R4-B.2: Multi-energy, Limited View Computed Tomography (CT)

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II. PROJECT DESCRIPTION

A. Project Overview

The development of energy selective photon counting detectors for X-ray sensing applications has created the possibility for significantly enhancing materials characterization capabilities relative to existing energy integrating or dual-energy systems. Energy integrating methods only provide information regarding material density, while dual energy systems, at best, can image both density and effective atomic number (or equivalently, spatial maps of Compton and photoelectric coefficients). In practice, the overlapping nature of the spectra employed in fielded dual energy systems, as well as the nature of X-ray physics, significantly complicates the stable recovery of atomic number/photoelectric coefficient (PE). Multi- or hyper-spectral forms of sensing, where data are collected over a large number of narrow energy bins in such a manner as to reflect both attenuation as well as X-ray scattering, have the potential to move X-ray based screening significantly beyond the limitations of the current state-of-the-art systems.

In more detail, the energy integrating and dual-energy methods recover information concerning the object of interest based on the way X-rays are attenuated as they pass through the medium. The attenuation properties reflect both the absorption of the X-rays as well as the scattering of the X-ray photons from the beam. For all fielded X-ray systems in use by DHS, these scattered photons are ignored. As the work in this project has begun to demonstrate, significant information is embedded in these photons. With appropriate processing, this information can greatly enhance materials characterization from X-ray data, specifically in the context of limited view systems currently under investigation and development. Indeed, in recent years, DHS has been exploring X-ray systems comprised of spatially fixed sources and detectors in contrast to traditional computed tomography (CT) types of systems where source/detector arrays rotate around the items being scanned. Complicating the development of these systems, the limited number of source-detector paths compared to

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1 The one exception here is the Morpho Yxlon XES 3000 system, which collects and processes diffracted photons. As we discuss shortly, the effort in this project is focused not on diffraction, but rather on Compton scattering. While both processes result in photons exiting the main X-ray beam, the physical processes underlying these modalities are distinct. Our focus here is on Compton scattering. Over the long term, there may well be reason to consider fusing data from both of these processes.
the full-scale CT case creates substantial challenges in terms of image formation, and ultimately, target detection. Using the detectors in these systems to collect scattered photons (in addition to the traditional attenuation-based data) significantly increases the information content in the data even for these fixed geometries. In this regard, the most interesting scattering process for the energy range of interest in this application domain, Compton scattering, is characterized by two key properties. First, the intensity of Compton scattering is directly proportional to the mass density near the event. Second, Compton scattering is inelastic, meaning that the energy of the photons shift after a scattering event, thereby necessitating the use of energy resolving detectors to usefully capture and quantify these processes. The shift in energy determines the direction in which photons are scattered. In a sense, this energy-dependent scattering direction very much “encodes” density at a specific location. These two properties have significant systems-level implications for DHS.

Realizing this potential required that we address several challenges in the first four years of this project. First, the physical processes and mathematical/computational models associated with these scattering processes are more complex than traditional attenuation imaging. The development of a model during Years 1 and 2, which links the observed data to the material properties of interest, was necessary to address the second challenge which has been the focus of our effort in Years 3 and 4: how we use these scattered photons in addition to traditional attenuation data to form images. Only after these image formation methods are in place can we quantify the true benefits of these new data; e.g., attainable image resolution and reduction in imaging artifacts, as well as target detection and false alarm rates.

The immediate significance of this project relative to the larger ALERT program lies in the potential of these models and associated processing methods to improve the accuracy of screening both checked baggage, as well as luggage inspected at the checkpoint. The algorithms at the heart of the current collection of TSA certified systems are not sufficient for the processing of the data that will be produced by the next generation of X-ray scanning systems. Even the state-of-the-art model-based iterative reconstruction methods are not designed to fully exploit the information provided by multi-/hyper-spectral X-ray data. Neither are they capable of addressing the challenges encountered when considering the severely limited view nature of the data provided by these fixed source/fixed detector systems. Our proposed approach to explore the utility of scattered X-ray information to materials characterization is intended to address both challenges, and to the best of our knowledge, is the only effort within the ALERT program with this focus.

Finally, we note the steps taken by this team in technology transition. As discussed in greater depth below, over the past 18 months or so, the initial promise of combining Compton scatter and traditional attenuation data was confirmed using simulation data by the Tufts-based PhD research assistant, Ms. Hamideh Rezaee, whose efforts have been directly supported by the ALERT center. Based on her results, the team from Tufts in collaboration with scientists from American Science and Engineering (AS&E) have, since mid-2016, been supported under a DHS “13-05” project to build a testbed system and associated processing methods to demonstrate the utility of combining energy resolved Compton scatter and attenuation data in a limited view geometry for imaging mass density and PE. Notably, imaging results obtained in the first half of 2017 using data from this testbed are showing benefits similar to those seen in Ms. Rezaee’s simulations. Transition of this work, initially seeded by ALERT, through AS&E is thus continuing with the submission of a proposal in April 2017 in response to DHS Broad Agency Announcement BAA HSHQDC-17-R-B0003 related to Advanced X-Ray Systems, for a project focusing on moving the Compton scatter tomography methods to Technology Readiness Levels 6-7. Moreover, based on exposure of the ALERT-supported work by the group at Tufts, Drs. Dan Strellis and Ed Morton at Rapiscan Systems reached out to Profs. Miller and Tracey in April 2017 to participate on a second full proposal to BAA HSHQDC-17-R-B0003 focusing on combining X-ray diffraction and attenuation data in a non-rotating source/detector system.
B. Year Two (July 2014 through June 2015) Biennial Review Results and Related Actions to Address

B.1. Strengths

- “Modeling of Compton scatter is a complex and challenging task; an accurate and efficient computational model would be quite valuable.”
- “The investigators have completed literature review and tool development in the first two years of the project, and laid out plans and milestones (development and validation of image formation algorithms) for the coming years. This reviewer agrees with both of them.”
- “The research methodology has been designed and executed with rigor. The investigators’ technical methodology is sound.”
- “Researchers presented comprehensive understanding of the field. They have strong background in one of the two main tasks they plan in the coming years: image reconstruction algorithm development. Thus, it is my opinion that they are in a good position to execute the plan.”
- “Transition pathway partners were clearly identified and use of research results were clearly presented.”

B.2. Weaknesses and Mitigation

- Weakness: “The approach revealed thus far indicates a highly exploratory methodology and there is some risk that the current path may lead to a negative result.”
  ○ Mitigation: Our ALERT-funded work since the Year 2 Biennial Review has indicated that, in simulation, we can in fact get quite stable and accurate reconstructions of density and photoelectric coefficients from limited angle Compton data especially as supplemented by, again, limited view absorption data. As discussed previously in this report, these results are being supported by similar reconstructions obtained using real data collected using the AS&E-Tufts testbed constructed under our 13-05 effort. Thus, the potential negative results are less and less of a concern.
- Weakness: “This project proposes another implementation of limited view CT and hence this reviewer is concerned about replicating other efforts in this area.”
  ○ Mitigation: We are very well aware of the state of limited view CT for security scanning at least to the extent to which it has been reported in the open literature. We feel that the approach we offer in its fusion of attenuation data and Compton scattered photons is rather unique.
- Weakness: “Transition is implied in the connections made with Analogic and Rapiscan. Although there appears to be active and engaged users, there is no evidence of an understandable agreement between these parties or a realistic vision/plan for how results will be transitioned.”
  ○ Mitigation: Transition is being affected through the current execution of the joint 13-05 project led by American Science and Engineering (AS&E) with Tufts as a subcontract, hopefully to continue under a 17-03 effort. To date, the models and processing methods developed with ALERT support have been transferred directly from the graduate student funded by ALERT to the post-doctoral researcher supported by 13-05. By the end of 13-05, these codes will be fully transitioned to the group at AS&E. As discussed in Sections III.A and III.B of this report, additional transition efforts are underway in the context of proposals involving the Tufts group with both AS&E, as well as Rapiscan Systems in response to DHS BAA HSHQDC-17-R-B0003.

