Anomaly Detection in Gamma-ray Radiation Spectra using Artificial Neural Network and Ant Colony Optimization

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Abstract

Detection of threatening radioactive sources is a crucial task for homeland security. One of the major challenges in radiation detection is to distinguish between the background radiation and the anomalous source radiation from the measured radiation spectrum at low source to background ratio. In this paper, an anomaly detection technique is proposed to detect anomalous Gamma-ray radiation spectra using machine learning. The method is based on dividing the radiation spectrum into two sub-spectra, where the background part of the second sub-spectrum is predicted from the first sub-spectrum through a neural network model. Hence, an anomaly spectrum is detected according to the difference between the predicted background radiation data and the measured values of the second sub-spectrum. The ant colony optimization is utilized to select, from the radiation spectrum, the values assigned to the first and second sub-spectra, where optimum prediction accuracy can be provided. To present the effectiveness of the proposed work, a performance comparison is conducted with both benchmark and a recent neural network-based method. The performance is evaluated using real data that represent both background and radioactive source radiation, which are measured through a network of detectors. Experimental results show that the proposed method outperforms the other methods in terms of the detection capability even at low source to background radiation ratios.

Full Text

Preamble

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Abstract: Detection of threatening radioactive sources is a crucial task for homeland security. One of the major challenges in radiation detection is distinguishing between background radiation and anomalous source radiation from the measured spectrum at low source-to-background ratios. This paper proposes an anomaly detection technique for gamma-ray radiation spectra using machine learning. The method divides the radiation spectrum into two sub-spectra, where the background component of the second sub-spectrum is predicted from the first sub-spectrum via a neural network model. An anomaly is detected based on the difference between the predicted background radiation data and the measured values of the second sub-spectrum. Ant colony optimization is utilized to select the spectral bins assigned to the first and second sub-spectra to achieve optimum prediction accuracy.

To demonstrate the effectiveness of the proposed approach, a performance comparison is conducted against both benchmark and recent neural network-based methods. The evaluation uses real data representing both background and radioactive source radiation, measured through a network of detectors. Experimental results show that the proposed method outperforms other methods in detection capability, even at low source-to-background radiation ratios.

Keywords: Anomaly detection; Machine learning; Neural Network; Ant colony optimization; Gamma-ray radiation spectrum.

Introduction

Radioactive sources are widely used for industrial, medical, agricultural, and research purposes. However, due to the dangerous effects of radiation on public safety, lost or stolen sources pose a major threat. Numerous radiation source incidents have occurred worldwide, as recorded by the International Atomic Energy Agency (IAEA) [1]. Consequently, radiation anomaly detection is a critical task for homeland security, enabling the identification of anomalous nuclear sources based on data from radiation detectors.

Anomaly detection is generally employed to identify observation instances that deviate from normal background radiation. In radiation detection, normal data represent typical background radiation, while anomaly data represent additional source radiation superimposed on the background. Detecting anomalous sources at low source-to-background ratios has always been challenging, as the anomalous source radiation is weak compared to the background.

Significant research efforts have been devoted to developing detection algorithms that enhance accuracy. Many radiation anomaly detection methods have been proposed in the literature. In [2], a detection algorithm based on energy windowing was presented, where the ratio between radiation data at low and high energies was used to discriminate between background and anomalous radiation. Various energy windowing methods were implemented in [3] to study their performance for radiation portal monitoring employed at international border crossings. Energy windowing methods are primarily designed for detecting radioactive materials with large count rates, which are considered threatening sources. However, at low source-to-background ratios, energy windowing techniques do not provide effective detection capability.

In [4,5], the spectral comparison ratios (SCR) method was studied, where ratios between the data of the first radiation spectral bin and those of other bins are used for anomaly detection. The method compares the count ratios of given radiation data with background data predicted using a Kalman filter at the time of detection. Certain radiation sources are considered by injecting simulated values into background data. Results showed that the SCR method can achieve good detection sensitivity for targeted sources, though this sensitivity comes at the cost of generality.

