Rough set models study on the fault knowledge acquisition for rotating water flooding units

WANG Hong-jun, Xu Xiao-li, and HAN Qiu-shi, Mechanical & Electrical Engineering Institute, Beijing Information Science & Technology University, Beijing 100192, China

Abstract: This paper researches the method that applies rough sets to fault diagnosis and performs the knowledge rule acquisition. It gives the method of attribute reduction and rule reduction for incomplete fault diagnosis system knowledge, uses discernibility matrix theory, and build rule confidence and coverage functions to evaluate the rules. It is applied to rule acquisition of the rotor fault diagnosis for the rotating water flooding units. There are 11 conditions of judgment in the original decision system. In the case of same decision classification, the system is reduced to 5 conditions of judgment. It uses new decision attribute to build the decision table of water flooding units, gets the rules for fault diagnosis, and verifies its effectiveness.

Keyword: Fault Diagnosis; Rule Acquisition; Rough Sets (RS) Theory

0 Introduction

When you perform fault diagnosis, there are a lot of actual experiences that can be applied, but the redundancy or loss of the symptom existed in these experiences affects the accuracy of fault diagnosis. Its rule acquisition is one of its bottlenecks. The diagnosis methods based on intelligent and knowledge such as fuzzy theory, neural network, expert system and pattern recognition, as well as fuzzy membership functions shall be determined factitiously. The problems such as difficulty in the knowledge acquisition of expert system, lack of samples training of neural network limit the applications of these methods. The redundancy, contradiction and uncertainty existed in the fault symptoms affect the generation of diagnosis rules, and go against actual applications of the knowledge. Rough set theory is capable of analyzing and treating various incomplete data such as inaccuracy, inconsistence and imperfection, finding out connotative knowledge, and opening out potential rules [1-3]. This paper researches the reduction methods of incomplete fault information system based on the rough sets and methods of rule knowledge acquisition.

1 The reduction of incomplete fault information system based on the rough sets

Classical rough sets is defined by lower and upper approximates (R* X and $R^{*}X$) of set X about rough sets of R. Decision table is special and important knowledge representation system. The rows of decision table are corresponded to the objects to be researched, and the columns are corresponded to the attributes of the objects. The information of objects is expressed by the attribute values of specified object. One attribute is corresponded to one equivalence relation. One table can be considered as defined one group of equivalence relation, i.e. knowledge base. One knowledge representation system to be processed by rough sets is expressed as $S=(U,A,V,f)$

Where S - knowledge representation system

U - non-null finite set of domain

A - attribute set, $A=C\cup D, C\cap D\neq\varnothing$

C - condition attribute sets

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First Author brief： Ms. WANG Hong-jun, born in 1966, Doctor, Professor. She focuses on the research on the advanced manufacturing technologies, fault diagnosis of Mechanical & Electrical systems and tendency prediction technologies. Second Author: Mr. Xu Xiao-li, born in 1951, Doctor, Professor, Doctor Advisor. He focuses on the research on the conditions monitoring of Mechanical & Electrical systems.

D -decision attribute sets

V -attribute range, $V = \cup_{a \in A} V_a$

f -information function, the value of every object x in the designated U under the attribute a.

In the fault diagnosis, C and D are called as symptom and decision attribute sets of faults respectively. In the fault diagnosis decision table, every example in the fault status domain is considered to be corresponded to one decision rule. The condition part of rules is determined by fault symptom attribute and its value, and the conclusion part of rules is determined by decision attribute and its value. For the rules in the table, not all of fault symptom attributes used in describing it are necessary. Some of them are redundant. The existence of redundancy symptom directly affects matching capacity when the decision rules are applied. Belong to incomplete information system. Fault diagnosis knowledge acquisition based on rough sets includes the steps such as building decision table, attribute reduction, attribute value reduction and rule reduction.

