A Fuzzy ART Network with Fuzzy Control for Image Data Compression

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Abstract - In this paper, the application of a Fuzzy ART (adaptive resonance theory) network with a fuzzy controller to (grayscale) 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 is used to adjust vigilance to seek a better compromise automatically. Therefore, the network is insensitive to the given initial vigilance values. Simulations are performed and the results indicate that this fuzzy-control-equipped Fuzzy ART 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 it 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. Since compression and distortion ratios depend on the source pictures and techniques used in the compression process; it is usually difficult to achieve the balance between those two ratios for various pictures in real-time environment. Trial-and-error may be used to search for the best tradeoff between distortion and compression ratios.

Fuzzy logic has been successfully used in many applications to control the process automatically. In this work, the incorporation of fuzzy controllers in the design of Fuzzy ART networks is investigated. The Fuzzy ART networks [4] has several advantages over the ART1 networks including less implementation cost and processing time, and the ability to handle the grayscale image. The rest of the paper is organized as follows. Section II describes the architecture and the learning algorithms of Fuzzy ART 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 LEARNING ALGORITHMS OF MFART AND MEASURE CRITERIA

The advantage of using adaptive resonance theory (ART) 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. The Fuzzy ART has two advantages. One is the ability to handle both binary and analog vectors and the other is less implementation cost and time. In this work, we proposed a modified Fuzzy ART (MFART) network which is the hybrid of ART1 and Fuzzy ART networks. The MFART counts the grayscale difference between the input and category and picks up the one has the minimum difference instead of using fuzzy min operator in Fuzzy ART.

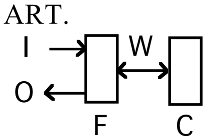


Fig. 1. The architecture of Fuzzy AR

The Learning Algorithm Of Modified Fuzzy ART [4]

Step 1: Initialize the vigilance parameter and weight vector of each uncommitted node j as follows:

$$0 \le \rho \le 1 \quad (1)$$

$$W_j = [1] \quad (2)$$

where W_j and ρ are the $2N$-dimensional weight vector and vigilance parameter respectively, and

N is the dimension of input vector before transformation.

Step 2: Transform the N-dimensional input vector I, whose components are in the interval [0,1], to $2N$-dimensional vector I' as follow before presenting it to F_1.

$$I' = (I_1, I_2, \ldots, I_N, I_{N+1}, I_{N+2}, \ldots, I_{2N}) \quad (3)$$

$$I_{N+i} = 1 - I_i \text{ for } i = 1, 2, \ldots, N \quad (4)$$

Step 3. The winning node (or category), say j, is the node with the weight vector (W_j) most similar to input I in terms of the minimum difference of grayscale value between the input I' and category j, that is, $(\sum_{i=1}^{2N} |I'_i - W_{ij}|)$, in layer C where $2N$ is the dimension of I'. In case of tie, one of them is to be selected arbitrarily.

Step 3: The selected category j is said to meet the vigilance criterion if the following inequality stand.

$$(\sum_{i=1}^{2N} |I'_i - W_{ij}|) \le N \times (1 - \rho) \quad (5)$$

Step 4: If resonance, go to Step 5; otherwise, the reset occurs and a new category (node) is 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 selected category J (either the winner j or new added category) as follows.

$$W_{iJ}^{new} = W_{iJ}^{old} \wedge I'_i \quad \text{for } i = 1, 2, \ldots, 2N \quad (6)$$

where $\wedge$ is the fuzzy min operator.

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

The Measure Criteria

The following criteria are used in this work mean absolute error (MAE), mean square error (MSE), single-to-noise-ratio (SNR), bit-per-pixel (BPP, compression ratio). They are defined as follows:

$$MAE = \left(\sum_{j=1}^{F} \sum_{i=1}^{N} |M_{ij} - M'_{ij}|\right) \Big/ NF \quad (7)$$

where M and M are the subimage in the original and reconstructed pictures respectively, N is the dimension of the input vector I or subimages M, and F is the total number of subimages

$$MSE = \sum_{j=1}^{F} \sum_{i=1}^{N} (M_{ij} - M'_{ij})^2 \Big/ NF \quad (8)$$

$$SNR = 10 \times \log(G^2 / MSE) \quad (9)$$

where G is the maximum grayscale value of picture.

$$BPP = (B \times N \times F) \Big/ (C \times B \times N + F \times \log_2 C) \quad (10)$$

where B is the bits per pixel in the original picture and C is the total number of categories formed during training.

