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Automated Detection of Radioisotopes from an Aircraft Platform by Pattern Recognition Analysis of Gamma-Ray Spectra

Brian W. Dess¹, John Cardarelli II², Mark J. Thomas³, Jeff Stapleton⁴, Robert T. Kroutil⁴, David Miller⁴, Timothy Curry³, Gary W. Small^{1,*}

¹Department of Chemistry & Optical Science and Technology Center, University of Iowa, Iowa City, IA 52242 USA

²CBRN Consequence Management Advisory Division, Environmental Protection Agency, 4900 Olympic Blvd., Erlanger, KY 41018 USA

³CBRN Consequence Management Advisory Division, EPA Office of Emergency Management, 300 Minnesota Ave, Kansas City, KS 66101 USA

⁴Kalman and Co., Inc., 5366 Virginia Beach Blvd., Ste. 303, Virginia Beach, VA 23462 USA

Abstract

A generalized methodology was developed for automating the detection of radioisotopes from gamma-ray spectra collected from an aircraft platform using sodium-iodide detectors. Employing data provided by the U.S Environmental Protection Agency Airborne Spectral Photometric Environmental Collection Technology (ASPECT) program, multivariate classification models based on nonparametric linear discriminant analysis were developed for application to spectra that were preprocessed through a combination of altitude-based scaling and digital filtering. Training sets of spectra for use in building classification models were assembled from a combination of background spectra collected in the field and synthesized spectra obtained by superimposing laboratory-collected spectra of target radioisotopes onto field backgrounds. This approach eliminated the need for field experimentation with radioactive sources for use in building classification models. Through a bi-Gaussian modeling procedure, the discriminant scores that served as the outputs from the classification models were related to associated confidence levels. This provided an easily interpreted result regarding the presence or absence of the signature of a specific radioisotope in each collected spectrum. Through the use of this approach, classifiers were built for cesium-137 (¹³⁷Cs) and cobalt-60 (⁶⁰Co), two radioisotopes that are of interest in airborne radiological monitoring applications. The optimized classifiers were tested with field data collected from a set of six geographically diverse sites, three of which contained either ¹³⁷Cs, ⁶⁰Co, or both. When the optimized classification models were applied, the overall percentages of correct classifications for spectra collected at these sites were 99.9 and 97.9 % for the ⁶⁰Co and ¹³⁷Cs classifiers, respectively.

*Corresponding author: gary-small@uiowa.edu, +1-319-335-3214 (Ph), +1-319-353-1115 (Fax).

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Keywords

Remote sensing; gamma-ray spectroscopy; cesium-137; cobalt-60; pattern recognition; airborne detection

1. Introduction

The ability to identify ground sources of radioisotopes from an airborne platform presents both useful capabilities as well as unique challenges. Determining that a specific radioisotope is present at a hazardous location can give insight regarding the nature of the hazard, offer important information for use in hazard management, and help determine the origin of the event being monitored (IAEA, 2003a). Airborne monitoring is particularly suited to surveying large areas to identify radioactivity from anthropogenic sources, thereby helping to define the boundaries of a contaminated site. Recent examples of the application of airborne radiation monitoring have included the use of gamma-ray spectrometers mounted on unmanned aerial vehicles (UAVs) to map contaminated areas surrounding the Fukushima Daiichi nuclear power plant in Japan, as well as legacy uranium mines in England (Connor et al., 2016; Martin et al., 2015; Sanada and Torii, 2015).

Remotely detecting specific radioisotopes in near real-time from an airborne platform presents several challenges. Operational concerns include the need for rapid interpretation of the large quantities of data acquired in an aerial survey, the hazards and logistical challenges of field experimentation related to methods development, and the expense of operating an appropriately equipped aircraft (Burr and Hamada, 2009; Huo et al., 2014; IAEA, 1991, 2003a; Owsley et al., 2010; Portnoy et al., 2011). False detections (false positives) and a lack of sensitivity have also been problems that have plagued efforts to detect specific radioisotopes reliably from the air (Burr and Hamada, 2009). These sensitivity limitations have been one of the motivations for the increased interest in the use of UAVs for airborne monitoring, as these vehicles can typically fly lower and slower than conventional manned aircraft (Connor et al., 2016), thereby facilitating the integration of larger gamma-ray signals.

In our view, a practical solution to addressing the challenges noted above has four key components: (1) automating the data interpretation step to provide near real-time feedback to the analyst (e.g., within seconds to minutes), (2) associating a level of confidence with each positive isotope-specific detection, (3) maximizing the extraction of information from the acquired gamma-ray spectra, and (4) developing a procedure to simulate isotope-specific gamma-ray spectral signatures to eliminate the need to measure actual radioactive sources in the field. This paper describes the development of signal processing and multivariate pattern recognition methodology that meets these requirements.

2. Material and methods

2.1 Overview

The data analysis approach taken here was the coupling of digital filtering and nonparametric linear discriminant analysis to produce classification models (classifiers) that

could be used to judge the presence or absence of the gamma-ray spectral signatures of specific radioisotopes. Novel features of this work include the development of confidence models to allow the output from the classification models to be associated with the percent probability of a correct detection. In addition, a data synthesis procedure was used to generate synthetic gamma-ray spectra for the purpose of defining the spectral components associated with a positive isotope-specific detection. The resulting spectra were used to train classification models. A conceptually similar procedure has been successfully used with passive infrared remote sensing data (Wan and Small, 2011).

This approach to gamma spectral analysis does not include the use of spectral stripping techniques (Aage et al., 2006; Furr et al., 1968). Spectral stripping has been widely used to remove interfering signals from gamma-ray spectra, but often requires prior knowledge of the site being monitored and the natural isotopes present. Thus, it can be difficult to apply in an automated way in near real time. The methodology presented here replaces the traditional spectral stripping step with a combination of digital filtering and multivariate pattern recognition, both of which can be applied in an automated manner.

