A Study on the Estimation of Gamma-Ray Source Positions Using Machine Learning with the Data of Different Activity Sources

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1. Introduction

In the disposal process, LILW is classified into short, medium, and long-lived waste according to its decay time. The radwaste is sealed in radwaste drums before disposal and one of the main issues has been monitoring the leakage of radioactive isotopes because of the possible leakage. Scanning the drums and tracing the location of any leak can reduce the risk of contamination to the environment as well as the operators.

In this study, the positions of gamma-ray source are estimated from the system that consists of a PSOF, two photon counters. The photon counting data of a 9 μCi Cs-137 source are measured as test data and evaluated using the ML (Machine Learning) model made of training data of a 41 μCi Cs-137 source to identify whether the ML model for the same gamma-ray source can estimate source positions with different radioactivity.

2. Methods and Results

2.1 Materials and Methods

The plastic scintillating optical fiber (PSOF) used in this study is BCF-12 (Saint Gobain Crystals). Table 1 lists some of the specific properties of BCF-12.

Table 1. Specific properties of BCF-12

Properties	**Value (Unit)**
Emission peak	435 (nm)
Decay time	3.2 (ns)
# of photons per MeV	~8000 (#)
Diameter	3.0 (mm)

In this study, two H11890-210 photon counters (Hamamatsu Photonics) are used to collect light signal from each end of the PSOF. Table 2 lists some of the specific properties of the photon counter.

Table 2. Specific properties of H11890-210

Properties	**Value (Unit)**
Spectral response	230 ~ 700 (nm)
Peak sensitivity wavelength	400 (nm)
Effective area diameter	8 (mm)

In the ML modeling and evaluation process, pre-processed photon counting data which means to be converted from absolute counts to relative counts are used to estimate the positions regardless of the activity of the source. The Keras framework with Tensorflow back-end engine in a Python environment is used for the construction of the ML model for the estimation of the source position. Nonlinear regression algorithm is used as the base of the model.

Theoretical estimations of the position of the gamma-ray source are conducted to compare derived from the photon counting data using the Beer-Lambert law of attenuation. In this study, the attenuation coefficient is calculated using the training data of ML model.

2.2 Experimental setup

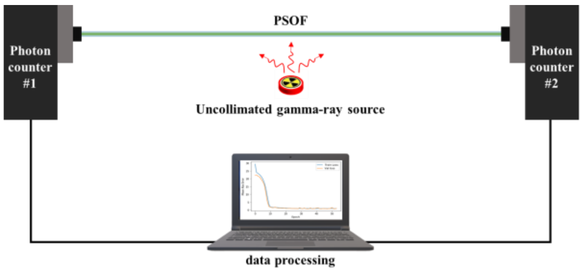

Fig. 1. Experimental setup

Figure 1 shows the experimental setup to measure the scintillation signals. A PSOF with a length of 1 m is connected to photon counters at both ends and the photon counting data are directly transferred to the computer. The source is positioned 5 cm below the PSOF. At 35 and 65 cm positions, the support bars are placed to keep the PSOF to be straight.

For the ML modeling and evaluation, 1,620 photon counting data at nine source positions between 10 to 90 cm are measured for the ML training data, and 180 photon counting data at 18 source positions are measured for the test data.

2.3 Results

To identify whether the ML model for the same gamma-ray source can estimate source positions with different radioactivity, the photon counting data of a 9 μCi Cs-137 source are measured to be used as test data and evaluated using the ML (Machine Learning) model made of training data of a 41 μCi Cs-137 source. The standard deviations of statistical fluctuation of test data for Cs-137 with 9 μCi are in the range of 1.8~2.9%.

Figure 2 and table 3 show the results for the position estimation error of the 9 μCi Cs-137 source test data using the Cs-137 ML model for a 41 μCi source. The results confirm that it is possible to use the ML position estimation model to the position of source with different activities, since 9 μCi Cs-137 source test results using Cs-137 ML model for 41 μCi source also show a lower overall error value compared with the theoretical position estimation result.

Table 3. Comparison between the overall error values

	ML estimation (cm)	Theoretical estimation (cm)
41 μCi Cs-137	1.15	4.27
9 μCi Cs-137	1.76	4.33

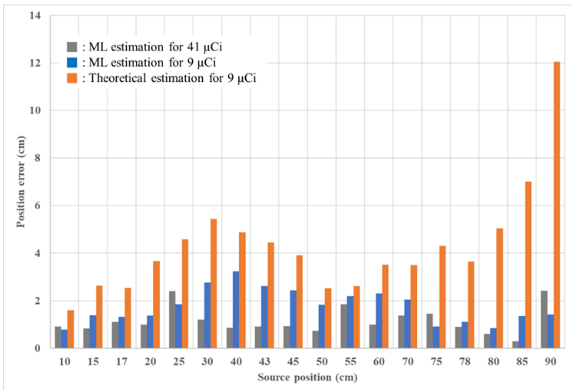

Fig. 2. ML model/theoretical position estimation error plot

3. Conclusions

In this study, the gamma-ray source position is estimated using a 1 m length PSOF, two photon counters and via ML data processing. The ML training data used 1,620 photon counting data at nine source positions between 10 to 90 cm. The test data used included 180 photon counting data at 18 source positions. To identify whether the ML model for the same gamma-ray source can estimate source positions with different radioactivity, the photon counting data of a 9 μCi Cs-137 source are measured as test data and evaluated using the ML (Machine Learning) model made of training data of a 41 μCi Cs-137 source. The results confirm that it is possible to use the ML position estimation model to the position of source with different activities.

Further studies will be conducted on the position estimation of gamma-ray sources using scintillation signals from complex geometry of PSOF, which can be used in the various and customized measurement of radiation.

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