Fault diagnosis of missile refrigeration system based on the belief rule base

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Abstract. In order to diagnose the fault of missile refrigeration system, aiming at the complex nonlinear relationship between the causes and symptoms of missile refrigeration system, we propose a method for fault diagnosis of refrigeration system based on the belief rule base (BRB). The method can use quantitative and qualitative information to establish a nonlinear model between input and output, and diagnose the system through optimization model. BRB can make comprehensive use of expert knowledge and historical data, which is more suitable for fault diagnosis. In order to address the problem of parameter inaccuracy in the initial BRB given by experts, combined with the information type of the failure of the refrigeration system, we use the chaotic particle swarm optimization learning model to train the initial BRB parameters given by experts to achieve the diagnosis of refrigeration faults in the refrigeration system. The experimental results show that the BRB after parameter optimization can better identify the state of the missile system and improve the accuracy of fault diagnosis.

1. Introduction

With the continuous development of infrared imaging seeker technology, the missiles’ ability to lock and hit targets has been constantly improved [1]. Air-to-air and ground-to-air missiles guided by infrared would pose a significant threat to tactical aircraft and is believed to be of great importance in the future wars [2]. However, for the new generation of ground-air infrared seeker technology, how to realize the cooling of seeker focal plane detector has become one of its main bottlenecks. Due to the continuous improvement of detector technology and higher chip integration, the thermal mass of the focal plane detector increases dramatically. Additionally, the performance of the missile refrigerator faces great challenges [3]. The failure of the refrigeration system often results from mass factors. Besides, the same failure may be triggered by many reasons. How to locate the fault quickly and accurately in complex system has become a hot issue in the research of the missile refrigeration system.

At present, the fault diagnosis technology mainly includes neural network, principal component analysis and expert system. The fault diagnosis method based on neural network relies on a large amount of historical data. However, this method fails to make full use of expert knowledge [4]. The method based on principal component analysis has a good effect on feature selection and dimensionality reduction of original data, but it requires a number of prior knowledge of the diagnostic object and some characteristics of the data [5]. The fault diagnosis method based on expert system can make full use of expert knowledge. However, strong subjectivity is usually embedded in the knowledge [6].
In order to solve the aforementioned problems, this paper proposes a belief rule based diagnosing method that identifies faults of missile refrigeration system. This method can not only effectively utilize valuable expert knowledge but also combine the data-driven method with the expert knowledge. Moreover, it can adjust the parameters set by the experts through the method of parameter optimization and establish the nonlinear model between input and output [7].

The rest of this paper is organized as follows: firstly, section 2 describes the method of belief rule base based on evidence reasoning and expounds the principle of parameter optimization. Then, for a certain type of missile refrigeration system, define the fault module's unique thermal code, select the parameter optimization objective function, and use the chaos particle swarm optimization algorithm to optimize the parameters. In section 3, the belief rule base database of the refrigeration system is established, and the relative Euclidean distance is used for error analysis. Afterwards, the fault diagnosis probability before and after optimization is compared.

2. Belief rule base inference methodology

2.1. The Structure of belief rule base

A general expression of the belief rule base rule:

\[ R_k: \text{If } x_1 = A_1^k \land x_2 = A_2^k \land \cdots \land x_m = A_m^k, \text{ Then } \left\{ \left( D_1, \beta_{1,k} \right), \ldots, \left( D_N, \beta_{N,k} \right) \right\} \]

Where, \( x_i (i = 1, 2, \ldots, M) \) represents the \( i \) th antecedent attribute in the \( k \) th rule. \( A_i^k (i = 1, 2, \ldots, M; k = 1, 2, \ldots, L) \) is the \( i \) th referential value of the antecedent attribute in the \( k \) th rule. \( M \) is the number of the antecedent attribute in the \( k \) th rule. \( L \) is the number of belief rules in the belief rules base. \( A_i^k \subseteq A_i, A = \{ A_i, j = 1, 2, \ldots, J \} \) represents the \( j \) th referential values of the \( i \) th antecedent attribute \( \theta_k (k = 1, 2, \ldots, L) \) is the weight of the \( k \) th rule and reflects the importance of the \( k \) th rule compared to other rules in BRB. \( \delta_i (i = 1, 2, \ldots, M) \) represents the weight of the \( i \) th antecedent attribute and reflects the importance of the attribute of the \( i \) th premise relative to other attributes of the premise. \( \beta_{i,k} (i = 1, 2, \ldots, N; k = 1, 2, \ldots, L) \) represents the belief of the \( j \) th output \( D_j \) in the \( k \) th rule.

