R4-B.1: Toward Advanced Baggage Screening: Reconstruction and Automatic Target Recognition (ATR)

Abstract—In transportation security applications, Computed Tomography (CT) scanners are widely used to scan checked baggage for threatening materials. Traditionally, images are reconstructed using direct methods, such as filtered back projection (FBP). Model-based iterative reconstruction (MBIR) potentially offers many important advantages over traditional methods for the security screening of checked baggage. It has the potential to reduce metal artifacts and improve resolution. All these improvements have the potential to improve the detection/false alarm tradeoff for CT security screening systems. Furthermore, automatic target detection and recognition from the scanned images can reduce the cost of human labors, help to extract important information and support human judgments. The objective of this research is to investigate the potential of MBIR algorithms for the security screening application. In addition, we aim to develop a new Automatic Target Recognition (ATR) system which will incorporate advanced segmentation, feature extraction and classification techniques in order to improve the current state-of-the-art ATR performance. To do this, we improved the existing MBIR algorithms, which are based on a monochromatic model for X-ray data, by estimating a polynomial for correction of nonlinear effects simultaneously with the image. We also built our new ATR system, which advances segmentation and classification over the standard software provided by ALERT. During the last project period, we successfully achieved better reconstruction images, which reduce artifacts caused by nonlinear attenuation behavior, such as beam hardening, scatter and other incompletely modeled attributes of the data and improved detection/false alarm score in the ATR system. We will continue to develop new techniques in order to further improve performance for challenging cases, such as images with cluttered objects and metal streaking artifacts.

I. PARTICIPANTS

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<tr>
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<tr>
<td>Name</td>
<td>Title</td>
<td>Institution</td>
<td>Email</td>
<td></td>
</tr>
<tr>
<td>Charles Bouman</td>
<td>Co-PI</td>
<td>Purdue University</td>
<td><a href="mailto:bouman@purdue.edu">bouman@purdue.edu</a></td>
<td></td>
</tr>
<tr>
<td>Ken Sauer</td>
<td>Co-PI</td>
<td>University of Notre Dame</td>
<td><a href="mailto:sauer@nd.edu">sauer@nd.edu</a></td>
<td></td>
</tr>
<tr>
<td>Dong Hye Ye</td>
<td>Post-Doc</td>
<td>Purdue University</td>
<td><a href="mailto:yed@purdue.edu">yed@purdue.edu</a></td>
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<tr>
<td>Pengchong Jin</td>
<td>PhD</td>
<td>Purdue University</td>
<td>2015</td>
</tr>
<tr>
<td>Benjamin Foster</td>
<td>PhD</td>
<td>Purdue University</td>
<td>2017</td>
</tr>
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II. PROJECT OVERVIEW AND SIGNIFICANCE

A. Research on reconstruction

X-ray CT for checked baggage scanning is among the most important elements of transportation security. The performance of image analysis algorithms is highly dependent on the quality of reconstruction imagery that is used as input to this analysis. When components of a reconstructed slice of a bag are poorly resolved or corrupted by artifacts, resulting from highly attenuating materials (such as metal objects), poor segmentation of materials may result in sufficient ambiguity in the bag’s content and require human intervention due to a “false alarm.” Any improvement in image quality is expected to reduce the number of such cases and reduce the cost of operation for the overall system.

The great majority of deployed CT systems utilize image reconstruction methods based on deterministic descriptions of the mapping from the data (sinogram) domain and the image domain. Variants of filtered back-projection are most common, and can be implemented at high frame rates appropriate for continuous-flow baggage scanning. Inversion methods based on more accurate descriptions of the instrument and modeling of reliability of data may demand more computation in their iterative solution, but show promise in related CT applications [1,2,3,4], which may transfer to the security arena. We call this class of methods “model-based image reconstruction” (MBIR) because they rely on relatively precise modeling of pixel/X-ray interactions, detector behavior, photon counting and electronic noise.

