F3-A5: Model-Based Iterative Reconstruction for Advanced Baggage Screening

Abstract—While traditional direct reconstruction algorithms such as filtered back projection (FBP) and direct Fourier method (DFM) depend on the analytic inversion of sinogram data, model-based reconstruction methods rely on iterative optimization of a statistical model of both the acquired data and the unknown image. Model-based iterative reconstruction (MBIR) potentially offers many important advantages over traditional methods of direct reconstruction for the security screening of checked baggage. It has the potential to reduce metal artifacts, improve resolution, reduce artifacts such as cupping that can systematically distort CT number estimates, incorporate tighter integration of reconstruction and segmentation, and support reconstruction of scanners with a small number of projections. All these improvements have the potential to improve the detection/false alarm tradeoff for CT security screening systems.

The objective of this research is to implement an MBIR algorithm on a widely deployed multislice helical CT security scanner, and assess qualitatively and quantitatively the improvements over direct reconstruction. The MBIR implementation entails the accurate modeling of both the system geometry, including subtle manufacturing deviations, as well as the photon and electronic noise characteristics. The quality assessment was carried out using a set of 12 vendor-provided bag scans, selected with the guidance of the ALERT Center. The results demonstrate significant quality improvements over the native DFM reconstructions, including improved metal artifact suppression, spatial resolution, and CT value uniformity.

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II. PROJECT OVERVIEW AND SIGNIFICANCE

While more traditional direct reconstruction algorithms such as filtered back projection (FBP) are founded on an analytic inversion of the projection measurements, model-based iterative reconstruction (MBIR) al-
gorithms approach the problem as an iterative optimization of a statistical model of both the acquired data and the unknown image. This structure allows an MBIR algorithm to incorporate specific details of geometry and physics of the scanner, as well as a statistical characterization of the objects being scanned. Advances in optimization algorithms, image models, and computational resources over recent years have allowed MBIR methods to be practically applied to medical image reconstruction for multi-slice helical scan CT [1,2,3,4,5]. The results of these studies support the view that model-based reconstruction can improve image quality and dramatically reduce X-ray dosage for medical applications. However, the field of security screening poses a different set of challenges from those in the medical application of CT, so questions remain for the potential advantages of model-based reconstruction in security applications.

In the baggage screening application, X-ray dosage reduction is not as critical a factor as in the medical case. However, model-based reconstruction holds promise in improving performance of EDS equipment through increased probability of detection (P_d), decreased probability of false alarm (P_{fa}), increasing the population of detected objects including additional HMEs, and reducing the mass per object required for detection. More specifically, MBIR has the potential to achieve these goals through:

- Reduced metal artifacts – Streaks resulting from metal artifacts can adversely affect segmentation algorithms, thereby degrading the P_d/P_{fa} tradeoff.
- Reduced noise – Effects such as photon starvation, which degrade image quality [8].
- Increased resolution – Improved resolution can better separate materials and detect smaller masses.
- Reduced beam hardening and scatter artifacts – Model-based reconstruction can be used to better model beam-hardening and scatter artifacts, thereby reducing cupping artifacts, and achieving more accurate estimates of CT number.
- Dual energy – Model-based dual energy reconstruction can achieve more accurate estimates of CT number and Z_{eff} by explicitly modeling beam hardening effects.
- Integrated reconstruction/segmentation – Model-based reconstruction allows for the direct integration of segmentation information into the prior model, which can potentially enhance the accuracy of CT number estimation [9,10].
- Reconstruction from limited view data – Model-based reconstruction offers the possibility of computing accurate reconstructions from finite view data (< 20 views), which in turn offers new alternatives in the concept of operation.

The objective of this research is to investigate and quantify the value of model-based reconstruction for baggage security screening and to develop novel methods for the improvement of model-based reconstruction in its application to CT security scanning of baggage. To this end, we have two main project-period goals, with the first being the implementation of a state-of-the-art model-based fully 3D reconstruction algorithm for a multi-slice helical security CT scanner, and the second goal being the evaluation of MBIR reconstruction quality relative to more standard reconstruction methods.

