One Fusion Approach of Fault Diagnosis Based on Rough Set Theory and Dezert-Smarandache Theory

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Abstract. There are the advantage of Rough Sets Theory and evidence theory for processing uncertain information, and one fusion approach of fault diagnosis based on the Rough Sets Theory and Dezert-Smarandache Theory. Firstly the abundant condition attribution was reduced through Rough Sets Theory, then evidence combining results of each reduced result were calculated through the basic probability assignment and normalized attribution significance. The diagnosis results were combined by DSmT combining equation. Finally the above method was applied to some equipment diagnosis to verify its effectiveness.

Introduction

The equipment fault diagnosis is important for equipment comprehensive support so the suited fault diagnosis methods research aiming at the equipment characteristic is very necessary. Generally, the equipment diagnosis information is uncertain, incorrect and incomplete, so the fault diagnosis is a uncertain reasoning and decision processing actually [1].

Rough Sets Theory has the advantage of processing uncertain, incorrect and incomplete data, and evidence theory is an effective uncertain reasoning method, so fusion research based on these two methods is more effective and correct for fault diagnosis. Relative to Dempster-Shafer Theory, Dezert-Smarandache Theory (DSmT) is a new evidence theory in 1992, which can express and process the uncertain and conflict information better and combine uncertain, high conflict and incorrect evidence resource expressed by belief function.

Rough Sets Theory

In 1982, Rough Sets Theory is proposed by Polish mathematician Z. Pawlak[2]. Rough Sets Theory is defined in the upper approximation set and lower approximation. Suppose U is the domain and R is the equivalence relation of U, P=(U,R) is named as Pawlak approximation space. $\forall X \subseteq U$,

$$\underline{R}(X)=\{x\in U \mid [x]_R \subseteq X\}=\bigcup\{[x]_R \mid [x]_R \subseteq X\} \tag{1}$$

$$\overline{R}(X)=\{x\in U \mid [x]_R \bigcap X \neq \Phi\}=\bigcup\{[x]_R \mid [x]_R \bigcap X \neq \Phi\} \tag{2}$$

as the upper approximation set and lower approximation of X to the approximation space (U,R), in which, $BN_R(X)=\overline{R}(X)-\underline{R}(X)$ is R boundary region of X, $POS_R(X)=\underline{R}(X)$ is R positive region of X, $NEG_R(X)=U-\overline{R}(X)$ is R negative region of X.

In Rough Sets Theory, the quad system $S=(U,A,V,f)$ is a knowledge representation system, in which U is the domain, A is attribute set, $V=\bigcup_{\alpha\in A} V_\alpha$, and V_α is the range of the property α. $f: U\times A \rightarrow V$ is an information function, it gives each attribute of each object an information value [3]. $M_{n\times n}$ is defined as relative core combined with all simple attribution,

$$CORE_C(D)=\{\alpha \mid (\alpha\in C)\wedge(\exists c_{ij},((c_{ij}\in M_{n\times n})\wedge(c_{ij}=\{\alpha\})))\} \tag{3}$$

The dependence degree between condition attribution C and decision attribution D is defined as

$$\gamma(C,D)=\frac{card[pos_C(D)]}{card(U)} \tag{4}$$

In which, $pos_C(D)=\bigcup_{X\in U/D}\underline{C}(X)$ is positive region of D in $IND(C)$, $card(\bullet)$ is the set cardinality. The attribution importance degree is defined as $SGF(a,R,D)=\gamma(R\bigcup\{a\},D)-\gamma(R,D)$.

DSmT

In 1967, Dempster proposed the evidence theory, then Shafer expanded and developed it, so the evidence theory is also called D-S Theory.In 2002, Dezert and Smarandache proposed DSmT[4-5].

Define a basic When the basic probability assignment function $m: D^U \to [0,1]$ is relative with the given evidence resource, that is

$$m(\phi)=0,\ \sum_{A\in D^U} m(A)=1 \tag{5}$$

Suppose there are the two independent, uncertain and high conflict resource B_1 and B_2 in the same identification framework and the two general basic probability assignment function $m_1(\bullet)$ and $m_2(\bullet)$, and the DSmT combining rules $m_{M^f}(\bullet)\equiv m(\bullet)\stackrel{\Delta}{=}[m_1\oplus m_2](\bullet)$ is defined as:

$$\forall A\neq\phi\in D^U \quad m_{M^f(U)}(f)\stackrel{\Delta}{=}[m_1\oplus m_2](A)=\sum_{\substack{X_1,\cdots X_k\in D^U\\(X_1\cap\cdots\cap X_k)=A}}\prod_{i=1}^{k} m_i(X_i) \text{ in which, } m_{M^f(U)}(\phi)=0 \tag{6}$$

Fusion Fault Diagnosis Model

The paper fusion the Rough Sets Theory and DSmT for fault diagnosis, firstly the uncertain and incomplete test data is preprocessed and condition attribution reduction and attribution value reduction to get the reduced decision table. Then, the basic probability assignment is calculated and the reduced condition attribution significance is calculated and normalized to get the evidence reasoning results. Finally, the evidence reasoning results are applied the DSmT combine rules to get the fault diagnosis results.The detail fault diagnosis process can see Fig.1.

