A Low-Power Multi-Nuclide Identification Algorithm for Portable Gamma Spectrometers

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Abstract

The multiple nuclides identification algorithm with low consumption and strong robustness is crucial for rapid radioactive source searching. This study investigates the design of a low-consumption multiple nuclides identification algorithm for portable gamma spectrometers. First, the gamma spectra of 12 target nuclides (including the background case) were measured to create training datasets. The characteristic energies, obtained through energy calibration and full-energy peak addresses, are utilized as input features for a neural network. A large number of single and multiple nuclide training datasets are generated using random combinations and small-range drifting. Subsequently, a multi-label classification neural network based on a binary cross-entropy loss function is applied to export the existence probability of certain nuclides. The designed algorithm effectively reduces the computation time and storage space required by the neural network and has been successfully implemented in a portable gamma spectrometer with a running time of tr $<$ 2 s. Results show that, in both validation and actual tests, the identification accuracy of the designed algorithm reaches 94.8%, for gamma spectra with a dose rate of d 0.5 μSv/h and a measurement time tm = 60 s. This improves the ability to perform rapid on-site nuclide identification at important sites.

Full Text

Abstract

A Low-Consumption Multiple Nuclide Identification Algorithm for Portable Gamma Spectrometers

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A low-consumption, robust multiple nuclide identification algorithm is crucial for rapid radioactive source detection. This study investigates the design of such an algorithm for portable gamma spectrometers. First, gamma spectra from 12 target nuclides (including background) were measured to create training datasets. Characteristic energies obtained through energy calibration and full-energy peak positions serve as input features for a neural network. Large numbers of single- and multiple-nuclide training datasets were generated using random combinations and small-range drifting. Subsequently, a multi-label classification neural network based on a binary cross-entropy loss function was applied to output the existence probability of specific nuclides. The designed algorithm effectively reduces computation time and storage requirements, and has been successfully implemented in a portable gamma spectrometer with a running time of less than 2 seconds. Results show that the identification accuracy reaches 94.8% for gamma spectra with a dose rate of approximately 0.5 μSv/h and a measurement time of 60 seconds, in both validation and actual tests. This improves the capability for rapid on-site nuclide identification at critical locations.

Keywords: Multiple nuclide identification, Low consumption, Portable gamma spectrometer, Multi-label classification

Introduction

Radionuclides are now widely used in medical, industrial, agricultural, and scientific research applications [1, 2]. Accidental leakage or incidents involving radionuclides can cause serious harm to people and the environment [3, 4]. A low-cost, effective nuclide identification algorithm suitable for portable gamma spectrometers can quickly determine the types of potential or unexpected radionuclides, enabling follow-up emergency response to minimize threats to public health and the environment [5–7].

Traditional nuclide identification methods utilize the most prominent features in gamma spectra—the position and area information of full-energy peaks—to search for and identify nuclides. These methods typically involve obtaining raw gamma spectrum data using digital multichannel analyzers, followed by smoothing, digital filtering [8], background subtraction [9], peak searching [10], and energy calibration [11–13]. This process ultimately establishes a functional relationship between full-energy peak positions and energies for nuclide identification. Such methods, which offer strong interpretability and rely on mature peak-search algorithms, have been widely adopted in various nuclide identification systems [14, 15].

However, for nuclides with multiple characteristic energies, or for spectra composed of multiple nuclides, the algorithm logic becomes complex and redundant, rendering traditional methods unsuitable for portable gamma spectrometers. Sequential Bayesian algorithms for nuclide identification represent statistical learning methods [16] that construct a screening process based on extracted energy and time information emitted by nuclide sources. While these methods perform well for single nuclides with low noise interference [17], they are easily affected by high background count levels. Additionally, the large computational requirements for multiple nuclides make sequential Bayesian methods impractical for deployment in portable gamma spectrometers [18, 19].

With the rapid development of artificial intelligence, neural networks have been widely applied to identification problems due to their powerful nonlinear mapping capabilities. The application of neural networks to identification tasks primarily involves extracting feature vectors, defining network structures, adjusting parameters, and calculating prediction results. In the field of nuclide identification, neural network applications aim to improve identification efficiency and reduce technical requirements for operators [20, 21].

