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1D Convolutional Neural Network-based Study for Pile-up Correction Considering Noise Effect

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1. Introduction

The pile-up pulses generate when two or more pulses are detected too closely in time to be distinguished as separate events. It can lead to a number of problems in radiation measurements. First is a reduction in the accuracy of the measured radiation intensity. The pile-up pulse has a higher amplitude than that of a single pulse, and its energy is a combination of the energies of the individual pulses. As a result, the measured intensity of the radiation is overestimated, and the energy spectrum obtained from the measurement is distorted. Also, a reduction of energy resolution can be generated because their energies are combined, leading to a loss of energy resolution in the detector.

To overcome the pile-up problems, several techniques have been developed such as pile-up rejection, and pile-up separation, in which overlapped pulses are separated based on the mathematical modeling of the pulse shape [1-3] or a numerical method [4-6]. But, they have several troubles. In case of pile-up rejection, count loss occur because it discards the impure signals. In case of pile-up separation, considerable effort and much time is required for correcting the signals.

Recently, deep learning-based technologies have been applied to various fields of radiation measurement. Among them, 1D CNN (Convolutional neural network), which extracts features from sequential data such as time series data or signals, has been proposed as a model for pulse height estimation because it has the advantage of being more effective in capturing complex patterns [7-8].

In this research, 1D CNN-based study for pile-up correction is conducted for Gamma-ray spectroscopy in high radiation environment. Pulse dataset is obtained experimentally. In order to evaluate the performance of the model due to noise, noise-added dataset is established by applying Gaussian random noise. After optimizing the CNN structure, evaluation results for noise-free, noise, and noise-mixed datasets are presented.

2. Material and Methods

2.1 Establishment of Dataset

To establish a dataset for the CNN model, piled-up pulse data measured in high radiation environments might be required. However, obtaining this data through an experiment was practically limited. To address this issue, in this study, we obtained individual, non-overlapping pulses through the experiment. And then we artificially synthesized each measured pulse, considering high radiation environments of more than 1Mcps, to create a piled-up dataset. Furthermore, in order to consider environmental characteristics commonly found in high radiation fields, noise was randomly added to the dataset.

Firstly, to obtain non-overlapped pulses, we constructed an experimental setup as shown in Figure 1. The experiment was conducted by using $LaBr_3$ scintillation detector (Saint-Gobain, 0.381 cm × 0.381 cm) which didn't have preamplifier. Sources of the point type (^{152}Eu (3.02 MBq), ^{137}Cs (2.92 MBq), ^{60}Co (2.54 MBq)) were used. The output signals from the detector were amplified by CAEN, A1423B and digitized by DT5730 which had 500 MSPS. The length of the measured pulse was 150 ns length approximately. They were recorded one by one in the window of the 1 us length which was corresponding to 500-channel-long signal. The height of a raw signal was obtained using the peak-finder function in the Scipy library.

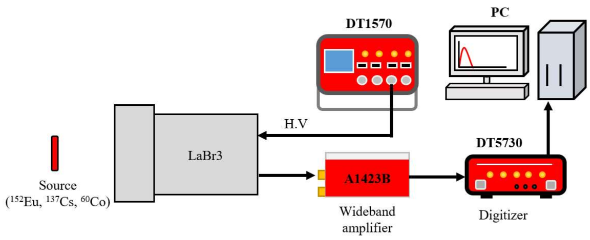

Fig. 1. Experimental setup

As a next step, we artificially synthesized the raw signal to make piled-up signals. The number of piled-up signals was determined in the range of 3 to 9 according to the probability of the Poisson distribution (λ=1). It means that pile-up rate was 100%. The occurrence of pile-up events was controlled by adjusting the timing among pulses, whose interval ranged from 10 ns to 100 ns. In this process, the Gaussian random noise (Its standard deviation was 0.1) was applied to raw signals to consider the noise effect on the CNN model.

As the last step, for piled-up signals, 32-channel-long samples around the peaks were sliced using the peak-finder. Those were used as input features of the CNN model. The dataset was composed of a total of $1.0×10^6$ sliced piled-up signals using $3.5×10^6$ raw signals. Out of the entire dataset, $6.0×10^5$ were used as training data, $2.0×10^5$ were used as validation data, and $2.0×10^5$ were used as test data. To evaluate the performance of the model depending on the presence of noise, we created three versions of the dataset for noise X, noise O, and noise mixed versions. Each of the three datasets was used to train a model, and the trained models were tested using the three versions of the dataset.

2.2 Optimization of 1D CNN model

The structure of the 1D CNN model was constructed in a Python environment using the Pytorch library. The model was optimized by analyzing performance factors calculated from training, verification, and testing based on noise-free datasets. The model was trained using a training set for 500 epochs using the Adam optimizer with a cosine annealing learning rate scheduler. The factors for the performance evaluation were utilized such as calculation time, learning time, results of loss function for training and validation, comparison between the reference spectrum and the predicted spectrum of CNN model, and average estimation accuracy of Eq. (1) for the pulse height.

$$\text{Estimation accuracy} = \frac{1}{n}\left(\sum_{1}^{n}(1 - abs\left(\frac{Pred.H - Act.H}{Act.H}\right) \times 100\right) \quad (1)$$

Figure 2 shows the optimization results of the 1D CNN structure for the estimation of pulse heights. Two convolutional layers contained 64, and 32 convolution filters. The length of convolution filters was set to 3 and the stride was set to 1. The maximum pooling layer was applied at the end of the last convolutional layer to extract the useful data. A flattening layer was the role of making the dimension of the output data into one dimension. The number of hidden layers was three. A rectified linear unit (ReLU) was used as an activation function for the convolutional and hidden layers.

