Gearbox fault diagnosis using data fusion based on self-organizing map neural network

Zhang Qiang¹,², Gu Jieying², Liu Junming², Tian Ying¹ and Zhang Shilei²

Abstract
This article aims to provide an efficient fault diagnosis method for gearbox. A self-organizing map–based fault model is developed to provide effective diagnosis of the faults of gearboxes using the gear signals extracted from gearboxes operating with zero and three different types of faults. The gear signals are collected by vibration and acoustic sensors, and pre-denoised using wavelet denoising and wavelet packet decomposition. The characteristic values are subsequently obtained using fast Fourier transform and infinite impulse response filtering. The results showed of the self-organizing map neural network diagnosis model can effectively diagnose gear fault information with a 95% diagnostic accuracy using four input characteristic values: (1) Y-axis vibration displacement amplitude, (2) Y-axis vibration acceleration amplitude, (3) acoustic emission energy amplitude, and (4) acoustic emission signal peak value. The proposed approach provides a novel method to more accurate diagnosis of gear fault pattern and improvement of working efficiency of mechanical instruments.

Keywords
Gearbox, vibration signal, acoustic emission signal, wavelet analysis, fault diagnosis system

Introduction
Gearboxes have been widely used in modern mechanical instruments as the key transmission components for change of speed and transmission of power. In transmission system, gearbox failure accounts for 78% of the total failures.¹ A faulty transmission system could result in heavy losses to the company or serious labor injuries. Therefore, predictive diagnosis of gearbox fault that provides effective detection of potential failure mode of the gearbox system prior to the accident is crucial for ensuring reliable operation and higher efficiency of the mechanical system.²³

The diagnosis of gearbox fault has been studied extensively by many domestic and foreign scholars. Lei et al.⁴ summarized the characteristics of faulty planetary gearbox vibration signals by collecting these signals from ordinary, solar, and planetary gear systems and comparing them with simulation results. Liu et al.⁵ proposed a characteristic value extraction method of gear fault based on the envelope analysis and time–frequency image of S transformation. The method was validated against fault simulations. Yang et al.⁶ proposed a method of gear fault diagnosis based on multi-scale fuzzy entropy of ensemble empirical mode decomposition (EEMD). The gear faults are diagnosed...

¹College of Mechanical and Electronic Engineering, Shandong University of Science and Technology, Qingdao, China
²School of Mechanical Engineering, Liaoning Technical University, Fuxin, China

Corresponding author:
Tian Ying, College of Mechanical and Electronic Engineering, Shandong University of Science and Technology, Qingdao, Shandong 266510, China.
Email: tianluoluo@sohu.com

Creative Commons CC BY: This article is distributed under the terms of the Creative Commons Attribution 4.0 License (https://creativecommons.org/licenses/by/4.0/) which permits any use, reproduction and distribution of the work without further permission provided the original work is attributed as specified on the SAGE and Open Access pages (https://us.sagepub.com/en-us/nam/open-access-at-sage).
by first extracting a complexity metric in different scales of the original signal, and then putting them into a least square support vector machine (LS-SVM) as characteristic values. Seokgoo and Joo-Ho\textsuperscript{7} propose a convolutional neural network method based on the signal segmentation, which is to divide the original signal into those at each tooth of the gear. The effectiveness of the method is validated by the data made from the gearbox test rig, in which the vibration and transmission errors are measured, respectively. Zeng et al.\textsuperscript{8} diagnosed different faulty gear signals using general singular value decomposition (SVD)-based subspace noise reduction algorithm. Yongzhi et al.\textsuperscript{9} proposed a fully unsupervised feature extraction method for “meaningful” feature mining, named disentangled tone mining, which can effectively extract the hidden “trend” associated with machinery health state. Dennis et al.\textsuperscript{10} introduce the combined use of the residual method and general linear chirplet transform using acoustic and vibration measurements from a single stage spur gearbox. Xihui et al.\textsuperscript{11} proposed a fault diagnosis method for planetary gears based on the entropy feature fusion of dual-tree complex wavelet transform (DTCWT) and optimized kernel Fisher discriminant analysis (OKFDA). Liming et al.\textsuperscript{12} proposed a new optimal demodulation subband selection method (ODSSM) for fault diagnosis of planetary gearbox, that can detect the gear fault in both simulation and experiment signals, and achieves improved demodulation performance than the other two methods. Ling et al.\textsuperscript{13} proposed a method of incipient fault feature enhancement based on the wavelet packet and the minimum entropy deconvolution (MED), and the vibration signal of the gearbox containing the incipient fault is decomposed by the wavelet packet, and the decomposed band is reconstructed to eliminate the noise component which is the initial enhancement of the fault feature. Liu et al.\textsuperscript{14} proposed a feature extraction and fault diagnosis method based on the variational mode decomposition, SVD, and convolutional neural network for the local weak feature information of planetary gears.

