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Generator Bearing Fault Diagnosis Based on Analytic Hierarchy Process and Binary-tree Support Vector Machine

ZHANG Xing-yuan[1], CHEN Minye[1], XU Hai-rong[1] and LI Pei-qi[1]

[1]*College of air-transport,ShangHai University Of Engineering Science, ShangHai 201620, China*
zhrhui@sina.com

Abstract

Binary-tree support vector machine (SVM) has such advantages as small repeated operation workload, fast classification speed and dead zone inexistence, but the structural design can influence the classification accuracy thereof. In order to rationally design the structure of the binary-tress SVM, a multi-classification algorithm (AHP-BSVM) combining analytic hierarchy process (AHP) and binary-tree SVM is proposed in this paper. Firstly, the analytic hierarchy process is adopted to establish the evaluation system model so as to comprehensively evaluate multiple influencing factors for determining the weight values of various faults; then, the faults are ordered by the weight values and the structure of the binary-tree SVM is determined according to the fault sequence; finally, the proposed algorithm is adopted for fault diagnosis and analysis. The simulation experiment shows: compared with other algorithms, the proposed algorithm has higher recognition accuracy and higher classification accuracy, and is applicable to multi-classification, thus having good promotion prospect.

***Keywords**: Binary-tree; Support vector machine; Analytic hierarchy process; Bearing fault diagnosis*

1. Introduction

As a new learning method [1] based on statistical learning theory, support vector machine (SVM) is originally used for solving the binary classification problem, but the multi-classification problems usually exist in practice. Therefore, one of the important contents in current SVM research is to promote the binary classification algorithm to the multi-classification field. SVM multi-classification extension strategy is mainly divided into two types: first, the global optimization method: all sub-classifier parameters are optimized in one formula, and this method seems to be simple, but the solving process is complex, thus rarely applicable to classification problems; second, the combined learning method: SVMs are combined to form multi-classifiers according to different strategy combinations, and such method includes one-to-many method, one-to-one method, decision-oriented acyclic graph method, binary-tree method, *etc*. [2] In allusion to k-mode classification problem, the one-to-many method needs to construct k binary classifiers, thus causing excessive repeated operation workload and slow calculation speed; the one-to-one method has fast calculation speed but needs to construct $k(k-1)$ binary classifiers, and the quantity of the classifiers is excessively increased along with the class increase; compared with the above two methods, the decision-oriented acyclic graph method has small operation workload and short calculation time, but has decision preference problem and random calculation accuracy; the binary-tree method needs k-1 binary classifiers, and has the features of small repeated operation workload, fast classification speed and dead zone inexistence, thus becoming a multi-classification method applicable to fault diagnosis, but the structural design can significantly influence the classification accuracy of the binary-tree support vector machine. Therefore, on the basis of the improvement of

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the existing binary-tree support vector machine, a multi-classification algorithm (AHP-BSVM) combining the analytic hierarchy process and the binary-tree SVM is proposed in this paper, and this method is applied to the generator bearing fault diagnosis.

2. Binary-tree Support Vector Machine

Binary-tree SVM classification principle is as follows: the multi-classification problem is firstly decomposed into a series of binary classification problems through binary-tree construction, and then SVM is adopted to realize binary classification. For training and testing binary-tree SVM, the classification is started at root node SVM, and the flow direction is determined according to the decision class till the class of the test sample is recognized. 1, 2,…,k modes are assumed for k-mode classification, and k-1 SVMs are needed, with the structure as shown in Figure 1.

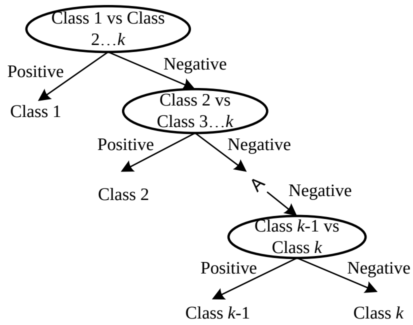

Figure 1. Binary-Tree Support Vector Machine Structure

There is no need for the binary-tree method to employ all binary classifiers for the test sample, and the operation can be terminated once the class is recognized, thus saving the test time. In the classifiers as shown in Figure 1, the first SVM is used to distinguish the first class among 1, 2,…k classes, the second SVM is used to distinguish the second class among 2, 3,…k classes, and so on, till the last two classes are distinguished by the k-1th SVM. The classification strategy as shown in Figure 1 is one of the classification strategies, and the classification sequence is 1, 2…k, totally k! classification sequences corresponding to k! structures. In the pattern recognition, the classification accuracy of the classifiers can be changed through the binary-tree structure design.

