Research on Welding Defect Detection Based on Visual Technology

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Abstract. Welding quality is crucial to components' safety and lifespan, while welding defects are unavoidable due to process parameters, material properties, and manual operations. Visual inspection via computer vision and deep learning well compensates for traditional techniques' shortcomings. This paper reviews visual-based welding defect detection methods with emphasis on deep learning applications, analyzes core challenges like image quality, micro-defect detection, small samples, and unbalanced data, and concludes future research directions: multimodal fusion, better micro-defect detection, dataset improvement, and few-shot learning. Research shows that deep learning combined with vision technology boasts notable advantages in automation, accuracy, and efficiency, boosting detection quality and advancing welding inspection towards greater intelligence and automation.

Keywords: Welding Defect Detection; Visual Technology; Testing methods.

1 Introduction

As an important material connection technology, welding is widely used in industrial manufacturing, aerospace, the construction industry, the electronic industry, and other fields. It is an indispensable key process in modern industry. However, many reasons, such as the mismatch of welding parameters, material problems, and welder technical problems, will cause welding defects. Welding defects will degrade the mechanical properties, weaken the structural integrity, and cause failure, and seriously affect the safety, reliability, functionality and service life of welded structures. Therefore, the detection of welding defects is particularly important [1].

At present, the five traditional testing methods are visual testing, radiographic testing, ultrasonic testing, magnetic particle testing and penetrant testing, but they all have their own limitations. Firstly, although the cost of manual visual inspection is low, it can only detect the surface and the speed and accuracy depend on the experience of the inspector. Although the shape and size of internal and external defects can be visually displayed by X-ray or γ - ray detection, it has a high cost and potential radiation hazards to human body. Although ultrasonic testing has strong penetration, high sensitivity to internal cracks and planar defects and is harmless to the human body, the results are not intuitive, and its interpretation depends on the technology and experience of operators and is affected by noise. Magnetic particle testing is very intuitive and sensitive to surface crack detection, but it is only applicable to ferromagnetic materials and can

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only detect surface or near surface defects. Although penetrant testing is applicable to any non-porous material, it is still unable to detect internal defects and requires high cleanliness of the material.

In order to avoid the shortcomings of traditional detection methods, the research on welding defect detection based on visual technology is particularly important. The information obtained by visual technology is more accurate and efficient, with a large amount of information and strong anti-interference ability. If deep learning is integrated into visual technology, through training a large number of defect samples, the model can automatically learn the defect characteristics, and the accuracy and efficiency of defect detection will be far higher than those of traditional methods, driving welding detection in the direction of high quality, high efficiency, and high intelligence [2]. For example, the Diaz Cano team, based on two-dimensional vision technology, combined with a high-resolution industrial camera to collect images, carries out the identification and classification of fillet welds, and the detection accuracy can reach more than 97% [3]. Therefore, this paper aims to systematically sort out the composition of the detection system based on visual technology in the welding defect detection, the welding defect detection method based on the deep learning visual technology, the challenges, and the future development trend.

2 Visual representation of welding defects

2.1 Typical weld defect characteristics

Welding defects will seriously affect the safety, integrity, and service life of welded structures. To detect welding defects, people first need to understand the characteristics of typical welding defects. Welding defects can be divided into external defects and internal defects. As shown in Table 1, Table 1 summarizes the characteristics and effects of typical internal and external welding defects.

Table 1. Characteristics of welding defects

Defect type	Describe	Influence
crack	Local cracking of welds or heat-affected zones	Stress concentration and bearing capacity reduction
Undercut	Groove at the weld edge	Stress concentration and fatigue strength reduction
Weld bead	Small metal nodules formed by the incomplete fusion of metals	Cause cracks and reduce mechanical strength
Pit	Low-lying part of the weld surface or end	Reduce effective cross-sectional area
Incomplete welding	Weld surface is not completely filled with the groove	Reduction of joint strength and effective working area
Blowhole	Voids are left in metal without gas escaping during welding	Reduction of weld compactness and joint strength

Slag inclusion	Non-metallic inclusions remain in the weld	Stress concentration reduces mechanical properties
Lack of penetration	Incomplete penetration at the root of the welded joint	Joint strength decreases, stress concentration

External defects. The external defects of welding mainly include cracks, undercuts, overlaps, pits, incomplete welding, etc.