In this paper, the methodology described above was used to develop classification models for two radioisotopes, cesium-137 (^{137}Cs) and cobalt-60 (^{60}Co). These radioisotopes are of interest in environmental monitoring applications because of their potential for being lost or stolen (^{60}Co) or their possible release in the event of nuclear power plant accidents (^{137}Cs). As an example, ^{137}Cs contamination will be present at the sites of the Chernobyl and Fukushima nuclear plant accidents for about 300 years due to the 30-year half-life of this radionuclide (NEA, 2002). The developed ^{60}Co and ^{137}Cs classification models were tested with field data collected under both controlled conditions and at a location in which 1960's-era nuclear weapons testing produced contamination that is still present today.

2.2 Equipment

The gamma-ray spectral data employed in this research were provided by the U. S. Environmental Protection Agency Airborne Spectral Photometric Environmental Collection Technology (ASPECT) program (Cardarelli II et al., 2015). In 2010, the ASPECT aircraft was an Aero Commander 680 fixed wing aircraft. It was equipped with two RS-500 Radiation Solutions gamma-ray spectrometer units (Radiation Solutions, Inc., Mississauga, ON), combined together for a total of eight $2\times 4\times 16$ inch (16.7 L) thallium-activated sodium iodide scintillation crystals. Each crystal was connected to a 1,024 multichannel analyzer (2.98 keV per channel). In 2014, the ASPECT technology was moved into a Cessna 208B Caravan which was equipped with three RS-500 Radiation Solutions gamma-ray spectrometer units for a total of 12 $2\times 4\times 16$ inch (25 L) thallium-activated sodium iodide scintillation crystals. Other detectors were also installed but were not used in acquiring the data presented here. During the data acquisition, altitudes above ground level (AGL) were determined by use of a radar altimeter mounted on the aircraft.

The ground area interrogated by each spectrum can be approximated by consideration of the data acquisition rate (1 spectrum/s), the average ground speed of the aircraft (~ 50 m/s), and the typical aircraft altitude (~ 100 m AGL) during the data collection runs. At a fixed position of the aircraft, Duval et al. have modeled the circle of investigation (COI) of the

spectrometer as a function of a number of parameters (Duval et al., 1971). For altitudes of ~100 m AGL, the radius of the COI for an integral of 50 % of the source yield was modeled to be approximately equal to the aircraft altitude (i.e., ~100 m for the data described here). Considering each acquired spectrum to be the result of viewing a series of overlapping circles whose centers span the 50 m traveled during one scan, the area interrogated was approximately elliptical in shape with a diameter of ~250 m along the flight track and ~200 m perpendicular to the flight track. While each acquired spectrum interrogated a relatively large area, radioactive sources at a target location could be pinpointed to within a few meters by flying a grid search pattern in which the individual lines of the grid were 15 to 30 m apart.

Data sets were derived from overflights of either (1) controlled sites at which commercial ^{137}Cs and ^{60}Co sources (activities of tens to hundreds of megabecquerels) were placed at known locations on the ground, (2) a location known to contain contamination from the Sedan nuclear weapon test, or (3) a nuclear power plant. The Sedan test was a shallow underground nuclear test (104 kT) conducted in July 1962 as part of Operation Plowshare, a program to investigate the use of nuclear weapons for civilian purposes. Data collected with both ASPECT platforms were used together in the work described below.

Gamma-ray spectra collected in the laboratory were also used in this work. The instrumentation employed was a Radiation Solutions RS-500 spectrometer similar to that described previously but comprising a single $4\times 4\times 16$ inch crystal rather than the large multi-unit array employed in the aircraft. The data collected in the laboratory were obtained by taking measurements of controlled radioactive sources at varying distances from the detector.

The computational work described here was performed with a custom-built computer utilizing two Xeon E5-2680 v2 10(20) core processors (Intel Corp., Santa Clara, CA) running at 3.6 GHz. This computer operated under Red Hat Linux (Version 6, Red Hat, Inc., Raleigh, NC). Software utilized in this research included in-house programs written in Fortran and compiled with the Intel Fortran Compiler (Version 10.0.023, Intel Corp.), in-house Linux shell scripts, MATLAB (The MathWorks, Natick, MA), Google Earth (Google, Inc., Mountain View, CA), ENVI/IDL (Exelis, Inc., Boulder, CO), and Origin Lab Pro 9 (OriginLab Corp., Northampton, MA).

2.3 Assembly of training set

The supervised pattern recognition methodology used in this work required the definition of a training set of known “analyte-active” and “analyte-inactive” spectra. The terms, analyte-active and analyte-inactive, denote, respectively, the cases in which a spectrum contains the signature of the specific radioisotope of interest (^{137}Cs or ^{60}Co) or does not contain the signature.

Pure-component spectra of ^{137}Cs and ^{60}Co are characterized by photopeaks near 662 keV for ^{137}Cs (technically this gamma ray is emitted from barium-137, the decay product of ^{137}Cs , but is traditionally associated with ^{137}Cs) and 1,173 and 1,333 keV for ^{60}Co . Pure-component spectra were collected by placing a known radioactive source in various

proximities to the detector. The data were accumulated at one scan per second and were subsequently co-added. The pure-component spectra were used in the generation of synthetic spectra that defined the analyte-active data class used in training and testing the classification models. In addition, 5,332 laboratory background spectra were obtained to supplement the background spectra collected in the field.

The pool of field background spectra used in the classifier development was assembled from aircraft overflights of 11 sites and consisted of 24 individual data collection runs. A total of 32,134 spectra were acquired from these runs. These spectra corresponded to altitudes spanning the range of 0 to 980 m AGL. Table 1 summarizes these background data. Included in the table are the altitudes flown at each site and a summary of the naturally occurring radiation sources present.

For the work described here, the inactive subset in the training sets for both ^{137}Cs and ^{60}Co contained 17,643 one-second spectra. This number of inactive spectra represents the remaining spectra in the pool of backgrounds after spectra were withheld for use in evaluating the computed classifiers and in generating synthetic active spectra. Spectra to be used in assessing the classifier performance were kept separated from spectra used in the training process.

