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EXTENTS AND LIMITS OF RADIOSCOPIC DETECTION OF NUCLEAR
MATERIALS IN CARGO CONTAINERS WITH TWO MEGAVOLTAGE ENERGY
BARRIERS

by

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ABSTRACT

Extents and Limits of Radioscopic Detection of Nuclear Materials in Cargo Containers with Two Megavoltage Energy Barriers

by

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The megavoltage X-ray technology is utilized for detecting nuclear materials in cargo containers. Interlaced response is obtained by switching rapidly between 6MeV and 9 MeV beams. It is known that the ratio of penetration levels of cargo contents taken at nominal and dual energies provides the information about atomic numbers of materials, and thus can also indicate the threat group. However, the identification is not straightforward if combinations of materials are present. The latter can lead to misdetections. It is imperative to know what are the extent and the limit of the currently employed technology, and how to carry out the inspection in real-time by balancing the human involvement and the computer assistance. We have performed experiments with Linatron K9, analyze data and conclude on an efficient system configuration. The following are addressed: (a) visualization the contents to produce an image suitable for the visual analysis, and (b) prompting the custom personnel on the presence and the location of suspicious objects.
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CHAPTER 1

INTRODUCTION

1.1 Introduction

Weapons of mass destruction (WMD) can be smuggled by terrorists by their shipping along with commercial goods in large containers. Of the special concern are fissile materials which could be used in nuclear weapons and radioactive materials that could be used in a “dirty bomb”. Radioactive materials, when they are heavy shielded may not be detected by radiation monitoring portals. However, the labor involved to physically open each container, extract and check the contents makes the inspection prohibitively long. Of the seven million cargo containers arriving through U.S. seaports every year, an extremely small percentage, i.e., 5-6% is ever examined [3].

Advanced dual-energy X-ray cargo inspection systems can play a crucial role in ensuring national security by providing a real-time inspection of cargo advancing through the customs. It is evident that both the speed and the robustness of the procedure are to be addressed and secured. In other words the inspection must be accurate and not obstructive for the traffic of commercial goods through the border. Transformed into the system properties, this means that the inspection is expected to be fast, with high true positive rates when threats or contraband is present and low false positive cases when there is no threat in the cargo. The task is challenging for numerous reasons and the major among them is the penetration limit through thick and high Z materials - fissile material that can be used in nuclear weapons or shielding material for dirty bomb material. However, knowing that threat materials are characterized by high atomic numbers, Z which are not conventional materials for commercial cargo, because normally, cargo contents do not
exceed iron or copper in atomic numbers \((Z = 26 \text{ or } 29)\), one can design the system around detection of high atomic numbers. Thus the higher atomic numbers found among container’s goods such as for example \(\text{Th}^{90}, \text{U}^{92}, \text{Pu}^{94}, \text{Pb}^{82}\) and \(\text{W}^{74}\) can be considered as a group of threats\[1\].

Radioscopic imaging with more than one X-ray energies allows for determining the material of scanned objects by exploiting differences in how the material interacts with X-rays at different energies\[4\]. With two energy levels the process involves taking X-ray projection of the same object and extracting information about the atomic number of the material by the ratio of the attenuation levels. This is possible because at some energy X-ray interacts via two different physical mechanisms related to the atomic number of the scanned material \[5\][6].

To study this technology we use a linear accelerator, Linatron K9 (based on a klystron) developed by Varian Security and Inspection Products. Electrons are accelerated before hitting a tungsten target, producing X-rays. The target is designed to produce a minimum focal spot size consistent with its high radiation output. Depending on the energy of individual photons three processes contribute to the aggregate attenuation of the polychromatic x-ray beam. First is the photoelectric absorption. This process occurs when the energy of photons in the beam is equal to or not much greater than the electron binding energies in the atoms of the attenuating medium. The photon transfers all its energy to an electron. The electron then has more than the binding energy of its shell and is ejected from the atom. When an X-ray photon has energy which is much greater than the binding energy of the electron with which it interacts, the Compton scattering becomes more important. Photons are deflected from their initial line of travel
and move in different directions with a lower speed. Finally, the pair production is characterized by the complete absorption and creation of electron-positron pair.

High-energy X-ray photons generated by the device are absorbed and scattered in varying amounts by the materials in their path, depending on their densities and atomic structure. On the far side of the scanned subject such as a cargo container, a linear CdWO₄ and photodiode detector array collects and records the photons passed through unabsorbed or unscattered, generating an electronic signal that is translated into an image. Two sets of collimators are used for the maximum scatter control and to narrow the beam to the detector area.

The exponential law of the attenuation of the gamma radiation is defined as a ratio of logarithmic transparencies at nominal and dual energies. It characterizes the material of the barrier irrespective to its thickness. This forms a physical principle of the material discrimination. The radioscopic transparency of a material with a mass thickness t and an atomic number Z, absorption coefficient µ for a bremsstrahlung beam with boundary energy Eₑ is expressed as a ratio of the radiation intensity before and after the penetration through the barrier:

\[
T(Eₑ, t, Z) = \frac{\int_{0}^{Eₑ} \frac{dp}{dEγ} (Eₑ, Eγ) e^{-\mu(Eγ, Z)} dEγ}{\int_{0}^{Eₑ} \frac{dp}{dEγ} (Eₑ, Eγ) dEγ} \tag{1}
\]

where the integrand function is a product of bremsstrahlung intensity according to the Schiff formula [7] and the detector response factor as[8]:

\[
\int_{Eγ}^{Eₑ} \frac{dp}{dEγ} (Eₑ, Eγ) dEγ
\]

\[
\int_{0}^{Eₑ} \frac{dp}{dEγ} (Eₑ, Eγ) dEγ
\]
\[
\frac{dp}{dE\gamma}(E, E_\gamma) = \frac{dI}{dE\gamma}(E, E_\gamma) \left[ 1 - e^{-\mu_{\text{tot}}(E_\gamma) \cdot t_{\text{at}}} \right] \frac{\mu_{\text{tot}}(E)_{\gamma}}{\mu_{\text{det}}(E)} \quad (2)
\]

Usually, the solution of the system cannot be found in general terms, as the barrier can represent a heterogeneous mixture of materials. As such, a number of unknown variables might exceed the number of equations. Two transparency profiles during irradiation of a barrier with nominal and dual boundary energies can be obtained, while atomic number and mass thickness of a material can be evaluated as a solution of a system of integral equations[9].

For monochrome gamma beam, let’s introduce \( R \) - a ratio of logarithmic transparencies (inverse value of absorption) at the nominal \( E_1 \) and dual \( E_2 \) boundary energies of bremsstrahlung as:

\[
R(E_1, E_2, t, Z) = \frac{\ln(E_{1, t, Z})}{\ln(E_{2, t, Z})} = \frac{\bar{\mu}_{\text{eff}}(E_1, t, Z)}{\bar{\mu}_{\text{eff}}(E_2, t, Z)} \quad (3)
\]

\( R \) in (3) is a constant and it uniquely characterizes the irradiated material.