2.2. Belief rule base reasoning

The inference of belief rule base is conducted by calculating the activation weight and integrating the activated rules through evidential reasoning algorithm. The activation weight refers to the reference degree of the rule to the input calculated according to the matching degree, rule weight and attribute weight.

Calculation of activation weight:

\[ \omega_h = \theta_h \prod_{i=1}^{M} (a_i^k)^{\overline{\delta_i}} / \sum_{h=1}^{H} \theta_h \prod_{i=1}^{M} (a_i^k)^{\overline{\delta_i}} \]

where \( \overline{\delta_i} \) is the weight calculation of relative attribute:

\[ \overline{\delta_i} = \delta_i / \max_{i=1,2,\ldots,M} \{\delta_i\} \]

\( a_i^k \) is the matching degree to which the \( i \) th input \( x_i \) matches the reference value \( A_i^k \). After obtaining \( \omega_h \), the evidence reasoning algorithm can be used to fuse the activated rules to obtain the final output of the belief rule base system:

\[ O(X) = \{ (D_j, \beta_j); j = 1, \ldots, N \} \]

where \( \beta_j \) is the belief of the latter item:
\[
\beta_j = \frac{u \left( \prod_{k=1}^{N} (\omega_k \beta_{j,k} + 1 - \omega_k \sum_{i=1}^{N} \beta_{j,k}) \right) - \prod_{k=1}^{N} (1 - \omega_k \sum_{i=1}^{N} \beta_{j,k})}{1 - u \left( \prod_{k=1}^{N} (1 - \omega_k) \right)}
\]

where \( u \) is the utility value:

\[
u = \left[ \sum_{k=1}^{N} \prod_{i=1}^{N} (\omega_k \beta_{j,k} + 1 - \omega_k \sum_{i=1}^{N} \beta_{j,k}) - (N - 1) \prod_{k=1}^{N} (1 - \omega_k \sum_{i=1}^{N} \beta_{j,k}) \right]^{-1}
\]

The antecedent attribute weight, rule weight and result belief degree in the belief rule base are all set by system experts out of experience, where subjectivity is always embedded. In order to select the optimal parameters of the belief rule base, Yang proposed the basic idea of optimizing the parameters of the belief rule base [8]. The specific structure of the optimal learning model of belief rule base is shown in figure 1.

The constraint conditions for optimization include: \( 0 \leq \delta_i \leq 1 \), \( 0 \leq \delta_e \leq 1 \), \( 0 \leq \beta_{j,k} \leq 1 \), \( \sum_{k=1}^{N} \beta_{j,k} = 1 \).

**Figure 1.** Belief rule base optimization learning model.

In addition, in order to obtain belief rule base with better performance, the reference values of the attributes of the preceding item and the attributes of the following item are included in optimization range and added to the above optimization learning model.

2.3. Input information transformation based on fuzzy semantic value

To select different parameters for the refrigeration system as inputs, we use expert knowledge to process the parameters. Expert knowledge is often expressed in the form of semantics and has ambiguity. To use expert knowledge to process related parameters, we set the semantic value and its referential value, and then calculate the matching degree to complete the conversion from numerical value to semantic value. After setting the semantic value and reference value, the matching degree \( \alpha_i^j \) can be obtained. The specific calculation method is as follows:

The matching degree \( x_i \) for \( A_{1,i} \) or \( A_{2,i} \) is 1, and the matching degree for other reference values is 0, when \( x_i \leq A_{1,i} \) or \( x_i \geq A_{2,i} \). And the matching degree of other reference values is 0, when \( A_{1,q} \leq x_i \leq A_{2,q+1} \) (\( q = 1,2,\ldots, J_i - 1 \)). The matching degree \( x_i \) of \( A_{1,q} \) and \( A_{2,q+1} \) is calculated as follows:

\[
\alpha_{i,q} = \frac{(A_{1,q+1} - x_i)}{(A_{1,q+1} - A_{2,q+1})}
\]

\[
\alpha_{i,q+1} = \frac{(x_i - A_{1,q})}{(A_{2,q+1} - A_{1,q})}
\]

