Research on the Algorithm of Avionic Device Fault Diagnosis Based on Fuzzy Expert System

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Abstract

Based on the fuzzy expert system fault diagnosis theory, the knowledge base architecture and inference engine algorithm are put forward for avionic device fault diagnosis. The knowledge base is constructed by fault query network, of which the basic element is the test-diagnosis fault unit. Every underlying fault cause's membership degree is calculated using fuzzy product inference algorithm, and the fault answer best selection algorithm is developed, to which the deep knowledge is applied. Using some examples, the proposed algorithm is analyzed for its capability of synthesis diagnosis and its improvement compared to greater membership degree first principle.

Keywords: fuzzy expert system; fault query network; fault answer best selection algorithm; fuzzy theory; test-diagnosis fault unit

As one of the most promising research domains of artificial intelligence (AI), fuzzy theory has been widely studied in recent years. Fuzzy reasoning can simulate human thought based on both fuzzy theory and fuzzy characteristic of knowledge. Combined with fuzzy reasoning, the idea of employing expert system to fault diagnosis for complicated non-linear system has got extensive attention.

Recently some approaches have been proposed for fuzzy reasoning method and knowledge base architecture, both of which are important components of fuzzy expert system (FES). Nevertheless, it still needs further study to apply FES to avionic device fault diagnosis (ADFD). Every fault cause’s membership degree was obtained by the fuzzy relationship matrix in Refs.[1-2], wherein the requirements of strictness and locality cannot be meet for diagnosis rules. In Refs.[3-4], by calculating the rule’s match degree or certainty grade, those rules with higher priority were selected from knowledge base. Using this inference method, the information provided by those rules with lower priority will be lost. Additionally, due to the high self-learning ability of neural network (NN), it was utilized to construct the knowledge base for fault diagnosis in Refs.[5-6]. However, sometimes the NN loses the IF-THEN rules’ comprehensibility, interpretability and Human expert’s prior knowledge[7].

The aim of this paper is to design the fuzzy inference algorithm and the knowledge base that consists of comprehensible IF-THEN rules for ADFD, which usually comes with the following difficulties: the less test-point for every phase of fault diagnosis, the complex fault hierarchy and the large number of fault category et al. To achieve so, this paper designs the knowledge base constructed by fault query network (FQN), which combines the testing with the diagnosis. In order to meet the requirements of strictness of IF-THEN rules, the fuzzy product inference engine[8] is applied for fault reasoning. Additionally, the fault...
answer best selection algorithm (FABSA) is proposed to satisfy the fault pervasion[9], by means of which the fault diagnosis result depends on the information of all IF-THEN rules and all fault symptoms instead of the only one with higher priority or higher membership degree.

1 Fuzzy Expert System Architecture

Generally, the avionic device is comprised by so many of sub-systems, so that the physical and logic relationships between each other are too complicated to represent the avionic device by mathematical model for this goal of accurate fault diagnosis. Prior knowledge, however, can be largely got together from device operation and maintenance. As the “shallow knowledge”, most of them are cases or rules that are valuable for ADFD. The knowledge base is just composed of the basic element IF-THEN rule using “shallow knowledge” recorded in a pre-specified format or applying machine self-learning algorithm. Associated with the information provided by the knowledge base, FES can diagnose the avionic device corresponding to the symptom shown out by employing the fuzzy inference engine. That is, the knowledge base and fuzzy inference engine are the two important components of FES[10] as shown in Fig.1.

![Fig.1 The architecture of fault diagnosis fuzzy expert system.](image)

It should be noted that the modified CHC genetic algorithm[11] is used for knowledge self-learning of the FES in this literature. Prior to generating the rule prototypes from the diagnosis cases, those original cases should be classified. Then the practical diagnosis rules are obtained by optimization using the modified CHC genetic algorithm.

2 Fault Query Network

It is known that the testing task cannot be performed completely for ADFD in one single step of testing so that the fault cause cannot be specified according to the result of the single step of testing even though the operator of ADFD is domain expert. Thus, the fault diagnosis accuracy depends on a series of testing, analysis and reasoning, where the interaction between knowledge base and operator is far more frequent. That is, knowledge base should release the next testing task efficiently in order to attain the more effective symptom as the input of fuzzy inference engine. To do so, this paper designs the architecture of knowledge base: fault query network, which consists of test-diagnosis fault unit (TDFU)[12-13].

