Research on Knowledge Acquisition of Motorcycle Intelligent Design System Based on Rough Set

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Abstract. In the intelligent design of motorcycle, a large number of data in the simulation or physical experiment are almost not utilized to guide our design and make decision for the design, so rough set theory is introduced to the intelligent design of motorcycle. Then, aim at experimental data of the engine piston performance, rough set theory is used. An attribute reduction algorithm of decision table based on discernibility matrix and heuristic value reduction algorithm are adopted. Knowledge is extracted from the data of performance experiment of the engine piston, in order to enrich knowledge base in motorcycle intelligent design system.

Keywords: Motorcycle; intelligent design; rough set; attribute reduction; value reduction

1 Introduction

Simulation analysis and physical testing are adopted to carry out research on the machine performance, but most of these tools are only as a verification of design result and are the lack of guidance and decision-making for design; At the same time, the results of test and analysis are mostly shown in the charts, graphs, etc., and interpretation and evaluation of results are lacked, so that the guiding role of the test and analysis for design has not been fully realized. With the simulation analysis and experimental research carried out, and a large amount of raw data about performance are accumulated, how to quickly extract valuable knowledge of motorcycle performance evaluation from a mass of data for guiding designer is a very urgent and meaningful questions.

Based on the above requirements, for the motorcycle engine piston test data and simulation features, rough set method is introduced. Knowledge acquisition based rough set is proposed. Experts level domain knowledge can be accessed to through processing and extraction of results on test and simulation analysis.

There are two main ways in the knowledge acquisition: First is obtained from experts in the field of expertise, and the second is directly accessed from the text or database. Expert domain knowledge for knowledge acquisition is got by artificial methods, and it will be inputted directly into the knowledge base. To acquire knowledge from text has two ways: One is to extract directly concepts and relationships from the text automatically. However, a fully automated approach is not always effective, because the text is often ambiguous, irregular knowledge. Therefore, if the machine does not have a certain amount of "background knowledge", the realization of fully automated access is not realistic. The second way is semi-automatic method, which requires the necessary knowledge engineer intervention [1-5].

2 Rough Set Theory

Definition 1 A decision table is an information system $S=<U, R, V, f>$, $R=C\cup D$ is a set of properties, subset C and D are respectively called condition attributes set and the result attribute set, D $\neq\varnothing$. If the result attribute set $D=\{d_1,d_2,\ldots,d_n\}$, the decision table can be decomposed into n different single decision-making table$\{S_1,S_2,\ldots,S_n\}$, where $S_i=<U, R_i, V_i, f_i>$, U is the domain, $R_i=C\cup\{d_i\}$ is a set of properties, subset C and subset $\{d_i\}$are respectively called condition attributes set and the result attributes set, $V_i=\bigcup_{r\in R_i} V_r$ is the set of attribute values , V_r indicates attribute values range of the property $r\in R_i$, that is the range of attribute r, f_i: $U\times R_i\rightarrow V_i$ is an information function.

Definition 2 On the knowledge representation system $S=(U, A, V, f)$, $P\subseteq A$, the indiscernibility relationship of attribute sets P is $ind(P)=\{(X,Y)\in(U\times U)|\forall a\in P, f(x,a)=f(y,a)\}$. Indiscernibility relation ind (P) is the equivalence relation on U, all the equivalence classes is educed by ind (P), denoted by U / P, which constitutes a partition of the domain U.

Definition 3 Knowledge representation system $S=(U,CUD,V,f)$, $\forall a\in C$, if $POS_{ind(C)}(ind(D)) = Pos_{ind(c-\{a\})}(ind(D))$, a is called unnecessary in C on D, otherwise, and is known as necessary in C on D. $POS_{ind(C)}(ind(D))$ is the set of all objects that are correctly classified to the every equivalence class U / D, namely equivalence class on the positive region of $ind(C)$ is derived from $ind(D)$. If each attribute of C is necessary, C is independent to D.

