Recognition of Fault State of RV Reducer Based on self-organizing feature map Neural Network

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Abstract. In order to accurately evaluate the working state of RV reducer, a fault identification method based on the fault identification model established by Self-Organizing Feature Map (SOM) Neural Network is proposed. Firstly, the data measured by the RV reducer test platform are analyzed by wavelet to obtain the wavelet coefficient. Then, combined with the efficiency data of RV reducer, the mean square frequency, center of gravity frequency and frequency variance of the two groups of data are calculated after Fourier transform and power spectrum analysis. After optimization, several eigenvalues are obtained. The eigenvalues are input into the competitive neural network and SOM neural network to establish the fault identification model. Finally, the results of the fault identification model established by the competitive neural network and SOM neural network are compared. The prediction results show that the fault identification model established by SOM neural network can effectively determine the working state of RV reducer.

1. Introduction
With the rapid development of society and the deep integration of industrial Internet of Things technology and artificial intelligence technology, industrial robots have been widely used in the Internet of Things. High-precision RV reducer is one of the core components of industrial robots. It can effectively reduce the speed at the joints of the robot so that it can run at a uniform speed. Once the RV reducer fails, it will cause huge losses to the entire factory, and in severe cases, it will cause harm to the operating workers. In view of many complex factors such as real-time dynamic changes and uncertain
conditions in the workshop, further fault diagnosis of the RV reducer can effectively reduce the loss of the factory and improve the efficiency of the factory. Therefore, the fault diagnosis of the reducer and bearing direction has been paid more and more attention by scholars [1-3]. People proposed a noise deep convolutional neural model (NOSCNN), which can identify faults under unknown operating conditions. A random noise layer was developed and added to the module of the NOSCNN model to improve its anti-interference ability. Xiao et al. [5] proposed a novel fault diagnosis method for rotating machinery. First, an improved LMD method was developed to decompose the vibration signal into a subset of the amplitude modulation/frequency modulation (AM-FM) product function (PF). Then, the time domain and frequency domain features are extracted from the selected PF, so that complex faults can be effectively identified. Due to the performance degradation of the fault diagnosis method caused by redundant features, a feature selection method combining SVM-RFE and MRMR is proposed to select salient features, which improves the performance of the fault diagnosis method. Bao Jihua et al. [6] used MATLAB to input the meshing frequency of the shaft gear to carry out spectrum analysis, power spectrum and axis trajectory analysis, and obtained the characteristic frequencies of the inner ring, outer ring, rolling element, and cage of the reducer. So as to get the operating state of the reducer. Kong Lingguo [7] used the manufacturer’s four-year reduction gear failure data as the basis, and used the fault tree analysis method to divide the faults into six categories according to the characteristics of the reducer, including the reducer oil leakage failure and the bearing failure, and carried out corresponding measures. Qualitative analysis and quantitative analysis. Li Qing [8] et al. proposed a new Non-convex penalty regularization sparse low-rank matrix, NPRSLM for the feature extraction of weak bearing faults.

The above literature provides a variety of fault diagnosis methods for the fault diagnosis of the reducer, but most of them are for large reducers. Because the fault signal of the small RV reducer is not easy to detect and the fault characteristics are not obvious, the research on the fault diagnosis of the small RV reducer is less, and some of them just put forward the theoretical scheme, and did not establish a diagnostic fault model to judge and classify. And there are many types of reducers, which require continuous diagnostic verification. A fault identification method based on SOM neural network is proposed.

The first step is to obtain the wavelet coefficient by wavelet analysis of the data measured by the RV reducer test platform.

In the second step, combined with the efficiency data of RV reducer, the mean square frequency, center of gravity frequency and frequency variance of the two groups of data are calculated after Fourier transform and power spectrum analysis, and several eigenvalues are obtained after optimization.

In the third step, the eigenvalues are imported into the competitive neural network and the self-organizing feature mapping network to establish the fault identification model.

2. The transmission mechanism and failure modes of the robot RV reducer

2.1. Selecting a Template (Heading 2)
The structure of the robot RV reducer is shown in Figure 1:
The structure of the RV reducer is a planetary gear structure, which is composed of a sun gear and two planetary gears in the middle. Its deceleration mechanism is a two-stage deceleration. For the first-stage reduction, the planetary gear is connected with the crankshaft to become the input for the second-stage reduction. The cycloidal gear is installed on the eccentric part of the crankshaft through rolling bearings. In addition, the needle teeth with only one more than the number of cycloidal wheels on the inside of the housing are arranged at the same pitch. If the fixed housing rotates the spur gear, the cycloid also performs an eccentric movement due to the eccentric movement of the crank shaft. At this time, if the crankshaft makes one revolution, the cycloid will rotate one tooth in the opposite direction to the crankshaft. This rotation is output to the shaft of the second reduction unit. This is a level 2 deceleration.

