Reduct Generation from Binary Discernibility Matrix: An Hardware Approach

Kanchan S. Tiwari, Ashwin G. Kothari, and Avinash G. Keskar

***Abstract*—Rough set theory is a powerful mathematical tool used for extracting useful rules from a huge database. We have proposed a Rough Set Machine which generates rules for classification applications. The classification task concentrates on predicting the value of the decision class for an object among a predefined set of classes' values. This rough set machine uses the concept of discernibility matrix for calculating the reducts, and using these reducts it generates the rules which are used for classifying the objects. The Reduct block is synthesized and downloaded on FPGA.**

***Index Terms*—Rough set, discernibility matrix, reduct , classification, FPGA .**

I. Introduction

The notion of rough set was introduced by Polish computer scientist Zdzislaw Pawlak in 1982.Rough set theory is a mathematical soft computing tool used for managing vagueness and uncertainty in data thereby resulting in extraction of useful information from database [1]. The rough set approach seems to be of fundamental importance to AI and cognitive sciences, especially in the areas of machine learning, knowledge acquisition, and decision analysis, knowledge discovery from databases, expert systems, inductive reasoning and pattern recognition. The rough set approach provides efficient algorithms for finding hidden patterns in data, minimal sets of data (data reduction), evaluating significance of data, and generating sets of decision rules from data. This approach is easy to understand, offers straightforward interpretation of obtained results, most of its algorithms are particularly suited for parallel processing. It deals with the classificatory analysis of information system. The main goal of the rough set analysis is to synthesize approximation of concepts from the acquired data [2].

An information system is normally characterized by huge attributes size. One of important aspect of rough set theory for knowledge acquisition involves the searching of some particular subsets of conditional attributes. It is well known that many of these attributes are redundant, superfluous, and irrelevant for rule discovery which needs to be eliminated since not only computation time increases exponentially with the size of database but also the quality of rules generated is degraded. Attributes reduction is a very important part of RST. It is defined as a process of selecting relevant attributes out of the larger set of candidate attributes. The relevant attributes are defined as attribute subset that has the same classification capability with the overall attributes. Since the attributes reduction reduces the size of databases, it enables the learning algorithms to operate more effectively and rapidly. Many attribute reduction algorithms have been proposed in recent years, such as Discernibility matrix based algorithms [4-7], Heuristic algorithms [3], etc. Softwares like RSES, ROSETTA etc has been developed for reduct construction [9]. The problem of computing all reducts belongs to the class of NP- Hard problems and the cost of finding the reduct is highly influenced by the size of object set and attribute set. Application of this type of rough set information processing has been typically conducted through the use of software running on conventional general-purpose microchips. Any type of such processing can be achieved easily when handled by software in this way. However, although high flexibility is achieved through software, software running on conventional microprocessors alone is not effective in handling applications requiring high speed processing.

For this reason, one method of achieving high speed processing is to develop specific hardware for the task and place it on microchips. Such hardware will speed the process of decision making and can be deployed in real time decision making systems. The application chosen for our research work is of object identification system by an intelligent robot. The paper is organized as follows: Section II presents a brief review of rough set theory concepts, Section III presents architecture for Discernibility matrix and reduct block; Section IV shows the simulation results; Section V talks about conclusion and future work.

II. Basic Concepts of Rough Set Theory

The rough set (RS) theory is founded on the assumption that with every object of universe we can associate some information. An information system (IS) is defined as a family of sets $S=<U, A, V, f>$, where U is a non-empty universe of objects, A is a finite non-empty set of attributes, V is the value set of A and f: $U \times A \rightarrow V$ is information function. Columns of an information table are labeled by attributes, rows - by objects and entries of the table are attribute values. Objects having the same attribute values are indiscernible with respect to these attributes and belong to the same block of the partition (classification) determined by the set of attributes.

Information systems with distinguished decision and condition attributes are called decision tables. A decision table is denoted by $DT=<U, C \cup D, V, f>$,where

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K. S. Tiwari is with the MESCOE, Pune, Maharashtra, India.

