Fault Diagnosis Method of Spacecraft Measurement and Control Equipment Based on Artificial Intelligence Technology

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Abstract: To solve the problems of fault diagnosis methods such as low versatility, difficulty in selecting feature parameters, and low efficiency of reasoning in spacecraft equipment, a fault diagnosis method for space equipment based on artificial intelligence is proposed. Feature selection and extraction, and then use the support vector machine to optimize the selected parameters, and finally through the application of simulation in the fault diagnosis of multiple types of space measurement and control equipment to verify the effectiveness of the system.

1 INTRODUCTION

The aerospace monitoring and control equipment has a complex structure, cross-coupling of subsystems, and a wide range of failure modes. Research on reliability modeling and analysis methods for complex aerospace monitoring and control equipment is an important guarantee for improving the automation level of aerospace monitoring and control equipment operation and management[1-3]. For complex large-scale measurement and control equipment, relying only on equipment operators using traditional methods for fault diagnosis and troubleshooting has greater limitations, applying artificial intelligence technology to the field of aerospace monitoring and control equipment fault diagnosis, through the establishment of fault diagnosis expert system, the equipment Faults are quickly and accurately located, and expert-level maintenance recommendations are proposed to provide new methods for fault diagnosis of measurement and control equipment.

The paper proposed a general method for fault diagnosis of spacecraft monitoring and control equipment based on genetic programming and support vector machines. From the selection of the original parameters of fault features of genetic programming, the optimization of characteristic parameters, SVM for fault diagnosis and other steps, the fault diagnosis method for space equipment based on artificial intelligence is studied. , To provide an effective guarantee for the safe and reliable operation of aerospace monitoring and control equipment.

2 GENETIC PLANNING ALGORITHM

2.1 Endpoint Sets and Function Node Sets

The set of endpoints contains the different types of variables and constants provided to the GP system and is the input to the program generated by the GP algorithm. The set of endpoints is the most basic element of the problem environment and results. For different problems, the meaning of the elements is also different. The selection of a function node set is a statement, an operation, and a function suitable for a GP operation, including an operator, a function operation, and some expressions.

2.2 Initial Population and Common Generation Methods

The initial population of the GP algorithm consists of a number of randomly generated individuals.

These individuals consist of a given function and various possible symbolic expressions. The process of generating the initial population can be seen as a blind search process in the program space. When generating the initial group of individuals, a function is first randomly selected in the function node set as the root node of the syntax tree; then, the same number of child nodes are selected according to the number of independent variables handled by the function. For each subtree starting from the child node, an element can be randomly selected from the union of the function node set and the end point set as the node of the subtree. If the selected function is a function, it will be repeated. The above operation process; if the selected end point, the subtree stops growing.

2.3 Fitness Evaluation

When the individuals in the population replicate, crossover, and mutate, the evaluation scale of the individual in the GP algorithm is called a fitness function. The fitness evaluation of the GP algorithm uses standardized fitness, initial fitness, adjusted fitness, and normalized fitness.

Standardization fitness is consistent with the maximization of fitness in genetic algorithms, and can be expressed in the following simple form:

$$S(i) = r_{\max} - r(i) \qquad (1)$$

In the formula, S(i) is the output value calculated by the individual i fitness, rmax is the maximum original fitness, and r(i) is the original fitness of individual i.

Primitive fitness is a measure of the natural description of the problem, usually obtained by directly calculating the absolute error between the individual's output and the expected output,

$$r(i) = \sum_{j=1}^{M} \left| S(i,j) - C(j) \right| \qquad (2)$$

In the formula, S(i,j) is the calculated output of the individual i at the jth input value; C(j) is the target expected value corresponding to the jth input value; M is the number of training samples.

The standardized fitness is adjusted, and the adjusted fitness a(i) of the individual i is calculated by the following equation.

$$a(i) = \frac{1}{1+S(i)} \qquad (3)$$

In general, $S(i) \geqslant 0$, then $a(i) \in [0,1]$. Therefore, the greater the adjusted fitness value, the better the individual. Adjusting the degree of fitness is better than the standard level of fitness for the best individual, especially when the standard fitness approaches zero, adjusting the degree of fitness can amplify small differences in standard fitness.

The normalized fitness degree is a selection method based on the fitness proportion, which is calculated by adjusting the fitness degree. The concrete expression is

$$n(i) = \frac{a(i)}{\sum_{k=1}^{M} a(k)} \qquad (4)$$

In the formula, M is the size of the population. The normalized fitness degree has the following three ideal characteristics: n(i) ∈ [0,1]; the greater the fitness value, the better the individual is:

$$\sum_{k=1}^{M} a(k) = 1.$$

2.4 Selecting Strategies

The GP algorithm selection strategy includes fitness proportion selection method, fitness ranking selection method, roulette selection method and tournament selection method.