The objective of this project is the improvement of MBIR in its specific application to security scanning. Because a major contributor to costly false alarms is poor image quality in the presence of the many metal objects that may be part of baggage, or packed within it, our primary focus is a technique to automatically compensate for beam hardening of metal. The technique separates metal from other image content and models the total attenuation as a polynomial function of both the total attenuation in metal, and the total in other materials. The coefficients of the polynomial, which will vary with the X-ray’s spectral shape, are estimated along with the image to allow the best fit to the sinogram data, eliminating some of the large inconsistencies due to beam hardening and other metal effects that force artifacts in images in an attempt to match data. A second thrust is variation in the weighting of measurements according to their approximate variances. The most direct model, taken from the Poisson log-likelihood function, dictates weighting proportional to received photon counts. However, the dynamic range of these counts may produce estimated images with disadvantageous properties, such as poor noise texture or unnecessary emphasis of artifacts in cases where the modeling of high-attenuation rays is inadequately accurate.

Both the advantages of generic MBIR and the enhancements of our beam-hardening correction approach are evaluated using the Imatron datasets shared among participants in the Task Order 3 “Research and Development of Reconstruction Advances in CT-based Object Detection Systems” effort supported by DHS Task Order Number HSHQDC-10-J00396. The iterative approaches show advantages in subjective image quality. The results in the project metrics for segmentation performance are mixed relative to standard, one-pass FBP.

B. Research on automatic target recognition

Automatic target detection and recognition from the scanned images can help to extract important information, and support human judgments. However, developing ATR systems is challenging due to metal presence and tight packing [5,6,7]. For example, metal introduces strong streaking artifacts with which ATR detects divided objects (see Fig. 1a on the next page). In addition, ATR may not be able to separate cluttered objects by tight packing (see Fig. 1b on the next page).
The objective of this research is to investigate and develop a new ATR system that can handle above-mentioned challenging cases. To do this, we will incorporate advanced computer vision algorithms upon the baseline software provided by ALERT. While recent research in computer vision has shown a lot of promising results in each ATR component, such as image denoising, image segmentation and object detection, most of them are for the application of natural images and very few have been applied to CT images, in particular, for security application. So the questions remain as to the potential advantages of the advanced techniques in ATR applications.

During the last project period, we successfully developed a new ATR system that incorporates advanced computer vision algorithms, such as shape filter and multi-label segmentation. We evaluate the performance using the standard specified metrics (i.e. probability of detection and probability of false alarm), and it already gives improvements over standard ATR. We will continue to develop new techniques, particularly in advanced feature extraction, in order to further improve the detection accuracy. With these results, we can propose potential directions for improvement of ATR in aviation security society.

III. RESEARCH ACTIVITY

III-1. RESEARCH ON RECONSTRUCTION MODEL

A. State-of-the art and technical approach

A.1 Based Iterative Reconstruction (MBIR) framework

MBIR works by formulating a mathematical optimization problem, which incorporates the model of both the measurement acquisition process during the scan and the image being reconstructed. A typical MBIR framework is used 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 measurement vector $y \in \mathbb{R}^m$, given the underlying true attenuation $x \in \mathbb{R}^n$ map; $p(x)$ is the prior distribution of $x$, and $x \geq 0$ indicates that each pixel must be non-negative. The first term in the optimization can be approximated by

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

Figure 1: Challenges in ATR for CT images: (a) Metal streaking artifacts divide objects detected by ATR; (b) ATR merges objects due to tight packing.
where $A \in \mathbb{R}^{M \times N}$ is the forward projection operator and $W = \text{diag}\{w_1, \ldots, w_M\} \in \mathbb{R}^{M \times M}$ is a diagonal weighting matrix.

The log prior term $\log p(x)$ controls the smoothness of the reconstructed image and also preserves local image structures. In this study, we used the $q$-Generalized Gaussian Markov Random Field ($q$-GGMRF) model [4] given by

$$-\log p(x) = \sum_{(i,j) \in C} a_{ij} \rho(x_i - x_j), \quad \rho(x_i - x_j) = \frac{|x_i - x_j|^p}{1 + |x_i - x_j|^q}, \quad 1 \leq q \leq p = 2.$$  

Combining the log likelihood term and the log prior term, we obtain the global objective function to be optimized as follows

$$\arg \min_{x \in \mathbb{R}^N} f(x) = \arg \min_{x \in \mathbb{R}^N} \left\{ \frac{1}{2} ||y - Ax||_2^2 + \sum_{(i,j) \in C} a_{ij} \rho(x_i - x_j) \right\}.$$  

