

COLOR IMAGES SEGMENTATION USING A SELF-ORGANIZING NETWORK WITH ADAPTIVE LEARNING RATE

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Abstract

In this paper, an approach based on self-organizing neural network with adaptive learning rate for color image segmentation is presented. It is well-known that the training speed depends on the choice of the learning rate. If the learning rate is small, the learning process is stable but at the expense of computation time. If the learning rate is too large, the estimation of the weights may diverge. The usual methods for this purpose are based on constant learning rate and because of its inflexibility; the cluster result is not so satisfactory. In this approach, self organized neural network has adaptive learning rate. It results in better convergence with equal quality compared to last works in this field. In simulation, training of the network using this approach is much faster than using a constant learning rate.

Keywords: neural network, self-organizing, learning rate, images segmentation, adaptive.

1 Introduction

Since color provides important cues for image processing and object recognition, color images are used in many applications. Nowadays, the techniques of image processing have been developed, but there are still some bottlenecks that are not solved. One of these which must be revised to solve relatively, is color image segmentation. The usual methods of segmentation are edge detection, region growing, region splitting and merging, histogram thresholding and clustering. But some of them, edge detection and histogram thresholding are not suitable for color images because the color component should not be processed separately in view of their interdependence [1]. The basic common idea of region segmentation methods is to modify the partition until all the regions of the image satisfy a given homogeneity criterion [2]. To perform a clustering of a color image, some strategies can be employed. The strategies generally differ on the dimension of the data used to cluster the image [3]. Segmentation of an image entails the division or separation of the image into regions of similar attribute. Surveys of image segmentation methods are given in references [4].

In recent years; using ANN approach in color image segmentation is seen in literature. This using has some advantages, but its costs must never be forgotten. Time consuming and hardware complexity are two important criteria to evaluate intelligent algorithms. Some authors have recently reported algorithms based on an NN which its requirement is SUN computers [5]. Regard to above criteria, the grade of this method of segmentation is not good. Some works have been done in adaptive learning rate. Some approaches have been presented in this area. In [6], new learning rate updating schemes for Self-organized Feature Maps (SOFM) and Generalized Learning Vector Quantization (GLVQ). Nachtsheim was presented an approach that is determined the learning rate parameter at each step of the iteration by attempting to find a double root of the quadratic cost function [7]. In [8] an adaptive learning rate to update the weights of a B-spline network with a scalar or multi-output is proposed. Negnevitsky and Ringrose have been developed several methods of accelerating learning using back-propagation [9]. In [10] a new theorem for the development and convergence analysis of supervised training algorithms with an adaptive learning rate for each weight has been presented.

In this paper we propose an approach which uses self organizing map neural network with adaptive learning rate to segment the color images. Comparing to other intelligent algorithms, better convergence with equal quality are the specifications of our approach.

The organization of this paper is as follows: Section 2 describes the color space used. Section 3 discusses the self-organizing neural network architecture and function. In Section 4 new adaptive approach is discussed and finally the conclusion is described in Section 5.

2 Choice of Color Space

All colors are seen in variable combinations of the so called primary colors red (R), green (G), and blue (B). The attribute generally used to distinguish one color from another are brightness, hue and saturation. Brightness embodies the chromatic notion. Hue is associated with the dominant wavelength in a mixture of light waves and represents dominant color. Saturation refers to the relative purity or the amount of white light mixed with the hue. Hue and saturation taken together and therefore a color may be characterized by its brightness and chromaticity. To facilitate the specification of colors in some standards, generally accepted way, a color space must be selected. There are several standard color spaces that are widely used in image processing e.g. RGB, CMY, HIS and YIQ. All of standard color space can be calculated from the tristimuli R, G, B by appropriate transformation. However, these models are not uniform color spaces [4]. The various color spaces exist because they present color information in ways that make certain calculations more convenient or because they provide a way to identify colors that is more intuitive. For example, the RGB color space defines a color as the percentages of red, green, and blue hues mixed together. Other color models describe colors by their hue (green), saturation (dark green), and luminance, or intensity. In this paper we used $L^*u^*v^*$ color space. In this color space, the difference between colors is computed using Euclidian distance. L^* represents the intensity and other elements, u^* and v^* are color chromaticities. The $L^*u^*v^*$ coordinate system, which has evolved from the $L^*a^*b^*$ and the $U^*V^*W^*$ coordinate systems, became a CIE standard in 1976. It is defined as:

$$L^* = \begin{cases} 25 \left(100 \frac{Y}{Y_0} \right)^{1/3} - 16 & \text{for } \frac{Y}{Y_0} \geq 0.008856 \\ 903.3 \frac{Y}{Y_0} & \text{for } \frac{Y}{Y_0} \leq 0.008856 \end{cases}$$

$$u^* = 13L^*(u' - u'_0), v^* = 13L^*(v' - v'_0)$$

Where:

$$u' = \frac{4X}{X + 15Y + 3Z}, v' = \frac{9Y}{X + 15Y + 3Z}$$

u'_0 and v'_0 are obtained by substitution of the tristimulus value X_0, Y_0, Z_0 for the reference white.