Let DT= (U, V, A) is fault diagnosis decision table, $U = \{x_1, x_2, ..., x_n\}$; A is attribute set, A=C∪D, C is condition attribute set, and D is decision attribute set; V=$\cup_{a \in A}$ **V** is attribute range, Va is attribute a range; $f : U \times A \rightarrow V$ is 一 information function, it designates the values of every object x in the U under the attribute a. For any $a \in A, x \in U, 有 f(x,a) \in V_a$. $a(x_i)$ is the value of sample individual on the fault symptom attribute a, D(x_i) is the value of sample individual on the fault decision attribute set. The discernibility matrix of DT is:

$$M(DT) = [c_{ij}]_{n \times n} = \begin{cases} \{a \in C : a(x_i) \neq a(x_j)\}, D(x_i) \neq D(x_j) \\ 0, D(x_i) = D(x_j) \\ \Phi, \forall a \in C, a(x_i) = a(x_j), D(x_i) \neq D(x_j) \end{cases} \quad (1)$$

According to the definition of discernibility matrix, when fault symptom attribute values of two samples are different, and can be differentiated with different values of some symptom attributes, the values of discernbility matrix elements corresponding to them are different symptom attribute sets of both symptom attribute values, that is, symptom attribute sets of both examples can be differentiated; when fault decision attribute values of two examples is the same, values of their corresponding discernibility matrix element is 0; when there is inconsistence between two samples (that is, the values of the attribute are the same, but the values of decision attribute are different), the values of corresponding elements is Φ.

With discernibility matrix, you can easily solve the reduction and core of attribute set A. Its discernibility function is $f_{M(S)}$, it is boolean function of m elements of variable $a_1, a_2, ..., a_m (a_i \in A, i = 1,2,...,m)$, it is the conjunctive of $\wedge c_{ij}$, and $\vee c_{ij}$ is the disjunctive of elements in the matrix term c_{ij}, $1 \leq j < i \leq n$, and $c_{ij} \neq \Phi$.

The core corresponding to discernibility matrix can be defined as matrix term set having one element in the discernibility matrix, which is

$$CORE(A) = \{a \in A : c_{ij} = (a)\} \quad (2)$$

Definition: For incomplete decision system $S = (U, C \cup \{d\}$, generalized decision function is defined as:

$$f_B\ (x) = \{d(y) \mid y \in S_B(x), B \subseteq C\} \quad (3)$$

Definition: If $C' \subseteq C$, $\forall B \subseteq C'$, if $f_{C'} = f_C$, $f_B \neq f_C$, C' is called as relative reduction of the S of incomplete decision system. One decision system can exist in more reductions.

To calculate the reduction of incomplete decision system, relative discernibility functions among the object $(x,y)\in U$ of decision system $S=(U,C\cup\{d\}$ are defined as:

$\Delta_C\ (x,y)=\{c \mid c\in C, d(y)\notin f_C(x),(x,y)\notin SIM(\{c\})\}$

Discernibility function of object x: $\Delta(x)=\bigwedge_{y\in\{z\in U \mid d(z)\notin f_C(x)\}} \vee\Delta_C(x,y)$

Discernibility function of decision system:

$$\Delta=\bigwedge_{(x,y)\in U\times\{z\in U \mid d(z)\notin f_C(x)\}} \vee\Delta_C(x,y)$$

Discernibility functionΔ of decision system can be converted into disjunctive normal form through the calculations, $\Delta=\bigwedge_{1\le i\le k}\vee\tau_i$

Where, k is the number of conjunctive sub normal form, $\tau_i\in 2^C$ and $\vee\tau_i$ are one conjunctive sub normal form of Δ. Then condition attribute reduction of decision system forms set $RED(C)=\{\tau_i \mid 1\le i\le k\}$, calculation method for condition attribute reduction of incomplete decision system can be obtained. The discernibility function of decision system is converted into disjunctive normal form, condition attributes in the each conjunctive sub normal form constitute one reduction of decision system.

After performing condition attribute reduction, the decision table can be reduced further by the reduction of the condition attribute values.

On the basis of the reduction of condition attribute and condition attribute value, rule reduction of decision table shall be performed. If decision table $DT=(U,C,D,V,f)$, $G\subseteq C\cup D$. Define $\wedge G=g_1\wedge g_2\wedge g_3\wedge\cdots\wedge g_i\wedge\cdots,其中 g_i\in G_x$ (其中 of which)

For any $x\in U$, G_x is the reduction of x's condition attribute value, and the rule belonging to x is : $\wedge(G_x)\to\wedge(D_x)$.

