Inspection method of combine assembly quality based on optimized VMD

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Abstract. Aiming at the problems of low assembly accuracy and difficult to detect assembly quality of combine, a method of combine assembly quality detection based on sparrow search algorithm (SSA) optimized variational mode decomposition (VMD) and particle swarm optimization (PSO) optimized least squares support vector machine (LSSVM) was proposed, Firstly, the sparrow search algorithm is used to obtain the optimal VMD decomposition modal parameter $K$ and penalty factor $\alpha$, then the combined vibration signal of combine harvester is decomposed into intrinsic modal components of different center frequencies by using the best parameter combination $[K, \alpha]$. Finally, the feature vector is used as the input of LSSVM classifier to classify different fault features. The analysis results show that the classification accuracy of SSA-VMD joint feature extraction method is 99.5%, which is 17.5% and 9.5% higher than ensemble empirical mode decomposition (EEMD) and fixed parameter VMD, which verifies the superiority of this method in the detection of combine assembly quality.

1. Introduction
The assembly quality inspection of combine is the last quality assurance link before the combine leaves the factory, and its assembly quality greatly affects the operation efficiency of combine[1]. It is difficult to judge the assembly quality of combine through traditional detection methods, so it is of great significance to improve the assembly quality by using modern processing methods. During the operation of the combine, the vibration signal contains rich fault information. Studying its vibration signal can diagnose the assembly quality of the combine. Time frequency analysis is a popular method for fault diagnosis. The signal decomposition algorithm of variational mode decomposition (VMD) is widely used in vibration signal processing. Mou Weijie et al. [2] decomposed the vibration signal of internal combustion engine by VMD, then extracted the image features for pattern recognition, and achieved good results. VMD processing effect is greatly affected by preset parameters.

In order to overcome the deficiency that VMD processing effect is affected by preset parameters, many scholars use intelligent optimization algorithm to optimize VMD parameters. Xiao et al. [3] used unsupervised learning algorithm self-organizing map (SOM) neural network to classify gear faults and compared with EMD. Li et al. [4] optimized VMD with whale optimization algorithm to obtain the best VMD decomposition parameters for radar signal noise reduction The accuracy of gear fault diagnosis is obviously higher than that of empirical mode decomposition algorithm.

The above VMD parameter optimization is based on the objective function with their own signal characteristics, and little attention is paid to the efficiency and accuracy of optimization calculation. In
order to solve the shortcomings of VMD manual setting parameters and the accuracy and convergence speed of some optimization algorithms, this paper proposes a new combine assembly quality detection method based on the combination of (sparrow search algorithm) SSA optimized VMD and particle swarm optimization (PSO) optimized least squares support vector machine (LSSVM).

2. Basic theory

2.1. SSA optimizes VMD
Variational mode decomposition (VMD) is a new and completely non-recursive method for solving variational problems. It seeks the optimal solution of the signal through the cross-direction multiplier iterative model to determine the optimal solution of each intrinsic mode function (IMF) [5-6]. The sparrow search algorithm (SSA) developed by Xue Jiankai and Shen Bo in 2020. It is a new swarm intelligence optimization algorithm that simulates sparrows' foraging behavior and anti-predation behavior. In SSA algorithm, there are discoverers, followers and scouts who update their positions according to their own rules to find the optimal position. More rules can be referred to as follows [7]. In this paper, a parameter adaptive VMD method based on SSA was introduced, which was used to detect the assembly quality of combine harvester. The basic idea of this method is to take Shannon entropy as the fitness function and use SSA algorithm to find the optimal VMD decomposition parameter combination.

2.2. Joint feature extraction
In order to meet the requirements of accurate diagnosis of assembly quality detection of combine harvester, a joint feature extraction method based on approximate entropy feature, time-domain feature and frequency-domain feature was proposed to extract fault information from vibration data more accurately. Approximate entropy is a linear parameter to measure the regularity and unpredictability of signal fluctuation. The higher the entropy value is, the higher the complexity of time series is. The application of approximate entropy to combine harvester vibration signal decomposition can reduce the operation time. The calculation process for time series is as follows [8]. Signal analysis in time domain refers to signal processing in time domain. The commonly use time domain analysis methods include mean square value, variance value and kurtosis value. The frequency domain feature analysis method analyzes the spectrum image by Fourier transform. Commonly used frequency domain analysis methods include gravity center frequency and mean square frequency. The frequency domain feature analysis method includes

3. Experimental design of assembly quality inspection

3.1. Data acquisition
In order to verify the effectiveness of the proposed method in the inspection of combine assembly quality, a real machine test of Dongfanghong 4LZ-9A2 combine was carried out in the Key Laboratory of Henan University of science and technology in July 2020. The faults of data acquisition and manual injection on the header of combine harvester are shown in Figure 1~2. There are four common fault states of manual injection: normal, auger misalignment, loose cutter transmission pressing wheel and cutter misalignment. Each signal sample is 200, the signal length is 2000, and the number is 0.1.2.3 respectively.
3.2. Quality Inspection Framework

This paper presents a method of assembly quality detection of combine based on SSA-VMD-PSO-LSSVM and joint feature extraction. The flow chart is shown in Figure 3.