C. State of the Art and Technical Approach

X-ray CT has been used widely in fields ranging from medical imaging [1] and non-destructive evaluation [2] to the investigation of the internal structures of geo-materials [3] and luggage screening [4], the application
of specific interest here. Motivated by a desire to construct spatial maps of material properties, increased attention has been given to X-ray based approaches in which information is extracted from observations of photons other than those associated with the incident beams. Of relevance to this project are X-ray fluorescence computed tomography (XFCT) [5] and Compton scatter tomography [6], each of which is based on distinct physical processes associated with the interaction of X-rays with matter. In the case of XFCT, used for example in micro-tomography applied to analyze biological samples [7], the sample is irradiated with a monochromatic synchrotron beam of low energy (less than 25 keV), which is still greater than the K-shell energy of the elements in the sample. Because of photoelectric interactions occurring between the X-ray photons and the atoms of the elements, fluorescence X-rays are produced and used as the basis for image reconstruction [8]. For Compton tomography, incoherent scattering [6] is the fundamental physical process giving rise to photons leaving the main beam. This modality has been considered for problems including analyzing human tissues [9]. While Compton scattering is most germane to the ideas we are pursuing for DHS, the mathematics of the models relating observations to material properties for XFCT and Compton tomography are quite similar. Thus, both modalities are informative to our longer-term interests in data processing and are reviewed here.

A wide range of image formation methods have been considered for both XFCT and Compton tomography. In the case of X-ray fluorescence, several different techniques have been developed to recover maps of attenuation and material density. For example, a statistical approach was introduced in [10] assuming a Poisson distribution for the data. Alternatively, an iterative data refinement technique has been provided in [11], which updates the unknown density and fluorescence attenuation at each iteration by minimizing a least square error type of objective function. At each iteration, one of the unknown quantities is replaced with the current value and the equations are solved for the other one. A joint penalized-likelihood Poisson objective function of the unknown element of interest's density and fluorescence attenuation map is introduced in [12] as a continuation of the work done in [10].

In most applications of XFCT, the unknown fluorescence attenuation map has been approximated as a linear combination of the density of the element and a modified version of the absorption attenuation, which may be a good approximation for low energies used for XFCT. It is not at all clear, however, that this approximation is suitable for the higher energies of interest here. Moreover, these studies have been restricted to cases in which a single, monochromatic source is used to illuminate the object which is rotated as a means of acquiring a diversity of views. For DHS applications, more restrictive, limited view geometries are more the norm and data may be acquired over a range of energies. Thus, while the physical model structure of XFCT and the general iterative reconstruction approaches considered to date are of interest and will motivate the ideas we consider, significant work remains in terms of adapting and extending these ideas to our application domain.

In addition to XFCT, Compton tomography provides a powerful tool for materials characterization [13]. Most of the research done on Compton scattering tomography can be divided into analytical and numerical approaches. A comprehensive review of the analytical solutions is provided in [14]. The ideas introduced in [15] are the basis of most of the research in the analytical domain. It is shown in [15] that the scattered beams collected by detectors located on a circular arc connecting the source to the detector, called the “isogonal line,” allow for a closed form reconstruction algorithm not unlike conventional filtered back projection. In a related study, a Radon-transform-like model for a rotating single source/single detector system is introduced in [16] and provides a closed form solution for recovering the electron density on the arcs passing through the source and detector for each point inside the object. Further developments in [17] show that a Chebyshev integral transform is also applicable to the arcs passing through each point inside the object, which confirms the results provided by [16]. The same idea has been employed in [18] for luggage screening applications. There it was shown that a combination of the proposed method and conventional attenuation tomography can produce a map of atomic numbers. However, the approach is not robust to the noise, necessitating the use of an ad-hoc pre-processing step of smoothing of the data. Although the analytical methods provide efficient, closed form solutions, they can only be applied to very specific data acquisition geometries. Only numerical
methods provide the flexibility to robustly process data for the more general class of systems currently of interest to DHS.

Most of the numerical work in Compton tomography has focused on recovering either the electron density or the total attenuation. A generalized Compton scattering transform that falls in the first category was proposed in [19] to reconstruct the attenuation map of the object of interest. The energy dependency of the attenuation coefficient at the scattering point was not considered there. In [20], the energy dependency of the attenuation is considered by approximating the attenuation as a linear function of energy. The algorithm tries to recover the total attenuation coefficient with an iterative minimization method and performed robustly in the presence of noise. The linear approximation to the attenuation holds in the cases that the range of energy change is small, which again is not the regime of interest in our work. One of the few studies seeking to recover the electron density combines three different interactions, fluorescence, Compton, and absorption of the X-ray with the elements within the sample [21] to directly estimate the unknown fluorescence attenuation map using Compton scattering measurements. Another approach in X-ray Compton tomography assumes the attenuation coefficient is known from a prior, traditional CT scan, resulting in a linear mapping from density to observations [22]. In addition to ignoring the dependence of attenuation on density, for the limited view problems of interest to us, it is far from clear that a high fidelity attenuation map will be in our possession.

To summarize, most the research to date in Compton tomography focuses on either analytical solutions which are suitable for limited system geometries or on the recovery of either attenuation or electron density over a limited energy range. We contend that to characterize the materials inside the object of interest for DHS applications, recovery of the electron density (or in our case, the mass density) along with attenuation is essential.

To illustrate the models and methods we have developed, we consider here a limited view system shown in Figure 1 in which pencil beams produced by each source with a specific energy spectrum, called “primary” raypaths, are scattered in different directions with different energies while passing through the object. We note that the attenuation data collected along these primary raypaths constitute a typical data set for absorption-based X-ray imaging methods.

For a given primary raypath, the total attenuated beam intensity is calculated at each detector as [23]

\[ g(r_s, r_d) = \int I(E_s) \left[ exp \left( - \int \mu(r', E_s) \delta_{(r', r_s)} \, dr' \right) \right] dE_s \]  \hspace{1cm} (1)

where \( I(E_s) \) is the initial intensity of the X-ray beam at energy \( E_s \) whose spectrum shown in Figure 2, \( \delta_{(r', r_s)} \) is a Dirac delta function supported along the primary raypath connecting the source position \( r_s \) to the detector located at \( r_d \), and \( \mu(r, E_s) \) is the absorption coefficient at energy \( E_s \). As stated earlier, the goal of this problem is material characterization, which requires in our case, recovery of mass density and photoelectric absorption coefficient, which are related to \( \mu \) according to [24].
\[ \mu(r, E_S) = N_A \frac{Z(r)}{A(r)} f_{KN}(E_S) \rho(r) + f_p(E_S) \rho(r) \]  

(2)

where \( \rho(r) \) is the mass density, \( N_A \) is the Avogadro number, \( Z(r) \) and \( A(r) \) are the atomic number and atomic weight, \( p(r) \) is the photoelectric coefficient, \( f_p(E_S) = E_S^{-3} \) and \( f_{KN}(E_S) \), the Klein-Nishina cross section, is

\[ f_{KN}(E_S) = \frac{1+\gamma}{\gamma^2} \left( \frac{1}{(1+2\gamma)^2} - \frac{1}{\gamma} \ln (1 + 2\gamma) \right) + \frac{1}{2\gamma} \ln (1 + 2\gamma) - \frac{1+3\gamma}{(1+2\gamma)^2} \]  

