Fault Degradation State Recognition for Planetary Gear Set Based on LVQ Neural Network

Bin Fan, Niaoqing Hu and Zhe Cheng

Abstract In order to ensure the safety and reliable operation of equipment, reduce accidents and economic loss caused by the mechanical fault or failure, prediction and health management (PHM) technology has attracted more and more attention. As the basis and starting point of fault prediction, degradation state recognition is one of the key steps of PHM, which directly affect the reliability of the equipment failure prediction and the selection of corresponding maintenance strategy. As to the degradation state recognition problem of planetary gear set, firstly, select the proper prognosis feature by evaluating various time-frequency features. Secondly, utilize the learning vector quantization neural network to recognize degradation state of planetary gear set. Finally, validate the effectively of presented method with pre-planted chipped fault experiment of planetary gear set. The results show that the proposed algorithm recognizes the multi-level degradation state effectively, and provide a useful reference for subsequent fault prediction.

Keywords Degradation state recognition · Prognosis feature · Neural network · Learning vector quantization

1 Introduction

As an important class of machinery and equipment in weaponry, transportation, electric power, petrochemical, and other fields, mechanical power transmission system is widely used and plays a crucial role in the domain of national defence and

B. Fan (✉) · N. Hu · Z. Cheng
Laboratory of Science and Technology on Integrated Logistics Support, College of Mechatronics and Automation, National University of Defense Technology, Changsha, China
e-mail: fanbin85510@163.com

N. Hu
e-mail: hnq@nudt.edu.cn

Z. Cheng
e-mail: chengzhe@nudt.edu.cn

P.W. Tse et al. (eds.), *Engineering Asset Management - Systems, Professional Practices and Certification*, Lecture Notes in Mechanical Engineering,
DOI 10.1007/978-3-319-09507-3_2

economy. With the high-speed improvement of industrial technological and science, mechanical power transmission system is becoming automation, precision, intelligent friendly, its performance and capabilities are gradually improve into perfection. Meanwhile, its structures become more and more complex, and the work environment is usually wretched, the failure or severe fault will lead to disastrous consequences, so the operational safety and reliability go into essential. Therefore, prediction and health management (PHM) technology has been widely concerned in many areas. Find the emergence of incipient fault as early as possible (early fault detection), to remove potential dangers of accidents; identify the current health state of equipment effectively (degradation state recognition), to formulate a reasonable maintenance plan; predict the failure time of equipment (fault prognosis and remaining useful life estimation), to avoid the accident and maximize the equipment effectiveness are three critical goals in PHM. Among them, the degradation state recognition provides a vital link between early fault detection and remaining useful life prediction, it need to be based on the results of former, and itself is prerequisite for latter [1].

Planetary gear set have compact structure, small volume, wide transmission ratio range and high efficiency, is a kind of widely used gear transmission system. Since long-term continuous work under high load and high speed condition, planetary gear set are susceptible to damage and failure, leading to transmission system work abnormally, and even more serious consequences. Therefore, the degradation state recognition for planetary gear system is essential [2, 3]. But due to the complexity of structure, its damage mode and dynamic response is different from the fixed axis gear system, so it is difficult to detect and identify the typical damage in planetary gear set just by some of traditional features. In addition, the difficulty of its dynamics modeling is large, the high accuracy of the model can't be guaranteed.

In contrast, artificial neural network is a simple and effective method. It regards the target system as a black box, relying solely on the characteristics of the input data, by simulating the way biological neural system works to get the desired output, to identify planetary gear set degradation states which is similar to a classification problem. Neural network is composed of large numbers of neurons interconnected, its special processing capability for nonlinear information, can overcome the disadvantages of traditional artificial intelligence methods in mode recognition, voice recognition, unstructured information processing and other nonlinear problems, so that in the nervous expert systems, pattern recognition, intelligent control, prognosis and other fields has been successfully applied. The vector quantization technique was originally evoked by Tuevo Kohonen in the mid 1980s, it introduced a mechanism of competition in neural network, and widespread used for classification and segmentation problems. Learning Vector Quantization (LVQ) network is a typical classification method which applying this technology [4].

