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Rolling bearing fault diagnosis based on data-level and feature-level information fusion

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Abstract: To address the limitation of single acceleration sensor signals in effectively reflecting the health status of rolling bearings, a rolling bearing fault diagnosis method based on the fusion of data-level and feature-level information was proposed. First, according to the impact characteristics of rolling bearing faults, correlation kurtosis rules were designed to guide the weight distribution of multi-sensor signals. These rules were then combined with a weighted fusion method to obtain high-quality data-level fusion signals. Subsequently, a feature-fusion convolutional neural network (FFCNN) that merges the one-dimensional (1D) features extracted from the fused signal with the two-dimensional (2D) features extracted from the wavelet time-frequency spectrum was designed to obtain a comprehensive representation of the health status of rolling bearings. Finally, the fused features were fed into a Softmax classifier to complete the fault diagnosis. The results show that the proposed method exhibits an average test accuracy of over 99.00% on the two rolling bearing fault datasets, outperforming other comparison methods. Thus, the method can be effectively utilized for diagnosing rolling bearing faults.

Key words: fault diagnosis; information fusion; correlation kurtosis; feature-fusion convolutional neural network

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With the rise of intelligent manufacturing, health monitoring systems for mechanical equipment and their key components have received increasing attention. Rolling bearings, which are commonly used standard parts, play a vital role in the safe and stable operation of rotating machinery. Consequently, the fault diagnosis of rolling bearings has become an industry consensus[1-3].

Previously, signal processing methods such as variational mode decomposition[4], synchrosqueezing transform[5], and stochastic resonance[6] were the preferred choices for fault diagnosis. However, in recent years, deep learning has emerged as a powerful tool, reducing the reliance on expert experience by automatically extracting features. This advancement has significantly promoted research in rolling bearing fault diagnosis[7]. Yuan et al.[8] converted one-dimensional vibration signals into wavelet time-frequency spectra and then used convolutional neural networks (CNNs) to diagnose bearing faults. Similarly, Che et al.[9] combined stacked denoising autoencoders with CNNs to diagnose bearing faults in noisy environments.

The widespread use of multi-sensor signal acquisition systems has introduced new opportunities and challenges for rolling bearing fault diagnosis. Compared with single-sensor signals, multi-sensor signals can provide a more comprehensive reflection of the bearing's health status, leading to improved fault diagnosis results. However, there is still no unified standard for multi-sensor information fusion. The selection of fusion levels—data-level fusion, feature-level fusion, and decision-level fusion—and the design of fusion methods still depend on specific tasks[10]. Song et al.[11] proposed a two-stage fusion method using acoustic signals, acceleration signals, and acoustic emission signals to detect compressor blade cracks. Similarly, Ma et al.[12] introduced a data-level fusion method based on kernel cosine similarity and a decision-level fusion method based on improved Dempster-Shafer evidence theory. Their results demonstrated that the proposed multilevel fusion method offers better blade crack detection performance and greater robustness.

To fully utilize multi-sensor information and enhance rolling bearing fault diagnosis, a rolling bearing fault diagnosis method based on data-level and feature-level fusion is proposed. First, according to the impact characteristics of rolling bearing fault signals, the correlation kurtosis (CK) rule is designed to guide the weight allocation of different sensors and obtain high-quality fused signals. Afterward, a feature-fusion convolutional neural network (FFCNN) is introduced to combine one-dimensional (1D) features extracted from the fused signal with two-dimensional (2D) features extracted from wavelet time-frequency spectra. Finally, these fused features are input into a Softmax classifier to complete the fault diagnosis of rolling bearings.

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1 Basic Theory

1.1 Data-level fusion based on correlation kurtosis rule

When a rolling bearing malfunctions, the periodic collision between the faulty part and other components generates an impact component in the acceleration signal, which is a crucial indicator of failure. Kurtosis, a statistical measure for capturing impact components in signals, is widely employed in the fault diagnosis of rolling bearings.