One commonly used approach for radiation anomaly detection is principal component analysis (PCA) [6-9]. PCA is typically applied for dimensionality reduction by projecting data onto a lower-dimensional space. In [6], an analysis investigated each principal component as an anomaly score for two radiation sources, showing that the first few principal components provide better anomaly scores than others. Another method in [9] detected anomalous data by evaluating the Mahalanobis distance between the principal components of given radiation data and those of normal observations. The classification performance of this method depends dramatically on the radiation source data.

To further improve anomaly detection performance, machine learning models are employed. Generally, machine learning-based anomaly detection techniques can be categorized as supervised, unsupervised, or semi-supervised, depending on the availability of training data labels. For radiation anomaly detection, semi-supervised learning is usually applied, where only labeled normal data instances are available for training. However, most recent radiation anomaly detection methods are based on neural networks [10-18] due to their significant classification performance, which requires supervised learning using labeled data. Consequently, neural network-based methods are typically employed for detecting and identifying specific radiation sources.

In [17], a multiphase neural network was trained, where each phase divides input data according to a given metric until high-accuracy classification is achieved in the final phase. In [18], fully-connected and convolutional neural network models were combined for radiation source detection. Feature values such as peak ratios, discrete cosine transform coefficients, and spectrum counts were extracted from radiation data for classification by the hybrid model. This method outperforms other neural network-based methods in detection accuracy, though training the hybrid model is more time-consuming than other neural network models.

Practically, designing a generic radiation anomaly detection method is carried out using only background radiation data, enabling detection of any anomalous source. Conventional neural network-based methods may not be suitable for non-specific anomalous radiation source detection. Recently, autoencoders —neural network structures typically used for compression or dimensionality reduction—have been employed to detect any anomalous radiation data. In [14], an autoencoder was trained using only background data to detect anomalous radiation based on the reconstruction error between the output and input of the autoencoder.

To the best of our knowledge, most recent methods can be categorized as classifier-based detection techniques, requiring supervised learning using anomalous measurements from specific sources. According to literature studies, classifier-based detection methods can achieve high classification accuracy. However, these methods have several general disadvantages. Practically, anomaly data samples are not commonly available for training classifier models. Additionally, after training, the detector cannot be tuned to adjust detection sensitivity to account for environmental changes that may impact the false alarm rate. Furthermore, receiver operating characteristics (ROC) cannot be computed for performance evaluation, which is a significant metric for visualizing tradeoffs between true alarm and false alarm rates [13].

In this work, a threshold-based radiation anomaly detection method is proposed using a neural network as a regression model to achieve high accuracy, where only background data are used for training. Anomaly detection is performed according to a numerical anomaly score value and a user-defined threshold, enabling easy adjustment of detection sensitivity by modifying the threshold value. The contributions of this work are summarized as follows:

1. Employing a neural network regression model to detect anomalies in radiation data using only normal data for model training.
2. Implementing a method for simulating anomalous data from normal data to consider different anomalies in model training.
3. Applying ant colony optimization to select the best parameter values for the proposed method.
4. Designing a fitness function for the optimization process that provides optimum detection performance.
5. Using real (normal and anomalous) radiation data, measured by a network of detectors, to evaluate the proposed method using receiver operating characteristics curves.

The rest of the paper is organized as follows: Section 2 provides a brief introduction to ant colony optimization. Section 3 explains the proposed work. Experimental results are illustrated in Section 4. Finally, Section 5 concludes the work.

2 Ant Colony Optimization

Ant Colony Optimization (ACO) is primarily used for solving discrete optimization problems. First presented by Colorni et al. [19], it simulates ant behavior in selecting the shortest path to a food source. Initially, ants explore different paths randomly, depositing a substance called pheromone on their path to the food source. When more ants traverse the same path, the pheromone concentration on that path increases. Typically, the path with the highest pheromone concentration represents the shortest path to the food source, so ants select paths with the highest pheromone concentration to reach the food source quickly.

For any meta-heuristic optimization method such as ACO, a solution space (S) and a fitness function (F) must be defined. The optimization algorithm then finds the solution S_{opt} that optimizes (maximizes or minimizes) the fitness function F. The objective of a discrete optimization problem is to select the best decision value for each of the D considered variables, where D is the dimension of the solution space. In ACO, the solution space represents the area between the nest and food source, divided into regions representing solution variables. For each region, a limited number of paths represent the corresponding decision values. Fig. 1 [Figure 1: see original paper] shows an example of a 4-dimensional solution space S = [s1, s2, s3, s4], where variables s1, s2, s3, and s4 have 6, 4, 5, and 3 decision values, respectively. The path selected by the kth ant represents the kth solution S_k = [s14, s22, s31, s42] as shown in Fig. 1.

