

# Evaluation of Fuzzy ARTMAP with DBSCAN in VLSI Application

K. A. Sumithradevi, Vijayalakshmi. M. N., Annamma Abraham. and Dr. Vasanta

**Abstract**—The various applications of VLSI circuits in high-performance computing, telecommunications, and consumer electronics has been expanding progressively, and at a very hasty pace. This paper describes a new model for partitioning a circuit using DBSCAN and fuzzy ARTMAP neural network. The first step is concerned with feature extraction, where we had make use DBSCAN algorithm. The second step is the classification and is composed of a fuzzy ARTMAP neural network. The performance of both approaches is compared using benchmark data provided by MCNC standard cell placement benchmark netlists. Analysis of the investigational results proved that the fuzzy ARTMAP with DBSCAN model achieves greater performance then only fuzzy ARTMAP in recognizing sub-circuits with lowest amount of interconnections between them The recognition rate using fuzzy ARTMAP with DBSCAN is 97.7% compared to only fuzzy ARTMAP.

**Keywords**—VLSI, Circuit partitioning, DBSCAN, fuzzy ARTMAP.

## I. INTRODUCTION

ADVANCES in semiconductor technology in the integration level of integrated circuits have enhanced many features, increased the performance; improved reliability of electronic equipment, and at the same time reduced the cost, power consumption and system size. As size and complexity of digital system has increased, more computer aided design tools are introduced into hardware design processes. There is Hardware/software [3] design methodology for embedded systems that seeks to satisfy system-level constraints by exploiting the synergy between hardware and software through their concurrent design [2]. During partitioning, design components are assigned to hardware and software implementation targets. The output of

the practitioner has a significant impact on the subsequent scheduling of software. The circuit partitioning problem arises in VLSI layout. Components called cells (or nodes) are to be laid out in two or more blocks. The cells are connected by wires, called nets. Nets connect two or more cells. Cells may be connected to more than one net. The netlist is the set of all nets to be partitioned. The netlist partitioning problem is known to be NP-hard [4]. The designers extensively rely on software tools for nearly every aspect of the development cycle, from circuit specification and design entry to the performance analysis, layout generation and verification. Partitioning is a problem that runs central to VLSI design automation, and one that has attracted a great deal of interest; a recent survey [1] lists almost 200 papers on the subject. In order to reduce the complexity of the design process, several intermediate levels of abstraction are introduced. Partitioning a circuit is necessary if it is too large to be accommodated on a single chip. A number of heuristic algorithms [5, 6, 7, 8, 9, 10] have been developed over the past three decades for various physical design problems. In this paper, we introduce DBSCAN algorithm for feature extraction which is capable of finding a better set of clusters that minimize the amount of investigation required and classifier as fuzzy ARTMAP to recognize the sub-circuits with lowest amount of interconnections between them.

This paper is organized as follows: In section 2, a brief introduction to the overview of the proposed system. Section 3 presents a new feature extraction method using DBSCAN algorithm that has not been used previously for Circuit partitioning in VLSI with fuzzy ARTMAP classification. Section 4 explains the structure of simplified fuzzy ARTMAP based in VLSI. Experimental results are presented in section 5 and conclusions are given in section 6.

## II. OVERVIEW OF PROPOSED SYSTEM

The sample circuit of the model is bipartite. The feature extractor obtains feature vector for subcircuit, and is sent to training or inference module. The SFAM (simplified fuzzy ARTMAP) [11] has two modules, i.e. training and inference module. The feature vector of training subcircuits and the categories to which they belongs are specified to SFAM's training module. Once the training phase is complete, the vector represents the subcircuit with minimum interconnection. The test subcircuit pattern which is to be recognize with minimum interconnection is fed to inference

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module. Classifications of sub circuits are done by associating the feature vector with the top-down weight vectors [12, 13] in SFAM. The system can handle both symmetric and asymmetric circuit. In symmetric pattern, only distinct portion of circuit is trained whereas in asymmetric (1/2n)th portion of circuit is considered.

### III. DBSCAN (FEATURE EXTRACTOR)

To separate the set D into subsets of similar densities Density-based algorithms is used [14]. In the best case they can find out the cluster number k routinely and categorize the clusters of random shape and size [15]. The runtime of this algorithm is in magnitude of  $O(n \log(n))$  for low-dimensional data. [16] A density-based cluster algorithm is based on two properties given below [14].

