Fault diagnosis of spraying workshop based on BP neural network

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Abstract. In this paper, for the failure of spraying workshop door switch, exhaust fan failure and other faults in the spraying workshop, a fault diagnosis algorithm based on the BP (Back Propagation) neural network is proposed to solve the fault diagnosis problem in the spraying workshop. First, the sensor network of the spraying workshop was built. Multi-source sensors were used to realize the dynamic perception of the on-site environment and equipment status. Through the preprocessing of multi-source heterogeneous data, a unified data template and interface were established. Secondly, the BP neural network algorithm is used to simulate and diagnose the possible faults in the spraying process. Finally, MATLAB test simulation proves its high accuracy of fault diagnosis.

Keyword. BP (Back Propagation) neural network; Fault diagnosis; Spraying workshop.

1. Introduction

The research of artificial neural network began in the 1940s and has been widely used. Artificial neural network has good self-organization, self-adaptability, self-learning ability and fault tolerance. It has the advantages of distributed storage of information and large-scale parallel processing of data. It is widely used in fault diagnosis, information processing, image processing and other fields. Become a research hotspot in the current artificial intelligence academic field [1-5]. The original neural network was a single-layer perceptual network, which could not deal with nonlinear problems. However, the actual problems in the spraying process were complex nonlinear problems, which limited the scope of application of neural networks. In the mid-1980s, David Runelhart and others solved the problem of learning the connection weights of the hidden layers of multi-layer neural networks. People call this multi-layer feedforward network for error correction as a BP neural network [6, 7]. BP neural network has strong nonlinear mapping ability and flexible network structure, and has a wide range of applications in fault diagnosis, function approximation, image recognition, etc. [8]. Therefore, when equipment failures occur in the spraying workshop, we use the method based on BP neural network to diagnose equipment failures, so as to guide the operators to make the next adjustments and finally solve the failure problems [9].
2. Principle and characteristics of BP neural network

BP neural network consists of input layer, hidden layer and output layer, which includes the forward propagation of signal and the backward propagation of error [10, 11]. Firstly, in the forward propagation, the input signal passes through the input layer and the hidden layer in turn. Through nonlinear transformation, it acts on the output layer and generates the output signal. If there is a big difference between the actual output signal and the expected output signal, it enters the backward propagation process of error. The back propagation of error is to propagate the error of the output signal through the hidden layer to the input layer, and distribute the error to all units of the neural network in each layer. The neural network in each layer is based on the obtained error, so as to adjust the weight of each layer. By adjusting the connection strength and threshold between the hidden layer node and the output layer node, the hidden layer node and the input layer node, the error decreases along the gradient direction. After repeated learning, the weights and thresholds corresponding to the minimum error are determined, and the training can be stopped [12]. Figure 1 shows the topology of a typical three-layer BP network.

![Figure 1. Topological structure of three-layer BP network.](image)

Now take the three-layer BP network shown in Figure 1 as an example to carry out algorithm derivation [13, 14]. It can be seen from Figure 1 that the structure of BP neural network includes the input layer, one or more hidden layers and the output layer. The nodes in the layer are connected with each other, and the nodes in the same layer are not connected with each other. For the input signal, it is necessary to propagate forward to the hidden layer node, and then the output signal of the hidden layer node is transmitted to the output layer after the activation function. The BP network learning process is shown in Figure 2.

![Figure 2. BP network learning flowchart.](image)
Compared with the feedback network, the feedforward network does not have feedback in the training process. The neurons are directly connected to the next layer from the upper layer, and the signal is unidirectionally transmitted from the input layer to the output layer. Its advantages are: simple structure, low requirements for programmers and strong learning ability; through the nonlinear transfer function, it can approximate any nonlinear function with any accuracy, and can obtain strong nonlinear processing ability through the combination of simple nonlinear processing units. This static nonlinear mapping is a very important performance. Because of the middle layer structure, the feedforward network can obtain higher-order statistical ability, especially when the input data is large, the ability of the network to obtain higher-order statistical performance is reflected. BP algorithm is particularly suitable for this feedforward network, and mature development, widely used.

