Nuclear Material Diversion Detection Using Intelligent Surveillance Based on Deep Learning

Se-Hwan Park[a,*], Byung-Hee Won[a], Hee-Sung Shin[a], Seong-Kyu Ahn[a], and Shin-Dong Kang[b]

[a] Korea Atomic Energy Research Institute, 111, Daedeok-daero 989beon-gil, Yuseong-gu, Daejeon, Republic of Korea

[b] IDOSI, 44, Seongsuil-ro 12-gil, Seongdong-gu, Seoul, Republic of Korea

[*]ex-spark@kaeri.re.kr-mail

1. Introduction

Deep learning is developed very quickly and it shows remarkable performance in many fields. Especially, the deep learning is applied to anomaly detection using surveillance video. Here, the anomaly is something that deviates from normal or is unexpected. In this application, a deep learning model is trained only with normal video sequence, and the anomaly can be detected if the abnormal sequence is mixed with the normal sequence in the video.

The surveillance is important to detect the diversion in a nuclear facility, and a complementary safeguards measure to the nuclear material accountancy. If an intelligent surveillance is developed to detect the diversion automatically without post analysis, the surveillance will play more important role in the safeguards.

Korea Atomic Energy Research Institute (KAERI) is developing safeguards techniques and safeguards system of a pyroprocessing to enhance the non-proliferation acceptability of the pyroprocessing. In the present work, our progress on the development of the intelligent surveillance in the pyroprocessing facility is presented.

2. Methods and Results

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

The virtual video data were produced with WITNESS Visionary Render (WITNESS VR). The process instruments inside the hot cell 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 transported the process material in the ER cell. A surveillance video camera was installed obliquely near the ER instrument. Fig. 1 is an image taken by the surveillance camera.

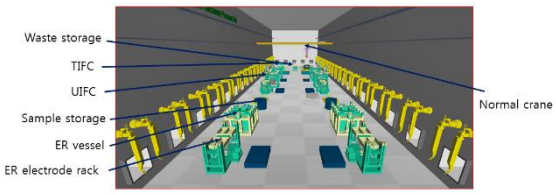

Fig. 1. Image taken with surveillance camera in the virtual ER cell.

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 operation 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 the ER instrument or before the TICF. All the abnormal data were not included to the normal data.

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 reproduce the output almost same to the original input if the characteristics of the input is similar to the normal data. However, if the characteristics of the input is very different from the normal data; anomaly, the trained autoencoder cannot reproduce the output. Based on this characteristics of the autoencoder, the anomaly; diversion can be detected with an autoencoder mode trained only 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 in the training.

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 loss of the autoencoder got larger when the anomaly video sequence was included to the test video.

3. Summary

KAERI is developing intelligent surveillance, which can be applied to detect the nuclear material diversion in a pyroprocessing facility. The virtual video data in the pyroprocessing hot cell were produced, and the autoencoder model was developed. The model can detect the diversion sequence in the virtual video data quite successfully. The following effort will be continued to implement this technique to the pyroprocessing safeguards

Our effort will help the effective and efficient safeguards implementation in future pyroprocessing facility.

ACKNOWLEDGEMENT

This work was supported by a National Research Foundation of Korea (NRF) grant funded by the Korean government's Ministry of Science and ICT (MSIT) (No. NRF-2017M2A8A5015084).

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