Spectral Unfolding of NaI(Tl) Scintillation Detectors Using an Untrained Neural Network

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1. Introduction

Gamma ray spectroscopy is the most commonly used technique for both qualitative and quantitative analysis of radioactive nuclides that emit gamma rays. A thallium-doped sodium iodide (NaI(Tl)) scintillation detector, known for its portability and high detection efficiency, has been widely used as an in-situ gamma spectrometer. However, its main drawback is poor energy resolution, making it challenging to distinguish overlapping peaks with similar energies or detect weak peaks. Thus, various unfolding methods [1-2] have been introduced as means to decompose Gaussian peaks in the measured spectrum to delta functions and infer their intensities. In this study, we present a novel unfolding method based on an untrained neural network-based unfolding method for both qualitative and quantitative analysis of NaI(Tl) gamma spectra.

2. Methods and Results

The untrained neural network-based unfolding method (UNU) can convert a measured spectrum into a fluence spectrum without training dataset. Instead, UNU needs the energy response functions of the detector to optimize the weight parameters of the neural network. A response function of a detector represents a relationship between the measured spectrum and the fluence spectrum. It can be described in discrete matrix form as follows:

$$\vec{S} = \vec{R}\vec{X}, \text{ where } S_i = \sum_{j=1}^{m} R_{ij} \cdot X_j \quad (1)$$

where the measured spectrum is represented by the *n*-dimensional vector $\vec{S}$ (with *n* channel bins), and $\vec{R}$ is a two-dimensional response matrix that contains the *n* channel bins of the detector within the discretized energy (*m* bin) of the incident gamma ray fluence vector, X_j. Because *i* is commonly different to *j*, mathematically this is an ill-conditioned problem having an infinite number of solutions (not all have physical meaning), therefore an unfolding method should be used.

Fig. 1 shows the strategy for spectral unfolding using an untrained neural network. First, we normalized the measured spectrum $\vec{S}$ by dividing it by the total counts, randomly initialized all weighting parameters in the network, and built the response matrix $\vec{R}$ of the used detector, computed by MCNP6.2 (Fig. 2). The structure of the neural network was composed of an input layer comprising 996 channels, which was identical to the 996 bins of the input spectrum, along with three hidden layers composed of 1992 channels and an output layer with 300 channels. The activation function of all hidden layers was defined as a softmax function. The characteristics of the softmax that turns a vector of numbers into a vector of probabilities which sum to one was suitable for effectively calculating the relative ratio for each energy. Namely, the neural network that receives the measured spectrum offers a fluence spectrum $\vec{X}$ based on the probability of the relative intensity in each energy bin. Then, the latent spectrum $\overrightarrow{S^*}$ was computed by equation (1), incorporating the response matrix $\vec{R}$ and the fluence spectrum $\vec{X}$. The error between input spectrum $\vec{S}$ and