4. Experiment and analysis

Taking the vibration signal acquisition process of header of combine as an example, sparrow search algorithm (SSA) is used to search for the optimal parameter combination of VMD. Among the sparrow search algorithms, the number of iterations is 20, the population of sparrow is 100, the proportion of discoverers is 20%, and the upper and lower bounds of sparrow patrol are respectively [10,10000], [2,200]. The curve of Shannon entropy value of fitness function changes with the number of iterations is shown in Figure 4: the figure shows that the minimum Shannon entropy value appears in the fifth
iteration, and then it has been convergent, indicating that the sparrow search algorithm has a fast convergence speed and strong global optimization ability, which is suitable for optimizing VMD parameters.

![Fitness iteration curve](image1)

Figure 4. Fitness iteration curve

![Time domain](image2)

Figure 5. SSA-VMD decomposes time domain

![Spectral spectrum](image3)

Figure 6. SSA-VMD decomposes spectral spectrum

The parameters combination is set to decompose the combine header vibration signal by VMD. The modal components and spectrum diagram of SSA-VMD decomposition are shown in Figure 5~6. Each IMF component decomposed has good independence and clear center frequency. In this paper, EEMD and fixed parameter VMD decomposition method $K=8, \alpha=987$ Decomposition method are used to compare the methods proposed [9].

In this paper. After EEMD decomposition, as shown in Fig.7~8, it can be seen that the six modal components generated by EEMD decomposition have frequency aliasing, and a large amount of noise is mixed in the first two components, making it difficult to extract useful information. The results show that the SSA-VMD method proposed in this paper can effectively overcome the mode aliasing phenomenon in EEMD algorithm and effectively extract the fault characteristics of combine vibration signal.
Figure 7. EEMD decomposes time domain

Figure 8. EEMD decomposes spectral domain

5. Comparison and analysis of classification accuracy of different features

In order to further verify the advantages of SSA-VMD-PSO-LSSVM and joint feature extraction, separate time-domain features, frequency-domain features, approximate entropy features and joint features are used to classify LSSVM. Figure 9 is a mixed matrix diagram of four features classified in LSSVM. According to the figure, the accuracy rate of time domain features is 74.5%, frequency domain accuracy is 84.5%, approximate entropy accuracy rate is 74.5% and joint feature is 97%. Only a few of the joint features are classified by mistake, and the rest are classified correctly, and classification is more accurate than other.

In order to improve the accuracy of the classifier, particle swarm optimization (PSO) algorithm is used to optimize LSSVM. The classification confusion matrix of four kinds of feature parameters in PSO-LSSVM is shown in Figure 10. It can be seen from the figure that the classification accuracy of time domain, frequency domain, entropy feature and joint feature reaches 79.5%, 88.5%, 87.5% and 99.5% respectively after LSSVM parameter optimization. Compared with LSSVM, the classification effect is significantly improved. Table 2 shows the comparison of classification accuracy of the proposed method in LSSVM and PSO-LSSVM.

Figure 9. Accuracy in LSSVM

Figure 10. Accuracy in PSO-LSSVM
5.1. Accuracy analysis of SSA optimized VMD parameters

EEMD and fixed parameter VMD are used to extract features for comparison. Table 1 shows the classification accuracy of different methods. It can be seen from table 1 that the classification accuracy of EEMD using joint features is 81.5%, the accuracy of fixed parameter VMD joint features is 88%, and the accuracy of the proposed method is 97%. After PSO optimization, the accuracy of EEMD joint features is increased by 2.5% The accuracy of the fixed parameter VMD joint feature is increased by 2%, and the accuracy of the proposed method is increased by 2.5%. Among the three methods, the classification accuracy of joint feature in LSSVM or PSO-LSSVM is higher than that of single feature, and the accuracy of the proposed method is also higher than that of EEMD and fixed parameter VMD. This experiment verifies the effectiveness of this method.

| Extracted features          | LSSVM (%) | PSO-LSSVM (%) |
|-----------------------------|-----------|---------------|
| Time domain                 | 74.5      | 79.5          |
| Frequency domain            | 84.5      | 88.5          |
| Entropy                     | 74.5      | 87.5          |
| Joint features              | 97        | 99.5          |
| EEMD-joint features         | 81.5      | 82            |
| VMD-Joint features          | 88        | 90            |
| SSA-VMD-Joint features      | 97        | 99.5          |

6. Conclusion

In this paper, a combined harvester assembly quality detection method to optimize VMD is proposed. SSA is used to quickly and accurately find the best decomposition parameter combination of VMD, and then the combined features are extracted for pattern recognition. Through experimental analysis, the combined features proposed in this paper have obvious advantages in classification. Therefore, this study has a certain potential value for the assembly quality inspection of combine harvester, and it can be applied to the assembly quality inspection of other machinery.

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