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Algorithms on Parameterized Rough-Intuitionistic Fuzzy Classification using a Threshold

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Abstract: Hybridization of Rough Sets with intuitionistic fuzzy sets is commonly in use for deriving several real time applications. However, due to limitations, the parameterized rough sets are found to be more effective than conventional RS Models due to its quality and accuracy. In this aspect, we describe three types of algorithms namely lower, upper and parameterized rough indexing algorithms to index the records of decision table with intuitionistic fuzzy decision attributes and the same are implemented using C Programming.

Keywords: Rough Sets, intuitionistic fuzzy sets, indexing, decision table

1. Introduction

Considering the importance of the theories on rough sets [4,5], fuzziness and intuitionistic fuzziness [1], a few hybridizing techniques are in practice. In Particular, G.Ganesan et. al.[2,3] developed naïve indexing technique using one threshold in intuitionistic fuzzy input. However, as Parameterized RS Model is effective than conventional RS Model, in this paper, we developed three kinds of indexing techniques using one threshold on intuitionistic fuzzy decision attribute of a decision table using parameterized RS Model.

This paper is organized into 6 sections. In 2nd Section, we narrate the basic mathematical concepts which are required for the forthcoming sections. In 3rd and 4th sections, we propose the lower and upper index algorithms respectively for a decision table with intuitionistic fuzzy decision attribute using one threshold and they are implemented using C Programming. In 5th section, both indexing algorithms are consolidated and parameterized rough indexing algorithm is proposed a decision table with intuitionistic fuzzy decision attribute using one threshold and the same has been implemented using C Programming and the paper ends with concluding remarks as 6th section.

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2. Mathematical Preliminaries

In this section, we describe the concepts of rough sets, fuzzy sets and intuitionistic fuzzy sets.

2.1 Rough Sets

Let U be a finite universe of discourse U and R be an equivalence relation on U. Let U/R = $\{X_1, X_2, \ldots, X_n\}$ denote the set of all equivalence classes of U induced by R. For a given input Y, the rough approximations are defined as $\underline{R}Y=\cup\{X\in U/R: Y\supseteq X\}$ and $\overline{R}Y=\cup\{X\in U/R: Y\cap X\neq\Phi\}$ where $\underline{R}Y$ and $\overline{R}Y$ are said to be R-lower and R-upper approximations of Y. The following algorithms may be implemented to compute Lower and Upper Rough Approximations.

<u>Algorithm of Lower Rough Approximations</u>

\\$X_1, X_2, \ldots, X_n$ – Equivalence Classes
\\ Y-Input

Let D=NULL
For i=1 to n do
    If Y is superset of X_i, then D= D $\cup$ X_i
Return D

<u>Algorithm of Upper Rough Approximations</u>

\\$X_1, X_2, \ldots, X_n$ – Equivalence Classes
\\ Y-Input

Let D=NULL
For i=1 to t do
    If Y $\cap X_i \neq$NULL then D= D $\cup$ X_i
Return D

Here, the Positive, Negative and Boundary Regions of a given set A are defined as the lower approximation of A, complement of the upper approximation of A and the difference between upper and lower approximations of A respectively.

2.2 Parameterization of RS Model

Since the conventional RS Model deals with mere inclusions and intersections in computing rough approximations, it has its own limitations and restrictions. For example, these conventional approximations consider only 100% inclusions in the computation and even ignore 99.9% inclusions. Hence, the Parameterized RS Model came into existence and for a given input A and $0 \leq \mu \leq \tau \leq 1$, the positive (POS(A)), boundary (BND(A)) and negative (NEG(A)) regions of A are defined respectively as follows:

$$POS(A) = \left\{ x \in U / \left| \frac{A \cap [x]}{[x]} \right| \geq \tau \right\}$$

$$BND(A) = \left\{ x \in U / \mu < \left| \frac{A \cap [x]}{[x]} \right| < \tau \right\}$$

$$NEG(A) = \left\{ x \in U / \left| \frac{A \cap [x]}{[x]} \right| \leq \mu \right\}$$

2.2 Rough and intuitionistic fuzzy Hybridization

Since Intuitionistic fuzziness is one of the effective tools whenever crisp data is not arrived, in this section, we describe the procedure of hybridizing it with rough approximations.

