LA-UR-12-20990
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Title: Final Progress Report: Isotope Identification Algorithm for Rapid and Accurate Determination of Radioisotopes Feasibility Study

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Intended for: Progress Report
Report

Final Progress Report: Isotope Identification Algorithm for Rapid and Accurate Determination of Radioisotopes Feasibility Study

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Abstract:

This is the final report of the project titled, "Isotope Identification Algorithm for Rapid and Accurate Determination of Radioisotopes," PMIS project number LA10-HUMANID-PD03. The goal of the work was to demonstrate principles of emulating a human analysis approach towards the data collected using radiation isotope identification devices (RIIDs). It summarizes work performed over the FY10 time period.

Introduction

The goal of the work was to demonstrate principles of emulating a human analysis approach towards the data collected using radiation isotope identification devices (RIIDs). Human analysts begin analyzing a spectrum based on features in the spectrum - lines and shapes that are present in a given spectrum. The proposed work was to carry out a feasibility study that will pick out all gamma ray peaks and other features such as Compton edges, bremsstrahlung, presence/absence of shielding and presence of neutrons and escape peaks. Ultimately success of this feasibility study will allow us to collectively explain identified features and form a realistic scenario that produced a given spectrum in the future. We wanted to develop and demonstrate machine learning algorithms that will qualitatively enhance the automated identification capabilities of portable radiological sensors that are currently being used in the field.

Work Performed

In the beginning we conducted 12 sessions in which we documented the processes and steps the spectroscopist used in receiving, opening and analyzing a spectrum. From these sessions, we extracted the steps common to the multiple separate analyses and also those that were unique to an individual spectrum analysis. The common steps suggest an overall structure for an algorithm whereas the unique ones point to analytical details that could complicate algorithm designs. This work is described in detail in a report titled, "Steps Toward Automated Gamma Ray Spectroscopy: How a Spectroscopist Deciphers an Unknown Spectrum to Reveal the Radioactive Source," February 25, 2010, LA-UR-

LA-UR-10-01009. This report was submitted as a progress report at the end of February 2010. In this work we were focusing on low resolution low statistics spectra.

We found the best approach that worked reasonably well was applying wavelet shrinkage denoising.[1] In this approach the spectrum is represented as a linear combinations of wavelet basis functions that capture spectral characteristics by means of a projection $\hat{S}(e)$ of the spectrum $S(e)$ onto a smooth subspace spanned by the localized wavelet basis functions $\{\psi_k^j\}_{k=0,\,j=1}^{\infty,\infty}$ centered at k and representing features at increasing scales j, and scaling functions that capture the largest scale background features at the coarsest scale J:

$$\hat{S}(e) = \sum_{j=1}^{J}\sum_{k=0}^{N_j}\langle S,\psi_k^j\rangle \psi_k^j(e) + \sum_{k=0}^{N_J}\langle S,\varphi_k^J\rangle \varphi_k^J(e) \quad \text{, where}$$

$$\langle S,\psi_k^j\rangle = \int_{-\infty}^{\infty} S(e)\psi_k^j(e)de, \quad \langle S,\varphi_k^J\rangle = \int_{-\infty}^{\infty} S(e)\varphi_k^J(e)de.$$

Once a wavelet transform is taken the signal is typically represented by a few high-magnitude coefficients and noise generally has low magnitude coefficients occurring at all scales j and positions k. Noise can then be removed by reducing coefficient magnitudes by a predetermined threshold commensurate with noise level in the signal. The signal is then reconstructed by the inverse wavelet transform using the processed wavelet coefficients. After that we applied simple maxima finding algorithm on the reconstructed denoised spectrum to extract feature locations. The wavelet toolkit from MATLAB was used to perform the work.[2]

We tried several wavelets, however the wavelet that worked best for the NaI(Tl) spectra was SYM4 or Symlet4. SYM4 is a near symmetric, orthogonal, relatively smooth wavelet. The scaling function and wavelet function for SYM4 is shown in Figure 1.

