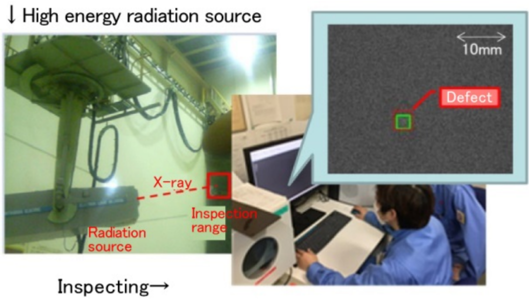
Development of High Accuracy Welding Defect Detection Technique for X-ray Images



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In the non-destructive inspection of welds of steam generators in nuclear power plants, radiographic testing (RT) using a high-energy radiation source and X-ray films is performed. Since the welds of the steam generator are thick, the contrast of defects in the RT image is low and the inspector is required to have high-level skill and concentrate for a long time in order to identify weld defects, which is a heavy burden. Therefore, in collaboration with the National Institute of Advanced Industrial Science and Technology, Mitsubishi Heavy Industries, Ltd. (MHI) has developed an image processing algorithm that can detect low-contrast defects with high accuracy and plans to apply this developed technology to an inspection support system that helps inspectors identify defects.

1. Introduction

RT of steam generators detects defects such as porosity (small cavities), poor penetration and slag entrainment that occur in welded joints. **Figure 1** is a schematic diagram of RT. This inspection targets thick metal materials with a thickness of about 100 mm and the contrast of defects in an RT image is low. Visibility is poor due to factors such as various types of noise including that caused by the radiation source, quantum mottling and graininess of the film(1), resulting in poor visibility. For this reason, the inspection requires high-level skill and concentration for long periods, which places a heavy burden on the inspector. Against this background, there is a need for automatic defect detection technology to assist inspectors, but it is difficult to detect defects with high accuracy using conventional image processing algorithms such as morphological operations. In recent years, machine learning technology that extracts features used for judgment by humans through deep learning and detects inspection targets automatically has come into practical use. However, it is difficult to apply this technology because it is not possible to prepare a sufficient number of actual defect samples for learning in the actual field.

In order to extract image features that are effective for identifying low-contrast defects from RT images, we employed two types of features: the statistical reach feature (SRF)(2), which is robust against noise and the higher-order local auto-correlation feature (HLAC)(3). Since only a small number of sample images containing defects could be obtained, we generated defect images in which the shape and noise of defects were simulated and used them as learning samples. We then constructed a defect discriminator using a support vector machine (SVM), which a machine learning method, to develop a system that can detect defects with high accuracy.

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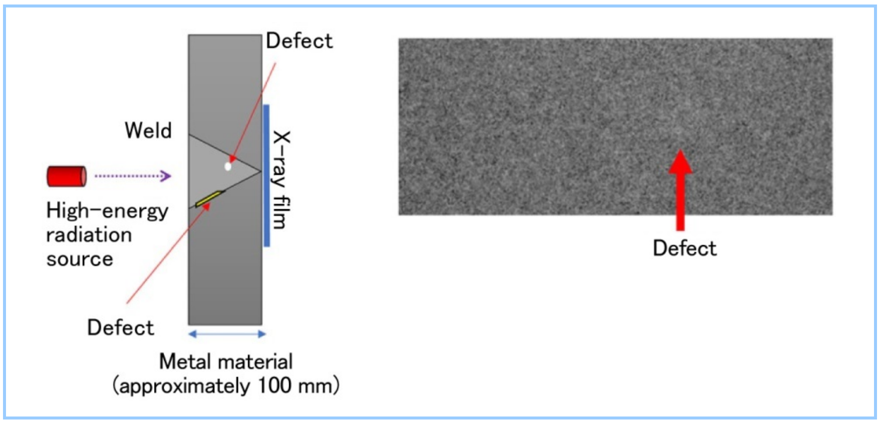


Figure 1 Overview of RT of weld (left) and RT film image (right)

2. Extraction of defect feature

2.1 Statistical reach feature (SRF)

A statistical reach feature (SRF) statistically expresses the magnitude of the relationship between the brightness I_o of a point of interest in the image and the brightness of its surrounding region C. Specifically, the feature is the ratio of the number of points with a higher brightness in the surrounding region than the point of interest and in this case it was defined in equations [1] and [2]. N_c is the number of pixels included in surrounding region C and I_i is the brightness of the ith pixel in surrounding region C.

$$SRF = \frac{1}{N_C} \sum_{i=1,\cdots N_C} \rho(i)$$

$$\rho(i) = \begin{cases} 1 & if\ \ I_i - I_o > 0 \\ 0 & othrewise \end{cases}$$

When the SRF is larger than 0.5, it can be determined that the point of interest has lower brightness than the surrounding region and when the SRF is smaller than 0.5, it can be determined that the brightness is higher than the surrounding region. **Figure 2** is a schematic diagram of the SRF. In the case shown in this figure, surrounding region C is defined as points on the circumference of a circle with a radius R centered on the point of interest. It can be seen that the SRF is less than 0.5 when the brightness is higher than the surrounding region, such as in the case of a defect.