(3)

and where \( \gamma = \frac{E_S}{(m_e c^2)} \). The ratio \( \frac{Z(r)}{A(r)} \) can be approximated to \( \frac{1}{2} \) for most of the elements [22]; therefore (2) can be summarized as

\[ \mu(r, E_S) = \frac{N_A}{2} f_{KN}(E_S) \rho(r) + f_p(E_S) \rho(r) \]  

(4)

If detectors are perfectly energy resolving, the polychromatic projection can be replaced by a monochromatic projection so that the attenuated intensity given in (1) simplifies to a set of linear equations with respect to density and the photoelectric absorption coefficient [25]; however, for the problem of interest in this paper, we consider detectors of finite energy resolution. For the imaging method discussed below, a linear model for attenuation is rather convenient. Toward that end, we consider the following discretized model for the attenuation data which exploits the fact that the energy dependence of the coefficients in (2) are well approximated as constant over the "bins" seen by the detectors even if \( I(E_S) \) varies more rapidly.

To discretize the attenuation model, we assume that the object area is discretized on a Cartesian grid with \( N_p = N \times N \) elements as shown in Figure 1. We also introduce discretized system matrix \( A \) where \( [A]_{ij} \) represents the length of that segment of primary raypath \( i \) passing through pixel \( j \) and \( [A]_i \) is the \( i\)-th row of \( A \). The size of \( A \) is given as \( N_{SD} \times N_p \), which is the product of the number of primary raypaths and number of pixels. For each primary raypath \( i = 1, \ldots, N_{SD} \) with detector energy bin \( E_m, m=1, \ldots, N_E \) and bandwidth of \( \Delta E \), the discrete equivalent to (1) is

\[ g(i, m) = \int_{E_m - \frac{\Delta E}{2}}^{E_m + \frac{\Delta E}{2}} I(ES) \left[ \exp\left(-[A]_i \mu(ES)\right) \right] dES \]  

(5)

where \( \mu(ES) \) is the lexicographically ordered vector of attenuation coefficients at energy level \( E_S \). Referring to (2), the terms that depend on energy are the Klein-Nishina cross section \( f_{KN}(E_S) \) and \( f_p(E_S) \), both plotted as functions of energy in Figure 3 (on the next page). Two characteristics of these graphs are important to us. First, \( f_p(E_S) \) is much smaller than \( f_{KN}(E_S) \), which implies that the data are much less sensitive to photoelectric variations than those of density, a fact we shall exploit when we discuss the imaging algorithm. Second, both functions vary little over the 1KeV windows (shown by the vertical lines in Fig. 3) over which the detectors in this study integrate energy. Thus we replace \( \mu(ES) \) with \( \mu(E_m) \) so that the term \( \exp\left(-[A]_i \mu(E_m)\right) \) can be factored out of the energy sum. Now, (5) simplifies to
from which we obtain the following model which is linear in the unknowns of interest:

\[ g_A(i, m) = -\log \left( \frac{g(l(m))}{l_m} \right) = [A]_i \mu(E_m) \]

where \( l_m = \frac{f_{EM}}{E_m - \frac{AE}{2}} I(E_S) dE_S \). After substituting \( \mu(E_m) \) given by (2), a set of equations linear with respect to density and photoelectric coefficients is obtained as

\[ g_A = K_A \rho + K_A p \]

where \( K_A \) is the discretized attenuation-density system matrix obtained from \( K_\rho \), \( f_{EM}(E_m)[A]_i \), \( K_A \rho \) is the discretized attenuation-photoelectric system matrix defined by \( f_p(E_m)[A]_i \) for \( i = 1, \ldots, N_{SD} \) and \( m = 1, \ldots, N_E p \) and \( \rho \) and \( p \) are lexicographically ordered vectors of density and photoelectric images respectively. The vector “\( g \)”. A consists of all the observed attenuation data as a function of source location, primary detector location, and energy. The number of elements in \( g_A \) is equal to \( N_A = N_{SD} \times N_p \), the product of the number of primary raypaths \( N_{SD} \) and energy bins \( N_p \).

While in principle a Poisson model is appropriate for describing the attenuation and scattered data [26], to focus initially on what can be learned from this new class of data in severely limited view geometries, we assume here that the only uncertainty in the data arises from typical additive, white Gaussian noise [27]. We leave it to future efforts to extend the ideas developed in this paper to the more complex, but very relevant and interesting, Poisson case. More specifically, the attenuation model after adding noise is defined by

\[ g_A = K_A \rho + K_A p + w_A \]

where \( w_A \) is a white Gaussian noise with zero mean and variance \( \sigma_A^2 \).

\[ g(r_{D'}, E') = \int I(E_S) [\int h(r_{D'}, r, E') S(r, \theta, E) f(r, r_S, E_S) \delta_{r_{D'}, r_S}(r) \rho(r) dr] dE_S \]

As discussed in previous reports, the model we have developed linking the number of Compton scattered photons absorbed by detector \( D' \) to the material properties of interest takes the form:

- \( f(r, r_S, E_S) \) is the attenuation of the beam intensity at energy \( E_S \) along the line connecting \( r \) and \( r_S \).
• $h(r_D, r, E_s)$ is the attenuation of the beam intensity at energy $E'$ where we describe below the relationship between $E'$, the energy of the photon emerging from the scattering event, and $E_s$, the initial energy of the photon;

• $\rho(r)$ is the mass density at the interaction point;

• $S(r, \theta, E_s)$ is the scattering factor; and

• $\delta_{r=r_s}(r)$ is a delta function along the line connecting the source to the primary detector.

It can be shown that (10) can be formulated as a set of equations nonlinear in the photoelectric coefficient and quasi-linear in density resulting in a measurement model taking the form

$$g_S = K_S(\rho, p)\rho + w_S$$

where $\rho$ and $p$ are lexicographically ordered vectors of density and photoelectric images respectively and $K_S(\rho, p)$ is the discretized scattering system matrix obtained from the integral kernel in (10). Note that this matrix depends on both density and photoelectric and thus is the source of the nonlinearity in the problem. The vector $g_S$ is comprised of all the observed scattered data as a function of source location, secondary detector location, and energy. The total number of elements in $g_S$ is defined by the number of all possible secondary raypaths and energy bins $N_e$ in detectors which is equal to $N_{se} - N_S \times N_p \times (N_D - 1) \times N_E$, the product of the number of sources $N_p$, number of detectors $N_p$, number of secondary raypaths $N_D - 1$ associated with each primary raypath, and energy bins $N_E$ at detectors. Finally, $w_S$ is a white Gaussian noise with zero mean and variance $\sigma_S^2$.

