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A New Parameter Reduction Method Based on Soft Set Theory

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Abstract

In order to solve the problems of large calculation and low efficiency of parameter reduction, a new parameter reduction method based on soft set theory is proposed. According to the importance degrees of parameters, this new parameter reduction method simplifies the reduction complexity brought by the equivalent classes in discernibility matrix, so that it not only improves the parameter reduction efficiency and quality, but also reduces the reduction complexity. Finally, comparing with other reduction methods, this new parameter reduction method based on soft set theory not only possesses feasibility and high efficiency, but also can make the reduction result more accurate.

Keywords*: soft set, parameter reduction, importance degree, discernibility matrix*

1. Introduction

Much information in our lives is imprecise and vague. Probability theory, rough set theory [1, 2] and fuzzy set theory [3, 4] can all solve these problems. However, they all have some limitations (lack of parametric tool), so that these limitations limit their applications in practical problems widely. In order to solve the problems, Molodtsov proposed the concept of soft set [5] in 1999. Soft set is a new mathematical tool to deal with uncertainty, vagueness and imprecision. At present, decision-making problems of soft set theory are the focus that many scholars study, while the parameter reduction is an important problem in them. Therefore, how to find a fast, simple and efficient reduction method is an important direction of worthy study.

Currently, there are some researches about the problems of parameter reduction based on soft set theory. For example, Maji *et al.,* proposed the concept of parameter reduction based on soft set theory [6]. Chen *et al.,* pointed out that the concept of parameter reduction based on soft set theory was irrational and proposed a parameter reduction method based on soft set theory, which can keep the optimal choice decision objects remain unchanged [7]. Zou *e. al.,* analyzed the cases that there was only one optimal choice object and multiple optimal choice objects respectively and proposed a new parameter reduction method based on the optimal choice objects [8]. According to the decision values, Ali *et al.,* classified the objects and reduced the parameters in the case that the classifications of the objects are unchanged [9]. Kumar *et al.,* reduced the parameters in the case that the classifications of the objects are unchanged, too [10]. Kong *et al.,* proposed the concept of the normal parameter reduction of soft set [11]. Ma *et al.,* improved the normal parameter reduction method of soft set and reduced the parameters on the basis of their importance degrees [12-15]. Xiao *et al.,* proposed a new parameter reduction method of bijective soft set [16]. Li *et al* studied the relationship between the soft set and the information system and proposed a new parameter reduction method based on soft set [17].

Based on above researches, in order to solve the problems of large calculation and low efficiency of parameter reduction, a new parameter reduction method based on soft set

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theory is proposed. An application of this new parameter reduction method based on soft set theory in the specific case proves its feasibility, high efficiency and accuracy.

2. Relationship between Soft Set and Information System

Definition 1: Given U is a finite non-empty universe of objects and E is a finite non-empty set of parameters. Let $A \subseteq E$, a pair (F, A) is called a soft set over U, where F is a mapping given by $F : A \to P(U)$.

In order to express the meaning of definition 1, a classic example is following:

Given $U = \{h_1, h_2, h_3, h_4, h_5, h_6\}$, $A = \{a_1, a_2, a_3, a_4, a_5, a_6, a_7\}$, where $h_1, h_2, h_3, h_4, h_5, h_6$ stand for the 6 houses respectively, $a_1, a_2, a_3, a_4, a_5, a_6, a_7$ stand for "expensive", "beautiful", "wooden", "cheap", "in green surroundings", "modern" and "in good repair" respectively. A soft set (F, A) describes the "attractiveness of houses" that a customer is going to purchase.

Suppose that we have

$(F, a_1) = \{h_1, h_4, h_5\}$;

$(F, a_2) = \{h_2, h_6\}$;

$(F, a_3) = \{h_1, h_3, h_5\}$;

$(F, a_4) = \{h_1, h_4, h_6\}$;

$(F, a_5) = \{h_1, h_3, h_6\}$;

$(F, a_6) = \{h_2, h_5\}$;

$(F, a_7) = \{h_2, h_3\}$.

