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Stepwise updating of optimal cut in multi-scale decision systems considering the dynamic changes of attributes

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Abstract: *The data processing under a multi-scale framework can satisfy the problem analysis from different perspectives, and the multi-scale rough set model promoted the development of multi-scale data analysis. The optimal cut in multi-scale decision systems can enable different objects to take different scales under the same attribute, and thus realize knowledge acquisition across granularity levels in multi-scale information systems. However, in practical applications under the network environment, the data in the information system often changes dynamically. In order to solve the dynamic updating of the optimal cut in multi-scale decision systems, the stepwise updating method of optimal cut while attributes dynamic changing in multi-scale decision systems are proposed based on the static stepwise optimal cut selection algorithm. Firstly, an initial cut combination and attribute sequence are determined from the original systems with unchanged information, which avoids the recalculating of attribute sequence when updating the optimal cut dynamically. Secondly, two simplified theorems for node consistence judgement are proposed, which can shorten the time of determining node consistence. Finally, a stepwise updating algorithm of optimal cut is proposed considering the dynamic changes of attributes. Multiple comparative experiments on the UCI standard dataset show that, compared with the static stepwise optimal cut selection method, the proposed dynamic updating algorithm can correctly obtain an optimal cut while significantly improving the computational efficiency.*

Keywords: *multi-scale decision system, optimal cut, dynamic updating*

1. Introduction

As one of the important research fields in data mining and knowledge representation, granular computing simulates human thinking by analyzing and solving the same problem at different granular levels, and reduces the complexity of problem solving by selecting appropriate granularity [1]. Rough set theory proposed by Professor Pawlak in 1982 played an important role in the development of granular computing research [2]. In rough set theory, a dataset is called an information system, the equivalence relation is used to carry out information granulation, and information granules are used as the basic units of computation to improve computational efficiency. In traditional rough set data analysis, each object can only take one value under each attribute, and data can only be analyzed in a single-scale framework.

However, in real life, data analysis from different levels is necessary to meet the practical needs. In view of this situation, Wu-Leung [3] first proposed a multi-scale rough set model in 2011, which deems that one object can have different scales and take different values under the same attribute, and calls an information system with multi-scale attributes as a multi-scale information system. The optimal scale selection under this model restricts that all attributes must take the same scale. Li et al. [4] extended the Wu-Leung model and believed that each attribute can have different scales and different attributes can be selected with different scales to form a single-scale information system. Currently, many scholars have studied this model from the aspects of optimal scale selection [5] and rule acquisition [6]. She et al. [7] further proposed a cut theory based on attribute granularity trees, holding that information granules can be combined between different levels of attribute granularity trees to achieve cross-granular combination of internal information, and proposed an optimal cut selection algorithm. Based on this, a stepwise optimal cut selection algorithm was proposed by author in [8], which can only acquire one optimal cut at a time, but compared with the algorithm in [7], it shortened the time significantly.

In fact, with the rapid growth of various data in information systems, data may change over time, which is usually reflected in the following three aspects: object change, attribute change, and attribute value change. In the part, scholars have already adopted the dynamic updating idea in various single-

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scale information systems for the approximation set acquisition, attribute reduction, and rule acquisition. However, in multi-scale information systems, there are few researches on dynamic updating. The dynamic updating algorithm for optimal scale acquisition while attribute values change in the traditional Wu-Leung model is discussed in [9], which takes the optimal scale in the original information system as the starting point of the optimal scale selection in the updated information system, reducing the search range and improving the computational efficiency to some extent. Similarly, the variation rule of the consistence of multi-scale systems based on the traditional Wu-Leung model was studies in [10] and a dynamic updating algorithm for the optimal scale while objects increased was proposed. These above researches mentioned explored the dynamic updating method of optimal scale selection in the traditional Wu-Leung model. Compared with the cut idea that can achieve cross-granular knowledge acquisition, the optimal scale in the traditional model has limitations, and there is still no research on the dynamic updating of optimal cut.

