The Application of Radial Basis Function (RBF) Neural Network for Mechanical Fault Diagnosis of Gearbox

Pengbo Wang¹

¹Institute of Solid Mechanics, Beihang University (Beijing University of Aeronautics and Astronautics), Beijing, 100191, P.R. China

Abstract. In this paper, the radial basis function (RBF) neural network is used for the mechanical fault diagnosis of a gearbox. We introduce the basic principles of the RBF neural network which is used for pattern classification and features a fast learning pace and strong nonlinear mapping capability; thus, it can be employed for fault diagnosis. The gearbox is a widely-used piece of equipment in engineering, and diagnosing mechanical faults is of great significance for engineers. A numerical example is presented to demonstrate the capability of the proposed method. The results indicate that the mechanical faults of a gearbox can be correctly diagnosed with a trained RBF neural network.

1. Introduction

Gearboxes are important pieces of equipment in industry. Gears are often damaged by collision or erosion, which leads to the gearbox malfunctioning. Mechanical faults in gearboxes may result in serious accidents; hence, the mechanical fault diagnosis of gearboxes is of great significance in engineering. Traditional mechanical fault diagnosis is mainly based on the examination of vibration features related to the faults. However, the workload involved with this approach is usually very large. Sometimes the vibration features are contaminated by noise, and the approach becomes inapplicable. Therefore, scholars have developed a more intelligent approach, the neural network, to diagnose mechanical faults.

Collected vibration features can be integrated into a neural network that can represent the complicated nonlinear relationship mapping from the vibration features to the mechanical faults [1]. Moreover, the neural network is robust to noise 0. The most widely-used neural network is the error back propagation (BP) neural network. However, an obvious disadvantage of BP neural networks is the slow learning speed 0. Thus, researchers developed the radial basis function (RBF) neural network, which possesses a high learning speed 0. In this study, we introduce the RBF neural network to the problem of mechanical fault diagnosis.

The remainder of this paper is organised as follows. In Section 2, the basics of the RBF neural network are briefly introduced. In Section 3, the procedure of using RBF neural network to diagnose the mechanical faults of a gearbox is presented. In Section 4, the different types of mechanical faults in the gearbox are discussed. In Section 5, a numerical example is provided to illustrate the feasibility of the proposed method, and Section 6 presents the conclusions of the study.

2. Basic principles of the radial basis function (RBF) neural network

A typical RBF neural network has three layers: the input layer, the hidden layer, and the output layer, as shown in figure 1. The relationship between the input and output can be described by the node
number of the hidden layer, \( J \), and the network weights, \( w_{jk} \), between the hidden layer and the output layer. The mapping between the input and output is thereby established through the neural network.

![Diagram](https://via.placeholder.com/150)

**Figure 1.** Topology structure of the RBF neural network.

The commonly-used radial basis functions are as follows:

\[
f(x) = \exp[-\frac{(x - c_j)^2}{\sigma_j^2}],
\]

\[
f(x) = \frac{1}{(x^2 + \sigma_j^2)^\alpha}, \quad (\alpha > 0),
\]

\[
f(x) = (x^2 + \alpha^2)^\beta, \quad (\alpha < \beta < 1).
\]

All these functions are radially symmetric, and the most commonly-used function is Gaussian:

\[
R_j(x) = \exp\left(-\frac{\|x - c_j\|^2}{2\sigma_j^2}\right), \quad j = 1, 2, \ldots, J,
\]

where \( x \) is the \( n \)-dimensional input vector; \( c_j \) is the center of the \( j \)-th RBF; \( \sigma_j \) is the \( j \)-th RBF width, which can be adjusted; \( J \) is the number of nodes in the hidden layer. The symbol \( \|x - c_j\| \) represents the norm of the vectors \( x \) and \( c_j \), which can also be regarded as the distance between the vectors \( x \) and \( c_j \).

As shown in Figure 1, the input layer represents the nonlinear mapping from \( x \) to \( R_j(x) \), and the output layer represents the linear mapping from \( R_j(x) \) to \( y_k \). The \( k \)-th output is a weighted summation of all RBFs, i.e.

\[
y_k = \sum_{j=1}^{J} w_{jk} \cdot R_j(x), \quad k = 1, 2, \ldots, K,
\]

where \( K \) is the number of outputs; \( w_{jk} \) is the weight between the \( j \)-th node of hidden layer and the \( k \)-th node of the output layer; \( J \) is the number of nodes in the hidden layer.

3. RBF neural network for mechanical fault diagnosis

The procedure of using an RBF neural network to diagnose the mechanical faults of a gearbox is illustrated in figure 2. The dynamic data is recorded from the gearbox, and then processed by signal-processing technologies, such as the wavelet transform or filtering. Thus, vibration features can be obtained. With these features, the RBF neural network can be established and trained, and after the
weights of the network have converged the network can be used. With given test features, the established network can diagnose the mechanical faults of the gearbox.

![Flowchart of the RBF neural network for mechanical fault diagnosis.](image)

**Figure 2.** Flowchart of the RBF neural network for mechanical fault diagnosis.

### 4. Mechanical faults of gearboxes

In this study, it is assumed that gearbox faults are all caused by the gears. We consider three states of the gear: ‘normal’, ‘root crack’, and ‘tooth broken’. The three states are illustrated in figures 3, 4, and 5, respectively.

