Radiation anomaly detection algorithms for field-acquired gamma energy spectra

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ABSTRACT

The Remote Sensing Laboratory (RSL) is developing a tactical, networked radiation detection system that will be agile, reconfigurable, and capable of rapid threat assessment with a high degree of fidelity and certainty. Our design is driven by the needs of users such as law enforcement personnel who must make decisions by evaluating threat signatures in urban settings. The most efficient tool available to identify the nature of the threat object is real-time gamma spectroscopic analysis, as it is fast and has a very low probability of producing false positive alarm conditions. Urban radiological searches are inherently challenged by the rapid and large spatial variation of background gamma radiation, the presence of benign radioactive materials in terms of the normally occurring radioactive materials (NORM), and shielded and/or masked threat sources. Multiple spectral anomaly detection algorithms have been developed by national laboratories and commercial vendors. For example, the Gamma Detector Response and Analysis Software (GADRAS) a one-dimensional deterministic radiation transport software capable of calculating gamma ray spectra using physics-based detector response functions, was developed at Sandia National Laboratories. The nuisance-rejection spectral comparison ratio anomaly detection algorithm (or N-SCRAD), developed at Pacific Northwest National Laboratory, uses spectral comparison ratios to detect deviation from benign medical and NORM radiation source and can work in spite of strong presence of NORM and or medical sources. RSL has developed its own wavelet-based gamma energy spectral anomaly detection algorithm called WAVRAD. Test results and relative merits of these different algorithms will be discussed and demonstrated.

Keywords: networked sensor, gamma spectroscopy, false alarm rate, spectroscopic anomaly, threat signature

1. BACKGROUND

This background describes methods used during search, localization, and identification operations when looking for illicit materials in urban areas. Radiological search is an inter-agency (often tactical) operation initiated and directed by law enforcement (LE) entities. With LE guidance and intelligence gathered by them, team(s) of searchers, properly equipped with the appropriate measurement and analysis tools, typically

- Find the point or extended sources of radiation in question.
- Localize the source(s) with certainty.
- Characterize the target source(s) in terms of radiation types (gamma, neutron, beta, etc.), energy (using high-purity germanium [HPGe] and tools for gamma spectroscopy), physical state of excitation (fission or not through use of a fission meter), and neutron directional distribution (by using shielded neutron assay probe, SNAP).
- Adjudicate the anomalous condition by inquiring further into the target source and make a determination of the threat conditions.
- Depending on the threat condition, the situation can get resolved in situ or may need further analysis through the Triage system.

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The operations detailed above are components of passive search. In active search an external stimulus, such as a pulsed neutron generator or a large neutron source, is used to “activate” the target sample in order to detect and analyze the prompt or beta-delayed neutrons and/or activation gamma rays. Associated particle identification (API) units use active interrogation techniques to image a fissioning source(s). Radiography, a variant form of active interrogation, uses tunable x-ray energy sources to make images of target objects (obscure by design or not) according to their atomic number (Z). Multiple energy beam bremsstrahlung photons are used to generate computer tomography of the target object for better contrasts in terms of the Z-value(s) of the target.

For operational simplicity search operations can be subdivided into two categories, namely static and mobile. In static search the detector(s) are stationary (portal monitors of various sizes and shapes stationed to radiologically monitor a flowing traffic in real-time), and they can be networked to provide comprehensive real-time radiological snap shots of a given area under surveillance remotely or in situ as required for the LE to make quick decisions. Static search systems are less prone to changing background radiation conditions. In mobile search systems the detectors are moveable; their effectiveness depends on the efficiency of the embedded software to reduce false (positive and negative) alarms and the ability to negotiate the spatial and temporal variation of the background radiation. Almost all mobile systems, except aerial systems, can be run in static mode. Mobile search can be further subdivided into functional teams performing

- Foot searches,
- Mobile ground searches,
- Mobile aircraft searches and
- Mobile search on water.

