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Deep Learning Based Rapid Tracking of Electromagnetic Radiation Source Position with Multiple Radiation Spectroscopy Detectors

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Rapid and accurate tracking of radiation sources during electromagnetic radiation emergencies is essential for minimizing human exposure and enabling prompt evacuation. In this study, we propose a deep learning–based electromagnetic radiation source tracking system using multiple NaI(Tl) radiation spectroscopy detectors. The training data was constructed via GATE simulation, and the coefficients measured from three detectors were converted into ratios to compensate for various differences in conditions between simulation and experimental data. A deep neural network model was designed and trained with these ratio-based datasets, and subsequently validated with experimental data acquired using Cs-137 sources and NaI(Tl) detectors. The trained model successfully predicted the X- and Y-coordinates of radiation sources with high accuracy. The deep learning–based localization achieved an average positional accuracy of 95.65 ± 2.65% in the experimental results, with accuracies exceeding 99% at certain positions. These findings confirm that the proposed deep learning approach enables rapid and accurate electromagnetic radiation source localization, with potential applicability to real-time electromagnetic radiation emergency response.

Keywords : deep leaning, radiation spectroscopy detector, electromagnetic radiation source position tracking, GATE

1. Introduction

Environmental radiation monitoring systems require rapid inspection and accurate identification of the source, along with accurate identification of the type of electromagnetic radiation source. This is especially true in situations involving the use of radioactive materials or the handling of electromagnetic radiation sources. Rapid location identification and evacuation are essential in the event of a radioactive material leak. Current environmental radiation monitoring systems utilize methods such as measuring the intensity of radiation and visualizing radiation to determine the location. Measuring the number and dose of radiation emitted from hazardous areas to locate sources has limitations in accurately identifying and visualizing the source. Furthermore, methods utilizing gamma cameras for imaging utilize collimators with very low sensitivity, making rapid detection difficult, hindering immediate location identification and emergency evacuation from the affected area [1-5].

To improve the shortcomings of these radiation monitoring systems, previous studies have deployed multiple high-sensitivity, non-collimator radiation spectroscopy detectors and tracked the location of electromagnetic radiation sources by calculating the number of radiation incident on each detector. Previously studied methods for tracking electromagnetic radiation sources have been studied in various ways. In an early study, simulation data was generated using Geant4 Application of Tomographic Emission (GATE), which can simulate the interaction between radiation and matter, and a location tracking method using multiple spectroscopy detectors was proposed based on this data [6, 7]. This method tracks the location of an electromagnetic radiation source by calculating the relative count ratio at each detector based on the inverse square law of the distance from the detector when the electromagnetic radiation source is emitted [8, 9]. Subsequently, the feasibility of this method was verified through experiments using a silicon photomultiplier (SiPM) detector, and a location tracking

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method applying the maximum likelihood position estimation (MLPE) was proposed using the simulation data. Subsequently, a non-collimator method was employed to track the location of the electromagnetic radiation source in an experiment using a radiation spectroscopic detector for extremely rapid detection, thereby ensuring the reliability of the electromagnetic radiation source location tracking method [10-15].

In this study, we build on previous research by applying deep learning methods to an electromagnetic radiation source location tracking method that combines simulation and experimental data to determine the feasibility of high-precision location tracking. We design a deep learning-based location tracking model, label the radiation count ratios of each detector obtained from simulation data according to location information, and train the deep learning model. We then apply the count ratio data based on location information obtained from actual experiments to evaluate the location tracking accuracy of the deep learning model.

2. Materials and Methods

2.1. GATE simulation for acquiring deep learning model training data

A GATE simulation was performed to obtain training data to be used in the deep learning model. The training data was obtained through interactions between radiation spectroscopy and radiation sources at various locations. The radiation source used in the simulation was Cs-137, which generated a total of 20 MBq of radiation. It was positioned 5 cm from the front of three 2″(diameter) × 2″(thickness) NaI(Tl) radiation spectroscopy detectors arranged at 10 cm intervals, as shown in Fig. 1. The radiation sources were positioned in a 21 × 21 array from 0 to 20 cm in the X direction and from 5 to 25 cm in the Y direction at 1 cm intervals. Data was obtained by performing the simulation 30 times for a total of 441 locations. The energy resolution of the detector used in the simulation was set to 10% based on the photopeak of 662 KeV of Cs-137.