In real life, data from different industries is constantly changing, and the attributes describing the objects will inevitably change as well. If taking the static optimal cut selection methods to handle dynamic data, all the data are still recalculated after the updating of the information system. The calculation cost is too high and the time cost is too high. Therefore, in the dynamic changing environment, it is of great significance to study the dynamic updating method of optimal cut. Based on the static stepwise optimal cut selection algorithm via multi-granularity attribute importance proposed by author previously in [8], and the stepwise updating method of optimal cut in multi-scale decision system considering the dynamic changes of attributes is furtherly researched. And the multiple comparative experiments on the UCI standard dataset validate the effectiveness of the proposed algorithm.

2. Preliminaries

Definition 1 [4]. A multi-scale decision table is a 2-tuple $S=(U,AT\cup\{d\})$ where $U=\{x_1,x_2,\cdots,x_n\}$ is the universe of discourse, $AT=\{a_1,a_2,\cdots,a_m\}$ is a nonempty finite set of conditional attributes, d is a decision attribute and the attribute $a_j\in AT$ has I_j levels of scale, then a multi-scale decision table can be expressed as $S=\{U,\{a_j^k|j=1,2,\cdots,m,k=1,2,\cdots,I_j\}\cup\{d\}\}$.

Definition 2 [7]. Let $S=(U,AT\cup\{d\})$ be a multi-scale decision table, the granularity tree T_j for attribute a_j can be construct as follows:

(1) The root node of T_j is labelled as a_j, the remaining nodes of T_j are labelled as v_j^k which represents the attribute value of a_j on the $k\mathrm{th}$ scale.

(2) For node v_j^k, $v_j^{k\downarrow}$ represents the set of objects whose attribute value is v_j^k under a_j^k.

(3) If the nodes $v_1,v_2,\cdots,v_n$ of T_j are all descendants of the node v, then $\{v_1{}^{\downarrow},v_2{}^{\downarrow},\cdots,v_n{}^{\downarrow}\}$ is a partition of $v^{\downarrow}$.

Definition 3 [7]. Let $S=(U,AT\cup\{d\})$ be a multi-scale decision table, the cut c_j is a set of nodes in granularity tree T_j of attribute a_j such that there exists one and only one node $v\in c_j$ (except root node) on the path from the root node to each leaf node.

Definition 4 [8]. Let $S=(U,AT\cup\{d\})$ be a multi-scale decision table, the family of all cut combination in S called the cut collection, denoted by $\wp$, where $\wp=\{(c_1,c_2,\cdots,c_m)|c_j\in\zeta_j,j=1,2,\cdots,m\}$. Obviously, the coarsest cut combination is $(I_1,I_2,\cdots,I_m)$ and the finest cut combination is $(1,1,\cdots,1)$, denoted by C_0.

$IND(C)=\{(x,y)|a_j^k(x)=a_j^k(y)=v,v\in c_j,c_j\in C\}$ is the equivalence relation derived from $C\in\wp$. Thus, $[x]_C=\{y\in U|(x,y)\in IND(C)\}$. If the attribute value under attribute a_j^k is v, let $IND(v)=\{(x,y)|a_j^k(x)=a_j^k(y)=v\}$, $IND(\bar{v})=\{(x,y)|a_j^k(x)\neq v,a_j^k(y)\neq v\}$.

Definition 5 [8]. Let $S=(U,AT\cup\{d\})$ be a multi-scale decision table, for $C\in\wp$, C is positive-region consistent to S if $POS_C(d)=POS_{C_0}(d)$. And C is said to be positive-region optimal cut of S if C is consistent to S and C' (if $\{C'\in\wp|C\prec C'\}\neq\varnothing$) is positive-region

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inconsistent to S.

3. The stepwise lower-bound cut selection algorithm in multi-scale decision systems

In the process of stepwise optimal cut selection, the result $C=(c_1,c_2,\cdots,c_m)$ is not only influenced by the attribute sequence τ but also depends on a given positive-region consistent lower-bound cut combination, denoted by $\underline{C}=\left(\underline{c_1},\underline{c_2},\cdots,\underline{c_m}\right)$. if not specified, it is usually $\underline{C}=C_0$. Thus, the $t\mathrm{th}$ step positive-region optimal cut $C^t=\left(c_{i_1},c_{i_2},\cdots,c_{i_t},\underline{c_{i_{t+1}}},\cdots,\underline{c_{i_m}}\right)$.

