Unfolding of Phoswich Detector Using Neural Network Method

Jae Cheon KIM,[a] Sang Kyung LEE,[b] Soon Young KIM,[a] Yong Kyun KIM,[c] Jong Kyung KIM,[a]
a Hanyang Univ. 17 Haengdang-dong, Seongdong-gu, Seoul, 133-791, Korea
b Seoul National Univ. San 56-1, Sillim-dong, Gwanak-gu, Seoul, 151-742, Korea
c Korea Atomic Energy Research Institute, Deokjin-dong, Yuseong-gu, Daejeon, Korea

1. Introduction

The neural networks are frequently used in a wide variety of data processing applications where real-time data analysis is required. Recently, the neural network has appeared as an alternative for unfolding the neutron or photon spectra.

The neural network approach has an advantage that most of the intense computation takes place during the training process. Therefore, once the neural network system is trained for a particular unfolding task, operation is relatively so fast compared with the previous matrix calculation to unfold the spectra.

2. Methods and Results

2.1 Prototype Phoswich Detector

The prototype phoswich detector, which was designed by KAERI, was used to develop the unfolding algorithm using the neural network method. The phoswich detector consists of CsI(Tl) and plastic scintillator for detecting the gamma and beta-ray, respectively. The plastic layer is 0.22 cm thick and the CsI(Tl) is 5.08 cm (2 inch) thick. The diameter of both crystals is 5.08 cm (2 inch).

For generation of the response function, the γ-ray source was assumed to be located vertically above and 100 cm away from the window of the phoswich detector. Figure 1 shows the cross sectional view of the phoswich detector used for this study.

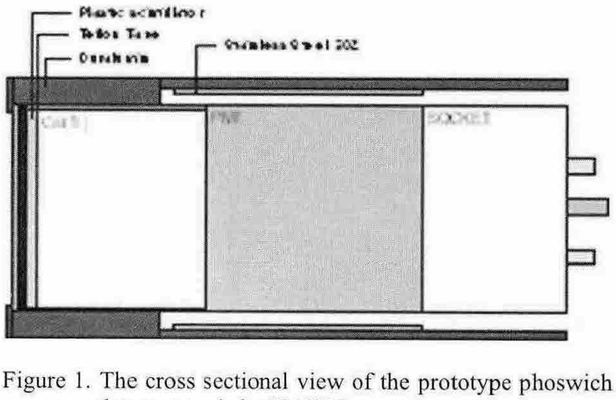

Figure 1. The cross sectional view of the prototype phoswich detector made by KAERI

2.2 Random-Sampled Gamma-ray Sources

To train the neural networks and review the unfolded spectra, 20 radioisotopes emitting the different γ-ray energy were mixed with random-sampled composition ratios. Using these mixed radioisotopes, total 50 cases with different composition ratios were sampled randomly. Among the 20 radioisotopes, ^{46}Sc and ^{60}Co emits two gammas, simultaneously. Therefore, these were assumed to emit the gammas with the same ratio at the same time.

Some phoswich detector response functions were generated from MCNP5 code calculations by employing 50 random-sampled mixed radioisotopes with different composition ratios. 40 samples were used for training our neural networks and 10 samples for algorithm evaluation as shown in Table 1.

Table 1. Random-sampled γ-ray sources

Isotope	Energy (MeV)	Case					
		Training			Evaluation		
		1		40	41		50
Sn-131	0.0241	0.063		0.065	0.036		0.085
Am-241	0.0595	0.072		0.013	0.024		0.093
Co-57	0.1221	0.001		0.074	0.089		0.009
Ce-141	0.1455	0.052		0.073	0.044		0.095
Ce-139	0.1658	0.058		0.001	0.050		0.091
Hg-203	0.2792	0.027		0.002	0.058		0.060
I-131	0.3645	0.023		0.026	0.040		0.027
Au-198	0.4118	0.052		0.062	0.040		0.102
Sr-85	0.514	0.029		0.081	0.066		0.013
Cs-134	0.6046	0.081	…	0.079	0.045	…	0.022
Cs-137	0.6616	0.065		0.065	0.055		0.028
Nb-95	0.7658	0.060		0.044	0.047		0.095
Mn-54	0.8348	0.011		0.053	0.029		0.003
Sc-46A	0.8892	0.062		0.042	0.066		0.059
Sc-46B	1.1205	0.062		0.042	0.066		0.059
Co-60A	1.1732	0.082		0.064	0.029		0.014
Na-22	1.2745	0.043		0.048	0.066		0.039
Co-60B	1.3325	0.082		0.064	0.029		0.014
La-140	1.5966	0.066		0.064	0.066		0.033
Y-88	1.8361	0.009		0.037	0.059		0.059

2.3 Stripping Method

The inverse matrix method, the stripping method, the folding iteration method, and so on has been proposed to unfold the γ-ray spectra. The stripping method is based on a successive subtraction of Compton background from higher to lower channels and widely applied for unfolding the γ-ray spectra [1].

