A NEW ART-1 NEURAL NETWORK INTERFACE MODEL ADOPTED FOR COLOR IMAGES RECOGNITION

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Abstract: *The theoretical outcomes and experimental results of new input interface for ART1 neural network applying in algorithms and software of image recognition are presented in this paper. It is well known that standard ART-1 network may process only binary images. The given fact limits application of ART-1 network for full color images recognition because conversion from color to binary form causes loss of the information and as a result two different colors inside one original image can be represented as the same value of binary color that produce a mistake during recognition. In the current paper, a new color interface for ART1 neural network has been developed, implemented in software and tested in real examples. As it will be shown below, new interface allow ART1 neural network to deal with color images in such tasks as image recognition and image segmentation.*

1. INTRODUCTION

Adaptive resonance theory was developed by Carpenter and Grossberg (Fauset, 1994). The ART-1 neural network is the first member of that theory, where implemented unsupervised learning model. General architecture of ART1 represented in the Fig.1.

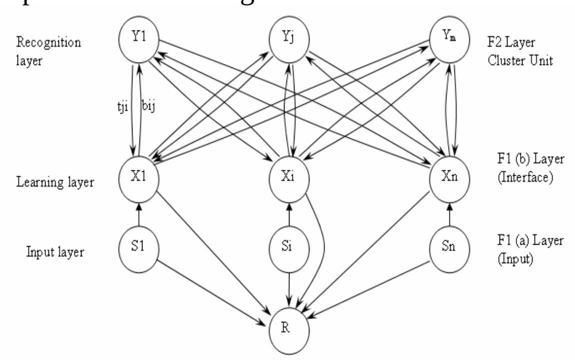

Fig.1 Typical Architecture of ART1.

The network contains three layers and reset unit, the input layer F1 (a) can accept the binary input vector only [1, 2]. It relates input pattern of images to one of the learned classes by vigilance parameter, which determines the degree of similarities and how close a new input image to a stored prototype. During learning new patterns may create new classes, but could not deform an existing memory [1]. As it was mentioned before, dealing with binary vectors greatly reduced a number of applications where ART1 can be applied. In current moment most popular applications of ART1 lay in such fields as data mining, data compression, image segmentation and image recognition.

In [3], 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 [4] for data compression some modified structure of ART1 applied in the paper [3]. The network contains a fuzzy controller to (grayscale) image data compression is presented. The data mining fields implemented and studied in paper [5], where proposes a Grid-based 3-tier ART1 classifier which operates an ART1 clustering data mining using grid computational resources with distributed GPCR data sets.

Image segmentation techniques has studied in [6] where the model, which is based on the adaptive resonance theory (ART) of Carpenter and Grossberg and on the self-organizing map (SOM) of Kohonen. The authors have designed the network SOMART, based on Fuzzy ART then they proposed the new model, SmART, which has been experimentally found to perform well in RGB color space, and is believed to be more coherent than Fuzzy ART. Some other methods for image segmentation used in [7] where ART has been applied for multispectral image segmentation of satellite images. According to results of [7] ART1 structure could classify the obscurity of satellite images better than ART2.

The image recognition represented by many publications where we can underline paper [8] where ART used for complex images recognition by composing reference images without learning all combinations of the reference images, [9] where described image processing techniques for extracting the cracks in a concrete surface crack image and the ART1-based RBF network for recognizing the directions of the extracted cracks. ART1 also used in some kinds of mobile communications, as example we can represent a paper [10] where the network was used for channel optimization. Analysis of modern publications allow to come to a conclusion that ART network most popular for image segmentation and recognition techniques and ART1 deal only with binary images. In this case development of new interface model that will enable ability of that network to process a color image will be considerable contribution to color image recognition techniques by ART1.