### A.2 Model-Based Iterative Reconstruction with simultaneous Beam Hardening Correction (MBIR-BHC)

It is well-known that the attenuation coefficient of materials depends on the energy of the X-ray, and the low-energy portion of the X-ray normally gets attenuated preferentially comparing to the high-energy portion, resulting in a physical effect known as the beam hardening. In practice, beam hardening can contribute to the reconstruction artifacts, such as metal streaks and cupping. Since most X-ray beams exhibit a broad energy-spectrum, a more accurate forward model that accounts for the broadness of the X-ray spectrum is given by

$$S(E) = \sum_{k} S_{k,\rho_k}(E)$$

where $S(E)$ is the normalized energy spectrum, $\mu_j(E)$ is the energy-dependent attenuation coefficient and the function $r_j(E)$ carries the energy-dependent behavior of the j-th pixel. In this study, we developed a novel model-based reconstruction algorithm, MBIR with Beam Hardening Correction (MBIR-BHC), which is able to simultaneously correct the beam hardening effect, and investigated the performance of MBIR-BHC on the baggage scan dataset.

In order to better model the data measurement and account for the beam hardening effect, in this study, we proposed a poly-energetic X-ray forward model, which is based on the assumption that different materials can be separated by their densities. We modeled the energy-dependent attenuations $\mu_j(E)$ as a convex combination of two basis materials given by

$$\mu_j(E) = x_j \left( (1 - b_j) \nu_j(E) + b_j \nu_H(E) \right)$$

where $\nu_j(E)$ and $\nu_H(E)$ are two energy-dependent basis functions of “low” and “high” density materials, and $0 \leq b_j \leq 1$ is the percentage of material in the j-th location that is of high density. Using this decomposition, we constructed a new forward projection model for the i-th projection as

$$E[Y_i \mid x] = h(p_{L,i}, p_{H,i}) = -\log \left( \int S(E) e^{-\nu_L(E) p_{L,i} - \nu_H(E) p_{H,i}} \, dE \right)$$

where $p_{L,i}$ and $p_{H,i}$ are two energy-independent material projections given by

$$p_{L,i} = \sum_{j=1}^{N} A_{i,j} x_j (1 - b_j), \quad p_{H,i} = \sum_{j=1}^{N} A_{i,j} x_j b_j.$$  

We further parameterized this nonlinear $h(\cdot)$ function using a joint polynomial of $p_{L,i}$ and $p_{H,i}$ given by

$$h(p_{L,i}, p_{H,i}) = \sum_k \sum_l \gamma_{k,l} (p_{L,i})^k (p_{H,i})^l$$
and the coefficients $\gamma_{k,l}$ will be simultaneously estimated in the optimization process. Incorporating the novel poly-energetic X-ray forward model, MBIR-BHC can be formulated as

$$\arg\min_{x \in R^n, b \in \{0, 1\}^m} \left\{ \frac{1}{2} \sum_{i=1}^{M} w_i \left( y_i - \sum_{k} \sum_{l} \gamma_{k,l}(p_{L,i}) \gamma_{l} \right)^2 + U(x,b) \right\},$$

where $U(x,b) = -\log p(x,b)$ denotes the negative log joint prior of $x$ and $b$ for regularization.

To further simplify the model, we assumed $b_j \in \{0, 1\}$ to be binary; therefore, each pixel can be of either low density material or high and the vector $b \in \{0, 1\}^M$ becomes a material segmentation of the reconstructed image. $U(x,b)$ is used for regularization over the image and the material segmentation. We modeled $U(x,b)$ as a two-layer hybrid Markov random field, illustrated in Figure 2. Mathematically, it can be formulated as

$$U(x,b) = \sum_{(s,r) \in C} \alpha_{s,r} \varphi(x_s - x_r) + \sum_{(s,r) \in C} \eta_{s,r} \delta(b_s \neq b_r) + \beta \sum_{j=1}^{N} (x_j - T)_+ (1 - b_j) + (T - x_j)_+ b_j,$$

where $\delta()$ is the discrete indicator function, $T$ is the pre-defined segmentation threshold, and $\alpha_{s,r}$, $\eta_{s,r}$, and $\beta$ are regularization weights for each potential functional. To optimize the overall objective function, we used the Newton-Raphson approximation techniques and ICD optimization.

