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A method of surface defect detection of magnesium alloy sheet based on convolutional neural network

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Abstract

In the rolling process of magnesium alloy sheet, the defects such as edge, fold and ripple are easilyappear on the surface of sheet and the mainlyinfluence factors are improper control of key process parameters, the quality of slab, the accuracy of processing equipment. It will seriously affect the surface quality if these defects are not detected timely and accurately.In order to solve this problem, a method of surface defect detection of magnesium alloy sheet based on convolutional neural network is proposed. The experiments show the detecting accuracy isabove 92%.

Keywords

Method, convolutional neural network.

1. Brief Introduction about detection techniques

Magnesium alloys have been widely used in industrial production, daily lifeand other fields.The surface quality of thesheet is an important indicator in the rolling process of magnesium alloy sheet. It can improve the quality of the sheetif the defectsare found as early as possible and the machine parameters are adjusted timely.In the early stage of detection methods, manual detection method[1] was used by most enterprises. Manual detection mainly relies on people's subjective impression. However, with the improvement of production speed,the detection standards are more and more strict and the disadvantages of manual detection are appeared that it is difficult to ensure accuratelydetects the different types of defects after long time work.With the development of photoelectric technology, pulsed eddy currentdetecting wayis the mainstream non-destructive testing technology, which has the advantages of simple operation, large detection depth and high resolution[2].The defects should be repeatedly detected in the pulsed eddy current detecting way,whichcannot meet the requirements of real-time detecting.With the development of deep learning, the appearance ofconvolutional neural network(CNN)[3] provides a new method of surface defect detection.The method shows many advantages in the fields of the speed and the accuracy because the feature extraction by human is not necessary.Therefore, it is proposed a method of surface defect detection of magnesium alloy sheet based on CNN, and the experiments show the detecting accuracy is above 92%.

2. Process analysis and modeling

Deep neural network [4]isestablished by an artificial neural network algorithm, in which the convolutional neural network is one of the successful models.It can directly take the image as the input, and has the ability of self-learning. Meanwhile, theconvolutional neural network’s structure tends to be simplified, and the training time is greatly shortened.

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It is a kind of feed-forward neural network[5] with multi-layer structure including convolutional layer,pooling layer,full connection layer and output layer

The convolution layer plays the most important role in the algorithm. Here,theconvolution calculation betweenthe 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 Eq.1.

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

Here, x_j^I represents the input of*j*th in the *I*convolution layer, x_i^{I-1}represents the output of *i*thfeature mapin the *I-1*convolution layer, $M_j$represents the all of the feature maps that *j*th feature map of the current layer are connected with theprevious layers, w_{ij}^Irepresentsthe convolution kernel between the *i*thfeature map of thepreviouslayersand the jth feature map in the currentlayer, andB^lrepresentthe bias of the*l* layer.

Thepooling layers are used to reduce the dimension of feature map without the excessive loss of the feature information.The common methods containmax_ pooling,mean_ pooling, stochastic_ pooling. The poolingprocess is shown in Eq.2.

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

Here, $pooling\_method(x_i^{l-1})$ represents the pooling operation of the *i*th feature mapin the*l-1*convolution layer.β^lrepresents the trainable parameter in *l*th layer,B^lrepresentsthe 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 Eq.3.

$$f_{\mathrm{out}}(\mathrm{x}) = \frac{\exp(\mathrm{x})}{\sum_{\mathrm{i}=1}^{\mathrm{n}} \exp(\mathrm{x_i})} \tag{3}$$

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.

The activation function used in this model is ReLU and is adopted in many network models, and in the convergencespeed is faster than sigmoid and tanh.

The CNN model designed in this paper is composed of 4 convolution layers, the activation functionis ReLu,and the input image size is adjusted as 256*256. The proper number of the model layers is designed according to the calculated receptive fieldin order thatthe features used in the final classification judgmentcovered all the information of the original image.Finally, the structure and parametersettingsof the model are shown in Fig.1.

Input(256*256)
Conv3-32+ReLu1
Maxpooling
Conv3-64+ReLu2
Maxpooling
Conv3-64+ReLu3
Maxpooling
Conv3-64+ReLu4
Maxpooling

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Fc-1024
Dropout
Softmax

Fig.1 The structure of the network

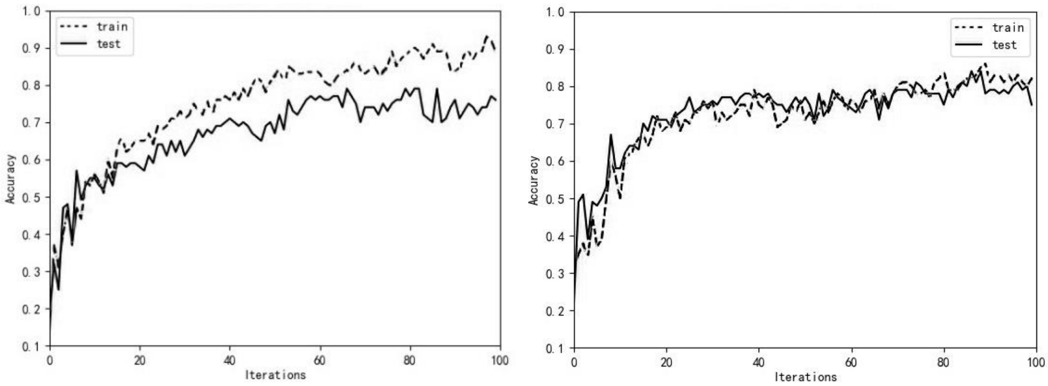
In theFig.1, the model contains 12 layers, theReLu function is used to activateneuronin every convolutional layer. The pooling layers isused toreduce the unnecessaryparametersin the end of every convolutional layer, all of the neuron will beconnected in the full connection layer, and the dropout layer is used toenhance the generalization performance of the model,finally, the Soft-Max function shows the result of classification.

