A New Type of ART2 Architecture and Application to Color Image Segmentation

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Abstract. A new neural network architecture based on adaptive resonance theory (ART) is proposed and applied to color image segmentation. A new mechanism of similarity measurement between patterns has been introduced to make sure that spatial information in feature space, including both magnitude and phase of input vector, has been taken into consideration. By these improvements, the new ART2 architecture is characterized by the advantages: (i) keeping the traits of classical ART2 network such as self-organizing learning, categorizing without need of the number of clusters, etc.; (ii) developing better performance in grouping clustering patterns; (iii) improving pattern-shifting problem of classical ART2. The new architecture is believed to achieve effective unsupervised segmentation of color image and it has been experimentally found to perform well in a modified $L^*u^*v^*$ color space in which the perceptual color difference can be measured properly by spatial information.

Keywords: ART2, similarity measurement, unsupervised segmentation, color image.

1 Introduction

With highly developed applications of color information in recent decades, the segmentation of color image has been given more and more attention. Various segmentation techniques have been proposed in the literature, amongst which the application of artificial neural networks (ANNs) comes to be attractive. ANNs have several advantages over many conventional computational algorithms, e.g., high degree of parallelism, nonlinear mapping, adaptivity, and error tolerance etc. Guo Dong [1] summarized different types of neural networks proposed for the segmentation of color image.

Both based on competitive learning there are two prevalent self-organizing network models: self-organizing map (SOM) of Kohonen [2] and adaptive resonance theory (ART) of Carpenter and Grossberg [3]. Although it has been commonly used in the unsupervised segmentation of color image [1], [4], SOM has following defects: (i) the map size should be defined in advance and can't be changed during learning; (ii) the learning is time-consuming. In comparison with it, ART is characterized by advantages: (i) no any prior knowledge of cluster

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number is needed; (ii) fast learning algorithm can be used. Adaptive resonance theory was introduced by Carpenter G. A. in 1976 who subsequently proposed three main types of ART network together with Grossberg S. [3], [5], [6].

In this paper, we cited ART2 network which can perform real-time unsupervised learning to analog input pattern, and overcome the disadvantage of most forward network that is easily running into local minimum [7], [8]. But the similarity measurement mechanism of ART2 is based on phase information of patterns that results in the loss of pattern magnitude and inhibits its application in segmentation of color image. Besides, pattern-shifting problem exists because the learning algorithm of classical ART2 is insensitive to gradually changed input patterns. In order to overcome these defects, various methods have been proposed in the literature [9], [10], [11], [12], [13], [14], but these improvements usually add more complexity to network in structure or in algorithms. By introducing a new mechanism of similarity measurement and a quick learning algorithm, we propose a new ART2 architecture without introducing complexity neither in structure nor in algorithms, and it is proved to be able to achieve effective color segmentation in perceptually uniform color space.

2 Structure and Algorithms of Classical ART2 Architecture

A classical ART2 architecture is shown in Fig. 1.

