Real-Time Airborne Gamma-Ray Background Estimation Using NASVD with MLE and Radiation Transport for Calibration

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Abstract

Helicopter-mounted gamma-ray detectors can provide law enforcement officials the means to quickly and accurately detect, identify, and locate radiological threats over a wide geographical area. The ability to accurately distinguish radiological threat-generated gamma-ray signatures from background gamma radiation in real time is essential in order to realize this potential. This problem is non-trivial, especially in urban environments for which the background may change very rapidly during flight. This exacerbates the challenge of estimating background due to the poor counting statistics inherent in real-time airborne gamma-ray spectroscopy measurements. To address this challenge, we have developed a new technique for real-time estimation of background gamma radiation from aerial measurements without the need for human analyst intervention. The method can be calibrated using radiation transport simulations along with data from previous flights over areas for which the isotopic composition need not be known. Over the examined measured and simulated data sets, the method generated accurate background estimates even in the presence of a strong, ^{60}Co source. The potential to track large and abrupt changes in background spectral shape and magnitude was demonstrated. The method can be implemented fairly easily in most modern computing languages and environments.

Keywords: background estimation, aerial search, radiological search, gamma detection, noise-adjusted singular value decomposition, maximum likelihood estimation

1.0 Introduction

Helicopter-mounted gamma-ray detectors can provide law enforcement officials the means to quickly and accurately detect, identify, and locate radiological threats over a wide geographical area. The ability to accurately distinguish radiological threat-generated gamma-ray signatures from benign, background gamma radiation in real time is essential in order to realize this potential. This problem is non-trivial, especially in urban environments for which the background may change very rapidly during flight over, for example, land-water interfaces and building materials containing large amounts of naturally occurring radioactive material (NORM). This exacerbates the challenge of estimating background due to the poor counting statistics from long standoff distances and short measurement times inherent in real-time airborne gamma-ray spectroscopy measurements.

To address this challenge, we have developed a new technique for real-time estimation of background gamma radiation from aerial measurements to support current efforts to significantly enhance the speed, accuracy, and precision of radiological threat detection, measurement, and localization over wide geographical areas. Background estimations from the current algorithm will be used as input, to provide a baseline for anomaly detection [1] and localization [2] algorithms.

A prodigious amount of work has been published regarding background estimation techniques, for which a summary is provided in recent literature [3]; although, it was mentioned that most of these techniques require human analyst intervention and were developed for high-count spectra,

1 high-resolution spectra, and/or spectra containing known sources. More recently, a background
2 estimation technique based on machine learning was developed to estimate the background
3 component in such low-count spectra containing unknown sources, without the need for human
4 intervention [3].

5 The technique described in this paper has also been developed to estimate the background for
6 low-count and low-resolution spectra containing unknown sources without the need for human
7 analyst intervention. The technique described herein is fairly simple and straight-forward to
8 implement using mathematical functions (e.g., singular value decomposition) that are available
9 in pre-existing libraries for several modern computing languages and environments. In addition,
10 we demonstrate that the sensitivity matrix, which is used for extracting the concentrations of the
11 major contributing background components, can be determined through the use of radiation
12 transport simulations. Traditionally, for airborne gamma-ray detection systems, this sensitivity
13 matrix is determined using empirical measurements over pads consisting of known material
14 composition [4].

15 The current algorithm uses data in the high-energy regions or channels of the data to estimate the
16 background signature in the lower channels. This same fundamental concept has been applied in
17 car-borne and airborne search of radioactive materials to determine the background contribution
18 to low-energy spectral windows, using a least-squares approach [5-6]. In this work, we apply
19 Poisson regression, using the method of maximum likelihood estimation (MLE) to estimate the
20 background counts in each channel of the spectrum. Poisson regression naturally incorporates
21 the Poisson statistical nature of the background spectra. To date, the current algorithm has only
22 been analyzed on data taken from a previous flight, in replay mode, to simulate real-time
23 background estimation.

We define gamma-ray background radiation as natural radiation emitted from soil (terrestrial), nearby building materials (e.g., concrete, asphalt, brick, aircraft itself), gamma rays from cosmic-ray showers, and atmospheric radon. The background estimation algorithm described herein assumes that the effect on threat detection metrics from benign nuisance sources of radiation, such as medical isotopes, can be taken into account by the consuming anomaly detection or source localization module, using nuisance-rejection as described in [1].

