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# Design of Fuzzy Adaptive Resonance Theory Structures with VLSI: A Design Approach

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**Abstract**

*The main objective is to present a mixed-mode VLSI implementation of the fuzzy-ART Structures. The proposed cells are composed of the following: current subtract circuit, multiplier/divider and the S-Z shapes circuit. The efficient performance can be achieved by the individual simulation of the new cells and, second, by the implementation of a decision making system that uses the Mamdani inference method and TMF cells as the knowledge base. Minimum and maximum circuits can be used for the implementation of the Mamdani inference method. The computation can be done in analog current mode. The design of Bias Column Peripheral Cell, Fuzzy-ART Array Cells along with the various Fuzzy-ART structures is to be done. The Measurement of "Column Bias" Cells, "Weight Currents" will be done. The results of above will be verified with the standard algorithm.*

**Keywords:**
Membership function, VLSI, decision making system, Adaptive resonance theory (ART), hardware implementations.

## I.Introduction

Adaptive resonance theory (ART) is a well-established neural network frame work developed by Grossberg et al. at the University of Boston, Boston, MA. The ART algorithms are neural categorizers that share some interesting properties. One of these properties is the online learning, that is, each time a new input exemplar is presented to the system, the system knowledge is updated online to incorporate that knowledge; the system learns while it performs. Another interesting property is that the system maintains a generalization capability which is controlled by a tunable vigilance subsystem. There is a vigilance parameter that tunes the coarness of the established categories. Setting the vigilance parameter to a low value increases the system generalization capability, thus the system tends to form coarser categories. Setting the vigilance parameter to a high value decreases the system generalization, and it tends to form finer categories, thus increasing the number of categories formed for the same set of input data.

## II. Fuzzy-ART Algorithm

The fuzzy-ART neural network is a clustering self organizing neural network for analog input patterns. Fig.1. represents the architecture of a fuzzy-ART network. The network is composed of an attention subsystem and an orienting or vigilance subsystem. The attention subsystem is composed of two layers. Layer F1 is the input layer. Input patterns b = (b1; b2; . . . ; bN) composed of N analog values are presented to the system. F2 is the category layer. The system categorizes each input pattern as belonging to one of the [y1; y2; . . ; yM] categories. The system stores a weight matrix fzijg of analog values that represents the categories learned by the system. Each category yj is represented by the weight vector zj composed of N analog values. The algorithmic flow diagram of the fuzzy-ART operation is depicted in Fig. 1(b). Initially all the interconnection weights zij are set to their maximum analog value "MAX." When an analog input vector b = (b1; b2; . . . ; bN) is applied to the system, each F1 layer cell receives an analog input component bi 2 [0; MAX]. Then, each F2

category computes its “choice function” Tj , which is a measurement of the similarity between the analog input pattern b and the analog weight template zj = (z1j; z2j ; . . . ; zNj) stored in category jTj =jb ^ zj j_ + jzj j (1) where ^ is the fuzzy MIN operator defined by (X ^ Y )i = min(Xi; Yi), jXj is the l1 norm jXj = Ni=1 jXij, and _ is a positive parameter called “choice parameter.” Layer F2 is a winner-takes-all (WTA) competition network. Each jth F2 cell gives an output yj which is “1” if that cell is receiving the largest Tj input and “0” otherwise. That is yJ = 1; if TJ = max (Tj) yj6=J = 0; otherwise. This way, the F2 layer selects the category J whose stored pattern zJ most closely resembles input pattern b according to the similarity criterion. The original fuzzy-ART algorithm states that
if more than one Tj is maximal, the category j with the smallest index is chosen. The different ways of resolving “ties” may result in some cases where the hardware system produce slightly different final categories than the theoretical fuzzy-ART algorithm for the same set of presentations of input patterns. However, this difference does not affect the functional objectives of the neural network categorizer. For the winning category J, the vigilance subsystem checks the condition _jbj _ jb ^ zJ j, where _ 2 [0; 1] is the so called vigilance parameter. If the condition is not satisfied, category J is disregarded by forcing TJ = 0. Layer F2 will again select the category with maximum Tj , and the vigilance criterion will be checked again. This search continues until a winning category is selected that fulfills the vigilance criterion. When a category J meeting the vigilance criterion is activated, its weights zJ are updated according to the learning rule zJ (new) = b ^ zJ (old). This learning rule is known as the fast-learning mode of the fuzzy-ART algorithm.

