Surface Flaw Detection of Industrial Products Based on Convolutional Neural Network

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Surface Flaw Detection of Industrial Products Based on Convolutional Neural Network

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Abstract. Surface flaw detection in industrial products is a typical application of image classification. By improving the structure of Convolutional Neural Network (CNN), for example, the first large-scale convolution kernel is replaced by a cascaded 3×3 convolution kernel; replaces the whole with a 1×1 convolution kernel and Global Average Pooling Connection layer; sets the appropriate batch_size, the convergence rate and convergence accuracy of the model are greatly improved. Experiments show that the proposed method has a classification accuracy of more than 96% in the detection of automotive hose surface flaws.

1. Introduction

Surface flaw detection has traditionally relied primarily on manual visual inspection. Long-term exposure to such monotonous appearance defects can easily cause visual fatigue of quality inspectors, thereby affecting detection efficiency and accuracy. The industrial production line has stable lighting conditions, and the single-line product type is fixed. It is more suitable for automatic detection of product surface flaws online by machine vision. Machine vision-based industrial product inspection system has application cases in textile, communication and other industries. Most of the existing application cases are digital image processing in the space domain. The surface of the product to be inspected is evaluated by comparing with the pre-stored standard product appearance template defect.

Based on the above background, an improved algorithm for surface defect detection based on improved convolutional neural network (CNN) [1] is proposed to improve the accuracy of defect detection. The CNN model is applied to the detection technology with high precision, non-contact and high reliability. It can save a lot of manpower, free people from tedious and repetitive labor, improve enterprise efficiency, ensure product quality and enhance enterprise competitiveness.

2. Method

2.1. Batch size

If the data set is small, it can be in the form of Full Batch Learning. There are at least two advantages to this: First, the direction determined by the full data set can better represent the sample population, thus more accurately towards the direction in which the extreme values are located. Second, because the gradient values of different weights are very different, it is difficult to select a global learning rate.

For larger data sets, the above two benefits have become two disadvantages: First, with the massive growth of data sets and memory limitations, it is becoming less and less feasible to load all the data at

once. Second, iteratively in the Rprop manner, due to the sampling difference between the various Batches, the gradient correction values cancel each other and cannot be corrected.

If the other extreme is used, only one sample is trained at a time, ie batch size = 1. This is Online Learning [2]. The error surface of a linear neuron in the mean square error cost function is a paraboloid with an ellipse in cross section. Using online learning, each correction direction is corrected by the gradient direction of the respective samples, and it is difficult to achieve convergence. As the picture shows:
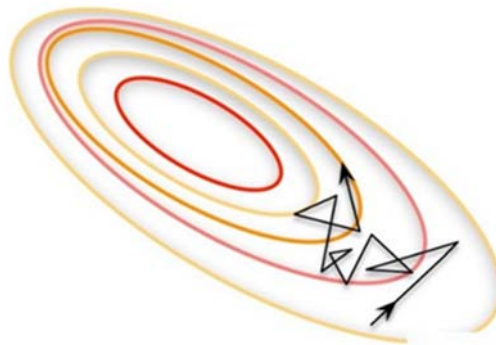

Figure 1. Direction of the gradient with batch size=1

Therefore, how to choose a suitable batch size is a problem that cannot be ignored in the field of deep learning.

2.2. Network structure

Input data uses a 3-color channel, and the original image is pre-processed and adjusted to 299*299 as the input to the network [3]. The initial convolutional layer and the pooled layer have a kernel size of 3*3, which resolves large-scale volume integration into multiple small-scale convolutions to reduce the amount of computation. Next, connect three Inception modules, and output the 2048-dimensional features of size 1*1*2028 through the last pooling layer. Finally, the linear regression of the design and the softmax classifier are used to classify the input images.

2.3. Data set

In this paper, the photo of the same type of hose produced on the same production line of a factory production workshop is taken as the test object, and the photos are collected by the high-definition camera on the production line. Collect photos of the same type of hose that are faulty and sort them by fault type. The classification criteria and the number of pictures are shown in the table below:

Table 1. Data Set Details

Picture type	Amount
Normal pipe photo	1000
Connector failure	1000
Bubble in pipe photo	500
Tin foil	500
Empty photo	1000
Other defects	300

We divided the data set into a training set, a validation set, and a test set at a ratio of 8:1:1[4].

3. Experimental results and analysis

Based on the CNN network structure design model introduced in Chapter 2, the learning rate is 0.001, the number of iterations is 1000, and the batch size is set to 1, 64, 128, and 512 respectively. Verify the set calculation results once [5]. The loss function value Loss of the network cross-validation and the correctness of the calculation result are selected as reference indicators, and the relationship between the number of iterations and the running time is analyzed.