The main fault types are roughly divided into six categories: oil leakage fault, bearing fault, gear fault, transmission shaft fault, box body fault, vibration and noise fault [7], among which RV reducer due to its small size and high precision, its fault The characteristics are relatively concealed and not easy to detect, so the RV reducer test experimental platform is used to collect the fault characteristics of the RV reducer.

The data used are provided for the RV reducer test platform built in the laboratory. The test platform structure is as follows:

The test platform is mainly composed of servo motor, torque sensor, RV reducer and force sensor. The power of servo motor is 750w, the range of torque sensor is 200, the range of torque sensor is 500, and the specification of magnetic powder brake is 1.5kw. The rotational speed of spindle is 406 r / min.
The input shaft and output shaft of RV reducer are mainly measured by torque sensor and force sensor. The RV reducer model is RV-20E. Samples were taken every 0.5 second, and 500-hour data were collected. The experiment was carried out at room temperature.

The experimental data collected are shown in Figure 3.

After the experiment, the torque, rotational speed and power show abnormal data. The reducer fails.

3. SOM neural network
SOM neural network learns and classifies according to the grouping of input vectors in the input space. In SOM neural network, neurons in the competition layer will try to identify the part of the input space adjacent to the neuron. The structure of SOM neural network is shown in Fig. 5 [9]:

![Figure 3 Partial data collected](image)

![Figure 4 Fault diagram of RV reducer](image)

![Figure 5 SOM neural network structure diagram](image)
Finally, complete content and organizational editing before formatting. Please take note of the following items when proofreading spelling and grammar:

Set the initial value of the weight between the input layer and the mapping layer with random number. The connection weights of c input neurons to output neurons are given smaller weights, where c is set to 5. Select the set \( S_0 \) of output neurons o ‘adjacent neurons’. Where \( S_0(t) \) denotes the set of ‘adjacent neurons’ of the neuron o of the moment \( t = 0 \) and \( S_0(t) \) denotes the set of ‘adjacent neurons’ of the moment \( t \). Area \( S_0(t) \) is shrinking over time.

\[
d_i = \|X - W_i\| = \sqrt{\sum_{j=1}^{c}(x_{ij} - o_{ij}(t))^2}
\]

In the formula, \( o_{ij} \) is the weight between the p neurons in the input layer and the o neurons in the mapping layer. By calculation, a neuron with the minimum distance is obtained, which is called a winning neuron, denoted as \( o^* \).

The formula for correcting the weights of output neuron \( o^* \) and its ‘adjacent neurons’ is as follows:

\[
\Delta o_{ij} = o_{ij}(t+1) - o_{ij}(t) = \eta(t)(x_{ij}(t) - o_{ij}(t))
\]

In the formula (2), \( \eta \) is a constant and \( 0 < \eta < 1 \) is reduced to 0 with time.

\[
\eta(t) = 0.2(1 - \frac{t}{10000})
\]

Calculate output \( t_o \):

\[
t_o = f(\min \|X - W_i\|)
\]

\( f(*) \) is generally \( 0 \sim 1 \) function or other nonlinear function.

There are two empirical formulas for determining the number of hidden layer neurons [10]:

\[
d_1 \times d_2 > a
\]

Among them, a is the total number of sample classifications, a is 2, d1 is the number of competitive row units, d2 is the number of competitive column units.

\[
d_1 = \sqrt{k + l + b} \quad \text{or} \quad d_2 = \sqrt{k + l + b}
\]

Where k is the number of input neurons, l is the number of output neurons, k is 5, l is 2, b is 1, the number of neurons is 3 * 3.

4. Establishment of SOM neural network fault identification model

4.1. Feature extraction

Figure 6 is obtained by haar wavelet transform.
As can be seen from the diagram, (a) group data waveform is relatively slow, showing a certain regularity, and (b) group data is dense, it is very chaotic, obviously, (a) group data for normal operation data, (b) group fault data. The wavelet coefficient is extracted.

Taking wavelet coefficients and efficiency as examples, the mean square frequency (MSF), center of gravity frequency (FC) and frequency variance (VF) are calculated respectively. The correlation functions are as follows:

\[
MSF = \frac{\int_{-\infty}^{\infty} f^2 S(f) df}{\int_{-\infty}^{\infty} S(f) df}
\]

\[
FC = \frac{\int_{-\infty}^{\infty} f S(f) df}{\int_{-\infty}^{\infty} S(f) df}
\]

\[
VF = \frac{\int_{-\infty}^{\infty} (f - FC)^2 S(f) df}{\int_{-\infty}^{\infty} S(f) df}
\]

In the formula, \( f \) denotes data and \( S(f) \) denotes power spectrum.