The digital and analog techniques constitute the two existent approaches for the hardware realization of fuzzy system. The features of these techniques make ones more suitable than the other in specific applications.

For the realization of an efficient fuzzy system, it is required that both techniques contemplate in its design the available time for the rule processing, the space to be occupied by the system and the power it must consume. The digital approach has a high degree of programmability, but it requires of an analog-digital and digital-analog converters for the interaction with the physical variables that the system works with, the system into an array that occupies a considerably great amount of space

The analog arrays count with a higher degree of difficulty to be programmed, but in terms of space occupation they are more effective arrays because of the reduced number of transistors necessary. Analog systems are preferred for its higher processing velocity and its reduced power consumption. Nevertheless, they present certain disadvantages in comparison with the digital systems, the lack of facility to use CAD (Computer Aided Design) tools for its design, and its major sensitivity to noise and distortion.

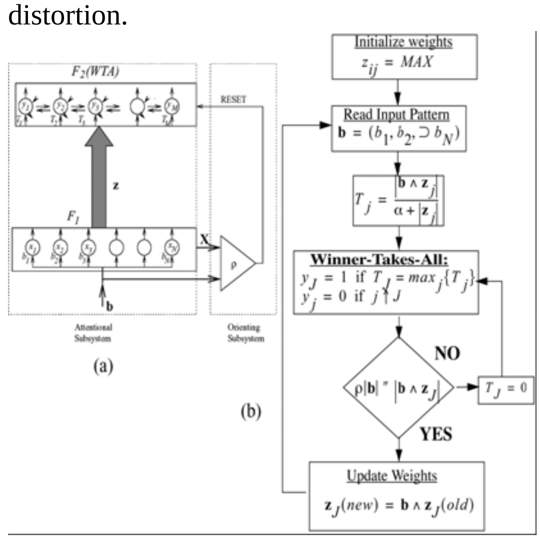


Fig. 1. (a)Topological structure of the fuzzy-ART architecture. (b) Flow diagram of the fuzzy-ART algorithm.

## III. Fuzzy-ART Cell Description

A fuzzy-ART cell has to perform the following operations:

1) Store an analog weight zij , which must be initially reset to its maximum analog value “MAX;”

2) Compute the component wise fuzzy-min operation between the analog stored value zij and the analog input component bi; this analog minimum value will be used in the computation of the choice function Tj and in the evaluation of similarity by the vigilance subsystem;
3) Implement the learning rule; when a category J is selected (yJ =1) that fulfills the vigilance criteria cells

## III. Design Aspects of Sub Cells:

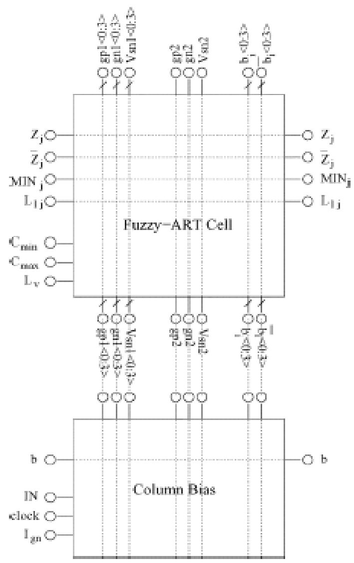


Fig. 2. Block diagram of the connections between the fuzzy-ART cell and the “bias column block.”

