Fault Diagnosis Based on Tree Heuristic Feature Selection and FS-DFV for Rolling Element Bearings

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Abstract. In order to make up for the deficiency of traditional single diagnosis in rolling element bearing fault diagnosis application, eliminate a large amount of redundant information and improve the classification effect of the aliasing mode, based on comprehensive analysis of the respective advantages of fuzzy set and tree search, this paper presents a joint rolling bearing fault diagnosis method based on tree-inspired feature selection and FS-DFV (Fuzzy Set and Dependent Feature Vector). The dependent feature vectors (DFV) can dig deeper the essential differences of the faults and improve the fault accuracy. By establishing the heuristic tree model, the tree type heuristic feature search strategy is designed, and the excellent feature selection criteria based on the density clustering with noise are proposed, and the conventional feature selection model is improved. In addition, fuzzy set are used to process the problem of extracting aliasing patterns in the DFV, and fuzzy membership is used to guide subsequent feature extraction of the alias modes. The proposed method is compared with the other four fault diagnosis methods. The experimental results show that the proposed method can effectively improve the diagnostic efficiency of the rolling bearing.

1. Introduction
In modern industry, rolling element bearing (REB) is one of the most basic components of rotating machinery [1]. It is widely used in aerospace [2], engineering manufacturing [3] and other industries. If the machine is operated for a long time, the rolling bearing part will be worn, peeled off, etc., and as a result, the service life of the machine will be reduced, and even the life of the personnel will be threatened, resulting in irreversible consequences. Therefore, the accurate condition monitoring and fault diagnosis of REB play an important role in ensuring the reliable operation of the machine. Effective diagnosis of the REB has become a hot spot in current research.

For REB, it is currently the most popular strategy to collect bearing vibration signals and perform fault diagnosis. In this way, predecessors have developed many analytical methods, such as envelope spectra and wavelet transforms [4-6]. Since the Empirical Mode Decomposition (EDM) method was proposed by Huang [7], the complex signal can be decomposed into simple signals in dealing with non-stationary and nonlinear data. Because of this feature, it is widely used in signal processing, and its advantages are more obvious than traditional signal processing [8-10]. The use of EDM to extract feature signals of rolling bearings does not effectively remove a large number of redundant features, so feature parsing has become the mainstream of optimization algorithms. Combining multi-scale entropy and least squares support vector machine, the rolling
bearing signal can be optimized to form a eigenvector containing only the main information and achieve significant improvement [11]. By combining the fast bearing empirical mode decomposition and the stochastic decrement technology bearing fault detection method, fault features can be quickly extracted and fault types analyzed [12]. The real-valued gravitational search algorithm (RGSA) is used to optimize the input weights and biases of ELM, and GSA is used to select important features from the composite feature set to achieve good results [13]. Among them, the dependent feature vector (DFV) proposed by Chen Xiaoyue was applied to the fault diagnosis of REB [14], and its unique characteristic organizational form opened up new diagnostic methods. At the same time, with the continuous optimization of intelligent algorithms, support vector machines, artificial neural networks and other classifiers are widely used in the fault diagnosis of rolling bearings [15-17], and have achieved good results. However, there are still the following problems: 1) Boundary effects and aliasing modes still exist. 2) The classification choice is too complicated.

Aiming at the above situation, this paper designs a tree heuristic feature search strategy, introduces fuzzy set to process aliased regions, and constructs fuzzy set and dependent vector (FS-DFV). DFV, in their unique organizational form, can fully exploit the characterization capabilities of each feature, and at the same time shield the interference of redundant information on classification. The addition of fuzzy set improves the efficiency and self-healing of fault diagnosis. Therefore, FS-DFV constructed by combining the advantages of the two can overcome the problem of poor discrimination in the aliasing area in fault diagnosis. Based on the improved intelligent optimization algorithm proposed in this paper, the fault diagnosis efficiency is improved, and the timeliness and practicality of the algorithm are increased.

