TESTING RCE NEURAL NETWORK FOR SKIN IMAGE SEGMENTATION

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Abstract: This paper describes my work with testing usability of a reduced Coulomb energy (RCE) neural network for skin segmentation task. Skin segmentation is an important task in computer vision. I describe three color spaces we used for skin segmentation (RGB, HSL and YCbCr). Also I briefly describe the RCE neural network. The segmentation results are described in the final section.

Keywords: RCE neural network, color spaces, skin segmentation

1. INTRODUCTION

The first important task in image processing is image segmentation. In most cases, the segmentation of color image is more useful than the segmentation of grayscale image. That is because color image contains much more information about image features than grayscale image. However, more complicated segmentation methods are required to deal with the segmentation of color images.

According to the usage of prior knowledge of the image, we can use unsupervised or supervised segmentation method. The unsupervised segmentation is mostly used when the image features are unknown, such as nature scene understanding, satellite image analysis etc. On the other hand, the supervised approach is mainly used in the applications where we can obtain samples of colors in advance, for example object tracking, face/gesture recognition and image retrieval etc. In supervised segmentation, we use samples of object colors for training the classifier. The image is segmented by assigning the pixel to one of the predefined classes. The common techniques of supervised segmentation are for example, maximum likelihood, decision tree, nearest neighbor and neural networks [1]. In our work we focused on supervised segmentation method, where we need just to decide if the pixel is a skin pixel or not. The simple techniques, such as color thresholding, are not accurate enough to distinguish between skin and background pixels. In this task, color learning is very important for training a good classifier. That is why we testing a different color representation for skin colors.

2. COLOR SPACES

For a proper color based segmentation is necessary to choose suitable color space [2, 3, 4, 5]. A color space is a method by which we can specify, create and visualize colors. Different color spaces are better for different applications. Below, three color spaces used for testing segmentation capabilities of RCE neural network are briefly described.

2.1. RGB

We start with standard RGB color space, Figure 1, because it is the most comprehensible for human eye. It is an additive color system based on tri-chromatic theory and Cartesian coordinate system. That means that mixing red, green and blue light can create a broad range of colors. RGB is easy to implement but nonlinear with visual perception [4].

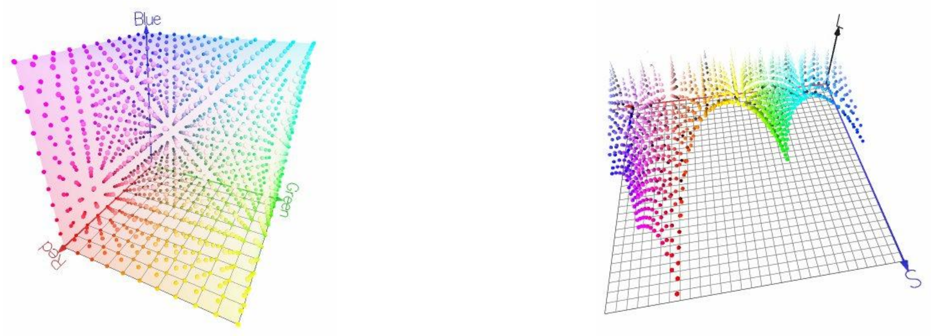

Figure 1: RGB (left) and HSL (right) color spaces

2.2. HSL

Since the RGB space does not mimic the higher level processes which allow the perception of color of the human visual system a HSL color model, Figure 1, was chosen as next. HSL is short for Hue, Saturation and Luminance and it is a closest to the actual human perception of color. Hue specifies the base color, the other two values then let you specify the saturation of that color and how bright the color should be. HSL is a simple transformation of RGB which preserve symmetries in the RGB cube [4].

2.3. YCBCR

As third an YCbCr color space was chosen because it is widely used in digital photography systems [6], where Y stands for luminance Cb is a blue difference and Cr is a red difference, see Figure 2.