### A.3 Data weighting matrix for metal artifact reduction

Recall that in the basic MBIR algorithm, the negative log likelihood function is approximated by

$$-\log p(y|x) = \frac{1}{2} (y - Ax)^TW(y - Ax) + c(\lambda),$$

where $W = \text{diag}\{w_1, \ldots, w_M\} \in R^{M \times M}$ is a diagonal weighting matrix. In general, the entries $w_i$ are effectively specifying the reliability of each measurement. The weighting scheme can be critical, especially when the dataset contains a lot of high density objects and many measurements become unreliable. In this study, we extended our previous study in the transition task [8] and explored an adaptive weighting scheme. Mathematically, to determine the weight for a particular projection, we pre-computed the metal projection of the initial reconstructed image $x^{(0)}_i$ (e.g. FBP, and determined the percentage $I_i$ of the metal projection in the projection) calculated as

$$I_i = \frac{\sum_{j=1}^{N} A_i,j x_j^{(0)} \delta(x_j^{(0)} \geq T)}{y_i},$$

where $T$ is the threshold used to segment the metal object, and the weight for the $i$-th projection is calculated as

$$w_i = I_i e^{-\eta} + (1 - I_i) e^{-\gamma},$$

This adaptation reduces weighting of data according to the proportion of metal in the given projection. The philosophy behind this innovation is that there is likely to be some inaccuracy in the modeling of metal projections, decreasing their relative reliability beyond the value indicated by variance purely from photon counting noise.

### A.4 A Modified likelihood model for abnormal measurement rejection

Depending on the objects being scanned, the actual measurements may not be always consistent with the physical assumption. One cause of the inconsistency is the beam hardening, a problem we address in the approach above. However, it is often the case that the defective measurements can come from various effects coupled together, such as beam hardening, scattering, metal partial volume, etc. Sometimes, it is difficult to
come up with a model that accounts for all these effects individually. Here, we consider another approach [9],
where we modify the conventional quadratic likelihood term and try to give less influence if the measure-
ment differs significantly from the theoretical model. Mathematically, we consider the family of the general-
ized Huber function as our modification to the original quadratic likelihood, given by
\[
-\log p(y|x) = \frac{1}{2} \sum_{i=1}^{M} H_{l,r}(\sqrt{w_j} \left( y_i - A_{ij} x \right))
\]
where the generalized Huber function is defined as
\[
H_{l,r}(\varepsilon) = \begin{cases} 
\varepsilon^2 & |\varepsilon| < L \\
2\tau L |\varepsilon| + L^2 (1 - 2\tau) & |\varepsilon| \geq L.
\end{cases}
\]

In this modified model, we control how much we fit the estimation to the actual measurement depending
on the difference of the normalized error sinogram. If the error sinogram entry is less than the threshold \(L\),
a normal quadratic penalty is used. If the error sinogram entry is greater than the threshold \(L\), indicating a
potential defective measurement entry, a linear penalty is used, reducing its effect to the total cost. In this
study, we set \(\tau = 0.5, L = 0.5\).

B. Reconstruction results

B.1 MBIR with metal-adaptive data weighting

We first consider our simplest approach to ameliorating metal artifacts, described in Section III-1 A.3 & A.4.
Many of these artifacts result from systematic errors in projections through highly attenuating materials due
to beam hardening and scatter, with photon counts possibly being higher than their true reliability dictates.
The reduction of weights for heavily metal-corrupted measurements encourages greater sinogram errors for
these measurements and allows the more reliable data plus the regularizing a priori model to suppress arti-
facts. Additionally, the transition from quadratic penalties on sinogram errors to absolute values for larger
deviations (the Huber model) builds in tolerance for these outlier data.