ACO is a population-based optimization method that operates iteratively, exploring a number of solutions per iteration. Fig. 2 [Figure 2: see original paper] shows the procedure for selecting the optimum solution using ACO optimization. The parameters to be defined are the number of solutions explored per iteration, initial pheromone concentration, and number of iterations N_{itr}. Initially, all solutions are assigned the same initial pheromone level. Then a set of solutions is selected randomly, and the fitness function evaluates each solution' s fitness value. Based on the fitness value, pheromone concentration for each explored solution (path) is updated [20], with higher pheromone concentration assigned to better solutions. A new set of solutions is selected for exploration based on the updated pheromone concentration levels. This process repeats for N_{itr} iterations. Finally, the solution with the best fitness value is selected as the optimum solution. More details about the ACO algorithm can be found in [19-23].

3.1 Neural Network-based Radiation Anomaly Detection

This subsection describes the proposed radiation anomaly detection method in detail. The method is based on the relationship between counts in the detected radiation spectrum RS, represented as follows:

$$RS = [C_1, C_2, \cdots, C_{N_b}]$$

where C_i is the radiation count measured at the ith spectral bin, and N_b is the total number of bins. The given radiation spectrum RS is divided into two sub-spectra denoted RS1 and RS2. In the proposed work, Set1 and Set2 represent two sets containing the bin numbers of spectrum RS from which the count values of RS1 and RS2 are selected, respectively:

$$RS1 = [R_{Set1[1]}, R_{Set1[2]}, \cdots, R_{Set1[N1]}]$$
$$RS2 = [R_{Set2[1]}, R_{Set2[2]}, \cdots, R_{Set2[N2]}]$$

where N1 and N2 are the total number of spectral bins selected for RS1 and RS2, respectively. A neural network model predicts the background counts of RS2 from the counts of RS1. Anomaly detection is performed according to the difference between measured RS2 and predicted background counts. Note that RS1 and RS2 can be represented as the summation of background and anomaly source counts:

$$RS1 = B_{RS1} + S_{RS1}$$
$$RS2 = B_{RS2} + S_{RS2}$$

where B_{RS1} and B_{RS2} are vectors of count values representing background radiation from the respective RS1 and RS2 sub-spectra, while S_{RS1} and S_{RS2} are vectors representing anomaly source radiation from RS1 and RS2 sub-spectra. For a background radiation spectrum, the count values of S_{RS1} and S_{RS2} should equal zero. Hence, for anomaly spectra, the difference between measured RS2 and predicted B_{RS2} is expected to be larger than for background spectra.

The neural network model is trained using background spectra, so the model' s output B_{RS2} equals RS2. A feature vector represents the model' s input, including sub-spectrum RS1. To provide effective prediction, the average count value of the radiation spectrum is used as a feature along with RS1 counts:

$$fv = [C_{avg}, r_1, r_2, \cdots, r_{N1}]$$

where C_{avg} is the average count value of the given RS spectrum, and r_i is the ith count value of the RS1 sub-spectrum. Fig. 3 [Figure 3: see original paper] shows the feature extraction process, where the feature vector is calculated from the given radiation spectrum.

To consider both normal and anomaly spectra in model training, a function generates simulated anomaly data from background spectra. Algorithm 1 shows the pseudo-code for generating an anomaly spectrum from a given normal spectrum. The algorithm modifies only the RS1 sub-spectrum of the given RS spectrum, so Set1 must be provided to the function. Two conditions are applied to generate realistic anomaly data: (1) anomaly counts must exceed background counts (values can only increase), and (2) not all bin values are modified simultaneously because each radiation source affects count values at specific energy levels. Therefore, N_p counts are selected for modification, where N_p is calculated using the rand_{int}(.,.) function that generates a random integer between given minimum and maximum values. As shown in Algorithm 1, the minimum and maximum values of N_p are 2 and N1/2, respectively. Moreover, the indices of the N_p count values are selected randomly from the range [1:N1] using the function Random_{selection}(N1, N_p).

