Progress in Welding Defect Detection Based on Visual Technology

Xucheng Feng

Harbin Institute of Technology, Heilongjiang Province,150001, China

fxc2024113174@outlook.com

Abstract. Welding defect detection is a crucial step in ensuring the safety of industrial manufacturing. The traditional manual visual detection and radiographic detection methods have low efficiency, high costs, and poor adaptability, which make it challenging to meet the needs of large-scale manufacturing. With the development of computer vision and machine learning methods, welding defect detection methods based on vision have become a research hotspot because of their non-contact, high efficiency, and intelligence. This paper reviews the research progress in this field. To begin with, the application scenarios and limitations of several traditional detection methods are introduced, and their shortcomings in dealing with a strong interference environment and identifying minor defects are emphasized. Then, the basic principle of machine learning and its application in weld defect detection are analyzed, and the innovative application of machine learning and deep learning technology in weld defect detection is discussed, including the excellent performance of support vector machine, random forest, convolutional neural network, transformer, and other models in feature extraction and classification. In addition, this paper also summarizes the key challenges currently facing us, including suppressing interference under extreme conditions, overcoming the bottleneck of high-precision detection, and addressing the obstacles to industrial implementation. Future research directions are identified, including multimodal data fusion, real-time adaptive control, lightweight models, and improving standardization and interpretability. Through technology integration and scene refinement, vision-based welding defect detection may transition from "passive recognition" to "active prediction", providing more efficient and accurate quality control solutions for intelligent manufacturing.

Keywords: Weld defect detection, Machine vision， Deep learning, Feature extraction, Smart manufacturing

1 Introduction

Various welding defects pose varying degrees of harm to the safe use of components and structures. Under the action of stress, severe welding defects can even lead to joint fracture and structural damage. Therefore, scientific and accurate defect detection is an essential means to ensure the welding quality of components. Welding

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defects can be categorized into surface defects and internal defects based on their location. Traditionally, surface defects can be detected by visual observation and measurement, while internal defects are commonly identified through ultrasonic flaw detection and radiographic flaw detection. It is challenging to precisely pinpoint tiny defects and effectively differentiate among various defect types [1]. In recent years, considerable research has been conducted on the application of machine vision technology in welding defect detection both domestically and abroad. Machine vision is a technology that utilizes machines to measure and judge, rather than relying on human eyes, offering the advantages of non-contact measurement and easy integration with automated production systems. Technology realizes the automatic detection of weld defects through image acquisition, feature extraction, and pattern recognition. Currently, machine vision has evolved from two-dimensional image recognition to three-dimensional stereo vision, and image acquisition technology is also continually improving. The new self-supervised learning framework and the mutual centered learning method enhance data efficiency and classification accuracy. In feature extraction, the application of deep learning and other methods enhances the accuracy and efficiency of feature extraction. In the aspect of image analysis and understanding, the application of deep learning, graph representation learning, and other methods provides more possibilities for the development of image analysis and understanding. In the future, with the further development of technology, the application prospects of machine vision will be broader. This article reviews the research progress in visual-based welding defect detection. Firstly, the basic principles of machine learning and its working mode in welding defect detection were introduced. In the main body of this article, the focus is on analyzing the new applications of machine learning in defect detection. Finally, the paper discussed the prospects for future research directions.

2 Fundamentals of Machine Learning

Machine learning is a branch of artificial intelligence. Computers solve problems by analyzing a given dataset and generating models based on the input data [2]. Machine learning is different from traditional programming. Traditional programming rules are only written in a computer language, and cannot be learned from data. Machine learning utilizes data to construct adjustable models, which are then employed to predict or classify new data. For some practical problems, due to the complexity of the code, it is tough to develop rule-based programs. When sufficient relevant data is available, machine learning can be utilized to address these problems.