In this paper, the degradation state recognition of chipped fault of planetary gear set was solved as a classification problem. Through evaluation of various commonly used features for the planetary gear set fault diagnosis, choose some suitable features among preferably to constitute input feature vectors, then use LVQ neural network approach to identify the degradation state of object system, and obtain a good results finally.

2 Learning Vector Quantization Neural Networks

2.1 Network Structure

Topologically, LVQ network consists of three layers, the input layer, hidden layer (competitive layer or Kohonen layer) and the output layer, the network architecture is shown in Fig. 1. Network between the input layer and hidden layer is fully connected, and in the hidden layer and output layer connection weights between neurons value is fixed at 1. Before training the network settings in the input layer and the hidden connections between neurons weights, training process, these weights are gradually modified. The output of competitive layer neurons and output layer neurons are all binary. When an input vector is sent to the network, the hidden neuron whose reference vector closest to the input vector will win the competition, thus produce a “1”, and the corresponding output neuron will give the class that input vector belonged to. The other hidden neurons are forced to produce a “0”. In LVQ network, each output unit has a known class, so it belongs to a kind of supervised competitive neural network.

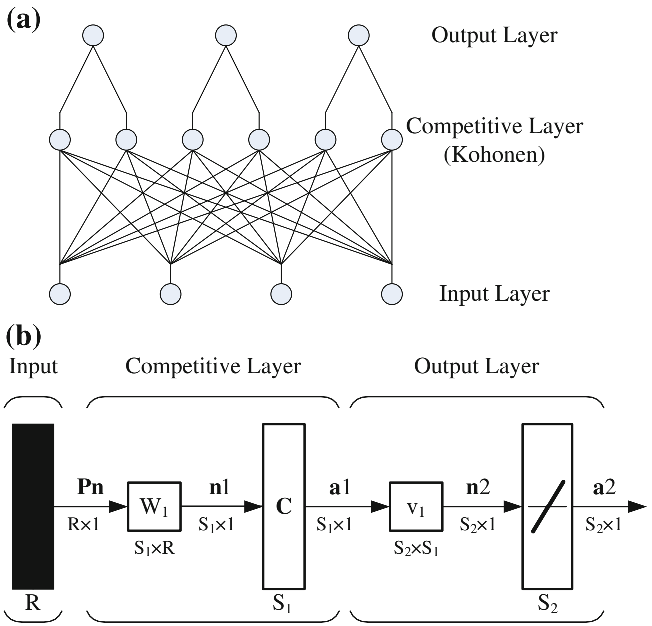

Fig. 1 The LVQ Network. **a** Topology of LVQ, **b** Architecture of LVQ

2.2 Tables, Figures and Pictures

Above all, define the input vector $X = (x_1, x_2,\ldots,x_R)$, wherein, R is the number of neurons in the input layer; the weights matrix between input layer and the competitive layer is $W^1 = (w_1^1, w_2^1, \ldots, w_{s1}^1)$, $w_i^1 = (w_{i1}^1, w_{i2}^1, \ldots, w_{iR}^1)$, w_{ij}^1 represents the weight between ith competitive layer neuron and jth input neuron, $i = 1, 2,\ldots,s_1$, $j = 1, 2,\ldots,R$, and s_1 is the number of competitive layer neurons. The output vectors of competitive layer is $V = (v_1, v_2,\ldots,v_{s1})$, the weights matrix between competitive layer and the output layer is $W^2 = (w_1^2, w_2^2, \ldots, w_{s2}^2)$, where $w_k^2 = (w_{k1}^2, w_{k2}^2, \ldots, w_{ks1}^2)$, w_{kr}^2 represents the weight between rth competitive layer neuron and kth output neuron, $k = 1, 2,\ldots, s_2$, $r = 1, 2,\ldots, s_1$, and s_2 is the number of output layer neurons. It can be classify the input vectors after learning of each neuron in the competitive layer by reference vectors. The class got by competitive layer learning is called subclass, and the class got by output layer learning is called the target class [4].

