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Surface Defect Detection Technique in Manufacturing Industry

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ABSTRACT: The comprehensive intelligent development of the manufacturing industry puts forward new requirements for the quality inspection of industrial products. This paper summarizes the current research status of machine learning methods in surface defect detection, a key part in the quality inspection of industrial products. First, according to the use of surface features, the application of traditional machine vision surface defect detection methods in industrial product surface defect detection is summarized from three aspects: texture features, color features, and shape features. Secondly, the research status of industrial product surface defect detection based on deep learning technology in recent years is discussed from three aspects: supervised method, unsupervised method, and weak supervised method. Then, the common key problems and their solutions in industrial surface defect detection are systematically summarized; the key problems include real-time problem, small sample problem, small target problem, unbalanced sample problem. Lastly, the commonly used datasets of industrial surface defects in recent years are more comprehensively summarized, and the latest research methods on the MVTec AD dataset are compared, so as to provide some reference for the further research and development of industrial surface defect detection technology.

KEYWORDS: surface, technique, defect, manufacturing, industry, detection, machine, deep learning, texture, method

I. INTRODUCTION

The continuous social development has made more and more high-tech industries gradually known to people, but many industries have increasingly higher requirements on the quantity and quality of raw materials, such as commutator as an important part of motor in the manufacturing industry, especially in vehicle manufacturing, ship manufacturing, aerospace equipment manufacturing and other industries. Therefore, the quality of the commutator surface directly determines its product quality. In addition, the commutator is very vulnerable to external influences in the process of production and processing, resulting in a variety of problems. For example, different raw materials, processing methods and manufacturing equipment will lead to a series of surface defects of the commutator such as scratches, cracks, oil stains, black spots, which not only affect the appearance to a certain extent, but also may have huge safety risks in quality. For instance, defects can reduce the physical properties of mechanical parts, such as corrosion resistance, wear resistance and fatigue strength, which will cause serious problems in the final product quality[1]. Consequently, how to find and locate defects in time during the production process has become an urgent problem in the commutator production industry.

With the rapid development of computer vision technology, mature application systems such as face detection, vehicle detection, speech recognition and text recognition have been widely used in various industries [2,3,4,5]. Computer vision-based surface defect detection technology for commutator has also developed rapidly [6], in which the product surface image is obtained through non-contact detection and optical automatic collection, and then, the specific features of the surface image are extracted using different algorithms. Computer vision is an artificial intelligence field that trains computers to understand and interpret the visual environment. Using digital pictures from cameras and videos, as well as deep learning models, machines can properly recognize and categorize things. The purpose of machine vision detection technology is to capture the surface image of the work piece using a camera rather than human eyes and then to assess if there are flaws on the surface of the work piece by processing the picture through a computer. Parsytec developed HTS-2 and HTS-2 W surface defect detection systems and applied the classifier technology based on artificial neural network to the field of commutator detection for the first time [7]. Harmonized System or Harmonized Tariff Schedule is represented by an HS or HTS code. The codes were created by the World Customs Organization (WCO) and are used to categorize and characterize items that are sold globally. In most situations, an HTS code must be allocated to a traded good in order to import or export it internationally. The HTS code must conform to the Harmonized Tariff Schedule of the country of import. HTS-2 column (2) has higher duty rates, which are necessary for nations that do not have regular commercial ties with the USA. The HTS lists the nations that are eligible for international trade program or are subject to column 2 tariff rates. Tolba combined decision theory, multi-scale features



with the neural network to get an optimal Bayesian classifier and applies it to flat and even defect detection of commutator surface [8]. However, it is difficult to maintain good detection performance in the day-to-day changing environment for the surface defect detection method of commutator based on machine learning and some shallow neural networks. Recently, the deep learning algorithm has been ranked first in the target detection challenge because of its high feature expression ability and high fitting, so it is a very competitive method to transplant the target detection method based on deep learning to the detection of surface defects of commutator. For many years, target detection techniques were investigated. Many classic target detection techniques came into being in the 1990s. Mainly conventional extraction techniques have been utilized to extract characteristics and then coupled with template matching algorithms or target identification classifications. Currently, there are two main types of framework for target detection algorithms based on deep learning: candidate box-based target detection and regression-based target detection.[9]