- (1) One to define a region  $C \subseteq D$ , which forms the basis for density analyses;
- (2) Another to propagate density information (the provisional cluster label) of C

In DBSCAN a region is defined as the set of points that lie in the  $\epsilon$ -neighborhood of some point p. if  $|C|$  exceeds a given Min Pts-threshold Cluster label propagation from p to the other points in C. The complete description of DBSCAN algorithm is provided in [15, 17, 18].

### IV. SIMPLIFIED FUZZY ARTMAP MODULE

The basic principle of Adaptive Resonance Theory (ART) was first introduced by Grossberg in 1976[11], whose structure resembles those of feed-forward networks. Fuzzy logic with the combination of Adaptive Resonance Theory gives Fuzzy ARTMAP is a class of neural network that perform supervised training of recognition pattern and maps in response to input vectors generated from DBSCAN algorithm [16] in this paper. Fuzzy ARTMAP [12] is a structural design which synthesizes the fuzzy logic with adaptive resonance theory neural network. Fuzzy ARTMAP is two layer network containing an input and output layer. In context of the circuit partitioning in VLSI design to recognize the subcircuit with minimum interconnection between them, the size of input layer is 4 and output layer is 10. Hence it outcomes in 2-10 layered Fuzzy ARTMAP model. For input vector I and cluster j from DBSCAN algorithm, Choice function given by:

$$CF_j(I) = \frac{|I \wedge W_j|}{\alpha + |W_j|} \quad (1)$$

where  $\alpha$  is small constant about 0.0000001,  $W_j$  is top-down weight

Winner node is one with highest activation /choice function, i.e

$$\text{Winner} = \max(CF_j) \quad (2)$$

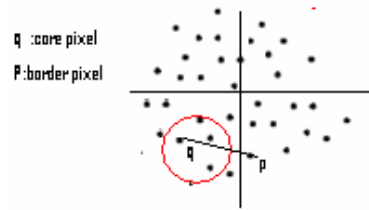


Fig. 2 Core and border pixel density connectivity mapping nonlinear data to a higher dimensional feature space

Match function which is very much used to find out whether the network must adjust its learning parameters is given by

$$MF_j(I) = \frac{|I \wedge W_j|}{|I|} \quad (3)$$

If  $MF_j(I) \geq \text{vigilance parameter } (\rho)$  then Network is in state of resonance, where  $\rho$  is in range  $0 \leq \rho \leq 1$ .

If  $MF_j(I) \leq \text{vigilance parameter } (\rho)$  then Network is in state of mismatch reset.

### V. RESULTS

The circuit is bipartite. The feature vectors of the subcircuit are extracted by using the generic approach of DBSCAN. Extracted features from the subcircuit, the vectors are fed into the fuzzy ARTMAP and the recognition of the subcircuit with minimum interconnection between them. The table 1 depicts the time required by DBSCAN for the 10 different way of bipartite sample circuits. It depicts that as the number of points considered in the subcircuit increases, the run time for extracting the feature also increases. The Table II depicts that as the vigilance parameter increases, the recognition rate also increases. From the table, it is clear that for vigilance parameter of 0.65, the recognition rate is almost most 97.7% which is the best recognition rate for subcircuit.

TABLE I  
FEATURE EXTRACTOR USING DBSCAN

Subcircuits	Number of Points	Run time in Secs
sample #1	23	2.5
Sample #2	45	3.8
Sample #3	38	2.9
Sample #4	53	4.1
Sample #5	56	4.3
Sample #6	70	6.9
Sample #7	65	5.3
Sample #8	72	7.2
Sample #9	35	2.5
Sample #10	75	7.6

TABLE II  
UNITS FOR EFFECT OF VIGILANCE PARAMETER ON RECOGNITION RATE

Vigilance Parameter	Recognition Rate
0.21	80.16%
0.32	88.56%
0.43	90.3%
0.56	95.3%
0.65	97.2%
0.75	97.3%
0.85	97.5%
0.87	97.6%

Graph in Fig. 3 shows the how vigilance parameter vary recognition rate. We found that at 0.65, recognition rate remain constant i.e. 97% around. Fig. 4 shows performance of DBSCAN Algorithm.

