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Application of Deep Learning to Detect Nuclear Material Diversion using Surveillance Video

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1. Introduction

Transuranic element (TRU) and uranium can be group recovered from spent fuel using pyroprocessing. Since most of the pyroprocessing process takes place inside hot cell, which has only limited transfer ports, the nuclear material measurement at the transfer port and surveillance in the hot cell can be very important to detect the nuclear material diversion in the pypoprocessing facility. However, it is very difficult to detect the diversion using the surveillance video in real time, since the people's attentiveness drops quickly. Also, since the size of surveillance video data is too large, large human and computer resource are required to store, transport, and analyze the data.

Recently deep learning has been developed very quickly and it has shown remarkable performance in many fields. Especially the deep learning is applied to the automatic anomaly detection using surveillance video. Here, the anomaly is defined as something that deviates from normal, or unexpected. And this approach has the possibility to be applied to the automatic nuclear material diversion detection using surveillance video.

In the present work, we produce the virtual surveillance video data of the pyroprocessing facility in normal and abnormal operation mode; diversion, and a deep learning model is develop to detect the abnormal operation automatically.

2. Methods and Results

2.1 Virtual Surveillance Video Data

Since it is very difficult to obtain enough surveillance video data inside the pyroprocessing hot cell, virtual video data were produced. The model facility is electro recovery cell (ER cell) of pyroprocessing facility.

The virtual video data were produced with WITNESS Visionary Render (WITNESS VR). The process instruments inside the hot cell model were reduced metal storage, U&UCl_3 storage, Electro Recovery (ER) instrument, sample storage, U ingot casting furnace, Liquid Cadmium Cathode (LCC) crucible storage, Trans Uranic ingot casting furnace (TICF), salt purifier, waste storage, U ingot storage, and TRU ingot storage. Two process lines with equal instrument arrangement were in the ER cell. A small crane transferred the process material in the ER cell. A surveillance camera was installed obliquely near the ER instrument. Figure 1 is an image taken by the surveillance camera.

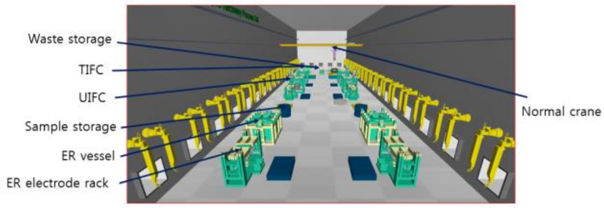

Fig. 1. Image taken with surveillance camera in the virtual ER cell

One campaign was composed of 2 times U recovery, 2 times U/TRU recovery, 2 times TRU Draw Down (DD), 2 times Rare Earth (RE) DD. Two process lines proceeded independently. The start time difference between the two process lines was changed to make various normal surveillance video data. Also the process time and the process material position were slightly changed.

Three type of abnormal surveillance video data were produced; large crane movement, diversion in the sample storage, and diversion of U/TRU product at ER vessel or TICF. All the abnormal data were not included to the normal data.

2.2 AutoEncoder Model

Autoencoder is one of the deep learning model. In the autoencoder, the input layer is compressed into short code, and then the shot code is decompressed into output, which is almost identical to the original input layer. After training the autoencoder only with the normal data, the trained autoencoder can produce the output similar to the original input if the input is close to the normal data. However, if the input is very different from the normal data; anomaly, the trained autoencoder cannot produce the output similar to the original input. Based on this characteristics of the autoencoder, the anomaly; diversion can be detected only training with the normal data.

An autoencoder model was developed and trained using the normal data of the virtual video data in pyroprocessing cell. Ten sequence surveillance images were used simultaneously for the training.

Figure 2 is one of detection result; the diversion in the sampling storage.

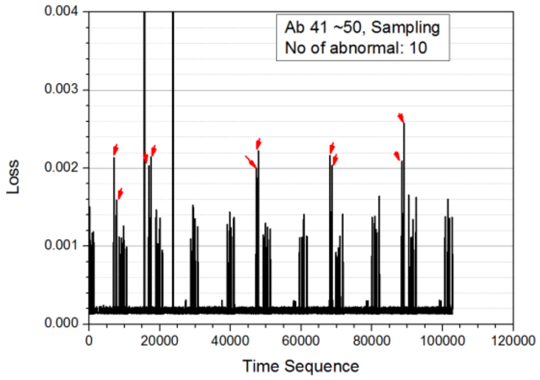

Fig. 2. Loss for the virtual camera data of diversion in the sampling storge

In figure 2, loss is the sum of difference between the input pixel data and the output pixel data. If the autoencoder reproduces the input well, the loss is small, and if the autoencoder cannot reproduce the input, the loss gets larger. The points of large loss in the figure 2 matches with the diversion time in the video data.

3. Conclusions

Surveillance can play more important role in the detection of nuclear material diversion if the diversion can be detected automatically with the surveillance without tedious analysis after a certain period of time. Deep learning technique, which shows amazing performance, has a potential to be combined with surveillance to detect the diversion in real time. In the present work, we develop an autoencoder model, and the model can detect the diversion for the virtual pyroprocessing surveillance camera video image. Our work shows the possibility that the automatic surveillance can be applied to help the diversion detection more effectively.

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Acknowledgement

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