1.1 Gamma ray scintillators as detectors

Inorganic scintillators, namely sodium iodide with thallium activator (NaI:Tl) and cesium iodide with thallium activators (CsI:Tl), are the industry’s workhorses. Recently, higher-resolution cerium-doped lanthanum bromide has made a big impact in the gamma ray scintillation detection area. The dopants are used to facilitate light production from the electrons, with a light conversion efficiency of ~13%. Optically coupled photomultiplier tube photocathodes create electrons that get multiplied by successive dynodes; finally, an anode pulse is collected, shaped, amplified, and discriminated against a discriminator voltage. These devices are found in many sizes, depending on the system (listed in order of sensitivity from best to worst): 2.5″ × 1.5″ × 8″ for backpack, 2″ × 4″ × 16″, 4 each, for the RSL mobile system, 1.5″ × 2″ for identiFINDER, and ½″ × 1″ cylinder CsI:Tl for Pager S. It must be kept in mind that the background counts increases when size goes up; an increase of size by a factor of 4 will give rise to an increase of sensitivity by a factor of 2. Calculating net counts over square root of background counts ($S/\sqrt{B}$) is a good measure of a system’s sensitivity..

A sensor’s “selectivity” is related to its resolution. The resolution determines the sensor’s ability to distinguish between two gamma rays having very close energies. Calculating full width half-maximum (FWHM) at a given energy from a differential pulse height spectrum is a measure of the sensor’s resolution. Sensors with higher resolution (lower FWHM) have better “selectivity.” Sensitivity and selectivity are not the same; sensitivity relates to gross counts, while selectivity relates to resolution. Compared to a 3″ × 3″ NaI:Tl crystal with 8% resolution at 1332 keV line from a ^{60}Co source, a 30% HPGe sensor with a resolution of FWHM of 2.2 keV is 1/3rd better in sensitivity but a factor of 48 better in selectivity.

Spectral sensitivity to the gamma ray energy spectrum depends on the signal-to-noise ratio, S/N. S/N is determined by ~ efficiency (ε)/$\sqrt{}$[background (B) * resolution (R)]. The relationship is that better resolution causes better S/N. Cherepy[1] has deduced that for the energy resolution range applicable to scintillators (from 4 to 15% at 200 keV), a false alarm rate (FAR) for identification of spectral anomalies can be expressed as FAR ~ $R^{3.4}/(S_{pp}/B_{TOT})^{0.54}$, where R is the resolution of the device, S_{pp} is the photopeak efficiency (product of stopping power and the photofraction), and B_{TOT} is the natural background including self-activity.

2. GADRAS

Dean Mitchell of Sandia National Laboratories developed an applications package, “Gamma Detector Response and Analysis Software,” or GADRAS.[2] GADRAS is a PC-based software package to simulate detector response and analyze unknown gamma energy spectra. It is a general-purpose application for the modeling and analysis of radiation detector responses of gamma spectroscopic instruments like scintillators, semiconductors, and neutron detectors working as proportional counters. It employs radiation source and detector response models to predict the response of user-defined detectors to chosen radioactive sources. It implements methods to identify radiation sources from their measured signatures, primarily the measured gamma spectrum and neutron count rate. Radiation source emissions are calculated using analytical and numerical radiation transport models. Detector responses are calculated using point models of the detector material, dimensions, collimation, and scattering environment. Analytical methods are implemented using linear and nonlinear regression techniques. The GADRAS Detector Response Function (GADRAS-DRF) computes the response of gamma ray and neutron detectors to incoming radiation. The capabilities include characterization of detector response parameters, plotting and viewing measured and computed spectra, analyzing spectra to identify isotopes, and estimating source energy distributions from measured spectra.

GADRAS-DRF can compute and provide detector responses quickly and accurately without having to go through full-blown Monte Carlo simulation of the scenario and surroundings, giving users the ability to obtain usable results in minutes or less.

Development of GADRAS started in 1985 for use in the Remote Atmospheric Monitoring Project (RAMP), which used low-resolution detectors to analyze airborne radionuclides. As of April 2010, the GADRAS application included six radiation analysis algorithms, gamma ray and neutron detector response functions, and support for radiation transport calculations. To identify radioactive sources creating a gamma ray spectrum, GADRAS matches an entire gamma ray spectrum against one or more known spectra. Figure 1 illustrates this approach. Many other algorithms focus on peaks in gamma ray spectra because they are the most obvious features. However, GADRAS analyzes the full spectrum for several reasons:

1. Peaks may overlap, making source identification ambiguous.
2. Most counts in a gamma ray spectrum are often outside the peaks, in which case using only peak data would ignore most of the data. For example, less than 3% of the counts in a spectrum for ^{238}U occur in the 1.001 MeV peak, the most prominent feature of its spectrum.
3. Counts outside the peaks help characterize the composition and thickness of intervening material. Because gamma rays interact with these materials, characterizing the materials improves the accuracy with which the gamma ray spectrum, as read by a detector, can be linked back to the gamma ray source. Arriving at a solution consistent with all the data increases confidence in the result.
4. The absence of counts in a region of a spectrum can be a clue to the identity of radioactive materials.
5. Using the entire spectrum helps analyze data from scintillators having low energy resolution because low resolution often precludes identification of peaks in the spectrum and helps analyze spectra of weak sources.