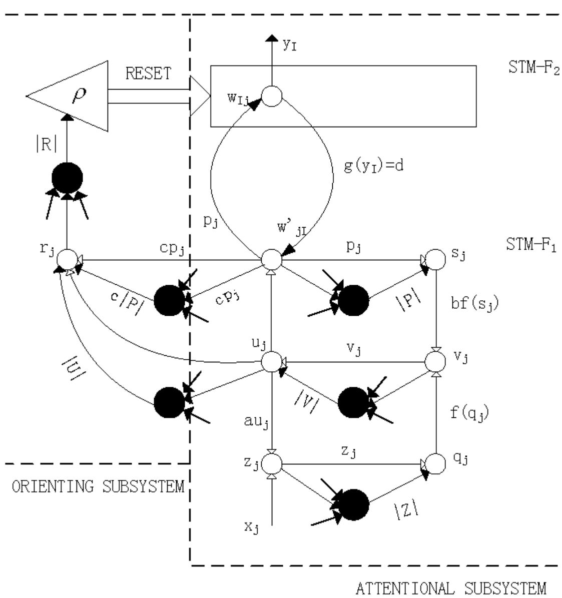


Fig. 1. A classical ART2 architecture

The network is partitioned by dashed lines into two subsystems. In attentional subsystem, STM-F_1 layer preprocesses input pattern to denoise and enhance contrast; the STM-F_2 layer keeps nodes to represent pattern prototypes, and $y_I = 1$ when node I is activated. Orienting subsystem executive similarity vigilance-testing between input pattern and activated pattern prototype. The bigger black circles mean calculation of modulus. Main algorithms of the classical ART2 network are as following [7]:

$$z_j = x_j + au \ , \tag{1}$$

$$q_j = \frac{z_j}{e + ||Z||} \ , \tag{2}$$

$$v_j = f(q_j) + bf(s_j) \ , \tag{3}$$

$$u_j = \frac{v_j}{e + ||V||} \ , \tag{4}$$

$$p_j = u_j + \sum_{i=0}^{m-1} g(y_i) w'_{ji} \ , \tag{5}$$

$$s_j = \frac{p_j}{e + ||P||} \ , \tag{6}$$

where,

$$f(x) = \begin{cases} x & if\ x \geq \theta \\ 0 & if\ x < \theta \end{cases} , \text{ and } g(y_j) = \begin{cases} d & if\ j = I \\ 0 & if\ j \neq I \end{cases} . \tag{7}$$

Activation mechanism runs under competitive selection described as:

$$T_I = \max\{T_i = \sum_{j=1}^{n} p_j w_{ij} \mid i = 1, 2, \ldots, m\} \ . \tag{8}$$

m is the maximal allowable number of categories; n is the dimension of input pattern; I is the category number of current active node; e is error parameter. System will carry out unsupervised learning when the pattern prototype stored in the current active node is successfully matched to the input pattern. With quick learning, instar and outstar connection weights w_{Ij} and w'_{jI} update by

$$w_{Ij} = w'_{jI} = \frac{u_j}{1-d} \ . \tag{9}$$

The similarity vigilance-testing of orienting subsystem processes with vector r described by

$$r_i = \frac{U_i + cPi}{||U|| + c||P||}, \text{ and } R = ||r|| \ . \tag{10}$$

If $R \geq \rho + e$, update the instar and outstar weights of current active node, otherwise, the active node should be reset and inhibited, and system should continue to search the most matching pattern prototype among the residual nodes. If no node passes vigilance-testing, create a new node, that is, create a new category.

According to the algorithms, there is $||U|| = 1$, and $||W_I|| = ||W'_I|| = ||U/(1-d)|| = 1(1-d)$. Consequently no magnitude information of original input patterns has been included during the similarity vigilance-testing. To some applications (for example, speech recognition) in which magnitude is not the invariant feature, classical ART2 network has been widely applied. But in some other cases, the magnitude must been considered. For example, in image recognition, sometimes we must adopt gray intensity or color chroma etc. Some transform algorithms maybe allow alternatively to get invariant feature independent of magnitude, but usually cost is huge. Therefore it is significant to modify classical ART2 so as to make magnitude an important feature. Following sections will describe in detail how to modify structure and algorithms to carry out recognition and classification with combination of phase and magnitude.

3 Modification of Structure and Algorithms

Modified ART2 architecture is shown in Fig. 2.