The kurtosis of the collected signal $x(n)$ is as follows:

$$K = \frac{\frac{1}{N}\sum_{n=1}^{N}[x(n)-\mu]^4}{\left\{\frac{1}{N}\sum_{n=1}^{N}[x(n)-\mu]^2\right\}^2} \tag{1}$$

where N is the length of $x(n)$; μ is the mean value of $x(n)$. According to Ref. [12], the correlation coefficient between the fused signal and the original multi-sensor signal is introduced as the weight, which can be calculated using

$$w_{\mathrm{f}} = \frac{1}{M}\sum_{i=1}^{M} \left| C(x_i, x_{\mathrm{f}}) \right| \tag{2}$$

where M represents the number of sensors; x_i represents the signal collected by the i-th sensor; x_{f} represents the fused signal; $C(\cdot)$ denotes the correlation coefficient between the two signals, x_i and x_{f}, and can be obtained as follows:

$$C(x_i, x_{\mathrm{f}}) = \frac{\sum_{n=1}^{N}[x_i(n)-\bar{x}_i][x_{\mathrm{f}}(n)-\bar{x}_{\mathrm{f}}]}{\sqrt{\sum_{n=1}^{N}[x_i(n)-\bar{x}_i]^2 \sum_{n=1}^{N}[x_{\mathrm{f}}(n)-\bar{x}_{\mathrm{f}}]^2}} \tag{3}$$

where $\bar{x}_i$ and $\bar{x}_{\mathrm{f}}$ are the mean values of x_i and x_{f}, respectively. Accordingly, the CK of the fused signal x_{f} is defined as follows:

$$C_K(x_{\mathrm{f}}) = w_{\mathrm{f}} K \tag{4}$$

As previously mentioned, kurtosis effectively captures the impact components in bearing fault signals, with higher kurtosis indicating a richer embedded impact component. Moreover, the incorporation of the correlation coefficient helps suppress noise in the fused signal. Consequently, a fused signal with a higher CK value exhibits clearer fault features and reduced noise interference, facilitating the diagnosis of bearing faults. Fig. 1 illustrates the structural diagram of the data-level fusion method based on the CK rule. The original collected multi-sensor signals are used as the training dataset, with weights randomly initialized for each sensor. A weighted fusion method[13] is employed to generate data-level fusion signals. The reciprocal of the CK value of the fused signal is designated as the loss function, and the adaptive moment estimation algorithm (ADAM) is utilized to train the weights of each sensor, aiming to attain the fused signal with the highest CK value. The training parameters for ADAM are configured as follows: a batch size of 64, a learning rate of 0.001, and 50 epochs.

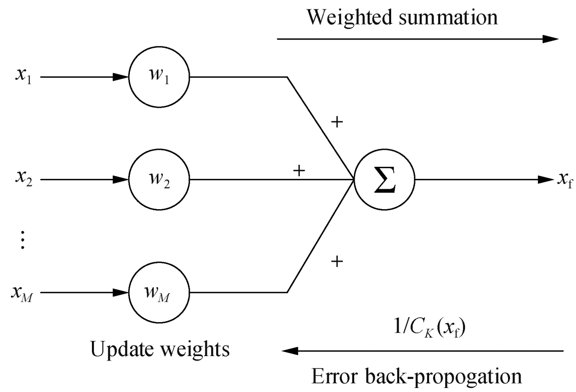

Fig. 1 Data-level fusion method based on the CK rule

1.2 Feature-fusion convolutional neural network

The extensive use of deep neural networks has led researchers to favor end-to-end methods, wherein the original one-dimensional acceleration signals are directly fed into the network. Xue et al. [14] highlighted that incorporating two-dimensional information aids in further extracting fault information from the signal and achieving improved feature representation. Hence, an FFCNN comprising a 1D-CNN and a 2D-CNN is proposed. The network parameters for each component are detailed in Table 1 and Table 2, respectively. Following feature extraction, the 1D and 2D features are concatenated to form fused features, which are then input into a Softmax classifier to complete the rolling bearing fault diagnosis.

