Classification-aware methods for explosives detection using multi-energy X-ray computed tomography

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Abstract

X-ray Computed Tomography (CT) is a powerful non-destructive technology used for baggage inspection. CT imaging is based on the X-ray attenuation of the scanned materials. In Multi-Energy Computed Tomography (MECT), multiple energy-selective measurements of the X-ray attenuation can be obtained. This provides more information about the chemical composition of the scanned materials than single-energy technologies and potential for more reliable detection of explosives.

We study the problem of discriminating between explosives and non-explosives using features extracted from the X-ray attenuation versus energy curves of materials. The features commonly used in conventional (dual-energy) systems are the photoelectric and Compton coefficients, which are based on an approximate physical model. We demonstrate that the detection performance can be improved by using different features obtained via classification-aware learning-based methods. The new approach can be incorporated in existing scanners and can also aid in the design of future multi-energy systems.

Motivation

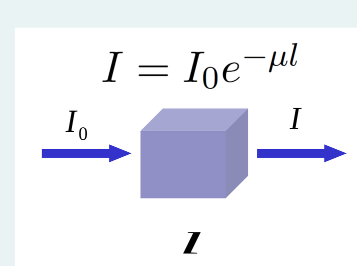
- In luggage inspection, **higher detection accuracy** and **lower false alarm rates** are needed.
- **Multi-Energy X-ray Computed Tomography (MECT)** is a non-destructive scanning technology with the potential for enhanced material discrimination.
- Through the principled application of **machine learning and optimization methods**, significant improvement of existing MECT systems may be obtained.

Our focus:

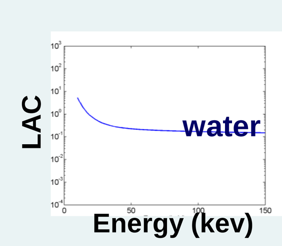
Optimizing information extraction from MECT measurements for increased discrimination between explosive and benign materials

Physical Model

- X-ray interaction with materials captured by the **Linear Attenuation Coefficient** (LAC): μ
- Function of X-ray energy
- Material "signature"
- MECT measurements contain LAC info.

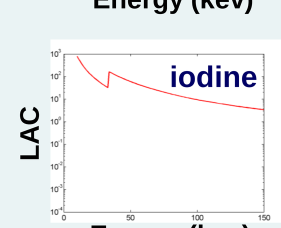


- Assumption: $\mu(E) = \underbrace{\sum_{i=1}^{N} a_i}_{\text{material-specific coefficients}} \underbrace{f_i(E)}_{\text{known energy-dependent basis functions}}$



- A common **physics-based representation** is [1]:

$$\mu(E) = \underbrace{a_P f_P(E)}_{\text{Photoelectric effect}} + \underbrace{a_C f_C(E)}_{\text{Compton scatter}}$$



- The problem: **photo-Compton model does not fit all materials and is not tuned for classification**.

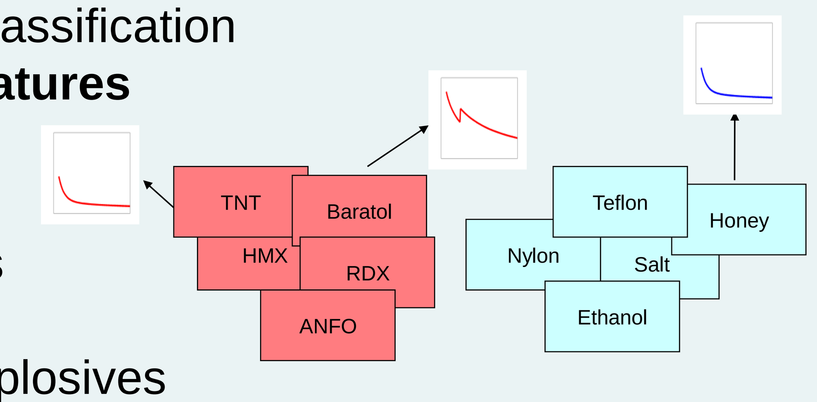
This material is based upon work supported by the U.S. Department of Homeland Security under Award Number 2008-ST-061-ED0001. The views and conclusions contained in this document are those of the authors and should not be interpreted as necessarily representing the official policies, either expressed or implied of the U.S. Department of Homeland Security.

