

Research on Fault Diagnosis of Aeronautic Gear Based on Permutation Entropy and SVM Method

Jia-Yin Liu*, Xiao-Guang Yu** and Qing-Kai Han***

Keywords : gear, feature extraction, fault diagnosis, permutation entropy, SVM.

ABSTRACT

The permutation entropy method is a new method for the spatial characteristics of time series. It can not only represent the complexity of the signal, but also can measure the uncertainty of a system or a piece of information. It can detect the dynamic mutations of time series of complex systems well. Small changes in time series data can be well demonstrated by it, which is beneficial to deal with nonlinear problems. It can be considered for fault diagnosis. Due to non-stationary operating conditions, driving force of the equipment, damping force, elastic force and its own non-linearity, the mechanical system usually exhibits strong complexity, nonlinearity and non-stationarity. Therefore, it is necessary to perform permutation and entropy analysis on the vibration signal. Support Vector Machines (SVM) is a new machine learning method. It can transform the non-linear non-separable model into a linear separable model by mapping the sample space to the high-dimensional feature space through nonlinear mapping, and construct an optimal classification hyperplane in the high-dimensional feature space, thereby achieve pattern recognition. Based on this, a gear fault diagnosis

method based on permutation entropy and SVM is proposed. First of all, starting from the phase space reconstruction theory, the permutation entropy method is used to calculate the entropy of the gear fault vibration signal, and the permutation entropy value and the normalized permutation entropy value can be obtained. Then, the permutation entropy value and the normalized entropy value are taken as the fault feature vector and input into the SVM and neural network classifier respectively for training. Finally, SVM and neural network classifiers are used to identify and classify the faults, and the classification results are compared. The method is applied to the gear experimental data. The analysis results show that this method still can effectively achieve gear fault diagnosis even in the case of small samples.

INTRODUCTION

During the operation of some mechanical equipment, the vibration signals of the machine usually present strong complexity, nonlinearity and non-stationary due to non-stationary operating conditions, driving force, damping force, elastic force of the equipment and non-linearity of the mechanical system itself. However, if only the traditional signal analysis method such as the Fourier transform are used, it is difficult to realize the quantitative description of these fault information, and it is not possible to completely satisfy the requirements for mechanical equipment fault diagnosis. Therefore, it is necessary to find an ideal method that can be used to analyze and deal with such complex, non-linear, non-stationary vibration signals. In recent years, with the development of nonlinear science, many nonlinear analysis methods have been applied to fault diagnosis of mechanical equipment. Lu (1999) studied the fractal dimension and its application in the fault diagnosis of rolling bearings. The fractal dimension was used as a feature to identify the faults of rolling bearings. Hou (2005) applied nonlinear theory such as chaos and Lyapunov exponent to the

Paper Received May, 2017. Revised March, 2018. Accepted July, 2018. Author for Correspondence: Xiao-Guang Yu.

** Postgraduate, School of Mechanical Engineering, Dalian University of Technology, Dalian, 116024, PR China. Collaborative Innovation Center of Major Machine Manufacturing in Liaoning, Dalian, 116024, PR China.*

*** Professor, School of Mechanical Engineering and Automation, Liaoning University of Science and Technology, Anshan, 114051, PR China.*

**** Professor, School of Mechanical Engineering, Dalian University of Technology, Dalian, 116024, PR China. Collaborative Innovation Center of Major Machine Manufacturing in Liaoning, Dalian, 116024, PR China.*

fault diagnosis of turbine engines. Wang (2000) studied the application of correlation dimension in fault diagnosis of large-scale units. Yan (2007) applied approximate entropy to the detection of mechanical system health. However, the calculation of the fractal dimension depends on the length of the data, which makes it computationally time-consuming and not suitable for on-line monitoring. The Lyapunov exponent is slower to calculate, which is less accurate and susceptible to noise. Approximate entropy as a method of time series complexity, its calculation also depends on the data length, the relative consistency is poor.

Permutation entropy (Bandt C et al., 2002) is an average entropy parameter that measures the complexity of one-dimensional time series. It has the advantages of simple calculation, fast calculation speed, strong anti-noise ability, etc., which can well detect dynamic mutations of complex systems and effectively extract non-stationary and non-linear fault features. Yan (2012) applied permutation entropy to feature extraction of vibration signals from rotating machinery, and compared permutation entropy with approximate entropy and Lempel-Ziv complexity. The results show that the permutation entropy algorithm can effectively detect and amplify dynamic changes of vibration signals. Liu (2007) introduced permutation entropy into the field of mechanical equipment fault diagnosis, studied the influence of permutation entropy of the vibration signals under different working conditions of the rolling bearing, embedding dimension and time delay on the calculation of the permutation entropy of the mechanical vibration signals, and observed and analyzed the influence of equipment state change and vibration shock on the calculation results of the permutation entropy. The results show that the permutation entropy can effectively detect the change of the state of the mechanical equipment and can be used as a parameter to detect the state change of the mechanical equipment. Liu (2008) analyzed the EEG signals before and after continuous brain work for a long time, extracted the permutation entropy of EEG signals, studied the relationship between the degree of brain fatigue and permutation entropy, and studied its variation under different brain fatigue conditions. Li (2008) applied the permutation entropy in the automatic machine condition monitoring and proposed that permutation entropy has great potential in terms of practicality and real-time.