Figure 2 shows improvements in cases with moderate amounts of corruption from metal. In each case, the
reconstruction of metal components is contained within a smaller region of support than in the FBP ver-
sions. The principal issue arising from inaccurate reconstruction of metal objects in security applications is
propagating artifacts corrupting other homogeneous materials. The rubber sheet atop the first row, the wa-
ter bottle in the lower right of the second, and both the water bottle and rolled rubber sheet of the third row
all have artifacts appreciably reduced. It is hoped that such improvements will prevent separation of single
materials into distinct segments. The segmentation results overlaying the image using the Stratovan’s Tum-
bler algorithm are shown in Figure 3 on the next page. It can be seen that the segmentations are improved.

Figure 2: Comparison of FBP reconstructions (left column) and MBIR with metal-adaptive data weighting (right column).
Scans are (top to bottom) numbers Medium_Clutter1_123, Medium_Clutter1_295.
B.2 Beam hardening correction in MBIR

In Section III-1.A.2 above, we introduce joint estimation of polynomial BHC parameters with imagery. In the results below, the correction is based on thresholding of the initial FBP image for a static, binary mask of high-density objects. The adaptation allowed by the optimal selection of the correction polynomial provides "relief" from especially large errors in locations where beam hardening causes inconsistencies.

In Figure 3, severity of artifacts is lessened as metal reconstructions become more spatially contained. One may speculate that the water containers will be better segmented in the MBIR images. However, sufficient corruption remains to damage the results of automated analysis. In the top and bottom rows of Figure 3, proper segmentation of the stacked rubber sheets is likely to be problematic in either column.

C. Major contribution

Our work related reconstruction included, most importantly, implementation of iterative reconstruction to match the Imatron scanner data, plus several variants of the basic MBIR algorithm. The algorithm we developed demonstrated some of the potential to handle the typical cases in security screening applications. The related work has been carefully studied and investigated, and the methodology we proposed has been carefully organized into a journal paper submitted for publication.

D. Future plans

The simultaneous beam hardening parameter estimation provides a framework for a relatively simple correction of artifacts. Reconstructed images show improvement visually, but the current version of MBIR applied to the provided data does not yet yield a clear overall win in the detection stage. Several aspects of the problem would deserve attention in subsequent, related research:

- Modeling aimed directly at metal characteristics: Our adaptations of MBIR have been relatively generic, attempting to perform beam-hardening correction and data down-weighting to compensate for the large errors encountered on metal projections. A number of more focused methods for metal correction are available, and could aid these efforts.

- Resolution boosting in rebinned data: There appear to be resolution limits in the data used in this study which may originate in the rebinning process. MBIR relies on accurate system modeling to create its benefits, and we should enhance our system model to include whatever resolution loss may affect the data.

- Advanced a priori image modeling: More sophisticated, adaptive stochastic image models may allow significantly smoother homogeneous regions in our reconstructions without sacrificing edge resolution.

III-2. RESEARCH ON AUTOMATIC TARGET RECOGNITION

A. State-of-the art and technical approach

Typically, an ATR system will consist of several separate processing units, including image segmentation, feature extraction and target classification (see Fig. 4 on the next page). Baseline ATR uses connected com-
ponent labeling (CCL) to segment objects in the CT scans. It then extracts the mass feature of each connected component and keeps only objects whose mass is higher than target definition. In following, we will give detailed descriptions about how we advance the baseline ATR system with computer vision algorithms.

**A.1 Image segmentation**

Image segmentation is a core step in ATR to assess material and morphological properties of the objects in the CT scan. Generally, CCL is used for segmentation in CT baggage scans. CCL first sets the foreground in the image and then uniquely labels subsets of connected components. When CCL sets the foreground, a morphological opening operation is usually used to prevent cluttering.

Even though CCL can find objects in the CT baggage scan, it is not enough to separate high cluttered objects as it takes account into only a local neighborhood. Moreover, streaking artifacts make it difficult to set the correct foreground, as streaking artifacts change the intensity significantly. In order to tackle these challenges, we further segment CCL results with our multi-label segmentation with metal artifacts.