In order to store soft set in the computer easily, the 0-1 two-dimensional table is used to represent soft set (*e.g.*, Table 1).

Table 1. Soft Set (F, A)

U	a_1	a_2	a_3	a_4	a_5	a_6	a_7
h_1	1	0	1	1	1	0	0
h_2	0	1	0	0	0	1	1
h_3	0	0	1	0	1	0	1
h_4	1	0	0	1	0	0	0
h_5	1	0	1	0	0	1	0
h_6	0	1	0	1	1	0	0

Definition 2: Given $S = (F, A)$ is a soft set over U, $I_S = (U, A, V, g_S)$ is called 2 valued information system induced by S, to any $x \in U, a \in A$, then

$$g_S(x, a) = \begin{cases} 1, x \in F(a) \\ 0, x \notin F(a) \end{cases} \quad (1)$$

Definition 3: Given $S = (F, A)$ is a soft set over U, (U, A, V, g) is a 2 valued information system induced by S, to any $B \subseteq A$, binary relation induced by S is defined as:

$$R_B = \{(x, y) \in U \times U : g(x, a) = g(y, a)(\forall a \in B)\} \quad (2)$$

3. Parameter Reduction Method Based on Soft Set Theory

3.1. Overview of Parameter Reduction

Parameter reduction is an important problem of soft set theory. Its practical significance is to delete redundant parameters for the optimal decision, so that the numbers of parameters are reduced to simplify the calculation and steps.

There is one-to-one relationship between soft sets and 2 valued information systems. Therefore, attribute reduction method in information system can be applied to parameter reduction of general soft set.

Definition 4: Given $S=(F,A)$ is a soft set over U, let $B\subseteq A$, if $R_B=R_A$ and $\forall a\in B$, all $R_B\neq R_{B-\{a\}}$ are right, then B is called the parameters reduction of S. Denoted as $\mathrm{Re}d(A)$.

Reduction is to make $R_B=R_A$.

If $a\in A$, $R_{A-\{a\}}=R_A$, then parameter a is unnecessary. Otherwise, it is necessary. The intersections of all parameter reductions are called core parameters. Denoted as $core(A)$. Therefore, $core(A)=\cap Red(A)$.

(1) If $a\in core(A)$, then a is called the core parameter.

(2) If $a\in\cup red(A)-core(A)$, then a is called the relative necessary parameter.

(3) If $a\in A-\cup red(A)$, then a is called the unnecessary parameter.

By definition 4, the core parameters are the intersections of all parameters reductions, and then they are the most vital parameters. If they are removed, then the classifications and decision results are changed. Hence, their importance degrees should be greatest. Relative necessary parameters are obtained after removing the core parameters from all parameters, and their importance degrees should be smaller than ones of the core parameters. Unnecessary parameters are the most unimportant, so, their importance degrees should be smaller than ones of the relative necessary parameters.

3.2. Determination of Importance Degrees of Parameters Based on Discernibility Matrix

Importance degrees of parameters are very important for the parameter reduction, because it can affect the reduction results.

Definition 5: Given $S=(F,A)$ is a soft set over U, (U,A,V,g) is a 2 valued information system induced by soft set S, let $|U|=n$, the importance degree of parameter a is defined as:

$$\gamma_a=\frac{\sum_{x\in U} g(x,a)}{n} \tag{3}$$

If all objects' values under parameter a are 1 (namely, each object under parameter a is attractive), then the importance degree of parameter a is 1. But this method of defining important degrees of parameters is not reasonable. Since each object under parameter a is attractive, then all objects' values under parameter a have no difference. Hence, this parameter has no influence on the decision result, and then its importance degree should be 0. In order to solve this defect, this paper proposes a method of determining importance degrees of parameters based on discernibility matrix.

