Original Research Article

Rolling bearing fault diagnosis based on WOA-VMD-YOLOv8

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Abstract: Rolling bearings are often in a state of high-speed operation, making them highly susceptible to failure. To address this issue, the WOA-VMD-YOLOv8 fault diagnosis model was designed by combining the advantages of Whale optimization algorithm (WOA), variational mode decomposition (VMD) and YOLOv8. The bearing vibration signals collected by Case Western Reserve University were used as experimental data. WOA was applied to optimize the VMD parameters, and the time-frequency diagrams of the WOA-VMD output signals were used as the dataset for YOLOv8. The experimental results show that, compared to the Wavelet Transform(WT)-YOLOv8, the WOA-VMD-YOLOv8 achieves better predictive performance for bearing faults, with Recall rate of 99.7%, mAP@0.5 of 99.5%, and mAP@0.5-0.95 of 99.4%. Therefore, the WOA-VMD-YOLOv8 demonstrates practical value in bearing fault detection technology.

Keywords: Fault diagnosis; Whale optimization algorithm; Variational mode decomposition; YOLOv8

1. Introduction

As a critical component of rotating machinery, rolling bearings play a significant role in the industrial field[1]. As rolling bearings are in high speed operation for a long time, they are very prone to failures and losses[2-4]. Therefore, it is of high practical significance to carry out fault diagnosis of rolling bearings to reduce the probability of equipment accidents.

In recent years, the use of vibration signals generated during the operation of rolling bearings for fault diagnosis has received the attention of many scholars. Common signal analysis methods include envelope demodulation, wavelet transform(WT), and empirical mode decomposition (EMD). However, WT relies on the choice of wavelet basis, EMD lacks a solid mathematical foundation and is prone to mode mixing and endpoint effects. When the characteristic signal is weak, the effectiveness of fault diagnosis becomes less evident. In 2014, K. Dragomiretskiy et al. proposed the Variational Mode Decomposition (VMD) algorithm. Since its inception, VMD has been widely applied in the field of mechanical fault diagnosis. VMD has a rigorous mathematical foundation and offers strong advantages in extracting features from nonlinear and non-stationary signals. However, the two parameters of the VMD need to be manually selected, and inappropriate choices can seriously affect the effectiveness of the algorithm.

The parameter optimization problem of VMD has been studied extensively. In 2018, Jiang et al. used the energy fluctuation spectrum to quickly determine the initial center frequency of potential patterns. Then, an optimization strategy guided by the center frequency was constructed to adaptively optimize the penalty factor to extract the optimal signal components. In 2019, Jiang et al. proposed a coarse-to-fine VMD decomposition strategy. First, the decomposition layers is initialized to 1, and VMD is iteratively applied to the signal to select the components containing the characteristic signal. Then, by adjusting the penalty factor, the frequency of the characteristic signal is made more prominent. However, neither of these methods can determine the optimal parameter combination for VMD.

To directly determine the optimal parameters for VMD and automatically detect bearing faults. In 2022, He et al. utilized an improved sparrow search algorithm to optimize the VMD parameters and employed a residual convolutional neural network for fault diagnosis, achieving an accuracy rate of 97.5%. Lin et al. optimized the VMD parameters using the Cuckoo Search algorithm and employed a Probabilistic Neural Network for fault identification, achieving an accuracy rate of 98.5%. However, both the sparrow search algorithm and the Cuckoo Search algorithm lack strong global search capabilities, making them prone to getting stuck in local optima. In addition, the inference time of neural network models is relatively long, which does not meet the requirements for real-time fault diagnosis. The Whale Optimization Algorithm(WOA) has a simple model and demonstrates strong global optimization performance. Mao et al. optimized the VMD parameters using WOA and selected suitable components based on Hausdorff distance. Simulations and experiments validated the effectiveness of the proposed method. In 2024, Liu et al. employed the YOLOv8 model for bearing defect detection, significantly improving detection efficiency and accuracy.

