ISSN: 2664-9640

Real time defect detection of transparent reflective film based on deep learning

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Abstract

The film surface defect detection system is used to detect the defect information of various kinds of thin film products in real time, classify and locate the film defects, completely replacing the artificial naked eye defect detection. The type and location of film defects can be obtained by real-time detection of film defects, which is of great significance for saving production cost, improving production efficiency and ensuring film quality. Therefore, the film defect real-time detection system has become an indispensable detection equipment in the high-speed film production line. At present, most of the film defect detection is to identify the type and location of defects manually, which is a time-consuming, labor-intensive and inaccurate detection method. By studying the traditional computer vision technology used in the defect detection of transparent reflective films, it is found that this process requires a lot of image preprocessing and complex feature extractors for special cases. In this study, a target detection method based on deep learning [1] Faster R-CNN [2] model is proposed to detect defects in thin films. 2000 film defect images with labels were collected to train the detection model. After training, the average accuracy (AP), detection speed and training time were used to evaluate the detection accuracy and calculation cost of the model. The experimental results show that the film defect detection system can detect the defects of transparent reflective film quickly and accurately with 86.32% at the speed of 12 frames per second. The research laid a foundation for the application of deep learning technology in the defect detection of transparent reflective film, and solved similar production management problems.

Keywords

Real time defect detection; Faster R-CNN; target detection; deep learning; computer vision.

1. Introduction

The transparency and reflection characteristics of the translucent film surface reduce the success rate of image processing algorithm. In order to improve the traditional deep learning Faster R-CNN, the general deep learning model is transferred to the specific learning model with different weights and outputs by pre training in the image task data set of coco. In this paper, we design feature extraction network, RPN network, classification network and model parameters to improve the detection performance of the model.

The defect detection based on computer vision is a non-contact and non-destructive automatic detection technology, which is a comprehensive technology that integrates the vision sensor imaging technology, image preprocessing technology, feature extraction technology, image segmentation technology and so on. In today's industrial information age, defect detection technology is widely used in food, building materials, steel, automobile agriculture and other fields . Defect detection technology has become one of the core technologies in the industrial production quality inspection system. The comprehensive defect detection technology with strong applicability and high accuracy can greatly improve the production efficiency of enterprises. Due to the great difference between products and raw materials, the defects of various products are diverse. It is difficult to extract the essential features of defects by conventional computer vision detection technology based on image preprocessing algorithm, image segmentation algorithm, image feature extraction and selection algorithm [3].

The market demand for plastic film of all walks of life is rising. The market scale of film industry will exceed 900 billion yuan in 2020 and increase year by year. Translucent film is widely used in various products and equipment to protect the easily damaged parts of the product and equipment. It is an important part of the product and equipment protection system, such as electronic equipment screen protection film, automobile glass explosion-proof film, etc. However, the defect detection of thin film production industry mainly relies on manual inspection and conventional computer vision detection methods. To some extent, manual testing can ensure the quality of products, but it is slow, high cost and unstable. Although using conventional computer vision to detect defects can improve the detection accuracy and unify the detection standards, the average cost is far less than the labor cost, but this process requires a lot of image preprocessing and complex feature extractors for special situations, which leads to low detection efficiency. In recent years, with the continuous development of artificial intelligence and computer vision technology, computer vision target detection and recognition technology based on artificial neural network and deep learning has made great breakthrough. Deep learning technology is widely used in the defect detection of steel, textile, glass and other industries, and has achieved good results. Therefore, the application of efficient detection technology based on deep learning in the film production process is an important way to improve the production efficiency of the film industry.

2. Related work

Through the in-depth study of defect detection methods, it is found that the design process of defect detection algorithm of conventional computer vision is complex, the generalization ability of algorithm is poor, and it is easy to be affected by the detection environment. However, the surface defects of translucent films have reflective properties and many kinds of defects, which makes the conventional defect detection method of computer vision not suitable for the detection of transparent film surface defects. In order to solve the above problems, this paper proposes a real-time detection method of film surface defects based on Faster R-CNN deep transfer learning. Therefore, in the second section, the traditional computer vision inspection technology and deep learning detection technology in industrial product defect detection are reviewed.

