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A Robust Approach for Small Bubble Detection in HANARO Core Using Consecutive Multi-Frames

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1. Introduction

HANARO, which stands for High-flux Advanced Neutron Application ReactOr, is a multi-purpose research reactor with a thermal output of 30 MW. It has a wide range of applications, including trace element analysis, medical and industrial isotope production, and nuclear fuel irradiation testing. The HANARO water pool is deliberately designed to be open and visible from the outside, enabling the observation of phenomena like Cherenkov radiation to aid in monitoring normal operation. CCTV can also capture the occurrence of bubbles in the water, which may be indicative of cracks in the nuclear fuel cladding. Early detection of this phenomenon through meticulous monitoring can be vital in ensuring the safe operation of the reactor. We conducted a study to detect small bubbles in CCTV video recording from the HANARO water pool. The industry is using a variety of computer vision techniques to detect and identify specific objects in CCTV. One of the classic image processing techniques for detecting changes in an image is the use of background modeling and background subtraction methods [1,2]. However, detecting bubbles in HANARO videos is a complex task due to the inclusion of water flow, requiring sophisticated preprocessing to model the background. Also, the background subtraction method is difficult to set a proper threshold for bubbles because they are very small and transparent, so the difference pixel value between the current frame and the previous frame is small.

Deep learning-based computer vision techniques include the object detection method, which detects specific objects in images or videos [3]. Single-frame based object detection techniques commonly used exhibit good performance in detecting large objects but show lower performance in detecting small objects [4,5]. When detecting bubbles in videos, using a single frame input with only momentary information makes it difficult to detect small and transparent bubbles. In this paper, we propose a multi-frame based deep learning model specialized in detecting small bubbles in the HANARO core. Due to the lack of video datasets, we synthesized small bubble-like objects in motion onto HANARO CCTV video. Furthermore, we utilized a consecutive of multi-frames as the input to the model to learn the characteristics of the bubbles as they move.

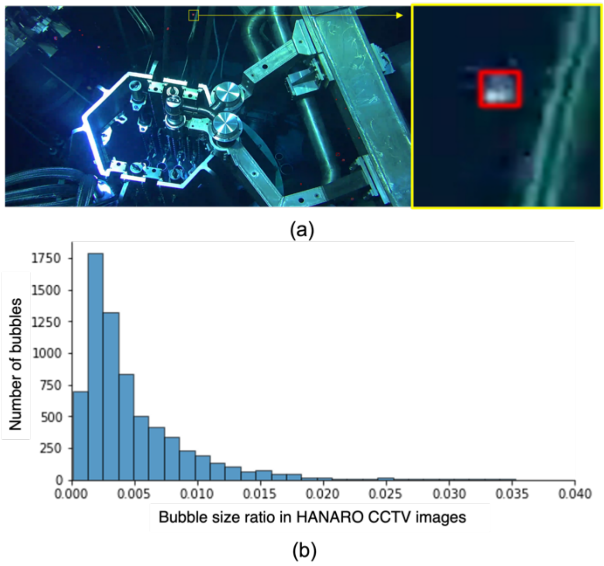

Fig. 1. Small bubbles in real HANARO CCTV images. (a) An example image of HANARO CCTV and enlarging the area within the red bubble annotation. (b) A statistic of occupied pixel numbers for bubble size ratio in HANARO CCTV images.

The synthetic bubble dataset was used to compare the bubble detection performance of the train with single-frame model and the muti-frame model. We also trained and evaluated proposed model by varying the number of consecutive frames used as input, specifically 3, 5, and 7, and analyzed the performance changes accordingly.