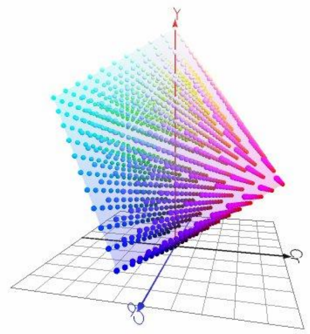

Figure 2: YCbCr color spaces

3. RCE NEURAL NETWORK

Reduced Coulomb energy (RCE) neural network is a supervised pattern classifier [7, 8, 9, 10]. It provides a way of region adjustment that is intermediate between Parzen-window and K-nearest-neighbor [2]. During the network training, the size of the hyper spherical window is adjusted in reference to the nearest point of a different category in feature space.

3.1. ARCHITECTURE

RCE neural network has three layers: the input (three color components), the prototype and the output (one neuron) layer. Used architecture is shown in Figure 3. Neurons in the prototype layer save the skin color information. Each neuron is fully connected to all neurons in a higher layer.

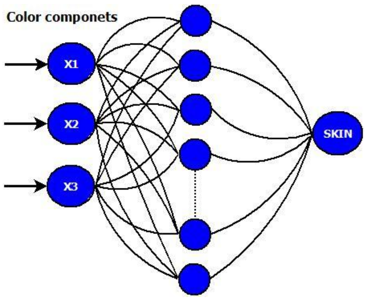

Figure 3: Architecture of RCE neural network

3.2. TRAINING

In our work we used modified training method called hierarchical prototype learning (HPL) introduced in [7]. Main advantage of this approach is that neurons in the prototype layer (color prototypes) have a different radius. Radius is decreasing from starting value r_{max} to r_{min} in every iteration step according to $r_{t+1} = \alpha r_t$, where α is learning rate. Such arrangement is advantageous because of better representation of color space. For all pixels in an input image and color prototypes the Euclidean distance is measured according to:

$$d(x_i, p) = \sqrt{\sum_{j=1}^{3} (p_j - x_{ij})^2} \qquad (1)$$

Where x_{ij} are color components of an input image and p_j are coordinates of one color prototype.

The pixel is considered as a skin pixel only if $d(x_i, p) < r$, where r is the radius of the prototype. For proper adjustment of all the prototypes radiuses the density of prototype D_p is defined as:

$$D_p = \frac{3N}{4\pi r^3} \qquad (2)$$

Where N is a number of pixels assigned to the prototype. If $D_p < D_{\min}$ the prototype p is rejected, otherwise is accepted and add in to the prototype layer.

3.3. SEGMENTATION

Given the test image, the supervised segmentation is performed by classifying each pixel as a skin pixel or image background. The pixel is classified as a skin pixel if it falls into any of color prototypes. Otherwise, it is regarded as the image background.

4. EXPERIMENTAL RESULTS

Usability of RCE neural network for skin (face) segmentation is tested in this section. The RCE neural network was implemented and tested in MATLAB programming environment.

4.1. TRAINING AND TESTING SETS

For all three color representations (RGB, HSL and YCbCr) was created a training set containing samples of a skin color from images of different peoples. It would be contra productive try to obtain color samples of the backgrounds (there are too many variants, not mentioning the different lightning). That is why the network only decides if it is a skin pixel or not. These three sets were used for training three RCE neural networks. For testing we used images of 30 peoples with different backgrounds, see Figure 5. Peoples in testing database [11] were not used for training networks.

4.2. DISTRIBUTION OF SKIN PIXELS IN COLOR SPACES

Figure 4 demonstrates distribution of skin pixels from the training sets in three different color spaces.

