

DOI: 10.19884/j.1672-5220.202310003

Acoustic Resonance Fast Detection Method of Harmonic Reducer Based on Support Vector Machine Algorithm

ENKHBAT Ganbayar, XU Yang*, ZHANG Yixin, XIE Guosheng
College of Mechanical Engineering, Donghua University, Shanghai 201620, China

Abstract: Assembly error abnormal quality testing of harmonic reducers is an important part of the pre-delivery process of manufacturers and focuses on abnormality assessment, which can reduce financial losses due to product recalls and further protect the interests of users and the reputation of manufacturers. Sound signals offer the benefit of simple and non-contact measurements for acoustic resonance testing and can facilitate pre-delivery fast factory testing of harmonic reducers. This paper presents an experimental method for sound data acquisition, feature extraction and analysis. Hammered excitation of a harmonic reducer is used to obtain acoustic datasets for both abnormal and normal harmonic reducers. Time and frequency domain features of the sound signals are extracted, and the classification algorithms of support vector machine (SVM), random forest (RF) and K-means are compared. The results show that the accuracy of SVM on the test set is 98.0%, that of RF is 95.0%, and that of K-means is only 53.0%. The SVM classifier's accuracy, recall, and F1 scores are high. Based on the SVM harmonic reducer quality detection model, the national instrument (NI) data acquisition card and Labview are used to design the harmonic reducer fast detection software for the harmonic reducer pre-delivery inspection of manufacturers.

Key words: harmonic reducer; acoustic resonance testing; feature extraction; classification analysis; support vector machine (SVM) algorithm

CLC number: TH17

Document code: A

Article ID: 1672-5220(2024)03-0289-09

Open Science Identity
(OSID)



0 Introduction

Musser^[1] introduced the fundamental concept of the harmonic reducer, also known as strain wave gearing (SWG). The advantages of harmonic reducers are small size, lightweight, no backlash, large torque, high transmission ratio and high efficiency. It is widely used in space science, robotics, energy and precision machine tools^[2]. There are currently numerous unresolved issues with the harmonic reducer. Harmonic reducers are small

and precise, and assembly errors or inadequate grease filling would result in factory anomalies. The abnormal harmonic reducer would negatively impact the operation. Harmonic reducers require strict quality detection before delivery.

In mass production, there are numerous harmonic reducer quality detection methods for pre-delivery, and non-destructive detection is the quickest^[3]. Existing non-destructive testing technology frequently employs a dynamic vibration test for harmonic reducer testing. Installed on a fixed platform and controlled by a motor, the harmonic reducer's vibration amplitude is measured to determine its quality. The disadvantages of this method are that its detection efficiency is very low, the disassembly and detection time of harmonic reducer is long, and the operation is complex. However, the detection accuracy is high.

At present, there are some studies on the fast detection of harmonic reducers. The fast detection of some bearings and other mechanical parts provides some references for the factory testing of harmonic reducers. For instance, Shiroishi et al.^[4] used vibration and acoustic emission measurements for bearing condition diagnostics. Wang^[5] studied crack identification of automotive brake pump support based on acoustic resonance testing. Jatzlau et al.^[6] executed the research on acoustic resonance spectroscopy to identify material defects in automotive and aerospace sample materials. Ju et al.^[7] have presented the acoustic resonance testing of sintered cogwheels for quality control. The assembly of the harmonic reducer is precise and the components are complex, so these methods cannot be directly applied to the pre-delivery fast detection of the harmonic reducer. There is a need to investigate and study the harmonic reducer to detect quality more rapidly and precisely, reduce the detection time, enhance the harmonic reducer's detection efficiency and reduce the cost of the method. Therefore, this paper presents a quality detection algorithm for the harmonic reducer based on a support vector machine (SVM)^[8-9], which solves the problems of long detection time, complex operation and low

Received date: 2023-10-11

Foundation item: National Natural Science Foundation of China (No. 52375528)

* Correspondence should be addressed to XU Yang, email: xuyang@dhu.edu.cn

Citation: ENKHBAT G, XU Y, ZHANG Y X, et al. Acoustic resonance fast detection method of harmonic reducer based on support vector machine algorithm[J]. *Journal of Donghua University (English Edition)*, 2024, 41(3): 289-297.

efficiency in traditional dynamic vibration detection of the harmonic reducer. This research paper is processed and analyzed in the following three stages.

1) A fast detection signal acquisition test platform is constructed, its data acquisition system is designed, and acoustic resonance testing (ART) experiments are conducted. The test collects the sound signals generated by the hammer excitation of the harmonic reducer.

2) Time and frequency domains are used to extract the feature characteristics of the acoustic resonance signal of the harmonic reducer. Acoustic resonance signal characteristics of the harmonic reducer are collected for training, and the application of SVM, random forest (RF), and K-means algorithms in harmonic reducer detection is compared.

