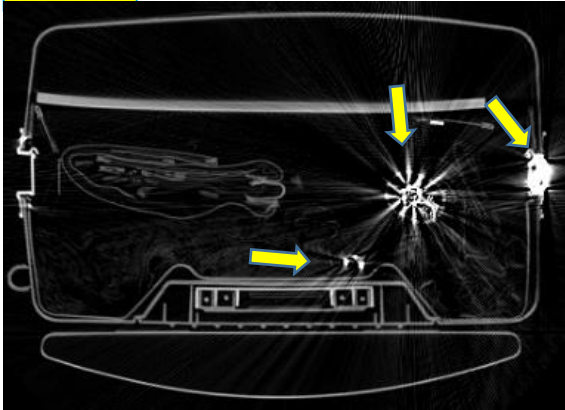
Water Doped Water Rubber Sheet



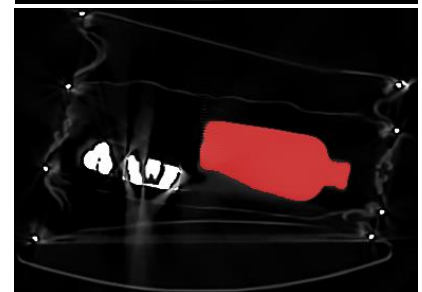
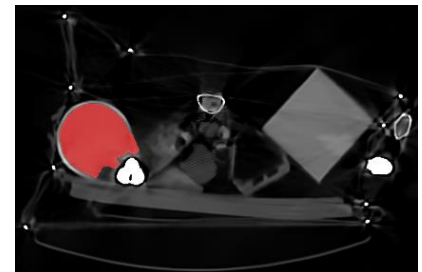
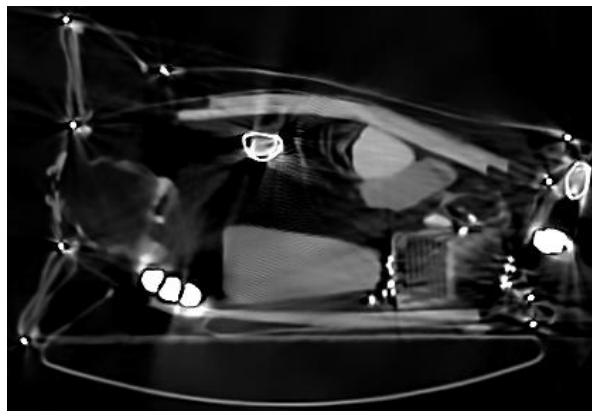
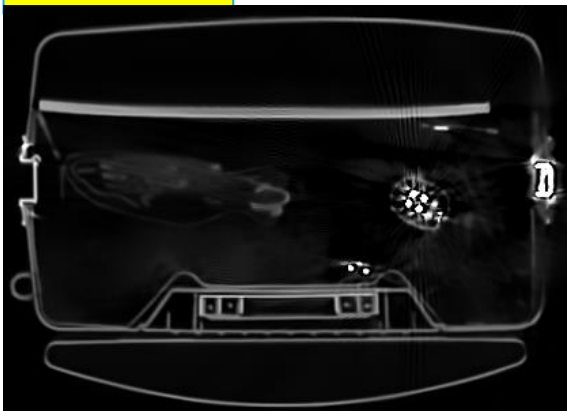
SSMART reduced cloud size.

Image Comparison

Xrec



SSMART



- Less streaking and shading artifacts
- Better homogeneous regions reconstruction
- Better segmentation

Massachusetts General Hospital and Harvard Medical School



Synho Do, PhD

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BIO NEWS PUBLICATIONS RESEARCH

Synho Do, PhD, is an Assistant in Physics at Massachusetts General Hospital, where he is a technical committee member of Webster Center for Advanced Research and Education in Radiation, and Instructor at Harvard Medical School. Dr. Do received the Ph.D. degree in Biomedical Engineering from University of Southern California. He is currently a member of IEEE Signal Processing Society, Bio-Imaging and Signal Processing (BISP). He is a MGH site PI for nVidia CUDA Research Center (CRC). Dr. Do's current research interests include statistical signal and image processing, estimation, detection, and medical signal and image processing, such as computed tomography. He has been a Co-Investigator for multiple medical imaging projects, and Co-PI/PI on medical (i.e., GE, Siemens, and Philips etc) and security (i.e., DHS, DARPA etc) image reconstruction projects.