2.1. Defect detection technology of traditional computer vision

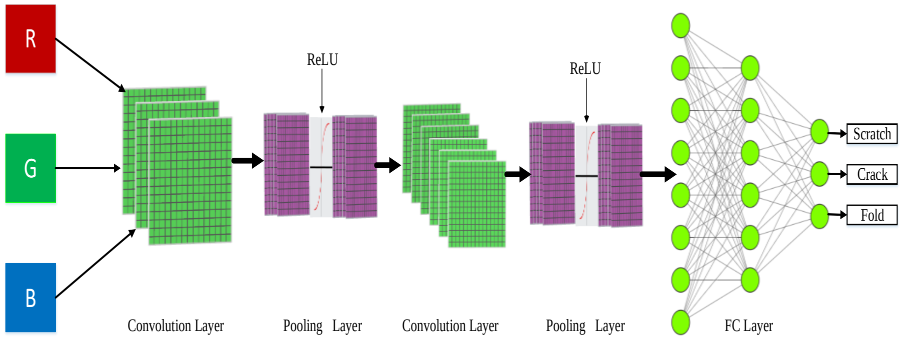

Figure 1 Defect detection model based on CNNs

In recent years, due to the poor anti-noise ability of traditional image segmentation algorithm, many scholars have improved the traditional defect detection algorithm in order to meet the needs of more accurate defect detection. Wang et al [4] proposed a method to detect surface defects of thin films by image processing and recognition technology. Chang et al [5] present a photothermal reflectance microscopy for detecting local defects inside optical films.

Through the study of a large number of traditional computer vision defect detection methods, it is found that the application of traditional computer vision technology in industrial production, to a certain extent, meets the needs of specific product defect detection. However, the traditional computer vision detection technology often has two limitations in product detection: on the one hand, it is necessary to design complex feature extractors based on obtaining high-quality images. On the other hand, the algorithm design is often aimed at a specific defect (such as crack) detection, and the algorithm has poor robustness. There are many kinds of defects in the translucent film, and the defect characteristics are reflective. The transparency and reflection characteristics of the translucent film surface reduce the success rate of the traditional computer vision algorithm, and the traditional computer vision technology is not suitable for the translucent film defect detection.

2.2. Defect detection technology based on deep learning

Deep learning can achieve complex function approximation by learning a kind of deep nonlinear network structure, represent the distributed representation of input data, and show a strong ability to learn the essential characteristics of data sets from a few sample sets [6]. Convolutional neural networks (CNN) [7] are widely used in image recognition and classification. Generally speaking, pattern recognition by machine includes digital image acquisition, image preprocessing, image feature extraction and data classification [8]. The success of LeNet, AlexNet, VGGNet [9] and other classical convolutional neural networks in image classification competition proves that CNN is the best way to extract features in image field. CNN is composed of three structures: convolution, activation and pooling. Image features are extracted from digital images and converted into specific feature spaces. These feature spaces are input into fully connected neural network (FCN). The mapping from input image to tag set is completed through full connection layer, that is to complete classification and get classification score. As Figure 1, defect detection model based on CNNs, using CNN to extract features does not need to design a complex feature extraction algorithm, and has achieved better detection results.

Yi et al [10] proposed an end-to-end defect recognition system for steel strip surface inspection. This system is based on the symmetric surround saliency map for surface defects detection and deep convolutional neural networks (CNNs) which directly use the defect image as input and defect category as output for seven classes of steel strip defects classification. Ozturk et al [11] transforms the single-value deviation input of traditional CNNs algorithm into deviation template, and proposes an effective method for glass surface defect segmentation.Wang et al [12] proposed a fabric defect detection method based on visual feature saliency and low rank recovery. This method is based on the monitoring fine-tuning of the fabric image database of convolutional neural networks (CNNs), and then more accurate deep neural network model is generated.