Compared with classical ART2, there are following modifications:

(1) Extracting magnitude of pattern before the original input pattern into F_1.
(2) Adapting minimum-win competitive rule in activation mechanism of F_2 nodes,

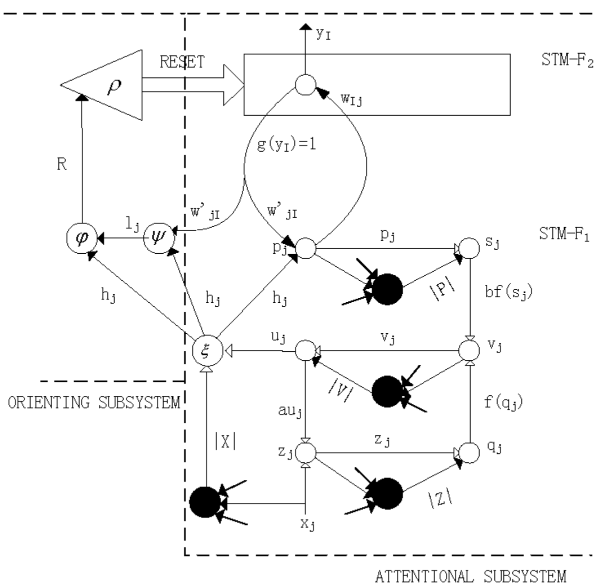


Fig. 2. The new ART2 architecture

$$D_i = ||P - W_i|| = \left(\sum_j (p_j - w_{ij})^2 \right)^{\frac{1}{2}} , \text{ and } D_I = \min(D_i) . \tag{11}$$

(3) Introducing three special functions to assistant similarity measurement between input pattern and stored pattern:

$$H = \xi(||X||, U) = ||X|| * U , \tag{12}$$

$$L = \psi(W_I', H) = \begin{cases} W_I' & if\ ||W_I'|| \neq 0 \\ H & if\ ||W_I'|| = 0 \end{cases} , \tag{13}$$

$$R = \phi(H, L, \delta) = \exp(-||H - L||/\delta) , \tag{14}$$

where, R is the final similarity measurement between two patterns for vigilance-testing.

(4) Quick weight adjustment (learning) algorithms:

$$w'_{jI}{}^{new} = w_{Ij}{}^{new} = \frac{1}{2}(||X|| \bullet u_j + w'_{jI}{}^{old}) . \tag{15}$$

By above modifications, the magnitude of original input pattern has been considered both during similarity vigilance-testing and weight adjustment. In addition, the stored pattern which is the closest to input pattern by Euclidian-distance will be activated.

4 Analysis of the New ART2 Network

The important modifications of the new ART2 architecture are similarity measurement and matching based on Euclidian-distance between pattern vectors. Then all modifications work together to appropriately apply spatial information to measure similarity, but keep the same foundation of classical ART2 network.

4.1 System Initialization

The processing nodes and downward connection weight are initialized to zero (same as classical ART2), but upward connection weight should be discussed forward. Initialization of upward connection weight aims to enable selecting or creating a new category when there is no existing category matching input pattern, but avoids to do so when there is matching category. So the initialization must make initial weight vectors far away from input pattern. In classical ART2 network, because competitive mechanism chooses the node of maximum weighted summation input as winner, upward channel vectors are usually initialized to evenly distributed random values inside a small zone, so new category's weighted summation is small and difficult to be chosen. Differently in the new ART2 network, competitive mechanism chooses the node of minimum Euclidian-distance as winner, so upward channel vectors should be initialized to be close to zeros in order to make the Euclidian-distance far enough between initial upward vector and input vector,

$$0 \leq w_{ij} \leq \beta \ , \tag{16}$$

where β is a mini constant values or mini random values inside a small zone. Notice that zeros are allowed here, because the Euclidian-distance is not zero between nonzero vector and zero vector.

4.2 STM-F$_1$ Self-stabilization Stage

The function of STM-F$_1$ in the new ART2 network is same as classical one that is to denoise and enhance contrast, but their operating process is somehow different mainly lying in the top pattern P:

$$p_j = h_j + \sum_{i=0}^{m-1} g(y_i) w'_{ji}, \text{ and } h_j = ||X|| \bullet u_j \ . \tag{17}$$

This top pattern P restores the magnitude information of input pattern. When there is no node in F$_2$ active, that is $g(y_i) = 0$, P represents middle pattern H.

