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Casting Defect Detection and Recognition Technology Based on Deep Learning

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ABSTRACT

Aiming at the existing casting defect detection and recognition technology based on deep learning, the limitations of traditional manual detection methods and the advantages of machine vision technology in improving detection accuracy and efficiency are discussed. The research status of casting defect detection is analyzed, including surface defect and internal defect detection technology, as well as image preprocessing, algorithm framework optimization and design innovation direction. By reviewing a variety of deep learning models and algorithms, such as CNN, transfer learning, lightweight models, and improved U-Net models, the potential of these techniques in improving the efficiency and accuracy of defect detection is demonstrated. In addition, this paper discusses the three key modules of visual defect detection technology: image acquisition, image preprocessing and image analysis, and compares the characteristics of one-stage and two-stage object detection algorithms. Finally, the main research directions of casting defect detection are summarized to provide directions for future research.

KEYWORDS

Deep learning; Casting defects; Defect detection; Machine vision

1. INTRODUCTION

Under In the field of industrial manufacturing, the control of product quality is particularly important. Casting as one of the industrial manufacturing technology, it plays a pivotal role in the field of industrial manufacturing. The casting process is a process in which molten metal is poured into the mold, cooled and solidified, and taken out. Casting technology is widely used in machinery manufacturing, automobile manufacturing, tool manufacturing. In complex and changeable working conditions, machines and equipment will inevitably produce unqualified products with defects such as scratches, gaps, surface bumps, edges and extra edges, resulting in a waste of resources. Therefore, defect detection of casting products is very critical.

The traditional defect detection technology is through manual visual inspection, by specialized technicians, through the human body's touch and vision to check whether the parts are qualified, this method is very time-consuming, but also wastes a lot of human resources. The traditional nondestructive testing technology for casting defects includes these five kinds: ultrasonic testing technology, ray testing technology, liquid penetration testing method, magnetic particle testing technology and eddy current testing technology. With the development of science and technology, machine vision in the field of computer can replace manual accurate measurement and analysis, improve production efficiency and product quality. In the field of casting defect detection, machine vision has played a role in improving the detection accuracy and work efficiency, timely troubleshoot the defects existing in the production products, and ensure the high quality and high efficiency of casting products.

Casting defect detection mainly includes surface defect detection and internal defect detection, and the innovation direction is mostly from image preprocessing, algorithm optimization and algorithm construction and design. Among them, Rohit Lal et al. developed a neural network combining two convolutional layers with Conv2d and Maxpoolong2d layers to achieve good detection effects on surface cracks and fins (outer protrusions) of castings [1]. Rupesh Gupta et al. proposed an integrated model for casting defect analysis by integrating the transfer learning ResNet50 model and the proposed convolutional neural network model [2]. Rohit Lal et al. proposed a lightweight model containing depthwise separable convolution and global average pooling layer, which constructs an efficient neural network model with different layers while reducing the number of parameters [3]. Haoyue Liu et al. proposed an innovative image registration method suitable for dynamic scenes. By mapping 3D reconstruction data to 2D mean curvature maps and combining ROI automatic generation technology, the efficiency and accuracy of online detection of casting surface defects are significantly improved, while avoiding the increase of calculation [4]. Liang Weizhong et al. used BERT pre-training model and BiLSTM-CRF model for feature extraction to improve the accuracy, recall rate and F1 value of magnesium alloy casting defect named entity recognition [5]. Xue Lin et al. proposed a casting DR Image defect detection algorithm based on deep learning. The U-Net model was improved by hybrid loss function and AdamW optimizer to achieve high-precision defect segmentation and detection [6]. Liu Xiaojia et al. studied an automatic recognition technology of casting defects based on Relief algorithm and Adaboost-SVM, which effectively improved the recognition performance of casting defects through image preprocessing, feature extraction and classifier construction [7]. Liu Tao achieved accurate edge extraction through machine vision and template matching algorithm, which improved the efficiency and accuracy of robot automatic burr removal [8]. Wei Bowen proposed a casting defect detection system based on laser ultrasound and convolutional neural network, which can effectively identify and grade the defects of metal castings [9]. Wang Fei and Zhang Suran proposed an automatic detection and recognition method of casting defects based on improved deep learning algorithm by fusing YOLOv3 network with multiple deep learning models and image preprocessing technologies such as Faster RCNN and Cascade RCNN network [10]. Li Chuang et al. proposed an improved YOLOv3 algorithm, which used data enhancement technology, lightweight network GhostNet, spatial pyramid pooling structure and channel attention mechanism, and introduced Focal Loss to improve the recognition accuracy of small targets [11]. Hongquan Jiang et al. proposed a casting defect region segmentation method based on dual-channel encoder-fusion decoding network, which effectively improved the segmentation accuracy and integrity of multi-scale fuzzy and weak texture defect regions [12]. Zhao Xiansheng et al. introduced Squeeze-and-Excitation module, balanced feature pyramid, variable convolution, CIOU Loss function, bidirectional recurrent neural network, etc., to improve the neural network model of YOLOv5 to realize automatic defect detection and grading classification [13]. Yan Xueshun et al. introduced histogram equalization method and Mosaic data augmentation strategy, and introduced SENet attention mechanism module to improve YOLOv5 backbone network [14]. Fu Jinlei improved the HTC network by using SE-ResNeXt as the backbone feature extraction network and introducing balanced feature pyramid, variable convolution, CIOU Loss function, and bidirectional recurrent neural network [15].

