An ART Network with Fuzzy Control for Image Data Compression

C. J. Wu, A. H. Sung, and H. S. Soliman
Department of Computer Science
New Mexico Tech.
Socorro, NM 87801-4682

Abstract - In this paper, the application of a simplified ART1 (adaptive resonance theory) network with a fuzzy controller to image data compression is presented. The unique feature of a vigilance parameter of ART allows the direct control of trade-off between compression ratio and image quality; the fuzzy controller can be used to adjust vigilance to seek a better compromise automatically. Furthermore, the decision table of this fuzzy controller is designed to guarantee convergence. Therefore, the network is insensitive to the given initial vigilance values. Simulations are performed and the results indicate that this fuzzy-control-equipped simplified ART1 network provides a promising technique for image data compression.

I. INTRODUCTION

The large amount of time and storage required to transmit pictorial data brings about the need of image data compression. In [1], the application of Adaptive Resonance Theory 1 (ART1) [2], [3], to image data compression was studied, and its performance was compared with CPN's and we showed that ART1 networks can be a promising alternative. In this work, another important issue for image data compression in real-time environment is studied. In general, the combination of compression and distortion ratios is a function of pictures and techniques used in the compression process; experimentally, some of the images will have profound effect on the compression process. It is rather difficult to obtain the balance between those two ratios for various pictures in real-time environment. For this reason, we usually use trial-and-error method to search for the better compromise of distortion and compression ratios.

Fuzzy logic has been successfully used in many applications to control the process automatically. In our work, the incorporation of fuzzy controllers in the design of simplified ART1 networks is investigated. The simplified ART1 networks has several advantages over the original ART1 networks including less implementation cost and processing time. The rest of the paper is organized as follows. Section II describes the architecture and the learning algorithms of simplified ART1 networks. The mechanism of fuzzy controller is introduced in section III. Simulation results are given in Section IV. At last, conclusions and discussions are given in section V.

II. THE ARCHITECTURE AND LEARNING ALGORITHMS OF SIMPLIFIED ART1

The advantage of using adaptive resonance theory (ART1) in image data compression is that it has an external control mechanism--the vigilance parameter--to control directly the trade-off between compression and distortion ratios. However, the ART1 has some disadvantages for this specific application as well [1]. One disadvantage is the possible large number of iterations which slow down the process of encoding each input presented to the network. In addition, we found out that the function of bottom-up weight matrix is just to decide the retrieval order of categories; therefore, we can compare the input with existing prototypes directly and eliminate the bottom-up weight matrix. The simplified ART1 (SART1) has two immediate advantages. Since the most similar prototype will be picked first, there is no need to check on other prototypes; hence, it runs much faster than the ordinary ART1 networks. The other advantage is less implementation cost since the SART1 only uses one weight matrix instead of two in the original ART1.

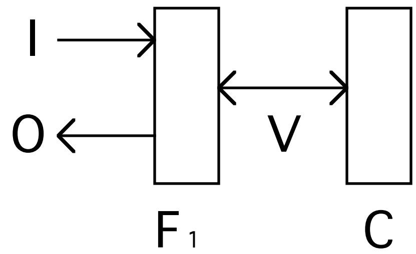


Figure 1. The architecture of simplified ART

The Learning Algorithm Of SART1

Step 1: Initialize the weight matrix and vigilance parameter as follows:

$$V = [1] \tag{1}$$

$$0 \le \rho \le 1 \tag{2}$$

where V and ρ are the weight matrix and vigilance parameter, respectively.

Step 2: Present the binary (unipolar) input vector I to F_1. The winning node, say j, is the node with the weight vector (V_j) most similar to input I in terms of the Hamming distance $(\sum_{i=1}^{M} |I_i - V_{ij}|)$ in layer C where M is the dimension of I. In case of tie, one of them is to be selected arbitrarily.

Step 3: Test the similarity between the prototype of winner j and the input pattern I by computing the following ratio:

$$\gamma = {(M - \sum_{i=1}^{M} |I_i - V_{ij}|)}\Big/{M} \tag{3}$$

Step 4: If $\gamma \ge \rho$, go to Step 5; otherwise, a new category (node) will be added to layer C unless there is no new node available. In that case, the operation terminates.

Step 5: Update only the weight vectors associated with the winner j as follows.

$$V_{ij}(t+1) = I_i V_{ij}(t) \quad \text{for} \ \ 1 \le i \le M \tag{4}$$

Step 6: If no new input vector, terminate the process; otherwise, get the next input vector and go back to Step 2.

