

IMAGE DATA COMPRESSION USING ART NETWORKS

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ABSTRACT:

In this paper an application of the ART1 (adaptive resonance theory) network in image data compression is studied, and the simulation results are compared with those using Counter-propagation networks (CPNs). The unique ability of ART to control the trade-off between compression ratio and image quality makes ART1 networks suitable for this application. Computer simulations indicate that ART1 networks can be an alternative for data compression.

INTRODUCTION

The large amount of time and storage required to transmit pictorial data brings about the need of image data compression. CPN (Hecht-Nielsen, 1987), which is self-organizing and combines a Kohonen layer with a Grossberg Outstar layer, has been shown a good candidate for this application (Chang, Soliman, and Sung 1992). In this work, ART1, Adaptive Resonance Theory 1, (Carpenter and Grossberg 1987) is studied and its performance is compared with CPNs. Apparently, ART1 has CPN's advantages such as faster learning and self-organization. In addition, ART1 has the vigilance parameter to control directly the trade-off between compression ratio and distortion ratio. Another factor affecting our choice is that we are concerned only with the quality of reconstructed pictorial data and the length of time needed to transmit data from source to destination, not the topological relation among nodes, which is the major feature of Kohonen networks (Kohonen 1982). One modification in similarity test of ART1 learning algorithm has been made to achieve error-free compression. The computer simulations indicate that ART1 networks perform as good as CPNs, therefore, it can be an alternative for data compression.

ART1 LEARNING ALGORITHM

In the process of compression, a picture is split into small frames. Those subimages are fed into an ART1 network for self-organization, and the outputs represent the category indices for those subimages. After learning, those indices and their corresponding prototypes are transmitted to the destination. The picture is then reconstructed according to those indices and prototypes. The benefit received from this operation is measured by the compression ratio (Q), which is computed as follows:

$$Q = NF / (C \cdot N + F \cdot \log_2 C) \quad (1)$$

where N is the dimension of the subimages, F is the total number of frames, and C is the total number of categories formed during learning. On the other hand, the price we pay is measured by the distortion ratio defined as follows:

$$E = \sum_{j=1}^F \sum_{i=1}^N (I_{ij} - I'_{ij})^2 \quad (2)$$

where I_{ij} is the value in the original image and I'_{ij} is the corresponding value in the reconstructed image. For image data compression, vigilance parameter is used to control the trade-off between Q and E .

The ART1 algorithm (Carpenter and Grossberg 1987, Zurada 1992)

Step 1. Enable all the nodes on the F_2 layer and initialize W (the weight matrix from F_1 to F_2), V (the pattern matrix from F_2 to F_1), and vigilance parameter (ρ) where both W and V are $N \times M$ matrices, N is the number of nodes on the F_1 layer, M is the number of nodes on the F_2 layer.

Step 2. Present the binary unipolar input vector (or subimage) to F_1 . The winning node on the F_2 layer is the one for which $W \cdot I$ is the largest.

$$y_j = \max_{m=1}^M \left(\sum_{i=1}^N W_{im} I_i \right) \quad (3)$$

where j is the winning node on the F_2 layer, and I is the input pattern. If all the committed nodes have been deactivated, an uncommitted node will be selected randomly unless there are no such nodes in which case the operation terminates.

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

$$\gamma = |I \cap V^{(j)}| / \|I\| = \sum_{i=1}^N V_{ij} I_i / \sum_{i=1}^N I_i \quad (4)$$

where \cap is the logical AND operator.

Step 4. If $\gamma \geq \rho$, go to Step 5; otherwise node j is deactivated by setting $y_j = 0$ and go back to Step 2.

Step 5. Update only the weights associated with the winning node j as follows:

$$W_{ij}(t+1) = \begin{cases} L / (1 - 1 + \sum_{i=1}^N V_{ij}(t) I_i) & \text{if } V_{ij}(t) I_i = 1 \\ 0 & \text{if } V_{ij}(t) I_i = 0 \end{cases} \quad (5)$$

where L is equal to 1.5 in this work.

$$\sum_{i=1}^N V_{ij}(t+1) = I_i V_{ij}(t) \quad (6)$$

Step 6. If there are no more inputs, terminate the program; otherwise get the next input vector and go back to Step 2.