3. Analysis of experimental data and results

A data sets shown as Tab.1 is used in the experiment, in which there are 5 types defect images including edge, fold, inclusion, ripple, scratch and so on. Because too little data will affect the detectionaccuracy， the data set is enhanced using flipping, shifting,zooming. Nevertheless, compared with others deep learning data set, the dataset in this paper is still not rich enough, which leads to over-fittingphenomenon. In order in solve this problem,the dropout technology is adopted to enhance the generalization performance of the network model. In order to verify the effect of the dropout technology,the comparison experimentsare carried out and the results are shown in the Fig.2.

Tab.1 Experimental dataset

Type	edge	fold	inclusion	ripple	scratch
Original dataset	261	185	166	232	74
Data enhancement dataset	400	370	332	400	296



(a)Without dropout technology (b) Using dropout technology

Fig.2 the result of contrast comparison experiment

In the Fig.2, thedashed lineexpresses the trainaccuracy and thesolid line expresses the test accuracy, there is a big gap between training accuracy and test accuracy before dropout technology is used. While, there are a small gap using dropout technology, which proves the effectiveness of thedropout technology.

Afterthenetwork model is designed,it is needed to be trained and in the paper, 75% of the entire data set is taken as the training dataset and the 25% as the prediction dataset. The train process of the model can bedescribed as following, (1) the network parameters are initialized randomly,(2) the dataset are loaded,(3) the probability of the image category is predicted by network calculation, (4) if the maximum number of iterations is not reached, the errors are calculated between the actual labels

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and the predicted results, which update the network parameters using back propagation algorithm(BP),(5) when the maximum iteration number is reached, the final defect detection result is got. The accuracy curve is shown in the Fig.3.

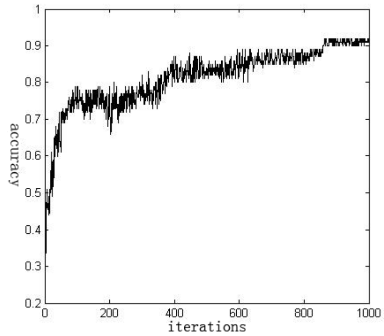

Fig.3 The results of detection

Specially,in order to verify the advantages of thealgorithmin this paper, at the same time, the SVM and Bayes methods are used in the data setsto detect the surface defection of magnesium alloy sheet.The accuracy comparison using above algorithmare shown in Tab.2.

Tab.2 The comparison of Accuracy

Model	accuracy %
CNN	92.0%
SVM	86.0%
Bayes	83.6%

It can be seen that the SVM method's recognition rate is 86.06% and the Bayes method'srecognition rate is 83.6%, the algorithm based onCNN in this paper,the accuracy achieves above 92.0%.By comparing the above experimental result, the algorithmin this paper is superior to traditional SVM and Bayes algorithm in defect detection.The validity of this algorithm is proved.

4. Conclusion

In this paper, a method of surface defect detection of magnesium alloy sheet based on CNN is proposed.Compared the detect accuracywith other methods, the algorithm in this paper hasa great advantage and the final detection accuracy is 92.0%.The next job is to optimize the topological structure of convolutional neural network, to reduce the complexity of the network and to improverecognition ratefurtherly.

References

[1] Yan Li; Kuai-She Wang, Chang-Rui Liu. Development Status of Surface Defects Inspection for Metal Plants. Materials Review, 2011; Vol:2. pp238-241

[2] Bing Song; San-Sheng Wang, Hua-AnHou, et al. Pulse eddy current testing technology and its applications in the 3A21 alumal defect detecting.Spacecraft Environment Engineering. 2016;Vol:33.pp606-611

[3] SejuneCheon; Han-Kang Lee, Chang-Ouk Kim, Seok-Hyung Lee. Convolutional Neural Network for Wafer Surface Defect Classification and the Detection of Unknown Defect Class. IEEE Transactions on Semiconductor Manufacturing. 2019;Vol:32.pp163-170.

[4] Hinton Geoffrey E; Osindero Simon. A fast learning algorithm for deep belief nets. Neural Computation, 2006;Vol:18.pp1527-1554

[5] Jiu-xiangGu; Zhen-hua Wang,Jason Kuen,et al. Recent Advances in Convolutional Neural Networks. Pattern Recognition,2018;Vol:77.pp354-377.