For simplicity, we use three row vectors to represent the three states. The row vector \([1, 0, 0]\) represents the ‘normal state’, the row vector \([0, 1, 0]\) represents the ‘root crack’ state, and the row vector \([0, 0, 1]\) represents the ‘tooth broken’ state. The relationships between the states and row vectors are listed in Table 1.

![The ‘normal’ state of the gear.](image)

**Figure 3.** The ‘normal’ state of the gear.

![The ‘root crack’ state of the gear.](image)

**Figure 4.** The ‘root crack’ state of the gear.
Figure 5. The ‘tooth broken’ state of the gear.

Table 1. Relationships between the gear states and row vectors.

| No. | Gear state  | Row vector |
|-----|-------------|------------|
| 1   | Normal      | [1, 0, 0]  |
| 2   | Root crack  | [0, 1, 0]  |
| 3   | Tooth broken| [0, 0, 1]  |

5. Numerical example

In this example, we use data from an automobile gearbox to demonstrate our proposed method. We have twelve groups of data in total, and within each group, eight parameters numbered from $P_1$ to $P_8$ represent the ten vibration features of the gearbox. Our aim is to use the RBF neural network to realize the mapping between the ten vibration features and the three gear states. In other words, we use the ten inputs to determine the three outputs.

We use nine groups of data as the sample data and three groups of data as the test data. The sample data listed in Table 2 is used to train the RBF neural network. The test data listed in Table 3 is then used to verify the correctness of the RBF neural network.

Table 2. Sample data for RBF neural network training.

| No. | $P_1$  | $P_2$  | $P_3$  | $P_4$  | $P_5$  | $P_6$  | $P_7$  | $P_8$  | Gear state   | Row vector |
|-----|--------|--------|--------|--------|--------|--------|--------|--------|--------------|------------|
| S1  | 0.6858 | 0.3876 | 0.2160 | 0.4776 | 0.4005 | 0.2199 | 0.3477 | 0.2821 | Normal       | [1, 0, 0]   |
| S2  | 0.6271 | 0.2841 | 0.4179 | 0.4161 | 0.7674 | 0.2702 | 0.2313 | 0.2646 | Normal       | [1, 0, 0]   |
| S3  | 0.1326 | 0.2640 | 0.3441 | 0.1689 | 0.9041 | 0.3449 | 0.4359 | 0.1287 | Normal       | [1, 0, 0]   |
| S4  | 0.7809 | 0.5145 | 0.2105 | 0.8133 | 0.4473 | 0.3989 | 0.2904 | 0.5733 | Root crack   | [0, 1, 0]   |
| S5  | 0.9670 | 0.6667 | 0.1686 | 0.9314 | 0.5616 | 0.4842 | 0.4275 | 0.4518 | Root crack   | [0, 1, 0]   |
| S6  | 0.1077 | 0.3447 | 0.3692 | 0.9981 | 0.5931 | 0.3744 | 0.1872 | 0.2496 | Root crack   | [0, 1, 0]   |
| S7  | 0.5277 | 0.7041 | 0.5487 | 0.5432 | 0.8766 | 0.1965 | 0.2322 | 0.6819 | Tooth broken | [0, 0, 1]   |
| S8  | 0.2172 | 0.5727 | 0.4019 | 0.7227 | 0.8526 | 0.1350 | 0.2472 | 0.3192 | Tooth broken | [0, 0, 1]   |
| S9  | 0.7902 | 0.6774 | 0.3495 | 0.3462 | 0.3223 | 0.1971 | 0.1831 | 0.7869 | Tooth broken | [0, 0, 1]   |

Table 3. Test data for RBF neural network check.

| No. | $P_1$  | $P_2$  | $P_3$  | $P_4$  | $P_5$  | $P_6$  | $P_7$  | $P_8$  | Gear state   | Row vector |
|-----|--------|--------|--------|--------|--------|--------|--------|--------|--------------|------------|
| T1  | 0.6303 | 0.2851 | 0.3894 | 0.4077 | 0.7803 | 0.3001 | 0.2259 | 0.2670 | Normal       | [1, 0, 0]   |
| T2  | 0.7779 | 0.5401 | 0.2133 | 0.8403 | 0.4503 | 0.3894 | 0.3004 | 0.5673 | Root crack   | [0, 1, 0]   |
| T3  | 0.7798 | 0.6705 | 0.3602 | 0.3513 | 0.3306 | 0.2049 | 0.1862 | 0.7791 | Tooth broken | [0, 0, 1]   |

The RBF neural network is built with the sample data, with 25 neurons in the hidden layer. The performance of the network is plotted in Figure 6. The results produced by the network are listed in Table 4, which indicates that faults can be effectively diagnosed with the RBF neural network.
6. Conclusion
In this paper, the RBF neural network and its basic principles were introduced for the mechanical fault diagnosis of gearboxes. The procedure of using the RBF neural network to diagnose the mechanical faults of a gearbox was put forward. A numerical example was provided to illustrate the proposed method, using twelve groups of data in total: nine groups were used as the sample data and three groups were used as the test data. We used three row vectors to represent the three states of the gearbox, and the RBF neural network was built with the sample data. After the network was trained, it was capable of predicting the state of the test data. The row vectors obtained using the RBF neural network on the test data were compared with the real states of the test data. The results indicate that the states predicted by the RBF neural network are consistent with the real states. This suggests that the mechanical faults of a gearbox can be correctly diagnosed with the trained RBF neural network.

7. References
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