In the process of stepwise optimal cut selection at each step, it is necessary to judge the nodes consistence under the current attribute. The following is the theorem 1 for judging the node consistence.

Theorem 1. Assuming that the $(t-1)\mathrm{th}$ step positive-region optimal cut is C^{t-1} and the attribute sequence is $\tau=a_{i_1}a_{i_2}\cdots a_{i_m}$, for node $v\in V_{i_t}$, if it satisfies $POS_{R(v)}(d)=POS_{C_0}(d)\cap v^{\downarrow}$, then the node v is positive-region consistent to the C^{t-1}.

Where, $R(v)=IND\left(C^{t-1}-\underline{c_{i_t}}\right)\cap IND(v)$, the $IND(v)$ is to restrict the equivalence relation $IND\left(C^{t-1}-\underline{c_{i_t}}\right)$ to the universe of discourse $v^{\downarrow}$ and let $POS_{R(v)}(d)=\left\{x\in v^{\downarrow}\mid [x]_{R(v)}\subseteq [x]_d\right\}$.

Consider using distance to characterize the similarity between two cut combinations.

Definition 6. For two cut c_1 and c_2, use $dist(c_1,c_2)$ to describe how many times c_1 needs to be coarsened and refined to reach c_2. Similarly, for cut combination C and $\underline{C}$, $dist\left(C,\underline{C}\right)=\sum_{j=1}^{m} dist\left(c_j,\underline{c_j}\right)$.

The following is the simplified consistence judgment theorem 2 of the nodes in the initial cut c_{i_t}.

Theorem 2. If $v\in c_{i_t}\cap \underline{c_{i_t}^{\Delta}}$, then the node v is region-positive consistent to the C^{t-1}.

Algorithm 1: Stepwise lower-bound cut selection algorithm based on sequence $reverse(\tau^{\Delta})$
Input: $S^{\Delta}=\{U,AT^{\Delta}\cup\{d\}\}$, $C^{\Delta}_{ini}=(c_1,c_2,\cdots,c_m)$, attribute sequence τ^{Δ}
Output: a lower-bound cut combination $\underline{C^{\Delta}}$ w.r.t C^{Δ}_{ini}
$\underline{C^{\Delta}}=\left(\underline{c_1^{\Delta}},\underline{c_2^{\Delta}},\cdots,\underline{c_m^{\Delta}}\right)=C^{\Delta}_{ini}$, $dif=POS_{C_0^{\Delta}}-POS_{C^{\Delta}_{ini}}$, $\overline{dif}=\{X\cap dif\neq\emptyset \mid X\in U/C^{\Delta}_{ini}\}$;
for a_{i_t} in $reverse(\tau^{\Delta})$ **do**
if $dif\neq\emptyset$ **do** $V^1_{i_t}=a^1_{i_t}(dif)$, $r1=\emptyset$;
for v in $V^1_{i_t}$ **do**
if $P=\left\{X\not\subset v^{\downarrow}, X\cap v^{\downarrow}\neq\emptyset \mid X\in\overline{dif}\right\}\neq\emptyset$ **do**
for X in P **do** $\overline{dif}-=X$; $//\partial(X)=\{d(y)\mid y\in X\}$
if $\lvert\partial(v^{\downarrow}\cap X)\rvert=1$ **do** $dif-=v^{\downarrow}\cap X$;
else do $\overline{dif}+=v^{\downarrow}\cap X$;
if $\lvert\partial(X-v^{\downarrow})\rvert=1$ **do** $dif-=(X-v^{\downarrow})$;
else do $\overline{dif}+=(X-v_{i_t}^{\downarrow})$;
else do $r1+=v$;
$V^1_{i_t}-=r1$, $\underline{c^{\Delta}_{i_t}}=\underline{c^{\Delta}_{i_t}}\wedge V^1_{i_t}$;
return $\underline{C^{\Delta}}$;

Before the simplified judgment theorem 2 can be applied, the lower-bound cut combination must be known. The following is the stepwise selection algorithm of lower-bound cut.