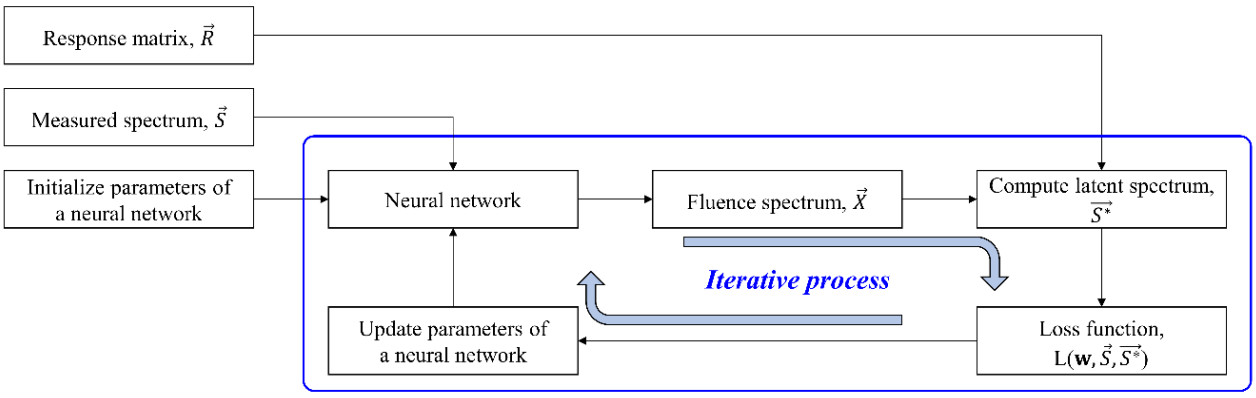


Fig. 1. Scheme of the untrained neural network-based unfolding method

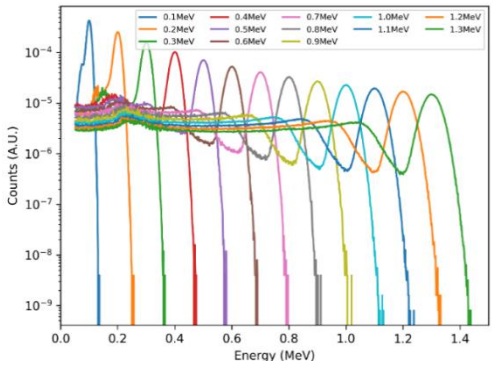
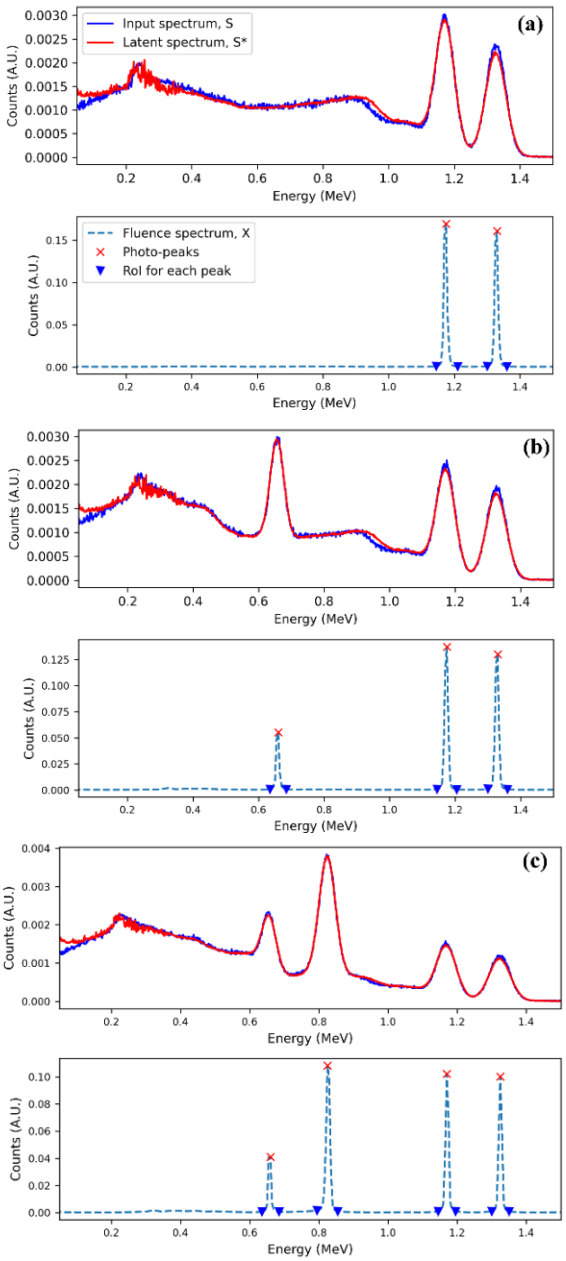


Fig. 2. Examples of response function of the used NaI(Tl) scintillation detector. The response matrix consisting of 300 response functions for mono-energies between 5 keV to 1.7 MeV was computed by MCNP6.2 with the high number of particle histories (10^8).



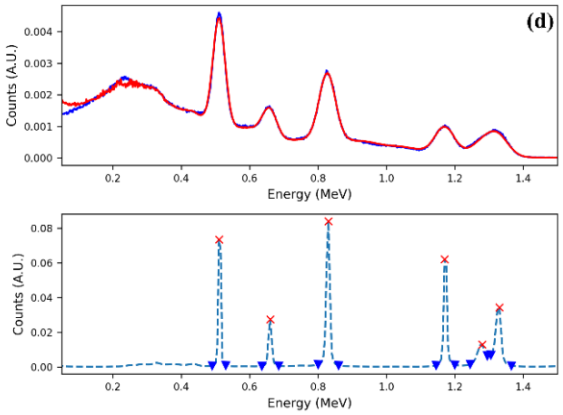


Fig. 3. Experimental results of UNU: measured spectra and latent spectra (first row), and fluence spectra with peak and RoI marks (second row)

Table I: Configuration of radioisotopes for each spectrum

Spectrum	Radioisotope			
	^{60}Co	^{137}Cs	^{54}Mn	^{22}Na
a	o			
b	o	o		
c	o	o	o	
d	o	o	o	o

latent spectrum $\overrightarrow{S^*}$ was calculated using a loss function, mean absolute error (MAE). Finally, the weight parameters of the neural network were updated to minimize the overall loss function using an optimization technique, Adam optimizer [3]. We iterated the above process for a preset number of times and selected the output fluence spectrum corresponding to the lowest value of the loss function.

We evaluated the performance of UNU using experimental data. A total of four spectra were obtained with different combination of four radioisotopes (Table I). The check sources were positioned 12 cm away from the detector and the measurement time was 5 min. Fig. 3 (a–d) depicts the results of the UNU for the measured spectra. The input spectra (blue solid line) and the latent spectra (red solid line) showed good agreement. Although the peaks in the fluence spectrum were not ideal delta functions, the unfolded spectra were acceptably decomposed, distinguishing even between gamma rays with nearly identical energies (1.275 MeV gamma rays from ^{22}Na and 1.332 MeV gamma rays from ^{60}Co). To quantitatively analyze relative intensities of each peak, we defined a specific region of interest (RoI) for each peak and considered the sum of all probabilities within that region as the relative intensity of the corresponding photo-peak energy. For all spectra, UNU accurately determine the relative intensities of each peak where the absolute errors were less than 2%.

3. Conclusions

In this study, we proposed a spectrum unfolding method using an untrained neural network for qualitative

and quantitative analysis of NaI(Tl) gamma spectrometers. It was proved that UNU can be automatically designed to find a fluence spectrum hidden within the measured spectrum, thereby solving the inverse problem outlined in equation (1). We believed that our proposed method would be extended to address various inverse problems in the field of the radiation measurement.

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