Fault Diagnosis Method for Certain Equipment Based on Case-based Reasoning

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Abstract: With the increasing complexity, information and intelligence of combat systems and weapons equipment, the traditional fault diagnosis technology can not meet the requirements of rapid and accurate fault diagnosis of equipment. In this paper, according to the fault characteristics and maintenance status of a certain type of equipment, combined with case-based reasoning technology, an equipment maintenance system which can realize intelligent query, case accumulation and fault reasoning is proposed. Finally, the feasibility of the method is proved by an example.

1. Introduction
The rapid upgrading of combat systems and weapons equipment makes the types of equipment increasingly rich and the system structure increasingly complex, which leads to the increasing difficulty of equipment support. A certain type of equipment contains a large number of mechanical, hydraulic, electrical and other parts, its fault form, mechanism is different, in the face of various forms of equipment failure, support personnel in most cases still use the traditional subjective diagnosis, instrument diagnosis and other methods, subjective diagnosis of individual differences are very large, belong to empirical judgment, poor accuracy; and instrument diagnosis cost is high, time-consuming and laborious, therefore, the existing methods are not easy to be efficient, fast troubleshooting, has been difficult to adapt to the combat scene of equipment maintenance rhythm.

In order to solve the problem of low efficiency of traditional fault diagnosis, many scholars combine intelligent diagnosis technology to construct fault diagnosis model and system, and put forward some intelligent fault diagnosis methods. Liu Baojie and others [1] use evidence theory and neural network integrated fault diagnosis method to solve the fault problem of hydraulic rocket launcher servo system. Zhou Rusheng and other [2] designed an expert system based on the characteristics of hydraulic system of missile launcher. Based on the particularity of ship hydraulic device and its fault, Yang Guang and other [3] established a fuzzy grey correlation diagnosis model. The above fault diagnosis method realizes the intelligent diagnosis of equipment fault, but the problem of knowledge rule construction and knowledge acquisition bottleneck exists in different degrees.

Aiming at this practical problem of this type of equipment, this paper puts forward a kind of equipment fault diagnosis method based on case reasoning, which can realize intelligent query, case accumulation and fault reasoning equipment maintenance system, in order to improve the ability of quick fault location and diagnosis of equipment.
2. Equipment fault diagnosis methodology

2.1. Equipment Fault Reasoning Architecture

The equipment fault reasoning method based on case reasoning is mainly composed of data acquisition, case base construction and fault diagnosis. The idea of solving the problem is to learn from the historical cases and solutions that have occurred, and to adjust and modify the historical similar cases in combination with the target case phenomenon. The fault diagnosis diagram is shown in figure 1.

![Diagram of fault diagnosis based on case reasoning]

2.2. Fault Case Library Construction

2.2.1. Fault data acquisition

The fault cases used in the invention mainly come from collecting and arranging the troubleshooting and maintenance records during the use of the equipment, including the fault maintenance manual, the maintenance service site work summary. The fault maintenance manual contains the description and solution of the common faults of the equipment by the equipment manufacturer and the user, including the fault phenomenon, the fault equipment, the fault cause, the fault location and so on. The collected fault data are sorted out uniformly, and the low value and redundant data items are eliminated to improve the quality and integrity of the case data.

2.2.2. Fault data classification

The fault case data is divided into mechanical system, electronic system and hydraulic system according to the equipment system.

2.2.3. Fault case feature extraction

Define the characteristic attributes of each failure case by standard, the characteristic attributes of each failure case can be expressed as Pi=(P_{i1},P_{i2},P_{i3},P_{i4}), (i =1,2,…, n), n is the number of fault cases.

Specifically, P_{i1} indicates the operating environment of the equipment, including temperature, humidity, salinity, altitude, recording this information provides a basis for the fault set to quickly match similar failures triggered in the same operating environment. P_{i2} means the equipment to which the fault belongs, which is three levels, which can be expressed as component level, part level, component level, each fault must record its component, part, component, if part, component level fault, it may not record low level. For example, hydraulic leg failure, the components are hydraulic cylinder seals, parts for hydraulic cylinders, components for hydraulic legs. This representation method can quickly
establish the correlation relationship for the subsequent failure of the same class and the same class parts. \( P_{i3} \) represents the fault phenomenon. By extracting the feature words input into the continuous information data, the key words of the fault phenomenon are obtained, which does not limit the number. This attribute is the core attribute of the system and the basis of analysis and reasoning. \( P_{i4} \) represents the fault solution, which corresponds to the \( P_{i3} \) attribute.

2.2.4. Fault classification into the case base

After the fault case feature is extracted, the fault feature is saved to the case library according to the equipment system type.