Cracks are the cracks with local cracks in the weld or heat-affected zone, which are the most dangerous defects. The section is bright. It may cause serious stress concentration, greatly reduce the bearing capacity, and crack propagation, resulting in instantaneous brittle fracture of the structure. It is characterized by straight line or irregular curve, including along the weld direction (longitudinal), perpendicular to the weld direction (transverse), crater (at the end of the weld), radial, etc. It is divided into hot crack and cold crack. Hot cracks occur at high temperature, and the section has oxidation color, while cold cracks occur after cooling, which may delay the appearance and brighten the section. Serious stress concentration, a significant decline in bearing capacity, and crack propagation will lead to the structure of instantaneous brittle fracture.

Undercut is a groove or depression along the base metal at the weld toe (the junction between weld and base metal), which is usually due to excessive arc heat or improper welding operation. It may lead to stress concentration and reduce the fatigue strength and bearing capacity of the structure. It is characterized by continuous or discontinuous grooves at the edge of the weld.

Weld beading is a metal beading formed when molten metal flows onto the unmelted base metal outside the weld during welding. It is usually caused by excessive welding current and slow welding speed, which may lead to stress concentration and cracks. Its characteristics are: there are many metal bumps outside the weld edge, and the shape is irregular.

Pits are local low-lying parts formed on the surface or back of the weld that are lower than the surface of the base metal. At the end of the weld, it is called a crater. It is usually because the electrode does not stay when the arc is stopped. It may reduce the effective cross-sectional area of the weld, the impurities in the crater are easy to gather, and the sudden change of shape causes stress concentration, which is easy to induce cracks. It is characterized by a depression on the surface or end of the weld.

Incomplete welding is a continuous or intermittent groove on the weld surface, and its filler metal is lower than the base metal surface. It is usually caused by too low welding current and too fast welding speed. It will reduce the effective working section of the weld and reduce the strength of the joint. It is characterized by: the weld metal does not fill the groove, resulting in the weld surface being lower than the base metal.

Internal defects. The internal defects of welding mainly include porosity, slag inclusion, incomplete fusion, and incomplete penetration.

Porosity is a cavity formed when the gas in the molten pool fails to escape before the metal solidifies during welding. Usually, the welding current is too small, or the welding speed is too fast, and the gas has no time to escape. It will reduce the effective working section of the weld and reduce the compactness and plasticity of the joint. It is characterized by spherical, oval, or wormlike cavities. It can be located inside the weld, on the surface, or throughout the weld. There are dense pores, strip pores, and single pores.

Slag inclusion is a non-metallic inclusion remaining in the weld after welding. It is usually because the slag removal between layers is not clean, or the welding current is too small, the molten pool solidifies too fast, and the slag has no time to float out. It may reduce the effective section of the weld and cause stress concentration. It is characterized by irregular shape, generally oxides, sulfides, etc. It can be a point, a strip or sheet.

Incomplete penetration is the phenomenon that the root of the joint is not fully penetrated during welding. It is usually because the welding current is too small and the welding speed is too fast. Similar to the lack of fusion, it seriously reduces the effective working section of the weld and causes serious stress concentration. It is characterized by continuous or discontinuous gaps at the root of the weld.

3 Defect detection during and after welding

The detection of welding defects is mainly divided into in-process detection and post-weld defect detection.

The traditional five non-destructive testing methods mainly belong to the post weld defect detection, which is to inspect the quality of the formed weld after the completion of the welding process and the cooling of the workpiece, judge whether there are defects such as pores, cracks, and lack of fusion in its internal or surface, and then evaluate whether the product is qualified. This method is direct and the standard is mature, but it can notaddress the defects that have been formed.

In the welding process detection focuses on process monitoring. It monitors key process parameters (such as current, voltage, arc sound, weld pool image, temperature field, etc.) in real time during the welding process, and compares and analyzes them with the preset high-quality weld process window, so as to judge whether the process is stable in real time, predict possible defects, and timely warn or adjust parameters to prevent defects from the source.