2. VISUAL DEFECT DETECTION TECHNIQUES

Defect detection is a very important technology in the field of machine vision, also known as automatic optical inspection or automatic surface inspection. It uses machine vision equipment to obtain images to determine whether there are defects in the collected images. The main goal of defect detection is to identify and locate defects on the surface of the product, such as bumps, stains, scratches, cracks, etc., as well as internal defects of the product. After the inspection, the detailed defect information is collected, so as to analyze the data of the target part, and the algorithm is used to make decisions to determine whether it meets the production standards. Visual defect detection mainly includes three modules: image acquisition, image preprocessing and image analysis.

Image acquisition: obtain two-dimensional grayscale image or three-dimensional depth image information of product surface by optical image sensing.

Image preprocessing: Image preprocessing operations such as noise reduction, enhancement, segmentation, and stitching are performed on the collected images in order to obtain regions of interest or input sizes more suitable for image detection algorithms, and the features that most easily distinguish defects from background are extracted through various image processing algorithms or their combinations.

Image analysis: Algorithms such as image comparison, statistical pattern recognition, machine learning or deep learning are used to identify possible defects from the background, classify and locate them.

2.1. Image Acquisition

With the rapid development of visual defect detection technology, the replacement of manual inspection by automated inspection is imminent. But there are still some problems and misunderstandings. In traditional manual inspection, the defect signs that people can observe by the naked eye can all capture the exact same defect by visual inspection. However, in the actual production work, inspectors can observe the parts from different angles by manually changing the position and posture of the parts, so as to make a comprehensive evaluation of the product. However, the static visual inspection technology is difficult to achieve large-scale Angle of view and light adjustment, and the visual defect detection technology will face severe challenges when detecting parts with complex structure and variable scale.

In the visual defect detection system, the image acquisition task is mainly carried out by the hardware such as light source, camera, lens, image acquisition card and vision processor. Therefore, the quality of the hardware directly affects the effect of product defect detection. For example, the information richness of the collected image, the image clarity, and the image file size will directly affect the processing speed and effect of the subsequent algorithm.

In order to achieve a good collection effect, the light source generally choose artificial light emitting diode, it is a common type of light source, the diode can adjust the Angle of the light, color and lighting mode for different parts; The camera is mainly used to capture the image of the detected object. Depending on the application requirements, different camera types can be selected, such as area-scan cameras, line-scan cameras, or high-speed cameras. The lens should be used in conjunction with the camera to focus the light to form a clear image. Lens selection depends on factors such as field of view size, working distance, and required resolution. The image acquisition card, also known as frame grabber, is used to transfer the image data captured by the camera to the processing system. The vision processor can be an integrated hardware unit or a PC-based system that is responsible for executing image processing algorithms and making judgments. In summary, the selection of hardware equipment for image acquisition is very important for visual defect detection.

2.2. Image Preprocessing

Image preprocessing is a key step in image processing and computer vision. Its purpose is to improve the quality of images and enhance the features of images, so as to provide higher quality inputs for subsequent image analysis and understanding tasks. Image preprocessing techniques include a variety of different operations. Here are some common image preprocessing methods: (1) Noise removal: Use filters to remove noise in the image, such as Gaussian filters, median filters, etc. (2) Contrast enhancement: adjust the contrast of the image to make the features in the image more obvious, such as histogram equalization or contrast limited adaptive histogram equalization; (3) Brightness adjustment: adjust the brightness of the image for easy observation and analysis. 4. Normalization and standardization: Scaling the image pixel values to a specific range, such as 0 to 1 or -1 to 1. Binarization: Converting an image into one that contains only two pixel values, typically black and white. (6) Edge detection: Detect edges in the image by algorithms, such as Canny edge detector, Sobel operator, etc. (7) Interpolation: During image resizing, interpolation algorithms (e.g., bilinear interpolation, bicubic interpolation) are used to reduce distortion. (8) Image segmentation: Segmentation of an image into regions or objects, typically for object recognition. 9. Normalization transformation: Transforms the image data into a specific distribution, such as a normal distribution.