II. REVIEW

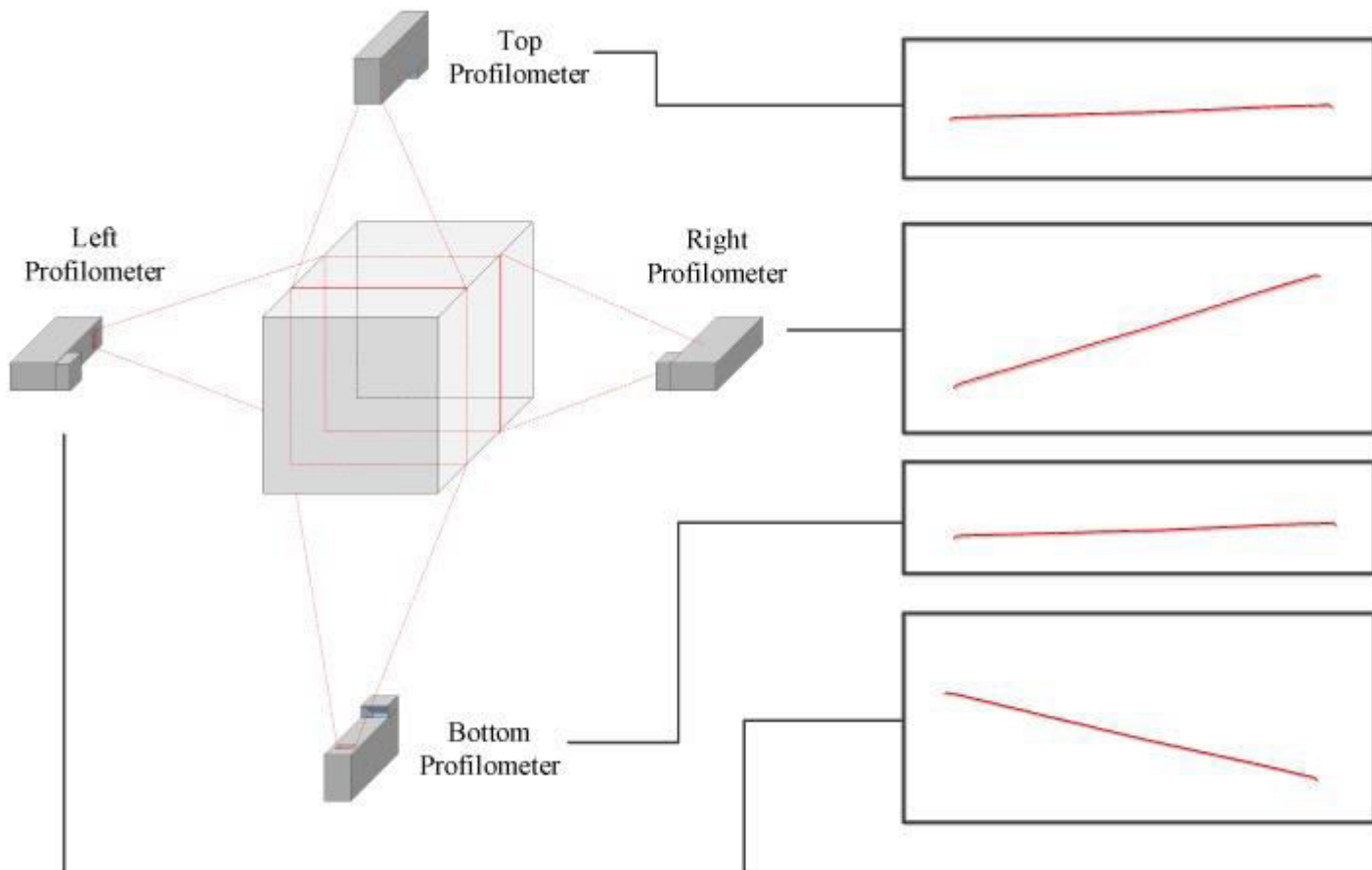
GIR-SHICK R proposed the first target detection framework R-CNN based on candidate boxes in 2012, followed by Fast R-CNN, Faster R-CNN and Mask R-CNN. Regression-based target detection methods are mainly based on You Only Look Once (YOLO) series, and Single Shot Multi-Box Detector (SSD) series. Face detection is a computer algorithm which recognizes human faces in digital pictures and is used in a number of applications. The psychological process through which people find and attention to faces in a visual situation is known as face detection. Vehicle detection attempts to offer vehicle counting, speed measurement, traffic accident identification, traffic flow forecasts, etc. Various sensors are utilized to collect traffic information continually generated. Speech recognition is accomplished using acoustic and linguistic modeling techniques. Language modeling connects sounds with word sequences to help discriminate between words that sound similar; acoustic modeling illustrates the link between linguistic units of speech and audio signals. Tedious data input for credit cards, receipts and commercial cards can be automated for text recognition. You may extract text from documents photographs, which you can use to enhance accessibility or to translate documents with the cloud-based API. Fortunately, the method based on deep learning can better overcome the complex changes brought by the practical application environment, because deep learning pays attention to the deep and automatic feature extraction of the model and carries out feature learning layer by layer from high to low, with a good ability of feature extraction and selection. However, the basic conditions of deep learning are a large amount of data as support and sufficient model training. However, in the study of commutator surface defects, because the data are basically collected by manual photography in the production workshop, resulting in small differences between samples and more repetitive data. Moreover, the actual amount of data collected is usually insufficient to meet the huge amount of data required by the deep learning target detection model, which requires transferring the relevant knowledge by the transfer learning from the existing deep learning target detection field to the commutator surface defect detection field to solve the practical problem [18]. The ImageNet dataset [19] is probably the best source data, which needs to transfer the feature expression ability of the network model trained based on the ImageNet dataset to the field of commutator surface defect detection and recognition. Because ImageNet image classification dataset has more than 1 million images, and in addition, edge, texture, space and other feature information are mainly used in the commutator surface defect detection and recognition, while ImageNet as the source data can extract rich and diverse image spatial feature information. Transfer is a method to profound learning (and machine learning), where knowledge is transmitted across models. It can accomplish a specific problem by employing a whole or part of a model that has now been trained to another task with transfer lessons. R-CNNs (Region Based Convolutional Neural Networks) are a kind of machine learning models used in computer vision, especially object detection.[10,11]

