Metal Surface Defect Detection Method Based on Machine Vision

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Abstract. Metal material is the core part of the strategic industrial fields such as aerospace, automobile manufacturing, precision electronics, energy equipment and so on. Its performance will determine the performance and reliability of industrial products. With the development of the times, the requirements for metal parts in industrial and other fields tend to be refined, complicated and slightly flawed, which may lead to chain problems such as performance degradation and sudden loss of life, and may even lead to safety accidents. In this context, the defect detection of metal surface will become an indispensable part of the future industrial intelligent production from the auxiliary link in traditional production. Based on this development status, this paper systematically studies the Chinese and English literature in the field of metal surface defect detection in recent years. Through a lot of reading, this paper not only summarizes the common defect types of metals, but also introduces the image processing and feature extraction in detail, and puts forward the relevant metal surface defect detection methods. The research results can not only provide reference for relevant enterprises, but also inspire subsequent researchers, and have a wide range of applications and academic inspiration.

Keywords: Metal surface defect, Imaging technology, feature fusion, attention mechanism.

1. Introduction

With the improvement of industry, people's demands for metal parts are getting more refined and involved. Metal parts play an irreplaceable role in the aerospace, manufacturing, and light - industry domains. Therefore, the detection technology of metal surface defects is becoming more and more important in the future and has become an indispensable part of related industries. Metal surface defects are caused by a series of uncertain factors such as ambient temperature, air humidity, raw materials and so on in the production process. Common defects such as pore inclusions, cracking, warping and so on [1]. These defects will not only affect the service life and performance of the product, but also bring fatal errors in extremely fine work such as precision instruments and aerospace engines.

Machine vision is a technology that integrates computer science and technology, optics, image processing and other disciplines. It is also a branch of the development of artificial intelligence. It captures the target through the camera and converts it into digital information, and controls the next operation according to the judgment result. Traditional machine vision methods mainly include image preprocessing, feature extraction and image segmentation [1]. However, in the face of practical challenges such as diverse defect shapes, complex backgrounds, and large noise interference, traditional methods often have limitations in generalization ability and detection accuracy.

With the development of deep learning and the improvement of metal surface requirements, artificial intelligence has shown great potential in metal surface defect detection. Deep learning models can automatically learn the deep features of defects, overcome the shortcomings of manual feature design in traditional methods, and significantly improve the accuracy of detection [2] [3]. The feature fusion method further improves the detection accuracy in complex scenes by integrating the prior knowledge of traditional methods and the feature learning ability of deep learning. The introduction of the attention mechanism simulates the selective attention characteristics of the human visual system and enhances the sensitivity of the model to small defects and key regions.

In this paper, the metal surface defect detection method based on machine vision is discussed, and the related methods and applications are sorted out. The follow-up content of this paper will first classify and introduce the common defect types of metal surfaces, then elaborate on the related imaging technology of metal image, then focus on the description of metal surface defect detection methods, and finally draw conclusions and prospects.

2. Defect Types and Applications

2.1. Detection Object and Typical Defect Types

China's rapidly developing metal industry has played an important role in the process of national industrialization. For example, as one of China's important basic industries, China's steel production will reach 1.02 billion tons in 2023 alone, accounting for more than half of global steel production. In the manufacture of metal parts, there are many kinds of defects on the metal surface, including but not limited to cracks, bubbles, pores, scratches, bumps, warpage and so on. These defects not only have an effect on the parts' appearance but also directly cut down their work efficiency and service life.

In general, the defects on the metal surface are separate, but there are also mixed defects. As shown in Fig.1, not only irregular surface micro-pits appeared continuously on the metal surface, but also scratches appeared. This seriously affects the performance and surface aesthetics of the product. If the parts produced by the metal processed by this block are applied to machinery with high requirements for metal surface accuracy, it may cause irreversible damage to the production machinery.

