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THE DESIGN OF PRECISION TEST TURNTABLE DIAGNOSIS SYSTEM BASED ON NEIGHBORHOOD ROUGH SETS

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ABSTRACT

A fault diagnosis system is designed for Precision Test Turntable (PTT) based on neighborhood rough sets. The fault diagnosis decision table is established, then on the base of the core and the easy gained attributes, the decision table is reduced by the forward greedy reduce algorithm. Finally, the logic rules are gained as the diagnosis rules. Neighborhood rough sets can compress sample space, and improves the efficiency of the diagnosis, and avoids information loss produced by the discretization of Pawlak rough sets as well. Based on the needs of the user, make the reduction contains the attributes which the user can easily get as much as possible. The results show that the method can detect the faults exactly, and it can improve the security and reliability of the PTT effectively.

Keywords: *Fault Diagnosis, Turntable, Neighborhood Rough Sets, Reduce*

1. INTRODUCTION

With the rapid development of high-tech field such as aerospace, astronautics, nuclear industry and robotics and all kinds of domestic applications, apparatus and control systems become more and more complicated, thus, an increasing demand for those systems needs to be safer and more reliable. The undetectable faults of the dynamic system can cause catastrophic aftermaths. Precision Test Turntable (PTT) has been widely used in defense technology of guidance for navigation allocation, satellite tracking and so on. PTT is the primary equipment for rating the inertial navigation systems and inertial devices. The performance of it can affect the testing precision, degree of belief and validity of simulation. There is an urgent need to solve how to detect the faults of the PTT. Fault detection and diagnosis technique provide a new way for improving the reliability and safety of those systems. Rough sets provide a new and effective way for the fault diagnosis.

Rough sets theory is a powerful mathematical tool proposed by Pawlak for dealing with inexact, uncertain or vague information, and a large number of studies have been focused on its development and applications. But rough sets based on equivalence relation cannot deal with numerical attributes directly. Lin proposed neighborhood rough sets in 1988. The neighborhood rough sets can deal with numerical attributes directly and without discrete. In this paper the neighborhood rough sets is used in fault diagnosis system of PTT. Experimental results show the diagnosis system can obtain ideal effect by setting the neighborhood model parameters appropriately.

2. THEORY OF NEIGHBORHOOD ROUGH SETS

Rough sets are based on equivalence and division. The discourse is divided into several disjoint subsets. It causes some samples that have the same characteristic but the different decision. And it is difficult to get exactly the same value of the sample to the classification described by numerical value. The neighborhood rough sets use neighborhood relation to substitute the equivalence, and it can make the samples which have the similar value and the same decisions.

Definition1. Let $NDT = <U, A, D>$ be a given neighborhood decision table. The dependence of the decision attributes D to the condition attributes B is $\gamma_B(D) = Card(\underline{N_B}D) / Card(U)$, and it can be marked as $B \Rightarrow \gamma D$.

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In neighborhood decision system $NDT = <U, A, D>$, let $a \in B \subseteq A$, if $\gamma_B(D) > \gamma_{B-a}(D)$, we define a is the necessary attribute in the B which relative to the classification decision D, else a is the unnecessary attribute. If $\forall a \in B$ are necessary attributes, then B is independent.

Definition.2 Let $NDT = <U, A, D>$ be a given neighborhood decision table and $B \subseteq A$, B is a reduction of A, if B satisfy the condition of below

Sufficient condition $\gamma_B(D) = \gamma_A(D)$

Necessary condition $\forall a \in B$, $\gamma_{B-a}(D) < \gamma_B(D)$

The first condition can ensure the positive region of B equal he positive region of A, so B can keep sufficient system information. The second condition can ensure every attribute is Necessary and there's no free attribute in B.

A greedy reduction algorithm based on user demand is proposed on the theory of neighborhood rough sets, and it will be applied to the fault diagnosis of PTT.

3. FAULT ANALYSIS OF PTT

PTT uses U-I-T structure, and use dual closed-loop control scheme of position loop and speed loop. PTT has high reliability, every component parts are subject to stringent checks. But the structure of PTT is complicated, and large numbers of component parts are used, therefore, it is inevitable in the future course of failure. The faults of PTT can be divided into five categories as follows: actuator faults, sensor failure, controller failure, mechanical failure and communication failure.

The fault expression of PTT is different, and is fuzzy. This state is the object of rough sets. A fault diagnosis system based on neighborhood rough sets is proposed. The describe characteristics of PPT have redundancy, and need to be eliminated. The reduction algorithm based on neighborhood rough sets is an effective method to eliminate the redundancy.

The decision table $S = (U, A)$ can be found based on the sketch of fault diagnosis for PTT and fault classification, which shown in Table.1. U is non-empty finite set of fault samples. $A = C \bigcup D$. C = {C1, C2, … , CM} is the condition attribute set include the fault characteristic vector of PTT. D= (D1, D2, …, DN) is decision attribute set include the decision vector of PTT that assume the PTT has N fault type class and the corresponding faults mode is $D_1, D_2, \cdots, D_N$.