To fulfill the goal, one of the polychromatic X-ray spectra must be at a high enough energy so that the pair production accounts for much of the attenuation. Typically 9 MeV is sufficient for this purpose. The other spectrum should be at an energy level that is significantly lower. However, since the X-ray dose output drops rapidly as the energy level decreases, too low energy will not be sufficient[4]. 6 MeV represents a good compromise between the energy and flux. Under the selected levels a library of \( R \) values can be obtained and further used for a table look-up for identification of a singled material [5]. In this thesis, we study the technology extents and limits, specifically we are interested in recognition of materials of interest behind the steel shields also, different
combinations of materials are considered to test false positive rate.

1.2 Outline of Thesis

The structure of this thesis closely follows the order in which the work was undertaken in response to the aims as they were initially conceived. It consists of five further chapters.

Chapter 2 presents overview of inspection technologies.

Chapter 3 focuses on device and calibration procedures, experimental setup and measurements.

Chapter 4 discusses the use of data analysis such as ratio, intensity, different segmentation algorithms, wavelet and Susan thresholding techniques to visualize the contents.

Chapter 5 illustrates the real cargo analysis for detection of suspicious materials.

Chapter 6 displays the operation of the developed prompter tool.

Finally, Chapter 7 summarizes the work done within the scope of this thesis and discusses the conclusions drawn from the work carried out. It also addresses the recommendations for the similar works that are intended to be done in the future.
CHAPTER 2

SURVEY OF INSPECTION TECHNOLOGIES

2.1 Introduction

Nuclear weapons contain SNM[16], which produces unique or suspect signatures that can be detected. It emits radiation, notably gamma rays (high-energy photons) and neutrons. SNM is very dense, so it produces a bright image on a radiograph (a picture like a medical x-ray) when xrays or gamma rays are beamed through a container in which it is hidden. Using lead or other shielding to attenuate gamma rays would make this image larger. Nuclear weapons produce detectable signatures, such as radiation generated by or a noticeable image on a radiograph. Other detection techniques are also available.

Nuclear weapons and SNM have various signatures by which they can be detected. As we will see, detection is difficult but not impossible. I will discuss five of these signatures.

Gamma rays:

Gamma rays[16] are high-energy photons emitted when an atomic nucleus decays to a lower energy state. The energies of gammas from a particular isotope may be depicted in a spectrum, which is a plot of energy versus number of counts at each energy level (Figure 1). The bottom axis is the energy and the vertical axis represents the counts. There are different peaks at different energy levels. This spectrum is unique to an isotope; if you can identify the spectrum, you can identify the isotope that caused the spectrum. However, there are several detection problems. A cargo container may hold items containing nonthreatening radioactive material, and dirt may generate background gamma rays. As a result, spectra of several radioactive isotopes may be commingled so
that the threat signature must be distinguished from the others. Another difficulty is that highly enriched uranium (HEU) is hard to detect because its main gamma ray—as we see on the far left in Figure 1—is a relatively low energy. If terrorists were to build a bomb, they would prefer to use HEU because, unlike plutonium, it can be used to make a gun-assembly bomb, the simplest design. Plutonium is easier to detect. Yet another problem is that dense material can be used to shield gamma rays.

Neutrons

Neutrons[16] offer a second signature. Plutonium and uranium to a much lesser extent emit neutrons spontaneously, but few other materials do, so detection of neutrons is suspicious.

![Figure 1 Gamma Ray Spectrum of HEU Taken with Geranium Crystal](image)

Figure 1 Gamma Ray Spectrum of HEU Taken with Geranium Crystal
Size and Density

Third, a bomb may be detected by its size and density[16]. High energy photons can be beamed through a cargo container to produce a radiograph, just like a medical x-ray. A nuclear weapon would show up on a radiograph because it is dense, as would lead shielding.

Muons

A fourth signature comes from muons[16], which are heavy, subatomic particles that are caused when cosmic rays strike the Earth’s upper atmosphere. They travel at nearly the speed of light.

Their mass and velocity make them very penetrating. When they strike matter, they are deflected in proportion to its density. The high densities of uranium and plutonium would result in a different deflection pattern than plastic.

Flourescence

Fifth[16], ultraviolet light causes certain materials to emit light in a process called fluorescence. The ultraviolet raises the electrons to a higher energy state, and they emit light when they drop back to a lower energy state. Similarly, when a nucleus is struck by photons of precisely the right energy, it will emit gamma rays in a spectrum unique to that isotope. This science that I have just discussed forms the basis for technology projects. A detector system has building blocks. Detector material captures photons or neutrons and converts their energy into measurable electrical pulses, algorithms process data, and computers to run the algorithms and provide a usable output, such as a display on a computer monitor.
2.2 Inspection Technologies:

Five technologies[16] illustrate the detection portfolio: (1) A new scintillator material to improve detector performance and lower cost. (2) GADRAS, an algorithm to determine the materials in a container by analyzing gamma-ray spectra. If materials are the “eyes and ears” of detectors, algorithms are the “brains.” (3) A third CAARS to detect material with high atomic number (Z, number of protons in an atom’s nucleus) based on the principle that Z affects how material scatters photons. (4) A system to generate a 3-D image of the contents of a container based on the principle that Z and density strongly affect the degree to which muons (a type of subatomic particle) scatter. (5) Nuclear resonance fluorescence imaging to identify materials based on the spectrum of gamma rays a nucleus emits when struck by photons of a specific energy.

2.2.1 Nanocomposite Scintillators:

One technology under development is a nanocomposite scintillator[16]. Many detector materials are plastics or crystals. Certain plastics like polyvinyl toluene (PVT) are rugged and cheap, and they can be made in large sheets. However, they have poor resolution of gamma ray spectra, so they cannot identify the source of radiation. As a result, they are prone to produce nuisance alarms.

Figure 2 is a spectrum taken with a PVT detector. It shows negligible detail. Contrast that with the spectrum from the germanium detector in Figure 1. Certain crystals, like high-purity germanium, have high resolution and can identify a substance emitting gamma rays, but they are small, delicate, and expensive. Los Alamos is currently mixing nanometer-size crystals in a plastic matrix to develop a detector material with the best
features of both; the Domestic Nuclear Detection Office (DNDO), the Defense Threat Reduction Agency (DTRA), and Los Alamos jointly fund this project.

2.2.2 GADRAS

The second technology[16] is Gamma Detector Response and Analysis Software (GADRAS), the gold standard of algorithms for analyzing a spectrum to determine what material(s) generated it. GADRAS originated in 1985 at Sandia and has continually been updated, especially after 9/11. While many spectrum analysis programs examine spectral peaks, GADRAS analyzes the entire spectrum, which is important because most data are outside the peaks, and shielding and multiple radioactive sources may subtract from or add to the spectrum.

2.2.3 CAARS

A third technology is Cargo Advanced Automated Radiography Systems (CAARS)[16]. DNDO started CAARS to develop next-generation radiography equipment for Customs and Border Protection (CBP) to screen cargo at ports of entry. The goal is to detect dense material like uranium, plutonium, or lead. Dense materials are more opaque to high energy x-rays than less dense materials, and both materials have similar opacity to lower energy x-rays. The pixel-by-pixel ratio of the two radiographs of a container taken with x-rays of higher and lower energy permits differentiation between dense and less dense material. One approach is to use two x-ray generators, one for each energy level. That requires a larger system, which is a problem where available space is at a premium, such as seaports. In another approach, Science Applications International Corporation (SAIC) and Accuracy Corporation developed a single so-called interlaced
accelerator that generates x-rays at both energy levels. This accelerator is expected to permit a much smaller system.