Even when the contrast of a defect is low, the emphasized image can be obtained by calculating the SRF for all pixels of the RT image and binarizing them with a fixed threshold value to make the brightness of the defect relatively different from that of the surrounding region (hereinafter, this image is referred to as the SRF image). In the case of a cavity defect in a weld, by calculating the SRF with the surrounding region set to the circle centered on the point of interest as shown in **Figure 3** and binarizing the values, a binarized image with the defective area emphasized as shown in **Figure 4** was obtained. In order to determine that its brightness was sufficiently higher than the surrounding region, a threshold value of 0.25 was used.

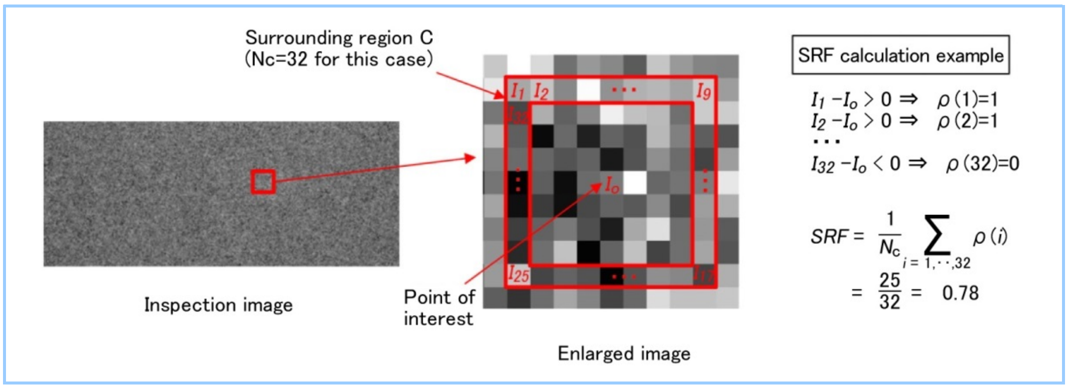


Figure 2 Schematic diagram of SRF

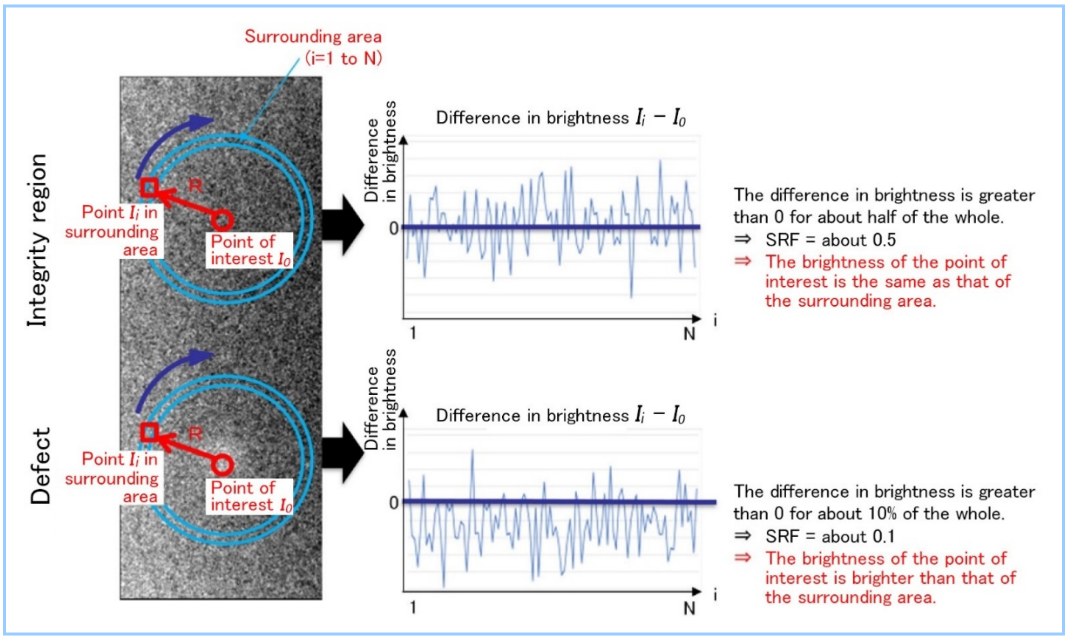


Figure 3 SRF of cavity defect in weld

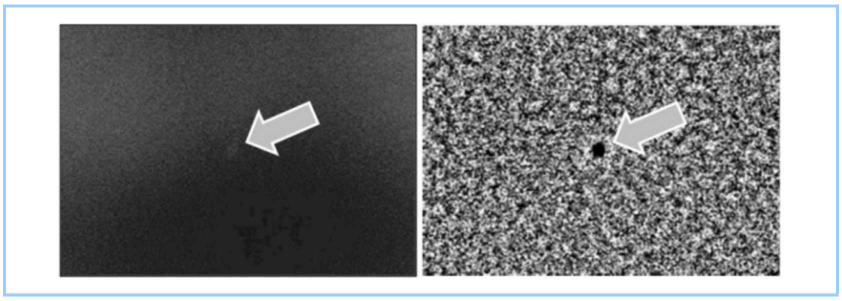


Figure 4 Input image (left) and SRF-emphasized defect image (right)

2.2 Higher-order local autocorrelation feature (HLAC)

In the SRF image shown in Figure 4, a mottled pattern appears even in an integrity region due to the influence of the quantum mottling, etc., peculiar to RT images. Therefore, the higher-order local autocorrelation feature (HLAC) extracted from the SRF image was used as an index to distinguish between small defects and mottled patterns of integrity regions.

HLAC expresses the local shape of a binary image as a 25-dimensional vector[3]. This makes it possible to express defects with different local shapes and mottled patterns of integrity regions as different vectors. In addition, the vector does not fluctuate significantly even when noise occurs. By taking advantage of these characteristics, it is made possible to distinguish between defects and integrity regions with high accuracy by machine learning described later.

3. Construction of defect discriminator using machine learning

3.1 Generation of simulated image

In general, machine learning requires a large number of learning samples, but only a small number of defect samples can be obtained. For this reason, we generated a large number of simulated images of defects as learning samples. It is difficult to generate defect images equivalent to real images, however, because there are few reference images, so we simulated the "defect shape" and "image noise" that can be expressed by the above two features.

The process of generating a simulated defect image is as follows. A simple defect model assuming a circular cavity defect was set and a simulated defect with the radius and concentration changed by random numbers was generated. Then this simulated image was superimposed on an image with noise equivalent to that of a real RT image, but the model creation was difficult because noise was caused by radiation sources, materials, films and a variety of other factors. Therefore, a simulated defect image was created by superimposing simulated defects on integrity regions randomly cut out from the actual RT image. As a result, various noise variations such as scratches on the film were included in the defect learning image.

3.2 Two-class discriminator using machine learning