Neural network algorithms for nuclide identification directly accept gamma spectra measured by digital multichannel analyzers as input and obtain identification results through nonlinear operations [22, 23]. Recent widespread application of machine learning to classification problems has promoted the development of nuclide identification based on neural networks. Various algorithms and principles have been applied to this task. For instance, a scintillation detector nuclide identification algorithm based on a deep neural network with multiple hidden layers was implemented for low-energy resolution applications [24]. Considering that energy spectra with 1024 or more channels are not suitable for direct use as network input, multiple nuclide identification methods for low-count cases have been realized by combining feature enhancement technology with one-dimensional neural networks to improve accuracy and applicability [25]. For convolutional neural networks (CNNs), a novel nuclide identification method based on the Hilbert-Huang transform and CNN was constructed, achieving high-precision identification by processing gamma pulse signals [26]. Using mixed nuclide gamma spectra simulated by Geant4, a trained CNN nuclide identification model demonstrated approximately 90% accuracy [27]. Additionally, background contrast nuclide identification methods can achieve high accuracy and rapid identification by comparing background signals with sample signals [28].

However, these methods do not maintain good interpretability of the extracted feature information. Moreover, the high dimensionality of feature information results in significant computational and resource consumption by the neural network, making deployment in portable equipment difficult. Second, for multiple nuclide identification, features from multiple nuclide spectra are often treated as features of a new single-nuclide spectrum, which significantly increases the sparsity of the multi-classification neural network [29]. Additionally, training

datasets in previous studies were typically simulated using Monte Carlo methods or collected under laboratory conditions [30, 31]. In portable gamma spectrometer applications, spectral features may change significantly due to temperature and regional variations, reducing the stability of these methods.

Therefore, this study designed a low-consumption, robust nuclide identification method suitable for portable gamma spectrometers. A peak-searching algorithm was developed to obtain full-energy peaks from gamma spectra, with the extracted characteristic energies serving as features. Subsequently, a multi-label classification neural network with a low node count was built, trained, and evaluated. The implementation achieved low energy consumption and good identification accuracy in the spectrometer.

Methods and Experiments

Classification problems represent important research topics in machine learning and can be divided into two categories: single-label classification and multi-label classification. Single-label classification is primarily used for problems where a sample belongs to only one category, with each output node representing a category. In multiple nuclide scenarios, single-label classification networks would need to enumerate all possible nuclide combinations, making them redundant and impractical [32]. In contrast, multi-label classification considers that a sample may belong to multiple categories simultaneously, making it suitable for multiple nuclide identification. For this reason, a multi-label classification neural network was designed to handle both single and multiple nuclide cases. The training and prediction processes are illustrated in Fig. 1 [Figure 1: see original paper].

A. Multi-Label Classification

As shown in Fig. 2 [Figure 2: see original paper], classification neural networks for single-label and multi-label tasks can share the same network topology. Let $\mathbf{o} = o_1, o_2, \cdots$ represent the output vector of the classification neural network. In single-label classification, the output vector satisfies $\sum o_i = 1$. Assuming o_3 is the maximum value, the prediction vector becomes $\mathbf{y} = [0, 0, 1, 0, 0]$, indicating that the input feature belongs only to the third label. In the multi-label case, the output vector satisfies $0 \leq o_i \leq 1$. Assuming $\tilde{o}_1, \tilde{o}_3, \tilde{o}_5$ all exceed a given threshold, the prediction vector becomes $\mathbf{y} = [1, 0, 1, 0, 1]$, indicating that the input feature vector belongs to the first, third, and fifth labels simultaneously, which meets the requirements for multiple nuclide identification.

Although single-label and multi-label classification neural networks can share the same topology, they differ in activation and loss functions. To avoid the logical redundancy of traditional nuclide matching methods and the high resource consumption of existing neural network algorithms, a loss function optimization method was designed to handle multi-label outputs.