The choice of image preprocessing depends on the specific application scenario and goal. For example, in medical imaging, you may want to enhance the contrast of an image to better visualize tissue; While in satellite image analysis, brightness and contrast may need to be adjusted to identify different terrain features. Through preprocessing, the accuracy and efficiency of image analysis can be significantly improved. The image preprocessing is programmed to realize the operation, where Figure 1 is the image to be processed, and Figure 2 is the histogram equalization. Figure 3 shows the comparison before and after adding histogram equalization results, and Figure 4 shows binarization.

Figure 1. Image to be processed

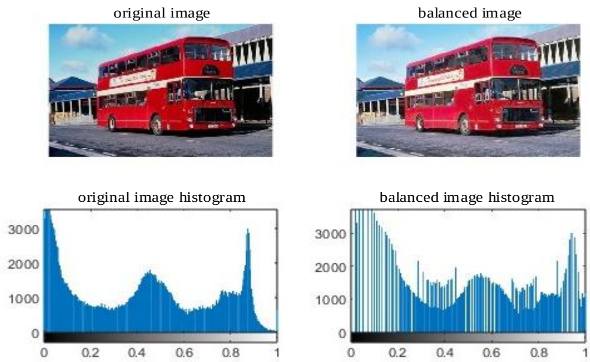

Figure 2. Histogram equalization

Figure 3. Comparison before and after adding histogram equalization results

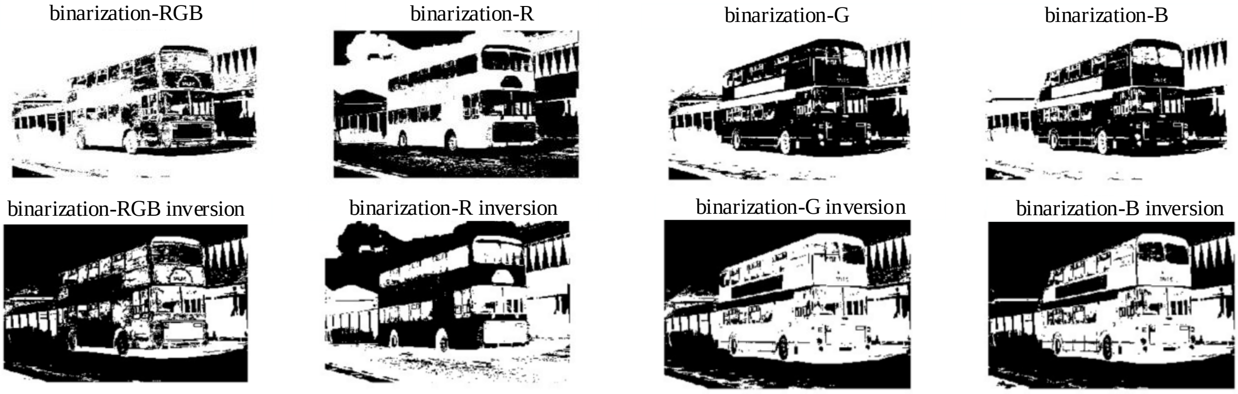

Figure 4. Binarization

2.3. Image Analysis

Image analysis refers to the process of processing, recognizing, understanding and interpreting digital images. This process covers a variety of techniques and methods from simple image processing to advanced image understanding and reasoning. The collected images are processed through a series of image preprocessing for image analysis, including feature extraction and analysis, image segmentation, object detection and recognition, image classification and recognition.

Firstly, the image feature extraction and analysis are carried out to extract representative features from the image, such as target object, texture, edge features and other information. The extracted features are analyzed and processed, such as dimensionality reduction to reduce data complexity, prevent overfitting, improve calculation speed, and help remove redundant information and noise in the data to highlight key features. At the same time, the high bit data can be mapped to two-dimensional or three-dimensional visualization.

Secondly, the image is segmented into several regions with semantic information, which facilitates the independent analysis and processing of each region and helps to locate and identify the target object or region in the image.