A live-time (~4 seconds) spectrum was taken from a mix of medical isotopes at a distance of 2.5 meters. The analysis, performed with GADRAS, is shown in Figure 1. GADRAS identified all medical radioisotopes in the mix and predicted quantitatively the relative strengths of the radioisotopes. A critical study of GADRAS applications to analyze special nuclear materials is available[3] in which the performance of GADRAS is compared with other gamma spectral analysis tools.

Note that Figure 1 shows how GADRAS can identify various materials (in this case a set of medical radioisotopes) despite background radiation. The top scale shows gamma ray energy in thousands of electron volts (keV); the left scale shows number of gamma ray counts at each keV level. Black bars at the upper edge of the blue area are the raw data that a gamma ray detector provides. Data are presented as bars rather than points to indicate one standard deviation uncertainties. The raw data cannot differentiate between gamma rays produced by different materials, as a 200 keV gamma ray from one substance is identical to a 200 keV gamma ray from another substance, and background radiation may hide gamma ray peaks from a material of interest. A count of gamma rays from a cargo container might produce a data set like this.

The main application of GADRAS is to support Triage/Reachback analysis. A radiation detection operator in the field, such as a Customs and Border Protection (CBP) officer, who finds a vehicle or cargo container that presents a suspicious radiation signature that cannot be easily resolved, can send the detection data (such as a gamma ray spectrum) to the Laboratories and Scientific Services section of CBP for a more detailed analysis. That analysis uses GADRAS.

Similarly, if that service is unable to resolve the matter, it can send the data to a secondary Reachback at the nuclear weapons laboratories, which also use GADRAS.

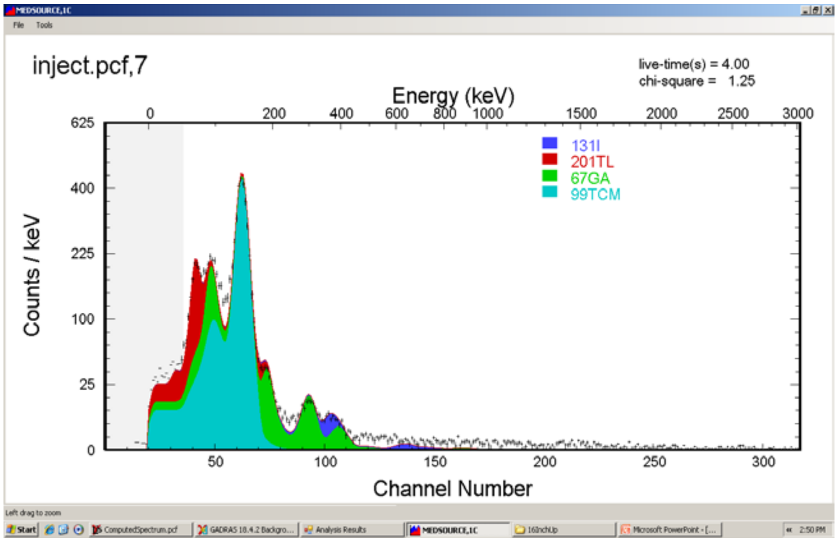


Figure 1. GADRAS solution for 4-second spectra with a mix of four medical radioisotopes of different strengths: ^{67}Ga (75 ±2) µCi; ^{99}Tc$_m$ (184 ±2) µCi; ^{131}I (7.4 ±0.4) µCi, and ^{201}Tl (70 ±2) µCi with a reduced χ^2- value of 1.25 per degree of freedom.

An example of using GADRAS to identify a complex source spectrum is described below. The scenario, a time-series data taken by a gross count measuring instrument shows the following profile:

- The first 10 seconds of data were with a backpack next to a static vehicle.
- The backpack is then carried into a location; the entrance of the building was crossed at around 60 seconds of the travel.
- The operator then walked past two suspects at a distance of 2′, walking at a slow pace.
- The operator next sat down as close as he could to the two subjects, approximately 3′ away.
- The operator was at the table for 60 seconds. Then, the two subjects left through a second entrance about 30′ away from the operator.
- After the two subjects left, the operator left the same way he came in and returned to the vehicle.