2.5 Genetic Manipulation

GP algorithm genetic operations include: copy, crossover, and mutation. Among them, the crossover operation is based on the rule that the higher the fitness value is, the better the probability of being selected is. From the current population, two parent individuals are randomly selected. The tree structure of two parent individuals is shown in Fig.1; then, from two A node is randomly selected as a cross point in the tree, and the entire sub-tree below the cross point is taken as a cross section (as shown by a dashed box in Fig.1).

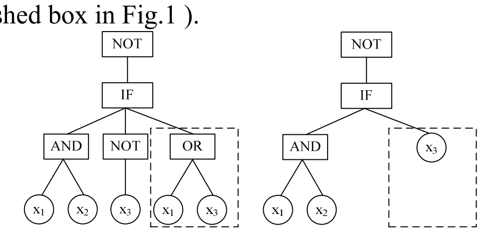

Figure 1: Tree structure of two parent individuals.

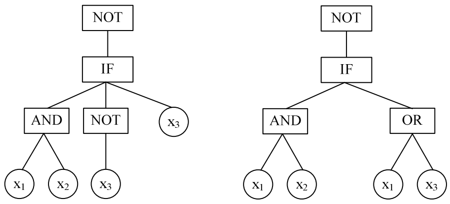

Figure 2: Tree structure of two individuals after crossover.

Two cross-sections selected in the two parent individuals are exchanged to generate two trees. The new tree is the two children of the next generation. The tree structure of the two individuals after the crossover operation is shown in Fig. 2.

2.6 Termination Criteria

The GP program is a process of highly parallel, local control and decentralized processing. The state of each stage is only determined by the genetic program group. The fitness index drives the group to constantly adapt to the changes of the environment, making the whole group adaptable development of.

3 AVIATION MEASUREMENT AND CONTROL EQUIPMENT FAULT FEATURE SELECTION AND EXTRACTION

3.1 The Selection of Fault Characteristics of the Original Parameters

In order to weaken the influence of factors such as process parameters and operating conditions of the aerospace measurement and control equipment on the diagnostic effect, and at the same time ensure sufficient sensitivity to equipment defects and faults, the selection of genetic operating parameters is usually selected to be sensitive to fault information. Given that dimensionless indices are used as genetic operands, genetic planning requires that the original indicators be optimized and combined. Therefore, it is necessary to prove that the combined feature parameters are still dimensionless parameters [4-5].

There are 2 dimensionless indicators, in the following format:

$$p_1 = \frac{a_1(d_1)}{a_2(d_1)} \quad (5)$$

$$p_2 = \frac{b_1(d_2)}{b_2(d_2)} \quad (6)$$

In the formulas, a_1 and a_2 represent two variables with dimension d1; b1 and b2 represent two variables with dimension d2. Let $V = p_1 + p_2$, then

$$V = p_1 + p_2 = \frac{a_1(d_1)}{a_2(d_1)} + \frac{b_1(d_2)}{b_2(d_2)} = \frac{a_1(d_1)b_2(d_2) + a_2(d_1)b_1(d_2)}{a_2(d_1)b_2(d_2)} = \frac{X_{12}(d_1d_2)}{X_{22}(d_1d_2)} \quad (7)$$

From the formula (7), we can see that V is the ratio of the two variables X_{12} and X_{22} with the same dimension (all d_1d_2), so it is still a dimensionless index. By the same token, it can be shown that after the arithmetic operations are performed on the dimensionless indicators, the results are still dimensionless.

3.2 Determination of Fitness Function

For the n-type d-dimensional sample set, contains N samples x1, x2, ..., xN, where N1 belongs to class ω 1, denoted as Ξ 1; N2 belongs to class ω 2, denoted as Ξ 2; Nn belongs to class ωn, denoted as Ξ n .

The average value of mi for mi samples is:

$$m_i = \frac{1}{N}\sum_{x\in\Xi} x \text{ , i=1,2,...,n} \quad (8)$$

The intra-class dispersion Di and the total intra-class average dispersion Dw are:

$$D_i = \sum_{x\in\Xi}(x-m_i)(x-m_i)^T \quad \text{i=1,2,...,n} \quad (9)$$

$$D_w = \frac{1}{n}\sum_{i=1}^{n} D_i \quad (10)$$

Sample class dispersion Dbij is

$$D_{bij} = \sum_{x\in\Xi}(m_i-m_j)(m_i-m_j)^T \quad \text{i}\neq\text{j} \quad (11)$$

Fitness function

$$F = \frac{\min(D_{bij})}{D_\omega} \quad (12)$$

Where Dbij represents the class spacing between the i-th and j-th classes. The numerator represents the minimum value of the dispersion between

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classes, and the denominator represents the average value of the dispersion within the class.

