FAULT ANALYSIS AND IDENTIFICATION OF MOTOR BEARING BASED ON ESMD AND SVM

Xuejun CHEN[1]*, Zhixin CUI[2], Jun SHEN[2], Lin MA[2]

Aiming at the non-stationary and non-linear characteristics of motor bearing vibration signal, a fault analysis and identification method of motor bearing based on extreme-point symmetric mode decomposition (ESMD) and support vector machine (SVM) is proposed. ESMD uses the optimal adaptive global mean to determine the optimal number of modal decomposition. The best IMF component of fault feature can be obtained by decomposing the vibration signal of motor bearing by ESMD algorithm. The energy of IMF components which contain the main fault features are extracted and normalized. The feature vectors are imported into SVM classification, and then the fault types are identified based on SVM classifier. It is verified by simulation experiment and database of Case Western Reserve University. Experimental results show that compared with empirical mode decomposition (EMD), this method can not only reduce the useless IMF components, but also effectively improve the signal decomposition accuracy and suppress the mode aliasing phenomenon in the process of EMD decomposition. Compared with the EMD-SVM method, the ESMD-SVM based method has higher accuracy. This method can provide a new idea for motor bearing fault analysis and identification.

Keywords: Motor bearing; Fault analysis; Identification; Extreme-point symmetric mode decomposition; Support vector machine

1. Introduction

The motor is widely used in the industrial field, and the bearing as an important component of the motor, the performance of the bearing directly determines the operation of the motor. According to relevant statistics, bearing fault accounts for 40% of the total faults in motor fault types, so it is of great significance to study the fault diagnosis of motor bearing [1-2].

There are many methods for motor bearing fault analysis and identification diagnosis, but the most common and effective method is to extract fault features and identify fault categories from vibration signals [3-4]. Due to the complexity of motor operating conditions, the vibration signal often contains noise and other interference signals, which makes it nonlinear and non-stationary. Traditional signal processing methods, such as Fourier transform and wavelet transform, have

[1] Key Laboratory of Fujian Universities for New Energy Equipment Testing, Putian University, Putian, China; * corresponding author: E-mail: cxjnet@126.com
[2] School of Mechanical Engineering and Automation, Fuzhou University, Fuzhou, China

good application effect on linear stationary signal [5-6], but they are not applicable to nonlinear and non-stationary signals. Aiming at the non-linear and non-stationary characteristics of vibration signals, Norden E. Huang proposed the Hilbert Huang transform (HHT) [7].

HHT firstly carries out empirical mode decomposition (EMD) on vibration signals to obtain the intrinsic mode functions (IMF) including the main frequency components, and then carries out Hilbert spectrum analysis (HSA) on these characteristic component signals [8-9]. For the analysis of nonlinear and non-stationary vibration signals, this method has achieved good results, but sometimes the accuracy of EMD decomposition is not high, and the mode aliasing phenomenon exists in the decomposition process.

In order to improve the inherent mode aliasing problem of EMD, based on EEMD method, reference [10] achieves the effect of denoising by adding Gaussian white noise to further reduce the impact of mode aliasing. However, its own white noise can not be effectively eliminated.

According to the problems existing in the practical application of EMD, Wang Jinliang and others proposed extreme-point symmetric mode decomposition (ESMD) in 2013 [11]. ESMD is a new development of HHT method. ESMD retains the characteristics of EMD adaptive decomposition signal, but uses internal extreme-point symmetry direct interpolation to replace the external envelope interpolation in EMD, and adopts the optimization strategy, introduces the optimal adaptive global mean (AGM) to determine the optimal screening times, and then obtains the optimal mode decomposition times [11-12]. The experimental results show that this method has more advantages than EMD.

Support vector machine (SVM) is a data classifier based on the statistical learning theory of data [13], which has the advantages of simple structure, short learning and prediction time, global optimization and so on. Therefore, in this paper, SVM classifier is used to identify the fault category of motor bearing.

