Modeling the Process of Color Image Recognition Using ART2 Neural Network

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Abstract: *This paper thoroughly describes the use of unsupervised adaptive resonance theory ART2 neural network for the purposes of image color recognition of x-ray images and images taken by nuclear magnetic resonance. In order to train the network, the pixel values of RGB colors are regarded as learning vectors with three values, one for red, one for green and one for blue were used. At the end the trained network was tested by the values of pictures and determines the design, or how to visualize the converted picture. As a result we had the same pictures with colors according to the network. Here we use the generalized net to prepare a model that describes the process of the color image recognition.*

Keywords*: Generalized nets, Neural networks, Adaptive resonance theory, Image color recognition, Bioinformation.*

Introduction

Adaptive resonance theory (ART) [2, 6] was introduced by Stephen Grossber in 1976. In this work ART2 [2, 3, 6] neural network [11], slow learning algorithm [5, 9, 12] for image processing of a picture is used. ART2 is designed to perform operation over continuous valued input vectors. It consists of two layers – the first one has complex units or neurons that support a combination of normalization and noise suppression. The second layer is a competitive one. Both of them are fully connected with bottom-up and top-down weights. In addition the bottom-up and top-down signals needed for the reset mechanism that takes the design whether or not the input vector takes place in the winner cluster. The neural network is learned by modification of bottom-up and top-down weights.

The slow learning algorithm according to [5, 12] can be expressed by the following steps:

Step 1. Initialize parameters a, b, Θ, c, d, e, α, ρ, b_j, t_j, where:

- S – input matrix with vectors $[s_1, s_2, ..., s_i, ..., s_n]$;
- a, b – fixed weights in the F_1 layer;
- Θ – noise suppression parameter;
- c – fixed weight used in testing for reset;
- d – activation of winning F_2 unit;
- e – small parameter using preventing division by zero;
- α – learning rate;
- ρ – vigilance threshold;
- b_j – initial bottom-up weights;
- t_j – initial top-down weights.

Step 2. While $s_i \le s_n$ for each input vector "*s* "do *Steps* from 3 to 8.

Step 3. Update F_1 unit activation:

$$u_i = 0,\ \ x_i = \frac{w_i}{e + \|w\|},\ \ q_i = 0,$$

where $\|w\|$ – vector normalization ($\sqrt{w_1^2 + w_2^2 + ... + w_n^2}$), $w_i = s_i$, $p_i = 0$, $v_i = f_i\left(x\right)$.

The activation function is $f\left(x\right) = \begin{cases} x, & \text{if}\, x \ge \theta \\ 0, & \text{if}\, x < \theta \end{cases}$.

Update F_1 activations again

$$u_i = \frac{v_i}{e + \|v\|},\ \ x_i = \frac{w_i}{e + \|w\|},\ \ q_i = \frac{p_i}{e + \|p\|}$$
$$w_i = s_i + a * u_i,\ \ p_i = u_i,\ \ v_i = f_i(x) + bf_i(q).$$

Step 4. Compute the signals to F_2 units:

$$y_j = \sum_j b_j p_i.$$

Step 5. While reset is true, do *Steps* 6 and 7.

Step 6. Find F_2 unit "J" with largest value ($y_J \ge y_j$ for $j = 1, 2, \ldots, m$).

Step 7. Check for reset:

$$u_i = \frac{v_i}{e + \|v\|},\ \ r_i = \frac{u_i + cp_i}{e + \|u\| + c\|p\|},\ \ p_i = u_i + dt_{Ji}.$$

If $\|r\| < p - e$ then $y_J = -1$ (inhibit J)
Reset is true; repeat *Step* 5.

If $\|r\| \ge p - e$
Reset is false; proceed to *Step* 8.

Step 8. Update weights for winning unit J

$$t_{Ji} = \alpha du_i + \left\{1 + \alpha d\left(d - 1\right)\right\} t_{Ji}$$
$$b_{iJ} = \alpha du_i + \left\{1 + \alpha d\left(d - 1\right)\right\} b_{iJ}$$

Go to Step 2.

The network consists of four clusters. It transforms the graphical information into RGB colors that are used for learning vectors, one for red [255 0 0], one for green [0 255 0], one for blue [0 0 255] and one for gray color [200 200 200].

