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A SURFACE DEFECT DETECTION METHOD OF THE MAGNESIUM ALLOY SHEET BASED ON DEFORMABLE CONVOLUTION NEURAL NETWORK

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In the rolling process of the magnesium alloy sheet, due to improper control parameters or inaccurate production equipment and other reasons, the surface of the magnesium alloy sheet is prone to appearance of edge crack, fold, inclusion, ripple, scratch and other defects. In order to improve the surface quality of the magnesium alloy sheet, a surface defect detection method based on deformable convolution neural network is proposed in the paper, which presents a higher detection accuracy than those traditional methods on the convolutional neural network (CNN), support vector machine (SVM) and Bayes. The experiment result shows the final detecting accuracy is greater than 95 %.

Key words: magnesium alloy, sheet, surface quality, defects, deformable convolution neural network

INTRODUCTION

In the rolling process of the magnesium alloy sheet, some defects are easy to appear on the sheet surface. It will seriously affect the quality of the sheet if the defects can not be detected in time. Therefore, the surface defects detection of the magnesium alloy sheet is a key in the production process of the magnesium alloy sheet. In the early stage of the surface defect detecting, the manual detection methods are widely used in the enterprises [1]. With the faster speed of production and the stricter standard of detection, the disadvantages of manual detection are emerged gradually, the eyes cannot adapt the speed of production and it is difficult to distinguish the small defects after long time work. With the development of the computer technology, some defects detection methods based on the machine vision are appeared. In [2] machine vision technology is used to detect the surface defect of the railway. According to the characteristics of the surface of rail, a new algorithm based on the faults localization technique is proposed. The final detection accuracy reaches 93 %. In [3] a metal defects detection method based on the pulse eddy current is proposed. In [4] an intelligent machine vision system is presented, which is based on support vector machine for detecting surface defects on packing boxes. The effective detection rate of the experimental results is 98,12 %. The methods based on the machine vision have faster detection speed and better performance on detection accuracy than the manual detection methods. However, those machine vision detection methods are based on artificial feature extraction, it is very difficult to learn the abstract representation, which leads to the poor detection result. In [5] a new deep learning model is proposed, which wins the image classification competition in ImageNet 2012. The model based on convolutional neural network (CNN) can automatically extract the map feature, which has been widely used in the field of defect detection [6]. However, the detection performance of the CNN methods obviously get poor when the defects are distorted. A large number of different position defect images are collected to solve this problem in the ordinary method. But, not all of the defects positions are wholly collected in the actual production of the magnesium alloy sheet. To improve further the detection accuracy, a surface defect detection method of the magnesium alloy sheet based on deformable convolution neural network is proposed in the paper, and the experimental result verifies the effectiveness of the algorithm.

THE CONVOLUTIOANAL NEURAL NETWORK

The convolutional neural network is one of the most successful models among these deep learning algorithms [7]. It can directly take the image as the input, and it has the ability of self-learning. Meanwhile, the convolutional neural network's structure tends to be simplified, and the training time is greatly shortened. The basic structure of CNN model includes the convolution layer, the pooling layer and the full connection layer.

The convolution layer plays the most important role in the algorithm. Here, the convolution calcula-

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tion between the feature map from the upper layer and the trainable convolution kernels, are finished to extract the feature information from the image. The process can be expressed as (1).

$$x_j^I = f\left(\sum_{i \in M_j} x_i^{I-1} \times w_{ij}^I + B^I\right) \qquad (1)$$

Here, x_j^I represents the jth input of the Ith convolution layer, x_j^{I-1} represents the output of ith feature map in the I-1 convolution layer, M_j represents all of the jth connected feature map with the previous layers, w_{ij}^I represents the convolution kernel between the ith feature map of the previous layers and the jth feature map in the current layer, and B^I represents the bias of the Ith layer.

The pooling layers are used to reduce the dimension of feature map without the excessive loss of the feature information. The common methods contain max_pooling, mean_pooling and stochastic_pooling. The pooling process is shown in (2).

$$x_j^l = f(\beta^l \times pooling\_method(x_i^{l-1}) + B^l) \qquad (2)$$

Here, $pooling\_method(x_i^{l-1})$ represents the pooling operation of the ith feature map in the l-1 convolution layer. β^l represents the trainable parameter in the lth layer, B^l represents the bias of layer l.

The function of the full connection layer is to connect with the neurons of the previous layer to form the whole information of the image. And the function of the output layer is to show the final classification result. In the output layer, a function called Soft-Max is used to calculate the probability of the category. The function is shown in (3).

$$_{out}(x) = \frac{\exp(x)}{\sum_{i=1}^{n} \exp(x_i)} \qquad (3)$$

Here, n is the number of classification, x_i is the output score of label i, the final result is normalized between [0, 1], the calculate result is the probability of each label, and the result of the maximum probability is the final output.