III. DISCUSSION

In this paper, a new commutator surface defect detection and recognition method is proposed based on transfer learning, in which the feature extraction layer learned by ResNet network in ImageNet is transferred to the commutator surface defect dataset, and the transferred feature layer covers a strong feature extraction ability. Specifically, firstly, the feature layer in Resnet-101 is transferred to the feature extraction layer in Faster R-CNN, a target detection network based on deep learning, and then, a new deep transfer learning network is constructed for commutator surface defect detection and recognition. In order to make full use of the multi-scale feature map in Resnet101, the regional referral network in Faster R-CNN is trimmed to adapt to the ResNet network, and the problem of missing detection due to the large-scale difference in the commutator surface defects is solved. Traditional approaches for detecting and recognizing strip surface defects are unable to adapt to the changing detection environment. A new deep transfer learning-based

strip surface defect detection method is suggested. The suggested approach has a greater level of accuracy and is better suited for strip surface fault identification.[12]

Big data analysis will be a dependable source of information extracted from sensors and actuators. The data gathered using the integrated telematic and real-time research capabilities are the bright advantage for self-driving automobiles. A sensor fusion system combining 3D camera sensor data with Lidar sensor data is proposed to achieve this goal . Object detection using deep learning models has shown promising results when it comes to detecting an object in pictures. The goal of this research is to use real-life pictures to annotate and locate medical face mask items. Its goal is to keep individuals safe from COVID-19 transmission .Goggles are an important aspect of any ski or snowboarding outfit since they protect your eyes from the weather and harm. Defects, particularly on the lens surface, are inherent in the ski goggles manufacturing business. A new approach based on machine vision is given to solve this challenge .In most cases, long products must be inspected completely, including their whole surface, in order to ensure their quality. In order to acquire images of the whole surface of a product, a set of sensors must be located around it. In this approach, four profilometers are placed around the product. A profilometer is a sensor made up of a camera and a laser. Each of these sensors acquires images of a part of the product defined by a point cloud as shown in Figure 1. The number and the place of the sensors must be set in such a way that the whole contour of the profile can be acquired. The sensors must also be placed so they acquire most of the surface perpendicular in order to acquire correctly the small cracks without occlusions.[13,14]



Profile acquisition.

IV. RESULTS

The four sensors are placed in two different measurement planes in order to avoid interferences between them while they are acquiring the projected laser line over the product. These interferences occur because the four profilometers



project the laser using the same wavelength. The acquisition of profiles by the set of sensors is synchronized using a signal that is triggered using an encoder signal. The encoder is placed in the production line so it sends a tick every 2 mm while the product is being moved. Once each part of the profile is acquired, the model is used to combine them. Each point cloud is aligned to a part of the model. This procedure is called registration. A partial model is defined as the set of arcs and segments, called primitives, that can be seen by a sensor. Therefore, four partial models must be defined in this example as the number of sensors is four.