Support Vector Machine (SVM) is a new machine learning method (Simon et al., 2004). It is based on statistical learning theory. The original sample space can be mapped to high-dimensional feature space by selecting appropriate mapping functions through specific nonlinear mapping, and the mapping functions are also called kernel functions. The kernel functions types include polynomial kernel functions, radial basis functions

and Sigmoid kernel functions, etc. The optimal classification hyperplane can be constructed in the high-dimensional feature space. It can be applied to pattern recognition of nonlinear and high-dimensional system described by multiple variables. It has the advantages of fast convergence and training with only a small sample. Chiang (2004) applied Fisher discriminant and support vector machines in fault diagnosis and found that the SVM is lower in terms of misclassification.

A gear fault diagnosis method based on permutation entropy and support vector machine (SVM) is proposed in this paper. Firstly, permutation entropy method is used to calculate the permutation entropy of the gear fault vibration signals, and the permutation entropy value and the normalized permutation entropy value are obtained. Then, the permutation entropy value and the normalized entropy value are taken as the fault feature vector and input into the SVM and neural network classifier respectively for training. Finally, SVM and neural network classifiers are used to identify and classify faults respectively to achieve gear fault diagnosis.

Compared with traditional feature extraction methods, the proposed method is not simply based on the statistical characteristics of time domain signals, but extracts dynamic mutation characteristics of vibration signals. Therefore, compared with traditional methods, this research method can better reflect the essential features of signal failure. The method proposed by the author is applied to gear experimental data. The experimental results show that this method can effectively distinguish the fault types of gears and is an effective fault diagnosis method.

PERMUTATION ENTROPY PRINCIPLE AND ALGORITHM

Permutation Entropy Algorithm

Supposing a time series $\{X(i) \mid i = 1, 2, \dots, n\}$, its phase space is reconstructed according to TAKENS Theorem, then the matrix can be obtained as follows:

$$\begin{bmatrix} x(1) & x(1+\tau) & \cdots & x(1+(m-1)\tau) \\ \vdots & \vdots & & \vdots \\ x(j) & x(j+\tau) & \cdots & x(j+(m-1)\tau) \\ \vdots & \vdots & & \vdots \\ x(K) & x(K+\tau) & \cdots & x(K+(m-1)\tau) \end{bmatrix}, (1)$$

$$j = 1, 2, \dots, K$$

Where m and τ respectively stand for embedding dimension and time delay, $K = n - (m-1)\tau$; every row in the matrix can be regarded as a reconstruction

component, a total of K reconstruction components. The j -th reconstruction component of $X(i)$ reconstruction matrix $(x(j), x(j+\tau), \dots, x[j+(m-1)\tau])$ is rearranged in ascending order according to the numerical size, and $j_1, j_2, \dots, j_m$ represent the index of the columns in which each element is located of reconstruction components, which is $x[i+(j_1-1)\tau] \leq x[i+(j_2-1)\tau] \leq \dots \leq x[i+(j_m-1)\tau]$, (2)

If the equal value in reconstruction components exists, which is

$$x[i+(j_1-1)\tau] = x[i+(j_2-1)\tau], \quad (3)$$

At this time it is sorted in accordance with the size of the value of i and j , which is when $j_1 < j_2$,

$$x[i+(j_1-1)\tau] \leq x[i+(j_2-1)\tau], \quad (4)$$

Therefore, for the resulting matrix which is reconstructed for any time series $X(i)$, every row can get a symbol sequence

$$S(l) = (j_1, j_2, \dots, j_m), \quad (5)$$

Where $l = 1, 2, \dots, k$, and $k \leq m!$, m -dimensional phase space maps different symbol sequences $(j_1, j_2, \dots, j_m)$, and there are $m!$ symbol sequences. Symbol sequence $S(l)$ is an arrangement in which (Feng et al., 2012). If the probability of each symbol sequence is $P_1, P_2, \dots, P_k$, then the k permutation entropy of different symbol sequences of time series $X(i)$ is defined as in eq.6 according to the form of Shannon entropy

$$H_p(m) = -\sum_{j=1}^k P_j \ln P_j, \quad (6)$$

When $P_j = 1/m!$, $H_p(m)$ reached the maximum $\ln(m!)$. $H_p(m)$ is usually normalized with $\ln(m!)$ for convenience, which is

$$0 \leq PE = H_p / \ln(m!) \leq 1. \quad (7)$$

Selection of Permutation Entropy Parameters

The calculation of the permutation entropy is related to the length of time series, the embedding dimension and the value of the delay. The experiment found that the result showed no significant difference when m took 4~6 and τ took 1~3. $m=5$ and $\tau=1$ are chose in this paper. Random signals with length of 1280, 2560, 5120, and 10240 are used in this paper to study the impact of the data length N on PE calculations, which is shown in Figure 1. It is found that the entropy difference is 0.0029 between the data with length of 5120 and the data with length of 2560 when $m=5$ and $\tau=1$, and the entropy difference is

0.0007 between the data with length of 5120 and the data with length of 10240. Therefore, it is appropriate to select the data whose length is larger than or equal to 5120. $m=5$, $\tau=1$ and $N=10240$ are chose in this paper.