Latest News

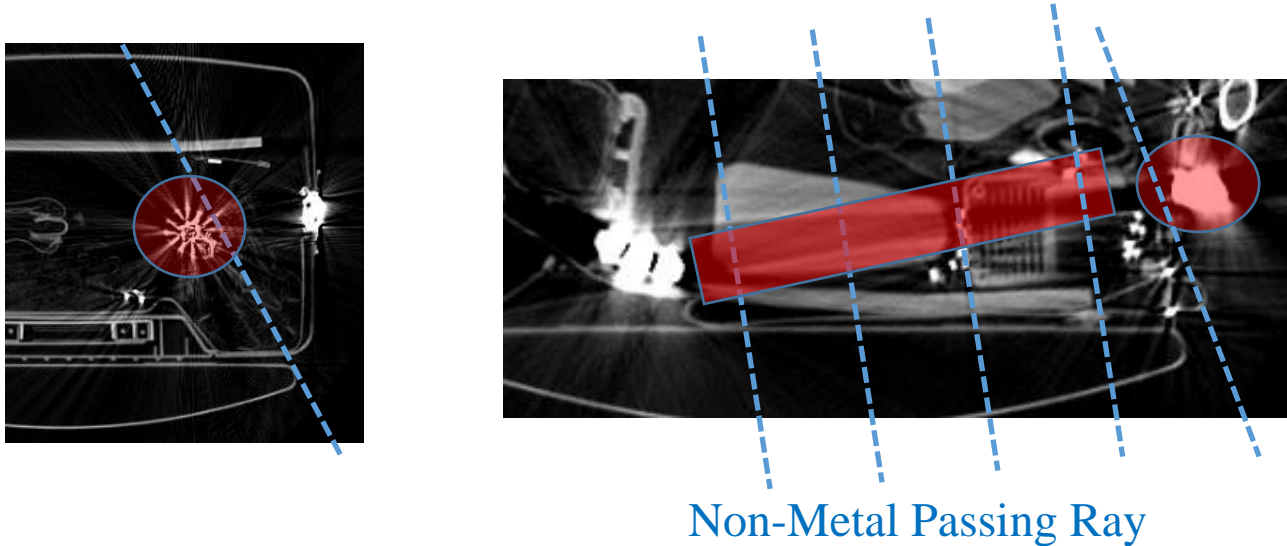
RSNA

DHS meeting

<http://scholar.harvard.edu/synho>

Nationality: U.S.A. (2013~present)

Algorithm : Main Idea



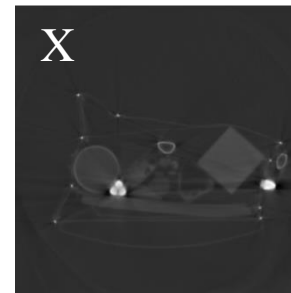
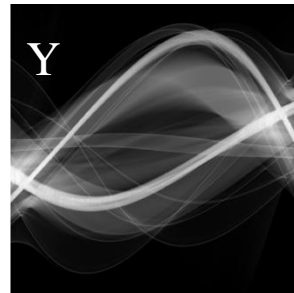
SSMART IDEA

1. Don't use bad data. → Throw it away
2. Let's use only non-metal passing rays for non-metal image reconstruction.
(Use only Blue Ray-sums)
3. Let's compensate metal passing ray with segmentation and re-projection.

How SSMART works ? (1/2)

Key Computations

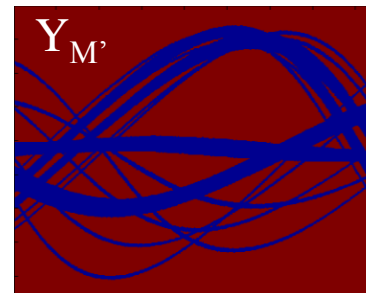
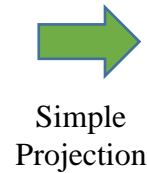
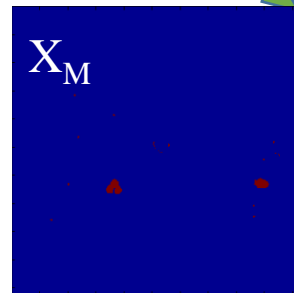
Lease-Squares solution



Original Sino.

Metal Component Selection
 $Th > \Delta$

Thresholding,
Element wise
Logical computation

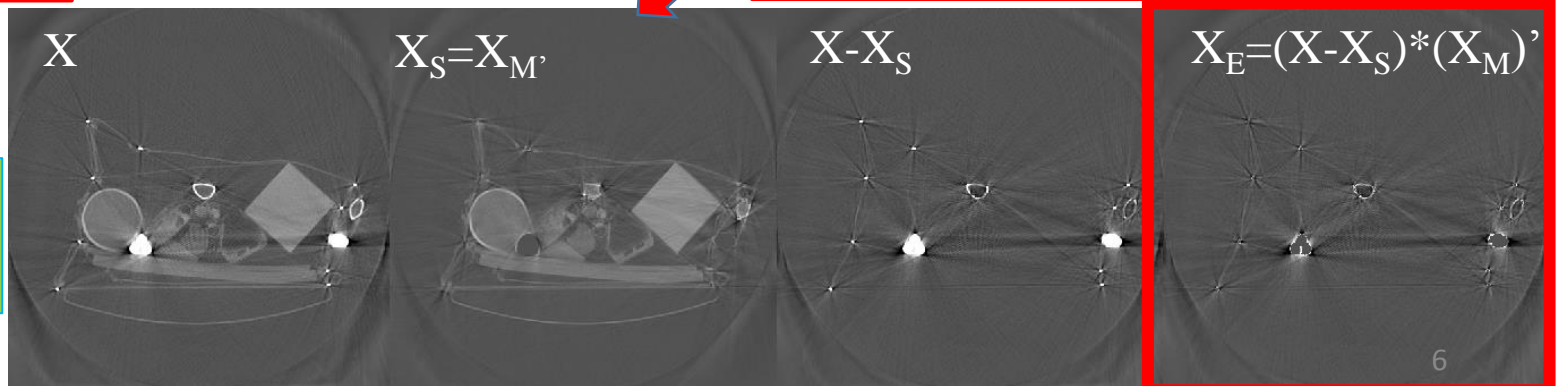


Binary Map:
Red=1
Blue=0

Sparse Reconstruction

A lot of math and computation.(Back-up slide)

Image subtraction
Element-wise
multiplication



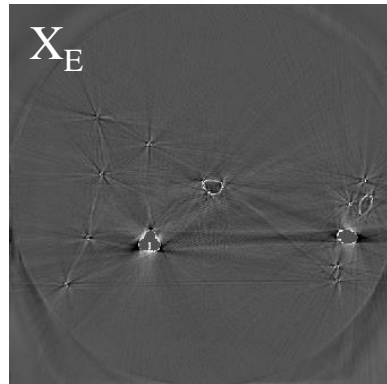
How SSMART works ? (2/2)

