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Turning Surface Roughness Classification Detection Based on Machine Vision

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Abstract: In the field of machining, surface roughness is an important parameter for evaluating the surface quality of workpieces. This paper takes the resnet18-based network and proposes an improved residual neural network, which improves the accuracy rate to a certain extent by introducing the attention mechanism. Experiments show that in the classification and identification of turning surface roughness, the improved model avoids artificial design characteristics compared with artificial networks, which can effectively meet the classification and detection needs of turning surface roughness.

Keywords: Roughness Classification; Convolutional Neural Network; Attention Mechanism; Residual Network.

1. Introduction

Surface roughness is the small spacing and small peaks in the processing surface. Inemptity A measure, which is an important indicator for measuring and evaluating the surface quality of machined parts. At present, the methods [1] for measuring surface roughness are mainly divided into contact and non-contact. When measuring by contact needle method, it is easy to scratch the surface, resulting in a large measurement error. Song Yong [2] used optical interference imaging technology to extract stripe information through the improved Niblack binary algorithm, and used the least squares method to establish a mathematical model to evaluate the height parameters and spacing parameters of surface roughness, and completed the surface roughness detection of optical components. However, non-contact measurement methods based on optics, such as interference and optical cutting, are difficult to be popularized in industrial manufacturing due to the high requirements for the measurement environment and the high cost of precision instruments used. With the development of big data technology and computer technology, many machine learning methods have been improved. By improving the texture extraction algorithm of GLCM (grayscale symbiosis matrix) characteristics and Tamura characteristics, Yang Yue[3] and others use support vector machines to establish the model relationship between texture characteristics and surface roughness, reducing the measurement. The quantitative error can qualitatively evaluate the surface roughness of the workpiece. By using the grayscale symbiosis matrix to extract the texture characteristic parameters of the surface image of the cylinder liner and use it as input, Lu Yanjun et alt.[4]uses traditional artificial neural networks to prove that the establishment of a 3D roughness detection model based on GRNN is based on multivariate regression analysis.(MRA) The detection model established has a smaller error and higher accuracy, but the artificial neural network requires artificial design features and many model parameters, which is complex in calculation, which is not conducive to training. Therefore, the deep learning method represented by convolutional neural network that can automatically extract features has attracted more and more attention from researchers.

In recent years, with the rise of artificial intelligence technology, the CNN network for image processing has also developed rapidly. Krizhevsky and others proposed AlexNet in the ImageNet competition in 2012, using ReLU as an activation function to introduce dropout. Regularized operation and data enhancement technology have won the competition with significant advantages, marking a major breakthrough in deep learning in the field of computer vision. Subsequently, convolutional neural networks have sprung up, and a series of improved classic networks have emerged, such as VGGNet, GoogleNet, ResNet, DenseNet, etc., which perform well in image processing tasks and are widely used. Yi Huai'an and others enhanced the data by adding milling simulation pictures, improving the feature extraction ability of the convolutional neural network Xception model, and improving the roughness classification detection results by 6.3%. Huang et al. proposed a model based on the adaptive deep fusion capsule network (ADFCNet), which alleviated the problem of the decline in the performance of the depth model caused by low illumination and environmental noise environment. Zhou Youxing and others [5] proposed an improvement by combining the attention mechanism of the convolutional layer filter and the batch normalization layer scaling coefficient. The DenseNet model shortens the time for the model to detect the surface of the workpiece and improves the detection accuracy. Fang Runji and others [6,7] proposed a milling surface roughness grade detection method based on width learning, which improved the model training speed and provided a new strategy for online measurement of visual roughness.

In summary, using the deep learning method of convolutional neural networks to detect surface roughness can improve the performance of the model from two angles, one is to enhance the data set, and the other is to integrate or improve the existing model. To this end, this paper designs an improved ResNet residual network. By integrating multi-scale convolution, it extracts rough image texture features from different scales. By introducing attention mechanisms, it adaptively re-weights the features of each channel and effectively uses channel information, so as to improve the roughness classification model. Classification performance and generalization ability to achieve accurate classification of workpiece surface roughness.

The implementation process of the turning surface roughness classification and detection system studied in this paper is shown in Figure 1. First, obtain the surface image of the sample block, then establish a data set, construct a network model, and then preprocess the data set and send it to the model training to solve the best network parameters, and save the model. Finally, design the system user interface to realize online classification.