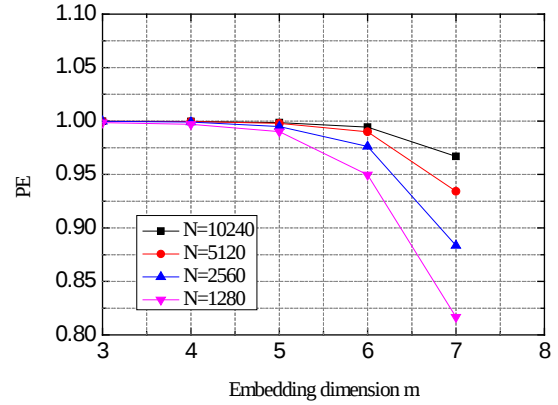


Fig. 1. The PE of random signals with different length.

GEAR FAULT DIAGNOSIS TEST

Experiment Equipment

The test is carried out on rotating machinery vibration fault test platform. The test platform mainly includes speed console, motor, pulley, axis, drive gear, driven gear, sensor and data collection system and so on. The motor is AC servo motor, whose power is 750W. The speed console regulates the speed, and the drive gear speed is 1160r / min when signals are collected. A CZ-0.5 magnetic brakes is connected in the terminal whose limit torque and slip power are 5N.m and 300W, which plays the role of load. Signal acquisition is completed by the NI 9234 acquisition card.

The number of drive gear teeth is 55, and the number of driven gear teeth is 75. The three states of the gears are tested, which includes normal state, broken teeth state and tooth error state. Experiment equipment is shown in Fig. 2, the three states of gears are shown in Fig. 3.

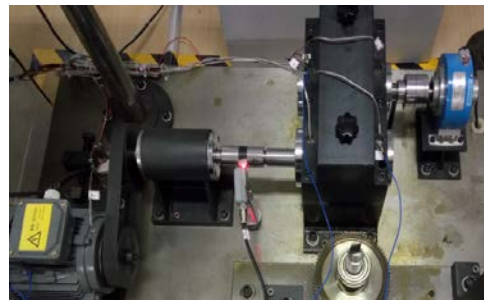


Fig.2. The experiment equipment.



(a) Normal gear



(b) Broken tooth fault

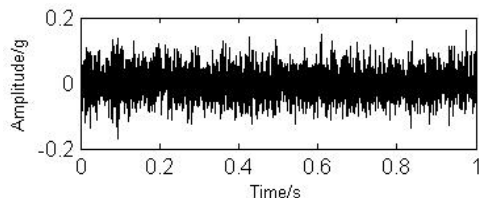


(c) Tooth profile error fault

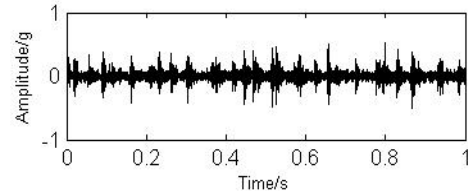
Fig.3. Three states of gears.

Signal acquisition

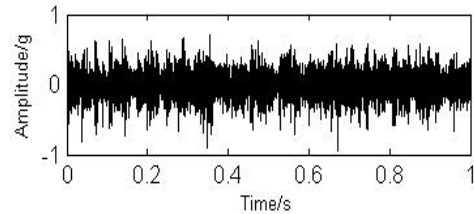
PCB-352C65 miniature waterproof acceleration sensor imported from the United States is applied, the measuring point is arranged on the bearing seat, and the sampling frequency is 10240Hz. The gears various states' vibrations are shown in Fig. 4.



(a) Normal gear



(b) Broken tooth fault



(c) Tooth profile error fault

Fig.4. The vibration signals of gears in various states.

The Permutation Entropy Analysis of Test Signals

Take the test signal of broken teeth fault of the aeronautic gear for example to analyze. Firstly, its phase space is reconstructed in accordance with TAKENS Theorem with MATLAB software, the process follows:

(1) The test signal of broken teeth fault $X = (-0.0225, -0.0269, -0.0138, 0.0060, \dots, -0.0122, -0.0230, -0.0617, -0.0615, -0.0399, 0.0073, 0.0677, \dots, -0.0180, -0.0237, -0.0205, 0.0018)$.

(2) Permutation entropy calculation results are influenced by embedding dimension m and delay time τ , therefore selecting these two parameters reasonably is necessary. It is found that the results differences are pointless when m takes 4~6 and τ takes 1~3. In this paper, $m=5, \tau=1$.