Through the previous work [2], the unfolding program of the phoswich detector using the stripping method was constructed. The 500 mono-energetic γ-ray sources whose energy was changed from 0 to 2.5MeV were used for constructing the γ-ray profile by MCNP5.

2.4 Neural Network Method

The neural network structure adopted for the unfolding γ-ray spectra is a successive form as illustrated in Figure 2. For example, the composition ratio of ^{88}Y calculated by the neural network for ^{88}Y is used as the input of the successive neural networks.

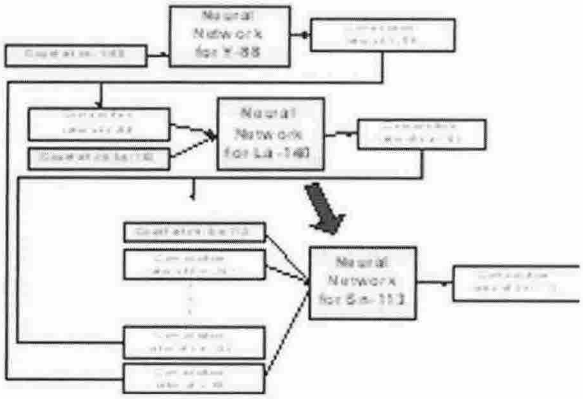

Figure 2. The neural network structure used for the unfolding algorithm

The structure used for this model is based on a three-layered feed forward network for each radioactive isotope. The inputs of the neural network of each individual isotope are the count at the channel in which the photopeak appears and the composition ratios of the isotopes emitting higher gamma energy.

Neural networks were trained by Scaled Conjugate Gradient algorithm [3]. The criterion for stopping the training is based on the mean square error (MSE). For all of the neural networks MSE reached less than 1×10^{-8}.

2.5 The Comparison between the Stripping Method and the Neural Network Method

Figure 3 shows the best and worst unfolded result, respectively. The RMSE (Root Mean Square Error) was 0.0074 and 0.0171, respectively. The average RMSE of the 10 cases was about 0.0127. In the case of the stripping method, the average RMSE was about 0.0007.

This unfolding program developed by using the neural network method has partially introduced a similar successive subtraction technique like the stripping method. Therefore, as shown in Figure 3, the comparison shows excellent agreements in radioisotope emitting the γ-ray energy bigger than of ^{137}Cs (~660 keV). On the other hand, the unfolded spectra do not match well in energy region less than ^{134}Cs.

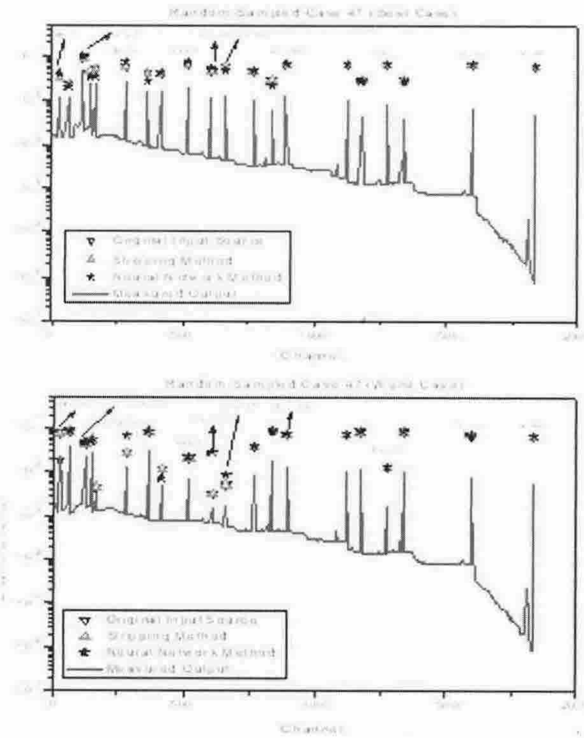

Figure 3. The comparison between the neural network method and the stripping method

3. Conclusion

The traditional approach like the stripping method is still superior to the neural network method. Nevertheless, the neural network method can calculate the unfolded spectra faster than the previous iterative method. Most of computing time for calculations would be needed in the training process. In addition, the unfolding program using the neural network method can avoid the complication from the intrinsic characteristics of real γ-ray detector.

Acknowledgement

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