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Development of Compensation System by Using Deep Learning Algorithm for Missing Radiation Data

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1. Introduction

If a nuclear power plant accident occurs, it is difficult for people to approach the accident area. In case of Chernobyl accident (1986), everyone who had exposed to radiation on the site was eventually caused to death [1].

A radiation sensor network system is the most effective way to monitor an accident situation at nuclear power plants. It can be collected the necessary nuclear radiation data right after the accident, even in places where people cannot enter. However, the sensors could be exposed to radiation above a certain level during the measurement process, causing inoperable and missing a part of data.

Therefore, we have a plan to use deep learning algorithms to compensate for the missing data. While traditional machine learning algorithms are used to discriminate selected features based on standardized data, a recently developed deep learning algorithms can show better classification ability by learning various features of data input from multiple layers [2].

This paper is organized into four sections. Section 2.1 describes the data preprocessing process, Section 2.2 explains the model used for data compensation, Section 3 shows the training and test results, and Section 4 summaries the direction of future research.

2. Methods

2.1 Data preprocessing

Before collecting the actual data, we created simulation data to train and test a deep learning model.

Fig. 1 shows an architecture of a virtual nuclear plant site consisting of grassy area absorbing radiation easily and buildings preventing radiation spread.

Fig. 2 illustrates a spread of radiation from the start point marked by red for 300 second simulation based on site map of Fig. 1. In order to obtain data set, we simulated four models with different starting points; one is for test data set and the others were used for train data. The one of three train data was displayed in Fig. 2 by a python library on the 160 by 160 pixel size.

In Fig. 3, there are two black boxes indicating the pixel death converting the pixel values to 0 that is an assumption of malfunctioning and/or missing sensors.