3) Based on the SVM harmonic reducer fast detection model, the harmonic reducer fast detection software is designed for the factory high-volume quality inspection of the harmonic reducer using the national instrument (NI) data acquisition card and Labview.

1 ART Sound Signal Acquisition and Feature Extraction

ART employs the sound vibrational properties of a harmonic reducer to detect defects^[10]. This means that measurements taken in one location can reveal flaws in any location^[11]. When the harmonic reducer is appropriately excited, the acoustic signals generated by the normal harmonic reducer and the abnormal harmonic reducer are distinct based on the principle of the acoustic mode theory, and the fault types of different frequencies and amplitudes will influence the acoustic signals^[12].

The abnormal detection acoustic data of LHSG, LHD and LCD series harmonic reducers (the Leadedrive Harmonic Drive Technology Co., Ltd., China) were collected by hammer knock detection experiment. The harmonic reducer is deemed defective if the detected amplitude exceeds the established threshold. Two methods are used to extract features from sound data. For the sound dataset used in the hammer knock detection experiment, the time-domain statistical feature reflects the signal's overall trend and variability. The frequency-domain statistic transforms the sound signal from the time domain to the frequency domain^[13]. These characteristics facilitate the differentiation between abnormal and normal sound signals.

1.1 Sound signal acquisition

The series of harmonic reducers used in the sound signal acquisition were LHSG-20-50-C-III and LHSG-20-50-C-I, which were tested by the traditional factory dynamic vibration method. Each harmonic reducer was marked with abnormal (Bad) or normal (Good). The end number of the rigid wheel is different from each other and added after "Good" and "Bad". For example, the part label code "Good180" represents the normal harmonic reducer, and 180 is the number of the rigid

wheel of the harmonic reducer.

The design of the experimental scheme is divided into an excitation system, a support mode, and a measurement and analysis system.

Excitation system: the hammer is a common excitation equipment, but hammer excitation has the advantages of simple operation and low cost. The method of hammer excitation is selected in the experiment to obtain the sound signal of the harmonic reducer^[14].

Support mode: the manner in which the melamine foam board is positioned on the ground reduces the occurrence of vibration after the hammer strikes the harmonic reducer and eliminates noise interference.

Measurement and analysis system: in this hammer knock detection experiment, DH8302 data signal acquisition equipment (Donghua Testing Co., Ltd., China) is used for measurement and analysis. This software enables the setting of acquisition parameters, the real-time visual observation of data during the acquisition, and data export after the acquisition. After the data were exported, signal processing and data analysis were performed using Python data analysis software.

The experimental platform contains a harmonic reducer, a hammer, a sound sensor, a melamine foam board, data signal acquisition equipment, and a personal computer (PC) with a measurement and analysis system. The selected equipment was used to build the hammer-knock-detection experimental platform, as shown in Fig. 1.

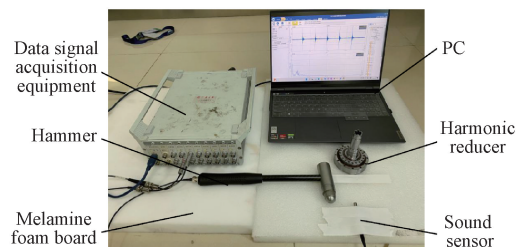


Fig. 1 Experimental platform for hammer knock detection

The DH8302 data signal acquisition equipment can precisely measure force, velocity, acceleration, etc. The microphone model of the sound sensor is MPA416 and the frequency ranges from 20 Hz to 20 kHz. The model of the hammer is WX-HM03. In this experiment, a metal hammer is chosen to excite the resonant frequency of the harmonic reducer in a higher frequency band. The instruments and equipment used in this experiment are shown in Table 1.

The experimental platform functions according to the following principles. The harmonic reducer is placed on the melamine foam board. The sound sensor is fixed on the melamine foam plate and the hammer is suspended above the front of the sound sensor. The hammer head is used to excite the harmonic reducer and collect the force signal of the hammer and the sound

response signal of the harmonic reducer at the same time. The input hammer excitation signal and the output sound response signal are gathered by data signal acquisition equipment and sent to the PC

terminal for real-time display and storage. The sampling frequency of the sound sensor is 10 000 Hz. The experiment platform sensor parameter settings during the sampling process are shown in Table 2.

Table 1 Instruments and equipment

Model number	Name	Remark
DH8302	Data signal acquisition equipment	Signal acquisition system
WX-HM03	Hammer	Excitation sound signal
MPA416	Sound sensor	Sound data signal collection
LENOVO, v480	PC	Test signal analysis and loading acquisition software
—	Melamine foam board	Noise interference reduction and elimination

Table 2 Experimental platform sensor parameter settings

Equipment	Unit	Sensor type	Channel	Input mode	Range	Accuracy
Hammer	N	WX-HM03	A11-02	IEPE	1 229	0.081 4 mV/N
Sound sensor	Pa	MPA416	A11-03	IEPE	166	51.9 mV/Pa

Each harmonic reducer was tested six times, with approximately one second between each knock. In a total of 1 440 experimental data groups, 810 groups of normal harmonic reducers and 630 groups of abnormal harmonic reducers were obtained.