2. DEVELOPING NEW INTERFACE MODEL

The aim of our work is adaptation of ART1 neural network for color image recognition. It is known, that ART1 model can handle only binary inputs but in real life many descriptive features are fuzzy, or partially present to some degree (James C Bezdek, James Keller Fuzzy models and algorithms for pattern recognition and image processing. Springer 2007). This fact plays a main limitation in applications of ART1 for color image processing. For adaptation the ART1 network for full color image recognition we suggest modification the network input interface (the S layer of ART1) according to method described below. The color image (24 or 32 bits images or "true color" format) generally is a bitmap where each pixel is convolution of RGB components [11-13]. In our work we dial only with RGB images because this format is "natural" for all image capturing devices like scanners and cameras, unlike some other formats (like HSI, HSV) that are popular in image processing techniques. Usually the value of each pixel in true color format represented as set of three bytes and each of them carry the information about red, green and blue colors, totally formed 24 bits per each pixel of source image [12], notice that the higher-order bits (D7) contain the majority of the visually significant data. The other bit planes contribute to more subtle details in the image [14]. Separating a digital image into its bit planes is useful for analyzing the relative importance played by each bit of the image, a process that aids in determining the adequacy of the number of bits used to quantize each pixel. Also, this type of decomposition we can use for adaptation of ART1 neural network to the recognition of color images. Let suppose that the length of input vector for standard ART1 network equal N, taking into account a 24 bits encoding of image format the length of ART1 input vector will be increased times. If number of clusters inside recognition layer equal M the increment of links inside "adapted network" and computation time will be increased times, that is too much for practical implementation. For simplification of network structure and to decrease a computation time, let's notice that color interface, cover all depth of source image colors that is redundant in practical implementations.

The minimum number of bits that we can use in input interface for ART1 is three, one each for red, green and blue colors; it is most significant bits (MSB) of source image. There is a guarantee that MSB alone will be sufficient for recognition because 3 bits encoding systems was one of the first to be used in the earliest color computers since it can represent not only the three primary colors but also secondary colors as well as black and white [8]. In this case, it is usual to refer to the color by the 3-bit value ranging from 0 (binary 000) to 7 (binary 111) forming totally 8 "basic" colors. In such a way the size of input vector of ART1 interface become MxNx3 bits where M and N are horizontal and vertical sizes of image. The source input image contains a full range of 24 bits colors, after passing the input interface all colors will be interpolated to 8 basic colors according to the table 1. Ability to color interpolation is new property in ART1 input interface that demonstrated in the figure 1.

$D7_r$	$D7_g$	$D7_b$	Color meaning
0	0	0	Black
0	0	1	Blue
0	1	0	Green
0	1	1	Cyan
1	0	0	Red
1	0	1	Violet
1	1	0	Yellow
1	1	1	White

Table 1 The colors range of ART1 color interface

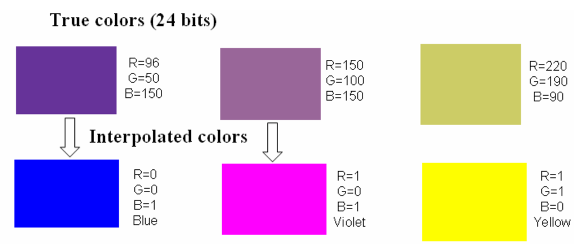

Fig.1. Interpolation Ability of ART1 Input Interface

Formation of input vector is illustrated in the Fig. 2.

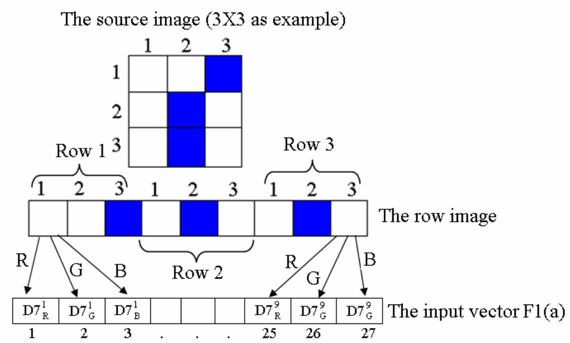

Fig.2 Formation of Input Vector in Example of 3X3 Image

As we can see, input image, that has a structure of 2D matrix transformed in F1(a) layer network's input interface to 1D binary vector with size MxNx3 bits (MxN pixels of source image, 3 bits per one color pixel).

Usually image recognition is performed using the parameters estimated or features extracted from the images, but in some specific applications like automatic number plate recognition or optical characters recognition direct use of pixel values can be considered as effective method.

3. SIMULATED RESULTS

To study the practical approaches of new ART1 structure the program implemented a color interface of ART1 neural network has been created using Borland Delphi 6.0 compiler [15, 16]. The program allow to recognize color characters recorded in BMP graphical formats, size of chars up 8X8 pixels to be able loading up 200 input vectors (images) with different vigilance parameter in the range 0.1...1 with maximum number of clusters equal 200. The graphical user interface of program that was created illustrated in Fig. 3.