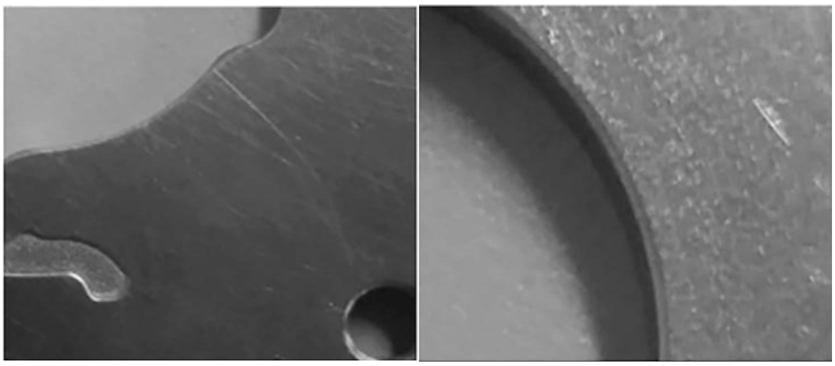

Figure 1. Pits and scratches on a metal surface [4]

2.2. Industrial Application Environment and Performance Requirements

China's demand for metals is huge, but the current smelting technology and manufacturing level cannot continue to improve the output and quality of metal parts. With the continuous improvement of China's industrialization level, the application of metal surface defect detection technology in many industries is becoming more and more popular. Its role is not only to improve the appearance and quality of products, but also directly related to the operation safety and service life of mechanical equipment. Steel, non-ferrous metals, automobile manufacturing, aerospace and other industries have put forward extremely high requirements for defect control of metal surfaces. For example, it inhibits the generation of small cracks or pits. In response to these requirements, the metal surface defect detection system needs to meet some key performance conditions.

First of all, the system should have a strong ability to distinguish and still accurately complete the identification of defect types when the gray values and texture features of different defects are highly similar. Secondly, sometimes similar defects are obviously different in scale and shape, and the problem of overlapping defect areas may occur in the actual acquisition process. The detection system must maintain the adaptability to multi-scale and complex shapes to avoid the loss of feature information caused by insufficient characterization. In addition, in view of the lack of clarity and blurred contour of some defect images, the system should also have high robustness, which can still ensure the stability and accuracy of the detection results under the condition of low-quality defect images. Finally, due to the shortcomings of low efficiency and poor generalization of traditional artificial feature methods, modern detection systems need more automated feature learning capabilities to meet the long-term application requirements in the current complex industrial environment.

Detecting metal surface defects is associated with the product's appearance quality and is extremely important for the application safety and lifetime extension of key components. If people improve the detection system in aspects of accuracy, multi-scale adaptability, and robustness, it can mainly meet the quality and safety needs of modern industrial production and give reliable support to the subsequent manufacturing process.

2.3. Industrial Application Environment and Performance Requirements

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Metal surface defect detection is not only related to the appearance quality of the product, but also plays a vital role in the application safety and life extension of key components. If the detection system can be improved in terms of accuracy, multi-scale adaptability and robustness, it can largely meet the requirements of modern industrial production for quality and safety, and provide reliable support for the subsequent manufacturing process.

3. Imaging Technology and Extraction Method

3.1. Imaging Technology and Extraction Method

Two-dimensional imaging technology mainly includes angle resolution technology [5], color resolution technology [6] and spectral resolution technology [7]. Since the materials used in metal parts are relatively uniform, the color will not change greatly. Therefore, in the detection of metal surface defects, angle resolution technology has gradually replaced color resolution and spectral resolution technology as the most widely used method because of its higher applicability. The basic principle of angle resolution technology is the surface scattering model [8]. In the detection, it is necessary to use a suitable light source [6] to directly illuminate the metal surface. According to the different roughness of the metal surface or the presence or absence of defects, different reflection phenomena will occur. According to the two-dimensional image obtained by the received optical path, the defect is detected by observing the background characteristics of the image.