So far, some studies have explored gear fault diagnosis using a variety of signal fusion methods,\textsuperscript{15,16} but the denoising effect of the signal is not obvious, resulting in inaccurate extraction of eigenvalues. Such an approach suffers from the drawback of low accuracy of the characteristic value extraction and long operating time due to the absence of signal fusion and poor performance of denoising, so there will be inefficient diagnosis, low diagnostic rate, and other issues. This article proposed a comprehensive method for diagnosing gear fault using both vibration and acoustic signals. This article used Daubechies 5 (db5) wavelet function to denoise the collected vibration signal and acoustic emission signal, and using wavelet packet decomposition to decompose the signal. The characteristic values were obtained by using fast Fourier transform (FFT) to transform the signal in the selected area and using infinite impulse response (IIR) method to filter it. The gear faults were diagnosed using identification mapping based on the self-organizing map (SOM) neural network, which improves the recognition accuracy by 10\%~20\%.

**Experimental method for fault diagnosis**

**Signal acquisition device**

The experimental setup for fault diagnosis is composed of inverter, motor, belt drive system, gearbox, and signal acquisition device. The vibration signal system comprises three vibration sensors (one for each axis X, Y, and Z), a signal modulator (SIRIUS constant current source module is used to adjust the vibration signal transmitter), and a data acquisition system (DEWE software). The range of XZD-YB vibration sensor is 0–20 mm/s, the sensitivity is 20 mV/mm/s\textsuperscript{6}5\%, and the linearity error is 6\%1\%. The acoustic signal acquisition system consists of SR150N acoustic emission sensor, preamplifier, acoustic emission acquisition device, and PC signal analysis system. The peak sensitivity of SR150N acoustic emission sensor is more than 265 dB, and the working frequency is 22–220 kHz. The range of XZD-YB vibration sensor is 0–20 mm/s, the sensitivity is 20 mV/mm/s\textsuperscript{±}5\%, and the linearity error is ±1%. The acoustic signal acquisition system consists of SR150N acoustic emission sensor, preamplifier, acoustic emission acquisition device, and PC signal analysis system. The peak sensitivity of SR150N acoustic emission sensor is more than 65 dB, and the working frequency is 22–220 kHz. The arrangement of the sensors is shown in Figure 1.

**Mode of the gearbox fault**

The gearbox is the key component in the experiment setup. The transmission gear of JZQ250 reducer is selected in the experiment. It has a transmission ratio of 31.5:1. The pulley ratio is 1. The gear ratio of the two gear sets are 85/14 and 83/16, respectively. The
motor provides power for the whole experimental device. It is the power source of gearbox drive system. Its rated power is 1.1 KW, rated frequency is 50 Hz, and rated speed is 1390 r/min. The gear mesh frequency is 61.05 Hz. The internal structure of the gearbox is shown in Figure 2.

In the process of gear operation, various kinds of failure will be mainly caused by fatigue as a consequence of a high number of operating cycles. These gear faults were simulated by following methods:

1. Gear tooth root crack fault: a small groove with a depth of 3 mm and a length of 30 mm is cut at the root of a gear by numerical control wire cutting.
2. Gear tooth wear fault: file a 3-mm deep groove on a tooth surface of a gear by filing.
3. Gear tooth broken fault: file a 30-mm long inclined surface with an angle of 150° at the root of a gear.

The present research studies the gear states of the wheel from the output shaft of the gearbox, being divided into four types: gear tooth root crack fault, gear tooth wear fault, gear tooth broken fault, and normal gear, as shown in Figure 3.

### Experimental procedures

The vibration and acoustic signals of the gearbox under normal operating condition and the three modes of faults were collected during the experiments. The detailed procedures are listed below:

1. Build experimental platform, install sensors, and label the corresponding locations of each sensor. All the sensors were fixed in place during the experiment and tested with signal testing prior to the experiment.
2. Install the fault-free gearbox and collect the vibration and acoustic signals from X, Y, and Z axis.
3. Dissemble the gearbox and replace the fault-free gear with gears that have gear tooth root crack fault, gear tooth wear fault, and gear tooth broken fault, respectively.
4. The experimental platform is cleaned up after the experiments are finished.

### Processing and analysis of vibration signal

#### Signal denoising

The acquisition frequency used in the experiment is 200 Hz. The signals are continuously collected for 1 min with 12,500 sample points in total. The collected image of vibration displacement signal, vibration speed signal, and vibration acceleration signal on X, Y, and Z axis is shown in Figure 4.