Multi-label segmentation are well-studied computer vision techniques that partition the spatially continuous image domain into multiple regions with minimal total perimeter [10-12]. Let \( Y = \{ y_s : s \in \{1, \ldots, S\} \} \) be the discrete vector that represents the image intensity at pixel \( s \) in three dimensional image space \( \Omega \). Multi-label segmentation partitions the image domain \( \Omega \) into \( R \) disjoint sub-regions \( \{ \Omega_r \}_{r=1}^R \). Let \( X = \{ x_s : s \in \{1, \ldots, S\} \} \) be the corresponding segmentation label at \( s \) denoted by discrete values \( 1 \) through \( R \). Then, segmentation problem can be modeled in MAP framework.

\[
\bar{X} = \arg\min_X f(Y|X, \phi) + p(X),
\]

where \( f(Y|X, \phi) \) represents the forward model given parameter \( \phi \), and \( p(X) \) is the prior model which regularizes total perimeter (i.e. MRF model). Typical forward model has \( L_2 \)-norm of difference between pixel intensity and pre-determined label intensity:

\[
f(Y|X, \phi) = \sum_{r=1}^R \sum_{s=1}^S (I_r' - I_s')^2,
\]

where \( I' \) is the parameter that represents the constant label intensity for \( \Omega \).

However, it is challenging to directly apply multi-label segmentation for CT images because the typical forward model \( f(Y|X, \phi) \) can not deal with metal artifacts and the parameters \( \phi = \{ I' \}_{r=1}^R \) are not adaptively estimated given images. Therefore, we develop the new multi-label segmentation that takes into account metal artifacts and adaptively estimates parameters. Toward this, we compute the metal artifacts based on the assumption that X-raying through the metal introduces random fluctuations to projection measurements and the variances of projection measurements are proportional to the metal artifacts. Let \( Z = \{ z_s : s \in \{1, \ldots, S\} \} \) be the discrete vector that represents metal artifact at pixel \( s \). With these estimated metal artifacts, we formulate the new multi-label segmentation problem.
\[
\left( \overline{X} \overline{\phi} \right) = \arg\min_{X, \phi} f(\overline{Y}, \overline{Z}|X, \phi) + p(X).
\]

It is worth mentioning that our new segmentation takes the input of estimated metal artifacts and adaptively estimates the parameters during optimization.

Here, we choose the forward model based on negative logarithm of Gaussian distribution.

\[
f(\overline{Y}, \overline{Z}|X, \phi) = \sum_{i=1}^{n} \sum_{s=1}^{S} \delta(x_i - r) \left[ \frac{1}{2\sigma_i^2} (y_i - b_i, z_i - \mu_i)^2 + \frac{1}{2} \log \sigma_i^2 \right]
\]

where \( \delta(. \) is the dirac-delta function, \((\mu, \sigma) \) are the mean and standard deviation for the object \( \Omega \), and \( b_i \) represents the material-specific weight for metal artifacts. (i.e. The level of metal artifacts for air and saline water are different).

Figure 5 presents the benefit of our multi-label segmentation with metal artifacts in ATR. In the input image 5a, there exists strong metal streak artifacts on the tightly packed powders. Compared with the Ground-Truth segmentation in 5b, CCL cannot separate merged objects by tight packing and fully identify the powder parts due to metal streak artifacts, as described in 5c. Our new multi-label segmentation with metal artifacts helps split merged objects tight packing while preventing the partial loss due to metal artifacts.

**A.2 Feature extraction**

For each segmented object, we need to determine whether it is target or non-target. For this task, we first need to transform the image data into the set of features that describe the properties of the segmented object. Baseline ATR provided by ALERT uses the mass of each segmented object as feature. However, mass itself is not sufficient to describe the complex properties of targets. Therefore, we construct high-dimensional features, which are widely used in literatures:

- Mass
• Mean
• Standard deviation
• Histograms
• Higher-order moments: skew, kurtosis, entropy
• Texture: wavelets

When performing analysis of complex data, one of the major problems originates from the number of features. Analysis of high-dimensional features generally requires a large amount of memory and computational time. Furthermore, parts of features can be redundant, which blurs the performance of analysis (curse of dimensionality). So, we apply feature-selection method called minimum-redundancy maximal-relevance (mRMR) [13] on high-dimensional features to find important features.

Figure 6 shows the most important feature selected by the mRMR method among high-dimensional features. mRMR selects the location of max histogram, as the most important feature reflecting that material-specific CT attenuation coefficient is the signature for target recognition.