In most of the bright field images of two-dimensional imaging, the bright field light path is used to detect the reflected light, the background is bright and the defect is dark; the dark domain light path is used to detect scattered light, and the background is dark and the defect is bright. Parallel light has good directivity and collimation. When parallel light irradiates a strongly reflective metal surface, most of the reflected light is specular reflection. Parallel light combined with dark field illumination, the resulting image gray difference is obvious, high contrast [1]. Aiming at the requirement of surface defect detection of metal stamping parts, Li Song and other scholars have innovatively proposed double light imaging technology. This technology can significantly improve the recognition ability of various defects on the metal surface by combining bright field lighting with dark field lighting at the same time [9]. It is foreseeable that the combination of multiple optical imaging methods will become an important development direction in this field. However, the two-dimensional imaging method has some problems with missing depth information when detecting metal surfaces with complex microstructures. For example, for three-dimensional defects such as pores and slag inclusions, two-dimensional image detection is difficult and the missed detection rate is high. Existing research shows that the combination of multi-angle illumination can alleviate the above problems, but it needs to be combined with three-dimensional imaging techniques such as structured light or laser scanning [10]. Three-dimensional imaging technology can effectively characterize the shape information such as wrinkles and bumps, by obtaining the depth coordinates and three-dimensional morphology characteristics of the object, but the detection sensitivity of micron-level defects is insufficient [11]. In the case that both imaging technologies have their limitations; there are also metal surface defect detection methods that combine two-dimensional and three-dimensional imaging technologies at this stage. Zhang et al. [12] proposed a detection method that combines two-dimensional grayscale and three-dimensional depth image information. This method calculates the potential relationship between the objects in the region of interest and then obtains the refined ROI saliency image through ROI seed extraction and local comparison operation. The pixel-level defect segmentation is realized on the grayscale image, which has good detection performance for surface depression defects [4].

The hybrid imaging detection technology combines the advantages of the two technologies to realize the collaborative processing of surface features and depth information. Under the condition of maintaining the same imaging parameters, the defect recognition accuracy is greatly improved compared with the detection scheme using only one technology.

3.2. Image Processing and Feature Generation

3.2.1. Image preprocessing

As the pre-processing of feature extraction, image preprocessing itself aims to improve the quality of the image, remove unnecessary interference, and perform pre-processing for subsequent feature extraction and image segmentation. Its core is to output an image with more distinctive features. The key steps are image filtering, contrast enhancement, geometric correction and radiometric correction. The above steps are described in detail below.

Image filtering is a technology that preserves the detailed features on the basis of retaining the original detail features of the image, and its purpose is to remove the image pollution problem [13]. Its core is to eliminate isolated noise and retain features and edge integrity. Traditional methods include mean filtering, median filtering, Gaussian filtering and bilateral filtering. Modern times take deep learning as a new research direction. The purpose of v contrast enhancement is to improve the single tone problem caused by the narrow area. Its principle can be simply divided into gray threshold segmentation, linear transformation and nonlinear transformation. Gray threshold segmentation is to set a threshold to further divide the image into different regions on the basis of graying. Geometric correction deals with different geometric distortions of the original image and the actual scene. There are two types of geometric correction: geometric coarse correction and geometric fine correction. The former is used for the cause of distortion, and the latter is corrected by the calculated distortion model. If the shape is processed, the image is segmented according to the threshold and then crossed to obtain an image with obvious features [14]. Radiation correction eliminates radiation errors caused by solar radiation and sensor properties. It is analyzed by the values of radiation or reflection calculated by the sensor [15], so the precision requirements of the sensor are high.

3.2.2. Feature extraction

The purpose of feature extraction is to extract data from the image and provide information and useful derived data to facilitate subsequent steps. Due to the different requirements of the feature points, the detection method is set separately based on different features. The traditional features include: geometric features, texture features, grayscale and so on. With the development of artificial intelligence, the abstract features obtained by convolutional neural networks are introduced. The corresponding features and description methods will be introduced below.

The types of geometric features are more complex. He mainly extracts information from shape, contour size and spatial relationship to detect. The edge contour or other features of the image can be sharpened first, and then processed using Fourier descriptors [16]. Moment features can also be used for detection [17]. And through the geometric matching [18] to detect, so as to complete the feature extraction. Texture features are widely used in industrial defect detection. It uses a mathematical model to fit the texture generation process and describes the texture through model parameters. With the help of deep learning features, convolutional neural networks can automatically extract texture features and further enhance the extraction of texture features. At present, there are also local spatial feature neural networks to further improve the ability to capture texture features [19]. Gray feature is the core part of machine vision. It changes color into light and shade, which greatly improves the difficulty of calculation and feature extraction. Its use of space is also very extensive, and can be based on pixel value, gradient, transform domain or local feature extraction. The extraction method has statistical features, gradient and edge features, and local binary [20].