To recover density and photoelectric images given both attenuation and scatter data, we solve the following least-squares optimization problem

$$\begin{align*}
(\hat{\rho}, \hat{p}) &= \underset{\rho, p}{\arg \min} w_1\|g_S - K_S(\rho, p)\rho\|^2_2 + w_2\|g_A - K_{A,\rho}\rho - K_{A,\rho}p\|^2_2 + R_\rho(\rho) + R_p(p|R)^{ref}
\end{align*}$$

where $\|g_S - K_S(\rho, p)\rho\|^2_2$ measures the mismatch between the scattering data and our prediction of the scattering data for a given $\rho$ and $\|g_A - K_{A,\rho}\rho - K_{A,\rho}p\|^2_2$ is the mismatch term between the attenuation data and predicted data. The regularization terms $R_\rho(\rho)$ and $R_p(p|R)^{ref}$ for density and photoelectric respectively stabilize the reconstruction by imposing prior information such as smoothness and $w_1$ and $w_2$ are weighting factors. Following [28], we set $w_1 = \frac{1}{\|\|\rho\|\|}$ and $w_2 = \frac{1}{\|\|p\|\|}$ to basically normalize the impact of the two data sets in the reconstruction process.

We use a cyclic coordinate decent method [29] for solving the optimization problem given in (12). At each iteration, density reconstruction is performed using estimate of the photoelectric coefficient from the previous iteration. Density reconstruction itself is an iterative procedure detailed. Subsequently, we use the current estimated density image to recover photoelectric coefficient image in another iterative process.

C.1. Density Reconstruction

With $\hat{p}_n$ representing our estimate of the photoelectric coefficient at iteration $n$ of the algorithm from (12), we update the density estimate by solving

$$\hat{\rho}_{n+1} = \underset{\rho}{\arg \min} w_1\|g_S - K_S(\rho, \hat{p}_n)\rho\|^2_2 + w_2\|g_A - K_{A,\rho}\rho - K_{A,\rho}\hat{p}_n\|^2_2 + R_\rho(\rho)$$

where the $R_p(\ .\ )$ term in (12) is not relevant as it does not depend on density.
To decrease the effect of noise and impose smoothness as a priori information for more accurate results, we employ here the edge preserving method considered in [30] for regularization. We start by recalling the conventional Tikhonov smoothness-based regularization approach defined as

\[ R_p(\rho) = \lambda_p \| L\rho \|_2^2 \]  \hspace{1cm} (14)

where \( \lambda_p \) is the regularization parameter, the value of which determines the balance between data mismatch and regularization terms, and \( L \) is a discrete gradient matrix including both vertical and horizontal derivatives computed as

\[ L = \begin{bmatrix} I \otimes L_1 \\ L_1 \otimes I \end{bmatrix} \]  \hspace{1cm} (15)

with \( I \) the \( N \times N \) identity (assuming we are reconstructing images containing \( N_p = N \times N \) pixels), \( \otimes \) is the Kronecker tensor product operator, and \( L_1 \) is the \((N-1) \times N\) derivative matrix

\[ L_1 = \begin{bmatrix} -1 & 1 & 0 & 0 & \cdots \\ 0 & -1 & 1 & 0 & \cdots \\ \vdots & \vdots & \vdots & \vdots & \ddots \\ 0 & 0 & \cdots & 0 & -1 \end{bmatrix} \]  \hspace{1cm} (16)

The edge-enhancing regularization methods developed in [30] is an iterative weighted Tikhonov approach in which the regularization matrix is updated in a manner that de-emphasizes the smoothing for locations in the image where edges are suspected. At iteration \( l \) the regularization term takes the form

\[ R_{p,l}(\rho) = \lambda_p \| D^{(l)} L\rho^{(l)} \|_2^2 \equiv \lambda_p \| M^{(l)} \rho^{(l)} \|_2^2 \]  \hspace{1cm} (17)

where \( D^{(l)} \) is a diagonal weighting matrix with elements between zero and one updated at iteration \( l \) and \( M^{(l)} = D^{(l)} L \). Those diagonal elements closer to one will enforce smoothness to the associated pixels, while the values closer to zero indicate that the associated pixels belong to the edge map and should be preserved. The pseudo-code for the iterative edge-preserving regularization is given in Table 1 (on the next page) with additional details and discussion provided in the paper to be submitted to the IEEE Transactions on Computational Imaging (see Section IV.B).

Because the regularization term is quadratic in \( \rho \), (13) is quasi-linear in the density, in that the density appears non-linearly in the structure of the matrix \( K_\rho \) but also in a linear manner as the vector upon which \( K_\rho \), \( K_{\lambda,\rho} \), and \( M \) operates. By stacking \( K_\rho \), \( K_{\lambda,\rho} \) and \( M \) (13) take the form:

\[ \hat{\rho}_{n+1} = \arg\min_{\rho} \left\| \begin{bmatrix} \sqrt{w_\gamma} g_\gamma \\ 0 \\ \sqrt{w_\lambda} K_\lambda(\rho, \hat{\rho}_n) \\ \sqrt{w_\lambda} K_{\lambda,\rho}(\rho, \hat{\rho}_n) \\ \sqrt{w_\lambda} K_{\lambda,\rho}(\rho, \hat{\rho}_n) \\ 0 \end{bmatrix} \rho \right\|_2^2 \equiv \arg\min_{\rho} \| \tilde{g} - \tilde{K}(\rho) \rho \|_2^2 \]  \hspace{1cm} (18)

This structure suggests an iterative approach for solving (18) detailed in Table 1 (on the next page). At each iteration, the scattering system matrix \( K_\rho \) and the edge preserving regularization matrix \( M \), are updated with the current estimate of density and “stacked” to create \( \tilde{K}(\rho) \) in (18). With the dependency of the matrices in (18) on density now effectively removed, we are left with a linear least squares problem for the vector \( \rho \)
multiplying $\overline{K}(\rho)$. We solve this system using the LSQR [31] method to obtain and update to the density. If the change from the last iteration is small, we stop. Otherwise, we rebuild the matrices and repeat.

We assume an initial estimate for the density, $\rho = \rho_0$ and $\rho = 0$ at the first iteration. Starting with an appropriate initial guess for the density is crucial to the success of the approach. There are several ways this could be accomplished. For example, attenuation based CT images have been shown to be useful in this regard [17]; however, for the limited view problems that are of most interest in this effort, reconstruction of the photoelectric and density from attenuation data is known to be a highly ill-posed problem. Thus, we are motivated to consider the multi-scale approach described and illustrated in last year’s report which is used only for the initial estimate of density (i.e., $n=0$); when we have essentially no prior information regarding the composition of the medium and for all subsequent iterations, (18) is solved at the finest scale using as the initial guess. At the first level, a coarse scale representation of the grid and density vector to be recovered is assumed and a constant density vector is considered as an initial guess to build the system matrix $K_S(.)$. The method in Table 1 is used to solve the problem at this spatial scale and the estimated density image at this level is “upscaled” using the Matlab function ‘imresize()’ employing nearest neighbor interpolation and used as an initial guess to build the system matrix at the next finer scale, and so on. After a few iterations, we achieve a good approximation of density vector in a desired scale size without any prior information about the density image. The block diagram of the multi-scale approach to estimate density with the edge-preserving regularization method is shown in Figure 4 (on the next page).

<table>
<thead>
<tr>
<th>Table 1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pseudo code for iterative quasi-linear solver</td>
</tr>
</tbody>
</table>

**Inputs:**

- $D^0 = I$
- $M = L$ gradient matrix
- $r_0 = \rho_n$ and $p = p_n$
- $\epsilon_0$ stopping criteria
- $\ell = 1$
- $\epsilon > \epsilon_0$

1: While $\epsilon > \epsilon_0$
2: Build $K_S(r_{l-1}, p)$
3: Set $v = D^{(l-1)} L r_{l-1}$
4: Normalize $v$ by setting $v \leftarrow v/\|v\|_\infty$
5: Map $d$ to $[0,1]$ by defining $d \leftarrow 1 - v, 0$
6: Define $D \leftarrow diag(d)$
7: Update $D^{(l)} \leftarrow DD^{(l-1)}$
8: Update $M = D^{(l)} L$
9: Find $r_l$ by solving (26) with LSQR
10: Define $\epsilon = \|r_l - r_{l-1}\|_2$
11: Increase $l$
12: Update $\rho_{n+1} = r_{l-1}$
13: End
After estimating density, the results can be used for photoelectric reconstruction.