2. ESMD-SVM Method

2.1. EMD

The core idea of EMD is to decompose the signal into the sum of IMF components and residual quantity including the main frequency components, according to the local characteristic time scale of the signal [14]. Its principle can be simply described as:

$$x(t)=\sum_{j=1}^{n}c_j+R \tag{1}$$

In formula (1), R is the residual quantity, that is, the residual term, c_j is the j-th IMF component, and n is the number of IMF components.

2.2. ESMD

ESMD is essentially the same as EMD. The difference is that ESMD introduces the optimal adaptive global mean to optimize the screening times, and uses the internal extreme-point symmetry interpolation to replace the outer envelope interpolation in EMD, which can reduce or even eliminate the mode aliasing in EMD to a certain extent. Meanwhile, ESMD also expands the two conditions that define the IMF to improve its decomposition accuracy. The expansion content is as follows:

(1) Regarding the adjacent and equal extreme-points as one, the local maximum points and the minimum points of the IMF are arranged staggered, and the maximum value is defined as positive and the minimum value is negative.

(2) In general, the IMF components are almost extreme-point symmetric.

Therefore, the whole ESMD decomposition process can be realized in seven steps.

(1) All the maximum and minimum points of the original signal Y are obtained and marked as $E_i(i=1,2\cdots n)$ in turn.

(2) Mark separately with $F_i(i=1,2\cdots n-1)$, the midpoints connected by line segments between adjacent extreme points, and supplement the midpoints F_0 and F_n of the left and right boundaries by a certain method.

(3) Using the above $n+1$ midpoints, construct P interpolation line $L_1,L_2\cdots L_p(P\geq 1)$, and take the average value L^*, namely:

$$L^*=\frac{L_1+L_2+\cdots+L_p}{P} \tag{2}$$

(4) Repeat the above steps (1)-(3) for $Y-L^*$ until L^* meets the pre-set termination condition, and then the first mode M_1 is obtained.

(5) Let $Y-M_1$ be the original signal and repeat the above steps (1) - (4) to obtain $M_2,M_3\cdots$ in turn until the extreme point of the final margin R is within the preset value.

(6) Change the value of the maximum screening times K, but ensure that K belongs to $[K_{\min},K_{\max}]$. repeat the steps (1) - (5) above to calculate the variance ratio. The calculation formula is as follows:

$$\frac{\sigma}{\sigma_0}=\sqrt{\frac{\sum_{i=1}^{n}(y_i-\bar{Y})}{\sum_{i=1}^{n}(y_i-r_i)}} \tag{3}$$

Where $Y=\{y_i\}$ -- the original data, $\bar{Y}=\left(\sum_{i=1}^{n}y_i\right)\Big/n$, $R=\{r_i\}$ -- the remainder is the AGM curve of the original data.

(7) Draw a graph of the change of σ/σ_0 with K, select the number of screenings corresponding to the minimum variance ratio, and repeat steps (1)-(4) to decompose a series of optimal IMF and residual *R*.

2.3. Fault Analysis and Recognition Based on ESMD-SVM

Compared with EMD, ESMD has strong decomposition ability, high decomposition accuracy, and can effectively suppress mode aliasing. Compared with other classification algorithms, SVM has the advantages of simple structure, short learning and prediction time, global optimization and so on [13]. The fault diagnosis steps of motor bearing based on ESMD-SVM are as follows:

(1) The vibration signal of motor bearing collected by data acquisition system is decomposed by ESMD method.

(2) The first n modal components including the main fault features are extracted from the ESMD decomposition results, and the energy of the first n modal components is calculated. The calculation formula is as follows:

$$E_i = \int_{-\infty}^{+\infty} \left| M_i(t) \right|^2 dt = \sum_{j=1}^{m} \left| M_{ij} \right|^2 \tag{4}$$

Where, $i = 1, 2 \cdots, n$ (n-the number of modal components); $j = 1, 2 \cdots, m$ (m-the number of data sampling points); M_{ij}-the amplitude of each IMF component.