2.0 Methodology

We anticipate that aerial surveys will be conducted at altitudes typically ranging from 150 ft. to 300 ft. At these altitudes, the gamma-ray background radiation induced by cosmic rays should be small compared to that from other sources, such as terrestrial radiation and radon. As a side note, the cosmic-induced gamma-ray energy spectrum is expected to have an approximately $E^{-1.3}$ energy dependence below a few MeV, where E is the gamma-ray energy [7].

Terrestrial radiation is generated from primordial radionuclides in the earth's crust. These radionuclides can be classified into three primary groups: 1) ^{40}K (K), 2) ^{235}U / ^{238}U and their progeny (U), and 3) ^{232}Th and its progeny (T). The radiation emitted from building materials, including the aircraft itself, is also likely to be mostly generated from these three primary radionuclide groups. The radon gamma-ray energy spectrum is structurally very similar to the U decay-series component, since its decay sequence contains ^{214}Pb and ^{214}Bi , which are the primary gamma-ray emitters of the U decay series radiation component [8]; although, the lower-energy photopeaks (e.g. 609 keV) are more pronounced in the radon contribution to the spectra, particularly at higher altitudes, due to its proximity to the aircraft relative to the ground surface [8].

1 As an intermediate step to estimate the background spectrum, the current algorithm estimates the
 2 K, U, and T soil concentrations, namely c_K (%), c_U (ppm), and c_T (ppm), respectively, using
 3 matrix equation (1), of the form $n_{3 \times 1} = S_{3 \times 3} c_{3 \times 1}$.

$$(1) \quad \begin{pmatrix} n_K \\ n_U \\ n_T \end{pmatrix} = \begin{pmatrix} S_{K,K} & S_{K,U} & S_{K,T} \\ S_{U,K} & S_{U,U} & S_{U,T} \\ S_{T,K} & S_{T,U} & S_{T,T} \end{pmatrix} \begin{pmatrix} c_K \\ c_U \\ c_T \end{pmatrix}$$

5 In this equation, the elements n_K , n_U , and n_T in vector n are the counts measured over channels
 6 corresponding to the gamma-ray energy windows defined in Table 1. These windows are
 7 recommended by the IAEA for airborne gamma-ray spectroscopy measurements taken with
 8 NaI(Tl) detectors [4]. The major contributing photopeaks to the standard K, U, and T windows
 9 are also shown in Table 1 and in Fig. 1. A description is provided in section 2.2 of how the
 10 NASVD algorithm is used, in real time, to obtain more accurate estimates of the true mean
 11 values of n_K , n_U , and n_T and thus c_K , c_U , and c_T . In equation (1), the sensitivity matrix S ,
 12 determined pre-flight, contains elements s_{ij} . These are the counts measured in energy window i
 13 from background component j , normalized by the concentration of j in the soil. In this work, S
 14 was determined using Monte Carlo radiation transport simulations, which are discussed in
 15 section 2.1.

16 Table 1. Standard windows for determining K, U, and T concentrations [4]. The major
 17 contributing photopeak to each window is shown.

Window	Nuclide	Energy Range (keV)
K	^{40}K (1460 keV)	1370 - 1570
U	^{214}Bi (1765 keV)	1660 - 1860
T	^{208}Tl (2614 keV)	2410 - 2810

18

19 In the current algorithm, since the primary objective is to simply estimate the background and
 20 not the actual K, U, and T concentrations in the soil, the cosmic and radon contributions to the
 21 background are not explicitly calculated. Rather, the MLE-based calibration procedure
 22 described later is relied upon to empirically fold these effects, as well as other extraneous effects,
 23 such as atmospheric conditions, into the background estimates.

