A LEARNING-BASED APPROACH TO EXPLOSIVES DETECTION USING MULTI-ENERGY X-RAY COMPUTED TOMOGRAPHY

Limor Eger\(^1\), Synho Do\(^2\), Prakash Ishwar\(^1\), W. Clem Karl\(^1\), and Homer Pien\(^2\)

\(^1\)Department of Electrical and Computer Engineering, Boston University, Boston, MA, USA.
\(^2\)Department of Radiology, Massachusetts General Hospital, Boston, MA, USA.

ABSTRACT

In this paper we consider the task of classifying materials into explosives and non-explosives according to features obtainable from Multi-Energy X-ray Computed Tomography (MECT) measurements. The discriminative ability of MECT derives from its sensitivity to the attenuation versus energy curves of materials. Thus we focus on the fundamental information available in these curves and features extracted from them. We study the dimensionality and span of these curves for a set of explosive and non-explosive compounds and show that their space is larger than two-dimensional, as is typically assumed. In addition, we build support vector machine classifiers with different feature sets and find superior classification performance when using more than two features and when using features different than the standard photoelectric and Compton coefficients. These results suggest the potential for improved detection performance relative to conventional dual-energy X-ray systems.

Index Terms— Multi-Energy X-ray tomography, Classification, Support vector machines, Dimensionality reduction, National security

1. INTRODUCTION

X-ray Computed Tomography (CT) is an effective non-destructive technology widely used for medical diagnosis and security purposes. With the use of CT, three-dimensional images of the inside of an object are generated based on its X-ray attenuation. Multi-Energy CT (MECT) is also capable of providing information about the chemical composition of the scanned materials. These attributes make MECT an attractive tool for explosives detection in luggage, as well as for medical applications, such as improved differentiation between contrast and non-contrast filled regions.

In MECT, multiple energy-selective measurements of the energy-dependent X-ray attenuation of an object are obtained. Material energy dependence is reflected in the linear attenuation coefficient (LAC) versus energy curve of a material. MECT measurements are used to estimate various material-specific parameters which are often the coefficients of a basis expansion of the LAC. These parameters can then be used to estimate quantities such as effective atomic number and density. A review of MECT can be found in [1].

Seminal work in the medical domain argued that the LAC space of low atomic number, biomedical materials (i.e. tissues) can be well approximated by a two-dimensional basis consisting of the photoelectric and Compton scatter components [2], whose coefficients can be found using only two CT scan energy spectra. Subsequent work retained this focus on a two-dimensional LAC representation, but used the LACs for two materials in the scene (e.g. soft tissue and bone) [3]. While some work has focused on extensions to include e.g. contrast agents, the dimensionality considered has remained very low. For explosives detection, however, the set of materials to be considered is much greater and more diverse. Therefore, considering higher-dimensional features and the possibility of features not limited to photoelectric and Compton coefficients is appropriate and our aim.

In this paper we focus on the behavior of the LACs and linear features extracted from them for the task of discriminating between explosive and non-explosive materials. The identification of material feature dimension and optimal LAC functionals can inform the design of next generation MECT systems and estimation methods for explosives detection. We demonstrate that the LACs of a set of explosive and non-explosive materials span a space that is significantly higher than two-dimensional. In addition, we examine the performance of classifiers constructed from various linear features extracted from the LACs. The results indicate that substantial improvements in material discrimination can be achieved when more than two features are used and that the optimal feature choice is not trivial. For example, if only two features are used, an optimized feature choice can dramatically outperform the conventional photoelectric and Compton coefficients. To our knowledge, this is the first work that attempts to systemically study the information available in the LACs for explosive detection.
The linear attenuation coefficient (LAC), denoted by $\mu$, is a quantity which characterizes how easily a material can be penetrated by a beam of X-rays. It originates from the Beer Lambert law: $I = I_0 e^{-\mu l}$, where $I_0$ and $I$ are the initial and final X-ray intensities at some energy level, and $l$ is the length of the X-ray path through a homogeneous material. A material’s LAC depends on the photon energy of the beam as well as on the elemental composition of the material. The units of the linear attenuation coefficients are inverse distance. For mixtures and compounds, the LAC is a weighted sum of the LACs of the constituent elements. Figure 1 shows examples of LACs of a few explosives and benign materials.