(3) The energy feature vector T is constructed by using E_i in (2), and T is normalized to get T^*:

$$T = \left[E_1, E_2, \cdots, E_n \right] \tag{5}$$

$$E^* = \left(\sum_{i=1}^{n} \left| E_i \right|^2 \right)^{\frac{1}{2}} \tag{6}$$

$$T^* = \left[\frac{E_1}{E^*}, \frac{E_2}{E^*}, \cdots, \frac{E_n}{E^*} \right] \tag{7}$$

(4) The T^* of training samples and test samples are used as feature vectors to input the multi-fault classification SVM classifier composed of SVM1, SVM2, SVM3 and SVM4. The data samples are trained and identified by SVM, and the fault classification of motor bearing and the accuracy of recognition results are finally output.

3. Simulation Signal Analysis

EMD and ESMD are both signal-based adaptive decomposition methods. Taking the simulation signal as an example, this paper analyzes and compares the ability of EMD and ESMD in signal decomposition and mode aliasing suppression. The superposition signal $z(t)$ of sine signal $x(t)$ and amplitude modulation signal $y(t)$ is taken as the original input signal, and its expression is as follows:

$$\begin{cases} x(t) = \sin(2\pi 50t) \\ y(t) = (1+0.6\sin(2\pi 4t))\cdot\sin(2\pi 90t) \\ z(t) = x(t) + y(t) \end{cases} \tag{8}$$

The time domain waveforms of $x(t)$, $y(t)$ and $z(t)$ are shown in Fig. 1.

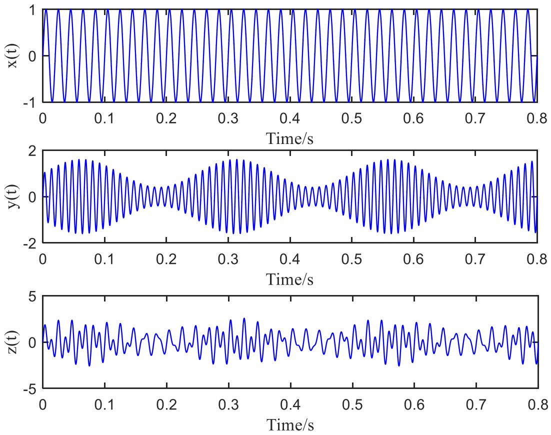


Fig. 1 Time domain waveform

EMD and ESMD methods are used to decompose $z(t)$, and the decomposition results are shown in Fig. 2 (a) and (b) respectively. It can be seen from the decomposition results that the signal features are mainly concentrated in IMF1 and IMF2 components, and the components after IMF3 can be regarded as interference due to their small amplitude. Comparing the decomposition results of the two methods, it can be seen that the decomposition amount of ESMD is less and the IMF component causing interference is less.

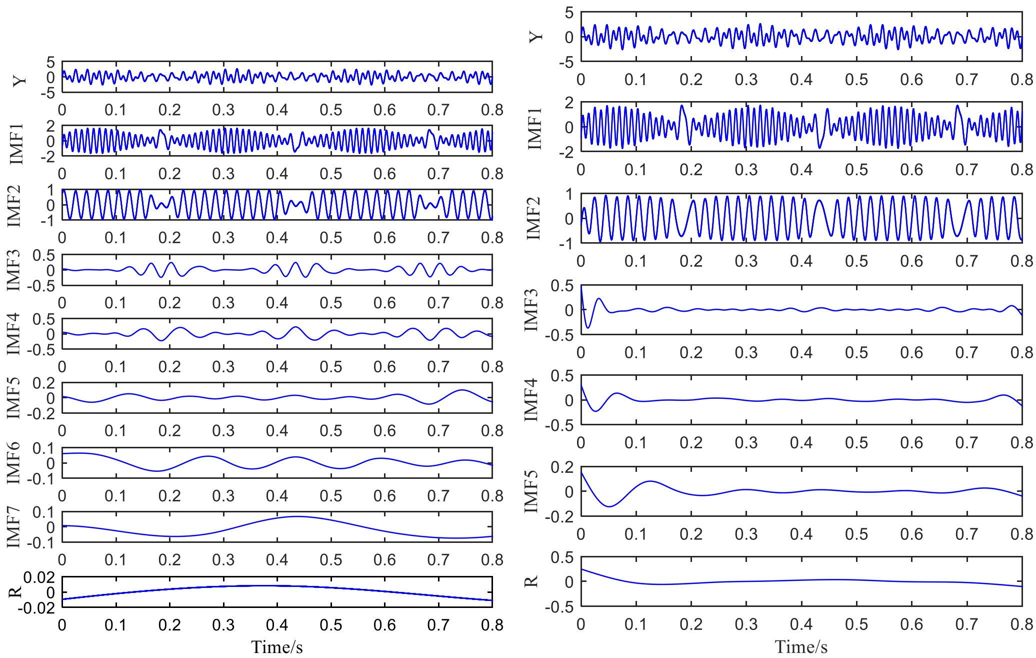
The results of correlation coefficient comparison between EMD and ESMD decomposition results and original signal are shown in Table 1. The higher the correlation between IMF and the original signal, the higher the decomposition accuracy and the better the decomposition effect. Otherwise, the decomposition accuracy is low and the decomposition effect is poor. It can be seen from Table 1 that the correlation coefficient of each IMF in the decomposition results of ESMD is higher, the decomposition ability is stronger, and the decomposition effect is better.