A single node in a BP neural network is called a perceptron. The composition of a single node is shown in Figure 3. It is introduced by Frank Rosenblatt, including input term, bias, weight, activation function, and output.

\[ \sum W_i X_i + b \]

Figure 3. The composition of a single node.

Input node: X1, X2, X3, weight: W1, W2, W3, bias: b, output node: output, activation function: f

The activation function is generally Sigmoid function, which is a common S-shaped growth curve in biology. In information science, it is used as the activation function of neural network to map variables to 0-1. Confirmation of node number in input layer, hidden layer and output layer:

\[ e = \sqrt{m + n + a} \] (1)

Among them, e is the number of hidden layer nodes, n is the number of output layer nodes, m is the number of input layer nodes, a is the adjustment constant between 1-10. When there is only one hidden layer, such BP neural network belongs to the traditional shallow neural network; When there are multiple hidden layers, such BP neural network belongs to deep learning BP neural network.

3. Sensor network construction

Hardware composition and layout of the control system in spraying workshop are shown in Figure 4. With the use of automatic spraying field sensors such as pose code discs, industrial cameras, thermometer/hygrometer/concentration meters, and proximity switches, the data can enter into the data acquisition PLC through different data interfaces for rapid pretreatment and structured coding. In case of security problems, users can handle the data remotely. The control signal is transmitted to the equipment control PLC through fiber and switches, and then sent to each piece of field actuating equipment. Finally, safe treatment can be executed according to the control instructions. The picture of the spraying workshop is shown in Figure 5. The physical layout of the sensors and equipment at the spraying site is shown in Figure 6. The sensor selection, deployment, function and output signal are shown in Table 1.

To address the inconsistent output signal formats of the camera, rangefinder, encoder, temperature-hygrometer, concentration meter and other multi sensors, different data acquisition interfaces are adopted to realize the real-time acquisition of the perception signals for the operation process and operation status of the painting equipment and the on-site environment. In addition, different signal
formats are digitized in real time to acquire real-time digital signals. Then, a unified interface data template is adopted to realize the unified expression and transmission of the collected data.

**Figure 4.** Hardware composition and layout of spraying workshop control system.

**Figure 5.** Internal structure of spraying workshop.

**Figure 6.** The physical layout of sensors and equipment at the spraying site.
Table 1. Sensor selection, deployment, function and output signal form.

| Label | Sensor name      | Deployment location                                                                 | Monitoring content                                                                                                                                                                                                 | Output signal          | Quantity |
|-------|------------------|--------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|------------------------|----------|
| 1     | Pose encoder     | Arranged on the drive motor shaft of the workpiece self-rotating mechanism and the reciprocating machine. Arranged on the inner wall of the spray booth, the specific position can be adjusted according to the key monitoring equipment to ensure that there is no dead corner for monitoring | Monitor parameters such as workpiece rotation angle, speed and acceleration.                                                                                                                                                  | High-speed pulse signal | 2        |
| 2     | Industrial camera| Deployed inside the spray booth, 0.3m above the ground.                                | Monitor the working status of various equipment, environment, resources and workpieces in the loading and unloading area and spray booth.                                                                                     | Video data             | 4        |
| 3     | Industrial thermometer | Deployed on the north wall inside the spray booth, 0.3m above the ground Deployed on the north wall inside the spray booth, 0.3m away from the ground | Monitor the temperature of the spray booth.                                                                                                                                                                                  | ASCII code data        | 1        |
| 4     | Industrial hygrometer | Deployed inside the spray booth, 0.3m away from the ground | Monitor the humidity in the spray booth.                                                                                                                                                                                  | ASCII code data        | 1        |
| 5     | Concentration meter | Deployed on the north wall inside the spray booth, 0.3m above the ground | Monitor VOC concentration in spray booth.                                                                                                                                                                                  | Analog voltage signal  | 1        |
| 6     | Laser rangefinder | Deploy on the carrier frame                                                          | Monitor the position of the vehicle and track status.                                                                                                                                                                    | Analog voltage signal  | 1        |
| 7     | Proximity switch | Arranged above and below the spray booth door                                            | Monitor the closing of the spray booth door.                                                                                                                                                                               | Switch signal          | 2        |
| 8     | Infrared detectors | Arrange at the front and rear of the carrier                                          | Detect whether there are obstacles in the direction of travel of the carrier vehicle.                                                                                                                                     | Switch signal          | 8        |

