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Color Image Segmentation Using Self Organizing Map Artificial Neural Network

Saeid Pashazadeh[1], Masume Kheyri[2]
Department of Information Technology[1], Department of Computer Engineering[2],
Faculty of Elec. & Comp. Engineering, University of Tabriz
Tabriz, Iran
pashazadeh@tabrizu.ac.ir, m.kheiri90@ms.tabrizu.ac.ir

Abstract: Segmentation of color images is one of the basic steps in most of image processing applications and quality of its result has great influence on future processes. A novel segmentation method using artificial neural network (ANN) for color image segmentation is proposed in this paper. For increasing color differences, images are represented in a modified L*u*v* color space. Self-organizing neural network with unsupervised learning is used for image segmentation based on color reduction. In color reduction, image colors are projected into a small set of prototypes using Self-Organizing Map (SOM) network. Results of this method can be considered as a near optimal segmentation with a low computation cost. Experimental results show that this system has a desirable ability for color image segmentation in computer vision applications.

Keywords: Image segmentation; Unsupervised learning; Self organizing map; Color space; Color reduction.

1. Introduction

Image segmentation is one the important and key process in numerous applications of computer vision. Segmentation is process of separating an image into different meaningful regions with homogenous characteristics using discontinuities or similarities of image's components. Quality of subsequent process on an image or video highly depends on quality of image segmentation. Segmentation of an image can be carried out using variety of methods. Most commonly used methods are as follows:

A. Histogram's Threshold Based Methods

These methods try to convert a multilevel image into a binary image. It assigns value of zero for background pixels and one for objects or foreground pixels of an image based on comparison with threshold value T that is intensity or color value. When T is constant, approach is called *global threshold* and otherwise it is called *local threshold*. When illumination of background is uneven, the global threshold methods do not produce correct answer and therefore multiple thresholds are used to solve this problem. Threshold selection is the most important issue in these approaches. These methods are popular due to their simplicity but they cannot process images whose histograms are nearly unimodal or target region is much smaller than the background area [1, 2].

B. Edge Detection Based Methods

These methods are considered as most useful approaches for image segmentation. They locate pixels that correspond to the edges of objects in image. They produce a binary image as result. Sobel, Prewitt and Laplacian operators are used in these methods. These algorithms are suitable for simple and noise-free images but they cannot easily identify a closed curve or banding when images have many edges and noises. So, they produce missing or extra edges [3-5].

C. Region Based Methods

Goal of these methods is to use image characteristics to map individual pixels of input images to sets of pixels called regions. These regions might correspond to an object or meaningful part of one an image. These methods use various techniques such as: Local techniques, Global techniques, splitting techniques and merging techniques. Quality of these algorithms depends on type of application and the size of the input image. If image were simple enough, simple local technique can be effective. However on difficult scenes, even the most sophisticate techniques may not produce a satisfactory segmentation [6-8].

D. Graph Based Methods

These methods use graph in which nodes represent image pixels and arcs represent neighboring of pixels. Segmentation is obtained by computing minimum weight that cut a graph into sub-graphs. Generally, these methods suffer from high computational complexity [9, 10].

E. ANN Based Methods

These methods can be considered as new category of methods that can be used for image segmentation. These networks have certain characteristics such as a high degree of parallelism, non-linear mapping, fault tolerancy, and acclimation that are suitable for image segmentation. These methods can be classified into two categories as follows:

- ✓ **Supervised Segmentation:** Supervised segmentation is commonly used in applications that sample of object color can be acquired in advance e.g., face recognition and image retrieval etc. Most commonly used techniques of these methods are Maximum Likelihood, Decision Tree and Nearest Neighbor [11].
- ✓ **Unsupervised Segmentation:** Unsupervised segmentation is widely used in applications where image features aren't known before such as nature scene understanding, satellite image analysis and so on.

Rest of paper is organized as follows: L*u*v* color space is presented in section 2. In section 3, SOM neural network is used for color images segmentation and finally results of experiments are presented.

2. Color Space

In most cases, segmentation of color image is more useful than segmentation of monochrome image. Because color image expresses much more image features than monochrome image. In fact, each pixel is characterized by a great number of combinations of R,G,B chromatic components such that each pixel usually contains 24 bit information.