III. THE CONTROL MECHANISM OF FUZZY CONTROLLER

Fuzzy logic has been successfully applied to automatic control [4]. Therefore, we propose to incorporate a fuzzy controller into the SART to achieve the automatic control during the compression process. In the algorithm above, the compromise of those two ratios is closely related to ρ. A high vigilance leads to low distortion and compression ratios. The relation of SART1 and fuzzy controller is depicted in Figure 2. The outputs of SART1 is the following two ratios:

(1) Generated Compression Ratio (GCR):

$$GCR = {NF}\Big/{C \cdot N + F \cdot \log_2 C} \tag{5}$$

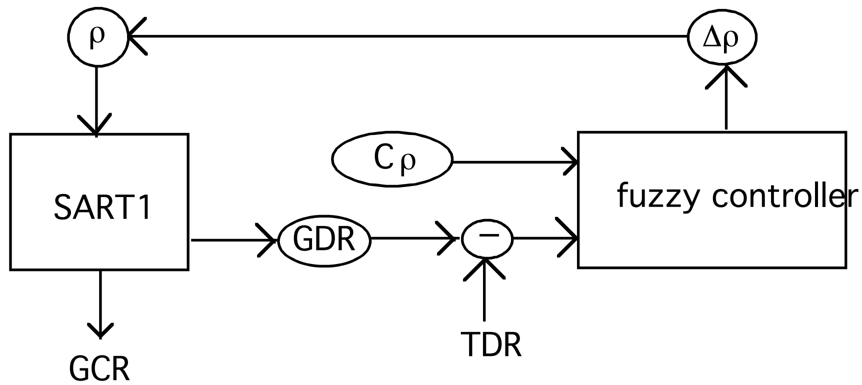
where N is the dimension of the input vectors or subimages, F is the total number of subimages, and C is the total number of categories formed during training.

(2) Generated Distortion Ratio (GDR):

$$GDR = (\sum_{j=1}^{F} \sum_{i=1}^{N} (I_{ij} - I'_{ij})^2 \Big/ NF) \times 100 \tag{6}$$

where I_{ij} is the value in the original image and I'_{ij} is the corresponding value in the reconstructed image. Since an accepted distortion ratio is our primary concern, we use the difference between the target and the actual distortion ratios (ΔE) to be one of the inputs from SART1 network to the fuzzy controller. The other input ($C\rho$) used by the fuzzy controller is the change of vigilance to detect the possible oscillation occurred in the process.

$$\Delta E = TDR - GDR \tag{7}$$
$$C\rho = \rho_t - \rho_{t-1} \tag{8}$$



GCR: generated compression ratio
GDR: generated distortion ratio
TDR: target distortion ratio

Figure 2. The schematic diagram of SART1 with fuzzy contrc

In general, the membership function of a fuzzy set *A*, μ_A, is defined as follows: [5]

$$\mu_A : X \rightarrow [0,1] \tag{9}$$

where X is the universal set. In this paper, seven fuzzy sets are used--PB (positive big), PM (positive medium), PS (positive small), ZE (zero), NS (negative small), NM (negative medium), and NB (negative big). Since we use the triangular type of membership functions (see Eq. 10), except fuzzy sets NB (see Eq. 11) and PB (see Eq. 12), the membership function of fuzzy sets can be characterized by three values--(left boundary, central value, right boundary). Hence, for any crisp value *x,* the membership values are decided as follow:

$$\mu_A(x) = \begin{cases} (x - L)/(C - L) & L \le x \le C \\ (x - R)/(C - R) & C \le x \le R \\ 0 & otherwise \end{cases} \tag{10}$$

$$\mu_{NB}(x) = \begin{cases} (x - R)/(C - R) & C \le x \le R \\ 1 & x \le C \\ 0 & otherwise \end{cases} \tag{11}$$

$$\mu_{PB}(x) = \begin{cases} (x - L)/(C - L) & L \le x \le C \\ 1 & x \ge C \\ 0 & otherwise \end{cases} \tag{12}$$

where C, L, and R are the central value, left boundary, and right boundary respectively and A={NM, NS, ZE, PS, PM}. For the input ΔE, let us choose the membership functions of the fuzzy sets to be as follows:

NB	(-100, -6, -3)	NM	(-5, -3, -1)	NS	(-2, -1, 0)
ZE	(-0.5, 0, 0.5)				
PS	(0, 1, 2)	PM	(1, 3, 5)	PB	(3, 6, 100)

For the input $C\rho$ and output $\Delta\rho$, the membership functions of fuzzy sets are defined as follows:

NB	(-1, -0.25, -0.1)	NM	(-0.15, -0.1, -0.05)	NS	(-0.1, -0.05, 0)

ZE (-0.025, 0, 0.025)
PS (0, 0.05, 0.1) PM (0.05, 0.1, 0.15) PB (0.1, 0.25, 1)

The decision table used by fuzzy controller is designed as follow to guarantee the convergence.

