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Research on the Method of Fault Diagnosis Based on Multiple Classifiers Fusion

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Abstract

In traditional fault diagnosis method, a large number of experiments are needed to get the optimal performance classifier which diagnoses type of fault. Because of classifier algorithm limit, there is no one classifier can be applied to all kinds of fault diagnosis. In order to avoid the disadvantages caused by single classifier approach, decision level fusion method based on multiple classifiers fusion is introduced in the field of fault diagnosis. The fusion method with fuzzy comprehensive evaluation is put forward and the basic evaluation model is set up. The reasonable distribution of classifiers weight that affects diagnosis result directly is vital. Firstly, the evaluation function which measures member classifier's diagnostic accuracy and correctness is constructed based on the theory of information entropy. Then, weights are distributed to each classifier with entropy coefficient according to the value of evaluation function. Experiments are carried out to demonstrate the effectiveness of the proposed method and results show that fault recognition rate after fusion is higher compared with the single classifier method.

Keywords*: multiple classifiers fusion, information entropy, fuzzy comprehensive evaluation, entropy coefficient, fault diagnosis*

1. Introduction

Fisrtly, the identification of fault type is the most important step of fault diagnosis [1]. The method with a certain kind of single neural network classifier is commonly used. In this mode, a large number of experiments are needed to obtain the enough priori knowledge in order to gain the best performance of the classifier [4]. Secondly, each classifier has its own algorithm. The study has shown that any classifier algorithm only can be well applied to a certain scope of application [5]. In practical application it become very difficult to seek the optimal classifier because of the finite samples. And the optimal classifier seeked only can be applied in a particular range due to the diversity and dynamic property of fault [6]. In recent years, the method of multiple classifiers fusion is proposed which can take the advantages of each single classifier and avoid or reduce the one-sidedness caused by the difference of the single classifier [5]. So the recognition rate of multiple classifiers fusion is often higher than that of the single classifier, therefore can even improve the efficiency and robustness [7].

The so-called multiple classifiers fusion is the synthesis results of each classifier according to certain rules. The two main problems needed to be solved are how to measure different classifiers' diagnosis abilities objectively and to perform diagnosis with the fusion rules. The decision level fusion by fuzzy comprehensive evaluation is presented in this paper. The system block diagram is shown in Figure 1.

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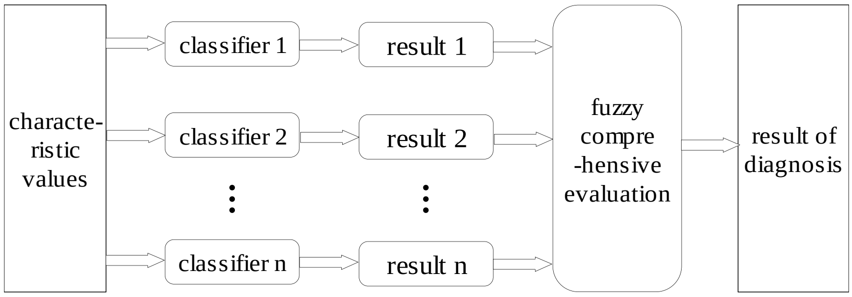

Figure 1. Block Diagram of Fault Diagnosis System Based on Multi-Classifier Fusion

2. The Fuzzy Model for Comprehensive Evaluation of Fault Diagnosis

The faults of complex system often have an unclear distinction boundary because of the coupling among subsystems. The more complex the system is, the fuzzier the boundaries between faults will be. So to a certain extent, the process of fault diagnosis can be considered as the process of fuzzy reasoning. This is the theoretical basis to solve the problem of fault diagnosis with fuzzy comprehensive evaluation method [8].

Fuzzy comprehensive evaluation is a mathematical tool used in decision-making. It's a method to analyze the 'fuzzy' things with the fuzzy mathematical method. The qualitative and quantitative evaluations are combined by the degree of membership in this method whose results are clear. It can solve the non-deterministic problem effectively.