A. G. Kothari and A. G. Keskar are with the VNIT, Nagpur, Maharashtra, India.

U, V and f are the same as defined above; $A=C\cup D$, C is a set of condition attributes, D is a set of decision attributes, and $C\cap D=\Phi$. Each row of a decision table determines a decision rule, which specifies decisions (actions) that should be taken when conditions pointed out by condition attributes are satisfied. The RS theory is based on the observation that objects may be indiscernible (indistinguishable) because of limited available information.

An information system can also be presented in terms of a Discernibility matrix. A Discernibility matrix is a basic method to search all the reducts of an information system. A Discernibility matrix is a square matrix in which rows and columns are objects, and cells are attribute sets that discern objects. Two objects are considered to be discernible if and only if they have different values for at least one attribute. The Discernibility matrix, denoted by M, for a decision table DT, of an Information system (IS) is given below:

$$c_{ij} = \begin{cases} \Phi & f_D(x_i) = f_D(x_j) \\ a \in A;\ a(x_i) \neq a(x_j)\},f_D(x_i) \neq f_D(x_j) & \text{----- I} \end{cases}$$

Using Discernibility matrix, Skowron and Rauszer[8] have proven several properties and constructed efficient algorithms related to information systems and decision tables e.g. reduct, core, dependencies.A reduct is any minimal subset of condition features, which discerns all pairs with different decision values and is complete if the deletion of any attribute of a reduct will make at least one pair of objects with different decision attribute values indiscernible.

The intersection of all reducts is called the core of the Decision Table. In this paper, we have implemented the algorithm of finding reduct using binary discernibility matrix proposed by [7].According to Susmaga's survey on Reduct calculation algorithms[10] , Discernibility matrix based algorithms were found to be more effective than traditional ones.Table 1 shows an information system consisting of 8 objects, U={x1,x2,x3,x4,x5,x6,x7,x8},eight condition attributes C={c1,c2,c3,c4,c5,c6,c7,c8},and one decision attribute{d}. Table 2 shows partial binary discernibilitymatrix for the information system in Table I.

TABLE I: INFORMATION SYSTEM.

	c1	c2	c3	c4	c5	c6	c7	c8	c2	***d***
x1	1	1	0	0	1	1	0	0	1	***1***
x	0	0	1	1	1	1	1	0	0	***2***
x3	1	0	1	1	1	1	0	0	0	***3***
x4	1	0	0	0	1	1	1	1	0	***4***
x5	1	1	1	1	0	0	0	1	1	***2***
x6	1	0	1	0	0	1	1	1	0	***3***
x7	1	1	1	0	0	0	1	1	1	***4***
x8	0	0	0	1	0	1	0	0	0	***1***

TABLE II: PARTIAL DISCERNIBILITY MATRIX.

	c1	***c2***	***c3***	***c4***	***c5***	***c6***	***c7***	***c8***	***c9***
X12	1	1	1	1	0	0	1	0	0
X13	0	1	1	1	0	0	0	0	1
X14	0	1	0	0	0	0	1	1	1
X15	0	0	1	1	1	1	0	1	1
X16	0	1	1	0	1	0	1	1	0
X17	0	0	1	0	1	1	1	1	1

III. ARCHITECTURE OF BINARY DISCERNIBILITY MATRIX

The block diagram of binary discernibility matrix is shown below in fig.1.The decision table is database obtained from a mobile robot multisensory system .The condition attributes in the decision table corresponds to infrared sensors values and the decision to be taken based on its value is stored the decision attribute column. The condition attributes are stored in C_RAM block and decision attributes are stored in D_RAM.The C_RAM and D_RAM values are latched in Registers on rising edge of clock.The addresses to these memories are generated by counter block.The D_RAM first value is compared with all successive values and if they differ then condition attributes are XORed .The resulting XORed string of data is stored in a RAM.Clk_ref is used to latch first value of D_RAM and X_RAM whereas clk_others are used for latching remaining values of condition and decision attributes.