In step 3, the result of $a_{i_t}^1(dif)$ represents the set of attribute values corresponding to the dif under $a_{i_t}^1$. In step 12, the result of $\underline{c_{i_t}^{\Delta}} \wedge V_{i_t}^1$ contains all the nodes in $V_{i_t}^1$ and is the closest cut to $\underline{c_{i_t}^{\Delta}}$.

4. Stepwise dynamic updating method of optimal cut in multi-scale decision systems

4.1. Attribute sequence and initial cut combination

In the process of dynamic stepwise optimal cut selection, to fully utilize the existing knowledge for applying the simplified judgement theorem 3 proposed in later sections, it is necessary to ensure that the current attribute order in τ^{Δ} is consistent with the relative order of attributes in the attribute sequence τ.

For the attributes in the original system, their optimal cuts are used as the initial point for the stepwise dynamic updating algorithm. while attribute a_m is deleted, initial cut combination $C_{ini}^{\wedge}=(c_1,c_2,\cdots,c_{m-1})$. While attribute a_{m+1} is added, its coarsest cut is used as the initial cuts, so initial cut combination $C_{ini}^{\vee}=(c_1,c_2,\cdots,c_m,I_{m+1})$.

4.2. Influenced domain of parent node and global equivalence

In the static stepwise selection algorithm, the reason why the parent node v is not selected as the optimal node is because of $POS_{\underline{C}}(d)\cap v^{\downarrow} \neq POS_{R(v)}(d)$. Let the part where the positive region becomes smaller be denoted as $E(v)$, which can be understood as the influenced domain of the parent node v, $E(v)=POS_{\underline{C}}(d)\cap v^{\downarrow}-POS_{R(v)}(d)$.

In the process of stepwise updating, the variable of global equivalence $R(U)=IND(U)=\{(x,y)|(x,y)\in U^2\}$ is introduced. Below is the updating process of $R(U)$.

(1) Compare the lower-bound cut combination $\underline{C}$ used for stepwise optimal cut selection in the original system with $\underline{C^{\Delta}}$ used for current system, if node $v\in \underline{c_j}$ is an ancestor of $v_1,v_2,\cdots,v_s$ in $\underline{c_j^{\Delta}}$, then updating $R(U)\cap=\left(IND(\overline{v})+\sum_{j=1}^{s} IND(v_j)\right)$.

(2) If there exists nodes in c_j^{Δ} that are finer than a node in c_j, then updating $R(U)$ as in (1).

(3) If the lower-bound cut for the newly added attribute a_{m+1} is $\underline{c_{m+1}^{\vee}}$, then updating $R(U)\cap=IND\left(\underline{c_{m+1}^{\vee}}\right)$.

4.3. Stepwise updating algorithm of optimal cut in multi-scale decision systems

The following is the simplified consistence judgment theorem of the parent nodes v_p to the C^{t-1}.

Theorem 3. If all the child nodes of node v_p in attribute a_{i_t} of S^{Δ} belong to c_{i_t} and are positive-region consistent to C^{t-1}, and $E(v_p)\cap POS_{C_0^{\Delta}}(d)\not\subset POS_{R(U)\cap R(v_p)}(d)$, then node v_p is not positive-region consistent to C^{t-1}.

