International Journal of Smart Home
Vol. 10, No. 3, (2016), pp.201-210
http://dx.doi.org/10.14257/ijsh.2016.10.3.20

Extension Neural Network Learning Algorithms and Models and their Applications in Fault Diagnosis of Rolling Bearing

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Abstract

Extension neural network is a new type of neural network that combines extension theory and artificial neural network. Extension neural network has been applied to pattern recognition, fault diagnosis and clustering. According to fault characteristics of rolling bearing, we propose a fault diagnostic method for rolling bearing based on extension neural network. We construct the fault diagnosis model based on extension neural network along with the learning algorithm, which are then applied to fault recognition of rolling bearing. Simulation experiment indicates that this algorithm is easy to implement and has small training error and fast convergence speed. The algorithm has both theoretical and practical value.

Keywords: *Extension neural network, Extension theory, Fault diagnosis, Learning algorithm, Model, Rolling bearing, Sample training*

1. Introduction

Rolling bearing is the most common component of machinery equipments. Rolling bearing is vulnerable to damage due to inappropriate assembly, poor lubrication, entry of water and foreign bodies, corrosion or overloading. Many intelligent fault diagnostic methods for rolling bearing have been proposed, and BP neural network is one of them [1-3]. Network structure, initial connection weight and threshold have large impact on network training, but their exact values are hard to determine. Moreover, BP neural network has the universal problems of low convergence speed and convergence to local minima. These defects lead to reduced diagnostic accuracy or even mistaken diagnosis. To improve this, BP neural network has been constantly optimized, for example, by combining wavelet analysis and BP neural network or through other modifications [4-7].

We propose a fault diagnostic method for rolling bearing based on extension neural network [8]. Extension neural network is the new form of neural network after fuzzy neural network, genetic neural network and evolutionary neural network. This type of neural network integrates extension system and neural network model and resolves the feature vector through interval-based classification and clustering [9-10].Besides excellent recognition effect, extension neural network has higher convergence speed compared with conventional neural networks using supervised learning algorithm; the new information is adapted rapidly. This study first analyzes the fault diagnostic methods for rolling bearing and expounds on the feasibility of using extension neural network to fault diagnosis. Then the extension neural network model is designed and the algorithm is presented. Finally, the validity and feasibility of the method were tested through simulation experiment and compared with other methods.

ISSN: 1975-4094 IJSH

2. Fault Diagnostic Methods for Rolling Bearing

According to the state variables, the methods for working state monitoring and fault diagnosis of rolling bearing can be based on temperature, oil sample analysis and vibration. Diagnosis based on vibration is easy and reliable and adapts to various working conditions, thus it has wider applications. By processing and analyzing the vibration signals measured by acceleration sensor, some feature vectors representing the working state of the rolling bearing can be extracted for fault recognition. The vibration signals measured by the sensor are usually broadband signals with high stochasticity. The amplitude parameters of vibration signals can be mathematically converted into feature vectors representing the operating state of the rolling bearing.

The commonly used amplitude parameters are root mean square (RMS), peak, kurtosis, peak factor, kurtosis factor, impulse factor, clearance factor and shape factor. RMS and peak are dimensional parameters, and the remaining are dimensionless parameters. Dimensional parameters heavily depend on historical data and are sensitive to changes of load and rotation speed, but dimensionless parameters are basically not affected by load and rotation speed. Therefore, there is no need to calculate the relative standard value or to compare with historical data; they are not affected by absolute levels of signals either. Even if the measuring points differ somewhat, the parameters calculated do not change obviously. We choose 5 dimensionless parameters to obtain the feature vectors representing the state of rolling bearing, namely, kurtosis, peak factor, impulse factor, clearance factor and shape factor.

Suppose the vibration signal collected is $x_i\,(i = 1, 2 \ldots, n)$ and n is the number of sampling points, then RMS is given by

$$X_{rms} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2} \tag{1}$$

The peak is

$$X_{peak} = \frac{1}{m}\sum_{j=1}^{m} x_{pj} \tag{2}$$

where x_{pj} is the m -th peak found in signal x_i using a specific peak counting method, $j = 1, 2 \ldots, m$; the kurtosis is calculated by

$$K = \frac{n\sum_{i=1}^{n} x_i^4}{X_{rms}^4} \tag{3}$$

The impulse factor is obtained by

$$K_r = \frac{\sum_{i=1}^{n} x_i^4}{n X_{rms}} \tag{4}$$

The shape factor is

$$S = X_{rms} / X_{av} \tag{5}$$

$$X_{av} = \frac{1}{n}\sum_{i=1}^{n-1} |x_i| \tag{6}$$

The clearance factor is

$$L = X_{peak} / X_r \tag{7}$$

$$X_r = \left(\frac{1}{n}\sum_{i=1}^{n} \sqrt{|x_i|}\right)^2 \tag{8}$$

The states of the rolling bearing include normal, fault of inner ring, fault of outer ring, fault of rolling body and fault of maintenance shelving.