3.1 Inspection during welding

The main purpose of process monitoring during welding is to detect the welding process in real time and ensure the stability of weld quality and process. On the one hand, welding defects can be found and treated in time. On the other hand, welding defects can be detected in real time without waiting for the completion of welding, saving time and cost.

Based on the research of existing real-time seam tracking technology, Nie Wenme's team developed a set of real-time seam tracking system for the ultrasonic testing process of high-frequency welded pipe with a length of less than 18 meters [4]. The system effectively solves the problem of weld deflection caused by axial bending of high-frequency welded pipe with a length of 12 to 18 meters, and overcomes the possible defect of missing inspection in ultrasonic testing. It can identify the position deviation of the weld in real time, and quickly adjust the probe frame so that the probe is always aligned with the centerline of the weld. Thus, the full coverage detection of high-frequency welded pipe welds can be realized, and the stability and reliability of weld quality can be significantly improved. This method provides a feasible technical way for on-line and real-time monitoring of welded pipe welds.

Aiming at the real-time monitoring problem of spatter in stainless steel high-power laser welding. Wang Cai team built a set of real-time visual monitoring methods, integrating lightweight deep learning and moving target tracking technology [5]. The dynamic welding process is captured by the high-speed camera system, and the image enhancement algorithm is used to effectively filter out the interference of metal vapor, so as to improve the identifiability of spatter features. The use of a dedicated lightweight detection network combined with automated labeling can significantly improve the detection efficiency while ensuring 96.7% recognition accuracy. Furthermore, the multi-target tracking mechanism is further introduced to realize the continuous tracking and behavior analysis of different splashes, and the key parameters such as splash size, motion speed and distribution law can be obtained in real time. This research provides effective technical support for real-time monitoring and process control of the welding process.

3.2 Post weld defect detection

Post weld defect detection is to detect the welding and its heat affected zone after the completion of the welding process, so as to evaluate various discontinuities or defects existing in the welding process and ensure that the product meets the design and safety requirements.

Aiming at the challenges such as the loss of fine-grained features and the difficulty of multi-scale fusion in the detection of welding surface defects, the Yan sun team proposed the deim-sfa detection model, as shown in Fig. 1. The model reduced the loss of small defect features by introducing the spatial information preserving subsampling module (SPD conv), integrated the efficient multi-scale attention mechanism (EMA) to enhance the focus on key areas, and built the feature focusing diffusion pyramid network (FTPN) to achieve the deep fusion of cross-scale features [6]. The experimental results show that the comprehensive detection performance of the model is significantly improved on the self built data set, which provides an effective solution for the intelligent detection of industrial weld quality while maintaining a low computational complexity.

Aiming at the problem of detecting small-scale defects on the surface of pipe welds, a lightweight visual detection model based on improved yolov7 is proposed, as shown in Fig. 2. By introducing the fourth small target special detection head in the network and integrating shallow details and deep semantic features, the perception of subtle defects is significantly improved [7]. In order to meet the deployment requirements of mobile terminals, the model uses deep separable convolution instead of standard convolution, which reduces the computational complexity to about one quarter of the original model while maintaining the accuracy. The improved model shows good robustness in a variety of lighting conditions and shooting angles, and the detection speed meets the requirements, which provides a feasible technical scheme for the weld quality detection of embedded equipment such as pipeline crawling robot.

