An Image Based Dual Energy Computerized Tomography Method for Detection of Explosive Objects

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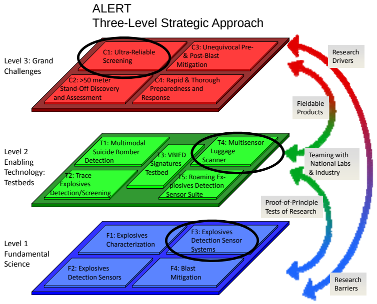
Abstract

We present a novel polychromatic dual energy computed tomography (CT) method for the detection of objects, particularly explosives, whose chemical properties are assumed to be known with some level of uncertainty. Specifically, we assume that chemical properties of materials are uniquely defined by energy independent Compton scatter and photoelectric absorption coefficients and particular type of explosives are characterized by an elliptical region in the Compton scatter photoelectric coefficient space. The solution, distinct images of Compton scatter and photoelectric absorption coefficients, is obtained via an optimization process where the prior knowledge about the characteristics of explosive objects is imposed as hard constraints. The boundaries of the explosive objects are determined by a level set approach and the background images are represented using a low order basis expansion method. Error in the photoelectric coefficient reconstruction is reduced by employing a regularizer which favors a photoelectric absorption image that is structurally similar to the Compton scatter image. A DICOM image of a CT scan of a duffle bag and an artificial image with piecewise constant objects with various shapes and intensities are used as phantoms. Computer simulations show that the algorithm successfully locates the explosive objects if any are present and provides an adequate characterization of background clutter. Therefore the algorithm can be implemented on a real CT scanner.



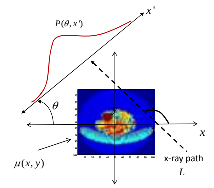
State of Art

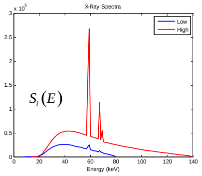
- Dual energy x-ray tomography allows material characterization[1].
- Used for large variety of applications such as
  - Non-destructive material evaluation
  - Aviation Security
  - Bone densitometry
- Filtered Back Projection (FBP) based methods for luggage screening [4]
- Image based iterative methods are efficient for medical imaging [5]

Research to Reality

- Opportunity to decrease false alarm rate for checked luggage scan for explosive materials
- Image based reconstruction is immune to artifacts such as scatter [2]
- The method can be tested with data from real scanners

Polychromatic CT Formulation





$S(E)$: X-ray energy spectrum
$M(\theta,x')$: Radon transform of the linear attenuation coefficient $\mu(x,y)$

$$M(\theta,x') = \int_L \mu(x,y)\delta(x\cos\theta + y\sin\theta - x')\mathrm{d}x\mathrm{d}y$$

$$P_i(\theta,x') = -\log\frac{y_{i,(\theta,x')}}{y_0}, \quad \text{where}$$

$$y_{i,(\theta,x')} \text{ is Poisson RV with mean } \bar{y}_{i,(\theta,x')} = \int S_i(E)e^{-M(\theta,x')}\mathrm{d}E + r_{i,(\theta,x')}$$

$$y_{0,i} = \int S_i(E)\mathrm{d}E, \qquad r_{i,(\theta,x')}: \text{ Known scatter signal}$$

$$\mu(x,y) = f_{KN}(E)a_c(x,y) + f_p(E)a_p(x,y)$$

$$f_p = 1/E^3 \quad f_{KN}: \text{ Klein-Nishina cross section}$$

- X-ray attenuation is due to Compton scatter and photoelectric effect
- Attenuation is a linear combination of energy dependent functions and space dependent Compton and PE coefficients
- Goal: determine the coefficients as a means of characterizing chemical composition of the scene
- Problem: vastly differing sensitivities complicate stable recovery of PE

Representation of Photoelectric and Compton Images

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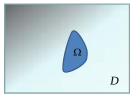
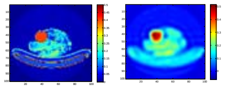
- Properties(Compton and P.E. coefficients) of objects are known to some degree
- For the objects, level set representation is suitable
- Basis expansion is used for level set function as well the background

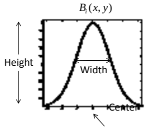
$$f(x,y;\boldsymbol{\alpha},\boldsymbol{\beta},a_{obj}) = \chi_\Omega(x,y;a)a_{obj} + [1-\chi_\Omega(x,y;\boldsymbol{\alpha})]\sum_i^N B_i(x,y)\beta_i$$

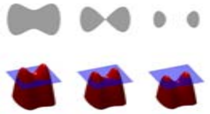


$T_i(x,y)$: "texture" basis functions for background
β_i: unknown expansion coefficients



$$\chi_\Omega(x,y) = \begin{cases} 1 & (x,y) \in \Omega \\ 0 & (x,y) \in D \setminus \Omega \end{cases}$$