3. Extension Neural Network

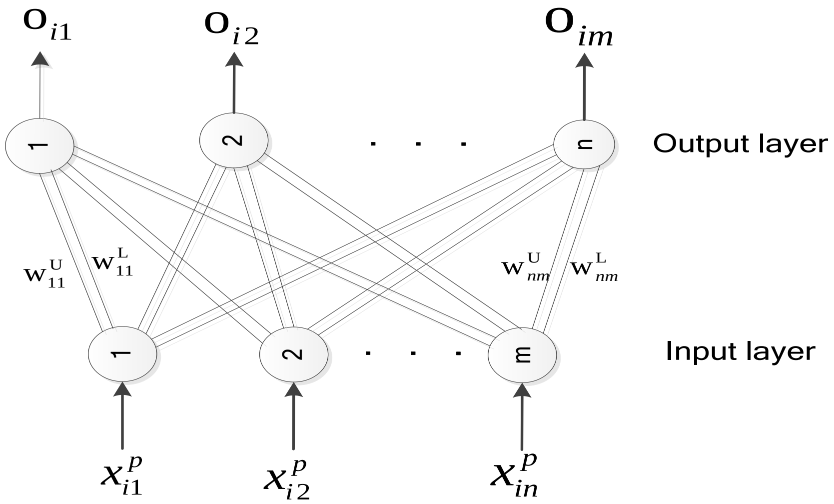

Figure 1. Architecture of Extension Neural Network

The issues of interval-based classification and clustering are very common, that is, the characteristic value to be classified lies within a finite interval. M. H. Wang presented an extension neural network with double weights of connection, as shown in Figure 1. The feature vector of the network is classified, clustered and recognized based on interval with high efficiency. There are the input layer and the output layer. The nodes of the input layer receive the input pattern, and the number of nodes is determined by the number of input feature vectors; the output layer produces the result of classification, and the number of nodes is determined by the number of categories. Only 1 node is activated each time to display the result of classification. The input layer and the output layer are connected by double weights. One weight represents the lower limit of classical domain of the feature, *i.e.*, the minimum; the other represents the upper limit of classical domain of the feature, *i.e.*, the maximum. The two weights connecting the j -th node of the input layer and the k -th node of the output layer are denoted by w_{kj}^L and w_{kj}^U, respectively, where L is the lower limit and U is the upper limit. This new neural network is the combination of extension theory and neural network, utilizing extension distance as a measure. As shown in formula (9), extension distance measures the degree of similarity between the sample and the clustering center. Neural network is capable of this due to its parallel processing and learning ability.

$$ED = \frac{|x - z| - \left(w^U - w^L\right)/2}{\left|\left(w^U - w^L\right)/2\right|} + 1 \tag{9}$$

Extension distance is the distance between point x and an interval $\langle w_{kj}^L, w_{kj}^U \rangle$, as shown in Figure 2. It can be seen that each classical domain has a different sensitivity and thus different extension distance. This can be utilized favorably in interval-based classification and recognition.