1.2 Sound signal feature extraction

After gathering sound signals, signal processing extracts features for subsequent abnormal detection and classification tasks.

1.2.1 Time-domain feature extraction

The sampling statistical analysis method for time-domain feature extraction can extract the feature data of the time-domain sequence signal. Time-domain feature data are the main parameter to measure time sequence signals such as sound and vibration^[15]. Time-domain features include signal parameters that can detect amplitude changes, such as mean value X_m , standard deviation X_{std} , root mean square X_{rms} , peak value X_p , root amplitude X_r , peak factor, peak-to-peak value, waveform factor, kurtosis and skewness^[16]. These features reflect the signal overall trend and fluctuations. The equations of various time-domain indicators are shown in Table 3.

The calculation result list of feature data in the time domain of five harmonic reducers is shown in Table 4.

Table 3 Dimensional feature equations in time domain

Parameter	Equation
X_m	$X_m = \frac{1}{N} \sum_{n=1}^N x(n)$
X_{std}	$X_{std} = \sqrt{\frac{1}{N-1} \sum_{n=1}^N [x(n) - x_m]^2}$
X_{rms}	$X_{rms} = \sqrt{\frac{1}{N} \sum_{n=1}^N x^2(n)}$
X_p	$X_p = \max x(n) $
X_r	$X_r = \left[\frac{1}{N} \sum_{n=1}^N \sqrt{ x(n) } \right]^2$

To analyze the different performances of abnormal and normal harmonic reducers in time-domain features, a statistical analysis was performed on the calculation results of the feature data of all abnormal and normal harmonic reducers, respectively, and average, maximum, and minimum values of the feature data distribution were obtained under two categories. The feature data of abnormal and normal harmonic reducers is shown in Table 5.

Table 4 Calculation results of time-domain feature data

Type	Equipment	Mean value	Standard deviation	Root mean square	Peak value	Root amplitude
Normal	Good4_3	0.002 312 316	0.150 067 491	0.150 085 305	6.251 98	0.141 512 917
	Good3_6	0.002 601 841	0.167 639 896	0.167 660 086	8.348 05	0.148 833 914
	Bad1_4	0.001 187 028	0.109 520 908	0.109 527 341	5.805 13	0.130 384 440
Abnormal	Bad2_1	0.004 237 721	0.117 659 873	0.117 736 163	5.810 31	0.122 283 286
	Bad3_5	0.000 630 381	0.120 286 858	0.120 288 509	5.844 78	0.145 087 064

Table 5 Distribution of time-domain feature data

Type	Characteristic	Mean value	Standard deviation	Root mean square	Peak value	Root amplitude
Normal	Average value	0.004 2	0.137 1	0.158 9	7.042 5	0.137 0
	Maximum value	0.008 0	0.182 9	0.202 9	10.925 0	0.182 9
	Minimum value	-0.000 7	0.082 8	0.115 4	2.588 0	0.082 8
Abnormal	Average value	0.005 0	0.145 3	0.164 2	7.630 7	0.145 4
	Maximum value	0.011 1	0.210 3	0.222 5	13.012 0	0.210 5
	Minimum value	0.000 2	0.092 1	0.116 0	3.597 0	0.092 1
Difference	Average value	16.0%	5.6%	3.2%	7.7%	5.8%

In Table 5, the different time-domain indexes of normal and abnormal average values distinguish the features of the harmonic reducer. It can be seen from Table 5 that the average time-domain feature data of the abnormal harmonic reducer are all higher than those of the normal harmonic reducer.

1.2.2 Frequency-domain feature extraction

To convert sound signals from the time domain to the frequency domain, the fast Fourier transform (FFT) is utilized^[17]. The feature data are subsequently extracted using statistical analysis. Various signal features are extracted in the frequency domain, including the signal's mean frequency, frequency spectrum centroid, root mean square frequency, spectrum bandwidth, frequency band energy ratio and frequency maximum position. These features facilitate the differentiation between abnormal and normal harmonic reducer sound signals.

Next, we perform a preprocessing step on the extracted features. The extracted frequency-domain and time-domain features are combined into a feature vector for classification analysis.

Combining frequency-domain and time-domain features into a single feature vector for classification analysis is advantageous because it provides a more comprehensive representation of the underlying patterns in the data. This integration captures both temporal and spectral information, allowing the classifier to benefit from complementary features and potentially improving performance. Additionally, it helps reduce dimensionality, simplifies model complexity and enhances generalization across different datasets and conditions.