In recent years, Faster R-CNN target detection method has been applied in many fields. Liu et al [13] proposed an end-to-end detection method based on Faster R-CNN， experimental results demonstrate that the proposed method can locate the fabric defect region with higher accuracy compared with the state-of- art, and has better adaptability to all kinds of the fabric image. Wang et al [14] proposed an automatic defect detection method for sewage pipeline based on Faster R-CNN. Ma et al [15] proposed a bullet appearance defect detection model

ISSN: 2664-9640

based on the improved Faster R-CNN. The proposed model uses a CNN that can automatically extract target features and has strong generalization ability.

3. Approach

3.1. Overview

By comparing the performance of various target detection frameworks in coco data set and voc2012 data set, the results show that Fast R-CNN has the highest detection efficiency. Fast R-CNN not only has higher average detection accuracy, but also can achieve detection speed of more than 10 FPS. Using Fast RCNN target detection technology to detect the defects of transparent film can fully meet the requirements of production efficiency and detection accuracy in the process of transparent film defect detection. Therefore, in this paper, the defect detection of transparent film in the actual production process is investigated. In view of the fact that the defect samples of transparent film are small, the film is reflective and the defect types are diverse, the deep learning mode training based on Fast R-CNN target detection model is carried out, and the real-time detection of surface defects of transparent film is realized. As shown in Figure 2, the overall design of real-time detection method for surface defects of transparent films based on deep learning of Fast R-CNN is introduced in detail from the following two aspects: Fast R-CNN model structure, model training method.

3.2. Overall structure of Fast R-CNN detection model

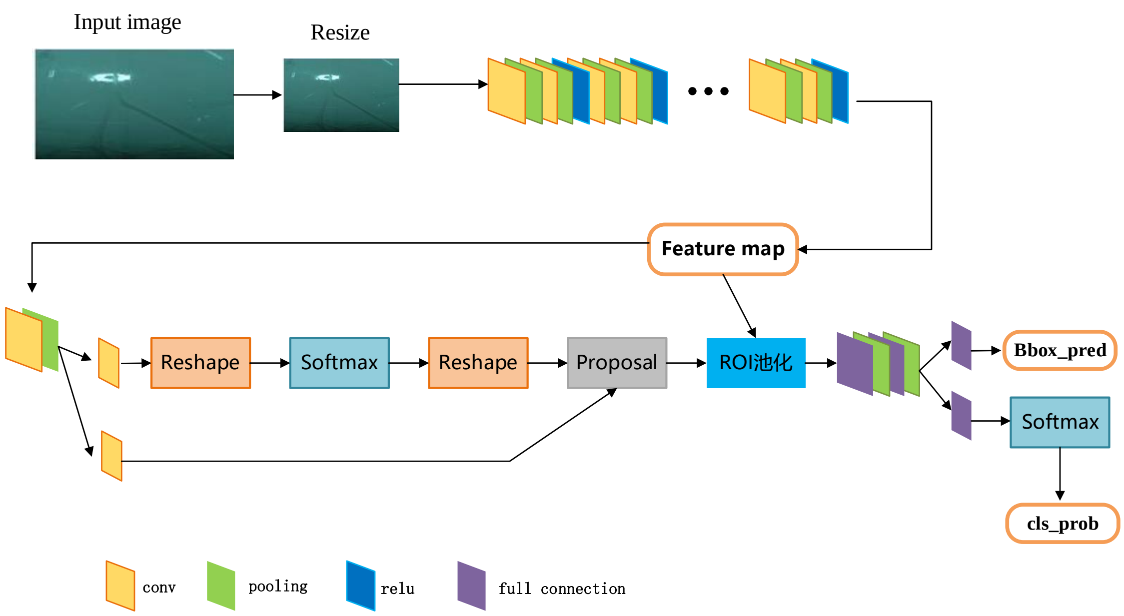

Figure 2 Fast R-CNN model structure

As shown in Figure 2, the surface defect detection process of transparent reflective film based on Fast R-CNN: the detection model of Fast R-CNN is usually composed of region proposal network (RPN) and Fast R-CNN detector. RPN and Fast R-CNN share the convolution layer by step training. Firstly, the resnet-101 convolutional neural network is used to extract the feature map of multi-scale image, and the RPN layer and full connection layer will share the feature map. Secondly, in RPN network (Fig. 3), on the one hand, the classification is realized by judging whether the anchors belong to positive or negative. On the other hand, the bounding box regression offset of anchors is calculated to obtain accurate proposals. The function of the proposal of RPN network is to synthesize the positive anchors and the corresponding border regression offset, and use non maximum suppression (NMS) to screen out the candidate frames.

