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Noise reduction approach of rolling bearing vibration signal based on GS-CDAE model

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Abstract

In response to the characteristics of non-stationary, non-linear, and susceptible to background noise interference in the fault signals of rolling bearings, a denoising method for vibrational signals of rolling bearings based on the grid search algorithm optimized convolutional denoising autoencoder (GS-CDAE) is proposed. The proposed model utilizes encoding and decoding operations to extract the underlying fault features and reconstruct the noisy signal back to its original form. Furthermore, the use of grid search algorithm to optimize the model hyperparameters has further enhanced the denoising performance and reduced the manual tuning effort. The experimental results show that the proposed model can effectively perform noise reduction reconstruction to output high-quality signals with an average loss value of 0.00502 under different signal-to-noise ratio interference, with good robustness and generalization performance. The visualization of the noise-reduced signal of the model also enhances the interpretability of the model.

Keywords

Fault diagnosis; rolling bearing; convolutional denoising autoencoder (CDAE); grid search algorithm.

1. Introduction

Rolling bearing as a key component of the rotating mechanism, widely used in various types of equipment. Due to its long-term exposure to high-speed, variable operating conditions, and high loads, as well as interference from adverse environmental factors, it is highly prone to failures. For example, signal processing methods such as short-time fourier transform (STFT) [1] and empirical mode decomposition (EMD) [2] are used.

In recent years, with the advancement of artificial intelligence technology and the promotion of intelligent manufacturing, deep learning (DL) models have achieved brilliant results in the fields of image recognition and speech recognition with their powerful feature extraction ability and nonlinear fitting ability [3-5]. Some scholars will start to apply deep learning models to the field of fault diagnosis [6-9]. For example, Che et al [10] proposed a domain adaptive deep belief network (DA-DBN) to solve the problem of lack of large number of labeled samples under the new working conditions.

To address the aforementioned issue, this study proposes a grid search algorithm-optimized Convolutional Denoising Autoencoder (GS-CDAE) model. The model first adds Gaussian white noise to the original data and then performs encoding operations using convolutional layers and pooling layers to transform the high-dimensional input features into a lower-dimensional representation. Then the model employs deconvolutional layers and up-sampling layers to

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perform decoding operations, converting the low-dimensional features back to high-dimensional features. The model is fine-tuned using the backpropagation algorithm, and the output is a denoised reconstructed signal. The grid search (GS) algorithm is also used to optimize the hyperparameters of the model, which improves the noise reduction performance of the model and reduces the workload of manual parameter tuning.

2. Grid Search Algorithm-Optimized CDAE for Vibration Signal Denoising

2.1. CDAE model parameter setting

The detailed parameters of the CDAE model designed in this paper are shown in Table 1, from which it can be seen that the structures of the encoder and decoder are completely symmetrical. Using Mean Square Error (MSE) as the loss function of the model, the smaller the loss value of MSE indicates that the reconstructed data is more similar to the original input data, and its expression is as follows:

$$MSE(y,\hat{y})=\frac{1}{n}\sum_{i=1}^{n}(x_i-y_i)^2 \tag{1}$$

where x_i denotes the i-th original data and y_i denotes the i-th reconstructed data.

Table 1 Detailed parameters of convolutional denoising auto-encoder

Index	layer	Kernel number	Kernel size	Stride	
1	Conv1D	18	128×1	1	Encoder
2	MaxPooling1D	—	2×1	—	
3	Conv1D	8	64×1	1	
4	MaxPooling1D	—	2×1	—	
5	Conv1D	3	1	1	
6	MaxPooling1D	—	2×1	—	
7	UpSampling1D	—	2×1	—	Decoder
8	ConvTranspose1D	3	1	1	
9	UpSampling1D	—	2×1	—	
10	ConvTranspose1D	8	64×1	1	
11	UpSampling1D	—	2×1	—	
12	ConvTranspose1D	18	128×1	1	

2.2. Signal noise reduction process based on GS-CDAE model

The diagnosis process of the complete GS-CDAE model, which is divided into 2 main steps: data pre-processing and noise reduction processing. The details are described as follows:

(1) data pre-processing: First, the bearing fault signals collected by sensors are stored in a data table in .csv format. Then, the sliding window algorithm is used for data augmentation to increase the number of samples. The dataset is then split into a training set and a test set in a 7:3 ratio. The training set is used to adjust the parameters of the model, while the test set is used to evaluate the classification performance of the model.