Proof. It is only proved here that when an attribute is added, the same is true when the attribute is deleted. In the static stepwise optimal cut selection algorithm in [8], when operating on attributes a_{i_t}, $R(v_p)=\bigcap_{j=1}^{t-1} IND(c_{i_j})\cap\bigcap_{j=t+1}^{m} IND\left(\underline{c_{i_j}}\right)\cap IND(v_p)=IND\left(C^{t-1}-\underline{c_{i_t}}\right)\cap IND(v_p)$ can be obtained. $R(U)$ is updated according to section 4.2 update procedure. When attribute a_{m+1} is added, thus there

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$R(U)\cap R(v_p)\subseteq \bigcap_{j=1}^{t-1} IND(c_{i_j}\wedge c_{i_j}^{\vee}) \cap \bigcap_{j=t+1}^{m} IND\left(\underline{c_{i_j}} \wedge \underline{c_{i_j}^{\vee}}\right) \cap IND\left(\underline{c_{m+1}^{\vee}}\right) \cap IND(v_p)$. In attribute sequence $\tau^{\vee}$, if attribute a_{i_t} precedes attribute a_{m+1} , there is $R^{\vee}(v_p)=\bigcap_{j=1}^{t-1} IND(c_{i_j}^{\vee})\cap\bigcap_{j=t+1}^{m} IND\left(\underline{c_j^{\vee}}\right)\cap IND\left(\underline{c_{m+1}^{\vee}}\right)\cap IND(v_p)$; if attribute a_{i_t} follows attribute a_{m+1}, there is $R^{\vee}(v_p)=\bigcap_{j=1}^{t-1} IND(c_{i_j}^{\vee})\cap \bigcap_{j=t+1}^{m} IND\left(\underline{c_{i_j}^{\vee}}\right)\cap IND(c_{m+1}^{\vee})\cap IND(v_p)$. In either case, there is $R(U)\cap R(v_p)\subseteq R^{\vee}(v_p)$, therefore, $POS_{R^{\vee}(v_p)}(d)\subseteq POS_{R(U)\cap R(v_p)}(d)$ is available. So if $E(v_p)\not\subseteq POS_{R(U)\cap R(v_p)}(d)$, there must be $E(v_p)\not\subseteq POS_{R^{\vee}(v_p)}(d)$. Because $E(v_p)\subseteq POS_{C_0}(d)\subseteq POS_{C_0^{\vee}}(d)$ and $E(v_p)\subseteq v_p{}^{\downarrow}$, so $E(v_p)\cap POS_{C_0^{\vee}}(d)\not\subseteq POS_{R^{\vee}(v_p)}(d)$ and $E(v_p)\cap POS_{C_0^{\vee}}(d)\subseteq POS_{C_0^{\vee}}(d)\cap v_p{}^{\downarrow}$ is available. In summary, $POS_{R^{\vee}(v_p)}(d)\neq POS_{C_0}(d)\cap v_p{}^{\downarrow}$, it can be seen that the node v_p is not consistent according to theorem 1.

For nodes in the initial cut combination, theorem 2 is applied first; for parent nodes of nodes in the initial cut combination, theorem 3 is applied first. If theorem 2 or 3 does not work, then theorem 1 is applied. According to these theorems, the algorithm 2 is given below.

Algorithm 2: stepwise optimal cut updating algorithm considering the dynamic changes of attributes
Input: $S^{\Delta}=\{U,AT^{\Delta}\cup\{d\}\}$, parent node set V_p, $E(v_p)$, $R(v_p)$, C, $\underline{C}$ and τ
Output: positive-region optimal cut C^{Δ} for a multi-scale decision system S^{Δ}
1 determine τ^{Δ} and C_{ini}^{Δ} based on section 4.1;
2 obtain a lower-bound cut combination $\underline{C^{\Delta}}$ according to algorithm 1;
3 Update $R(U)$ according to the process (1) and (3) in section 4.2;
4 $C^{\Delta}=(c_1^{\Delta},c_2^{\Delta},\cdots,c_m^{\Delta})=(\varnothing,\varnothing,\cdots,\varnothing)$, $t=0$, $C^0=\underline{C^{\Delta}}$;
5 **for** a_{i_t} *in* τ^{Δ} **do**
6 $r1=\varnothing$, $t+=1$;
7 **for** v *in* c_{i_t} **if** $v\notin \underline{c_{i_t}^{\Delta}}$ **do** //according to theorem 2
8 **if** v *is inconsistent* (*theorem* 1) **do**
9 select the optimal node from top to bottom and store it in $c_{i_t}^{\Delta}$;
10 Update $R(U)$ according to process (2) in Section 4.2 and $r1+=v$;
11 $c_{i_t}-=r1$, $r1=\varnothing$, $r2=\varnothing$;
12 **for** v *in* c_{i_t} **if** v *is not the coarsest node* **do** //the parent node of v is denoted as v_p
13 **if** $Q=T[i_t].Children(v_p)\subseteq c_{i_t}$ and $Q\cap(r1\cup r2)=\varnothing$ **do**
14 **if** $v_p\in V_p$ and v_p *is inconsistent* (*theorem* 3) **do** $r2+=Q$;
15 **else if** v_p *is inconsistent* (*theorem* 1) **do** $r2+=Q$;
16 **else do** $r1+=Q$, $c_{i_t}+=v_p$;
17 $c_{i_t}^{\Delta}+=(c_{i_t}-r1)$, $C^t=C^{t-1}_{i_t\text{th}=c_{i_t}^{\Delta}}$;
18 **return** C^{Δ};

