Deep Learning Based Bubble Detection and Core Thermal Power Prediction for Safety of Nuclear Power Plants

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1. Introduction

Nuclear power plants are protected and shielded under normal operations, so there is no radioactive release causing harm to people. However, there is a risk that radiation can be released into the environment in the event of some accidents on the nuclear control system. To address these safety issues, there have recently been several attempts to manage safety by applying artificial intelligence and statistical techniques in research reactors [1, 2].

First, we apply our deep learning algorithms to detect bubbles around the reactor core to determine the abnormal condition. The reason is bubble prevents heat release from the nuclear fuel cladding and makes it easier for corrosion products to adhere to the surface of the nuclear fuel cladding. To detect this kind of effect, we create virtual bubbles and applied Faster R-CNN model for detecting bubbles. Unreal software is used to acquire virtual bubbles and synthesize them with CCTV images of research reactors.

Second, we analyze the correlation between core thermal power and pixel values of the images by applying statistical techniques. In particular, we consider the correlation with the reactor power as the blue light intensifies based on Cherenkov effect. For this purpose, the values of the RGB, HSV, and YUV channels in the image were analyzed.

Our main contributions are summarized as follows. We train and test the Faster R-CNN model with bubble images to propose a deep learning model for anomaly detection. The next is we analyzed the relationship between the pixel value of the CCTV image and core thermal power of the HANARO.

The rest of the paper is organized as follows. We provided methods and results of deep learning model and statistical analysis for the safety of the reactor, Then the conclusion of this work and its future work.

2. Methods and Results

2.1 Deep learning-based bubble detection

We created a dataset based on the CCTV images obtained from the HANARO research reactor in Fig. 1-2. The size of input images is 1280×720. We utilize Unreal software to generate virtual bubbles in Fig. 1. A dataset was made by changing the angle, velocity, and frequency of bubbles for most realistically abnormal conditions of the reactor core. We used Fast R-CNN deep learning model as the baseline and optimized learning

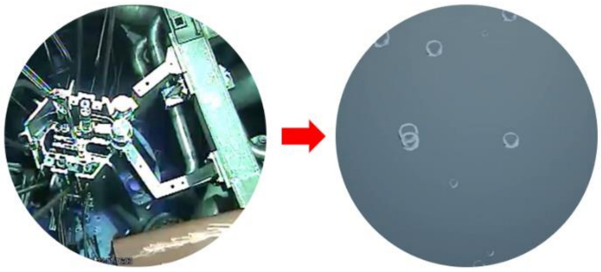

Fig. 1. Images of HANARO research reactor and virtual bubbles

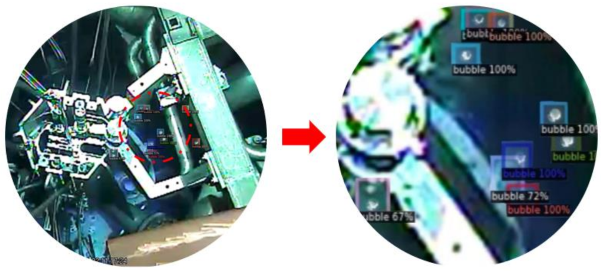

Fig. 2. Virtual bubble occurs and detects it as our deep learning model.

model as the baseline and optimized the model parameters for bubble detection in Fig. 3.

Our model was initialized by pre-trained ImageNet model and using a learning rate of $2.5e^{-3}$ for 250k iterations with 8 batch size. Momentum is 0.9 and weight decay is set to $1e^{-4}$. We conducted experiments to demonstrate the performance evaluation of our bubble detection model using the precision, recall, and F1-score. The dataset is consists of training, validation, and test sets of 2000, 300, and 1000 images, respectively. The precision, recall, F1-score of the test dataset is 83%, 81%, and 82%, respectively.

2.2 Correlation between image data and core thermal power

We analyzed the correlation between the CCTV image pixel values and the Cherenkov effect using statistical techniques named Pearson correlations. The dataset for analysis synchronized the image with the core thermal power of the HANARO reactor every second in Fig. 4.
We normalized pixel values of image channels to 0 and 1 for comparative analysis. This allowed us to correlate the pixel value of the image with the core thermal power. The whole process is as follows. First, we cropped a region of interest (ROI) which would occur the Cheren

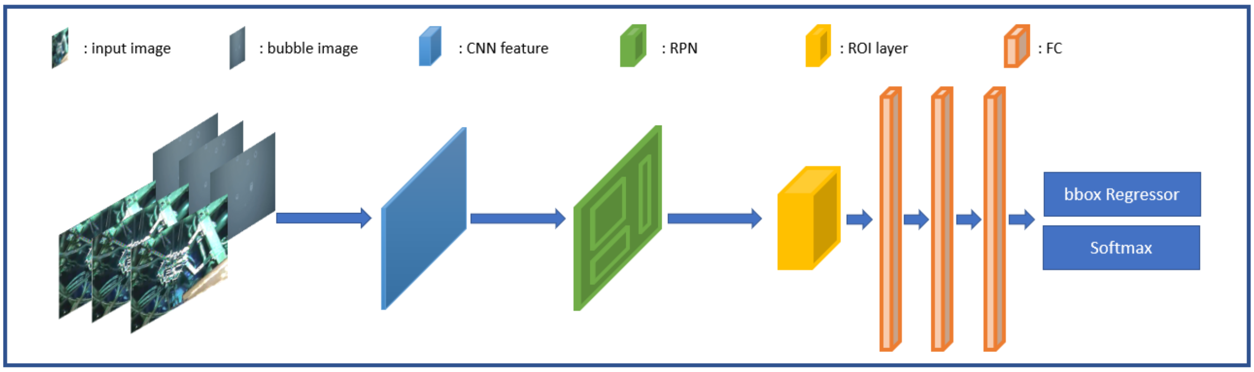

Fig. 3. Virtual bubble occurs and detects it as our deep learning model.