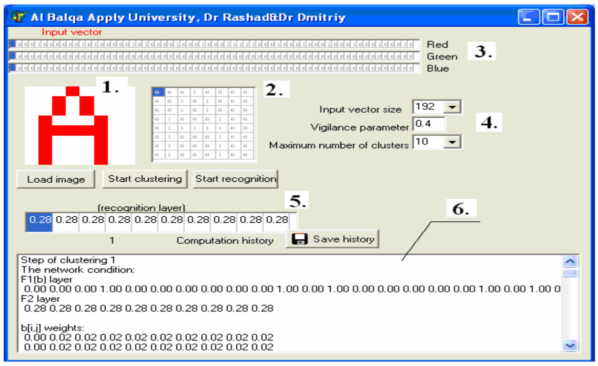

Fig. 3 Graphical User Interface of ART1 Color Recognition Program

The graphical user interface is representing a set of program elements: 1. – a source color image; 2 - the source image represented in binary form; 3. – the input of ART1 neural network (here the input is separated R,G,B components for obviousness reason, but in input of ART structure all bits formed single vector 192 bits as showed in the figure 2); 4. – the set of adjusted parameters such as input vector size (read only property related to the size of image), vigilance parameter, that is a variable in the range 0.1...1 and will be discussed below, maximum number of clusters is variable in the range 3...200; 5 – the vector of F2 condition of ART1 structure; 6 – computation history that trace all condition of network during all steps of recognition process.

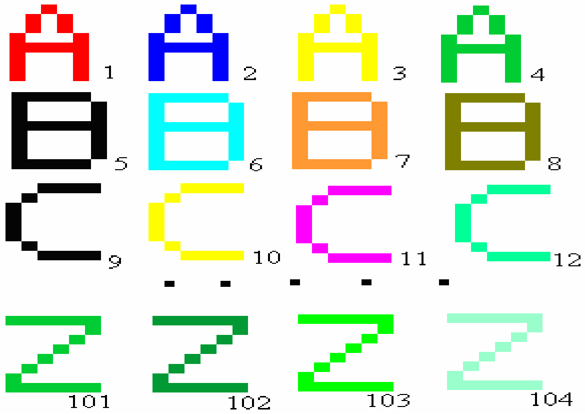

Fig. 4 The samples of chars used during network testing

For testing the accuracy of neural network recognition the set of samples representative letters of the Latin alphabet (A...Z) has been constructed.

The set includes 26 different chars, 4 random colors per each char, it's totally 104 symbols located in external graphical files (BMP format). The appearance of sample chars inside the set showed in Fig. 4, note that each char was numbered. Thus, initial parameters of the network are input vector size equal 192 bits, number of clusters 104, vigilance parameter from 0.4 to 1 with incremental step 0.1. Experimental work was broken on 2 parts: clustering of training set by neural network and recognition. During clustering the learning set (chars recorded in BMP files numbered in ascending order) forwarded to the network input. During recognition initial numbers of files were shuffled in random order and then sent to the input again. Recognition set was included 65% percents of training dataset, by other words, the training and recognition sets was disjoined with overlapping 65%. The output of the network (one output per one input file) is the number of recognized cluster. Thus, entrance parameters of a neural network are:

1. Input vector size =64 bits
2. Vigilance parameter (was vary from 0.4 to 0.8)
3. Maximum number of clusters = 104

The output parameter: number of cluster (or clusters if input char belong to few learning images)

We have provided two researches, first of them purposed to estimate abilities of the network to recognize the patterns with same object by different colors and second one to estimate statistical properties of the network at various values of vigilance parameter.

The result of first research represented in Table 2, input sequence means the numbers of input samples (Fig. 4). In first test we used lower vigilance parameter equal 0.4 and result shows that ever in low vigilance it is possible to recognize the colors of pattern. In this test the red, green and blue 'A' chars recognized correctly but yellow char (sample number 3) clustered as green (sample number 4). We can explain this fact that binary representation of red, green and blue color is 100,010,001 accordingly (all bits is different), yellow 110 - first bit cross linked with middle bit of green color. In second test all chars recognized correctly due moderate vigilance parameter. The third test shows ability of network for color interpolation, so pattern 8 (dark grey) interpolated as pattern 5 (black). This ability is easy to explain in next example: the hexadecimal representation of black is 00H(Red),00H(Green),00H (Blue), for dark grey - 00H (Red), 70H (Green), 70H (Blue), but in 3 bits notation the bit D7 equal zero for both colors and as result dark grey color interpolated to black in input interface.

