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Radioactive Source Localizing Radiation Portal Monitor using Convolutional Neural Network

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1. Introduction

Radiation portal monitors (RPM) have been deployed at nation's borders to screen individuals, vehicles or cargos at borders or security facilities to thwart smuggling of illicit radiological source and materials for nuclear weapons. The utilization of RPMs is not limited to detecting radioactive sources. Depending on which technology integrated with RPMs, diverse functions can be implemented RPMs. The various applications have been developed in the direction of convenient to operators such as radioisotope identification[1-4] and localization and tracking of radioactive sources[5-7]. This paper is focused on a technique to localize radioactive source using a deep learning algorithm.

2. Methods and Results

2.1 Convolutional Neural Network

Convolutional neural network (CNN) is one of the deep learning algorithm, and known that CNN has powerful performance to analyze 2D visual data. It generally utilized for image and natural language processing

Similar with general neural networks, CNN consists of an input, output layer and multiple hidden layers. Differently from typical neural network system, CNN has convolution layer, pooling layer and fully connected layers. Fig. 1 shows a schematic of conventional convolutional neural network system.

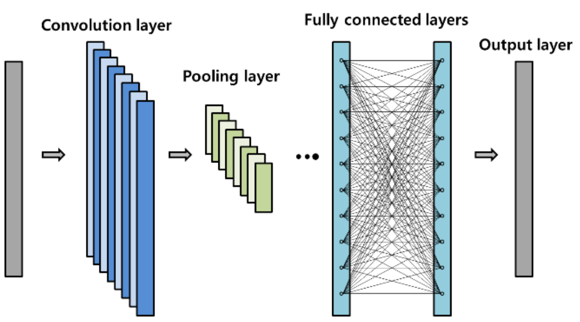

Fig. 1 A schematic of a convolutional neural network

2.2 Radioactive Source Localizing RPM

To estimate the position of radioactive source, a set of NaI(TI) scintillation detector which has a volume of $4 \times 4 \times 16$ in^3 are utilized. Totally, 4 detectors are installed at the RPM frame. A region of interest (ROI) is set equivalent to the cross sectional size of containers, which satisfies ISO standard. Positions of detectors are determined as tri-sectional points of ROI. After then, we defines 25 position areas. The size of area is concerning the number of training samples. The number of the areas can be enlarged if the number of samples are enough. Following figure shows a schematic of source localizing RPM system with detailed dimensions.

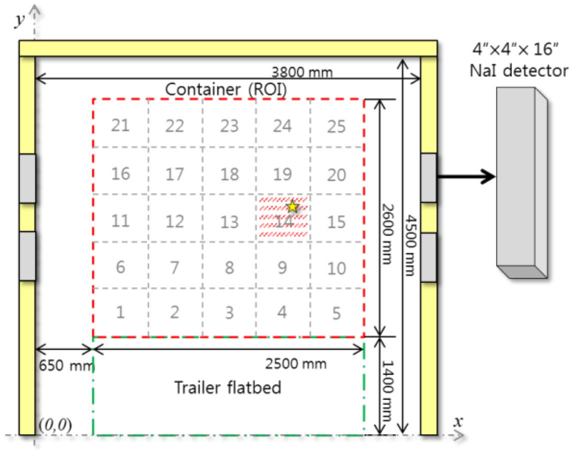

Fig. 2 A schematic of source localizing RPM system

Using the measured quantities from these detector, a machine that localizes radioactive source will be trained by convolutional neural network.

2.3 Training & Test

Training and test data have been generated by MCNP6[9] simulations. Co-60 is utilized as source. Training samples are achieved by simulations with regularly distributed source data for all sections. Totally, 2025 samples (81 samples per section) are utilized as training data. For test samples, 1250 simulation results (50 data per section) with randomly distributed source data are utilized for all sections. To confirm the localization performance correctly, test samples are generated as follows. Firstly, generate a random source distribution for a grid. Secondly, make source distributions for all section by matching generated data on each section.

3. Simulation result

To confirm the performance of radioactive source localizing RPM, a convolutional neural network was implemented in the Python with the TensorFlow library[10]. As mentioned above, 81 samples per sections were utilized for training, and 50 data per sections were used for test. Fig. 3 shows test results in forms of confusion matrix.

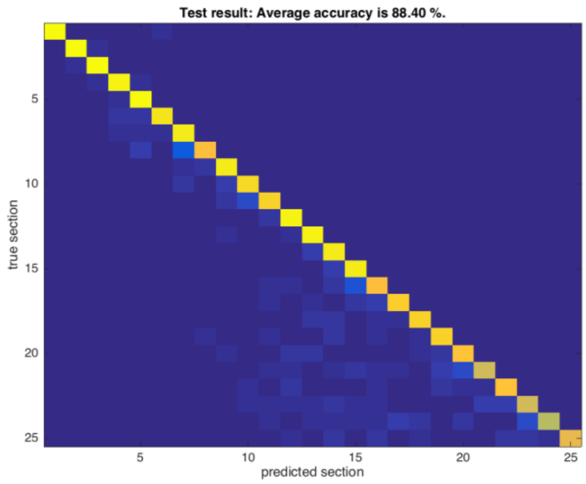

Fig. 3 Simulation result

4. Conclusions

By simulation study, the possibility to implement a deep-learning based radioactive source localizing RPM has been verified. Using a convolutional neural network, we confirms that it is possible to achieved accuracy over than 88 % in ideal with only 81 samples per section. Now we fabricated the RPM system. After the fabrication, we will confirm the performance of the RPM with real experimental data.

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