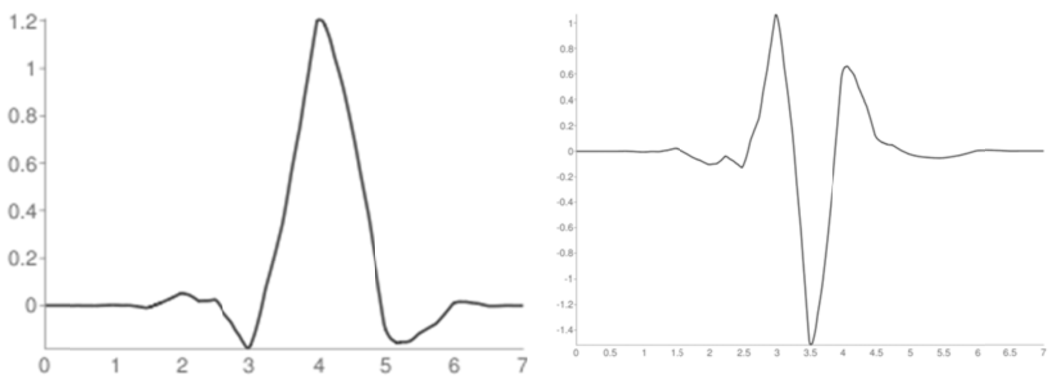

Figure 1: To the left is a scaling function and to the right is a wavelet function for SYM4.

[1] David L. Donoho. "Denoising via soft thresholding," IEEE Transactions on Information Theory, 41:613–627, May 1995

[2] http://www.mathworks.com/products/matlab/

Application of the Method

Typical data collected at US borders using RIIDs (Radiation Isotope Identification Device) are low resolution data collected for a live time anywhere from half to 1 minute. The measurement dead time can also be large. Often the calibration is not perfect.

Figure 2 shows a spectrum acquired from a CardioGen-82 shipment. CardioGen-82 is a radionuclide generator that provides Rb-82 for positron emission tomography (PET) myocardial perfusion imaging (MPI). The Rb-82 is produced from its precursor Sr-82. The generator may also contain contaminant radionuclides such as Sr-85.[3] The vertical lines in the figure mark where the Rb-82 gamma-rays would show up if the calibration was perfect.

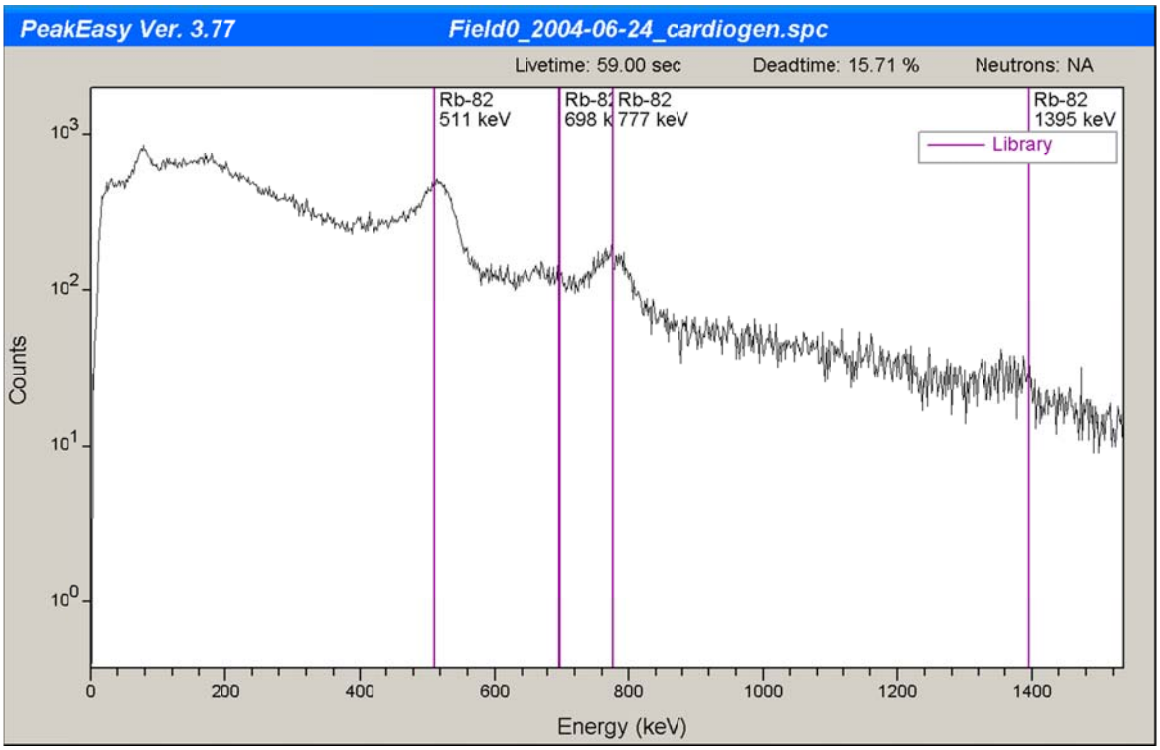

Figure 2: Data collected from a Cardiogen-82 shipment. Note the dead time is more than 15%. Live time is 59 sec.