The current subtract circuit is shown in fig. 3. This circuit is in the charge of the subtraction of the current I2 from I1. While I1>I2 the circuit’s output current is the result of the subtraction and when I1<I2 the output is equal to zero. The mirror formed by transistor M1, M2, M3, M4 is in charge of introducing current I1 into node 4. The result of the subtraction is taken from node 4 by the mirror formed by M7, M8. The mirror is in the charge also preventing the output current from being negative, this is the reason why the output current is equal to zero when I1<I2.

1.Current Subtract Circuit

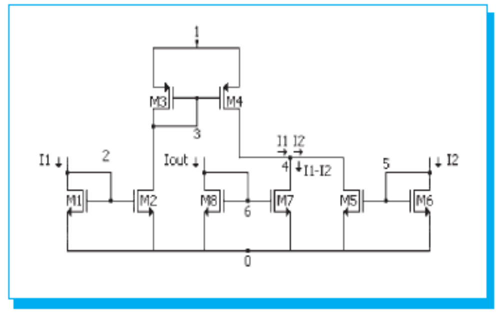


Fig. 3. Current Subtract Circuit

2. Multiplier/Divider:

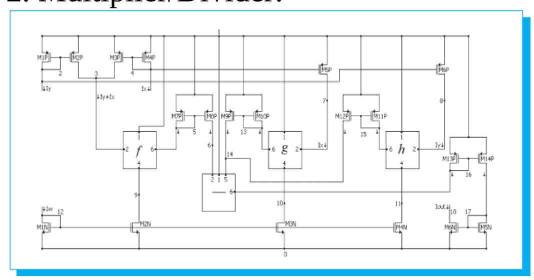

Fig. 4 Multiplier/Divider circuit

The multiplier/divider circuit is based on the Generalized Tran lineal Principle is as shown in Fig. 4. Using the Generalized Tran lineal Principle we were able to perform the wanted output function using a series of operations. It is based on Kickoff’s Voltage Laws.

3. Circuit for S-Z Shapes

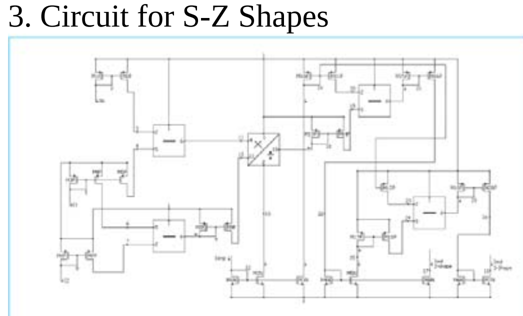

Fig. 5. Circuit for S-Z Shapes

The basic fuzzy cell for the construction of the membership function. This cell delivers in its output S and Z function depending on the input parameter I1, I2.

## 4. TMF Circuit

Fig 6. Shows the schematic that represents the TMF circuit. It is able to generate asymmetric and symmetric membership function. The performance of all the cells that composed TMF circuit.

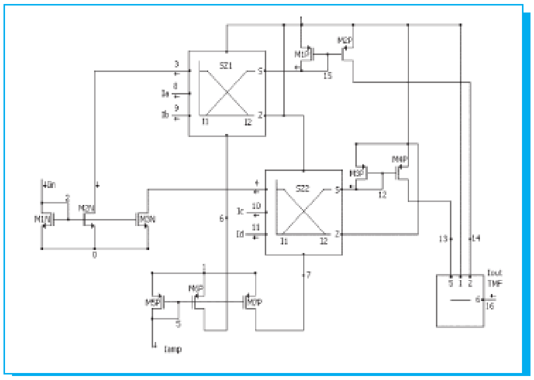


Fig. 6. TMF Circuit

## 5. Maximum Detection Circuit

The Maximum and minimum Detection circuit are necessary for the implementation of the decision making system based on the mamdani inference method.

A maximum detection circuit with two inputs is shown in Fig. 7 as below. This circuit is based on a very simple operation and the cascade connection of various circuit of this kind composes the maximum detection circuit.