![Saline water and Rubber with histograms](image)

(a) Saline water  (b) Rubber

Figure 6: Most important feature selected by mRMR: (a) saline water, (b) rubber; mRMR selects the location of max histogram as the most important feature. This reflects that material-specific CT number (attenuation coefficient) is the key of representing targets.

A.3 Target classification

Given extracted and selected features, we feed them into the classifier that determines whether the segmented object is target or not. Baseline ATR provided by ALERT uses the simple threshold classifier for one-dimensional mass feature. Since our new features are multi-dimensional (after feature selection), we need the advanced classifier that can deal with high-dimensional features.

Toward this, we use a support-vector machine (SVM) [14] classifier. SVM is a popular high-dimensional classifier in computer vision. SVM finds a hyper-plane that separates two groups by training the algorithm on a pre-classified set. From this pre-classified set, SVM selects a relatively small number of samples that are close to the opposite group. These samples are called support vectors and define the hyper-plane by maximizing margins between them.

While the SVM classifier is very effective in finding the hyper-plane, selecting the type of hyper-plane is very important. If the hyper-plane is too stiff, then the classifier may not perfectly separate the two groups. On the other hand, if the hyper-plane is too flexible, then the classifier will overfit the data. We determine the type of hyper-plane by the non-linear Gaussian kernel that maps the data to a space where linear separation is possible:

\[ K(u, v) = e^{-(\|u-v\|)^2}, \]
where \( u \) and \( v \) are using feature vectors and \( \mathcal{Y} \) is a model parameter. We automatically estimate the model parameter by cross-validation on pre-classified set.

Table 1 shows Probability of Detection and Probability of False Alarm scores on 188 baggage scans with our segmentation and classification methods. Compared with baseline ATR provided by ALERT, our segmentation significantly improves probability of detection. This indicates that our segmentation algorithm better separates cluttered objects while dealing with metal artifacts. SVM classification then significantly decreases the probability of false alarm while mis-classifying a few targets. This reflects the benefit of the SVM classifier in ATR.

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<th>Baseline</th>
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<td>Probability of Detection</td>
<td>0.70</td>
<td>0.93</td>
<td>0.89</td>
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<td>Probability of False Alarm</td>
<td>0.24</td>
<td>0.56</td>
<td>0.16</td>
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Table 1: Probability of Detection and Probability of False Alarm - Our Segmentation significantly improves the probability of detection compared with baseline ATR. Our Classification significantly decreases the probability of false alarms while mis-classifying a few targets.

B. Major contributions

We have developed and implemented a new ATR system for CT baggage scans, and adapted the advanced image segmentation, feature extraction, and target classification in computer vision to a particular security screening CT systems. The major contributions are listed in the following:

- Image Segmentation
  - Metal Artifact Detection
  - Multi-label Segmentation with Metal Artifact

- Feature Extraction
  - High-dimensional features
  - Feature Selection

- Target Classification
  - Supervised Support Vector Machine
  - Non-linear Kernel for the Hyper-plane

Evaluation using a realistic set of passenger baggage scans demonstrated significant quality improvement in terms of probability of detection and probability of false alarms. The proposed segmentation algorithm splits the merged objects by tight packing and corrects the partial loss due to the metal artifacts. Our classification helps differentiating targets from non-targets, decreasing false alarms. These are all factors that can lead to improved threat detection in ATR systems.

C. Future plans

In the near term, we will continue to refine our ATR system to produce higher probability of detection and lower probability of false alarm. To do this, we will investigate advanced features and classifiers to decrease the probability of false alarm while not ignoring targets. For example, we will try Gabor features that model the behavior of cells in the visual cortex and Deep Learning classifier that models the neuron network in the brain. Also, we plan to compare our ATR system with other commercial ATR systems provided by vendors. Once this task is complete, we will identify the most challenging cases (corner case) including severe metal artifacts or systematic errors in CT number and formulate improved forward and prior models in our seg-
mentation algorithm in order to enhance segmentation quality. We hope that this will ultimately improve the probability of detection.