Many color spaces such as RGB, CIE XYZ, CIE L*u*v*, CIE L*a*b*, HSL, YUV and YIQ are used in the segmentation of color image. A color image is uniform if equal distance in color space corresponds to equal perceived color difference. Many color spaces are non-uniform. For example RGB color space is far from exhibiting the perceptual uniformity, it does not the way that human perceive colors. In HSL color space, different computations are involved around 60°, which introduce the visible discontinuities in color space [12]. Nonlinear R'G'B', YUV, CIE L*u*v* and modified CIE L*u*v* are four color spaces that score well in perceptual uniformity in studies of Riemersma [13]. He concluded that performance of the modified CIE L*u*v* is better than other color spaces. In [14, 15] Hunt and Nemcsics studied perception in a complex environment and Matkovic proposed the formulas of CIE L*u*v* color space as follows [16]:

$$\begin{cases} L^* = 10\sqrt{Y} \\ u^* = 13L^*\,(u' - u'_n) \\ V^* = 13L^*(v' - v'_n) \end{cases} \qquad (1)$$

L* is luminance component of modified L*u*v* color space and Y is component of XYZ color space. XYZ color space can be computed from RGB color space using following 3*3 conversion matrix [17]:

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} 0.412453 & 0.357580 & 0.180423 \\ 0.212671 & 0.715160 & 0.072169 \\ 0.019334 & 0.119193 & 0.950227 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \qquad 2)\,($$

u* and v* in Eq. 1 are color components of modified L*u*v* color space. u* axis varies from green to red and v* axis changes from blue to yellow. u' and v' are acquired from XYZ color space as follows [18]:

$$u' = \frac{4X}{X + 15Y + 3Z} \quad v' = \frac{9Y}{X + 15Y + 3Z} \qquad (3)$$

We compute u'_n , v'_n for the reference white X_n, Y_n, Z_n . (RGB = (255, 255, 255)).

Figure 1 shows color distributions in RGB and Modified L*u*v* color space and Figure 2 displays original image in two different color space.

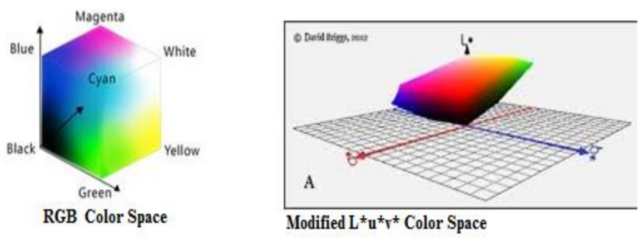

Figure 1: Color distributions in RGB$\in [0\ ,255]$ and modified L*u*v* color spaces

$L^* \in [0, 159.69]$, $u^* \in [-127.86,\ 242.09]$, $v^* \in [-179.49, 169.13]$

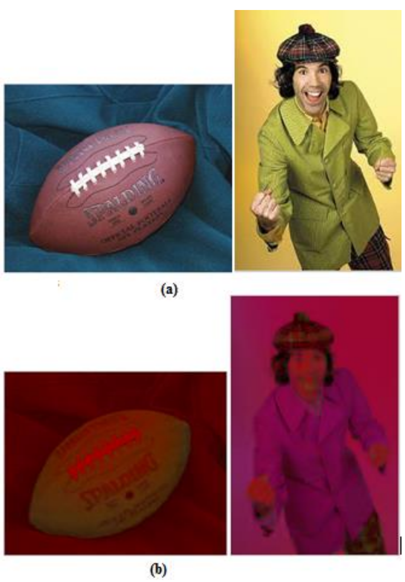

Figure 2: (a) Original Images in RGB Color Space. (b) Original Images in Modified L*u*v* Color Space.

3. Self -Organizing Map

Let Assume that color space in color space segmentation is R^3 and a transformation T carries out a projection of color points from color space into a lower dimensional space R^d as follows:

$$X \in R^3 \overset{T}{\Rightarrow} Y \in R^d \quad d < 3 \qquad (4)$$

There are linear and nonlinear techniques for this conversion such as PCA, ICA. In comparison with these techniques, SOM has advantages of nonlinear projection [19]. SOM is one of the most famous ANN models that use competitive unsupervised learning. This means that its learning does not require human intervention and completes with low information about inputs of network.

Assume that $X = \{x_1, x_2, \dots, x_n\}$ is a set of color pixels in modified L*u*v* color space ($R^3_{L^*u^*v^*}$) and it is projected from R^3 space into a two dimensional with SOM learning. A two-layered SOM neural network with rectangular topology as is shown in Figure 3 is used for this transformation.