Taking the LHSG-20-50-C-I harmonic reducer as an example, the normal harmonic reducer numbered Good170 and the abnormal harmonic reducer numbered Bad170 are observation objects here. FFT is used to convert the sound signal of the harmonic reducer from the time domain to the frequency domain. The difference between the normal harmonic reducer and the abnormal harmonic reducer is observed, and the frequency-domain diagram are shown in Fig. 2

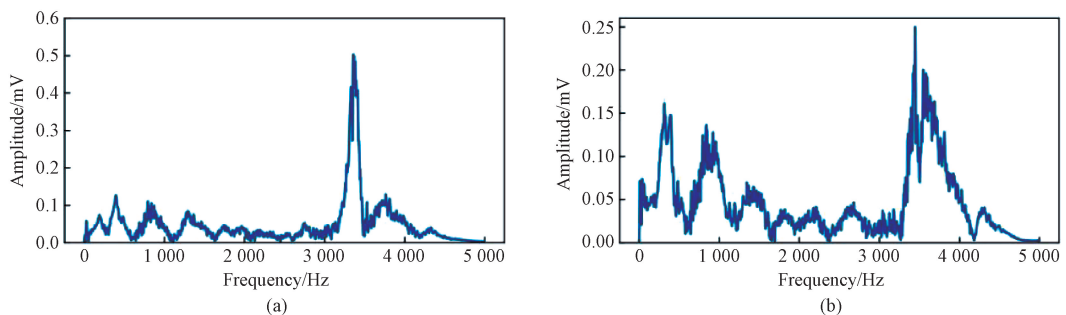


Fig. 2 Comparison of frequency domain of normal and abnormal harmonic reducers: (a) Good170; (b) Bad170

As can be seen from Fig. 2, the frequency distribution of normal and abnormal harmonic reducers is quite different, and the energy proportion under each frequency component is shown in Table 6.

The frequency component of the normal harmonic reducer is mainly concentrated in the frequency band [2 900, 3 300). In contrast, for the abnormal harmonic

reducer, the energy proportion in the frequency band [0, 1 000) changes to 32.61%, and the energy proportion in the frequency band [2 900, 3 300) decreases to 10.71%. The energy in the frequency band [3 300, 3 900) increases from 16.05% to 24.83%. It can be found that FFT can classify the sound signal of the harmonic reducer hammer knock experiment well.

Table 6 Energy proportion comparison of normal and abnormal harmonic reducers under each frequency component

Frequency/Hz	Energy proportion/%	
	Normal harmonic reducer	Abnormal harmonic reducer
[0, 500)	12.01	18.12
[500, 1 000)	8.31	14.49
[1 000, 2 900)	21.92	21.15
[2 900, 3 300)	30.51	10.71
[3 300, 3 900)	16.05	24.83
[3 900, + ∞)	4.30	4.21

Then normalizing the features is necessary to eliminate the dimensional influence between different features. Standard scaler standardizes the data with zero mean and unit variance.

2 Data Classification Analysis Algorithm

Fast detection for harmonic reducer's acoustic resonance primarily entails sound signal acquisition and feature extraction. Furthermore, executing data classification on extracted sound data is a crucial step in realizing the pre-delivery quality fast detection experiment. After extracting sound data features from the harmonic reducer, selecting an appropriate feature classification algorithm and a corresponding model is another crucial step in achieving the qualification check and evaluation of harmonic reducers.

SVM is a powerful machine learning algorithm developed by Vapnik and Cortes to solve regression and classification problems using statistical learning. The fundamental basis of SVM is statistical learning theory and structural risk minimization. SVM solves the problem of small sample machine learning more effectively compared to the neural network method, and the convergence speed is faster when it is applied to machine learning. It uses a small number of training samples known as support vectors to find the optimal hyperplane, maximize the difference between classes, distinguish one class from others, and classify logarithmic data points. SVM uses the kernel method and linear and nonlinear transformations to transform data into a high-dimensional space for regression and classification. It differentiates between two classes based on the linear distance between them. This linear spacing is implemented, and when the data is converted to higher dimensions, it tends to expand the data to find the linear spacing between the to-be-separated classes. SVM is a common classification model whose purpose is to identify hyperplanes and enhance the model generalization ability by minimizing classification errors.

Now assume that there are two types of data, a total of X training samples, in which each training sample i can

be expressed as (x_i, y_i) , where $i = 1, 2, \dots, X$, $x_i = [x_{1i} \ x_{2i} \ \dots \ x_{yi}]^T$. It means that the sample contains y_i -dimensional features. $Y_i \in Y = \{-1, 1\}$ is the classification mark of the sample, the blue dot is labeled as 1, and the red dot is labeled as -1 . It is named the decision boundary.

$$\omega^T x_i + d = 0, \quad (1)$$

where ω is the weight vector; d is the bias. When $y = 2$, $x_i = [x_{1i} \ x_{2i} \ y_i]^T$, and then X training samples can be visualized on a two-dimensional plane with x_{2i} as the horizontal coordinate and x_{1i} as the vertical coordinate.