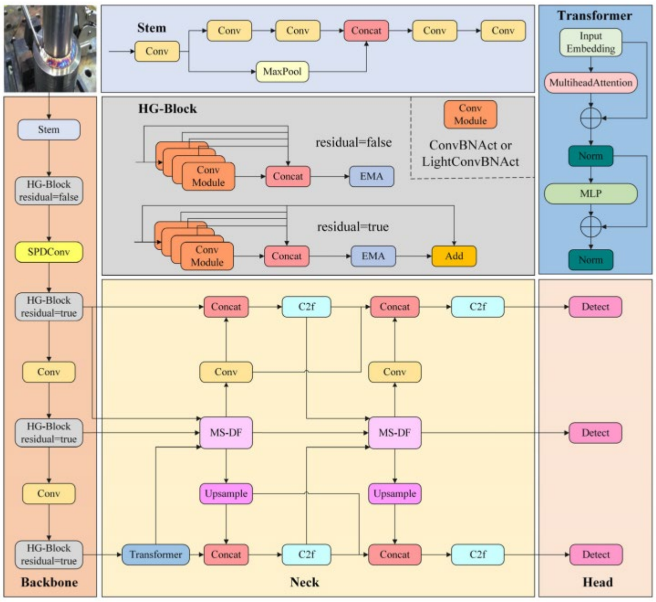

Fig. 1.deim-sfa overall architecture [6]

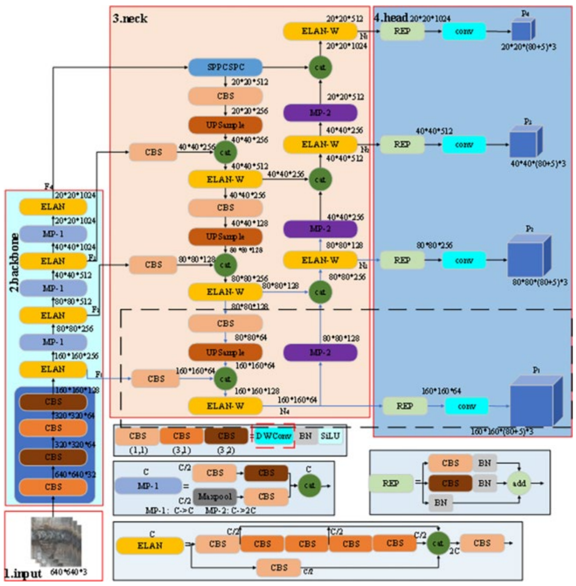

Fig. 2. improved lightweight visual inspection model of YOLOv7 [7]

4 Welding defect detection method based on deep learning vision technology

After a large number of data model training, the visual technology welding defect detection method based on deep learning can automatically identify the defect characteristics according to the characteristics of welding defects, and the processing is more automatic, which significantly improves the efficiency and reliability of detection, and has become an important method in the field of welding defect detection.

4.1 Image Acquisition System

Image acquisition is an important part of welding defect detection, and the image acquisition determines whether the subsequent data processing and enhancement, feature extraction, and recognition can continue. At present, the main image acquisition systems are mainly divided into two-dimensional vision systems and three-dimensional vision systems.

2D-vision system. The 2D-vision system is the most widely used and the most mature scheme at present, especially good at detecting the welding defects on the surface. Mainly through the analysis of the two-dimensional image of the weld area, using its gray, texture, contrast changes to identify defects.

Diaz Cano team used the high-resolution industrial camera ensenson35 based on 2D-vision, combined with the yolov8 algorithm, to recognize and classify the fillet welds in 2D-vision images, and the accuracy of fillet weld detection exceeded 97% [3].

Based on the active two-dimensional linear structure laser vision, the Weiming Li team can effectively and accurately identify a variety of welds under the interference of extreme noise, such as welding strong arc light by integrating the IPCE algorithm with the linear structure laser vision sensor composed of an industrial camera, linear structure laser, and filter [8].

Although the 2D-vision system is widely used in the field of welding defect detection, it still has some shortcomings that are difficult to overcome, mainly because it lacks three-dimensional information and depends too much on the surface state, and is vulnerable to external interference such as spatter and lighting conditions. Therefore, it can be combined with 3D-vision in practical applications.

3D-vision system. The 3D-vision system vision can obtain the three-dimensional shape data of the weld, has a more flexible perspective, provides a new dimension for the detection, and can overcome the surface interference of two-dimensional vision, which is more robust in the detection ofworkpieces with complex surface state, and is becoming the key technology to solve the problem of complex defect detection.

