# Target identification in multi- and dual-energy computed tomography

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## Abstract

We seek to exploit dual- and multi-energy measurements in computed tomography (CT) to characterize material properties as well as object geometry. Material characterization is performed by decomposing the scene into Compton and photoelectric (PE) scattering functions. While well motivated physically, this inversion is challenging due to the lack of sensitivity in the data to photoelectric variations. Moreover, our prior knowledge for materials of interest is imperfect. We propose a model-based, polyenergetic iterative approach which includes patch based regularization terms to stabilize inversion, and uses level set methods to localize explosives or contraband based on imperfect prior information. The approach appears promising for future dual- and multi-energy CT systems.

## Relevance & State of the Art

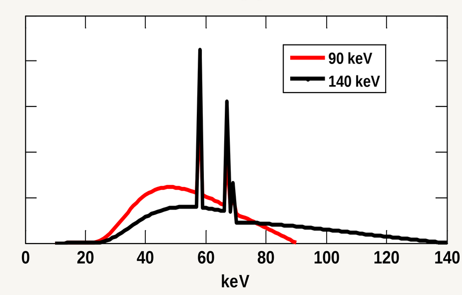
Improved materials characterization through advanced CT systems is a key technology for baggage or carry-on luggage screening in airports and other environments. Previous work [2,4,5] has used physics-based material descriptions that apply to the wide range of materials seen in luggage, but which lead to difficulty in stably estimating material parameters (such as PE coefficients). In addition, there is a need to make use of existing but imperfect characterizations of the material properties of explosives. This project is extending recent DHS-funded work [2,3] and will lead to concept validation on actual scanner data.

## Technical Approach

### Physical Model and Approach

**Dual- or multi-energy scanners** can exploit energy-dependence of X-ray absorption to obtain material identification.

Dual-Energy Spectra




1) We capture energy dependence with a polyenergetic physical model:

$$[\bar{\mathbf{Y}}]_i = \int S(E) e^{-\mathbf{A}_{i*}\mu(E)} dE$$

2) We express data as sum of **physics-based** basis functions - giving **Compton scatter** and **photoelectric effect** images [4,5]

$$\mu(x,y,E) = \underbrace{f_{KN}(E)\, a_c(x,y)}_{\text{Compton scatter}} + \underbrace{f_p(E)\, a_p(x,y)}_{\text{photoelectric effect (PE)}}$$

Note, PE inversion is much less stable due to low sensitivity

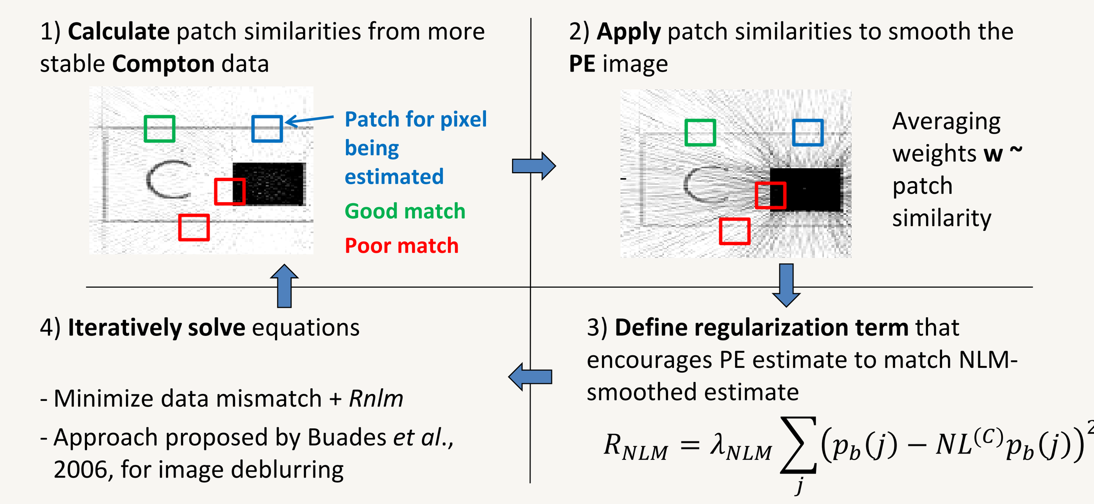
3) We apply **iterative reconstruction** algorithms [2]