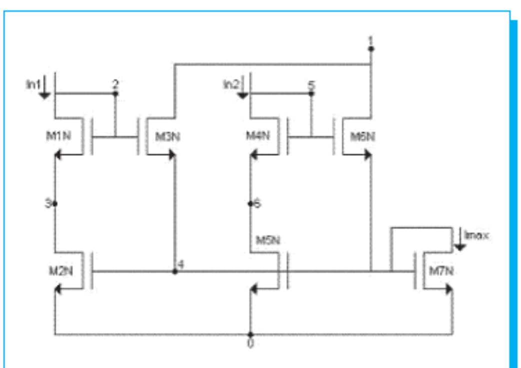


Fig.7. Maximum Detection Circuit with two inputs

## 6. Minimum Detection Circuit

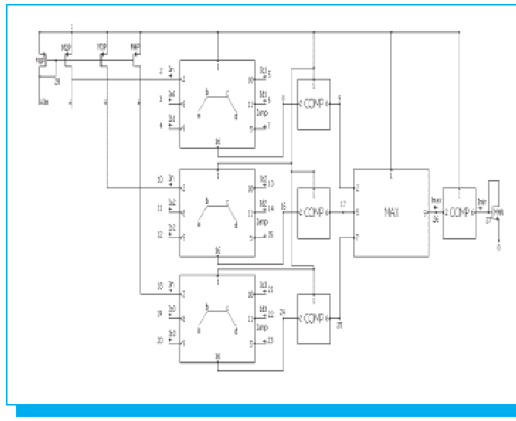


Fig. 8 Minimum Detection Circuit

The minimum detection circuit is obtained as the complement of the maximum of the complements and the circuit is as shown by Fig. 8. The minimum detection operator can be implemented by the complement sub-circuits connected to the n inputs and outputs of the maximum detection circuit**.**

## 7. Decision Making System

The cell described in past section will be taken for the implementation of a fuzzy decision making system. This structure is based on a mamdani inference method (MIN-MAX inference).

The mamdani inference method is used commonly for its simplicity and high implementation efficiency, this method is also as MIN-Max inference. It uses the MIN t-norm as the implication function and MAX s-norm as the aggregation operator.

If water temperature and ambient temperature then cold water tap condition

| | Water Temperature | Ambient Temperature | Cold Water Tap Condition |
|---|---|---|---|
| 1 | Cold | Cold | Close a lot |
| 2 | Warm | Cold | Close a little |
| 3 | Cold | Warm | Close a little |
| 4 | Warm | Warm | Do nothing |
| 5 | Hot | Cold | Open a little |
| 6 | Cold | Hot | Open a little |
| 7 | Warm | Hot | Open a little |
| 8 | Hot | Hot | Open a lot |
| 9 | Hot | Warm | Open a lot |

Fig. 9. Input-output relationship for the decision making system

This method is an inference mechanism based on based rules of the form:

Rule1:if if x1 is A1'and x2 is A2' then y is B'

Rule2: if x1 is A12'and x2 is A22' then y is B'.

## IV. Expected Results:

Result obtained by Fuzzy ART algorithm is compared with the measured output of Fuzzy ART cell by using Tanner Tool.

## V. Conclusions:

This work presents a significant improvement in the performance of the cells initially proposed by Camacho. The technology used was scaled from 0.8µm to o.18 µm. It represents a great improvement in terms of the circuit area utilization.

The TMF circuit offers a clear advantage over the other designs. Since it is also able to generate programmable symmetrical and asymmetrical membership function. It also shows a greater flexibility by being constituted by independent cells.

The decision making system not only proved the efficient performance of the proposed cells, it also demonstrated the precision with which a fuzzy system is able to obtain conclusions using rules. It also permits the creation of n-rule system with any decision purpose. Another action line for the future is the study of the design of Bias Column Peripheral Cell; Fuzzy-ART Array Cells along with the various Fuzzy-ART structures is to be done. The Measurement of "Column Bias" Cells, "Weight Currents" will be done. The results of above will be verified with the standard algorithm.

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