Perform spectrum and instantaneous frequency analysis on IMF1 and IMF2 in the decomposition results of EMD and ESMD. The two modal components spectrograms after EMD and ESMD decomposition are shown in Fig. 3 (a) and (b) respectively. And Fig. 4 (a) and (b) respectively show the instantaneous frequency diagrams of the two modal components after the decomposition of EMD and ESMD. Comparing Fig. 3 (a), (b) and Fig. 4 (a), (b), it can be seen that the modal aliasing phenomenon is obvious in the decomposition result of EMD, and the ESMD decomposition method can effectively suppress the modal Aliasing phenomenon.

Table 1

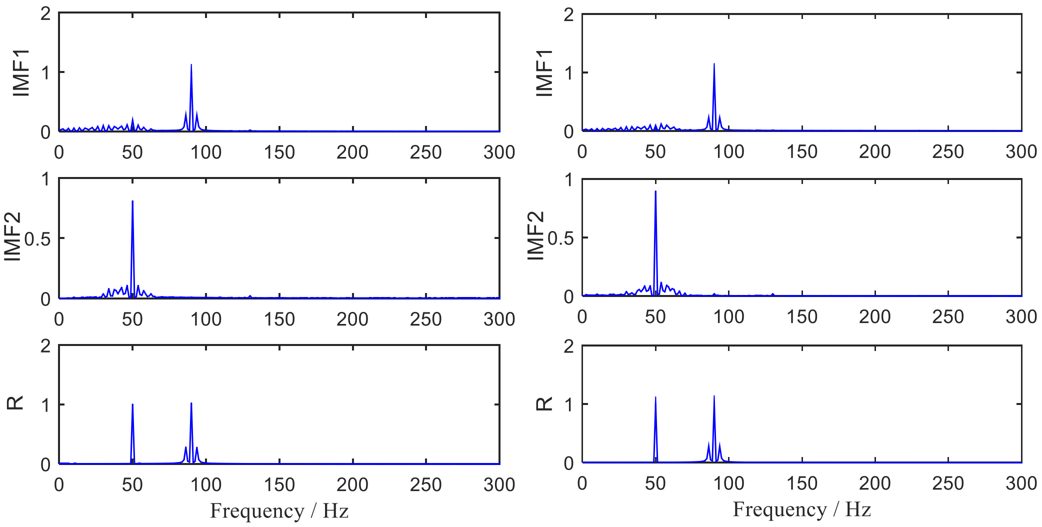
Correlation coefficients between EMD and ESMD decomposition results and original signals

Decomposition component	EMD	ESMD
IMF1	0.9383	0.9538
IMF2	0.9464	0.9553
IMF3	0.0029	0.0345
IMF4	0.0105	0.0286
IMF5	0.0137	0.0427
IMF6	0.0151	/
IMF7	0.0103	/
R	0.0039	0.0379



