APPLICATION OF MODIFIED BP NN IN AIRCRAFT ENGINE FAULTS DIAGNOSIS

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Abstract

BP algorithm has faults of low convergence rate and running into local minima easily. In this paper, a modified BP algorithm named MBP is proposed. MBP brings random noises into BP. Random noises make NN not stabilized in local minima point and go into global minima point finally. In global minima point, effect of random noises will be weakened, and the network will go on converging. And random noises in MBP increase convergence rate of NN, which decrease learning time of network greatly. MBP adopts staggered learning method, which make NN reach very high precision in a very short time. From what mentioned above we can see that MBP has advantages of high convergence rate, high precision and making easily. So MBP has a wide application perspective.

This paper also gives out an example of the application of MBP, in which we apply it in an aircraft engine faults diagnosis system. In civil aviation, aircraft engine faults diagnosis needs abundant experiences, which only experts have. But training an expert needs so long a time that amount of experts can not meet the demand of civil aviation. Aircraft engine faults diagnosis system, which makes use of learning and association abilities of NN and uses NN to learn experiences of aircraft engine faults diagnosis experts, can help aircraft engine maintenance personnel in aircraft engine faults diagnosis. And experiments have verified its usability. In this example, we compare the performance of MBP and BP. The result verifies the advantage and usability of MBP.

1 Introduction

BP NN is a kind of mature artificial neural network, which is widely used in many areas. BP NN is a kind of multilayered network. By learning teacher information, BP NN can remember the information in the form of weights and thresholds. BP NN has the ability of association. That is if a NN is trained by teacher information that is enough to describe the property of the system, when the input data is not teacher input data, we can get the output desired.

Learning of BP NN is divided into two courses. One is forward propagation, the other is backward propagation. Forward propagation uses forward calculation algorithm to calculate output data from input data. Backward propagation uses the difference between actual output data and teacher output data to adjust weights and thresholds in the network, the aim of which is to reduce the difference between actual output data and teacher output data. The algorithm of backward propagation is gradient decent algorithm, which has faults of low convergence rate and going into local minima easily. In backward propagation algorithm, the modification of weights relies on one rank derivative of error function. When there are many local minima points in the answer space, if initial values of weights are not proper, the network will run into local minima and can not get out. And when the output of a nerve cell is close to saturation area, the output of the nerve cell will be inactive to the modification of weights, which will reduce convergence rate of network greatly. This article will put forward a modified BP algorithm named MBP algorithm, which can make NN go into global minima point and increase its convergence rate.

2 MBP Algorithm

In back propagation algorithm, when there are local minima points in the answer space, if the initial values of weights are not proper, the modification of weights and thresholds will run into local minima. At this time, the error between teacher output data and actual output data is still high, but modifications of weights and thresholds by some teacher data that make error lower will be changed by other teacher data, which makes error higher, so the network can not get out from the local minima. And when output of a nerve cell is close to the saturation area, output of the nerve cell will be inactive to the modification of weights, which will decrease the convergence rate of the network greatly. We can overcome the faults mentioned above by adding random noises into back propagation algorithm.

Let's take 3 layers MBP NN for example. 3 layers MBP NN includes one input layer, one invisible layer and one output layer. Its structure is shown in figure 1.

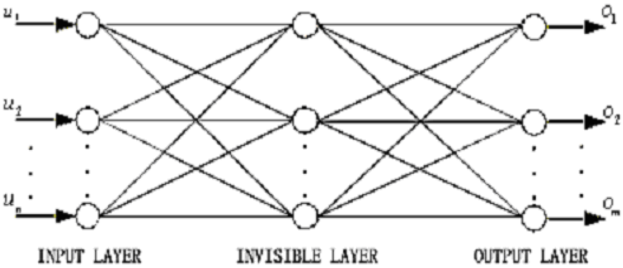

Fig.1 structure of 3 layers MBP NN

Input data is u_i ($i \in \{1,2\cdots,n\}$, n is amount of nerve cells of input layer), output data of invisible layer is y_j ($j \in \{1,2\cdots,l\}$, l is amount of nerve cells of invisible layer), output data of output layer is o_k ($k \in \{1,2\cdots,m\}$, m is amount of nerve cells of output layer), W_{ij} is weight between No. i nerve cell of input layer and No. j nerve cell of invisible layer, W_{jk} is weight between No. j nerve cell of invisible layer and No. k nerve cell of output layer, θ_j is threshold of No. j nerve cell of invisible layer and θ_k is threshold of No. k nerve cell of output layer.