This spectrum (without performing a calibration) was then denoised by using wavelet shrinkage method. A simple maxima finding algorithm was used to locate the maxima. Figure 3 shows the data from figure 2 (blue cross marks), denoised spectrum (solid red line) and feature locations found by the maxima algorithm after the spectrum is denoised. The feature were found at energies 78 keV, 112.5 keV, 168 keV, 516 keV, 661.5 keV, 774 keV and 1356 keV.

[3] http://www.cardiogen.com/patients.html

The 78 keV feature in the spectrum is from lead X-rays (around 72 and 74 keV) generated in the lead shielding of CardioGen-82.

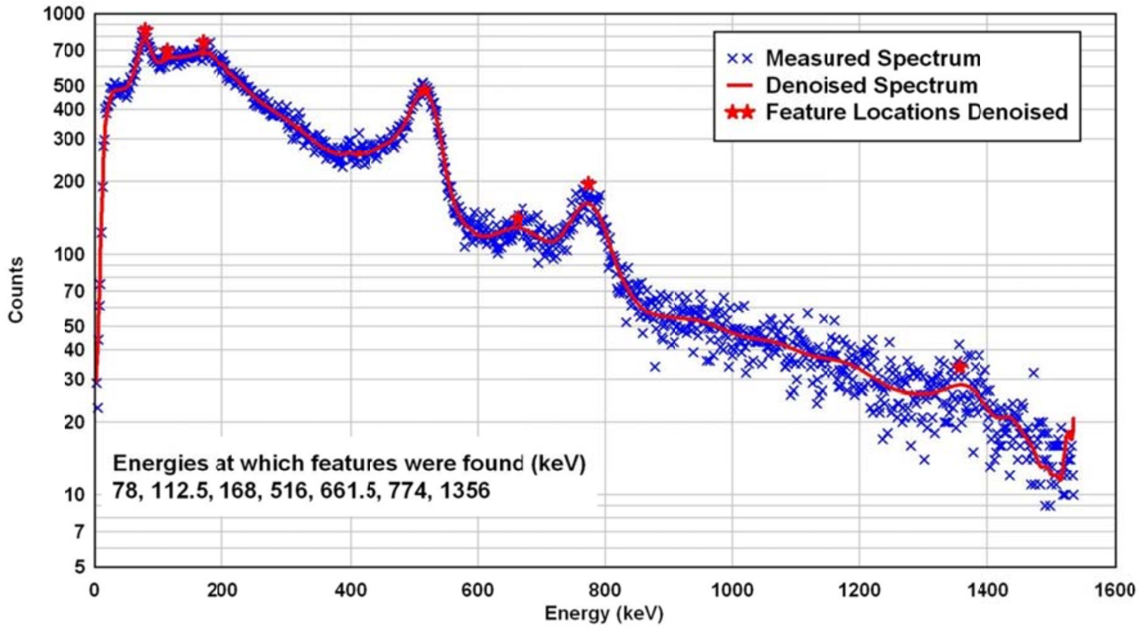

Figure 3: CardioGen-82 measured spectrum (same as in Figure 2) along with denoised spectrum of the data (solid red line) and locations found by the maxima finding algorithm.

Work up to this point was presented at the RadSensing2010 meeting at the Argonne National Laboratory in Chicago, Illinois.[4]

Understanding method sensitivity to the statistical fluctuation

We have tried to test our de-noising algorithm experimentally by collecting a spectrum from the same source with the same detector and the same configuration in a short period of time. In principle, the only difference between the spectra would be the statistical fluctuations. At least one issue we are attempting to understand is how sensitive the de-noised spectra are to statistical fluctuations in the original data. Seven spectra were taken. Six of the spectra were taken for 60 seconds. Inadvertently, one of the spectra was taken for 64 seconds. In some of the plots and tables which follow, the 64 second spectrum in included to show how much different (or not) it is. Table 1 summarized the live times and total number of counts for each spectrum – numbered 0 through 6. Figure 4 shows the source and detector configuration used in the measurements, which were taken with an identiFINDER (Thermoelectric) hand-held detector and a 90.35 μCi ^{137}Cs source.