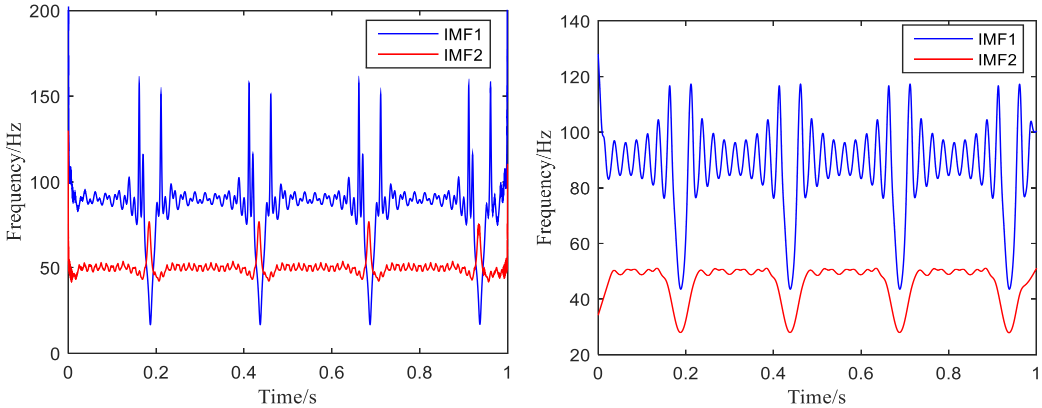
(a) The decomposition results of EMD method. (b) The decomposition results of ESMD method

Fig. 2 EMD and ESMD decomposition results



(a) The spectrogram of EMD decomposition (b) The spectrogram of ESMD decomposition

Fig. 3 The spectrogram



(a) The instantaneous frequency of EMD (b) The instantaneous frequency of ESMD

Fig. 4. The instantaneous frequency diagram

4. Fault diagnosis of motor bearing

Take the experimental database of motor bearing fault of Case Western Reserve University as the data source of this experiment [14]. The experimental platform is shown in Fig. 5. In the experiment, artificial faults were created on the inner and outer rings and rolling elements of motor bearings to simulate the natural fault categories of motor bearings. Data collection is performed on the fan side and the drive side with a sampling frequency of 12 kHz [15-17]. In this paper, 60 sets of fan end data are randomly selected, including 15 sets of normal data, inner ring fault data, outer ring fault data, and rolling element fault data. The number of data sampling points for each group is set to 3600. The 60 groups of data are divided into test samples and training samples. Among them, 40 groups are training samples and 20 groups are test samples.

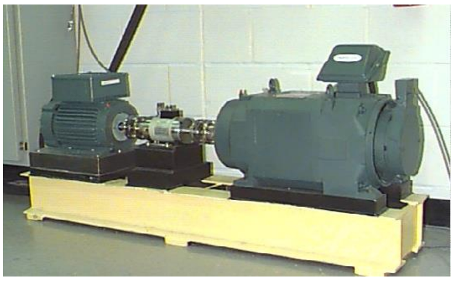


Fig. 5 No-load circuit model of single-phase transformer

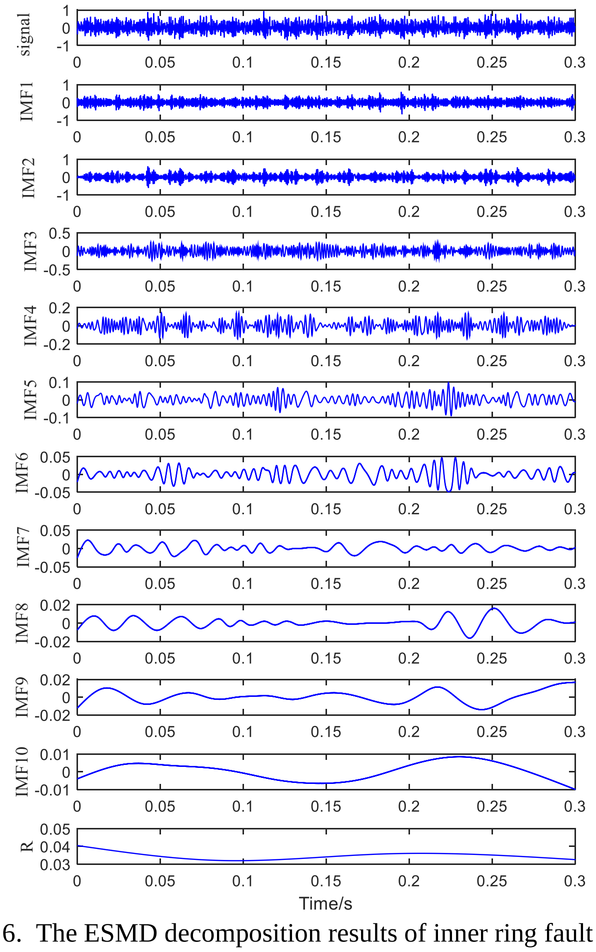
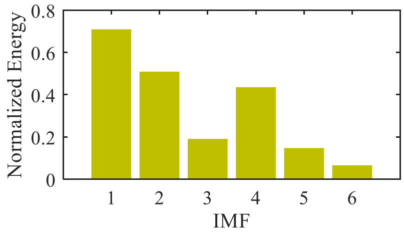