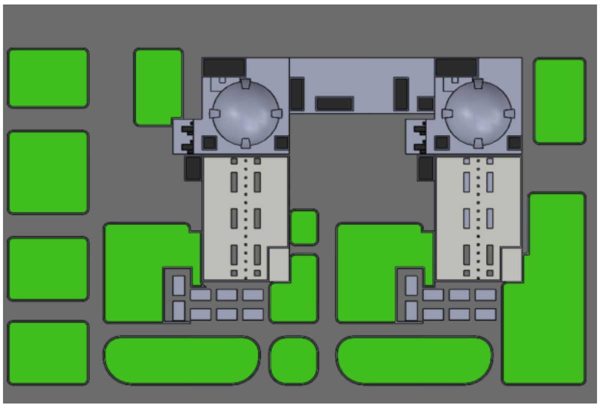

Fig. 1. Virtual Nuclear Power Plant

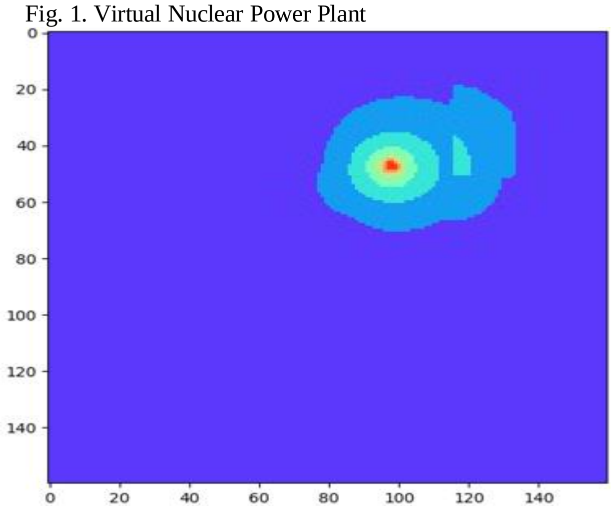

Fig. 2. Radioactivity map at 300 s

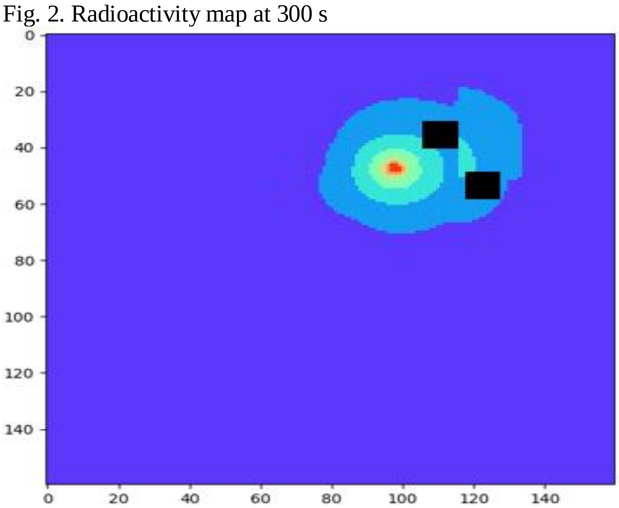

Fig. 3. Radioactivity map where some pixels are dead indicating sensor missing data

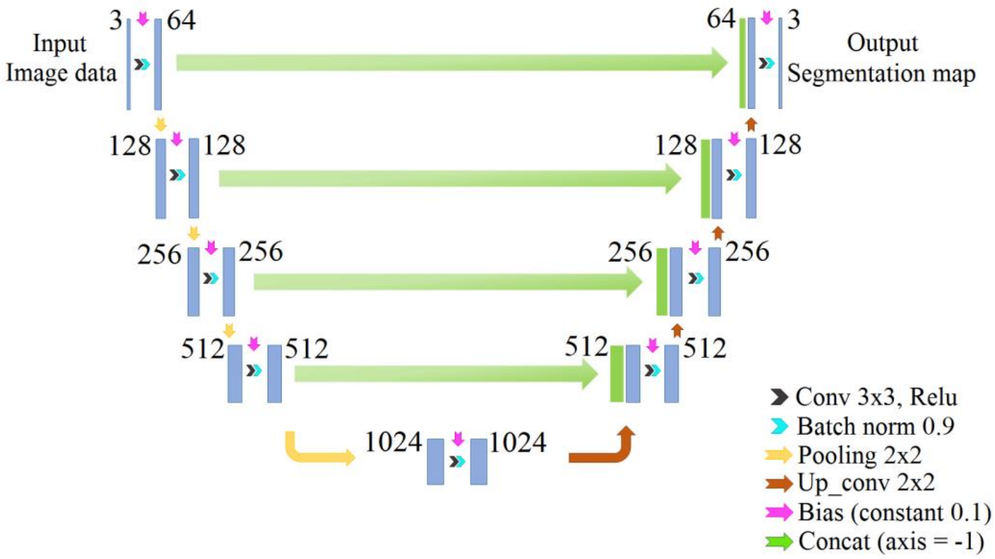

Fig. 4. A conventional U-net architecture

Fig. 2 data was used as label data and Fig. 3 data was used as input data, respectively.

The next section will discuss the deep learning model we used.

2.2 U-net Model

Convolutional neural networks (CNN) is suitable artificial neural network for image classification. For example, in the imagenet large scale visual recognition challenge (ILSVRC) [3], Alex-Net (1st, ILSVRC 2012), VGG-Net (2st, ILSVRC 2014), Google-Net (1st, ILSVRC 2014), and Res-net (1st, ILSVRC 2015) based on CNN received high ranked awards with better results than other models not kind of CNN [4].

So we used a U-net model based on CNN. U-net has some advantages over other CNN models. U-net can be computed faster than other models because dose not overlap in convolution layer and is not easy to trade off (bias-variance trade off) because it has a special layer represented by gray arrows in Fig. 4. The special layer is concatenated the one layer on the contracting path with the other layer on the expansive path. This process makes it possible to recover the data lost in the up-convolution process [5].

The U-net model used in this work consists of a 3x3 size convolution layer, activation function using leaky-relu, concatenated layer (concat layer), 2x2 max-pooling, and 2x2 size up-convolution.