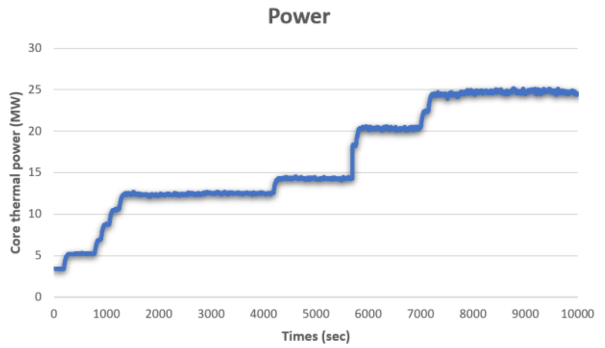

Fig. 4. This chart shows a change in HANARO core thermal power with time change.

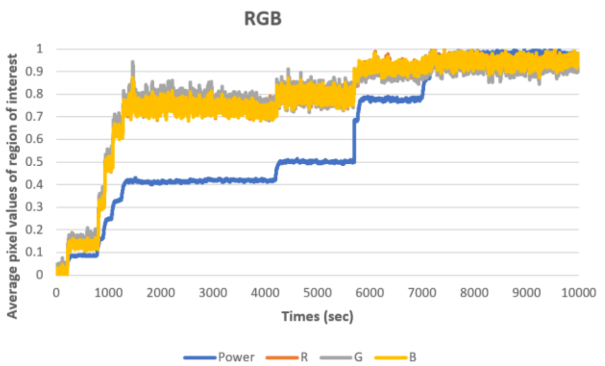

Fig. 5. This chart represents the average pixel values of the RGB in the region of interest over time.

-kov effect. Second, the ROI images split into three images channels: RGB, HSV, and YUV in Fig. 5-7. Third, we correlated the core thermal power of the reactor with each image channel.

The experimental results show that most image channels have a linear relationship between average pixel values of ROI images and HANARO core thermal power over time in Fig. 5-7. We also obtained the Pearson correlations coefficient for image channels and power over time to digitize linear relationships in Table 1. The Pearson correlation coefficient is close to 1 except for V channel of YUV, indicating that there is a linear relationship. Overall, these experiments show that the

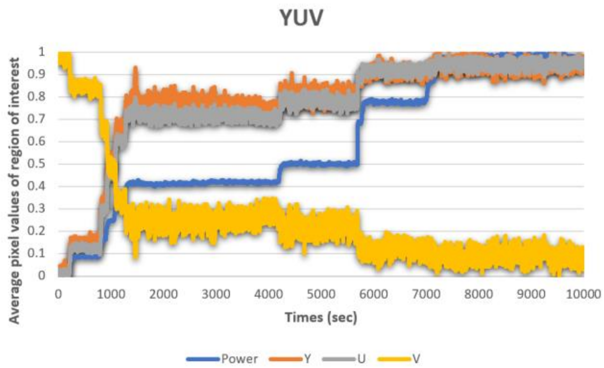

Fig. 6. This chart represents the average pixel values of the YUV in the region of interest over time.

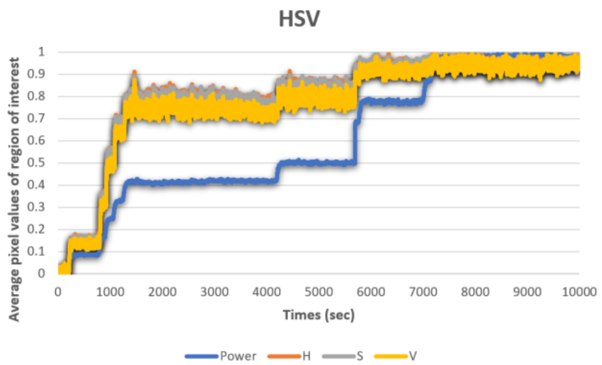

Fig. 7. This chart represents the average pixel values of the HSV in the region of interest over time.

possibility of predictability of core thermal power using a pixel value of image.

Table I: Pearson correlation coefficient between image channels and core thermal power.

	Red	Green	Blue
Core thermal power (MW)	0.8393	0.8254	0.8541
	Hue	Saturation	Value
	0.8142	0.8174	0.8537
	Y	U	V
	0.8348	0.8751	-0.8216

3. Conclusions

In this paper we introduced deep learning models and statistical analysis for better safety management of nuclear control systems. In future work, we will attempt to improve the performance of deep learning-based bubble detection model. Moreover, we will proceed with core thermal power prediction by image pixel values using deep learning model.

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