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Estimation of radioactive contamination depth through NaI(Tl) gamma spectroscopy analysis using ANN

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1. Introduction

Depth estimation of contaminated soil by Cs-137 is a crucial issue for effective decommissioning and safe decontamination. Prediction of contamination depth is economically important because disposal of radioactive waste imposes cost during the decommissioning process. If Cs-137 spends a considerable long time near the plants' root, it can be included human food chains. On the other hand, the deep penetration of Cs-137 in the basement result in groundwater contamination.[1] Mapping the depth distribution of contaminated soil for a large decommissioning site is an essential element to ensure the safety of the nearby area.

Traditional intrusive methods such as core sampling have been widely used to investigate the depth distribution of Cs-137, but it is expensive and time-consuming. Therefore, nondestructive methods have been studied extensively in recent years. Among the several methods, Lead plate and Collimator methods use a heavy structure with the detector and require multiple measurements. Various methods that use specific peaks of the spectrum like peak-to-valley is inaccurate about the distorted and noisy spectrum. Some of them need additional experiments or simulations to establish a prior model. Depth estimation applying Bayesian inference[2] achieved higher accuracy with the only single measurement using NaI(Tl) detector. Although, the Bayesian inference is inconsistent with real-time estimation. The real-time scanning of large areas and the fast announcement of restrictions about land use is needed to minimize the damage to nearby residents.

To succeed in real-time depth estimation of Cs-137, this paper applied a machine learning algorithm, Artificial Neural Network(ANN). This paper aims to develop an optimized ANN for estimation of the accurate depth of where Cs-137 is located. We also showed that the ANN model works well for the spectrum under various measurement conditions like gain-shift and short acquisition time.

2. Methods and Results

2.1 Experimental Setup

The experimental part of this study was carried out to obtain the base spectrum for the generation of training data. Figure 1, shows the experimental setup which composed of a sandbox and 2-inch diameter NaI(Tl) detector with a cylindrical lead collimator of 2cm thickness. The inner dimensions of the sandbox were 50 cm in length, 40 cm in width, 40 cm in height, and it's acrylic wall thickness was 0.3 cm. The Cs-137 source with radioactivity of 0.94 μCi was buried in fine silica sand. The distance between the sand surface and the geometrical center of the detector was 6 cm, and Cs-137 source was placed in sand in the depth of 0, 1, 3, 5, 7, 10, 15, 20, 25, 30, 40, and 50 cm. The spectra to be used as the basis of the training set were measured for 50 minutes to ensure the accuracy of training data. The measurement time of test spectra was chosen as 10 sec, 1 min, and 10 min to evaluate ANN's prediction ability about short acquisition time. The gain was not carefully adjusted to see the ability of the trained model to overcome the gain change of the detection system

2.2 Training Data Establishment

The quality and quantity of training data determine ANN's performance. To construct enough amount of training data set, set of PMF(probability mass function) about each spectrum measured with the different situations; depth(0 ~ 50 cm) and gain(0.92 ~ 1.08). By inputting the total count value to the constructed PMF, it is possible to generate an infinitely large amount of spectra as the input value is changed. Before the build of PMF, the base spectrum of each PMF should be determined. Part of the total count corresponding to the background spectrum was removed from the spectrum. The construction of base spectra at an interval of 1cm between 0 to 50 cm was achieved through the linear interpolation within the measured base spectra. (Figure 1.) Each spectrum was further expanded with 17 different gains. A total of 867 base spectra with different depths and gains produced a set of PMF.

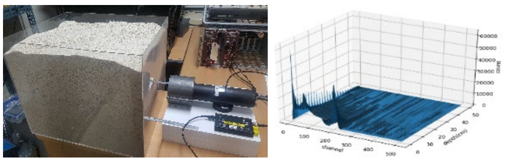

Fig. 1. Experimental setup and Spectra obtained as a result of interpolation

The total count as input to PMF was determined by the following Eq(1).

$$N_{tot} = AP\delta\varepsilon t \quad (1)$$

where A is activity(Bq), P is total x-ray and gamma-ray emission probability(s^{-1}), δ is the intrinsic efficiency of the detector, ε is the correction coefficient due to attenuation, t is acquisition time. A and P are the property of radioactive source, δ is experimentally determined.[3] ε can be described as Eq(2).

$$\varepsilon = \frac{1}{4\pi(h+z)^2} e^{-\mu_A h} e^{-\mu_s z} \quad (2)$$

where h is the detection height from the surface of the soil(cm), z is the buried depth of source(cm), μ_A and μ_s are attenuation coefficients of soil and air which determined by fitting the experimental values(cm^{-1}). The Cs-137 with 0.94, 0.7, 0.5 μCi activity and acquisition time with 10, 60, 600, 1500, 3000 sec were substituted to Eq(1). The total count values from the substitution result became input data for each PMFs created above. As a result, a total of 13005 training sets were created, and 20% of them were used as validation sets during the training process.