Definition 4 knowledge representation system $S=(U, C\ U\ D, V, f)$, $B\subseteq C$, if $pos_{ind(B)}(ind(D)) = Pos_{ind(C)}(ind(D))$, and B is independent to D, B is called reduction with C relative to D, and is denoted $red_D(C)$. It should be noted that reduction of C is not the only. the intersection of all D reduction in C is D core of C, which is denoted by core D (C) = $\cap$redD (C) .

Definition 5 The decision table system $S=<U, R, V, f>$, $R=P\cup D$ is a set of attributes, the subset P = {ai | i = 1, ..., m} and D = {d}, respectively, is called the condition attribute set and decision attribute set, $U=\{x_1,x_2,\ldots,x_n\}$ is the domain, $a_i(x_j)$ is the value the property a_i in the sample x_j. $C_D(i, j)$ is the element of column i row j in the identification matrix, the identification matrix can be defined as follows:

$$C_D(i,j)=\begin{cases}\{a_k \mid a_k \in P \wedge a_k(x_i) \neq a_k(x_j)\}, d(x_i) \neq d(x_j) \\ 0, d(x_i) = d(x_j)\end{cases} \quad (1)$$

Where i, j = 1, ..., n.

2.1 Attribute Reduction Algorithm

Based on the concept of discernibility matrix of decision table , we can get the following attribute reduction algorithm through discernibility matrix and logical operation [5].

1) The discernibility matrix of decision table is calculated C_D;

2) The corresponding logic expressions L_{ij} is established by using C_{ij}(C_{ij}≠0 , C_{ij}≠∅) in the discernibility matrix.

$$L_{ij} = \underset{a_i \in C_{ij}}{V} a_i \quad (2)$$

3) When all the disjunction logical expression L_{ij} are conjunctive, CNF L can be got:

$$L = \underset{C_{ij}\neq 0, C_{ij}\neq\varnothing}{\wedge} L_{ij} \quad (3)$$

4) L is converted to disjunctive normal form:

$$L' = \underset{i}{\vee} L_i \quad (4)$$

5) Attribute reduction results output. Each conjunction entry of disjunctive normal form corresponds to attribute reduction result. The attributes that each conjunction item contains compose a set of condition attributes after being reduced.

Process can be seen from the above, disjunction logical expression L_{ij} created in step 2 of the algorithm is a lot, which will result in increasing the computational time when logical formulation is reduced. Therefore, certain measures need to be taken to further streamline the process of attribute reduction. It can be found through the discernibility matrix that, if there is a matrix element, its value is a collection of element containing a single attribute, it indicates that the necessary attribute is to distinguish between the matrix elements corresponding to two samples, and is the only distinction between the two sample properties. The collection of the attributes included these elements in discernibility matrix is actually the relative attribute nuclear of deciding-table system. So first of all, these attributes can be removed, but the value of the matrix element containing the nuclear attributes will be change to 0 to get a new matrix, and then in the new basis matrix, the algorithm 2,3,4 step can be implemented. Disjunctive logic expressions can be given. Finally the result of attribute reduction can be got through adding all the nuclear attributes to each conjunction item in disjunctive normal formal.

2.2 Value Reduction Algorithm of Decision Table

Through attribute reduction, the unnecessary attributes for decision-making in the decision tables can be omitted, then a simplified decision table can be achieved. This is beneficial to found the attributes that play role in decision-making classification. However, the attribute reduction is, to some extent, to remove the redundant attribute in the decision table, but not fully remove redundant information in the decision table. Therefore, the decision table needs to be further processed to be more streamlined decision-making table, i.e. reduction of decision table values.

Heuristic value reduction algorithm:

Input: Information system T (assuming the system has only one decision attribute)

Output: a value reduction T' of T.

1) The condition attributes of information table are inspected by column. If you remove the column, conflict of the records occurs, then keep the value of the property of conflict records; Otherwise, if there are duplicate records, the property value of duplicate records will be recorded as "*"; For other records, the property value is marked "?";

2) Possible duplicate records are deleted, and each record containing the mark "?" is examined. If the property value that is not marked can make decision, it will mark from"?" To "*"; Otherwise, it will mark from"?" to the original property value; if all the condition attributes of a record are mark, the mark "?" was changed to the original property value;

3) Remove record that all condition attributes are marked "*" , and possible duplication records after removing;

4) If only one condition attribute values between the two records are different, and the property of a record is marked as "*", then if the property value that is not mark can determine the decision-making for the record, then delete the other one record; Otherwise, delete the record.