24

2.1. Determination of Sensitivity Matrix

In this work, the sensitivity matrix S is determined as a function of altitude through the use of Monte Carlo radiation transport simulations. Simulations using MCNP5 [9] were performed with a model consisting of the helicopter above a $1 \times 1 \times 0.0015 \text{ km}^3$ volume of soil and with an air density of $1.199 \times 10^{-3} \text{ g/cm}^3$. The air was modeled with the following properties; a temperature of 20° C , a barometric pressure of 1013.25 mbar, and a relative humidity of 50%. The helicopter was modeled at altitudes ranging from 100 ft. to 900 ft. in 100 ft. increments. A surface source was placed on top of the soil consisting of gamma rays from the K, U, and T background components developed from a previous background modeling effort [7]. The individual K, U, and T components of the detector response were tallied separately in the simulations, and the Gaussian energy broadening feature was applied, as implemented in MCNP. The K, U, and T spectra are shown in Fig. 1, using log-scale on the dependent axis, and offset for clarity. These K, U, and T detector response components were then normalized by the respective K, U, and T concentrations modeled in the soil, namely 412 Bq of K per kg of soil (Bq/kg), 34 Bq/kg for U, and 45 Bq/kg for T. Converting these units from Bq/kg to per cent and parts per million [10], these concentrations translate to 1.32% K, 2.75 ppm U, and 11.1 ppm T. Matrix elements $s_{K,K}$, $s_{U,U}$, and $s_{T,T}$ of S are shown in Fig. 2 as a function of the helicopter altitude, as modeled in the simulation, above the homogenous soil volume. Exponential fits to these plots are also shown in Fig. 2. From the simulations, the off-diagonal elements of S also closely followed a decaying exponential trend with altitude. Therefore, in the current background estimation algorithm, each of the individual elements of S are stored as exponential functions of height, which is read in real-time from the aircraft's altimeter.

Fig. 1. Individual K, U, and T contributions to the response of the helicopter-mounted NaI(Tl) gamma-ray detectors, from the MCNP5 background simulations.

Fig. 2 Sensitivity matrix elements $s_{K,K}$, $s_{U,U}$, and $s_{T,T}$ as a function of altitude from the MCNP5 simulations.

In geological surveying applications of airborne spectroscopy, measurements to determine the sensitivity coefficients as a function of altitude (height) are typically taken over a test strip (calibration range). The test strip should have, among several other properties, accessibility to surface measurements and uniform concentrations of K, U, and T [4]. The attenuation coefficients for each window are determined by fitting an exponential curve to a plot of the stripped count rates (count rates from each component to its respective window) as a function of the equivalent height, H_e , of the aircraft at a standard temperature and pressure (STP) of 0° C and 1013.25 mbar, respectively. H_e is defined in equation (2) for measurements taken at an actual height of H , a temperature of T (°C), and a barometric pressure of P (mbar) [4].

$$(2) \quad H_e = H \times \frac{273.15}{T + 273.15} \times \frac{P}{1013.25}$$

In Table 2, attenuation coefficients, μ , determined in this manner from previously measured data are compared with the results obtained from the simulations in this work, adjusted to STP using (2). The linear attenuation coefficients for the K, U, and T windows for the simulations agree with data taken from previous measurements conducted by the IAEA [4] within 3%, 5%, and 2%, respectively.

Table 2. Linear attenuation coefficients calculated from exponential fits to the simulated results compared with previous measurements.

Window	μ from simulations in current work (m^{-1})	μ from previous measurements (m^{-1}) [4]
K	9.17×10^{-3}	9.45×10^{-3}
U	8.67×10^{-3}	8.28×10^{-3}
T	7.72×10^{-3}	7.83×10^{-3}

2.2. Determination of K, U, and T Concentrations

The K, U, and T concentrations (c_K , c_U , and c_T) are estimated in real time from the data taken during flight. It is very difficult to obtain even moderately precise estimates of the c_K , c_U , and c_T from raw (un-processed) one-second airborne spectra due to the significant inherent noise from poor counting statistics. Therefore, noise-adjusted singular value decomposition (NASVD) [11] was used in real time to smooth the measured one-second spectra to improve the c_K , c_U , and c_T estimates. For large airborne gamma-ray spectrometric surveys, the NASVD typically reduces the fractional errors in c_K , c_U , and c_T by 14%, 42%, and 37%, respectively, relative to extracting these concentrations directly from the raw spectra [12]. The NASVD is applied by scaling the measured, observed spectra so that they have unit variance in each of their channels, accomplished as follows [12]. Prior to the SVD operation, each of the observed spectra is divided, channel by channel, by the least-squares fit of the average spectrum to the respective observed spectrum. A matrix is formed from these scaled (noise-adjusted) spectra, and the SVD is applied to this matrix. The resulting principle components from the SVD are then multiplied, channel by channel, by the average spectrum to reverse the scaling. The noise-adjustment, in effect, flattens the observed spectra and thus reduces the variation that the principle components from the SVD operation must span.

