Chapter 28
Design Knowledge Reduction Approach Based on Rough Sets of HCI

Qing Xue, Qi-qi Yin, Li-ying Feng and Min-xia Liu

Abstract With the application of high-tech in the battlefield, the battlefield environment became complicated. Whether the weapon is easy to use or not depended on its interface, and determines the success or failure of the war. In order to design weapon display interface and improve the usability of interactive system, an approach to adaption reasoning based on rough sets is proposed. Condition attributions of decision tables in the knowledge systems could be reduced, and it simplified the adaption inference rules and related human-computer interface design knowledge, which could be applied into the design practices easily. And concise friendly adaptive human-computer interface could be designed to improve the efficiency of operations.

Keywords Context · Decision table · Rough set · Weapon display interface

28.1 Introduction

The theory of rough sets was originally proposed by Pawlak as a formal tool for modeling and processing intelligent systems characterized by insufficient and incomplete information (PawIak 1991; PawIak 1982). Its main advantage is that through rough set we can find the connection and characteristics of the data and extract the implied rules without the apriori knowledge and additional information (Zhou and Wu 2011).

Q. Xue (✉) · Q. Yin · M. Liu
Institute of Industrial Engineering, Beijing Institute of Technology,
Beijing, China
e-mail: sdjlqq@126.com

L. Feng
Beijing Institute of Technology Zhuhai, Zhuhai, China

E. Qi et al. (eds.), *The 19th International Conference on Industrial Engineering and Engineering Management*, DOI: 10.1007/978-3-642-38391-5_28,

A domain U and a equivalence relation R of U is given in the rough set, $\forall A \subseteq U$. The upper and downer approximate set of A is:

$$\overline{R}(A) = \{x|[x]_R \cap A \neq \varnothing\}$$
$$\underline{R}(A) = \{x|[x]_R \subseteq A\}$$

If $\overline{R}(A) \neq \underline{R}(A)$, then said that set A is rough set of equivalence relation R in domain U (Li and Cercrone 2005; Miao and Li 2008).

Because of the large quantity of targets, complex cooperation relations and frequent tactical movements in modern wars, it is very difficult to accept an increasing number and types of data, and process them into information of weapon system (Zhang et al. 2003; Pawlak 2002). In order to improve the efficiency of operations and avoid misoperation, concise and friendly interface of multimedia becomes more and more important. But in the design process, weapon context information is complex, changeable and indistinguishable. In this paper, the authors defined the weapon context as follows: context is to decide or influence weapon display control calculation and the information of man-machine interactive process, which may come from users, equipments and systems, the external environment, and other entities. If we establish all interfaces corresponding to all the context knowledge respectively, this will be a very big job (Zhang and Liang 1996; Wang et al. 2006). And there is a lot of information to deal with in the system, which is a complicated constraint-based reasoning process.

At present, the basic methods of uncertain measurement in the rough set theory are (Zhang et al. 2001): Precision, rough membership function, attribute dependency attribute significance, inclusion degree and conditional information entropy etc. Zhang (Cai and Yao 2009) has put forward the concept of inclusion degree as a measurement of rough set data analysis, indicating that every measurement can be concluded as inclusion degree. Beauboude et al. (Dai and Li 2002) introduced a method of measuring the uncertainty of rough set based on information entropy, which is better to reflect and can measure the uncertainty more precisely.

Design knowledge reduction approach based on rough sets of weapon display interface is put forward in this paper.

28.2 Design Knowledge Expression System

We get the knowledge acquisition through the knowledge representation system, and find useful information through analyzing the original data. We should take the original knowledge expression into a new target expression form (easily for computer process). Knowledge discovery based on the rough set theory, mainly use such an effective knowledge expression-information list. The basic elements of information list are the set of samples. Knowledge of samples described through designating properties (characteristics) and their property values (characteristic value) of the samples.

Table 28.1 Part of the decision table

U	C				D
	Con_1 Target distance (km)	Con_2 Target speed (m/s)	…	Con_m Target type	Against measure
X_1	24	500		Cruise missile	D_1
X_2	18	300		Boomer fighter	D_2
X_3	6	280		Tactical missile	D_3
…	…	…		…	
X_n	35	560		Air-to-ground missile	D_t

Through observing the practical operation situation and the use of weapons' interface to get a record form, it can be considered as a knowledge representation system, KRS for short. In the KRS table, row presents research objects; and column presents attribute (Cheng and Sun 2007; Wei et al. 2006). A list can be regarded as a cluster of equivalence relation of attributes' definition, and this kind of list is usually called the decision table.

