Multi-Radioisotope Identification Using Convolutional Neural Networks Trained with Two-Dimensionally Transformed Gamma Spectrum Data Measured Using CsI(Tl) Spectrometer

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1. Introduction

Radioisotope Identification (RIID) algorithms for gamma-ray spectroscopy are widely used to quantify or identify the radioactive materials in medical, industrial, and scientific fields. High-purity germanium (HPGe), $LaBr_3$, NaI(Tl), and CsI(Tl) gamma spectrometers are commonly used to measure radioisotopes (RIs).

NaI(Tl) and CsI(Tl) spectrometers are also commonly used in practical monitoring due to their low price, high detection efficiency and easy production in a variety of sizes and shapes. a complex and accurate gamma spectrum unfolding algorithm must be used to realize reliable and effective RIID owing to the low energy resolution [1]. The challenging aspects in gamma spectrum unfolding tasks pertain to spectral data smoothing, background subtraction, and overlapping peak separation. In this context, it is necessary to identify suitable mathematical methods according to the application and optimal parameters in an iterative manner.

convolutional neural networks (CNNs) can give the ability to quantify and identify the radioactive materials without the gamma spectrum unfolding tasks by pattern recognition to identify characteristics in spectrum through learning. The use of CNNs for RIID [2-6] is recent, and research is necessary to enhance the RIID performance of CNNs. In this study, one-dimensional (1-D) gamma spectral data of RI mixtures, measured using a CsI(Tl) spectrometer, are transformed to two-dimensional (2-D) image data with the method we suggest, which are used as training inputs for the CNNs. The performance of models trained using the 1-D and transformed 2-D data is compared and evaluated.

2. Methods

2.1 Experimental setting

The experimental setup to measure the energy spectrum is as shown below in Fig. 1. A cube-shaped CsI(Tl) crystal (Amcrys, 13 × 25 × 51 mm^3) with PTFE reflector (1 mm) is coupled to 4 SiPMs (SensL microFC 60035, 6×6 mm^2) to which a +28 V is applied each. A preamplifier is used to convert the radiation-induced charges into a voltage and an amplifier is used to for pulse shaping. The generated pulses are digitized by Analog-to-digital converters(ADC). Then, they are sorted, stored and transferred to PC by Field Programmable Gate Array (FPGA). 8 γ-ray sources (^{241}Am, ^{57}Co, ^{137}Cs, ^{60}Co, ^{22}Na, ^{133}Ba, ^{109}Cd, ^{54}Mn) are all standard radioactive sources and placed at a distance of 20 mm in front of the CsI(Tl) crystal. They are measured for more than about 1 minute with standard sources so that the typical spectral shapes can be sufficiently displayed.

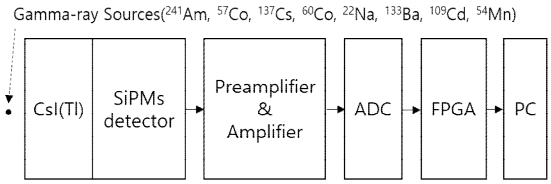

Fig. 1. Schematic of the experimental setup for measurement of pulse height spectrum for γ-ray sources

2.2 Data Generation

Datasets are generated by data synthesis of the spectra. First, pulse height spectra of single RIs (^{241}Am, ^{57}Co, ^{137}Cs, ^{60}Co, ^{22}Na, ^{133}Ba, ^{109}Cd and ^{54}Mn) obtained from the experiment are all normalized to one, respectively. Each spectrum s of single RI becomes the base element for the synthetic spectrum of multiple RIs, multiplied by synthesis coefficient c which is randomly selected. The synthesized artificial spectrum S can be expressed as a linear combination of the base spectrum with the coefficient as in equation (1).

$$S_i(x) = \sum_j^N c_{ji}\, s_j(x) \quad \left(\sum_j^N c_{ji} = 1\right) \qquad (1)$$