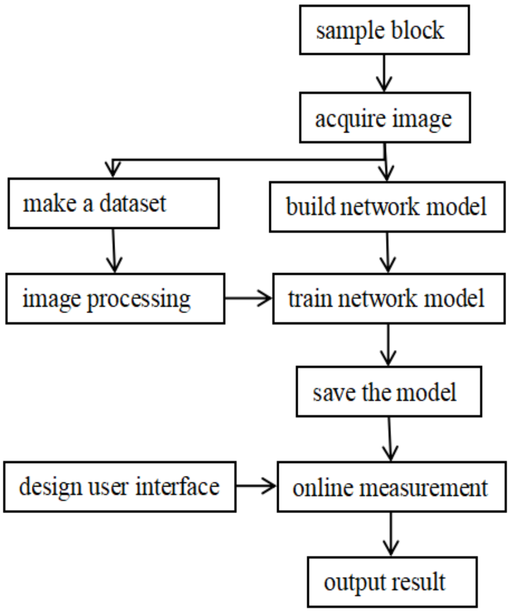

Fig 1. Classification system implementation flow chart

2. Dataset

2.1. Image Acquisition System

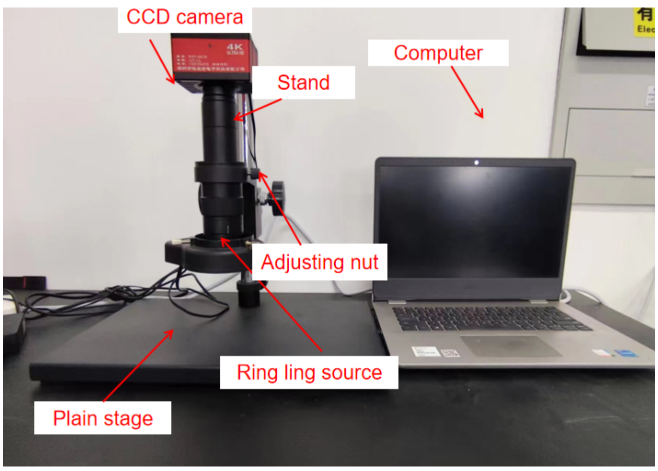

Fig 2. Image acquisition system

In order to prepare the data set required for model training, it is necessary to collect surface images of aluminum samples. The image acquisition system is mainly composed of a ring light source, a connected bracket, an industrial camera, an adjustment nut and a laptop. The ring light source mainly provides uniform light, so that the camera can better capture the surface roughness information of the sample block. The base of the joint bracket plays a connecting and fixing role. In order to obtain high-quality pictures, the camera adopts a high-resolution CCD industrial camera model WST-4KCH. During the collection process, keep the objective lens multiple unchanged, and adjust the distance between the objective lens and the surface of the sample block by adjusting the nut to achieve clear focus. Laptops are mainly used to receive and save collected pictures by connecting with industrial cameras to facilitate the processing of subsequent data. The stage is located under the ring-shaped light source, which is mainly used to place the sample block. When collecting, pay attention to the side of the sample block being collected facing up. The physical object of the image acquisition system is shown in Figure 2.

2.2. Preparation and Division of Data Sets

The image acquisition system uses a high-resolution industrial camera to collect 20 surface images of different roughness levels of standard turning samples provided by a manufacturer in the same experimental environment, and the resolution size of each image is 7680 x 4320. The original image of the surface of the sample with different roughness levels is shown in Figure 1. Due to the original images collected The number is small. In order to improve the robustness of the model to the data set and reduce the overfitting problem that may be caused by the small data set, appropriate cropping, adjusting saturation, changing brightness, mirroring technology and other methods are used to enhance the data, and then pasting the corresponding roughness grade mark on these pictures through the online image marking tool. Sign and preprocess the grayscale of the image, so as to obtain a total of 5 roughness levels of turning surface roughness data set consisting of 3,960 pictures. Figure 3 is a grayscale data set picture. In the experiment of this paper, the sample data is randomly disrupted, divided into training sets and test sets according to a ratio of 4:1, and the image size is normalized into 224 x 224 and sent into the model for training. The specific division and quantity of data set samples are shown in Table 1.

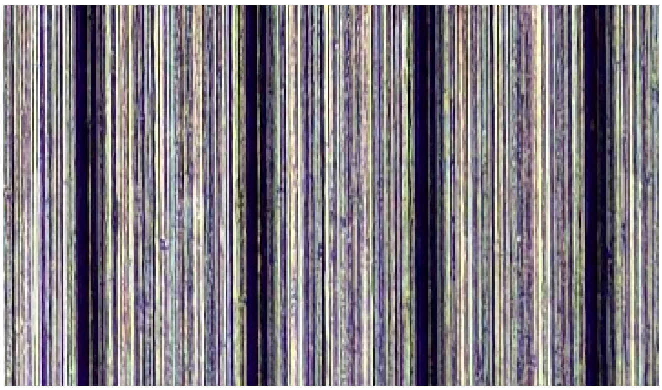

Fig 3. Pre-processed Ra12.5 picture example

Table 1. Dataset division and quantity

Table 1 Dataset division and quantity Roughness	12.5	6.3	3.2	1.6	0.8	Total
Training set	608	640	640	640	640	3168
Test set	152	160	160	160	160	792
Total	760	800	800	800	800	3960

3. Model Design

3.1. Basic Network

This paper selects the ResNet18 network as the basic network model. By using residual connections in the network as an effective technical means, the ResNet convolutional neural network model solves the problem that traditional deep networks are prone to gradient disappearance or gradient explosion during reverse propagation, thus deepening the number of network layers and improving the learning ability and performance of the model. The residual structure is shown in Figure 4.