The count rate vs. time correlation can be tabulated as shown in Table 1. The time profile and associated summed spectral data are shown in the screen shot in Figure 2. The suspect target spectra for approximately one minute (while the operator was sitting close to the subject source) is shown in Figure 3. Finally, a stable background spectra was extracted during a period of about 83 seconds and is shown in Figure 4.

Table 1. Count rate vs time correlation for source spectrum

Time Start (sec)	Time End (sec)	Average Counts per Second	Standard Deviation	Comment
1	10	355.3	22	Background at vehicle
28	58	756.7	139.2	Movement causes fluctuation
61	75	761.5	27.2	Stable local background
77	136	916.3	31	Stable Source term
138	166	729	117	Motion involved
167	196	385.8	18.7	Stable background
197	216	728	116	Movement causes fluctuation
217	246	361	16	Stable background outside the structure

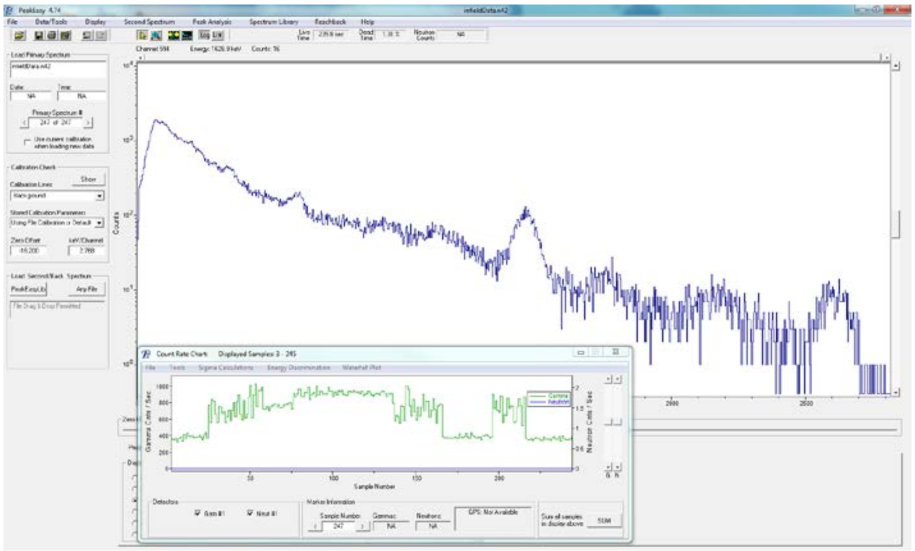


Figure 2. The green histogram is time series data of the gross counts only. The gamma energy spectra collected over the entire duration is shown in blue on the top. The gamma-ray energy covered is from 0 to 3000 keV.

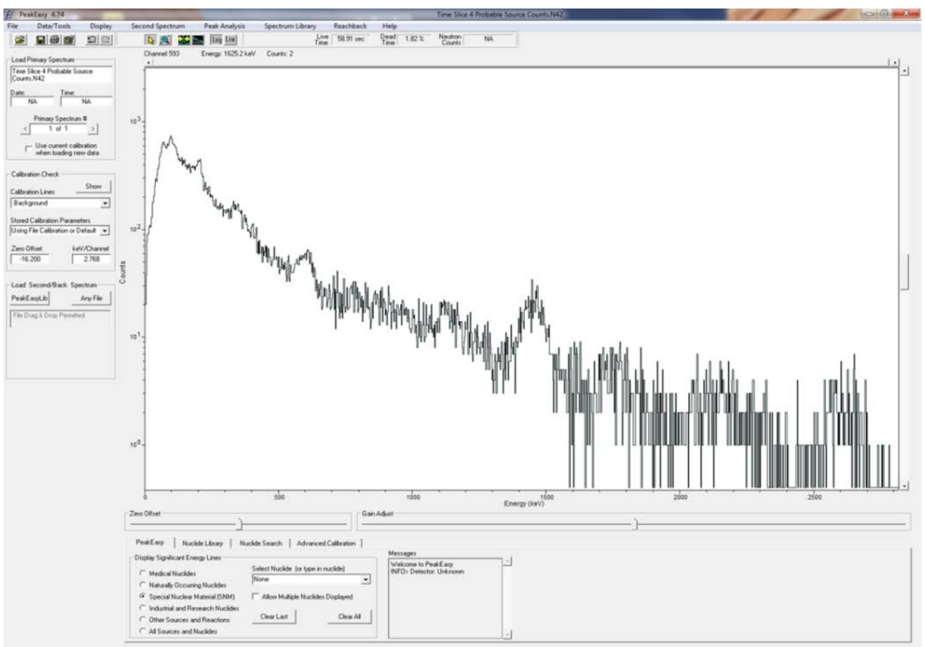


Figure 3. One minute's worth of spectral data collected 3′ away from the source.