Jin, Lei's team used a multilinear structured light 3D vision sensor inspired by the laser triangulation method to accurately capture and analyze the three-dimensional shape distortion of light strips caused by surface concave defects. Combined with the patch core, they built a detection system that can effectively resist surface interference and directly detect the depth of defects [9]. Chen, Chao's team successfully achieved accurate measurement of weld pore depth by introducing a line laser 3D sensor for 3D scanning, and overcame the industry problem that 2D vision could not quantitatively detect defects [10].

Huang, Hanjie team has developed a set of aluminum tank weld defect detection system based on 3D vision , which collects high-precision point cloud data through Haikangwei line of sight laser contour scanner, and realizes the accurate identification and classification of defects such as pores, craters and undercuts [11]. It effectively overcomes the limitation of 2D vision which is vulnerable to environmental interference, and can more accurately quantify the geometric morphology of defects, and promote industrial detection from qualitative judgment to a new level of quantitative analysis.

However, the acquisition speed of 3D vision system is limited, which is difficult to meet the real-time detection requirements, and the cost is high. Therefore, in the actual manufacturing scene, the combination of 2D and 3D vision can achieve a hybrid detection scheme with complementary advantages, so as to achieve the best balance between speed, accuracy and cost.

4.2 Image data preprocessing and enhancement

In the actual manufacturing scene, the data of image acquisition are often affected by different factors, so the data characteristics become complex. Due to the influence of different lighting conditions, working conditions, shooting angle, and workpiece pose, the collected images also have significant differences in key quality indicators such as resolution, contrast and noise level. In order to make the features of welding defects in the image more obvious and easy to extract and identify, it is particularly important to preprocess and enhance the image data.

Qin Wei adopted the combined enhancement strategy of Gaussian noise injection and image flipping, simulated industrial imaging interference by adding normal distribution noise, and expanded the sample perspective by using geometric flipping [12]. Enhanced dataset expansion provides a data base with higher quality and wider coverage for subsequent model training.

Jia Chen team. Effectively expanded the diversity of the data set by performing data enhancement operations such as rotation, translation, flipping and brightness adjustment on the welding image data, thus improving the generalization ability of the model, improving the performance of the model in different welding scenarios, and making it more accurate in detecting defects such as dents, welding slag, scratches and bubbles [13].

Aiming at the common problems of low contrast and high gray image in welding defect detection, Liangliang Li's team. Proposed IMFF-WD method [14]. Through the detailed information extraction algorithm of multi-scale Gaussian kernel, combined with particle swarm optimization (PSO) algorithm to optimize the threshold, to enhance the contrast and detail of the image, so as to make the defect feature more prominent.

4.3 Image feature extraction and recognition

Welding defects often appear in small areas of welded joints, and the shape, color, contrast and other characteristics of these defects may be very subtle or not obvious in the image. In order to effectively detect these defects, it is necessary to extract meaningful features through image processing technology, so as to achieve accurate defect recognition.

Qinwei et al. Deformable convolution (DCNV3) enhanced the adaptability of the model to irregular weld morphology. The hybrid attention mechanism focused on key feature areas through channels and spatial attention, and the dynamic focus loss function (wise IOU) significantly optimized the positioning accuracy of small targets [12]. Through these optimization strategies, the accuracy of the model in weld defect detection has been significantly improved.

Liangliang Li constructed an IMFF-WD model and designed an interpretable detection model for dual path feature extraction and fusion, so that defects that are usually difficult to identify can be effectively extracted and detected in low contrast welding images [14]. It provides a new solution for high-precision detection of welding quality, and has a strong industrial application potential.

Vinod Vasan et al. Extracted a variety of statistical features from images by using a series of image segmentation techniques, including fast Fourier transform (FFT), gray level co-occurrence matrix (GLCM), gray level difference method (GLDM), texture analysis and discrete wavelet transform (DWT), which enhanced the ability of defect recognition [15]. The extracted features are dimensionally reduced to improve the computational efficiency and prevent over fitting. It shows that the integration method combining different types of features significantly improves the classification accuracy of the model, and finally achieves 93.12% accuracy in the detection of welding defects.