Fig. 6. The ESMD decomposition results of inner ring fault data

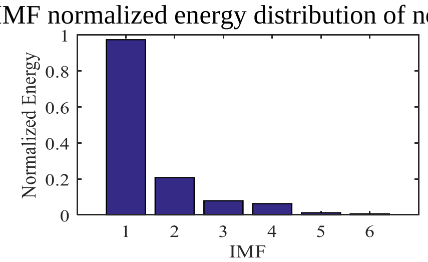
First, 60 sets of sample data are decomposed by ESMD. The ESMD decomposition results of a group of motor bearing inner ring faults are shown in

Fig. 6. From the ESMD decomposition results, it can be seen that the fault frequency information of motor bearings mainly contains the first few modes.

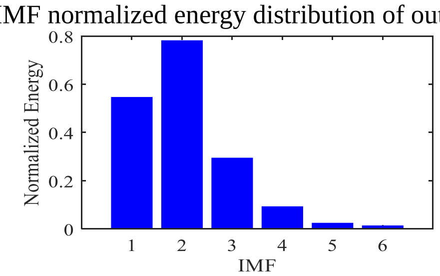
In this paper, the first six modal components are selected for research, and their energy is calculated, the energy eigenvector is constructed and normalized. The first six IMF normalized energy distributions of the four bearing fault categories are shown in Fig. 7.



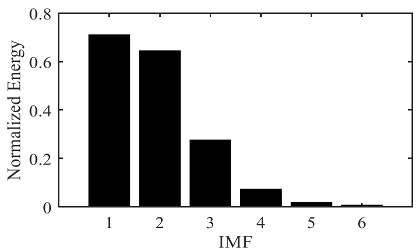
(a) The IMF normalized energy distribution of normal data



(b) The IMF normalized energy distribution of outer ring fault



(c) The IMF normalized energy distribution of inner ring fault



(d) The IMF normalized energy distribution of rolling element fault

Fig. 7 The IMF normalized energy distribution histogram

And Fig. 7 (a), (b), (c) and (d) are normalized energy distribution histograms of IMF for normal, inner ring, outer ring and rolling element respectively. Comparing the IMF normalized energy distribution histogram of these four kinds of bearing fault categories, it can be seen that the energy distribution of each IMF is obviously different after ESMD decomposition for different kinds of bearing fault signals. Therefore, the normalized energy value of each IMF is taken as the feature vector of SVM. The extracted feature vectors are shown in Table 2.

Four kinds of label sets are set in the SVM classifier: “1” for normal, “2” for inner ring fault, “3” for outer ring fault and “4” for rolling element fault. The above feature vectors are input into the multi-fault SVM classifier composed of SVM1, SVM2, SVM3 and SVM4 for training, and then imported into the test set. The test results are shown in Fig. 8. In order to show that ESMD-SVM method has more advantages, EMD-SVM method is used for the same data, and the test results are shown in Fig. 9.