DESIGN OF THE CONVOLUTION NEURAL NETWORK STRUCTURE

Generally, the performance of the detection is depending on the depth of convolution neural network because a number of the feature maps can make the model completely extract the features for the image. However, with the deepening of network depth, the number of feature maps and the amount of computation is increasing, the speed of training and detection is getting slower. Considering the characteristics of the surface image of the magnesium alloy sheet, the training time, the accuracy and speed of detection and the applicability of the network model, how to choose the appropriate network structure is a key problem. In order to ensure the network model have the appropriate number of network layers, the different number of the convolution layers are designed and the detection result is shown in Table 1.

In the Table 1, it can be seen that the network model have a good performance with four convolution layers, and the detection accuracy is 92 %, with the increase of convolution layers, the detection accuracy decreases, so the number of convolution layers of the network model is chosen as four. For the input layer, the defect sample image size is 256*256.

Table 1 **The detection accuracy of the different convolution layers**

Convolution layers	The accuracy/ %
4-CNN	92
5-CNN	90
6-CNN	89
7-CNN	91
8-CNN	87

The proper number of the model layers is designed according to the calculated receptive field in order that the features used in the final classification judgment can cover all the information of the original image. Finally, the structure and parameter settings of the model are shown in Table 2.

Table 2 **The parameters of the convolution neural network**

The name of the layers	Parameters
Input	256*256
Conv	3*3, 3*3, 3*3, 3*3
Pool	2*2
FC	1 024
Output	5

In the Table 2, for the input layer, the defect sample image size is 256*256, and the size of convolution kernel is 3*3. For the pool method, the max_pooling is used and the size is 2*2. In the fully connected layer, it can generate a 1 024-dimensional feature vector. In output layer, the classification results are displayed.

After the selection of the convolution layers and the design of parameters for each layer, the convolution neural network model for the surface defect detection of the magnesium alloy sheet is established, and its structure is shown in Figure 1.

During the progress of detection, the defects have different size, different form, and different angle. Because the ability of the convolution neural network model to solve the deformation defect is insufficient, in order to improve the accuracy of defect detection when the deformation defects occur on the surface of the rolling magnesium alloy sheet, a deformable convolution neural network is proposed.

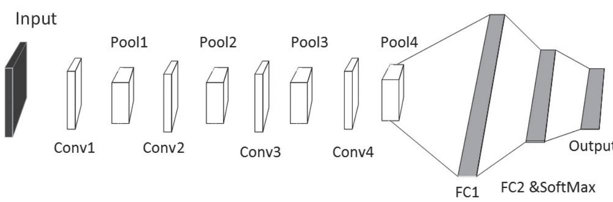

Figure 1 The structure of convolution neural network

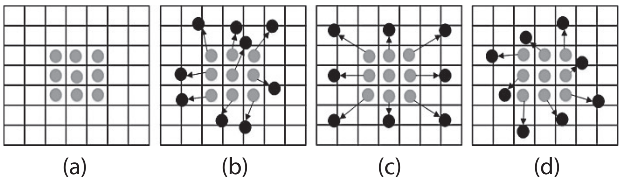

Figure 2 Illustration of the deformable convolutions in 3 × 3 standard

DESIGN OF THE DEFORMABLE CONVOLUTION NEURAL NETWORK STRUCTURE

The traditional CNN methods show a poor performance when the defects are deformed. In [8], a deformable convolution is proposed in which an offset is added in the sampling position to obtain a larger receptive field. The sampling filter can deform freely. The deformable convolution is shown in Figure 2.

Figure 2(a) shows the sampling position of the traditional convolution. Figure 2(b) shows the random sampling position of the deformable convolution. Figure 2(c) shows the enlarged sampling position. Figure 2(d) shows the rotated sampling position.

In the traditional 2D convolution, for an input feature map x and the output feature map y, the mathematical model of convolution can be shown as

$$y(p_n)=\sum_{p_n R} W(p_n)*x(p_0+p_n) \qquad (4)$$

Here, R defines a sampling position for the 3 × 3 kernel, which respectively enumerate all the positions in the output feature map y , and R = {(-1,-1), (1, 0), …,(0, 1),(1, 1)}. W (·) is the weight corresponding to the sampled values.

In deformable convolution, it adds the 2D offsets $\{\Delta p_n | n = 1,\cdots,N\}$ to the regular grid sample locations to freely form deformation of the sampling filters, where N represents the number of the sampling position. The mathematical model of deformable convolution shown in (5) and the process is shown in Figure 3.

$$y(p_n)=\sum_{p_n R} W(p_n)*x(p_0+p_n+p_n) \qquad (5)$$

Here, the sampling position is irregular and offset is located in $p_n + \Delta p_n$. The offset is typically fractional, which should be converted to the integer using the bilinear interpolation and it is shown as (6).

$$x(p)=\sum_{q} G(q,p)*x(q) \qquad (6)$$

Where p represents any position ($p = p_0 + p_n + \Delta p_n$), enumerates all the spatial positions of feature map x. G (·) is the bilinear interpolation kernel. G is a 2-D vector, which can be separated into two 1-D vectors. As shown in (7).

$$Gq,p=g(q_x\ ,p_x)*g(q_y,p_y) \qquad (7)$$

$$\begin{aligned} g(q_x,p_x)&=max(0,1-|q_x-p_x|)\\ g(q_y,p_y)&=max(0,1-|q_y-p_y|)\end{aligned} \qquad (8)$$

Here, (7) can be fast to compute as (8).