For a given finite universe of discourse U and for the equivalence relation, denote the quotient space as $U/R = \{X_1, X_2, \ldots, X_n\}$. Lat A be an intuitionistic fuzzy subset of U. For a given threshold α (ranging between 0 and 1), define $A[\alpha]=\{x \in U/\delta_A(x)>\alpha \text{ and } \gamma_A(x)<1-\alpha\}$ where δ_A, γ_A represent membership and non-membership values in A respectively. The lower and upper rough approximations of A are given by $A_\alpha = \underline{A[\alpha]}$ and $A^\alpha = \overline{A[\alpha]}$ respectively.

3. Lower Indices in a Decision Table with Intuitionistic Fuzzy Decision Attribute

In this section, an algorithm is introduced to compute the lower index using parameterized rough approximations. In the algorithm, single threshold is used on an intuitionistic fuzzy input A and using square and square root functions, the lower indices are obtained. Also, we illustrate the algorithm for a decision table with a intuitionistic fuzzy decision attribute.

Algorithm (alpha, A, x)
//Algorithm to obtain index of x an element of universe of discourse
//Algorithm returns the index

1. Let x_index be an integer initialized to M

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```
2. Pick the equivalence class K containing x.

3. If  U(y)=0 for all y belongs to K
Begin
   x_index=-x_index
   goto 7
End

4. If  U(y)=1 for all y belongs to K
   goto 7

5. Compute “POS of A[alpha]”

6. If “ x belongs to POS of A[alpha]”
While (“x belongs to POS of A[alpha]”)
   Begin
 alpha= sqrt(alpha) //square root of alpha
 x_index=x_index+1
 Compute “POS of A[alpha]”
End