The registration procedure is carried out in two phases: first, a coarse registration is done by aligning the centroid and the orientation of the point cloud and the partial model, then a fine registration is done using the ICP algorithm. After the registration procedure, the differences between the model and the acquired point cloud are calculated. For each point in the point cloud, its closest point in the model is calculated and called the corresponding point. A coordinate origin in the profile contour must be defined in order to represent the position of each point in the contour by a single number, the arc-length from the origin to the point. If the application is suitable to be used for many types of the same product, this origin point must be set carefully so it has the same meaning in every type of profile. [15,16]

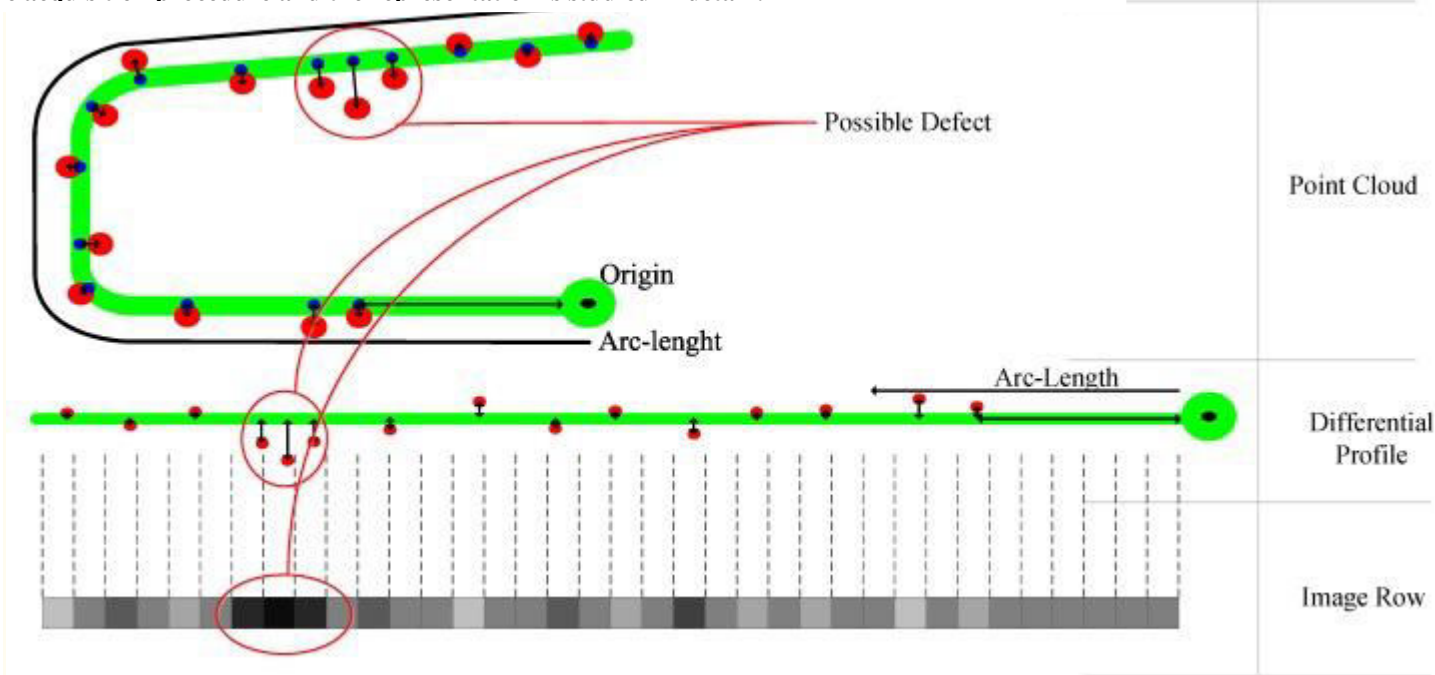
Then, each point is transformed into a new one that represents the position of its corresponding point in the profile and its distance between the point and its corresponding point. Then, the new point cloud is defined by points that have two coordinates: the arc-length of the profile from the origin to the corresponding point and the distance from the point to its corresponding point. The result of this step is called the differential profile, as shown in Figure 2. In this figure the acquired points, in red, are compared with their corresponding points in the model, in blue. The translation into the differential profile is shown calculating the distance between the point and its corresponding point (red-blue) and the arc-length between the corresponding point and the origin (blue-black).