Fig. 2 shows the relationship between Loss and the number of training iterations. It can be seen from the figure that in the initial stage of training, that is, STEP (the number of iterations) is less than 300, since the model parameters are randomly set, the batch size is relatively oscillating regardless of the size; In the middle and later period, when the batch size is small, Loss will have a small oscillation during the training process. For example, the batch size=1, that is, the blue polyline in the figure, the Loss oscillation is obvious when STEP=500 and STEP=800, and the batch size becomes larger as the batch size becomes larger. The fold line tends to be flat in the later stages of training. It indicates that the size of batch size does have an impact on the oscillation of the cross-validation loss function value Loss during model training. The larger the batch size, the smoother the Loss and the better the convergence effect.
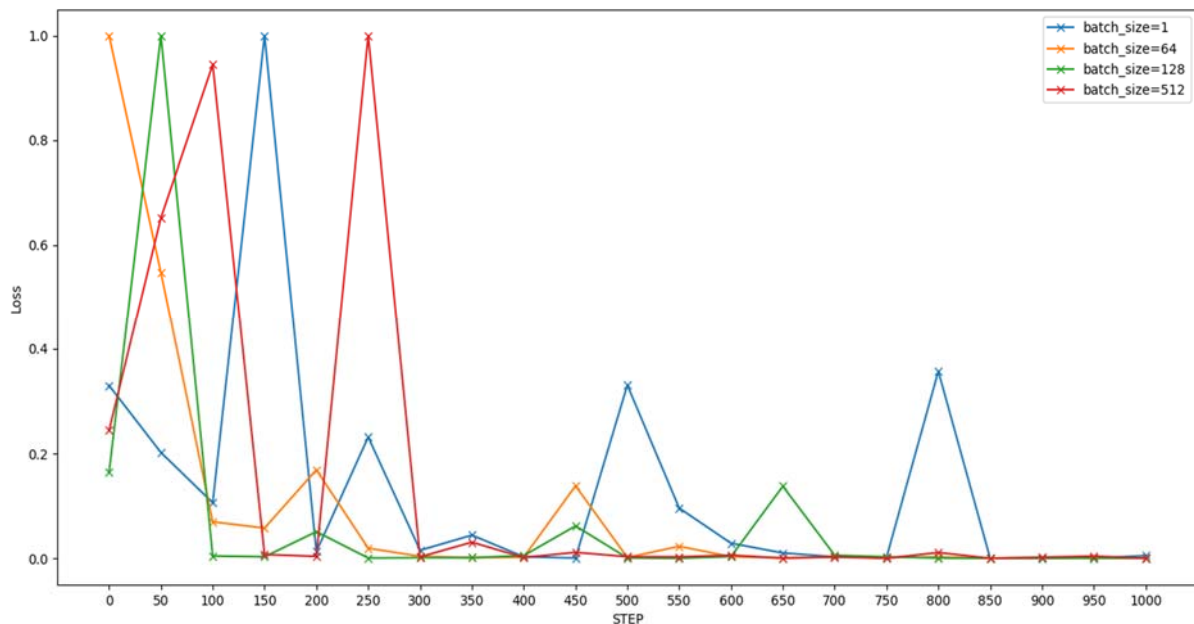

Figure 2. Relationship between Loss and training iterations

Fig. 3 The polyline of the models calculated correct rate as a function of the number of iterations. It can be seen that with different batch size settings, the correct rate will tend to be 100% as the number of iterations increases, but the slope of the correct rate rises differently. The smaller the batch size setting, the lower the slope. As the batch size becomes larger, the correct rate will tend to 100% faster. That is, to achieve the same correct rate, the larger the batch size setting, the iteration required for model training. The smaller the number.
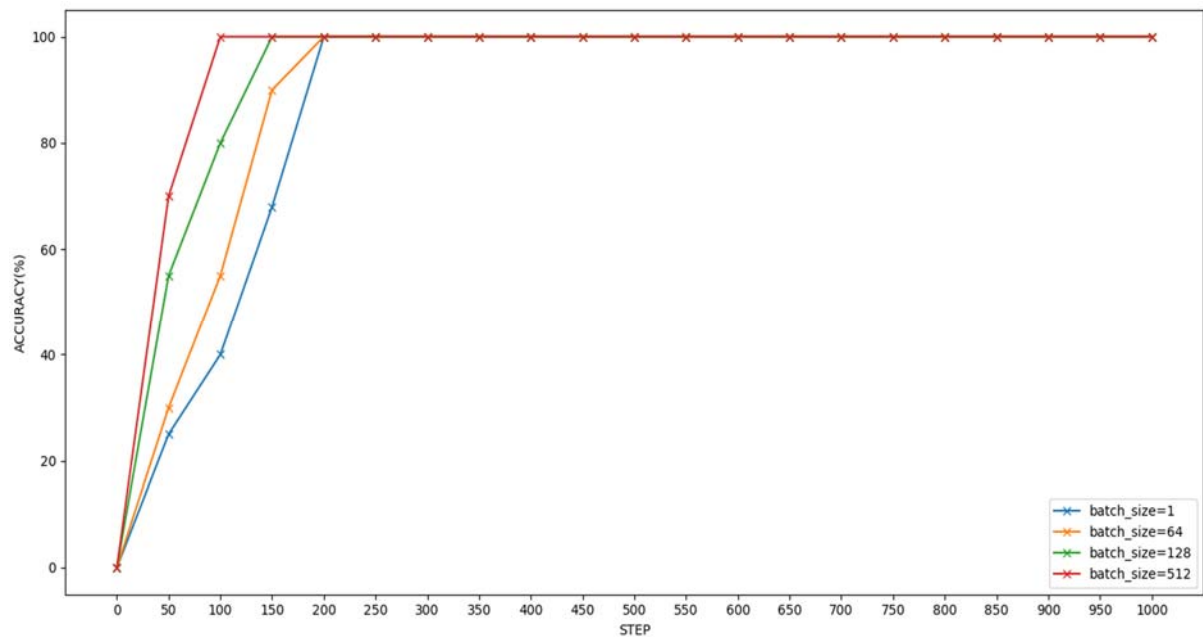
Figure 3. The correct rate varies with the number of training iterations