To implement the NASVD in real time, a dynamic buffer of the past 15 one-second raw spectra, each containing 1024 channels, was stored in a 15×1024 matrix. At each second in flight, the most recently-measured spectrum was placed into this matrix along with the previously-measured 14 raw spectra. Traditionally [11-12], the resulting smoothed spectra are obtained from the NASVD by multiplying the unit PCs (eigenvectors) by the sum of the counts in each raw, respective spectrum prior to reconstruction. In this work, however, slightly, yet

consistently more accurate background estimates were obtained by forming a smoothed version, x , of the recently-measured raw spectrum according to equation (3). In (3), v_1 , v_2 , and v_3 are first three, lower-order principle components (PCs) obtained by applying the NASVD over the dynamic buffer matrix. Coefficients r , s , and t in (3) were determined by fitting x to the recently-measured raw spectrum using ordinary least squares (OLS).

$$(3) \quad x = rv_1 + sv_2 + tv_3$$

More robust fitting techniques and the use of greater than three PCs have been employed but have not appreciably improved the background estimates on the examined data sets.

The counts, n_K , n_U , and n_T are obtained from the K, U, and T energy windows in the NASVD-smoothed spectrum. Using S , matrix equation (1) is then solved for concentration vector c , containing c_K , c_U , and c_T . Results are shown in Table 3 for the average c_K , c_U , and c_T estimates using the current algorithm, at a nominal flying altitude of 100 ft., over a fairly homogenous region of the Government Wash 7.5-Minute Quadrangle near Las Vegas, Nevada. These results are compared to interpolated values over United States Geological Survey (USGS) Maps [13]. It should be noted that the USGS maps are fairly sparse in this region, but can serve as a rough estimate. The agreement is generally good between the estimated c_K , c_U , and c_T values. The larger discrepancy in the values for c_T is likely due to the low level of counts within the high-energy T window, for which the detection efficiency is lower.

Table 3. Comparison of c_K , c_U , and c_T estimates

concentrations	This work (100 ft.)	Interpolated USGS [13]
c_K (%)	0.57	0.51
c_U (ppm)	3.11	3.27
c_T (ppm)	3.09	2.56

2.3. MLE-Based Calibration

One method by which the background contribution in each channel of the measured spectrum could be estimated during flight is by determining the c_K , c_U , and c_T using the method described in section 2.2 and then using these concentrations to scale the K, U, and T spectra from the simulations. This method provided good estimates for higher regions of the background spectrum, but overshoot the actual background in the lower energy regions, less than approximately 80 keV. A graph comparing the 30 min. average spectrum measured over the homogeneous region of Government Wash is compared with the MCNP-simulated spectrum in Fig. 3. The simulated spectrum has been scaled to the K, U, and T concentrations estimated in this work, listed in Table 3, for this geographical area. The discrepancy between the measured and simulated spectra is likely a result of the detector electronics effects below approximately 40 keV (measurements using NaI often set the lower discriminator close to 40 keV) and lack of sufficient detail in the model, such as attenuating materials, up to 80 keV. Over-estimations of the K, U, and T concentrations made these low-energy discrepancies more apparent. Also, due to the assumptions made in the MCNP5 simulations, estimating the background in this way would likely require cosmic and radon corrections, particularly at the higher search altitudes.

Fig. 3 Comparison between measured and MCNP-simulated spectra over the homogenous region of Government Wash.