5 Challenges and future trends

5.1 Current major challenges

In the process of welding defect detection, although deep learning and image processing technology have made significant progress, they still face many challenges. First of all, the welding environment is complex, and the image may be affected by light changes, surface reflection, Weld Geometry diversity, noise and other factors, resulting in low image contrast and blurred details, which brings difficulties to feature extraction and recognition. Even for the same type of defects, the images under different shooting conditions may differ greatly. It is sometimes difficult to ensure the applicability to all working conditions by relying only on a single image enhancement or preprocessing method [16]. Secondly, some defects account for a small proportion in the image, the characteristics are not obvious, and are easy to be covered by background or noise. The performance of traditional target detection or segmentationnetworks in small target detection and precise positioning is still limited. Although the detection effect can be improved through multi-scale feature fusion, attention mechanism, and other methods, it is still difficult to achieve stable and high-precision recognition in the complex industrial background [16]. In addition, the welding defect samples are often far less than the "normal weld" samples, and some defect types (such as cracks, incomplete welding, undercut, etc.) have low occurrence frequency but high harm, which causes the imbalance of training concentration categories, and the deep learning model is easy to over fit most categories, and the recognition ability of a few categories is insufficient [17].

5.2 Future research directions and trends

In order to meet the current challenges, future research can carry out in-depth exploration in the fields of multimodal data fusion, the combination of multi-scale feature extraction and attention mechanism, small sample learning, and self-monitoring learning, and promote the further development of welding defect detection technology.

Firstly, multimodal data fusion is an important research direction. Welding defect detection not only depends on a single visual image data, but also combines different types of sensor data, such as two-dimensional images, three-dimensional point clouds, infrared imaging, etc., which can provide richer information for defect detection, effectively improve the accuracy of detection, and comprehensively analyze and identify welding defects. Especially in complex working conditions, it can make up for the shortcomings of a single visual system, and the recognition rate is better than that of the traditional two-dimensional visual sensor [18].

Secondly, the combination of multi-scale feature extraction and attention mechanism is also a direction worthy of further exploration. The detection of small defects is still a major challenge in the detection of welding defects. Although the existing deep learning model performs well in most defect detection, it is still insufficient in the detection of small defects (such as microcracks, shallow pores, etc.). Future research can enhance the recognition ability of the model for small targets and small defects by introducing more advanced multi-scale feature extraction technology and attentionmechanisms [6]. This can not only improve the accuracy of defect detection, but also reduce the occurrence of missed detection and false detection.

In addition, small sample learning and self-supervised learning will become effective means to solve the problem of unbalanced data in welding defect detection. Most of the current data sets lack labeled defect samples, especially small samples and rare defect types, which makes model training very difficult. Through small sample learning, transfer learning, data enhancement, and other technologies, the performance of the model in the absence of sufficient annotation data can be greatly improved [19]. In addition, technologies such as Gan can be used to generate more defect samples to help train more robust models. Some studies also show that the self-supervised learning method can learn more feature information from the unlabeled data, and further improve the generalization ability of the model in practical applications.

6 Conclusion

This study systematically summarizes the limitations of traditional welding defect detection methods, and discusses the application of visual technology, especially the deep learning method, in welding defect detection in detail. Through the analysis of existing research, it is found that the application of traditional detection methods in actual production is limited, which can not effectively deal with the complex types of welding defects and their different detection requirements. In contrast, the combination of deep learning and visual technology, through automatic feature learning and efficient image processing, can significantly improve the accuracy and efficiency of welding defect detection, especially in complex environments.

However, although deep learning technology has made significant progress in welding defect detection, it still faces challenges such as inconsistent image quality, unbalanced defect samples, and difficulty in detecting small defects. Future research should focus on multimodal data fusion, less sample learning, and self-monitoring learning methods to further improve the generalization ability and detection accuracy of the model. In addition, the combination of multi-scale feature extraction and attention mechanism is expected to further improve the recognition ability of the model for micro defects, and provide more reliable technical support for intelligent detection in industrial production.

In a word, deep learning combined with visual technology has brought revolutionary progress for welding defect detection, and has a broad application prospect. With the continuous progress of technology, welding defect detection based on visual technology will gradually replace the traditional methods, and play an important role in ensuring welding quality, improving production efficiency and reducing production costs.

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