To address the aforementioned issues and facilitate rapid and accurate diagnosis of bearing faults, this study designed a bearing fault detection model based on WOA-VMD and YOLOv8. First, a bandpass filter is applied to preprocess the vibration signals, filtering out some noise components. Then, WOA is used to optimize the VMD parameters. Next, the preprocessed signal is decomposed using WOA-VMD to obtain the reconstructed signal. The time-frequency figure of the reconstructed signal is plotted to create the training and validation datasets. Finally, the YOLOv8 model is trained, and its performance is validated.

2. Theory of WOA-VMD-YOLOv8

The VMD algorithm and WOA algorithm have been extensively introduced in numerous papers. Therefore, this paper will not provide a detailed description. VMD is an adaptive, non-recursive denoising algorithm that is well-suited for removing noise from nonlinear and non-stationary signals. However, VMD requires manual selection of two parameters, and inappropriate combinations can significantly affect the denoising performance of VMD. The WOA algorithm has a simple model and demonstrates good global optimization capabilities. Therefore, this study utilizes WOA to optimize the VMD parameters. Then, WOA-VMD is used to decompose the signal and obtain the reconstructed signal. Finally, the dataset of YOLOv8 is produced and the model is trained. The theory of WOA-VMD-YOLOv8 is shown in **Figure 1**.

The specific implementation steps are as follows:

Step1: Preprocess the original signal using a bandpass filter;

Step2: Initialize the WOA parameters and the WOA is uesd to optimize the VMD parameters.

Step3: The preprocessed signal is decomposed using WOA-VMD, resulting in several Intrinsic Mode Functions (IMFs).

Step4: All IMFs are summed to obtain the reconstructed signal.

Step5: The time-frequency representation of the reconstructed signal is plotted, and the YOLOv8 dataset is obtained.

Step6: YOLOv8 is used for model training, and the bearing fault detection results are output.

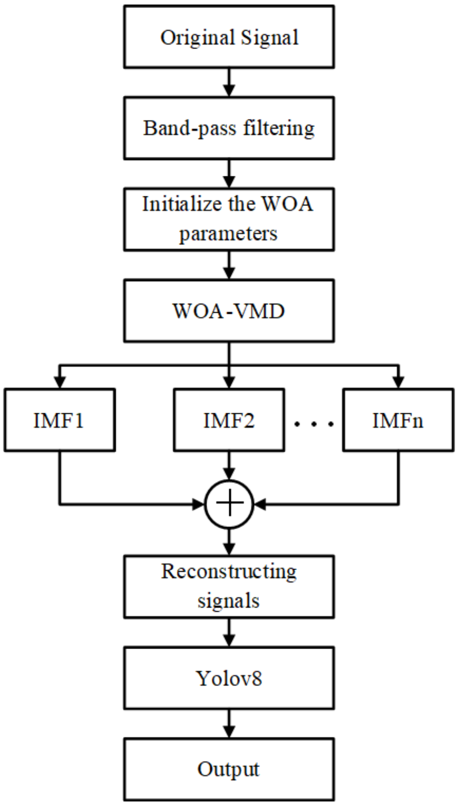

Figure 1. The theory of WOA-VMD-YOLOv8.

3. Experimental results

3.1. Data processing

In this paper, the bearing vibration signals collected by Case Western Reserve University were used as experimental data to validate the effectiveness of the WOA-VMD-YOLOv8. The drive-end data (105.mat) were processed using WT and WOA-VMD, and the results of the signal envelope spectrum analysis are shown in **Figure 2**.

