A NEW ROLLER BEARING FAULT DIAGNOSIS METHOD BASED ON VMD ENERGY ENTROPY AND BSOA-LSSVM

AO HUNG LINH
Faculty of Mechanical Engineering, Industrial University of Ho Chi Minh City
aohunglinh@iuh.edu.vn
DOIs: https://doi.org/10.46242/jstiuh.v64i04.4888

Abstract. This paper presents a new method for roller bearing fault diagnosis based on least square support vector machine (LSSVM) with parameters optimized by Backtracking Search Optimization Algorithm (BSOA), namely BSOA-LSSVM. First, roller bearing acceleration vibration signals are decomposed into functions by using Variational Mode Decomposition (VMD) method. Second, initial feature matrices are extracted from those functions by energy entropy to obtain feature matrix. Third, these values serve as input vector for BSOA - LSSVM classifier. Experimental results showed that the proposed method gave the higher classification accuracy (100%) and shorter computational time than other method.
Keywords. Variational Mode Decomposition; fault diagnosis; energy entropy; Backtracking Search Optimization Algorithm; least square support vector machine.

1 INTRODUCTION

The roller bearing is an intermediate element between the stationary part and the rotating part. Roller bearing failure can create a terrible failure, so bearing failure diagnosis plays an important role in ensuring continued system operation. Therefore, the diagnosis of roller bearing faults is a focus of this paper. Roller bearing failure diagnosis includes three stages: data collection, feature extraction, and pattern recognition, of which the latter two stages play an important role. When a bearing failure appears, fault characteristic information extraction is difficult because the roller bearing vibration signal is a non-stationary signal. Feature extraction consists of signal decomposition and feature extraction. The signal decomposition methods consists of Empirical Mode Decomposition (EMD) [1], Mean Decomposition (LMD)[2], Local-scale Characteristic Decomposition (LCD)[3]. Generally, these methods decompose an oscillating signal into the sum of component and residual signals. However, the LMD, EMD, and LCD methods have disadvantages such as end effects and mode mixing because of the sifting process. These effects make the signal decomposition results inefficient, so these methods do not adapt themselves to signals, especially roller bearing vibration signals. Recently, Dragomiretskiy et al. [4] have proposed the method of Variational Model Decomposition (VMD) to decompose the signal. This method surmounts the shortcomings of the EMD, LMD, and LCD methods and gives high efficiency. The component signals are feature extracted to form feature matrices using the methods of frequency ratio analysis [5], energy entropy [6], and the single value decomposition method (SVD) [7]. The feature extraction stage aims to reduce the input matrix size for the object recognition step.

Pattern recognition methods include using discriminable predictive model class discrimination (VPMCD) [8], artificial neural networks (ANNs) [9] and support vector machines (SVM) [10]. The disadvantage of VPMCD is that it is difficult to set the variable parameters of model. The support vector machine method has the advantage over ANN that it has high generalizability with a small number of training samples. This is very suitable when dealing with technical problems that are very expensive to collect large numbers of samples. LSSVM proposed by Suyken [11] is a modified version of SVM to reduce the computational workload. In the process of training by the LSSVM, a least squares error function is recommended to obtain a linear set of equations in dual space. Thus, the data training problem is reduced to just solving a set of linear equations instead of quadratic like in SVM. LSSVM shows the effect performance in prediction accuracy, fast computation, and high classification. However, the challenge for LSSVM users is the selection of the parameters of this model. The parameters of this model include penalty factor and Kernel parameter. Usually, the selection of these parameters is based on heuristic search algorithms. Heuristic algorithms are often used to select and search parameters for LSSVM such as Genetic Algorithm (GA)[12], Differential Evolution algorithm (DE)[13], Particle Swarm Optimization (PSO)[14]. Recently Backtracking Search Optimization Algorithm (BSOA) was proposed for the optimization problem

[15]. This algorithm showed outstanding advantages in solving optimization problems when compared with GA and PSO algorithms. Therefore, in this paper, we propose to use the BSOA as a tool for selecting parameters for the LSSVM classifier.

In this paper, we use VMD method combined with energy entropy (EE) operator for feature extraction and BSOA-LSSVM classifier for fault identification. The bearing acceleration vibration signals are first decomposed into component functions by the VMD method. These component functions are then extracted into a feature matrix by the EE operator. The feature matrices are used as the input matrix for the LSSVM classifier. The parameters of the LSSVM set are optimized by the BSOA to generate the BSOA-LSSVM classifier. The experimental results show that the BSOA-LSSVM classifier gives higher classification results and shorter time when compared with the GA-LSSVM and PSO-LSSVM classifiers with the same input data. The paper is arranged as follows: Section 1 presents VMD method and VMD energy entropy, Section 2 presents Backtracking Search Optimization Algorithm, Section 3 presents optimization of LSSVM parameters based on BSOA. Section 4 presents the application of BSOA-LSSVM to diagnose bearing failure and the experimental process along with the results presented in section 5. Section 6 presents the conclusion of the paper.