2.3. Fault inference based on RBF neural network

RBF neural network has the advantages of fast convergence speed and good nonlinear mapping ability in fault diagnosis. During the whole fault reasoning process, the RBF neural network is equivalent to a similarity computing network, and the similarity between the vector of the feature element of the target case and the vector of the known case feature element is calculated by the incentive function of the hidden layer. [4-5]

RBF network structure is shown in figure 2, with three layers: input layer, hidden layer and output layer.

![RBF Network structure diagram](image)

In this method, the fault case after word segmentation, feature extraction, the feature is vectorized, and according to the word frequency weight into a vector, as the input of the RBF neural network. The input vector is \( X = [x_1, x_2, \ldots, x_n]^T \), generated by the fault phenomenon in the fault case; the output vector is \( Y = [y_1, y_2, \ldots, y_m]^T \), is the cause of the fault.

The hidden layer uses a Gaussian function whose weighted network output is:

\[
y_j(x) = \sum_{i=1}^{h} \omega_{ij} g(x) = \sum_{i=1}^{h} \omega_{ij} \exp \left( -\frac{\| x - c_i \|}{\sigma_i^2} \right), \quad (i = 1, 2, \ldots, h; \quad j = 1, 2, \ldots, m)
\]

Where the \( y_j(x) \) is the output of the j node of the output layer, \( g(x) \) is the output of the i node of the hidden layer, and the \( \omega_{ij} \) is the from the hidden layer to the output layer, and the \( c_i, \sigma_i \) is the center and variance of the Gaussian function at the i node, the \( \| \cdot \| \) is the distance between the input \( x \) and \( c_i \). \( n \), \( h \), \( m \) is the number of nodes in each layer.

2.4. Fault diagnosis process

The steps of fault diagnosis are as follows:

Step 1, obtain the historical fault case data of the equipment, preprocess, classify and extract the historical fault case data in turn, get each kind of corresponding feature attribute, and establish the fault case database accordingly;

Step 2, use the case data in the fault case database to train the RBF neural network and get the trained RBF neural network;

Step 3, feature extraction for diagnostic faults. After extracting the feature attributes of the target case, the TF-IDF keyword extraction algorithm is used to extract the feature of the case, mainly to
extract the key words of the case. The key words with high word frequency and low word frequency in other cases in case library are obtained and quantified simultaneously.

Step 4, the case retrieval reasoning. Query past cases through key feature attributes, that is, retrieve case base. After quantifying the extracted key feature attributes, all the cases in the case library are clustered according to word vectors to find the cases with the same feature attributes as the target cases, that is, similar cases. The fault features of each similar case are transformed into word vectors and input the trained RBF neural network.

Step 5, output diagnostic results. According to the output of the RBF neural network, the fault cases with high similarity are selected to locate the fault and find the fault cause and its solution.

Step 6, case study adjustment. According to the output results, if the same source case as the target case is retrieved, the definite solution is obtained, the target problem can be solved, and the target case is given up in order to avoid redundancy. If a source case similar to the target case is retrieved, the proposed solution to the target case is obtained by the solution of the similar case, and the case correction is carried out according to the actual situation, and then the solution is determined and saved to the case base as a new case.

3. Examples of fault diagnosis

The verification system of this fault diagnosis method is based on the operation page of Windows operating system, B/S architecture, operating and debugging in Pycharm2018.1.3 and Java8.0 programming environment, using Python3.8 programming language to develop, and the system database using MySQL database. The system consists of three main modules: fault case input module, case reasoning module and system management module. The system framework structure is shown in figure 3.

| Car Type: Loading | Type: Vehicle No.3 | Temperature: 5°C | Humidity: 58% |
|-------------------|--------------------|------------------|--------------|
| Pressure: 976hpa  | Altitude: 400 m    | Salinity: 1 ppm  | Diurnal temperature difference: 10°C |
| Fault feature 1: hoisting operation | Fault feature 2: hoisting | Fault feature 3: slow execution |

The system quantifies the fault feature words, and the results are shown in Table 2.
Table 2 Quantification of fault characteristics

| 0.20933745 0.   0.   0.   0.   0.40317551 |
| 0.   0.   0.   0.40317551 0.   0.34371327 |
| 0.   0.   0.34371327 0.   0. |
| 0.   0.   0.   0.   0.34371327 |
| 0.   0.   0.   0.18259963 0.15317089 |
| 0.   0.   0.44536465 0.   0. |
| 0.   0.   0.   0.   0.34371327 |
| 0.14665195 0.   0. |

The fault characteristics after vectorization are clustered, and the results are shown in Table 3.

