Compton Scatter Imaging

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This material is based upon work supported by the U.S. Department of Homeland Security, Science and Technology Directorate, Office of University Programs, under Grant Award 2013-ST-061-ED0001 and through contract #HSHQDC-15-C-B0012. The views and conclusions contained in this document are those of the authors and should not be interpreted as necessarily representing the official policies, either expressed or implied, of the U.S. Department of Homeland Security.

ADSA15-Next Generation Screening Technologies and Processes for the Checkpoint

So What, Who Cares

- What space/topic/area is being addressed?
  - X-ray-based baggage inspection
  - Nominally carryon but methods are more broadly applicable
- What problem have you solved?
  - Improve detection performance for severely limited view systems
- How have you solved the problem?
  - Similar to dual energy CT case:

Photoelectric + Compton → Material Maps → Detection

  - In limited view cases, DE image formation is at best challenging
  - We have development a new iterative reconstruction methods fusing traditional absorption data with Compton scatter photons

Compton Scatter Photons = Additional Raypaths → Improved Imaging → Improved Material Maps → Improved Detection

- So what? Who cares?
  - Demonstrating the (potential) value of information typically thrown away
  - Ultimately increase P_d, decrease P_{fa} etc.

The Team

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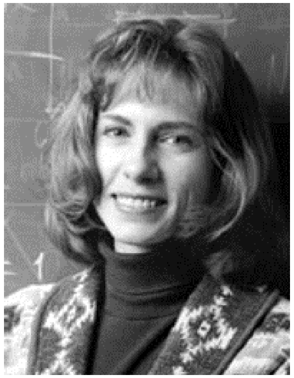
Jeff Denker



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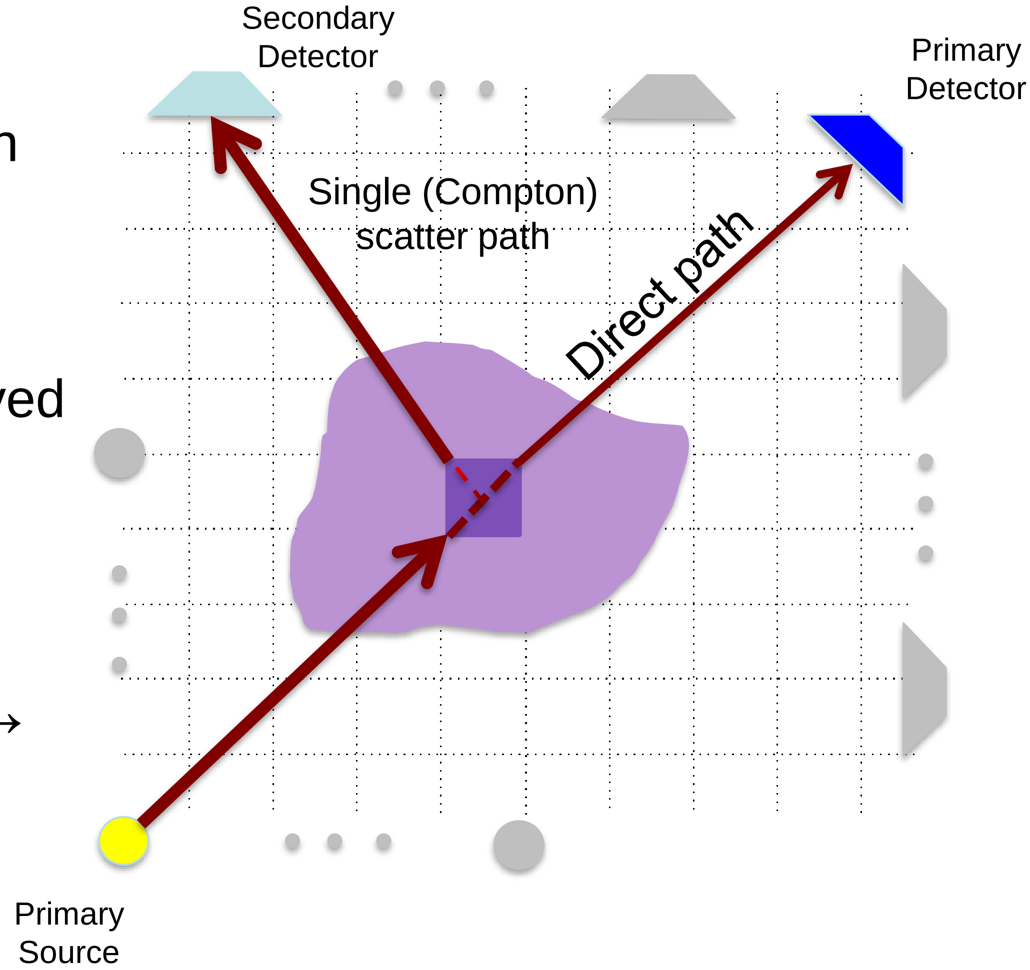
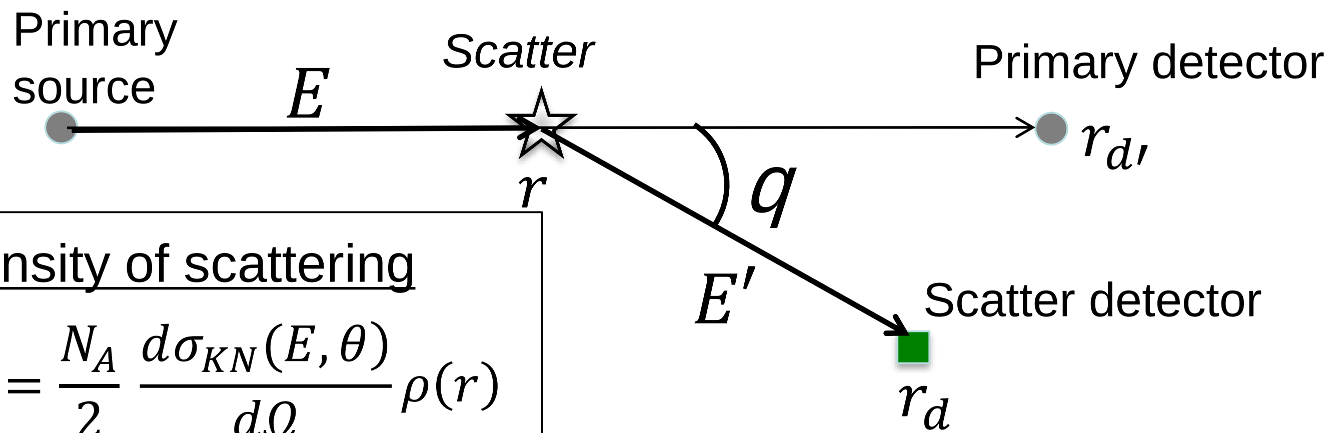
Background

- Ultimate goal: Improved detection
- Scenario of interest: few, fixed sources where traditional DE image formation will break down
- Approach:
  - Measure Compton Scatter = additional raypaths
  - Combined with energy resolved data (~100 few keV bins/detector)
- Rationale
  1. Improved ability to resolve photoelectric and density →
  2. Improved ability to characterize materials →
  3. Improve detection



Compton Scatter



Intensity of scattering

$$S(r,\theta,E) = \frac{N_A}{2}\frac{d\sigma_{KN}(E,\theta)}{d\Omega}\rho(r)$$

Change in direction

$$\cos\big(\theta(r,r_D,r_{D'})\big) = \frac{r-r_D}{|r-r_D|}\cdot\frac{r-r_{D'}}{|r-r_{D'}|}$$

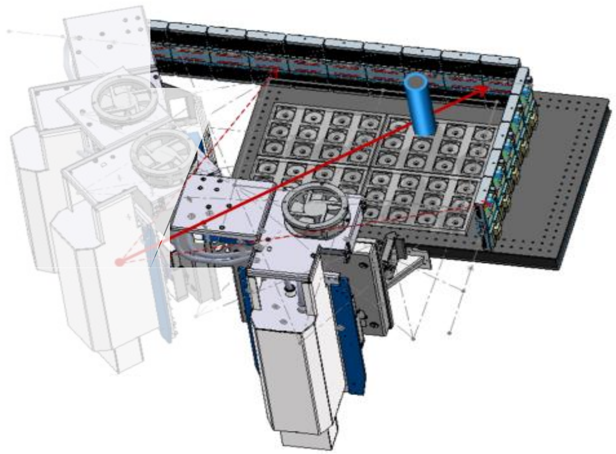
Change in energy

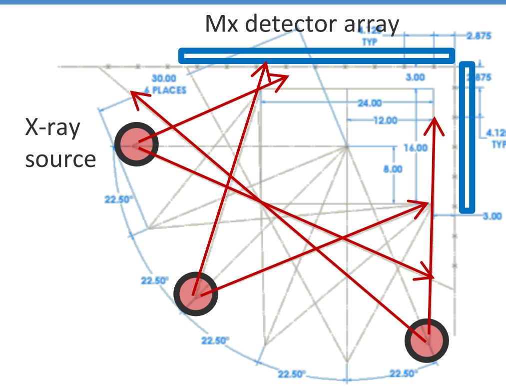
$$E' = \frac{E}{1+\frac{E}{m_e c^2}\Big(1-\cos\big(\theta(r,r_D,r_{D'})\big)\Big)}$$

- From these physics we construct a computational model connecting maps of density and photoelectric absorption to energy resolved observation of attenuated and scattered photons.
- Use model as the basis for imaging

Is the model accurate?