2 VMD ENERGY ENTROPY

2.1 Variational mode decomposition (VMD)

The VMD method is an adaptive orthogonal signal decomposition method. This is a powerful method for sampling and anti-interference. VMD can decompose a real signal *x(t)* into some component function $u_k(t)$ [4]. Here, each major u_k form should be compressed around a central point. VMD's proposal can be summarized as a constrained transformation problem:

$$\min_{\{u_k(t)\},\{\omega_k\}} \left\{ \sum_{k=1}^{K} \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) * u_k(t) \right] e^{-j\omega_k t} \right\|_2^2 \right\} \quad (1)$$

$$s.t \sum_{k=1}^{K} u_k\ (t) = x(t)$$

where $u_k(t)=\{u_1(t), u_2(t),\dots, u_k\}$ and $\omega_k=\{\omega_1, \omega_2,\dots,\omega_k\}$ respectively are component and central frequency of them.

The Lagrange multiplier method and the quadratic penalty method are included in Eq.1 to transform the constrained variable problem into the unconstrained variable problem. The Lagrange parameter L is represented as follows:

$$L(\{u_k\},\{\omega_k\},\lambda) = \alpha \sum_{k=1}^{K} \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) * u_k(t) \right] e^{-j\omega_k t} \right\|_2^2 + \| x(t) - \sum_{k=1}^{K} u_k\ (t) \|^2 + \langle \lambda(t), x(t) - \sum_{k=1}^{K} u_k\ (t) \rangle \quad (2)$$

Details of the VMD method are presented in [4]. The number of component functions u_k determines the signal decay time and the classification time of the LSSVM classifier. The larger the number of component functions, the higher the computational time cost. In this paper, we choose the number of component functions to be 3 because important information is often contained in the first components. After decomposing the bearing acceleration vibration signal into component functions, in the next step, these component functions are extracted into characteristic matrices by energy entropy operator.

2.2 VMD Energy Entropy

The resonance frequency components are produced in the roller bearing vibration signals correspond to different faults. To illustrate this change case, the VMD energy entropy is proposed in this paper.

If n u_k are obtained by using the VMD method to decompose the roller bearing vibration signal *x(t)* where the energy of the n u_k is $E_1,E_2, . . . ,E_n$, respectively; then, due to the orthogonality of the VMD decomposition, the sum of the energy of the n u_k should be equal to the total energy of the original signal. As the $\{u_1(t),u_2(t),\dots,u_n(t)\}$ include different frequency components, $E=\{E_1,E_2,\dots,E_n\}$, forms an energy distribution in the frequency domain of roller bearing vibration signal, and then the corresponding VMD energy entropy is designated as

$$H_{EN} = -\sum_{i=1}^{n} p_i \log p_i, \quad (3)$$

where $p_i = E_i/E$ is the percent of the energy of $u_i(t)$ in the whole signal energy ($E = \sum_{i=1}^{n} E_i$), and E_i is presented as:

$$E_i = \int_{-\infty}^{+\infty} |u_i(t)|^2 \, dt, (i = 1,2, \dots, m) \quad (4)$$

Fig. 1 (a), (b), (c), and (d) show the vibration acceleration signals of the roller bearing that is normal, with inner-race fault, with out-race fault, and with ball fault, respectively. Table 1 shows that the energy entropy of each roller bearing vibration signal is different because of the uncertain energy distribution and frequency range. Therefore, the LSSVM classifier will be effective in identifying roller bearing conditions based on these energy entropy values.