The designed neural network consists of an input layer, two hidden layers, and

an output layer, with all layers fully connected. The computational formula between layers is defined as $\mathbf{o} = f(\mathbf{lW} + \mathbf{b})$, where $\mathbf{o}$, $\mathbf{l}$, $\mathbf{W}$, and $\mathbf{b}$ denote the data vector of the current layer, data vector of the previous layer, weight matrix, and bias vector, respectively. When the network converges during training, the weight matrix of each layer becomes fixed. The function $f(\cdot)$ represents the activation function, which introduces nonlinear factors enabling the network to learn and represent complex nonlinear relationships. Input layer data consist of a feature vector containing characteristic energies from the measured spectrum, with dimensionality discussed in the following subsection.

For the output layer, the data constitute a 12-dimensional prediction vector indicating the existence probability of 12 target nuclides (with background spectra treated as a nuclide type). The sigmoid activation function was selected for the output layer, differing from the softmax function used in single-label classification. It is defined as $\sigma(x) = \frac{1}{1+e^{-x}}$, with derivative $\sigma'(x) = \sigma(x)(1-\sigma(x))$. The sigmoid function effectively maps network outputs to the range [0, 1] and is particularly suitable for models requiring probability interpretation.

The loss function quantifies the difference between predicted and true values, representing the discrepancy between real and predicted probability distributions in this network design. The output of the k-th node, O_k, can be regarded as the predicted presence probability of the k-th target nuclide and follows a Bernoulli distribution. The probability density function is defined as $P(Y_k) = O_k^{Y_k}(1-O_k)^{1-Y_k}$. In a sample set $\mathbf{Y}$ containing N samples, the occurrence frequency of event Y_k can be determined, though its true probability $\tilde{O}_k$ remains unknown. Maximum likelihood estimation is applied to estimate $\tilde{O}_k$. The likelihood function is $\log P(\mathbf{Y}) = \sum_{i=1}^{N} \log P(Y_{ik}) = \sum_{i=1}^{N} [Y_{ik} \log O_k + (1 - Y_{ik}) \log(1 - O_k)]$. By taking the derivative and setting it to zero, the estimated O_k representing the maximum point can be calculated. During one training epoch utilizing all N samples, the loss function for the k-th node is defined as $\text{Loss}_k = -\sum_{i=1}^{N} [Y_{ik} \log O_k + (1-Y_{ik}) \log(1-O_k)]$, where Y_{ik} represents the true k-th label of the i-th input sample. By continuously minimizing this optimized loss function, the predicted existence probability approaches the true existence probability.

For undefined network hyperparameters, an optimization process was implemented using random search to select hyperparameters and evaluate model performance. This approach identifies optimal hyperparameters across a wide range and provides an initial training set. By analyzing training results, the hyperparameter region converges more effectively. The Keras-Tuner toolkit was utilized for hyperparameter searching, with node numbers for the first and second hidden layers set to 30 and 26, respectively. The dropout rate for hidden layer neurons was 0.5, and the learning rate was 0.001.

The designed multi-label classification neural network was built, trained, and tested using the Keras library in Python 3.9. In the backpropagation algorithm, the Adam optimizer was applied to adjust network parameters and minimize

the loss function [33]. The number of training epochs was set to 20,000.

B. Feature Extraction

A portable gamma spectrometer was used to measure spectra from 12 nuclides (including background) at a dose rate of $d \approx 0.5$ μSv/h and measurement time $t_m = 60$ s. The self-developed portable gamma spectrometer is shown in Fig. 3 [Figure 3: see original paper]. It comprises a $1 \times 2 \times 4$ inch CsI scintillator detector and a signal processing circuit. Signals from the scintillator detector are amplified, shaped, counted, and analyzed by the signal processing circuit, which incorporates a low-power ARM chip. Energy calibration is performed using LuO powder surrounding the scintillator crystal. By analyzing fluctuations in the decay energy peaks of ^{176}Lu in LuO, energy-scale coefficients are adjusted to achieve calibration.

The measured nuclides include industrial nuclides (^{241}Am, ^{133}Ba, ^{60}Co, ^{137}Cs, ^{152}Eu, ^{22}Na, ^{54}Mn), natural nuclides (^{40}K, ^{232}Th), and medical nuclides (^{131}I, ^{99m}Tc, ^{177}Lu). The measured gamma spectra serve as original samples, from which features are extracted to construct training datasets. The characteristic energies of the spectra are utilized as elements in feature vectors, enhancing algorithm robustness, generalizability, and interpretability under higher dose rates or longer measurement times.

