Photopeak unfolding from plastic gamma spectra using a convolutional autoencoder

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1. Introduction

Plastic scintillation detectors have been widely used in various fields in radiation detection and measurements owing to its unique characteristics, but they have poor spectroscopic capabilities. To overcome this weakness, various methods have been reported for plastic scintillation detectors to be have spectroscopic capabilities. However, most of them are focused on identification of radioactive materials. Several of them allow plastic scintillation detectors to identify and quantify gamma ray sources, but they are not able to be applied to plastic gamma spectra containing statistical uncertainties. In this paper, we proposed a deep learning model to unfold full energy peaks (FEP) for pseudo gamma spectroscopy of plastic gamma spectra.

2. Materials and method

2.1 Convolutional Autoencoder

Autoencoder is one of the representative generation models in artificial neural networks. Autoencoder is consisting of encoder and decoder layers; In the encoder layers, input signals are compressed in the lower dimension, which is called as code. In the decoder layers, output signals are reconstructed in the identical dimension to input signal from codes. Previously, we developed a deep autoencoder for Compton edge reconstruction from plastic gamma spectra, and its performance was proven by measured plastic gamma spectra for single and multiple isotopes. [1] This study may be similar with our previous research, but we developed an advanced deep learning model, convolutional autoencoder (CAE), and applied it to unfolding of FEP. Figure 1 shows structure of developed CAE model. Hyper parameters of our model were tuned by a Bayesian optimization method [2].

2.2 Experimental setup

EJ-200 which has cylindrical shape with diameter of 30 mm and height of 50 mm was used as plastic scintillation detector. For signal processing, DP5G, a pulse processor by the Amptek, was used. Operating high voltage was supplied by NHQ 224M, a high voltage supplier by the ISEG.

The aluminum dark box was used to reduce background radiation, whose internal dimension is width of 590 mm, height of 430 mm and length of 890 mm. Detector was placed on the bottom plate of the box. For gamma ray sources, ^{22}Na, ^{54}Mn, ^{57}Co, ^{60}Co, ^{109}Cd, ^{133}Ba, ^{137}Cs and ^{152}Eu, isotope products by the Eckert & Ziegler, were used. Position of sources was set to 1.25 cm away from the detector window, and measured for various measurement periods. Energy calibration of measured spectra was conducted using parametric optimization method [3].

2.3 Monte Carlo simulation

MCNP 6.2 was used to simulate plastic gamma spectra. Experimental environment was implemented as simulation geometry, and composition and densities of materials were defined by referring material data report [4]. Pulse height tally with Gaussian energy broadening

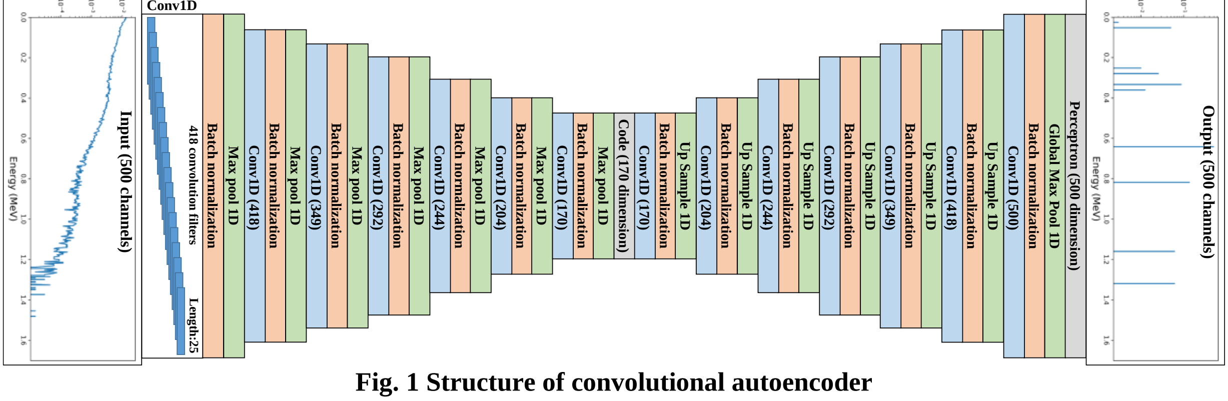


Fig. 1 Structure of convolutional autoencoder

(GEB) card was used to simulate distribution of energy deposition in a plastic scintillation detector. To simulate energy broadening effects of plastic gamma spectra, GEB card was activated when simulating distribution of energy deposition using pulse height tally. GEB coefficients were calculated by parametric optimization [3] using experimental spectra with measuring period of an hour. Used GEB coefficient is 0.0004 for "a", 0.3704 for "b" and -0.4999 for "c".