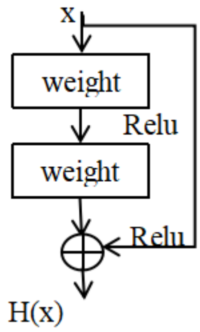

Fig 4. Residual structure

If x is the input of the residual structure, F(x) is the characteristic mapping after the input x passes through the weight layer, H(x) is the characteristic mapping of the residual structure, and the right path is the identity mapping, then this process can be expressed by formula (1):

$$H(x) = F(x) + x \quad (1)$$

3.2. Multi-scale Convolutional Module

The first layer of the ResNet18 basic network convolution selected in this paper uses 7×7 convolutional kernels, large convolutional kernels will introduce more parameters, increase the amount of network computing, and may also lead to the loss of some feature information and other problems, and considering that the acquired roughness surface image adjacent to the roughness level has a certain similarity. Therefore, comprehensive network expenses and dataSet and other factors, in order to improve the ability to perceive the overall features of the input image, multiple convolutional nuclei of different sizes are used to carry out multi-scale convolution operations to capture a variety of local feature information of rough images at different scales, thus enhancing the ability of model classification and identification. The multi-scale convolutional module is shown in Figure 5. The multi-scale convolutional module first passes through a 1x1 convolution, and then accesses a convolutional network composed of a 3x3 convolution, two series of 3x3 convolutions, and three series of 3x3 convolutions and three parallel paths.

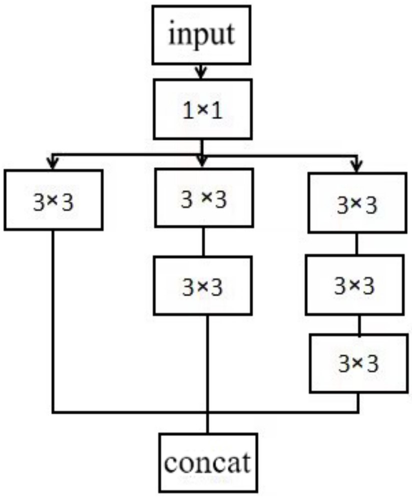

Fig 5. Multi-scale convolutional module

3.3. Attention Mechanism

The CBAM attention mechanism includes the channel attention module and the spatial attention module, which enhance the characteristic weight beneficial to classification tasks from the two dimensions of channel and space respectively, and suppress irrelevant interference. The two are used in series as shown in Figure 6.

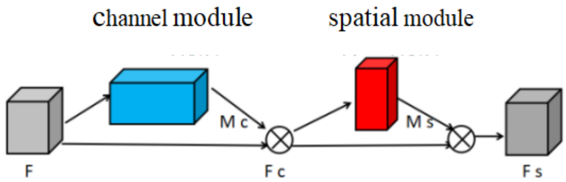

Fig 6. CBAM attention mechanism

In the CBAM module, for the input size is H×W feature diagram F, the channel attention module first uses maximum pooling and average pooling to generate 2 1×One×C's one-dimensional vector, and then send these two vectors to the multi-layer perception machine with weight sharing, and then add the results and go through the sigmoid activation function, so as to obtain the channel attention weight Mc, whose size is 1×One×C. Finally, F and Mc are multiplied to obtain the characteristic graph Fc, whose size is the same as that of the characteristic diagram F. The calculation process of channel attention is shown in equation (2) (3):

$$Fc = Mc(F) \otimes F \quad (2)$$

Among them,

$$\begin{aligned} Mc(F) &= \sigma\{MLP[AvgPool\ (F)] + MLP[MaxPool\ (F)]\} \\ &= \sigma\{W_1[W_0(F^c_{avg})] + W_1[W_0(F^c_{\max})]\} \end{aligned} \quad (3)$$

In the formula:

Mc——Channel attention weight;

Avgpool——Average poolization;

Maxpool——Maximum pooling;

W0, W1——The weight of the hidden layer;

Σ——Sigmoid activates the function.