The raw signals contain very dense noise signals. To obtain the characteristic value of each different fault, the original signal spectrums were preprocessed for denoising using db5 wavelet function and soft-thresholding denoising method. The signals obtained from all X, Y, and Z axes were denoised with five levels.
layers of wavelet functions. Figure 5 shows the denoised signal for gear in normal condition.

Figure 5 shows that the all the signals were amplified after the wavelet denoising process. The attenuation of the noise resulted in higher signal-to-noise ratio, which is particularly significant for vibration acceleration signal. By comparing the denoised signal with the original signal, it was found that the most notable change in the signal diagram could be obtained from the Y-axis. The amplitude of the signal is varied significantly after denoising. However, the diagram revealed weak periodicity of the vibration velocity signal, while the displacement and acceleration signals are not ideal for extraction of characteristic value. Therefore, a wavelet packet decomposition was performed to reconstruct the vibration displacement and acceleration signals.

**Wavelet packet decomposition**

Wavelet packet decomposition can decompose a signal into different frequency bands. The more the layers of decomposition, the higher the resolution in the frequency domain. Wavelet packet decomposition and reconstruction technology can more accurately decompose the signal into high frequency and low frequency, which is good for signal analysis and eigenvalue extraction.

The experiment adopts three-layer wavelet packet decomposition technology, and the tree diagram of
Wavelet packet decomposition is shown in Figure 6. Where $Y$ is the decomposed waveform, $L$ is the low-frequency waveform, $H$ is the high-frequency waveform, and the number represents the number of decomposition layers. The decomposition relationship is as follows

$$Y = \text{LLL}_3 + \text{HL}_3 + \text{LH}_3 + \text{HHL}_3 + \text{LLH}_3 + \text{HLH}_3 + \text{LHH}_3 + \text{HHH}_3$$

db12 wavelet is used to decompose the acoustic emission signal. To facilitate identification, eight frequency bands are defined as $A1$, $A2$, $A3$, $A4$, $A5$, $A6$, $A7$, and $A8$.
The decomposition algorithm of wavelet packet is shown in formula (1), formula (2), and formula (3).

\[ g_l^n(t) = \sum_{l} d^{2n}_l W_n(2^l - l) \]  

(1)

\[ d^{2n}_l = \sum_{k} a_{k-2n} d^{1+1,n}_k \]  

(2)

\[ d^{2n+1}_l = \sum_{k} b_{k-2n} d^{1+1,n}_k \]  

(3)

Figure 7 shows the reconstructed gear vibration signal in normal condition after wavelet packet decomposition. The frequency band of the wavelet packet decomposition is in accordance with the values listed in Table 1.

By analyzing the vibration displacement signal and vibration acceleration signal reconstructed by wavelet packet decomposition, the energy of the vibration signal is mainly distributed in A0–A3 (0–50 Hz), which is in a relatively low-frequency band in the whole signal frequency domain. The ratio of A4–A7 frequency band to total energy is low. The amplitude of the signal for different gears remains almost the same for vibration frequencies higher than 50 Hz. Therefore, the frequency higher than 50 Hz can be treated as noise band in the experimental signal spectrum. To extract the characteristic value of the vibration signal more effectively, the vibration displacement and acceleration signals are filtered using an IIR filter after FFT process, which only allows frequencies from 0–50 Hz to pass. Figures 8 and 9 show the signal spectrum after filtration.

**Extraction of characteristic value**

In this experiment, the signal acquisition time is 60 s, and the sample data are 10 groups, with 10 s as a time period. The characteristic values of the experiments were obtained by taking the root mean square of the 200 sample points after FFT transformation. Table 2 shows the characteristic values of the gear signal under four different conditions.

**Processing and analysis of acoustic emission signal**

The acoustic signals were collected with a sampling frequency of 200 kHz, sampling time of 60 s, and total sample points of 12,800 in the experiment. The raw signal spectrum revealed significant periodic change of acoustic emission signal from gear under normal condition to gear with fault. The raw signals were processed with wavelet packet decomposition and reconstruction method for mitigating noise and enhance
signal-to-noise ratio. Figure 10 shows the reconstructed acoustic emission signals, and their corresponding frequency bands are summarized in Table 3.

The calculation result from the reconstructed signal shows that most of the energy is concentrated in the A2, A3, and A4 frequency bands (12.5–50 kHz). In the
The article selected the peak value of the root mean square amplitude of the energy in A2–A4 frequency bands as the characteristic values. Figures 11–14 show the acoustic emission signal after FFT transform.