![Gamma Ray Spectrum of HEU Taken with PVC](image.png)

**Figure 2** Gamma Ray Spectrum of HEU Taken with PVC

2.2.4 Muon Tomography

The fourth technology is muon tomography[16]. Recall that muons are highly penetrating subatomic particles. Los Alamos, through a cooperative research and development (R&D) agreement with Decision Sciences Corporation, has developed an algorithm to calculate the track of individual muons entering and exiting a cargo container. Calculating the deflection of each track is used to determine density of each
volume element and locate dense material. This equipment is large but does not generate radiation because it uses naturally-occurring muons, potentially making the equipment of particular value for inspecting cars with passengers inside, such as at border crossings.

2.2.5. Nuclear Resonance Fluorescence

A fifth technology is nuclear resonance fluorescence (NRF)[16]. Bombarding an isotope with x-rays of the right energy level can cause the nucleus to emit gamma rays. The gamma rays are emitted in all directions, so by placing a detector behind the object to be detected relative to the x-ray beam, it is possible to detect only those gamma rays that are scattered backwards, minimizing interference from the x-ray beam. Because the gamma spectrum is unique to each isotope, this technique indicates which isotopes are present; for example, it can differentiate between U235, which can be used in a gun-assembly bomb, and U238, which cannot. Note that the gamma spectrum produced by NRF is different than the spectrum emitted through radioactive decay. Passport Systems is developing this system under contract to DNDO.

Conclusion

PVT radiation detectors could detect radiation but could not identify isotopes, and shielding SNM might defeat detection. Radiographic equipment could reveal dense objects, but relied on operator skill to flag potential threats. It might be possible to hide a nuclear artillery shell in a cargo of dense objects, and it would be difficult to pick out a small piece of SNM. Resolving alarms required time-consuming methods, such as using hand-held radioisotope identification devices or unpacking a container.

Dual-energy radiography detects high-Z material automatically. EZ-3D reveals high-Z material hidden in medium-Z material, and might be able to differentiate SNM from
other high-Z material. These approaches detect useful signatures, but have drawbacks as well, such as low signal strength, complexity, high cost, or large size. The task is to utilize these signatures and minimize drawbacks in a system that can be fielded. Other technologies, such as improved detector material and improved algorithms, also have the potential to improve detection capability.

In the medium term (5-10 years), there are promising opportunities to develop new technologies, such as muon detection systems. In the long term (10-20 years) detection could benefit from advances in nanotechnology and organic semiconductors.
CHAPTER 3

EXPERIMENTAL SETUP AND MEASUREMENTS

As explained in chapter 1, dual energy megavoltage radioscopy is considered in this work.

3.1 Device and Calibration Procedures

The experiments we have conducted aimed to reveal the capabilities of the system to distinguish materials in combinations. The outline of Linatron K9 used in the experiments and the imaging chain are shown in Fig.3. Complete and aligned radiography system consists of klystron type accelerator, linear detector array, a single reference detector, collimators, a motion table and a data acquisition computer with proper configuration setting similar to the setup shown in Fig.1. The source is made of tungsten (W), and the primary collimator is made of lead (Pb) of 300 mm length. It has a 4 mm vertical opening. The secondary collimator is 200 mm Pb with a vertical opening of 14 mm and 25 mm acrylic gap. A moving table can travel from 100 mm above beam plane to 500 mm below the beam plane at 50 to 800 mm/sec. This mimics the moving cargo in a horizontal direction. A stationary table is used for additional experiments setting, such as steel shield plates. The wall of the detector box shield is 100 mm Pb with a vertical opening of 13 mm and 22 mm acrylic gap. The linear detector array has 449 CdWO₄ channels at 4.6 mm pitch along 6.5 meter radius arc. Internal apertures are as 4 mm high by 4 mm opening per channel. The angle subtended by detector is 17.6°. The main purpose of the primary collimator, the secondary collimator and the shield wall of the detector box is to precisely control the beam shape and the scatter removal to minimize corresponding noise.

In general, K-9 Linatron and detectors operate in interlaced mode by cycling between
HiE and LoE pulses. All images are taken at 333pps (pulses per second) in interlaced mode, half of those are high energy (HiE) pulses and half are of low energy (LoE). In that mode the beam is set to 475rad/min at 1m at 200pps. The scan in moving up is ranged between 440mm to 0mm. The scan speed is performed as fast as 166.67mm/s. 448 detectors by 880 views (pulses) produce an image.

In the measurements, some materials have been placed onto the moving table mimicking the cargo moving through the gantry bay. The shielding steel or lead plates were placed on the stationary table. The offset and the gain calibration are performed with X-ray off and with the steady state high mode beam, respectively. The detector electronics have two banks, each used for every other view (line of data). The offset calibration is performed with x-ray off. The gain calibration is performed with the steady state high mode X-ray beam. When a radiograph is generated, the system is linearly normalized net detector signal (detector reading minus offset).

In a perfect world, pixel value should be 0 when X-ray is off and 60,000 when X-ray is running high mode beam

X-ray intensity fluctuates from pulse to pulse even in the steady state mode and there is a complication from the difference between HiE (High Energy, i.e., nominal energy) and LoE (Low Energy) pulses. HiE pulse in the interlaced mode may also be slightly different from that in steady state high mode. These are taken care of in the following steps. After performing the offset calibration and the gain calibration in the steady state high mode, a radiography scan is run in the steady state high mode.
We calculate an average pixel value in the region with no object and no motion stage. It should be around 60,000 and let’s call it “Steady”. Then, a radiography scan is performed in the interlaced mode. For each detector (0:447), we calculate the average pixel value of odd number views in the region with no object and no motion stage and repeat the same for even numbered views. The larger average values are associated with HiE pulses and should be near 60,000. Let’s call them “InterHiE[i=0:447]”. The smaller average values are associated with LoE pulses and let’s call them “InterLoE[i=0:447]”. The #447 (out of 0 to 447) detector is a reference detector located behind the first collimator that monitors beam intensity.

After an object radiograph is taken in interlaced mode we first identify whether an odd numbered or an even numbered views are associated with HiE or LoE pulses. There
is no digital communication between detectors and K-9 accelerator and the first view can
be either HiE or LoE. The accelerator is setup in a way that the LoE dose per pulse is
slightly lower than the HiE dose per pulse. We identify HiE and LoE by the reference
detector readings. Let’s call pixels from HiE pulse “HiE[i=0:447, j]” and pixels from LoE
pulse “LoE[i=0:447, j].”

The next step is an additional normalization (correcting the average difference
between the steady state high mode pulses and the LoE and HiE pulses in the interlaced
mode) and the reference correction (correct X-ray source instability).

\[
HiE^P[i = 0:447, j] = HiE[i = 0:447, j] \times \frac{\text{Steady}}{\text{InterHiE}[i = 0:447]} \times \frac{HiE[i = 447, j]}{\text{InterHiE}[i = 447]}
\]

\[
LoE^P[i = 0:447, j] = LoE[i = 0:447, j] \times \frac{\text{Steady}}{\text{InterLoE}[i = 0:447]} \times \frac{LoE[i = 447, j]}{\text{InterLoE}[i = 447]}
\]

In the equations, the first correct term is an additional normalization and the second
term is a reference correction.

