Fault Diagnosis of Planetary Roller Screw Mechanism Based on Bird Swarm Algorithm and Support Vector Machine

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Abstract. Intelligent fault diagnosis of rotating machinery has been widely developed in recent years due to the improvement of computing power, but how to identify the fault states of planetary roller screw mechanism is a difficult problem in practical industrial applications. A fault diagnosis method for planetary roller screw mechanism is proposed by combining with bird swarm algorithm (BSA) and support vector machine (SVM), which shows strong advantages in solving small sample, nonlinear and high-dimensional identification problems, and the bird swarm algorithm with high optimization accuracy and good robustness. In this paper, the vibration data of the planetary roller screw mechanism in two states with and without grease are collected, and features are extracted from the time domain, frequency domain and time-frequency domain, respectively. The predicted accuracy of SVM and BSA-SVM is compared, and the feasibility of the proposed method is verified.

1. Introduction
Planetary roller screw mechanism (PRSM) is a very important transmission element in precision drive system, which can realize the mutual transformation between rotary motion and linear motion based on the characteristics of large thrust [1], high-precision [2] and higher speeds [3], and is widely used in precision machine tool [4], robots [5], medical equipment [6] and other fields. Figure 1 shows the structure of PRSM.

Figure 1. The structure of PRSM.
on PRSM have mainly focused on load distribution [11], meshing principle [12], thermal characteristic analysis [6], kinematic analysis [13] and so on. There are few literature studies on the fault diagnosis of PRSM. Therefore, using machine learning technology to recognize fault state of PRSM is particularly urgent.

The work proposes a feasible manner to identify the different states of PRSM. A fault diagnosis method based on BSA-SVM for PRSM is developed, the framework of this paper is arranged as follows. After introducing the characteristics of PRSM and the importance of fault diagnosis in Section 1, Section 2 briefly describes the process of optimizing parameters of SVM by BSA. Section 3 analyses the predicted results of BSA-SVM and SVM. In Section 4, the conclusions are presented.

2. BSA-SVM
Bird swarm algorithm (BSA) is a new biological heuristic algorithm proposed by Meng et al. [14] in recent years, according to the biological behaviors of birds in nature. Support vector machine (SVM) is a Machine learning algorithm widely used in classification and regression. But the penalty parameter $c$ and kernel parameter $g$ of SVM have a great effect on the predicted results. Therefore, the BSA-SVM is a fault diagnosis method optimizing parameters of SVM by BSA. The BSA-SVM model can be described in detail as follows.

1) Initialize the BSA parameters. When iteration number $t$ equal to 0, the initial position of individual in the population need satisfy

$$c_{\text{min}} \leq x(i,1) \leq c_{\text{max}}$$

(1)

$$g_{\text{min}} \leq x(i,2) \leq g_{\text{max}}$$

(2)

where, $c_{\text{min}}$ and $c_{\text{max}}$ are the minimum and maximum in the range of parameter $c$ respectively. $g_{\text{min}}$ and $g_{\text{max}}$ represent the minimum and maximum in the range of parameter $g$.

At the same time, the size of bird population $N$, iteration times $M$, flight frequency $FQ$, and foraging probability $P$ are set (Step 1).

2) Calculate fitness values. The fitness value of each bird is calculated according to the fitness function, and the optimal position of individual and colony is determined by the fitness value (Step 2).

3) Update position. At the beginning of each iteration, it is determined whether $t/FQ$ has a remainder. If there is a remainder, the individual bird group only carries out foraging behavior or vigilance behavior. Otherwise, birds are divided into producers and beggars. Their positions are updated (Step 3).

4) Update best positions of individual and group. If the current position of the individual is better than its previous best position, the current position becomes its own best position, and the current best position of the flock is also updated.

5) Whether the maximum number of iterations has been reached will be judged. If the iteration ends, go to step 6. Otherwise, go back to step 3 (step 5).

6) Output the best parameters. The optimal parameters are used to train the SVM, and the test set is used for prediction.

The specific flow of the BSA-SVM model can be summarized as Figure 2.

![Figure 2](image.png)

**Figure 2.** The optimization process of BSA-SVM model.
3. Experiment and analysis

In the running process of PRSM, grease failure is one of the most common fault. And grease have a significant impact on the performance of PRSM. Grease failure will aggravate the wear, increase the heat at work, cause a decline in PRSM precision, produce deformation, and eventually lead to the entire PRSM break. In a word, grease failure usually appears before the PRSM whole fracture. Therefore, reasonable judgment on whether grease in the working process is present in PRSM effectively guarantees the PRSM running safety. And it can timely remind the operator whether to add grease to PRSM and provide certain judgment basis. Figure 3 indicates the working state of PRSM with or without grease.

![Figure 3. The working state of PRSM: (a) without grease (b) with grease.](image)

Figure 4 shows the PRSM failure test bench, and it consists of four parts, motor, reducer, PRSM and hydraulic load system. The motor drives the reducer, which drives the PRSM to run. And the PRSM pushes the hydraulic load to reciprocate. The vibration acceleration sensor is located at the upside of the nut and the sampling frequency is 20480Hz.

![Figure 4. The PRSM failure test bench.](image)

| Table 1. The working condition of PRSM. |
|----------------------------------------|
| Working state | speed (r/min) | load (KN) |
|---------------|---------------|-----------|
| With grease   | 6             | 9         |
|               | 40            | 3.5       |
| Without grease| 6             | 9         |

Three working conditions are shown in Table 1. There are 48 samples of train data and 12 samples of test data in each working condition, so there are totally 288 samples of train set and 72 samples of test set. Kernel function of SVM is selected as RBF function, the range of kernel parameter $g$ and penalty parameter $c$ are set as $[0,100]$, the population number is 30, the number of iterations is 50, and the flight frequency $FQ$ is 10. When parameters of SVM are not optimized, penalty parameter $c$ and kernel parameter $g$ are respectively set as 1 and 0.5.
Fault characteristics are extracted from the time domain, frequency domain and time-frequency domain respectively, and transmitted to the BSA-SVM network. The iterative process diagram of three domains are shown in Figure 5, 6.

![Figure 5](image1)

(a) Curve of fitness in the iterative process diagram of train: (a) time domain; (b) frequency domain; (c) time-frequency domain.

![Figure 6](image2)

(a) The scatter plot of parameter selection in the iterative process diagram of train: (a) time domain; (b) frequency domain; (c) time-frequency domain.

![Figure 7](image3)

Figure 7. The predicted accuracy of test data before and after optimization.

By comparing $c$ and $g$ after optimization with before optimization, the difference is relatively large, so they have a great impact on the accuracy of prediction. As shown in Figure 7, the predicted accuracy of test data before and after optimization is compared.

It can be seen from the Figure 7 that after optimization, the prediction accuracy in the time domain, frequency domain and time-frequency domain all has been greatly improved. In three domains, the predicted accuracy is respectively 83.33%, 83.33% and 72.22%. It indicates that BSA-SVM can improve classification accuracy and is a feasible fault diagnosis method of PRSM.

4. Conclusion

In this paper, a fault diagnosis method for the PRSM is proposed. The vibration acceleration data with grease and without grease is collected. Then, the fault features, which are extracted from the time domain, frequency domain and time-frequency domain respectively, are input to BSA-SVM and SVM. The
results shown that the accuracy of test data using the BSA-SVM model is better than that of the SVM. Also, the results illustrate that different kernel parameter and penalty parameter of SVM have a greater effect on the results of prediction. Moreover, the effectiveness of the proposed PRSM fault diagnosis method is verified.

5. References

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