A Poisson regression technique was developed to produce a set of basis vectors using spectra measured during previous flights. This technique is based on the assumption that the counts in each channel of the background spectrum are Poisson-distributed and can be modeled as a linear combination of the individual K, U, and T spectra as in (4). In (4), y_i is simply the estimate, produced by the Poisson regression technique, of the background portion of counts in the i -th channel of a spectrum.

$$(4) \quad y_i = a_i c_K + b_i c_U + c_i c_T$$

In (4), a_i , b_i , and c_i are unknown scaling coefficients corresponding to the i -th channel and are determined through optimization by the Poisson regression. Using this mathematical model, a method based on maximum-likelihood estimation (MLE) can be applied to a calibration set of data taken over a previous flight, ideally under similar conditions. This is described mathematically by (5).

$$f_i = \sum_{j=1}^N (y_{i,j} - Y_{i,j} \log y_{i,j}) \quad (5)$$

In (5), the subscript j is added to show that $y_{i,j}$, and thus constants a_i , b_i , and c_i through relation (4), are optimized over N calibration spectra, each denoted by j . The term $Y_{i,j}$ is the actual, observed number of counts in calibration spectrum j , and f_i is the so-called objective function for channel i . This objective function is found by taking the negative-log of the Poisson distribution function in parameter $Y_{i,j}$ with assumed distribution mean $y_{i,j}$. This objective function, f_i , is then minimized by finding the optimum values of $y_{i,j}$, and thus parameters a_i , b_i , and c_i . It is noted that minimizing the negative-log likelihood is equivalent to maximizing the log-likelihood. In implementing this approach, the Newton-Raphson method was used, and OLS was used to generate an initial estimate for this iterative procedure. An MLE calibration using 1000 spectra, obtained from slightly less than 17 minutes of flight time, was found to be sufficient and required less than three seconds to perform using MATLAB [14] on a desktop computer having a 2.3 GHz processor. Therefore, more sophisticated quasi-Newton algorithms, although more efficient than the Newton-Raphson method, were not investigated to minimize (5).

The result of this MLE-based calibration procedure is a 1024×3 scaling matrix containing the a_i , b_i , and c_i 's for each of the 1024 channels in the spectrum. This method was used to produce scaling matrices at 100 ft., 200 ft., and 400 ft. flight altitudes over the heterogeneous region of Government Wash. During background estimation, linear interpolation over flight altitude, read from the altimeter, was used to calculate the scaling matrix. To estimate the background, as each raw spectrum is measured during flight, this matrix can be multiplied by the vector c containing c_K , c_U , and c_T determined using the method described in section 2.2. It should be noted that this

matrix is also altitude-dependent, for which the b_i 's, which can also be viewed as the empirically-determined U basis vector, is shown in Fig. 4.

Fig. 4 The U basis vector, determined using the MLE-based calibration procedure, as a function of flight altitude.

3.0 Results

Results are shown in Fig. 5, for which a ^{60}Co source was placed in the homogenous region of Government Wash using scaling matrices calculated by performing the MLE-based calibration method described in section 2.3. The nominal flying altitude was 100 ft. The spectrum labelled ^{60}Co and the estimated background spectrum are for a one-second snapshot during the flight at which the ^{60}Co source generated the largest number of counts in the gamma-ray detectors. This number was slightly over twice the gross count rate of the average background, which is also shown in Fig. 5. This average background was taken over the same homogenous region during a previous flight with no source present other than background and therefore is considered ground truth for this scenario. These results are encouraging in that the current algorithm produced a smoothed, accurate estimate of the background and was not noticeably affected by the strong,

1 fairly high-energy ^{60}Co source. In the observed one-second spectrum, the counts within the K,
2 U, and T energy regions, listed in Table 1, were 224, 44, and 21, respectively.

3
4 Fig. 5 Background spectrum estimate over a homogenous region of Government Wash with ^{60}Co
5 source present.

6 The three PCs from the NASVD, which were used to fit the one-second ^{60}Co spectrum shown in
7 Fig. 5, are given in Fig. 6 as a function of energy. In the Fig. 6 inset, the first two PCs are given
8 between 1400 keV and 2800 keV to illustrate the primary photopeaks, listed in Table 1, in each
9 of the background components. The third PC consisted entirely of noise at these high energies
10 and is therefore, for the purpose of clarity, not shown in the Fig. 6 inset. With (3), a linear
11 combination of these three PCs was used to fit, and to the extent possible, project unwanted noise
12 out of the one-second ^{60}Co spectrum in order to reduce the uncertainty of the total counts within
13 the K, U, and T energy windows. Equation (1) was then used to determine the K, U, and T
14 concentrations from the counts within these three windows in the spectral fit. The three basis
15 vectors, determined from the MLE calibration procedure described in section 2.3, were then

- 1 scaled by these calculated K, U, and T concentrations to generate the final background estimate
2 shown in Fig. 5.