Basis Selection Methods

- View problem as **2-class classification**: explosive vs. benign
- Use labeled data
- Find basis functions f_i tuned for classification
- Use resulting coefficients a_i as **features**

Data:

- Sampled LAC-curves of materials
  - 141-dimensional vectors
  - 124 explosives and 195 non-explosives from difference sources, e.g. [2,3])



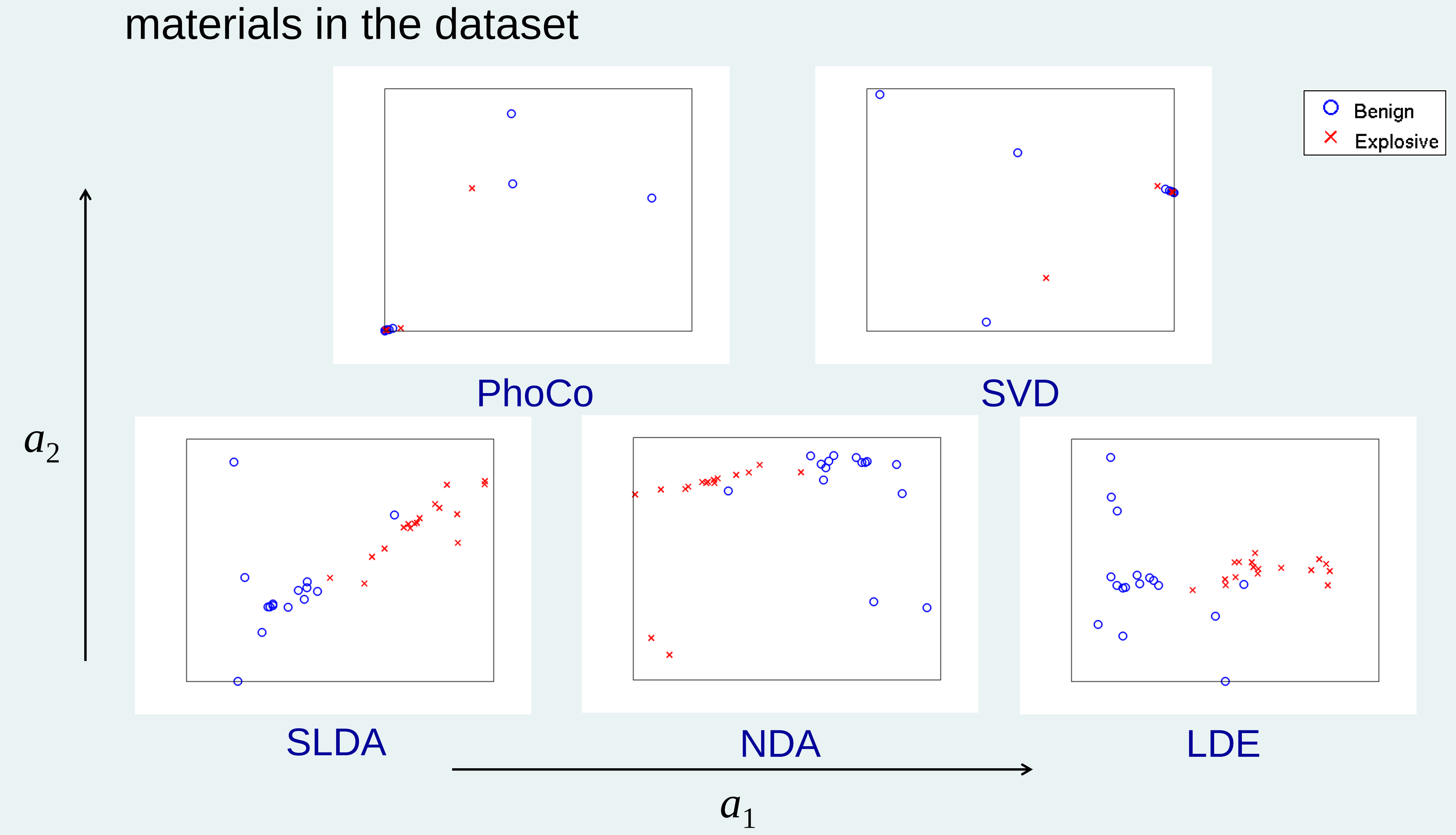
Methods examined:

- Photo-Compton model (PhCo)
- Singular Value Decomposition (SVD) [4]
- Sequential Linear Discriminant Analysis (SLDA) [5]
- Non-parametric Discriminant Analysis (NDA) [6]
- Local Discriminant Embedding (LDE) [7]
- Energy-level selection with ROC criterion (EnLR)

Method	PhCo	SVD	SLDA	NDA	LDE	EnLR
Adaptive?	x	✓	✓	✓	✓	✓
Classification-aware?	x	x	✓	✓	✓	✓