Table 1. The decision table of fuzzy controller.

		C ρ						
		NB	NM	NS	ZE	PS	PM	PB
Δ E	NB	PM	PS	ZE	ZE	PS	PM	PB
	NM	PS	PS	ZE	ZE	PS	PM	PM
	NS	PS	PS	ZE	ZE	PS	PS	PS
	ZE	ZE	ZE	ZE	ZE	ZE	ZE	ZE
	PS	NS	NS	NS	ZE	ZE	NS	NS
	PM	NM	NM	NS	ZE	ZE	NS	NS
	PB	NB	NM	NS	ZE	ZE	NS	NM

The convergence of this fuzzy controller is guaranteed by the following three special design criteria and one constraint to avoid possible infinite oscillations:

(1) $\Delta\rho$ should not be bigger than $C\rho$ in terms of fuzzy sets.

(2) Whenever the oscillation is observed (through the decision table), $\Delta\rho$ should be smaller than $C\rho$ in terms of fuzzy sets. For example, if ΔE is PB and $C\rho$ is PB, then $\Delta\rho$ is at most jump back NM.

(3) If ρ is equal to zero and GDR is smaller than TDR, the process is terminated since it makes no sense have negative ρ in ART networks.

(4) $0 \le TDR \le 1$

However, the convergence does not mean that the system will always find the proper ρ, which generates the TDR, if it exists.

The membership value of entry ij in the decision table is decided as follow:

$$M_{ij} = \min(M_i, M_j) \tag{13}$$

where M_i and M_j are the membership values of ΔE and $C\rho$, respectively. The crisp output $\Delta\rho$ of fuzzy controller is decided as follow: [6]

$$\Delta\rho = \sum_{i=1}^{K}\sum_{j=1}^{N} f(M_{ij})C_{ij} \Big/ \sum_{i=1}^{K}\sum_{j=1}^{N} f(M_{ij}) \tag{14}$$

where N is the number of fuzzy sets, $f(M_{ij})$ and C_{ij} are the membership and central values of entry ij in the decision table respectively. The process will be terminated when $\Delta\rho$ reaches 0.

IV. SIMULATION RESULTS

Experiments are performed on two pictures of 256^2 black-and-white pixels using the simplified ART1 network with fuzzy controller. Simulation results of ten randomly generated initial vigilance values using 8x8 subimages are listed in Table 2. As shown, the system is insensitive to the given initial ρ's and the final ρ's are staying in the target range. The reconstructed images of "goat" and "monkey" along with their original pictures are shown in Fig. 3.

(a) (b)

(c)
(d)

Figure 3: The comparison between original and reconstructed images (a) the original image of the goat (b) the reconstructed image of the goat (c) the original image of the monkey (d) the reconstructed image of the monkey.

Table 2. Simulation results of simplified ART1 with fuzzy controller (DDQ=18.5%)

		Initial ρ									
		0.38	0.58	0.13	0.15	0.51	0.27	0.1	0.19	0.12	0.86
Goat	final ρ	0.667	0.670	0.667	0.667	0.686	0.661	0.689	0.640	0.663	0.710
	GCQ	10.240	10.240	10.240	10.240	10.039	10.240	9.942	10.240	10.240	9.846
	GCE(%)	21.013	21.013	21.013	21.013	18.292	21.013	17.165	20.764	21.013	17.038
Monkey	final ρ	0.665	0.657	0.665	0.667	0.660	0.670	0.703	0.704	0.705	0.610
	GCQ	9.309	9.309	9.309	9.309	9.309	9.309	9.225	9.225	9.225	9.309
	GCE(%)	19.136	19.136	19.136	19.136	19.136	19.136	17.899	17.899	17.899	19.136

where DDR, TDR, and GCR are the desired distortion ratio, target distortion ratio, and generated compression ratio, respectively.

V. CONCLUSIONS AND DISCUSSIONS

Since we can not predict the proper vigilance value in advance, with the help of fuzzy controller, the ART1 network can be insensitive to a given initial vigilance values. Nevertheless, our computer simulations show that the final vigilance will converge to the target range. In addition, the simplified ART1 (SART1) used in this work has two advantages over the original one--less processing time and implementation cost. Hence, the image data compression using SART1 with fuzzy controller in the real-time environment is promising. The on-going research is to extend this architecture to accommodate the gray scale and color pictures as well as tune-up the fuzzy controller to keep the final vigilance as close as possible to the target value.

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