# Algorithm Development for Detecting a Crane on Surveillance Camera in Pyroprocessing Based on Machine Learning Technique

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## 1. Introduction

Containment and Surveillance (C&S) system is one of the main safeguards measures to monitor major locations in a facility handling nuclear materials. Especially it is expected that the role of surveillance will become more important in pyroprocessing facilities having cell based structure. Surveillance under isolated and separated space of a pyroprocessing facility can achieve a significant level of performance and reliability. However, the introduction of many surveillance equipment has a disadvantage that it requires a lot of human resources to confirm normal and abnormal conditions. This issue about human resource is a burden not only for IAEA but also for facility operator. Therefore, it is necessary to develop algorithm that automatically detect normal and abnormal conditions in order to introduce many surveillance devices while minimizing manpower.

In this study, the algorithm development was performed by using the hypothetical surveillance camera in electro-refining cell, which is the main process cell of pyroprocessing. The key technology to check operation condition automatically is to detect any object to classify normal and abnormal conditions. The movement of a crane can be an important factor in monitoring within electro-refining cell. The algorithm to detect the crane, which indicates transportation of process materials in main processes, has been developed based on the hypothetical video data showing process condition in the electro-refining cell.

## 2. Method & Results

The hypothetical camera which monitors the main processes in a fixed position of electro-refining cell has been utilized in this study. Fig. 1 shows a frame obtained by the hypothetical surveillance camera. As shown in the Fig., the camera was installed at the start of the processes and electro-refining process begins sequentially from near the camera to far away. The crane moves to transfer process materials according to process schedule.

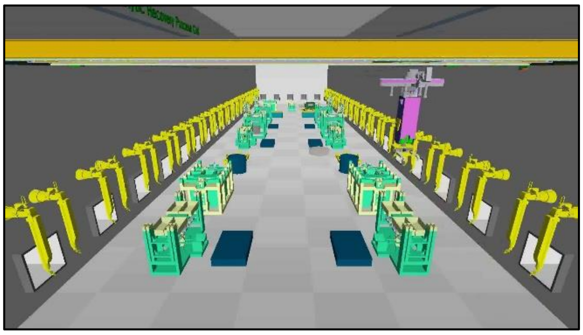
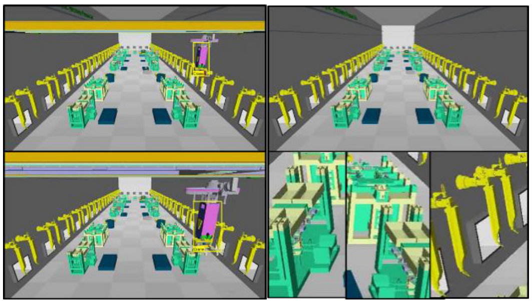


Fig. 1. Screen of Hypothetical Surveillance Camera.

The cascade classifier [1], which is a type of machine learning technique, has been applied to detect crane object in this study. The first step to utilize the cascade classifier is to generate training data set. Fig. 2 shows some training data generated as positive images and negative images. Positive images show the frames having crane and the region of crane marked as Region of Interest (ROI). These frames were obtained from the hypothetical video. Since there are various crane shapes and sizes depending on the distance and position between the camera and the crane, the positive images were considered to reflect the relevant information. Negative images show the scenes without a crane. These images without a crane help the cascade classifier distinguish crane from background. 1,316 positive images and 2,812 negative images were used to train the classifier in this study.



(a) Positive Images (b) Negative Images

Fig. 2. Training Data Set.

The cascade classifier has been trained based on the positive and negative images and then the trained classifier to detect a crane has been evaluated using the hypothetical video data. There are three cases in the algorithm that can indicate false detection results. In the first case, the classifier falsely detects crane on a screen having no crane. In the second case, the classifier dose not detect anything on a screen where a crane exists. In the last case, the classifier indicates two or more cranes on a screen having only one crane. There are total 13,223 frames in the video having 460 seconds length. All false cases have been analyzed for whole frames. Table 1 shows the evaluation result of false detection. As shown in the table, only 3 times of incorrect detection were occurred among 837 frames having no crane. It shows good performance when a crane is out of camera. However, about 20% and 14% among the frames having a crane were failed to correctly detect a crane by detecting wrong object or nothing. It particularly shows poor performance when a crane was located near to the camera or far to the camera.

Table 1. Evaluation Result of False Detection

| Case | Number of Failures | Probability of Failures |
|---|---|---|
| Case 1: crane detection in the frame having no crane | 3 | 0.36% |
| Case 2: crane detection failure in the frame having a crane | 1721 | 13.89% |
| Case 3: two or more cranes detection in the frame having a crane | 2511 | 20.27% |

## 3. Conclusion

The study on detecting a crane in the hypothetical video obtained surveillance camera was performed. The machine learning technique, called as cascade classifier, was applied for crane detection. 1,316 positive images among total 13,223 frames were used for training the classifier. The trained classifier showed good performance when there was no crane on the surveillance screen. On the other hand, about 34% false detection was occurred when there was a crane on the screen. These false detection rate can be reduced by increasing training data set and optimizing some parameters of the classifier. It is expected that the algorithm for detecting important objects would be useful for building considerably efficient and reliable C&S system in pyroprocessing facility.

## ACKNOWLEDGEMENT

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## REFERENCES

[1] Viola, P., and M. J. Jones. "Rapid Object Detection using a Boosted Cascade of Simple Features." Proceedings of the 2001 IEEE Computer Society Conference. Volume 1, 15 April 2001, pp. I-511-I-518.