**Definition 1** TDFU consists of seven-element model \((N T A B R Q E)\), where

1. \(N\) is the symbol of a TDFU. As the unit address, \(N\) is used to orient the TDFU in FQN. Obviously, \(N\) and TDFU are one-to-one corresponding.
2. \(T\) represents the set of test-task to be released,
   \[ T = \{t_1, t_2, \ldots, t_n\} \]
3. \(A\) represents the set of all of the fault symptoms. Every element of \(A\) represents a standard fuzzy subset with corresponding \(T\),
   \[ A = \{a_1, a_2, \ldots, a_k\} \]
4. \(B\) represents the set of all of the diagnosis answers for a TDFU. Every element of \(B\) will be assumed as the address of the next TDFU if diagnosis needs another phase testing-diagnosis based on the current TDFU,
   \[ B = \{B_1, B_2, \ldots, B_j\} \]
5. \(R\) represents the set of IF-THEN rules. The confidence of every rule is denoted by \(CF\),
   \[ R = \{r_1, r_2, \ldots, r_m\} \]
(6) \( Q \) represents the set of the distances between every underlying fault cause and ideal fault answer. The greater the distance is obtained, the less possibility corresponding fault occurs,

\[
Q = \{ \Gamma_1, \Gamma_2, \ldots, \Gamma_j \}
\]

(7) \( E \) represents the inference function of current TDFU. It is carried out by product inference engine together with FABSA for every TDFU,

\[
E: A \times A \times \cdots \times A \times B \rightarrow Q
\]

Under Definition 1, the FQN consists of a number of TDFUs. As an example, a FQN with three of the max numbers of testing-diagnosis phase is shown in Fig.2, where \( \Gamma_{ij} \) represents the distance between the \( j \)th underlying fault cause and the ideal fault answer for the \( i \)th TDFU. The definition of \( \Gamma_{ij} \) is given in Section 3.2.

This paper will not completely describe a FQN for ADFD due to the complexity of avionic device. In order to describe how the FQN is constructed, an example of one TDFU of an airborne-radio is shown in Fig.3. After diagnosis reasoning in previous TDFU, the corresponding current TDFU is addressed for the current phase of testing-diagnosis. First, according to the testing task assigned by \( T \), the operator will perform the following three measurement indexes: whole-machine signal parameter, controller voltage for frequency switch turned on, and controller voltage for frequency switch turned off. Then, according to IF-THEN rules of \( R \) FES will combine \( E(\cdot) \) with FABSA to obtain the distances \( \{ \Gamma_{\text{Transceiver}}, \Gamma_{\text{Controller}} \} \) between every element of set \( B\{\text{Transceiver}, \ldots, \text{Controller}\} \) and ideal fault answer.

![Fig.2 The knowledge base of expert system.](image)

![Fig.3 A test-diagnosis fault unit for an airborne-radio.](image)

### 3 Fuzzy Reasoning Algorithm

Traditionally, the fuzzy relationship matrix was applied to represent the relationship between the vector of symptom and the vector of cause in fuzzy diagnosis\([14]\). The vector of cause is denoted by

\[
Y = \{ y_1, y_2, \ldots, y_n \}
\]

(1)

The vector of Symptom is denoted by

\[
X = \{ x_1, x_2, \ldots, x_n \}
\]

(2)

The matrix of fuzzy relationship matrix is denoted by\([14]\)

\[
R = \begin{bmatrix}
\tilde{r}_{11} & \tilde{r}_{12} & \cdots & \tilde{r}_{1n} \\
\tilde{r}_{21} & \tilde{r}_{22} & \cdots & \tilde{r}_{2n} \\
\vdots & \vdots & \ddots & \vdots \\
\tilde{r}_{m1} & \tilde{r}_{m2} & \cdots & \tilde{r}_{mn}
\end{bmatrix}
\]

(3)
The relationship between $X$ and $Y$ is represented as\cite{14}
\begin{equation}
Y = X \cdot R
\end{equation}

then\cite{8, 14}
\begin{equation}
y_j = \bigcup_{i=1}^{n} (x_i \cap r_{ij}) , j = 1, 2, \cdots, n
\end{equation}

The knowledge base is composed of IF-THEN rules, which construct the aforementioned FQN. Furthermore, the relationship among those rules with locality is fuzzy union. Hence, it is infeasible to apply fuzzy relationship matrix for ADFD. Assume that there is only one rule for the knowledge base, IF $A_1$ and $A_2$ and $A_3$, THEN $B_1$.