First, an SRF image in which defects were emphasized by SRF extraction processing was generated and then the HLAC was extracted(4). Classification thereof into two classes, a defect and an integrity region, was performed by a discriminator using machine learning. The machine learning used SVM and was performed with simulated defect images and integrity region images. At the time of this machine learning, various parameters were set so that no defects were false negative and the number of false positive detections was minimized with respect to the defect and integrity region images that were taken.

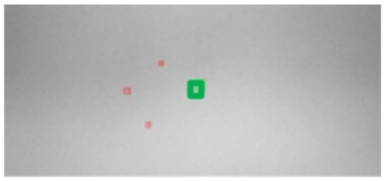
The integrity region learning images were selected in two stages. First, several thousand images were randomly extracted from many integrity region images and used for machine learning. At this stage, many false positive detections occurred. These false positive detections were used as integrity regions for the second round of machine learning. These was noise caused by many factors such as scratches on the film and using it again for learning resulted in the suppression of false positive detections.

3.3 Evaluation with actual application

In order to evaluate the accuracy of the algorithm developed this time, we conducted a comparative experiment with the conventional defect detection algorithm. In this experiment, 17 film-scanned images containing 27 defects were used as samples for evaluation.

Table 1 lists the evaluation results. The conventional method of detecting weld defects using RT images performs segmentation by morphology calculation and binarization and then determines features such as size, maximum brightness, average brightness and variance of brightness using the threshold values. With the conventional method, there were false negative defects and more than 100 false positive detections per film. With the method developed this time, on the other hand, no defects were false negative and the number of false positive detections per film was 5.8 on average, which was a significant improvement compared to the conventional algorithm.

Table 1 Detection rate, number of false negative defects and number of false positive detection

	Conventional method	Developed method
Detection result Green: True positive detection Red : False positive detection		
Detection rate (%)	81.5 (22/27)	100 (27/27)
Number of false negative defects [part]	5	0
Number of false positive detection [part per film]	115	5.8

4. Conclusion

We have built a system that automatically detects false positive detections from RT images containing low-contrast defects using a feature extraction method and machine learning. This system has sufficient performance to help inspectors identify defects and is expected to be used for double-checking and screening for inspections to significantly reduce the burden on inspectors. Currently, the applicability of this system is being evaluated by inspectors using actual images. It was also confirmed that the generation of simulated defects can be effectively used as learning samples, so this system is expected to be introduced quickly even in applications for which it is difficult to sample defect images.

References

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