The differential profile from each profilometer can be merged into a single differential profile that can be used as a row of an image. Each pixel has two dimensions in millimeters depending on the resolution of the sensor and the acquisition frequency. The whole image can be seen as a differential map of the surface of the product. Each row of the output images is the result of merging the four differential profiles that form each complete profile. Therefore, the dimension that each row represents in millimeters is set by the acquisition frequency of the sensors. In the same way, the dimensions on the columns axis must be set according to the resolution of the sensors.

The value of each pixel is set so it has a direct translation in millimeters to real-world dimensions. To do so, the measuring range must be translated into the [0,255] range defined by an 8-bit image. There may be some pixels with no associated data depending on the position of the points on the contour of the product. These spots with no data are represented with an exact zero value on the differential map that will be translated into a 127 value when formatting the image. These images can be viewed with a common program, so both inspectors and customers can access the raw information. As the gray value of the pixels can be directly transformed into millimeters, the images can also be used to measure defects and other objects. This format allows the storage of dimensional information in an efficient way. The format has several advantages: the images can be viewed easily by inspectors and customers, the defects can be measured directly in the images by looking at the gray value, and the detection can be carried out using common computer vision algorithms that use an image as input. [17,18]

The procedure of acquiring and representing a profile from a point cloud to an image is shown schematically. This figure shows how a defect can be represented in the point cloud, the differential map and also in the image. This figure also shows some spots with no-data that are formatted with 127 value. Taking into account the measuring range, each gray value represents 0.03 mm. This resolution should be enough to be used in many types of products. One of the products with high-quality requirements is train track rails, which must meet surface tolerances up to 0.35 mm, as is set in the European Standard for defects in the head of the rail.

The acquisition procedure and the representation is studied in detail .



Acquisition and scheme

V. CONCLUSION

An effective threshold segmentation algorithm for coefficient of variation is proposed. This algorithm overcomes the disadvantage of using only one threshold per iteration in repeated threshold segmentation. It also utilizes the sliding window used in adaptive threshold segmentation, which reduces the amount of calculation and improves detection efficiency. The system structure of the whole system is designed, and the system is divided into imaging module, fault detection software module, and storage management module. According to different principles of detection methods, different image capturing methods are given. The overall process of defect detection software is designed, and the design and implementation of basic software units are introduced in detail. This paper analyzes the design of the steel strip surface defect detection system based on machine vision. According to the application requirements of machine vision technology, based on the surface quality of strip steel, the detection of surface defects is adjusted and optimized for the design of this article. Experiments prove that the method designed in this paper is very effective. We hope that the research in this article can provide a theoretical basis for the design method of steel surface defect detection system based on machine vision.[19]

At present, most retinal blood vessel extraction methods are mainly used for normal retinal images. Therefore, when applied to a large range of lesion images, it is difficult to accurately extract blood vessels due to the interference of lesions and other nonvascular structures, and a large number of nonvascular structures cannot be filtered. In addition, this article focuses on vascular bone extraction and vascular structure segmentation methods suitable for retinal imaging. Analyze the characteristics of defects, and find the entry point for detecting defects. According to the edge feature, uneven texture feature, and uneven defect feature, the defect detection method based on edge feature, the defect detection method based on unequal texture feature, and the defect detection method based on irregular feature are proposed. The techniques and theories on which this method relies are introduced and discussed. The steel industry occupies an important position in China's economic industry. It can be regarded as the main core of manufacturing. This is an intensive industry that has accumulated a lot of capital and energy. Although China produces a large amount of steel every year, the quality of various steel products in China is obviously not as good as that of developed countries. In the quality of steel products, the importance of surface quality is self-evident, but improving quality is always difficult. Improving the surface quality of steel is of great significance to improving market competitiveness. Accurate detection of steel plate surface defects and the establishment of a steel plate surface defect evaluation system are important conditions for improving the quality of steel plates. This article makes full use of the image data of steel surface defects and introduces artificial intelligence methods to classify and identify steel defects and target detection. It solves the problem of long iteration time of ant colony optimization algorithm and particle optimization algorithm.

The algorithm is easy to fall into local optimization, improves the classification accuracy of the support machine, optimizes the optimization process, and is made of steel.[20]

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