If decision table $DT=(U,C,D,V,f)$, for any $x\in U$, the sets of all rules about x are defined as $Rule\ (x)$. For any $X\subseteq U$, Definition: $Rule\ (X)=\bigcup\{Rule\ (x) : x\in X\}$

If $RD\subseteq Rule(U)$, for any $x\in U$, $RD\cap Rule(x)\neq\Phi$, and for any $RD'\subseteq RD$, $RD'\cap Rule(x)\neq\Phi$ is ineffective, RD is called as rule reduction of decision table.

2 Evaluation of diagnosis rules

Because inconsistent fault examples are possibly contained in the fault diagnosis decision table, and the performances of diagnosis rules are different, the decision rules after the reduction are measured and evaluated properly using the confidences of rules as evaluation indicator. If $\{rule_1, rule_2,\cdots, rule_n\}$ is a generalized decision rules set, every $rule_i$ determines one sequence $c_1(rule_i), c_2(rule_i),\cdots, c_n(rule_i), d_1(rule_i), d_2(rule_i),\cdots d_m(rule_i)$, where $C'=\{c_1,c_2,\cdots,c_n\}$ is subset of decision table condition attribute set, D={d} is decision attribute. The confidence of rules is expressed using the value of rough membership function:

$$\alpha(rule_i)=\frac{card\ (C'(rule_i)\bigcap D(rule_i)))}{card\ (C'(rule_i))} \quad (4)$$

$card(C'(rule_i))\neq 0$, $card(C'(rule_i)\bigcap D(rule_i))$ expresses the number of examples meeting with condition attribute $C'(rule_i)$ and decision attribute $D(rule_i))$ of rule $rule_i$, and $card(C'(rule_i)$ expresses the number of examples meeting with condition attribute $C'(rule_i)$ of rule $rule_i$. Therefore, it reflects the reliability of rules.

If $\alpha(rule_i)=1$, rules are determinacy rules; while $0<\alpha(rule_i)<1$, rules are possibility rules. The greater confidence is, the greater the reliability of rules is. When rule acquisition has been implemented, identify determinacy decision rules and possibility decision rules using the confidence of rules, and perform rule combination. Introduce the coverage of decision rules to express the coverage of this decision rules in the same type decisions in the decision table. The coverage of rules is defined as:

$$\operatorname{cov}(rule_i)=\frac{card(C'(rule_i)\cap D(rule_i))}{card(D(rule_i))} \tag{5}$$

$card(D(rule_i))\neq 0$, $card(C'(rule_i)\cap D(rule_i))$ expresses the number of examples meeting with condition attribute $C'(rule_i)$ and decision attribute $D(rule_i))$ of rule $rule_i$, $card(D(rule_i)$ expresses the number of examples meeting with decision attribute $D(rule_i)$ of rules $rule_i$. It represents the proportion of the examples supporting the $rule_i$ and examples having the same decision part as the $rule_i$ in the whole decision table, and reflects the coverage of rules. Consider the confidence of rules and the coverage of rules. The decision rules containing inconsistent information can be measured properly to solve the problem that decision rules cannot be used resulting from inconsistent information. Obtained rules are stored into knowledge base for object-oriented intelligent fault diagnosis system, and become the criterion of fault diagnosis.

3. Knowledge acquisition of large rotating machinery based on the rough sets

According to the experiences and actual fault characteristics from the sites, build the decision table as shown in the table 1, where c1, c2, c3, … c9, c10, c11 are diagnosis symptom conditions: vibration dominant frequency, normal frequency, vibration stability, vibration direction, vibration change varying with rotary speed, phase characteristic, axes track, vibration change varying with the loads, vibration change varying with lubricating oil temperature, vibration change varying with the flow, vibration change varying with outlet pressure. The d is the conclusion of diagnosis decision, and d1, d2, …, d10 are corresponding to shaft bending, temporary bending, asymmetry, cracks, misalignment, damaged couplings, different supporting rigid of bearing, damaged radial bearings, loosed supporting, impact and friction fault etc. The vibration dominant frequency: 1 (2 × fundamental frequency), 2 (fundamental frequency and fractional harmonic), 3 (fundamental frequency, and secondary, third high-order harmonics as well as 1/ 2, 1/ 3, 1 /5 order harmonics); Normal frequency: 1 (2 × fundamental frequency), 2 (high-order harmonic), 3 (fundamental frequency); vibration stability: 1 (stable), and 2 (instable); vibration direction: 1 (radial, axial), 2 (radial; vibration change varying with rotary speed: 1 (no change), 2 (change); phase characteristic: 1 (stable), 2 (instable); axes track: 1 (ellipse), 2 (disorder); vibration changes varying with the loads, lubricating oil temperature, flow, and outlet pressure: 1 (no change), and 2 (change).