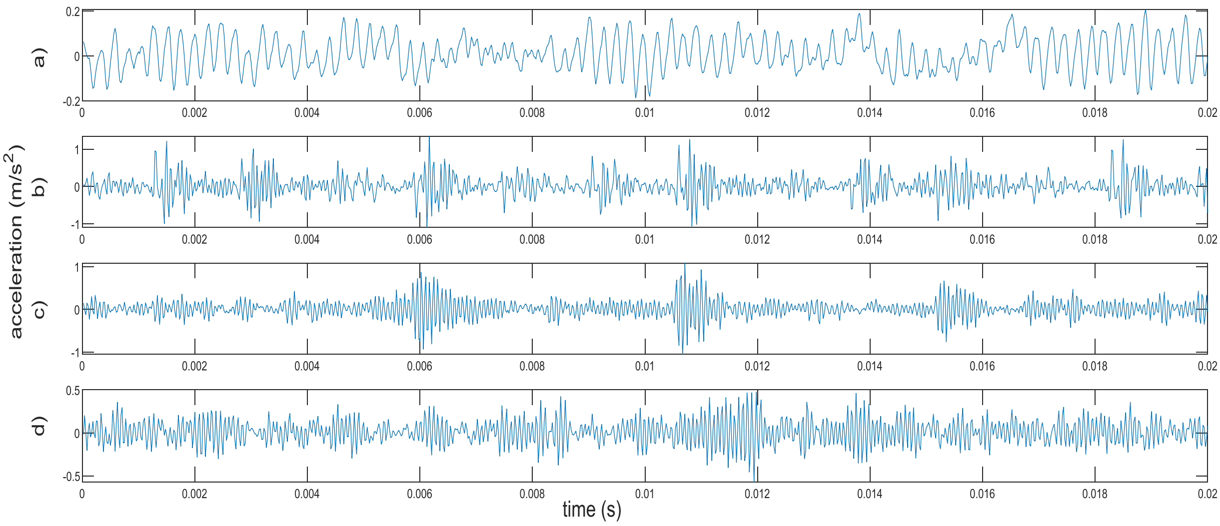

Figure 1 The vibration acceleration signals of the normal (a), inner-race fault (b), outer-race fault (c), and ball fault roller bearing (d)

Table 1 The VMD energy entropies of the vibration signals of the roller bearing with different fault

Inner-race fault ($\times 10^3$)	Out-race fault ($\times 10^3$)	Ball fault ($\times 10^3$)	Normal ($\times 10^3$)
866	539	709	899

3 BACKTRACKING SEARCH OPTIMIZATION ALGORITHM (BSOA)

The BSOA is an adaptive search algorithm that includes three basic genetic operators, mutation, crossover, and selection to produce test individuals. The BSOA algorithm consists of six steps as follows [15]: (i) Problem definition and algorithm parameters; (ii) Initialization; (iii) Selection-I; (iv) crossover and mutation; (v) Selection -II; (vi) End. The procedure of the BSOA algorithm is shown in Fig. 2.

Problem definition and algorithm parameters:

$$min\, f(x) \quad (5)$$

$$subject\ to\ \mathbf{x}_i \in R_i = [l_i, u_i], i = 1,2, \dots N$$

where $f(x)$ is a fitness function, $\mathbf{x} = (x_1, x_2, \dots, x_N)$ is the vector of decision variables, R_i is the range of feasible values for the i-th decision variable, and N is the number of decision variables, l_i and u_i are the lower and upper bounds of the i-th decision variable, respectively;

Initialization: The initial population P_0 are generated and evaluated and a historical population P_0 is also started. The memory of BSOA is constituted.

Selection-I: The current population P is randomly determined to be recorded as the historical population $P0$. Then the individuals of P_0 are mixed up.

Mutation: The mutation P_i operator is created by an initial version of the new population P_j, according to Eq. (1). P_i is the result of the individuals movement ($P_0 - P$) and the motion amplitude $F = k \cdot rndn$ where

$rndn \sim N(0,1)$, N is the standard normal distribution, k value is adjusted empirically during prior simulations. This paper uses k=3. In Eq. (1), F controls the amplitude of the search-direction matrix (P_0 - P).

$$P_i = P_j + F(P_0 - P) \quad (6)$$

Crossover: The elements of P are crossed randomly with the operator from P_I aims to generate the final version of P_j.

Selection-II: The elements from P_j are selected to have better fitness than elements of P, then P_j replaces them in P. Therefore, new evolved individuals are only received by P. After reaching the stopping conditions, the best solution which found is returned.

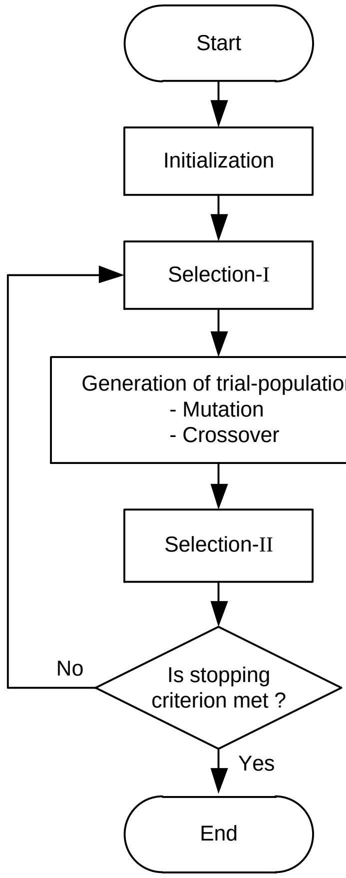

Figure 2 Flowchart of BSOA

4 BSOA BASED LSSVM PARAMETERS OPTIMIZATION

4.1 Least square support vector machine (LSSVM)

LSSVM was proposed by Suykens [11] to decrease the computational workload of SVM, which applies by using equality instead of inequality constraints. LSSVM has solved the following convex optimization problems with good generalization ability and tries to find the optimal separating hyperplane. Suppose $\{(x_i, y_i)|i=1,2,\ldots,l\}$ as training set of sample number is l. The sample of x_i , i=1,2,…,l corresponds to the category of $y_i \in (-1,1)$, the objective function and constraint condition are shown as follows:

$$\begin{cases} \min \quad J(w,e) = \frac{1}{2} w^T w + \frac{1}{2}\gamma \sum_{i=1}^{l} e_i^2 \\ s.t.\ y_i(w^T \varphi(x_i) + b) = 1 - e_i, \quad i = \{1,2,\ldots,l\} \end{cases} \quad (7)$$

where, e_i are slack variables and $\gamma \geq 0$ is a penalty factor/ regularization parameter.

The values of γ will affect the training results of the LSSVM model. The low value of γ means a model with high training errors and oppositely the high γ value does not permit any slack variables and consequently increases model complicity. Therefore, it is critical to find proper value for γ and it is one of LSSVM tuning parameter that should be adjusted conscientiously. The Lagrange function can be define:

$$L(w,b,e,\alpha) = \frac{1}{2}w^T w + \frac{1}{2}\gamma \sum_{i=1}^{l} e_i^2 - \sum_{i=1}^{l} \alpha_i \{y_i(w^T\varphi(x_i)+b) - 1 + e_i \quad (8)$$

where, the α_i values are the Lagrange multipliers, which can be positive or negative. The optimal condition is as follows:

$$\frac{\partial L}{\partial w} = 0; \frac{\partial L}{\partial b} = 0; \frac{\partial L}{\partial e_i} = 0; \frac{\partial L}{\partial \alpha_i} = 0 \quad (9)$$

The matrix equation can be obtained easily as follows:

$$\begin{bmatrix} 0 & Y^T \\ Y & \Omega + I/\gamma \end{bmatrix} \begin{bmatrix} b \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ \bar{I} \end{bmatrix} \quad (10)$$

where $Y^T = [y_1, y_2, \dots, y_l]$; I is unit matrix; $\bar{I} = [1; 1; \dots; 1]$; $\alpha = [\alpha_1, \alpha_2, \dots, \alpha_l]$; $\Omega = y_i y_j \varphi^T(x_i)\varphi(x_j) = y_i y_j K(x_i, x_j)$; $K(x_i, x_j)$ is Kernel function of SVM; *i*, *j*=1,2,…*N*.

The LSSVM classifier in the dual space can be obtained as follows:

$$f(x) = sgn\left[\sum_{i=1}^{l} \alpha_i y_i K(x, x_i) + b\right] \quad (11)$$

In this paper, Gauss radial basic function (RBF) is utilized to map the samples into a higher dimension feature space which can make LSSVM get better performance and generalization, as shown in Eq. (7).

$$K(x, x_i) = exp\left(\frac{-\|x - x_i\|^2}{2\sigma^2}\right) \quad (12)$$

where σ is a Kernel parameter.

Summary, the parameter pair (γ, σ) affect the classification efficiency of LSSVM, in which the penalty factor γ is mentioned in Eq. (7) and σ is a Kernel parameter mentioned in Eq. (12). The proper selection of two parameters will affect the learning performance of LSSVM. Therefore, these parameter pair values must be optimized to obtain effective classification accuracy, which can be done by the BSOA.

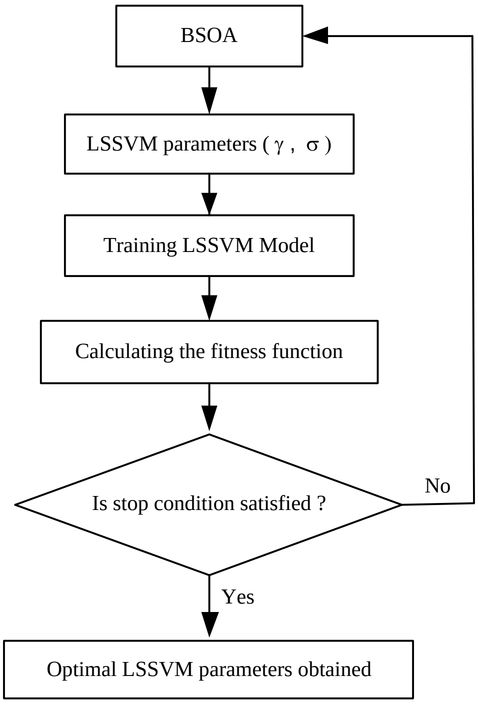

Figure 3. The parameter optimization flowchart of LSSVM based on BSOA

4.2 Parameters optimization of LSSVM based on BSOA

As mentioned in previous studies[12,13], LSSVM parameters strongly influence the classifier performance. The selection of optimal parameters for LSSVM is mainly based on user experience. In this paper, we propose to use BSOA to optimize the LSSVM parameters.