According to part of the provided data, the decision table has been constructed as shown in Table 28.1:

In Table 28.1, domain $U = \{x_1, x_2, \ldots, x_n\}$ means that there are n contexts and interface mode records; condition attribute set $C = \{Con_1, Con_2, \ldots, Con_m\}$ mean that there are m different weapon equipment contexts, such as presenting target distance, and presenting target speed. Decision attribute set $D = \{UI_1, UI_2, \ldots, UI_t\}$means that there are t different interfaces.

28.2.1 *Pretreat the Decision Table*

In order to obtain valuable knowledge from the decision table, the original data must be pretreated first. The common pretreatment mainly includes two aspects: totalize the incomplete data and discrete normalize the attribute value (Wei 2006).

28.2.1.1 Totalize the Incomplete Data

The context information of battlefield environment is often incomplete. For example, sensor errors may cause target information lost partly. Therefore, before establishing the decision table, totalize the incomplete data is very necessary. KRS contains incomplete data, taking Table 28.2 as an example. Totalizing the incomplete data method is presented as follows.

Table 28.2 is a KRS which contains incomplete data. It records the context information Con_1, Con_2 and the corresponding interface decision attributes D.

Table 28.2 KRS which contain incomplete data

U	Con_1 Target distance (km)	Con_2 Target speed (m/s)	D Against measure
X_1	15	500	D_1
X_2	25	680	D_2
X_3	10	400	D_3
X_4	3.5		D_4
X_5	6	800	D_5

(1) Elimination method

Delete the row record which has attribute values missing, and get a complete decision table. In Table 28.2, the object X_4 should be deleted. Obviously, this method is very simple, and we use it when in the decision table the incomplete information object number is far less than complete information data; otherwise, we cannot use this method.

(2) Compensation method

For the KRS which contain incomplete data, we use the following approaches to add the missing data and complete the KRS:

(i) According to the actual requirements, take incomplete attribute value as a kind of special value; (ii) Using statistical principle, assess the missing attribute values according to the rest of the record object attribute value. If the missing value is numerical, take the arithmetic mean value of this property in other objects as a supplement; and if the missing value is no-numerical, take the highest frequency value of this property in other objects as the supplement. In Table 28.2, the arithmetic mean value of Con_2 in other objects is $(500 + 680 + 400 + 800)/4 = 595$. We take 595 as a supplement. In addition, there are some other methods of compensation, such as condition combination compensation method, and compensation method based on the indiscernibility relation.

28.2.1.2 Discrete Normalize the Attribute Value

The weapon context information with numerous types, some are numerical while some not, some are continuous while others not, and they have different value confines and measurement units. It is hard to create a decision table with clear structure, if we do not discrete normalize the attribute value. Discrete normalize the attribute value must meet the needs of the two aspects: One hand, the dimension of the attribute value should be reduced. On the other hand, the information loss should be avoided to the greatest extent. There are two ways of discrete normalize the attribute value.

(1) Partial discretization and normalization

In this method, we consider only one attribute in the decision table. As for a continuous attribute a, with its range $[a_{\min}, a_{\max}]$, discrete and normalize mean the generating set of a group, $\{[d_1, d_2], [d_2, d_3], \ldots [d_{n-1}, d_n]\}$ and $d_1 = a_{\min}, d_n = a_{\max}$. When they are in the same range of values, we use $(a_{\max} - a_{\min})/k = (d_2 - d_1) = (d_3 - d_2) = \cdots (d_n - d_{n-1})$ as a division. If the number of the attributes is m, and there are k levels, every sample size of value range is m/k.

(2) Global discretization and normalization

In this method we manipulate all the attributes in the decision table, such as the method based on Boolean logic and rough set theory. Main processes of operation are as follows: the attribute values can be shown by the set and symbolic which are used to represent the gap between contact attribute values; disjunction types are used to represent different decisions; conjunction expressions are used to represent the disjunction types and could be translated into disjunction types; discretization results could be obtained from one of the disjunction types.

28.2.2 Reduce the Decision Table

When we design the weapon human-computer interface, there are many data samples and condition attributes in the decision table. The decision table is very complex, and it is hard to find the implied knowledge from the data. The reduction process of decision table is deleting the redundant data, reducing condition attribute dimensionality and reducing the sample size.