The membership degrees of $A_1$, $A_2$ and $A_3$ are 0, 0.5, and 0.6 respectively, which are attained via their membership functions. By using fuzzy relationship matrix and Eq.(5), the following inequation is derived:
\begin{equation}
\mu_b = \mu_{a_1 r_{11}} + \mu_{a_2 r_{21}} + \mu_{a_3 r_{31}} \geq 0
\end{equation}

Clearly, Eq.(6), by which $\mu_b$ is not always equal to zero when $\mu_{a_1} = 0$, is inconsistent with the locality of IF-THEN rules. To guarantee to meet the requirement for this characteristic feature of rules, this paper demonstrates that the modified product inference engine can be applied to the FES of ADFD in Section 3.1.

3.1 Product inference engine algorithm

Product inference engine has been successfully applied to various control system nowadays. The engine function\cite{8} is given by
\begin{equation}
\mu_{B'}(y) = \max_{x \in U}[\sup_{x \in U}(\mu_{A'}(x)\prod_{i=1}^{n} \mu_{A_i}(x_i)\mu_{B}(y))]
\end{equation}
where $n$ denotes the number of input dimension and $M$ denotes the number of IF-THEN rules in knowledge base. The IF-THEN rules have the following forms\cite{8}:

Rule $R_i$: IF $x_1$ is $A_{i_1}$ and ... and $x_n$ is $A_{i_n}$, THEN $y$ is $B_i$.

The relationship of fuzzy union among the IF-THEN rules of ADFD is satisfied by using the above-mentioned product inference engine. Besides, the mamdani product strategy applied to IF part ensures the IF-THEN rule’s locality insofar as the THEN part of a rule follows only if all conditions of the IF part are satisfied. As the input of inference engine, the testing-task assigned by TDFU is fuzzified by singleton-shape membership function\cite{8},
\begin{equation}
\mu_{A'}(x) = \begin{cases}
1 & x = x^* \\
0 & \text{otherwise}
\end{cases}
\end{equation}

The membership degree of every rule’s THEN part corresponding to an element of the set $B$ is equal to 1 if it is just the fault answer. Otherwise, the degree is equal to zero. The membership function\cite{8} is written as
\begin{equation}
\mu_{B}(y) = \begin{cases}
1 & y = y^* \\
0 & \text{otherwise}
\end{cases}
\end{equation}

The confidence of every rule denoted by $\mu_B$ is viewed as the rule degree, which represents the possibility that the THEN part happens given the occurrence of the condition of IF part. That is, the confidence can be considered as a product factor of the fault membership degree for Eq.(7). In that case, using Eqs.(8)-(9), Eq.(7) can be modified as\cite{8}
\begin{equation}
\mu_{B'}(y) = \prod_{i=1}^{n} \mu_{A_i}(x_i) \cdot \mu_{C_{F_i}} y = y_l (l = 1, 2, \cdots, M)
\end{equation}
where $\mu_{C_{F_i}}$ denotes the confidence of the $l$th rule.

In practice, every underlying fault answer, the element of set $B$, is discrete in the solution space. As shown in Eq.(10), the membership degree of any point not equal to one element of $B$ must be zero. That is, the final fault answer must be selected from the set $B$. Therefore, what Eq.(10) assesses is the membership value at which the element of set $B$ occurs actually.

3.2 Fault answer best selection algorithm

Several fuzzy diagnosis approaches have been discussed for selecting final fault answer from the set $B$. Most of them\cite{14} are based on the greater membership degree first principle, e.g., threshold value principle algorithm, max subordination principle algorithm, et al.
However, this paper aims at the fault diagnosis for avionic device composed of so many sub-systems, which have fault relevance as well as fault pervasion, that it is impossible to analyze them independently by each other. While two given sub-systems’ fault can be represented as two elements of set $B$ contained in TDFU, either one symptom may be caused by both of them or one sub-system fault that possibly causes another sub-system fault does not show remarkable symptom. That is, the diagnosis by the greater membership degree first principle is not comprehensible and complete because of the complicated relationship among the sub-systems of avionic device.