3.3. Defect Recognition and Detection

3.3.1. Target detection

The core of target detection is ' localization + classification '. In the image, it can mark the location of possible defects by drawing the bounding box, and at the same time, determine the category of defects. Common methods can be divided into two categories: one is the ' two-stage method ', which first finds the potential area and then classifies it; the other is the ' single-stage method ', which directly predicts bounding boxes and categories in one step. These methods usually combine contextual information and different forms of bounding box regression strategies to achieve a balance between detection accuracy and computational efficiency [21]. Compared with the classification method that only judges ' defective or non-defective ', target detection is more suitable for dealing with complex situations where multiple defects may exist in an image at the same time. It can directly give the location and type of each defect, which is convenient for online early warning, sorting and statistical analysis [22]. Therefore, in many review studies, target detection is often considered as one of the two key technologies of surface detection (the other is semantic segmentation), in which target detection mainly undertakes the role of rapid screening and station-level decision-making linkage, and provides pre-support for subsequent fine-grained evaluation [23].

3.3.2. Semantic segmentation

Semantic segmentation assigns semantic labels to each position in the image in a pixel-level manner, generating a binary or multi-class mask of the defect area. [24] In the metal surface scene, this pixel-level modeling can more ideally describe the continuity and connectivity of fine cracks and pitting corrosion under low contrast and weak boundary conditions, and provide a basis for subsequent calculation of indicators such as size and area [25].

Semantic segmentation is more suitable for precision measurement than detection, which only gives the bounding box. It can give the specific outline of the defect, which is convenient for the subsequent fatigue evaluation of the metal as a whole. Pixel-level results can also support the automatic generation of statistics such as defect area, length, curvature, and density, which are often used for repair determination [26]. In the review and empirical research, the segmentation method has been widely used in the quality inspection of steel or aluminum strips and plates, and is usually superior to the detection frame-only scheme in terms of boundary sharpness and morphological consistency indicators [26,23].

4. Metal Surface Defect Detection Method

4.1. Detection Method Based on Feature Fusion

You Only Look Once (YOLO) is derived from single-stage detection: the entire image is forwardly propagated once while completing ' positioning + classification ', pursuing end-to-end (one-time) and real-time. Starting from v3, YOLO has gradually been shaped into a common three-stage structure: the backbone extracts features, the middle connection layer (Neck) is responsible for cross-layer information flow connectivity, and finally the head outputs results in parallel on multiple scales.

The feature fusion network is located between the Backbone and the Head, and its role is to combine features of different resolutions and different semantic levels. The shallow features have the characteristics of high resolution and sufficient details, but the semantics are weak. However, the deep features have strong semantics, but the resolution is small. Many kinds of metal surface defects are small, weak and unclear, and a single scale is easy to miss. However, if the multi-scale information is fused at the Neck, the ' details ' and ' semantics ' can be used simultaneously to improve the visibility of small targets, positioning stability and robustness to complex textures or reflections [27,28].

The workflow of ' fusion ' is to ' align ' first and then ' merge ': the feature maps from different layers are first aligned by up and down sampling, and then the number of channels is aligned by 1 × 1 convolution, and then three common strategies are used for fusion-addition fusion: pixel-by-pixel channel-by-channel addition, low overhead; convolution after stitching: stitching in the channel dimension, and then 3 × 3 convolution 'stirring 'information, strong expression; weighted addition: learning weights for each scale, so that more discriminative scales account for a larger proportion of the effect [28].

The feature pyramid network (FPN) proposed by Lin et al. firstly takes a feature map with the strongest semantics but the smallest resolution from the deepest layer of the network. After up sampling, it is horizontally added to the shallow feature map of the same size in the previous layer, and the obtained results are then upsampled and added. In this way, a set of pyramid features from large to small is finally obtained, and each layer has both ' high semantics ' and higher resolution, which means that small targets can use deep semantic information in the high-resolution layer, and large targets can still be stably detected in the low-resolution layer [29]. On the COCO dataset, after connecting FPN to Faster R-CNN, compared with the baseline of ' using only a single scale feature ', the average recall (AR) of candidate boxes increased by about 8 percentage points, the overall AP increased by about 2.3 percentage points, and the inference speed was still about 5 FPS, indicating that it achieved a good balance between accuracy and speed [30].