3.2 Materials and Objects

Following materials have been selected:

Step wedges of plastic (acrylic and polyethylene), aluminum (Al), steel and lead (Pb) for
material calibration;

- 1” and ½” steel plates (up to 17” total);
- 2”×4”×8” lead bricks.
• Five depleted Uranium (DU) cubes of 75cc, 100cc, 150cc, 200cc and 400cc, a 4”×6” ×1.25” oval shape DU piece;
• Five tungsten cubes of 75cc, 100cc, 150cc, 200cc and 400cc.
• Five tin cubes of 75cc, 100cc, 150cc, 200cc and 400cc.
• Wood boards of 15.5” and 16”.

Wedges were used for various thicknesses of same or mixed materials; steel plates have been used as shields.

We have performed ten sets of experiments: A4, A5, A6, A7, A8, B4, B6, B7, B8, B9. The materials and structures are described below and displayed in Fig.4
3. Exp A6

4. Exp A7

5. Exp A8

6. Exp B4(Top)
Steel is selected to be a shield material because it is a most common commercial material. Thus one can expect the cargo contents of combination of steel with other types. Also, steel is a good candidate for shielding, compared for example to aluminum whose penetration is high, or to lead whose penetration levels is approaching those of nuclear materials and thus can even enhance the detection of threats. In the following we describe materiala/objects per experiment.

\textit{A4:} Fig.2 (1). Steel step wedges.
Left (top down): 1mm, 0.25”, 0.5”, 1”, 1.5”, 2.25”, 3”, 4”, 6”, 8”;
Right (top down): 2”, 4”, 6”, 8”, 10”; 
Middle: 2”, 4”.

\textit{A5:} Fig.2 (2). Plastic step wedges

Front step wedge (top down): 0.125”, 0.25”, 0.5”, 1”, 1.5”, 2”, 3”, 4”, 5”, 6”, 7”, 8”, 8”, 12” 16”; Stack of boards (added to the right): eighteen 1” thick boards; White bricks at the back (added to the middle and the right section): 8.5”
A6:  Fig.2 (3). Lead step wedges

Step wedge in front (top down): 0.0625”, 0.125”, 0.25”, 0.5”, 1”, 1.5”, 2”, 3”, 4”

Add on the back (left to right): 4”, 3”, 2”, 1”.

A7:  Fig.2 (4). Aluminum step wedge.

Front left wedge (left to right): 4”, 8”, 12”, 16”

Front right wedge (left to right): 0.25”, 0.5”, 1”, 2”, 3”; 4”, 6”; 8”;

Block at back: 24”

A8:  Fig.2 (5). Variety

Left column (top down): Aluminum, 4”, 8”, 12”, 16”;

2nd column (top down): plastic 2.25”, 4.5”, 6.75”, 9”; wood 15.5”;

3rd column (top down): lead 1”, 2”, 3”, 4”;

4th column (top down): tin 150cc, tungsten 150cc, lead 400cc;

5th column (top down): steel 2” and 4”

B4:  Fig.2 (6): DU objects shielded.

Steel step wedge thickness: 1”, 2”, 3”; 4”, 5”

Behind 5” and 4” steel (left): DU cubes 400cc and 200cc;

Behind 3” and 2” steel (middle): DU cubes 150cc and 100cc;

Behind 1” steel (right): 75cc DU, 75cc tungsten and 75cc tin;

Inside the box: an oval shaped DU).

B6:  Fig.2 (8). DU and W

Left: DU cubes 200cc and 400cc;

Middle: DU cubes 75cc, 100cc and 150cc;
Right: W cubes of 75cc, 100cc and 150cc;

Inside the box: an oval shaped DU.

B7: Fig.2 (9). Variety

Left: Aluminum step wedge, 0.5”, 1”, 1.5”, 2”, 2.5”, 3”, 3.5”, 4.25”;

Middle: tin cubes, 75cc, 100cc and 150cc;

Right: tungsten cubes, 200cc and 400cc;

Bottom: two same lead wedges, 4”, 3”, 2”, 1”; placed as shown in Fig.6 (10).

B8: Fig.2 (11): DU cubes shielded.

Left: steel wedge 2”, 4”; 

Back: steel wedge 5”, 4”, 3”, 2”, 1”;

Inside the box: an oval shaped DU.

Left next to the box: DU cubes, 75cc, 100cc;

Front: Aluminum wedge: 2”, 1.5”, 1”, 0.5”;

B9: As shown in Fig.2 (12): Du in a toolbox (clutter).

Inside the tool box: DU cubes of 75cc and 100cc;

In front of the box: an oval shaped DU in a box, as shown in Fig.2 (7).

Right next to the box: DU cubes of 150cc and 200cc;

In experiments B6 and B7, fifteen 1’ steel plates are used as shields and placed between objects and the device by adding then one by one per experiment within the set.

In B9, only 1’ steel plate is used as a shield assuming that this thickness mimics the container walls.
Conclusion

This chapter has explained the various experimental setup for measurements and device and calibration procedures to perform the dual energy radioscopy.
CHAPTER 4

DATA ANALYSIS

4.1 Ratio Analysis

We have calculated mean ratio values for objects/materials at known positions within the test images. Plots of a single or a pair of materials in combination are presented in Figures 5. From the figure, the ratio below for example 1.5 could be a threshold for clear identification of DU and some other high Z materials, but not in the presence of shields. One can observe also that with one to four inches of steel shields and then between 13 and 15 inches of thickness a variety of objects in combination produce similar values for R. Thus these thicknesses can be used wisely for hiding threats or misleading the inspection. So it can be concluded that the efficiency of the ratio analysis is limited, but it can be performed at first for identification of suspicious spots. A straight forward approach would be a hard ratio thresholding (RT). The result of such processing shown in Fig.4 is affected greatly by the scatter noise. It should be mentioned that the ratio of the background (air) is 1, thus a care to be taken to subtract the background.

For automated prompting the alert signal is to be generated based on the cummulative count of the suspicious pixels per area. The shape analysis can be made available after postprocessing of the results, such as morphological filtering.

If noise is concerned, then both geometry of the system and the offset introduced by the object motion between the scans are to be taken into account. It should be mentioned that the noise is to be estimated on both HiE and LoE images and only then the ratio is calculated. The noise is observed to be signal dependent. For example, the material itself, object shape and the geometry are significant parameters of the scatter. Under the real-
time requirements, de-noising prior to ratio calculation can take a considerable time on 16-bit 7386 x 1450 images of a real cargo.