C.2. Photoelectric Reconstruction

Having the density image estimated, from (18) the photoelectric sub-problem takes the form

$$\hat{\rho}_{n+1} = \text{argmin}_p w_1 \| \mathbf{g}_S - K_S(\hat{\rho}_n, p)\hat{\rho}_n \|_2 + w_2 \| \mathbf{g}_A - K_{A,p} \hat{\rho}_n - K_{A,p}p \|_2 + R_p(p|I^{ef})$$

where $\hat{\rho}_n$ is the final estimate of density image at previous iteration as a solution to (18) and $R_p(p|I^{ef})$ is the photoelectric regularization term.

In contrast to the density problem, photoelectric recovery is a non-linear least squares optimization problem which we solved using the Levenberg-Marquardt method [32]. The approach requires the Jacobian matrix of the objective function which is given in our previous report.

To stabilize the photoelectric problem, we have used patch-based non-local mean (NLM) regularization method [33] which benefits from the accuracy with which density can be recovered. In this approach the photoelectric reconstructed image is conditioned on a reference image $I^{ef}$ which we take as $\hat{\rho}_{n=1}$, the density estimate obtained after the first iteration of the algorithm. Mathematically, the NLM regularization can be written in the form of quadratic regularization as

$$R_p(p|I^{ef}) = R_{NLM}(\hat{\rho}_{n=1}) = \lambda_p \| (I - W)p \|_2^2$$

where $I$ is the identity matrix, $W$ is the weigh matrix which is calculated based on the reference image [34], and $\lambda_p$ is the regularization parameter. By stacking the $K_S(\hat{\rho}_n, p)\hat{\rho}_n$, $K_{A,p} \hat{\rho}_n$ and $(I - W)p$ vectors, (19) can be written as

$$\hat{\rho}_{n+1} = \text{argmin}_p \left\| \begin{bmatrix} \sqrt{w_1} \mathbf{g}_S \\ \sqrt{w_2} (\mathbf{g}_A - K_{A,p} \hat{\rho}_n) \end{bmatrix} - \begin{bmatrix} \sqrt{w_1} K_S(\hat{\rho}_n, p)\hat{\rho}_n \\ \sqrt{w_2} K_{A,p}p \\ \sqrt{\lambda_p} (I - W)p \end{bmatrix} \right\|_2^2 \equiv \text{argmin}_p \| \tilde{q} - \tilde{Q}(p) \|_2^2$$

Figure 4: Block diagram of multi-scale approach. An estimate of density $\rho_{(k-1)}$ at scale $k-1$ first resized to the current scale $k$ then a new estimation $\rho_k$ at the current scale obtained via density estimation (using the algorithm in Table 1).
C.3. Results

To evaluate the performance of our proposed method, we consider a limited view system of the form provided in Figure 1. The area to be imaged is taken to be 20 cm × 20 cm. Three rotating pencil beam sources each with a spectrum shown in Figure 2 are located in the center of the left and bottom edges and left-bottom corner of the scanning area. Forty-one detectors with the width and height of 0.1 cm are equally spaced along the top and right edges.

All data are generated assuming a uniform grid of 50 × 50 pixels covering the $400\text{cm}^2$ region. For the multiscale processing method, five uniform grids of $10 \times 10$, $20 \times 20$, ..., $50 \times 50$ are employed for the unknown mass density. We have generated synthetic data for two different phantoms consisting of different materials with moderate to high attenuation properties shown in Figure 5 below. The phantom is relatively complicated with three circular objects consisting of water, delrin and graphite. The characteristics of the materials used in these phantoms such as density and photoelectric attenuation coefficients are taken from the XCOM database [35].

![Figure 5](image)

Figure 5: Simulated phantoms. Density and Photoelectric (at the energy level of 20 KeV) ground truth images of different objects.

Attenuation data is collected in the range of 20-120 KeV with the energy resolution of $\Delta E = 1\text{KeV}$ for density and photoelectric coefficient reconstruction. Because of the size of the resulting data set (123 primary raypaths times 40 scatter detectors per raypath times 100 energy bins = 4.92e + 5 observations), we have chosen to bin the scattered data into 5 KeV intervals to reduce the computational overhead of the processing. To consider measurement and discretization noise, a signal-to-noise (SNR) ratio of 50 dB is assumed for both attenuation and scattering measured data.

In the cyclic decent method, at each iteration, to reconstruct density the estimates of the photoelectric coefficient and density from previous iteration are required. At the initial iteration, $n = 0$, the estimation of density $\hat{\rho}_0$ requires photoelectric coefficient $\hat{p}_0$ which we take as $\hat{p}_0 = 0$. The density is initialized with $\rho_0 = \frac{4}{\text{g/cm}^3}$. For the photoelectric reconstruction at $n = 0$, $\hat{p}_1$ is used. The Levenberg-Marquardt method is initialized with $\rho_0 = 0$ and for $n > 1$ $\hat{p}_{n-1}$ is used.

The regularization parameters $\lambda_\rho$ and $\lambda_p$ are determined using the discrepancy principle [36] since the variance of the noise is assumed known. In theory, these parameters should be selected by first discretizing the space of both parameters $\lambda_\rho$ and $\lambda_p$, then calculating the reconstructions of density and photoelectric for all the points on this two-dimensional discretized space and computing the value of the discrepancy function for each of these reconstructions. The optimal parameters and associated reconstructions output by the
algorithm would be those associated with the minimum of the discrepancy function. Given the computational burden of the reconstruction process this approach is not feasible. Hence, we employ the following suboptimal method. At iteration $n = 1$ for density reconstruction where $\hat{\rho}_0 = 0$, each scale of the multi-scale reconstruction process is repeated for 25 logarithmically spaced values of $\lambda_\rho$ between $10^{-4}$ and $10^5$. At each scale, we choose that estimate of density which minimized the discrepancy function

$$F_{D,\rho}(i, k) = \frac{1}{\tau} \| r_{i,k} \|_2^2 - \sigma^2$$

for $i = 1, 2, ..., 25$ and $k = 1, 2, ..., 5$ and where $r_{i,k} = \hat{g} - \tilde{K}_{i,k}(\hat{\rho}_{i,k})\hat{\rho}_{i,k}$ is the regularized residual of the density reconstruction defined in (18), $\tau$ is the number of the elements of the data vector, $i$ indexes the regularization parameter, $k$ corresponds to the scale level and $\sigma^2$ is the noise variance. For $n > 1$, we use as $\lambda_\rho$ the value of this parameter associated with the reconstruction selected at the finest scale of the $n = 1$ iteration. Again, at iteration $n = 1$, where the density estimate $\hat{\rho}_1$ is used for reconstruction of the photoelectric coefficient, the optimization problem in (19) is performed 25 times for 25 logarithmically spaced values of $\lambda_\rho$ between 0.01 and 100. The optimal $\lambda_\rho$ of the first iteration is used for all subsequent iterations $n = 2, 3, ..., n$. The criteria to select the regularization parameter is minimizing the discrepancy principal function similar to (21).