The learning rule of LVQ neural network combines characteristics of competitive learning and supervised learning. Requires a set of input vectors and their corresponding target classes to train the network, here each target output vector t_j, $j = 1, 2,\ldots,Q$, just has only one component is 1, the other components are all 0. The columns of W^2 represent different subclasses, and rows represent different classes. There is only one component in each column of W^2 is 1, indicating that this subclass belong to the corresponding category. Once defined, W^2 is unchanged.

LVQ network learning is carried out through iteratively update W^1 with improved Kohonen rules for the W^1, specifically speaking, at each iteration, sent an input vector X to the network, and in competitive layer, compute the distances between X and each reference vector, the neuron i^* corresponding to the shortest distance wins competition, so set the i^*th element of output V to 1. Vector Y can be calculated as follows:

$$Y = W^2 V \tag{1}$$

Obviously, there is only one nonzero element in Y. Assumed its number is k^*, that is, X is assigned to class k^*. If X is classified correctly, i.e. $y^* = t_{k^*} = 1$, then move weights of the winner neuron near to X, and update the weights as follows:

$$i^{*\,w^1}(t+1) = i^{*\,w^1}(t) + \eta\left(p(t+1) - i^{*\,w^1}(t)\right) \tag{2}$$

If X is classified incorrectly, i.e. $y^* = 1$, but $t_{k^*} = 0$, which means that the wrong hidden layer neurons wins, then move the weights of this neuron away from X, update the weights as follows:

$$i^{*w^1}(t+1) = i^{*w^1}(t) - \eta\Big(p(t+1) - i^{*w^1}(t)\Big) \quad (3)$$

where $\eta \in (0,1)$ is the learning rate, illustrating the adjustment rate of the process for adjusting the weight matrix. $i^{*w^1}(t)$ represents the weights of the i^*th neuron in competitive layer at time t. After network training, each neuron move toward near to vectors of the class it belongs to, and away from vectors belong to the other classes.

3 Feature Choosing and Evaluation

Before the training of LVQ network, it needs to build the input feature vector first. There are many common features used for fault diagnosis or prediction of gearbox, but 21 kinds of them are concerned in this paper [5–7], and are numbered #1–21 in sequence.

Time-domain feature: mean, mean square amplitude, rms, variance, peak, peak to peak, margin factor, crest factor, shape factor, pulse factor, skewness, kurtosis, etc.

Frequency-domain features or **statistical-based features**: FM0, M6A, M8A, NA4, MRS, NF1, NSR, NSR1, spectral kurtosis, etc.

But too many features is a burden of networks, much time is needed to calculate the results, however, the results are not always ideal. In order to solve this problem, a process of feature evaluation and choosing is necessary. By the feature evaluation, choose one or many more suitable features from the feature set above, and construct LVQ network input vector with selected features.

Feature evaluation is assessment of features' sensitivity based on the distance between them. The evaluation rule is: the smaller distance between the feature and other features in the same class, and the larger distance between different classes of the feature, the more sensitive the feature is. Evaluation method can be described as four steps as follows [8].

Step 1: Calculating the average distance of the same class data $d_{i,j}$

$$\begin{gathered} d_{i,j} = \frac{1}{N(N-1)} \sum_{m,n=1}^{N} \left| p_{i,j}(m) - p_{i,j}(n) \right| \\ m,n = 1,2,\ldots,N; m \neq n; i = 1,2,\ldots,K; j = 1,2,\ldots,M \end{gathered} \quad (4)$$

where, N is the number of samples; K is the number of features; M is the number of different classes; $p_{i,j}(m)$, $p_{i,j}(n)$ are sample m and n, i and j represent the number of features and classes, respectively. And then getting the average distance of M classes D_i

$$D_i = \frac{1}{M}\sum_{j=1}^{N} d_{i,j} \tag{5}$$

Step 2: Calculating the average distance between different classes data D'_i:

$$q_{i,j} = \frac{1}{N}\sum_{n=1}^{N} p_{i,j}(n) \tag{6}$$

$$D'_i = \frac{1}{M(M-1)}\sum_{u,w=1}^{M} \left| q_{i,u} - q_{i,w} \right| \qquad u, w = 1, 2, \ldots, M;\ u \neq w \tag{7}$$

where, $q_{i,u}$, $q_{i,w}$ are the average value of N samples of the same feature i in class u and w, respectively.