After a new information table is obtained through the reduction, all the property values are the core of table, every record corresponds to a decision rule respectively.

3 Knowledge Acquisition of Engine Piston Performance Based on Rough Set

In the motorcycle intelligent design system, the knowledge acquisition will have access to expert experience, book knowledge processed and abstracted into knowledge base. By operation of the system ,the knowledge is constantly improved and modified. While the potential knowledge is identified and extracted from the large amount of simulation analysis and experimental test results, revealing the inherent law that the implicate in the data, so as to provide decision support for development and design, CAE technology and physical test are to achieve position from design verification to the design guidance and design decisions.

From the reference [6] section 6.3.1, study of orthogonal testing on piston performance shows that, orthogonal design method to ensure that the various levels of each factor mix respectively once in the test, so orthogonal table used is completely the indiscernibility relationship collection. Since rough set theory emphasize the indiscernibility relation between objects of the collection, in order to use rough set theory to acquire knowledge, combined with reference [6], Chapter 6, the forecasting method of neural network, the results of orthogonal test in the table 6.2 are extended analyze. Through random combination of multiple experimental conditions and the BP network [7], the prediction results are obtained in Table 1. At the same time equidistant partitioning algorithm is used, the test conditions and test results are processed, the results are shown in Table 2.

Table 1. Results of Piston Orthogonal Experimental Analysis & Results of BP Neural Network

No.	*A*	*B*	*C*	*D*	*E*	friction power /kw	power /kw	fuel consumption (g/kw.h)	Noise dB(A)
1	1	1	1	1	1	2.93	64.04	259.3	108.1
2	1	2	2	2	2	2.68	64.17	259.2	108.2
3	1	3	3	3	3	2.4	64.1	259.5	106.8
4	1	4	4	4	4	2.33	63.02	259.5	108.2
5	2	1	2	3	4	3.04	64.06	259.6	108.1
6	2	2	1	4	3	2.93	64.07	259.7	108.5
7	2	3	4	1	2	2.43	65.02	258.5	108
8	2	4	3	2	1	2.17	6.3.85	259.1	108.2
9	3	1	3	4	2	2.52	64.02	259.6	108.3

10	3	2	4	3	1	2.36	63.99	259.6	108.2
11	3	3	1	2	4	2.23	64.37	259	108.1
12	3	4	2	1	3	1.92	64.18	259.2	108.4
13	4	1	4	2	3	1.77	63.78	260.6	107.6
14	4	2	3	1	4	1.7	63.78	259.2	108.2
15	4	3	2	4	1	1.61	64.19	259.5	108.6
16	4	4	1	3	2	1.41	64.09	259.5	109.2
17	1	2	3	3	2	2.76	64.26	259.49	106.99
18	2	3	3	2	4	2.18	63.76	259	107.24
19	3	2	2	2	4	1.85	64.14	259.05	108.24
20	4	2	4	2	3	1.64	64.15	259.73	107.83
21	1	3	2	2	2	2.34	63.948	259.22	107.68
22	3	4	4	4	4	1.59	63.052	259.43	108.98
23	2	4	3	3	1	2.07	63.80	259.35	107.

Because there are five conditions property, set up materials piston skirt and cylinder liner clearance A, the domain is X = [10,140], the X is divided into 5 grades, ie X = {-2, -1,0,1 , 2}. Also set up the domain B of piston head and cylinder liner clearance, the domain is Y = [40,340], is divided into five grades, namely, Y = {-2, -1, 0, 1, 2}. Also set up the piston pin offset C , the domain Z = [0.05, 1.55], divided into 5 grades, ie Z = {-2, -1,0,1,2}. Set up the piston skirt length D, the domain W = [40, 61], is divided into five grades, namely, W = {-2, -1,0,1,2}. the domain of E liner surface roughness RMS is V = [0.1,9.10], divided into 5 grades, ie V = {-2, -1,0,1,2}, the domain of friction power F is U = [1.41,3.04], divided into five grades, namely U = {-2, -1,0,1,2}.