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{density_results.png}
\caption{Density simulation results with scattering and attenuation data of different scales at n=1. The combination of scattering and attenuation datasets increases the performance of the density reconstruction in such limited-view systems by taking advantage of scattering data in enforcing the structure of the object and attenuation data in increasing the accuracy of the reconstructed amplitudes. (a),(b),(c),(d), and (e) show density reconstruction results.}
\end{figure}
The stopping criteria for the overall method is defined based on density convergence, which means if the current estimation of density satisfies the convergence condition then the reconstruction of photoelectric using the final estimation of density will conclude the cyclic coordinate decent procedure. Based on [37], the stopping criterion used here is

\[ \| \hat{\rho}_n - \hat{\rho}_{n-1} \| < \epsilon (1 + \| \hat{\rho}_{n-1} \|) \]  

(23)

where \( \epsilon \) is a small, positive number defining the accuracy of the final result is taken as \( 10^{-2} \) here.

To evaluate the performance of the proposed method quantitatively, we have calculated the two-norm of the relative mean square error (RMSE) for each of density and photoelectric images using

\[ \text{RMSE} = \frac{\| \hat{I} - I_{\text{true}} \|_2^2}{\| I_{\text{true}} \|_2^2} \]  

(24)

Where \( \hat{I} \) is the reconstruction of either the density or the photoelectric image and \( I_{\text{true}} \) is the corresponding ground truth image.

Density reconstructions derived from a combination of both attenuation and scattering information at the first iteration are shown in Figure 6. These images clearly demonstrate the advantages (quantitative and qualitative) of employing both types of data. Specifically, both the geometric structure of the objects as well as the pixel-by-pixel estimates of the density value are recovered successfully and are significantly more accurate than the finest scale results displayed in Figure 7 where in (a) only attenuation data were employed and in (b) only scatter data were used. Figure 6 also provides evidence of the utility of the multi-scale approach. The multi-scale approach starting from the grid with the size of 10×10 ending with the grid of the size of 50×50 is applied to the phantom. The method performed well using a spatially constant initial guess for the density and zero for the photoelectric absorption. Specifically, we see a monotonic decrease in the RMSE as well as qualitative improvements as we refine the scale.

![Figure 7: Density simulation results at final scale using (a) only attenuation and (b) only scatter data.](image)

Provided in Figure 8 (on the next page) are the photoelectric reconstructions after one iteration of the algorithm using only attenuation, only scatter, and both. As with the density, the benefits of employing both sources of data are rather stark here. Moreover, as analyzed in greater depth in the paper to be submitted to the IEEE Transactions on Computational Imaging, the accuracy with which we can recover photoelectric is also influenced to a great degree by the use of the NLM regularization scheme.
Finally, in Figure 9 and Figure 10 (on the next page) we display the density and photoelectric reconstructions using both data sets for the second and third iterations of the algorithm. While the results for even the first iteration were rather good, especially given the limited view nature of the problem, we do see both quantitative and qualitative improvements from the continued processing. Indeed, with $\epsilon = 0.01$, the first convergence criterion in (23) is achieved for $n = 3$.

Figure 8: Photoelectric reconstruction results after one iteration using (a) only attenuation data; (b) only scatter data; and (c) both attenuation and scatter data.

(a) $\text{RMSE} = 0.5868$  
(b) $\text{RMSE} = 0.4039$  
(c) $\text{RMSE} = 0.1783$

Figure 9: Density simulation results for (a) the second and (b) the third iterations of the algorithm.

(a) $\text{RMSE} = 0.0725$  
(b) $\text{RMSE} = 0.0687$
We stress that the results presented here are representative of the general behavior of the processing method we have developed under support from the ALERT Center. In the paper to be submitted to the IEEE Transactions on Computational Imaging discussing this effort, a more extensive set of examples is provided highlighting the benefits of the approach on a second phantom and providing greater justification for advantages of fusing attenuation and scatter data. In addition, we anticipate by the end of the summer of 2017, a second paper will be submitted to the journal Optics Express arising from our 13-05 effort with AS&E, detailing a similar set of results and analogous conclusions this time using experimental data.

D. Major Contributions

- Phase 2, Year 4: The initial image formation method developed in Year 3 has been refined as we have tested the approach on test cases far more complex than those considered during Year 3. Specifically, we have achieved the objectives in Year 4 that were outlined in the Year 3 project report. First, we have developed an objective method based on the discrepancy principle for choosing the regularization parameters defining the cost functions used as the basis for estimating both the mass density and photoelectric (PE) images from X-ray observations. Second, we have augmented the Compton data with energy resolved attenuation data and demonstrated the gain achieved from the fusion of these two data types. Finally, building on our prior efforts in multi-energy CT, we have developed a method for stabilizing the recovery of the PE image which is based on the use of a non-local means (NLM) regularization scheme.

- Phase 2, Year 3: We have demonstrated a method for joint recovery of both density as well as photoelectric coefficient from severely limited view, multi-energy Compton scatter data. The overall approach is based on a variational formulation of the imaging problem. Physical intuition has guided the specific method used to solve this problem. Initial results on simulated data were quite promising.

- Phase 2, Year 2: We have developed a tractable, analytical model capable for X-ray scattering and attenuation. The model has been instantiated in the form of a Matlab-based code that will be made accessible to the broader DHS community. We believe that the model can be used effectively and efficiently in the context of image reconstruction methods seeking to recover spatial maps of electron density and photo-electric absorption information from limited view, multi-energy X-ray data.

Figure 10: Photoelectric simulation results for (a) the second and (b) the third iterations of the algorithm.
Phase 2, Year 1: Our initial efforts under Phase 2 of ALERT support involved the development of a computational forward model for multi-energy, limited view X-ray scanner modeled on the AS&E CANSCAN system—the limited view system which was to form the basis for the 13-05 project. At the start of Phase 2, Year 2, we decided to move away from this absorption-only model as we began to explore the potential for scattered photon data to address the many challenges associated with the processing of limited view information.

E. Milestones

Below are the Year 4 and Year 5 Milestones for this project (see underlined text) along with progress made or to be made for each milestone:

1. **Year 4, Milestone 1:** The evaluation of the current method on more complex simulation data as well as real data generated under our 13-05 effort. This milestone has been completed. Details can be found in Section II.C of this report and the manuscript submitted for publication to the *IEEE Transactions on Computational Imaging*.

2. **Year 4, Milestone 2:** Extension of the processing methods. More specifically, based on our multi-energy, limited view CT work over the past seven years, we anticipate that more complex scenarios will result in the failure of the current method for recovering the photoelectric coefficient. To address this issue will require the development of regularization strategies that exploit our ability to stably recover the density profile to "help" estimate photoelectric maps. This milestone has been completed. As noted previously in this document, a regularization scheme based on non-local means ideas has been employed for allowing structural information found in the relatively accurate recovery of the mass density to guide the reconstruction of the photoelectric absorption coefficient. Details can be found in Section II.C of this report and the manuscript submitted for publication to the *IEEE Transactions on Computational Imaging*.

3. **Year 5, Milestone 1:** Continue to explore the issue with stable recovery of photoelectrical attenuation for mixed material problems where high density objects are present. Given the success we have seen in the first half of 2017 under the AS&E/Tufts 13-05 effort, we shall not consider this milestone. The refinements in the processing associated with high density objects are better addressed in the context of a transition effort such as that proposed under the proposal submitted with AS&E in response to BAA SHQDC-17-R-B000.