4. Fault diagnosis based on BP neural network

Since the BP neural network has the characteristics of good memory, fast convergence and strong stability, the BP neural network is applied to the fault diagnosis of automatic painting process in this paper. The fault in the automatic spraying process can be diagnosed by a total of seven fault parameters, including exhaust fan stop warning lights(X1), spray gun pressure(X2), spray gun flow(X3), laser ranging(X4), spray room temperature(X5), spray room humidity(X6) and spray room concentration (X7). The parameters of the automatic spraying process are feature extracted to form a feature vector composed of seven parameters. After fuzzy processing, the quantitative fuzzy feature vector is obtained to form the input sample information.

Through the analysis of the automatic spraying process, four fault modes are summarized, including equipment suddenly stopped running(S1), spray atomization unsatisfactory(S2), carrier vehicle overrunning(S3), temperature / humidity / concentration anomaly (S4). In order to ensure the accuracy of diagnosis, four cases of each fault mode are selected for training. Sixteen sets of fault data as shown
in table 2 are used to form a simulation sample library. These seven performance parameters are taken for the input layer and the fault form for the output layer. The corresponding relationship between the fault form and the output mode is shown in Table 3. 0.9 on the diagonal of the output mode corresponds to different fault modes.

Table 2. Failure samples after fuzzy processing.

| X1 (0/1) | X2 | X3 | X4/mm | X5/℃ | X6% | X7% | Class |
|----------|----|----|-------|------|-----|-----|-------|
| Fault1   | 0  | 0.02 | 0.04 | 0.5  | 35  | 80  | 35    | S1    |
| Fault2   | 0  | 0.04 | 0.03 | 5    | 40  | 40  | 45    | S1    |
| Fault3   | 0  | 0.05 | 0.05 | 1    | 20  | 20  | 50    | S1    |
| Fault4   | 0  | 0.08 | 0.01 | 0    | 18  | 35  | 66    | S1    |
| Fault5   | 0  | 0.2  | 0.3  | 7    | 27  | 35  | 15    | S2    |
| Fault6   | 0  | 0.3  | 0.05 | 6    | 25  | 70  | 20    | S2    |
| Fault7   | 0  | 0.06 | 0.5  | 5.5  | 18  | 54  | 24    | S2    |
| Fault8   | 0  | 0.4  | 0.35 | 4.5  | 19  | 60  | 12    | S2    |
| Fault9   | 0  | 0.04 | 0.42 | 12   | 29  | 58  | 16    | S3    |
| Fault10  | 0  | 0.02 | 0.045 | 10.5 | 27  | 47  | 17    | S3    |
| Fault11  | 0  | 0.04 | 0.034 | 15   | 22  | 39  | 12    | S3    |
| Fault12  | 0  | 0.06 | 0.047 | 17   | 18  | 56  | 11    | S3    |
| Fault13  | 1  | 0.06 | 0.015 | 3.5  | 17  | 59  | 15    | S4    |
| Fault14  | 1  | 0.05 | 0.034 | 2    | 25  | 63  | 20    | S4    |
| Fault15  | 1  | 0.03 | 0.04 | 1.5  | 20  | 66  | 12    | S4    |
| Fault16  | 1  | 0.02 | 0.015 | 5.5  | 15  | 72  | 17    | S4    |