(3) Reconstruct the phase space of the test signal of broken teeth fault according to the formula (1). The sample data includes 10240 points which are divided into 80 groups, and every 128 sampling points are grouped. Take the group 1 to group 4 for example, and 124×5 order matrix can be obtained respectively.

$$[x] = \begin{bmatrix} -0.0225 & -0.0269 & -0.0138 & 0.0060 & 0.0092 \\ -0.0269 & -0.0138 & 0.0060 & 0.0092 & -0.0050 \\ -0.0138 & 0.0060 & 0.0092 & -0.0050 & -0.0185 \\ 0.0060 & 0.0092 & -0.0050 & -0.0185 & 0.0150 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ -0.0503 & -0.0342 & -0.0057 & 0.0138 & -0.0048 \\ -0.0342 & -0.0057 & 0.0138 & -0.0048 & 0.0085 \\ -0.0057 & 0.0138 & -0.0048 & 0.0085 & 0.0290 \\ 0.0138 & -0.0048 & 0.0085 & 0.0290 & 0.0418 \end{bmatrix}$$

$$[x]=\begin{bmatrix} -0.0114 & -0.0471 & -0.0317 & 0.0165 & 0.0413 \\ -0.0471 & -0.0317 & 0.0165 & 0.0413 & 0.000935 \\ -0.0317 & 0.0165 & 0.0413 & 0.000935 & -0.0196 \\ 0.0165 & 0.0413 & 0.000935 & -0.0196 & -0.0150 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ -0.1069 & -0.1751 & -0.1703 & -0.1247 & -0.0967 \\ -0.1751 & -0.1703 & -0.1247 & -0.0967 & -0.1267 \\ -0.1703 & -0.1247 & -0.0967 & -0.1267 & -0.1173 \\ -0.1247 & -0.0967 & -0.1267 & -0.1173 & -0.0439 \end{bmatrix}$$

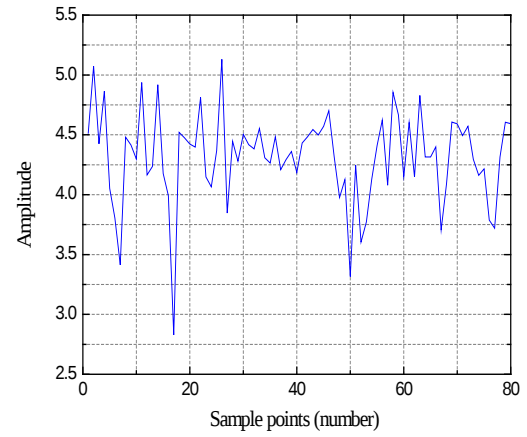
$$[x]=\begin{bmatrix} 0.0537 & 0.1619 & 0.2164 & 0.2222 & 0.1647 \\ 0.1619 & 0.2164 & 0.2222 & 0.1647 & 0.1342 \\ 0.2164 & 0.2222 & 0.1647 & 0.1342 & 0.1322 \\ 0.2222 & 0.1647 & 0.1342 & 0.1322 & 0.1066 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0.0795 & 0.0137 & -0.0268 & -0.0023 & 0.0265 \\ 0.0137 & -0.0268 & -0.0023 & 0.0265 & 0.0172 \\ -0.0268 & -0.0023 & 0.0265 & 0.0172 & -0.0184 \\ -0.0023 & 0.0265 & 0.0172 & -0.0184 & -0.0322 \end{bmatrix}$$

$$[x]=\begin{bmatrix} -0.0365 & -0.0215 & 0.0089 & -0.000064 & -0.0490 \\ -0.0215 & 0.0089 & -0.000064 & -0.0490 & -0.0986 \\ 0.0089 & -0.000064 & -0.0490 & -0.0986 & -0.0454 \\ -0.000064 & -0.0490 & -0.0986 & -0.0454 & -0.0113 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ -0.0089 & 0.0100 & 0.0071 & -0.000077 & 0.0100 \\ 0.0100 & 0.0071 & -0.000077 & 0.0100 & 0.0089 \\ 0.0071 & -0.000077 & 0.0100 & 0.0089 & 0.0333 \\ -0.000077 & 0.0100 & 0.0089 & 0.0333 & 0.0076 \end{bmatrix}$$

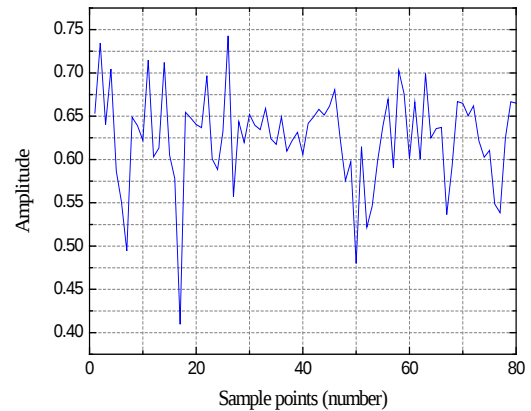
Then process data using Matlab software according to the formula (2)~(7) to calculate permutation entropy and normalized permutation entropy. Repeat these steps for the other groups to calculate permutation entropy and normalized permutation entropy similarly. Permutation entropy and normalized permutation entropy of the first four groups of the test signals of broken teeth fault are listed in Table 1. Test data of other two states is processed in accordance with the procedure above similarly. The changes of permutation entropy of the test signals of gears' various states are showed in Fig. 5.