For each target radioisotope, an active training subset of 8,000 synthetic spectra was generated from a single pure-component spectrum. The pure-component spectrum was randomly scaled to account for variation in signal intensities in the field and then added to a randomly selected background spectrum to generate a synthetic active spectrum. For each synthesized spectrum, the corresponding background spectrum was taken from a pool of 5,000 field backgrounds. These spectra were selected as representative from the overall background pool of Table 1 by use of the subset selection algorithm of Carpenter and Small (Carpenter and Small, 1991; Small et al., 1991). The pool of 5,000 backgrounds did not overlap with those in the inactive class of the training set. This data synthesis procedure is depicted graphically in Fig. 1.

Varying the signal strength in the generated synthetic active spectra was achieved through the use of a scaling coefficient, $\alpha_{\min}$, that served to adjust the signal level in the pure-component spectrum such that a continuous range of intensities was achieved down to a level that could not be detected. In the generation of spectrum i , a specific scaling coefficient, α_i , was defined as $\alpha_i = \alpha_{\min} Z_i$ where Z_i was a randomly selected value taken from the sequence defined in $Z_i \in [((1 \dots n) - 1) / (n - 1)] \cdot 99 + 1$ where n is the total number of active spectra to be generated.

An optimization procedure was used to determine a value of $\alpha_{\min}$ that produced a range of signal strengths such that $15 \pm 2.0\%$ of the active class could not be detected (i.e., false-negative errors). This ensured that the separating boundary corresponding to any resulting classification model would be pushed as closely as possible to the analyte-inactive data class, thus defining the boundary between positive and negative detections.

While the nominal value of 15% missed detections was somewhat arbitrary, preliminary experiments confirmed that at this signal level, there would still be missed detections even

after all parameters related to the classifier were optimized. Thus, there was no danger of the classification boundary being placed in an arbitrary location between completely separated data classes. If the classes are completely separated, the resulting boundary does not adequately define the transition from an active spectrum to an inactive spectrum.

The optimization of $\alpha_{\min}$ used a spectral segment (region-of-interest) of 120 (^{137}Cs) or 160 (^{60}Co) points (channels) centered on the analyte (isotope) peak region (e.g., the peak at 662 keV for ^{137}Cs) and a preprocessing digital filter chosen to be representative by visual inspection of filtered spectra. Classification models were computed by the use of nonparametric linear discriminant analysis (LDA) methodology (Tou and Gonzalez, 1974). The specific implementation used here was developed by Small and co-workers (Kaltenbach and Small, 1991; Shaffer and Small, 1996).

An arbitrary starting value of $\alpha_{\min} = 0.1$ was used to initialize the optimization. The value of $\alpha_{\min}$ was then increased or decreased to meet the target of 85.0 ± 2.0 % correct classification of the analyte-active (isotope-specific) class. This optimization was performed separately for ^{137}Cs and ^{60}Co , producing $\alpha_{\min}$ values of 8.540×10^{-3} and 4.225×10^{-2} , respectively. These values indicate that the ^{60}Co pure-component spectrum had to be scaled approximately five times higher than the corresponding spectrum of ^{137}Cs in order to generate spectra that met the correct classification threshold of 85.0 ± 2.0 %.

2.4 Spectral preprocessing for background correction

All spectra were preprocessed before submission to the pattern recognition procedure in order to suppress sources of variance unrelated to the signature of the specific radioisotope. The preprocessing consisted of three sequential steps: (1) scaling to normalize the spectra as a function of aircraft altitude, (2) digital filtering to enhance the signal-to-noise (S/N) ratio, and (3) selection of the most informative region of the gamma-ray spectrum for use in defining the pattern that was subsequently submitted to the classification model. Each of these steps is described below.

2.4.1 Altitude scaling—Gamma-ray spectra are sensitive to altitude because of the interaction of gamma rays with atmospheric constituents. The initial scaling step attempted to bring the spectra onto a common intensity scale. The scaling was performed by $s' = s * \exp^{(0.00524 \cdot a)}$ where s' is the scaled spectrum, s is the unsealed spectrum, a is the altitude of the aircraft in meters AGL as determined by the radar altimeter, and 0.00524 m^{-1} is an attenuation factor based on a nominal aircraft operational height (IAEA, 2003b). Because a single attenuation factor was used in implementing the scaling at each point in all spectra, this altitude correction step was imprecise. The attenuation factor is dependent on both the altitude and the specific gamma-ray energy. However, despite its limitations, the altitude scaling step did serve to contract the data space and facilitate the application of the subsequent pattern recognition methods. After this first scaling step, digital filtering was performed on the scaled spectrum.

2.4.2 Digital filter architecture—Digital filters were used to suppress unwanted features in the gamma-ray spectra. The filtering operation decomposes a spectrum into a sum of sine and cosine waveforms and attenuates the amplitude of these waveforms as a

function of frequency. This allows the suppression of both low-frequency (i.e., slowly varying) and high-frequency (i.e., rapidly varying) spectral features, thus allowing the attenuation of both baseline artifacts and noise.

Both finite impulse response (FIR) and infinite impulse response (HR) filters were investigated for their suitability as preprocessing tools for gamma-ray spectra. The tested FIR filter was designed with a Chebyshev Type II architecture while the HR filter was designed using the elliptic architecture (Oppenheim et al., 1983). When applied to the detection of ^{137}Cs , it was found that the HR filter results were consistently superior to those obtained with the FIR filter. This improved performance was attributed to the faster roll-off in the filter passband that is achievable with HR filters (Chen, 2001; Daniels, 1974; Oppenheim et al., 1983; Schlichtharle, 2011; Williams, 1988). No problems with regard to HR filter stability were observed. On the basis of these results, elliptic HR filters were selected for use in subsequent work with both ^{137}Cs and ^{60}Co .

2.4.3 Optimization of digital filters—Both bandpass and lowpass filters were investigated. The design of each bandpass filter required the following parameter settings: (1) attenuation of the first stopband, (2) location of the trailing edge of the first stopband, (3) location of the beginning of the passband, (4) passband attenuation, (5) location of the trailing edge of the passband, (6) location of the beginning of the second stopband, and (7) attenuation of the second stopband. These parameters were designated on a decibel (dB) scale for the filter magnitude (degree of attenuation) and a normalized 0.0 to 1.0 scale for the frequency axis. Lowpass filters required settings for (1) attenuation of the passband, (2) location of the trailing edge of the passband, (3) location of the beginning of the stopband, and (4) attenuation of the stopband.