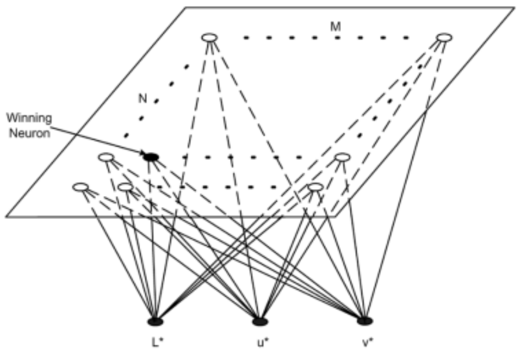

Figure 3: Two-layered SOM Network with Rectangular Topology that is Used in Color Space Transformation.

Three inputs (L*u*v*) are fully connected to the neurons in a 2D plane. The connections have the weight values to the neuron i which is presented with $w_i = [w_{i1}, w_{i2}, w_{i3}]^T$

A. Training of Network

The SOM training in unsupervised manner is presented in this part of paper.

- ✓ **Initialization:** In first step, we define SOM network: the weight vector $w_i(0)$ of the i^{th} neuron is randomly initialized. Rectangular topology for ANN and Gaussian neighborhood function is used in this paper. Neighborhood radius $r = 16,5$ and learning rates $\alpha = 0.05\ ,0.02$ are used in different iterative. Different size of SOM ANN such as 16×16, 4×4 for color reduction, and finally 2×2 network size is used for segmentation. Figure 4 shows the topologies of trained network with different network sizes for segmentation of person image of Figure 2(b).

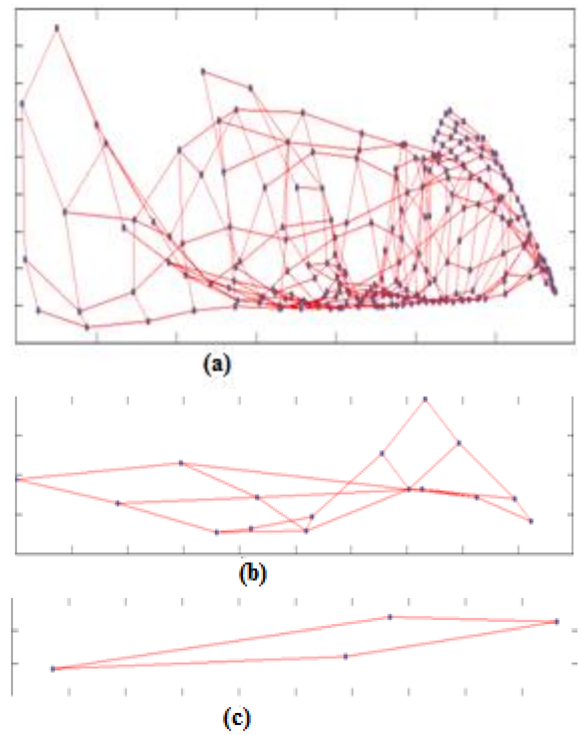

Figure 4: Map of Trained Network for Person Image (a) Network with Size is 16×16 (b) Network with Size is 4×4 (c) Network with Size is 2×2.

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- **Input:** The image colors are iteratively used to train the network for few times. During the training, each color point **x** is cyclically chosen from the data set, and presented to all neurons on the map simultaneously.

- **Competition Step:** At time $\boldsymbol{t}$, color point $\boldsymbol{X}(\boldsymbol{t}) = [\boldsymbol{l}(\boldsymbol{t}), \boldsymbol{u}(\boldsymbol{t}), \boldsymbol{v}(\boldsymbol{t})]^{\boldsymbol{T}}$ is presented to the network. The "winning neuron" **c** is computed with the shortest distance between color point and weight vectors by

$$\|x(t) - w_c(t)\| = min_i\{\|x(t) - w_i(t)\|\} \quad (5)$$

Where

$$C = arg\,min_i\,\{\|X(t) - w_i(t)\|\}$$

- **Cooperation Step:** The topological neighbors of winning neuron say **C** are determined by Gaussian function centered **C** with the effective scope of $\mathbf{R_c(t)}$

- **Update Weight Step:** The weights of winning neuron **C** and its neighbor neurons are updated based on the following neighborhood function.

$$w_i(t+1) = \begin{cases} w_i(t) + \alpha(t) h_{ci}[X(t) - w_i(t)] & \text{if } i \in R_c(t) \\ w_i(t) & \text{Otherwise} \end{cases} \quad (6)$$

Where $\alpha(t)$ is the learning factor and h_{ci}(t) is the neighborhood function centered on the winning neuron C.