Table 1 1D-CNN network structure parameters

No.	Layer	Kernel size	Channel size	Stride
1	1D-Conv 1	3	16	1
2	1D-MaxPool	2		2
3	1D-Conv 2	3	32	1
4	1D-MaxPool	2		2
5	1D-Conv 3	3	64	1
6	1D-MaxPool	2		2
7	1D-GAP		64	

Table 2 2D-CNN network structure parameters

No.	Layer	Kernel size	Channel size	Stride
1	2D-Conv 1	3 × 3	16	1 × 1
2	2D-MaxPool	2 × 2		2 × 2
3	2D-Conv 2	3 × 3	32	1 × 1
4	2D-MaxPool	2 × 2		2 × 2
5	2D-Conv 3	3 × 3	64	1 × 1
6	2D-MaxPool	2 × 2		2 × 2
7	2D-GAP		64	

2 Proposed Method

Building upon the aforementioned, Fig. 2 illustrates the flowchart of the proposed rolling bearing fault diagnosis method, integrating data-level and feature-level fusion. The specific steps are outlined as follows:

1) Collect multichannel signals using multiple acceleration sensors positioned at various locations.

2) Employ the CK rule to allocate weights to each channel signal, utilizing a weighted fusion method to produce the data-level fusion signal.

3) Utilize wavelet transform to derive the wavelet time-frequency spectra corresponding to the fused signals.

4) Input the 1D acceleration signals and 2D wavelet time-frequency spectra into the FFCNN to extract fused features.

5) Integrate these features with the Softmax classifier to determine the health status of the bearing, thereby completing the rolling bearing fault diagnosis.

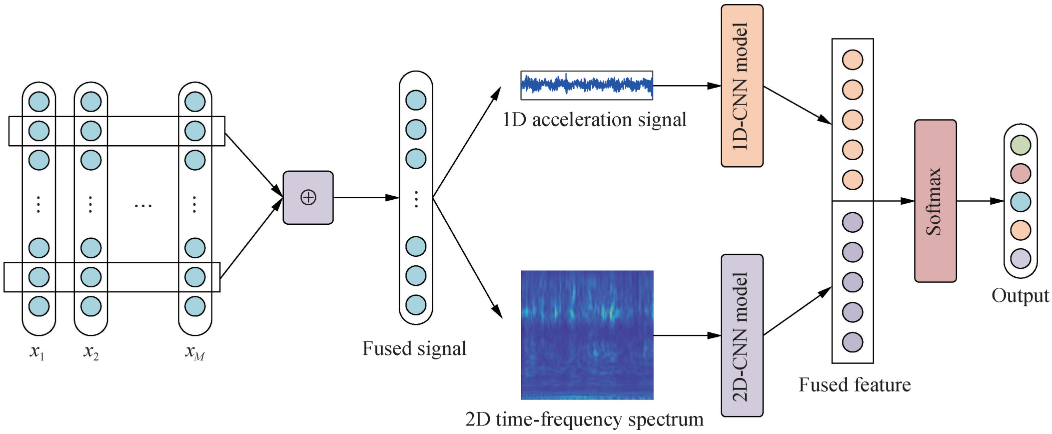

Fig. 2 Flowchart of the proposed method

3 Case Study

3.1 Case 1

To assess the effectiveness of the proposed method, the bearing fault dataset from Southeast University was used for testing purposes.

3.1.1 Introduction of dataset

The experimental setup is depicted in Fig. 3, and detailed experimental parameters are presented in Ref. [15]. Here, only the dataset is introduced. Data from channel 2, channel 3, and channel 4, representing the acceleration signals of the planetary gearbox in directions x, y, and z, are selected for testing purposes. Following the data-level fusion of these three-channel data, the resulting fused signal dataset is presented in Table 3. In the experiment, five bearing states were established: normal, rolling ball fault, inner race fault, outer race fault, and combination fault, labeled 0, 1, 2, 3, and 4, respectively. The experiment was conducted under two distinct working conditions, denoted 20-0 and 30-2, corresponding to different speed-load configurations. A total of 500 samples were collected under each working condition, with each sample having a length of 2 048. The size of the corresponding wavelet time-frequency spectrum was 227 × 227 × 3. Samples with the same bearing status under both working conditions were assigned the same label. Consequently, there were 1 000 samples for each bearing state. The training set and the test set were divided in a ratio of 4∶1.