2. Methods and Results

2.1. Synthetic Bubble with HANARO CCTV video

The bubbles generated during actual HANARO operation have stability issues and are sparse, so the dataset acquired during the maintenance period of operation was used for this study. It includes images of small bubbles generated from the core and has a resolution of 1080x1920. In Fig. 1 (a), it shows an example of HANARO CCTV images containing actual bubbles that are very small in size. Also, the Fig. 1 (b) shows the percentage of pixels occupied by the bubble bounding box to the total resolution, and we can see

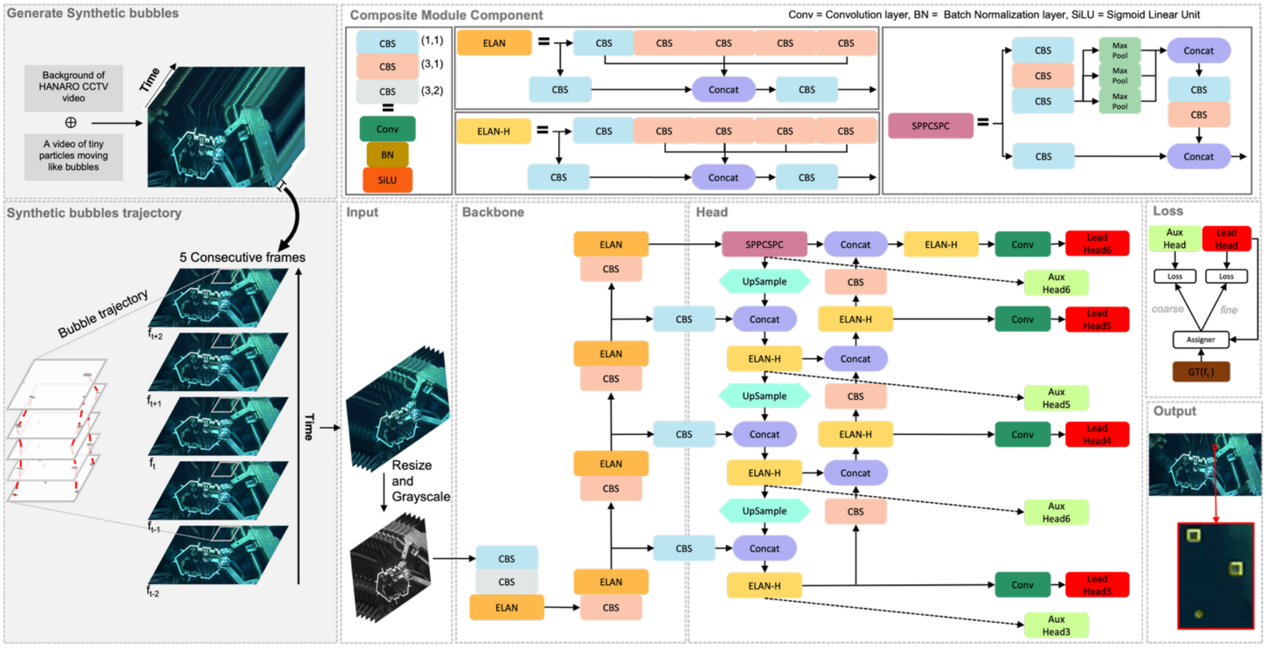

Fig. 2. Generate the synthetic bubbles and proposed model structure using consecutive multi-frames.

that all bubbles are 0.4% or less in size. Using only real-world data was not enough to serve as training data for a deep learning-based object detection model. Therefore, we used the HANARO core image as a background to generate synthetic training data with the addition of a moving object with a circular shape. The synthetic bubbles are small, transparent, and non-uniformly shaped with movement to mimic the appearance and movement of real bubbles. The synthetic data generation was performed based on the Python OpenCV library. First, we extracted a non-bubbling sequence from the HANARO CCTV. In total, two background sequences were extracted, one used for training and validation, and the other for testing. The training-validation sequence is 9.57 seconds long and consists of 287 frames, and the test is 4.97 seconds long and consists of 149 frames. A total of 30 synthetic bubble videos are generated, resulting in 5,740 training-validation images and 1,490 test images.