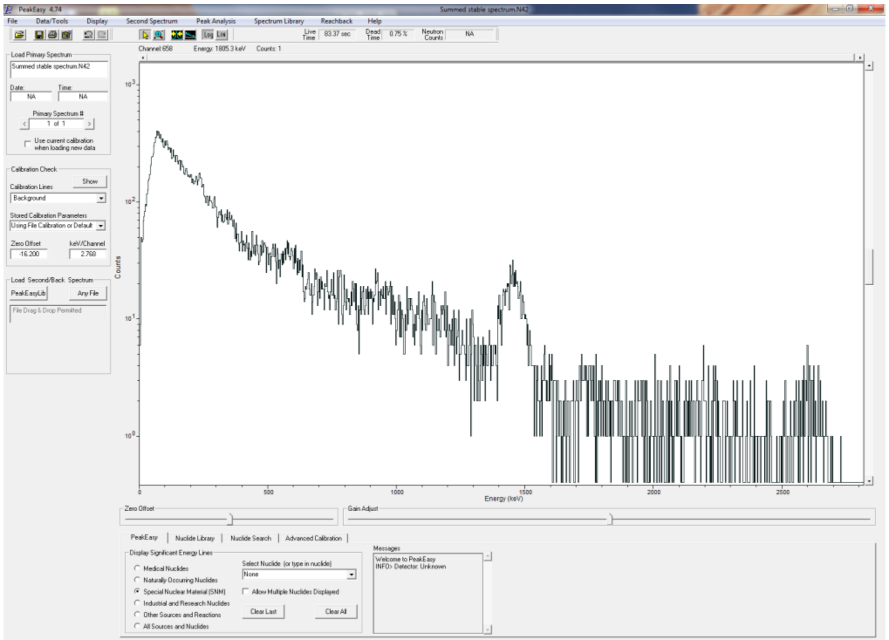


Figure 4. A background spectrum collected for about 83 seconds.

The GADRAS detector geometry dimensions were modified from a 3″ × 3″ cylinder to a 1.75″ × 2.75″ × 8″ backpack sensor. Figure 5 shows the GADRAS setup used for this analysis, and the resultant GADRAS multiple linear-regression analysis is shown in Figure 6.