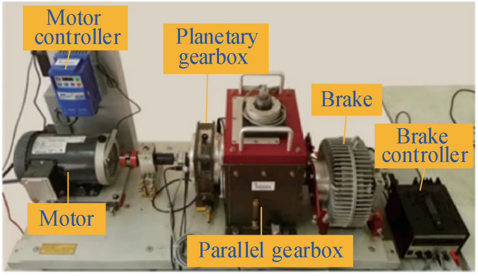

Fig. 3 Southeast University bearing test bench

Table 3 Southeast University bearing dataset

Bearing states	Training dataset/ Testing dataset	Label
Normal	800/200	0
Rolling ball fault	800/200	1
Inner race fault	800/200	2
Outer race fault	800/200	3
Combination fault	800/200	4

3.1.2 Assessing the effectiveness of the proposed method

To evaluate the effectiveness of the data-level fusion method based on the CK rule, besides the fused signals, the signals from channel 2, channel 3, channel 4, and the mean fusion signals are taken as inputs. Each result represents the average of 10 trials. As illustrated in Fig. 4, regarding the original signal, diagnostic accuracy is highest for signals collected from channel 2 (98.20%), while channel 3 yields the lowest accuracy (88.20%). Notably, the mean fusion signals fail to surpass the diagnostic accuracy achieved by channel 2 signals, indicating that an unreasonable weight distribution may hinder the exploitation of the complementary information from multichannel signals. The proposed method, which utilizes the CK rule to allocate weights to multichannel signals, achieves the highest diagnostic accuracy of 99.00%. Furthermore, the FFCNN effectively utilizes both 1D and 2D features to attain a more comprehensive representation of the bearing fault state, outperforming single-input methods. This confirms the effectiveness of the proposed two-level fusion method.

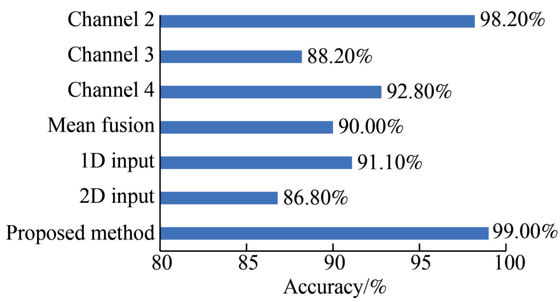

Fig. 4 Diagnostic results of different inputs

To elucidate the functioning mechanism of the FFCNN, the original 1D signals, the original 2D wavelet time-frequency spectra, features extracted by 1D-CNN, features extracted by 2D-CNN, and the fused features are visualized using the t-distributed stochastic neighbor embedding (t-SNE) method[16]. As depicted in Fig. 5, the samples of the original signal appear mixed, making it challenging to directly distinguish between different bearing fault states. However, following 1D-CNN and 2D-CNN processing, the extracted features demonstrate considerable capabilities in differentiating between fault states. Moreover, the FFCNN maximizes the complementarity between 1D and 2D features, enhancing its capacity to distinguish between fault states. This further underscores the effectiveness of the proposed FFCNN in extracting rolling bearing fault features. Considering that samples with the same fault state under the two working conditions are regarded as the same label, samples of the same category aggregate into two clusters. This indicates the method's capability to discriminate between different working conditions as well.

3.1.3 Comparison with other methods

To further validate the superiority of the proposed method, several relevant methods are selected for comparison: SDAE[17], WDCNN[18], MSCNN[19], Shen's method[20], 2MNet[21], and MLVAF-CNN[22]. Among them, 2MNet and MLVAF-CNN are both data-level and feature-level fusion methods, and their input is the original 3-channel signals. SDAE, WDCNN, MSCNN, and Shen's method utilize the fused signal according to the CK rule. The experimental results are depicted in Fig. 6. Although other methods achieve diagnostic accuracy higher

