Preliminary study on the machine learning models to predict radiation source directions

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1. Introduction

Once radioactive material is released from a Nuclear Power Plant (NPP) during an accident, it is crucial to understand the behavior of the radioactive plume in real time. It serves as an important decision-making factor in establishing and implementing resident protection measures in the early stages of an accident. However, it is difficult to understand the behavior of radioactive plumes in real-time based on actual measurement data.

In a previous study, Long Short-Term Memory (LSTM), a deep learning model, was applied to an atmospheric diffusion model to predict the diffusion of radioactive materials from NPP [1]. However, this model has limitations in real-time applications when an actual accident occurred. The study using artificial intelligence to predict radioactive source positions was also conducted. For example, an optical fiber-based system that utilizes machine learning techniques to find the location of a radiation source in one dimension was developed [2]. This system is limited by the requirement to position the radioactive source directly beneath the optical fiber. In addition, several studies have utilized drones equipped with radiation detectors to measure and visualize contaminated areas from the air [3, 4]. These studies mainly focus on visualizing or inverse modeling contaminated areas. In that, there are limitations in accurately determining the direction and location of unknown sources in the air.

Previous studies provide an important foundation for predicting the diffusion of radioactive plumes and developing systems for tracking the position of radiation sources. However, further study using actual real-time measurement data is needed to assess their applicability.

In this study, as a preliminary study for predicting the location of a radiation source, we conducted to predict the direction of the radiation source using two CZT sensors that can be mounted on a drone. Data measured using two CZTs were set as input data, and the angle of the source from the detection device was set as output data. Nonlinear regression analysis and an artificial neural network model were employed for prediction.

2. Methods and Results

2.1 Experimental data acquisition and generation

The experimental setup required to collect the data for learning are shown in Fig. 1. Two CZT sensors are placed at a 90-degree angle, and the data measured from the two CZTs were collected and processed through a detection device and transmitted to the PC. Cs-137 source was used for the experiment. The source was placed at distances of 0 cm, 3.5 cm, and 7 cm from the CZT, respectively, and its position was changed at 15-degree intervals from the detection device. Each position was measured once, and a total of 21 measurement data were collected.

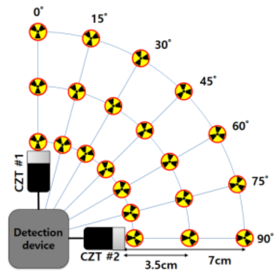


Fig. 1. Experimental setup for collecting measurement data.

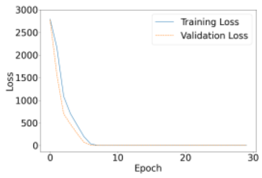
In order to train a machine learning model, a sufficiently large amount of data is needed. Statistically acceptable data were generated and used for model learning [5]. When the number of measurements increases, radioactivity measurements follow the Poisson distribution, and it approximates the normal distribution if the count value is large. In the Poisson distribution, the variance is equal to the mean, and if the count value ‘n’ is obtained by measuring once, ‘n’ can be considered the mean [6]. Since 95.45% exists within the range of the mean ± 2 sigma, random data distributed within the range was generated for learning at each position. The number of data per position, including random data, is 100, and the total data used for learning is 2,100.

2.2 Machine learning method

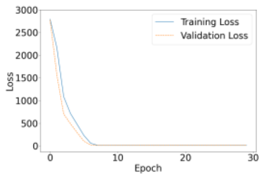
The measured values of CZT #1 and CZT #2 are used as input, and the angles between the detection device and radioactive source is used as the output value. Learning was divided into three categories based on the distance from the detection device. For learning, input data was converted into ratios for each dataset. For example, if count values measured by two CZTs are 9000 and 1000, respectively, each value was converted to 0.9 and 0.1, which are divided by the sum of the two values. Additionally, for normalization, the maximum and minimum values of each column were set to 1 and 0, respectively, and then the data were converted to a ratio between 0 and 1. The training data and validation data were used in an 8:2 ratio. For prediction, the Keras library of the Python program, a nonlinear regression analysis model, was used.

2.3 Prediction results

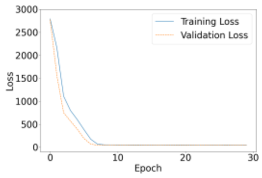
Figure 2 shows the change in the loss for training and validation data as the number of epochs increases. The loss means the difference between the predicted value and the actual value. The smaller the loss, the closer the predicted value is to the actual value. In an ideal scenario, the loss decreases as the epoch progresses. Loss values at each distance are 2.97, 13.21, and 46.98.



(a) 0 cm

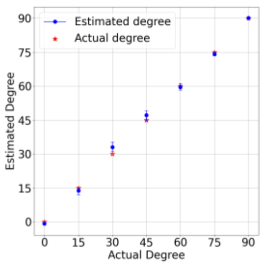


(b) 3.5 cm

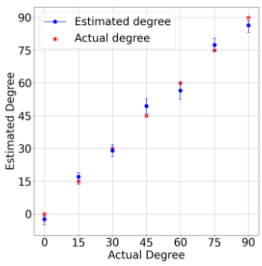


(c) 7 cm

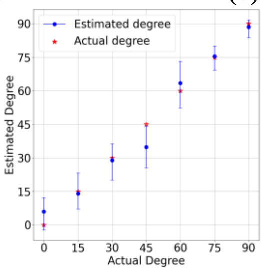
Fig. 2. Loss functions of training and validation data by increasing epoch.



(a) 0 cm



(b) 3.5 cm



(c) 7 cm

Fig. 3. Evaluation results of the machine learning model.

Table I: Comparison of the actual and predicted degree by distances

Distance (cm)	Degree (°)		
	Actuality	Prediction	Difference
0	0	-0.79	0.79
	15	13.82	1.18
	30	33.01	3.01
	45	47.12	2.12
	60	59.61	0.37
	75	74.12	0.88
	90	90.12	0.12
3.5	0	-2.34	2.34
	15	17.10	2.10
	30	29.08	0.92
	45	49.38	4.38
	60	56.54	3.46
	75	77.38	2.38
	90	86.33	3.67
7	0	5.99	5.99
	15	14.02	0.98
	30	28.92	1.08
	45	34.86	10.14
	60	63.49	3.49
	75	75.50	0.50
	90	88.48	1.52

Figure 3 and Table I present the results of comparing the values predicted by the model with the actual values. In Fig. 3, the red asterisk represents the actual value, the blue dot represents the average of the predicted values, and the blue line represents the maximum/minimum of the predicted values. In Table I, "Prediction" refers to the mean, while "Difference" refers to the absolute value of the difference between the actual value and the predicted value. As shown in the figure and table, the farther the distance from the detection device, the larger the deviation of the predicted value. Additionally, when the distance is 7 cm, there is a slight difference between the actual and predicted values at 0 and 45 degrees.

3. Conclusions

In this study, two CZT sensors were placed at 90 degrees and the radioactive source direction was predicted using data from measuring radioactive source at various positions. The Keras library of the Python program was used to learn the model. The input data are the measurements of CZT #1 and #2, and the output data is the angle between the source and detector.

As a result, it was confirmed that although the deviation of the predicted value increased as the distance between the source and the detector increased, it was possible to predict the source direction in 2D through machine learning. In this study, synthetic data was used to confirm the applicability of machine learning. However, for future study, we plan to utilize actual measurement data to conduct detailed study on the source positions and directions.

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