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Deep learning-based air bubble detection for HANARO

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1. Introduction

Recently, nuclear safety regulations have been strengthened worldwide owing to the accident at the Fukushima nuclear power plant in Japan [1]. As part of this initiative, one of the target facilities is the HANARO reactor core, and studies are being conducted at this research reactor to improve its defense-in-depth (DID) [2-3]. DID is a safety philosophy that guides all nuclear facilities in their design, construction, inspection, operation, and regulation to ensure their safe and efficient operation. To enhance DID at HANARO, one approach being employed involves the use of CCTV image data analysis to support HANARO operators. Our study is to detect air bubbles in the HANARO reactor core. To achieve this, we analyzed the characteristics of air bubbles, generated a synthetic dataset [4], and utilized a Faster R-CNN deep learning model [5-6], that was optimized for bubble detection.

2. Preliminary

HANARO [7] is a multi-purpose research reactor designed as an open tank-in-pool type, with the inside of the reactor being monitored by a CCTV camera. One important aspect of this monitoring is the detection of air bubbles that may arise from cracks in the fuel cladding of the reactor core, which is one of the operator's tasks. Monitoring air bubbles is an exhausting task due to their small size and the fact that their shape can vary depending on rotation, viewpoint, and occlusion.

3. Dataset

Images of the HANARO reactor core were obtained using a CCTV camera, and bubble characteristics were analyzed based on images of the process of discharging air inflow during the maintenance period. This analysis allowed us to create a synthetic dataset for bubble detection using a deep learning model. Utilizing image processing techniques, we generated a dataset by extracting bubble images from their respective backgrounds and inserting them into images. Due to the varying sizes and transparency levels of the bubbles, 2,000 synthetic datasets were generated with diverse sizes, positions, angles, and transparency, as illustrated in Fig. 1.

4. Methods

The air bubble detection algorithm comprises two sequential steps, which are applied to every frame. The first step involves identifying regions of interest (ROIs) through background subtraction. The second step employs a deep learning-based object detection model. The utilization of a fixed CCTV camera enables this system to effectively detect air bubbles in the HANARO reactor core.

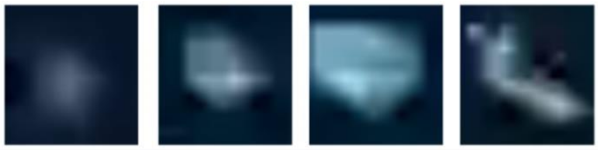

Fig. 1. Air bubble image generated from synthetic datasets.

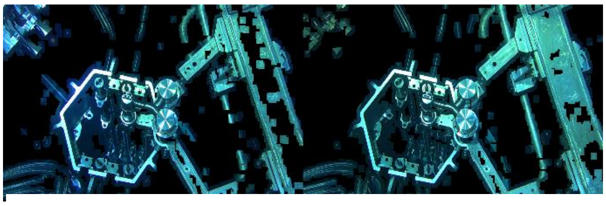

Fig. 2. An algorithm was used to remove the background from the image, resulting in a black mask covering the background.

4.1 Background subtraction

As the CCTV camera installed around the core of the nucleus is fixed, the difference between the image containing the background and the moving air bubbles can be utilized during the image preprocessing stage. The background subtraction algorithm used is based on gaussian mixture models, which select appropriate gaussian distribution values for each pixel and are robust in removing background even when lighting conditions change, as shown in Fig 2. The resolution of the images to which the algorithm was applied is 1920×1080, with an average speed of over 80 frames.

4.2 Deep learning-based object detector for air bubbles

Our algorithm was designed using deep learning-based techniques for detecting air bubbles in images, as shown in Fig.3. To achieve this, the architecture of Faster R-CNN was optimized with hyperparameters to train on small size and transparent bubble objects. The algorithm consists of three parts: feature extraction, region proposal network, and multitask learning.

The ResNet was used as the backbone feature extraction, and feature pyramid network (FPN) was used to improve the scale invariance of air bubble objects. The FPN is applied on the feature vector of ResNet-101 having different resolutions (1/4, 1/8, 1/16, 1/32), and top-down approach with lateral connections. Next, we use a region proposal network (RPN) for end-to-end training to generate regions in air bubbles. The RPN operates on a feature map with five levels of FPN to generate anchor boxes and predict the presence of air bubbles within each anchor box. The anchor box used in

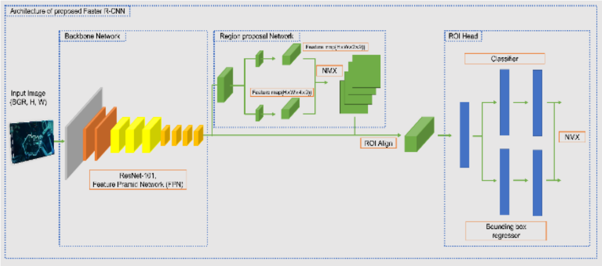

Fig. 3. Deep learning bubble detection model structural diagram

our algorithm is a bounding box with a predetermined ratio and size that is based on the size of the bubble object. The size of the bubbles in our dataset ranges mainly between 50 and 500 pixels. To accommodate this range, we adjusted the anchor box to have five different scale levels of 32, 64, 128, 256, and 512 pixels. Finally, the multi-task learning algorithm makes use of three inputs: the feature vector from FPN, proposal box from RPN, and ground truth boxes obtained from images. The feature maps generated by the FPN are selected depending on the region proposals generated by the RPN. A non-maximum suppression (NMS) algorithm is then used to select region proposals with high class scores. Following the selection process, the model is trained using multitask learning using equation (1).

$$L(p,u,t^u,v) = L_{cls}(p,u) + \lambda[u \geq 1]L_{loc}(t^u,v). \quad (1)$$

The log loss function is utilized by the L_{cls} function to classify air bubbles. The predicted class scores are denoted by p, while the ground truth class scores are denoted by u. The L_{loc} function is used to predict the coordinates of the bounding box that surrounds the air bubble in the image. The predicted bounding box coordinates is represented by v, while the ground truth bounding box coordinates is represented by t^u.

5. Experiments

We evaluate the qualitative performance analysis of the air bubble detection model. We used a dataset of air bubbles produced during the maintenance period to generate both single and multiple bubbles within the HANARO reactor core, as shown in Fig 4. The two images were created by detecting air bubbles during HANARO reactor core maintenance. Columns from left to right represent single and multiple bubble detection results.

6. Conclusion

In this paper, we propose an image-based air bubble detection system in the HANARO reactor core. To address the issue of an insufficient air bubble dataset, the synthetic dataset was created and used to train a deep learning model optimized for detecting air bubbles in HANARO reactor core. More efforts will be made to

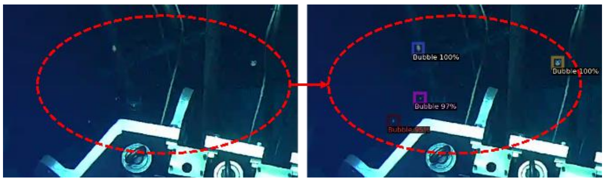

Fig. 4. Examples of qualitative air bubble detection on the HANARO reactor core. Columns from left to right correspond to original image and image with detected bubbles.

generate synthetic data and obtain real-world test datasets from the HANARO reactor core. It is expected that these additional measures will improve the performance of the bubble detection model. In order to validate the efficacy of the bubble detection model, qualitative experiments will be conducted.

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