- **Iteration Step:** The next color point is presented to the network at time t+1. The learning rate α and neighborhood radius **R** is linearly reduced which is formed as follows:

$$\alpha(t+1) = \alpha(0)\left(1.0 - {}^{t}/_{T}\right) \quad (7)$$

$$R(t+1) = R(0)\left(2.0 - {}^{t}/_{T}\right) \quad (8)$$

Where T is the number of color points for training. The new "winning" neuron is chosen by repeating the procedure from step 2 until all iterations have been made. Initial values of some parameters in the experiments are t=T, α=0, R=1.

4. Experimental Results

Images of Figure 2(a) in the form of modified L*u*v* color space as are shown in figure 2(b) are presented to ANN for segmentation. Figure 5 shows result of our experiments. Figures 5(a), 5(b) show respectively result of segmentation and color reduction using a SOM with 16×16 and 4×4 network topologies. In each experiment, original images presented to SOM network as input. For better image segmentation, we reduced size of topology to 2×2 and segmentation result was as is shown in figure 5(c).

5. Conclusion

In this paper a novel segmentation method for color images represented that was based on using ANN with unsupervised learning. For increasing color difference between pixels of an image and improving segmentation quality, color images was transformed to modified L*u*v* color space.

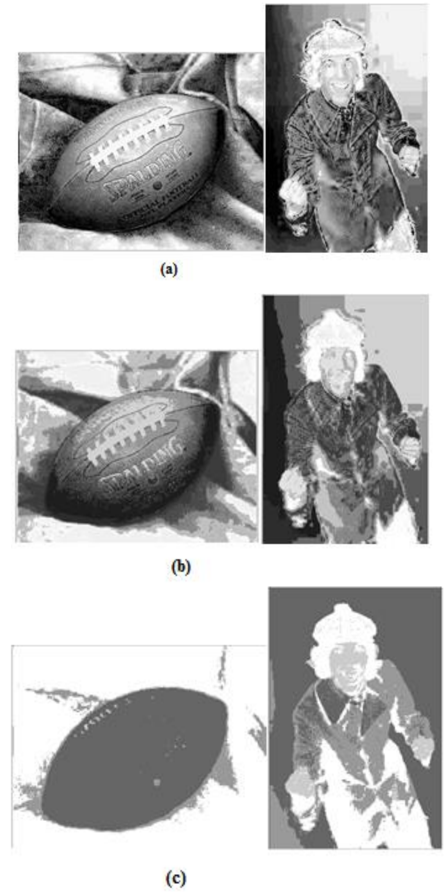

Fig. 1. (a) Result of segmentation after training SOM network with 16×16 topology size (b) Result of segmentation with a SOM network using 4×4 topology (c) Result of segmentation using 2×2 topology.

Then a two SOM layer network with square topology is used for color reduction and segmentation of image. Experiments with two different images and three different SOM networks were done and presented. Experimental results show that using SOM ANN with unsupervised leaning yields satisfactory segmentation results. Using this proposed method can produce near-optimal segmentation with a low computation cost.

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Authors profile

Saeid Pashazadeh is Assistant Professor of Software Engineering and chair of Information Technology Department at Faculty of Electrical and Computer Engineering in University of Tabriz in Iran. He received his B.Sc. in Computer Engineering from Sharif Technical University of Iran in 1995. He obtained M.Sc. and Ph.D. in Computer Engineering from Iran University of Science and Technology in 1998 and 2010 respectively. He was Lecturer in Faculty of Electrical Engineering in Sahand University of Technology in Iran from 1999 until 2004. His main interests are modeling and formal verification of distributed systems, computer security, wireless sensor/actor networks, and applications of artificial neural networks. He is member of IEEE and senior member of IACSIT and member of editorial board of journal of electrical engineering at University of Tabriz in Iran.

Masume Kheyri is M.Sc. student of Computer Engineering in the field of Artificial Intelligence in Faculty of Electrical and Computer Engineering at University of Tabriz in Iran. She received her B.Sc. degree in Computer Engineering from Urmia University of Iran in 2008. Her current research interests are artificial neural network and their applications.