**Extraction of characteristic value**

The signal spectrum from Figures 11–14 revealed that the acoustic emission energy is mainly concentrated between 15 and 40 kHz, while the energy associated with other frequency bands is insignificant. Such result is consistent with the findings obtained using wavelet packet decomposition and reconstruction method, which suggests that the characteristic value extracted using space energy associated with each node is effective. The peak value of the root mean square amplitude of the energy in A2–A4 frequency bands was taken as the characteristic value. One set of the results is shown in Table 4.

| Gear condition            | Vibration displacement signal (mm × 10⁻⁵) | Vibration acceleration signal (g × 10⁻⁵) |
|---------------------------|------------------------------------------|----------------------------------------|
| Normal                    | 1.55                                     | 0.78                                   |
| Tooth root crack           | 2.12                                     | 1.04                                   |
| Tooth wear                | 3.41                                     | 2.35                                   |
| Tooth broken              | 2.60                                     | 1.50                                   |

**Table 3.** The bands of wavelet packet decomposition and reconstruction corresponding to each node.

| Node | Frequency range (kHz) |
|------|------------------------|
| A1   | 0–12.5                 |
| A2   | 12.5–25                |
| A3   | 25–37.5                |
| A4   | 37.5–50                |
| A5   | 50–62.5                |
| A6   | 62.5–75                |
| A7   | 75–87.5                |
| A8   | 87.5–100               |

Figure 10. Signal reconstruction of acoustic emission signal by wavelet packet decomposition. (a) Gear under normal condition. (b) Gear with tooth root crack fault. (c) Gear with wear fault. (d) Gear with tooth broken fault.
Discussions on recognition results

SOM network training

SOM neural network consists of an input layer and a competitive layer, where the number of input neurons is $m$ and the competitive layer is a $a \times b$ two-dimensional (2D) planar grid. The input layer is fully connected with every single neuron, which forms a topological distribution for inputting signal characteristics. Such topology is capable for input of characteristic value of the signals as shown in Figure 15.

The vibration displacement energy amplitude, vibration acceleration energy amplitude, acoustic emission signal energy, and the acoustic emission signal peak value were taken as the four characteristic values for input vectors $[x_1, x_2, x_3, x_4]$ in the SOM neural network. The learning rate and step in the classification stage are 0.9 and 1000, respectively. The learning rate and the default value of the neighbor distance are 0.02 and 1, respectively. The competitive layer consists of $6 \times 6 = 36$ neurons. A hexagonal topology structure was used with a training step of 200.

Figure 16 shows that the competitive neuron for normal condition P1, tooth root crack P2, tooth wear P3, and tooth broken P4 are 31, 1, 36, and 6, respectively. Their corresponding locations in the topology structure are revealed in the same figure. By labeling the position of all the neurons in Figure 16, it was found that there

| Gear condition       | Energy | Peak value ($V \times 10^{-3}$) |
|----------------------|--------|-------------------------------|
| Normal               | 54.68  | 14.26                         |
| Tooth root crack     | 44.86  | 8.75                          |
| Tooth Wear           | 64.77  | 15.26                         |
| Tooth break          | 75.00  | 17.54                         |

Table 4. The characteristic sample value of the four acoustic emission signals.
exist significant differences of fault mode in the topological structure.

The blue hexagon in Figure 17 represents 36 neurons and the straight line between each neuron represents their connection. The color of each diamond indicates the distance between adjacent neurons, where a dark color is equivalent to a longer distance and larger mismatch between two different fault modes. When it is difficult to determine the mode of the fault pattern, the distance between neurons can help with judging the degree of wear.

Figure 17 shows that the different modes of fault are associated with different neurons. Such mapping is summarized in Table 5.

### Analysis of experimental results

To test the accuracy of the SOM neural network for fault diagnosis, 100 different experiments were performed to collect the vibration and acoustic emission signal of gears under four different conditions. Twenty sets of test samples were randomly selected from the collected signals. After the vibration and acoustic emission signals were processed and analyzed using the SOM neural network model, 76 of 80 samples were identified with the correct mode of fault. The identification error may be due to noise interference during the signal collection. The accuracy of the gear fault diagnosis is around 95%.

Because the denoising method and recognition model are established accurately, the recognition accuracy increases by 10%–20% compared with the previous research results.