Table 3 Fault characteristic clustering results

| Category 1 | 10°C,40%,1076hpa,500m,0.8ppm,15°C, loading vehicle, No.4 vehicle, hoisting operations, hoists, pulsation |
| 10°C,40%,1076hpa,500m,0.8ppm,15°C, loading vehicle, No.5 vehicle, hoisting operation, lifting gear, no reversing |
| 10°C,40%,1076hpa,500m,0.8ppm,15°C, loading vehicle, No.5 vehicle, hoisting operations, hydraulic pressure gauges, pointers, fluctuations |
| Category 2 | 10°C,35%,1276hpa,500m,0.8ppm,15°C, loading vehicle, No.9 vehicle, hoisting operation, insufficient thrust, reduced speed, unstable work |
| 10°C,35%,1276hpa,500m,0.8ppm,15°C, loading vehicle, No.8 vehicle, hoisting operation, insufficient thrust, reduced speed, unstable work |
| Category 3 | 10°C,35%,1276hpa,500m,0.8ppm,15°C, loading vehicle, No.3 vehicle, hoisting operation, hoists, no response |
| 10°C,35%,1276hpa,500m,0.8ppm,15°C, loading vehicle, No.4 vehicle, hoisting operation, lifting gear, reversing, slow movement |
| 10°C,35%,1276hpa,500m,0.8ppm,15°C, loading vehicle, No.9 vehicle, hoisting operations, hoists, reversing, impact, noise |

After clustering, the fault features of each case are transformed into word vectors and the radial basis function neural network is input. The similarity between each case and the input case is obtained and sorted. According to the similarity from high to low, the fault features and solution features of the case are displayed, as shown in Table 4.

Table 4 Similar case presentations

| Case 1: |
| Fault characteristics:5°C, 58%, 976hpa, 400m, 1ppm, 10°C, loading vehicle, No.3 vehicle, slow execution, hoisting operation |
| Solution features : ['first check the amount of hydraulic oil, the amount of oil in accordance with the regulations, eliminate the shortage of hydraulic oil tank; then check the connection joints, the joints are well connected, eliminate the problem of airtight air entry; finally check the piston pump.'] |
| Similarity :1.0 |
| Case 2: |
| Fault characteristics:5°C, 58%, 976hpa, 400m, 1ppm, 10°C, loading vehicle, No .5 vehicle, hoisting operation, hoisting gear, slow reversing movement |
| Solution features: ['first check the hydraulic oil quantity, the oil filter is not blocked; then check the connection mechanism is not abnormal; then check the corresponding direction of the one-way valve, no abnormal; finally check the reversing valve, Found that the armature contact point wear in the

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Case 3:
Fault characteristics: 10℃, 58%, 976hpa, 400m, 0.6ppm, 10℃, loading vehicle, No.4 vehicle, hoisting operation, hoisting gear, no response.
Solution features: ['first check the loading vehicle power supply is normal, hydraulic oil quantity conforms to the regulations; Then check the piston pump, found that the piston ball head broken, resulting in pump shaft can not rotate, should be replaced after troubleshooting. ']
Similarity :0.936

According to the diagnostic results, the similarity between case 1 and target case is 1.0. Check the corresponding solution to get the cause of the failure. According to the plan, check the hydraulic oil quantity, related connection joint, if no problem, replace the piston pump, you can troubleshoot. The actual troubleshooting situation is that there is a gap wear between the plunger of the piston pump and the cylinder block, resulting in the loss of seal.

Compared with the traditional fault knowledge processing and fault diagnosis methods, this method only needs to retrieve the most similar existing cases from the case base without the rule of complete acquisition of knowledge, so it is not troubled by the bottleneck problem of knowledge acquisition. In addition, in the face of the same fault problem, it can directly call the last reasoning result without re-matching according to the rules, so it has the performance of fast problem reasoning, query and solution.

4. Conclusion
This paper introduces a fault diagnosis method based on case reasoning, which applies artificial intelligence technology to a certain type of equipment, and selects suitable reasoning technology for the unique fault diagnosis data of the equipment. It breaks the problem of difficult fault diagnosis of traditional support equipment and improves the efficiency of equipment support. By using the key feature attributes to search, the efficiency of case retrieval is improved, especially when the number of case data in the fault case database is more and more, the advantage of retrieval speed will be obvious. In the process of operation, high precision reasoning results are obtained by global optimization of core parameters. Furthermore, thanks to the strong self-study ability of RBF neural network, the field ability of this method will gradually improve with the increase of fault cases.

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