New Development of Intelligent Detection Technology for Complex Aerospace Castings Ray Flaw Detection

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Abstract: Complex castings of light alloys such as aluminum, titanium and magnesium are widely used in high-end national defense equipment such as aerospace. The main means of internal defect detection are "X-ray flaw detection two-dimensional DR Manual division parameter adjustment and film shooting + manual visual experience evaluation + manual trial and error three-dimensional positioning". The three links are highly dependent on manual labor, and defects are easy to miss and mis-detect, and the efficiency is low, resulting in potential safety risks for equipment. Therefore, a new idea of intelligent casting inspection in the whole process of path planning, automatic machine assessment and 3D defect positioning is proposed. A defect recognition and evaluation model based on casting knowledge and deep learning is established, an inspection path optimization and planning algorithm based on quality key points, and a 3D defect reconstruction and position technology based on multi-angle 2D images. The results of engineering application or test verification show that the accuracy of casting defect assessment exceeds 98% (miss detection is close to 0), full-size filming without blind area, and 3D positioning error is less than 2%, which is expected to transform manual inspection into intelligent inspection of the whole process of filming, scoring and positioning.

Keywords: Defect 3D positioning; Internal defect detection; Light alloy castings; X-ray inspection images

1 Introduction

Light alloy castings, such as titanium, aluminum, and magnesium, are widely used in critical aerospace and defense applications, including engine casings, air intake ducts, and ribbed plates, which are typical titanium alloy aerospace components. The precision casting process for light alloys involves multiple stages, including wax removal, baking, melting, and pouring, with any anomaly in these steps potentially leading to internal defects. To ensure the reliability and safety of critical light alloy castings for aerospace equipment, radiographic inspection and 3D defect positioning have become essential procedures before installation. Current detection methods rely heavily on manual adjustments in image acquisition parameters and visual inspection, resulting in lengthy processes with a high likelihood of missed or misidentified defects. Furthermore, existing methods for internal defect positioning depend on manual analysis of X-ray images, which makes it difficult to intuitively obtain information about defect depth and size, leading to low-quality and inefficient defect positioning and repair. Therefore, there is an urgent need to shift from manual inspection to a fully intelligent detection process encompassing imaging, evaluation, and defect positioning.

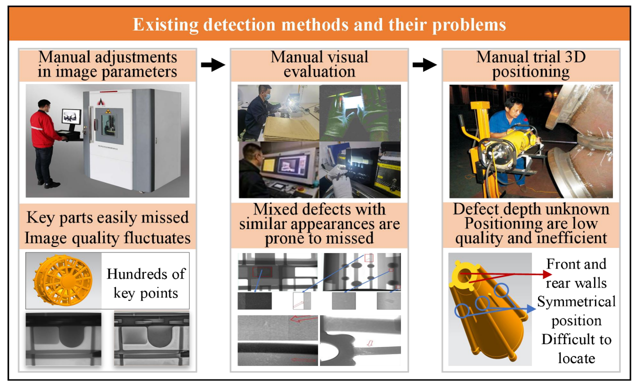

Figure 1. Existing detection methods and their problems

2 Experimental procedure

(1) To improve the efficiency of radiographic path planning, we first introduced the concept of quality control points[1], which were identified based on a feature point extraction algorithm applied to the casting. Next, we generated a cylindrical surface of motion around the 3D model of the casting, representing the potential positions of the radiation source, and map the quality control points onto this surface. Finally, using a genetic algorithm, we generated the optimal movement paths for the radiation source, the workpiece platform, and the imaging plate, drawing 3D curves to complete the path planning process.

(2) To achieve automated online radiographic image evaluation, we first developed the ASCUnet (Ameliorated Skip Connection Unet) model. We embedded an efficient, lightweight attention module[2] at appropriate positions within the Unet architecture to build an attention-enhanced multiscale feature pyramid. Additionally, we proposed a data augmentation strategy tailored for X-ray defect segmentation in light alloy castings and used transfer learning to train the ASCUnet model. Finally, comparative tests and validation showed that the model achieved a segmentation accuracy of 98% for multiscale defect detection.

(3) To achieve intelligent 3D defect positioning, we first integrated filtering and morphological processing techniques to extract defect contours from the images. Next, we constructed a coordinate dimensionality elevation model to transform 2D image defect coordinates into 3D defect coordinates on the casting[3]. Finally, we calculated the intersections between the radiographic rays and the casting model, established a boundary feature polyhedron, and developed an algorithm for defect morphology reconstruction. The results demonstrated that the relative error in 3D defect positioning was less than 2%.

3 Result and discussion

To validate the performance of ASCUnet, we created a titanium alloy dataset and trained seven semantic segmentation models, including Res50DeepLabV3+, for comparison with ASCUnet, with the results shown in Figure 1. Define the defect detection accuracy:

$$\eta = \frac{T-M}{T} \times \frac{D-F}{D} \qquad (1)$$

Data analysis indicated that the total number of actual defects(T) was 259, with 260 defects detected(D), 4 false positives(F), and 0 missed defects(M). The defect detection accuracy(η) was 98.46%.

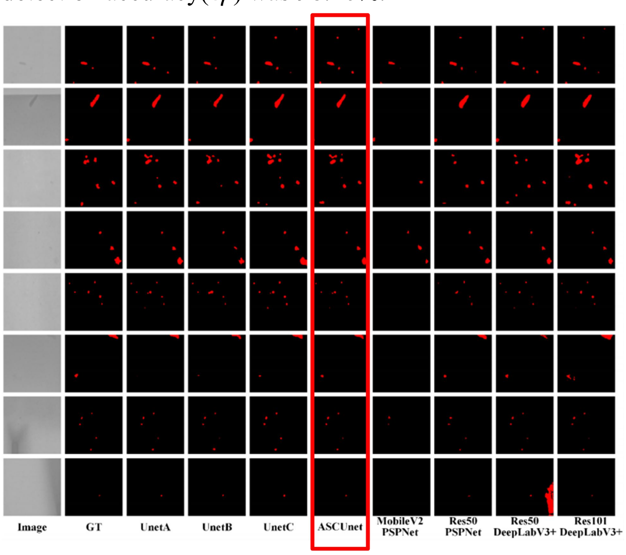

Figure 2. Comparison results of the eight models

To verify the accuracy of 3D defect positioning, we simulated 3D positioning for hole-type and crack-type defects, calculating the centroid coordinates of the feature polyhedra obtained from positioning, the centroid coordinates of the simulated defects in the model, the model dimensions, and the relative positioning error. The results are presented in Table 1.

Table 1. Defect positioning result quantification table (CG means the center of gravity)

Object	X	Y	Z
Model size	81.77	81.77	43.81
CG of Defect A	-2.145	-8.776	19.264
CG of Result A	-1.858	-9.085	20.014
Relative error	0.35%	0.38%	1.71%
CG of Defect B	-1.040	10.392	32.471
CG of Result B	-0.828	10.216	32.679
Relative error	0.26%	0.22%	0.47%

4 Conclusion

We propose a new approach for intelligent casting inspection that integrates radiographic path planning, automated image evaluation, and 3D defect positioning. This includes developing a defect recognition and evaluation model that combines casting expertise with deep learning, an optimized inspection path planning algorithm based on quality control points, and a technique for 3D defect reconstruction and positioning using multi-angle 2D images. Engineering applications and test validation demonstrate that our method can achieve an image evaluation accuracy of over 98%, full-size radiographic inspection with no blind spots, and a 3D positioning error of less than 2%. This approach is expected to transform manual inspection into a fully intelligent process encompassing imaging, evaluation, and positioning.

Acknowledgments

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