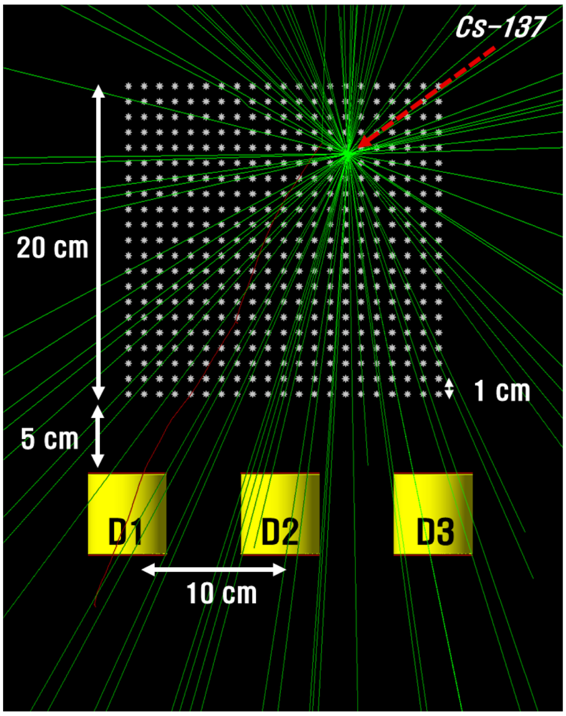

Fig. 1. (Color online) Schematic diagram of the radiation spectroscopy system in GATE.

2.2. Deep learning model

Deep learning is a technology that mimics the human brain's neural network, learning from large data sets and predicting outcomes through multilayer neural networks. This study applied this technique to radiation source location tracking. To achieve this, a multilayer perceptron (MLP)-structured deep neural network (DNN) model was designed using Pytorch 2.0.1 [16].

The training data used in the deep learning model was converted to a ratio, representing the number of radiations detected by each detector. This approach compensates for coefficient discrepancies between simulations and experiments, allowing for direct application of experimental data to the trained model. Using 13,230 data points acquired from three detectors through simulation, six ratios were derived: D2/D1, D3/D1, D1/D2, D3/D2, D1/D3, and D2/D3. The ratio data was labeled with the actual radiation source locations to form a training dataset. The model designed in this study consists of an input layer, three hidden layers, and an output layer. The hidden layers consist of 512, 512, and 256 neurons, respectively, and learn the input coefficient ratio data. The output layer is designed to independently predict the X and Y coordinates of the radiation source. The rectified linear unit (ReLU) activation function in the hidden layer is used to ensure nonlinearity and mitigate the gradient vanishing problem that can occur during the learning process. Furthermore, the model consists of forward propagation, loss calculation, backpropagation, and optimization stages, which are repeated to minimize the model's loss.

To prevent overfitting, which occurs due to excessive reliance on specific neurons during the learning process, the dropout technique was applied, randomly disabling 30% of the neurons. Huber loss was used as the loss function, and Adam was used as the optimization

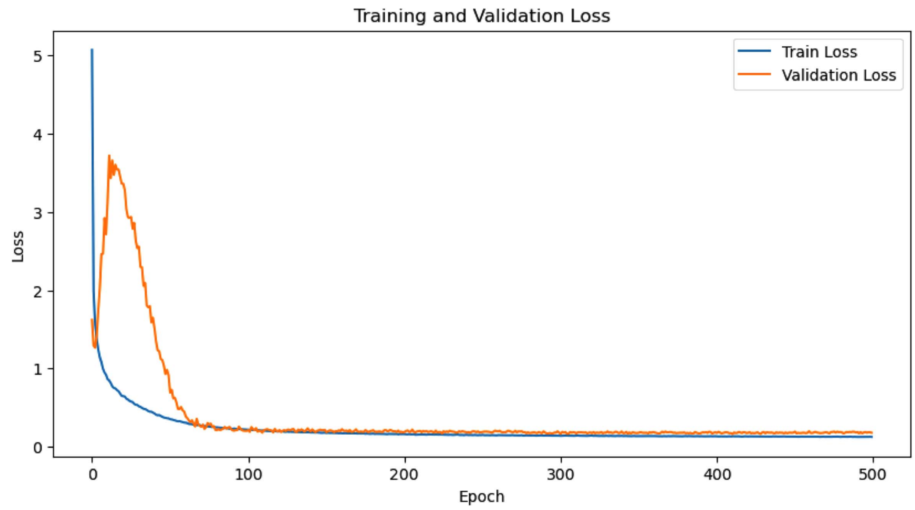

Fig. 2. (Color online) Variation of training and validation loss during the training process of the deep learning model.

algorithm. The batch size was set to 32 and the learning rate to 0.0001. The appropriate number of training epochs was determined to be 500, based on analysis of training and validation loss trends, as shown in Fig. 2 [17, 18].