The fourth test also demonstrated good network color interpolation, during test patterns 101-103 interpolated as green, last pattern number 104 recognized as white color because source color too bright (all D7 bits equal one).

Test number	**Vigilance parameter**	**Learning sequence**	**Input sequence**	**The network outputs (number of cluster)**	**Note**
1.	0.4	1,2,3,4	1,4,3,2	1,3,3,2	Small vigilance parameter caused clustering into 3 clusters
2.	0.75	1,2,3,4	1,4,3,2	1,4,3,2	All patterns recognized correctly
3.	0.75	5,6,7,8	8,6,5,7	5,6,5,7	Pattern 8 (dark grey) recognized as pattern 5 (black)
4.	0.75	101,102,103,104	104,101,103, 102	102,101, 101,101	All patterns clustered into two clusters (see explanation below)

Table 2 Testing the recognition ability of the network

To study the recognition accuracy of the network we generated additional set of Latin alphabet (A...Z), but only native colors were included to this set (red, green, blue, yellow). The statistical parameter sensitivity calculated according with equation 1[17-19].

Test number	Vigilance parameter	Learning sequence	The number of true positives	The number of mistakes	Sensitivity
1.	0.4	124 files	70	54	0.56
2.	0.5	124 files	96	28	0.77
3.	0.6	124 files	112	12	0.90
4.	0.7	124 files	119	5	0.96
5.	0.8	124 files	119	5	0.96

Table 3 Testing of recognition ability of the network

$$Sensivity = \frac{Number\ of\ true\ positives}{Number\ of\ true\ positives + Number\ of\ false\ Negatives} \quad (1)$$

The result of our presented paper is represented in Table 3. The results shows that the network is able to recognize different colors in vigilance parameter ranged 0.7 - 0.8. Less value of vigilance reducing sensitivity of network, on the other hand moderate vigilance can't increase an accuracy of recognition ability of neural network.

4. CONCLUSION AND FUTURE WORK

It is known, that the standard ART1 network is intended for work with a binary input vector and this fact complicates using of ART1 technology for color images recognition In our paper we have elaborated a new color interface for ART1 neural network and have shown recognition ability and accuracy in example of color chars recognition. New interface allow to use any color depth from one (binary color images) to eight (true color images) but in proposed work we have shown that in applied applications is possible to use binary colors that is three bits colors encoding and in this case ART1 neural network has interpolation ability that allow to interpolate any input color to the nearest color listed in Table 1.

Our investigations show, that good results of ART1 recognition (the sensitivity at level 0.96) it is possible to get when the value of vigilance parameter located in the range 0.7-0.8. The less value reducing network sensitivity, high value cause increment a time of learning and recognition

Conducted researches have shown efficiency of proposed approach to color image recognition, but suggested method has one disadvantage: even with using binary color images (1 bit encoding) the size of ART1 neural network increased three times to compare with standard ART binary network. If we deal with 4 bits encoding the size of network will be growth up 12 times. That is why we apply this technology for chars recognition because for real images with size more than 100X100 pixels computations hold too much time (up few minutes). That is why our future work will be concentrated in the field of parallel processing implementation of ART1 neural network for color image recognition. Further development of suggested method lies in applications of "color adapted" ART1 network in problems where is necessity for objects recognition that are similar in form but different in coloring. As a future work to be done by others, some problems of biomedical engineering such as automated blood cells counting or counting a numbers of microorganisms in microscopic frames that may be appropriate for new ART1 interface model.

REFERENCES

[1] Carpenter, G.A. and S. Grosberg, 1987. Massively parallel architecture for self-organizing Neural pattern recognition, Machine// computer vision. Graphics and Image Processing, 37: 45115.

[2] Faulset, L., 1994. Fundamentals of Neural Networks. Architectures, Algorithm and Applications. New Jersey, Prentice Hall Int., pp: 461.