On the other hand, for visual inspection, the ratio signal itself can be efficiently interpreted by human. As it can be seen, objects of the threat group are seen clearly at up to 13 inches of steel shields in Fig.6 (8)–(20) and at some extent at higher shield thicknesses. A simple pseudocoloring with a proper color assignment per material group can make the ratio signal itself quite useful. For example, in Fig.5 we show the ratio signal and its colored version corresponding to Fig.7(15); red color indicates a threat material and a non-commercial material such as tungsten.
Fig.5. Unfolded ratio plots per material with and w/o shields.
1. Exp A4 No Shield
2. Exp A5 No Shield
3. Exp A7 No Shield
4. Exp A8 No Shield
5. Exp A8 No Shield
6. Exp B4 No Shield
7. Exp B6 No Shield
8. Exp B6 1 Shield
9. Exp B6 2 Shield
10. Exp B6 3 Shield
11. Exp B6 4 Shield
12. Exp B6 5 Shield
13. Exp B6 6 Shield
14. Exp B6 7 Shield
15. Exp B6 8 Shield
16. Exp B6 9 Shield
17. Exp B6 10 Shield
18. Exp B6 11 Shield
19. Exp B6 12 Shield
20. Exp B6 13 Shield
21. Exp B6 14 Shield
22. Exp B6 15 Shield
23. Exp B7 No Shield
24. Exp B7 1 Shield
Fig. 6. Hard thresholding with $T=1.4$. 
Fig. 7. (left) Ratio signal and (right) pseudocolor version of a setup with 15 inches of steel shield.

4.2 Intensity Analysis

Knowing that X-rays penetrate through low Z materials at 9 MeV and absorbed merely by high Z materials, one can design an automated procedure for finding spots of high absorption, and thus pointing to suspicious areas. Their analysis is to be carried out based on the mean ratio value. Fig.8 displays the intensity distribution per material versus thickness of the steel shields.
As it can be seen from the figure, the intensity itself is not indicative. Three inches of steel make difficult visual examination of the contents (see, Fig. 9). Image enhancement techniques can be employed for improving the image qualities. For visualizing data, histogram stretching or logarithmic rescaling work to a certain extend towards the better
visibility behind the shields. For automated processing, a simple k-means or Fuzzy C-means clustering is able to segment images.
21. Exp B6 14 Shield
22. Exp B6 15 Shield
23. Exp B7 No Shield
24. Exp B7 1 Shield
25. Exp B7 2 Shield
26. Exp B7 3 Shield
27. Exp B7 4 Shield
28. Exp B7 5 Shield
29. Exp B7 6 Shield
30. Exp B7 7 Shield
31. Exp B7 8 Shield
32. Exp B7 9 Shield
33. Exp B7 10 Shield
34. Exp B7 11 Shield
35. Exp B7 12 Shield
36. Exp B7 13 Shield
37. Exp B7 14 Shield
38. Exp B7 15 Shield
39. Exp B8 No Shield
40. Exp B8 1 Shield
4.3 Fuzzy C-means

The next step involves segmentation based on the fuzzy C-means (FCM) [17] clustering method. This creates segments for further analysis. The FCM algorithm is an iterative procedure that finds clusters in data by exploiting the concept of fuzzy membership: instead of assigning a pixel to a single cluster, each pixel is assigned different membership values on each of the groups. This is done by minimizing an objective function $J$,

$$J = \sum_{i=1}^{N} \sum_{j=1}^{C} \mu_{ij} \|x_i - c_j\|^2$$

where

$$c_j = \frac{\sum_{i=1}^{N} \mu_{ij}^m x_i}{\sum_{i=1}^{N} \mu_{ij}^m}$$

$$\mu_{ik} = \frac{1}{\sum_{j=1}^{C} \left(\frac{\|x_i - c_j\|}{\|x_i - c_k\|}\right)^{\frac{2}{m-1}}}$$
If after one iteration of the algorithm the value of $J$ is smaller than before it means the algorithm is converging or getting closer to a good separation of pixels into clusters; $N$ is the number of pixels in the image; $C$ is the number of clusters used in the algorithm; $\mu$ is the membership table of $N \times C$ entries which contains the membership values of each data point and each cluster; $m$ is a fuzziness factor (a value larger than 1); $x_i$ is the $i^{th}$ pixel in $N$, $c_j$ is $j^{th}$ cluster in $C$; $|x_i - c_j|$ is the Euclidean distance between $x_i$ and $c_j$.

The procedure is as follow.

1. Initialize $\mu$ with random values between zero and one; but with the sum of all fuzzy membership table elements for a particular pixel being equal to 1.
2. Calculate a first value for $J$ using (6).
3. Calculate the centroids of the clusters $c_j$ using (7).
4. Calculate the fuzzy membership table using (8).
5. Recalculate $J$ by (6).
6. Go to the step 4) until a stopping condition was reached.

The process stops when either a given number of iterations is executed in which we can consider that the algorithm achieved a ‘good enough’ clustering of the data, or the difference between the values of $J$ in consecutive iterations is small (smaller than a user-specified parameter $\varepsilon$), therefore the algorithm has converged. In our experiment, the parameters are set as follows: $C = 8$; $m = 2$; maximum iteration is 100 and the results are as shown in the fig. below.

The “penetration” ability is extended to see behind 8 inches of steel. The time to complete the procedure is 8.7 sec on the experimental images in MATLAB environment. This approach lends itself to the shape based analysis. For example, if the axi-symmetry is
a property of containers for nuclear materials, the analysis can be aimed at finding the symmetry features.

4.4 K-Means Clustering

K-means (MacQueen, 1967)[18] is one of the simplest unsupervised learning algorithms that solve the well known clustering problem. The procedure follows a simple and easy way to classify a given data set through a certain number of clusters (assume k clusters) fixed a priori. The main idea is to define k centroids, one for each cluster. These centroids should be placed in a cunning way because of different location causes different result. So, the better choice is to place them as much as possible far away from each other. The next step is to take each point belonging to a given data set and associate it to the nearest centroid. When no point is pending, the first step is completed and an early groupage is done. At this point we need to re-calculate k new centroids as barycenters of the clusters resulting from the previous step. After we have these k new centroids, a new binding has to be done between the same data set points and the nearest new centroid. A loop has been generated. As a result of this loop we may notice that the k centroids change their location step by step until no more changes are done. In other words centroids do not move any more. Finally, this algorithm aims at minimizing an objective function, in this case a squared error function. The objective function

\[
J = \sum_{j=1}^{k} \sum_{i=1}^{n} \left\| \mathbf{x}_{ij} - c_{j} \right\|^2
\]
where \( \| x_i^{(j)} - c_j \|^2 \) is a chosen distance measure between a data point \( x_i^{(j)} \) and the cluster centre \( c_j \), is an indicator of the distance of the \( n \) data points from their respective cluster centres.

The algorithm is composed of the following steps:

1. Place \( K \) points into the space represented by the objects that are being clustered. These points represent initial group centroids.
2. Assign each object to the group that has the closest centroid.
3. When all objects have been assigned, recalculate the positions of the \( K \) centroids.
4. Repeat Steps 2 and 3 until the centroids no longer move. This produces a separation of the objects into groups from which the metric to be minimized can be calculated.

In Fig. 10 we show the results with number of classes as 9. The “penetration” ability is extended to see behind 10 inches of steel. The time to complete the procedure is 7.8 sec on the experimental images in MATLAB environment. This approach lends itself to the shape based analysis. For example, if the axi-symmetry is a property of containers for nuclear materials, the analysis can be aimed at finding the symmetry features. Further increase of the number of clusters, say up to 17 will allow for “seeing” behind 11-14 inches of steel, but a certain level of noise is introduced which hinders the extraction of the shape features. Fig. 11 shows the result of such segmentation for the shield of 14 inches. Although it supports the visual inspection, the time to complete also increases.
Fig. 10. Segmentation of images of B6 experiment with k-means (9 clusters).
Fig. 11 Segmentation of images of B6 experiment with k-means (17 clusters).
4.5. Edge Detection Using Scale Multiplication

Wavelet transform [19] is considered to be useful in detection of edges because of its multiscale and multiresolution properties. In wavelet domain, the edge structures present observably at each sub-band and noise gets suppressed by increase in scale.