To make the decision boundary classify all samples correctly and maximize the classification margin, the decision boundary should meet the following conditions:

$$y_i(\omega^T x_i + d) \geq 1. \quad (2)$$

The calculated classification interval margin is

$$f(\omega) = \frac{\|\omega\|^2}{2}. \quad (3)$$

The problem of constructing the optimal hyperplane is further transformed into the problem of solving under constraints:

$$\min_{f(\omega)} \frac{1}{2} \|\omega\|^2, \quad (4)$$

$$s. t. \ y_i(\omega^T x_i + d) \geq 1, \ i = 1, 2, \dots, X.$$

To solve ω that minimizes the loss function, the loss function is transformed from the initial form into the Lagrange multiplier form:

$$L(\omega, d, \alpha) = \frac{\|\omega\|^2}{2} - \sum_{i=1}^X \alpha_i [y_i(\omega^T x_i + d) - 1], \quad (5)$$

$$\alpha_i \geq 0, \ i = 1, 2, \dots, X,$$

where α_i is the Lagrange multiplier.

The constrained optimization problem depends on the saddle point of the Lagrange function, and the partial derivative of the solution of the optimization problem concerning ω and d :

$$\max \alpha = -\frac{1}{2} \sum_{i=1}^X \sum_{j=1}^X \alpha_i y_i (x_i x_j) y_j \alpha_j + \sum_{j=1}^X \alpha_j, \quad (6)$$

$$\sum_{j=1}^X \alpha_j y_j = 0, \ j = 1, 2, \dots, X,$$

$$\alpha_j \geq 0, \ j = 1, 2, \dots, X,$$

where α_j is the Lagrange multiplier.

Through Eq. (6) and constraint conditions, the optimal decision boundary can be obtained as follows:

$$\omega^* x_i + d^* = 0, \quad (7)$$

where ω^* is the two-dimensional vector pointing perpendicular to the hyperplane; d^* is the distance of the closest point on the hyperplane to the origin.

The optimal decision function is

$$f(\mathbf{x}) = \text{sng}((\boldsymbol{\omega}^* \mathbf{x}_i) + d^*) = \text{sng}\left(\left(\sum_{j=1}^X \alpha_i^* y_i(\mathbf{x}_i, \mathbf{x}_j)\right) + d^*\right), \mathbf{x} \in \mathbf{R}^{y_i}, \quad (8)$$

where α_i^* is Lagrange multiplier.

In the face of an indivisible linear problem in reality, it is not easy to completely separate sample points through the hyperplane. The concept of soft margin is introduced, and Eq. (3) is rewritten as

$$\begin{aligned} & \min \frac{1}{2} \|\boldsymbol{\omega}\|^2 + C \sum_{i=1}^X \xi_i, \\ & \text{s. t. } y_i(\boldsymbol{\omega}^T \mathbf{x}_i + d) \geq 1 - \xi_i, \\ & \xi_i \geq 0, i = 1, 2, \dots, X, \end{aligned} \quad (9)$$

where C is a constant which minimizes the solution for which ξ_i get larger. Hence, C is an important parameter and decides the appropriate hyperplane of the classifier. In this case, the value range of α_i changes to $0 \leq \alpha_i \leq C$, $i = 1, 2, \dots, X$.

When dealing with nonlinear problems, mapping functions can be introduced to transform them into a specific high-dimensional space, and then the nonlinear problems are transformed into linear problems. This process can be expressed as

$$f(\mathbf{x}) = \text{sng}\left(\sum_{i=1}^X \alpha_i^* y_i K(\mathbf{x}_i, \mathbf{x}) + d^*\right), \quad (10)$$

where $K(\mathbf{x}_i, \mathbf{x})$ is a mapping function, also known as a kernel function including linear kernel function, polynomial kernel function, Gaussian kernel function, etc.

3 Experiment and Results

Time-domain statistics and frequency-domain statistics yielded 13 eigenvalues, and frequency bands were divided into seven frequency bands according to the frequency band of sound, which meant seven eigenvalues for a total of 20 eigenvalues. The above 20 indicators were used as inputs for SVM, RF and K-means

algorithms during the process of feature engineering. The ratio of the test set to the training set was 2 : 8, and the classification accuracy score of the test set was determined.

We determined the average algorithm time, the accuracy, the classification report and the confusion matrix for SVM, RF and K-means prediction results. These metrics help to comprehend the model performance. The comparison of the three algorithms' accuracy is shown in Table 7.