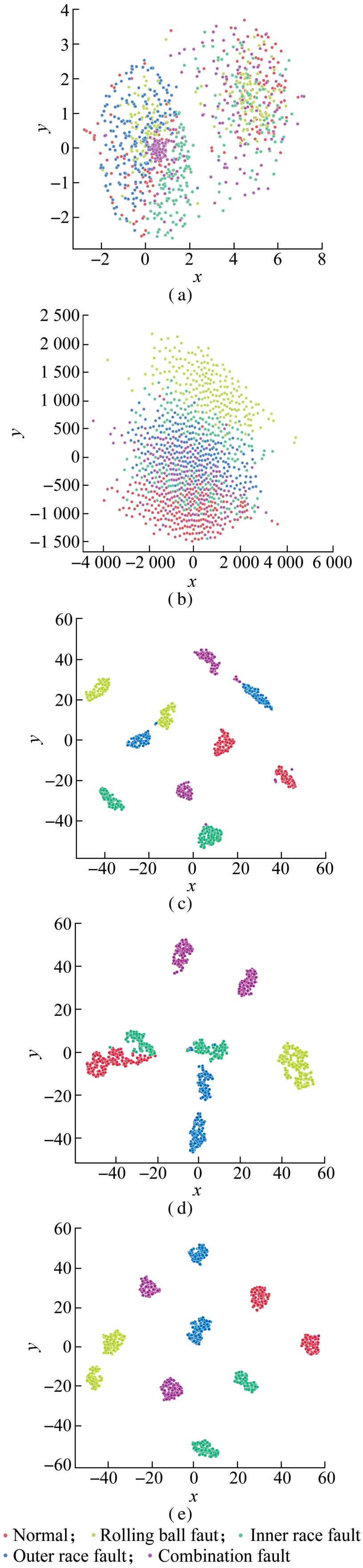

Fig. 5 Visualization results of different features. (a) 1D acceleration signals; (b) 2D wavelet time-frequency spectra; (c) Features extracted from 1D-CNN; (d) Features extracted from 2D-CNN; (e) Fused features

than 94%, the proposed method exhibits the highest accuracy, 99.00%, demonstrating its superiority.

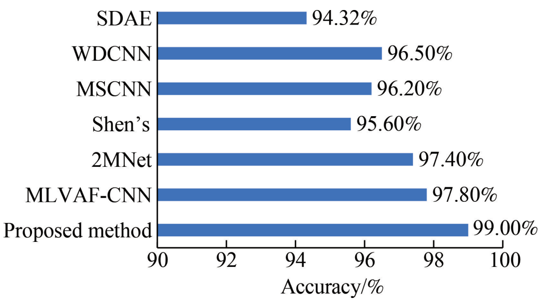

Fig. 6 Test results of different methods

3.2 Case 2

3.2.1 Introduction of dataset

To further validate the effectiveness of the proposed method in diagnosing rolling bearing faults, a dataset from a marine rudder propeller slewing bearing is utilized for testing. The specific bearing model is SKR31326. As depicted in Fig. 7, a three-axis acceleration sensor is positioned on the slewing bearing seat to gather signals.

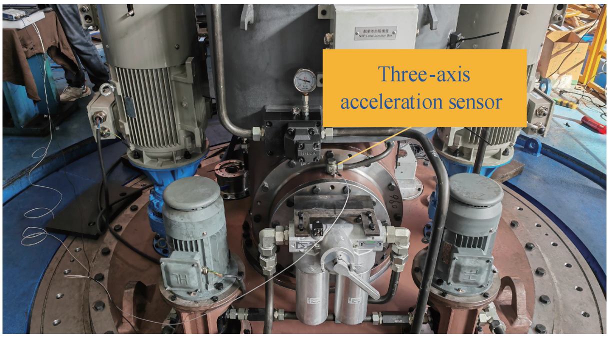

Fig. 7 Marine rudder propeller slewing bearing test bench

As depicted in Fig. 8, the experiment comprised two bearing states: normal and inner race fault, labeled as 0 and 1, respectively. To induce an inner race fault, a 2 mm crack was machined onto the inner race of the bearing using electrical discharge machining. The experiment was conducted under two distinct working conditions, with rotation speeds of 485 and 750 r/min, respectively. A total of 400 samples were collected under each working condition. The sample length was set to 2 048, with the corresponding size of the wavelet time-frequency spectrum also being $227 \times 227 \times 3$. Similarly, samples with the same bearing state under the two working conditions were assigned the same label. Consequently, there were 800 samples for each bearing state, with the training dataset and testing dataset divided in a 4∶1 ratio. Further details of the dataset are provided in Table 4.