Step 3: Calculating the sensitivity factor, it can be defined as follows:

$$\alpha_i = D'_i / D_i \tag{8}$$

wherein, α_i can reflect the difficulty of classifying M classes use feature i, larger α_i denotes that feature i is more sensitive to different classes, and more suitable for being input vector of network.

Step 4: Sort all features according to α_i from large value to small value, and then choose features for network input vector. First of all, take the first feature as neural network input vector, and then train the network and calculate the test result. Secondly, increase in the number of features one by one, and repeat the calculate process. During certain training epochs, when the training performance, i.e. the Mean Squared normalized Error (MSE) of classification for training samples, decline to 5×10^{-2} or less, it believed that the selected features are enough sensitive to correctly identify M different classes states, and have no further use for other features. Conversely, if training performance is much larger than 10^{-1}, the input vector to add the next feature, until it meets the threshold.

4 Validation

The helicopter transmission fault simulation platform is shown as Fig. 2, it can be used to simulate pitting, chipped, cracks, wearing and other kinds of faults of the planetary gear set system which is the key components of helicopter transmission system. Its design principle is shown as Fig. 3. The drive motor simulates the helicopter engines, and generates driving force; the shaft angle of straight bevel gears 1 and 2, can be used to simulate the spiral bevel gear transmission; #1 and #2

Fig. 2 Helicopter transmission system fault simulation platform

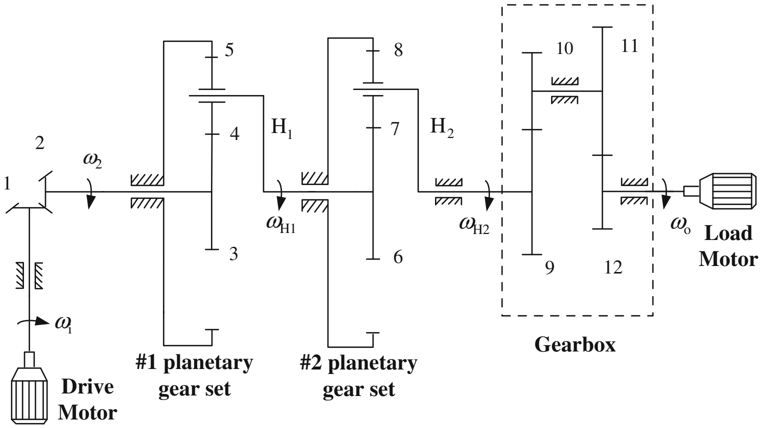

Fig. 3 Illustration of the structure of fault simulation platform

planetary gear sets are used to simulate the helicopter's main reducer; the gearbox can regulate the transmission characteristics between the load motor and the planetary gear set, the load motor also simulates the resistance torque by the rotor shaft. During the experiment, through replacing defective gear, we can study the operating characteristics of transmission system under typical fault condition or evolution of the specific components. Degradation state recognition for the sun gear of planetary gear set is main focus of this paper.

Utilize the simulation platform to take the pre-planted fault experiments. Implant four different severity levels chipped fault in the sun gear of #1 planetary gear set respectively, set the sample frequency is 5 kHz, speed is 1,000 r/min. The acquisition signals include: rotate speed, the horizontal vibration signals (X1) and vertical vibration signals (Y1) of #1 planetary gear set, as well as vertical vibration signals of #2 planetary gear set (Y2). Take 20 samples for every kind of signals, and each sample contains 5,000 points, as shown as Fig. 4.