The penalty parameter γ and the kernel parameter σ in the Gaussian kernel function are considered as optimization variables while the test error is a suitable measure of the optimization problem. The objective function is the test error of the SVM and is represented as follows:

$$G(\gamma, \sigma) = \text{Test\_Error}_{LSSVM}(\gamma, \sigma) \quad (13)$$

where $G(\gamma,\sigma)$ is a fitness function and $Test\_Error_{LSSVM}(\gamma,\sigma)$ is define:

$$Test\_Error_{LSSVM} = \frac{Number\ of\ incorrect\ classification\ in\ test\ samples}{Total\ number\ of\ samples\ in\ test\ set} \quad (14)$$

In general, the BSOA was integrated to LSSVM training procedure to obtain the optimal parameters for maximizing the classification accuracy and generalization capability of the LSSVMs. Initially, each individual in the first generation is randomly obtained. The LSSVM algorithm normally calculated the corresponding output weights matrix for each individual. Then, BSOA can be applied to find the fitness measurement for each individual in the population. This process was repeated until the stopping condition was reached. When the evolution is finished, the optimal parameters of the LSSVM were ready to perform the classification. The procedure of BSOA-LSSVM algorithm is shown as follow (Fig.3):

5 APPLICATION OF BSOA-LSSVM TO ROLLER BEARING FAULT DIANOSIS

5.1 Data Acquisition

The data of the Case Western Reserve University Bearing Data Center Website (CWRUBDCW) was used with the kind permission of Professor Loparo [16]. The test stand included a 2 hp Reliance Electric motor, a torque transducer/encoder, a dynamometer, and control electronics. The sample frequency was 485063 Hz and the motor speed was 1772 rpm. The deep groove ball bearing manufactured by SKF was used in this test stand. The drive end bearings are of the 6205-2RS JEM type. The test bearings of electro-discharge machining with fault diameters of 0.007 inches were selected. The roller bearings with the four conditions (normal (NOR), inner-race fault (IRF), outer-race fault (ORF), and ball fault (BF)) include 432 samples. The number of collection samples is divided into 3 parts, one part for testing and 2 parts for training. Table 2 shows collection of vibration signal samples.

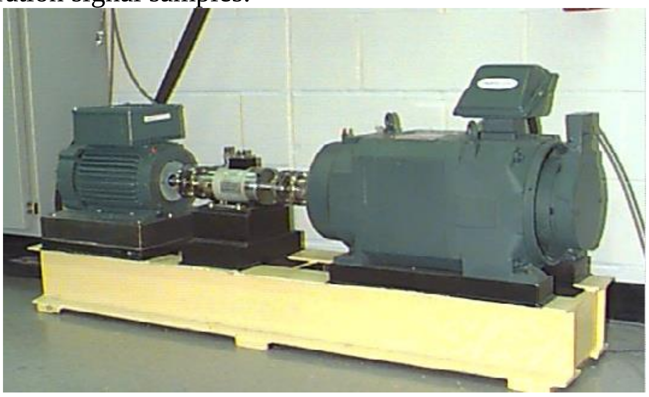

Figure 4 Roller bearing vibration data collection model, extracted from [16]

Table 2 Collection of vibration signal samples

Roller bearing conditions	Class	Collection samples	Training samples	Test samples
Inner-race fault (IRF)	1	108	72	36
Outer-race fault (ORF)	2	108	72	36
Ball fault (BF)	3	108	72	36
Normal (NOR)	4	108	72	36

5.2 Application

It can be seen from the above analysis that the VMD energy entropies of the vibration signal of the roller bearings with different work conditions and fault samples are obviously different, which shows that the energy of each u_k changed when the roller bearing went wrong. In this paper, it is adopted that taking the energy feature of each u_k as the BSOA-LSSVM input vector, the work condition and fault patterns of the roller bearing can be identified effectively. The flow chart of the roller bearing fault diagnosis method based on VMD energy entropy and BSOA-LSSVM is shown in Fig. 5.

(1) Use the VMD to decompose the roller bearing vibration signals into a number of component functions u_k . Because the fault information of the roller bearing was mainly included in the first

three components, the first three components u_k were selected to form the initial feature vector matrix.

(2) Calculate the total energy E_i of the component functions u_k;

$$E_i = \int_{-\infty}^{+\infty} |u_i(t)|^2\, dt, (i = 1,2, \dots, m) \quad (15)$$

(3) Build feature vector Z with the energy as element, namely VMD-EE vector

$$Z = [E_1, E_2, \dots, E_m] \quad (16)$$

(4) Divide the feature vector data into two groups: the training and the testing group.