In the actual battlefield, the situation of the battlefield is diversity and uncertainty. Sometimes, we got the same sample information, but we made different decisions; so it is an inconsistent decision table. When we process the inconsistent decision table, we usually transfer it into a consistent table. The reduction method is as follows:

(1) Firstly, merge the repeat record and reserve the inconsistent part;

(2) Secondly, simplify the condition attributes. Delete every condition attribute in turn, if the table changed into inconsistent, the attribute cannot be reduced, or it can be reduced;

(3) Thirdly, simplify the decision rule. On the basis of above, delete an attribute for every decision rule. If the table changed into inconsistent, the attribute cannot be reduced, or it can be reduced. Then get the core value table of decision;

(4) Finally, according to the core value table generated the simplest decision table. That is to say, if we delete some core value, the decision rule is the same with others, so it is the simplest decision table.

The core part of above method is, specific algorithm of reducing attribute, and it is shown as follows (Meng et al. 2008):

Algorithm: The algorithm of reducing attributes

Input: condition set $C = \{a_i | i = 1, 2, \ldots, n\}$, and decision set D;

Output: the minimum reduction decision table.

Let $B = CORE_D(C), A = C - CORE_D(C)$.

Step1. [Is $|B| = 0$?], if $|B| = 0$, $RED_D(C) = C$ and exit; else, calculate and go to Step4.

Step2. For each a_iÎ A, calculate $k_{B\grave{E}\{a_i\}}(D)$

Step3. For a_iÎ A, satisfied $k_{B\grave{E}\{i\}}(D) = \min\left(k_{B\grave{E}\{i\}}(D)\right)$; $A = A - \{a_i\}, B = B \cup \{a_j\}$

Step4. If $((k_B(D)) = k_C(D)$, then $RED_D(C) = B$; else go to step2.

Through reducing the decision table, we get a more simple decision rule. Not only reducing redundant data, but also improving the decision efficiency obviously. It can help to establish a simple expression from context space to interface design space. Using this method can realize the adaptive interfaces easily.

28.3 The Design of a Weapon Defense Interface

The rapid development of modern optoelectronic technology, greatly promotes the military photoelectron technology to be mature and perfect. In military applications, the photoelectric precision technology and photoelectric detection technology develop extensively and rapidly. Currently it became a more perfect equipment system (Mi and Li 2009). This example is the generation of optoelectronic countermeasure interface in different battlefield situation. The condition attributes are target distance a_1 (km), target type a_2, target speed a_3 (m/s), and route shortcut a_4 (km); and decision attributes d, which are different interfaces with different optoelectronic countermeasures. In this example the decision attribute d are information apperceive 1, laser alarm 2, laser countermeasure 3, smoke set 4, and optical camouflage 5.

According to the provided data, construct the original decision table as shown in Table 28.3.

28.3.1 Attribute Discredited

Before establishing the final decision table, the original decision table should be discredited. In this paper, due to the attributes have different nature, we use local discrete method and adopt experts subjective designed to discrete the attributes. Discrete standards are provided by application unit shown in Table 28.4.

Table 28.3 Original decision table

Sample no.	a_1	a_2	a_3	a_4	d
1	24	Helicopter	380	20	1
2	16	Cruise missile	560	13	2
3	6	Helicopter	360	5	3
4	2	Cruise missile	540	1	2
5	15	Tactical missile	1200	16	2
6	25	Boomer fighter	760	22	1
7	0.06	Air-to-ground missile	460	0.05	4
8	12	Helicopter	340	8	2
9	30	Boomer fighter	660	15	1
10	0.9	Air-to-ground missile	740	0.7	4
11	18	Air-to-ground missile	800	14	2
12	0.05	Cruise missile	700	0.02	5
13	5	Air-to-ground missile	350	18	1
14	3	Helicopter	320	1	4
15	8	Tactical missile	780	7	3
16	26	Boomer fighter	680	15	2
17	0.08	Air-to-ground missile	460	0.06	5
18	7	Tactical missile	1000	5	3
19	5	Tactical missile	750	2	4
20	8	Cruise missile	720	6	3
21	17	Boomer fighter	780	12	2

Table 28.4 Discrete standards

	1	2	3	4	5
A_1	Above 10	5–10	0–5		
A_2	Helicopter	Boomer fighter	Cruise missile	Air-to-ground missile	Tactical missile
A_3	0–250	250–500	500–750	750–1000	Above 1000
A_4	Above 15	7–15	0–7		

In Table 28.4, A_1 represents target distance, A_2 represents target type, A_3 represents target speed, A_4 represents route shortcut. The decision table after discrete is shown in Table 28.5.