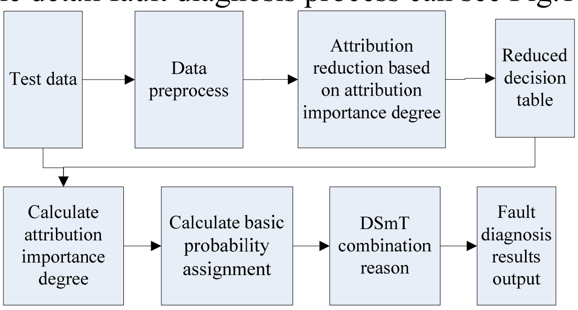

Fig.1 Fusion Fault Diagnosis process

Application Example

The paper discusses some airborne radio equipment fault diagnosis, the test data is extracted as fault examples and the above method is applied to get the diagnosis results. Table1 gives the test data of the familiar fault phenomenon "airborne radio", in which the fault symptom is expressed attribution reduction C= {+5V voltage C_1, UUT receiver voltage C_2, UUT receiver power C_3, UUT sender voltage C_4, UUT sender voltage C_5, 1553B bus C_6}, the decision attribution D= {d_1, d_2, d_3}, "d_1"is fault synchronous module, "d_2" is fault front panel module, "d_3" is fault master control microcomputer module. The 8 times test fault data is extracted in Table1, in which the data from the 1st time to the 6th time is diagnosis sample, the 7th time data is the normal sample, the 8th time data is the verified sample. Through the equipment normal work interval, the above data can discretizated and the original decision table is gotten.

Table1 fault samples and original decision table

	C_1		C_2		C_3		C_4		C_5		C_6		D
(1)	5.1	1	27.5	1	25	0	22.5	0	120	0	50	0	d_1
(2)	5.0	1	28.0	1	35	0	27.5	1	180	0	35	0	d_1
(3)	5.25	2	22.5	0	15	0	28.5	1	500	2	30	0	d_2
(4)	4.85	0	30.5	2	35	0	28.5	1	250	1	110	2	d_2
(5)	5.0	1	26.5	1	100	2	25.0	0	170	0	210	2	d_3
(6)	4.7	0	23.0	0	20	0	27.0	1	120	0	220	2	d_3
(7)	0	0	0	0	0	0	0	0	0	0	0	0	normal
(8)	5.2	2	24.5	0	70	1	27.5	1	110	0	20	0	d_2

Calculate the discernibility matrix of the previous 6 time test samples, and the relative *core*={C_4,C_6}. In the discernibility matrix, the all including core sets is extracted, it is found that the sets also contain the condition attribution "C_1", "C_2", "C_3" and "C_5". Then, calculate the appearing their times through the attribution importance degree algorithm, we can get the relative reduction RED_1={C_1,C_4,C_6}和RED_2={C_2,C_4,C_6}and the reduced decision table is Table2.

Table2 the reduction table

No.	RED_1			RED_2			D
	C_1	C_4	C_6	C_2	C_4	C_6	
(1)	1	0	0	1	0	0	d_1
(2)	1	1	0	1	1	0	d_1
(3)	2	1	0	0	1	0	d_2
(4)	0	1	2	2	1	2	d_2
(5)	1	0	2	1	0	2	d_3
(6)	0	1	1	0	1	2	d_3
(7)	0	0	0	0	0	0	normal

Then, take C_1,C_4,C_6 or C_2,C_4,C_6 as r_1,r_2,r_3 or R_1,R_2,R_3 to combine the evidence r or R, and take d_1,d_2,$d_3$and normal as frame of discernment $\Theta1, \Theta2, \Theta3, \Theta4$ .The basic probability assignment of RED_1={C_1,C_4,C_6} is gotten as Table 3.

Table3 the basic probability assignment

	Θ1	Θ2	Θ3	Θ4
r_1	0	1	0	0
r_2	0.25	0.5	0.25	0
r_3	0.5	0.25	0	0.25

Calculate the attribution importance degree of RED_1={C_1,C_4,C_6}relative to D, we can get $SGF(C_1,D)$=2/7, $SGF(C_4,D)$=2/7, $SGF(C_6,D)$=4/7, then normalize the attribution importance degree to get the basic probability assignment λ_1=0.25, λ_2=0.25, λ_3=0.5, the evidence combined results can be gotten as Table4. Use the same way the RED_2={C_2,C_4,C_6} combined results is gotten as Table4.

Table4 RED_1 and RED_2combined results

	Θ1	Θ2	Θ3	Θ4
r	0.3125	0.25	0.0625	0.125
R	0.214	0.357	0..214	0.214

DSmT combined rules are applied to calculate the Table4 results, and the results are in Table6.

Table6 DSmT combined results

	d_1	d_2	d_3	$d_1 \cap d_2$	$d_1 \cap d_3$	$d_2 \cap d_3$	*normal*
r+R	0.16	0.19	0.053	0.17	0.076	0.067	0.027

Through contrasting the fault diagnosis results, it is likely to be "d_2" , and it is accordance with the real test result. So the above method is valid.

Summary

The paper gives one fusion method based on Rough Sets Theory and DSmT, which has some processing advantage of uncertain information. The application example verified its validity. It providers the new approach of the information fusion methods for equipment fault diagnosis.

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