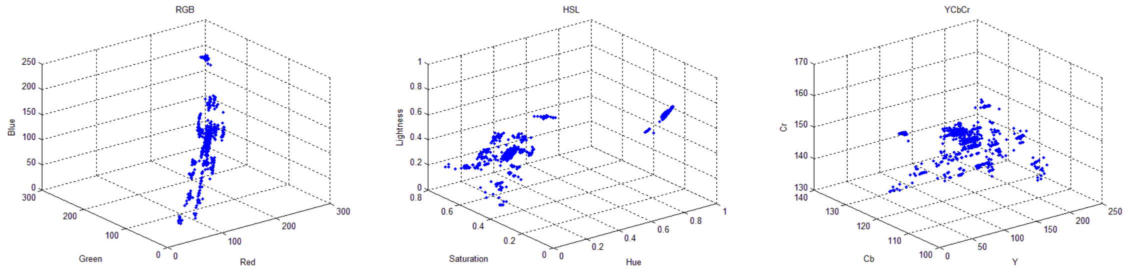

Figure 4: Distribution of skin color points in RGB (left), HSL (mid) and YCbCr (left) color spaces

4.3. SEGMENTATION RESULTS

After creating training sets, we train three networks using the HPL algorithm. The samples of results are shown in Figure 5. The learning rate was same for all three nets, $\alpha = 0.8$.