After STM-F$_1$ self-stabilization, top pattern P is sent to feature representation field through upward channel for similarity matching in order to search the node with the shortest Euclidian-distance to pattern P. Calculate all Euclidian-distances of instar connection weight vectors to P. If $D_I = \min(D_i)$, then activate node I. There are some instances which should be considered:

(1) If define the maximum number of categories in advance, and no node has been executed that is never learned, when all topward channel vectors have the same initial values, system may chose to active one node randomly or according to index number, otherwise minimum-win rule still works.
(2) If define the maximum number of categories in advance, and all learned nodes have been inhibited because of not passing vigilance-testing, execute as instance (1) among residual unlearned nodes.
(3) If not define the maximum number of categories in advance, and all new nodes are dynamically added, then there is just one node initially. It is chosen when input the first pattern, and create new node dynamically if the following pattern does not match it, the rest may be deduced by analogy. Because new node will be created only when all learned nodes have been inhibited, input pattern may be directly stored into the new category.
(4) Quick searching: directly chose or create a new node will greatly shorten searching time. It means that when the node with the minimum Euclidian-distance among all learned nodes don't pass vigilance-testing the others will also not pass.

4.3 Vigilance Testing

When a node in F$_2$ is activated, its downward channel vector will be sent to orienting subsystem for similarity vigilance-testing together with middle-level pattern of input. If node I is activated, there are several possibilities:

(1) It is an unexecuted node. $W_I' = 0$, such that by Eq. (13) and (14) there are

$$L = H \text{ and } R = 1 \; . \tag{18}$$

That means two patterns are the same, so undoubtedly the node will pass vigilance-testing

(2) It is an executed node. $W_I' \neq 0$, by Eq. (12), (13), (14) there is

$$R = \exp\left(-||W_I' - ||X|| * U||/\delta\right) \; . \tag{19}$$

By defining

$$D_I' = ||W_I' - ||X|| * U|| \; , \tag{20}$$

and vigilance parameter ρ , the requirement for passing vigilance-testing is

$$\exp(-D_I'/\delta) \geq \rho \Rightarrow D_I' \leq (-\ln\rho)\delta \; . \tag{21}$$

With a determinate ρ, all those input patterns located inside a super-sphere with W_I' as center and $(-\ln\rho)\delta$ as radius will pass vigilance-testing. It is obvious that super-sphere's radius linearly varies with δ , therefore the selection of δ directly decides clustering precision. In addition, with defined δ the super-sphere's radius logarithmically varies with vigilance parameter, so selection of ρ can also regulate classifying precision. Based on that, δ and ρ should be appropriately selected according to actual application background.

4.4 Weight Adjustment (Learning)

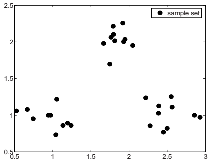
Weight learning in this paper is a kind of quick algorithms of approximate mean vector. By analysis of articles [9], [10] the learning algorithms of classical ART2 usually result in pattern shifting, and it can be improved by adapting varied K-means as weight learning algorithm. In article [10] the activated times K of each node is recorded, and new weight update by

$$W^{new} = \frac{1}{k}((k-1)W^{old} + input) \tag{22}$$

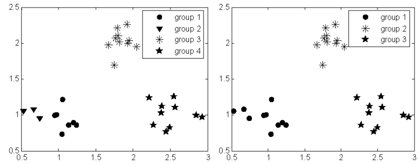
By this method, the new weight vector more correctly represent clustering center of a category with combination of all learned patterns and the new input pattern. The disadvantage is having to add a mechanism in network to record K, and it becomes not important after enough learning. We adapt approximate mean defined by Eq. (15) that avoids recording mechanism while sufficiently simulate the idea of varied K-mean algorithm.

