Development of Integrated Monitoring System for Defect Detection of SFR's Internal Structures

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1. Introduction

Operating the Sodium Fast Reactor (SFR) at temperatures of 500 ℃ or higher introduces significant thermal stress due to substantial temperature fluctuations within the reactor structure. The primary failure modes identified in these conditions include ratcheting deformation and a combination of creep and fatigue damage resulting from repeated thermal loading. To address these challenges, the design of the SFR prioritizes structural integrity, assessing failure modes such as creep fatigue, inelastic strain, and buckling. This study highlights the critical need for regular in-operation inspections throughout the lifespan of an SFR to ensure its structural integrity and safety.

The reactor container is particularly vital, necessitating the development of a monitoring and diagnostic system to detect physical deformations caused by thermal ratcheting and crack defects arising from creep fatigue. However, the use of liquid sodium as a coolant presents unique challenges, as it renders conventional optical inspection technologies, commonly employed in light water reactors, impractical [1, 2]. The prolonged use of sodium coolant also demands materials with high corrosion resistance, complicating ultrasonic evaluations of resulting welds [3]. Furthermore, sodium's opacity precludes visual inspections, endoscopic evaluations, or television camera assessments of surfaces submerged in sodium, necessitating reliance on ultrasonic methods for in-service inspections of reactor vessel internals.

For external assessments of the SFR, both acoustic bulk waves and guided waves can be employed. In the bulk wave approach, ultrasonic probes are placed along the main vessel's wall to generate bulk waves that travel through the wall and penetrate the vessel. This method enables telemetric evaluations of internal components and may support Non Destructive Testing (NDT) procedures, mimicking the effectiveness of probes located within the reactor. However, energy dissipation at each interface may reduce the signal-to-noise ratio, complicating measurement accuracy. Therefore, enhancing defect identification precision through techniques such as super resolution or noise filtration during ultrasonic image acquisition is crucial.

Significant research efforts have been directed toward developing ultrasonic techniques capable of visualization in opaque environments. Despite these advancements, the degradation of data quality at elevated temperatures remains a concern, potentially leading to inaccuracies in detecting structural deformations. To address these issues, former study proposed the application of an Artificial Intelligence (AI) model for monitoring defects in the internal structures of the SFR [4, 5]. In these studies, the Yolov7 AI model developed for object detection was applied to images detected by an ultrasonic device to check for defects in the internal structures of SFR. To improve the object detection performance, the Enhanced Super Resolution Generative Adversarial Network (ESR-GAN) deep learning AI model for super-resolution of images and the Sobel noise filtering algorithm were applied to conduct tests. Therefore, we developed for a defect detection monitoring system for SFR's internal structures by combining two AI models and noise filtering algorithms.

In this study, we developed a web-based integrated monitoring system that integrates all the previously developed models to perform real-time defect detection and data management. The system light-weight the model by uploading it to the triton inference server in the form of TensorRT to improve AI model serving and speed, and showed the benefits of Application Programming Interface (API) conversion and speed improvement of AI models by applying the inference server. In addition, the system changed to the Yolov8 model, which is an upgrade from the existing object detection model Yolov7, and confirmed the improvement in inference speed compared to the previous one.

2. Methodology and system design

2.1. Defect detection with artificial intelligence model

Ultrasound scanning is an effective and safe method for inspecting concealed or hard-to-reach metallic structures, making it particularly valuable for defect detection. In this context, C-scan technology has been specifically developed to facilitate the examination of sodium fast reactor (SFR) components, providing real-time, high-resolution images that significantly improve the efficiency and accuracy of the inspection process. The C-scan system is optimized for reliable operation in high-temperature sodium environments. For our study, we initially acquired C-scan data in water at room temperature (25 ℃) using an ultrasonic guide tube sensor.

To enhance our dataset, we integrated the collected C-scan data with images generated through image augmentation techniques. While this approach yielded approximately 80% accuracy, the use of distortion techniques in the augmented data introduced critical challenges in defect detection. To address these issues, we employed two methodologies: deep learning super-resolution and a filtering algorithm for image data, both aimed at improving the object detection performance of the AI model by enhancing data quality.

The ESR-GAN model, which features a network architecture incorporating skip connections in the convolutional layers and generator network, was utilized to improve performance. Additionally, we implemented Sobel image filtering algorithm to reduce image noise and further enhance image quality. These processes are shown in Fig. 1.