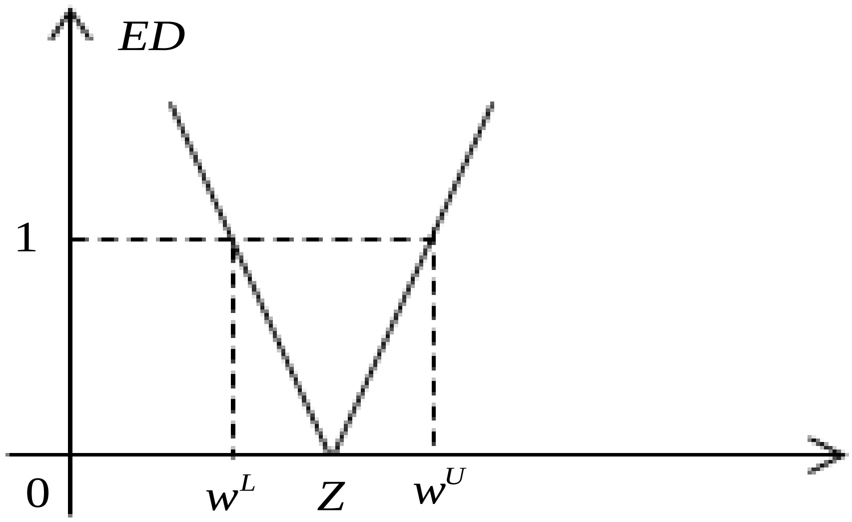

Figure 2. Extension Distance

Extension neural network is a type of supervised learning. The learning system can adjust the parameters according to the difference between the known output and the actual output. Then the knowledge structure will be reorganized to constantly improve the performance. The supervised learning algorithm with extension neural network can be described as follows:

Suppose the training sample set is $X = \{X_1, X_2, \ldots, X_{N_p}\}$, where N_p is the total number of samples in the sample set; the i -th sample is $X_i^p = \{X_{i1}^p, X_{i2}^p, \ldots, X_{in}^p\}$ and n is the total number of sample features.

The matter-element model in extension theory is used to determine the initial weight connecting the input and the output. The initial central point for each category is calculated. After the input of the i -th training sample and the corresponding category p , the distance between the training sample X_i^p and the k -th category is calculated using extension distance according to formula (10):

$$ED_{ik} = \sum_{j=1}^{n} \left[\frac{\left| x_{ij}^p - z_{kj} \right| - \left(w_{kj}^U - w_{kj}^L \right) / 2}{\left| \left(w_{kj}^U - w_{kj}^L \right) / 2 \right|} + 1 \right], k = 1, 2, \ldots, n_c \tag{10}$$

The value of k^* is determined to make $ED_{ik^*} = Min\{ED_{ik}\}$. If $k^* = p$, then the extension distance of the next sample is calculated; otherwise, the center of category corresponding to p -th category and k^* -th category and the connection weight are adjusted, as in formula (11)-(14):

(1) Adjustment of the center of category

$$z_{pj}^{new} = z_{pj}^{old} + \eta \left(x_{ij}^p - z_{pj}^{old} \right) \tag{11}$$

$$z_{k^*j}^{new} = z_{k^*j}^{old} - \eta \left(x_{ij}^p - z_{k^*j}^{old} \right) \tag{12}$$

(2) Adjustment of connection weight

$$\begin{cases} w_{pj}^{L(new)} = w_{pj}^{L(old)} + \eta\left(x_{ij}^{p} - z_{pj}^{old}\right) \\ w_{pj}^{U(new)} = w_{pj}^{U(old)} + \eta\left(x_{ij}^{p} - z_{pj}^{old}\right) \end{cases} \tag{13}$$

$$\begin{cases} w_{k^*j}^{L(new)} = w_{k^*j}^{L(old)} + \eta\left(x_{ij}^{p} - z_{k^*j}^{old}\right) \\ w_{k^*j}^{U(new)} = w_{k^*j}^{U(old)} + \eta\left(x_{ij}^{p} - z_{k^*j}^{old}\right) \end{cases} \tag{14}$$

Where η is the learning speed. The two weights are adjusted as shown in Figure 3, from which the changes of the extension distance can be seen. With $ED_A > ED_B$, the center of category for sample x_{ij} changes from A to B. Thus the learning process is in essence the adjustment of weights corresponding to the p-th and the k^*-th category. This makes the neural network faster and the information update more effective compared with other supervised learning algorithms.