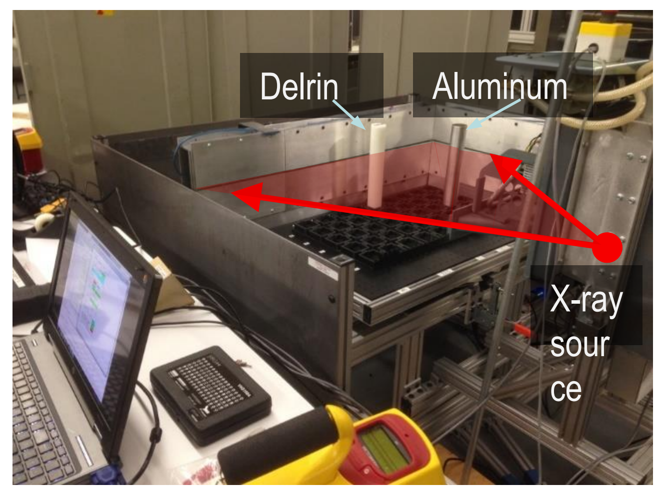
Test Apparatus





Schematic top view of apparatus
(end view of notional tunnel)

- Elementary target configuration consists of two image targets, each with a 2” diameter circular cross section:
  - Delrin (CH$_2$O) Z_{eff} ~ 7 ρ = 1.4 g/cm^3
  - Aluminum (Al) Z = 13 ρ = 2.7 g/cm^3



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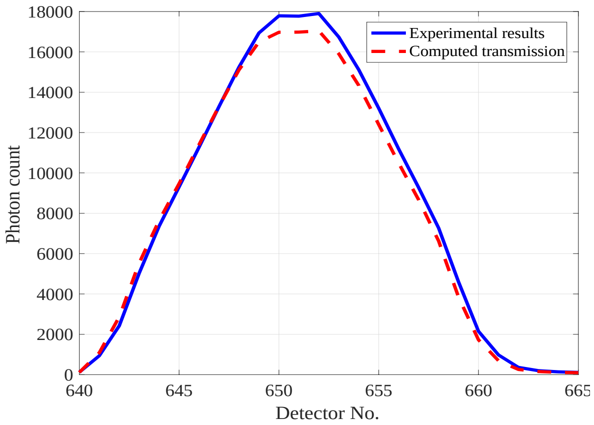
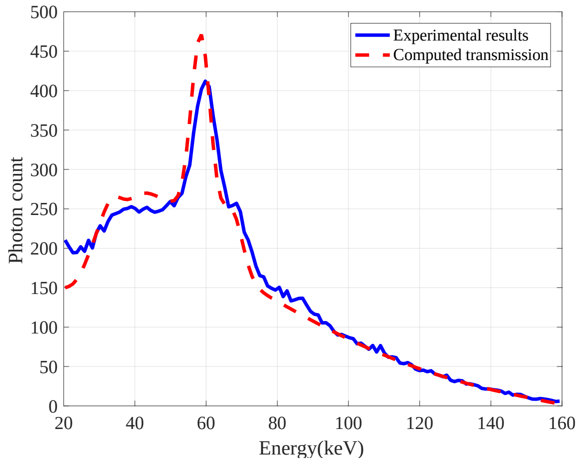
Tx model validation: Delrin and Aluminum, 2” cylinders

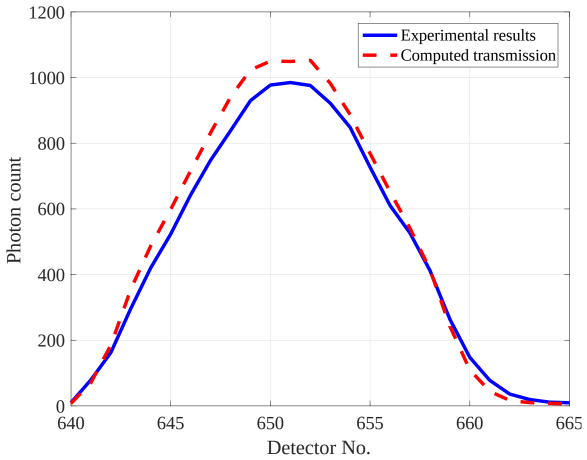
Energy-summed, vs. beam | Multi-energy spectra, peak beam

Delrin





Aluminum



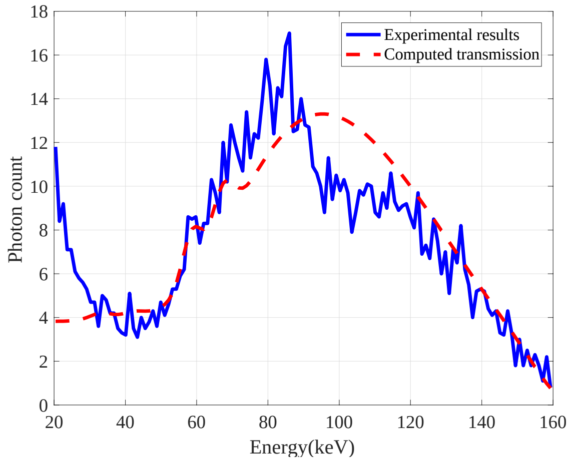


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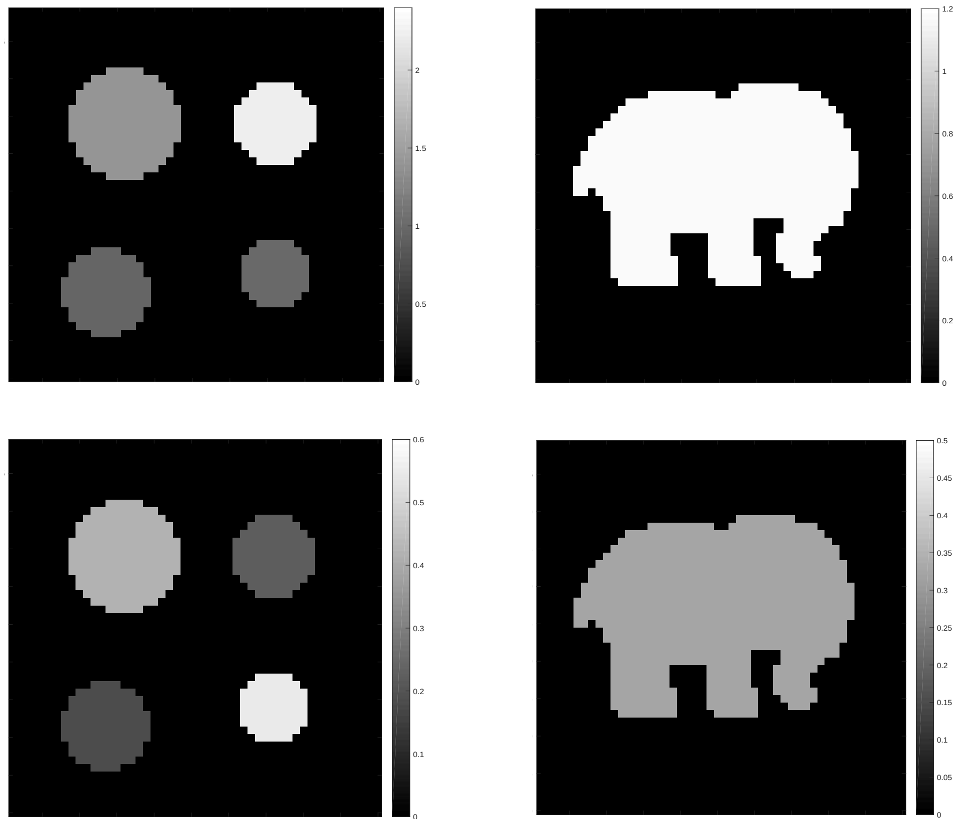
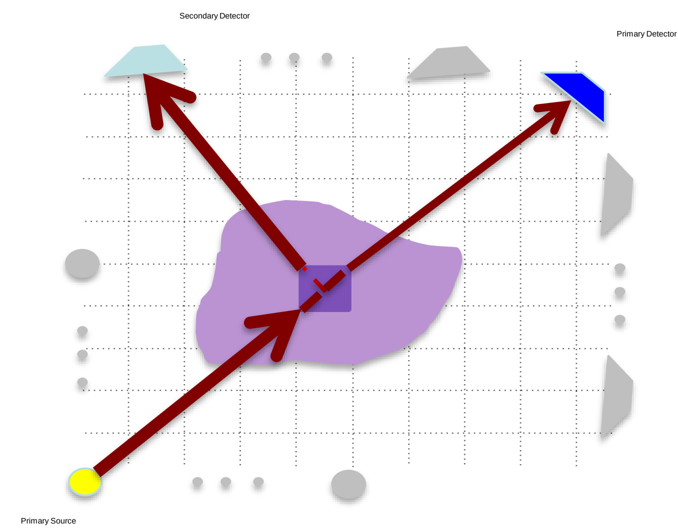
Image Formation: Initial Results