Key Computations

Re-projection

Element-wise
Subtraction

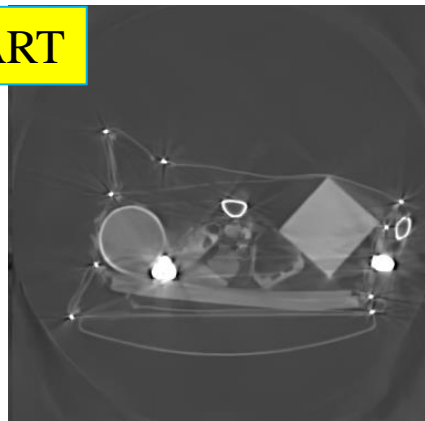
Image Reconstruction



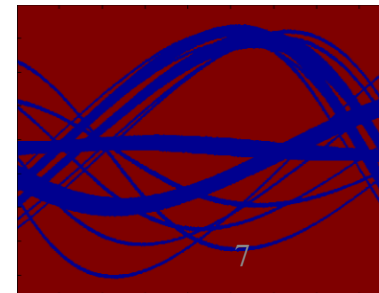
Segmented artifacts are projected to Sinogram domain



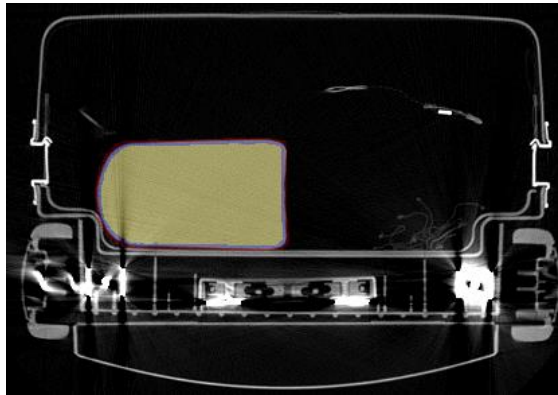
SSMART



Note that Y_E has positive and negative values and not bounded in Y_M map.



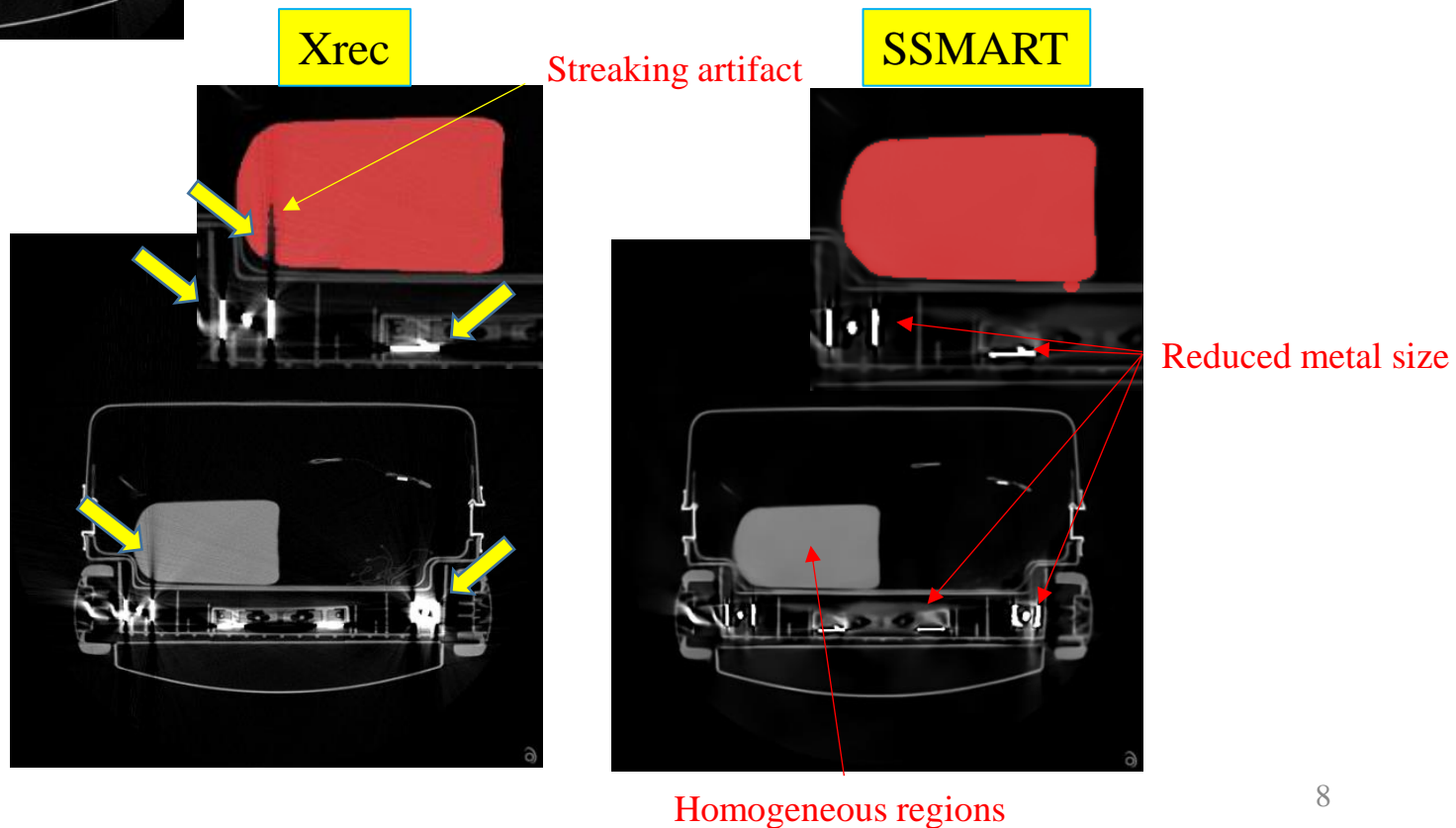
Streak artifacts reduction & segmentation (1/2)