Three factors are needed for any model of fuzzy comprehensive evaluation [9].

(1) the factor set

(2) the judgment set

(3) the single factor evaluation

According to the features of multiple classifiers fusion fault diagnosis, these three facts are determined individually in order to establish the basic model of fuzzy comprehensive evaluation.

2.1. Factor Set

The definition of the factor set is the object composed of various factors in the evaluation.

Each single member classifier's output can be seen as a decision. Each decision must be taken into account to form the final decision by fusion. Therefore, each single member classifier is a factor of the factor set. If the number of member classifiers is *n*, denoted as $U = \{u_1, u_2 \cdots, u_n\}$.

2.2. Judgment Set

The definition of the judge set is the object consists of the comments.

All types of fault diagnosis constitute the judgment set. If the number of fault type is *m*, then $V = \{v_1, v_2, \cdots, v_m\}$.

2.3. Single Factor Judgment

The definition of the single factor evaluation judgment is each factor's judgment. It is a fuzzy mapping from U to V , $u_i \mapsto (r_{i1}, r_{i2}, \cdots, r_{im})$.

In multiple classifiers fusion of fault diagnosis, the output of the single classifier can be seen as a single factor's judgment. The output of single factor judgment must be a fuzzy set. However, most of the classifier's output is not a fuzzy set due to its algorithm. Therefore the reformation of classifier output is needed. The form of classifier output can be converted in the form of membership degree of the fault type. If r_{ij} is membership degree for a certain fault type v_j which is given by a certain member of classifier U_i, then r_{ij} must to meet two conditions.

$$\begin{cases} 0 \le r_{ij} \le 1, \quad (i = 1,2,\cdots,n;\ j = 1,2,\cdots,m) \\ \sum_{j=1}^{m} r_{ij} = 1, \quad (i = 1,2,\cdots,n) \end{cases}$$

All the member classifiers' outputs are combined to form a matrix R which is called the evaluation matrix.

$$R = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1m} \\ r_{21} & r_{22} & \cdots & r_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ r_{n1} & r_{n2} & \cdots & r_{nm} \end{bmatrix}$$

Then factor set *U*, judgment set *V* and single factor judgment *R* construct the model of the fuzzy comprehensive evaluation.

3. Method of Deciding the Weight of Each Member Classifier

In view of the limits of classifier's algorithm, the contribution of each member classifier output in final diagnosis decision is not the same. So each member classifier must be weighted. The weight value is the equitable and objective reflection of the classification ability which is very important to the fusion results.

3.1. Accuracy of Fault Diagnosis

Qualitatively speaking, the bigger the degree of membership's range between the various fault types is, the clearer the fault type is and the higher the diagnostic accuracy is , then the result is becoming more important in the final decision. If the degree of membership's range between the various fault typesis smaller, then the fault type is the more blurred and the diagnostic accuracy is lower, therefore the results is less important in the final decision.

The information entropy is a measurement of the degree of information uncertainty. The bigger the information entropy is, the higher the uncertainty degree will be; the smaller the information entropy is, the lower the uncertainty degree will be.

If $X = \{x_1, x_2, \cdots, x_i\}$ is a finite discrete random variable, $P_i = P\{X = x_i\}$, then the information entropy is:

$$H(X) = \sum p_i \log \frac{1}{p_i} = -k \sum p_i \ln \frac{1}{p_i} \tag{1}$$

Where $0 < p_i < 1, \sum p_i = 1$, k is a constant.

Based on the research results of literature[10], the constraints of P_i can be promoted as $0 \le p_i \le 1, \sum p_i = 1$, k is a constant.

Therefore, the concept of information entropy can be used to measure each member classifier's accuracy quantitatively in the diagnosis. The information entropy of each member classifier output is calculated. The smaller the information entropy value is, the higher the accuracy and reliability of diagnosis will be.

The output of each member classifier $R_i = \{r_{i1}, r_{i2}, \cdots, r_{im}\}$ (i=1,2,... n) can be seen as a discrete variable. By the above analysis, r_{ij} satisfies the information entropy formula's constraint conditions.