Definition 6: Given $S=(F,A)$ is a soft set over U, (U,A,V,g) is a 2 valued information system induced by soft set S, to any $x_i,x_j\in U$, distinguishing parameter set of the objects x_i and x_j is defined as:

$$d(x_i, x_j) = \{a \in A : g(x_i, a) \neq g(x_j, a)\} \tag{4}$$

$D(S) = \{d(x_i, x_j) : x_i, x_j \in U\}$ is called the discernibility matrix of soft set S.

The properties obtained by definition 6 are following:

(1) $d(x_i, x_i) \subseteq A$;

(2) $d(x_i, x_i) = \phi$;

(3) $d(x_i, x_j) = d(x_j, x_i)$;

(4) $B \subseteq A$, $R_B = R_A \Leftrightarrow B \cap d(x_i, x_j) \neq \phi$;

(5) if $|d(x_i, x_j)| = 1$, then the parameter in $d(x_i, x_j)$ is a core parameter.

Proof: (1) ~ (3) can be proved by definition 6.

(4) Adequacy: Given $\exists d(x_i, x_j) \neq \phi$, which makes $B \cap d(x_i, x_j) \neq \phi$, to any $a \in B$, $g(x_i, a) = g(x_j, a)$, then $(x_i, x_j) \in R_B$. Since $d(x_i, x_j) \neq \phi$, then there must be $b \in A$, which makes $g(x_i, b) \neq g(x_j, b)$. Thus $(x_i, x_j) \notin R_A$. Therefore, $R_B \neq R_A$ and $R_B = R_A$ are contradictory.

Necessity: Given $R_B \neq R_A$, then $R_B - R_A \neq \Phi$. Let $(x_i, x_j) \in R_B - R_A$, we have $(x_i, x_j) \in R_B$ and $(x_i, x_j) \notin R_A$, then $d(x_i, x_j) \subseteq A - B$. Therefore, $B \cap d(x_i, x_j) = \phi$ and $B \cap d(x_i, x_j) \neq \phi$ are contradictory.

In summary, this property is proved.

(5) We can get $B \cap d(x_i, x_j) \neq \phi$ by the property (4). Since $|d(x_i, x_j)| = 1$, then there is only one parameter in $d(x_i, x_j)$. Let the parameter is a, we have $B \cap d(x_i, x_j) = \{a\}$. Thus $a \in B$ .Therefore, parameter a is necessary. In summary, this property is proved.

By definition 6, when two objects' values in the universe are equal, they have no difference. Namely, the objects x_i and x_j can't be distinguished. Therefore, $d(x_i, x_j) = \phi$. When the objects x_i and x_j in the universe can be distinguished, $d(x_i, x_j)$ is the set of parameters that can distinguish the object x_i from the object x_j. In a word, the appearing parameters in the discernibility matrix are contributory for distinguishing objects, that is to say, these parameters are important and have different importance degrees. In order to reflect these parameters' importance truly, we can use the appearing times of a certain parameter and its proportion in $d(x_i, x_j)$ to define its importance degree. In the discernibility matrix, the more appearing times are and the larger its proportion is, it can distinguish more objects and has greater contribution. Therefore, its importance degree is bigger. On the contrary, its importance degree is smaller.

Definition 7: Given $S = (F, A)$ is a soft set over U, (U, A, V, g) is a 2 valued information system induced by soft set S, let $|U| = n$, $d(x_i, x_j)$ is the distinguishing parameter set of the objects x_i and x_j, to any $a \in A$, the importance degree of parameter a is defined as:

$$D_a = \frac{\sum_{i,j=1,2\cdots n} \frac{|a \cap d(x_i, x_j)|}{|d(x_i, x_j)|}}{K} \tag{5}$$

where $K = \frac{n \times (n-1)}{2}$ is the total number of distinguishing parameter set in the upper triangular or lower triangular of the discernibility matrix (we only need calculate the half $d(x_i, x_j)$, because the discernibility matrix is a symmetric matrix).