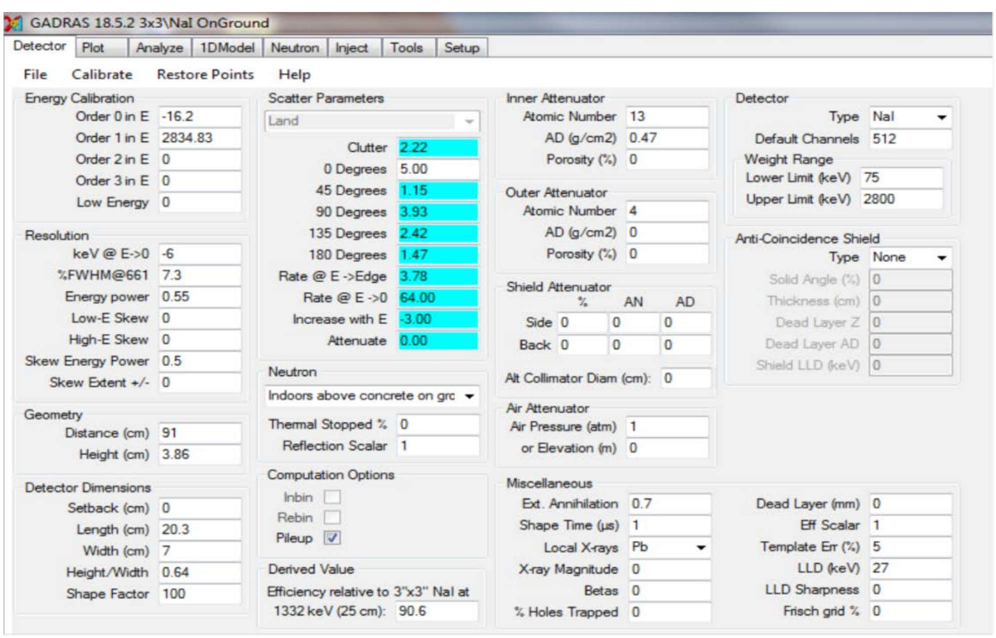
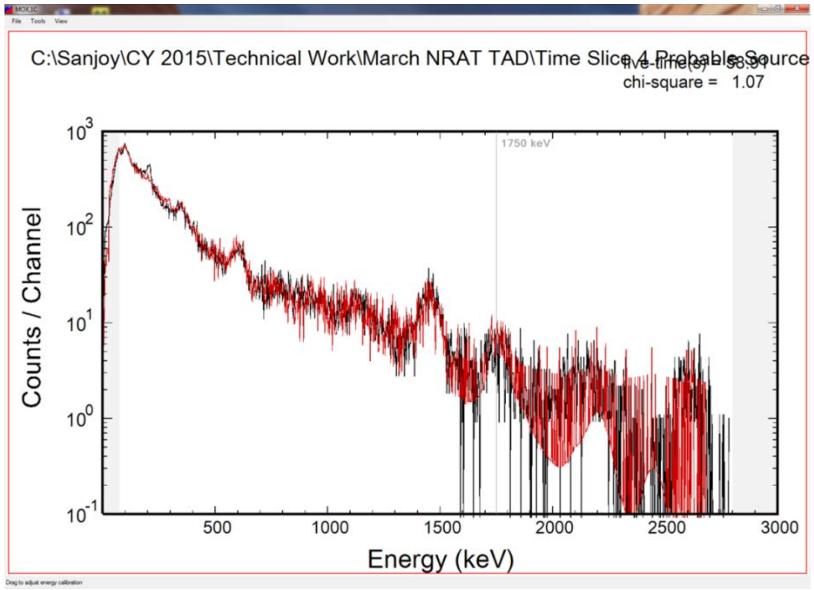


Figure 5. The GADRAS detector size and shape was modified from the standard 3″ x 3″ cylindrical form to the size and shape of sensor consistent with infield backpack use. This caused an efficiency loss of about 9% as shown, in the figure.



************** MULTIPLE LINEAR REGRESSION ANALYSIS **************

detector name : 3x3\NaI On Ground
distance (cm) : 91
foreground spectrum: C:\Sanjoy\CY 2015\Technical Work\March NRAT TAD\Time Slice 4 Probable Source Counts.pcf,1
background spectrum: C:\Sanjoy\CY 2015\Technical Work\March NRAT TAD\Time slice 1 Background.pcf,1
collect date/time :
reduced chi-square : 1.072 weight range (keV): 72-2799
relative background: 1.000 background unc (%): 0.000
mult-regres. coeff.: 0.662 template error (%): 5.000
GainShift (%) : 0.000

Source	Activity(Ci)	Weight(gm)	AN	AD
URANIUMINSOIL	7.9 +/- 0.1	NA	91.0	1.2
MOX	4.3 +/- 0.2	NA	91.0	1.2

URANIUMINSOIL,7.98 Ci{91.0,1.2}+MOX,4.36 Ci{91.0,1.2}

Figure 6. Multi-regression analysis results show a fit to the database of isotopes and finds a match with a combination of uranium in soil and possible mixture of metal oxide fuel with a χ^2 of 1.07 per degree of freedom. The experimentally measured count rate is 918.8 and the modeled count rate is 918.2. The details of GADRAS analysis is shown below

To summarize, the spectra taken at the target location are consistent with that from a few-gram quantity of mixed oxide fuel (MOX) and uranium in soil (not enriched). The materials are not weapons-grade elements and no apparent threat of WMD exists. One word of caution, however; the MOX fuel is radiologically HOT that's why the Curie content of the materials is very high (MOX is basically plutonium oxide and depleted uranium oxide), so the actual mass is well within the range of 0.5 to 5 g. For all practical purposes, MOX is as hazardous as spent fuel and should be handled as such. Personnel in pursuit of these materials have to be careful not to expose themselves to MOX for prolonged time periods.

