Surface Defect Detection of Strip-Steel

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Surface-defect detection is crucial for assuring the quality of strip-steel manufacturing. Strip-steel surface-defect detection requires defect classification and precision localization, which is a challenge in real-world applications.

defect detection | data augmentation | Coordinate Attention | Atrous Spatial Pyramid Pooling | loss function | real-time detection

1. Introduction

The need for strip-steel has gradually increased across all sectors of society as the social economy has expanded. Yet, quality control in strip-steel manufacturing has always been a severe concern for industrial production. Many defects, including scratches, burrs, iron scales, contamination, inclusions, and bright marks, may appear during the manufacture of strip-steel due to variables including the production raw materials, rolling technique, and system control. These defects, in addition to the strip's surface, significantly reduce the strip's high-temperature resistance, corrosion resistance, wear resistance, and strength. As a result, improving strip-steel quality and production efficiency requires a rapid and accurate strip-steel surface-defect-detection method.

Methods for detecting early strip-steel surface defects include manual sampling, eddy current detection, magnetic flux leakage detection, infrared detection, laser scanning detection, and others [1]. The manual sampling method includes picking and detecting defect samples using the naked eye. This detection method easily fatigues inspectors and is a great test of the inspector's dedication and level. The eddy current detection is a non-destructive testing method based on electromagnetic induction theory. When detecting large areas, the detecting speed cannot meet the demands of high-speed strip-steel manufacturing lines.

The magnetic flux leakage detection is limited in the types of defects, and it is unsuitable for faults with minor flaws. Due to infrared's limited capacity for absorption, the accurate classification of defect categories is not possible using infrared detection technology for strip defects. The laser scanning detection method dramatically reduces the effectiveness and applicability of this method because the dust and substances on the production line will affect the reflection of light.

At the end of the 20th century, due to the rapid development of CCD technology, conventional machine-vision-detection methods made tremendous strides in recognizing strip defects. Traditional machine-vision-detection methods have a number of benefits over earlier detection methods, including improved dependability, increased efficiency, and enhanced practicability. This detection approach still necessitates manual feature extraction, which is detrimental to boosting industrial production efficiency and industry automation.

Deep learning has advanced quickly in recent decades, with applications ranging from autonomous driving to image identification, natural language processing, intelligent predictions, and so on. To fully automate industrial quality detection, deep learning technology solutions are progressively being implemented in strip surface-defect detection.

The use of convolutional neural networks (CNN) to extract defective features for classification produced good results [2][3][4][5]; however, defect location remained a challenge. There are two types of object detection algorithms: one-stage and two-stage algorithms. The one-stage algorithms are represented by the you only look once (YOLO) series of algorithms, single shot multiBox detector (SSD), RetinaNet, etc. The two-stage algorithms are represented by Fast Region-CNN (Fast R-CNN), Faster R-CNN, Mask R-CNN, Cascade R-CNN, etc.

The one-stage algorithms conduct unified classification and regression directly and do not produce regional recommendations. This type of algorithm has low accuracy but outperforms the two-stage algorithm in terms of the detection speed. The two-stage algorithms generate some region proposals before classification and regression. This algorithm has high accuracy; however, the detection speed is slow. Many academics have undertaken successful studies on strip-steel surface defect recognition using algorithms, such as YOLO [6], SSD [7], YOLOv3 [8], RetinaNet [9], and Faster R-CNN [10][11][12].

2. Traditional Strip-Steel Surface-Detection Approaches

Traditional approaches for detecting strip-steel surface defects based on machine vision may be divided into three main categories: those that are based on local anomaly [13][14][15][16], those that use template matching [17][18][19][20][21], and those that use machine learning [22][23][24][25].

(1) Local anomaly: The texture of the picture under test is analyzed in order to detect normal behavior that does not adhere to an explicit definition. In the space domain, one-stage and two-stage statistical approaches, such as the covariance matrix [13], the weighted covariance matrix [14] and the Weibull model [15][16], are used. In the frequency domain, the spectrum features are extracted by means of wavelet and Fourier transforms.