In this work, N_D background radiation spectra represent the normal dataset, divided into N_{tr} and N_{ts} spectra for training and testing, respectively. Fig. 4 [Figure 4: see original paper] presents the training procedure for the NN model using the N_{tr} background radiation spectra. The N_{tr} spectra are divided equally into two groups: Group 1 and Group 2. As shown in Fig. 4, Group 1 spectra are used to generate anomaly data through the generate_{anomaly} function. From each spectrum, the feature vector is calculated and the sub-spectrum RS2 is selected. The neural network model is trained to predict sub-spectrum RS2 from the feature vector fv of the given spectrum RS.

After training, the proposed radiation anomaly detection is applied according to the block diagram in Fig. 5 [Figure 5: see original paper]. The sub-spectrum S_{RS2} corresponding to the anomaly source is calculated from RS2 and predicted B_{RS2} as:

$$S_{RS2} = RS2 - B_{RS2}$$

Based on the count values of S_{RS2}, spectrum RS can be classified as background or anomaly. For a background spectrum, counts calculated for S_{RS2} should equal zero. However, calculated counts may exceed zero due to neural network prediction error. Therefore, for a given normal/anomaly radiation spectrum, classification is performed based on the Mahalanobis distance between S_{RS2} and the prediction error. First, error is calculated for each radiation spectrum in the training background set to provide an error matrix E of size N2 $\times$ N_{tr}:

$$E = [e_1, e_2, \cdots, e_{N_{tr}}]$$

where e_i is the error vector of length N2 between sub-spectrum RS2 and predicted B_{RS2} corresponding to the ith background radiation spectrum. Then, for a given spectrum, the Mahalanobis distance is calculated between the corresponding sub-spectrum S_{RS2} and error matrix E as:

$$d_M = \sqrt{S_{RS2}^T \cdot \Sigma^{-1} \cdot S_{RS2}}$$

where d_M is the Mahalanobis distance and Σ is the N2 × N2 covariance matrix calculated from the error vector matrix E. Finally, anomaly detection is performed by comparing the calculated Mahalanobis distance d_M with a user-defined detection threshold thrd, as shown in Fig. 5.

3.2 Parameter Optimization

In the proposed method, selection of spectral bins for Set1 and Set2 affects detection performance. Therefore, an optimization process is carried out before applying the anomaly detection method to provide optimum selection according to detection accuracy. The ACO technique performs the required optimization. First, a fitness function is designed to represent performance as a function of the two sets (Set1 and Set2). Then, ACO selects the optimum sets that maximize the fitness function.

For this optimization problem, the solution space includes all feasible sets for Set1 and Set2. Spectral bin numbers in Set1 and Set2 are selected from the N_b bins of the given radiation spectrum, where bin numbers included in Set1 are not included in Set2. Accordingly, bin numbers assigned to Set1 and Set2 can be calculated from a vector V_b of N_b binary values:

$$V_b = [b_1, b_2, \cdots, b_{N_b}]$$

The binary value of b_i indicates assignment of the ith spectral bin number to either Set1 or Set2 according to:

$$Set1 = \{i | b_i = 1\}$$
$$Set2 = \{i | b_i = 0\}$$

To search for optimum values of vector V_b, the solution space must include all feasible combinations, which may be huge for large N_b, decreasing optimization convergence rate. Since meta-heuristic optimization techniques are designed for multi-dimensional solution spaces, vector V_b is divided into D sub-vectors of length L bits. Each sub-vector is converted to a decimal value to provide a D-dimensional vector X:

$$X = [x_1, x_2, \cdots, x_D]$$

where x_i is the ith decimal value calculated from V_b according to:

$$x_i = \text{Bin2Dec}(V_b[(i-1)L + 1 : iL])$$

where Bin2Dec(.) converts a list of binary bits to the corresponding decimal value. The number of bits L equals N_b/D. The solution space is defined by range [X_{min}, X_{max}] such that:

$$X_{min} = [1, 1, \cdots, 1]$$
$$X_{max} = [2^L - 2, 2^L - 2, \cdots, 2^L - 2]$$

The minimum and maximum values of x_i are 1 and 2^L - 2, ensuring only the least significant bit of corresponding binary values equals 1 and 0, respectively, as shown in Fig. 6 [Figure 6: see original paper]. Thus, the minimum number of bins assigned to either Set1 or Set2 from each sub-vector of V_b equals 1.