Then, target detection and recognition are carried out, and the specific target objects in the recognition image are determined by the corresponding target detection algorithm, and their position, shape and category or label are determined. After that, post-processing is carried out to process the results of detection and recognition, including removing invalid or overlapping bounding boxes and screening candidate boxes with high detection efficiency to improve the detection accuracy and stability.

Then, the image is classified and recognized, the image is divided into different defect categories, and the image content is recognized and understood. Common classifiers include support vector machine, k nearest neighbor, decision tree, and convolutional neural network in deep learning.

2.4. Object Detection Algorithm

The object detection process in deep learning includes image preprocessing and analysis. According to the degree of labeled data required, object detection models are mainly divided into three categories: fully supervised, unsupervised and weakly supervised methods. Among them, fully supervised learning is the most commonly used due to its wide applicability, and its typical representative is Convolutional Neural Network (CNN). CNN is mainly applied to three types of tasks in the field of industrial defect detection: image recognition, defect localization (object detection) and image segmentation, which promotes the significant development of this technology.

The core of CNN is to use the convolution layer to automatically extract the local features of the image (such as edges and corners), and to greatly reduce the number of model parameters and improve the training efficiency through the weight sharing mechanism (the same convolution kernel is applied to the whole image). By stacking multiple convolutional layers, CNNS can build a spatial hierarchy and achieve layer-by-layer abstraction from low-level to high-level features. The following pooling layer is used to compress the spatial size of the feature map and enhance the robustness of the feature to position changes.

With its excellent feature extraction ability, CNN is particularly good at dealing with complex and diverse defect patterns, and has become an indispensable core technology in modern visual inspection systems.

At present, in the detection network, the object detection algorithms composed of CNN are mainly divided into two categories in structure, which are two-stage object detection algorithms and single-stage object detection algorithms. Among them, the one-stage object detection algorithm uses a single neural network to perform feature extraction and object detection at the same time, and outputs the location, class and probability of the defect. The representative algorithms are YOLO, SSD and RetinaNet. The two-stage object detection algorithm uses two networks, region selection network: generate candidate regions that may contain the object, and usually use a sliding window to move on the feature map to predict multiple candidate regions for each location. Object Detection network: Classifies and predicts bounding boxes for each candidate region. Therefore, the two-stage target detection algorithm has the characteristics of high precision. Representative algorithms are: Faster R-CNN, Mask R-CNN, and Cascade R-CNN. Table 1 below shows the comparison of single-stage and two-stage object detection algorithms.

Table 1. Comparison of one-stage and two-stage object detection algorithms

Features	One stage	Two-stage
speed	fast	slow
accuracy	low	high
Complexity	Simple	complex
Applicable scenarios	Real-time object detection Low latency applications	High accuracy Object detection Object segmentation and recognition

The main advantage of single-stage detectors is that they are very fast, which makes them suitable for application scenarios that require real-time responses, such as video surveillance, autonomous driving, etc. However, compared with the two-stage detectors, the one-stage detectors may be deficient in accuracy because they do not have a dedicated candidate region generation step to improve the localization accuracy. Nevertheless, single-stage detectors can still achieve very high detection performance through various optimization methods, such as improved network structures, loss functions, and feature fusion techniques. The advantage of two-stage detection networks is their accuracy and robustness to target scale changes, and the disadvantage is that they spend a lot of time and resources, so they may not be suitable for real-time processing. Whether to use a one-stage or two-stage object detection algorithm depends on the specific application requirements. If real-time object detection or low latency is required, a one-stage detection algorithm is the better choice. If high-precision object detection, object segmentation or recognition is required, the two-stage detection algorithm is a better choice.

Object detection algorithms are widely used in visual defect detection techniques. The algorithm can be trained using labeled defect image datasets to identify and locate defect regions in images. After training, the object detection model can be applied to new images to automatically detect defects.

3. SUMMARY

This paper focuses on the survey of deep learning driven casting defect detection and recognition technology. In the field of industrial manufacturing, casting quality control is very important.

Traditional detection methods mainly rely on manual visual inspection, which has the disadvantages of low efficiency and high labor cost. With the progress of technology, machine vision technology gradually replaces manual work with its higher detection accuracy, effectively improving production efficiency and product quality. Casting defects are mainly divided into two types: surface defects and internal defects. The current research focuses on the construction of high-quality datasets, the improvement of image preprocessing methods, and the optimization and design of the algorithm framework. This paper further analyzes the three core modules of the visual defect detection system: visual information acquisition, image preprocessing and image analysis. At the same time, the one-stage and two-stage object detection algorithms are compared and analyzed, covering their differences in detection speed, accuracy, model complexity and application scenarios.

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