2.4. Chaos particle swarm optimization algorithm

Chaos particle swarm optimization algorithm is used to optimize the parameters of the initial belief rule base. Particle swarm optimization (PSO) is a swarm intelligence algorithm, which is derived from the study of bird behaviour. Chaos thinking is an optimization mechanism that avoids falling into local optimality in the process of parameter optimization by experiencing all state laws in a certain range without repetition and relying on its randomness. Chaos iteration is introduced into the particle swarm optimization algorithm, and chaos iteration is used to guide local optimal \( P_{best} \) and global optimal \( G_{best} \). We choose the logical mapping \( x_{n+1} = \mu x_n (1 - x_n) \) \((0 < x_n < 1, n = 1,2,3,\ldots)\), where \( \mu \) is the control parameter and the value of \( \mu \) is 4. The specific algorithm steps are as follows:
1) Initialize the particle swarm and set relevant parameters. Set the population size as $n$ and the initial position and velocity of particles within the range, calculate the fitness of each particle, and then set $P_{\text{best}}$ and take the best as $g_{\text{best}}$.

2) Calculate the velocity and position of the particle. And check whether it is in the constraint region. If so, it will be updated; otherwise, it will not be updated.

3) Evaluate the adaptive value of each particle. For each particle, it is compared between the current position and the historical position. And then update the corresponding $P_{\text{best}}$ and $g_{\text{best}}$.

4) According to the formula $P_{t+1} = P_t + c_t v_{t+1} - d_t$, update the particle position and calculate the function value. If it is better than the previous $P_{\text{best}}$, update the $P_{\text{best}}$ and check whether it is needed to reset $g_{\text{best}}$. According to the formula $l_{t+1} = \mu l_t (1-t_c)$, update $l_{t+1}$.

5) According to the formula $g_{t+1} = g_t + c_t r_{t+1} - d_t$, update $g_{\text{best}}$ and calculate the function value. If it is better than before, reset and update $l_{t+1}$.

6) Check the termination conditions. If the maximum number of iterations or the increment of the optimal adaptation value is less than the given threshold value, then stop the iteration. Otherwise, return to step 2.

2.5. Parameter optimization based on one-hot code

In view of the attribute characteristic value which represents as the discrete conclusion data, the consequent conclusions of the belief rule base are coded by one-hot code, and the original discrete attribute characteristic is extended to Euclidean space. Euclidean distance between calculated data is:

$$E(D) = \| \hat{y}_m - y_m \|_2$$

The Euclidean distance between system output and actual output is taken as the objective function of parameter optimization:

$$f(x) = \frac{1}{t} \sum_{t=1}^{T} \| \hat{y}_m - y_m \|_2$$

where $\hat{y}_m$ is the belief structure corresponding to the input of the $m$th group, namely the diagnostic output of the system, and $y_m$ is the one-hot code corresponding to the actual output corresponding to the input of the $m$th group [9].

3. Experiments

3.1. Case analysis

The refrigeration system is a key component of the infrared seeker of this type of airborne missile, which is generally composed of refrigeration unit, detector, filter and pipeline. This system is mainly used for refrigeration before target detection to reduce detection noise to a reasonable level. Refrigeration failure is a common fault of this type of missile, which means that the detection noise cannot be reduced to the specified level within the specified time after the refrigeration is started.

According to the experience of experts, the reasoning of failure may include the following situations: A) detector fault. Although the temperature drop, the noise voltage of refrigeration signal do not drop after refrigeration, which is much higher than the theoretical value, while the refrigeration flow did not drop significantly. B) refrigeration failure. The noise voltage of refrigeration signal decreased after refrigeration, which is slightly larger than the theoretical value, but the cooling flow did not decrease significantly. C) nitrogen pipeline failure. The noise voltage of refrigeration signal decreases after refrigeration, and the refrigeration flow decreases greatly.

Thus, the parameters related to refrigeration mainly include refrigeration signal noise and refrigeration flow. For the refrigeration signal noise, a set of semantic reference values is defined, $A' = \{\text{Normal, Large, Very Large}\}$. For the refrigeration flow, a set of semantic reference values is defined, $A'' = \{\text{Very Small, Small, Normal}\}$. 
3.2. Establishment of belief rule base

According to the working characteristics, test data and expert experience of refrigeration system, the semantic value and corresponding reference value are set. In view of the fault diagnosis of refrigeration system, three reference values are selected for the refrigeration noise voltage and refrigeration flow.

On this basis, according to experts' understanding of the nonlinear and complex relationship between its external characteristic parameters and various components of the refrigeration system. Combined with the data analysis after demilitarization, the initial belief rule database was established, as shown in table 1.