else

While (“x NOT belongs to POS of A[alpha]”)
   Begin
 alpha= sqr(alpha) //square of alpha
 x_index=x_index-1
 Compute “POS of A[alpha]”
End
7. Return x_index
```

3.2 Experimental Results

Consider the following decision table with 10 records namely 1, 2,3,4,5,6,7,8,9 and 10 with three conditional attributes namely Attr_1, Attr_2, Attr_3 and an intuitionistic fuzzy decision attribute.

	Attr_1	Attr_2	Attr_3	Decision	
				Membership	Non-Membership
1	Violet	Pink	Violet	0.6	0.2
2	Pink	Violet	Red	0.7	0.1

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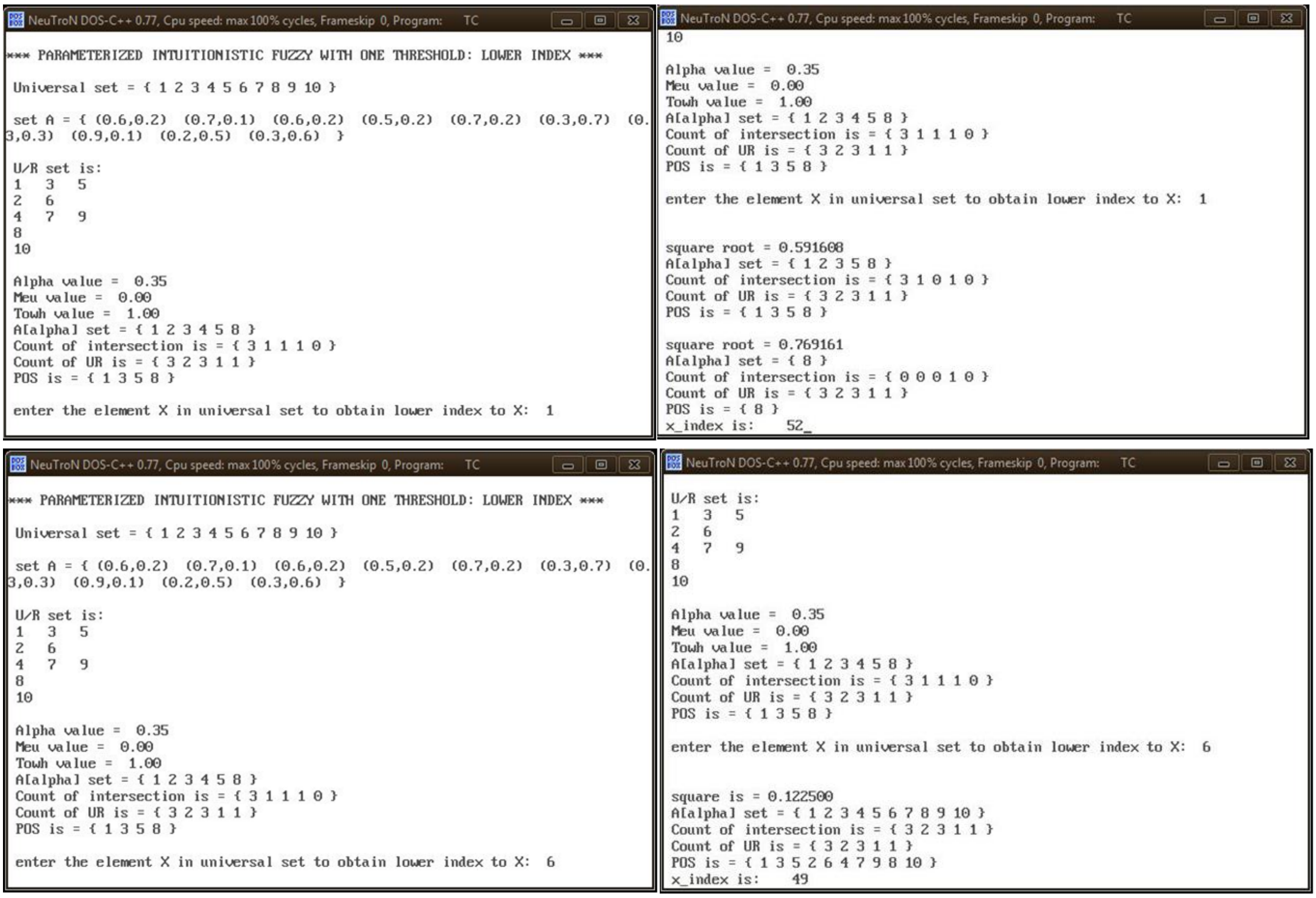
3	Pink	Pink	Violet	0.6	0.2
4	Purple	Red	Black	0.5	0.2
5	Black	Pink	Black	0.7	0.2
6	Purple	Violet	Pink	0.3	0.7
7	Violet	Red	Black	0.3	0.3
8	Violet	Black	Purple	0.9	0.1
9	Red	Red	Pink	0.2	0.5
10	Black	Purple	Black	0.3	0.6

It may be noticed that the records are grouped according the similarity for each key or group of keys. i.e., the records are grouped as follows: For Attr_1, the grouping are {(Violet, {1,7,8}), (Red,{9}), (Pink, {2,3}), (Black, {5,10}), (Purple, {4,6}) }. For Attr_2, the grouping are {(Violet,{2,6}), (Red,{4,7,9}), (Pink,{1,3,5}), (Black,{8}), (Purple,{10})} and for Attr_3, we obtain {(Violet, {1,3}), (Red,{2}), (Pink,{6,9}), (Black,{4,5,7,10}), (Purple,{8})}.

The above example is implemented in C by using Attr_2 as the key and the threshold as 0.35 we obtain the lower index of 1 as 52 and the lower index of 6 as 49



4. Upper Indices in a Decision Table with Intuitionistic Fuzzy Decision Attribute

In this section, we propose an algorithm to compute an upper index using parameterized rough approximations. In this algorithm, an intuitionistic fuzzy input A is considered and using a single threshold. For each element, the upper index is obtained using square and square root functions. Also, we illustrate the algorithm for a decision table with an intuitionistic fuzzy decision attribute.

4.1 Algorithm for Upper index of an element