ISSN: 2664-9640

Finally, each region proposal obtained corresponds to a target score and location information. Finally, the obtained region proposals are further refined by Fast R-CNN detector to obtain more accurate classification and boundary box positioning. Next, we will introduce the principle of surface defect detection of transparent reflective film based on Fast R-CNN and our work in this study.

3.3. Model training

3.3.1. RPN training

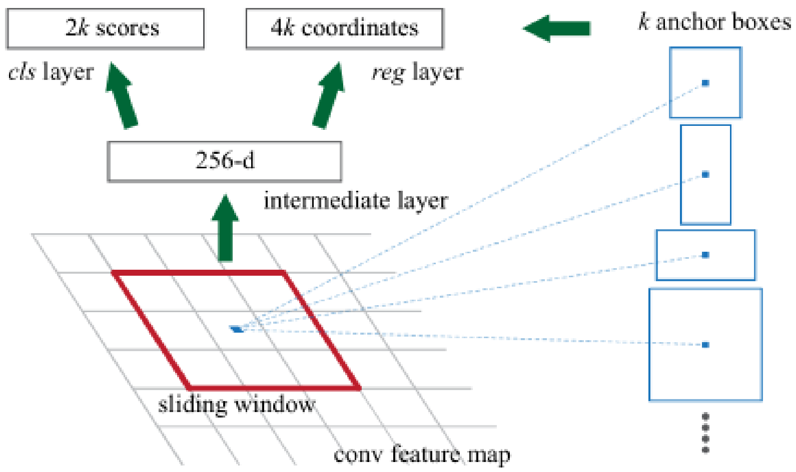

Figure 3 RPN training

In the process of transparent film detection, its defect detection accuracy and detection efficiency demand is high, so we choose Faster R-CNN model based on RPN for defect detection. The 3 × 3 sliding window is projected to a lower dimensional feature. This lower dimensional feature is convoluted by two 1 × 1 convolution kernels and activated by ReLU function. This conv feature map is fed into two sibling fully-connected layers—a box-regression layer and a box-classification layer. On the other hand, at each sliding-window location, we simultaneously predict k region proposals by using anchors. There are 3 scales with anchor box areas of 128^2 , 256^ 2 , and 512^ 2 pixels, and 3 aspect ratios of 1:1, 1:2, and 2:1 in this study. Therefore, each sliding-window location will predict 9 region proposals, the box-regression layer will predict 4*9 co-ordinates for the proposals and the box-classification layer outputs 2*9 scores which indicate the probabilities of the regions containing a defect or not.

After the above process, the region proposals output by RPN also contains many bounding boxes with high overlap rate. In order to preserve some unique bounding boxes with little overlap, non-maximum suppression (NMS) is applied to reduce the overlapping regions by merging proposals that have high intersection of Union (IOU). Setting the NMS threshold = 0.7, we take the boundary box with high confidence, which is about 2000 in training and 30 in testing.

3.3.2. Faster R-CNN training

We take the pre trained model weight as the training initialization weight. In the training process, as shown in Fig. 2, this process adopts the supervised learning training method, and uses the VGG-16 convolutional neural network as the image feature extraction network. Fast R-CNN uses ROI pooling to extract proposals features. First, ROI pooling proposals maps different size proposals from RPN to uniform size proposal vectors. Then, combined with these uniform size proposal vectors and feature maps, a fixed size proposal feature map was calculated from shared CNN. Finally, the proposal feature map is input into the full connection layer and softmax layer to implement the proposals classification, and each proposals will be attached with defect

ISSN: 2664-9640

probability scores. The regression layer again classifies proposals by bounding box expression and classification, so as to obtain more accurate relative coordinates of the bounding box. Finally, the trained model framework is used to detect the defects of transparent films.