After training, the deep learning model received the coefficient ratio data for each detector obtained through experiments as input and used it to predict the X and Y coordinates of the radiation source. This process is depicted in Fig. 3 [19, 20].

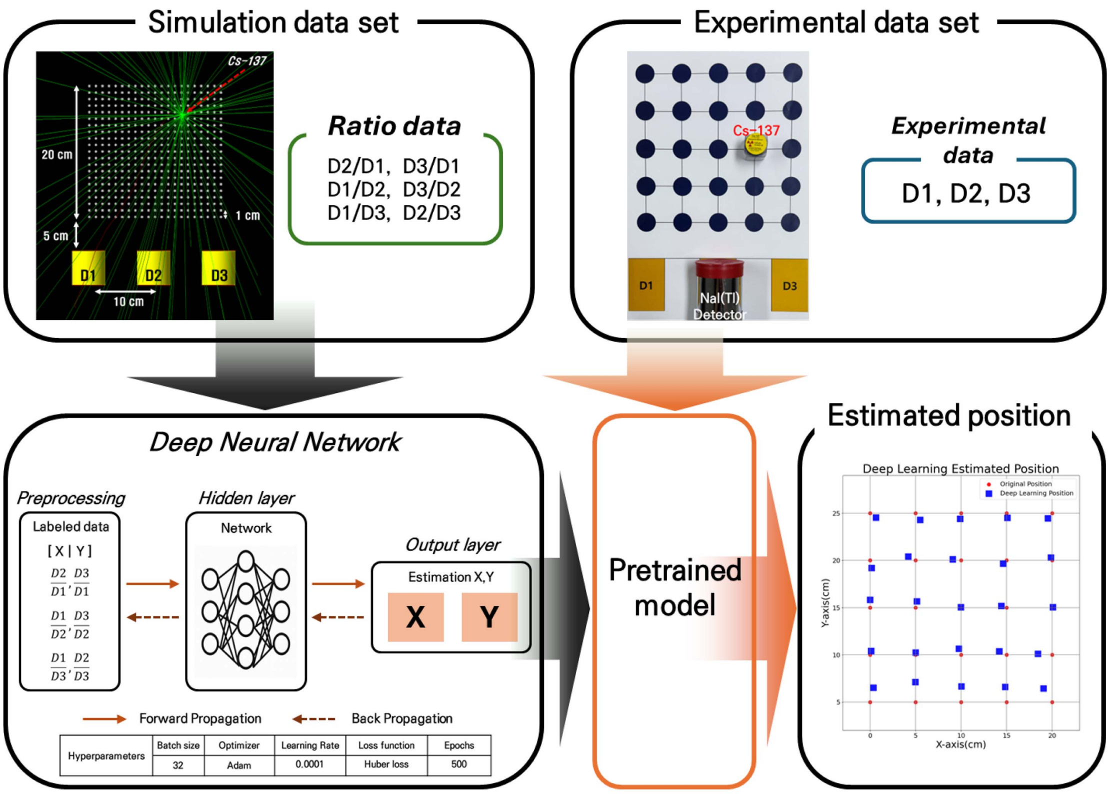

Fig. 3. (Color online) Schematic diagram of the deep learning model for position estimation using GATE simulation data and experimental data acquired with a NaI(Tl) detector. The model is trained with radiation count ratios according to source position and predicts the X and Y coordinates through separated pathways.

2.3. Deep Learning Model Validation Experiment Data Collection

The number of radiation sources per location for application to the deep learning model was measured through experiments. The detector used in this experiment is a radiation spectroscopy (MODEL 905-3, ORTEC) manufactured based on a NaI(Tl) scintillator. The detector used in the experiment consists of a NaI(Tl) scintillator, a photomultiplier tube, and a signal processing module. A high-voltage device (MODEL 556, ORTEC) was used to apply voltage. Afterwards, a main amplifier (DUAL SPEC AMP 855, ORTEC) was used for signal amplification, and the signal was transmitted to a computer through a multi-peak analyzer (ASPEC-927, ORTEC). This transmitted signal was converted into an energy spectrum using analysis software (MAESTRO, ORTEC) and the coefficients of the photopeak region were extracted [21-25]. As shown in Fig. 4, three Cs-137 sources with a total radioactivity of approximately ~2 μCi were used in the experiment, stacked one on top of the other. As shown in Fig. 5, the experimental environment was configured identically to the simulation environment. A single detector was used, and the distance between each detector was set to 10 cm, allowing for movement and counting of radiation. The distance between the radiation sources was designed to be 5 cm, and the number of incident radiations at each of 25 locations for 60 minutes was acquired, and the number of incident radiations on each detector was converted into a ratio and applied.

