

## Reconstruction of Compton Edges in Plastic Gamma Spectra using Deep Autoencoder

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### 1. Introduction

Analysis on plastic gamma spectra is one of the most challenging tasks in radiation measurement, because of energy broadening effect and absence of full energy peak. To overcome these weaknesses, deep autoencoder model is addressed to reconstruct Compton edges not shown in plastic gamma spectra because of energy broadening effect. If Compton edges are shown in gamma spectra, it is possible to conduct direct pseudo gamma spectroscopy.

### 2. Materials and Methods

#### 2.1 Deep autoencoder

Autoencoder is a model of artificial neural networks which copies input signals to output. Figure 1 shows a schematic of an autoencoder model. Autoencoder is consisting of encoder and decoder part. Encoder is called as a recognition network, and it maps input signal into internal code. Decoder is called as a generative network, and it reconstructs output signal from internal code. If only encoder part is used once trained, data set can be represented as internal code whose dimension is smaller than data set. If noise signals are added into training data, autoencoder learns to reject noises. Therefore, autoencoder is typically used for dimension reduction or noise rejection of data set.

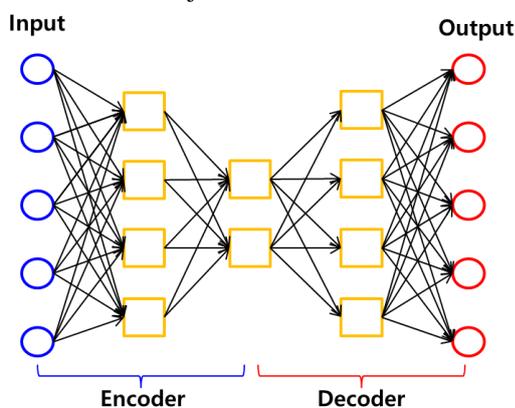


Fig. 1 Architecture of Autoencoder

#### 2.2 Experimental setup

A polystyrene crystal (cylinder type, dia.  $30 \times 50$  mm, EJ technology) coupled with a PMT (R2228, HAMAMATSU) and a preamp (E990-501, HAMAMATSU) was used as plastic scintillation detector. Optical grease (BC630, Saint-Gobain) was spread at the junction between the crystal and PMT for optical coupling. For optical shielding, the crystal was wrapped by Teflon and black friction tapes. A pulse processor (DP5G, Amptek) was used as a shaping amp and a multichannel analyzer. A high voltage supplier (NHQ 224M, ISEG) was used to supply operating voltage of the detector. Experiments to measure gamma spectra were conducted in an aluminum dark box for replenishment of optical shielding. The dark box consists of 10-mm-thick aluminum case with internal space of  $440 \times 440 \times 899$  (W  $\times$  H  $\times$  L) mm. Detector was placed on the shelf of the dark box, and the window of the detector was located at the center of the dark box.  $^{22}\text{Na}$ ,  $^{60}\text{Co}$  and  $^{137}\text{Cs}$  were used as gamma ray sources, and the position of source was fixed at 5 cm from the detector window. Energy calibration was conducted by a parametric optimization method [1].

#### 2.3 Monte Carlo simulation

To simulate plastic gamma spectra, geometry of simulation was implemented as analogous to experimental setup as possible using MCNP 6.2 [2]. Compositions and densities of materials were defined by referring a material data report [3]. Gamma ray sources were defined as point sources. F8 tally was used to simulate spectral response of each source, and history number was set from  $10^4$  to  $10^6$ . Energy bins for F8 tally were defined as identical to energy calibrated channel bins. To acquire ideal and energy broadened pulse height distribution, F8 tallies were defined with and without GEB card respectively. Coefficients "a", "b" and "c" for GEB card was calculated by a parametric optimization method [1] using experimental spectra as analogous with measurement data as possible.

### 3. Results

Deep autoencoder was implemented in the Python environment using the Tensorflow [4] and the KERAS

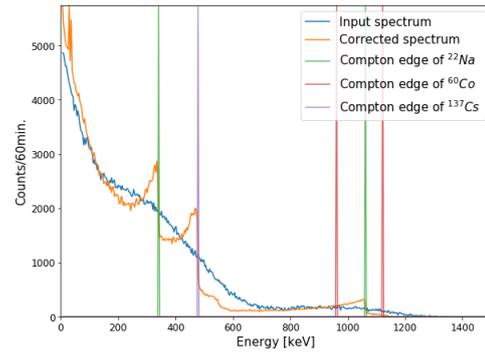
[5] libraries. Hyper parameters for our autoencoder model were determined by trial and error. To train deep autoencoder, training and validation sets for GEB case were given as input, and those for ideal case were given as desired output. In general, noise signals are added into data set for autoencoder to have ability of noise reduction. However, it is almost as if noise signals are already included in our data set because the data set was created by simulation with history numbers from  $10^4$  to  $10^6$ .