4. **Year 5, Milestone 2:** The second focus of the work in Year 5 will be system design. The interaction of the Tufts group with the scientists and engineers at American Science and Engineering (AS&E) under 13-05 has brought to our attention the need for tools and methods that can inform the design of scanning systems. Understanding the impact of a wide number of variables on one’s ability to simultaneously resolve closely spaced objects and distinguish materials of interest would be of great use as part of the initial system design effort. These variables include:
   a. X-ray data types including attenuation, Compton scatter, diffraction, and backscatter.
   b. Number, location, and spectral structures of X-ray sources for each data type.
   c. Number, location, sizes, and energy resolution characteristics of detectors for each data type.

These issues shall be the focus of our work in Year 5. Specifically, we shall fuse the physical models and variationally-based image formation methods we have with analytical methods, such as Cramer-Rao bound analysis or Monte-Carlo simulation to provide a powerful collection of tools for addressing these fundamental design tasks.
F. Future Plans

The primary focus of the work in this last year will be on the development of analytical methods for quantifying the tradeoffs and subsequently supporting the optimization of system design. Please see the discussion under Section II.E above for the details of the effort. The major risk with this approach is one of computational burden. Cramer-Rao analysis, which is based on a statistical bound, may not provide sufficient accuracy in terms of predicting performance, especially in the case where the bound is too loose. Rectifying the situation will require the use of Monte-Carlo methods, which are computationally burdensome. This means it will be necessary to think carefully about how to limit the range of possibilities to be explored via Monte-Carlo methods and how to implement the methods in a computationally efficient manner. The former will be addressed by consulting with our collaborators from AS&E and Rapiscan to gain insight into how to best constrain the design space. The latter will be addressed using the computational platform that has been purchased with the 2017 supplement granted by ALERT to Tufts for the acquisition of a high-performance computing tools.

We anticipate a conclusion to the basic research focus of this project by June 30, 2018, at which time the following products should be produced:

1. Transition of the models and image formation methods to AS&E via the 13-05, and potentially, the HSHQDC-17-R-B0003 funding mechanisms
2. Two journal papers
   a. The first is in preparation and will be submitted by July 31, 2017 to the *IEEE Transactions on Computational Imaging*. This paper will cover the physical models and processing methods associated with fusion of energy resolved, sparse view Compton scatter and attenuation data for purposes of mapping mass density and photoelectric attenuation.
   b. The second paper will focus on the use of these models as the basis for rapid and accurate system design trade studies.

A sixth year of effort on this project would allow for several possible transition efforts. First, it is unlikely in a year that the systems analysis ideas will be packaged in a form that would be suitably user friendly to make them of interest to our industrial colleagues and collaborators. Thus, one avenue of effort would be to complete this task, specifically working closely with the groups at AS&E and Rapiscan (see Sections III.A and III.B below) to ensure the utility of the final product. A second potential focus of effort would be to consider an integrated approach and associated system architectures for full scale fusion of potentially all X-ray data types employed by DHS. Of greatest interest would be the addition of diffraction data into the processing; however, backscatter X-ray (used in personnel screening) may also bring some benefit. Indeed, as detailed in Section III.A, Tufts has been included on a proposal submitted by Rapiscan Systems in response to BAA HSHQDC-17-R-B0003 focusing on combining X-ray diffraction and attenuation data in a non-rotating source/detector system. A sixth year of ALERT support could be put toward building on this work (should it be funded) by "adding in" the Compton data. The goal here would be to develop a theoretically justified framework by which these three data types (attenuation, diffraction, and Compton scatter) could be fused in a model-based manner to obtain a single, coherent, integrated picture of the scene. Even if not implementable in a realizable, fielded system, this analysis provides a bound for how well we could ever do in meeting the DHS's needs using X-ray data and could easily be incorporated into the system design tool just discussed. From that work, we can then carefully and rationally consider tradeoffs which allow for real-world implementation while simultaneously minimizing performance losses. Such an effort would contribute to the ability of DHS to quickly and accurately identify and resolve threats in both checked luggage and baggage at the checkpoint using both well-established X-ray methods (attenuation, backscatter), as well as data types that have over the past decade begun to show promise (diffraction and Compton scatter).
III. RELEVANCE AND TRANSITION

A. Relevance of Research to the DHS Enterprise

The most immediate value of the research in this project to the DHS Enterprise lies in the potential of these models and processing methods to improve the accuracy of screening checked baggage, as well as luggage inspected at the checkpoint. The algorithms at the heart of the current collection of TSA certified systems are not sufficient for the processing of the data that will be produced by the next generation of X-ray scanning systems. Even state-of-the-art model-based iterative reconstruction methods are not designed to fully exploit the information provided by multi- and hyper-spectral X-ray data. Neither are they capable of addressing the challenges encountered when considering the severely limited view nature of the data provided by these fixed source/fixed detector systems. Our approach to explore the utility of scattered X-ray information to materials characterization is intended to address both challenges, and to the best of our knowledge, is the only effort within the ALERT program with this focus.

We are seeking to address challenges associated with automated scanning and threat detection in both checked luggage and baggage that is inspected at checkpoints. The overall goal is to determine spatial maps of material properties in an automated manner from multi-energy X-ray data collected in limited view types of geometries characteristic of many systems currently under development by DHS contractors. Any metric that quantifies the accuracy of the material maps can be used to evaluate the performance of our work including:

- Confusion matrices capturing the percentage of correctly and incorrectly labeled pixels for scenarios where ground truth is known.
- If one is concerned with purely binary problems (threat object versus all other types of materials), then receiver operating curves plotting detection probabilities versus false alarm measures could be developed.
- Finally, we could visualize accuracy using uncertainty cloud analysis developed as part of ALERT Task Order 3 and employed initially in “Tracey, Brian H., and Miller, Eric L. Stabilizing dual-energy X-ray computed tomography reconstructions using patch-based regularization. Inverse Problems, Vol. 31, No. 10 (2015),” and again in the paper we shall be submitting to the IEEE Transactions on Computational Imaging. These clouds would plot the average value and one standard deviation ellipse of the distribution of photoelectric and electron density over known target regions in our reconstructions. In comparing multiple candidate processing methods, smaller ellipses and means closer to ground truth are indicators of higher accuracy.

From a broader perspective, there is strong reason to believe that the ideas developed in this project can have impact on a far more diverse collection of problems relevant to the DHS Enterprise. Here we point to two recent interactions between the group at Tufts and DHS vendors:

1. In April 2017, Dr. Miller was contacted by Dr. Dan Strellis, Director of R&D Technical Programs at Rapiscan Systems, regarding interest in the following two collaborative efforts:
   a. The first focused on the Tufts group hosting a PhD student, Mr. James Webber, from the University of Manchester in the UK for a three-month visit to the United States. Mr. Webber’s dissertation, funded in part by Rapiscan, concerns the development of analytical methods for Compton scatter image formation. Dr. Strellis felt that there would be value for Mr. Webber, Rapiscan, and Tufts in exploring the combination of these analytical methods, which are computationally efficient but typically require specific sensing geometries, with the more flexible but computationally intensive iterative methods being considered at Tufts. Because of these conversations, Mr. Webber will be staying at Tufts from June to September 2017. During which time, Mr. Webber, the group from Tufts, and Rapiscan will be exploring ideas for advanced X-ray reconstruction...
methods for limited view systems employing energy resolved attenuation and Compton scatter data types.

b. In addition to hosting Mr. Webber, Dr. Strellis has included support for Tufts in Rapiscan’s proposal entitled *Stationary Gantry Checkpoint CT with In-line X-ray Diffraction* which was submitted in April 2017 in response to the RFP HSHQDC-17-R-B0003 from DHS. This project again considers the problem of image formation from limited view X-ray data, but rather than the fusion of Compton scatter and attenuation data, the focus here is on combining X-ray diffraction data with attenuation information.

