Research on Classification of Surface Defects of Hot-rolled Steel Strip Based on Deep Learning

Chao WANG¹, Yu-ting LIU¹, Ya-ning YANG²*, Xiang-yu XU² and Tao ZHANG¹

¹College of Electromechanical Engineering, Dalian Minzu University, Dalian Liaoning 116605, China
²College of Electromechanical & Information Engineering, Dalian Minzu University, Dalian Liaoning 116605, China

*Corresponding author

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Abstract. Surface defect is one of the important factors affecting the quality of hot-rolled steel strip. Aiming at six typical surface defects of hot-rolled steel strip, a method of surface defect classification based on deep learning is proposed. Based on the Convolutional Neural Networks model and the surface defect data set of Northeast University, the proposed method is verified by experiments. The experimental results show that the recognition rate of surface defects is up to 98.6%, and the detection speed is about 60ms, which meets the requirements of accuracy and speed in industry. The classification and recognition technology of hot strip surface defects proposed in this paper not only has certain theoretical value, but also has practical application prospects.

Introduction

Hot-rolled steel strip, as one of the products of iron and steel industry, is widely used in automotive, electrical, chemical, shipbuilding and other industries, and has a great development space in the next few years. The apparent quality of hot-rolled steel strip is an important factor affecting its performance. However, due to the influence of equipment, raw materials and manufacturing technology, different types of defects on the surface of hot-rolled steel strip are formed in the production process, such as patches, crazing and inclusion[1]. These defects do not affect the apparent quality of steel products, and are easy to cause rust, stress concentration, cracking and other quality problems, which greatly reduces the performance and service life of steel products.

At present, manual inspection is the main method to detect the surface defects of hot-rolled steel strip in industry. This process is not only time-consuming and laborious, but also high error rate [2]. With the continuous development of image processing technology, machine learning method has gradually replaced the traditional method of manual detection, and has been applied in large-scale production practice [3]. The surface defect detection method of machine learning is generally divided into two parts: pretreatment and feature extraction. To a certain extent, this method depends on the accuracy of feature extraction. However, the extraction of features often requires manual work, and the accuracy of detection still has some room to improve.

In order to solve the above problems, a defect detection and classification method based on deep learning is proposed. The deep learning network model has higher autonomous learning ability and does not need to extract the features of two-dimensional images manually. It also reduces the process of image pre-processing, solves the complexity and uncertainty of manual feature extraction, and reduces the influence of man-made factors to the maximum extent. In this paper, six typical defect samples of hot-rolled steel strip have been tested, and high detection rate has been obtained, and training and recognition time has been reduced.
Relate Work

In reference [4], a semi-supervised learning method for classification of steel surface defects was proposed by D. He et al. This method is based on convolutional automatic encoder (CAE) and semi-supervised generation anti-network (SGAN). The CAE is trained by unlabeled data, and the trained CAE coder is fed back to the network layer (softmax) to form a new classifier. Then SGAN is introduced to semi-supervised learning to improve the generalization ability of the method. In reference [5], a classification method of steel strip surface defects based on deep Convolutional Neural Networks was proposed by Y. Liu et al. Based on the GoogLeNet model, this method adds an identity mapping, to a certain extent, and improves the original method to a certain extent. In reference [6], a defect classification method based on Convolutional Neural Networks was proposed by S.Y. Zhou et al. This method can learn two parts at the same time: feature extraction and training classifier, which can effectively realize the classification of defects.

Experiment

Dataset. In order to train and classify deep learning, the dataset in the surface defect database of Northeast University (NEU) is adopted [7]. The dataset consists of 1800 defect images, including six typical surface defects of hot-rolled steel strip rolled-in scale (RS), patches (Pa), crazing (Cr), pitted surface (PS), inclusion (In), scratches (Sc). Each defect type has 300 sample images. An example of each defect type is given in Fig. 1.

![Figure 1. Typical defect types of hot-rolled steel strip.](image)

Model. The deep learning model used in the experiment is Convolutional Neural Networks (CNN) model [8]. It is a feedforward neural network with Convolutional layer, Pooling layer and Fully Convolutional layer. A typical Convolutional Neural Networks model is shown in Fig. 2.