Let's take sigmoid function as the conversion function of nerve cell, its formula is :

$$f(x) = \frac{1}{1+\exp(-r_0 x)} \qquad (2.1)$$

Error function is double multiplication error function:

$$E = \frac{1}{2}\sum_{k=1}^{m}(T_k - o_k)^2 \qquad (2.2)$$

Formulas of forward propagation are:

$$y_j = f(\sum_{i=1}^{n} W_{ij}u_i - \theta_j) \quad j \in \{1,2\cdots,l\} \qquad (2.3)$$

$$o_k = f(\sum_{j=1}^{l} W_{jk}y_j - \theta_k) \quad k \in \{1,2\cdots,m\} \qquad (2.4)$$

Formulas of modified backward propagation are:

$$\delta_k = (T_k - o_k)o_k(1-o_k)r_0 \quad k \in \{1,2\cdots,m\} \qquad (2.5)$$

$$\delta_j = y_j(1-y_j)r_0\sum_{k=1}^{m}\delta_k W_{jk} \quad j \in \{1,2\cdots,l\} \qquad (2.6)$$

$$W_{jk}(t+1) = W_{jk}(t) + \alpha\delta_k(y_j + \xi(t+1)) \quad \xi(t+1) \in [0,0.8] \qquad (2.7)$$

$$\theta_k(t+1) = \theta_k(t) - \beta\delta_k\eta(t+1) \quad \eta(t+1) \in [0,0.8] \qquad (2.8)$$

$$W_{ij}(t+1) = W_{ij}(t) + \alpha\delta_j(u_i + \zeta(t+1)) \quad \zeta(t+1) \in [0,0.8] \qquad (2.9)$$

$$\theta_j(t+1) = \theta_j(t) - \beta\delta_j\psi(t+1) \quad \psi(t+1) \in [0,0.8] \qquad (3.0)$$

In functions above, $\xi(t+1), \eta(t+1), \zeta(t+1)$ and $\psi(t+1)$ are random noises. They are positive real number that are not larger than 0.8.

As to modification of weight, random noise has two functions. Firstly, it can magnify the modification value of weight, which will make modification of weight faster, and then increase convergence rate of the network. Even when output of some a nerve cell is in saturation area, if only there is high error between the output data and teacher output data, the random noise will make the nerve cell active to modification of weight value. Secondly, it will increase randomicity of modification of weight, which can help the network get out from local minima point.

As to modification of threshold. Multiplying the modification value of threshold by a positive real number that lower than 1 has two functions too. Firstly, it can reduce the rate of modification of threshold. From formula (2.3) and (2.4) we can see, it will increase the change value of the output, which will increase the rate of modification of the network. Secondly, it can increase the randomicity of the modification of the network, then will do good to getting out from local minima point.

But random noise will strengthen the surge of parameters of NN, which will possibly make NN jump out from global minima. So MBP adopts staggered learning method. At start time, we use random noise in learning of NN, which can make NN get out from local minima point and go into global minima region. When error of network is smaller than some a value that can be called sign value, the network is thought to be in its global minima region already. That is to say that the NN has found its gradient decent direction. Random noise is gotten rid of, which can reduce the surge of network and the network goes on converging to its global minima point. Staggered learning method can make NN reach very high precision in a short time.

The steps of learning of MBP NN is:

1. Initialize parameters of NN ;
2. Set values to $r0$, α , β and sign value;
3. Learn teacher information using MBP algorithm ;
4. If error is small enough then stop learning and save NN parameters. Else if error is smaller than sign value then get rid of random noise, and go to step 3. Else if error is higher than sign value then add random noise to NN and go to step 3.

3 Using MBP NN in Aircraft Engine Faults Diagnosis System[1]

Aircraft engine faults diagnosis is one of the important works of maintenance of aircraft in civil aviation. Aircraft engine faults diagnosis needs a lot of experiences, which only experts have. Training an aircraft engine faults diagnosis expert needs so long a time that amount of experts can not meet the demand of civil aviation. Artificial neural network has abilities of learning and association, so we can use it to learn experiences of experts and help aircraft engine maintenance personnel in aircraft engine faults diagnosis. Aircraft engine faults diagnosis system is just based on the principle mentioned above and BP NN is used in it. Experiments have verified its usability.

Aircraft engine faults diagnosis system uses fault phenomenon of aircraft engine as input data. The system adopts four aircraft status monitoring data as its input data. They are rotate speed of low pressure compressor (NL), rotate speed of high pressure compressor (NH), temperature of exhaust (EGT) and the flux of fuel (FF). Its output data is twelve kinds of fault pattern.