2.3 Artificial Neural Network optimization

Hyperparameter in machine learning means the values are preset before the learning process begins. To find the optimal value of hyperparameter the Bayesian Optimization was applied. Bayesian Optimization simultaneously reflects 'prior knowledge' when researching new hyperparameter values each time. Since it is more efficient than simply repeating randomization, it has better performance than the other existing methods like Random search during the same time. The input distribution of each hyperparameter was determined within the range we want to examine, and Bayesian optimization was done using the Python package GPyOpt version 1.2.6. Table 1. shows the optimized value of each hyperparameter which applied to ANN constructed through the Python package Keras, version 2.3.1. Hyperparameter optimization was performed for 4 cases with the different number of hidden layers of ANN, and as a result, the structure with one hidden layer with the best performance was selected as the final model.

Table 1. Optimal value of hyper-parameters of ANN

No. of neuron in input layer	**No. of neuron in hidden layer**	**Drop out rate in input layer**	**Drop out rate in input layer**	**Learning rate**	**Batch size**	**Activation function**
1135	1297	0.2356	0.3748	0.0015	3000	ReLu

To effectively reflect changes according to the depth of the spectrum, the counts from channels 15 to 444 out of a total of 512 channels were put as input. As a loss function for monitoring the performance of ANN, Mean Squared Error (MSE) was used.

2.4 Results

The regression result is represented in figure 2 indicate the closeness among the true depth and predicted depth from ANN about spectra measured for 10 min. The fitted equation in the graph shows the accuracy of the trained model. The slope of the fitted equation is 1.0376, it means ANN well estimated the depth from the input spectrum. Since the effect of noise and statistical error increases due to the decrease in the count, it is observed that the accuracy of prediction decreases when the depth is more than 35 cm. However, all predicted values are included in the 95% confidence interval up to 30 cm. This is a more advanced result than 21 cm obtained through Bayesian inference under the same experimental conditions.

As a result of testing with a short measurement time spectrum, the accuracy of the model was relatively degraded and the regression results were underestimated compared to the actual values. Spectrum with extremely short acquisition time increases statistical fluctuation and the features of the spectrum due to the change in the depth do not appear well.

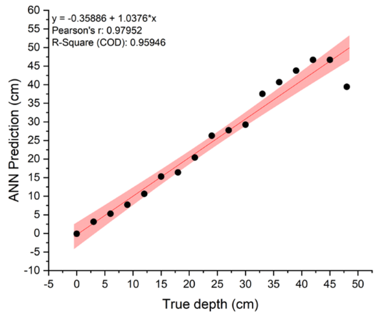

Fig. 2 Regression plot between ANN prediction and true depth for spectrum with 10 min acquisition time

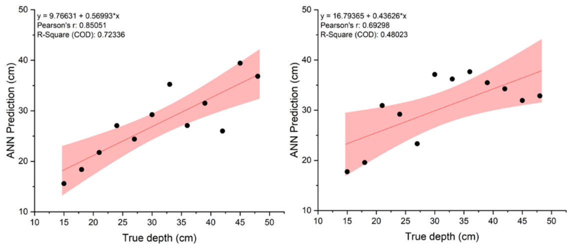

Fig. 3 Regression plot between ANN prediction and true depth for spectrum with 1 min and 10 sec acquisition time

3. Conclusions

In this study, ANN was applied to evaluate the depth contaminated by Cs-137 in real-time. A maximum reliable estimated depth is improved over recent research results. It was shown that depth evaluation is possible even in harsh environments such as gain shift or short measurement time. Further research should be directed at determining how to enhance the performance for a short acquisition time spectrum for fast inspection of large areas. Furthermore, the model will be developed to enable estimation of the radioactivity along with the depth.

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