N is the total number of RIs (8, in this study), and c_{ji} represents the synthesis coefficient randomly selected between 0 and 1, corresponding to the relative activity of RI j for the ith random generation. The sum of the eight synthesis coefficients for each i is 1. Under these spectral synthesis conditions, 15,000 1-D spectral data points for multiple radiation sources in various ratios can be generated without additional experimentation. As inputs for CNN learning, 15,000 2-D input data are prepared in addition to the 15,000 1-D input data. The transformation method of 1-D to 2-D data can be summarized as follows: We sequentially cut 39 channels in the 1-D spectral data and arrange them to form 39 rows. The obtained 2-D image data sized 39 × 39 is different from the typical spectrum image but has the same information as the 1-D data sized 1 × 1521.

2.2 CNNs For RIID

CNNs are trained to extract and identify the best feature such as the photo peak and Compton continua for identifying and quantifying RIs in a mixture of RIs. To compare the performance of CNN models, 15,000 1-D spectral data points and 15,000 2-D data points

transformed from the 1-D data are prepared. We split each set of the 15,000 data points into training, validation, and test sets in the ratio 67:13:20 through random splitting. Therefore, for each dataset, the training, validation, and test sets include 10,000, 2,000, and 3,000 data points, respectively.

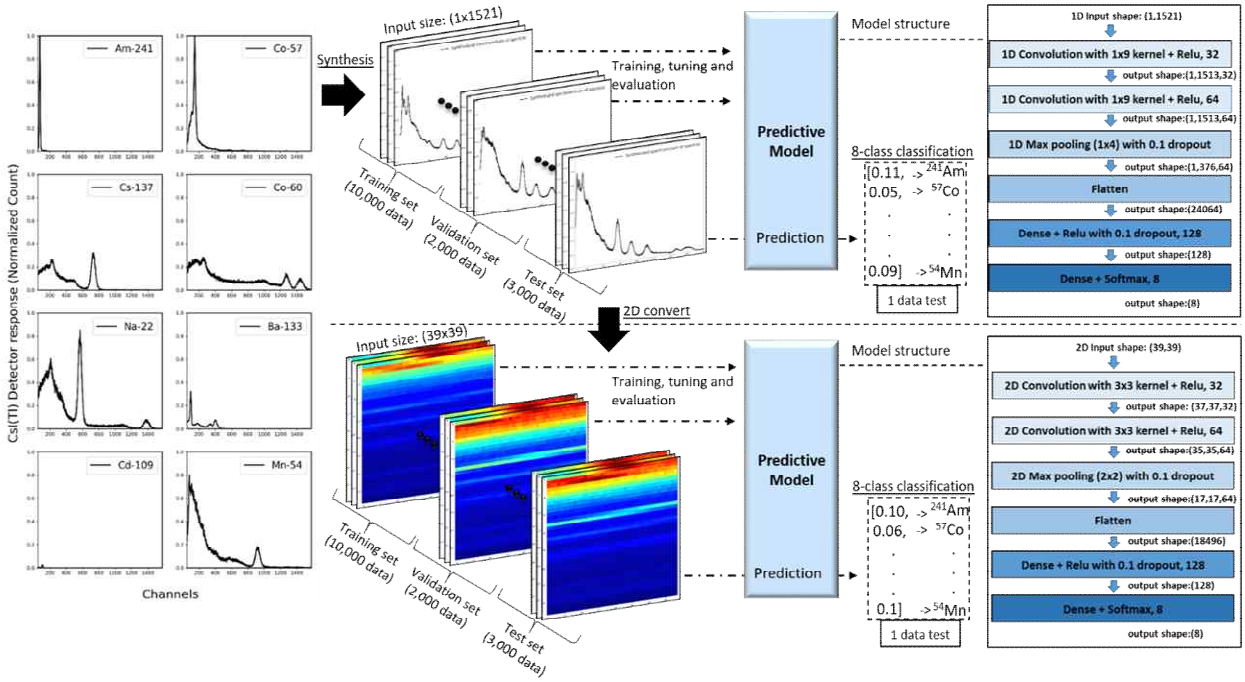

Fig. 2. Training process based on 1-D spectra and transformed 2-D image data for multi-RIID using CNNs, and CNN model summary.

