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Simulation Study of Radioactive Source Localizing Radiation Portal Monitor using Support Vector Machine

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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 machine learning algorithm.

2. Methods and Results

2.1 Support Vector Machine

SVM is an classification learning tool developed by Vladimir Vapnik[8]. This algorithm has been developed theoretically and applied in not only data mining problems but pattern recognition problems.

SVM is an alternative machine learning method to polynomial, radial basis function and multi-layer perceptron classifiers. SVM is basically an extension of neural network and linear classifier. General neural network method is solving optimization problem with non-convex and non-constraint minimization problem. However, SMV is solving optimization problem with quadratic programing with inequality constraints.

There are linear separable data extracted from 2 classes(true and not true) on N-dimensional space. The hyper planes dividing classes can be represented as

$$w_1x_1 + w_2x_2 + \cdots + w_Nx_N + b = 0 \qquad (1)$$

where, w_n is normal vector, x_n is points and b is a distance from origin to hyper-plane.
There are a number of hyper planes that distinguishing true from not true classes. Each of them is utilized as a classifier. To choose the best classifier that classifying classes optimally, the concept of margin is utilized. The margin of the classifier can be defined as the width of the plane when the plane for width is reached any point while the width is widened gradually in 2 vertical directions of the plane. The margin can be formulated with the distance between a plane and a point.

$$d = w^T A + B/\|w\| \qquad (2)$$

where, w is normal vector and A is a point.
When largest margin is found, reached points are called support vector and the hyper plane divides the margin in half is called optimal separating hyper plane.
Support vector machine is a learning method for finding support vector.

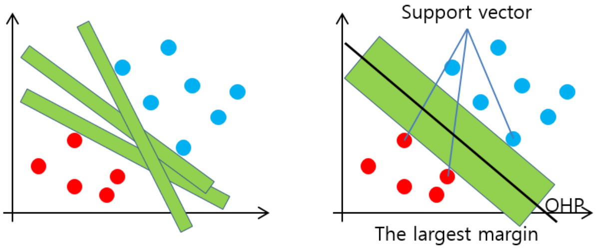

Fig. 1. Schematics of the margin, optimal hyper plane and support vectors

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 4×4×16 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 9 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 RPM structure with detailed dimension and concept of radioactive source localizing.

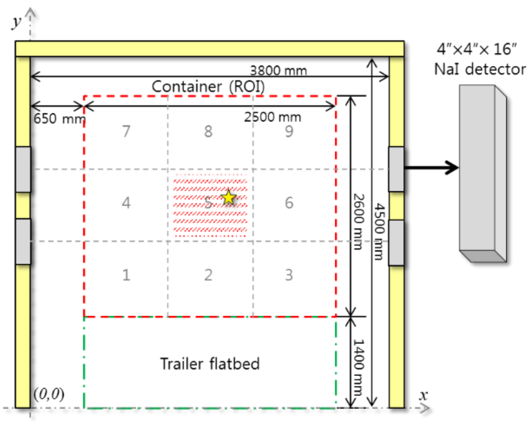

Fig. 2. A schematic of RPM system

Using the measured quantities from these detector, a machine that localizes radioactive source will be trained by support vector machine. To train the machine, detector measurements should be necessary. To simulate detector signals, MCNP6[9] is used. Fig. 3 is a 3D modeling of the RPM system achieved using the MCNPX Visual Editor.

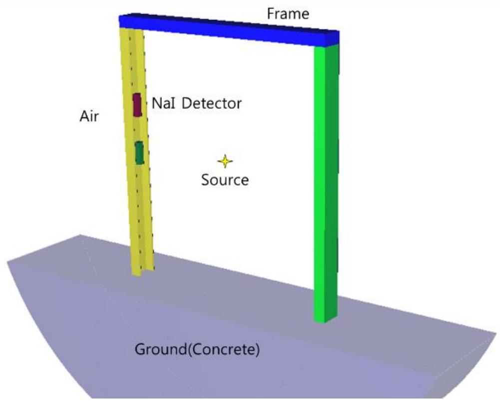

Fig. 3 3D modeling of RPM structure in MCNP simulation

2.3 Training & Test

Training and test data have been generated by monte carlo simulations. Co-60 is utilized as source. Training samples are achieved by simulations with regularly distributed source data for all sections. Totally, 2250 samples (250 samples per section) are utilized as training data. For test samples, 450 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 support vector machine was implemented in MATLAB environments. As mentioned above, 250 samples per sections were utilized for training, and 50 data per sections were used for test. Fig. 4 shows test results in forms of confusion matrix.

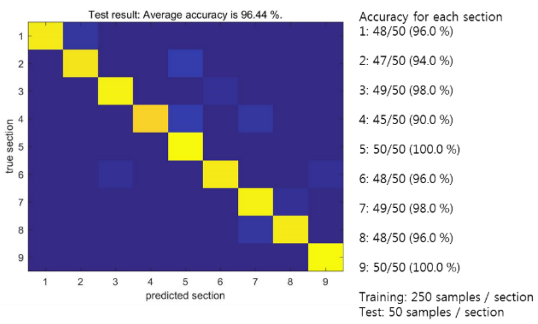

Fig. 4. Simulation result.

4. Conclusions

By simulation study, the possibility to implement a machine learning based radioactive source localizing RPM has been verified. Using support vector machine, we confirms that it is possible to achieved accuracy over than 90 % in ideal. Now we are fabricating the RPM system. After the fabrication, we will confirm the performance of the RPM with real experimental data.

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