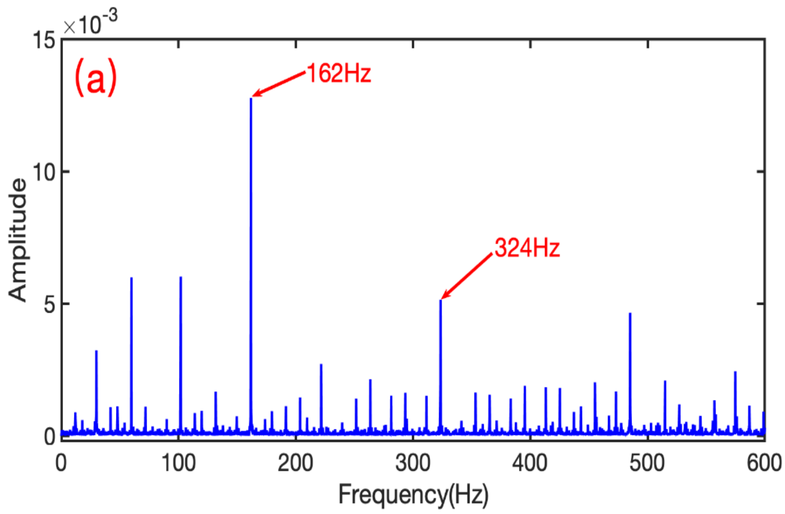

Figure 2. *(continued)*

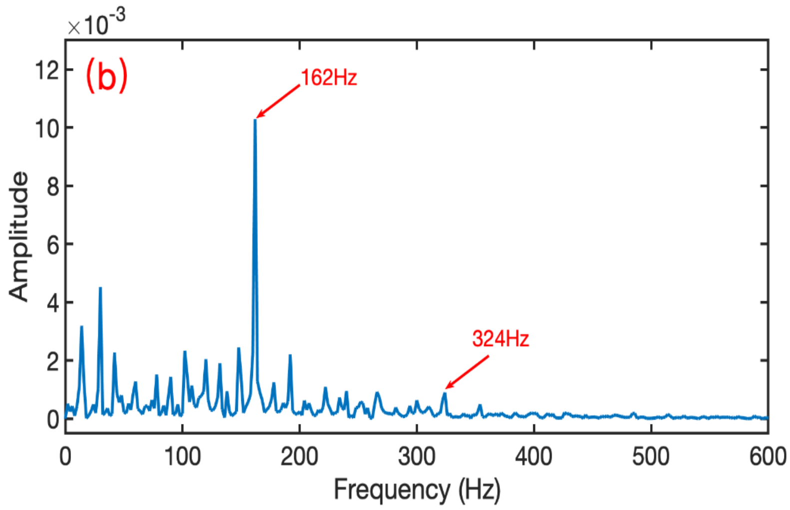

Figure 2. Envelope spectrum of the output signal (a) WT, (b)WOA-VMD.

It is evident that both WT and WOA-VMD output signals contain the characteristic frequency of 162 Hz and its second harmonic. Additionally, the WOA-VMD output signal shows less noise compared to WT.

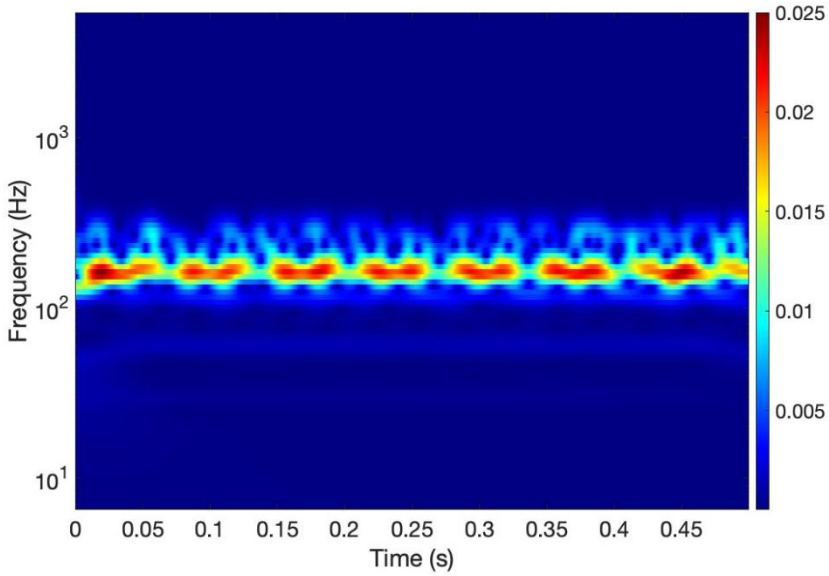

Figure 3. Time-frequency diagram of the WOA-VMD output signal.