Fig. 8 Inner race fault

Table 4 Marine rudder propeller slewing bearing dataset

Bearing states	Training dataset/ Testing dataset	Label
Normal	640/160	0
Inner race fault	640/160	1

3.2.2 Effectiveness of the proposed method

The specific results from 10 tests are depicted in Fig. 9. The diagnostic accuracy of the proposed method exceeds 99.00%, sufficiently demonstrating its effectiveness in diagnosing rolling bearing faults. Given that this is solely a binary classification problem, different related methods are not compared here. According to the test results from the two datasets, the proposed method exhibits exceptional performance in rolling bearing fault diagnosis.

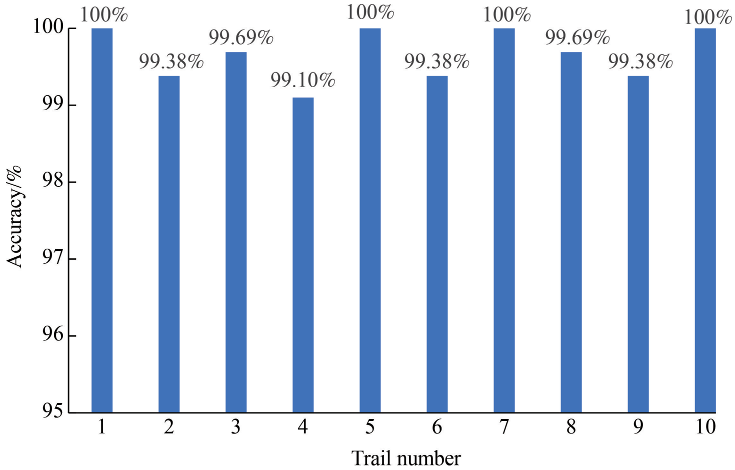

Fig. 9 Test results of marine rudder propeller slewing bearing fault diagnosis

4 Conclusions

1) A weighted fusion method based on the CK rule is used to perform data-level fusion of multichannel signals. The resulting fused signal exhibits more pronounced fault features, facilitating subsequent feature extraction.

2) An FFCNN, capable of effectively leveraging both 1D and 2D features to generate fused features, is introduced. Experimental results demonstrate that these fused features are more sensitive to bearing fault states.

3) Evaluation of the Southeast University bearing dataset and the marine rudder propeller bearing dataset reveals the effectiveness of the proposed rolling bearing fault diagnosis method, which integrates data-level and feature-level information fusion. The method exhibits outstanding fault diagnosis performance, with an average diagnostic accuracy of over 99.00%, markedly outperforming other diagnostic methods.

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基于数据级和特征级信息融合的滚动轴承故障诊断

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摘要:针对单一加速度传感器信号难以充分反映滚动轴承健康状态的问题,提出了一种基于数据级和特征级信息融合的滚动轴承故障诊断方法. 首先,根据滚动轴承故障的冲击特性,设计了相关峭度规则来指导多传感器信号的权重分配,结合加权融合方法获得高质量的数据级融合信号;随后,设计了一个特征融合卷积神经网络(FFCNN),对从融合信号中提取的一维(1D)特征和从小波时频谱中提取的二维(2D)特征进行融合,获得滚动轴承健康状态的充分表征;最后,将融合后的特征输入 Softmax 分类器,完成故障诊断. 结果表明,所提方法在 2 个滚动轴承故障数据集上平均测试准确率均高于 99.00%,优于其他对比方法,可用于滚动轴承的故障诊断.

关键词:故障诊断;信息融合;相关峭度;特征融合卷积神经网络

中图分类号:TH165; TH17