Research on Fault Diagnosis Method of Train Rolling Bearing Based on Variational Modal Decomposition and Bat Algorithm-Support Vector Machine

Jin zhenzhen\textsuperscript{1,a}, He deqiang\textsuperscript{1,b*}, Chen yanjun\textsuperscript{1,c}, Liu chenyu\textsuperscript{1,d}, Shan sheng\textsuperscript{2,e}

\textsuperscript{1} College of Mechanical Engineering, Guangxi University, Guangxi Nanning 530004; \textsuperscript{2} Zhuzhou CRRC Times Electric Co., Ltd, Hunan Zhuzhou 412001

\textsuperscript{a} email: sdkjdxjz@163.com, \textsuperscript{c} email: yjchen2010@qq.com, \\
\textsuperscript{d} email: 595083431@qq.com, \textsuperscript{e} email: shansheng@csrzic.com

\textsuperscript{*} corresponding author: \textsuperscript{b*} email: hdqlqy@gxu.edu.cn

Abstract: Aiming at the problem that the vibration signal of train rolling bearing presents nonlinear and non-stationary characteristics, which leads to the difficulty of fault feature extraction, a fault diagnosis method of train bogie rolling bearing based on variational mode decomposition (VMD) and bat algorithm optimization support vector machine (BA-SVM) is proposed. Firstly, the center frequency method is used to determine the K value of VMD algorithm. Then, the original signal is decomposed into a series of intrinsic mode components and the distribution entropy of each component is calculated as the feature vector, and the bat algorithm is used to optimize the model parameters of support vector machine. Finally, the BA-SVM model is used for fault pattern recognition of train rolling bearing. The experimental results show that this method can effectively extract the fault characteristics of train rolling bearings and realize fault diagnosis, and the recognition rate is better than that of the comparison method.

1. Introduction

With the development of urban rail transit system, the running speed of the train is increasing, and the carrying capacity is increasing, which brings challenges to the safe operation of the train. As one of the key components of the train, bogie rolling bearing runs at high speed under heavy load for a long time, and the temperature and humidity of the operating environment change rapidly, which intensifies the occurrence of rolling bearing fault. Therefore, it is of great significance to accurately grasp the state of rolling bearing and accurately diagnose the fault of rolling bearing to ensure the safe and stable operation of the train. Vibration signal analysis is a common method for fault diagnosis of rolling bearings. However, due to the nonlinear and non-stationary characteristics of vibration signals, the effective extraction of fault characteristics of rolling bearings is restricted. Therefore, scholars have applied wavelet transform (WT)\textsuperscript{[1]}, empirical mode decomposition (EMD)\textsuperscript{[2]}, variational mode decomposition \textsuperscript{[3]}and other methods to deal with rolling bearing vibration signal, and achieved good results. Variational Mode Decomposition (VMD) proposed by K.Dragomiretskiy\textsuperscript{[4]} can effectively separate the frequency of each signal component, and avoid the problems of insufficient generalization of WT and mode mixing of EMD. In order to extract the feature vector of fault signal, information entropy is introduced into mechanical equipment fault diagnosis. The commonly used information entropy mainly includes sample entropy\textsuperscript{[5]}and permutation entropy\textsuperscript{[6]}, but the sample entropy has the shortcomings of large amount of
calculation and slow calculation, and the permutation entropy does not consider the difference between
the vibration amplitude. Dispersion entropy is an index to measure the complexity and irregularity of
time series. It overcomes the shortcomings of permutation entropy, such as slow calculation of large-
scale data, and the influence of mutation signal on it is small. It has good ability to characterize nonlinear
fault characteristics [7].
Rolling bearing fault diagnosis is a typical small sample pattern recognition problem, Support Vector
Machine (SVM) has the characteristics of simple structure, good generalization performance, and has
outstanding advantages in dealing with small sample pattern recognition problems [8]. However, pattern
recognition ability of SVM is easily affected by penalty coefficient and kernel function parameters. Bat
algorithm (BA) [9] is a heuristic search algorithm proposed by Professor Yang based on swarm intelligence
in 2010, which is an effective method for searching the global optimal solution. It has a good advantage
in training neural network [10], which provides a solution for improving SVM parameter optimization.
Based on the above analysis, combined with the advantages of various algorithms, a train rolling
bearing fault diagnosis method based on VMD and BA-SVM is proposed in this paper. Firstly, VMD is
used to decompose the vibration signal into a series of intrinsic mode components, and the distribution
entropy of each component is calculated as the feature vector. Then, the BA algorithm is used to optimize
the parameters of SVM, and the BA-SVM model is obtained. The BA-SVM model is used to identify
the fault of rolling bearings. Finally, the optimal comparison with the existing similar methods shows
that the proposed method can accurately identify the fault type of rolling bearings, and has certain
advantages.