Table 1. The permutation entropy and normalized permutation entropy

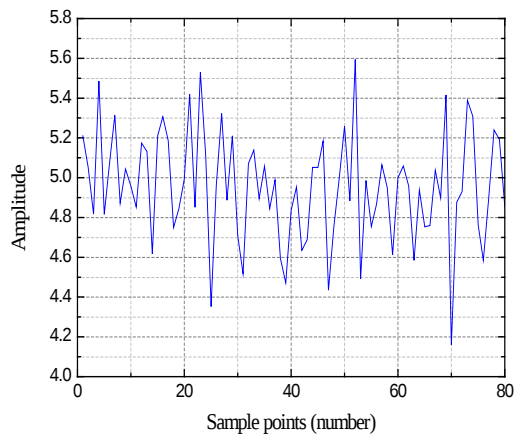
permutation entropy	5.2109
	5.0521
	4.8169
	5.4860
normalized permutation entropy	0.7545
	0.7315
	0.6974
	0.7943



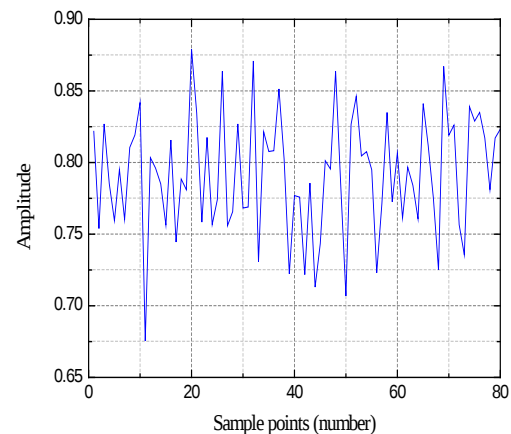
(a) Permutation entropy of normal signal of gear



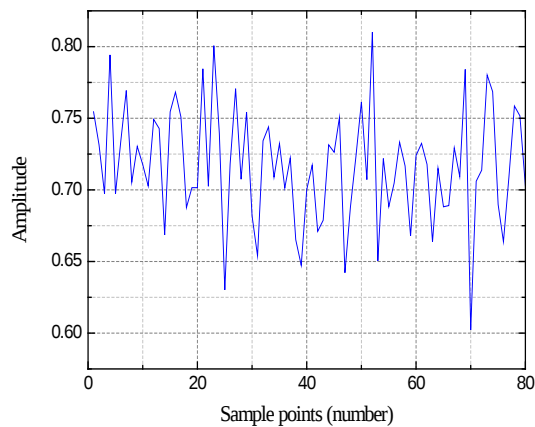
(b) Normalized permutation entropy of normal signal of gear



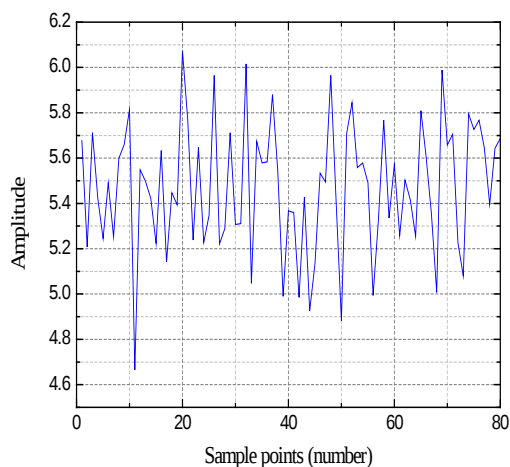
(c) Permutation entropy of the signal of gear with broken tooth fault



(f) Normalized permutation entropy of the signal of gear with tooth profile error fault



(d) Normalized permutation entropy of the signal of gear with broken tooth fault



(e) Permutation entropy of the signal of gear with tooth profile error fault

Fig.5. Analysis diagram of permutation entropy of the test signal of various states.

The permutation entropy of the normal signal is about 4.25, and the normalized permutation entropy is about 0.625, which are shown in Fig. 5 (a) and (b). The permutation entropy of the signal with broken tooth fault is about 5, and the normalized permutation entropy is about 0.725, which are shown in Fig. 5 (c) and (d). The permutation entropy of the signal with tooth error fault is about 5.5, and the normalized permutation entropy is about 0.8, which are shown in Fig. 5 (e) and (f). It is found that the characteristics of the permutation entropy and normalized entropy of every gear state are different, which shows that the permutation entropy can be used as the characteristic basis of gear fault classification.