In order to achieve the first goal, we continue the development of a fully 3D MBIR CT algorithm. The models therein are adapted to a widely deployed multi-slice helical CT security scanner. Modifications in the forward modeling demonstrate a significant reduction in image artifacts in the presence of diverse and highly attenuating materials. The model-based reconstructions are compared to slice-rebinned direct Fourier (DFM) reconstructions, which is a method chosen mainly for its computational advantages. The comparative evaluation is facilitated by a set of vendor-provided scans, including suitcases containing clothing and typical contents (e.g. laptop computers, liquid containers, other electronics), and also standard control items used for quantitative evaluation. The more significant modeling improvements, and the evaluations are summarized in the following sections.
III. RESEARCH AND EDUCATION ACTIVITY

A. State-of-the-Art and Technical Approach

The Figures 1 a) and b) below illustrate the comparison between state-of-the-art filtered back projection and the model-based iterative reconstruction (MBIR) method implemented on a 64 slice GE scanner. Notice the substantial noise reduction, improved resolution and reduced artifacts of the MBIR reconstruction as described in [4]. Below we give a more detailed mathematical description of the model-based reconstruction method we have implemented.

MAP Reconstruction

Model-based reconstruction works by incorporating a model of both the tomographic scanner and the image being reconstructed. A typical approach is to compute the maximum a posteriori (MAP) estimate given by

$$\hat{x} = \arg\min_{x \geq 0} \{-\log p(y|x) - \log p(x)\}$$

where $p(y|x)$ is the conditional distribution of projection data vector $y$ given the true image $x$, $p(x)$ is the prior distribution of $x$, and $x \geq 0$ indicates that each voxel must be non-negative. In this study, we use a 2nd order Taylor series approximation of the log likelihood term [1], resulting in

$$-\log p(y|x) \approx \frac{1}{2} (y - Ax)^T D (y - Ax) + c(\lambda)$$

where $j_i = \log(\lambda_{0,i}/\lambda_i)$, $\lambda_i$ and $\lambda_{0,i}$ are the detector $i$ measurements from the target and air-calibration scans respectively, matrix $A$ is a forward projection operator, and $D$ is a diagonal weighting matrix given by $D = \text{diag}\{d_1, \ldots, d_M\}$. For the computation of the forward projection matrix $A$, we used the distance driven forward model described in [4,5].

The log prior term $\log p(x)$ controls the smoothness of the reconstructed image, and its selection is key in minimizing artifacts and enhancing resolution, particularly when the scanning geometry limits spatial sampling. In this approach, we use the q-GGMRF model of [5,6], which is a generalization of the GGMRF of [3]. Our prior model has the form

$$p(x) = \frac{1}{Z} \exp \left\{\frac{-1}{q\sigma^2} \sum_{i=1}^{N} b_{ij} \phi(\Delta)\right\}$$

where $\phi(\Delta)$ has the form of the q-GGMRF prior, given by $\phi(\Delta) = |\Delta|^{q/p} / [1 + |\Delta|^{q/p}]$. After combining, the global objective function to be minimized is the following,

$$f(x) = \frac{1}{2} |y - Ax|_D^2 + \frac{1}{q\sigma^2} \sum_{i=1}^{N} b_{ij} |\Delta|^{q/p} / [1 + |\Delta|^{q/p}]$$

1 Dose calc: Anatomy = 1/2 Pelvis, 1/2 Abdomen = DLP (45*5*0.19) + (45*5*0.015) = 0.43+0.34 = 0.77
ICD Algorithm

Our MBIR implementation uses iterated coordinate descent (ICD) for minimization of the MAP cost function [1,2,6]. The ICD algorithm has the form

\[
\text{Initialize } x \text{ and } s = y - Ax \\
\text{For each voxel } s \{ \\
\quad \theta_1 = -A_i D s_i, \quad \theta_2 = A_i D A_i, \\
\quad x_s \leftarrow \arg\min_{u \geq 0} \left\{ \theta_1(u - v) + \frac{1}{2} \theta_2(u - v)^2 + \sum_{s \in n} \rho(u - x_s) \right\}
\}
\]

where \( n \) is the set of neighboring voxels to \( s \), and \( \theta_1 \) and \( \theta_2 \) are the first and second derivatives of the likelihood function with respect to the voxel \( x_s \). In order to solve the 1-D optimization problem, we use the methods of surrogate functions [7].