The convolution layer is for creating feature maps by identifying the feature of each section after filters stride image data [6].

The activation function is that determines whether the extracted feature value is valid. Among the various functions, Leaky-relu is following the formula below.

$$\mathrm{F(x)} = \max(a * x,\ x),\ when \gg a$$

Max pooling layer is to perform calculations for the overlap between image and filter after convolution, using only the largest value in filtering data each filter. Then the image data is highlighted.

Up-convolution is similar to up-sampling not only increasing the size, but also retaining the feature. So, it does not lose feature values during convolution.

3. Result

Fig. 5 shows (a) compensated image for missing data by U-net, (b) image with dead pixels, and (c) ground truth (GT). The results of the compensation simulation for the loss of radioactive map data through deep learning could support the proposed method working properly.

In Table I, the error rate was calculated by comparing the U-net image pixel data with the GT image pixel data in the damaged coordinate.

Unfortunately, Fig. 5 (a) image is not clear due to the construction of the resolution of the input data and the learning model. In the case of the input data, a low resolution images were extracted in the data preprocessing. On the other hand, the learning model, a blurry image was taken out of learning based on the entire image data, not a necessary part of the image.

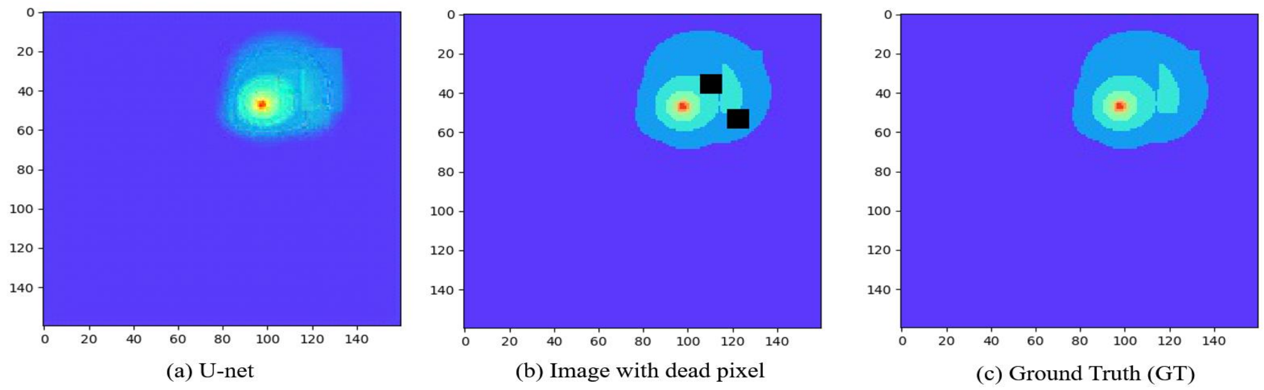

Fig. 5. Simulation data comparison: (a): Radioactivity map image restored by U-net. (b): Radioactivity map image with random dead pixels.

TABLE I: Compare the error rate for each coordinate

(X, Y)	U-net	GT	Average error rate (%)
(109, 37)	(0.11, 0.907,0.845)	(0.184, 0.925, 0.769)	82.94
(114, 33)	(0.0462, 0.662, 0.938)	(0.0863, 0.616, 0.976)	80.89
(121, 50)	(0.119, 0.75, 0.931)	(0.255, 0.89, 0.902)	75.94

4. Conclusions

This paper presents a method for compensating missed sensor data from a radiation sensor network by using a deep learning algorithm. With this method, the missed data can be compensated for the data of the entire sensor network. The compensation accuracy for the three sample points as missed data was over 75%.

However, since radiation data is extremely sensitive to safety issues, the accuracy should be much higher as well as the problem on the low resolution image should be resolved.

For the conference presentation, we will show better performances by revising and analyzing the deep learning model.

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