3. PRINCIPAL COMPONENT ANALYSIS

Principal component analysis (PCA) is a multivariate statistical tool that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. The number of principal components is less than the number of original variables. The transformation is defined in such a way that the first principal component has the largest possible variance and accounts for as much of the variability in data as possible. Each succeeding component in turn has the highest variance possible under the constraint that it is orthogonal to the preceding components. The resulting vectors are an uncorrelated orthogonal basis set. The principal components are orthogonal because they are eigenvectors of the covariance matrix, which is symmetric. PCA is sensitive to the relative scaling of the original variables.

The goals of PCA, dimensionality reduction and independence, are achieved by transforming a multivariate data set in such a manner that only a small fraction of new, uncorrelated, dimensions (principal components), are needed to retain nearly all of the variation present in the original data set. For any particular energy resolution, the number of principal components (dimensions) required to explain a particular desired fraction of the variation in the original data (e.g., 99.9%) provides a measure of the information content available in the original spectral population. As a qualitative example of PCA application we use three pairs of individual radioisotopes, ^{137}Cs, ^{235}U, and ^{239}Pu, to obtain six separate spectra of gamma ray energy as collected by a sodium iodide–based detector, a typical radioisotope identification device (RIID) called identiFINDER.[4] The scaling of the counts was done by first converting counts, C, to square root of counts, √C, and then dividing the √C values by the maximum value of √C so the entire spectra is normalized to unity at the maximum. Figure 7 shows the six spectra, two for each of the above-mentioned isotopes.

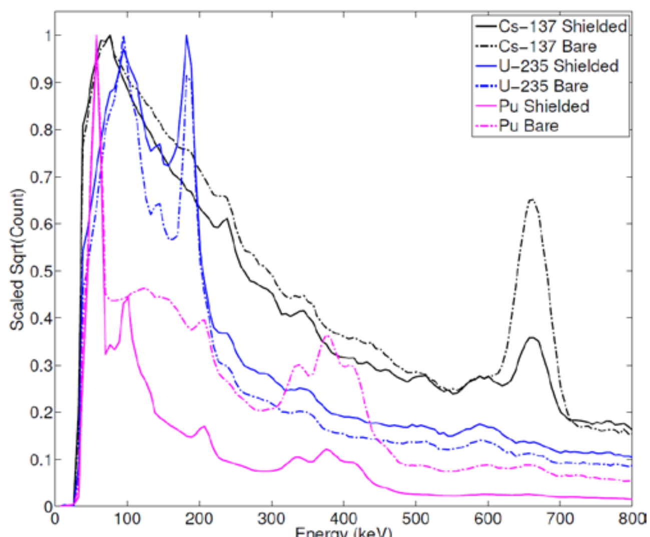


Figure 7. Two scaled spectra from each of ^{137}Cs, ^{235}U, and ^{239}Pu, in the gamma energy range from 0 to 800 keV.

Following the PCA analysis method prescribed in Ref. 5, we found a way to display the "within isotope" variability as well as "between isotope" variability. Figure 8 describes the same six spectra in reduced, two-dimensional space by three pairs of points (clusters). The values of the two coordinates in Figure 8 are chosen so that the distances between each of the 15 ($^6C_2$) possible spectral pairs are very closely approximated (using multidimensional scaling) by the distances as computed using ordinary Euclidian distance applied to the 2-component values. Each isotope has a unique thumb print that can be regarded as a cluster of points in the 2-component space.

4. WAVRAD

In radiation detection, real-time alarm systems are needed that appropriately alarm near sources and do not provide a large number of spurious alarms elsewhere. When too many false alarms are present, it may be easy to become complacent in the field, ignoring alarms that require attention. WAVRAD (wavelet-assisted variance reduction anomaly detection) is an algorithm that mathematically compares features of a spectra to a collection of the previous spectra over a given time period. This algorithm has been shown to reduce the number of spurious alarms and does not depend on a source library of data. In addition, this algorithm points to areas in the spectra that give cause for the alarm, providing the field expert with additional information over just an alarm. Finally, this algorithm is insensitive to slow changes over background radiation levels in the field.