Since portable gamma spectrometers with scintillator detectors typically have lower energy resolution and can identify fewer nuclides, the feature vector size was set to eight elements (empty elements are filled with zeros) to achieve identification capability within three nuclide types. This significantly reduces the number of input nodes and computational burden [22]. The following peak-searching algorithm was designed for feature extraction.

Considering the spectrometer's computing power and the reliability of smoothed spectral data, the smoothing algorithm employs the 7-point barycenter method, expressed as:

$$s_i = \frac{1}{64}(20s_i + 15s_{i-1} + 15s_{i+1} + 6s_{i-2} + 6s_{i+2} + s_{i-3} + s_{i+3})$$

where s_i indicates the count of the i-th channel in the spectrum. For spectral boundaries, the symmetry method is used for processing. The smoothing weight factors are all positive, ensuring the smoothed spectrum data remain positive and exhibit good smoothing performance for spectra with high background counts.

Given the characteristics of high background noise and low energy resolution, a symmetric zero-area peak-searching algorithm was adopted, which effectively suppresses high background and resolves overlapping peaks. Its expression is defined as:

$$\tilde{s}_i = \sum_{j=-t}^{t} C_j s_{i+j}$$

where $\sum_{j=-t}^{t} C_j = 0$ and $\tilde{s}$ represents the transformed spectrum. The first derivative of the Gaussian function is utilized as the transformation function:

$$C_j = \frac{j}{\sigma^2} e^{-j^2/2\sigma^2}$$

where $j \in \{-t, -t+1, \cdots, 0, \cdots, t-1, t\}$ and σ is the variance of the Gaussian function. In the transformed spectrum, zero points correspond to alternative peak positions. To avoid interference from miscellaneous peaks and boundary noise, two criteria are applied: the area ratio between two adjacent zero points (f_1) and the distance between them (f_2) serve as discrimination standards. When the positive extreme value of the transformed spectrum divided by its standard deviation exceeds a set threshold f, the point is identified as a peak position.

Figure 4 [Figure 4: see original paper] illustrates the peak-searching process for background, single-nuclide, and multiple-nuclide spectra. The characteristic decay energies of ^{176}Lu (201.8 keV and 306.8 keV) were used for energy calibration. For the portable gamma spectrometer, energy calibration was performed periodically during background measurement but not during identification. To ensure calibration stability and minimize interference from ^{176}Lu in nuclide identification, different values for f_1, f_2, and f were selected. The smoothing algorithm demonstrates good performance, ensuring non-negativity of spectra around peak regions, while the transformation process effectively removes background. The peaks marked in Figs. 4(f) and 4(i) represent full-energy peaks for single and multiple nuclide cases, respectively, confirming the effectiveness of the designed peak-searching algorithm.

C. Dataset Construction

Using the designed feature extraction algorithm, full-energy peaks of 12 nuclides were obtained from 1200 measured spectra (100 spectra per nuclide). Characteristic energies were calculated based on the spectrometer' s energy-scale coefficients. Table 1 lists the characteristic energies of measured nuclides obtained through the peak-searching algorithm and energy calibration. The algorithm proves effective for gamma rays with high branching ratios emitted by the nuclides.

The data in Table 1 demonstrate noticeable errors between obtained energies and standard characteristic energies. Considering detector drift under varying environmental temperatures, the extracted datasets for single nuclides were expanded within a range of $±$2%. Consequently, the training dataset size for each single nuclide increased from 100 to 500 samples. Different expanded single-nuclide characteristic energies were then combined to create multiple-nuclide characteristic energy vectors, with the number of non-zero elements kept at eight or fewer. Multiple-nuclide labels were formed by linearly superposing single-nuclide labels. This process generated datasets containing 18,500 input feature vectors. All input feature vectors were normalized and randomized to reduce positional sensitivity and enhance model generalizability.