In a trained network, the picture is splitting up in matrix that consists of testing vectors with three elements. Finding cancer diseases, especially in areas such as in the brain, different glands, etc., is very important for the early diagnostics of cancers. In the presence of such cancerous cells the fact that in x-ray and nuclear magnetic resonance those types of cells are colored differently from the healthy ones, is used. Here we want to recognize the x-ray [10] and nuclear magnetic resonance (NMR) [4] images and those pixels that enter in cluster responding to the red (or specific) color are regarded as a part of NMR image and it will be colored in black. The pixels that enter in cluster responding to the gray color are regarded as a part of x-ray image and it also will be colored in black. In case where pixels are obtained by the blue or green cluster it will be colored in white and if it does not gets anywhere it will also be colored in white.

Generalized net model

Initially the following tokens enter the Generalized Net (GN) [1].

- in place L_1 – one token with an initial characteristic "Input matrix of pictures".
- in place L_2 – one token with an initial characteristic "Structure of neural network and number of clusters".
- in place L_3 – one token with an initial characteristic "Learning vectors".

On the first step in place L_{11} there is a token that start procedure.

The GN-model in Fig. 1 is introduced by the following set of transitions:

Z_1 – "Converting pictures to the input vector";
Z_2 – "Training of the Neural Network";
Z_3 – "Determine cluster of input vector";
Z_4 – "Determine values pixels of the picture";
Z_5 – "Converting output vector to picture".

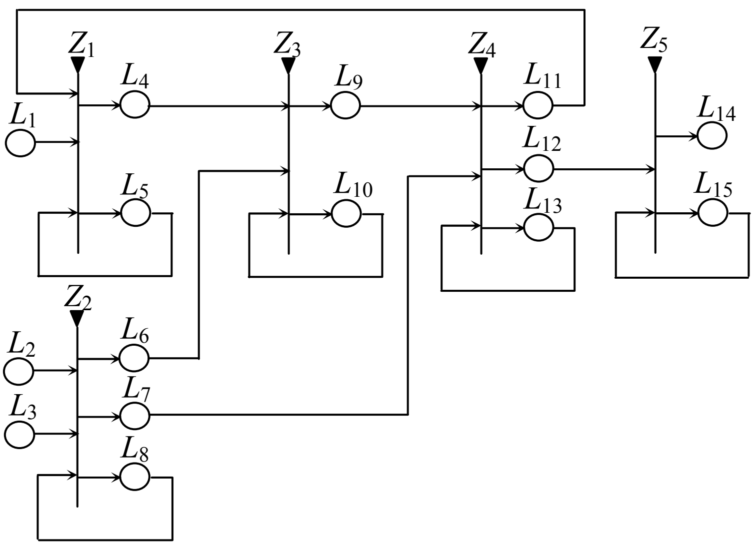

Fig. 1 GN model of the process of color recognition
using ART2 neural network

GN-model consists of five transitions with the following description:

$$Z_1 = \left\langle \{L_1, L_5, L_{11}\}, \{L_4, L_5\}, R_1, \vee\left(L_1, \wedge\left(L_5, L_{11}\right)\right)\right\rangle,$$

where

$$R_1 = \begin{array}{c|cc} & L_4 & L_5 \\ \hline L_1 & false & true \\ L_5 & W_{5,4} & true \\ L_{11} & false & true \end{array},$$

and $W_{5,4}$ = "There is an active signal for the next input vector".

Token that enters place L_5 from places L_1 or L_5 does not obtain new characteristic. Token that enters place L_4 from place L_5 obtains a characteristic "input test vector". Token that enters place L_5 from place L_{11} obtains a characteristic "request for next input vector from the matrix".

$$Z_2 = \left\langle \{L_2, L_3, L_8\}, \{L_6, L_7, L_8\}, R_2, \vee\left(L_8, \wedge\left(L_2, L_3\right)\right)\right\rangle,$$

where

$$R_2 = \begin{array}{c|ccc} & L_6 & L_7 & L_8 \\ \hline L_2 & false & true & false \\ L_3 & false & true & false \\ L_8 & W_{8,6} & W_{8,7} & true \end{array},$$

and $W_{8,6} = W_{8,7}$ = "The neural network is trained".

Token that enters place L_8 obtains a characteristic "Trained Neural Network". Token that enters place L_6 from place L_8 does not obtains new characteristic. Token that enters place L_7 from place L_8 obtains a characteristic "Conditions for winner clusters".

$$Z_3 = \left\langle \{L_4, L_6, L_{10}\}, \{L_9, L_{10}\}, R_3, \vee\left(L_6, \wedge\left(L_4, L_{10}\right)\right)\right\rangle,$$

where

$$R_3 = \begin{array}{c|cc} & L_9 & L_{10} \\ \hline L_4 & false & true \\ L_6 & false & true \\ L_{10} & W_{10,9} & true \end{array},$$

and $W_{10,9}$ = "There is a result from ART2 NN".