Picture adapted from Wikipedia

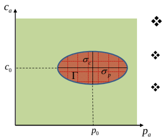
$$\chi_\Omega(x,y;\boldsymbol{\alpha}) = H\left(\sum_{i=1}^{N_b} B_i(x,y)\alpha_i\right)$$

- Traditionally, sample on a dense grid and estimate samples (e.g., distance function)
- Leads to numerical issues
- Parametric representation of the level set function is beneficial
- RBF's Arranged on a regular grid , provide local control of geometry
- Optimize Heights

Reconstruction Algorithm

- Solution via a constrained optimization problem
- Penalized least squares approximation for Poisson log-likelihood [3]

$$\begin{aligned} &\text{minimize} && F(\boldsymbol{\theta},\boldsymbol{\lambda}) = \frac{1}{2}(K(\boldsymbol{\theta})-\mathbf{m})^T \Sigma (K(\boldsymbol{\theta})-\mathbf{m}) + R(\mathbf{a}) \\ &\text{subject to} && (p_a,c_a) \in \Gamma \\ &&& ([\mathbf{B\beta}]_i,[\mathbf{B\alpha}]_i) \notin \Gamma, \quad \text{for} \quad i=1,\dots,N_p \end{aligned}$$



- Allowable values for the contrast of the object is represented by an elliptical region in ca pa space
- Also corresponds to pairs of values that cannot be found in the reconstruction of the background
- Two sets of non-linear inequality constraints

$$g_1(p,c) = \frac{(c_a-c_0)}{\sigma_c^2} + \frac{(p_a-p_0)}{\sigma_p^2} - 1$$

$$g_{2,i}(p,c) = -\frac{([\mathbf{B\beta}]_i - c_0)}{\sigma_c^2} + \frac{([\mathbf{B\alpha}]_i - p_0)}{\sigma_p^2} + 1, \quad \text{for} \quad 1=1,\dots,N_p$$

$$\Downarrow$$

$$\begin{aligned} &\text{minimize} && F(\boldsymbol{\theta},\boldsymbol{\lambda}) = \frac{1}{2}(K(\boldsymbol{\theta})-\mathbf{m})^T \Sigma (K(\boldsymbol{\theta})-\mathbf{m}) + R(\mathbf{a}) \\ &\text{subject to} && g_1(p_a,c_a) \le 0 \\ &&& g_i(\boldsymbol{\beta},\boldsymbol{\alpha}) \le 0, \quad \text{for} \quad i=1,\dots,N_p \end{aligned}$$

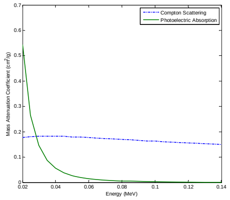
- First term in $R(\mathbf{a})$ penalizes oversized objects

$$R_1(\mathbf{a}) = \lambda_1 \|\boldsymbol{\chi}_\Omega\|_1$$

- Second is a correlation type of metric enforces the structural similarities between two images

$$R_2(\boldsymbol{\beta},\boldsymbol{\alpha}) = \lambda_2 \left(\frac{\|D\mathbf{B}\boldsymbol{\beta}\|^2 \|D\mathbf{B}\boldsymbol{\alpha}\|^2}{(D\mathbf{B}\boldsymbol{\beta})^T (D\mathbf{B}\boldsymbol{\alpha})} - 1 \right)^2$$

D: gradient matrix



- Solution is obtained via an exact penalty method where one transforms the constrained problem to an unconstrained one

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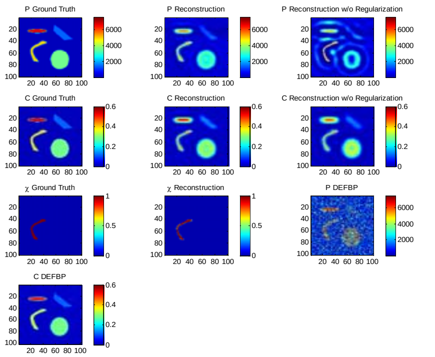
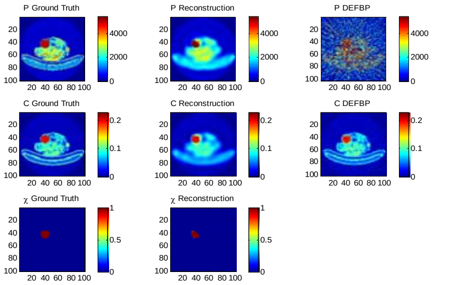
Reconstruction Examples

- 40dB white Gaussian noise simulates detector read-out noise
- 150 Projections for 30 uniformly distributed angles between 0° and 180°
- 20x20cm images are discretized into 100x100 pixels
- 4x4 pixel sized background basis functions
- 144 expansion coefficients for the object function
- Comparison with a dual energy filtered back projection method





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