According to the results, the following conclusions can be drawn. The SVM algorithm performs better and faster than the RF algorithm and the K-means algorithm. By comparing the three algorithms, it is obtained that the speed and the accuracy of the SVM algorithm are high, with an accuracy of 98.0% in 0.049 ms, whereas the RF algorithm achieves an accuracy of 95.0% within 0.370 ms, and the K-means algorithm only achieves 53.0% within 1.760 ms. The SVM algorithm's prediction speed, accuracy, recall rate, and F1 score for classes 0 (Good) and 1 (Bad) indicate that the SVM algorithm can classify the data categories fastest.

In conclusion, the SVM algorithm with time-domain and frequency-domain statistics is more accurate and advantageous for the harmonic reducer hammer knock classification task. To visualize the classification outcomes, principal component analysis was used to reduce the test data to two dimensions, and scatter plots were generated. Mixing two different sets of variables in scatter plots is often done to visually explore relationships, correlations, or patterns between variables from distinct sets. This approach allows for a comparative analysis. The key is to provide clarity through labeling and visual distinctions to ensure that the audience understands the context and relationships being depicted. The scatter plots of SVM, RF, and K-means are shown in Fig. 3. The confusion matrices of SVM, RF, and K-means are shown in Fig. 4.

Table 7 Comparison of SVM, RF and K-means algorithm accuracy

Quality detection model	Accuracy of SVM/%		Accuracy of RF/%		Accuracy of K-means/%	
	Training set	Test set	Training set	Test set	Training set	Test set
Accuracy	99.0	98.0	97.0	95.0	61.0	53.0
Precision	98.6	98.5	96.4	96.0	64.0	54.0
Recall	98.5	98.0	95.0	94.5	64.3	54.0
F1 score	99.0	98.5	96.1	95.0	59.0	52.5
Macro average	99.3	99.0	97.0	96.0	60.0	54.0
Weighted average	99.0	99.0	97.2	95.0	63.0	55.0
Prediction speed/ms	0.049		0.370		1.760	

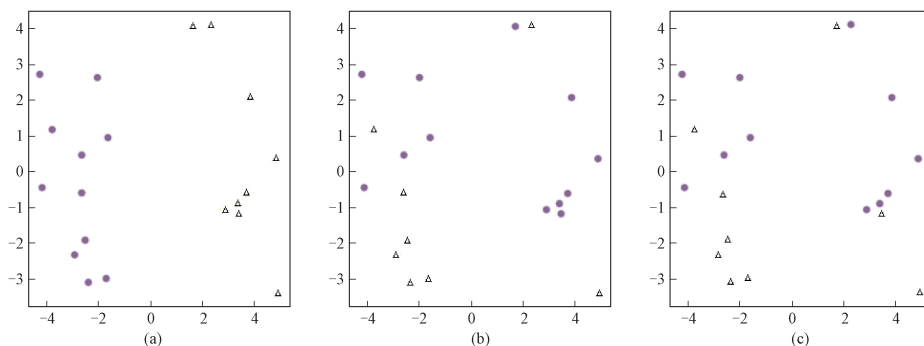


Fig. 3 Scatter plots: (a) SVM; (b) RF; (c) K-means

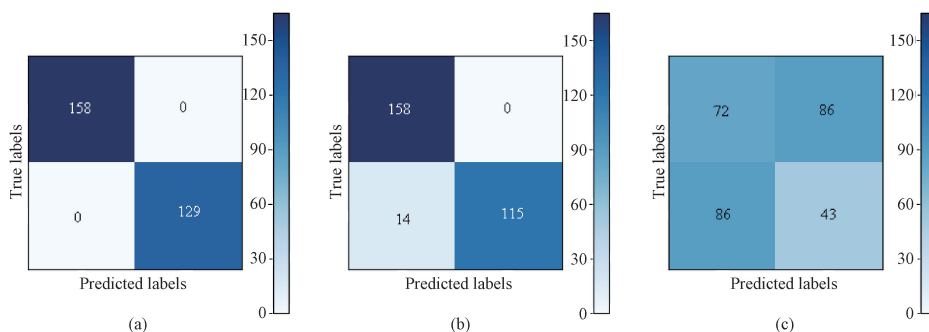


Fig. 4 Confusion matrices: (a) SVM; (b) RF; (c) K-means

In Fig. 4, the sub-diagonals in the confusion matrix of the test sets are both 0, indicating that the model has a strong generalization ability on the test sets, and the accuracy of the test sets is 98.0%. This shows that the SVM algorithm can be used for harmonic reducer classification and can effectively identify abnormal states.

To make the designed algorithm be used for the fast detection of the harmonic reducer, NI data acquisition card and Labview were used to design the fast detection software of the harmonic reducer. The computer adopts Intel(R) Core(TM) i5-10400F CPU 2.90 GHz; the GPU is NVIDIA GeForce GTX1660; the system type is a 64-bit Windows 10 operating system. Figure 5 shows the login interface of the fast detection software of the harmonic reducer.