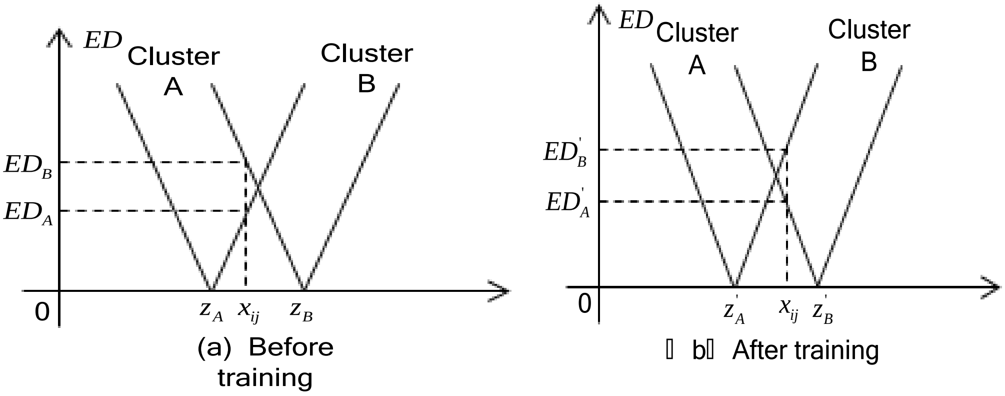

Figure 3. Comparison of Weights before and after Training

The extension neural network exhibits greater advantages in interval-based classification and recognition. The algorithm is easier and the connection weights have more explicit physical meanings. This method has been already applied in data classification, pattern recognition, fault diagnosis, state monitoring, and intelligent control of road traffic [11-12]. If fault diagnosis of rolling bearing is considered an issue of interval-based pattern recognition, the extension neural network will be fit for fault diagnosis and recognition of rolling bearing.

4. Simulation Experiment and Analysis

To verify the validity and reliability of extension neural network model in fault diagnosis of rolling bearing, training and simulation analysis were performed under Mat lab environment.

4.1. Data Processing

Activation function is very important in network training. The input of the activation function should be values lying within the interval [0-1]. Therefore, the raw data required for network training have to be initialized first so that the values are within the interval [0-1].

The sample data are normalized by

$$x_{io} = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \tag{15}$$

Where x_{io} is the normalized i-th characteristic parameter; x_i is the original i-th characteristic parameter; $x_{\min}$ is the minimum value of the i-th characteristic parameter; $x_{\max}$ is the maximum value of the i-th characteristic parameter.

One hundred groups of experimental data were taken and normalized for network training. Some of the experimental data are shown in Table 1.

Table 1. Training Samples

State of the rolling bearing	Peak factor	Shape factor	Impulse factor	Clearance factor	Kurtosis
Normal (1 0 0 0 0)	0	0	0.0013	0	0
	0.0074	0.0335	0.0015	0.0032	0.0106
	0.0043	0.0223	0	0.0047	0.0053
Fault of the outer ring (0 0 1 0 0)	0.2462	0.1508	0.0947	0.0964	0.0999
	0.2535	0.1061	0.0968	0.0971	0.0810
	0.2665	0.0894	0.0937	0.0994	0.0908
Fault of the inner ring (0 1 0 0 0)	0.5520	0.3017	0.2581	0.3094	0.2316
	0.5452	0.2793	0.2611	0.2988	0.2036
	0.5502	0.2458	0.2717	0.3115	0.2347
Fault of the rolling body (0 0 0 1 0)	0.6615	0.5251	0.5195	0.4710	1.0000
	0.6738	0.4413	0.5225	0.4732	0.9667
	0.6665	0.4749	0.5225	0.4769	0.9758
Fault of the maintenance shelving (0 0 0 0 1)	1.0000	1.0000	0.9812	1.0000	0.8206
	0.9797	0.9777	1.0000	0.9960	0.7759
	0.9846	0.9727	0.9847	0.9857	0.7600

4.2. Network Training

Matter-element models for 5 states of the rolling bearing were constructed first, namely, normal (N_1), fault of outer ring (N_2), fault of inner ring (N_3), fault of rolling body (N_4), and fault of maintenance shelving (N_5). The inputs were peak factor (c_1), shape factor (c_2), impulse factor (c_3), clearance factor (c_4) and kurtosis (c_5). The limited domain was determined according to sample data.