Phantom #1 | Phantom #2

Density

Photoelectric



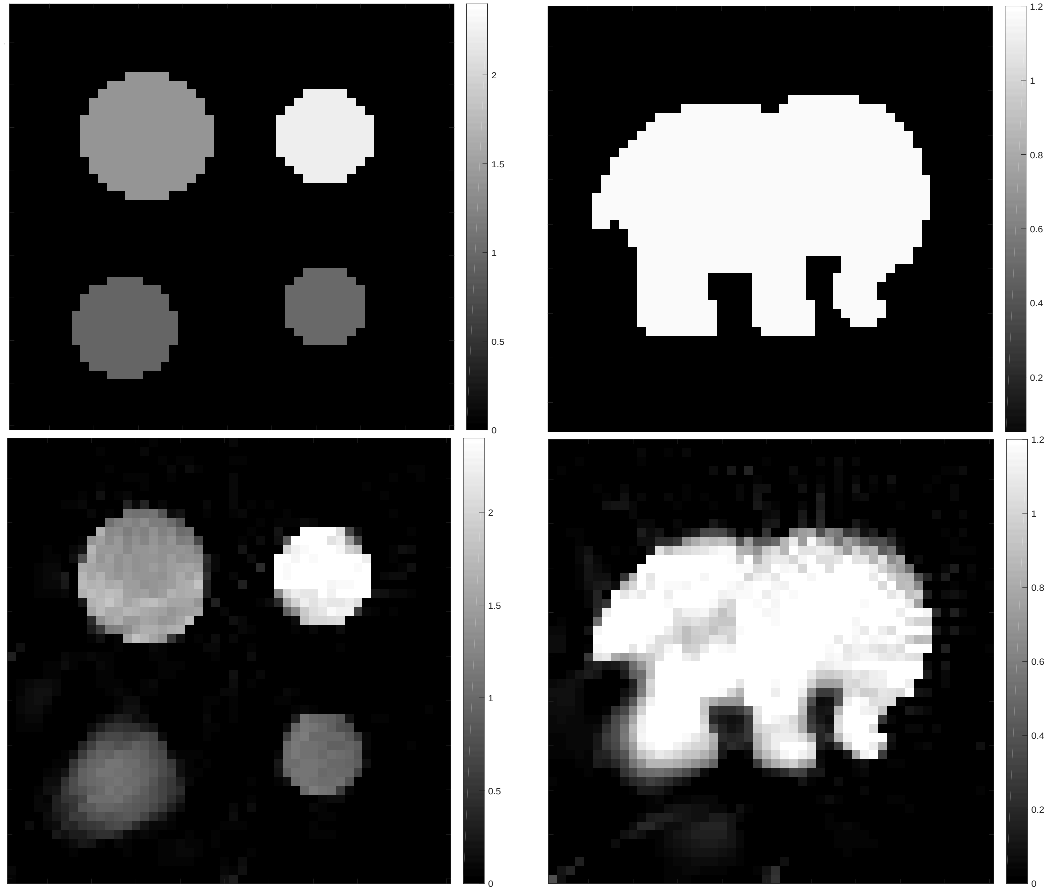


Initial Results

Density Reconstruction

Phantom #1 Phantom #2

Phantom #1:
0-2.4 g/cm

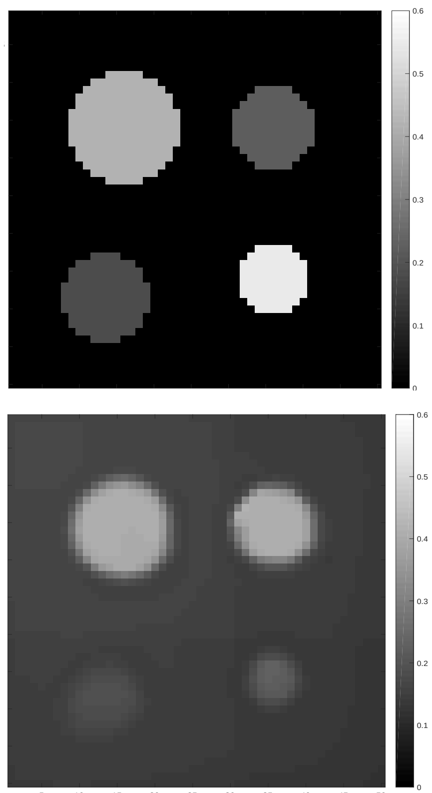


Phantom #2:
0-1.2 g/cm

Initial Results

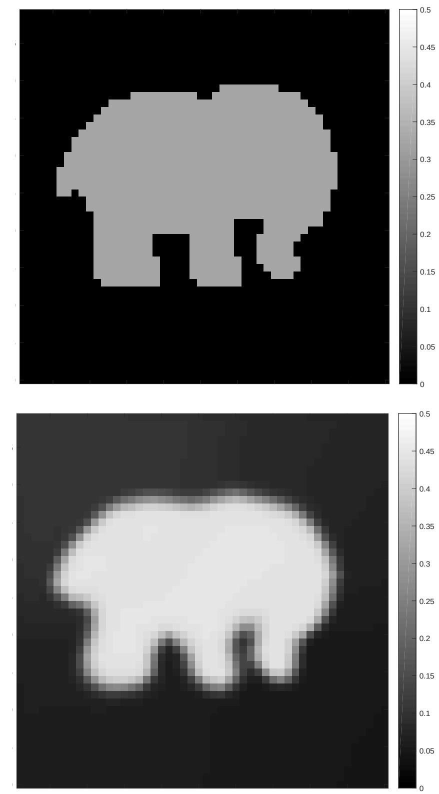
Photoelectric Reconstruction

Phantom #1



Phantoms 1: 0-.6 cm^{-1}

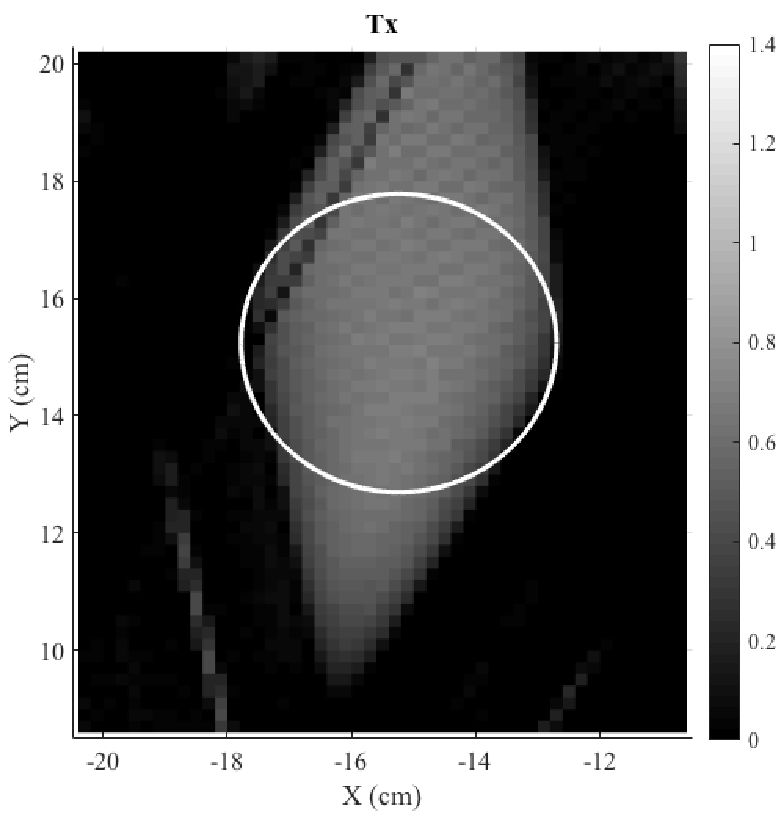
Phantom #2

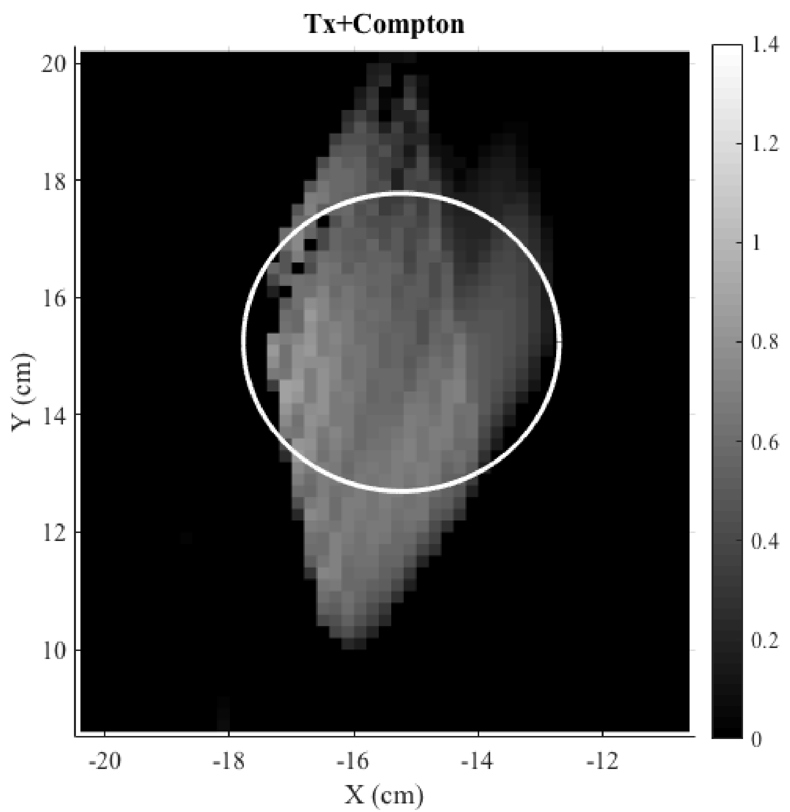


Phantom 3: 0-.5 cm^{-1}

Real Data: Initial Results

- Two views, 0 and 45 degrees source locations
- Low count data, averaging over 10 slots each with 0.1 sec observation





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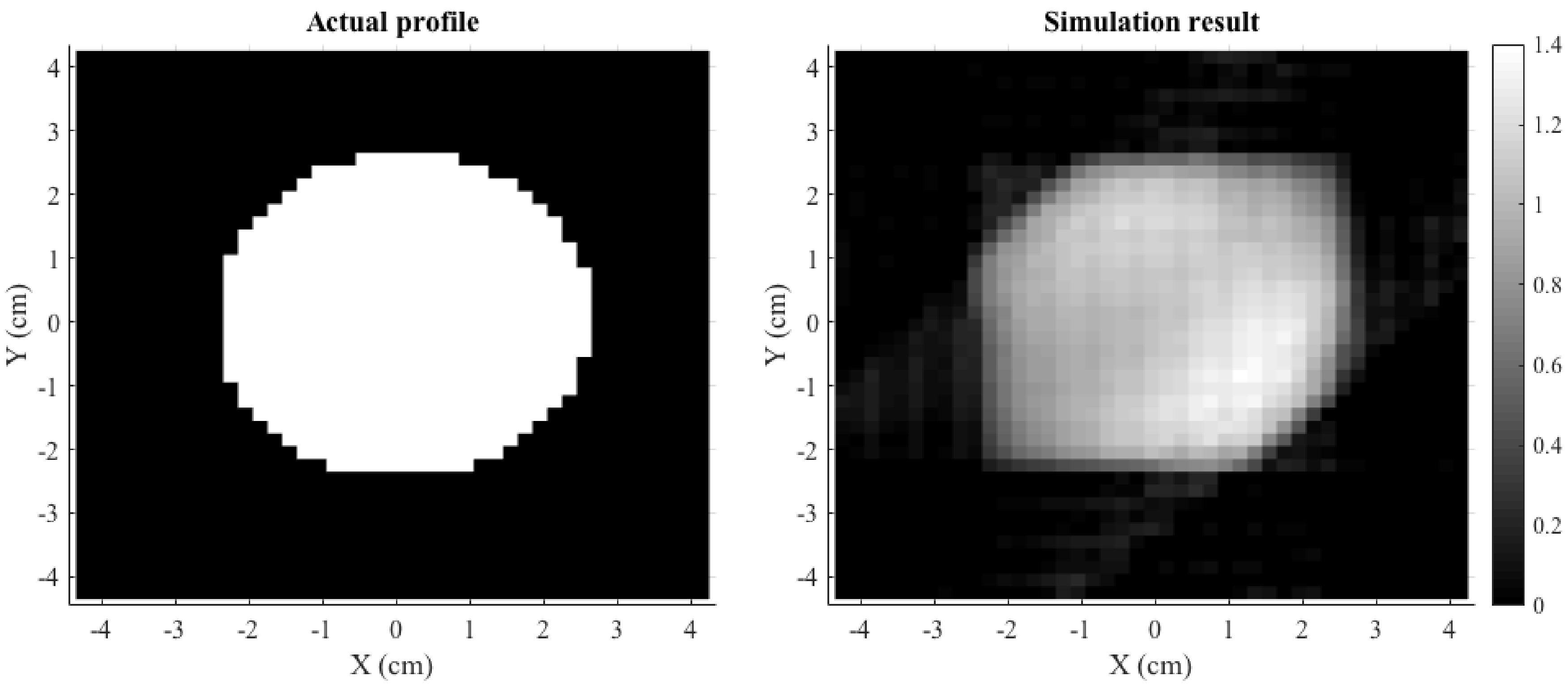
Looking Ahead to Better Data: Simulation Results

- Three views, 0, 45 and 90 degrees
- <u>High count data are assumed</u>



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Conclusion

- Moving toward the conclusion that multi-energy scatter data can be fused with traditional absorption data to (substantially) improve imaging in limited view geometries
  - Certainly true in simulation.
  - Confident (at least ELM is) that this will be demonstrated from real data
- Materials ID to be explored in coming months
- Operationalization is not trivial
  - Scattered photons take time to collect.