The properties obtained by definition 7 are following:

(1) $\forall a \in A$, $0 \le \frac{|a \cap d(x_i, x_j)|}{|d(x_i, x_j)|} \le 1$;

(2) $\forall a \in A$, $0 \le D_a \le 1$;

(3) $\forall a, b, c \in A$, if a is the core parameter, b is the relative necessary parameter, and c is the unnecessary parameter, then $D_a > D_b > D_c$.

Proof: (1) Let $a \cap d(x_i, x_j) = \phi$, then $\frac{|a \cap d(x_i, x_j)|}{|d(x_i, x_j)|} = 0$.

Let $a \cap d(x_i, x_j) \neq \phi$:

If $d(x_i, x_j) = \{a\}$, then $\frac{|a \cap d(x_i, x_j)|}{|d(x_i, x_j)|} = 1$.

If there are at least 2 parameters in $d(x_i, x_j)$, then $|d(x_i, x_j)| > 1$. Hence, $0 < \frac{|a \cap d(x_i, x_j)|}{|d(x_i, x_j)|} < 1$.

In summary, $0 \le \frac{|a \cap d(x_i, x_j)|}{|d(x_i, x_j)|} \le 1$ is proved.

(2) To any $a \in A$, let $a \notin d(x_i, x_j)$, we have $a \cap d(x_i, x_j) = \phi$. Thus $D_a = 0$. Hence, parameter a does not appear in the discernibility matrix, and then it has no effect on the distinction of objects.

To any $a \in A$, let $a \in d(x_i, x_j)$:

If there is only a parameter in every $d(x_i, x_j)$, then $D_a = 1$.

If there are at least 2 parameters in every $d(x_i, x_j)$, then $0 < \frac{|a \cap d(x_i, x_j)|}{|d(x_i, x_j)|} < 1$. Hence, $0 < D_a < 1$.

In summary, $0 \le D_a \le 1$ is proved.

(3) If a is the core parameter, b is the relative necessary parameter, and c is the unnecessary parameter, then the appearing times of parameter a are more than b , and its proportion is bigger than b . While, the appearing times of parameter b are more than c , and its proportion is bigger than c . Hence,

$$\sum_{i,j=1,2\cdots n} \frac{|a \cap d(x_i, x_j)|}{|d(x_i, x_j)|} > \sum_{i,j=1,2\cdots n} \frac{|b \cap d(x_i, x_j)|}{|d(x_i, x_j)|} > \sum_{i,j=1,2\cdots n} \frac{|c \cap d(x_i, x_j)|}{|d(x_i, x_j)|}$$

So we can get

$$\frac{\sum_{i,j=1,2\cdots n} \frac{|a \cap d(x_i, x_j)|}{|d(x_i, x_j)|}}{K} > \frac{\sum_{i,j=1,2\cdots n} \frac{|b \cap d(x_i, x_j)|}{|d(x_i, x_j)|}}{K} > \frac{\sum_{i,j=1,2\cdots n} \frac{|c \cap d(x_i, x_j)|}{|d(x_i, x_j)|}}{K}$$

Therefore: $D_a > D_b > D_c$.

3.3. Reduction Method Based on Importance Degrees of Parameters

Definition 8: Given $S = (F, A)$ is a soft set over U , $d(x_i, x_j)$ is a distinguishing parameter set of the objects x_i and x_j , discernibility function can be defined as:

$$\Delta(S) = \wedge\{\vee\{a \mid a \in d(x_i, x_j)\} : x_i, x_j \in U, \forall a \in A\} \quad (6)$$

Reduction results are obtained by seeking the minimal disjunctive normal form of $\Delta(S)$.

Because the discernibility matrix is a symmetric matrix, lots of repeated parameters emerge. If the discernibility function is used to reduce parameters, then calculation of reduction will be large. Moreover, efficiency will be low. Besides, the reduction results will not be unique. Therefore, in order to solve these problems, a reduction method based on importance degrees of parameters is proposed.