[4] Mohini Rawool-Sullivan, "Isotope Identification Algorithm for Rapid and Accurate Determination of Radioisotopes," LA-UR 10-03583, May 28, 2010, presented at the SNM Movement Detection / Radiation Sensors and Advanced Materials Portfolio Review, RadSensing2010

Table 1: *Summary of the total number of counts and the live time for each spectrum number.*		
Spectrum number	Total counts	Live time (seconds)
0	71106	60
1	71811	60
2	71392	60
3	71624	60
4	71911	60
5	75934	64
6	71617	60

Table 1 summarizes the total number of counts and the live time for each spectrum number.

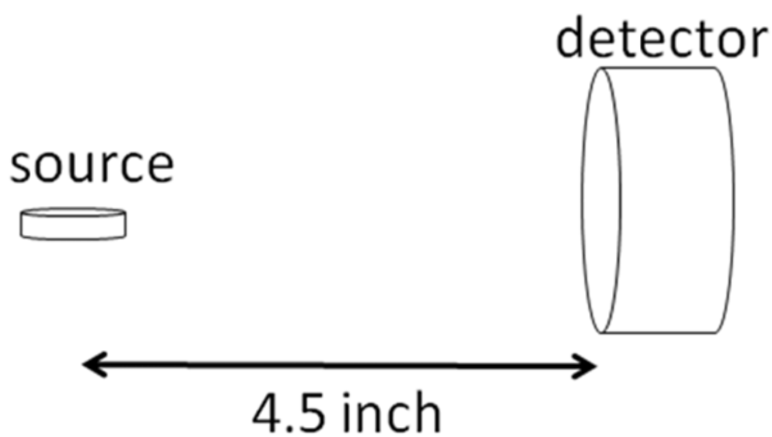

Figure 4 shows the configuration of the source and detector. The source was 4.5 inches from the front surface of the NaI detector.

Table 1 below shows the χ^2/N_{chan} – *chi-squared per degree of freedom for each combination of raw Cs-137* spectra

Table 1: The χ^2/N_{chan} – *chi-squared per degree of freedom for each combination of raw Cs-137* spectra						
χ^2/N_{chan}	**Data 1**	**Data 2**	**Data 3**	**Data 4**	**Data 5**	**Data 6**
Data 1	**0.0**					
Data 2	**0.754**	**0.0**				
Data 3	**0.800**	**0.705**	**0.0**			
Data 4	**0.812**	**0.812**	**0.736**	**0.0**		
Data 5	**1.016**	**0.877**	**0.730**	**0.868**	**0.0**	
Data 6	**1.013**	**0.896**	**0.747**	**0.867**	**0.867**	**0.0**

Table 2 below shows the χ^2/N_{chan} – chi-squared per degree of freedom for each combination of denoised Cs-137 spectra

Table 2: The χ^2/N_{chan} – *chi-squared per degree of freedom for each combination of denoised Cs-137* spectra						
χ^2/N_{chan}	**Data 1**	**Data 2**	**Data 3**	**Data 4**	**Data 5**	**Data 6**
Data 1	**0.0**					
Data 2	**0.743**	**0.0**				
Data 3	**0.815**	**0.707**	**0.0**			
Data 4	**0.802**	**0.818**	**0.728**	**0.0**		
Data 5	**1.023**	**0.863**	**0.734**	**0.844**	**0.0**	
Data 6	**0.978**	**0.911**	**0.732**	**0.879**	**0.855**	**0.0**

The differences in the de-noised spectra seem to have been largely associated with differences in the raw data above the photo-peak.

Conclusions

The Wavelet shrinkage denoising may provide a way of doing robust feature identification in a low-statistics gamma-ray spectrum. We also applied this method to the spectra collected from CZT (CdZnTe detectors) and $LaBr_3$ detectors with similar success. This method is most suitable for low statistics gamma-ray spectra. The differences in the de-noised spectra seem to have been largely associated with differences in the raw data above the photo-peak.

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