2. Feature evaluation

Whether or not the heuristic tree can select the most effective features, feature evaluation plays a decisive role. Therefore, this paper adopts two aspects of single feature evaluation and feature set evaluation to comprehensively evaluate, so as to ensure the high efficiency of selected features in fault diagnosis.

2.1. The evaluation of one feature

In pattern characterization and pattern recognition, the selected features must be able to distinguish different faults. At the same time, the compactness of the fault data is very good under this feature. In order to achieve these indicators, this paper proposes a density-based clustering evaluation method. Density-based spatial clustering of applications with noise (DBSCAN) can be divided into any cluster, and noise can be filtered out. The figure 1 is based on density clustering and fault clustering comparison.

![Figure 1. Density clustering scatter diagram](image)

2.2. The evaluation of a feature set

The smaller the Euler distance in the same sample class, the better the sample size is better, the greater the Euler distance between the different sample classes, which indicates that the two samples based on this feature have a large distance interval, which can be very good for fault diagnosis. Euler distance is often used to measure the advantages and disadvantages of feature subset in pattern recognition.
\[
    d_{ij} = \frac{1}{h \times k} \sum_{m=1}^{h} \sum_{n=1}^{k} MSE(i(m), j(n))
\]

Formula: MSE is Euler distance, \(i(m)\) and \(j(n)\) are two data sets respectively, \(h\) and \(k\) correspond to the number of data contained in these two datasets respectively. \(D_{ij}\) is an average Eulerian distance.

3. search strategy

3.1. feature selection

Based on the above feature evaluation, the most effective feature is selected and the complex sample space is divided into only one type of sample, and the features used are recorded. The optimized feature subset is formed, and the flow chart of fuzzy dependent feature selection is showed in figure 2.

![Figure 2. Flowchart of hierarchical fuzzy feature selection method based on classification tree](image)

3.2. Feature extraction based on fuzzy set

In order to deal with the aliasing mode, this paper introduces fuzzy sets. The most important part of fuzzy set is the construction of fuzzy membership degree. There is no specific form of fuzzy membership function. Variance is often used to describe whether discrete variable distribution is compact. As shown in equation (2), \(D_i\) represents the \(i\)th subspace. The compactness of the fault on feature \(x\), the smaller its value indicates better compactness.

\[
    D_i = \frac{1}{n} \left( (x_1 - \bar{x}_i)^2 + (x_2 - \bar{x}_i)^2 + \ldots + (x_n - \bar{x}_i)^2 \right)
\]

Where \(n\) represents the number of feature \(x\) in one of the fault samples in the subspace; \(x_n\) represents the \(n\)th eigenvalue of a fault sample; \(x_i\) represents the mean of the eigenvalues of the \(i\)th fault sample in the subspace.

According to the structure of the tree search, the sample mean and variance of each fault in the parent sample space of the aliased region are selected as a mean sample set and a variance sample set, and the equation (3),(4) is as follows. When judging for each aliased region, the corresponding variance and mean of each fault sample are different.

\[
    \bar{X}_i = \{ \bar{x}_1, \bar{x}_2, \ldots, \bar{x}_n \}
\]

\[
    D_i = \{ d_1, d_2, \ldots, d_n \}
\]

The difference between the eigenvalues scattered in the fuzzy region and each fault in the fault space under this feature is used to make the difference. The absolute value of the result is worse than the above, and the membership function the equation 5 is as follows:

\[
    \mu_{x_i}(x_j) = e^{-\frac{|x_j - \bar{X}_i|}{D_i}}
\]