(2) Template matching: Defect detection is achieved by conducting location operations on the defect-free template image and the image to be examined, such as similarity computation or image registration. During detection, the approaches are readily influenced by the imaging environment, and the spatial location, light qualities, and geometric properties of objects in the picture will also change significantly.

(3) Machine learning: The procedure consists of image processing, feature extraction, and defect classification using models. Typical classifiers consist of SVM, K-nearest neighbor, and decision tree, among others. Numerous

scholars have also improved the detection performance of the strip-steel surface-defect detection classifier by studying and bolstering the classifier's performance [22][23][24][25].

The aforementioned approaches necessitate substantial professional knowledge, require hand-crafted extracting features, are susceptible to environmental influences, and are not conducive to complete industrial automation.

3. Strip-Steel Surface-Detection Approaches of Deep Learning

In deep learning, strip-steel surface-defect detection is possible using three approaches: object detection, semantic segmentation, and GAN.

(1) Object detection: Li et al. [6] proposed an end-to-end detection approach based on improved YOLO, including 27 convolutional layers in the improved network. Lin et al. [7] proposed an improved SSD detector for defect localization and a ResNet50 network for defect classification.

Zhang et al. [8] proposed a CP-YOLOv3-dense detection approach that preferentially uses convolutional networks to classify pictures and then locates defects. Cheng et al. [9] proposed a deep neural network for differential channel attention and adaptive spatial feature fusion based on the RetinaNet detection network. Refs. [6][7][8][9] used the one-stage algorithm, which has significant speed benefits; however, the two-stage algorithm's precision is better. In [6], the approach is less feasible.

Refs. [7][8] separated the work of defect localization and classification into two phases in the defect detection process, which costs greater detection time. In [8], the classification priority concept was applied to a single image with a single defect but not to a single image with multiple defects. In [9], adaptive feature fusion resulted in an increase in the computation and model parameters, as well as a prolonged in the model inference process. In [10][11][12], these approaches are all based on the Faster R-CNN architecture.

He et al. [10] proposed two distinct deep networks as convolutional layers, ResNet34 and ResNet50, to generate multi-level features from convolutional neural networks and fuse them into one feature. Ren et al. [11] substitutes the backbone network VGG's convolution with a depthwise separable convolution and introduces center loss. Tang et al. [12] adopted Resnet50 as the backbone network, while also introducing the attention and MSMP module. These approaches of two-stage [10][11][12] are extremely precise in detecting strip defects; however, they do not fulfill the actual manufacturing process speed requirements.

(2) Semantic segmentation: Praveen et al. [26] explored two encoders, ResNet and DenseNet, based on U-Net on the Severstal dataset, employing migration learning to obtain excellent results in classification and segmentation tasks. Dong et al. [27] proposed a pixel-level surface-defect detection system based on pyramid feature fusion and global context attention network (PGA-Net), which was experimentally validated on several defect datasets and yielded great results. Bao et al. [28] proposed a novel TGRNet network that employs triple to segment defect and

background areas and multi-graph reasoning to explore the similarity between different images. These approaches are all pixel-level defect detection methods, which are more accurate for defect identification and location. Still, the training and inference process takes longer than the object detection method.

(3) GAN: Liu et al. [29] proposed a GAN-based strip-steel surface-defect detection approach that uses the GAN generator’s second to last output layer as the feature layer and normal samples to conduct single-class classification by comparing the characteristics of normal and abnormal samples. This approach can perform unsupervised learning on a limited number of samples; however, it can only categorize single-class flaws and cannot locate defects.

The deep learning methodology has a significant benefit over traditional strip surface-defect detection approaches in that the extraction is automated, thereby, eliminating the need to extract features manually. Manual feature extraction is a time-consuming and challenging task that demands high-level expertise.

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