To compare reconstruction results with desired spectral data, a mean absolute percentage error (MAPE) was used as loss function, which is described as following equation.

$$\text{MAPE} = \frac{100\%}{n} \sum_{i=1}^n \frac{O_i - I_i}{O_i} \quad (1)$$

where,  $n$  is the number of channel bins,  $i$  indicates  $i^{\text{th}}$  channel bin,  $O$  is Compton edge reconstructed output, and  $I$  is ideal spectrum given as desired output.

Deep autoencoder was trained with established training and validation sets for 500 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 model was tested using generated test set. Figure 2 show examples of Compton edge reconstruction results for measured spectra of single and multiple radioisotopes.



(c)  $^{22}\text{Na}$  &  $^{137}\text{Cs}$

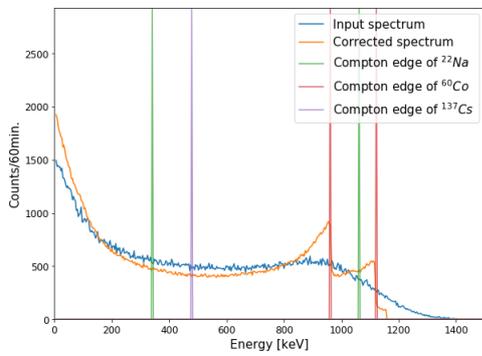
Fig. 2 Compton edge reconstruction results

#### 4. Conclusion

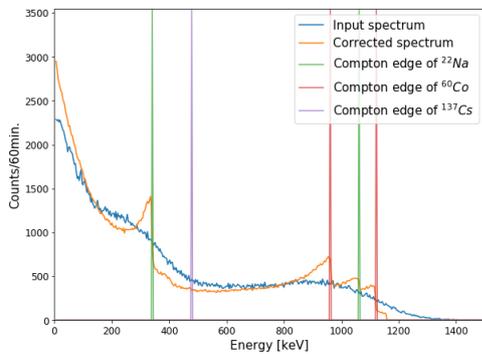
A deep autoencoder model was presented to reconstruct Compton edges in plastic gamma spectra. Deep autoencoder was trained not only to reconstruct Compton edges but to reduce measurement noises by designing data set generation procedure which measurement noises were included in. As shown in experimental results, it successfully reconstructed Compton edges in plastic gamma spectra with measurement noises. Therefore, it was possible to conduct direct pseudo gamma spectroscopy using energy broadening corrected results.

#### REFERENCES

- [1] B. Jeon, J. Kim, M. Moon and G. Cho, Parametric optimization for energy calibration and gamma response function of plastic scintillation detectors using a genetic algorithm, Nuclear Instrument and Methods in Physics Research A, Vol. 930, pp. 8-14, Jun 2019.
- [2] R.J. McConn Jr, C.J. Gesh, R.T. Pagh, R.A. Rucker and R.G Williams III, Compendium of material composition data for radiation transport modeling, Technical report PNNL-15870, Rev 1, Pacific Northwest National Laboratory, Richland, Washington, 2011.
- [3] C. J. Werner, J. S. Bull, C. J. Solomon, F. B. Brown, G. W. McKinney, M. E. Rising, D. A. Dixon, R. E. Martz, H. G. Hughes, L. J. Cox, A. J. Zukaitis, J. C. Armstrong, R. A. Forster and L. Casswell, MCNP6.2 release notes, Report LA-UR-18-20808, Los Alamos National Laboratory, Los Alamos, New Mexico, 2018.
- [4] F. Chollet, KERAS, 2015. Software available from {<https://keras.io>}.
- [5] M. Abadi, A. Agarwal, P. Barham, E. Brevdo, Z. Chen, C. Citro, G. S. Corrado, A. Davis, J. Dean, M. Devin, S. Ghemawat, I. Goodfellow, A. Harp, G. Irving, M. Isard, R. Jozefowicz, Y. Jia, L. Kaiser, M. Kudlur, J. Levenberg, D. Mane, M. Schuster, R. Monga, S. Moore, D. Murray, C. Olah, J. Shlens, B. Steiner, I. Sutskever, K. Talwar, P. Tucker, V. Vanhoucke, V. Vasudevan, F. Viegas, O. Vinyals, P. Warden, M. Wattenberg, M. Wicke, Y. Yu and X. Zheng, TensorFlow: Large-scale machine learning on heterogeneous systems, 2015. Software available from {<https://www.tensorflow.org>}



(a)  $^{60}\text{Co}$



(b)  $^{22}\text{Na}$  &  $^{60}\text{Co}$