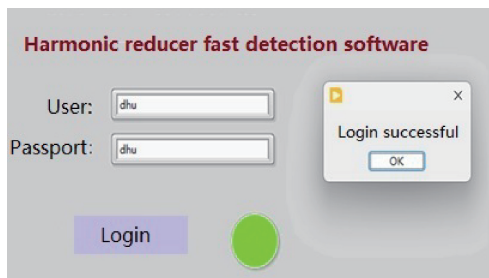


Fig. 5 Harmonic reducer fast detection software login interface

The signal acquisition and analysis module can collect the sound pressure signals of the four channels at the same time. The interface of the signal acquisition and the analysis module of the harmonic reducer fast detection software is shown in Fig. 6.

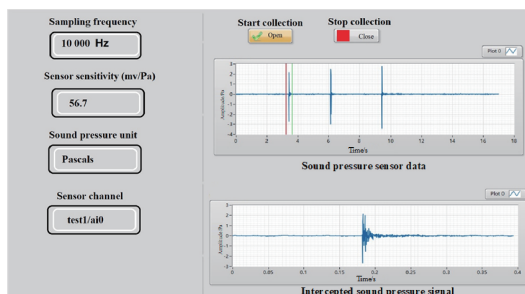


Fig. 6 Signal acquisition and analysis module interface

The signal analysis module of the software can intercept the signal and analyze the frequency domain. The hammer signal of the harmonic reducer was intercepted and the SVM was trained for 300 rounds. The trained SVM algorithm model was used to detect the quality of the harmonic reducer. The interface is shown in Fig. 7.

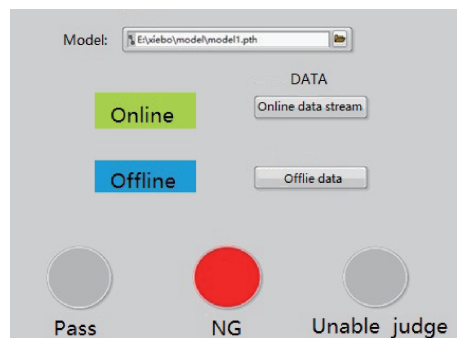


Fig. 7 Quality determination interface of harmonic reducer

Figure 8 shows the interface of model training results. The accuracy of detection, training time and test

time can be seen from Fig. 8, and the training process of the model can also be seen.

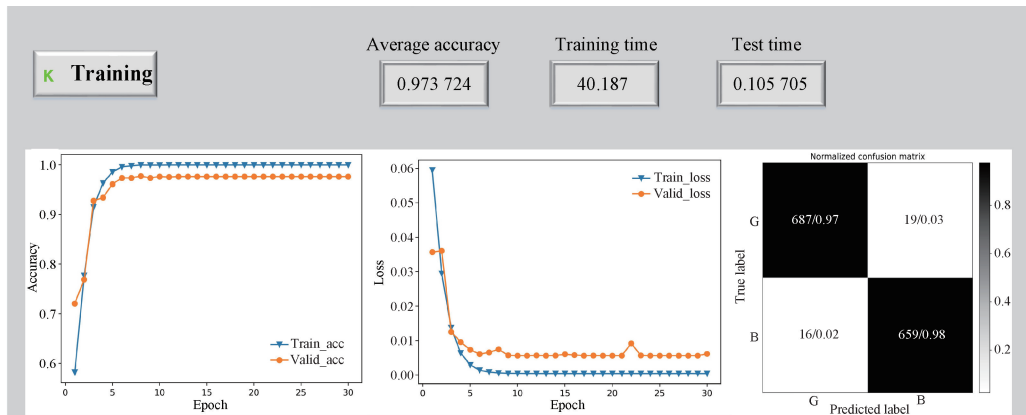


Fig. 8 Model training result interface

4 Conclusions

The manufacturer's pre-delivery fast detection of the harmonic reducer quality is completed based on the acoustic resonance sound signal method in different scenarios and tasks. The ongoing advancements in acoustic resonance fast detection research are poised to revolutionize post-mass production factory inspection methods.

Specific conclusions are as follows.

1) The comprehensive hammer knock detection experiment for the harmonic reducer quality detection is conducted based on acoustic resonance signals. After gathering sound signals, the features of the acoustic resonance signals are extracted for subsequent quality detection and classification tasks.

2) The performance of SVM, RF and K-means algorithms was verified on the same test set. Using the hammer knock detection dataset, the classification model accuracy is validated through experiments, and the qualification classification of a harmonic reducer is obtained. The classification results of SVM, RF, and K-means algorithms are compared. It is found that the SVM algorithm has the best performance, with an accuracy of 98.0% in 0.049 ms on the test set.

3) A harmonic reducer pre-delivery fast detection software is designed based on the SVM. A robust and efficient detection solution would be provided.