Table 1 Fault diagnosis decision table of large rotating machinery

u	c1	c2	c3	c4	c5	c6	c7	c8	c9	c10	c11	d
1	1	1	1	1	1	1	1	1	1	1	1	d1
2	1	1	2	1	1	1	1	1	2	1	1	d2
3	1	2	2	1	1	*	1	2	1	1	1	d3
4	1	1	2	2	1	*	*	1	2	1	1	d4
5	1	3	1	1	1	*	*	2	2	1	1	d5
6	1	4	1	1	1	2	*	2	2	1	1	d6
7	1	1	2	2	2	*	*	2	2	1	1	d7
8	1	2	2	2	2	2	*	1	2	*	1	d8
9	2	1	2	1	2	2	*	1	2	1	1	d9
10	3	5	2	2	2	*	*	*	2	*	1	d10

Using the discernibility matrix method of knowledge acquisition system based on rough sets, obtained discernibility function of diagnosis rules is:

$$(c_3 \vee c_9) \wedge (c_1 \vee c_5 \vee c_6) \wedge c_4 \wedge (c_5 \vee c_8) \wedge c_2 .$$

The discernibility function of the system is converted into disjunctive normal form, you can evaluate 6 reductions of the system:

$$\{c_2,c_3,c_4,c_5\},(c_2,c_4,c_5,c_9\},\{c_1,c_2,c_3,c_4,c_8\},\{c_1,c_2,c_4,c_8,c_9\},$$

$$\{c_2,c_3,c_4,c_6,c_8\},\{c_2,c_4,c_6,c_8,c_9\}$$

There are 11 conditions of judgment in the original decision system. When this incomplete decision system has been processed using rough set theory, system reductions are 4 to 5 conditions of judgment only in the case of the same decision type. Identify necessary key symptoms for fault diagnosis, and eliminate redundant conditions. The effect of the reduction shall be measured using attribute reduction rate:

$$E = (1 - \frac{card(C_O)}{card(C_F)}) \times 100\% ,$$

$card(C_O)$ is minimum number of obtained reduction symptom attribute, and $card(C_F)$ is the number of condition attributes in the original decision table. The attribute reduction rate represents the percentage of reduced attributes in the original decision table condition attributes, and reflects the amounts of redundancy information in the fault symptom attribute. It is seen that fault attribute reduction rate of large rotating machinery reaches about 80%.

Table 2 Fault diagnosis decision table of water flooding units

Fault samples

u	K	0.42f-C1	0.75f-C2	1f-C3	2f-C4	3f-C5	5f-C6	7f-C7	d	
X1	1	1	1	1	0	0	1	0	D1-油膜振荡	oil film oscillation
X2	3	1	1	1	0	0	0	0	D1	
X3	3	1	1	0	1	1	1	1	D1	
X3	1	1	1	0	0	1	0	0	D1	
X3	1	0	1	0	0	0	0	0	D1	
X6	1	0	0	1	1	1	1	0	D2-不平衡	unbalance
X7	1	0	0	1	0	1	0	0	D2	
X8	1	0	0	1	0	1	1	1	D2	
X9	2	0	0	1	0	0	0	0	D2	
X10	1	1	1	1	0	0	1	0	D2	
X11	2	1	1	1	0	0	0	0	D2	
X12	1	0	1	1	0	0	0	0	D2	
X13	1	0	0	0	1	1	1	0	D3-不对中	misalignment
X14	2	0	0	0	1	0	0	0	D3	
X15	1	0	0	1	1	1	1	0	D3	
X16	1	0	0	1	0	1	1	1	D3	
X17	3	1	1	0	1	1	1	1	D3	
X18	1	1	1	0	0	1	0	0	D3	
X19	1	0	0	1	1	0	0	0	联轴器故障	coupling failed
X20	1	1	0	0	0	0	0	0	D4-正常	