In fact, the membership values computed by Eq.(10) of the elements of set $B$, some of which may be greater than zero, can also interpret the sub-system fault’s dependency on each other. Traditional approaches, however, determine the fault cause that has greater membership degree. Either, re-reasoning and backward-reasoning are applied to further diagnosis after some of fault causes with less membership degree have been neglected. Hence, those methods using the greater membership degree first principle lost the information of symptom with less membership degree. This paper will introduce an approach that can make full use of all of the information of symptom. The following definitions$^{[15]}$ are given first:

**Definition 2** $d_{UV}$ denotes the relation alienation degree between sub-system $U$ and sub-system $V$ in system $B$. $d_{UV} \in (0,1)$, “0” represents that $U$ is the same to $V$ and “1” represents that $U$ and $V$ are inter-independent. Note that both $U$ and $V$ are viewed as the fault causes for ADFD.

**Definition 3** The ideal fault answer denoted by $I$ is the centroid fault answer$^{[15]}$ of all underlying fault causes in set $B$ which contains $U$ and $V$. It may be excluded by set $B$. The best fault answer denoted by $F$ is the nearest fault cause to the ideal fault answer.

**Definition 4** The distance between $U$ and $I$ is denoted by $\Gamma_U$ which can be determined from:

$$\Gamma_U = \frac{\sum_{i=1}^{M} \mu_{B_i}(x^*) \cdot d_{UI}}{\sum_{i=1}^{M} \mu_{B_i}(x^*)}$$  \hspace{1cm} (11)$$

where $M$ is the number of IF-THEN rules in set $R$. If there is no rule with duplicate consequent, $M$ will be equal to the number of underlying fault causes. Fig.4 shows the relationship among $B$, $I$, $U$ and $V$.

![Fig.4 The relationship of every fault in fault space.](image)

Since the ideal fault answer $I$ may be excluded by set $B$ according to Definition 3, it is unnecessary to obtain $I$ from set $B$. On the other hand, by using Eq.(11) the distance between any underlying fault cause and ideal fault answer can be computed. It will be used as the selection criterion of the best fault answer in this contribution.

The membership degree vector of set $B$ derived from Eq.(10) is normalized as follows

$\hat{\mu} = \{\hat{\mu}_{B_1}, \hat{\mu}_{B_2}, \cdots, \hat{\mu}_{B_M}\}$  \hspace{1cm} (12)

where

$$\hat{\mu}_{B_i} = \frac{\mu_{B_i}}{\sum_{j=1}^{M} \mu_{B_j}}$$  \hspace{1cm} (13)$$

The vector $Q$ aforementioned can be determined from Eq.(11),

$$Q = \{\Gamma_1, \Gamma_2, \cdots, \Gamma_M\} = \hat{\mu} \cdot D$$  \hspace{1cm} (14)$$

$$D = \begin{bmatrix}
    d_1 & d_2 & \cdots & d_M \\
    d_2 & d_2 & \cdots & d_2 \\
    \vdots & \vdots & \ddots & \vdots \\
    d_M & d_M & \cdots & d_M
\end{bmatrix}$$  \hspace{1cm} (15)$$

where $D$ denotes the matrix of relation alienation...
degree with \( d_{ij} = d_{ji} \) and \( d_{ij} = 0 \). As the deep knowledge, \( D \) can be provided by domain experts.

The possibility of fault cause increases and underlying testing cost decreases as the element of set \( B \) gets closer to the ideal fault answer. Definition 4 and Eq.(14) show how every underlying fault cause’s membership degree can alter the value of \( \Gamma_U \). In other words, this approach takes into account all of the membership degrees of every element of set \( B \) to ensure the completeness of fault symptom information.

4 Example Analysis

In this section, an example of knowledge base for ADFD of a helicopter will be introduced to jointly diagnosis reasoning by product inference engine and the fault answer best selection algorithm.

The diagnosis involves starting from one TDFU’s set \( R \) that consists of prior knowledge either provided by domain experts or derived by any self-learning method.

\[ R_1: \text{If } x_1 \text{(receiver audio output)} = A_{3,1} \text{ and } x_4 \text{(transmitter transmission power)} = A_{3,4}, \text{ then } y \text{ is } B_1 \text{ (receiver low frequency amplifier fault)} \] with \( \mu_{C_1} (0.7) \);

\[ R_2: \text{If } x_2 \text{(sensitivity)} = A_{3,2} \text{ and } x_4 \text{(transmitter transmission power)} = A_{3,4}, \text{ then } y \text{ is } B_2 \text{ (receiver high frequency amplifier fault)} \] with \( \mu_{C_2} (0.7) \);

\[ R_3: \text{If } x_3 \text{(receiver output value range)} = A_{3,3} \text{ and } x_4 \text{(transmitter transmission power)} = A_{3,4}, \text{ then } y \text{ is } B_3 \text{ (receiver automatic gain control circuit fault)} \] with \( \mu_{C_3} (0.5) \);

\[ R_4: \text{If } x_1 \text{(receiver audio output)} = A_{3,1} \text{ and } x_2 \text{(sensitivity)} = A_{3,2} \text{ and } x_4 \text{(transmitter transmission power)} = A_{3,4}, \text{ then } y \text{ is } B_4 \text{ (transmitting channel fault)} \] with \( \mu_{C_4} (0.8) \), where \( x_i \) denotes the measurement of \( t_i \) with \( t_i \in T \) , and \( T \) contains the following elements:

- receiver audio output,
- sensitivity,
- receiver output value range,
- transmitter transmission power;

\( A_{ij} \) denotes the fuzzy subset corresponding to the \( i \)th measurement index for the \( j \)th rule with \( A_{ij} \in A \); \( y \) denotes the final fault answer of current TDFU; \( B_i \) denotes the underlying fault cause with \( B_i \in B \), and \( B \) contains the following elements:

- receiver low frequency amplifier fault,
- receiver high frequency amplifier fault,
- receiver automatic gain control circuit fault,
- transmitting channel fault;

and \( \mu_{C_i} \) denote the confidence of the \( i \)th rule of \( R \) with 0.7, 0.7, 0.5, and 0.8 respectively.

Depending on the measurement values of every index and the membership functions of every element of set \( A \), the normalized membership degree vector \( \bar{B} \) of fault answer can be computed by Eq.(10),

\[ \bar{B} = \{ \bar{\mu}_{B_1}, \bar{\mu}_{B_2}, \bar{\mu}_{B_3}, \bar{\mu}_{B_4} \} = \{ 0.5, 0.2, 0.3, 0 \} \] (16)

By putting Eq.(16) into Eq.(14), the vector \( Q \) can be obtained,

\[ Q = \bar{B} \cdot D = \{ 0.26, 0.08, 0.42, 0.42 \} \] (17)

where

\[ D = \begin{bmatrix} 0 & 0.1 & 0.8 & 0.6 \\ 0.1 & 0 & 0.1 & 0.3 \\ 0.8 & 0.1 & 0 & 0.2 \\ 0.6 & 0.3 & 0.2 & 0 \end{bmatrix} \] (18)

It follows from Eqs.(16) and (17) that while \( B_1 \) (receiver low frequency amplifier fault) with the maximal membership degree has the most remarkable fault symptom, the \( \Gamma' \) of \( B_2 \) (receiver high frequency amplifier fault) is the smallest in the set \( B \). This means that other fault with remarkable symptom may be caused by \( B_2 \) though \( B_2 \) has not remarkable symptom. This case can be interpreted by matrix \( D \) with \( d_{31} = d_{33} = 0.1 \) and \( d_{34} = 0.3 \), from which \( B_2 \) is more active in set \( B \) and has tight relativity with other elements. Consequently, the operator should pay more attention to \( B_2 \) in order to improve the diagnosis efficiency and decrease the testing cost.

In addition, the vector \( Q \) can be computed by Eq.(19) in the case that the elements of \( B \) are homogeneous absolutely,

\[ Q = \bar{B} \cdot D = \{ 0.25, 0.4, 0.35, 0.5 \} \] (19)
where
\[
D = \begin{bmatrix}
0 & 0.5 & 0.5 & 0.5 \\
0.5 & 0 & 0.5 & 0.5 \\
0.5 & 0.5 & 0 & 0.5 \\
0.5 & 0.5 & 0.5 & 0
\end{bmatrix}
\]  
(20)

Observe that the ascending order of the elements of \( Q \) is consistent with the descending order of the membership degree of elements of set \( B \). Therefore, this method in this contribution can induce the same diagnosis result with those of approaches based on greater membership degree first principle when the elements of \( B \) are homogeneous absolutely.

5 Conclusions

This paper proposes the architecture of knowledge base and fuzzy inference algorithm to satisfy the characteristic features of ADFD. The knowledge base is constructed by FQN, which consists of TDFU defined as a seven-element model. Associated with the modified product inference engine, the fault answer best selection Algorithm designed in this paper can extract the optimal fault answer by the matrix of relation alienation degree. The completeness of this approach for ADFD mainly lies in the consideration of the shallow knowledge and deep knowledge as well as the membership degree of every fault cause. The example shows that besides the completeness and accuracy for ADFD, this method has compatibility with traditional approaches applied by greater membership degree first principle.

References


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