[3] C. J. Wu, A. H. Sung, and H. S. Soliman, "Image Data Compression Using ART Networks," in Proc. Artificial Neural Networks In Engineering, 1993, pp. 417-422

[4] Wu, C.J.; Sung, A.H.; Soliman, H.S., “An ART network with fuzzy control for image data compression”, Fuzzy Systems, 1994. Proceedings of the Third IEEE Conference on Volume , Issue , 26-29 Jun 1994 Page(s):1743 - 1748 vol.3

[5] Kyu Cheol Cho , Da Hye Park, Jong Sik Lee. Computational Grid-Based 3-tier ART1 Data Mining for Bioinformatics Applications // Fuzzy Systems and Knowledge Discovery, Springer Berlin / Heidelberg; Volume 4223/2006; pages 522-531, ISBN 978-3-540-45916-3

[6] N.C. Yeo, K.H. Lee, Y.V. Venkatesh, S.H. Ong. Colour image segmentation using the self-organizing map and adaptive resonance theory // Image and Vision Computing, Volume 23, Issue 12, 1 November 2005, Pages 1060-1079

[7] Y.Rang Sanseri, P. Thitimajshima, S. Kanotai. Multispectral Image segmentation using ART1/ART2 neural networks//22-nd Asian conference of remote sensing, Thailand, 2001

[8] V. P. Tret'yakov and S. G. Mikhailov. A neural network algorithm for complex binary image recognition requiring no presegmentation // Biomedical Engineering Volume 29, Number 4 / July, 1995, p 171-176

[9] Kwang-Baek Kim, Kwee-Bo Sim, Sang-Ho Ahn. Recognition of Concrete Surface Cracks Using the ART1-Based RBF Network // Advances in Neural Networks - ISNN 2006, Volume 3972/2006, p. 669-675.

[10] Kwang-baek Kim, Cheul-woo Roв, Kwang-eui Leeв. Enhanced ART1-based Self-Organizing Supervised Learning Algorithm for Channel Optimization in Mobile Cellular Networks// IJCSNS International Journal of Computer Science and Network Security, VOL.6, No.4, April 200694 Manuscript received April 5, 2006.

[11] B. Moore, D. Touretzky, ART1 and pattern clustering, in //Proceedings of the connectionist models summer school. Morgan Caufmann, LosAltros, CA, 1998, pp. 174–185.

[12] Gonzalez, R.C. and R.E. Woods, Digital Image Processing. 1992, Reading, Massachusetts: Addison-Wesley. 716.

[13] Castleman, K.R., Digital Image Processing. Second ed. 1996, Englewood Cliffs, New Jersey: Prentice-Hall.

[14] F. van der Heijden, “Image Based Measurement Systems”, Wiley Publishing, 1994.

[15] Kerman F., Miitchell C. Programming and Problem Solving With Delphi. UK INTERNATIONAL ED, Pearson Higher Education Date Published: 2001 ISBN: 0321204417

[16] Rachele, Warren Learn Object Pascal with Delphi. Wordware Publishing inc. ISBN: 1556227191.

[17] Carpenter GA, Markuzon N. ARTMAP-IC and medical diagnosis: Instance counting and inconsistent cases. Neural Networks 1998; 11:323-336

[18] Markram H, Tsodyks M. Redistribution of synaptic efficacy between neocortical pyramidal neurons. Nature 1996; 382:807–810

[19] In L.C. Jain, B. Lazzerini & U. Halici (Eds.), Innovations in ART Neural Networks ISBN: 3790812706 Pub. Date: January 2000 Series: Studies in Fuzziness and Soft Computing , Vol. 43 2000, XII, 258 p., 69

[20]G.T.Raju,S.Khandige. ART Neural Network based Clustering Agent for Use access Patterns\\Computational Intelligence 2005, 487-042. ISBN: 0-88986-479-9;

[21]Hecht-Nielsen,Robert, Neurocomputing, Addison-Wesley, ISBN 0-201-09255-3, 1990.

[22] Maren, Alianna, and Harston, Craig, and Pap, Robert, Handbook of Neural Computing Applications, Academic Press, ISBN 0-12-546090-2, 1990

[23] Schalkoff, R. J., Pattern Recognition: Statistical, Structural, and Neural Approaches, John Wiley & Sons, New York, NY, 1992.