Fig. 4. (Color online) Three Cs-137 sources were stacked for the experiment, and the sources were placed at the central height of the detector to ensure measurement accuracy.

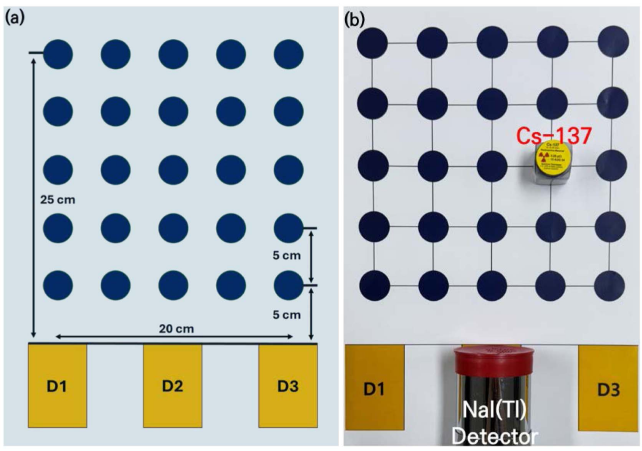

Fig. 5. (Color online) Experimental design and actual setup for radiation source localization. (a) Simulation-based schematic of detector and source placement. (b) Image of the experimental setup using a Cs-137 source with NaI(Tl) detectors.

2.4. Location accuracy assessment

The ratio of the radiation coefficient at each location of the radiation spectroscopy obtained in the experiment was used as the experimental data of the deep learning model to track the location. As shown in Fig. 6, the error rate of the location of each radiation source was defined as the error between the actual location of the radiation source and the location of the radiation source predicted by the deep learning model, *w*, and was calculated by dividing it by the total distance (system length (cm)) along which the detectors were arranged, and is expressed by the following equation [9].

$$\mathrm{error}(\%) = \frac{\mathrm{w(cm)}}{\mathrm{system\ length(cm)}} \times 100 \tag{1}$$

3. Results

A deep learning model was trained using labeled data,

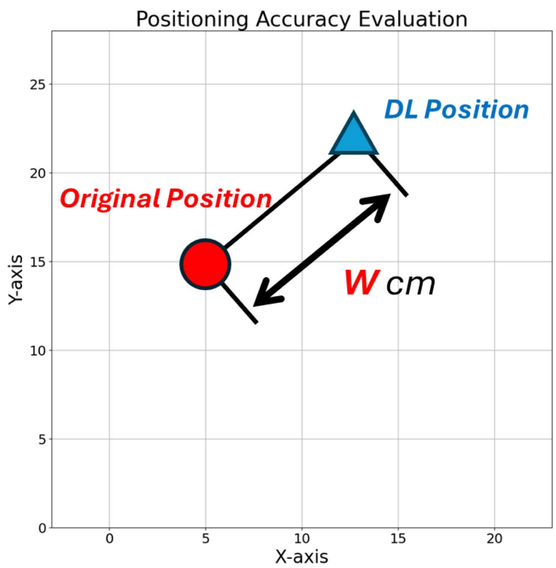

Fig. 6. (Color online) Error evaluation of the deep learning–based source localization. The distance w represents the discrepancy between the actual source position and the position predicted by the deep learning model, and the error rate was obtained by normalizing this distance with respect to the overall detector array length.