**Challenges and proposed solutions***:*

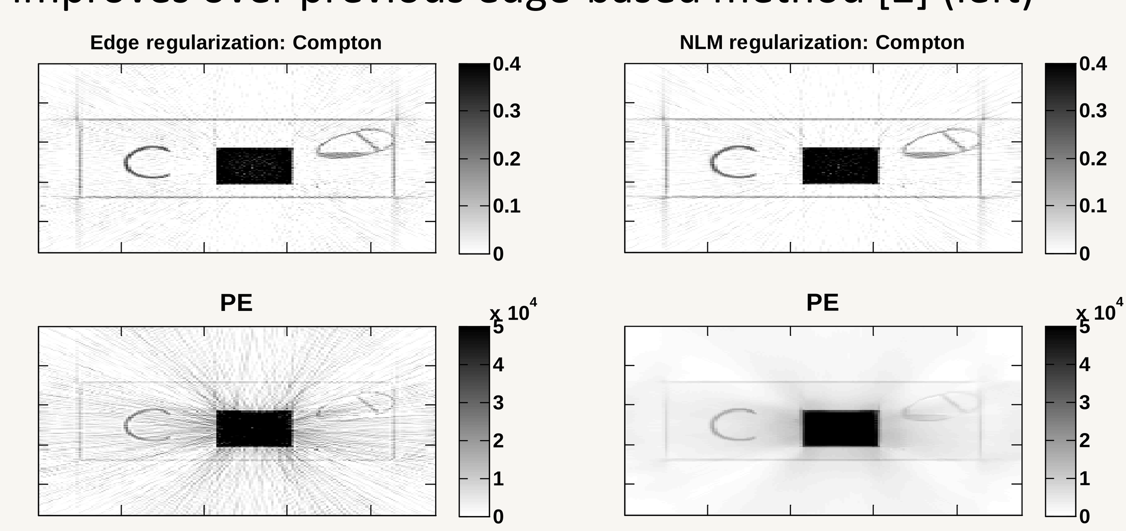
- Develop methods to **stabilize PE image reconstruction**
  - Make use of **patch-based regularization** techniques
- **Exploit imperfect knowledge** of materials of interest
  - Use **level sets to find "foreground",** i.e. objects of interest

### Patch-based Stabilization of PE image Inversion

Intuition: Overall geometry is expected to be similar between Compton and PE, so use Compton image to guide PE reconstruction

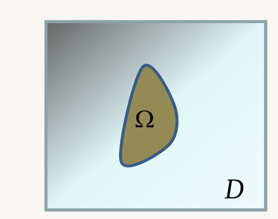



For suitcase phantom, patch-based result (right) improves over previous edge-based method [2] (left)




### Level Set Localization of Materials of Interest

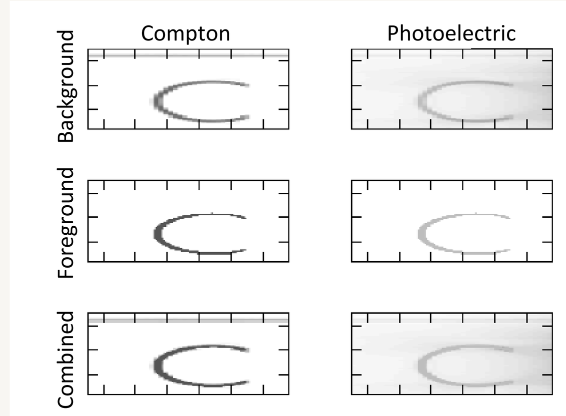
We use Parametric Level Sets (PaLS) [8] to identify the *foreground,* i.e. location of targeted materials