For the real-time requirements of the production line, many studies regard " integrating information more effectively " as the first priority. For example, BiFPN is used in industrial detection networks to allow useful clues from different scales to flow in both directions, merge by weight, and retain key information as much as possible. In this way, in the case of mixed background and different target sizes, the recall rate and positioning can be improved, while the computational overhead is not much increased, which is suitable for online deployment [31].

For three-stage structures such as YOLO, Neck's multi-scale fusion has become a fixed link in the evolution of serialization, providing an input basis for subsequent detection heads to make stable predictions at multiple scales at the same time. [28]

4.2. Detection Method Based on Attention Mechanism

Attention can be understood as an adaptive ' gain control ', which automatically amplifies the signal useful for defect discrimination and suppresses the redundant response related to the background in the feature map. For the common small-scale, low-contrast, and blurred boundary defects on the metal surface, this mechanism is similar to the role of feature fusion, and can also significantly improve visibility and discrimination, making the detection more stable under complex texture and reflective interference.

Attention usually works along two paths: the first is the path at the channel level. The importance vector of each channel is obtained by global aggregation of the whole feature, and then it is multiplied back to the original feature as a weight to determine the feature type; the second is the path at the spatial level, which generates an attention heat map at the pixel position to give a higher weight to the area more like the defect, thereby determining the location of the occurrence [30]. The two can be combined in sequence or in parallel to strengthen the ability to ' select types, select locations ' at the same time.

In the three-stage detector, the insertion position and function of attention are different. If it is placed in the early or middle layer of the Backbone, it helps to enhance the perception of weak texture and reduce the weakening effect of background texture on the detail layer. If it is placed at the fusion node of the Neck, it can be selectively retained or suppressed during multi-scale merging, leaving more scale information that is more helpful to small targets; if it is located before the Head, it is equivalent to the ' refinement ' link before output, which improves the stability of positioning and classification [28]. For metal surface detection, the benefits of attention are reflected in two aspects: one is to make the target with a small proportion of pixels such as fine cracks and pitting more prominent in the feature map, reducing the possibility of missed detection; second, through the enhancement of neighborhood consistency and context, the defect boundary is more coherent, and the false alarm caused by factors such as reflection, roll pattern and oil stain is reduced [31]. On the GC10-DET amplification data set, after introducing the global attention mechanism into YOLOv5s, compared with the baseline, Precision increased by 5.3 %, mAP @ 0.5 increased by 1.4 %, mAP @ 0.5: 0.95 increased by 1.7 %, and the inference speed did not decrease. This result shows that the false positives are reduced and the real-time performance is controllable [32].

Attention will bring additional calculations and parameters. When introducing, it is necessary to preferentially select lightweight implementations, locally insert key layers, and cooperate with data augmentation and reweighting to alleviate overfitting under small samples and domain shift. In the evaluation, the accuracy side indicators (AP_S, positioning error) and the inference side indicators (delay, FPS, memory and power consumption) are reported at the same time to ensure deployment under real-time and computing power constraints [27, 28].

5. Conclusion

With the continuous development of the manufacturing industry, it is bound to put forward more stringent requirements for the accuracy and quality of metals, and the detection of metal defects will become more important in industrial production. This paper systematically reviews the relevant literature on metal surface defect detection methods based on machine vision, comprehensively summarizes the defect types and imaging technologies of metal surfaces, and focuses on the application principles of feature fusion and attention mechanisms in metal surface defect detection. The frontier detection mechanism is introduced in detail, which can not only popularize science for people who do not understand related industries, but also sort out ideas and inspire innovation for those engaged in related industries. Looking forward to the future, in the face of increasing industrial precision standards, it will inevitably lead to more efficient, more robust and more intelligent metal detection algorithms and engineering solutions. The hope is that this paper will provide backing for follow-up studies on metal surface defects and add to future detection technology. It can be predicted that only by deeply integrating the interpretability of traditional image processing methods with the powerful sensing capabilities of advanced technologies such as deep learning and constructing a hybrid intelligent detection framework can people fully meet the complex and diverse application requirements of future industries.

Authors Contribution

All the authors contributed equally and their names were listed in alphabetical order.

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