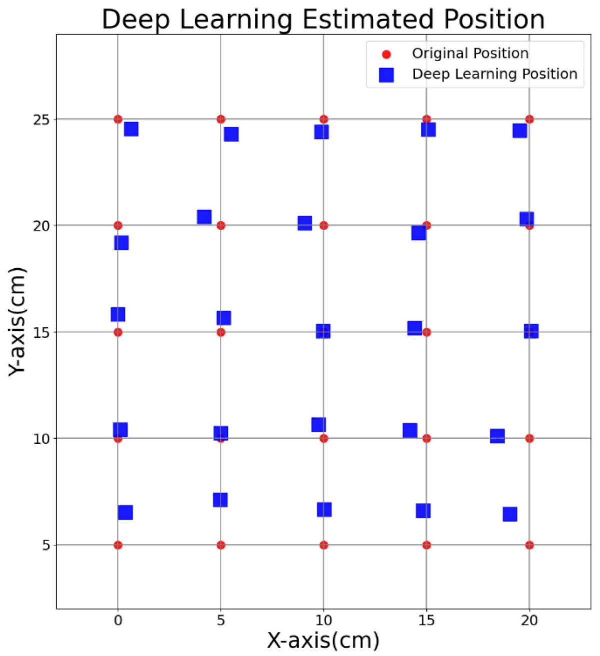

Fig. 7. (Color online) Comparison of the original source positions with those predicted by the deep learning model. Red markers represent the true source locations, while blue markers denote the positions estimated by deep learning.

which included coordinates and radiation count ratios for each location obtained through simulation. The radiation count ratios at all locations obtained through experiments were then used as inputs to evaluate the error rate of a deep learning-based radiation source location tracking system.

Fig. 7 shows the actual locations of the radiation sources marked with red markers, and the coordinates resulting from the deep learning-based location tracking are marked with blue square markers. Excellent agreement between the actual and tracked locations was observed at all locations.

Table 1 shows the error rates for each location. The maximum predicted accuracy was 99.73%, while the minimum predicted accuracy was 89.46%. Of the 25 locations, 19 were predicted with an accuracy of 95% or higher, with an error distance of less than 1 cm, demonstrating extremely high accuracy. Accuracy was particularly high at (10,15) and (20,15), with accuracy rates of 99.73% and 99.43%, respectively. The location with the lowest error rate was (5,5), with a location accuracy of 89.46%. The average accuracy across all locations was 95.65 ± 2.65%.

Table 1. Error rate of deep learning estimation relative to original positions.

DL Position error rate(%)						
Y \ X	0	5	10	15	20	Average
5	7.87	10.54	8.31	8.05	8.55	8.66
10	2.06	1.27	3.43	4.48	7.83	3.81
15	4.18	3.46	0.27	3.04	0.57	2.30
20	4.03	4.56	4.72	2.55	1.64	3.50
25	3.87	4.27	3.07	2.47	3.58	3.45
Average	4.40	4.82	3.96	4.12	4.43	4.35

4. Discussion and Conclusions

Various environmental radiation monitoring methods are being developed for radiation detection, making them essential for rapid evacuation in the event of a radioactive material leak. Currently, gamma cameras are used to image radiation source locations. These require collimators with very small apertures, limiting location detection and rapid evacuation through imaging. To overcome these limitations, a radiation source location tracking system using a non-collimating spectroscopy detector was developed for rapid detection and source identification. Research has also been conducted to improve accuracy and achieve faster source location detection than existing methods. To achieve this, a deep learning model was trained based on GATE simulation data and applied to experimental data acquired using an actual NaI(Tl) radiation spectroscopy detector to estimate the location of the radiation source. To compensate for the absolute differences between the simulation and experimental data, coefficient values were converted to ratios for training and prediction. By labeling the ratios and X and Y positions before application, a deep learning-based location tracking model was implemented that can be directly applied to real-world data. The results of this study confirmed a very high accuracy of 95.65 ± 2.65% for the deep learning model, demonstrating a high accuracy of over 95% at 19 locations, and over 99% in position prediction accuracy at two locations. However, the error rate was relatively high at a distance of 5 cm from the detector. This is considered to be due to the difference in the radiation count generated due to the difference in the area where the radiation emitted from the source interacts with the scintillator at close distances from the detector. The Cs-137 source used in the experiment has a very low activity of approximately 2 μCi, so a long measurement time was required to acquire a large amount of experimental data. However, the photopeak count value was stable because it was higher than the background radiation level. In addition, the use of a radiation spectroscopy detector allowed for the distinction of different radiation sources through their photopeaks, enabling the location of each source to be tracked with high accuracy.

This study was conducted in the laboratory to verify feasibility before conducting a real-world demonstration. Therefore, the experimental area was set to an area where implementation was feasible. Furthermore, the activity of the available radiation sources was very low, limiting the experimental area. Based on this study, future research will conduct experiments in a wider area to determine applicability. Furthermore, since the current study focuses on a single radiation source, further research on the diffusion of radioactive liquids is necessary. Therefore, we plan to continue this research in the future.

By reproducing accident scenarios, such as radioactive material leaks, through simulations and building data based on these simulations to design a deep learning-based location tracking system, it is expected that human radiation exposure can be minimized by quickly identifying the location of radiation sources in real-world situations.

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