```
Algorithm (alpha, A, x)
//Algorithm to obtain index of x an element of universe of discourse
//Algorithm returns the index
1. Let x_index be an integer initialized to M

2. Pick the equivalence class K containing x.

3. If  U(y)=0 for all y belongs to K
Begin
    x_index=-x_index
    goto 7
End

4. If  U(y)=1 for all y belongs to K
    goto 7

5. Compute "NEG of A[alpha]"

6. If " x belongs to NEG of A[alpha]"
While ("x belongs to NEG of A[alpha]")
    Begin
  alpha= sqr(alpha) //square of alpha
  x_index=x_index-1
  Compute "NEG of A[alpha]"
End

else

While ("x NOT belongs to NEG of A[alpha]")
    Begin
  alpha= sqrt(alpha) //square root of alpha
  x_index=x_index+1
  Compute "NEG of A[alpha]"
End
7. Return x_index
```

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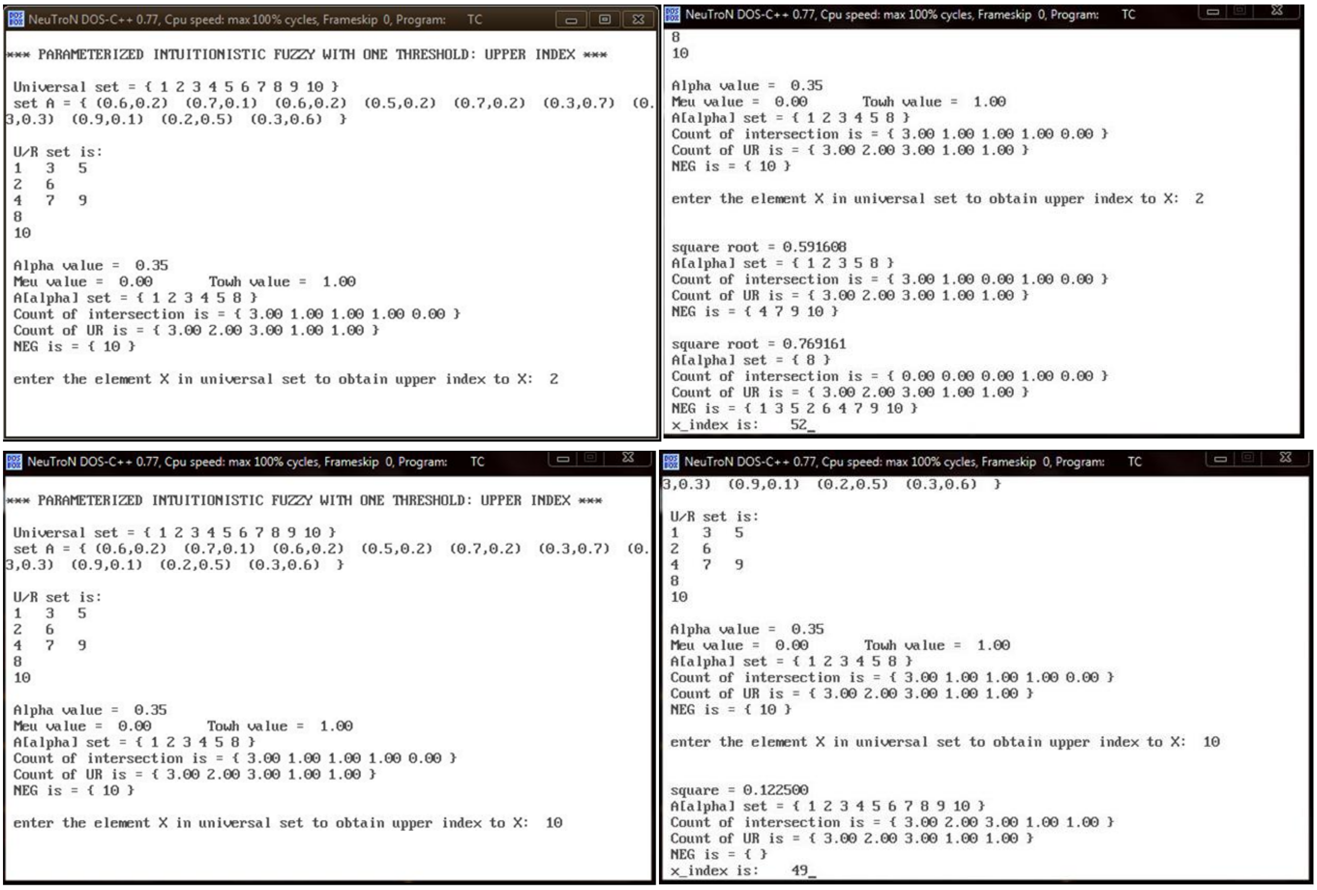
4.2 Experimental Results

In the example, the upper indices of 2 and 10 are computed as 52 and 49 respectively.