2.2 Bubble Detector using Consecutive Multi-Frames

Consecutive multi-frames are used to take advantage of the features of bubble movement while offsetting the small and transparent nature of bubbles that can interfere with bubble detection. We modified a model from YOLOv7 that performed well for real-time object detection and used it in our study [6]. Fig. 2 shows the overall structure of the bubble detection model using consecutive multi-frames. On the left-hand side, there are two gray sections. The upper section presents a simplified diagram of the process used to generate synthetic bubble videos, which involves adding synthetic bubbles to HANARO core images. The lower section showcases an example of a continuous frame from a specific point in time with details of the synthetic bubble trajectory. This represents five consecutive multi-frames constructed by sequentially concatenating four adjacent frames, f_{t+1}, f_{t+2}, f_{t-1}, and f_{t-2}, including frame f_t at time t. In general, the color of bubbles does not play a significant role in distinguishing them from the background. Bubbles are usually made of transparent or semi-transparent material and primarily resemble the color of the surrounding water. Therefore, we converted the multi-frames to grayscale and resized them to 1280x1280 for memory efficiency [7]. The backbone, and heads based on the YOLOv7 and using composite module. There are several composite module that are commonly used in backbone-head for feature extraction and object detection tasks. The CBS composite module applies convolution, batch normalization, and the sigmoid linear unit function sequentially to the input feature map. Meanwhile, the ELAN and ELAN-H composite modules take this idea even further by combining multiple CBS modules together. The SPPCSPC module, which stands for Spatial Pyramid Pooling with Constrained Spatial Positional Constraints. This module is designed to obtain multi-scale object information while keeping the size of the feature maps unchanged. It can accurately identify objects at different scales, making it a valuable module for precise object detection in various applications. To enhance the training of the network, a label assigner mechanism was introduced, which assigns soft labels based on both the network's predictions and the ground truth. This mechanism is optimized by predicting the lead head and using the ground truth to obtain labels for both the training of the lead head and the auxiliary head simultaneously. This mechanism works well for low-resolution object detection[8]. Finally, the output of the propose model is shown in the bottom right Fig. 2. The location of predicted small bubbles in the CCTV image are marked with a yellow box.

2.3 Result

In Table I, we compare the performance of models trained with the different numbers of input frames. The evaluation metrics used were precision, recall, F1 score, Average Precision at a 0.5 Intersection over Union (AP@0.5). It was evaluated based on synthetic bubble images generated for testing. As shown in Table 1, the precision of trained with 3 frame, 5 frame, and 7 frame models exceeded that of the base model by 93.3%, 92.8%, and 92.4%, respectively. According to AP@0.5 evaluation metrics, the performance of multi-frame model was 95%, 94.9%, and 93.3%, respectively. This shows a 12.4% improvement in bubble detection performance when using 3 frames compared to the base model. In results, we can see that AP@:0.5 degrades in performance as the number of frames increases.

Table I: Performance comparison of different frames on synthetic bubbles

Model	Precision	Recall	F1	AP@:.5
base	86.0	70.1	77.2	82.6
3 frames	93.3	90.8	92.0	95.0
5 frames	92.8	91.6	92.2	94.9
7 frames	92.4	90.1	91.2	93.3

3. Conclusions

In this paper, we generate a synthetic video bubble dataset and propose a multi-frame method to detect bubbles occurring in HANARO water pool. As a result, models trained over a single frame had more false positives than models trained over multiple frames. This suggests that multiple frames are effective in distinguishing bubbles from the background. Also, It can be interpreted that the use of adjacent frames at one point in time would have maximized the bubble's motion and intrinsic properties to improve detection performance. The model proposed in this paper has not been evaluated in a real-world bubble environment. In future work, we would like to evaluate performance using real bubbles generated in HANARO core, and apply vision techniques that can be utilized for imaging, such as optical flow and tracking, to our research.

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