2D Example

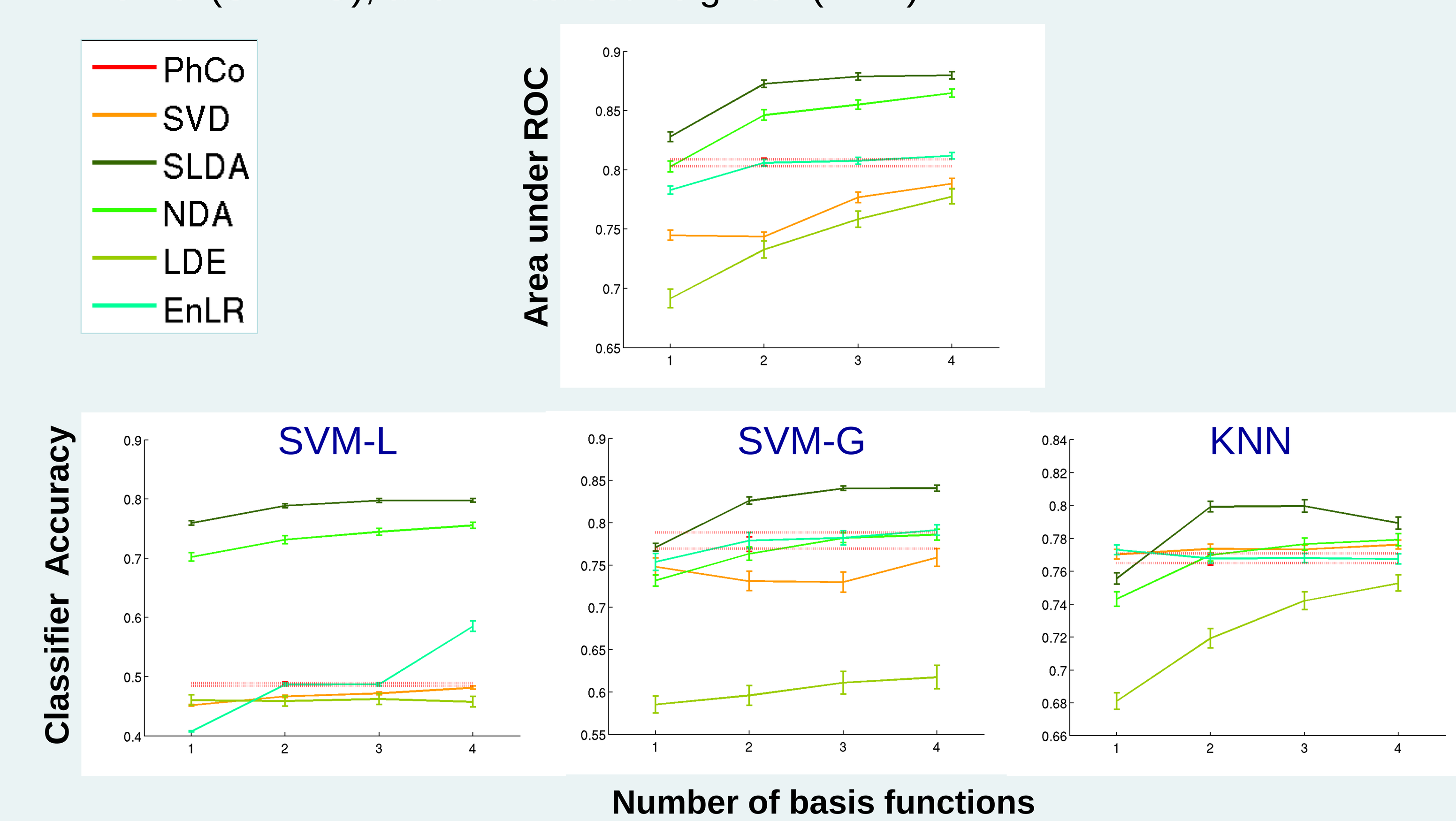
- Chose randomly 20 explosives and 20 benign materials to compose example dataset
- For each basis selection method:
  - Obtained basis functions f_1 and f_2
  - Calculated the corresponding coefficients a_1 and a_2 for each of the materials in the dataset



Separability is higher using classification-aware methods.

Feature Performance

- Evaluated features by :
  - **Area Under the ROC (AUC)**
  - **Classifier Accuracy**
- The experiment:
  - Step 1: Divide data randomly into training (50%) and testing (50%)
  - Step 2: Apply basis selection methods to training data to obtain basis fns f_i
  - Step 3: Train the classifier using coefficients a_i of the training data
  - Step 4: Calculate AUC using coefficients a_i of the test data
  - Step 5: Test the classifier using coefficients a_i of the test data
  - Step 6: Repeat steps 1-5 and calculate average AUC and Classifier Accuracy
- We used three classifiers: SVM with linear kernel (SVM-L), SVM with Gaussian kernel (SVM-G), and K-nearest-neighbor (KNN)



- **It is possible to do better than with photo-Compton.**
- **Benefit of increased dimensionality depends on choice of classifier.**

Summary

- Material discrimination can be enhanced by using more than two multi-energy features and when using features different than the standard photoelectric and Compton coefficients.
- Results of this study may lead to an improved CT based explosive detection system.
- Next step: Incorporating the basis selection procedure into the complete MECT problem.

References:

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