Now let's use a group of samples of aircraft engine fault diagnosis system to compare the performance of MBP algorithm with that of BP algorithm. There are 12 samples in the group of samples. A 3 layers NN is used. It has 4 input nerve cells, 16 invisible nerve cells and 12 output nerve cells. Let $r0 = 0.45$, $\alpha = 0.3$, $\beta = 0.8$ and sign value=0.2. Let target average error of 12 samples be 0.00005. That is the whole error is 0.0006. The error change curve of MBP is shown in figure 2:

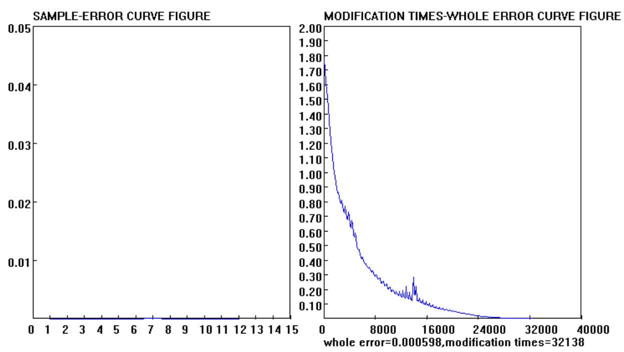

Fig. 2 Error change curve of MBP NN when target whole error is 0.0006

The modification times of MBP NN is 32138.

The error change curve of BP NN when modification times is 100000 is shown in figure 3:

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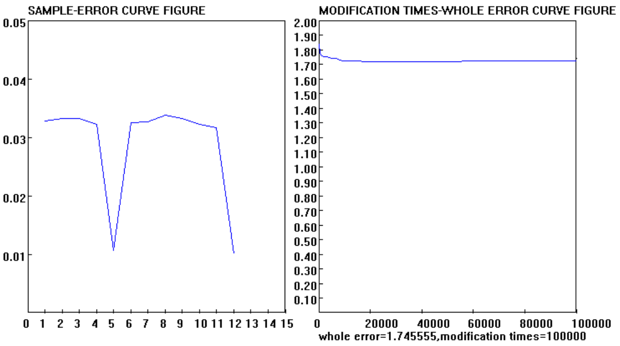

Fig. 3 Error change curve of BP NN when modification times is 100000

After 100000 times modification, whole error of BP NN can merely reach 1.745555.

So we can see that performance of MBP algorithm is much better than BP algorithm. MBP has advantages of high precision and high convergence rate.

Let input data be teacher input data, the table below shows the comparison between teacher output data and actual output data that are calculated by using trained MBP NN whose target average error is 0.00005:

Table 1 Comparison between teacher output data and actual output data

1	Teacher output	0.800 0.200 0.200 0.200 0.200 0.200 0.200 0.200 0.200 0.200 0.200 0.200
	Actual output	0.795 0.206 0.197 0.200 0.200 0.200 0.197 0.189 0.208 0.200 0.200 0.200
2	Teacher output	0.200 0.800 0.200 0.200 0.200 0.200 0.200 0.200 0.200 0.200 0.200 0.200
	Actual output	0.200 0.802 0.204 0.201 0.199 0.200 0.212 0.195 0.201 0.200 0.200 0.200
3	Teacher output	0.200 0.200 0.800 0.200 0.200 0.200 0.200 0.200 0.200 0.200 0.200 0.200
	Actual output	0.200 0.202 0.796 0.199 0.200 0.200 0.192 0.201 0.201 0.200 0.200 0.200
4	Teacher output	0.200 0.200 0.200 0.800 0.200 0.200 0.200 0.200 0.200 0.200 0.200 0.200
	Actual output	0.200 0.200 0.199 0.799 0.200 0.200 0.198 0.197 0.203 0.200 0.201 0.200
5	Teacher output	0.200 0.200 0.200 0.200 0.800 0.200 0.200 0.200 0.200 0.200 0.200 0.200
	Actual output	0.200 0.206 0.194 0.199 0.800 0.200 0.201 0.189 0.209 0.200 0.202 0.200
6	Teacher output	0.200 0.200 0.200 0.200 0.200 0.800 0.200 0.200 0.200 0.200 0.200 0.200
	Actual output	0.200 0.200 0.200 0.200 0.200 0.800 0.200 0.199 0.201 0.200 0.200 0.200
7	Teacher output	0.200 0.200 0.200 0.200 0.200 0.200 0.800 0.200 0.200 0.200 0.200 0.200
	Actual output	0.199 0.200 0.198 0.199 0.200 0.200 0.794 0.188 0.208 0.200 0.200 0.200
8	Teacher output	0.200 0.200 0.200 0.200 0.200 0.200 0.200 0.800 0.200 0.200 0.200 0.200
	Actual output	0.200 0.201 0.200 0.200 0.200 0.200 0.201 0.796 0.204 0.200 0.200 0.200
9	Teacher output	0.200 0.200 0.200 0.200 0.200 0.200 0.200 0.200 0.800 0.200 0.200 0.200
	Actual output	0.200 0.199 0.202 0.200 0.200 0.200 0.203 0.200 0.799 0.200 0.200 0.200
10	Teacher output	0.200 0.200 0.200 0.200 0.200 0.200 0.200 0.200 0.200 0.800 0.200 0.200
	Actual output	0.200 0.200 0.200 0.200 0.200 0.200 0.201 0.199 0.200 0.800 0.200 0.200
11	Teacher output	0.200 0.200 0.200 0.200 0.200 0.200 0.200 0.200 0.200 0.200 0.800 0.200
	Actual output	0.200 0.203 0.198 0.199 0.200 0.200 0.204 0.199 0.200 0.200 0.801 0.200
12	Teacher output	0.200 0.200 0.200 0.200 0.200 0.200 0.200 0.200 0.200 0.200 0.200 0.800
	Actual output	0.200 0.200 0.200 0.200 0.200 0.200 0.199 0.200 0.201 0.200 0.200 0.800