  - Likely need to process scatter data in specific regions of interest
  - Computational burden is not small but methods are embarrassingly parallelizable
  - Work needed to understand trade-space comprised of computational architecture (CPA, FPGA, GPU), speed, and cost.
- May also be value in supporting effort in numerical linear algebra
- The story of this work is IMHO a nice example of how basic ALERT research can be moved out of the campus lab and toward actual application

BACKUP

Compton Scatter

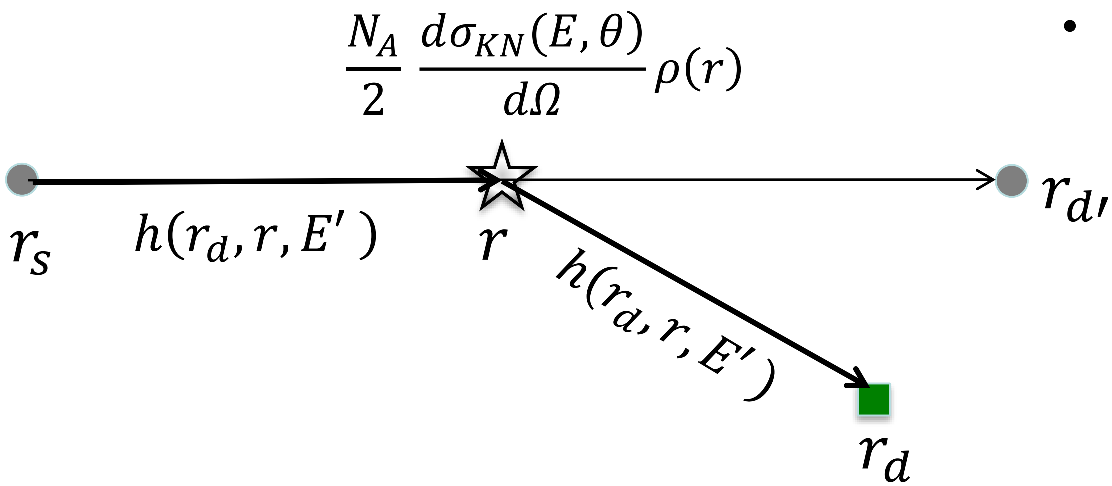
- Hypothesis: Some energy leaving the main bean can be usefully recovered and ultimately improve detection performance
- Dominant process of interest here is Compton Scatter
- Inelastic scattering of an incoming X-ray photon by an electron

Discrete Compton Scatter Model

$$g = K(\rho, p)\rho + \mathcal{N}(0, \delta^2)$$

- Data vector aggregates information as a function of
  - Source-Primary Detector pair, $(r_s, r_d,)$
  - Secondary detector: r_d
  - Energy: E'
- Nice structure:
  - Kind of linear in density
  - Will be exploited in processing
- For system with relatively few primary raypaths
  - Compton scatter gives many more “looks”
  - But signal strength lower. Either lower SNR or increased integration time
- Settle for additive white Gaussian noise for now. Poisson later.