The working state and the fault type of the gear can be judged by permutation entropy through the analysis above. But that's not enough, it is necessary to introduce the support vector machine to train and test the fault type.

SUPPORT VECTOR MACHINE PRINCIPLE

The basic idea of SVM can be illustrated in two classification situation of Fig. 6 (Zhang, 2000). SVM is developed from the optimal hyperplane in the case of linearly separable. There are two types of samples in Fig. 6, H is the classification line, and H1 and H2 are the straight lines that cross all kinds of samples nearest to the classification line and are parallel to the classification line. The distance between H1 and H2 is the classification interval. The optimal classification line is a classification line which can classify two classes correctly and minimize the classification interval.

The classification line equation is $kx+b=0$, which can be normalized, so that the linearly separable sample set (x_i, y_i) , $i=1, \dots, l$, $x \in R^d$, $y \in \{-1, +1\}$, which satisfies

$$y_i[(kx_i)+b]-1 \geq 0 (i=1, 2, \dots, l). \quad (8)$$

At this time, the classification interval is equal to $2/\|k\|$, and maximizing the interval is equivalent to minimize $\|k\|^2$. The training sample points on H_1 , H_2 are the support vectors.

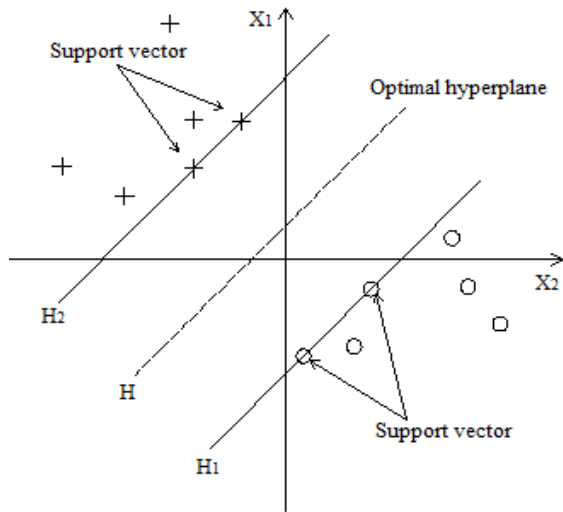


Fig.6. The optimal hyperplane

The multi-classification support vector machine algorithm includes one-to-one method and one-to-many classification method (Chapelle et al., 2002; Keerthi, 2002). The advantages and disadvantages of the two methods are compared by Chih (2002), and the conclusion that one-to-one classification method is better is drawn, which is more suitable for practical engineering applications. One-to-one method is applied in this paper. For given training data sample sets of w classes (x_i, y_i) , $i=1, 2, \dots, n$, $x_i \in R^d$, $y_i \in \{1, 2, \dots, w\}$ (9)

All possible two types of classifiers are constructed in w categories' samples, every two types of classifiers only uses two types of training samples in w categories to train. A total of $w(w-1)/2$ two types of classifiers can be constructed.

In the classification of test data samples, voting decision method is applied, and it is also called max wins decision method. It needs to construct $w(w-1)/2$ two types of classifiers. The test sample x is entered to two types of classifiers which are constructed by the class m samples and the class n samples. If the classification function

$$f^{mn}(x) = \text{sign} \left\{ \sum_{i=1}^n \alpha_i^{mn} y_i^{mn} K(x_i, x) + b^{mn} \right\} \quad (10)$$

Where $\text{sign}\{\}$ is symbol function and $K(x_i, x)$ is kernel function.

If the output result shows that x belongs to class m , then a vote will be added to class m ; if the output result shows that x belongs to class n , then a vote will be added to class n . After the test sample x is classified with all $w(w-1)/2$ two types of classifiers, which class gets the most votes in w classes, then determine that test sample x belongs to which class.

Common kernel functions include three types, which are polynomial kernel function, radial basis kernel function and Sigmoid kernel function.

GEAR FAULT DIAGNOSIS BASED ON PERMUTATION ENTROPY AND SVM

The permutation entropy and the normalized permutation entropy of the different states' gears are taken as the feature vectors of the support vector machines, which are entered to the Support Vector Machine for fault pattern recognition. The specific procedure is as follows:

(1) Samples are collected according to certain sampling frequency f respectively in the normal state of the gear, the broken tooth failure of the gear, and the tooth error fault state of the gear.

(2) Test signals of three states are used with K sampling points as a group. The permutation entropy and the normalized permutation entropy are calculated and several permutation entropy and normalized permutation entropy features are obtained. The fault types are classified into three classes, and the first m features of the permutation entropy and the normalized permutation entropy features of three classes are selected as the eigenvalue vectors.

(3) The eigenvalue vectors are entered to the support vector machine to train the Support Vector Machine.

(4) The combination of the last n features of the permutation entropy and normalized permutation entropy features of three classes are selected as the eigenvectors of the test set, which are regarded as the input of the SVM classifier. The output of the SVM classifier is used to determine the operating state and fault type of the gears.