(2) Reduction processing: The CDAE model is first initialized based on a set of hyperparameters filtered by the GS algorithm. Then, the divided training and test sets are fed into the CDAE model after adding Gaussian white noise with different signal-to-noise ratios.

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The original signal features are mined by unsupervised learning, the noise distribution is learned adaptively and noise reduction is performed, and the noise-reconstructed high-quality signal is output.

3. Optimization research with different optimizer

In this section, we will investigate the impact of the aforementioned optimizers on the model's accuracy. To ensure fairness in the experiments, we keep the other hyperparameters of the model constant and only change the optimizer. We use the dataset with 0dB signal-to-noise ratio as the input for the model. The experimental results are shown in Table 5 and Figure 1. It can be seen from the figure that when the model uses AdaGrad as the optimizer although it is the smoothest, it tends to fall into the local optimal solution, so the loss value is much lower than the other three optimizers, and after 100 iterations, the model still does not fully converge and also shows a decreasing trend. The SGD optimizer starts to converge after about 80 iterations, with a maximum training time of 13 min 42 s. The RMSProp optimizer smooths out the fluctuations after about 60 iterations, with a training time of 12 min 9 s.

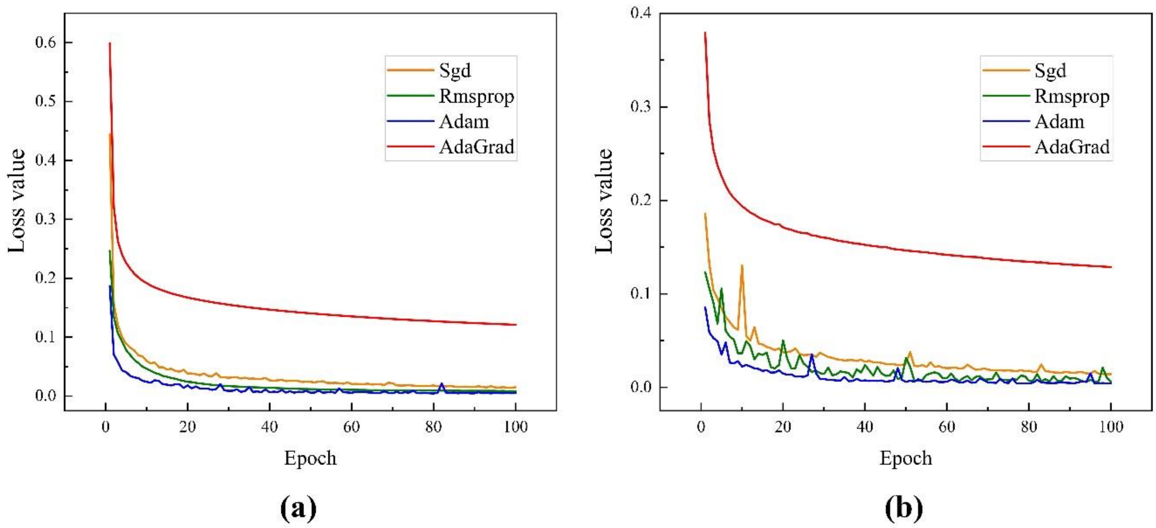

Fig. 1 Loss curve of models under different optimizers (a) Train set loss value (b) Test set loss value

4. Conclusions

In this paper, a GS-CDAE model is proposed to clean the noise-disrupted vibration signal while outputting the noise-reduced signal to provide a high-quality signal for subsequent fault diagnosis work. The experimental results show that CDAE uses the fault signal with noise added as input, adapts to the noise distribution by unsupervised learning, and then outputs a noise-reduced reconstructed signal. At the same time, the elu activation function is used instead of the traditional relu activation function, which effectively alleviates the problem of gradient disappearance during the training of the CDAE model, and its left side has soft saturation to make the model more robust to noise disturbance.

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