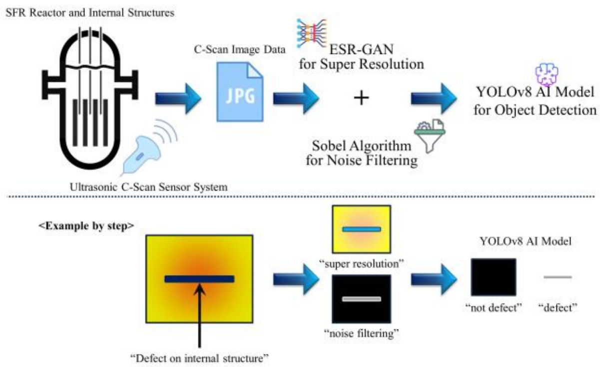

Fig. 1. Process of defect detection for SFR's invisible environment of internal structure

2.2. Integrated monitoring system

As we changed AI model from Yolov7 used in our previous research to Yolov8, AI model became increasingly large and slow to infer. For this reason, Yolov8 model can benefit when Graphics Processing Unit (GPU) uses in terms of performance, but the cost is very high. Therefore, in our research, light-weight of the model is conducted necessary in order to run efficiently.

For light-weight the AI model, it is usually to convert the model trained with PyTorch or TensorFlow to ONNX or TensorRT format. However, it is needed to write separate inference code for using the converted model, and it is hard to write the inference code in C++ for improving performance. Therefore, we used triton inference server.

The triton inference server is an open-source software optimized for high-performance inference and provides inference capabilities for various model formats, especially TensorRT. So it can be inferred AI models faster than loading them from a traditional local or hub. TensorRT is a model optimization engine that can help improve deep learning services by optimizing trained deep learning models to increase inference speed by several orders of magnitude to several orders of magnitude. By converting pre-trained AI models to TensorRT engine and utilizing it, you can get good inference performance.

In this project, we applied two methodologies; triton inference server and TensorRT. And to the pre-trained Yolov8, it is implemented the API to test the function using WebUI shown as Fig. 2.

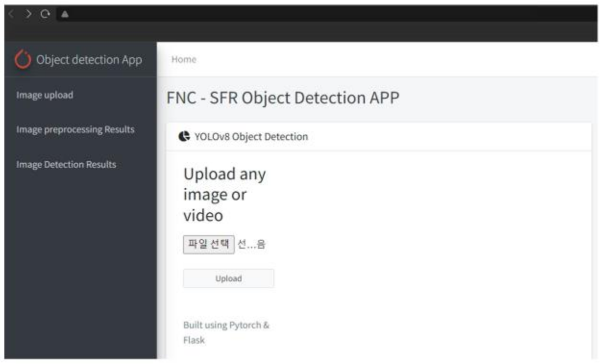

Fig. 2. WebUI of integrated monitoring system

3. Experimental setup and results

We evaluated the defect detection performance between Yolov7 and Yolov8 using the integrated monitoring system by inputting the C-scan data previously mentioned. The input C-scan data is a sample of arbitrary generated defects, and the evaluation was performed by extending the sample to data with various types of defects using data augmentation techniques. The Fig. 3 is defect detection example of C-scan image data from defected sample and augmented data used it.

Fig. 3. Example of defect detection using that arbitrary generated defect data (a) and augmented data (b)

And to assess defect detection, the effectiveness of the AI model was measured by calculating confidence scores, which are crucial for determining object detection accuracy. A comparative analysis was performed to evaluate the model's performance between Yolov7 and Yolov8, considering the application of super-resolution and noise filtering algorithms. The resulting performance metrics, presented in Table I, offer a detailed depiction of the model's capabilities across various defect data shapes.

Table I: Comparison of defect detection performance

Confidence score for evaluating defect detection			
AI Model	Optional	C-scan data	
		Line shape	Augmented
Yolov7	n/a	0.57	0.86
	With ESR-GAN and Sobel algorithm	0.70	0.87
Yolov8	n/a	0.73	0.87
	With ESR-GAN and Sobel algorithm	0.89	0.90

To compare the defect detection outcomes between Yolov7 and Yolov8, with and without the application of ESR-GAN and the Sobel algorithm, we presented the defect detection accuracy as confidence scores. The results indicated that Yolov8 outperformed Yolov7 regarding improved defect detection accuracy, and when super-resolution and noise filtering techniques were better than it is not applied.

4. Conclusion

In Table I, the evaluation outcomes derived from the test dataset indicate that Yolov8 demonstrates superior defect detection capabilities compared to Yolov7, as reflected in the varying confidence scores. These scores represent the likelihood that a given component is defective; however, their numerical values alone do not provide sufficient accuracy for definitive defect classification. In contrast, utilizing Yolov8 for defect detection after applying super-resolution and noise filtering on the same datasets results in confidence scores that increase by up to 21.9%. These findings highlight the critical role of super-resolution and noise filtering in enhancing the effectiveness of Yolov8 for defect detection, making these techniques essential components of image processing and analysis protocols.

In the near future, we will conduct tests for defect detection using C-scan data obtained from liquefied sodium. It is anticipated that our developed model can effectively detect defects in the internal structure of SFR, which operate within an invisible environment. Additionally, we plan to extend our research to include the assessment of samples with replicated defects in an opaque liquid sodium environment. This iterative process of validation and optimization will enhance our integrated monitoring system, allowing it to serve as effective defect detection for SFR applications.

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