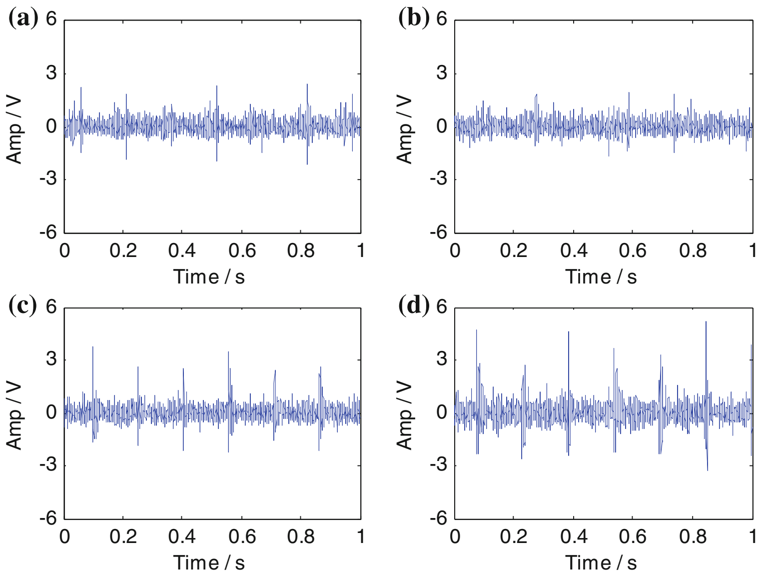

Fig. 4 The different fault level samples of signal X1. **a** level 1, **b** level 2, **c** level 3, **d** level 4

Data processing can be on the procedure as follows:

(1) Extract features from the data obtained before, and get 21 kinds of features to constitute a feature set for each data.
(2) Feature evaluation. Evaluate all features in the feature set of three vibration signal of the different positions respectively, and obtain the result shown as Fig. 5. It is not difficult to find that the sensitive factors of features from different position vibration signals have obvious difference.
(3) Input feature vector construction. According to the above rules, build the feature vector for the three kind of signals respectively. For the signal X1 and Y1, only one feature need to constitute the input vector, which are #18 feature (NF1) and #11 feature(skewness); for the signal Y2, need 7 features to

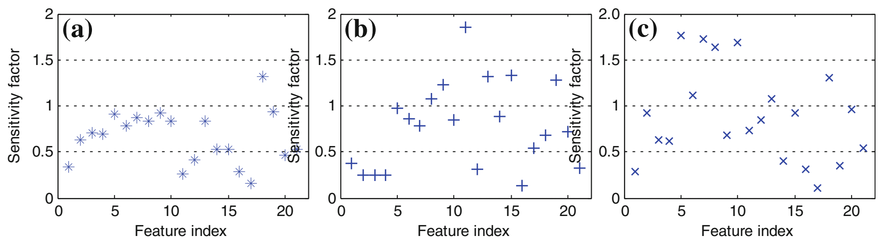

Fig. 5 The results of feature evaluation. **a** X1, **b** Y1, **c** Y2

constitute the input vector, include features #5(peak), #6(peak to peak), #7 (margin factor), #8(crest factor), #10(pulse factor), #13(FM0) and #18(NF1).

(4) Network training. Take 5 samples from every group degradation data samples, total 20 samples as the training data set, and the remaining 60 samples as the validating data. Use neural network toolbox in Matlab software to create an LVQ network and train the network. During the training process, it requires to fix the learning rate η and the number of competitive layer neurons by cross-validation. For signal X1, $s_1 = 11$, $\eta = 0.19$; for signal Y1, $s_1 = 4$, $\eta = 0.04$; for signal Y2, $s_1 = 4$, $\eta = 0.06$.

(5) Degradation state recognition. According to the characteristic of LVQ network, the features of input vector can be taken as the network input directly without normalization. Create an LVQ network with function *newlvq* in neural network toolbox, and after network training, it can be used to identify the state of validation samples. To avoid too long training time, set the training epochs to 300. During the LVQ network training, because of the initialization of competitive layer weights contain some randomicity, the network is a little different from itself after training again, and the recognition results are not exact same. So in order to reduce the fortuity of result, calculating 10 times for every condition, then take the mean of them, and obtain the final recognition result as shown in Table 1.