To accommodate multiple dynamic updates, let $R(v_p)=R(v_p)\cap R(U)$ and $E(v_p)=E(v_p)-POS_{R(v_p)}(d)$ when v_p is judged to be inconsistent by theorem 3 in step 14.

5. Experiments and analysis

Two datasets are collected from the University of California, Irvine (UCI) Machine Learning Repository UCI standard datasets. The detailed information of these datasets is listed in alphabetical order in Table 1. The experimental environment is AMD Ryzen 5 3500U, 8.00 memory and Microsoft

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Windows 11 64 bit. The programming language is Python3.8.

Table 1: Dataset Information.

Datasets	Instances	Features	Classes
Glass identification	214	9	6
Seeds	210	7	3

5.1. Comparative experiments under dataset Glass identification and Seeds

For datasets Glass identification and Seeds, use the process of creating multi-scale decision tables in [8] to multiscale them. In this subsection, the parameter h is set to 1 by default.

In the experiment, the stepwise updating algorithm of optimal cut considering the dynamic changes of attributes proposed in this paper is compared with the static stepwise optimal cut selection algorithm in [8]. For the dataset Glass Identification and Seeds, the last condition attribute is taken as the changing attributes. Figure 1 shows attribute granularity trees, and Table 2 lists the granularity tree corresponding to the attributes under dataset Glass Identification, as well as the lower-bound cut, initial cut, and optimal cut of each attribute obtained by algorithm 2 after adding attribute. It also lists the parent node v_p w.r.t the initial cut and the parent node that can be judged as inconsistent according to theorem 3. Similarly, Table 3 lists the relevant data for the 6 attributes of dataset Seeds.