A grid search procedure was used to identify optimal settings for the lowpass and bandpass filter parameters. For both filter types, the attenuation of the passband and stopband(s) was fixed at 1.0 and 30.0 dB, respectively. For the bandpass filters, the passband width was varied over the range of 0.010 to 0.060 in steps of 0.005 (normalized frequency units) in conjunction with moving the left passband edge from 0.010 to 0.020 in steps of 0.001. For each set of passband parameters, the two stopband positions were set such that the distance between the edges of the passbands and stopbands (i.e., the transition bands) was always 0.005. This provided stable filter designs across the frequency range studied while also producing a sharp roll-off of the filter passband. The lowpass filter values had a starting passband edge of 0.00085 and a stopband edge of 0.001 (normalized frequency units). The stopband was incremented to 0.005 normalized frequency in steps of 0.0025 with the transition band width kept constant. These parameter ranges were selected on the basis of a preliminary visual analysis of filtered spectra.

The grid search to optimize the filter parameters was performed in conjunction with studies of the length and position of the optimal spectral segment used to define the patterns submitted to the LDA calculations. This allowed an optimal digital filter to be identified for use with each tested spectral segment. Fig. 2 illustrates the operation of a digital filter in converting a raw spectrum into a pattern.

2.4.4 Selection of spectral segments—As depicted in Fig. 2, all classification models were based on multidimensional patterns corresponding to a single contiguous segment (region-of-interest) in the filtered spectra. The segments studied contained both peak and baseline information in order to define the transition between the presence and absence of the radioisotope signatures of interest.

A two-step procedure was employed to identify the optimal length and location of the spectral segment used with each classifier. An initial study of segment length was performed in conjunction with a coarse study of the segment position. Segment lengths investigated were 504, 563 and 578 keV for ^{60}Co (170, 190 and 195 spectral channels) and 355, 414 and 444 keV for ^{137}Cs (120, 140 and 150 channels). For ^{60}Co , starting points of channels 330 to 380 (980 to 1129 keV, increment of 2 channels) were used for each segment length. The corresponding starting points for ^{137}Cs were 166 to 220 (492 to 653 keV, increment of 2 channels). These search ranges were selected on the basis of preliminary work that identified the most promising spectral regions, as well as consideration of software limitations and the scale of the required computations.

For each spectral segment investigated, the full grid search of digital filter parameters was applied, and individual classification models were developed for each combination of parameters. The classification performance of the resulting models was used to select the optimal filter and segment parameters. Once an optimal segment length was determined, a more extensive investigation of the segment position was performed. Details regarding this optimization step are provided in the Results section below.

2.5 Monitoring set and classifier selection

Once computed, the classification models were tested with analogous patterns not used during the training process. This assessment was performed with a monitoring set composed of synthetic active spectra supplemented by a set of field and laboratory inactive spectra. The monitoring set was used to select a single classifier for final testing with the prediction data sets.

The active class in the monitoring set was built with the same parameters used to construct the training set, but the random number generator seeds employed in the scaling process and in the selection of which background to use were altered. The same set of 5,000 background spectra used in generating the training actives was also employed in producing the monitoring set. For ^{137}Cs and ^{60}Co , respectively, 4,000 and 5,000 synthetic active spectra were generated for use in the monitoring set. For the inactive class employed in testing the ^{137}Cs classifiers, 5,000 spectra selected from the pool of field backgrounds described in Table 1 were used along with 3,697 laboratory background spectra. The inactive class of the ^{60}Co monitoring set contained 7,939 field backgrounds.

2.6 Prediction testing

Final testing of the selected classifiers was performed with field data containing either controlled sources, the remnants of manmade radiological events (e.g., nuclear fallout), or no

radioisotope emissions. Each of the six sites is described in Table 2. Three sites were known to contain ^{137}Cs , while two sites had ^{60}Co . Three of the sites had neither ^{137}Cs nor ^{60}Co .

In assembling this set of prediction data, spectra were visually inspected for the presence of the signature of the specific radioisotope. When evaluating the performance of the computed classifiers, classification percentages were computed on the basis of these visual inspections. Spectra where neither an inactive or active designation could be assigned with confidence were removed from the prediction set for the respective isotope. For data collected at the *Mine* site, 13 spectra were removed that had missing altitudes and thus could not be used with the altitude scaling operation described previously.

As indicated in the table, various altitudes were flown during the data collections. Because gamma-ray signal intensities weaken with increasing altitude due to scattering effects, the same map location could yield a positive or negative detection decision depending on the altitude of the aircraft when the corresponding spectrum was acquired.

2.7 Development of confidence models

The output of the LDA pattern recognition method is a discriminant score that encodes the distance of the pattern to the separating boundary placed between the data classes by the training procedure. Positive discriminant scores correspond to the active class (i.e., the active side of the class separation boundary corresponding to a positive isotope identification), while negative scores denote the inactive class (i.e., where the specific isotope is not present). In principle, there should be greater confidence in the classification as the distance to the decision boundary increases (Duda et al., 2001; Jurs and Isenhour, 1975; Tou and Gonzalez, 1974). To assign confidence levels to the classifications, a model was constructed for each classifier relating discriminant scores to the percentage of correctly classified patterns.

To build these models, sites that contained a broad range of signal intensities were needed to account for either weakly active spectra the classifier misses, or unusual inactive spectra that are falsely classified. For the optimized ^{137}Cs and ^{60}Co classifiers, respectively, the *Sedan* and *Desert Rock* prediction sites (Table 2) were used to build the confidence models.

The procedure for generating a confidence model involved collecting the discriminant score values from the prediction site for a given classifier. These scores were sorted and placed into bins to allow the percent correct classification per bin to be calculated. In computing the classification percentages, the class assignments made during the visual inspections of the prediction data files were used as the “true” active and inactive designations for each spectrum.