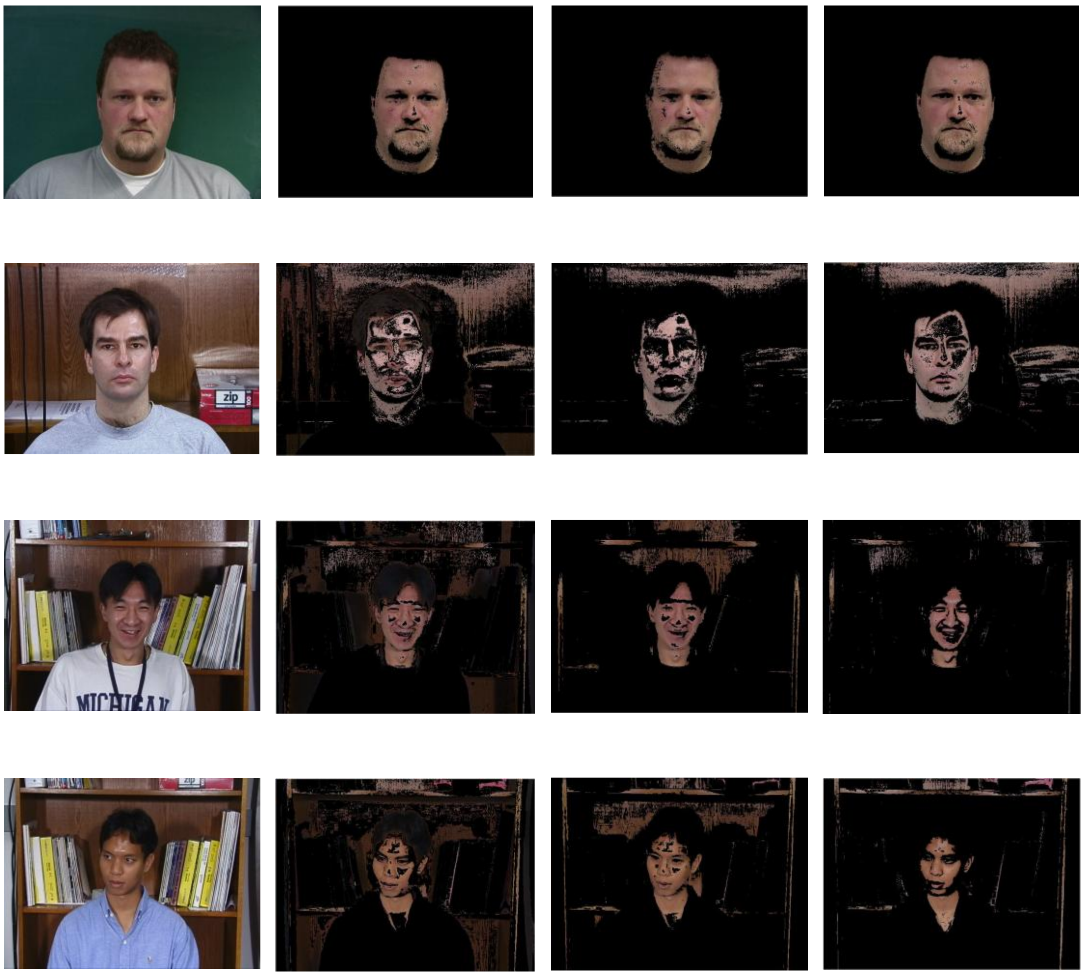

Figure 5: From left: Original image, segmentation result using RGB, HSL and YCbCr color spaces

For networks using RGB and YCbCr color space was radius range set as $r = \langle 50,1 \rangle$ and minimum density for acceptance color prototype was $D_{min} = 6.0*10^{-3}$. For the network using HSL color space was the parameters: $r = \langle 0.5,0.01 \rangle$ and $D_{min} = 6.0*10^{4}$. From the results we can say that YCbCr color space seems slightly more suitable for skin segmentation than the others. But mainly we confirm that RCE neural networks are suitable for skin segmentation of variety of different people and backgrounds.

5. CONCLUSION

In this article we described three different color spaces (RGB, HSL and YCbCr), which we used for testing the RCE neural network for skin segmentation task. Also we present a basic description of the RCE neural network with HPL algorithm. From the results of segmentation of 30 different people with various backgrounds we can say that RCE neural network is suitable for skin segmentation in color images.

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REFERENCES

[1] Power, P. W., Clist, R. S.: *Comparison of supervised learning techniques applied to color segmentation of fruit images*, in Proc. SPIE Intelligent Robots and Computer Vision XV: Algorithms, Techniques, Active Vision, and Material Handling, vol. 2904, Boston, MA, Nov. 1996, pp. 370–381.

[2] Duda R.O., Hart P.E., Stork D.G.: *Pattern classification*, 2ed., Wiley, ISBN 0471056693, 738p, , 2000.

[3] Kwok, NM, Ha, QP, Fang, G.: *Effect of color space on color image segmentation*. Proc. of Second International Congress on Image and Signal Processing, pp. 1–5. (2009)

[4] Gonzalez, R.C., Woods, R.E.: *Digital image processing*. Prentice Hall, New Jersry (2008)

[5] Lucchese, L., Mitra, S. K.: *Color image segmentation: A state-of-art survey*, in Proc. Indian Nat. Sci. Acad. (INSA-A), vol. 67-A, New Delhi, India, Mar. 2001, pp. 207–221.

[6] Poynton, C.A.: *A technical introduction to digital video*. John Wiley, New York (1996)

[7] Guo, D., Ming X., , *Color clustering and learning for image segmentation based on neural networks*, Neural Networks, IEEE Transactions on, vol.16, no.4, pp.925-936, July 2005

[8] Chang, T., Xiao, N., , *Improved RCE neural network and its application in human-robot interaction based on hand gesture recognition*, Information Science and Engineering (ICISE), 2010 2nd International Conference on , vol., no., pp.1260-1263, 4-6 Dec. 2010

[9] Chao, S., Ngai, M. K., Tianran R., *A Restricted Coulomb Energy (RCE) Neural Network System for Hand Image Segmentation*, Computer and Robot Vision (CRV), 2011 Canadian Conference on , vol., no., pp.270-277, 25-27 May 2011

[10] Xiaoming, Y., Xing, Z.: *Hand Posture Recognition in Gesture-Based Human-Robot Interaction*, Industrial Electronics and Applications, 2006 1ST IEEE Conference on, vol., no., pp.1-6, 24-26 May 2006

[11] M. B. Stegmann, B. K. Ersbøll, and R. Larsen. FAME – a flexible appearance modeling environment. IEEE Trans. on Medical Imaging, 22(10):1319–1331, 2003