EXPERIMENTAL RESULTS

For some critical pictorial data, we might want to have error-free compression, i.e., mapping each unique input pattern to a unique category cell on the F_2 layer. Thus, an identical picture can be reconstructed after the transmission. Unfortunately, the ART1 networks (Carpenter and Grossberg 1987) can not guarantee an error-free compression even when we use the strictest vigilance, 1. We depict this problem by the example in Figure 1. In this example, ART1 networks can not distinguish pattern A from pattern B by using vigilance 1 if we present pattern B first then pattern A. Since pattern B is presented first, an uncommitted node of F_2 (category 1 or node 1) will store it immediately. Then if pattern A is presented next, node 1 on the F_2 layer will be the winning node first according to the Weber Law Rule since all the input patterns or prototypes are subsets of those uncommitted nodes which have initial values 1. Thus, the input pattern A will be assigned to category 1 as well because

$$\sum_{i=1}^N V_{i1} A_i / \sum_{i=1}^N A_i = \rho = 1$$

Clearly, an ART1 network can not distinguish a new input pattern from the stored category prototype of winning node under equation (4) if the set of black pixels of this new input pattern is a subset of the black pixels of the stored prototype. Therefore, some distortion will be introduced during the process. The approach used in his work is to count directly the number of different bits between the new input pattern and a stored category prototype instead of using the inner product

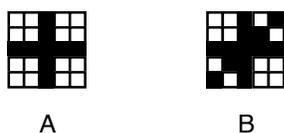


Figure 1: Two patterns to demonstrate the updating operations of the category prototypes.

(or logical AND) operation. In other words, we use the equation (7) to replace equation (4).

$$\gamma = (N - \sum_{i=1}^N |I_i - V_{ij}|) / N \quad (7)$$

where I and V are binary unipolar vector and matrix, respectively.

The experiments are performed on three pictures of 256^2 black-and-white pixels. Simulation results of this modified ART1 networks are listed in Table 1 with those using CPNs (Chang, Soliman, and Sung 1992). Also, the reconstructed images of "Bear" of four operations, including supervised CPN, CPN with KFM (Kohonen Feature Map) layer, CPN with FSO, Frequency Sensitive Self-Organization, (Fang 1992) layer, and ART1 with $\rho = 0.01$, along with the original picture are shown in Figure 2. As shown, ART1 networks perform as good as CPNs in terms of compression ratio (Q) and distortion ratio (E). Also, despite the supervised CPN has higher compression ratio and lower distortion ratio than other CPNs and ART, the severe loss of the object's edges makes the recognition very difficult; therefore, it may not be suitable for practical use. By adjusting the vigilance parameter from 1 to near 0, ART1 performs from error-free compression to highly compressed operation. Moreover, the picture quality control and parameter value assignment are more direct in ART. This makes ART1 networks very attractive for use in real time environments.

Table 1: Simulation results of ART1 and CPNs (Frame Size = 16)				
Image	Network's Types	ρ (for ART1) or Learning Types(for CPN)	Q	E(%)
Boy	CPN	S	7.88	23.12
	ART1	0.01	7.95	26.37
House	CPN	S	7.88	18.92
	ART1	0.01	7.95	20.67
Bear	CPN	S	7.88	10.42
	CPN(with KFM layer)	US	2.86	17.98
	CPN(with FSO layer)	US	3.82	17.64
	ART1	0.01	3.94	20.83

S is the supervised learning and US is the unsupervised learning.

CONCLUSIONS AND DISCUSSIONS

In this paper the application of ART1 networks in image data compression has been studied. A modified similarity test that counts the number of differing bits between an input pattern and the stored prototypes instead of using their inner products gives ART1 networks the ability to perform error-free compression. The computer simulation results indicates ART1 networks perform as good as CPNs in terms of compression ratio and distortion ratio in those cases that we analyzed. Though more simulations are needed to draw a concrete conclusion of the comparison between ART and CPN, the initial simulation results indicate that the use of ART in data/image compression is promising.

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