The time-frequency diagram of the WOA-VMD output signal is shown in Figure 3. It can be observed that periodic characteristic signals are present. Based on the characteristic frequencies of bearing faults, it can be determined that an inner ring fault exists in the bearing.

3.2. Model comparison

The WOA-VMD and WT is applied to process the Inner Race fault, Outer Race fault, and Rolling Element fault data in the dataset, creating a dataset for YOLOv8. The WOA-VMD-YOLOv8 and WT-YOLOv8 are used to make predictions on the test set, further analyzing the performance of the WOA-VMD-YOLOv8. **Figure 4** and **Figure 5** illustrate the Recall-Confidence Curve and Precision-Confidence Curve of the WOA-VMD-YOLOv8, respectively. It can be seen that the model training performance is well.

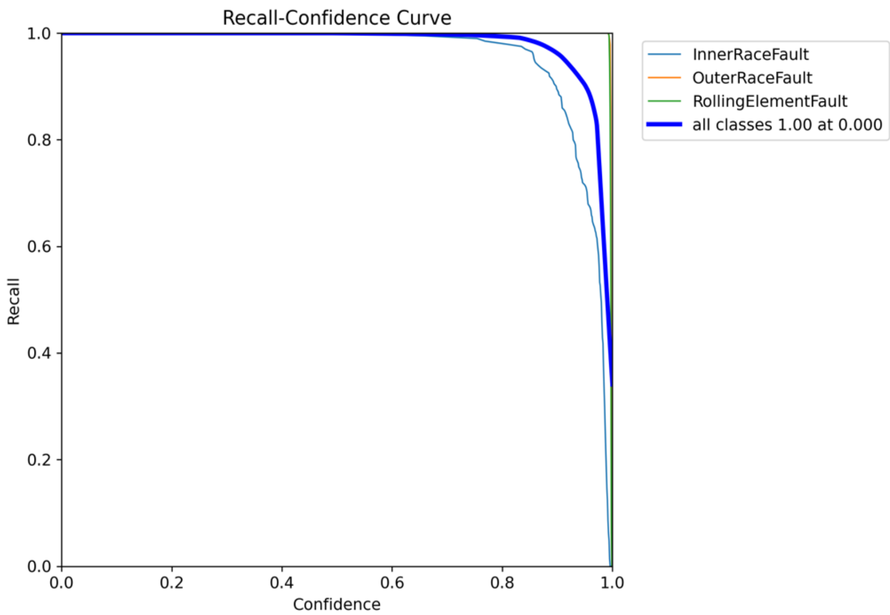

Figure 4. Recall-confidence curve.