Therefore the member classifier's output entropy formula is

$$e_j = -K\sum r_{ij} \ln r_{ij} \tag{2}$$

Where the value of the constant K is related to the number of fault type m[10], take $K = \dfrac{1}{\ln m}$.

3.2. Correctness of Fault Diagnosis

If $X = \{x_1, x_2, \cdots, x_i\}$ is a finite discrete random variable, $p_i = P\{X = x_i\}$, then the probability distribution is $(p_1, p_2, \cdots, p_i)$. When the sequence of elements is changed in this vector, the new probability distribution $(p'_1, p'_2, \cdots, p'_i)$ is gotten. The relation between these two probability distributions is as formula (3).

$$H(p_1, p_2, \cdots, p_i) = H(p'_1, p'_2, \cdots, p'_i) \tag{3}$$

This is the symmetry properties of information entropy. The value of information entropy is independent with the sequence of the single factor judgement vector R_i. But if the position of r_{ij} is changed in R_i, then the fault type is likely to change that even leads to the wrong diagnosis result. That is to say, if the diagnosis of a certain member classifier is wrong, then the formula (2) can not measure the ability of the classifier objectively. If the single factor judgement vector R_i gives the wrong fault type, then this judgment is invalid. So inview of this phenomenon, the formula (2) is improved as formula (4) .

$$e_j = \begin{cases} -K\sum_{i=1}^{m} r_{ij} \ln r_{ij}, & (when\ result\ is\ correct) \\ 1, & (when\ result\ is\ not\ correct) \end{cases} \tag{4}$$

When a classifier's output results in an improper diagnosis of fault, define the value of entropy is 1, which can reduce the comprehensive evaluation's effect to a minimum.

3.3. Member Classifiers' Weights

A certain number of known samples are selected to test for each member classifier. The entropy values of all the outputs of member classifiers are calculated according to the formula (4). In order to eliminate the influence caused by individual factors, $\overline{e_j}$ the average entropy of each member classifier is calculated .

The degree of deviation

$$d_j = 1 - \bar{e}_j, \quad j = 1, 2, \cdots, n \tag{5}$$

Each member classifier weight is

$$\omega_j = \frac{d_j}{\sum_{j=1}^{n} d_j} \tag{6}$$

4. Fusion of Multiple Classifiers

The weight of each member classifier is determined by the method mentioned in part 2. The weight matrix $A=\{\omega_1,\omega_2,\cdots,\omega_n\}$ is obtained. Then the output of multiple classifiers fusion is

$$B = A \circ R \tag{7}$$

Where B is the fusion output.

Because the matrix A and R are both normalized, so the matrix of B is also normalized [9]. According to the principle of maximum membership, we can get the final diagnosis results.

5. Experiment

According to the location and degree, the bearing wear fault are divided into ten types which includes ball bearing retention's severe and mild wear, inner ring's severe wear and mild wear, outer ring's severe and mild wear, ball's mild, moderate and severe wear and normal. Four measuring points are chosen as shown in Figure 2. The type of sensor in measuring point 1,2,3 are all acceleration sensors and the type of sensor in measuring point 4 is a noise sensor.