As can be seen from Table 1, there are four decision attribute in the table, belong to more decision-making. Therefore, according to the method described by definition 1, Table 1 is divided into four equivalent of a single decision table by the decision attribute, that is, the condition attributes of the four tables are identical, decision-making is not same. Namely, condition attributes such as the friction power, power, fuel consumption, noise, and the decision attribute for the friction power, this single decision table is shown in Table 2. Analysis shows that, when Table 1 is converted to four single decision tables, the table has not duplicate records in the condition attributes, so objects of a single decision-making table are still 23. The single decision table aiming to friction power is as an example that all data are analyzed and processed, and extracted the rule.

3.1 Attribute Reduction

When the decision attribute is "f = friction power", so that Q = decision attribute set = {f}, P = condition attribute set = {a, b, c, d, e}, then
$IND(P)=\{\{1\},\{2\},\{3\},\{4\},\{5\},\{6\},\{7\},\{8\},\{9\},\{10\},\{11\},\{12\},\{13\},\{14\},\{15\},\{16\},\{17\},\{18\},\{19\},\{20\},\{21\},\{22\},\{23\}\}$,
$IND(Q)=\{\{1,5,6,17\},\{2,3,7,9\},\{4,8,10,11,18,21,23\},\{12,13,19\},\{14,15,16,20,22\}\}$,
$POS_P(Q)=U$.

The domain U is consistent with P relative to Q, which shows that the decision table decision table is completely determined, the table does not contain inconsistent information.

Table 2. Decision Table System of Piston Performance

	Condition attribute					Decision attribute
U	Materials piston skirt and cylinder liner clearance *a*	piston head and liner clearance *b*	piston pin offset *c*	piston skirt length *d*	liner surface roughness RMS *e*	friction power f

1	-2	-2	-2	-2	-2	2
2	-2	-1	-1	-1	-1	1
3	-2	1	1	1	1	1
4	-2	2	2	2	2	0
5	-1	-2	-1	1	2	2
6	-1	-1	-2	2	1	2
7	-1	1	2	-2	-1	1
8	-1	2	1	-1	-2	0
9	1	-2	1	2	-1	1
10	1	-1	2	1	-2	0
11	1	1	-2	-1	2	0
12	1	2	-1	-2	1	-1
13	2	-2	2	-1	1	-1
14	2	-1	1	-2	2	-2
15	2	1	-1	2	-2	-2
16	2	2	-2	1	-1	-2
17	-2	-1	1	1	-1	2
18	-1	1	1	-1	2	0
19	1	-1	-1	-1	2	-1
20	2	-1	2	-1	1	-2
21	-2	1	-1	-1	-1	0
22	1	2	2	2	2	-2
23	-1	2	1	1	-2	0

$\mathrm{IND}(P\backslash\{a\})=\{\{1\},\{2\},\{3\},\{4,22\},\{5\},\{6\},\{7\},\{8\},\{9\},\{10\},\{11\},\{12\},\{13\},\{14\},\{15\},\{16\},\{17\},\{18\},\{19\},\{20\},\{21\},\{22\},\{23\}\}$

$\mathrm{POS}_{(P\backslash\{a\})}(Q)=\{1,2,3,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,23\}$

Similarly:

$\mathrm{POS}_{(P\backslash\{b\})}(Q)=\{1,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,22,23\}$

$\mathrm{POS}_{(P\backslash\{c\})}(Q)=U=\mathrm{POS}_P(Q)$

$\mathrm{POS}_{(P\backslash\{d\})}(Q)=U=\mathrm{POS}_P(Q)$

$\mathrm{POS}_{(P\backslash\{e\})}(Q)=U=\mathrm{POS}_P(Q)$

It can be seen that, attributes c, d, e may be omitted relatively to the decision attribute f, but it can not be omitted at same time. The properties a and b that are relative to the decision attribute f can not be deleted, so