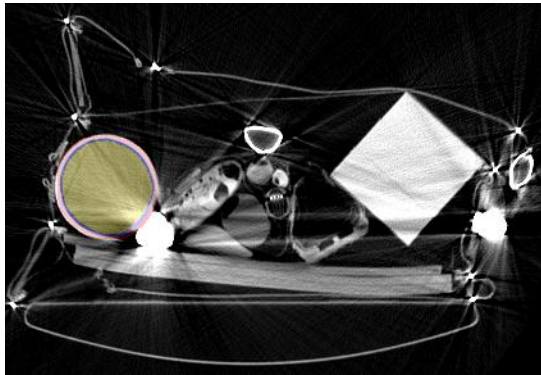
Ground Truth

SSMART improved image:

1. Reduced metal size
2. Suppressed streaking artifacts
3. Cleaner homogeneous regions
4. Better segmentation



Streak artifacts reduction & segmentation (2/2)



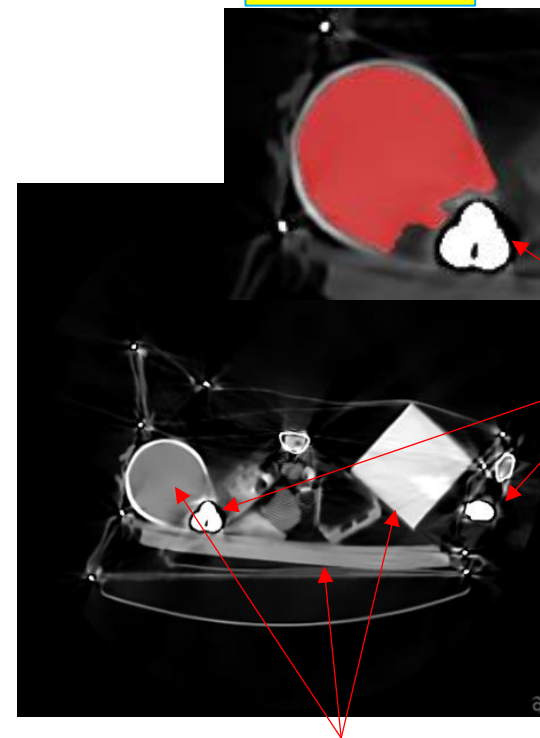
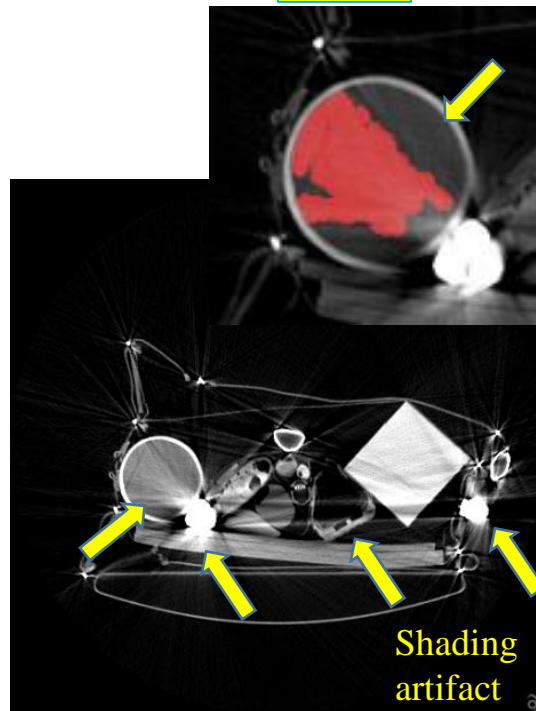
Ground Truth

SSMART also improved Image:

1. Shading artifacts
2. Big metal boundaries

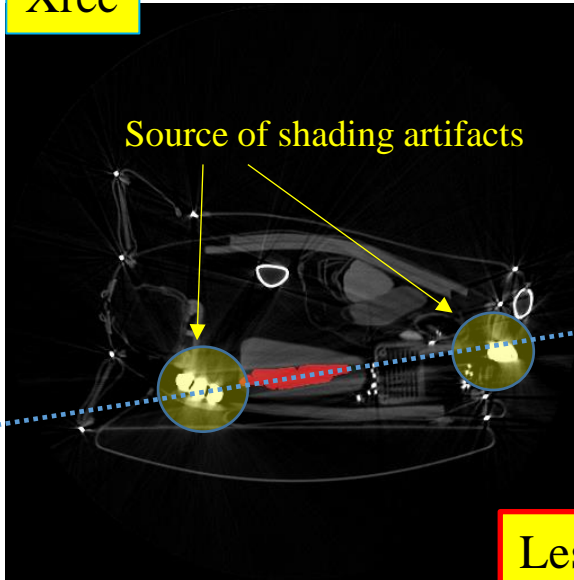
Xrec

SSMART



Shading Artifacts & Segmentation

Xrec

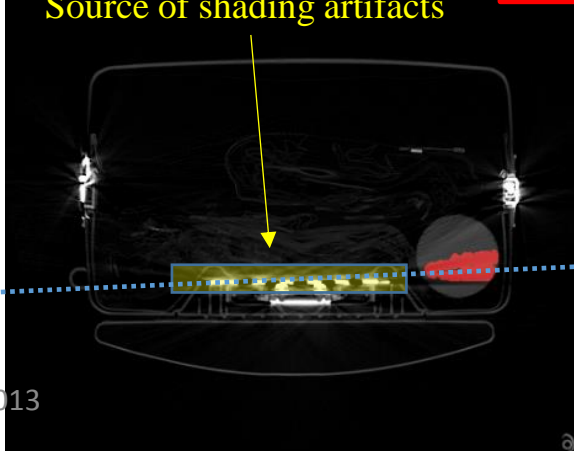


SSMART



Less reliable measurements corrupt whole fidelity term.
→ Hard to correct with regularization term.
→ So, better not to use.

