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Application of Artificial Intelligence Technology in Industrial Defect Detection

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Abstract: ***Defects are inevitable in the production process of products, and these defects can have an impact on the appearance and even functionality of the product. Defect detection is of great significance in improving product quantity, ensuring industrial safety, and environmental protection. This article analyzes from the perspective of commonly used defect point detection methods and introduces the problems and solutions currently encountered in industrial defect point detection. With the continuous development of new detection technologies and artificial intelligence, industrial defect point detection will move towards higher accuracy and efficiency, creating more value for enterprises. At the same time, the development of detection technology will promote the intelligent process of industrial production.***

Keywords: Artificial intelligence; Testing technology; Industrial production; Defect detection.

1. Introduction

In modern industrial production, the presence of defects often leads to a decline in product quality and even affects the entire production process. Through industrial defect point detection, these defects can be detected and eliminated in a timely manner, thereby improving product quality. In addition, this also helps to reduce the after-sales costs and reputation losses caused by defective products for enterprises.

With the arrival of the Industry 4.0 era, intelligent manufacturing and automated production have become important trends in industrial development. In this context, industrial defect detection, as a key link to ensure product quality and production safety, is becoming increasingly important. Traditional manual detection methods have problems such as low efficiency and poor accuracy, making it difficult to meet the high standards of modern industrial production. Therefore, the application of artificial intelligence technology (AI) in industrial defect detection has gradually become a research hotspot [1-3]. Deep learning is an important branch of the AI field, which performs well in areas such as image recognition and speech recognition. In industrial defect detection, deep learning algorithms can automatically extract defect features and achieve high-precision defect recognition by training a large amount of sample data. Deep learning algorithms have demonstrated outstanding application value in industrial defect detection. With the rapid development of machine vision and industrial automation, deep learning technology has become an effective solution for defect detection due to its high precision and efficiency [4-6]. Deep learning algorithms, especially convolutional neural networks (CNNs), can automatically learn features from images, videos, or sensor data and perform efficient defect detection. Its applications mainly focus on image classification, object detection, attribute recognition, etc. It can determine whether there are defects in the image, locate the defect area, and recognize the type, size, position, and other attributes of the defect. In addition, generative adversarial networks are also used to generate images containing defects to improve the accuracy of training and testing [7-9]. The application of deep learning algorithms has greatly improved the automation and intelligence level of industrial defect detection. Convolutional neural networks (CNN) have been widely used in the detection of metal surface defects, textile defects, and other defects. Machine vision is one of the important applications of AI in the industrial field, which simulates human visual functions to achieve automatic detection and recognition of industrial products. In industrial defect detection, machine vision technology can capture product images in real time and quickly and accurately detect defect locations and types through image processing and analysis algorithms [10]. Although natural language processing (NLP) technology has limited direct applications in industrial defect detection, its indirect role in industrial production processes cannot be ignored. For example, NLP can be used to analyze textual data such as production logs and maintenance records, extract useful information, and help engineers quickly locate potential defect causes.

2. Methods and Techniques for Detecting Industrial Defects

There are currently two main methods for detecting industrial defects: traditional detection methods and computer vision based detection methods. The main difference between traditional detection methods and computer vision detection methods is that traditional detection methods rely on various sensors to obtain data information and determine whether there are defects. And computer vision methods use cameras to obtain image data and understand the content of the images.

2.1 Traditional Detection Methods

Traditional detection methods mainly include optical detection, electromagnetic detection, ultrasonic detection, laser detection, etc. These methods can detect defects to a certain extent, but there are problems such as low detection accuracy and reliability, and limited detection range. Simultaneously detecting equipment requires a certain amount of cost and maintenance in the later stage [11-13].

2.2 Defect Point Detection based on Digital Image Processing

The method based on digital image processing relies on information such as color, texture, and shape to make judgments. For defective areas, there is usually a significant difference in pixel values compared to the surrounding normal areas, which can be determined based on gradient information.

Usually, in order to reduce computational costs, the RGB three channel images captured by the camera are converted into grayscale images. Then use filtering algorithms to remove interference noise from the background, highlighting the features of the foreground. The commonly used filters include mean filtering, median filtering, maximum minimum value filtering, bilateral filtering, etc. Sometimes it is necessary to perform morphological operations on photos to better highlight the foreground. Common morphological processing algorithms include dilation, erosion, open operation, close operation, top cap, and black cap. After obtaining a relatively clean foreground, edge detection operators are used to extract foreground information. Common edge detection operators include Sobel, Laplacian, Roberts, Canny, etc. Finally, the contour is determined through contour search to obtain contour information.

The defect detection algorithm based on digital image processing has good detection effect and high accuracy. However, this method has relatively high environmental requirements and is suitable for scenes with fixed backgrounds and relatively prominent foreground contours. Such image processing makes contour extraction relatively easy. However, in scenes where there is a lot of noise in the background and the contour of the object to be detected is difficult to extract, it is difficult to handle [14-16].

2.3 Based on Artificial Intelligence Image Processing

The emergence of artificial intelligence and machine learning technologies has brought new changes to industrial defect detection. Through methods such as deep learning and image recognition, automatic recognition and localization of defects have been achieved, significantly improving the accuracy and efficiency of detection.