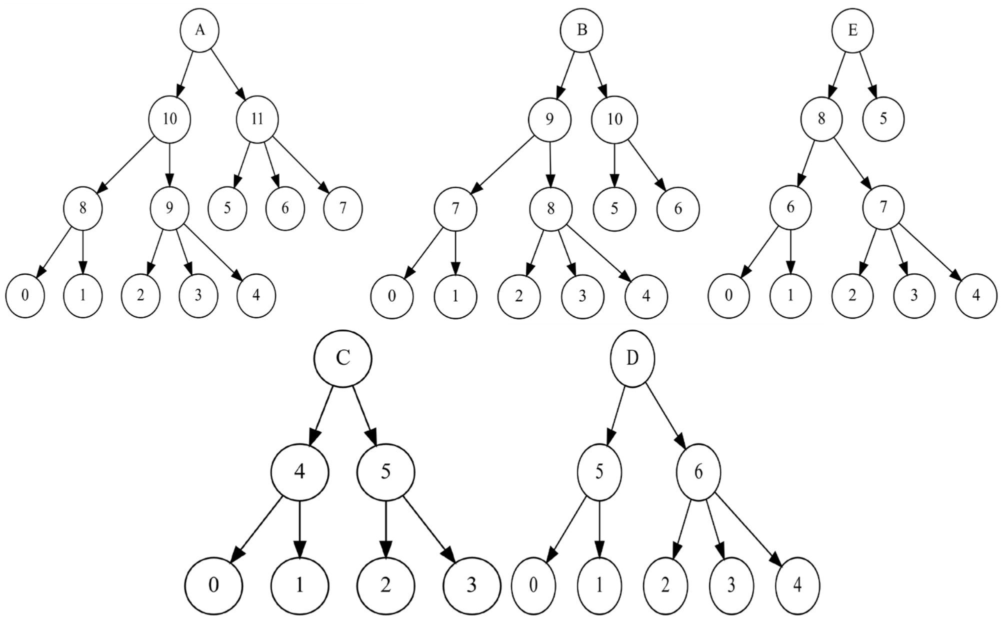

Figure 1: Attribute granularity trees.

Table 2: The changes of optimal cut after a_9 added on dataset Glass Identification.

<table>
<tr><th>Granularity tree</th><th>attribute</th><th>$\underline{C}^{\vee}$</th><th>$C^{\vee}_{ini}$</th><th>$C^{\vee}$</th><th>V_p</th><th>Theorem 3</th></tr>
<tr><td rowspan="4">Tree A</td><td>a_1</td><td colspan="3">$\{0,1,2,3,4,11\}$</td><td colspan="2">$\{8,9\}$</td></tr>
<tr><td>a_2</td><td colspan="3" rowspan="3">$\{8,2,3,4,11\}$</td><td colspan="2" rowspan="3">$\{9\}$</td></tr>
<tr><td>a_5</td></tr>
<tr><td>a_7</td></tr>
<tr><td rowspan="2">Tree B</td><td>a_4</td><td colspan="2">$\{0,1,2,3,4,10\}$</td><td>$\{7,8,10\}$</td><td>$\{7,8\}$</td><td>$\varnothing$</td></tr>
<tr><td>a_8</td><td colspan="3">$\{0,1,8,10\}$</td><td colspan="2">$\{7\}$</td></tr>
<tr><td>Tree C</td><td>a_3</td><td colspan="3">$\{4,5\}$</td><td colspan="2">$\varnothing$</td></tr>
<tr><td rowspan="2">Tree D</td><td>a_6</td><td colspan="3">$\{5,6\}$</td><td colspan="2" rowspan="2">$\varnothing$</td></tr>
<tr><td>a_9</td><td>$\{0,1,6\}$</td><td>$\{5,6\}$</td><td>$\{0,1,6\}$</td></tr>
</table>

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Table 3: The changes of optimal cut after a_7 deleted on dataset Seeds.

Granularity Tree	attribute	$\underline{C}^\wedge$	$C^\wedge_{ini}$	$C^\wedge$	V_p	Theorem 3
Tree C	a_1	$\{4,5\}$			$\varnothing$	
	a_2	$\{0,1,2,3\}$	$\{4\}$	$\{0,1,2,3\}$	$\{4\}$	
	a_5	$\{0,1,2,3\}$			$\{4,5\}$	
Tree D	a_3	$\{2,3,4,5\}$			$\{6\}$	
	a_4	$\{0,1,2,3,4\}$	$\{5\}$		$\{5\}$	
Tree E	a_6	$\{0,1,2,3,4,5\}$			$\{6,7\}$	

According to the results in Table 2, only the initial cut of attributes a_4 and a_9 needs to be updated, and $dist(C^\vee_{ini}, C^\vee) = 3$. In algorithm 2, except for the two parent nodes $\{7,8\}$ in attribute a_4 that cannot be quickly judged as positive-region inconsistent by theorem 3 and need to be judged by theorem 1, all other attributes with parent nodes can be judged as inconsistent by theorem 3.

According to the results in Table 3, it can be seen that only the initial cut of attribute a_2 needs to be updated, while the other attributes can remain unchanged, and $dist(C^\wedge_{ini}, C^\wedge) = 1$. In algorithm 2, the parent nodes in the attribute a_2, a_3, a_4, a_5 and a_6 can all be quickly judged as positive-region inconsistent by theorem 3, which greatly reduces the running time of the algorithm.