Normal value of equipment

| Y1 | Y2 | Y3 | Y4 | Class |
|----|----|----|----|-------|
| Fault1 | 0.9 | 0.1 | 0.1 | 0.1 | S1    |
| Fault2 | 0.1 | 0.9 | 0.1 | 0.1 | S2    |
| Fault3 | 0.1 | 0.1 | 0.9 | 0.1 | S3    |
| Fault4 | 0.1 | 0.1 | 0.1 | 0.9 | S4    |

In order to verify the practicability of the BP neural network, the actual fault data is used for testing. Select 7 parameters: X1=0, X2=0.35, X3=3.45, X4=5mm, X5=23℃, X6=50%, X7=15%. The diagnosis result is: (0.1008, 0.8996, 0.1007, 0.1017). The second number is 0.8996, the diagnosis result is the second type of fault, and the spray paint atomization is not ideal. The actual measurement result is that the thickness of the spray paint layer is too large, and the diagnosis result is consistent with the actual measurement result. It can be seen from Figure 7 and Table 4 that the results of these 16 fault identifications are completely consistent with the manual diagnosis results of the experts on site. It can be seen that the correct rate of fault diagnosis based on BP neural network is 100%, which shows that the use of BP neural network for fault diagnosis is indeed efficient and practical.
Figure 7. Comparison of test results and prediction results.

Table 4. BP neural network fault diagnosis results.

| Test patterns | Y1     | Y2     | Y3     | Y4     | Class |
|---------------|--------|--------|--------|--------|-------|
| Fault1        | 0.8993 | 0.1218 | 0.0761 | 0.1090 | S1    |
| Fault2        | 0.9323 | 0.0962 | 0.0793 | 0.1034 | S1    |
| Fault3        | 1.1317 | -0.2450| 0.2867 | -0.4600| S1    |
| Fault4        | 0.6594 | 0.1704 | 0.4934 | -0.2663| S1    |
| Fault5        | 0.1038 | 0.9225 | 0.0960 | 0.0860 | S2    |
| Fault6        | 0.0887 | 0.9190 | 0.0887 | 0.0991 | S2    |
| Fault7        | 0.1230 | 0.8846 | 0.1256 | 0.0844 | S2    |
| Fault8        | 0.1006 | 0.9294 | 0.0746 | 0.0917 | S2    |
| Fault9        | 0.0777 | 0.1275 | 0.9392 | 0.0830 | S3    |
| Fault10       | 0.0771 | 0.1132 | 0.9744 | 0.0708 | S3    |
| Fault11       | 0.0226 | 0.0741 | 0.9076 | 0.0909 | S3    |
| Fault12       | 0.1213 | 0.0751 | 0.9127 | 0.0752 | S3    |
| Fault13       | 0.1156 | 0.0828 | 0.1694 | 0.9226 | S4    |
| Fault14       | -0.0073| 0.0562 | 0.1956 | 0.9414 | S4    |
| Fault15       | 0.1191 | 0.0924 | 0.1443 | 0.9294 | S4    |
| Fault16       | 0.1375 | 0.0353 | 0.2384 | 0.9277 | S4    |
5. Conclusion
In this paper, first analyze the historical background of the formation of BP neural network, explain the necessity and importance of the formation of the network, and then briefly introduce the principles and characteristics of the BP neural network, including the composition of the network and how the network is run and process data, and confirm the number of nodes in the input layer, hidden layer, and output layer. Then, a case study was carried out, and 7 fault signs and 4 fault types were determined. In addition, in order to ensure the accuracy of diagnosis, two cases of each failure mode are selected for training, and the actual Y value is obtained according to the X parameter and compared with the expected Y value. It is found that the expected Y value is highly correlated with the actual Y value within a certain range. Finally, it is concluded that BP neural network has a good application prospect in the fault diagnosis of spraying process.

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