$\mathrm{CORE}_Q(P)=\{a，b\}$

Table 3. Identification Matrix Revised by Core Attributes

0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	*cd*	0	0	0	0	0	0
		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	*cde*	0	0
			0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
				0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
					0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
						0	0	0	0	0	0	0	0	0	0	0	*cde*	0	0	0	0	0
							0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
								0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
									0	0	0	0	0	0	0	0	0	*cde*	0	0		0
										0	0	0	0	0	0	0	0	0	0	0	0	0
											0	0	0	0	0	0	0	0	0	0	*cde*	0
												0	0	0	0	0	0	0	0	0	0	0
													0	0	0	0	0	0	0	0	0	0
														0	0	0	0	0	0	0	0	0
															0	0	0	0	0	0	0	0
																0	0	0	0	0	0	0
																	0	0	0	0	0	0
																		0	0	0	0	0
																			0	0	0	0
																				0	0	0
																					0	0
																						0

The property c, d and e are the relative properties nuclear of the decision-making table. According to 2.1 section, attribute reduction algorithm based on discernibility matrix and logical operation, when discernibility matrix of decision-making table is calculated, these two properties can be removed first, while at the time the value of the elements that contains the nuclear attribute in the matrix will rewritten to 0 , then obtained a new matrix. New matrix of which elements are modified is showed in Table 3.

According to Table 3, CNF L can be got.

$$L=(c\vee d\vee e)\wedge(c\vee d) \qquad \textbf{(5)}$$

After simplification, disjunctive CNF L ' was obtained.

$$L'=c\vee d \qquad \textbf{(6)}$$

After the nuclear properties are added to conjunctive items, reduction results $(a\wedge b\wedge c)\vee(a\wedge b\wedge d)$ can be obtained, i.e. producing two new decision table, attributes in the table are respectively as a, b, c and a, b, d. Reduction results obtained ($a \wedge b \wedge c$) as new decision-making table is treated.

Table 4. Attribute Reduction Result of Friction Power

U	condition attribute			decision attribute	U	condition attribute			decision attribute
	Materials piston skirt and cylinder liner clearance *(a)*	piston head and cylinder liner clearance（*b*）	eccentricity of piston pin（*c*）	friction power（f）	U	Materials piston skirt and cylinder liner clearance (*a*)	piston head and cylinder liner clearance（*b*）	eccentricity of piston pin *(c)*	friction power（f）
1	-2	-2	-2	2	12	1	2	-1	-1
2	-2	-1	-1	1	13	2	-2	2	-1
3	-2	1	1	1	14	2	-1	1	-2
4	-2	2	2	0	15	2	1	-1	-2
5	-1	-2	-1	2	16	2	2	-2	-2
6	-1	-1	-2	2	17	-2	-1	1	2
7	-1	1	2	1	18	-1	1	1	0
8	-1	2	1	0	19	1	-1	-1	-1
9	1	-2	1	1	20	2	-1	2	-2
10	1	-1	2	0	21	-2	1	-1	0
11	1	1	-2	0	22	1	2	2	-2

3.2 Value reduction

The new decision Table 4 is got from the reduction result ($a \wedge b \wedge c$) . By analyzing the data in the table, the table does not contain inconsistent information. However, when value reduction algorithm is carried out, there will be inconsistencies between samples. Therefore decision-making rules are treated as follows. That is part of the decision rules for inconsistency, assuming it can not be simplified, the value of these attributes is fully retained. For the consistent part of the decision-making rule, and inconsistent part of it together, and then only to examine whether the property value of the same part of the decision rule may be eliminated. If you eliminate the value of some properties, its positive field changes, or data table becomes inconsistent, then the property can not be omitted. Thus, data tables that may be consistent and inconsistent are handled by a unified approach. According to the above approach, the value reduction resulting are shown in Table 5, each row of which represents a decision rule.