In actual application, aircraft engine faults diagnosis system uses NN to get diagnosis data and calculates probability of every fault that is identified. And outputs diagnosis result based on the probability at last. Through using in actual aircraft engine faults diagnosis, the correction ratio of aircraft engine faults diagnosis system is 92%. The table below lists part of the actual diagnosis results.

Table 2 Diagnosis result of aircraft engine faults

1	Engine Model	JT9D-7R4G2
	Input Data	NL=0.200 NH=0.200 EGT=3.000 FF=0.400
	Output Data	0.246 0.344 0.117 0.271 0.081 0.329 0.170 0.205 0.310 0.714 0.450 0.165
	Diagnosis Result	3.0BLEED OPEN, PROBABILITY=7.7%; 3.5BLEED OPEN, PROBABILITY=24%; 8TH BLEED LEAK, PROBABILITY=21.5%; HPC LEAF ERROR, PROBABILITY=18.3%; HPC FAULT, PROBABILITY=85.7%; LPC FAULT, PROBABILITY=41.7%;
	Actual Faults	HPC FAULT

2	Engine Model	PW4056
	Input Data	NL=-0.200 NH=-0.200 EGT=10.000 FF=0.400
	Output Data	0.129 0.228 0.257 0.858 0.145 0.228 0.256 0.158 0.303 0.381 0.183 0.160
	Diagnosis Result	3.5BLEED OPEN, PROBABILITY=4.7%; 3.0+3.5BLEED OPEN, PROBABILITY=9.5%; TCC SYSTEM OFF, PROBABILITY=100%; 8^{TH} BLEED LEAK, PROBABILITY=4.7%; 15^{TH} BLEED LEAK, PROBABILITY=9.3%; HPC LEAF ERROR, PROBABILITY=17.2%; HPC ERROR, PROBABILITY=30.2%;
	Actual Faults	TCC SYSTEM OFF
3	Engine Model	PW4056
	Input Data	NL=0.000 NH=-0.200 EGT=10.000 FF=0.200
	Output Data	0.108 0.220 0.276 0.688 0.171 0.237 0.387 0.114 0.318 0.459 0.337 0.146
	Diagnosis Result	3.5BLEED OPEN, PROBABILITY=3.3%; 3.0+3.5BLEED OPEN, PROBABILITY=12.7%; TCC SYSTEM OFF, PROBABILITY=81.3%; 8^{TH} BLEED LEAK, PROBABILITY=6.2%; 15^{TH} BLEED LEAK, PROBABILITY=31.2%; HPC LEAF ERROR, PROBABILITY=19.7%; HPC FAULT, PROBABILITY=43.2%; LPC FAULT, PROBABILITY=22.8%;
	Actual Faults	TCC SYSTEM OFF

4 Conclusions

From what mentioned above, we can conclude that performance of MBP algorithm is better than that of BP algorithm. By using MBP algorithm, we can get high convergence rate, high precision and can avoid running into local minima. MBP algorithm has a wide application perspective.

Aircraft engine faults diagnosis system can help aircraft engine maintenance personnel in faults diagnosis of aircraft engine. Using learning and association abilities of NN, it can diagnose faults of aircraft engine with high precision. So it has usability in aviation aircraft engine maintenance.

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