The number of bins was varied to assess the ability to define the functional relationship between discriminant score and classification percentage. Fig. 3 illustrates the effect of the number of bins in building the confidence model for the ^{137}Cs classifier. In this case, dividing the discriminant score range into 100 bins was adequate to allow the data to be fit accurately. Using too few bins produced poor definition of the curvature of the function, while too many bins yielded a noisy response. Various functional forms of the model were

investigated, with the bi-Gaussian function providing the best overall fit to the active and inactive sides of the data. For the case of 100 bins in Fig. 3B, the coefficient of determination for the bi-Gaussian fit was 0.999. Given the parameters of the fitted function, discriminant score cutoffs could be estimated corresponding to any classification percentage. These classification percentages were then equated to confidence levels associated with the discriminant scores for both the active and inactive data classes.

3. Results

Table 3 displays the results of the segment length optimization, demonstrating that segment lengths of 150 (444 keV) and 190 points (563 keV) were optimal for ^{137}Cs and ^{60}Co , respectively. Once the segment lengths were chosen, these parameters were maintained for the more fine-tuned starting point optimization. The parameters associated with the optimization of the starting point are presented in Table 4.

Following the optimization of the starting point, the top performing classifiers were extracted from the monitoring results and are shown in Table 5 and compared to the results obtained from predicting the patterns in the training set. The top performing classifiers were then tested against the full set of prediction data. Table 6 lists the classification statistics obtained for each site in the prediction set, as well as the results tabulated across all the prediction sites. It should be emphasized that none of the prediction data were used at any step of the classifier development work.

The classification results summarized in the tables were translated into visual imagery by plotting each discriminant score at the map coordinates corresponding to the aircraft location at the time of the spectral acquisition. The resulting plot was then overlaid on a satellite image of the measurement site. Figs. 4–6 display the images generated by the ^{137}Cs and ^{60}Co classifiers when applied to the *Desert Rock*, *Wings-Runway*, and *Sedan* sites, respectively. The color coding used in the image was derived from the developed confidence models and is detailed in the figure captions. Briefly, light blue, green, yellow, and red symbols denote isotope-specific detections of increasing confidence, while dark blue, purple, and black symbols specify classification of spectra as analyte-inactive with increasing confidence levels. Locations coded as red and black are judged to be analyte-active and analyte-inactive, respectively, with > 99 % confidence.

In order to characterize the sensitivity of the classifiers, Fig. 7 A plots every fourth of the 881 gamma-ray spectra from the overall prediction set correctly classified as analyte-active by the optimized ^{137}Cs classifier. Figure 7B plots every fourth of the 347 spectra that corresponded to missed ^{137}Cs detections. These were spectra in which the ^{137}Cs signature was judged to be present by visual inspection but that the classifier did not judge to be analyte-active. Figs. 8A and 8B display the corresponding plots for the 15 correct ^{60}Co classifications and 11 missed detections (every other spectrum plotted in both sets).

4. Discussion

The results presented demonstrate that a successful methodology has been developed for building and optimizing radioisotope classifiers using pattern recognition methods. The

correct radioisotope was detected at each of the prediction sites where it was found to exist by visual inspections of the collected gamma-ray spectra. In addition, as presented in Table 6, the overall rate of false detections was extremely low ($< 0.1\%$ for both classifiers). This can be seen visually in the image plots in Figs. 4–6 where the source locations are clearly observed with no spurious detections at random locations. When both active and inactive detection decisions are considered together, the overall successful classification rate was 99.9 % for ^{60}Co (17,834 correct classifications out of 17,846 active and inactive spectra in the prediction set). The corresponding correct classification rate for ^{137}Cs was 97.9 % (16,985 correct classification out of 17,349 active and inactive spectra).

Inspections of the spectra plotted in Figs. 7 and 8 reveal that the great majority of the analyte signals are weak and that the ^{60}Co signals are weaker than ^{137}Cs . This is reflected in the increased number of missed detections for ^{60}Co . For the 11 ^{60}Co missed detections, nine had confidence levels $< 51\%$ for the *inactive* data class, indicating these spectra were very close to the classification boundary and were effectively indeterminate in terms of class identity.

To characterize the signal strengths associated with both the correct classifications and missed detections, the signal-to-noise (S/N) ratio was computed for the the spectra corresponding to the correct and missed detections. To remove the curved baseline artifact derived from atmospheric scattering of gamma-rays, a quadratic regression model was fitted to each spectrum using the regions of 900–1,000 and 1,500–1,600 keV for ^{60}Co and 400–500 and 800–900 keV for ^{137}Cs . The quadratic model was the simplest regression model that allowed the curvature of the baseline to be fit adequately.

The predicted baseline was subtracted from each spectrum, followed by estimation of the baseline noise as the standard deviation of the baseline-corrected spectral intensities over the ranges of 900–1,000 keV for ^{60}Co and 800–900 keV for ^{137}Cs . Signal values were taken as the mean of 1,159–1,180 keV in the baseline-corrected spectra for ^{60}Co and 650–670 keV for ^{137}Cs . These regions corresponded to a 20 keV band centered on the spectral peaks (1,173 keV for ^{60}Co and 662 keV for ^{137}Cs). Ratios of the computed signal and noise values produced estimates of the S/N ratios for the groups of correct and missed detections.

For ^{60}Co , the median S/N ratio for the correct classifications was 3.4, with values ranging from 1.5 to 6.4. The corresponding values for the missed detections were a range of 0.3 to 2.6 with a median S/N ratio of 1.4. These values illustrate again that the ^{60}Co spectra are very weak and that the developed ^{60}Co classification model is operating near the classical limit of detection (LOD) of 3.0 in terms of S/N ratio (Winefordner and Long, 1983).

The corresponding results for ^{137}Cs show a similar trend. The median S/N ratio for the correct detections was 5.2, while the corresponding value for the missed detections was 2.4. Values of the S/N ratios for the correct detections reached a maximum at 84.8, reflecting the presence of some strong ^{137}Cs signals, particularly at the Sedan prediction site. Among the correct detections, 781 of the 881 spectra (88.6 %) had S/N values > 3.0 , while 834 (94.7) had S/N values > 2.5 . These results suggest the ^{137}Cs classifier is also operating near the classical LOD specified by a S/N ratio of 3.0.

