Preliminary study on the estimation of radioactive source position using plastic scintillating fiber and machine learning

Jinhong Kim [a], Seung Hyun Kim [a], Si Won Song [a], Jae Hyung Park [a], Jin Ho Kim [a], Tae Seob Lim [a], Bongsoo Lee [a*]
[a] *Department of energy systems engineering, Chung-Ang University, 84, Heuk-Seok ro, Seoul, Korea*
[*] *Corresponding author: bslee@cau.ac.kr*

1. Introduction

Plastic scintillating fiber (PSF)s have many advantageous features such as high sensitivity, electro-magnetic interference, fast response and flexibility as a radiation detecting tool. Especially, their capability to transfer the scintillating signal allows them to be a long-range measuring sensor. On the other hand, precisely measuring the attenuation coefficient of a PSF is not easy and enough length of PSF is needed, so the theoretical method to estimate the position of radioactive source using a PSF has limit in accuracy.

In this study, the 1-dimensional radioactive source position estimating system with a PSF is developed and machine learning (ML) model is made with the photon counting data from the system. ML model is evaluated with test data which are separately obtained from the system.

2. Methods and Results

2.1 Materials

The 1-dimensional radioactive source position estimating system is very simple and consists of a PSF, two photon counting modules.

The PSF used in this study is BCF-12, which is produced by Saint-Gobain crystals. The 3.0 mmΦ core is made of polystyrene, and the 90 mm thickness single-layered cladding is made of polymethyl-methacrylate. To create scintillating signal, the core contains fluorescent dopants. The refractive indices of core and cladding are 1.6, 1.49, respectively. For the scintillating signal, the emission peak of BCF-12 is 435 nm and the decay time of signal pulse is 3.2 ns. To prevent signal loss, black tube jacketing and customized connectors are prepared. The customized connectors are used at both ends of the PSF, make the distance of PSF tip and detector window is minimized and maintained with a gap.

The light signal detector used in this study is photon counting module whose model name is H11890-210, which is produced by Hamamatsu photonics. The specific properties of photon counting module are as follows; photocathode area size is 8 mmΦ, detectable wavelength range is from 230 to 700 nm, detect wavelength peak is 400 nm, typical dark count is 50 s^{-1}.

To obtain experimental data, the 49 μCi Co-60 check source is used.

2.2 Experimental setup and results

Figure 1 shows the experimental setup to measure the light signals from Co-60 gamma ray source. A single strand of PSF with 1 m length is connected to photon counting modules at both ends with customized connectors. The Co-60 source is located below 5 cm from the PSF, and the data are obtained from 10 to 90 cm along the PSF by the same intervals of the source position. For the random position estimation test, test data are obtained at the position of 17, 43, 78 cm as well as the training data position.

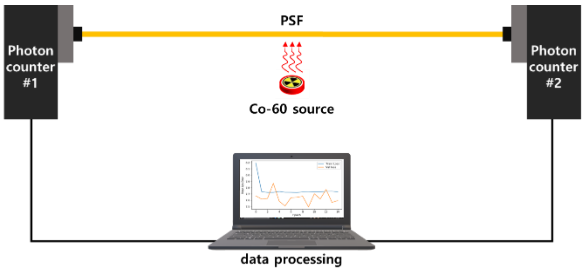

Fig. 1. Experimental setup schematics.

At each measuring position, 20,000 photon counting data are obtained for the training data, and 5,000 data are obtained separately for the test data.

The theoretical method to estimate the position of the source is based on the equation shown in below.

$$x = \frac{L}{2} + \frac{1}{2\mu}\ln\frac{I_2}{I_1} \qquad (1)$$

where,

x: estimated position of the source, L: length of fiber, μ: attenuation coefficient of fiber, I: counted number of photons.

The parameter used in this study to evaluate the accuracy in the position estimation is mean absolute error (MAE), which is widely used to evaluate the regression AI model. The estimated position MAE value of the experimental data calculated from the theoretical method is 6.11 cm.

2.3 Machine learning model

Figure 2 shows relatively processed scintillating signals, which are both shaped linearly. The Python linear regression machine learning algorithm is used to create the position estimating model with the relatively processed signals.

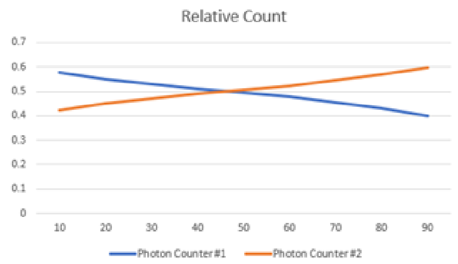

Fig. 2. Photon signals which is relatively processed.