References

- [1] MUSSER C W. The harmonic drive [J]. *Machine Design*, 1960, 14: 160-173.
- [2] MASOUMI M, ALIMOHAMMADI H. An investigation into the vibration of harmonic drive systems [J]. *Frontiers of Mechanical Engineering*, 2013, 8(4): 409-419.
- [3] ZHAO Y Q. Damage detection and performance

evaluation of harmonic reducer based on sound signal and acoustic emission [D]. Shanghai: Donghua University, 2023. (in Chinese)

- [4] SHIROISHI J, LI Y, LIANG S, et al. Bearing condition diagnostics via vibration and acoustic emission measurements [J]. *Mechanical Systems and Signal Processing*, 1997, 11(5): 693-705.
- [5] WANG H C. Research on crack identification of parts based on resonance acoustic nondestructive testing technology [D]. Taiyuan: North University of China, 2019. (in Chinese)
- [6] JATZLAU P, MÜLLER M, GROSSE C U. Identification of flawed CFPR samples using local acoustic resonance spectroscopy (LARS) [C]// 19th World Conference on Non-Destructive Testing. Munich: DGZfP, 2016.
- [7] JU Y C, KRALJEVSKI I, NEUNÜBEL H, et al. Acoustic resonance testing of small data on sintered cogwheels [J]. *Sensors*, 2022, 22(15): 5814.
- [8] ZHANG S N, WANG F L, YOU F Q, et al. Robust least squares support vector machine based on robust learning algorithm and its application [J]. *Control and Decision*, 2010, 25(8): 1169-1172, 1177. (in Chinese)
- [9] CERVANTES J, GARCIA-LAMONT F, RODRÍGUEZ-MAZAHUA L, et al. A comprehensive survey on support vector machine classification: applications, challenges and trends [J]. *Neurocomputing*, 2020, 408: 189-215.
- [10] HEINRICH M, VALESKE B, RABE U. Efficient detection of defective parts with acoustic resonance testing using synthetic training data [J]. *Applied Sciences*, 2022, 12(15): 7648.
- [11] YIN Y, XIE L F, HUANG T B. A deep learning method for magnetic tile internal defect inspection based on acoustic vibration [J]. *China Measurement & Test*, 2020, 46(3): 32-38. (in Chinese)

- [12] TANDON N, CHOUDHURY A. A review of vibration and acoustic measurement methods for the detection of defects in rolling element bearings [J]. *Tribology International*, 1999, 32(8): 469-480.
- [13] XU Y, XIE G S, SHENG X W, et al. The invention relates to a method and device for a quick inspection of harmonic speed reducer; CN, 202211211977.9 [P]. 2022-09-30. (in Chinese)
- [14] LI M, YANG J H, WANG X J. The cyclic spectrum density method based on entropy and its application to the fault diagnosis of rolling bearings[J]. *Journal of Vibration Engineering*, 2015, 28(1): 164-174. (in Chinese)
- [15] YU Y, LI Y, YANG P, et al. Improved wavelet threshold function and ACEWT method for feature extraction of acoustic emission signals from rolling bearing faults [J]. *Journal of Vibration and Shock*, 2023, 42(17): 194-202. (in Chinese)
- [16] SCHNABEL S, GOLLING S, MARKLUND P, et al. The influence of contact time and event frequency on acoustic emission signals [J]. *Proceedings of the Institution of Mechanical Engineers, Part J: Journal of Engineering Tribology*, 2017, 231(10): 1341-1349.
- [17] LIU M H, LU J G, ZHANG J K, et al. Fault diagnosis of gearbox rolling bearing based on VMD energy entropy[J]. *Coal Mine Machinery*, 2023, 44(10): 173-175. (in Chinese)

基于支持向量机算法的谐波减速器声学共振快速检测方法

ENKHBAT Ganbayar, 徐 洋*, 张熠鑫, 解国升

东华大学 机械工程学院, 上海 201620

摘要: 谐波减速器的装配误差异常质量检测是制造商交货前的重要流程。该检测重点关注异常评估, 可以减少因产品召回而造成的经济损失, 进一步保护用户的利益和制造商的声誉。声音信号为声学共振测试提供了简单非接触式测量的基础, 并且有助于工厂在谐波减速器交货前进行快速测试。该文提出了一种声音数据采集、特征提取和分析的试验方法。利用谐波减速器的锤击激励, 获得了异常和正常谐波减速器的声学数据集。提取了声音信号的时域和频域特征, 比较了支持向量机 (support vector machine, SVM)、随机森林 (random forest, RF)、K-means 这三种分类算法。结果表明, SVM 在测试集上的准确率为 98.0%, RF 的准确率为 95.0%, K-means 的准确率仅为 53.0%。SVM 分类器的准确率、召回率和 F1 分数都很高。基于 SVM 谐波减速器质量检测模型, 利用 NI 数据采集卡和 Labview 软件, 设计了谐波减速器快速检测软件, 可用于厂家谐波减速器出厂前检测。

关键词: 谐波减速器; 声振测试; 特征提取; 分类分析; 支持向量机