3 Structure and Training of SOM Network

The SOM, introduced by Kohonen [11] is one of the most appealing topics in the neural network field. The development of SOM is motivated by a distinct feature of the human brain. This type of network is based on competitive learning; the output neurons of the network compete among themselves to be activated or fired, with the result that only *one* output neuron, or one neuron per group, is on at any one time. In this manner, there is a winner-takes-all neuron. In an SOM, the neurons are the nodes of a lattice that is one or two dimensional. Higher-dimensional is not common. In the course of competitive learning process, the neurons selectively tuned to various input patterns or classes of input patterns. SOM provide a bridge between two levels of adaptation:

- 1- Adaptation rules formulated at microscopic level of a single neuron.
- 2- Formation of experimentally better and physically accessible patterns of feature selectivity at the microscopic neural layer.

The principal goal of the SOM is to transform an incoming signal pattern of arbitrary dimension into a one- or two-dimensional discrete map, and to perform this transformation adaptively in a topologically ordered fashion.

SOM represents a feed forward structure with a single computational layer consisting neurons arranged in row and column (The number of rows or columns can be single). All neurons in the network should be exposed to a sufficient number of different realization of the input pattern to ensure that the self-organization process has a chance to mature properly.

There are three essential processes involved in the formation of the self-organizing map:

- 1-Competition: The neurons in a competitive layer distribute themselves to recognize frequently presented input vectors. For each input pattern, the neurons in the network compute the respective values of a discriminant function. This discriminant function provides the basis for competition

among the neurons. The winner of the competition is the neuron which has the largest value of discriminant function.

2-Cooperation: The winning neuron determines the spatial location of a topological neighborhood of excited neurons, thereby providing the basis for cooperation among such neighboring neurons.

3-Synaptic Adaptation: In this process, the excited neuron is enabled to increase their individual values of discriminant function in relation of input pattern through suitable adjustment applied to their synaptic weights. In this way, the response of the winner to the subsequent application of a similar input pattern is enhanced.

Using these processes the SOM network can learn to detect regularities and correlations in their input and adapt their future responses to that input accordingly. The neurons of competitive networks learn to recognize groups of similar input vectors. Self-organizing maps learn to recognize groups of similar input vectors in such a way that neurons physically near each other in the neuron layer respond to similar input vectors [12].

Self-organizing Maps have been commonly used since their first description in a wide variety of problems, as classification, feature extraction, pattern recognition and other related applications. The basic SOM consists of a 2-dimensional lattice L of neurons. Each neuron $n_i \in L$ has an associated weight vector $W_i \in R^n$. The lattice is either rectangular or hexagonal with the connections within L determining the neighborhoods of a given neuron. Training the SOM involves first randomly initializing all the weight vectors and then sequentially presenting each training sample.

Each $X \in R^n$ is presented as an input vector to all neurons in the network, and the winning neuron N_c with weight vector W_c is determined so that:

$$\|X - W_c\| = \text{Min}_i \{ \|X - W_i\| \} \quad (1)$$

The winner and all the neurons within N_c are update by the learning rule:

$$W_{k+1}^i = \begin{cases} W_k^i + \alpha_k [X_k - W_k^i] & \text{if } i \in N_c \text{ and } i = c \\ W_k^i + \beta_k [X_k - W_k^i] & \text{if } i \in N_c \text{ and } i \neq c \\ W_k^i & \text{if } i \notin N_c \end{cases} \quad (2)$$

Where α_k, β_k are the respective learning rates of the winning neuron and its neighbors at the k^{th} iteration. The neurons in a specific neighborhood of

the winning neuron then have their weight vectors adjusted to be closer to the input vector according to a parameterized learning function. Each neuron is then assigned the label of the type for which it ‘fired’ the most. Classification can then take place by presenting data and labeling with the label of the winning neuron each time [13]. In traditional method α_k, β_k decreases monotonically with time:

$$\begin{aligned} 1^{\text{st}} \text{ stage: } \alpha_k &= \alpha_0 \times 1.5^{-k}, & \beta_k &= \beta_0 \times 1.5^{-k} \\ 2^{\text{nd}} \text{ stage: } \alpha_k &= \frac{\alpha_0}{k^3}, & \beta_k &= \frac{\beta_0}{k^3} \end{aligned} \quad (3)$$

Where α_0, β_0 are the initial values, and $\alpha_0 < \beta_0$.

