Machine learning method for automatic rating of metal corrosion test specimens

Gen-yong Huang
(Jiangxi Technical College Manufacturing, Nanchang, P.R. China)
584079435@qq.com

Key words: automatic rating; machine learning; crossover entropy; normalization;

Abstract: Combining machine learning normalization and improved weight initialization method with normalized automatic generation initialization method, the iteration period is attenuated, the weight decay will be maintained when the weight is reduced, and the sub-pixel pixel matching between the five-frame deformed fringe pattern is realized by using the mark with certain characteristics, and the phase-shifted deformed fringe pattern is extracted to obtain the truncated phase of the workpiece surface. The deformed fringe pattern obtains the phase of the workpiece surface, obtains the data that accurately reflects the metal corrosion test piece, and realizes the machine learning method for the automatic evaluation of the metal corrosion test sample and the test piece.

Introduction

Machine learning was first proposed in 1998 to train a workstation using state-of-the-art technology to achieve high accuracy. The speed of training means it is a good tool for solving deep learning purposes. At the same time, the high-speed laser grating stripe projection system designed by multi-faceted rotating prism converts the time-modulated precision line laser signal into a high-frame rate, high-brightness, high-density, high-precision precision grating stripe by scanning. Combine more and more powerful computers, train larger network capabilities, and develop powerful normalization techniques to mitigate over-fitting and reflect phase and feature point data of metal corrosion test specimens and test specimens. The field of extremely active research is currently driving the development of automatic rating equipment for metal corrosion test pieces[1].

Stroboscopic stripe projection acquisition system

The laser is used to emit a laser beam, which is laterally focused by a focusing lens, and is diverged in the longitudinal direction by a cylindrical mirror to form a fine line laser. The high-speed rotation of the prism reflects the surface of the object to be measured, and the driving circuit controls and synchronizes. The rotation speed of the motor and the laser are turned on and off, and the exposure time and exposure time of the high-speed camera are controlled to acquire the laser grating stripe image, and the high-speed rotating multi-face prism realizes the spatio-temporal conversion of the modulation signal. In the system, the laser control frequency, duty cycle, lighting off time, motor speed, prism number, working distance parameters determine the mode and characteristics of the projected laser grating stripe, because the time signal is currently engineering. The physical quantity can be precisely controlled. Therefore, the stroboscopic system can instantaneously and accurately control the projection and mode change of the grating stripe, and
perform background and corrosion region segmentation on the metal image to obtain a three-dimensional characteristic of the corrosion pattern which can be quantitatively analyzed.

**Improve the learning method of neural network**

By replacing the quadratic cost function with a cross-cost function, a neuron containing several input variables is trained, and the weights corresponding to $x_1$, $x_2$, ... are $w_1$, $w_2$, ... and offset $b$. The output of a neuron is $a = \delta (z)$, where $z = \sum j W_j X_j + b$ is the weighted sum of the input, and crossover entropy cost function of this neuron is defined as [1,2]:

$$ C = -\frac{1}{n} \sum_i [y \ln a_i + (1 - y) \ln (1 - a_i)] $$

Where, $C$ is the total number of training data, the sum is carried out on all training input $x$, and $y$ is the corresponding target output.

The cross-entropy of a neuron has extended to many multilayer neural network neurons, assumed that $y = y_1, y_2, ...$ is the output target neuron, and $a_1, a_2, ...$ actual output values that define cross-entropy as follows

$$ C = -\frac{1}{n} \sum_i [y_i \ln a_i^j + (1 - y_i) \ln (1 - a_i^j)] $$

Then, a cost function that does not include $\delta (z)$ is selected. For a training sample $x_i$, its cost $C = C_{x_i}$ satisfies:

$$ \frac{\partial C}{\partial w_j} = x_i (a - y) \frac{\partial C}{\partial a} = (a - y) $$

To solve the problem of decreased learning speed, the greater the cost function selected initial error, Neuron faster, derived from the cross entropy with the chain rule:

$$ \frac{\partial C}{\partial b} = \frac{\partial C}{\partial a} \sigma (z) $$

Using $\delta \cdot (z) = \delta (z)(1 - \delta (z)) = a(1 - a)$, the last equation becomes:

$$ \frac{\partial C}{\partial a} = \frac{a - y}{a(1 - a)} $$

To integrate this equation with $a$, get:

$$ C = -[y \ln a + (1 - y) \ln (1 - a)] + \text{constant} $$

In which constant is an integral constant. This is a single training sample's contribution to the cost function. In order to obtain the overall cost function, it is necessary to average all of the training samples.