Compton Scatter Model



- Single scatter model
  - Propagate (attenuate) source to image point
  - Scatter at image point
  - Propagate image point to secondary detector

$$g(r_d, E') = \int I(E) \int h(r_d, r, E') \frac{N_A}{2} \frac{d\sigma_{KN}(E,\theta)}{d\Omega} h(r, r_s, E)\rho(r)\,dr\,dE$$

$$= \int K(r_d, r, E; \rho, p)\rho(r)\,dr$$

Compton Scatter Model

- Compton Scatter- Continuous form

$$g(\boldsymbol{r}_{D'}, E') = \int I_0(E_S)\left[\iint h_2(\boldsymbol{r}_{D'}, \boldsymbol{r}, E') S(\boldsymbol{r}, \theta, E) h_1(\boldsymbol{r}, \boldsymbol{r}_S, E_S) l_{\boldsymbol{r}_D, \boldsymbol{r}_S}(\boldsymbol{r}) \rho(\boldsymbol{r}) d\boldsymbol{r}\right] dE_S$$

$$h_2(\boldsymbol{r}_{D'}, \boldsymbol{r}, E') = \Omega_D exp\left(-\int \mu(\boldsymbol{r}', E') l_{\boldsymbol{r}_{D'}, r}(\boldsymbol{r}') d\boldsymbol{r}'\right)$$

$$h(\boldsymbol{r}_2, \boldsymbol{r}_1, E_S) = exp\left(-\int \mu(\boldsymbol{r}', E_S) l_{\boldsymbol{r}_2, \boldsymbol{r}_1}(\boldsymbol{r}') d\boldsymbol{r}'\right)$$

$$\mu(\boldsymbol{r}, E) = N_A \frac{z(r)}{A(r)} \rho(r) f_{KN}(E) + p(\boldsymbol{r}) f_p(E)$$

- Compton Scatter- Discrete form

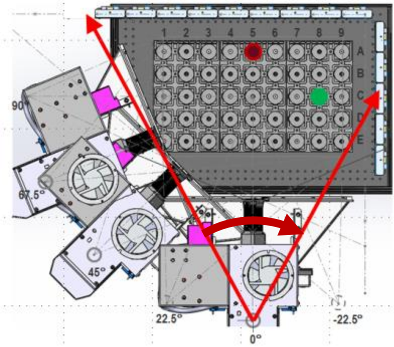
$$g = K(\rho, p)\rho + \mathcal{N}(0, \delta^2)$$

scattered data

discretized scattering system

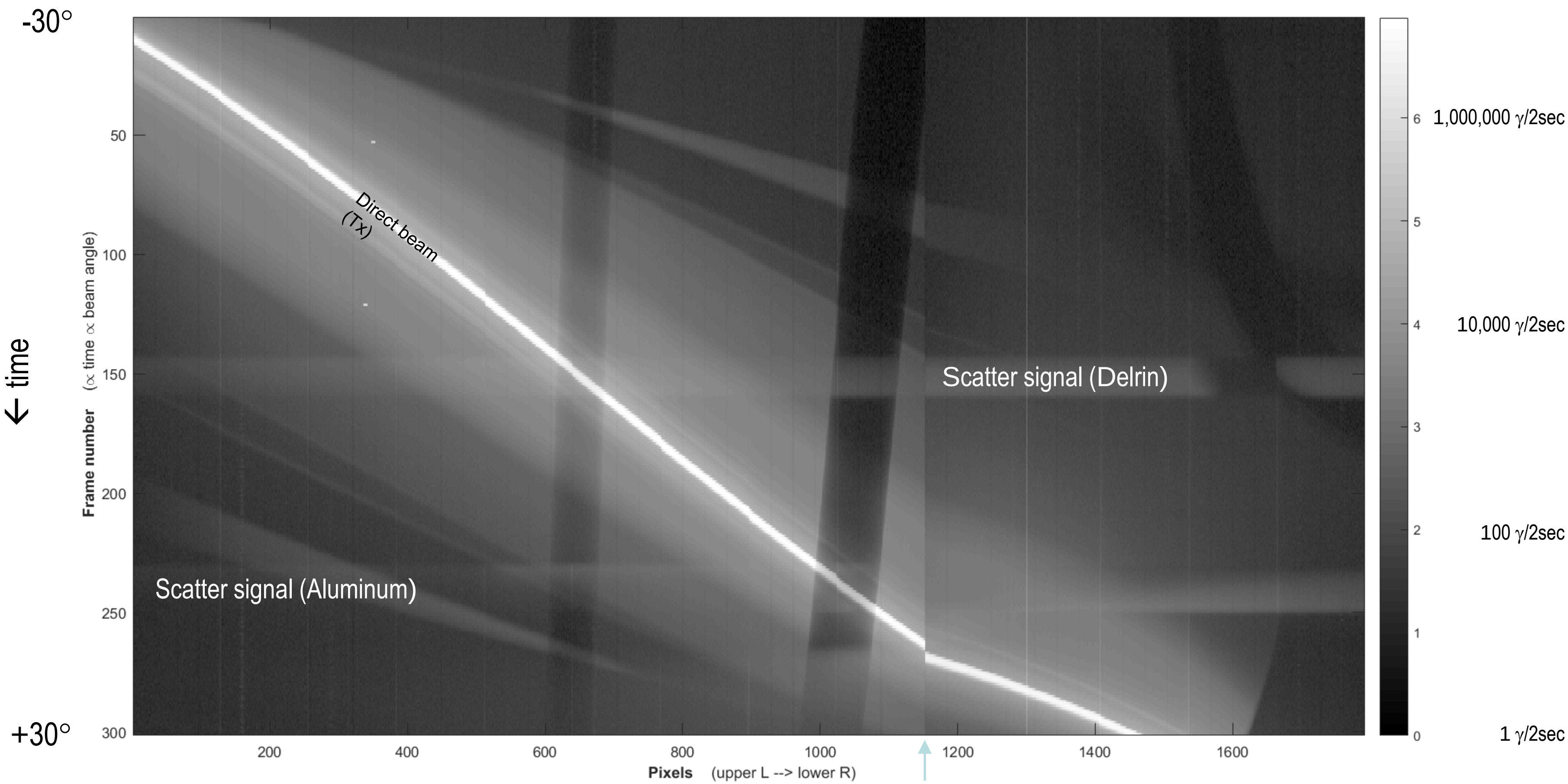
measureme nt noise

Amplified by Log10 scaling (grayscale)



Low signals emphasiz

Color indicates counts/pixel per 2.0 sec time period
(all energy channels summed)



Horizontal detector array　　Corner gap　　Vertical detector array

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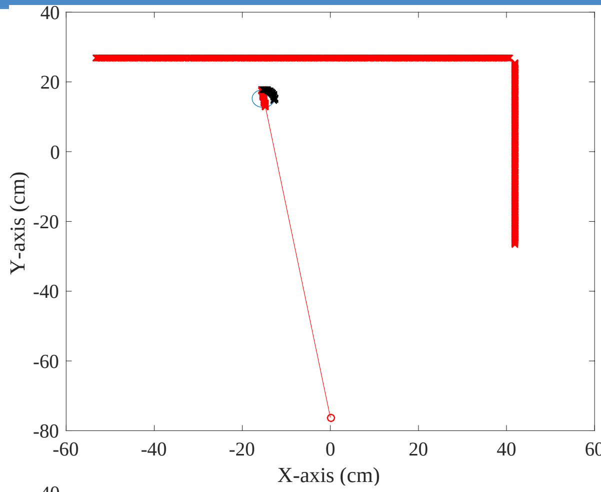
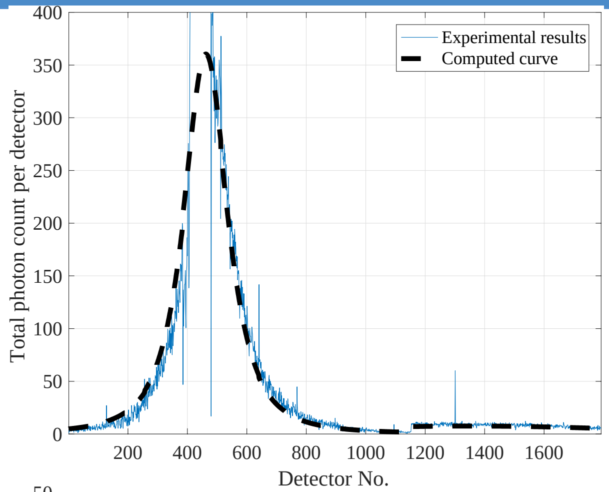
Scatter model validation: Varying target positions