```
NeuTroN DOS-C++ 0.77, Cpu speed: max 100% cycles, Frameskip 0, Program: TC
*** PARAMETERIZED INTUITIONISTIC FUZZY WITH ONE THRESHOLD: UPPER INDEX ***

 Universal set = { 1 2 3 4 5 6 7 8 9 10 }
 set A = { (0.6,0.2)  (0.7,0.1)  (0.6,0.2)  (0.5,0.2)  (0.7,0.2)  (0.3,0.7)  (0.
3,0.3)  (0.9,0.1)  (0.2,0.5)  (0.3,0.6)  }

 U/R set is:
 1   3   5
 2   6
 4   7   9
 8
 10

 Alpha value =  0.35
 Meu value =  0.00        Towh value =  1.00
 A[alpha] set = { 1 2 3 4 5 8 }
 Count of intersection is = { 3.00 1.00 1.00 1.00 0.00 }
 Count of UR is = { 3.00 2.00 3.00 1.00 1.00 }
 NEG is = { 10 }

 enter the element X in universal set to obtain upper index to X:  2
```

```
NeuTroN DOS-C++ 0.77, Cpu speed: max 100% cycles, Frameskip 0, Program: TC
 8
 10

 Alpha value =  0.35
 Meu value =  0.00        Towh value =  1.00
 A[alpha] set = { 1 2 3 4 5 8 }
 Count of intersection is = { 3.00 1.00 1.00 1.00 0.00 }
 Count of UR is = { 3.00 2.00 3.00 1.00 1.00 }
 NEG is = { 10 }

 enter the element X in universal set to obtain upper index to X:  2


 square root = 0.591608
 A[alpha] set = { 1 2 3 5 8 }
 Count of intersection is = { 3.00 1.00 0.00 1.00 0.00 }
 Count of UR is = { 3.00 2.00 3.00 1.00 1.00 }
 NEG is = { 4 7 9 10 }

 square root = 0.769161
 A[alpha] set = { 8 }
 Count of intersection is = { 0.00 0.00 0.00 1.00 0.00 }
 Count of UR is = { 3.00 2.00 3.00 1.00 1.00 }
 NEG is = { 1 3 5 2 6 4 7 9 10 }
 x_index is:    52_
```

```
NeuTroN DOS-C++ 0.77, Cpu speed: max 100% cycles, Frameskip 0, Program: TC
*** PARAMETERIZED INTUITIONISTIC FUZZY WITH ONE THRESHOLD: UPPER INDEX ***