Table 2. Matter-Element Model of States of Rolling Bearing

State of rolling bearing	Matter-element model
Normal	$R_1=(N_1,C,v_1)=\begin{bmatrix} N_1 & c_1 & \langle 0\sim 0.050\rangle \\ & c_2 & \langle 0\sim 0.051\rangle \\ & c_3 & \langle 0\sim 0.040\rangle \\ & c_4 & \langle 0\sim 0.050\rangle \\ & c_5 & \langle 0\sim 0.110\rangle \end{bmatrix}$
Fault of the outer ring	$R_2=(N_2,C,v_2)=\begin{bmatrix} N_2 & c_1 & \langle 0.045\sim 0.375\rangle \\ & c_2 & \langle 0.050\sim 0.245\rangle \\ & c_3 & \langle 0.040\sim 0.253\rangle \\ & c_4 & \langle 0.049\sim 0.275\rangle \\ & c_5 & \langle 0.081\sim 0.351\rangle \end{bmatrix}$
Fault of the inner ring	$R_3=(N_3,C,v_3)=\begin{bmatrix} N_3 & c_1 & \langle 0.357\sim 0.612\rangle \\ & c_2 & \langle 0.232\sim 0.451\rangle \\ & c_3 & \langle 0.179\sim 0.579\rangle \\ & c_4 & \langle 0.289\sim 0.491\rangle \\ & c_5 & \langle 0.202\sim 0.612\rangle \end{bmatrix}$
Fault of the rolling body	$R_4=(N_4,C,v_4)=\begin{bmatrix} N_4 & c_1 & \langle 0.597\sim 0.887\rangle \\ & c_2 & \langle 0.447\sim 0.942\rangle \\ & c_3 & \langle 0.552\sim 0.899\rangle \\ & c_4 & \langle 0.475\sim 0.909\rangle \\ & c_5 & \langle 0.839\sim 1\rangle \end{bmatrix}$
Fault of the maintenance shelving	$R_5=(N_5,C,v_5)=\begin{bmatrix} N_5 & c_1 & \langle 0.871\sim 1\rangle \\ & c_2 & \langle 0.931\sim 1\rangle \\ & c_3 & \langle 0.897\sim 1\rangle \\ & c_4 & \langle 0.889\sim 1\rangle \\ & c_5 & \langle 0.603\sim 0.872\rangle \end{bmatrix}$

The weights were initialized using matter-element model, and the network was trained according to the above algorithm. The error convergence curve is shown in Figure 4 with learning speed of 0.1.

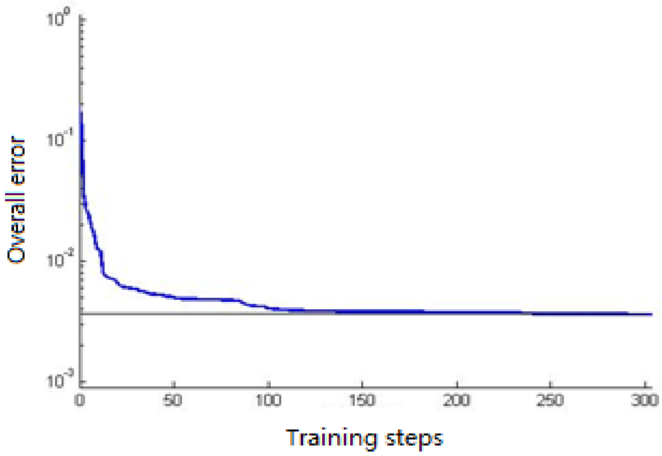

Figure 4. Error Convergence Curve

4.3. Comparative Analysis

Table 3. Comparison between Different Models

Neural network model	ENN model	BP neural network model
Network structure	5-5 (2 layers)	5-12-5 (3 layers)
Learning speed	0.1	Variable learning speed
Number of connection weights	50	300
Step length	200	350
Error	0.0041	0.0088

We compared the proposed model with the conventional BP neural network. It can be seen from the table that both two models can accurately diagnose and recognize the faults of the rolling bearing, but the ENN model is superior in network structure, learning speed and learning time (Table 3). BP neural network has 3 layers, which are input layer, hidden layer and output layer, with neuron number of 5, 12 and 5, respectively; the number of connection weights is 300. ENN model has only 2 layers, the input layer and the output layer, and the number of connection weights is 50. As to the learning speed, the learning error converges to 0.0041 after 200 steps using ENN model, while the error converges to 0.0088 after 350 steps using BP neural network. Thus ENN model not only satisfies the actual need in fire disaster warning, but also with improved performance.

5. Conclusion

This article describes the structure, algorithm and simulation with the new extension neural network. Experiment shows that the method is reliable and superior compared with conventional neural networks. When applied to fault diagnosis of rolling bearing, the algorithm exhibits the advantages of simple design, faster convergence and smaller error. It is suitable to be used as a new fault diagnostic method for rolling bearing.

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