Concrete thought of reduction method based on importance degrees of parameters is following:

(1) Importance degrees of all parameters are obtained by the discernibility matrix.

(2)According to the important degrees of parameters, the reduction steps are following:

(a) When important degrees of all parameters are unequal, the parameter of the max importance degree is put in the reduction set, and all distinguishing parameter sets that contain this parameter are removed. And so on, until all distinguishing parameter sets are null. At this time, obtained reduction set is the reduction result.

(b) When important degrees of some parameters are equal:

If importance degrees of the core parameters are equal, then these core parameters are put in the reduction set, and all distinguishing parameter sets that contain these parameters are removed. And so on, until all distinguishing parameter sets are null. At this time, obtained reduction set is the reduction result.

If importance degrees of all core parameters are unequal, then disjunctive result of these equal parameters is put in the reduction set, and all distinguishing parameter sets that contain these parameters are removed. And so on, until all distinguishing parameters sets are null. At this time, obtained reduction set is the reduction result.

Concrete steps of the parameter reduction method based on importance degree of parameters are following:

Input: soft set $S=(F,A)$

Output: Reduction result

Step 1: According to the soft set, distinguishing parameter set $d(x_i,x_j)$ is obtained, and then the discernibility matrix $D(S)$ is constructed.

Step 2: According to the discernibility matrix $D(S)$, the importance degrees of all parameters are obtained.

Step 3: According to the importance degrees of all parameters, the reduction set is obtained. Hence, the reduction result is obtained.

4. Example Analysis

Somebody wants to buy a car. Given there are 6 kinds of cars, the universe $U=\{h_1,h_2,h_3,h_4,h_5,h_6\}$, there are 12 factors to consider, the parameter set $A=\{a_1,a_2,a_3,a_4,a_5,a_6,a_7,a_8,a_9,a_{10},a_{11},a_{12}\}$, $a_1,a_2,a_3,a_4,a_5,a_6,a_7,a_8,a_9,a_{10},a_{11},a_{12}$ stand for "price", "configuration", "environment protection", "customer service", "security", "performance", "fuel consumption", "style", "brand", "comfort", "space", "maneuverability" respectively. The Table 2 reflects “attractiveness of houses” that a customer is going to buy.

Table 2. Soft Set (F, A)

U	a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8	a_9	a_{10}	a_{11}	a_{12}
h_1	1	1	0	0	1	1	1	1	0	1	0	0
h_2	0	0	0	0	1	1	1	0	0	1	1	0
h_3	0	1	0	1	0	0	1	0	0	0	1	0
h_4	0	1	1	0	0	0	1	1	0	1	0	0
h_5	1	1	0	1	0	0	1	1	0	1	0	0
h_6	0	0	0	0	0	1	1	0	0	1	1	1

According to the data in Table 2, the concrete steps of the new parameter reduction method based on soft set theory are following:

Step 1: According to the soft set, distinguishing parameter sets are obtained, and then the constructed discernibility matrix is following:

$$\begin{bmatrix} \phi & a_1, a_2, a_8, a_{11} & a_1, a_4, a_5, a_6, a_8, a_{10}, a_{11} & a_1, a_3, a_5, a_6 & a_4, a_5, a_6 & a_1, a_2, a_5, a_8, a_{11}, a_{12} \\ & \phi & a_2, a_4, a_5, a_6, a_{10} & a_2, a_3, a_5, a_6, a_8, a_{11} & a_1, a_2, a_4, a_5, a_6, a_8, a_{11} & a_5, a_{12} \\ & & \phi & a_3, a_4, a_8, a_{10}, a_{11} & a_1, a_8, a_{10}, a_{11} & a_2, a_4, a_6, a_{10}, a_{12} \\ & & & \phi & a_1, a_3, a_4 & a_2, a_3, a_6, a_8, a_{11}, a_{12} \\ & & & & \phi & a_1, a_2, a_4, a_6, a_8, a_{11}, a_{12} \\ & & & & & \phi \end{bmatrix}$$