 Universal set = { 1 2 3 4 5 6 7 8 9 10 }
 set A = { (0.6,0.2)  (0.7,0.1)  (0.6,0.2)  (0.5,0.2)  (0.7,0.2)  (0.3,0.7)  (0.
3,0.3)  (0.9,0.1)  (0.2,0.5)  (0.3,0.6)  }

 U/R set is:
 1   3   5
 2   6
 4   7   9
 8
 10

 Alpha value =  0.35
 Meu value =  0.00        Towh value =  1.00
 A[alpha] set = { 1 2 3 4 5 8 }
 Count of intersection is = { 3.00 1.00 1.00 1.00 0.00 }
 Count of UR is = { 3.00 2.00 3.00 1.00 1.00 }
 NEG is = { 10 }

 enter the element X in universal set to obtain upper index to X:  10
```

```
NeuTroN DOS-C++ 0.77, Cpu speed: max 100% cycles, Frameskip 0, Program: TC
3,0.3)  (0.9,0.1)  (0.2,0.5)  (0.3,0.6)  }

 U/R set is:
 1   3   5
 2   6
 4   7   9
 8
 10

 Alpha value =  0.35
 Meu value =  0.00        Towh value =  1.00
 A[alpha] set = { 1 2 3 4 5 8 }
 Count of intersection is = { 3.00 1.00 1.00 1.00 0.00 }
 Count of UR is = { 3.00 2.00 3.00 1.00 1.00 }
 NEG is = { 10 }

 enter the element X in universal set to obtain upper index to X:  10


 square = 0.122500
 A[alpha] set = { 1 2 3 4 5 6 7 8 9 10 }
 Count of intersection is = { 3.00 2.00 3.00 1.00 1.00 }
 Count of UR is = { 3.00 2.00 3.00 1.00 1.00 }
 NEG is = { }
 x_index is:    49_
```

5. Parameterized Rough Indices in a Decision Table with Intuitionistic Fuzzy Decision Attribute

In this section, by hybridizing the algorithms described in sections 3 and 4, parameterized rough indices are obtained for each element of the Universe of discourse. Similar to the above algorithms, by applying square and/ or square root functions on the threshold of the intuitionistic fuzzy input A, the rough indices are obtained accordingly. The algorithm is illustrated for a decision table with an intuitionistic fuzzy decision attribute.

5.1 Algorithm for Rough index of an element

Algorithm (alpha, A, x)

//Algorithm to obtain index of x an element of universe of discourse

//Algorithm returns the index

1. Let x_index be an integer initialized to M

2. Pick the equivalence class K containing x.

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```
3.  If  U(y)=0 for all y belongs to K
Begin
    x_index = -x_index
    goto 7
End

4.  If  U(y)=1 for all y belongs to K
    goto 7

5.  Compute POS of A[alpha], NEG of A[alpha], BND of A[alpha]

6.  If  " x belongs to POS of A[alpha]"
While (" x belongs to POS of A[alpha]")
    Begin
alpha= sqrt(alpha) //square root of alpha
  x_index=x_index +1
  Compute POS of A[alpha]
End

else

7.  If  " x belongs to NEG of A[alpha]"

While ("x belongs to NEG of A[alpha]")
    Begin
alpha= sqr(alpha) //square of alpha
  x_index=x_index-1
  Compute "NEG of A[alpha]"
End
else
    Begin
beta = alpha
Compute NEG of A[beta]
while("x NOT belongs to(POS of A[alpha] U NEG of A[beta]")
Begin
alpha = sqr(alpha) // square of alpha
beta = sqrt(beta) // square root of beta
compute POS of A[alpha] U NEG of A[beta]
x_index=x_index+1
End
If "x belongs to POS of A[alpha]"
```