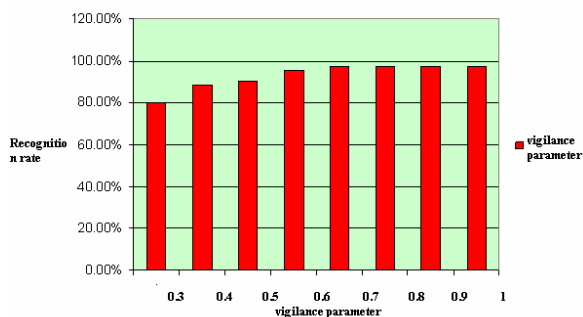


Fig. 3 Recognition rate versus vigilance parameter

Feature Extractor for DBSCAN

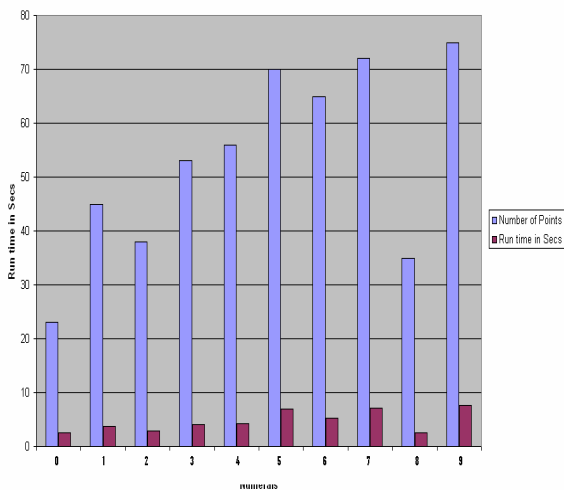


Fig. 4 Performance of DBSCAN Algorithm

## VI. CONCLUSION

In this paper recognition of subcircuit with minimum interconnection between them is done using fuzzy ARTMAP neural network by using DBSCAN as the feature extractor. Software is simulated for eight and six nodes. Tested successfully in partitioning these nodes to arrive minimum interconnection between them. Experimental results shows that the recognition rate using DBSCAN with fuzzy ARTMAP is best compared to only fuzzy ARTMAP. Classification is done at rate of better cut size using DBSCAN –fuzzy compared to ARTMAP. Fig. 5 shows the screen shots of the module use to recognize the subcircuit with minimum interconnection using DBSCAN with fuzzy ARTMAP.

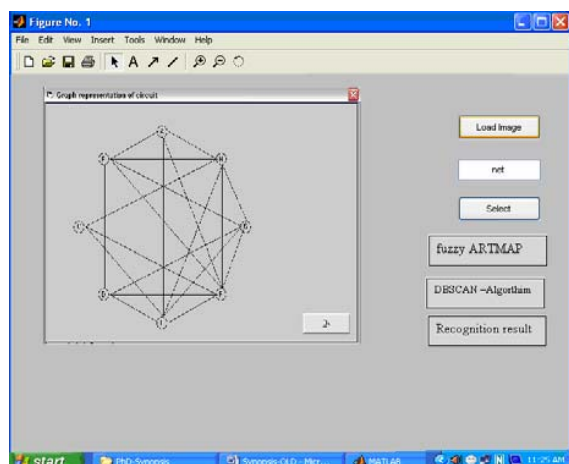


Fig. 5 Screen shots of recognizer model of DBSCAN with fuzzy ARTMAP

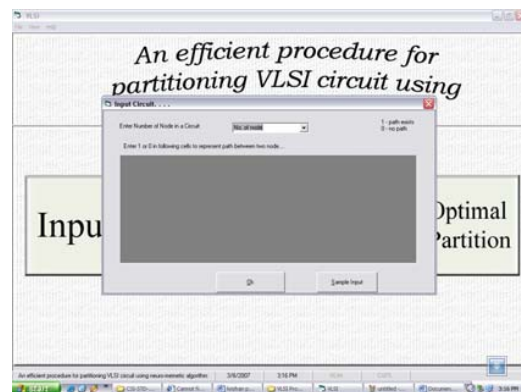


Fig. 6 Screen shot gives a user the choice for selection of 6 or 8 nodes

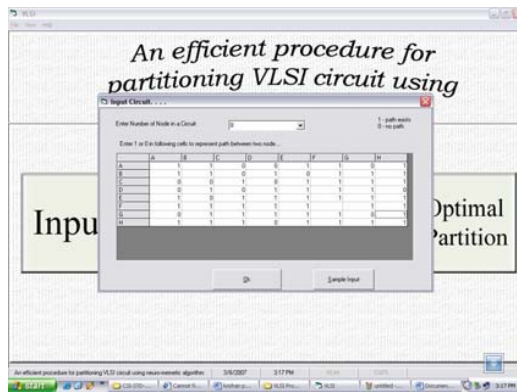


Fig. 7 Screen shots shows the input for eight nodes

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