Step 2: According to the discernibility matrix, the importance degrees of all parameters are following:

$$D_{a_1} = 0.112,\ D_{a_2} = 0.096,\ D_{a_3} = 0.074,\ D_{a_4} = 0.113,\ D_{a_5} = 0.127,\ D_{a_6} = 0.116,\ D_{a_7} = 0,$$
$$D_{a_8} = 0.109,\ D_{a_9} = 0,\ D_{a_{10}} = 0.066,\ D_{a_{11}} = 0.109,\ D_{a_{12}} = 0.078$$

The ranking result of the importance degrees of all parameters is following:

$$D_{a_5} > D_{a_6} > D_{a_4} > D_{a_1} > D_{a_8} = D_{a_{11}} > D_{a_2} > D_{a_{12}} > D_{a_3} > D_{a_{10}} > D_{a_7} = D_{a_9}$$

Steps 3: The reduction result is following:

$$\{a_1, a_4, a_5, a_6\}$$

The reduction result obtained by the new parameter reduction method in this paper is compared with the reduction results obtained by reduction methods in the papers [14, 17]. The reduction results are following:

	The reduction method in the paper [14]	The reduction method in the paper [17]	The reduction method in this paper
Reduction result	$\{a_1, a_2, a_6, a_{10}\}$ $\{a_1, a_2, a_5, a_{10}, a_{12}\}$ $\{a_2, a_4, a_5, a_6, a_8, a_{10}, a_{12}\}$	$\{a_1, a_4, a_5\}$ $\{a_4, a_5, a_{11}\}$ $\{a_4, a_5, a_8\}$ $\{a_1, a_5, a_6, a_8\}$ *etc*	$\{a_1, a_4, a_5, a_6\}$
Time complexity	$O(mn)$	$O(1)$	$O(mn^2)$

Analysis of reduction results:

The time complexity of reduction method in the paper [14] is $O(mn)$ (where m stands for the number of the parameters, n stands for the number of the objects). But this method determines the importance degrees of the parameters by definition 5. To a certain degree, this method is unreasonable. Besides, reduction results are not unique or accurate.

The time complexity of reduction method in the paper [17] is $O(1)$. But this method is very complex to calculate the reduction results by the discernibility function. Moreover, reduction results are not unique or accurate.

The time complexity of reduction method in this paper is $O(mn^2)$. But this method in this paper is more reasonable. Moreover, the process of reduction is simpler and faster. Besides, the reduction result is unique and accurate.

Through the above analysis, from the view of feasibility, the specific example shows that the new reduction method in this paper is feasible.

From the view of reduction results, reduction results obtained by the methods in the papers [14, 17] are not unique or accurate. However, the reduction result obtained by the method in this paper is unique. Hence, the new reduction method in this paper can make the reduction result more accurate.

From the view of reduction methods, the importance degrees of parameters given by this paper are more reasonable. Therefore, the reduction result is more reasonable.

From the view of efficiency, the new reduction method in this paper has simpler operation, smaller calculation and higher reduction efficiency.

5. Conclusions

In order to solve the problems of large calculation and low efficiency of parameter reduction, the definition of determining importance degrees of parameters is given. Based on it, a new parameter reduction method based on soft set theory is proposed. This new parameter reduction method simplifies the reduction complexity brought by the equivalent classes in discernibility matrix, so that it not only improves the parameter reduction efficiency and quality, but also reduces the reduction complexity. The specific example verifies that the new reduction method in this paper is feasible. Moreover, comparing with other different reduction methods, this new parameter reduction method based on soft set theory not only makes the reduction result more reasonable and accurate, but also has simpler operation, smaller calculation and higher reduction efficiency.

This paper focuses on parameter reduction methods based on soft set theory. Attribute reduction of the decision-making soft set will be the focus of next research.

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