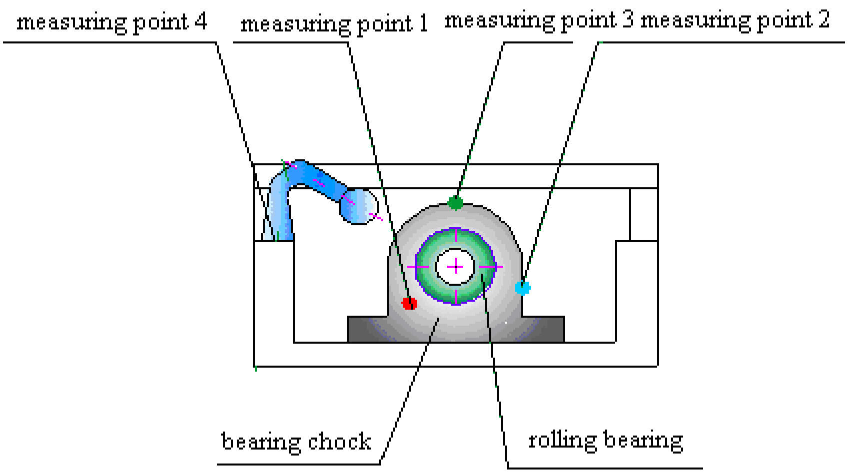

Figure 2. Layout of Sensors

BP, RBF and SVM are chosen as the members of the classifier and all the members of classifiers judge the fault type respectively. Please note that the output of these three classifiers must to be converted to the membership degree of fault types.

The output of BP and RBF classifier can be treated as formula (8).

$$r_{ij} = \frac{x_{ij}}{\sum_{j=1}^{m} x_{ij}} \tag{8}$$

where r_{ij} is the membership degree of fault type, x_{ij} is the original output of BP or RBF classifier.

The parameter of 'prob_estimates' can be set in the program of SVM. The outputs are converted to the form of fault type's probability [11].

100 groups of sample data are chosen to determine the weights of BP, RBF and SVM. The weights of the classifiers are 0.3717, 0.2416 and 0.3867. In order to validate the proposed method, another 50 groups of sample are chosen to test. Some results of the experiment are shown in Table 1.