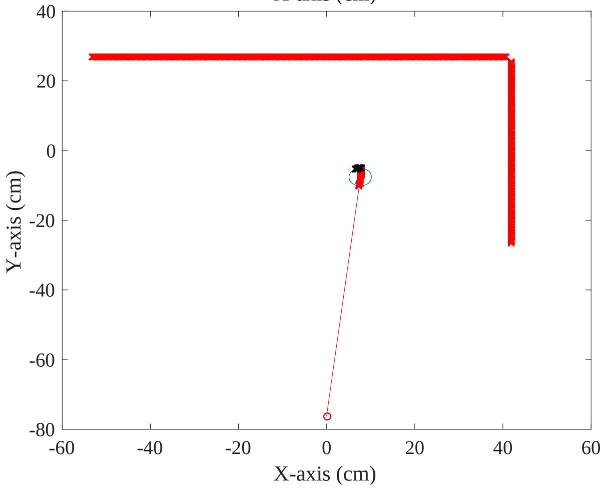
Delrin target loc. D6 Delrin target loc. A3

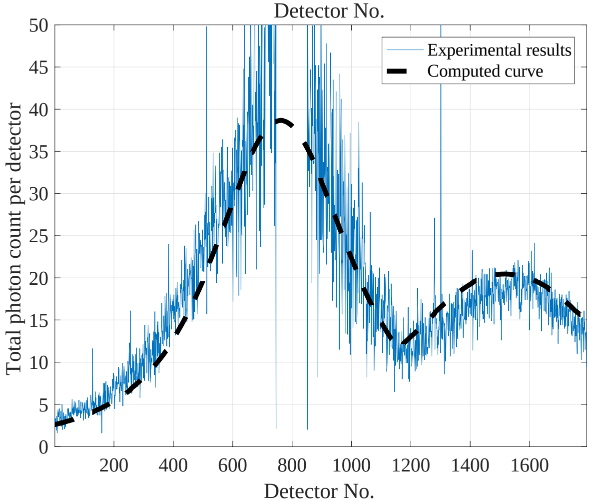
Problem configuration

Energy-summed, vs. detector









Underlying scattering is fairly isotropic; position cues are largely from solid angle effects

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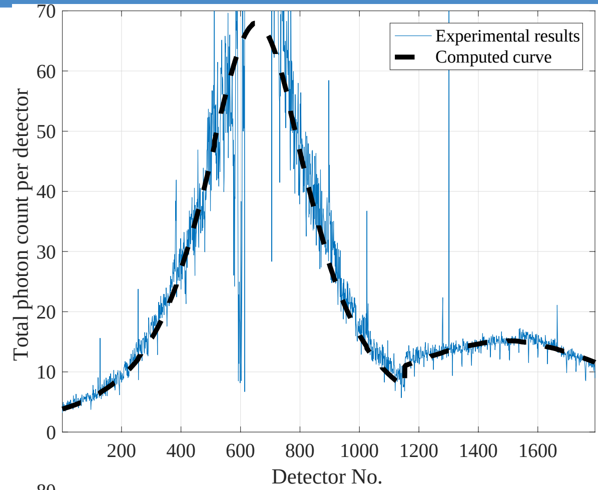
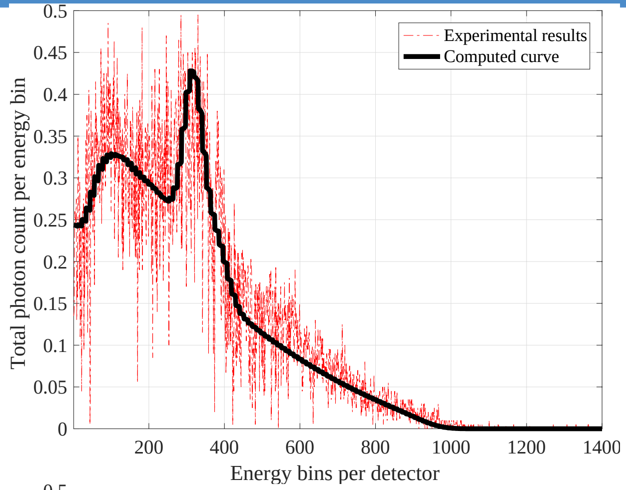
Scatter model validation: Spectra and effect of dwell time

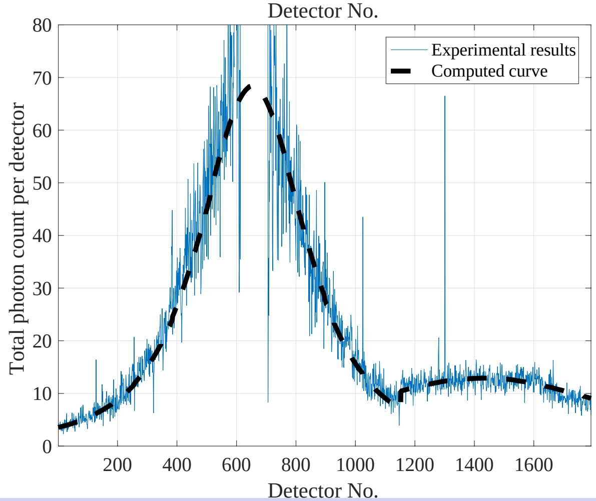
Energy-summed, vs. detector | Multi-energy spectra, peak beam

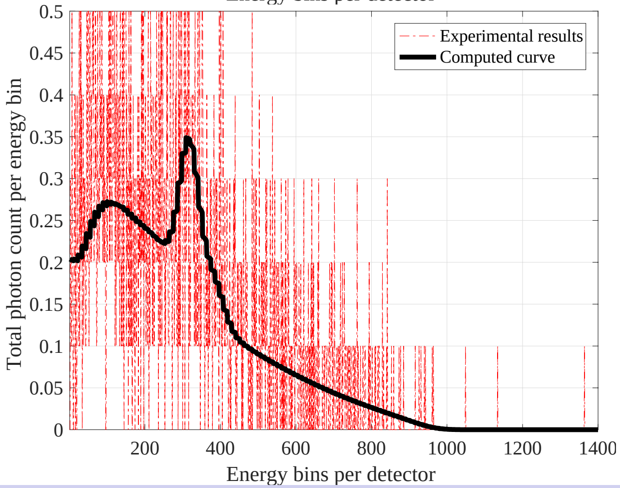
Graphite, 20 sec integration





HDPE, 1 sec integration





Model predicts spectral shape well; longer integration time reduces statistical noise

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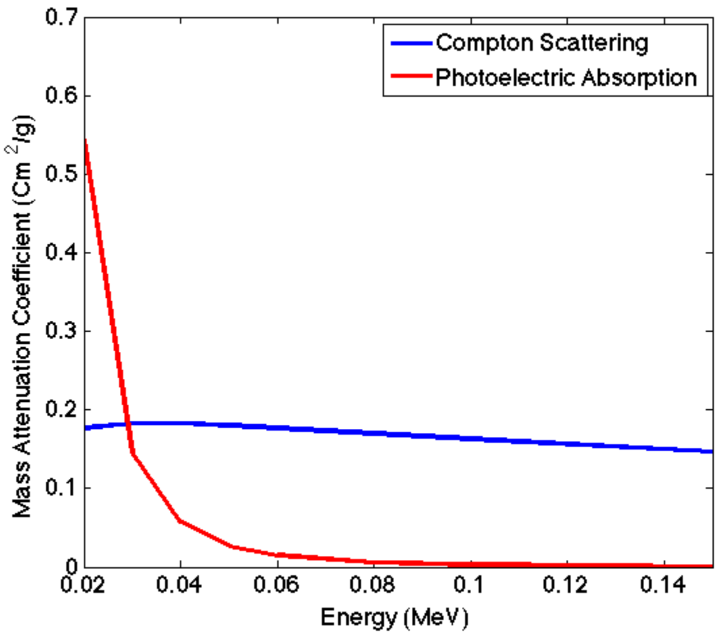
Inverse Problem

$$(\hat{\rho}, \hat{p}) = \underset{\rho,p}{\text{argmin}} \underbrace{\|g - K(\rho,p)\rho\|_2^2}_{\text{data mismatch}} + \underbrace{R_\rho(\rho) + R_p(p)}_{\text{regularization}}$$

- Solution approach
  - Impact of photoelectric on data is small
  - Assume it can be ignored and first solve for density
  - After density recovered, estimate photoelectric
- Could iterate, but leave that for later



Density Reconstruction

$$\hat{\rho} = \underset{\rho}{\operatorname{argmin}} \|g - K(\rho, 0)\rho\|_2^2 + R_\rho(\rho)$$