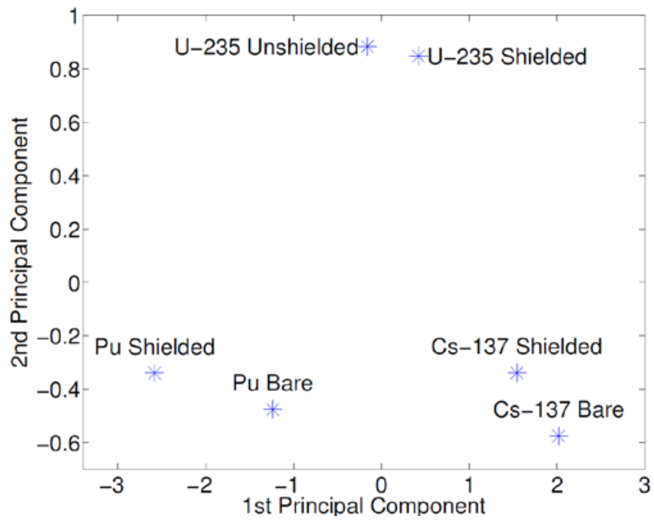


Figure 8. There is a recognizable clustering of same isotope data points whether the spectrum was from a bare or shielded source for each of the three isotopes. The complex energy spectrum has been reduced to a two-dimensional plot, still bearing the identity of the isotopes.

WAVRAD provides a general algorithmic approach for real-time anomaly detection, impervious to common detector limitations (e.g., poor resolution, imperfect or non-linear calibration, gain shift due to environmental reasons). The algorithm uses an approach based on the continuous wavelet transform for variance reduction, formation of an expectation from recent measurements, followed by evaluation of the deviation between the current measurement and the expectation using methods from linear algebra.

Radiological search depends on the successful execution of two principal steps: (1) recognition of radiological anomalies in the dynamic background, and (2) identification of the source of the radiological anomaly for determination of the threat potential and characteristics.

The recognition of a radiation anomaly must be performed in real time using only “sparse" data, such as a spectrum acquired over a one-second interval. This may include scenarios in which the detector is in motion, whether it is transported by aircraft, automobile or carried by a human or automaton. Dynamic search methods based solely on gross count rates perform quite poorly in terms of spurious alarm rates and/or sensitivity. Other methods that utilize spectral information, such as template matching, applications of PCA concepts, or utilization of ratios of specific spectral window sums, are generally more sensitive and exhibit fewer false alarms. However, such methods tend to rely on one or more of the following: (a) a relatively small selection of target radioactive isotopes and shielding configurations; (b) optimizations based on a training dataset; (c) fixed detector calibration and resolution; or (d) complex computations performed in conjunction with data acquisition. For most realistic scenarios, at least one of these attributes is unsatisfactory. Real-world search operations are best aided by focusing on the recognition of the presence of a spectral anomaly, which informs and drives further data collection in the appropriate temporal/spatial location, permitting an actionable identification of the actual source of the anomaly.

In light of the challenges presented by the radiological search mission, an effective algorithm must have the following attributes:

- Provides alarms in real time.
- Provides a clearly interpretable cause for alarm.
- Depends only on data collected during current operational cycle, i.e., does not require training on a limited dataset.
- Does not depend on any source library.
- Is insensitive to detector calibration or resolution imperfections, and “slow” gain shifts caused by issues like thermal drift.
- Is impervious to “slow” changes in background radiation level and composition.

The approach is broken into several distinct steps:

- The determination of an expected spectral shape for comparison with the given measurement will be chosen.
- An energy-dependent collection of scale parameters will be chosen.
- A variance-reducing transform based on the scale parameters will be defined.
- A collection of semi-norms and thresholds will be selected for the output of the transform.
- The transform output coupled with the expected spectral shape will lead to the formation of a deviation vector.
- The collection of semi-norms and thresholds will be used to evaluate the deviation vector for the presence of a spectral anomaly.

5. CONCLUSION

Commercially available hand-held or vehicle-mounted and portal gamma ray detection and radioisotope identification systems suffer from limited scintillator energy resolution, spatial and temporal variation of background, and the presence of a ubiquitous, widely varying terrestrial mix of naturally occurring radioactive materials. Legitimate use and transport of radioactive materials for medicinal purpose or other nuclear power plant–related operations, or planned waste management work also complicate matters. Commonly used RIIDS do not perform well in real-time data evaluation mode. It is imperative that one or many of the smart algorithms discussed in this paper be embedded in the data acquisition system of the devices to have higher success rates (true positive alarm) and fewer false (positive or negative) alarm rates. The Department of Homeland Security, Customs and Borders Patrol, and other government agencies are actively looking for solutions to develop better identification tools. With modern-day fast computers having higher computing power, real-time data acquisition with multiple front-end identification algorithms running are feasible and being implemented in commercial applications.

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