Table 1. Part of Experiment Results

fault type	the outputs of the member classifier		the output by fusion
	BP	0.0106 0.0141 0.0027 0.0077 0.1055 0.1033 0.0054 0.1108 0.0091 **0.6309**	
00000 00001	RBF	0.0606 0.0063 0.0580 0.0837 0.0947 0.0109 0.0255 0.0953 0.1188 **0.4461**	0.0299 0.0102 0.0272 0.0310 0.0900 0.0493 0.0251 0.0713 0.0399 **0.6261**
	SVM	0.0293 0.0088 0.0316 0.0204 0.0721 0.0215 0.0438 0.0183 0.0203 **0.7339**	
	BP	0.0050 0.0053 0.0003 0.0014 0.0051 0.0030 0.0007 0.0073 0.0056 **0.9663**	
00000 00001	RBF	0.2019 0.0651 0.0558 0.1088 0.5109 0.0556 0.0183 0.0989 **0.5948** 0.1899	0.0723 0.0240 0.3015 0.0338 0.1359 0.0245 0.0119 0.0413 0.1529 **0.4193**
	SVM	0.0561 0.0162 **0.7446** 0.0181 0.0273 0.0257 0.0187 0.0380 0.0183 0.0369	
	BP	0.0309 0.0566 0.0239 0.0352 **0.6910** 0.0359 0.0366 0.0158 0.0160 0.0580	
00001 00000	RBF	0.1209 0.0723 0.0191 0.0409 **0.3783** 0.0177 0.0179 0.0844 0.1044 0.1440	0.0496 0.0436 0.0189 0.0362 **0.6392** 0.0270 0.0294 0.0332 0.0394 0.0833
	SVM	0.0230 0.0133 0.0140 0.0343 **0.7525** 0.0243 0.0296 0.0180 0.0214 0.0696	
	BP	0.0205 0.0309 0.0008 0.0175 **0.8359** 0.0263 0.0051 0.0191 0.0356 0.0082	
00001 00000	RBF	**0.2209** 0.0723 0.0191 0.0409 0.1783 0.0177 0.0179 0.0844 0.2044 0.1440	0.0699 0.0341 0.0103 0.0296 **0.6448** 0.0234 0.0177 0.0345 0.0709 0.0648
	SVM	0.0230 0.0133 0.0140 0.0343 **0.7525** 0.0243 0.0296 0.0180 0.0214 0.0696	
	BP	0.0228 0.0026 0.0069 0.0025 **0.8804** 0.0127 0.0080 0.0300 0.0205 0.0137	
00001 00000	RBF	0.0696 0.0190 0.0616 0.0430 0.0447 0.0238 0.0117 0.0304 **0.6746** 0.0216	0.0694 0.0076 0.0231 0.0132 **0.3440** 0.0150 0.2382 0.0607 0.1748 0.0541
	SVM	0.1140 0.0052 0.0146 0.0049 0.0155 0.0116 **0.6011** 0.1091 0.0108 0.1133	
	BP	**0.9492** 0.0011 0.0006 0.0124 0.0007 0.0008 0.0031 0.0003 0.0125 0.0194	
01000 00000	RBF	0.0287 **0.7378** 0.0425 0.0309 0.0399 0.0175 0.0137 0.0230 0.0232 0.0427	0.3635 **0.5449** 0.0137 0.0143 0.0108 0.0067 0.0086 0.0068 0.0109 0.0198
	SVM	0.0096 **0.9471** 0.0084 0.0058 0.0024 0.0057 0.0106 0.0030 0.0016 0.0058	
	BP	0.0090 **0.8033** 0.0392 0.0112 0.0057 0.0052 0.0616 0.0470 0.0130 0.0047	
10000 00000	RBF	**0.7440** 0.0512 0.0227 0.0158 0.0092 0.0634 0.0245 0.0030 0.0144 0.0519	0.5272 **0.3142** 0.0233 0.0097 0.0057 0.0237 0.0366 0.0222 0.0099 0.0275
	SVM	**0.8898** 0.0083 0.0085 0.0044 0.0034 0.0167 0.0201 0.0104 0.0042 0.0342	
	BP	0.0055 0.0057 **0.8892** 0.0069 0.0162 0.0218 0.0015 0.0260 0.0126 0.0145	
00100 00000	RBF	**0.2008** 0.0837 0.1175 0.1748 0.0004 0.0762 0.0293 0.1150 0.1277 0.0745	0.0632 0.0284 **0.6377** 0.0501 0.0202 0.0413 0.0223 0.0535 0.0515 0.0316
	SVM	0.0328 0.0157 **0.7209** 0.0137 0.0364 0.0383 0.0380 0.0416 0.0414 0.0212	
	BP	0.0018 0.0008 0.0048 0.0030 0.0001 0.0039 **0.9715** 0.0059 0.0044 0.0038	
00000 10000	RBF	0.1055 0.0744 0.0184 0.0796 0.0100 **0.4352** 0.0584 0.0259 0.0686 0.1239	0.0278 0.0204 0.0082 0.0253 0.0047 **0.4654** 0.3789 0.0156 0.0197 0.0341
	SVM	0.0042 0.0056 0.0052 0.0128 0.0057 **0.9279** 0.0094 0.0184 0.0038 0.0070	
	BP	0.0001 0.0005 0.0028 0.0001 0.0031 **0.9855** 0.0023 0.0027 0.0015 0.0016	
00000 10000	RBF	0.0714 0.0334 0.0273 0.0884 0.0359 0.0527 **0.5426** 0.0894 0.0251 0.0337	0.0288 0.0099 0.0103 0.0234 0.0142 0.3911 **0.4647** 0.0354 0.0085 0.0140
	SVM	0.0297 0.0042 0.0069 0.0052 0.0112 0.0312 **0.8604** 0.0330 0.0048 0.0135	

6. Conclusions

The experiment results show that the fault type can be diagnosed correctly if the members of classifier's conclusions are the same. If there is a conclusion conflict between single classifiers, about 70% of the sample can identify the fault types after fusion correctly. The diagnosis rate can be improved effectively. Fault's membership degree after the fusion between the maximum membership degree of fault membership between single member classifier and minimum value, that is to say, the final result after fusion depends on the result s of each member classifier. Measurements must be taken to ensure member classifier's correctness. The classifier fusion method based on fuzzy comprehensive evaluation belongs to the soft decision fusion method. The output of each member classifier is the judgment for various faults which presents the membership degree of each type of fault. The experiments prove that this method can effectively improve the recognition rate of fault.

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