![Figure 2. Convolutional Neural Networks model.](image)
Convolution layer is a layer in which the input data is extracted for feature extraction. By convolution, a set of images can be generated for subsequent use. The pooling layer is mainly used to reduce the size of the data and reduce the computation of subsequent feature images. Full connection layer is a kind of nonlinear classifier called multi-layer perceptron, which has excellent ability of nonlinear classification. After continuous convolution and pooling, an image can be converted from binary data to vector data and sent to the full connection layer for classification. In the classification process, not only the Convolutional Neural Networks can be optimized, but also the learned features can be optimized.

**Environment Construction and Setting Training Parameters.** Experiments based on the following hardware and software environments: Intel quad-core processor, Samsung main hard disk, Nvidia Quadro P4000 graphics card, CUDA-10.0, CUDNN-10.0 deep learning library, 64 GB memory, Windows 10 operating system, Image processing software HALCON.

It is necessary to set the parameters of the pre-training network model before training the dataset. The selection of the parameters has a significant impact on the training process of the classifier. According to the six different defect types trained in the experiment, the setting parameters are shown in Table 1.

| Model parameters                  | Value  |
|-----------------------------------|--------|
| batchsize                         | 32     |
| InitialLearningRate               | 0.0012 |
| LearningRateStepEveryNthEpoch     | 5      |
| LearningRateStepRatio             | 0.1    |
| NumEpochs                         | 20     |
| Momentum                          | 0.8    |
| WeightPrior                       | 0.0001 |

**Analysis of Results**

In this experiment, 210 images from each defect data set are used as training set, 30 images as verification set, and 60 images as test set. The training results are shown in Fig. 3. The confusion matrix can be obtained by applying the test set to the classifier, as shown in Table 2.
Table 2. Confusion Matrix.

| Predicted classes | Ground truth labels |
|-------------------|---------------------|
|                   | RS | Pa | Cr | PS | In | Sc |
| RS                | 60 | 0  | 0  | 0  | 0  | 0  |
| Pa                | 0  | 58 | 0  | 0  | 0  | 2  |
| Cr                | 0  | 0  | 60 | 0  | 1  | 0  |
| PS                | 0  | 1  | 0  | 60 | 0  | 0  |
| In                | 0  | 0  | 0  | 0  | 59 | 0  |
| Sc                | 0  | 1  | 0  | 0  | 0  | 58 |

According to Table 2, the accuracy rate and regression rate of each defect category and the overall accuracy rate can be calculated. The formula for calculating the accuracy is as shown in Eq. 1.

\[
\text{Precision} = \frac{TP}{TP + FP}
\]  

(1)

The formula for calculating the regression rate is shown in Eq. 2.

\[
\text{Recall} = \frac{TP}{TP + FN}
\]

(2)

The overall accuracy formula is shown in Eq. 3.

\[
\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}
\]

(3)

In formula (1), formula (2), formula (3), the real value of TP (True Positive) is positive, and the model considers it to be the number of positive. The real value of FN (False Negative) is positive, however, the model considers it to be the number of negative. The real value of FP (False Positive) is negative, but the model considers it to be the number of positive. The real value of TN (True Negative) is negative, and the model considers it to be the number of negative.

The final test results of the test set are shown in Table 3:

Table 3. Training set test results.

| Classification | Precision | Recall | Accuracy |
|----------------|-----------|--------|----------|
| RS             | 100%      | 100%   |          |
| Pa             | 96.6%     | 96.6%  |          |
| Cr             | 98.4%     | 100%   |          |
| PS             | 98.4%     | 100%   |          |
| In             | 100%      | 98.3%  | 98.6%    |
| Sc             | 98.3%     | 96.6%  |          |

| Time for inspection | 60ms |

Summary

A defect classification method based on deep learning is proposed to detect defects on the surface of hot-rolled steel strip. Compared with the traditional machine vision method, this method improves the accuracy and efficiency of hot strip surface defect detection. At the same time, this method has a strong ability of defect recognition. By setting training parameters, the classification and training of data sets can be realized effectively. In the experimental results, the training of six types of defects can achieve a higher recognition accuracy. In addition, the recognition speed of each image defect is about 60 Ms, which can meet the demand of on-line real-time detection in industrial production, and has a practical application prospect. In the future, more industrial product image defect classification will be applied to the deep learning network model used in this paper, so as to provide better reference value for the automation application of industrial products.
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