At present, SVM multi-classification method based on binary-tree has been researched more or less. A fault priority dependent binary-tree multi-stage classifier realization method based on SVM can be used to determine the binary-tree classifier structure according to the fault occurrence frequency sequence, namely: the fault state with high occurrence frequency is firstly recognized. In literatures [3~4], the classification sequence is designed according to the distribution condition of different classes of samples in the high-dimensional characteristic space so as to firstly distinguish the class with wide distribution scope or large between-class distribution distance, namely: the class which can be most easily distinguished in the sample space is firstly recognized.

3. Binary-tree Fused SVM

3.1. Decision Preference

The structure of the binary support vector machine is not unique. As explained above, for k-classification problem, the binary tree totally has k! structures, and different structures can result in different classification accuracies and results.

In the example as shown in Figure 1, if the division accuracy of different hierarchies are respectively *p1, p2,…pk*, and the class division accuracy is *l*, then division accuracies of all fault classes are respectively as follows:

$$\begin{cases} l_1 = p_1 \\ l_2 = p_1 \cdot p_2 \\ \vdots \\ l_{k-1} = l_k = p_1 \cdot p_2 \cdots p_k \end{cases} \tag{1}$$

The following formula can be obtained according to the above equations.

$$l_1 > l_2 > \cdots l_{k-1} = l_k \tag{2}$$

Namely, for the binary-tree classifier at lower hierarchy, the corresponding class recognition accuracy of SVM is lower, and the recognition rate of SVM at lower hierarchy depends on that at the upper hierarchy, and the recognition rate of SVM at lower hierarchy can be ensured only when SVM at upper hierarchy can accurately recognize the class. Based on such characteristics of the binary-tree structure, if one standard is adopted to measure each class, then the class firstly recognized should be the class with strict standard, and the whole binary-tree classifier can be ensured to have high classification accuracy only when the class with strict standard is relatively accurately recognized. In literatures [3~4], the class most easily distinguished in the sample space is recognized; on this basis, the maximum voting mechanism algorithm is adopted in literature [5] to construct the binary tree.

The value degree is adopted in this paper to comprehensively measure all classes. In the pattern recognition, a set of evaluation system is established to integrate various indexes to compare the weight values of various classes. All classes are ordered according to the weight values so as to design the binary-tree structure according to this sequence and accordingly recognize the class with large weight value. The larger weight value indicates higher recognition accuracy and shorter recognition time, thus overall ensuring relatively high classification accuracy. The binary-tree structure determined as above depends on the weight values of various classes in all classes, and compared with the binary-tree structure randomly determined, such binary-tree structure can save time and has higher diagnosis and better diagnosis effect.

3.2. AHP Fused Binary-Tree SVM

The binary-tree structure mentioned above can significantly influence the classification accuracy of the whole binary-tree support vector machine, and the improvement in this paper lies in the binary-tree structure designed on the basis of analytic hierarchy process. Specifically, the evaluation system based on the analytic hierarchy process can combine the fault practice and the expertise to design the important indexes able to influence the value degree, and then multiple indexes are combined to measure the value degrees of all faults in order to obtain the weight value of each fault, which can determine fault recognition sequence, and finally the binary-tree structure is constructed on the basis of this sequence.

As a multi-target and multi-criteria decision analysis method, the analytic hierarchy process (AHP) aims at decomposing the evaluation target into a multi-stage indexes and introducing 1~9 proportion scales to judge the relative importance of each factor [6]. Meanwhile, the complex problem is decomposed into multiple hierarchies and multiple factors so as to implement simple comparison and calculation among various factors, thus to obtain the weight values of different solutions and provide the basis for selecting the optimal solution[7].

In the analytic hierarchy process, the importance of each factor in the evaluation system is comprehensively considered in order to maximally rationalize the weight value of each index. Specifically, the model for the binary-tree support vector machine based on analytic hierarchy process is mainly established through the following steps.

(1) Establish the hierarchical structure

The model is usually divided into three hierarchies, namely: target hierarchy, criterion hierarchy and solution hierarchy, wherein the hierarchical relationship is connected by lines. For the evaluation system based on fault diagnosis, the target hierarchy is the fault value degree, the criterion hierarchy is used to measure the influencing factor of the fault, and the solution hierarchy is the fault state. Bearing fault is a common generator fault caused by poor lubrication, improper assembly, *etc*., and can result in the abnormal bearing operation due to fatigue wear [8]. Therefore, it is significant to research the bearing fault diagnosis.

Based on the practical conditions of the generator bearing in this paper, the measurement indexes of the criterion hierarchy are determined as follows: sample distribution scope of each fault in high-dimensional characteristic space *B1*, fault occurrence frequency *B2*, diagnosis based loss recovery *B3* and between-class distance of each fault in high-dimensional characteristic space *B4*. Accordingly, the weight value in the evaluation system is the centralized reflection of fault recognition rate, actual occurrence probability and theoretical division difficulty. Specifically, four states ---- normal state, inner ring fault, outer ring fault and ball bearing fault are selected as the classification objects, and the hierarchical structure established thereby is as shown in Figure 2.

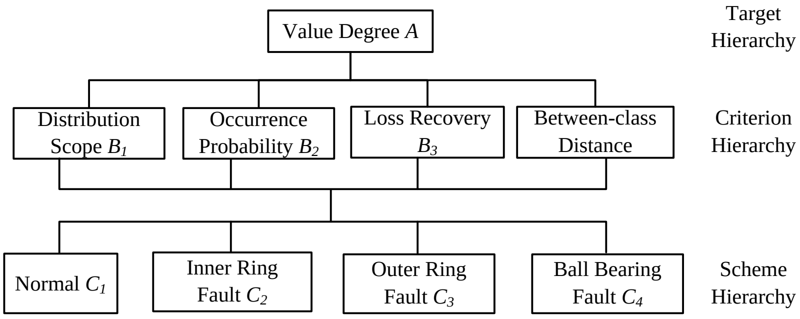

Figure 2. Hierarchical Structure Based on Bearing Fault Diagnosis

(2) Construct comparison matrix

In order to qualify the quantitative analysis results, the pair-wise comparison is implemented for the importance of the elements at the same hierarchy to a certain criterion of the upper hierarchy. Specifically, the judgment matrix is constructed as follows:

$$\mathrm{A} = (a_{ij})_{n\times n} \tag{3}$$

Where *aij* is the specific value of the importance of elements *ai* and *aj* to the criterion hierarchy, and judgment matrix **A** has the following characteristics:

$$\begin{cases} a_{ij} > 0 \\ a_{ij} = 1/a_{ji} \\ a_{ii} = 1 \end{cases} \tag{4}$$

The importance of the elements at the same hierarchy is usually valuated according to 1~9 proportion scales, and the specific meaning thereof is listed in Table 1.

Table 1. Proportion Scales of Judgment Matrix and Meaning

Scale	Meaning
1	In two-factor comparison, the two factors have the same importance.
3	In two-factor comparison, the former factor is slightly more important than the later factor.
5	In two-factor comparison, the former factor is obviously more important than the later factor.
7	In two-factor comparison, the former factor is greatly more important than the later factor.
9	In two-factor comparison, the former factor is extremely more important than the later factor.
2，4，6，8	The median value of the above adjacent judgments.

In the bearing faults mentioned in this paper, the judgment matrix of criterion hierarchy *B* constructed on the basis of diagnosis experience relatively to target *A* is as follows:

$$\mathrm{A}=\begin{bmatrix} 1 & 3 & 3 & 5 \\ 1/3 & 1 & 1 & 3 \\ 1/3 & 1 & 1 & 3 \\ 1/5 & 1/3 & 1/3 & 1 \end{bmatrix} \tag{5}$$

(3) Calculate the weight value according to the judgment matrix

There are many methods for finding the weight value through judgment matrix, including summation method, minimum angle method, eigenvector method, *etc*. Specifically, the eigenvector method is adopted in this paper. Firstly, the maximum eigenvalue λ max of judgment matrix A is calculated; then, the corresponding eigenvector (with all components more than 0) is found according to Formula (6).

$$AW=\lambda_{\max}W \tag{6}$$

Where λ max is the maximum eigenvalue of matrix A, *W* is the eigenvector thereof and is normalized to obtain the weighted vector.

Through calculation, the maximum eigenvalue λ max of judgment matrix A is λ max=4.043 and the weighted vector *W* is *W*=(0.520, 0.201, 0.078).

(4) Matrix consistency check

The consistence check includes the following steps:

① Calculate the consistency index of the judgment matrix;

$$CI=\frac{\lambda_{\max}-n}{n-1} \tag{7}$$

② According to the order of the matrix, check the average random consistency index RI in Table 2;

Table 2. Average Random Consistency Index

Order	1	2	3	4	5	6	7	8	9
RI	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45

③ Calculate consistency ratio *CR*;

$$CR=\frac{CI}{RI} \tag{8}$$

If *CR*<0.1 is true, matrix A is regarded to have satisfactory consistency and should be accepted; or else, matrix A should be abandoned or the data of matrix A should be properly adjusted. Actually, CR=0.016<0.1 is obtained through verification, thus indicating that matrix A has acceptable consistency.