2. At the ADSA16 Workshop held in Boston on May 2-3, 2017, Dr. Jeffrey Schubert of American Science and Engineering approached Dr. Miller to discuss the application and extension of the methods developed in this project and the AS&E/Tufts 13-05 effort to two problems in addition to checked luggage scanning; namely cargo and vehicle inspection as well as automated/robotic inspection of suspicious packages and potential suitcase bombs.

To be sure, the work with Rapiscan as well as the discussions cited in item #2 in the above list with AS&E are preliminary; however, they are a clear indication of interest from multiple equipment manufacturers in transitioning the basic research ideas developed by the group at Tufts with ALERT support to several problem areas of direct concern to DHS.

B. Potential for Transition

As indicated previously in this document, the Tufts group being supported by ALERT is also teamed with American Science and Engineering (AS&E) on a 13-05 project that is focused on constructing a system designed specifically to implement the processing methods being developed in this project. To a substantial degree, this project was founded on preliminary results obtained by the Tufts research assistant, Ms. Hamideh Rezaee, indicating the potential utility of Compton Scatter Tomography for addressing challenges associated with limited view, fixed source/detector systems of interest to DHS. Since mid-2016, the team from AS&E and Tufts have built a testbed system and associated processing methods to further develop these ideas. Initial imaging results obtained in the first half of 2017 using real, experimental data from this testbed are showing similar benefits as Ms. Rezaee saw in her simulations. Transition of this work (initially seeded by ALERT) through AS&E is thus continuing with the writing of a proposal in response to BAA HSHQDC-17-R-B0003, for a project focusing on moving the Compton scatter tomography methods to TRL 6-7. As this AS&E 13-05-based system embodies the physical models and image formation methods whose development was funded by ALERT, it represents a primary transition product for the work in this project.

In addition to this work with AS&E, there are several other transition pathways for our work, detailed in Section III.A.

C. Transition Pathway

Please see Section II.B for a detailed treatment of these issues. To summarize:

1. We have an on-going 13-05 funded effort with AS&E which is focused on transitioning directly the ideas in this project (fusion of energy resolve Compton scatter and attenuation data for materials characterization in limited view systems). That effort is due to conclude in the summer of 2017.

2. As of the writing of this document, the Tufts group anticipates being part of a follow-on proposal with AS&E to DHS to continue the development and transition of these methods such that the resulting system is at a Technology Readiness Level of Six or Seven. The white paper for this full proposal has been accepted; however the proposal itself is still being written.

3. The Tufts group has been included on a Rapiscan full proposal to DHS RFP HSHQDC-17-R-B0003 in
which the iterative reconstruction ideas developed in this project will be employed in the context of a limited view system combining X-ray attenuation and diffraction data. If supported, the period of performance for that project is Oct. 1, 2017 – Sept. 30, 2019.

4. Starting in the summer of 2017, the Tufts group will be engaging with Rapiscan and their collaborators from the University of Manchester in the exploration of new methods for Compton Scatter Tomography. At the current time, it is impossible to say where this work will lead vis a vis transition, but again the very existence of this effort goes to the interest of industry in the work being performed at Tufts under support from ALERT.

5. The Tufts group anticipates continued collaboration with AS&E in the application of the ideas from ALERT project R4-B.2 to problems in cargo and vehicle screening, but also potentially to other challenges, such as tomographic imaging of left-parcels. As with item #4 above, transition along these pathways is certainly in the future; however, there is good reason for optimism of success given the long and successful collaboration between Tufts and AS&E, which originated due to ALERT and has been supported in many ways both by ALERT as well as DHS S&T.

In addition to the collaborations with AS&E and Rapiscan, the team at Tufts is very willing to present the work discussed in this report at future ADSA Workshops and ALERT Industrial Advisory Board meetings.

D. 

Customer Connections

Please see Section II.E for details. The contacts and collaborators of the Tufts team are specifically:

- At AS&E: Drs. Aaron Couture and Jeffrey Schubert. We meet weekly to review our joint 13-05 effort.
- At Rapiscan: Dr Dan Strellis. We anticipate meeting with the Rapiscan group at least once or twice over the summer of 2017 in support of Mr. Webber’s visit to the United States. Should the HSHQDC-17-R-B0003 proposal be supported, weekly or bi-weekly meetings will likely begin.

We also note that in addition to the X-ray imaging work being done at Tufts, through ALERT, the Tufts team has also established a working relationship with Pendar Technologies in Cambridge MA. Specifically, Tufts will be a subcontractor to Pendar technologies on a DHS-funded SED-V project. The Tufts component of the program will be focused on computer vision methods to support the Pendar-developed hyperspectral imaging (HSI) system for standoff detection and identification of trace chemicals on vehicles. The Tufts PI for the project, Prof. Shuchin Aeron, will be developing computer vision methods for automatically identifying from RGB video regions such as door handles where HSI data are to be collected. Tufts co-PI, Prof. Eric Miller, will support the development of inversion methods for identifying the chemical compounds and their concentrations from the HSI data. Our primary contact at Pendar is Dr. Mark Witinski. We have been in contact with the Pendar group multiple times in 2016-2017. Once the SED-V contracting is complete, we anticipate weekly or bi-weekly meetings.

IV. PROJECT ACCOMPLISHMENTS AND DOCUMENTATION

A. 

Education and Workforce Development Activities

1. Outcomes that Relate to Educational Improvement or Workforce Development

   a. The two students who have worked on this project both have benefitted greatly from the experience. Mr. Jonathan Foley received his Master’s in Electrical and Computer Engineering from Tufts University in the spring of 2015, where his thesis work focused on image analysis and target enhancement for three-dimensional, limited view X-ray CT data. This effort represented for him an opportunity to apply and extend the ideas he learned in the classroom to a problem of immediate practical relevance. Specifically, he employed advanced image processing techniques.
for contrast enhancement of features, which in turn significantly improved the identifications of objects of interest in luggage. Additionally, he was able to apply computer science theory to improve the efficiency of the algorithms necessary for data transforms between physically collected linear absorption data and mathematically modeled spatial density arrays. Upon graduation, Mr. Foley was hired as a Technical Support Engineer at Cognex Corp (Natick MA), a leading supplier of industrial machine vision systems, in no small part because of the direct applicability of the methods he explored in his MS thesis work to the problem so interest to Cognex.

b. The second student, Ms. Hamideh Rezaee, is currently pursuing her Ph.D. in Electrical and Computer Engineering at Tufts under full support from ALERT. This project has provided her with a special educational opportunity to engage in fundamental research on a problem that is of intense interest to a wide range of people. By attending the ALERT Program Review in March 2015, where Prof. Miller made an oral presentation to the review committee and the attending community about the progress of her project, Ms. Rezaee had the opportunity to experience firsthand, the high level of interest and relevance in her work. As noted previously in this document, Ms. Rezaee’s work and results were the basis for what has been a very successful collaboration between Tufts and AS&E in transitioning her work via a 13-05 effort. In the remaining year of her Ph.D. studies, Ms. Rezaee will be provided with a rather unique experience where the results of her efforts will be directly translated to our industrial partner, and via the ADSA workshops, disseminated to a broader community of researchers from academia, corporate labs, and the government.

B. **Peer Reviewed Journal Articles**

**Pending –**


C. **Peer Reviewed Conference Proceedings**


D. **Other Presentations**


V. **REFERENCES**