$$ C = \frac{1}{n} \sum_i [y \ln a_i + (1 - y) \ln (1 - a_i)] + \text{constant} $$

The constant here is the average of all the individual constants, so the equation uniquely determines the form of the cross, and adds a constant term that yields the result in a natural and simple way. Meanwhile, the application of the flexible definition of a maximum of a new kind of neural network output layer, and $S$ layer, the calculated weighted input $z_i^j = \sum l W_i l a_i l + b_i$, in this application called a flexible layer on a maximum function $Z_{jl}$. According to this function, the activation value of the $j$th neuron is:

$$ a_j^i = \frac{\sum e^{z_j}}{\sum_j e^{z_j}} $$

Among them, the denominator is the sum of all the output neurons.
Increasing the number of training samples and reducing the size of the network is a way to reduce over-fitting. Large networks have a greater potential than small networks, and use a standardized technique with only a fixed network and a fixed training set to mitigate over-fitting. Attenuation while applying weight (weight decay) or a normalized L2 adding an additional term to the cost function item, normalized cross entropy is:

\[ C = -\frac{1}{n} \sum_{i=1}^{n} \left[ y_i \ln a_i^y + (1-y_i) \ln(1-a_i^y) \right] + \frac{\lambda}{2n} \sum w^2 \]

Wherein the first item is the expression of a routine cross-entropy, the second square and all weights added now and then using a factor \( \frac{\delta}{n^2} \). A quantization adjustment is made, where \( \lambda > 0 \) is called a normalization parameter and \( n \) is the size of the training set.

In stochastic gradient descent not normalized by an average of \( n \) samples of small quantities of training data to estimate \( \frac{\partial C}{\partial w} \). Therefore, the normalized learning rules for stochastic gradient descent become equations:

\[ w \rightarrow w - \frac{\eta \lambda}{n} w - \frac{\eta}{m} \sum \frac{\partial C}{\partial w} \]

The latter term is performed on the small batch data \( x \) of the training samples, and \( C_x \) is the unnormalized cost of each training sample. This is actually the same as the usual rule for random gradient descent, except that there is a factor of \( 1-h\lambda/n \) with a weight reduction, in order to be consistent with the previous denormalization case, the normalized learning rule of the bias is given completely:

\[ b \rightarrow b - \frac{\eta}{n} \sum \frac{\partial C}{\partial b} \]

This is also the sum on the small batch data \( x \) of the training sample.

**Experiment and result analysis**

In order to collect the metal corrosion test sample and the test piece image, a sinusoidal grating is generated by computer programming, projected onto the surface of the workpiece on the assembly line, the measurement grating is sent equidistantly, and the CCD is controlled to acquire the deformed stripe, which is collected by the image acquisition card to the computer. Inside, the test piece is in-line detected, the first frame deformed fringe pattern is collected by the measuring grating, and the third frame deformed fringe pattern is collected by the measuring grating, and the pixels are matched, and the third frame pixel is mapped to the first The deformed fringe pattern after 1 frame of pixel coordinates can be used to perform pixel matching and coordinate mapping on the 2, 4, and 5 frame deformed stripes by the same method, and a phase shift deformed fringe pattern in which 5 frames of pixels and object points are completely matched can be obtained. The three-dimensional shape of the specimen reconstructed after phase unwrapping and height mapping. Extend training data through a number of small rotations on all machine learning training samples, using a network of 800 feed forward neurons with a learning rate of \( \eta = 0.5 \) and a normalized parameter of \( \lambda = 5.0 \), training 30 on all training data sets. During the iteration period, the image recognition accuracy rate reached 90.9%. Of course, in the later stages of training, the learning process is close to saturation. If the logarithm is used as the abscissa, the result is shown in Figure 1. Then, the experiment is performed on the data of "elastic distortion", through this special metal. The image distortion method of corrosion state and environmental parameter information finally
achieves 96.3% recognition accuracy. The application demonstrates all types of training data to extend the network experience, which is more conducive to the formation of rating strategy and improve system stability[2].

![Classification Accuracy Graph]

**figure 1** classification accuracy in the later period of training

**Acknowledgements**

2016 Jiangxi Provincial Department of Education Science and Technology Project "metal corrosion test sample and specimen automatic rating system development (GJJ151487)"

2017 Research on Teaching Reform of Higher Education Institutions in Jiangxi Province "Research on Project-Driven Teaching Model - Reform and Practice of Robocup Competition Course in Higher Vocational Colleges(JXJG-17-74-3)"

**Reference**:
