Defect Diagnostics of Rolling Element Bearing Using Fuzzy Dichotomy Technique*

Bo-Suk YANG**, Young-Chun JO**
and Dong-Soo LIM**

The monitoring and diagnostics of the bearing have been received considerable attention for many years because the majority of problems in rotating machines are caused by faulty bearings. The malfunction of rotating machinery in plants due to some defects may cause shutdown of the plants, resulting in high maintenance cost. Overly generalized predictions are problematic due to concept classification. In particular, the boundaries among classes are not always clearly defined. To avoid such problems, the idea of fuzzy classification was proposed. In this paper, in order to automatize the diagnosis of a rolling element bearing using the fuzzy classification along with their construction algorithm, the fuzzy dichotomy technique as an acquisition of structured knowledge from field case history data is used for validating the diagnosis capability.

Key Words: Classification, Fuzzy Dichotomy Technique, Rolling Element Bearing, Defect Diagnostics

1. Introduction

The rolling element bearing has been widely used in industrial rotating machinery of various kinds such as motors, gas turbines and pumps. But the rolling element bearing has a very low damping capacity in comparison with the oil film bearing. Therefore in the case where resonance occurs in a rotating shaft system or when the bearing is broken down by fatigue that is caused by periodic stress which is generated by the partial defect of a bearing, these may be a serious industrial disaster or economic losses⁽¹⁾. Thus, a lot of research has been done on defect diagnosis by using the vibration characteristics of rolling element bearings. And facility maintenance based on the construction of a diagnosis system is very important in preventing danger and saving costs⁽²⁾.

The diagnostics of the causes of vibration requires an indepth knowledge of the dynamics of

rotating machines and their operation principles, and a great deal of experience. However, the operators in plants are usually not experts on the vibration of rotating machines. Thus, expert systems have been developed to help the operators diagnose the vibration causes for predictive maintenance⁽³⁾.

An expert system comprises an inference engine and a knowledge base. The expert systems systematically configure data on vibration causes and phenomena obtained from field experiences, and infer the causes for vibration phenomena in diagnostic steps. Thus, most of the expert systems systematize the inference processes of the expert with probabilistic methods adapted from the field.

Overly generalized prediction is a serious problem in concept classification. In particular, the boundaries among classes are not always clearly defined. For example, there are usually uncertainties in diagnoses based on measured data. To avoid such problems, the idea of fuzzy classification was proposed. Instead of determining a single class for any given case, fuzzy classification predicts the degree of possibility for every class.

Knowledge acquisition from data is very important

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** School of Mechanical Engineering, Pukyong National University, San 100 Yongdang-dong, Nam-ku, Pusan 608-739, Korea. E-mail: bsyang@dolphin.pknu.ac.kr

in knowledge engineering. A popular and efficient method is the Iterative Dichotomizer 3 (ID3) algorithm proposed by Quinlan⁽⁴⁾, which makes a decision tree for classification from discrete data. In the ID3, the attribute which has a maximized information gain among all attributes is selected and it starts to make a subtree. A decision tree is generated by repeating this process. C4.5 developed from ID3, can process both discrete and continuous attribute values. C4.5 is an efficient method when the number of attribute value can be divided in two⁽⁵⁾. However, uncertainty always exists in the real world. Fuzzy dichotomy algorithm (FID3)⁽⁶⁾⁻⁽¹⁰⁾ is extended to apply to a fuzzy set of data and generates a fuzzy decision tree using a membership function defined by a user for all attributes. FID3 is robust in processing continuous values, in allowing multiple diagnostics and in generating good results for the causes with attribute values around class boundaries.

In this paper, first a training set is made by using a cause-result matrix which represents the cause and symptoms of a defect in the rolling element bearing. And then a test set is constructed using real diagnostic cases in the field. By using both sets, FID3 is applied for the defect diagnostics of the rolling element bearing and compared with C4.5 for accuracy of classification. Then the effectiveness and possibility of diagnosis is verified.

2. Fuzzy Dichotomy Algorithm (FID3)

The ID3 algorithm applies a set of data and generates a decision tree for the purpose of classifying the data. Whereas the fuzzy ID3 (FID3) algorithm is extended to apply to a fuzzy set of data (several data with membership grades) and generates a fuzzy decision tree using fuzzy sets defined by a user for all attributes⁽⁵⁾⁻⁽⁷⁾. A fuzzy decision tree consists of nodes for testing attributes, edges for branching by test values of fuzzy sets defined by a user and leaves for deciding class names with certainties. FID3 is very similar to ID3, except ID3 selects the test attribute based on an information gain which is computed using the probability of ordinary data but FID3 uses the probability of membership values for data. The information gain $G(A_i, D)$ for the attribute A_i by a fuzzy set of data D is defined by

$$G(A_i, D) = I(D) - E(A_i, D) \quad (1)$$

where

$$I(D) = - \sum_{k=1}^n (P_k \cdot \log_2 P_k) \quad (2)$$

$$E(A_i, D) = \sum_{j=1}^m (P_{ij} \cdot I(D_{F_{ij}})) \quad (3)$$

$$P_k = \frac{|D_{C_k}|}{|D|}, \quad P_{ij} = \frac{|D_{F_{ij}}|}{\sum_{j=1}^m |D_{F_{ij}}|} \quad (4)$$

Comparing the P_k value from Eq. (2) with that of C4.5, P_k is computed as the ratio of the number of data which has each value of class in the ID3 and C4.5. However, the value of P_k is applied to the ratio of the membership value of the data in FID3. By using the membership function, it can process a continuous value easily, and can represent an attribute value around the class boundaries more flexibly. Assume that there is the attribute of "height". If the attribute value of the "height" is above 170 cm, then that value can be represented as "tall" and "short" for the lower value in the C4.5. Although there is not a big difference between 169.5 cm and 171.2 cm, in real, it is classified into "tall" and "short" for the process of the classification. However, we can represent an attribute value around the boundaries suitably by using the membership function in the FID3. Thus, it can be explained as membership grades such as 0.9 for 169.5 cm and 0.85 for 171.5 cm when it uses the triangular membership function in which the membership value for 170 cm is given as 1.

In Eqs. (1)-(4), assume that we have a set of data D for attributes $A_1, A_2, \dots, A_l$ and one classified class $C = \{C_1, C_2, \dots, C_n\}$ and fuzzy sets $F_{i1}, F_{i2}, \dots, F_{im}$ for the attributes A_i (the value of m varies on every attribute). Let D_{C_k} be a fuzzy subset in D whose class is C_k and $|D|$ the sum of the membership values in a fuzzy set of data D . Then an algorithm to generate a fuzzy decision tree is as follows:

1) Generate the root node that has a set of all data, i.e., a fuzzy set of all data with a membership value of 1.

2) If a node t with a fuzzy set of data D satisfies the following conditions, then it is a leaf node and assigned by the class name (more detailed method is described below).

(1) Information content I (minbuildIN) $\leq$ selected threshold value

(2) Information gain G (minGain) $\leq$ selected threshold value

3) If it does not satisfy the above conditions, it is not a leaf and the test node is generated as follows:

(1) For $A_i (i=1, 2, \dots, l)$, calculate the information gains $G(A_i, D)$, to be described below, and select the test attribute $A_{\max}$ that maximizes them.

(2) Divide D into fuzzy subsets $D_1, D_2, \dots, D_m$ according to $A_{\max}$, where the membership value of the data in D_j is the product of the membership value in D and the value of $F_{\max, j}$ of the value of $A_{\max}$ in D .

(3) Generate new nodes $t_1, t_2, \dots, t_m$ for fuzzy subsets $D_1, D_2, \dots, D_m$ and label the fuzzy sets $F_{\max, j}$ to edges that connect the nodes

Table 1 Normalized bearing frequency

No.	FTF	BSF	BPFO	BPFI
6306	0.383	2.025	3.064	4.936
6307	0.383	2.013	3.064	4.936
6308	0.384	2.039	3.072	4.928
6309	0.380	1.955	3.040	4.960
6310	0.381	1.981	3.048	4.952
6311	0.382	2.002	3.080	4.920
6312	0.383	2.020	3.080	4.920
6313	0.384	2.036	3.072	4.928
6314	0.385	2.050	3.064	4.936
6315	0.385	2.062	3.056	4.944
Average	0.383	2.021	3.065	4.935

between t_j and t .

- (4) Replace D by $D_j(i=1, 2, \dots, m)$ and repeat from 2) recursively.

3. Defect Diagnosis of Rolling Element Bearing

3.1 Defect frequency of rolling element bearing

Rolling element bearings generate four specific defect frequencies and harmonics. The four dominant defect frequencies of the rolling element bearing are classified by their location; on the inner race, the outer race, the balls or rollers, or the cage (or train). The inner race defect frequency is referred to as the ball pass frequency of inner race (BPFI), the outer race as the ball pass frequency of outer race (BPFO); the ball defect frequency is called the ball spin frequency (BSF), and the defects on the cage, the fundamental train frequency (FTF). In the case where the inner race is rotating and the outer race is stationary, the formulas for calculating these specific frequencies are

$$FTF = \frac{f_r}{2} \left[1 - \frac{B_d}{P_d} \cos \phi \right] \quad (5)$$

$$BSF = \frac{P_d}{2B_d} (f_r) \left[1 - \left(\frac{B_d}{P_d} \right)^2 \cos^2 \phi \right] \quad (6)$$

$$BPFO = N(FTF) \quad (7)$$

$$BPFI = N(f_r - FTF) \quad (8)$$

where f_r is rotating speed (rps) of inner race, B_d is ball diameter, P_d is pitch diameter, N is number of balls and ϕ is contact angle. In Eqs. (5)–(8), as the four specific defect frequencies are a function of f_r , the equations can be normalized by f_r .

Table 1 gives examples of the normalized frequencies for some deep grooved ball bearings (No. 6306–6315). We know that bearings represent similar defect frequencies regardless of the bearing number.

3.2 Applications

The training set for diagnosis is shown in Table 2. The training set is based on a cause–result matrix of a rolling element bearing and indicates all defects which can happen. Continuous attributes are selected as the defect and sideband frequencies. Classes are

Table 2 Training set

No.	Attribute		Class
	Defect frequency	Sideband frequency	
1	0.0905	0.0337	Inner race defect
2	0.2728	0.0672	Inner race defect
3	0.1132	0.0345	Outer race defect
4	0.2268	0.1140	Outer race defect
5	0.1119	0	Ball defect
6	0.0210	0	Cage defect
⋮	⋮	⋮	⋮
80	0.2821	0.1121	Outer race defect

Table 3 Test set for defect diagnosis

No.	Attribute		Class
	Defect frequency	Sideband frequency	
1	0.0520	0.0342	Outer race defect
2	0.1125	0	Outer race defect
3	0.2820	0	Outer race defect
4	0.0903	0	Inner race defect
5	0.1815	0	Inner race defect
6	0.2723	0.0337	Inner race defect
⋮	⋮	⋮	⋮
99	0.0743	0.0128	Ball defect
100	0.0070	0	Cage defect

divided into inner race, outer race, ball and cage defects, because they often occur in rolling element bearings. The total numbers of training sets are 80.

Table 3 shows that the test set, based on diagnostic cases generated in the field, was constructed to confirm whether a trained decision tree diagnoses bearing defects well or not. The total number of cases is 100. Among these cases there are 47 outer race, 34 inner race, 11 ball and 8 cage defects respectively. When the class is an outer race defect, four unknown attribute values are included in the sideband frequency attribute.

Figures 1 and 2 show the membership function for defect and sideband frequency, respectively. After the membership function is normalized by an operating frequency (f_r), the normalized maximum membership function is used to renormalize it from 0 to 1. The membership function of a defect frequency attribute is constituted by the triangular membership function which is represented using up to 10th harmonics of defect frequencies of Eqs. (5)–(8) as an attribute value. The membership function of a sideband frequency attribute is represented using up to 5th harmonics including the sideband frequencies of four defect frequencies and an operating frequency, that is, a total of five attribute values.

The performance of FID3 was compared to that of C4.5 in Table 4. The result and accuracy was

Fig. 1 Membership function for fault frequency

Fig. 2 Membership function for sideband frequency

compared for a case which has an unknown attribute and one that does not respectively. The threshold value of minimum information content (minbuildIN) is 0.2 and minimal gain (minGain) is 0.

Table 4 shows that FID3 has a better result compared to C4.5 with respect to classification accuracy. In this case, since two attributes (defect frequency and sideband frequency) are continuous values, the results show the merit of FID3 which can efficiently process continuous values. Unknown attribute values are used when the class is a sideband frequency of an outer race defect. And in Table 4, the reason why both cases have an identical accuracy irrespective of the unknown attribute values is because the cases can be classified without the effect of a sideband frequency. Among 100 cases, FID3 misclassified (misdiagnosed) three cases. After investigating the results, we found that in one of the three cases mistaken data had been included in the test set and the two other cases were not trained in the training set. This example often occurs in the field, and the accuracy can be increased by decreasing these mistakes.

Figure 3 simply indicates a fuzzy decision tree

Table 4 Comparison of classification accuracy

	With undefined attribute	Without undefined attribute
FID3	97%	97%
C4.5	73%	73%

Fig. 3 An example of fuzzy decision tree

based on a training set. The defect frequency attribute of two attributes is selected, and then the fuzzy decision tree begins to divide. And multi-diagnosis is possible by representing the number of cases belonging to every classes for each node.

Based on the above good results, a more accurate diagnosis is applied by separating class more precisely. When the information of the frequency domain is usually used, it is known that approximately 80% of the rolling element bearing failures are processed by following four stages based on experience⁽²⁾. L_{10} is the number of hours that 90% of a group of bearings should attain or exceed prior to onset of fatigue failure.

1) Stage 1 (Approximately 10% to 20% L_{10} Life Remaining)

Only the high order frequency of defect frequency will appear slightly. So, unless specific signal processing methods (enveloping process) are used, defect signals cannot be acquired.

2) Stage 2 (Approximately 5% to 10% L_{10} Life Remaining)

The natural frequency of the bearing appears in the frequency spectrum. Defect frequency and harmonics are generated.

3) Stage 3 (Approximately 1% to 5% L_{10} Life Remaining)

Many harmonics of the defect frequency appear in the spectrum. And the sidebands of rotating speed appear around the bearing defect frequency. As the bearing defect gets worse, the harmonics of sideband

Fig. 4 Membership function for sideband of rotating frequency

increases.

4) Stage 4 (Approximately 1 hour to 1% L_{10} Life Remaining)

Many harmonics of the sideband are present around the bearing defect frequency. As the bearing continues to degrade, the discernable bearing defects and the component natural frequencies actually begin to disappear and are replaced by a random broadband high frequency "noise floor" which can extend far down into the spectrum, obliterating discrete frequency peaks. Since bearing damage typically will increase exponentially during the final 10% to 20% of its life, a bearing should not be used in stage 4.

Class is divided in detail, by using the above failure processing stages. Namely, classes of inner and outer race defects are separated up to stage 3 and also the cases belonging to the remaining 20% of a failure path is added by two inner and outer race defects respectively. So the total numbers of classes is divided into 12. Usually a bearing is replaced before stage 4, so stage 4 is not included. The cases belonging to the remaining 20% of a failure path are represented by stage 3 which indicates the condition of defect well. The attribute number is too short to be expressed by the 12 classes, so it is extended up to 5. Therefore attributes consist of defect frequency and sideband frequency (namely, FTF, f_r , BPFO, BPFI). The membership function is constituted with ascending order for each attribute. The membership function of defect frequency is the same as that of the former membership function.

The membership function for sideband of rotating frequency is represented up to 5th harmonics by dividing the previous sideband frequency in Fig. 4. The last three membership functions for sideband frequency are also constituted using the same form.

Table 5 shows the training set for diagnosing rolling element bearings. The total number of case is 246. The initials of the classes represent the abbrevia-

Table 5 Training set

No.	Attribute					Class
	Defect Frequency	Sideband frequency				
		FTF	f_r	BPFO	BPFI	
1	0.7273	0	0	0	0	I-1-1
2	0.0909	0	0.1667	0	0	I-1-2
3	0.2728	0	0	0	0.500	I-1-3
4	0.0909	0	0.8333	0	0	I-2
5	0.6364	0	0	0	0	I-3
6	0.4516	0	0	0	0	O-1-1
7	0.0570	0	0	0.1667	0	O-1-2
8	0.3952	0	0.6667	0	0	O-1-3
9	0.0570	0	0.3333	0	0	O-2
10	0.2258	0	0	0	0	O-3
11	0.2234	0.8333	0	0	0	Ball
	⋮	⋮	⋮	⋮	⋮	⋮
246	0.0212	0	0	0	0	Cage

Table 6 Test set for defect diagnosis

No.	Attribute					Class
	Defect Frequency	Sideband frequency				
		FTF	f_r	BPFO	BPFI	
1	0.2728	0	0.1667	0	0	I-1-3
2	0.2820	0	?	0	0	O-1-3
3	0.1486	0.1664	0	0	0	Ball
4	0.2830	0	0	0	0	O-1-2
5	0.1109	0	0	0	0	Ball
6	0.0210	0	0	0	0	Cage
7	0	0	0	0.1663	0	O-1-2
8	0.1690	0	0	0	0	O-3
:	:	:	:	:	:	:
100	0.3632	0	0.4990	0	0	I-1-3

Table 7 Comparison of classification accuracy

	With undefined attribute	Without undefined attribute
FID3	81%	81%
C4.5	56%	52%

tion of inner and outer race defect, and the numbers next to it indicate the failure path and failure stage respectively. When failure path is 1, the path represents that approximately 80% of the rolling element bearing is damaged, and path 2 and 3 indicate the last 20% which is damaged by other failure paths included only in stage 3. For example, O-1-3 represents O is outer race defect, 1 is path 1 and 3 is stage 3 respectively.

The test set is shown in Table 6. The total numbers of test sets are 100. The classes of test set are constituted by 42 of O-1-3, 8 of O-1-2, 29 of I-1-3, 3 of I-1-2, 10 of ball and 8 of cage defects respectively. The test set includes the 8 unknown attribute values for the rotating speed of a sideband frequency attribute. A question mark (?) represents the unknown attribute value in Table 6. First, the decision tree is constituted by a training set and then it is compared with C4.5 to discover whether it can classify real cases or not by using a test set.

Table 7 shows the performance of FID3 compared with that of C4.5. The classification accuracy was compared for a case which have an unknown attribute

and one that does not. The threshold value of minimum information content (minbuildIN) is 0.2 and minimal gain (minGain) is 0.

The result of Table 7 is not accurate compared to that of Table 4, but FID3 has good accuracy compared to C4.5 in the Table 7. The cases of misclassification are 19 out of 100. The 19 misclassification cases show some cases which are classified with the same defect are misclassified in the precision diagnosis stage. For example, O-1-2 is misdiagnosed to O-1-3. Others are the cases where an inner race defect or outer race defect is misclassified to a ball defect. Accuracy is decreasing, because practically it is very difficult to distinguish the failure stage exactly. That is, when the failure stage is precisely separated like this case, it is thought that misclassification increases due to the above difficulty. Generally, the cases that have unknown attribute values have a high error rate compared to the case without unknown attribute values. But the result of C4.5 is opposite because it is thought that C4.5 cannot carry out the classification due to the many continuous attributes.

4. Conclusions

In this paper, a fuzzy dichotomy algorithm (FID3) which can process the continuous attribute was introduced for the defect diagnosis of a rolling element bearing. By using both a training and test set, FID3 is applied for the defect diagnostics of a rolling element bearing and compared with C4.5 for accuracy of classification and capability. As a result, all attributes that were applied to this paper are continuous, and FID3 showed much higher accuracy than C4.5. That is, it can carry out defect diagnosis better than C4.5. From the viewpoint of diagnosis by classification, the execution of classification diagnosis with better accuracy can reduce the maintenance time and cost, and help with productivity enhancement by decreasing incorrect decisions in equipment maintenance, that is, the number of wrong diagnosis. FID3 can express the continuous value as well as discrete value easily compared to previous C4.5. It can be easily applied to a multi-diagnosis situation and has an excellent advantage for expressing the boundary value. Besides it has a good capability for data that includes many noises to some extent.

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