Evaluation of each selected solution X is performed through a fitness function. Fig. 7 [Figure 7: see original paper] shows the procedure of the designed fitness function. First, Set1 and Set2 are calculated from solution vector X via a mapping function that converts X to the corresponding binary vector V_b. Then, Set1 and Set2 are calculated from V_b according to (10). Since the proposed work predicts background sub-spectrum B_{RS2} from either normal or anomaly RS spectra using a neural network model, the fitness function evaluates detection performance in terms of prediction accuracy for given Set1 and Set2. As shown in Fig. 7, data pairs (fv, B_{RS2}) calculated from given spectra are divided into training and testing groups for the neural network model:

$$M_{tr} + M_{ts} = N_{tr}$$

where M_{tr} and M_{ts} are the numbers of data used for training and testing, respectively. The fitness value evaluates solution X according to model prediction accuracy:

$$f_{fitness} = \frac{1}{e_p}$$

where e_p is the prediction error represented by the average Euclidean distance between predicted and actual B_{RS2} over all M_{ts} testing data. After the optimization process selects the optimum solution, the corresponding Set1 and Set2 are calculated.

4 Experimental Results

This section evaluates and compares the performance of the proposed method with other radiation anomaly detection methods. Performance is calculated using radiation spectra measured at the Savannah River National Laboratory's Low Scatter Irradiator (LSI) facility [24]. Measurements were performed by 18 stationary radiation detectors deployed at different locations in an 8 m $\times$ 8 m room. Each detector measures count rates at 21 energy bands covering the range from 42 keV to 2776 keV. Normal (background) data were collected by measuring radiation spectra in the room without radioactive sources, as shown in Fig. 8 [Figure 8: see original paper]. Anomaly radiation spectra were measured from Cesium-137 and Cobalt-57 sources to provide three anomaly datasets: DS1, DS2, and DS3. Fig. 9 [Figure 9: see original paper] shows the layout of radiation detectors and sources inside the room for collecting spectra in the three anomaly datasets. The number of radiation spectra measured by each detector in each anomaly dataset is denoted by N_A. Table 1 presents the parameter values used for generating datasets and implementing the proposed method, selected experimentally.

Detection accuracy depends on the source-to-background ratio (SBR) [11]. In this work, SBR is calculated for each detector as:

$$SBR_l = \epsilon \cdot \frac{MGC_l - MGC_{BG}}{MGC_{BG}}$$

where SBR_l is the source-to-background ratio for the lth detector, is a scaling factor, MGC_{BG} is the mean gross count of training background radiation spectra, and MGC_l is the mean gross count of radiation spectra measured by the lth detector. The gross count is the summation of all count values in the radiation spectrum. MGC_{BG} and MGC_l are calculated as:

$$MGC_{BG} = \frac{1}{N_{tr}} \sum_{i=1}^{N_{tr}} GC_{BG}[i]$$

$$MGC_l = \frac{1}{N_A} \sum_{j=1}^{N_A} GC_l[j]$$

where GC_{BG}[i] and GC_l[j] are gross count values of the ith and jth spectra from background radiation and radiation detected by the lth detector, respectively. Fig. 10 [Figure 10: see original paper] presents SBR values for some detectors, with scaling factor set to 10. As shown, SBR decreases as the distance between the radiation source and detector increases. Detector readings with very low SBR values represent only background radiation. Therefore, only spectra measured by detectors with SBR values exceeding a defined threshold thr_{SBR} are considered anomaly spectra. The SBR value and threshold thr_{SBR} represent ground truth for anomaly data. The threshold thr_{SBR} is calculated based on observation of radiation spectra at different SBR values. Fig. 11 [Figure 11: see original paper] shows the average background spectrum and four average spectra measured at different SBR values. Radiation detected at SBR = 0.49 can be considered background radiation. Performance comparison is conducted at four SBR thresholds: 0.5, 0.7, 0.9, and 1.