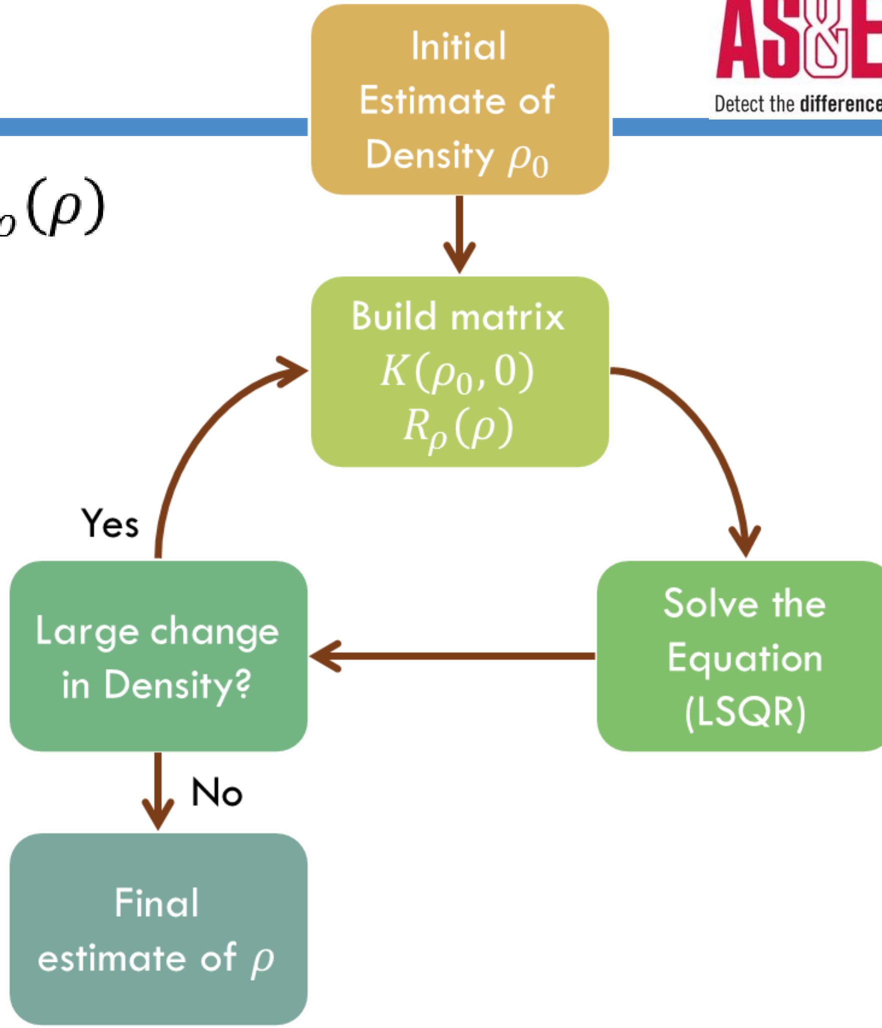
- **Regularization**
  - Gradient-based

    $$R_\rho(\rho) = \lambda_\rho \|L\rho\|_2^2$$

  - Iterative Edge-Enhancing [1]

    $$R_{\rho,\ell}(\rho) = \lambda_{\rho,\ell} \left\|D^{(\ell)} L\rho\right\|_2^2$$

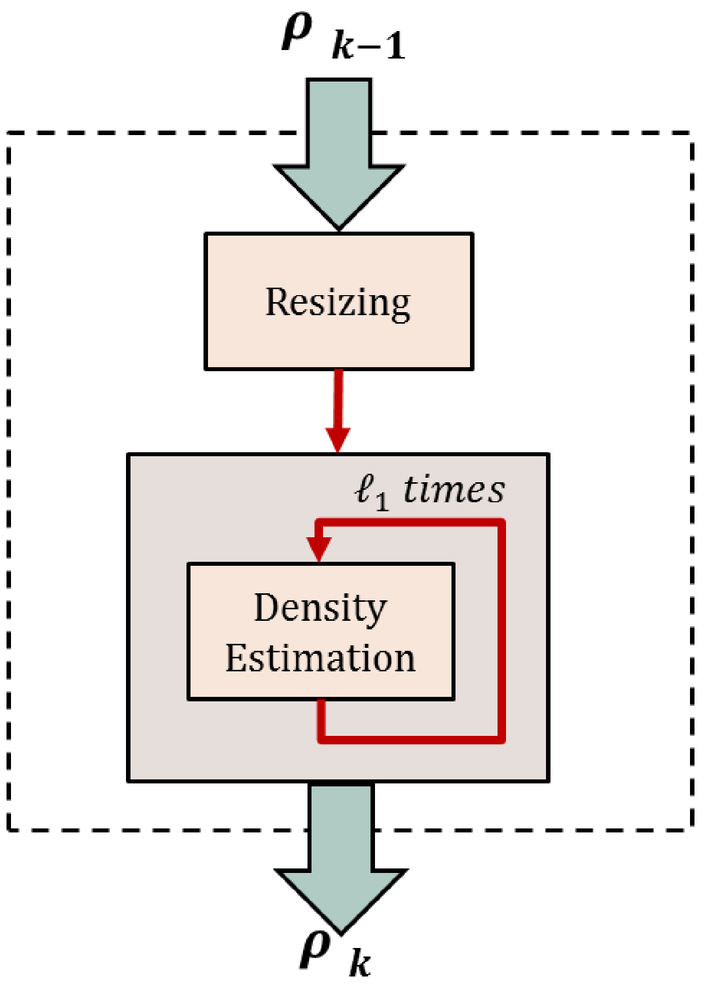
  - All λ_ρ chosen to minimize MSE (Clearly needs to be changed)
- **Initial Guess**
  - Attenuation based CT images
  - Constant background image



[1] Oguz Semerici, "Image Formation Methods for Dual Energy and Multi-Energy Computed Tomography," PhD Thesis, Dept. of ECE Tufts University, October 2012.

Multi-Scale Approach

- Initial efforts recovering density using fine scale grid of pixels did not work out so well.
- Multi-scale approach worked out much better
  1. Begin at coarse scale, $NR \times NC$, representation
  2. Initialized as a constant density image
  3. Estimate ρ
  4. Interpolate onto finer grid
  5. Goto 3 until fine enough
- Regularization parameter updated at every scale



Edge-Enhancing Regularization

- Gradient-based regularization penalizes all high differences even edges
- Edge-enhancing regularization de-emphasizes the smoothing for the edge locations in the image
- Diagonal elements on the weighting matrix determine whether a pixel belongs to the edge map
  - Closer to one : enforce smoothness
  - Closer to zero : should be preserved

$$R_{\rho,\ell}(\rho) = \lambda_{\rho,\ell} \left\| D^{(\ell)} L\rho \right\|_2^2$$

Inputs:

- $D^{(0)} = I$
- **L gradient matrix**
- **Estimate of** ρ **for** $\mathbf{k} = 0,1,\ldots$