Source of shading artifacts



Problem Cases

Xrec

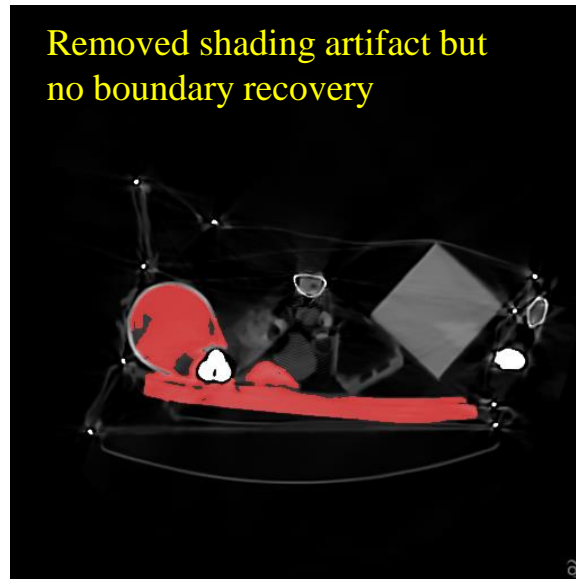
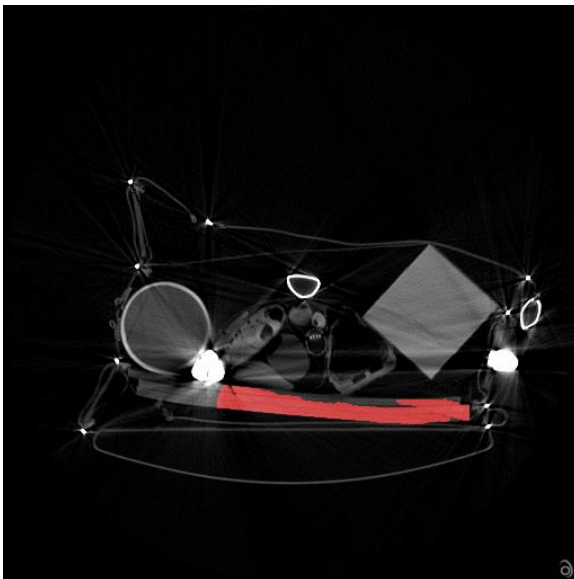
SSMART

Slice #28



Parameter
Selection
Problem

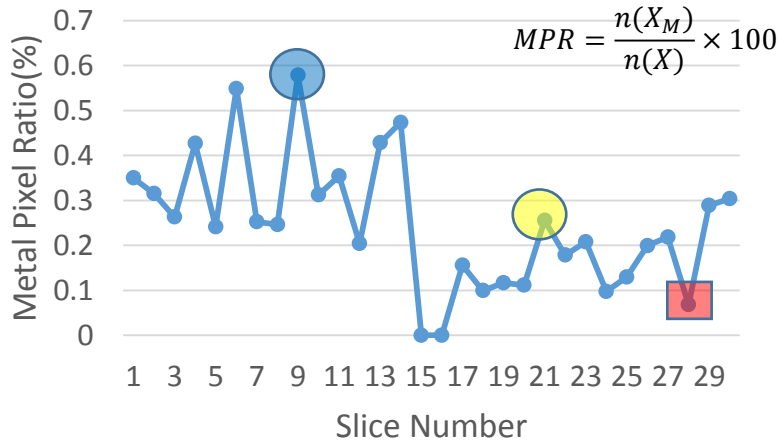
Slice #1



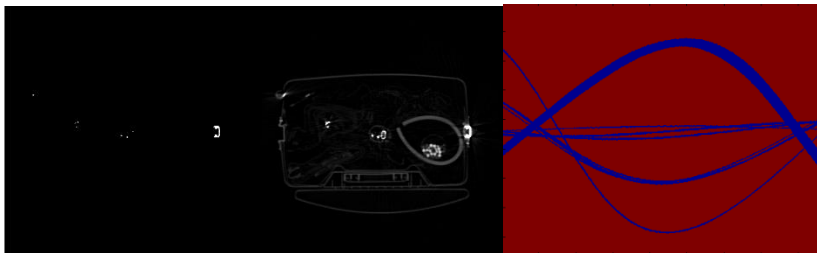
Need Dual
Energy ?

Sparseness vs. SSMART parameters

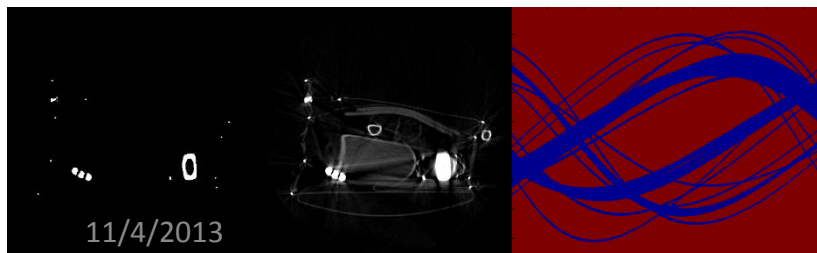
Metal Pixel Ratio (%)