5.2. Comparative analysis of the operational efficiency of dynamic and static algorithms on different datasets

To verify the effectiveness of the proposed stepwise updating algorithm, the static optimal cut selection algorithm proposed by author in [8] and the proposed algorithm 2 in this paper were compared through experiments on two UCI datasets. In the experiment, the last conditional attribute in each dataset was selected as the changing attribute, and the value of parameter h was set as 1, 3, 5, 7 and 9 to obtain different multi-scale decision tables. The experimental results for attribute addition are shown in Figure 2, and the experimental results for attribute deletion are shown in Figure 3. The y-axis on the left represents the computation time of the algorithm, and the y-axis on the right represents the distance between the initial cut combination C^Δ_{ini} and the optimal cut C^Δ by definition 6.

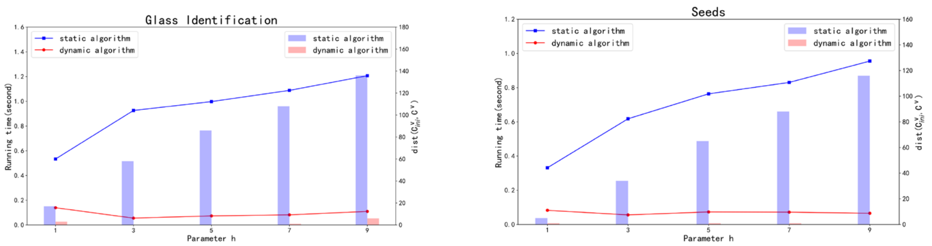

Figure 2: Comparison of running time and $dist(C^\vee_{ini}, C^\vee)$ between dynamic and static algorithms.

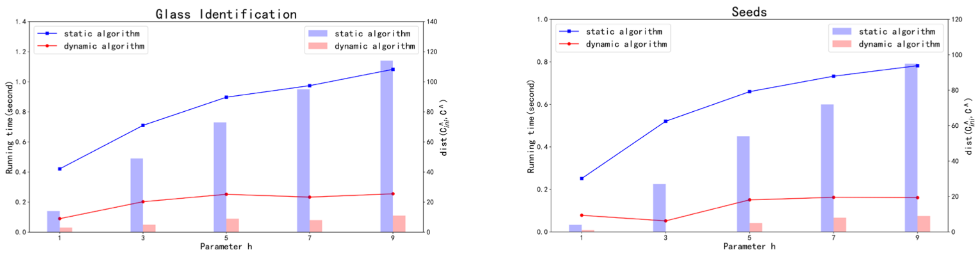

Figure 3: Comparison of running time and $dist(C^\wedge_{ini}, C^\wedge)$ between dynamic and static algorithms.

Through the above experiments, it can be seen that compared with the static stepwise optimal cut

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selection algorithm proposed by author in [8], the initial cut combination and the optimal cut obtained by algorithm 2 proposed in this paper have smaller distance and higher similarity. Moreover, by simplified judgment theorems 2 and 3, the time cost of stepwise updating of optimal cut is reduced greatly.

6. Conclusions

In view of the dynamic change of multi-scale information system, the static stepwise selection method cannot use the knowledge obtained in the original optimal cut selection process, and more time will be spent to recalculate all the data. The stepwise dynamic updating method of optimal cut in multi-scale information systems considering the changes of attributes is focusly researched. By taking the optimal cut obtained from the original information system as the initial cut combination to search, keeping the relative order of attributes, and utilizing the knowledge obtained from the stepwise optimal cut selection under the original information system, the consistence judgment of some nodes in the updated information system is simplified, the time cost is saved greatly. By synthesizing two static stepwise selection algorithms, a stepwise dynamic updating algorithm of optimal cut in multi-scale decision systems considering the changes of attributes is proposed. Experimental results on UCI datasets show that the proposed dynamic updating algorithm significantly improves computational efficiency compared with the static stepwise selection algorithm while attributes dynamic changing in multi-scale decision systems.

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