For most defect detection tasks, we not only need to know if there are defects, but also need to know the location information of the defect points. Therefore, we need to use object detection algorithms to achieve this requirement. With the rapid development of computer hardware in recent years, more and more excellent object detection algorithms have been designed. Object detection algorithms can be divided into two categories: one-stage detection algorithms and two-stage object detection algorithms. The two-stage algorithm is represented by the R-cnn series algorithm. The One stage algorithm is represented by YOLO and SSD. The biggest difference between these two types of algorithms is the generation of erroneous candidate boxes. The two-stage algorithm will recommend candidate boxes with defects and then determine their category and location information. Single stage algorithms such as Ssd and yolo do not require candidate boxes, but directly utilize convolutional neural networks to achieve classification and regression tasks [17-18].

There are various platforms on which object detection algorithms are deployed in production environments. Some are deployed on regular x86 computers, some on GPU graphics processors, and some on embedded devices. Different deployment plans will be selected based on different usage scenarios. With the development of miniaturization models, more and more scenarios are using object detection algorithms based on embedded devices. So it is necessary to replace the backbone network of the object detection algorithm with a lightweight network. Currently, commonly used lightweight backbone networks include MobileNet, GhostNet, ShufflleNet, EfficientNet, and further reduce the number of model parameters through methods such as model quantization.

Image segmentation technology has also been used in defect point detection[19]. Compared with object detection, image segmentation can not only detect category information and location information of defect points, but also accurately detect contour information of defects. Based on the contour and range of the defect point, it is very easy to obtain information about the area, perimeter, center point, and width of the defect point's location. According to the difference in segmentation functions, it can be divided into image segmentation methods based on fully convolutional networks and image segmentation methods based on Mask R-CNN [20-21].

3. Challenges and Solutions for Industrial Defect Detection

In recent years, there have been numerous use cases in the field of industrial defect detection based on digital image processing and artificial intelligence technology. Compared to traditional defect point detection, there has been a qualitative leap in effectiveness, but there are still some issues that need to be addressed.

3.1 Data Collection

The image captured by the camera is the source of the data. The data acquisition part of industrial defect point detection systems is usually composed of cameras and light sources. The light source for defect point detection based on digital image processing is a very important hardware device that provides illumination for the detection system. When generating some mechanical parts, the reflectivity of different batches of parts varies. Some parts have low reflectivity, which can result in better detection results. However, some parts have high reflectivity, which can cause overexposure in the images captured by the camera. It is difficult for the algorithm to achieve dynamic adaptive adjustment. The current common practice is to generate different programs by adjusting algorithm parameters for different models of components. Before producing different models of products, different programs need to be imported.

3.2 Complex Environment

There are high requirements for the robustness of algorithms and the generalization ability of models in complex scenarios. A model with a large number of parameters can be used to train samples in the scene. The larger the number of parameters, the more samples are needed. Otherwise, the model is difficult to converge and the accuracy cannot be guaranteed.

3.3 Insufficient Sample Data

The problem of insufficient sample size arises in defect point detection methods based on artificial intelligence. The training of deep learning models requires a large amount of data to support the accuracy of the models. Usually, overfitting and underfitting problems are encountered during model training. For most production environments, the production conditions are already relatively mature, and there are not many defective products produced during the production process. So there are too few photos of defective products, and the samples in the dataset are not enough to support training a usable model. Usually, for this situation, it is necessary to optimize the backbone network and reduce its parameters. On the other hand, data can be enhanced to expand the sample size in the dataset.

4. Future Development Trend of Industrial Defect Detection

The future development of defect point detection based on artificial intelligence includes the following aspects: (1) improving the quality of image acquisition. The hardware facilities such as light sources and cameras are the direct sources of raw detection data. Good light sources and cameras can produce images that are relatively easy to process, greatly reducing the workload of image filtering. (2) With the development of convolutional neural networks, more and more algorithms have emerged. Each algorithm has its own advantages and disadvantages. Choose the appropriate algorithm based on the current situation. Especially for handling situations with limited data samples. (3) Nowadays, more and more production scenarios are using defect point detection algorithms based on computer vision. How to transfer the parameters of a trained model to another familiar product without reducing accuracy and detection speed also needs further research [3]. The integration and development of industrial defect point detection with other industrial technologies, such as the Internet of Things, big data, cloud computing, etc., will achieve the integration and intelligence of detection systems.

5. Conclusion

Industrial defect point detection technology has received widespread attention and application in recent years, and defect detection methods based on digital image processing and artificial intelligence technology have achieved significant results. The article provides a detailed analysis and discussion on target detection algorithms, image segmentation techniques, challenges and solutions for industrial defect point detection, as well as future development trends.

Object detection algorithms and image segmentation techniques play a key role in industrial defect point detection. The field of object detection has a wide range of applications. In addition, deploying models based on lightweight backbone networks on embedded devices can effectively improve detection speed.

In industrial defect detection, data collection, environmental complexity, and limited sample data are the main challenges faced. To address these issues, methods such as adjusting algorithm parameters, optimizing models, and enhancing data can be adopted to improve detection accuracy and robustness. The future development trends include improving image acquisition quality, algorithm optimization, model migration, and the integration of industrial defect point detection with other industrial technologies. In summary, industrial defect point detection technology has made significant progress in the fields of artificial intelligence and digital image processing, but still requires continuous exploration and development.

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