3
4 Fig. 6 The three PCs from NASVD used to fit the one-second ^{60}Co spectrum shown in Fig. 5.
5

6 The same calibration data over the complex, heterogeneous region of Government Wash was
7 used to estimate the background during a ~2 hour flight over an urban area containing both
8 Oakland, CA and Berkeley, CA. The flight was conducted at an altitude of 300 ft. The results
9 are shown in Fig. 7 for the worst (largest) and typical (median) chi-square fit to the
10 corresponding measured, one-second spectra. The worst-fit spectrum was taken over the San
11 Francisco Bay and had a count rate approximately 10 times lower than the spectrum with the
12 typical fit. This spectrum has been divided by a factor of 10 in Fig. 7 for clarity. No ground
13 truth background estimates were available for these background estimates; although, the results
14 are quite encouraging in that estimates agree fairly well with the low-energy regions of the

1 measured spectra using calibration data over a very different region. In MATLAB, a single
2 background estimate required an average of 0.0267 seconds on a computer with a 2.3 GHz
3 processor.

4
5 Fig. 7 Background estimates at 300 ft. altitude over an urban area containing both Berkeley, CA
6 and Oakland, CA.

7
8 One of the more challenging data sets that was investigated was one for which the helicopter
9 flew several times over a land-water interface. The background count rate changes significantly
10 when traversing over this interface, since the background measured over water is almost entirely
11 from radon and cosmic components. These results are shown in terms of gross counts for
12 representative paths of land to water in Fig. 8 and in Fig. 9 for water to land flight paths. As
13 shown, when flying from land to water, there is an approximately 15-second lag in the algorithm.
14 The discrepancy was not as great when flying from water to land, but the reason for this is
15 unknown. A smaller dynamic buffer of 10 rather than 15 spectra was applied, but did not appear

to significantly improve the agreement between the estimated and measured background, as illustrated in Fig. 8 and in Fig. 9.

Fig. 8 Estimated vs. measured count rate for flight path from land to water at an altitude of 100 ft.

Fig. 9 Estimated vs. measured gross count rate for flight path from water to land at an altitude of 100 ft.

A simulated scenario was also investigated, in which a step change of c_K and c_T were inserted into the simulation. The purpose of this exercise was to determine how well the dynamic buffer

with NASVD could adjust to large and abrupt changes in background. The K, U, and T empirical basis vectors from the homogenous region of Government Wash were extracted from the actual flight spectra, measured at an altitude of 100 ft, using the MLE method described in section 2.2. The scenario was developed by scaling these basis vectors by the calculated c_K , c_U , and c_T values shown in Table 3, until the step change. At a point precisely in the middle of the flight, c_K was multiplied by 10, c_T was divided by 10, and c_U was left unchanged. Poisson noise was added to simulate the noise in the spectra. This may represent a somewhat unrealistic scenario for which the ^{40}K and ^{232}Th background components suddenly change beneath the helicopter. The results are shown in Fig. 10, which illustrates the spectrum that the helicopter would theoretically measure immediately prior to the step change, the actual background at the instant of the step change, and the estimated background signature. As one may expect, the estimated background significantly underestimates the ^{40}K peak; although, the background estimate is much closer in agreement at the lower energies of interest for radiological search. The same calibration matrix from the Government Wash complex region was used for this scenario to calculate the background estimates.

Fig. 10. Results of a simulated scenario for which a large step change in c_K and c_T were inserted into the simulated background.

4.0 Conclusions

A new technique for real-time estimation of background gamma radiation from aerial measurements for radiological search has been developed using a combination of Monte Carlo calculations, NASVD, and MLE for calibration. It has been demonstrated to be accurate and robust against contamination even in the presence of a strong ^{60}Co source. The algorithm produced accurate background estimates for rural and urban environments using calibration data from a flight over a very different area. Results from a simulated scenario indicate that the algorithm has good potential to track large and abrupt changes in background spectral shape and magnitude. In MATLAB the average time to produce a background estimate was 0.0267 seconds on a computer with a 2.3 GHz processor. The algorithm can be implemented fairly

easily using the built-in mathematical libraries and functions available in most modern computing languages and environments.