Using MCNP simulation, 200,000 plastic gamma spectra were simulated. Corresponding to simulated spectra, FEP spectra were generated manually by referring emitted gamma energies and their intensities. Generated spectra paired by GEB and FEP were used as dataset to train our CAE model.

3. Results

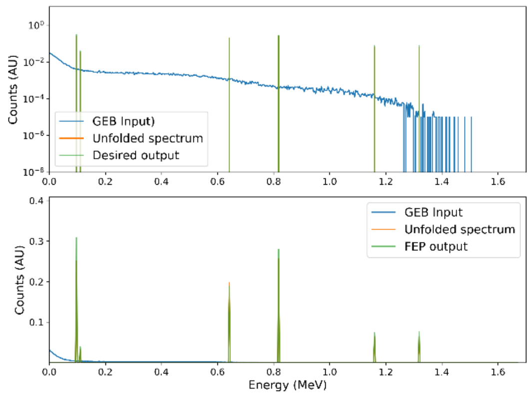
CAE was implemented in the Python environment using the Tensorflow 2.0 library [5]. Among generated dataset, 160,000 of them were used as training set, 30,000 of them were used and validation set and 10,000 of them were used as test set.

To compare unfolding results with full energy peak spectra, a mean squared logarithmic error (MSLE) was used as loss function, which is described as following equation.

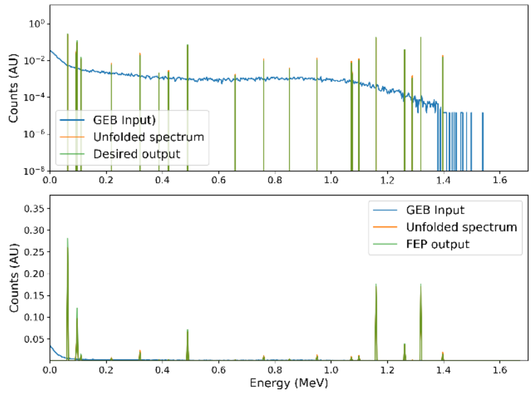
$$MSLE = (1/N)\sum_{n=1}^{N}\{\log(y_n+1)-\log(\hat{y}_n+1)\}^2 \quad (1)$$

where, i means channel number, N is the total number of channels, y_n means n^{th} value in FEP spectrum, and $\hat{y}_n$ means n^{th} value in unfolded spectrum.

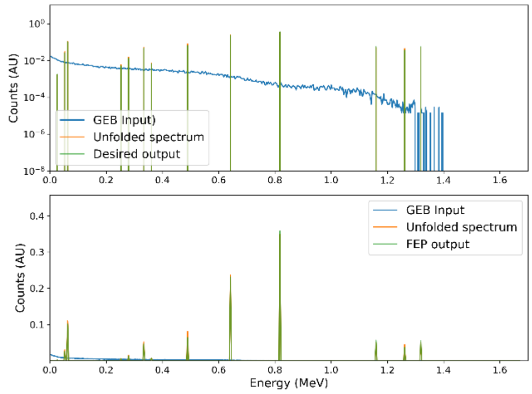
CAE was trained with established training and validation sets for 300 epochs. For callback functions, model check point option was activated to save the best model built during training procedure, and the best model in training procedure was used as final model. Performance of trained CAE was tested using generated test set. Figure 2 show examples of unfolding results for simulated spectra of single and multiple radioisotopes in test set.



(a) ^{54}Mn&^{57}Co&^{60}Co&^{137}Cs



(b) ^{22}Na&^{57}Co&^{60}Co&^{109}Cd&^{152}Eu



(c) ^{22}Na&^{54}Mn&^{60}Co&^{109}Cd&^{133}Ba&^{137}Cs

Fig. 2 Unfolding results for several spectra in test set

4. Conclusion

A CAE was presented to unfold FEPs from plastic gamma spectra. By unfolded FEPs, identification and quantitation of gamma ray sources are possible for plastic scintillation detectors. It can be utilized for identification and quantitation of radioactive materials in radiation portal monitors or spectroscopic dosimetry using plastic scintillation detectors.

ACKNOWLEDGEMENT

This research was funded by the Ministry of Oceans and Fisheries, KIMST project no. 20200611.

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