The wavelet transform is just the projection of signal onto the wavelet bases. Mathematically, the wavelet transform of the function $f(x)$ at the scale $2^j$ and position $x$ is

$$W_\varphi = f(x)\varphi_{2^j}(x) = \int_{-\infty}^{\infty} f(t)\varphi_{2^j}(x-t)dt$$

$$W_\psi = f(x)\psi_{2^j}(x) = \int_{-\infty}^{\infty} f(t)\psi_{2^j}(x-t)dt$$

Where $W_\varphi$ is wavelet co-efficient and $W_\psi$ are wavelet coefficients (horizontal, vertical and diagonal), $t$ is the translation parameter, $\varphi(x)$ and $\psi(x)$ are scaling and wavelet functions defined by

$$\varphi(x) = 2^{-j/2}\varphi(2^{-j}x)$$

$$\psi(x) = 2^{-j/2}\psi(2^{-j}x)$$

The wavelet transform is implemented using low pass filter and high pass filter. Initially low-pass filter is applied on the whole image row wise and then column wise followed by down-sampling. Then high-pass filter is applied. This leads to four sub-bands namely low-low (LL), low-high (LH), high-low (HL) and high-high (HH). The transform can be done recursively by working on the LL channel produced in the previous decomposition step. The whole process is illustrated below:
Algorithm:

Initially, wavelet decomposition is performed on the original image as explained above. The decomposition is done up to two levels. This produces approximate coefficients and detailed coefficients at all levels. Haar, db2 and db4 wavelets are used in this case.

The main aim of this experiment is to find edges which are obtained by detailed coefficients. So, these coefficients are only processed keeping approximate coefficients untouched. Initially, the detailed wavelet coefficients in all the sub-bands are thresholded independently such that all the coefficients below this threshold are set to zero keeping remaining coefficients intact. The reason for setting all the lower coefficients to zero is to avoid unwanted processing with these coefficients which may otherwise affect in future. In other words, it may include noise after multiplying scales. This threshold is calculated using Donoho’s hard thresholding equation which is given by \( \sigma \sqrt{\frac{2 \log n}{n^2}} \). The deviation ‘\( \sigma \)’ is median absolute deviation which is explained later. For thresholding, a
small parameter $\beta$ is multiplied to the obtained threshold in order to remove noise. This value varies in between 1.5-4 depending upon the contrast of the image. The detailed coefficients at first and second level are then multiplied. In other words, the horizontal (Vertical, Diagonal) sub-band coefficients at second level are multiplied by the horizontal (Vertical, Diagonal) sub-band coefficients at first level. This is illustrated for horizontal sub-band in the figure below. Same strategy is used for vertical and diagonal sub-bands.

Thus, the original 1st level sub-band coefficients are modified by these scale multiplication values. All the coefficients are then converted to absolute values because coefficients with either higher positive values or higher negative values signify edges.

The thresholding is done using Donoho’s [2] method and is given by

$$\sigma \sqrt{2 \log n^2}$$

where ‘$\sigma$’ is median absolute deviation and it is given by

$$\sigma = 1.4826 \times \text{median} \left( \text{abs (w-median (w))} \right)$$

It is noted that all the three sub-bands are thresholded independently. Finally those coefficients whose value is greater than the obtained threshold represent edges. The
other values which are less than threshold are set to zero. Now the corresponding wavelet coefficients in three sub-bands are added in order to find edges across different orientations.

In Fig 13, we show the results with Haar, db2 and db4 wavelets. The “penetration” ability is extended to see behind 8 inches of steel. This approach lends itself to the shape based analysis. For example, if the axisymmetry is a property of containers for nuclear materials, the analysis can be aimed at finding the symmetry features.
Fig 13.a. Haar wavelet results of images of B6 experiment.
Fig13.b. db2 wavelet results of images of B6 experiment.
Fig. 13.c. db4 wavelet results of images of B6 experiment.
4.6. SUSAN Algorithm

The SUSAN algorithm for edge and corner detection was developed by S.M. Smith [20]. The algorithm principle is the use of a circular mask centered on each pixel of an image, and the computation of the number of pixels inside of the mask with a similar gray-level as the central pixel. The number of pixels or "area" computed from the mask is called USAN or "Univalue Segment Assimilating Nucleus". The USAN area contains information about the image structure around the neighborhood surrounded by the mask. The SUSAN principle is based on the fact that each pixel in an image has an area associated to the pixel with similar intensity levels. The USAN area has a maximum when the nucleus is on a uniform region. The USAN area reduces to 50% in regions close to an edge, and it reduces to around 25% in regions close to a corner. This property determines the detection of edges and corners in the image.

Edge and corner detection

The SUSAN algorithm for edge and corner detection follows the usual image processing techniques: from an input image, a predefined mask is scanned across the image, applying a set of rules with the local data, to obtain an enhanced edge image. The algorithm uses a circular mask to assure an isotropic response. The most used mask contains 37 pixels although it is possible to use a small 3x3 pixel mask with good results. The mask is placed on each image pixel, and the intensity value of each pixel inside the mask is compared with the central pixel value. The comparison result is given by the following equation:

\[
\text{compare}(r, r_0) = \begin{cases} 
1 & \text{if } |I(r) - I(r_0)| \leq t \\
0 & \text{if } |I(r) - I(r_0)| > t 
\end{cases}
\]
where $r$, is the position of the mask central pixel, $r$ is the position of any other pixel inside the mask, $I(r)$ is the intensity of pixel $r$, $t$ is a threshold for the intensity difference, and compare is the result of the comparison. The threshold $t$ determines the minimum contrast to detect features in the image. A value of 25 is adequate for most real images. The number of pixels with similar intensity to the central pixel value can be obtained with the following equation:

$$n(r_0) = \sum_r \text{compare}(r, r_0)$$

this value defines the USAN area for pixel $r$. The USAN area value is then compared to a constant geometric threshold $g$, which is set to $3n_{\text{ima}}/4$ for edge detection, or $g = n_{\text{ima}}/2$ for corner detection, where $n_{\text{ima}}$ is the maximum value for $n$. The value of $g$ is larger than 50% needed to detect an edge in order to add some noise rejection capabilities to the algorithm. However, the geometric threshold is not critical for the precise detection of edges. The initial edge detection response is obtained by applying the following equation:

$$\text{response}(r_0) = \begin{cases} 
g - n(r_0) & \text{if } n(r_0) < g \\
0 & \text{otherwise} \end{cases}$$

Equation 3 is the formulation of the SUSAN principle. If the USAN area is small, the response to edges will be higher. The SUSAN algorithm can be generalized as follows [7]:

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1. Use a circular mask centered on each image pixel.

2. Count the number of pixels inside the mask with similar intensity to the nucleus intensity.

3. Subtract the USAN area from the geometric threshold to detect edges and/or corners.

4. Compute the momentums of the USAN area to obtain the direction of the edges. Look for false positives by computing each USAN centroid and their contiguity.