Token that enters place L_{10} from place L_4 obtains a characteristic "Winner cluster was determined". Token that enters place L_{10} from place L_6 stays in all time of life of GN and does not obtain new characteristic. Token from place L_{10} enters place L_9 with a characteristic

"Winner cluster was determined". Token that enters place L_{10} from place L_{10} does not obtain new characteristic.

$$Z_4 = \left\langle \{L_7, L_9, L_{13}\}, \{L_{11}, L_{12}, L_{13}\}, R_4, \vee\left(L_9, \wedge\left(L_7, L_{13}\right)\right) \right\rangle,$$

where

$$R_4 = \begin{array}{c|ccc} & L_{11} & L_{12} & L_{13} \\ \hline L_7 & \mathit{false} & \mathit{false} & \mathit{true} \\ L_9 & \mathit{false} & \mathit{false} & \mathit{true} \\ L_{13} & W_{13,11} & W_{13,12} & \mathit{true} \end{array},$$

and $W_{13,11}$ = "The value pixel of picture was determined", $W_{13,12}$ = "The values of pictures were determined".

Token that enters place L_{11} from place L_{13} obtains a characteristic "Request for next input vector". Token that enters place L_{12} from place L_{13} obtains a characteristic "Converted values of the picture". Token that enters place L_{13} from place L_7 stays in all time of life of GN and does not obtain new characteristic. Token from place L_9 unites with one token from place L_7 in place L_{13} and obtains a characteristic "Tested pixel value". Token that enters place L_{13} from place L_{13} does not obtain new characteristic.

$$Z_5 = \left\langle \{L_{12}, L_{15}\}, \{L_{14}, L_{15}\}, R_5, \vee\left(L_{12}, L_{15}\right) \right\rangle,$$

where

$$R_5 = \begin{array}{c|cc} & L_{14} & L_{15} \\ \hline L_{12} & \mathit{false} & \mathit{true} \\ L_{15} & W_{15,14} & \mathit{false} \end{array},$$

and $W_{15,14}$ = "The values of the pictures were converted".

Token that enters place L_{15} from place L_{12} obtains a characteristic "Converted values of pictures". Token that enters place L_{14} from place L_{15} obtains a characteristic "Visualization of the pictures".

Results and discussion

In order to test the algorithm we use one random picture taken from the [7, 8] (Fig. 2). The first picture is an x-ray image of a hand and the second is a NMR image of a human skull. Both pictures are used for testing the ART2 neural network for finding cancerous cells in a given color. In our case, we use black color for training the neural network [255 0 0]. After the processing, the result picture with the recognized colors is shown in the Fig. 3.

The colors that were not taken into account were depicted in white color. As it can be seen from the resulted x-ray image after testing into the network there are black spots that surrounds the black object and the explanation is we recognize gray color and pixels values in range of [1 1 1] to [244 244 244] are regarded as a gray color.

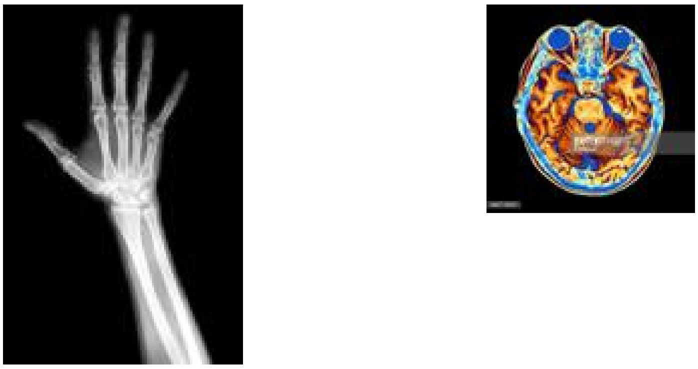

Fig. 2 Original pictures

Fig. 3 Pictures after testing

The result pictures after the recognition can be used for diagnostics, finding cancerous cells as well as performing surgery operations with absolute accuracy in the human organs.

Conclusion

The neural network was learned by slow learning of ART2 and each cluster was presented by different colors. The neural network was tested by x-ray and NMR images in .jpg format. As a result of the training process, two figures are presented. It was shown that ART2 neural network successfully recognize x-ray and nuclear magnetic resonance images. The algorithm might be implemented in hospitals in order to support medical stuff for more precisely establish their diagnosis.

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