The results illustrate that LVQ network can effectively identify the four levels fault signals for different positions. Wherein, for signals X1, only a few samples are misidentified as other states in level 3 fault state, the recognition rate reaches 88 %, meanwhile fault samples in level 1, 2 and 4 fault states have been all correctly identified. For signals Y1, fault samples in level 4 fault states have been all correctly identified, there are small amount of misidentified fault samples in other states. Recognition rates for level 1, 3 fault states are around 95 %, and that for level 2 fault states is lower, about 86.7 %. For signals Y2, fault samples in level 1 fault states have been all correctly identified, there are small amount of misidentified fault samples in other states. Recognition rates for level 3, 4 fault states are above 90 %, only for level 2 fault states is about 80 %. Generally, the total recognition rates for three signals are all more than 90, 97 %(X1), 94.3 %(Y1), 92.2 %(Y2) respectively, and demonstrate the effectiveness of LVQ neural network on the degradation state recognition for the experimental data.

Table 1 Identify results of chipped fault based on LVQ network

Fault level	Recognition rate		
	X1 (%)	Y1 (%)	Y2 (%)
Level 1	100.0	96.0	100.0
Level 2	100.0	86.7	80.0
Level 3	88.0	94.7	92.0
Level 4	100.0	100.0	96.7
Total	97.0	94.3	92.2

From the recognition results, it can also be found that, recognition rates are higher for weak fault (level 1) and severe fault (level 4), while other two intermediate fault states are relatively difficult to distinguish, prone to misidentification. In addition, not only feature evaluation results, but also the final recognition results have significant difference for the vibration signals obtained at the different positions. In this paper, the recognition results of signals X1 and Y1 which more closer to the faulty sun gear is better than results of signal Y2.

5 Conclusion

In this paper, we applied the LVQ neural network to identify the degradation state for the sun gear chipped fault of planetary gear set. After the introduction of the structure and characteristic of LVQ network, firstly analyzed the feature evaluation method of input vectors, and then carried out the pre-planted fault experiment with helicopter transmission system simulation platform, acquired enough fault data samples. Finally, trained the network and validated the proposed approach with experiment data. The result illustrated that LVQ network can recognize the degradation state of data samples effectively, and Recognition rate is above 90 %.

Acknowledgment Financial support: This investigation was partly supported by National Natural Science Foundation of China under Grant No. 51075391 and No. 51205401, the Specialized Research Fund for the Doctoral Program of Higher Education of China under Grant No. 20114307110017.

References

1. He ZJ, Chen J, Wang TY, Chu FL (2010) Theories and application of machinery fault diagnostics. Higher Education Press, Beijing
2. Cheng Z, Niaoqing Hu, Gao J (2011) An approach to detect damage quantitatively for planetary gear sets based on physical models. Adv Sci Lett 4(4/5):1695–1701
3. Cheng Z, Niaoqing H, Zhang X (2012) Crack level estimation approach for planetary gearbox based on simulation signal and GRA. J Sound Vib 331(26):5853–5863
4. Sumathi S, Paneerselvam S (2010) Computational intelligence paradigms: theory and applications using MATLAB. CRC Press, New York
5. Samue Paul D, Pines Darryll J (2005) A review of vibration-based techniques for helicopter transmission diagnostics. J Sound Vib 282(1–2):475–508
6. Wu B, Saxena A, Patrick R , Vachtsevanos G (2005) Vibration monitoring for fault diagnosis of helicopter planetary gears. In: Proceedings of the 16th IFAC World congress on disc, Prague, Cesko, 4–8 July 2005
7. Abdulrahman SS, Sharaf-Eldeen YI (2011) A review of gearbox condition monitoring based on vibration analysis techniques diagnostics and prognostics. In: Conference proceedings of the society for experimental mechanics series 8
8. Yang BS, Han T, An JL (2004) ART-KOHONEN neural network for fault diagnosis of rotating machinery. Mech Syst Signal Process 18(3):645–657

http://www.springer.com/978-3-319-09506-6

Engineering Asset Management - Systems, Professional Practices and Certification
Proceedings of the 8th World Congress on Engineering Asset Management (WCEAM 2013) & the 3rd International Conference on Utility Management & Safety (ICUMAS)
Tse, P.W.T.; Mathew, J.; Wong, K.; Lam, R.; Ko, C.N. (Eds.)
2015, XXVIII, 1811 p. 755 illus., 543 illus. in color. In 2 volumes, not available separately., Softcover
ISBN: 978-3-319-09506-6