Table 2

Feature vector

Data type	Sample number	E1/E*	E2/E*	E3/E*	E4/E*	E5/E*	E6/E*
Normal data	1	0.7509	0.5053	0.1872	0.4321	0.1438	0.0625
	2	0.5229	0.7037	0.1478	0.2785	0.3458	0.1112
	3	0.5869	0.5970	0.2154	0.4244	0.2564	0.0832
Inner Ring fault	1	0.5449	0.7799	0.2929	0.0913	0.0228	0.0120
	2	0.7365	0.6373	0.2257	0.0430	0.0066	0.0029
	3	0.6449	0.7175	0.2527	0.0710	0.0164	0.0067
Outer Ring fault	1	0.9731	0.2072	0.0785	0.0625	0.0120	0.0060
	2	0.9734	0.2113	0.0659	0.0588	0.0102	0.0047
	3	0.9746	0.1991	0.0818	0.0590	0.0167	0.0056
Rolling element fault	1	0.7099	0.6439	0.2735	0.0724	0.0176	0.0065
	2	0.6984	0.6622	0.2335	0.1357	0.0273	0.0076
	3	0.7081	0.6332	0.3031	0.0746	0.0157	0.0066

The accuracy of ESMD-SV is 95%, and EMD-SVM is 85%. Compared with Fig. 8 and Fig. 9, the detection accuracy of ESMD-SVM method is higher, and the recognition effect of motor bearing fault category is better.

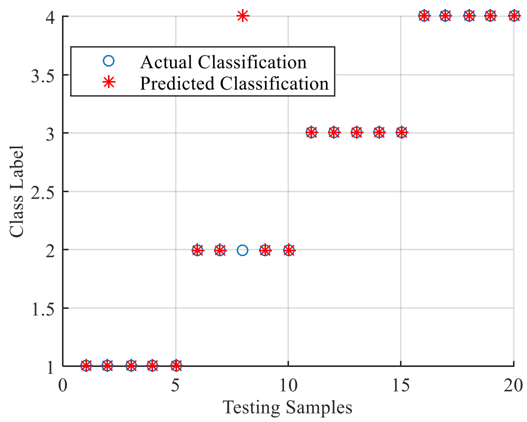


Fig. 8 ESMD-SVM method test results

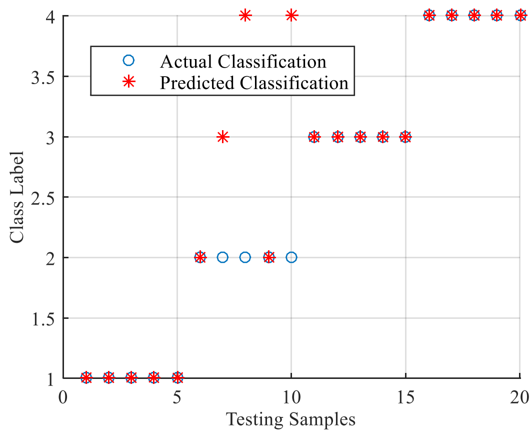


Fig. 9 EMD-SVM method test results

5. Conclusions

Aiming at the non-stationary and non-linear characteristics of motor bearing vibration signal, a method based on pole symmetric mode decomposition is proposed to decompose the bearing vibration signal. The simulation results show that the ESMD decomposition method has stronger decomposition ability, higher precision, stronger ability to suppress mode aliasing and better effect than the popular EMD decomposition method.

The energy distribution histogram of each IMF component after ESMD decomposition is quite different for different fault types of bearings. The energy of each IMF component is used as a feature vector to input SVM for training, and the fault types of test samples are identified. Finally, through the analysis of engineering examples, the ESMD-SVM and EMD-SVM are compared. The experimental results show that the former has higher recognition rate and better effect for motor bearing fault. This ESMD-SVM provides a new method for fault identification with non-stationary and non-linear characteristic signals.

Acknowledgements

This work is supported by the Natural Science Foundation of Fujian Province of China (2018J01511), and the Program for New Century Excellent Talents in Fujian Province University (2018047).

R E F E R E N C E S

[1]. *An Qingguo, Qin Cheng, Guo Liwei, Liang Yongchun*,“Kurtosis filter in feature extraction for incipient motor bearing fault diagnosis”, in Electric Machines and Control, **vol. 18**, no. 6, 2014, pp. 55-60.