Detection technique performance is typically evaluated using detection rate. However, in most anomaly detection problems, normal data quantity exceeds anomaly data quantity, as noted in Table 1. Thus, detection rate does not provide an accurate metric due to dataset imbalance. This work provides accurate performance measurement through true positive rate (TPR), false positive rate (FPR), and detection precision, defined as:

$$TPR = \frac{TP}{TP + FN}$$

$$FPR = \frac{FP}{FP + TN}$$

$$Precision = \frac{TP}{TP + FP}$$

where TP is true positives (anomaly data correctly detected), FP is false positives (normal data incorrectly detected as anomaly), FN is false negatives, and TN is true negatives. TP is evaluated using anomaly spectra, while FP is evaluated using testing background radiation spectra. Total normal and anomaly data quantities equal N_{ts} and N_A, respectively.

To adequately illustrate detection performance, receiver operating characteristics (ROC) curves are presented, calculating TPR and FPR for different detection thresholds th_{r_i}. First, anomaly scores are calculated for all training background radiation spectra. For the proposed method, the anomaly score is the Mahalanobis distance d_M. Then, detection threshold th_{r_i} is calculated as:

$$th_{r_i} = \mu_d + k_i \cdot \sigma_d$$

where _d and σ_d are the mean and standard deviation of anomaly score values for background spectra, and k_i is the ith value from a user-defined range. The threshold providing the best detection performance is selected as:

$$th_{rd} = \arg\max_i (TPR_i - FPR_i)$$

where TPR_i and FPR_i are calculated for the ith threshold th_{r_i}.

Performance comparison is conducted between the proposed method and three anomaly detection techniques from [4,14,25]: PCARAD (Principal Component Analysis-based Radiation Anomaly Detection) [25], SCRRAD (Spectral Comparison Ratio-based Radiation Anomaly Detection) [4], and ARAD (Autoencoder-based Radiation Anomaly Detection) [14]. Performance is evaluated using data from each detector with SBR exceeding thr_{SBR}, with final performance presented by averaging calculated performance across all selected detectors.

Figs. 12, 13, and 14 [FIGURE:12-14] show ROC curves for the proposed method (NNRAD—Neural Network-based Radiation Anomaly Detection) and methods from [4,14,25,26] for datasets DS1, DS2, and DS3, respectively. TPR and FPR decrease as detection threshold th_{rd} increases, and vice versa. At the same FPR values, methods providing higher TPR are considered superior in detection capability. Results show the proposed method provides better detection than other methods at all considered thr_{SBR} values. For thr_{SBR} = 1, the proposed method and methods from [4,14] show almost identical performance. For smaller thr_{SBR} values, detection capability becomes more challenging, with different methods achieving varying accuracy.

Precision is calculated using detection threshold th_{rd} selected according to (22). Tables 2-5 [TABLE:2-5] compare the proposed method with methods from [4,14,25] in terms of precision for thr_{SBR} = 0.5, 0.7, 0.9, and 1, respectively. Results demonstrate the proposed method outperforms others in detection precision, even at low source-to-background ratios (small thr_{SBR} values).

5 Conclusion

This paper presented an anomaly detection method to distinguish between background and anomalous gamma-ray radiation spectra. The method divides the radiation spectrum into two sub-spectra and models their relationship through a neural network, enabling prediction of one sub-spectrum' s background radiation from the other. For a given radiation spectrum, the error between the sub-spectrum and its predicted background values measures the anomaly score via Mahalanobis distance. To incorporate anomaly data in neural network training, a function was designed to simulate various anomaly spectra from available normal spectra. Furthermore, ACO optimized selection of spectral bins assigned to each sub-spectrum for optimum detection performance. A fitness function was designed where neural network prediction error represented the fitness value to be optimized. The proposed method was evaluated and compared with other methods using real radiation data measured by a detector network. Experimental results showed the proposed method' s detection capability surpasses other methods, even at low source-to-background ratios.

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Data Availability Statement: This manuscript has no associated data.

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Note: Figure translations are in progress. See original paper for figures.