2. Theoretical method

2.1 Variational modal decomposition

The VMD decomposition algorithm is a process of solving variational problems. When the VMD
algorithm is used for signal decomposition to iterate K intrinsic modal components IMF, the
corresponding variational model is as follows [4]:

\[
\min_{\{u_{k}\}} \left\{ \sum_{t=1}^{T} \left\| \left( \delta(t) + \frac{j}{\pi t} \right) * u_{k}(t) \right\|_{2}^{2} \right\}
\]

In this model, \( f \) is the input signal, \( t \) is the time, \( \delta \) is the Dirac distribution,
\( \{u_{k}\} = \{u_{1}, u_{2}, \ldots, u_{K}\} \) represents the K natural modal components IMF, and \( \{w_{k}\} = \{w_{1}, w_{2}, \ldots, w_{K}\} \) is
the frequency center of each IMF. The Lagrange function is introduced to solve the optimal solution of
the constrained variational problem. There are:

\[
L\left(\{u_{k}\}, \{w_{k}\}, \lambda\right) = \alpha \sum_{k} \left\| \left( \delta(t) + \frac{j}{\pi t} \right) * u_{k}(t) \right\|_{2}^{2} + \frac{\lambda}{2} \left\| f(t) - \sum_{k} u_{k}(t) + \frac{\lambda(t)}{2} \right\|_{2}^{2} + \left\langle \lambda(t), f(t) - \sum_{k} u_{k}(t) \right\rangle
\]

In the formula, \( \alpha \) is the secondary penalty factor, and \( \lambda \) is the Lagrange operator. To obtain the
saddle point of the Lagrange function through the alternating direction multiplier algorithm, that is, the
optimal solution of the constrained variational model, the modal component \( u_{k} \) and the center frequency
\( w_{k} \) can be obtained as:
\[ u_{i+1}(w) = \frac{\hat{f}(w) - \sum_{j=1}^{n} \hat{u}_j(w) + \frac{\dot{x}(w)}{2}}{1 + 2\alpha (w - w_i)} \]  

\[ \hat{w}_{i+1} = \frac{\int w |\hat{u}_i(w)|^2 \, dw}{\int |\hat{u}_i(w)|^2 \, dw} \]  

2.2 BA optimized SVM

Bat algorithm (BA) is a search algorithm that simulates bats using sonar system to pursue prey and avoid obstacles. The specific process of SVM parameter optimization using BA algorithm is shown in Figure 1.

Fig.1 Flow chart of BA-SVM

3. Fault diagnosis model

The main steps of the rolling bearing fault diagnosis method based on VMD and BA-SVM proposed in this paper are shown in Figure 2:

Fig.2 Flow chart of fault diagnosis

4. Case analysis

In this paper, the vibration signals collected by a rolling bearing test rig designed and processed by a
research institute is used as the test data. The speed is 1309 r/min and the sampling frequency is Fs = 10240 Hz. Four types of samples are selected in this paper, including normal operation, outer ring fault, inner ring fault and rolling element fault. Each fault type includes 12 groups of samples, and each sample contains 2048 sampling points.

4.1 Modal number determination and VMD decomposition
According to the flow chart shown in Figure 2, the first is to determine the parameter K of VMD by using the center frequency. The number of modal decomposition K value has great influence on VMD effect, when K is small, it will filter out important information; When K is large, the decomposition will produce mode mixing. Taking the inner ring failure as an example, the penalty factor adopts the default value of 2000. Table 1 below shows the center frequencies corresponding to different K values when the inner ring fails. It can be seen that when K=6, the center frequencies of IMF4 and IMF5 components are closer, and when K=7, the center frequencies of IMF5 and IMF5 components are closer, may lead to modal aliasing, so K is more appropriate to choose 5.

| K  | IMF1  | IMF2  | IMF3  | IMF4  | IMF5  | IMF6  | IMF7  |
|----|-------|-------|-------|-------|-------|-------|-------|
| 3  | 1200  | 3287  | 4075  |       |       |       |       |
| 4  | 850   | 2544  | 3578  | 4195  |       |       |       |
| 5  | 507   | 1990  | 3072  | 3718  | 4320  |       |       |
| 6  | 235   | 1534  | 2550  | 3448  | 3789  | 4426  |       |
| 7  | 227   | 1410  | 2356  | 3181  | 3653  | 3919  | 4587  |

4.2 Calculation of Spread Entropy
Through analysis, the number of the decomposition layers of the four states are all 5. Five modal components are decomposed by VMD and the distribution entropy values of each component are calculated.

In order to express the feature extraction effect of rolling bearing features more intuitively, this paper averaged the distribution entropies of rolling bearing normal, inner ring failure, outer ring failure and rolling element failure to obtain the mean value distribution curve of rolling bearing VMD distribution entropy as shown in Figure 3.