5. Conclusions

The work described in this paper is an enabling methodology for automating the detection of specific radioisotopes from any aircraft platform (fixed-wing, rotary, UAV). Detection decisions are made on individual spectra in near real time with an associated level of confidence. Rather than having to review thousands of spectra collected during an aerial survey, the analyst is freed to focus on only a small number of likely target spectra. The use of multivariate patterns to represent the data rather than simple univariate peak intensities or peak ratios allows the shape of the isotope spectral signature to be incorporated into the detection decision. This helps to increase the selectivity of the classification model, thus allowing the detection of weak signatures while minimizing the number of false positives.

In developing the classification models, no field measurements are required with an active radioactive source. The only data requirements are a single laboratory gamma-ray spectrum of the specific radioisotope and a set of representative background spectra collected in the field. Use of an optimization procedure to identify the best spectral processing parameters allows the unbiased identification of spectral regions of interest that would not necessarily be chosen by simple visual inspection of the spectra. For example, as presented in Table 5 and Fig. 2, the optimized segment of 635 – 1079 keV for ^{137}Cs is shifted to the right side of the characteristic peak at 662 keV. This segment avoids the variability in the spectral baseline that is found to the left side of the peak as a consequence of atmospheric scattering of the upwelling gamma rays.

Going forward, follow-on work will assess the degree to which the presented methodology can work with spectral peaks that are increasingly overlapped with the Compton scattering region of the gamma-ray spectrum that occurs below 400 keV. This spectral region, visible in Figs. 1 and 2, contains an altitude-sensitive spectral background that results from the scattering of upwelling gamma-rays through interactions with atmospheric constituents. Suppression of this background is a focus of current efforts.

Removing these background signatures may also define a path toward increasing the performance of the developed classification models. Examination of the spectra plotted in Figs. 7 and 8 and the associated calculation of S/N ratios suggest the current classification models can work reliably down to S/N ratios of approximately 3.0. However, as observed in Figs. 7B and 8B, visual detections can still be made below this threshold. Work is ongoing to increase the performance of the classifiers such that they operate as well as a visual analysis.

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References

- Aage HK, Korsbech U, Bargholz K, Bystom S, Wedmark M, Thorshaug S, 2006 Experiences with area specific spectrum stripping of NaI(Tl) gamma spectra. *Radiation Protection Dosimetry* 121, 108–121. [PubMed: 16488919]

- Burr T, Hamada M, 2009 Radio-Isotope Identification Algorithms for NaI Gamma Spectra. *Algorithms* 2, 339–360.
- Cardarelli II J, Thomas M, Kroutil R, Small G, Desss B, Stapleton J, Miller D, Curry T, 2015 Real-time isotope identification and mapping capabilities of the U.S. Environmental Protection Agency's Airborne Spectral Photometric Environmental Collection Technology, Nuclear Terrorism and National Preparedness: NATO Science for Peace and Security Series B: Physics and Biophysics. Springer, Dordrecht, pp. 105–116.
- Carpenter SE, Small GW, 1991 Selection of Optimum Training Sets for Use in Pattern Recognition Analysis of Chemical Data. *Anal. Chim. Acta* 249, 305–321.
- Chen C-T, 2001 Digital Signal Processing: Spectral Computation and Filter Design, 1 ed Oxford University Press Inc, New York, New York.
- Connor D, Martin PG, Scott TB, 2016 Airborne radiation mapping: overview and application of current and future aerial systems. *International Journal of Remote Sensing* 37, 5953–5987.
- Daniels RW, 1974 Approximation Methods for Electronic Filter Design. McGraw-Hill, New York.
- Duda RO, Hart PE, Stork DG, 2001 Pattern Classification, 2 ed John Wiley & Sons, Inc., New York.
- Duval JS Jr., Cook B, Adams JAS, 1971 Circle of Investigation of an Air-borne Gamma-Ray Spectrometer. *J. Geophys. Res.* 76, 8466–8470.
- Furr AK, Robinson EL, Robins CH, 1968 A spectrum stripping technique for qualitative activation analysis using monoenergetic gamma spectra. *Nuclear Instruments and Methods* 63, 205–209.
- Huo Y, Xu P, Li Z, Li S, Gou Z, 2014 Fast Radioactive Nuclide Recognition Method Study Based on Pattern Recognition. *Sensors & Transducers* 163, 103–106.
- IAEA, 1991 Airborne Gamma Ray Spectrometer Surveying, in: IAEA (Ed.), Technical Reports Series. IAEA, Austria.
- IAEA, 2003a Guidelines for radioelement mapping using gamma ray spectrometry data, in: IAEA (Ed.). IAEA, Austria.
- IAEA, 2003b Guidelines for radioelement mapping using gamma ray spectrometry data Jurs PC, Isenhour TL, 1975. *Chemical Applications of Pattern Recognition*. John Wiley & Sons, Inc.
- Kaltenbach TF, Small GW, 1991 Development and Optimization of Piecewise Linear Discriminants for the Automated Detection of Chemical Species. *Anal. Chem.* 63, 936–944.
- Martin PG, Payton OD, Fardoulis JS, Richards DA, Scott TB, 2015 The use of unmanned aerial systems for the mapping of legacy uranium mines. *Journal of Environmental Radioactivity* 143, 135–140. [PubMed: 25771221]
- NEA, 2002 Chernobyl: assessment of radiological and health impacts Organisation for Economic Co-Operation and Development - Nuclear Energy Agency, Paris.
- Oppenheim AV, Willsky AS, Young IT, 1983 Signals and Systems. Prentice-Hall, Inc., Englewood Cliffs, New Jersey.
- Owsley LMD, Okopal G, Salaymeh SR, 2010 New Directions in Radioisotope Spectrum Identification, in: Laboratory AP (Ed.), Aiken, South Carolina.
- Portnoy D, Feuerbach R, Heimberg J, 2011 Global parameter optimization for maximizing radioisotope detection probabilities at fixed false alarm rates. *Nucl. Instrum. Meth. A* 652, 29–32.
- Sanada Y, Torii T, 2015 Aerial radiation monitoring around the Fukushima Dai-ichi nuclear power plant using an unmanned helicopter. *Journal of Environmental Radioactivity* 139, 294299. [PubMed: 25053518]
- Schlichtharle D, 2011 Digital Filters: Basics and Design, 2 ed Springer.
- Shaffer RE, Small GW, 1996 Improved Response Function for the Simplex Optimization of Piecewise Linear Discriminants. *Chemom. Intell. Lab. Syst.* 32, 95–109.
- Small GW, Carpenter SE, Kaltenbach TF, Kroutil RT, 1991 Discriminant analysis techniques for the identification of atmospheric pollutants for passive Fourier transform infrared interferograms. *Anal. Chim. Acta* 246, 85–102.
- Tou JT, Gonzalez RC, 1974 Pattern Recognition Principles. Addison-Wesley, Canada.
- Wan B, Small GW, 2011 Synthetic training sets for the development of discriminant functions for the detection of volatile organic compounds from passive infrared remote sensing data. *Analyst* 136, 309–316. [PubMed: 20953478]