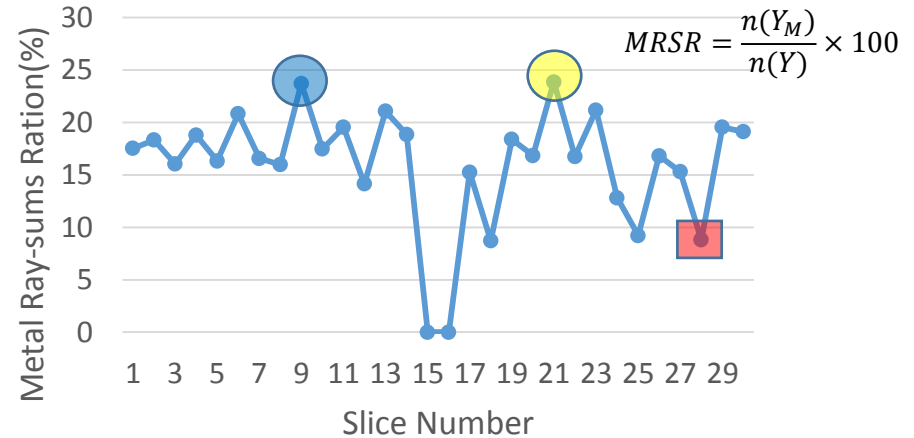
Slice #28



Slice #9



Metal Ray-Sums Ratio (%)

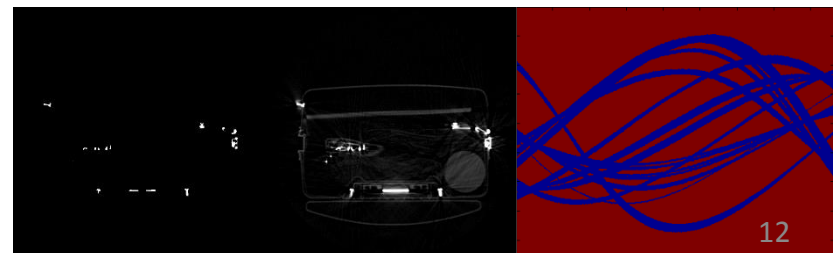


Slice Number

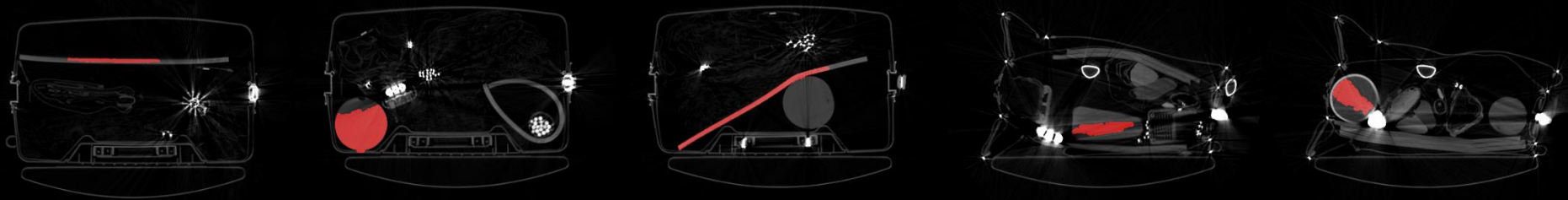
SSMART parameter adjustment needs:

1. MPR and/or MRSR
2. Metal pixel intensity
3. Metal size

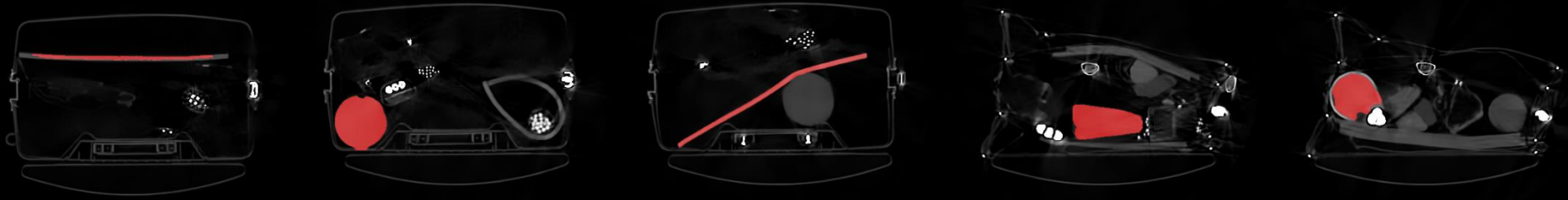
Slice #21



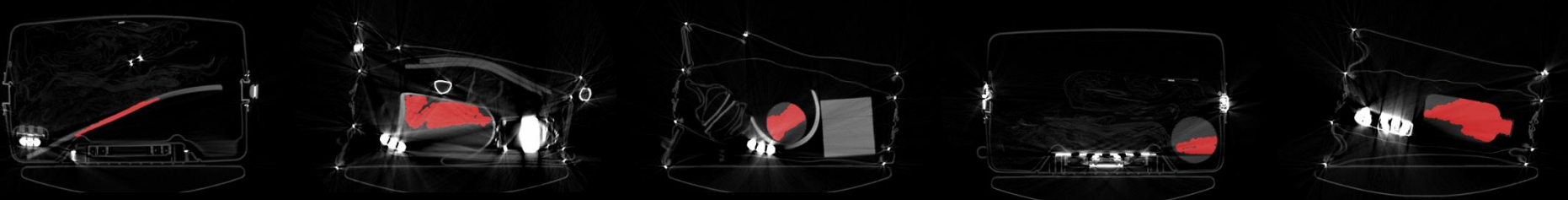
Xrec



SSMART



Xrec



SSMART



Summary

Strength

- Works well with small dense metal components.
- Great performance with a few objects.
- Removes low frequency shading artifacts.
- Improve homogeneity in uniform objects.

Weakness

- Not good for many metal components.
- Generates new streak artifacts when MPR & MRSR are high.
- Threshold sensitive.
- Additional projection required.