4. Experiment and evaluation

As shown in the figure 4, in our transparent film defect detection, the ultimate goal is to find the type and location of defects contained in the image, and the detection results are usually represented by a rectangular boundary box. The defect detection model we use is trained on the defect scratch data set. In the process of experimental verification, we use the new image of defect without training for training, and finally evaluate the model through the results of positioning and classification.

Model evaluation needs to calculate precision and recall, true positive, false positive, true negative and false negative. In the evaluation of the real-time detection model for the surface defects of translucent reflective film, the accuracy is calculated $Precision = TP/(TP + FP)$ and recall = $Recall = TP/(TP + FN)$ draw the P-R curve, and calculate the area under the P-R curve is the average accuracy AP; defined as the ratio of the intersection and union of the areas of two rectangular frames as the intersection ratio, $IOU = A \cap B / A \cup B$, if the IOU threshold is set higher, the positioning frame is more accurate, and the recall rate is reduced In the experiment, IOU = 0.5. As shown in the Figure 5, the final model evaluation result shows that the average detection accuracy is 86.32%, which meets the robustness in the detection process, which proves the effectiveness of our method.

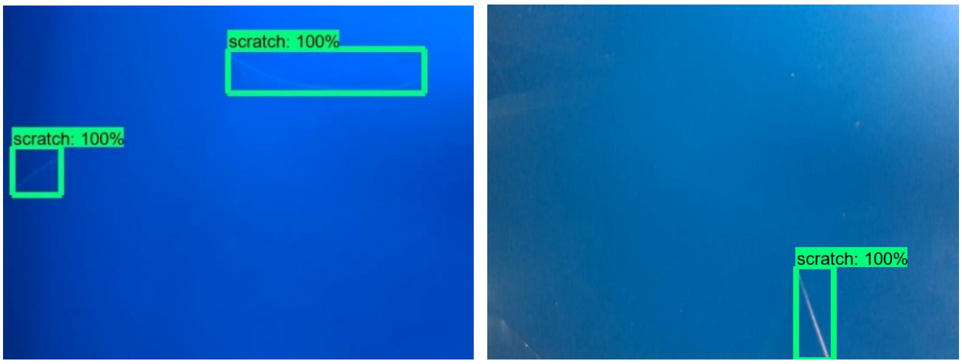

Figure 4 Experimental defect detection results

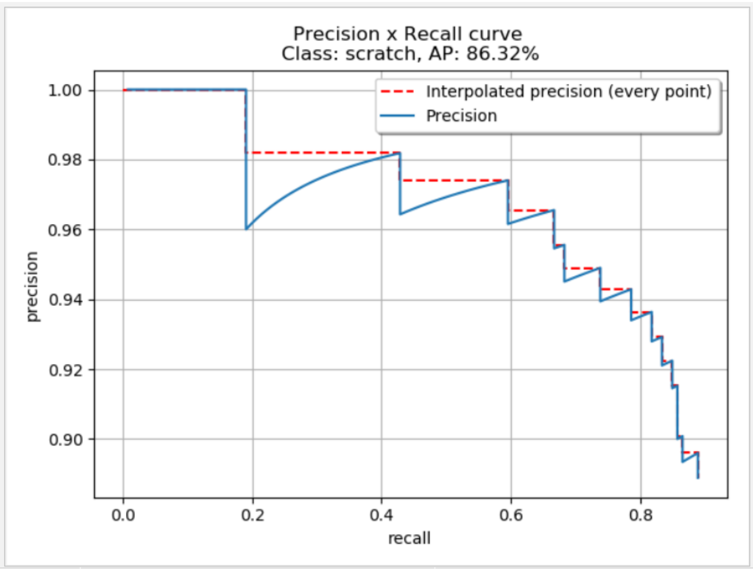

Figure 5 Detection average accuracy

ISSN: 2664-9640

5. Conclusion

According to the test results, the average detection accuracy is 86.32%, and the surface defects can be detected in real time, and the defects can be classified and located. The effectiveness of the real-time detection algorithm for the surface defects of transparent films is verified. The application of this method to the defect detection is of great significance to ensure the production quality of the films. At the same time, it lays a theoretical foundation for the application of deep learning technology in transparent film defect detection, and has important practical significance to solve similar production management problems.

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