The calculation of power spectrum requires Fourier transform to determine the frequency, and the obtained data are Fourier transformed to obtain Fig. 7.

The maximum amplitude of normal data is 262, and the maximum amplitude of fault data is 265. The data after Fourier transform are brought into the power spectrum to obtain Fig. 8.
Figure 8 Power spectrum analysis

It can be seen from the above figure that the power spectrum trend of fault data is similar to that of normal data, and the power spectrum of fault data is slightly larger than that of normal data. The power spectrum is brought in to calculate the mean square frequency (MSF), center of gravity frequency (FC) and frequency variance (VF). Since the center of gravity frequency is number, it is used to calculate the frequency variance, so it is not used as a feature. After calculation, several groups of data are obtained. After screening, a total of five groups of data become effective features. As shown in Figure 9.

Figure 9 Wavelet coefficient mean square frequency first band diagram

It can be seen from Fig. 9 that the normal data are generally high on both sides and low in the middle, and the kurtosis of most single peaks is similar, showing certain regularity. The fault data is high and low random distribution, and the steepness between the peaks is very different, showing a chaotic trend.
Figure 10  Wavelet coefficient mean square frequency second band diagram

It can be seen from Figure 10 that the normal data is higher in the middle and lower on both sides, and the value is higher in the 27th and 35th groups, while the fault data is higher in the 5th and 18th groups, and shows a small fluctuation trend to the right.

Figure 11  Frequency variance first band of wavelet coefficients

It can be seen from Fig. 11 that the trends of normal data and fault data are similar to those in Fig. 9, but the values are smaller than those in Fig. 7.
Figure 12  Second band of frequency variance of wavelet coefficient

It can be seen from Figure 12 that the peaks and valleys of normal data show a trend of large amplitude in the middle and small amplitude on both sides, while the fault data show a trend of high on the left and low on the right.

Figure 13  Efficiency mean square frequency diagram

It can be seen from Figure 13 that the distribution of normal data is relatively average, the amplitude of the whole data fluctuates little, the fault data is chaotic, the amplitude is large or small, and there is no regularity.

The five groups of features are input into the competitive neural network and SOM neural network respectively, and the fault diagnosis model is established. The diagnosis results are as follows:

Table 1  Comparison between Competitive Neural Network and SOM Neural Network

| Sample number | Actual category | Victory neuron number ( competitive neural network ) | Victory neuron number ( SOM neural network ) |
|---------------|-----------------|------------------------------------------------------|---------------------------------------------|
| 1             | 1               | 2                                                    | 2                                           |

9
In table 1, 1 represents the normal running state and 2 represents the fault state. In the statistical figure of winning neurons in Fig. 14, the number of neurons was from left to right, and from bottom to top, the number of neurons increased in turn, and the number of the upper right corner was 9. It can be
seen from the figure that the nine neurons in the SOM neural network have numbers, which means that there are no dead neurons in the SOM neural network, and the label of each neuron represents the state of a class of reducer at operation.

In the distance distribution of adjacent neurons in Figure 15, the darker the color is, the farther the distance between the two adjacent neurons is. It is obvious from the figure that No. 1, 4, 7, 8 neurons represent the fault state and 2, 3, 5, 6, 9 neurons represent the normal operation state. Table 1 shows that the accuracy of competitive neural network is only 19.44 %, while the accuracy of SOM neural network is 86.1 %. It can be clearly seen from table 1 and the above analysis results that SOM neural network has better performance than competitive neural network in dealing with more complex data.

5. Conclusions
1) The data measured by the RV reducer test platform are analyzed by wavelet to obtain the wavelet coefficient. Combined with the efficiency data of RV reducer, the mean square frequency, center of gravity frequency and frequency variance of the two groups of data are calculated after Fourier transform and power spectrum analysis. After optimization, several eigenvalues are obtained. The eigenvalues are input into the competitive neural network and SOM neural network to establish the fault identification model.
2) By comparing the actual operation state of RV reducer with the predicted state, it is verified that the neural network can establish the accuracy and feasibility of the RV reducer fault diagnosis model.
3) Timely and accurate judgment of the running state of RV reducer is conducive to timely maintenance of RV reducer, which can effectively help factories and enterprises to reduce losses, and can also help RV reducer test manufacturers to improve the accuracy of RV reducer test data to a certain extent, so as to achieve the purpose of improving enterprise efficiency.

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