D4 - normal

In the actual applications, vibration signal analysis technology is popular. Select the reduction $\{c_2,c_3,c_4,c_5\}$ to build new decision system of water flooding units. According to fault characteristics of water flooding units, {c2} vibration dominant frequency is the basis for differentiating equipment vibration faults. The conditions and conditions c1 are combined and built into new decision system as shown in the table 2. After the reduction, obtained decision rules and its confidence and coverage as shown in table 3.

Table 3 The rules for fault diagnosis of water flooding units

NO.	Rules	Confidence	Coverage
DI-1	(c2,1), (c5,0)	0.625	0.56
D1-2	(c2,1),(c3,1)	0.50	0.44
DI-3	(c2,1), (c4,1)	0.50	0.33
DI-4	(c2,0), (c3,1) (c4,0)	0.50	0.10
D2-1	(c2,0), (c4,0) (c5,1)	0.66	0.22
D2-2	(c2,0) (c3,1) (c4,0)	0.80	0.57
D2-3	(c2,1), (c3,1)	0.66	0.44
D2-4	(c5,0) (c3,1)	0.54	0.66
D2-5	(c4,1) (c3,1)	0.33	0.10
D3-1	(c2,0), (c4,1)	0.25	0.22
D3-2	(c2,0), (c5,1) (c3,0)	1	0.10
D3-3	(c2,0), (c4,1)	0.66	0.44
D3-4	(c3,1)(c4,1)	0.33	0.11
D3-5	(c2,0), (c5,1) (c4,0)	0.25	0.10
D3-6	(c2,0) (c5,1) (c4,0)	0.50	0.10
D3-7	(c5,0) (c4,1)	0.66	0.22
D4	(c3,1) (c5,0) (c4,1)	1	1
D5	(c2,0), (c4,0) (c3,0)	1	1

From relative discernibility function of the rules, evaluate its corresponding reduction, finally determine relative reduction of diagnosis rules d1 to d10: $\{c_2,c_3\},(c_2,c_3,c_4,c_5\},\{c_2,c_4\},\{c_4,c_5\},\{c_2\},\{c_2\},\{c_2,c_4,c_5\},\{c_2,c_4\},\{c_2,c_4,c_5\},\{c_2\}$

Assume that there is/are one or more rule(s) in the obtained rules sets, and that the conclusion is consistent, obtained rules are directly stored in the knowledge base for object-oriented intelligent fault diagnosis system, and becomes the criterion of fault diagnosis. if more rules are obtained, and their conclusions are inconsistent, the rule having higher confidence and coverage shall be selected to become the criterion of fault diagnosis.

f the threshold of the confidence is set to >=0.3, coverage>=0.22, you can establish the following fault diagnosis rules base

The rules for unbalance fault: are

IF 0.75F=1 AND 1F=1, THEN D=D2 (unbalance). Confidence=0.66 Coverage=0.44

IF 1F=1, AND 3F=0, THEN D=D2 (unbalance). Confidence=0.54 Coverage=0.66

IF 0.75F=0 AND 2F=0 AND 3F=1 THEN D=D2 (unbalance). Confidence=0.66 Coverage=0.22

IF 0.75F=0 AND 1F=1 AND 2F=0 THEN D=D2 (unbalance). Confidence=0.80 Coverage=0.57

In the decision system built by system reduction, there is possibly redundant condition in the some diagnosis rules. If diagnosis rules and conditions of judgment are more, then the comparison and matching operation between fault symptom and conditions of judgment is complex. At this time, you can eliminate further redundant condition attributes depending on the relative reduction of the diagnosis rules; identify the key points of the faults. To reduce the signal processing process, you can select the reduction having minimum number of attribute in order to reduce the number of the sensors and costs.

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