The prepared inputs are used to train and test the CNNs by using the open source Keras library in the Python environment [7]. The performance of the trained CNN models is evaluated in terms of the mean magnitude of relative error (MMRE) between the test values (actual relative activity) and predicted values (predicted relative activity). The MMRE for each RI can be defined as in equation (2).

$$MMRE_j\ (\%) = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{(y_{ji}-\bar{y}_{ji})}{y_{ji}}\right| \times 100(\%) \quad (2)$$

y_{ji} and $\bar{y}_{ji}$ are the test and predicted values of the activity for RI j at the ith sampling, respectively. n is the sampling number for the test set.

The generation and training processes of 1-D spectra and transformed 2-D image data for multi-RIID using CNNs are illustrated in Fig. 2.

3. Results and Discussions

Model training is performed 10 times for each model to estimate the mean MMRE and uncertainty. Notably, the MMRE is calculated by sampling test values greater than 0.01 and the corresponding predicted values because the two models cannot predict relative activities of RIs less than 1%. The performance values (MMREs) of CNN models trained with 1-D spectral inputs and transformed 2-D inputs are shown in Fig. 3. A smaller MMRE indicates a smaller difference between the actual and predicted values, representative of superior performance. The model trained using 2-D inputs exhibits a higher performance for seven (241Am, 57Co, 60Co, 22Na, 133Ba, 109Cd, 54Mn) of eight RIs. Specifically, this model exhibits a significantly a smaller MMRE and uncertainty for 109Cd than those associated with the model trained with 1-D inputs. Both models achieve reasonably small MMRE values of approximately 4% or less, except in the cases of 133Ba and 109Cd.

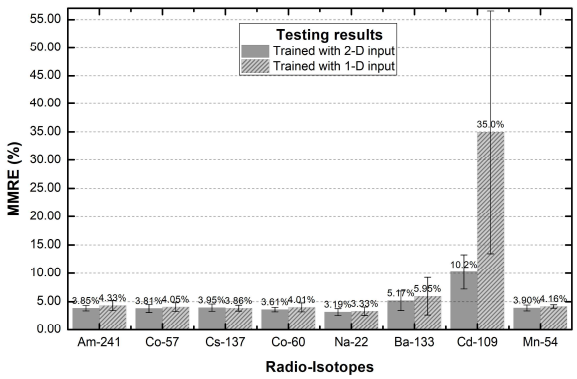

Fig. 3. Mean magnitude of relative error (MMRE) between the actual and predicted activities for each RI in a mixture of RIs. The sampling range of test values is 0.01–1.00. Error bars (uncertainty) pertain to the standard deviation of the mean ($\pm 1\sigma$).

For both models, the MMRE for 109Cd is significantly larger than those for other RIs, primarily because the

normalized spectrum of 109Cd (Fig. 2) is significantly smaller than those of other RIs. Thus, the models cannot accurately predict the relative activity of 109Cd as the feature associated with 109Cd is not prominent and is hidden in the RI mixture spectrum.

4. Conclusions

We use two types of CNNs to identify and quantify RIs in a mixture of RIs through a gamma spectrum measured using a CsI(Tl) spectrometer. One model is trained with raw 1-D spectral data, and the other model is trained with the 2-D data transformed from 1-D data using the method. We compare the RIID performance of the two models. The model trained with the transformed 2-D data outperforms the model trained with the 1-D data. Therefore, the proposed method of transforming 1-D spectra into 2-D data is a promising approach for training CNNs for RIID. Future work can be aimed at enhancing the model by considering the effects of the backgrounds, distance, count, and peak shift to facilitate the practical application of the CNN model in diverse fields.

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