Forward Projector

Multi-slice helical CT has a cone-beam structure where a gantry (X-ray source and detector array) rotates around an object in a helical scan path as shown in Figure 2. The detector array typically consists of hundreds of channels and several rows. An integral component of the MBIR algorithm is the forward model for how a given image scene produces the observed measurements. We use a linearized distance-driven forward projector in this work [4,5].

Multi-Core Parallelization

In order to reduce reconstruction time, we have parallelized the algorithm using p-threads on a multicore, shared memory architecture. Figure 3 illustrates how each core is assigned a range of image slices. Then a single core updates one z-line at a time by updating the voxels in sequence along the z coordinate. This approach is motivated by considerations of cache efficiency.
Non-homogeneous ICD Algorithm

In order to further reduce the number of CPU cycles required for convergence, we use the non-homogeneous ICD method described in [7]. In this approach, updates are focused on voxels that are expected to require the greatest number of updates. A "V map" is maintained to track the voxel locations having the greatest change at the last ICD update, and voxels at the top of the list are selected for further updates. Figure 4 illustrates the flowchart of the NH-ICD algorithm.

Afterglow Correction

X-ray scintillation detectors exhibit a property called afterglow, which is a residual signal in the scintillation crystal that remains after the incident X-rays are removed. This signal decays exponentially with multiple time constants associated with different physical characteristics of the scintillator. In a continuous scan mode, as occurs in a helical system, the afterglow effect results in a smoothing of the measurements since each given measurement is affected by the beam's position over its recent history. If the sampling rate of the system is on the order of the afterglow time constants or greater, this smoothing can be de-convolved to compensate for afterglow.

In this work we employed an afterglow correction filter described in [11] on the raw scanner measurements. Figure 5 illustrates the effect of afterglow correction for the MBIR reconstructions. This example shows an axial slice with significantly improved resolution as a result of the correction.

Fan Angle Offset

Image reconstruction algorithms in general assume an exact geometry of the system. Subtle manufacturing deviations can generate unwanted distortions if not accounted for in the reconstruction. One example in a helical system is the placement of the X-ray source and the detector panel on the rotating gantry. A small deviation in the detector panel position with respect to the center of rotation can produce displacement errors as shown in the native DFM reconstruction in Fig 6(a).

A strong benefit of MBIR is the ability to incorporate geometrical variations directly into the model. Figures 6(a) and (b) illustrate the effect of incorporating a small offset of the X-ray fan angle. The spatial shift distortion becomes undetectable after the correction.

Figure 4: Flowchart of NH-ICD algorithm

Figure 5 (above): Effect of afterglow correction on image reconstruction. (a) is an MBIR reconstruction from raw scan data, and (b) is the same algorithm applied to the afterglow corrected data.

Figure 6 (left): Effect of modeling a manufacturing deviation in the detector panel location. The DFM reconstruction in (a) demonstrates the distortion as a period offset visible along edges parallel to the z-axis. The MBIR reconstruction in (b) accounts for the detector offset directly in the forward model.
Data Weighting Matrix Transformation

Recalling the log-likelihood function approximation,

$$-\log p(y | x) \approx \frac{1}{2} (y - Ax)^T D (y - Ax) + c (\lambda)$$

we see the entries of the diagonal matrix $D$ specify the weights of each of the sinogram entries, $y_i$, in the MAP estimate. The entries $D_{ii}$ are in effect specifying the reliability of each measurement in determining the image, $x$. The result $D = \text{diag}\{\lambda_1, \lambda_2, \ldots, \lambda_M\}$ was derived from an approximation of the likelihood assuming a Poisson model of the photon counts. We explored alternate weightings in this matrix to improve reconstruction quality.

Figure 7 shows the result of defining the weightings as $D_{ii} = (\lambda_i / \lambda_{ij})^{\frac{1}{2}}$. The modified weighting produces an improvement in the variance and texture in the reconstruction of a uniform material.

Reconstruction Results

More extensive image reconstruction results and quantitative evaluation of relative performance may be available on request from Morpho Detection, Inc.