Table 1. Initial belief rule base.

| No | A′ | A″ | Fault location belief structure |
|----|----|----|----------------------------------|
| 1  | N  | VS | (T, 0.00), (Z, 0.06), (D, 0.94) |
| 2  | N  | S  | (T, 0.00), (Z, 0.17), (D, 0.83) |
| 3  | N  | N  | (T, 0.34), (Z, 0.32), (D, 0.34) |
| 4  | L  | VS | (T, 0.00), (Z, 0.00), (D, 1.00) |
| 5  | L  | S  | (T, 0.00), (Z, 1.00), (D, 0.00) |
| 6  | L  | N  | (T, 0.00), (Z, 0.51), (D, 0.49) |
| 7  | VL| VS | (T, 0.48), (Z, 0.00), (D, 0.52) |
| 8  | VL| S  | (T, 0.81), (Z, 0.00), (D, 0.19) |
| 9  | VL| N  | (T, 1.00), (Z, 0.00), (D, 0.00) |

For the output of the belief rule base, the specific fault location is expressed in the form of one-hot code, as shown in table 2.

Table 2. Belief rule base output items and their encoding.

| Serial number | Consequent conclusions | One-hot code |
|---------------|------------------------|--------------|
| T             | Detector fault         | 100          |
| Z             | Refrigeration failure  | 010          |
| D             | Nitrogen line failure  | 001          |

,where, the attribute weight $\delta_1$ and $\delta_2$ is 1. To reduce the subjective bias contained in the initial belief rule base, the initial belief rule base is optimized in the following parts of this paper.

3.3. Belief rule base optimization

Chaos particle swarm optimization learning model is used to optimize the initial belief rule base. The optimized belief rule base is shown in table 3, and the reference values of the former and latter attributes after optimization are shown in table 3, where the weight value of the optimized attribute is $\delta_1=0.4994, \delta_2=0.4995$.

Table 3. The optimized belief rule base.

| No | A′ | A″ | Fault location belief structure |
|----|----|----|----------------------------------|
| 1  | N  | VS | (T, 0.0362), (Z, 0.1115), (D, 0.8523) |
| 2  | N  | S  | (T, 0.2954), (Z, 0.3356), (D, 0.3690) |
| 3  | N  | N  | (T, 0.0535), (Z, 0.7152), (D, 0.2313) |
| 4  | L  | VS | (T, 0.0381), (Z, 0.0306), (D, 0.9313) |
| 5  | L  | S  | (T, 0.0527), (Z, 0.7820), (D, 0.1653) |
| 6  | L  | N  | (T, 0.0865), (Z, 0.0716), (D, 0.8419) |
| 7  | VL| VS | (T, 0.5706), (Z, 0.1051), (D, 0.3243) |
| 8  | VL| S  | (T, 0.7090), (Z, 0.0757), (D, 0.2153) |
| 9  | VL| N  | (T, 0.8424), (Z, 0.0691), (D, 0.0885) |
The weights of the optimized rules from rule 1 to rule 9 are: 0.6524, 0.0172, 0.5797, 0.6979, 0.1717, 0.0766, 0.3407, 0.6692, 0.3953.

3.4. Results
In this paper, mean squared error (MSE), root mean squared error (RMSE) and mean absolute error (MAE) were used to compare the diagnostic effect. The smaller the distance, the closer the diagnosis result is to the actual situation, and the smaller the error, the better the diagnostic effect. The Euclidean distance and Manhattan distance were selected to analyse the error of the refrigeration fault diagnosis effect of the belief rule base with the training data, and the pre-optimization and post-optimization MSE, RMSE and MAE were obtained [10]. The diagnostic errors of the training data are shown in figure 2 and figure 3.

As can be seen from figure 5 and figure 6, overall, the optimized belief rule base distance is small, which means the diagnostic effect of training data is bettered. After calculation, the error comparison is shown in the following table:

| Diagnostic error | Before optimization | After optimization |
|------------------|---------------------|--------------------|
| RMSE             | 0.8515              | 0.6526             |
| MSE              | 0.7250              | 0.4259             |
| MAE              | 1.0803              | 0.6478             |

4. Conclusion
This paper proposes a fault diagnosis method of missile refrigeration system based on belief rule base. The initial belief rule base is established by using expert knowledge, the fault location is coded by one-hot code, and the initial belief rule base is optimized by historical fault data. The experimental results show that the method is feasible and can provide advice for the maintenance of airborne missile in the process of fault diagnosis.

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