10% out of 300,000 data are separated for the validation of model. The activation function of the model is rectified linear unit function and the optimizer is Adam, shown in the figure 3.

Require: α
Require: $\beta_1, \beta_2 \in [0, 1)$
Require: $f(\theta)$
Require: θ_0

$m_0 \leftarrow 0$
$v_0 \leftarrow 0$
$t \leftarrow 0$

while θ_t not converged **do**
$t \leftarrow t + 1$
$g_t \leftarrow \nabla_\theta f_t(\theta_{t-1})$
$m_t \leftarrow \beta_1 \cdot m_{t-1} + (1 - \beta_1) \cdot g_t$
$v_t \leftarrow \beta_2 \cdot v_{t-1} + (1 - \beta_2) \cdot g_t^2$
$\widehat{m}_t \leftarrow m_t / (1 - \beta_1^t)$
$\widehat{v}_t \leftarrow v_t / (1 - \beta_2^t)$
$\theta_t \leftarrow \theta_{t-1} - \alpha \cdot \widehat{m}_t / (\sqrt{\widehat{v}_t} + \varepsilon)$
end while

return θ_t

Fig. 3. The algorithm of optimizer Adam.

Where,

α: stepsize, β_1 and β_2: exponential decay rates for the moment estimates, $f(\theta)$: stochastic objective function with parameters θ, θ_0: initial parameter vector

The parameter used in this study is as follows; learning rate=0.001, β_1=0.9 and β_2=0.999. The number of hidden layers is 2, and the number of nodes is 32 at both hidden layers. All of nodes are densely connected.

Randomly selected validation data are used for the stop-modeling, by tracking validation loss and there is no reduction of validation loss while 10 times of epochs are completed. As a result, the overfitting of model does not occurred.

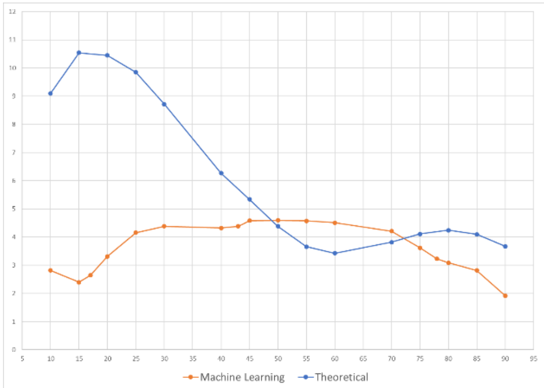

Fig. 4. Comparison between the MAE of ML test results and theoretical calculation at each test position.

Table I: Total MAE of ML test results and theoretical calculation

	Theoretical	ML
MAE (cm)	6.11	3.66

Figure 4 and Table I show the MAE values of ML test results and theoretical calculation, both at each test position and total average value. From 10 to 45 cm and 75 to 90 cm position, ML model predicts the source position more precisely, showing relatively gradual change of MAE value. And the test results measured besides training data position (17, 43, 78 cm position) show that the ML model has capability of estimating any positions with the light intensity data.

3. Conclusions

In this study, the 1-dimensional radioactive source position estimating system with a PSF is developed and ML model is made to enhance the accuracy in the estimation of the source position. ML model is evaluated with separately obtained test data and shows 40.1% of improvement ratio compared to the theoretical calculation.

Further studies are needed to optimize the linear regression model and to develop non-linear regression model.

ACKKNOWLEDGEMENTS

This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korean government (MSIT)
(No. 2016M2B2B1945255, 2020M2D2A2062457)

REFERENCES

[1] Carly Whittaker et al., Transmission Loss Measurements of Plastic Scintillating Optical Fibres, Optical Materials Express, Vol. 9, No. 1, 2019.

[2] Sang Don Lee et al., Plastic Scintillation Fibers for Radiological Contamination Surveys, EPA/600/R-17/370, 2017.

[3] Plastic Scintillating Fibers Datasheet, Saint-Gobain Ceramics & Plastics, Inc.

[4] Photon Counting Head H11890-210 Datasheet, Hamamatsu Photonics.
[5] G. F. Knoll, Radiation Detection and Measurement 4th edition, John Wiley & Sons, New York, 2010.
[6] Diederik P. Kingma, Jimmy Lei Ba, Adam: A Method for Stochastic Optimization, ICLR Conference, 2015