Future Research Topic

- More **accurate system model** would improve image quality. (Now, pencil-beam ray model and some artifacts near COR)
- Test with **raw sinogram** (less pre-processed) coupling with accurate system model. (Now, '.clp' is used)
- SSMART **parameters** can be adjusted by sparseness measurements. (Now, same parameters for all slices)
- **Multi-level iterative threshold method** can be tested. (Now, regardless pixel intensity and size of metal, all metal pixels are treated equally)

Back-up Slides

How SparseRecon works ?

- SparseRecon is a modification of “image de-blurring” [1,2]
- Iterative shrinkage algorithm

$$\hat{x} = \operatorname{argmin} \frac{1}{2} \|y - Ax\|^2 + \lambda \rho(x)$$

x: image, y: sinogram, A: system matrix, λ : weighting parameter, and

$$\rho(x) = |x| - s \log\left(1 + \frac{|x|}{s}\right)$$

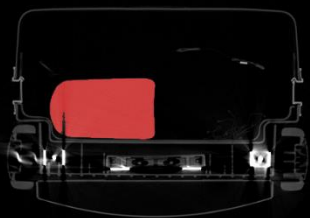
which leads to near $L1$ -norm for small value of $s > 0$ ($s=0.0001$ in our case).

- The new component : $A = H[\Psi, \Phi]$
 Ψ and Φ are two $n \times n$ unitary matrices. And H is a conventional forward system matrix
- Therefore, the algorithm becomes to minimize:

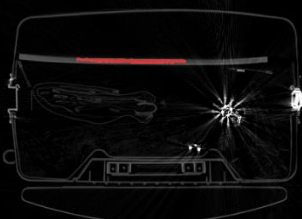
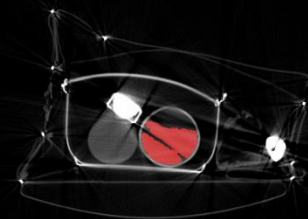
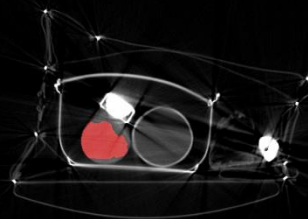
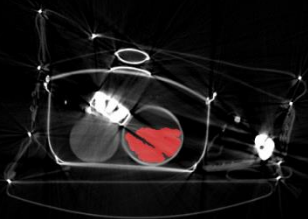
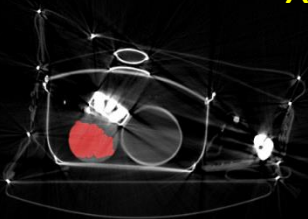
$$\hat{x} = \operatorname{argmin} \frac{1}{2} \|y - H(\Psi x_\Psi + \Phi x_\Phi)\|^2 + \lambda \rho(x_\Psi) + \lambda \rho(x_\Phi)$$

- [1] M. A. Figueiredo, R. D. Nowak, and S. J. Wright, "Gradient projection for sparse reconstruction: Application to compressed sensing and other inverse problems," *Selected Topics in Signal Processing, IEEE Journal of*, vol. 1, pp. 586-597, 2007.
- [2] M. Elad, B. Matalon, and M. Zibulevsky, "Coordinate and subspace optimization methods for linear least squares with non-quadratic regularization," *Applied and Computational Harmonic Analysis*, vol. 23, pp. 346-367, 2007.

Xrec



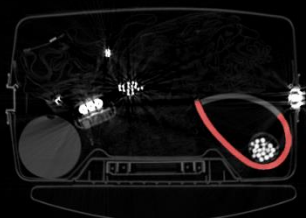
a



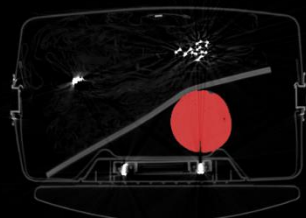
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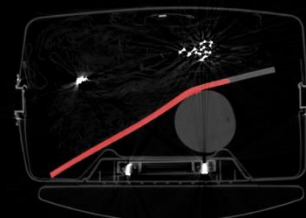
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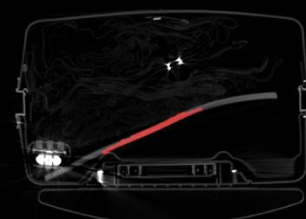
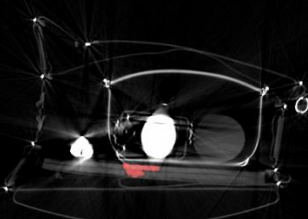
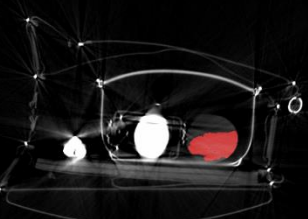
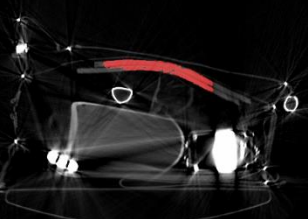
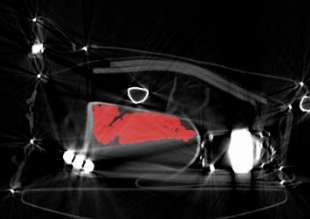
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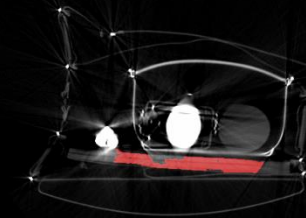
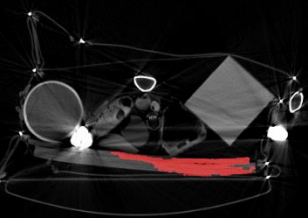
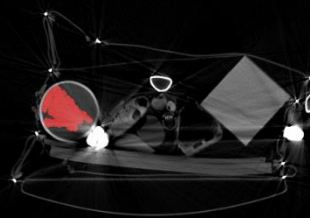
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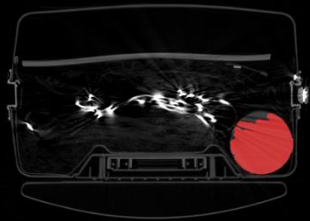