(5) Calculate the relative weight value of the solution hierarchy to the total target

Only the weight vector of each element in criterion hierarchy *B* to target *A* is obtained through the above calculation, but the ultimate purpose is to obtain the weight vector of each element in solution hierarchy *C* to target *A*. Therefore, it is necessary to respectively calculate the weight vector of each element in solution hierarchy *C* to criterion hierarchy *B* according to the above method, and then integrate the weight vectors obtained thereby to finally obtain the total weight vector.

As a result, the integral model based on analytic hierarchy process and binary-tree support vector machine is established, and this model is used for the motor bearing fault diagnosis. Specifically, the corresponding structure diagram is as follows:

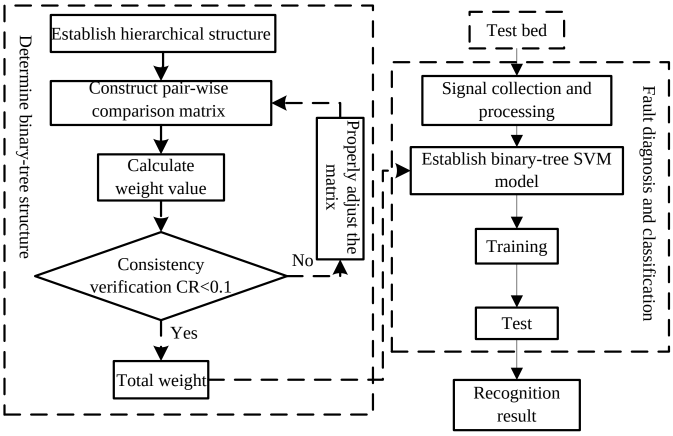

Figure 3. Bearing Fault Diagnosis Structure Diagram

4. Simulation Experiment

4.1. Data Source

In order to verify the effectiveness of the improved generator bearing fault diagnosis algorithm, the bearing fault data provided by Case Western Reserve University, U.S. are adopted for the simulation experiment, and meanwhile the comparison algorithms are also provided for relevant data analysis. Specifically, 50 groups of sample data are respectively collected under four states ---- normal state, outer ring fault, inner ring fault and ball bearing fault, totally 200 groups of data, wherein 120 groups of data are used for training and 80 groups of data are used for test.

Figure 4 shows one group of time-domain waveforms of the vibration signals respectively under different fault states ---- normal state, outer ring fault, inner ring fault and ball bearing fault (from the top down).

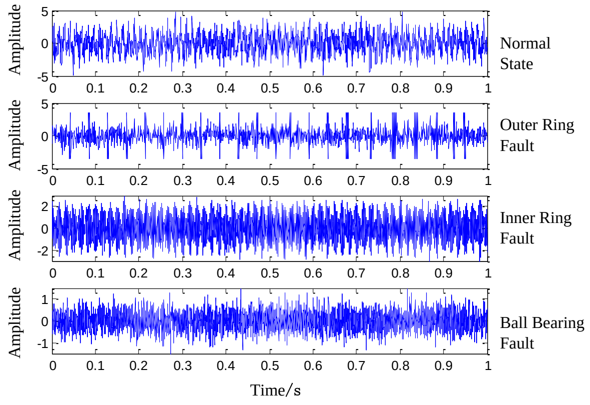

Figure 4. Vibration Time-Domain Waveform

4.2. Fault Feature Extraction

In Figure 4, the vibration signal has noise interference and corresponding harmonic wave in the low-frequency stage, thus unsuitable for direct fault feature diagnosis, but should be correspondingly processed. Wavelet packet entropy theory can be used to process the vibration signal of the faulty generator and effectively extract the fault features in the signal [9]. Therefore, based on the wavelet packet entropy theory, db3 wavelet is adopted for the three-layer wavelet packet decomposition of the vibration signal [10], and the signal is decomposed to have eight sub-frequency bands at the third layer. Specifically, the wavelet packet decomposition for the outer fault signal is as shown in Figure 5.

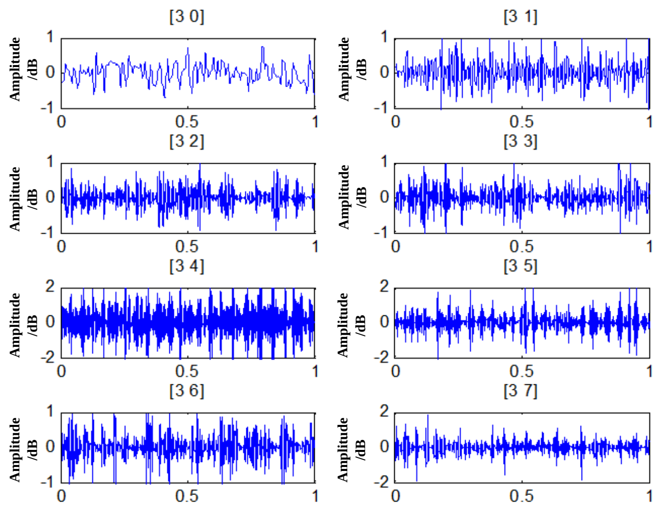

Figure 5. Wavelet Packet Decomposition Diagram

The entropy of each sub-frequency band is calculated to obtain the proportion of the entropy of each sub-frequency band in the total energy of the third layer. Subsequently, the relative energy of each frequency band is regarded as the elements to construct an eight-dimensional eigenvector as fault data sample input SVM [11].

4.3. Result and Analysis

According to relevant calculation, the combined weight values of the solutions of the bearing fault diagnosis model based on analytic hierarchy process and binary-tree SVM relatively to the target are (0.151, 0.238, 0.210, 0.401), and CR value is CR=0.024<0.1, thus indicating that the combined weight has good consistency. Therefore, the bearing fault diagnosis sequence is as follows: ball bearing fault, inner ring fault, outer ring fault, normal state.

In order to improve calculation accuracy, the genetic algorithm is adopted to optimize the two important parameters able to influence SVM performance ---- kernel parameter and penalty parameter for realizing good effect [12]. RBF (Radial Basis Function) kernel function is adopted for SVM.

$$K(x,y)=\exp(-\frac{\|x-y\|^2}{2\delta}) \tag{9}$$

After the genetic algorithm is adopted to optimize SVM parameters, parameter δ is set as 4 and penalty parameter C is set as 224.

Firstly, the eigenvector of 120 groups of training samples is sent into the binary-train support vector machine for training; then, 20 groups of training samples are randomly extracted for training so as to calculate the training accuracy. Additionally, 80 groups of test samples are selected to test and verify the generalization ability and the fault-tolerant ability thereof, thus to statistically calculate the test accuracy. Specifically, M1 represents the proposed algorithm, and in order to verify the effectiveness of the proposed algorithm, M1 is respectively compared with M2, M3, M4, M5 and M6, wherein the binary-tree structure of M2 algorithm is designed according to the fault frequency, the binary-tree structure of M3 algorithm is designed according to the sample distribution scope, M4 represents the one-to-many method, M5 represents the one-to-one method, and M6 represents the decision-oriented acyclic graph method. The comparison result is as shown in Table 3.

Table 3. Fault Diagnosis Results of these Multi-Classification Algorithms

Algorithm	SVM Quantity	Diagnosis Time/s	Training Accuracy/%	Test Accuracy/%
M1	3	3	100	95.9
M2	3	6	99.2	94.5
M3	3	8	98.5	94.8
M4	4	14	97.6	93.6
M5	6	7	100	96.8
M6	6	4	97.6	91.2

According to the above comparison table, compared with other algorithms, the binary-tree support vector machine based on analytic hierarchy process and the one-to-one method have relatively high diagnosis accuracy, and the improved algorithm needs shorter diagnosis time and less SVMs. Therefore, the improved algorithm proposed in this paper has high diagnosis efficiency, high classification accuracy and good fault recognition ability.

5. Conclusion

A generator bearing fault diagnosis method based on analytic hierarchy process (AHP) and binary-tree support vector machine (SVM) is proposed in this paper. Specifically, multiple influencing factors able to influence classification accuracy are considered in the proposed algorithm, the analytic hierarchy process is adopted to calculate the weight values of various faults so as to determine the fault classification sequence according to these weight values. Meanwhile, different methods are adopted for the simulation experiment for the bearing fault diagnosis, and the experiment result shows that the proposed algorithm has high diagnosis efficiency, good classification accuracy and feasibility & effectiveness in bearing fault diagnosis, thus providing a new thought for bearing fault diagnosis.

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Authors

Zhang Xingyuan, She received her PhD in traffic information engineering and control from Tongji university in Shanghai, China. She is currently a lecturer in ShangHai University Of Engineering Science. Her research interest is mainly in the area of fault diagnosis, reliability engineering. She has published several research papers in scholarly journals in the above research areas.