Due to space limitations, the eigenvectors of the first five groups' signals of gears in three states are listed in table 2.

Table2.The eigenvectors under three states of the gears

	Permutation entropy	Normalized permutation entropy
Normal	4.5147	0.6537
	5.0740	0.7346
	4.4239	0.6405
	4.8652	0.7044
	4.0521	0.5867
Broken tooth	5.2109	0.7545
	5.0521	0.7315
	4.8169	0.6974
	5.4860	0.7943
	4.8158	0.6972
Tooth error	5.6763	0.8218
	5.2074	0.7539
	5.7119	0.8270
	5.4230	0.7852
	5.2451	0.7594

The first 60 features of permutation entropy and normalized permutation entropy features in the three classes are regarded as the training set, and the combination of the last 20 features is regarded as the test set. There are 180 sets of training data and 60 sets of test data. The number of permutation entropy features of gears in three states is listed in table 3.

Table3.The number of characteristics of permutation entropy in 3 status

Fault type	SVM classification number	Number of permutation entropy features	Number of normalized permutation entropy features
Normal gear	1	80	80
Broken tooth fault	2	80	80
Tooth error fault	3	80	80

Multi - class Support Vector Machine theory is used to train the data, and the radial basis kernel function is chosen as kernel function. The classification prediction chart of the test set is shown in Fig. 7.

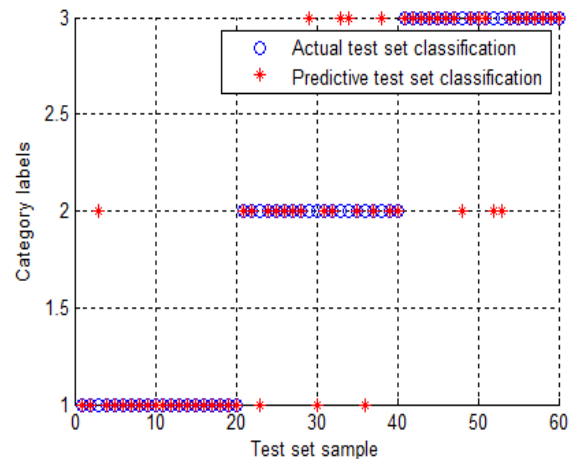


Fig.7. The classification prediction graph of Test set

The classification accuracy rate is 81.6667%, which can be seen from Fig. 7.

In order to compare the classification effect between the support vector machine and BP neural network, the BP neural network is designed according to the dimension of the eigenvector and the number of the gears' fault states. The input layer and output layer nodes of the neural network are respectively 6 and 3, and the number of hidden layer nodes are empirically chosen to be 8. Sigmoid-type function is chosen as the activation function of the hidden layer and the output layer. The maximum number of training steps is set to 1000, and the error index is respectively 0.02, 0.01 and 0.005. The network with the same training samples and test samples as the SVM is trained and tested. The performance comparison of the two classifiers is shown in table 4.

Table4.The comparison of two classification methods

Network type	Number of the test set	The correct number of classification	Classification accuracy rate
Radial basis SVM	60	49	81.6667%
BP network (6 -8 -3, $\delta=0.02$)	60	47	78.33%
BP network (6 -8 -3, $\delta=0.01$)	60	45	75%
BP network (6 -8 -3, $\delta=0.005$)	60	46	76.67%

The classification accuracy of support vector machine is higher than that of neural networks, which can be seen from table 4. It shows that Support Vector Machine still has good ability of prediction and promotion in the case of small samples.

CONCLUSIONS

A gear diagnosis method based on permutation entropy and SVM is proposed in this paper. The permutation entropy algorithm is used to detect the dynamic mutation of the time series and extract the permutation entropy eigenvalue vector, and then SVM pattern recognition is performed. The working state of the gear is determined according to the SVM pattern recognition result. The following conclusions are obtained through analysis:

(1) The eigenvalues extracted from the original data actually reflect the essential characteristics of the original data. The SVM method maps the eigenvalue space of the original data to the high-dimensional feature space through nonlinear mapping, and the optimal classification hyperplane is constructed in the high-dimensional feature space. The disadvantages of slow convergence rate and infinite sample size of the neural network are overcome and more effective classification can be implemented in the SVM method.

(2) SVM is compared with BP when the number of training samples is same, and the analysis results show that SVM can more effectively identify the characteristic information of gear fault. The choice of neural network structure and type, neural network producing local extremum and lacking of theoretical basis are avoided by the SVM method.

(3) The permutation entropy algorithm is a new method to detect the complexity and dynamic mutation of time series. It has the advantages of simple calculation, fast calculation speed, strong anti-noise ability and suitable for online monitoring. The permutation entropy and SVM method is introduced into the gear fault diagnosis, and the results show that this method can effectively identify the working state of gears.

ACKNOWLEDGMENT

This work has been supported by the National Natural Science Foundation of China (No. 51775257).