- Model the Compton and PE images as a spatially varying background, and a homogenous "foreground"
- Region Ω is *parameterized* using shape functions
- Prior knowledge is used to constrain the material values allowed in foreground region
- If bag does not contain material of interest, region Ω disappears – thus method *detects* and *segments* object

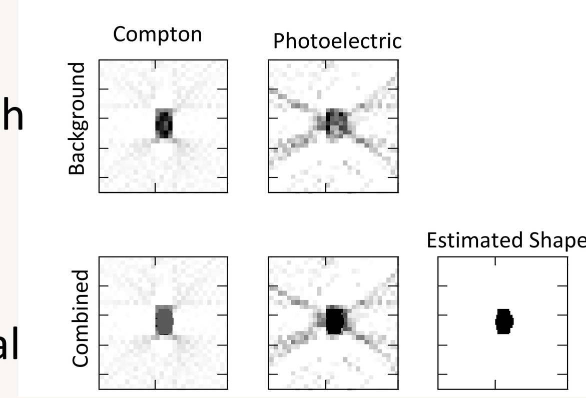
**Example 1: suitcase phantom**

- Initial reconstruction is background only
- Foreground reconstruction is done at higher resolution
- **Approach lets us focus computation** where needed




**Example 2: high-noise case**

- Background estimate has high variation in estimates
- Foreground result **stabilizes the estimates** (within 5% of ground truth), aiding material identification




## Accomplishments Through Current Year

- Reformulated previous work to improve computational efficiency, enabling processing of realistic-sized datasets and actual scanner data.
- First application of NLM regularization [6] to dual-energy tomography (to our knowledge).
- Demonstration of approach on phantom data and initial results on real scanner data.

## Future Work

- Explore the use of state-of-the-art convex solution methods that allow parallel processing.
- Apply recent advances in non-local means denoising [7] to further improve regularization.
- Prove out approaches on multi-energy scenarios.
- Quantify performance on real scanner data.

## Transition Strategy

- Our project is funded under the ALERT Task Order 3 project, which seeks to improve many aspects of CT reconstruction for luggage.
- Along with other participants, we will present our results to industry at a Technical Interchange in October 2013.
- We have presented earlier versions of this work to vendors.
- We are actively participating with local firms to explore avenues for improving future DHS luggage scanning capabilities.

## Publications Acknowledging DHS Support

[1] B. Tracey and E. Miller, "Geometric image formation for target identification in multi-energy computed tomography", SPIE DSS 2013, conference paper 8746-27, May 2, 2013.

[2] O. Semerci and E. Miller, "A Parametric Level-Set Approach to Simultaneous Object Identification and Background Reconstruction for Dual-Energy Computed Tomography," IEEE Trans. Image Processing, 21, 2719-2734, May 2012.

[3] B. Tracey, E. Miller, O. Al-Kofahi, et al, "Denoising Approaches for X-Ray Personnel Screening Systems , Paper 97, IEEE Technologies for Homeland Security Conference,November 2012.

## Relevant Publications

[4] Z. Ying, R. Naidu, and C. Crawford, "Dual energy computed tomography for explosive detection," J. of X-ray Sci. and Tech. 14(4), 235-256, 2006.

[5] R. Alvarez and A. Macovski, "Energy-selective reconstructions in x-ray computerized tomography," Phys. Med. Biol. 21(5), 733-744, 1976.

[6] A. Buades, B. Coll, and J.-M. Morel, "Image enhancement by non-local reverse heat equation," Technical report, CMLA, 2006.

[7] Y. Wu, B. Tracey, et al, , "James-Stein type center pixel weights for non-local means image denoising," Signal Processing Letters, IEEE 20, 2013.

[8] A. Aghasi, M. Kilmer, and E. Miller, "Parametric level set methods for inverse problems," SIAM J. Imaging Sciences 4(2), 618-650, 2011.

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