(5) Train and test the BSOA-LSSVM classification model to classify the actual roller bearing fault conditions. After training, the optimal parameters of BSOA-LSSVM are γ and σ are used to test the samples. A set of BSOA-LSSVM(i) i=1,2,3,4 are constructed to identify bearing conditions IRF, ORF, BF and NOR listed in Table 2. In order to define the condition of roller bearing, first, $BSOA\text{-}LSSVM_1$ was first used to separate the IRF condition from another condition by setting the these conditions as y = +1 and the other conditions as y = −1. Second, $BSOA\text{-}LSSVM_2$ was used to separate the ORF condition from other condition by setting outer-race fault as y = +1 and the other condition as y = −1. Third, $BSOA\text{-}LSSVM_3$ was used to separate the BF condition from other condition by setting BF as y = +1 and the other condition as y = −1. Because the data set had only got four conditions that needed to be identified, the rest was NOR condition.

Table 2 Classifier BSOA-LSSVM model

Classifier model	Roller bearing condition			
	IRF	ORF	BF	NOR
$BSOA\text{-}LSSVM_1$	(+1)	(-1)	(-1)	(-1)
$BSOA\text{-}LSSVM_2$	(-1)	(+1)	(-1)	(-1)
$BSOA\text{-}LSSVM_3$	(-1)	(-1)	(+1)	(-1)
$BSOA\text{-}LSSVM_4$	(-1)	(-1)	(-1)	(+1)

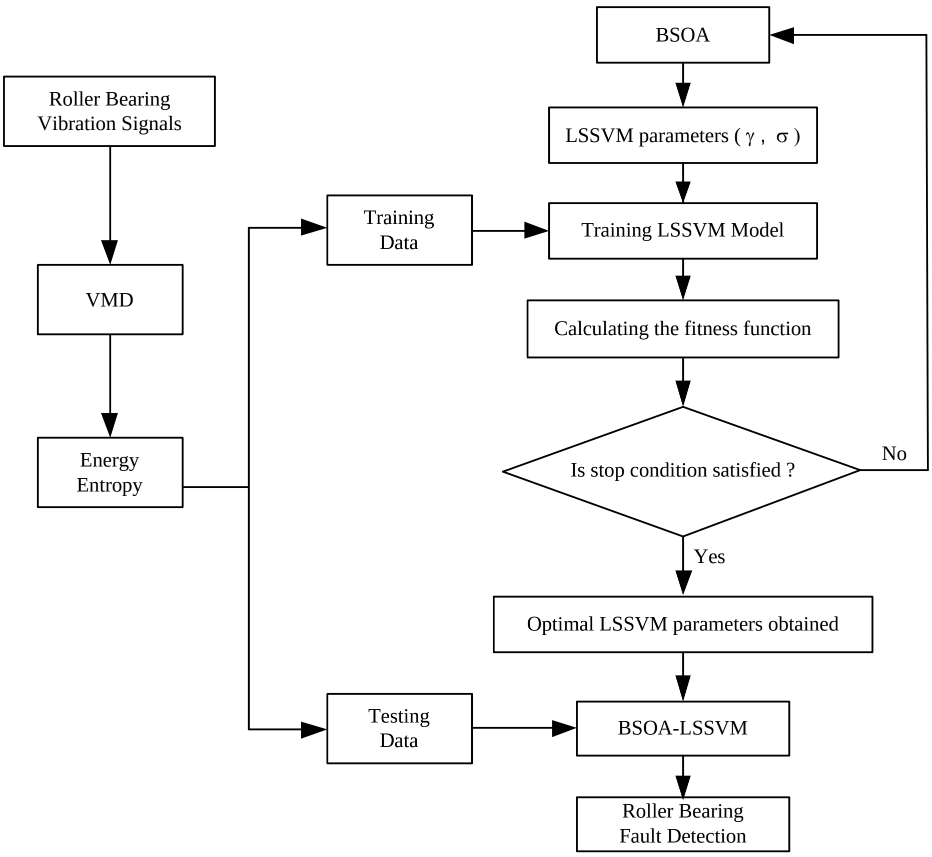

Figure 5. Roller bearing fault detection method based on VMD-EE and BSOA-LSSVM

6 RESULT AND DISCUSION

Results of this paper are show in Table 3. In order to make a fair performance evaluation comparison, the same original vibration signals were chosen. The roller bearing signals were also decomposed into IMFs using the EMD method [1]. Three IMFs were chosen, and they were arranged from high to low, according to the frequency components, as $c_1(t)$, $c_2(t)$, $c_3(t)$, and then the fault feature vector Z was obtained according to Eq.(14). Next, the BSOA-LSSVM was used to identify the various patterns. The identification results of the test samples based on the VMD preprocessing are shown in Table 4 and are compared with those using EMD. The optimal parameters of the classifiers of the 2 methods are presented in Table 4. From Table 4, it is shown that the classification results of the proposed method give the best classification accuracy (0%) compared to the EMD method. At the same time, the program running time of the VMD-EE- BSOA -LSSVM method is shorter than that of EMD-EE-BSOA-LSSVM method.