Decision attribute value f is discretized into five zones, namely the information system has five concepts. Based on the reduction results of Table 5, some of rules are analyzed as follows.

Table 5. Value Reduction Results of Vriction Power

	condition attribute			decision attribute		condition attribute			decision attribute
R	Materials piston skirt and cylinder liner clearance (*a*)	piston head and cylinder liner clearance (*b*)	eccentricity of piston pin (*c*)	friction power (f)	*R*	Materials piston skirt and cylinder liner clearance (*a*)	piston head and cylinder liner clearance (*b*)	eccentricity of piston pin (*c*)	friction power (f)
1	-2	-2	-2	2	10	1	—	-1	-1
2	-2	-1	-1	1	11	2	-2	—	-1
3	-2	1	1	1	12	2	-1	—	-2
4	-2	2	2	0	13	2	1	—	-2
5	-1	—	2	1	14	2	2	—	-2
6	-1	—	1	0	15	-2	-1	1	2
7	1	-2	—	1	16	-2	1	-1	0
8	1	-1	2	0	17	1	2	2	-2
9	1	1	—	0					

A rule of the concept R=2 is

$(114<a\leq 140) \wedge (100<b\leq 160) \longrightarrow (r=-2)$ |1

This rule covers 40% samples of the concepts r=-2 in Table 1. Its meaning is: If the clearance value between piston skirt and cylinder material is among 114~140μm, and the clearance value between piston head and cylinder is among 100~160μm, the friction power value is among 1.41 ~ 1.736kw, its credibility is equal to 1.

A rule of the concept R=-1 is

$(88 < a \leq 114) \wedge (0.35 < c \leq 0.65) \rightarrow (r = -1)$ | 1

This rule covers 66.7% samples of the concepts r=-1 in Table 1. Its meaning is: If the clearance value between piston skirt and cylinder material is among 88~140μm, and the eccentricity of piston pin is among 0.35~0.65μm, the friction power value is among 1.736 ~ 2.062kw, its credibility is equal to 1.

A rule of the concept R=0 is

$(10<a\leq 36) \wedge (280<b\leq 340) \wedge (1.25<c\leq 1.55) \longrightarrow (r=0)$ |1

This rule covers 16.7% samples of the concepts r=0 in Table 1. Its meaning is: If the clearance value between piston skirt and cylinder material is among 10~36μm, and the clearance value between piston head and cylinder is among 280~340μm, and the eccentricity of piston pin is among 1.25~1.55μm, the friction power value is among 2.062 ~ 2.388kw, its credibility is equal to 1.

A rule of the concept R=1 is

$(10<a\leq 36)\wedge(100<b\leq 160)\ \wedge(0.35<b\leq 0.65)$—>$(r=1)$ |1

This rule covers 25% samples of the concepts r=1 in Table 1. Its meaning is: If the clearance value between piston skirt and cylinder material is among 10~36μm, and the clearance value between piston head and cylinder is among 100~160μm, and the eccentricity of piston pin is among 0.35~0.65μm, the friction power value is among 2.388~2.714kw, its credibility is equal to 1.

A rule of the concept R=2 is

$(10<a\leq 36)\wedge(40<b\leq 100)\ \wedge(0.05<b\leq 0.35)$—>$(r=2)$ |1

This rule covers 25% samples of the concepts r=2 in Table 1. Its meaning is: If the clearance value between piston skirt and cylinder material is among 10~36μm, and the clearance value between piston head and cylinder is among 40~100μm, and the eccentricity of piston pin is among 0.05~0.35μm, the friction power value is among 2.714~3.04kw, its credibility is equal to 1.

4 Conclusion

The rough set method is adopted to identify and extract the potential knowledge from the experiment result, and the inherent laws implication behind these data are revealed. The results show that rough set theory is adopt to acquire knowledge, not only the attributes that have important influence on decision-making information can be found, but also redundant information of information table may be deleted. Thus the final decision table has not only the simplified information, but also not affect the original decision table information. Using the extracted knowledge, reasoning process of neural network can be explained, and it can provide decision support for the designer, improving the intelligence level of intelligent design system.

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