28.3.2 Reduction the Decision Table

Given that the condition set of decision table is $C = \{a_1, a_2, a_3, a_4\}$, and decision attribute set is $D = \{d\}$. Let the initial attribute core is $\mathrm{CORED}(C) =$. From the decision table, we get that $U/C = \{\{X_1\}, \{X_2\}, \{X_3\}, \{X_4\}, \{X_5\}, \{X_6\}, \{X_7\}, \{X_8\}.\{X_9, X_{16}\}, \{X_{10}\}, \{X_{11}\}, \{X_{12}\}, \{X_{13}\}, \{X_{14}\}, \{X_{15}\}, \{X_{17}\}, \{X_{18}\}, \{X_{19}\}, \{X_{20}\}, \{X_{21}\}\}$, and $U/D = \{\{X_1, X_6, X_9, X_{13}\}, \{X_2, X_4, X_5, X_8, X_{11}, X_{16}, X_{21}\},$

Table 28.5 The decision table after desecrating

Sample no.	a_1	a_2	a_3	a_4	d
1	5	1	2	1	1
2	4	3	3	2	2
3	3	1	2	3	3
4	2	3	3	3	2
5	4	5	5	1	2
6	5	2	4	1	1
7	2	4	2	3	4
8	4	1	2	2	2
9	5	2	3	2	1
10	2	4	3	2	4
11	4	4	4	2	2
12	1	3	3	3	5
13	5	4	2	1	1
14	2	1	2	3	4
15	3	5	4	2	3
16	5	2	3	2	2
17	1	4	2	3	5
18	3	5	5	3	3
19	2	5	3	2	4
20	3	3	3	3	3
21	4	2	4	2	2

Table 28.6 The decision table after reducing

Sample no.	a_1	a_3	a_4	d
1	5	2	1	1
2	4	3	2	2
3	3	2	3	3
4	2	3	3	2
5	4	5	1	2
6	5	4	1	1
7	2	2	3	4
8	4	2	2	2
9	5	3	2	1
10	2	3	2	4
11	4	4	2	2
12	1	3	3	5
13	5	2	1	1
14	2	2	3	4
15	3	4	2	3
16	5	3	2	2
17	1	2	3	5
18	3	5	3	3
19	2	3	2	4
20	3	3	3	3
21	4	4	2	2

Table 28.7 The minimum reduction decision table

Sample no.	a_1	a_3	a_4	d
1,13,6				1
2,5,8,11,21	4			2
3,15,18,20	3			3
4	2		3	2
7,14	2	2		4
9	5	3	2	1
10,19	2		2	4
12,17	1			5
16	5	3	2	2