The original fault diagnosis decision table includes many numerical values and many redundancy values. It cannot be used as a rule directly for fault diagnosis. The rough sets cannot deal with the numerical values directly. And the discretization will cause the loss of information. A neighborhood rough sets reduce algorithm based on user needs is proposed. It can avoid the information loss caused by discretization. The algorithm based on user need can make the reduction contains the easy access attributes.

Table 1 The original fault diagnosis decision table

U	C1	C2	…	Ci	…	CM	D
X1	C11	C21	…	Ci1	…	CM1	D1
…	…	…	…	…	…	…	…
Xj	C1j	C2j	…	Cij	…	CMj	Dj
…	…	…	…	…	…	…	…
XN	C1N	C2N	…	CiN	…	CMN	DN

4. REDUCE ALGORITHM BASED ON NEIGHBORHOOD ROUGH SETS

The main scheme of the reduction algorithm is to gain the core attributes of decision table, and gain the reduction of the decision table on the base of the core, so the redundant attributes are deleted. Attributes reduction and feature selection is one of most important applications in rough sets. It shows the dependency between the attributes and gets the

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important attributes, so it has important value no matter in theory analysis or in practice application.

The core is the attributes which will decrease the class information of the system for delete it.

Let $S=<U,A,D>$ be a given decision table and $a\in A$. The significance of a is defined as [8]:

$$SIG(a,A,D)=\frac{|POS_A(D)|}{|U|}-\frac{|POS_{A-\{a\}}(D)|}{|U|}$$

Let $NDT=<U,A,D>$ be a neighborhood decision system and $a\in A$. If $SIG(a,A,d)>0$, then $a\in CORE(DT)$ .So the core can be defined as $CORE(DT)=\{a\,|\,SIG(a,A,d)>0\}$.

With the definition and properties of the significance we can gain some theory as follows:

Theorem1. Let $NDT=<U,A,D>$ be a neighborhood decision table and $B\subseteq A$. If $\forall a'\in A-B$ satisfy $SIG(a',B,d)=0$, B is the reduction of A, and $\forall a\in CORE(DT)$ satisfy $a\in B$.

Proof: If $\forall a'\in A-B$ satisfy $SIG(a',B,d)=0$, then $a'\notin CORE(NT)$ and $\gamma_B(D)=\gamma_A(D)$. According to the definition 2, we can gain that B is a reduction of A. Let attribute $a\in A$ and a satisfy $SIG(a,A,D)>0$, then $\gamma_A(D)-\gamma_{A-\{a\}}(D)>0$. If delete a from A, the classification of the decision table will decrease. So $a\in B$ for $\forall a\in CORE(DT)$.

Based on the Occam's Razor, the theory of rough sets holds the reduction which has the minimum attributes is the best reduction. But the research of the Small Sample Size (SSS) problem shows that the complexity of classification machine does not depends on the dimension of practice; it depends on the VC dimension. The reduction which has the minimum attributes cannot keep that the gained classification has the minimum VC dimension [10]. We also find in practice that

In practice, we found the attribute reduction amount is not the less the better. Sometimes the smaller number of attributes increased decision-making rules. Some condition attributes are difficult to obtain, so the accessible condition attributes should be in the core. Based on this idea, we can get Theorem 2 and Theorem 3.

Theorem 2: Let $NDT=<U,A,D>$ be a neighborhood decision table and $E\subseteq A$. E is the set of attributes which can be easy gained in practice. $CORE(DT)$ is the core of A. So

$CORE(DT)-CORE(DT)\cap E$ is the core of $A-E$.

Proof: It can be easy proved by the definition of the core.

Theorem 3: Let $NDT=<U,A,D>$ be a neighborhood decision table. $B\subseteq A$ and B is the reduction of A. $E\subseteq A$ and E is the set of attributes which can be easy gained in practice. If $E\subseteq B$, then B is the better reduction of A in practice. If $E\not\subset B$, $B'=B\cup E$ still include all the classification information of A.

Proof: It can be easy proved by the definition of the reduction.

A greedy algorithm based on neighborhood rough sets can be gained according to theorem1to 3. First the core attributes must be found. Then attributes which can be easily gained in practice and will be added to the core in order to let the core satisfy the requirement of engineering practice.

Algorithm 1: Forward greedy reduce algorithm based on neighborhood rough sets

Input: $IS=<U,A,d>$, $A=C\cup D$. E is the attributes set that can easy gained in practice. Nei_value is the size of the neighborhood.