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 MFART to achieve the automatic control during the compression process. The relation of MFART and fuzzy controller is depicted in Figure 2. The two inputs, ΔE and $C\rho$, to fuzzy controller are defined as follows:

$$ADR = (MAE / G) \times 100 \quad (11)$$

where G is the maximum grayscale value.

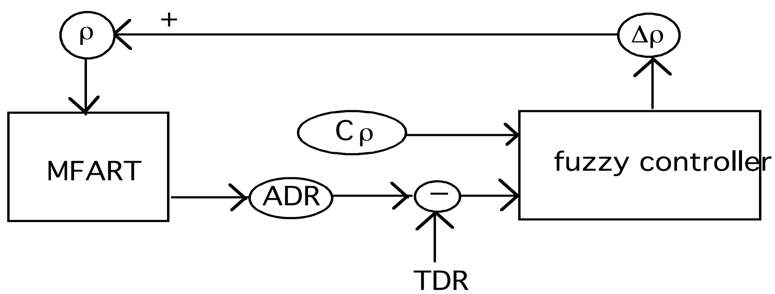
$$\Delta E = TDR - ADR \quad (12)$$

$$C\rho = \rho_t - \rho_{t-1} \quad (13)$$

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

$$\mu_A : X \to [0,1] \quad (14)$$

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)--for those inputs and output of fuzzy controller.



ADR: generated distortion ratio
TDR: target distortion ratio
Figure 2. The schematic diagram of MFART with fuzzy contro

Their membership functions are defined in Eq. 15-17 and in the form of (left boundary, central value, right boundary).

$$\mu_A(x)=\begin{cases}(x-L)/(C-L) & L\le x\le C\\ (x-R)/(C-R) & C\le x\le R\\ 0 & otherwise\end{cases}\quad(15)$$

$$\mu_{NB}(x)=\begin{cases}(x-R)/(C-R) & C\le x\le R\\ 1 & x\le C\\ 0 & otherwise\end{cases}\quad(16)$$

$$\mu_{PB}(x)=\begin{cases}(x-L)/(C-L) & L\le x\le C\\ 1 & x\ge C\\ 0 & otherwise\end{cases}\quad(17)$$

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, we 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.

Table 1. The decision table of fuzzy controller.

ΔE \ Cρ	NB	NM	NS	ZE	PS	PM	PB
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 feedback from controller to MFART $\Delta\rho$ is decided as follow: [6]

$$\Delta\rho=\left(\sum_{i=1}^{K}\sum_{j=1}^{L}M_{ij}\times V_{ij}\right)/\sum_{i=1}^{K}\sum_{j=1}^{L}M_{ij}\quad(19)$$

where K and L are the number of rows and columns in the decision table respectively, and M_{ij} is the value of entry *ij* in the decision table. V_{ij} is decided by the following algorithm to guarantee that $\Delta\rho$ will be smaller than $C\rho$ in terms of crisp value to force the convergence, that is, $\Delta\rho$ reaches 0 and the process will terminates.

Step 1. Calculate the corresponding crisp values of fuzzy membership value M_{ij}.

$$T=u_A^{-1}(M_{ij})\quad(20)$$

where u_A^{-1} is the inverse function of u_A and A is the corresponding fuzzy set of M_{ij}. Please note there might have more than one value generated by u_A^{-1}.

Step 2. Pick up the biggest T, say T_J, whose absolute value--$|T_J|$--is smaller than $|C\rho|$, that is, $V_{ij}=|T_J|$. Otherwise, $V_{ij}=0$.

IV. SIMULATION RESULTS

Experiment is performed on Lena, of $512x512$ pixels with 256 grayscale using the

Modified Fuzzy ART network with fuzzy controller. It is well known that the presented order of subimage will affect the system performance. To eliminate this effect, each subimage is reassigned to a cluster which has the minimum grayscale difference with this subimage after the initial categories are formed. Simulation results with parameters-- $TDR = 3.0(\%)$, initial $\rho = 0.5$, and *4x4* frames--are listed in Table 2.

Table 2. Simulation results of Modified Fuzzy ART and fuzzy controller with frame size=16

	Initial ρ	final ρ	CLS	BPP	MAE	MSE	SNR	ADR
Lena	0.5	0.607	38	0.394	7.904	159.132	26.11	3.1

MAE: mean absolute error CLS: the cluster number
MSE: mean square error BPP: bit per pixel
SNR: single-to-noise ratio ADR: actual distortion ratio

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 Modified Fuzzy ART has two advantages over the ART1--less processing time and implementation cost. Hence, the image data compression using MFART with fuzzy controller in the real-time environment is promising. The on-going research is to tune-up the fuzzy controller to keep the final vigilance as close as possible to the target value.

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Figure 3: The reconstructed image of Lena

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