Results

Identification Accuracy Indicators

Hamming Loss is a common evaluation metric in machine learning and classification problems, particularly for multi-label tasks where each sample can have multiple labels. It measures dissimilarity between predicted and actual labels using Hamming distance, which quantifies the number of differing bits between binary strings. Specifically, Hamming Loss is calculated as the average number of misclassified labels across an entire test dataset. It evaluates both individual label predictions and overall sample predictions, providing an intuitive measure of classifier performance. Lower Hamming Loss indicates higher accuracy, calculated as:

$$\text{Hamming Loss} = \frac{1}{mq}\sum_{i=1}^{m}\sum_{j=1}^{q}\left[y_{ij} \neq \tilde{y}_{ij}\right]$$

where m is the number of tested samples, q is the label dimension, y_{ij} is the j-th element of the real label for the i-th sample, and $\tilde{y}_{ij}$ is the j-th element of the prediction.

However, Hamming Loss primarily focuses on overall similarity and may fail to capture local characteristics. To address this limitation, this study introduces a stricter evaluation method called the exact match ratio (EMR), which considers only predictions that match true labels exactly as effective results. EMR is defined as:

$$\text{EMR} = \frac{1}{m}\sum_{i=1}^{m}\mathbb{I}(y_i = \tilde{y}_i)$$

where m is the number of tested samples, y_i is the real label for the i-th sample, $\tilde{y}_i$ is the prediction, and $\mathbb{I}(\cdot)$ is the indicator function. EMR is stricter than Hamming Loss because partially correct predictions are not considered effective. For both metrics, smaller values indicate better network performance.

Identification Test

In this study, 14,800 gamma spectra were used as training and validation datasets, while 3,700 gamma spectra served as test datasets. Training accuracy iteration processes for both datasets were recorded over 20,000 epochs, as shown in Fig. 5 [Figure 5: see original paper]. Validation accuracy converged to 0.967. Two identification tests were performed: a validation test using 3,700 validation spectra and an actual test using 900 spectra measured under both unshielded and shielded conditions.

Using the trained network, validation datasets including single, double, and triple nuclides were tested. Table 2 lists the average neural network output for each node under single-nuclide cases, where background is also considered a single-nuclide case. The 12 values in each row represent the average output of the 12 network nodes for a specific nuclide case. Figure 6 [Figure 6: see original paper] illustrates the distribution of network outputs for corresponding nodes

under single-nuclide cases, with bold numbers in Table 2 and red lines in Fig. 6 indicating the average output of corresponding nodes.

Tables 3 and 4 list average neural network outputs for dual- and triple-nuclide cases, respectively, excluding background. This is because dual- and triple-nuclide cases including background can be reduced to single- and dual-nuclide cases. Based on possible combinations of target nuclides in industrial and medical applications, 16 dual-nuclide cases and 12 triple-nuclide cases were tested. Figures 7 [Figure 7: see original paper] and 8 [Figure 8: see original paper] illustrate network output distributions for dual- and triple-nuclide cases.

Following validation dataset testing, an actual test was conducted under unshielded and shielded conditions (using a 10 mm lead brick). To verify algorithm validity and feasibility under challenging energy resolution and complex background interference, several single, double, and triple nuclide types were randomly selected for 100 repeated identification tests under both conditions. All shielded spectra were excluded from training datasets, though the nuclides were included in the output layer. Figure 9 [Figure 9: see original paper] shows peak-searching results for unshielded and shielded multiple-nuclide cases.

Discussion

Identification Accuracy

As shown in Fig. 6, for single nuclides with similar decay energies, the average output of corresponding nodes is relatively lower than for other nuclides. For example, the decay characteristic energies of 364.5 keV and 637.0 keV for ^{131}I are close to the 356.0 keV of ^{133}Ba and the 661.7 keV of ^{137}Cs, indicating small differences between their input vectors after normalization. A similar situation occurs between ^{241}Am, ^{177}Lu, and ^{99m}Tc. These small differences are likely treated as noise signals, causing reduced output from corresponding nodes. Nevertheless, Table 2 shows that outputs from corresponding nodes remain significantly different from other nodes.