4 SUPPORT VECTOR MACHINE PARAMETER OPTIMIZATION

Select 50 sets of data from the data samples of A1 and A2 as the training samples of the support vector machine. Set the initial population number N of the genetic algorithm to 100, the crossover probability Pc=0.7, the mutation probability Pm=0.15, and terminate the algebra For 400, training and parameter optimization are performed. The optimization results are: C3=47.26, σ3=1.74.

5 SIMULATION

In the experimental process, the collected data is first calculated according to the calculation formula of each characteristic parameter of the aerospace measurement and control equipment, and margin index L, peak factor C, kurtosis factor K, waveform of each group of measurement and control equipment can be obtained. RMS ratio Rv and other parameters, Table 1 gives the calculation results of 10 domain parameter values under different working conditions.

Table 1: Time-frequency parameter values when the aviation measurement and control equipment is damaged.

Parameter Number	Rv	C	K	L
1	78.4652	1.9878	2.4908	2.2325
2	97.4409	1.9080	2.5642	2.9842
3	96.7694	1.9631	2.9067	2.9487
4	89.0543	1.9884	2.4554	2.8225
5	98.6545	1.8774	2.3211	2.3221
6	87.4321	1.8998	3.2323	2.9885
7	103.7689	1.9990	3.1221	3.3417
8	101.2321	1.9567	2.9003	2.5663
9	100.4531	1.9899	2.3425	2.7888
1	103.2321	1.9996	2.7888	3.4175

In the experiment process, the data from the lubricating oil spectral analysis data of the aerospace measurement and control equipment in the complete working phase, and according to the time sequence of the spectrum analysis to obtain the original data sequence of the metal content of the aviation measurement and control equipment, as shown in Fig. 3.

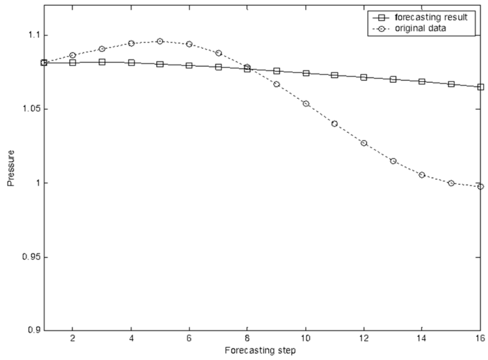

Figure 3: Raw data sequence of metal content.

The data sequence is processed relative to each other, and then the data is subjected to zero processing to obtain a new Al metal relative content time series {xi}. Relative data processing, and then the data after the zero treatment to get the new relative content of Al time series. According to the calculation formula of the embedding dimension, the FPE value corresponding to different embedding dimensions shown in Fig. 4 can be calculated. From Figure 4, we can see that when it is equal to 10, the FPE value is the smallest, that is, the best embedding dimension is 10.

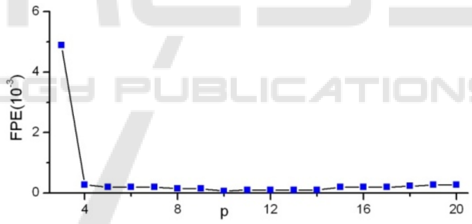

Figure 4: The FPE values corresponding to different embedding dimensions.

6 CONCLUSIONS

Genetic programming is used to select the features of aerospace monitoring and control equipment, and the parameters of aerospace monitoring and control equipment are optimized using regression SVM, which makes the optimized state diagnosis model of aerospace monitoring and control equipment have higher accuracy. Under the given device parameter alert value, the support vector machine can be used to diagnose the status of aerospace monitoring and control equipment in a relatively long range, which can provide an important basis for the health

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monitoring of space monitoring and control equipment.

REFERENCES

1. WANG Wanyu,TAO Sunjie,FENG Xuxiang. Design of fault diagnosis expert system for remote sensing satellite receiving system [J]. Telecommunication Engineering,2015,55(5):491-496.
2. ZHOU Qijun,ZHAO Qiuying,ZHU Mingming. TT&C systemfault diagnosis method based on fault tree[J]. Modern Elec—tronics Technique,2015,38(7):103-106.
3. WANG Weihong,LI Jun. Improved edit distance algorithm base on local variability[J]. Computer Engineering,2015,41(7):294-298.
4. WANG Hua,LIU Huanmin,DUAN Huifen. Case-basedreasoning method in fault diagnosis expert system of inertial navigation system [J]. Journal of Chinese Inertial Technology,2009,17(5):614-617.
5. Baker J.E.. Adaptive selection methods for genetic algorithms[J], Proc. of the Intel Conf. on Genetic Algorithms and Their Applications, 2008:101~111

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