Several concepts can be explored to improve the accuracy of the background estimations. For example, the sensitivity matrix used for extracting c_K , c_U , and c_T from the measured spectra in this work was determined using Monte Carlo simulations, with the helicopter modeled parallel to the soil. Currently, simulations are being performed to take into account several angular orientations of the helicopter. Incorporating the results of these simulations to determine the sensitivity matrix may improve the background estimates, for instance, when the helicopter is turning during flight, which would likely skew the measured background spectra toward lower energies. Incorporation of radon and cosmic effects may also potentially improve the validity of (3) and thus the background estimates. Good detector gain stabilization is required for this algorithm, since it relies heavily on calibrated data. Also, since the Gaussian energy broadening feature as implemented in MCNP was used in this work to determine S , the resolution of the detection system must be known prior to and remain fairly constant across the calibration and survey flights.

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6.0 References

- [1] D. M. Pfund, R. C. Runkle, K. K. Anderson, and K. D. Jarman, "Examination of Count-Starved Gamma Spectra Using the Method of Spectral Comparison Ratios," *IEEE Trans. Nucl. Sci.*, vol. 54, no. 4, pp. 1232-1238, Aug. 2007.
- [2] K. D. Jarman, E. A. Miller, R. S. Wittman, and C. J. Gesh, "Bayesian Radiation Source Localization." *Nucl. Technol.*, vol. 175, No. 1, pp. 126-334, 2011.
- [3] M. Alamaniotis, J. Mattingly, and L. H. Tsoukalas, "Kernel-Based Machine Learning for Background Estimation of NaI Low-Count Gamma-Ray Spectra," *IEEE Trans. Nucl. Sci.*, vol. 60, No. 3, pp. 2209-2221, 2013.
- [4] "Airborne Gamma-Ray Spectrometer Surveying," International Atomic Energy Agency, Technical Report Series, No. 232, 1991.
- [5] H. K. Aage and U. Korsbech, "Search for Orphan Radioactive Sources Based on NaI Gamma Spectrometry," *Appl. Radiat. and Isot.*, vol. 58, pp. 103-113, 2003.
- [6] H. K. Aage, et al, "Experiences with Area Specific Spectrum Stripping of NaI(Tl) Gamma Spectra," *Radiat. Prot. Dosim.*, vol. 121, No. 2, pp. 108-121, 2006.
- [7] G. A. Sandness, J. E. Schweppe, W. K. Hensley, J. D. Borgardt, and A. L. Mitchell, "Accurate Modeling of the Terrestrial Gamma-Ray Background for Homeland Security Applications," *IEEE Nucl. Sci. Conf. R. (NSS/MIC)*, vol. N06-5, pp. 126-133, 2009.
- [8] B. R. S. Minty, "Multichannel Models for the Estimation of Radon Background in Airborne Gamma-Ray Spectrometry," *Geophysics*, vol. 63, No. 6, pp. 1986-1996, 1998.

- 1 [9] MCNP X-5 Monte Carlo Team, "MCNP – A General Purpose Monte Carlo N-Particle
2 Transport Code, Version 5," LA-UR-03-1987, Los Alamos National Laboratory, Los Alamos,
3 NM, 2003.
- 4 [10] IAEA, "Construction and Use of Calibration Facilities for Radiometric Field Equipment,"
5 Technical Report 309, Vienna: International Atomic Energy Agency, 1989.
- 6 [11] J. Hovgaard, 1997. "A New Processing Technique for Airborne Gamma-Ray
7 Spectrometer Data (Noise Adjusted Singular Value Decomposition)," *Am. Nucl. Soc. Sixth*
8 *Topical Meeting on Emergency Preparedness and Response*, pp. 123-127, San Francisco, April
9 22-25, 1997.
- 10 [12] B. Minty and P. McFadden, "Improved NASVD Smoothing of Airborne Gamma-Ray
11 Spectra," *Explor. Geophys.*, vol. 29, pp. 516-523, 1998.
- 12 [13] J. S. Duval, J.M. Carson, P.B. Holman, and A.G. Darnley, "Terrestrial Radioactivity and
13 Gamma-Ray Exposure in the United States and Canada." U.S. Geological Survey, Washington,
14 D.C, 2005, Revised 2009.
- 15 [14] MATLAB version 7.14.0.739. Natick, Massachusetts: The MathWorks Inc., 2012.