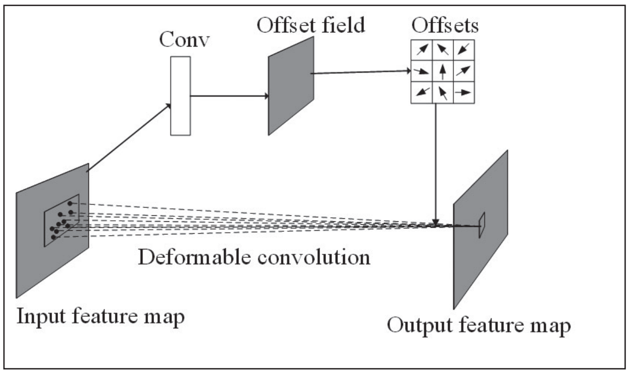

Figure 3 The process of the 3 × 3 deformable convolution

The offset can be learned by back propagation algorithm. Comparing with the standard convolution, the deformable convolution includes the shape definition of the standard convolution, and it can transform its own shape according to the requirements of feature extraction, which provides more choice for the convolution neural network in feature extraction. And the shape of the deformable convolution can automatically adjust, so it has a higher adaptability to feature extraction of new samples.

The deformable convolution neural network model is designed as 12 layers in this paper. The model includes 4 convolution layers, and every deformable convolution layer respectively contains 32, 64, 64 and 64 convolution kernels, and the size of deformable convolution kernels are 3 × 3.

EXPERIMENT AND ANALYSIS

The defect image sets are used in the experiment, in which there are 5 kinds of typical defects shown as Figure 4.

The defects include edge crack (a), fold (b), inclusion (c), ripple (d) and scratch (e). In order to improve the generalization ability of the deformable convolution neural network model, the data augmentation method such as flip, zoom, shift, scale and blur are used. In the original data set which is collected from actual production process, the number of defects is 4 000. After data augmentation method is implemented, the number of the defects can reach 10 000. The defect samples must be transformed into the acceptable size of the deforma-

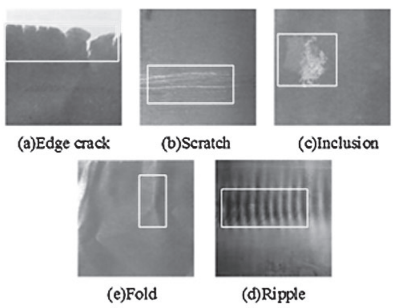

Figure 4 Five kinds of typical defects image

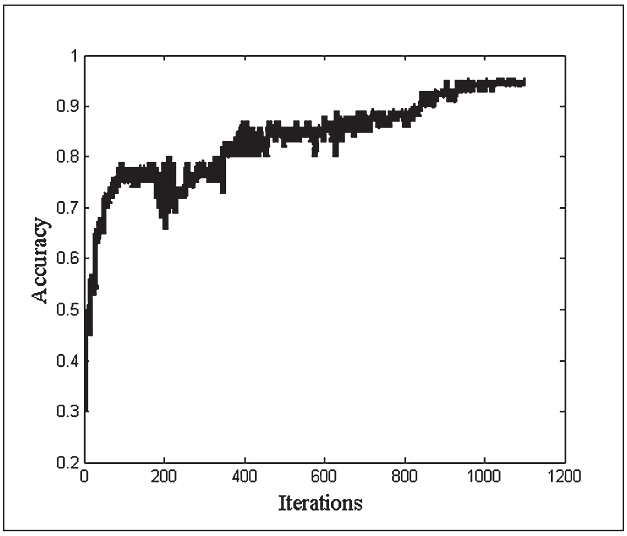

Figure 5 The accuracy of the deformable convolution neural network model

ble convolution neural network model. In order to avoid the insufficient judgment of the model for these small defects, the adjusted image size is 256*256 during the normalization process.

The detection results using deformable convolution neural network model are shown in Figure 5.

In Figure 5, the number of iterations is 1 100, at the beginning of the iterations, the accuracy is lower. With the increase of the iterations, the detection accuracy increased gradually. In the end, the detection accuracy can reach 95,7 %.

In order to verify the advantages of the deformable convolution neural network model, the SVM, Bayes detection method is used on the same data set for the contrast experiment. The SVM recognition rate is 86,06 %, the Bayes recognition rate is 83,6 %, and the CNN recognition accuracy rate is 92,1 %, while the Deform-CNN recognition accuracy rate is 95,7 %. By comparing the above experiment results, it can be clearly seen that the deform-CNN is much better than the SVM, Bayes and the CNN in defect detection accuracy, which are verified the effectiveness of the algorithm in detecting surface defect of the magnesium alloy sheet.

CONCLUSION

In this paper, a surface defect detection method of the magnesium alloy sheet based on deformable convolution neural network is proposed. The method has a good performance in detection accuracy and the capacity of the deformation defects. Compared with others machine vision detection methods, the deform-CNN has obvious advantages in feature extraction and much better recognition accuracy.

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Note: The responsible translators for English language is Lihua Cai—University of Science and Technology Liaoning, China