4 New SOM Network Training

The new adaptive algorithm uses the steepest descent for optimal computation of the step size in each iteration. This adaptive method is based on the gradient descent optimization. In this approach the latest learning rate and latest changes in weights are used to generate new learning rate. We have the derivative of the cost function J with respect to α_k [14]:

$$\begin{aligned} \frac{\partial J(W_{k+1})}{\partial \alpha_k} &= 0 \\ \frac{\partial J(W_{k+1})}{\partial \alpha_k} &= \frac{\partial J(W_{k+1})}{\partial W_{k+1}} \cdot \frac{\partial W_{k+1}}{\partial \alpha_k} \\ \frac{\partial J(W_{k+1})}{\partial W_{k+1}} &= X_{k+1} - W_{k+1} \\ \frac{\partial W_{k+1}}{\partial \alpha_k} &= X_k - W_k \\ (X_{k+1} - W_{k+1}) \cdot (X_k - W_k) &= 0 \end{aligned} \quad (4)$$

Substituting Eq. (2) in Eq. (4) and doing some mathematical operation, we get:

$$\alpha_k = \frac{X_{k+1}X_k - X_{k+1}W_k - W_kX_k + W_k^2}{X_k^2 - 2X_kW_k + W_k^2} \quad (5)$$

The algorithm is briefly shown in Figure 1. The α_k in this algorithm is obtained by Eq. (5) and $F(X_k, W_k)$ is equal to $\alpha_k[X_k - W_k^i]$.

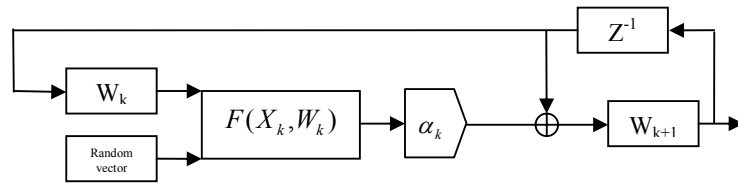
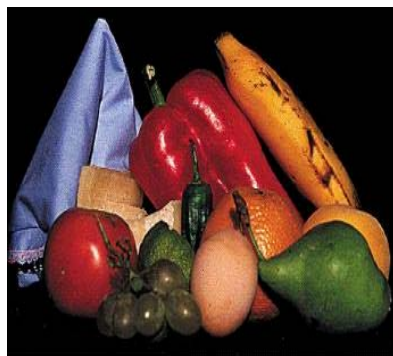


Figure 1.Computational algorithm.

The main advantage of the new algorithms is its convergence rate in weights which is very fast. The convergence speed of this method makes it appropriate for online applications Figure.4 shows that convergence of adaptive learning rate is faster than traditional adaptive algorithm using SOM.

The domain clusters are shown in images in Figure.2, and Figure.3. The details of color images segmentation have been discussed completely in [5].



(a)



(b)

Figure 2.(a) Original “Fruits” image, (b) Segmented “Fruits” image using 8×8 map

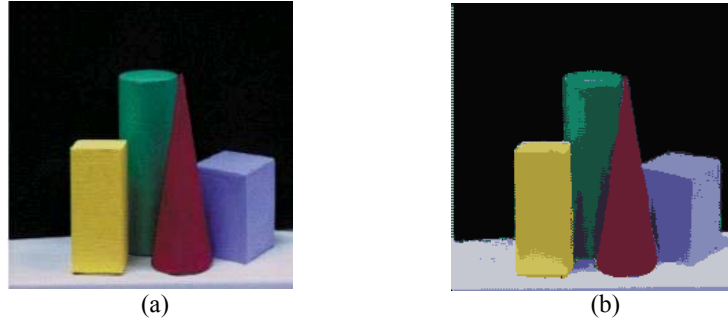


Figure 3.(a) Original “Plants” image, (b) Segmented “Plants” image using 16×16 map

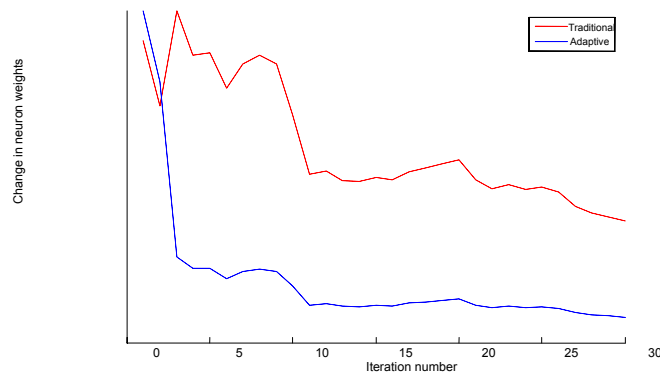


Figure 4.Change in neuron weights w_{ij} against the iteration number

5 Conclusion

In this paper a self-organizing neural network with adaptive learning rate for color image segmentation has been presented. Because of fast convergence in using SOM with adaptive learning rate, it can be applied in online applications. Beside of better convergence the results show equal quality compared to previous works.

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