5 Experimental Results and Analysis

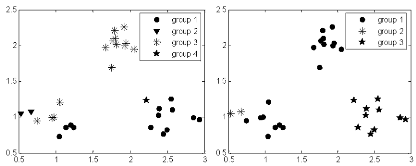
To describe the design and application of the new ART2 architecture, we carried out some experiments in this paper.



(a) samples



(b) $\rho = 0.9, 0.85$ from left to right



(c) $\rho = 0.996, 0.99$ from left to right

Fig. 3. Sample set and classifying results. (a) is samples distribution; (b)showed classifying results of the new ART2 network given parameters $a = b = 10, \theta = 0.01, \delta = 5, e = 0$; (c) showed classifying results of the classical ART2 network given parameters $a = b = 10, \theta = 0.01, c = 0.1, d = 0.9, e = 0$.

5.1 Performance in Classifying Clustering Groups

Sample set includes thirty randomly distributed data points which are expected at points $(1, 1)$, $(2, 2)$, and $(2.5, 1)$ respectively disturbed by noise of Gaussian distribution. The samples and classifying results are shown in Fig. 3. In Fig. 3(a) we can visually perceive that all samples are distributed as three clustering groups. The experimental results have shown that the new ART2 is more suitable for group clustering data than the classical ART2 architecture.

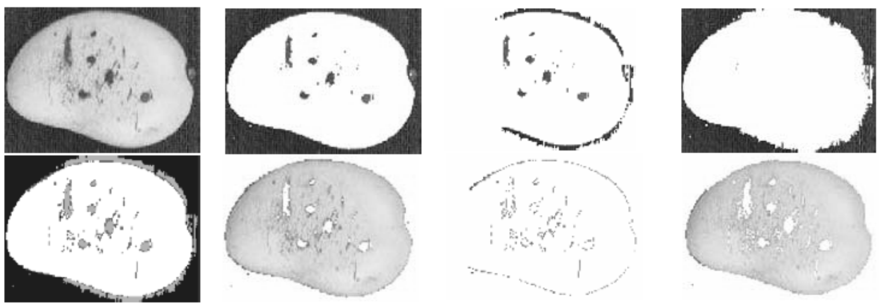
5.2 Segmentation of Color Image

With the advantages described above, it is believed that the new ART2 architecture should be able to achieve effective segmentation of color image in perceptually uniform color space. In this paper, we conducted all experiments in a modified CIE$L^*u^*v^*$ color space in which the perceptual color difference can be measured properly by spatial information [15]. In [1], Gu Dong has given detailed steps for the conversion from RGB to modified CIE$L^*u^*v^*$.

A. Segmentation of Artificial Color Image

Given an artificial color image in which several perceptually close colors are nested, experiments were designed to test the classifying ability of the new ART2 architecture. Results have been shown in Fig. 4.

Fig. 4. Artificial color image and segmentation results with the new ART2 network. From left to right they are the original image and segmentation results given parameters $a = b = 5, \theta = 0.1, \delta = 1, e = 0$ with different vigilance testing $\rho = 0.85, 0.9$ and 0.95 respectively.



(a) (b) (c)

Fig. 5. Natural color image and segmentation results with the new ART2 network. By column, (a) showed original image and final segmentation; given parameters $a = b = 5, \theta = 0.1, \delta = 1, e = 0.01$, (b) showed segmentation results with $\rho = 0.8$; (c) showed the subsegmentation of (b) with $\rho = 0.9$ and $\rho = 0.85$ from top to bottom.

B. Segmentation of Natural Color Image

Fig. 5 has shown the segmentation results of natural color image with the new ART2 network.

6 Conclusion

The new ART2 architecture proposed in this paper introduces a new similarity mechanism without changing the classical ART2 foundation, and the modifications of structure and corresponding algorithms work together to improve network's performance in grouping clustering data and have been experimentally found effective in color image segmentation in uniform color space. Of course there still is need for more work to make the new network generally applicable. For example: how to preprocess data to make sure the spatial compactness; and how to select parameters appropriately? That will be our next goal.

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