Table 3. Classification results of VMD-EE and BSOA-LSSVM method

Test samples	E1 ($\times 10^3$)	E2 ($\times 10^3$)	E3 ($\times 10^3$)	BSOA - SVM1 classifier	BSOA - SVM2 classifier	BSOA - SVM3 classifier	Identification results
(1) IRF	179.48	376.17	908.99	(+1)			Inner-race fault
(2) IRF	153.01	363.92	918.77	(+1)			Inner-race fault
(3) IRF	168.85	355.00	919.48	(+1)			Inner-race fault
(4) IRF	151.43	325.78	933.24	(+1)			Inner-race fault
(5) IRF	213.35	408.66	887.40	(+1)			Inner-race fault
(6) ORF	28.66	11.37	999.52	(-1)	(+1)		Outer-race fault
(7) ORF	23.46	160.11	986.82	(-1)	(+1)		Outer-race fault
(8) ORF	12.37	172.70	984.90	(-1)	(+1)		Outer-race fault
(9) ORF	9.43	100.37	994.91	(-1)	(+1)		Outer-race fault
(10) ORF	13.68	14.51	999.80	(-1)	(+1)		Outer-race fault
(11) BF	147.40	156.55	976.61	(-1)	(-1)	(+1)	Ball fault
(12) BF	123.73	111.84	985.99	(-1)	(-1)	(+1)	Ball fault
(13) BF	114.00	123.66	985.76	(-1)	(-1)	(+1)	Ball fault
(14) BF	150.09	175.63	972.95	(-1)	(-1)	(+1)	Ball fault
(15) BF	350.59	173.22	920.37	(-1)	(-1)	(+1)	Ball fault
(16) NOR	448.16	890.01	83.87	(-1)	(-1)	(-1)	Normal
(17) NOR	416.73	906.23	71.37	(-1)	(-1)	(-1)	Normal
(18) NOR	418.42	906.04	63.34	(-1)	(-1)	(-1)	Normal
(19) NOR	312.57	947.78	63.37	(-1)	(-1)	(-1)	Normal
(20) NOR	313.12	947.15	69.76	(-1)	(-1)	(-1)	Normal

Table 4. Table comparing the results of the classification of bearing failure of the classifiers VMD-EE-BSOA-LSSVM with EMD-EE-BSOA-LSSVM method.

Method	Training samples	Test samples	Optimal γ	Optimal σ	Average cost time (s)	Average test error (%)
VMD-EE-BSOA-LSSVM$_1$	288	144	6627.62	15.08	**25.32**	**0**
EMD-EE -BSOA-LSSVM$_1$	288	144	12573.08	13.67	27.15	2.63
VMD-EE-BSOA-LSSVM$_2$	216	108	7230.50	30.55	**21.24**	**0**
EMD-EE -BSOA-LSSVM$_2$	216	108	21089.81	0.85	23.16	1.51
VMD-EE-BSOA-LSSVM$_3$	144	72	31444.94	23.27	**17.26**	**0**
EMD-EE -BSOA-LSSVM$_3$	144	72	15349.49	7.67	19.31	0

7 CONCLUSION

Because of the non-stationary and energy characteristics of bearing failure signals, a failure diagnosis method based on VMD-EE and BSOA-LSSVM is proposed in this paper. VMD is first used to preprocess different types of signals into component functions. The energy entropy operator is then used to characterize these component functions to generate the input matrix for the LSSVM classifier. The input matrix is used as training and testing data for the LSSVM classifier. After training, BSOA-LSSVM gave the optimal pair of values (γ,σ) for testing. The test results show that the proposed method has the highest accuracy when compared with other method.

ACKNOWLEDGMENT

The author thanks Professor K. A. Loparo of Case Western Reserve University for allowing the use of data from the Bearing Data Center for this paper.

TÀI LIỆU THAM KHẢO

[1] N. Huang *et al.*, "The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis," *Proceedings of the Royal Society of London. Series A: Mathematical, Physical and Engineering Sciences,* vol. 454, pp. 903-995, 1998.

[2] J. S. Smith, "The local mean decomposition and its application to EEG perception data," (in eng), *Journal of the Royal Society, Interface,* vol. 2, no. 5, pp. 443-454, 2005.

[3] J. Z. Junsheng Cheng, Yu Yang, "A nonstationary signal analysis approach-The local characteristic-scale decomposition method," *Journal Vibration Engineering,* vol. 25, no. 2, pp. 215–220, 2012.