3 How Machine Learning Works in Welding Defect Detection

According to the presence or absence of "labels" in training data, machine learning can usually be divided into three categories: supervised learning, unsupervised learning, and reinforcement learning. Supervised learning is most used in welding defect detection, and its training model usually includes inputs and corresponding expected outputs (labels). The model learns these input-output pairs to predict the production of new data, thereby completing the recognition and classification of weld images. Anvar et al. proposed ShuffleDefectNet, which achieved an accuracy of 99.75% on the NEU dataset [3]. With the breakthrough of convolutional neural networks (CNNs) in feature extraction, deep learning-based detection methods have gradually become mainstream. Significant breakthroughs have been made in terms of detection accuracy and efficiency. According to different task architectures, single-stage models (such as YOLO series and SSD) directly predict defective locations and categories through an end-to-end network, allowing them to meet the demand for fast detection through lightweight design and real-time optimization. Two-stage models are based on region-CNN. The CNN extracts hierarchical structures in low-level to high-level features of images. The He K team extended the Faster R-CNN model by adding branches, and in all testing tasks, the model's performance exceeded that of all independent model schemes at the time [4]. And the hybrid models (such as RefineDet) attempt to balance the contradiction between speed and accuracy. For example, Rong Liang et al. constructed a RefineDet model by introducing an attention mechanism, which significantly improved the localization accuracy of occluded small targets while maintaining efficient detection speed [5]. Besides, Swin Transformer innovatively introduces hierarchical structures and sliding window mechanisms, significantly optimising computational efficiency while preserving global modelling capabilities. Generative Adversarial Networks (GANs) provide innovative solutions to the core challenges of sparse and imbalanced industrial defect datasets. The integrated application of these technologies has delivered significant performance leaps.

4 Innovative Applications of Machine Learning in Welding Defect Detection

The introduction of machine learning (ML) technology has led to transformative breakthroughs in automated welding defect detection, demonstrating significant advantages, particularly in feature optimization, classification model design, key technology integration, and enhanced detection performance [6].

4.1 Feature Optimisation and Innovative Applications of Classification Models

The core challenge in weld defect detection lies in extracting discriminative features from noisy X-ray or optical images and constructing robust classifiers.

Support Vector Machines (SVM). SVMs serve as the cornerstone for welding defect classification due to their exceptional generalisation capabilities, particularly in classifying small-sample, high-dimensional data. By employing kernel techniques (e.g., RBF kernel, polynomial kernel), SVMs map raw image features (such as grayscale statistics, texture features GLCM, shape descriptors) into high-dimensional or even infinite-dimensional spaces. Within this space, they construct optimal hyperplanes to achieve linear separability for complex defects. After loading and optimising the DOA-SVM for training, Feng Zhiqiang's team established a welding defect recognition model. Multiple experimental sets were designed to validate this approach. Results demonstrated 98.03% accuracy in identifying six weld quality categories, accompanied by short training/prediction times, as well as strong generalization capabilities, meeting the requirements for online welding quality inspection [7]. SVM’s key advantages lie in its ability to handle high-dimensional feature spaces and nonlinear classification boundaries.

Random Forest (RF). RF effectively overcomes the overfitting issue of individual trees by integrating multiple decision trees. Its inherent support for high-dimensional feature inputs and parallel computing capabilities make it particularly effective in welding defect detection. Its core innovations lie in multi-feature fusion, feature importance evaluation, and ensemble learning.

Regarding multi-feature fusion, RF can simultaneously process various feature types (e.g., numerical, categorical, geometric, textural, spectral) and automatically learn complex relationships between features to achieve complementary information.

Regarding feature importance evaluation, RF provides feature ranking based on Gini impurity or out-of-bag (OOB) error. Kumar et al. applied RF to analyse time-frequency domain features extracted from ultrasonic welding inspection signals, precisely identifying key frequency band features that are most critical for crack detection. This provides clear guidance for sensor optimisation and feature engineering. RF's feature selection capability significantly optimises model inputs, enhancing computational efficiency and model interpretability.

Ensemble learning primarily enhances robustness by combining the wisdom of multiple models. A single model may fail under specific defect or noise conditions. Ensemble methods (e.g., Boosting, Bagging, Stacking) combine predictions from numerous base learners (often SVM, RF, KNN, etc.), significantly improving overall system accuracy and robustness. For weld image defect assessment using ensemble learning, Zhang Huiming integrated ensemble voting and averaging methods with multi-convolutional neural network detection and multi-object detection approaches. Compared to standalone models, the integrated system achieved a maximum classification accuracy of 99.3% and a maximum mAP50 of 0.911 for object detection. This model demonstrated significantly greater detection stability under substantial noise interference than any single model, highlighting the value of ensemble strategies in addressing the complexity of real industrial environments [8].