In conventional CT, the polychromaticity of the X-ray photons is ignored and the reconstructed quantity is an averaged attenuation coefficient. In MECT the LAC is usually decomposed with respect to some energy-dependent basis functions and the coefficients of the decomposition are reconstructed and used for material discrimination.

2.1. Decomposition of the linear attenuation coefficient

One of the first models for the LAC was presented by Alvarez and Macovski [2]. Based on the two main physical phenomena which affect the LAC - the photoelectric effect and Compton scatter - the following two-dimensional representation was proposed

$$\mu(\epsilon) = a_c f_c(\epsilon) + a_p f_p(\epsilon),$$  \hspace{1cm} (1)

where $\epsilon$ is the energy level, $a_c$ and $a_p$ are characteristic positive constants of the material, and $f_c(\epsilon)$ and $f_p(\epsilon)$ are the energy dependencies of Compton scatter and photoelectric effect respectively, which are independent of the material (see Fig. 2). The advantage of this model is that it has a physical interpretation and can be used to directly estimate physical parameters such as the effective atomic number and density. The disadvantage is that it can only describe low-atomic-number materials whose absorption edges are outside the energy range of interest, since the basis functions are smooth. For instance, the LAC of lead styphnate, which is shown in Fig. 1, cannot be represented with these two functions.

Alternatively, Clinthorne et al. [3] used the mass attenuation coefficients (LACs scaled by density) of two materials as the energy-dependent basis functions. The assumption in this representation is that the scanned object is composed of those materials. For example, if the basis materials are chosen as soft tissue and bone, the LAC can be written as

$$\mu(\epsilon) = \rho_b \mu_b(\epsilon) + \rho_s \mu_s(\epsilon),$$  \hspace{1cm} (2)

where $\rho_b$, $\rho_s$ are the relative densities, and $\mu_b(\epsilon)$ and $\mu_s(\epsilon)$ are the mass-attenuation coefficients of bone and soft tissue respectively. This model works well when there are a few known materials in the scene, which is mostly the case in the medical domain. However, it becomes problematic when considering a suitcase with potentially many unknown materials. A more general representation of the LAC was suggested by Lehmann and Alvarez [4]

$$\mu(\epsilon) = \sum_{k=1}^{N} a_k f_k(\epsilon),$$  \hspace{1cm} (3)

where $a_k$ are the material-dependent coefficients, $f_k(\epsilon)$ are energy basis functions, and $N$ is the number of components. In contrast to representations (1) and (2), in (3), the basis functions are general functions of energy which may not have a physical interpretation. Lehmann and Alvarez investigated the dimensionality of the attenuation coefficients of biological materials. They applied Singular Value Decomposition (SVD) to the matrix whose columns contain the attenuation curves of a set of elements commonly found in biological materials. They concluded that for biological materials within the diagnostic range of energies, a two-dimensional linear vector space representation of the LAC is sufficiently accurate. In addition, they observed that if a material with an absorption edge is included in the set (e.g., a contrast agent) then
two basis functions will not be enough to represent the set. In our work we focus on materials which are relevant to the problem of explosives detection. The goal is to find an accurate low-dimensional representation of the LAC for the materials in this domain. We apply the framework of Lehmann and Alvarez to a set of explosives and benign materials. The SVD analysis shows that a two-dimensional representation is not sufficient to describe the curves. We take this framework one step forward and consider the problem of classifying the materials into explosives and non-explosives based on the coefficients of the LAC decomposition. The classification results vary with the choice of basis functions and the number of coefficients used.

3. EXPERIMENTS AND RESULTS

3.1. Understanding the space of the LACs

We made a list of materials consisting of 84 examples of explosives and 40 examples of non-explosives, with a total of $N_m = 124$ materials. The explosives and their chemical formulas were taken from the 1985 LLNL explosives handbook [5]. Since there is no standardized list of relevant non-explosive materials, we chose materials which have appeared in literature and web resources. For each material, using its chemical formula, we constructed its LAC by linearly combining the attenuation coefficients of its constituent elements according to their relative weights [6]. In total, there were 23 distinct elements across all the materials that were used in our experiments. For each material $m$, we sampled its LAC every 1 keV from 10 keV to 150 keV, for a total of $N_c = 141$ energy levels, and arranged these values into a vector denoted by $\mu_m$.