Where \(x_i\) is the \(j\)th fault point that falls in the fuzzy region, and \(\bar{X}_i\) is the average value of the \(i\)th fault sample characteristic; \(D_i\) is the variance of the fault type to which the \(i\)th fault point belongs;
When establishing a FS-DFV each virtual node is set as a fuzzy set correction part (FSCS) to determine which kind of fault each aliased area characteristic value belongs to because the sample mean and variance in the membership function are a data set. Therefore, in each judgment, the obtained fuzzy membership degree value is also a set of numerical values, and the largest value is selected to determine the basis for assigning the value of the aliased region. The equation 6 is as follows, FS-DFV Extraction tree combining fuzzy set with DFV is showed in figure 3.

$$\mu_A(x) = \max(\mu_A(x_1), \mu_A(x_2), ... \mu_A(x_n))$$

![Figure 3. FS-DFV extraction tree combining fuzzy set with DFV](image)

4. Fault diagnosis

This section describes experimental and engineering applications based on the above theory. Figure 4 shows the fault diagnosis flow. Figure 5 shows the comparison of the DFV and FS-DFV extraction rates. Figure 6 shows the three-dimensional view of the failure types before and after the FS-DFV treatment. Table 1 shows the diagnostic rates of DFV and FS-DFV on a probabilistic neural network, and table 2 shows the comparison of five vectors for fault diagnosis.

![Figure 4. Flow chart of fault diagnosis](image)  
![Figure 5. The comparison of the DFV and FS-DFV](image)
Table 1. FS-DFV fault diagnosis results

| Fault classes | FS-DFV the diagnostic rate | DFV the diagnostic rate |
|---------------|-----------------------------|-------------------------|
| FF_1          | 100%                        | 91.32%                  |
| FF_2          | 100%                        | 99.04%                  |
| FF_3          | 97.57%                      | 95.44%                  |
| FF_4          | 100%                        | 100%                    |
| FF_5          | 100%                        | 100%                    |
| FF_6          | 100%                        | 100%                    |
| FF_7          | 96.18%                      | 90.49%                  |
| FF_8          | 97.21%                      | 93.38%                  |

Table 2. Comparison of fault diagnosis of rolling bearing

| Feature vector | The average diagnostic rate | The feature extraction time (ms) | The training time (ms) | The testing time (ms) |
|---------------|-----------------------------|---------------------------------|------------------------|-----------------------|
| FS-DFV        | 98.87%                      | 114                             | 377                    | 254                   |
| DFV           | 96.62%                      | 109                             | 369                    | 258                   |
| SSF           | 95.26%                      | 219                             | 380                    | 249                   |
| FSR           | 71.24%                      | 221                             | 393                    | 246                   |
| AF            | 96.71%                      | 2793                            | 1435                   | 1243                  |

In table 2, by comparing the other four methods, the average diagnostic efficiency of the FS-DFV fault diagnosis method is better than the other four methods, thus verifying the efficiency of this method. The corresponding time is also within a reasonable range. The time used for the diagnosis method based on FS-DFV is far less than that of the original feature. This shows that the FS-DFV can be used to represent the fault samples to obtain a satisfactory diagnosis efficiency. By comparing with
the DFV, the edge blurring process can improve the insufficiency of the DFV and improve the accuracy.

5. Conclusions
In this paper, a fault diagnosis algorithm for REB is proposed, which combines the FS-DFV and tree search. In the fault diagnosis, a fuzzy set is introduced. The fuzzy membership function can be used to deal with the edge problem effectively. Combining tree search and density clustering, the key features of the fault are screened to determine the structure of the FS-DFV, and the validity of the fuzzy membership is verified by the extraction of the FS-DFV of the original data. The experiment shows that the method is high in the extraction of FS-DFV. Efficiency. By the probability neural network, the five of feature vector fault diagnosis is compared. The FS-DFV should be compared with the other four of feature vector in the fault diagnosis efficiency because of the effect of the other four of feature vector, and the time it takes in the ideal range. The comprehensive fault diagnosis method based on FS-DFV and tree type heuristic feature selection has both breakthrough accuracy and excellent computational efficiency. It is an excellent fault diagnosis method.

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