5. Apply non-maximum suppression, thinning and subpixel estimation if necessary.

In Fig. 14, we show the results with Susan threshold results. The “penetration” ability is extended to see behind 8 inches of steel. This approach lends itself to the shape based analysis. For example, if the axi-symmetry is a property of containers for nuclear materials, the analysis can be aimed at finding the symmetry features.
4.7. New Visualization Method Based on Processing Low and High Energy Images With Stationary Wavelet (HLSW)

A flowchart of this algorithm [21] is displayed in Fig. 2. It proceeds as follows:
(1) Wavelet Decomposition. In order to obtain approximation coefficients and detail coefficients, we perform SWT on low and High respectively. To obtain a high quality image, wavelet basis function db4 and scale 1 are appropriate.

(2) Coefficients Enhancement. The approximation coefficients and detail coefficients obtained in step 2 are weighted via multiplying weighting coefficients, respectively. Smooth regions in image are represented mainly by approximation coefficients and details mainly by detail coefficients. Therefore, image can be enhanced by enhancing approximation coefficients and weakening detail coefficients.

(3) Wavelet Reconstruction. The enhanced fusion image can be obtained by implementing ISWT using the approximation coefficients and detail coefficients obtained in step 3.

Fig.15 Block diagram of HLSW method.
B6 0 inch Shield

B6 1 inch Shield

B6 2 inch Shield

B6 3 inch Shield
B6 8 inch Shield

B6 9 inch Shield

B6 10 inch Shield

B6 11 inch Shield
4.8. Adaptive Thresholding Algorithm

In this section we propose to detect target materials based on both ratio and intensity.
values. In Fig.9 we plot the signature (blue line marked with rectangles) of the ratio versus intensity of HiE. Based on the analysis of the signature we derive an algorithm which is parameter-controlled, however is easy to implement. We assume that a minimum thickness of DU object is 1.25” that corresponds to the oval DU object in the experiments. The following data are used:

Mean value of intensity signal, $I_{\mu 9}$ for HiE;

Mean Ratio value, $R_m$ and $\sigma_R$, std of $R$;

Standard deviation of HiE, $\sigma_9$.

The following thresholds are calculated:

$$T_9 = I_{\mu 9} + \sigma_9;$$

$$R_T = R_m + 0.1\sigma_R$$

The ratio threshold for the oval DU is shown in red on Fig.17.

The processing is performed in a square $w \times w$ window. The size of the window, $w$ is set experimentally and is recommended to be 5-7 to accommodate the statistics and not to span across the boundaries of small DU cubes, for example. Processing is performed in a following fashion:

Slide the window of $w \times w$ pixel by pixel and calculate $I_9$ -mean value in the window of HiE image, $I_6$-mean value in the window of LoE image, and the mean of ratio $R_m$.

The final decision on whether it is a suspicious material or not is made by checking the following system of inequalities:

$$\begin{cases} I_9 \leq T_9 \\ R_m \leq R_T \end{cases} \quad (4).$$

If system (4) is satisfied, the window is classified as ‘suspicious’ and marked “1”,
otherwise it is considered as ‘benign’, or ‘0’. This way a binary map of suspicious spots is produced on a pixel by pixel basis.

The result of the AT algorithm are presented in Fig.18. A summary per experiment is as follows:

A4: Steel thicker than 12” shows up.

A5: 42.5” of plastic is disregarded.

A6: Lead thicker than 3” shows up.

A7: Aluminium of 40” is filtered out, but shows up when superimposed on 16” of iron (tabletop).

A8: Aluminium up to 16”, plastic up to 9”; wood of 15.5” and 2.09” tin (150cc) are discarded. Lead thicker than 2.9” (400cc) and 2.09” tungsten (150cc) are shown.

B4: 1.66” of tin is clear. DU and 1.67” tungsten (75cc) are detected with steel shields up to 5”.

B6: DU or tungsten thicker than 1.25” can be detected with steel shields up to 15”, but steel thicker than 8” will increasingly make the result difficult to analyze (false positives).

B7: Aluminium up to 4.25” is disregarded even with steel up to 15”. Tin up to 2.09” (150cc) is not detected even when with steel up to 15”. Lead thinner than 2” will not be detected, but 2” of Pb with steel more than 1” is detected. Tungsten thicker than 2.3” (200cc) is found even with steel up to 15”. But steel thicker than 8” makes the result difficult to analyze.

B8: DU objects show up behind steel up to 5” combined with Al up to 2”.

B9: DU is detected behind one steel plate and in the clutter.
Although results are not perfect in terms of detecting all the pixels in the object, at least a meaningful portion of that is preserved. The TP and FP rates are calculated under the ground truth which is the area of the objects of interest in pixels. Overall True Positive is 77.2%, and the overall False Positive is 3.64%. However, these numbers are not self explanatory, because they do not consider the degradation of the shape such as shrinking due to pixel misdetections or merging of neighboring objects to an unrecognizable shape. Thus, as such they cannot be considered as a metric.

The algorithm completes in 4 seconds on experimental images and can be further optimized for real-world implementation.
33. Exp B7 15 Shield 34. Exp B9 No Shield 35. Exp B9 1 Shield

Fig. 18. Detection based on Adaptive Thresholding.

4.9 Analysis of the Results

- We brief below our observations:
- The look-up in the library of the ratio signatures is feasible for a singled out material only which is not a case for a real cargo loaded with various goods.
- The visual analysis of the ratio images facilitated by image enhancement techniques is available for up to 15 inches of steel shields which is the maximum used in experiments.
The mean ratio analysis per object is available upon successful segmentation. The latter is carried out on the intensity image, particularly on HiE images. The success of the segmentation depends mainly on the intensity variation, or on the width of the intensity histogram and the power of the segmentation technique. In the experiments the segmentation using k-means clustering is available up to 15 inches of steel, but additional post-processing is required for the automated shape analysis.

The developed AT algorithm combines both ratio and intensity data for the analysis and shows a good performance. It is also meets the time requirements defined by DNDO. The algorithm demarcates the areas better that its counterpart, i.e., ratio based thresholding. The generated output demands on postprocessing to be further used by the shape analyzer.

The overall conclusion about availability of shape information by the automaton is that it would need a laborious processing and employment of pattern recognition methods. On the contrary, trained personnel can look further at “suspicious” spots to analyze shapes. Human intelligence discriminates objects in the background even in highly noisy images. This means that the combination of automated routines and the visual analysis can make the inspection accurate and performed in real-time.

We have evaluated std of the ratio signal. The plot is presented in Fig.19. It shows that high thicknesses or high Z are featured by higher std values due to scattering. It follows, however not directly, that std can be utilized as an additional classification feature. The future research can be directed to the development of
efficient classification for example based on Neural Network or Support Vector
Machines with input features such as mean ratio, mean intensity and std of
intensity and the ratio signals.

- Given that the ratio is useful for a single material only, the results are
couraging. The penetration level is established for hidden objects if any are 15
inches of steel. It is apparent that the manifest data can be useful for adjusting
parameters and validating the results of radiography.