Williams AB, 1988 Electronic Filter Design Handbook. McGraw-Hill, New York.
Winefordner JD, Long GL, 1983 Limit of Detection. Anal. Chem. 55, 712A–724A.

- Automated detection of ^{137}Cs and ^{60}Co by airborne gamma-ray spectroscopy
- Supervised pattern recognition of digitally filtered gamma-ray spectra
- Methods development does not require field data of radioactive sources
- Detection decisions supplied with % confidence for ease of interpretation
- Methodology demonstrated with aerial surveys of six field sites

Fig. 1.

Visual representation of the generation of a synthetic active spectrum containing the signature of ^{137}Cs . In this example, the pure-component spectrum of ^{137}Cs in the upper left panel is multiplied by 0.62 to scale it to a previously optimized range.

Fig. 2.

A raw inactive spectrum (red) and ^{137}Cs active spectrum (blue) from the *Desert Rock* site (A) are converted into patterns (B) for pattern recognition using the described preprocessing procedures. The plot in panel B demonstrates how the dimensionality of the data is reduced and the S/N ratio is increased. The digital filtering parameters and segment selection correspond to the optimized values for the ^{137}Cs classifier (Table 5).

Fig. 3.

Plots showing the relationship of the percentage of patterns correctly classified to the corresponding discriminant scores produced by the optimized ^{137}Cs classifier. Each classification percentage is computed within a bin defined by an upper and lower discriminant score. These plots demonstrate how the shape of the transition to 100 % correct classification changes with bin size. Panels A, B, C, and D correspond to 50, 100, 200, and 300 bins, respectively. The use of 100 bins was judged to be optimal in defining the shape of the curve well without introducing artifacts.

Fig. 4. Images produced by the application of the optimized ^{137}Cs (upper) and ^{60}Co (lower) classifiers to gamma-ray spectra collected during overflights at various altitudes of the *Desert Rock* prediction site. Both classifiers performed well, detecting the commercial point sources of ^{137}Cs and ^{60}Co placed on opposite ends of an airport runway. Red, yellow, green, light blue, dark blue, purple, and black symbols correspond, respectively, to the following confidence levels: > 99 % active, 90–99 % active, 70–90 % active, <70 % active, <70 % inactive, 70–99 % inactive, and > 99 % inactive.

Fig. 5.

Images produced by the application of the optimized ^{137}Cs (upper) and ^{60}Co (lower) classifiers to gamma-ray spectra collected during overflights at various altitudes of the *Wings Runway* prediction site. Both classifiers performed well, detecting the two commercial point sources of ^{137}Cs placed on opposite ends of an airport taxiway, as well as the single weaker source of ^{60}Co placed near the middle of the same taxiway. Red, yellow, green, light blue, dark blue, purple, and black symbols correspond, respectively, to the following confidence levels: > 99 % active, 90–99 % active, 70–90 % active, < 70 % active, < 70 % inactive, 70–99 % inactive, and > 99 % inactive.

Fig. 6. Images produced by the application of the optimized ^{137}Cs (upper) and ^{60}Co (lower) classifiers to gamma-ray spectra collected during overflights at various altitudes of the *Sedan* prediction site. This is a site of 1960's-era underground nuclear testing. A widespread area of ^{137}Cs is still present, centered near a crater in the upper middle portion of the image that marks the blast site. There is no known presence of ^{60}Co at this location. Both classifiers performed well, detecting a wide distribution of ^{137}Cs with no false positives of ^{60}Co . Red, yellow, green, light blue, dark blue, purple, and black symbols correspond, respectively, to

the following confidence levels: > 99 % active, 90–99 % active, 70–90 % active, < 70 % active, < 70 % inactive, 70–99 % inactive, and > 99 % inactive.

Fig. 7. Plots of ^{137}Cs -active spectra in the prediction set correctly determined as active (A) and those for which the apparent ^{137}Cs signature was missed by the classification model (B), Assessments of correct and incorrect classifications were based on visual inspections of the spectra for the ^{137}Cs peak in the region of 660 keV. Every fourth spectrum in each corresponding data set is plotted.

Fig. 8. Plots of ^{60}Co -active spectra in the prediction set correctly determined as active (A) and those for which the apparent ^{60}Co signature was missed by the classification model (B). Assessments of correct and incorrect classifications were based on visual inspections of the spectra for the ^{60}Co peaks in the region of 1170 and 1330 keV. The apparent peak in the region of 1460 keV in some of the spectra derives from naturally-occurring potassium-40. Every other spectrum in each corresponding data set is plotted.

Table 1.

Field background data used in classifier development.