REFERENCES

- Bandt C, Pompe B. "Permutation entropy: a natural complexity measure for time series," *Physical Review Letters*, Vol.88 No.174102(2002).
- Chiang L H, Kotanchek M E, Kordon A K. "Fault Diagnosis Based on Fisher Discriminant Analysis and Support Vector Machines," *Computers & Chemical Engineering*, Vol.28, pp.1389-1401 (2004).
- Chapelle O, Vapnik V, Bousquet O, et al. "Choosing Multiple parameters for support vector machines," *Machine Learning*, Vol.46, pp.131-159 (2002).
- Chih-Wei Hsu, Chih-Jen Lin. "A Comparison of methods formulticlass support vector machines," *IEEE Trans. on Neural Networks*, Vol.13, pp.415-425 (2002).
- Feng F Z, Si A H, Rao G Q, et al. "Early Fault Diagnosis Technology for Bearing Based on Wavelet Correlation Permutation Entropy," *Journal of Mechanical Engineering*, Vol.29, pp.73-79 (2012).
- Hou Rongtao, Wen Bangxi, Zhou Wei. "Research on Fault Diagnosis Technology of Turbogenerator Based on Modern Nonlinear Theory," *Journal of Mechanical Engineering*, Vol.41, pp.142-147(2005).
- Keerthi S S. "Efficient tuning of SVM hyperparameters using radius/margin bound and iterative algorithms," *IEEE Trans. On Neural Networks*, Vol.13, pp.1225-1229 (2002).
- Liu Y B, Long Q, Feng Z H, et al. "Detection Method for Nonlinear and Non-stationary Signals," *Journal of Vibration and Shock*, Vol.26, pp.131-134(2007).
- Liu J P, Zhang C, Zheng C X, et al. "Mental Fatigue Analysis Based on Complexity Measure of Multichannel Electroencephalogram," *Journal of Xi'an Jiaotong University*, Vol.42, pp.1555-1559 (2008).
- Li X L, Ouyang G X, Liang Z F. "Complexity Measure of Motor Current Signals for Tool Flute Breakage Detection in End Milling," *[J]. International Journal of Machines Tools and Manufacture*, Vol.48, pp.371-379(2008).
- Lu Zhimin, Xu Jinbiao. "Fractal Dimension and Its Application in Fault Diagnosis of Rolling Bearings," *Journal of Mechanical Engineering*, Vol.35, pp.88-91(1999).
- Simon Haykin Write, Ye S W, Shi Z Z Interpret. "Neural Network Theory," Beijing: Machinery Industry Press (2004).
- Wang Weijun, Wu Zhaotong. "Application of Correlation Dimension in Fault Diagnosis of Large-scale Rotating Machinery," *Journal of Vibration Engineering*, Vol.13, pp.229-234 (2000).
- Yan R, Gao R X. "Approximate Entropy as a diagnostic tool for machine health monitoring," *Mechanical Systems & Signal Processing*, Vol.21, pp.824-839(2007).
- Yan R Q, Liu Y B, Gao R X. "Permutation entropy: A nonlinear statistical measure for status characterization of rotary machines," *Mech. Syst. Signal Process*, Vol.29, pp.474-484(2012).
- Zhang X G. "Introduction to statistical learning theory and support vector machines," *Acta*

Auto-matica
Sinica ,Vol.26 ,pp.32-42(2000).

基於排列熵和 SVM 方法的齒輪故障診斷研究

劉佳音 韓清凱

大連理工大學機械工程學院
遼寧重大裝備製造協同創新中心

於曉光

遼寧科技大學 機械工程與自動化學院

摘要

排列熵方法是一種針對時間序列的空間特性的新方法，它不但能表徵信號的複雜性，而且能夠度量一個系統或一段資訊的不確定性。它能夠很好地檢測出複雜系統時間序列的動力學突變等，時間序列資料的細小變化可以通過它很好地展現出來，有利於處理非線性問題，可以考慮將其應用於故障診斷。機械系統由於非平穩運行工況、設備的驅動力、阻尼力、彈性力以及本身的非線性等原因，其振動信號通常呈現出強烈的複雜性、非線性和非平穩性，因此需要對振動信號進行排列熵分析。SVM (Support Vector Machines) 是一種新的機器學習方法，它通過非線性映射將樣本空間映射到高維特徵空間的辦法可使非線性不可分模式變為線性可分模式，並在高維特徵空間中構造出最優分類超平面，進而實現模式識別。基於此，提出了基於排列熵和SVM的齒輪故障診斷方法。首先從相空間重構理論入手，採用排列熵方法對齒輪故障振動信號進行排列熵計算，得到排列熵值與歸一化排列熵值；然後將排列熵值與歸一化排列熵值作為故障特徵向量，分別輸入到SVM與神經網路分類器進行訓練；最後，分別採用SVM與神經網路分類器進行故障識別與分類，對比分類效果。將該方法應用於齒輪實驗資料，分析結果表明，即使在小樣本情況下，此方法仍可有效實現齒輪的故障診斷。