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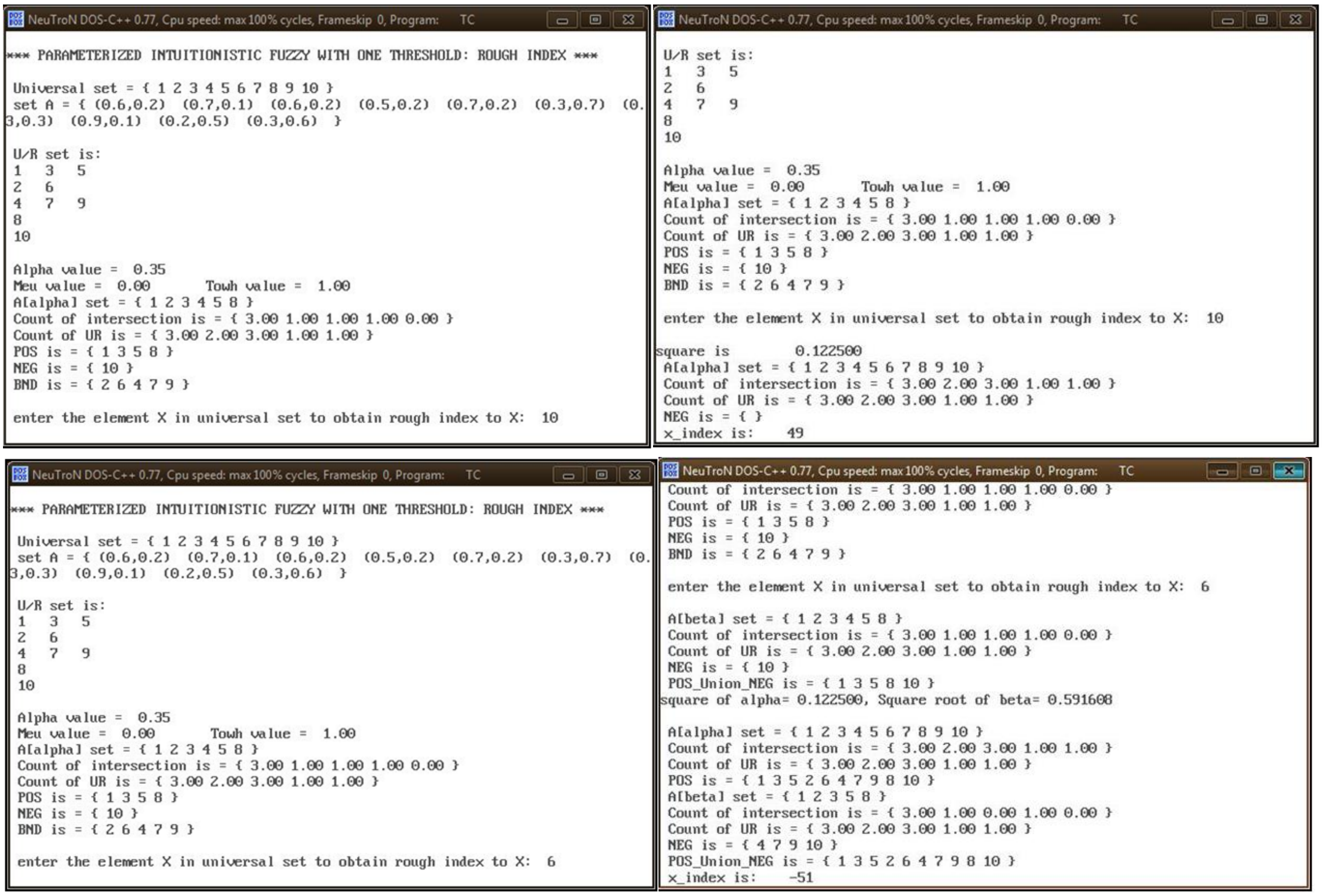
x_index = -x_index
End
8. Return x_index

5.2 Experimental Results

In the above example, the parameterized rough indices of 6 and 10 are -51 and 49 respectively.



6. Conclusion

In this paper, we implemented three algorithms using C Programming for computing parameterized rough indices of the records of the decision table with intuitionistic fuzzy decision attributes.

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