Site number	Location	Terrain	Altitude range ^a (m)	Runs	Spectra	Natural Isotopes ^b
1	Southern US	Urban	100 – 950	4	4497	⁴⁰ K, U _{nat} , Pos. Ann.
2	Southwest US	Reservoir	150 – 950	1	1622	⁴⁰ K, U _{nat} , Pos. Ann.
3	Central US	Reservoir	40 – 950	2	5575	⁴⁰ K, U _{nat} , Pos. Ann.
4	Midwest US	Lake/ Fields	80 – 950	2	1850	⁴⁰ K
5	West Coast	Coastal/ Urban	100 – 950	6	4843	⁴⁰ K
6	Mountain US	Plateaus/ Desert	130 – 131	1	873	⁴⁰ K, U _{nat} , Pos. Ann., ²³² Th
7	Southeast US	Southeastern Coastal	70 – 950	1	1262	U _{nat} , Pos. Ann.
8	Southern US	Temperate/ Urban	100 – 950	1	518	⁴⁰ K, U _{nat} , Pos. Ann., ²³² Th
9	Southern US	Suburban	100 – 980	3	8565	U _{nat} , Pos. Ann.
10	Southern US	Urban	0 – 950	2	1578	⁴⁰ K, Pos. Ann.
11	Eastern US	Forest	100 – 950	1	951	⁴⁰ K, ²³² Th, Pos. Ann.

^aAltitude in m AGL specified.^bNatural radiation sources: potassium-40 (⁴⁰K), natural uranium (U_{nat}), thorium-232 (²³²Th), positron annihilation (Pos. Ann.).

Table 2.

Description of prediction sets.

Site name	Location	Terrain	Altitude range ^a (m)	Analyte	Active	Inactive	Removed	Total ^b
Desert Rock	Western US	Desert/Airport	19 – 951	¹³⁷ Cs ⁶⁰ Co	38 16	1,039 1,063	2 0	1,079
Sedan	Western US	Desert	100 – 951	¹³⁷ Cs ⁶⁰ Co	1,173 0	3,047 4,715	495 0	4,715
Wings-Runway	East Coast US	Forested/Airport	70 – 220	¹³⁷ Cs ⁶⁰ Co	17 10	359 366	0 0	376
Wings-Power Plant	East Coast US	Coastal	280 – 380	¹³⁷ Cs ⁶⁰ Co	0 0	3,038 3,038	0 0	3,038
Mine	Southwest US	Low Mountains	60 – 850	¹³⁷ Cs ⁶⁰ Co	0 0	4,415 4,415	13 13	4,428
Transit	Southern US	Varies	50 – 500	¹³⁷ Cs ⁶⁰ Co	0 0	4,223 4,223	0 0	4,223
Total	--	--	--	¹³⁷ Cs ⁶⁰ Co	1,228 26	16,121 17,820	510 13	17,859

^aAltitude above ground level specified.^bTotal spectra collected. For sites in which spectra were declared to be of indeterminate classification, the total number of spectra is greater than the sum of the active and inactive spectra.

Table 3.Monitoring results from segment length study for ^{60}Co and ^{137}Cs .

^{60}Co Classifiers				
Segment length (pts/keV)	Starting point (pts/keV)	Digital filter ^a	False (%)	Missed (%)
195/578	360/1070	s0.025p0.03p0.055s0.06ap1as30	0.189	10.920
190/563	330/980	s0.02p0.025p0.05s0.055ap1as30	0.353	10.620
170/504	338/1004	s0.005p0.01p0.085s0.09ap1as30	0.239	10.999
^{137}Cs Classifiers				
Segment length (keV)	Starting point (keV)	Digital filter ¹	False (%)	Missed (%)
150/444	214/635	p0.025s0.03ap1as30	0.000	13.480
140/414	204/605	s0.005p0.01p0.06s0.065ap1as30	0.000	15.040
120/355	172/510	s0.005p0.01p0.06s0.065ap1as30	0.000	13.860

^aFor a bandpass filter specified as “s *a* p *b* p *c* s *d* ap *e* as *f*”, the stopband edges were *a* and *d*, the passband edges were *b* and *c*, the attenuation in the passband was *e* and the attenuation in the stopbands was *f*. For a lowpass filter specified by “p *a* s *b* ap *c* as *d*”, the passband edge was *a*, the stopband edge was *b*, the attenuation in the passband was *c* and the attenuation in the stopbands was *d*.

Table 4.Classifier optimization parameters for ^{60}Co and ^{137}Cs .

^{60}Co Classifiers		
Segment length	Starting point range	Starting point increment
563 keV (190 pts)	891–1189 keV (300–400 pts)	2.98 keV (1 pt)
Number of digital filters	Number of starting points	Total number of classifiers
286	101	7150
^{137}Cs Classifiers		
Segment length	Starting point range	Starting point increment
444 keV (150 pts)	474–653 keV (160–220 pts)	2.98 keV (1 pt)
Number of digital filters	Number of starting points	Total number of classifiers
286	61	4290

Table 5.

Best classifier performance with monitoring and training sets.

	⁶⁰ Co	¹³⁷ Cs
Segment length	563 keV (190 pts)	444 keV (150 pts)
Starting point	980 keV (330 pts)	635 keV (214 pts)
Digital filter ^a	s0.02p0.025p0.05s0.055ap1as30	p0.025s0.03ap1as30
False classification % training	0.0	0.0
Missed classification % training	3.9	2.5
False classification % monitoring	0.4	0.0
Missed classification % monitoring	10.6	13.5

^aFor a bandpass filter specified as “s *a* p *b* p *c* s *d* ap *e* as *f*”, the stopband edges were *a* and *d*, the passband edges were *b* and *c*, the attenuation in the passband was *e* and the attenuation in the stopbands was *f*. For a lowpass filter specified by “p *a* s *b* ap *c* as *d*”, the passband edge was *a*, the stopband edge was *b*, the attenuation in the passband was *c* and the attenuation in the stopbands was *d*.

Table 6.

Prediction results organized by location.

Site	¹³⁷ Cs results			⁶⁰ Co results		
	False (%)	Missed (%)	Sources identified?	False (%)	Missed (%)	Sources identified?
Desert Rock	0.0	2.6	Yes	0.09	25.0	Yes
Sedan	0.6	29.0	Yes	0.0	N/A	Not present
Wings-Runway	0.0	35.3	Yes	0.0	70.0	Yes
Wings-Power Plant	0.0	N/A	Not present	0.0	N/A	Not present
Mine	0.0	N/A	Not present	0.0	N/A	Not present
Transit	0.0	N/A	Not present	0.0	N/A	Not present
Overall results	0.1	28.3	All identified	0.006	42.3	All identified