III-3. RESEARCH ON ELECTRON MICROSCOPY

A. State-of-the-art and technical approach

Given the success with CT reconstruction, segmentation and target recognition, we applied developed techniques to Electron Microscopy. Scanning Electron Microscopy – Focused Ion Beam (SEM-FIB) imaging is used to view nanoscale particles for a variety of applications. For security applications, it is desirable to view the imaged particles separately from their surroundings, preferably as a full three-dimensional volume. As such, one of the main tasks at hand is to perform a segmentation to isolate the particle(s) of interest from their surrounding environment. The image data that SEM-FIB produces is directly viewable as a “stack” of cross-sectional images of the particle; i.e. no tomographic operations are necessary to transform the data into natural images. We employ MBIR techniques to denoise and regularize our SEM-FIB data (cross-section images) using neighboring “slices” in preparation for segmentation, which at present is performed on individual slices using the region-growing algorithm. Once denoising and segmentation is complete, the segmented slices are viewed together as the volume of a particle (or particles).

A.1 De-noising

We are interested in the bonding properties of the particles, and as such are most concerned with the edge of particle that takes up the majority of the image. We then aim to transform the image into a binary image, where every pixel contained within the particle is “true” and every particle outside the particle is “false” (in the transformed images, “true” and “false” are represented by their integer analogs, 1 and 0, respectively).

There are multiple challenges that we face in producing a good binary image. The first is that the raw images are fairly noisy, and obscure the true shape of the particle edge. To address this problem, we employ a model-based denoising algorithm that models the noise as zero-mean Gaussian and assumes that each pixel is related to its 26 neighbors in 3D space, per the generalized Gaussian Markov random field (GGMRF) model. The algorithm uses iterative coordinate descent (ICD) optimization to bring the image closer to its MAP estimate over the course of a specified number of iterations. Figure 7b is the image that results when this MBIR algorithm is applied to the raw image in Figure 7a. The edge of the particle is much sharper, and is much more robust when applying the segmentation procedures described in the following section.

A.2 Segmentation

The constituent parts of the segmentation procedure are:

1. Use a region-growing algorithm to construct large segments of the image and threshold appropriately to ensure that one of these regions aligns with the edge of the particle.

2. Convert the segmented image into a binary image, where the previously alluded-to “edge-segment” represents one value and all other pixels take the other value.

3. “Fill in” the areas of the particle that do not yet belong to the “edge-segment.”

Figure 8 on the next page has been created using this procedure. This procedure is repeated for all slices in a stack after they have been denoised, and are then read into a MATLAB function where they are displayed.
together as a volume, per Figure 4: It is worth noting that the inside particle is well separated from outside particle.

![2D Binary Mask and Denoised SEM-FIB Image](image)

**Figure 8. Segmentation Result on the SEM-FIB Image or “Slice”:** (a) 2D Mask, (b) Stack of 2D Slices.

### B. Major contributions

So far, we have developed a segmentation procedure that is faster and more robust than the state-of-the-art method. The speed improvements have come from devising an efficient segmentation routine, while the robustness improvements have come from employing an MBIR routine to clarify the edges of the nanoparticles imaged by the FIB-SEM system.

### C. Future plans

We are still in the early stages of development of the denoising/segmentation procedure. There are many potential improvements to our work. In the short term, we are working toward improving our forward model of the stack of slices, as the thickness of the stack when the present image is collected is known to be a parameter of the image. This parameter is as-yet unaccounted for in the forward model part of our MAP estimate. Our next task is likely the implementation of a segmentation algorithm that is faster. Our hope is that we can assemble a cohesive denoising/segmentation software package, since these two constituent parts of our procedure are by and large disjointed.

### IV. 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 while minimizing the cost related secondary inspection. We have shown that an alternative method of MBIR and ATR provides the sort of quality improvement that is likely to move the detection/false alarm probability curve above its present placement. The reconstruction/segmentation dealing with merged/divided objects by tight packing/metal artifacts is a significant gain, and we are confident that this will translate into more efficient automated detection performance.

### V. PROJECT DOCUMENTATION AND DELIVERABLES

#### A. Peer reviewed journal articles

**Pending-**


B. Peer reviewed conference proceedings


C. Software developed

1. Our principal focus has been algorithm development in implementation of ATR for the CT baggage scan screening. Transition into application is envisioned with subsequent work on computational efficiency.

VI. REFERENCES

dependency, max-relevance, and min-redundancy”, Pattern Analysis and Machine Intelligence, pp. 1226-1238, 2005

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