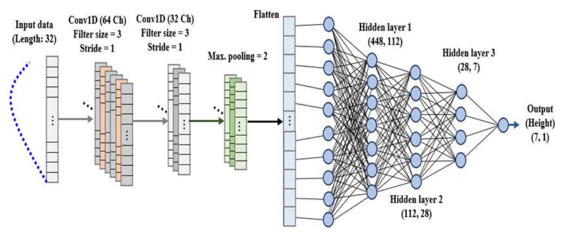

Fig. 2. Schematic of 1D CNN model for pile-up correction

3. Result and Discussion

3.1 Predicted result without the noise effect

Figure 3 shows the reference and piled-up spectra, as well as the predicted spectrum for piled-up spectrum without noise pulses using a 1D CNN model. The result of the pile-up correction from the piled-up spectrum was a good agreement for the reference spectrum and the average estivation accuracy was calculated as 99.302 %. This result implies that our model has the ability to restore the intrinsic energy resolution of the detector even though the signal is superimposed for the absence of noise effects.

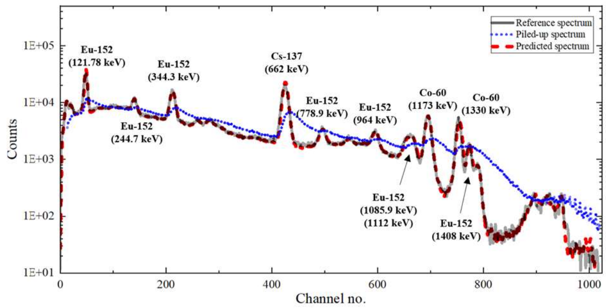

Fig. 3. Reference spectrum and piled-up spectrum, predicted spectrum of pile-up correction results for 1D CNN model.

3.2 Predicted result with the noise effect

Figure 4 presents predicted results (^{60}Co peaks) of 1D CNN model according to the kinds of training dataset based on three cases. Most results show a good correction performance in the range below 1 MeV. However, in previous studies, resolution degradation and peak shift were found in the adjacent peaks of ^{60}Co mentioned [8]. Accordingly, Figure 4 presents only the results for ^{60}Co peaks for efficient analysis. The three datasets used in the training were noise-free datasets (Noise X), only noise datasets (Noise O), and mixed datasets with and without noise (Noise mixed). For each model trained with three datasets, we tested the performance on pile-up correction based on 1D CNN models using three different types of datasets. The test results for noise X show a good agreement for all training models. However, peak shift was observed in models trained with the dataset containing only noise pulse. On the other hand, in the case of the test result on Noise O, it was confirmed that the model trained with Noise X datasets didn't respond effectively to overlapped noise pulses. In other models, resolution degradation was found in adjacent peaks of ^{60}Co. Lastly, the test results on the Mixed noise dataset show that pile-up correction didn't perform well for the noise dataset in the case of the model trained with the Noise X dataset. However, other models gave good prediction results similar to the reference spectrum. In particular, the model trained with the mixed noise dataset had a good result as an estimation accuracy of 98.86%, which was better than the model trained with the dataset that included only noise pulses (98.52%).

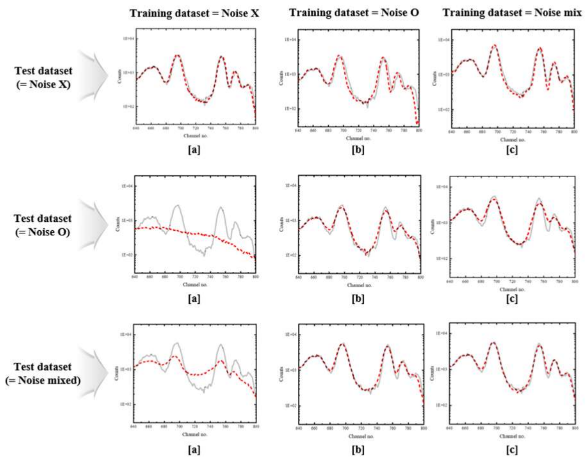

Fig. 4. Predicted results of 1D CNN model according to the kinds of training dataset based on three cases.

4. Conclusion

In this study, we conducted 1D CNN-based study for pile-up correction considering noise effect. As a result, our model had a good correction performance for pile-up pulses with the noise when the mixed noise dataset was used as training dataset. However, we hadn't fully solved the problem of energy resolution degradation at adjacent peaks (^{60}Co) observed in previous studies [8]. In future works, we will perform a comparative study using other models and choose the best pile-up correction model for radioisotope identification & analysis in a high-radiation environment.

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