Quantitative Evaluation

Comparisons between MBIR and DFM reconstructions were measured using the ANSI N42.45-2011 standard (American National Standard for Evaluating the Image Quality of X-ray CT Security-Screening Systems). The test article used for the evaluation is shown in Figure 8. The reconstructions were evaluated for streak suppression, resolution, and noise equivalent quanta (NEQ) as shown in Figures 9, 10, and 11 below and on the following page.

Figure 8: Test article used for quantitative evaluation (from ANSI N42.45-2011). The cross section on the right shows the region used for streak evaluation, consisting of an acetal copolymer cylinder containing 4 tungsten alloy pins aligned with the z-axis. The voxel variance is assessed within the 4cm x 4cm ROI, as well as along the diagonal lines.

Figure 9: Streak evaluation using the ANSI N42.45-2011 test article. The slices for the DFM and MBIR reconstructions are shown along with the pixel profiles along the northeast diagonal. The table contains the mean and standard deviations for the pixels in the 4cm x 4cm ROIs, as well as along the diagonals. The CTRL results are from an adjacent section of the test article that is free of the tungsten pins. Quantitative analysis is available on request from Morpho Detection, Inc.
B. Major Contributions

We have designed and implemented a fully 3D model-based reconstruction algorithm for multi-slice helical scan CT data, adapted the algorithm to a particular security screening CT system, and evaluated the model-based reconstructions comparing to more standard reconstruction methods. Evaluations using a realistic set of passenger bag scans, as well as NIST control scans, demonstrated significant quality improvements afforded by an MBIR approach. The model-based approach improved resolution, resistance to streaking, noise suppression, CT value uniformity, and consistency. These are all factors that can lead to improved threat detection in EDS systems.

IV. FUTURE PLANS

The transition task research here documented consisted of applying the basic, published form of MBIR to data from a TSA-certified scanner. Several innovations in the forward model improved performance, but the great majority of our work was consumed in creating the code for the generic algorithm and comparing its performance to that of conventional reconstruction. As explained in our component of the proposal for renewal of the ALERT Center’s funding, the next phase of this research should reach far deeper into aspects of the problem specific to baggage scanning for security. The first advance envisioned for the next year will be in tailoring our a priori image models to the security task. The current models have shown utility in medical imaging, in which texture in representations of human tissue must match certain expectations among radiologists. However, many of these traits may be of little consequence in security scans. Given that our target is primarily manufactured materials, the models of image content should be adjusted to increased probabilities of constant-valued regions and boundaries between materials. We will benefit from our experience in the field of “discrete tomography” in these efforts.

This modeling approach will provide a first step toward combined reconstruction and segmentation. Sequential execution of these two functions is inherently suboptimal; we will therefore seek a tractable, stable approach to identifying densities, and therefore materials, as the parameters of the reconstructed images. Admittedly, a problem formulated in this manner poses potentially difficult, non-convex optimization tasks. The potential gains, however, appear to very well merit the effort.

A goal that could, depending on task order descriptions, be either short- or long-term, is dramatic computational speed-up of our algorithm. This economically critical component of the problem also was not part of the transition task, but will be of primary importance on any path to the marketplace. In addition to implementation on parallel computing machinery, it will be critical that algorithmic innovations allow reduction in total operation counts and improved data access patterns.
V. RELEVANCE AND TRANSITION

Our transition task was, by its very design, highly relevant to the goals of DHS in improving detection of threats in checked baggage. We have shown that an alternative method of image reconstruction provides the sort of quality improvement, on data from a currently certified scanner, that is likely to move the detection/false alarm probability curve above its present placement. The reduction of artifacts and enhanced resolution of boundaries shown above is qualitatively a significant gain, and we are confident this will translate into more efficient automated detection performance.

VI. LEVERAGING OF RESOURCES

The project was conducted in cooperation with Morpho Detection, Incorporated, manufacturer of the TSA-certified scanner from which our data was extracted. Morpho has expressed interest in the commercial potential of our work for incorporation into their airport scanning systems. Commercial interest from Morpho and other vendors will depend on large reductions in computation time, as mentioned above as a future research direction.

VII. PROJECT DOCUMENTATION AND DELIVERABLES

A. Software Products

Our principal focus has been algorithm development in implementation of MBIR for the certified scanner. Transition into application is envisioned with subsequent work on computational efficiency.

VIII. REFERENCES