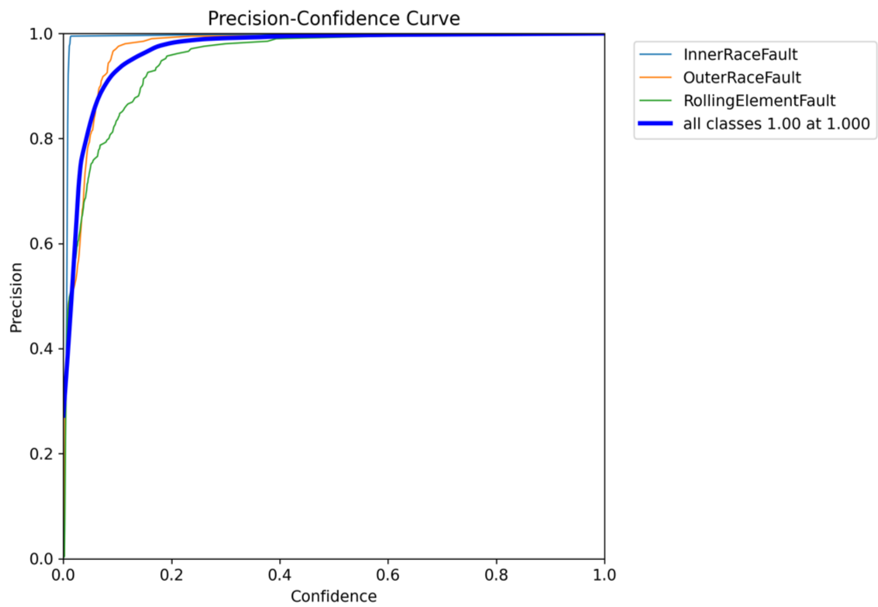

Figure 5. Precision-confidence curve.

Table 1. Comparative performance metrics of WOA-VMD-YOLOv8 and WT-YOLOv8.

Algorithm	Recall	mAP@0.5	mAP@0.5-0.95
WT-YOLOv8	99.3%	98.9%	98.5%
WOA-VMD-YOLOv8	99.7%	99.5%	99.4%

Table 1 shows Comparative Performance Metrics of WOA-VMD-YOLOv8 and WT-YOLOv8. The WOA-VMD-YOLOv8 has Recall rate of 99.7%, mAP@0.5 of 99.5%, and mAP@0.5-0.95 of 99.4%, with all performance metrics superior to the WT-YOLOv8.Therefore, the WOA-VMD-YOLOv8 demonstrates excellent fault detection performance and possesses significant practical value.

4. Conclusion

To enable rapid and accurate diagnosis of rolling bearing faults, this study designed a bearing fault diagnosis model based on WOA-VMD and YOLOv8. First, a bandpass filter is applied to preprocess the vibration signals, filtering out some noise components. Then, the VMD is optimized using WOA to obtain the optimal parameters. Next, WOA-VMD decomposes the preprocessed signal to obtain the reconstructed signal. Plot time-frequency images of the reconstructed signals and produce training and test sets. Finally, the YOLOv8 model is trained. The results show that WOA-VMD-YOLOv8 has Recall rate of 99.7%, mAP@0.5 of 99.5%, and mAP@0.5-0.95 of 99.4%, with all performance metrics superior to the WT-YOLOv8. Therefore, WOA-VMD-YOLOv8 demonstrates significant application value.

However, the reconstructed signal is obtained by summing up all IMFs, which results in a higher noise component still retained in the reconstructed signal. In the future, research will be carried out to address this issue and the YOLOv8 model will be improved appropriately.

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Funding

1. Jiangsu Provincial Vocational College Students' Innovation and Entrepreneurship Cultivation Program, Jiangsu Maritime Institute (GX-2024-023).

2. Scientific Research Project of Jiangsu Maritime Institute (2024ZKzd02).

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References

[1] X. Zhang, Q. Miao, Z. W. Liu, et al. An Adaptive Stochastic Resonance Method Based on Grey Wolf Optimizer Algorithm and Its Application to Machinery Fault Diagnosis[J], ISA transactions, 2017, 71: 206-214.

[2] G. Wang, J. W. Xiang. Remain useful life prediction of rolling bearings based on exponential model optimized by gradient method[J], Measurement, 2021, 176:109161.

[3] M. M. Manjurul Islam, Alexander E. Prosvirin, Jong-Myon Kim. Data-driven prognostic scheme for rolling-element bearings using a new health index and variants of least-square support vector machines[J], Mechanical systems and signal processing, 2021, 160:107853.

[4] L. B. Cosme, W. M. Caminhas, M. F. S. V. D'Angelo, et al. A Novel Fault-Prognostic Approach Based on Interacting Multiple Model Filters and Fuzzy Systems[J], IEEE Transactions on Industrial Electronics, 2019, 66(1):519-528.