Fig. 19. STD of the ratio signal per material and thickness.
Based on the above, we conclude that the system configuration is to be of a combination of automated procedures for locating materials of interest and visualization techniques and visual inspection. The first part is responsible for ratio/intensity based analyses; image enhancement and segmentation in a region of interest. This way, both the time requirements can be met and the accuracy can be secured. However, there is a certain level of false positive misidentifications of the material type due to the limits of the described technology.
CHAPTER 5

REAL TIME CARGO ANALYSIS

5.1 Materials and Objects

For a real container analysis, we used four different objects of materials as: Iron (M1: diameter = 2.5” and length = 8”, M2: length = 5”, width = 2.5cm and height = 2.5cm), brass (length = 10.4 cm, width = 3.5 cm and height = 4.5cm), tungsten (M1: diameter = 7.8” and length = 1.5”, M2: diameter = 7.8” and width = 1.6”) and lead (length = 6”, height = 2”, width = 4”) for 0, 2, 4, 6, 8 and 10 inches of the steel shield. Fig. 20 shows the setup in the test cell.

Fig. 20. Measuring levels in the test cell.
5.2 Analysis

An example 9MeV image with a 0” steel shield is enhanced and analyzed, as shown in Fig. 21 and Fig. 22.

![Fig. 21 Original image.](image1)

Further experiments have been performed on the real cargo container loaded with same objects as above. The purpose of this experiment is to examine the resolution ability of the technology. The test objects have been placed on the floor.

![Fig. 22. Coloring per material type.](image2)
The profiling method is applied for subtracting the container from the image. This is done by identifying the “drops” in the profile function, i.e. two global minima and one global minimum, respectively. The resulted signal is shown in Fig. 23.

Based on the utilization of intensity, ratio and shape analyses the objects of interests are located, as shown in Fig. 24, Fig.25 and Fig. 26.

Fig.23 (a) Full image (32 bit); (b) profile function; (c) Subtracted container.
This shows that the system can detect this small object in the cargo and the overall processing time didn’t exceed the limit established for the time of advancing the cargo through the system, i.e., 5 minutes of time. In fact it took three minutes to analyze a complex scene.
Finally, a Graphical User Interface (GUI) is developed for furnishing the technology with an interactive tool of processing, visualization and manipulation the images.

The GUI encapsulates the automatic material identification algorithms with a minimal user involvement and also provides the means for the user to interact with the overall material detection process as for example, to define the number of classes, to zoom into a region of interest, or to outline a specific part of the image for processing. It has been implemented in a PC-Windows environment, using JAVA. The chosen software platform ensures maximum flexibility for the development and makes possible future porting to other environments, such as UNIX. More specific actions supported by the GUI are:

- Open, save or visualize partitions.
- Denoising algorithms such as wavelet, median filters.
- Image enhancement techniques such as logarithmic rescaling, contrast improvement and brightness adjustment.
- Image operations such as obtaining a negative image, ratio calculation, morphological filtering.
- Segmentation using FCM, k-means.
- Pseudo coloring using the developed for the application a look up table.

The implemented GUI supports the intuitive specification by the user of the initial selection of parameters and constraints, as well as corrections to the results being produced by automatic procedures.

Below fig. 27 shows some of the screenshots of image processing tool.
Ratio image

The ratio image is given by the ratio of low image pixel value by high image pixel value.

The result of ratio image is as shown in Fig. 27.a.

(a) Low, High and Ratio Image

Logarithmic enhancement

The logarithmic transform creates an image suitable for a human observer. The former is defined as conversion

\[ s = c \times \log(r + 1) \]
where $c$ is a fixed scaling constant,

$$c = \frac{\max(I)}{\log(1 + |r|)}$$

and max($I$) is the maximum intensity of the pixel; $r$ is the value of the input pixel and $s$ is the corresponding value of the output pixel.

The result of logarithmic enhancement for high image is as shown in the Fig.27.b.

Morphological Filtering

The two principal morphological operations are dilation and erosion (Haralick et al. 1992; Boomgaard et al. 1992)[22]. Dilation allows objects to expand, thus potentially filling in small holes and connecting disjointed objects. Erosion shrinks objects by etching away (eroding) their boundaries. These operations can be customized for an application by the proper selection of the structuring elements, which determines exactly how the objects will be dilated or eroded. Basically, the structuring element is used to probe the image to find how it will fit, or not fit, into the image object(s). The dilation process is performed by placing the structuring element on the image and sliding it across the image in a manner similar to convolution. The difference is in the operation performed. It is best described in a sequence of steps.

- If the origin of the structuring element coincides with a “0” in the image, there is no change; move to the next pixel.
- If the origin of the structuring element coincides with a “1” in the image, perform the OR logic operation on all pixels within the structuring element.
(b) Logarithmic enhancement of Hi image

Fig. Disc type structuring element of $7 \times 7$ pixels.
To apply the morphological operation to the gray-level image, we can treat the image as a sequence of binary images and operate on each gray level as if it were the “1” value, assuming everything else to be “0.” The resulting images can then be combined by laying them on top of each other and “promoting” each pixel to the highest gray level value coincident with that location. In our experiment, a disc structuring element of $7 \times 7$ pixels was used.

Fig shows the morphological output of ratio image

Fuzzy C-means segmentation

As described in chapter 5, the fuzzy C-means segment the image, in to number of $k$ different clusters. In this tool we can select the number of clusters, fuzziness and maximum of iterations to run the experiment. The figure shows the result of fuzzy C-means for high image for $k=8$ clusters.
(c) Morphological result of ratio image
K-means segmentation

As described in chapter 5, the k-means segment the image, in to the number of k clusters. In this tool we can select the number of clusters, and maximum of iterations to run the experiment. The figure shows the result of k-means for high image for k=8 clusters.
In order to visualize the suspicious objects in the image pseudo coloring technique is used. Fig 27.e. shows the pseudo coloring output of high image, the red in color are suspicious objects.
f) Pseudo coloring of logarithmic enhancement

Figure 27 Shows the screenshots of Java image processing tool.
CHAPTER 7

CONCLUSION AND FUTURE WORK

7.1 Conclusion

In this thesis we have evaluated the system properties of a cargo inspection system based on megavoltage X-ray radioscopy for detecting certain objects representing materials of the threat group from the perspective of real-time implementation. The latter requirement strictly limits the complexity of data processing algorithms and requires a limited data to be presented to operators for attaining the operational goals. An efficient use of intensity and ratio signals allows for detecting small objects of a threat group behind 15 inches of steel based on the derived AT algorithm. The proposed algorithm is fast enough to meet the real-time requirements. The algorithm is expected to produce an alert signal and point to suspicious spots. Simple yet computationally efficient visualization techniques allows for focused screening and shape analysis by operators. Extents and limits of the technology in terms of penetration levels and accuracies are presented.

7.2 Future Work

Among a number of possible ways for handling the problems we consider the use of advanced classifiers such as for example Neural Network or Support Vector Machine for marking each pixel based on the features calculated in a certain neighborhood. Use ratio, std and the intensity as classification features. Cluster pixels of similar classes using the distance metric. Used advanced techniques for segmentation of the intensity image and analyzed the shape.
Image de-noising for scatter removal in low and high energy images, respectively is another pathway for improving visual analysis and detection efficiency. For that, an accurate model of a source, collimator, system geometry is to be taken into account to guarantee the success of the filtering.
REFERENCES


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