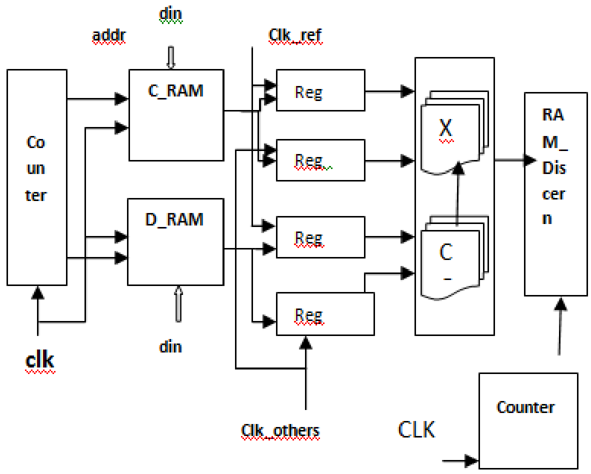

Fig. 1. Binary discernibility matrix.

IV. ARCHITECTURE OF REDUCT CALCULATOR BLOCK

The discernibility matrix block output acts as an input to Reduct Calculator Block. Reduct block assumes initial value of reduct vector to be zero of size equal to number of condition attributes. It calculates the significance of each attribute and the attribute having higher significance is retained. The significant attribute calculation goes through two iterations, during first iteration the occurrence of each attribute is stored in a variable and the attribute having unique maximum value is marked as a part of reduct vector. However if there exists more than one unique maximum value, reduct calculation goes to next phase of calculating significant attribute which involves computing length of corresponding column attributes , where length corresponds to sum of each row. The minimum amongst the sum value is marked as in indispensable attributes and the corresponding bit is set in the reduct vector. The attribute marked in reduct vector is masked in discernibility matrix and the operations are repeated till it becomes empty.

V. Simulation Results

The simulation results of discernibility matrix and reduct calculator block integrated together are shown in fig 2.A clk of 20 ns is used as master clock for generating addresses of RAM.Clk_ref and clk_other is derived from so as to latch reference values of both condition and decision RAM. We have shown a sample simulation for 4 condition attributes , 4 class decision system consisting of 4 objects.rd1 and rx1 are the reference values latched for comparison with successive values.The output of discernibility matrix is shown in dismat and reduct vector is shown by reduct_m.The reduct is available approximately after 950 ns.

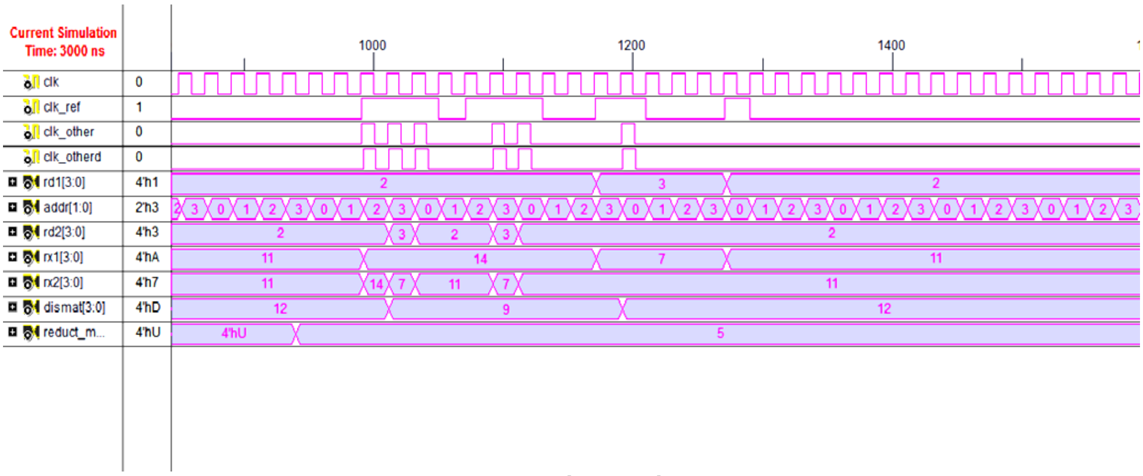

Fig. 2. Simulation results

VI. Conclusions and Results

In this paper, architecture of Binary Discernibility matrix and reduct calculator block of rough set processor have been designed and implemented in VHDL.This work is in support for the development of rough set processor. A dedicated hardware for approximate reasoning will relieve the main processor from computational overhead, thereby increasing the speed of the operation. Our future work is develop a rule block and integrate it with RSM.

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