### Conclusion

1. In this article, two signal fusion methods of vibration and acoustic emission are used to construct the SOM neural network to construct the gear fault diagnosis model, which greatly improves the recognition accuracy.
2. After preprocessing the vibration signal with wavelet denoising and wavelet packet decomposition, the characteristic of different gear fault can be represented by the Y-axis vibration displacement and acceleration signal in the frequency domain obtained using FFT transform and IIR filter.
3. Through wavelet packet decomposition, reconstruction, and FFT signal transformation, it was found that the energy is concentrated in the frequency bands from A2 to A4. The root mean square and the peak value of vibration
amplitude of the energy extracted from A2 to A4 can be used as the characteristic values for gear fault diagnosis.

4. The recognition model constructed in this article has been tested by experiments, and the accuracy of fault diagnosis is about 95%, which can be potentially used as a novel technique for diagnosing gear fault and improving efficiency of mechanical instruments.

Declaration of conflicting interests
The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding
The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This study was financially supported by the National Natural Science Foundation Fund of China (Projects No. U1810119, 51774161 and 51804151), Development of National Key Laboratory of Mineral Processing Science and Technology (BGRIMM-KJSKL-2017-20), and Youth Research Projects in Colleges and Universities of Liaoning Provincial Department of Education of China (LJ2017QL018) and Taishan Scholar Program of Shandong Province.

ORCID iD
Gu Jieying https://orcid.org/0000-0001-9778-1103

References
1. Zhang Z and Wang X. Application of fault diagnosis technology in gear box detection. Metal Equip 2017; S2: 282–284.
2. Wu L, Yang Z, Yang L, et al. Common methods and development trend of mechanical equipment fault diagnosis. Metal Equip 2017; S2: 318–321.
3. Wang H, Zhang Q and Xie F. Dynamic tension test and intelligent coordinated control system of a heavy scraper conveyor. IET Sci Meas Technol 2017; 11(7): 871–877.
4. Lei Y, Tang W, Kong D, et al. Vibration signal simulation and fault diagnosis of planetary gearboxes based on transmission mechanism analysis. J Mech Eng 2014; 50(17): 61–68.
5. Liu J, Liu Y, Jiang P, et al. Extraction of gear fault features based on the envelope and time-frequency image of S transformation. J Vib Shock 2014; 33(1): 165–169.
6. Yang W, Zhang P, Wang H, et al. Gear fault diagnosis based on multiscale fuzzy entropy of EEMD. J Vib Shock 2015; 34(14): 163–167.
7. Seokgoo K and Joo-Ho C. Convolutional neural network for gear fault diagnosis based on signal segmentation approach. Struct Health Monit 2019; 18(5–6): 1401–1415.
8. Zeng M, Yang Y, Zheng J, et al. μ-SVD based denoising method and its application to gear fault diagnosis. J Mech Eng 2015; 51(3): 95–103.
9. Yongzhi Q, Yue Z, Miao H, et al. Gear pitting fault diagnosis using disentangled features from unsupervised deep learning. Proc IMechE, Part O: J Ris 2019; 233(5): 719–730.
10. Dennis H, Dunant H, Gethin W, et al. Gear fault diagnosis using the general linear chirplet transform with vibration and acoustic measurements. J Low Freq Noise V A 2019; 38(1): 36–52.
11. Xihui C, Gang C, Yong L, et al. Fault diagnosis of planetary gear based on entropy feature fusion of DTCWT and OKFDA. J Vib Control 2018; 24(21): 5044–5061.
12. Liming W, Yimin S and Zheng C. Optimal demodulation subband selection for sun gear crack fault diagnosis in planetary gearbox. Measurement 2018; 125: 554–563.
13. Ling Z, Jing D, Darong H, et al. The incipient fault feature enhancement method of the gear box based on the wavelet packet and the minimum entropy deconvolution. Syst Sci Control Eng 2018; 6(3): 235–241.
14. Liu C, Cheng G and Chen X. Planetary gears feature extraction and fault diagnosis method based on VMD and CNN. Sensors 2018; 18(5): E1523.
15. Qu Y, He D and Jae Y. Gearbox tooth cut fault diagnostics using acoustic emission and vibration sensors—a comparative study. Sensors 2014; 14(1): 1372–1393.
16. Cheek KT, Phil I and David M. A comparative experimental study on the diagnostic and prognostic capabilities of acoustics emission, vibration and spectrometric oil analysis for spur gears. Mech Syst Signal Pr 2007; 21(1): 208–233.
17. Thoret-Bauchet Q, Velep P, Guingand M, et al. Simulations of the dynamic response of planetary gears in the presence of localised tooth faults. Proc IMechE, Part C: J Mech 2019; 233(21–22): 7121–7223.
18. Jialin L, Xueyi L, David H, et al. A domain adaptation model for early gear pitting fault diagnosis based on deep transfer learning network. Proc IMechE, Part O: J Ris 2020; 234(1): 168–182.