Output: Reduction B of decision table

1: $\varnothing\to CORE$, $E\to CORE$, $A=A-E$

2: For i=1 to size(C)

3: Calculate γ_{A-ai}

4: Calculate $SIG(a_i,A,d)$

5: If $SIG(a_i,A,d)>0$ $CORE\cup\{a_i\}\to CORE$

End if

6: End for

7: $CORE\to B$

8: Do

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9：For each $a \in C - B$, Calculate $SIG(a, B, d)$
End for

10 ： Select a_k that satisfy $SIG(a_k, B, D) = \max(SIG(a_i, B, D)$

11：$B \cup \{a_k\} \to B$

12：Until $\forall a_i$ ：$SIG(a_i, B, d) = 0$

13：Return B

In algorithm 1, new characters are added on the base of the core attributes. Repeated calculating can be avoided by this method. On the base of the core attributes and use the greedy search strategy, the max significance attributes were added in the chosen character subset until the significance of attributes will not be increased by adding any attributes. In step 11, there will not have the max significance require the new add attribute; if the stop rule in the search of Algorithm.1 is kept, it can ensure the character subset have the same sufficient system information with the raw data.

5. RESULTS ANALYSIS OF PTT FAULT DIAGNOSIS

The faults of PTT measure system include overvoltage of power-amplifier, under-voltage of power-amplifier, physical damage of inductosyn, physical damage of rotary transformer and no coupling. The original fault decision table can be found based on the historical measurement data shown in Table.2. There are 320 fault examples, 5 types of faults, 7 fault characteristic properties in Tab.2. And C5 is the more accessible attribute than others.

The original fault decision table shown in Table.2 is reduced by the greedy search algorithm based on neighborhood rough sets. The neighborhood size parameter Nei_value=0.01, additional attribute significance stop threshold is 0.1. Firstly C5 is added to the core by the attribute significance and accessible. Final reduce set is {C2, C4, C5, C7}.

Assume I1, I2, I3 are three neighborhood of condition attribute C2. J1, J2, J3 are three neighborhood of condition attribute C4. K1, K2, K3 are three neighborhood of condition attribute C5. L1, L2, L3 are three neighborhood of condition attribute C7.

Diagnostic decision rules can be established by the reduction fault diagnosis decision table and shown in Table.3.

Table 2 The fault diagnosis decision table

U	C_1	C_2	C_3	C_4	C_5	C_6	C_7	D
X_1	10.440	10.208	10.829	15.869	10.777	12.959	10.298	F_1
X_2	11.088	10.039	11.124	19.591	10.302	10.483	10.222	F_1
X_3	11.284	11.056	11.368	12.075	14.219	11.182	10.746	F_2
X_4	10.854	10.074	11.266	15.099	13.416	9.989	11.288	F_2
X_5	12.094	12.089	10.188	13.566	10.730	10.245	10.640	F_3
X_6	10.230	12.171	10.755	12.286	10.482	11.066	11.212	F_3
X_7	10.551	12.146	10.311	15.912	10.855	11.374	10.675	F_4
X_8	10.826	12.766	10.497	12.431	11.422	10.824	13.478	F_4
X_9	11.470	11.072	10.921	13.785	10.515	13.478	11.678	F_5
X_{10}	11.401	10.417	10.306	18.292	10.817	11.292	10.616	F_5
X_{11}	…	…	…	…	…	…	…	…

Table 3 Diagnostic decision rules

Rule	Description
Rule1	IF $C_2 \in \{I_2, I_3\}$ & $C_7 \in L_3$ Then D=F_4
Rule2	IF $C_2 \in I_1$ & $C_5 \in K_1$ & $C_7 \in \{L_2, L_3\}$ Then D=F_5
Rule3	IF $C_2 \in \{I_2, I_3\}$ & $C_4 \in J_1$ & $C_7 \in L_2$ Then D=F_3
Rule4	IF $C_2 \in \{I_2, I_3\}$ & $C_4 \in J_3$ Then D=F_4
Rule5	IF $C_4 \in J_3$ & $C_7 \in L_1$ Then D=F_1
Rule6	IF $C_5 \in \{K_2, K_3\}$ Then D=F2

When the samples are obtained, the neighborhood is calculated firstly, and then diagnosis the faults based on the if-then rules in Table.3. After 50 simulated fault test experiment, 48 times diagnosis the fault type of the PTT, the correct rate is 96%. Diagnostic error due to the

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samples is polluted by noise and the wrong neighborhood is obtained. The disadvantage of this method is unable to detect the weak pre-fault signals.

6. CONCLUSION

Neighborhood rough sets can reduce the samples effectively and not changing the original accuracy of classification. It compresses sample space, improves the efficiency of the diagnosis, and avoids information loss produced by the discrete of Pawlak rough sets. Based on the needs of the user, make the reduction contains the attributes which the user can easily get as much as possible. Through practical operation, the PTT with faults diagnosis system operated stable and possess high reliability. At present, the PTT has completed a number of real comprehensive test missions, and the proposed algorithm can be widely used.

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