[2]. *Li Yuanjun, Sun Jixuan*,“Car motor bearing fault diagnosis based on fault feature extraction and recognition stages”, in Journal of Electronic Measurement and Instrumentation, **vol. 33**, no. 2, 2019, pp. 56-63.
[3]. *Su Wencai, Ahang Shutuan, He Yingzheng*,“Fault Diagnosis of Motor Bearing Based on ESMD and Fast Kurtogram”, in Micromotors, **vol. 52**, no. 1, 2019, pp. 6-10.
[4]. *Wang H., Lin Y., Liao Y.*, "Fault diagnosis of tamper rolling bearing based on IPSO algorithm for optimizing FSVM ", in U.P.B. Sci. Bull. Series D, **vol. 80**, no. 4, 2018, pp.81-90.
[5]. *Li Y, Xu M, Wang R, Huang W*,“A fault diagnosis scheme for rolling bearing based on local mean decomposition and improved multiscale fuzzy entropy”, in Journal of Sound and Vibration, **vol. 360**, 2016, pp. 277-299.
[6]. *Zhang Shuqing, Xu Jiantao, Jiang Anqi*,“Fault Diagnosis of Bearings Based on Extreme-point symmetric Mode Decomposition and Probabilistic Neural Network”, in China Mechanical Engineering, **vol. 28**, no. 4, 2017, pp. 425-431.
[7]. *Zhou Xiaolong, Yang Gongyong, Liang Xiuxia, Li Jiafei*,“Fault Diagnosis of Rolling Bearings Based on EMD reconstruction and SVM”, in Journal of Northeast Dianli University, **vol. 36**, no. 6, 2016, pp. 71-76.
[8]. *Xia P, Xu H, Lei M, Ma Z*,“An improved extreme-point symmetric mode decomposition method and its application to rolling bearing fault diagnosis”, in Journal of Vibroengineering, **vol. 20**, no. 8, 2018, pp. 2810-2824.
[9]. *Li Yingming, Zhao Chenxiao, Tan Qian*,“Classification method for long period ground motions based on component decomposition with HHT”, in Journal of Vibration and Shock, **vol. 37**, no. 7, 2018, pp.164-171+219.
[10]. *Guo Di, Wang Y, Yu L, Pu Y, Jiang J, Min J, Zhang W*, "Application of EEMD singular value energy spectrum in gear fault identification", in U.P.B. Sci. Bull., Series D, **vol.83**, no. 3, 2021, pp.29-42.
[11]. *Wang J L, Li Z J*,“Extreme-point symmetric mode decomposition method for data analysis”, in Advances in Adaptive Data Analysis, **vol. 5**, no. 3, 2013, pp. 1350015.
[12]. *Wang J, Li Z*,“The ESMD method for climate data analysis”, in Climate Change Research Letters, **vol. 3**, no. 1, 2014, pp. 1-5.
[13]. *Wang Xin, Yan Wenyuan*,“Fault diagnosis of roller bearings based on the variational mode decomposition and SVM”, in Journal of Vibration and Shock, **vol. 36**, no. 18, 2017, pp. 252-256.
[14]. *Chen X, Yang Y*,“De-noising for vibration signals based on local mean decomposition”, in IECON 2017-43rd Annual Conference of the IEEE Industrial Electronics Society, IEEE, 2017, pp.3298-3303.
[15]. Zhu Y, Tang S, Quan L, Jiang W, Zhou L,“Extraction method for signal effective component based on extreme-point symmetric mode decomposition and Kullback–Leibler divergence”, in Journal of the Brazilian Society of Mechanical Sciences and Engineering, **vol. 41**, no. 2, 2019, pp. 100.
[16]. *Cheng Junsheng, Wang Jian, Gui Lin*,“An improved EEMD method and its application in rolling bearing fault diagnosis”, in Journal of Vibration and Shock, **vol. 37**, no. 16, 2018, pp. 51-56.
[17]. *Zhu Y, Jiang W, Kong X*,“Adaptive extraction method for trend term of machinery signal based on extreme-point symmetric mode decomposition”, in Journal of Mechanical Science and Technology, **vol. 31**, no. 2, 2017, pp. 493-500.