[4] K. Dragomiretskiy and D. Zosso, "Variational Mode Decomposition," *IEEE Transactions on Signal Processing,* vol. 62, no. 3, pp. 531-544, 2014.

[5] H. Ao, J. Cheng, Y. Yang, and T. K. Truong, "The support vector machine parameter optimization method based on artificial chemical reaction optimization algorithm and its application to roller bearing fault diagnosis," *Journal of vibration and control,* vol. 2013, no. 2013, 2013.

[6] H. Ao, J. Cheng, K. Li, and T. K. Truong, "A Roller Bearing Fault Diagnosis Method Based on LCD Energy Entropy and ACROA-SVM," *Shock and Vibration,* vol. 2014, no. 2014, pp. 1-6, 2014.

[7] J. Cheng, D. Yu, J. Tang, and Y. Yang, "Application of SVM and SVD Technique Based on EMD to the Fault Diagnosis of the Rotating Machinery," *Shock and Vibration,* vol. 16, p. 519502, 2009.

[8] R. Raghuraj and S. Lakshminarayanan, "VPMCD: variable interaction modeling approach for class discrimination in biological systems," *FEBS Lett,* vol. 581, no. 5, pp. 826-30, 2007.

[9] W. S. McCulloch and W. Pitts, "A logical calculus of the ideas immanent in nervous activity," *The bulletin of mathematical biophysics,* vol. 5, no. 4, pp. 115-133, 1943.

[10] V. N. Vapnik, *The Nature of Statistical Learning Theory; Springer: New York*. 1995.

[11] J. A. K. Suykens and J. Vandewalle, "Least Squares Support Vector Machine Classifiers," *Neural Processing Letters,* vol. 9, no. 3, pp. 293-300, 1999/06/01 1999.

[12] X. Pan, Z. Xing, C. Tian, H. Wang, and H. Liu, "A method based on GA-LSSVM for COP prediction and load regulation in the water chiller system," *Energy and Buildings,* vol. 230, p. 110604, 2021/01/01/ 2021.

[13] B. Lin and X. Gu, "Soft sensor modeling based on DE-LSSVM," *Huagong Xuebao/Journal of Chemical Industry and Engineering (China),* vol. 59, pp. 1681-1685, 07/01 2008.

[14] X. Gao, H. Wei, T. Li, and G. Yang, "A rolling bearing fault diagnosis method based on LSSVM," *Advances in Mechanical Engineering,* vol. 12, no. 1, p. 1687814019899561, 2020/01/01 2014.

[15] P. Civicioglu, "Backtracking Search Optimization Algorithm for numerical optimization problems," *Applied Mathematics and Computation,* vol. 219, no. 15, pp. 8121-8144, 2013/04/01/ 2013.

[16] L. K. A. (2003, 1 Nov.). *Bearings vibration dataset, Case Western Reserve University*. Available: https://engineering.case.edu/bearingdatacenter/download-data-file (Accessed on September 10, 2022)

PHƯƠNG PHÁP MỚI CHẨN ĐOÁN HƯ HỎNG Ổ LĂN DỰA TRÊN TOÁN VMD ENTROPY NĂNG LƯỢNG VÀ BSOA-LSSVM

AO HÙNG LINH
Khoa Công nghệ Cơ khí, Trường Đại học Công nghiệp Thành phố Hồ Chí Minh
aohunglinh@iuh.edu.vn

Tóm tắt. Bài báo này giới thiệu một phương pháp mới để chẩn đoán hư hỏng ổ lăn dựa trên máy véc tơ hỗ trợ bình phương tối thiểu (LSSVM) với các thông số được tối ưu bởi thuật toán tối ưu hóa tìm kiếm ngược (BSOA) gọi là BSOA-LSSVM. Trước tiên, phương pháp phân rã mô hình biến đổi (VMD) được dùng để phân rã những tín hiệu dao động gia tốc của ổ lăn thành các hàm thành phần. Sau đó, phương pháp entropy năng lượng được sử dụng để trích xuất các hàm thành phần này thành các ma trận đặc tính đầu vào. Thứ ba, các ma trận đặc tính này được dùng làm ma trận đầu vào cho bộ phân loại BSOA-LSSVM. Kết quả thực nghiệm cho thấy phương pháp đề xuất cho độ chính xác phân loại cao hơn (100%) và thời gian ngắn hơn so với các phương pháp khác với dữ liệu thu thập được.

Từ khóa. Phương pháp phân rã mô hình biến đổi; chẩn đoán hư hỏng; entropy năng lượng; thuật toán tối ưu hóa tìm kiếm ngược; máy véc tơ hỗ trợ bình phương tối thiểu.

Received on: 14/11/2022

Accepted on: 06/03/2023