![Fig.3 Mean value of VMD dispersion entropy of rolling bearing](image)

The entropy value reflects the uniformity of the signal, the uniform distribution of the entropy value is large, and vice versa. The vibration signal of the rolling bearing is relatively stable under normal conditions. In the case of a fault, the signal will be concentrated in the fault characteristic frequency band to varying degrees and fluctuate greatly. As can be seen from Figure 3 above, the entropy value of the rolling bearing in the normal state is generally higher than the fault state. The law of measured vibration signal entropy conforms to the theory of dispersion entropy, which proves the rationality of
using dispersion entropy to extract the fault characteristics of rolling bearings.

4.3 Fault pattern recognition

The method in Section 4.2 is used to construct the feature vector set, and 12 groups of samples are extracted for each state. Among them, 8 groups of samples are the training set, and 4 groups of samples are the test set. The class labels of normal state, inner loop fault, outer loop fault and rolling element fault are 1, 2, 3 and 4, respectively. The bat algorithm is used to optimize the support vector machine (BA-SVM) for fault classification and recognition. The results of state pattern recognition are shown in Figure 5. It can be seen from Figure 4 that the BA-SVM model with the spread entropy as the input can accurately identify four states, and the recognition rate reaches 100%.

![Failure mode recognition result](image)

In order to verify the superiority of the method in this paper, the same data samples were used to directly calculate the original signal of the spread entropy and support vector machine method (DE-SVM), the spread entropy and particle swarm optimization support vector machine method (DE-PSO-SVM) to identify the fault mode of rolling bearing, the results are shown in Table 2. The comparison of the three methods shows that the method proposed in this paper can accurately identify the failure mode, and the recognition effect is the best.

| Serial number | Diagnosis method         | Diagnostic result |
|---------------|--------------------------|-------------------|
| 1             | VMD-DE-SVM               | 87.5%             |
| 2             | VMD-DE-PSO-SVM           | 93.75%            |
| 3             | VMD-DE-BA-SVM            | 100%              |

5. Conclusions

Aiming at the problem that the vibration signal of train rolling bearing is nonlinear and non-stationary, and it is difficult to extract feature, a fault diagnosis method based on VMD and BA-SVM is proposed in this paper. The following conclusions are obtained:

(1) VMD algorithm can separate the modal components of different frequency bands, and can effectively suppress noise interference; The distribution entropy can reflect the complexity of vibration signal, which is reasonable as fault feature vector.

(2) The VMD is used for signal decomposition, the distribution entropy is used for fault feature extraction, and the BA-SVM is used to identify the fault mode. Compared with other methods, the proposed method can accurately identify four types of modes, and the recognition rate is 100%. It proves
that this method has certain advantages in the fault diagnosis of rolling bearings.

Acknowledgments

The research was supported by the Natural Science Foundation of Guangxi Province of China [grant number 2017GXNSFDA198012], Nanning Excellent Young Scientist Program [grant number RC20190204] the Science and Technology Planning Project of Nanning [grant number 20193127] and the Innovation Project of Guangxi Graduate Education [grant number YCSW2020017].

References

[1] Kankar, P. K., Sharma, S. C., & Harsha, S. P. (2011). Rolling element bearing fault diagnosis using wavelet transform. Neurocomputing, 74(10), 1638-1645.
[2] Rai, A., & Upadhyay, S. H. (2017). Bearing performance degradation assessment based on a combination of empirical mode decomposition and k-medoids clustering. Mechanical Systems and Signal Processing, 93, 16-29.
[3] Cheng, Y., Wang, Z., Chen, B., Zhang, W., & Huang, G. (2019). An improved complementary ensemble empirical mode decomposition with adaptive noise and its application to rolling element bearing fault diagnosis. ISA transactions, 91, 218-234.
[4] Dragomiretskiy, K., & Zosso, D. (2013). Variational mode decomposition. IEEE transactions on signal processing, 62(3), 531-544.
[5] Zhao, S.T, Ma,L., Zhu, J.P., et al. (2020). Mechanical fault diagnosis of high voltage circuit breaker based on CEEMDAN sample entropy and FWA-SVM [J].Power automation equipment , 40(03):181-186.
[6] Li, C.W., Li,W.P., Pang,B., et al. (2020). Rolling bearing fault diagnosis based on EEMD related permutation entropy [J]. Modular Machine Tool and Automatic Manufacturing Technology, 08: 1-4.
[7] Rostaghi, M., & Azami, H. (2016). Dispersion entropy: A measure for time-series analysis. IEEE Signal Processing Letters, 23(5), 610-614.
[8] Shifei, D., Bijingjuan, Q., & Hongyan, T. (2011). Review of Support Vector Machine Theory and Algorithm Research [J]. Journal of University of Electronic Science and Technology, 1, 2-10.
[9] Yang, X. S. (2010). A new metaheuristic bat-inspired algorithm. In Nature inspired cooperative strategies for optimization. NICOSS 2010. Berlin, pp. 65-74.
[10] Khan, K., & Sahai, A. (2012). A comparison of BA, GA, PSO, BP and LM for training feed forward neural networks in e-learning context. International Journal of Intelligent Systems and Applications, 4(7), 23.