We created a matrix $M_{N_c \times N_m}$, with the sampled attenuation coefficients as columns, and calculated its SVD:

$$M = \begin{bmatrix} \mu_1 & \mu_2 & \ldots & \mu_{N_m} \end{bmatrix} = USV^T \quad (4)$$

where the columns of $U$ and $V$ are the left and right singular vectors, respectively, and $S$ is a diagonal matrix with the singular values on the diagonal. The singular values $s_i$ and top two singular vectors $u_i$, $i = 1, 2$ are shown in Fig. 3. The singular values plot strongly indicates that the dimensionality of the LAC space is greater than 2. For instance, whereas the MSE with the top 2 singular vectors is 0.1824, with the top 10 singular vectors the MSE is 9.57E-11. It is also interesting to observe that the singular vectors have very different characteristics when compared to the photoelectric and Compton basis function of Fig. 2. The singular vectors can be regarded as an alternative set of energy-dependent basis functions that are better tuned for accurately and efficiently approximating a given family of LAC curves.

3.2. Effect of feature choice on classification performance

As discussed in Sec. 2, materials are associated with their LAC curves and thus discrimination of materials is equivalent to discrimination of their LAC curves. The linear decomposition of a material’s LAC relative to a family of basis functions, given by equation (3), provides a representation for the material in terms of the projection coefficients $a_k$, $k = 1, \ldots, N$. Since the coefficients of the decomposition can potentially be reconstructed from MECT measurements, we regard these coefficients as our features. The challenge is to choose a small set of basis functions so that the coefficients of the explosives would be well separated from the coefficients of the non-explosives. From a machine-learning viewpoint, we are looking for coefficients which would serve as good features for an explosives versus non-explosives classification task.

3.2.1. Feature dimensionality

In this experiment we tested the effect of feature dimensionality on classification performance. For each material $m$ of our example materials, we projected the LAC $\mu_m$ onto the left singular vectors, to obtain a vector $c_m$ of coefficients:

$$c_m = [c_{m1}, c_{m2}, \ldots, c_{mN_c}]^T = \mu_m^T U \quad (5)$$

For dimensions $d = 1, \ldots, 20$, we took as features the coefficients corresponding to the first $d$ singular vectors.
Based on these features, we trained a Support Vector Machine (SVM) classifier \cite{7} on 80\% of the labeled examples and tested it on the remaining 20\% of examples. The correct classification rate was estimated by repeating the training and testing phases over 1000 independent trials and computing the simple average of the correct classification rates across the trials. The percentage of training data which turned out to be support vectors varied from almost 100\% for \( d = 1 \) to about 50\% for \( d = 20 \). The results for the average correct rate are displayed in Fig. 4. It can be seen that the average correct rate generally increases with dimension. The performance improves from about 66\% for two coefficients to almost 85\% for 10 coefficients. Thus not only is the LAC much better estimated with more than 2 basis functions, the better estimation quality also translates to a significant improvement in the classification performance.

3.2.2. Feature choice

In this experiment we constrained the dimensionality of the feature vector to 2 and studied the effect of feature choice on the classification performance. We projected the example LACs onto 6 different combinations of two singular vectors out of the first four, and used those coefficients as features: \( \{ c_{m_i}, c_{m_j} \} \), \( i, j \in \{1,2,3,4\} \), \( i \neq j \), \( m = 1, \ldots, N_m \). We also computed the photoelectric and Compton coefficients of the LACs (Eq. (1)) and used them as features in our test for classification performance. We trained and tested an SVM classifier as in Sec. 3.2.1. The results in Fig. 5 show that the choice of features is not trivial. An unexpected combination of two SVM coefficients provides the highest performance (the coefficients corresponding to the 1st and 4th singular vectors). In addition, it can be seen that it is possible to do better than with the photoelectric and Compton decomposition.

4. CONCLUDING REMARKS

We studied the problem of explosives detection using features related to the LAC curve. Our analysis of the space of the curves for a set of materials of interest demonstrated that two components are insufficient for accurate description of the curves and that a higher dimensional representation is needed. The classification experiments showed that classification performance improves significantly by using the coefficients of a more accurate representation. Continuing with this type of analysis may lead to an optimal choice of features to reconstruct from MECT measurements for the purpose of accurate explosives detection with a low false alarm rate. Interesting directions for future work include finding better choices for basis functions and incorporating the source spectrum and detector response into the analysis.

5. REFERENCES