The spatial attention module then calculates the maximum pooling and average pooling of the feature map Fc, and obtains two dimensions of H.×W×1's characteristic map and splice it on the channel dimension, and through a 7×The convolution operation of 7, at this time, the number of channels is 1, and finally the activation function is connected to the size of H.×W×1's spatial attention weight Ms, and then multiply Fc by Ms to complete the feature calibration on the spatial dimension, and get the output feature map Fs with the same size as the input size.The spatial attention calculation process is shown in Formula (4) (5):

$$Fs = Ms(Fc) \otimes Fc \quad (4)$$

Among them,

$$Ms(Fc) = \sigma(f^{7\times7}([AvgPool(F); MaxPool(F)])) = \sigma(f^{7\times7}([F^s_{avg}; F^s_{\max}])) \quad (5)$$

In the formula, f7×7 means that the size of the convolutional nucleus is 7.×The convolutional operation of 7.

4. Experimental Environment and Evaluation Indicators

4.1. Experimental Platform and Hyperparameter

In order to test the roughness of the design to identify the classification effect of the model, it is necessary to send the established turning surface roughness image data set to the model for training and testing. The training experimental environment and parameters of the roughness classification identification model designed in this paper Configuration: The deep learning framework adopted isPyTorch, the programming language is python, the development software is Pycharm, the processor is Intel Core i7-14700K, the system running memory is 16GB, the graphics card is NVIDIA RTX-A4000, the graphics memory is 16GB, and the 64-bit Wi Ndows10 professional operating system.

4.2. Model Evaluation Indicators

This paper adopts Accuracy, Precision, Recall Recall and F1-score as the evaluation indicators of model training. To fully evaluate the complexity and operation efficiency of the model, the parameter quantity and calculation volume are also taken as evaluation indicators.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FN} + \text{FP} + \text{TN}} \quad (6)$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (7)$$

$$\text{Re call} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (8)$$

$$\text{F1} - \text{score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (9)$$

In the formula: TP predicts the positive sample as the number of positive samples for the model; FN predicts the positive sample as the number of negative samples for the model; FP predicts the number of negative samples as positive samples for the model;

TN predicts the negative sample as the number of negative samples as the model;

5. Experiments and Analysis

5.1. Model Training

This text The roughness classification model adopts batch operation during training and testing, and each batch contains 32 roughness images; Using Adam network optimizer and cross-entropy loss function, the learning rate is initially set to 0.01. The maximum number of model training is 200 times, and each parameter at this time is selected for model training.

Figure 6 shows the change in the accuracy of the verification set identification during the training process. It can be seen that the model tends to converge when iterating 50 times, and its accuracy rate no longer changes significantly.

5.2. Confusion Matrix

The identification results of the test model on the data set, the real label and model prediction results of each test sample are counted, and the five-classified confusion matrix is obtained as shown in Figure 7. It can be seen from the test results that the average prediction accuracy of the model is 94%. The results show that the improved model can easily distinguish the surface images of standard samples with 5 levels of turning roughness of Ra0.8~Ra12.5.

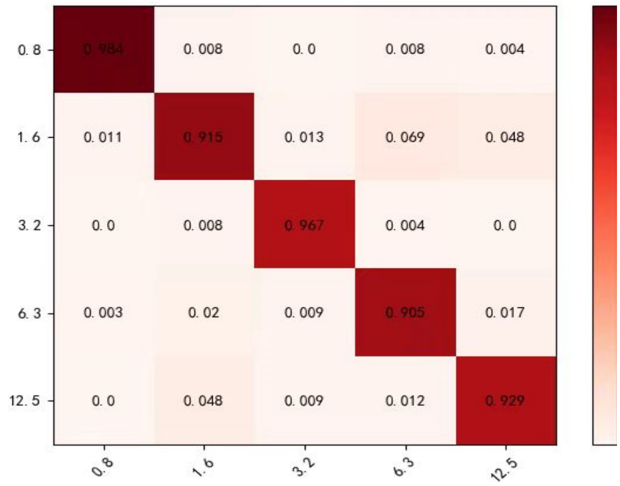

Fig 7. Confusion matrix

6. Test

In order to realize the online measurement of surface roughness, this research has developed a surface roughness detection software. By loading the trained network model, it realizes the grade detection of the input surface image and displays the results. Load the model and randomly enter the picture with a roughness of 1.6 for detection. The detection interface is shown in Figure 8.

Fig 8. Roughness online detection test diagram

7. Conclusion

By adding multi-scale convolution and attention mechanisms, the improved Resnet-18 network has an accuracy rate of 94% on the 5 types of turning surface roughness classification detection data set. The model's parameter size is 1.15M, which can better balance the complexity and classification accuracy of the model. The model can realize the surface roughness value detection of turning parts within a certain range of roughness values, and classify different roughness values. The detection efficiency and identification accuracy are high, which can meet the actual detection needs.

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