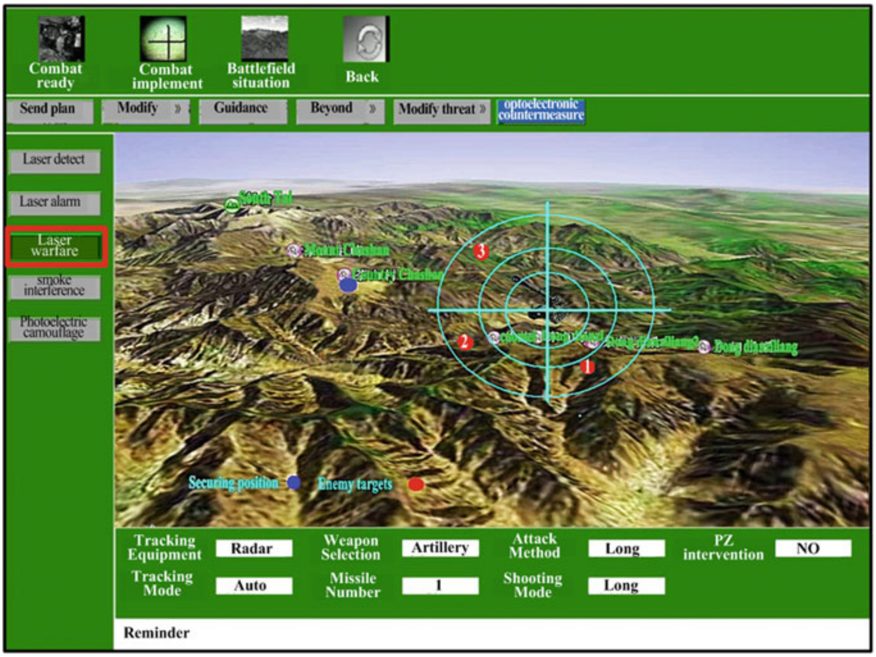

Fig. 28.1 Adaptive human-computer interface of weapon system

$\{X_3, X_{15}, X_{18}, X_{20}\}, \{X_7, X_{10}, X_{14}, X_{19}\}, \{X_{12}, X_{17}\}\}$. According to the algorithm, we get, $POS(C,D) = \{\{X_1\}, \{X_2\}, \{X_3\}, \{X_4\}, \{X_5\}, \{X_6\}, \{X_7\}, \{X_8\}, \{X_9\}, \{X_{10}\}, \{X_{11}\}, \{X_{12}\}, .\{X_{13}\}, \{X_{14}\}, \{X_{15}\}, \{X_{16}\}, \{X_{17}\}, \{X_{18}\}, \{X_{19}\}, \{X_{20}\}, \{X_{21}\}\}, k_C(D) = 19/21$. So the decision Table 28.5 is inconsistent. And we get that inconsistent of decision table is because sample X_9 and sample X_{16} have the same condition attributes but different decision attributes. After remove a_1, get $k_{C-\{a_1\}}(D) = 11/2^1 \neq k_C(D)$, so cannot be remove. That is to say, a_1I CORED(C). Similarly, we can obtain the dependency of other condition attributes to the decision attribute D, $k_{C-\{a_2\}}(D) = 15/2^1 \neq k_C(D)$, $k_{C-\{a_3\}}(D) = 19/21$, $k_{C-\{a_4\}}(D) = 19/21$. Minimum attribute reduction set is $\{a_1, a_3, a_4\}$. Table 28.6 shows the decision table after reducing.

Similar attribute reduction, remove the decision table redundant condition attribute value, and with the same rules, finally obtained such as the minimum reduction decision table shown in Table 28.7.

The reduced decision table made the task context and optoelectronic countermeasure form decision knowledge simply. Then we reasoned and simplified the design rules. In addition, these rules more simplified than the original records.

28.3.3 Example

Weapons systems require a good real-time and stability, so we choose VxWorks as the system platform, and use WindML development tools to develop weapon system interface. We have got the reduction decision table above, and made the goal situation and photoelectric form decision knowledge simplified. The adaptive interface for against measures can be obtained according to the sensed actual context and decision reasoning rules. It is shown in Fig. 28.1.

28.4 Conclusion

In this paper, we used rough sets to reduce conditional attributions of decision tables' in the knowledge systems. Also we extracted key attributes from a lot of original data and established simple expression from context space to interface design space. The adaptive interfaces realized easily using this method.

References

Cai L, Yao X (2009) Attribute reduction algorithm based on rough set theory. J Sichuan Univ Sci Eng 22:34–37 (in Chinese)

Cheng S, Sun S (2007) Adaptive human-computer interaction user modeling based on rough sets. Comp Sci 34:48–52 (in Chinese)

Dai JH, Li YX (2002) Study on discretization based on rough set theory. In: Proceedings of 1st international conference on machine learning and cybernetics, Piscataway, IEEE Press, pp 1371–1373

Li J, Cercrone N (2005) Empirical analysis on the geriatric care data set using rough sets theory. Tech Report, CS-2005-05

Meng J, Liu Y, Mo H (2008) New method of packing missing data based on rough set theory. Comp Eng Appl 6:175–177 (in Chinese)

Mi R, Li X (2009) The knowledge reduction in incomplete fuzzy decision information system. J Wuhan Univ Sci Eng 22(3):24–28 (in Chinese)

Miao D, Li D (2008) Rough sets theory algorithms and application. Tsinghua University Press, Beijing (in Chinese)

PawIak Z (1982) Rough sets. Int J Comp Inf Sci 15:341–356

PawIak Z (1991) Rough sets-theoretical aspects of reasoning about data. Kluwer Academic Publishers, Dordrecht

Pawlak Z (2002) Rough sets and intelligent data analysis. Inf Sci 147:1–12

Wang X, Cai N, Yang J, Liu X (2006) Methods of rough set uncertainty measure based on approximation precision and condition information entropy. Acad J Shanghai Jiao Tong Univ 51(7):1130–1134

Wei D (2006) Research on rough set model and knowledge deductions for incomplete and fuzzy decision information system, Nanjing University, Nanjing (in Chinese)

Wei D, Zhao Y, Zhou X (2006) A rough set approach to incomplete and fuzzy decision information system. 2006 IEEE 6th world congress on intelligent control and automation, June 2006

Zhang W, Liang Y (1996) The theory of uncertainty reasoning. Publishing Houses of Xi'an Jiaotong University, Xi'an

Zhang W, Wu W, Liang J (2001) Rough set theory and method. Science Press, Beijing, pp 182–185

Zhang W, Liao X, Wu Z (2003) An incomplete data analysis approach based on rough set theory. Pattern Recognit Artif Intell 16:158–163 (in Chinese)

Zhou L, Wu W (2011) Characterization of rough set approximations in atanassov intuitionistic fuzzy set theory. Comp Math Appl 62:282–296