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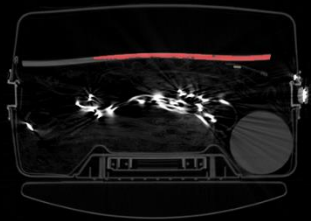


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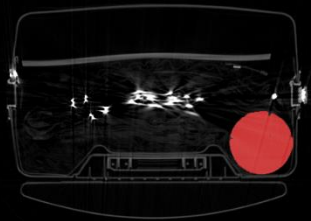




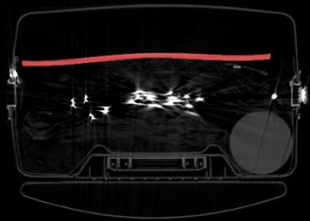
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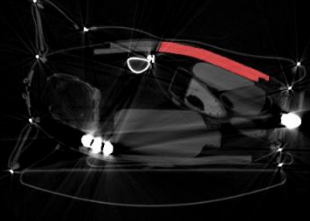
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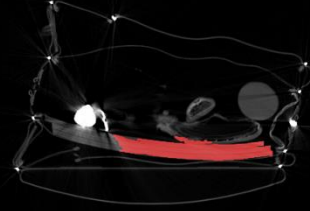
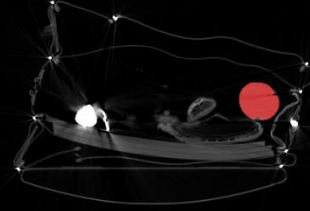
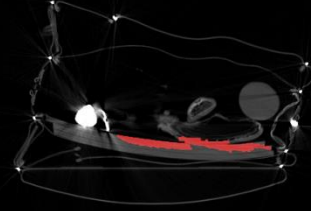
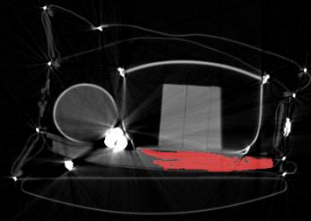
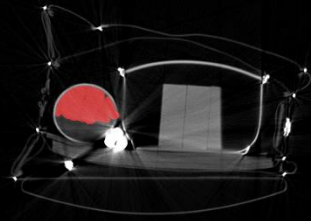
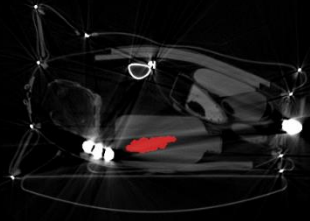
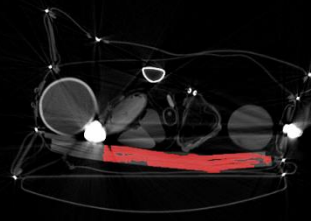
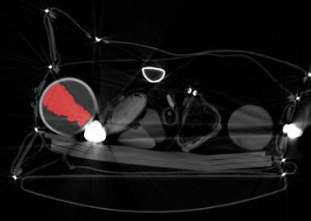
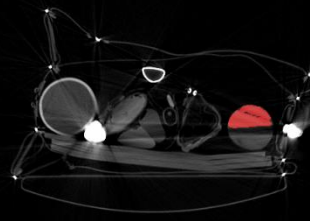
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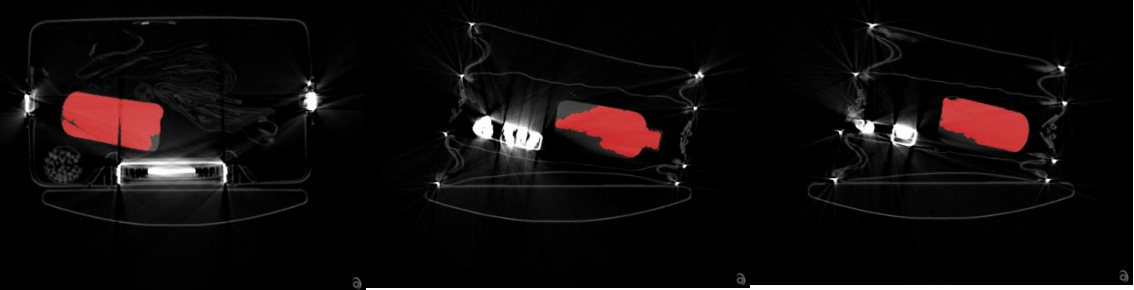
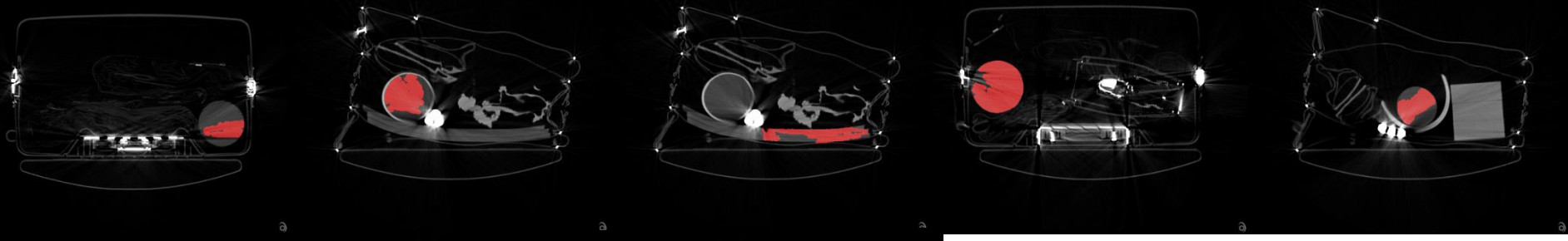


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SSMART