1: **for iterations** $\mathbf{k} = 1,\ldots$

2: **Set** $v = D^{(k-1)} L\rho_{\mathbf{k}-1}$

3: **Normalize** v **by setting** $v \leftarrow v/\|v\|_\infty$

4: **Map** d **to** $[0,1]$ **by defining** $d := 1 - v.^p$

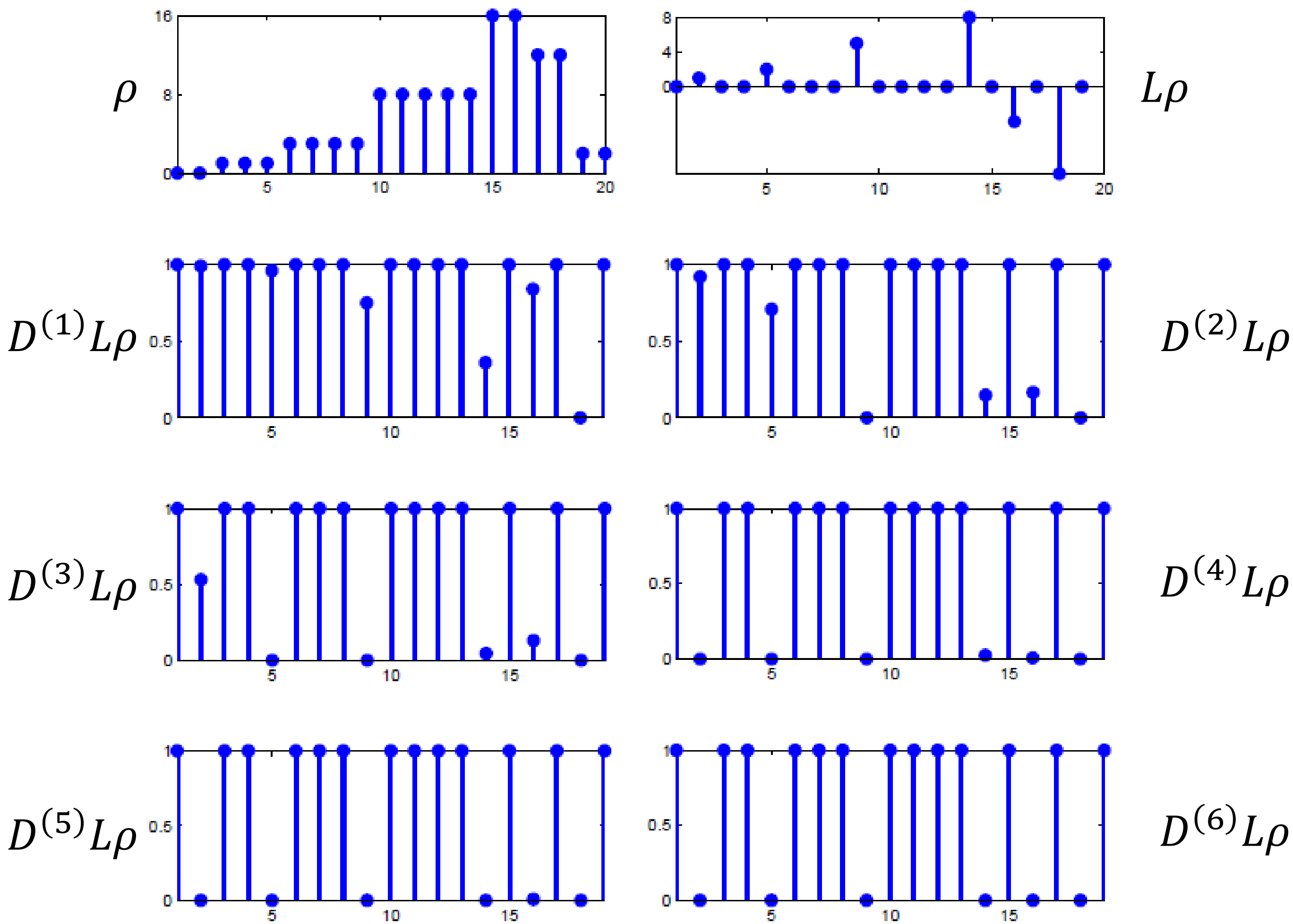
5: **Define** $D := diag(D)$

6: **Update** $D^{(\mathbf{k})} \leftarrow DD^{(\mathbf{k}-1)}$

7: **end**

Edge-Enhancing Regularization

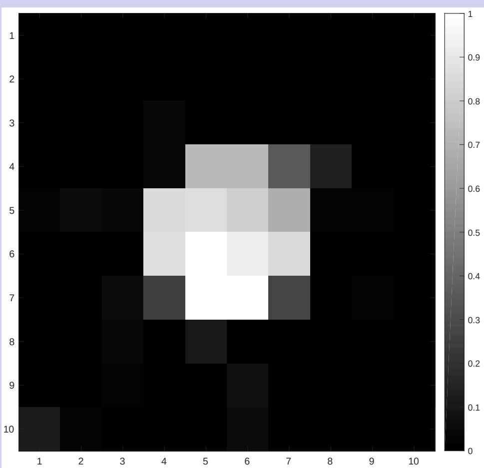
$$R_{\rho,l} = \lambda_{\rho,l} \left\| D^{(l)} L\rho \right\|_2^2$$



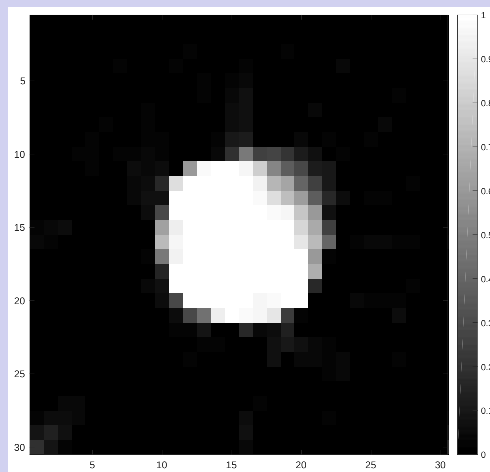
Simulation Results

Phantom #3

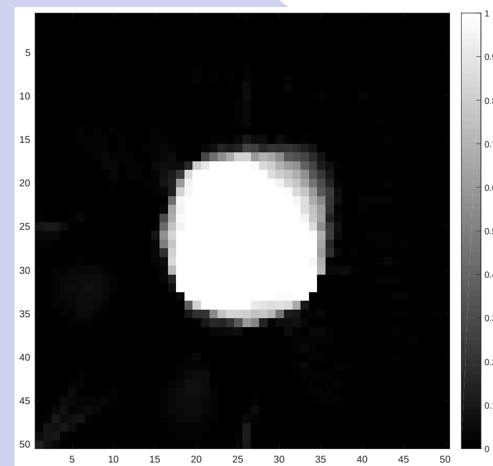
Density Estimation: Iterative Edge-Enhancing Regularization



Scale 1
10×10



Scale 3
30×30



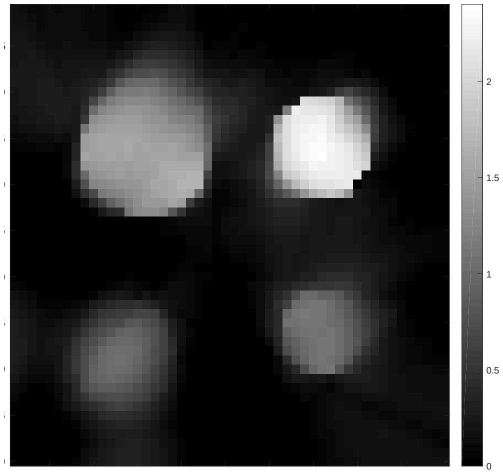
Scale 5
50×50

Initial Results

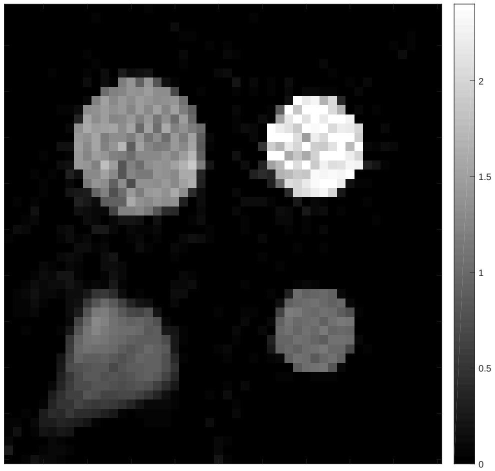
Density Reconstruction

Value of Heterogeneous Data

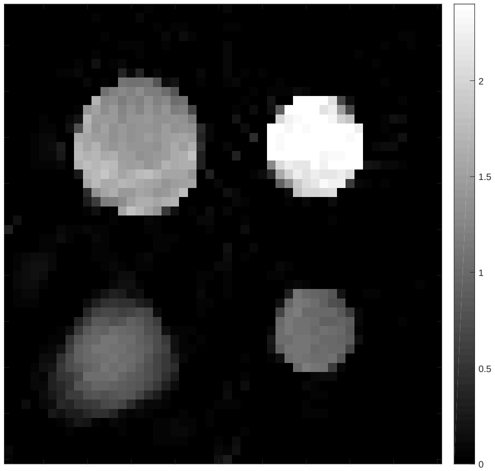
Only Attenuation Data



Only Scatter Data



Attenuation and Scatter Data



Photoelectric Estimation

$$\hat{p} = \underset{p}{argmin} \|g_{scat} - K_{scat}(\rho_t, p)\rho_t\|_2^2 + \|g_{att} - K_{att}(\rho_t, p)\|_2^2 + R_p(p)$$

- Joint attenuation and Compton Scatter inversion
- Non-linear least squares optimization problem
- Levenberg-Marquardt method [2]
- Patch-based non-local mean (NLM) regularization [3]
- Constant background image as initial guess

[2] D.W. Marquardt, “An algorithm for least-squares estimation of nonlinear parameters,” Journal of the Society for Industrial and Applied Mathematics, pages 431–441, 1963.
[3] Brian H. Tracey and Eric L. Miller, “Stabilizing dual-energy X-ray computed tomography reconstructions using patch-based regularization,” Inverse Problems, 31(10), 05004, September 2015

Patch-based Regularization

$$R_p(p) = R_{NLM}(p|\rho^{ref}) = \lambda_p \|(I - W)p\|_2^2$$

- Reduce noise artifacts
- Brings demising step into inversion process
- Calculates weighting matrix using density estimation as reference image

$$W(i,j) = \frac{1}{Z(i)} exp\,(-\frac{\sum_{\delta\in\Delta}\left(\rho^{ref}_{(i+\delta)} - \rho^{ref}_{(j+\delta)}\right)^2}{h^2})$$

$$Z(i) = \sum_j W(i,j)$$

[2] D.W. Marquardt, “An algorithm for least-squares estimation of nonlinear parameters,” Journal of the Society for Industrial and Applied Mathematics, pages 431–441, 1963.

Scaling Up: Parallel MPI Matlab code

- A parallel MPI Matlab code is developed to speed up the inversion process and reduce the memory cost
- The code distributes the algorithm such that each processing unit will process data from a single incident beam
- The code uses efficient memory storage where only the necessary beam-cell intersections are stored
- The memory is reduced by more than 20 times while the algorithm speed depends linearly on the number of processers

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