For dual-nuclide results in Fig. 7 and Table 3, and triple-nuclide results in Fig. 8 and Table 4, the decline in corresponding node outputs is caused not only by similar decay characteristic energies but also by mutual interference within dual- and triple-nuclide training datasets. For example, in the ^{241}Am–^{60}Co case, the weight of ^{241}Am in its input vector approaches zero after normalization because normalization divides all feature vectors by the largest characteristic energy value in the datasets. The characteristic energy of ^{241}Am and the largest characteristic energy were 63.2 keV and 1452.1 keV, respectively, causing a decline in the ^{241}Am node output. Nevertheless, the 12 values in each row of Tables 3 and 4 show relatively significant differences between correct and other nodes, and by choosing an appropriate threshold, high identification accuracy can be achieved.

Based on the above analysis, the threshold for determining nuclide presence was

set at 0.4. If a node's output exceeds 0.4, it indicates presence of the corresponding nuclide. Using this threshold, Hamming Loss and EMR were calculated as 0.013 and 0.052, respectively, yielding a complete identification accuracy of $1 - \text{EMR} = 94.8\%$. Compared to full-spectrum identification methods achieving 90.0% accuracy (considering only six nuclides) [22], the proposed algorithm demonstrates higher accuracy and superior multiple-nuclide identification capability. As shown in Fig. 9, full-energy peak positions can be accurately determined in both unshielded and shielded multiple-nuclide cases, highlighting the effectiveness of the peak-searching method. After 100 repetitions per case, Hamming Loss, EMR, and complete identification accuracy for each case are listed in Table 5 . Total Hamming Loss and EMR were 0.007 and 0.016, respectively, with an overall actual test accuracy of $1 - \text{EMR} = 98.4\%$. Although shielding can alter peak shapes and characteristics due to energy resolution challenges and complex background interference, good identification results were achieved for both conditions, demonstrating algorithm effectiveness and robustness.

The algorithm can be further developed to include additional standard nuclides. Incorporating new standard nuclides typically reduces identification accuracy. This study considered eleven common nuclides and their combinations. To include new sources, their gamma spectra must be measured or their full-energy peak data obtained directly. These characteristic energies can then be combined with existing nuclides to update training datasets. Directly used full-energy peak data should account for uncertainties based on detector performance (e.g., peak drifting or resolution changes). The output layer should also be expanded to include all considered nuclides. Expanding output nodes slightly increases resource consumption and may reduce chip identification accuracy. However, previous neural network methods required expanding the output layer to include not only considered nuclides but also their combinations, leading to significant chip resource consumption. The decrease in identification accuracy primarily depends on the proximity of new nuclides' characteristic energies to existing ones; greater differences result in smaller effects.

Complexity Analysis

Time and space complexities are fundamental concepts describing the computational resources required by an algorithm. Time complexity refers to the computational work needed and reflects execution time growth with input size. For CNNs, time and space complexities are given by:

$$\text{Time} \propto \sum_{l=1}^{L} M_l^2 K_l^2 \tilde{C}_{l-1} \tilde{C}_l, \quad \text{Space} \propto \sum_{l=1}^{L} (K_l^2 \tilde{C}_{l-1} \tilde{C}_l)$$

where M_l and K_l denote feature map and kernel side lengths, respectively. CNNs typically consist of multiple convolutional, pooling, and fully connected layers with high dimensionality, significantly increasing time and space complexities [36, 37]. The algorithm designed in this study achieves shorter running times

and lower resource consumption, with practical testing demonstrating execution within 2 seconds on an ARM chip.

Conclusion

This study measured gamma spectra of 12 common nuclides using a portable gamma spectrometer. Features were extracted and combined to generate multiple-nuclide feature vectors. Considering spectrum drift influence, the extracted spectral datasets were expanded within a $±$2% range. A low-consumption, robust nuclide identification method capable of execution within 2 seconds on an ARM chip was developed. Experimental results show that for a dose rate of $d \approx 0.5$ μSv/h and measurement time $t_m = 60$ s, the proposed model achieved at least 94.8% identification accuracy. Furthermore, actual testing achieved 98.4% accuracy, meeting basic requirements for nuclide screening and monitoring. Future work will focus on further improving identification speed, potentially processing real-time spectra or pulses using deep reinforcement learning methods to enable early warnings and nuclide identification.

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