Fig. 4 reflects the relationship between correct rate and training time. After training for a certain period of time, the correct rate line corresponding to different batch size will eventually tend to 100%, but it will show a difference in the process of increasing the correct rate. First, the slope of the polyline is different. Under the current data set, the smaller the batch size is, the larger the slope is. Secondly, after setting the same number of iterations, the size of batch size significantly affects the training time. The smaller the batch size is, the earlier the training ends. On the contrary, the larger the batch size is, the slower the training is. As shown in the figure, the blue polyline (batch size=1) ends at about TIME=40, and the red polyline (batch size=512) does not end until TIME=120.
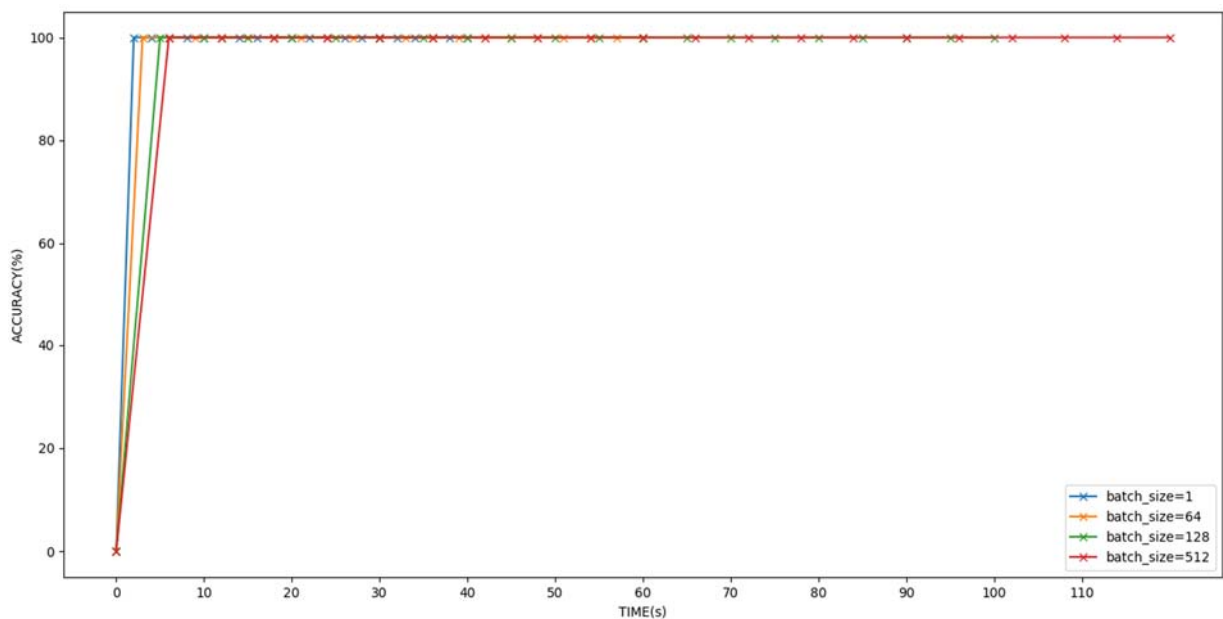

Figure 4. Correct rate changes with training time

Usually, training a model is mainly concerned with two indicators: training speed and model convergence. The above experimental results show that the size of batch size has a great influence on the convergence effect of the model loss function and the length of time for model training. When training the model, the same number of iterations, the larger the batch size setting, the better the model convergence effect, but the longer the training time required; the smaller the batch size is, the faster the training speed will be, but the model convergence effect is not necessarily good. Analyze the distribution law of the data set, find a suitable empirical value through experiment, and then expand the experience, apply the empirical value to a similar data set, make the model training convergence effect, and the training speed is faster. It is an effective method.

4. Conclusion
Product surface flaw detection is a multi-classification problem. In this paper, CNN is applied to flaw detection, and the accuracy rate is close to 100%. Compared with the traditional manual detection method, the efficiency and accuracy of detection are improved, and the labor force is released. In addition, the experiment proposed to find the batch size adapted to the data set, on the basis of ensuring the accuracy of the model training, speed up the training and save the training time.

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