4.2 Deep Integration with Traditional Image Processing Techniques

Purely data-driven ML models sometimes struggle with precise defect localisation and segmentation. Integrating ML with traditional image processing techniques can enhance localisation accuracy. During detection, after ML preliminarily identifies suspected defect areas, applying morphological operations (e.g., opening/closing operations, morphological reconstruction) effectively removes noise points, smooths defect boundaries, and connects fragmented sections, significantly improving segmentation quality. After identifying spatter regions in weld pool images using SVM, Wu et al. employed morphological filtering for refinement, substantially improving measurement accuracy for spatter size and location. When multiple defect targets are closely adhered, ML classifiers may misclassify them as a single entity. The watershed algorithm effectively separates touching objects, resolving adhesion issues. By embedding the watershed algorithm into their RF-based weld bubble detection workflow, RF first identifies large regions that potentially contain multiple adhered bubbles. The watershed algorithm then performs fine segmentation based on image gradient information, successfully addressing false positives and false negatives caused by bubble adhesion, thereby improving localization accuracy by approximately 15% [9]. Another team also employed a filtering approach. Chunyuan Gong et al. proposed a novel compensation filtering method (CFM) that builds upon traditional techniques. The original point cloud is segmented into several independent groups, smoothed to obtain compensation values, and then the filtered point cloud is fused with these compensation values to extract surface features. This method can reduce noise by approximately 80% and better identify defect features [10].

4.3 New Approaches to Three-Dimensional Networks

Submillimeter-scale microdefects (such as microcracks and lack of fusion) are challenging to identify due to their characteristic dimensions approaching the imaging resolution limit. For three-dimensional defect reconstruction, Hanjie Huang et al. employed a planar correction algorithm that adjusts contour line slopes based on gradient information to minimise the impact of system disturbances during weld data acquisition. Subsequently, surface features of the weld, including curvature and the direction of the normal vector, were extracted to identify porosity, pitting, and undercut defects. A dual-alignment template matching approach ensured comprehensive extraction and measurement of defect regions. Finally, the detected defects were classified based on their morphology. This approach elevated the accuracy rate for detecting and classifying typical welding defects to over 97.1%, with precision reaching 98.9% for different defect types (including porosity, undercut, and pitting) [11].To balance efficiency and accuracy, Liang Feng's team proposed a novel approach: a lightweight deep learning-based network, UWD-Net, for ultrasonic welding surface defect detection. This enables comprehensive extraction of complex defect information, enhancing the network's feature extraction capabilities. However, this method is not yet ready for industrial implementation. Future efforts will explore knowledge distillation techniques to reduce computational demands and boost detection efficiency, while designing and optimising loss functions tailored to defect types to enhance the model's generalisation capabilities [12].

5 Conclusion

This paper provides a comprehensive review of the research advancements in detecting welding defects using visual technologies. The traditional methods are constrained in terms of efficiency, cost, and adaptability. However, machine vision technology has become a focal point of research owing to its non-contact nature, high efficiency, and intelligent merits. Machine learning approaches, such as SVM and RF, demonstrate outstanding performance in feature extraction and classification. Deep learning models, such as CNN and Transformer, further enhance detection accuracy and generalization capabilities, facilitating a transition from manual feature selection to automatic feature learning. Strategies such as ensemble learning and multimodal fusion significantly enhance the system's robustness in complex industrial environments.

Nevertheless, significant challenges remain in suppressing interference under extreme conditions, achieving high-precision identification of minute defects, addressing insufficient model generalisation, overcoming the scarcity of high-quality annotated data, and mitigating high industrial deployment costs. Future research should focus on multimodal data fusion, lightweight model design, the development of real-time adaptive detection systems, and the standardization of model interpretability. This will drive the transformation of weld defect detection from passive recognition to proactive prediction, providing more reliable quality control support for intelligent manufacturing.

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